Detecting the Conceptual Evolution of Social Inequality in Sociology

KANYAO HAN, JIAWEI DENG, and JUNJIE YUE

1 INTRODUCTION

Social inequality regarding race, gender, class, and other social identities is a key issue in our society as well as a crucial topic in many fields of social studies. Undoubtedly, the conceptual perception of social inequality is evolving over time. For example, Gang et al. [7] investigates the evolution of gender and ethnic stereotypes through text mining of news over the past 100 years. Though there have been a number of scholars investigating the conceptual evolution of gender and ethnic stereotypes based on text mining of news [6, 7, 9], little is known about the conceptual evolution in scholarly work, especially in the field of sociology which focuses mainly on a variety of social inequality issues not limited to gender and ethnicity. Different from media news that often explicitly embody social stereotypes, the sociology papers aim mainly to analyze and criticize such stereotypes and other social inequality. We thus aim to explore how the conceptual discussion, analysis, and criticism of social inequality problems evolve in sociology papers. In other words, our task is to detect how sociology papers talked about social inequality in more than one century.

In the domain of sociology, especially in the sub-domain of sociology of knowledge, sociologists often investigate sociology papers to trace the evolution of sociological knowledge and discussion mainly though human reading [1]. However, because there are numerous top journal papers which are often very lengthy (over 30 pages), it is difficult and time-consuming to explore all papers by human reading. In view of this difficulty, we need computational models to explore them.

However, most state-of-the-art computational methods are developed based on practical needs, such as indexing, classification, recommendation, sentence generation, among others, and benchmark datasets often used in computer science such as news and reviews. Social studies may be not interested in these tasks. They care more about analysis, interpretation, and explanation often based on texts with unique characteristics. In view of this, this project aims to modify and adapt text mining and machine learning methods, previously developed based on conventional computer science tasks and benchmark datasets, to detect the conceptual evolution of social inequality in prestigious sociology journals. Therefore, our focus will be on new ways of using and evaluating topic modeling and word embedding for the purpose of analysis. It is worth noting that, compared to pure substantial analysis, we are more interested in the application and evaluation of machine learning models in social data mining for analysis. This paper, accordingly, will focus more on the technical aspects in terms of application and evaluation for analysis rather than substantial analysis of conceptual evolution itself.

2 DATA PREPROCESSING

2.1 Data Collection

The first step of data collection was to identify representative sociology journals. Our selection was based on the result of a journal reputation survey conducted by Erin McDonnell and Dustin Stoltz [8]. We selected 5 top generalist journals : American Sociological Review (ASR), American Journal of Sociology (AJS), Social Forces (SF), Social Problems (SP), and Demography (DE). Annual Review of Sociology was excluded from our selection because it only publishes literature review papers rather than original research papers. We then downloaded journal papers published from 1895 to 2021, leveraging Web of Science and Endnote. We also downloaded a meta-information dataset that contains the publication information of these papers, such as publication year, and matched it to the papers we downloaded. A few papers were missing in our downloaded dataset for several reasons, such as copywrite and database access issues as well as digitization issues faced by papers published decades or even a century ago. However, we assume that missing papers would not have substantial impacts on our research since the missing proportion is not large.

2.2 Preprocessing

PDF files are not readable directly by the machine, we converted them to txt files through a Python package called Textract and stored all texts in a dataframe by matching them to their corresponding journal and year of publication. We then cleaned and preprocessed all texts as follows:

- Remove copyright information
- Remove numbers and punctuation
- Convert all string into lowercase
- Remove stop words and rare words
- Lightly lemmatize texts
- Detect and remove strings before abstracts, citations in body, and references.

3 STRUCTURAL TOPIC MODELING

3.1 Principle

Topic models are unsupervised probabilistic models that aim to find the semantic clusters in documents. They are most dominantly used for the analysis of large text corpus. As the rapid development of social media platforms, topic modeling is widely utilized in those text such as blogs and tweets as well. The Latent Dirichlet Allocation(LDA) models [2], being the most well-known type of models, are the most fundamental ones as well. However, metadata are neglected in LDA and are not taken into account in the model function and it is based on the word frequency. Structured topic modeling(STM) is proposed to address those problems [12]. What differs STM from LDA is that it allows correlations between topics. In addition, STM can incorporate covariates and metadata in the analysis of text. The model is primarily affected by two components: topic prevalence and topic content. Topic prevalence is defined as the proportion of a document devoted to a topic which is implemented as a global Dirichlet distribution that are shared by all topics in LDA. It is replaced with logistical normal distributions with a mean vector parameterized as a function of the covariates. As for topic content, it is the word rates used in mentioning the certain topic. The definition of the word distribution over a topic is an exponential model which is similar to a multinomial logistic regression, which consist of the frequency of occurrence deviations of each word, and the deviation of word to certain topics, covariates and their correlations.

