Sequencing Legal DNA

NLP for Law and Political Economy

11. Global Semantics

Q&A Page

bit.ly/NLP-QA11

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Machine understanding of text **discourse.**

- good summaries of long texts: extraction of relevant information, discarding of irrelevant information.
- question answering: retrieving evidence and answers from large corpora
- storytelling: enriched text generation that understands characters and their relationships.

Outline

Knowledge Graphs

- A structured graph representing facts (and assertions?) as tuples.
- Entities are nodes, relations are edges:
  - (head entity, relation, tail entity)

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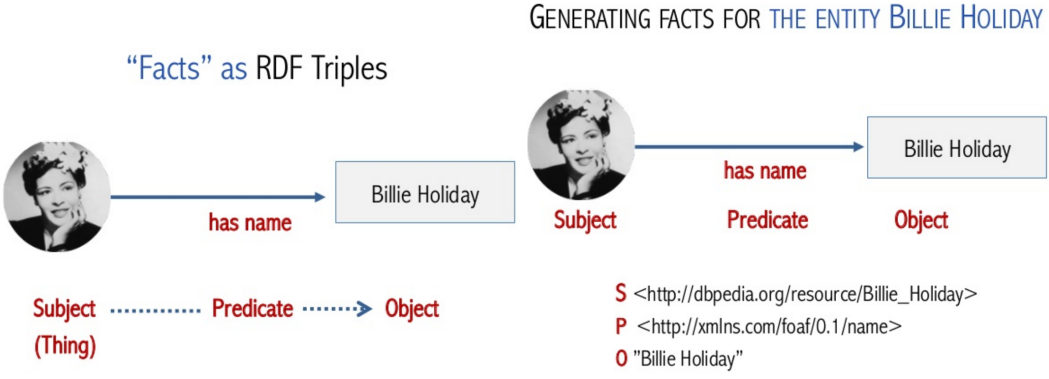
- E.g., DBPedia: crowd-sourced effort to extract structured information from Wikipedia and make it available as linked open data.



Relation Extraction

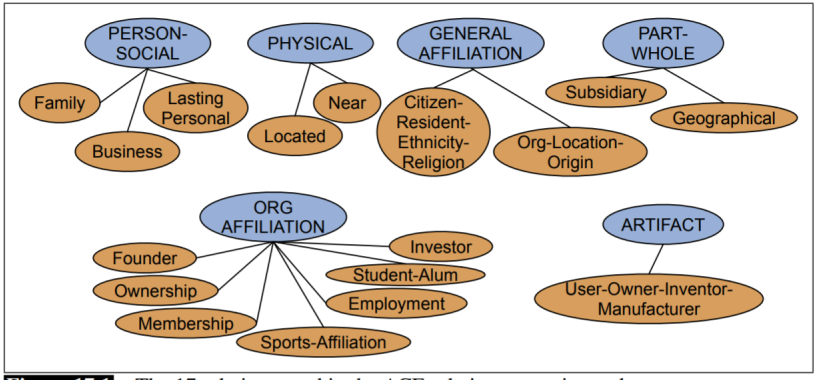


Figure 17.1 The 17 relations used in the ACE relation extraction task.

Relations	Types	Examples
Physical-Located	PER-GPE	**He** was in **Tennessee**
Part-Whole-Subsidiary	ORG-ORG	**XYZ**, the parent company of **ABC**
Person-Social-Family	PER-PER	**Yoko**'s husband **John**
Org-AFF-Founder	PER-ORG	**Steve Jobs**, co-founder of **Apple**...

Figure 17.2 Semantic relations with examples and the named entity types they involve.

