D001 Economic Analysis of Non-Standard Data

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6. Word Embeddings Without Neural Nets

Outline

Words Embedding with Local Contexts

- Properties of Word Embeddings
- How do I use Word Embeddings?

Bias in Language

Outline

Word Embeddings

- "Word embeddings" often refer to GloVe or Word2Vec – these are particular (popular) models for producing word embeddings.
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    → rather than predicting some metadata, they predict the co-occurence of neighboring words.
  - “You shall know a word by the company it keeps”
- From high-dimensional sparse representations to low-dimensional dense representations

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** of the vocabulary (e.g. "income"), each column c represents another word (e.g. "tax") or linguistic **context** in which words can occur (e.g. "... pay corporate ___ tax to the relevant ...")
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  - Popular embeddings (glove and word2vec) generally use 5- or 10-word context windows
- 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 have a **spatial interpretation** $\rightarrow$ geometric distances between word vectors reflect semantic distances between words.

GloVe Embeddings

- Pennington et al (2014) GloVe (Global Vectors for Word Representation) is embedding technique to represent words as dense vectors to capture semantic relationships between words
- Input: C_{ij} = local co-occurrence counts between words $i, j \in \{1, ..., n_w\}$ within some co-occurrence window, e.g. ten words.

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

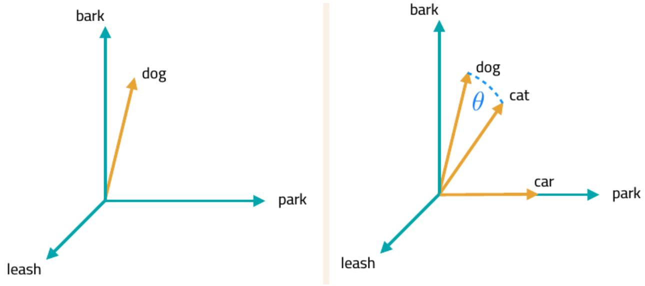
$$\min_{\boldsymbol{w}} \sum_{i,j} f(C_{ij}) \left(w_i^T w_j - \log(C_{ij}) \right)^2$$

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 $\{v_1 = \boldsymbol{M}_{[w_1,:]},\ v_2 = \boldsymbol{M}_{[w_2,:]}, \ldots\}$, 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":



- The standard metric for comparing vectors is cosine similarity:

$$\cos\theta = \frac{v_1 \cdot v_2}{||v_1||||v_2||}$$

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

Word Vectors can produce Document Vectors

$$\vec{D} = \sum_{w \in D} a_w \vec{w}$$

- The "continuous bag of words" representation for document D is the sum, or the average (potentially weighted by a_w), of the vectors $\vec{w}$ for each word w in the document.
  - word vectors $\vec{w}$ constructed using GloVe or Word2Vec (pre-trained or trained on the corpus).
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- Arora, Liang, and Ma (2017) provide a "tough to beat baseline", the SIF-weighted ("smoothed inverse frequency") average of the vectors:

$$a_w = \frac{\alpha}{\alpha + p_w}$$

where p_w is the probability (frequency) of the word and $\alpha = .001$ is a smoothing parameter.

What do Word Embeddings Capture? (Budansky and Hirst, 2006)

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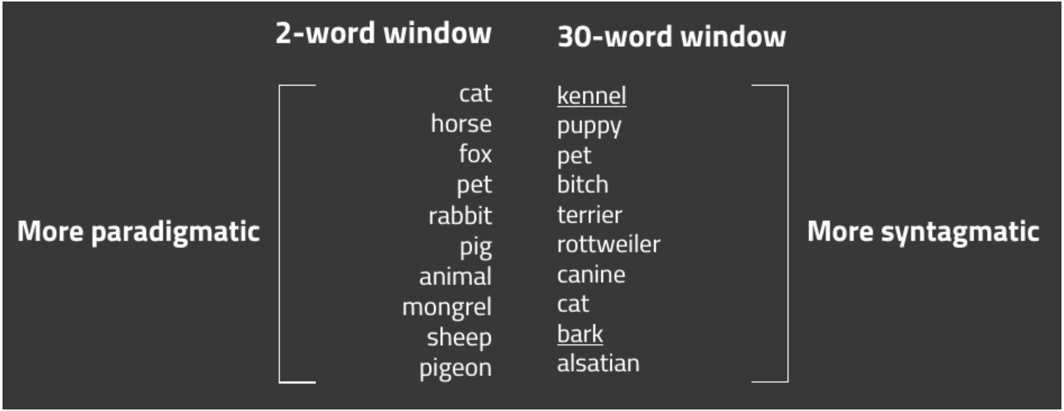
- Word embeddings will recover one or both of these relations, depending on how contexts and associated are constructed.

