

# *Word Vectors - IV*

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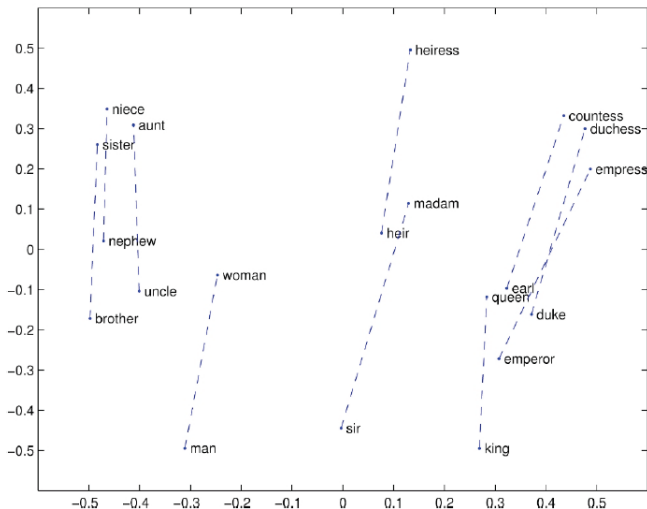
CSE, IIT Kharagpur

February 3rd, 2017

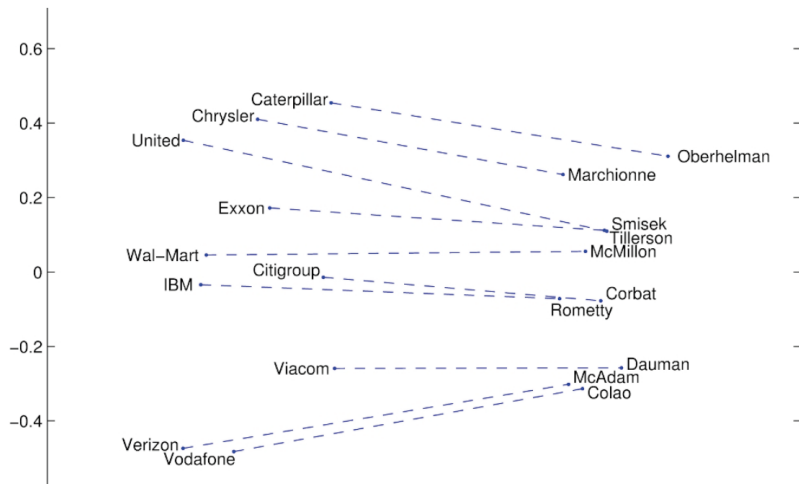
## On Board

- CBOW / Skip-Gram: Form of the objective / error function for gradient descent?
- $f(P_{ij})$  in Glove: Why should it give low weight in the regression to low co-occurrences?
- How is Glove faster than CBOW / Skip-Gram?

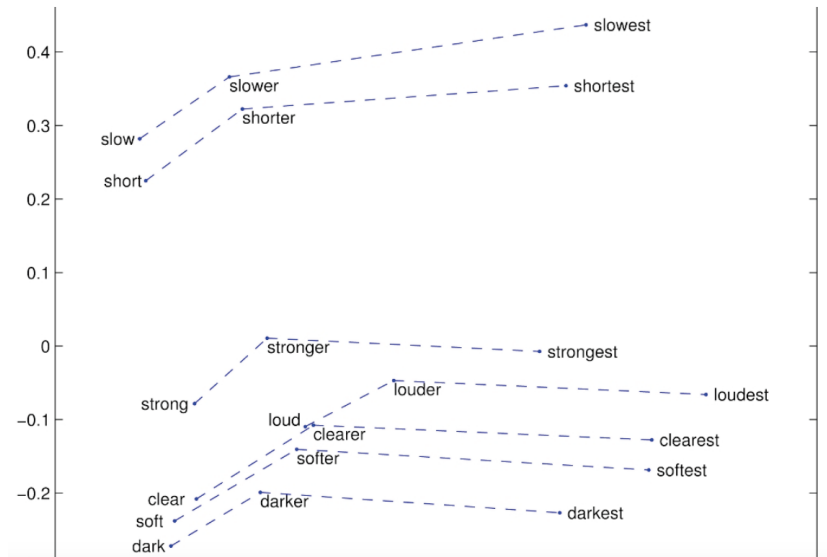
# Glove Visualisations



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## *t*-distributed Stochastic Neighbor Embedding

