Insight
Centre for Data Analytics

#InsightDL2018

DEEP LEARNING WORKSHOP

Dublin City University
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Day 1 Lecture 5

Word Embeddings

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UPC
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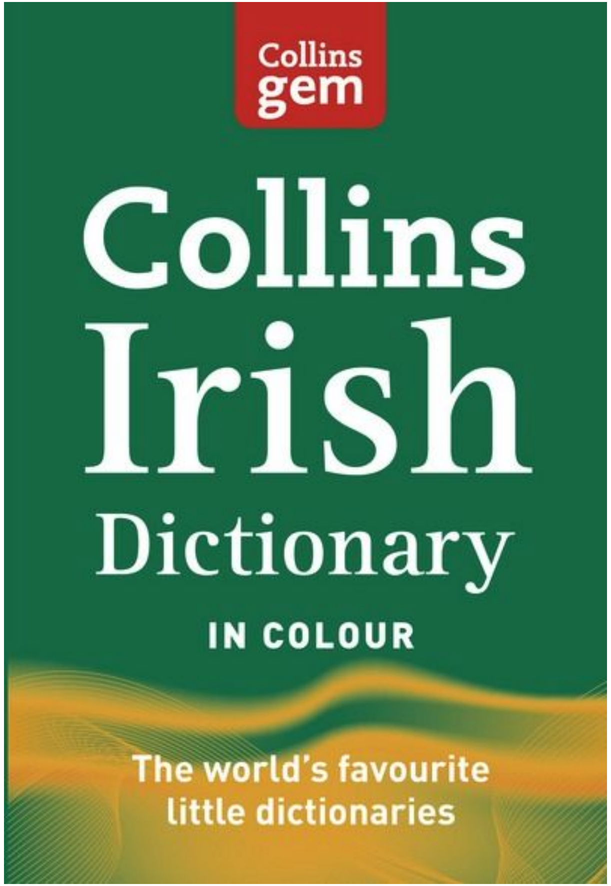
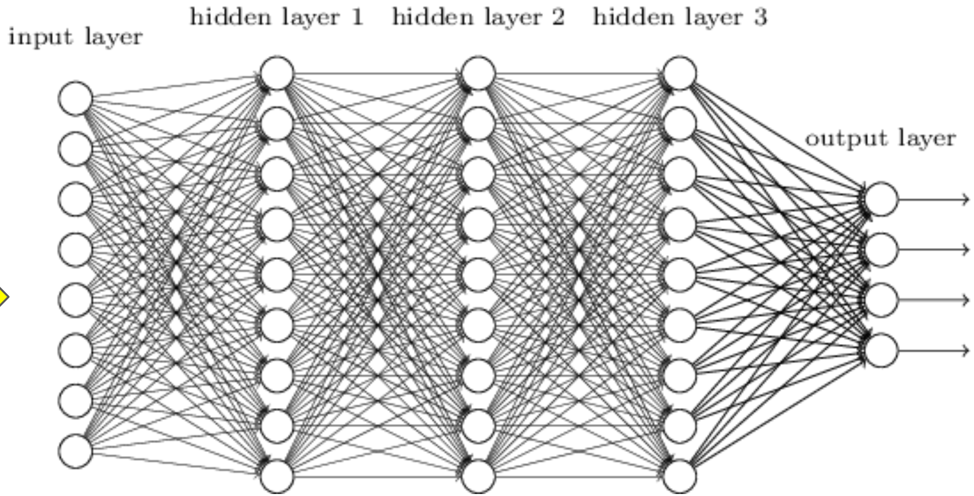
Motivation


Collins gem
Collins Irish Dictionary
IN COLOUR
The world's favourite little dictionaries

?


input layer
hidden layer 1
hidden layer 2
hidden layer 3
output layer

One-hot encoding

Example: letters. |V| = 30

```
'a': x = 1
'b': x = 2
'c': x = 3
.
.
.
'.': x = 30
```

One-hot encoding

Example: letters. |V| = 30

```
'a': x = 1
'b': x = 2
'c': x = 3
.
.
.

'.': x = 30
```

We impose fake range ordering

One-hot encoding

Example: letters. |V| = 30

```
'a': x^T = [1,0,0, ..., 0]
'b': x^T = [0,1,0, ..., 0]
'c': x^T = [0,0,1, ..., 0]
.
.
.
'.': x^T = [0,0,0, ..., 1]
```

One-hot encoding

Example: words.

cat: x^T = [1,0,0, ..., 0]
dog: x^T = [0,1,0, ..., 0]
.
.
house: x^T = [0,0,0, …,0,1,0,...,0]
.
.
.

