Natural Language Processing for Law and Social Science

5. Word Embeddings

In-Class Presentation: Ash, Jacobs, MacLeod, Naidu, and Stammbach (2020) "Unsupervised extraction of rights and duties from collective bargaining agreements"

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6. Answer the research question!

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  - the vector of features, $\boldsymbol{x}_i$, is itself a compressed representation of the unprocessed document $\mathcal{D}_i$.
- Further: the learned parameters $\hat{\theta}$ can also be understood as a **learned compressed representation of the whole dataset**:
  - it contains information about the training corpus, the text features, and the outcome classes.

Information in $\hat{\theta}$

Say we train a multinomial logistic regression on a bag-of-words representation $\boldsymbol{x}_i$ to predict classes $\boldsymbol{y}_i$:

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- θ is an interesting object. How can we use it?
- e.g.:
  - cluster the column vectors $\rightarrow$ which outcome classes are similar/related.
  - cluster the row vectors $\rightarrow$ which input features are similar/related.

$\hat{\theta}$ Contains Word Embeddings

$\theta =$ matrix of parameters learned from logit, relating words to outcomes.

- If $\boldsymbol{x}$ is a bag-of-words representation for a document consisting of a list of tokens $\{w_1, ..., w_t, ..., w_n\}$, we can write

$$\boldsymbol{x} = \frac{1}{n}\sum_{t=1}^{n} x_t$$

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- We can construct a **document vector**

$$\vec{\boldsymbol{d}} = \frac{1}{n}\sum_{t=1}^{n_i} \theta_t$$

  the sum of the n_y-dimensional word representations (the row vectors from above).

  - this is called the "continuous bag of words (CBOW)" representation (Goldberg 2017).
  - Note that $\vec{\boldsymbol{d}} = \theta \cdot \boldsymbol{x}$, we thus call θ a **word embedding matrix**.

Outline

Word Embedding with Local Context

- "Word embeddings" often refer to Word2Vec or GloVe – these are particular (popular) models for producing word embeddings.
  - the goal: represent the meaning of words by the neighboring words – their **contexts**.
  - these models get good performance on a range of similarity, analogy, and prediction tasks.

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  - these models get good performance on a range of similarity, analogy, and prediction tasks.
- "You shall know a word by the company it keeps":
  - "He filled the **wampimuk**, passed it around and we all drunk some."
  - "We found a little, hairy **wampimuk** sleeping behind the tree."

Words and Contexts

A long line of NLP research aims to capture the distributional properties of words using a **word-context matrix** $\boldsymbol{M}$:

- each row w represents a **word** (e.g. "income"), each column c represents a linguistic **context** in which words can occur (e.g. "corporate ___ tax").
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  - A matrix entry $\boldsymbol{M}_{[w,c]}$ quantifies the strength of association between a word and a context in a large corpus.
- each word (row) $\boldsymbol{M}_{[w,:]}$ gives a distribution over contexts.
  - different definitions of contexts and different measures of association $\rightarrow$ different types of **word vectors**.
  - these vectors often have a **spatial interpretation** $\rightarrow$ geometric distances between word vectors reflect semantic distances between words.

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  - ...
- Etc.

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- Better: **Point-wise mutual information** (PMI):

$$f_M(w,c) = \frac{\Pr(w,c)}{\Pr(w)\Pr(c)} = \frac{\frac{\#(w,c)}{n_D}}{\frac{\#(w)}{n_D}\frac{\#(c)}{n_D}} = \frac{n_D\#(w,c)}{\#(w)\#(c)}$$

where $\#(w)$ and $\#(c)$ are the corpus counts for w and c, respectively.

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- $\boldsymbol{M}$ is $n_w \times n_c$
  - if c is drawn from from the vocabulary of a reasonably large corpus, the associated word vectors $\{v_1 = \boldsymbol{M}_{[w_1,:]}, v_2 = \boldsymbol{M}_{[w_2,:]}, \ldots\}$ are too high-dimensional to be useful.

