

# Illinois cases linguistic analysis

Davide Carletti and Francesco Tomaselli

University of Milan

**Abstract.** Court judgments temporal analysis

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## 1 Introduction

The goal of this project is to study words among the temporal axis in court decisions. More precisely, we aim to find information about relevance and frequency of single or multiple terms, and also to discover correlations between them.

The work is accessible at <https://illinois-cases-analysis-webapp-qka7d4ktbaew.a.run.app/>.

## 2 Research question and methodology

The goal of the project is to analyze, from a collection of court decisions, the relevance of terms in time while also gathering information about possible correlations between them. The reasons to perform such a study are various, firstly, one could find interesting and unexpected correlations between terms, also, studying them in time could reveal a change of context of some words.

The research question is focused in particular on three main areas of interest: narcotics, weapons and investigations. Thus, words related to this three main sets are the most interesting ones to analyze.

### 2.1 Initial idea

In the first place, the methodology aimed to divide the dataset into the three main areas, corresponding to the area of interests previously introduced. Having documents divided in areas, would have made possible to topic modelling and language modelling on the three areas, possibly considering the temporal factor in the process.

This approach would have allowed to directly confront the three sets also in a temporal way, showing differences in the language and topics between words regarding drugs, narcotics and investigations respectively.

Some scientific literature has been explored and tested, based on the idea of *Guided topic modelling* but it has been soon discovered that the dataset comprehended many other topics other than the three main areas of interest. [1] Another drawback was the fact that even when finding promising results with the guided method, the three topics were somehow intersecting too much, probably because the area of interests are closely related to each other in real life.

## 2.2 Refined methodology

After coming to a dead end with the approach presented in the previous Subsection, we opted for a different overall methodology, guided topic modelling shifted towards a classical one and the temporal analysis is performed with an heavy use of word embeddings.

## 3 Experimental results

### 3.1 Dataset preprocessing

The dataset in use is the Illinois Bulk Dataset, that contains 183146 cases with 194366 judges opinions.

The first step of the preprocessing is to merge the opinions about a case into one, obtaining a single document for each dataset entry. Then, each document goes through a text cleaning and tokenization phase, where the first part is done with the help of regular expressions, while the second uses Spacy to obtain a list of terms.

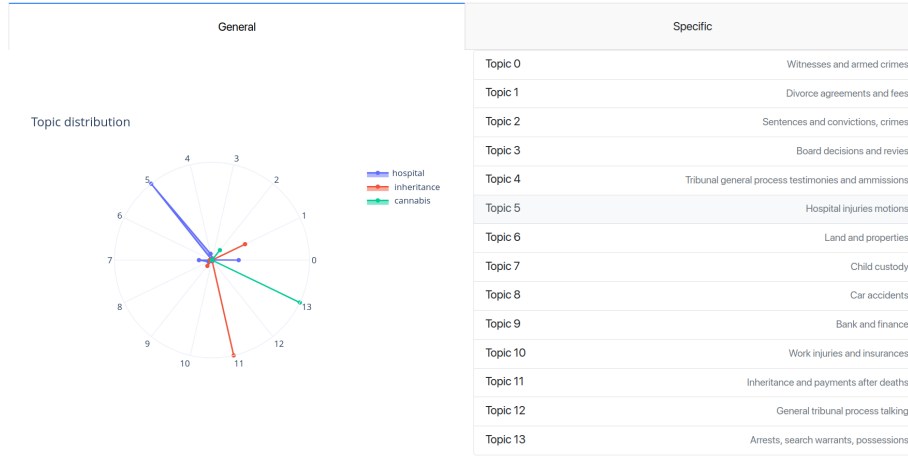
### 3.2 Word of interest expansion

The project started with a collection of relevant words for three categories, namely weapons, narcotics and investigations. The idea is to preserve these words in each preprocessing phase, especially when filtering out words that do not meet a required frequency in the dataset. To have a better set of interesting words to keep we opted to expand them using pre-trained word embeddings, the *GoogleNews* models. The process consists of finding similar words for each word of interest, checking that these words are in the dataset, with a manual final review to remove unnecessary or wrong words.

### 3.3 Topic modelling

To have an overview of the topics discussed on the dataset a Latent Dirichlet Allocation model is trained on the tokenized texts. One of the key parameters of such a model is the number of topics, and, given the fact that cases could potentially talk about anything, an *Halving search* is performed to find a good value.

