Applied Machine Learning for Business Analytics

Lecture 8: Frontiers in NLP

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Agenda

1. Representation Learning in NLP
2. Word Embeddings
3. Neural Networks for NLP
4. Attention is all you Need
5. Introduction to BERT
6. From GPT to ChatGPT
7. Fine-tuning vs Prompt Engineering

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.

Representation learning

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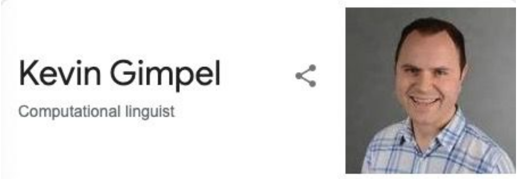
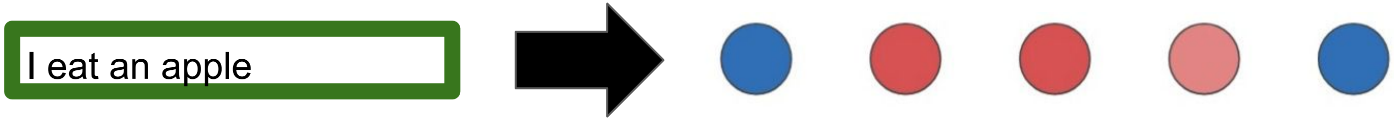




Text

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

Symbolic NLP	Statistical NLP	Neural NLP	?
1950 - early 1990s	1990s - 2010s	Present	Future

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

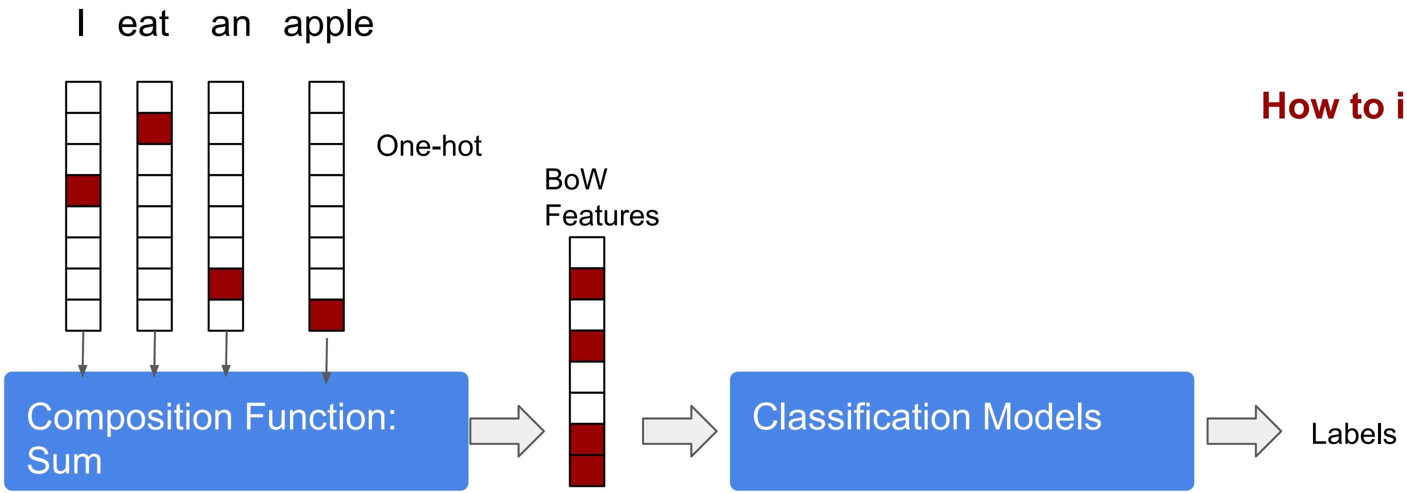
Limitations of document-Term matrix

- 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?

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

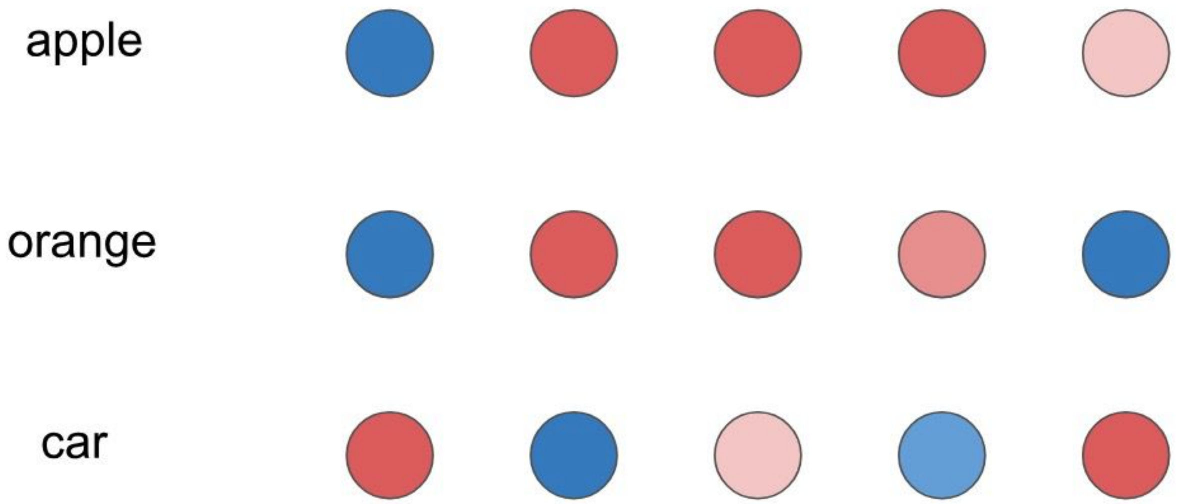
Word representation

- 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

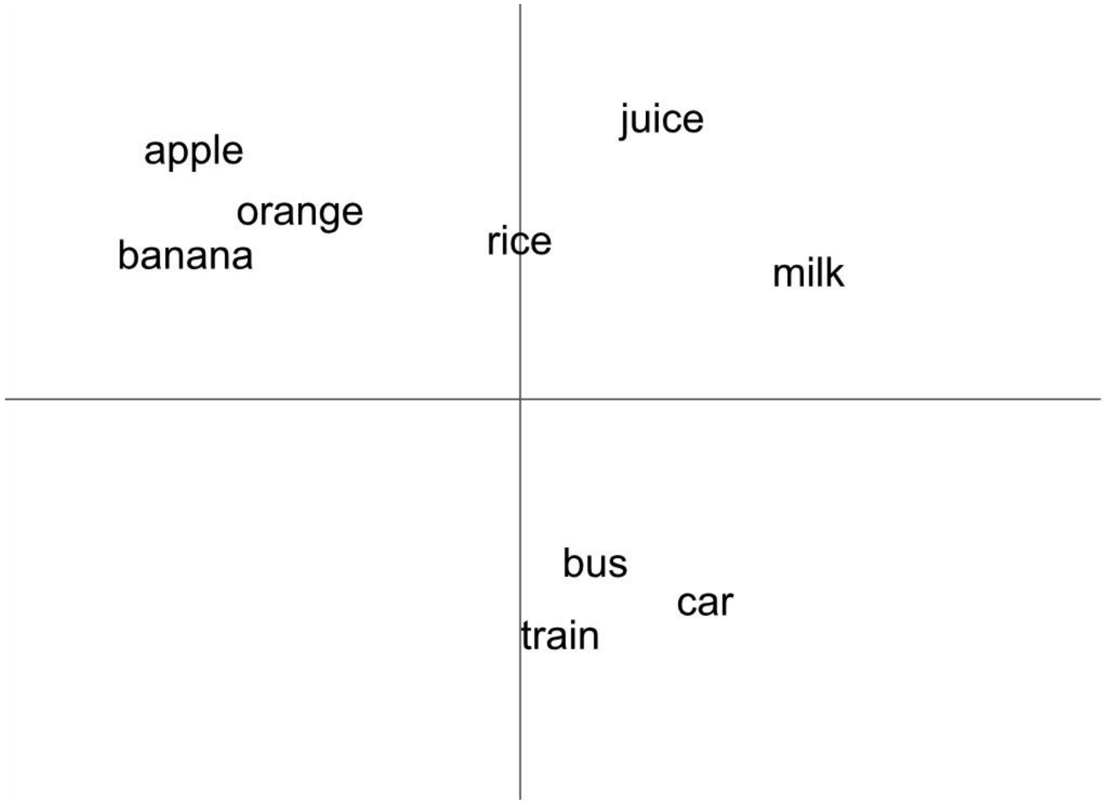
- Words should be encoded into a low-dimensional and dense vector



Word vectors

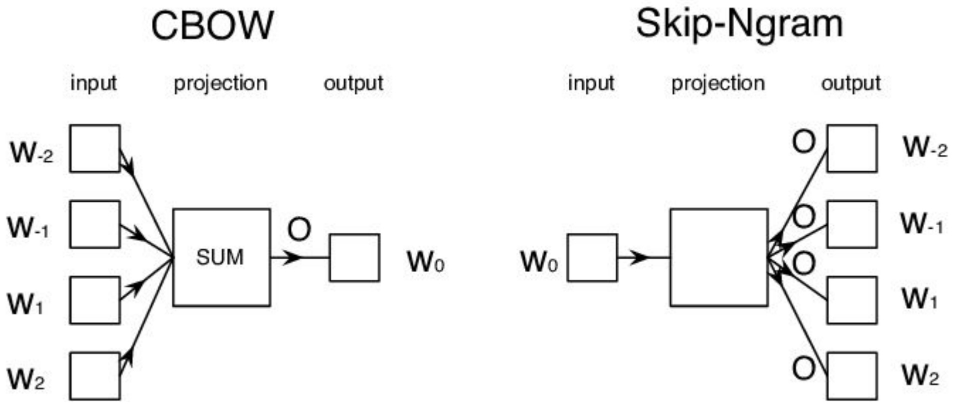
Project word vectors in a two-dimensional space. And visualize them!

Similar words are close to each other.

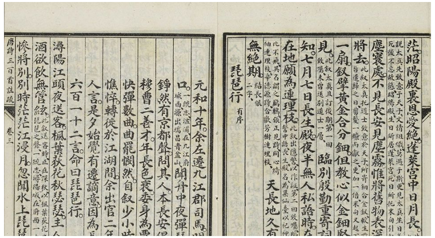


Word2Vec

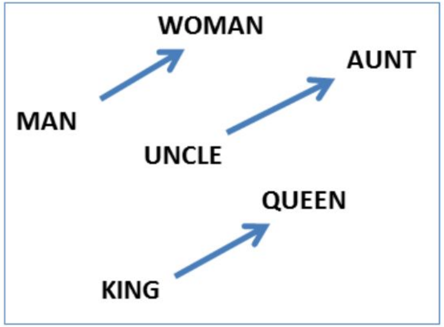
- A method of computing vector representation of words developed by Google.
- Open-source version of Word2Vec hosted by Google (in C)
- Train a simple neural network with a single hidden layer to perform word prediction tasks.
- Two structures proposed Continuous Bag of Words (CBoW) vs Skip-Gram



Word2Vec as BlackBox



input, output



Corpus **Word2Vec Tool** **Word Embeddings**

A Good Visualization for Word2Vec

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

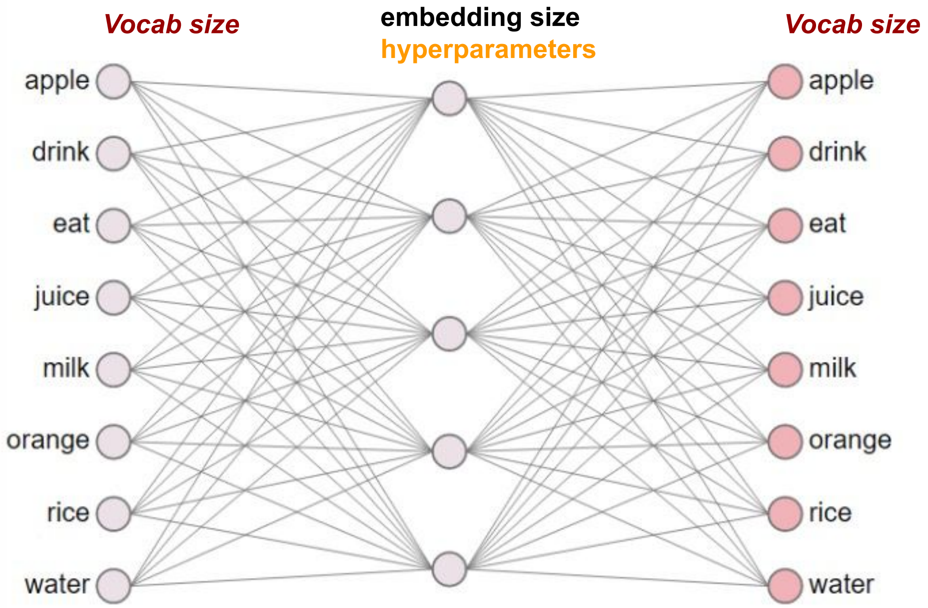
Target

- 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



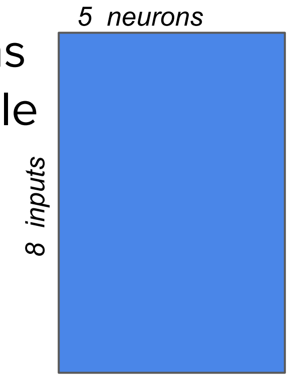
Structure Highlights:

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

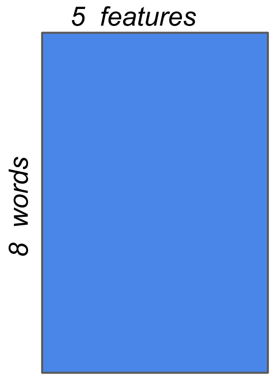
From Xin Rong 2016

Hidden layer

Hidden Layer Weights Matrix



Word Vector Look Up Table



- **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**

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

=

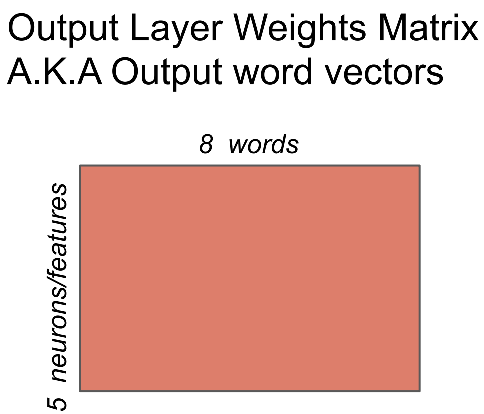
Word vector for “eat”

