Self-Supervised Learning Word Representations

CSCI 601 471/671
NLP: Self-Supervised Models

https://self-supervised.cs.jhu.edu/sp2023/

[Slide credit: Chris Manning, John Canny, Reda Bouadjenek, and many others]

HW Poll

- How was it?

- **A note about solutions:**
  - We will not release solutions.
  - But we will be as clear as we can in our grading.
  - If there are any lingering questions about homework solutions, come discuss during office hours.

Recap

- Inherently, there is no meaning to symbols:

"apple" ≈ 01100001011100000111000001101100011001 01

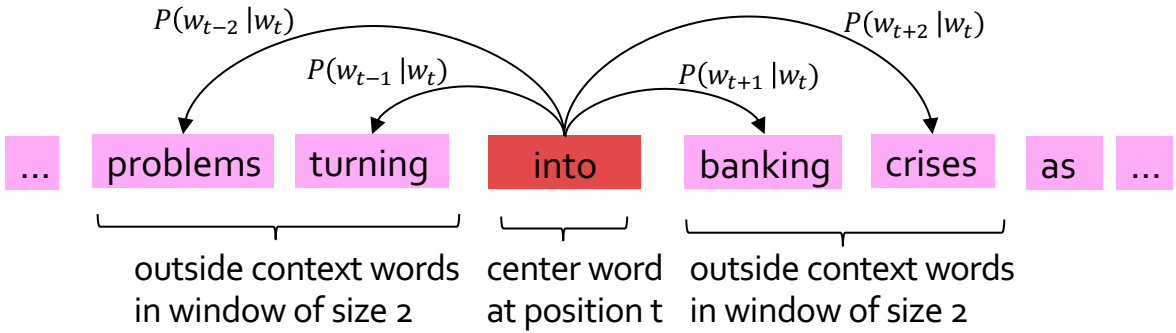
- Lots of literature on mapping **symbols** to their **"meaning"** (e.g., formal semantics)
- **Focus of this class:** distributional semantics —learning ***some*** meaning by regurgitating language use.
  - **Simplest form:** learning word representations via Word2Vec

Recap: Word2Vec Probabilities

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

If o and c tend to co-occur, they should have similar representation.

$$P(w_{t-2}|w_t) = p(\text{problems}|\text{into}) = \frac{\exp\left(u_{\text{problems}}^T v_{\text{into}}\right)}{\sum_{x \in V} \exp(u_x^T v_{\text{into}})}$$



Recap: Word2Vec Objective Function

- Minimize the objective function (log-likelihood) via Gradient Descent.

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

text length

window size

- Derivatives of "center" vectors: $\frac{\partial}{\partial v_c}J(\theta) = ?$
- Derivatives of "outside" vectors: $\frac{\partial}{\partial u_c}J(\theta) = ?$

We will derive the gradients with respect to the "center" vectors. Similar calculations for "outside" vectors (homework!!)

Chapter: Self-Supervised Meaning of "Words": Continued

1. ~~Human language and word meaning~~
2. ~~Word2vec overview~~
3. ~~Word2vec objective function and~~ gradients
4. Inspecting the resulting word vectors
5. Extrinsic evaluation of word vectors

Computing the Gradients for Word2Vec

- Minimize the objective function (log-likelihood):

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

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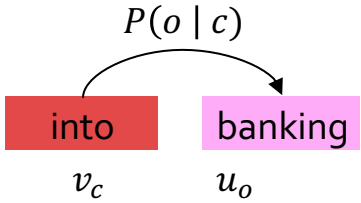
(distributive property)

?

Computing the Gradients for Word2Vec (2)



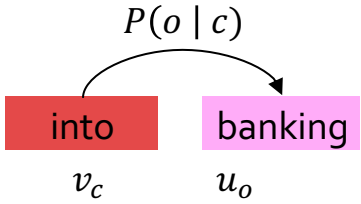
$$\frac{\partial}{\partial v_c} \log P(c \mid o; \theta) = \frac{\partial}{\partial v_c} \left[\log \frac{\exp(u_o^T v_c)}{\sum_{x \in V} \exp(u_x^T v_c)} \right]$$

$$= \frac{\partial}{\partial v_c} \left[\log \exp(u_o^T v_c) - \log \sum_{x \in V} \exp(u_x^T v_c) \right]$$

$$= \frac{\partial}{\partial v_c} [\log \exp(u_o^T v_c)] - \frac{\partial}{\partial v_c} \left[\log \sum_{x \in V} \exp(u_x^T v_c) \right]$$ (distributive property)

$$\frac{\partial}{\partial v_c} [\log \exp(u_o^T v_c)] = \frac{\partial}{\partial v_c} [u_o^T v_c] = u_o$$

Computing the Gradients for Word2Vec (3)