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  - dense, rather than sparse.
- **similarity measures between rows of $\boldsymbol{W}$ approximate similarity measures between rows of $\boldsymbol{M}$**

GloVe Embeddings

Pennington et al (2014) (GloVe = Global Vectors) learns vectors without a neural net

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Learn word vectors $\boldsymbol{w} = (w_1, ..., w_i, ..., w_{n_w})$, initialized randomly and $w_i \in (-1, 1)^{n_E}$, to solve

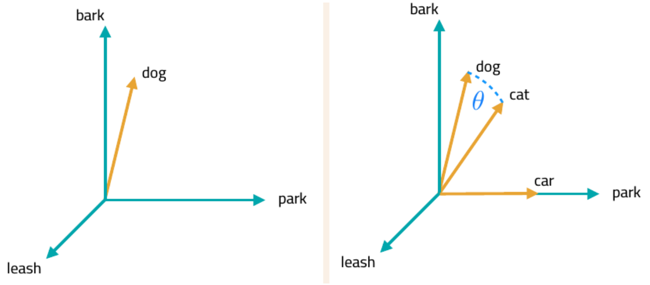
$$\min_{\boldsymbol{w}} \sum_{i,j} f(C_{ij}) \left(w_i^T w_j - \log(C_{ij}) \right)^2$$

where $f(\cdot)$ is weighting function to down-weight frequent words.

- Minimizes **squared difference** between**:**
  - **dot product of word vectors,** $w_i^T w_j$
  - **empirical co-occurrence,** $\log(C_{ij})$
    [Arora et al (2016) put the PMI here instead of co-occurence counts]
- Intuitively: words that co-occur should have high correlation (dot product)

Word Similarity

- Once words are represented as vectors, we can use linear algebra to understand the relationships between words:
  - Words that are geometrically close to each other are similar: e.g. "dog" and "cat":



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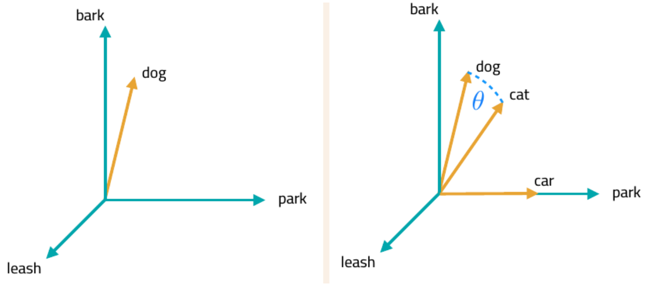

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- Thanks to linearity, can compute similarities between groups of words by averaging the groups.

In-Class Presentation: Gennaro and Ash (EJ 2022)

Outline

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- Embeddings:
  - PCA reductions of the word count vectors
  - LDA topic shares

Categorical Embeddings = dense representations of categorical variables

Say we have a binary classification problem with outcome Y:

- we have a high-dimensonal categorical variable (e.g. area of law with 1000 categories)
- including dummy variables A for each category in your ML model is computationally expensive.

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(2) is similar to what embedding layers do in neural nets.

In deep learning, an embedding layer is matrix multiplication:

$$\underbrace{h_1}_{n_E \times 1} = \underbrace{\omega_E}_{n_E \times n_w} \cdot \underbrace{x}_{n_x \times 1}$$

- x = a categorical variable (e.g., representing a word)
  - one-hot vector with a single item equaling one. Input to the embedding layer.
- ω_E = the matrix of learnable parameters.
- h_1 = the first hidden layer of the neural net
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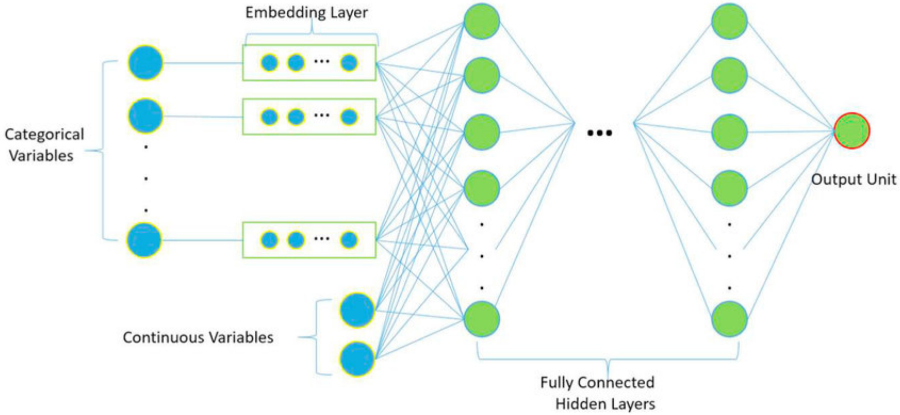

The embedding matrix ω_E encodes predictive information about the categories, has a spatial interpretation when projected to two dimensions.

