Sequencing Legal DNA

NLP for Law and Political Economy
ETH Zurich, Spring 2021

Welcome to the course!

Instructions before we begin:
(1) Turn on video and set audio to mute
(2) In Participants panel, set zoom name to "Full Name, School, Dept/Major"
(ex: "Leon Smith, ETH Computer Science")
(3) Say "hi" in the chat

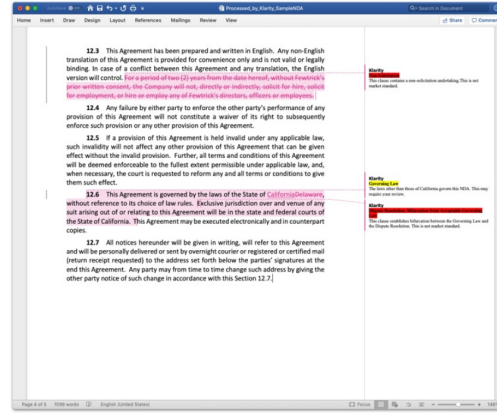
Klarity reviews NDAs under commercial market standard.

👌 Klarity highlights standard language in green.

👀 Language that requires your attention is in yellow.

👿 Non-market standard language and red-flags are in red.

Language that is not marked is boilerplate and doesn't deserve your attention.



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

- Fight Corporations
- Beat Bureaucracy
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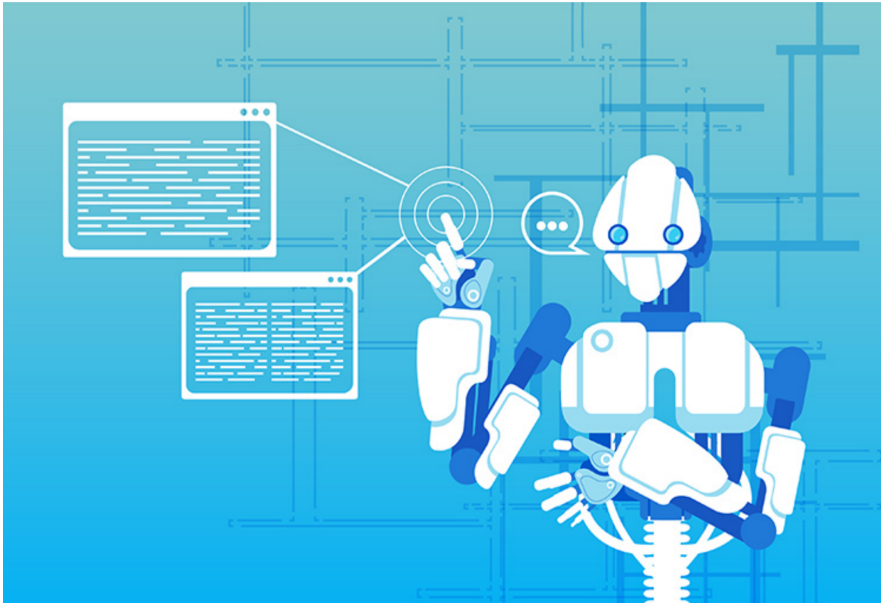
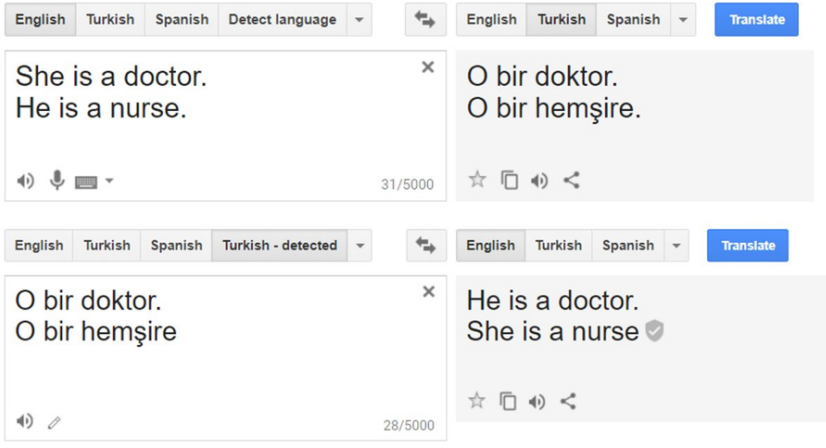
Your Court-Appointed Chatbot – Is Artificial Intelligence Threatening the Legal Profession?



