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Word Embeddings

2/05/25

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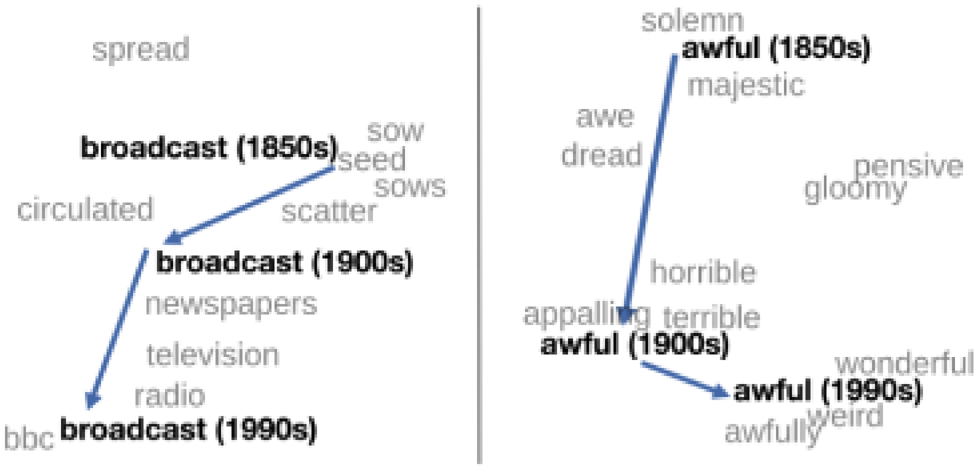
Background: Word Representations

Motivation

- Core question in understanding cultural and language evolution: how do words change meaning over time?



How can we represent meaning of a word?

Hamilton, William L., Jure Leskovec, and Dan Jurafsky. "Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change." Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). 2016.

Motivation

- Can we use language analysis to identify and measure stereotypes?

- Example from last week:
  - Using PMI scores, Wikipedia articles about women tend to talk personal life more
  - Might we expect words like “family”, and “marriage” to be women-associated?

How can we measure “associations” between words?

Wagner, Claudia, et al. "It's a man's Wikipedia? Assessing gender inequality in an online encyclopedia." *Proceedings of the international AAAI conference on web and social media*. Vol. 9. No. 1. 2015.

How might we represent words?

"Lexical Semantics"

- Dictionary definition
- Lemma and word forms
- Senses

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pepper [**pep**-er] **SHOW IPA**

See synonyms for: pepper / peppered / peppering on Thesaurus.com

noun

1. a pungent condiment obtained from various plants of the genus *Piper,* especially from the dried berries, used whole or ground, of the tropical climbing shrub *P. nigrum*.
2. any plant of the genus *Piper*.: Compare pepper family.

A sense or "concept" is the meaning component of a word.

How might we represent words?

"Lexical Semantics"

- Dictionary definition
- Lemma and word forms
- Senses
- Relationships between words or senses
- Taxonomic relationships
- Word similarity, word relatedness

