

# Legal Linking: Citation Resolution and Suggestion in Constitutional Law

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## Abstract

The paper describes a dataset and system for linking paragraphs from court cases to clauses or amendments in the US Constitution. We implement a neural architecture for matching two paragraphs, taking training data from online databases in a distantly-supervised fashion. In experiments on a manually-annotated evaluation set, we find that our proposed system noticeably outperforms a simple rules-driven baseline. Qualitatively, this performance gap seems largest for indirect links between documents, which suggests that our system might be useful for answering political science and legal research questions or discovering novel links. We release the dataset along with a small set of manual annotations to foster future work.

## 1 Introduction

Authors of legal texts are frequently interested in understanding how their document relates to a knowledge base or to some reference text or corpus. Because legal reasoning relies on references to preexisting precedent, identifying the documents or document sections (e.g. court cases; constitutional provisions) that relate to the author’s current argument or topic of interest is an important task. However, constructing these reference links is labor-intensive, particularly if the set of reference texts is large or the link is ambiguous. Automating this linkage task therefore offers useful assistance for authors of legal texts.

Linking systems of this kind are also useful for answering important political science and legal research questions. For example, in US Constitutional law, the Supreme Court has anecdotally appeared more receptive to arguments that combine

multiple Constitutional rights.<sup>1</sup> However, without an automated linking system, identifying instances of rhetorical “commingling” of rights is labor-intensive. Outside the American context, even simple data on the frequency with which judges invoke particular constitutional rights are difficult to gather. A generic, automated system capable of inferring links between sections of judicial opinions and related legal texts<sup>2</sup> would therefore be valuable for legal and political science researchers.

With this motivation, we present a method for linking Supreme Court decisions to the US Constitution. Our model operates on the level of short pieces of text, such as paragraphs, and gives a binary decision between pairs of texts, marking a true or null link. In our experiments, we find that our system offers lower precision but noticeably higher recall than a rules-driven baseline, with improved overall performance on a manually-tagged evaluation set. Qualitatively, this performance gap appears largest for paragraphs that contain abstract or indirect references to Constitutional provisions, which suggests that the model we propose might also be useful for discovering new links not identified by existing techniques.

## 2 Related Work

In the legal domain, initiatives including the Cornell Legal Information Institute have constructed standardized citation ontologies to assist rules-based resolution of format-related entity ambiguity (see [Casanovas et al. \(2016\)](#) for an overview). However, these systems are not designed to infer citations to users based on plain-text excerpts,

<sup>1</sup>For example, *Lamb’s Chapel v. Center Moriches Union Free School District* (508 U.S. 384) and other religious speech cases successfully combine free speech and free exercise of religion arguments. See, e.g., [McCloskey and Levinson \(2016, 162-163\)](#) for further discussion.

<sup>2</sup>E.g. other national constitutions ([Elkins et al., 2014](#)).

which is our problem of interest. Schwartz et al. (2015) propose a topic model-based approach that suggests citations to relevant US Supreme Court caselaw based on user-inputted free text. Because this system only draws links between excerpts and full Supreme Court cases, it is coarser than ours, but provides perhaps the closest point of comparison in the legal domain (Branting, 2017). A closer comparison point is Nomoto (2018), who propose an approach that infers paragraph-level citation links between published scientific papers.

The methods that we adopt to solve this problem draw inspiration from several fields in natural language processing (NLP) and machine learning including multilabel classification (Boutell et al., 2004; Nam et al., 2014), dataless classification (Chang et al., 2008), citation resolution (Duma and Klein, 2014), and entity linking (Ratinov et al., 2011; Shen et al., 2015). Our method of collecting training data is reminiscent of distant supervision techniques (Mintz et al., 2009).

### 3 Data Collection

To obtain training data, we draw on the Cornell Legal Information Institute (Cornell LII)’s repository of US Supreme Court opinion texts.<sup>3</sup> We began by scraping all text associated with all opinions available through the Cornell LII site. For each case, we then removed all HTML markup, editorial information, and other non-opinion language (e.g. footnotes, case summaries, or front matter), and split the remaining text into paragraphs. For each paragraph, we then checked whether that paragraph contained a hyperlink to a section of the US Constitution. If any hyperlinks were present, we store the paragraph and linked Constitution section(s) as training pair(s). Finally, we removed any duplicate paragraphs. This process left us with a total dataset of  $\sim 328k$  unique paragraphs, of which  $\sim 8k$  contained at least one link, and a total of  $\sim 11k$  links.

