Natural Language Processing (CS-472) Spring-2023

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Overview of this week's lecture

Word Representations

- Localist Representation
- Distributional Semantics
- word2vec embeddings
- GloVe embeddings

Denotation

Home: A place to live in

Childish: Like a child

Plant: A manufacturing facility, Photosynthetic organisms, An action of putting into place

Mostly Used in Formal Communication

Every word in natural languages has a Denotation and a Connotation

Denotation

Home: A place to live in

Childish: Like a child

Plant: A manufacturing facility, Photosynthetic organisms, An action of putting into place

Mostly Used in Formal Communication

Connotation

Home: Security, Family, Shelter

Childish: Innocent, Stupid, Immature

Plant: Colonise, Conceal

Mostly Used in Poetry and Literature

How do computers understand the meaning of a word?

- By using **WordNet**: A thesaurus containing lists of synonyms and hypernyms.

https://wordnet.princeton.edu/

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Synonyms

Good:

noun,	Goodness
noun,	Commodity
adj,	Good
adj,	Honourable
adj,	Beneficial
adv,	Well
adv,	Thoroughly

Hypernyms

Panda:

- Animal
- Carnivores
- Mammal
- Physical Entity
- Living Thing
- Placental
- Vertebrate

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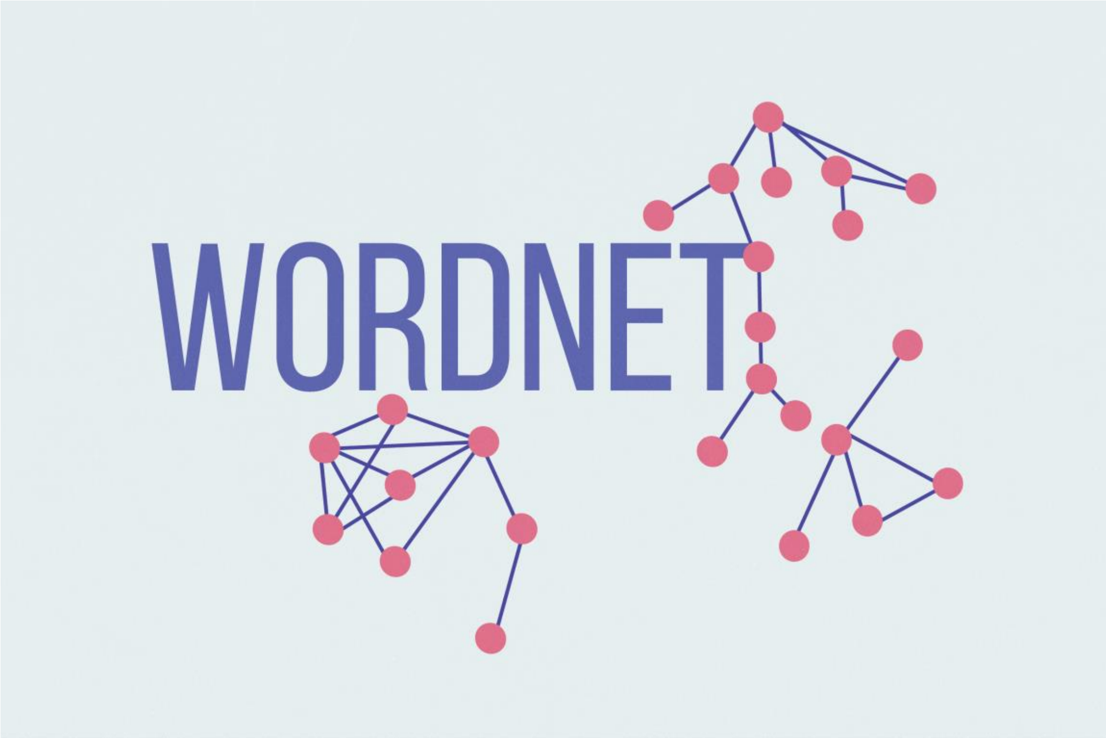
WordNet is like Swiss Army Knife of NLP.

- Missing new meaning of words.
    - Wicked, Badass, Wizard, Ninja
    - Very difficult to keep up-to-date



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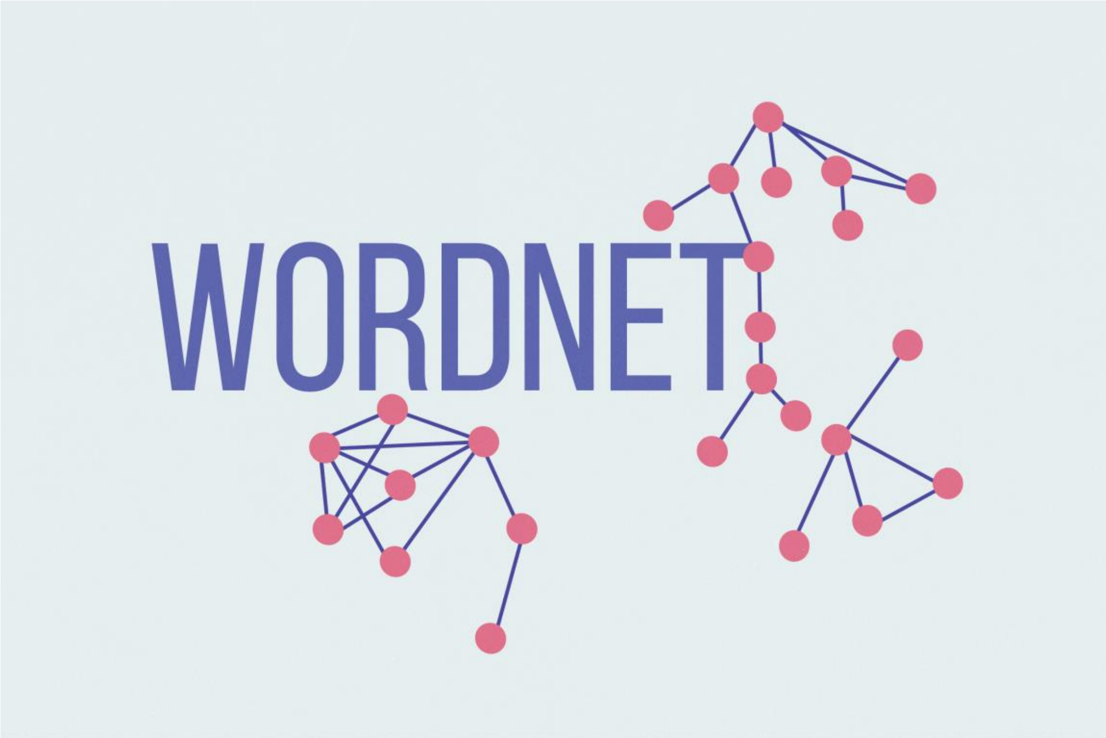

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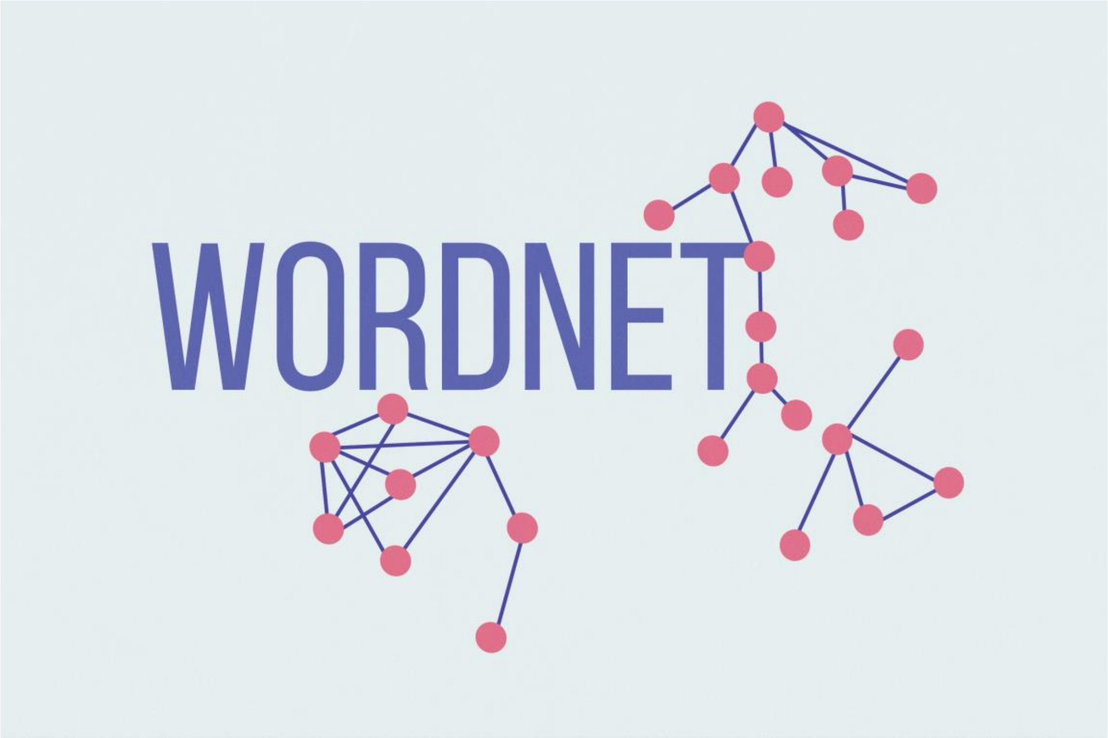
- Requires manual labour to curate.
    - What’s the purpose of AI, then?



