Applied Machine Learning for Business Analytics

Lecture 7: From BoW to Word2Vec

Lecturer: Zhao Rui

Agenda

1. Representation Learning in NLP
2. Word Embeddings
3. Neural Networks for NLP

1. Representation Learning

Representation learning

- We need to develop systems that read and understand text the way a person does, by forming a representation of the text, and other context information that humans create to understand a piece of text.

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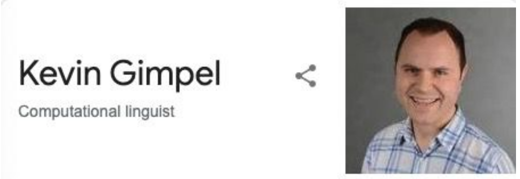
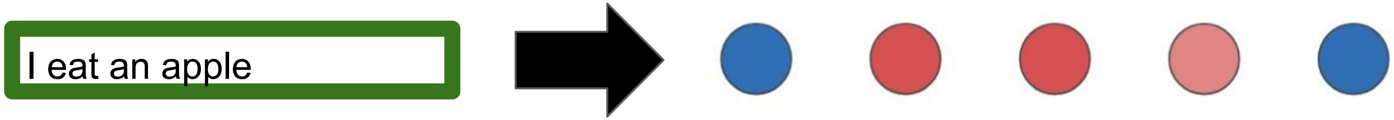




Text

Numerical Representation

The learned representation should capture high-level semantic and syntactic information.

History of NLP

- Now, neural nlp models are able to achieve state-of-arts results in all tasks.
- Before neural nlp:
  - Symbolic NLP: rule-based system (derived from linguistic)
  - Statistical NLP: data-driven and use statistical methods

Statistical NLP

- Starting from Document-Term Matrix
  - It contains the co-occurrence information
  - Bag-of-Words: n-gram as features
  - TF-IDF: frequency of words to measure importance
  - Matrix Decomposition:
    - SVD->Latent Semantic Analysis
    - Probabilistic model-> Topic Model

Corpus

D0: I eat an apple every day
D1: I eat an orange every day
D2: I like driving my car to work

Document-Term Matrix

	an	apple	car	day	driving	eat	every	like	my	orange	to	work
0	1	1	0	1	0	1	1	0	0	0	0	0
1	1	0	0	1	0	1	1	0	0	1	0	0
2	0	0	1	0	1	0	0	1	1	0	1	1

Bag-of-Words

TF-IDF

Latent Semantic Analysis

Topic Models

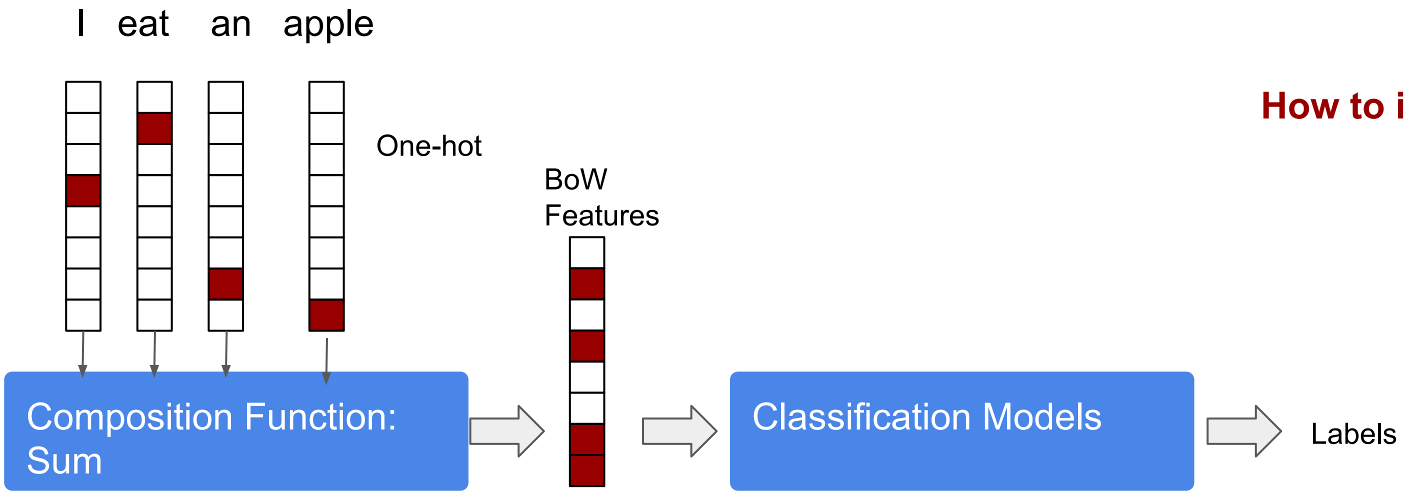
Limitations of document-Term matrix

- Too strong assumption: all words are independent of each other
    - | *orange* - *peach* | < | *orange* - *car* |
- Can not capture the order information in the sequence
- High dimensionality due to large size of vocabulary

	an	apple	car	day	driving	eat	every	like	my	orange	to	work
0	1	1	0	1	0	1	1	0	0	0	0	0
1	1	0	0	1	0	1	1	0	0	1	0	0
2	0	0	1	0	1	0	0	1	1	0	1	1

A new perspective on BoW

- Each word in vocab is represented in one-hot embedding
- Sum one-hot vectors of the words in a sentence
- The final vector is the representation for the given sentence and then fed into a classifier.



How to improve?

Statistical NLP

- D3: apple car
  - Word vector: one-hot ones
    - Apple: 0 1 0 0 0 0 0 0 0 0 0 0
    - Car: 0 0 1 0 0 0 0 0 0 0 0 0
  - Sum of two word vectors
    - apple vec + car vec
  - Document vector:
    - 0 1 1 0 0 0 0 0 0 0 0 0

Corpus

D0: I eat an apple every day
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Document-Term Matrix

	an	apple	car	day	driving	eat	every	like	my	orange	to	work
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1	1	0	0	1	0	1	1	0	0	1	0	0
2	0	0	1	0	1	0	0	1	1	0	1	1

Neural NLP

2001	Neural language models
2008	Multi-task learning
2013	Word embeddings
2013	Neural networks for NLP
2014	Sequence-to-sequence models
2015	Attention
2015	Memory-based networks
2018	Pretrained language models

