CS 2731
Introduction to Natural Language Processing

Session 10: Vector semantics, word2vec

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September 29, 2025

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Course logistics: quiz and homework

- Quiz in class **this Wed Oct 1.** Readings to review:
  - Session 9: J+M 4.5-4.8, 4.13, 4.16
  - Session 10: J+M 5-5.2, 5.5-5.8, 5.10
  - You will have 10 minutes to complete the quiz (until 2:40pm)
- Homework 2 has been released. Is **due next Thu Oct 9**
  - Michael will post the Kaggle competition soon (probably tomorrow)

Course logistics: project

- Next project deliverable: project proposal due Oct 16
    - Michael will post the requirements soon
    - For now, focus on finding related literature and datasets
    - Finding out what evaluation metric to use may require looking at other chapters of the textbook
    - Feel free to email or book office hours with Michael to discuss
- We have $150 total as a class to use on OpenAI LLM credits
- Michael is still looking into open-source models set up on School of Computing and Information servers

Start running notebook: examine word2vec embeddings

- Click on this nbgitpuller link
  - Or find the link on the course website
- Open **session10_word2vec.ipynb**
- Run the first 2 cells while we go through slides, as they take awhile

Overview: vector semantics, static word embeddings

- Vector semantics
- Distributional semantics
- Types of word vectors
- Word2vec
- Bias in word vectors
- Coding activity: explore word vectors

Vector semantics

Semantics: the study of meaning

Word representations in NLP draw on 2 areas of semantics

a. Vector semantics

b. Distributional semantics

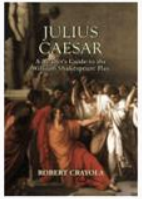
Vector semantics

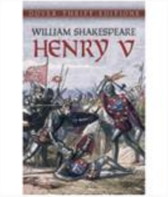
Modeling semantics as points in vector space

- Words or other text segments are represented by vectors
- Multiple dimensions
- Nearer = more similar words

Term-document matrix: word vectors

Two words are similar if their vectors are similar.





	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	6	117	0	0

Slide adapted from David Mortensen, Jurafsky & Martin

Pairs of similar words?

Similarity and relatedness

- Synonyms: big/large, couch/sofa, automobile/car
- Similar: sharing some element of meaning
  - coffee/tea, car/bicycle, cow/horse
- Related: by a semantic field
  - coffee/cup, scalpel/surgeon

Slide adapted from Jurafsky & Martin

Distributional semantics

Distributional semantics

"The meaning of a word is its use in the language" [Wittgenstein 1953]

"You shall know a word by the company it keeps" [Firth 1957]

"If A and B have almost identical environments we say that they are synonyms" [Harris 1954]

Slide adapted from Jurafsky & Martin

Distributional semantics

Define the meaning of a word by its **distribution in language use**: its neighboring words or grammatical environments.

You Learn Words by Using Distributional Similarity

Consider

- A bottle of pocarisweat is on the table.
- Everybody likes pocarisweat.
- Pocarisweat makes you feel refreshed.
- They make pocarisweat out of ginger.

What does *pocarisweat* mean?

Slide credit: David Mortensen

You Know Pocarisweat by the Company It Keeps

From context words humans can guess *pocarisweat* means a beverage like **coke**.
How do you know?

- Other words can occur in the same context
- Those other words are often for beverages (that you drink cold)
- You assume that *pocarisweat* is probably similar

So the intuition is that **two words are similar if they have similar word contexts**.

