

Strategies for political-statement segmentation and labelling in unstructured text

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Abstract

Analysis of parliamentary speeches and political-party manifestos has become an integral area of computational study of political texts. While speeches have been overwhelmingly analysed using unsupervised methods, a large corpus of manifestos with by-statement political-stance labels has been created by the participants of the MARPOR project. It has been recently shown that these labels can be predicted by a neural model; however, the current approach relies on provided statement boundaries, limiting out-of-domain applicability. In this work, we propose and test a range of unified split-and-label frameworks—based on linear-chain CRFs, fine-tuned text-to-text models, and the combination of in-context learning with constrained decoding—that can be used to jointly segment and classify statements from raw textual data. We show that our approaches achieve competitive accuracy when applied to raw text of political manifestos, and then demonstrate the research potential of our method by applying it to the records of the UK House of Commons and tracing the political trajectories of four major parties in the last three decades.

1 Introduction

Among the genres used by politicians to communicate with each other and voters, two of the most important ones are party manifestos and speeches made in deliberative assemblies, such as the House of Commons in the UK or the Bundestag in Germany. These sources are publicly available, but their sheer volume makes manual analysis of them a very challenging task, and the study of party manifestos and parliamentary debates has become one of the cornerstones of computational analysis of political texts (cf., among others, Fišer et al., 2022; Arroyo, 2022; Müller and Proksch, 2023).

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While members of the research community share an interest in analysing the stances expressed by politicians towards different issues, the particular approaches taken for these two types of texts have largely differed.

The analysis of party manifestos has, to a large extent, coalesced around the labelling scheme developed in the framework of the MARPOR project (Volkens et al., 2021) and used to manually annotate manifestos from more than 60 countries, written in almost 40 languages.¹ MARPOR labels are attached to *statements*, semantically coherent units on the sentence or sub-sentence level. These labels correspond to political issues, such as national defence or migration, but often encompass both an issue and a particular stance towards that issue. For example, label 504, ‘Welfare state expansion’, is assigned to ‘Favourable mentions of need to introduce, maintain or expand any public social service or social security scheme.’ Therefore, by means of simply counting different labels assigned to statements from a particular manifesto, it is possible to obtain a rather fine-grained representation of the political program expressed therein.

Until recently, efforts to assign these labels automatically had been largely unsuccessful and limited in scale (Dayanik et al., 2022). It has been then shown by Nikolaev et al. (2023)² that contemporary multilingual models can be used for adequate cross-lingual analyses. However, their approach relies on the availability of statement boundaries, not provided by existing NLP tools, which limits the practical applicability of the trained models.³

¹<https://manifesto-project.wzb.eu/information/documents/corpus>

²And concurrently, albeit in a less rigorous fashion, by Burst et al. (2023b,a).

³It has been argued by Däubler et al. (2012) that sentences, which NLP tools do aim to identify, are valid units of analysis in computational analyses of political texts. The MARPOR annotation practices remain prevalent, however, and this is the setting we are targeting in this study.

Conversely, the study of parliamentary debates, where labelled corpora are non-existent and the basic unit is usually a whole speech, has overwhelmingly relied on unsupervised exploratory methods, such as topic modelling, or even manual analysis, and targeted simple binary categories and aggregate scales (Abercrombie and Batista-Navarro, 2020; Nanni et al., 2022; Skubic and Fišer, 2024).⁴

The MARPOR categorization scheme has proven to be a powerful tool for political-text analysis, applicable to almost any text in this domain,⁵ and the fact that labelled data and models trained on them only exist for party manifestos is largely a technical obstacle. Therefore, in this work we aim to solve the problem of projecting the MARPOR annotations to any running text.

In order to do this, we experiment with a series of models, spanning the landscape of Transformer-based architectures.

As a first step, we replace the encoder-based statement-level classifiers proposed by Nikolaev et al. (2023) and Burst et al. (2023b) with a linear-chain CRF layer (Lafferty et al., 2001) that learns to predict statement boundaries jointly with MARPOR labels using raw manifesto texts. This pipeline is very memory efficient and provides quick training and inference. However, its ability to understand label sequences is limited by the expressive power of linear-chain CRFs, motivating investigation of autoregressive models.

As a more expressive but also more computationally demanding alternative, we propose using a pre-trained T5-family model that is fine-tuned to split large textual chunks into statements and label these statements at the same time.

Finally, we try to solve the task by using in-context learning, i.e. forgoing fine tuning and providing labelled examples during inference with a state-of-the-art decoder-only model.⁶

We show that, even though fine-tuned T5-type models produce the best in-domain results, their

⁴A limited attempt at applying the MARPOR coding scheme to parliamentary data, again on the speech level, has been made by Abercrombie and Batista-Navarro (2022), but it relies on a rather strong assumption that the whole speech revolves around the same narrow topic.

⁵Cf. an analysis of judges' decisions using this framework by Rosenthal and Talmor (2022).

⁶Nikolaev et al. (2023) showed that using long-input BERT-type model for directly predicting a scaling score, RILE, produced bad results, and it seems that language models are in general poorly suited for regression. Therefore in this study we only experiment with statement-level classification, which has additional practical benefits.

high computational demands and slow inference limit their practical applicability to large-scale out-of-domain experiments. For such cases, the CRF-based model makes for a better choice, showing a slight performance degradation on in-domain evaluation but orders-of-magnitude faster inference.

Equipped with our CRF model, capable of efficiently segmenting and labelling statements from raw text, we perform an exploratory analysis of the UK parliamentary records.⁷ We further discuss the problem of the parliamentary data being out-of-domain, especially in terms of label sequences, and propose to mitigate it using model ensembling.

2 Data

We target the same original-language and translated subsets of the MARPOR dataset as used by Nikolaev et al. (2023).⁸ Out of the two settings explored in their paper, leave-one-country-out and old-vs.-new, we adopted the former as it is more challenging.

Since training and testing larger models on all 41 countries from their dataset is not practicable, we adopted the following approach: after a complete preliminary analysis done using the XML-R + CRF approach, we split the countries into quartiles based on the test-set performance. We then selected a country from the middle of the each quartile and used this country's manifestos as a test set for subsequent experiments. For each of the test countries we also used the same set of dev-set-countries' manifestos when training the CRF and fine-tuning Flan T5.⁹

The dataset for the exploratory analysis of parliamentary records is described in § 6.

