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Using Word Order in Political Text Classification with Long Short-term Memory Models

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Abstract

Political scientists often wish to classify documents based on their content to measure variables, such as the ideology of political speeches or whether documents describe a Militarized Interstate Dispute. Simple classifiers often serve well in these tasks. However, if words occurring early in a document alter the meaning of words occurring later in the document, using a more complicated model that can incorporate these time-dependent relationships can increase classification accuracy. Long short-term memory (LSTM) models are a type of neural network model designed to work with data that contains time dependencies. We investigate the conditions under which these models are useful for political science text classification tasks with applications to Chinese social media posts as well as US newspaper articles. We also provide guidance for the use of LSTM models.

Keywords: statistical analysis of texts, machine learning, computational methods, Automated content analysis

Political scientists have increasingly turned to computational methods to code texts as they analyze larger and larger corpora that human coders alone could not easily handle. In many cases, models that are computationally simple and easy to interpret are ideal because more complicated models do not improve classification accuracy (Grimmer and Stewart 2013). However, for some tasks, "Nonlinear methods that can make effective use of word order have been shown to produce more accurate predictors than the traditional" methods (Johnson and Zhang 2016). While political science research has, in some cases, expanded beyond single-word (unigram) text models (Spirling 2012; Grimmer and Stewart 2013; Lucas *et al.* 2015; Han *et al.* 2018), it has yet to make use of models that account for more complex time dependencies among words.

For a simple example of time dependence in a text classification context, imagine a researcher is trying to categorize whether congressional representatives support a bill based on their speeches about that bill. A method that only uses a count of the words in a speech would have a hard time distinguishing between a congress person who said, "Some people may disagree, but I support this bill" and another who said, "I disagree with people who support this bill." Both sentences contain the words "disagree" and "support."

Even in this relatively simple example, an *n*-gram model, a model that counts phrases of *n*-length rather than unigrams, would probably fail to classify both sentences accurately. To accurately classify the second sentence, the *n* in the *n*-gram model would need to be at least six. This would include the *n*-gram "I disagree with people who support." However, once *n* increases much beyond 2, *n*-grams become too rare to train a classifier. This six-word *n*-gram would likely be unique in the corpus, preventing a model from using information from other texts to draw

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inferences about whether it increases or decreases the likelihood the document containing it supports the bill.

We introduce long short-term memory (LSTM) models, which are an especially useful recurrent neural network (RNN) model for text analysis under the conditions we describe below. Neural network models allow researchers to stack nonlinear equations to represent complex data processes (for further explanation, see Section 2.2).[1] Instead of memorizing set phrases, RNN models, neural network models that incorporate information from previous steps in their current calculation, allow researchers to directly evaluate word context by treating documents as sequences of words and modeling the time dependencies between earlier and later words in documents. New software packages, specifically TensorFlow and Keras (Chollet *et al.* 2015; Abadi *et al.* 2016), which are now available for both R and Python (we use Python 3), simplify the implementation of these models.

The contributions of this paper are both empirical and instructional. The empirical contribution is to test the performance of LSTM models against a variety of competing models in different use cases political scientists are likely to face. Competing models examined here include: naive Bayes, support vector machines (SVM), extra trees, and gradient boosting machines (GBM). To examine different use cases, we explore applications classifying both Chinese social media posts and US newspaper articles.[2] In the applications, we vary the size of the training datasets, the balance of the categories in the data, and the length of documents in the corpus. From these applications, we derive a set of heuristics to aid political scientist in model selection decisions. The instructional contribution is to explain how LSTM models work and provide guidance and code templates for their use.[3]

Because the optimal machine-learning model is often task-dependent, we can only offer heuristics rather than hard and fast rules for model selection. We endeavor to offer useful guidance to researchers wishing to choose among machine-learning models while also being mindful that results can vary for different tasks. LSTM models are more likely to perform well relative to competitors when classification is highly context-dependent, meaning that a set of keywords or *n*-grams, by itself, is insufficient to categorize texts. If taking a phrase out of context changes its theoretical meaning, then LSTM models are more likely to perform better. For example, if a researcher wants to categorize documents based on whether they promote discriminatory discourse, racial slurs in documents criticizing the usage of such slurs should be treated differently than the same words in documents that deploy the words as slurs.

Before using an LSTM model, researchers need a dataset with thousands of texts from the categories they want to classify already labeled by humans. In general, the more data, the more likely the LSTM model will outperform other models. LSTM models are well suited to both short and long texts, although these two cases may call for different preprocessing procedures. The more evenly distributed the categories to be classified in the data are, that is, the more balanced the data is among the categories, the better are the LSTM models to likely perform relative to alternatives. LSTM models are more appropriate when the researcher wants to accurately classify documents rather than to understand why documents are placed in particular categories.

This paper proceeds as follows. The first section lays out the uses of text classification in political science. The second section explains what neural network models are and how they work, building up to an explanation of LSTM models. The third section contains several empirical applications that compare the performance of LSTM models against alternatives and uses these

1 See Beck, King, and Zeng (2000) for an application of neural network models to conflict data.
2 The US newspapers application comes from Baum, Cohen, and Zhukov (2018).
3 See Appendix Section 5.7 for detailed advice about implementing an LSTM model, and see Chang and Masterson (2019) for code templates and replication materials.

applications to derive lessons for the use of LSTM models in political science. The final section offers concluding comments.

1 Text Categorization in Political Science

Political scientists often want to classify texts into categories based on their content. For example, a researcher might want to classify congressional speeches based on their ideological content (Diermeier *et al.* 2012), classify whether documents describe a Militarized Interstate Dispute (D'Orazio *et al.* 2014), classify whether political speeches invoke nationalist themes, or classify news articles on the Cold War based on the narratives they use (Krebs 2015). Once the classification of a document is known, its class can be used as a variable in later analysis.

Supervised machine learning is appropriate for these kinds of classification tasks. In supervised learning, a subset of the data along with its "true" prediction is fed to the model, so the model can learn what predictors (in the case of text classification, predictors are the words of a document and the order they appear in) correspond to what predictions (the categories the documents are being classified into). This subset of the data is referred to as the "training set." The researcher then uses the model to predict the class of previously unseen documents to evaluate performance. This previously unseen set of data that is used to evaluate the model is called the "test set."

Sometimes writers use the phrases "validation set" and "test set" interchangeably, but with neural networks, a validation set is distinct from a test set (Prechelt 1998). The validation set is like the test set in that the model is not allowed to train on it, but it is used during each iteration of training to evaluate whether the model's classification of out-of-sample data has improved. If the model goes too many steps without improving, then training will end early to prevent overfitting. This is known as "early stopping." Early stopping is useful because a neural network will usually pass through all of the training data multiple times during training.