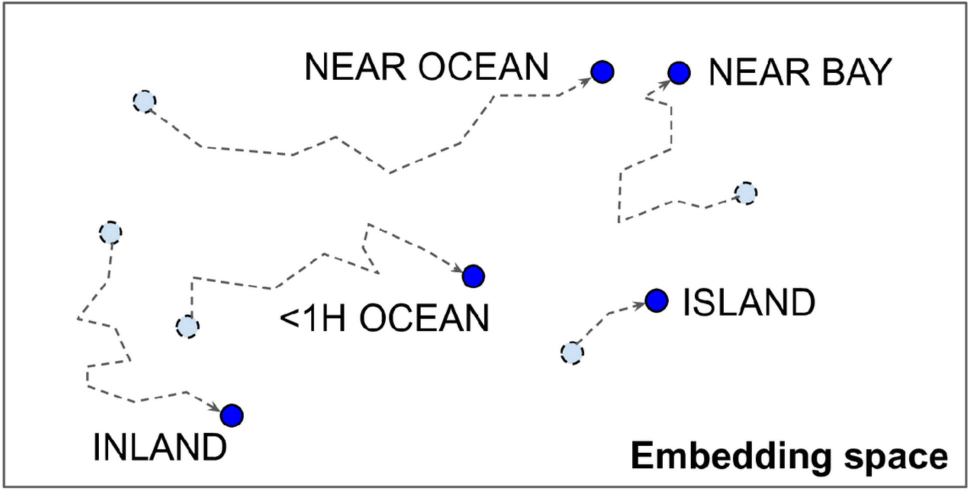

Figure 13-4. Embeddings will gradually improve during training

Embedding Layers versus Dense Layers

- An embedding layer is statistically equivalent to a fully-connected dense layer with one-hot vectors as input and linear activation.
  - dense layers might fit the data better, since you can use ReLU activation.
  - embedding layers are much faster; should use them when you have 10 or more categories.

Outline

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- Documents are lists of word indexes $\{w_1, w_2, ..., w_{n_i}\}$.
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$$\boldsymbol{X} = \begin{bmatrix} x_1 & \dots & x_L \end{bmatrix}$$

where

$$\underbrace{x_j}_{n_E \times 1} = \underbrace{\boldsymbol{E}}_{n_E \times n_w} \cdot \underbrace{w_j}_{n_w \times 1}$$

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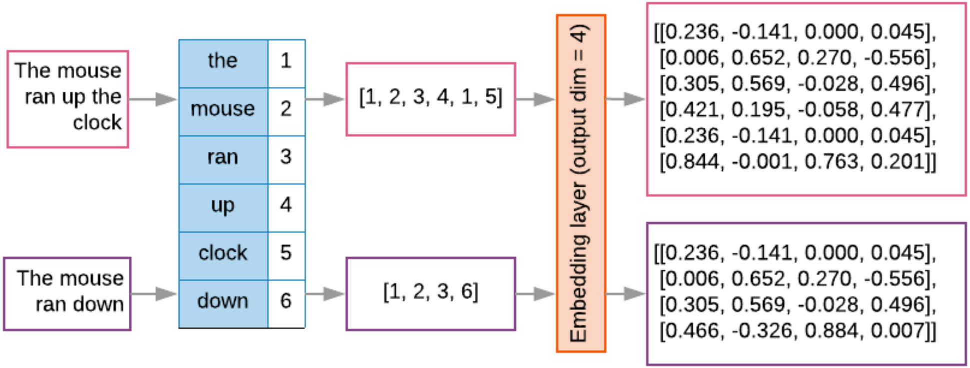
- $\boldsymbol{X}$ is flattened into an $L * n_E$ vector for input to the next layer.