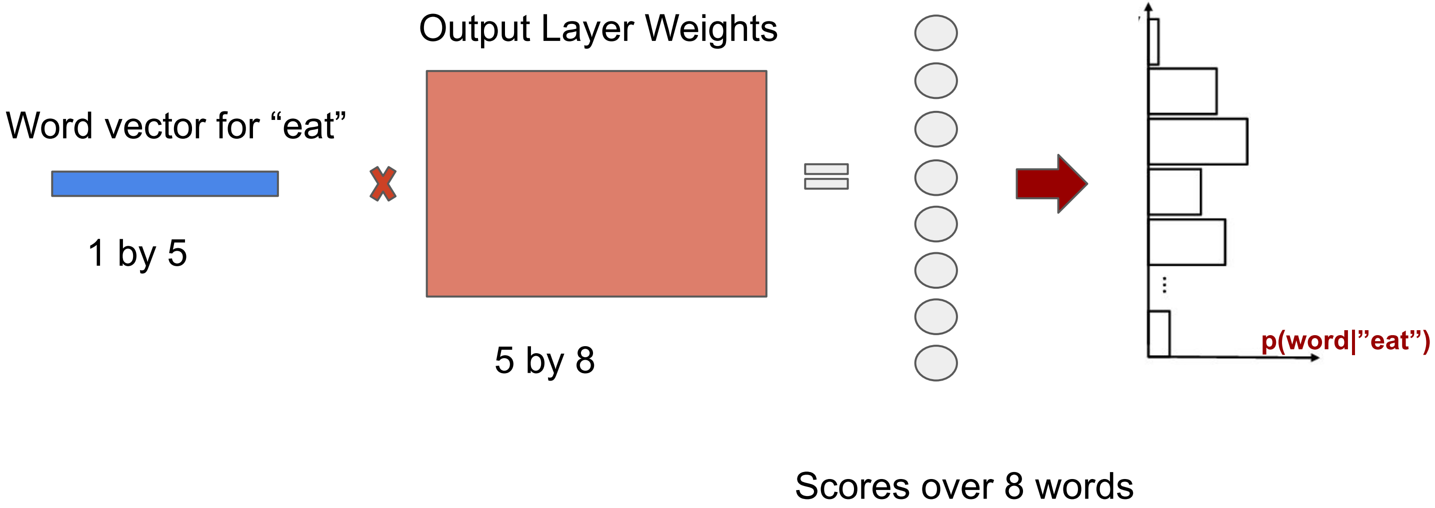
0.96, 1.5, 1.37, 0.34, 1.04

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**

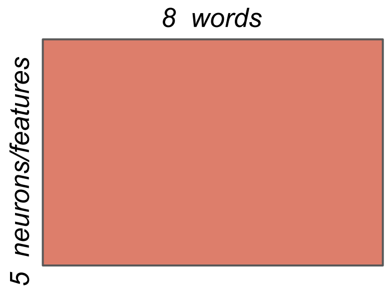




Output layer

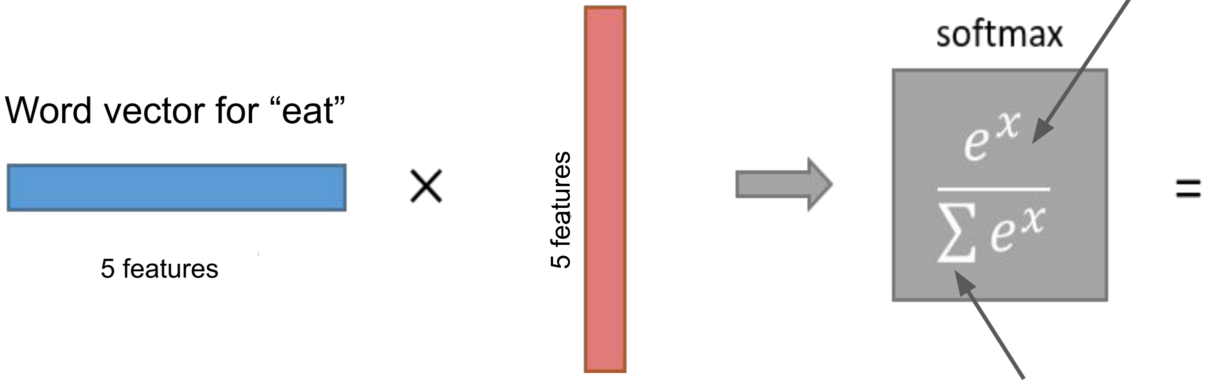
- Softmax Classifier
- Output word matrix denoted as **OVec**

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



Output weights for “apple”

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

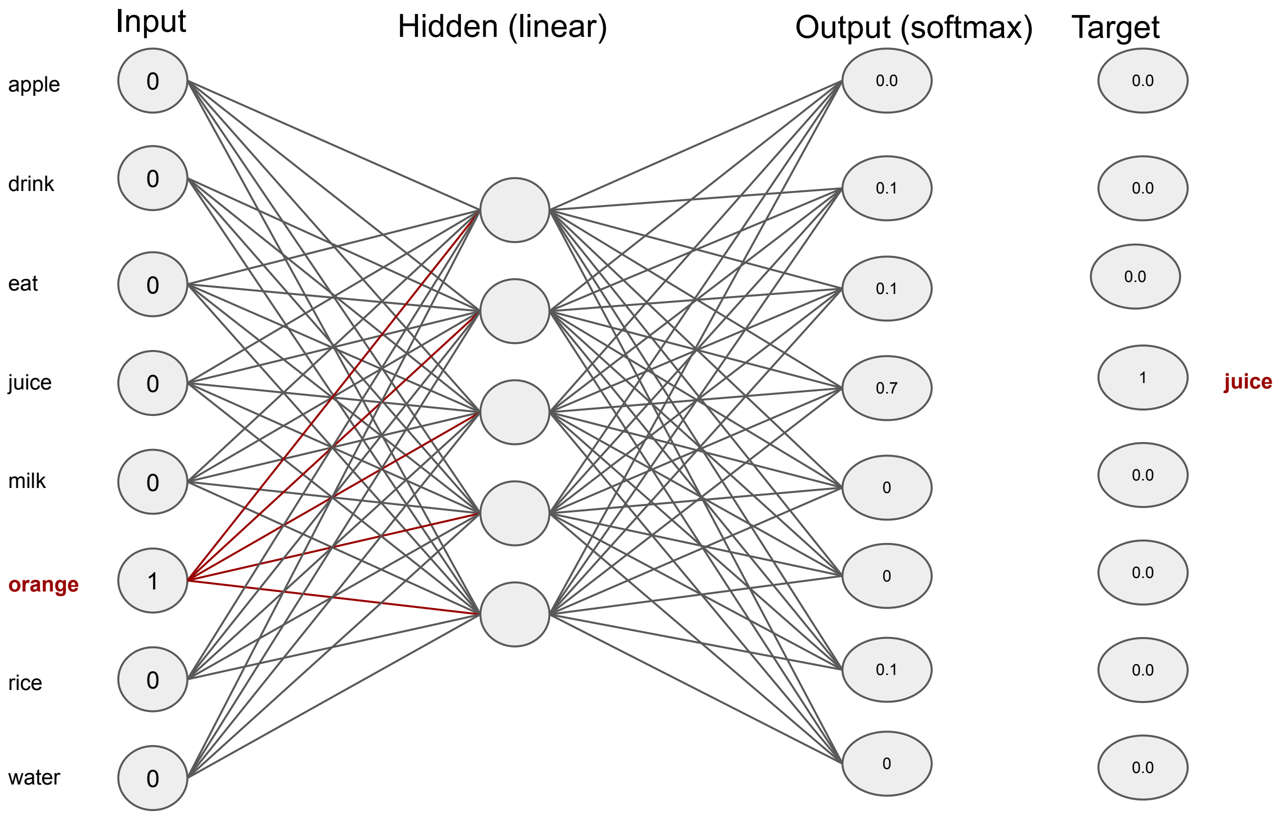


Probability that if you randomly pick a word nearby “eat”, that it is “apple”

p(apple|eat)

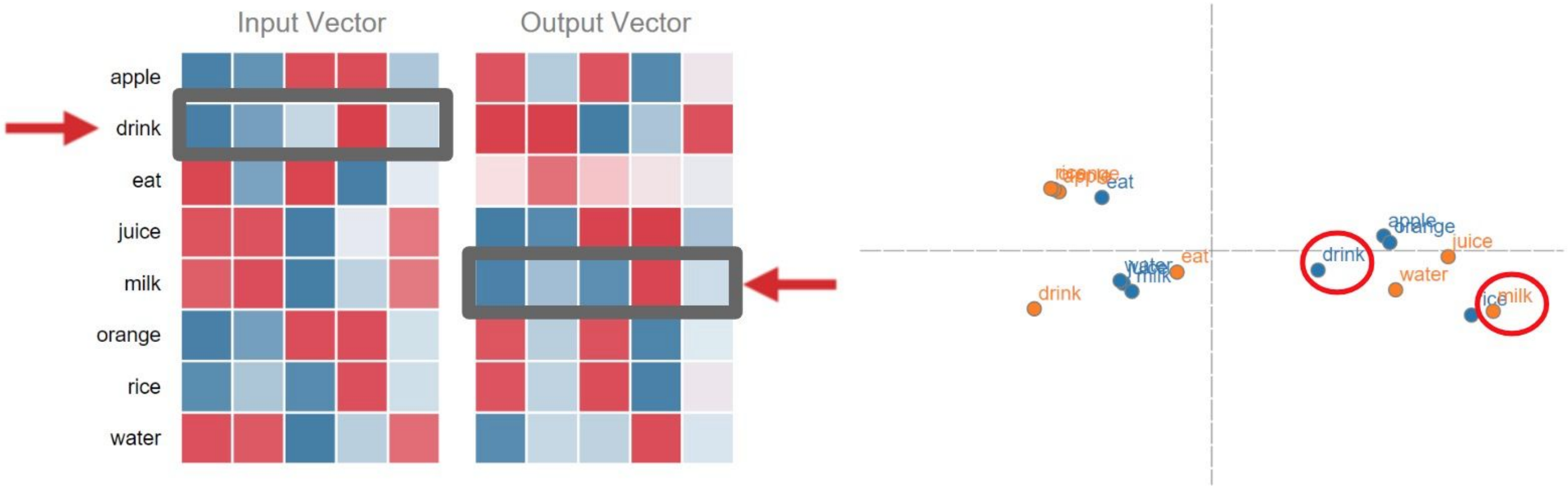
e^(IVec[eat]*OVec[apple]) + e^(IVec[eat]*OVec[juice]) + e^(IVec[eat]*OVec[drink])+e^(IVec[eat]*OVec[other vocab words])

Word2Vec



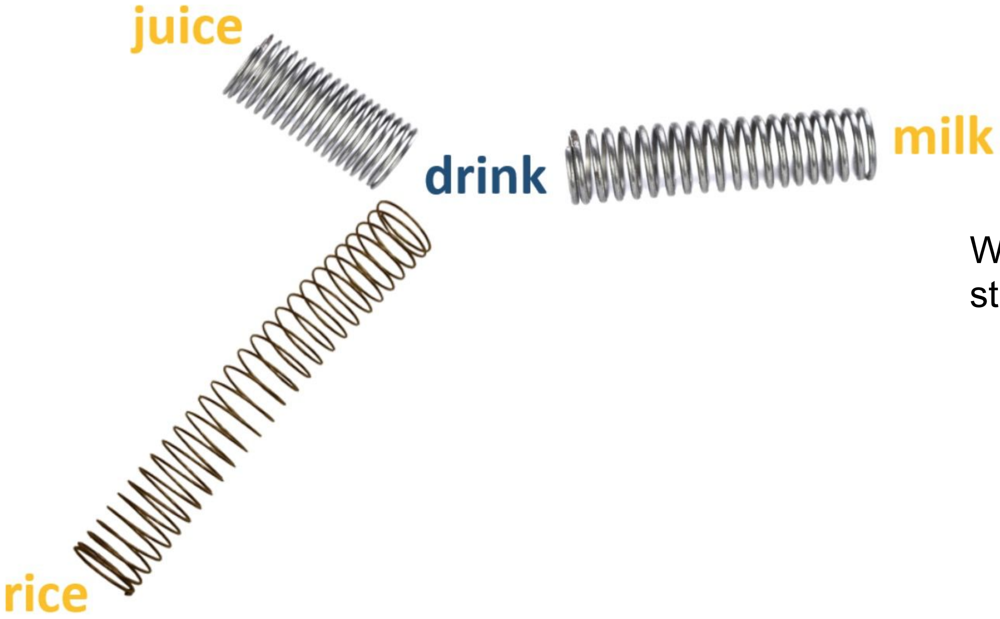
Then, we can compute the loss and call gradient descent to update model parameters.

Updating word vectors



From Xin Rong 2016

A force-directed graph



What decides the strength of the string?

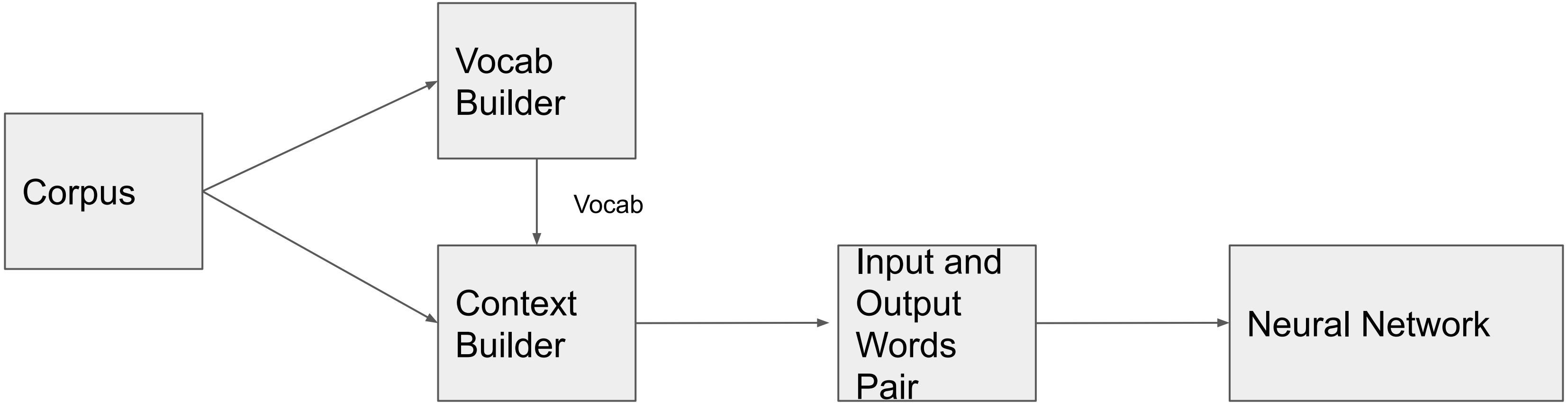
Idea behind Word2Vec

- 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

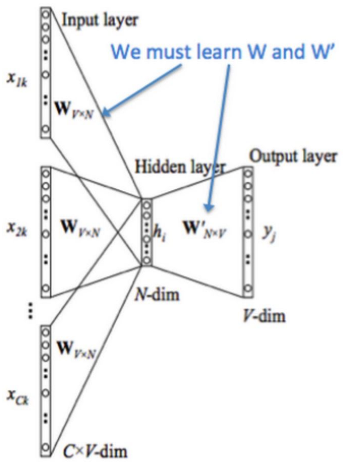
CBoW

- 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

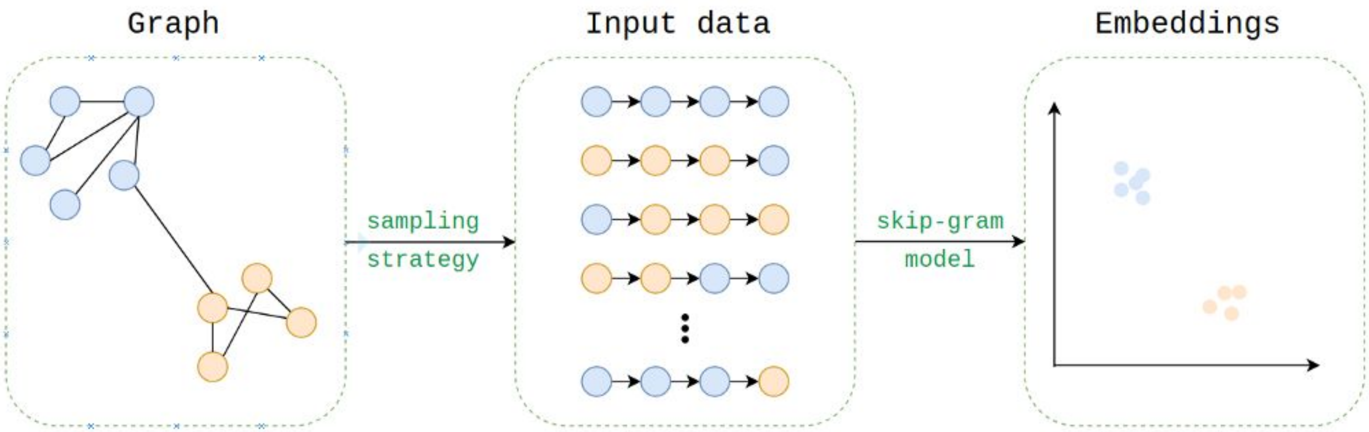
Input x
(give,a,at,the)

Target y
talk



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.

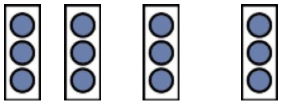


3. Neural Networks for NLP

Sequence of words

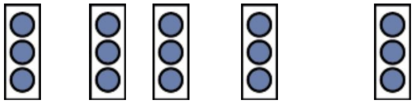
- Each sentence or document can be regarded as a sequence of vectors.
- The shape of matrix depends on the length of sequence. However, the majority of ML systems need fixed-length feature vectors.
- One simple solution: average the sequence of vectors, just like bag-of-words (abandon order information).

