

# Joint Sentence-Document Model for Manifesto Text Analysis

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## Abstract

Election programs (so-called manifestos) are published verbal declaration of the intentions, motives, or views of the political party. Political scientists use manifestos to understand policy relevant themes discussed and also quantify a party's position on the left-right spectrum. Rather than handling the two tasks separately, we propose a joint sentence-document model for sentence level thematic classification and document level position quantification using manifestos in different languages. In order to handle text from multiple languages we exploit continuous neural embeddings for semantic text representation. We have empirically shown that the proposed joint model performs better than state-of-art approaches using manifestos from thirteen countries which are written in six different languages.

## 1 Introduction

Among many actors, political parties are at the core of contemporary democratic systems. One of the widely used dataset by political scientists includes the Comparative Manifesto Project (CMP) dataset, initiated by (Volkens et al., 2011), that collects party election programs (so-called manifestos) from elections in many countries around the world. The goal of the project is to provide a large data collection to support political studies on electoral processes. A sub-part of the manifestos has been manually annotated at sentence-level with one of over fifty fine-grained political themes, divided into 7 coarse-grained topics (schema is given in Table 5). While manual annotations are very useful for political analyses, they come with two major drawbacks. First, it is very

time-consuming and labor-intensive to manually annotate each sentence with the correct category from a complex annotation scheme. Secondly, coders' preferences towards particular categories might cause annotation inconsistencies and affect comparability between manifestos annotated by different coders (Mikhaylov et al., 2012). In order to overcome these challenges, fine and coarse-level manifesto sentence classification was addressed using supervised machine learning techniques (Verberne et al., 2014; Zirn et al., 2016). Nonetheless, manually coded manifestos remain the crucial data source for studies in computational political science (Lowe et al., 2011; Nanni et al., 2016).

Other than the sentence level labels, the manifesto text also has document level signals which quantifies its position in the left-right spectrum (Slapin and Proksch, 2008). Though sentence level classification and document level quantification tasks are inter-dependent, existing work handle them separately. Whereas, we propose a joint sentence-document model to handle both the tasks together. Overall, the contributions of this work are given as follows:

- We empirically study the utility of multi-lingual embeddings for cross-lingual manifesto text analysis — at sentence and document level.
- We evaluate the effectiveness of solving sentence and document level tasks together.
- We study the value of *country* information used in conjunction with text for document level regression task.

## 2 Related Work

The recent adoption of NLP methods had led to significant advances in the field of Computational

Social Science (Lazer et al., 2009) including political science (Grimmer and Stewart, 2013). Some popular tasks addressed with political text include party position analysis (Biessmann, 2016); political leaning categorization (Akoglu, 2014; Zhou et al., 2011); stance classification (Sridhar et al., 2014); identifying keywords, themes & topics (Karan et al., 2016; Nallapati et al., 2004; Ding et al., 2011); emotion analysis (Rheault, 2016) and sentiment analysis (Bakliwal et al., 2013). These works use manifestos, political speech, news articles, floor debates and social media posts.

With the advancement of computational resources, large scale comparative political text analysis has gained the attention of political scientists, where the objective is to analyze large amounts of data uniformly in order to make it comparable (Lucas et al., 2015). For example, rather than analyzing the political manifesto of a particular party during an election, mining different manifestos across countries over time can provide deeper comparative insights on political change.

Existing classification models, except (Glavaš et al., 2017), utilize discrete representation of text (i.e., bag of words). Also most of the work analyze manifesto text at country level. Recent work has shown the use of neural embeddings for multi-lingual manifesto text coarse-level topic classification (7 major categories) (Glavaš et al., 2017). In (Glavaš et al., 2017) authors show that multi-lingual embeddings are more effective for cross-lingual coarse-level manifesto text topic classification using labeled data across languages. In this work, we focus on cross-lingual fine-grained thematic classification (57 categories in total), where we have labeled data across all the languages.

