Methods to Plan for the Smart City

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Abstract

Smart cities are now prevalent around the world, in large part because the smart city promises to create a more efficient, equitable, innovative, competitive, sustainable and livable community. Most definitions of the smart city emphasize innovations in Information and Communication Technologies (ICTs). Consequently, definitions are overly 'tech-heavy' or aspirational and vague. The confidence placed on ICTs and the aspiration and vagueness could overlook the impacts of employing the new suite of ICT innovations. Even with smart city literature that covers innovations like artificial intelligence/machine learning (AI/ML), we argue that there is insufficient knowledge from both theoretical and methodological perspectives. We do not know enough about the impacts of smart city innovations on those who plan for the smart city. Moreover, the field would benefit from a more abductive interpretation, using those same AI/ML tools, of the smart city. Our research question is: how do researchers and practitioners plan for the smart city using automated technologies?

We begin by revisiting the studies on Planning Support Systems (PSS), which is a term that encompasses computer-based tools customized for urban planning. We compare PSS with ICT tools available in smart cities. We also compare the evolution of the terms and find that challenges in use of PSS, such as technocracy, opacity, digital divides, wicked problems and the role of civic participation, might reappear in the smart city. We are particularly concerned with issues that arise from using automated technologies like ML to plan for the smart city. As ML methods become more accessible, practitioners interested in the smart city are in the danger of adopting these new tools without thorough discussion of the limits of those tools, including a lack of transparency, exacerbation of social inequality and even obviation of the need for planners. PSS has moved through

stages of being overly optimistic only to fall well short of expectations. Lessons of PSS can help deflate the hyperbole about the smart city and its emerging technologies.

Beyond the theoretical exploration, we conduct a case study on how the smart city is interpreted in Canada. The Smart Cities Challenge (SCC) was launched by the Canadian federal government in 2017. Canadian communities, whether urban or rural, were eligible to apply for the SCC grant. Applications also came from Indigenous communities. We employed topic modelling, an unsupervised classification form of ML, to perform a bottom-up analysis of 137 grant applications, approximately 1.5 million words, from the SCC. These documents corresponded to two stages of the SCC, which we chose to analyze separately so we could track the evolution of thinking in what communities wanted from smart cities and what communities thought the federal government wanted to hear about smart cities. The findings and our arguments are separated into two chapters. One concentrates on the algorithmic deployment; the other explains the results.

ML methods are increasingly used to research the smart city, in part because they are widely available in easy-to-use software. We argue that the automation implied by those ML algorithms are not as automated as one thinks. ML encompasses considerable amounts of human intervention, in which humans participate in the loop of ML and likely influence the results. Our case study provides an opportunity to implement topic modelling and, in doing so, identify all the human interventions during the process. By explicating the human intervention, we hope to bolster the usability of automated technologies to research the smart city. The explication is accomplished by exploring the concept of human-centered ML (HCML). Our identification of human intervention is framed by issues of visibility, explainability, trustworthiness, and transparency. While HCML helps, its continued emphasis on computational solutions to enjoin humans-in-the-loop, still fails short of assisting non-experts in comprehending these tools.

In applying topic modelling to the SCC grant applications, we had four main findings related to the subject matter of smart cities. First, the Canadian smart cities have moved beyond an early stage that heavily emphasizes data and technologies. Canadian smart cities are unlikely a rebranding of urban cybernetics, which represents a command-and-control system. Second, topics show little difference between urban and rural areas regarding the level of technological sophistication. This disputes the notion that only cities can be smart. This research also reveals the issues of importance of rural and remote Indigenous communities as they are increasingly interested in becoming smart cities. Third, what constitutes technological innovation varies considerably over regions, as some communities would regard big data analytics and AI/ML as an innovative technology while some might employ Geographic Information Systems as a novel tool even though it has been used by municipalities since the 1980s. Cultural distinctions also exist. Citizen and urban development is the dominant topic in most applications from Quebec communities. Topics related to language, culture and education prevail in Indigenous communities.

Finally, by modelling the original applications and 20 finalist proposals separately, we were able to identify 40 percent of the finalists and the four winners. The dominant topics proposed by the four winners included data solutions, youth/ child & culture, education, food & agriculture and housing & energy, which, we argue, are what the federal government thinks “smarter” than other topics. The comparison between finalist proposals to their original applications shows that health care is the most significant topic in smart city initiatives, where health is broadly defined to include community health as well as urban development.

We conclude that ‘automated’ technologies like ML are useful to plan for the smart city. This should be tempered by consideration of human choices that impact data input, model output and interpretation of results. Automated technologies imply effortless use and objectivity in extracting knowledge from large volumes of data. These ICTs can fail to address needed socio-political considerations, another form of human intervention, in public decision-making. In terms of future research, we can develop new approaches, beyond HCML, to guide appropriate use of ML by non-experts. We can apply and test various ML methods in empirical cases of smart city initiatives around the world. It would be worth exploring technologies like deep learning to discover its potential in the smart city and compare it to PSS and ML. We hope our research provides researchers and practitioners with useful knowledge, instruments and experiences to plan for the smart city, in Canada and around the world.

Résumé

Les villes intelligentes sont désormais répandues dans le monde entier, en grande partie parce que la ville intelligente promet de créer une communauté plus efficace, équitable, innovante, compétitive, durable et vivable. La plupart des définitions de la ville intelligente mettent l'accent sur les innovations dans les technologies de l'information et de la communication (TIC). Par conséquent, les définitions sont trop «technologiques» ou ambitieuses et vagues. La confiance accordée aux TIC ainsi que les aspirations et le manque de précision pourraient négliger les impacts de l'utilisation de la nouvelle série d'innovations TIC. Même avec la littérature sur les villes intelligentes qui couvre des innovations telles que l'intelligence artificielle / l'apprentissage automatique (IA / ML), nous soutenons que les connaissances sont insuffisantes tant du point de vue théorique que méthodologique. Nous ne savons pas assez sur les impacts des innovations de la ville intelligente sur ceux qui planifient la ville intelligente. De plus, le domaine bénéficierait d'une interprétation plus abductive, utilisant ces mêmes outils d'IA / ML, de la ville intelligente. Notre question de recherche est la suivante: comment les chercheurs et les praticiens planifient-ils la ville intelligente à l'aide des technologies automatisées?

Nous commençons par revenir sur les études relatives aux systèmes d'aide à la planification (SAP), terme qui englobe les outils informatiques personnalisés pour l'urbanisme. Nous comparons le SAP aux outils TIC disponibles dans les villes intelligentes. Nous comparons également l'évolution des termes et constatons que les défis liés à l'utilisation du SAP, tels que la technocratie, l'opacité, les fractures numériques, les problèmes pernicieux et le rôle de la participation civique, pourraient réapparaître dans la ville intelligente. Nous sommes particulièrement préoccupés par les problèmes liés à l'utilisation de technologies automatisées telles que le ML pour planifier la ville intelligente. À mesure que les méthodes de ML deviennent plus accessibles, les praticiens

intéressés par la ville intelligente risquent d'adopter ces nouveaux outils sans discussion approfondie des limites de ces outils, y compris un manque de transparence, une exacerbation des inégalités sociales et même une élimination du besoin de planificateurs. SAP a franchi les étapes d'être trop optimiste pour ne pas répondre aux attentes. Les leçons de SAP peuvent aider à dégonfler l'hyperbole sur la ville intelligente et ses technologies émergentes.

Au-delà de l'exploration théorique, nous réalisons une étude de cas sur la façon dont la ville intelligente est interprétée au Canada. Le Défi des villes intelligentes (DVI) a été lancé par le gouvernement fédéral canadien en 2017. Les collectivités canadiennes, qu'elles soient urbaines ou rurales, étaient admissibles à la subvention du DVI. Les demandes provenaient également des communautés autochtones. Nous avons utilisé la modélisation thématique, une forme de classification non supervisée du ML, pour effectuer une analyse ascendante de 137 demandes de subvention, soit environ 1,5 million de mots, provenant du DVI. Ces documents correspondaient à deux étapes du DVI, que nous avons choisi d'analyser séparément afin de suivre l'évolution de la réflexion sur ce que les communautés attendaient des villes intelligentes et ce que les communautés pensaient que le gouvernement fédéral voulait entendre sur les villes intelligentes. Les résultats et nos arguments sont séparés en deux chapitres. L'un se concentre sur le déploiement algorithmique ; l'autre explique les résultats.

Les méthodes de ML sont de plus en plus utilisées pour rechercher la ville intelligente, en partie parce qu'elles sont largement disponibles dans des logiciels faciles à utiliser. Nous soutenons que l'automatisation impliquée par ces algorithmes de ML n'est pas aussi automatisée qu'on le pense. Le ML englobe des quantités considérables d'interventions humaines, dans lesquelles les humains participent à la boucle de ML et influencent probablement les résultats. Notre étude de cas offre l'opportunité de mettre en œuvre une modélisation thématique et, ce faisant, d'identifier toutes les interventions humaines au cours du processus. En expliquant l'intervention humaine, nous espérons renforcer la convivialité des technologies automatisées pour rechercher la ville intelligente. L'explication est accomplie en explorant le concept de ML centrée sur l'homme (HCML). Notre identification de l'intervention humaine est encadrée par des questions de visibilité, d'explicabilité, de fiabilité et de transparence. Bien que HCML aide, son accent continu sur les solutions informatiques pour enjoindre les humains dans la boucle, échoue toujours à aider les non-experts à comprendre ces outils.

En appliquant la modélisation thématique aux demandes de subvention du DVI, nous avons eu quatre conclusions principales liées au thème des villes intelligentes :

- Premièrement, les villes intelligentes canadiennes sont allées au-delà d'un stade précoce qui met fortement l'accent sur les données et les technologies. Il est peu probable que les villes intelligentes canadiennes réorganisent la cybernétique urbaine, qui représente un système de commandement et de contrôle,
- Deuxièmement, les sujets montrent peu de différence entre les zones urbaines et rurales en ce qui concerne le niveau de sophistication technologique. Cela conteste l'idée que seules les villes peuvent être intelligentes. Cette recherche révèle également les enjeux importants des communautés autochtones rurales et éloignées, qui souhaitent de plus en plus devenir des villes intelligentes,
- Troisièmement, ce qui constitue une innovation technologique varie considérablement selon les régions, car certaines communautés considéreraient l'analyse des mégadonnées et l'IA / ML comme une technologie innovante, tandis que d'autres pourraient utiliser les systèmes d'information géographique comme un outil novateur, même s'il est utilisé par les municipalités depuis les années 1980. Des distinctions culturelles existent également. Le développement citoyen et urbain est le sujet

dominant dans la plupart des applications des communautés québécoises. Les sujets liés à la langue, à la culture et à l'éducation prévalent dans les communautés autochtones.

- Enfin, en modélisant séparément les candidatures originales et les 20 propositions finalistes, nous avons pu identifier 40% des finalistes et les quatre gagnants. Les sujets dominants proposés par les quatre lauréats comprenaient les solutions de données, les jeunes / enfants et la culture, l'éducation, l'alimentation et l'agriculture ainsi que le logement et l'énergie, qui, selon nous, sont ce que le gouvernement fédéral juge «plus intelligents» que d'autres sujets. La comparaison entre les propositions finalistes et leurs applications originales montre que les soins de santé sont le sujet le plus important des initiatives de villes intelligentes, où la santé est définie au sens large pour inclure la santé communautaire ainsi que le développement urbain.

Nous concluons que les technologies «automatisées» comme le ML sont utiles pour planifier la ville intelligente. Cela devrait être tempéré par la prise en compte des choix humains qui ont un impact sur la saisie des données, la sortie du modèle et l'interprétation des résultats. Les technologies automatisées impliquent une utilisation sans effort et une objectivité dans l'extraction des connaissances à partir de grands volumes de données. Ces TIC peuvent ne pas répondre aux considérations sociopolitiques nécessaires, une autre forme d'intervention humaine, dans la prise de décision publique. En termes de recherche future, nous pouvons développer de nouvelles approches, au-delà de HCML, pour guider l'utilisation appropriée du ML par des non-experts. Nous pouvons appliquer et tester diverses méthodes de ML dans des cas empiriques d'initiatives de ville intelligente à travers le monde. Il vaudrait la peine d'explorer des technologies comme l'apprentissage en profondeur pour découvrir son potentiel dans la ville intelligente et le comparer aux SAP et ML. Nous espérons que notre recherche fournira aux chercheurs et aux praticiens, des connaissances, des instruments et des expériences utiles pour planifier la ville intelligente, au Canada et dans le monde.

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Chapter 1: Introduction to Methods to Planning for the Smart City

1.1 Introduction

With increasingly advanced Information and Communication Technologies (ICTs), cities are primed for a technological revolution. Like prior industrial revolutions that were marked by innovations in power systems (steam and electricity) and digitization; "the Fourth Industrial Revolution", driven by interdisciplinary innovations across ICT, biological and physical fields, will result in a profound societal transformation in the way we live, work and relate to one another. The Fourth Industrial Revolution, according to the founder of the World Economic Forum, is distinguished from prior revolutions, in terms of its increased velocity, geographic scope, and broad impact (Schwab, 2016). Innovations such as artificial intelligence (AI), drones, the Internet of Things, autonomous vehicles, cloud computing and mobile devices mean that "Ordering a cab, booking a flight, buying a product, making a payment, listening to music, watching a film, or playing a game—any of these can now be done remotely" (Schwab, 2015). These changes hold important implications for a rapidly urbanizing world, promising an urban knowledge economy of fast-paced and customized responsiveness. Amidst these promises, the Fourth Industrial Revolution also is accompanied by ethical concerns, like inequality caused by automated technologies disrupting the labor market.

ICTs in this transformation promise that cities will become more efficient through automating the industrial process, more equitable by assisting public participation with digital tools, more innovative because of crowdsourcing solutions, more competitive due to greater economic opportunities and more sustainable and livable since sensors are monitoring extreme weathers or disasters in real time (Albino, Berardi & Dangelico, 2015).

Smart cities embrace numerous and occasionally conflicting goals. Despite being a concept for three decades now (Batty 2013), researchers have not settled on goals and characterizations of the smart city (Anthopoulos 2015; Ching and Ferreira 2015; Cocchia 2014). For the purposes of this chapter, we will rely on a definition from Townsend (2013, p. 15) for smart cities, "places where information and communication technologies (ICT) are combined with infrastructure, architecture, everyday objects, and even our bodies to address social, economic, and environmental problems." The definition is overly 'tech-heavy' and it fails to recognize the varied ways that cities and communities may choose to adopt and present their own characterizations. Townsend's definition does allow us to examine the role that analytics play in planning for the goals of a smart city.

To plan for a smart city with new ICTs like artificial intelligence/machine learning (AI/ML) and big data, practitioners have employed computer-based tools to assist in planning the city since the 1960s (Klosterman, 1997). A set of computer-based tools now have become collectively known as Planning Support Systems (PSS). PSS also refers to a scholarly and professional field researching the development of computer-based tools for urban planning (Geertman & Stillwell, 2004). With emerging technologies like deep learning, a component of AI that employs neural networks, more ICT tools are available to support planners in the city and researchers of the city. These tools have the potential to address the grand and complex challenges that cities are facing (Geertman et al., 2017). There are all sorts of promises attached to AI/ML: they are increasingly available in software libraries; they are relatively easy to use given the sophistication of their analysis; they generate actionable insights from large volumes and velocities of data; and many have the appearance of objectivity because they are inductive and do not rely on a priori judgements. The problem is that these new tools can be opaque "black-boxes", in which the processes are heuristic and outcomes are emergent (Brauneis & Goodman, 2018).

Planners have experience in applying tools with some of these properties, for example agent-based modelling whose outcomes can be likewise emergent. Overall, these new tools, like deep learning, are not nearly as transparent and outcomes as explanatory as the equations embedded in traditional PSS. Because of increased accessibility, planners and others interested in the smart city are in danger of uncritically adopting these new tools.

We are interested in the ways that ICT advances, whether traditional or new, help us interpret the smart city. We investigate the issues with the Smart Cities Challenge (SCC) launched by the Canadian federal government in 2017. We were presented with this novel opportunity to study how smart cities are interpreted in Canada. Here the term "smart city" is characterized by leveraging innovation, data and interoperable technology to improve the lives of residents in a community (Infrastructure Canada, 2017). Infrastructure Canada strategically used the term community and not city, both to reflect the dramatic population gradient in Canada and to encourage applications from rural and remote (Indigenous) communities. Applications came from single cities and from aggregations of multiple smaller communities. Instead of delivering a priori characterizations of smart cities, we have at our disposal 137 primary texts containing approximately 1.5 million words. Since these were applications to a grant program, the documents are relatively similar in tone and content, thus allowing for an 'apples-to-apples' comparison. The applications were submitted in two stages, which we could analyze separately and track the evolution of thinking in what communities wanted and what communities though the federal government wanted to hear. We can find out what communities considered salient and interrogate the tools that we use to find this out.

1.2 Research Question

The aim of this research is to investigate the computational tools used to interpret "the smart city" concept. By interpret we mean clarify its nature (definitions, aspirations, goals), explain the tool, and track the historical evolution of the tools used in the smart city and how they have evolved. We provide insights into issues related to transparency and automation of smart city solutions; we explore a specific ML method to address a lack of methodological clarity in common use of the tool; and finally, we analyze smart city initiatives proposed in the SCC. The SCC is used as a case study with which to apply the ML method, topic modelling, illustrating the advances and limits of data-driven techniques and presenting how to adopt the techniques to conduct best practice. The interpretation of the smart city based on the SCC will provide valuable experiences and principles for PSS and smart city researchers, urban planners and policy makers to plan for the smart city.

The following research questions guide the research and provide a clear sense of the research topic. The main research question is:

How do researchers and practitioners plan for the smart city using automated technologies?

Definitions of the smart city are ambiguous but, beyond Townsend (2013), refer to initiatives that apply innovation, data and interoperable technology to improving the lives of residents in a community (Infrastructure Canada, 2017). PSS is regarded as a scholarly and professional field researching the development of computer-based tools for urban planning. Interactions between the smart city and PSS are in terms of how new technologies can influence and be included in PSS, also how PSS links the smart city to a traceable research field. Therefore, we examine the possibility to integrate PSS within the smart city for the purpose of understanding how to plan for the smart city.

Automated technologies here include Internet of Things, cloud computing, big data analytics or AI/ML. Since characteristics of the smart city are partially determined, even defined, by automated technologies, we believe a case study to apply the technologies to researching the smart city per se will disclose details that contribute to planning for the smart city. We focus on two technologies in this thesis: planning support systems and a type of unsupervised natural language processing called topic modelling. We break down our research question into following sub-questions:

1. What is the relationship between the traditional tools of urban planners and tools and processes implied in the smart city?
2. How is machine learning used to interpret the smart city?
3. How automated is machine learning in interpreting the smart city?
4. What constitutes the smart city in Canada as identified by machine learning?

1.3 Research Focus and Relevance

We answer the research questions in three steps. First, in Chapter 2, we comprehensively review the evolution of PSS and its role as cities, their governments and stakeholders, propose to become ‘smart.’ We compare PSS and the tools available in the smart cities. We identify their potential commonalities as well as divergences and explore the path toward integrating PSS within the smart city. Chapter 2 functions as the literature review of the thesis and also answers sub-question 1 and 2 by revealing the relationship between PSS and the smart city and demonstrating the difficulties and investigating the durable tensions in their integration.

In Chapter 3, we recall extant methods to research the smart city and argue for the necessity of moderating the use of automated technologies to study the nature of the smart city with an insight that automated algorithms are not as automated as one thinks. We conduct a case study that applies a specific ML method (i.e., automated technology), topic modelling, to analyze the primary texts from the SCC for interpreting the smart city. We inspect implementation details of topic modelling and recognize all the human intervention during the process. Human intervention is a way to have humans participate in the loop of

ML methods and influence results interpretation. Chapter 3 serves as the methodological chapter of the thesis. It answers sub-question 2 and 3 through uncovering the pros and cons of the use of automated technologies in a practical case and proposing the human-centered ML to exemplify the adoption and improvement of automated technologies regarding how to address issues like technocracy and opacity (i.e., not usable and transparent).

Chapter 4 presents the best practice of the topic modelling on the SCC texts so as to clarify the smart city. The chapter addresses the answer to the sub-question 4 by revealing, contextualizing and illustrating 33 topics of importance to Canadian communities. Synthesizing the answers to the four sub-questions will respond to our main research question from theoretical (Chapter 2), methodological (Chapter 3) and experimental (Chapter 4) perspectives. By addressing the research question, we hope to provide researchers and practitioners with useful knowledge, instruments and experiences to plan for the smart city.

The last chapter, Chapter 5, concludes the thesis, summarizes essential findings and proposes possible directions for future research.

Reference

Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. Journal of Urban Technology, 22(1), 3-21.

Anthopoulos, L. G. (2015). Understanding the smart city domain: A literature review. In Transforming city governments for successful smart cities (pp. 9-21). Springer, Cham.

Batty, M. (2013). Big data, smart cities and city planning. Dialogues in human geography, 3(3), 274-279.

Brauneis, R., & Goodman, E. P. (2018). Algorithmic transparency for the smart city. Yale JL & Tech., 20, 103.

Ching, T. Y., & Ferreira, J. (2015). Smart cities: Concepts, perceptions and lessons for planners. In Planning support systems and smart cities (pp. 145-168). Springer, Cham.

Cocchia, A. (2014). Smart and digital city: A systematic literature review. In Smart city (pp. 13-43). Springer, Cham.

Geertman, S., & Stillwell, J. (2004). Planning support systems: an inventory of current practice. Computers, Environment and Urban Systems, 28(4), 291-310.

Geertman, S., Allan, A., Pettit, C., & Stillwell, J. (2017). Introduction. Planning Support Science for Smarter Urban Futures. Cham, Switzerland: Springer Nature.

Infrastructure Canada (2017). Smart Cities Challenge Applicant Guide. Retrieved on May 18, 2019 from https://impact.canada.ca/sites/default/files/2017-11/SCC_Applicant_Guide.pdf

Klosterman, R. E. (1997). Planning Support Systems: A New Perspective on Computer-Aidded Planning. Journal of Planning education and research, 17(1), 45-54.

Schwab, K. (2016). The fourth industrial revolution. New York: Crown Publishing.

Schwab, K. (2015). The Fourth Industrial Revolution: What It Means and How to Respond. December 12, 2015. Foreign Affairs. https://www.foreignaffairs.com/articles/2015-12-12/fourth-industrial-revolution

Townsend, A. M. (2013). Smart Cities: Big Data, Civic Hackers, and the Quest for a New Utopia. New York: WW Norton & Company.

The Preface of Chapter 2

Chapter 2 aims to answer the main research question of "how do researchers and practitioners plan for the smart city using automated technologies?". Here, we explore the relationship of the practitioners to the smart city by comparing the traditional tools of urban planners and the technical processes implied in the smart city. The exploration situates the smart city in the context of urban planning and compares it to a traceable research area Planning Support Systems (PSS) that also studies tools used to support practitioners including planners. The investigation of the commonalities as well as divergences between PSS and the smart city allows us to refer to historical concepts in PSS research that might indicate issues and concerns need to be addressed or discussed when planning for the smart city. Chapter 2 functions as the literature review of the thesis since it tracks the evolution of the concept of the smart city.

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Zhibin Zheng conceptualized and designed the study, conducted the literature review and wrote the manuscript. Zhibin Zheng and Renee Sieber, his supervisor, reviewed the manuscript together. Renee Sieber offered advice on reorganizing ideas and restructuring the manuscript. Renee Sieber contributed some ideas and inspired Zhibin Zheng to rethink the study. Zhibin Zheng revising the manuscript together with Renee Sieber. Renee Sieber also provided help regarding the English language by editing or guiding Zhibin Zheng to edit the manuscript. Zhibin Zheng and Renee Sieber finally approved this version to be published.

Chapter 2: Planning Support Systems and Science Beyond the Smart City

Abstract

Technologies, like artificial intelligence (AI) and big data, are just two of the innovations that may change the tools and roles of planners. Many of these innovations are becoming embedded in smart city initiatives. This paper questions the relevance of the predominant tools of planning, planning support systems (PSS), as cities think of adopting smart city initiatives. We compare the evolution of PSS to that of smart cities. Comparisons between changes in PSS and the short history of smart cities show that what constitutes a smart city complicates a path forward in integrating the two. We see potential challenges in the adaptation of PSS, related to concepts of technocracy and opacity, digital divides, wicked problems, and the role of civic participation in the planning process. We are particularly concerned with the possibility of automated systems obviating the need for PSS and planners. We conclude by exploring ways to solve planning problems with AI while remaining cautious about a 1960s- type hyperbole about the smart city.

Keywords: Planning Support Systems (PSS), Smart City, Wicked Problems, Urban Planning, Urban Planners, Artificial Intelligence

2.1 Introduction

From the early days of graphic overlay methods (McHarg & Mumford, 1969) and cold war urban models (Light, 2003), planning has always had a creative tension with computational technology. What were computationally-intensive initiatives in the 1960s transformed into routine task supports in 1980s and to more qualitative communicative decision support systems in the 1990s (Klosterman, 1997). Collectively these became what is known as planning support systems (PSS), a working definition of which is a set of computer-based tools that have been customized to assist the practice of planning (Geertman & Stillwell, 2004). Another way to think of PSS is digitally-enabled planning, planning that depends on technologies. Planning is increasingly impacted by innovations like Artificial Intelligence (AI), big data and the Internet of Things, technologies that promise to introduce even more hardware, software and data into the daily life of the planner.

Many of the afore-mentioned technological advances are embedded in the concept of the smart city. The promises are that the ideals and technologies of smart cities will produce cities that are more efficient (e.g., through automated transit scheduling), equitable (e.g, via online platforms that ease provision of feedback about public service delivery), innovative (e.g., with new sources of data such as real time crowdsourcing), competitive (e.g., with greater opportunities for entrepreneurs and high-tech companies), and sustainable and livable (e.g., by real time monitoring of stormwater infrastructure) (Albino, Berardi & Dangelico, 2015). The concept of smart cities certainly implies that planners should be involved in smart design and operation. However, the tools of planners will be impacted by new technologies in a way that could change traditional processes included in PSS, such as support for civic participation and decision making. This could lead to a role change of planners.

This paper presents critical issues in interactions between the tools of planning (i.e., PSS) and the new technologies of smart cities. We first trace the origin and track the evolution of PSS, noting that PSS has shifted from the demand for technocratic approaches to the necessity of incorporating the political and human nature of planning. In examining the short history of smart cities, we find that smart city initiatives often blur the boundaries between tools/ data and aspirations that are supposed to fulfill the rhetoric of being smart.

We argue that difficulties of characterizing the smart city complicate a path forward in expanding PSS to include new technologies. A further comparison finds commonalities in terms of technocracy and opacity and differences in considering digital divides and the changing role of civic participation in the planning process. Looking beyond smart cities, we are especially concerned with the ways that smart city hardware/ software packages may supplant existing tools and obviate the need for planners altogether. By revisiting early critiques that planning problems are wicked problems (Rittel & Webber, 1973), we note that the complexity of planning derives from the lack of definitive rules and imbalances in political power, not from a lack of data or processing power.

We conclude with moves in the smart city and PSS to integrate AI. With AI, PSS can alternately automate human decision making or foster a new form of urban planning that can be called “neoplanning”, similar to “neogeography”. The former will reduce citizens to training datasets for automated decisions; the latter could engage broader publics for collective design. Either way planners may become less necessary (e.g., as uncreative work and high-structured tasks are automated, or planners become facilitators of collective design). We should remain cautious about the hyperbole of the smart city or any advances in technology as it relates to planning. PSS has been through stages of being overly optimistic only to fall short of reality. The lessons of PSS can help moderate the hype.

2.2 Planning Support System (PSS) Evolution and Tensions

Planning Support System (PSS) represents an accumulation of five decades of research and practice (Klosterman, 1997) and provides lessons for initiatives like the smart city. An initial way to examine PSS is through definitional changes. Researchers have variously characterized PSS by emphasizing the geographic components (i.e., GIS) (Harris & Batty, 1993), collaborative features (Klosterman, 1999), and utility and usability (Pelzer, 2015).

The most general definition appears to be a set of computer-based tools that assist planners in activities specific to the practice of planning (Geertman & Stillwell, 2004).