Most similar words to dog, depending on context window size



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

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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.

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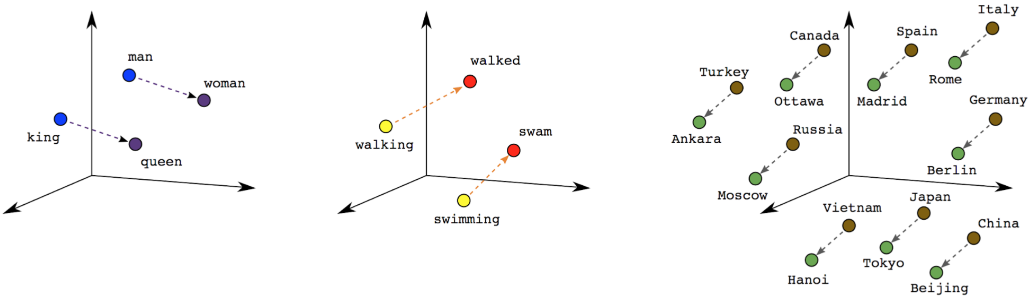
- Relatedly, antonyms are often rated similarly, have to be careful with that.

Vector Directions ↔ Meaning

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



Male-Female Verb Tense Country-Capital

Word Embeddings for Analogies

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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)

Outline

Tokenizing for Word Embeddings

- Need to think about what's the right way to pre-process data
  - drop capitalization
  - punctuation is optional
  - add special tokens for start of sentence and end of sentence
  - don't drop stopwords/function-words
  - for out-of-vocab words, substitute a special token or replace with part-of-speech tag

Which word-embedding?

- 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.

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

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

Limitations

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

- **n-grams**: does not produce embeddings for multi-word phrases
- **rare words**: a word that shows up just once or twice won't be well-defined
- **polysemy**: you get one vector for multiple senses of a word
  (e.g. "**glass** of water" vs "window **glass**")

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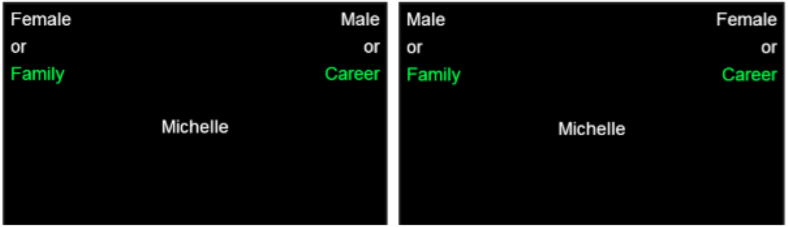

- Comparing reaction times across trials with different word pairs:
  - subjects tend to be slower and more error-prone in assignments against stereotype (e.g. “Michelle” goes to “Female or Career”).

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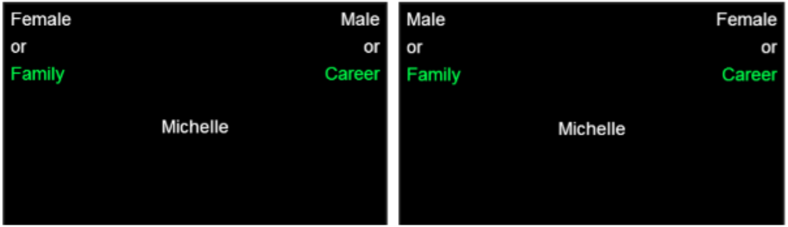

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  - subjects tend to be slower and more error-prone in assignments against stereotype (e.g. “Michelle” goes to “Female or Career”).
  - IAT score = difference in reaction time between stereotype-consistent and stereotype-inconsistent rounds.