3 Methods

The problem of jointly segmenting and classifying statements from text is an example of a span identification, or extraction, task. In spite of the fact that all models we use rely on the same underlying Transformer architecture, they demand different approaches to task operationalisation and input/output encoding. We specify them below.¹⁰

⁷A secondary study of Australian data is reported in the Appendix.

⁸Available at <https://osf.io/aypxd/>

⁹The test countries with their respective dev-set countries are as follows: Denmark (Netherlands, Turkey), Netherlands (Mexico, Slovakia), Bulgaria (Chile, Georgia), Uruguay (Austria, Czech Republic).

¹⁰The training code for the study will be uploaded to a public repository in case of acceptance.

3.1 CRF

Input formatting. Following standard practice, we encode the statements using the BIO scheme (Ramshaw and Marcus, 1995) and use a sequence-labelling model to predict token-wise labels. As the spans we are extracting form a total cover of our texts, the O label is ultimately only used for padding and BOS/EOS tokens.

The architecture. Our model combines a linear-chain CRF with a pre-trained XLM-RoBERTa (XLM-R) encoder (Conneau et al., 2019) providing token-wise emission scores for the CRF. Due to XLM-R’s multi-lingual pre-training, we are able to directly use manifestos in their original languages.

As the political manifestos we train on are significantly larger than our encoder’s context window, we divide the input text into multiple overlapping windows, feed these windows to our encoder independently, and stitch together the contextualized representations obtained from the centre of each window for use as input to the CRF. In this way, we can process sequences of arbitrary length, while still ensuring that each token’s representation was generated with adequate context to both left and right.

During inference, we feed entire documents as input to our model in this manner, irrespective of length, while during training, for performance reasons, we limit model inputs to 1024 tokens, yielding a maximum of four overlapping windows. A complete description of our model, including hyperparameters and splitting procedures, is provided in Appendix B.

Training. For each cross-validation split, we initialize our encoder with pre-trained XLM-R weights and randomly initialize all other model weights. We jointly optimize all model weights on negative-log-likelihood loss using mini-batch gradient descent. During training, we periodically calculate the model’s F_1 -score on the held-out development set in order to guide early stopping. After twenty such evaluations with no improvement, we terminate training, retaining model weights from the training step that yielded the highest dev-set F_1 -score.

3.2 Fine-tuned Flan-T5

We use the pre-trained version of Flan T5 XL from HuggingFace¹¹ as the base model. Since Flan T5

is English only, we use the translated version of the dataset.

Input formatting. Thanks to using relative attention Flan T5 is able to handle contexts of arbitrary length. However, due to high memory constraints we split the MARPOR manifestos input into chunks of 260 tokens, as defined by the model’s tokeniser. Input consisted of raw text, and the output consisted of input statements followed by their MARPOR label followed by a triple tilde.¹² A sample input-output pair is shown in Appendix C.

Training. The model was trained with the standard cross-entropy loss using the AdamW optimiser (Loshchilov and Hutter, 2019) with the learning rate of 10^{-5} for 5 epochs, and we selected the checkpoint that performed best on the dev set for testing.¹³ We then decoded greedily at test time.

3.3 In-context learning with Llama 3.1

Our final model is an in-context learning approach utilizing Llama 3.1 8B Instruct (Dubey et al., 2024), an instruction-tuned large language model. We use the provided model weights as-is and do not further fine tune this model. As Llama 3.1 does not support the vast majority of languages present in the MARPOR corpus, we again use English-language translations of the manifestos.

In order to obtain useful predictions from this pre-trained model, we leverage few-shot in-context learning (Brown et al., 2020; Wei et al., 2022) with decoding-time constraints.

We present the model with a short English-language system message, tasking it with segmenting and classifying claims from a provided snippet from a party manifesto. We then present a fabricated chat history of thirty task-response pairs. For each of these, a user message presents a snippet of a party manifesto, and an agent message parrots the same text back, inserting statement labels after each statement. These in-context learning examples are drawn uniformly randomly from the training partition, agent responses reflecting gold-

¹²Originally we experimented with splitting labelled statements with line-breaks, but line-breaks were replaced by single spaces during decoding. The fine-tuned model also refused to reconstruct triple tildes, but it consistently replaced them with <unk>, which we then used to extract statements.

¹³We used the same cross-entropy loss to select the checkpoint and not span-extraction and label-prediction accuracy. The latter would be beneficial, but inference with T5 XL is very slow, so we only used it for the test set.

¹¹<https://huggingface.co/google/flan-t5-xl>

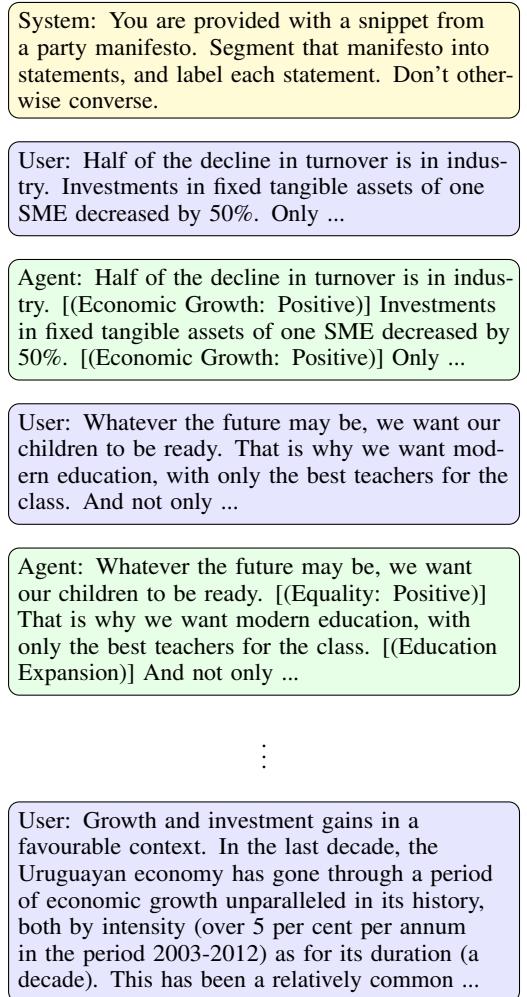


Figure 1: An example of an in-context learning prompt, comprising natural-language instructions, in-context learning examples, and the input text. The instructions are shown verbatim; in-context learning examples shown are real examples from the dataset but are truncated for space. The model’s response to this prompt, decoded with constraints, will constitute the prediction for the input text.

standard segmentations and labellings. Statements are labelled by the English name of their category titles, parenthesized [(like this)]. By using descriptive English names, as opposed to numeric IDs, the model can leverage existing semantic knowledge obtained from its pre-training when assigning labels to statements.