Number of words, |V| ?

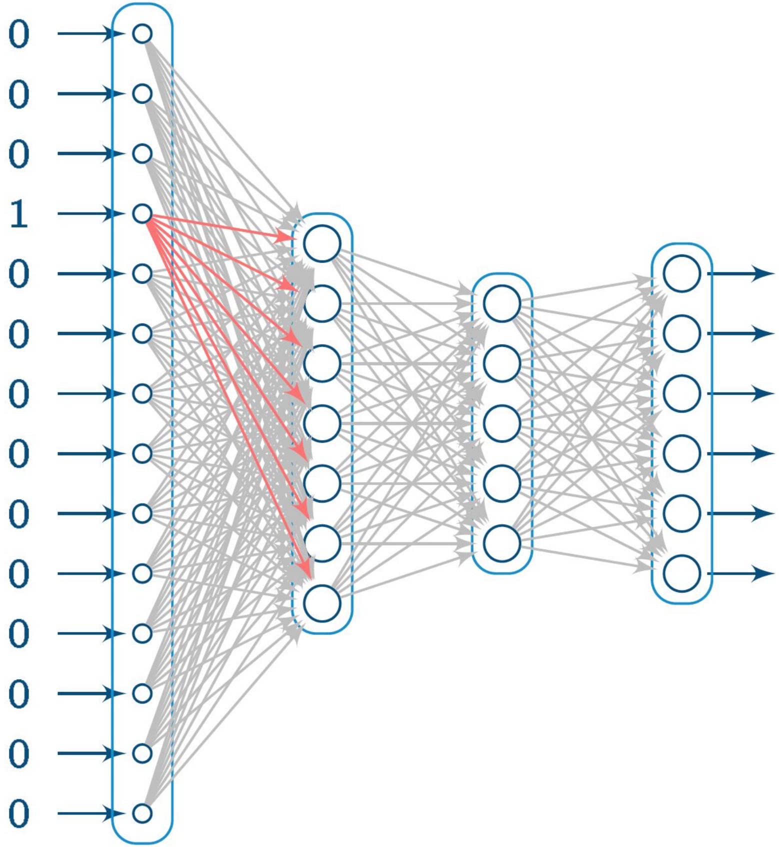
B2: 5K
C2: 18K
LVSR: 50-100K
Wikipedia (1.6B): 400K
Crawl data (42B): 2M

One-hot encoding

- Large dimensionality
- Sparse representation (mostly zeros)
- Blind representation
    - Only operators: ‘!=’ and ‘==’

Projection to a word embedding

The one-hot is linearly projected to a embedded space of lower dimension with matrix E for learned weights (=fully connected).



Projection to a word embedding

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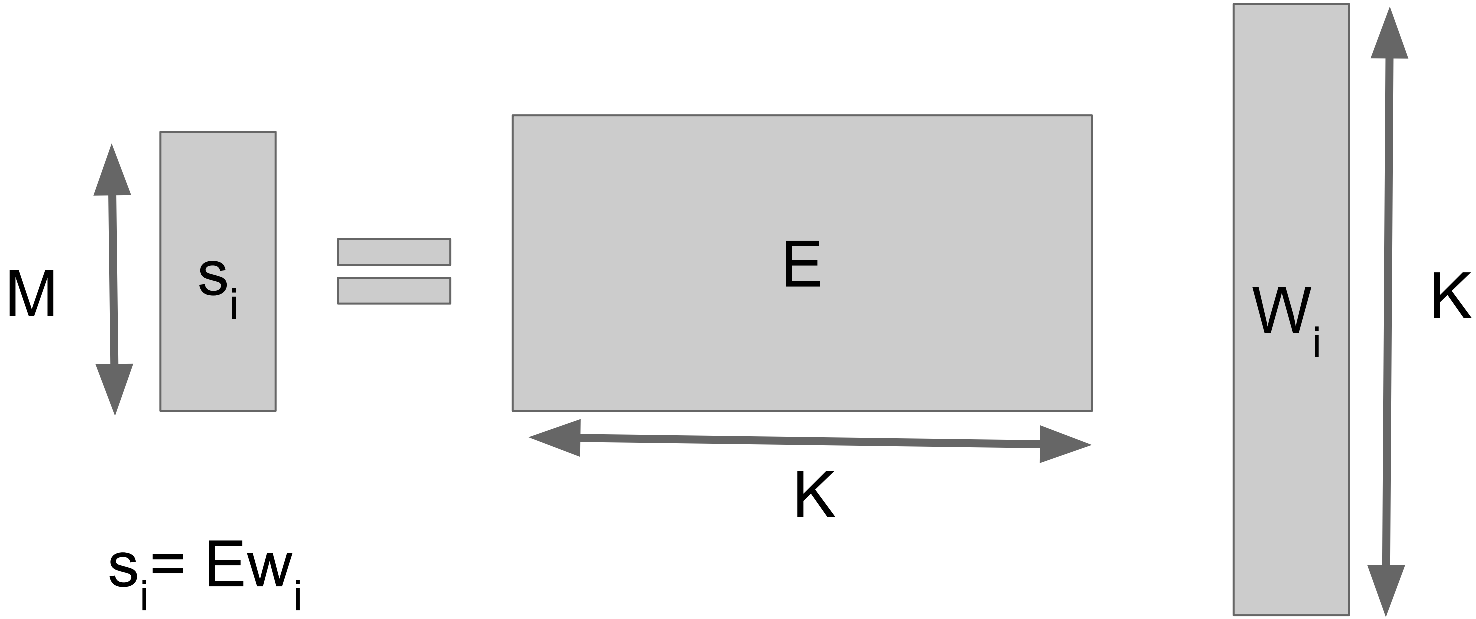