I hate this movie



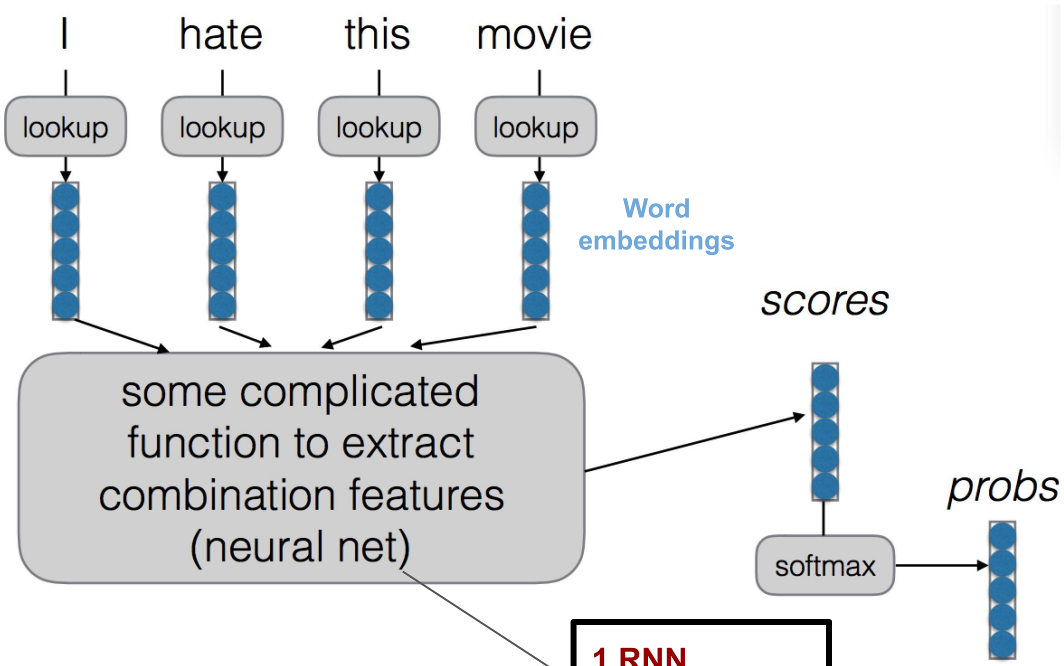
4 by d

This is my favorite movie.



5 by d

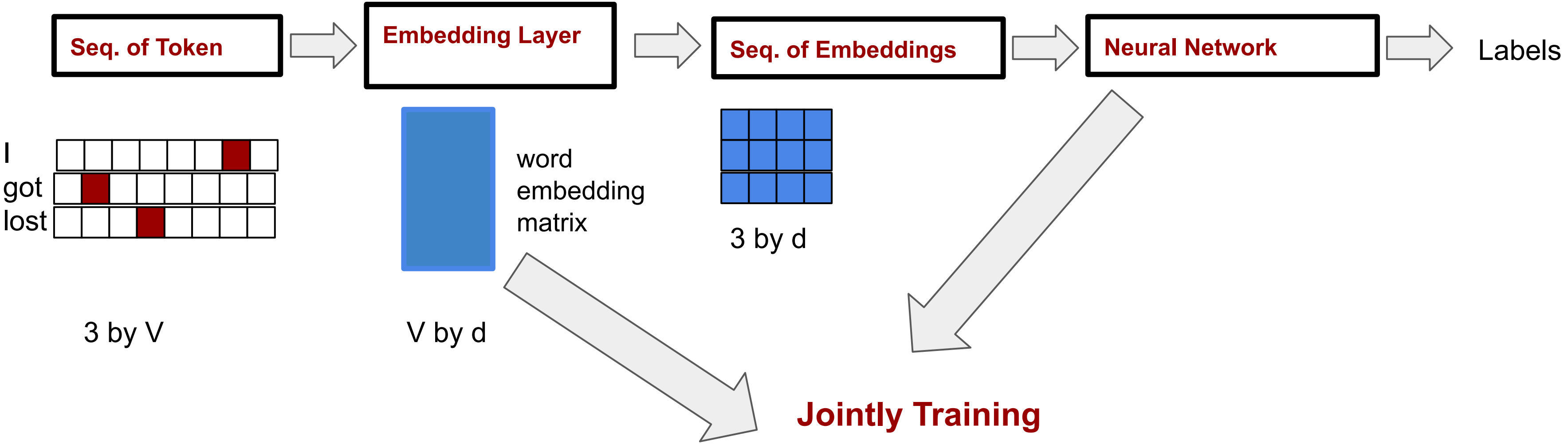
Complex semantic



1 RNN
2 CNN
3 Attention
etc

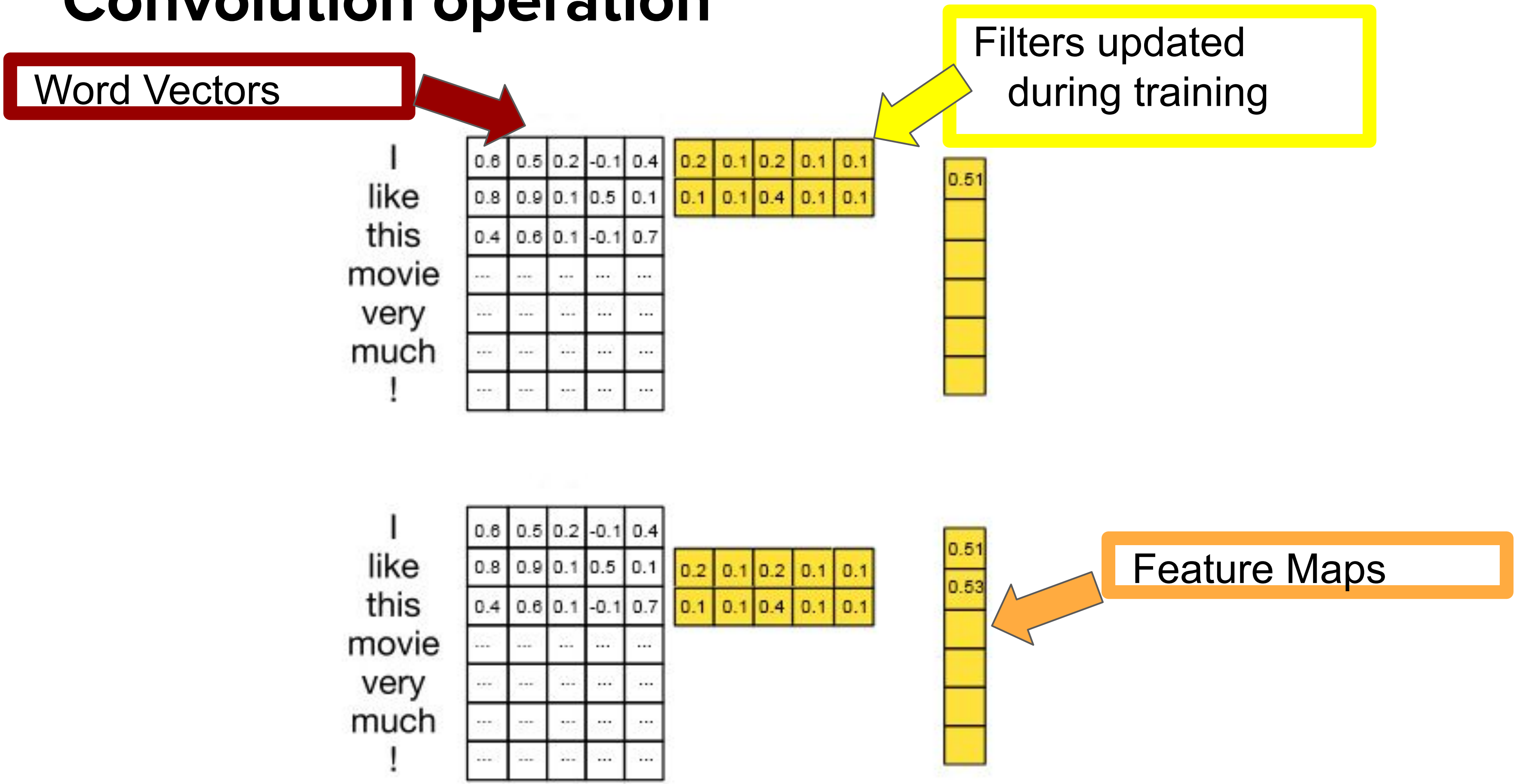
Word Embeddings is the foundation for deep learning's applications on NLP

Neural networks for NLP

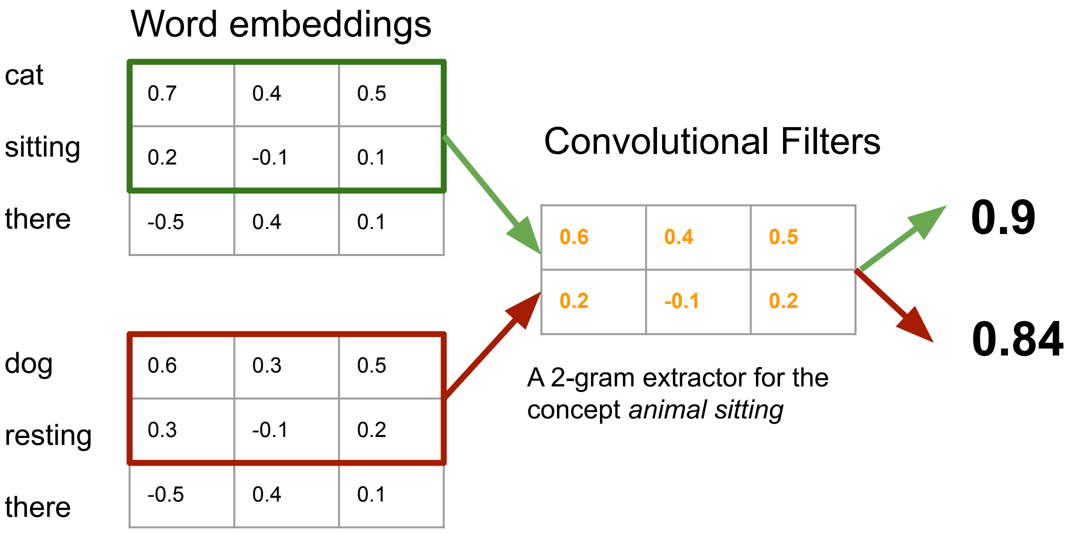


- Learn from Scratch: Random initialize the word embedding matrix and update the matrix and neural network parameters in the specific task
- Pre-train: Got pre-trained word embeddings as the embedding layer and only update neural network parameters in the specific task
- **Pre-train then fine tune**

Convolution operation



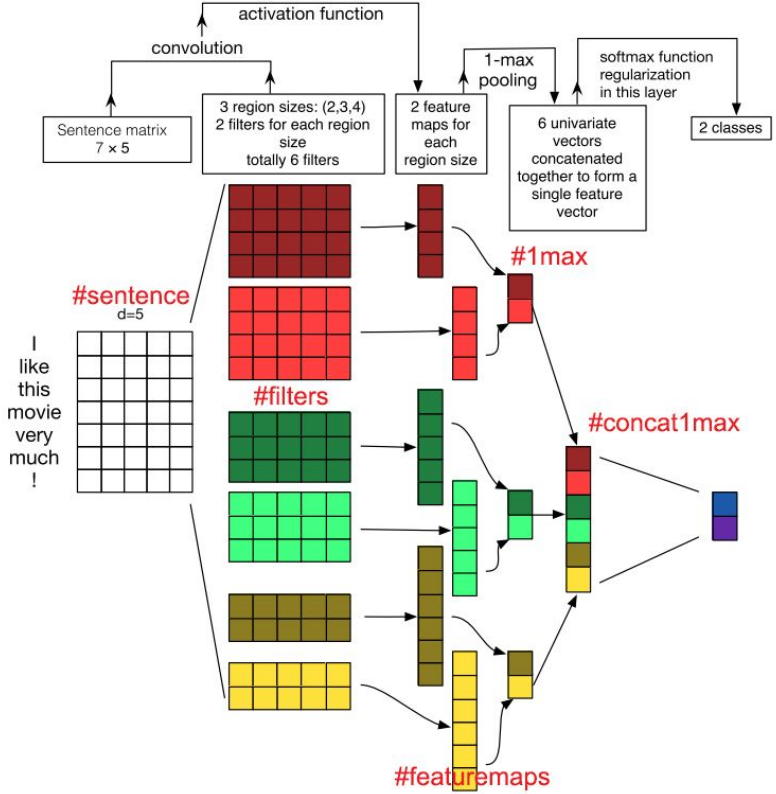
Toy example



- 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

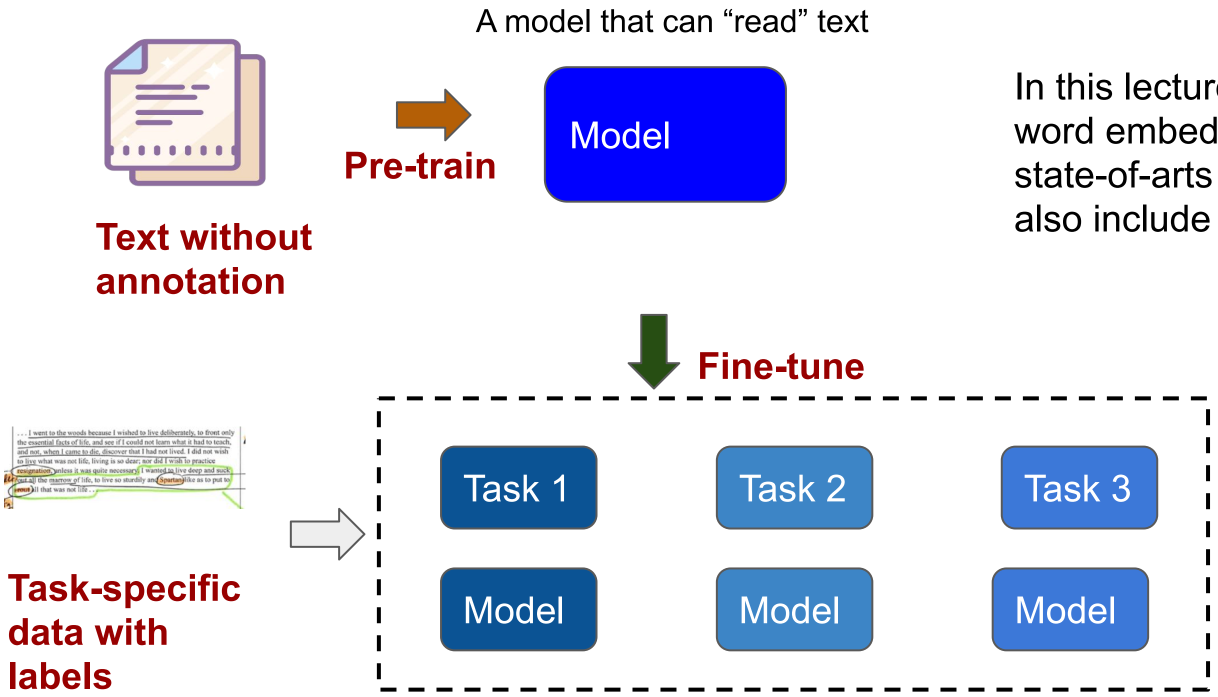


From Zhang 2015

How to build word embedding layer

- 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

Pre-train then Fine-tune



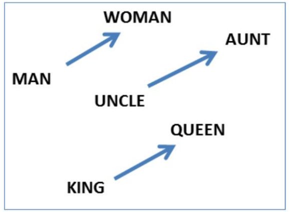
In this lecture, the model is only referred to word embedding matrix. However, in state-of-arts NLP techniques, the model will also include the following neural network.