Language Models can be Biased



Source: fastai NLP course.

OPENAI'S NEW MULTITALENTED AI WRITES, TRANSLATES, AND SLANDERS

A step forward in AI text-generation that also spells trouble

By James Vincent | Feb 14, 2019, 12:00pm EST

Howard, co-founder of Fast.AI agrees. “I’ve been trying to warn people about this for a while,” he says. “We have the technology to totally fill Twitter, email, and the web up with reasonable-sounding, context-appropriate prose, which would drown out all other speech and be impossible to filter.”

https://transformer.huggingface.co/doc/distil-gpt2

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- This course focuses on applications of **natural language processing** in **law** and **social science**.

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- Scientific goals:
  - Understand the motivations and decisions of judges and public officials through their writings and speeches.
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- Engineering goals:
  - Develop tools for "sequencing legal DNA" – machine interpretation and generation of legal documents.

What we will do

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4. **Word/document embedding for identifying dimensions of language**.
5. **Discourse analytics – summarization, question answering.**

Why did you sign up for this course?

https://www.menti.com/hxkrdszbyg

- What are your goals for this course?
- What would you like to be able to do better afterward?
- Are you more interested in the data science or social science aspects?

Lecture Times

- Mondays, 1215h-14h, on Zoom.
- ~10 minute break, 13h-1310h

Online Lecture Norms

Let's make the most of online learning!

- Lectures will be recorded, but live attendance is required and absences require permission of instructor.
- Keep video on if connection allows.
- Stay muted when not talking.
- To make questions or comments, use the "raise hand" function.

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- To make questions or comments, use the "raise hand" function.
- We will keep track of course participation through in-class activities (e.g. zoom polls, group work).

Online Course Materials

- Course Syllabus (see chat).
- Course Reading List:
  - `https://bit.ly/NLP-reading-list`
- Course Repo:
  - `https://github.com/elliottash/legal_dna_2021`

Teaching Assistants

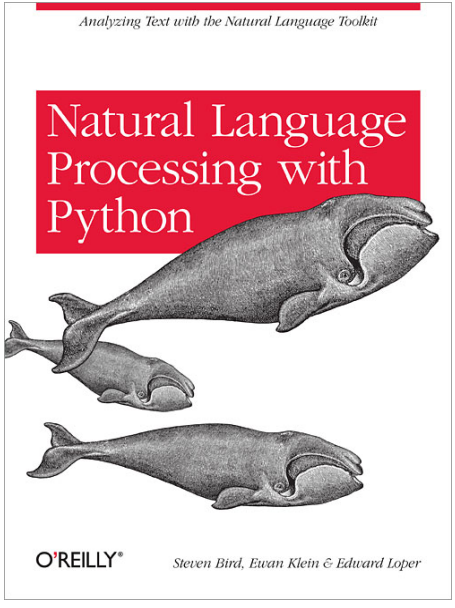
- Dominik Stammbach (dominik.stammbach@gess.ethz.ch)
- Claudia Marangon (claudia.marangon@gess.ethz.ch)
- TA Sessions: Fridays, 2pm-3pm
  - will go over code notebooks, homeworks, and some additional material
  - not mandatory – attend if you are new to the tools.
  - we will also post recordings.
- TA Office Hours: Mondays, 4pm-5pm
  - can answer questions about lectures and notebooks.

