자연어 처리 DAY 1

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1.

Intro to Natural Language Processing(NLP)

Academic Disciplines related to NLP

Trends of NLP

Goal of This Course

- Natural language processing (NLP), which aims at properly understanding and generating human languages, emerges as a crucial application of artificial intelligence, with the advancements of deep neural networks.

- This course will cover various deep learning approaches as well as their applications such as language modeling, machine translation, question answering, document classification, and dialog systems.

Academic Disciplines related to NLP

Natural language processing (major conferences: ACL, EMNLP, NAACL)

- Includes state-of-the-art deep learning-based models and tasks
- Low-level parsing
  - Tokenization, stemming
- Word and phrase level
  - Named entity recognition(NER), part-of-speech(POS) tagging, noun-phrase chunking, dependency parsing, coreference resolution
- Sentence level
  - Sentiment analysis, machine translation
- Multi-sentence and paragraph level
  - Entailment prediction, question answering, dialog systems, summarization

Academic Disciplines related to NLP

Text mining(major conferences: KDD, The WebConf (formerly, WWW), WSDM, CIKM, ICWSM)

- Extract useful information and insights from text and document data
  - e.g., analyzing the trends of AI-related keywords from massive news data
- Document clustering (e.g., topic modeling)
  - e.g., clustering news data and grouping into different subjects
- Highly related to computational social science
  - e.g., analyzing the evolution of people's political tendency based on social media data

Information retrieval (major conferences: SIGIR, WSDM, CIKM, RecSys)

- **Highly related to computational social science**
  - This area is not actively studied now
  - It has evolved into a recommendation system, which is still an active area of research

Trends of NLP

- Text data can basically be viewed as a sequence of words, and each word can be represented as a vector through a technique such as Word2Vec or GloVe.

- RNN-family models (LSTMs and GRUs), which take the sequence of these vectors of words as input, are the main architecture of NLP tasks.

- Overall performance of NLP tasks has been improved since attention modules and Transformer models, which replaced RNNs with self-attention, have been introduced a few years ago.

- As is the case for Transformer models, most of the advanced NLP models have been originally developed for improving machine translation tasks.

Trends of NLP

- In the early days, customized models for different NLP tasks had developed separately.

- Since Transformer was introduced, huge models were released by stacking its basic module, self-attention, and these models are trained with large-sized datasets through language modeling tasks, one of the self-supervised training setting that does not require additional labels for a particular task.
  - e.g., BERT, GPT-3 …

- Afterwards, above models were applied to other tasks through transfer learning, and they outperformed all other customized models in each task.

- Currently, these models has now become essential part in numerous NLP tasks, so NLP research become difficult with limited GPU resources, since they are too large to train. ☹

2.
Bag-of-Words

Bag-of-Words

Bag-of-Words Example (NaiveBayes Classifier)

Bag-of-Words Representation

- **Step 1. Constructing the vocabulary containing unique words**
  - Example sentences: “John really really loves this movie“, “Jane really likes this song”
  - Vocabulary: {“John“, “really“, “loves“, “this“, “movie“, “Jane“, “likes“, “song”}

Bag-of-Words Representation

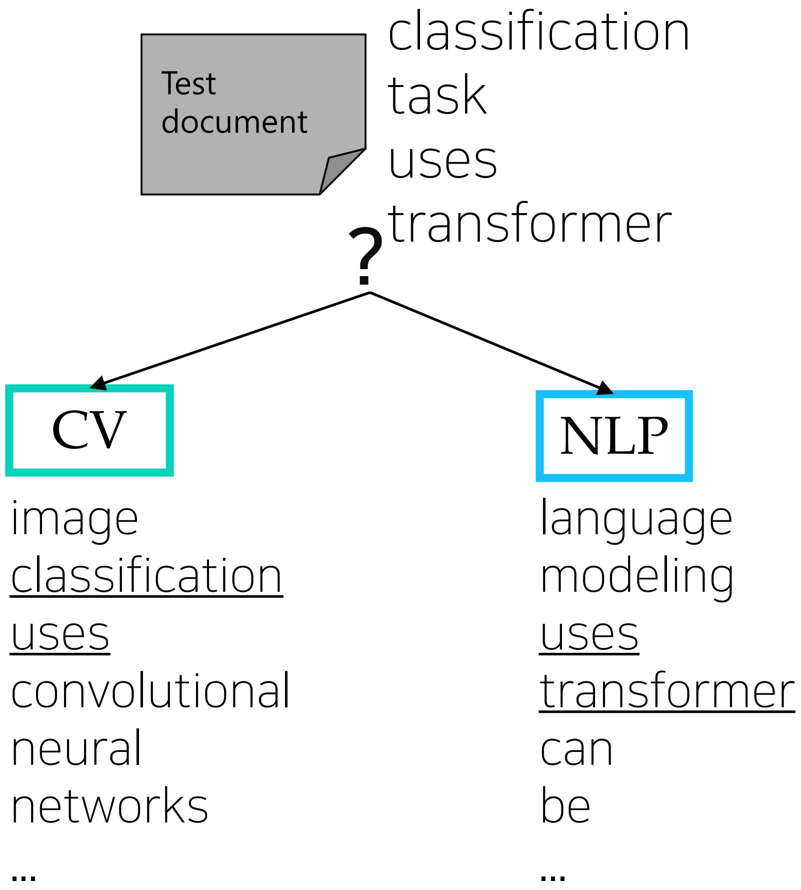
- Step 2. Encoding unique words to one-hot vectors
  - Vocabulary: {“John“, “really“, “loves“, “this“, “movie“, “Jane“, “likes“, “song”}
    - John: [1 0 0 0 0 0 0 0]
    - really: [0 1 0 0 0 0 0 0]
    - loves: [0 0 1 0 0 0 0 0]
    - this: [0 0 0 1 0 0 0 0]
    - movie: [0 0 0 0 1 0 0 0]
    - Jane: [0 0 0 0 0 1 0 0]
    - likes: [0 0 0 0 0 0 1 0]
    - song: [0 0 0 0 0 0 0 1]
- For any pair of words, the distance is $\sqrt{2}$
- For any pair of words, cosine similarity is 0

Bag-of-Words Representation

- **A sentence/document can be represented as the sum of one-hot vectors**
  - Sentence 1: “John really really loves this movie“
    - John + really + really + loves + this + movie: [1 2 1 1 1 0 0 0]
  - Sentence 2: “Jane really likes this song”
    - Jane + really + likes + this + song: [0 1 0 1 0 1 1 1]

NaiveBayes Classifier for Document Classification

Bag-of-Words for Document Classification



Test document

classification
task
uses
transformer

?