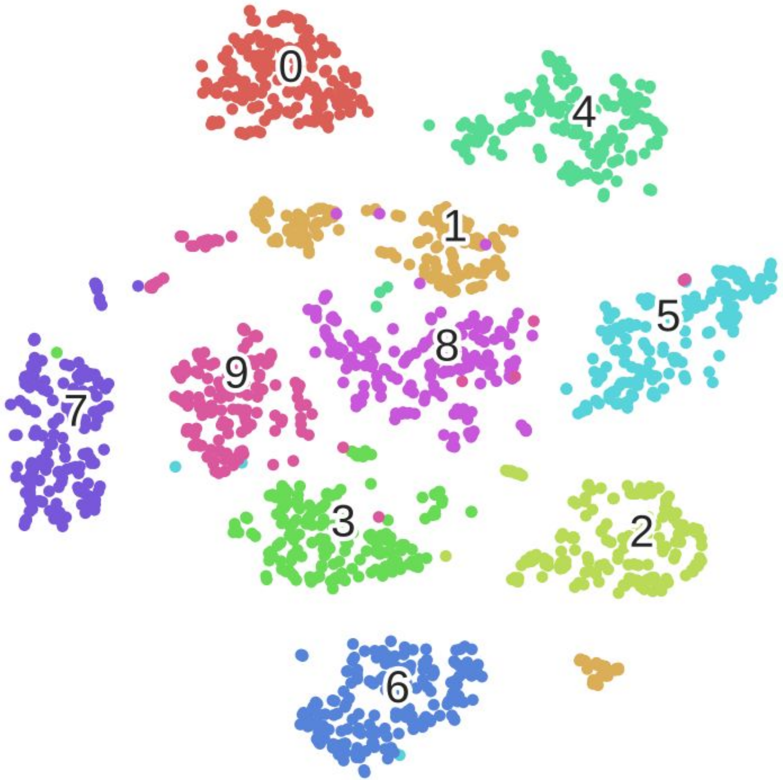
$s_i = Ew_i$

Projection to a word embedding

t-SNE

Embed high dimensional data points (i.e. feature codes) so that pairwise distances are preserved in local neighborhoods.

s_i



Maaten & Hinton. [Visualizing High-Dimensional Data using t-SNE](). Journal of Machine Learning Research (2008).