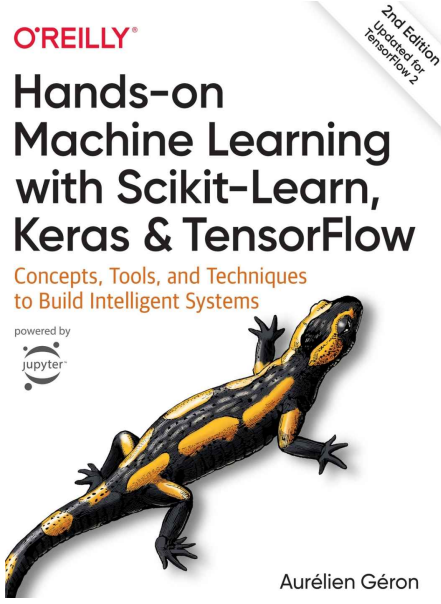
Course Communication

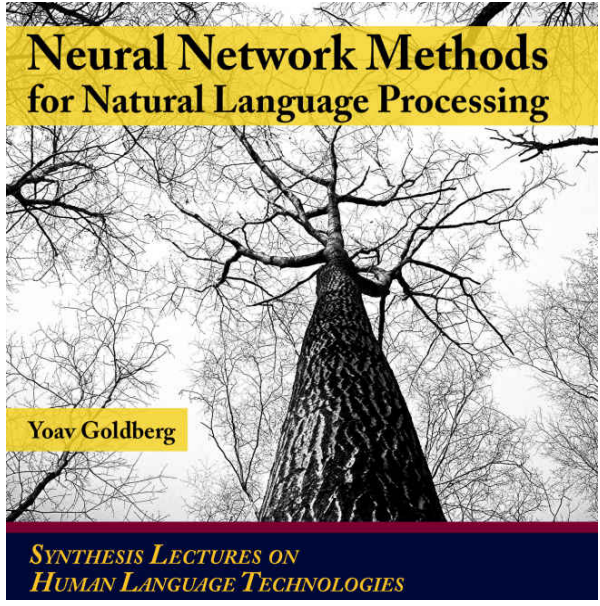
- Course communication will be done through eDoz.
- Post questions/concerns on the weekly course Q&A padlets.
- I will be available in the zoom 5 minutes early, during the mid-lecture break, and for 10 minutes after the end of lecture.
- Will schedule meetings with students doing projects.

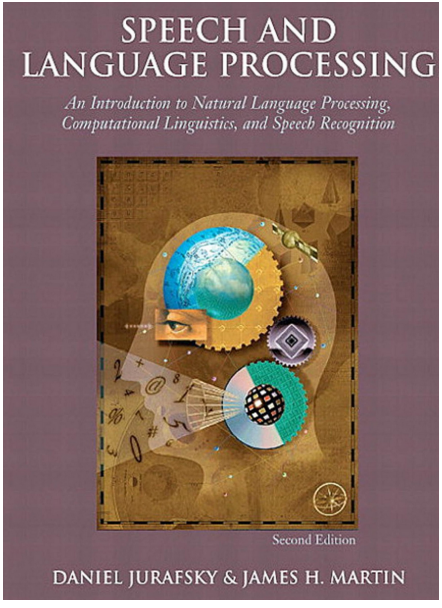
Syllabus has a long readings list

- There are only a couple of required readings (highlighted).
- Other readings can be used as reference:
  - to complement the slides
  - to be used for reading response essays (more next week)
  - lit review for projects


Analyzing Text with the Natural Language Toolkit
Natural Language Processing with Python
O'REILLY®
Steven Bird, Ewan Klein & Edward Loper


O'REILLY
2nd Edition
Updated for TensorFlow 2
Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow
Concepts, Tools, and Techniques to Build Intelligent Systems
powered by
jupyter
Aurélien Géron


Neural Network Methods
for Natural Language Processing
Yoav Goldberg
Synthesis Lectures on
Human Language Technologies


SPEECH AND
LANGUAGE PROCESSING
An Introduction to Natural Language Processing,
Computational Linguistics, and Speech Recognition
Second Edition
DANIEL JURAFSKY & JAMES H. MARTIN

Python is a Course Pre-Requisite

- Python 3 is ideal for text data and natural language processing.
  - Can use Anaconda or download the packages we need to a pip environment.
  - See the syllabus for list of packages we will use.
- In first TA session this Friday, can try to help with setup questions.

Course Workload

3 ECTS credits $\approx$ 90 hours of work

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- 12 lectures, 1.75 hours each $=$ 21 hours
- 10 NLP programming homework assignments, ~1.5 hours each $\approx$ 15 hours
- Required readings (two papers and a few short articles/snippets) $\approx$ 6 hours
- 3 response essays, ~6 hours each $\approx$ 18 hours
- Final assignment / take-home test, 2 hours
- $\approx$ **62 required hours.**

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- $\approx$ 28 hours at student discretion:
  - 12 optional TA sessions, 1 hour each $\approx$ 12 hours
  - leaves ~16 hours for additional study time

Course Projects

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- About twice as much out-of-class work expected
  - previous course projects have turned into conference/journal publications.
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- Information session after Week 2 lecture (~10 minutes)
  - we have a list of potential topic ideas.