Slide credit: David Mortensen

Sample Contexts of ± 7 Words

sugar, a sliced lemon, a tablespoonful of	**apricot**	preserve or jam, a pinch each of,
their enjoyment. Cautiously she sampled her first	**pineapple**	and another fruit whose taste she likened
well suited to programming on the digital	**computer**.	In finding the optimal R-stage policy from
for the purpose of gathering data and	**information**	necessary for the study authorized in the

	aardvark	computer	data	pinch	result	sugar ...
⋮						
apricot	0	0	0	1	0	1
pineapple	0	0	0	1	0	1
digital	0	2	1	0	1	0
information	0	1	6	0	4	0
⋮						

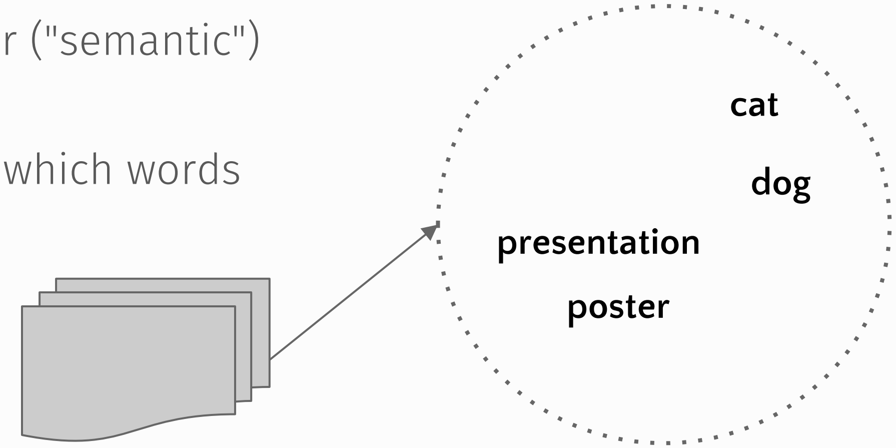
Slide credit: David Mortensen

Types of word vectors

Shared Intuition: Words are Vectors of Numbers Representing Meaning

- Model the meaning of a word by "embedding" it in a vector space.
- The meaning of a word is a vector of numbers:
  - Vector models are also called **embeddings**
  - Often, the word *embedding* is reserved for *dense* vector representations
- In contrast, word meaning is represented in many (early) NLP applications by a vocabulary index ("word number 545"; compare to one-hot representations)

- Similar words are nearby in vector ("semantic") space
- Build "semantic space" by seeing which words are nearby in text



Slide adapted from David Mortensen

There are Two Kinds of Vector Models

- **Sparse embeddings** (vectors from term-document matrix)
  - long (length of 20,000 to 50,000)
  - sparse: most elements are 0
- **Dense embeddings** (Word2vec)
  - short (length of 50-1000)
  - dense (most elements are non-zero)


Slide adapted from David Mortensen, Jurafksy & Martin

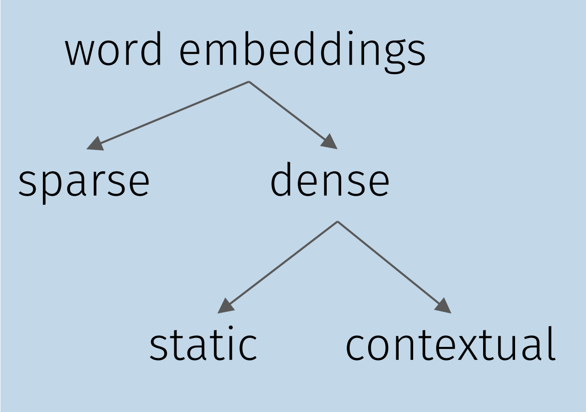
Dense Vectors Have Three Advantages over Sparse Vectors

1. Short vectors may be **easier to use as features** in machine learning (less weights to tune).
2. Dense vectors may **generalize better** than storing explicit counts.
3. They may do **better at capturing synonymy**:
    - *car* and *automobile* are synonyms
    - But, in sparse vectors, they are represented as distinct dimensions
    - This fails to capture similarity between a word with *car* as a neighbor and a word with *automobile* as a neighbor

Slide credit: David Mortensen

Methods for learning short, dense word embeddings

- Static, neural embeddings
  - Fixed embeddings for word types
  - Word2Vec, GloVe
- Contextual embeddings
  - Embeddings for words vary by context
  - ELMo, BERT, LLMs



Word2vec

Word2vec [Mikolov et al. 2013]

- Instead of counting words, train a classifier on a binary prediction task
  - Is w_1 likely to show up near w_2?

