Text Data in Business and Economics

Basel University – Autumn 2024

6. Word Embeddings Without Neural Nets

What have we been doing? ***Learning representations*** of the data

- Dictionary methods: document is represented as a count over the lexicon
- N-grams: document is a count over a vocabulary of phrases
- Topic models: document is a vector of shares over topics
- Text classifiers: produces $\hat{\boldsymbol{y}}_i = f(\boldsymbol{x}_i; \hat{\theta})$, a vector of predicted probabilities across classes for each document i.
  - This vector of class probabilities is a **compressed** **representation** of the outcome-predictive text features $\boldsymbol{x}_i$
  - the vector of features, $\boldsymbol{x}_i$, is itself a compressed representation of the unprocessed document $\mathcal{D}_i$.
- For topic models or classifiers: 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 outcomes.

Information in $\hat{\theta}$: Preview of Word Embeddings

θ = 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

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

  - where x_t is an n_x-dimensional one-hot vector – all entries are zero except equals one for the word at t.

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- Let θ_t be the row of θ corresponding to the word w_t: a **word embedding** for w_t containing the outcome-relevant information for that word.
- 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 $\vec{\boldsymbol{d}} = \theta \cdot \boldsymbol{x}$, and thus θ is a **word embedding matrix**.

Outline

Words and Local Contexts

How do I use Word Embeddings?

Bias in Language

Word Embeddings

- "Word embeddings" often refer to Word2Vec or GloVe – these are particular (popular) models for producing word embeddings.
  - **Previously:** focus on global document counts or predict an outcome
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    - → rather than predicting some metadata, they predict the co-occurence of neighboring words.
- 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** (e.g. "income"), each column c represents a linguistic **context** in which words can occur (e.g. "... pay corporate income ___ to the relevant ...").
  - A matrix entry $\boldsymbol{M}_{[w,c]}$ quantifies the strength of association between a word and a context in a large corpus.
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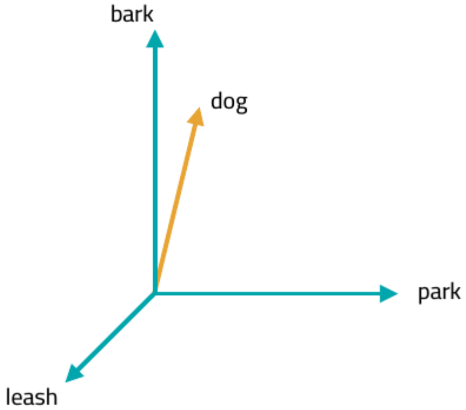
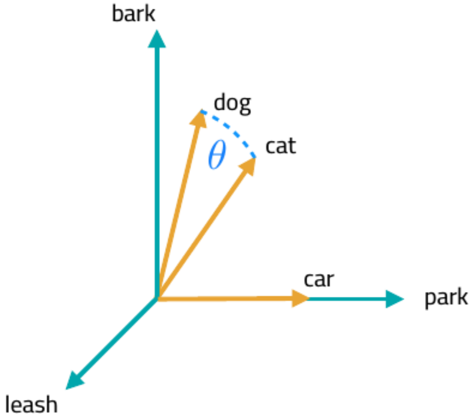
  - Popular embeddings (word2vec and glove) generally use 5- or 10-word windows as the context.
- each word (row) $\boldsymbol{M}_{[w,:]}$ gives a distribution over contexts.
  - different definitions of contexts and different measures of association $\rightarrow$ different types of **word vectors**.
  - these vectors have a **spatial interpretation** $\rightarrow$ geometric distances between word vectors reflect semantic distances between words.

