COMPUTATIONAL SOCIAL SCIENCE FOR NONPROFIT STUDIES:
DEVELOPING A TOOLBOX AND DATABASE FOR THE FIELD

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Abstract

How can computational social science (CSS) methods be applied in nonprofit and philanthropic studies? This paper summarizes and explains a range of relevant CSS methods, and highlights key applications in our field. Based on a typical design of empirical social science research, we define CSS as a set of computationally intensive empirical methods for *data organization*, *concept representation*, *data analysis*, and *visualization*. What makes the computational methods "social" is that the purpose of using these methods is to serve empirical social science research, such that theorization can have a solid ground. We illustrate the promise of CSS in our field by using it to construct the largest and most comprehensive database of scholarly references in our field so far, the Knowledge Infrastructure of Nonprofit and Philanthropic Studies (KINPS). Furthermore, we show that through the application of CSS in the analyses of the KINPS, our field's knowledge and knowledge producing activities can be advanced, which is a core requisite for the development of our field as a discipline. We conclude the article with cautions for using CSS and suggestions for future research directions implementing CSS and the KINPS.

Keywords: Computational social science, nonprofit, philanthropy, Knowledge Infrastructure of Nonprofit and Philanthropic Studies, KINPS

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Since Computational Social Science (CSS) was coined in 2009 (Lazer et al. 2009), it has been widely experimented in many social science disciplines, including sociology, political science, and public administration (e.g., Anastasopoulos and Whitford 2019; Edelmann et al. 2020; Hollibaugh 2019). Recently, the field of nonprofit studies also have begun to apply computational methods, such as social network analysis, machine learning, and automated text analysis (e.g., Chen and Nakazawa 2017; Fyall, Moore, and Gugerty 2018; Litofcenko, Karner, and Maier 2020; Paarlberg, Hannibal, and McGinnis Johnson 2020; Yang, Zhou, and Zhang 2019). We start this article by explaining CSS and introducing its applications in nonprofit and philanthropic studies. We illustrate the promise of CSS for our field by applying CSS to create a bibliographic database aspiring to cover the entire literature of nonprofit and philanthropic studies. The article concludes with a critical reflection of the application of CSS in our field.

Computational Social Science for Nonprofit Studies: A Toolbox of Methods

All empirical analysis methods are computational to some extent, but why are some of them framed as "computational social science methods" (CSS) and others not? Is it just a fancy but short-lived buzzword, or a new methodological paradigm that is fast evolving?

Empirical studies of social sciences aim at building social theories typically include two essential parts: theorization and empirical research. This is illustrated in Figure 1, which displays the structure of empirical social science studies (Shoemaker, Tankard, and Lasorsa 2003; Cioffi-Revilla 2017). Theorization focuses on developing concepts and the relationship among these concepts, while empirical research emphasizes representing these concepts using empirical evidence and analyzing the relationship between concepts (Shoemaker, Tankard, and Lasorsa 2003, 51). The relationship between theorization and empirical research is bidirectional—researchers can be either theory-driven (i.e., deductive), data-driven (i.e., inductive), or a combination of both. Quantitative and qualitative studies, and studies with different research questions, may vary in discourse, but they typically follow a similar rationale as Figure 1 illustrates.

CSS has been widely discussed but poorly framed—an important reason causing many scholars' perception that the CSS is only a buzzword but not a methodological paradigm. We define CSS as *a set of computationally intensive empirical methods employed in social science research for data organization, concept representation, data analysis, and visualization*. What makes computational methods "social" is the objective to serve empirical social science research, such that theorization can have a solid ground (i.e., completing the deductive or inductive cycle). Solely focusing on computational methods would be classified as "data science" or "computer science."