https://www.kamperh.com/slides/ruder+kamper_indaba2018_talk.pdf

2. Word Embeddings

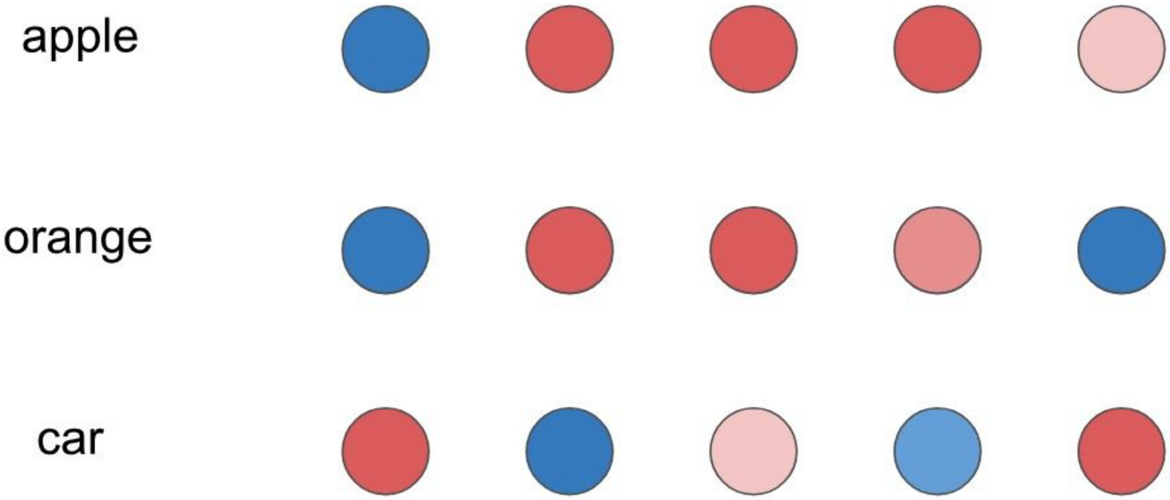
Word representation

- How to represent words in a vector space

apple	[0 0 0 0 0 **1** 0 0 0 0 0 0 0 0 0 0 0 0 ... 0 0 0 0 0 0]
orange	[0 0 0 0 0 0 0 0 0 0 0 0 0 **1** 0 0 0 0 ... 0 0 0 0 0 0]
car	[0 0 0 0 0 0 0 **1** 0 0 0 0 0 0 0 0 0 0 ... 0 0 0 0 0 0]

Distributed representation

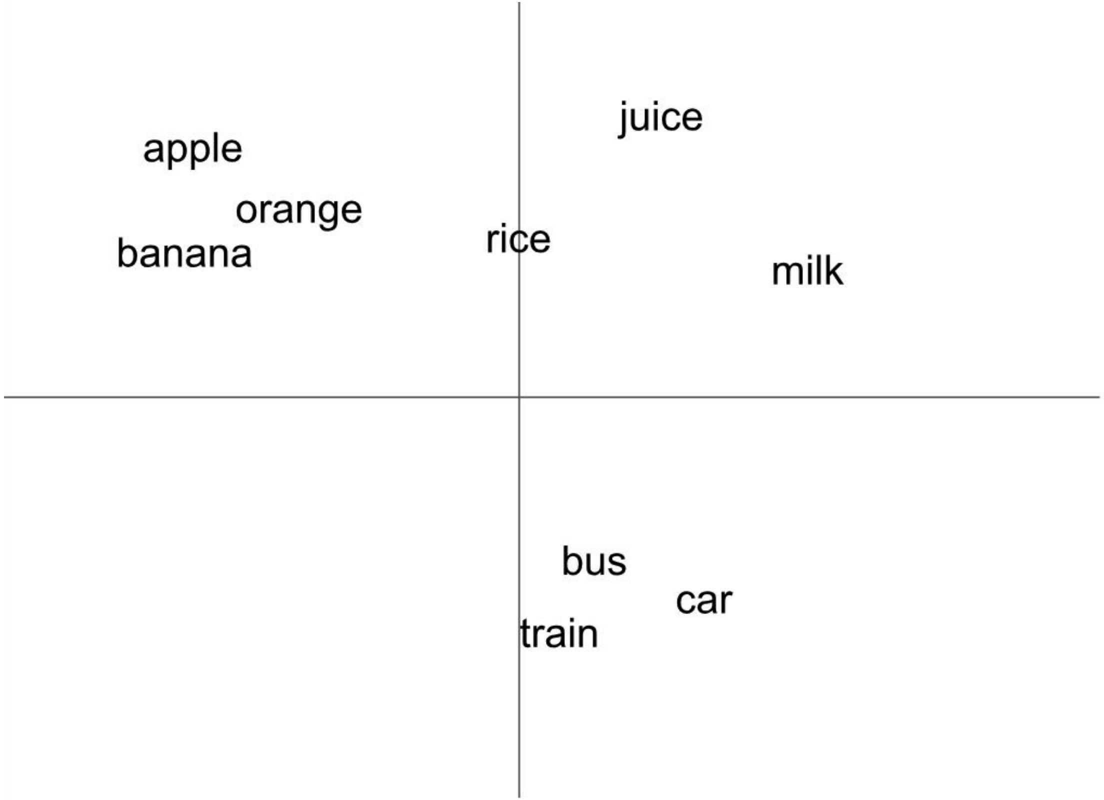
- Words should be encoded into a low-dimensional and dense vector



Word vectors

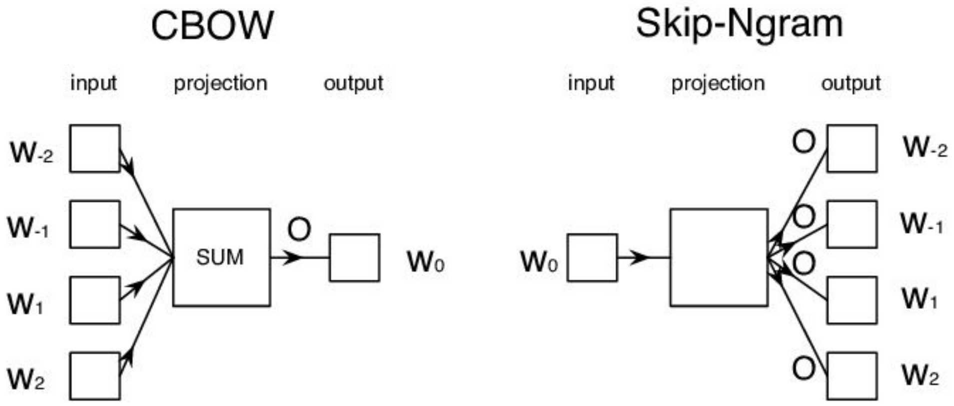
Project word vectors in a two-dimensional space. And visualize them!

Similar words are close to each other.

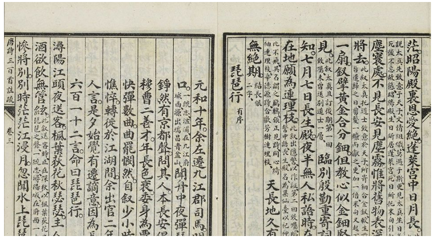


Word2Vec

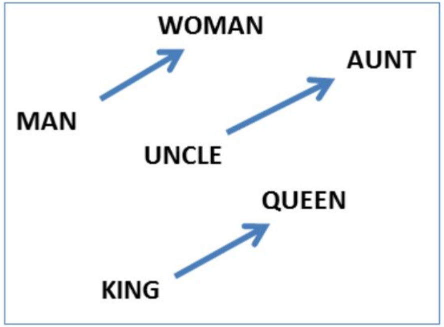
- A method of computing vector representation of words developed by Google.
- Open-source version of Word2Vec hosted by Google (in C)
- Train a simple neural network with a single hidden layer to perform word prediction tasks.
- Two structures proposed Continuous Bag of Words (CBoW) vs Skip-Gram



