

Sequencing Legal DNA

NLP for Law and Political Economy

12. Legal NLP

`bit.ly/NLP-QA12`

Outline

Tools for Legal NLP

Wrapping Up

Legal Texts

- ▶ Legislation
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 - ▶ hierarchical structure, extensively cross-referenced.

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 - ▶ e.g., tax agency should decide whether a gift counts as income.
- ▶ Judicial opinions
 - ▶ when a dispute arises over the meaning of a statute or regulation, a judge decides.
 - ▶ judge will write an opinion, citing statutes and previous caselaw, explaining the interpretation.

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 - ▶ however:
 - ▶ definitions are often specified elsewhere in the document
 - ▶ extensive and pivotal citations to other documents
 - ▶ when provisions are contested, ambiguity might be used to overcome conflict.

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 - ▶ *In U.S. v. 171-02 Liberty Ave.* (E.D.N.Y. 1989), government seized Greco’s drug den under forfeiture statute for property involved in crime.
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- ▶ Analysis of legal language requires **natural language understanding**.

Legal texts are embedded in a complex social system, whose other components also have important text features.

▶ **Institutions**

- ▶ constitutions/charters/treaties

▶ **Elections and policymaking**

- ▶ campaign ads, parliamentary debates, proposed bills

▶ **Media**

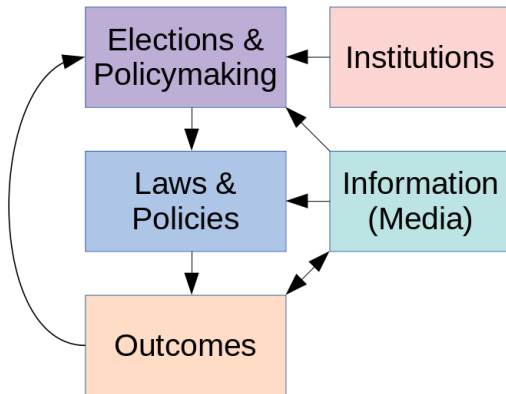
- ▶ newspaper articles, TV transcripts, lobbying, academic research

▶ **Laws and policies**

- ▶ legislation, regulation, judicial opinions

▶ **Outcomes**

- ▶ contracts, culture



Uses of NLP in legal practice

`https://emerj.com/ai-sector-overviews/
ai-in-law-legal-practice-current-applications/`

- ▶ discovery/diligence: find relevant documents during litigation, or during company acquisitions.
- ▶ legal research: find relevant statutes/caselaw to support arguments.
- ▶ contract analysis: document templates, find unusual or missing provisions.
- ▶ question answering: match clients with a lawyer who can answer it
- ▶ judicial analytics: predict judge decisions (not really NLP focused yet)

Argument Mining

Automated extraction of inference structure in natural language (more data is needed)

Argument from example

<i>Premise</i>	In this particular case, the individual a has property F and also property G .
<i>Conclusion</i>	Therefore, generally, if x has property F , then it also has property G .

Argument from cause to effect

<i>Major premise</i>	Generally, if A occurs, then B will (might) occur.
<i>Minor premise</i>	In this case, A occurs (might occur).
<i>Conclusion</i>	Therefore, in this case, B will (might) occur.

Practical reasoning

<i>Major premise</i>	I have a goal G .
<i>Minor premise</i>	Carrying out action A is a means to realize G .
<i>Conclusion</i>	Therefore, I ought (practically speaking) to carry out this action A .

Argument from consequences

<i>Premise</i>	If A is (is not) brought about, good (bad) consequences will (will not) plausibly occur.
<i>Conclusion</i>	Therefore, A should (should not) be brought about.

Argument from verbal classification

<i>Individual premise</i>	a has a particular property F .
<i>Classification premise</i>	For all x , if x has property F , then x can be classified as having property G .
<i>Conclusion</i>	Therefore, a has property G .

Table 1.1: The five most frequent schemes and their definitions in Walton’s scheme-set

Interpreting Black Box Text Classifiers using LIME

1. Generate new texts by randomly *removing* words from the original document.
2. Form predictions \hat{y} from black box model for these perturbed documents.
3. Train lasso on dataset of binary features for each word, equaling one if word appears, to predict \hat{y} .
 - ▶ weight by proximity to initial data point (one minus the proportion of words dropped)

```
exp = explainer.explain_instance(test_example,  
                                classifier.predict_proba, num_features=6)
```

Prediction probabilities

atheism	0.58
christian	0.42

atheism

Posting 0.15
Host 0.14
NNTP 0.11
edu 0.04
have 0.01
There 0.01

christian

Text with highlighted words

From: johnchad@triton.unm.edu (jchadwic)
Subject: Another request for Darwin Fish
Organization: University of New Mexico, Albuquerque
Lines: 11
~~NNTP-Posting-Host~~: triton.unm.edu

Hello Gang,

~~There~~ ~~have~~ been some notes recently asking where to obtain the DARWIN fish.
This is the same question I ~~have~~ and I ~~have~~ not seen an answer on the net. If anyone has a contact please post on the net or email me.