For document level quantification task, many works use label count aggregation of manually annotated sentences as features (Lowe et al., 2011; Benoit and Däubler, 2014) and other works use dictionary based supervised methods (word-scores), unsupervised factor analysis based techniques (wordfish) (Hjorth et al., 2015; Bruinsma and Gemenis, 2017). Since the latter techniques use discrete word representation, they cannot be used for multi-lingual setting. In (Glavas et al., 2017), authors leverage neural embeddings for EU parliament speech text quantification task with two pivot texts for extreme left and right positions. They represent the documents using

word embeddings averaged with TF-IDF scores as weights. All these approaches handle sentence and document-level tasks separately.

### 3 Manifesto Text Analysis

In the CMP, trained annotators categorize manifesto sentences into one of the 57 fine-grained political categories (shown in Table 5) that are grouped into seven policy areas: External Relations, Freedom and Democracy, Political System, Economy, Welfare and Quality of Life, Fabric of Society and Social Groups. Political parties either write their promises as a list of sentences or structured as paragraphs (example is given in Figure 4) which can provide more information related to topic coherence. Also the length of document, measured as number of sentences, varies between manifestos. The typical length (number of sentences) we computed using digitized manifestos (948 in total) from 13 countries — Austria, Australia, Denmark, Finland, France, Germany, Italy, Ireland, New Zealand, South Africa, Switzerland, United Kingdom and United States, is  $516.7 \pm 667$ . Variance in the number of sentences across documents in conjunction with class imbalance makes the automated thematic classification a challenging task.

A sentence is split into multiple segments, if it discusses unrelated topics or different aspects of a larger policy. An example sentence split into two is given below

We need to address our close ties with  
our neighbours (107) as well as the  
unique challenges facing small business  
owners in this time of economic hard-  
ship. (402)

Scenarios where split sentences discuss different topics, as in the example given above, are not common.<sup>1</sup> Also the segmentation was shown to be inconsistent and to have no effect on quantifying proportion of sentences discussing various topics and document level regression tasks (Däubler et al., 2012). Hence, similar to previous works (Biessmann, 2016; Glavaš et al., 2017), we consider the sentence level classification as a multi-class single label problem. We use the segmented text when available (especially for evaluation), and complete sentences otherwise.

<sup>1</sup>In (Däubler et al., 2012), using a sample of 15 manifestos, authors noted that around 7.7% split sentences discuss different topics

A manifesto as a whole can be positioned on the left-right spectrum based on the proportion of topics discussed. We use the RILE score, which is defined as the difference between count of sentences discussing left and right topics (Budge and Laver, 1992),

$$RILE = \sum_{r \in R} per_r - \sum_{l \in L} per_l \quad (1)$$

where,  $R = \{104, 201, 203, 305, 401, 402, 407, 414, 505, 601, 603, 605, 606\}$  and  $L = \{103, 105, 106, 107, 202, 403, 404, 406, 412, 413, 504, 506, 701\}$ , “ $per_{xyz}$ ” denotes share of each topic (xyz) as given in Table 5, per document. Note that the RILE score is provided almost for all the manifestos in CMP dataset, but the sentence level annotations are provided only for a subset of manifestos.

## 4 Proposed Approach

We propose a joint sentence-document model to classify manifesto sentences into one out of 57 categories and also quantify document level RILE score. The joint formulation is not only to capture the task inter-dependencies but also to efficiently use annotations at different levels of granularity (sentence and document) — RILE score is available for 948 digitized manifestos from 13 countries, whilst sentence level annotations are available only for 235 manifestos. We use a Hierarchical Neural Network for modeling sentence level classification and document level regression tasks. The proposed architecture is given in Figure 1. Since the text across countries is multi-lingual in nature, we use neural embeddings to represent words ( $e_w$ ). We refer to the total set of manifestos available for training as  $D$ , subset of it which are annotated with sentence level labels (one out of 57 classes) as  $D_s$ . We denote each manifesto as  $d$ , which has  $l_d$  sentences  $s_1, s_2, \dots, s_{l_d}$ .