Illustration



Word2Vec

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- How does it learn the meaning of the word "fox"?
  - By comparing true instances of the word fox ("The <u>quick brown</u> **fox** <u>jumps over</u> the lazy dog")
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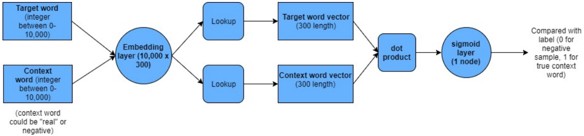
- Word2Vec learns embedding vectors for the target word ("fox") and context words (neighbors of "fox") to distinguish true from false samples.

Word2Vec Negative Sampling Objective

The dataset is a collection of context pairs indexed by i:

- $y_i = 1$ means correct (it appeared in the corpus)
- $y_i = 0$ means incorrect (it was randomly drawn $\rightarrow$ **negative sample**).



- Both words are looked up in the same embedding matrix.
- The concatened embeddings $[\boldsymbol{w}; \boldsymbol{c}]$ are input to a dense layer (no activation) then to sigmoid output:

$$\hat{y}(w, c) = \text{sigmoid}(([\boldsymbol{w}; \boldsymbol{c}] \cdot \omega_0) \cdot \omega_1)$$

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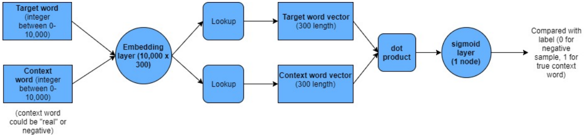

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- Word2Vec minimizes the binary cross-entropy

$$\min_{\boldsymbol{w},\boldsymbol{c},\omega} L(\boldsymbol{w},\boldsymbol{c},\omega) = -\sum_{i=1}^{n_D}[y_i \log \hat{y}_i(\boldsymbol{w},\boldsymbol{c},\omega) + [1-y_i]\log(1-\hat{y}_i(\boldsymbol{w},\boldsymbol{c},\omega))]$$

How does Word2Vec relate to the $\boldsymbol{M}$ matrix?

- Word2Vec produces embedding matrices $\boldsymbol{W}$ and $\boldsymbol{C}$.
  - generally, context embeddings are discarded after training.
- Levy and Goldberg (2014):
  - If we take $\tilde{\boldsymbol{M}} = \boldsymbol{W}\boldsymbol{C}'$, word2vec is equivalent to factorizing a matrix $\boldsymbol{M}$ with items

$$\boldsymbol{M}_{[w,c]} = \text{PMI}(w, c) - \log a$$

    where a is a constant calibrating the amount of negative sampling.

Check for Understanding

1. What is the difference/connection between an embedding layer and a word embedding?
2. What does negative sampling mean in general, and in the case of Word2Vec?
3. What are the main differences between Word2Vec and GloVe?

Word Embeddings Encode Linguistic Relations

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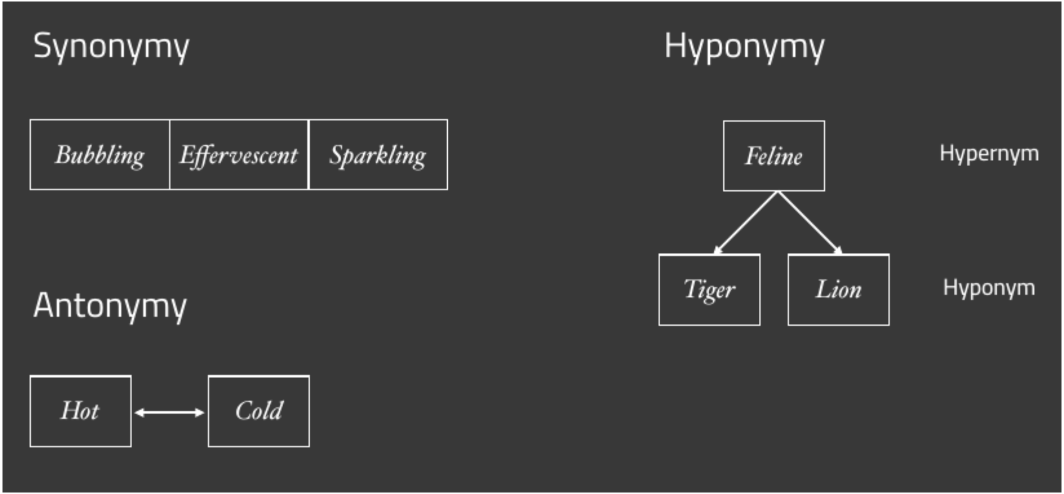