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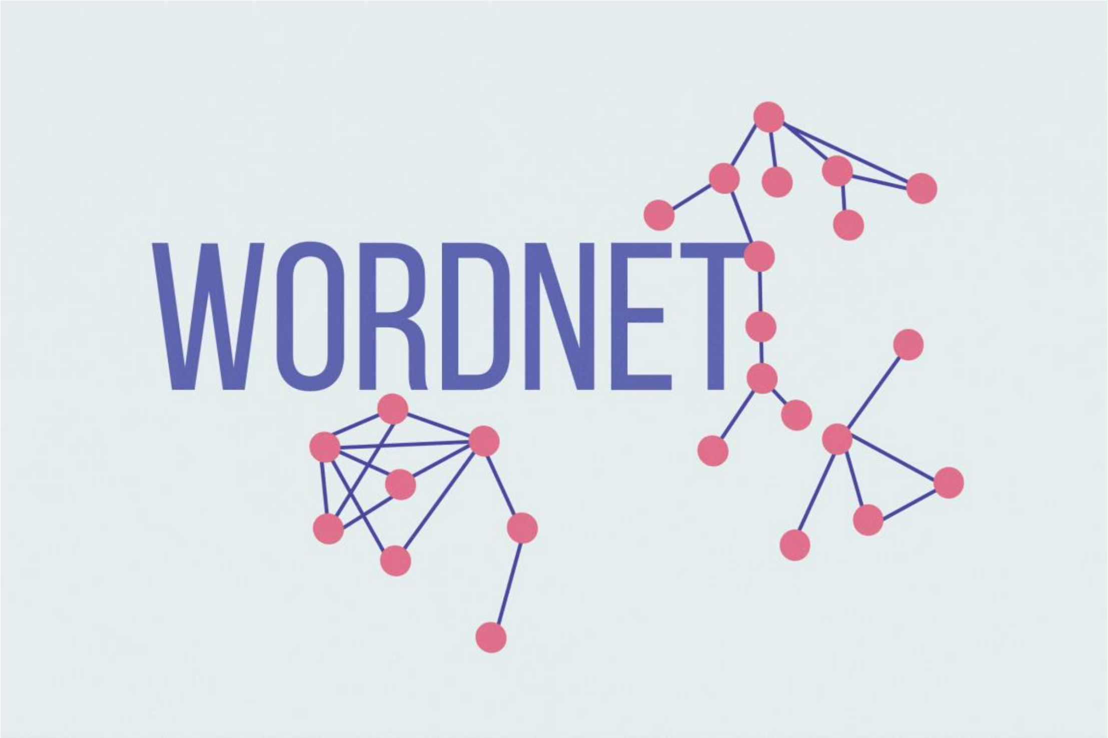
    - What’s the purpose of AI, then?
- Can’t compute accurate word similarity.
    - No partial resemblance
    - Has only fixed synonym set



Computers cannot understand words

- **Localist Representation:** Consider words as discrete symbols.
  - It was practiced in traditional NLP (up until 2012).
  - Example: One-Hot Encoding

Leopard	1	0	0	0	0	0
Sofa	0	1	0	0	0	0
Spider	0	0	1	0	0	0
Panther	0	0	0	1	0	0
Chair	0	0	0	0	1	0
Give	0	0	0	0	0	1

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  - Each vector is orthogonal to all others (what does it mean?)
  - Sparse matrix

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Gave	0	0	0	0	0	0	1	0	0
Gives	0	0	0	0	0	0	0	1	0
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- Learn to encode similarity in the word representation.
  - Smart and efficient

Representing words by their context is better than localist representation

- **Distributional Semantics:** A word’s intended meaning is determined by the context it appears in.

"You shall know a word by the company it keeps"
(J.R. Firth, 1957)

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- Use many contexts of a word w to make representation of w.
  - The prime minister urged the nation to plant a tree to preserve environment.
  - The prime minister inaugurated a plant to manufacture cars.
  - The prime minister emphasised that the research in plant biology is important.
  - The prime minister cautioned that the opposition may plant fake news about him.

John R. Firth
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Represent each word by a vector of real numbers

- Makes a smaller and dense vector for each word, such that it's similar to the vectors of words that co-occur in similar context.

$$Plant = \begin{bmatrix} +0.285 \\ -0.188 \\ +0.892 \\ -0.109 \\ -0.349 \\ +0.543 \\ +0.271 \\ +0.018 \end{bmatrix}$$

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- The example word vector for the word ‘plant’ is an 8-dimentional vector.

    - In practice, the dimensions of this vector can range from hundreds to thousands.

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- These word vectors are also called word embeddings or word representations.

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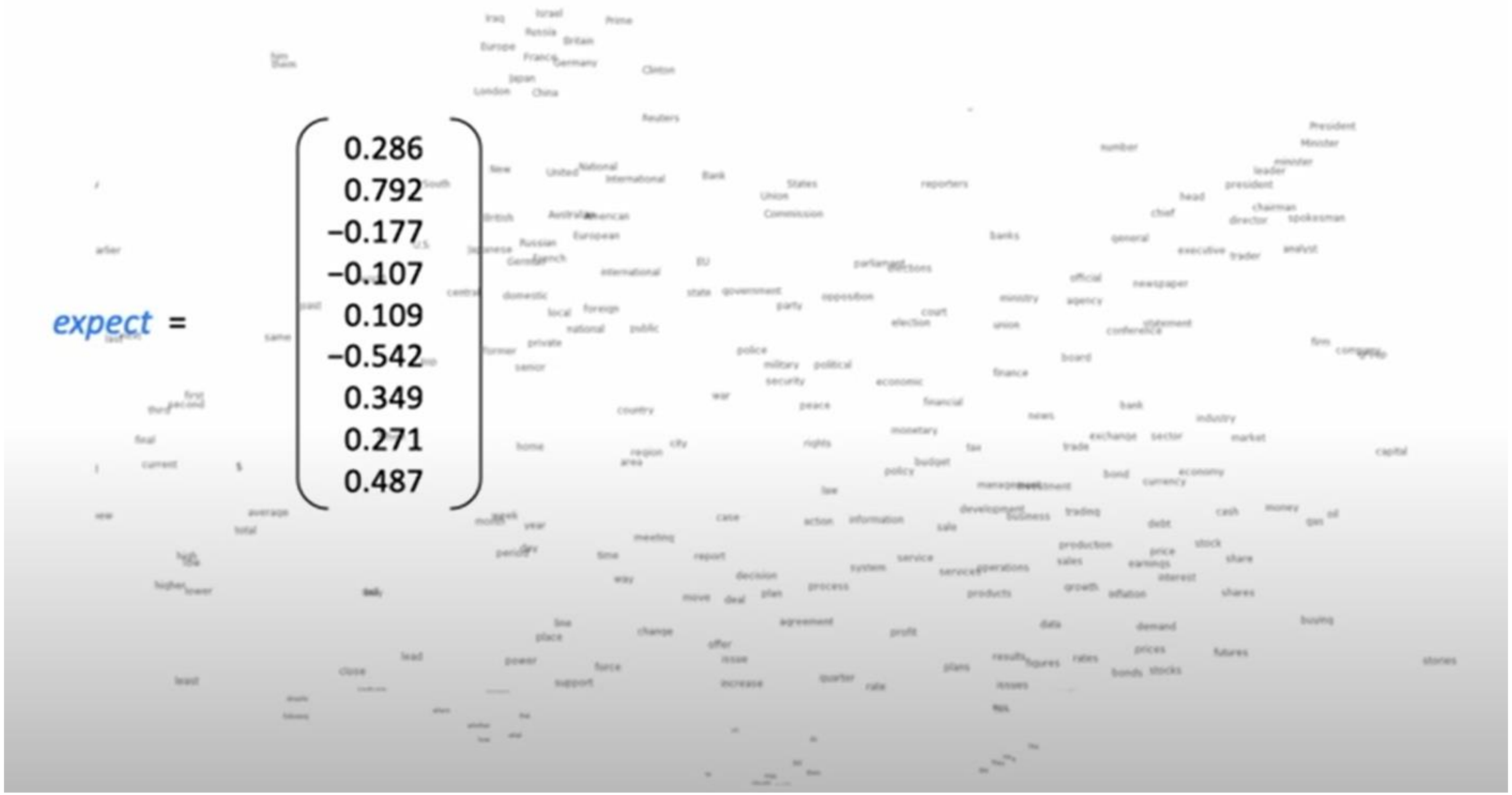
Word embeddings can be visualised in vector space



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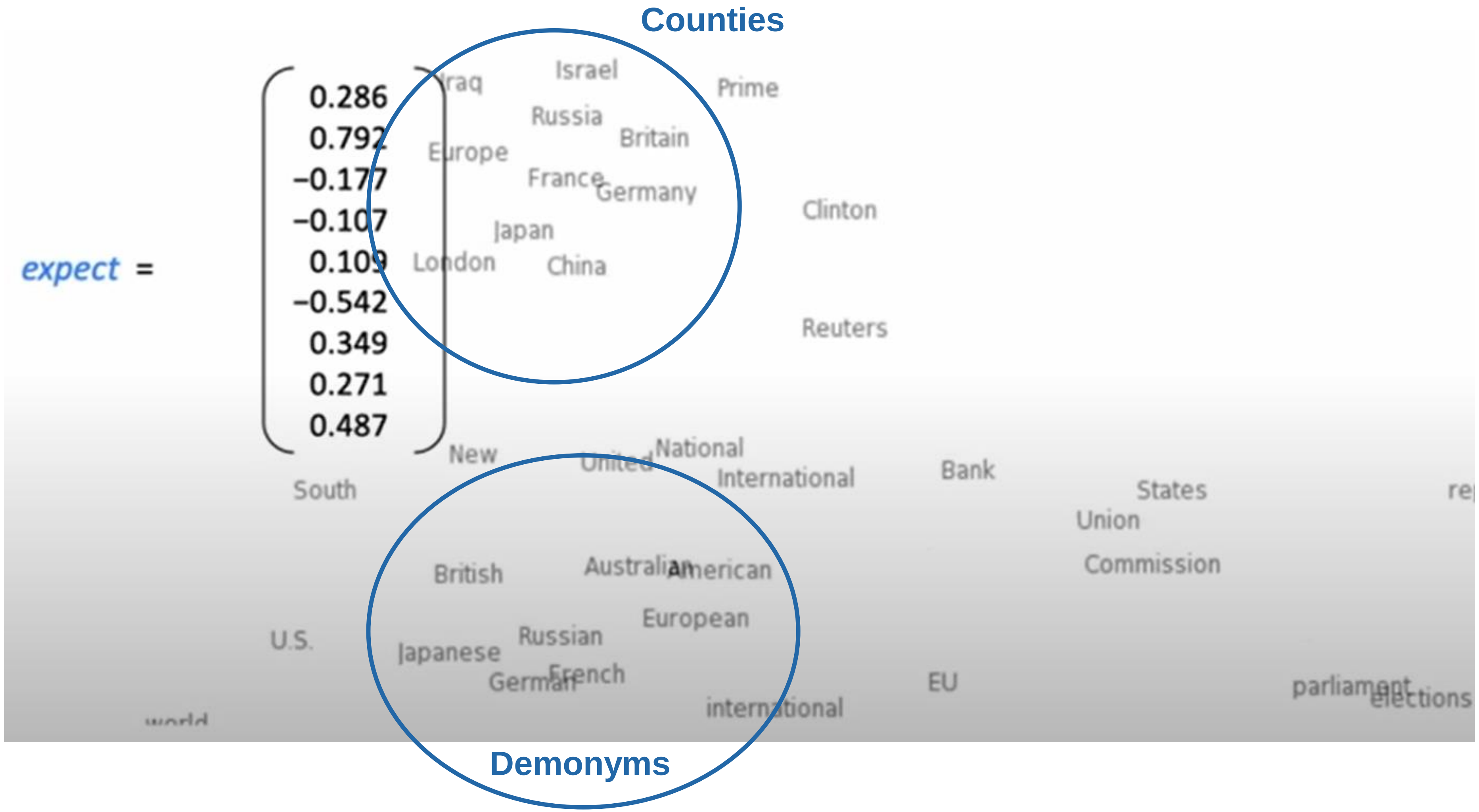