Word Embeddings in the 2-Dimensional Space





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:

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

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- 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.
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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)

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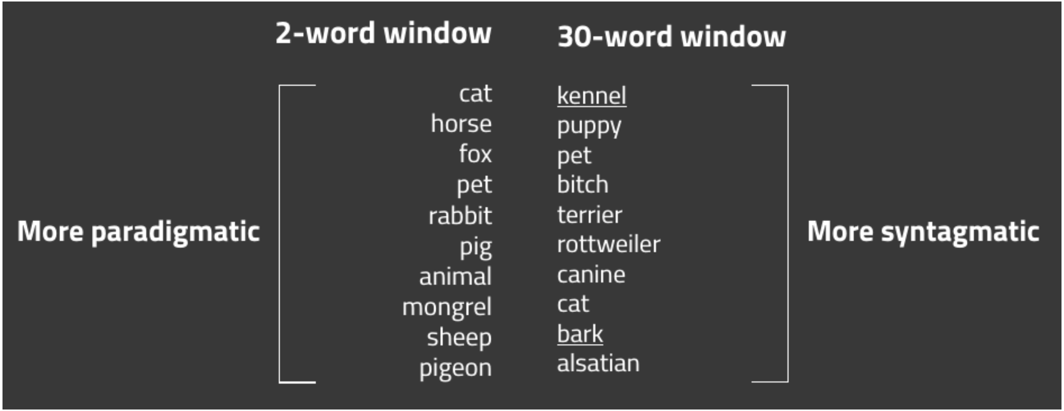
- Word embeddings will recover one or both of these relations, depending on how contexts and associated are constructed.

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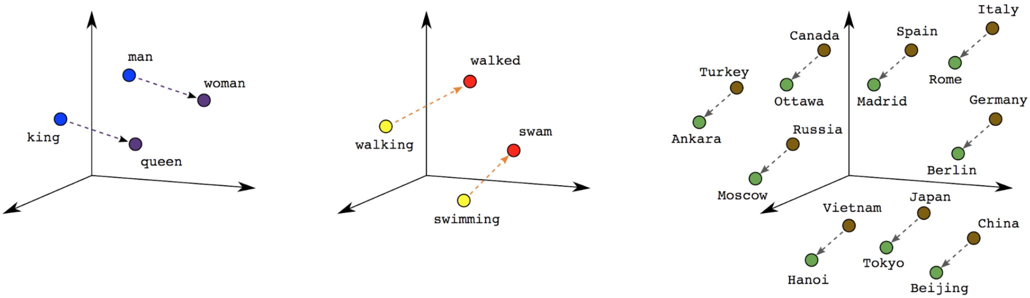
- Relatedly, antonyms are often rated similarly, have to be careful with that.

Vector Directions $\leftrightarrow$ Meaning

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



Male-Female Verb Tense Country-Capital

Word Embeddings for Analogies

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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.

Outline

Tokenizing for Word Embeddings

- Need to think about what's the right way to pre-process data
  - drop capitalization
  - punctuation is optional
  - don't drop stopwords/function-words
  - 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

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 (hashed) 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

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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.

Limitations

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

- **polysemy**: you get one vector for multiple senses of a word
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Scientists attending ACL work on **cutting edge** research in NLP

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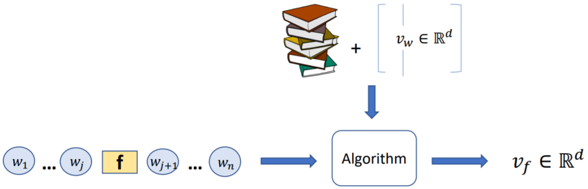
- Goal of Khodak et al (2018): produce embeddings "a la carte" given a context:

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



Input: A feature in context(s)

Output: Good quality embedding

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.
- Arora et al (2018) prove that for vectors produced by a generative language model, there exists a matrix A such that

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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:

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

Outline

Implicit attitudes

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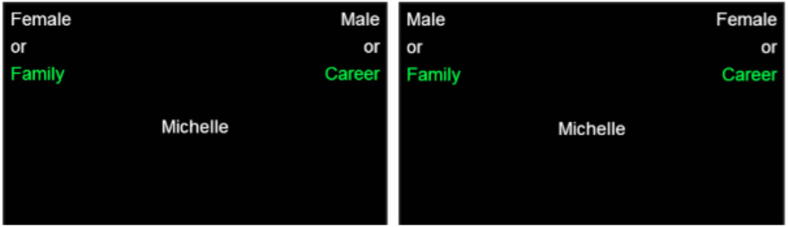

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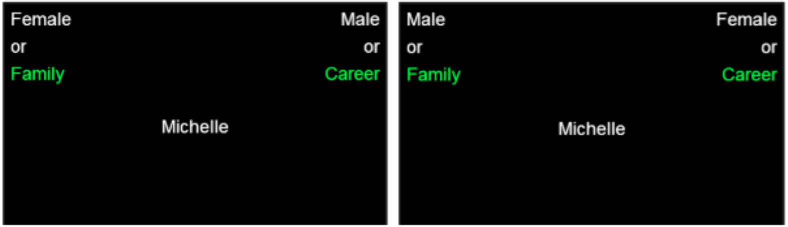

- Comparing reaction times across trials with different word pairs:
  - subjects tend to be slower and more error-prone in assignments against stereotype (e.g. "Michelle" goes to "Female or Career").
  - IAT score = difference in reaction time between stereotype-consistent and stereotype-inconsistent rounds.

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

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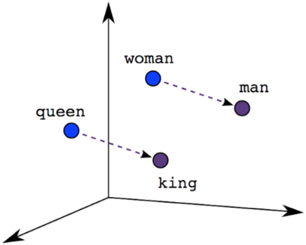

Analogies

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

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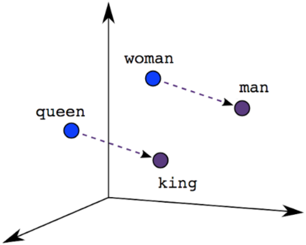

Analogies

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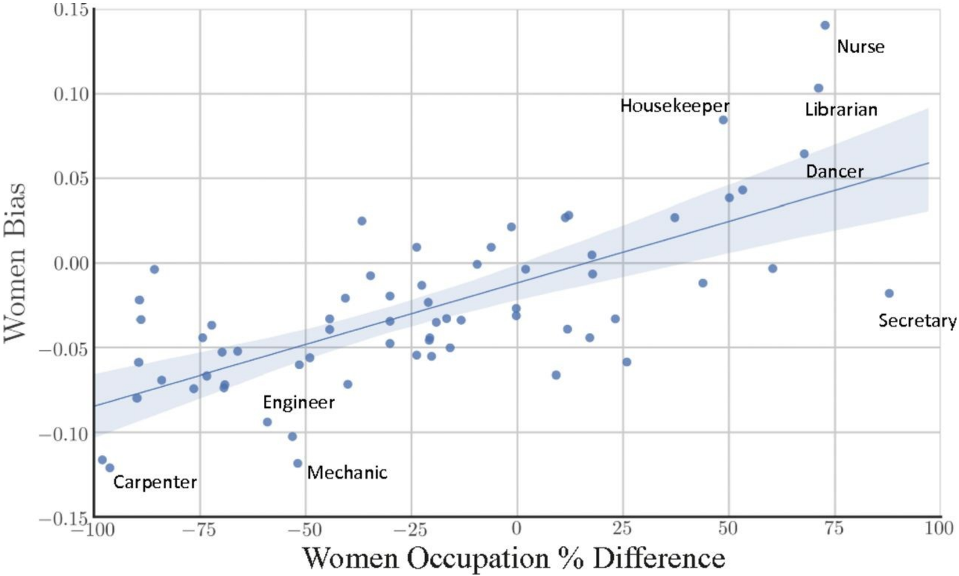
- Male names vs. Female names:
  - Career words (e.g. professional, corporation, ...) vs. family words (e.g. home, children, ...)
  - Math/science words vs arts words

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



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