We opt for an halving search since the number of topics could be anything, we fixed a range between ten and thirty and training each model to then evaluate results would take a huge amount of time. Halving search mitigates the problem, as it trains firstly on smaller datasets, select the best models, and retrain on bigger slices of data until a final model is found. This methodology can be ten times faster then grid search. The selection criterium for the search is the Log Likelihood of each model. The search revealed that the optimal number of topics is 14. An overview of the found topics can be seen on Figure 1 on the facing page.



**Fig. 1.** Generic topic distribution for the words hospital, inheritance and cannabis

The results are promising but the words of interest, namely a collection of narcotics, investigation and weapons terms, are merged together in a few topics.

To solve the issue we decide to run topic modelling on a subset of the previous topics with the same technique as before. The result is similar, we find again 14 topics, but this time they are much more specific, an example of specific topic distribution can be seen on Figure 2 on the next page, with an in depth topic analysis on Figure 3 on the following page

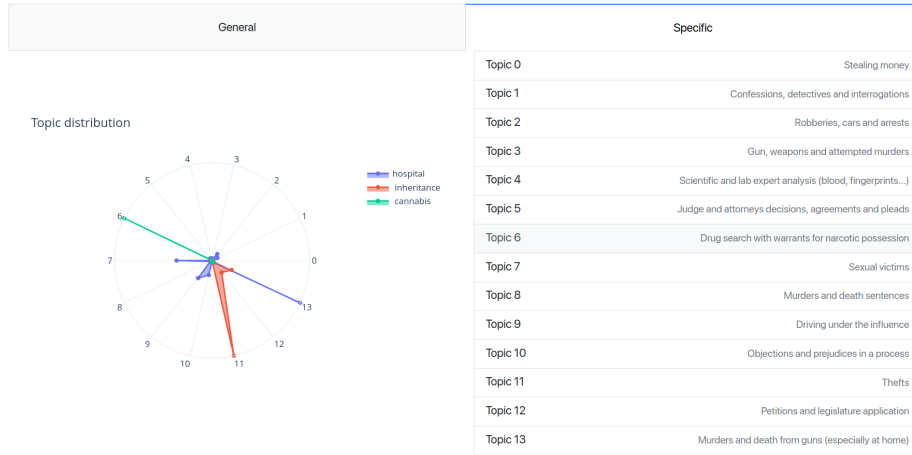
As stated on Subsection 2.1 on page 1, the first idea was to guide the topic modelling process to find three main topics, but the applied methodology failed on numerous occasions to perform well, we believe that running two phases of topic modelling provided in a similar result, while discovering much more about the dataset.

### 3.4 Temporal word embeddings

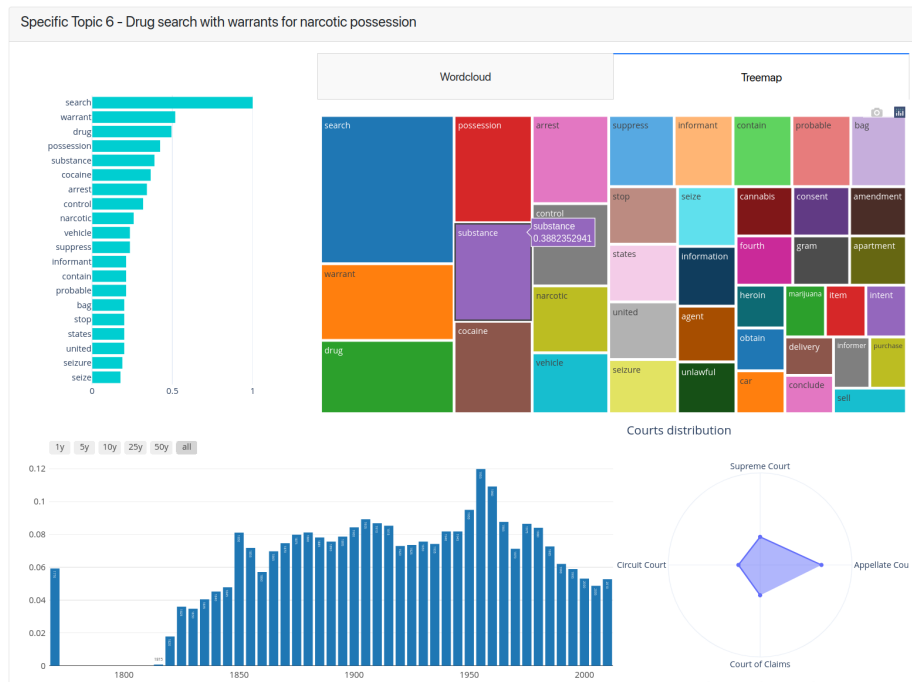
One of the objective of the project is to find correlations among words and one tool that can be used is word embeddings. The technique assigns a real vector of a given dimensions to each word in the document collection, creating a way to directly compare the context similarity between two terms.