Information Extraction

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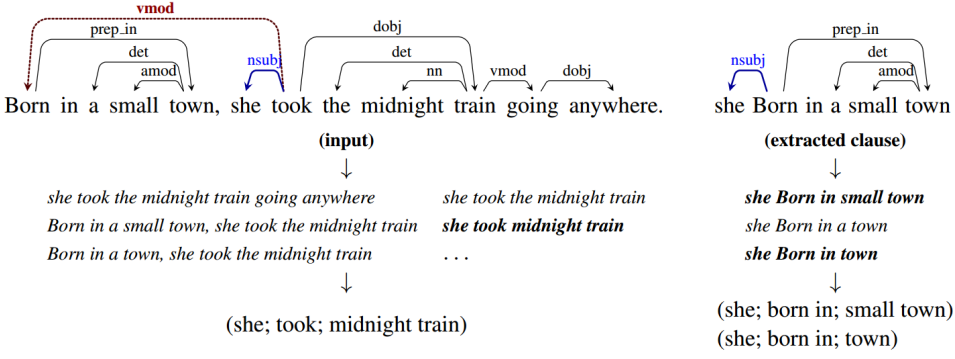
- Manual information extraction is too costly.
- Can use relation extraction from text to fill in the knowledge graph.
- Rule-based approach:
  - use dependency parse to extract relations (e.g. Bank et al 2007, Fader et al 2011, Angeli et al 2015):



  - filters: relation must contain a predicate; subject and object must be noun phrases.
  - thresholds: aggregate over large corpora and keep only frequent (therefore potentially reliable) relations.

Soares et al (2019): Contrastive Learning for Relations

- English Wikipedia:
  - use named entity recognition and co-reference resolution to assign unique ID's.
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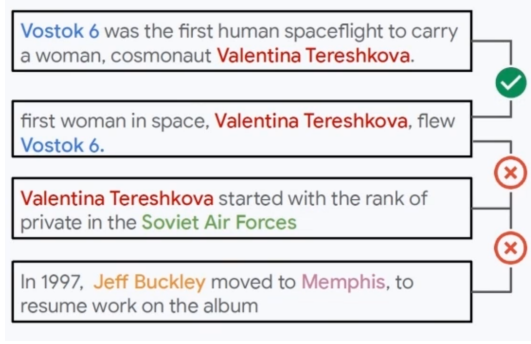
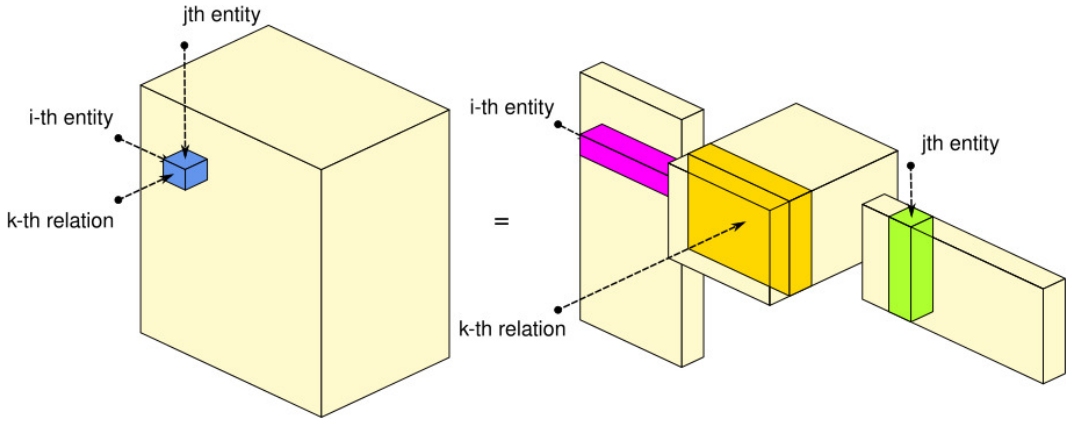
Negative sampling objective:

- Positive samples:
  - statements with the same two entities
- Negative samples:
  - same entity, one other entity
  - two different entities



Knowledge Graph Embeddings



- Many proposed approaches for embedding KG entities, for example by predicting the presence of a bilateral relation.

