Using Natural Language Processing to Analyze Political Party Manifestos from New Zealand

by

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COMPUTER SCIENCE AND INFORMATION SYSTEMS

To My Family

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TABLE OF CONTENTS

LIST OF FIGURES

Figure

LIST OF TABLES

Table

LIST OF ABBREVIATIONS

NLP Natural Language Processing

MMP Mixed-Member Proportional System

SMDP Single-Member-District Plurality System

MRG Manifesto Research Group

MARPOR Manifesto Research on Political Representation

TF-IDF Term-Frequency Times Inverse Document Frequency

BERT Bidirectional Encoder Representation from Transformers

MLM Masked Language Modelling

NSP Next Sentence Prediction

UMAP Uniform Manifold Approximation and Projection

HDBSCAN Hierarchical Density-Based Spatial Clustering of Applications with Noise

ABSTRACT

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This study explores how natural language processing (NLP) can supplement content analyses of political documents, particularly the manifestos of political parties. NLP is particularly useful for tasks such as: estimating the similarity between documents, identifying the topics discussed in documents (topic modeling), and sentiment analysis. This study applies each of these techniques to the study of political party manifestos. Document similarity may be used to gain some insight into the way parties change over time and which political parties are successful at bringing attention to their policy agenda. Categorizing text into topics may help objectively categorize and visualize the ideas political parties are discussing. Finally, sentiment analysis has the potential to show each political party's attitude towards a policy area/topic. This study specifically applies these techniques to the manifestos produced by the political parties of New Zealand, from 1987 to 2017 (a period of significant party system change in New Zealand). It finds that NLP techniques are promising, though there is a need for significant fine-tuning.

CHAPTER I

Introduction

Text is a common and rich source of data in political science research. However, while there has been a proliferation of studies that use natural language processing (NLP) to analyze political texts, there are yet important opportunities to expand the use of NLP, and indeed, some of the best known and readily available sources of text in the field of political science could benefit from the application of recently developed and powerful NLP techniques. This study applies NLP techniques to one of the richest sources of text in political science: the manifestos of political parties.

Party manifestos present a challenge for NLP applications because they are longer and more complex than many of the documents computer scientists have worked with while developing NLP methods. For example, many NLP methods have been developed on shorter documents, such as product reviews. Often, theses documents are labeled and thus are suitable for supervised machine learning. On the other hand, manifestos are easier to work with than many of the other documents analyzed by political scientists (such as political speeches and news media). They contain much less extraneous text (such as ads and procedures) and they are written to express policy ideas more directly.

Party manifestos have been used by political scientists to objectively estimate various types of information produced by political parties, including: their ideologi-

cal positions, the positions they take on particular policy areas, and the ideas they are trying to promote. Because manifestos can be gathered over many years and across many countries, they also allow researchers to track the behavior of political parties across time and across many countries. Thus, the information gleaned from party manifestos has been used to explore many other political phenomena, including: the relation between parties and voters, the role of parties in parliament, and the translation of party programs into policy.

NLP has the potential to contribute to the analysis of manifestos in a variety of ways. NLP can be used to estimate: the similarity between documents, the topics or entities discussed in a document/corpus, and the sentiment expressed towards topics/entities. This study applies each of these estimation techniques to the analysis of manifestos. These techniques may help reveal: how party ideology evolves over time, how party positions on specific topics evolve over time, which parties may be most successful in promoting their policy ideas, and how political reforms can influence all of these dynamics. In later research, these techniques might reveal further insights when applied to other political texts, such as legislative speeches and political news media.

This study specifically focuses on the manifestos produced by the political parties of New Zealand, from 1987 to 2017. During this period, New Zealand experienced significant party system change, which provides an opportunity to use a quasi-experimental research design. The study finds that NLP techniques appear promising for the analysis of long political texts, though there remains a need for significant fine-tuning.

1.1 Related Work

Analyses of political texts can be described as having evolved along two paths: one created by political scientists and the other by computer scientists. Political scientists

have long analyzed text such as legislative speeches *Poole and Rosenthal* (2001), newspapers *Hayward and Rudd* (1999), and party manifestos *Volkens et al.* (2013). In its early stages, the data collection process was driven by hand-coding. More recently, it has been enhanced by automated coding performed on machine-readable texts. Most of this automated coding has relied mainly on "bag-of-words" approaches, involving frequencies of words or n-grams *Weber* (1990); *Neuendorf* (2017); *Krippendorff* (2018).

Computer scientists have also long been interested in text, including political texts. They have developed natural language processing (NLP) methods (such as those described by *Jurafsky and Martin* (2008) and *Manning and Schütze* (2002)) to perform tasks such as the following: estimating the similarity between documents (often to perform search activities), topic modeling (to detect topics discussed in texts), estimating sentiment (to detect attitudes towards products and ideas), voice recognition, and chat bots that respond to users.

Recently, there has been a rise in political science studies that apply techniques developed by computer scientists. There are now studies in the top political science journals using topic modeling (e.g., *Parthasarathy et al.* (2019)), supervised machine learning to categorize texts (e.g., *Chang and Masterson* (2020)), and sentiment analysis (e.g., *Soroka et al.* (2015)). At the same time, there has been a rise in studies of political texts led by computer scientists. These studies, for example, apply cutting edge algorithms to the detection of ideology (e.g., *Iyyer et al.* (2014); *Baly et al.* (2020); *Liu et al.* (2022)) and the detection of misinformation or fake-news (e.g., *Yang Zen et al.* (2021); *Pavlov and Mirceva* (2022)).