Here is an example to make this process more concrete. A political scientist wants to code speeches by members of different political parties based on whether they contain nationalist appeals. She will first use human coders to code a subset of the documents as either nationalist or not nationalist. These documents will form the training set and the validation set. Further, some labeled documents are withheld to compose a test set. Once she settles on a model that achieves a desired level of accuracy, the researcher can now use this model to code documents that were not previously labeled by human coders. We explore the kinds of text classification tasks for which LSTM models will be most useful to political scientists.

2 LSTM Models

2.1 The Texts

Unlike most text classification models that analyze texts as a matrix of word or *n*-gram counts, LSTM models analyze texts as a sequence of word identifiers. The corpus is converted from words to unique numbers that identify each word. For example, in a corpus that contains 1000 words, the most common word might be represented as 1 and the least common as 1000.

Here we show the difference between these ways of processing texts with an example of a corpus composed of two sentence-long documents. The first document is "I went to the store today," and the second document is "You went in the store." For a traditional model, the corpus would be represented as a matrix of word counts with a row representing each document:

$$corpus = \begin{bmatrix} I & in & store & the & to & today & you & went \\ 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 & 1 & 1 \end{bmatrix}$$

This matrix does not contain information about the order the words appear in each document. For LSTM models, documents must be represented as sequences of word identifiers. For example, the first document might be represented with the sequence [5 1 2 3 4 6]. In this example, the second document would be represented as [7 1 8 3 4].[4]

Before feeding the sequences to the LSTM model, all sequences must be made the same length. This is not an inherent requirement of LSTM models, but it facilitates computation during batch training (training when more than one set of documents and labels are fed to the model at once). The most common way to get documents to a single length is to pick a maximum length that a document is allowed to take, for example, the length of the longest document in the corpus, and pad all documents to that length by adding 0s to the end. In our two-document corpus, the second document would become [7 1 8 3 4 0].[5]

When using neural network text classification models, it is common to process the texts with word embedding first to transform each word from a single number to a vector that contains information about how the word is similar to other words in the corpus. This can be thought of as a feature generation process that creates more usable information from the data for the model to train on. Word embedding is not required to use LSTM models and is not the focus of this paper. Here we will provide a brief introduction to word embedding with further information in Appendix Section 5.3 and sources that interested readers can pursue for further detail.[6]

Word embeddings learn about the similarities among words in the corpus and create vectors of weights for each word indicating where that word falls on dimensions that are learned from the data. These similarities are learned by using words in sentences to predict the words surrounding them. Typically, they maximize the probability of the next word w_t, given previous words h, with a softmax function. Score(w_t, h) calculates the probability of word w_t appearing in context h (see Appendix Section 5.3 for more information about how word embeddings are trained and computed in practice).[7]

$$P(w_t|h) = \text{softmax}(\text{score}(w_t, h)) = \frac{\exp\{score(w_t, h)\}}{\sum_{\text{word}}^{\text{vocabulary size}} \exp\{\text{score}(w', h)\}}. \quad (1)$$

This probability is normalized over the score for all the other words w' in context h.

2.2 Neural Network Models

LSTM models take word order into account by allowing their interpretation of the current time step (word in the sequence) to be dependent on previous time steps (previous words in the sequence). The reason LSTM models take the functional form they take, as with many machine-learning models, is that this form has been found to work well empirically (Greff *et al.* 2016). This section explains the model's functional form in comparison with other machine-learning models. We first introduce vanilla neural networks. Next, we build up to RNNs and finally LSTM models. Afterward, we briefly discuss how training is conducted.

2.2.1 Neural Networks and Deep Learning

Neural networks may appear radically different than other models at first, but "they are just nonlinear statistical models" (Friedman, Hastie, and Tibshirani 2001, 392). All neural network models have matrices of weights and vectors of biases as parameters that are learned from the

4 We convert texts to sequences with the Keras Tokenizer and texts to word count matrices using Scikit-learn's CountVectorizer.

5 The value chosen for padding, in this case 0, can be set so that the model does not interpret it as a word during training. To do this in Keras, set the argument "mask_zero" equal to "True" for the word embedding.

6 For academic treatments of word embedding, see Mnih and Kavukcuoglu (2013), Mikolov *et al.* (2013a), and Han *et al.* (2018). For accessible, applied introductions, see Ruizendaal (2017) and TensorFlow (2018).

7 This equation is adapted from TensorFlow (2018).

data. These are analogous to the parameters in a regression (Friedman, Hastie, and Tibshirani 2001, 395).

Neural networks are composed of nonlinear equations. This nonlinearity is what enables neural networks to be used in "deep learning" where arbitrarily many equations are stacked on top of each other to create a single model. The ability to construct a model out of a series of equations this way allows earlier equations in the model to extract features that later equations train on. This means a "major difference between deep learning and traditional pattern recognition methods is that deep learning automatically learns features from big data, instead of adopting handcrafted features" (Liang *et al.* 2017, 5). If the equations were linear, then neural network models could reduce to a single equation by adding up all the equations (Friedman, Hastie, and Tibshirani 2001, 394). For this reason, linear regression models can be thought of as a special case of neural network models where $\sigma = 1$ (see Equation 2). For example, if two logistic regressions are estimated in a row and the prediction of the first regression is a predictor in the second regression, this would be a simple neural network model with two equations.

A simple neural network might have a nonlinear function σ (usually the sigmoid function), a bias scalar b, and an i-length weight vector W_i, where i indexes the sample.[8]

$$f(x) = \sigma(b + W_i x_i). \tag{2}$$

The values of the weight and bias are the parameters (θ) that the model learns over time.

Deep learning models are useful when the "true function" (referring to the true data generating process or the ideal function that maximizes the classification of out-of-sample documents that we would like our classifier to learn) is complex and nonlinear (Bengio 2009). However, when a simpler model can accurately represent the data, deep learning models may add needless complexity.

Even when deep learning models increase accuracy, they present the researcher with less interpretable parameters than traditional models, creating a trade-off between accuracy and interpretability.[9] This problem is not unique to neural networks. Other models, like SVM, share this issue (Cortez and Embrechts 2013). Such models are best when a researcher wishes to train a model to accurately classify texts based on a training set rather than understand why texts fall into particular categories (Friedman, Hastie, and Tibshirani 2001, 408).

2.2.2 *Recurrent Neural Networks*

In equation (2), there are no terms that depend on previous steps. This means that vanilla neural networks cannot take into account previous words when interpreting in the current word. In contrast, RNNs have terms that depend on previous steps, which allow this (Elman 1990). The functional form of an Elman RNN is

$$\begin{aligned} h_t &= \sigma_h(W_h x_t + U_h h_{t-1} + b_h) \\ y_t &= \sigma_y(W_y h_t + b_y), \end{aligned} \tag{3}$$

where t indexes each time step, x_t is a D-dimensional vector of predictors, h_t is the D-dimensional prediction of the first equation, y_t is the D-dimensional prediction of the second equation, the weights W and U are square, D-dimensional transition matrices, b is a D-dimensional bias vector, and the σ are nonlinear functions (Jernite *et al.* 2017, p. 3). In this model, h_t is estimated first

8 For simplicity, we set the number of hidden units equal to 1 here.

9 Researchers are working to increase the interpretability of neural network parameters. See, for example, Olden and Jackson (2002), Yosinski *et al.* (2015).