CV

image
classification
uses
convolutional
neural
networks
…

NLP

language
modeling
uses
transformer
can
be
…

NaiveBayes Classifier for Document Classification

Bayes' Rule Applied to Documents and Classes

- For a document *d* and a class *c*

$$c_{MAP} = \underset{c \in C}{\operatorname{argmax}} \; P(c|d)$$

MAP is "maximum a posteriori" = most likely class

$$= \underset{c \in C}{\operatorname{argmax}} \; \frac{P(d|c)P(c)}{P(d)}$$

Bayes Rule

$$= \underset{c \in C}{\operatorname{argmax}} \; P(d|c)P(c)$$

Dropping the denominator

NaiveBayes Classifier for Document Classification

- **Bayes' Rule Applied to Documents and Classes**
  - For a document *d*, which consists of a sequence of words *w*, and a class *c*
  - The probability of a document can be represented by multiplying the probability of each word appearing
  - $P(d|c)\mathrm{P}(c) = P(w_1, w_2, \ldots, w_n|c)\mathrm{P}(c) \rightarrow \mathrm{P}(c)\prod_{w_i \in W} P(\mathrm{w}_i|c)$ (by conditional independence assumption)

NaiveBayes Classifier for Document Classification

- Example
  - For a document *d*, which consists of sequence of words *w*, and a class *c*

	Doc(d)	Document (words, w)	Class (c)
Training	1	Image recognition uses convolutional neural networks	CV
	2	Transformer can be used for image classification task	CV
	3	Language modeling uses transformer	NLP
	4	Document classification task is language task	NLP
Test	5	Classification task uses transformer	?

- $\mathrm{P}(\mathrm{c_{cv}}) = \frac{2}{4} = \frac{1}{2}$
- $\mathrm{P}(\mathrm{c_{NLP}}) = \frac{2}{4} = \frac{1}{2}$

NaiveBayes Classifier for Document Classification

- Example
  - For each word $\mathbf{w}_i$ we can calculate conditional probability for class $\mathbf{c}$
    - $P(w_k|c_i) = \frac{n_k}{n}$, where n_k is occurrences of w_k in documents of topic c_i

Word	Prob	Word	Prob
$P(w_{\text{"classification"}}\|c_{\text{CV}})$	$\frac{1}{10}$	$P(w_{\text{"classification"}}\|c_{\text{NLP}})$	$\frac{1}{13}$
$P(w_{\text{"task"}}\|c_{\text{CV}})$	$\frac{1}{10}$	$P(w_{\text{"task"}}\|c_{\text{NLP}})$	$\frac{2}{13}$
$P(w_{\text{"uses"}}\|c_{\text{CV}})$	$\frac{1}{10}$	$P(w_{\text{"uses"}}\|c_{\text{NLP}})$	$\frac{1}{13}$
$P(w_{\text{"transformer"}}\|c_{\text{CV}})$	$\frac{1}{10}$	$P(w_{\text{"transformer"}}\|c_{\text{NLP}})$	$\frac{1}{13}$

NaiveBayes Classifier for Document Classification

- For a test document d_5 = “Classification task uses transformer”
  - We calculate the conditional probability of the document for each class
  - We can choose a class that has the highest probability for the document

– $P(\mathrm{c_{CV}}|d_5) = \mathrm{P(c_{CV})} \prod_{\mathrm{w\in W}} P(\mathrm{w}|\mathrm{c_{CV}}) = \frac{1}{2} \times \frac{1}{10} \times \frac{1}{10} \times \frac{1}{10} \times \frac{1}{10} = 0.00005$

– $P(\mathrm{c_{NLP}}|d_5) = \mathrm{P(c_{NLP})} \prod_{\mathrm{w\in W}} P(\mathrm{w}|\mathrm{c_{NLP}}) = \frac{1}{2} \times \frac{1}{13} \times \frac{2}{13} \times \frac{1}{13} \times \frac{1}{13} \approx 0.00003$

Word	Prob	Word	Prob
$P(w_{\text{"classification"}}\|c_{\mathrm{CV}})$	$\frac{1}{10}$	$P(w_{\text{"classification"}}\|c_{\mathrm{NLP}})$	$\frac{1}{13}$
$P(w_{\text{"task"}}\|c_{\mathrm{CV}})$	$\frac{1}{10}$	$P(w_{\text{"task"}}\|c_{\mathrm{NLP}})$	$\frac{2}{13}$
$P(w_{\text{"uses"}}\|c_{\mathrm{CV}})$	$\frac{1}{10}$	$P(w_{\text{"uses"}}\|c_{\mathrm{NLP}})$	$\frac{1}{13}$
$P(w_{\text{"transformer"}}\|c_{\mathrm{CV}})$	$\frac{1}{10}$	$P(w_{\text{"transformer"}}\|c_{\mathrm{NLP}})$	$\frac{1}{13}$

3.

Word Embedding: Word2Vec, GloVe

What is Word Embedding?

Word2Vec

GloVe

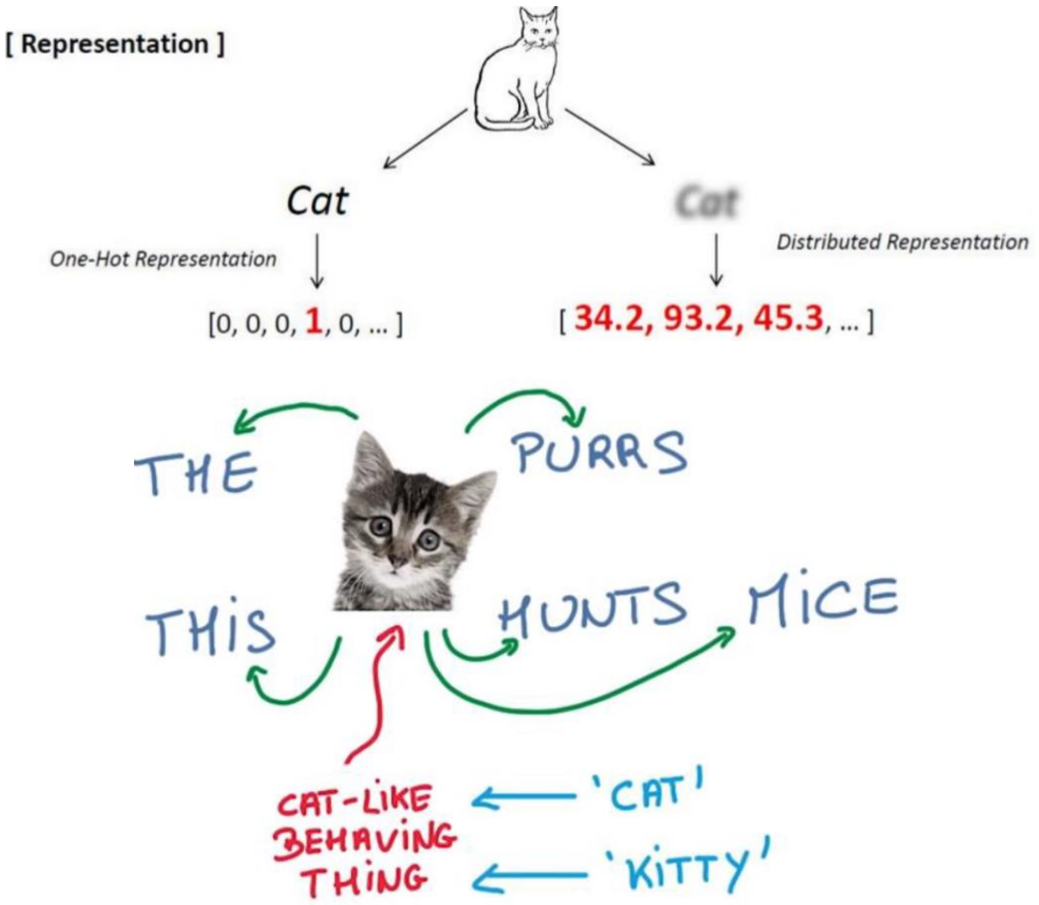
What is Word Embedding?

