CS 4120: Natural Language Processing

Instructor: Prof. Lu Wang
Northeastern University
Webpage: www.ccs.neu.edu/home/luwang

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## Logistics

- Next Tuesday: in addition to regular course content, TA will use half an hour to discuss the common problems seen in assignment 1.
  - Output format is incorrect, or no output at all
  - Code not runnable
- Grades, comments, and rubrics will be released by today. Feel free to reach out to TA during office hour if you have any question wrt grading.

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## Neural language models

- Skip-grams
- Continuous Bag of Words (CBOW)
- Math details can be found at https://cs224d.stanford.edu/lecture_notes/notes1.pdf (not required for this course)

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## Prediction-based models: An alternative way to get dense vectors

- **Skip-gram** (Mikolov et al. 2013a), **CBOW** (Mikolov et al. 2013b)
- **Idea**: Learn embeddings as part of the process of word prediction
- **Implementation**: Train a neural network to predict neighboring words
- Advantages:
  - Fast, easy to train (much faster than SVD)
  - Available online in the `word2vec` package
  - Including sets of pretrained embeddings!

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## Word2vec

- Popular embedding method
- Very fast to train
- Code available on the web
- Idea: **predict** rather than **count**

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## Word2vec

- Given a sentence:

... lemon, a tablespoon of **apricot** jam a pinch ...

- Instead of **counting** how often each word *w* occurs near "*apricot*"
- Train a classifier on a binary **prediction** task:
  - Is *w* likely to show up near "*apricot*"?
- We don't actually care about this task
  - But we'll take the learned weights (will be discussed later) as the word embeddings

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## Brilliant insight: Use running text as implicitly supervised training data!

- A word near *apricot*
  - Acts as gold 'correct answer' to the question
  - "Is word *w* likely to show up near *apricot*?"
- No need for hand-labeled supervision
  - The idea comes from **neural language modeling**
    - Bengio et al. (2003)
    - Collobert et al. (2011)

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## Word2Vec: **Skip-Gram** Task

- Now we have positive samples.
- Where do the "negative samples" come from?

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## Word2Vec: **Skip-Gram** Task

- Word2vec provides a variety of options. Let's do
  - "skip-gram with negative sampling" (SGNS)

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## Skip-gram algorithm

1. Treat the target word and a neighboring context word as positive examples.
2. Randomly sample other words in the lexicon to get negative samples
3. Use logistic regression (will discuss formulation later) to train a classifier to distinguish those two cases
4. Use the weights as the embeddings

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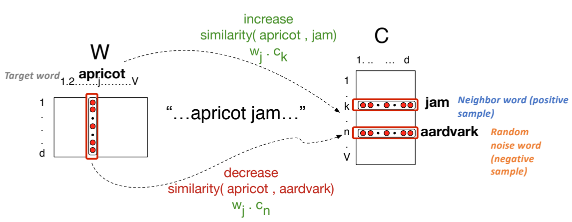


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## Skip-gram Training Data

- Training sentence:

... lemon, a tablespoon of apricot jam a pinch ...
c1 c2 target c3 c4

Assume context words are those in +/- 2 word window

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## Skip-gram Goal

- Given a tuple (t,c) = target, context
  - (*apricot*, *jam*) -> +
  - (*apricot*, *aardvark*) -> -
- Return probability that c is a real context word (or not):
  - P(+|t,c)-> positive
  - $P(-|t,c) = 1-P(+|t,c)$ -> negative

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## How to compute p(+|t,c)?

- Intuition:
  - Words are likely to appear near similar words
  - Model similarity with dot-product!
  - Similarity(t,c) $\propto t \cdot c$
- *Problem:*
  - *Dot product is not a probability!*
    - *(Neither is cosine)*

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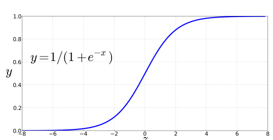
## Turning dot product into a probability

- The sigmoid lies between 0 and 1:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

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## Turning dot product into a probability

$$P(+|t,c) = \frac{1}{1+e^{-t\cdot c}}$$

$$P(-|t,c) = 1 - P(+|t,c) = \frac{e^{-t\cdot c}}{1+e^{-t\cdot c}}$$

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## For all the context words:

- Assume all context words are independent

$$P(+|t,c_{1:k}) = \prod_{i=1}^{k} \frac{1}{1+e^{-t\cdot c_i}}$$

$$\log P(+|t,c_{1:k}) = \sum_{i=1}^{k} \log \frac{1}{1+e^{-t\cdot c_i}}$$

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## Skip-gram Training Data

- Training sentence:

... lemon, a tablespoon of apricot jam a pinch ...

c1 c2 t c3 c4

- Training data: input/output pairs centering on *apricot*
- Assume a +/- 2 word window

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## Skip-gram Training Data

- Training sentence:

... lemon, a tablespoon of apricot jam a pinch ...

c1 c2 t c3 c4

- Training data: input/output pairs centering on *apricot*
- Assume a +/- 2 word window

**positive examples +**

| t | c |
|---|---|
| apricot | tablespoon |
| apricot | of |
| apricot | preserves |
| apricot | or |

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## Skip-gram Training Data

- Training sentence:

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**positive examples +**

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- For each positive example, we'll create *k* negative examples.
- Any random word that isn't *t*

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## Skip-gram Training Data

- Training sentence:

... lemon, a tablespoon of apricot jam a pinch ...

c1 c2 t c3 c4

**positive examples +**

| t | c |
|---|---|
| apricot | tablespoon |
| apricot | of |
| apricot | preserves |
| apricot | or |

**negative examples -** *k=2*

| t | c | t | c |
|---|---|---|---|
| apricot | aardvark | apricot | twelve |
| apricot | puddle | apricot | hello |
| apricot | where | apricot | dear |
| apricot | coaxial | apricot | forever |

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## Choosing noise words (we've seen this!)

- Could pick w according to their unigram frequency P(w)
- More common to chosen then according to $p_\alpha(w)$

$$P_\alpha(w) = \frac{count(w)^\alpha}{\sum_w count(w)^\alpha}$$

- α= 0.75 works well because it gives rare words slightly higher probability
- To show this, imagine two events p(a)=.99 and p(b) = .01:

$$P_\alpha(a) = \frac{.99^{.75}}{.99^{.75} + .01^{.75}} = .97$$

$$P_\alpha(b) = \frac{.01^{.75}}{.99^{.75} + .01^{.75}} = .03$$

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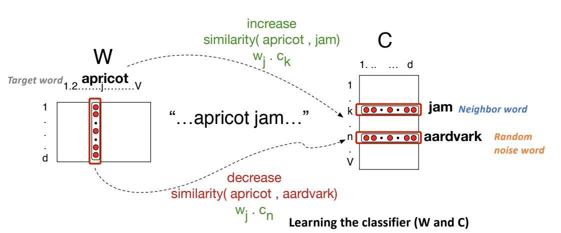


**Learning the classifier (W and C)**
Iterative process on training data. Then adjust the word weights to make the positive pairs more likely and the negative pairs less likely.

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## Setup

- Let's represent words as vectors of some length (say 300), randomly initialized.
- So we start with 300 * V random parameters
- Over the entire training set, we'd like to adjust those word vectors such that we
  - Maximize the similarity of the target word, context word pairs (t,c) drawn from the positive data
  - Minimize the similarity of the (t,c) pairs drawn from the negative data

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## Formally

- We want to maximize the following objective

$$\sum_{(t,c)\in +} logP(+|t,c) + \sum_{(t,c)\in -} logP(-|t,c)$$

- Maximize the + label for the pairs from the positive training data, and the – label for the pairs sampled from the negative data.

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## Focusing on one target word t:

$$\begin{aligned} L(\theta) &= \log P(+|t,c) + \sum_{i=1}^{k} \log P(-|t,n_i) \\ &= \log \sigma(c \cdot t) + \sum_{i=1}^{k} \log \sigma(-n_i \cdot t) \\ &= \log \frac{1}{1+e^{-c \cdot t}} + \sum_{i=1}^{k} \log \frac{1}{1+e^{n_i \cdot t}} \end{aligned}$$

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Logistic regression

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## Train using gradient descent (not required)

- Idea: gradually changing W and C
- Finally learns two separate embedding matrices W and C
- Can use W and throw away C, or merge them

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## Summary: How to learn skip-gram embeddings

- Start with V random 300-dimensional vectors as initial embeddings
- Use logistic regression, the second most basic classifier used in machine learning after naïve bayes
  - Take a corpus and take pairs of words that co-occur as positive examples
  - Take pairs of words that don't co-occur as negative examples
  - Train the classifier to distinguish these by slowly adjusting all the embeddings to improve the classifier performance
  - Throw away the classifier code and keep the **embeddings**.