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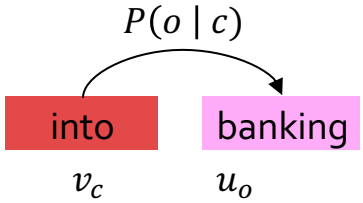
(distributive property)

Computing the Gradients for Word2Vec (4)



$$\frac{\partial}{\partial v_c}\left[\log \sum_{x \in V} \exp(u_x^T v_c)\right] = \frac{1}{\sum_{x \in V} \exp(u_x^T v_c)} \times \frac{\partial}{\partial v_c} \sum_{x \in V} \exp(u_x^T v_c)$$

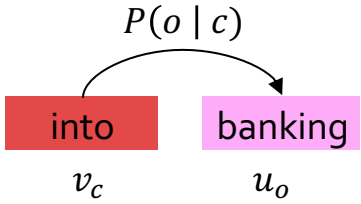
$$\frac{\partial}{\partial x} \log(f(x)) = \frac{1}{f(x)} \frac{\partial f}{\partial x}$$

$$= \frac{1}{\sum_{x \in V} \exp(u_x^T v_c)} \times \sum_{x \in V} u_x \exp(u_x^T v_c)$$

$$\frac{\partial}{\partial x} \exp(f(x)) = \frac{\partial f}{\partial x} \times \exp(f(x))$$

$$= \sum_{x \in V} u_x \times P(x \mid c; \theta)$$

Computing the Gradients for Word2Vec (5)



- Putting things together:

$$\frac{\partial}{\partial v_c} \log P(c \mid o) = u_o - \sum_{x \in V} u_x \times P(x \mid c)$$

the current representation of o

The expected (weighted avg) representation of the words that tend to co-occur with c.

Intuition: This gradient incentivizes representation of o to be more similar to the avg representation of words co-occurring with c.

Pop Quiz

- What is the computational complexity of the followings?
  (assume that $P(o|c)$ is pre-computed we just need to look it up)

$$\frac{\partial}{\partial v_c}\log P(c\,|o) = u_o \;-\; \sum_{x\in V} u_x \times P(x\,|c)$$

(A) O(d)
(B) O(|V|)
(C) O(|V|+d)
(D) O(|V|.d)

$$\frac{\partial}{\partial v_c}J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{\substack{-m\le j\le m\\ j\neq 0}}\frac{\partial}{\partial v_c}\log P\left(w_{t+j}\,|w_t;\theta\right)$$

(A) O(T)
(B) O(T.m)
(C) O(T.m.|V|)
(D) O(T.m.|V|.d)

Stochastic Gradient Descent

- Challenge: $J(\theta)$ is a function of all windows in the corpus (potentially billions!)
  - So computing $\nabla_\theta J(\theta)$ is very expensive to compute
  - You would wait a very long time before making a single update!
- Very bad idea!

$$\frac{\partial}{\partial v_c} J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{\substack{-m \le j \le m \\ j \neq 0}} \frac{\partial}{\partial v_c} \log P(c \mid o)$$

- Solution: Stochastic gradient descent (SGD)
  - Repeatedly **sample windows and instances**, and update after each one

- This resolves the complexity of $\sum_{t=1}^{T} \sum_{\substack{-m \le j \le m \\ j \neq 0}}$ but what about $\frac{\partial}{\partial v_c} \log P(c \mid o)$?

Skip-gram with Negative Sampling

- Let's see where the complexity is:

The expensive computation: O(|V|.d)

$$\log P(o|c) = \log \frac{\exp(u_o^T v_c)}{\sum_{x \in V} \exp(u_x^T v_c)} = \log \exp(u_o^T v_c) - \log \sum_{x \in V} \exp(u_x^T v_c)$$

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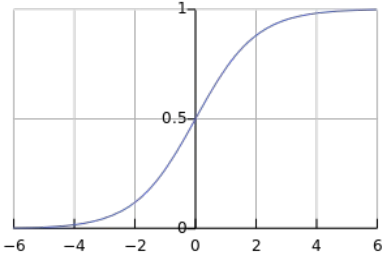
$$\log P(o|c) = \log \frac{\exp(u_o^T v_c)}{\sum_{x \in V} \exp(u_x^T v_c)} = \log \exp(u_o^T v_c) - \log \sum_{x \in V} \exp(u_x^T v_c)$$

- **Idea:** rather than enumerating over all vocabulary, let's sample!

$$J_{NS}(\theta) = -\log \sigma(u_o^T v_c) - \sum_{k \in \{K\ samples\}} \log \sigma(-u_x^T v_c)$$

  - Maximize the prob that outside word co-occurs w/ the center
  - Minimize the prob of noise/random words far from the center (negatives)

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



Skip-gram with Negative Sampling (2)

- Have to be careful with sampling negative examples
  - Challenge: uniform sampling will sample a lot of stop-words that are very popular.
- Mikolov et al. proposed to sample: $p(w_i) = f(w_i)^{3/4} \Big/ \sum_j f(w_j)^{3/4}$
  - Assigns more prob to less frequent words. No theory backing, but works!