Pragmatics

When a diplomat says yes, he means 'perhaps';

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- ▶ language use depends on the context.
 - ▶ e.g. social identity, relationships, setting, conversation history, shared knowledge...
- ▶ this is mostly unexplored in NLP.

Quote Detection

Automated extraction of quotations and speaker

- ▶ Direct quotations are fully enclosed in quotation marks:
 - ▶ X said, "Taxes will go up next year."
- ▶ Indirect quotations paraphrase the original utterance:
 - ▶ X says that taxes will go up next year.
 - ▶ According to X, taxes will go up next year.
- ▶ Java package: <https://github.com/christianscheible/qsamples>

Speech Acts

Some statements are meant to perform actions

“We hold the defendant guilty.”

“I declare them husband and wife.”

“I bequeath this watch to my brother.”

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- ▶ **assertives** commit a speaker to the truth of the expressed proposition, e.g. reciting a creed
- ▶ **directives** cause the hearer to take a particular action, e.g. requests, commands and advice
- ▶ **commissives** commit a speaker to some future action, e.g. promises and oaths
- ▶ **expressives** express the speaker's attitudes and emotions towards the proposition, e.g. congratulations, excuses and thanks
- ▶ **declarations** change the reality in accord with the proposition of the declaration, e.g. baptisms, pronouncing someone guilty or pronouncing someone husband and wife

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- ▶ Important for legal NLP, but hardly any research about this

“Target-Based Speech Act Classification in Political Campaign Text”

Subramanian, Cohn, and Baldwin (2019), $N = 258$ docs, 6609 sentences:

Utterance	Speech act	Target party	Speaker
Tourism directly and indirectly supports around 38000 jobs in TAS.	<i>assertive</i>	NONE	LABOR
We will invest \$25.4 million to increase forensics and intelligence assets for the Australian Federal Police	<i>commissive-action-specific</i>	LIBERAL	LIBERAL
Labor will prioritise the Metro West project if elected to government.	<i>commissive-action-vague</i>	LABOR	LABOR
A Shorten Labor Government will create 2000 jobs in Adelaide.	<i>commissive-outcome</i>	LABOR	LABOR
Federal Labor today calls on the State Government to commit the final \$75 million to make this project happen.	<i>directive</i>	LIBERAL	LABOR
Good morning everybody.	<i>expressive</i>	NONE	LABOR
The Coalition has already delivered a \$2.5 billion boost to our law enforcement and security agencies.	<i>past-action</i>	LIBERAL	LIBERAL
Malcolm Turnbull's health cuts will rip up to \$1.4 billion out of Australians' pockets every year	<i>verdictive</i>	LIBERAL	LABOR

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Speech act	%	Kappa (κ)
<i>assertive</i>	40.8	0.85
<i>commissive-action-specific</i>	12.4	0.84
<i>commissive-action-vague</i>	6.6	0.73
<i>commissive-outcome</i>	4.9	0.72
<i>directive</i>	1.7	0.92
<i>expressive</i>	1.9	0.88
<i>past-action</i>	6.3	0.76
<i>verdictive</i>	25.4	0.82

Table 3: Speech act agreement statistics

Speech act	MLP _{ELMo}	Our approach
<i>assertive</i>	0.77	0.80
<i>commissive-action-specific</i>	0.65	0.69
<i>commissive-action-vague</i>	0.45	0.48
<i>commissive-outcome</i>	0.28	0.39
<i>directive</i>	0.58	0.59
<i>expressive</i>	0.55	0.58
<i>past-action</i>	0.45	0.48
<i>verdictive</i>	0.48	0.61

Table 6: Speech act class-wise F1 score.

The World's First Robot Lawyer

The DoNotPay app is the home of the world's first robot lawyer. Fight corporations, beat bureaucracy and sue anyone at the press of a button.

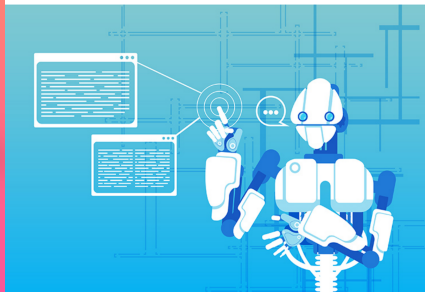
[Sign Up/Login](#)

THINGS YOU CAN DO WITH DONOTPAY

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Your Court-Appointed Chatbot – Is Artificial Intelligence Threatening the Legal Profession?



