Using machine learning and text mining to classify fuzzy social science phenomenon: the case of social innovation

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Abstract
Classifying social science concepts by using machine learning and text-mining is often very challenging, particularly due to the fact that social concepts are often defined in a vague manner. In this paper, we put forward a first conceptual step to overcome this challenge. By using the case of social innovation, which has 252 distinct definitions, we qualitatively demonstrated that these definitions group around four different themes where various definitions utilise one or multiple of these criteria in different combinations to define social innovations. We designed an experiment where a database of social innovation projects annotated i) based on an overall understanding and ii) based on a decomposed definition of four criteria. As a next step, we will test the performance of various model specification on these two approaches.

Introduction
We live in machine-learning age. The advent of artificial intelligence and the underlying machine-learning processes is more and more evident in the daily life from transport systems to productions. Similarly, the way natural sciences is conducted now benefits greatly from machine learning. This trend of utilising machine learning has also being increasingly explored in social sciences. However, one particular problem relating to the applications in social science is that most concepts are defined in a comparatively vague manner due to the differential understandings of them in their respective literatures. This makes employing machine-learning challenging as in most cases it requires a well-defined definition of the phenomenon to be classified and/or large amounts of data. This challenge is often attenuated when large amounts of data is not readily available due to the nature of the social phenomenon in question.

In this paper, we propose a conceptual approach to employ machine learning in classifying complex and fuzzy social science concepts. Our approach involves decomposing the social science concept in question to smaller, comparatively more analytically defined components through an extensive qualitative literature review of the differential understandings of the concept.

To test the suitability of our approach, we compare the performance of a machine learning model to classify entities related to the complex and vaguely defined social science concept of social innovation. We implemented two models: one is based on our approach of decomposing the definition of social innovation and another based on the conventional method of classifying entities based on undecomposed definition of social innovation.

The Case of Social Innovation

We use social innovation as a case study to illustrate our approach. Social innovation is broadly defined as "new ideas (products, services and models) that simultaneously meet social needs (more effectively than alternatives) and create new social relationships or collaborations" (European Commission, 2010). Prominent examples include the historical origins of the co-operative movement, hospices, model villages as well as the modern projects such as microfinance, fair trade, the Big Issue, online activism platforms and specific technological solutions that benefit disadvantaged groups such as blind people or refugees . While the most diffused examples of social innovation originates from the Victorian era, it is rapidly growing phenomenon thanks to the increased availability of social media and also the possibility of real-time collaboration through online tools. Social innovation has a huge potential to improve the lives of people where conventional innovation fails the challenge. In fact, social innovation featured heavily in UN Sustainable Development Goals for 2030.

While the importance and the increasing uptake of the concept of social innovation are detailed above, the exact definition of the concept of social innovation is complex and hotly debated in social science and policy literature. Taking its roots from the classics of Karl Marx , Max Weber and Emile Durkheim, the concept of social innovation started being used extensively in 1960s and since then the exact meaning of the concept have been subject of a debate. Edwards-Schachter and Wallace (2017) report that there are at least 252 variations of the concept. This cacophony of the definitions makes any data collection exercise more difficult but it is particularly challenging for a machine learning based approach, which requires a fairly clean and analytical understanding of the subject matter.

To overcome this hurdle, based on Edwards-Schachter and Wallace's (2017) idea, we have conducted a qualitative literature review to establish some common themes in the myriad of definitions. We have established that there are in fact four common themes in the definitions of social innovation (see Table 1 for a summary). While nuances between each of these themes are vastly varying, the broad themes are about social objectives, social interaction between actors or actor diversity, social outputs and innovativeness. However, different definitions include different combinations and different number of these themes (e.g. the EU definition we used above emphasises social objectives and actors interaction).

We used these four common themes in various definitions as distinct criteria in our model. We created four different classifiers for each of these four criterion. This kind of flexible and modular approach not only allows us to add more granularity to a complex concept but also it provides us the flexibility later on to deconstruct and construct any definition.

Table 1. Decomposed Definition of Social Innovation

Element of definition	**Criteria description**
Objectives	The project primarily or exclusively satisfies (often unmet) societal needs, including the needs of particular social groups; or aims at social value creation.
Actors and actor interactions	Satisfy one or both of the following: i. **Diversity of Actors:** Project involves actors who would not normally involve in innovation as an economic activity, including formal (e.g. NGOs, public sector organisations etc.) and informal organisations

	(e.g. grassroots movements, citizen groups, etc.). This involvement might range from full partnership (i.e. project is conducted jointly) to consultation (i.e. there is representation from different actors). ii. **Social Actor Interactions:** Project creates collaborations between "social actors", small and large businesses and public sector in different combinations. These collaborations usually involve (predominantly new types of) social interactions towards achieving common goals such as user/community participation. Often, projects aim at significantly different action and diffusion processes that will result in social progress. Often social innovation projects rely on trust relationships rather than solely mutual-benefit.
Outputs/Outcomes	Project primarily or exclusively creates socially oriented outputs/outcomes. Often these outputs go beyond those created by conventional innovative activity (e.g. products, services, new technologies, patents, and publications), but conventional outputs/outcomes might also be present. These outputs/outcomes are often intangible and they might include the following but not limited to: - change in the attitudes, behaviours and perceptions of the actors involved and/or beneficiaries - social technologies (i.e. new configurations of social practices, including new routines, ways of doing things, laws, rules or norms) - long-term institutional/cultural change
Innovativeness	There should be a form of "implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method". The project needs to include some form of innovative activities (i.e. scientific, technological, organisational, financial, and commercial steps intending to lead to the implementation of the innovation in question). Innovation can be technological (involving the use of or creating technologies) as well as non-technological. The innovation should be at least "new" to the beneficiaries it targets (even if it is not new to the world).