After these 30 in-context learning examples, we present a final user message, this time presenting a snippet of a manifesto taken from the test partition. At this point, the model is left to generate a continuation response labeling and segmenting this snippet. Figure 1 illustrates a prompt built in this way.

As we are specifically interested in statement segmentations and labellings, and not in a conversational response the model was instruction-tuned to provide, we make use of decoding-time constraints to severely limit the possible output space. At each time-step, we only consider possible continuations that either (i) parrot the next token as was present in the input snippet, (ii) begin a statement label tag, or (iii) continue a previously-begun statement label tag in a way that can lead to a legal tag with a valid statement name. A token trie is used to efficiently track legal continuations for already-begun tags.

In this way, every allowed response corresponds one-to-one with a possible segmentation and labelling of the input sequence. As greedy decoding might lead the model to commit to tokens with no legal high-probability continuations, we decode from this constrained model with beam search of beam width three.

3.4 Evaluation

We evaluate the models on two tasks: (i) statement segmentation and MARPOR-label prediction and (ii) a ‘downstream’ task of political scaling, i.e. assigning to political texts numerical scores that characterise their position on a certain continuum. We use F_1 -scores for (i) and target the Standard Right–Left Scale, a.k.a. the RILE score, as the most commonly used political scale. It is computed using the following formula:

$$\text{RILE} = \frac{R - L}{R + L + O} \quad (1)$$

R and L stand for the number of right- and left-leaning statements in the target manifesto, respectively, and O stands for other statements. The categories making up the R and L groupings are shown in Table 4 in the Appendix. See Volkens et al. (2013) for more details.

4 Results

With the leave-one-country-out cross-validation setting, we obtain one set of model predictions for one test country. For the CRF-based model, where all 41 countries were processed, we analyse our results on the union of by-country predictions. For Flan T5 XL and Llama, we report the results for each test country individually.

4.1 CRF-based segmentation

Table 1 summarises the performance of the CRF-based model in terms of macro-averaged F_1 -scores

Model	Precision	Recall	F_1	RILE
CRF	41.3	40.7	40.7	0.74
CRF+Oracle	48.0	50.0	48.6	0.75
Baseline (XLM-R)	–	–	44	0.73
Baseline (MT)	–	–	44	0.71

Table 1: The results of predicting MARPOR labels and RILE scores for held-out manifestos. Precision, recall, and F_1 -scores are weighted by support in the true labels. Performance on RILE is measured as Spearman correlation of computed and gold scores. MT denotes using an English SBERT encoder with translated inputs.

	Denmark	Netherlands	Bulgaria	Uruguay
CRF	45.4	42.33	41.2	33
Flan	48.3	43.5	40.1	37.5
Flan+	40	37.7	37.9	31.1
ICL	32.7	31.3	24.9	25.1
CRF	40.72	40.95	38.72	24.96
Flan	45.52	43.3	42.7	34.3
Flan+	39.4	37.2	39.6	28.4
ICL	29.34	30.89	26.88	22.97

Table 2: F_1 -scores for extracted and labelled spans in the test sets. Micro-averaged scores are in the upper part of the table, and the lower part presents scores averaged by manifesto. Flan+ stands for combining span extraction using Flan T5 XL with label assignment using Nikolaev et al.’s SBERT-based model. ICL is Llama 3.1 8B Instruct.

for exact span-and-label matches, weighted by class frequency, and compares its results with those from Nikolaev et al. (2023) where, as in all other prior work, gold statement boundaries were assumed.

We find that after replacing gold statement boundaries and a unigram-based classifier by an end-to-end CRF model we obtain the results that differ by less than four percentage points. We can interpret numerical differences in F_1 -scores as the result of two factors: differences in the two models’ competency at *classifying* claims, and additional challenges introduced by the task of determining claim *boundaries*, which are only faced by our model.

We can attempt to disentangle these two factors by providing our model with an oracle for span boundaries. This can be accomplished at decoding time by constraining (Papay et al., 2022) our CRF output as follows: our CRF *must* output some begin tag wherever the true label sequence has a begin tag, and it *must not* output a begin tag wherever the true label sequence does not have a begin tag.

	Denmark	Netherlands	Bulgaria	Uruguay
CRF	0.67	0.79	0.54	0.9
Flan	0.84	0.9	0.45	1
Flan+	0.78	0.86	0.59	1
ICL	0.71	0.78	0.62	1

Table 3: RILE scores computed using predicted labels. See the caption of Table 2 for model abbreviations.

In this way, we can ensure that our model’s statement boundaries match the true boundaries, while still allowing our CRF to choose which MARPOR category to assign to each statement.

Under this setting, we find that our model actually outperforms the classifier-based baseline by more than 4 percentage points. As both models use XLM-R as an encoder, we cannot ascribe this performance difference to quality of latent representations. Instead, we suspect that our CRF-based model’s ability to model interactions between adjacent statement labels gives it an edge against the classifier-based baseline, which must predict statement labels independently.

Interestingly, even though our oracle-free model loses to the baselines on F_1 , it still leads to better estimates of manifesto-level RILE scores, which was the main target for Nikolaev et al. (2023). Mistakes made by the new model therefore seem to be less ‘damaging’ in the sense that, e.g., left-leaning stances are not identified as neutral or right-leaning.

4.2 Text-to-text and in-context learning

The analysis above highlights the importance of incorporating sequential information in political-statement labelling. Given that the CRF is hamstrung by its inability to model non-immediate context, we can expect autoregressive models attending to long histories to outperform it. Large language models with decoders are a natural fit for this task.