Question/Comment Padlets

Question/Comment Padlets

- We have a dedicated question/comment padlet for each lecture week.
- The URL's will be of the form `http://bit.ly/NLP-QA#`, where # is the week number, 2 through 13.
  - e.g. this week is `http://bit.ly/NLP-QA01`
  - e.g. next week is `bit.ly/NLP-QA02`, etc
- Please post things before class, we will go over them at the beginning of each lecture.

Other questions?

Big Data, Big Analytics

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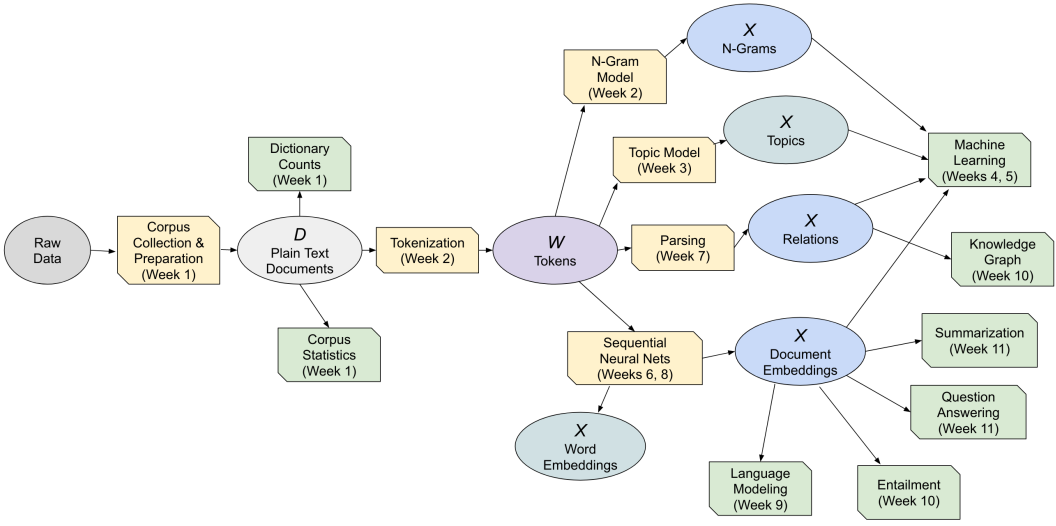
- Where are these trends most salient?
  - **law** and **political economy**
  - The social phenomena of interest – **legal and political institutions** – are composed of thousands, potentially millions, of lines of **unstructured text**.
  - We cannot read them – somehow we must teach the computers to read them for us.