### 4.1 Sentence Level Model

We represent each sentence using average embedding of its constituent words,  $s_i = \frac{1}{|s_i|} \sum_{w \in s_i} e_w$ . The average embedding representation is given as input to hidden layer with rectified linear activation units (ReLU) to get the hidden representation, which is defined as

$$H_{s_i} = \max(0, a)$$

where,  $a = \mathbf{W}_s^\top s_i$ . Finally, the predictions are obtained using a softmax layer, which takes the

hidden representation as input and gives probability of 57 classes as output.

$$\hat{Y}_{s_{ik}} = \frac{e^{H_{s_i}^\top w_{pk}}}{\sum_{j=1}^K e^{H_{s_i}^\top w_{pj}}}$$

We use cross-entropy loss function for sentence level model. For sentences in  $D_s$ , with ground truth labels  $Y_s$  (one-of-K encoding), the loss function is given as follows

$$L_S(D_s, Y_s) = -\frac{1}{\sum_{i=1}^{D_s} l_{d_i}} \sum_{i=1}^{D_s} \sum_{j=1}^{l_{d_i}} \sum_{k=1}^K Y_{s_{ijk}} \ln \hat{Y}_{s_{ijk}} \quad (2)$$

### 4.2 Joint Sentence-Document Model

Using the Hierarchical Neural Network, we model both sentence level classification and document level regression tasks together. In the combined model, we use unrolled (time-distributed) neural network model for the sentences in a manifesto. Here, the model minimizes cross-entropy loss for sentences over each temporal layer (1 to  $n$ ). We use average-pooling to create document representation with individual sentence representations. We concatenate hidden representation ( $H_s$ ) and predicted output distribution ( $\hat{Y}_s$ ) of sentences before average-pooling.<sup>2</sup>

$$S_r = \frac{1}{|l_{d_i}|} \sum_{s \in d_i} [\hat{Y}_s, H_s]$$

RILE varies from -100 to +100, we scale it to a range between -1 and +1. So, we use tanh layer finally to get regressed output with  $z = \mathbf{W}_r^\top H_d$ , where  $H_d = \text{ReLU}(\mathbf{W}_d^\top S_r)$ , as input.

$$\hat{y}_d = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

Since it is a regression task, we minimize mean-squared error loss function between the predicted  $\hat{y}_d$  and actual rile scores  $y_d$ .

$$L_d(\hat{Y}_d, Y_d) = \frac{1}{|D|} (\hat{Y}_d - Y_d)^\top (\hat{Y}_d - Y_d) \quad (3)$$

Overall, the combined loss function using (2) and (3) for the joint model is

$$\alpha \times L_s(D_s, Y_s) + (1 - \alpha) \times L_d(\hat{Y}_d, Y_d) \quad (4)$$

<sup>2</sup>We observed that the concatenated representation performed better than using either hidden representation or output distribution