Thus, political scientists and computers scientists are heading in similar directions, but there is currently space to merge the knowledge of the two fields more directly and purposefully. Perhaps this space can be partially filled by attempting to apply cutting edge computer science methods to important political science texts and the

questions they were collected to attempt to answer. In this study, recently-developed NLP techniques are applied to the analysis of political party manifestos.

The manifestos have already been analyzed via hand-coding. Such an approach has its advantages, but it also has significant disadvantages that NLP may help address. One important limitation, for example, is that the methods of hand-coding were designed to be comparable over a wide range of countries and thus the coding team made the choice to create a set number of topics, a priori *Volkens* (2001). Such a decision is difficult or perhaps impossible to change, because of the hand-coding resources involved. NLP may be able to provide an important supplement in such cases.

There have been attempts to analyze manifestos with automated coding techniques. These are, however, frequency-based approaches not informed by some of the breakthroughs NLP researchers have made available today (e.g., *Laver et al.* (2003)). This thesis seeks to apply the products of some these breakthroughs, particularly to the analysis of the manifestos produced by the political parties of New Zealand.

1.2 Case Background

This thesis focuses on manifestos from New Zealand ,first, because the manifestos are written in English, and some NLP techniques were particularly developed for English texts *e.g., lexicon-based sentiment estimators). More importantly, New Zealand provides a quasi-experimental setting in which to explore NLP techniques.

For most of its history, New Zealand's voters elected their legislators via a single-member-district-plurality (SMDP) system, in which the candidate winning the most votes (not necessarily a majority) wins the district/seat. In the 1990s, however, New Zealand switched to a German-style mixed-member proportional system (MMP) that produces relatively pure proportional results. Since 1996, over half (65 out of 120) of the members of the New Zealand parliament are still elected via SMDP, however, the

remaining 55 seats are allocated via compensatory, proportional representation *Johnston and Pattie* (2002). That is, the remaining seats are awarded to parties according to the percentage of the national vote that they receive, minus the number of seats they win in the single-member districts. Any party that wins at least 5 percent of the vote or that wins at least one seat in the single-member district part of the ballot is entitled to a share of legislative seats roughly proportional to the share of votes they received.

These changes along with factors such as a long-term trend towards party dealignment *Vowles* (1995) led to a significant fragmentation of the party system. In 1993 (the last election under the SMDP system), the two largest parties (Labour and National) garnered over 95 percent of the seats, on slightly less than 70 percent of the vote; while in 1996 (the first election under the MMP system), the two largest parties captured only 67.5 percent of parliamentary seats on 62 percent of the vote. Furthermore, while only two parties won at least 5 percent of the seats in 1993, five parties won over 5 percent of the seats in 1996.

The electoral reforms and changes to the party system likely produced several information effects that may be captured by NLP methods. First, electoral and party systems should affect the number of issue areas considered by the political system. Specifically, more proportional systems with higher numbers of parties should encourage political competition along a broader range of issue areas *Lijphart* (1999). Second, because proportional/multiparty systems also tend to be associated with more parties that are small, extreme, and ideological, they should be associated with a broader spectrum of political ideas. That is, proportional/multiparty systems should represent a wider range of positions on a left-right scale and in most other policy areas (such as taxation and environmental policy) than do less-proportional/fewer-party systems *Katz* (1997).

Thus, under more proportional electoral systems smaller parties will tend to have

more space to introduce new and sometimes controversial ideas. Topic modeling, thus, may detect that New Zealand's political discourse became more diverse under its new MMP system. With document similarity analyses, it may be possible to observe how a party's ideology evolves over time and which small parties are more successful in getting the larger parties to adopt or respond to their agenda. With sentiment analysis, it may be possible to observe how a party's positions change on specific issues over time, and whether this behavior matches theoretical expectations.

CHAPTER II

Materials and Methods

This chapter introduces the data used in this study, particularly the manifestos produced by New Zealand's political parties around the time of a major electoral reform. It also introduces the three NLP techniques used to analyze these manifestos: document similarity, topic modeling, and sentiment analysis.

2.1 Data

A significant advantage of analyzing manifestos is that they are readily accessible via the Manifesto Project Database. This database grew out of the efforts of the Manifesto Research Group (MRG 1979-1989) and the Comparative Manifestos Project (CMP 1989-2009), and is now currently maintained and expanded by Manifesto Research on Political Representation (MARPOR) *Volkens et al.* (2021). The Manifesto Project Database makes available the manifestos of over 1000 political parties, from over 50 countries, from 1945 to the present. The database also makes available the results of hand-coded content analyses for every manifesto. This hand coding required the support of coders from over 50 countries.

This study particularly analyzes a subset of the manifesto corpus: the political party manifestos produced by New Zealand's political parties, for the elections that took place between the years 1987 and 2017. New Zealand holds elections every three

years, and that amounts to 12 elections, during that period. Roughly 11 parties produced 61 manifestos during that time period. Prior to the electoral reforms (in 1996), only 3 parties were producing manifestos - that were collected by researchers. By 2017, roughly 6 parties were producing manifestos.