Word2Vec as BlackBox



input, output

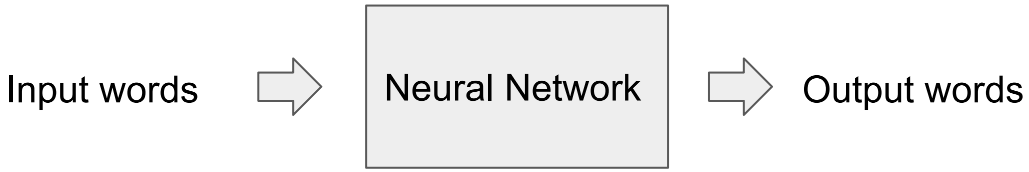


Corpus

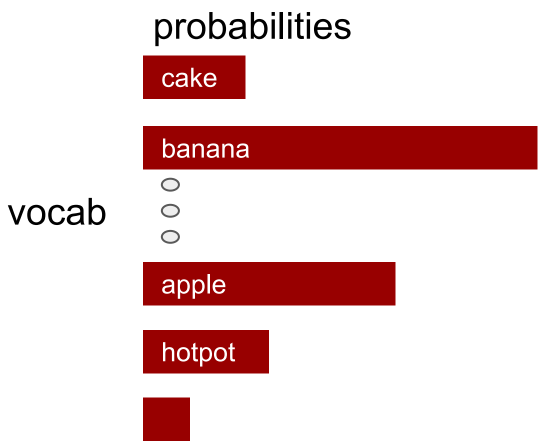
Word2Vec Tool

Word Embeddings

Use NN to predict word



Eat



Self-supervised learning

A Good Visualization for Word2Vec

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

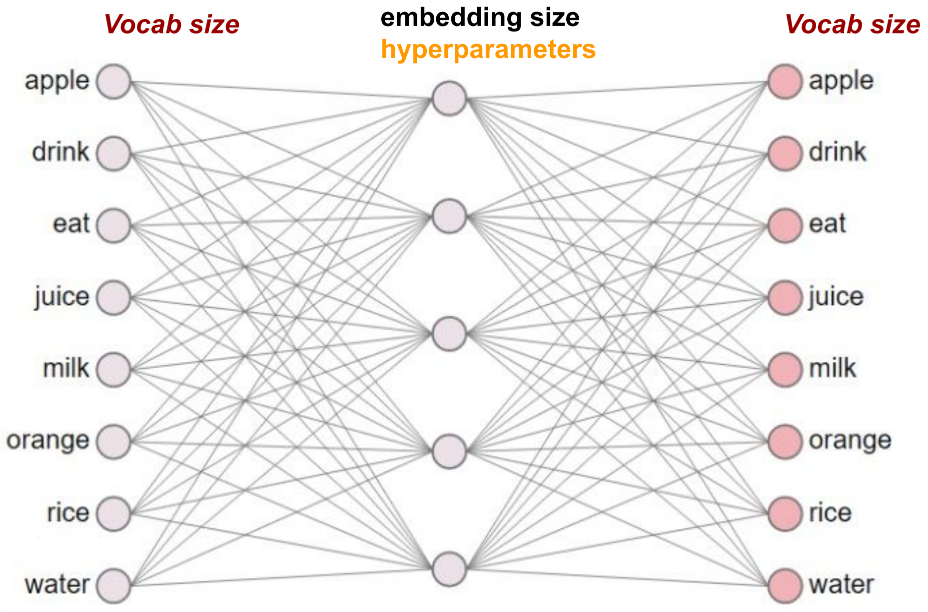
Target

- Given a training corpus, we prepare a list of N (input_word, output_word).
- Objective Function: Maximize probability of all the output words given the corresponding input words.

$$\mathbf{J}(\theta) = \prod_{i=1}^{N} p(w^i_{output} | w^i_{input}, \theta)$$

Neural network parameters that will be optimized

Model architecture



Structure Highlights:

- input layer
  - one-hot vector
- hidden layer
  - linear (identity)
- output layer
  - softmax

From Xin Rong 2016

Input layer

Give the training pair: eat -> apple (given eat, predict apple)

- 8 unique words are in the corpus so that the input layer has 8 neurons
- The index of eat is 3 in the vocab
- The input vector of the x(eat) would be:

One-hot vector

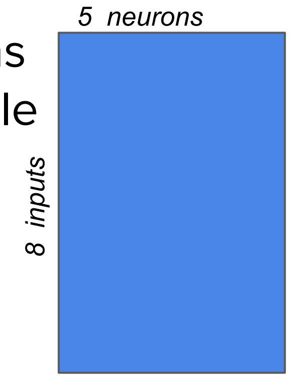
[0,0,1,0,0,0,0, 0]

Index of eat

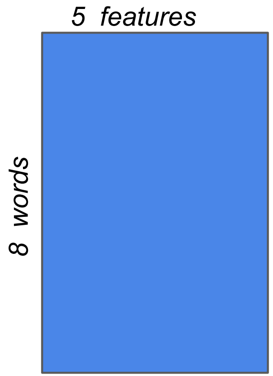
Hidden layer

- **Linear-activation** function here
- **5** neurons are the word vec. dimensions
- This layer is operating as a 'lookup' table
- Input word matrix denoted as **IVec**

Hidden Layer Weights Matrix



Word Vector Look Up Table



One-hot vector

[0,0,1,0,0,0,0, 0] ✗

Index of eat

1.06	2.91	0.29	1.39	0.33
1.60	1.12	0.29	0.74	0.21
0.96	1.50	1.37	0.34	1.04
0.53	2.11	0.76	2.51	0.20
0.31	0.64	2.08	0.24	1.23
1.40	1.36	0.01	1.69	1.95
2.97	2.13	0.86	0.90	2.21
1.05	0.80	2.18	2.43	1.57

=

Word vector for "eat"

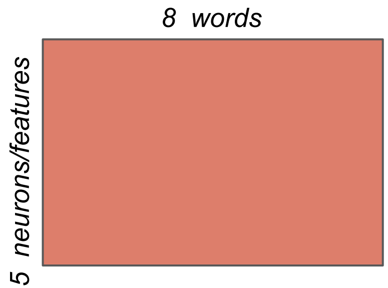
0.96, 1.5, 1.37, 0.34, 1.04

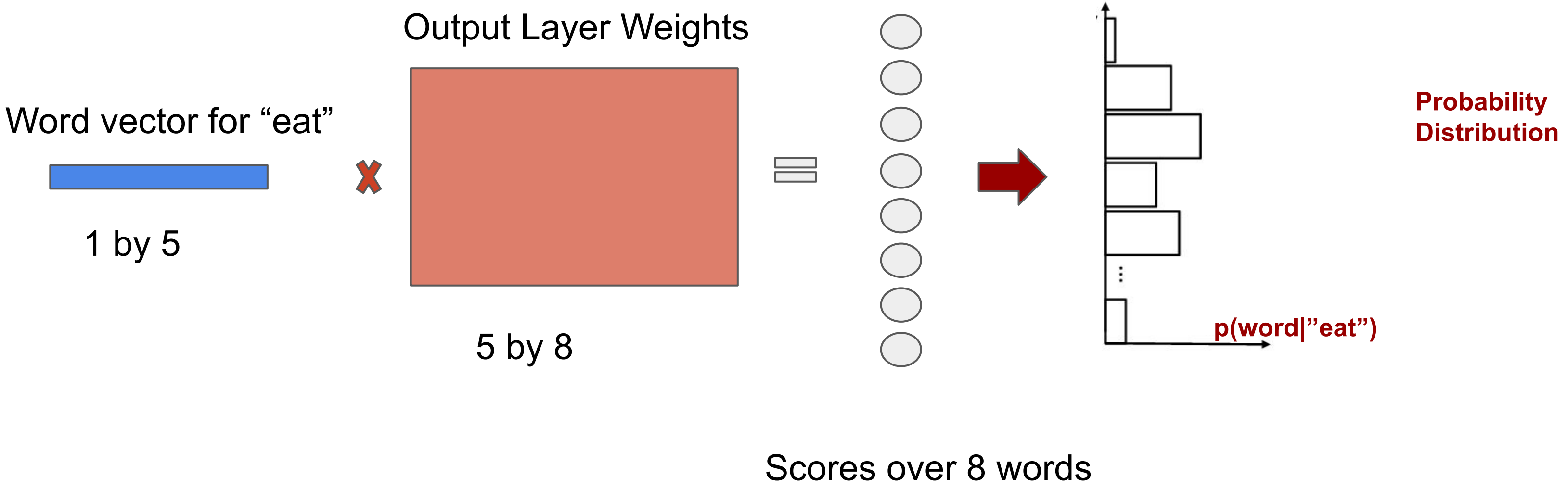
This is a **projection/look up** process: given the index of the word, we take the ith row in the word vector matrix out

