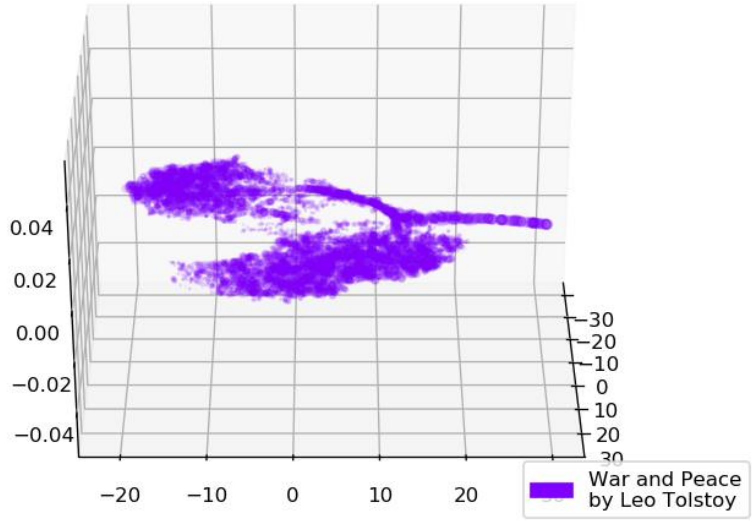


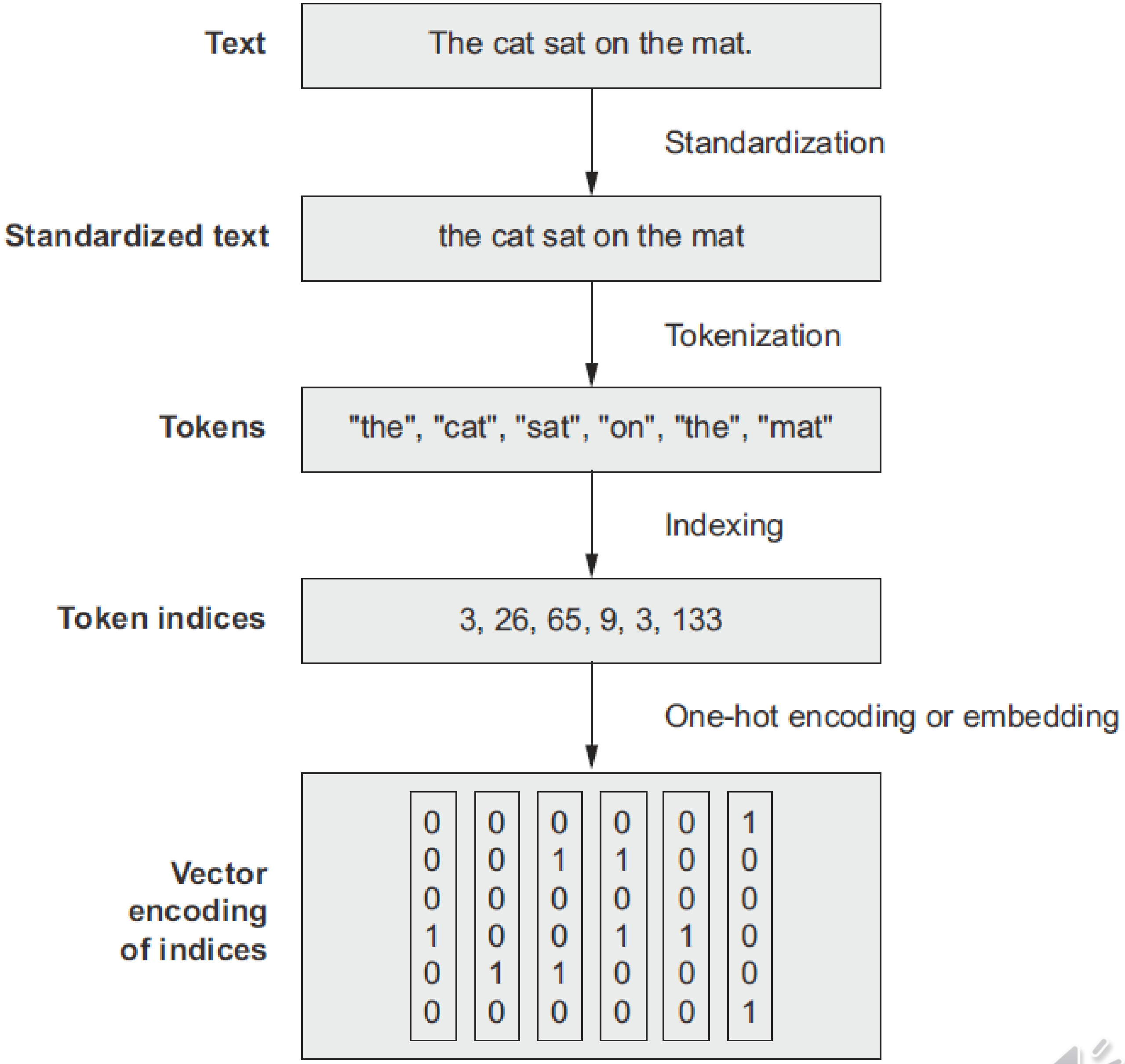
word2vec

Kuan-Ting Lai

2022/4/25

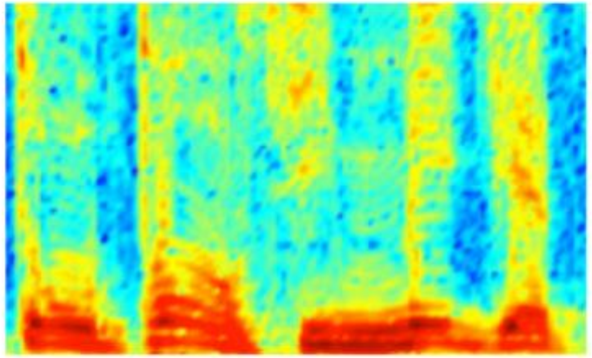
Natural Language Processing (NLP)

- Preprocessing
  - Convert words into vectors first



Why Word Embeddings?

AUDIO



Audio Spectrogram

DENSE

IMAGES

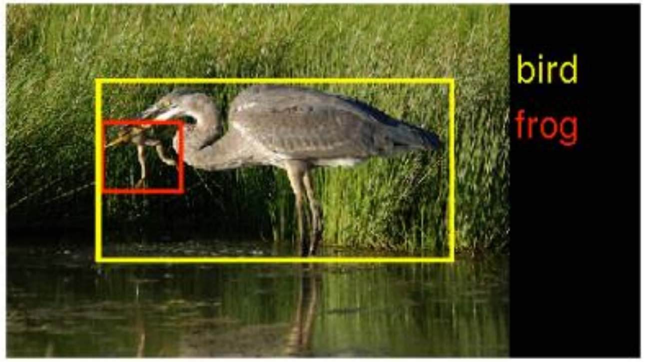


Image pixels

DENSE

TEXT

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

Word, context, or document vectors

SPARSE

https://www.tensorflow.org/tutorials/representation/word2vec

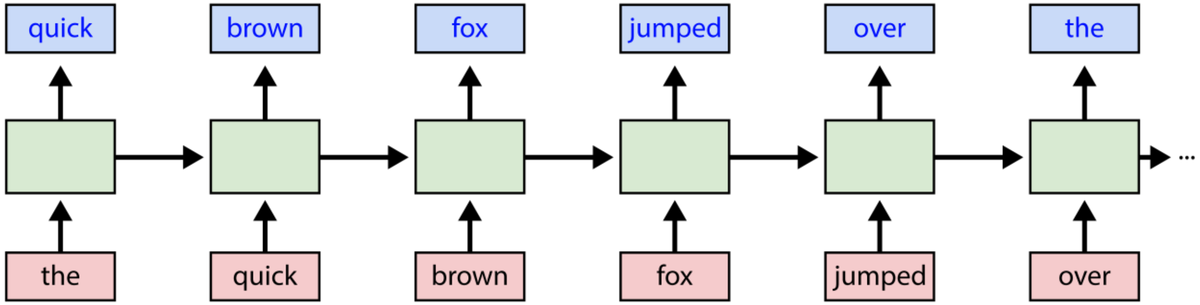
Word2vec (Word Embeddings)

- Embed one-hot encoded word vectors into dense vectors

- Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg S. Corrado, and Jeff Dean. "Distributed representations of words and phrases and their compositionality." In *Advances in neural information processing systems*, pp. 3111-3119. 2013.

Bag-of-words vs. Sequence Model

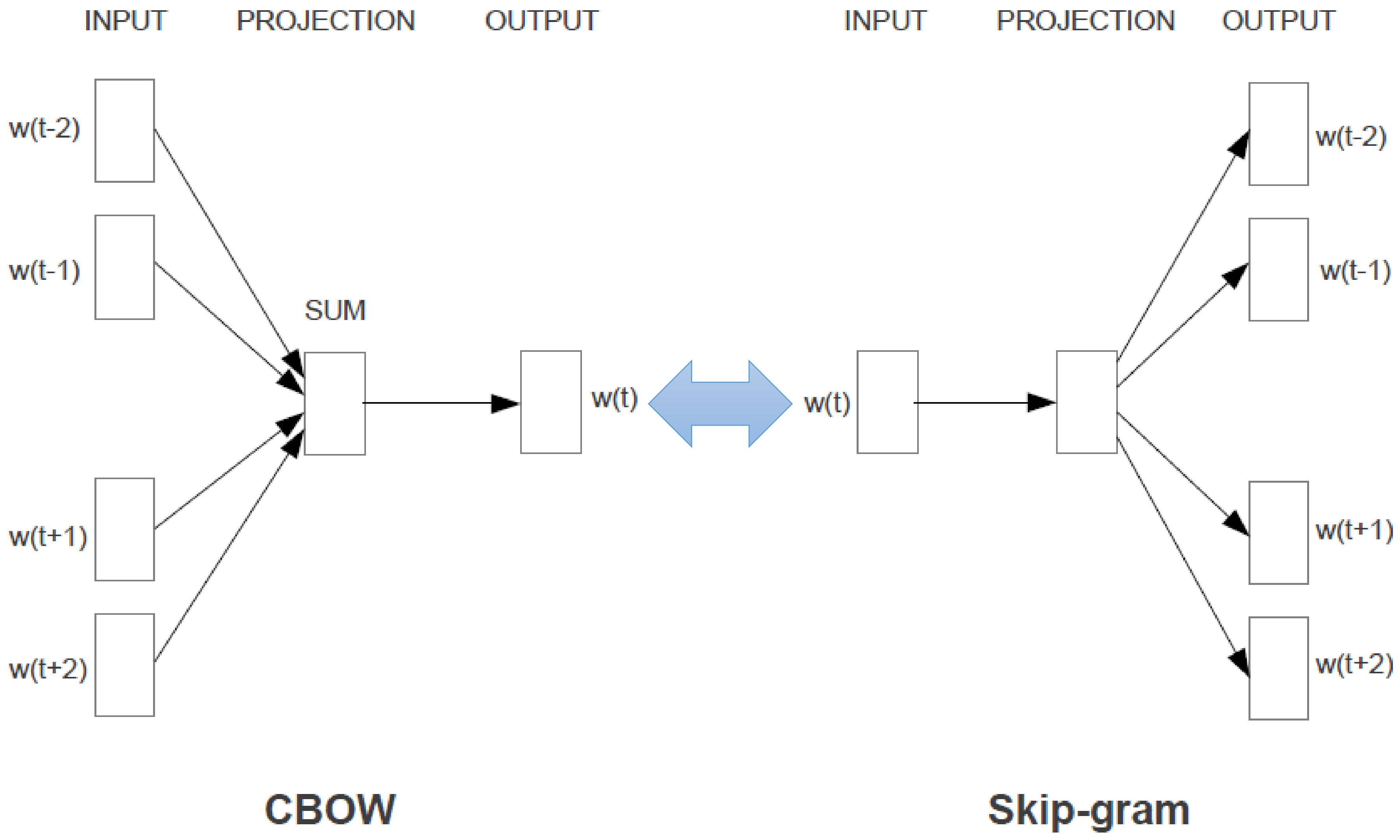
The quick brown fox jumped over the lazy dog