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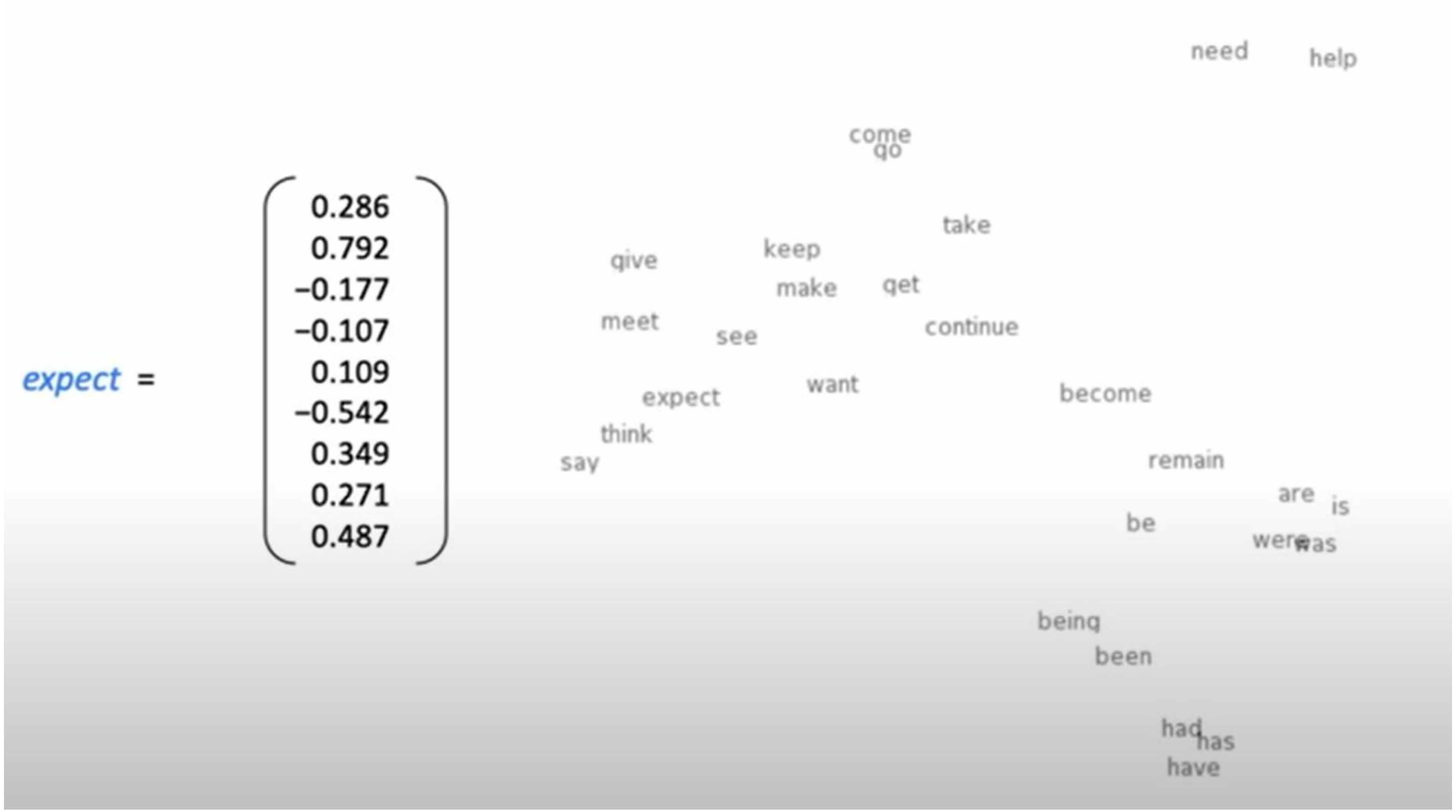
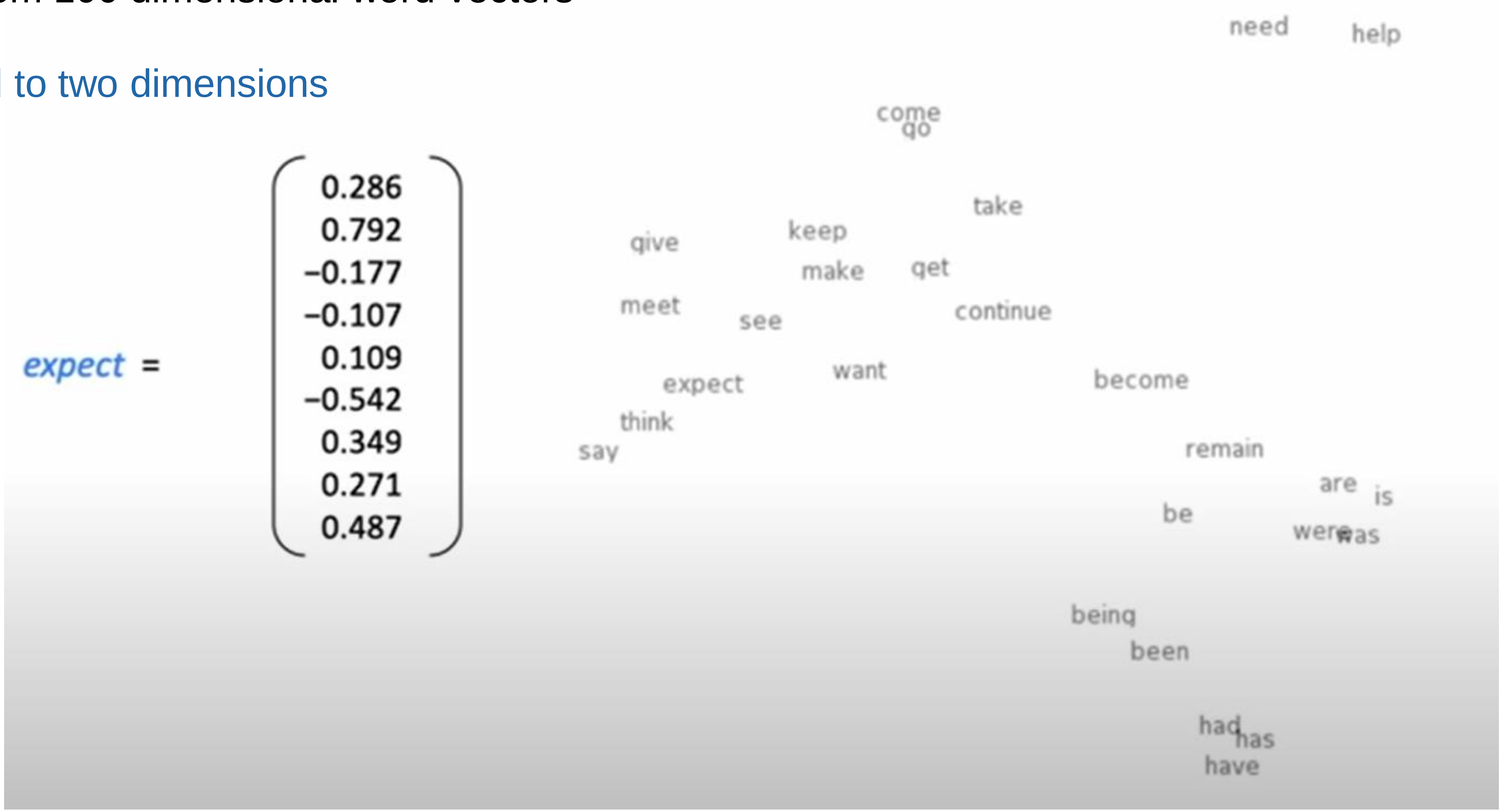


Word embeddings can be visualised in vector space

- Generated from 100 dimensional word vectors
  - Reduced to two dimensions



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word2vec is a famous algorithm used to create word vectors

- Have a large corpus of text.
- Represent each word in a fixed vocabulary by a vector (already?).
- Go through each position t in the text that has a centre word c and a context word o.

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- Have a large corpus of text.
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- Go through each position t in the text that has a centre word c and a context word o.
- Use the similarity of the word vectors c and o to calculate the probability $P(o|c)$, or vice versa.
- Keep updating the word vectors to maximise this probability.

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How to compute the probability of a context word given a centre word?

- Process of computing $P(w_{t+j}|w_t)$, where j is the size of context window:

$\boldsymbol{For\ j = 1}$

The prime **minister** inaugurated a pant to manufacture cars.

Centre word w at position t, (w_t)

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$P(w_{t-1}|w_t)$ $P(w_{t+1}|w_t)$

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How to compute the probability of a context word given a centre word?

- Process of computing $P(w_{t+j}|w_t)$, where j is the size of context window:

$For\ j = 2$

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- To know the meaning of the word minister, we predict what words come in context of the word minister.

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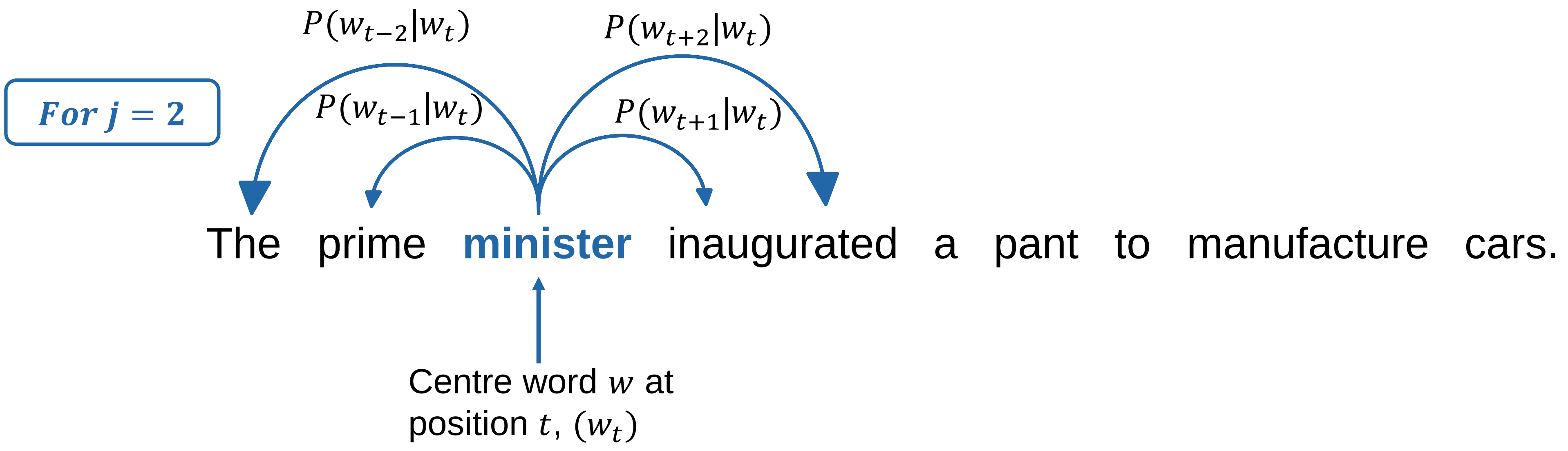

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Once the representation of minister is done, move on to the next word.