Inspecting this data, we noticed that the annotation was inconsistent and incomplete. For example, not all paragraphs with the phrase “First Amendment” linked to the First Amendment. To solve this problem, we manually created a small list of rules for annotation. The list contained about 100 rules, and consisted mainly of mapping amendment names (“Seventh Amendment” or “7th Amendment”) to the correct label. We

<sup>3</sup><https://www.law.cornell.edu/>

also included several representative phrases, such as “free speech”, “due process clause”, and others. After this annotation, we had  $\sim 36k$  paragraphs with at least one link, and  $\sim 41k$  links total.

Though convenient, this process creates certain trivial dependencies between linked paragraphs, which might limit a model’s ability to generalize. Because hyperlinks and rules are associated with text, all linked paragraphs necessarily contain strings that correspond to the linked Constitution section. For example, all paragraphs that link to the First Amendment necessarily contain strings such as “First Amendment”, “1st Amendment”, or “Amendment I”. A model trained on this dataset would likely treat the presence/absence of strings like these as strong classification signals, which is undesirable if the goal is to identify links between paragraphs that do not explicitly mention the name of the linked paragraph. To break these trivial dependencies, we therefore create a second “stripped” dataset, in which we delete 50% of the hyperlink or rule strings. We delete only half because presence of a phrase such as “First Amendment” is still a strong linking signal which we would like to preserve. In our evaluations, we assess model performance on both the original and “stripped” datasets separately.

#### 3.1 Manual Annotations

To assess model performance, we hand-annotated Constitutional references in all paragraphs ( $n = 1241$ ) from an additional four Supreme Court cases: *Griswold v. Connecticut* (381 U.S. 479), *Miranda v. Arizona* (384 U.S. 436), *US v. Nixon* (418 U.S. 683), and *Texas v. Johnson* (491 U.S. 397). We emphasize that these cases were *not* selected randomly. Since most Supreme Court cases infrequently reference the Constitution, we chose these cases because they litigate important constitutional law questions, and are therefore likely to contain a high density of positive examples with which to assess model performance.

These five cases provide two other desirable properties for an evaluation set. First, each of these cases addresses a different legal issue (e.g. criminal rights in *Miranda*; free speech in *Texas v. Johnson*). As a result, each case is likely to contain references to a distinct set of Constitutional provisions. Second, these cases also vary substantially in rhetorical style. For example, Justice Douglas’s opinion in *Griswold* famously ref-

erences the “penumbras” of various Constitutional provisions in order to identify a right to privacy. Since most of these references consist of passing references to standard provision names (e.g. “First Amendment”; “Due Process Clause”), we expect the links in *Griswold* to be “easy” to predict. By contrast, *US v. Nixon* tackles abstract questions of Presidential power and is more likely to indirectly reference Constitutional language, thus providing a substantial challenge, and room to grow.

## 4 Methods

Our data is defined in terms of input documents  $D$ , and reference documents  $C$ . The goal of the task is to link an input document  $d \in D$  to zero or more reference documents. Formally, we will create a model of the form  $h(d) \rightarrow \mathbf{y}$ , where  $\mathbf{y} \in \{0, 1\}^{|C|}$  and  $\mathbf{y}_i = 1$  if  $d$  is to be linked to document  $c_i \in C$ . If  $\mathbf{y} = \{0\}^{|C|}$ , this means that  $d$  links to no paragraph (true for most pieces of text, including this paragraph).

### 4.1 Rule-based

An intuitive baseline is to use the rules defined for the annotation process as the entire labeling strategy. Instead of applying these rules to the training data, we apply them to the test data directly. As with any rule-based system, we would expect that this achieves high precision and low recall.

### 4.2 Neural Network Model

In addition to the rule-based baseline, we model this problem using a neural network-based classifier. We use a variant of the so-called Binary Relevance framework (Boutell et al., 2004; Nam et al., 2014), which builds a separate classifier for each label. As such, the problem decomposes to building  $C$  separate classifiers:  $h(d) \rightarrow \{h_i(d)\}_{i=1}^{|C|}$ , where  $h_i(d) \rightarrow \{0, 1\}$ .

Inspired by work in dataless classification (Chang et al., 2008), a key observation in our

Model	P	R	F1
Rules	<b>88.2</b>	48.3	62.4
Neural Network (original)	87.7	48.3	62.3
Neural Network (stripped)	74.6	<b>58.7</b>	<b>65.7</b>

Table 1: Results on the manually annotated test set. The top row uses the rule based classifier. The bottom two rows use the neural network model trained on the original and stripped training sets respectively.

model is that each element in the output vector  $\mathbf{y}$  represents a *document*, not just a label. Under this observation, we can create a meaningful representation for each label which gives an additional signal for classification. As such, we use the index  $i$  to retrieve  $c_i$ , and rewrite the decision function as  $h_i(d, c_i) \rightarrow \{0, 1\}$ . Ultimately, we define a single model for all  $h_i(\cdot)$  as follows:

$$h_i(d, c_i) = \max[f(d2v(T(d)) \cdot d2v(T(c_i)))]$$

Where  $T$  is a token embedding function,  $d2v$  is a document embedding function, and  $f$  is a feed forward neural network layer that projects to two dimensions. The  $\max$  function is only used for prediction, not during training. Loosely speaking, the function  $h_i$  can be understood as measuring the similarity between the vector representations of  $d$  and  $c_i$ . We used allennlp to build our systems (Gardner et al., 2017).