To understand the mechanism of topic modeling, there are some assumptions we need to have in mind while implementing. The first assumption is that all documents in a corpora consists of different topics. Those topics use similar groups of words. Second, documents are defined as probabilistic distribution of latent topics. Unlike words that can be seen in each document, those topics remain latent until further delve into the corpus by leveraging algorithms like topic models. Third, topics are probability distributions of words as well. Under these assumptions, the creation of a new document can be described as follows. First, the total number of words is given. For each words, we firstly choose a topic for it based on the probability distribution of a topic mixture and then choose a word based on the word distribution of that topic. The twofold procedure will continue until all words are created.

STM works backwards. For each word in a document, we randomly assign a topic to it and assume that all topic assignments except the current one is true. In each iteration, we will update the assignment based on the two proportions mentioned above. Finally, we will reach a steady state where all assignments make sense.

3.2 Parameter Tuning and Model Performance

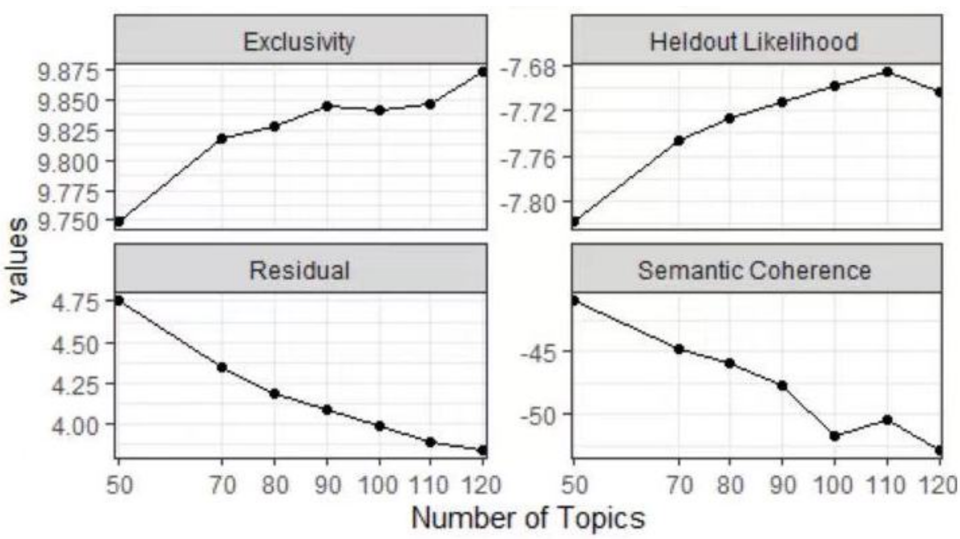

Fig. 1. Diagnostic Values by Number of Topics. We use four metrics (mainly based on heldout likelihood) shwon in the figure to select the number of topics.

To find the optimal number of topics, we have run multiple models and evaluate the results by different metrics including exclusivity, heldout likelihood, residual and semantic coherence. As it is noticeable in the diagnostic metrics, 110 has the largest result on heldout likelihood among the values ranging from 50 to 120 and 10 as the increment. In addition, the measurements of exclusivity and semantic coherence are similar between models using 100 and 110 as number of topics, which also validates our choice of using 110 as the input parameter of the STM model.

3.3 Results and Human Evaluation

Statistical metrics such as held-out likelihood and semantic coherence can be used for model performance evaluation, but it does not always signify whether the results are interpretable or, in other words, whether a topic has human-identifiable semantic meaning [5]. We further evaluate our model based on topic identification, diversity and graininess, domain knowledge, and meanings in vector spaces.

3.3.1 Topic Identification

We use the term topic identification to refer to whether human can easily identify what a topic represents for and distinguish it from other topics. We leveraged top words calculated by four metrics (highest probability, frequency and exclusivity, lift, and score) to measure whether the meaning of a topic can be easily identified.

- Highest probability words are the most frequent words that may appear under this topic.
- FREX contains words that are both frequent and not shared by other topics. It can often distinguish similar or related topics when they have similar highest probability words.

Table 1. Top Words for Topic 10

Metrics	Top Words
Highest Prob	jewish, jew, soviet, russian, israel, russia, party, communist, state, socialist, israeli, economic, country, nazi, society, eastern, union, europe, socialism, political
FREX	soviet, israeli, russian, nazi, ussr, israel, russia, jewish, antisemitism, jew, kibbutz, hungarian, nonjewish, fascist, moscow, socialism, socialist, communist, postcommunist, basque
Lift	pravda, jewry, israeli, nonjewish, ruble, soviet, moscow, basque, armenian, nonjews, czechoslovak, jewishness, russian, trotsky, ussr, postcommunist, zionism, kyrgyzstan, kibbutz, leningrad
Score	jew, soviet, jewish, russian, israeli, russia, nazi, communist, israel, socialist, antisemitism, kibbutz, socialism, ussr, palestinian, hungary, poland, fascist, nonjewish, nationalism

Table 2. Topics Correlated with Topic 10

Topic	Correlation
30	0.248
87	0.248
108	0.232
35	0.164
63	0.152
39	0.138
98	0.132
2	0.131
69	0.126

- Lift and score are another two metrics used to rank words.