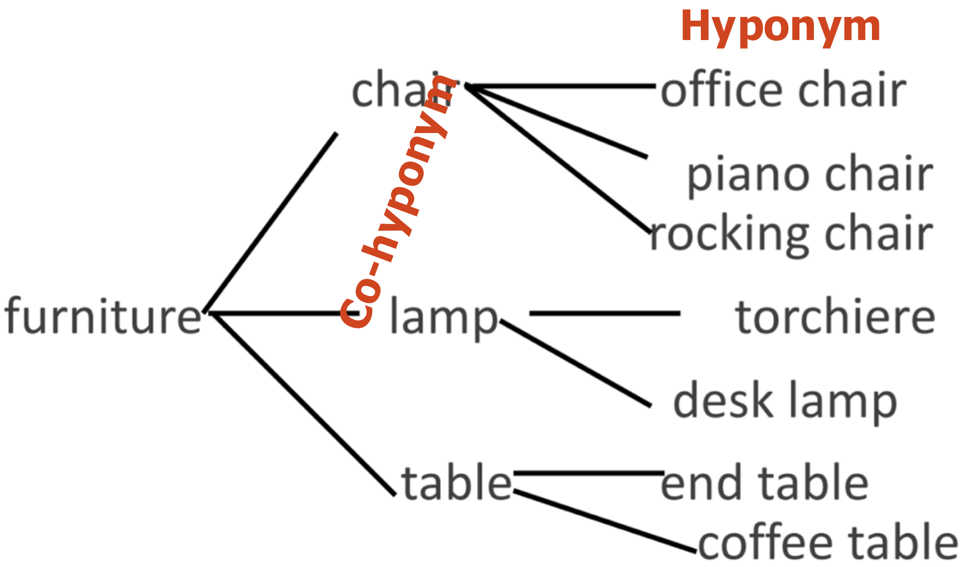
Relations between words

- **Synonyms** have the same meanings in some or all contexts
  - Couch / sofa, car / automobile
  - [Note that there are no examples of perfect synonymy]

- **Antonyms** senses that are opposite with respect to one feature of meaning
  - Dark / light, short / long, slow / fast
  - [Otherwise they are very similar]
  - [Antonyms can define a binary opposition or be at opposite ends of a scale]

Relations between words

- **Hypernym** / **Hyponym** (superordinate / subordinate)
  - One sense is a hyponym of another if the first sense is more specific, denoting a subclass of the other



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Annotated Resources for Lexical Semantics

- https://wordnet.princeton.edu/
- (python packages)

WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: pepper Search WordNet

Display Options: (Select option to change) Change

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations
Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **pepper**, common pepper, black pepper, white pepper, Madagascar pepper, Piper nigrum (climber having dark red berries (peppercorns) when fully ripe; southern India and Sri Lanka; naturalized in northern Burma and Assam)
  - *part meronym*
  - *member holonym*
  - *substance meronym*
  - *direct hypernym* | *inherited hypernym* | *sister term*
- S: (n) capsicum, **pepper**, capsicum pepper plant (any of various tropical plants of the genus Capsicum bearing peppers)
- S: (n) **pepper**, peppercorn (pungent seasoning from the berry of the common pepper plant of East India; use whole or ground)
- S: (n) **pepper** (sweet and hot varieties of fruits of plants of the genus Capsicum)

Verb

- S: (v) **pepper** (add pepper to) *"pepper the soup"*
- S: (v) **pepper**, pelt (attack and bombard with or as if with missiles) *"pelt the speaker with questions"*

How might we represent words?

"Lexical Semantics"

- Dictionary definition
- Lemma and word forms
- Senses
- Relationships between words or senses
- Taxonomic relationships
- Word similarity, word relatedness
- Semantic frames and roles
- Connotation and sentiment

How to represent a word

- Until the ~2010s, in NLP words == atomic symbols
- **One-hot** representations in vector space:

1	0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0	0
0	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	0	0	1
0	0	1	0	0	0	0	1	0
...	...	...	...	...	...	...	...	...
0	0	0	0	0	0	1	0	0
the	drinks	were	strong	but	the	tacos	were	bland

V

$\boldsymbol{w}$ = the drinks were strong but the tacos were bland

0	0	...	0	0	0	0	1	tacos
0	0	...	0	1	0	0	0	burritos
0	0	...	0	0	1	0	0	drinks
0	0	...	0	0	0	0	1	leader
0	1	...	0	0	0	0	0	president
0	0	...	1	0	0	0	0	bland

How to represent a word

- Until the ~2010s, in NLP words == atomic symbols
- **One-hot** representations in vector space:

	1	0	0	0	0	1	0	0	0
	0	0	0	0	1	0	0	0	0
	0	1	0	0	0	0	0	0	0
	0	0	0	1	0	0	0	0	0
	0	0	0	0	0	0	0	0	1
	0	0	1	0	0	0	0	1	0
	…	…	…	…	…	…	…	…	…
	0	0	0	0	0	0	1	0	0
w =	the	drinks	were	strong	but	the	tacos	were	bland

V

Good things:

- Useful for coding *identity*
- Can do matrix operations:
  - Feed into machine learning models
  - Matrix decompositions

How to represent a word

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- **One-hot** representations in vector space:

	1	0	0	0	0	1	0	0	0
	0	0	0	0	1	0	0	0	0
	0	1	0	0	0	0	0	0	0
	0	0	0	1	0	0	0	0	0
	0	0	0	0	0	0	0	0	1
	0	0	1	0	0	0	0	1	0
	...	...	...	...	...	...	...	...	...
	0	0	0	0	0	0	1	0	0
w =	the	drinks	were	strong	but	the	tacos	were	bland

V

Bad things:

- Sparse representations that scale with vocabulary size
- "tacos" is orthogonal to "burritos"
- How can we encode word *similarity* (not just identity)?