Further, adding constraints on the decoding or an explicit copy mechanism is a natural way of simplifying the task of regenerating the input, and we did add constrained decoding to Llama 3.1. Preliminary tests of fine-tuned Flan T5 XL, however, showed that the model very rarely garbles the input, so in the interest of simplicity and decoding speed (see § 5) we resorted to the greedy strategy.

The results for span extraction and labelling are shown in Table 2. With extracted spans, gold-label-weighted F_1 becomes less interpretable, and we revert to simple micro-averaging and macro-averaging across manifestos. The correlations be-

tween RILE scores computed using predicted and gold labels for all models are shown in Table 3. The test countries can be roughly split in three groups in terms of model performance.

The first group consists of Denmark and Netherlands. Both these countries have large test sets, with manifestos written in comparatively well-resourced Western European languages. This ensures higher quality of both multilingual embeddings (used by the CRF model) and the MT models, which provide inputs to LLMs. In both cases, we see the same outcome: the vanilla Flan T5 XL is a clear winner in terms of classification accuracy, with the CRF model a more or less close second.

In terms of downstream RILE scores, Flan T5 is again the best model, but the second place is now taken by the combination of Flan-derived spans with SBERT-assigned labels, and the CRF model loses even to the Llama-based model, whose accuracy is very low. This further reinforces the conclusions by Nikolaev et al. (2023) that when it comes to computing RILE scores, the nature of the errors made by a given models becomes more important than its actual accuracy.

The second group consists of Uruguay, which is a very hard label-prediction task (Flan T5 attains an F_1 -score of 37.5, and all others do even worse), but a much easier scaling task, with correlations everywhere close to 1. The latter result, however, should be taken with a grain of salt since the test-set size is small (4 manifestos).

Finally, the most complicated case is presented by Bulgaria, which is closer to Uruguay in terms of span and label accuracy, with a minimal difference between CRF and Flan T5 in terms of the F_1 -score, but where the best performance on RILE is attained by the Llama-based setup. Most intriguingly, the performance of Flan T5 on the RILE task is the worst among all the models.

If we regard Bulgaria as a sort of outlier with high-variance results induced by lower-quality embeddings or translations, we may tentatively conclude that

1. Using a fine-tuned Transformer-based model for span extraction and labelling provides a modest boost in performance over the CRF-based approach, even without constrained decoding.
2. Conversely, using constrained decoding for multi-label classification in the in-context-

learning setting does not yet lead to good results. This may be overcome by resorting to larger models or longer contexts; however, see § 5 below.

3. In contrast to exact label prediction, RILE-based scaling seems to be an easy task, with even constrained Llama 3.1 providing results on par with those reported by Nikolaev et al. (2023). This suggests that for coarse-grained analysis bypassing fine-tuning is already a valid strategy.

5 Discussion of computational demands

In this section, we contrast computational demands of different approaches. We show that while training demands of even bigger models that we use are manageable, given access to typical research-grade infrastructure, inference on them becomes limited to hundreds, at most thousands of examples, which limits their applicability to larger corpora in computational political science numbering millions of data points.

5.1 Training

CRF + XLM-R has relatively low demands for training, particularly when taking into account its much lower memory footprint than most modern autoregressive models: training required 6.87 GiB of GPU memory, and up to six independent models could be trained simultaneously on a single NVIDIA RTX A6000 GPU. In this parallel training regime, each training process took about 1.08 seconds to complete a single training step with a batch size of one.

Fine-tuning **Flan T5 XL** is moderately demanding: while training on four NVIDIA A100 40 gigabyte GPUs, one batch of two 260-token inputs takes approximately 1.3 seconds for a forward and a backward pass. While this is comparable to the CRF, fine-tuning Flan T5 XL requires approximately 60 gigabytes of GPU memory, limiting the ability to perform such fine-tuning on lower-end hardware and precluding the parallelisation of multiple training runs as was possible for the CRF-based model.

The in-context-learning setup does not demand a training stage.

5.2 Inference

Not relying on autoregression and benefiting from a smaller model size, inference was quite fast with

the **CRF** model, averaging just over 3000 tokens per second.¹⁴ Furthermore, as was the case with training, the model’s small memory footprint allowed multiple inference procedures to be parallelised on a single GPU.

With sequential decoding in inference, the time demands of the two autoregressive models are almost prohibitive: **Flan T5 XL** performed inference at a rate of 26 tokens per second, and **Llama 3.1 8B**, requiring a long context for in-context-learning examples and beam-search decoding, averaged just under 3 tokens per second. Such slow inference time makes these models infeasible to apply to large corpora such as UK or Australian Hansard for targeted experiments.

6 Analysis of parliamentary debates

We now turn to the analysis of parliamentary data to show how our raw-text-capable CRF-based model can be applied in another domain. While it is likely less powerful than fine-tuned Flan T5 XL, it is incomparably faster in inference and can be used to process large corpora without access to massive computational resources.

6.1 Preliminaries

We apply our model to the records of parliamentary debates published as so-called Hansards in the UK and some of the Commonwealth countries. Our primary data come from the UK version of Hansard,¹⁵ with a similar analysis for Australia presented in Appendix G. There is no published dataset of UK parliamentary debates annotated with CMP labels.¹⁶ Therefore our analysis is exploratory, and it may be validated by evaluating the reasonableness and insightfulness of the revealed trends.

Preliminary analysis of the labels assigned by the CRF model demonstrated that, apart from the core of semantically relevant statements, it often assigned more general or technical statements that MARPOR labels as ‘Other’ to other classes, most likely because topic sequences in the manifesto data differ significantly from those in parliamentary speeches. In order to mitigate this issue, we re-

¹⁴For comparability, all inference speeds are reported in terms of Flan T5 XL tokenisation.

¹⁵<https://hansard.parliament.uk/>

¹⁶Abercrombie and Batista-Navarro (2022) assigned CMP labels to a set of *motions*, i.e. statements calling for a vote on a bill, and used these as gold labels for speeches responding to this motion. The choice of the label, however, depends on the contents of the bill and not on the text of the motion itself.

sorted to conservative model ensembling, and only included in the analysis statements on which our model and the classifier by Nikolaev et al. (2023)—with statement boundaries provided by the CRF model—agreed. This happened in 38% of cases (39.6% on the Australian Hansard), which gives around 7 million statements for analysis. A randomised manual inspection of statements given different labels (see examples in Appendix D) showed that the performance of the ensemble model is good both in terms of statement boundaries and assigned labels. The only problematic category is 305, ‘Political authority’, which seems to lack a coherent core in the source data and competes with ‘Other’ for general or procedural statements.