Take Topic 10 shown in Table 1 for example, we can find that the 4 lists of top words are slightly different, but we can still tell that this topic refers to totalitarianism because all these lists of topic words contains Fascism- and Stalinism-related words, such as Nazi, Jews, communist, and Soviet. Another information we can obtain from this topic is that sociology papers may often compare Fascism with Stalinism when they discuss totalitarianism. In this topic, jewish, soviet, communist, are in the highest probability words which means this topic is related to the Former Soviet Union, and communist party.

The meanings of the vast majority of topics from our model can be easily identified as Topic 10.

3.3.2 Topic Diversity

The 110 topics from model covering a variety of substantial issues in sociology in a long history, including but not limited to family, race, gender and sexuality, and environment protection, law and legal policies, politics, class, education, and military, among many others. Besides these substantial sub-fields in sociology, the results also capture other topical information such as methodology, theory, and generic information (e.g. country names).

3.3.3 Topic Graininess

Many topics are also fine-grained. Figure 2 shows the correlation matrix of all topics, in which the lighter area indicates closer relation. After an investigation of correlated topics, we find that some of the topics can be fine-grained sibling topics and belong to a higher-level (more coarse-grained) field. For example, Topics 1, 2, and 30 shown in Table 2 are sibling topics and belong to a parental field related to child-care in a broader sense, according to the top words for these three topics shown in Table 3. Specifically, Topics 1, 2, and 30 can represent society-level, motherhood-level,

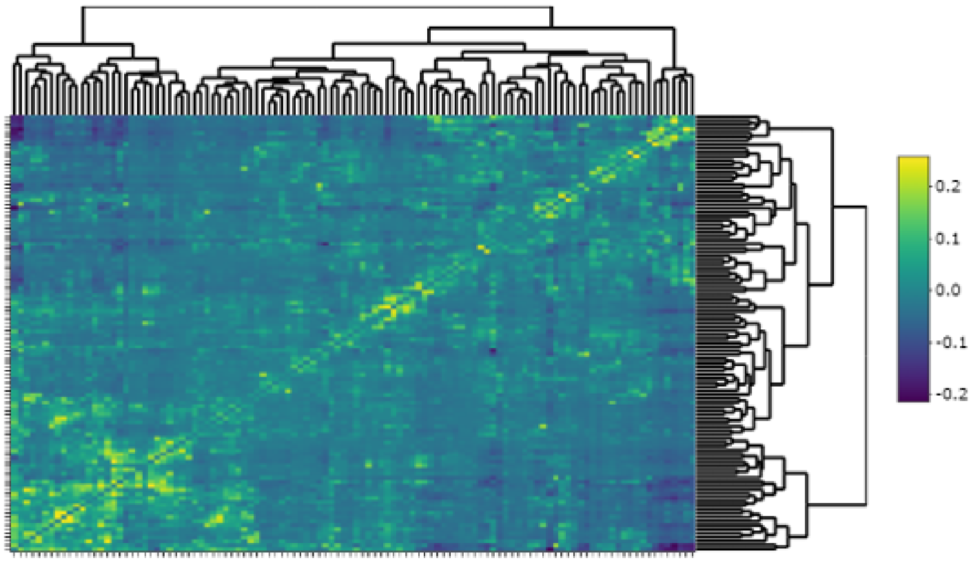

Fig. 2. Topic Correlation Matrix

Table 3. Top Words for Sibling Topics 1, 2, and 30

Topic	Metrics	Top Words
1	Highest Prob	child, care, mother, number, childrens, likely, may, guest, downloaded, household, age, parent, support, year, one, foster, characteristic, time, also, childcare
	FREX	child, care, foster, orphan, childcare, preschool, signi, childrens, youngest, caregiver, childsupport, immunization, rearing, speci, award, yes, cant, placement, mother, childrearing
2	Highest Prob	woman, married, among, status, number, year, first, domestic, mother, may, one, young, motherhood, likely, however, study, since, education, never, also
	FREX	woman, motherhood, childless, domestic, lactation, amenorrhea, married, sexrole, ried, menstruation, childrearing, breast, currently, childbirth, feeding, never, ever, resumption, marriedwomen, active
30	Highest Prob	amily, household, living, structure, head, type, child, home, member, live, extended, arrangement, economic, single, kin, adult, among, one, alone, status
	FREX	family, fily, kin, head, coresidence, headship, living, household, singleparent, extended, arrangement, headed, nuclear, alone, familial, live, femaleheaded, filies, structure, extendedfamily

and household-level child-care, respectively, even though we can give them the same parental tag child-care. In addition sibling topics, some topics are correlated to Topic 1 without any sibling relationships. For example, Topic 35 refers to quantitative methods (especially regression analysis), which implies that the field represented by Topic 1 often uses quantitative methods.