Learning from Knowledge Graph Relations

- Knowledge graph embeddings can be used to fill in missing relations.

e.g., parents of a person are often married, so

(John, parent of, Anne) + (Mary, parent of, Anne) $\rightarrow$ (John, married to, Mary)

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EXAMPLES OF PATHS LEARNED BY PRA ON FREEBASE TO PREDICT WHICH COLLEGE A PERSON ATTENDED

Relation Path	F1	Prec	Rec	Weight
(draftedBy, school)	0.03	1.0	0.01	2.62
(sibling(s), sibling, education, institution)	0.05	0.55	0.02	1.88
(spouse(s), spouse, education, institution)	0.06	0.41	0.02	1.87
(parents, education, institution)	0.04	0.29	0.02	1.37
(children, education, institution)	0.05	0.21	0.02	1.85
(placeOfBirth, peopleBornHere, education)	0.13	0.1	0.38	6.4
(type, instance, education, institution)	0.05	0.04	0.34	1.74
(profession, peopleWithProf., edu., inst.)	0.04	0.03	0.33	2.19

Language models and knowledge graphs

Hayashi et al (2019):

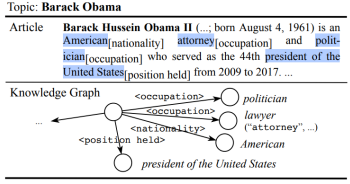

Figure 1: Overview of our task of language modeling conditioned on structured knowledge. For a given topic, we want to learn an LM that leverages the knowledge graph through relations when modeling the text.

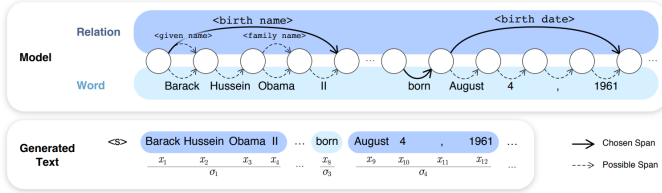

Figure 2: While generating, our model switches between the two sources, namely "Relation" and "Word". Nodes represent hidden states up to each token, and edges represent possible span matches, *i.e.*, choice of latent variables. In this example, we show one choice of latent variables with solid lines, and other options as dashed lines. We also show an "annotation" of the token sequence by the spans and sources we choose.

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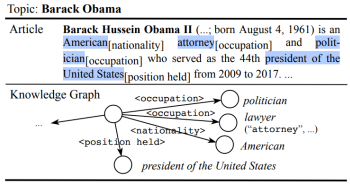

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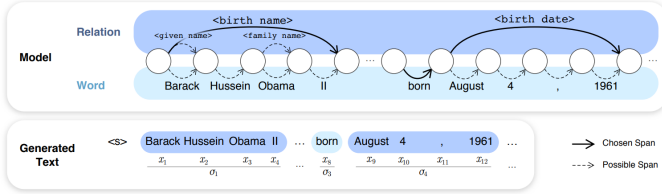

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Wang et al (2020):

- Language models *are* knowledge graphs
- iterate over entity pairs, search LM attention weights for highest-probability phrase that connect them.
- construct / complete knowledge graph with these LM outputs.

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The Problem with BERT/GPT

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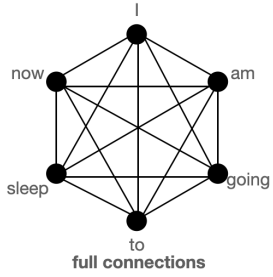

$$h_i = \sum_{j=1}^{n_L} a(x_i, x_j) x_j, \forall i \in \{1, ..., n_L\}$$

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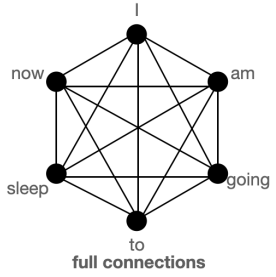

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- Long-document transformers like BigBird try to approximate fully connected attention while enforcing sparsity between some/most tokens.

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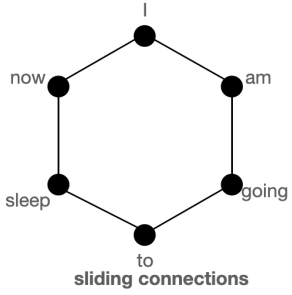

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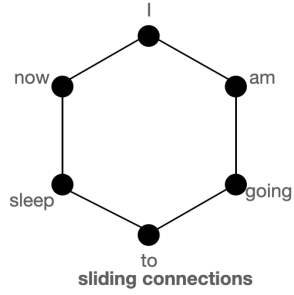