- Express a word as a vector
- 'cat' and 'kitty' are similar words, so they have similar vector representations → short distance
- 'hamburger' is not similar with 'cat' or 'kitty', so they have different vector representations → far distance

Word2Vec

- An algorithm for training vector representation of a word from context words (adjacent words)
- Assumption: words in similar context will have similar meanings

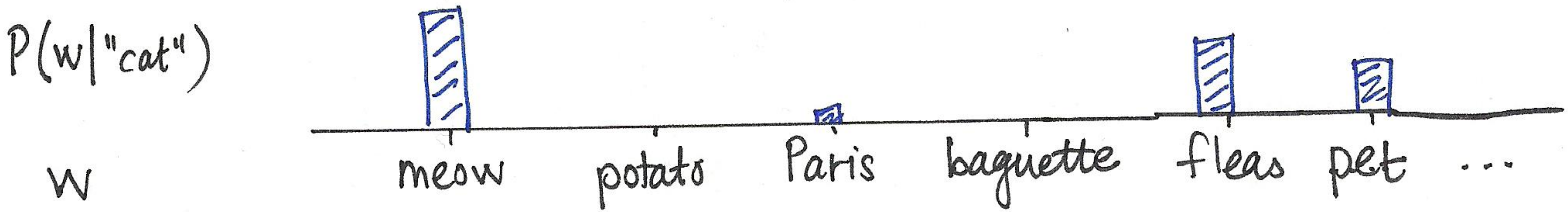
- e.g.,
  - The cat purrs.
  - The cat hunts mice.



Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

Idea of Word2Vec

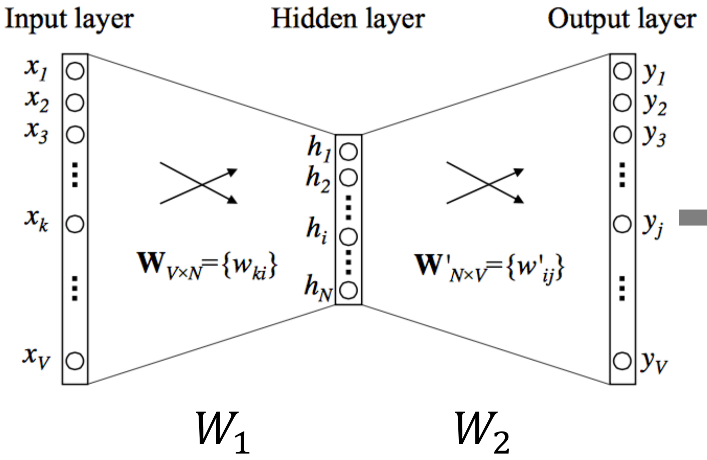
- "You shall know a word by the company it keeps" –J.R. Firth 1957
- Suppose we read the word "cat"
  - What is the probability P(w|cat) that we'll read the word w nearby?



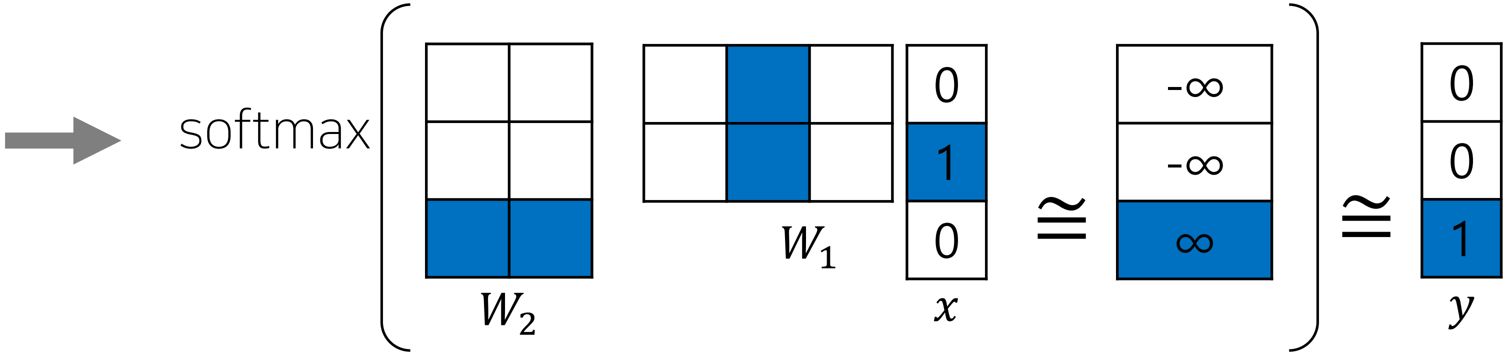
- Distributional Hypothesis: The meaning of "cat" is captured by the probability distribution P(w|cat)

Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

How Word2Vec Algorithm Works



$$y = \text{softmax}(W_2 W_1 x)$$

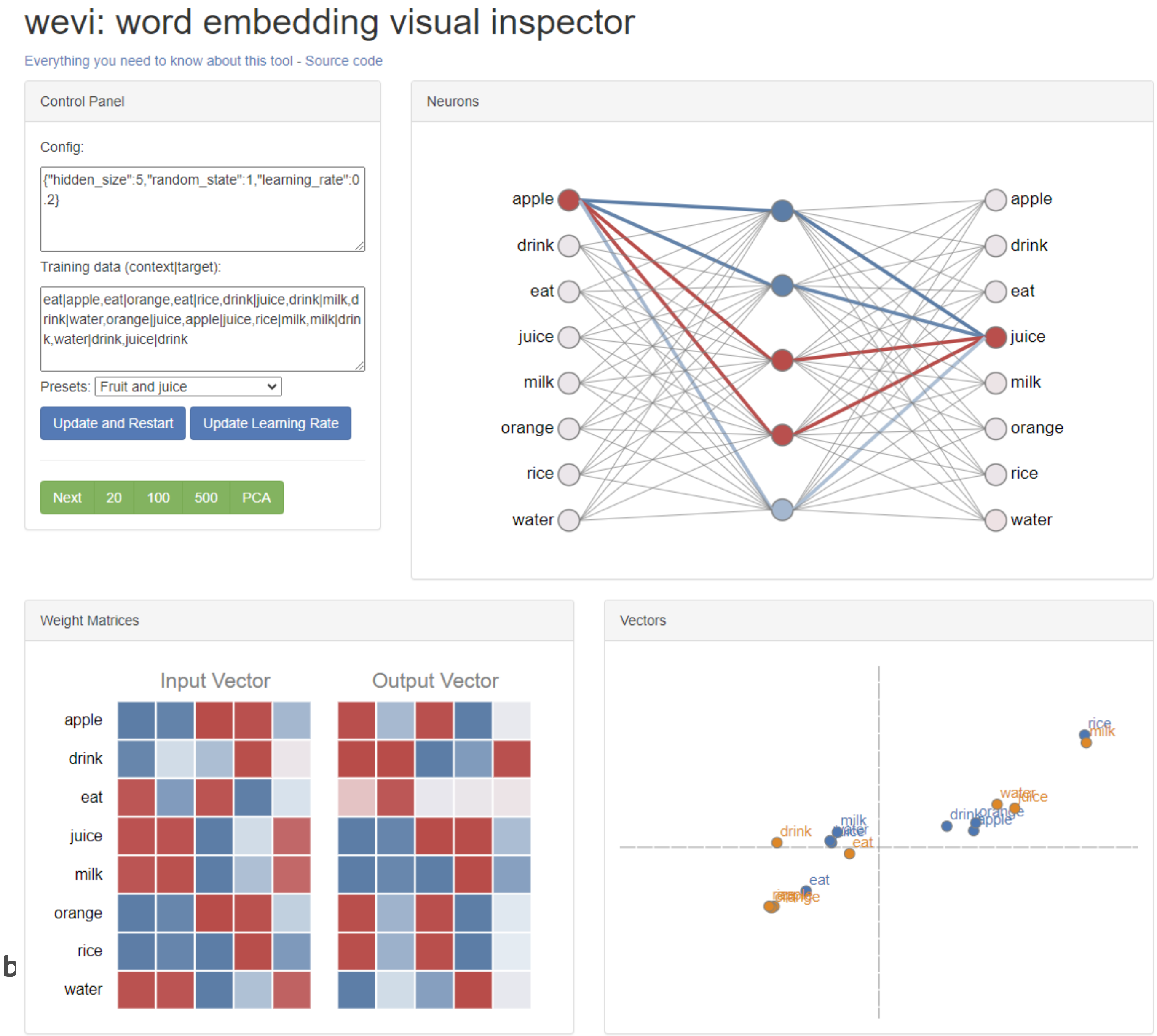


- Sentence : "I study math."
- Vocabulary: {"I", "study" "math"}
- Input: "study" [0, 1, 0]
- Output: "math" [0, 0, 1]
- Columns of W_1 and rows of W_2 represent each word

- E.g., 'study' vector : 2nd column in W_1, 'math' vector : 3rd row in W_2.
- The 'study' vector in W_1 and the 'math' vector in W_2 should have a high inner-product value.

Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

Another Example



wevi: word embedding visual inspector

Everything you need to know about this tool - Source code

Control Panel

Config:

```
{"hidden_size":5,"random_state":1,"learning_rate":0.2}
```

Training data (context|target):

```
eat|apple,eat|orange,eat|rice,drink|juice,drink|milk,drink|water,orange|juice,apple|juice,rice|milk,milk|drink,water|drink,juice|drink
```

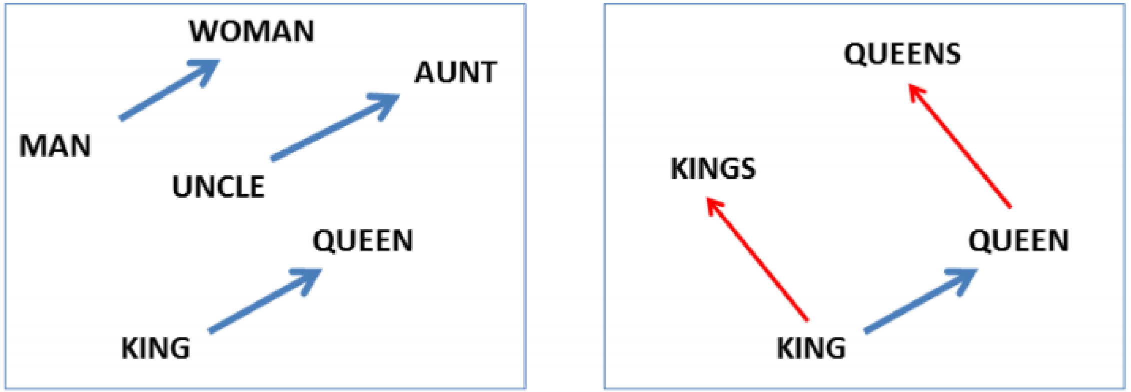
Presets: Fruit and juice

https://ronxin.github.io/wevi/

- A vector representation of ‘eat’ in W_1 has similar pattern with vectors of ‘apple’, ‘orange’, and ‘rice’ in W_2
- When the input is 'eat', the model can predict 'apple', 'orange’, or 'rice’ for output, because the vectors have high inner product values

Property of Word2Vec

- The word vector, or the relationship between vector points in space, represents the relationship between the words.
- The same relationship is represented as the same vectors.



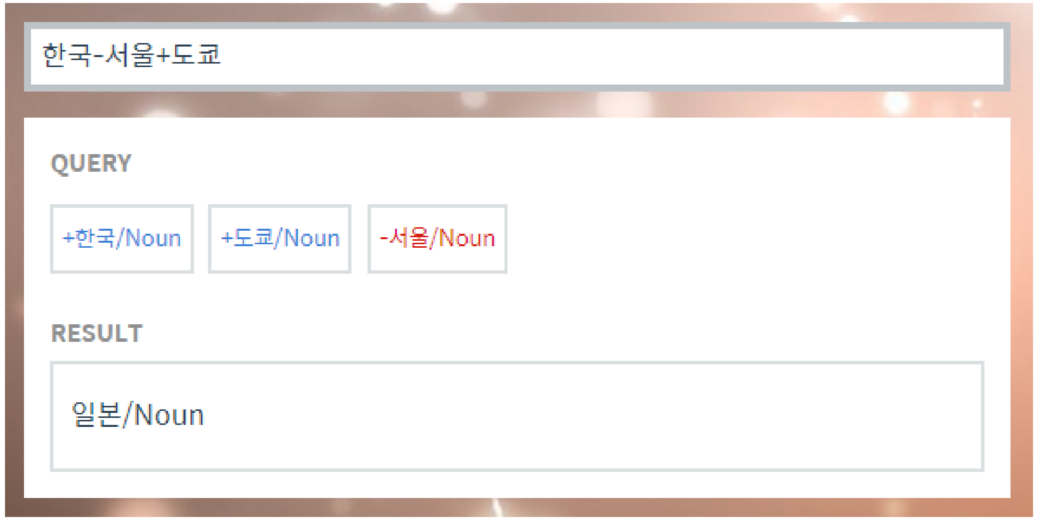
(Mikolov et al., NAACL HLT, 2013)

- e.g.,
- vec[queen] – vec[king] = vec[woman] – vec[man]

Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

Property of Word2Vec – Analogy Reasoning

- Korean Word2Vec : http://w.elnn.kr/search



한국-서울+도쿄

QUERY

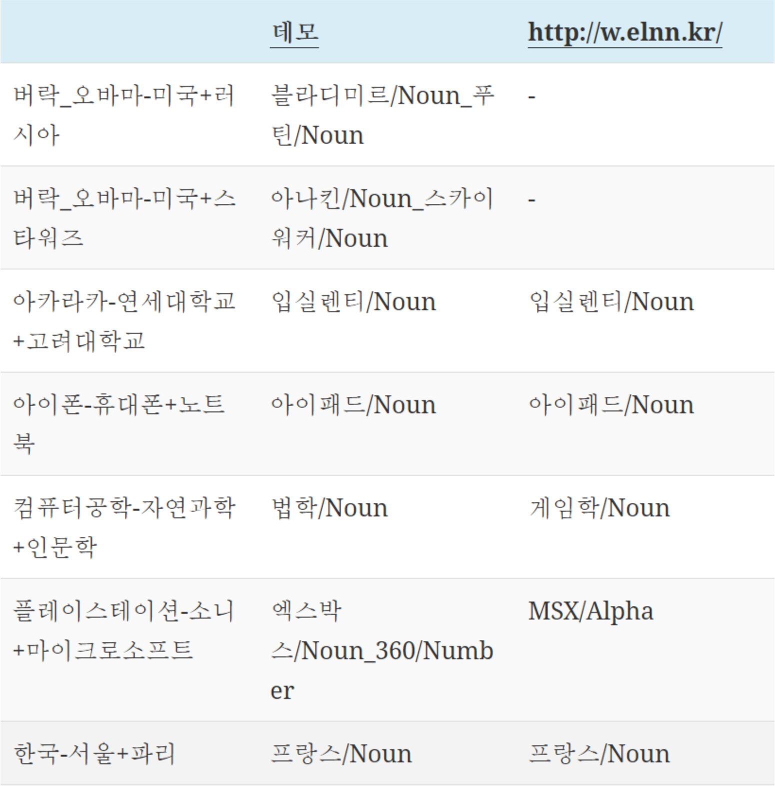
+한국/Noun +도쿄/Noun -서울/Noun

RESULT

일본/Noun

Property of Word2Vec – Analogy Reasoning

- More examples: http://wonjaekim.com/archives/50



	데모	http://w.elnn.kr/
버락_오바마-미국+러시아	블라디미르/Noun_푸틴/Noun	-
버락_오바마-미국+스타워즈	아나킨/Noun_스카이워커/Noun	-
아카라카-연세대학교+고려대학교	입실렌티/Noun	입실렌티/Noun
아이폰-휴대폰+노트북	아이패드/Noun	아이패드/Noun
컴퓨터공학-자연과학+인문학	법학/Noun	게임학/Noun
플레이스테이션-소니+마이크로소프트	엑스박스/Noun_360/Number	MSX/Alpha
한국-서울+파리	프랑스/Noun	프랑스/Noun

Property of Word2Vec – Intrusion Detection

- Example: https://github.com/dhammack/Word2VecExample

- Word intrusion detection
  - staple hammer saw drill
  - math shopping reading science
  - rain snow sleet sun
  - eight six seven five three owe nine
  - breakfast cereal dinner lunch
  - england spain france italy greece germany portugal australia

Application of Word2Vec

- **Word2Vec improves performances in most areas of NLP**
  - Word similarity
  - Machine translation
  - Part-of-speech (PoS) tagging
  - Named entity recognition (NER)
  - Sentiment analysis
  - Clustering
  - Semantic lexicon building

Application of Word2Vec – Machine Translation

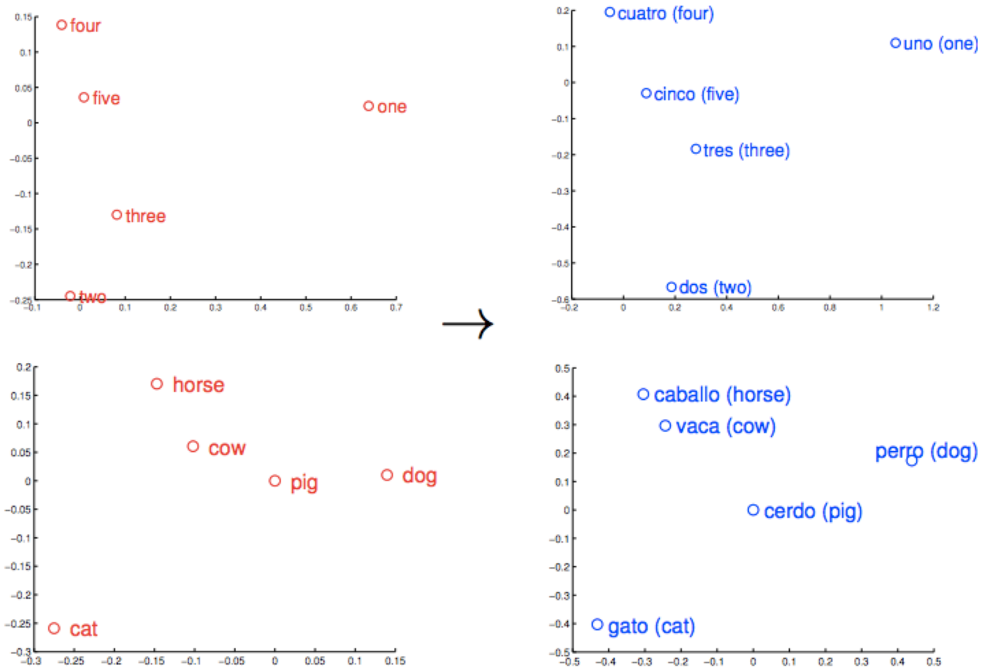
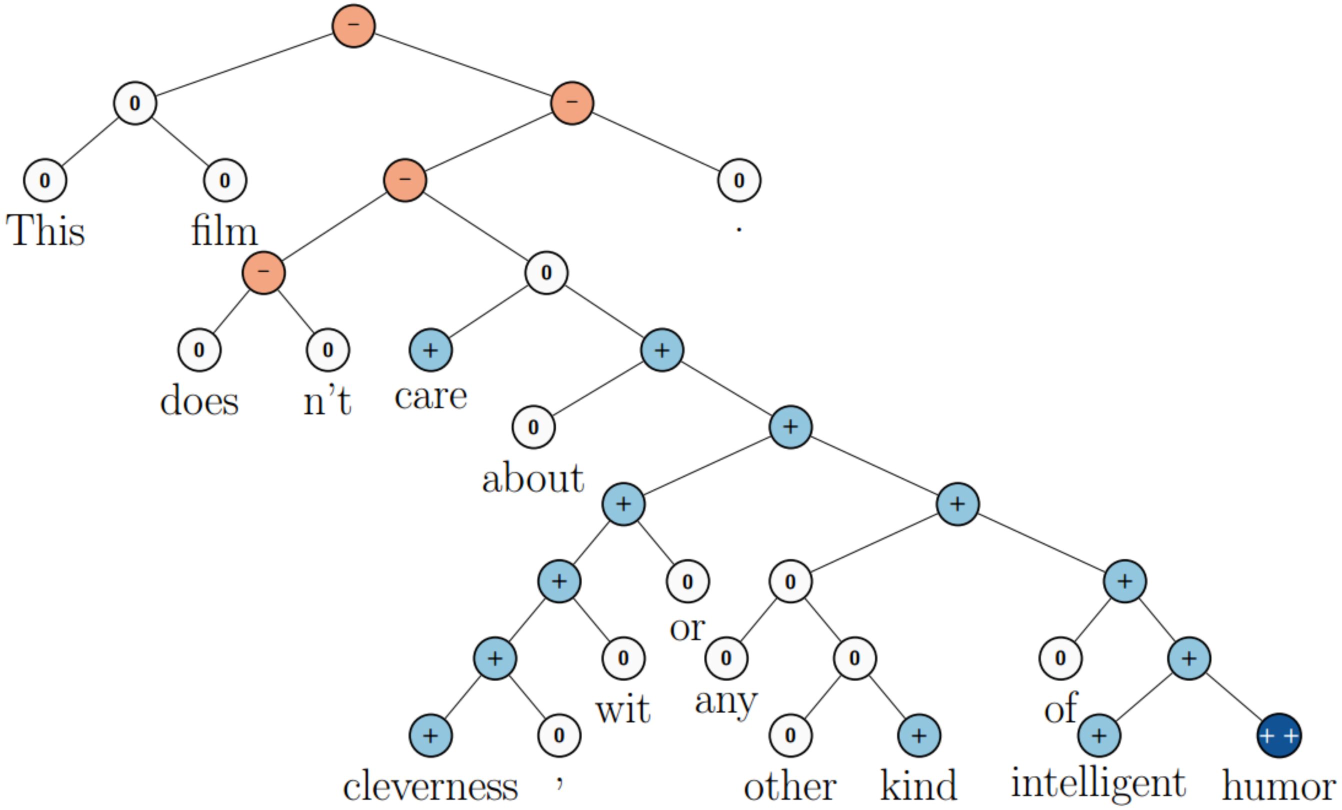


Figure 1: Distributed word vector representations of numbers and animals in English (left) and Spanish (right). The five vectors in each language were projected down to two dimensions using PCA, and then manually rotated to accentuate their similarity. It can be seen that these concepts have similar geometric arrangements in both spaces, suggesting that it is possible to learn an accurate linear mapping from one space to another. This is the key idea behind our method of translation.