Projection to a word embedding

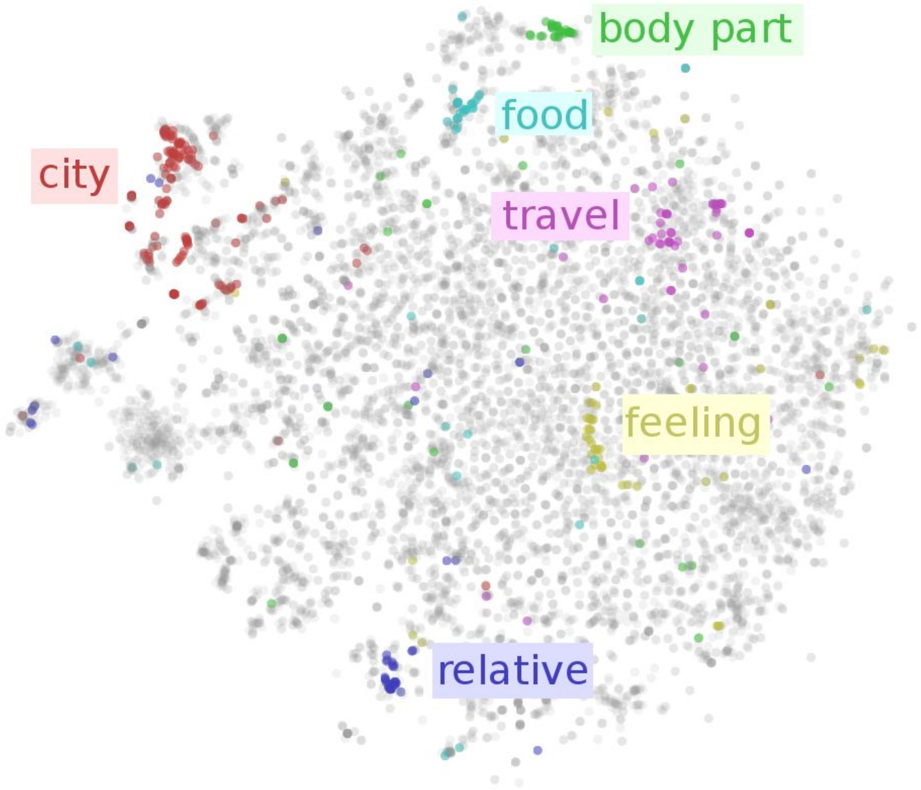
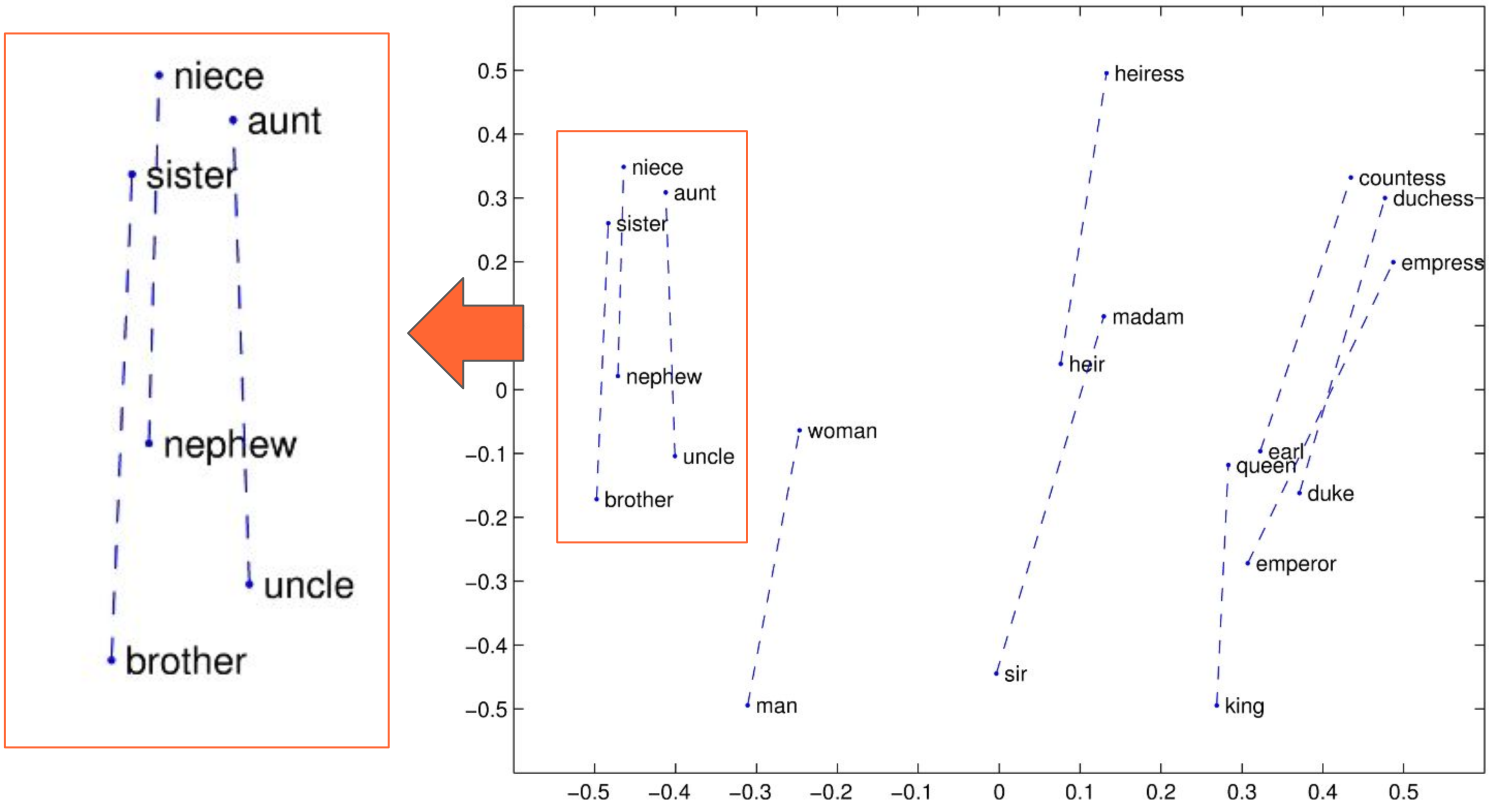