These manifestos were analyzed using the following NLP techniques: estimating the similarity between documents, identifying the topics discussed in documents, and sentiment analysis. Document similarity may help reveal how the ideology of each party changes over time (particularly in relation to one another) and which minor parties are more successful at gaining the attention of the major parties. Topic modeling techniques may detect the topics parties promote and if there were more topics discussed by the party system as whole, after the electoral reforms. Sentiment analysis techniques may help gauge a party's position on the topics discovered by topic modeling. The methodology of each of these techniques is briefly discussed in the remainder of this chapter. Each of these techniques has important limitations, which are discussed in the final chapters.

2.2 Document Similarities

A task to which NLP is frequently applied is the estimation of the similarity between documents (e.g., books, articles, sentences, and even search terms). Once a document is converted to a mathematical object (i.e., a vector) a similarity measurement can be calculated, often using the cosine similarity. The cosine similarity is the cosine of the angle between two vectors, which yields the angular distance between the vectors.

There are multiple ways to turn documents into vectors. One vector type commonly used for this task is the TF-IDF (term-frequency times inverse document frequency) vector. TF-IDF vectors are frequency vectors that adjust the count of each word by the number of documents in which the word occurs.

Another commonly used vector type is Word2vec, which accounts for the words around each word, how the neighbors of a word affect the overall meaning of a statement. It learns the meaning of words by processing a large corpus of unlabeled text; it searches for words that tend to be near each other. All words in a corpus are represented by numerical vectors containing scores associated with dimensions of meaning. It can take significant time to create such vectors, but fortunately, pre-trained representations are available. Word2vec techniques can be applied to entire documents (such as manifestos) and the resultant vectors can then be compared for similarity. This can be done using the Doc2vec algorithm, which is an unsupervised learning algorithm that produces vector representations of entire documents (and can also be applied to sentences and paragraphs).

This study relies on BERT (Bidirectional Encoder Representation from Transformers) vector representations.[1] BERT was developed by Google and is considered a state-of-the-art NLP technique. It is trained on unlabeled text including Wikipedia and Book corpuses. BERT uses transformer architecture (an attention model) to learn embeddings for words. It involves two pre-training steps: Masked Language Modelling (MLM) and Next Sentence Prediction (NSP). The training text is represented via three embeddings: token embeddings, segment embeddings, and position embeddings.

2.3 Topic Modeling

Topic modeling can help reveal what policy issues the political parties wish to emphasize. As mentioned, one expectation is that more proportional systems with higher numbers of parties should encourage political competition along a broader range of issue areas. Thus, we should expect that New Zealand's party system brought attention to more issues after its reforms than before. This is where the quasi-experimental

[1]The representations were created using the SentenceTransfomer package for Python.

analysis is more directly applied.

This section compares the number of issues covered by the party system in the three elections before the reform (1987, 1990, 1993) and the three elections after the reform (1999, 2002, 2005). Topic modeling analysis was performed on all the manifestos appearing during each of these periods. The 1996 election is left out, because it was the first election under the new MMP system. Thus, it is regarded here as a transition period. This design thus matches Campbell and Stanley's description of a one-group pretest-posttest quasi-experimental design *Campbell and Stanley* (1963), where a group (New Zealand's party system) is observed prior to being exposed to an event (major electoral reform) and then it is observed again after the event.

This study applies NLP techniques to identify the topics political parties are discussing. It is expected that the topics discussed and emphasized vary across political parties and across time, and thus, unsupervised topic modeling techniques are required. This study specifically applies the topic modeling technique developed by Grootendorst *Grootendorst* (2020), which leverages sentence transformers and c-TF-IDF (a class-based variant of TF-IDF) to create dense clusters that yield interpretable topics.[2]

In this technique, BERT transformer embeddings are used to convert documents into numerical data. BERT extracts word embeddings based on the context of the word. Many pre-trained models are available, which helps reduce processing time and can produce more accurate representations of words and sentences. To find topics, documents with similar topics are clustered together, using the UMAP (Uniform Manifold Approximation and Projection) dimensionality reduction algorithm. UMAP stores a high portion of the information of the high-dimensional local structure in a structure of lower dimensionality.

After dimensionality reduction, the documents are clustered using HDBSCAN

[2]The topic modeling presented here was carried out using Grootendorst's Python pacakge, BERTopic

(Hierarchical Density-Based Spatial Clustering of Applications with Noise), a density-based algorithm. HDBSCAN does not force all data points to cluster, it treats some as outliers. The parameters of HDBSCAN can be tweaked to control the number of topics returned, which may be necessary when the system is returning hundreds of topics.

To derive topics from clustered documents (to extract what makes each set of documents unique compared to the other), a class-based variant of TF-IDF (c-TF-IDF) is used. TF-IDF algorithms basically compare the importance of words between documents. Here, a cluster is treated as a single document, to which a TF-IDF algorithm is applied. The resulting TF-IDF score would demonstrate the important words in a topic. The higher the score, the more representative it should be of its topic – the score is a proxy for information density. The top 10 to 20 words (with the highest scores) can be selected to visualize what may be the focus of a topic. Topic sizes can be used to gauge how frequently certain topics appear.