Bag-of-words

- Count-based methods:
  - how often some word co-occurs with its neighbor words
  - Latent Semantic Analysis
- Predictive methods:
  - Predict a word from its neighbors
  - Continuous Bag-of-Words model (CBOW) and Skip-Gram model

Continuous Bag-of-Words vs. Skip-Gram



N-Gram Model

- Use a sequence of N words to predict next word
- Example N=3
  - (The, quick, brown) -> fox

Skip-Gram Model

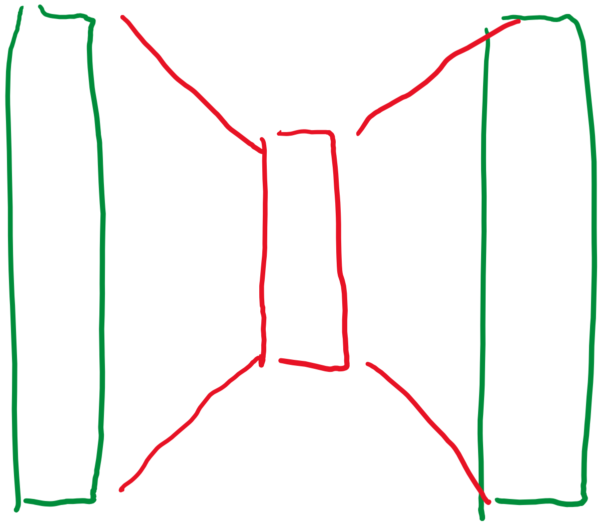
- Window size of 2

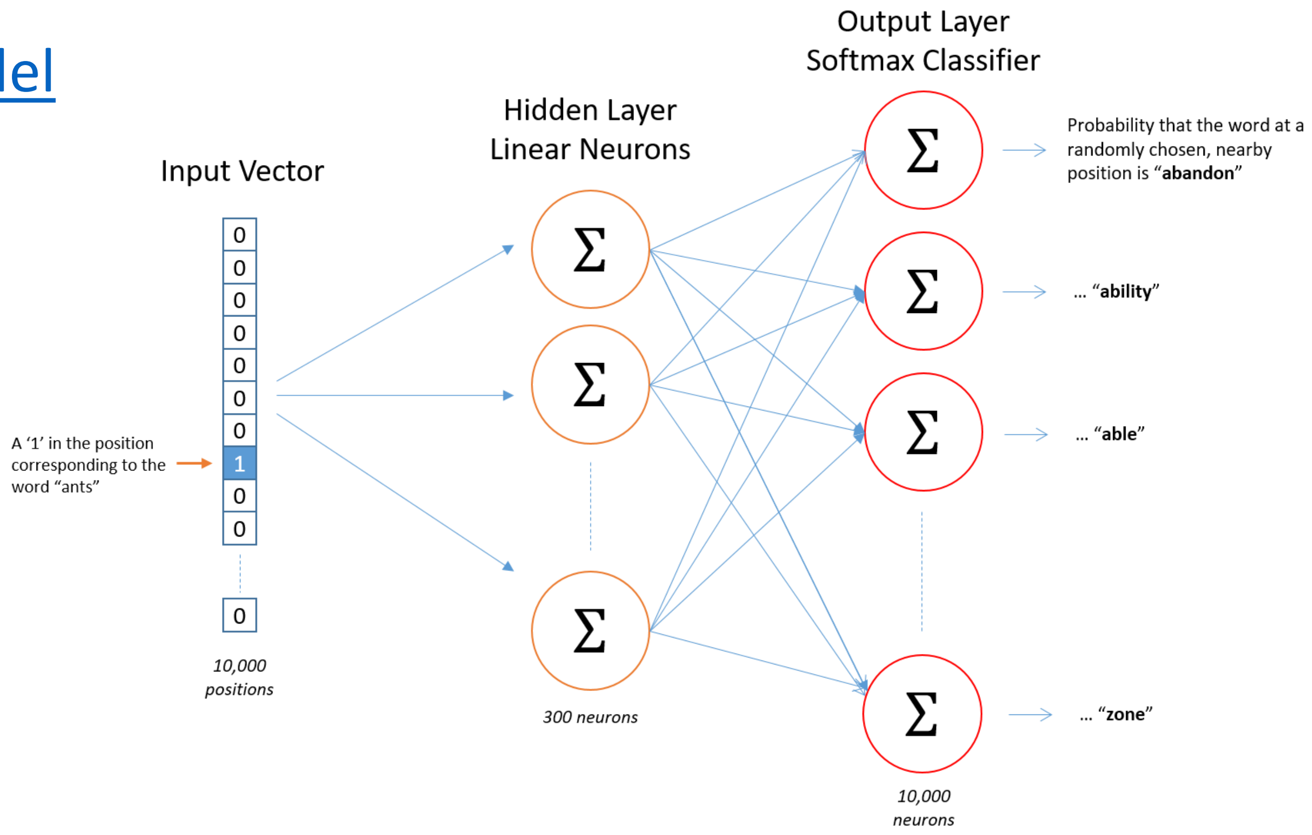
Source Text	Training Samples
The quick brown fox jumps over the lazy dog. ⟹	(the, quick) (the, brown)
The quick brown fox jumps over the lazy dog. ⟹	(quick, the) (quick, brown) (quick, fox)
The quick brown fox jumps over the lazy dog. ⟹	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown fox jumps over the lazy dog. ⟹	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Word2Vec Tutorial

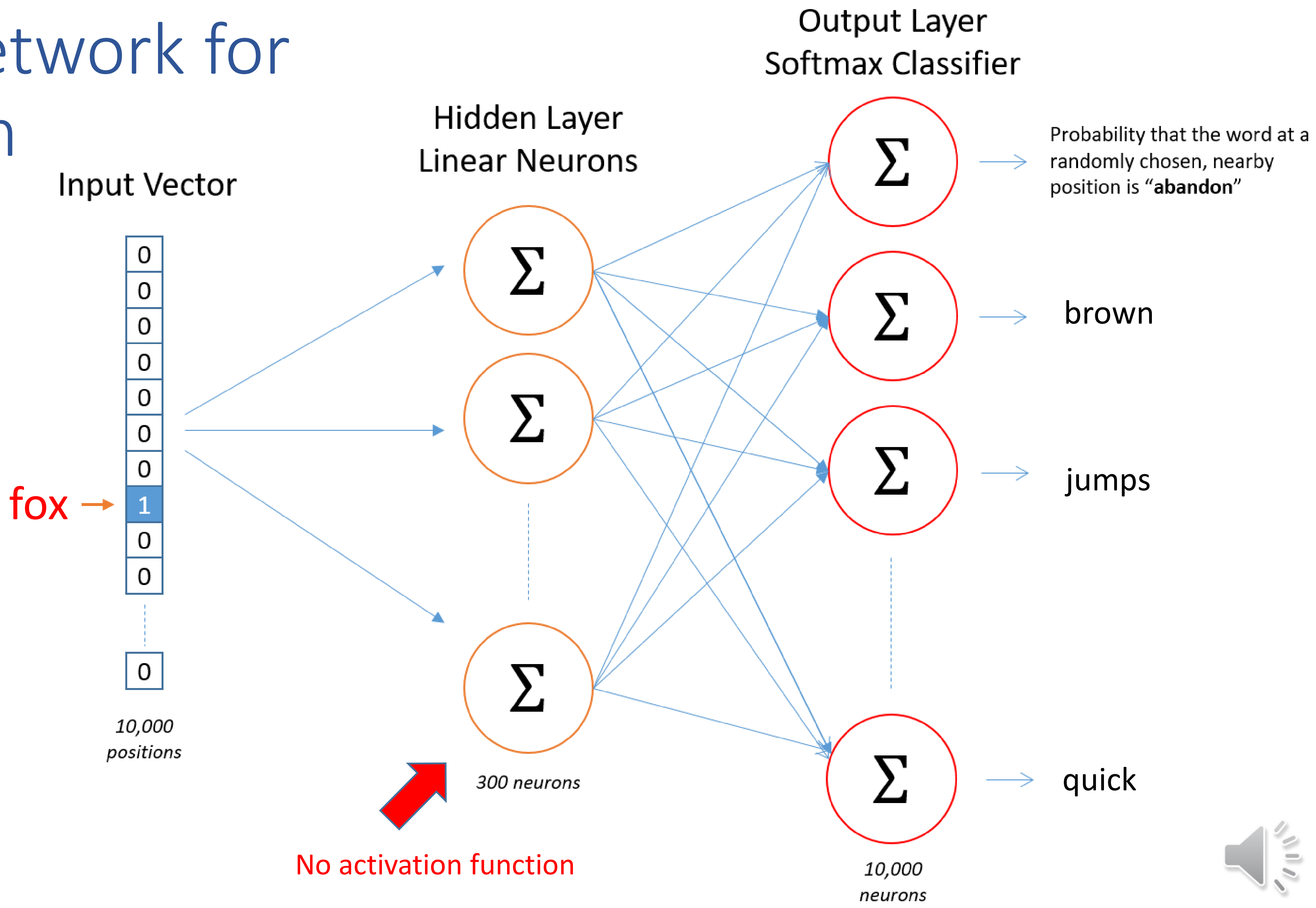
- [Word2Vec Tutorial - The Skip-Gram Model]
- [Word2Vec Tutorial - Negative Sampling]