**Objective:** Given a set of  $N$  high-dimensional objects  $x_1, \dots, x_N$ , learn a  $d$ -dimensional map  $y_1, \dots, y_N$  (with  $y_i \in \mathbb{R}^d$ ) such that the new similarities  $q_{ij}$  reflect the old similarities  $p_{ij}$  as closely as possible, i.e., the KL-divergence between the two similarity distributions is minimized

$$KL(P||Q) = \sum_{i \neq j} p_{ij} \log \frac{p_{ij}}{q_{ij}}$$

# *Intrinsic Evaluation*

- Word vector distances and their correlation with human judgements
- Example dataset: WordSim353

Word 1	Word 2	Human (mean)
tiger	cat	7.35
tiger	tiger	10.00
book	paper	7.46
computer	internet	7.58
plane	car	5.77
professor	doctor	6.62
stock	phone	1.62
stock	CD	1.31
stock	jaguar	0.92

## *Skip-gram: using evaluation on analogy testing*

- **Dimensions:** 300 dimensions work the best
- **Window size:** 8 words around each center word works well.
- **More training time and data helps!!**



## *Problem with word vectors*

Multiple senses of a given word get the same representation!!

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Huang et al., “Improving Word Representations via Global Context and Multiple Word Prototypes”, ACL 2012.

## *Basic Idea*

Cluster words windows around words, retrain with each word assigned to multiple different clusters, e.g., bank<sub>1</sub>, bank<sub>2</sub> etc.

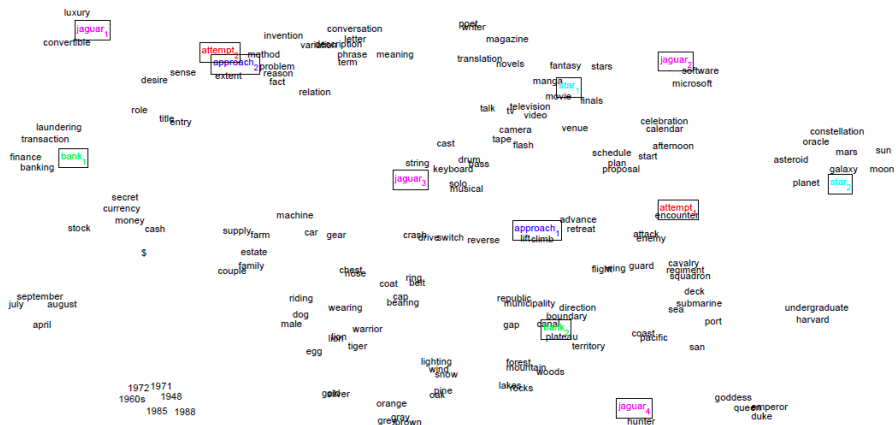
# Multiple Word Prototypes: Nearest Neighbors

Center Word	Nearest Neighbors
bank_1	corporation, insurance, company
bank_2	shore, coast, direction
star_1	movie, film, radio
star_2	galaxy, planet, moon
cell_1	telephone, smart, phone
cell_2	pathology, molecular, physiology
left_1	close, leave, live
left_2	top, round, right

Code and dataset:

<http://www.socher.org/index.php/Main/ImprovingWordRepresentationsViaGlobalC>

# Multiple Word Prototypes: Visualization



# Cross-lingual applications: Word Embeddings

## *Cross-lingual information retrieval task*

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Query is in one language and documents in another language

## *Obtaining common representations for words in multiple languages*

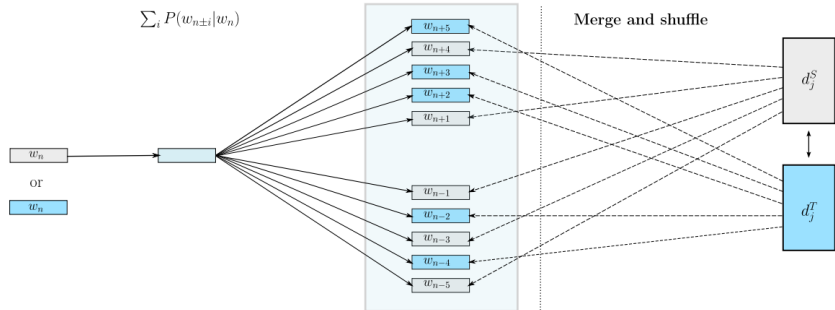
So that you can visualize words in multiple languages in the same space

# Bilingual Word Embeddings: Merge and Shuffle

Input: Pivot word representation

Output: Context representations

Aligned document pair



Vulić, Ivan, and Marie-Francine Moens. "Monolingual and cross-lingual information retrieval models based on (bilingual) word embeddings." SIGIR 2015.

- The previous approach requires a comparable corpora. What if you do not have such corpora?
- Suppose you have a dictionary to start with, what would be an approach?