Similarity vs. Relatedness (Budansky and Hirst, 2006)

- Semantic **similarity**: words sharing salient attributes / features
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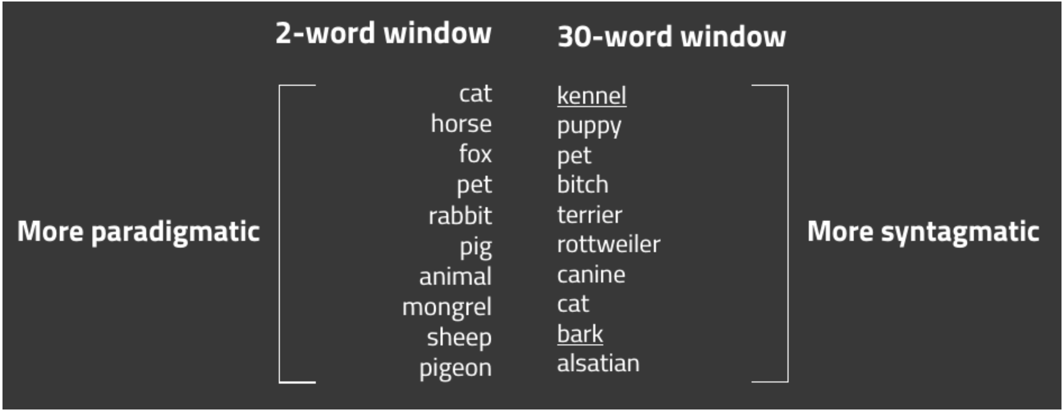
- Word embeddings will recover one or both of these relations, depending on how contexts and associated are constructed.

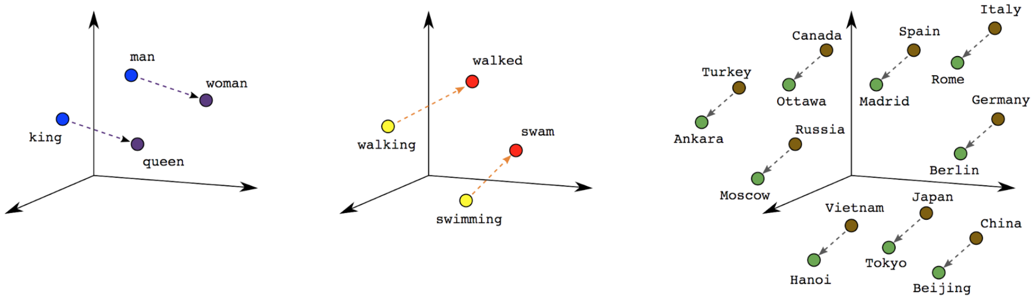
Most similar words to dog, depending on context window size



- Small windows pick up substitutable words; large windows pick up topics.

Vector Directions ↔ Meaning

- Intriguingly, word2vec algebra can depict conceptual, analogical relationships between words:



Male-Female Verb Tense Country-Capital

Word Embeddings for Analogies

$$vec(king) - vec(man) + vec(woman) \approx vec(queen)$$

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- More generally: The analogy $a_1 : b_1 :: a_2 : b_2$ can be solved (that is, find b_2 given a_1, b_1, a_2) by

  $$\arg\max_{b_2 \in V} \cos(b_2, a_2 - a_1 + b_1)$$

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where V excludes (a_1, b_1, a_2).
- Often works better with normalized vectors (so that one long vector doesn't wash out the others)
- Levy and Goldberg (2014) recommend the following "CosMul" metric which tends to perform better:
$$\arg\max_{b_2 \in V} \frac{\cos(b_2, a_2)\cos(b_2, b_1)}{\cos(b_2, a_1) + \epsilon}$$
  - requires normalized, non-negative vectors (can transform using $(x + 1)/2$)
  - ϵ is a small smoothing parameter.