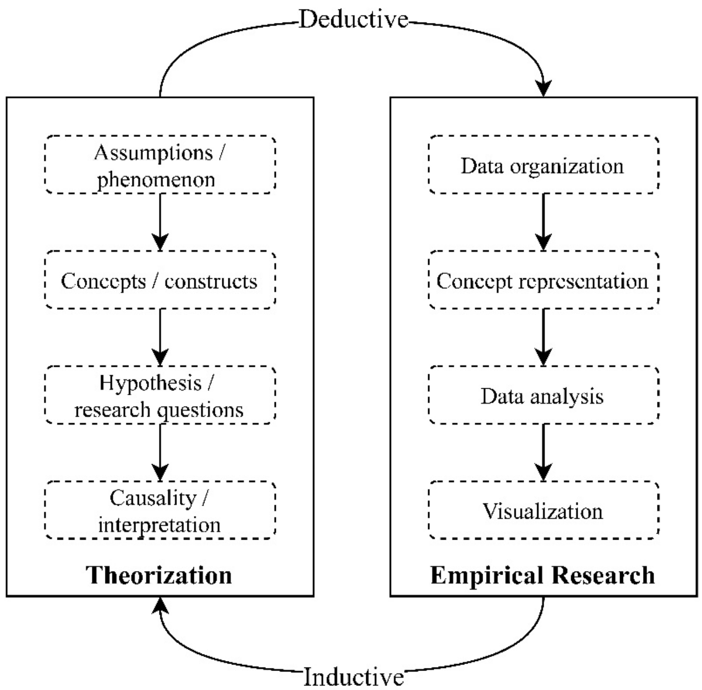

Figure 1: Structure of empirical social science studies. A diagram summary of Shoemaker, Tankard, and Lasorsa (2003), adapted by the authors of this paper.

CSS uses computationally intensive methods for the actions classified as empirical research in Figure 1: data organization, concept representation, data analysis, and visualization. *Data organization* methods help store and represent data efficiently. This is especially relevant when dealing with heterogeneous, messy, and large datasets. *Concept representation* focuses on using computational methods to operationalize concepts, for example, using sentiment analysis in natural language processing to scale political attitudes. These computational methods are very different from, but can be integrated with, traditional operationalization methods (e.g., developing survey questions and experimental interventions). Compared to traditional statistical analysis, *data analysis* in CSS typically consumes more computational resources. The *visualization* of CSS illustrates data points using graphs that enable human-data interaction, so that consumers can closely examine the data points of interests within a massive dataset.

Table 1 presents a list of the most commonly used computational methods. The following sections briefly introduce each of them and provide applications in nonprofit studies. Our purpose is not to be comprehensive and exhaustive, but to introduce these methods in non-jargon language within the framework of social science studies and provide readers resources to get familiar with CSS. Extensive details and source codes related to this paper are available via the Open Science Framework (OSF) repository (https://osf.io/nyt5x/).

Table 1: Common computational social science methods and their roles in empirical studies

Computational methods	Empirical component of social science studies			
	Data organization	Concept representation	Data analysis	Visualization
Relational database	X			
Tidy data	X		X	X
Natural language processing		X		X
Network analysis		X	X	X
Machine learning		X	X	

Relational Database

The entity-relationship (ER) model has been a fundamental data modeling method, allowing for representing real-world entities and relationships and storing them as tables in a database (Bachman 1969; Codd 1970). An ER model is a network of strictly interrelated objects describing real-world entities using particular domain knowledge. Creating an ER model is a crucial step before building any database. Also known as a database schema, the ER model describes entity types and relationships between those entities (P. P.-S. Chen 1976). Entities are represented as tables with unique identifiers known as primary keys, while relationships are represented by using foreign keys.

Many social science studies have been applying the notions of relational database, either implicitly or explicitly. Ma et al. (2017) constructed a relational database on characteristics and activities of Chinese foundations. The database schema in that paper is a good example illustrating the use of primary and foreign keys. In a similar way, data from different sources can be matched using unique countries (Wiepking and Handy 2015) or nonprofit organizations (De Wit, Bekkers, and Broese van Groenou 2017) as primary keys.

Tidy Data

It is essential to normalize data before importing it to a relational model or analysis, such that the redundancies and null values in the dataset can be minimized. Wickham (2014) coined and introduced the practices of "Tidy Data", which offer guidelines to standardize the data cleaning process. Tidy Data as a standard starts by encouraging Codd's (1970) third normal form. It also describes how to identify untidy or messy data. For example, if the columns of a dataset represent instances but not the attributes of those instances, the dataset needs to be reorganized so that the columns represent attributes and rows represent instances. This is particularly important for analyzing and visualizing longitudinal data, in which observations are organized as rows and attributes as columns (Wickham 2014, 14).

