Nobody expects the Spanish Inquisition: Which events drive topic change in Australian parliaments? *

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We use a structural text model to explore the effect of various events on what was said in Australian state and federal parliaments from the mid-1800s through to 2017. We find that: 1) changes of government are associated with topic changes only when there is also a change in the party in power; 2) polling results appear dissociated from parliamentary topics; 3) economic changes, such as financial crises have a significant effect; and 4) other events, such as an unexpected attack tend not to have a prolonged change.

Keywords: text analysis, politics, Australia

Introduction

New governments often go to some trouble to be different to the governments they replace. For instance, Kevin Rudd's apology to Indigenous Australians was not supported by John Howard and then one of Tony Abbott's first acts was to repeal Rudd's carbon tax. Similarly, significant events such as the 9/11 attacks or the Great Recession have often altered the course of a government. However it is not so clear which events drive changes, for how long these changes persist, and what was given up due to the change.

In this paper we examine text records of what was said in Australian state and federal parliaments from the mid-1800s through to 2017. We use the Structural Topic Model (STM) of Roberts, Stewart and Airoldi (2016) to impose structure such as correlation between days. We then construct a **[XYZ]** model to examine changes at various types of events, including: changes in government; changes in the political environment (as defined by polling or other results); changes in economic conditions; and other significant events (such as the 9/11 attacks or the Bali bombings).

We find **[INSERT RESULTS]**.

Our paper applies a topic model to a dataset of larger-scale parliamentary text records from multiple Australian parliaments. A forecasting model is then used to construct a counterfactual. Our work fits into a growing literature that considers text as a input to more usual quantitative techniques, rather than requiring separate analysis. While using text as data has well-known shortcomings, it allows larger-scale analysis that would not be viable using less-automated approaches and so it can identify patterns that may otherwise be overlooked.

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Data

Parliamentary text data

Following the example of the UK a daily text record called Hansard of what was said in Australian parliaments has been made available since their establishment.[1] Hansard records and their equivalents are an increasingly popular source of data as new methods and reduced computational costs make larger-scale analysis easier. For instance, the digitisation of the Canadian Hansard, Beelen et al. (2017), allowed Whyte (2017) to examine whether parliamentary disruptions in Canada increased between 1926 and 2015 and Rheault and Cochrane (2018) to examine ideology and party polarisation in Britain and Canada. In the UK, Duthie, Budzynska and Reed (2016) analysed Hansard records to examine which politicians made supportive or aggressive statements toward other politicians between 1979 and 1990 and Peterson and Spirling (2018) examined polarisation. In New Zealand, Curran et al. (2017) modelled the topics discussed between 2003 and 2016, and Graham (2016) examined unparliamentary language between 1890 and 1950. And in the US Gentzkow, Shapiro and Taddy (2018) examine congressional speech records from 1873 to 2016 to find that partisanship has risen in the past few decades.

Australian Hansard records have been analysed for various purposes, but usually not at larger-scale. For instance, Rasiah (2010) examined Hansard records for the Australian House of Representatives to examine whether politicians attempted to evade questions about Iraq during February and March 2003. And Gans and Leigh (2012) examined Australian Hansard records to associate mentions by politicians of certain public intellectuals with neutral or positive sentiment.

Australian parliaments generally make their daily Hansard records available online as PDFs and these are considered the official release. There is a more limited set of XML records available in some cases.[2] There are 65,000 **[UPDATE]** Hansard records available across the state and federal parliaments (Table 1) **[UPDATE NUMBERING]**. As with any larger-scale data process, there are various issues with some of the PDFs and the known ones are detailed in the Appendix.

Parliament	House	Years used	Number of records
Commonwealth	House of Representatives	1901 - 2017	7,873
	Senate	1901 - 2017	**[TBD]**
Queensland	Legislative Assembly	1860 - 2017	**[TBD]**
	Legislative Council	1860 - 1922	**[TBD]**

[1] While Hansard is not necessarily verbatim, it is considered close enough for text-as-data purposes. For instance, Mollin (2008) found that in the case of the UK Hansard the differences would only affect specialised linguistic analysis. Edwards (2016) examined Australia, New Zealand and the UK, and found that changes were usually made by those responsible for creating the Hansard record, instead of the parliamentarians.