3.3.4 Temporal Trends

To justify the model based on our prior knowledge of actual historical events, we led some experiments that are trending in history:

- LGBT Issue in 1980s
- Totalitarianism during WWII

Table 4. Top Words for Topic 64

Metrics	Top Words
Highest Prob	sexual, adolescent, behavior, relationship, sex, gay, peer, partner, drinking, lesbian, alcohol, friend, intercourse, respondent, girl, romantic, heterosexual, may, wave, dating
FREX	sexual, gay, sexuality, lesbian, adolescent, bisexual, drinking, homosexuality, romantic, alcohol, heterosexual, pornography, dating, intercourse, homosexual, sexually, queer, drinker, pubertal, harassment
Lift	pubertal, bisexual, heterosexuality, orgasm, nonheterosexual, lgbtq, hookup, sexual, heteronormative, petting, homophobia, homosexuality, gaylesbian, pornography, sexuality, gay, queer, debut, testosterone, puberty
Score	sexual, adolescent, gay, lesbian, heterosexual, intercourse, bisexual, romantic, samesex, girl, pubertal, sexuality, drinking, peer, sex, partner, homosexuality, pornography, alcohol, behavior

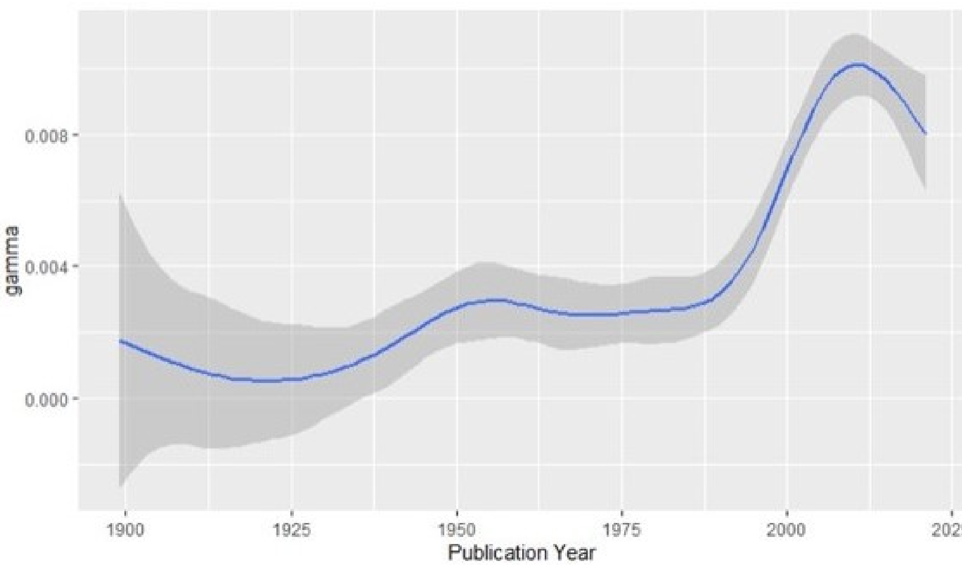

Fig. 3. Temporal Trends of LGBT Issue

Topic 64 refers obviously to LGBT issues. Figure 3 shows its temporal trends. The uphill was started to rise between 1975 and 2000, which was accurately corresponding to history. The rise of LGBT issue was taking place in the 1980s due to large social movement for LGBT rights. Therefore, it is a great examination to our model based on historical events.

Another topic is about totalitarianism, as we have mentioned before. The politics of totalitarianism of the time in Germany and Former Soviet Union, took place around WWII. In the 1940s, the radical rightism of Hitler and leftism of Starling brought totalitarianism into its peak. Then after that decade, totalitarianism gradually fell and we can observe the trend of downhill of totalitarianism.

To summary, using domain knowledge to evaluate the performance of topic model is also a very important to for interpretation use.