Natural Language Processing

Natural Language Processing (NLP) aims at getting computers to process human language for analysis or understand and communicate using human language (Bird, Klein, and Loper 2009; Grimmer and Stewart 2013). Named entity recognition (NER), text classification, and sentiment analysis are the most commonly used NLP tasks.

NER is the task of extracting nouns, names, and strings from unstructured texts. Methods in NER have been useful through relying on graphical models such as Hidden Markov Models (HMM) and Conditional Random Fields (CRF; Settles 2004). The current state-of-the-art methods rely on the latest advancements in contextual embedding such as the Bidirectional Encoder Representations from Transformers (BERT), which is a deep learning model which can be fine-tuned for specific NLP tasks such as NER (Devlin et al. 2019). Text classification uses supervised or unsupervised algorithms to classify texts into known or unknown categories that are relevant to research questions, and sentiment analysis (SA) applies machine-learning algorithms to grouping or scaling the attitudes of texts (Grimmer and Stewart 2013).

Scholars have already been using NLP methods in studying nonprofits. For example, researchers have tried to apply text classification techniques to grouping nonprofit activities in the United States (Fyall, Moore, and Gugerty 2018; Ma 2020a) and Austria (Litofcenko, Karner, and Maier 2020). Sentiment analysis or topic modeling can find latent clusters or the meaning of texts in large amounts of text data from websites, social media, interviews, open-ended survey questions, or other texts. In public administration and political science, these methods are applied to analyzing meanings of political speeches, assembly transcripts, and legal documents (Gilardi, Shipan, and Wüest 2020; Mueller and Rauh 2018; Parthasarathy, Rao, and Palaniswamy 2019). In sociology, text mining may be useful to extract the semantic aspects of social class, identity, or social interactions (Kozlowski, Taddy, and Evans 2019; Schröder, Hoey, and Rogers 2016; van de Rijt et al. 2013). As Evans and Aceves (2016, 43) state, "although ML and NLP cannot reproduce the subtlety of a creative researcher who brings a life of prior associations to their analysis, computational methods trained on big data can generate many suggestive, subtle associations beyond the sensitivity of human perception and the capacity of human memory."

However, these methods are still in development, and not all datasets are sources of insightful concepts. Automated methods should not be a goal in itself, and sometimes manual coding may be a more precise method to answer research questions (Varese 2013; Wasif 2020).

Network Analysis

The notion of social relations and human networks has long been existent in sociology, but modern network analysis methods only gained momentum since the mid twentieth century, along with the rapidly increasing computational power (Scott 2017, 12–13). Networks exist of vertices (nodes) and edges (links), and network analysis uses the mathematical fundamentals of graph theory to solve problems such as finding the shortest path between two vertices or the importance of each node. Typically, researchers use three levels of analysis in network analyses: nodal, ego, and complete network levels (Wasserman and Faust 1994; Scott 2017). At the nodal level, research questions usually focus on the attributes of nodes (e.g., gender, age, and education). At the ego level, the measures consider the node of interest and its neighbors (e.g., degree centrality). At the complete network level, attributes of the entire network are calculated (e.g., density and community detection).

Nonprofits scholars have been using metrics of network analysis to operationalize various concepts. For example, network density and centrality are useful instruments for measuring social capital (Herzog and Yang 2018; Xu and Saxton 2019; Yang, Zhou, and Zhang 2019). Nakazato and Lim (2016) use an alternative community currency database to analyze relationships between participants' monetary transactions. Social media data can also be subtracted and organized (Guo and Saxton 2018; Xu and Saxton 2019).

A disadvantage of using social media platforms is that not all platforms allow public access to their data, which may enormously decrease generalizability. Collaboration with social media users may help to overcome a too large dependency on (commercial) platforms. For instance, Bail, Brown, and Mann (2017) offered advocacy organizations an app with insights in their relative Facebook outreach, asking nonpublic data about their Facebook in return. Network analysis has been also applied to studying inter-organizational collaboration (Bassoli 2017; Shwom 2015), resource distribution (Lai, Tao, and Cheng 2017), interlocking board networks (Ma and DeDeo 2018; Paarlberg, Hannibal, and McGinnis Johnson 2020; Ma 2020b), and the structure of civil societies (Diani, Ernstson, and Jasny 2018; Seippel 2008).