Output layer

- Softmax Classifier
- Output word matrix denoted as **OVec**

Output Layer Weights Matrix
A.K.A Output word vectors





Output layer

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Output Layer Weights Matrix
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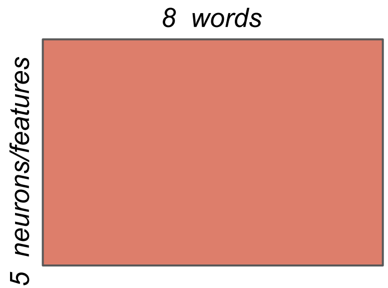
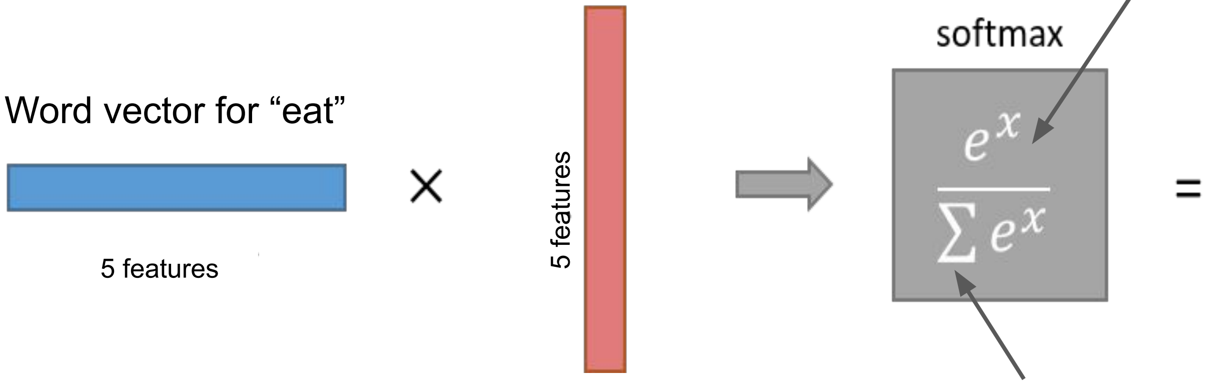


Output weights for “apple”

e^(IVec[eat]*OVec[apple])

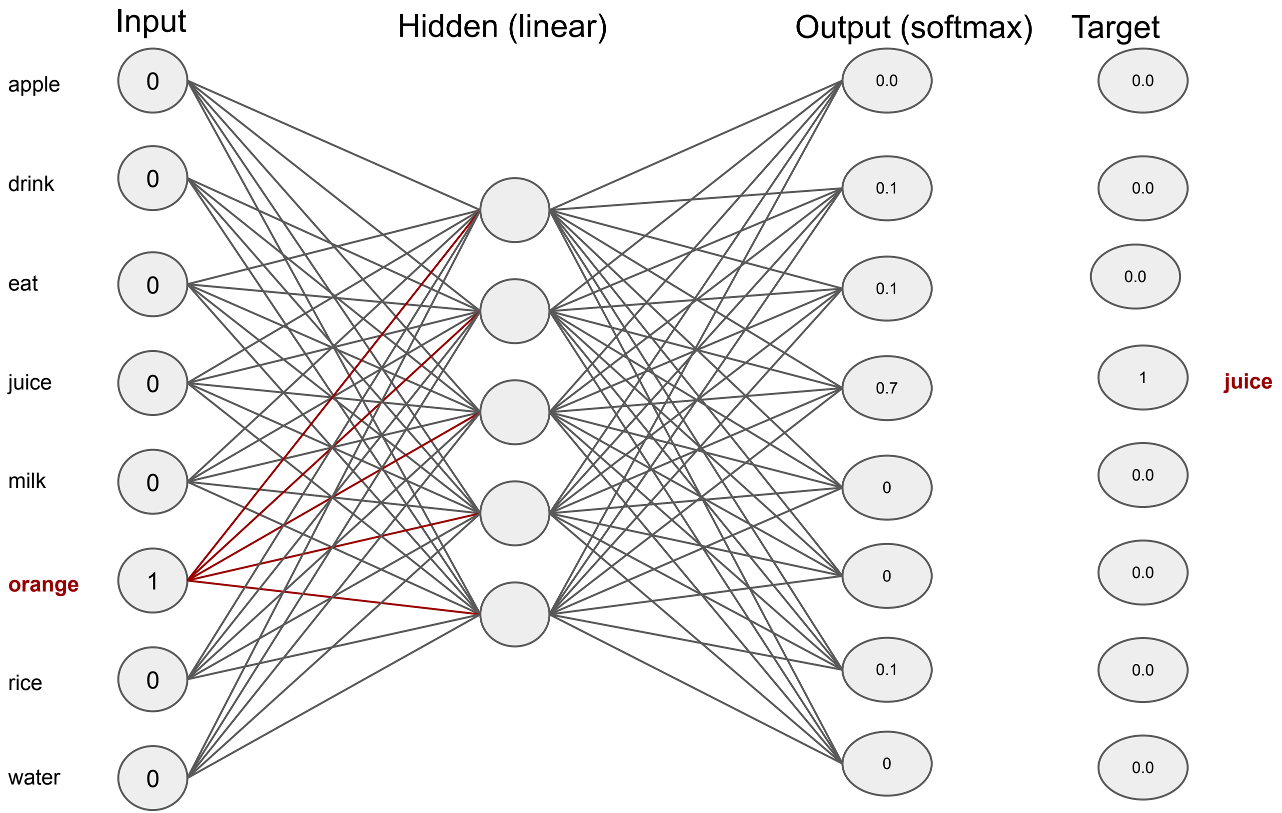


Probability that if you randomly pick a word nearby “eat”, that it is “apple”

p(apple|eat)