2.4 Sentiment Analysis

Many sentiment analysis techniques attempt to determine the sentiment (positive or negative) of documents or sentences, and even parts of sentences (aspects). Much of the aspect-based sentiment analysis (ABSA) research conducted to date focuses on the analysis of product reviews, which tend to be short and relatively structured – at least when compared to longer documents, such as the manifestos analyzed in this study. Thus, this study currently focuses on detecting sentiment in sentences, particularly by applying the VADER (Valence Aware Dictionary for sEntiment Reasoning) algorithm to each sentence in a manifesto that contains at least one of the words returned by the topic modeling analysis.

VADER is a rule-based sentiment analysis algorithm developed by Hutto and Gilbert *Hutto and Gilbert* (2014). VADER sentimental analysis relies on a dictionary

that maps lexical features to emotion intensities known as sentiment scores. Hutto maintains the dictionary and Python package used in this analysis.[3]

The algorithm finds keywords in a document and maps each one to numerical scores or weights in the dictionary (or "mapping"). Stems, lemmas, or n-gram tokens can be used in the dictionary. Vader recognizes that words such as 'love', 'enjoy', 'happy', 'like' convey a positive sentiment. It also recognizes the basic context of these words, particularly modifying words that can change the sentiment. It can recognize that a statement such as "did not love" is a negative statement. It also understands the emphasis implied by capitalization and punctuation (such as "ENJOY"), as well as emoticons (such as happy faces).

Scores are summed for each keyword in a document. The sentiment score of a text can be obtained by summing up the intensity of each word in the text. Thus, VADER is able to address both polarity (positive/negative) and intensity of emotion.

As mentioned, this study focuses on detecting sentiment in sentences, particularly by applying the VADER algorithm to each sentence in a manifesto that contains at least one of the words returned by the topic modeling analysis. Here it is specifically applied to the sentences containing the words associated with environmentally friendlier transportation (discussed and displayed in the following chapter): rail, trains, buses, cycling. That is, to estimate the support that each political party shows towards environmentally friendlier forms of transportation, the polarity of each sentence containing at least one of these words is calculated. Then, the average is calculated for all the sentences appearing in each party's manifesto.

[3]The Python package is called vaderSentiment.

CHAPTER III

Results

This chapter presents the results of applying the three NLP techniques to the New Zealand manifestos. The next three sections present the results of the document similarity analysis, topic modeling, and sentiment analysis.

3.1 Manifesto Similarities

It is difficult to observe patterns when comparing all the manifestos simultaneously. Thus, the tables in this section present the document similarities for one party at a time, and only for the two major parties: National and Labour. Each column compares the manifesto produced by that party for that year's election with: the manifestos other parties produced for that year's election, and the manifestos of past elections (its own as well as those of other parties). Each column does not show comparisons with manifestos from future elections. This latter comparison adds little theoretical value because we would need to assume that parties anticipate what they themselves or the other parties will say years into the future.

The comparisons with past and present manifestos can provide insights into how a party is responding to other parties and how successful parties (especially minor parties) were in bringing attention to their ideas. Because this analysis uses mainly basic BERT embeddings, it is difficult to determine if a party is adopting policy

positions that are similar to another party's policy positions, or whether it is mainly talking about the same issues raised by an opposition party. Nonetheless, the output produced by the BERT embeddings appear to hint at important insights – that may be more clearly observed in future work.

Table 3.1 tracks how the similarity between the Labour Party manifestos and the manifestos of other parties changed across time. In the top row is displayed each Labour Party manifesto, sequentially by year. Manifestos that are most similar to Labour's manifesto for that year appear closest to the top of that column. Labor Party manifestos are colored blue and a darker shade is used for more recent manifestos. Other parties are shaded in other colors, and darker shades are used for more recent manifestos (see table caption for color coding scheme).

First, it should be noted that Labour Party manifestos are perfectly correlated with themselves (similarity scores equal 1), and that similarity scores are relatively high with several other manifestos. This latter result may indicate that parties are talking about similar issues, though they may take different positions on those issues.

Second, by the time of the most recent elections, Labour's manifestos become more consistently similar to those of the Progressive Party (particularly the Progressive Party's 2002 manifesto). This result suggests that the Labour Party's policy agenda may have become more progressive, in recent years - and this result appears corroborated by recent news evaluations of Labour's positions *Cave* (2020).

On the other hand, there is also some recent – though less consistent – similarity with ACT's 2002 manifesto, which is a relatively centrist document. There are also elections when the Labour Party manifestos are relatively similar to the manifestos of the National Party, its long-time rival. Thus there is a need to fine tune this technique, so that it may be possible to more clearly distinguish the dynamics in play here. Did Labour become more progressive? Did other parties become more progressive? Is labor just talking about the same issues, but not necessarily taking

LP 1987	LP 1990	LP 1993	LP 1996	LP 1999	LP 2002
NP 1987	NP 1987	NP 1987	DP 1987	NP 1993	NP 1990
DP 1987	DP 1987	LP 1987	NP 1987	ACT 1999	NZF 1999
	NP 1990	NP 1990	NZF 1996	NP 1987	NZF 1996
	LP 1987	All 1993	LP 1993	NP 1999	NP 2002
	DP 1990	NP 1993	NP 1990	NP 1996	LP 1993
		DP 1987	LP 1987	LP 1993	All 1999
		LP 1990	ACT 1996	All 1993	All 1996
		DP 1990	NP 1996	DP 1987	NP 1996
			NP 1993	NZF 1999	Prog 2002
			All 1996	LP 1990	NZF 2002
			LP 1990	All 1999	LP 1987