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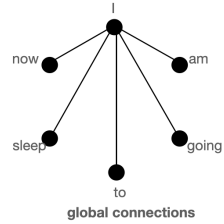

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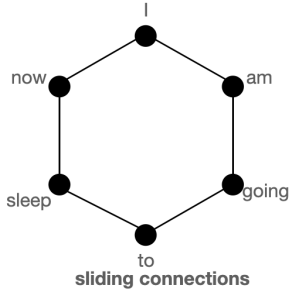

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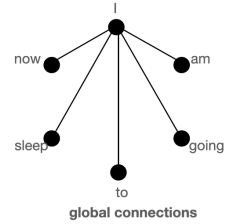

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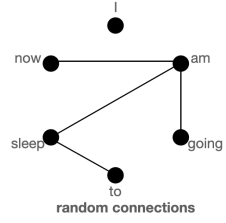

(3) Pick some random tokens j to be included in $a(\cdot)$.

BigBird's Block Sparse Attention

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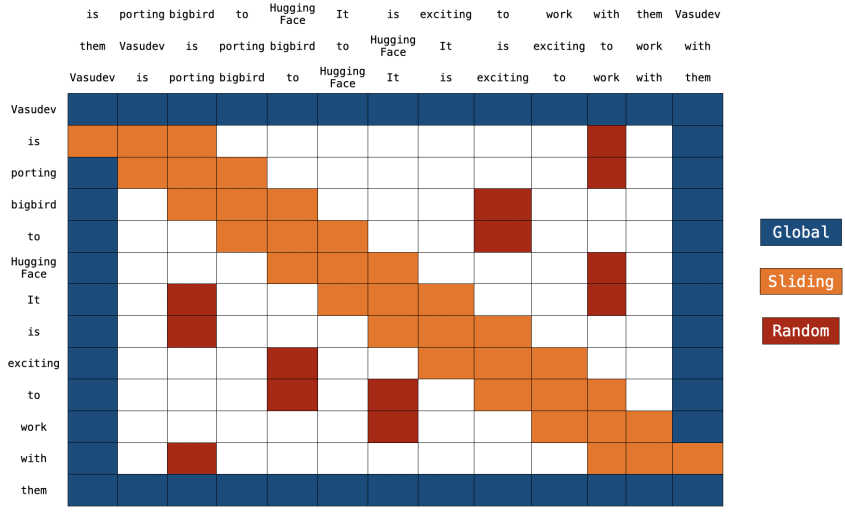


- Block sparse attention is an efficient implementation of these three alternative attention mechanisms: Each token attends to sliding tokens, some global tokens, & some random tokens.
- Extends the context window from 512 tokens to 4096 tokens, superior on long-document tasks.

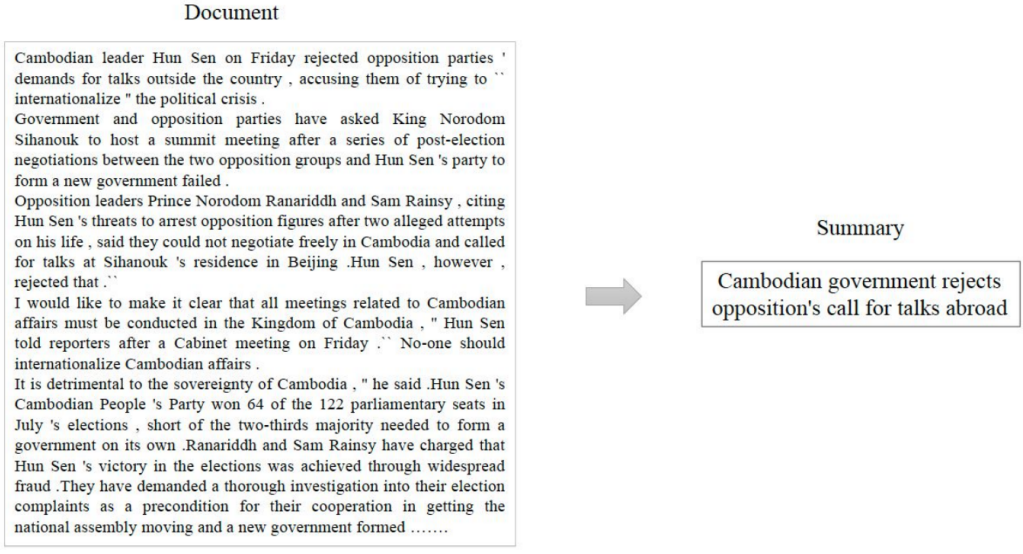
Outline

Text Summarization

Goal: produce a shorter version of a text that contains the most relevant or important information.

