Big Data Analytics & Applications

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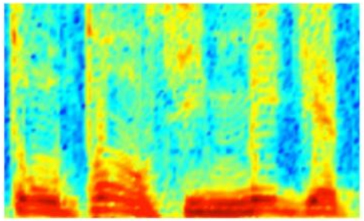
Why Word Embedding

- Natural language processing systems traditionally treat words as discrete atomic symbols, provide no useful information to the system regarding the relationships that may exist between the individual symbols

AUDIO



Audio Spectrogram

DENSE

IMAGES

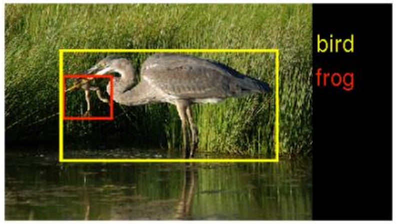


Image pixels

DENSE

TEXT

0	0	0	0.2	0	0.7	0	0	0	...	...

Word, context, or document vectors

SPARSE

One-Hot Representation

- Represent a word as a one-hot vector
  - Example: He studies machine learning

Dictionary									
	He	studies	machine	learning	is	interesting	supports	big	data
v_{He}	1	0	0	0	0	0	0	0	0
v_{is}	0	0	0	0	1	0	0	0	0
v_{big}	0	0	0	0	0	0	0	1	0
v_{data}	0	0	0	0	0	0	0	0	1

- How large is this dictionary (universe set)?
  - Penn Treebank dataset: ~50K
  - Google 1T dataset: 13M

Issues of One-Hot Vector

- High-dimensional
- Sparse
- Fixed dimensionality (cannot represent new words)
- Orthogonal semantic similarity between pair of words

$$\langle v_{king}, v_{queen} \rangle = \langle v_{king}, v_{professor} \rangle = 0$$

	Dictionary						
	king	queen	professor	interesting	supports	big	data
v_{king}	1	0	0	0	0	0	0
v_{queen}	0	1	0	0	0	0	0
$v_{professor}$	0	0	1	0	0	0	0

Distributional Representation

- "You shall know a word by the company it keeps" (John R. Firth, 1957)
- A word is characterized by its context

Dictionary						
	royal	palace	duke	speech	university	research
v_{king}	1	1	1	1	0	0
v_{queen}	1	1	1	1	0	0
$v_{professor}$	0	0	0	1	1	1

$$\langle v_{king}, v_{queen}\rangle > \langle v_{king}, v_{professor}\rangle = \langle v_{queen}, v_{professor}\rangle$$