LP 2005	LP 2008	LP 2011	LP 2014	LP 2017	
Prog 2002	NP 2005	Prog 2002	LP 1993	Prog 2002	
NP 1996	Prog 2005	ACT 2002	ACT 2008	ACT 2002	
All 1999	NZF 2002	LP 1987	GP 2014	NP 1987	
LP 1999	LP 1993	ACT 1999	NP 1990	LP 1999	
NP 1993	NP 1990	NP 2005	UF 2014	NP 1999	
NP 1999	NZF 1999	NZF 1999	ACT 2002	NP 2008	
ACT 1999	LP 1987	DP 1990	Prog 2002	ACT 1999	
UF 2002	ACT 2002	All 1999	LP 2005	NZF 2014	
LP 1993	Prog 2002	ACT 2008	UF 2002	Prog 2005	
Maori 2005	ACT 2008	NZF 2011	NP 2011	NP 2011	
Prog 2005	ACT 1996	UF 2002	NP 2002	GP 2011	

Table 3.1: Similarity Between the Labour Party and Other Parties
Color coding is used to help visualize the similarity of the Labour Party to other parties across time. More recent manifestos appear in darker shades. Manifestos that are most similar to Labour's manifesto for that year appear closest to the top of that column. LP = Labour Party (blue), NP = National Party (grey), Act = Act Party (purple), All = Alliance (light red), Prog = Progressive Party (darker red), GP = Green Party (green), MP = Maori Pacific (yellow), DP = Democratic Party (light yellow), NZF = New Zealand First (brown), UF = United Future (violet).

more progressive positions?

Table 3.2 tracks how the similarity between the National Party manifestos and the manifestos of other parties changed across time. In the top row is displayed each National Party manifesto, sequentially by year. National Party manifestos are colored grey and a darker shade is used for more recent manifestos. First, it should be noted that National Party manifestos are perfectly correlated with themselves

(similarity scores equal 1), and that similarity scores are relatively high with several other manifestos. Again, this latter result may indicate that parties are talking about similar issues, though they may take different positions on those issues.

NP 1987	NP 1990	NP 1993	NP 1996	NP 1999	NP 2002
DP 1987	NP 1987	NP 1987	NP 1993	NP 1996	LP 1993
LP 1987	LP 1987	LP 1993	NP 1990	NP 1993	All 1993
	DP 1987	LP 1987	NP 1987	All 1999	NZF 2002
	LP 1990	All 1993	NZF 1996	LP 1999	All 1999
	DP 1990	DP 1987	All 1993	ACT 1999	LP 2002
		LP 1990	LP 1987	NP 1987	NP 1999
		NP 1990	LP 1993	All 1993	NP 1990
		DP 1990	ACT 1996	LP 1987	Prog 2002
			DP 1987	LP 1993	ACT 1996
			LP 1990	DP 1987	LP 1987
			LP 1996	NP 1990	NZF 1999

NP 2005	NP 2008	NP 2011	NP 2014	NP 2017	
Prog 2005	NP 1999	ACT 2008	LP 1999	ACT 2008	
LP 1993	NP 1993	Prog 2005	Maori 2008	NP 2011	
NP 1987	Prog 2002	NP 1987	NP 2011	NZF 1999	
Prog 2002	NP 1987	ACT 2002	NP 1993	Prog 2005	
NZF 1999	Prog 2005	LP 2002	NP 1996	LP 1993	
LP 1987	LP 1999	Prog 2002	ACT 2014	NP 1987	
NZF 2002	ACT 2002	ACT 1999	Prog 2005	LP 2008	
ACT 2002	LP 1993	LP 1993	NP 1987	NP 2005	
NP 1990	NP 1996	NP 2005	ACT 1999	NZF 2011	
ACT 1996	LP 1987	LP 1999	NP 1999	Prog 2002	
NP 1999	ACT 1999	UF 2008	NP 2005	NP 1996	

Table 3.2: Similarity Between the National Party and Other Parties
Color coding is used to help visualize the similarity of the Labour Party to other parties across time. More recent manifestos appear in darker shades. Manifestos that are most similar to National's manifesto for that year appear closest to the top of that column. LP = Labour Party (blue), NP = National Party (grey), Act = Act Party (purple), All = Alliance (light red), Prog = Progressive Party (darker red), GP = Green Party (green), MP = Maori Pacific (yellow), DP = Democratic Party (light yellow), NZF = New Zealand First (brown), UF = United Future (violet).

Second, National's manifestos are consistently more similar to older National manifestos, especially in 2008 and 2014. Like Labour, National's manifestos do show some similarity with the manifestos of the Progressive Party, along with those of

New Zealand First and ACT. These results may indicate that the National Party is focusing on the same policy issues, though not necessarily taking the same positions. If the preferences of New Zealand's society have become more similar to those espoused by the Progressive Party, it would be reasonable for the National Party to gravitate in that direction, as well. Further research would be required, however, to fully determine the nuances of these dynamics.