3.3.5 Vector Space

Finally, we may also explore the vector spaces created by the document vectors consisting of topic proportions. Each paper can be seen as a vector with 110 dimensions, and each dimension indicates a specific topic with a value of proportion. We used T-SNE to reduce the 110-D to 3-D and visualize

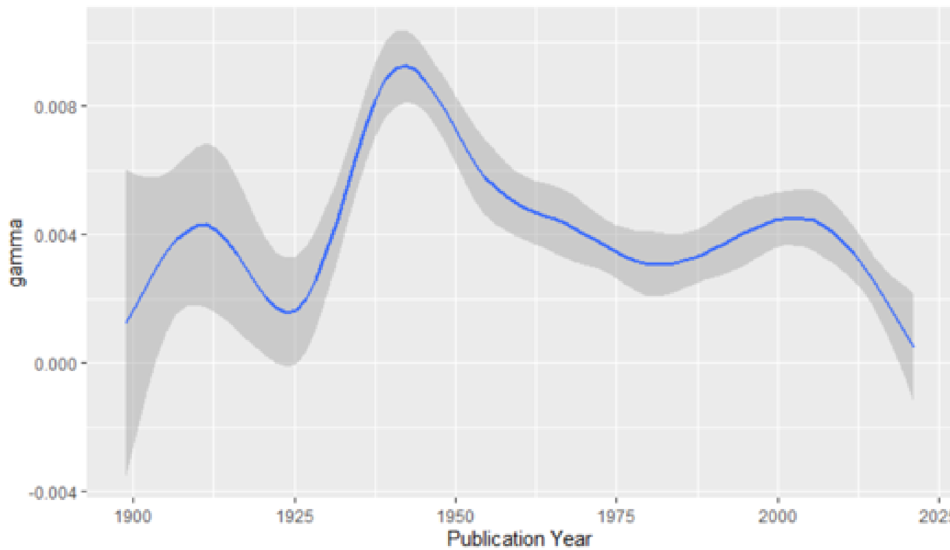

Fig. 4. Temporal Trends of Totalitarianism

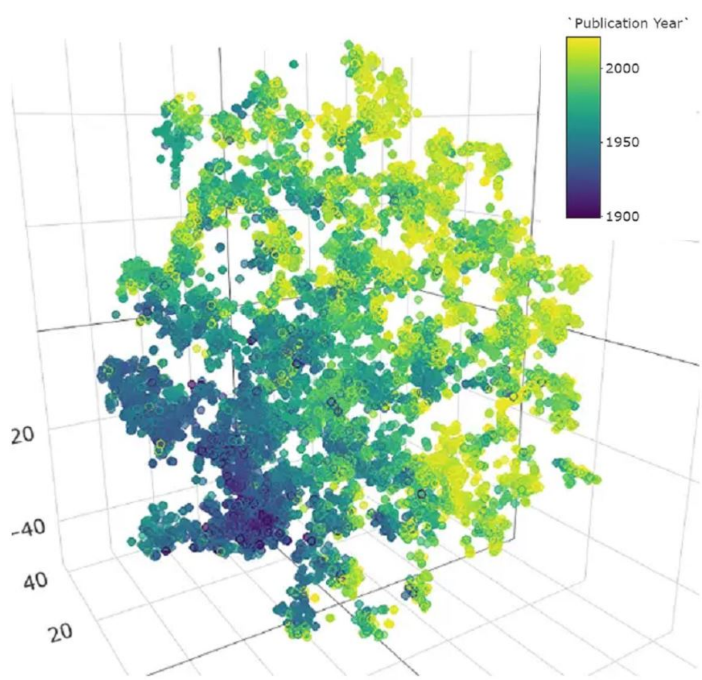

Fig. 5. Vector Space for 110 Topics showing the developing trend of sociological issues

the evolution of papers based on the year they published. The overall pattern of the evolution of sociological issues is diverging as time passed by. In the 1900s, the papers are more likely clustered or converged together. Then with the development of society and passing of time, the topics are more separated which means there are different genres or categories. In the most recent decades, the points in the spatial diagram are more sparse and diverged, indicating the strong diversity of social issues and sociological papers.

4 WORD EMBEDDING

4.1 Interpretable Word Embedding

Topic model can provide us with high-level information because each topic refers to a field. However, we also want to know how the discussion or use of a topic or concept evolved over time. In light of this, we further use word embedding to investigate our data.

It is well-known since the birth of Word2Vec [11] that word vectors and the vector spaces can be interpreted in terms of complex meanings and contexts. For example, in the Word2Vec model trained based on Google news, man to woman can be analogized to programmer to homemaker [3]. In the domain of computer science, since word embedding algorithms are mainly used for vectorizing sentences or documents for further classification and language model building, computer scientists usually regard some of these relations as bias and try to design methods to debias vector space [10] instead of uncover interpretable information from texts. As mentioned in Introduction, there has been a few studies aiming to uncover gender and ethnic stereotypes from news [4, 7, 9], but little is known about how we can adapt similar methods to scholarly work or social data for social studies tasks.

4.2 Text Preprocessing and Parameter Choosing for interpretation

One problem for Word2Vec result is that each word only has one vector, and we cannot add meta-information (such as publication year) because the meta-information is based on document rather than word. Our method to add meta-information into word vectors is to replace the words we are interested with the combination of a year label and these words. For example, "*And how do family and religious changes in adolescence and young adulthood alter **delinquency** trajectories?*" will be replaced with "*And how do family and religious changes in adolescence and young adulthood alter **2009_delinquency** trajectories?*" if we are interested in the concept delinquency. In this way all target concepts can contain temporal information. When we train a word embedding model, these words will only be modeled based on the contexts in a specific year.