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

4. Attention is all you Need

Attention Is All You Need

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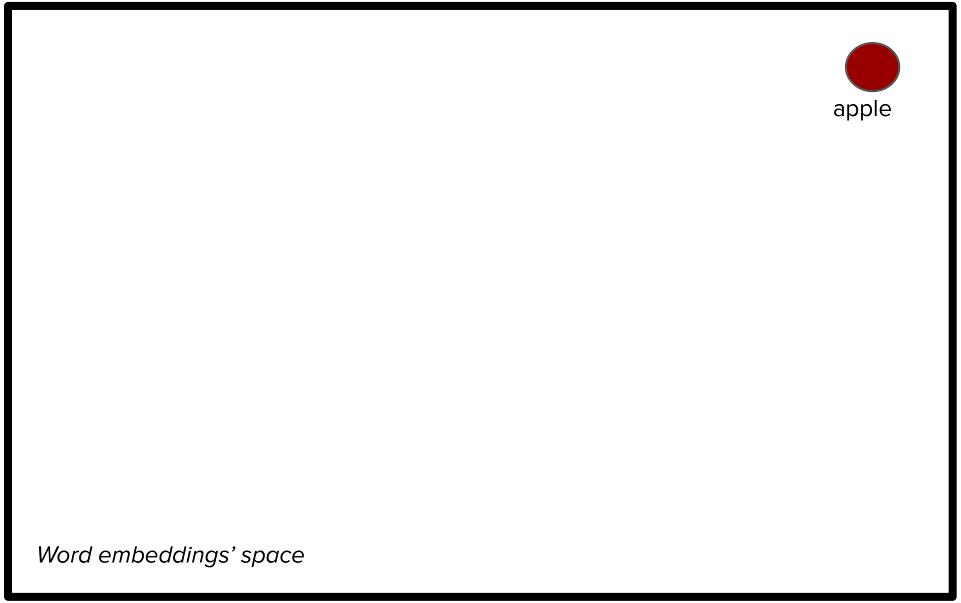
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

https://proceedings.neurips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

Word Embeddings

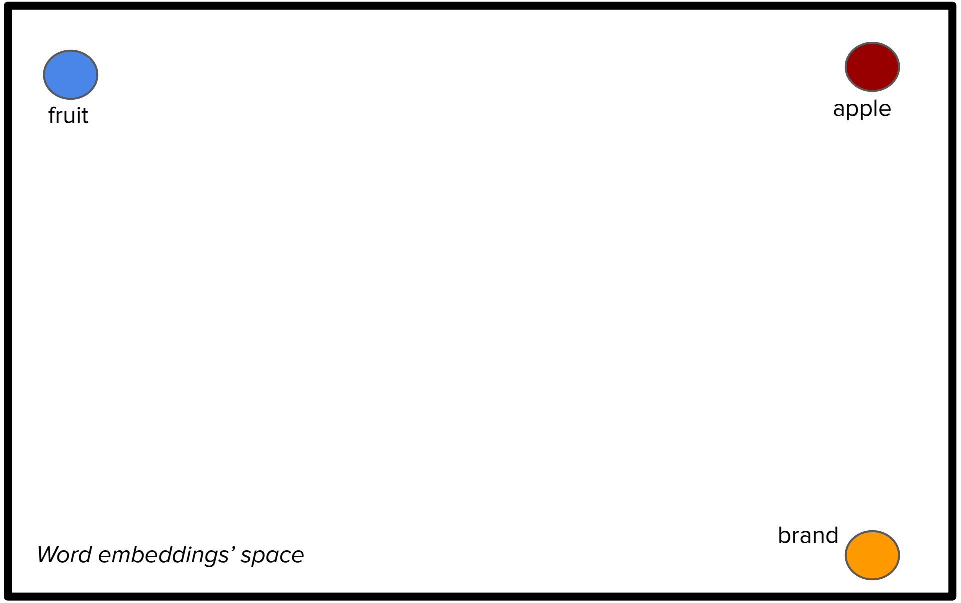
- **Apple** in two sentences:
  - Sentence 1: My favorite fruit is **apple**
  - Sentence 2: Solution: My favorite brand is **apple**



One embedding has multiple senses

Contextualized Word Embeddings

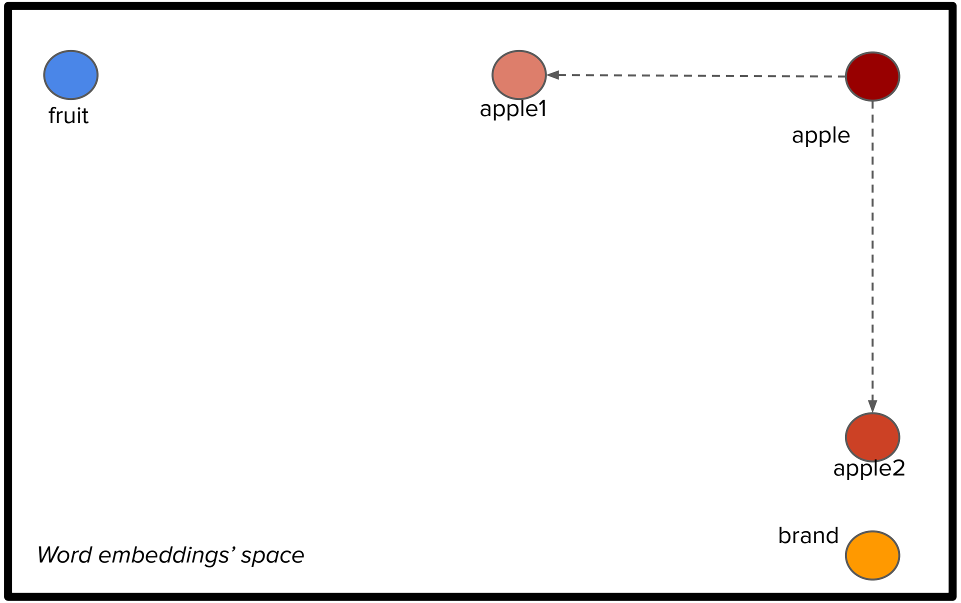
- Telling context in words
  - Sentence 1: My favorite fruit is **apple1**
  - Sentence 2: Solution: My favorite brand is **apple2**



From nearby words, we can guess two different meanings of this word (i.e., food and brand)

Contextualized Word Embeddings

- Telling context in words
  - Sentence 1: My favorite fruit is **apple1**
  - Sentence 2: Solution: My favorite brand is **apple2**



1. In sentence 1, move the word embedding of apple towards the word "fruit"
2. In sentence 2, move the word embedding of apple toward the word "brand"

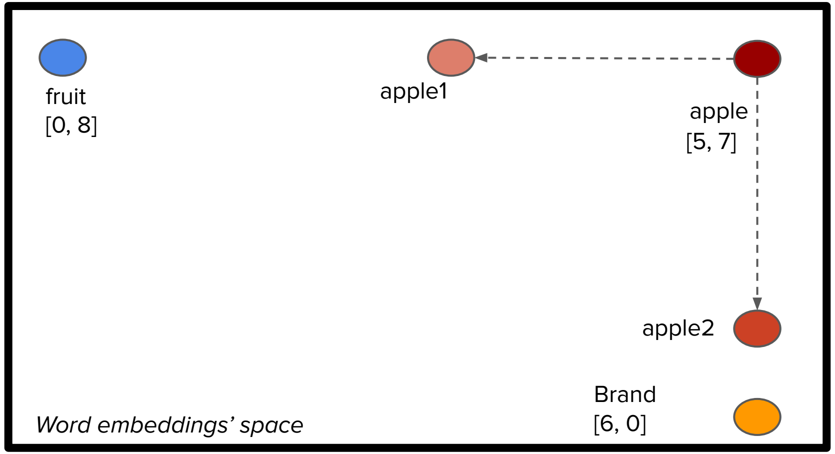
This is how attention will work

How to move one word closer to another one

- Average two words
  - apple1 = 0.8*apple + 0.2*fruit = [4.0, 7.2]
  - apple2 = 0.9*apple + 0.1*brand = [5.1, 6.3]

Similarity/Attention

Embeddings



Attention mechanism is able to learn multiple embeddings for the same word in multiple sentences

How to derive similarity

- **Apple** in two sentences:
  - Sentence 1: My favorite fruit is **apple**
  - Sentence 2: My favorite brand is **apple**
- Why we move apple to fruit in sentence 1? Instead of other words as “my” and “is”
- It is based on the similarity!

How to derive similarity

- In good embeddings, the similarity between two irrelevant words would be zero, while the similarity between the related pair would be high

	my	favourite	fruit	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
fruit	0	0	1	0	0.25
is	0	0	0	1	0
apple	0	0	0.25	0	1

	my	favourite	brand	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
food	0	0	1	0	0.11
is	0	0	0	1	0
apple	0	0	0.11	0	1

How to derive similarity

- The diagonal entries are all 1
- The similarity between any irrelevant words is 0 (for simplicity)
- The similarity between apple and fruit is 0.25 while the one between apple and brand is 0.11 considering apple is used more often in the same context as fruit

	my	favourite	fruit	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
fruit	0	0	1	0	0.25
is	0	0	0	1	0
apple	0	0	0.25	0	1

	my	favourite	brand	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
food	0	0	1	0	0.11
is	0	0	0	1	0
apple	0	0	0.11	0	1

How to derive similarity

- Contextualized Target Word = The sum of a product between the similarity between target word and context word * context word
- We should also normalize the similarity along the sentence
- Therefore
  - my (in the sentence 1) = my
  - apple (in the sentence 1) = 0.2 * fruit + 0.8 * apple

	my	favourite	fruit	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
fruit	0	0	1	0	0.25
is	0	0	0	1	0
apple	0	0	0.25	0	1

	my	favourite	brand	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
food	0	0	1	0	0.11
is	0	0	0	1	0
apple	0	0	0.11	0	1

Attention Mechanism

Sentence i: My favourite fruit is apple

	my	favourite	fruit	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
fruit	0	0	1	0	0.25
is	0	0	0	1	0
apple	0	0	0.25	0	1

New Word Index	Attention Step
my_i	my
favourite_i	favourite
fruit_i	0.8*fruit+0.2*apple
is_i	is
apple_i	0.2*fruit+0.8*apple

Here, we only use the same embedding for attention weights and the base vectors

Self-Attention Layer

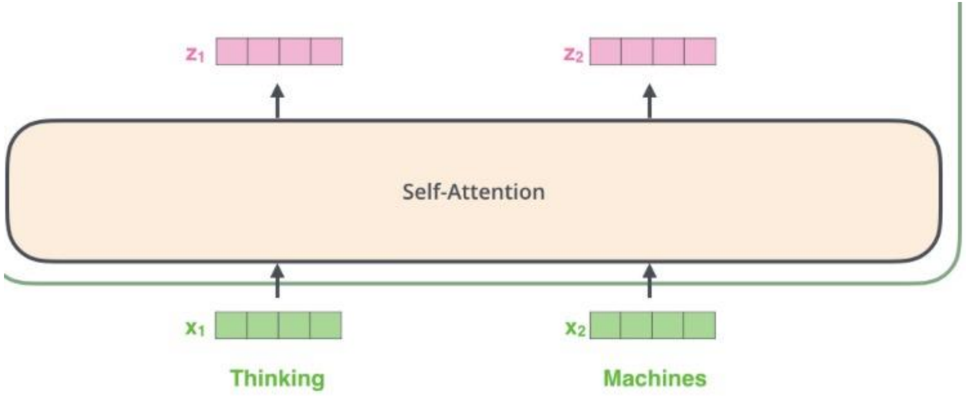
Sentence i: My favourite fruit is apple

	my	favourite	fruit	is	apple
my	1	0	0	0	0
favourite	0	1	0	0	0
fruit	0	0	1	0	0.25
is	0	0	0	1	0
apple	0	0	0.25	0	1

New Word Index	Attention Step
my_i	my
favourite_i	favourite
fruit_i	0.8*fruit+0.2*apple
is_i	is
apple_i	0.2*fruit+0.8*apple

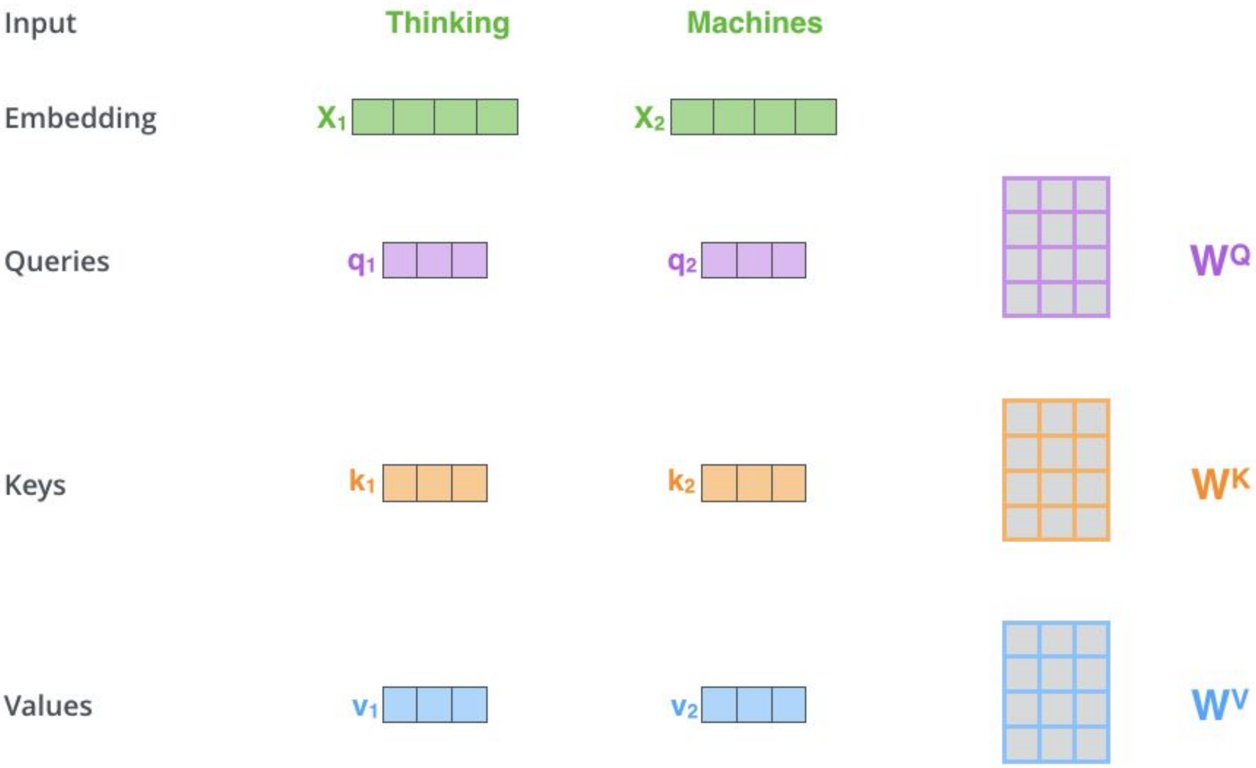
Query, Key and Value vector would be created for each word