Caliskan, Bryson, and Narayanan (*Science* 2017)

- "We replicated a spectrum of known biases, as measured by the Implicit Association Test, using a widely used, purely statistical machine-learning model trained on a standard corpus of text from the World Wide Web. . . "

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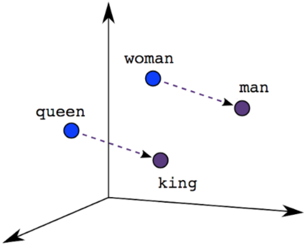

Analogies

- king : queen :: man : woman
- walked : walking :: swam : swimming

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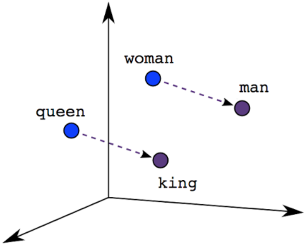

Analogies

- king : queen :: man : woman
- walked : walking :: swam : swimming
- **man : programmer :: woman : homemaker**
- **he : physician :: she : nurse**

Example Stimuli

- Targets:
  - **Flowers**: aster, clover, hyacinth, marigold, poppy, azalea, crocus, iris, orchid, rose, bluebell, daffodil, lilac, pansy, tulip, buttercup, daisy, lily, peony, violet, carnation, gladiola, magnolia, petunia, zinnia.
  - **Insects**: ant, caterpillar, flea, locust, spider, bedbug, centipede, fly, maggot, tarantula, bee, cockroach, gnat, mosquito, termite, beetle, cricket, hornet, moth, wasp, blackfly, dragonfly, horsefly, roach, weevil.

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- Attributes:
  - **Pleasant**: caress, freedom, health, love, peace, cheer, friend, heaven, loyal, pleasure, diamond, gentle, honest, lucky, rainbow, diploma, gift, honor, miracle, sunrise, family, happy, laughter, paradise, vacation.
  - **Unpleasant**: abuse, crash, filth, murder, sickness, accident, death, grief, poison, stink, assault, disaster, hatred, pollute, tragedy, divorce, jail, poverty, ugly, cancer, kill, rotten, vomit, agony, prison.

Results

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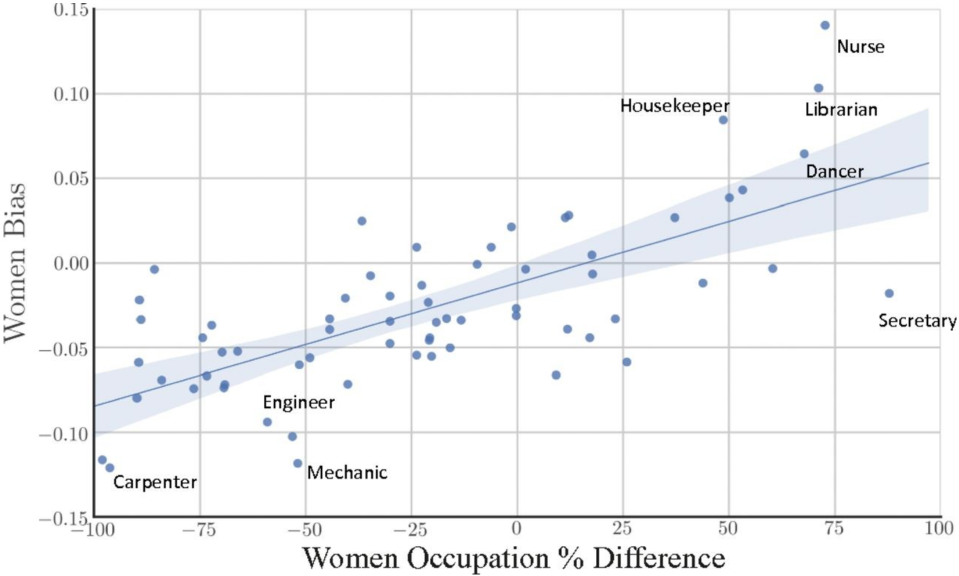
  - European-American names vs. African-American names
- Male names vs. Female names:
  - Career words (e.g. professional, corporation, ...) vs. family words (e.g. home, children, ...)
  - Math/science words vs arts words

Garg, Schiebinger, Jurafsky, and Zou (PNAS 2018)



Women's occupation relative percentage vs. embedding bias in Google News vectors.