[2] Tim Sherratt makes these XML records available as a single download and also presents them in a website (http://historichansard.net/) that can be used to explore Commonwealth Hansard records from 1901 to 1980. Commonwealth XML records from 1998 to 2014 are available from Andrew Turpin's website, and from 2006 through today from Open Australia's website.

Parliament	House	Years used	Number of records
New South Wales[3]	Legislative Assembly	1856 - 2017	**[TBD]**
	Legislative Council	1856 - 2017	**[TBD]**
Victoria	Legislative Assembly	1856 - 2017	**[TBD]**
	Legislative Council	1851 - 2017	**[TBD]**
Tasmania[4]	House of Assembly	1856 - 2017	**[TBD]**
	Legislative Council	1856 - 2017	**[TBD]**
South Australia[5]	House of Assembly	1857 - 2017	**[TBD]**
	Legislative Council	1840 - 2017	**[TBD]**
Western Australia[6]	Legislative Assembly	1890 - 2017	**[TBD]**
	Legislative Council	1832 - 2017	**[TBD]**

The formatting of the Hansard records changes between the different parliaments and over time. We use R scripts to convert the PDFs into daily text records.[7] These scripts are primarily based on: the `PDFtools` package of Ooms (2018*a*); the `tidyverse` package of Wickham (2017); the `tm` package of Feinerer and Hornik (2018); the `lubridate` package of Grolemund and Wickham (2011); and the `stringi` package of Gagolewski (2018). The functions of those packages are supported by: the `furrr` package of Vaughan and Dancho (2018); and the `tictoc` package of Izrailev (2014). Some error is introduced at this stage because many of the records are in a two-column format that need to be separated, and the PDF parsing is not always accurate especially for older records. An example of the latter issue is that 'the' is often parsed as 'thc'. These errors are fixed when they occur at scale and can be identified. The `hunspell` package of Ooms (2017) is also used to help find spelling issues.

[ADD PICTURE OF HANSARD RECORD AND THE SUBSEQUENT TEXT RECORD?]

These daily records are the main data used in this paper, however the daily records are also further divided into individual-level records. Sometimes these are just short interjections or notes that are not specific to any particular politician, such as 'Honourable members interjecting'. Interjections are interesting in their own right, for instance Whyte (2017) analysed them in a Canadian context for the period 1926 to 2015 to find that female MPs were more likely to be interrupted than male MPs, but do not usually contribute much to defining the topics being discussed that day.

Usually the disaggregation into individual-level records is done by identifying politicians' names in particular patterns. For instance, when the Hansard record is trying to indicate that a person is speaking, as opposed to being mentioned (for more on the political effect of being mentioned see Alexander (2018)), often the name is in upper case (e.g.

[3] The NSW Legislative Council was established earlier than 1856, however the earlier Hansard records have not been through an independent OCR process and were not used in this paper. However, the Google Tesseract OCR engine as implemented by Ooms (2018*b*) provided useful data and these could be used in the future.

[4] **[Update this, depending on final Tassie records]**.

[5] **[Update this, depending on final SA records]**.

[6] **[Update this, depending on final WA records]**.

[7] An example of the workflow and some reduced-detail scripts are provided in the Appendix. The full set of scripts are available on request.

'Mr WHITLAM' or 'Mr MENZIES'); followed by a dash or colon; or are next to some title within brackets. There is substantial variation in how the person making a statement is identified. Again some error is introduced at this stage because of inconsistencies over time and between the parliaments, as well as the errors introduced during the PDF parsing stage. There is considerable variance but on average each daily record had 250 **[UPDATE]** individual-level records, resulting in roughly 15 million rows **[UPDATE]** across the state and federal parliaments.

Text usually needs to be pre-processed before topic models can be used. The specific steps that we take are to remove numbers and punctuation and to change all the words to lower case. Then the sentences are deconstructed and each word considered individually. In addition to the packages already mentioned, in this step the R scripts to do this use the `tidytext` R package of Silge and Robinson (2016).

