Natural Language Processing

Shangbin Feng

Xi'an Jiaotong University

wind_binteng@stu.xjtu.edu.cn

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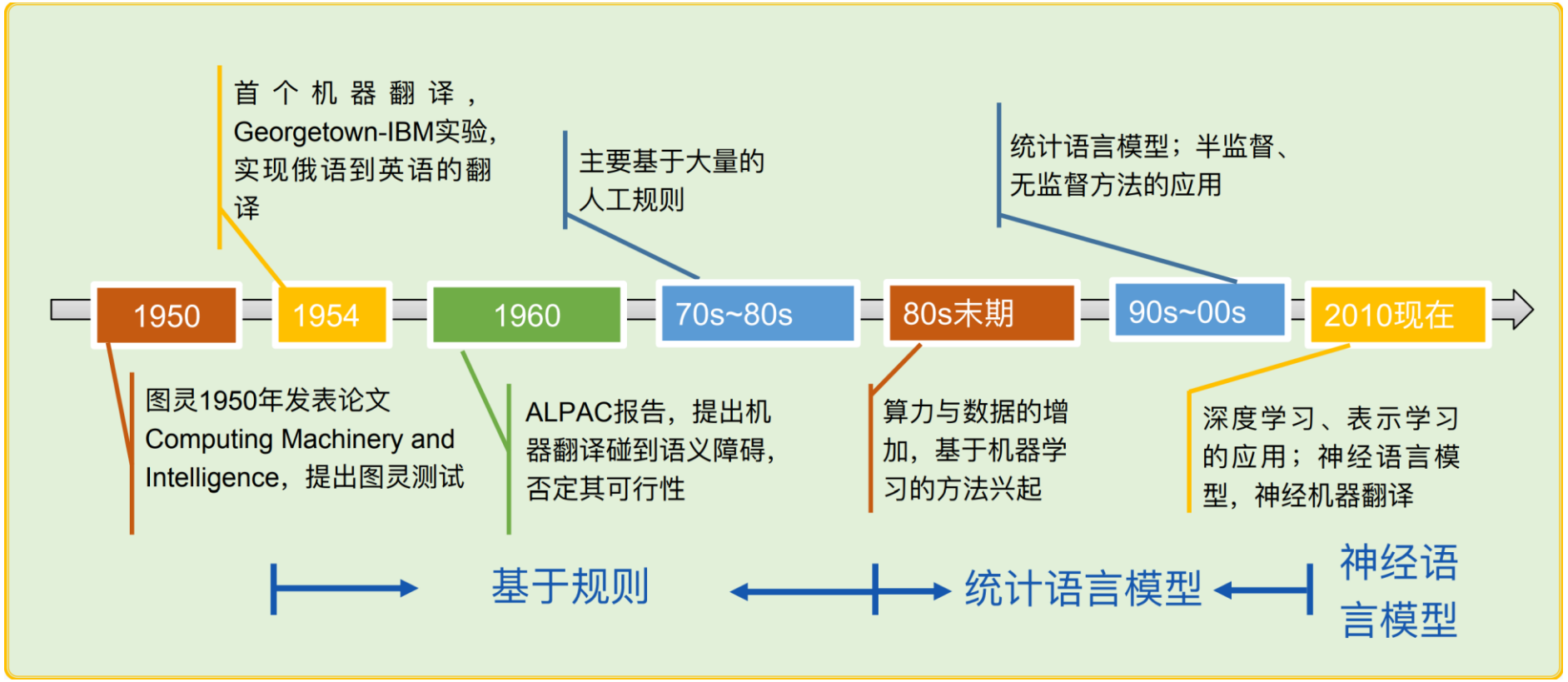
Contents

- Introduction to NLP
- Word Embedding and RNNs
- Attention and Transformers
- Self-supervised Learning
- Pre-trained Language Models

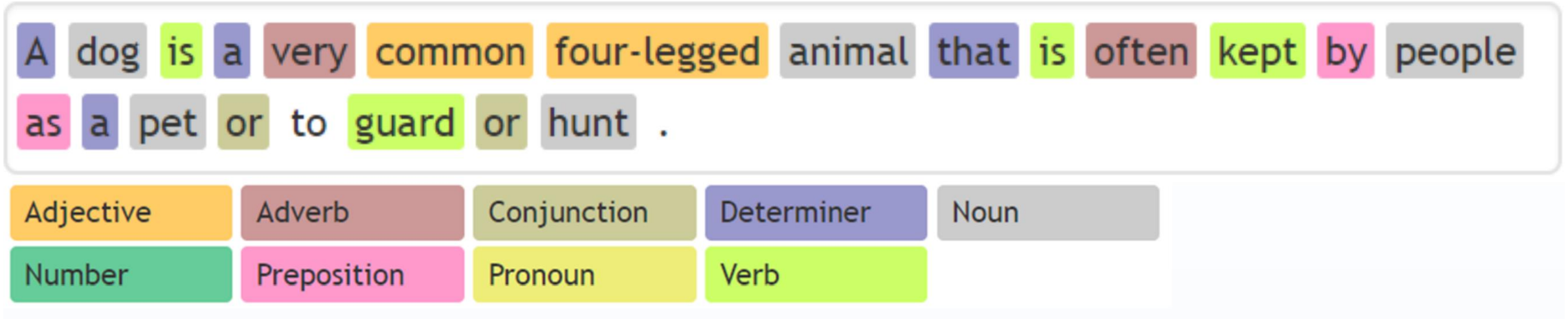
What is NLP?

- Natural Language Processing

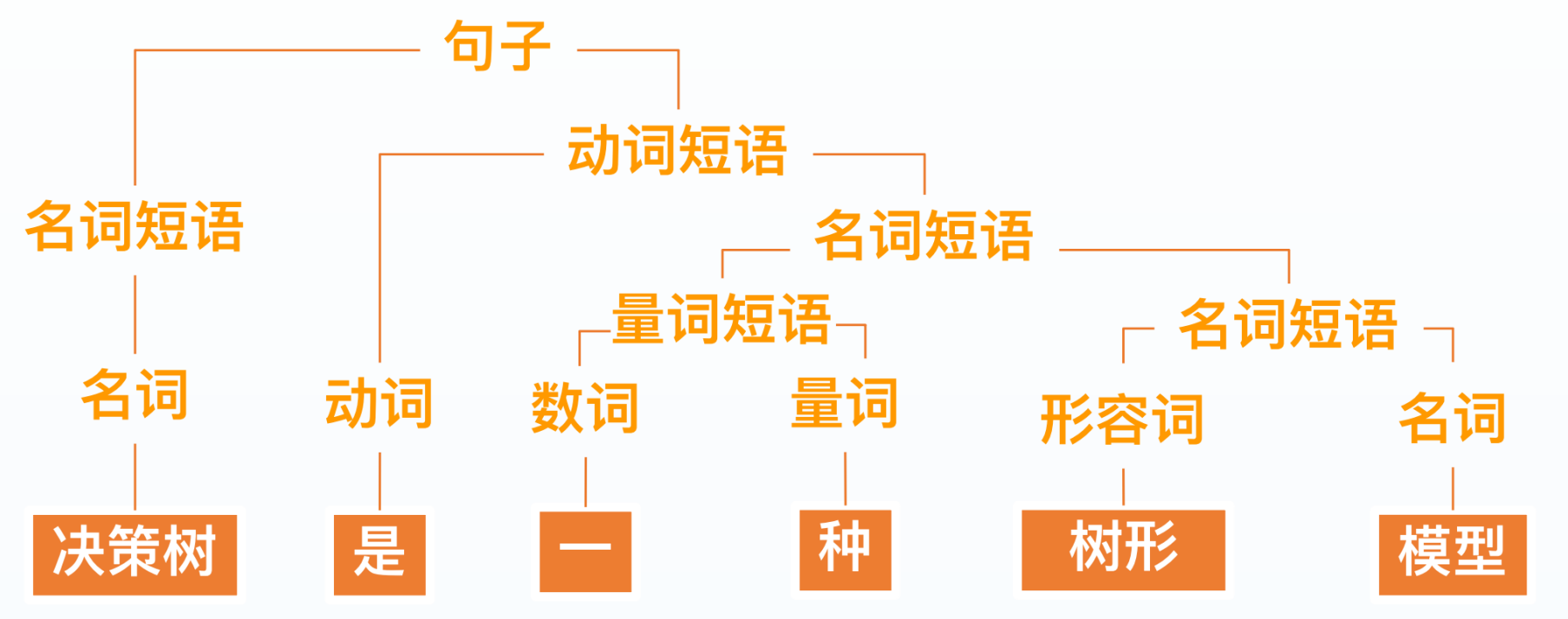


https://en.wikipedia.org/wiki/Natural_language_processing#History

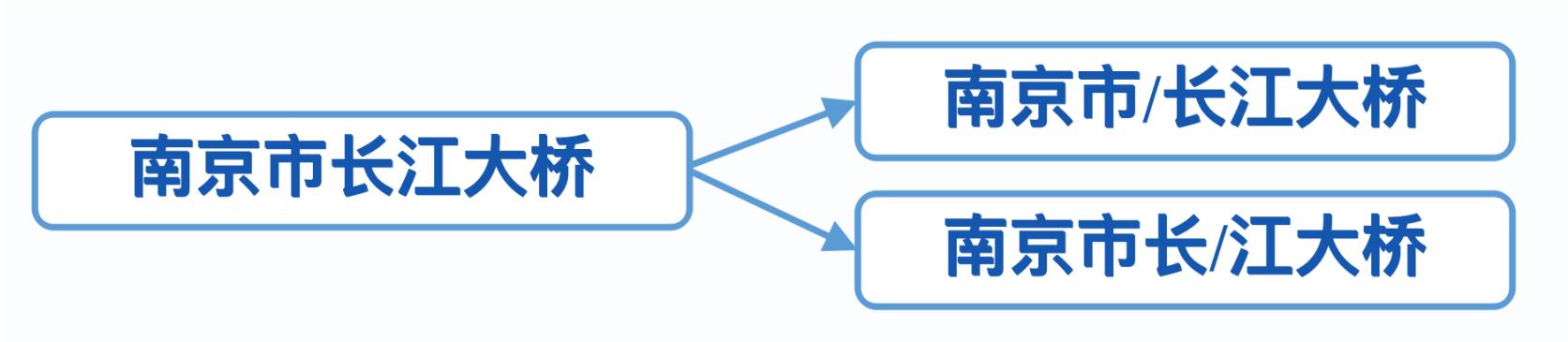
Task 1: PoS Tagging



Task 2: Parsing



Task 3: Tokenization



Task 4: Machine Translation

Task 5: Named Entity Recognition

Obama is the president of the United States

Jim bought 300 shares of Acme Corp. in 2006

Task 6: Text Classification

- ✓ 垃圾邮件过滤
- ✓ 情感识别
- ✓ 新闻分类
- ✓ 色情文档识别

Task 7: Question Answering

Task 8: Sentiment Analysis

- ✔ 《复联3》是一部史无前例的电影
- ✔ 让人有些绝望的电影结局
- ✔ MIUI8系统还算流畅，功能多，人性化，但是广告不能完全关闭

Task 9: Coreference Resolution

- ✔ 甲队打败了乙队，他们更强
- ✔ 虽然甲队打败了乙队，但他们都很强

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Why word embedding?