Pre-trained word embeddings

- In many settings (e.g. a small corpus), better to use pre-trained embeddings.
- e,g, spaCy's GloVe embeddings:
  - one million vocabulary entries
  - 300-dimensional vectors
  - trained on the Common Crawl corpus
- Can initialize models with pre-trained embeddings, can fine-tune as needed.

Parts of Speech and Phrases

- In the default model multiple senses of a word are merged.
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- The default model only works by word, but "new york $\neq$ "new" + "york"
  - can tokenize phrases together (see Week 2 lecture) before training.

The black sheep problem

- The trivial or obvious features of a word are not mentioned in standard corpora.
- For example, although most sheep are white, you rarely see the phrase "white sheep".
  - so word2vec sometimes tells you sim(black,sheep) $>$ sim(white,sheep).

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  - so word2vec sometimes tells you sim(black,sheep) $>$ sim(white,sheep).
- This is really important when interpreting results using embeddings to anayze beliefs/attitudes.
- Relatedly, antonyms are often rated similarly, have to be careful with that.

Review: NLP "Bias" is statistical bias

- Self-supervised learning algorithms like Word2Vec learn ***all*** dimensions of word associations; not just ones we are most interested in.
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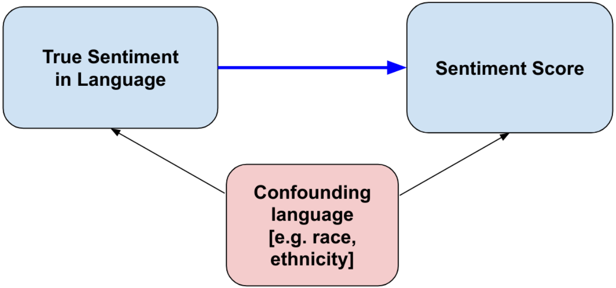
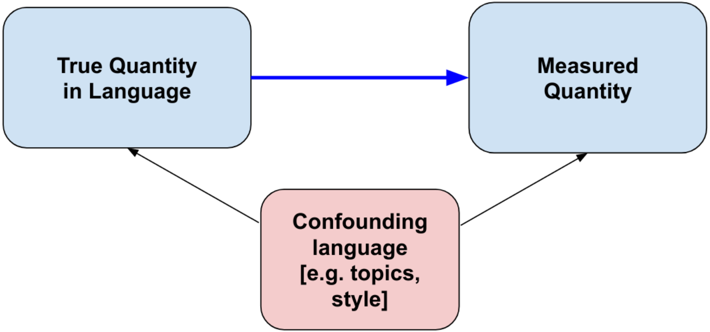
- Self-supervised learning algorithms like Word2Vec learn ***all*** dimensions of word associations; not just ones we are most interested in.
  - e.g., true expressions of attitudes or perceptions.
- e.g., using embeddings to scale social group words in a positive-to-negative dimension can learn correlated associations, not just sincere expressions of such attitudes:

```
text_to_sentiment("Let's go get Italian food")
2.0429166109
text_to_sentiment("Let's go get Chinese food")
1.4094033658
text_to_sentiment("Let's go get Mexican food")
0.3880198556
```

```
text_to_sentiment("My name is Emily")
2.2286179365
text_to_sentiment("My name is Heather")
1.3976291151
text_to_sentiment("My name is Yvette")
0.9846380213
text_to_sentiment("My name is Shaniqua")
-0.4704813178
```



Self-Supervised Models Learn Confounders



- self-supervised language models like Word2Vec learn all lingusitic associations in language.
  - the measured associations might reflect attitudes/perceptions, or might reflect something else.