Table 1. Summary of model differences.

	Tree-based model	NN	RNN	LSTM
Parameters interpretable	Yes	No	No	No
Short time dependence	No	No	Yes	Yes
Long time dependence	No	No	No	Yes

Note: This is not intended to imply that models with these characteristics are "better" than models without them. NN stands for neural network. RNN stands for recurrent neural network, and LSTM stands for long short-term memory. Random forest is an example of a tree-based model.

and then used as a predictor for y_t. The subscripts $_h$ and $_y$ indicate the equation the components belongs to. In the case of text analysis, each word or word vector is a time step.

RNNs allow time dependencies to be addressed to some extent. However, RNNs have difficulty separating signal context from noise context. Far away words are only sometimes helpful in interpreting the current word. This makes traditional RNNs impractical to train. Interested readers should see Hochreiter (1998).

2.2.3 *LSTM Models*

To address this, computer scientists added a series of equations to RNN models that store information for evaluating long time dependencies and determine how this information should be updated. This resulted in LSTM models (Hochreiter and Schmidhuber 1997a; Gers, Schmidhuber, and Cummins 2000). What information is stored to evaluate long time dependencies and whether or not this information is updated are determined by parameters the model learns from the data. The equations in LSTM models are estimated in a sequence with the predictions of previous equations becoming predictors in subsequent equations. This is similar to the way prediction h_t becomes a predictor in the equation to predict y_t in the RNN model in the previous section.

The following equations show the prediction process for LSTM models for every time step t. We give the dimensions of each term below. These dimensions depend on the dimensions of the predictors D and the number of hidden units H, which is a hyperparameter.[10] x_t is a D-dimensional vector of predictors, W is a $D \times H$ weight matrix, U, and V are square, H-dimensional weight matrices, and b is an H-dimensional bias vector with subscripts indicating the equation to which they correspond. The left-hand side of each equation is an H-dimensional prediction vector. σ indicates the sigmoid function.[11] Keep in mind that the weights and biases are the trainable parameters or the parameters that take values that maximize accuracy based on the training data.

The first equation makes a prediction, g_t, which can be conceptualized as a weighted sum of information the model takes in from the current word or word vector x_t and the previous prediction of the final equation in the model h_{t-1}.

$$g_t = \sigma(W_g x_t + U_g h_{t-1} + b_g). \tag{4}$$

The sigmoid function ensures that the values of this initial prediction is between 0 and 1. These values are used in equation (7) to weigh how much information from the current word should be stored for use in making predictions based on future words. A 0 means no new information will be stored, and a 1 means all of the new information will be stored. The weights and bias vector in this equation allow the model to use information from the training set to decide which predictors are important for classification and, hence, should receive a higher weight. The term $U_i h_{t-1}$ is the

10 For simplicity, we assume the batch size is 1.

11 These equations are adapted from Hochreiter and Schmidhuber (1997a), Gers, Schmidhuber, and Cummins (2000), Theano Development Team (2017).

previous prediction h_{t-1} weighted by the weight matrix U_i. In this way, the weight that the model puts on a predictor, in the case of text analysis a word or word vector, depends on how the model evaluated the previous predictor.

Next, the model evaluates how the information stored to model long time dependencies would change based on the current predictor and the previous prediction:

$$\widetilde{C_t} = \tanh(W_c x_t + U_c h_{t-1} + b_c). \tag{5}$$

Next the model evaluates whether and how much information previously stored to evaluate long time dependencies should be erased or 'forgotten':

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f). \tag{6}$$

This value along with the prediction of equations (4) and (5) is used in the following equation that computes the new value of the information stored to evaluate long time dependencies. In this way, the model will decide to retain or discard information from the past based on the values of the weigh matrices W_f and U_f as well as the bias b_f. Information for evaluating long time dependencies might be maintained, in part or whole, all the way to the end of a document, or it might be forgotten immediately depending on the values of these parameters.

Given the values of g_t (equation (4)), $\widetilde{C_t}$ (equation (5)), and f_t (equation (6)), the model computes C_t, which is the new state of the information stored to evaluate long time dependencies:

$$C_t = g_t \circ \widetilde{C_t} + f_t \circ C_{t-1}.^{12} \tag{7}$$

The information used to evaluate long time dependencies, C_t, is used to calculate the prediction below. Further, this information becomes C_{t-1} in the next step. In this way, the model uses the information it has decided is useful to retain from previous steps in the calculation of the current prediction.

Given the new information about long time dependencies in the data, C_t, the model computes o_t:

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o C_t + b_o). \tag{8}$$

This value places a weight on the final prediction. It serves a role similar to the prediction of equation (4), controlling the flow of information through the model.

Finally, the model calculates the final prediction as a function of the o_t from equation (8) and the value of information stored to evaluate long time dependencies, C_t, from equation (7):

$$h_t = o_t \circ \tanh(C_t). \tag{9}$$

Neural network models are usually adapted to the problem they are applied to. To produce a single prediction between 0 and 1 for each text, our model ends in a logistic regression. See Appendix Section 5.5 for the full models we use. In practice, researchers often use bidirectional models that contain two LSTM models (Graves and Schmidhuber 2005). One model reads the documents forward and the other reads the documents backwards. These models can pick up on different predictors and sometimes improve classification. The predictions of these models are then concatenated and sent to the final prediction equation, in our case, a logistic regression.

12 "$\circ$" in these sets of equations denotes the Hadamard product rather than the dot product.

2.2.4 *Training*

The parameters begin at random values. To minimize misclassifications, neural network models iteratively adjust the parameters slightly and then check for improvement. These adjustments improve the fit if misclassifications decrease (for more information, see Appendix Section 5.2). How much the parameters are adjusted at each step is determined by the learning rate, which is a parameter set by the researcher (see Appendix Section 5.7.1 for advice on optimizing the hyperparameters of neural network models). An analogy can be drawn to the expectation–maximization algorithm that is familiar to political scientists from maximum likelihood estimation. Both algorithms initialize the parameters at random values and then repeatedly iterate using different estimates of the parameters until convergence.

3 Applications

3.1 Purpose

We use four applications to show LSTM models' performance in different contexts. Because LSTM models differ in more than one way from alternative models, it is difficult to pinpoint exactly *why* the LSTM model performs better in any one task. Our purpose is instead to show the *kinds* of tasks where LSTM models perform well. The first three applications use a dataset of posts from the Chinese website Weibo, which is similar to Twitter. These posts are classified as either political or not political. The first application shows that in a large balanced dataset, ideal conditions for any classifier, LSTM models can outperform the alternatives. The second application shows that even as the size of this dataset is decreased by randomly sampling subsets of it, the LSTM model continues to perform well. The third shows that if we make this dataset unbalanced, the performance of the LSTM model decreases relative to competitors.