One-hot Encoding

$$
\begin{aligned}
apple &= [1\ 0\ 0] \\
banana &= [0\ 1\ 0] \\
pineapple &= [0\ 0\ 1]
\end{aligned}
$$

- Problems
  - Embedding size
  - transductive
  - No meaning in it

motel = [0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]

hotel = [0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

Idea

- “You shall know a word by the company it keeps.”

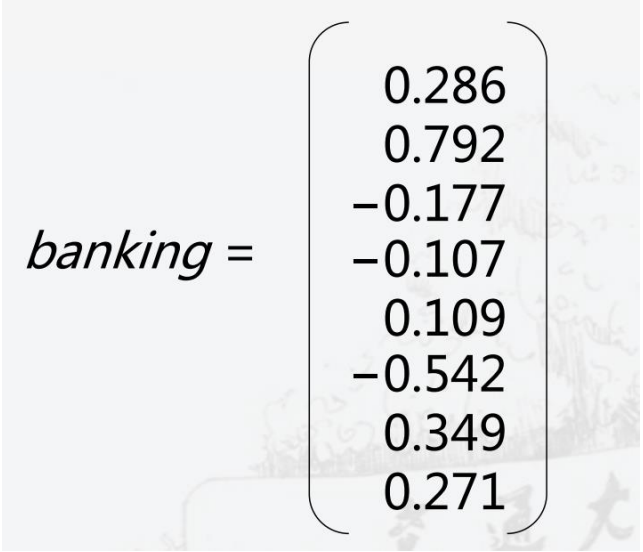
...government debt problems turning into banking crises as happened in 2009...

...saying that Europe needs unified banking regulation to replace the hodgepodge...

...India has just given its banking system a shot in the arm...

Word Embedding

- Distributed embedding
- Dense vector
- Word vector
- Word representation
- Distributed representation



- Limited dimension / word meaning included

Word2Vec

- “You shall know a word by the company it keeps”
  - CBOW
  - Skip-gram

CBOW

- Continuous bag of words

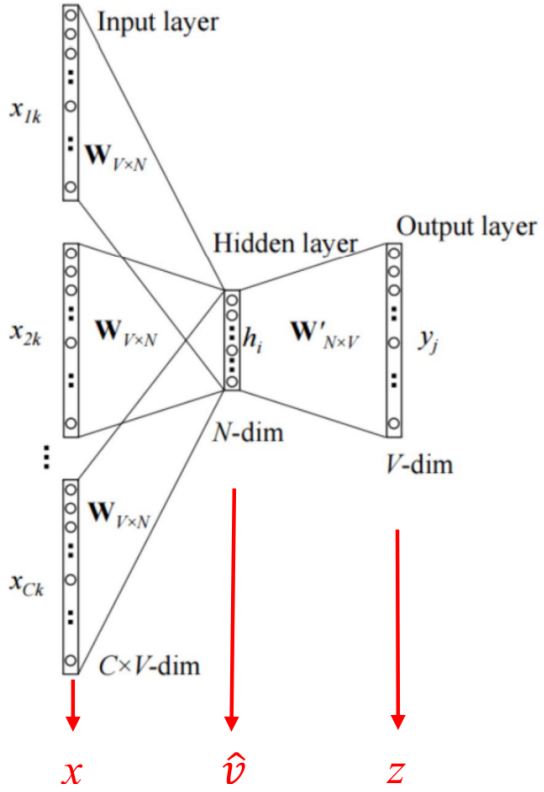
1. Generate one-hot word vectors for the input context of size m:
   $(x^{c-m}, \ldots, x^{c-1}, x^{c+1}, \ldots, x^{c+m} \in R^{|V|})$.

2. Get embedded word vectors for the context.
   $v_{c-m} = x^{c-m} \cdot W, \ldots, v_{c+m} = x^{c+m} \cdot W \in R^N$

3. Average context word vectors get $\hat{v}$.
   $\hat{v} = \frac{v_{c-m+\cdots+} v_{c+m}}{2m} \in R^N$

4. Generate a score vector z.
   $z = \hat{v} \cdot W' \in R^{|V|}$

5. Turn the score vector into probabilities $\hat{y}$.
   $\hat{y} = softmax(z)$



Skip-gram

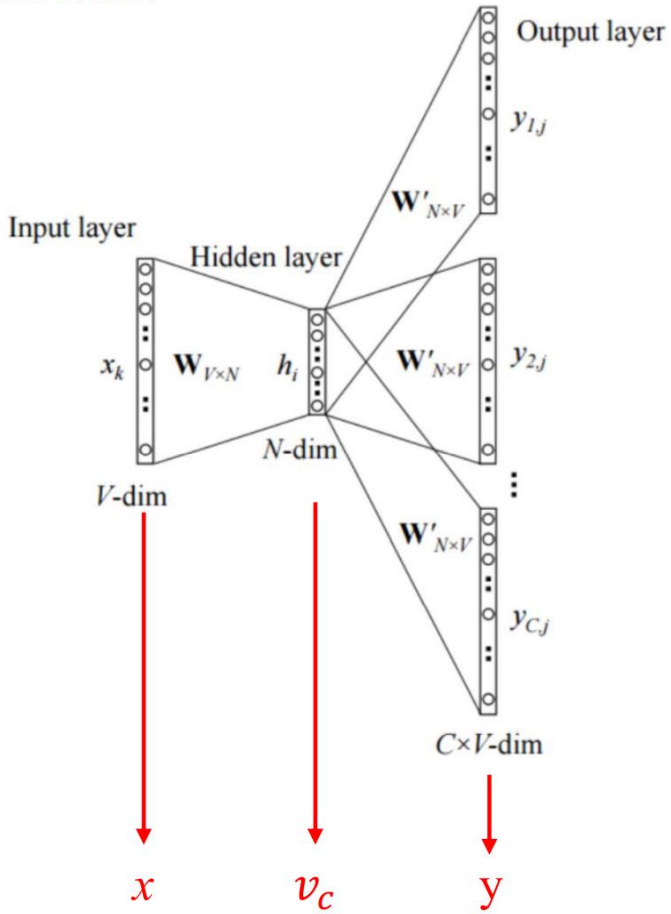
1. Generate one-hot input vector $x \in R^{|V|}$ of the center word.

2. Get embedded word vectors for the center word.
   $v_c = x \cdot W \in R^N$

3. Generate a score vector z.
   $z = v_c \cdot W'$

4. Turn the score vector into probabilities $\hat{y}$.
   $\hat{y} = softmax(z)$

5. Note that $\hat{y}_{c-m}, \ldots, \hat{y}_{c-1}, \hat{y}_{c+1}, \ldots, \hat{y}_{c+m}$ are the probabilities of observing context word.



Summary of Word2Vec

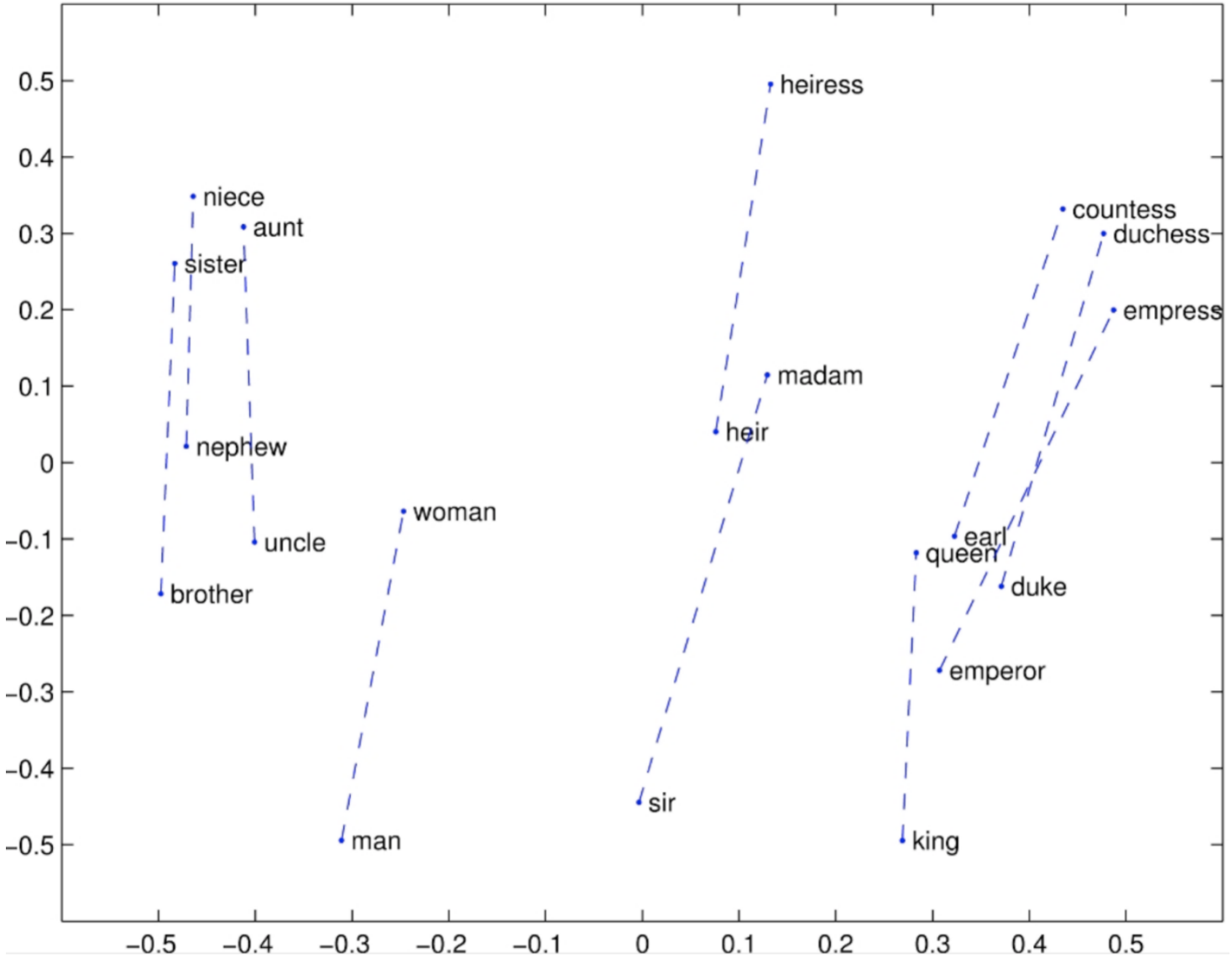
- What's the idea?
- What's the difference between CBOW and Skip-gram?

- Problem of vocabulary size
  - Negative sampling & hierarchical softmax

How do we evaluate word embeddings?