For parameter tuning, an important prerequisite is that our dataset is large. Specifically, even though we only have 15,000 papers, most papers are very lengthy (over 30 pages) and can provide a lot of information about words relations. Therefore, our parameters mainly follow the common parameters for large-scale dataset. We removed rare words which occur in data below 25 times, the dimension size is 300 since increasing the size over 300 will not increase model performance too much. We also do not need to pass the whole dataset too many times and can only use a small negative sampling to speed up model training. The only parameter we pay attention to is the window size. A very typical window size in conventional computer science tasks is 5. This is because they often need interchangeable words rather than related word in a broader sense. Interchangeable word means words with similar grammatical and semantic meaning such as synonym, antonym, or words with similar functions or characteristics such as apple and banana as well as China and US. However, in our task, we do not care much about interchangeable words. Instead, we focus more on the use of concepts in larger contexts. Therefore, we use a larger window size. We tried both 10 and 30 window sizes and will also analyze impacts on results brought by different window sizes.

Table 5. Top Similar Words from Models with Different Window Sizes

Sexuality 10	**Sexuality 30**	**Race 10**	**Race 30**
2015_sexuality	homophobia	2019_race	2019_race
2019_homosexual	homophobic	2018_race	2018_race
2008_sexuality	2019_homosexual	2015_race	2013_race
hetero	hetero	2017_race	2015_race
2017_sexuality	2015_sexuality	2013_race	2012_race
homophobia	abuser	2013_race	2017_race
2016_sexuality	2008_sexuality	2016_race	2010_race
2014_sexuality	promiscuous	2010_race	2011_race
2009_sexuality	2009_sexuality	2011_race	2009_race
homophobic	survivorhood	1988_race	2016_race
2018_sexuality	2014_sexuality	2007_race	2007_race
2006_sexuality	straightidentied	2005_race	1988_race
normativity	heterosexist	2009_race	2014_race
2011_sexuality	heteronormativity	2021_race	1998_race
misrecognized	effeminate	1997_race	1999_race
heteronormativity	2011_sexuality	2014_race	ethnicity
homo	heteronormative	1999_race	2005_race
straightidentied	erotic	1998_race	2000_race
2002_sexuality	butch	2004_race	1980_race
2016_homosexual	2007_sexuality	1985_race	1990_race
2017_homosexual	sexualized	1989_race	monoracial
butch	2006_sexuality	1994_race	2004_race
2005_homosexual	promiscuity	1979_race	latinoas
2018_homosexual	womanhood	2008_race	2008_race
nonheterosexual	2009_homosexual	1987_race	latinao
gaylesbian	2018_homosexual	1992_race	ethnoracially
promiscuous	crazy	2000_race	hypodescent
heterosexist	gaslighting	1999_race	1981_race
heteronormative	2017_sexuality	2003_race	1997_race
abuser	2017_homosexual	2006_race	2006_race

4.3 Window Size

Table 5 shows the similar words (discussion contexts) for the concept sexuality in 2019 and race in 2020 from two models with different window size. For the concept sexuality in 2019, the result from 10-window model contains more year-labeled concept of sexuality than that from 30-window model. As we know, concepts of sexuality with different year-labels are in nature the same word sexuality and have similar semantic meaning overall and thus interchangeable. In other words, the first model gives more weight on interchangeable words while the second model gives more weight on related words. The results are similar in the second example for the concept race in 2020. In the 10-window model, all top similar words are year-labeled concepts, while in the 30-window model, at least there are some related words. Therefore, for the purpose of our analysis, a larger window size will be preferred. This is very different from conventional computer science that prefer small window size and evaluate the results based on their tasks.

Table 6. Topic Similar Words for Two Concepts in Different year

1974_Sexuality	**1997_Sexuality**	**2019_Sexuality**	**1981_China**	**1996_China**	**2018_China**
rapist	sexual	homophobia	1981_immigration	hannum	2013_china
machismo	1981_sexuality	pomophobic	fled	1993_china	beijing
bw	kinsey	2015_race	exile	1997_china	guangdong
blacknowhite	promiscuity	hetero	bloody	2008_china	2015_china
lynchers	pomeroy	2015_sexuality	brewery	nee	postmao
blacksthe	extramarital	abuser	massacre	walder	guanxi
bestiality	libidinal	2008_sexuality	burning	nees	sichuan
culpability	incest	promiscuous	mecca	2003_china	yunnan
harsher	effectual	2019_sexuality	crushed	2001_china	shaanxi
tort	hetero	survivorhood	valparaiso	2010_china	jiangxi
assault	huk	2014_sexuality	nomad	markettransition	deng
rape	affectual	straightidentied	fisherman	marketreform	shandong
lien	intercourse	heterosexist	banned	zhou	2019_china
expectan	freud	heteronomativity	pogrom	tianjin	hubei
supremacist	abstinence	effeminate	cargo	1988_china	jilin
racist	virginity	2011_sexuality	tourist	bian	jiangsu
inroad	2006_sexuality	heteronormative	johnstown	1995_china	yuan
clair	2014_sexuality	erotic	forcibly	1992_china	2016_china
inflict	mclennan	butch	sojourner	walders	hunan
threat	2016_sexuality	2007_sexuality	colonist	marketization	guizhou