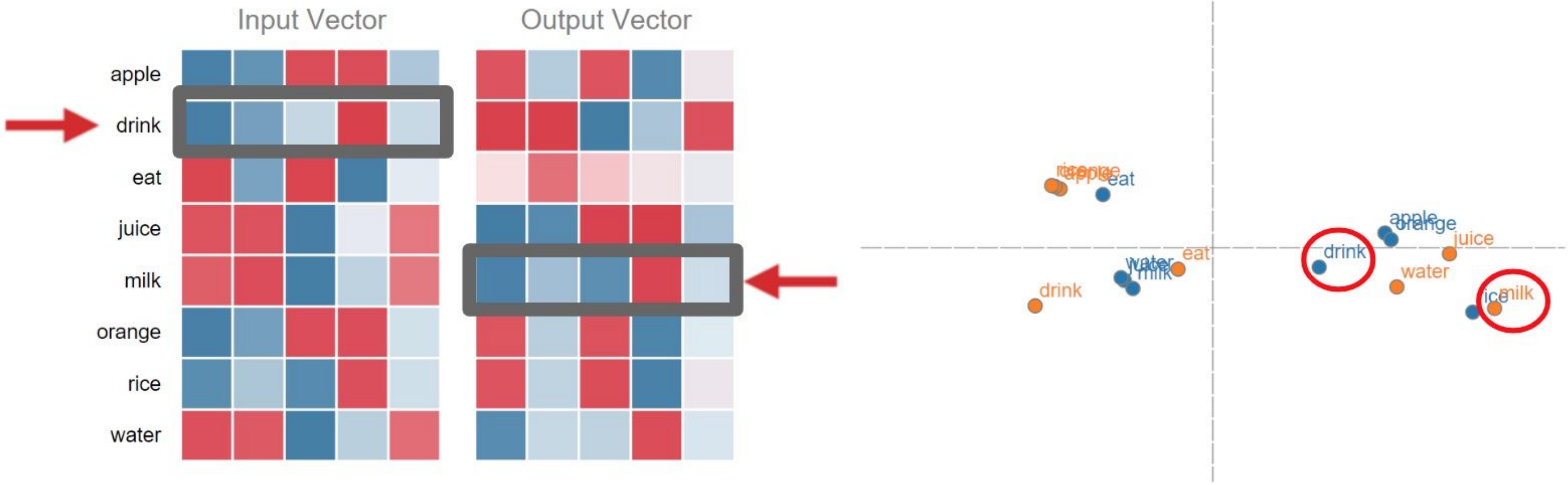
e^(IVec[eat]*OVec[apple]) + e^(IVec[eat]*OVec[juice]) + e^(IVec[eat]*OVec[drink])+e^(IVec[eat]*OVec[other vocab words])

Word2Vec



Then, we can compute the loss and call gradient descent to update model parameters.

Updating word vectors



From Xin Rong 2016

Input vs output word vectors

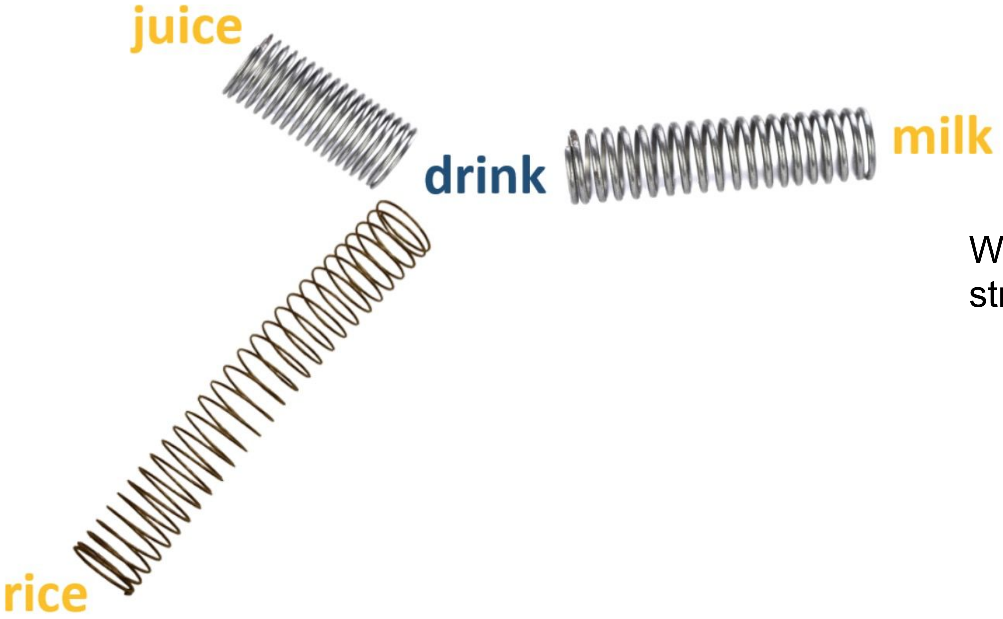
- Input matrix: semantics **encoder** from word index to semantics
- Output matrix: semantics **decoder** from semantics to probability distributions over words
- In most cases, input word vectors are used. Some have observed that combinations of these two vectors may perform better

	Vector size	Overall	Semantic	Syntactic
DVRS	300	0.41	0.59	0.26
DVRS	1024	0.43	0.62	0.28
SG	300	**0.64**	**0.69**	**0.60**
SG	1024	0.57	0.60	0.55
Add 300-DVRS, 300-SG	300	0.64	0.72	0.58
Concatenate 300-DVRS, 300-SG	600	**0.67**	**0.74**	**0.60**
Add 1024-DVRS, 1024-SG	1024	0.60	0.66	0.55
Concatenate 1024-DVRS, 1024-SG	2048	0.61	0.68	0.55
Concatenate DVRS-1024, SG-300	1324	0.66	0.73	**0.60**
Oracle DVRS-1024, SG-300	1024/300	0.70	0.79	0.62

Table 2: Performance on word analogy problems with vectors trained against the first 10^9 bytes of Wikipedia.

Garten, 2014

A force-directed graph



What decides the strength of the string?

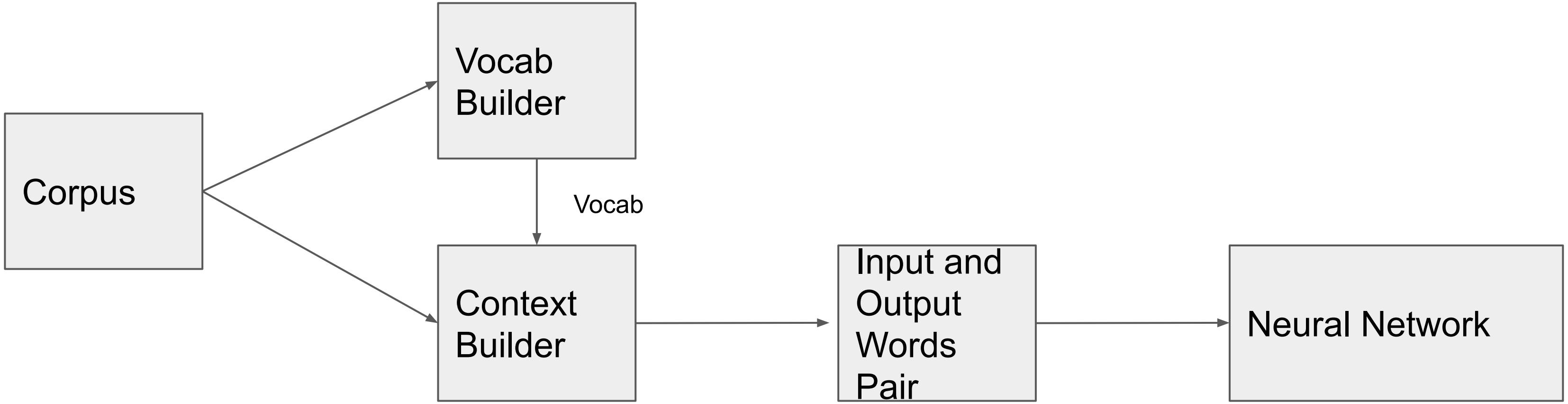
Idea behind Word2Vec

- Feature vector assigned to a word will be adjusted if it can not be used for accurate prediction of that word's context.
- Each word's context in the corpus is the teacher sending error signals back to modify the feature vector.
- It means that words with similar **context** will be assigned similar **vectors**!