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The updates in word vectors in made using Objective Function

- For each position $t = 1, \ldots, T$, predict context words within a window of fixed size m, given centre word w_t.

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

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- How to calculate $P(w_{t+j}|w_t)$?

  - Go to the next slide.

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$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

$\exp$ makes everything positive.
$u_o^T v_c$ is just dot product of the two vectors. (what does dot products do?)
Normalise over entire vocabulary. (why?)

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$$softmax\ (x_i) = \frac{\exp(x_i)}{\sum_{j=1}^{n} \exp(x_j)}$$

    - $softmax$ amplifies probability of the largest x_i, while still assigning some probability to other classes.

Train the model using any optimisation algorithm

- Training a model **simply** means finding (optimising) suitable parameters of the model to minimize the cost function.

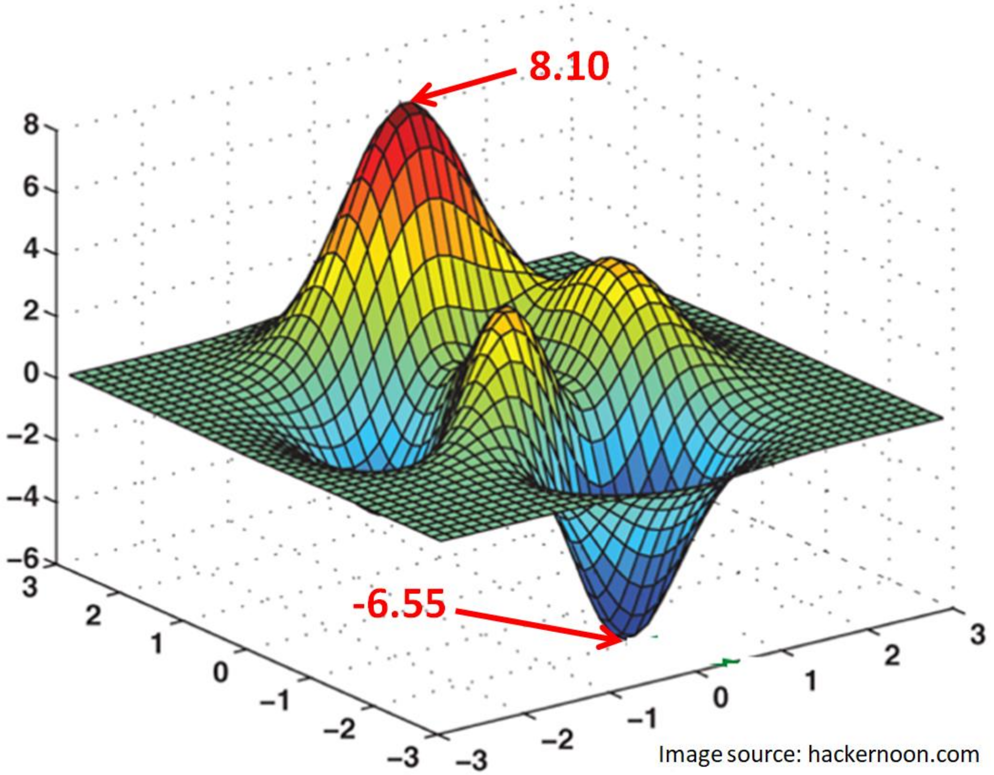

Image source: hackernoon.com

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- In practice,

    - Evaluate the model with any given weights θ (initially random)
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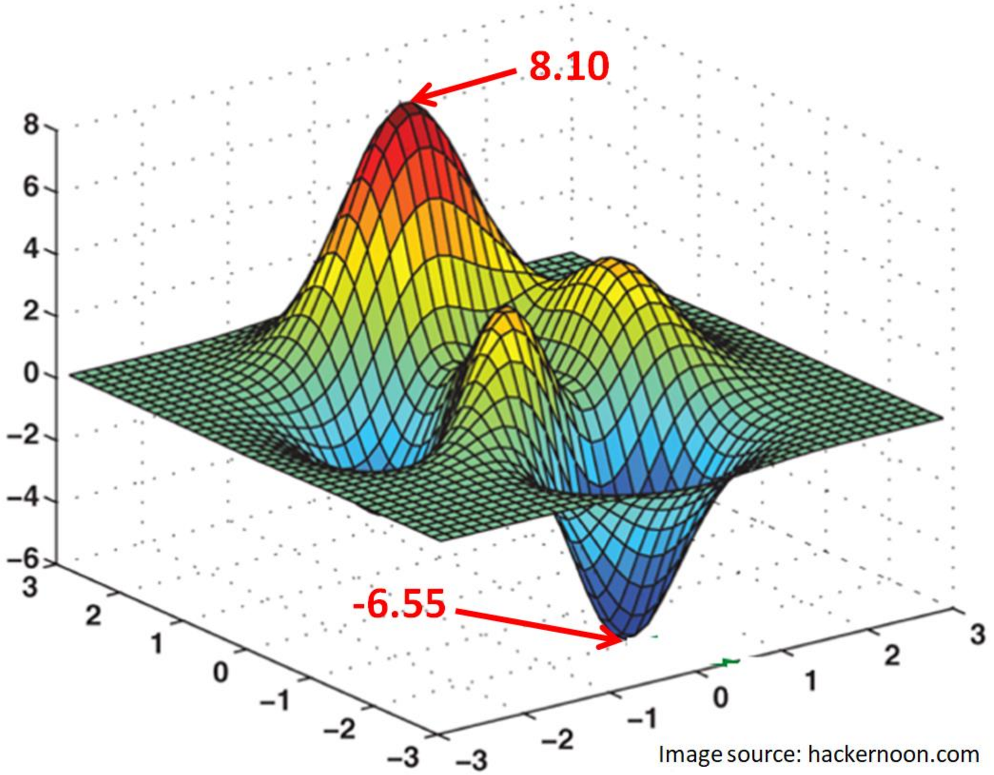
    - Calculate gradient with respect to each weight
    - Follow the slop (up or down?) to find optimal parameters.



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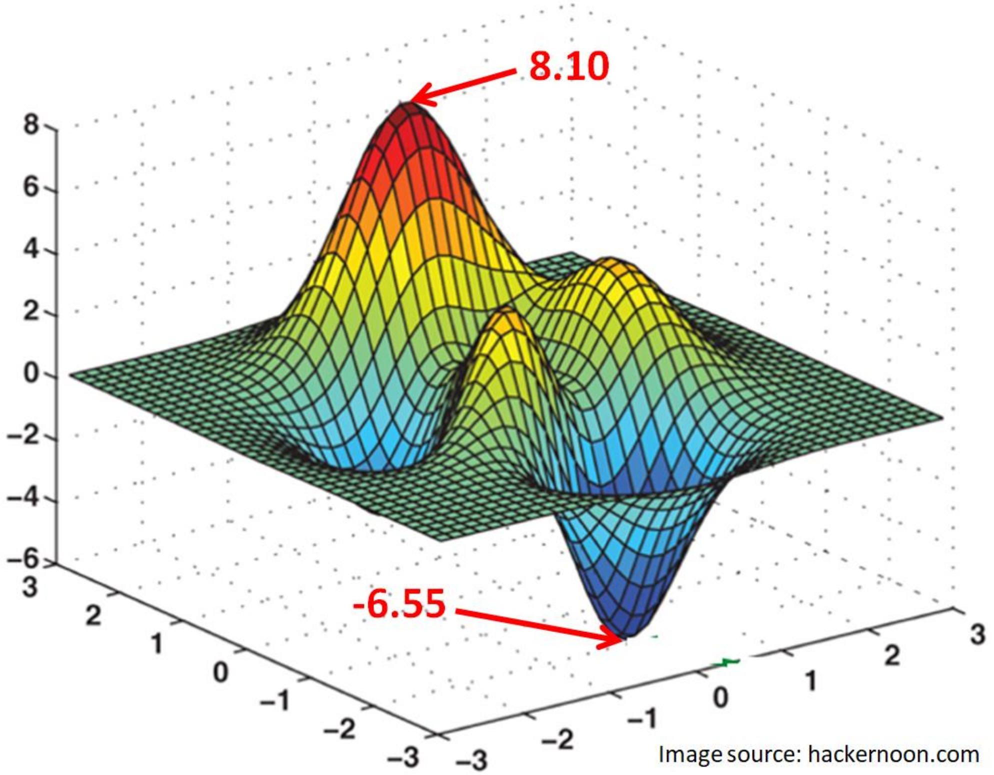
- With d-dimensional vector for each word and V-dimensional vocabulary, θ represents a vector of the dimensions $\mathbb{R}^{2dV}$.

    - θ consists of the contents of word vectors.



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Additional details on word2vec

- Why we have two vectors u_w and v_w for each word?
  - Easy to optimise. But what to do with the second vector after optimisation?
  - One vector for each word from the outset can also work.
- There are two main implementations of word2vec algorithm.
  - Skip-Gram (SG): Predicts context words given centre word.
  - Bag of Words (BOW): Predicts centre word from (a bag of) context words
  - Which model we discussed?

