- Word Meaning (lexical)

What do words mean?

- Next thought: look in a dictionary
- http://www.oed.com/

Words, Lemmas, Senses, Definitions

lemma

sense

definition

pepper, *n.*

Pronunciation: Brit. /ˈpɛpə/, U.S. /ˈpɛpər/

Forms: OE **peopor** (*rare*), OE **pipcer** (transmission error), OE **pipor**, OE **pipur** (*rare*

Frequency (in current use):

Etymology: A borrowing from Latin. **Etymon:** Latin *piper*.

< classical Latin *piper*, a loanword < Indo-Aryan (as is ancient Greek *πέπερι*); compare Sa

I. The spice or the plant.

1.

a. A hot pungent spice derived from the prepared fruits (peppercorns) of the pepper plant, *Piper nigrum* (see sense 2a), used from early times to season food, either whole or ground to powder (often in association with salt). Also (locally, chiefly with distinguishing word): a similar spice derived from the fruits of certain other species of the genus *Piper*; the fruits themselves.

The ground spice from *Piper nigrum* comes in two forms, the more pungent *black pepper*, produced from black peppercorns, and the milder *white pepper*, produced from white peppercorns: see BLACK *adj.* and *n.* Special uses 5a, PEPPERCORN *n.* 1a, and WHITE *adj.* and *n.*[1] Special uses 7b(a).

2.

a. The plant *Piper nigrum* (family Piperaceae), a climbing shrub indigenous to South Asia and also cultivated elsewhere in the tropics, which has alternate stalked entire leaves, with pendulous spikes of small green flowers opposite the leaves, succeeded by small berries turning red when ripe. Also more widely: any plant of the genus *Piper* or the family Piperaceae.

b. Usu. with distinguishing word: any of numerous plants of other families having hot pungent fruits or leaves which resemble pepper (1a) in taste and in some cases are used as a substitute for it.

c. *U.S.* The California pepper tree, *Schinus molle*. Cf. PEPPER TREE *n.* 3.

3. Any of various forms of capsicum, esp. *Capsicum annuum* var. *annuum*. Originally (chiefly with distinguishing word): any variety of the *C. annuum* Longum group, with elongated fruits having a hot, pungent taste, the source of cayenne, chilli powder, paprika, etc., or of the perennial *C. frutescens*, the source of Tabasco sauce. Now frequently (more fully ***sweet pepper***): any variety of the *C. annuum* Grossum group, with large, bell-shaped or apple-shaped, mild-flavoured fruits, usually ripening to red, orange, or yellow and eaten raw in salads or cooked as a vegetable. Also: the fruit of any of these capsicums.

Sweet peppers are often used in their green immature state (more fully ***green pepper***), but some new varieties remain green when ripe.

Lemma pepper

- Sense 1: spice from pepper plant
- Sense 2: the pepper plant itself
- Sense 3: another similar plant (Jamaican pepper)
- Sense 4: another plant with peppercorns (California pepper)
- Sense 5: *capsicum* (i.e. chili, paprika, bell pepper, etc)

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

Relations between senses: Synonymy

- Synonyms have the same meaning in some or all contexts.
  - filbert / hazelnut
  - couch / sofa
  - big / large
  - automobile / car
  - vomit / throw up
  - water / H_20

Relation: Similarity

Words with similar meanings. Not synonyms, but sharing some element of meaning

```
car, bicycle
cow, horse
```

Ask humans how similar 2 words are

word1	word2	similarity
vanish	disappear	9.8
behave	obey	7.3
belief	impression	5.95
muscle	bone	3.65
modest	flexible	0.98
hole	agreement	0.3

SimLex-999 dataset (Hill et al., 2015)

Relation: Word relatedness

- Also called "word association"
- Words can be related in any way, perhaps via a semantic frame or field
    - `car, bicycle`: **similar**
    - `car, gasoline`: **related**, not similar

Relation: Antonymy

- Senses that are opposites with respect to only one feature of meaning
- Otherwise, they are very similar!