Additional information

Data from other sources are useful to complement the parliamentary text data. For instance, although the name, party, and division represented are contained in Hansard records they are inconsistent. Also non-Hansard information about the politicians can inform the analysis. This includes: date of birth and date of death; sex; date of entry to parliament and exit from parliament; some aspects of their pre- and post-parliamentary career; some aspects of their parliamentary career, such as ministry appointments; and electoral information such as primary and two-party-preferred results.

The main sources for this additional supplementary information are the handbooks supplied by the various parliaments (Table 2).

Parliament	House	Source
Commonwealth	House of Representatives	Parliamentary Handbok
	Senate	**[TBD]**
Queensland	Legislative Assembly	**[TBD]**
	Legislative Council	**[TBD]**
New South Wales	Legislative Assembly	**[TBD]**
	Legislative Council	**[TBD]**
Victoria	Legislative Assembly	**[TBD]**
	Legislative Council	**[TBD]**
Tasmania	House of Assembly	**[TBD]**
	Legislative Council	**[TBD]**
South Australia	House of Assembly	**[TBD]**
	Legislative Council	**[TBD]**
Western Australia	Legislative Assembly	**[TBD]**
	Legislative Council	**[TBD]**

The additional information from the handbooks had many errors and it was supplemented by data from the Australian Dictionary of Biography and Wikipedia.[8]

[8] An example of the additional information is provided in the Appendix. The datasets are available on

Model

The main model that we use in this paper is the Structural Topic Model (STM) as implemented by the `stm` R package of Roberts, Stewart and Tingley (2018). The basis of this type of topic modelling is the Latent Dirichlet Allocation (LDA) model of Blei, Ng and Jordan (2003). In this section a brief overview of both the LDA model and the STM approach is provided and then the specifics of how we consider events in this setting are discussed.

Latent Dirichlet Allocation

When the text data is being modelled at the day level then each day's Hansard record needs to be classified by its topic. Although more- or less-fine levels of analysis are possible. Sometimes Hansard records includes titles that make the topic clear. But not every statement has a title and the titles do not always define topics in a well-defined and consistent way, especially over longer time periods. One way to get consistent estimates of the topics discussed in Hansard is to use the LDA method of Blei, Ng and Jordan (2003), for instance as implemented by the R package 'topicmodels' by Grün and Hornik (2011).

The key assumption behind the LDA method is that each day's text, 'a document', in Hansard is made by speakers who decide the topics they would like to talk about in that document, and then choose words, 'terms', that are appropriate to those topics. A topic could be thought of as a collection of terms, and a document as a collection of topics. The topics are not specified *ex ante*; they are an outcome of the method. In this sense, this approach can be considered unsupervised machine learning. Terms are not necessarily unique to a particular topic, and a document could be about more than one topic. This provides more flexibility than other approaches such as a strict word count method. The goal is to have the words found in each day's Hansard group themselves to define topics.

As applied to Hansard, the LDA method considers each statement to be a result of a process where a politician first chooses the topics they want to speak about. After choosing the topics, the speaker then chooses appropriate words to use for each of those topics. More generally, the LDA topic model works by considering each document as having been generated by some probability distribution over topics. For instance, if there were five topics and two documents, then the first document may be comprised mostly of the first few topics; the other document may be mostly about the final few topics (Figure 1).

Similarly, each topic could be considered a probability distribution over terms. To choose the terms used in each document the speaker picks terms from each topic in the appropriate proportion. For instance, if there were ten terms, then one topic could be defined by giving more weight to terms related to immigration; and some other topic may give more weight to terms related to the economy (Figure 2).

Following Blei and Lafferty (2009), Blei (2012) and Griffiths and Steyvers (2004), the process by which a document is generated is more formally considered to be:

1. There are $1, 2, \ldots, k, \ldots, K$ topics and the vocabulary consists of $1, 2, \ldots, V$ terms. For each topic, decide the terms that the topic uses by randomly drawing distributions

request.