3.2 Topic Modeling of Manifestos

Figures 3.1 and 3.2 display the results of the topic modeling analysis. It can first be observed that the topic modeling approach returned many topic areas, for each of the two periods (the two-party system period versus the multiparty system period). It can also be observed that more distinct topics were discussed under the multiparty system.

In the three elections before the reform, roughly 104 issues were discussed by the political parties. In the three elections after the reforms, roughly 170 issues were discussed by the political parties.[1] When overlapping is taken into account, the conclusion is more pronounced. In the three elections before the reform, roughly 18 issues were discussed by the political parties. In the three elections after the reforms, roughly 34 issues were discussed by the political parties.[2]

The figures also provide more detail about the largest (most frequent) topics. The largest topics are numbered in the figure and their word composition is displayed in the caption below the figure. The largest topics in figure 1 include health care, families, fishing, and so on. The largest topics in figure 2 include transport, taxation, housing, and so on.

[1] A t-test shows this difference is statistically significant at least at the 0.01 level, though it should be noted that the sample size is n = 2.

[2] A t-test shows this difference is statistically significant at least at the 0.05 level, though it should be noted that the sample size is n = 2.

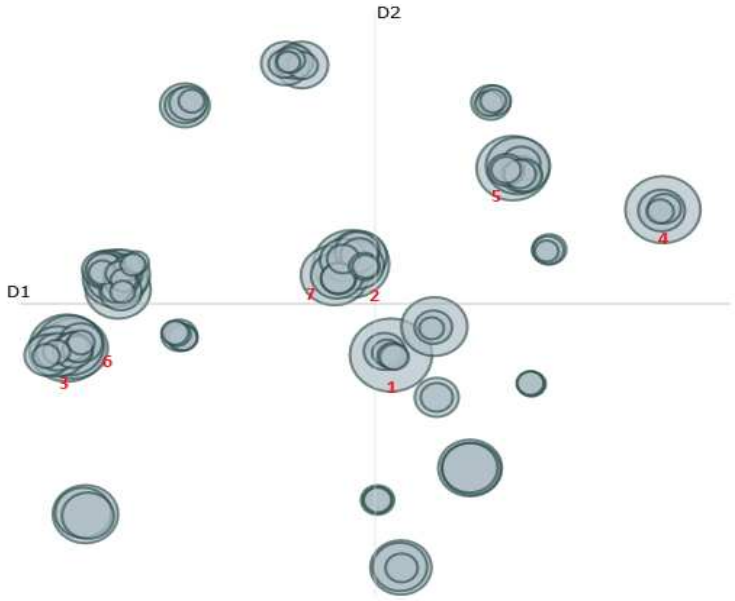

Figure 3.1: Intertopic Distance Map: Pre-reform Topics
Topic 1: health, hospitals, public, care, hospital, system, patients, services, quality, national. Topic 2: families, children, family, parents, childcare, child, support, social, subsidy, stress. Topic 3: fishing, fisheries, fish, quota, aquaculture, recreational, management, commercial, industry, percent. Topic 4: relations, industrial, unions, employment, union, workers, bargaining, employers, contracts, equity. Topic 5: trade, export, markets, imports, products, tariffs, marketing, market, overseas, goods. Topic 6: environmental, environment, conservation, natural, management, sustainable, resource, resources, accounts, mineral. Topic 7: tax, taxation, small, taxes, businesses, business, duties, applies, definition, which.

The topics produced by this topic modeling approach appear reasonable - have high face validity. Table 3.3 shows a topic cluster that appears to be about transportation and perhaps more specifically about environmentally friendly transportation:

Table 3.3: Example Topic

Top 10 Words	**Importance Value**
transport	0.065317291
rail	0.04883337
electric	0.03538137
trains	0.027568078
buses	0.027568078
cars	0.024513584
cycling	0.023804225
auckland	0.023682579
safer	0.02330147
vehicles	0.022399063

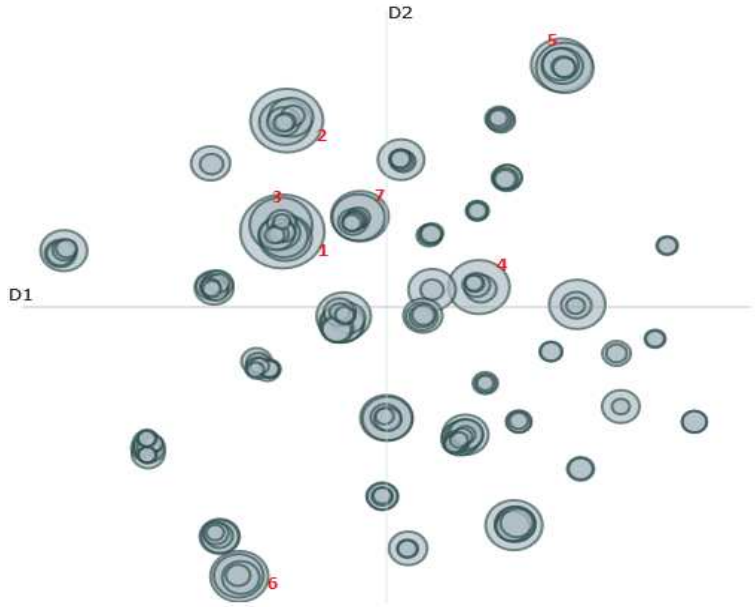

Figure 3.2: Intertopic Distance Map: Post-reform Topics
Topic 1: transport, road, rail, roads, roading, safety, traffic, infrastructure, congestion, transit. Topic 2: tax, taxation, taxes, rate, income, lower, company, corporate, personal, higher. Topic 3: housing, tenants, houses, state, income, low, rental, rent, accommodation, house. Topic 4: defence, force, forces, maritime, air, capability, allies, navy, peace, army. Topic 5: they, but, we, delivered, it, what, let, now, more, win. Topic 6: radio, broadcasting, television, tvnz, spectrum, fm, air, music, tv, nz. Topic 7: export, business, value, small, growth, economy, exports, commerce, wealth, businesses.