For this task we used Gensim's Word2Vec implementation and trained different models in three ways:

1. *Global model*: trained on the entire document collection, with 100 components vectors;
2. *One year models*: they are trained on subsets of the dataset divided by years;
3. *Ten years models*: trained on epochs of 10 years each.



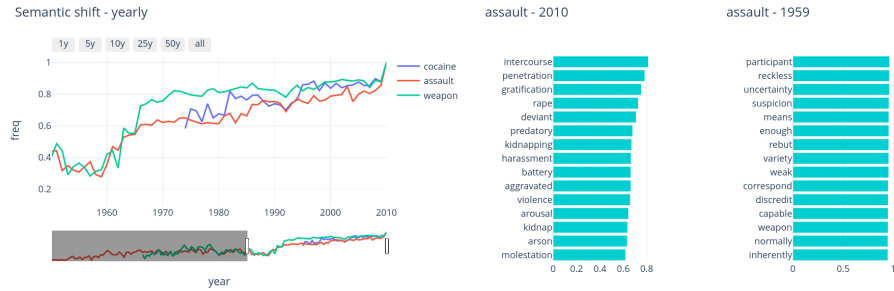
**Fig. 2.** Specific topic distribution for the words hospital, inheritance and cannabis



**Fig. 3.** Detailed topic analysis for the drug warrant specific topic.

The first model gives information about the whole dataset, it can be used to compute similar words queries, while the others can be exploited to find context and semantic shifts among the temporal axis. Taking inspiration from the *Hist-Words* work on semantic shift, we start by aligning the models, and then find, given a word and a base year, the similarity of that word in time with respect to the base year. [2] This approach can reveal if a word changed semantic or context, and when, with respect to a given year, an example can be seen in Figure 4.

Similarly, the ten year models are aligned, but this time, given a term, we compute the difference among two consecutive epochs. The idea is similar to the previous one but slightly different, this time a drop in the similarity sequence reveals a change of meaning from an epoch to the other, the resulting sequence can be seen in Figure 5 on the next page.

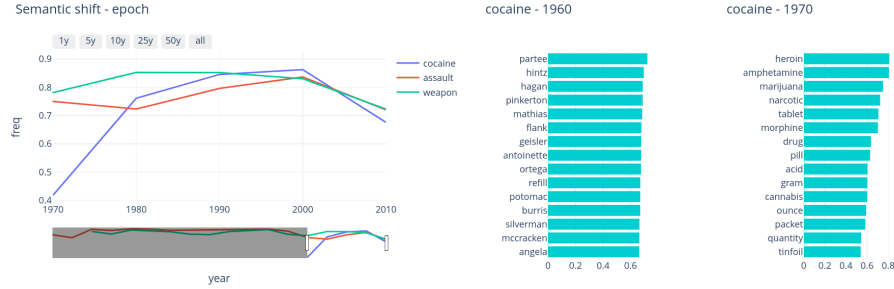


**Fig. 4.** Semantic shift of the word cocaine, assault and weapon with respect to the year 2010. A drop of the assault curve in 1959 correspond to a different context with respect to the base year, as proven by the different similar words.

### 3.5 Webapp

In order to visualize and explore the results of the analysis, a web interface has been developed. Through the UI, the user can search multiple words united, separated by ", ", and/or compare words, separated by "-"; the app will show various interesting sections, one focused on the analysis of the searched words:

- Top 15 words of similar context of the searched words, using word embeddings).
- Frequency graph of documents in time containing the searched words.
- Semantic shifts of the searched words, both by epoch, two adjacent epochs of 10 years, and by single year. If the user clicks on a point of the graph, the contexts of the selected word in the different selected years/epochs will be showed, allowing the comparison of contexts which helps understanding the evolution of words meaning and usage during time.



**Fig. 5.** Similarity between consecutive epochs of the terms cocaine, assault and weapon. Comparing the similar words, we can see that the drop of the cocaine curve around 1970 correspond to a shift in context.