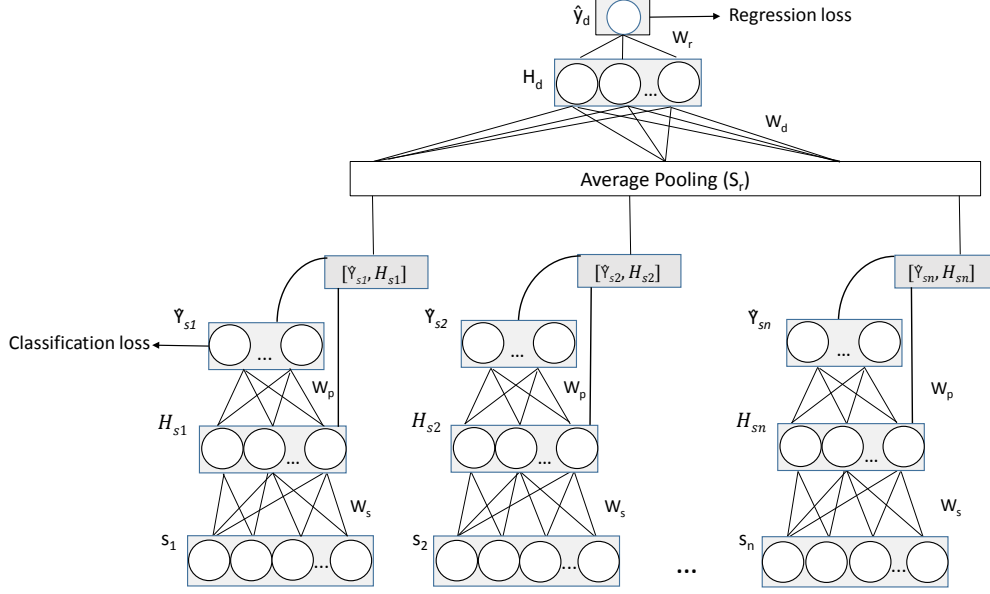


Figure 1: Hierarchical Neural Network for Joint Sentence-Document Analysis.  $s_1, s_2, \dots, s_n$  are input sentences,  $W_s$  and  $W_p$  are shared across unrolled sentences.  $\hat{Y}_{s_i}$  denotes 57 classes and  $\hat{y}_d$  denotes the estimated RILE score

where  $0 \leq \alpha \leq 1$ .<sup>3</sup> We evaluate both cascaded and joint training for this objective function. We use Adam optimizer (Kingma and Ba, 2014) for parameter estimation.

**Cascaded Training:** In this approach sentence level model is trained using  $D_s$ , to minimize  $L_s(D_s, Y_s)$  in (2), and the pre-trained model is used to obtain document level representation  $S_r$  for all the manifestos in training set,  $D$ . Then the document level regression task is trained to minimize  $L_d(\hat{Y}_d, Y_d)$  in (3). Here, the sentence level model parameters are fixed when the document level regression model is trained using  $S_r$ .

**Joint Training:** Like in cascaded training, sentence level model is pre-trained using labeled sentences. Then the entire network is updated by minimizing the joint loss function (4). Here the sentence level model uses both labeled and unlabeled data, where the updates using unlabeled data is influenced by document level objective.

<sup>3</sup>We set  $\alpha=0.3$  empirically which gave maximum score for both sentence and document level tasks. We observed a tradeoff in performance with different  $\alpha$ , with lesser  $\alpha$  (0.1), document level correlation increases while sentence level F-score decreases. Higher value of  $\alpha$  (0.9) gives performance closer to cascaded training

The proposed architecture evaluates the effectiveness of posing sentence-level topic classification task as a precursor to solve document level RILE prediction, rather than learning a model directly. We also study the effect of quantity of annotated text at both sentence and document level for RILE prediction task. Finally, the document level RILE score estimation can be replaced with any other task in the proposed architecture — expert survey or voter survey scores.

## 5 Experiments

As mentioned earlier, we use manifestos collected and annotated by political scientists at CMP. In this work, we used digitized manifestos from 13 countries, 948 in total which are written in 6 different languages — Danish (Denmark), English (Australia, Ireland, New Zealand, South Africa, United Kingdom, United States), Finnish (Finland), French (France), German (Austria, Germany, Switzerland) and Italian (Italy). Out of the 948 manifestos, 235 are annotated with sentence level labels (Table 5). We have RILE scores for all the 948 manifestos. Statistics about number of annotated documents and sentences with fine-grained labels (from Table 5) across languages is given below.