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## (Dense) Word embeddings you can download!

- **Word2vec** (Mikolov et al.) https://code.google.com/archive/p/word2vec/
- **Fasttext** http://www.fasttext.cc/
- **Glove** (Pennington, Socher, Manning) http://nlp.stanford.edu/projects/glove/

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## Evaluating embeddings

- Compare to human scores on word similarity-type tasks:
  - WordSim-353 (Finkelstein et al., 2002)
  - Stanford Contextual Word Similarity (SCWS) dataset (Huang et al., 2012)
- TOEFL dataset:
  - *Levied is closest in meaning to:*
    - ***imposed**, believed, requested, correlated*

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## Properties of embeddings

- Nearest words to some embeddings (Mikolov et al. 2013)

| **target:** | Redmond | Havel | ninjutsu | graffiti | capitulate |
|---|---|---|---|---|---|
| | Redmond Wash. | Vaclav Havel | ninja | spray paint | capitulation |
| | Redmond Washington | president Vaclav Havel | martial arts | grafitti | capitulated |
| | Microsoft | Velvet Revolution | swordsmanship | taggers | capitulating |

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## Properties of embeddings

*Similarity depends on window size C*

- C = ±2 The nearest words to *Hogwarts:*
  - *Sunnydale*
  - *Evernight*
- C = ±5 The nearest words to *Hogwarts:*
  - *Dumbledore*
  - *Malfoy*
  - *halfblood*

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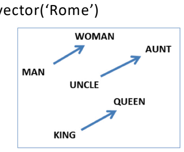
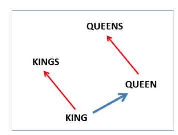
## Analogy: Embeddings capture relational meaning!

vector(*'king'*) - vector(*'man'*) + vector(*'woman'*) ≈ vector('queen')

vector(*'Paris'*) - vector(*'France'*) + vector(*'Italy'*) ≈ vector('Rome')

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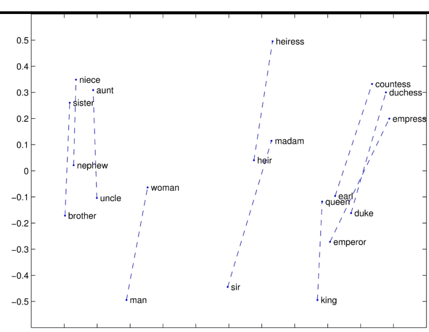


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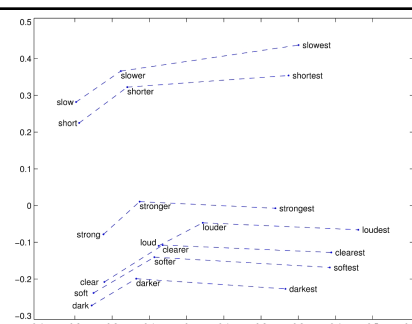


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## Embeddings can help study word history!

- Train embeddings on old books to study changes in word meaning!!

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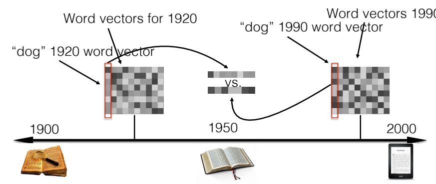
## Diachronic word embeddings for studying language change!