- Still not good enough $\cdots$

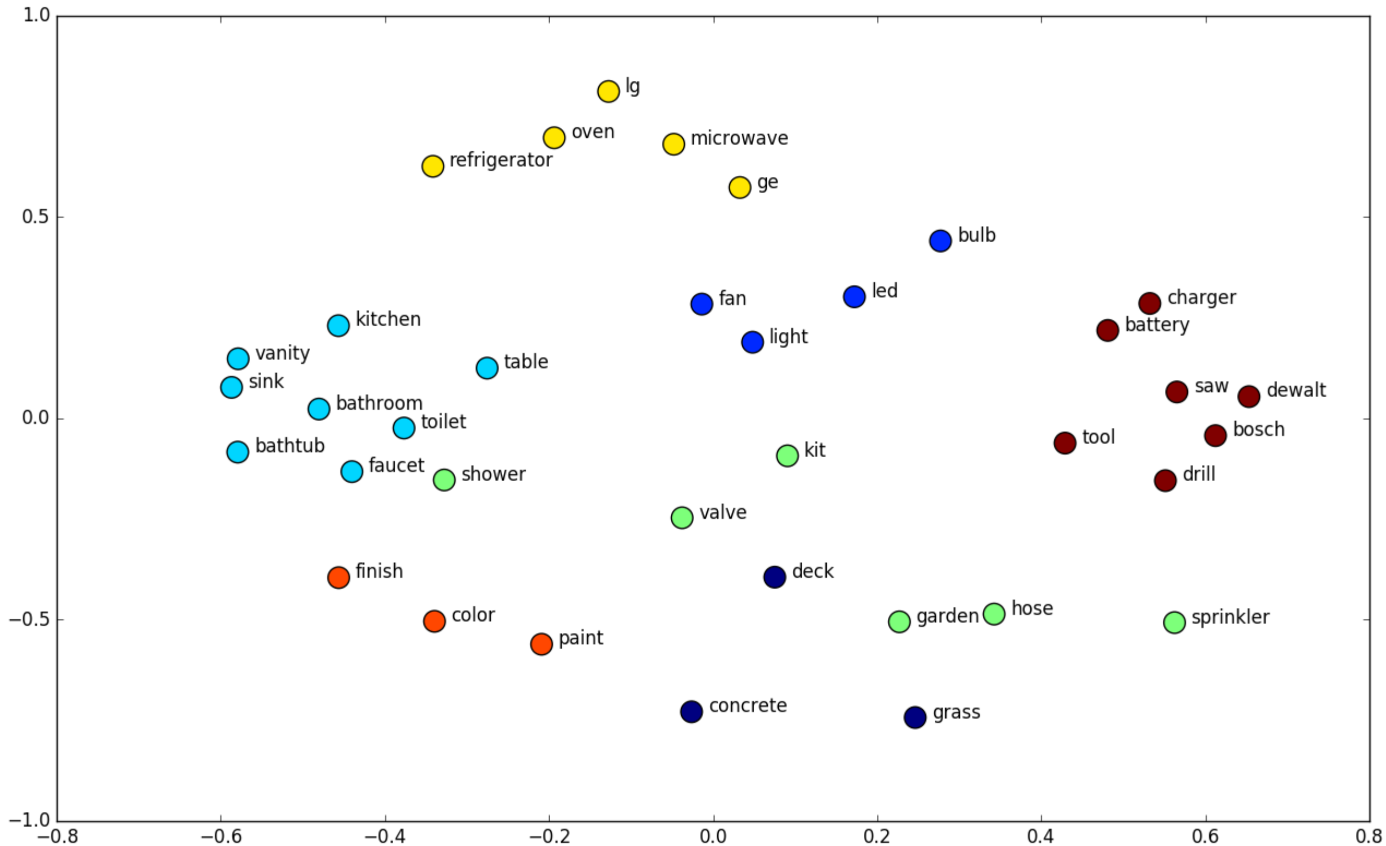
Vector Representation

- The vector space is spanned by semantic "concepts"
- Each word is represented by a distribution of weights over these concepts
  - The representation of a word is spread across all of the concepts in the vector
  - Each concept in the vector contributes to the definition of many words

	Concepts			
	Royalty	Masculinity	Femininity	Celebrity
v_{king}	0.9	0.9	0.1	0.9
v_{queen}	0.8	0.2	0.9	0.8
v_{actor}	0.1	0.8	0.2	0.7