- Intrinsic evaluation
- Extrinsic evaluation

Intrinsic Evaluation



Extrinsic Evaluation

- Use word vectors on downstream tasks

Glove

- Word embeddings by Christopher Manning @ Stanford

- Global Vectors for Word Representations
- https://nlp.stanford.edu/projects/glove/

- Download
  - Code
  - Trained word embeddings

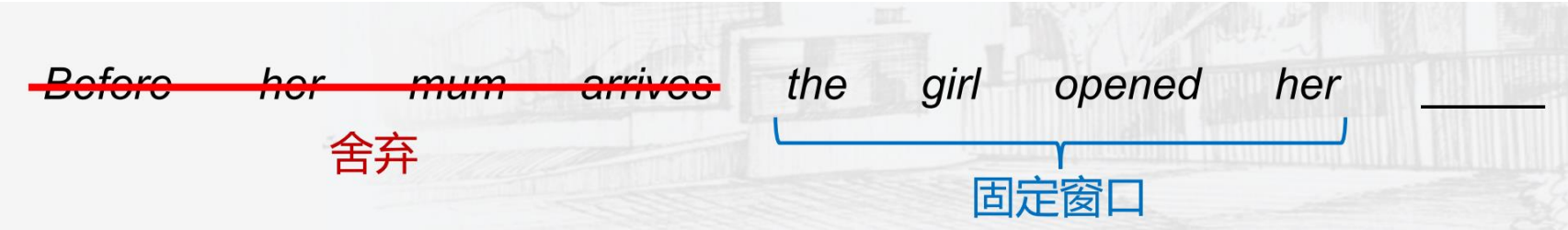
Language Model (LM)

- The girl opened her _____
  - Laptop
  - Books
  - …

- A language model tries to **predict the next word (token)** given the previous token sequence.

$$P(x^{(t+1)}|x^{(t)}, \ldots, x^{(1)})$$

Context window



Linear Layer LM

- Problem
  - Window size
  - W parameter size
  - Never enough W

输出层

$$\hat{y} = softmax(Uh + b_2) \in \mathbb{R}^{|V|}$$

隐藏层

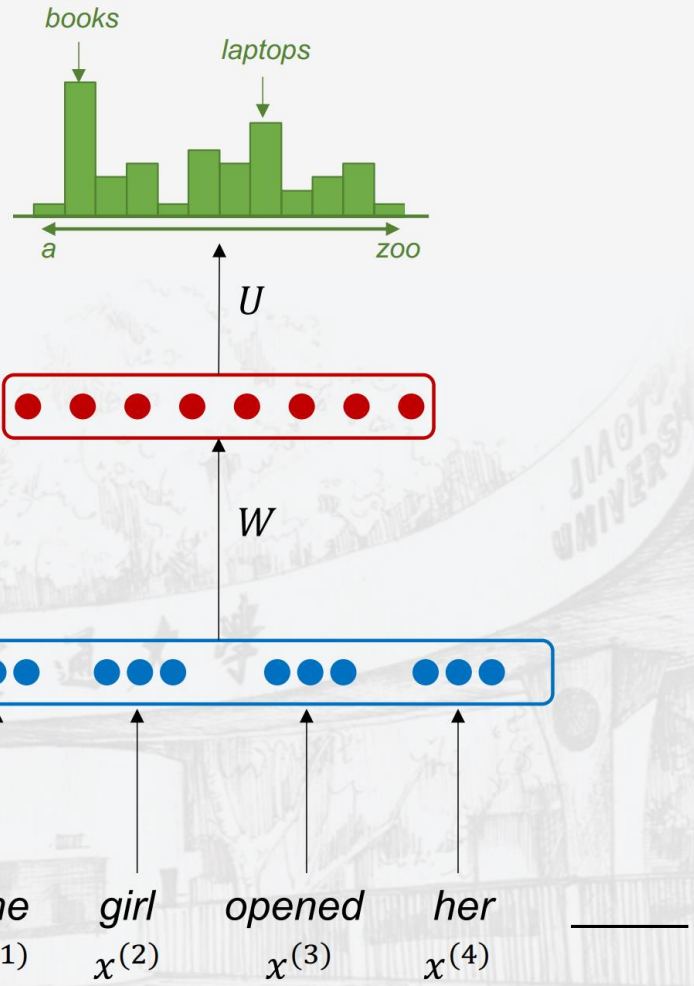
$$h = f(We + b_1)$$

连接嵌入式词向量（word embeddings）

$$e = [e^{(1)}; e^{(2)}; e^{(3)}; e^{(4)}]$$

词向量（one-hot、分布式表示 .....）

$$x^{(1)}, x^{(2)}, x^{(3)}, x^{(4)}$$



Recurrent Neural Networks (RNNs)

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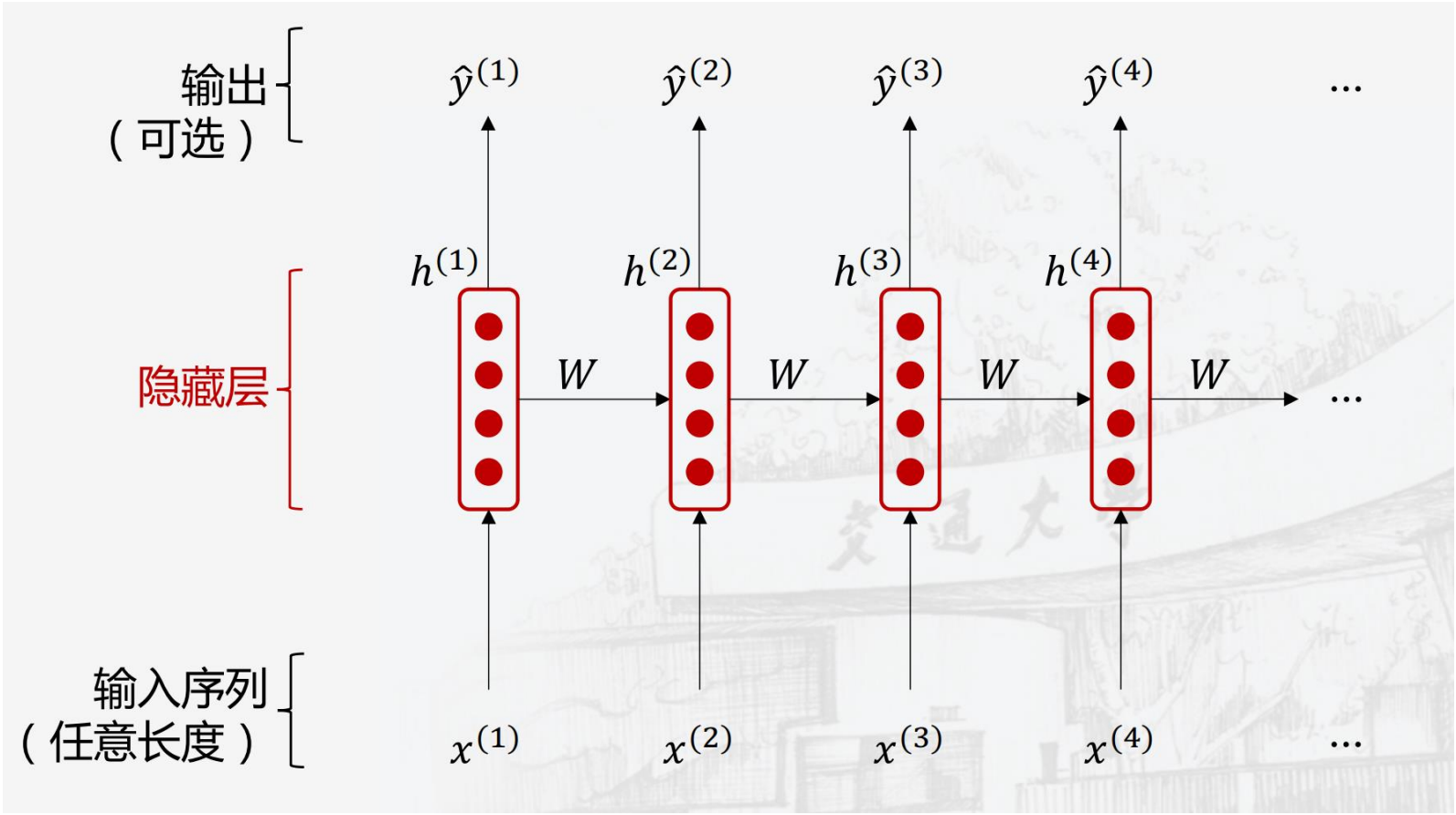