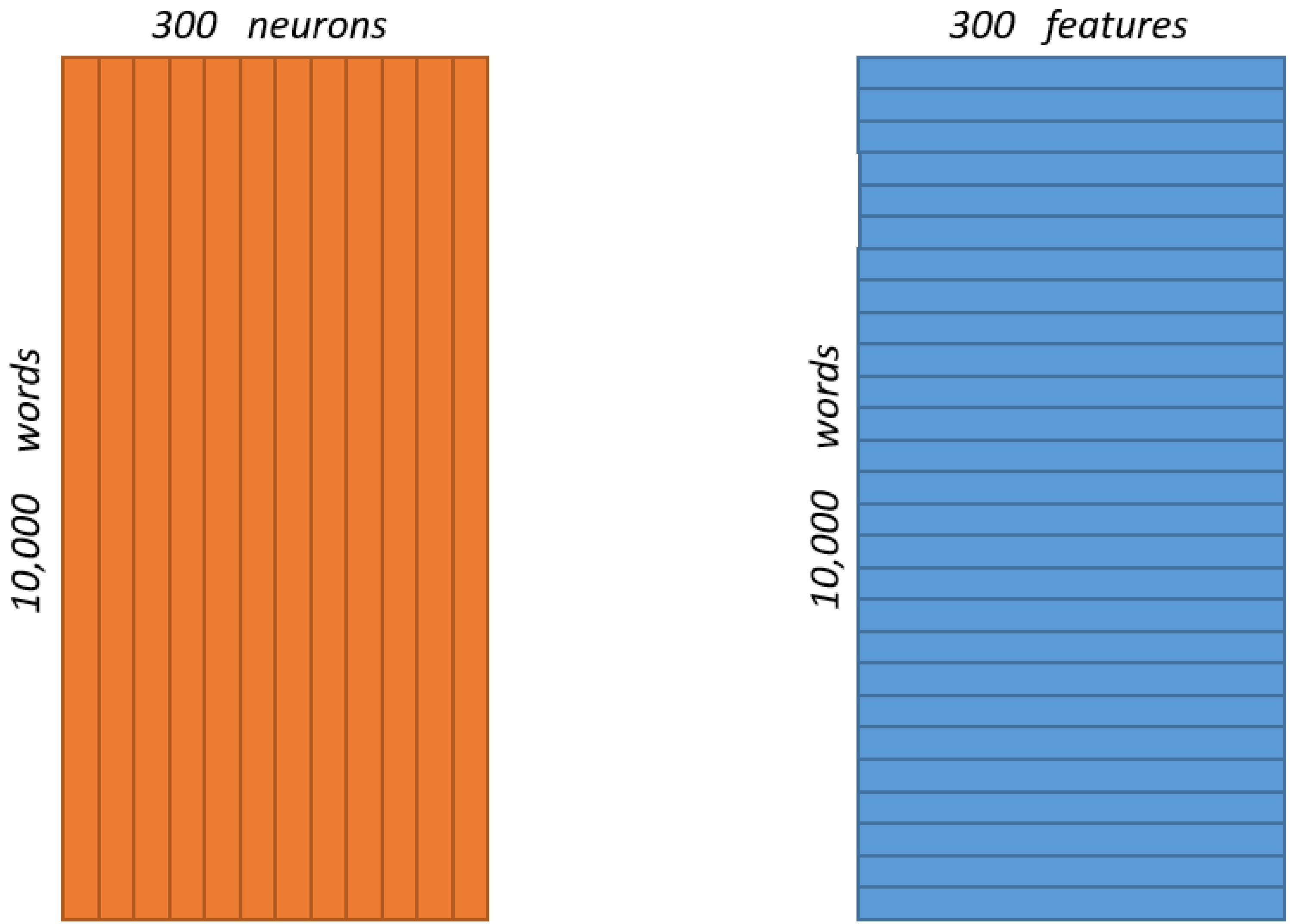


Chris McCormick, http://mccormickml.com/tutorials/

Neural Network for Skip-Gram



Hidden Layer Weight Matrix → *Word Vector Lookup Table!*



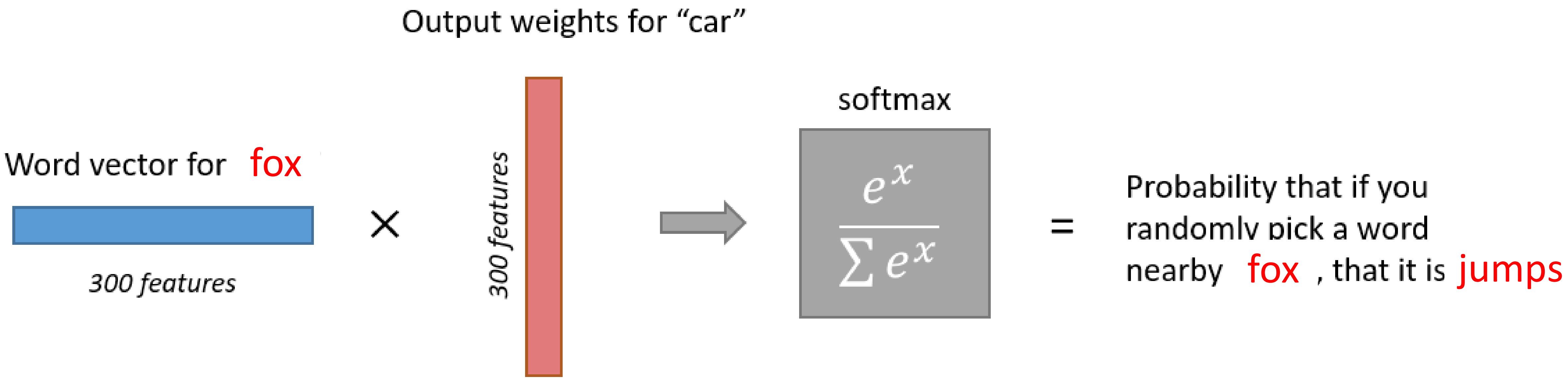
Hidden Layer as Look-up Table

- One-hot vector *selects* the matrix row corresponding to the “1”

$$\begin{bmatrix}0 & 0 & 0 & \boxed{1} & 0\end{bmatrix} \times \begin{bmatrix}17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25\end{bmatrix} = \begin{bmatrix}10 & 12 & 19\end{bmatrix}$$

The Output Layer (Softmax)

- Output probability of nearby words (e.g., “jumps” next to “fox”)
- Sum of all outputs is equal to 1



Softmax Function

- $P(w_t|h) = softmax(score(w_t, h)) = \frac{e^{\{score(w_t,h)\}}}{\sum_{word\ w'\ in\ vocab.} e^{\{score(w',h)\}}}$

- $score(w_t, h)$ computes compatibility of word w_t with the context h (dot-product is used)

- Train the model by maximizing its log-likelihood:
  - $-\ logP(w_t|h) = score(w_t, h) - log\left(\sum_{word\ w'\ in\ vocab.} e^{\{score(w',h)\}}\right)$

Sampling Important Words

- Remove non-informative word "the"

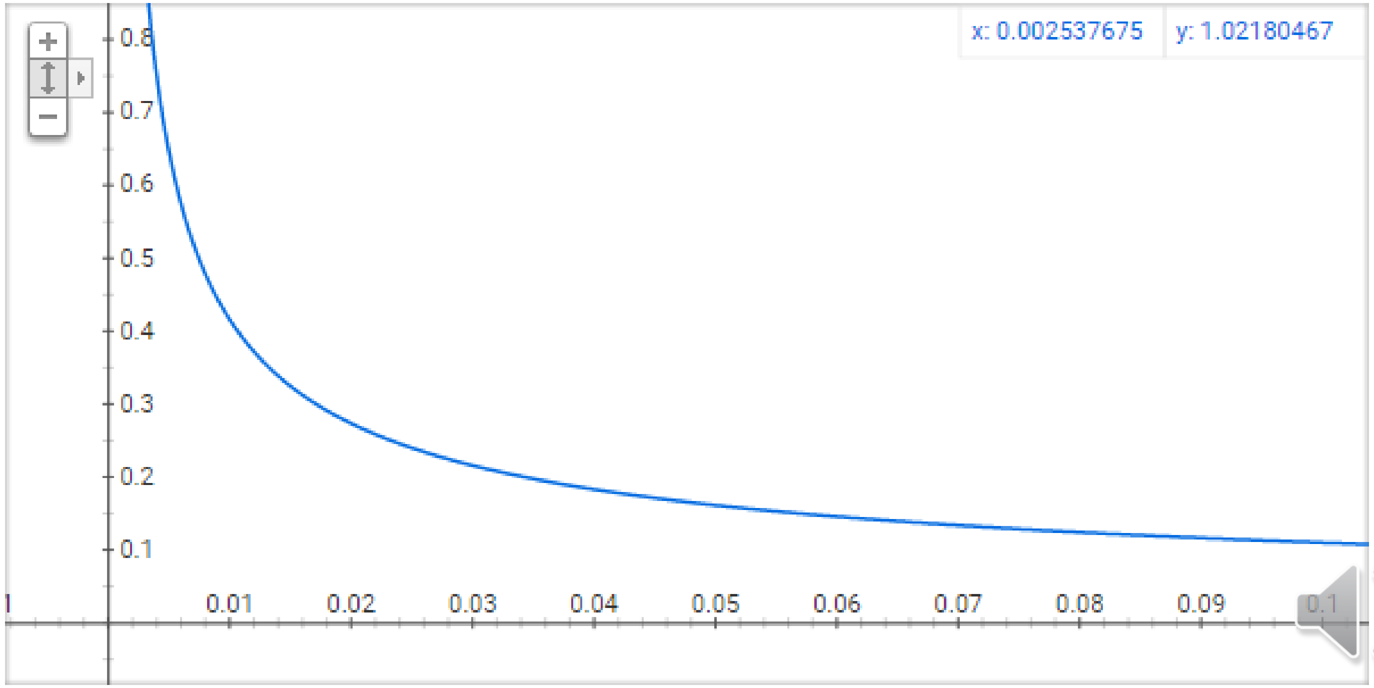
Source Text	Training Samples
The quick brown fox jumps over the lazy dog.	(the, quick) (the, brown)
The quick brown fox jumps over the lazy dog.	(quick, the) (quick, brown) (quick, fox)
The quick brown fox jumps over the lazy dog.	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown fox jumps over the lazy dog.	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

Probability of Keeping the Word

- $z(w_i)$ is the occurrence rate of word w_i
- $\mathrm{P}(w_i)$ is the keeping probability

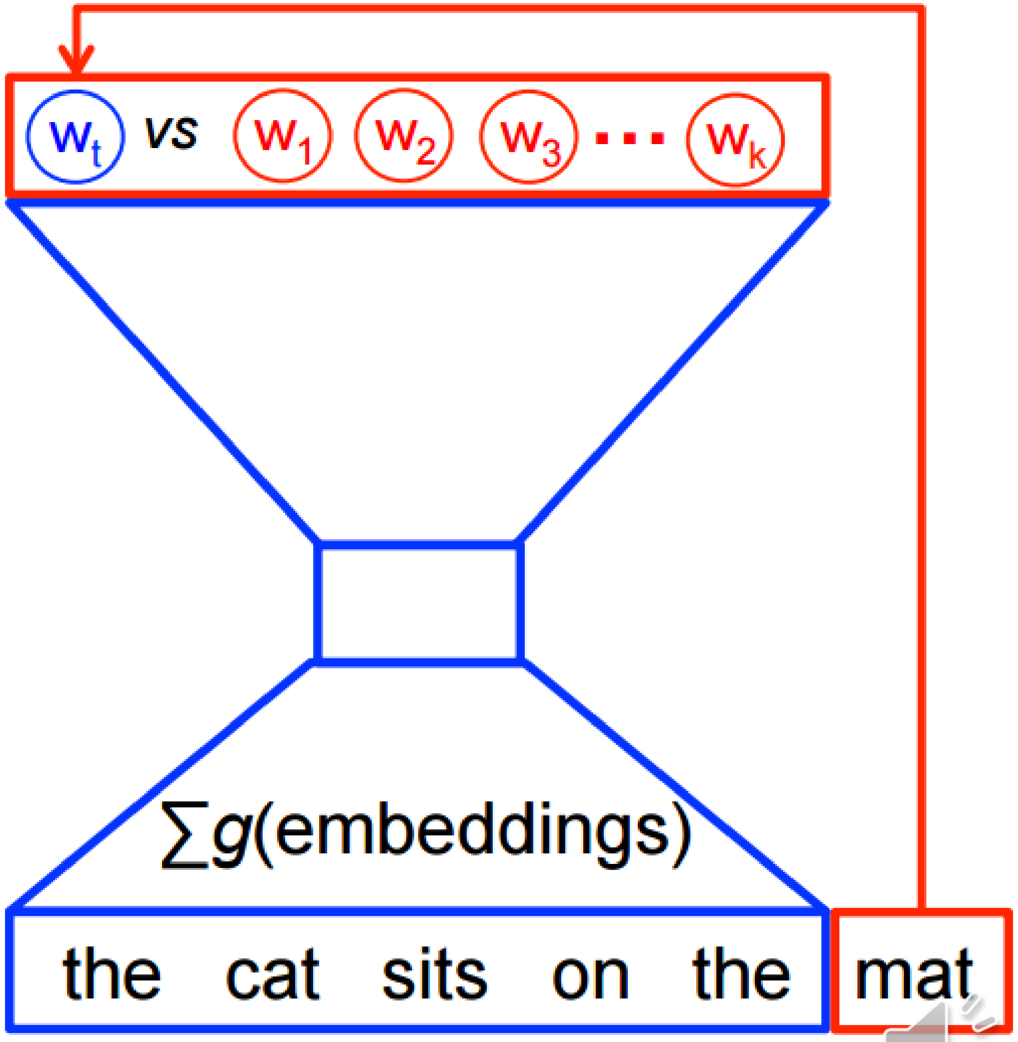
$$P(w_i) = \left(\sqrt{\frac{z(w_i)}{0.001}} + 1\right) \cdot \frac{0.001}{z(w_i)}$$