Self-Attention Layer

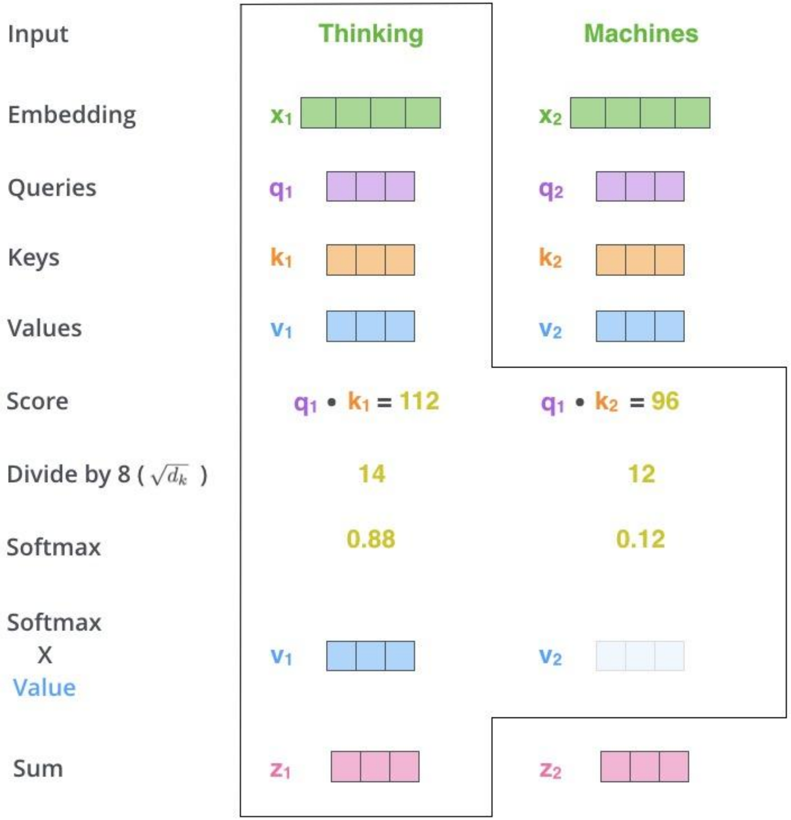


A sequence of vectors in,
A sequence of vector out

Self-Attention Layer

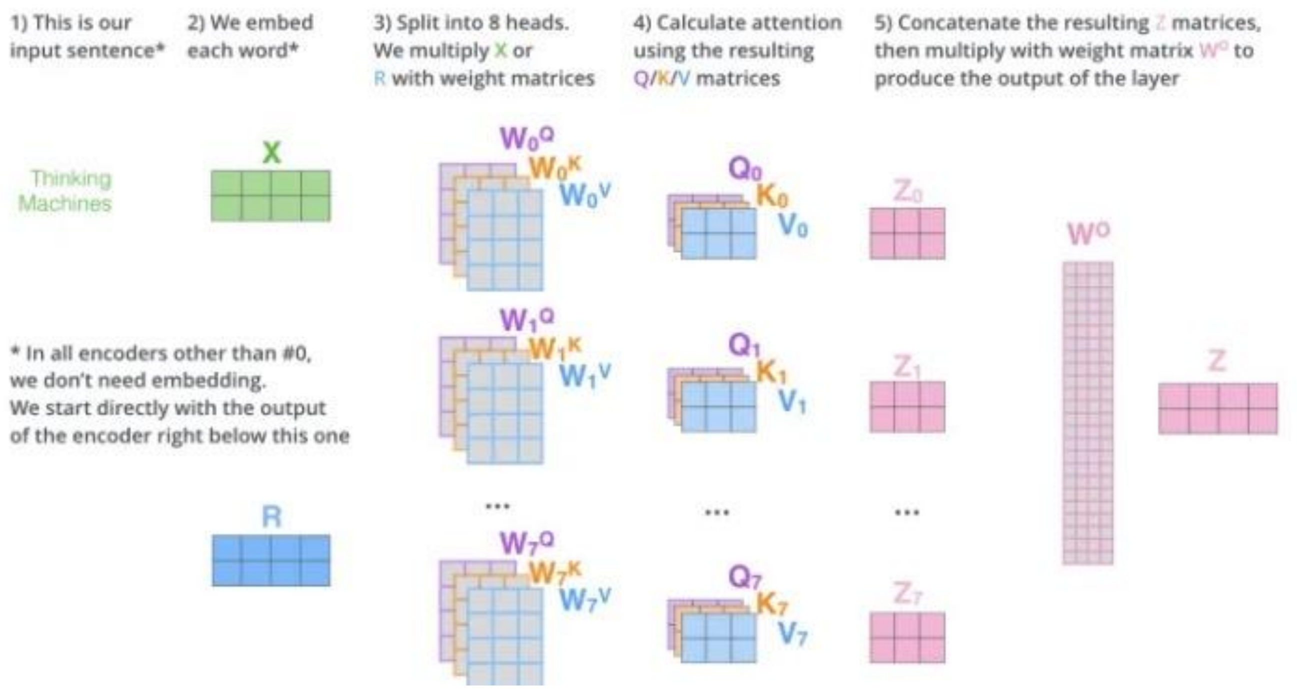


Self-Attention Layer



Each pair of q, k, v transformation is corresponding to each neuron. In attentional layer, we call it multihead (multi-neurons)

MultiHeadAttention



What are model parameters?

MultiHeadAttention in Keras

```
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers import MultiHeadAttention
```

```
target = tf.keras.Input(shape=[6, 16])

# assume it is a sentence of 6 words. Then, each word has a
```

```
layer = MultiHeadAttention(num_heads=1, key_dim=2)
output_tensor, attention_scores = layer(target, target, return_attention_scores=True)
print(output_tensor.shape)
print(attention_scores.shape)
```

```
(None, 6, 16)
(None, 1, 6, 6)
```

```
for matrix in layer.weights:
    print(matrix.shape)
```

```
(16, 1, 2)
(1, 2)
(16, 1, 2)
(1, 2)
(16, 1, 2)
(1, 2)
(1, 2, 16)
(16,)
```

MultiHeadAttention in Keras

```
layer = MultiHeadAttention(num_heads=3, key_dim=2)
target = tf.keras.Input(shape=[6, 16])
output_tensor, attention_scores = layer(target, target, return_attention_scores=True)
print(output_tensor.shape)
print(attention_scores.shape)
```

```
(None, 6, 16)
(None, 3, 6, 6)
```

```
for matrix in layer.weights:
    print(matrix.shape)
```

```
(16, 3, 2)
(3, 2)
(16, 3, 2)
(3, 2)
(16, 3, 2)
(3, 2)
(3, 2, 16)
(16,)
```

MultiHeadAttention in Keras

If we change the key_dim from 2 to 5?

```
layer = MultiHeadAttention(num_heads=3, key_dim=2)
target = tf.keras.Input(shape=[6, 16])
output_tensor, attention_scores = layer(target, target, return_attention_scores=True)
print(output_tensor.shape)
print(attention_scores.shape)
```

```
(None, 6, 16)
(None, 3, 6, 6)
```

```
for matrix in layer.weights:
    print(matrix.shape)
```

```
(16, 3, 2)
(3, 2)
(16, 3, 2)
(3, 2)
(16, 3, 2)
(3, 2)
(3, 2, 16)
(16,)
```

https://github.com/rz0718/BT5153_2023/blob/main/codes/lab_lecture08/Attention_Layer_in_Keras.ipynb

Keras Implementation

https://keras.io/examples/nlp/text_classification_with_transformer/

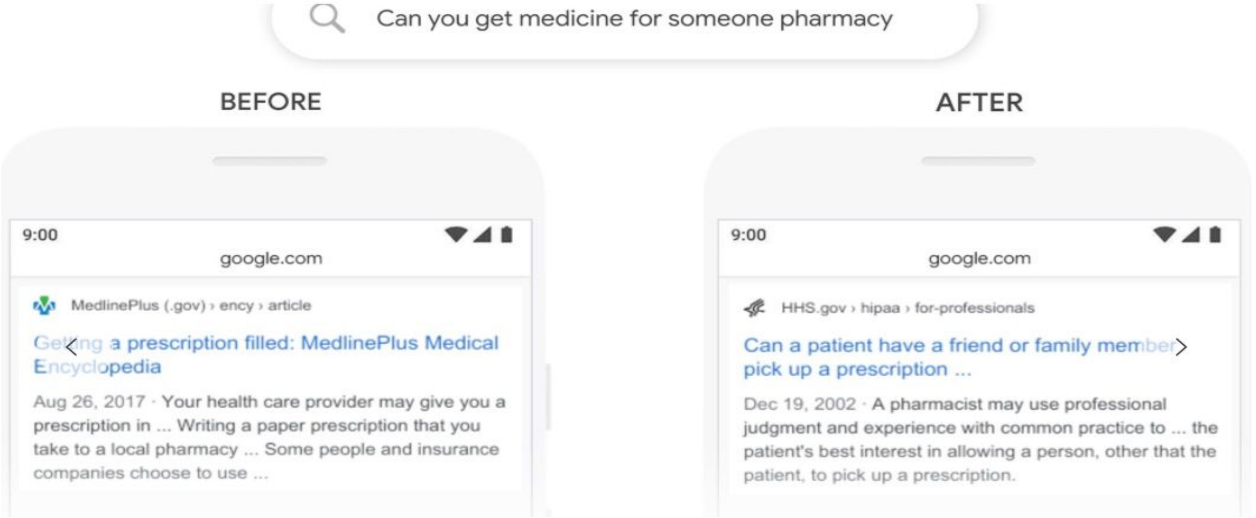
Details Behind Transformer

1. https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/
2. http://jalammar.github.io/illustrated-transformer/

Visualizing Ichiban!!!

5. Introduction to BERT

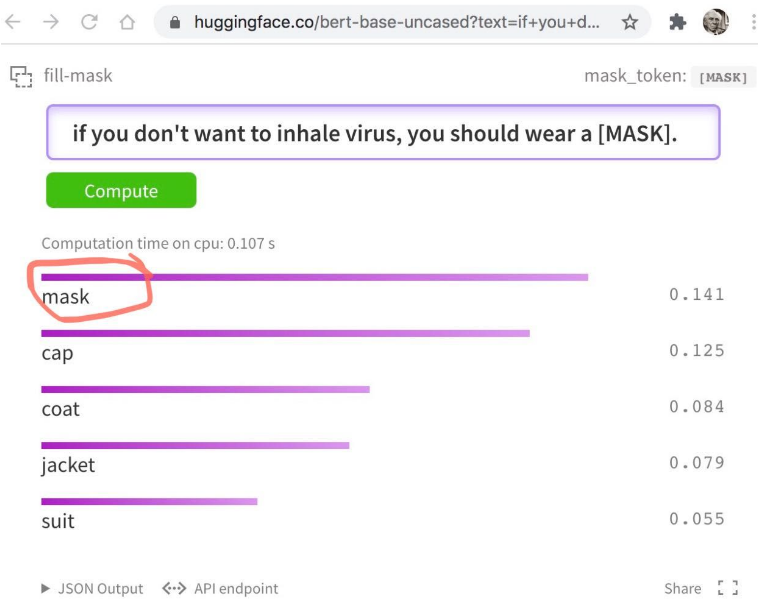
BERT in Google Search



With the latest advancements from our research team in the science of language understanding--made possible by machine learning--we're making a significant improvement to how we understand queries, representing the biggest leap forward in the past five years, and one of the biggest leaps forward in the history of Search.

https://blog.google/products/search/search-language-understanding-bert/

BERT vs Somebody



Try:
https://huggingface.co/bert-base-uncased?text=if+you+don%27t+want+to+inhale+virus+is%2C+you+should+wear+a+%5BMASK%5D

Extraction-based QA using BERT

```
question = "What can we learn in NUS?"
answer_text = "The National University of Singapore (NUS) is the national research university of Singapore. \
               Founded in 1905 as the Straits Settlements and Federated Malay States Government Medical School, NUS is the oldest higher education institution in Singapore. \
               It is consistently ranked within the top 20 universities in the world and is considered to be the best university in the Asia-Pacific. \
               NUS is a comprehensive research university, \
               offering a wide range of disciplines, including the sciences, medicine and dentistry, design and environment, law, arts and social sciences, engineering, business, computing and music \
               at both the undergraduate and postgraduate levels."
```

BERT

```
print('Answer: "' + answer + '"')
```

```
Answer: "sciences , medicine and dentistry , design and environment , law , arts and social sciences , engineering , business , computing and music"
```

```
question = "What does NUS mean?"
answer_text = "The National University of Singapore (NUS) is the national research university of Singapore. \
               Founded in 1905 as the Straits Settlements and Federated Malay States Government Medical School, NUS is the oldest higher education institution in Singapore. \
               It is consistently ranked within the top 20 universities in the world and is considered to be the best university in the Asia-Pacific. \
               NUS is a comprehensive research university, \
               offering a wide range of disciplines, including the sciences, medicine and dentistry, design and environment, law, arts and social sciences, engineering, business, computing and music \
               at both the undergraduate and postgraduate levels."
```

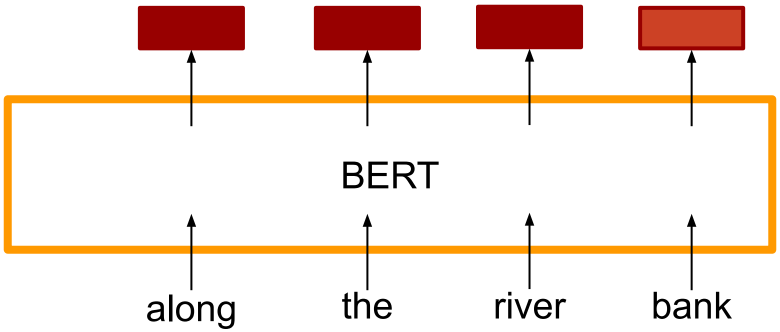
BERT

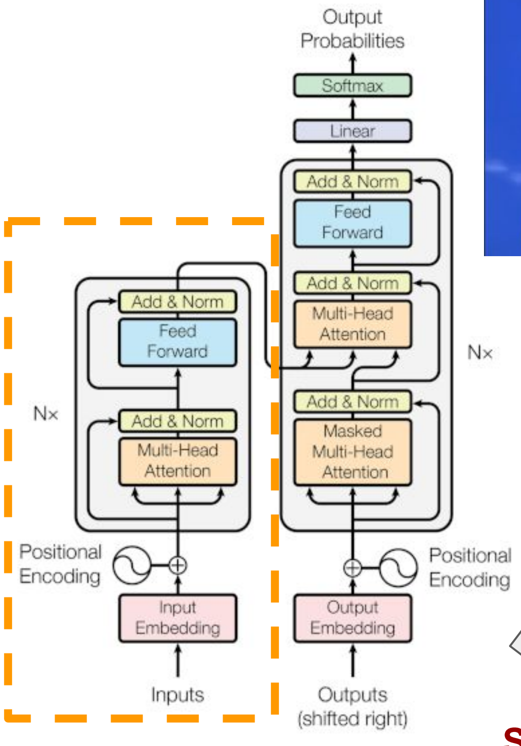
```
print('Answer: "' + answer + '"')
```

```
Answer: "national university of singapore"
```

What is BERT

- **B**idirectional **E**ncoder **R**epresentations from **T**ransformers (**BERT**)
- BERT: Encoder of Transformer,



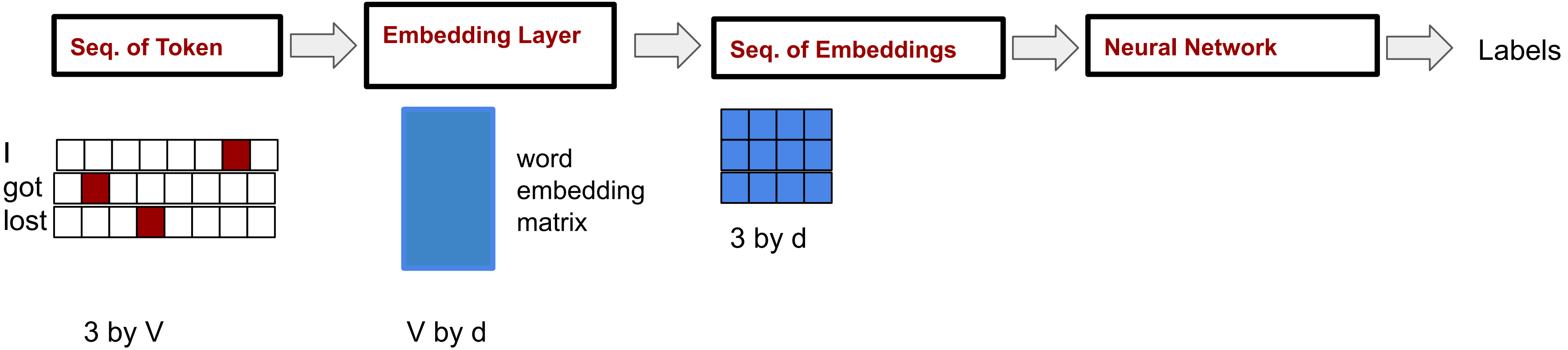


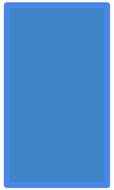
Transformer

Given a sequence of words, generate a sequence of vectors and then can be used for various NLP tasks

Solve Seq2Seq Task

Neural Networks for NLP





Each word has a fixed vector

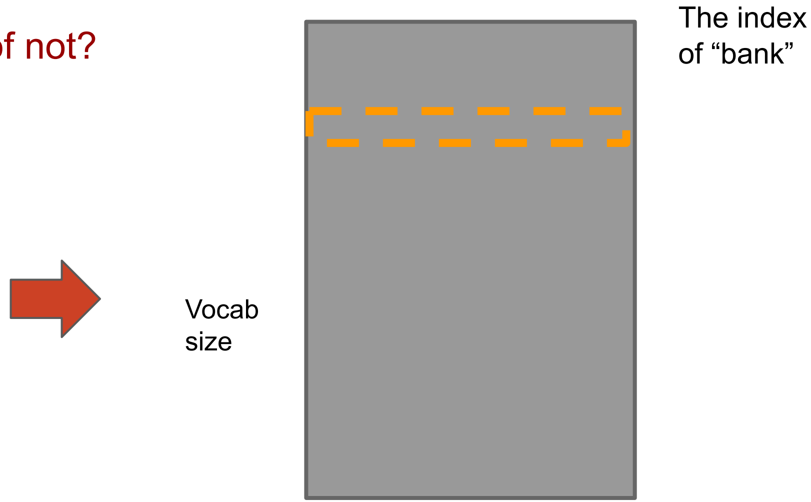
Can not address multi-sense problem!