Figure: Christopher Olah, Visualizing Representations

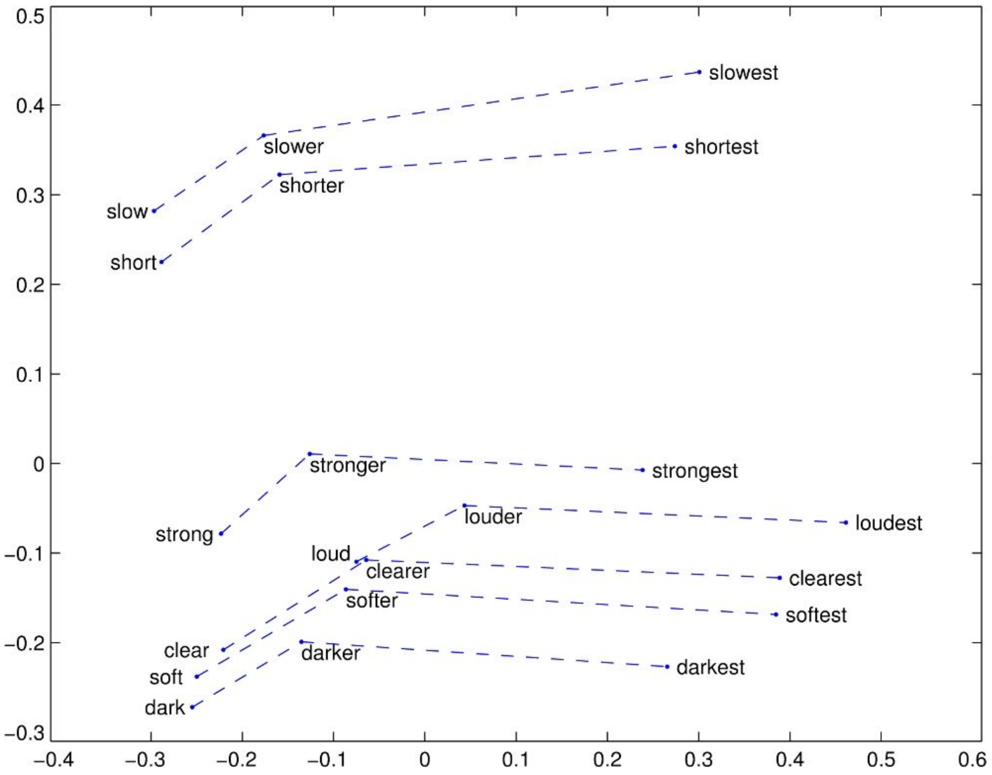
Projection to a word embedding



Man-Woman

Pennington, Jeffrey, Richard Socher, and Christopher Manning. ["Glove: Global vectors for word representation."]() EMNLP 2014