- **Idea:** rather than enumerating over all vocabulary, let's sample!

$$J_{NS}(\theta) = -\log \sigma(u_o^T v_c) - \sum_{k \in \{K\ samples\}} \log \sigma(-u_x^T v_c)$$

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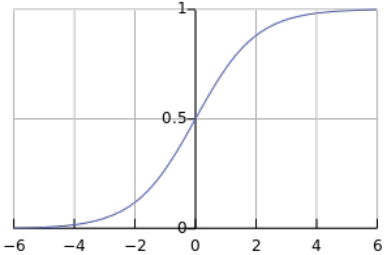

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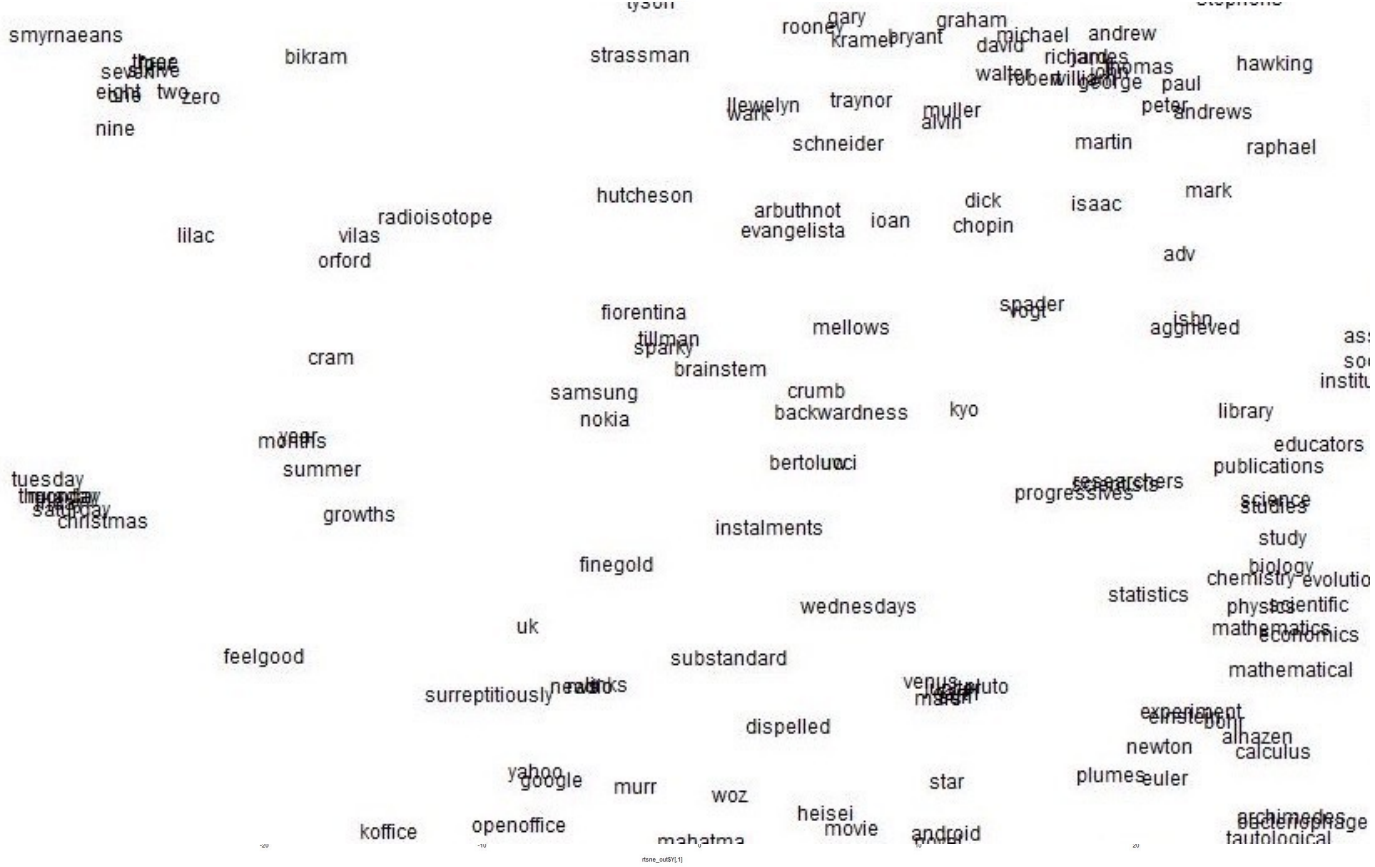
Word2Vec maximizes objective function by putting similar words nearby in space