The fourth application compares an LSTM model with the SVM classifier deployed in another political science paper that classifies US newspaper articles based on whether they contain rape culture, specifically rape culture in the form of expressing empathy for the person accused of rape (Baum, Cohen, and Zhukov 2018). The point of this application is to show that LSTM models can sometimes improve classification accuracy under nonideal conditions where the classes are severely imbalanced. The purpose of this application is *not* to criticize original paper.

3.2 Classifying Weibo Posts

We evaluate how models perform classifying a subset of posts we collected from June 25, 2014 through June 15, 2015 that were hand-coded as either containing political content or not (see Appendix Section 5.1 for a full explanation of data collection, coding rules, and selection of the subset). The subset is balanced, containing 5,346 political posts and 5,345 nonpolitical posts. These posts are selected from a much larger dataset of posts. While the true prevalence of political posts is unknown, we estimate that less than 5% of the posts we originally collected are political.

We select several alternative document classifiers to compare our LSTM model against.[13] To get comparable accuracy scores, we focus only on models that assign an individual classification for each document. The first method we compare with is SVM, which is "the most widely used (and arguably the best) of the existing methods" (Hopkins and King 2010, 239).[14] We also compare against both multinomial naive Bayes and Bernoulli naive Bayes, which are commonly used as baselines to compare classifiers against (D'Orazio *et al.* 2014, 232–233). Finally, we compare against the extra-trees classifier, which is similar to the random forest classifier but is more computationally efficient and, in some cases, more accurate (Geurts, Ernst, and Wehenkel 2006). Extra-trees models are a useful comparison both because they are nonlinear and because they fit

13 To implement each of these competing models as well as the vectorizers we combine with them, we use Scikit-learn (Pedregosa *et al.* 2011).

14 We use linear kernel SVM following D'Orazio *et al.* (2014, 235).

multiple randomly chosen models to the data, allowing them to capture complexity. This makes it a potential nonneural network model that researchers could use to classify documents that contain complex and nonlinear predictors.

We also combine these models, in some cases, with one of two different vectorizers in an attempt to improve their performance. The first is Word2vec (W2V). W2V is a type of word embedding that changes a corpus of words from unique identifiers that contain no information about how words relate to each other into a vector space where similar words are closer to each other.[15] The second is term frequency–inverse document frequency (TFIDF). TFIDF gives more weight to words that are rare in the corpus but common in a particular document and, hence, more likely to be distinguishing.[16]

We do not compare against other variants of LSTM models because the largest study of LSTM model performance concluded that "The most commonly used LSTM architecture (vanilla LSTM) performs reasonably well on various datasets and using any of eight possible modifications does not significantly improve the LSTM performance" (Greff *et al.* 2016). We do not compare against RNNs because LSTM models converge more quickly (Hochreiter 1998), which eliminates what one might expect to be the gain from using the simpler RNN model. Further, LSTM models are preferable over RNNs for "nontrivial tasks"(Hochreiter and Schmidhuber 1997b, 478), where a trivial task is a problem that is quickly solvable by random search, making deep learning unnecessary in the first place.[17] Finally, we do not compare against MLP because, at least for classification tasks, MLP tends to offer no advantage over SVM (Osowski, Siwek, and Markiewicz 2004).[18]

To express uncertainty around our accuracy scores, we draw five training and test sets from the data for each model and report the mean, minimum, and maximum test accuracy scores.[19] The train/test splits are stratified to ensure class balance. Traditional 95% confidence intervals cannot be used because supervised learning models like SVM and LSTM models are not founded on probability distributions (Hopkins and King 2010, 239). The size of the training dataset for each model in each test is four-fifths of the full dataset or 8,552 posts. The remaining 2,139 posts are used as the test set.

For the LSTM models, one-tenth of the training set is split off to use as a validation set (see Section 1 on why validation is different with neural network models). Some readers might worry that our test is not a fair comparison because the LSTM model uses a validation set and the others do not. However, the LSTM model does not train on the validation set (James *et al.* 2013, 178). We independently tune the hyperparameters of all the models using cross-validation. In this way, the competing models also get the advantage of using the full dataset to set their hyperparameters, so cross-validation to optimize the hyperparameters of competing models with tunable hyperparameters takes the place of a validation set for these models (James *et al.* 2013, 178). If the LSTM model forgoes a validation set and is set to stop after 11 passes through the data, the results are substantially the same (see Appendix Section 5.6).

We preprocess the data in the same way for all the models. The classifiers are classifying posts in the original Chinese, which we segment using Jieba (Sun 2015). For this application,

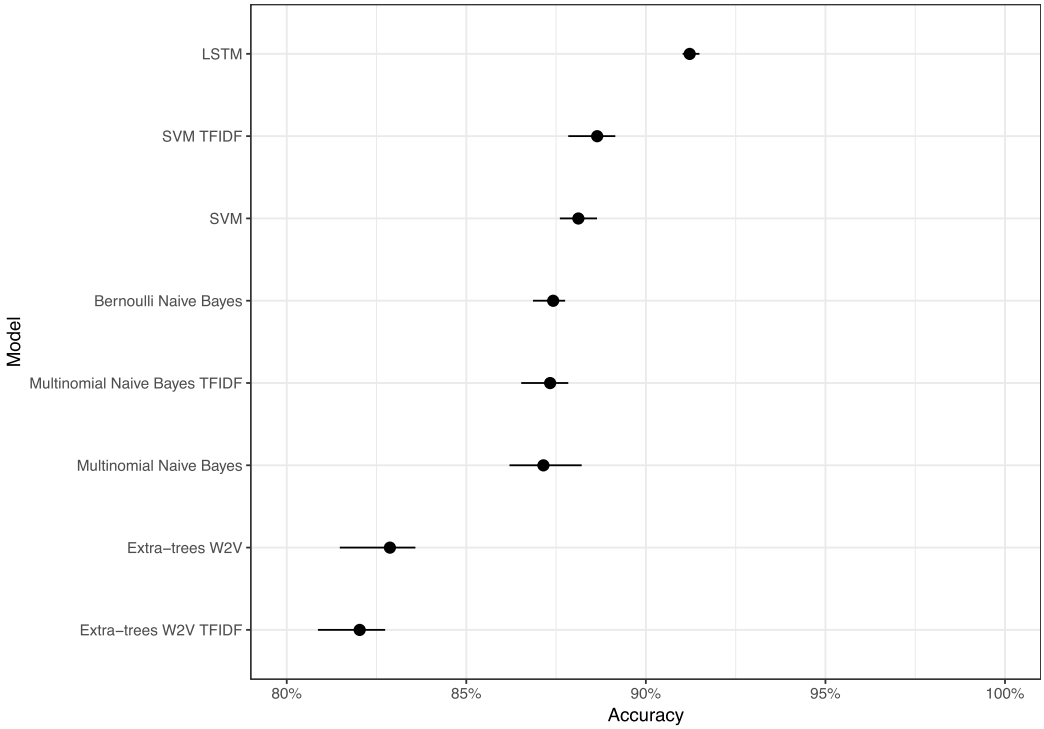
15 A full explanation of W2V is beyond the scope of the paper, but see the discussion of embeddings in Section 2.1 and Appendix Section 5.3. For an accessible introduction to W2V, see (Google 2017). For a more detailed academic treatment, see (Mikolov *et al.* 2013b).