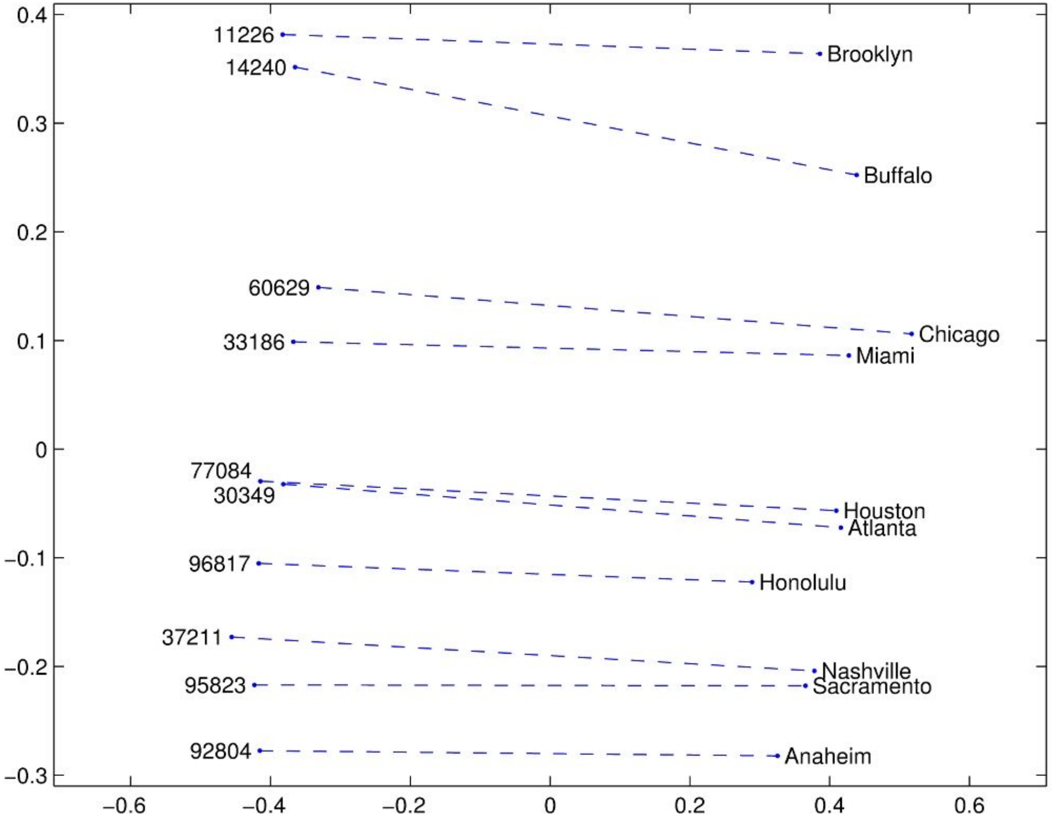
Projection to a word embedding



Comparative-superlative

Pennington, Jeffrey, Richard Socher, and Christopher Manning. ["Glove: Global vectors for word representation."]() EMNLP 2014

Projection to a word embedding



City-Zipcode

Pennington, Jeffrey, Richard Socher, and Christopher Manning. ["Glove: Global vectors for word representation."]() EMNLP 2014

Projection to a word embedding

- Represent words using vectors of dimension *d* (~100 - 500)
- Meaningful (semantic, syntactic) distances
- Dominant research topic in last years in NLP conferences.
- *Good* embeddings are useful for *many* other tasks