Slide adapted from Jurafsky & Martin

Word2vec [Mikolov et al. 2013]

- Instead of counting words, train a classifier on a binary prediction task
    - Is w_1 likely to show up near *apricot*?

Slide adapted from Jurafsky & Martin

Word2vec [Mikolov et al. 2013]

- Instead of counting words, train a classifier on a binary prediction task
  - Is w_1 likely to show up near *apricot*?

- Take the learned classifier weights as the word embeddings

Slide adapted from Jurafsky & Martin

Word2vec [Mikolov et al. 2013]

- Instead of counting words, train a classifier on a binary prediction task
  - Is w_1 likely to show up near *apricot*?

- Take the learned classifier weights as the word embeddings
- Training techniques: skip-gram and CBOW

Slide adapted from Jurafsky & Martin

Word2vec: training supervision

- Self-supervision [Bengio et al. 2003, Collobert et al. 2011]
- Use naturally occurring text as labels
- A word c that occurs near *apricot* in the corpus counts as the gold "correct answer" for supervised learning

Slide adapted from Jurafsky & Martin

Word2vec training overview

1. Positive examples: the target word w and a neighboring context word c_{pos}
2. Negative examples: Randomly sample other words c_{neg} in the lexicon to pair with w
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights (W, C) as the word embeddings

Slide adapted from Jurafsky & Martin

Training for Embeddings

- We do not know what W and C are. So we learn them through an iterative process.
- We use a large corpus as a training data
- We also randomly sample the corpus to find words that are NOT in the context—negative sampling.

A	soothsayer	bids	you	beware	the	Ides	of	March	.
				c_1	c_2	t	c_3	c_4	

Positive Examples		Negative Examples			
t	c	t	c	t	c
ides	beware	ides	aardvark	ides	twelve
ides	of	ides	puddle	ides	hello
ides	March	ides	where	ides	dear
ides	the	ides	coaxial	ides	forever

Slide credit: David Mortensen

Word2vec: learning embeddings

- Start with randomly initialized context *C* and target word *W* matrices
- Go through the positive and negative training pairs, adjusting word vectors such that we:
  - Maximize the similarity of the target word, context word pairs (w, c_{pos}) drawn from the positive data
  - Minimize the similarity of the (w, c_{neg}) pairs drawn from the negative data.

Slide adapted from Jurafsky & Martin

Skip-gram classifier

Classifier input pairs:

(target word *w*, context word *c*)