Raw Data
Corpus Collection & Preparation (Week 1)
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Topic Model (Week 3)
X Topics
Parsing (Week 7)
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Sequential Neural Nets (Weeks 6, 8)
X Word Embeddings
X Document Embeddings
Machine Learning (Weeks 4, 5)
Knowledge Graph (Week 10)
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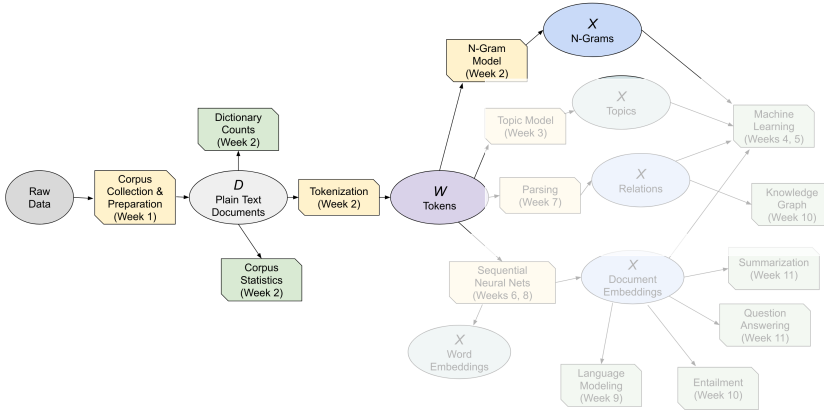
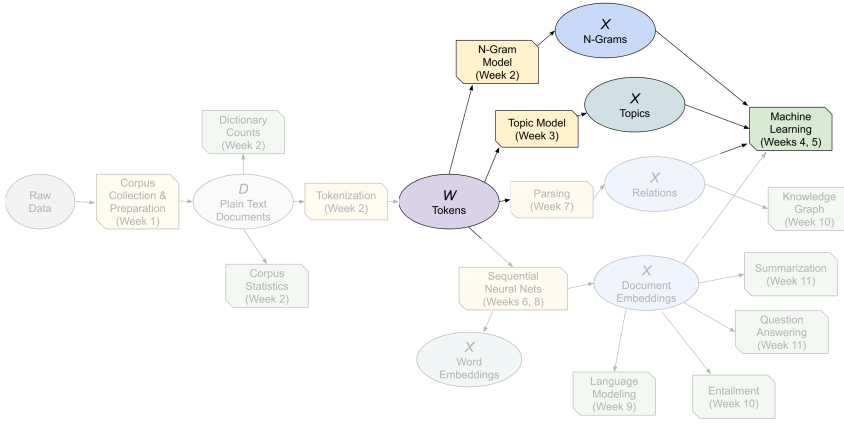
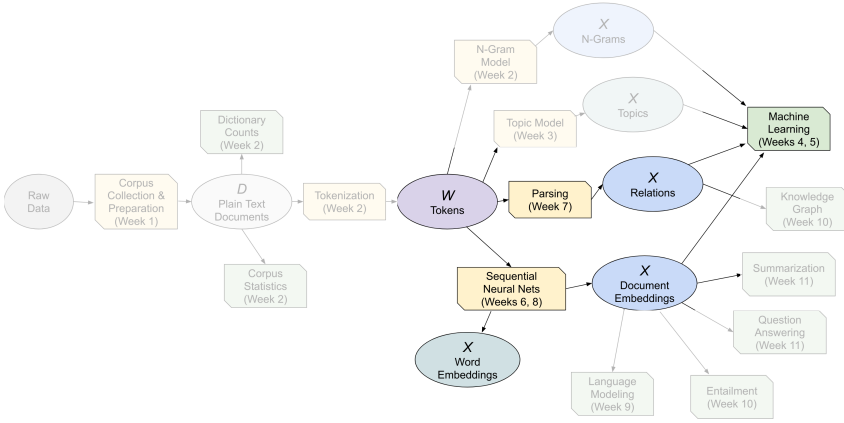


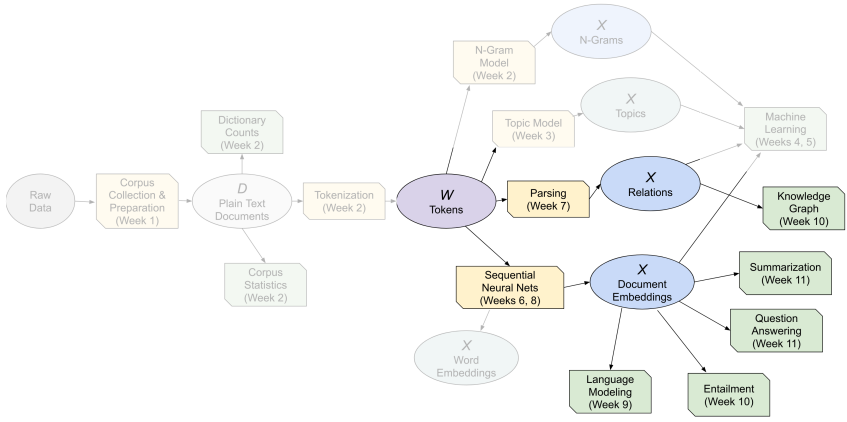
- Week 01 Introduction
  - Intro to Corpora
  - Text Complexity Methods
  - Dictionary Methods
- Week 02 Tokenization
  - N-grams
  - Word pieces
  - Parts of Speech
  - Named Entity Recognition