Graph for (sqrt(x/0.001)+1)*0.001/x



Negative Sampling

- Problem: too many parameters to learn at training
- Solution
  - Select only few other words as negative samples (output prob. = "0")
  - Original paper selected 5 – 20 words for small datasets. 2 – 5 words work for large datasets

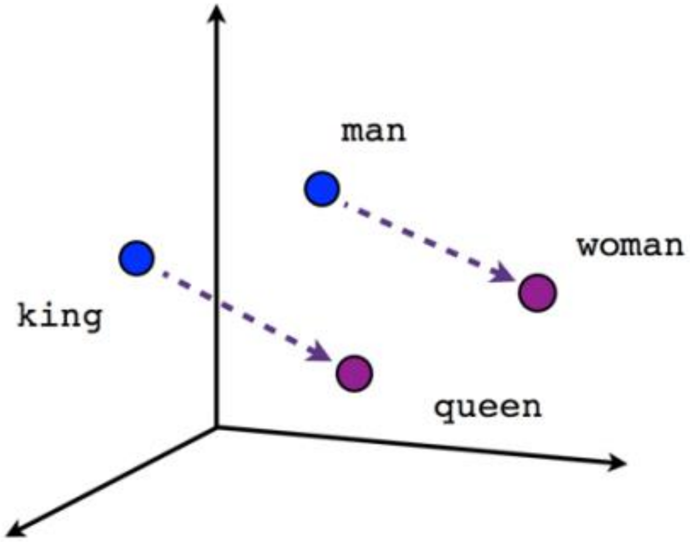


Negative Sampling

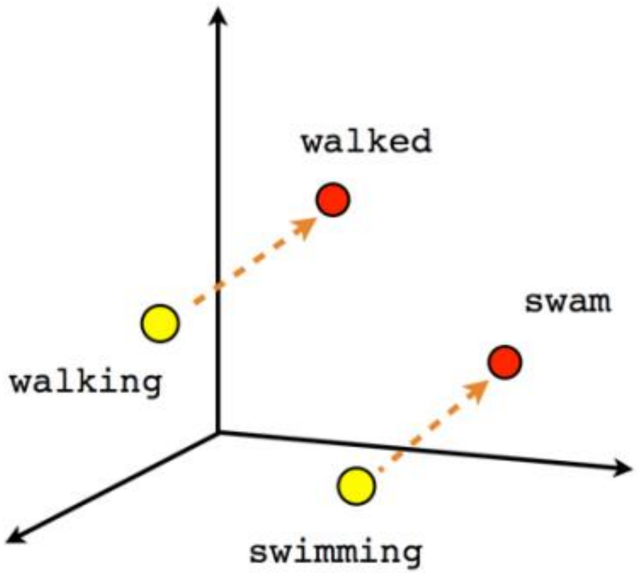
- $P(w_t|h) = softmax\big(score(w_t, h)\big) = \frac{e^{\{score(w_t,h)\}}}{\sum_{word\ w'\ in\ vocab.} e^{\{score(w',h)\}}}$
- $logP(w_t|h)$= $score(w_t, h) - log\left(\sum_{word\ w'\ in\ vocab.} e^{\{score(w',h)\}}\right)$

- Negative sampling reduces the number of words in the second terms

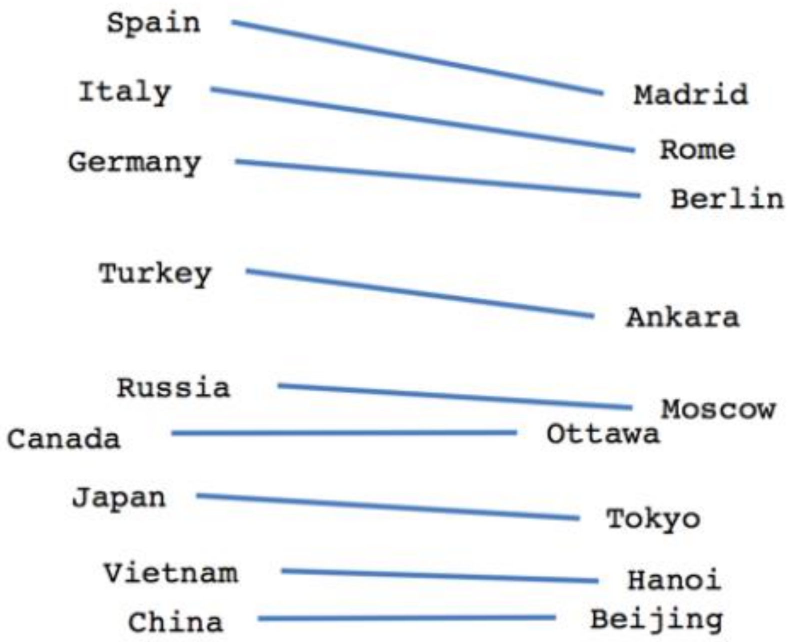
Evaluate Word2Vec



Male-Female



Verb tense



Country-Capital

Vector Addition & Subtraction

- vec(“Russia”) + vec(“river”) $\approx$ vec(“Volga River”)
- vec(“Germany”) + vec(“capital”) $\approx$ vec(“Berlin”)
- vec(“King”) - vec(“man”) + vec(“woman”) $\approx$ vec(“Queen”)

Embedding in Keras

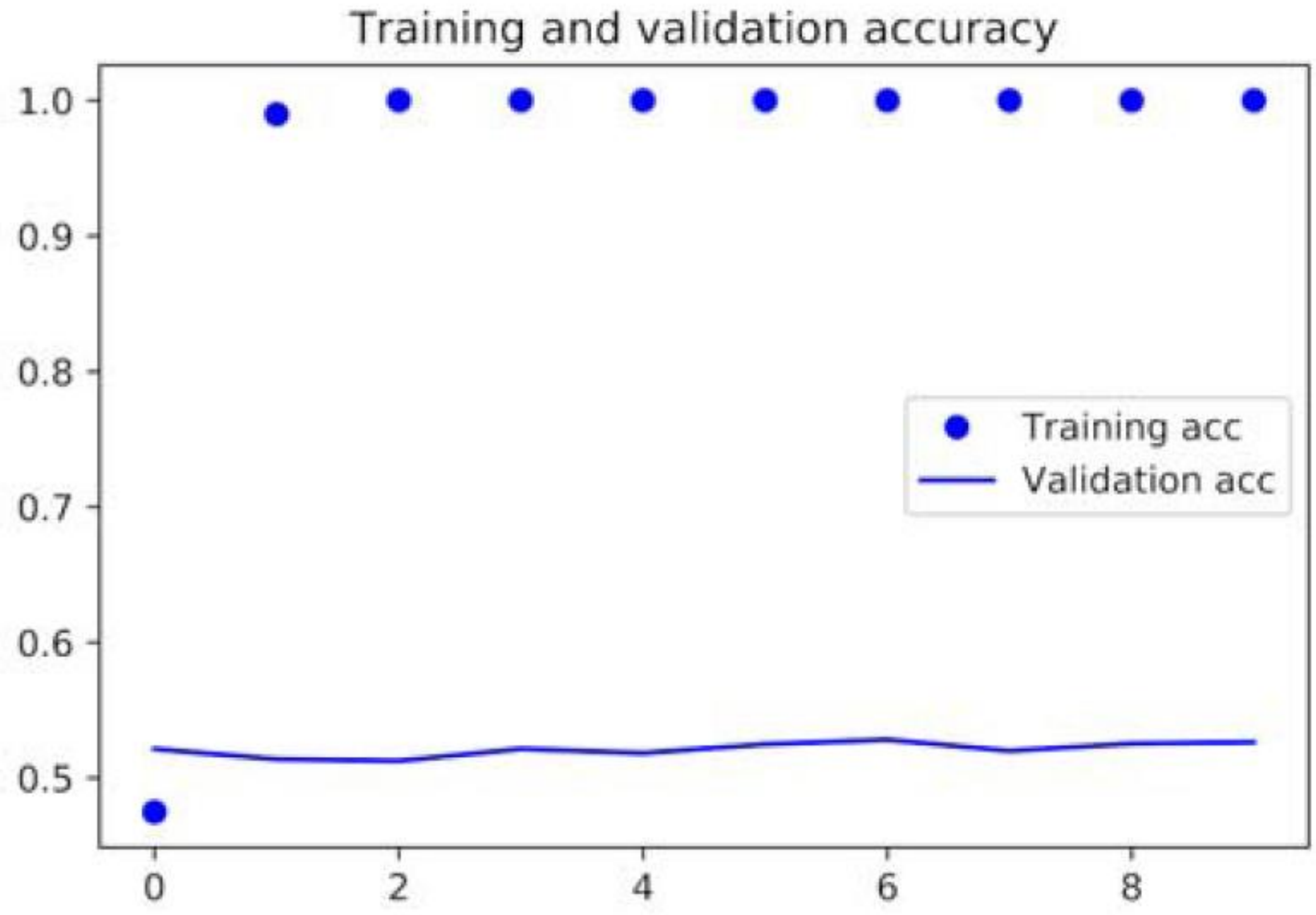
- Input dimension: Dimension of the one-hot encoding, e.g. number of word indices
- Output dimension: Dimension of embedding vector

```
from keras.layers import Embedding

embedding_layer = Embedding(1000, 64)
```

Using Embedding to Classify IMDB Data

```
from keras.datasets import imdb
from keras import preprocessing
from keras.models import Sequential
from keras.layers import Flatten, Dense, Embedding
max_features = 10000  # Number of words
maxlen = 20           # Select only 20 words in a text for demo
(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=max_features)
# Turn the lists of integers into a 2D integer tensor of shape (samples, maxlen)
x_train = preprocessing.sequence.pad_sequences(x_train, maxlen=maxlen)
x_test = preprocessing.sequence.pad_sequences(x_test, maxlen=maxlen)

model = Sequential()
# Specify the max input length to the Embedding layer so we can later flatten the embedded
# inputs. After the Embedding layer, the activations have shape (samples, maxlen, 8).
model.add(Embedding(10000, 8, input_length=maxlen))
model.add(Flatten())
model.add(Dense(1, activation='sigmoid'))
model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
history = model.fit(x_train, y_train, epochs=10, batch_size=32, validation_split=0.2)
```