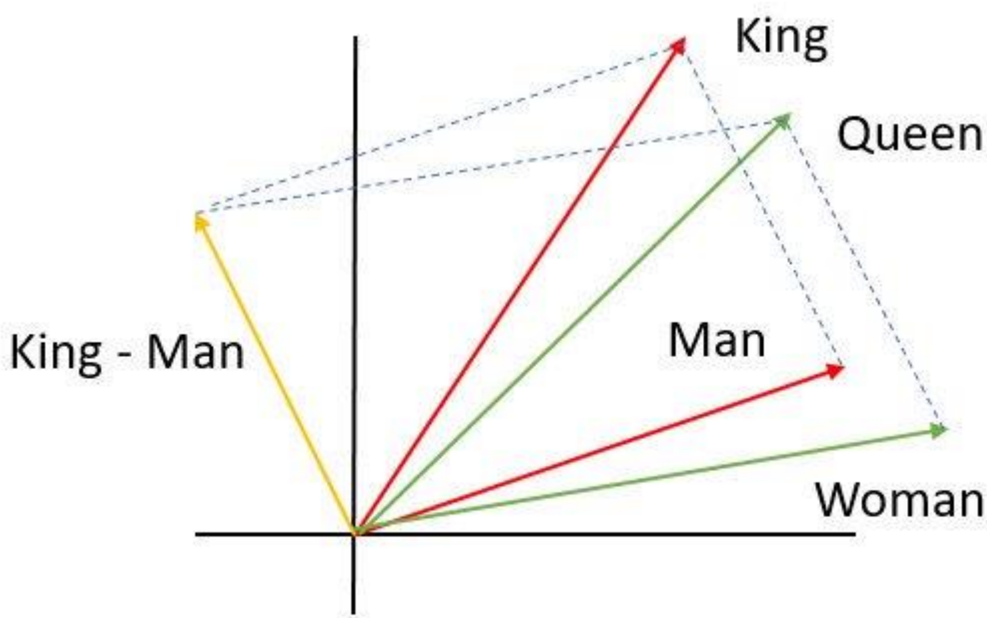
Vector Representation

- An illustration of 2-D vector representation



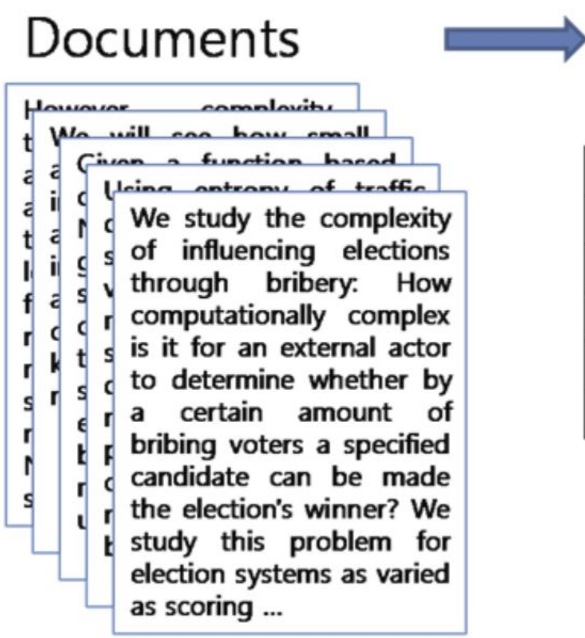
How to Learn Word Vectors?

- How to find semantic concepts – bases
- How to assign weights – vectors
- How to define similarity/distance – metric



A Simple Vector Representation

- A word is represented by the documents (bases of the vector space) in which it appears
- A document is represented by the words it contain (i.e., bag-of-words representation for the document)