Training Word Embeddings

Next word prediction

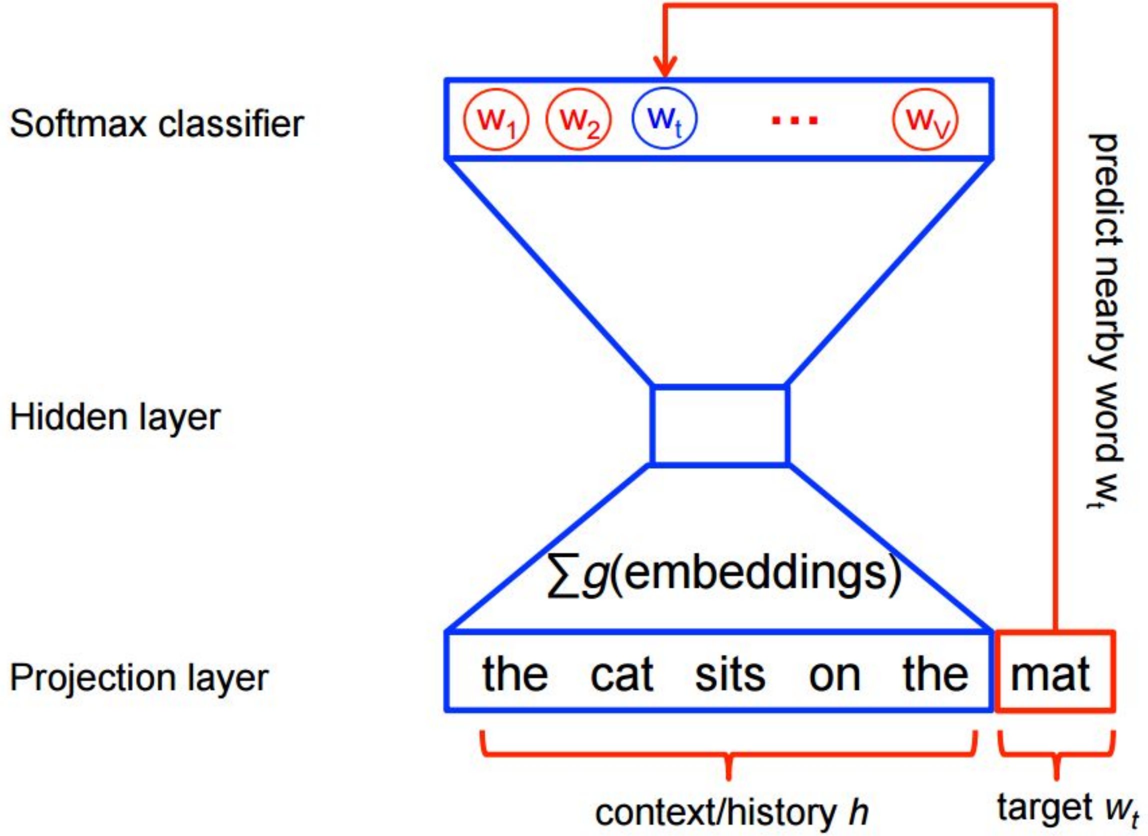
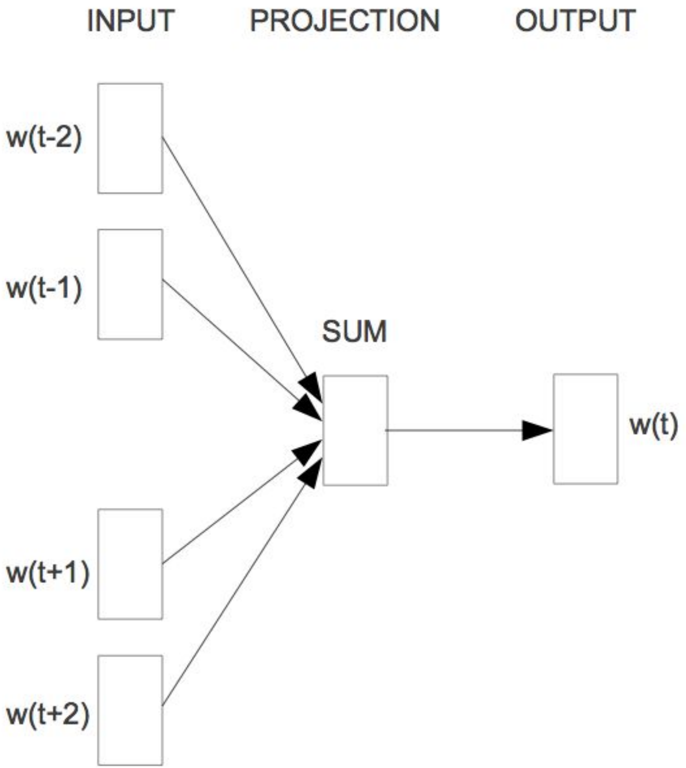


Figure:
TensorFlow tutorial

Bengio, Yoshua, Réjean Ducharme, Pascal Vincent, and Christian Jauvin. "A neural probabilistic language model." Journal of machine learning research 3, no. Feb (2003): 1137-1155.