Training Embedding Model on IMDB



GloVe: Global Vectors for Word Representation

- Developed by Stanford in 2014
- Based on Matrix Factorization of Word Co-occurrence
- https://nlp.stanford.edu/projects/glove/
- Assumption
  - Ratios of word-word co-occurrence probabilities encode some form of meaning

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

Using Pretrained Word Embedding Vectors (2-1)

```
# Preprocessing the embeddings
glove_dir = './glove/'
embeddings_index = {}
f = open(os.path.join(glove_dir, 'glove.6B.100d.txt'))
for line in f:
    values = line.split()
    word = values[0]
    coefs = np.asarray(values[1:], dtype='float32')
    embeddings_index[word] = coefs
f.close()
print(‘Found %s word vectors.’ % len(embeddings_index))# 400000 word vectors.

# Create a word embedding tensor
embedding_dim = 100
embedding_matrix = np.zeros((max_words, embedding_dim))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if i < max_words:
        if embedding_vector is not None:
            # Words not found in embedding index will be all-zeros.
            embedding_matrix[i] = embedding_vector
```

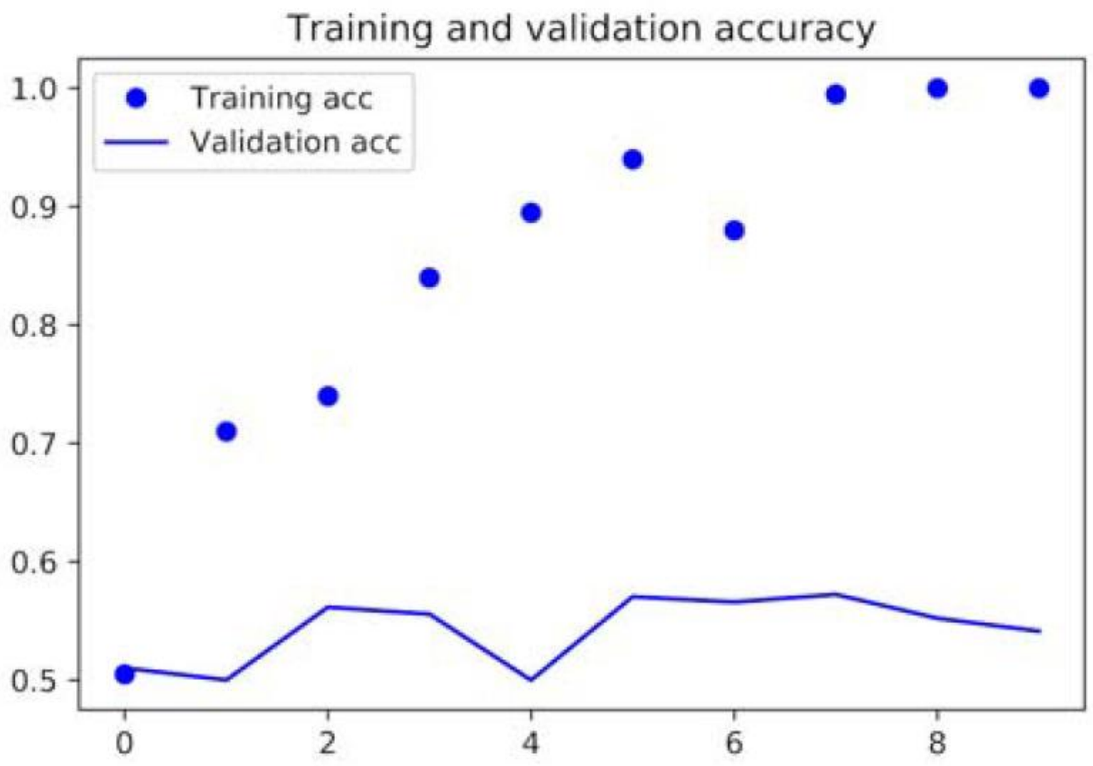
Using Pretrained Word Embedding Vectors (2-2)

```
from keras.models import Sequential
from keras.layers import Embedding, Flatten, Dense

model = Sequential()
model.add(Embedding(max_words, embedding_dim, input_length=maxlen))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()

# Load the GloVe embeddings in the model
model.layers[0].set_weights([embedding_matrix])
model.layers[0].trainable = False

model.compile(optimizer='rmsprop', loss='binary_crossentropy', metrics=['acc'])
history = model.fit(x_train, y_train,
                    epochs=10, batch_size=32, validation_data=(x_val, y_val))
model.save_weights('pre_trained_glove_model.h5')
```

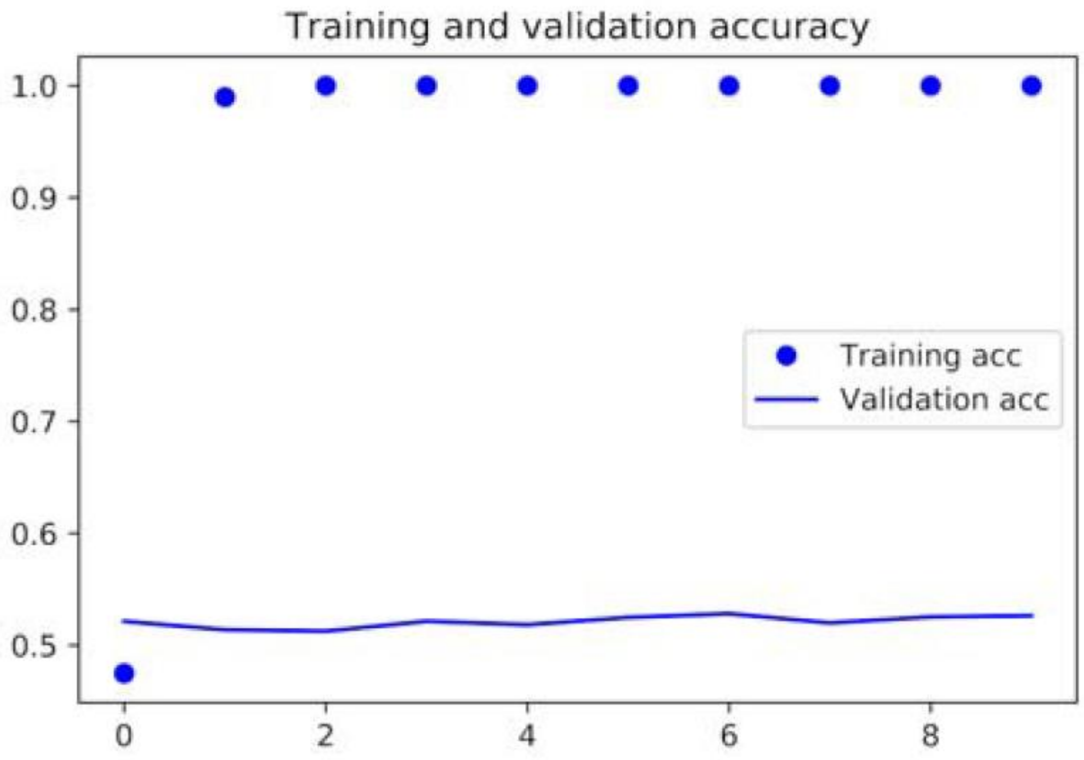
https://github.com/fchollet/deep-learning-with-python-notebooks/blob/master/6.1-using-word-embeddings.ipynb