We use off-the-shelf multi-lingual word em-



Lang.	# Docs (Ann.)	# Sents (Ann.)
da	175 (36)	32161 (8762)
en	312 (94)	227769 (73682)
fi	97 (16)	18717 (8503)
fr	53 (10)	24596 (5559)
de	216 (65)	146605 (79507)
it	95 (14)	40010 (4918)
Total	948 (235)	489858 (180931)

Table 1: Statistics of dataset, ‘Ann.’ refers to annotated. *da* - Danish, *en* - English, *fi* - Finnish, *fr* - French, *de* - German, *it* - Italian

beddings<sup>4</sup> to represent words. We chose embeddings trained using translation invariance approach (Ammar et al., 2016), with size 512 for our work, since we found it empirically better compared to other approaches. As mentioned in Section 4.1, we use average embedding as sentence representation. Optimal model parameters we found for the proposed model (Figure 1) are  $|H_s| = 300$ ,  $|H_d| = 10$ . We first compare traditional bag-of-words discrete representation with distributed neural representation for words for fine-grained thematic classification, under mono-lingual training setting (*Mono*). Hence we compare the following approaches.

Bag of words (*BoW-LR*, *BoW-NN*): We use TF-IDF representation for sentences and build a model for each language separately. We use Logistic Regression classifier, which is the state-of-art approach for fine-grained (57 classes) manifesto sentence classification (Biessmann, 2016). We refer to this approach as *LR*. We also use Neural Network classifier, which we refer as *NN*.

Language-wise average embedding (*AE-NN<sub>m</sub>*): We build a Neural Network classifier per language, with average neural embedding as sentence representation.

Since distributed representation allows to leverage text across languages, we evaluate the following approaches with combined training sentences across languages (*Cross*).

Convolutional Neural Network (*CNN*): CNN was shown to be effective for cross-lingual manifesto text coarse-level (7 major domains as

shown in Table 5) topic classification (Glavaš et al., 2017). So, we evaluate CNN with a similar architecture — single convolution (32 filters with window size 3), single max pooling layer and finally a softmax layer. We use neural embeddings to represent words. Similar to (Glavaš et al., 2017) we combined training instances across all the languages.

Combined average embedding (*AE-NN<sub>c</sub>*): We build a Neural Network classifier with training instances combined across languages, with average neural embedding as sentence representation. This is our proposed approach for sentence-level model.

Commonly for all empirical evaluation, we compute micro-averaged performance with 80-20% train-test ratio across 10 runs with random split (at document level), where the 80% split also contains sentence level annotated documents proportionally. Neural Network model has a single hidden layer commonly for all the sentence and document level approaches. We compute F-score<sup>5</sup> to evaluate sentence classification performance. Sentence classification performance is given in Table 2. In the mono-lingual setting (Table 2), using word embeddings did not provide better performance compared to bag-of-words (except for *en* which was the source language for obtaining multi-lingual embeddings). Under cross-lingual setting, *AE-NN<sub>c</sub>* is the sentence level Neural Network model. We use *AE-NN<sub>c</sub>* in the *cascaded training* for obtaining document level *RILE* prediction. Note that in *cascaded training*, sentence and document level models are trained separately in a cascaded fashion. Joint-training results where the sentence model is trained in a semi-supervised way together with document level regression task is referred to as *AE-NN<sub>c</sub>*. We observed that *JT<sub>s</sub>* has a comparable performance with *AE-NN<sub>c</sub>*. Also CNN, *AE-NN<sub>c</sub>* and *JT<sub>s</sub>* use combined training instances across languages. Except for *da* and *it* cross-lingual training performs better than mono-lingual setting.

For document level regression task, following are the baseline approaches. Note that we use tanh output for all the models, since the range of re-scaled *RILE* is from -1 to +1.