For the sake of robustness, we further restrict ourselves to statements made by members of four major parties, the Conservative Party, the Labour Party, the Liberal Democrats (LibDems), and the Scottish National Party (SNP), between 1990 and 2019. As Figure 3 in Appendix E shows, the number of statements made by each party is roughly proportional to its success in the preceding elections, with Conservatives and Labour dominating throughout and SNP overtaking LibDems after 2015.

6.2 Party trajectories

In order to trace political evolution of major UK parties as reflected by statements their members made in the House of Commons, we use path diagrams. Each data point represents a distribution of CMP labels attached to statements made by a party in a given year. To derive the axes, we use non-negative matrix factorization with 2 components¹⁷ trained on the original CMP data with label counts aggregated by manifesto. This provides us with a ‘universal salience baseline’. We then use the trained model to project UK parliamentary data on the same axes.

The results of this procedure are shown in Figure 2. Similar to previous work on political-text scaling (Rheault and Cochrane, 2020; Ceron et al., 2023), an axis emerges that can be understood as politically left-vs.-right. In our case, the first component portrays both Conservatives and Labour as largely centrist parties, with Labour spending several years (2015–2019) as a more left-wing one. This ties in nicely with the fact that in 2015–2020 the party was lead by Jeremy Corbyn, who was noted for leading the party towards the radical left

¹⁷Implemented in scikit-learn.

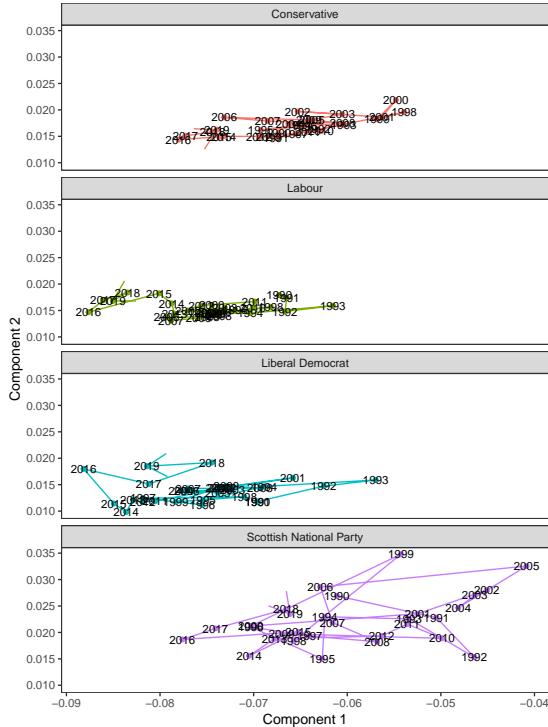


Figure 2: Political trajectories of major UK parties traced by projecting yearly salience vectors of CMP categories in their parliamentary speeches using non-negative matrix factorization and the original CMP data as the training set.

(Goodger, 2022). LibDems, a centre-left party, is also to the left of Conservatives, while SNP, social democratic in terms of its social and economic policies but with a distinct nationalistic agenda (Mitchell et al., 2011), shown as the most right-wing one.¹⁸

Our analysis can be contrasted by that by Rheault and Cochrane (2020, 12), who used averaged word embeddings. They portray Labour as strictly to the left of Conservatives at all times with LibDems always occupying middle ground. Given the amount of convergence and shared values, e.g. on the expansion of welfare state, among the British political parties (Quinn, 2008; Goodger, 2022), this picture seems too simplistic.

7 Related work

As far as we are aware, no prior work addresses the problem of assigning MARPOR labels to raw text, and the efforts were focused on providing higher-level stance or scaling analyses. For example, Subramanian et al. (2018) provided manifesto-

¹⁸The more traditional way of placing each of the parties on the right–left scale using the MARPOR RILE formula (Volkens et al., 2013) is shown in Appendix F.

level scaling scores by aggregating over LSTM-based representations of sentences and taking into account historical RILE values, while Liu et al. (2022) present a model for determining ideology and stance, where both target values are encoded as binary or 3-element scales.

The problem of automatically assigning contentful MARPOR labels to statements in party manifestos was first addressed on a smaller scale by Dayanik et al. (2022) and Ceron et al. (2023), and then in a larger cross-lingual setting by Nikolaev et al. (2023) and Burst et al. (2023b,a). All these studies assumed, however, that gold statement boundaries are provided, which contrasts with the fact that many MARPOR statements consist of sub-sentences, which demands a dedicated span-extraction module.

The necessity of completely splitting the input into sub-sentence-level chunks contrasts our setting with span-extraction tasks, such as NER, and more straightforward sentence-segmentation settings, where the need for domain-specific approaches has also been recognised. In the latter area, CRF- and encoder-based approaches continue to demonstrate strong results, cf. Brugger et al. (2023) for a domain-specific example and Frohmann et al. (2024) for a general model. In a manner similar to ours, McCarthy et al. (2023) contrast CRF-based approaches to text segmentation to using LLMs with constrained decoding.

8 Conclusion

The analysis of political texts has long been impeded by the absence of a model providing identification and fine-grained semantic labelling of statements. In this work, we show that it is possible to assign statement boundaries and stance labels at the same time. Using well-proven methods, a BERT-type encoder with a CRF layer, we reach good performance on the manifesto data and then demonstrate that our model can provide insightful analyses of parliamentary data in the standard MARPOR framework. We furthermore show that better results can potentially be attained using simple fine-tuning of a large text-to-text model, but its low inference speed precludes its use for large-scale exploratory studies. Finding ways of accelerating inference on high-volume raw-text segmentation and analysis is an important avenue for future work.

Limitations

For in-domain performance, the breadth of languages covered made an in-depth qualitative analysis impossible, as the majority of manifestos were written in languages not spoken by the authors. For the autoregressive models, computational costs prevented us from performing a full-scale comparison against the CRF across all 41 countries. Due to a lack of labeled data for the parliamentary debates domain, we were unable to quantitatively evaluate our models' out-of-domain performance. Furthermore, our exploratory analysis of parliamentary debates was limited to two English-speaking countries.