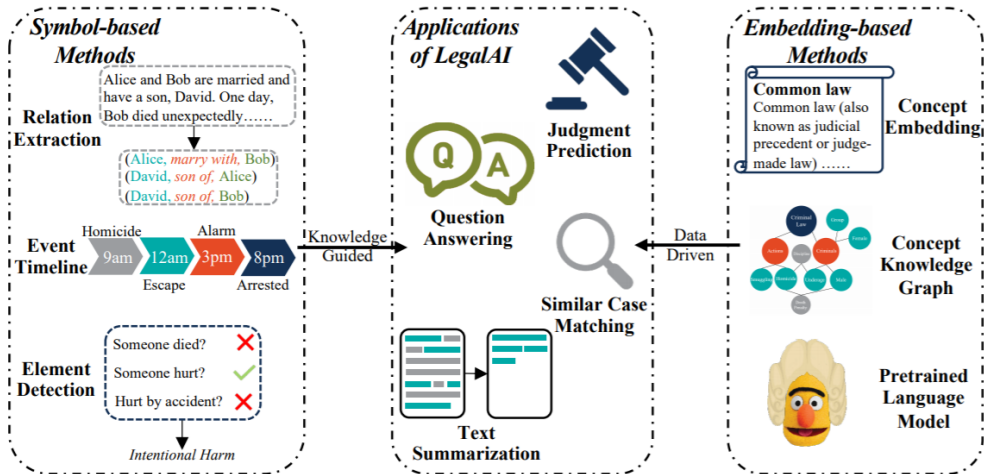


Figure 1: An overview of tasks in LegalAI.

<https://arxiv.org/pdf/2004.12158.pdf>

Dangers of Legal NLP systems

- ▶ We discussed previously how GPT might flood the internet with machine generated text, e.g. fake news
 - ▶ is there a similar risk with legal language models?

Limits of Judicial Support Systems

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- ▶ (Lack of) transparency in judicial support systems:
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- ▶ NLP systems do not generalize to new types of cases.
 - ▶ e.g., judicial prediction systems would not account for new laws/legislation.
- ▶ Teaching a legal NLP system to understand rare evidence, and to understand new laws, would require something much closer to **legal artificial intelligence**.

Legal Vagueness and Value Judgments



- ▶ Even if the AI could read new laws, there is the problem of legal vagueness:
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 - ▶ How will the AI decide in this circumstance?
- ▶ Making choices in the presence of vagueness or indeterminacy requires value judgements.
 - ▶ What counts as a “good” outcome? Is it even measurable?



Philosophical Issues

- ▶ What does it mean to surrender the implementation of legal interpretation and judicial decision making to machines?
- ▶ What are the long-term implications for the system and its adaptiveness to change?
 - ▶ what are the political and cultural impacts?
 - ▶ how does it affect trust in the system and motivation to appeal?

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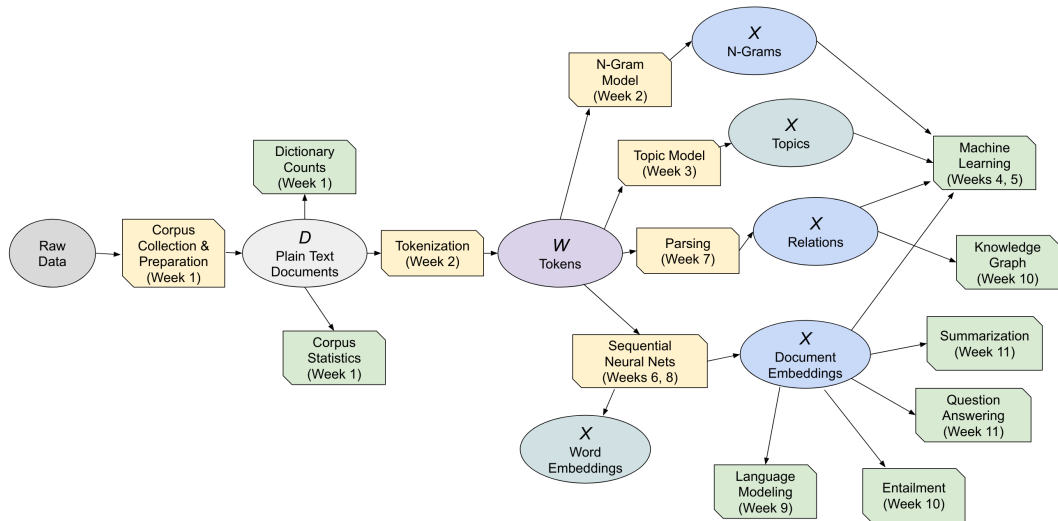
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- ▶ Learning objectives:
 1. **Implement and evaluate natural language processing pipelines.**
 2. **Apply NLP tools to support legal practice.**
 3. **Understand how (not) to use NLP tools for measurement in social science.**



Review Section Next Week

- ▶ We will have a set of practice questions to review for next week.
- ▶ Please post questions, or lists of slide numbers, you would like to review:

<https://padlet.com/eash44/dhaakb2xkgad88jl>

Next Term: “Building a Robot Judge” Course

- ▶ In the fall term, I teach a complementary course focusing on machine learning and causal inference:
 - ▶ “Building a Robot Judge: Data Science for Decision-Making” (851-0760-00L)
- ▶ Not a lot of overlap:
 - ▶ non-text data (tabular datasets, computer vision)
 - ▶ a lot more on causal inference
 - ▶ distinguishing prediction from decision-making
- ▶ Similar setup in terms of course credits:
 - ▶ 3 credits for the lectures/assignments, 2 additional credits for a project.

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