"You shall know a word by the company it keeps" - by Firth (1957)

Input and output words

- How to select them from corpus
- Skip-gram and CBoW differ here



Skip-Gram

- Task Definition: given a specific word, predict its nearby word (probability output)
- Model input: source word, Model output: nearby word
- Input is one word, output is one word
- The output can be interpreted as prob. scores, which are regarded as how likely it is that each vocabulary word can be nearby your input word.

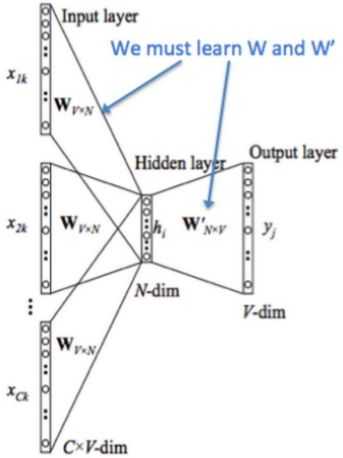
give a talk at the

Input x	Target y
talk	give
talk	a
talk	at
talk	the

CBoW

- Task Definition: given context, predict its target word
- Model input: context (several words), Model output: center word
- Input is several words, output is one word
- Core Trick: **average** these context vectors for prob. score computing

give a **talk** at the ⇒ **Input x (give,a,at,the)** **Target y talk**



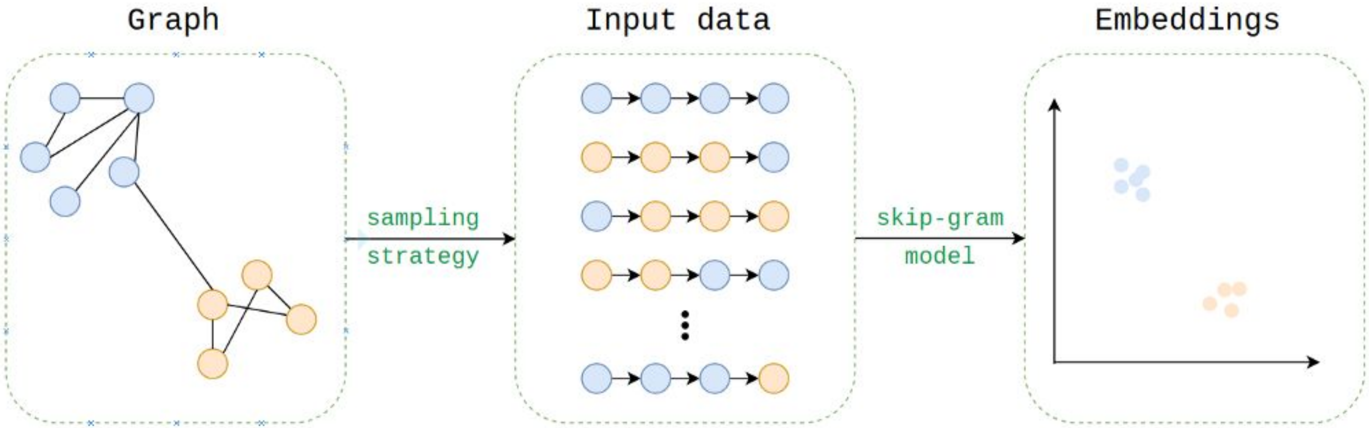
Skip-Gram vs CBoW

- Skip-gram:
  - Learning to predict the context by the center word
- CBoW:
  - Learning to predict the word by the context

- ? : several times faster to train the ?
- ? : works well with small amount of the training data, represents well even rare words or phrases.

Embedding for graph data

- Embeddings can be extended beyond NLP domain
- Embeddings can be learned for any nodes in a graph
- Nodes can be items, web pages and so on in user clicked stream data
- Embeddings can be learned for any group of discrete and co-occurring states.

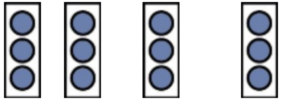


3. Neural Networks for NLP

Sequence of words

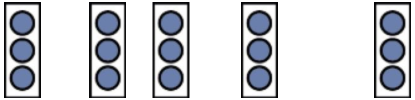
- Each sentence or document can be regarded as a sequence of vectors.
- The shape of matrix depends on the length of sequence. However, the majority of ML systems need fixed-length feature vectors.
- One simple solution: average the sequence of vectors, just like bag-of-words (abandon order information).

I hate this movie



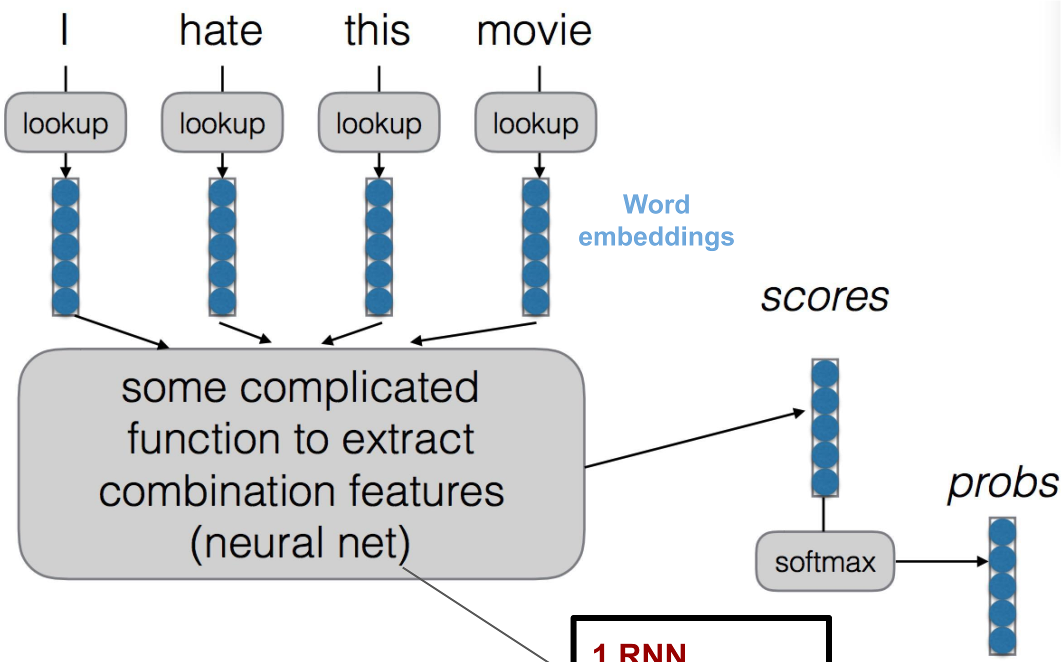
4 by d

This is my favorite movie.