- obvious applications in law / legal practice.
- not proven: dimension reduction or information extraction for social science measurement.

Single Document Summarization



Source: Chan Young Park, Dan Jurafsky Slides

- **Extractive summarization:**
  - create the summary from phrases or sentences in the source document(s)
  - SOTA: Fine-tune BERT on corpora to predict predict start and end tokens of annotated summary sentences.

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- **Abstractive summarization:**
  - express the ideas in the source documents using (at least in part) different words
  - SOTA: fine-tune **Big Bird Pegasus** to reconstruct provided summaries.

Summarization with Human Feedback (Stiennon et al 2020)

Collect a large, high-quality dataset of human comparisons between summaries, train a model to predict the human-preferred summary, and use that model as a reward function to fine-tune a summarization policy using reinforcement learning

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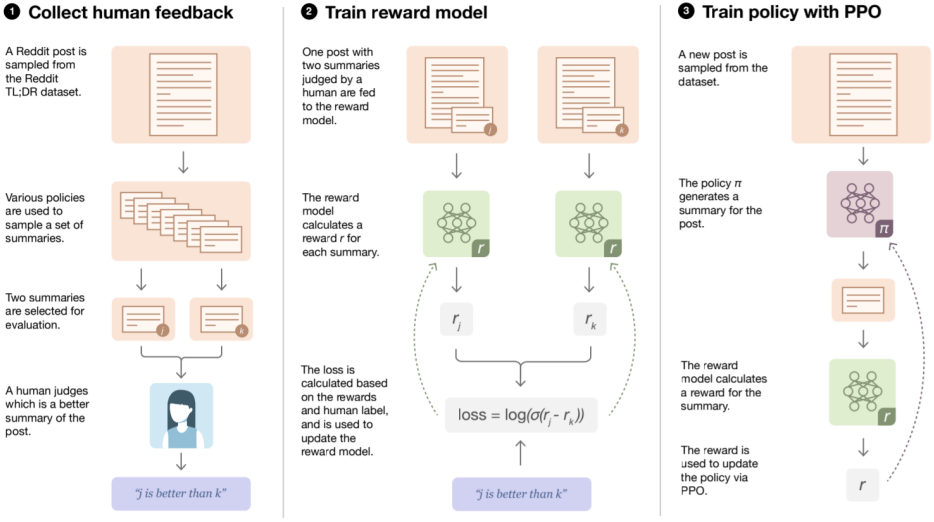
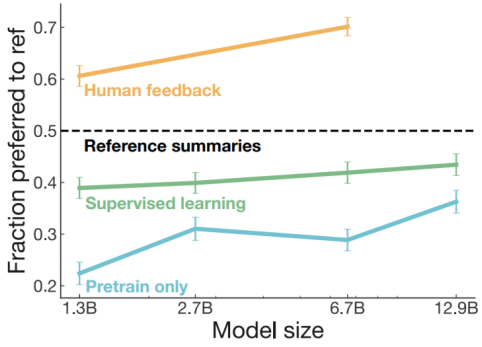


Figure 2: Diagram of our human feedback, reward model training, and policy training procedure.



[r/dating_advice] **First date ever, going to the beach. Would like some tips**
Hey Reddit! I (20M) would like some tips, because I have my first ever date tomorrow (although I've had a gf for 3 years, but no actual dating happened), and we're going to the beach.

I met this girl, we have mutual friends, at a festival a few days ago. We didn't kiss, but we talked, held hands, danced a bit. I asked her to go on a date with me, which was super hard as it is the first time I've asked this to anybody. What I mean to say is, it's not like a standard *first* date because we already spent some time together.