  `dark/light` `short/long` `fast/slow` `rise/fall`

  `hot/cold` `up/down` `in/out`

- More formally: antonyms can
  - define a binary opposition or be at opposite ends of a scale
    - `long/short, fast/slow`
  - Be *reversives*:
    - `rise/fall, up/down`

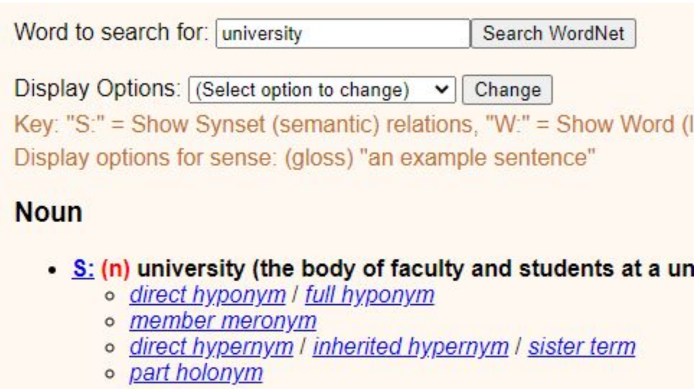
Relation: Superordinate/ subordinate

- One sense is a **subordinate** of another if the first sense is more specific, denoting a subclass of the other
  - *car* is a subordinate of *vehicle*
  - *mango* is a subordinate of *fruit*
- Conversely **superordinate**
  - *vehicle* is a superordinate of *car*
  - *fruit* is a superodinate of *mango*

Superordinate	vehicle	fruit	furniture
Subordinate	car	mango	chair

http://wordnetweb.princeton.edu/perl/webwn

- **Concepts** or word senses
  - Have a complex many-to-many association with **words** (homonymy, multiple senses)
- Have relations with each other
  - Synonymy
  - Antonymy
  - Similarity
  - Relatedness
  - Superordinate/subordinate, basic level
  - Connotation



- Meaning (distributional)

How about a radically different approach?

Ludwig Wittgenstein

- PI #43:

  "The meaning of a word is its use in the language"

Let's define words by their usages

- One way to define "usage":
- words are defined by their environments (the words around them)

- Zellig Harris (1954):
- **If A and B have almost identical environments we say that they are synonyms.**

What does recent English borrowing *ongchoi* mean?

- Suppose you see these sentences:
  - Ong choi is delicious **sautéed with garlic**.
  - Ong choi is superb **over rice**
  - Ong choi **leaves** with salty sauces
- And you've also seen these:
  - …spinach **sautéed with garlic over rice**
  - Chard stems and **leaves** are **delicious**
  - Collard greens and other **salty** leafy greens
- Conclusion:
  - Ongchoi is a leafy green like spinach, chard, or collard greens

Ongchoi: *Ipomoea aquatica "Water Spinach"*

空心菜
kangkong
rau
muống
...

Yamaguchi, Wikimedia Commons, public domain

A new model of meaning focusing on distributional similarity

- Each word = a vector
  - Not just "word" or word45.
- Similar words are "nearby in space"

We define a word as a vector

- Called an "embedding" because it's embedded into a space
- The standard way to represent meaning in NLP
- **Every modern NLP algorithm uses embeddings as the representation of word meaning**
- Fine-grained model of meaning for similarity

Intuition: why vectors?

- Consider sentiment analysis:
  - With **words**, a feature is a word identity
    - Feature 5: 'The previous word was "terrible"'
    - requires **exact same word** to be in training and test
  - With **embeddings**:
    - Feature is a word vector
    - 'The previous word was vector [35,22,17…]
    - Now in the test set we might see a similar vector [34,21,14]
    - We can generalize to **similar but unseen** words!!!

2 kinds of embeddings

- tf-idf (alternatively PPMI)
  - Information Retrieval workhorse!
  - A common baseline model
  - **Sparse** vectors
  - Words are represented by (a simple function of) the **counts** of nearby words
- Word2vec
  - **Dense** vectors
  - Representation is created by training a classifier to **predict** whether a word is likely to appear nearby
  - In later chapters we'll discuss extensions called **contextual embeddings**

- Dense vectors

Sparse versus dense vectors

- tf-idf vectors are
  - **long** (length |V|= 20,000 to 50,000)
  - **sparse** (most elements are zero)
- Alternative: learn vectors which are
  - **short** (length 50-1000)
  - **dense** (most elements are non-zero)

Sparse versus dense vectors

- Why dense vectors?
  - Short vectors may be easier to use as **features** in machine learning (fewer weights to tune)
  - Dense vectors may **generalize** better than explicit counts
  - They may do better at capturing synonymy:
    - *car* and *automobile* are synonyms; but are distinct dimensions
      - a word with *car* as a neighbor and a word with *automobile* as a neighbor should be similar, but aren't
  - **In practice, they work better**

- Word2vec: The classifier

Embeddings you can download!