Training Word Embeddings

Word2Vec: Continuous Bag of Words



`the cat climbed a tree`

Given context:

`a, cat, the, tree`

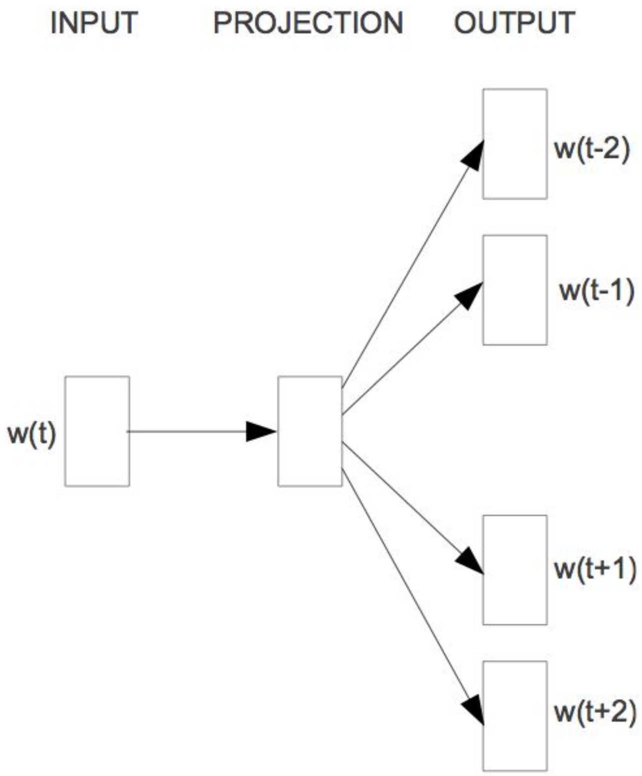
Estimate prob. of

`climbed`

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. ["Distributed representations of words and phrases and their compositionality."]() NIPS 2013

Training Word Embeddings

Word2Vec:
Skip-gram



`the cat climbed a tree`

Given word:

`climbed`

Estimate prob. of context words:

`a, cat, the, tree`

(It selects randomly the context length, till max of 10 left + 10 right)

Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. "Distributed representations of words and phrases and their compositionality." NIPS 2013

Training Word Embeddings

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

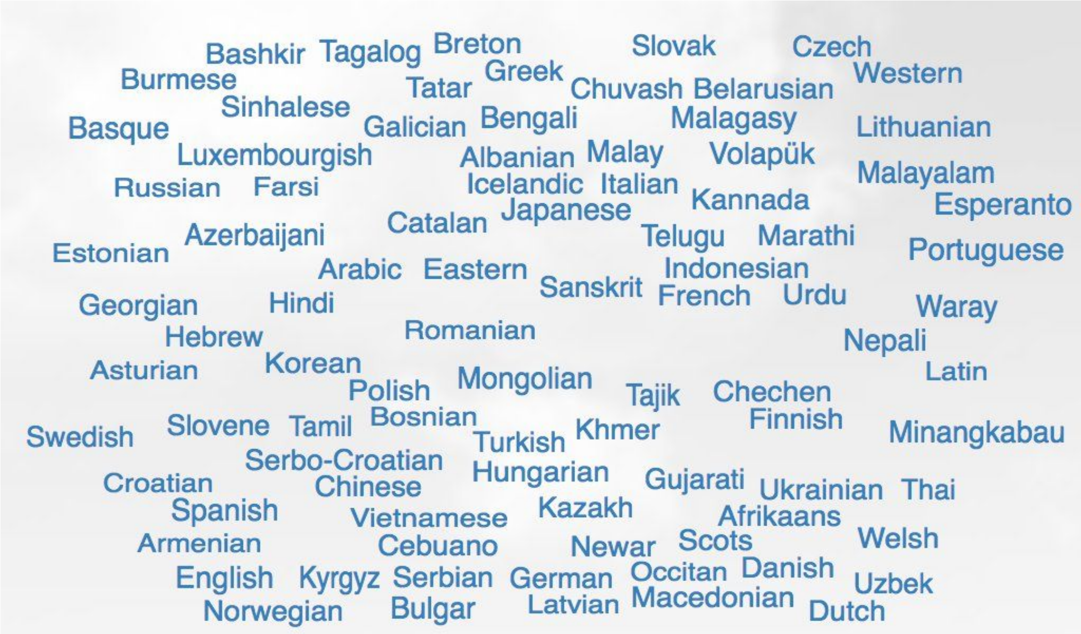
Based on non-zero co-occurrence matrix

The ratio of probabilities encodes some crude form of meaning associated with the abstract concept of thermodynamic phase.

Pennington, Jeffrey, Richard Socher, and Christopher Manning. "Glove: Global vectors for word representation." EMNLP 2014

Multilingual Embeddings

Pre-trained Word Embeddings for 90 languages trained using FastText, on Wikipedia.



facebook research

Questions?