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Appendix

A RILE categories

MARPOR categories used for computing the RILE score are shown in Table 4.

B Model details

This appendix details the specifics of our CRF-based-model architecture and training procedure.

Right emphasis	Military: Positive, Freedom, Human Rights, Constitutionalism: Positive, Political Authority, Free Enterprise, Economic Incentives, Protectionism: Negative, Economic Orthodoxy, Social Services Limitation, National Way of Life: Positive, Traditional Morality: Positive, Law and Order, Social Harmony
Left emphasis	Decolonisation, Anti-imperialism, Military: Negative, Peace, Internationalism: Positive, Democracy, Regulate Capitalism, Market, Economic Planning, Protectionism: Positive, Controlled Economy, Nationalisation, Social Services: Expansion, Education: Expansion, Labour Groups: Positive

Table 4: The MARPOR categories used for calculating the RILE score.

B.1 Model architecture

As an encoder, we used the XLM-RoBERTa (Conneau et al., 2019) pretrained model, with weights obtained from HuggingFace. As almost all inputs exceeded the 512-token context length of this model, we adopted an overlapping-window approach to encoding longer sequences.

After tokenizing documents in their entirety, we define a number of overlapping 512-token windows to use as independent inputs to our encoder. A new window starts every 256 tokens, such that, except for the start and end of the text, each token is part of exactly two windows. These windows are all used as independent inputs to XLM-RoBERTa, yielding two separate representations for each interior token (one for each window that token is a part of). We take the embeddings from the central half of each window (tokens indexed 64 to 192) and concatenate these to form our input representations – this results in exactly one contextualized vector for each input token and always ensures that these vectors are calculated with adequate left- and right-context.

Our BIO labeling scheme leaves us with 275 labels. We pass our input representations through a 275-unit linear layer in order to obtain emission scores for our CRF. Transition scores are stored explicitly in a 275×275 weight matrix, which is initialized randomly.

B.2 Training

We optimize all parameters jointly, fine-tuning the XLM-RoBERTa weights while learning weights for our linear layer and transition matrix. We utilize the Adam optimizer (Kingma and Ba, 2015) with an initial learning weight of 5×10^{-6} . Due to the length of our documents, we use a batch size of 1. We further limit documents to a length of 1024 during training.

Every 2000 training steps, we evaluate model F_1 -score on the held-out development set in order to guide early stopping. After twenty such evaluations with no improvement, we terminate training, retain-

ing model weights from the training step which yielded the highest in dev-set F_1 -score.

The 41 splits were trained in parallel across a number of NVIDIA GeForce GTX 1080 Ti and NVIDIA RTX A6000 GPUs. Training time varied significantly per split but was generally on the order of about 4 days.

C Flan T5 XL input-output example

Input: We want to renovate the quality society in the current quantity society. In a quality society, we do not always have to do more, but better. Quality means services and sustainable products that do not waste energy and natural resources. In working life, quality means fairness, equality and enjoyment – and that everyone can participate. The quality of life is improved by having more time for family and loved ones. We want stone-foot shops, domestic services, village economy promote the export of environmental technology and computer games. We want the goods purchased not only to be able to carry home but also to be used, and we want them to be repaired or repaired by professionals. Work must continue to be done at hand and without it, because a green quality society is a society for everyone. The aim of green policy is to restore a more gentle, equal and environmentally friendly society. From single use to sustainability: products, goods, nature and climate must last from generation to generation. We want an eco-efficient economy based on services, knowledge and knowledge, where healthier and more long-term people can influence their own lives. We want a more diverse nature, a more nuanced environment and a richer cultural environment. We want a world where children do well to live.

Output: We want to renovate the quality society in the current quantity society. 416~~~In a quality society, we do not always have to do more, but better. 416~~~Quality means services 504~~~and sustainable products that do not waste energy and natural resources. 416~~~In working life,

quality means fairness, equality and enjoyment – and that everyone can participate. 701~~~The quality of life is improved by having more time for family and loved ones. 603~~~We want stone-foot shops, domestic services, village economy 408~~~promote the export of environmental technology and computer games. 410~~~We want the goods purchased not only to be able to carry home but also to be used, and we want them to be repaired or repaired by professionals. 416~~~Work must continue to be done at hand and without it, because a green quality society is a society for everyone. 701~~~The aim of green policy is to restore a more gentle, equal and environmentally friendly society. 416~~~From single use to sustainability: products, goods, nature and climate must last from generation to generation. 416~~~We want an eco-efficient economy based on services, knowledge and knowledge, where healthier and more long-term people can influence their own lives. 416~~~We want a more diverse nature, a more nuanced environment 501~~~and a richer cultural environment. 502~~~We want a world where children do well to live. 706

D Sample of statements labelled by the ensemble model

In this section, we provide 10 random statements from the UK Hansard for five random MARPOR labels assigned by our consensus ensemble model.

201 ‘Freedom and Human Rights’

- We hear about the freedom and liberty of the individual yet every so often we see on the Order Paper another of these county council Bills or something of the sort that includes this requirement to give prior notice of processions and demonstrations.
- At the very least, it should be an offence to impersonate another person for the purpose of obtaining compulsory access to personal information.
- My right hon. and hon. Friends believe that the civil rights of the citizen come first and foremost.
- He had come to similar conclusions over 10 years ago on the same basis — that Parliament could no longer safeguard the liberties of the individual.
- — to unconditionally release Nelson Mandela and the other political prisoners
- As from 11 November this year, individuals will have the right to demand access to any data held about them on police computer systems and, where appropriate, to have such data corrected or erased.
- That, apparently, is what the Prime Minister means by freedom of choice.
- The applicant is not told whether information about him or her is held on computer.

- Clause 2(1) is most important as it balances the competing interests of freedom of information with the protection of the individual’s privacy.
- It would be an offence for those responsible for the operation of the police national computer wrongly to disclose such personal information.