Method and Data

We employ the European Social Innovation Database (ESID) in our study. ESID is a comprehensive database of social innovation projects that employs text-mining techniques to collect data about social innovation from the publicly available websites. The methodology used in ESID to populate social innovation projects semi-automatically initially uses currently available databases, lists, case study repositories, and mappings of social innovation projects in order to obtain initial data about social innovations. This phase includes the following steps (see Figure 1 for graphical representation):

1. Compose a list of social innovation sources.
2. Crawl the project description pages from the listed sources.
3. Crawl project websites, if they were available in the social innovation source.
4. Translate the crawled texts to English (if they are not in English).

5. Manually annotate a set of projects. The projects are annotated whether they satisfy social innovation criteria by human coders.
6. Create machine learning models for classifying projects for specific social innovation criteria.
7. Obtain additional features about the project, such as information about organisations involved, location, etc.

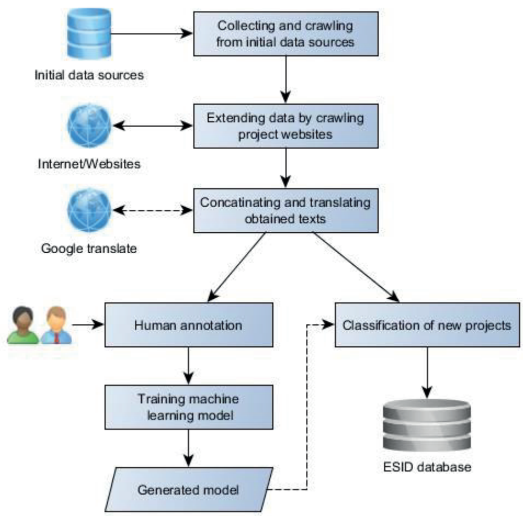

Figure 1. Workflow of a classification of social innovation criteria.

After dropping projects we don't have any available websites or textual information or information less than 350 characters, ESID preliminary contained 3560 projects.

In order to make a data set for supervised machine learning-based approach, we organised a set of data annotation workshops. The annotators were PhD students and research staff whose research is associated with the areas of innovation and social innovation. We created a single document for each project which was a combination of the project description available in the original data source and also the text available on the project websites.

The annotators were asked to annotate sentences that present how a project met defined social innovation as a whole or in terms of the decomposed criteria (objectives, actor interaction, outputs, innovativeness). Annotators were asked to give a score at the document (i.e. project) level for the whole project based on an overall understanding of social innovation as well as based on each of the four decomposed criteria (as presented in Table 1). The document level marks were in the range of 0-3:

- 0 – criteria not satisfied
- 1 – criteria weakly satisfied
- 2 – criteria partially satisfied
- 3 – criteria fully satisfied

Our annotations involved at least two independent annotators (three annotators where there is disagreement between two annotators). We have obtained 728 annotated documents from three annotation workshops out of a total of 3560 projects initially included in the ESID. Of 728 annotations, 120 included annotations based on an overall understanding.

The dataset created during the annotation task was used for training and validation of the machine learning-based approach. The classifier is created for each social innovation criteria (objective, actors, outputs, innovativeness) as well as an overall understanding of the concept.

We have created and evaluated multiple classifiers for each of the criteria. The classifiers that were used were Naive Bayes, decision trees, random forests, long short-term memory recurrent neural networks (LSTM) (Sundermeyer et al, 2012), convolutional neural networks (LeCun et al., 2015) and stacked LSTM and convolutional neural networks (Wang et al., 2016).

The naive Bayes, decision trees and random forests classifiers used bag-of-words language models, with stemmed tokens and excluded stopwords (using Rainbow stop-word list[1]). Also, the naive Bayes, decision trees and random forests used unigram, bigrams, trigrams, and fourgrams as features. The neural network implementations relied on neural language model (Glove embeddings (Peninngton et al., 2014)). Long short-term memory recurrent neural networks (LSTM) classifiers were using a single layer with 100 neurons and a dense layer outputting the class. The convolutional neural network architecture consisted of three layers of convolutional networks with 512 filters in the first layer, 256 in the second and 128 in the third layer. The ensemble architecture consisted of the three-layered described convolutional network whose output was input to LSTM neural network.

Since dataset was not balanced, having more negative instances than positive, we also performed an experiment with balancing data by oversampling the class that had minority instances and adding new negative instances.

Next Steps

As a next step, we plan to construct two different classification models: one based on an overall understanding of the social innovation and the other based on our approach of analytically decomposing the definition of social innovation to four different criteria. We will then be able to compare the performance of these two models to each other and to reveal the added benefit of our approach. We also plan to explore the how the performance difference changes in these two approaches based on specific model specifications.

Conclusion

In this paper, we put forward a first conceptual step to utilise machine learning to classify complex and fuzzy social science concepts. By using the case of social innovation which has 252 distinct definitions, we qualitatively demonstrated that these definitions group around four different themes where various definitions utilise one or multiple of these criteria in different combinations to define social innovations. We designed an experiment where a database of social innovation projects annotated i) based on an overall understanding and ii) based on a decomposed definition of four criteria. As a next step, we will test the performance of various model specification on these two approaches.

[1] http://www.cs.cmu.edu/ mccallum/bow/rainbow/

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