Vector-space representation

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

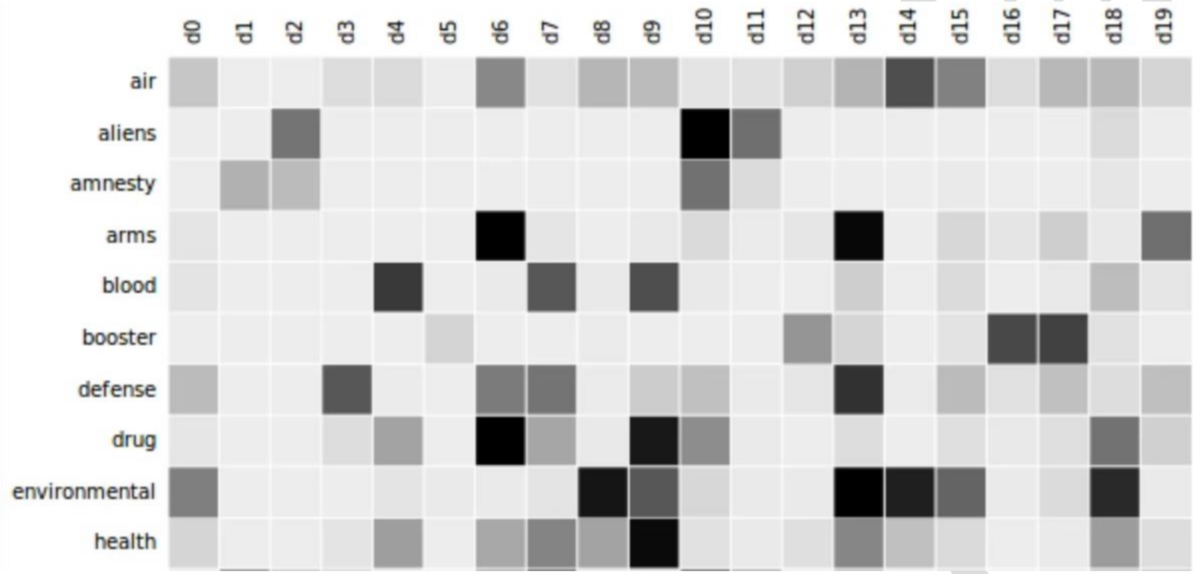
Term-document matrix

Issues of Doc-Word Co-occurrence

- Number of concepts (bases) is too large
- Concepts (bases) are not orthogonal
- High-dimensional
- Sparse
- Meaningless function words
- etc.

Latent Semantic Analysis

- Represent a corpus as a document-word co-occurrence matrix (frequency, tf-idf, etc.) – relational data



- Factorize the document-word co-occurrence matrix to find latent components – semantic concepts

Latent Semantic Analysis

- Latent semantic analysis (LSA) is a technique of analyzing relationships between a set of documents and the terms they contain by producing a set of concepts related to the documents and terms.
- LSA assumes that words that are close in meaning will occur in similar documents (the distributional hypothesis).
- LSA applies singular value decomposition (SVD) to find latent concepts $A = USV^\top$
- Words are then compared by taking the cosine of the angle between the two vectors.

Latent Semantic Analysis

- LSA applies singular value decomposition (SVD) to find latent concepts $A = USV^\top$
  - A: $m \times n$ word-document co-occurrence matrix
  - U: $m \times k$ orthogonal matrices for representing words
  - V: $n \times k$ orthogonal matrices for representing documents
  - S: $k \times k$ diagonal singular value matrix
  - Select $k' \ll n, k' \ll m$ for a low-rank approximation of A

A = **U** x **S** x **Vt**

A:

	d1	d2	d3	d4
a	6	7	1	0
b	8	6	0	1
c	6	9	8	5
d	0	1	8	8
e	2	0	9	7
f	2	0	7	7

U:

	f1	f2	f3	f4
a	0.24	-0.51	0.08	0.06
b	0.25	-0.54	-0.64	-0.23
c	0.58	-0.28	0.57	0.13
d	0.42	0.37	0.16	-0.68
e	0.44	0.34	-0.24	0.66
f	0.39	0.29	-0.40	-0.09

S:

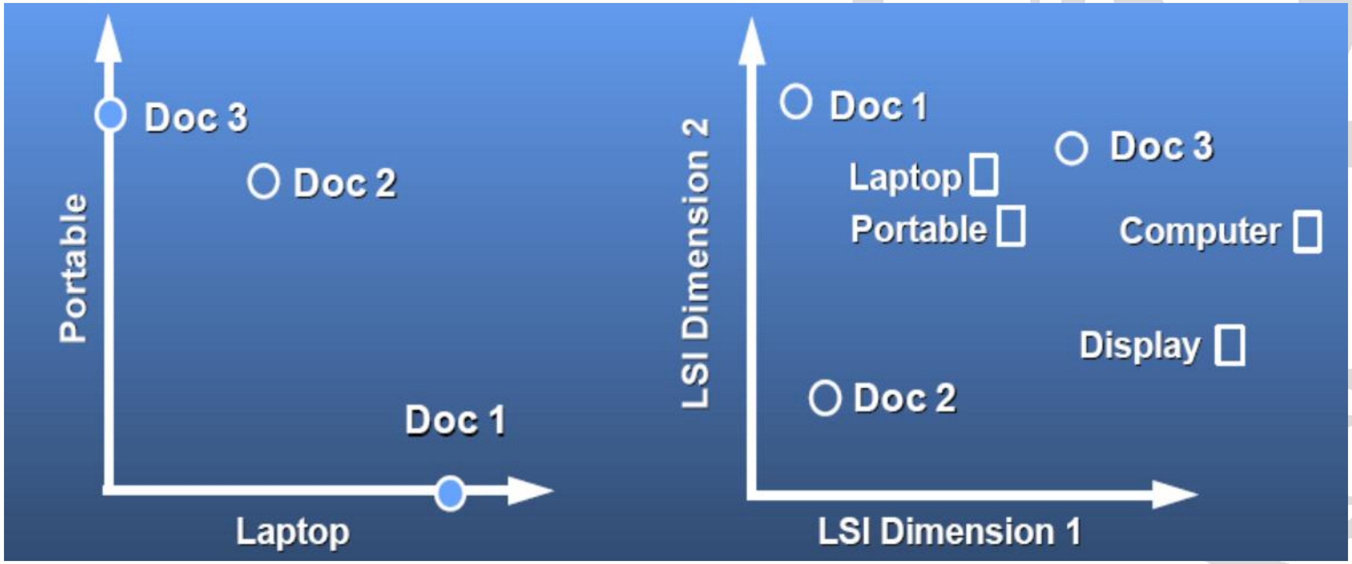
	f1	f2	f3	f4
f1	23.1	0	0	0
f2	0	14.3	0	0
f3	0	0	3.5	0
f4	0	0	0	1.5