PSS reflects a digital turn in planning. The original concept of PSS traces back to computer-assisted/ automated planning in the 1960s. Klosterman (1997) reviewed computer-assisted planning and information systems to both define PSS and identify its role in planning. The turn towards computers was accompanied by a shift in planning, from a “design” process to an “applied science” in 1960s. The applied science approach was reflected in large scale land-use/ transportation models and municipal integrated information systems (Brewer, 1973; Danziger, 1977). It was thought that a digital turn, dominated by technical experts, could result in cities being managed in a technocratic manner. Assumptions were that, with sufficient data and robust analysis, one could achieve the desired rationality, as well as a systematic and objective accounting of urban spaces (Harris, 1968). Early on, Klosterman was cautious about computer’s prevalence in planning. The push towards large scale models carried assumptions of the rational planning model in which planning data and its processing were value-free. Those computer models encountered significant failures in 1970s (Lee 1973), which resulted “less from the limitations of hardware and software than from a limited understanding of the proper role these tools should play in planning” (Klosterman, 1997: 46).

In the 1980s, stimulated by the prevalence of microcomputers, a kind of proto-PSS became standard for supporting planner’s routine tasks, such as storing data, creating charts, or monitoring budgets (Klosterman, 1997). Advances in hardware and software overcame their initial computational limitations and subsequently responded to some of the original critiques (Lee 1973). Just as planning practices was eased by “quotidian” computing, the discipline began to grapple with a post-rationality (Alexander, 1988) transitioning from an expertise-led planning to a more qualitative communicative approach

(Healey, 1992). The ultimate approach to producing plans, policies, or guidelines was considered to occur not through analytic processing but through consensus building. Only in this way, could decisions approximate the public interest (Glass, 1979; Innes, 1996; Healey, 1992). Instead of “plan for”, planners needed to “plan with” the public (Klosterman, 1999). This extended to digitally-enabled planning, with some tools developed to support public collaboration (Klosterman, 1999; Simonovic & Bender, 1996). We saw a movement to greater inclusion of people and the political concerns but ongoing tensions remained between the quantitative and the qualitative, the analytic and the communicative. Increasingly as planning was facilitating open communication and enabling public participation, planning supports were often solely about efficiency and computational power.

The 1990s saw an explosion of software and hardware tools, which opened up contemporary research in PSS. In 1993, the term PSS was coined by Harris and Batty as both a way to encapsulate important dimensions of these varied tools (Harris & Batty, 1993). One may regard any computer-based tool as a PSS, supporting routine tasks or facilitating basic communications (e.g., emails, online forums) and analysis (e.g., spreadsheets). However, planners were looking to tools that were customized to support planning-specific needs. These included job forecasting spreadsheets, land suitability mapping, and environmental impact assessments. Planners often developed their own tools, like decision support systems (DSSs) to support both civic participation in planning as well as analytic capacity (Sharda, Barr, & McDonnell, 1988; Coutinho-Rodrigues, Simão, & Antunes, 2011; Dye & Shaw, 2007; Jankowski & Richard, 1994). Several of these were built as applications of geographic information system (GIS), which municipalities began adopting in large numbers (Budić, 1994). GIS once was conceived as a “silver bullet” for every planning task (Klosterman, 1997). The introduction of GIS forced us to re-conceive

PSS because, although GIS was useful to planners, it was not specifically built with planning in mind and required considerable modification (e.g., with data or scripts) to directly address planning needs (Klosterman, 1997). Only later did we see innovations in GIS like geodesign that targeted planning (Batty, 2013).

Numerous PSSs have been developed over the decades but they have been accompanied by low levels of adoption. A global survey on planning practitioners points to a lack of awareness of PSS or indifference to its value (Vonk et al., 2005). Recent research suggests that “there are too many tools out there;” PSSs are neither user-friendly nor can they meet end-users’ requirements (Shah & Read, 2018). There continue to be insufficiency in technical training and high-resolution data to adapt them to a local level. Importantly, the unfriendliness of PSSs reflects on issues of planners’ comprehension and public understanding, where PSS essentially functions as a blackbox (Geertman & Stillwell, 2004). If the public fails to understand how PSS handles particular problems then the public cannot sufficiently convey its opinions and defend its interests. Making sense of decisions is one fundamental goal of civic participation, which ensures valid discussion among diverse stakeholders (Innes, 1996) and reduces risks underlying controversial plans or decisions (Alexander, 1988). Opacity in a technical system can frustrate planner usage as well as civic participation in consensus building.

Geertman (2017) concludes that PSS might never be a valuable tool in planning. However, “it seems that with the growing attention to the ‘smart city’ concept, planning practice is opening up much more widely to technological innovation and support, including PSS” (Geertman, 2017: 74). There have been novel PSS applications, such as moving to web-based (Pettit et al., 2013; Pettit, Tice, & Randolph, 2017) and open-source (Pettit et al., 2013; Santé, Pacurucu, Boullón, García, & Miranda, 2016), incorporating advancing temporal analysis (Deal, Pan, Timm, & Pallathucheril, 2017a), embracing crowdsourcing solutions (Kahila-Tani et al., 2015; Pánek & Pászto, 2017), and being data driven (Ghavami, Taleai, & Arentze, 2016; Semanjski, Bellens, Gautama, & Witlox, 2016). PSS is accompanied by new buzzwords like “web 2.0”, “Internet of Things”, “streaming data”, “natural language processing”, and “actionable analytics”. Advances in technology are changing the original or generating new process of planning beyond beyond just being more digitally-enabled.

Over the decades, PSS has evolved form the purely quantitative to the integration of the qualitative. In this evolution, we saw tensions of PSS between being technocratic and being inclusive. We also transitioned, ironically, from a scarcity of tools in which we had grand ambitions (e.g., model an entire city) to abundance of tools with smaller ambitions. To some extent this is because planning problems were identified early on as wicked, ill-structured or unstructured problems (Rittel and Webber, 1973). The wickedness of planning problems is not from insufficiencies in data or processing power. This caused equity and advocacy planners to continue their skepticism about whether planning problems could ever be sufficiently handled by technologies (Deal, Pan, Pallathucheril & Fulton, 2017b; Pelzer, Geertman, Van der Heijden & Rouwette, 2014). We see similar tensions (and possibly even a retrenchment) play out in smart cities. We argue that one significant difference is that the planner and his/her tools could be written out of the continued evolution of tools useful to manage and plan for the city.

2.3 The Emerging Smart City

Shifts in PSS mirror changes in planning, for example, from being design-oriented to an applied science. PSS also has moved from being purely quantitative in its approach to including qualitative content. There is no similar evolution in smart cities, although there are commonalities, like in challenges of deriving a single agreed-upon definition. Researchers have discussed the concept of “smart city” or its equivalents for some time

(Burchell, Listokin, & Galley, 2000; Daniels, 2001; Hall et al., 2000). At the same time, researchers have struggled with a comprehensive understanding of the neologism (Albino et al., 2015; Batty et al., 2012; Ching & Ferreira, 2015; Hollands, 2008; Luque-Ayala & Marvin, 2015; Nam & Pardo, 2011; Neirotti, De Marco, Cagliano, Mangano, & Scorrano, 2014). According to these authors, smart cities can be viewed variously as intelligent machines and people, sites of learning and innovation, entrepreneurial, self-promotional, knowledge-intensive, data-driven, technology-driven, connected, mobile, shared, participatory, equitable, resilient, adaptive, sustainable, livable, and green. Absent a settled-upon a definition, we cannot easily say that the concept of smart cities has evolved. Indeed, the smart city has served as a kind of "magic concept" (Pollitt & Hupe, 2011), so dilute yet "normatively attractive" and suggestive of consensus that it wins plaudits from everyone who hears of it even though there are no easy ways to operationalize the concept (Hollands 2008). Townsend (2013) broadly defines the smart city as a place where information and communications technologies are combined with infrastructure, architecture, everyday objects, and even our bodies to address social, economic, and environmental problems. Under this broad definition, smart cities have become a catch-all term for any technology about municipal services like providing e-services on website (City of Kitchener, 2017), or providing public wifi (Halifax Region, 2018).

Usage of the adjective 'smart' suggests a broad transformation brought by new technologies to the urban context (Nam & Pardo, 2011). However, a large part of smart city discourse is pure technology, for example as seen in the evaluation of Smart City Challenge applications in Canada (Robinson, 2018). The smart city takes advantage of sensors (e.g., cellphones, pollution counters), new software architectures (e.g., big data analytics, cloud computing, AI), and data (e.g., big data from crowdsourced social media) (Cardone et al., 2013; Harrison et al., 2010; Jin, Gubbi, Marusic, & Palaniswami, 2014;

Kitchin, 2011, 2014a; Neirotti et al., 2014; Zanella, Bui, Castellani, Vangelista, & Zorzi, 2014), to improve critical infrastructure and services including urban planning, management and governance. Globally, billions of devices, the Internet of Things, are sharing data and AI applications are emerging in many domains including public health (e.g., disease surveillance), public safety (e.g., facial recognition in CCTV cameras), environment (e.g., air quality monitoring), and transportation (e.g., traffic lights, transit scheduling) (Ark, 2018). Compared to the 1960s when PSS was proposed, the technologies of smart cities (i.e., hardware, software, and algorithms) are vast and suggest that many municipal processes can now be automated. Indeed, the classical illustration of the smart city is the giant urban control center in Rio de Janeiro, Brazil which suggests that massive amount of data can be passively collected via integrated sensors as well as real-time monitoring of transportation, police, and environmental issues (Ching & Ferreira, 2015). Unlike the modest PSS of the 1970s, the abundance of smart city tools seems to empower planners to finally achieve those grand ambitions.

Embedded within the smart city are considerations that it should move beyond technology to include people and politics. Nam and Pardo (2011) note that “smart” is greater than an efficient response to a set of instructions; smartness can be realized only when the “intelligent” system satisfies public or social needs. Although innovation in smart cities has the potential to automate municipal processes, supplanting the “quotidian” computing in 1980s, public or social needs are still expected to be solved by politics, not by technologies. The smart city, it is argued, must be a human-led and political exercise (Luque-Ayala & Marvin, 2015). Ching and Ferreira (2015) emphasize humans throughout their categorization of smart cities. “Smart machines” need to integrate with informed organizations; smart cities depend on partnerships and collaboration, and learning and adaptation.

Collaborations among municipal governments, communities, business, research institutions, it is argued, is the true driver of urban innovation. Boston's "participatory urbanism", for example, aims to engage citizens through mobile applications, websites, SMS, the "Community PlanIT" gaming platform, the "Open Government Portal", and the "Data Boston" portal (Osgood, 2013). San Francisco opened its Mayor's Office of Civic Innovation to foster entrepreneurship and host idea-generating platforms such as "unhackathons" to improve collaboration (Lee, 2012). Only when cities invest in human and social capital, will those cities reap desired benefits (Ching & Ferreira, 2015). Notions of investment and human capital lead to concerns that smart cities are conductive to neoliberalism (Luque-Ayala & Marvin, 2015). The consequence of neoliberalism in smart cities can mean the commodification of residents (who serve the city and its private sector stakeholders as "mobile bipedal data providers"), the view of the city as no more than a provider of services (e.g., pothole repairs), and the privileging of efficiency over effectiveness (e.g., improved bus service along well-travelled routes). The tension in smart cities is not only between pure technology and human-led approaches but also more hyperbolic, between a city being democratic or trending neoliberal.

It should be noted that definitions of smart cities are goal- or future-oriented. This aspirational orientation is oft-mentioned in the literature (Albino et al., 2015; Burchell et al., 2000; Harrison & Donnelly, 2011; Nam & Pardo, 2011; Neirotti et al., 2014; Viitanen & Kingston, 2014), where smart city initiatives can be seen as a response to global urbanization as well as enhance urban resilience in face of increasingly serious social, economic, and environmental challenges. According to United Nations (2018), at least 55 percent of world's population (4.2 billion) lives in cities; that number is expected to increase to 68 percent (6.7 billion) by 2050. The complexity of settling large populations and operating mammoth infrastructures lead to various urban problems, for example, inequality, unemployment, air pollution, and traffic congestion (Albino et al., 2015; Nam & Pardo, 2011). In this context, smart city initiatives seek to anticipate changes and provide technology-based solutions to ensure metropolitan prosperity (Neirotti et al., 2014), for example, developing self-driving cars to solve the parking problems and smoothing the traffic in future cities; building an intelligent system to assist doctors for enhancing medical care. It is worth noting that these solutions tend not to be developed inhouse by government or planners but tend to come from large private sector firms (e.g., IBM, Huawei) (Woods & Goldstein, 2014), which differentiate PSS from the technology of smart cities.

2.4 A Look Inside the Integration of PSS and the Smart City

Above we see potential commonalities as well as divergences between PSS and smart cities. The question is whether the common elements are sufficient or the divergences are too great to integrate PSS and the smart city. Frameworks have been proposed for this integration, for example via "Planning Support Sciences" (Geertman, Allan, Pettit & Stillwell, 2017a), to address low adoption rates as well as align with data science, urban science, and urban informatics. Although individuals have investigated numerous approaches to integrating PSS and smart cities (Geertman, Allan, Pettit & Stillwell, 2017b), we argue that a loosely coupled framework cannot guide the integration. These activities may be best practices but are spread across different domains and can be dedicated to separate (niche) problems. We suggest that any framework to integrate PSS into smart cities requires more than thinking of data and data-relevant technologies. We worry that the current integration of planning tends towards the technocratic and frustrates planning practitioners with less technological expertise.

PSS and smart cities are not a simple "alignment" relationship because this can hide a complex set of dynamics. We now consider the difficulties of integrating PSS and smart cities, investigates tensions when attempting integration, and explores the possibilities of PSS being supplanted and even the need of planners being obviated in smart city initiatives.

2.4.1 Difficulties of Integrating PSS and The Smart City

Integration of PSS and smart cities is complicated because neither concept is easily characterized, albeit for different reasons. The concept of PSS has evolved over the decades and has achieved a stable definition (Geertman & Stillwell, 2004). That being said, changes in the planning field (from design-oriented to applied science to communicative practice) and in computer technology (i.e., from large-scale models to DSS and GIS) has resulted in dominant characteristics responsive to different periods. Smart cities definitions show no sign of settling (Albino et al., 2015). Instead they represent a cacophony of voices, which have implications for any implementation. The cacophony manifests in different practices: some smart city initiatives read as quite political (e.g., pursuing an equitable city); some are fairly technological (e.g., real-time transit monitoring); some are comprehensive (e.g., sustainable and smart buildings); whereas some are "shallow" (e.g., free public wifi). The difficulties of their integration first derive from the question of exactly what PSS should integrate with.

Integration is tightly linked to hardware/software/data interoperability. Gabrielsen (2017) argues that interoperability, for example via the Internet of Things, is "built into" smart cities. Smart cities are promoted, in part, because the seamless device-to-device sharing of information should creates greater efficiency as people move in space and time (Kitchin, 2014b). Numerous technological barriers limit the interoperability of smart cities like lack of data standards (Ahlgren, Hidell, & Ngai, 2016). Because many smart city initiatives serve different visions, the actuality of being smart may just be a loosely coupled batch of technologies. (Nam & Pardo, 2011: 286) maintain that "IT infrastructure and applications are prerequisites, but without real engagement and willingness to collaborate and cooperate between public institutions, private sector, voluntary organizations, schools and citizens there is no smart city". Insufficient institutional collaboration also broadens the gap between different applications. We can integrate specific technologies into PSS, but that does not holistically represent a smart city. The people and politics discussed in smart cities are what PSS have become concerned with and could become an afterthought over time. PSS, therefore, is likely to serve a small niche amongst the grand urban system agenda that is the smart city initiative. The precise placement of that niche is unclear.

A goal of integration is that smart city technologies and initiatives would improve the adoption of PSS (Geertman, 2017). As discussed above, PSS has been constrained by low levels of adoption caused by unfriendliness and unsatisfying solutions to planners (Shah & Read, 2018). It is quite possible that low adoption rates can be partially attributed to the fact that many of these disparate tools are not interoperable or repurposable ("one-offs"). By integrating with smart cities, the hope is that PSS can overcome inherent defects. We already know that smart cities are not as interoperable as promised. Smart cities may be largely "smoke and mirrors," aspirations without coordinated operationalization (Gaffney and Robertson 2016) or little more than "technology demonstrations" (Boorsma 2017). Smart cities largely remain proofs of concept rather than initiatives that achieve any of their objectives. At its own forum, Cisco admitted that three-quarters of Internet of Things projects fail (Hall, 2017). "The current reality of smart cities is that there aren't any. At the end of the day, most so-called smart cities are just cities with a few or several standout smart projects" (Smith 2017). We should be cautious of adoption of smart city technologies providing grounded lessons for PSS.

2.4.2 Durable Tensions When Integrating PSS and Smart Cities

Two tensions likely will remain even if some integration issues are resolved. The first pertains to the role of technology as a solution to urban problems. Smart cities not only do not seem to have learned from earlier data-driven approaches, of which PSS is one, but appear doomed to repeat them. Second, and related to this, is the furtherance of neoliberalism induced by smart cities, of which PSS researchers have attempted to resist.

Townsend, who wrote the formative book on smart cities, asserts that "[t]he urge to bring scientific methods to urban planning seems to reappear every few decades" (Townsend, 2015: 203). Smart cities could represent such a reappearance and a rebranding of what is essentially a technocratic urge to manage the unmanageable. Goodspeed (2015) reviews early critiques about past technocratic approaches like urban cybernetics and command-and-control and concludes that improvements in data and computing power cannot construct a model to handle urban complexity. Smart city initiatives, like Waterfront Toronto spearheaded by Sidewalk Labs (Alphabet/Google), "should be a model for using technology and data as tools to enhance personal connections and the urban environment" (Doctoroff & Schmidt 2017). Waterfront TO, the largest proposed smart city in North America "could make living in cities cheaper, healthier, greener, more convenient and even more exciting" Echoing what happened in 1960s, this reads as more of the "technology and data (and the technocrats who supervise them) will solve the wicked problems of the city" this time with GPUs (for supporting unprecedentedly intensive computation of deep learning, an advanced and prevalent AI technique) instead mainframes. The technology changes but the urban problems remain intractable and technocracy remains irresistible.

Cartwright (1973) identified a dilemma in planning tools: planning problems have increased in complexity even as planning tools were developing rapidly to efficiently solve simple problems. Here, "complexity" means a problem involving ever more incalculable and unspecified factors. PSS has advanced beyond planning tools when Cartwright proposed the dilemma; however, there is no equivalent breakthrough in dealing with problems of high complexity. Integrating smart city technologies and PSS may change little in terms of the wickedness of planning problems. The introduction of automation via AI could exacerbate the durability of planning problems. Use of AI perpetuates the idea that advanced software can optimize urban functioning. However, most AI is trained on data with the biases of the contributors and programmers and it can conflict with certain societal values such as racial equality (Beira & Feenberg, 2018; Pasquale, 2015). Use of AI also perpetuates opacity because of the nature of how machine learning works, the challenge in explaining AI, and the lack of predictability of AIs response to new situations (Burrell 2016). AI does little to advance the aspirational goals of smart cities, including correctives to imbalances in political power. Technocratic and data-driven approaches may further marginalize vulnerable groups (e.g., the have-nots, the elder) through new ways (e.g., where big data can obscure minority voices) (Hardt, 2014).

Townsend further argues that cities rationalized by data-driven scientific ideas and plans might be anti-democratic (Townsend, 2015). Inclusion of people and politics in smart cities appears similar to the preconditions that PSS be communicative but inclusion is a durable problem that is further complicated in smart cities and might even enhance a neoliberal approach to a city's constituents.

Most smart city initiatives seek to expand civic participation. Inclusion of civil society organizations was a requirement for the Canadian federal government's Smart City Challenge (Robinson, 2018). Participation in the smart city is envisioned as engagement from those already participating and more people participating, which can be achieved by utilizing wireless mobile devices and web 2.0 (Cardone et al., 2013; Oliveira, 2017). Smart cities also seek to harness the big data generated by citizens (Berthon, et al., 2015). This crowdsourced data can foster a new form of participation, "passive participation" (Tenney & Sieber, 2016), through which passively-collected data are analyzed for better informing decisions. Innovations in civic participation afforded by smart city technologies do not reduce the digital divide because of the opacity and because digital literacies are usually not built into these data-driven solutions (Helbing et al. 2019). Instead of improving civic participation, they may damage it.

Passive participation involves the harvesting of informal content (e.g., Tweets) or the tracking of individual behaviors (e.g., commuter information). The idea is that tracking people in space-time is superior to having them attend city council meetings and tracking achieves a better sense of intent (e.g., lingering outside a subway station could imply poor intermodal transit connections). This kind of passivity may be afforded by the ambient tracking of smart city technologies but is controversial in planning. Healey (1992) proposes "planning through debate" by developing the idea of inter-subjective reasoning, supporting which is essential to a communicative PSS. Passive participation, enabled by Internet of Things, big data analytics and AI, leaves out the communicating and reasoning process. The knowledge, instead, is structured by hidden patterns in big data. During the process, people can be reduced to training datasets, which likely results in the loss of information about social contexts where diverse interests come from and can further automation as the data is fed into AI.

Passive participation, like other smart city initiatives, could represent a commodification of a city and its residents (Leszczynski, 2012). Data-driven approaches could turn individuals into measurable units, the aggregated data of which could offer a new revenue source for cities. In the Waterfront TO case, we have begun to see early signs of the monetization potential from the ambient tracking of individuals (Johnson et al., 2017). Streaming data at a high spatial and temporal resolution will provide private sector stakeholders like Sidewalk Labs enormous detail on what people do and likely desire. This data can better inform Alphabet's advertising offerings like Google Adsense and Analytics. Smart city initiatives, especially when they involve public private partnerships, can further the idea that the relation between the city and its residents is one of consumers and producers (and who is the consumer and who is the producer shifts over time). PSS and tools like DSS, have evolved to see citizens as active participants in a complicated political city. We are wary of this new iteration that suggests durable problems can easily be solved by more technologies, more data and more technical experts to run them to optimize urban functioning.

2.5 Conclusion and Outlook: Potential for PSS and Planning in An Era of Smart Cities

Moves to integrate PSS and smart cities might improve the functioning of PSS, for example through appropriate of the visual analytics available in smart city "dashboards" (Kitchin & McArdle, 2018). Greater use of smart city technologies might further automated handling of planning problems. Following researchers like Healey (1997), investing smart cities with lessons learned by PSS might enable broader civic engagement in planning activities. Conversely, the integration can be muddy because inconsistent definitions and a lack of recognition that there are intractable problems in planning that are not ameliorated by more technology. New technologies might increase trends towards technocracy as well as opacity in planning process, enlarge inequities caused by digital divides and differential capabilities in comprehending data and data analysis.

The dominance of smart cities in new forms of PSS might jeopardize the role of planners in planning the city. Planning is already challenged from civil society and non-state actors, a kind of do-it-yourself planning. There are instances in which civil society uses technology similar to DSS to produce analyses superior to those of planners (Sieber, 2006). There are instances in which government believes the private sector can better plan cities. Leszczynski (2012) reports on a case in the US where town councillors rejected additional funding for GIS because Google Maps was considered sufficient for planning analysis. We discussed how residents are becoming important sources of planning data. PSS could be developed to support crowdsourcing under the coordination of planners. Planners' roles might shift to facilitators and translators of technologies.

Employing new technologies in the smart city could release planners from uncreative work as highly structured planning tasks are automated. It is also possible that planners might become unnecessary as their tasks automated. Automated systems promise to better understand and anticipate the public's needs through harvesting and analyzing data from, for example, the Internet of Things, then decide which services to supply where. These systems diminish the interventions from governments, including planners. PSS also become less essential to support planners since planning tasks are replaced by smarter machines. Eventually, PSS and planners might be omitted, or at least shut out of planning the smart city. Likewise, residents in this process might be reduced to training datasets and further commodified as their relation with the state shifts. To preclude the omission, Batty argues for planners to play an active role in the future automation of the smart cities, "to begin to tame AI and to establish the right kinds of regulatory structure, to invoke serious ethical principles and to ensure that the increasing polarizing effects of information technologies are dealt with appropriately" (Batty, 2018: 4).

Ultimately, the integration of the smart city and PSS is bidirectional, which means they shape each other. The smart city has significant impacts on PSS; whereas PSS can deflate the hyperbole about the smart city. PSS has traversed through stages of being overly optimistic only to fall well short of expectations. Lessons of PSS should be revisited to tackle anticipated challenges in the smart city. In current smart city era, the essential concerns of employing technologies in planning remain the same. Humans and messy politics matter. Technocratic and data-driven approaches should not supplant communicative and democratic methods in urban planning.

Reference

Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart Cities: Definitions, Dimensions, Performance, and Initiatives. Journal of Urban Technology, 22(1), 3-21. doi:10.1080/10630732.2014.942092.

Alexander, E. R. (1988). After rationality. Society, 26(1), 15-19.

Ahlgren, B., Hidell, M., & Ngai, E. C. H. (2016). Internet of things for smart cities: Interoperability and open data. IEEE Internet Computing, (6), 52-56

Ark, T. V. (2018). How Cities Are Getting Smart Using Artificial Intelligence. Retrieved on November 21, 2018, from https://www.forbes.com/sites/tomvanderark/2018/06/26/how-cities-are-getting-smart-using-artificial-intelligence/#a2c455838036.

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., . . . Portugali, Y. (2012). Smart cities of the future. The European Physical Journal Special Topics, 214(1), 481-518. doi:10.1140/epjst/e2012-01703-3

Batty, M. (2013). Defining geodesign (= GIS + design ?) Environment and Planning B: Planning and Design. volume 40, pages 1 – 2.

Batty, M. (2018). Artificial intelligence and smart cities. Environment and Planning B: Urban Analytics and City Science, Vol. 45(1) 3–6.

Beira, E., & Feenberg, A. (2018). Technology, Modernity, and Democracy: Essays by Andrew Feenberg.

Berthon, P., Pitt, L., Kietzmann, J. & McCarthy, I. (2015). CGIP: Managing Consumer-Generated Intellectual Property. California management review. 57. 43-62. 10.1525/cmr.2015.57.4.43.

Boorsma, B. (2017). A New Digital Deal: Beyond Smart Cities. How to Leverage Digitalization for the Benefit of our Communities. Uitgeverij Boekscout， Netherlands: Boekscout BV.

Brewer, G. D. (1973). Politicians, bureaucrats, and the consultant: A critique of urban problem solving. Basic Books.

Budić, I. Z. D. (1994). Effectiveness of geographic information systems in local planning. Journal of the American Planning Association, 60(2), 244-263.

Burchell, R. W., Listokin, D., & Galley, C. C. (2000). Smart growth: More than a ghost of urban policy past, less than a bold new horizon. Housing Policy Debate, 11(4), 821-879. doi:10.1080/10511482.2000.9521390

Burrell, J. 2016. How the Machine 'Thinks': Understanding Opacity in Machine Learning Algorithms. Big Data and Society 3(1): 1-12

Cardone, G. F., L.; Bellavista, P.; Corradi, A.; Borcea, C.; Talasila, M.,; Curtmola, R. (2013). Fostering ParticipAction in Smart Cities: A Geo-Social Crowdsensing Platform. IEEE Communications Magazine, 51(6), 112–119.

Cartwright, T. J. (1973). Problems, Solutions and Strategies: A Contribution to the Theory and Practice of Planning. Journal of the American Institute of Planners, 39(3), 179-187. doi:10.1080/01944367308977852

Ching, T.-Y., & Ferreira, J. (2015). Smart Cities: Concepts, Perceptions and Lessons for Planners. In Planning Support Systems and Smart Cities (pp. 145-168).

City of Kitchener. (2017). On Demand (Digital Kitchener). Retrieved on November 12, 2018, from https://www.kitchener.ca/en/city-services/on-demand.aspx#Explore-new-opportunities-to-enhance-online-services

Coutinho-Rodrigues, J., Simão, A., & Antunes, C. H. (2011). A GIS-based multicriteria spatial decision support system for planning urban infrastructures. Decision Support Systems, 51(3), 720-726. doi:10.1016/j.dss.2011.02.010

Doctoroff D. and Schmidt E. (2017). Why toronto is the ideal place to build a neighbourhood of the future. Retrieved on November 19, 2018, from https://www.theglobeandmail.com/opinion/why-toronto-is-the-ideal-place-to-build-a-neighbourhood-of-the-future/article36614593/

Dye, A. S., & Shaw, S.-L. (2007). A GIS-based spatial decision support system for tourists of Great Smoky Mountains National Park. Journal of Retailing and Consumer Services, 14(4), 269-278. doi:10.1016/j.jretconser.2006.07.005

Daniels, T. (2001). Smart Growth: A New American Approach to Regional Planning. Planning Practice and Research, 16(3-4), 271-279. doi:10.1080/02697450120107880

Danziger, J. N. (1977). Computers, local governments, and the litany to EDP. Public Administration Review, 28-37.