There are more advanced ways of using network analysis. For example, network analysis can be done at all three levels of analysis at the same time, answering more complex sociological questions (e.g., Lazega, Jourda, and Mounier 2013; Müller, Grund, and Koskinen 2018). Networks can be analyzed even without real-world data, for example, Shi et al. (2017) show how different organizational strategies affect their membership rates by simulating different scenarios.

Machine Learning

Machine learning (ML) tries to learn the features of a dataset (Molina and Garip 2019). Known as supervised machine learning (SML), a parametric model (e.g., a linear regression model or neural network model) can be fitted to a labelled dataset to estimate the parameters of the model. It aims at estimating complex functions that would transform, link, or correlate inputs to outputs from existing data with the sole purpose of making predictions on new data. In SML, models rely on optimization strategies such as ordinary least squares where the goal is to minimize the difference between the square of the error between the predicted and the expected value of the function. Some SML models used for classification and prediction include regression, decision trees, random forest, ensemble models, neural networks, and deep learning models.

The ML algorithms can also rely on non-parametric approaches to find the features of the input data, which is known as unsupervised machine learning (UML). The main task of UML is to cluster the data inputs according to a metric. There are no classes or labels associated with the input data; hence UML is often used in exploratory analysis, such as dimensionality reduction and representation learning. The simplest form of unsupervised learning is the K-means clustering algorithm.

ML can have a wide range of applications. For example, ML algorithms were experimented in analyzing nonprofit mission statements (Litofcenko, Karner, and Maier 2020, 233; Ma 2020a), public institutions' tweets (Anastasopoulos and Whitford 2019) and political fundraising and voting behavior (Bonica 2018). However, ML methods also suffer from numerous challenges, particularly the issue of interpretability resulting from the black-box effect—predictive modeling often relies on training complex functions which provide little explanation on how those results are obtained--. Along with the advancement of ML programming languages, ML methods are becoming more accessible to researchers. However, researchers should be cautious with the parameters and caveats that are pre-specified by existing ML packages.

Applying the Methods: The Knowledge Infrastructure of Nonprofit and Philanthropic Studies

To advance our field, studying its knowledge and knowledge producing activities is crucial. CSS provides excellent tools to do so. By applying the newest advancements in computational methods, we created a unique database to advance in this direction: the Knowledge Infrastructure of Nonprofit and Philanthropic Studies (KINPS). The KINPS aims to provide the most comprehensive knowledge base for nonprofit and philanthropic studies created so far. Next, we introduce the KINPS and provide examples showing how scholars can use the KINPS to advance the much-needed theory and paradigm development in our field.

Data Sources of the KINPS

The KINPS currently builds on three primary data sources: 1) Over 67 thousand bibliographical records of nonprofit studies between 1920s-2018 from Scopus (Ma and Konrath 2018); 2) Over 19 thousand English records from the Philanthropic Studies Index maintained by the Philanthropic Studies Library of Indiana University–Purdue University Indianapolis; And 3) Google Scholar, the largest bibliographic database to date (Martín-Martín et al. 2018). The online supplementary document contains the details of each source.

Database Construction Methods

Constructing the database primarily involves three tasks: 1) normalizing and merging heterogeneous data records; 2) establishing a classification of literature; 3) building a knowledge graph of the literature. Each of the three tasks requires the application of various computational methods introduced earlier.

Normalizing and merging heterogeneous data records. The bibliographic records from different sources are in different formats, so the first task is to normalize these heterogeneous entries using the same database schema and following the principles of relational databases. This task is especially challenging when different data sources record the same article as Figure 2 illustrates.