Vt:

	d1	d2	d3	d4
f1	0.37	0.38	0.65	0.53
f2	-0.55	-0.63	0.37	0.38
f3	-0.69	0.59	0.27	-0.21
f4	0.26	-0.29	0.59	-0.69

Latent Semantic Analysis

- After applying SVD to the word-document co-occurrence matrix and obtain the factorization $A = USV^\top$
  - U: similar words have large inner products
  - V: similar documents have large inner products
  - Related word and document have large inner products



word2vec

- Latent semantic analysis (LSA)
  - Low-rank factorization of the co-occurrence matrix
  - Latent space can be interpreted as latent concepts
  - Words are vector representations in the latent space
- word2vec
  - Word vectors are positioned in the vector space such that words that share common contexts in the corpus are located in close proximity to one another in the space
  - Predict surrounding words (skip-gram)
  - Also can be used represent similarity

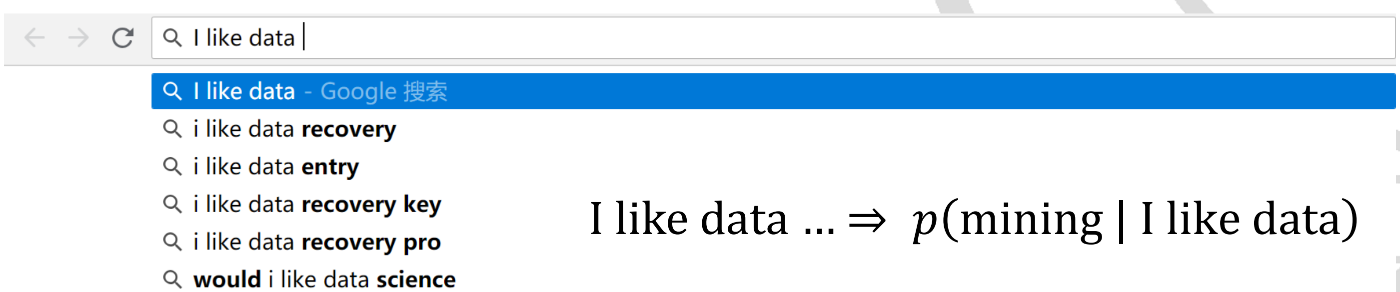
[1] Mikolov (2013). "Efficient Estimation of Word Representations in Vector Space".

Language Model

- A statistical language model is a probability distribution over sequences of words $w_1, \dots, w_N$
- Given such a sequence, it assigns a probability $p(w_1, \dots, w_N)$ to the whole sequence
  - Rank possible sentences (e.g., spelling correction)

$$p(\text{“I like data analytics”}) > p(\text{“I like Dota analytics”})$$
$$p(\text{“I like data analytics”}) > p(\text{“Data analytics likes I”})$$

  - Generate possible sentences (e.g., autocomplete query)



$$\text{I like data} \dots \Rightarrow p(\text{mining} \mid \text{I like data})$$

n-gram Language Model

- The probability of a word only depends on the previous $n-1$ words, known as an n-gram model

$$p(w_1, \dots, w_N) = \prod_{i=1}^{N} p(w_i | w_1, \dots, w_{i-1}) \approx \prod_{i=1}^{N} p(w_i | w_{i-(n-1)}, \dots, w_{i-1})$$