Application of Word2Vec – Sentiment Analysis



Application of Word2Vec – Image Captioning

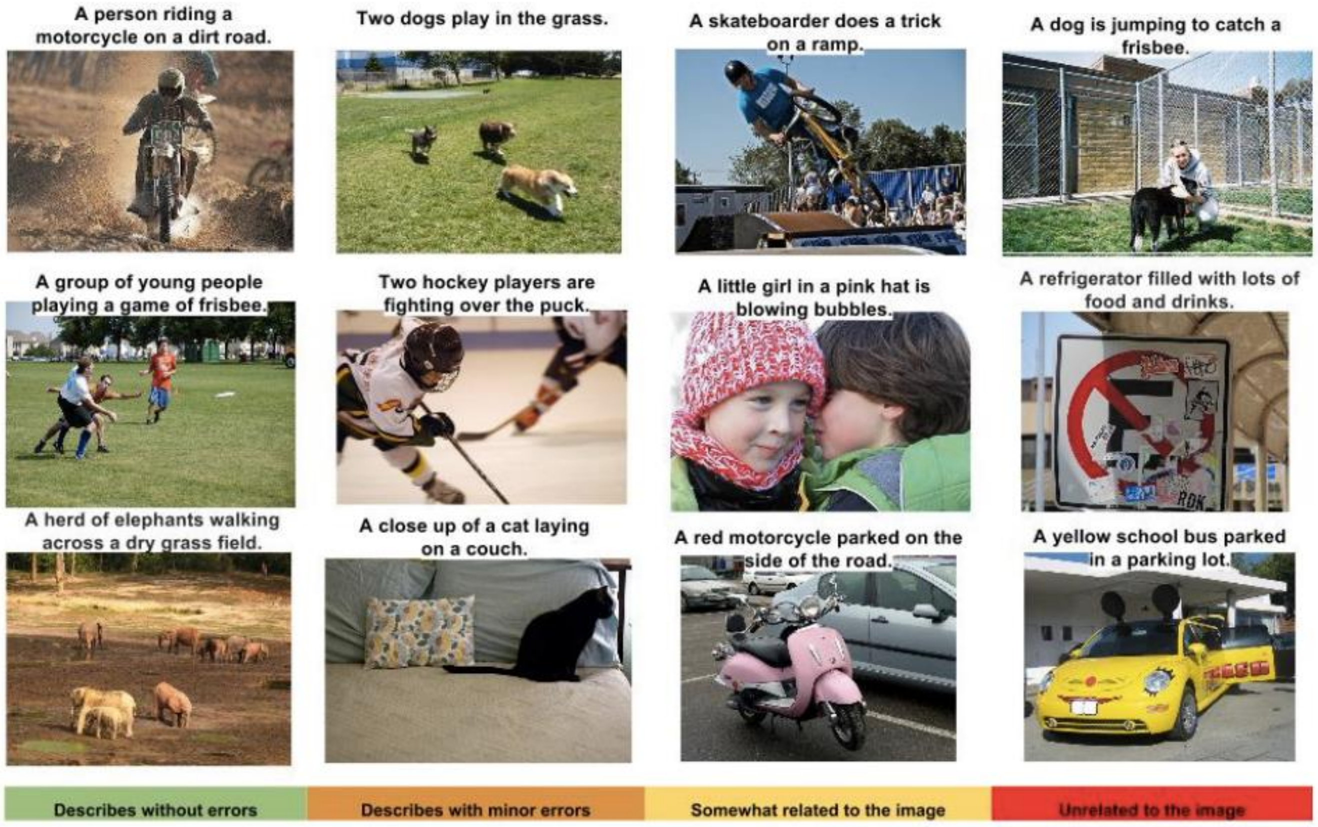

A person riding a motorcycle on a dirt road.
Two dogs play in the grass.
A skateboarder does a trick on a ramp.
A dog is jumping to catch a frisbee.
A group of young people playing a game of frisbee.
Two hockey players are fighting over the puck.
A little girl in a pink hat is blowing bubbles.
A refrigerator filled with lots of food and drinks.
A herd of elephants walking across a dry grass field.
A close up of a cat laying on a couch.
A red motorcycle parked on the side of the road.
A yellow school bus parked in a parking lot.
Describes without errors
Describes with minor errors
Somewhat related to the image
Unrelated to the image

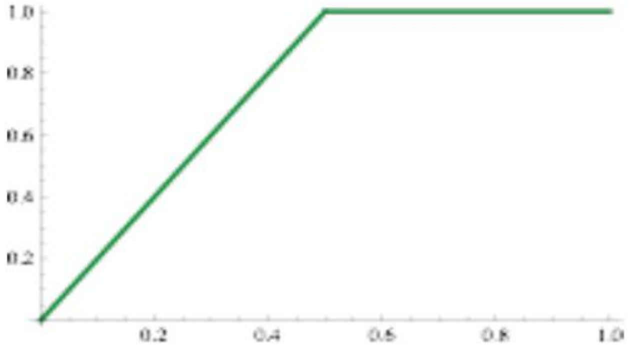
Figure 5. A selection of evaluation results, grouped by human rating.

GloVe: Another Word Embedding Model

GloVe: Global Vectors for Word Representation

- Rather than going through each pair of an input and an output words, it first computes the co-occurrence matrix, to avoid training on identical word pairs repetitively.
- Afterwards, it performs matrix decomposition on this co-occurrent matrix.

$$J(\theta) = \frac{1}{2} \sum_{i,j=1}^{W} f(P_{ij})(u_i^T v_j - \log P_{ij})^2 \quad f \sim$$