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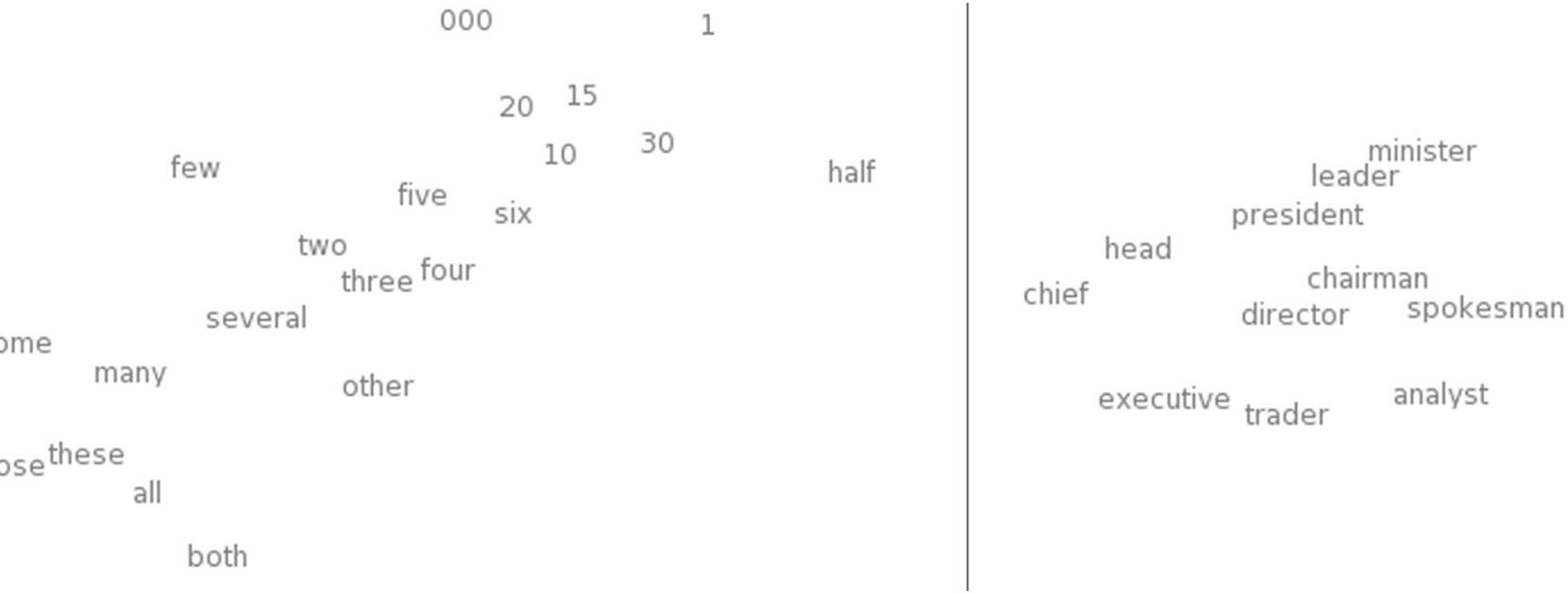


Left: Number Region

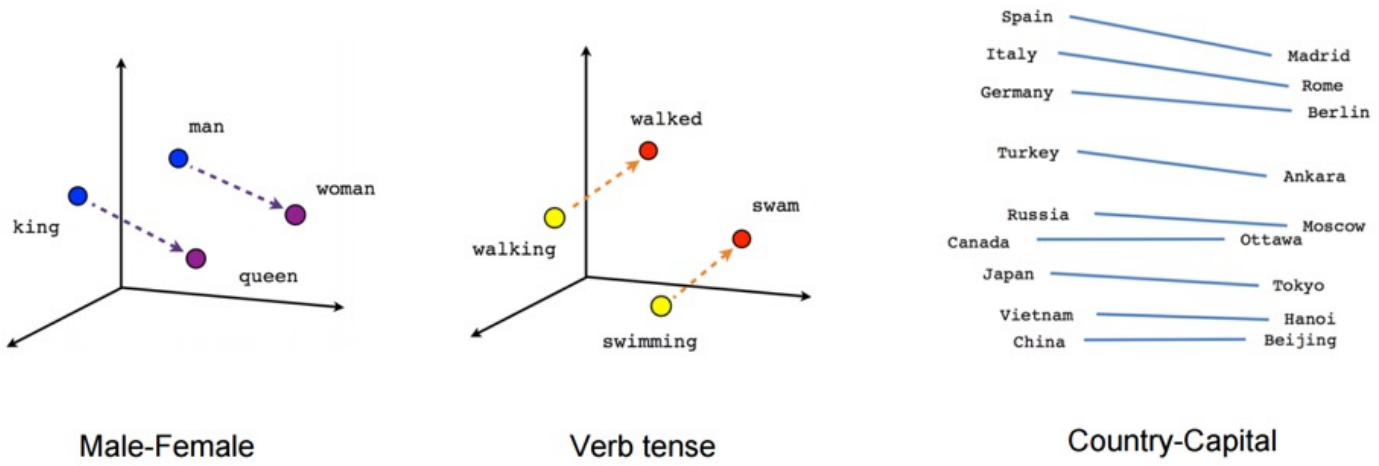
Right: Jobs Region

Also try: https://projector.tensorflow.org/

["Deep Learning, NLP, and Representations" by Chris Olah]

vec(“woman”)–vec(“man”) ≃ vec(“aunt”)–vec(“uncle”)

vec(“woman”)–vec(“man”) ≃ vec(“queen”)–vec(“king”)



Male-Female Verb tense Country-Capital

This can be interpreted as “France is to Paris as Italy is to Rome”.