I'm really nervous and excited. I'm going to pick her up tomorrow, we're cycling to the beach which will take 30 minutes, and then what? I'm a bit scared. Should I bring something (the weather, although no rain and sunny, is not super so no swimming), should we do something. I'd like all the tips I can get. Thanks!

Human written reference TL;DR	**6.7B supervised model**	**6.7B human feedback model**
First date after 3 years in a relationship, going to the beach, terrified. What to bring with me, what to do?	Going on a date with a girl I met a few days ago, going to the beach. What should I bring, what should we do?	Going on my first ever date tomorrow, cycling to the beach. Would like some tips on what to do and bring. I'm a bit nervous and excited. Thanks!

Table 1: Example of post and samples on the TL;DR dataset, chosen to be particularly short. For random samples (along with posts), see Appendix H and our website.

Outline

Open Question Answering and Claim Verification

Perhaps the most difficult global semantics tasks:

- Open question answering:
  - Answer any question.
  - "What are the responsibilities of the mayor of Zurich?"
- Open claim verification:
  - Check whether a plain-text claim is true or false.
  - "Zurich has the highest per-capita income of any city in Europe."

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- Open claim verification:
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  - "Zurich has the highest per-capita income of any city in Europe."
- Both problems are solved using information retrieval pipelines:
  - search large corpora or knowledge graphs for evidence
  - use evidence to answer the question or check the claim

Information Retrieval for Question Answering

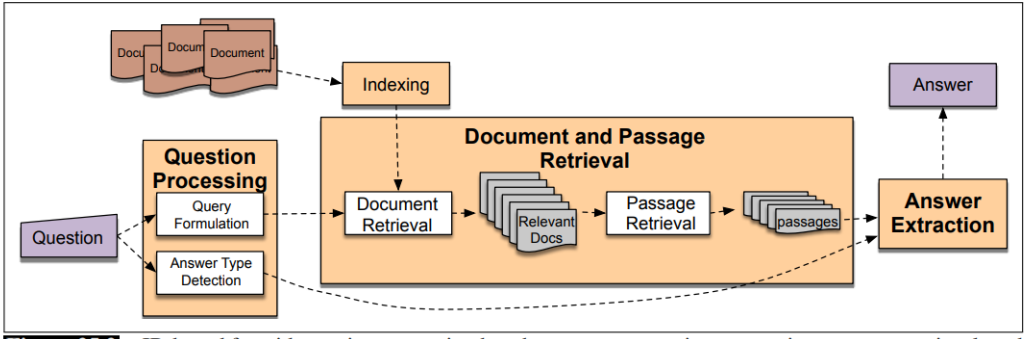

Figure 25.2 IR-based factoid question answering has three stages: question processing, passage retrieval, and answer processing.

- e.g., IBM Watson is a fast search engine over a knowledge base.

Automated Claim Verification

Claim *(by Minister Shailesh Vara)*
"The average criminal bar barrister working full-time is earning some £84,000."
Verdict: FALSE *(by Channel 4 Fact Check)*
The figures the Ministry of Justice have stressed this week seem decidedly dodgy. Even if you do want to use the figures, once you take away the many overheads self-employed advocates have to pay you are left with a middling sum of money.

1. Claim spotting (what to fact check – facts vs opinions, etc)
2. Evidence retrieval
3. Evidence filtering
4. Fact-check claim given evidence (textual entailment)

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- Problem: requires exact word overlap (not synonyms).
  - alternatives use embeddings, e.g. S-BERT (but separate problem of how to encode long documents).
  - then can do fast approximate search over dense vectors (e.g. Faiss, Johnson et al 2017)
  - BM25 still usually does better, but this is being actively researched

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- Claim verification:
  - take retrieved evidence as the premise, and the claim as the hypothesis, and do textual entailment (also like in Week 10).

How can we use global semantics in social science?