Vectorise the data to speed up computations

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$$

$$\begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix} \quad \begin{bmatrix} \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \\ \bullet & \bullet & \bullet & \bullet & \bullet \end{bmatrix}$$

U

Outside Words

V

Centre Words

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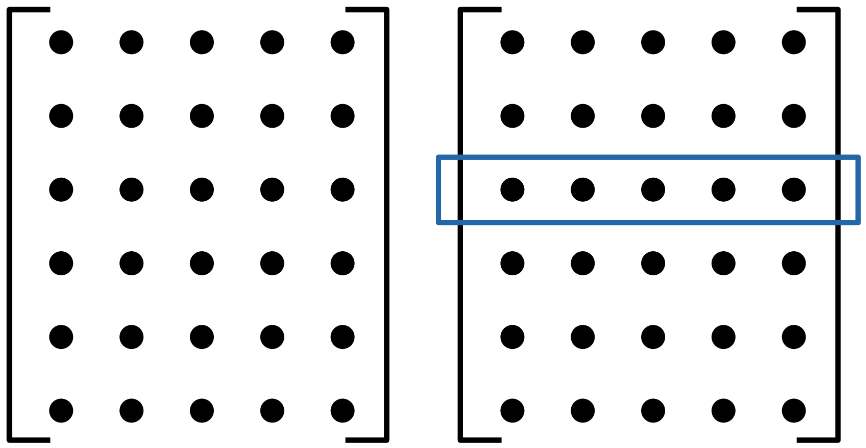

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$U . v_i^T$
Vector of Dot Products

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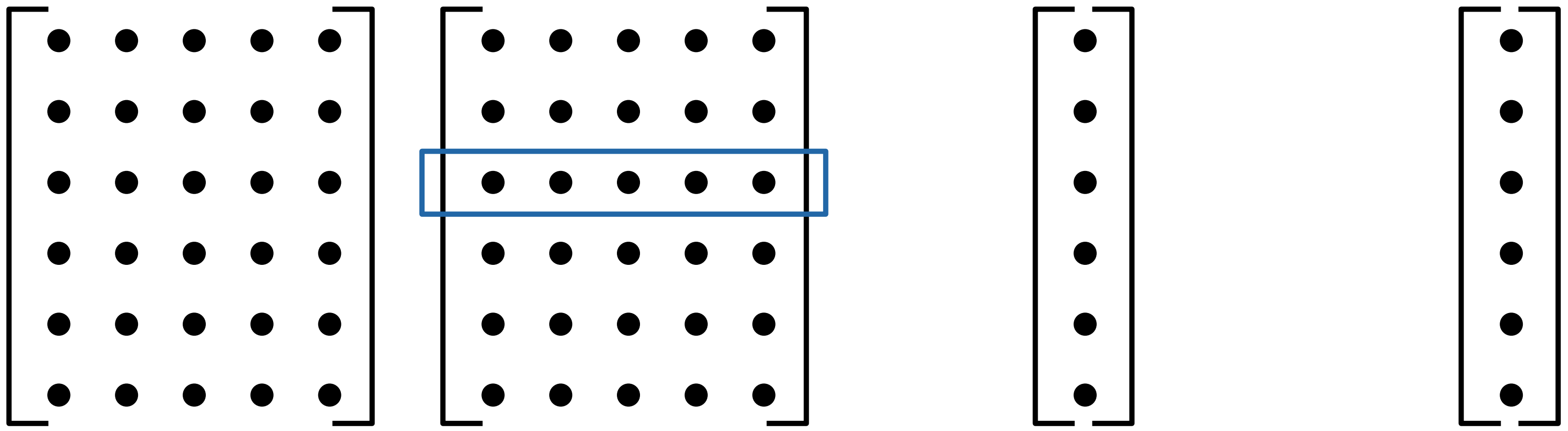

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$U.v_i^T$
Vector of Dot Products

$Softmax(U.v_i^T)$
Probability Distribution

Vectorise the data to speed up computations

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- The $softmax$ distribution may fall victim to high frequency words. How to fix it?

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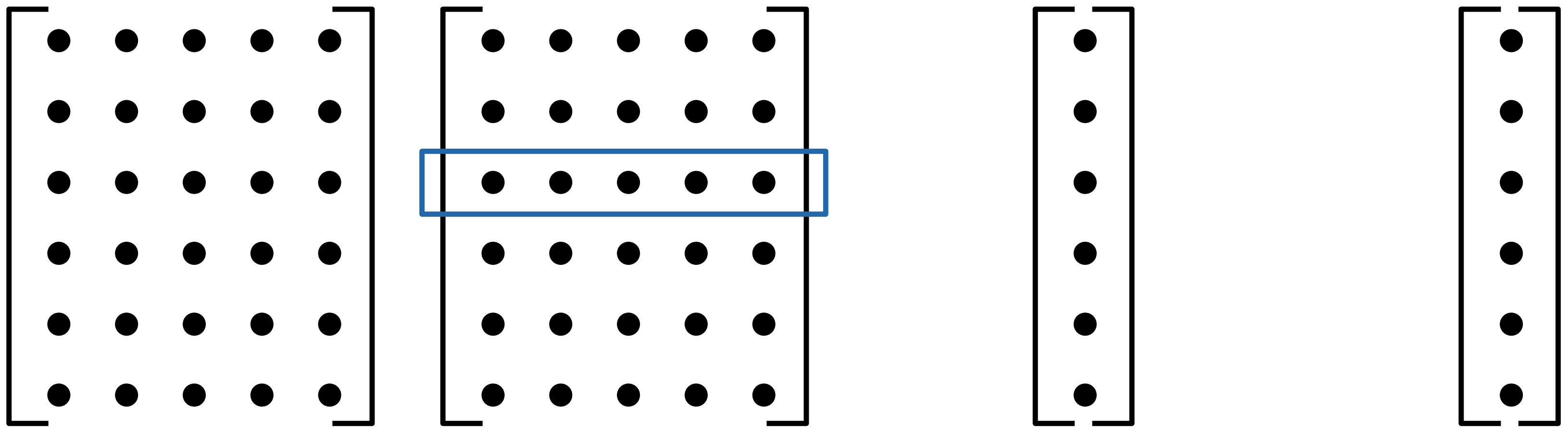

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$Softmax(U.v_i^T)$
Probability Distribution

Gradient Descent is an accurate but slow optimization algorithm

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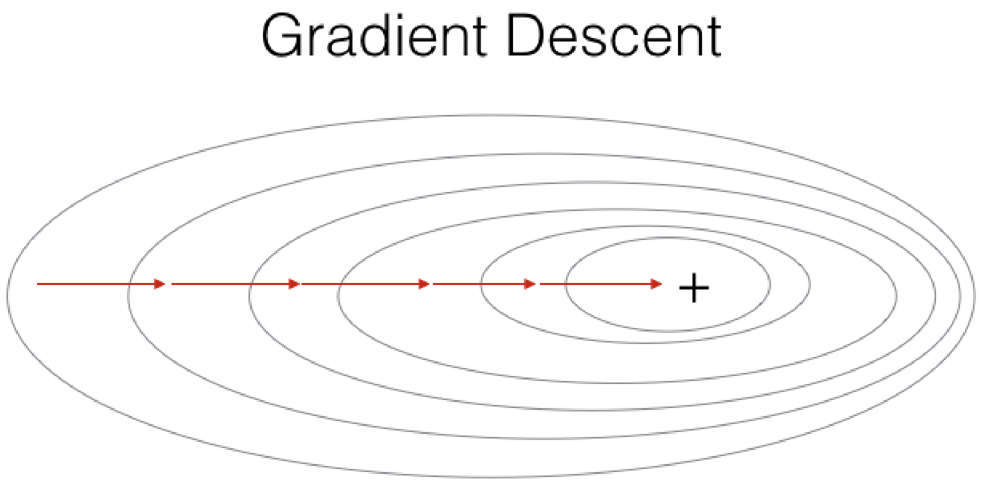

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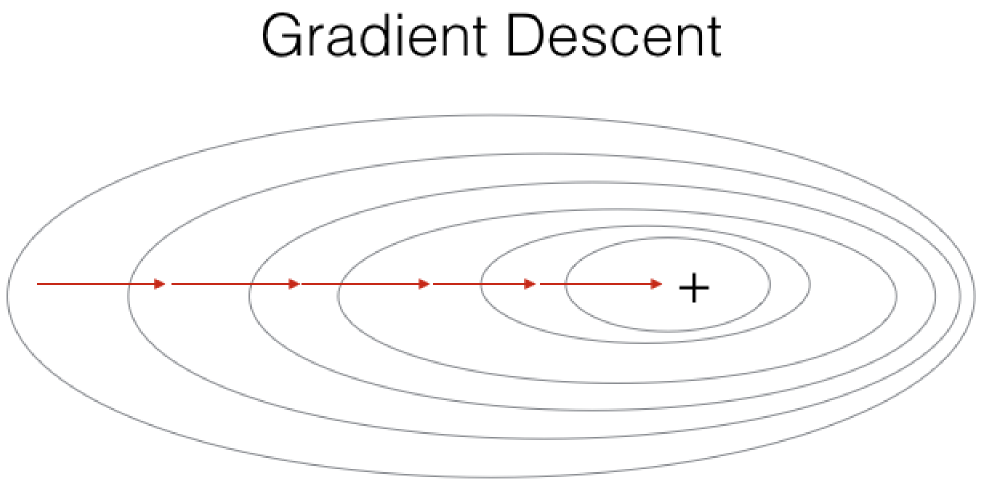
- Update equation for single parameter is,

$$\theta_i^{new} = \theta_i^{old} - \alpha \frac{\partial J(\theta)}{\partial \theta_i^{old}}$$

- Update equation for all parameters is,

$$\theta^{new} = \theta^{old} - \alpha \nabla_\theta J(\theta)$$



Gradient Descent is an accurate but slow optimization algorithm

- Training a model **simply** means finding (optimising) suitable parameters of the model to minimize the cost function.

- Update equation for single parameter is,

$$\theta_i^{new} = \theta_i^{old} - \alpha \frac{\partial J(\theta)}{\partial \theta_i^{old}}$$

- Update equation for all parameters is,

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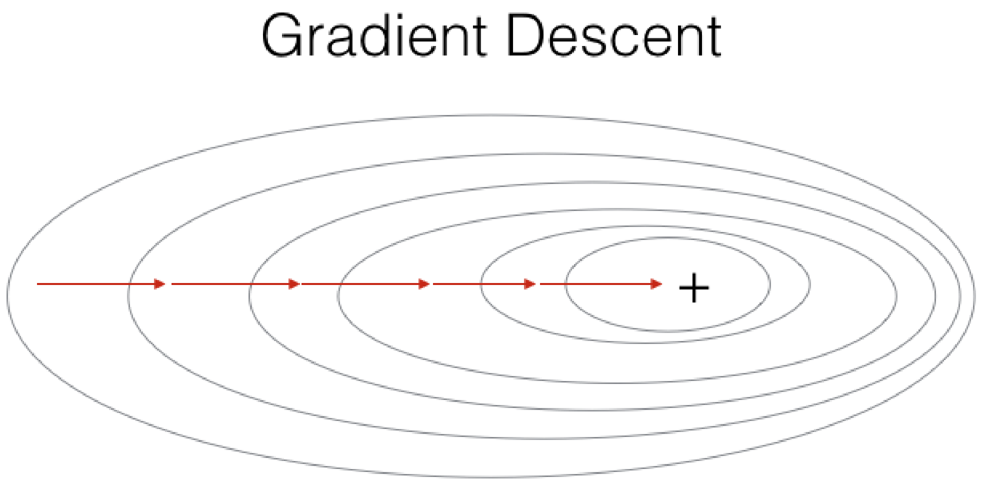
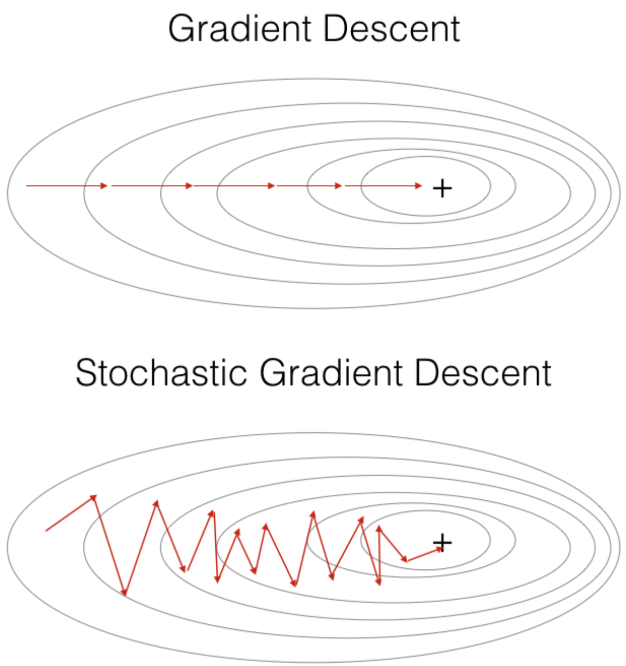
- Gradient descent is an old, time-tested but very slow optimisation algorithm.
    - Can we make it faster?