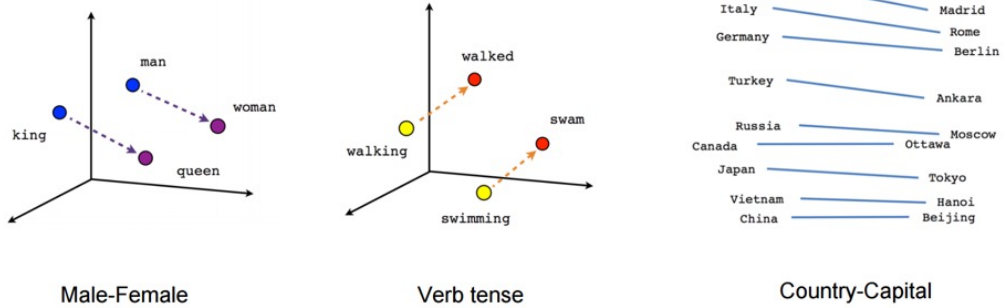
[Linguistic Regularities in Continuous Space Word Representations. Mikolov et al. 2013]

Evaluating Word Vectors: Word Analogies

- Evaluate word vectors by how well their cosine distance after addition captures intuitive analogical relations.

a:b :: c:?

$$d = \arg\max_i \frac{(x_b - x_a + x_c)^T x_i}{||x_b - x_a + x_c||}$$



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A relation is defined by the vector displacement in the first column. For each start word in the other column, the closest displaced word is shown.

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
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Mismatch Between Cosine and Dot Product

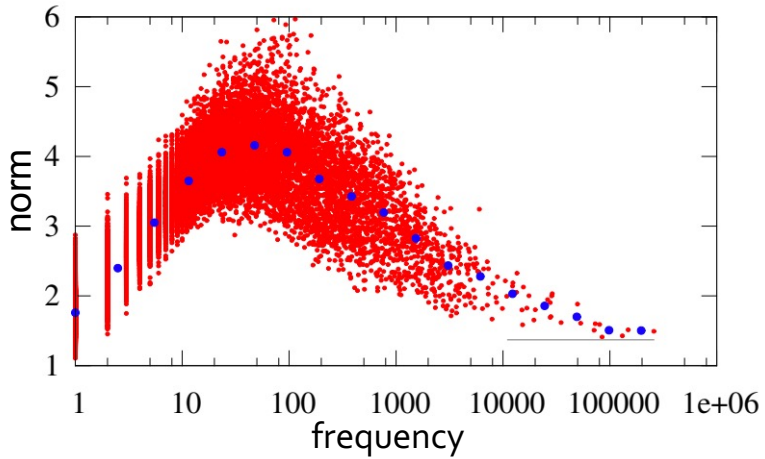
- **Observation:** there a mismatch between Word2Vec objective and cosine distance!

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

$$\text{distance}(x, y) = \cos(v_x, v_y) = \frac{v_x^T v_y}{\|v_y\| \|v_x\|}$$

1. Why use cosine distance instead of dot product?
   - Term frequencies affect the embedding norms.
   - Without normalization, frequent terms would seem more similar.

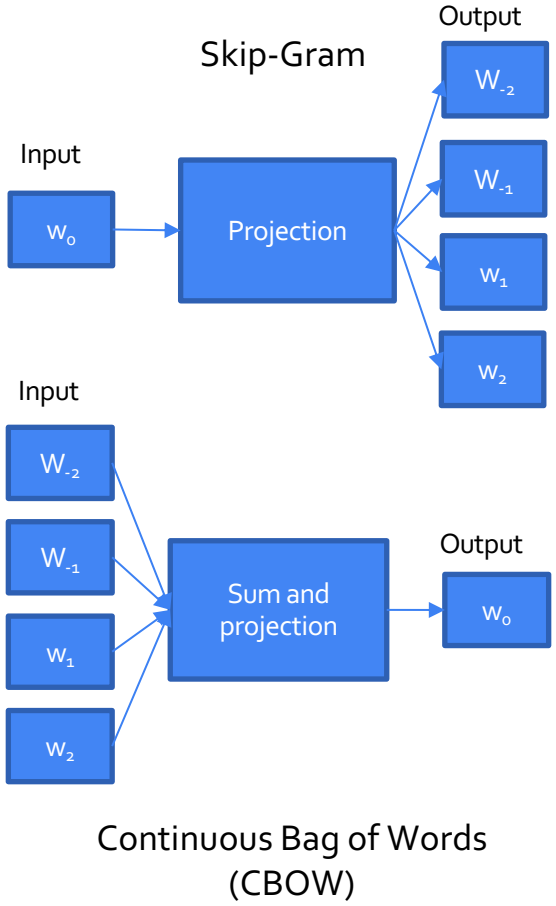
2. Why not change W2V objective to not use cos?
   - ¯_(ツ)_/¯
   - It's possible that the resulting vectors would conflate semantic similarity and frequency.