RNN LM

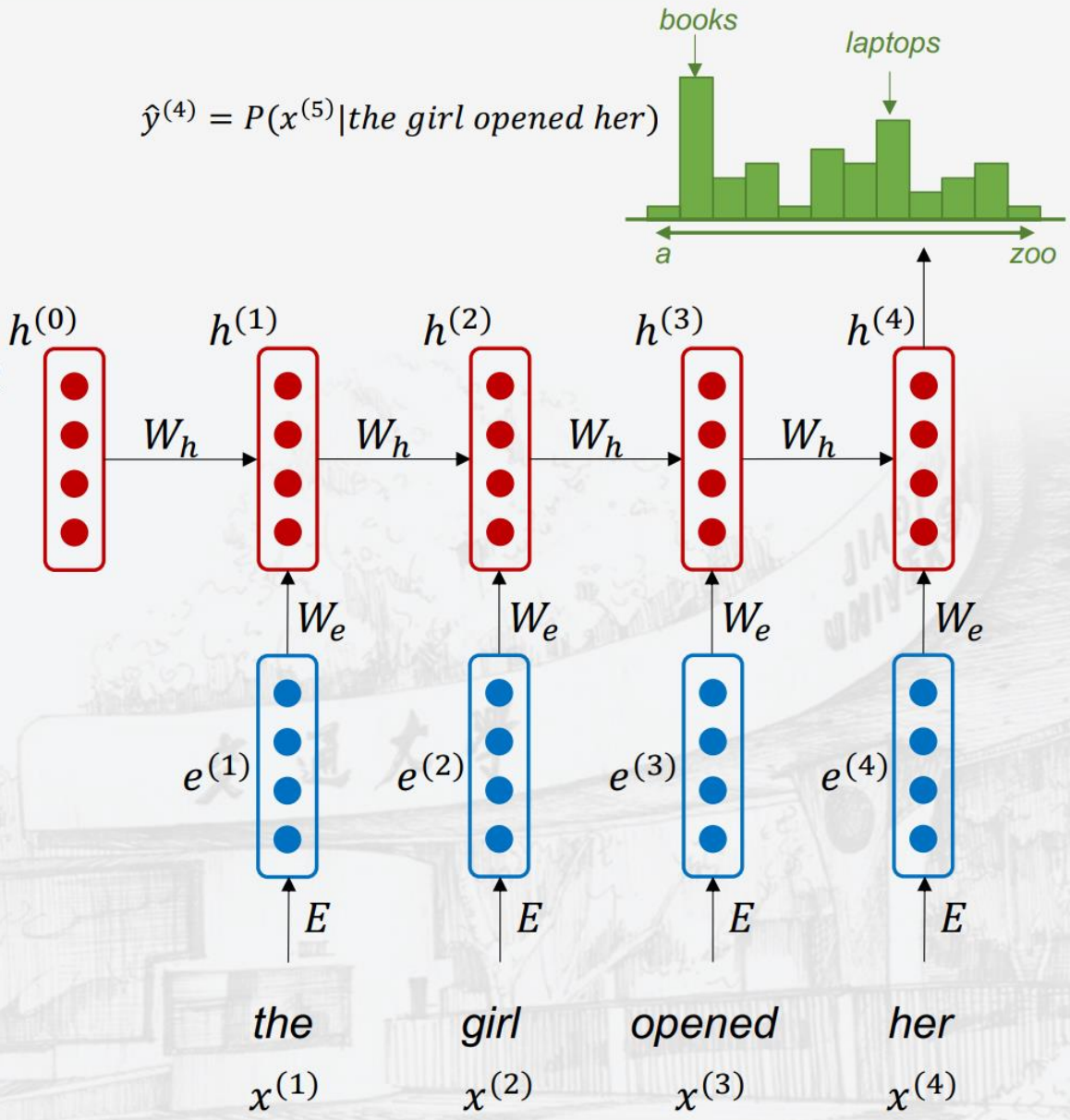
基于递归神经网络的LM

优点

- 可处理任意长度句子；
- 第 t 步的计算（理论上）使用了前面多步的信息；
- 模型体量不随着输入变长而增加；
- 每一步使用同一个 W ，降低计算量。

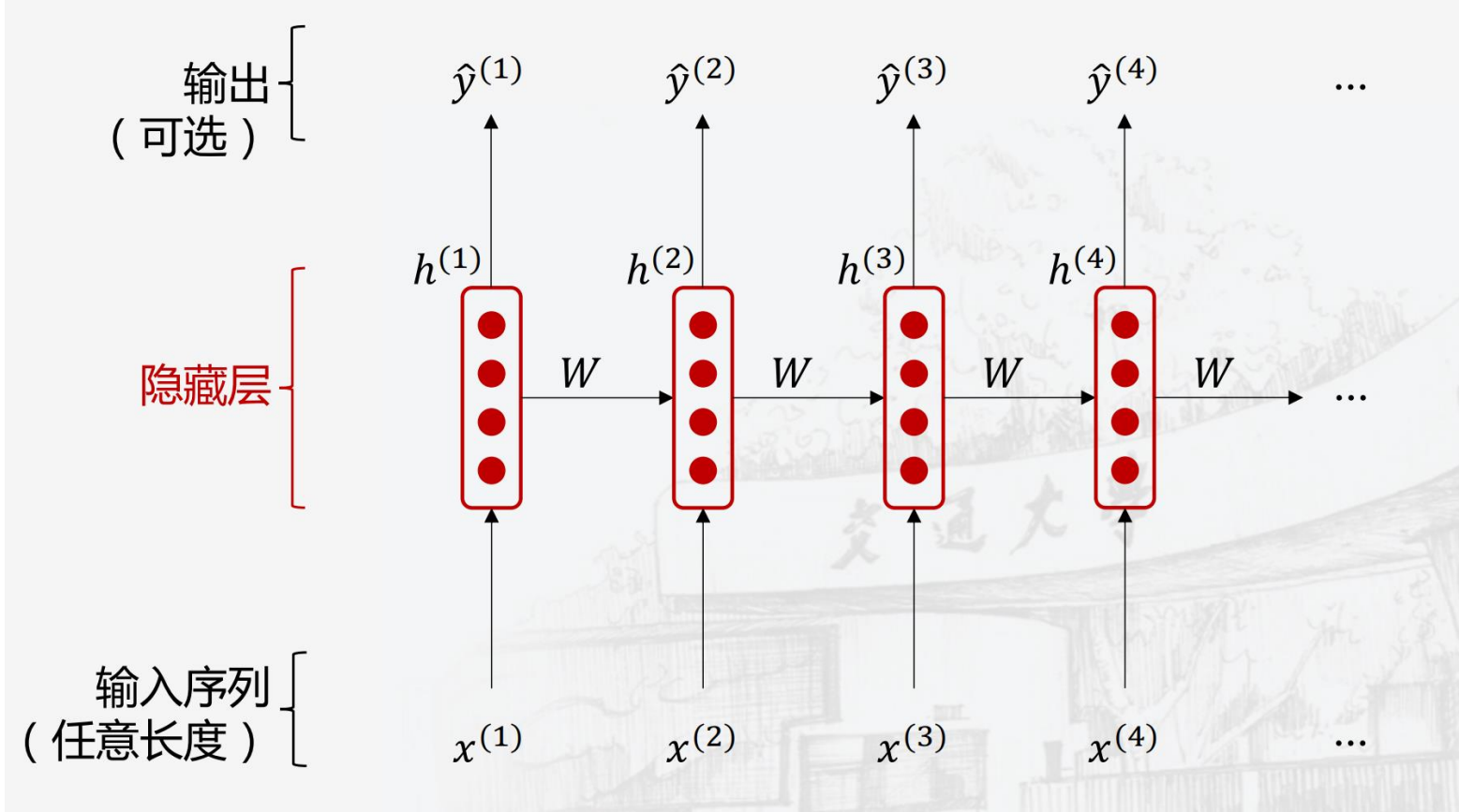
缺点

- 递归计算缓慢；
- 实际上，将前面很多步的信息完整传递是困难的。



Important Issues

- When do we initialize W?
- When do we initialize h(0)?



Text Classification with RNN

基于递归神经网络的LM

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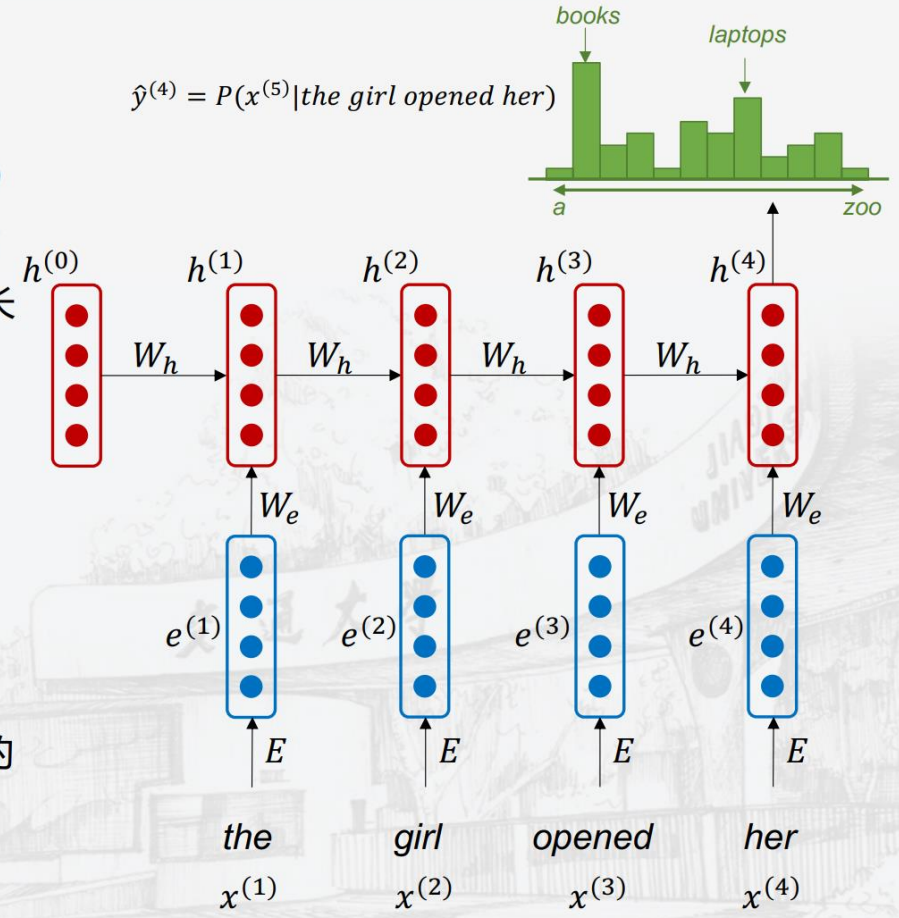
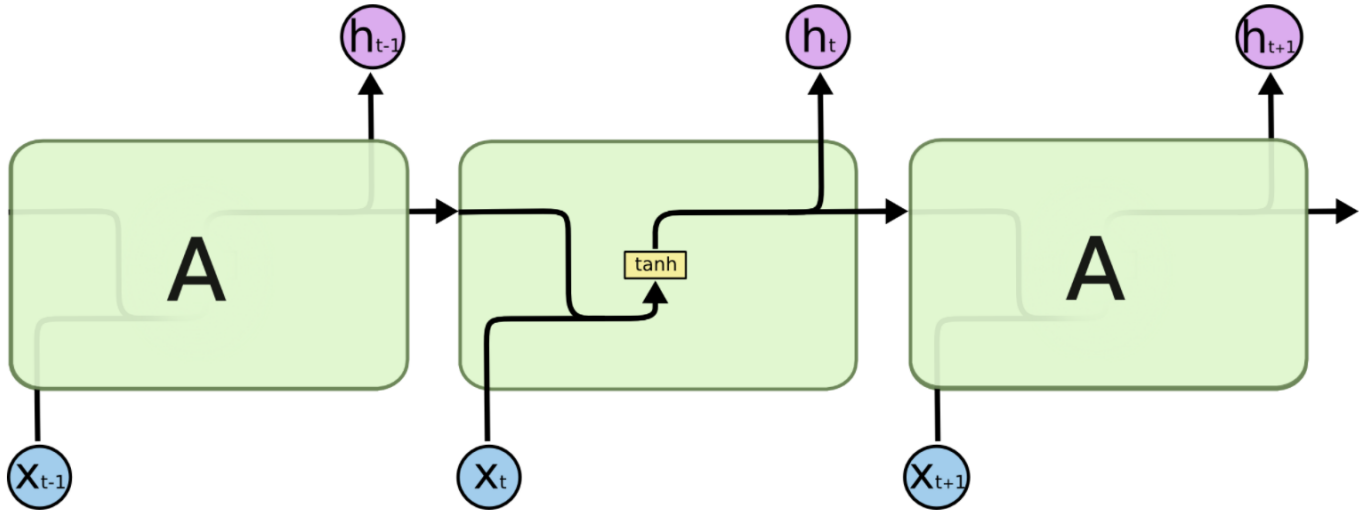