Stochastic Gradient Descent is sloppy but fast

- Less accurate but more time and memory efficient.
    - Can do more with the same resources.
- Updates are made based on a randomly selected window of word.



https://www.youtube.com/watch?v=UmathvAKj80

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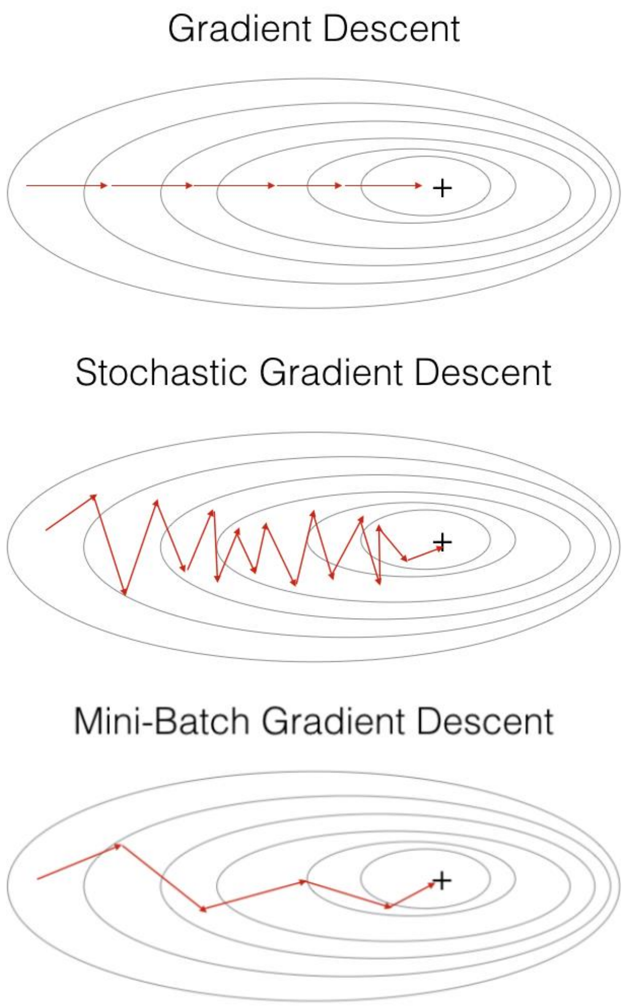

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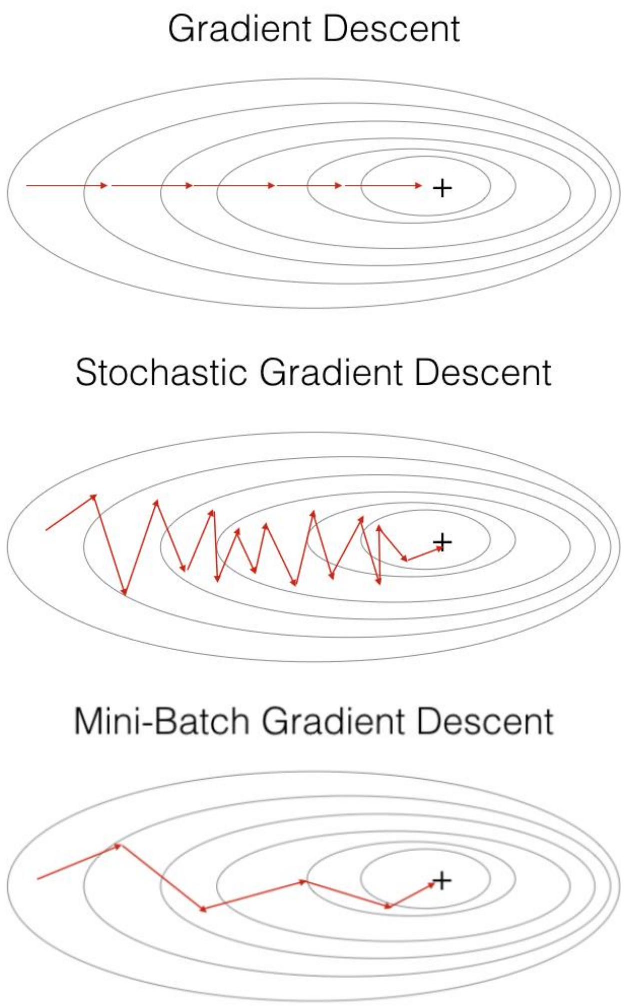
  - **Solution?**

$$\nabla_\theta J(\theta) = \begin{bmatrix} 0 \\ . \\ . \\ . \\ \nabla v_i \\ 0 \\ . \\ . \\ \nabla u_i \\ 0 \\ . \\ . \end{bmatrix} \in \mathbb{R}^{2dV}$$



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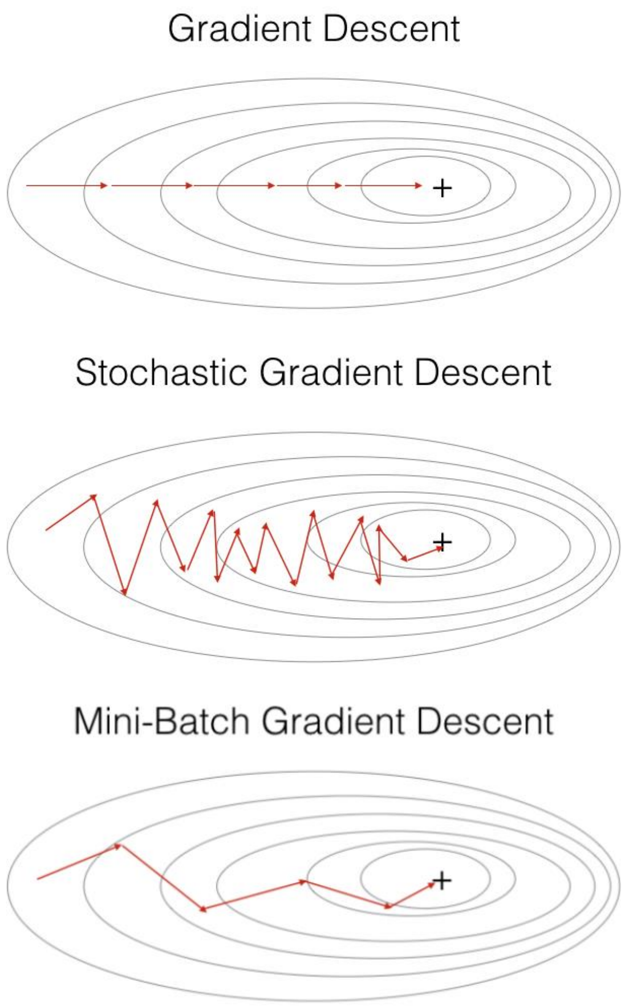
- The SGD has the problem of sparsity though.
    - **Solution?** Update only those word vectors that appear in the minibatch.

$$\nabla_\theta J(\theta) = \begin{bmatrix} 0 \\ \cdot \\ \cdot \\ \cdot \\ \nabla v_i \\ 0 \\ \cdot \\ \cdot \\ \nabla u_i \\ 0 \\ \cdot \\ \cdot \end{bmatrix} \in \mathbb{R}^{2dV}$$



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There is something wrong with the existing word2vec model

- Naïve $softmax$ is simpler but expensive.

$$P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp u_w^T v_c}$$

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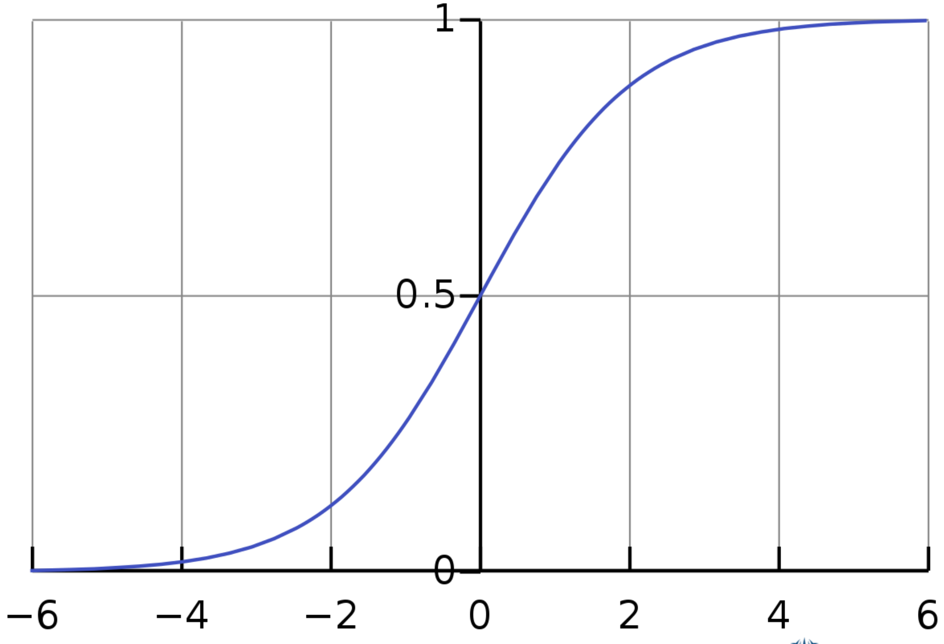
- We may get similar performance using sigmoid function with significantly reduced computations.

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



Negative Sampling can improve training efficiency of Skip-Gram

- What's negative sampling?

  - Train binary logistic regression for each word in the numerator for a true pair vs several noise pairs (negative samples).