Encoding word similarity

- How can we encode word similarity (not just identity) in word representations?
- Consider encountering a new word: *tezgüino*
  - A bottle of *tezgüino* is on the table
  - Everybody likes *tezgüino*
  - Don’t have *tezgüino* before you drive
  - We make *tezgüino* out of corn

context

term	1	2	3	4
tezgüino	1	1	1	1
loud	0	0	0	0
motor oil	1	0	0	1
tortillas	0	1	0	1
choices	0	1	0	0
wine	1	1	1	0

Word-word co-occurrence matrix

Apples are green and red.
Red apples are sweet.
Green oranges are sour

-	apples	are	green	and	red	sweet	oranges	sour
apples	2	2	1	1	2	1	0	0
are	2	3	1	1	2	1	1	1
green	1	1	2	1	1	0	1	1
and	1	1	1	1	1	0	0	0
red	2	2	1	1	2	1	0	0
sweet	1	1	0	0	1	1	0	0
oranges	0	1	1	0	0	0	1	1
sour	0	1	1	0	0	0	1	1

https://www.baeldung.com/cs/co-occurrence-matrices

Distributional hypothesis

- These representations encode **distributional** properties of each word.
- The **distributional hypothesis**: words with similar meaning are used in similar contexts.

"The meaning of a word is its use in the language." [Wittgenstein 1943]

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

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

How to encode context

Really really big

context

term	**1**	**2**	**3**	**4**	…
tezgüino	1	1	1	1	
loud	0	0	0	0	…
motor oil	1	0	0	1	
tortillas	0	1	0	1	…
choices	0	1	0	0	…
wine	1	1	1	0	

sparse

How to encode context

- **TF-IDF**
- **Word2Vec**
- Not covering other methods: e.g. Brown clusters, Matrix factorization

TF-IDF

Encoding Context with TF-IDF

- Consider a matrix of word counts across documents: **term-document matrix**

Words like *the*, *it*, *they* are not very discriminative, we can do better than raw counts

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

word vector

Bag-of-words document representation

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Encoding Context with TF-IDF

- TF-IDF incorporates two terms that capture these conflicting constraints:
  - **Term frequency (tf):** frequency of the word t in the document

$$tf_{t,d} = \log(count(t,d) + 1)$$

Encoding Context with TF-IDF

- TF-IDF incorporates two terms that capture these conflicting constraints:
  - **Term frequency (tf):** frequency of the word t in a cluster (or "class")

$$tf_{t,c} = \log(count(t,d) + 1)$$

  - Document frequency (df): number of documents that a term occurs in
  - **Inverse document frequency (idf):**

$$idf_t = \log(\frac{N}{df_t})$$

Higher for terms that occur in fewer documents

  - (N) is the number of documents in the corpus

Encoding Context with TF-IDF

- TF-IDF incorporates two terms that capture these conflicting constraints:
  - **Term frequency (tf):** frequency of the word t in the document

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  - Document frequency (df): number of documents that a term occurs in
  - **Inverse document frequency (idf):**

$$idf_t = \log\left(\frac{N}{df_t}\right)$$

Higher for terms that occur in fewer documents

  - (N) is the number of documents in the corpus

- **TF-IDF** combines these two terms: $tf\text{-}idf_{t,d} = tf_{t,d} * idf_t$

Encoding Context with TF-IDF

- Consider a matrix of word counts across documents: **term-document matrix**

We could use TF-IDF here instead of counts

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

word vector

Bag-of-words document representation

Notes about TF-IDF

- Very useful way of creating *document embeddings*
  - Designed for and still excels at **document retrieval**
  - Often useful as features for classification models

- We could use variants of *log-odds with a Dirichlet prior ratios* or *topic models* to create document or word embeddings

- Word-embedding use cases of TF-IDF are not as common

Dimensionality Reduction

- TF-IDF representations are still sparse
  - Wikipedia: ~29 million English documents. Vocab: ~1 million words.
- Sparse vs. dense vectors:
  - Short vectors often easier to use as features in a classifier (fewer parameters).
  - Dense vectors may generalize better than storing explicit counts.
  - May better capture synonymy
  - In practice, they just work better [Baroni et al. 2014]

- How do we build dense vectors?