RNN Problems

- Long-term dependencies

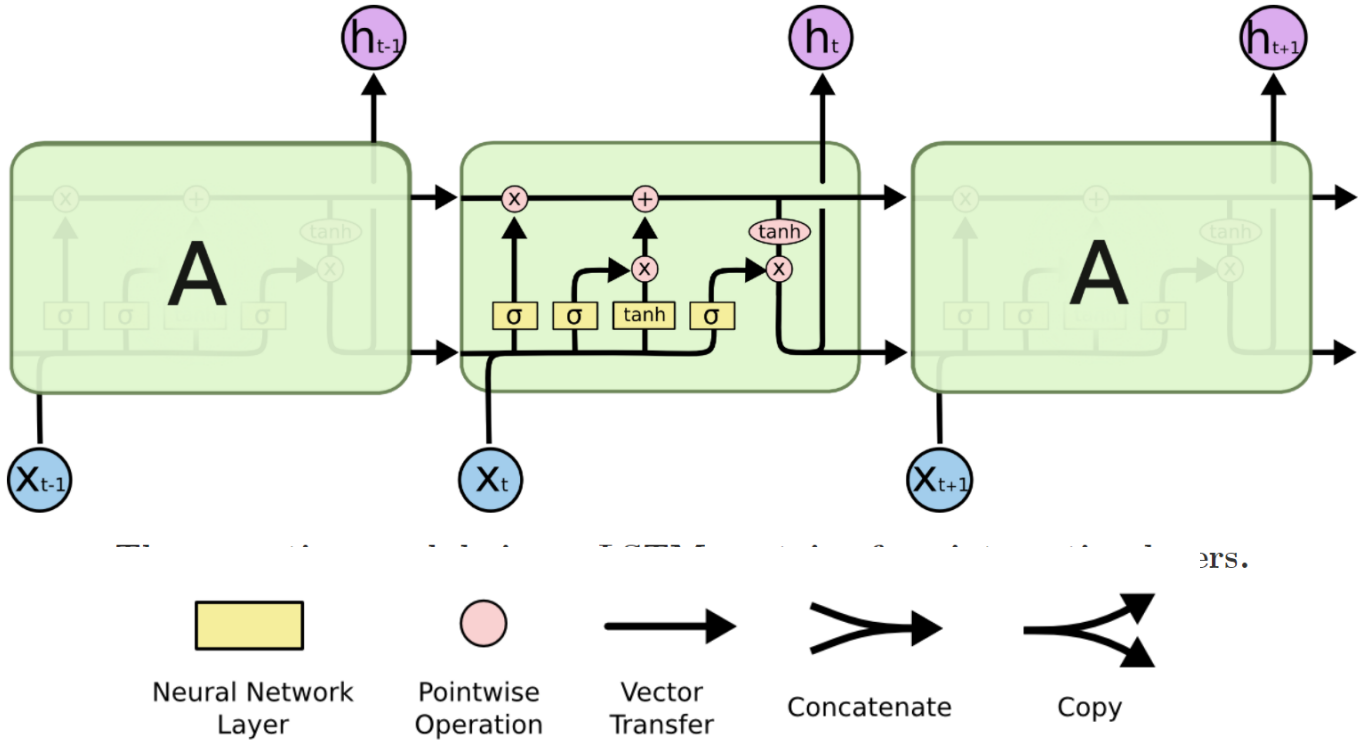
- Vanishing gradient problem



https://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM comes to the rescue

- Long short-term memory



Summary

- NLP tasks
- “You shall know a word by the company it keeps”
- Word2Vec
  - CBOW
  - Skip-gram
- Language Model
- RNN and LSTM

Take a break!

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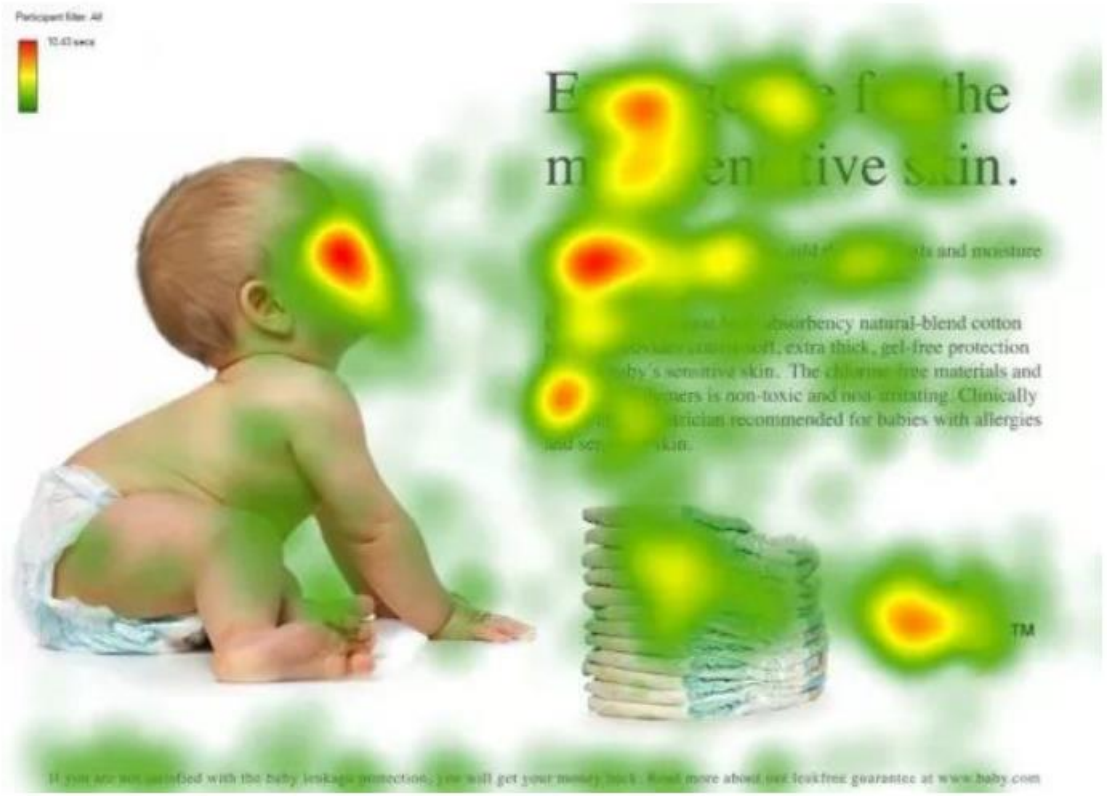
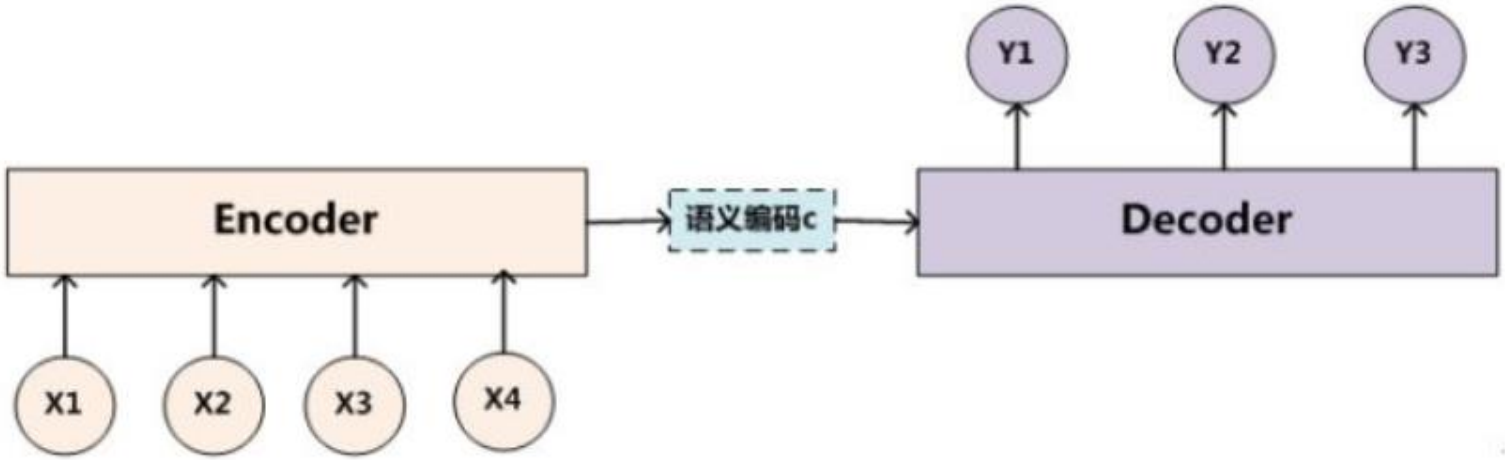
Attention



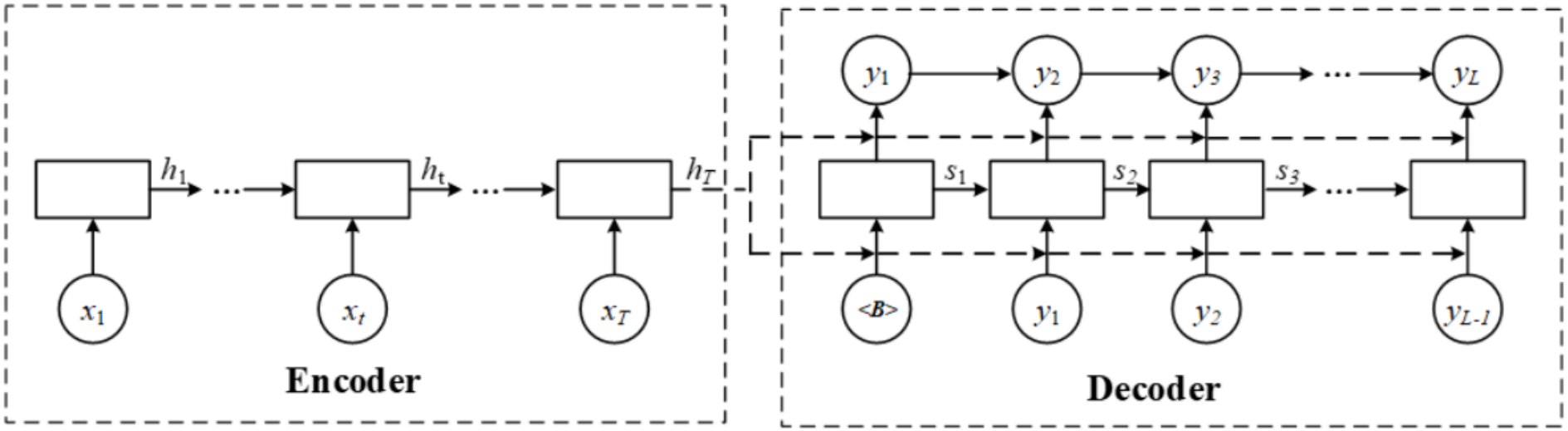
Encoder-Decoder Architecture

- Sequence-to-sequence



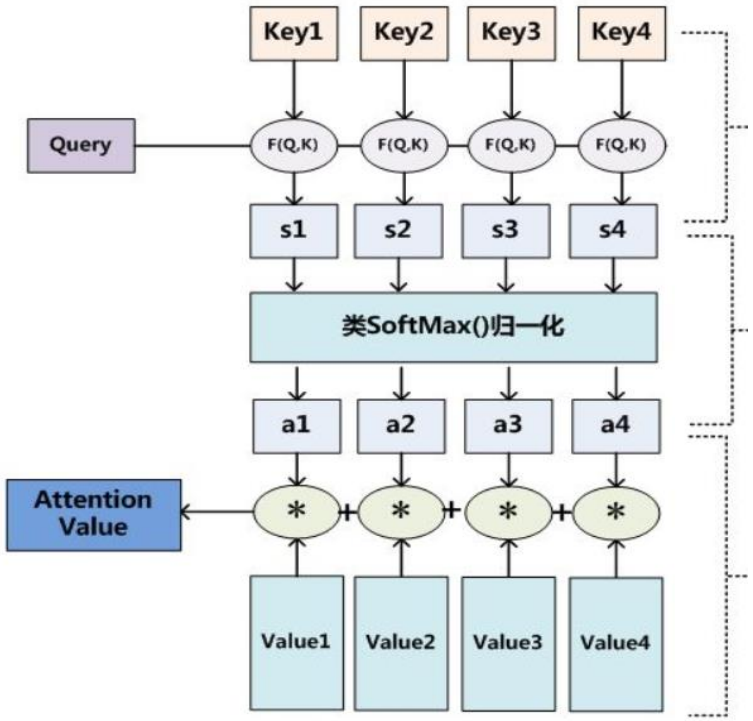
Machine Translation

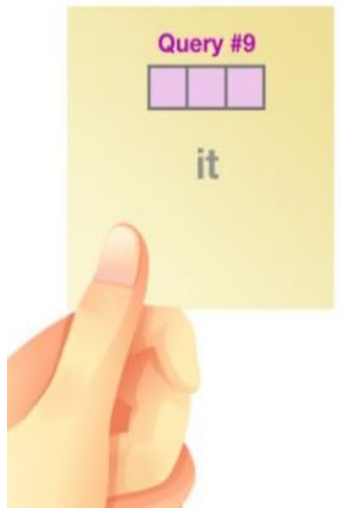
- Encoder: RNN Decoder: RNN
  - What is the input of the decoder?
  - When does the output sequence stop?