Classifying IMDB Reviews

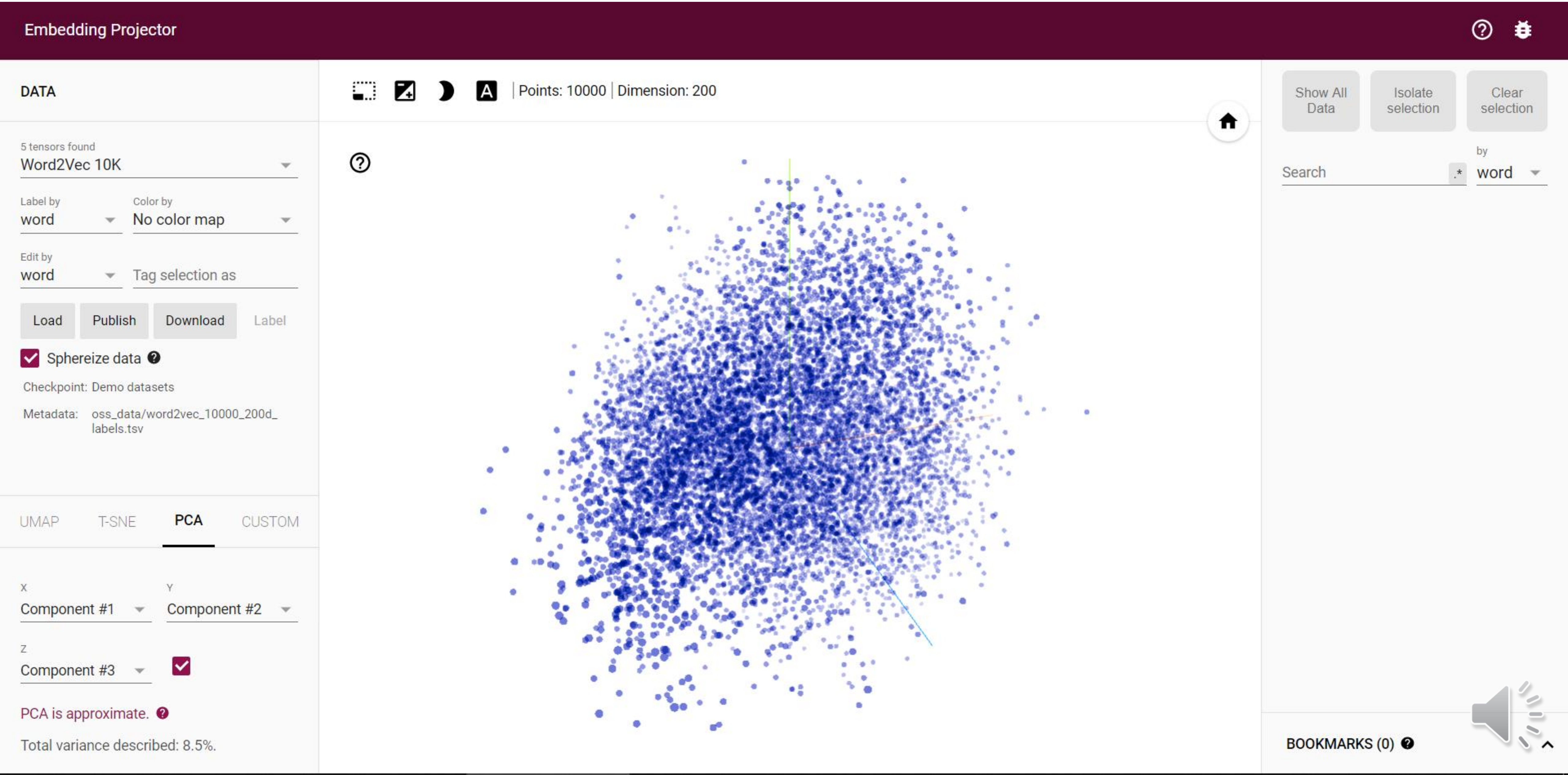
With pretrained Glove vectors

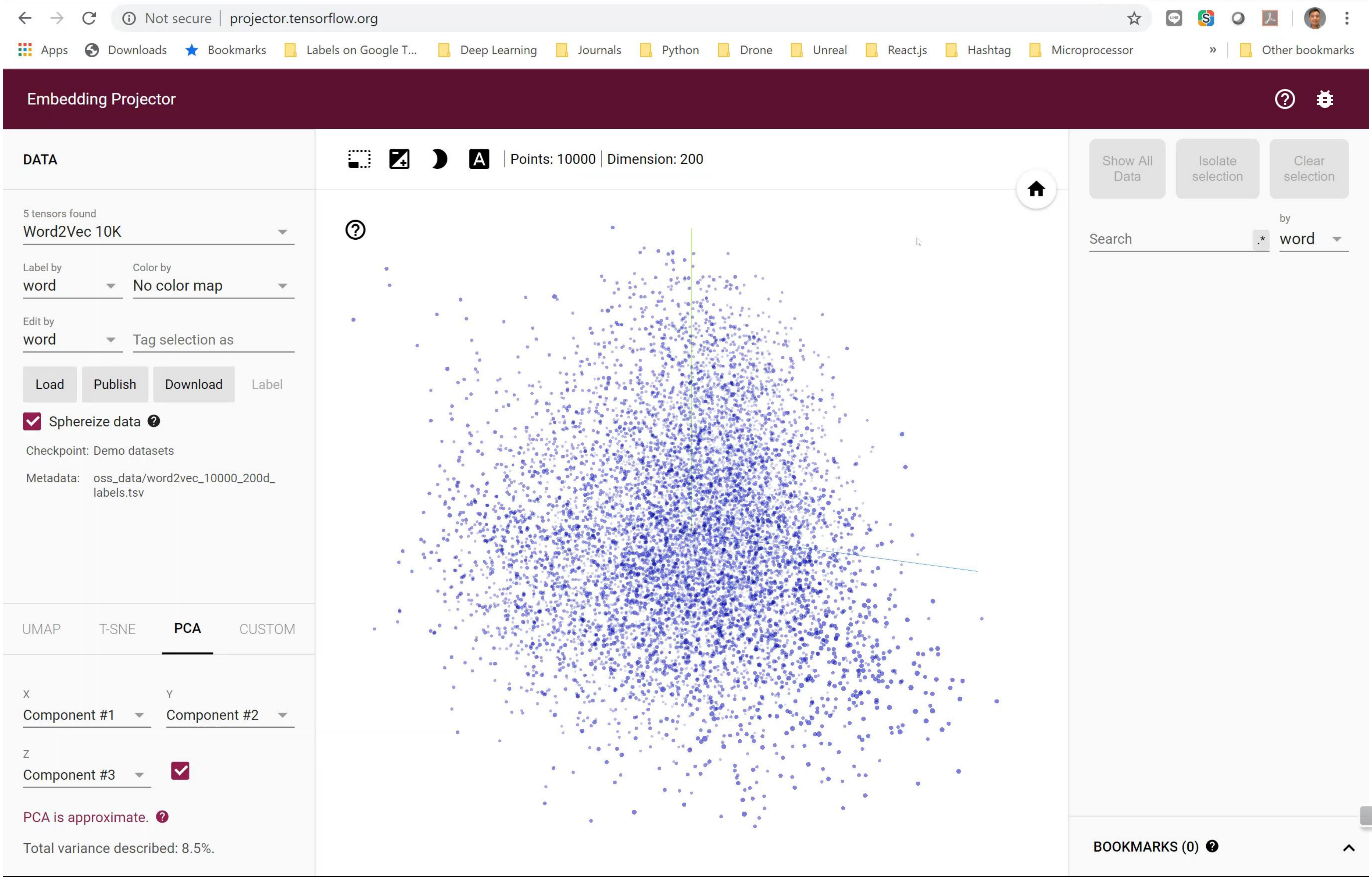


Without pretrained embedding model



Embedding Project (projector.tensorflow.org/)





Not secure
projector.tensorflow.org
Apps
Downloads
Bookmarks
Labels on Google T...
Deep Learning
Journals
Python
Drone
Unreal
React.js
Hashtag
Microprocessor
Other bookmarks
Embedding Projector
DATA
5 tensors found
Word2Vec 10K
Label by
word
Color by
No color map
Edit by
word
Tag selection as
Load
Publish
Download
Label
Sphereize data
Checkpoint: Demo datasets
Metadata: oss_data/word2vec_10000_200d_labels.tsv
UMAP
T-SNE
PCA
CUSTOM
X
Component #1
Y
Component #2
Z
Component #3
PCA is approximate.
Total variance described: 8.5%.
Points: 10000
Dimension: 200
Show All Data
Isolate selection
Clear selection
by
Search
word
BOOKMARKS (0)

Neighbors of “Learning”

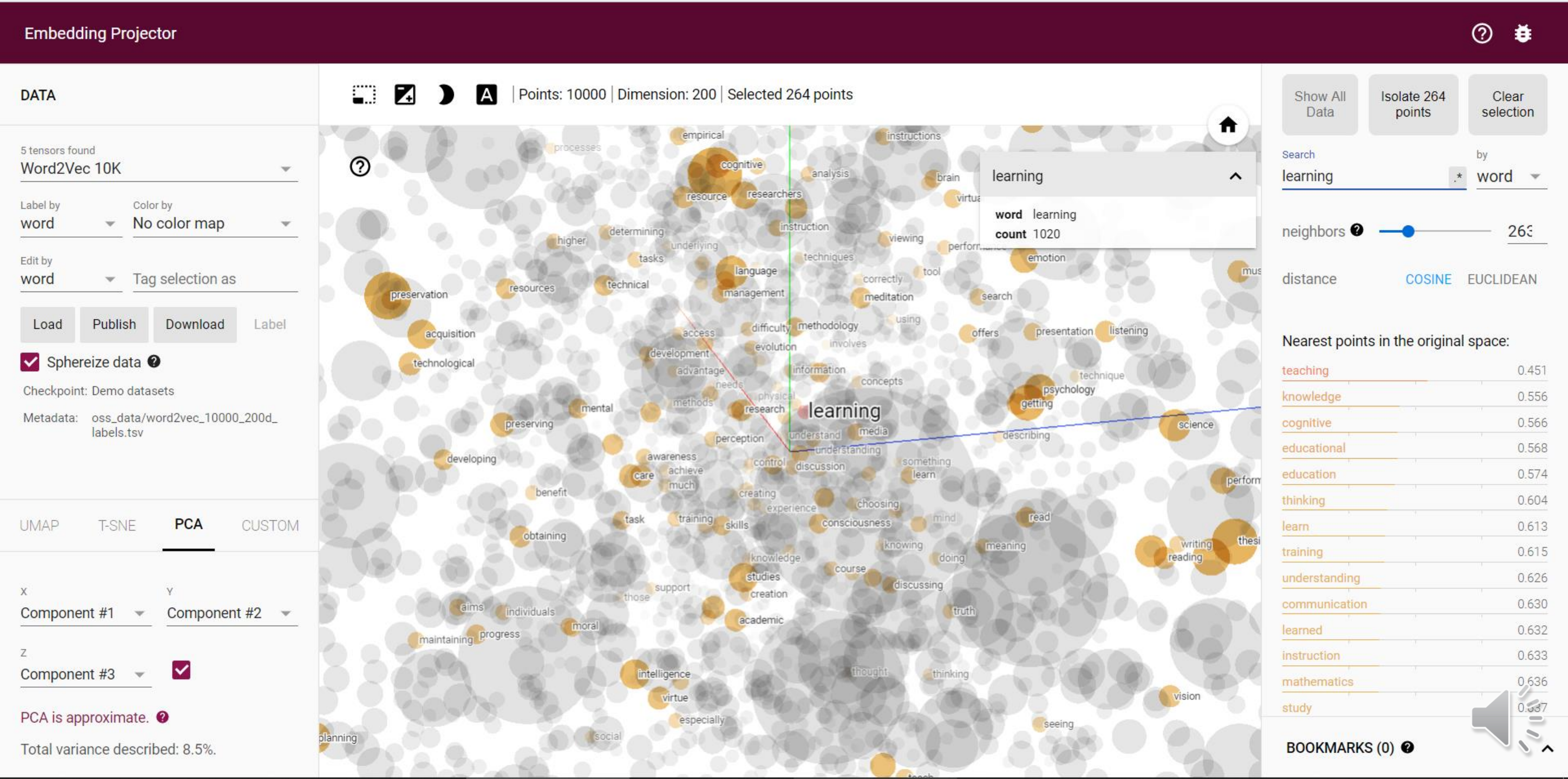
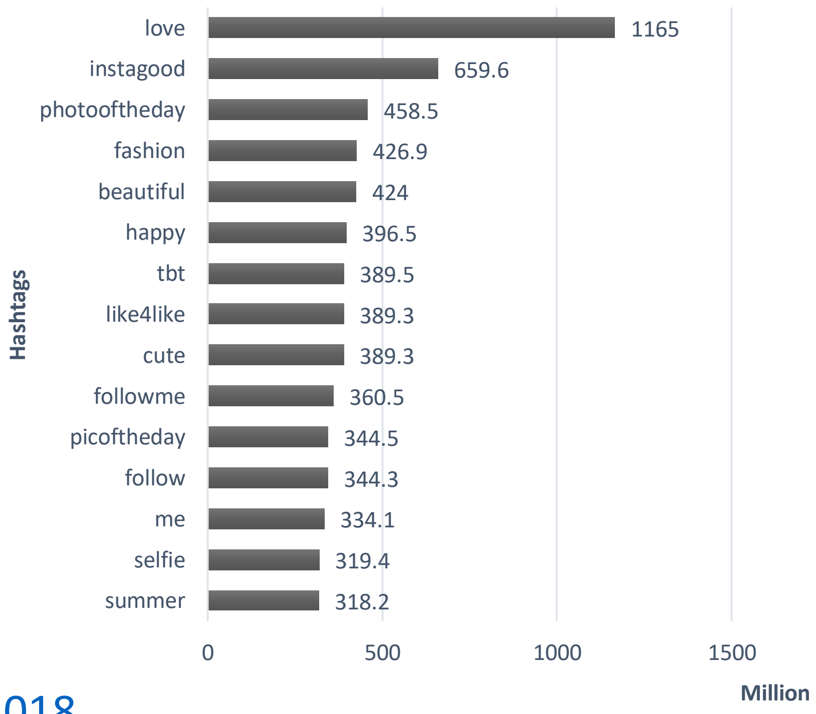


Image Hashtag Recommendation

- Hashtag => a word or phrase preceded by the symbol # that categorizes the accompanying text
- Created by Twitter, now supported by all social networks
- Instagram hashtag statistics (2017):



[Latest stats: izea.com/2018/06/07/top-instagram-hashtags-2018](izea.com/2018/06/07/top-instagram-hashtags-2018)

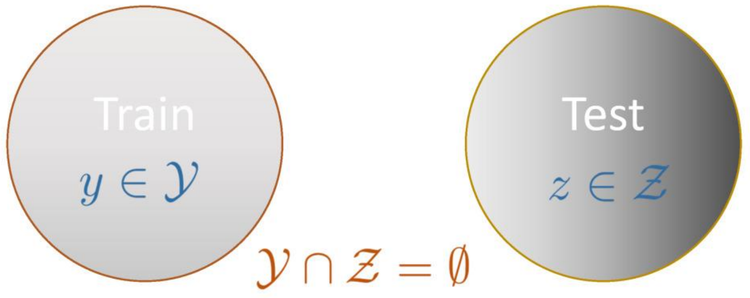
Difficulties of Predicting Image Hashtag

- Abstraction: #love, #cute,...
- Abbreviation: #ootd, #ootn,…
- Emotion: #happy,…
- Obscurity: #motivation, #lol,…
- New-creation: #EvaChenPose,…
- No-relevance: #tbt, #nofilter, #vscocam
- Location: #NYC, #London

Zero-Shot Learning

- Identify object that you've never seen before
- More formal definition:
  - Classify test classes *Z* with zero labeled data (Zero-shot!)