<sup>4</sup><http://128.2.220.95/multilingual>

<sup>5</sup>Harmonic mean of precision and recall, [https://en.wikipedia.org/wiki/F1\\_score](https://en.wikipedia.org/wiki/F1_score)

<i>Lang.</i>	Mono-lingual			Cross-lingual		
	<i>BoW-LR</i>	<i>BoW-NN</i>	<i>AE-NN<sub>m</sub></i>	<i>CNN</i>	<i>AE-NN<sub>c</sub></i>	<i>JT<sub>s</sub></i>
da	0.29	<b>0.35</b>	0.24	0.30	0.28	0.30
en	0.36	0.38	<b>0.42</b>	0.40	<b>0.42</b>	0.41
fi	0.21	0.29	0.26	<b>0.30</b>	0.27	0.26
fr	0.28	0.36	0.24	0.36	0.37	<b>0.38</b>
de	0.30	0.31	0.31	0.31	0.31	<b>0.33</b>
it	0.32	<b>0.33</b>	0.25	0.30	0.32	0.26
Avg.	0.32	0.34	0.35	0.34	<b>0.36</b>	0.35

Table 2: Micro-Averaged F-measure. Best scores are given in bold under each language setting

Bag of words (*BoW-NN*): We use TF-IDF representation for documents and build a Neural Network model for each language.

Average embedding (*AE-NN<sub>d</sub>*): We use average embedding of words in the document as representation, with Neural Network model.

Bag-of-Centroids (*BoC*): Here the word embeddings are clustered into  $K$  different clusters using K-Means clustering algorithm, and words in each document are assigned to clusters based on its euclidean-distance ( $dist$ ) to cluster-centroids ( $C$ ).

$$cluster(word) = \underset{k}{\operatorname{argmin}} dist(C_k, word)$$

Finally, each document is represented by the distribution of words mapped to different clusters (1 X  $K$  vector). We use a Neural Network regression model with bag-of-centroids representation. Results with  $K=1000$ , which performed best is given in Table 3.

Sentence level model and RILE formulation (*AE-NN<sub>c</sub><sup>rile</sup>*): Here the predictions of sentence level model in the cascaded approach (*AE-NN<sub>c</sub>*) are used directly with RILE formulation (equation (1)) to derive RILE score for manifestos.

Cross-lingual scaling (*CLS*): This is a recent unsupervised approach for multi-lingual political speech text positioning task (Glavas et al., 2017). Authors use average word-embeddings weighed by TF-IDF score to represent documents.<sup>6</sup> Then a graph is con-

structed using pair-wise distance of documents. Given two pivots texts for extreme left and right positions  $[-1, +1]$ , label propagation approach is used to quantify other documents in the graph.

RILE score regression performance results are given in Table 3. We evaluate document level performance using mean-squared-error (MSE) and Pearson correlation ( $r$ ). The proposed approach performance, using cascaded training with fixed sentence model parameters is referred to as *Cas<sub>d</sub>* and jointly trained model is referred to as *JT<sub>d</sub>*. Overall we the jointly trained model performs best for document level task, with a comparable performance at sentence level.

### 5.1 Quantity of Annotation

We measure the importance of annotated text at sentence and document level for RILE score regression task. We vary the percentage of labeled data, while keeping the test sample size at 20%

Approach	MSE(↓)	$r$ (↑)
<i>BoW-NN</i>	0.054	0.23
<i>AE-NN<sub>d</sub></i>	0.057	0.14
<i>BoC</i>	0.052	0.33
<i>AE-NN<sub>c</sub><sup>rile</sup></i>	0.060	0.35
<i>CLS</i>	—	0.24
<i>Cas<sub>d</sub></i>	0.050	0.41
<i>JT<sub>d</sub></i>	<b>0.044</b>	<b>0.47</b>

Table 3: RILE score prediction performance. Best scores are given in bold. CLS assigns -1 and +1 for extreme manifestos and propagates the values on a graph. Since they solve it as a classification problem, MSE is not applicable. ↑ indicates higher is better, ↓ indicates lower is better

<sup>6</sup>We use this aggregate representation since it was shown to be better than word alignment and scoring approach (Glavas et al., 2017)

as before. In the first setting, we keep the training ratio of documents at 80%, within that 80% we increase the proportion of documents with sentence level annotations — from 0 (document average embedding setting,  $AE-NN_d$ ) to 80%. Results are given in Figure 2. Similarly, in the other setting, we keep the training set with 80% sentence level annotated documents (which is  $\sim 20\%$  of the total data), and add documents (with only RILE score), increasing the training set from 20 to 80%. Results of this study are given in Figure 3. We observe that, jointly-trained model uses sentence level annotations more effectively than cascaded approach (Figure 2) — even with less sentence level annotations. Also, with less document level signal (upto 40%) for training, both the approaches perform similarly ( $r$ ). As the training ratio increases, joint-training leverages both sentence and document level signals effectively.