  - The goal is to maximise probability for true pair (an actual neighbour) and minimise probabilities for negative labels. (How to pick negative labels?)

https://arxiv.org/pdf/1310.4546.pdf

Skip-Gram model with negative sampling

- The objective function changes to

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T} J_t(\theta)$$

$$J_t(\theta) = \underbrace{\log \sigma(u_o^T v_c)}_{\text{Positive Sample}} + \underbrace{\sum_{j=1}^{k} \mathbb{E}_{j\sim P(w)}\left[\log \sigma(-u_j^T v_c)\right]}_{\text{Negative Samples}}$$

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- Sampling of negative pairs is not completely random.

$$P(w) = \frac{U(w)^{3/4}}{Z}$$

  - Here $P(w)$ is the distribution of noise and $U(w)$ is unigram distribution (just a histogram if each word in a corpus). Raising unigram to ¾ helps compensate sampling of rarer and frequent words.

https://arxiv.org/pdf/1310.4546.pdf

The content discussed so far is taken from original word2vec papers

Efficient Estimation of Word Representations in Vector Space

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Distributed Representations of Words and Phrases and their Compositionality

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Co-occurrence is another criterion to estimate word similarity

- With huge amount of data (which we usually have), simply counting co-occurrences can also provide statistically significant information.

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  - **Using a window:** Similar to word2vec, captures **syntactic** and **semantic** information using a window around each word.

  - **Over the whole document:** Provides **topics** leading to Latent Semantic Analysis.

    - LSA deals with representation of text data in terms of latent features and reducing the dimensionality of original data.

Let’s make a window based co-occurrence matrix

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	I	Like	Artificial	Intelligence	Pizza	Enjoy	Driving	.
I	0	2	0	0	0	1	0	2
Like	2	0	1	0	1	0	0	0
Artificial	0	1	0	1	0	0	0	0
Intelligence	0	0	1	0	0	0	0	1
Pizza	0	1	0	0	0	0	0	1
Enjoy	1	0	0	0	0	0	1	0
Driving	0	0	0	0	0	1	0	1
.	2	0	0	1	1	0	1	0

Co-occurrence matrix suffers from a few problems

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    - How? **Singular Value Decomposition**.
        - Data-driven dimensionality reduction technique tailored for specific problem.
        - SDV is the basis for PCA.
        - Google uses it for page ranking.
        - Facebook uses it for facial recognition.

https://www.youtube.com/watch?v=gXbThCXjZFM
https://www.youtube.com/watch?v=vSczTbgc8Rc

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- Co-occurrence matrix was explored to discover meaningful semantic directions in the low-dimensional projections of embeddings.

- The performance was acceptable but not extraordinary.

Many hacks are used to improved the performance of co-occurrence matrix

- To fix the problem of frequently occurring words,
  - Scaling (log scaling) the counts in the cells of co-occurrence matrix can greatly help.
  - Applying ceiling function, $\min(X, t)$, where $t \approx 100$.
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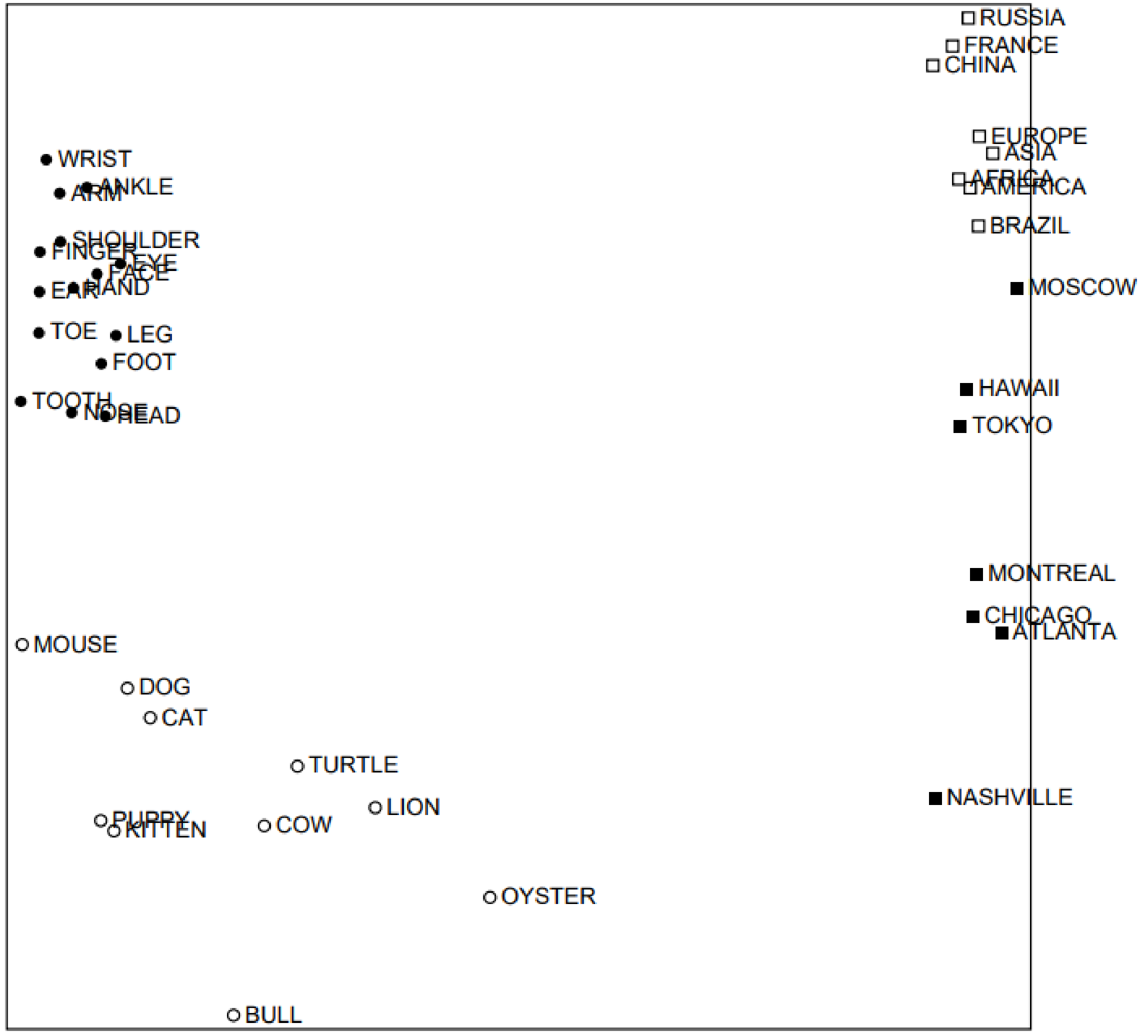
- Instead of counts, use Pearson correlation.
    - Tells about correlation plus strength of correlation.

Interesting patterns emerge from word vectors using these transformations



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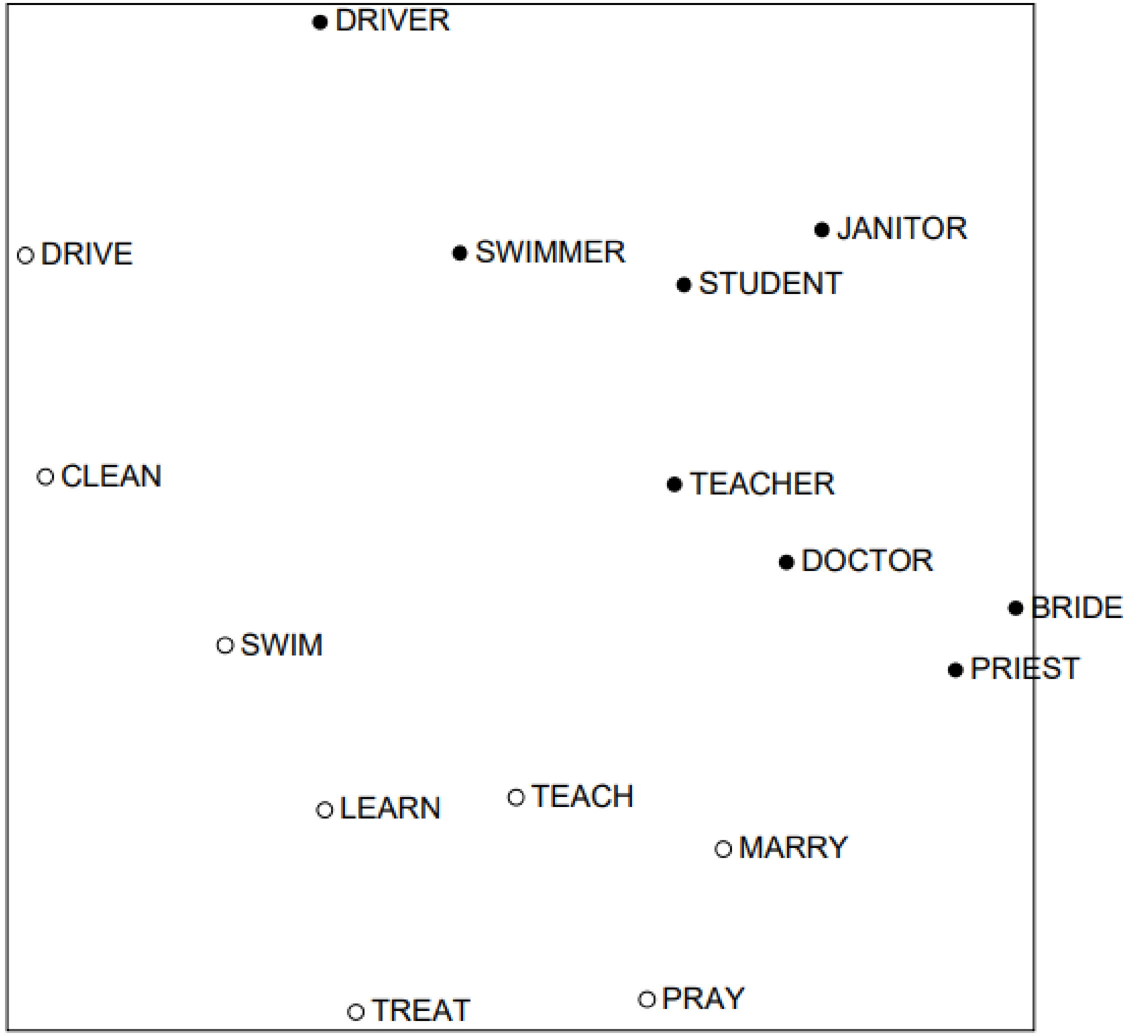