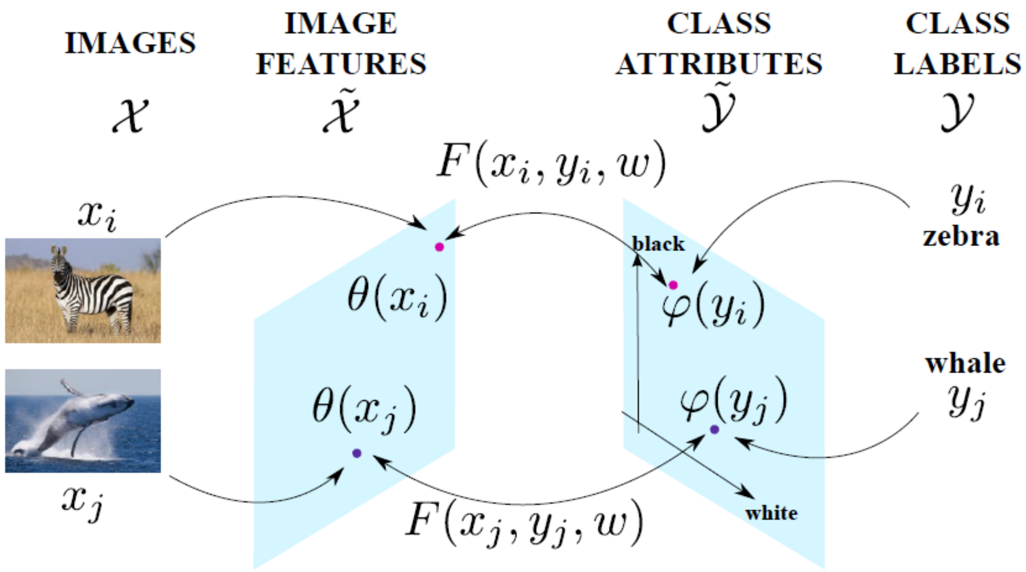
Data: $x \in \mathcal{X}$



Objective: $f : \mathcal{X} \rightarrow \mathcal{Z}$

Zero-Shot Formulation

- Describe objects by words
  - Use attributes (semantic features)

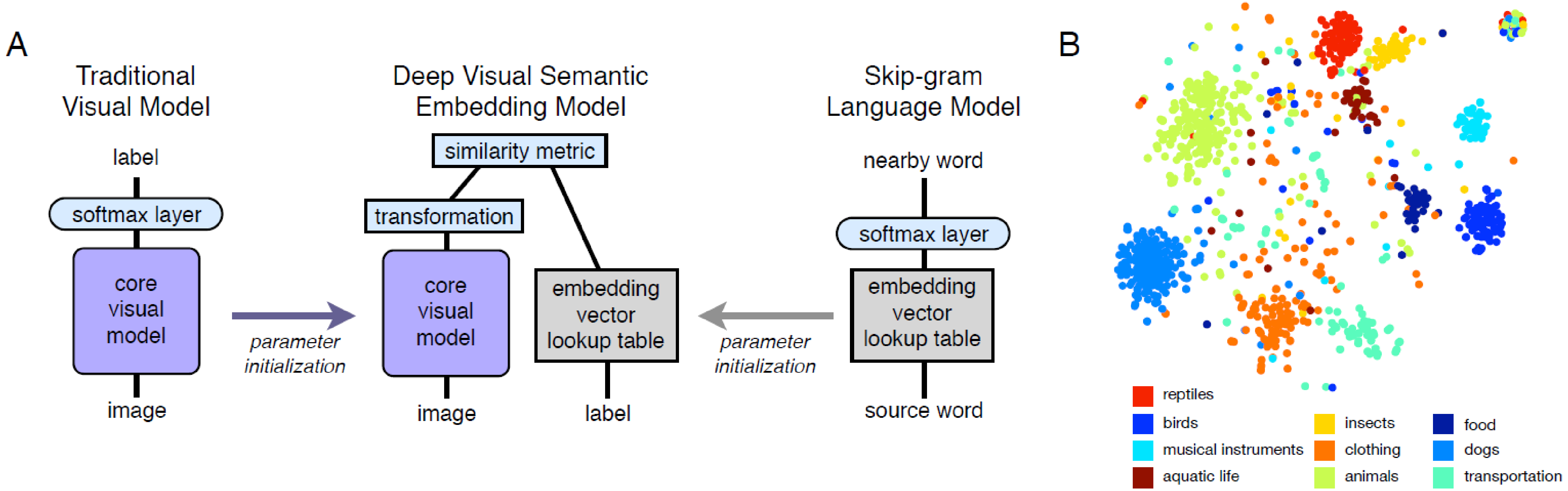


$$F(x, y; W) = \theta(x)^T W \phi(y)$$

DeViSE – Deep Visual Semantic Embedding

- Google, NIPS, 2013

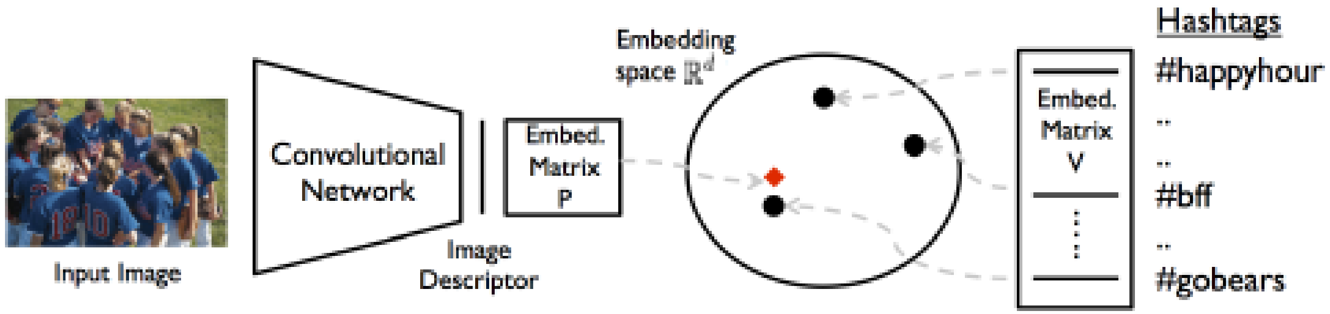
Model	200 labels	1000 labels
DeViSE	31.8%	9.0%
Mensink et al. 2012 [12]	35.7%	1.9%
Rohrbach et al. 2011 [17]	34.8%	-



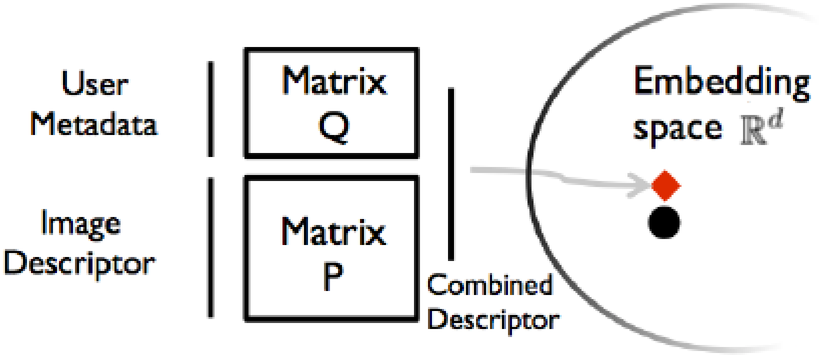
User Conditional Hashtag Prediction for Images

- E. Denton, J. Weston, M. Paluri, L. Bourdev, and R. Fergus, “User Conditional Hashtag Prediction for Images,” *ACM SIGKDD*, 2015 (Facebook)
- Hashtag Embedding: $f(x, y) = \Phi_I(x)^\top \Phi_H(y)$
- Proposed 3 models:

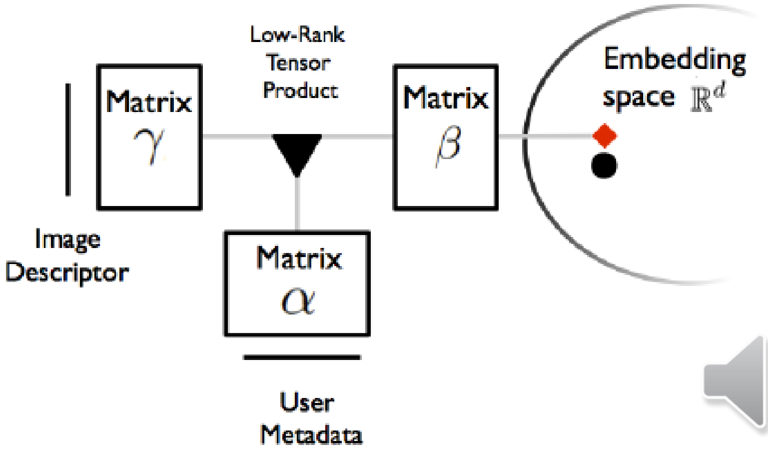
1. Bilinear Embedding Model



2. User-biased model



3. User-multiplicative model



User Profile and Locations

Age	Females	Males
13-17	#mcm	#like
	#bestfriend	#lmp
	#love	#throwback
	#lovehim	#squad
	#mce	#wce
	#latepost	#throwback-
	#bestfriends	#thursday
	#boyfriend	#family
	#loveher	#workflow
	#loveyou	#selfie
		#wcm
43-47	#100happydays	#photoshop-
	#mcm	#express
	#love	#wcw
	#sisters	#goodtimes
	#cousins	#prouddad
	#lovehim	#throwback-
	#latergram	#thursday
	#loveher	#selfie
	#bff	#salute
	#youcampperfect	#blessed
		#zijasummit14
		#familyfirst