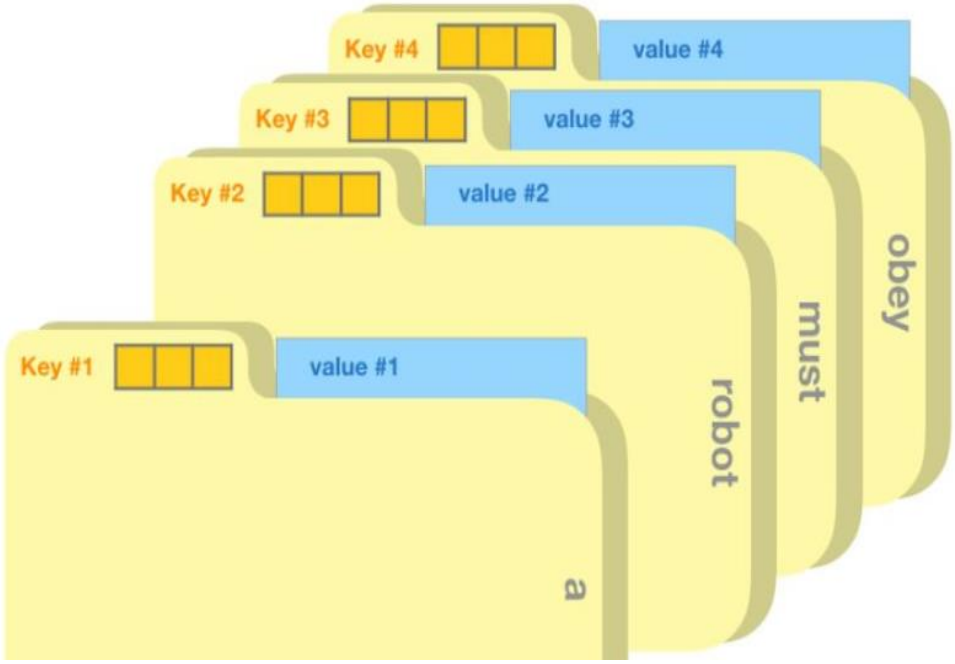


QKV Attention

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$



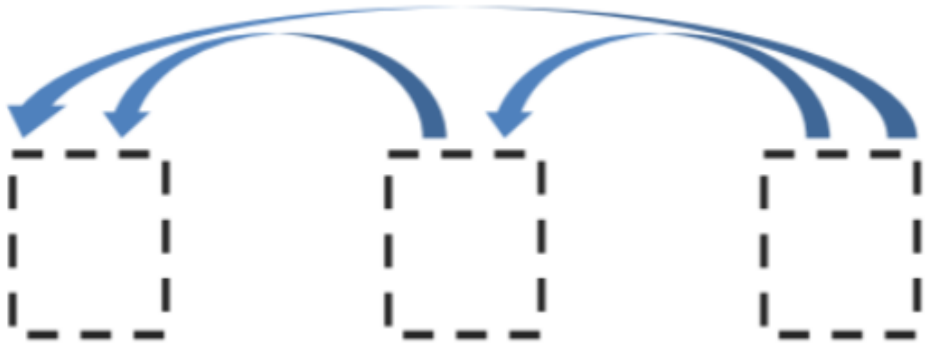




Self-attention in NLP

- Q=K=V

Masked Self-attention



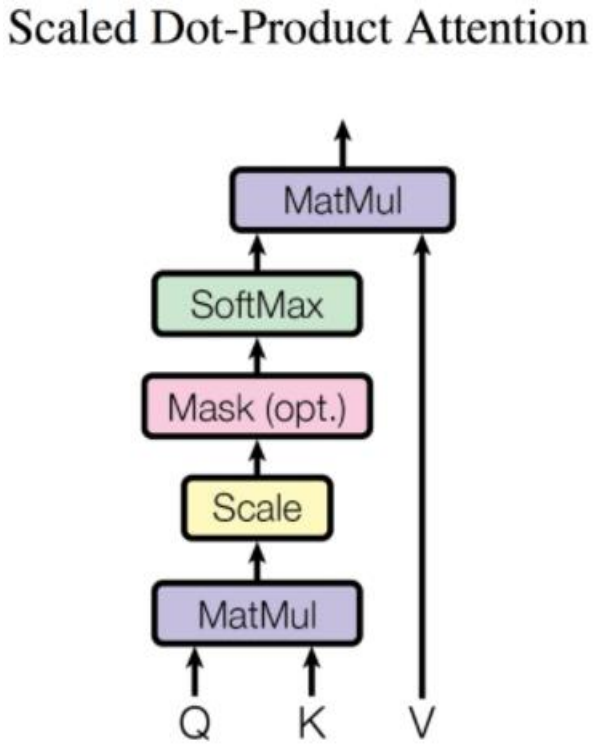
Multi-head attention

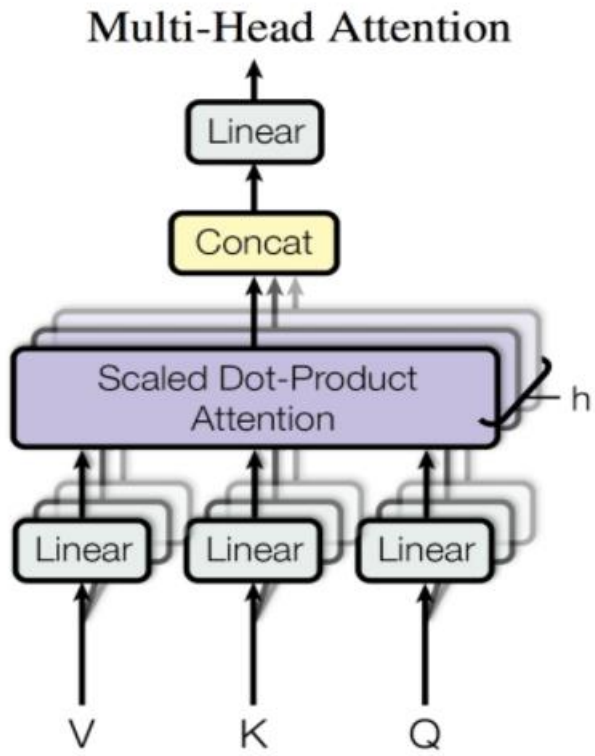
$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

$$MultiHead(Q,K,V) = Concat(head_1, head_2, \cdots head_h)W^o$$

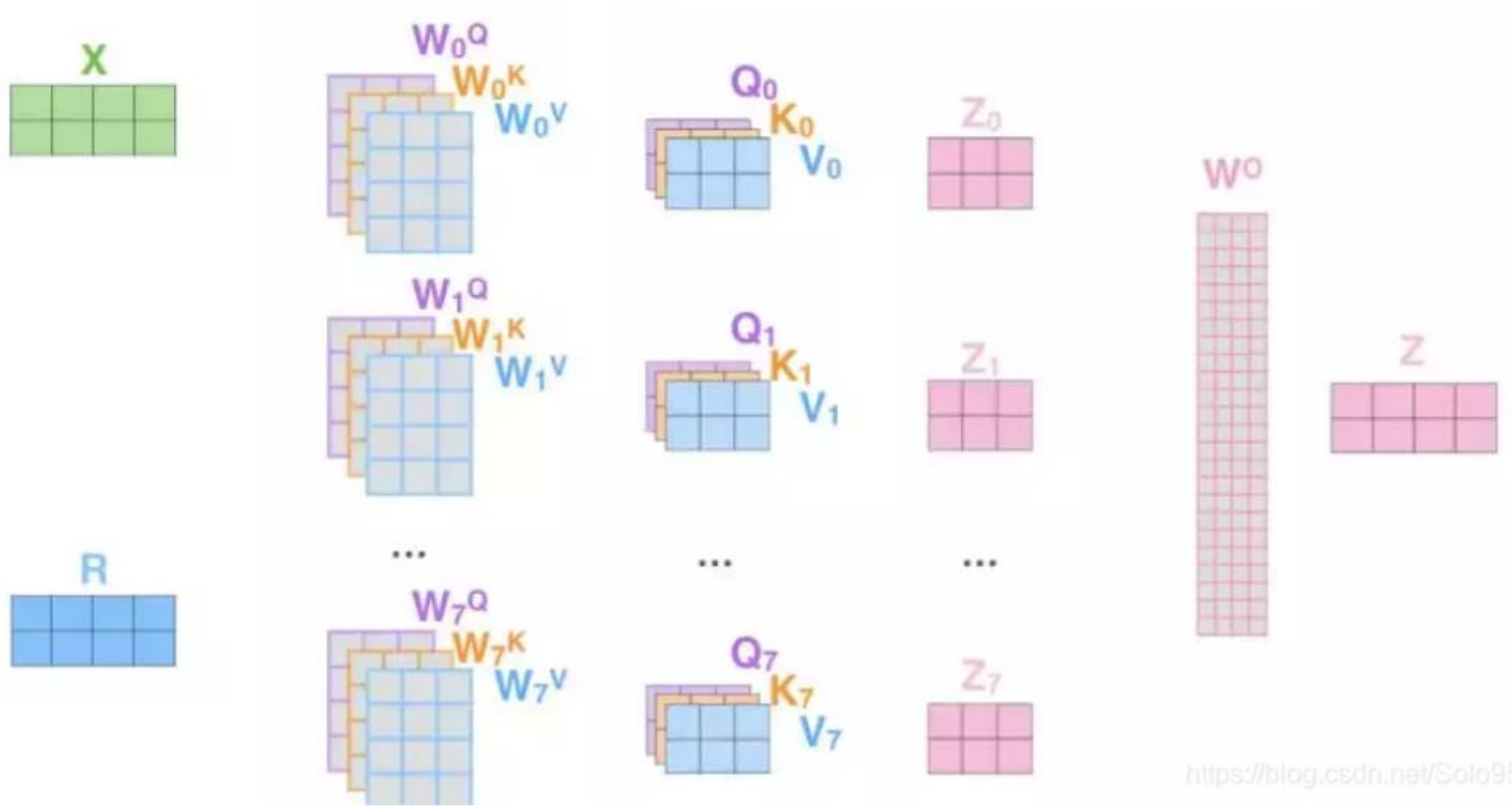
- Project onto more subspaces
- Dimension reduction