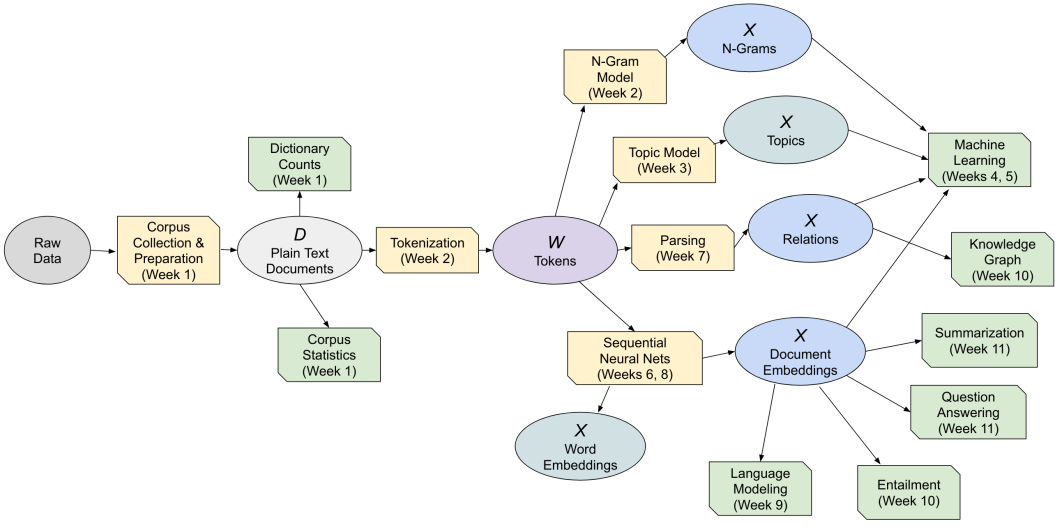
- Week 03 March 8 Dimensionality and Distance
  - SVD
  - NMF
  - Topic Models
  - Text-based ideal points
- Week 04 March 15 Machine Learning for NLP
  - text regression
  - text classification
  - elastic net, logistic regression, xgboost
- Week 05 March 22 Deep Learning for NLP
  - multilayer perceptrons
  - recurrent neural nets



- Week 06 March 29 Word Embeddings
  - word2vec, glove
- Week 07 April 12th Parsing and Relation Extraction
  - syntactic / semantic parsing
  - relation extraction
- Week 08 April 26th Transformer Embeddings
  - birectional transformer architectures (e.g. BERT, RoBerta)
  - document embeddings



- Week 09: May 3rd Language Modeling
  - autoregressive transformers (e.g. GPT)
  - transformer autoencoders (e.g. BART)
  - conditioned generation
- Week 10: May 10th Local Semantics
  - entailment
  - stance detection
  - knowledge graphs
- Week 11: May 17th Global Semantics
  - summarization
  - question answering
  - claim checking
- Week 12: May 31st Causal Inference with Text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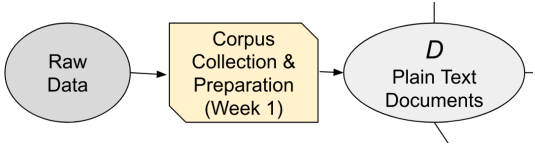
Corpora



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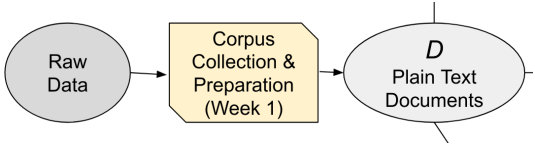

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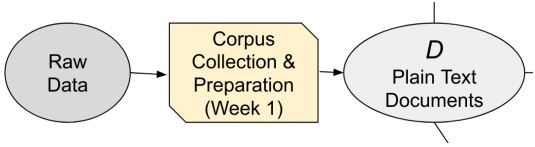

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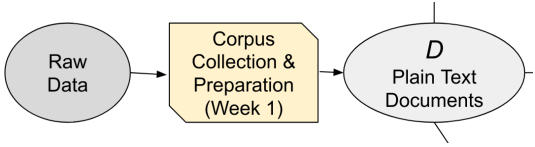

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  - The trick is figuring out how to retain valuable information.
- The tools from Weeks 2 (Tokenization) and 3 (Dimension Reduction) are focused on this step:
  - transforming an unstructured corpus D to a usable matrix X.

What counts as a document?

The unit of analysis (the "document") will vary depending on your question.

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Zoom Poll 1.1

Handling Corpora

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  2. run a web scraper in selenium
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  3. do pre-processing on corpora, e.g. to remove HTML markup, fix errors associated with OCR.
- All of the tools that we discuss in this class are available in many languages, and machine translation is now extremely good and automatable.