  - Bigram ($n = 2$) language model

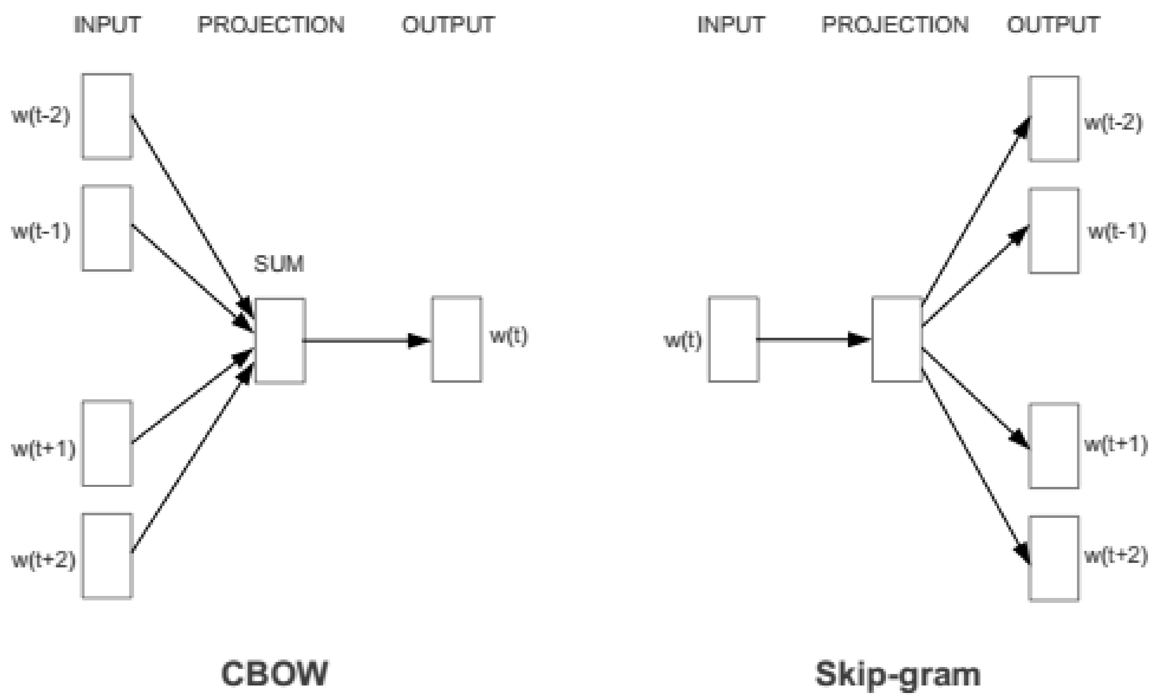
$$\begin{aligned} & p(\text{“I like data analytics”}) \\ \approx\ & p(\text{I} \mid \langle s \rangle) p(\text{like} \mid \text{I}) p(\text{data} \mid \text{like}) p(\text{analytics} \mid \text{data}) p(\langle /s \rangle \mid \text{analytics}) \end{aligned}$$

- The conditional probability can be calculated from n-gram model frequency counts

$$p\left(w_i \middle| w_{i-(n-1)}, \dots, w_{i-1}\right) = \frac{\#(w_{i-(n-1)}, \dots, w_{i-1}, w_i)}{\#(w_{i-(n-1)}, \dots, w_{i-1})}$$

CBOW and Skip-Grams

- word2vec can use either continuous bag-of-words (CBOW) or continuous skip-gram to produce a distributed representation of words



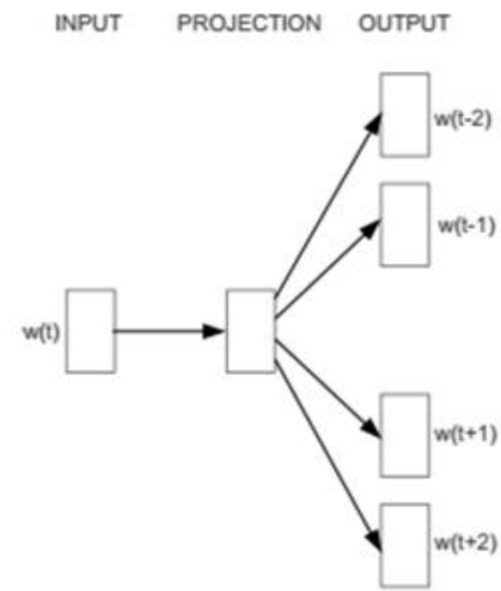
Objective of word2vec (Skip-gram)