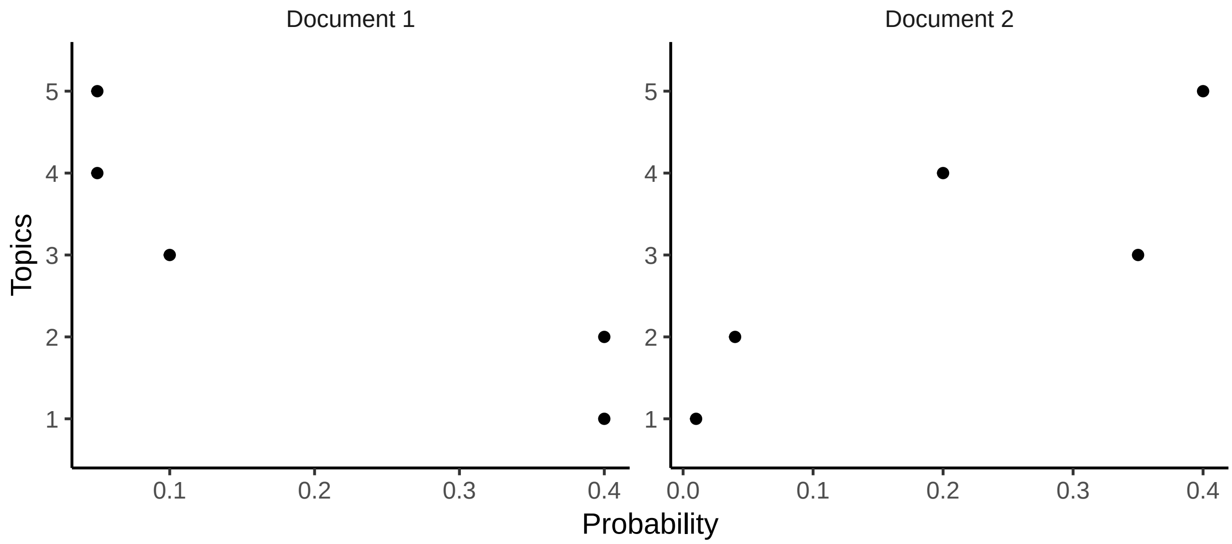

Figure 1: Probability distributions over topics for two documents

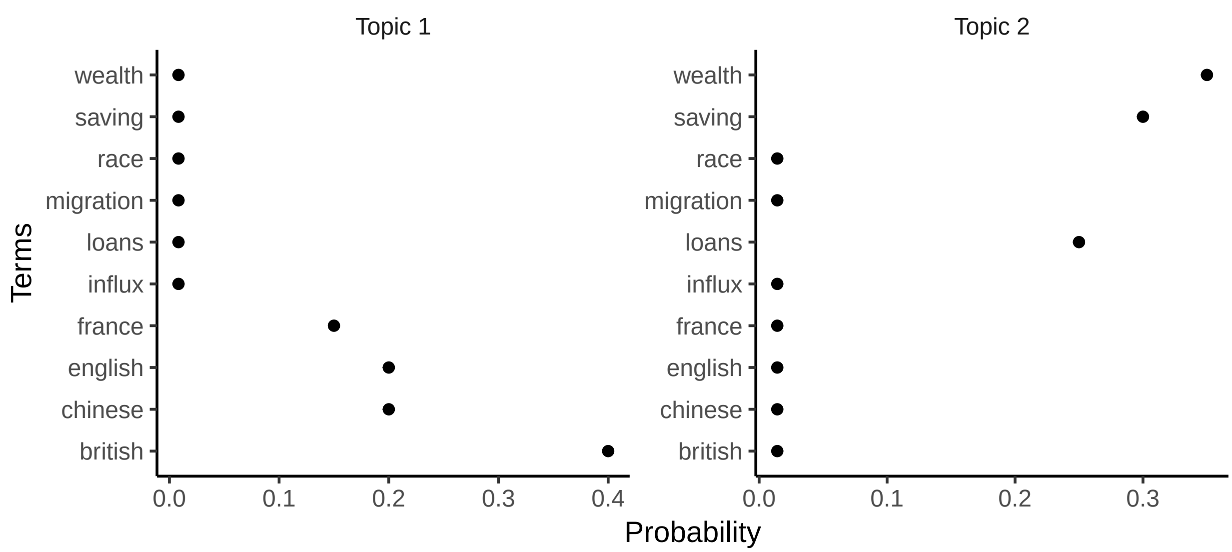

Figure 2: Probability distributions over terms

over the terms. The distribution over the terms for the kth topic is β_k. Typically a topic would be a small number of terms and so the Dirichlet distribution with hyperparameter $0 < \eta < 1$ is used: $\beta_k \sim \text{Dirichlet}(\eta)$.[9] Strictly, η is actually a vector of hyperparameters, one for each K, but in practice they all tend to be the same value.