The full set of words captures a focus on transportation. A subset of the words – rail, trains, buses, cycling – suggests this topic is more specifically about environmentally friendly forms of transportation.

3.3 Sentiment Analysis of Manifesto Sentences

Table 3.4 shows the scores returned by VADER for a small sample of sentences from the Green Party's manifesto. Each sentence contains at least one of the key words produced by the subset of the topic discussed above (rail, trains, buses, or cycling). The polarity appears relatively positive, as may be expected from the Green Party (GP) on this issue.

To get a sense of the total support each party shows on this issue, an average

Table 3.4: Sample of VADER Scores for Each Sentence

Party	**Text**	**Polarity Vader**
GP	Support locating clusters near transport hubs (rail lines, ports etc).	0.4019
GP	Expand the nationwide network of cycle/pedestrian trails.	0.3182
GP	Promote rail as a great way to travel and seek to make it more available and reliable.	0.7717
GP	All goods and services produced or sold in New Zealand to meet quality and sustainability standards (eg energy and recycling standards).	0.2732
GP	Fast, electric rail lines eliminate pollution and create healthier, congestion-free cities.	0.2732
GP	Safe walking and cycling for kids.	0.4404
GP	Allocate $50m a year for four years to build modern, convenient walking and cycling infrastructure around schools: separating kids and other users from road traffic, giving a safe choice for families	0.6486
GP	Get half of kids walking or cycling to school by 2022: reducing congestion; improving health and learning; saving families time and money	0.4215
GP	Better funding will enable more frequent buses on existing routes.	0.4404

score is calculated across all the sentences containing the key words. The average score for each party, along with the number of sentences containing the key words, is reported in table 3.5 below. The average scores appear reasonable. The Green Party appears to show by far the highest level of support for environmentally friendlier forms of transportation. It has the highest number of related sentences (65) and the highest average polarity (0.36). It is much less of an emphasis for other parties (fewer sentences), and they have considerably less positivity towards that issue.

Table 3.5: Average VADER Score for Each Party on Environmentally Friendlier Transportation

Party	**Number of Sentences**	**Avg Polarity Vader**
ACT	-	-
GP	65	0.359523
LP	18	0.1463
Maori	2	0.08895
NP	29	0.15811
NZF	7	0.025414

It may be possible to expand this approach to analyze all the topics returned by a topic modeling analysis. One obstacle, however, is that the topics returned by the topic modeling performed earlier can be relatively generic. The topic on taxes, for example, contains the words "increase" and "decrease." Thus a sentiment analysis may be misleading in such cases.

To mitigate this obstacle, a topic modeling analysis was performed on only the Green Party's 2017 manifesto. Such an approach returns more distinct topics with usually more distinct positions. Thus a sentiment analysis of these topics is more likely to produce valid polarity scores. To gauge the other parties' stances towards these topics, only their 2017 manifestos were used.

Figure 3.3 displays each of the party's average VADER score for each of the top 25 topics returned from the Green Party's 2017 manifesto. These scores are weighted by the log of the number of times a party mentions the topic in their manifesto. It is reasonable, then, to see that the Green Party (the red dot) tends to have a high positive score on most of these issues. On issues such as "energy, renewable", "water, drinking" and "needs, learning, schools" the Green Party has the highest positively polarity, which matches expectations.

For some issues, such as "housing," all the parties are clustered relatively close together. Such clustering may indicate that there is broad consensus on such issues. Some issues have a wider variation of support, including "weapons, security, peace" and "human, rights, violations."

An interesting and perhaps surprising result is the polarity scores on issues such as "marine, mining, whales." Almost all the parties appear to show low support for this topic, but the Maori Party is considerably less supportive.

While the results of this section appear quite reasonable, there are some concerns left to address. The current approach likely suffices to capture a party's attitude (polarity) towards an issue, particularly when the goal is to compare the polarity of

Figure 3.3: Average Vader Polarity for Multiple Topics
Topics in this figure were created by applying topic modeling to only the Green Party's 2017 manifesto. The scores are weighted by the log of the numbers of rows in which one of the topic words appears, for each party's manifesto. Only manifestos from the 2017 election were used in this analysis.

several parties, but the accuracy is likely reduced by applying VADER to complete sentences – which may contain more than one target topic.

Problems such as multiple targets, are likely addressed more effectively by ABSA

methods. However, most ABSA techniques have been developed for shorter, more structured documents, such as product reviews. Not surprisingly, then, ABSA techniques under-performed the VADER method presented in this study. This is a promising area to continue researching.