Figures


Scaled Dot-Product Attention
MatMul
SoftMax
Mask (opt.)
Scale
MatMul
Q
K
V


Multi-Head Attention
Linear
Concat
Scaled Dot-Product Attention
h
Linear
Linear
Linear
V
K
Q

Figure


X
R
W_0^Q
W_0^K
W_0^V
W_1^Q
W_1^K
W_1^V
W_7^Q
W_7^K
W_7^V
Q_0 K_0 V_0
Q_1 K_1 V_1
Q_7 K_7 V_7
Z_0
Z_1
Z_7
W^O
Z
https://blog.csdn.net/Solo9

Multi-head Self-attention

- Where Q=K=V for this:

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

$$MultiHead(Q,K,V) = Concat(head_1, head_2, \cdots head_h)W^o$$

Figure

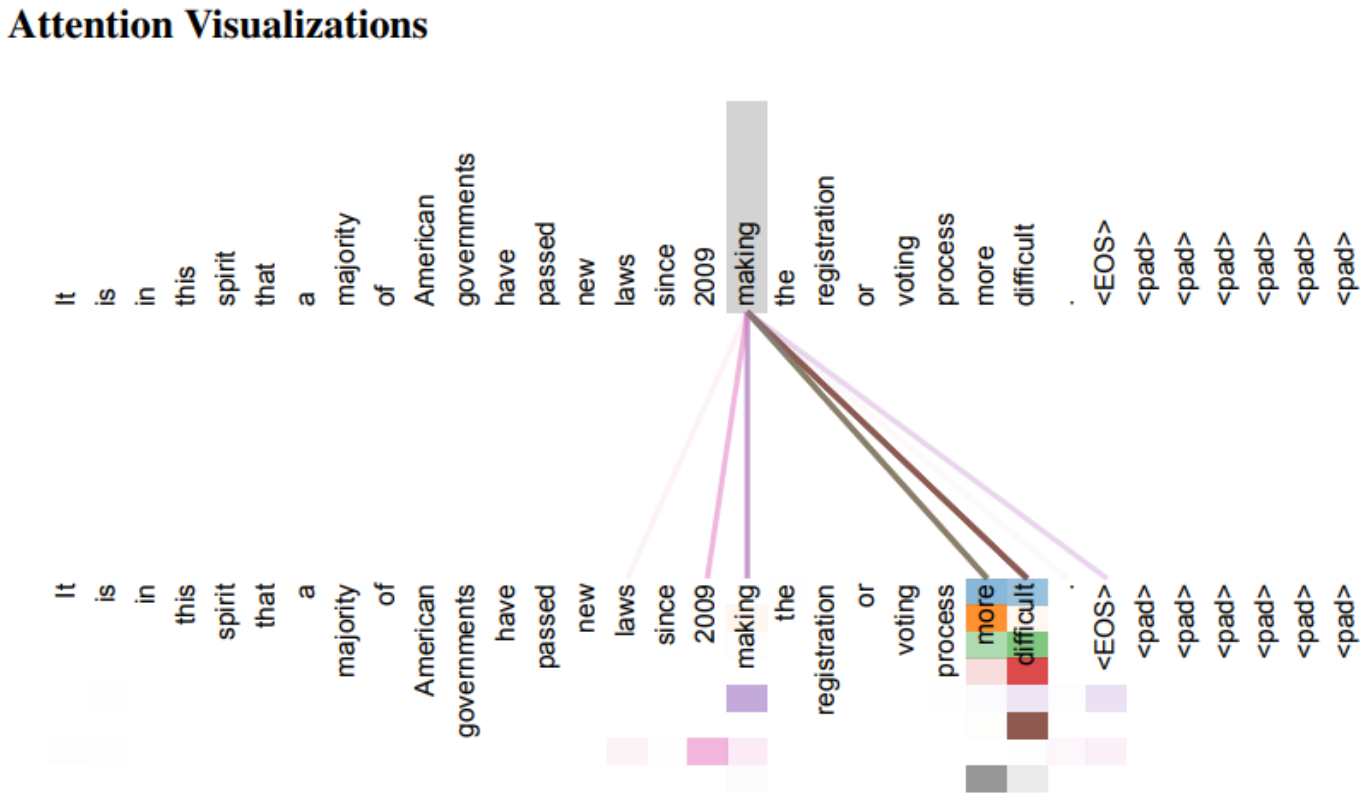
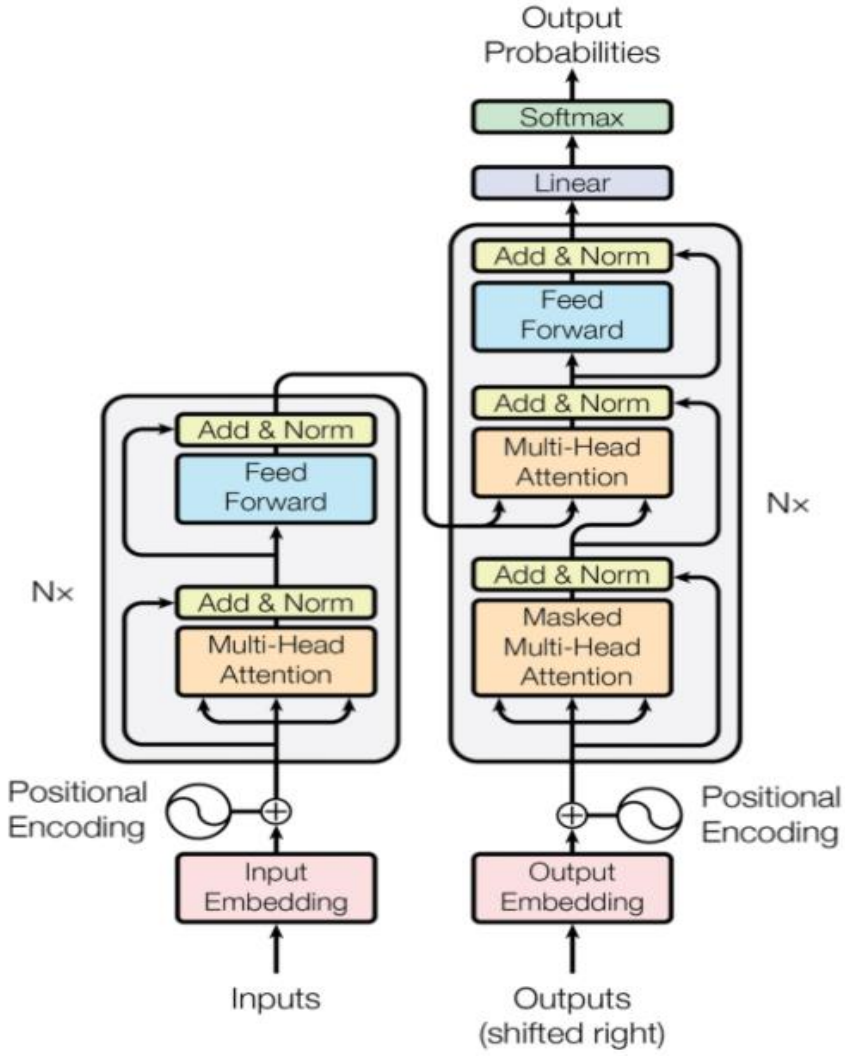


Figure 3: An example of the attention mechanism following long-distance dependencies in the encoder self-attention in layer 5 of 6. Many of the attention heads attend to a distant dependency of the verb 'making', completing the phrase 'making...more difficult'. Attentions here shown only for the word 'making'. Different colors represent different heads. Best viewed in color.

Transformers

- “Attention is All You Need”
  - Encoder and decoder
  - Residual connection
  - Positional encoding



Summary

- QKV attention
- Self-attention and in NLP
- Multi-head attention
- transformers

Take a break!

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Revisit: Language Model

- A language model tries to **predict the next word(token)** given the previous token sequence.

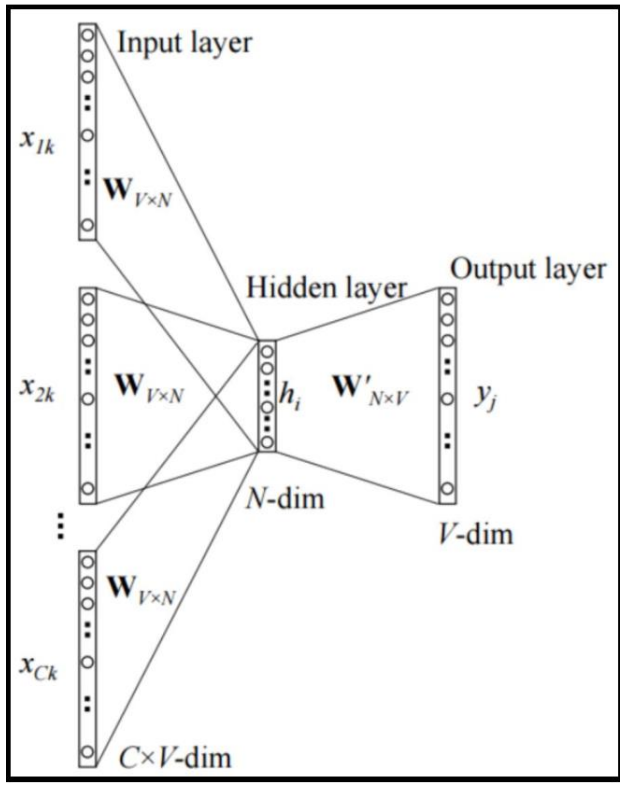
$$P(x^{(t+1)}|x^{(t)}, \ldots, x^{(1)})$$

- RNN Language Model

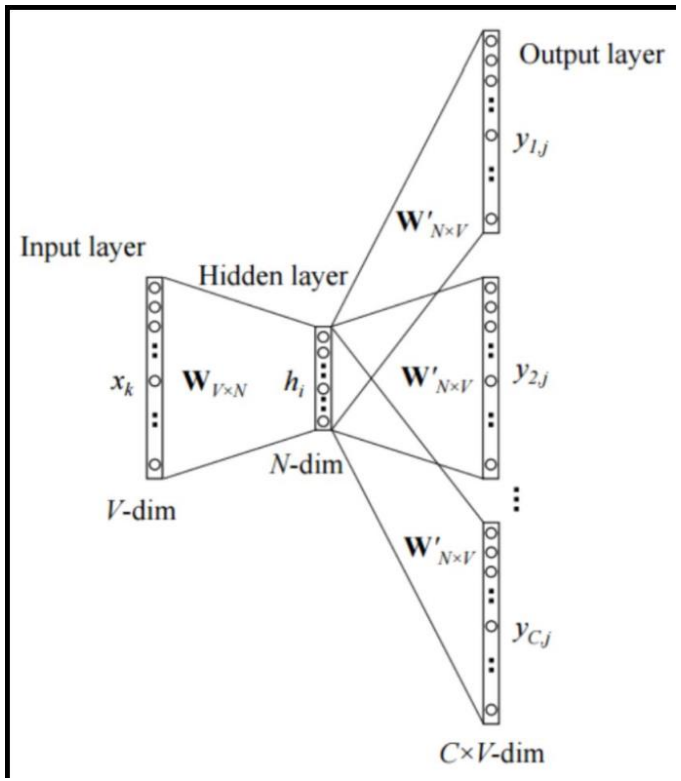
- How to train an RNN language model?