202 ‘Democracy’

- Will not that be the right time to enter into new discussions?
- It also requires us to reassess, as a House, the control that we believe we should exercise on behalf of the people, of the means that we use to protect them.
- Let us not be kidded — democracy affects local government.
- The Minister who piloted through the Elections (Northern Ireland) Act 1985 — that unwanted piece of legislation — will be well aware that any attempt to filter and vet electors when they present themselves at the entrance to the polling station is illegal under that Act.
- Its chairman, John Hosking, and others have taken a considerable interest in the subject.
- Will the Leader of the House give us his views on the prospects for a debate on an issue affecting democratic debate in the House?
- Is it in order for a group such as the Amalgamated Engineering Union parliamentary Labour group to be a sponsor of a Bill in the House, because it must surely include Members of the other place as well?
- As Winston Churchill said, a democracy is an imperfect form of government.
- The more one studies that view, however, the more ineffective a weapon it has proved to be for Oppositions over the past 30 years.
- Therefore, I shall be as helpful as I can during the Committee stage, provided that Ministers participate fully in the process.

601 ‘National Way of Life: Positive’

- A further consequence of the contradiction between the Government’s budgetary and monetary policies is that we shall increase the attractiveness of the United Kingdom as a haven for the world’s footloose funds.
- Thereby they will lift a burden from the backs of the British people.
- Should it fail, we must use our best endeavours both before and after independence to ensure that nothing disrupts that country.
- To do that, they had to have their own citizenship.
- They lit bonfires in Marlborough, they had cream teas in Ramsbury, they had special children’s fetes in Great Bedwyn and smaller fetes in Little Bedwyn.
- As hon. Members know, this is Derby day.
- Subject to the same safeguards, I believe that the existing law should be extended to provide the same protection for Her Majesty the Queen and the royal family as is now available to foreign embassies and diplomats.
- I am convinced that, by those standards, Britain could do better.

- I believe that they see themselves more as Londoners now than they did even 18 months ago.
- Is it not true that even if they all arrived tomorrow morning, that would still represent only 3 per cent. of the British birth rate and there would still be a net outflow of emigrants from this country?

603 ‘Traditional Morality: Positive’

- We are told that the income tax reduction for the average family is 75p–80p.
- Does she realise that any delay will mean that five times the number of babies born in that group will either be born either dead or with a severe handicap?
- According to Government figures, 25,000 people who are unemployed and registered for work are unmarried childless couples living together as man and wife.
- They are brought out at births, deaths and funerals and, when I visit the Sikh temple in my constituency, they are offered as hospitality and a welcome to worship.
- It could be argued — this is why the previous Labour Government backed down on proposals which did not go as far as the present ones — that it is more likely that at the age of 60 family commitments will have decreased.
- I have listened carefully to the hon. Gentleman’s speech in which he has ranged widely from the Old Testament to the Rocky mountains and back to confessions.
- When I was a little boy I was told that I had to work twice as hard as everybody else because I did not have a father.
- The old system undoubtedly constituted a tax on marriage in exactly the same way as the former allowance of double tax relief on mortgages for unmarried persons was a tax on marriage.
- My husband agreed to have another baby and now I am six months pregnant and we are both overjoyed.
- He should stop believing as gospel everything that he reads in the newspapers.

305 ‘Political authority’

- We know the problems, as we have said many times in this House.
- That is true.
- I was delighted to say the same to you in a similar debate at almost exactly the same time last year.
- I am grateful for that reply.
- I shall come to the Conservative manifesto.
- He is quite right.
- Perhaps you can help me by saying whether it is in order to listen to a point of order raised by Liberal Members, all of whom have been absent until 45 minutes ago, who have come into the debate just recently and seem to be voting —
- He brought a deputation to my Department last Thursday, and I was extremely impressed by the responsible and well argued approach adopted by the councillors and officials whom I met and by the way that the case had been prepared in some documents which I found compelling reading.
- The Minister looks askance at that comment, but he is the only one who has held office in that Department for four years.

- I realise that it has been a long evening for Conservative Members and that a large number are being forced to stay here in case the Opposition require a vote to be held later tonight.

E Hansard UK statistics

Statistics of the number of statements made by member of the four major parties in the House of Commons are shown in Figure 3.