[Measuring Word Significance using Distributed Representations of Words]

Word2Vec: Variants

- What we just saw is the **Skip-Gram** model.
  - Predict context ("outside") words (position independent) given center
- There is also a **CBOW** (continuous-bag-of-words) variant.
  - Predict center word from (bag of) context words
- Additional efficiency:
  - The current gradient computation w/ softmax function is expensive.
  - Alternative: Negative Sampling



Continuous Bag of Words (CBOW)

Word Embeddings: Big Picture

- There are a variety of approaches:

- **Gradient-based algorithms:**
  - Skip-gram/CBOW (Mikolov et al.), GloVe (Pennington et al.)
  - NNLM, HLBL, RNN (Bengio et al; Collobert & Weston; Huang et al; Minh & Hinton)

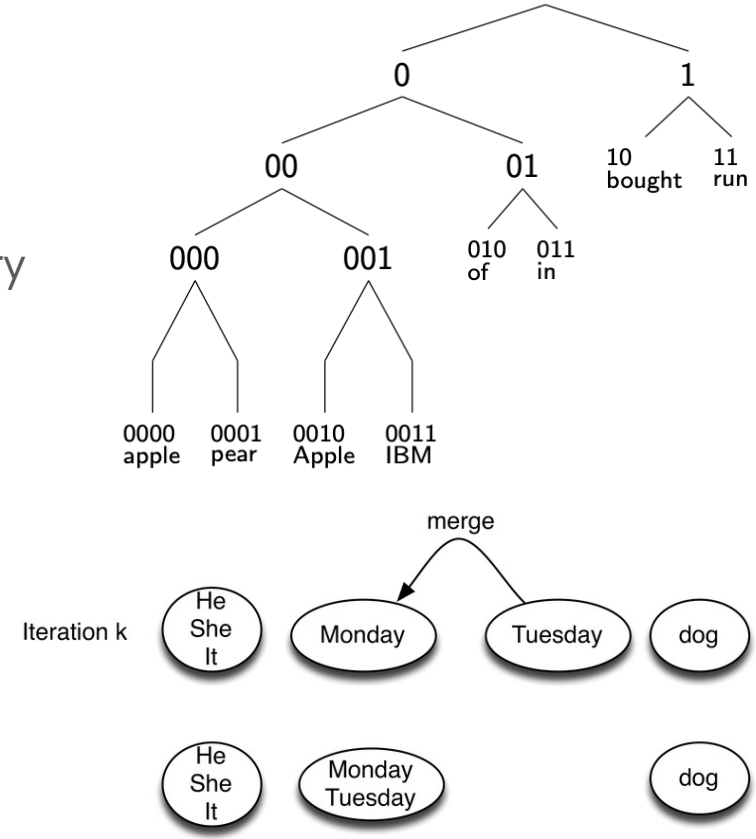
Scales with corpus size
Better representations Captures complex patterns

- **Count-based:**
  - LSA, HAL, COALS, Hellinger-PCA (Lund & Burges; Rohde et al; Lebret & Collobert; Deerwester et al)
  - Brown clustering (Brown et al.)