Classifier output: probabilities that *w* occurs with *c*

$P(+|w, c)$

$P(-|w, c) = 1 - P(+|w, c)$

Slide adapted from Jurafsky & Martin

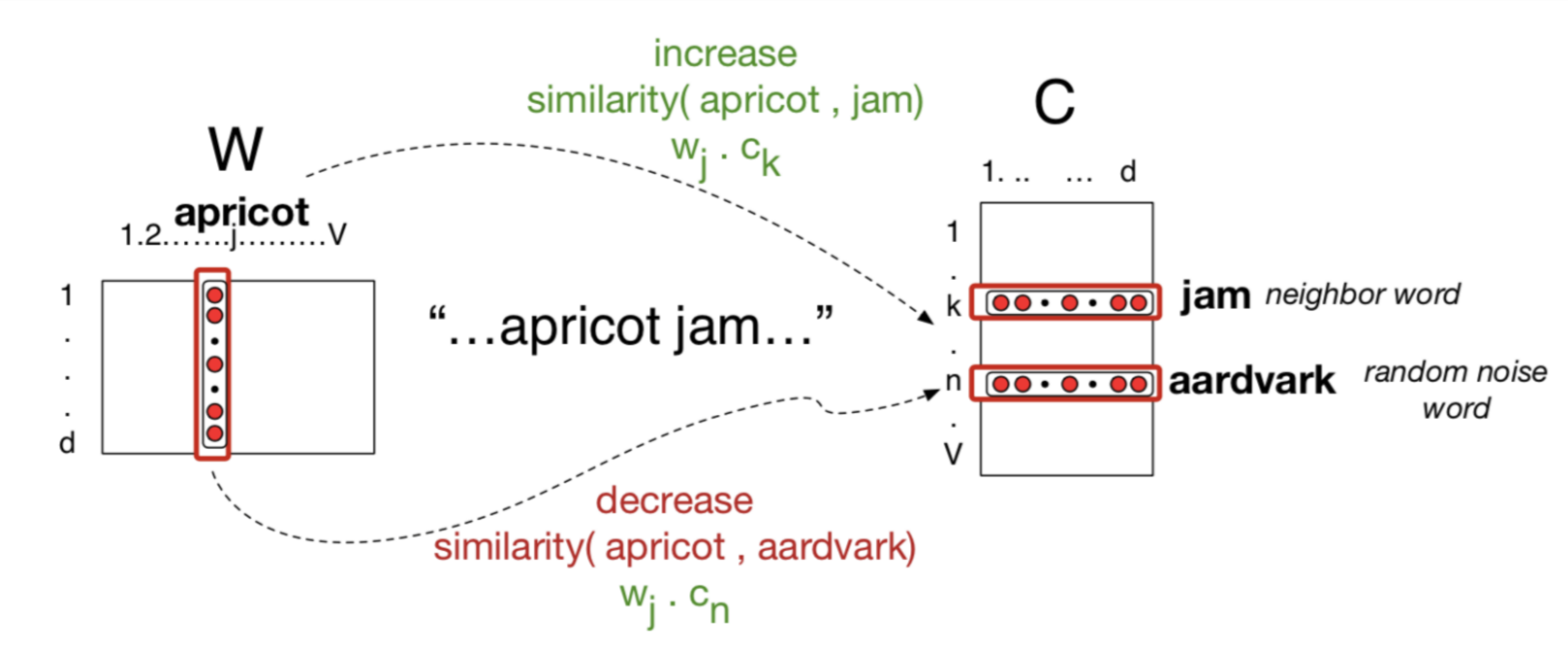
Skip-gram classifier: calculating probabilities

- From input vectors, need to compare for similarity
- Start with dot product: sim(**w**,**c**) ≈ **w** · **c**
- To turn this into a probability, use the sigmoid function from logistic regression:

$$P(+|w,c) = \sigma(c \cdot w) = \frac{1}{1+\exp(-c \cdot w)}$$

Slide adapted from Jurafsky & Martin

Training for Embeddings



Slide adapted from David Mortensen, Jurafsky & Martin

Reminder: one step of gradient descent

- Direction: We move in the reverse direction from the gradient of the loss function
- Magnitude: we move the value of this gradient $d/dw\ L(P(+|w,c) + P(-|w,c))$ weighted by a learning rate η
- Higher learning rate means move w faster

Slide adapted from Jurafsky & Martin

Loss function for one *w* with c_{pos} , c_{neg1} ...c_{negk}

Maximize the similarity of the target with the actual context words, and minimize the similarity of the target with the *k* negative sampled non-neighbor words.

$$
\begin{aligned}
L_{\mathrm{CE}} &= -\log\left[P(+|w,c_{pos})\prod_{i=1}^{k}P(-|w,c_{neg_i})\right] \\
&= -\left[\log P(+|w,c_{pos})+\sum_{i=1}^{k}\log P(-|w,c_{neg_i})\right] \\
&= -\left[\log P(+|w,c_{pos})+\sum_{i=1}^{k}\log\left(1-P(+|w,c_{neg_i})\right)\right] \\
&= -\left[\log\sigma(c_{pos}\cdot w)+\sum_{i=1}^{k}\log\sigma(-c_{neg_i}\cdot w)\right]
\end{aligned}
$$