- Maximize the log likelihood of the context words $w_{t-m}, w_{t-m+1}, \dots, w_{t-1}, w_{t+1}, w_{t+2}, \dots, w_{t+m}$, given w_t
  - m is usually 5~10

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

- Use softmax to model $p(w_{t+j}|w_t)$

$$p(w_{t+j}|w_t) = \frac{\exp(v_{w_{t+j}} \cdot v_{w_t})}{\sum_{w'} \exp(v_{w'} \cdot v_{w_t})}$$



Skip-gram

Optimization of word2vec

- How to minimize the objective of word2vec to obtain v_{w_t} for $w_1, \dots, w_T$? – Gradient descent
  - Let the current center word be c and one of its context word be s, then the conditional probability becomes

$$p(s|c) = \frac{\exp(v_s \cdot v_c)}{\sum_{w'} \exp(v_{w'} \cdot v_c)}$$

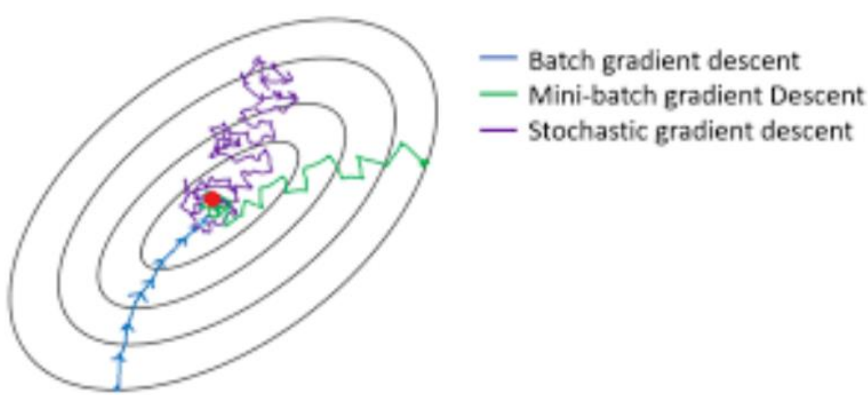
  - The gradient of the log likelihood w.r.t. v_c is

$$\frac{\partial \log p(s|c)}{\partial v_c} = v_s - \sum_w \frac{\exp(v_w \cdot v_c)}{\sum_{w'} \exp(v_{w'} \cdot v_c)} v_w = v_s - E_{w \sim p(w|c)} v_w$$