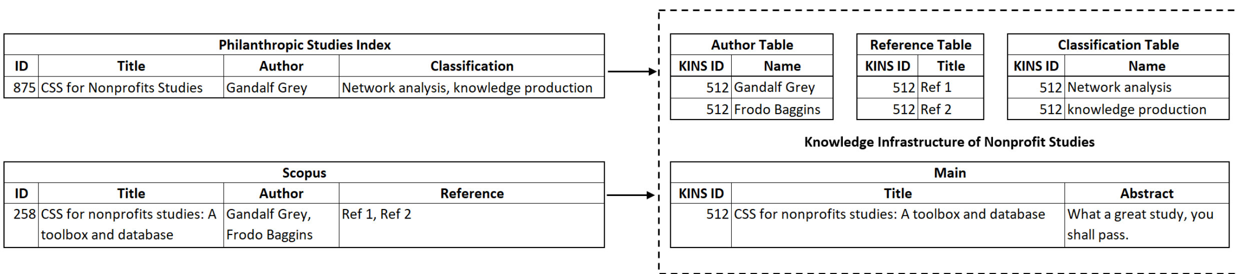

Figure 2: An example of data normalization.

To normalize and retain all the information of an article from different sources, the schema of the KINPS should achieve a fair level of "completeness" that can be evaluated from three perspectives: schema, column, and population (Ma et al. 2017). *Schema completeness* of the KINPS measures the degree to which the database schema can capture as many aspects of an article as possible. As Figure 2 illustrates, the schema of the KINPS include both "Reference Table" and "Classification Table." *Column completeness* measures the comprehensiveness of attributes for a specific perspective. For example, only the KINPS has the "Abstract" attribute in the "Main" table. *Population completeness* refers the extent to which we can capture the entire nonprofit literature. It can be evaluated by the process for generating the corpus, which was detailed in Ma and Konrath (2018, 1142).

Another challenge is disambiguation, a very common task while merging heterogeneous datasets. As Figure 2 shows, records of the same article from different sources may vary slightly. The disambiguation process uses NLP methods to measure the similarity between different records: we first converted two strings to word vectors, then calculated the cosine of the angle between the two vectors

(Jurafsky and Martin 2019, 103). This process helped us link over 3,100 records from different sources with high confidence. Technical details, source codes, and similarity results are in the OSF repository.

Establishing a classification of literature. Classification reflects how social facts are constructed and legitimized from a Durkheimian perspective (Durkheim [1912] 2012). A classification of literature presents the anatomy of scholarly activities and also is the basis for building knowledge paradigms in a discipline or research area (Kuhn 1970). What is the structure of knowledge production by nonprofit scholars, how does the territory evolve time, and what are the knowledge paradigms in the field? To answer such fundamental questions the literature of nonprofit and philanthropy needs to be classified.

We first classified the references in the KINPS using state-of-the-art advancements in ML and NLP (Devlin et al. 2019). After merging data records from different sources, 14,858 records were labeled and have abstract texts. We used the title and abstract texts as input and classification labels as output to train a machine-learning algorithm. After the classification algorithm (i.e., classifier) was trained and validated, it was used to predict the classifications of all 60 thousand unlabeled references in the KINPS. The source codes with annotations are available in the OSF repository.

The classification in the KINPS should be developed with extreme prudence because it may have profound influence on shaping the research themes in our field. We made a great effort to assure that the classification is relevant, consistent and representative. First, the original classification was created by a professional librarian of nonprofit and philanthropic studies[†] between the late 1990s and 2015. Second, we normalized the original classification labels following a set of rules generated by three professors of philanthropic studies and two doctoral research assistants with different cultural and educational background. Third, we invited a large group of nonprofit scholars (approximate 75 nonprofit and philanthropic studies scholars) to revise the predicted results, and used their feedback to fine-tune the algorithm. In future use of the database, continuously repeating this step will be necessary to reflect changes in research themes in the field. Lastly, if scholars find our classification unsatisfactory, they can follow our code scripts to generate a classification system that may better fit their own research questions.

Building a knowledge graph of the literature. From the perspective of disciplinary development, three levels of knowledge paradigm are crucial to understand the maturity of a discipline. Concepts and instruments are *construct paradigms* (e.g., social capital), which are the basis of *thematic paradigm*[‡] (e.g., using social capital to study civic engagement). By organizing different thematic paradigms together, we are able to analyze the *metaparadigms* of our knowledge (Bryant 1975, 356).