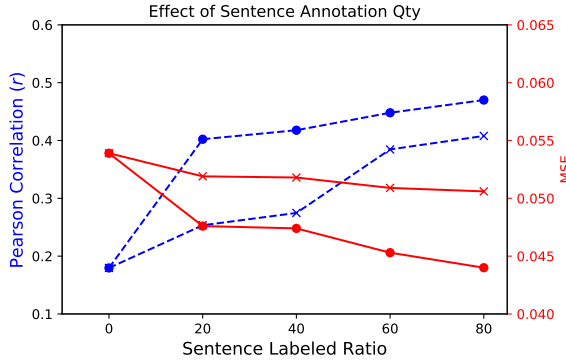


Figure 2: Fixing 80% training documents with RILE score, ratio of documents with sentence level annotations is varied.  $\times$  denotes  $Cas_d$  and  $\circ$  denotes  $JT_d$

## 5.2 Use of Country Information

Since the definition of left-right varies between countries, we study the influence of *country* information in the proposed model with *joint-training*. We use two ways to incorporate country information: (a) *stack* — one-hot encoding (13 countries, 1 X 13 vector) of each manifesto’s *country* is concatenated with hidden representation of the document ( $S_r$  in Figure 1) (b) *non-linear stack* — one-hot-encoded country vector is passed through a hidden layer with tanh non-linear activation and concatenated with  $S_r$ . With both the models we observed mild improvement in correlation (given in Table 4).

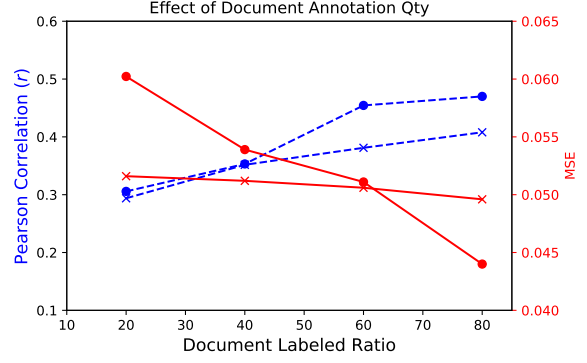


Figure 3: Fixing 80% training documents with sentence level annotations, ratio of documents with RILE score is varied.  $\times$  denotes  $Cas_d$  and  $\circ$  denotes  $JT_d$

Approach	MSE	$r$
stack	0.045 (0.001 $\downarrow$ )	0.49 (0.02 $\uparrow$ )
non-linear stack	0.048 (0.004 $\downarrow$ )	0.48 (0.01 $\uparrow$ )

Table 4: RILE score prediction performance with *country* information. Difference compared to  $JT_d$  is given within paranthesis.  $\uparrow$  – improvement,  $\downarrow$  – decrease in performance

## 6 Conclusion and Future Work

In this work we evaluated the utility of a joint sentence-document model for sentence level thematic classification and document level RILE score regression tasks. Our observations are as follows: (a) joint model performs better than state-of-art approaches (b) joint-training leverages sentence level annotations more effectively than cascaded approach for RILE score regression task, but doesn’t provide significant gains for sentence level task. There are many extensions possible to the current work. First is to handle class imbalance in the dataset with a cost-sensitive objective function. Secondly, CNN gave a comparable performance with Multi-layer Perceptron (NN), which motivates the need to evaluate an end-end sequential architecture. Off-the-shelf embeddings leads to out-of-vocabulary scenarios. It could be beneficial to adapt word-embeddings with manifesto corpus. Finally, background information such as country can be leveraged more effectively.