Deal, B., Pan, H., Timm, S., & Pallathucheril, V. (2017a). The role of multidirectional temporal analysis in scenario planning exercises and Planning Support Systems. Computers, Environment and Urban Systems, 64, 91-102. doi:10.1016/j.compenvurbsys.2017.01.004

Deal, B., Pan, H., Pallathucheril, V., & Fulton, G. (2017b). Urban Resilience and Planning Support Systems: The Need for Sentience. Journal of Urban Technology, 24(1), 29-45. doi:10.1080/10630732.2017.1285018

Festinger, L. (1962). A theory of cognitive dissonance (Vol. 2). Stanford university press.

Gabrielsen, K. R. (2017). Interoperability in Smart Cities (Unpublished master's thesis). Department of Design, Norwegian University of Science and Technology. Throndheim, Norway.

Gaffney, C. and Robertson, C. (2016). Smarter than Smart: Rio de Janeiro's Flawed Emergence as a Smart City. Journal of Urban Technology. 25 (3).

Geertman, S., & Stillwell, J. (2004). Planning support systems: an inventory of current practice. Computers, Environment and Urban Systems, 28(4), 291-310. doi:10.1016/s0198-9715(03)00024-3

Geertman, S. (2017). PSS: Beyond the implementation gap. Transportation Research Part A: Policy and Practice, 104, 70-76. doi:10.1016/j.tra.2016.10.016

Geertman, S., Allan, A., Pettit, C., & Stillwell, J. (2017a). Introduction. Planning Support Science for Smarter Urban Futures. Cham, Switzerland: Springer Nature.

Geertman, S., Allan, A., Pettit, C., & Stillwell, J. (2017b). Planning Support Science for Smarter Urban Futures. Cham, Switzerland: Springer Nature.

Ghavami, S. M., Taleai, M., & Arentze, T. (2016). An intelligent spatial land use planning support system using socially rational agents. International Journal of Geographical Information Science, 31(5), 1022-1041. doi:10.1080/13658816.2016.1263306

Glass, J. J. (1979). Citizen participation in planning: the relationship between objectives and techniques. J Am Plann Assoc, 45(2), 180-189. doi:10.1080/01944367908976956

Goodspeed, R. (2015). Sketching and learning: A planning support system field study. Environment and Planning B: Planning and Design, 43(3), 444-463. doi:10.1177/0265813515614665

Halifax Region. (2018). Halifax Smart Cities Proposal. Retrieved on November 12, 2018, from https://static1.squarespace.com/static/5a8f1f898a02c7aa4b11be71/t/5af091b6562fa7c6f4b30aa1/1525715408245/Smart+Cities+Bid_8.5x11_May+4+2018_DIGITAL.PDF

Hall, R. E., Bowerman, B., Braverman, J., Taylor, J., Todosow, H., & Von Wimmersperg, U. (2000). The vision of a smart city(No. BNL-67902; 04042). Brookhaven National Lab., Upton, NY (US).

Hall, K. (2017). Three-quarters of IoT projects are failing, says Cisco. Retrieved on November 18, 2018, from https://www.theregister.co.uk/2017/05/23/threequarters_of_iot_projects_are_failing/

Hardt, M. (2014). How big data is unfair: Understanding unintended sources of unfairness in data driven decision making. Retrieved on November 21, 2018, from https://medium.com/@mrtz/how-big-data-is-unfair-9aa544d739de

Harris, B. (1968). Computer and Urban Planning. Socio-Econ. Plan. Sci., 1, 223-230.

Harris, B., & Batty, M. (1993). Locational Models, Geographic Information and Planning Support Systems. Journal of Planning Education and Research, 12, 184-198.

Harrison, C., Eckman, B., Hamilton, R., Hartswick, P., Kalagnanam, J., Paraszczak, J., & Williams, P. (2010). Foundations for Smarter Cities. IBM Journal of Research and Development, 54(4), 1-16. doi:10.1147/jrd.2010.2048257

Harrison, C., & Donnelly, I. A. (2011). A THEORY OF SMART CITIES.Paper presented at the 55th Annual Meeting of the ISSS, Hull, UK.

Healey, P. (1992). Planning through debate: the communicative turn in planning theory. Town planning review, 63(2), 143-162.

Healey, P. (1997). Collaborative planning: Shaping places in fragmented societies. UBc Press.

Helbing, D., Frey, B. S., Gigerenzer, G., Hafen, E., Hofstetter, M. H., ven den Hoven, J., Zicari, R. V. & Zwitter, A. (2019). Will Democracy Survive Big Data and Artificial Intelligence? Towards Digital Enlightenment. Essays on the Dark and Light Sides of the Digital Revolution. Springer. pp 73-98

Hollands, R. G. (2008). Will the real smart city please stand up? City, 12(3), 303-320. doi:10.1080/13604810802479126

Innes, J. E. (1996). Planning Through Consensus Building: A New View of the Comprehensive Planning Ideal. Journal of the American Planning Association, 62(4), 460-472. doi:10.1080/01944369608975712

Jankowski, P., & Richard, L. (1994). Integration of GIS-based suitability analysis and multicriteria evaluation in a spatial decision support system for route selection. Environment and Planning B: Planning and Design, 21(3), 323-340.

Jin, J., Gubbi, J., Marusic, S., & Palaniswami, M. (2014). An Information Framework for Creating a Smart City Through Internet of Things. IEEE Internet of Things Journal, 1(2), 112-121. doi:10.1109/jiot.2013.2296516

Johnson, P., Sieber, R., Scassa, T., Stephens, M. & Robinson, P. 2017. The cost(s) of geospatial open data. Transactions in GIScience 21, 3: 434–445.

Kahila-Tani, M., Broberg, A., Kyttä, M., & Tyger, T. (2015). Let the Citizens Map—Public Participation GIS as a Planning Support System in the Helsinki Master Plan Process. Planning Practice & Research, 31(2), 195-214. doi:10.1080/02697459.2015.1104203

Kitchin, R. (2011). The Programmable City. Environment and Planning B: Planning and Design, 38(6), 945-951. doi:10.1068/b3806com

Kitchin, R. (2014a). Big Data, new epistemologies and paradigm shifts. Big Data & Society, 1(1). doi:10.1177/2053951714528481.

Kitchin, R. (2014b). The real-time city? Big data and smart urbanism. GeoJournal, 79(1), 1-14.

Kitchin, R. and McArdle, G. (2018). Urban data and city dashboards: Six key issues. In Kitchin, R., Lauriault, T. P. and McArdle, G. (eds). Data and the City. Routledge, London.

Klosterman, R. E. (1997). Planning Support Systems: A New Perspective on Computer-Aidded Planning. Journal of Planning education and research, 17(1), 45-54.

Klosterman, R. E. (1999). The What if? collaboration planning support system. Environment and Planning B: Planning and Design, 26, 393-408.

Lee Jr, D. B. (1973). Requiem for large-scale models. Journal of the American Institute of planners, 39(3), 163-178.

Lee, E. (2012). San Francisco's secret sauce—Innovation drives livability and sustainability. Presented at meeting of the minds conference October 9–11, 2012. http://cityminded.org/talk/ san-franciscos-secret-sauce-innovation-drives-livability-and-sustainability. Accessed March 18, 2013.

Leszczynski, A. (2012). Situating the geoweb in political economy. Progress in Human Geography 36 (1): 72-89.

Light, J. S. (2003). From warfare to welfare: Defense intellectuals and urban problems in Cold War America. JHU Press.

Luque-Ayala, A., & Marvin, S. (2015). Developing a critical understanding of smart urbanism? Urban Studies, 52(12), 2105-2116. doi:10.1177/0042098015577319.

McHarg, I. L., & Mumford, L. (1969). Design with nature. New York: American Museum of Natural History.

Nam, T., & Pardo, T. A. (2011). Conceptualizing Smart City with Dimensions of Technology, People, and Institutions. Paper presented at the The 12th Annual International Conference on Digital Government Research.

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in Smart City initiatives: Some stylised facts. Cities, 38, 25-36. doi:10.1016/j.cities.2013.12.010.

Oliveira, E. (2017). Citizen Empowerment and Innovation in the Data-Rich City. Journal of Urban Technology, 24(2), 111-114. doi:10.1080/10630732.2017.1333841

Osgood, C. (2013). Interview. Boston Mayor's Office of New Urban Mechanics (MONUM), January 23, 2013.

Pasquale, F. (2015). The black box society: The secret algorithms that control money and information. Harvard University Press.

Pánek, J., & Pászto, V. (2017). Crowdsourcing Mapping and Participatory Planning Support System: Case Study of Brno, Czechia. In Advances in Cartography and GIScience(pp. 61-73).

Pelzer, P. (2015). Usefulness of Planning Support Systems: Conceptual perspectives and practitioners' experiences (Doctoral dissertation, InPlanning).

Pelzer, P., Geertman, S., Heijden, R., & Rouwette, E. (2014). The added value of planning support systems: A practitioner's perspective. Computers, Environment and Urban Systems, 48, 16-27.

Pettit, C. J., Klosterman, R. E., Nino-Ruiz, M., Widjaja, I., Russo, P., Tomko, M., . . . Stimson, R. (2013). The Online What if? Planning Support System. In Planning Support Systems for Sustainable Urban Development(pp. 349-362).

Pettit, C. J., Tice, A., & Randolph, B. (2017). Using an Online Spatial Analytics Workbench for Understanding Housing Affordability in Sydney. In Seeing Cities Through Big Data(pp. 233-255).

Pollitt, C., & Hupe, P. (2011). Talking about government: The role of magic concepts. Public Management Review, 13(5), 641-658.

Rittel, H. W., & Webber, M. M. (1973). Planning problems are wicked problems. Man-made Futures, 26(1), 272-280.

Robinson, P. (2018). The Future of Canadian Smart Cities: Early Signals from the Smart City Challenge and Sidewalk Labs' Quayside. Presentation at 2018 Association of Collegiate Schools of Planning Annual Conference. Buffalo, NY.

Santé, I., Pacurucu, N., Boullón, M., García, A. M., & Miranda, D. (2016). An open source GIS-based Planning Support System: Application to the land use plan of La Troncal, Ecuador. Transactions in GIS, 20(6), 976-990. doi:10.1111/tgis.12223

Semanjski, I., Bellens, R., Gautama, S., & Witlox, F. (2016). Integrating Big Data into a Sustainable Mobility Policy 2.0 Planning Support System. Sustainability, 8(11). doi:10.3390/su8111142

Sharda, R., Barr, S. H., & McDonnell, J. C. (1988). Decision Support System Effectiveness: A Review and An Empirical Test. Management science, 34(2), 139-159.

Shah, S. & Read, A. (2018). Needs Assessment of Water-Related Decision Support Tools. Oral presented at 2018 Association of Collegiate Schools of Planning Annual Conference. Buffalo, NY.

Sieber, R. (2006). Public participation geographic information systems: A literature review and framework. Annals of the association of American Geographers, 96(3), 491-507.

Simonovic, S. P., & Bender, M. J. (1996). Collaborative planning-support system: an approach for determining evaluation criteria. Journal of Hydrology, 177, 237-251.

Smith, K. (2017). The The Inconvenient Truth about Smart Cities. Retrieved on November 15, 2018, from https://blogs.scientificamerican.com/observations/the-inconvenient-truth-about-smart-cities/

Tenney, M., & Sieber, R. (2016). Data-Driven Participation: Algorithms, Cities, Citizens, and Corporate Control. Urban Planning, 1(2), 101-103.

Townsend, A. M. (2013). Smart cities: Big data, civic hackers, and the quest for a new utopia. WW Norton & Company.

Townsend, A. (2015). Cities of data: Examining the new urban science. Public Culture, 27(2 (76)), 201-212.

United Nations. (2018). World Urbanization Prospects The 2018 Revision. United Nations Publications.

Viitanen, J., & Kingston, R. (2014). Smart Cities and Green Growth: Outsourcing Democratic and Environmental Resilience to the Global Technology Sector. Environment and Planning A, 46(4), 803-819. doi:10.1068/a46242

Vonk, G., Geertman, S., & Schot, P. (2005). Bottlenecks Blocking Widespread Usage of Planning Support Systems. Environment and Planning A, 37(5), 909-924. doi:10.1068/a3712

Woods, E., & Goldstein, N. (2014). Navigant research leaderboard report: Smart city suppliers. Assessment of Strategy and Execution for, 15.

Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of Things for Smart Cities. IEEE Internet of Things Journal, 1(1), 22-32. doi:10.1109/jiot.2014.2306328.

The Preface of Chapter 3

Chapter 3 uses machine learning (ML) to explore the main research question of “how do researchers and practitioners plan for the smart city using automated technologies?” in a methodological way. This chapter reports on extant methods to research the smart city. This context allows us to argue why we need to mediate automated technologies when we use ML to study the nature of the smart city. A specific ML method, topic modelling, is employed to interpret the smart city through analyzing the primary texts from the Canadian federal government’s Smart Cities Challenge (SCC) grant. This chapter inspects the implementation details of topic modelling for investigating all the human intervention and understanding their influence on results interpretation. We identify the pros and cons of using automated technologies, which offer caveats for continued usage. We apply human-centered ML (HCML) to exemplify issues of usability by non-experts when they adopt the automated technologies. Because there are numerous issues to consider about the methodology, we decide to split the discussion of the methods from the results of topic modelling on the SCC (Chapter 4). As an independent manuscript, Chapter 4 will contain some overlaps with Chapter 3 to be complete and comprehensible. Whereas Chapter 4 ultimately presents more of the salient themes in the smart city discourse and how we interpret them from modelling results, Chapter 3 serves as the methodology of the thesis to support Chapter 4’s discovery and interpretation.

We plan to submit this chapter to *GeoJournal*.

Zhibin Zheng conceptualized and designed this study, collected and analyzed the data, preliminarily interpreted the results and drafted the manuscript. Zhibin Zheng and Renee Sieber, his supervisor, reviewed the manuscript together. Renee Sieber offered advice on reorganizing ideas and restructuring the manuscript. Zhibin Zheng ran the topic modelling and crafted the paper as the implementation of topic modelling. Renee Sieber suggested HCML as a framework to more clearly identify a more clear gap for this study to fill. Zhibin Zheng revisited the manuscript together with Renee Sieber. Renee Sieber also provided help in terms of the English language by editing or guiding Zhibin Zheng to edit the manuscript. Zhibin Zheng and Renee Sieber finally approved this version to be published.

Chapter 3: Human-Centered Machine Learning Methods to Interpret the Smart City

Abstract

Smart cities are often characterized by big data analytics and computational advances used to analyze the large volumes, velocities and variety of data generated by a wide range of sensors, social media, government documents and other materials. Whereas smart city analysis frequently emphasizes, for example, feature detection (e.g., autonomous vehicles) or quantitative measures (e.g., from Internet of Things devices); a considerable amount of this data is qualitative and text-based, whether from social media or government documents. In urban science, researchers employ unsupervised machine learning (ML) methods including text mining, graph analysis and topic modelling. "Unsupervised" refers to a bottom-up and abductive approach that makes inferences from datasets without the need for pre-identification of results or other forms of human oversight. Unsupervised ML methods are increasingly used in social sciences research so as to more efficiently conduct qualitative data analysis than methods that extensively involve humans. The deployment of unsupervised ML methods implies that out-of-the-box tools, relatively opaque and automated, lead to quicker and more insightful and objective results. However, far from automated or objective these methods require considerable amounts of human intervention. A field of research called Human-Centered ML (HCML) acknowledges that non-automated humans can play a role in ML. HCML, as a set of methods, can still be algorithm-driven as opposed to human-centered. We argue for a user-centered deployment of ML methods that foreground the choices the researcher makes in interpreting the smart city. To exemplify the roles of domain users/researchers in ML methods, we apply topic modelling to primary texts from the Canadian Smart Cities Challenge (SCC). In the process of discussing the emergent topics, we identify fifteen implementation steps of human intervention in topic modelling, throughout data collection to results interpretation stages. These steps serve to counter increasing opacity of ML methods and uncritical usage. Investigating the human intervention we hope can improve the design of a more user-centered deployment of ML methods.

Keywords: smart city, human-centered, machine learning, topic modelling

3.1 Introduction

Over three decades of research and practice (Batty, 2013), we have accumulated a vast corpus of data to interpret the smart city. This big data can be sourced to crowdsourcing, for example by analyzing the contents of social media to gauge public sentiments. The data can also come from sensors, like streaming traffic data analytics to improve the transportation system. Beyond data available on social media or collected by sensors to sense the smart city, large volumes of texts can help us interpret the smart city. Texts range from academic literature, proposals, reports or working papers to documents accumulated by governments like hansards, committee reports, building inspections and purchase orders.

Numerous data-driven methods from machine learning (ML) and artificial intelligence (AI) disciplines hopefully can extract valuable insights and actionable items about the smart city. Of them, natural language processing (NLP) offers an opportunity to deal with large textual data through automating the analysis. NLP comprises a set of methods to computationally provide semantic understanding, process, translate, and/or analyze large amounts of natural language data (Manning & Schütze, 1999). In the fields of urban science, NLP has been recognized as an important approach to analyze texts and support decision making based on the extracted semantics and public sentiment (Chen et al., 2017; Hagen et al., 2015; Wilson et al., 2020). Topic modelling is the most popular NLP technique employed in the urban science studies (e.g., Hasan & Ukkusuri, 2014; Kling & Pozdnoukhov, 2012; Resch el al., 2016), for example to identify urban activity patterns/dynamics by extracting topics and implications from massive social media texts (e.g., Twitter, Facebook).

ML like NLP is attractive for several reasons. First, much of the data generated in smart cities is big, in volume and velocity. Conventional labour-intensive research methods can limit the amount of this big textual data that can be analyzed since "the work is tedious and difficult for humans to do reliably at scale" (Crowston, Allen & Heckman, 2012: 523). Second, ML is considered to be a "bottom-up" quantitative method for smart city research that supposedly removes preconceptions of researchers using qualitative data analysis (Yu, Jannasch-Pennell & DiGangi, 2011). With conventional methods, researchers might be stuck in a cycle that repeats previous theories instead of uncovering new findings about the smart city. Third, ML might be better suited to the complexity of smart cities. The complexity not only arises from the variety of smart city practices but also from highly contextualized characteristics of each practice. The prevalence of single case studies (e.g., Mahizhnan, 1999) attests to the ways that researchers investigate smart cities, a method not easily generalizable so as to add more cities in analysis. Fourth, ML speaks to a "why not" attitude. Why not use all the data we now have? We conduct a case study on applying topic modelling to interpreting smart cities proposed in bulk texts submitted to the Canadian Smart Cities Challenge (SCC). The SCC texts consist of over hundred documents containing about 1.5 million words. The documents are sufficiently diverse, coming from different communities across Canada, to offer rich data for the study of smart cities. Perhaps we can extract central themes across all these proposals.

The tension with ML techniques like NLP is that they are not as automated as we would like. For example, topic modelling needs specific configurations to be usable. A researcher must intervene at several points in the use of topic modelling: in the selection of data, any transformation of that data (e.g., changing interval data to ordinal data) or labeling the data for training algorithms (in supervised learning). In other words, topic modelling requires a considerable amount of human intervention in the process. NLP for smart city research and practice may be popular but users are not explaining all the decisions needed to achieve useful results. Indeed, this is part of the growing opacity of ML methods. In those applications of topic modelling, little is written that deeply interrogates the human judgement calls. Instead topic modeling is used relatively uncritically as a tool that is "pulled off the shelf" and applied according to default parameters set by data scientists or other developers. We are worried that as it becomes easier to use, it will be blindly adopted.

The fear is that results using ML will be algorithm-driven rather than human-centered (Lee et al., 2017), which is important so we fully understand the impacts of smart cities beyond simply their technical innovations. The field of human-centered machine learning (HCML) recognizes that, even as we increasingly use ML, humans remain key components in optimizing ML outputs (Holzinger et al., 2019). We include smart city researchers, that is domain-based social scientists who may wish to adopt ML methods without possessing a deep knowledge of the algorithms. As will be seen, even if HCML is proposed, human-as-researcher can be ignored.

In this chapter, we employ topic modelling to retrieve information and extract topics from SCC applications and proposals. The topics function to synthesize these SCC documents and appear to automatically generate new knowledge. We then explicate steps where the researcher needs to make various choices that influence the outcomes we herald as interpretations of the smart city.

3.2 Review of Methods to Research the Smart City

Methods to research the smart city include a mix of qualitative and quantitative approaches. Cocchia (2014) utilized a meta-synthesis of smart city research from 1993 to 2012 and conducted analysis from perspectives of time, terminology, definition, typology and geography of smart city development. Mosannenzadeh and Vettorato (2014) implemented a keyword analysis of the literature to identify research questions of why, what, who, when, where and how in terms of the creation of smart cities. Case studies are common; Ching and Ferreira (2015) studied six smart cities, Boston, San Francisco, Amsterdam, Stockholm, Singapore and Rio de Janeiro to interrogate their assumptions about automation and intelligent functions, partnership and collaboration, learning and adapting and investments for the future in smart city initiatives. Alawadhi et al (2012) conducted interviews with government officials and managers who were responsible for smart city initiatives. These represent the prevalent approaches to clarifying the nature of the smart city and drawing comparisons among cities.

The smart city often is featured by a dashboard for integrating data collected by sensors (Suakanto, Supangkat & Saragih, 2013). There are numerous quantitative examples of this sensing of the city. Experts can monitor the environment to provide better city service such as air quality management (Shah & Mishra, 2016), predict parking availability (Zheng, Rajasegarar & Leckie, 2015), improve sustainable energy efficiency (Jaradat et al., 2015) and enhance healthcare effectiveness (Cook et al., 2018). Social media and crowdsourcing offer another means of city sensing. Goodchild (2007) characterizes "citizens as sensors" and a sensor network consisting of humans with the observational capacity, technical connectivity and the intelligence to interpret the local conditions they sense. Some researchers believe social media offers the city a new infrastructure of civic engagement participation and situational awareness (Ahmed et al., 2016; Lee & Kwak, 2012; Tenney & Sieber, 2016). The potential is for "[m]illions of city dwellers [to] share their observations, thoughts, feelings, and experiences about their city through social media updates" (Doran, Gokhale & Dagnino, 2013: 1323). The challenge is to obtain meaningful information, to see the signal through the noise, which is why even qualitative data is assessed, for example to conduct sentiment analysis, through algorithms like those in NLP discipline.

3.2.1 Topic Modelling to Research the Smart City

NLP is a set of automated techniques that can be used to clarify the nature of and sense the smart city. NLP refers to a discipline with dependency on computational linguistics, representing a large area of research and applications on text analysis (Crowston et al., 2012). Liddy (2003: 2126) defines NLP as

> a theoretically motivated range of computational techniques for analyzing and representing naturally occurring texts at one or more levels of linguistic analysis for the purpose of achieving human-like language processing for a range of tasks or applications.

Like other forms of ML, NLP attempts to model human thought through analyzing and understanding natural language, which includes algorithms, methodologies and tools to study grammatical, syntactic and semantic structures of texts (Guetterman et al., 2018). Yu et al. (2011) compared text mining with content analysis and concluded that text mining leads to highly consistent results and offers reliability similar to qualitative research (e.g., content analysis). Tierney (2012) proposed graph analysis to more easily discover themes from data at a large scale and the method can be adopted to different domains. Zerr et al. (2013) mined public opinions on a topic with an emphasis on protecting contributors' privacy. Jacobi, Van Atteveldt and Welbers (2016) promoted topic modelling to address the challenge of analyzing the unprecedented amounts of data faced by journalists. They explained how topic modelling works; how researchers can use them and how the results can be interpreted. Topic modelling is the most well-developed and accessible set of NLP algorithms for qualitative research.

Topic modelling can be traced back to the 1990s (Deerwester et al., 1990). Topic modelling algorithms include latent semantic indexing (LSI), probabilistic latent semantic analysis (PLSA) and Non-Negative Matrix Factorization (NMF) (O'Neill et al., 2016). Built on PLSA, Blei, Ng and Jordan (2003) created Latent Dirichlet Allocation (LDA). Compared with conventional methods like content analysis, LDA can extract latent (i.e., hidden but waiting to be discovered) meaning from texts by identifying their statistical (probabilistic) relations instead of just by counting word frequencies (Mohr & Bogdanov, 2013). Documents, whether a set of government reports or a set of tweets, start as "bags-of-words", where word co-occurrences within the bags produce latent patterns (i.e., topics). LDA calculates the probability of every word occurring in every topic, as well as the probability of every topic discussed in subsets of the documents (Mohr & Bogdanov, 2013). In other words, mapping the distribution of words into topics shows co-occurrence patterns of words clustering across documents (Jacobi et al., 2016).

Note that topic modelling or LDA is not just statistically sophisticated and useful, it is also convenient and usable. Many well-developed libraries (e.g., Gensim, Scikit Learn, BERT and R) have built-in topic modelling functionality. These libraries also provide supportive analytics and visualization tools to assist topic interpretation, which is user-friendly for non-experts to apply. Topic modelling has become increasingly prevalent in urban science, for example, to extract semantics from social media data and hopefully inform public decision making (e.g., Hasan & Ukkusuri, 2014; Kinoshita, Takasu & Adachi, 2015; Kling & Pozdnoukhov, 2012). Topic modelling possesses the potential to be applied to clarifying the nature of the smart city although its use is nascent. Like most ML methods, topic modelling promises automation and insights, which might be fallacious without acknowledging how much human intervention actually happens during the process of building a topic model.

3.2.2 From Automated to Human-Centered ML

An early definition of ML is a field of study that gives computers the ability to learn without being explicitly programmed (Samuel, 1959). In other words, the ML did not require human intervention. Samuel had the computer 'watch' over tens of thousands of games and code itself to play checkers. The program sought to "understand" what were good and bad board positions and ultimately became a better player than its developer. Mitchell (1997: 2) more formally defined ML as "a computer program [that] learn[s] from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E". The learning process is often posed as absent humans, as algorithms automatically analyze data (Fiebrink & Gillies, 2018). Developing automated algorithms seems to be a fundamental objective of ML (Holzinger et al., 2019). Holzinger et al. term these algorithms "automated Machine Learning" (aML) as recent studies have started conceiving of a new human-centered perspective of ML to act as a corrective to the disadvantages of automatic approaches.

Automated approaches, while convenient and potentially insightful, consume sizeable resources (e.g., computing power) and require massive amounts of data, for example to train a topic model. Most ML algorithms are considered black-boxes, in which the mathematical principles are too complex to understand. There is now a substantial literature on Fairness, Accountability and Transparency in ML that concerns itself with the ethical problems of that opacity (Mittelstadt et al., 2016). One identified problem of automated approaches is that they are not truly automatic. The term automation conceals considerable human efforts, including bias, in choosing and adapting algorithms, collecting (e.g., lemmatizing) data, and deciding what to model in the beginning (Gillies et al., 2016).

To address the ethical concerns and better integrate people into ML development, researchers have proposed an approach called HCML. Riedl (2019: 2) provides a justification,

> At the heart of human-centered AI is the recognition that the way intelligent systems solve problems—especially when using machine learning—is fundamentally alien to humans without training in computer science or AI. We are used to interacting with other people, and we have developed powerful abilities to predict what other people will do any why.

HCML can be broadly explained as “combin[ing] human insights and domain expertise with data-driven predictions to answer societal questions” (Chancellor, Baumer & de Choudhury, 2019: 1). There are slight variants of HCML. Human-in-the-Loop (HITL) is an approach in which humans can be used to train or test an algorithm rather than only adjust models before or after the learning process (Holzinger et al., 2019). HITL tends to be more algorithmic-driven, in that humans are used to optimize or correct the algorithms, for example by validating intermediate results or annotating texts. Chellapilla and Simard

(2005) engaged humans, via CAPTCHA, to determine the smallest task that is both human and machine readable. Interactive Machine Learning (iML) commonly refers to ML approaches that have an user-facing design, usually for generating training examples for algorithmic learning. Fails and Olsen (2003) utilized iML to an image segmentation task by having users iteratively provide corrective feedback to the learner after examining its output.