Fast-ish training
Sub-par representations

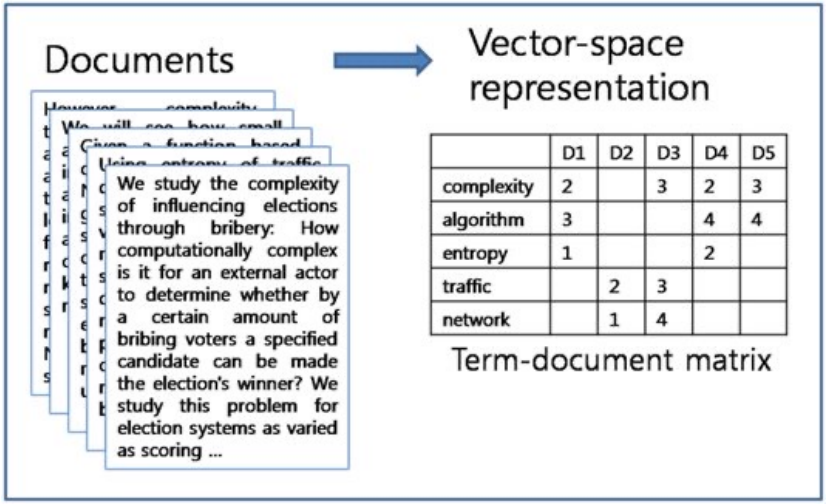
Brown Clusters

- Creates a binary tree for all words in a dictionary
- Algorithm sketch:
  1. Initialize with isolated nodes (words)
  2. Iteratively merge subtrees, so as to maximize some probabilistic notion of co-occurrence.
  3. Continue until everything connected
- Resulting word representation are sequence of 0's and 1's connecting a word to the tree root
- Note:
  - Result is hard cluster
  - Runs in O(|V|^3)



[Class-Based n-gram Models of Natural Language, Brown et al. 1992]

Latent Semantic Analysis



	D1	D2	D3	D4	D5
complexity	2		3	2	3
algorithm	3			4	4
entropy	1			2	
traffic		2	3		
network		1	4		

- Alg sketch:
  1. Create **word-document co-occurrence matrix**: each value is the number of appearances of that term in that doc.
  2. Use SVD (or a similar matrix decomposition alg) to create low-dimensional representation for words

$$A_{mxn} \approx U_{mxr} \quad \Sigma_{rxr} \quad V^T_{rxn}$$

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Extrinsic Evaluation of Word Vectors: Classification Recap

- Supervised learning: we have a training dataset consisting of samples

$$D = \{\mathbf{x}_i, y_i\}_{i=1}^{N}$$

- $\mathbf{x}_i$ are inputs, e.g., words, sentences, documents, etc.
- y_i are labels (one of C classes) we try to predict, for example:
  - Sentiment labels (+/–), named entity types, buy/sell decisions, word senses, etc.

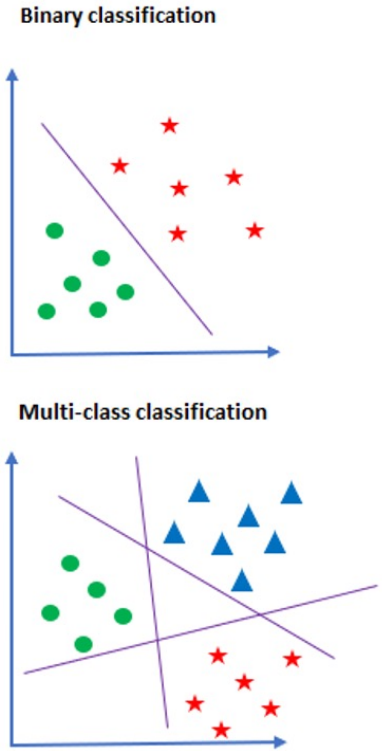
Classification Intuition

- Training data: $D = \{\mathbf{x}_i, y_i\}_{i=1}^{N}$

- Linear separators:
  - Visualization of input vectors in 2D space
  - Linear decision boundary (hyperplane) for two classes:

$$f(\mathbf{x}) = \boldsymbol{w}.\mathbf{x}$$

- **Model:** multiclass classification, each $y_i \in \{0, \dots, C\}$
  - Softmax classifier
  - Acts like a combination of multiple linear classifiers



Classification with Softmax Classifier (Logistic Regression)

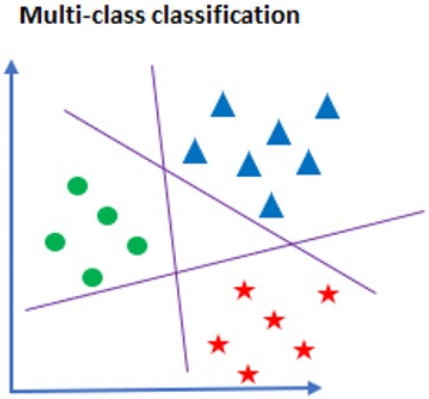
1. Compute the score assigned to each class:
   $f_c(\mathbf{x}) = \boldsymbol{w}_c.\mathbf{x}\ \ \forall c \in C$ and parameters: $\boldsymbol{W} = [\boldsymbol{w}_1, \ldots., \boldsymbol{w}_C]^\top \in \mathbb{R}^{C \times d}$

2. Pass them through the Softmax to get probabilities:

$$\sigma(\boldsymbol{z})_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)}, \boldsymbol{z} = [z_1, \ldots., z_C]$$

Putting it together:

$$p(x|\boldsymbol{W}) = \frac{\exp(\boldsymbol{w_c}.\mathbf{x})}{\sum_{\boldsymbol{c'}} \exp(\boldsymbol{w_{c'}}.\mathbf{x})}, \qquad \boldsymbol{W} = [\boldsymbol{w}_1, \ldots., \boldsymbol{w}_C]^\top$$