4.4 Concepts in Vector

Table 6 also shows two examples about temporal trends of concept uses. The first is about sexuality. In 1974, the discussion of sexuality is more related to direct gender and racial inequality such as violence. In 2001, the discussion are more related to sexuality itself. In 2019, the discussion is closely tied to queer issues because of the dominance of queer theory in this field, according our prior domain knowledge. Another concept is the word "China". Besides the similar words related substantial research content, we can also find that there are more and more province and city names over time. It means the sociological study about China was moveing from treating china as an abstract and uniform entity to acknowledging its diversity.

4.5 Visualization

Finally, we can also visualize the results for initial exploration. Since word2vec is based on cosine similarity, which will be hard to read in visualization when there are many vectors, we converted cosine similarity to Euclidean distance through L2 normalization. We then used dimensionality reduction and interactive visualization methods to explore the relations between words.

Basically, as Figures 6 and 7 show, we can plot our target words (such as year-labeled concept sexuality and homosexual) as well as their similar words on this 3-D vector space. When zooming into a specific region in the diagram. We can observe the colored embedded words with their year-label to analyze their relationships. The distance in the vector space implies how relevant two concepts are. The similar (orange) words consist of the context in which these target words are talking about over time.

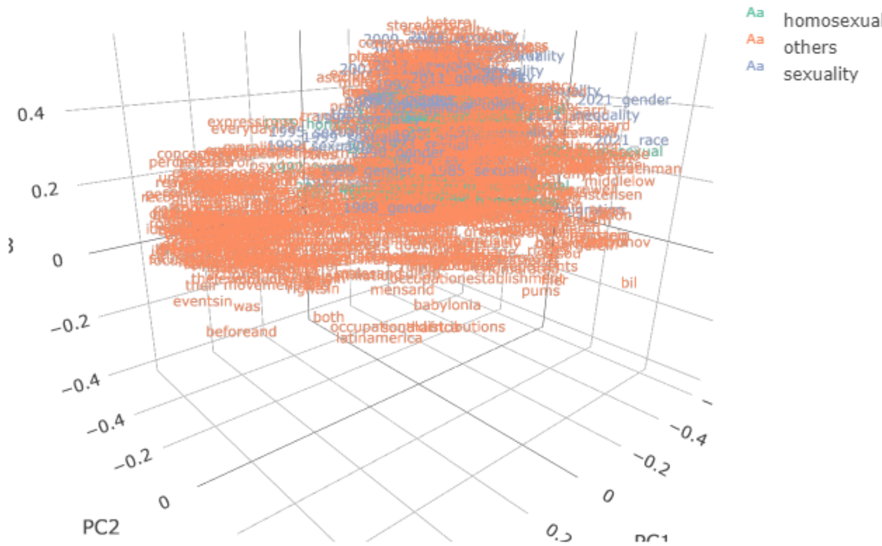

Fig. 6. Vector Space of Word Embedding - Overview

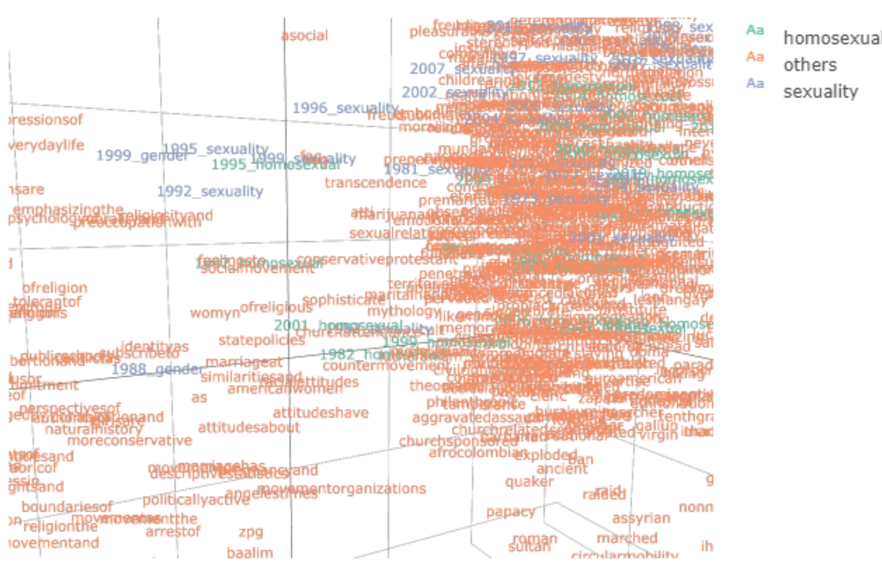

Fig. 7. Vector Space of Word Embedding - Closeview

5 CONCLUDING DISCUSSION

In this paper we applied structural topic models and Word2Vec models to detect the conceptual evolution of social inequality in sociology papers. Different from the prior works using these two methods which mainly focus on conventional data preporcessing and model evaluation metrics such as held-out likelihood, we focus more on the application and evaluation in terms of interpretation. First, we need prior domain knowledge to evaluate these models for the purpose of intrepreation and explanation. In both word embedding and topic modeling, we demonstrate that many results from our models are consistent with our knowledge of historical events. Second, intrepretation model may need new criteria for parameter tuning. For example, in computer science, the window size in embedding models should not be too large, while in our task, larger window sizes are preferred. Third, we also need to preprocess data to cater to our need, such as adding temporal information in Word2Vec model through year label before model training. Finally, vector spaces from both topic model and word embedding results are meaningful, we still need more methods to uncover the meaning.

6 OTHER NOTES