HCML refers to diverse problems, methods, technologies and theories as reviewed by Fiebrink and Gillies (2018). Consequently, there are no single definitions of the concepts or syntheses of goals. Zhou and Chen (2018a) come the closest and yet they use these as a way to organize chapters instead of providing definitions or synthesis. We borrow their chapter organization to distill four general characteristics of HCML: visible, explainable, trustworthy and transparent. Visible builds on the large body of research conducted in Human-Computer Interfaces (HCI) and refers to the need to visualize and enable interactivity of ML (Sacha et al., 2017). Visible is operationalized, for example as interacting with the ML processes (via a user interface), providing visual analytics, and displaying (e.g., mapping) probabilities or clusters (Chen et al., 2016; Sacha et al., 2017). Explainable refers to the interpretability of ML to developers and end users, for instance highlighting which parts of a feature influences its classification or why inferences are made (e.g., based on keywords) (Doshi-Velez & Kim, 2017; Zhou & Chen, 2018b). The classic definition for trust is the ability of one entity to rely on another as they are in a relationship with each other (Gambetta, 1988); for ML, trustworthy is usually operationalized by listing, rating and aggregating measures of risk (cf., Canada's Directive on Automated Decision Making, https://www.tbs-sct.gc.ca/pol/doc-eng.aspx?id=32592). Transparency refers to how algorithms act on the data, generate data, how the algorithm deals with uncertainty and how to better connect the end users with the thought processes of the algorithm developers (Zhou & Chen, 2018b).

As much as terms like "trustworthy" evoke a kind of qualitative human engagement in the process of ML, HCML tends to be highly computational. Zhou and Chen (2018b) argue that the trouble with characteristics like explainable ML are that the methods come from AI/ML experts and not domain (e.g., social science) users. It also could be in the way human-centered is conceived. In their review of the HCML literature, Chancellor et al. (2019) found five different representations of humans, from patient to ML object to person--their study area was ML analysis of mental health as expressed through social media. They argue that different representations of humans pose a problem for interdisciplinary research, since disciplines use the same words but the underlying semantics profoundly and substantially differ. This creates "a paradoxical representation within HCML of the human as being both in the "subject" and "object" positions, where humans are both centered and prioritized in the analyses but are also the object of machine learning techniques" (Chancellor et al., 2019: 3). HCML shares characteristics with the urban science/smart city mentioned above, which can treat humans as data points, sensors to be analyzed and aggregated. Instead of considering humans as engaged citizens, that approach can reduce people to data sources for more efficient city operations (Mattern, 2017). Following on Zhou and Chen (2018a), we believe Chancellor et al. (2019) missed a sixth category: human-as-researcher. Chancellor et al. (2019: 16) argue that, among their five categories, "HCML uniquely risks dehumanizing individuals because of the paradoxical contrast of its human-centered commitments and the ways of knowing in AI and machine learning". That argument could just as easily refer to social scientists (the beneficiaries of the research) using data science methods, who could be diminished to tool users applying default parameters instead of more actively engaging in the methods. We advocate for a qualitative approach in considering humans as researchers and the choices they make in the development and deployment of ML, in this case, topic modelling.

Ultimately, there is a push-and-pull impulse to automate the sensing of the smart city, aided in large part by big data, whether generated by sensors or legacy government documents. This data-driven approach is coupled with a growing realization of the limits of this automation, that a comprehensive interpretation of the smart city is not free of bias or human intervention. There is a push to bring the human back in. This re-centring of the human is what drives our research.

3.3 Method and Case Study

To investigate how human intervention works in smart city research, we conduct a case study, where we use topic modelling to extract topics from the SCC texts and interpret the smart city based on the topics. This section presents the methodological details of applying topic modelling so that we then can identify the human intervention during this process.

3.3.1 Case Study: Interpret the Smart City via the SCC

The Canadian federal government launched the SCC competition in November 2017 to encourage Canadian communities to propose projects that would improve the lives of their residents through innovation, data and interoperable technology (Infrastructure Canada, 2017). By March 5 of 2019, the federal government received 130 applications from 199 communities (communities could apply jointly) and 20 proposals from 34 finalists (communities whose applications were admitted) (Infrastructure Canada, 2017; 2018). SCC applications or proposals are supposed to support smart city initiatives as varied as managing autonomous vehicles (in Vancouver's proposal) or data governance (in Montreal's proposal). From these finalists, the federal government, on May 20 of 2019, recognized four winners and awarded them with grants from $5 to $50 million.

We collect the documents from the local governments' official websites; 13 applications not available online nor offered by the corresponding communities. Overall, our choice of SCC documents allows us to conduct an 'apple-to-apple' comparison because the documents were grant applications written in a relatively standardized format. The results of those topic models are reported in the next chapter.

We choose to separately analyze the two stages of the SCC: the grant application stage and final proposal stage. We create two corpora, one that combines 117 original applications and one that combines 20 finalist proposals. We then create a topic model for each corpus. Our goal is to see if we can identify any changes from the first to second stage.

3.3.2 Data Preprocessing

As a first step to topic modelling, we clean the data. Real world data can be noisy, for example, caused by improper entry, sensor failures or system error. It can also be irrelevant (e.g., less contribute to the goal of analysis) or contain missing attributes (i.e., incomplete or insufficient data records) (Famili et al., 1997). Only after cleaning can we apply the algorithms to the data.

Several steps are required so data is ready to use. The first problem is that documents are written in two languages because Canada at the federal level is officially bilingual. Since the majority (117 out of 137) are in English, we decide to translate the 20 documents that are in French to English. We employ Google's Neural Machine Translation (NMT) to conduct the document conversion. A second problem is the noise in our data. These are manual processes. We remove words, including "Canada", "smart", "cities" or "challenge", "application", "proposal" and names of communities and provinces, that are less informative for answering research questions and consume resources for analysis. We replace acronyms with original spelled-out words to increase the readability and prevent them from becoming noise. Last, we use a standard Natural Language Toolkit (NLTK 3.5) stop words list of 128 English words that are ignored by most searching engines, which eliminated what is another traditional component of noise in NLP called “stop words” like “a”, “an”, “the”, “in”, “on” and “to”.

A corpus is a compilation of documents, represented by a word matrix, and yet the modelling treats the documents, vectors in the matrix, separately. This is why the modelling requires both a sufficient number of documents and an adequate length of each document. In practice, there is no determination of an adequate size of corpus. Blei et al. (2003) apply LDA to two corpora of 5,225 abstracts and 16,333 articles; numerous examples of topic modelling do not approach this size of corpora (e.g., Kling & Pozdnoukhov, 2012; Leydesdorff & Nerghes, 2017; Mohr and Bogdanov, 2013). In our corpora, each of the 117 SCC applications contains approximately 8,000 words; each of the 20 SCC proposals contains over 30,000 words. Individual documents may be adequate in length but there may be an insufficient number of them. Hence, we choose to divide each application into eight equal chunks and each proposal to 32 chunks to generate more “documents”. From this, we obtain 936 chunks for the first model and 640 chunks for the second model, where each document contains approximately 1,000 words. We base our choices in comparison to some previous studies (e.g., Leydesdorff & Nerghes, 2017; Mohr and Bogdanov, 2013) although few articles explain why these operations are necessary nor what constitutes optimization.

Topic modelling requires a word matrix instead of raw text as inputs (Blei et al., 2003). Raw text should first be tokenized and vectorized. With tokenization, we break the texts up into lists of words without space and punctuation. We lemmatize the lists of words by reducing them into their base terms (“proposed”, “proposing” and “proposed” becomes “propos”). This yields a total number of 14,963 unique terms from SCC grant applications and 13,083 unique terms from SCC final proposals. We vectorize the lists of terms by using software to create a matrix showing the relationship between every term to every other term. As with similar studies, we employ functions in the Gensim library to conduct the above processing. Other libraries (e.g., Scikit-Learn library) are also useful.

3.3.3 Model Building

A topic model results from the application of a topic modelling algorithm to a corpus. We choose LDA, one of the most popular topic modelling algorithms, to build our models (e.g., Hasan & Ukkusuri, 2014; Kinoshita et al., 2015; Kling & Pozdnoukhov, 2012). Compared to LSA and NMF that analyzes documents independently, LDA analyzes documents (e.g., the 936 separate word vector matrices) together during the modelling process by assuming that every document is more or less related to all topics. Since we are more interested in inter-document similarity than in difference, we feel that LDA is better suited for interpreting the smart city by summarizing cases across Canada. We also choose an extant function in the Gensim library to implement LDA. Gensim has been used in other smart city research that applies topic modelling (e.g., Pereira, 2017). The library has various useful functions like a visualization tool, pyLDAvis, for displaying topics in a model. Per below, Gensim also provides functions to assess coherence and perplexity.

Topic modelling does not automatically determine an optimal number of topics. (Other parameters that we leave as default, per Jacobi et al., 2016). Topic coherence (Röder et al., 2015) and perplexity (Blei et al., 2003) are two common measures for suggesting the number of topics. Similar to other studies (e.g., Jacobi et al., 2016), we run topic modelling multiple times with different numbers of topics. We calculate the topic coherence score each time and examine the topics to see whether the topics can be easily explained and interpreted. Values of coherence scores range between 0 and 1; a higher coherence score indicates a better topic model (Jacobi et al., 2016). Ideally, as the number of topics increases, the coherence score increases and then slows its increase, coalescing around a maximal coherence value (Röder et al., 2015). After convergence, an increase in the number of topics will lead to more overlap among topics (Röder et al., 2015). The earliest the coherence score achieves its maximal value is ideally considered the optimal number of topics for LDA. In practice, the convergence is based on probabilities instead of a specific value and the coherence scores do not monotonically increase (the values move up and down even when converging). We argue that it is more appropriate to seek for an optimal range instead of an optimal number of topics based on coherence score. Within the range, we then consider the explainability and interpretability of the model to finally determine the number of topics. We do this process twice to generate two models. Each model consists of multiple clusters of words, where each cluster represents a topic. We call one model the grant application model (GAM) and another the final proposal model (FPM).

3.3.4 Post-processing

Even though topic modelling can rapidly synthesize a large volume of text, the utility of those results are not immediately apparent after modelling. One essentially obtains a probabilistic set of word clusters. It is not immediately obvious what these clusters mean or how distributed these clusters are. We conduct three visualizations to enhance the resulting topics of GAM and FPM. The visualizations, together with cosine measures, contribute to comparing topics of two models to detect any changes from the SCC application stage to proposal stage. These post-processing steps help us in labelling the topics.

Our first visualization is the standard in the field, a visualization that shows the intertopic distance map. We use pyLDAvis to create the map through reducing the multi-dimensional topic-term distribution matrix into a two-dimensional distance matrix. The outputs are shown on interactive HTML files. Note that the patterns of word distribution are latent; the topics are only a cluster of terms but are not explicitly labelled. Labelling topics is a common practice in topic modelling (e.g., Crowston et al., 2012), which is not necessary but often done for the convenience of interpretation. The label of a topic usually refers to the primary and secondary terms or with n-grams. We use this visualization as well as examine the 30 most frequent terms of a topic to generate the label.

Our second visualization is of the geographic distribution of topics. We geocode the predominant topic of each application with the centroid of that community's longitude and latitude. Geovisualization integrates geographical context into our interpretation by showing any can reveal any spatial patterns in the use of topics.

The last visualization is co-words mapping. Co-words mapping infers the semantic structures of words based on the words' networks of co-occurrence. Leydesdorff and Nerghes (2017) regard topic modelling as an improvement over co-words mapping, although they demonstrate that topic modelling does not outperform co-words mapping when dealing with a small corpus (document numbering less than 1,000). They argue that topic models generated from a small corpus are less interpretable, but they also note that "the qualitative interpretability of topics in terms of words does not inform us about the quality of the clustering of the documents in the set" (Leydesdorff and Nerghes, 2017: 1032). Although we use small corpora, it remains to be discussed whether our topic models are interpretable and cluster the words well. Co-words mapping is not a post-processing of the results (i.e., not on models), but reprocessing the data (i.e., corpora). We compare co-words maps with topic models to triangulate the results of topic modelling.

We also wish to evaluate differences and similarities between the two corpora. Cosine measure is a frequently used method to quantify similarity between topic models (e.g., He et al., 2009; Ramage et al., 2009), which contribute to explaining the models and inferring changes. Note that post-processing of topic modelling makes the results more interpretable; nevertheless, it might be a simplification that supports users' arguments with bias. The arguments based on this process should not be exclusive and reject other possibilities to interpret the results. For example, the visualizations are all in a two-dimensional plane where we project a multi-dimensional topic-term distribution matrix. Inferring arguments from the post-processing should have further reflection.

3.4 Results and Discussion

In this section, we present the results of the case study. We then discuss all the ways in which an ostensible automated process requires human choices in the parameterization and interpretation of results.

3.4.1 Preliminary Statistics of Words/Terms

Figures 1 and 2 show a 'first pass' in assessing the models generated from the grant applications and final proposals by examining the predominance of terms. It is unsurprising that the terms "datum" and "technology" are the most popular terms in both sets of documents since the rhetoric of the smart city is so aligned with data-driven and technology-based solutions. Cohen (2015) is one of many researchers who track the evolution of smart cities. Cohen (2015) proposes three simultaneous generations of smart cities that can frame the terms we observe in the corpora. "Datum" and "technology" exemplify the first generation, "Technology-Driven" smart cities. In the second generation, the core value of smart cities shifts to "Technology Enabled, City Led" (Cohen, 2015). This value can be inferred in terms such as "service," "provide," "support," "plan," and "development". The third generation of smart cities is about "Co-Creation" (Cohen, 2015) that is reflected in terms like "include," "engagement," "create," "make," and "design". The corpora cohere with the smart city literature and Cohen's smart city evolution.

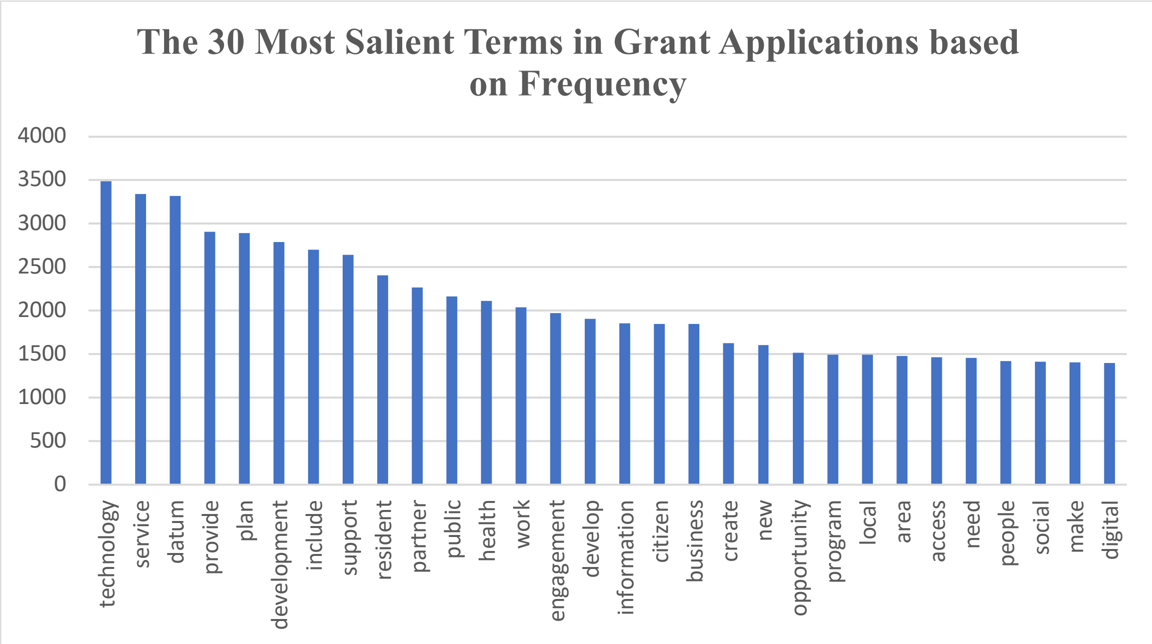

Figure 1. The 30 Most Frequent Terms in Grant Application

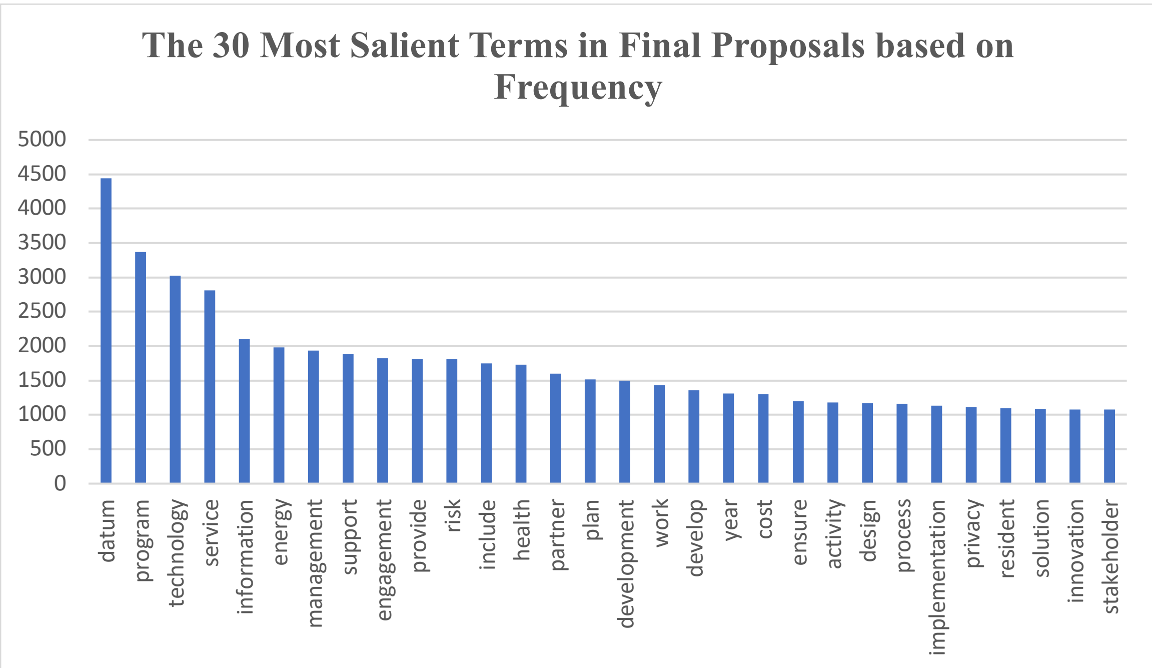

Figure 2. The 30 Most Frequent Terms in Final Proposals

One ‘take away’ from Figures 1 and 2 is that many terms (technology, service, datum, provide, plan, development, include, support) that might emerge in a topic model are not particularly useful for analysis. One needs to “scrub” a corpus of high frequency terms or low frequency terms. We might wish to examine the corpus for words that, for a domain like smart city, are irrelevant because those words are likely to appear and are thus noise. This is an under investigated issue with topic modelling: how non-automated and non-inductive the approach actually is and how much one has to manipulate the text to optimize results.

3.4.2 Topics Distribution in GAM and FPM

Topics generated by the two topic models, GAM and FPM, are presented in Tables 1 and 2. Table 1 shows the 20 topics of GAM, ranked according to how much each topic contributes to the overall model. For each topic, the number of applications to which that cluster of terms appeared are displayed in the table. The topic contribution rate is the term/token probability, which aggregates the frequency of the over ten thousand terms in the corpus divided by the frequency of that term in the corpus. Word probability normalizes different terms in the corpus and measures the degree to which a topic captures specific terms in the corpus. In the last column, we list the ten most frequent terms associated with each topic. Table 2 contains the same columns as Table 1 except that the word “proposal” replaces “application”, showing the thirteen topics generated for the FPM.

Table 1. Topics of GAM

Topic Names	Applications Counted	Topic Contribution (TC) %	The 5 Most Frequent Terms
Partnership	117	10.3	partner, provide, partnership, design, development
Digital Services	117	9.0	service, datum, information, access, provide
Public Consultation	117	7.4	idea, activity, citizen, consultation, meeting
Economic Opportunity	117	7.0	business, economic, opportunity, local, economy
Citizen & Urban Development	117	6.9	citizen, urban, develop, development, technology
Transportation/ Mobility	113	6.4	transportation, mobility, active, travel, public
Urban Planning	117	6.3	plan, strategy, development, support, strategic
Management	117	6.1	management, partner, ensure, implementation, process
Youth/ Child	117	5.9	youth, social, child, people, belong
Data Solutions	116	5.8	datum, innovation, technology, solution, develop
Public Engagement	117	5.3	engagement, resident, survey, public, feedback
Connected Technology	116	4.9	technology, digital, platform, datum, new
Demography	117	3.6	population, achieve, statement, resident, province
Culture, Education & Language	116	2.8	world, knowledge, language, facilitate, traditional
Innovation	103	2.8	provide, preliminary, innovation, information, technology
Utilities Cost	114	2.8	cost, increase, waste, year, reduce
Housing & Energy	97	2.7	energy, housing, building, affordability, affordable
Safety & Emergency Response	110	2.6	safety, emergency, area, sensor, public
Health Care	59	1.1	health, senior, healthy, care, social
Food & Agriculture	17	0.3	food, farm, agriculture, farmer, affirm

Table 2. Topics of FPM

Topic Names	Proposals Counted	Topic Contribution (TC) %	The 5 Most Frequent Terms
Public Engagement	19	15.3	engagement, stakeholder, activity, resident, provide
Risk & Management	20	15.1	risk, management, program, plan, governance
Health Care	20	13.1	health, technology, service, resident, vision
Data Solutions	20	9.1	datum, mobility, partner, technology, open
Information Privacy	20	8.3	information, datum, privacy, personal, security
Youth/ Child & Culture, Education	20	7.7	youth, indigenous, child, support, program
Digital Services	20	6.3	service, technology, user, solution, connect
Housing & Energy	20	5.5	program, energy, housing, service, year
Food & Agriculture	19	5.5	food, agora, farm, support, rural
Transportation/ Mobility	20	4.9	mobility, transportation, indicator, transit, prosperity_partnership
Innovation & Budget	20	4.0	innovation, fund, makerspace, development, funding
Housing & Culture	19	3.0	inuit, housing, construction, building, home
Utilities Cost	20	2.2	cost, total, year, subtotal, source

With topics, we can observe how little technologies are mentioned in the applications. For instance, we fail to see a prevalence of terms like AI or autonomous (autonomous vehicles) emerging as terms with significant probability (the only exception is drones, which is related to agriculture). Neirotti et al. (2014) makes a distinction between "hard" technical domains like transportation and energy and soft domains like culture. The corpora reveals a prevalence of soft domains like public engagement and youth/child. The emphasis placed on non-explicitly technological themes suggests that, for Canadian smart communities, smartness does not need to equate with technical innovations. Chapter 4 contains far greater detail about the implications of the distributions, the distinctness of Canadian "cities" compared to other smart cities, and the impact of choosing the term community over city.

To further assist in interpreting topics, we utilize a standard visualization of topic models with pyLDAvis. The first set of snapshots (Figures 3 to 5) show the modelling results of the GAM. Figure 3 exhibits the 30 most frequent probabilistic terms in the original grant applications as well as the 20 topics/clusters of GAM. Each topic is represented by a circle with the circle size indicating the contribution of this topic to the model. The two topics, with a small size (topic contribution rate), appear on the left of the two-dimensional distance map and indicate that these two are less connected with other topics and may have unique insights that a researcher can investigate. Numerous topics overlap with each other, which indicates close relationships among some topics.

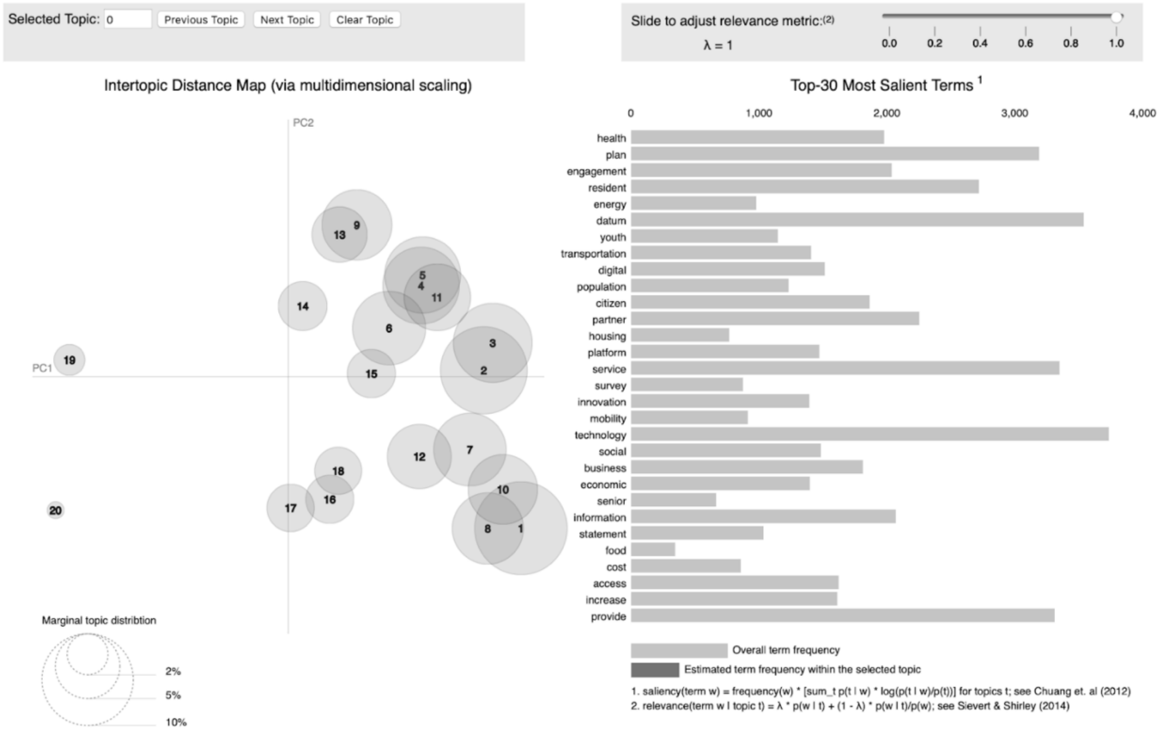

Figure 3. Interactive HTML of GAM (from pyLDAVis)

In typical LDA visualizations (here generated as an HTML), users can move the cursor to a topic and the page will highlight this topic with its 30 most frequent terms (Figure 4). If the cursor is on one of the most frequent terms, the page will display the contribution of this term to each topic through changing the size of topic circles (Figure 5). Topic 14, utilities cost is unsurprisingly distinct, in terms of associated terms, from other topics; whereas Topics 4 (Economic Opportunity), 5 (Citizen & Urban Development), and 11 (Public Engagement) exhibit considerable overlap. Despite differences associated terms, a researcher may not wish to treat these topics as strikingly different from each other.