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Word2Vec

Word2Vec

- Instead of counting how often each word w occurs near “corn”, train a classifier on a binary prediction task: Is w likely to show up near “corn”?
- Don’t actually care about performing this task, but we’ll take the learned classifier weights as the word embeddings
- Training is self-supervised: no annotated data required, just raw text!

Word2Vec: Two Algorithms

- Context bag-of-words (CBOW): predict current word using context
  - $P(w_t \mid w_{t+1}, \ldots, w_{t+k}, w_{t-1}, \ldots, w_{t-k})$

- Skip-gram: predict each context word using current word
  - $P(w_{t+1}, \ldots, w_{t+k}, w_{t-1}, \ldots, w_{t-k} \mid w_t)$

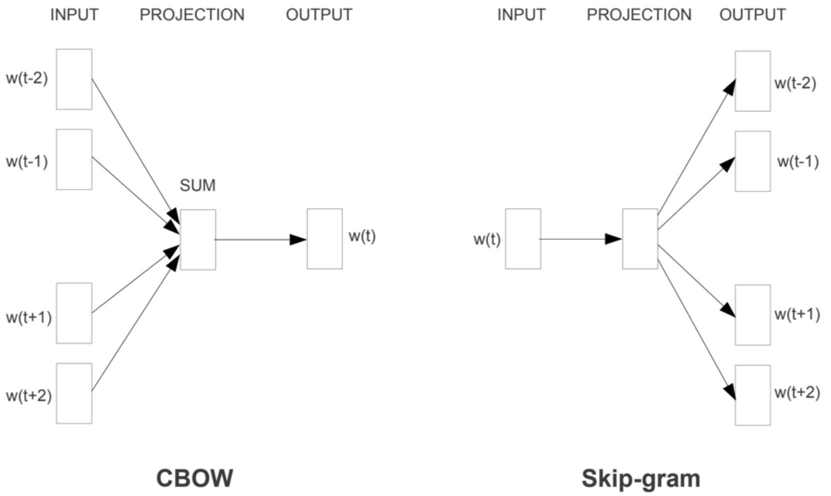


Figure 1: New model architectures. The CBOW architecture predicts the current word based on the context, and the Skip-gram predicts surrounding words given the current word.

Skip-gram: Probabilities

… that Europe needs unified **banking** regulation to replace the hodgepodge …

w_{t-3} w_{t-2} w_{t-1} w_t w_{t+1} w_{t+2} … w_{t+5}

We want to train a model to output $P(w_{t+j}|w_t)$. We define:

$$P(w_{t+j}|w_t) = P(o \mid c) = \frac{\boxed{\exp(\boxed{u_o^T v_c})}}{\boxed{\sum_{i=1}^{V} \exp(u_i^T v_c)}}$$

Dot product (similarity metric)
Larger dot product = larger similarity

softmax function

o = index of outside (context) word
c = index of center word (w_t)
V = vocab size

u = vector for word as outside (context)
v = vector for word as center

Skip-gram: How do we learn u and w?

… that Europe needs unified **banking** regulation to replace the hodgepodge …

w_{t-3} w_{t-2} w_{t-1} w_t w_{t+1} w_{t+2} … w_{t+5}

m = 5

Data Likelihood: probability of any context word given center word (maximize)

[Note we're assuming conditional independent]

$$L = \frac{1}{T}\prod_{t=1}^{T}\prod_{-m\leq j\leq m, j\neq 0} P(w_{t+j}|w_t,\theta)$$

Objective Function: negative log probability (minimize)

$$L = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0} \log P(w_{t+j}|w_t,\theta)$$

Skip-gram: How do we learn u and w?

$$L = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-m\leq j\leq m, j\neq 0} \log P(w_{t+j}|w_t, \theta)$$