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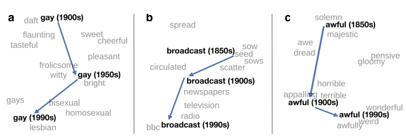
## Visualizing changes

*Project 300 dimensions down into 2*




~30 million books, 1850-1990, Google Books data

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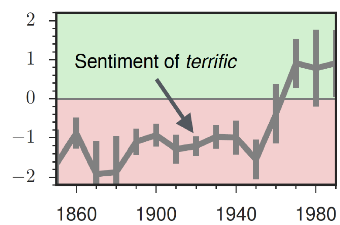
## The evolution of sentiment words

*Negative words change faster than positive words*

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## Embeddings and bias

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## Embeddings reflect cultural bias

Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. "Man is to computer programmer as woman is to homemaker? debiasing word embeddings." In *Advances in Neural Information Processing Systems*, pp. 4349-4357. 2016.

- Ask "Paris : France :: Tokyo : x"
  - x = Japan
- Ask "father : doctor :: mother : x"
  - x = nurse
- Ask "man : computer programmer :: woman : x"
  - x = homemaker

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## Embeddings reflect cultural bias

Caliskan, Aylin, Joanna J. Bruson and Arvind Narayanan. 2017. Semantics derived automatically from language corpora contain human-like biases. Science 356:6334, 183-186.

- Implicit Association test (Greenwald et al 1998):
  - How associated are concepts (*flowers*, *insects*) & attributes (*pleasantness*, *unpleasantness*)?
  - Studied by measuring timing latencies for categorization.
- Psychological findings on US participants:
  - African-American names are associated with unpleasant words (more than European-American names)
  - Male names associated more with math, female names with arts
  - Old people's names with unpleasant words, young people with pleasant words.

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  - Male names associated more with math, female names with arts
  - Old people's names with unpleasant words, young people with pleasant words.
- Caliskan et al. replication with embeddings:
  - African-American names (*Leroy, Shaniqua*) had a higher GloVe (another word embeddings learning method) cosine similarity with unpleasant words (*abuse, stink, ugly*)
  - European American names (*Brad, Greg, Courtney*) had a higher cosine with pleasant words (*love, peace, miracle*)
- Embeddings reflect and replicate all sorts of pernicious biases.

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## Embeddings as a window onto history

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

- The cosine similarity of embeddings for decade X for occupations or adjectives (e.g. teacher or smart) to male vs female names
  - Find its correlation with the actual percentage of women teachers in decade X

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## History of biased framings of women

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

- Embeddings for competence adjectives are biased toward men
  - *Smart, wise, brilliant, intelligent, resourceful, thoughtful, logical, etc.*
- This bias is slowly decreasing

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## Embeddings reflect ethnic stereotypes over time

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

- Princeton trilogy experiments
- Attitudes toward ethnic groups (1933, 1951, 1969) scores for adjectives
  - *industrious, superstitious, nationalistic*, etc
- Cosine of Chinese name embeddings with those adjective embeddings correlates with human ratings.

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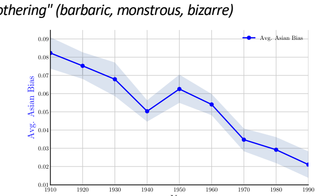
## Change in linguistic framing 1910-1990

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

*Change in association of Chinese names with adjectives framed as "othering" (barbaric, monstrous, bizarre)*

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## Changes in framing: adjectives associated with Chinese

Garg, Nikhil, Schiebinger, Londa, Jurafsky, Dan, and Zou, James (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences*, *115*(16), E3635–E3644

| 1910 | 1950 | 1990 |
|---|---|---|
| Irresponsible | Disorganized | Inhibited |
| Envious | Outrageous | Passive |
| Barbaric | Pompous | Dissolute |
| Aggressive | Unstable | Haughty |
| Transparent | Effeminate | Complacent |
| Monstrous | Unprincipled | Forceful |
| Hateful | Venomous | Fixed |
| Cruel | Disobedient | Active |
| Greedy | Predatory | Sensitive |
| Bizarre | Boisterous | Hearty |

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## Directions

- Debiasing algorithms for embeddings
  - Bolukbasi, Tolga, Chang, Kai-Wei, Zou, James Y., Saligrama, Venkatesh, and Kalai, Adam T. (2016). Man is to computer programmer as woman is to homemaker? debiasing word embeddings. In *Advances in Neural Information Processing Systems*, pp. 4349–4357.
- Use embeddings as a historical tool to study bias

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