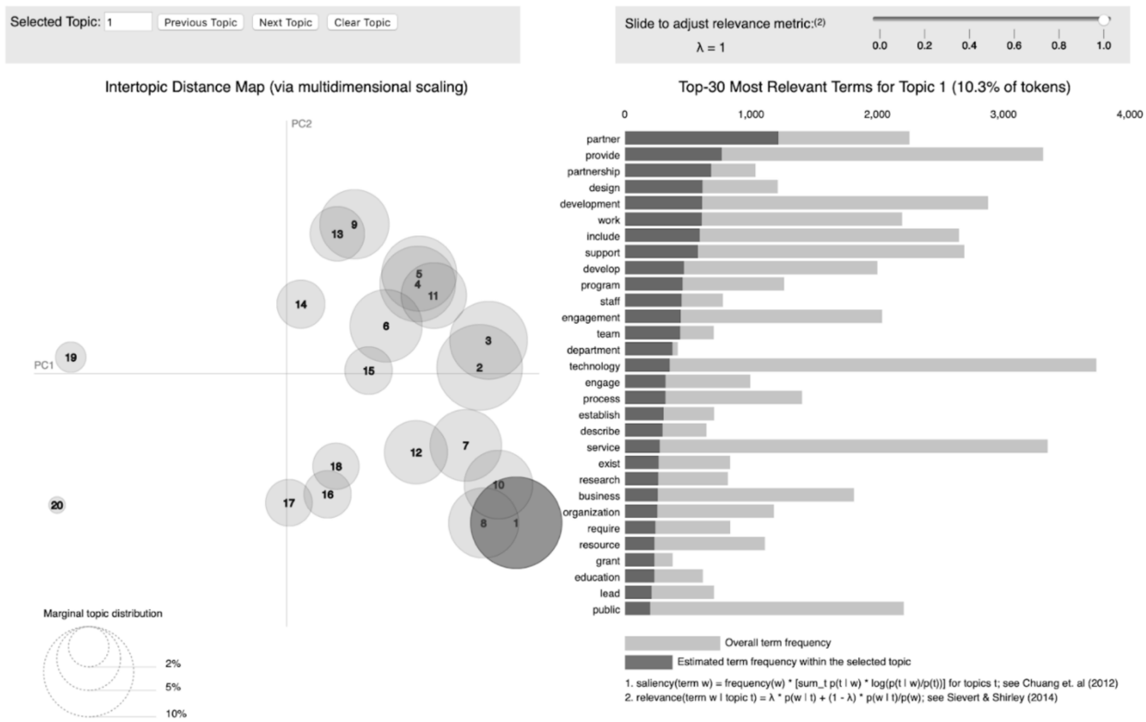

Figure 4. GAM Topic One "Partnership" and Its Top-30 Most Frequent Terms

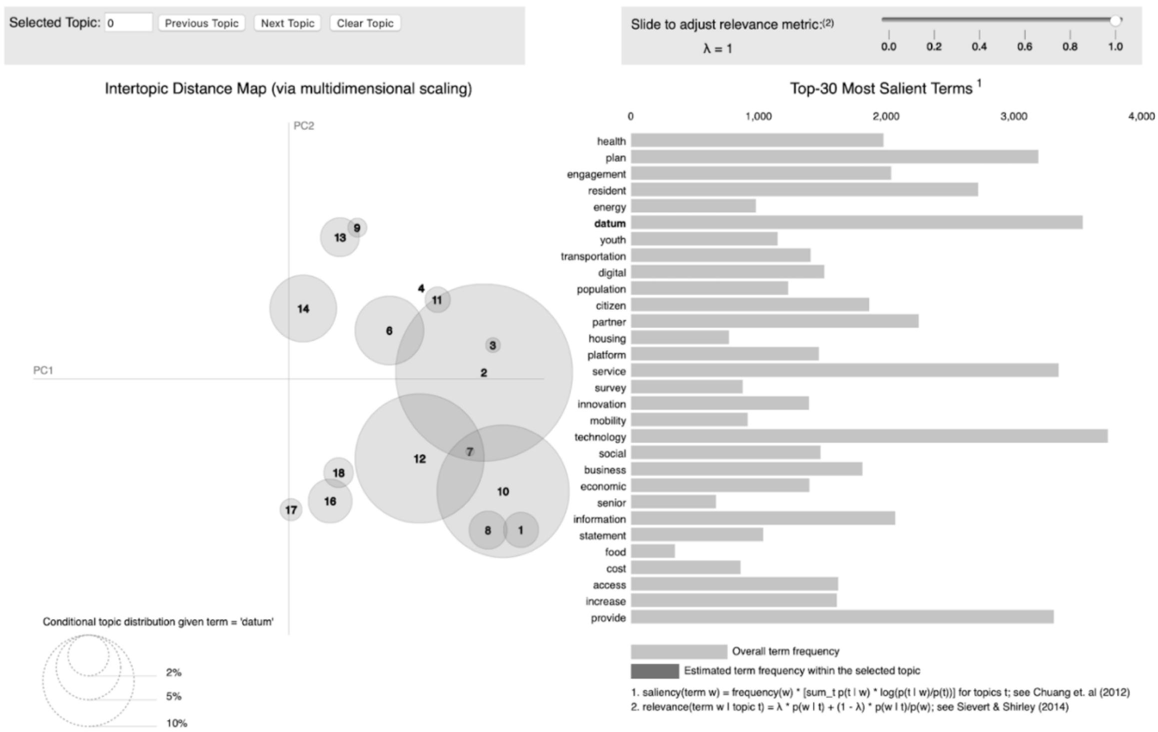

Figure 5. The Contribution of "Datum" to Each Topic of GAM

The snapshot above (Figure 6) presents the modelling results of the FPM, which shows the 13 topics and 30 most frequent terms associated with those topics. Similar to the first snapshot, Figure 6 also suggests distant topics and overlapped topics worth investigating for potential inference. Likewise, the cursor movements in the HTML can function for highlighting topics and its most frequent terms.

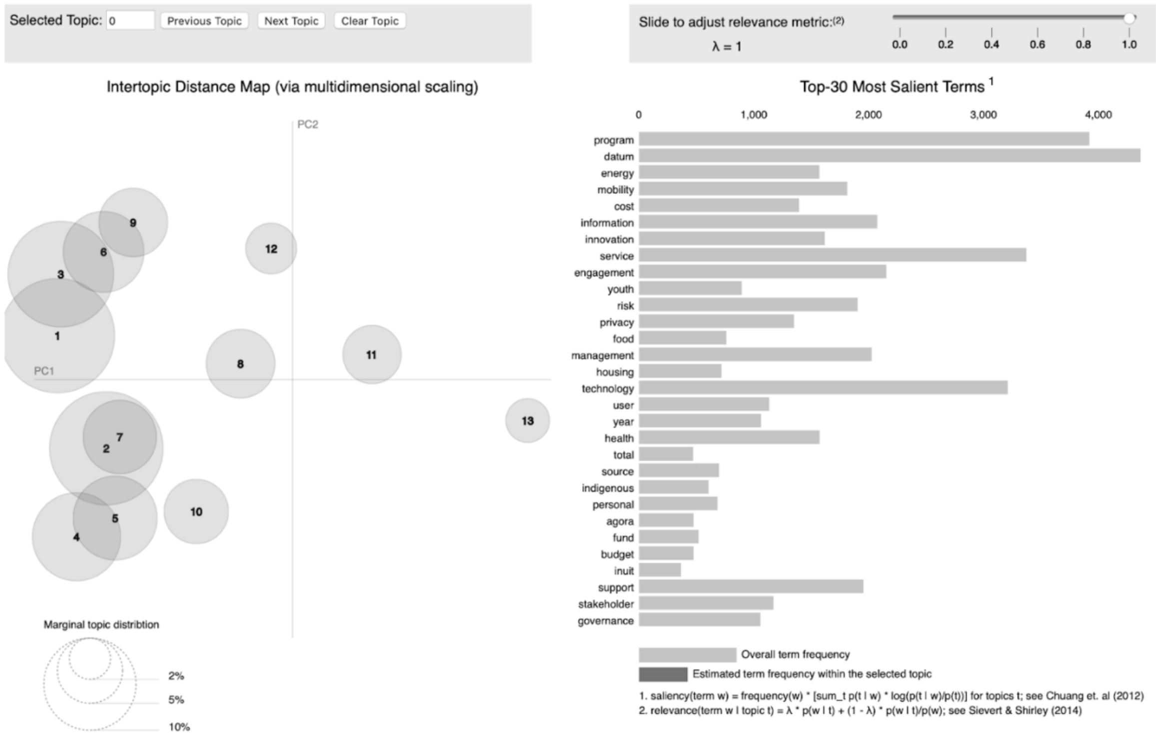

Figure 6. Interactive HTML of FPM (from pyLDAVis)

3.4.3 Geographic Topics Mapping

We can create maps showing geographic clustering of the dominant topic of grand applications and final proposals. Figures 7 and 8 show snapshots of two interactive online maps[1] that locate the dominant topics as centroids of cities and communities submitting

[1] The web map of dominant topics of each grant application: https://www.google.com/maps/d/viewer?mid=1pgdQBbnsFXzBarVtQj0MOPoVIrahxDsz&ll=59.31909286797678%2C-99.15641693295981&z=4
The web map of dominant topics of each final proposal: https://www.google.com/maps/d/viewer?mid=1ugnYDKWyTuOsoIFJ_6wnNsLIFItWP3Bj&ll=59.42129324719199%2C-99.03983025000002&z=4

applications. Fifteen out of twenty GAM topics appear as the dominant topic in an application in Figure 7. The fifteen topics are categorized into six categories, for mapping convenience (less check boxes, easier to interact), that are “data, technology & connectivity”, “economy, partnership & innovation”, “housing, energy & resource”, “transportation, safety & emergency”, “citizen, urban development & public consultation” and “culture, education & youth”. Figure 8 displays eleven FPM topics appearing as the dominant topic in a proposal. The eleven FPM topics are categorized into more categories since they are less related to each other. The categories are “data, technology & connectivity”, “management & engagement”, “transportation”, “privacy”, “housing, energy & culture”, “health”, “food” and “culture, education & youth”. In both interactive maps, we can select all or any of the areas for descriptions of dominant topics.

Figure 7. The Map of Dominant Topics in Grant Applications

Figure 8. The Map of Dominant Topics in Final Proposals

3.4.4 Triangulation: Co-words Mapping

The co-words mapping results in two density maps (Figures 9 and 10) of grant applications and final proposals. Each density map contains a group of clusters of terms that are compared with the topics. Frequent terms in the clusters are reflected in larger size and higher opacity on the map. Generally, the co-words clusters reflect the topics extracted (terms in topic can be found in co-words maps). The most frequent terms cluster on particular topics like innovation and youth/child in Figure 9 and utility cost and youth/child in Figure 10. The mapping appears to triangulate the interpretation of the topic modelling and the choice of labels.

Figure 9. Density Map of Co-Words Mapping of Grant Applications

Figure 10. Density Map of Co-Words Mapping of Final Proposals

3.4.5 Evaluation: Coherence and Cosine Similarity

One goal of our project is to compare corpora to determine whether themes have evolved from the first stage of the SCC to the final stage. Prior to comparison across models, it is necessary to examine whether topics within each model are sufficiently coherent. If topics in a model are unrelated and challenging to interpret collectively, then the similarity between topics of two models cannot be assessed. Figure 11 illustrates the relation between the coherence score and the number of topics in GAM; Figure 12 does the same for the FPM. A coherence score initially increases with the number of topics. The convention is to choose the number of topics when coherence becomes stable at a range (Röder et al., 2015), in this study it is between 0.40 and 0.50. We ultimately decide on 20 topics for GAM and 13 topics for FPM.

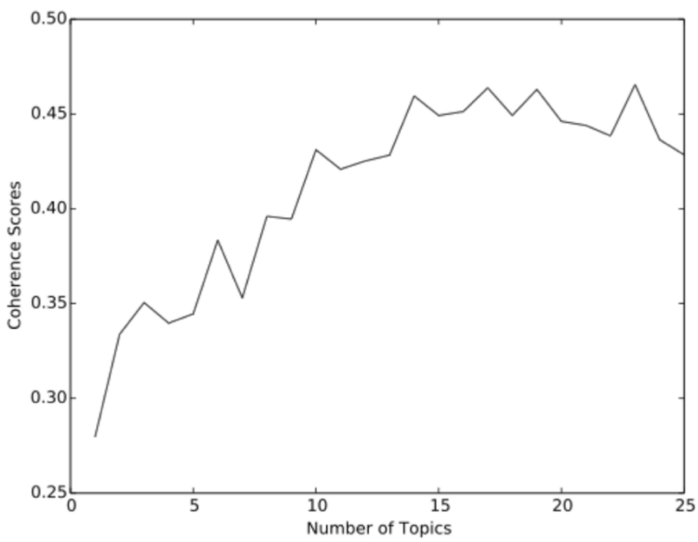

Figure 11. Coherence Scores of GAM over Different Topic Numbers

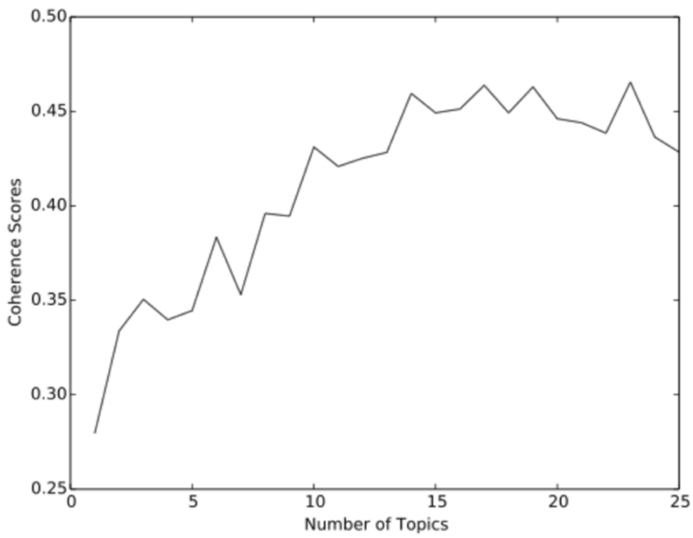

Figure 12. Coherence Scores of FPM over Different Topic Numbers

After the examination of model coherence, we can compare results from cosine similarity (Table 3). We compare every pair of GAM-FPM topics (260 comparisons) and calculate the cosine similarity score of each pair. Scores in bold represent a pair of a FPM topic and its most similar GAM topic. Underlined scores represent pairs of a GAM topic with their most similar FPM topic. Ten pairs of topics have a score in bold and underlined; those scores range from 0.381 to 0.673. Based on topic similarity, we are able to determine which topics should be discussed together and which should be further explored (Aletras & Stevenson, 2014). For example, the topic public engagement in FPM appears related to both the topics public consultation and public engagement in the GAM. It is worth exploring what is contained in proposals in which the FPM topic health care is significant because it corresponds to multiple GAM topics. A topic might not be the best unit of analysis or interpretation since, as indicated, there could be subclusters within a topic that can suggest nuances within the two sets of modelling results.

Table 3. Cosine Similarity Matrix of GAM and FPM Topics

FPM Topics / **GAM Topics**	Public Engagement	Risk & Management	Health Care	Data Solutions	Information Privacy	Youth/ Child & Culture, Education	Digital Services	Housing & Energy	Food & Agriculture	Transportation / Mobility	Innovation & Funding	Housing & Culture	Utilities Cost
Partnership	0.459	0.535	0.357	0.285	0.128	0.333	0.263	0.197	0.250	0.114	0.266	0.145	0.051
Digital Services	0.339	0.213	0.386	0.533	**0.518**	0.242	**0.575**	0.203	0.194	0.186	0.129	0.084	0.030
Public Consultation	0.504	0.243	0.313	0.167	0.115	0.222	0.103	0.042	0.161	0.114	0.147	0.142	0.021
Economic Opportunity	0.213	0.147	0.347	0.093	0.058	0.280	0.155	0.053	0.432	0.080	0.152	0.107	0.032
Citizen & Urban Development	0.230	0.122	**0.466**	0.189	0.054	0.168	0.200	0.052	0.186	0.105	0.114	0.139	0.027
Transportation/ Mobility	0.149	0.104	0.285	0.215	0.139	0.084	0.202	0.051	0.105	**0.568**	0.053	0.047	0.013
Urban Planning	0.226	0.435	0.233	0.139	0.062	0.208	0.108	0.081	0.191	0.098	0.126	0.060	0.027
Management	0.342	**0.629**	0.259	0.309	0.182	0.200	0.236	0.122	0.159	0.127	0.208	0.144	0.151
Youth/ Child	0.219	0.135	0.368	0.073	0.084	**0.673**	0.112	0.080	0.181	0.096	0.053	0.121	0.016
Data Solutions	0.348	0.274	0.451	**0.597**	0.262	0.218	0.242	0.074	0.292	0.100	**0.339**	0.112	0.037
Public Engagement	**0.660**	0.132	0.232	0.065	0.061	0.115	0.043	0.052	0.086	0.156	0.038	0.057	0.036
Connected Technology	0.173	0.164	0.379	0.574	0.311	0.153	0.438	0.056	0.217	0.106	0.166	0.072	0.026
Demography	0.181	0.091	0.284	0.084	0.149	0.159	0.076	0.058	0.127	0.113	0.044	0.044	0.036
Culture, Education & Language	0.210	0.142	0.183	0.123	0.106	0.253	0.157	0.041	0.099	0.059	0.091	0.145	0.046
Innovation	0.173	0.185	0.308	0.215	0.284	0.154	0.306	0.051	0.170	0.105	0.267	0.036	0.074
Utilities Cost	0.154	0.131	0.167	0.209	0.175	0.139	0.102	0.092	0.235	0.231	0.138	0.087	**0.381**
Housing & Energy	0.056	0.080	0.082	0.054	0.044	0.073	0.054	**0.570**	0.057	0.062	0.073	**0.377**	0.118
Safety & Emergency Response	0.173	0.190	0.226	0.110	0.183	0.107	0.138	0.034	0.154	0.080	0.062	0.082	0.025
Health Care	0.100	0.005	0.430	0.006	0.094	0.020	0.018	0.011	0.043	0.013	0.003	0.008	0.015
Food & Agriculture	0.003	0.001	0.003	0.005	0.011	0.000	0.001	0.001	**0.595**	0.001	0.000	0.003	0.004

3.4.6 Human Intervention in the Topic Modelling

We have demonstrated the utility of topic modelling to interpret the smart city. We also have alluded to the numerous choices that researchers must make as a part of the process and the interpretation of results. To show how the tool is far from automated, we summarize human intervention in the application of topic modelling to documents of the SCC. Table 4 organizes the steps in which human judgement is required. We further structure the steps by whether they exhibit characteristics of HCML: visible, explainable, trustworthy and transparent.

Table 4. Human Intervention in the Application of Topic Modelling to the SCC

Stages	Implementations	Human Intervention/Judgement Calls	HCML Characteristics
Data Collection	1. Collect available SCC applications and proposals	The choice of research subject, study area, corpus	Explainable
Preprocessing	1. Translate French documents into English	The manner or software used to translate, choice of which items to translate (e.g., the minority language to the majority or the converse)	Transparent
	2. Clean non-value-adding and noisy words	The words that are less informative and noisy, also stop words	Explainable, Transparent
	3. Equally divide each document into chunks	The number and length of documents in the corpus	Explainable, Trustworthy, Transparent
	4. Tokenize and lemmatize the documents	The forms of words (e.g., nouns, verbs) to remain	Explainable
	5. Vectorize the words	The ways to encode vectors from documents (e.g., frequency vectors, distributed representation)	Explainable, Transparent
Model Building	1. Choose algorithm to build topic models	The process of modelling	Explainable, Trustworthy, Transparent
	2. Determine the number of topics for a model	The number of clusters of words expected in a corpus	Explainable, Trustworthy, Transparent
Post-processing	1.Identify the dominant topic of each document	Manipulation and presentation of statistical indicators of topic models	Explainable, Transparent
	2. Identify the most representative document of each topic		
	3. Triangulate the topic modelling results	Comparison to other techniques (here co-words mapping)	Explainable, Transparent, Visible
	4. Comparison across models	Determination of similarity between models	Explainable, Transparent
Results Interpretation	1. Labelling	Assignment of a name to a word cluster	Explainable
	2. Visualization	Methods of visualization (here LDAVis, geographic visualization, co-words mapping)	Visible, Explainable
	3. Contextualization	Review of community contexts, original documents	Explainable, Trustworthy, Transparent

Even though it precedes the ML, human intervention starts at the data collection stage. As aforementioned, the assumption in topic modelling is for a certain level of homogeneity of documents in the corpus, whether they are tweets, which are actually highly structured records, or grant applications and proposals. Consequently, we make decisions on what to model based on having a sufficiently large volume of homogeneous documents. The decisions at this early stage can influence how we later interpret the topic modelling results.

Judgement calls are more obvious at the data preprocessing stage as all analysis models require the data to be prepared subsequent to data collection. For instance, we might have to change the data structure (e.g., data formats or levels of granularity to be processed) (Famili et al., 1997). Restructuring data requires care since bias can be introduced even in the choice of translation mechanism (human or machine). Google's NMT translates a whole sentence at a time and improves on word to word translation. But might still not be as competent as a human translator. We decide to employ NMT since manual translation will consume tremendous amounts of time and energy. Explicating the translation mechanism increases the transparency of this process.

We have to identify which words are noisy for topic modelling, which demands a solid understanding about the nature of the data and the domain. It is common in topic modelling to eliminate so-called "non-value-adding" words including stop words. Lists of stop words provided by popular NLP libraries vary slightly. Researchers can expand the list by adding corpus-specific stopwords, although expanding the list has proved to be of little use for improving the outcome (Schofield, Magnusson & Mimno, 2017). One of the most subjective judgement calls is removing high frequency words and low frequency words (e.g., that only occur in a single document (Asmussen & Møller, 2019). For example, high frequency words like “Canada”, “challenge”, “application” and “proposal” could lead to unwanted and meaningless co-occurrence patterns in this study. Low frequency words, like a specific placename mentioned in a document from a particular community, provide little benefit in producing topics that should reflect the whole corpus. Cleaning non-value-adding words saves computational resources to generate the models and reduces the possibility of resulting in ‘low value’ and obvious topics. It renders the topics more explainable. At minimum these removals must be made transparent to ensure repeatability. It is worth examining the sensitivity of topics to these removals.

We determine the number and length of documents in a corpus for topic modelling by dividing them into chunks. Based on how LDA works, which tracks co-occurrence of words across documents, the division likely will not change the overall outcome but it may change how we interpret them. A naturally-occurring cluster of words could be separated. For example, we might be splitting the grant applications’ methods sections, which might result in a relevant concept being split across topics. Second, the distribution of words across documents, now actually, is across chunks. If we need to identify dominant topics of particular applications, we have to add up topic contributions of chunks belonging to the same applications. Our explanation of the effects of this dividing process depends on the understanding of the LDA algorithm, so it is important to make the LDA algorithm less opaque for users. The effects can be regarded as “risks” that are explicitly listed for a trust that the influence on modelling results are traceable and uncertainty embedded in the dividing process will not significantly alter the results.

Tokenization breaks texts into lists of words for modelling, which does not change any semantic information but does alter the semantic structure. Lemmatization changes the information to be modeled and needs further explanation for the judgement call. Some researchers might only keep particular forms of words to customize their topic modelling (e.g., Martin & Johnson, 2015). In this study, we retain all the nouns, verbs, adjectives and adverbs to have a corpus closer to the source, although this reduces consolidating verb tenses. Vectorization also affects the modelling in terms of the ways to encode vectors. Two different ways to encode vectors are: (1) frequency vectors by returning a count of each word in its position in the vector and (2) distributed representation by embedding words in space along with similar words based on their context. The former usually leads to sparse vectors to represent documents; whereas, the latter results in representation of documents in a feature space. A major advantage of the latter is being able to detect the similarity between specific documents even if they do not share terms. Since we will not compare individual documents, we use the former encoding. Numerous tools are available for frequency vectors encoding and may pose little difference regarding the implementations. However, words, their order and co-occurrence, can produce different meanings in a sentence, which will influence how to understand the texts. The issue of data sparsity (i.e., a lack of word co-occurrence patterns) is so important in short messages, like Twitter, that researchers are frequently turning to topic modelling like biterm (Yan et al., 2013). In larger corpora, frequency vectors can be realized based on bigram (2 adjacent words), trigram (3 adjacent words) or higher n-grams transformation. We use the doc2bow function in Gensim to vectorize documents based on trigrams. Although trigarm transformation is more computationally expensive than vectorizing individual words, it ensures that we will not miss information on phrases composed of up to 3 words. The explainability and transparency of this vectorization process is critical as it offers the possibility to discuss any issues that might happen when quantifying the qualitative data for algorithmic analysis.

We choose LDA as the algorithm to generate topic models although other algorithms (e.g., LSA, NMF) can be used. As noted, LDA assumes that every document is somewhat related to all topics. Its probability distribution should lead to a more intuitive analysis process like humans reading relevant documents certainly with some prior knowledge. Compared to LSA or NMF, LDA "heavily" processes the texts to make the modelling easier to explain and trust in general. Even if explainable, LDA does complicate transparency.

We also need to determine the number of topics in a model by examining its coherence score. There is no set threshold in the literature and researchers are silent on the appropriate number of topics (cf., Jacobi et al., 2016). The number of topics will decide the granularity of a topic, which can slightly change how we interpret the model (during the cosine similarity we found informative subclusters). We argue that examining coherence scores is not a sufficient indicator to determine the optimal number of topics but human intervention is required to iteratively explore the interpretability of the topics.

Post-processing of topic models starts with manipulating and presenting statistical indicators from topic modeling. Some statistical indicators are simple like probabilities of individual words. Post-processing extends to identification: ranking the topics, finding the most representative document of each topic. Each is useful for interpretation of results. To a certain extent, these appear as the most objective quantitative aspects of topic modelling.

We employ co-words mapping in two ways: as a visual interpretation (see below) and a triangulation of topic modelling results. The hope is that a good topic model will converge at similar results if we compare it to another technique (e.g., running LSA, biterm). Triangulation can affirm or complement the interpretation; it reveal potential issues.

To compare the models generated by topic modelling, we compare corpora and also measure similarities between pairs of topics from different models. There are multiple ways to define the similarity including simple word overlap, cosine similarity, Jarcard distance or KL-divergence (Wang et al., 2019). Different measurements will lead to different similar pairs of topics. We decide to employ cosine similarity since it is a well-documented method designed to measure similarity between vectors in feature space. Consequently, this type of measure can be used as an assessment of explainability and transparency. Here is where post-processing requires significant domain knowledge to see whether the comparison "makes sense" and not add more difficulties in interpreting and understanding the results.

One clear instance of human intervention in topic modelling is the assignment of labels. The literature often just presents the labels, without detailing the decision making process (e.g. Jacobi et al., 2016). We examined the top 30 terms associated with each cluster. This is still a judgement call, and can embed our own biases about the relative importance of individual terms. Topic 12 in GAM is relatively clear. Its cluster of terms "technology, digital, platform, datum, new, enable, open, network, connectivity, solution" for us encapsulate new digital technologies for networking and connectivity. Compare that to the fifteenth cluster, which is "provide, preliminary, innovation, information, technology, select, service, area, number, letter". We needed to refer back to the most representative application of this topic, which was the Town of Halton Hills, ON. The application states that the town "will become the leading 21st century low carbon community by accelerating the adoption of electric vehicles through the development and deployment of a network of Internet connected electric car charging stations". Referring back to obtain that nuance allows for a reasoned explanation about the topic label, but it could be difficult if the corpus is very large.

Visualization provides a more intuitive presentation of modelling results. For example, the distance between topics in LDAvis can identify whether two topics are statistically related. As with mapping, visualization can suggest patterns of which we may be unaware when merely seeing the textual results. Geographic distribution of topics informs us which particular topics are clustered. There is a vast literature on biases introduced by visual inspection of patterns (e.g., Monmonier, 2018). Visualization is not a large part of our research but the qualitative and quantitative aspects of visualization can affect our judgement on what part of results to interpret and how to interpret.

Contextualizing the modelling results is also critical to the interpretation. Even if the SCC documents are summarized into topics, we still need to revisit the documents for the best explanation of those topics. It is unnecessary to revisit all documents but certain documents like the most representative document of a topic, should provide needed insight. The review is a manual action depending on researchers' knowledge and ability to match topics in suitable contexts and make inferences. This interrogation also affirms trustworthiness. Trust and transparency are additionally important because research in smart cities may have an impact on policy and resource allocation. Algorithmic transparency is always a concern of applying ML methods in public decision-making (Brauneis & Goodman, 2018). Conveying the results of ML is difficult to explain because of the complexity of technical details, which may make policy makers suspicious of an opaque system. If and when policy makers know there is human intervention into what appears to be an objective, bottom up solution. These countervailing aims must be balanced when deciding which ways and to what extent we make the interpretation explainable.

From Table 4, we identified twelve implementation steps reflecting explainability, ten indicating transparency, four informing trustworthiness and two showing visibility. Explainability is the most frequently observed characteristic throughout the stages of building topic models. Here implementation details that influence modelling results should be clarified by understandable terms to non-experts, while a critical question is when we need to seek for the clarifications and explanations. In this study, we need explanations for implementation steps requiring domain knowledge. If a step is indifferent to human judgement, it has no need to be explainable.