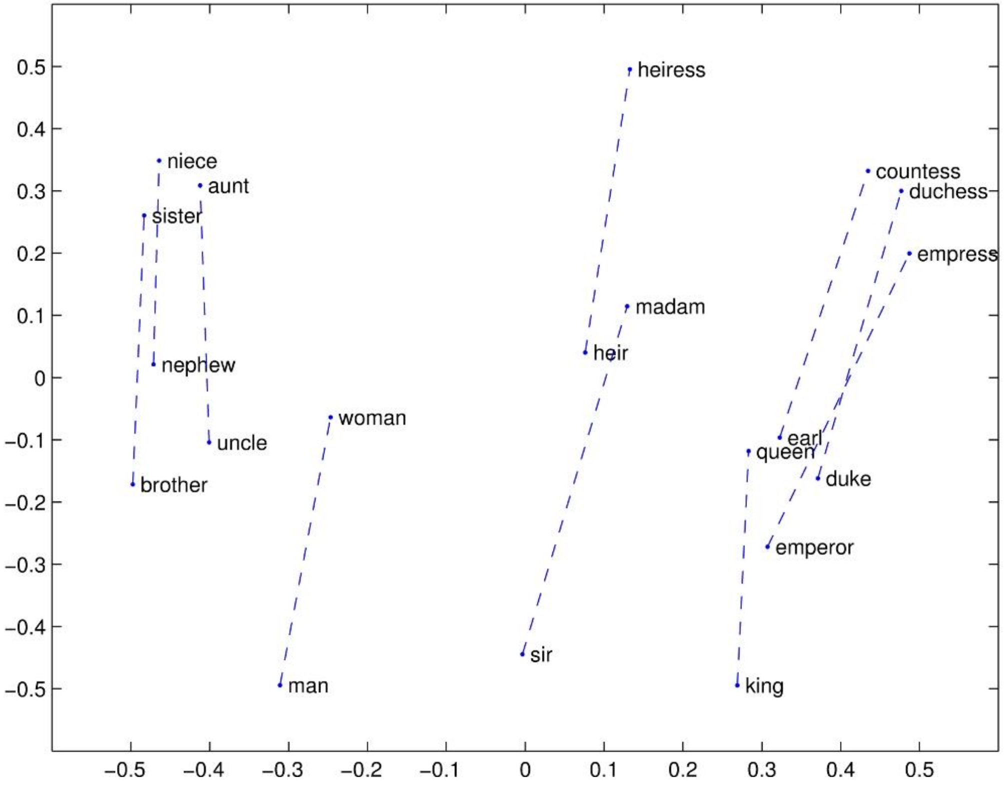


- Fast training
- Works well even with a small corpus

GloVe: Global Vectors for Word Representation, EMNLP'14

Property of GloVe – Linear Substructure

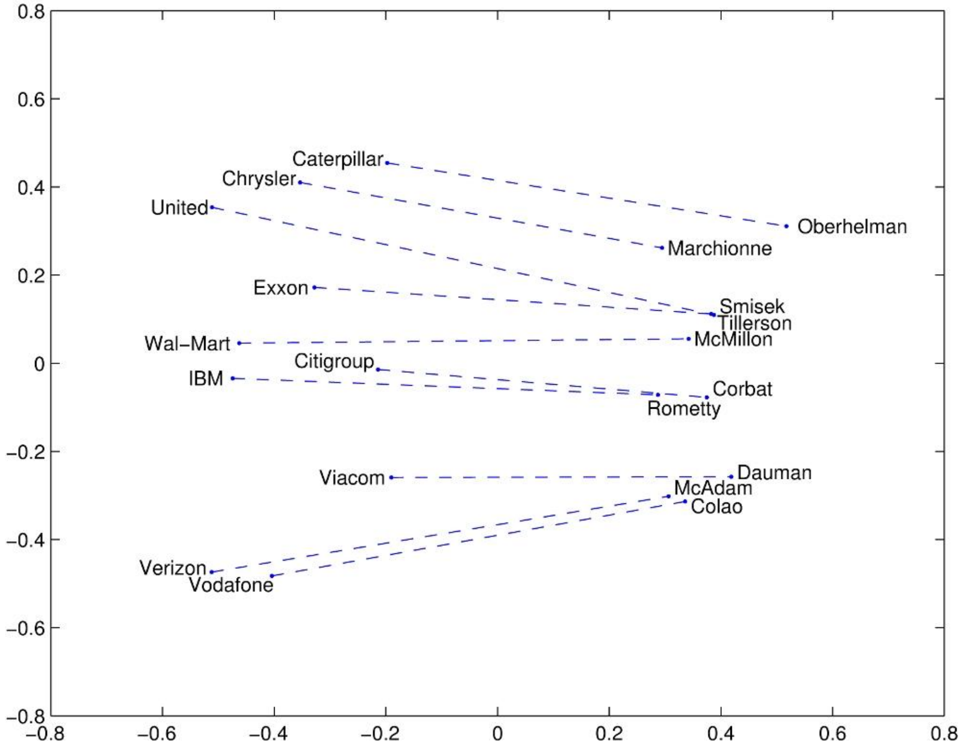
- man - woman



Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

Property of GloVe – Linear Substructure

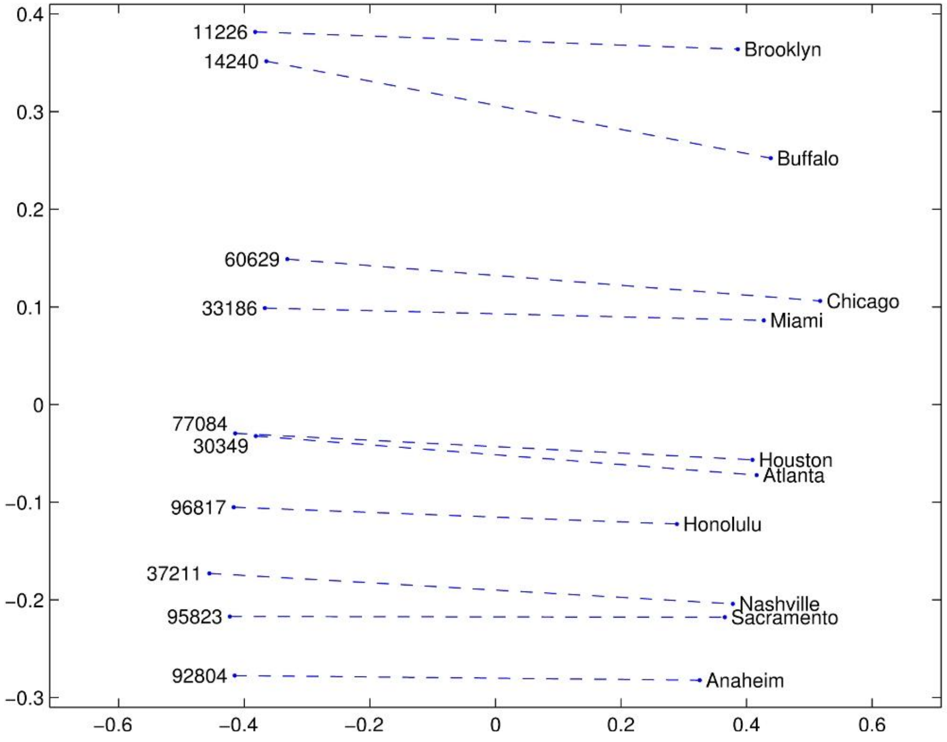
- company – ceo



Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

Property of GloVe – Linear Substructure

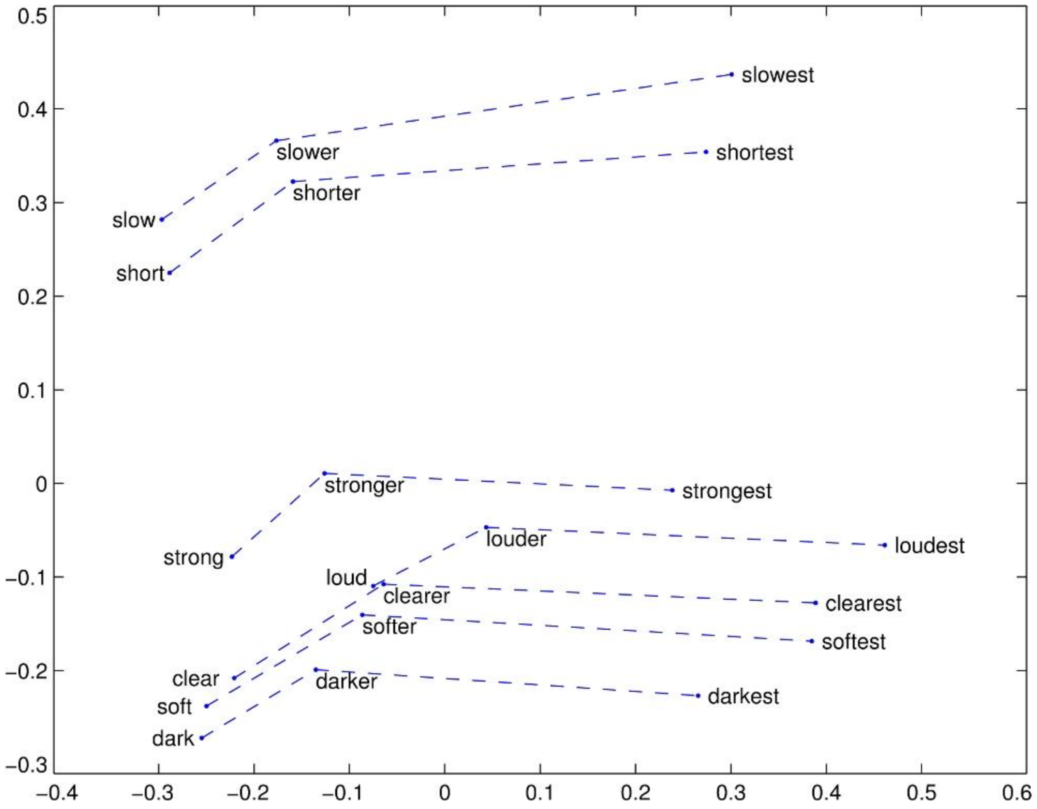
- city – zip code



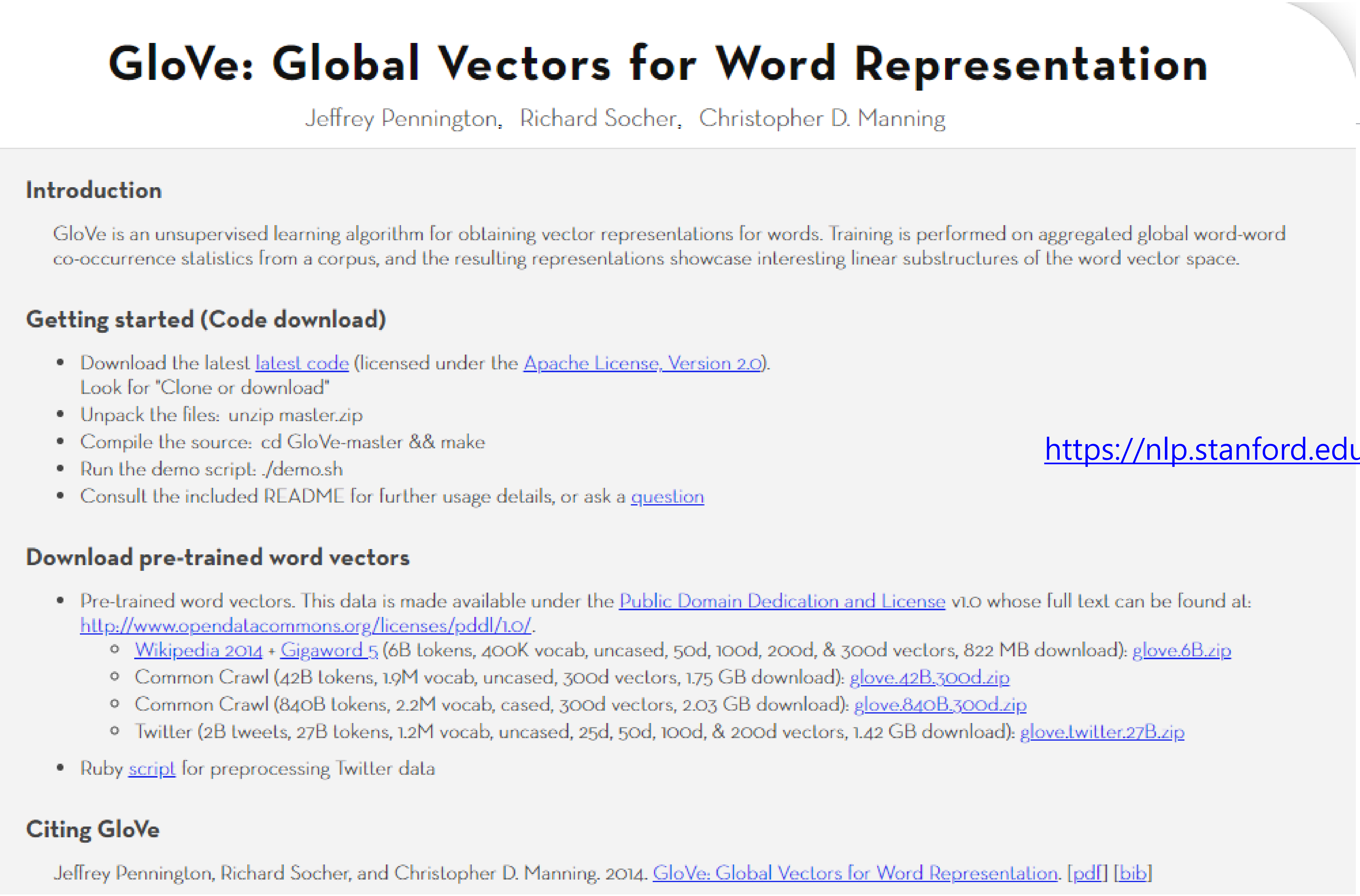
Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13

Property of GloVe – Linear Substructure

- comparative – superlative



Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13



GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, Christopher D. Manning

Introduction

GloVe is an unsupervised learning algorithm for obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.

Getting started (Code download)

- Download the latest latest code (licensed under the Apache License, Version 2.0). Look for "Clone or download"
- Unpack the files: unzip master.zip
- Compile the source: cd GloVe-master && make