[†] We very much appreciate [name omitted for blind review] for her enormous valuable work.

[‡] The original study analyzes a specific discipline (i.e, sociology). We adapted the name (i.e., "sociological paradigm") to fit the study of other disciplines and research areas.

We can use a network graph to analyze the structure and paradigms of the knowledge in our field (Boyack, Klavans, and Börner 2005). Figure 3 illustrates the knowledge structure of nonprofit and philanthropic studies based on the KINPS.

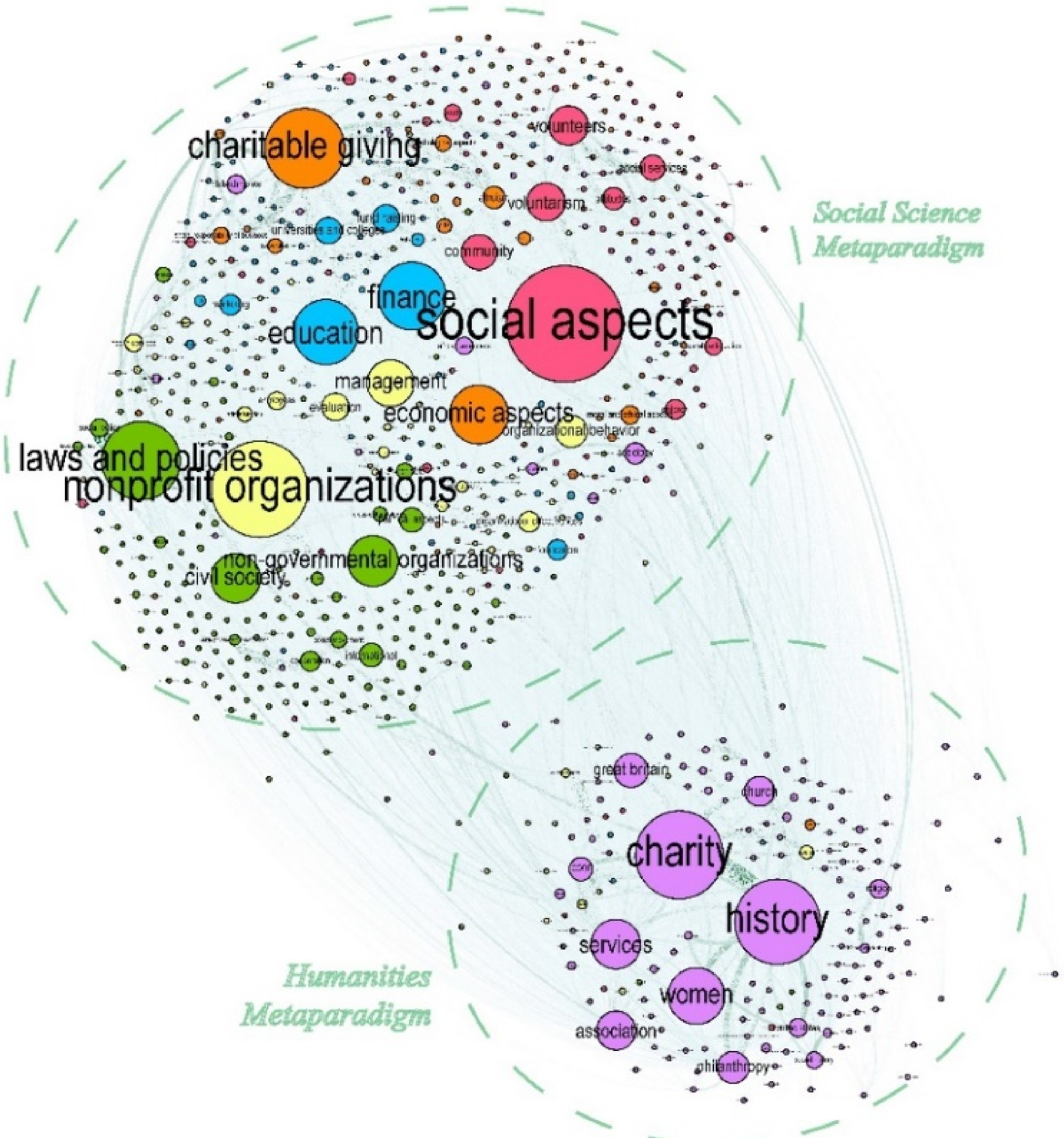

Figure 3: The Knowledge Structure of Nonprofit and Philanthropic Studies.