In most studies, there will often be problems, and the results may be not good as expected. However, in this project, the performance of our model, for the purpose of interpretation, is better than our expectation. It may be because sociology papers are often very lengthy and can provide a lot of information for modeling, compared to short texts such as tweets and online review. Therefore, we do not change our planned analysis.

Our team worked together throughout all the project, from data collection to result interpretation. To be honest, both data collection and model building in our project were very time-consuming. Each member in our team shared the workload. For example, each member collected parts of data and tested parts of models with different parameters, and then all the data and results were merged together.

REFERENCES

[1] Andrew Abbott. 2021. *Department and discipline.* University of Chicago Press.

[2] David M. Blei, Andrew Y. Ng, Michael I. Jordan, and John Lafferty. 2003. Latent Dirichlet Allocation. *Journal of Machine Learning Research* 3, 4/5 (2003), 993 – 1022. http://www.library.illinois.edu.proxy2.library.illinois.edu/proxy/go.php?url=http://search.ebscohost.com.proxy2.library.illinois.edu/login.aspx?direct=true&db=asn&AN=12323372&site=eds-live&scope=site

[3] Tolga Bolukbasi, Kai-Wei Chang, James Zou, Venkatesh Saligrama, and Adam Kalai. 2016. Man is to computer programmer as woman is to homemaker? debiasing word embeddings. *arXiv preprint arXiv:1607.06520* (2016).

[4] Aylin Caliskan, Joanna J Bryson, and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. *Science* 356, 6334 (2017), 183–186.

[5] Jonathan Chang, Jordan Boyd-Graber, Chong Wang, Sean Gerrish, and David M Blei. 2009. Reading tea leaves: How humans interpret topic models. In *Neural information processing systems*, Vol. 22. Citeseer, 288–296.

[6] Tessa ES Charlesworth, Victor Yang, Thomas C Mann, Benedek Kurdi, and Mahzarin R Banaji. 2021. Gender stereotypes in natural language: Word embeddings show robust consistency across child and adult language corpora of more than 65 million words. *Psychological Science* 32, 2 (2021), 218–240.

[7] Nikhil Garg, Londa Schiebinger, Dan Jurafsky, and James Zou. 2018. Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences* 115, 16 (2018), E3635–E3644.

[8] Dan Hirschman. 2020. Devilish details: a reputational ranking of generalist and specialist sociology journals. https://scatter.wordpress.com/2020/01/29/devilish-details-a-reputational-ranking-of-generalist-and-specialist-sociology-journals/. Accessed: 2021-02-20.

[9] Austin C Kozlowski, Matt Taddy, and James A Evans. 2019. The geometry of culture: Analyzing the meanings of class through word embeddings. *American Sociological Review* 84, 5 (2019), 905–949.

[10] Kaiji Lu, Piotr Mardziel, Fangjing Wu, Preetam Amancharla, and Anupam Datta. 2020. Gender bias in neural natural language processing. In *Logic, Language, and Security.* Springer, 189–202.

[11] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Efficient estimation of word representations in vector space. *arXiv preprint arXiv:1301.3781* (2013).
[12] Margaret E Roberts, Brandon M Stewart, and Edoardo M Airoldi. 2016. A model of text for experimentation in the social sciences. *J. Amer. Statist. Assoc.* 111, 515 (2016), 988–1003.