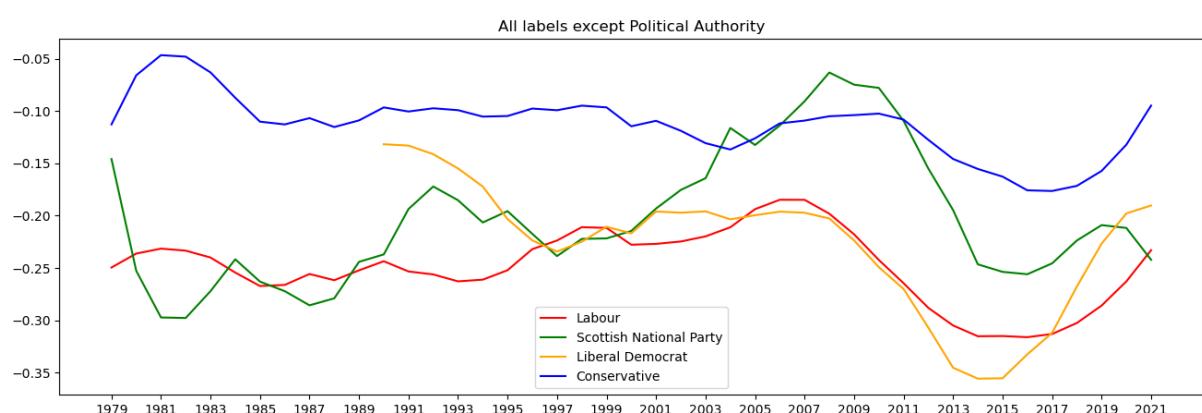
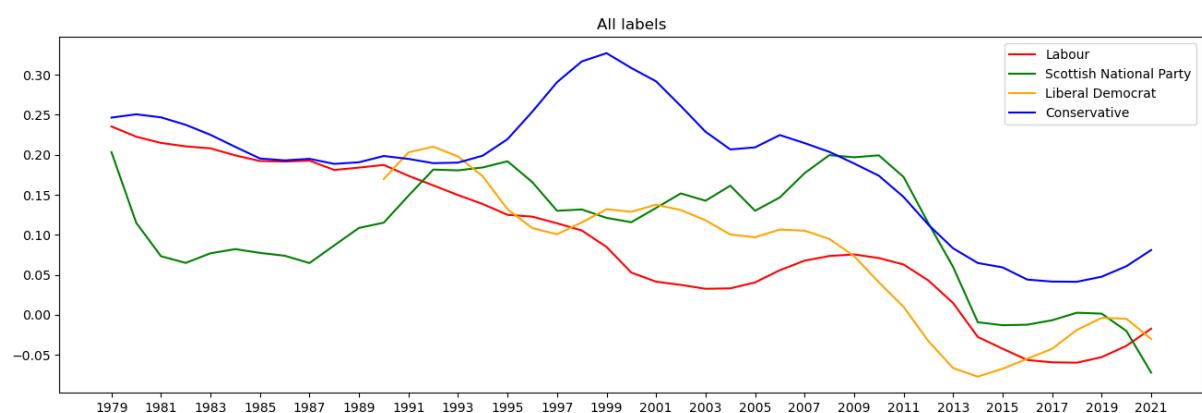
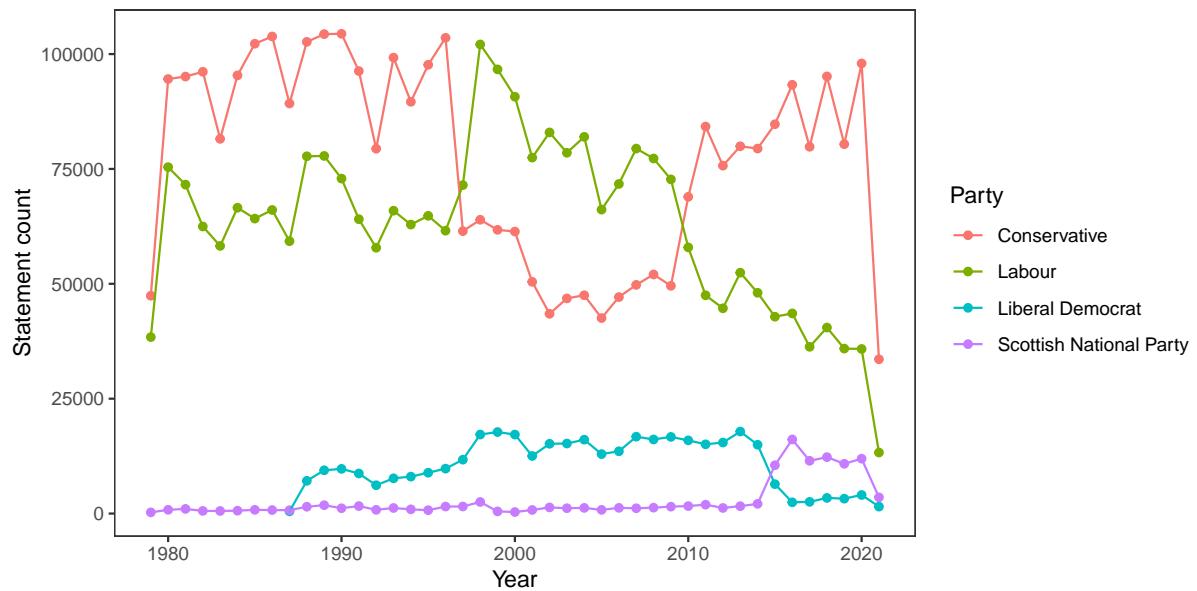
F RILE scores of major UK parties

RILE scores computed on all available data from the UK Hansard are shown in Figure 4 (all labels) and Figure 5 (all labels except 305, ‘Political authority’, which is equally overpredicted for all parties and does not influence their mutual differences but shifts all RILE scores to the right).

Conservatives are consistently portrayed as the most right-wing party, with SNP briefly overtaking them in the run-up to the referendum on Scottish independence, which took place in 2014. After the independence was rejected by the voters, SNP returned to its other traditional focus on social-welfare issues.

G Trajectories of Australian parties

Original XML files published by the Australian Parliament and provided by [Sherratt \(2019\)](#) were used to extract the statements for analysis. Only the subset from 1998 till 2005 was analyzed. See [Katz and Alexander \(2023\)](#) for a more up-to-date dataset. The results of the application of NMF-based analysis to the data are shown in Figure 6.



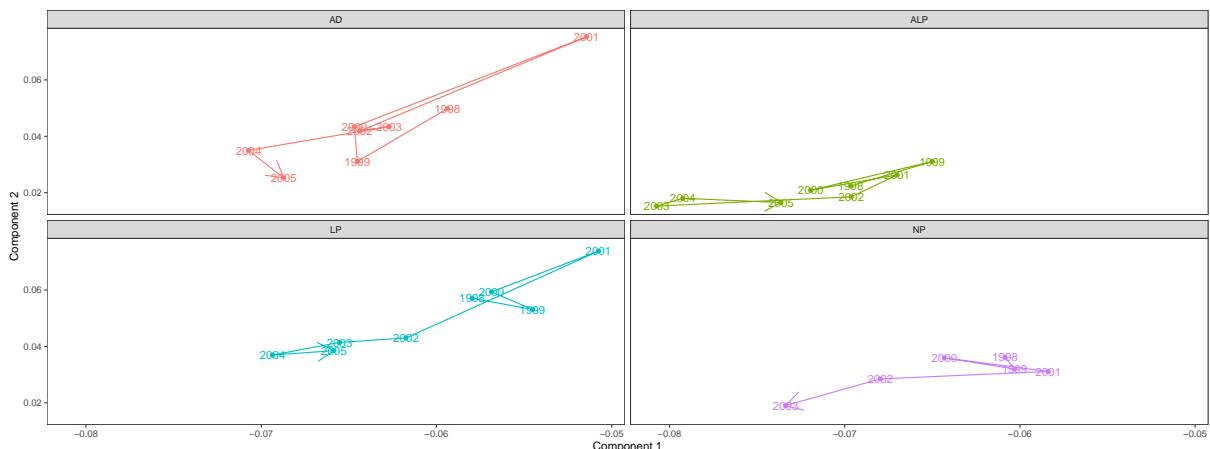


Figure 6: Political trajectories of four major Australian parties traced by projecting yearly salience vectors of CMP categories in their speeches in Parliament (both House of Representatives and Senate) using non-negative matrix factorization and the original CMP data as the training set. AD: Australian Democrats; ALP: Australian Labour Party; LP: Liberal Party; NP: National Party.