Multiple Senses of Words

- It is safest to deposit your money in the bank.
- All the animals lined up along the river bank.
- Today, blood banks collect blood.

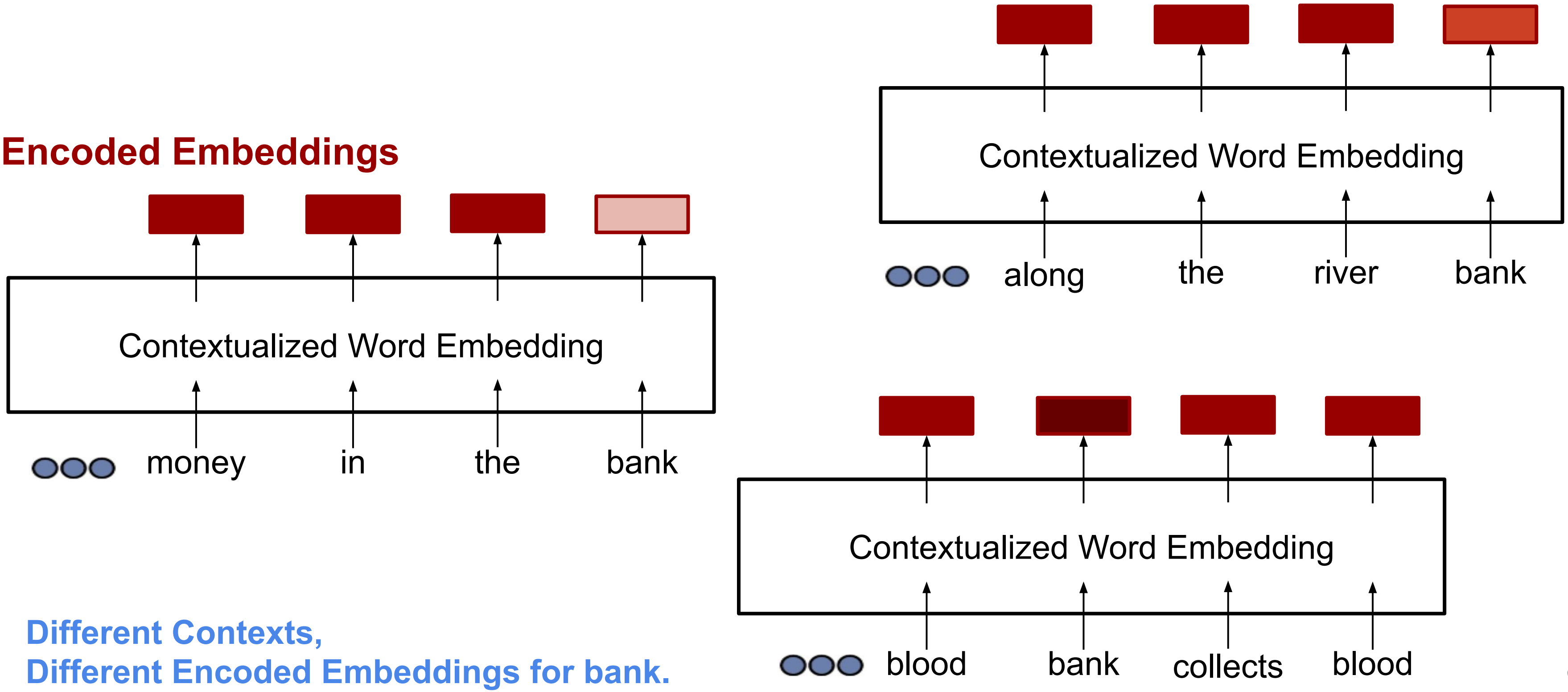
The third sense of not?

Word2Vec, Fasttext,Glove and other word embedding models



Contextualized Word Embeddings

Encoded Embeddings



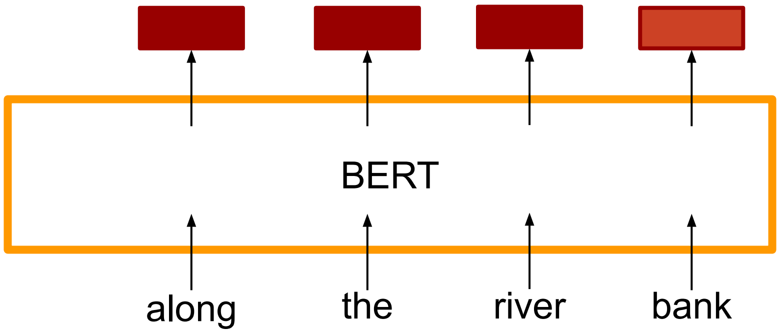
Different Contexts,
Different Encoded Embeddings for bank.

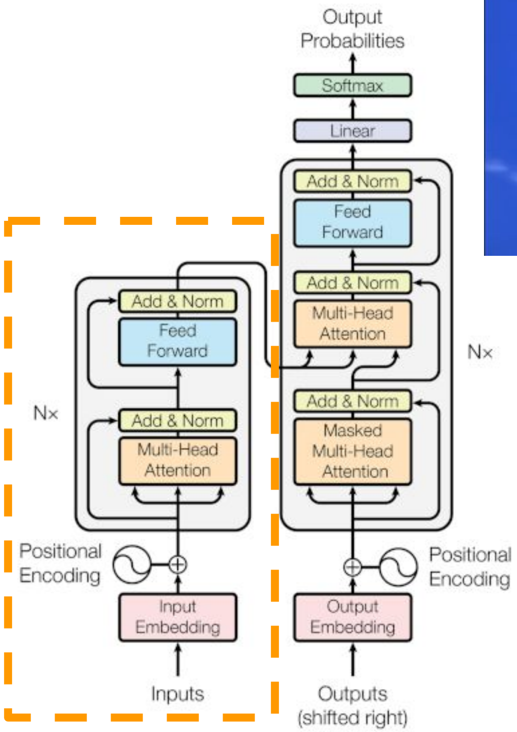
Embeddings generated from BERT

Cos-similarities among vectors of "apple" in different context

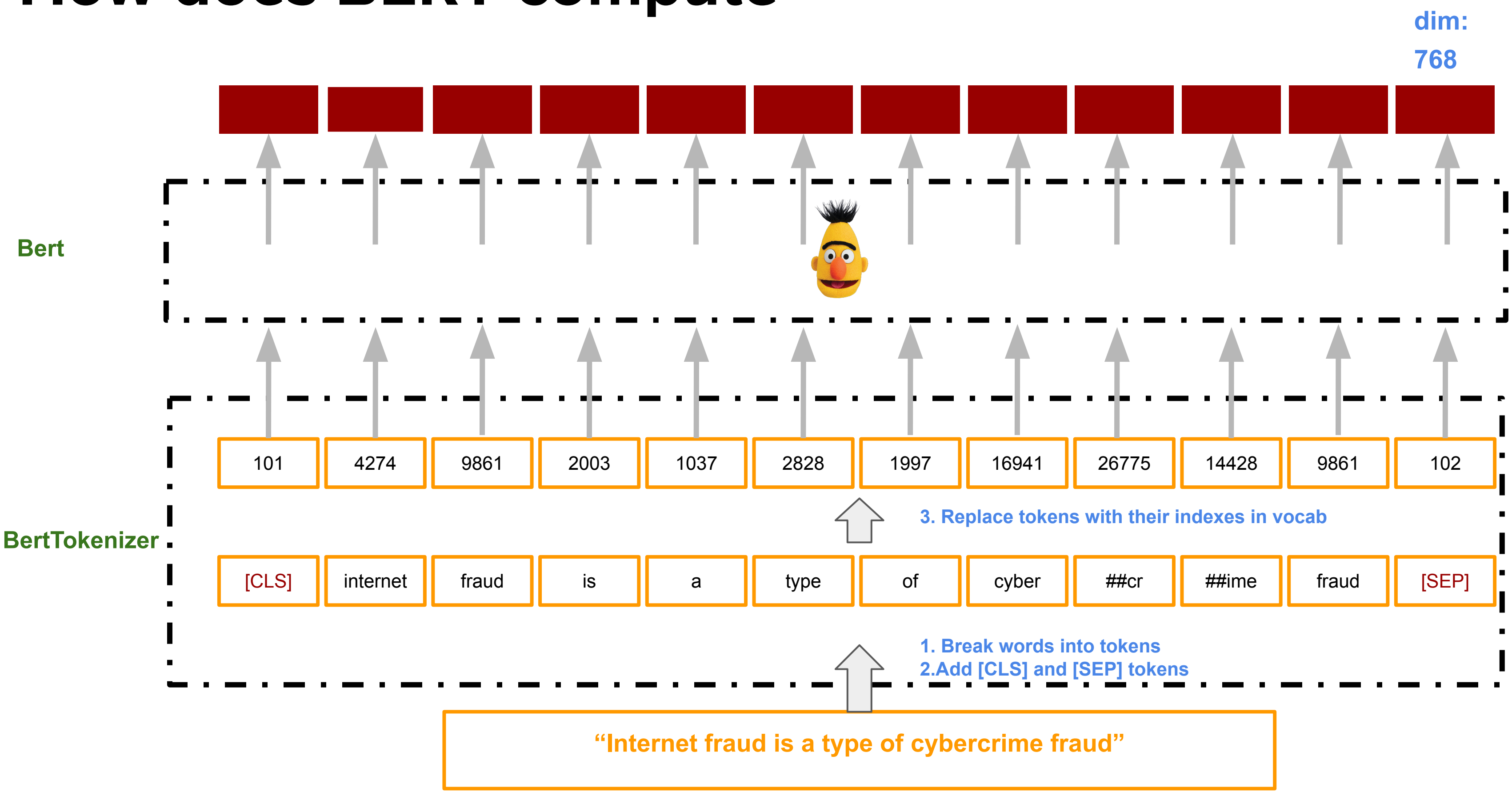
BERT

- **Bidirectional Encoder Representations from Transformers (BERT)**
- BERT: Encoder of Transformer,

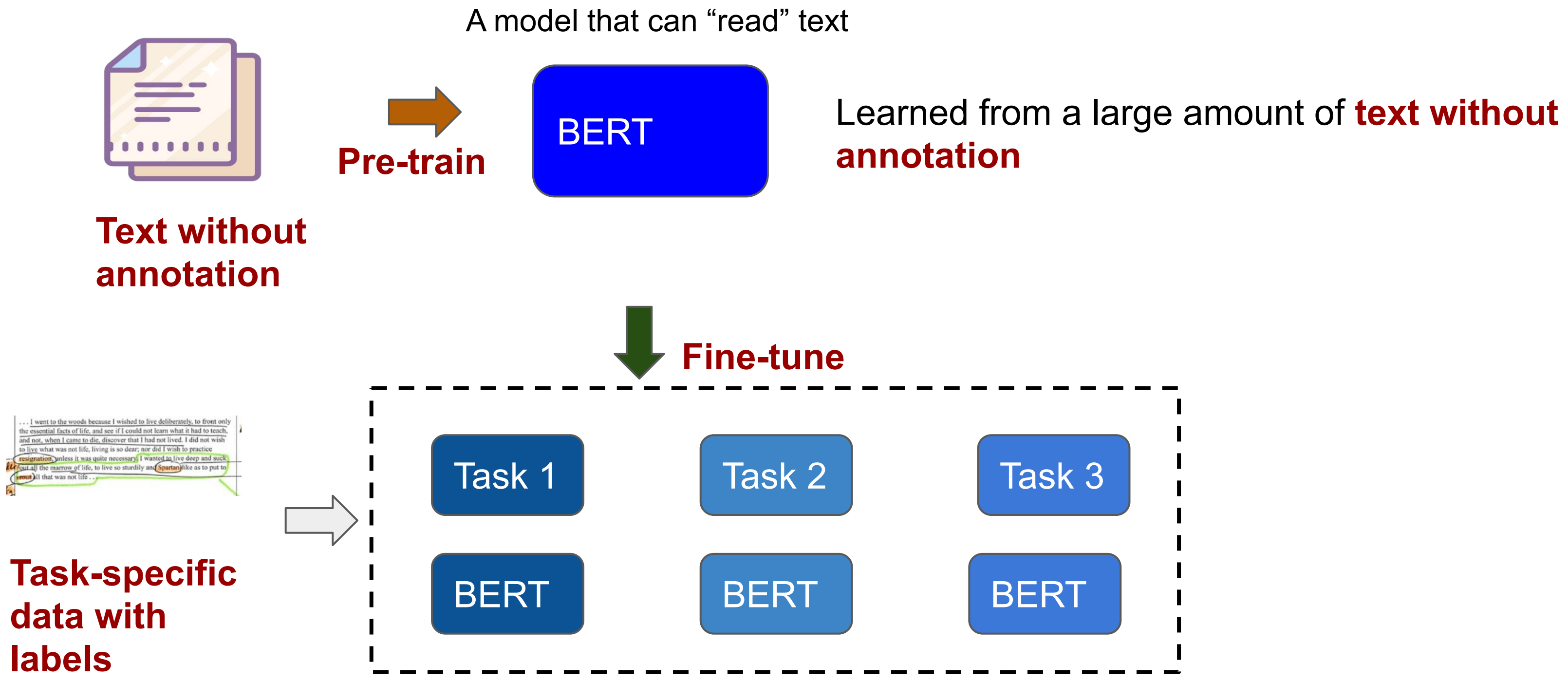




How does BERT compute

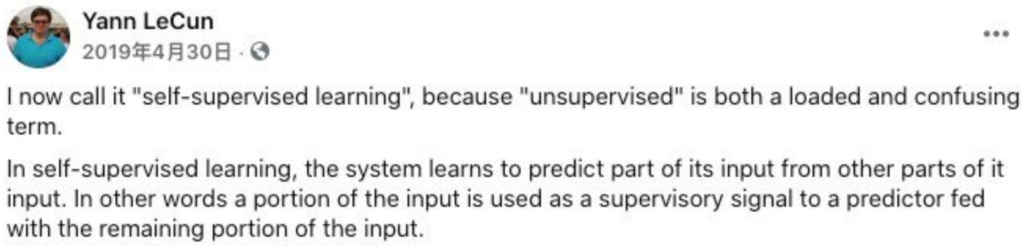


How to use BERT



How to Pre-Train

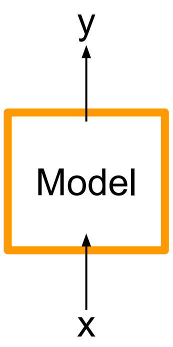
The answer is **self-supervised learning**.



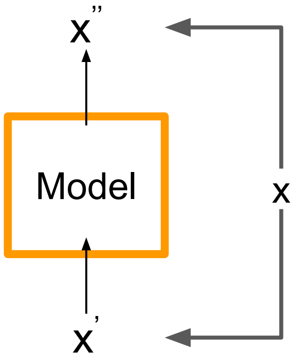
Yann LeCun
2019年4月30日 ·

I now call it "self-supervised learning", because "unsupervised" is both a loaded and confusing term.

In self-supervised learning, the system learns to predict part of its input from other parts of it input. In other words a portion of the input is used as a supervisory signal to a predictor fed with the remaining portion of the input.