Transparency is the second most frequently observed characteristic. Here, transparent implementation refers to the algorithmic learning process that can be presented to domain users. If an implementation step contains judgement calls that are influenced by how the algorithm is designed to process data and handle uncertainty, we argue this step should be transparent. Much of the time, algorithms are opaque due to their complexity, which hinders connecting users with the original developers. It might be difficult to make a step transparent; therefore opacity requires trust from domain users and reducing risks. Instead of dwelling on every implementation detail and eliminating all risks, we will need a more realistic way to identify and measure the risks. In this study, we trust LDA for building topic models. We have to know a method's merits and demerits compared to other algorithms. We need to understand how data input (i.e., the number and length of documents in the corpus) may alter modelling results. We should be aware of the influence of the predetermined topic numbers. We could miss nuance in specific documents as we examine output in a purely quantitative bottom-up analysis. Some risks of the employment of topic modelling, specifically LDA, may be unavoidable. We argue that managing risks is vital to a trustworthy user-centered deployment of ML.

Visibility is the least observed characteristic, but it is also important to a user-centered deployment of ML. It contributes to the interpretation of modelling results through an intuitive presentation of the results from different perspectives (i.e., interactive graphs, geographic maps and word density maps). The visualization happens at the end of our implementation so users' reactions to the visual products are only captured in the interpretation stage. We argue that visualization/visual analytics can be further integrated in early stages of user-centered deployment of ML and HCML has numerous examples to guide us in that effort (Sachaa et al., 2017).

3.5 Conclusion

This chapter interrogates the use of a specific ML method, topic modelling, to extract themes from sets of government documents. We argue that unsupervised and bottom-up learning like topic modelling is not as out-of-box and automated as rhetorically promised for qualitative research. Our example case is grant applications to the 2017-2018 SCC program run by the Government of Canada's federal agency, Infrastructure Canada. The case study demonstrates the substantial amounts of human intervention required during the process of building topic models. We track the judgement calls, which begin at the data collection stage and continue through to the results interpretation stage. We were guided by HCML but identified a gap. Much of HCML is computational and directed towards human-as-subject, not human-as-researcher. The field fails to address the needs of non-computational researchers, who already may have trouble understanding the internals of the technology. We attached importance to the HCML characteristics of being explainable, transparent, trustworthy and visible when implementing topic modelling in a user-centered way (users refer to researchers). These characteristics can serve as a schema for a real-world practice of HCML as long as they can be well integrated in detailed implementation. For example, visualization needs to be more interactive with both users and ML components so that users' feedback can be referred to in an iterative modelling process. However, we should be aware that users with domain knowledge (researchers) do not react to models based on their intuition from graphs or maps. Again, our notion of HCML wants to avoid the human-as-subjects assumption but as users. Current studies of HMCL are mostly from perspectives of computer science instead of social/political science. We argue for an open research challenge at the intersection of social science and ML research, whose solution could lead to more usable and useful ML applications and less uncritical adoption.

Reference

Ahmed, K. B., Radenski, A., Bouhorma, M., & Ahmed, M. B. (2016). Sentiment analysis for smart cities: state of the art and opportunities. In Proceedings on the International Conference on Internet Computing (ICOMP) (p. 55). The Steering Committee of The World Congress in Computer Science, Computer Engineering and Applied Computing (WorldComp).

Alawadhi, S., Aldama-Nalda, A., Chourabi, H., Gil-Garcia, J. R., Leung, S., Mellouli, S., ... & Walker, S. (2012, September). Building understanding of smart city initiatives. In International conference on electronic government (pp. 40-53). Springer, Berlin, Heidelberg.

Aletras, N., & Stevenson, M. (2014). Measuring the similarity between automatically generated topics. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, volume 2: Short Papers (pp. 22-27).

Asmussen, C. B., & Møller, C. (2019). Smart literature review: a practical topic modelling approach to exploratory literature review. Journal of Big Data, 6(1), 93.

Batty, M. (2013). Big data, smart cities and city planning. Dialogues in human geography, 3(3), 274-279.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. Journal of Machine Learning Research, 3(Jan), 993-1022.

Brauneis, R., & Goodman, E. P. (2018). Algorithmic transparency for the smart city. Yale JL & Tech., 20, 103.

Chancellor, S., Baumer, E. P., & de Choudhury, M. (2019). Who is the "Human" in Human-Centered Machine Learning: The Case of Predicting Mental Health from Social Media. Proceedings of the ACM on Human-Computer Interaction. Article No.: 147: 1-32 https://doi.org/10.1145/3359249

Chellapilla K & Simard PY. 2005. Using Machine Learning to Break Visual Human Interaction Proofs (HIPs). In LK Saul, Y Weiss, & L Bottou (eds), Advances in Neural Information Processing Systems 17 (pp. 265–72). MIT Press, Cambridge, MA.)

Chen, D. Bellamy, RKE, Malkin, PK, Erickson, T. (2016). Diagnostic Visualization for Non-expert Machine Learning Practitioners: A Design Study. In 2016 IEEE Symposium on Visual Languages and Human-centric Computing, 87-95.

Chen, N. C., Zhang, Y., Stephens, M., Nagakura, T., & Larson, K. (2017). Urban Data Mining with Natural Language Processing: Social Media as Complementary Tool for Urban Decision Making.

Ching, T. Y., & Ferreira, J. (2015). Smart cities: Concepts, perceptions and lessons for planners. In Planning support systems and smart cities (pp. 145-168). Springer, Cham.

Cocchia, A. (2014). Smart and digital city: A systematic literature review. In Smart city (pp. 13-43). Springer, Cham.

Cohen B. (2015). The 3 Generations Of Smart Cities: Inside the development of the technology driven city. Retrieved on October 08, 2015. https://www.fastcompany.com/3047795/the-3-generations-of-smart-cities

Cook, D. J., Duncan, G., Sprint, G., & Fritz, R. L. (2018). Using smart city technology to make healthcare smarter. Proceedings of the IEEE, 106(4), 708-722.

Crowston, K., Allen, E. E., & Heckman, R. (2012). Using natural language processing technology for qualitative data analysis. International Journal of Social Research Methodology, 15(6), 523-543.

Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K., & Harshman, R. (1990). Indexing by latent semantic analysis. Journal of the American society for information science, 41(6), 391- 407.

Doran, D., Gokhale, S., & Dagnino, A. (2013, August). Human sensing for smart cities. In Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (pp. 1323-1330).

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608.

Fails, J. A., & Olsen Jr, D. R. (2003, January). Interactive machine learning. In Proceedings of the 8th international conference on Intelligent user interfaces (pp. 39-45).

Famili, A., Shen, W. M., Weber, R., & Simoudis, E. (1997). Data preprocessing and intelligent data analysis. Intelligent data analysis, 1(1), 3-23.

Fiebrink, R., & Gillies, M. (2018). Introduction to the special issue on human-centered machine learning.

Gambetta, Diego. 1988. Trust: Making and Breaking Cooperative Relations. Oxford: Blackwell.

Gillies, M., Fiebrink, R., Tanaka, A., Garcia, J., Bevilacqua, F., Heloir, A., ... & d'Alessandro, N. (2016, May). Human-centred machine learning. In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems (pp. 3558-3565).

Goodchild, M. F. (2007). Citizens as sensors: the world of volunteered geography. GeoJournal, 69(4), 211-221.

Guetterman, T. C., Chang, T., DeJonckheere, M., Basu, T., Scruggs, E., & Vydiswaran, V. V. (2018). Augmenting qualitative text analysis with natural language processing: methodological study. Journal of medical Internet research, 20(6), e231.

Hagen, L., Ö. Uzuner, C. Kotfila, T. M. Harrison and D. Lamanna. (2015). Understanding Citizens' Direct Policy Suggestions to the Federal Government: A Natural Language Processing and Topic Modeling Approach. 48th Hawaii International Conference on System Sciences, Kauai, HI, 2015, pp. 2134-2143, doi: 10.1109/HICSS.2015.257.

Hasan, S., & Ukkusuri, S. V. (2014). Urban activity pattern classification using topic models from online geo-location data. Transportation Research Part C: Emerging Technologies, 44, 363-381.

He, Qi, Bi Chen, Jian Pei, Baojun Qiu, Prasenjit Mitra, and Lee Giles. 2009. Detecting topic evolution in scientific literature: how can citations help? In Proceedings of the 18th ACM Conference on Information and Knowledge Management (CIKM ’09), pages 957–966, Hong Kong, China.

Holzinger, A., Plass, M., Kickmeier-Rust, M., Holzinger, K., Crişan, G. C., Pintea, C. M., & Palade, V. (2019). Interactive machine learning: experimental evidence for the human in the algorithmic loop. Applied Intelligence, 49(7), 2401-2414.

Infrastructure Canada (2017). Smart Cities Challenge Applicant Guide. Retrieved on May 18, 2019 from https://impact.canada.ca/sites/default/files/2017-11/SCC_Applicant_Guide.pdf

Infrastructure Canada (2018). Smart Cities Challenge Finalist Guide. Retrieved on May 18, 2019 from https://impact.canada.ca/en/challenges/smart-cities/finalist-guide

Jacobi, C., Van Atteveldt, W., & Welbers, K. (2016). Quantitative analysis of large amounts of journalistic texts using topic modelling. Digital Journalism, 4(1), 89-106.

Jaradat, M., Jarrah, M., Bousselham, A., Jararweh, Y., & Al-Ayyoub, M. (2015). The internet of energy: smart sensor networks and big data management for smart grid.

Kinoshita, A., Takasu, A., & Adachi, J. (2015). Real-time traffic incident detection using a probabilistic topic model. Information Systems, 54, 169-188.

Kling, F., & Pozdnoukhov, A. (2012, November). When a city tells a story: urban topic analysis. In Proceedings of the 20th international conference on advances in geographic information systems (pp. 482-485).

Lee, G., & Kwak, Y. H. (2012). An open government maturity model for social media-based public engagement. Government information quarterly, 29(4), 492-503.

Lee, T. Y., Smith, A., Seppi, K., Elmqvist, N., Boyd-Graber, J., & Findlater, L. (2017). The human touch: How non-expert users perceive, interpret, and fix topic models. International Journal of Human-Computer Studies, 105, 28-42.

Leydesdorff, L., & Nerghes, A. (2017). Co-word maps and topic modeling: A comparison using small and medium-sized corpora (N< 1,000). Journal of the Association for Information Science and Technology, 68(4), 1024-1035.

Liddy, E.D. (2003). Natural language processing. In M.A. Drake (Ed.), Encyclopedia of library and information science (pp. 2126–2136). New York, NY: Marcel Decker.

Mahizhnan, A. (1999). Smart cities: the Singapore case. Cities, 16(1), 13-18.

Manning, C. D., & Schutze, H. (1999). Foundations of statistical natural language processing. Cambridge Massachusetts: MIT Press.

Mattern, Shannon. 2017. A City Is Not a Computer. Places Journal. https://placesjournal.org/article/a-city-is-not-a-computer

Martin, F., & Johnson, M. (2015, December). More efficient topic modelling through a noun only approach. In Proceedings of the Australasian Language Technology Association Workshop 2015 (pp. 111-115).

Mitchell, T. M. (1997). Machine Learning, 1st ed. New York, NY, USA: McGraw-Hill, Inc.

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society 3, 2, 2053951716679679.

Mohr, J. W., & Bogdanov, P .(2013). Topic models. what they are and why they matter. Poetics, 31, 545-569.

Monmonier, M. 2018. How to Lie with Maps, 3rd Ed. ChicagoL: University of Chicago Press

Mosannenzadeh, F., & Vettorato, D. (2014). Defining smart city. A conceptual framework based on keyword analysis. TeMA-Journal of Land Use, Mobility and Environment.

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in Smart City initiatives: Some stylised facts. Cities, 38, 25-36.

O'Neill, J., Robin, C., O'Brien, L., & Buitelaar, P. (2016). An analysis of topic modelling for legislative texts. CEUR Workshop Proceedings.

Pereira, J. F. F. (2017). Social media text processing and semantic analysis for smart cities. arXiv preprint arXiv:1709.03406.

Ramage, D., Hall, D., Nallapati, R., & Manning, C. D. (2009, August). Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora. In Proceedings of the 2009 conference on empirical methods in natural language processing (pp. 248-256).

Resch, B., Summa, A., Zeile, P., & Strube, M. (2016). Citizen-centric urban planning through extracting emotion information from twitter in an interdisciplinary space-time-linguistics algorithm. Urban Planning, 1(2), 114-127.

Riedl, M. O. (2019). Human-centered artificial intelligence and machine learning. Human Behavior and Emerging Technologies, 1(1), 33-36.

Röder, M., Both, A., & Hinneburg, A. (2015, February). Exploring the space of topic coherence measures. In Proceedings of the Eighth ACM International Conference on Web Search and Data Mining, 399-408.

Sacha, Dominik, Michael Sedlmair, Leishi Zhang, John A. Lee, Jaakko Peltonen, Daniel Weiskopf, Stephen C. North, and Daniel A. Keima. 2017. What you see is what you can change: Human-centered machine learning by interactive visualization. Neurocomputing 268: 164-175 https://doi.org/10.1016/j.neucom.2017.01.105

Samuel, A. L. (1959). Some studies in machine learning using the game of checkers. IBM Journal of research and development, 3(3), 210-229.

Schofield, A., Magnusson, M., & Mimno, D. (2017, April). Pulling out the stops: Rethinking stopword removal for topic models. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers (pp. 432-436).

Shah, J., & Mishra, B. (2016, January). IoT enabled environmental monitoring system for smart cities. In 2016 international conference on internet of things and applications (IOTA) (pp. 383-388). IEEE.

Suakanto, S., Supangkat, S. H., & Saragih, R. (2013, June). Smart city dashboard for integrating various data of sensor networks. In International Conference on ICT for Smart Society (pp. 1-5). IEEE.

Tenney, M., & Sieber, R. (2016). Data-driven participation: Algorithms, cities, citizens, and corporate control. Urban Planning (ISSN: 2183-7635), 1(2), 101-113.

Tierney, P. J. (2012). A qualitative analysis framework using natural language processing and graph theory. International Review of Research in Open and Distributed Learning, 13(5), 173-189.

Wang, X., Fang, A., Ounis, I., & Macdonald, C. (2019, April). Evaluating Similarity Metrics for Latent Twitter Topics. In European Conference on Information Retrieval (pp. 787-794). Springer, Cham.

Wilson, S., Magdy, W., McGillivray, B., Garimella, K., & Tyson, G. (2020, May). Urban Dictionary Embeddings for Slang NLP Applications. In Proceedings of The 12th Language Resources and Evaluation Conference (pp. 4764-4773).

Yan, Xiaohui, Jiafeng Guo, Yanyan Lan, Xueqi Cheng. (2013). A Biterm Topic Model for Short Texts. International World Wide Web Conference, May 13–17, 2013, Rio de Janeiro, Brazil. ACM 978-1-4503-2035-1/13/05.

Yu, C. H., Jannasch-Pennell, A., & DiGangi, S. (2011). Compatibility between text mining and qualitative research in the perspectives of grounded theory, content analysis, and reliability. Qualitative Report, 16(3), 730-744.

Zerr, S., Tran, N. K., Bischoff, K., & Niederée, C. (2013). Sentiment analysis and opinion mining in collections of qualitative data. In Proceedings of the 1st International Workshop on Archiving Community Memories at iPRESS (Vol. 2013).

Zheng, Y., Rajasegarar, S., & Leckie, C. (2015, April). Parking availability prediction for sensor-enabled car parks in smart cities. In 2015 IEEE Tenth International

Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP) (pp. 1-6). IEEE.

Zhou, Jianlong, and Fang Chen. 2018a. Human and Machine Learning: Visible, Explainable, Trustworthy and Transparent. Springer. Cham, Switzerland.

Zhou, Jianlong and Fang Chen. 2018b. 2D Transparency Space--Bring Domain Users and Machine Learning Experts Together. In.., pages 3-20.

The Preface of Chapter 4

Chapter 4 answers the main research question of "how do researchers and practitioners plan for the smart city using automated technologies?" by presenting topic modelling of applications to the Canadian Smart Cities Challenge (SCC) grant program. It allows us to see, abductively, how cities and the federal government interpret the smart city. This chapter exhibits, contextualizes and interprets the results of 33 smart city topics of importance to Canadian communities, to demonstrate that the use of automated technologies to plan for the smart city can introduce new insights into existing smart city research. This interpretation of modelling results is based on the background provided by Chapter 2 and the methodology in Chapter 3.

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Zhibin Zheng conceptualized and designed this study, collected and analyzed the data, interpreted the results and drafted the manuscript. Zhibin Zheng and Renee Sieber, his supervisor, reviewed the manuscript together. Renee Sieber offered advice on reorganizing ideas and restructuring the manuscript. Renee Sieber suggested restructuring of the discussion sections and added insights that made the interpretation of results more aligned with the research question. Zhibin Zheng revisited the manuscript together with Renee Sieber. Renee Sieber also provided help in terms of the English language by editing or guiding Zhibin Zheng to edit the manuscript. Zhibin Zheng and Renee Sieber finally approved this version to be published.

Chapter 4 Interpreting the Smart City through Topic Modelling

Abstract

In November 2017, the Canadian federal government launched the Smart Cities Challenge (SCC) to encourage Canadian communities to propose projects that would improve the lives of their residents through innovation, data and interoperable technology. This granting program provided a unique opportunity to investigate what communities across the world might mean when they propose becoming a smart city and how different contexts shape their initiatives. Instead of delivering an *a priori* characterization of the smart city, we analyze the grant proposals: 137 primary texts containing approximately 1.5 million words. To efficiently handle this large textual dataset, we employ a machine learning method, topic modelling, to extract latent semantics that allow us to interpret the smart city. We derive 33 topics of importance to Canadian communities and generate four main findings. First, topics reveal a prevalence of "soft" and non-explicitly technological themes that demonstrate that smartness does not equal "tech". Canadian smart communities proposed initiatives that move beyond a first generation technology-driven model and toward technology-enabled, city-led and citizen co-creation models. Second, topics related to rural, regional and Indigenous communities challenge our notion of the "city" in the smart city. Third, cosine similarity allows us to compare original applications to those of finalists to infer what constitutes "smarter." Fourth, our approach suggests a bottom-up empirical interpretation of the smart city beyond conventional research methods, including identifying 40 percent of the finalists and the four winning cities.

Keywords: smart city, topic modelling, urban-rural contrast, community, technology

4.1 Introduction

The concept of the smart city is prevalent in discourses about global urbanization, where data-driven and technology-based solutions promise efficiency, social equality, public safety, inclusiveness, innovativeness and sustainability (e.g., Albino, Berardi & Dangelico, 2015; Neirotti et al., 2014). Fueled by these promises, the Canadian federal government issued the Smart Cities Challenge (SCC) competition in November 2017 (Infrastructure Canada, 2017). By April 24, 2018, the federal government received 130 individual or group grant applications from 199 communities. On June 1, 2018, the government announced 20 finalists (some were groups of multiple communities). The finalists then had support from the government to develop a final proposal that was submitted by March 5 of 2019 (Infrastructure Canada, 2018). On May 20, 2019, the government awarded four grants, from $5 million to $50 million Canadian to help winners implement smart city initiatives.

With more than 100 SCC applications, we have an unparalleled opportunity to extend our knowledge of what constitutes ‘smart’ and ‘city’. We can explore, for instance, the ambivalent role of technology in the smart city literature (Albino et al., 2015) by seeing how much technology was proposed in the SCC applicants and, by extension, infer how much technology applicants believed the government wanted to see proposed. The applications also enable us to move beyond highly cited cities like Toronto, Barcelona or New York (e.g., Bakıcı, Almirall & Wareham, 2013; Robinson & Coutts, 2019; Shelton, Zook & Wiig, 2015). For example, few studies have considered rural communities that possess the aspiration of being smart (Shearmur, Charron & Pajevic, 2019; Spicer, Goodman & Olmstead, 2019). The federal government allowed any Canadian community, large or small, Indigenous or non to be considered a “smart city”. Grant applications and final proposals came from both urban areas with high population density (4,300 persons/sq km) and rural areas with low population density (less than 400 persons/sq km) (Statistics Canada, 2018a). We have the opportunity to discover what rural communities think are smart and contrast that with urban communities.

The literature tells us that communities diversify their applications by content or geography (e.g., Ching & Ferreira, 2015). An additional value of these documents is that they are in a relatively standardized format since communities followed the guidelines from the federal government. The standardization provides us with a suitable corpus for topic modelling and also reduces an "apples-to-oranges" comparison of dissimilar content and media. We choose to group the grant applications and the final proposals as separate corpora. Comparing the two corpora offers a window into the federal government's vision of what is smart enough as well as an applicant's perception of how the federal government characterizes smart.

We use topic modeling, an unsupervised machine learning and natural language processing method, to analyze 137 applications containing approximately 1.5 million words. Traditional methods to interpret the smart city, like literature reviews, content analysis and case studies, may not be the best choice when presented with a large amount of qualitative data (Crowston, Allen & Heckman, 2012). Topic modelling, a form of text mining amenable to big data, allows for a relatively bottom-up and abductive means to understand how Canadian communities design their smart cities.

In the next section, we review the literature on what constitutes the smart city. We then describe topic modelling in terms of data preparation and implementation. We present the results, followed by an in-depth discussion on how the results nuance our understanding of what constitutes cities and smartness. This dataset and method allow us to move beyond theory and empirically interpret the smart city.

4.2 Literature Review

The concept of the smart city is at least 30 years old (Batty, 2013; Harrison & Donnelly, 2011; Nam & Pardo, 2011). Since 2010, there has been growing interest with advances in technology and maturation of the concept (Anthopoulos, 2015; Cocchia, 2014). One would think that we would now know what constitutes a smart city; however, the extant literature increasingly blurs the concept (cf., Albino et al., 2015). “Smart”, which early on referred to planned growth as opposed to sprawl (Batty, 2013), now overlaps with normative terms like “connected”, “participatory”, “resilient”, “sustainable”, “innovative”, “entrepreneurial” or “livable” (Hollands, 2008). The smart city now contains so many desirable attributes that it functions as a *tabula rasa*, a “magic concept” (Pollitt & Hupe, 2011) onto which anyone can project their aspirations. The smart city becomes eminently adaptable such that it is difficult to determine when a community qualifies as smart.

Technology, particularly information and communications technology (ICT), plays a significant role in characterizing “smartness”. How much technology is necessary? Neirotti et al. (2014) divide these into “hard” and “soft” domains, distinguished by the degree of dependence on technology. Hard domains like transportation, construction and environmental monitoring are assumed to be more amenable to technologies that allow services to be automated. In soft domains like culture, education and social inclusion, ICTs have limited role and are not necessarily directed to, for example, processing real-time data. Nonetheless, the smart city exhibits a bias to a technology-dominant discourse, where technical innovation, realtime and big data or artificial intelligence (AI) are preferred over human development.

Ultimately a smart city may represent a rebundling of less innovative existing projects or a rebranding of older concepts like the command-and-control of urban cybernetics (Goodspeed, 2015) or a reimagining of a surveillance-filled dystopia (Zuboff, 2019). A strong connection of smartness to technology can reflect an ideology that technology is necessary to control otherwise unmanageable geographies. The iconic example of a technologically-enabled centralized control is the control room photograph of a bank of monitors and data dashboards from the famous smart city project in Rio de Janeiro, Brazil (Goodspeed, 2015). The imagery evokes an urban cybernetic ideal (Goodspeed, 2015); however, its implementation was found to be marketing over technology in service of its residents (Gaffney & Robertson, 2018).

Cohen (2015) suggests that the smart city has evolved away from its high-tech rhetoric, what Cohen (2015) calls the first generation smart city. In these “technology-driven cities”, private firms persuade cities to adopt technology, without municipal employees necessarily understanding how the technology works or how it affects their residents’ well-being. In the second generation of smart city, “Technology Enabled, City Led” communities lead the implementation of smart city initiatives; technology assists rather than seeks to control residents. Citizen engagement becomes increasingly significant to the smart city as the implementation evolves. The “Co-Creation” third generation smart city takes advantage of an inclusive partnership and bottom-up innovation with city residents.

A tacit assumption is that the smart city is densely urban, in large part because the city is the presumed locus of technical innovation. This ‘it can only occur in cities’; urban-centred focus is increasingly challenged (Spicer et al., 2019; Shearmur et al., 2019). Urban areas need not be the sole beneficiaries of innovation; rural areas can benefit from technology in many ways including connections to urban centres, improvements to service delivery and increased opportunities for rural residents (Spicer et al., 2019). Making rural areas smarter could achieve a greater return-on-investment than in urban areas (Shearmur et al., 2019). Shearmur et al. (2019) remind us of the technological sophistication of rural areas in sectors like agriculture. Despite benefits, significant barriers hinder rural areas' goals of becoming smart, including a lack of resources like attracting a skilled workforce or connecting to broadband service (Spicer, et al., 2019). A rural area may need to achieve the characteristics of the city to be smart. Indeed, Shearmur et al. (2019: 2) reveal a paradox (translated from the French), "[t]he intelligent rural area therefore begins to be considered, even if, paradoxically, it forms part of a contest that promotes the smart city. That is, the rural world will become intelligent only if it urbanizes."

Smart city equals urban is one assumption that reveals an undercurrent of universalism in the concept. That is, a smart city connects technology with the interests of communities and the well-being of their residents that is independent of place (Dameri, 2013). A convenient theoretical construct, this fails to reflect the reality of implementation of a smart city. Many researchers acknowledge the unique cultural identity of cities that must be accounted for in smart city implementation (Han & Hawken, 2018). Obviously Barcelona, an often-cited example, is not Columbus, Ohio but that may not prevent technology firms from presenting one-size fits-all technological solutions. Part of the uniformity is the creation of standards so cities can be compared in terms of how smart (innovative, creative, open) they are (Hollands, 2008). Cities with varied identities pursue smartness for different reasons. For example, smart cities in Asia, Europe or North America look to share data, increase innovation, improve e-service or adopt green policies. In contrast, smart cities in Middle/South America and Africa look to attract foreign investment, move to more of a knowledge economy, or enhance ICT access in rural areas (Cocchia, 2014). Smart cities exhibit rich and diverse practices rather than a single-dimensional race to the top of some world city ranking (Han & Hawken, 2018). The tension between this universality/homogeneity and particularity is one aspect that we examine in this paper.

The smart city therefore is an ambiguous concept that complicates standardized analysis (Mosannenzadeh & Vettorato, 2014). We neither know what constitutes smart, or smarter, nor do we know what constitutes a city. The SCC provides us with an opportunity to empirically obtain some answers for over 100 communities.

4.3 Methods and Data

To understand how communities in Canada conceptualize smart cities, and by implication, how the Canadian federal government envisions the smart Canadian city, we extract semantics from a large volume of SCC documents. We perform topic modelling on two stages of the SCC: 117 grant applications[2] and on 20 final proposals, which results in two models respectively named grant application model (GAM) and final proposal model (FPM). Since a finalist, who was admitted to the second stage, also submitted a grant application, separate corpora prevent double counting the responses. We also create two topic models under the hypothesis that differences between the original grant applications and final proposals imply what communities viewed as smart and what the federal government viewed as smarter.

We employ topic modeling since it has proved to be an efficient and reliable technique for text mining (Baumer et al., 2017; Jacobi, Van Atteveldt & Welbers, 2016; Mohr & Bogdanov, 2013). Topic modeling identifies the occurrence and topological relations of words in text documents. The method is considered heuristic because it learns how the words cluster and therefore characterize those documents. Clusters become the corpus's themes or topics, although one needs to label and thus assign meaning to the clusters. Topic modelling assumes that there are a fixed number of topics and those topics

[2] There were 130 submissions at the grant application stage but 13 of them were neither available online nor offered by the corresponding communities.

act as containers for storing words. The key is to distribute words from all the documents into those containers.

Previous examples show that topic modelling works best with relatively homogeneous content and/or format. For example, content can be tweets (Resch et al., 2016), newspaper articles (Jacobi et al., 2016) or books (Tangherlini & Leonard, 2013). The SCC provides us that uniformity. For the SCC, applicants highlighted specific community needs and contexts in their submissions but they followed government guidelines. They were likely influenced by what they believed the grantor wanted in terms of a smart city. Consequently, they might discuss similar topics and thus align with the best practices of topic modelling.

Next we illustrate the three steps to accomplish topic modelling and compare the two models (i.e., GAM and FPM). First, we preprocess data through language translation, text cleaning and vectorization. Second, we choose a topic modelling method, Latent Dirichlet Allocation (LDA), to create models. Topics of the models will reveal characterizations of the smart city and allow us to focus on specific communities, whose initiatives we wish to examine further. Third, we employ cosine similarity at two levels: comparing corpora of GAM and FPM and comparing topics within the two models.