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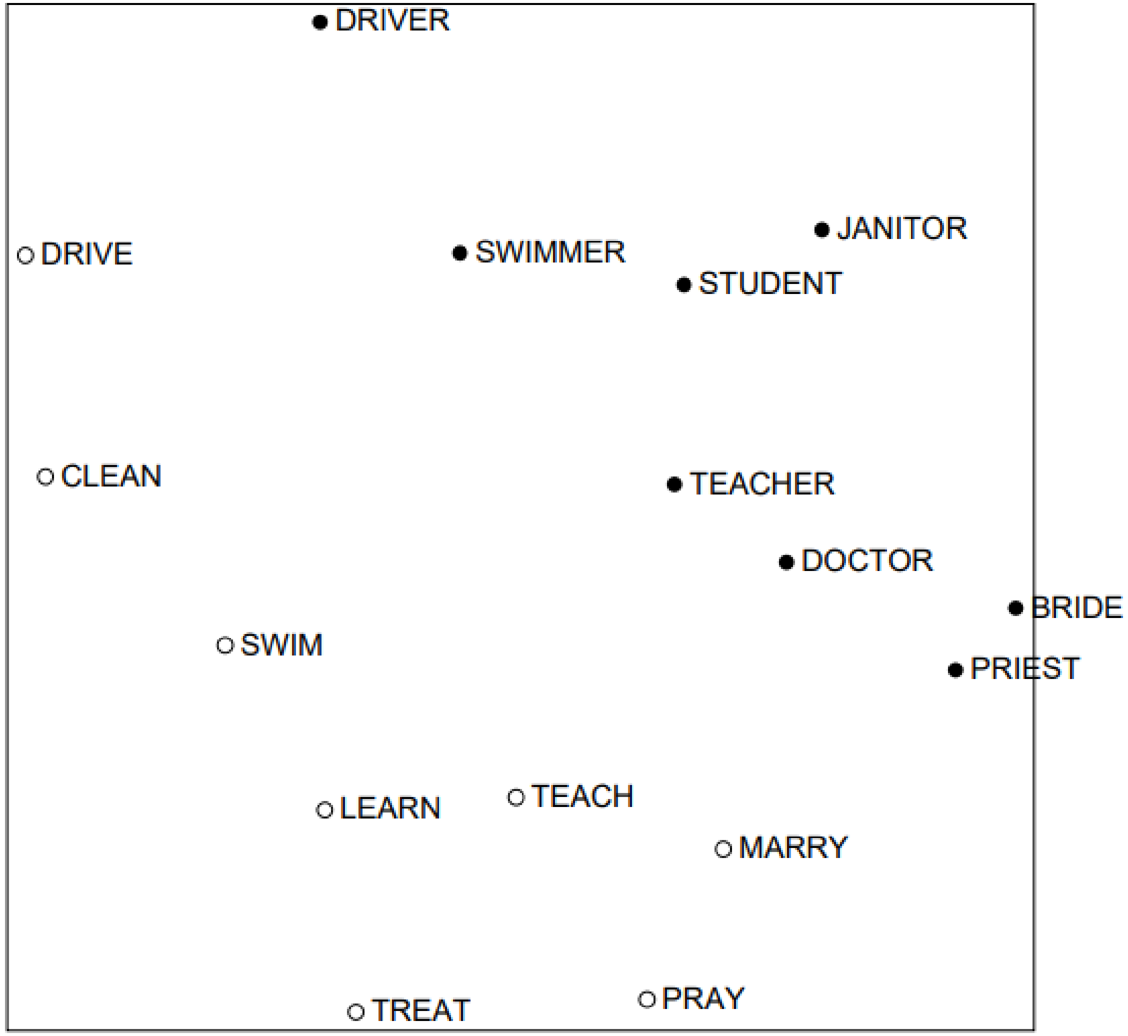

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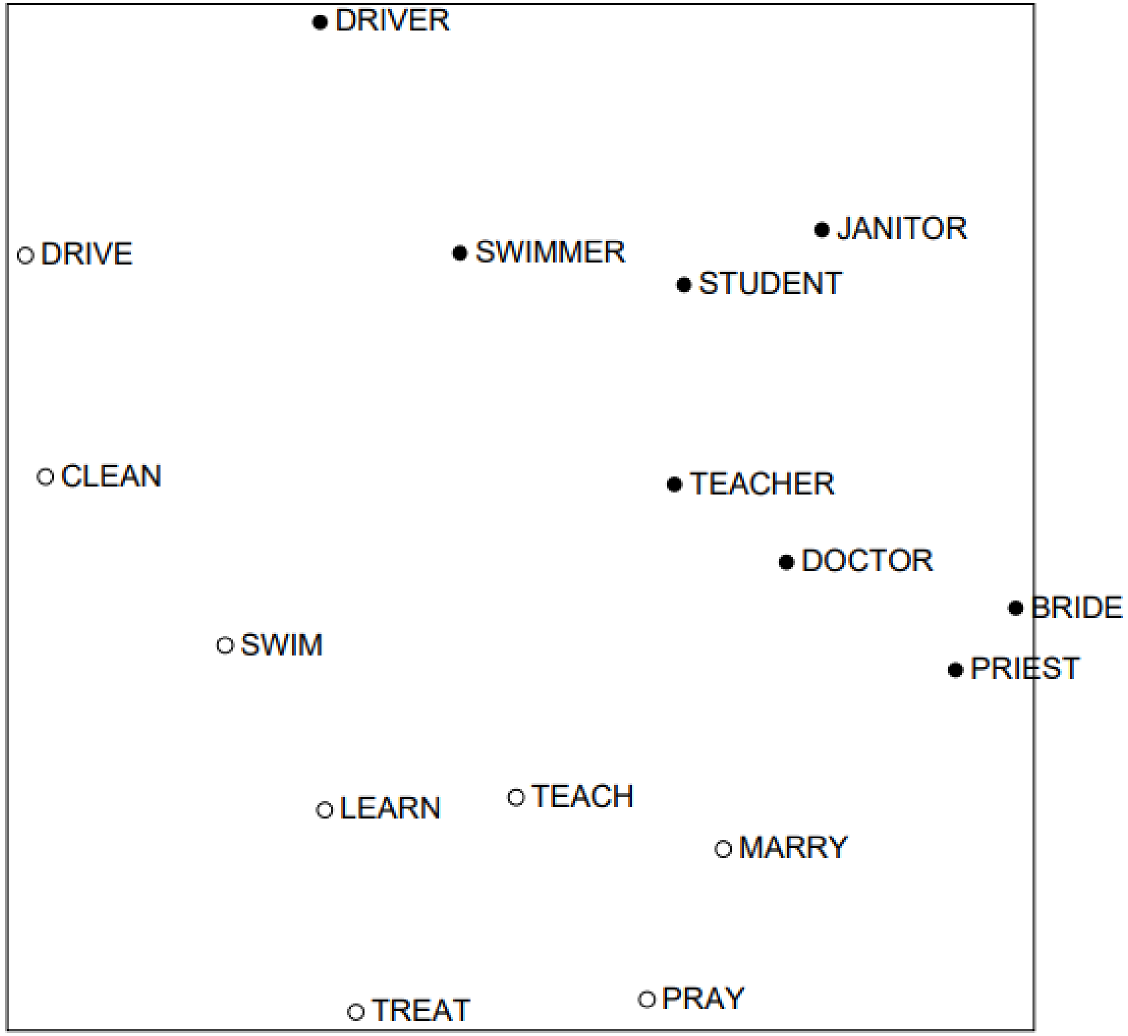
- Lesson?

  - Even with simply counting word occurrences (with some hacks, of course), we can still make reasonably good word representations.



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Count-based and neural-based models have their merits and demerits

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- Fast training.
- Efficient usage of statistics.
- Mostly good for capturing word similarities.
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Neural-Based

- Scales well with corpus size.
- Can capture complex patterns other than word similarities.
- Performs well on other tasks also.
- Due to sampling words, memory is not an issue.
- Inefficient usage of statistics.

Combining counts and neural methods can produce better embeddings

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- **Objective:** Obtain components of meaning as linear operations in vector space without (many) hacks.

- **Contribution:** Ratios of co-occurrence probabilities can encode meaning components.

Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)

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Ratio of co-occurrence probabilities should be linear in this vector space

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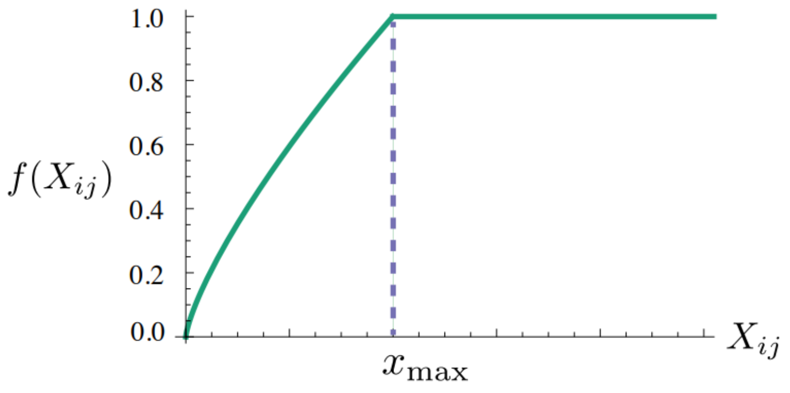

Figure 1: Weighting function f with $\alpha = 3/4$.

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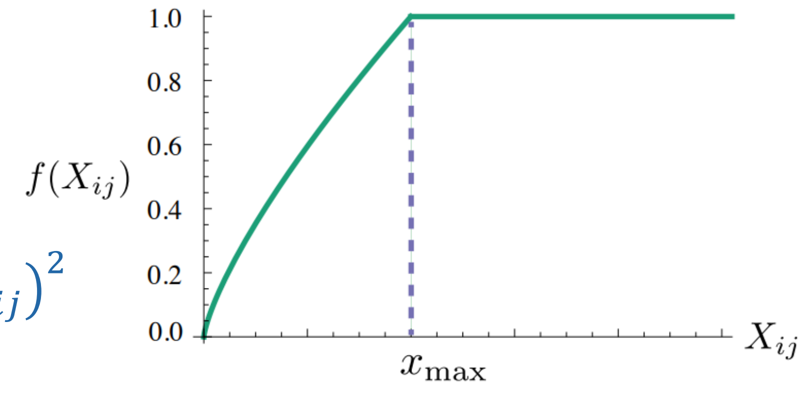

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- GloVe trains faster, is scalable, and has better performance with small corpora and small vectors compared to word2vec

GloVe Results

- Nearest words to frog:
  - Frogs
  - Toad
  - Litoria
  - Leptodactylidae
  - Rana
  - Lizard
  - Eleutherodactylus

GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, Christopher D. Manning
Computer Science Department, Stanford University, Stanford, CA 94305
jpennin@stanford.edu, richard@socher.org, manning@stanford.edu

Litoria

Leptodactylidae

Rana

Eleutherodactylus

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