CHAPTER IV

Discussion

Applying NLP to key texts analyzed by political scientists appears promising. In this study, it was applied to political party manifestos, which are difficult to analyze in comparison to documents such as product reviews. Still, it was possible to observe that current NLP methods can provide important insights that supplement past work.

First, document similarity can provide some insights into the behavior of political parties. It can detect how parties position themselves relative to other parties, across multiple elections. It can also detect which minor parties are most successful at having their ideas either adopted by the major parties or responded to by the major parties.

Second, topic modeling can provide objective insights into the policy issues the parties talk about. This finding can be considered a useful supplement to existing content analyses of the manifestos, which use set numbers of topic categories and subcategories.[1] Even if the unsupervised approach used here suffers from some inaccuracies, it can still give us very useful insights into how electoral systems affect the diversity of political discourse. It was possible to observe that multiparty systems likely produce a more diverse political discourse than do single-member-district systems.

Finally, sentiment analysis can capture the support parties show towards particu-

[1]Such an approach facilitated comparisons over a wide range of countries irrespective of cultural and socio-economic differences.

lar policy ideas - like those found using topic modeling. The results have face validity, and they also appear to be a good supplement to existing hand-coded approaches. It can be efficiently applied to any new categories missed by hand coding or generated by changes in coding strategies. NLP offers a more flexible approach to identifying party positioning, though its accuracy is likely lower than that of hand coding.

In sum, current NLP methods can provide important insights that supplement past work. With fine-tuning and some technological breakthroughs, these methods could become more than supplementary. They might make it possible to ask new questions and detect previously overlooked patterns. Such possibilities are discussed in the concluding chapter.

CHAPTER V

Conclusion and Future Work

This section discusses key limitations of the methods applied in this thesis. The analyses performed here can likely benefit from significant fine-tuning. First, each type of NLP analysis performed in this study would likely benefit from more appropriate vector representations, especially vector representations that captured a party's attitude towards a policy issue.

Document similarity would clearly benefit from such an improvement. It would allow it to more accurately compare manifestos and thereby to more clearly establish whether a party's manifesto is similar to another party's manifesto because they are talking about the same issues or because they hold similar positions on those issues.

More fine-tuned ABSA techniques might improve the accuracy of measurements of a party's attitude on an issue (polarity measurements). Such accuracy may allow a more nuanced tracking of the behavior of political parties. It may allow for the detection of new patterns, such as whether parties are using strategies such as prevarication or pandering. Unfortunately, this kind of fine-tuning could take significant effort, time, and technological breakthroughs; thus, it is left for future work.

Another important avenue for future work would involve expanding the analysis to more cases. This study presented evidence from one country, but manifestos are available for more than 50 countries. Expanding this kind of NLP analysis to all the

manifestos from all the countries might allow for the detection of new patterns. A major limitation, however, is that most of the manifestos in the MARPOR database are not in English. Thus, such an analysis would involve applying algorithms that can either translate text to English or handle different languages.

A final avenue for future work would involve expanding the analysis to different sources of text. The techniques applied to manifestos in this study could lead to more substantive insights when applied to other texts in the political realm. For example, when applied to the news media, it may be possible to observe which parties are more successful in getting their ideas disseminated to the broader society.

APPENDICES

APPENDIX A

Underlying Technologies

A.1 UMAP

UMAP (Uniform Manifold Approximation and Projection) is a dimension reduction technique. It can be used to reduce non-linear dimensionality and to create comprehensible visualizations. The algorithm relies on three assumptions about the data: the data is uniformly distributed on Riemannian manifold, the Riemannian metric is locally constant (or can be approximated as such), the manifold is locally connected.

From these assumptions it is possible to model the manifold with a fuzzy topological structure. The embedding is found by searching for a low dimensional projection of the data that has the closest possible equivalent fuzzy topological structure.

A.2 HDBSCAN

HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) is a clustering algorithm that does not require a user to pre-set the number of clusters. It works by starting at an arbitrary point. It then finds all points within

the core-defining boundary (eps). If there are less than minSamples (the minimum number of points required to form a dense region) within the eps, this point is labeled noise. Otherwise, the point is labeled a core sample and assigned a new cluster label. Then, all the neighbors within the eps are visited. If they have not been assigned a cluster, they are assigned that new cluster label. Then their neighbors are visited, and so on.

DBSCAN has several benefits. Because it does not require a pre-set number of clusters, it can be used in unsupervised settings. It can also capture complex shapes. It can also identify points that are not part of any cluster (i.e., outliers). It also scales well to relatively large datasets.

A.3 VADER

VADER (Valence Aware Dictionary for sEntiment Reasoning) is a sentiment analysis algorithm that uses human-designed rules. These rules are stored in a dictionary that assigns numerical scores to various words in a lexicon. For example, a word like "good" would receive a positive numerical value, and a combination of words like "very good" would receive a higher positive numerical value. Adding a negator to the front of that combination - "not very good" - would produce a strongly negative numerical value. The dictionary can use words, stems, lemmas, and n-gram tokens.

VADER searches for key words in a text document that appear in the dictionary. The scores for each word in the document can then be added up to produce a total sentiment score for that document.

VADER's human-designed rules were developed and are maintained by *Hutto and Gilbert* (2014). It can be applied using the Python package vaderSentiment, which is maintained by Hutto (see https://github.com/cjhutto/vaderSentiment).

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