In this network graph, nodes represent the classifications labels established in the preceding section, two nodes are connected if a reference is labelled with both subjects, and the edge weight indicates the times of connection. The nodes are clustered using an improved method of community detection and visualized using a layout that can better distinguish clusters (Martin et al. 2011; Traag, Waltman, and van Eck 2019). Details and source codes are available in the OSF repository.

As Figure 3 shows, there are two metaparadigms in our field: *humanities* and *social science metaparadigms*. We encourage readers to discover the key references related to the different paradigms via our online user interface, introduced below. The humanities metaparadigm includes historical studies of charity, women, church, and philanthropy and many other topics. The social science metaparadigm includes five thematic paradigms represented in different colors. For each paradigm we mention key topics: 1) the *Sociological paradigm* includes the study of local communities and volunteering; 2) the *Economic paradigm* includes research on giving and taxation; 3) the *Finance paradigm* includes research on fundraising, marketing, and education; 4) the *Management paradigm* studies evaluation, organizational behavior, and employees, and prefers "nonprofit organizations" in discourse; 5) the *Political and policy paradigm* includes research on law and social policy, civil society, and social movements, and prefers "non-governmental organizations" in discourse. More thematic paradigms can be found by fine-tuning the community detection algorithm (e.g., Heemskerk and Takes 2016, 97), which will be part of future in-depth analysis of the KINPS.

For educational purposes, we can construct a coherent, inclusive and evidence-based curriculum based on these paradigms. For publication purposes, it is essential to strategically establish and posit journals appropriately (Walk and Andersson 2020). Academic associations can use the knowledge graph and paradigms to strategically build our scholarly community and facilitate conversations between groups with different knowledge paradigms.

Figure 3 also reveals the empirical evidence that support some anecdotal observations of our field. First, the research area is truly interdisciplinary. It includes both humanities and social science metaparadigms, and we can find numerous thematic paradigms within the metaparadigms. Second, the research field is usually termed "nonprofit and philanthropic studies" because it includes two metaparadigms—social science disciplines prefer to use "nonprofit" and "nongovernmental" in their discourses, while humanities prefer "philanthropy" and "charity." Third, in different thematic paradigms of social sciences, "nonprofit" is preferred in the discourse of management and finance, and "nongovernmental" is preferred in studying politics, policy, and law. Although the paradigmatic discourse influences the use of a specific term to describe the object under investigation, different research themes have been forming a coherent and intra-connected knowledge community.

Overall, the empirical examples here provide us crucial instruments for the study and mature development of our field. Nonprofit scholars have been talking about intellectual cohesion and knowledge paradigms as indicators of this field's maturity (Young 1999, 19; Shier and Handy 2014; Ma and Konrath

2018). Future studies can build on existing literature, the KINPS database, and the computational methods introduced in the proceeding section.

Using the KINPS: A Cloud Platform for Data Interaction

The KINPS database is stored using MySQL, which is a powerful industrial database platform but not user-friendly. We built a data platform using Tableau that allows users to interact with the dataset intuitively (https://jima.me/?KINPS).

Facing the Future of Nonprofit Studies: Promoting Computational Methods in Our Field

We strongly believe that computational social science methods provide a range of opportunities that could revolutionize nonprofit and philanthropic studies. First, CSS methods will contribute to our field through its novel potential in theory building. Computational methods can be used with both inductive and deductive approaches (Edelmann et al. 2020), and they can analyze "old" research questions using new methods. Using computational methods, researchers can generate, explore, and test new ideas at a large scale. For the KINPS, we did not formulate a priori expectations or hypotheses on the structure of nonprofit and philanthropic studies. The knowledge graph merely visualizes the connections between knowledge spaces in terms of disciplines and methodologies. As such it is a purely descriptive tool. Now that it is clear how themes are studied in different paradigms and which vocabularies are emic to them, we can start to build mutual understanding and build bridges between disconnected knowledge spaces. Also we can start to test theories on how knowledge spaces develop (Shwed and Bearman 2010; Frickel and Gross 2005).