- Word2vec (Mikolov et al)
- https://code.google.com/archive/p/word2vec/

- Glove (Pennington, Socher, Manning)
- http://nlp.stanford.edu/projects/glove/

Word2vec

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

Word2vec

- 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 classifier weights as the word embeddings
- Big idea: **self-supervision**:
    - A word c that occurs near apricot in the corpus asks as the gold "correct answer" for supervised learning
    - No need for human labels
    - Bengio et al. (2003); Collobert et al. (2011)

Word2Vec: Skip-Gram Task

- Word2vec provides a variety of options. We'll do:

  skip-gram with negative sampling (SGNS)

Approach: predict if candidate word *c* is a "neighbor"

1. Treat the target word *t* and a neighboring context word *c* as **positive examples**.
2. Randomly sample other words in the lexicon to get negative examples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

Skip-Gram Training Data

- Assume a +/- 2 word window, given training sentence:

  …lemon, a [tablespoon of apricot jam, a] pinch…

- c1 c2 [target] c3 c4

Skip-Gram Classifier

- (assuming a +/- 2 word window)

…lemon, a [tablespoon of apricot jam, a] pinch…

- c1 c2 [target] c3 c4

- Goal: train a classifier that is given a candidate (**w**ord, **c**ontext) pair
- (apricot, tablespoon)
- (apricot, aardvark)
- …
- And assigns each pair a probability:
- $P(+|w, c)$

Similarity is computed from dot product

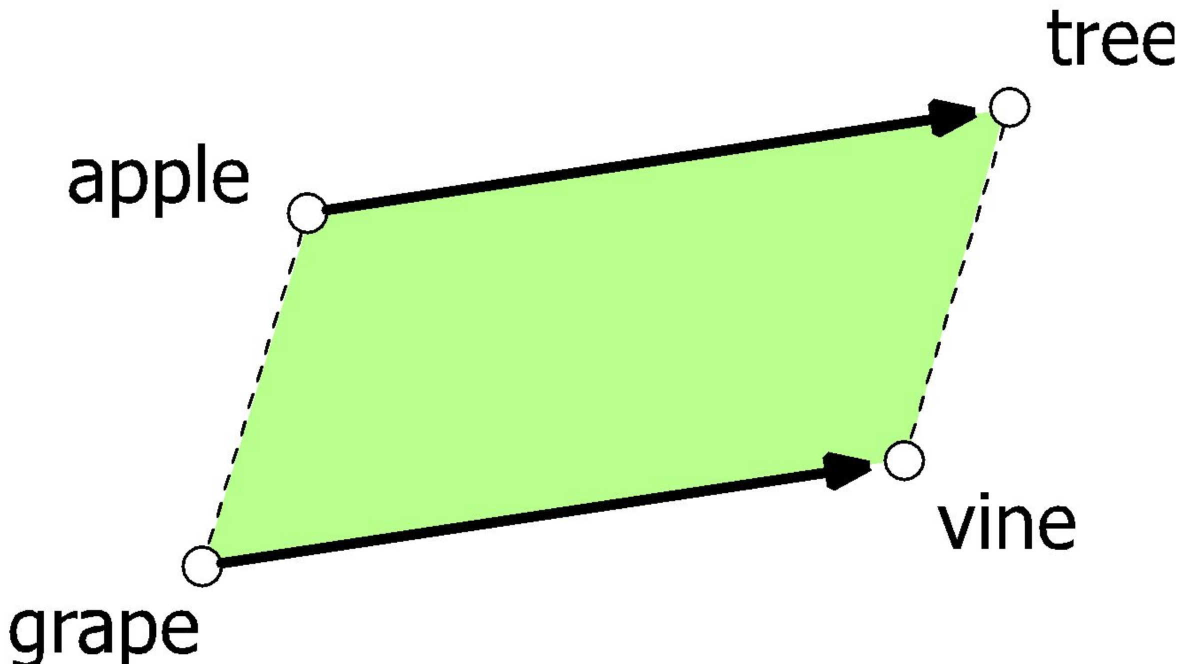
- Remember: two vectors are similar if they have a high dot product
  - Cosine is just a normalized dot product
- So:
  - Similarity(w,c) $\propto$ w · c
- We'll need to normalize to get a probability
  - (cosine isn't a probability either)