For the token embedding layer  $T$ , we used the BERT base cased pretrained embeddings (Devlin et al., 2018), as provided by huggingface.<sup>4</sup> For the document embedding layer  $d2v$ , we used a bidirectional LSTM with hidden size 300, 2 layers, and dropout 0.5. This embedder converts a sequence of embeddings into a fixed length by running the bidirectional LSTM over the sequence and concatenating the resulting context vectors from each direction.

Since the training data is wildly imbalanced towards unmatched paragraphs, we employ two tricks in our training. First, as a preprocessing step, we selected all examples with links, but subsampled the unmatched examples such that there was an equal number of matched and unmatched. Second, we downweighted all negative examples in training by a factor of 10. This deals with the fact that every positive example for one class is a negative example for all other classes, and also that the quality of annotation is unsure, as in (Liu et al., 2003).

### 4.3 Evaluation

During training, we tuned according to a split of the original train data. Since this data is automatically generated, it is not a good indicator of performance. Instead, we report all of our results on the manually annotated test set, described in Section 3.1. Since the decision from most of the classifiers

<sup>4</sup><https://github.com/huggingface/pytorch-pretrained-BERT/>

Input sentence	Rule Pred.	NN Pred.
The defendant argued that their right to <b>free speech</b> had been chilled.	First Amendment	First Amendment
This was a <b>Second Amendment</b> case.	Second Amendment	Second Amendment
This was a <b>Ninth Amendment</b> case.	Ninth Amendment	Unmatched
The court argued that the punishment was not only cruel, but also unusual.	Unmatched	Eighth Amendment
We sometimes forget how long it has taken to establish the privilege against self-incrimination.	Unmatched	Fifth Amendment

Table 2: A comparison of predictions from the rule-based system and the neural network model (stripped). **Bold text** represents text matching a rule. The last example is taken from the manually annotated test examples.

will be 0, we evaluate the outputs of our model using F1 measure, calculated without regard to any individual class.

Upon publication, we will release all code and data (including the manually annotated test set), along with trained models.

## 5 Results and Analysis

Table 1 shows our main quantitative results. As expected, the rules-based approach gives high precision but low recall on the manually annotated test set. Interestingly, the model trained on the original (unstripped) data performs almost identically to the rules-based approach. This also matches our expectations, and highlights how deterministic training data can lead to overfitting. Finally, the stripped results are in the third row of the table. Here, the precision is lower but the recall is considerably higher, leading to a jump in F1 performance. We consider this an encouraging first step, which shows that the rule-stripping approach is important to prevent the model from simply re-learning deterministic training set rules.

In Table 2, we show some examples of predictions from the rule-based system and our model. The table has three sections, corresponding to examples on which 1) both models are correct, 2) only rule-based is correct, and 3) only the neural network is correct.

The example from the second section (“Ninth Amendment case”) is interesting in how it contrasts with the nearly identical sentence above it (“Second Amendment case”). Naturally, the rule-based system correctly tags both, but the neural network is only correct on the “Second Amendment” sentence. This is likely because of imbalances in the training data, such that sentences with

the phrase “Second Amendment” are common, but sentences with the phrase “Ninth Amendment” are much less common. In fact, in the training split we used, the phrase “Ninth Amendment” appeared less than 20 times out of nearly 50K examples.

The bottom section shows the power of the neural network model. Words such as “cruel”, “punishment”, and “unusual” are distinctive of the Eighth Amendment, even though they are used in a different order. Similarly, the “privilege against self-incrimination” is a common paraphrase of language used in the Fifth Amendment. Examples like these are readily identifiable by humans but are difficult to capture in a rules-based framework, and demonstrate our model’s value.

## 6 Conclusions

We have introduced a new task for linking portions of text from Supreme Court cases to the US Constitution, some data supporting this task (although with incomplete annotations), and some baseline models, including a rule-based system and a neural network system. Although the neural network system outperforms the rule-based system, there is still a further exploration to be done both in the direction of automatic or distant labeling, and in problem modelling. We look forward to other researchers using this dataset for future work.

From a practical perspective, we anticipate that this dataset could be used to give valuable insights on research questions of interest to the world of political science. For example, these data could be used to study which amendments tend to see higher litigation rates according to the period in the Supreme Court, or rhetorical co-citation of Constitution sections.



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