2. Decide the topics that each document will cover by randomly drawing distributions over the K topics for each of the $1, 2, \ldots, d, \ldots, D$ documents. The topic distributions for the dth document are θ_d, and $\theta_{d,k}$ is the topic distribution for topic k in document d. Again, the Dirichlet distribution with the hyperparameter $0 < \alpha < 1$ is used here because usually a document would only cover a handful of topics: $\theta_d \sim \text{Dirichlet}(\alpha)$. Again, strictly α is vector of length K of hyperparameters, but in practice each is usually the same value.
3. If there are $1, 2, \ldots, n, \ldots, N$ terms in the dth document, then to choose the nth term, $w_{d,n}$:

   a. Randomly choose a topic for that term n, in that document d, $z_{d,n}$, from the multinomial distribution over topics in that document, $z_{d,n} \sim \text{Multinomial}(\theta_d)$.
   b. Randomly choose a term from the relevant multinomial distribution over the terms for that topic, $w_{d,n} \sim \text{Multinomial}(\beta_{z_{d,n}})$.

Given this set-up, the joint distribution for the variables is (Blei (2012), p.6):

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}, w_{1:D,1:N}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p\left(w_{d,n}|\beta_{1:K}, z_{d,n}\right) \right).$$

Based on this document generation process the analysis problem, discussed next, is to compute a posterior over $\beta_{1:K}$ and $\theta_{1:D}$, given $w_{1:D,1:N}$. This is intractable directly, but can be approximated (Griffiths and Steyvers (2004) and Blei (2012)).

After the documents are created, they are all that we have to analyse. The term usage in each document, $w_{1:D,1:N}$, is observed, but the topics are hidden, or 'latent'. We do not know the topics of each document, nor how terms defined the topics. That is, we do not know the probability distributions of Figures 1 or 2. In a sense we are trying to reverse the document generation process – we have the terms and we would like to discover the topics.

If the earlier process around how the documents were generated is assumed and we observe the terms in each document, then we can obtain estimates of the topics (Steyvers and Griffiths (2006)). The outcomes of the LDA process are probability distributions and these define the topics. Each term will be given a probability of being a member of a particular topic, and each document will be given a probability of being about a particular

[9] The Dirichlet distribution is a variation of the beta distribution that is commonly used as a prior for categorical and multinomial variables. If there are just two categories, then the Dirichlet and the beta distributions are the same. In the special case of a symmetric Dirichlet distribution, $\eta = 1$, it is equivalent to a uniform distribution. If $\eta < 1$, then the distribution is sparse and concentrated on a smaller number of the values, and this number decreases as η decreases. A hyperparameter is a parameter of a prior distribution.

topic. That is, we are trying to calculate the posterior distribution of the topics given the terms observed in each document (Blei (2012), p. 7):

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N} | w_{1:D,1:N}) = \frac{p\left(\beta_{1:K}, \theta_{1:D}, z_{1:D,1:N}, w_{1:D,1:N}\right)}{p(w_{1:D,1:N})}.$$

The initial practical step when implementing LDA given a collection of documents is to remove 'stop words'. These are words that are common, but that don't typically help to define topics. There is a general list of stop words such as: "a"; "a's"; "able"; "about"; "above"... An additional list of words that are commonly found in Hansard, but likely don't help define topics is added to the general list. These additions include words such as: "act"; "amendment"; "amount"; "australia"; "australian"; "bill"... A full list can be found in Appendix **??**. We also remove punctuation and capitalisation. The documents need to then be transformed into a document-term-matrix. This is essentially a table with a column of the number of times each term appears in each document.