Second, CSS methods combine features of what we think of as 'qualitative' and 'quantitative' research in studying nonprofits and voluntary actions. The prototypical qualitative study relies on a small number of observations to produce inductive knowledge based on a human interpretation of textual data, such as interviews with foundation leaders. The prototypical quantitative study relies on a large number of observations to test predictions based on deductive reasoning with statistical analysis of numerical data, such as scores on items in questionnaires completed by volunteers. The prototypical CSS study relies on a large number of observations to produce inductive knowledge based on an exploratory statistical analysis of textual or numerical data. Computational methods like machine learning can help researchers to inductively find clusters, topics or classes in the data (Molina and Garip 2019). These classifications can then be used in statistical analyses that may involve hypothesis testing. With automated sentiment analysis in NLP, it becomes feasible to quantify emotions, ideologies, and writing style such as valence, intensity, and complexity in text data. These can be used to analyze reports on the work of nonprofit organizations (e.g., Farrell 2019; Lecy, Ashley, and Santamarina 2019). Computational social science methods can also be used to analyze audiovisual content, such as pictures and videos. To provide one example: CSS methods will allow to study the use of pictures of recipients of donations in fundraising materials, and how characteristics of these pictures are correlated with amounts donated by donors.

Third, a promising strength of CSS methods are the principles of open science including the high standards for reproducibility typically applied. Public sharing of data and algorithms provides a citation advantage (Colavizza et al. 2020) and advances the development of tools and knowledge in our field. For instance, Lecy and Thornton (2016) developed and shared an algorithm linking federal award records to recipient financial data from Form 990s. Across our field, there is an increasing demand for data transparency. With the current article, we not only provide access to the KINPS database, but also source codes with detailed annotations for reproducing, reusing, and educational purposes.

As promising and relevant the potential contributions of CSS to the field are, there are also concerns and risks we need to mitigate when implementing CSS in nonprofit and philanthropic studies. There are ample examples of unintended design flaws in CSS that can lead to serious biases in outcomes for certain populations, resulting in discriminatory practices and maintaining or even contributing to increasing inequalities. The ML algorithms can reproduce biases hidden in the training dataset, and then amplify these biases while applying the trained algorithms at scale.

To extend the caution to the KINPS, our bibliographic database as it stands now certainly lacks diversity. Most of the research included in the KINPS is conducted on "WEIRD" participants, that is, from Western, Educated, Industrialized, Rich and Democratic countries (Henrich, Heine, and Norenzayan 2010). Results based on these populations are unlikely to be applicable to all mankind. The KINPS also lacks disciplinary diversity as most of these references are social science literature. The roles of humanities in our field can be underestimated. In addition, thematic diversity is also a concern. Because the KINPS mostly covers academic articles, the database is limited to those topics that are only interested to scholars. These topics do not necessarily reflect the most relevant topics in nonprofit and philanthropic studies, or those with highest societal relevance. Improving the KINPS will be an ongoing and collective effort.

For future research implementing CSS in nonprofit and philanthropic studies, we see great opportunities, as long as the applications carefully consider the potential limitations, biases, and weaknesses that are inherent in CSS methods. We end this article with a few ideas for future research.

With a larger community of international scholars, we will be working to expand the KINPS to include academic publications in additional languages, starting with Chinese. We encourage interested scholars to contact us to explore options for collaboration. Furthermore, the KINPS is an ideal starting point for meta-science in our field. With linked citation data, it is possible to conduct network analyses of publications, estimating not only which publications have been highly influential, but also which publications connect different subfields of research. Researchers can find publications that are similar to key publications of interest through co-citation networks. Furthermore, by extracting results of statistical tests, it is possible to quantify the quality of research—at least in a statistical sense—through the lack of errors in statistical tests, and the distribution of p-values indicating p-hacking and publication bias. In the future, algorithms may be developed to automatically extract effect sizes for statistical meta-analyses. We highly encourage scholars to use KINPS and advance nonprofit and philanthropic studies toward a mature discipline and a place of joy.

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