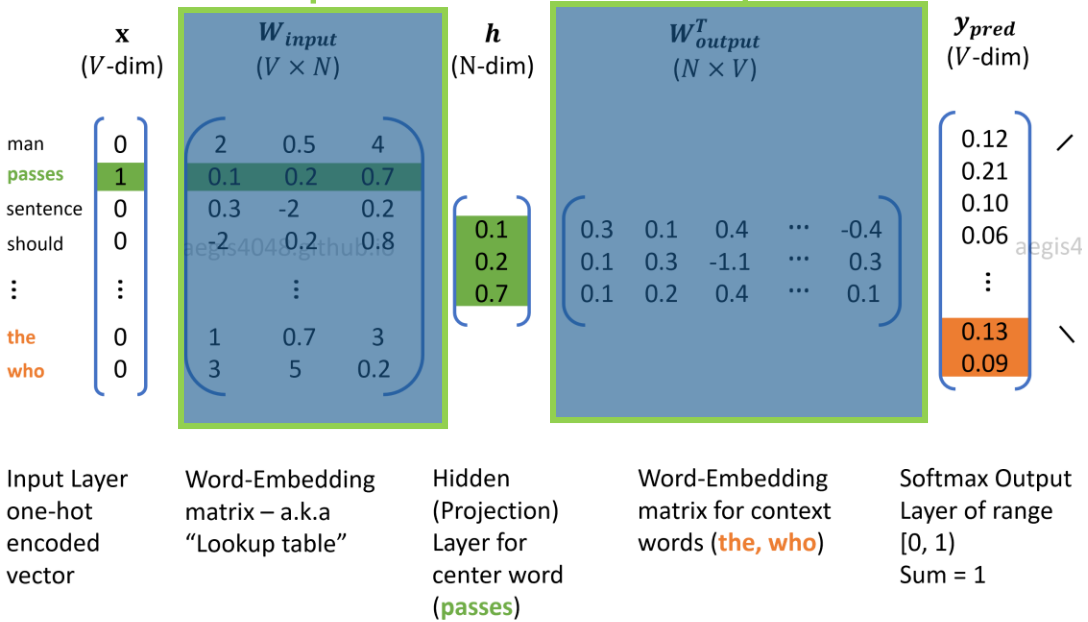
$$P\left(w_{t+j}\middle|w_t\right) = P(o \mid c) = \frac{\exp(u_o^T v_c)}{\sum_{i=1}^{V}\exp(u_i^T v_c)}$$

- Gradient-based estimation (e.g. stochastic gradient descent)
  - Start with uninformed guess for u and w (e.g. random)
  - Iteratively change u and w in the way that locally best-improves the guess
  - Computing gradients (e.g. derivatives) of the objective function with respect to u and w inform how to change them

$$\frac{\exp(u_o^T v_c)}{\sum_{i=1}^{V} \exp(u_i^T v_c)}$$

"v" input vector matrix

"u" output vector matrix



N = number of dimensions in embeddings (parameter you choose)

At the end of training we've learned 2 sets of embeddings: we can average them or just keep one of them

https://aegis4048.github.io/demystifying_neural_network_in_skip_gram_language_modeling

Quiz

Consider three categories of words that have different relationships in our favorite dataset of Democratic and Republican congressional speech.

A. Synonyms that are nearly interchangeable like “death-tax” and “estate-tax”, but tend to be used by different party members

B. Words that are used by different individuals and have different meanings, but tend to appear in identical sentences like “Texas” and “New York” (example sentence: “My constituents from Texas”)

C. Words that tend to co-occur in the same speech, but maybe not the same sentences. For example a speech healthcare might refer to “insurance” and “doctors”

1. Let’s we construct TF-IDF word embeddings (from a term-document matrix) over the corpus. Which of the above categories do expect to have similar embeddings (select all that apply)?
2. Let’s we construct CBOW Word2Vec embeddings. Which of the above categories do expect to have similar embeddings (select all that apply)?
3. Let’s we construct Skip-gram Word2Vec embeddings. Which of the above categories do expect to have similar embeddings (select all that apply)?