In-Class Presentation: Caliskan, Bryson, and Narayanan (*Science* 2017)

Tokenizing for Word Embeddings

- capitalization?
- punctuation?
- stopwords/function-words?
- can add special tokens for start of sentence and end of sentence
- for out-of-vocab words, substitute a special token or replace with part-of-speech tag
  - or use FastText embeddings (more below)

Can cluster word embeddings to produce topics

Cluster #	Top 10 Words
174	complicate, depend, crucial, illustrate, elusive, focus, important, straightforward, elide, critical
134	implausible, problematic, exaggeration, skeptical, ascribe, discredit, contradictory, weak, exaggerate, supportable
75	reverse, AFFIRM, affirm, vacate, reversed, REMANDED, forego, foregoing, forgoing, remands
70	importation, import, ecstasy, marihuana, illicit, opium, distilled, export, phencyclidine, narcotic
178	perverse, sensible, tempt, unlikely, unwise, anomalous, would, easy, costly, attractive
32	phrase, meaning, word, synonymous, language, interpret, noun, wording, verb, adjective
169	circumscribe, endow, unfettered, vest, unlimited, boundless, broad, constrain, exercise, unbounded
85	hundred, thousand, many, million, huge, massive, large, enormous, most, dozen
28	emphasis, bracket, alteration, citation, footnote, italic, ellipsis, petcitation, idcitation, punctuation
138	logo, symbol, stylized, imprint, emblem, grille, prefix, lettering, suffix, crosshair
181	wilful, carelessness, recklessness, careless, intentional, willful, conscious, reckless, unintentional, wantonness
158	rigorous, demanding, heightened, reasonableness, rigid, heighten, objective, deferential, flexible, particular
55	agreement, contract, contractual, promise, novation, repudiate, guaranty, enforceable, novate, repurchase
197	summation, admonish, sidebar, prosecutor, admonishment, mistrial, curative, questioning, remark, recess
120	scrivener, typographical, reversible, plain, harmless, clerical, invited, clear, requiresthe, instructional
15	adjudicatory, adjudicative, adversarial, judicial, rulemaking, decisionmaking, administrative, meaningful, rulemake, agency

Clustered word embeddings in judicial opinions, from Ash and Nikolaus (2020)

"Enriching word vectors with subword information" (Bojanowski et al 2017)

- each word is represented as a bag of (hashed) character n-grams. (e.g., spicy = (spi, pic, icy)).
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- learn embeddings for the character segments, and construct word embedding by summing over the segment embeddings
- competitive with word2vec in standard tasks; better in some languages.
- produces good embeddings for unseen words.

Standard word embeddings (e.g. word2vec/glove) have a number of limitations:

- **polysemy**: you get one vector for multiple senses of a word
  (e.g. “**glass** of water” vs “window **glass**”)

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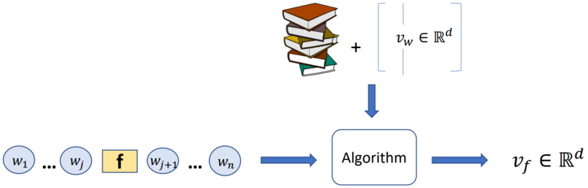
- Goal of Khodak et al (2018): produce embeddings "a la carte" given a context:

Given: Text corpus and high quality word embeddings trained on it



Input: A feature in context(s)

Output: Good quality embedding for the feature

A la carte embeddings

- Given a target word f and its context c, define

$$v_f^{avg} = \frac{1}{|c|} \sum_{w \in c} v_w$$

the average vector for the words in the context.

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- The "induction matrix" A can be learned with a least-squares (linear regression) objective

$$A^* = \arg\min_A \sum_w |v_w - A v_w^{avg}|_2^2$$

  where w indexes over all the tokens in the corpus.

- empirically:

$$\text{cosine}(v_f, A^* v_f^{avg}) \geq 0.9$$

In-Class Presentation: Kozlowski, Evans, and Taddy (ASR 2019)

Discussion: Social Science with Embeddings

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- In what domains is this relevant?
  - social media, news media, politics, legal, scientific, ...
- Does language matter?
  - Djourelova (2020): style change from “illegal” to “undocumented” immigrant softened attitudes toward immigration.

Check for Understanding

1. How would it affect my word embeddings to use co-occurence within paragraph, rather than within sentence?
2. How would it my embeddings to drop function words in a pre-processing step?
3. What is the black sheep problem in the context of word embeddings?
4. Think of a setting (and explain) where:
   - using pre-trained embeddings would not work.
   - using embeddings with subword information would help a lot
   - using a la carte embeddings is necessary

Outline

Examples: Confounders in Measurement from Text

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- Policy priorities → predicted probability of speeches/laws being about a particular policy topic.