16 A full explanation of TFIDF is beyond the scope of this article. For examples of political science papers that use TFIDF, see Burscher, Vliegenthart, and De Vreese (2015) and Baum, Cohen, and Zhukov (2018).

17 For a more recent comparison of LSTM vs. RNN performance, see (Chung *et al.* 2014).

18 Of course there may be exceptions to this because the performance of models varies with tasks, but the goal of this paper is to introduce LSTM models to political science and make general statements about how they tend to perform in various tasks compared with competing models rather than definitively demonstrating that LSTM models dominate all conceivable competing models in any single application.

19 For the traditional models this is done with 5-fold cross-validation. Because the LSTM model needs a third dataset for the validation set, each dataset drawn for the LSTM model is a random stratified draw from the data.



The bars show the minimum and maximum scores for 5 draws of train and test sets from the data while the points show the mean score. The full dataset is 10,691 posts. Each model uses a balanced training dataset of 8,552 posts or 80% of the full dataset. The remaining 2,139 are used in the test set. In the case of LSTM, one-tenth of the training set is split off to use as a validation set. The hyper-parameters for each model are tuned independently.

Figure 1. Classifying political vs. nonpolitical Weibo posts.

we find that all the methods, not just LSTM, perform better when stop words, words that are so common that they are usually considered not meaningful for classification, and punctuation are *not* removed. This might be because social media posts are short, so the further removal of information decreases accuracy. For this reason, we do not remove stop words or punctuation. Chinese has no conjugation, so stemming (taking words down to their root so that, for an English example, "run," "running," and "ran" count as the same word) is not necessary.

As shown in Figure 1, the mean accuracy of the LSTM model is over 2.53 percentage points higher than the next-best model (SVM TFIDF). A 2.5 percentage point increase may not sound like much, but this is actually quite a large difference. To put it into perspective, the next-best model's mean accuracy is only about 1.2 percentage points higher than the best performing of the naive Bayes models. This means the improvement from switching from SVM TFIDF to an LSTM model for this dataset is more than double the improvement from switching to SVM TFIDF from Bernoulli naive Bayes, which is typically used as a baseline model. The LSTM model consistently performs better across every train and test set drawn. The worst performing LSTM test is still over 2 percentage points more accurate than that of the best performing test for SVM TFIDF. Table 2 shows how these models perform on precision (identifying nonpolitical posts as not political) and recall (identifying political posts as political). The LSTM model outperforms the other models on both metrics.

Here are two examples of posts from the data where word context is important for correct classification, and SVM TFIDF incorrectly classifies the post while LSTM classifies it correctly. The first post appears to be about friendship, but in the context of the Asia-Pacific Economic Cooperation (APEC) conference leaving Beijing, it is actually pointing out that the government manipulates pollution levels to make China look good to international audiences but allows pollution to return once the world's attention is elsewhere.

Table 2. Precision and recall.

Model	Precision	Recall
LSTM	0.914 (0.011)	0.913 (0.014)
SVM TFIDF	0.887 (0.006)	0.887 (0.006)
SVM	0.882 (0.005)	0.881 (0.005)
Bernoulli naive Bayes	0.874 (0.003)	0.874 (0.003)
Multinomial naive Bayes TFIDF	0.874 (0.005)	0.873 (0.006)
Multinomial naive Bayes	0.873 (0.007)	0.871 (0.007)
Extra-trees W2V	0.829 (0.008)	0.829 (0.008)
Extra-trees W2V TFIDF	0.821 (0.007)	0.820 (0.007)

Note: The mean scores from the five train and test set draws are shown with standard errors in parentheses. Precision measures whether the models identify nonpolitical posts correctly, and recall measures whether the model identifies political posts correctly.

> 'APEC' has gone, and our old friends [air pollution] have returned to us. [Our old friends] never abandon us or give us up. Such friends are absolutely loyal.
> 'APEC' 走了, 我们的老朋友以不抛弃、不放弃的步伐又回到了我们身边, 这 样的朋友绝对够义气!

The second post is actually non-political. However, because "climb onto the wall" (翻墙) often means bypassing the Great Firewall, SVM TFIDF classifies it as political, even though the phase does not have that meaning in this context.

> A while ago, I suddenly wanted to go to the Internet cafe to go online. I went to the school wall and climbed onto the wall. Surprisingly, just when I climbed up, a school security guard came and called to me in the distance. I said, "Is it possible to come in to the school and find someone?" Security: "No! Get out right away!" Then I got out. . .
> 前阵子在学校突然想去网吧上网, 于是就到学校围墙翻墙出去, 谁知刚爬上去, 就听到学校保安在远处叫我下来, 然后我就对他说: "进来找个人可以不?" 保 安: "不行! 马上给我出去!" 后来我就他妈被赶了出来. . .