During our nation's darkest hours, Americans have strived mightily and succeeded in meeting the challenges of their times. The question before us is whether we will do the same during this bright moment; whether we will seize this moment to bring more prosperity and progress to more Americans than ever before; whether, having finally conquered our financial deficits, we will have the courage to conquer the other deficits – in health care, in education, in the environment – that challenge us today.

601  
606  
410  
305

Figure 4: Democratic Party of USA, 2000 —  $\int$  denotes sentence segment. 601 - National Way of Life: Positive, 606 - Civic Mindedness: Positive, 410 - Economic Growth: Positive, 305: Political Authority

CMP Coding Scheme	
<ul style="list-style-type: none"> <li>Domain 1: External Relations               <ul style="list-style-type: none"> <li>101 Foreign Special Relationships: Positive</li> <li>102 Foreign Special Relationships: Negative</li> <li>103 Anti-Imperialism</li> <li>104 Military: Positive</li> <li>105 Military: Negative</li> <li>106 Peace</li> <li>107 Internationalism: Positive</li> <li>108 European Community/Union: Positive</li> <li>109 Internationalism: Negative</li> <li>110 European Community/Union: Negative</li> </ul> </li> <li>Domain 2: Freedom and Democracy               <ul style="list-style-type: none"> <li>201 Freedom and Human Rights</li> <li>202 Democracy</li> <li>203 Constitutionalism: Positive</li> <li>204 Constitutionalism: Negative</li> </ul> </li> <li>Domain 3: Political System               <ul style="list-style-type: none"> <li>301 Decentralisation</li> <li>302 Centralisation</li> <li>303 Governmental and Administrative Efficiency</li> <li>304 Political Corruption</li> <li>305 Political Authority</li> </ul> </li> <li>Domain 4: Economy               <ul style="list-style-type: none"> <li>401 Free Market Economy</li> <li>402 Incentives: Positive</li> <li>403 Market Regulation</li> <li>404 Economic Planning</li> <li>405 Corporatism/Mixed Economy</li> <li>406 Protectionism: Positive</li> <li>407 Protectionism: Negative</li> <li>408 Economic Goals</li> <li>409 Keynesian Demand Management</li> <li>410 Economic Growth: Positive</li> </ul> </li> </ul>	<ul style="list-style-type: none"> <li>411 Technology and Infrastructure: Positive</li> <li>412 Controlled Economy</li> <li>413 Nationalisation</li> <li>414 Economic Orthodoxy</li> <li>415 Marxist Analysis</li> <li>416 Anti-Growth Economy: Positive</li> <li>Domain 5: Welfare and Quality of Life               <ul style="list-style-type: none"> <li>501 Environmental Protection</li> <li>502 Culture: Positive</li> <li>503 Equality: Positive</li> <li>504 Welfare State Expansion</li> <li>505 Welfare State Limitation</li> <li>506 Education Expansion</li> <li>507 Education Limitation</li> </ul> </li> <li>Domain 6: Fabric of Society               <ul style="list-style-type: none"> <li>601 National Way of Life: Positive</li> <li>602 National Way of Life: Negative</li> <li>603 Traditional Morality: Positive</li> <li>604 Traditional Morality: Negative</li> <li>605 Law and Order: Positive</li> <li>606 Civic Mindedness: Positive</li> <li>607 Multiculturalism: Positive</li> <li>608 Multiculturalism: Negative</li> </ul> </li> <li>Domain 7: Social Groups               <ul style="list-style-type: none"> <li>701 Labour Groups: Positive</li> <li>702 Labour Groups: Negative</li> <li>703 Agriculture and Farmers: Positive</li> <li>704 Middle Class and Professional Groups</li> <li>705 Underprivileged Minority Groups</li> <li>706 Non-economic Demographic Groups</li> </ul> </li> <li>000 No meaningful category applies</li> </ul>

Table 5: Left topics are given in red and right topics are given in blue



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