Judge Age and Writing Style

Ash, Goessmann, and MacLeod (2021)

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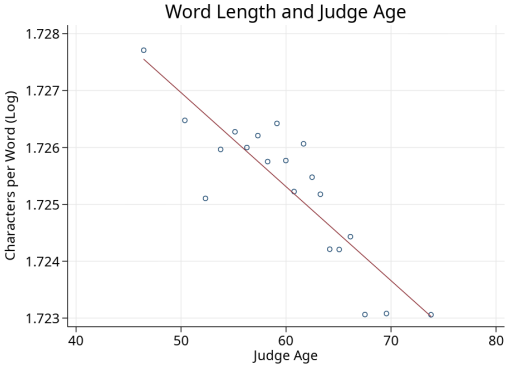

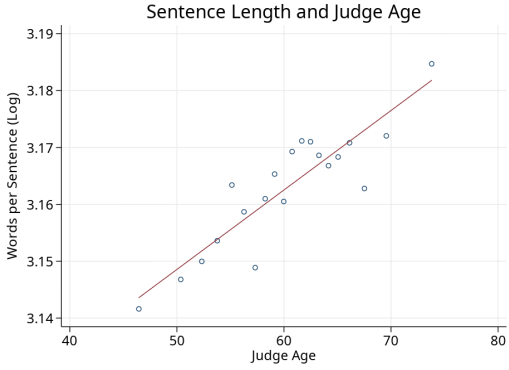

Optimal legal complexity

Katz and Bommarito (2014)

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- More detail is needed in law to properly target incentives to activities and groups.
  - but there are costs to understanding/following complex laws, so there is a trade off.
- Analyzing this issue empirically requires a measure of complexity/detail.
  - e.g., compressing a text file with gzip, and then taking the ratio of the compressed file size to decompressed file size, gives a measure of entropy or structure in the document.

Number of Words $\neq$ Word Entropy

Measuring Complexity (Katz and Bommarito 2014)

Five largest and smallest titles by token count

Title	Tokens	Tokens per section
Public Health and Welfare (Title 42)	2,732,251	369.22
Internal Revenue Code (Title 26)	1,016,995	487.07
Conservation (Title 16)	947,467	200.48
Commerce and Trade (Title 15)	773,819	336.88
Agriculture (Title 7)	751,579	274.00
President (Title 3)	7,564	120.06
Intoxicating Liquors (Title 27)	6,515	144.78
Flag and Seal, Seat of Govt. and the States (Title 4)	5,598	119.11
General Provisions (Title 1)	3,143	80.59
Arbitration (Title 9)	2,489	80.29

Five highest and lowest titles by word entropy

Title	Word entropy
Commerce and Trade (Title 15)	10.80
Public Health and Welfare (Title 42)	10.79
Conservation (Title 16)	10.75
Navigation and Navigable Waters (Title 33)	10.67
Foreign Relations and Intercourse (Title 22)	10.67
Intoxicating Liquors (Title 27)	9.01
President (Title 3)	8.89
National Guard (Title 32)	8.50
General Provisions (Title 1)	8.49
Arbitration (Title 9)	8.24

Overview of Dictionary-Based Methods

- Dictionary-based text methods use a pre-selected list of words or phrases to analyze a corpus.
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  - use regular expressions for this task (see notebook)
- Corpus-specific: counting sets of words or phrases across documents
  - (e.g., number of times a judge says “justice” vs “efficiency”)
- General dictionaries: WordNet, LIWC, MFD, etc.

Measuring uncertainty in macroeconomy

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For each newspaper on each day since 1985, submit the following query:

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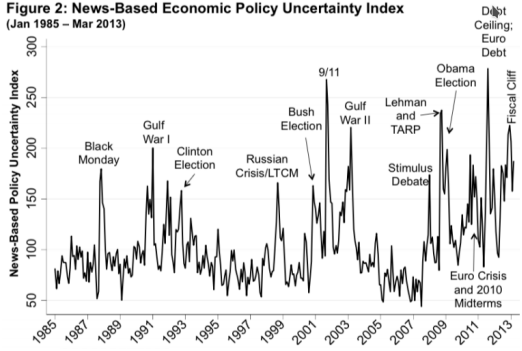

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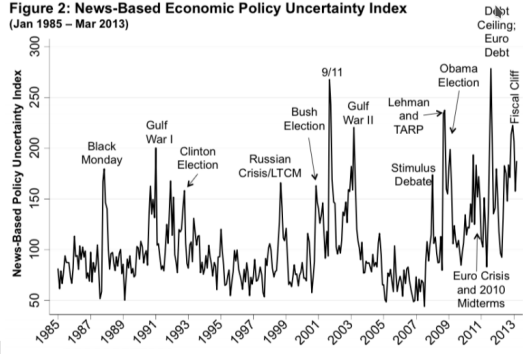

- but see Keith et al (2020), showing some big problems with this measure (`https://arxiv.org/abs/2010.04706`).