4.3.1 Data Preparation and Vectorization

Before cleaning and vectorizing, we need to translate some SCC documents. Canada is officially bilingual so the applications and proposals were written in English or French. We employ Google Translate to convert three French applications into English ones. Google's Neural Machine Translation translates whole sentences at a time, which can rearrange and adjust text to better resemble human speech (Turovsky, 2016). We conduct spot checks on the translated documents and compare them to the originals so as to assess consistency in meaning. Our belief is that the translation would not interfere with the topic modelling.

Not all words are useful in topic modelling. Some words in corpora occur with too frequency to be informative and consume computational resources without generating topics that answer research questions (Jacobi et al., 2016). We remove words like “Canada”, “smart”, “cities” or “challenge”, “application”, “proposal” and names of communities and provinces. These words frequently appear but do not provide insights and might obscure other important themes. We also replace acronyms with original spelled-out words to increase interpretability.

The next step is vectorization of the corpora. There are three components of this process (Jacobi et al., 2016; Tong & Zhang, 2016). First, we split a corpus into lists of words and delete spaces and punctuation, which is called tokenization. Second, we lemmatize the text, for example, removing past tense and plurals, so variations on a word could be analysed as a single word. Finally, we remove “stop words” (e.g., “a”, “an”, “the”, “in”, “on”, “to”, “have”), which could slow down processing and add only marginal benefits. This yields a total number of 14,963 unique terms from SCC grant applications and 13,083 unique terms from SCC final proposals. After these components, we use doc2bow function in Gensim’s dictionary Application Programming Interface to generate vectors. Word (term) vectorization essentially creates a matrix showing the relationship of every term to every other term (Blei et al., 2003). We then need to algorithmically group the vectors to create topics.

4.3.2 Topic Modelling

Several established algorithms can be applied to topic modelling, including Latent Semantic Analysis (LSA), probabilistic LSA (pLSA), and LDA. Among them, LDA is the most popular in urban science (Kling & Pozdnoukhov, 2012). All the algorithms are probabilistic in that they cluster terms in a corpus showing the greatest likelihood to be in a topic. Both the order of terms in a document (e.g., application) and documents in a corpus matter in LDA, which makes LDA a more refined probabilistic analysis than the other algorithms (Blei et al., 2003).

Topic modelling requires we predetermine the number of topics. The number determines the granularity, or level of detail, of the model (Jacobi et al., 2016). There is no set rule to ascertain a number into which LDA should assign the terms. Determining the number of topics creates a trade-off since “the goal is to describe the data with fewer dimensions (topics) than are actually present, but with enough dimensions so that as little relevant information as possible is lost” (Jacobi et al., 2016: 93). Topic coherence (Röder et al., 2015) can be used to score topics through the semantic similarity of terms within a topic, essentially evaluating the chosen number of topics. Values of topic coherence scores typically are between 0 and 1; a higher topic coherence score indicates a better topic model. We calculate topic coherence scores of both GAMs and FPMs over a different number of topics. As usual, scores increase at first place and then stabilize regardless of the addition of new topics. We extract 20 clusters of terms (i.e., topics) for GAM and 13 clusters of terms for FPM, which are the first number at which the coherence scores stabilized. With the number of topics determined, we finally have two topic models: SCC grant applications and final proposals. Compared to GAM, the FPM has a corpus composed of much fewer documents so it is reasonable to reduce the number of FPM topics. Consequently, the FPM may contain a coarser representation of topics and each FPM topic may contain multiple subtopics (word clusters) similar to a GAM topic.

4.3.3 Topic Comparison

We are interested in comparing the two corpora to see whether we can infer government preferences in terms of what constitutes smartness. For this we use the cosine measure, which is frequently applied to evaluate the similarity between corpora (cf., Batmanghelich et al., 2016; Vulić, De Smet & Moens, 2011) and among topics (e.g., He et al., 2009;

Ramage et al., 2009). A cosine measure can be used even if corpora are dissimilar in size because it assesses the angle--the cosine--between one corpus's word vectors and another's to compare how well they align. A similarity score varies from 0 to 1. Measures of sufficient similarity (i.e., how close to 1) vary but other authors affirm that 0.5 and above are considered similar (Vulić et al., 2011). We obtain a score of 0.861, which means the two corpora have very similar distribution of words.

After gauging the similarity of corpora, we then use cosine measure to compare topics in the GAM and FPM. We calculate a cosine similarity score for each pair of GAM-FPM topics. There is no definitive threshold of similarity scores to determine if two topics are similar or dissimilar. Instead, how similar the topics are is influenced by how much the topics are disaggregated. The greater are the number of topics, the greater the specificity of the representation of each topic and the higher the likelihood of a high similarity measure (Aletras & Stevenson, 2014; Jacobi et al., 2016). Small corpora to ours (1.5 million words) limit the disaggregation and therefore reduce the prospect of strong "matches". We can still detect partial similarity (as low as 0.25 and as high as 0.70) because, as Jacobi et al. (2016) observes, the measure is detecting word clumping within topics. When there is a small value of similarity score, we cannot simply claim that the result of a pairwise comparison is negative. There can be still an opportunity to identify and report comparable topics.

4.4 Results

Before we detail the topics that emerged from the two models, GAM and FPM, we first obtain a sense of how many Canadians were represented in the SCC. There was wide variation in the population sizes of communities that submitted applications, from a minimum of 185 residents to a maximum of 2,731,571 residents. The total number of population implicated in the SCC was 21,892,278, which means that the program constituted about 60 percent of the entire Canadian population of 37 million (Statistics

Canada, 2018b). Some of those communities are from vast areas; for example, the application from the Nunavut Association of Municipalities include 24 communities from Northern Canada with a population of 35,944. It stretches over 1,877,000 square kilometers and contains less than one person (0.019) per square kilometer.

The federal government disaggregated grant applications into different prize categories. One prize of $5 million was open to all communities under 30,000 people; two prizes of $10 million were open to all communities under 50,000 people; and another prize of $50 million was open to communities regardless of population (Infrastructure Canada, 2017). Of the 130 original applicants and 20 finalists, ultimately $5 million was awarded to the Town of Bridgewater in the Province of Nova Scotia; $10 million to City of Guelph and County of Wellington in the Province of Ontario and to Nunavut Communities in the Territory of Nunavut and $50 million to City of Montreal in the Province of Quebec.

4.4.1 Topic Model: GAM

Table 5 shows the 20 topics of GAM, ranked according to the contribution rates of topics. For each topic, the number of applications to which that cluster of terms appeared are displayed in the table. The topic contribution rate is the word/ token probability, which aggregates the frequency of the over ten thousand terms in the corpus divided by the frequency of that term in the corpus. Word probability normalizes different terms in the corpus and measures the degree to which a topic captures specific terms in the corpus. To some extent, “Applications Counted” and “Topic Contribution” indicate the popularity of a topic.

We then identify the most representative application (MRA) for each topic. The topic contribution to the MRA refers to the sum of the frequency of each term in a topic that belongs to a particular application, divided by the frequency of that term in the application. This is how we determine the MRA. In the last column, the table lists the ten most frequent terms associated with each topic.

Table 5. Topics of GAM and the Most Representative Applications

Topic Names	Topic Contribution (TC) %	Most Representative Application (MRA)	TC to the MRA %	The 5 Most Frequent Terms
Partnership	10.3	Frog Lake First Nation	26.4	partner, provide, partnership, design, development
Digital Services	9.0	Strathcona	31.4	service, datum, information, access, provide
Public Consultation	7.4	Mashteuiatsh	24.2	idea, activity, citizen, consultation, meeting
Economic Opportunity	7.0	Powell River	32.9	business, economic, opportunity, local, economy
Citizen & Urban Development	6.9	Coaticook	32.9	citizen, urban, develop, development, technology
Transportation/ Mobility	6.4	Dieppe	34.8	transportation, mobility, active, travel, public
Urban Planning	6.3	Williams Lake	23.1	plan, strategy, development, support, strategic
Management	6.1	Saint-Nazaire	19.4	management, partner, ensure, implementation, process
Youth/ Child	5.9	Nunavut Association	29.4	youth, social, child, people, belong
Data Solutions	5.8	Guelph & Wellington	23.6	datum, innovation, technology, solution, develop
Public Engagement	5.3	Stratford	15.1	engagement, resident, survey, public, feedback
Connected Technology	4.9	Cote Saint-Luc	27.5	technology, digital, platform, datum, new
Demography	3.6	Banff	12.9	population, achieve, statement, resident, province
Culture, Education & Language	2.8	Biigtigong Nishnaabeg	24.6	world, knowledge, language, facilitate, traditional
Innovation	2.8	Halton Hills	16.8	provide, preliminary, innovation, information, technology
Utilities Cost	2.8	Kelsey, the Pas, Cree Nation of Opaskwayak	21.9	cost, increase, waste, year, reduce
Housing & Energy	2.7	Cree Nation of Eastmain	45.4	energy, housing, building, affordability, affordable
Safety & Emergency Response	2.6	Richmond	23.0	safety, emergency, area, sensor, public
Health Care	1.1	Airdrie Area	14.1	health, senior, healthy, care, social
Food & Agriculture	0.3	Halifax Regional	64.8	food, farm, agriculture, farmer, affirm

We assign a name to each topic (i.e., cluster of terms) by reviewing the top 30 terms, more than that listed in the table. It is straightforward to assign topic names to most clusters. For example, the first cluster of terms “partner, provide, partnership, design, development, work, include, support, develop, program” suggest partnerships that are created to develop smart initiatives. The twelfth cluster of terms “technology, digital, platform, datum, new, enable, open, network, connectivity, solution” for us encapsulate new digital technologies for networking and connectivity.

A few instances prove to be challenging because of seemingly distinct terms. The fifteenth cluster is “provide, preliminary, innovation, information, technology, select, service, area, number, letter”. To name this topic, we refer to its MRA, in which the Town of Halton Hills, ON. The application states that the town “will become the leading 21st century low carbon community by accelerating the adoption of electric vehicles through the development and deployment of a network of internet connected electric car charging stations". To us, that speaks to innovation. In Topic 6, transportation and mobility are found to refer to the same domain in smart cities. Topic 9, youth and child, is inclusive of the population under 18 years. Topics sometimes underscore the interconnections of somewhat dissimilar terms. An investigation of applications associated with Topic 14, "culture, education & language", finds applications in which Indigenous communities describe the connections between education and their unique cultural and linguistic practices.

Most topics occur in over 80 percent of applications. This reflects applications coalescing around what constitutes the smart city and how the GAM generates only 20 topics covering the entire corpus. Popular topics like partnership, digital services and public engagement, capturing a large portion of terms, appear in most applications. The least popular topics like health care and food & agriculture occur in the fewest applications (59 and 17, respectively). Note that topic modelling needs careful curation since higher performance topics, like partnership, can be anodyne and therefore add little value to a deeper understanding of topics significant to specific communities (Lim, Kim & Maglio, 2018). No community would likely reject the need for partnerships in developing a smart city. By contrast, low performing topics like "culture, education & language" could indicate needs of a smaller but important segment of Canadian society.

4.4.2 Topic Model: FPM

Table 6 shows the thirteen topics generated for the FPM. This table contains the same columns as Table 5 except that the word "proposal" replaces "application". Most topics in FPM are straightforward to name; only the twelfth cluster of terms is not apparent. That topic's most representative proposal (MRP) from the Cree Nation of Eastmain, QC illustrates how housing issues are rooted in the history of Indigenous communities and the legacy of government interventions in that history.

Inclusive of “housing & culture”, six of thirteen topics involve multiple subjects. For example, Topic 2 shows that risk management is an important part of management in general. Topic 6 joins culture to education and relates them to youth/ child. Students before K12 are foci for education programs that also include cultural subjects in proposals from Indigenous communities. Topic 11 uncovers the importance of funding and budgets to innovation. The increasing proportion of multi-subject topics results from FPM’s coarser representation of topics, but also implies that the communities see issues as interconnected.

Table 6. Topics of FPM and the Most Representative Proposals

Topic Names	Topic Contribution (TC) %	Most Representative Proposal (MRP)	TC to the MRP %	The 5 Most Frequent Terms
Public Engagement	15.3	Airdrie Area	28.9	engagement, stakeholder, activity, resident, provide
Risk & Management	15.1	Richmond	25.5	risk, management, program, plan, governance
Health Care	13.1	Cote Saint-Luc	26.8	health, technology, service, resident, vision
Data Solutions	9.1	Montreal	32.4	datum, mobility, partner, technology, open
Information Privacy	8.3	Kelsey, the Pas, Cree Nation of Opaskwayak	19.6	information, datum, privacy, personal, security
Youth/ Child & Culture, Education	7.7	Biigtigong Nishnaabeg	31.3	youth, indigenous, child, support, program
Digital Services	6.3	Saskatoon	20.9	service, technology, user, solution, connect
Housing & Energy	5.5	Bridgewater	36.1	program, energy, housing, service, year
Food & Agriculture	5.5	Guelph and Wellington	27.5	food, agora, farm, support, rural
Transportation/ Mobility	4.9	Greater Victoria	20.8	mobility, transportation, indicator, transit, prosperity_partnership
Innovation & Budget	4.0	Nunavut Association	22.4	innovation, fund, makerspace, development, funding
Housing & Culture	3.0	Cree Nation of Eastmain	27.7	inuit, housing, construction, building, home
Utilities Cost	2.2	Tri-Council Region	13.1	cost, total, year, subtotal, source

Based on the contribution rates, topics of “public engagement”, “risk & management” and “health care” rank at the top, together capturing 43.5 percent of total terms. The rest account for between two and nine percent. The number of proposals counted provides little information about the relative popularity of a topic since every topic appears in almost all the proposals.

4.4.3 Differences between Topics of GAM and FPM

We compare every pair of GAM-FPM topics (260 comparisons) and find the highest similarity score of each topic in the comparison (Table 7). Scores in bold are those of pairs of a FPM topic and its most similar GAM topic. Underlined scores represent those of pairs of a GAM topic and its most similar FPM topic. Ten of thirteen FPM topics' scores are bold and underlined; the similarity of topic names demonstrates the consistency of our labelling activities. Scores of the predominant matches range from 0.226 to 0.673.

Table 7. Related Topics of GAM and FPM Based on Similarity Scores

(bold refers to the highest similarity score of all GAMs compared to each FPM topic; underlined refers to the highest similarity score of all FPMs compared to each GAM topic. Topic contributions are the same as those in Tables 5 and 6.)

FPM Topics	Topic Contribution (TC) to FPM %	Related GAM Topics	TC to GAM %	Cosine Similarities
Public Engagement	15.3	Public Engagement	5.3	<u>**0.660**</u>
		Public Consultation	7.4	<u>0.504</u>
Risk & Management	15.1	Management	6.1	<u>**0.629**</u>
		Partnership	10.3	<u>0.535</u>
		Urban Planning	6.1	<u>0.435</u>
Health Care	13.1	Citizen & Urban Development	6.9	<u>**0.466**</u>
		Health Care	1.1	<u>0.430</u>
		Innovation	2.8	<u>0.308</u>
		Demography	3.6	<u>0.284</u>
		Safety & Emergency Response	2.6	<u>0.226</u>
Data Solutions	9.1	Data Solutions	5.8	<u>**0.597**</u>
		Connected Technology	4.9	<u>0.574</u>
Information Privacy	8.3	Digital Services	9.0	**0.518**
Youth/ Child & Culture, Education	7.7	Youth/ Child	5.9	<u>**0.673**</u>
		Culture, Education & Language	2.8	<u>0.253</u>
Digital Services	6.3	Digital Services	9.0	<u>**0.575**</u>
Housing & Energy	5.5	Housing & Energy	2.7	<u>**0.570**</u>
Food & Agriculture	5.5	Food & Agriculture	0.3	<u>**0.595**</u>
		Economic Opportunity	7.0	<u>0.432</u>
Transportation/ Mobility	4.9	Transportation/ Mobility	6.4	<u>**0.568**</u>
Innovation & Funding	4.0	Data Solutions	5.8	**0.339**
Housing & Culture	3.0	Housing & Energy	2.7	**0.377**
Utilities Cost	2.2	Utilities Cost	2.8	<u>**0.381**</u>

Table 7 shows four kinds of relations among topic pairs, 1 to 1 (the greatest similarity occurs between the subclusters of one topic to the subclusters of another topic), 1 to n and n to 1 (i.e., subclusters of one topic correlate or overlap with several {n} topics) and n to n (i.e., subclusters of several topics mutually relate to each other). Digital services is an example of the 1:1 relationship. The FPM topic youth/child & culture, education exemplifies a 1:n relationship. Unsurprisingly, it associates with the two GAM topics of youth/child and culture, education and language. Pairs with a 1 to n relation indicate that the GAM results in a better disaggregation of topics than the FPM. Pairs with an n to 1 relation suggest an emerging FPM topic. For instance, information privacy was not extensively discussed in the original applications although related concepts appear in GAM topic, digital services.

Among pairs with an n to n relation, we thought that two topics we labelled innovation and innovation & budget should correspond. However, innovation & budget in FPM corresponds with data solutions in GAM; whereas the GAM topic innovation shares similarity with the FPM topic health care. This could be a result of incorrect or partial labels since we examined a limited number of terms. The cosine measure utilizes the over ten thousand terms to calculate the similarity.

The FPM topic health care represents a domain that covers multiple subjects. Unexpectedly, its most similar GAM topic is citizen & urban development. Although health is not one of the top-30 frequent terms in this GAM topic, we find occurences of concepts related to health care, including citizen/ people/ population, quality of life, and technology. Topic modeling can reveal non-obvious linkages among subclusters according to concepts communities, as opposed to researchers, find connected.

4.5 Discussion

Our topic models help us understand what the smart city means to Canadian communities, what the Canadian federal government suggests constitutes the smart city, and inferentially, how communities write applications that they believe have the best chance of success. We then track the dynamics of the SCC through the similarities among topics.

4.5.1 What Constitutes the Canadian Smart "City"

Modelling results are consistent with the literature, in that no clear definition emerges of what constitutes a smart city. Instead, Canadian smart city initiatives vary to match specific geographic needs, from data and technologies to public participation, and from transportation to health care. Communities envision the smart city through different approaches even as they all assert their potential to become smart. Where the SCC differs from the literature is the prevalence of topics not intrinsically connected to technology and the influence of a rural voice in the discourse of smart cities.

Recall that Neirotti et al. (2014) divide smart city initiatives into “hard” and “soft” domains. Hard domain initiatives like transportation/mobility, energy grids, healthcare and public safety are more amenable to technological solution; whereas, soft domains related to education and culture and social inclusion are less obviously connected to technology. Neirortti et al. regard food and agriculture as hard domains applying technologies like drones or robots. For us, food and agriculture exist as both hard (as seen in GAM) and soft domains (as seen in FPM), the latter of which relate to values held by rural communities. In addition to food and agriculture, the SCC sheds light on subjects not normally associated with the technicity of the smart city, like those important to Indigenous populations (cf., culture, education & language). Unlike Neirotti et al. (2014), where culture is an adjunct to entrepreneurship in numerous smart city implementations, preserving culture is an existential issue for certain Canadian communities.

Similar to Neirotti et al. (2014), our research suggests that soft domains require more contextualization than hard domains. However, Neirotti et al. (2014) place contextual factors (e.g., level of technological development; institutional factors) into discrete categories. Discretization defeats the importance of context because context should not be so neatly “typed”. Attention to place-specific factors also points to tailored solutions that could reveal more insights into local issues and what constitutes smart to that particular community. The predominant GAM application for culture, education & language is from the Biigtigong Nishnaabeg First Nation. The topic of culture, education or language is not ostensibly associated with the smart city. Reviewing the “raw” application, we find that the community built an education program empowered by technologies like cloud computing, mobile applications, open data, and video analytics. By delivering both Nishnaabe knowledge and modern K-12 Science, Technology, Engineering, and Math knowledge, Biigtigong Nishnaabeg communities hope their youth can attain full language literacy in the endangered Nishnaabe language and are “more holistically Nishnaabe” due to … their knowledge of the roles of our Nishnaabe worldview in modern technological society” (grant application from Biigtigong Nishnaabeg). Sometimes the technical, for us the topic modelling, must be put aside to re-examine the base data.

With the exception of Indigenous applications, topics' appearance show little difference between urban and rural areas, which reinforces arguments that rural areas can be as technical as cities (Shearmur et al. 2019). Topics like culture, education & language are proposed by rural communities alongside hard domain topics, like housing & energy. Agriculture (smart farming, see above) is highly technologically sophisticated even as it rarely appears in the smart city literature. We find that food & agriculture is not strictly rural but appears in both urban and rural applications. For example, the most representative application, Halifax Regional Municipality, includes both the City of Halifax, the largest city in Nova Scotia and its surrounding rural areas. This may be atypical to more uniformly dense communities but suburban communities may encompass rural extents as well. Topics can potentially be used to detect these differences in density.

What is innovative in one community may not be in another. In their grant applications, the Cities of Surrey and Vancouver sought to leverage autonomous vehicles and big data analytics to improve transportation systems. Conversely, the City of Bromont proposed numerous transportation improvements, whether cutting edge or conventional (e.g., increased cycling to take advantage of their 100km trail network). One strong example of innovation divergence concerns the Frog Lake First Nation, which proposed to map unofficial garbage dump sites with geographic information systems (GIS). GIS is hardly a new technology in municipalities (Harris & Batty, 1993); yet it is wholly new for many small communities in Canada. Frog Lake First Nation appears to be an innovation "laggard" compared with the cities like Surrey and Vancouver, although communities possess different understanding of smartness. Because we lack consensus on what constitutes a smart city, a laggard in certain technologies is not necessarily a laggard in the smart city.

Topic models also reveal cultural distinctions not only between urban and rural areas. Community applications from the Province of Quebec expressed a distinct cultural identity compared to other Canadian provinces. This difference is primarily manifest with language systems where French, instead of English, is the official and predominant language spoken in Quebec (Statistics Canada, 2016). The cultural difference is further embedded in "a vision of society that recognizes community participation as a fundamental exercise in citizenship and democracy, and as a means for empowering citizens" (Laforest, 2007: 172). Applications from the majority of Quebec communities cluster keywords into the topic "citizen & urban development". Place- and cultural specificity is found in other countries (e.g., Catalonia in Spain, Southern US States versus Northern US States). Smart city rhetoric and technological implementations can obscure these differences (Sepasgozar et al., 2019).

4.5.2 What Constitutes the Canadian "Smart" City?

The Canadian federal government chose not to define a smart city but rather characterized an approach "to achieve meaningful outcomes for residents by leveraging the fundamental benefits that data and connected technology have to offer" (Infrastructure Canada, 2017: 2). In the application guide, the federal government listed multiple visions of a smart city: having residents "feel safe and secure", "earn a good living", "move around my community", "enjoy a healthy environment", "be empowered and included in society" and "live an active and healthy life" (Infrastructure Canada, 2017). The vague and aspirational messages allowed for broad interpretation and contrasted with reminders that proposals be rooted in connected technology.

There is no practical metric that encompasses all smart cities, since initiatives will likely be customized to each community. However, we have a unique opportunity via the SCC to analyze how cities interpreted SCC instructions and infer what the government viewed as sufficiently smart to be selected as finalist and winner. We utilize a variety of means to extrapolate what constitutes smarter. This includes investigating topic choices among finalists and winners, reviewing similarity scores and examining topic contribution rates. Our determination is both qualitative as well as quantitative.

From 130 applicants, the federal governments selected 20 finalists and four winners. Applicants who made it to the finalist stage were "smarter" relative to those who did not; topics in FPM should therefore represent smarter concepts. Dominant topics (topics with highest contribution rates) for finalists cover a mix of hard domains like data solutions, utilities cost and housing & energy, and soft domains like culture, education & language and health care. Eight of the finalists' applications emerged as the most representative application of a GAM topic. One could argue then that the GAM identifies 40 percent of the finalists and thus indicates what is sufficiently smart to make it to the next stage of the competition. Dominant topics in the winning proposals include data solutions for Montreal; youth/ child & culture, education for Nunavut; food & agriculture for Guelph/Wellington; and housing and energy for Bridgewater. All the winning proposals appeared in the list of the most representative proposals of a FPM topic, which means the FPM identifies all the SCC winners. We argue that the federal government considers the dominant topics of the winners to be smarter than other topics.

We can utilize similarity scores to assess smartness. Table 7 shows GAM topics with the highest similarity to a corresponding FPM topic (see bolded scores). Several of the FPM topics are matched with two or more GAM topics, although only one of the GAM topics holds the highest similarity (i.e., bolded scores). Since these represent subclusters, the component with the greatest similarity constitutes smarter. For example, the subcluster of public engagement in FPM constitutes smarter involvement with residents than mere consultation. Health care is particularly illustrative of “smarterness”. One might think that applications explicitly linked to health would be privileged. However, health’s most similar GAM topic is citizen & urban development, which indicates a broader categorization to community health that includes quality of life. An example is Nunavut Communities, one of the finalists and winners whose application proposed to improve mental health among the Nunavummiut.

The relative topic contribution rates of the FPM topics exhibited in Table 7 also can suggest what constitutes smarter. There is a natural break between the first three topics and the rest. The top three topics, public engagement, risk & management and health care, have a large contribution rate of over 13 percent. Finalists were actually told to emphasize public engagement, risk, management, data, technology, and privacy in their final proposal (Infrastructure Canada, 2018) so for this exercise we will not count FPM topics 1, 2, 4, and 5 as automatic indicators of smartness. This suggests an emphasis on health care secured a spot as a finalist.

Insight into the differences in topics between non-finalists and finalists/winners reveal clues to smarterness. Let us compare the two largest cities in Canada, Toronto and Montreal. Toronto is heralded as the epitome of smart cities in Canada (Tierney, 2019) yet it was not accepted as a finalist. The goal of its grant application was to “reduc[e] poverty of children”. However, its top three topics, according to the GAM, were digital services, partnership and economic opportunity. Youth/child ranks fifth, after data solutions. The topics therefore disclose an inconsistency between an ostensible statement of intent and actual emphasis. In contrast, Montreal showed greater consistency at the grant application stage. The goal of Montreal's original application was to"innovat[e] mobility and access to food through a co-creation and citizen participation process." Examining its predominant topics, citizen & urban development ranked first and public consultation, second. Transportation was fourth (although food & agriculture was 16th). Communities can be "smarter" not only in the presentation of ideas but also in their justification and contextualization.

4.5.3 Where is Technology in the Canadian Smart City?

In the SCC, the federal government posited data and connected technology as a means to achieve aspirational goals of Canadian communities. A strong emphasis on technology/data when characterizing a smart city questions whether the Canadian smart city represents a rebranding of urban cybernetics as well as Cohen's (2015) first generation model of technology-driven initiatives.

Instructions for the initial grant applications suggested communities mention specific technologies to accomplish their projects. There were frequent references to AI, augmented reality (AR), virtual reality (VR), cloud computing, Internet of Things (IoTs), mobile applications, enterprise solutions, and big data analytics. With the exception of terms mobile, drone, robotic, many of which were related to agriculture, these words fail to emerge as keyword descriptors of topics. A possible explanation is that the Canadian smart city might not be technology-driven. Or it might imply that communities feel the need to add the buzzwords as a way of being smart city-compliant.

Alongside a lack of "high-tech" keywords, no keyword or topic like efficient, effective, control or system emerge in the GAM or FPM. Canadian communities appeared far removed from a vision of urban cybernetics. The closest cybernetics-relevant keyword we could find was “monitor”. Dashboards appear in the corpora (e.g., “real-time analytic dashboard” from the District of Squamish, BC). Dashboards can serve as a kind of an urban cybernetics, Rio de Janeiro-type control room because they are “underpinned by [the same] naive instrumental rationality, are open to manipulation by vested interests” (Kitchin et al., 2015: 6). Nonetheless, the term “dashboards” fails to rise to the level of keywords or topics. Indeed, the term dashboards tends to substitute for “apps” that are geared towards public engagement. The phrases public dashboard, citizen dashboard, community dashboard, customized dashboard, personal dashboard, resident dashboard, and tailored dashboard appear in our corpora.

Instead of viewing applications as demonstrative of Cohen’s (2015) first generation of technology-driven solutions, our topic models suggest that applications better match Cohen’s second and third generations of smart cities. Whereas technology remains part of a smart city; it increasingly does not dominate. The prevalence of soft domains suggests that communities embraced Cohen’s second generation, in which communities practice technology enabled, city-led approach. GAM topics like youth/ child, culture, education & language, and health care suggest that Canadian communities prioritized community interests over technology or the private sector interests (i.e., those providing smart city technologies). Many of the soft domain topics increase in popularity in FPM.