Supervised



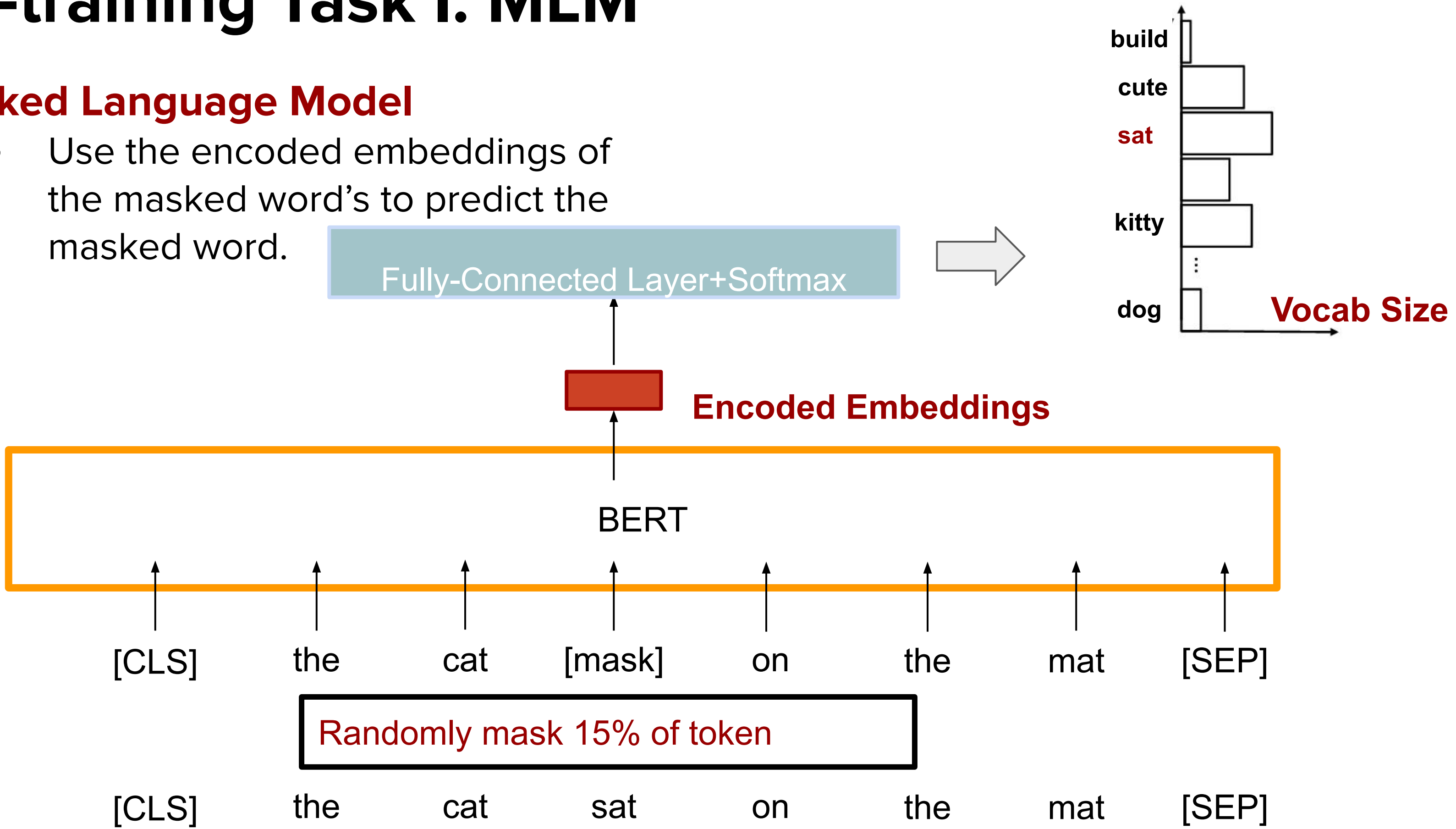
Generated by Rules

Self-Supervised

Automatically generate some kind of supervisory tasks

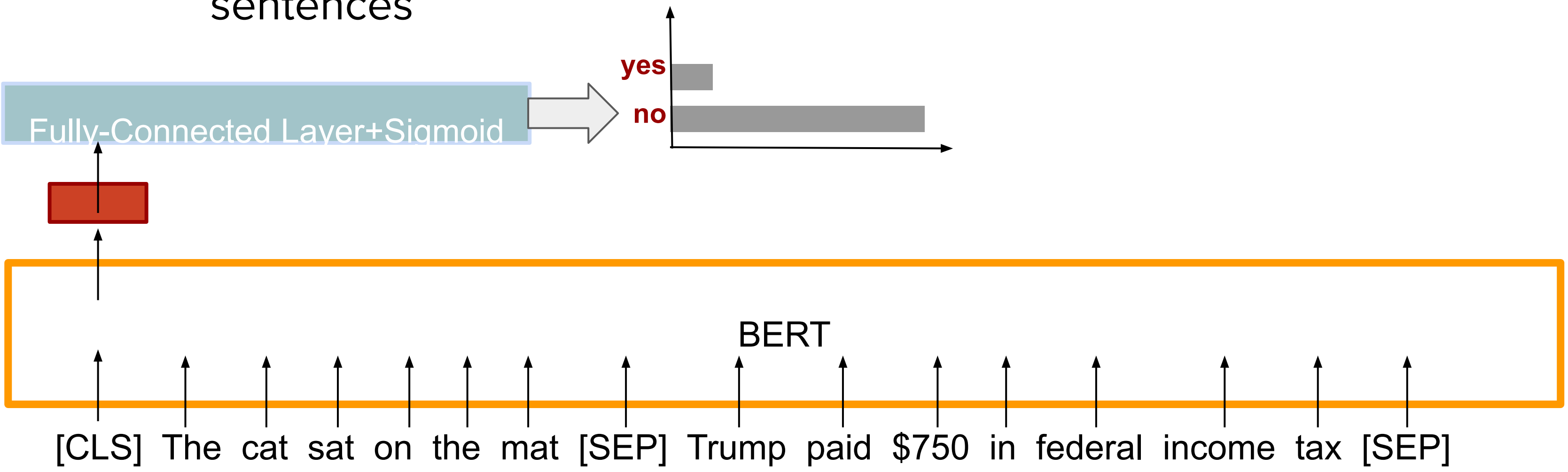
Pre-training Task I: MLM

- **Masked Language Model**
  - Use the encoded embeddings of the masked word's to predict the masked word.



Pre-training Task II: NSP

- **Next sentence prediction**
  - Given two sentences A and B, is B likely to be the sentence followed by A?
  - Make bert good at handling relationships between multiple sentences



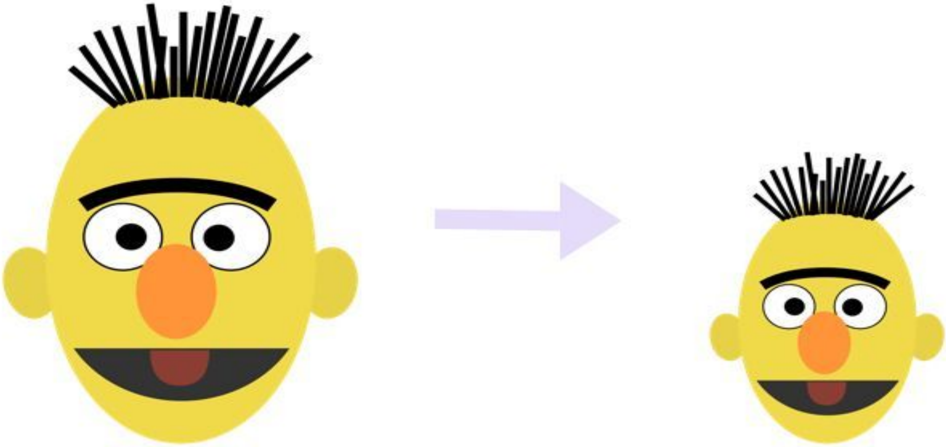
Huge Model Size

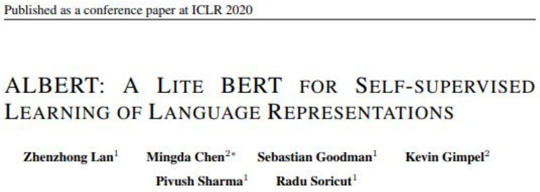
12 attention heads
110 million model parameters

Training of $\text{BERT}_{\text{BASE}}$ was performed on 4 Cloud TPUs in Pod configuration (16 TPU chips total).[13] Training of $\text{BERT}_{\text{LARGE}}$ was performed on 16 Cloud TPUs (64 TPU chips total). Each pre-training took 4 days to complete.

16 attention heads
345 million model parameters

Smaller Model




Published as a conference paper at ICLR 2020

ALBERT: A LITE BERT FOR SELF-SUPERVISED LEARNING OF LANGUAGE REPRESENTATIONS

Zhenzhong Lan[1] Mingda Chen[2*] Sebastian Goodman[1] Kevin Gimpel[2]
Pivush Sharma[1] Radu Soricut[1]


DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter

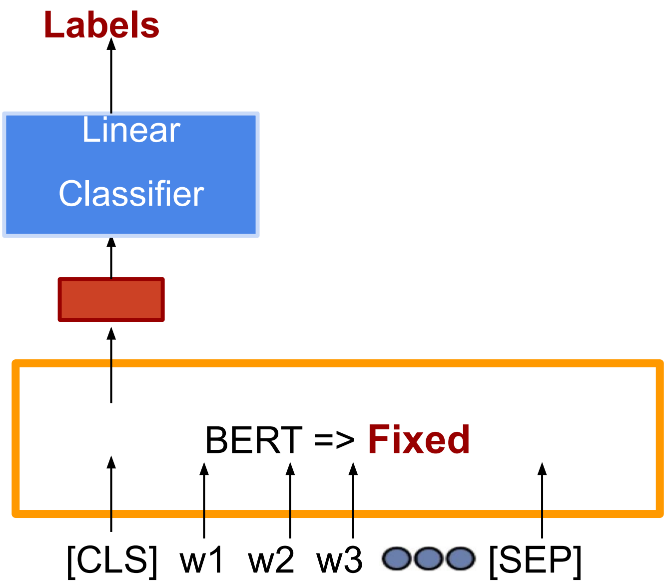
Victor SANH, Lysandre DEBUT, Julien CHAUMOND, Thomas WOLF
Hugging Face
{victor,lysandre,julien,thomas}@huggingface.co

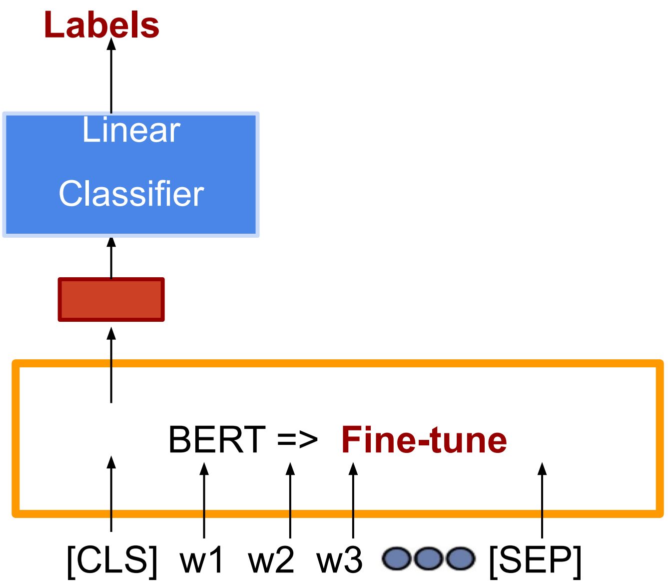
Abstract

Good summary:
http://mitchgordon.me/machine/learning/2019/11/18/all-the-ways-to-compress-BERT.html

BERT Usage I

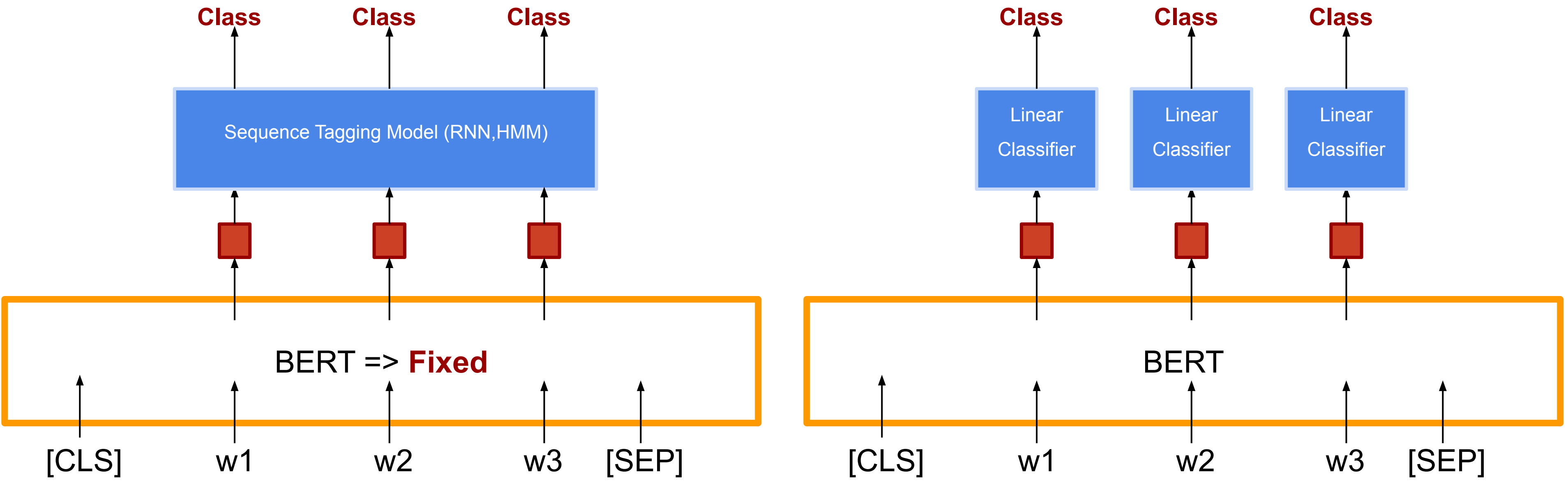
- **Input: Single Sentence Output: Class**
    - Sentiment Analysis
    - Document Classification





BERT Usage II

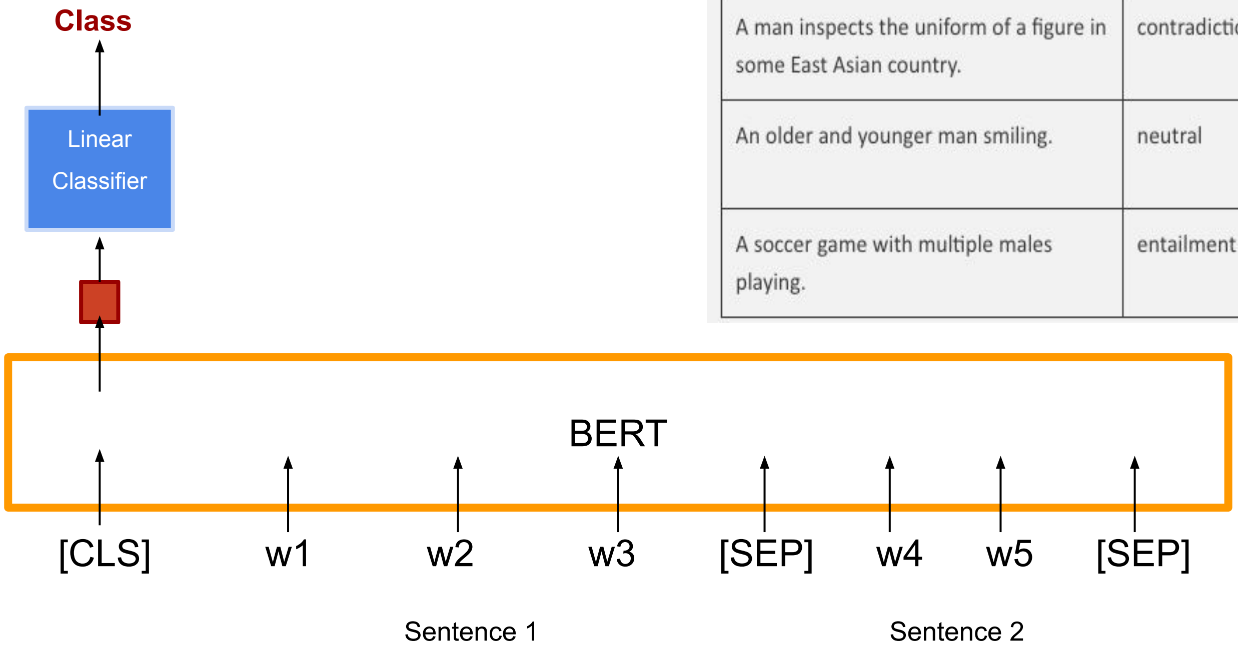
- **Input: Single Sentence Output: Class**
  - NER, POS Tagging



BERT Usage III

- **Input: Two Sentences Output: Class**
    - Natural Language Inference

Premise	Label	Hypothesis
A man inspects the uniform of a figure in some East Asian country.	contradiction	The man is sleeping.
An older and younger man smiling.	neutral	Two men are smiling and laughing at the cats playing on the floor.
A soccer game with multiple males playing.	entailment	Some men are playing a sport.