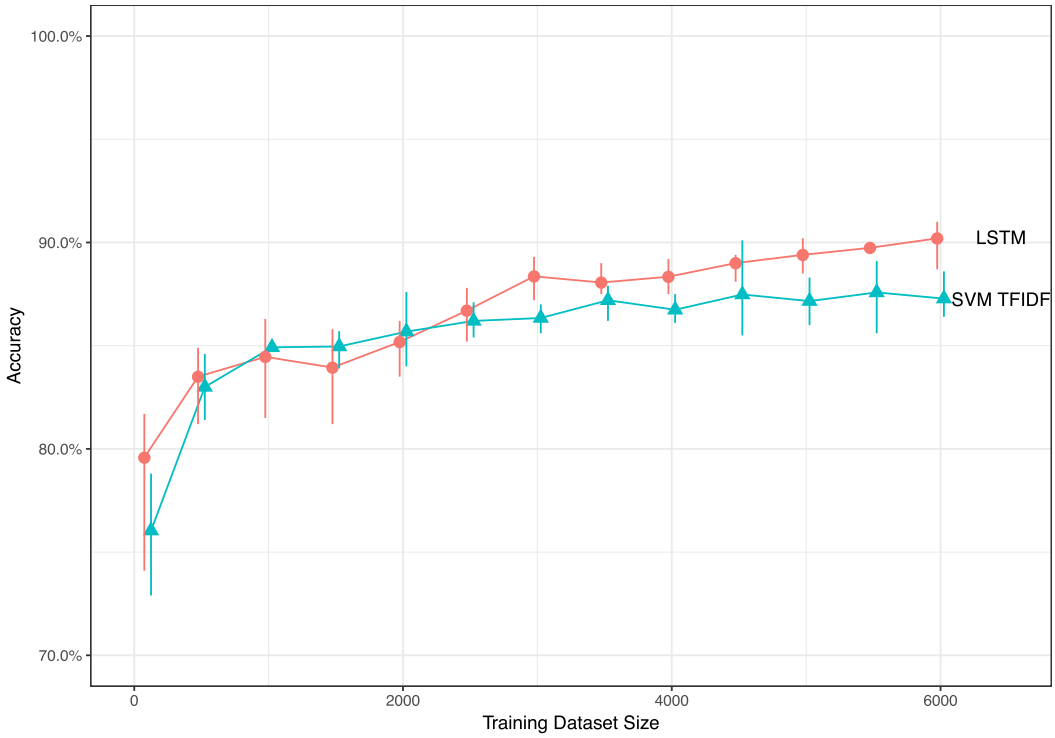
3.2.1 *Computation Time*

Another important performance metric is speed. LSTM models do take longer than traditional models to train. In this application, our LSTM model takes 2 minutes and 51 seconds to train and test for one draw from the data. This is when running the model on a desktop with an NVIDIA GeForce GTX 760 GPU and 7 gigabytes of RAM. This is a relatively old GPU that has exactly the minimum computing power required to run NVIDIA's Deep Neural Network library (see Appendix Section 5.7.4). If the model is instead run on the Intel Core i5 CPU of one of the authors' laptops with 3 gigabytes of RAM, it takes 5 minutes and 40 seconds.[20] In comparison, SVM takes about 20 seconds to train and test for one draw from the data on the laptop. This time difference has the biggest impact when tuning hyperparameters because the researcher will need to run the model repeatedly with different parameters. The good news is that researchers can automate this process and perform other tasks while tuning takes place. We have provided scripts to facilitate this.[21]

20 This CPU has four cores, but because of memory limitations, all models run on the CPU are run on a single core.
21 Chang and Masterson (2019).

3.3 Classifying with Small Samples

In this section, we test how the two models that performed best on the full dataset, the LSTM model and the SVM TFIDF model, perform on random, balanced subsamples of the data. The purpose of this is to examine how LSTM model performance changes as the size of the training set shrinks. Good performance with relatively small training samples is important for political science uses because it is expensive and time consuming to code large training datasets. We start with a randomly selected balanced training dataset of 6,000 posts taken from the original data. We then decrease the size of the training dataset by intervals of 500. We also include a test where the training dataset only contains 100 posts. The models are evaluated on a randomly selected balanced test set of 1,000 posts. We repeat this process five times for each training dataset size to get minimum, maximum, and mean scores. The LSTM model uses a validation set of one-tenth the size of the training set.



Each model trains on 5 randomly selected balanced training sets of the targeted size from the full dataset. These models are then evaluated on a randomly selected balanced test set of 1,000 posts. The bars show the minimum and maximum scores while the points show the mean score. The LSTM models use a validation set that is 10% of the size of the training set. To keep the comparison consistent, the hyper-parameters for each model are same as the independently tuned hyper-parameters on the full dataset from the previous section. Points are jittered along the x-axis to aid visual comparison.

Figure 2. Accuracy with changing sample sizes.

As shown in Figure 2, the LSTM model continues to achieve higher mean scores than the SVM TFIDF model until the size of the training dataset drops below 2,500 posts. While collecting large training sets can be costly,[22] LSTM will generally provide greater returns to researchers willing to pay this cost because they hit the point of diminishing returns from added data more slowly.

3.4 Classifying with Unbalanced Data

Political scientists often work with unbalanced data, meaning data where one category is more common than another. To compare performance with unbalanced data, we add additional

22 See, however, Carlson and Montgomery (2017), Benoit *et al.* (2016) for advice on using crowdsourcing to facilitate this process.

Table 3. Unbalanced Weibo results.

Metric	LSTM	SVM	GBM
Accuracy	0.993 (0.001)	0.991 (0.000)	0.921 (0.041)
Precision	0.913 (0.012)	0.964 (0.002)	0.649 (0.276)
Recall	0.960 (0.007)	0.993 (0.001)	0.639 (0.213)
Penalized	Yes	Yes	No

Note: The mean scores from five train and test set draws are shown with standard errors in parentheses. Precision measures whether the models identify nonpolitical posts correctly, and recall measures whether the model identifies political posts correctly.

nonpolitical posts to create a dataset with 45,000 nonpolitical posts and 5,346 (about 10% of the total) political posts.[23] Unbalanced sets like this are difficult for models to train on because models will tend to classify every post as not political and get 90% accuracy.

One way to deal with this challenge is to penalize incorrect classifications of the less common category more heavily. Another way to deal with class unbalance is to use gradient boosting. GBM are a tree-based model that uses gradient boosting. Interested readers should see Montgomery and Olivella (2018). Because GBM train sequentially, they are able to devote more trees at each step to the class that they classify incorrectly (Weiss 2004). Other techniques for dealing with unbalanced data include undersampling the more common class and synthetic minority oversampling (SMOTE). These methods are beyond the scope of this paper, but interested readers should see Liu, Wu, and Zhou (2009) on undersampling and Chawla *et al.* (2002) and Fernández *et al.* (2018) on SMOTE. Here we compare an LSTM model and an SVM model, which penalize misclassification in inverse proportional to the frequency of categories in the data, with GBM.

As shown in Table 3, both SVM and LSTM perform well with accuracy of over 99% and precision and recall over 90%. However, SVM notably outperforms LSTM on precision and recall. As the application in Section 3.5 reveals, SVM does not always outperform LSTM on unbalanced datasets, but it is reasonable to expect that unbalanced data will increase the performance of SVM in the comparison with LSTM, holding the task constant. This is because neural network models perform best on tasks with a "high signal-to-noise ratio" (Friedman, Hastie, and Tibshirani 2001, 408). It is tempting to dismiss GBM's performance as poor, but it is classifying over 90% of posts correctly with *balanced* accuracy (meaning precision and recall are approximately equal). This improves on models not adjusted to handle unbalanced data, which would achieve similar levels of accuracy but with near 0 recall.

3.5 Classifying US Newspaper Articles

Baum, Cohen, and Zhukov (2018) train an SVM TFIDF classifier to classify US newspaper articles on various indicators of rape culture. We choose the indicator, empathy for the accused, where their classifier performs the least well and examine whether an LSTM model can offer improvement. We suspect that contextual information may improve classification of this variable because it is important to know *who* the article is expressing empathy for, the victim or the accused.

We follow the practices of the original authors by removing stop words, punctuation, and stemming.[24] We also follow the original authors in using the "pooled" dataset that contains

23 However, this sample is still more balanced than full sample of Weibo posts we collect, which we estimate to contain less than 5% political posts.

24 We use the Natural Language Toolkit package to remove stop words and tokenize the newspaper articles (Bird, Klein, and Loper 2009). We use the SnowballStemmer from this package to stem English words.

Table 4. Comparing newspaper classifiers.