Sentiment Analysis

Extract a "tone" dimension – positive, negative neutral

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- standard approach is lexicon-based, but they fail easily: e.g., "good" versus "not good" versus "not very good"
- flair's pre-trained sentiment model uses a context-sensitive neural net
- Off-the-shelf scores designed for online writing – may not work for legal text, for example.
  - Hamilton et al (2016) and Zorn and Rice (2019) show how to make domain-specific sentiment lexicons using word embeddings (more on this later).

WordNet

- English word database: 118K nouns, 12K verbs, 22K adjectives, 5K adverbs

The noun "bass" has 8 senses in WordNet.
1. bass[1] - (the lowest part of the musical range)
2. bass[2], bass part[1] - (the lowest part in polyphonic music)
3. bass[3], basso[1] - (an adult male singer with the lowest voice)
4. sea bass[1], bass[4] - (the lean flesh of a saltwater fish of the family Serranidae)
5. freshwater bass[1], bass[5] - (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
6. bass[6], bass voice[1], basso[2] - (the lowest adult male singing voice)
7. bass[7] - (the member with the lowest range of a family of musical instruments)
8. bass[8] - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

Figure 19.1 A portion of the WordNet 3.0 entry for the noun *bass*.

- Synonym sets (synsets) are a group of near-synonyms, plus a gloss (definition).
  - also contains information on antonyms (opposites), holonyms/meronyms (part-whole).

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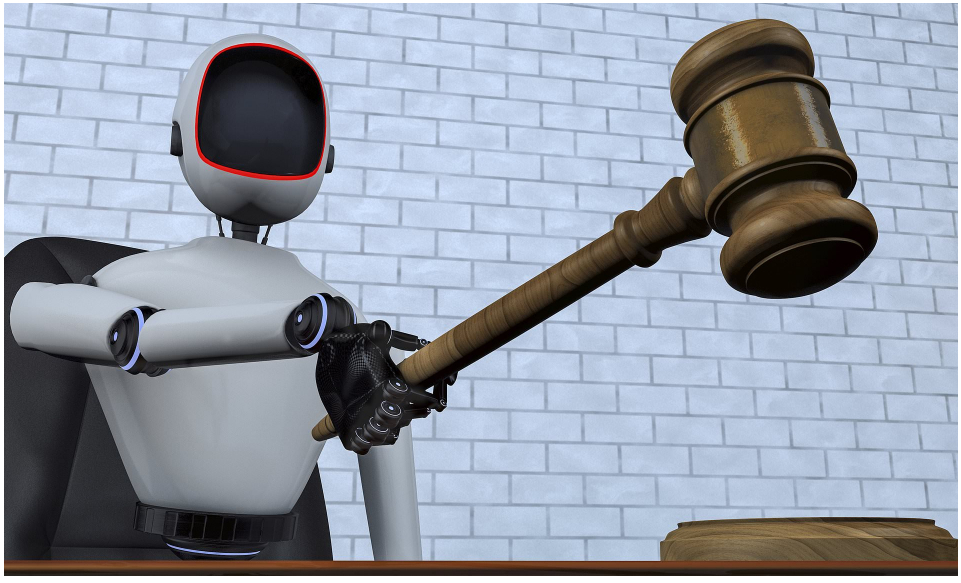
- Mohammad and Turney (2011):
  - code 10,000 words along four emotional dimensions: joy–sadness, anger-fear, trust-disgust, anticipation-surprise
- Warriner et al (2013):
  - code 14,000 words along three emotional dimensions: valence, arousal, dominance.

First Homework Assignment

Homework Assignments Page: `http://bit.ly/NLP-HW`

- First homework: practice with some of the tools we already mentioned in today's lecture.
- to be uploaded via EduFlow on Moodle by next Tuesday March 2nd.
- More info in the example code notebook, and in the first TA session on Friday.



Meeting Adjourned!