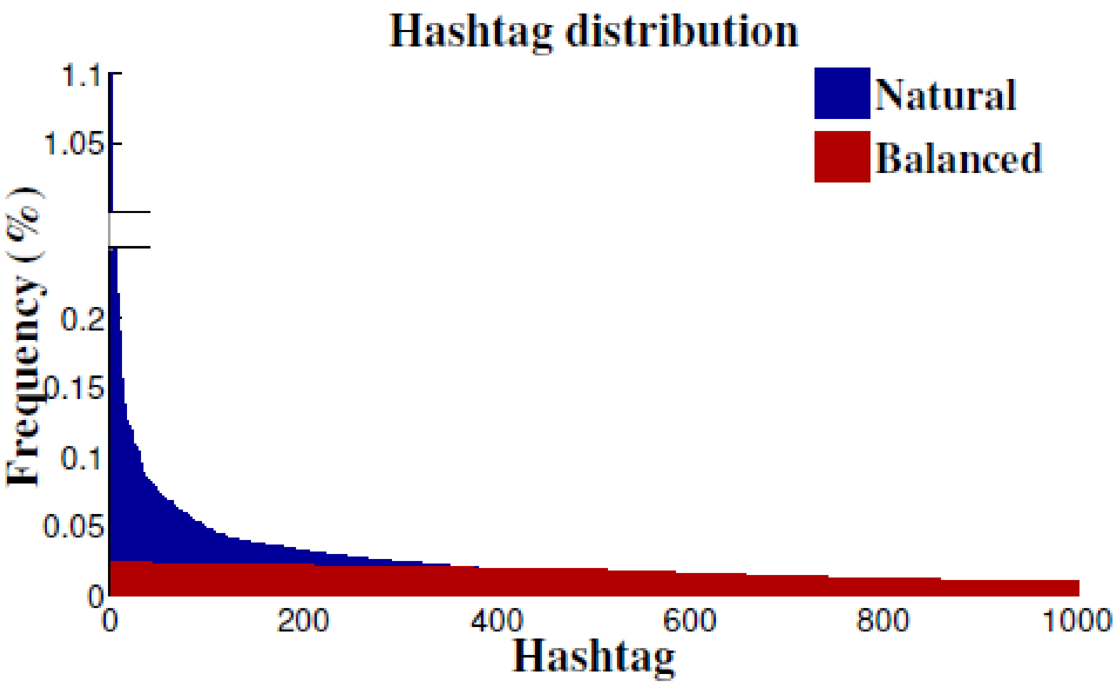
Gender	15-17 years old	43-47 years old
Female	#wcw	#100happydays
	#mcm	#blessed
	#bestfriend	#goodtimes
	#tb	#family
	#ss	#love
	#bestfriends	#photogrid
	#throwback	#latergram
	#latepost	#cousins
	#like	#sundayfunday
	#selfiesunday	#friends
Male	#wcw	#goodtimes
	#like	#blessed
	#throwback	#love
	#squad	#family
	#tb	#photoshop-
	#lmp	#express
	#mcm	#photogrid
	#ss	#sundayfunday
	#wce	#friends
	#selfiesunday	#zijasummit14
		#prouddad

Sydney	Toronto
#melbourne	#toronto
#sydney	#tbt
#australia	#canada
#spring	#vancouver
#beach	#fall
#grandfinal	#throwback
#sunshine	#blessed
#sun	#ilovethiscity
#nz	#vancity
#newzealand	#vscocam
#bali	#tb
#happy	#cntower
#nofilter	#goodmorning
#wellington	#hoco
#springbreak	#montreal
#bondi	#wcw
#afl	#tdot
#thailand	#lateupload
#stkilda	#downtown
#city	#beautiful

Meta data	Possible values
Age	13 – 114
Gender	Male, Female, Unknown
Home City	GPS coordinates
Country	United States, Canada, Great Britain, Australia, New Zealand

Facebook's Experiments

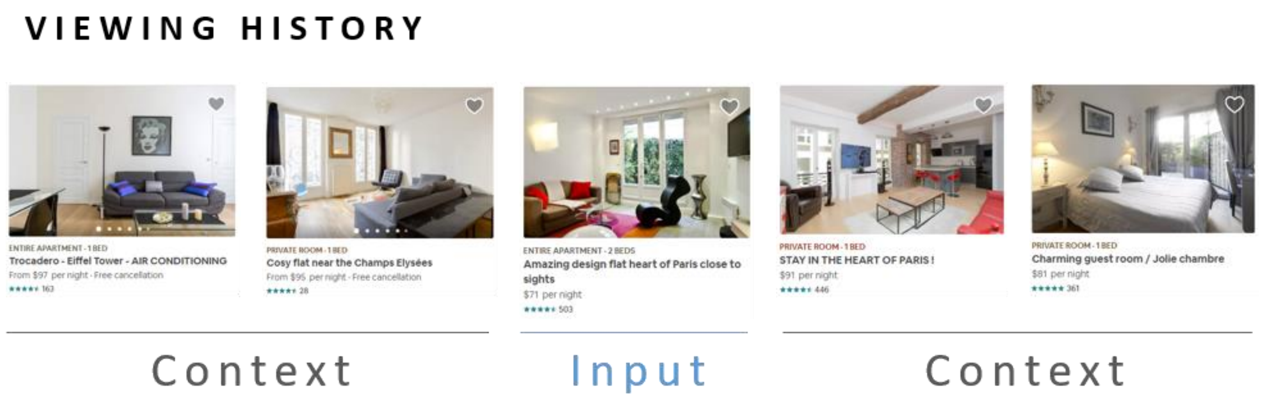
- 20 million images
- 4.6 million hashtags, average 2.7 tags per image
- Result

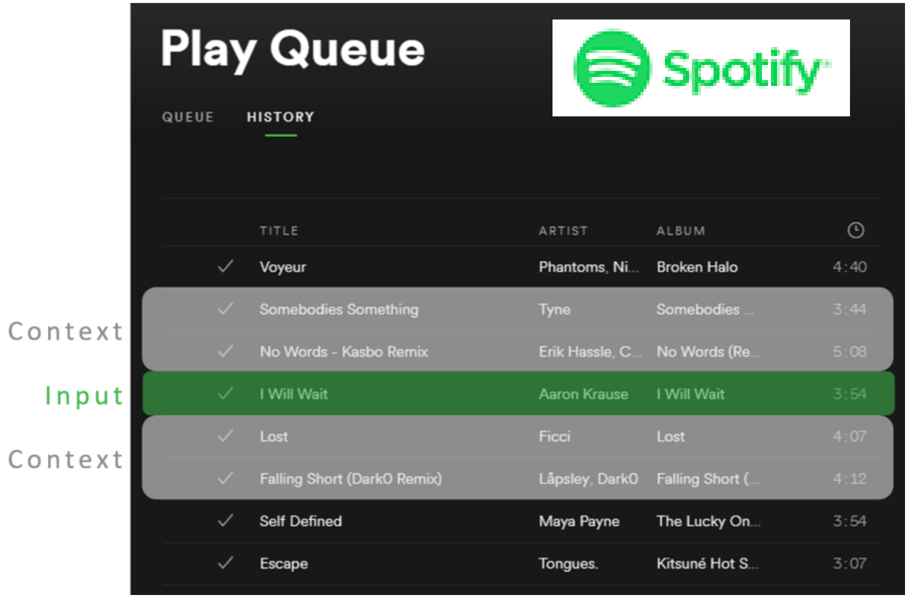


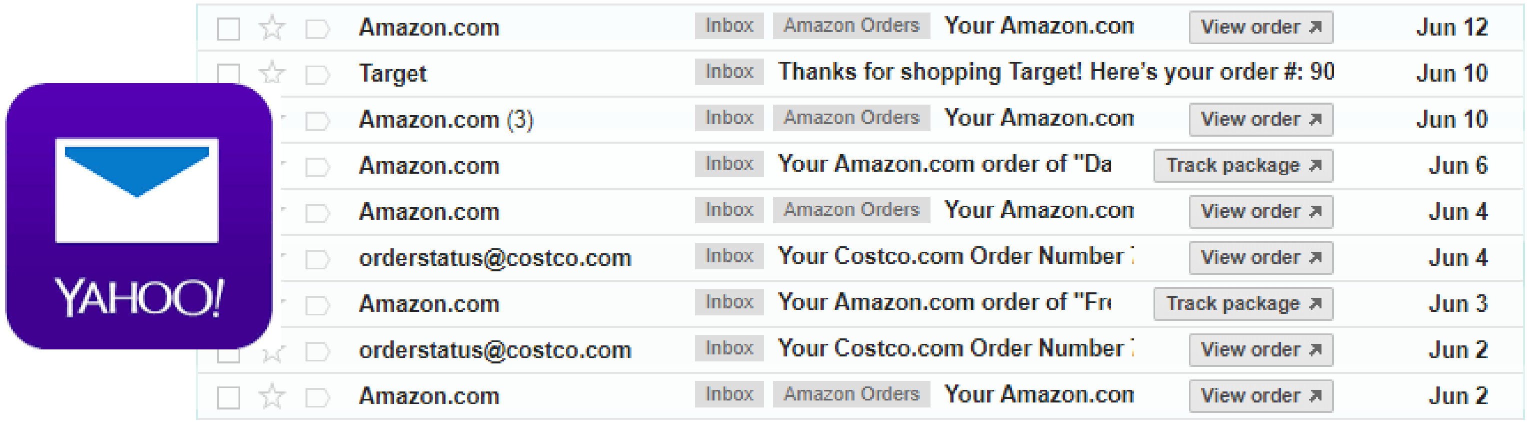
Method	d	K	P@1	R@10	A@10
Freq. baseline	-	-	3.04%	5.63%	9.45%
Bilinear	64	-	7.37%	11.71%	18.69%
Bilinear	128	-	7.37%	11.69%	18.44%
Bilinear	256	-	6.75%	10.84%	17.25%
Bilinear	512	-	6.50%	10.83%	17.17%
User-biased	64	-	9.02%	13.63%	21.88%
User-biased	128	-	9.00%	13.67%	21.83%
User-biased	256	-	8.48%	13.03%	20.96%
User-biased	512	-	7.98%	12.51%	20.05%
3-way mult.	64	50	8.95%	13.66%	21.82%
3-way mult.	64	100	9.03%	13.81%	22.04%
3-way mult.	64	200	8.96%	13.81%	22.05%
3-way mult.	64	300	9.00%	13.74%	21.96%
3-way mult.	64	400	8.96%	13.65%	21.82%

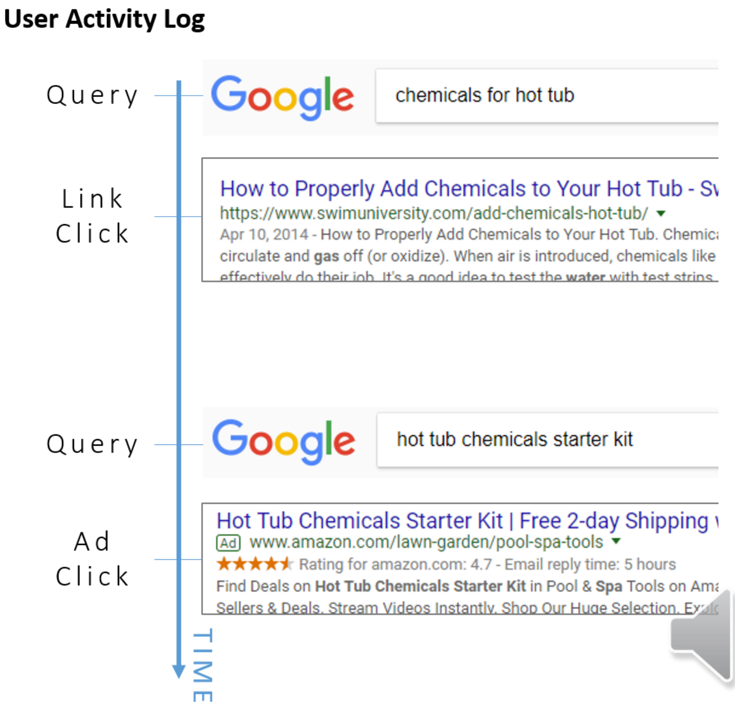
Real World Applications

mccormickml.com/2018/06/15/applying-word2vec-to-recommenders-and-advertising/









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