Group Activity

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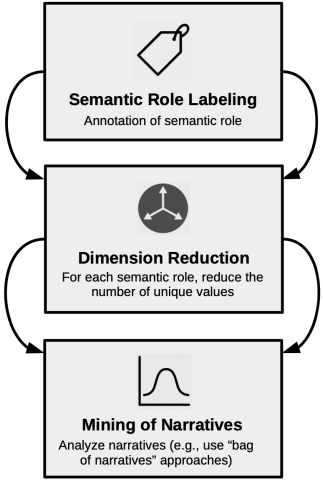
- But relative to the other tasks, it is not well-researched.
- Meanwhile, "narratives" are also of major interest in social science, e.g. political economy:

"Higher taxes will hurt the economy."

"Immigrants steal our jobs."

"Murderers deserve the death penalty."

Ash, Gauthier, and Widmer (2021), "Mining Narratives from Large Text Corpora"



Methods Review: Text Data in Social Science

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- **TF-IDF with clustering**: e.g., Hoberg and Phillips (JPE 2016), categorizing industries in SEC filings to measure concentration.
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- **Supervised learning to scale a dimension in text**: e.g. Gentzkow and Shapiro (Ema 2010), Gentzkow, Shapiro, and Taddy (Ema 2019), measuring partisanship of language in congressional speeches / newspapers; Osabruegge, Ash, and Morelli (PA 2021) doing cross-domain topic classification in political text.
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- **Semantic role labeling**, extracting agents, actions, patients, and attributes (**Ash, Gauthier, and Widmer 2021**).

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- We decompose each statement S_j into a role sequence:

$$S_j = \{\text{Agent},\ \text{Negation},\ \text{Verb},\ \text{Patient}\}$$

Main Challenge: High Dimensionality

Summary statistics from U.S. Congressional Record

	All narratives	**Complete narratives**
Sentences	6,405,907	1,456,308
Statements	27,157,787	2,045,488
Agents, raw	4,000,807	2,045,481
Agents, raw unique	706,332	412,061
Patients, raw	13,111,368	2,045,487
Patients, raw unique	3,543,212	758,804
Verbs, raw (cf. statements)	27,157,787	2,045,488
Verbs, raw unique	24,807	10,788

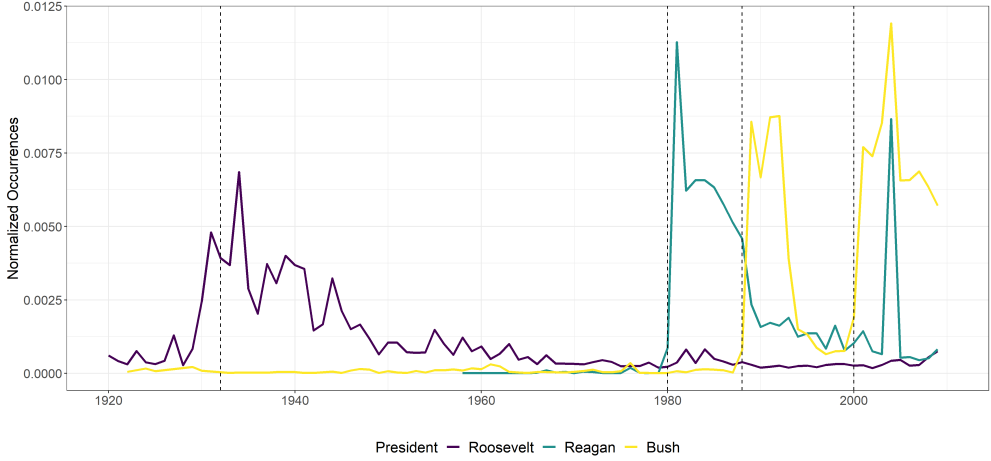
Dimension Reduction: Verbs (Dictionary Approach)

- Replace verbs by their most common synonym (from WordNet)
  - "**make**": make, create, produce, establish, build, ...
  - "**provide**": provide, offer, furnish, cater, ...
  - "**use**": use, employ, utilize, expend, habituate, ...
- Where possible, replace negated verbs by their (non-negated) most common antonym
  - **Example**: "can't find job" becomes "lose job"

Verb	Count
make	2374401
take	1055386
see	482254
provide	462867
give	377449
go	299348
have	287331
get	215879
do	206180
use	204300

Dimension Reduction: Agents and Patients (NER)