Slide adapted from Jurafsky & Martin

Word2vec training process

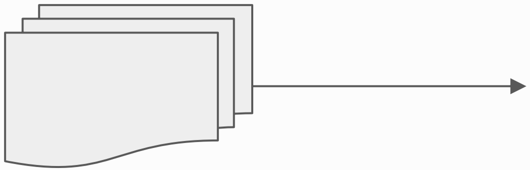
Updates on C and W

$$\underbrace{c_{pos}^{t+1}}_{\text{new context weights}} = \underbrace{c_{pos}^{t}}_{\text{old context weights}} - \underbrace{\eta}_{\text{learning rate}} \underbrace{[\sigma(c_{pos}^{t} \cdot w^{t}) - 1]}_{\text{derivative of loss wrt } c_{pos}}$$

$$\underbrace{w^{t+1}}_{\text{new target word weights}} = \underbrace{w^{t}}_{\text{old context weights}} - \underbrace{\eta}_{\text{learning rate}} \left[\underbrace{[\sigma(c_{pos} \cdot w^{t}) - 1]c_{pos} + [\sigma(c_{neg_i} \cdot w^{t})]c_{neg_i}}_{\text{derivative of loss wrt } w} \right]$$

Slide adapted from Jurafsky & Martin

Summary: How to learn word2vec embeddings



cat	[0.31, 0.24, 0.07, 0.65 ...]
dog	[0.37, 0.29, 0.06, 0.63 ...]
presentation	[0.65, 0.93, 0.16, 0.78 ...]
poster	[0.57, 0.82, 0.21, 0.73 ...]

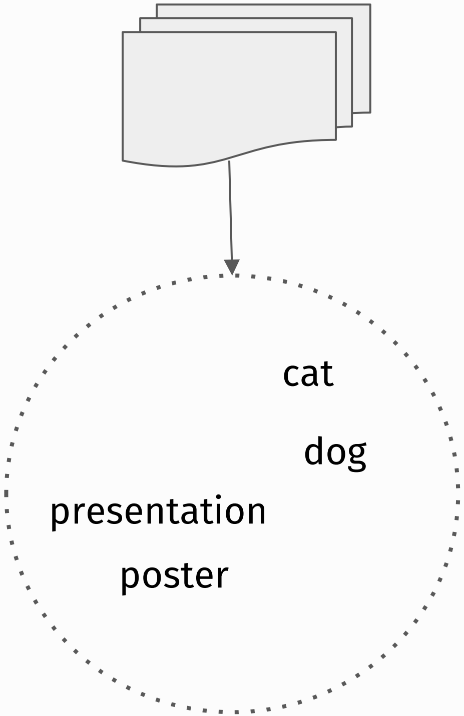
Summary: How to learn word2vec embeddings

1. Start with randomly initialized word embeddings
2. From a corpus, extract pairs of words that co-occur (positive)
3. Extract pairs of words that don't co-occur (negative)
4. Train a classifier to distinguish between positive and negative examples by slowly adjusting all the embeddings to improve the classifier performance
5. Keep the weights as our word embeddings

Slide adapted from Jurafsky & Martin

Final embeddings

- Can add representations for a word in W and in C together for final word vector for w_i
- Can just keep W and throw away C
- Can find "nearest neighbors" of certain words with cosine similarity in embedding space



Slide adapted from Jurafsky & Martin

There are Tools and Resources Available for Training and Using Embeddings

- **Pretrained embeddings**
  - Skip-gram
  - CBOW
  - fastText
  - GloVe
- **Training your own embeddings**
  - You can easily train skip-gram, CBOW, and fastText embeddings with `gensim`
  - Straightforward Python interface

Slide credit: David Mortensen

Embeddings reflect cultural biases [Bolukbasi et al. 2016]

- Paris : France :: Tokyo : *Japan*
- Sexist occupational stereotypes
  - father : doctor :: mother : *nurse*
  - man : computer programmer :: woman : *homemaker*
- Would be problematic to use embeddings in hiring searches for programmers

Slide adapted from Jurafsky & Martin

Conclusion: vector semantics, static word embeddings

- NLP typically represents words as vectors in spaces where distance ≈ semantic similarity
- Word2vec learns static embeddings (vectors) for words by predicting which words occur together in training data
- These embeddings are effective in downstream NLP tasks, but also reflect social biases of training data text

Coding activity

Notebook: examine word2vec embeddings

- Click on this nbgitpuller link
    - Or find the link on the course website
- Open **session10_word2vec.ipynb**