Model	Truncation	Accuracy	AUC
LSTM	100 words	0.852 0.838–0.870	0.986 0.985–0.986
LSTM	339 words	0.863 0.851–0.872	0.985 0.983–0.985
SVM TFIDF	NA	0.804 0.802–0.807	0.750 0.720–0.770

Note: The mean score from the train and test set draws are shown with the range between the best and worst scores below.

multiple entries for articles where their human coders disagree.[25] This dataset contains 21,911 human-labeled articles.

For all of our LSTM models on Weibo posts, we preserved the length of every post by padding them to the length of the longest post. While this is possible to do for longer documents, it is impractical in terms of computation time and resource demands (the longest article is over 3,000 words). For the LSTM model, we first try truncating the post to the first 100 words to see if performance is satisfactory. To address the possible concern that this truncation may somehow bias the comparison in favor of LSTM, we show that the results are essentially unchanged if truncation is extended to the mean length of newspaper articles in the dataset (339 words). The results for SVM TFIDF we report come directly from Baum, Cohen, and Zhukov (2018) where SVM TFIDF was allowed to train on the entire length of the articles.

Baum, Cohen, and Zhukov (2018) do not report precision and recall, but they report out-of-sample accuracy as well as area under the receiver operating characteristic (ROC) curve, so we compare these two metrics.[26] Baum, Cohen, and Zhukov (2018) report results both for 10-fold cross-validation as well as 10 trials of random re-sampling with a 75/25 train/test split. We compare against their classifier's 10-fold cross-validation results, which are its best. However, for our own model, we use random re-sampling with a 75/25 train/test split, which makes the training set of our model smaller than that of the model we are comparing against. We do not use a validation set in this application.

The categories are unbalanced. Only about 1 in every 6.89 articles expresses empathy for the accused. For this reason, it is important to focus on area under the curve (AUC) in addition to accuracy because a model could predict that every article is a 0 (contains no empathy for the accused) and achieve out-of-sample accuracy of about 88%. To prevent our model from doing this, we penalize misclassification in inverse proportion to the observed class frequencies.[27]

The results in Table 4 show that the LSTM model outperforms the SVM TFIDF model from the original paper by about 5 percentage points in accuracy (6 points when truncation is extended to 339 words). The model improves the AUC by approximately 23 percentage points. This indicates that many more of the true positives are correctly classified as containing empathy for the accused by the LSTM model. We speculate that the size of the improvement is larger here than in the Weibo post application because of the greater importance of context for understanding whether an article is expressing empathy and, if so, for whom the newspaper article is empathizing. Parsing empathy may even require going a sentence or two back in the text, making it a good case for

25 In the original paper, Baum, Cohen, and Zhukov (2018) take the median classification as the truth for these cases. We take the mode because otherwise there are 12 cases where articles receive a classification of 0.5 rather than a 1 or a 0, which is not compatible with the binary loss function we use.

26 We use TensorFlow's streaming_auc function to calculate our model's AUC performance. This approximates the AUC with a Riemann sum.

27 Baum, Cohen, and Zhukov (2018) do not mention whether they adjust for class imbalance, but our own testing of SVM TFIDF models on this dataset suggest that they do because without adjustment, these models will also predict 0 for every example (results available from authors upon request).

applying an LSTM model. LSTM models are able to parse features like this because they extract features the model has learned are useful for interpreting words or word vectors that may occur later in documents (see Section 2.2). This application also shows that, at least for some cases of unbalanced data, LSTM can outperform SVM TFIDF.

4 Conclusion

LSTM models perform best relative to traditional models in applications with large training sets where words within documents have complex context-dependent relationships. LSTM models perform less well relative to traditional models as the amount of unbalance among categories in the data increases. LSTM models are adaptable to a wide variety of tasks and can classify texts on any basis the researcher desires provided they have adequate training data. Our examples are binary, mutually exclusive tasks for the sake of simplicity, but LSTM models can classify texts into more than two categories as well as in situations where categories are not mutually exclusive. Further, LSTM models can classify texts regardless of their language. We hope that the guidance we provide about the use of these models along with our code templates facilitates the use of these models in future political science applications.

Future work should continue to explore the relatively untapped political science potential of LSTM models. For example, LSTM models have applications for time-series forecasting that may prove useful for political scientists working with event data (Maknickiene and Maknickas 2012). This is because the characteristics that allow LSTM models to learn long time dependencies, such as the relationship between the words at the beginning of a document and the words at the end of a document, can be applied to time-series data where predictors from the past have systematic yet complex relationships with events in the future.

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Supplementary materials

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References

Abadi, M., A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, and M. Devin et al. 2016. "Tensorflow: Large-Scale Machine Learning on Heterogeneous Distributed Systems." Preprint, arXiv:1603.04467.

Baum, M. A., D. K. Cohen, and Y. M. Zhukov. 2018. "Does Rape Culture Predict Rape? Evidence from U.S. Newspapers, 2000–2013." *Quarterly Journal of Political Science (QJPS)* 13(3):263–289.

Beck, N., G. King, and L. Zeng. 2000. "Improving Quantitative Studies of International Conflict: A Conjecture." *The American Political Science Review* 94(1):21–35.

Bengio, Y. 2009. "Learning Deep Architectures for AI." *Foundations and Trends in Machine Learning* 2(1):1–127.

Benoit, K., D. Conway, B. E. Lauderdale, M. Laver, and S. Mikhaylov. 2016. "Crowd-Sourced Text Analysis: Reproducible and Agile Production of Political Data." *American Political Science Review* 110(2):278–295.

Bird, S., E. Klein, and E. Loper. 2009. *Natural Language Processing with Python*. Sebastopol, CA: O'Reilly Media, Inc.

Burscher, B., R. Vliegenthart, and C. H. De Vreese. 2015. "Using Supervised Machine Learning to Code Policy Issues: Can Classifiers Generalize across Contexts?" *The ANNALS of the American Academy of Political and Social Science* 659(1):122–131.

Carlson, D., and J. M. Montgomery. 2017. "A Pairwise Comparison Framework for Fast, Flexible, and Reliable Human Coding of Political Texts." *American Political Science Review* 111(4):835–843.