BERT Usage IV

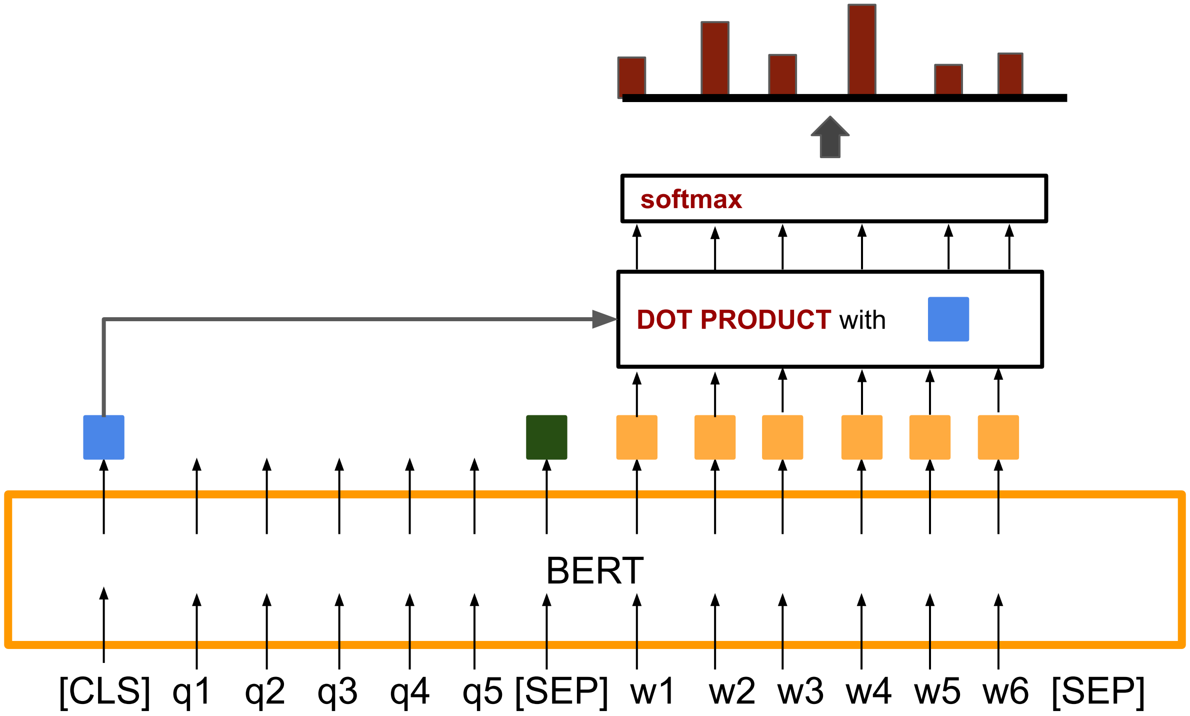
- Extraction-based Question Answering (SQuAD):
    - Input: two “sentences” (Question and Reference Text)
    - Output: start and end positions in Reference (Answer)

Question: How many parameters does BERT-large have?

Reference Text: BERT-large is really big... it has 24 layers and an embedding size of 1,024, for a total of 340M parameters! Altogether it is 1.34GB, so expect it to take a couple minutes to download to your Colab instance.

BERT Usage IV

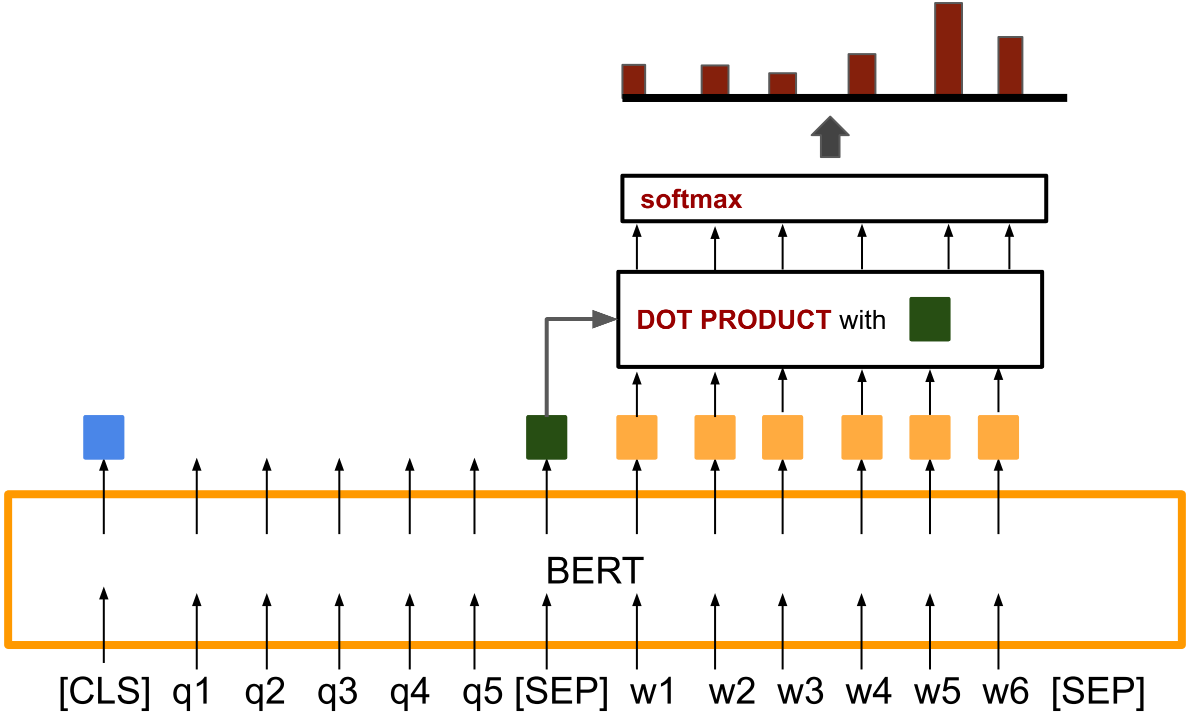
- Extraction-based Question Answering (SQuAD):
    - Question {q1,q2,q3,q4,q5} Reference Text{w1,w2,w3,w4,w5,w6}



The starting position for answer in reference is 4

BERT Usage IV

- Extraction-based Question Answering (SQuAD):
  - Question {q1,q2,q3,q4,q5} Reference Text{w1,w2,w3,w4,w5,w6}



The starting position for answer in reference is 4

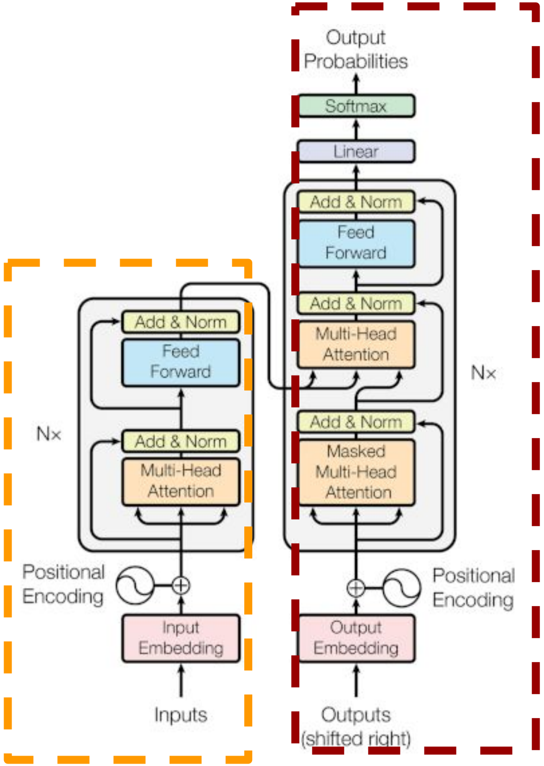
The ending position for answer in reference is 5

The answer is w4w5

BERT, GPT and Transformers

BERT

Encoder
Maksed “Language” Model



Transformer

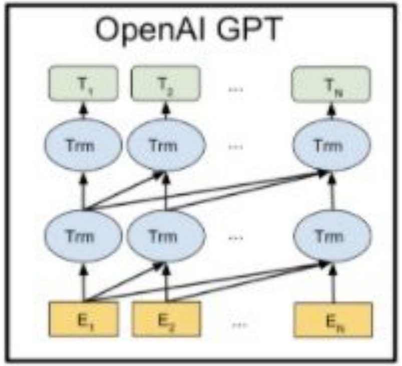
GPT2
GPT3

OpenAI

GPT-3, an autoregressive language model with 175 billion parameters

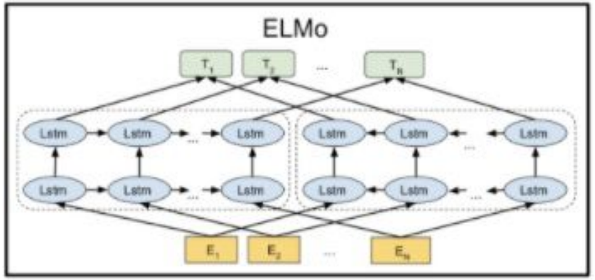
Decoder
Language Model

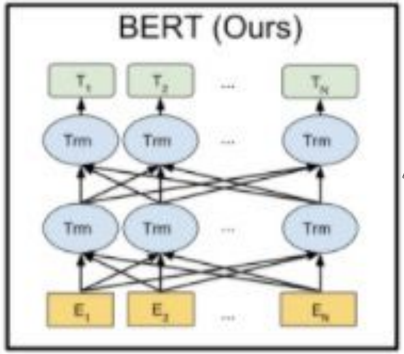
BERT and other Pre-trained Models



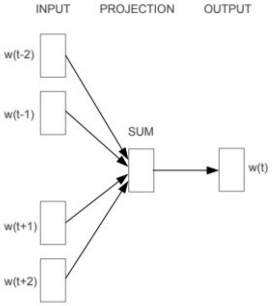
From
single-directional to
Bi-directional

From RNNs to
transformers





From FCNs to
transformers



CBOW

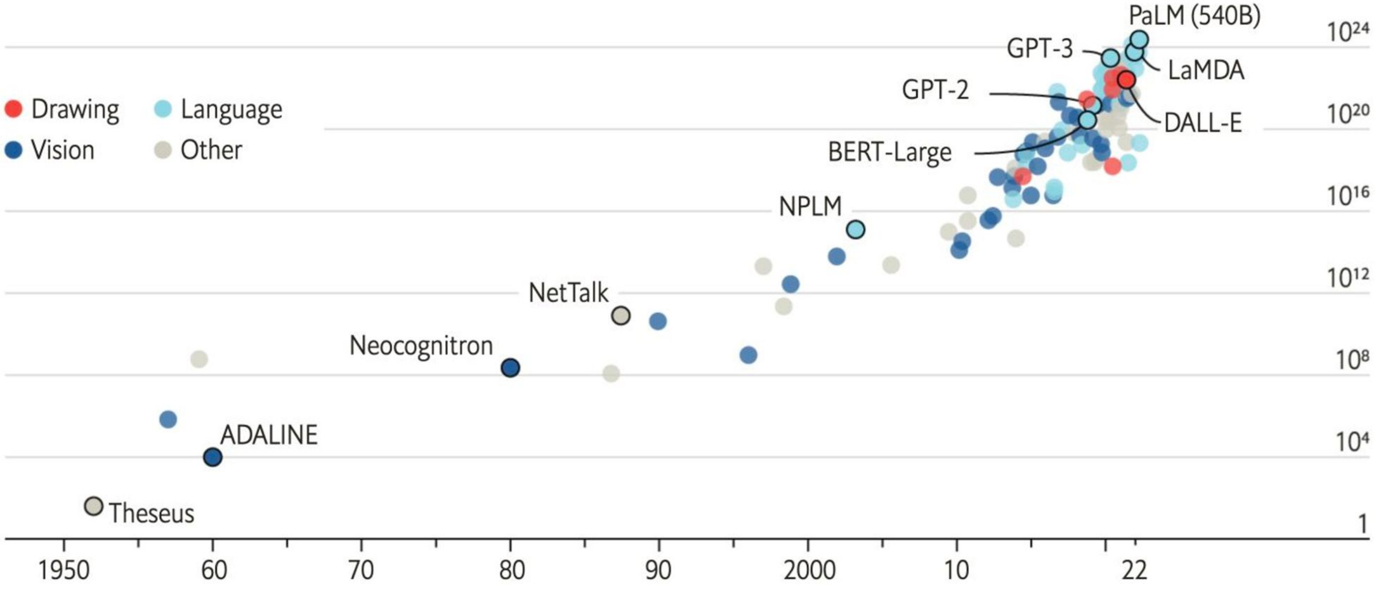
https://lilianweng.github.io/lil-log/2019/01/31/generalized-language-models.html

Pre-training

The blessings of scale

AI training runs, estimated computing resources used

Floating-point operations, selected systems, by type, log scale



Sources: "Compute trends across three eras of machine learning", by J. Sevilla et al., arXiv, 2022; Our World in Data

Pre-training

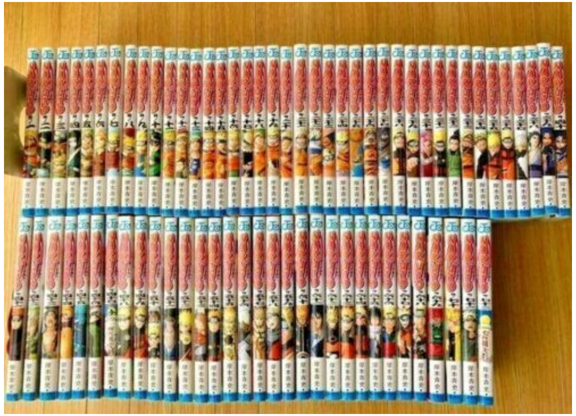
GPT versions

	Architecture	Parameter count	Training data
GPT-1	12-level, 12-headed Transformer decoder (no encoder), followed by linear-softmax.	0.12 billion	BookCorpus:[8] 4.5 GB of text, from 7000 unpublished books of various genres.
GPT-2	GPT-1, but with modified normalization	1.5 billion	WebText: 40 GB of text, 8 million documents, from 45 million webpages upvoted on Reddit.
GPT-3	GPT-2, but with modification to allow larger scaling.	175 billion	570 GB plaintext, 0.4 trillion tokens. Mostly CommonCrawl, WebText, English Wikipedia, and two books corpora (Books1 and Books2).

https://en.wikipedia.org/wiki/Generative_pre-trained_transformer

How Large is 570GB

Read Naruto 270K times



And GPT3 brain is also so huge having 175 billion words.

GPT3 is already powerful

- GPT3 can do everything that Chatgpt can do
    - https://pub.towardsai.net/crazy-gpt-3-use-cases-232c22142044
- Why not achieve the hype as ChatGPT?
    - It is a language model that is learned from all text across the open internet
    - GPT3 is a genius but do not know our humans' preference

6. From GPT to ChatGPT

What is ChatGPT

- It is a language model
  - A mapping function: take a few words in, generate another word
  - Pre-trained by **large-scale** unannotated corpus
  - Fine-tuned by limited annotated dataset (33k)

What is business analytics

Business analytics is the practice of using data analysis and statistical methods to make informed business decisions. It involves the use of techniques such as data mining, data visualization, and predictive modeling to identify patterns and insights within data that can inform business strategies and actions.

Business analytics can help organizations improve their decision-making by providing data-driven insights into areas such as customer behavior, market trends, product performance, and operational efficiency. By analyzing data from various sources, such as customer surveys, social media, and sales reports, businesses can identify opportunities for growth, optimize their operations, and make more informed decisions.

Business analytics is a broad field that encompasses many different techniques and approaches, including descriptive analytics, which focuses on summarizing and visualizing data; predictive analytics, which uses statistical modeling and machine learning to make predictions about future outcomes; and prescriptive analytics, which suggests optimal courses of action based on data analysis.

Overall, business analytics is a powerful tool for businesses of all sizes and industries, and

7. Fine-tuning vs Prompt Engineering

Next Class: Model Evaluation