- Identify named entities using spaCy
- Replace the 500 most frequent named entities (personalities, places, ...) by a unique token



Dimension Reduction: Agents and Patients (Embedding Clusters)

Take agent/patient phrases that are not captured by NER:

- Encode each (e.g., “health care”, "income tax credit") as phrase embedding
- Train k-means clustering on phrase embeddings (batch of 50,000 speeches)
  - $\rightarrow$ 500 additional entity clusters
- Labeled by the most frequent token in the cluster

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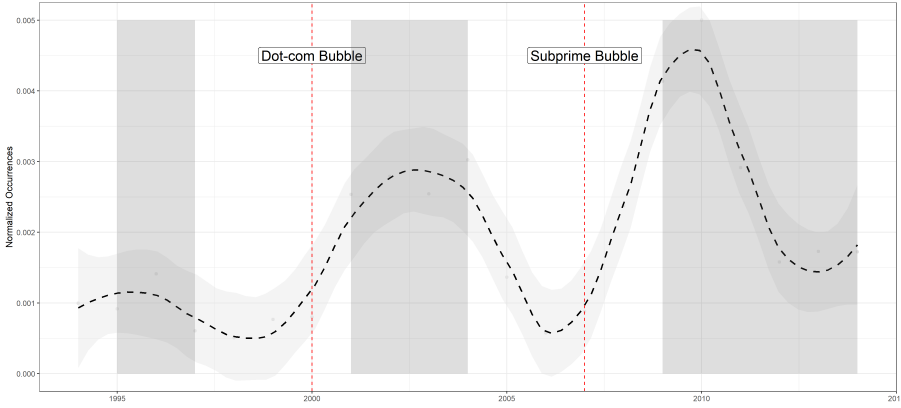
- “**american**”: american people, million american, american taxpayer, many american, american public, every american, american citizen, american family, american worker
- “**government**”: government, local government, federal government, government official, american government, government employee, government operation, branch government
- “**job**”: job, good job, million job, american job, outstanding job, great job, job do, excellent job, job creation, do job
- “**money**”: money, great money, percent money, tax money, public money, monies, good money, people money, make money, use money

Agent	Count	Patient	Count
president	310228	job	144314
people	298532	do	115236
american	218049	be	112563
man	215616	thing	90334
government	174977	money	87056
anyone	161031	service	86167
administration	124774	call	84745
company	121730	american	84220
law	105464	matter	83270
program	101246	family	77324

Raw sentences and their mined narratives

- "President, I think the administration has begun to address the overseas basing issue."
  $\rightarrow$ (administration, address, foreign policy)
- "As always, God bless and protect our troops and their families."
  $\rightarrow$ (god, bless, troop)
  $\rightarrow$ (god, protect, troop)
- "We need to pay attention to agriculture and the survival of the family farm as other countries protect and subsidize their farmers."
  $\rightarrow$ (country, protect, farmer)
  $\rightarrow$ (country, subsidize, farmer)

Narratives Capture Major Events: "people lose job" and Economic Crises



Narratives Capture Political Partisanship

Top Democrat Narrative Statements			
Agent	**Verb**	**Patient**	**Odds Ratio**
people	make	billions	8.92
company	denies	benefits	7.33
medicare	benefits	a lot	5.80
president bush	took	government	4.42
worker	lost	job	4.40
agency	receives	grant	3.18
children	have	benefit	3.06
people	lost	job	2.95
people	make	year	2.850
millions of americans	lost	job	2.785

Top Republican Narrative Statements			
Agent	**Verb**	**Patient**	**Odds Ratio**
government	borrows	money	0.471
president	balanced	budget	0.464
americans	pay	tax	0.461
god	bless	country	0.457
president	made	hearings	0.456
citizens	abide	law	0.448
government	sponsors	economy	0.435
people	buy	benefits	0.429
act	appropriates	fund	0.416
doctor	takes	care	0.406

Narratives as Worldviews

- At the document or speaker level, we obtain a list of relationships between entities.
- This list may also be represented as an adjacency matrix (network representation).
- The resulting graphs uncover the broader connections between narratives.

`https://sites.google.com/view/trump-narratives/accueil`