After the dataset is ready, the R package 'topicmodels' by Grün and Hornik (2011) can be used to implement LDA and approximate the posterior. It does this using Gibbs sampling or the variational expectation-maximization algorithm. Following Steyvers and Griffiths (2006) and Darling (2011), the Gibbs sampling process attempts to find a topic for a particular term in a particular document, given the topics of all other terms for all other documents. Broadly, it does this by first assigning every term in every document to a random topic, specified by Dirichlet priors with $\alpha = \frac{50}{K}$ and $\eta = 0.1$ (Steyvers and Griffiths (2006) recommends $\eta = 0.01$), where α refers to the distribution over topics and η refers to the distribution over terms (Grün and Hornik (2011), p. 7). It then selects a particular term in a particular document and assigns it to a new topic based on the conditional distribution where the topics for all other terms in all documents are taken as given (Grün and Hornik (2011), p. 6):

$$p(z_{d,n} = k | w_{1:D,1:N}, z'_{d,n}) \propto \frac{\lambda'_{n\rightarrow k} + \eta}{\lambda'_{.\rightarrow k} + V\eta} \frac{\lambda'^{(d)}_{n\rightarrow k} + \alpha}{\lambda'^{(d)}_{-i} + K\alpha}$$

where $z'_{d,n}$ refers to all other topic assignments; $\lambda'_{n\rightarrow k}$ is a count of how many other times that term has been assigned to topic k; $\lambda'_{.\rightarrow k}$ is a count of how many other times that any term has been assigned to topic k; $\lambda'^{(d)}_{n\rightarrow k}$ is a count of how many other times that term has been assigned to topic k in that particular document; and $\lambda'^{(d)}_{-i}$ is a count of how many other times that term has been assigned in that document. Once $z_{d,n}$ has been estimated, then estimates for the distribution of words into topics and topics into documents can be backed out.

This conditional distribution assigns topics depending on how often a term has been assigned to that topic previously, and how common the topic is in that document (Steyvers and Griffiths (2006)). The initial random allocation of topics means that the results of early passes through the corpus of document are poor, but given enough time the algorithm converges to an appropriate estimate.

The choice of the number of topics, k, affects the results, and must be specified *a priori*. If there is a strong reason for a particular number, then this can be used. Otherwise, one way to choose an appropriate number is to use a test and training set process. Essentially, this means running the process on a variety of possible values for k and then picking an appropriate value that performs well.

One weakness of the LDA method is that it considers a 'bag of words' where the order of those words does not matter (Blei (2012)). It is possible to extend the model to reduce the impact of the bag-of-words assumption and add conditionality to word order. Additionally, alternatives to the Dirichlet distribution can be used to extend the model to allow for correlation. For instance, in Hansard topics related the army may be expected to be more commonly found with topics related to the navy, but less commonly with topics related to banking. This motivates the use of the Structural Topic Model, described in the next section.

Structural Topic Model

Overview and example

[TBD]

Note that each of the states and the Commonwealth are treated independently here. Future work could expand the model to better understand, and allow, for correlation between them.

Considering events

[TBD]

Results

Political events

> *When you change the government, you change the country.* Paul Keating.

Change of government.

Polling events

> *The only poll that matters is the one on election day.* John Howard.

[TBD]

Economic events

Major economic changes.
[TBD]

External events

> *Events, dear boy, events.* Attributed to Harold Macmillan.

Major event such as 9/11 attacks, or economic change.

Summary and conclusions

What could happen if we had longer terms. Eg GST needed multiple generations of politicians but carbon tax couldn't because it was one generation.

Text analysis has well-known biases and weaknesses and is a complement to more detailed analysis such as qualitative methods and case studies. We consider the results presented in this paper, as well as many of those results of the larger text-as-data research program, as fitting within findings based on other methods.

Appendix

Document sources

Where from?
  Which years are being used (not non-OCRd)

Dataset issues

Which PDFs are missing or have no content, etc.

Example workflow

Example of the workflow from PDF to text

PDF to CSV issues

Insert graph of stop words over time.

Selection of number of topics

Robustness of results

Here we change the number of sitting days considered either side of an event. The results in the main section of the paper are for the nearest ten days either side of an event. Here are show that the results are essentially the same if the nearest one, two, five, and twenty days either side of an event.

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