More surprisingly the prevalence of topics and keywords related to public engagement suggest that Canadian smart cities have moved towards Cohen’s third generation of smart cities, in which citizens co-create the smart city. The GAM includes topics of public consultation, public engagement and citizen & urban development, as well as keywords like citizens, residents, stakeholders, engage, and participate. The increase in popularity of topic public engagement in FPM explicates communities’ intent to involve citizens in smart city projects. For example, the City of Montreal proposed a responsible deployment of technology that supports citizen engagement approaches. One of their smart city strategies defined a co-creation model that integrated citizens in decision-making through employment of new technologies, design of governance mechanisms and development of shared and common property.

4.6 Conclusion

This research applies topic modeling to reveal what constitutes the Canadian smart city and how these emergent topics relate to the prevalent discourse. To analyse the applications/proposals from those communities, we apply LDA topic modelling. We combine the texts into two corpora, one for the initial applications and one for the proposals. We then perform a cosine similarity to ensure we can compare these two corpora and their topics.

Four findings arise from our topic modelling and similarity comparison. First, topics reveal a prevalence of “soft”, non-explicitly technological themes, that demonstrate that smartness does not equal “tech”. The failure of neologisms like AI or IOT to emerge as keywords suggests that we need other determinants for the ubiquitous “Top 10” smart cities lists. Increasingly, the distinction between “soft” and “hard” domains represents a false choice in the smart city. Data and connected technology permeate every aspect of cities and it is problematic to create an ordinality that prioritizes hard domains over soft domains. The Canadian smart city is unlikely to represent a rebranding version of urban cybernetics; instead, it is evolving in the direction of embracing more soft domains that also are less committed to urban areas. The smart city, at least in Canada, appears to have moved beyond the technology-driven phase toward technology-enabled, city-led and citizen co-creation phases.

Second, topics related to rural, regional and Indigenous communities challenge our notion of the "city" in the smart city. A smart "city" may be a sparsely populated area. What constitutes a technological innovation can vary from rural to urban areas. In the future, rural communities may have an increasingly important role in the smart city discourse, for example as testbeds that combine hard and soft domains. Regardless of rural-urban context, a country will invariably contain multiple cultural and geographic identities, which puncture the universalism of smart city initiatives.

Third, cosine similarity allows us to show an evolution in thinking about the smart city to infer what constitutes "smarter", that is what communities and the federal government identify as smarter. Communities proposing certain domain(s), for example health care, are smarter. Certain domains may be irrelevant to the needs of a specific community and they possess neither the capacity nor the skills to master the technical skills or force fit a particular domain to a critical community need. We do not want to label communities as less smart just because of a comparison to communities with greater resources.

Last, our approach suggests a bottom-up empirical interpretation of the smart city beyond conventional research methods, including identifying 40 percent of the finalists and the four winning cities. Our findings offer a useful albeit imperfect inference of what the federal government considered smart, smarter, and smartest. Did the federal government pre-determine the smart topics (e.g., health)? Were there political considerations related to the geographic distribution of awardees? Topic modelling is not ideal for the political calculus of government but it does provide a quantified analysis of large amounts of qualitative text.

Reference

Albino, V., Berardi, U., & Dangelico, R. M. (2015). Smart cities: Definitions, dimensions, performance, and initiatives. Journal of urban technology, 22(1), 3-21.

Aletras, N., & Stevenson, M. (2014). Measuring the similarity between automatically generated topics. In Proceedings of the 14th Conference of the European Chapter of the Association for Computational Linguistics, volume 2: Short Papers (pp. 22-27).

Anthopoulos, L. G. (2015). Understanding the smart city domain: A literature review. In Transforming city governments for successful smart cities (pp. 9-21). Springer, Cham.

Bakıcı, T., Almirall, E., & Wareham, J. (2013). A smart city initiative: the case of Barcelona. Journal of the knowledge economy, 4(2), 135-148.

Batmanghelich, K., Saeedi, A., Narasimhan, K., & Gershman, S. (2016, August). Nonparametric spherical topic modeling with word embeddings. In Proceedings of the conference. Association for Computational Linguistics. Meeting (Vol. 2016, p. 537). NIH Public Access.

Batty, M. (2013). Big data, smart cities and city planning. Dialogues in human geography, 3(3), 274-279.

Baumer, E. P., Mimno, D., Guha, S., Quan, E., & Gay, G. K. (2017). Comparing grounded theory and topic modeling: Extreme divergence or unlikely convergence?. Journal of the Association for Information Science and Technology, 68(6), 1397-1410.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. Journal of machine Learning research, 3(Jan), 993-1022.

Ching, T. Y., & Ferreira, J. (2015). Smart cities: Concepts, perceptions and lessons for planners. In Planning support systems and smart cities (pp. 145-168). Springer, Cham.

Cocchia, A. (2014). Smart and digital city: A systematic literature review. In Smart city (pp. 13-43). Springer, Cham.

Cohen B. (2015). The 3 Generations Of Smart Cities: Inside the development of the technology driven city. Retrieved on October 08, 2015. https://www.fastcompany.com/3047795/the-3-generations-of-smart-cities

Crowston, K., Allen, E. E., & Heckman, R. (2012). Using natural language processing technology for qualitative data analysis. International Journal of Social Research Methodology, 15(6), 523-543.

Dameri, R. P. (2013). Searching for smart city definition: a comprehensive proposal. International Journal of Computers & Technology, 11(5), 2544-2551.

Gaffney, C., & Robertson, C. (2018). Smarter than smart: Rio de Janeiro's flawed emergence as a smart city. Journal of Urban Technology, 25(3), 47-64.

Goodspeed, R. (2015) Sketching and learning: A planning support system field study. Environment and Planning B: Planning and Design, 43(3): 444-463.

Han, H., & Hawken, S. (2018). Introduction: Innovation and identity in next-generation smart cities. City, culture and society, 12, 1-4.

Harris, B., & Batty, M. (1993). Locational models, geographic information and planning support systems. Journal of Planning Education and Research, 12(3), 184-198.

Harrison, C. and Donnelly, I.A. (2011), 'A theory of smart cities', paper presented at the Fifty-fifth Annual Meeting of the International Society for the Systems Sciences (ISSS), Hull, 17–22 July.

He, Qi, Bi Chen, Jian Pei, Baojun Qiu, Prasenjit Mitra, and Lee Giles. 2009. Detecting topic evolution in scientific literature: how can citations help? In Proceedings of the 18th ACM Conference on Information and Knowledge Management (CIKM '09), pages 957–966, Hong Kong, China.

Hollands, R.G. (2008) Will the real smart city please stand up? City. 12(3): 303-320.

Infrastructure Canada (2017). Smart Cities Challenge Applicant Guide. Retrieved on May 18, 2019 from https://impact.canada.ca/sites/default/files/2017-11/SCC_Applicant_Guide.pdf

Infrastructure Canada (2018). Smart Cities Challenge Finalist Guide. Retrieved on May 18, 2019 from https://impact.canada.ca/en/challenges/smart-cities/finalist-guide

Jacobi, C., Van Atteveldt, W., & Welbers, K. (2016). Quantitative analysis of large amounts of journalistic texts using topic modelling. Digital Journalism, 4(1), 89-106.

Kitchin, Rob, Tracey P. Lauriault & Gavin McArdle. 2015. Knowing and governing cities through urban indicators, city benchmarking and real-time dashboards. Regional Studies, Regional Science 2, 1, 6-28.

Kling, F., & Pozdnoukhov, A. (2012, November). When a city tells a story: urban topic analysis. In Proceedings of the 20th international conference on advances in geographic information systems (pp. 482-485). ACM.

Laforest, R. 2007. State and Community Sector Relations: Crisis and Challenges in Quebec. The Philanthropist 20, 3, 171-184.

Lim, C., Kim, K. J., & Maglio, P. P. (2018). Smart cities with big data: Reference models, challenges, and considerations. Cities, 82, 86-99.

Mohr, J. W., & Bogdanov, P. (2013). Introduction—Topic models: What they are and why they matter.

Mosannenzadeh, F., & Vettorato, D. (2014). Defining smart city. A conceptual framework based on keyword analysis. Tema. Journal of Land Use, Mobility and Environment.

Nam, T., & Pardo, T. A. (2011, June). Conceptualizing smart city with dimensions of technology, people, and institutions. In Proceedings of the 12th annual international digital government research conference: digital government innovation in challenging times (pp. 282-291).

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in Smart City initiatives: Some stylised facts. Cities, 38, 25-36.

Pollitt, C. and Hupe, P. (2011). Talking about government: The role of magic concepts. Public Management Review, 13(5), 641-658.

Ramage, D., Hall, D., Nallapati, R., & Manning, C. D. (2009, August). Labeled LDA: A supervised topic model for credit attribution in multi-labeled corpora. In Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing: Volume 1-Volume 1 (pp. 248-256). Association for Computational Linguistics.

Resch, B., Summa, A., Zeile, P., & Strube, M. (2016). Citizen-centric urban planning through extracting emotion information from twitter in an interdisciplinary space-time-linguistics algorithm. Urban Planning, 1(2), 114-127.

Robinson, P., & Coutts, S. (2019). The case of Quayside, Toronto, Canada. In Smart City Emergence (pp. 333-350). Elsevier.

Röder, M., Both, A., & Hinneburg, A. (2015, February). Exploring the space of topic coherence measures. In Proceedings of the eighth ACM international conference on Web search and data mining (pp. 399-408). ACM.

Sepasgozar, S. M., Hawken, S., Sargolzaei, S., & Foroozanfa, M. (2019). Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. Technological Forecasting and Social Change, 142, 105-116.

Shearmur, R., Charron, M., & Pajevic, F. (2019). Pourquoi seules les villes sont-elles qualifiées d'intelligentes? Un vocabulaire du biais urbain. The Canadian Geographer/Le Géographe canadien. 1–13 DOI: 10.1111/cag.12573

Shelton, T., Zook, M., & Wiig, A. (2015). The 'actually existing smart city'. Cambridge Journal of Regions, Economy and Society, 8(1), 13-25.

Spicer, Z., Goodman, N., & Olmstead, N. (2019). The frontier of digital opportunity: Smart city implementation in small, rural and remote communities in Canada. Urban Studies.

Statistics Canada (2016). Census Profile, 2016 Census. Retrieved on November 13, 2019 from https://www12.statcan.gc.ca/census-recensement/2016/dp-pd/prof/details/Page.cfm?Lang=E&Geo1=PR&Code1=24&Geo2=&Code2=&Data=Count&SearchType=Begins&SearchPR=01&B1=All

Statistics Canada (2018a). Canada goes urban. Retrieved on August 1, 2019 from https://www150.statcan.gc.ca/n1/pub/11-630-x/11-630-x2015004-eng.htm

Statistics Canada (2018b). Population estimates on July 1st, by age and sex. Retrieved on May 20, 2019 from https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=1710000501

Tangherlini, T. R., & Leonard, P. (2013). Trawling in the Sea of the Great Unread: Sub-corpus topic modeling and Humanities research. Poetics, 41(6), 725-749.

The World Bank (2018). Urban Population (% of Total Population) - Canada. Retrieved on Nov15, 2019 from https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=CA

Tierney, T. F. (2019). Toronto's Smart City: Everyday Life or Google Life?. Architecture_MPS.

Tong, Z., & Zhang, H. (2016). A Text Mining Research based on LDA Topic Modelling. In International Conference on Computer Science, Engineering and Information Technology (pp. 201-210).

Turovsky, B. (2016). Found in translation: More accurate, fluent sentences in Google Translate. Retrieved on July 20, 2019, from https://blog.google/products/translate/found-translation-more-accurate-fluent-sentences-google-translate/

Vulić, I., De Smet, W., & Moens, M. F. (2011, June). Identifying word translations from comparable corpora using latent topic models. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies: short papers-Volume 2 (pp. 479-484). Association for Computational Linguistics.

Zuboff, S. (2019). Toronto is surveillance capitalism's new frontier. Toronto Life. Retrieved on Sept 10, 2019 from https://torontolife.com/city/toronto-is-surveillance-capitalisms-new-frontier/

Chapter 5: Conclusion and Future Research Direction

In this thesis, we sought to answer the research question "how do researchers and practitioners plan for the smart city with automated technologies?" We broke down this question into four sub-questions:

1. What is the relationship between the traditional tools for urban planners and tools and processes implied in the smart city?
2. How is machine learning used to interpret the smart city?
3. How automated is machine learning in interpreting the smart city?
4. What constitutes the smart city in Canada as identified by machine learning?

5.1 Findings and Contributions

The research questions are worth exploring because, even though the smart city has been proposed, initiated and researched, the smart city as a concept has not 'settled' on a well recognized definition or framework. Seawalls to combat the impacts of climate change; bicycle lanes that existed long before any smart city initiative; regional proposals for durable 'old tech' broadband; all of these are accorded smart city status. Consequently, concepts around the smart city have only become more confusing. Partially due to this "all-inclusive" characteristic, researchers such as Hollands (2008) argue that the smart city becomes a somewhat vague and non-operational concept. New researchers, like me, have less understanding of what constitutes a smart city than was originally proposed.

This vagueness, combined with the furious pace of information and communications technology (ICT) innovation like artificial intelligence/machine learning (AI/ML) and big data, impacts the field of urban planning and urban planners. The smart city, as concept and practice introduces new tools to assist in planners' decision-making and raises concerns about transparency and automation of the tools as planners use them.

In Chapter 2, we tracked a path toward integrating Planning Support Systems (PSS) with all that is proposed in the smart city. PSS can be defined as a set of computer-based tools that can be customized to support the practice of planning (Geertman & Stillwell, 2004). The definition of PSS is well-established compared to the vagueness of the smart city. Unsurprisingly, that renders integration difficult.

We reviewed the literature and found different evolutionary paths of PSS. PSS have evolved from the technocratic roots to include humans as part of a participatory practice. PSS practitioners and researchers have recognized the sheer difficulty of 'wicked problems' presented by issues in the city and have attempted to build that into the tools. We argued that emerging technologies like AI/ML--the tools implicated in the smart city--could automate urban planning tasks (e.g., Tenney & Sieber, 2016) in a way that could jeopardize the role of planners and supplant their PSS. ICT innovations in the smart city could be driven by non-planners like software engineers; they could be 'wrapped' in easy-to-use interfaces and result in a kind of 'neoplanning' or DIY planning. We anticipate planners' roles shifting to be facilitators or coordinators of these innovations.

If the GUIs are easy to use then this could open up civic participation to greater collaboration, especially since a source of the data comes from new non-expert sources like social media (e.g., Brabham, 2009). The availability of social media generated by the public coupled with the automation offered through the smart city might transform traditional forms of civic participation into a 'passive participation' (Tenney & Sieber, 2016). This might defeat the promise of greater civic collaboration. Overall, this synthesis prevents us from being overly optimistic about the capability of new tools introduced by the smart city to automate urban planning, which might exacerbate the opacity and technocracy in the planning process.

AI/ML is often viewed as a magical solution that will automatically generate knowledge and semantic understanding from messy data; whereas, current solutions based on AI/ML are far from an out-of-box tool to use for researchers or practitioners (Holzinger et al., 2019). Topic modelling is a popular method in smart city research and practice, although it has yet to be widely adopted as a method to analyze government documents about the smart city. We used it to analyze large textual data, extracting themes that represent clusters of keywords. We applied topic modelling and documented the various steps in which human judgement was required. We introduced the concept of human-centered machine learning (HCML) to categorize the various steps at which interventions were needed. We found that human intervention permeates every step from early data collection to results interpretation. "Explainable" was the most frequently observed characteristic in our topic modelling deployment, which focuses on interpretability of ML to social science developers and end users (Doshi-Velez & Kim's, 2017). "Transparent" was a second observed characteristic that emphasized the design process to better understand developers' thoughts and their handling of biases (Zhou & Chen, 2018). The deployment of ML also needed to be "trustworthy" since algorithms could not always be sufficiently transparent. "Visible" was the least observed characteristic but it contributed to the interpretation through relatively intuitive and interactive presentations of modelling results. Future integration of visual analytics into ML deployment could benefit in considering more users' feedback and centering humans in the process (Sacha et al., 2017). Even as we learned from the HCML literature, its continued emphasis on computational solutions to enjoin humans-in-the-loop still falls short of non-expert comprehension.

We applied topic modelling to interpret smart cities in Canada. Topic modelling offers an abductive process to apply ML in bottom-up data analysis. We extracted topics that not only reflected data, technologies and connected technology--those items one might expect from smart cities--, but also about partnership, economic opportunities, citizens and urban development and public participation. The modelling results show that Canadian cities are not 'stuck' in what Cohen (2015) calls the first generation smart city, a kind of technological determinism that will lead to improved urban life. Instead we saw an evolution towards city-led and the citizen co-creation generations (Cohen, 2015). Neirotti et al. (2014) distinguish between hard and soft domains, the former of which would more likely appear in Cohen's (2015) first generation smart city, while the topics extracted do not overly emphasize hard domains like transportation, housing and energy that are more amenable to technological applications. We argued that Canadian smart cities are unlikely to retreat to a kind of urban cybernetics because few keywords resembled those characterizing command-and-control systems.

The smart "city" in Canada is not exactly a city. Infrastructure Canada (2017) expanded on who was eligible, from urban centres to rural towns and remote Indigenous communities; aggregations of towns and rural areas could apply together. Unsurprisingly, topics related to food and agriculture are more attached to the rural and remote contexts. Rural communities proposed both hard and soft domains and demonstrated that high levels of technological sophistication does not only reside in urban centres. What also was innovative to this study into the smart city was the emergence of Indigenous communities and their visions of smart communities like language and cultural preservation. This research indicates that rural and remote communities will play increasingly important roles in the smart city discourse and dispute the notion that only cities can be smart.

What constituted technological innovation varied considerably. The Cities of Surrey and Vancouver proposed to leverage autonomous vehicles and big data analytics to build a smart transportation system; whereas the City of Bromont planned to improve their transportation systems, some of which included conventional and existing systems (i.e., increasing cycling to exploit their 100km trail network). Geographic Information Systems is not a new technology used by municipalities, but it is new for many small communities in Canada, like Frog Lake First Nation. Those communities are laggards compared with cities like Surrey and Vancounver. We argue that they are laggard in smart city practice since we lack consensus on what constitutes smartness.

The modelling results further suggest, beyond Indigenous in rural areas and non-Indigenous in urban areas, cultural distinctions result in different smart city initiatives. A good example is the Province of Quebec, which showed a distinct culture identity compared to other Canadian provinces. Beyond language differences--Quebec is predominantly French-speaking compared to the rest of Canada, topics indicate different recognitions of citizenship and democracy (Laforest, 2007). Topics found in the proposals from most Quebec communities emphasized citizen and urban development. A characterization of a smart city as technological can obscure these cultural distinctions (Sepasgozar et al., 2019) and emphasizes a universality while overlooking the diversity of smart cities.

We modelled the original applications separate from the 20 finalist proposals. Our use of topic modelling was able to identify 40 percent of the finalists and the four winners. We found that the dominant topics, including data solutions, youth/ child & culture, education, food & agriculture and housing & energy, proposed by the winners cover both hard and soft domains. We argued that the federal government considers these dominant topics of the winning proposals to be “smarter” than other topics. We compared the finalists’ applications to the original applications and found that health care arose as the most significant topic to illustrate smartness and indicated a broader categorization to community health including urban development that influences quality of citizens’ lives. Health is a broad category, encompassing citizen & urban development in the original applications and improving mental health among the Nunavummiut. “Automated” technologies like ML provide a useful approach to researching and planning for the smart city, although human efforts on explanation and interpretation are still important regarding the political considerations implicit in which communities were ultimately selected.

5.2 Reflection and Outlook

As in any research, there will be concerns that need further reflection. Herein, we have three points to discuss. First, previous research and practices do not provide clear guidelines for how to compare PSS and smart cities. Second, few rules can be followed, other than “follow the defaults”, to appropriately use ML in smart city research. Third, there is a potential lack of generalization because the initiatives were in Canada. As part of these discussions, we propose future research directions to further and extend our research into applying automated technologies in the smart city.

First, it would have been helpful to have well-established guidelines. In Chapter 2, our concern is that there is no guide for our comparison of PSS and the smart city. A few researchers tried to investigate the relationship between PSS and the smart city (Geertman, Goodspeed & Stillwell, 2015). We took a historical stance to discuss the relationship between PSS and the smart city, as we reviewed the evolution of PSS and revisited concepts like urban cybernetics and wicked problems. We consider these concepts partially because we assume emerging technologies will replicate traditional computer-based tools in the inability to adequately handle the complexity of planning problems. It is important to develop guidelines in assessing the socio-political and human aspects of emerging tools and fill the gap in understanding the difference between new technologies used in the smart city and traditional computer-based planning tools.

Second, we could investigate the assumptions and defaults. These were suggested in our table in Chapter 3. We can run the model with variations in stop words and lemmatization. For example, we can compare models in which we remove different high and low value words. We can compare coherence scores with other methods (e.g., perplexity) to determine the “appropriate” number of topics. We can run the model several times with multiple numbers of topics and compare the expression of clusters in those models. We can use the cosine measure to compare topics from the model runs. We may need to find other statistical tests for our comparison so we can identify the sensitivity of these defaults. Model parameters could be pushed even further to assist in smart city research. Numerous Natural Language Processing (NLP) techniques, like sentiment analysis (e.g., Zerr et al., 2013) and graph theory (e.g., Tierney, 2012), can be used to analyze textual data about smart cities. We can conduct the same investigation on these techniques against the HCML characteristics we referred to and expand our user-centered deployment of ML to broader applications.

In Chapter 3, we borrowed the concept of HCML from computer science to direct the use of ML in smart city research. HCML incorporates a broad diversity of approaches to apply ML (Fiebrink & Gillies, 2018). HCML continues to mix concepts like interactive ML (iML) and human-in-the-loop (HITL) and most research is still highly computational as human intervention is driven by algorithmic convenience. A less computational approach may be something like society-in-the-loop (SITL) proposed by Rahwan (2018). Rahwan regards SITL as an integration of HITL and the concept of a ‘social contract’, which represents a result of societal and political development “that can provide the efficiency and stability of sovereign states, but which also ensures the sovereign implements the general will of the people, and is held in some way accountable for violations of fundamental rights” (Rahwan, 2018: 4). The SITL paradigm advocates for greater interaction between the government and citizens and greater consideration of social problems like resolving tradeoffs between the different values and assessing benefits and costs of different stakeholders (Rahwan, 2018). Note that, while inspirational, Rahwan's is a proposal that will require empirical test cases and practice.

Given the diversity of smart city practices, we acknowledge that smart cities in other continents like Asia or Europe or in the neighbouring country, United States, can differ from those in Canada (Cocchia, 2014). Building on Chapter 4 future research can adapt the methodology based on topic modelling to investigate smart cities outside Canada. Topic modelling is bottom-up so its results entirely depend on the documents that are examined in the corpus. The same methods can be used but the interpretation of the smart city will certainly change to reflect those different contexts. Cosine similarity measures still can be used to compare our model with the model generated by a different corpus. Should there be another SCC, we can compare the original model to the model generated by the new corpus.

We began this research with an a priori assumption that the smart city needs a unified definition, which was overthrown by our modelling results. We can neither have a universal explanation of smartness, nor regard the smart "city" literally as a city. This research introduced more questions than it resolved: is a unified definition still necessary for the smart city? For example, is it important to clearly distinguish what does and does not constitute a smart city so cities do not merely appropriate the term and rebrand existing projects? Will the smart city ever be free of technocratic impulses, especially as AI/ML continues to advance at the high velocities, AI/ML will likely become ever more abstract and opaque, and big data analytics is increasingly adopted? Considering the speed of innovation, will AI/ML ever be sufficiently transparent to the non-experts, without sacrificing ease-of-use? How much domain users (e.g., planners) or researchers will be necessary and able to actively engage in the ML process rather than being uncritical tool users? Will smart cities even exist as a term in five years?

We suggest future research to continue to address the above questions. As just one example, we can interrogate the benefits and necessity of ML applications for urban planning tasks and, built on best practices, investigate the capability of planners to keep up with those innovative methods regarding when they can make judgement calls during AI/ML deployment and interpretation. Answers to a question like this might be implicated in the understanding of the difference between emerging technologies and traditional PSS, in exploration of new paradigms like SITL for guiding the governmental use of ML, and in empirical cases and practices that test various ML methods to validate output. This study reveals some preliminary, hopefully illuminating, results on how to center humans in ML methods so that they can be appropriately adopted to assist in public decision-making. Much work needs to be accomplished in this big research direction.

Reference

Brabham, D. C. (2009). Crowdsourcing the public participation process for planning projects. Planning Theory, 8(3), 242-262.

Cocchia, A. (2014) Smart and Digital City: A Systematic Literature Review. In: Dameri, R.P. and Rosenthal-Sabroux, C., Eds., Smart City: How to Create Public and Economic Value with High Technology in Urban Space, Springer, Cham, 13-43.

Cohen B. (2015). The 3 Generations Of Smart Cities: Inside the development of the technology driven city. FastCompany. Retrieved on October 08, 2015. https://www.fastcompany.com/3047795/the-3-generations-of-smart-cities

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint arXiv:1702.08608.

Fiebrink, R., & Gillies, M. (2018, June). Introduction to the special issue on human-centered machine learning. ACM Transactions on Interactive Intelligent Systems 8(2), 7:1–7:7.

Geertman, S., & Stillwell, J. (2004). Planning support systems: an inventory of current practice. Computers, Environment and Urban Systems, 28(4), 291-310. doi:10.1016/s0198-9715(03)00024-3

Geertman, S., Goodspeed, R., & Stillwell, J. (Eds.). (2015). Planning support systems and smart cities. Cham, Switzerland: Springer.

Hollands, R. G. (2008). Will the real smart city please stand up? City, 12(3), 303-320. doi:10.1080/13604810802479126

Holzinger, A., Plass, M., Kickmeier-Rust, M., Holzinger, K., Crişan, G. C., Pintea, C. M., & Palade, V. (2019). Interactive machine learning: experimental evidence for the human in the algorithmic loop. Applied Intelligence, 49(7), 2401-2414.

Infrastructure Canada (2017). Smart Cities Challenge Applicant Guide. Retrieved on May 18, 2019 from https://impact.canada.ca/sites/default/files/2017-11/SCC_Applicant_Guide.pdf

Laforest, R. (2007). State and Community Sector Relations: Crisis and Challenges in Quebec. The Philanthropist 20, 3, 171-184.

Neirotti, P., De Marco, A., Cagliano, A. C., Mangano, G., & Scorrano, F. (2014). Current trends in Smart City initiatives: Some stylised facts. Cities, 38: 25-36.

Rahwan, I. (2018). Society-in-the-loop: programming the algorithmic social contract. Ethics and Information Technology, 20(1), 5-14.

Sacha, Dominik, Michael Sedlmair, Leishi Zhang, John A. Lee, Jaakko Peltonen, Daniel Weiskopf, Stephen C. North, and Daniel A. Keima. (2017). What you see is what you can change: Human-centered machine learning by interactive visualization. Neurocomputing 268: 164-175 https://doi.org/10.1016/j.neucom.2017.01.105

Sepasgozar, S. M., Hawken, S., Sargolzaei, S., & Foroozanfa, M. (2019). Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies. Technological Forecasting and Social Change, 142: 105-116.

Tenney, M., & Sieber, R. (2016). Data-Driven Participation: Algorithms, Cities, Citizens, and Corporate Control. Urban Planning, 1(2), 101-103.

Tierney, P. J. (2012). A qualitative analysis framework using natural language processing and graph theory. International Review of Research in Open and Distributed Learning, 13(5), 173-189.

Wang, Y., & Xu, W. (2018). Leveraging deep learning with LDA-based text analytics to detect automobile insurance fraud. Decision Support Systems, 105, 87-95.

Zerr, S., Tran, N. K., Bischoff, K., & Niederée, C. (2013). Sentiment analysis and opinion mining in collections of qualitative data. In Proceedings of the 1st International Workshop on Archiving Community Memories at iPRESS (Vol. 2013).

Zhou, Jianlong and Fang Chen. (2018). 2D Transparency Space--Bring Domain Users and Machine Learning Experts Together. In Zhou, J., and Chen. F., (eds.), Human and Machine Learning: Visible, Explainable, Trustworthy and Transparent, pages 3-20, Cham: Springer.