5 by d

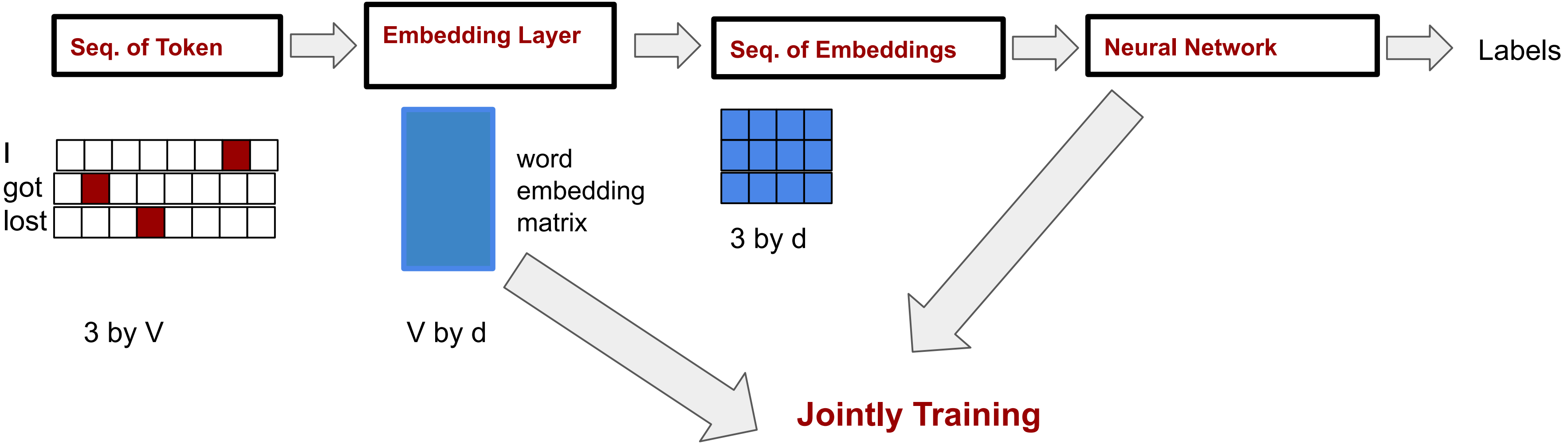
Complex semantic



1 RNN
2 CNN
3 Attention
etc

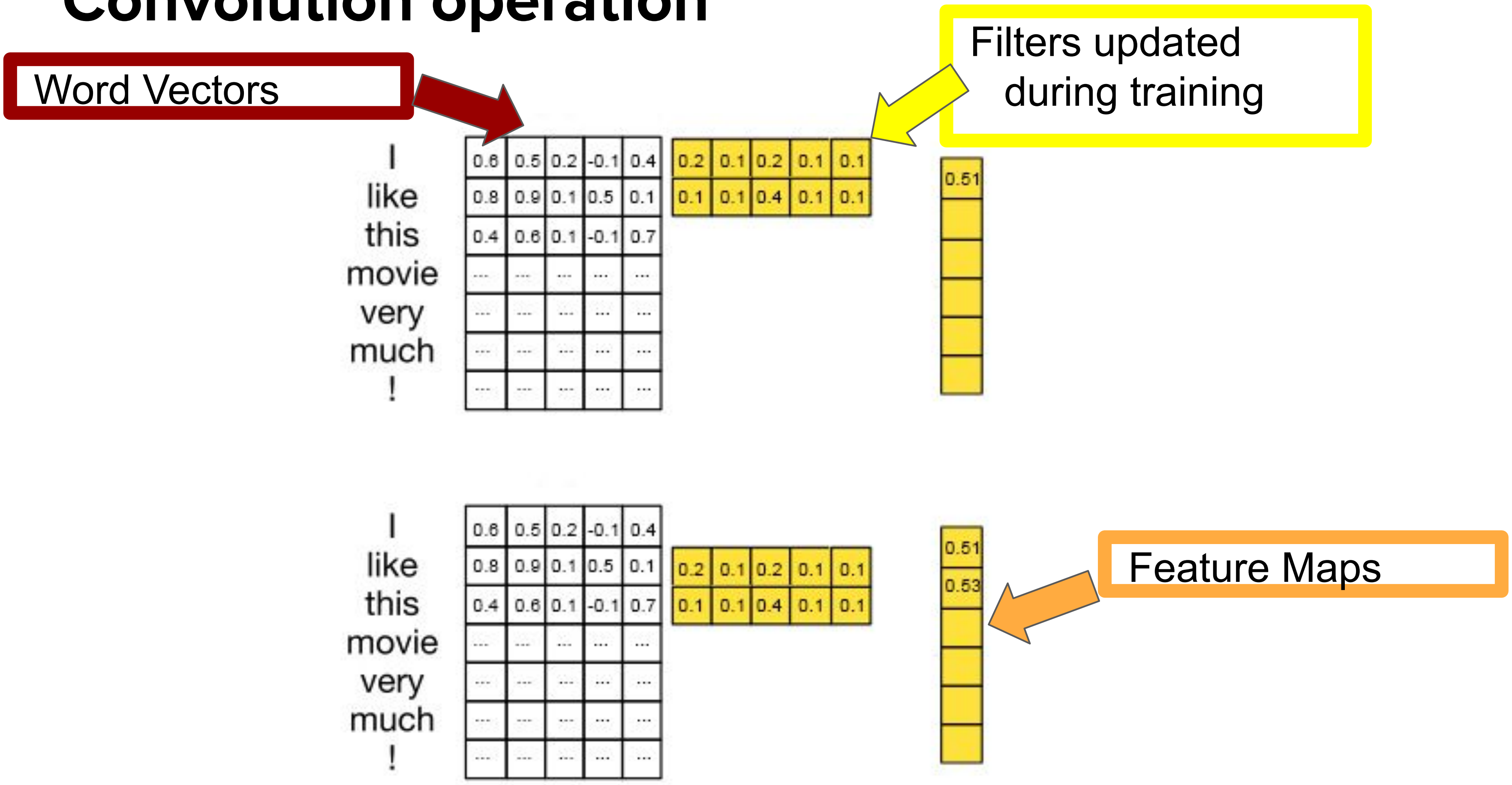
Word Embeddings is the foundation for deep learning's applications on NLP

Neural networks for NLP



- Learn from Scratch: Random initialize the word embedding matrix and update the matrix and neural network parameters in the specific task
- Pre-train: Got pre-trained word embeddings as the embedding layer and only update neural network parameters in the specific task
- **Pre-train then fine tune**