- Run the demo script: ./demo.sh
- Consult the included README for further usage details, or ask a question

Download pre-trained word vectors

- Pre-trained word vectors. This data is made available under the Public Domain Dedication and License v1.0 whose full text can be found at: http://www.opendatacommons.org/licenses/pddl/1.0/.
  - Wikipedia 2014 + Gigaword 5 (6B tokens, 400K vocab, uncased, 50d, 100d, 200d, & 300d vectors, 822 MB download): glove.6B.zip
  - Common Crawl (42B tokens, 1.9M vocab, uncased, 300d vectors, 1.75 GB download): glove.42B.300d.zip
  - Common Crawl (840B tokens, 2.2M vocab, cased, 300d vectors, 2.03 GB download): glove.840B.300d.zip
  - Twitter (2B tweets, 27B tokens, 1.2M vocab, uncased, 25d, 50d, 100d, & 200d vectors, 1.42 GB download): glove.twitter.27B.zip
- Ruby script for preprocessing Twitter data

Citing GloVe

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. [pdf] [bib]

https://nlp.stanford.edu/projects/glove/

References

- Word2Vec
  - Distributed Representations of Words and Phrases and their Compositionality, NeurIPS'13
- GloVe
  - GloVe: Global Vectors for Word Representation, EMNLP'14

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Thank You.