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When is measurement confounding important?

- By itself, producing measurements that are biased by confounders might not be a problem.
- e.g.:
  - an NLP-based essay grading system that learns confounders $\rightarrow$ not a problem unless tudents learn about it and strategically alter their essays.

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  - probably won't matter for in-domain summary statistics
  - but would matter a lot for summary statistics in a new domain
- even in-domain, will matter for assessing the causal effect of a treatment, e.g. the electoral cycle:
  - elections might cause politicians to focus on social issues rather than economic issues,
  - if social/economic issues are confounded with partisanship, the resulting estimates are biased.

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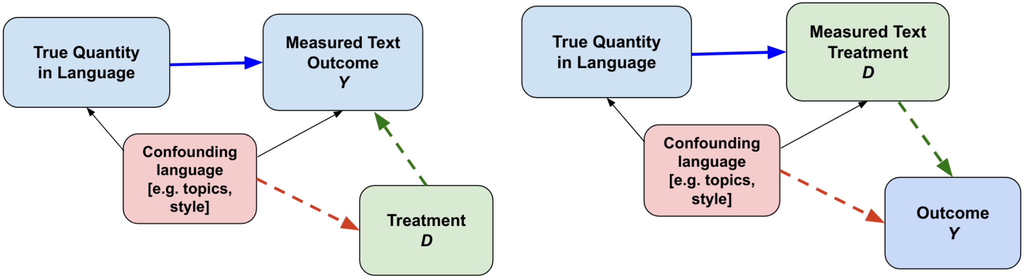

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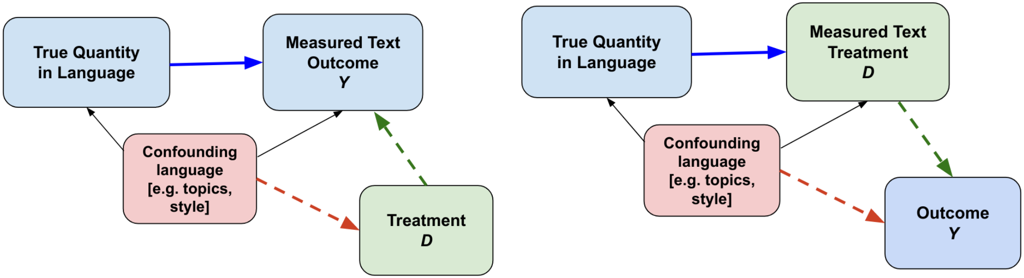

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  - e.g.: estimating the effect of politician speech sentiment on his/her reelection chances?

Steps for de-biasing

- Language features that are often confounded with the quantity of interest:
  - stopwords
  - named entities: person/organization/place names
- These can be dropped during pre-processing to reduce the influence of confounders in subsequent measurements.
- Can control for topic or style features or other potential confounders in regressions, or shuffle named entities.

De-Biasing Word Embeddings

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- Bolukbasi et al (NIPS 2016):
  - “Geometrically, **gender bias is first shown to be captured by a direction in the word embedding**.“
  - “Second, gender neutral words are shown to be linearly separable from gender definition words in the word embedding.”
  - “Using these properties, we provide a methodology for modifying an embedding to remove gender stereotypes, such as the association between the words receptionist and female, while maintaining desired associations such as between the words queen and female.”

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  - "Geometrically, **gender bias is first shown to be captured by a direction in the word embedding**."
  - "Second, gender neutral words are shown to be linearly separable from gender definition words in the word embedding."
  - "Using these properties, we provide a methodology for modifying an embedding to remove gender stereotypes, such as the association between the words receptionist and female, while maintaining desired associations such as between the words queen and female."
- But: Gonen and Goldberg (2019):
  - ***"... we argue that this removal is superficial. While the bias is indeed substantially reduced according to the provided bias definition, the actual effect is mostly hiding the bias, not removing it. The gender bias information is still reflected in the distances between 'gender-neutralized' words in the debiased embeddings, and can be recovered from them..."***