Convolution operation



Toy example

Word embeddings

cat	0.7	0.4	0.5
sitting	0.2	-0.1	0.1
there	-0.5	0.4	0.1

dog	0.6	0.3	0.5
resting	0.3	-0.1	0.2
there	-0.5	0.4	0.1

Convolutional Filters

0.6	0.4	0.5
0.2	-0.1	0.2

A 2-gram extractor for the concept *animal sitting*

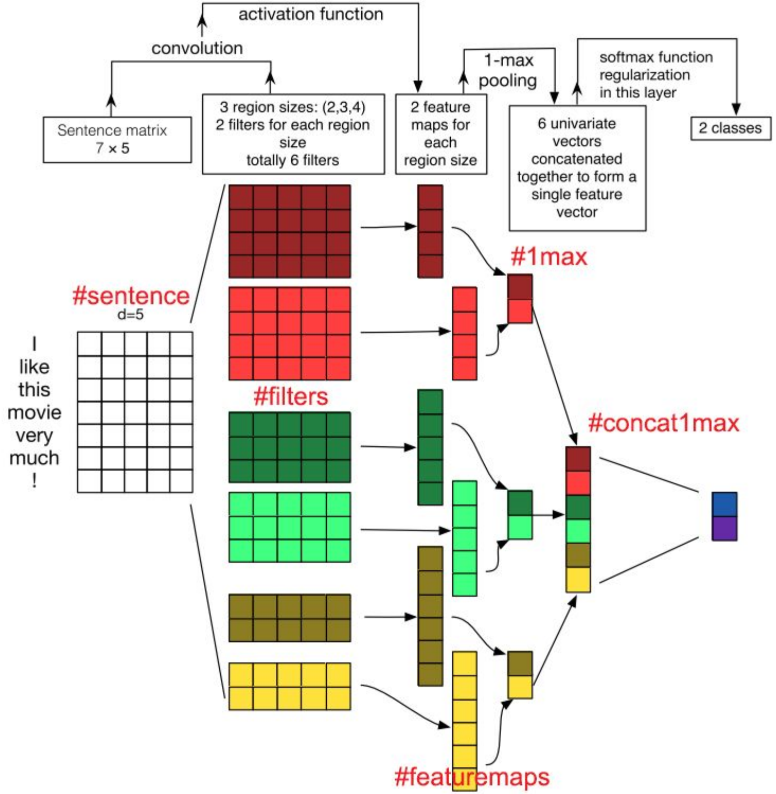
0.9

0.84

- This convolution provides high activations for 2-grams with certain meaning
- Can be extended to 3-grams, 4-grams, etc.
- Can have various filters, need to track many n-grams.
- They are called 1D since we only slice the windows only in one direction

Why is it better than BoW?

CNN framework

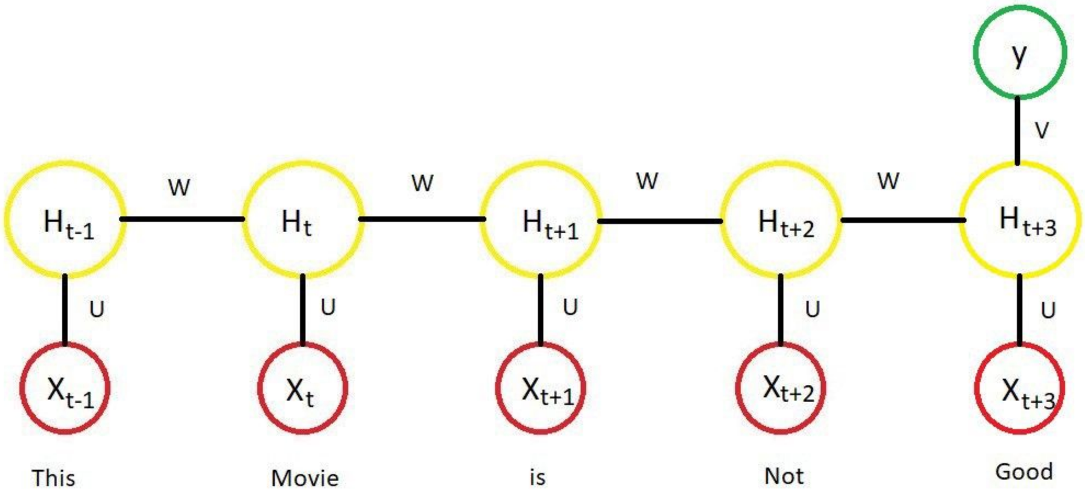


From Zhang 2015

RNN framework

This movie is not good -> sentiment label

U, W, V: RNN's parameters
H: Hidden Outputs
X: Word Embeddings
y: Labels



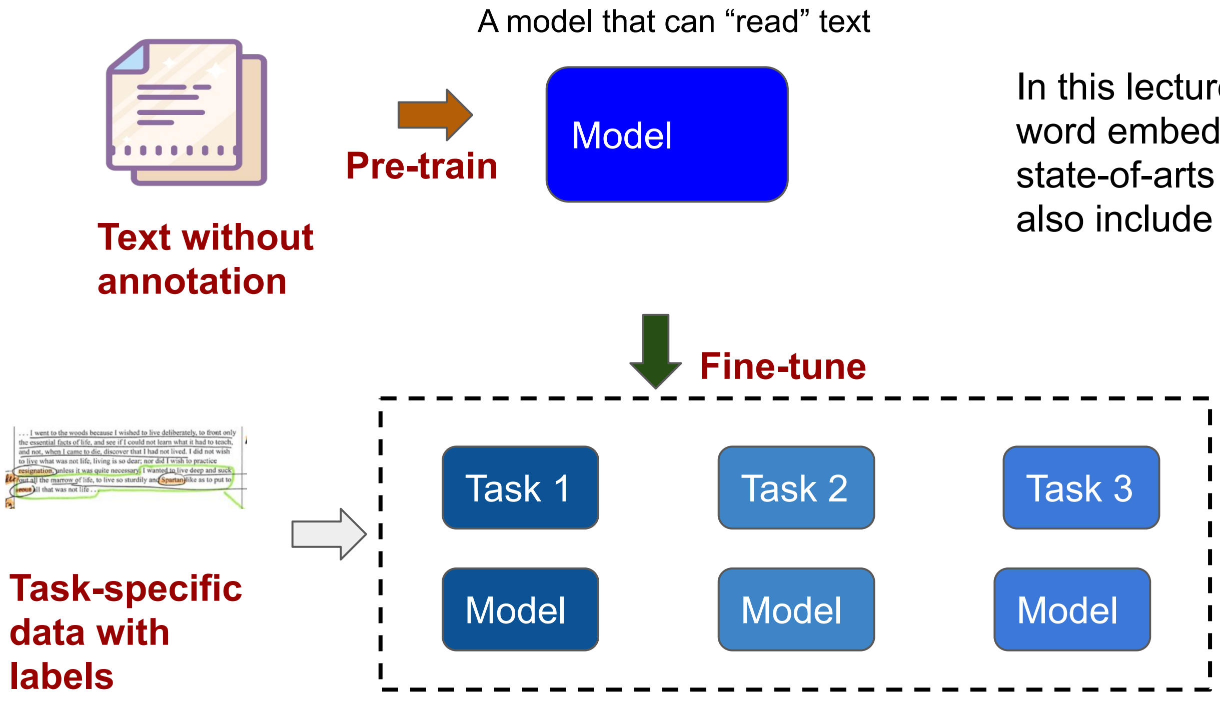
Multiple Channels

- Learn from Scratch: Random initialize the word embedding matrix and update the matrix and neural network parameters in the specific task
- Pre-train: Got pre-trained word embeddings as the embedding layer and only update neural network parameters in the specific task
- Pre-train then fine tune

How to build word embedding layer

- Like image, CNN is applied on R-G-B channels
- For NLP, different word embeddings can be regarded as different channels

Pre-train then Fine-tune



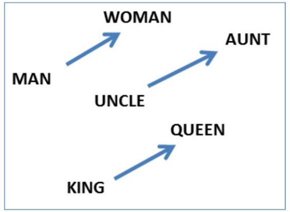
In this lecture, the model is only referred to word embedding matrix. However, in state-of-arts NLP techniques, the model will also include the following neural network.

Is Word2Vec good enough?

- Can not capture different senses of words (context independent)
  - Solution: Take the word order into account
- Can not address Out-of-Vocabulary words
  - Solution: Use characters or subwords

Corpus

Word2Vec Tool



Word Embeddings used for downstream tasks

Next Class: Transformers