The kinds of neighbors depend on window size

- **Large windows** (C= +/- 5) : nearest words are related words in same semantic field
  - *Hogwarts* nearest neighbors are Harry Potter world:
    - *Dumbledore, Half-blood, Malfoy*
- **Small windows** (C= +/- 2) : nearest words are similar nouns, words in same taxonomy
  - *Hogwarts* nearest neighbors are other fictional schools
    - *Sunnydale, Evernight, Blandings*

Analogical relations

- The classic parallelogram model of analogical reasoning (Rumelhart and Abrahamson 1973)
- To solve: *"apple is to tree as grape is to _____"*
- *Add $\overrightarrow{\textit{apple}} - \overrightarrow{\textit{tree}}$ to $\overrightarrow{\textit{grape}}$ to get $\overrightarrow{\textit{vine}}$*

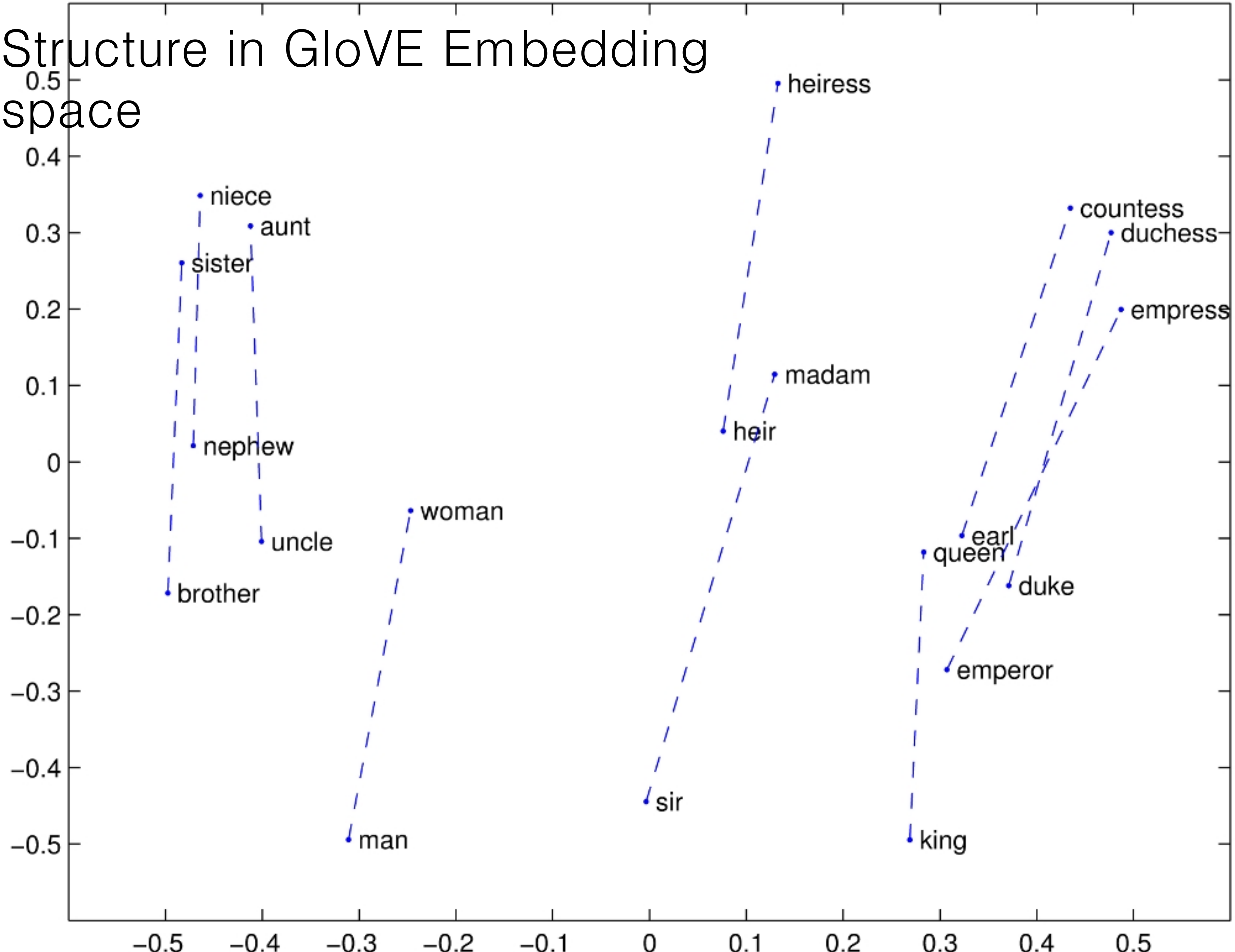


Analogical relations via parallelogram

- The parallelogram method can solve analogies with both sparse and dense embeddings (Turney and Littman 2005, Mikolov et al. 2013b)
- $\overrightarrow{\text{king}} - \overrightarrow{\text{man}} + \overrightarrow{\text{woman}}$ is close to $\overrightarrow{\text{queen}}$
- $\overrightarrow{\text{Paris}} - \overrightarrow{\text{France}} + \overrightarrow{\text{Italy}}$ is close to $\overrightarrow{\text{Rome}}$
- For a problem a:a*::b:b*, the parallelogram method is:

$$\hat{b}^* = \underset{x}{\operatorname{argmax}} \ \text{distance}(x, a^* - a + b)$$

Structure in GloVE Embedding space



Caveats with the parallelogram method

- It only seems to work for frequent words, small distances and certain relations (relating countries to capitals, or parts of speech), but not others. (Linzen 2016, Gladkova et al. 2016, Ethayarajh et al. 2019a)

- Understanding analogy is an open area of research (Peterson et al. 2020)

Embeddings as a window onto historical semantics

Train embeddings on different decades of historical text to see meaning shift

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

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change. Proceedings of ACL.

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 *NeurIPS*, 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

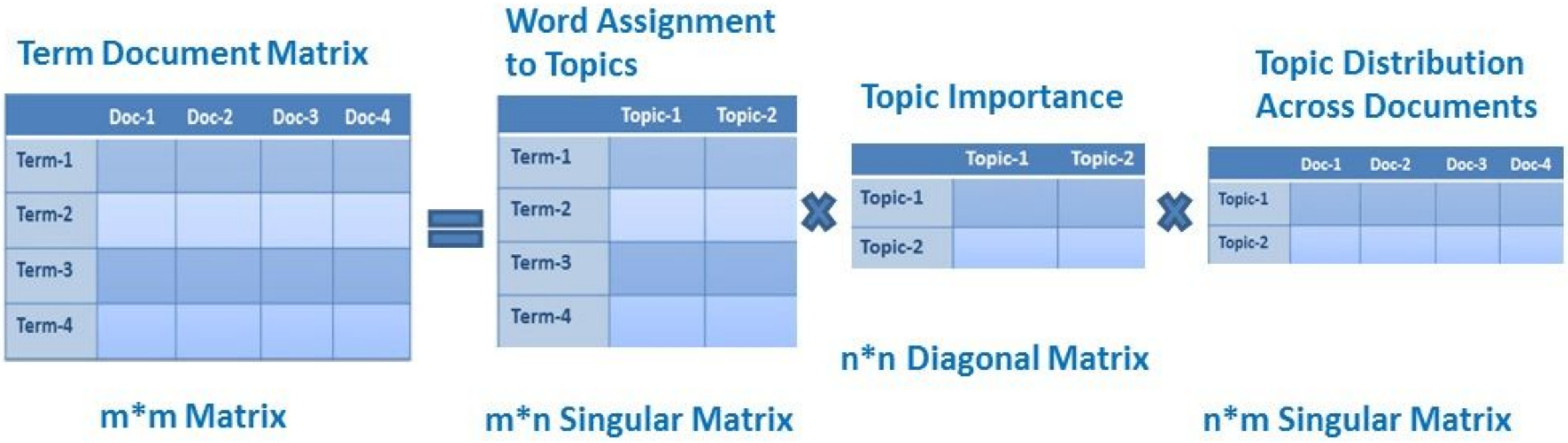
Algorithms that use embeddings as part of e.g., hiring searches for programmers, might lead to bias in hiring

Historical embedding as a tool to study cultural biases

Garg, N., Schiebinger, L., Jurafsky, D., and Zou, J. (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. Proceedings of the National Academy of Sciences 115(16), E3635–E3644.

- Compute a **gender or ethnic bias** for each adjective: e.g., how much closer the adjective is to "woman" synonyms than "man" synonyms, or names of particular ethnicities
  - Embeddings for **competence** adjective (*smart, wise, brilliant, resourceful, thoughtful, logical)* are biased toward men, a bias slowly decreasing 1960-1990
  - Embeddings for **dehumanizing** adjectives (barbaric, monstrous, bizarre) were biased toward Asians in the 1930s, bias decreasing over the 20th century.
- These match the results of old surveys done in the 1930s

Student QA: Densify sparse



https://www.datacamp.com/tutorial/discovering-hidden-topics-python