Note: during inference we can just pick the class with the highest score $\hat{y} = \ \mathrm{argmax}_{c \in C} \boldsymbol{w}_c.\mathbf{x}$

Classification with Softmax Classifier (Logistic Regression)

- **Training:** for a collection of training example $(\mathbf{x}_i, y_i)$ optimize the parameters $\boldsymbol{W} = [\boldsymbol{w}_1, \ldots, \boldsymbol{w}_C]$ to
  - maximize the probability of the correct class y_i,
  - minimize the negative log probability of that class y_i: $-\log \frac{\exp(\boldsymbol{w}_{y_i}.\mathbf{x}_i)}{\sum_c \exp(\boldsymbol{w}_c.\mathbf{x}_i)}$

- Objective for full dataset $D = \{\mathbf{x}_i, y_i\}_{i=1}^N$: $J(\boldsymbol{W}) = \frac{1}{N}\sum_i -\log \frac{\exp(\boldsymbol{w}_{y_i}.\mathbf{x}_i)}{\sum_c \exp(\boldsymbol{w}_c.\mathbf{x}_i)}$

- Minimization via gradient descent:
  - Programming assignment for HW2!
  - Word embeddings for sentiment classification

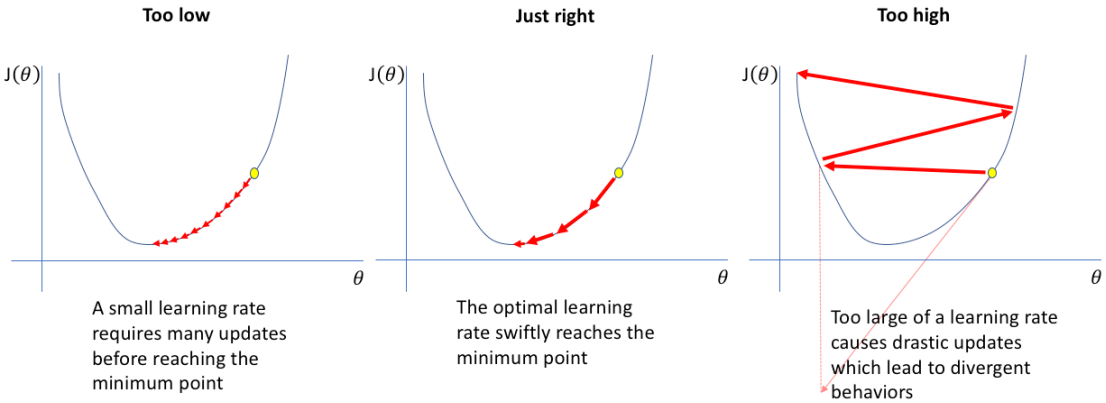
$$\nabla_{\boldsymbol{W}} J(\boldsymbol{W}) = \begin{bmatrix} \nabla_{\boldsymbol{w}_1} \\ \vdots \\ \nabla_{\boldsymbol{w}_C} \end{bmatrix} \in \mathbb{R}^{C \times d}$$

Aside: Setting the Step Size in Gradient Descent

- What is a good value for step size α?

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

  - If α = too small, it may be too slow
  - If α = too large, it may oscillate



- It may take trial-and-errors to find the sweet spot.
- Another trick is to define a "schedule" for gradually reducing the learning rate starting from a large number.
  - More on this in the homework! ☺

[figure from: https://www.jeremyjordan.me/nn-learning-rate/]

Limitations of Word Embeddings: Lack of Compositionality

- Lexical Semantics: focuses on the meaning of individual words.
- Compositional Semantics: meaning depends on the words, and on how they are combined.

Limitations of Word Embeddings: Lack of Compositionality

- Lexical Semantics: focuses on the meaning of individual words.
- Compositional Semantics: meaning depends on the words, and on how they are combined.
  - From HW:

Now, consider sentiment analysis on a phrase in which the predicted sentiments are

$$f(s;\theta) = \theta \cdot \text{repr}(s),$$

for some choice of parameters θ. Prove that in such a model, the following inequality cannot hold for any choice of θ:

$$f(\texttt{good};\theta) > f(\texttt{not good};\theta)$$
$$f(\texttt{bad};\theta) < f(\texttt{not bad};\theta)$$

Limitations of Word Embeddings: No Word Senses

- Most words have lots of meanings!
  - Especially common words
  - Or those that existed for a long time
- Example: "bear"
  - A mammal (🐻)
  - Something difficult (*the oven is a bear to clean*)
  - To accept (*couldn't bear the pain*)
  - To have features (*bears a likeness of her mom*)
  - To contain (*old-bearing shale*)
  - To hold in mind or emotions (*bear malice*)
  - …
- Do word vectors capture word senses?

Today's Recap

- W2V training and broader family of word embeddings
- Building classifiers with word embeddings
- Next time: moving beyond words by modeling sequences.