- Topic distribution of the searched words, both generic and areas of interest-specific topics. By clicking on the showed radar chart, or on the lateral list of topics, the selected topic info will be loaded in the below section.
- Most important words of the selected topic. There are three ways of visualization: a barchart with the first 15 words, a Wordcloud with the first 80 and a Treemap with the first 50.
- Topic distribution over time and over the different Illinois courts.

The application has been developed in Python.

**3.5.1 Webapp developing technology** In order to fastly create an interesting interface, three python-based frameworks for web developing have been considered:

- Voila and ipywidgets. Because the whole project has been developed using Jupyter notebooks, it would have been natural to develop the webapp in a new notebook. ipywidgets allow to create dynamic elements and behaviour to a Jupyter Notebook, while Voila allows to have better design and the possibility to run the notebook as if it was a web page, hiding all the code and markdown of the notebook itself.
- Dash. It consists in a point-&-click interface to models written in Python, vastly expanding the notion of what's possible in a traditional "dashboard." It is the main solution for data scientists and engineers in order to put complex Python analytics in the hands of business decision-makers and operators.
- Streamlit. Similar to Dash.

Voila and ipywidgets have been discarded because of the technical requirements needed to run and understand a Jupyter notebook; even if the complexity could have been partially hidden, the graphics component of ipywidgets are not so captivating as it would have been required from a website which main goal was to be easy to use and undestand, while providing a nice design.

Dash and Streamlit are really similar one to another, with both offering beautiful interfaces easy to deploy. Dash has been chosen because of its popularity and presence in the data science applications world, but Streamlit is quite new but in the last years it has gained a lot of popularity and attention.

In all three frameworks, and particularly in Dash, the workflow is pretty similar; the design elements of the UI are defined in an HTML-style using the framework Python libraries predefined classes, while the user-generated events are captured using callback functions, which connect the input elements (e.g. a button which has been clicked) to output elements (e.g. a graph), defining the required processing and manipulation of output elements.

**3.5.2 Cloud hosting** Since the developed webapp prototype shows some potential in finding interesting trends about words, we decided to host the project on a public domain, in order to give anyone the possibility to make queries without a technical knowledge or any installation requirement.

Firstly, many free-to-use hosting sites of Python web applications have been tested, such as PythonAnywhere and Heroku, but all of them allowed a too small free tier, for instance of one gigabyte of disk. Because of the large data that it is used to show the various statistics, to give reference the word embeddings models take up five gigabytes of space, it was not possible to use any of them.

Google Cloud Platform has been chosen to host the webapp. In order to do so, a Docker image has been created, starting from the directory of the webapp. The image has been sent to Google Cloud through a build phase which created an online container of 16GB of memory and 4 CPUs, the last and only combination allowed which permitted also to load all the required files. Google Cloud offers a huge Free Tier, but because of the demanding configuration, the monthly cost is expected to be around three dollars. One downside of the selected hosting method is that the container instance is active only during the period in which requests are served, thus, if no other instance is active, the container has to be launched from an idle state, taking about three or four minutes to be accessible, due to the amount of files that it has to load in order to make all the analysis functionality available.

## 3.6 Interesting findings

We now present a collection of interesting findings with the developed tools. The webapp allows to search for single or combinations of words, and the data on context change and topics can reveal really interesting trends in time.

The first one is about murders, in particular the difference of context between murders involving men and women. In the first case, the topics associated with the combination murder-man are theft related, while in the second case, murder-woman is associated with the sexual victims topic. Searching for murder and rape reveals similarity with kidnaps and robberies.

A second finding is about the context change of the word drug, in fact, the ten year epoch similarity drops between 1940 and 1950, in the first case the

word is associated with groceries, while in the second the word shifted towards a narcotic context.

If we associate the words drug and death we find that overdose is the closets word in term of vector distance.

Another example is the change of context of the word homosexual, in the 60s it is associated with words such as deviate, aggressive, unnatural, while in modern times it refers to sexual orientation.

Analyzing the word assault, we can see that in the 60s it was associated with armed crimes, while in modern days it has a sexual crime context.

Finally, in the most similar words with respect to home and murder combined we can find boyfriend, girlfriend and fiance.

## 4 Concluding remarks

## References

1. Jagarlamudi Jagadeesh, Daumé III Hal and Udupa Raghavendra. ACL 2012. Incorporating Lexical Priors into Topic Models.
2. William L. Hamilton, Jure Leskovec, and Dan Jurafsky. ACL 2016. Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change.