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Skip-gram

$$\frac{\exp(u_o^T v_c)}{\boxed{\sum_{i=1}^{V} \exp(u_i^T v_c)}}$$

- Problem:
  - Denominator is computationally expensive! O(VK)
  - Solutions:
    - Hierarchical softmax O(log V)
    - Negative Sampling O(1)

Skip-gram: Negative sampling

$$\frac{\exp(u_o^T v_c)}{\sum_{i=1}^{V} \exp(u_i^T v_c)}$$

Encourage center word and context word to have similar vectors

Encourage center word and all other words to have different vectors

- Intuition: we don’t need to down-weight all other words at once, we can chose a small number of negative samples

Skip-gram: Negative sampling

$$P(o \mid c) = \frac{\exp(u_o^T v_c)}{\sum_{i=1}^{V} \exp(u_i^T v_c)} \longrightarrow \frac{1}{1 + \exp(-u_o^T v_c)}$$

- New objective (single context word, k negative samples)

$$\log P(o_+|c) + \sum_{i=1}^{k} \log(1 - P(o_i|c))$$

- (Problem changes from multiclass to binary)

Choosing negative samples

- Generally choose frequent words
- Could choose purely based on frequency P(w)
- In practice, $P_\alpha(w) = \frac{count(w)^\alpha}{\sum_w count(w)^\alpha}$ with $\alpha = 0.75$ works well (gives rare words slightly higher probability)

Recap

- We want meaningful representations of words that we can use for corpus analytics (and other things)
- By defining a fake task, predicting context from a word (skip-gram) or a word from context (CBOW), we can learn meaningful vector
  - Our training objective specifically encourages words that co-occur together or occur in similar contexts to have similar vectors
- Actual implementation requires additional tricks for reducing computational complexity

Pre-trained Word2Vec Embeddings

- https://code.google.com/archive/p/word2vec/
- You can train embeddings on your own data
- Depending on your application, you can also start with embeddings trained on large data set

Other word embeddings: GloVe [Pennington et al. 2014]

- https://nlp.stanford.edu/projects/glove/
- "Global Vectors"
- Model is based on capturing global corpus statistics
- Incorporates ratios of probabilities from the word-word cooccurrence matrix (intuitions of count-based models) with linear structures used by methods like word2vec

Other word embeddings: fasttext [Bojanowsi et al. 2017]

- Word2vec can’t handle unknown words and sparsity of rare word-forms (e.g. we should be able to infer ”milking” from “milk” + “ing”)
- Uses subword models, representing each word as itself plus a bag of constituent n-grams, with special boundary symbols < and > added to each word.
- Each word is represented by the sum of all of the embeddings of its constituent n-grams. Unknown words can be represented by just the sum of the constituent n-grams.

Gensim: Python Package for working with word embeddings

```
>>> from gensim.test.utils import common_texts
>>> from gensim.models import Word2Vec
>>>
>>> model = Word2Vec(sentences=common_texts, vector_size=100, window=5, min_count=1, workers=4)
>>> model.save("word2vec.model")
```

https://radimrehurek.com/gensim/models/word2vec.html

Takeaways

- Intuitive ideas behind representing words as vectors
- Distributional Hypothesis
- Basic ideas behind TF-IDF weighting
- Basic ideas behind Word2Vec
  - Difference between CBOW and Skip-gram
  - Practical challenges
- *Know where your embeddings came from and how they were made*

Next Class

- How do we know if our embeddings work?
- What do we do with them?

Acknowledgements and Resources

- Slide content drew heavily from Emma Strubell and Yulia Tsvetkov's slides: http://demo.clab.cs.cmu.edu/11711fa20/slides/11711-04-word-vectors.pdf

- Resources:
  - Lecture Notes from Stanford NLP class on word embeddings https://web.stanford.edu/class/cs224n/readings/cs224n_winter2023_lecture1_notes_draft.pdf
  - Efficient Estimation of Word Representations in Vector Space (original word2vec paper) https://arxiv.org/pdf/1301.3781.pdf
  - Distributed Representations of Words and Phrases and their Compositionality (negative sampling paper) https://proceedings.neurips.cc/paper_files/paper/2013/file/9aa42b31882ec039965f3c4923ce901b-Paper.pdf
  - Jurafsky and Martin textbook Chap 6: https://web.stanford.edu/~jurafsky/slp3/6.pdf