Chang, C., and M. Masterson. 2019. "Replication Data for: Using Word Order in Political Text Classification with Long Short-Term Memory Models." https://doi.org/10.7910/DVN/MRVKIR, Harvard Dataverse, V1.
Chawla, N. V., K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. 2002. "SMOTE: Synthetic Minority Over-Sampling Technique." *Journal of Artificial Intelligence Research* 16:321–357.
Chollet, F. et al. 2015. *Keras*. GitHub. https://github.com/fchollet/keras.
Chung, J., C. Gulcehre, K. Cho, and Y. Bengio. 2014. "Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling." Preprint, arXiv:1412.3555.
Cortez, P., and M. J. Embrechts. 2013. "Using Sensitivity Analysis and Visualization Techniques to Open Black Box Data Mining Models." *Information Sciences* 225:1–17.
Diermeier, D., J.-F. Godbout, B. Yu, and S. Kaufmann. 2012. "Language and Ideology in Congress." *British Journal of Political Science* 42(01):31–55.
D'Orazio, V., S. T. Landis, G. Palmer, and P. Schrodt. 2014. "Separating the Wheat from the Chaff: Applications of Automated Document Classification Using Support Vector Machines." *Political Analysis* 22(2):224–242.
Elman, J. 1990. "Finding Structure in Time." *Cognitive Science* 14(2):179–211.
Fernández, A., S. Garcia, F. Herrera, and N. V. Chawla. 2018. "Smote for learning from imbalanced data: progress and challenges, marking the 15-year anniversary." *Journal of Artificial Intelligence Research* 61:863–905.
Friedman, J., T. Hastie, and R. Tibshirani. 2001. *The Elements of Statistical Learning*, vol. 1 *(Springer Series in Statistics)*. New York: Springer.
Gers, F. A., J. Schmidhuber, and F. Cummins. 2000. "Learning to forget: Continual prediction with LSTM." *Neural Comput.* 12(10):2451–2471.
Geurts, P., D. Ernst, and L. Wehenkel. 2006. "Extremely randomized trees." *Machine Learning* 63(1):3–42.
Google. 2017. Vector Representation of Words. www.tensorflow.org/tutorials/word2vec.
Graves, A., and J. Schmidhuber. 2005. "Framewise Phoneme Classification With Bidirectional LSTM and Other Neural Network Architectures." *Neural Networks* 18(5-6):602–610.
Greff, K., R. K. Srivastava, Jan Koutník, B. R. Steunebrink, and J. Schmidhuber. 2016. "LSTM: A Search Space Odyssey." *IEEE Transactions on Neural Networks and Learning Systems* 28(10):2222–2232.
Grimmer, J., and B. M. Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* 21(03):267–297.
Han, R., M. Gill, A. Spirling, and K. Cho. 2018. "Conditional Word Embedding and Hypothesis Testing via Bayes-by-Backprop." Working Paper.
Hochreiter, S. 1998. "The Vanishing Gradient Problem During Learning Recurrent Neural Nets and Problem Solutions." *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems* 6(02):107–116.
Hochreiter, S., and J. Schmidhuber. 1997a. "Long Short-Term Memory." *Neural Computation* 9(8):1735–1780.
Hochreiter, S., and J. Schmidhuber. 1997b. "LSTM Can Solve Hard Long Time Lag Problems." In *Advances in Neural Information Processing Systems*, edited by M. C. Mozer, M. I. Jordan, and T. Petsche, 473–479. Cambridge, MA: MIT Press.
Hopkins, D. J., and G. King. 2010. "A Method of Automated Nonparametric Content Analysis for Social Science." *American Journal of Political Science* 54(1):229–247.
James, G., D. Witten, T. Hastie, and R. Tibshirani. 2013. *An Introduction to Statistical Learning*, vol. 112. New York: Springer.
Jernite, Y., E. Grave, A. Joulin, and T. Mikolov. 2017. "Variable Computation in Recurrent Neural Networks." In *5th International Conference on Learning Representations, ICLR 2017*.
Johnson, R., and T. Zhang. 2016."Supervised and Semi-Supervised Text Categorization using LSTM for Region Embeddings." Preprint, arXiv:1602.02373.
Krebs, R. R. 2015. "How Dominant Narratives Rise and Fall: Military Conflict, Politics, and the Cold War Consensus." *International Organization* 69(04):809–845.
Liang, H., X. Sun, Y. Sun, and Y. Gao. 2017. "Text Feature Extraction Based on Deep Learning: A Review." *EURASIP Journal on Wireless Communications and Networking* 2017(1):211.
Liu, X., J. Wu, and Z. Zhou. 2009. "Exploratory Undersampling for Class-Imbalance Learning." *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 39(2):539–550.
Lucas, C., R. A. Nielsen, M. E. Roberts, B. M. Stewart, A. Storer, and D. Tingley. 2015. "Computer-Assisted Text Analysis for Comparative Politics." *Political Analysis* 23(2):254–277.
Maknickiene, N., and A. Maknickas. 2012. *Application of Neural Network for Forecasting of Exchange Rates and Forex Trading*. Vilnius Gediminas Technical University Publishing House Technika, 122–127.
Mikolov, T., K. Chen, G. Corrado, and J. Dean. 2013a, "Efficient Estimation of Word Representations in Vector Space." Preprint, arXiv:1301.3781.
Mikolov, T., I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. 2013b. "Distributed Representations of Words and Phrases and Their Compositionality." In *Advances in Neural Information Processing Systems*, edited by C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, 3111–3119. Cambridge, MA: MIT Press.

Mnih, A., and K. Kavukcuoglu. 2013. "Learning Word Embeddings Efficiently with Noise-Contrastive Estimation." In *Advances in Neural Information Processing Systems*, edited by C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, 2265–2273. Cambridge, MA: MIT Press.

Montgomery, J. M., and S. Olivella. 2018. "Tree-Based Models for Political Science Data." *American Journal of Political Science* 62(3):729–744.

Olden, J. D., and D. A. Jackson. 2002. "Illuminating the Black Box: a Randomization Approach for Understanding Variable Contributions in Artificial Neural Networks." *Ecological Modelling* 154(1):135–150.

Osowski, S., K. Siwek, and T. Markiewicz. 2004. "Mlp and SVM Networks-a Comparative Study." In *Proceedings of the 6th Nordic Signal Processing Symposium, 2004. NORSIG 2004*, 37–40. Espoo, Finland: IEEE.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. "Scikit-learn: Machine Learning in Python." *Journal of Machine Learning Research* 12:2825–2830.

Prechelt, L. 1998. "Early Stopping-But When?" In *Neural Networks: Tricks of the Trade*, 55–69. Heidelberg: Springer.

Ruizendaal, R. 2017. "Deep Learning #4: Why You Need to Start Using Embedding Layers" *Towards Data Science*, July 17. https://towardsdatascience.com/deep-learning-4-embedding-layers-f9a02d55ac12.

Spirling, A. 2012. "US Treaty Making With American Indians: Institutional Change and Relative Power, 1784–1911." *American Journal of Political Science* 56(1):84–97.

Sun, J. 2015. Jieba. Version 0.38. https://github.com/fxsjy/jieba.

TensorFlow. 2018. Vector Representations of Words. https://www.tensorflow.org/tutorials/representation/word2vec.

Theano Development Team. 2017. LSTM Networks for Sentiment Analysis. http://deeplearning.net/tutorial/lstm.html.

Weiss, G. M. 2004. "Mining with Rarity: a Unifying Framework." *ACM Sigkdd Explorations Newsletter* 6(1):7–19.

Yosinski, J., J. Clune, A. Nguyen, T. Fuchs, and H. Lipson. 2015. "Understanding neural networks through deep visualization." Preprint, arXiv:1506.06579.