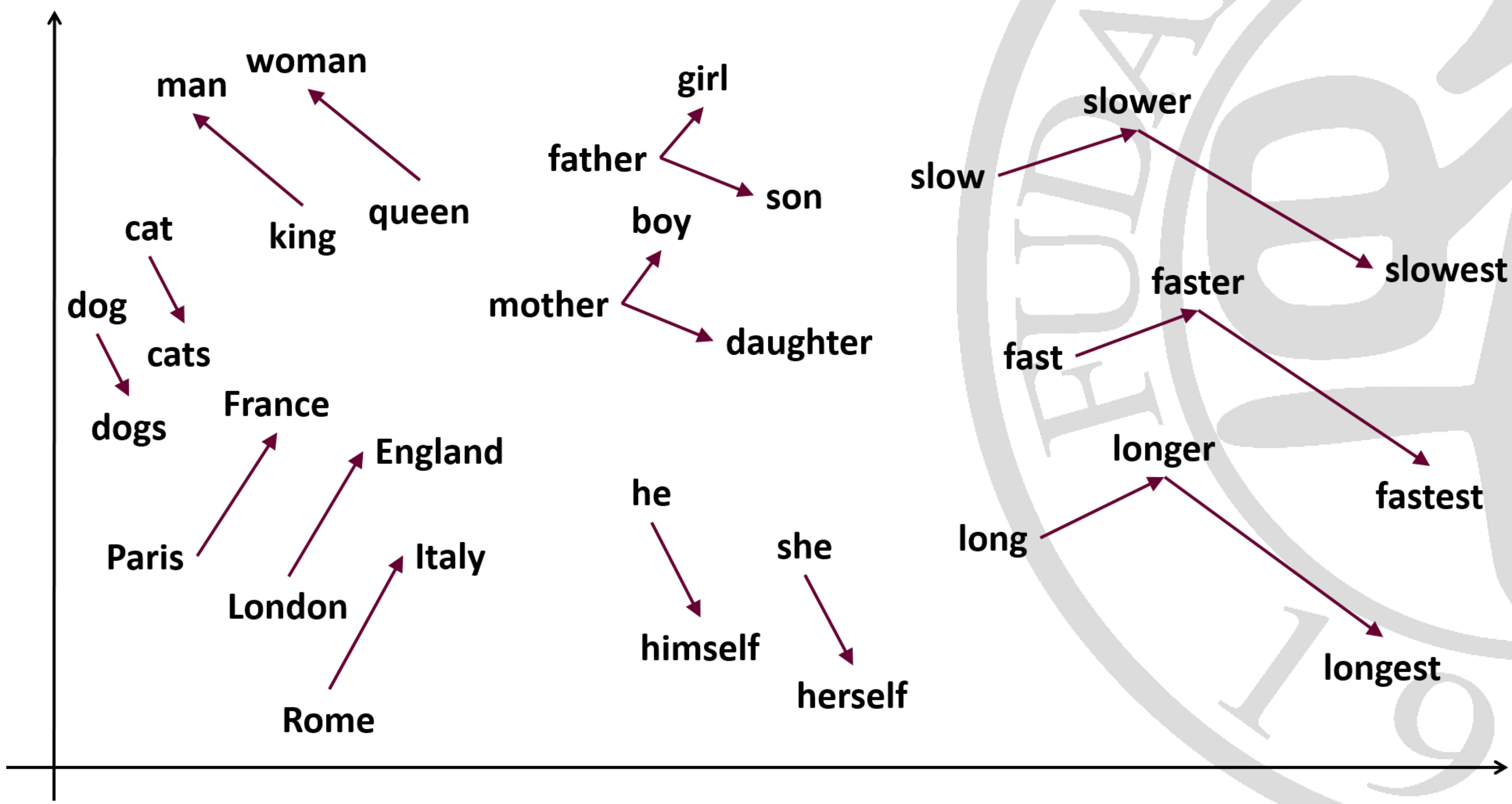
  - Alternate minimize $J(\theta)$ w.r.t. v_{w_t} for $w_1, \dots, w_T$

Optimization of word2vec

- Gradient descent
  - Let $J(\theta) = \frac{1}{n}\sum_{i=1}^{n} J_i(\theta)$
  - update rule: $\theta \leftarrow \theta - \frac{\eta}{n}\sum_{i=1}^{n} \nabla J_i(\theta)$
- Stochastic gradient descent
  - Replace $\frac{1}{n}\sum_{i=1}^{n} \nabla J_i(\theta)$ by the gradient at a single example $\nabla J_i(\theta)$
  - At each iteration randomly select an example i and update: $\theta \leftarrow \theta - \eta \nabla J_i(\theta)$



Word Embedding with word2vec



Summary

- Vector space models (VSMs) represent words in a continuous vector space where semantically similar words are located in close proximity to one another
- All methods depend on the distributional hypothesis, which states that words that appear in the same contexts share semantic meaning
- There are two main categories: count-based methods (e.g. Latent Semantic Analysis), and predictive methods (e.g. neural probabilistic language models).

Project: Word Embedding

- Dataset:
  - Public available word embedding datasets (e.g., https://github.com/kudkudak/word-embeddings-benchmarks)
  - Or text data collected by yourself
- Method:
  - Use latent semantic analysis or word2vec techniques to embed English words
- Experiments:
  - Project the embeddings onto the 2-D space (using tool t-SNE) to visualize the results
  - And discuss the observations from the visualization

Thanks

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