Revisit: Word2Vec

- “you shall know a word by the company it keeps”
- CBOW

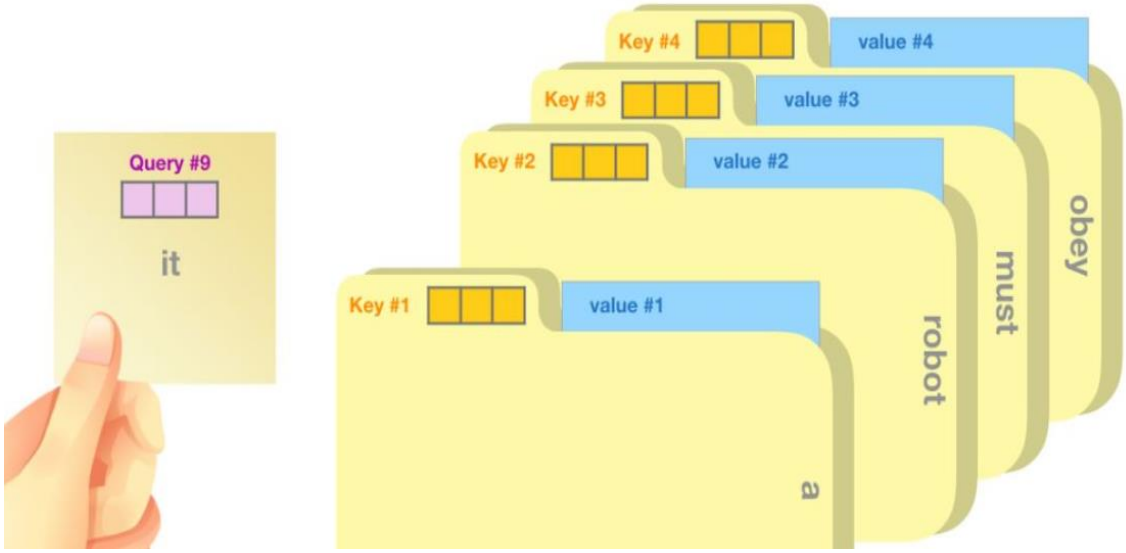


Skip-Gram



Revisit: Attention Mechanism

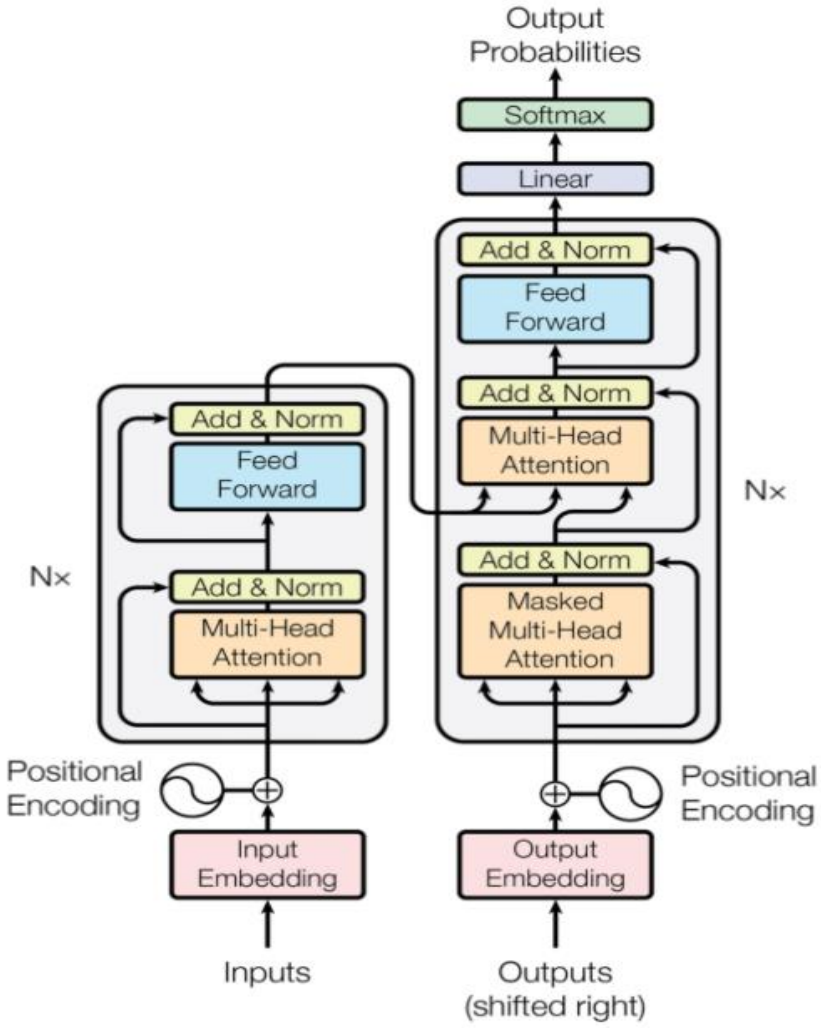
- Query-Key-Value Framework
- Self-attention
  - Q=K=V
- Masked self-attention
  - Only K V before the current token
- Multi-head attention
  - Just like multiple convolution kernels



Revisit: Transformer

- Positional encoding
  - Why and how
- Residual connection
- Input & output
- Why is it faster than RNN?

- Multi-layer transformer encoder?



Motivation

- Data annotation has always been the soft spot…

- Few-shot learning
- Unsupervised leanring
- Semi-supervised learning

- Self-supervised learning

Definition

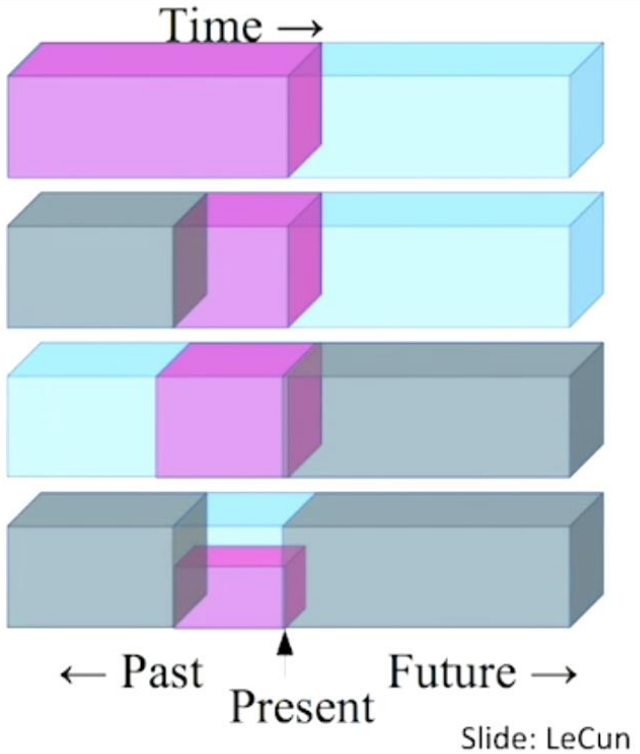
- Framing a supervised learning task in a special form where **predict only a subset of information using the rest**

- In which way, both inputs and labels are provided by the dataset

But

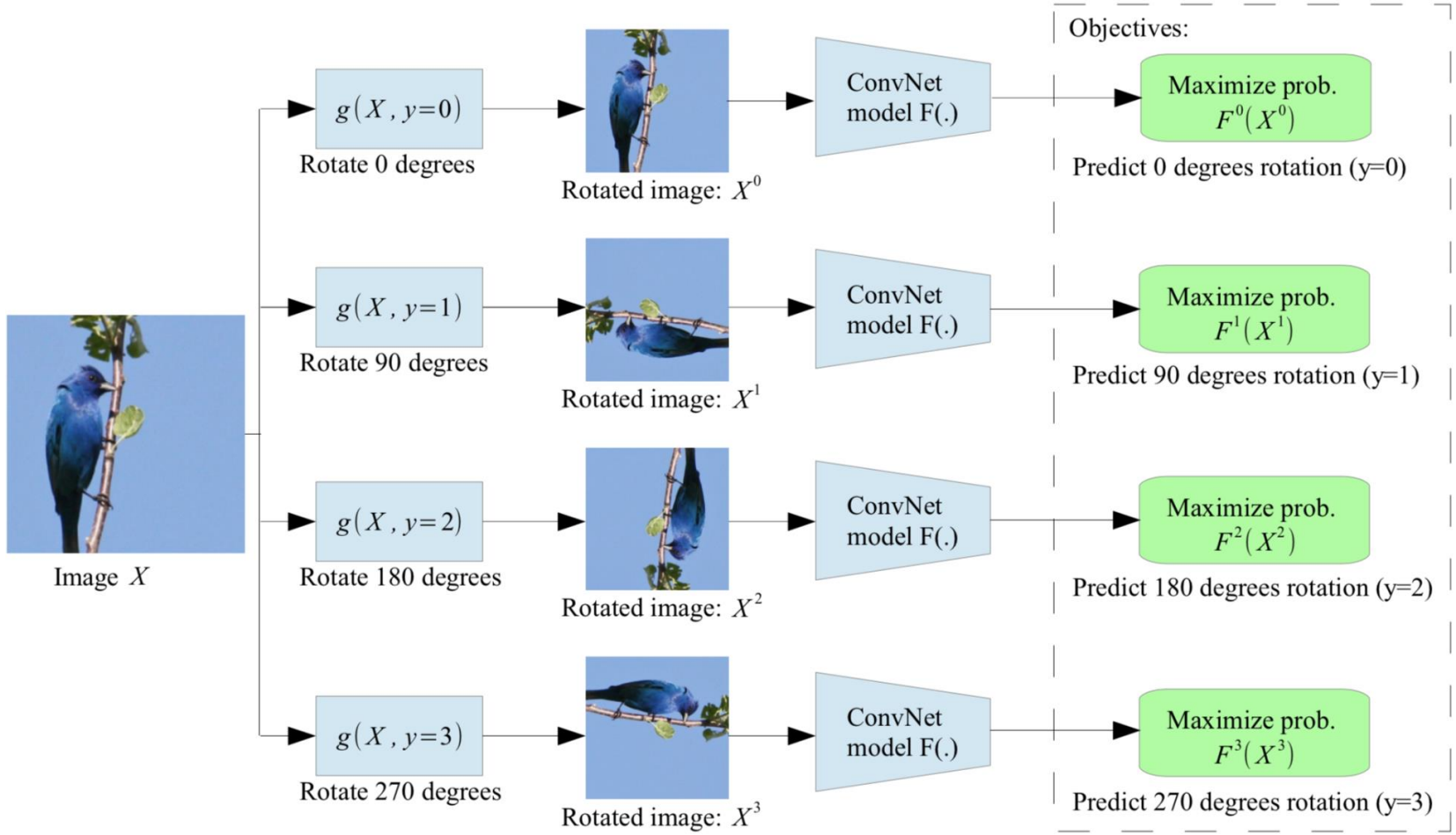
- How do we decide which to predict?

- Predict any part of the input from any other part.
- Predict the future from the past.
- Predict the future from the recent past.
- Predict the past from the present.
- Predict the top from the bottom.
- Predict the occluded from the visible
- Pretend there is a part of the input you don't know and predict that.



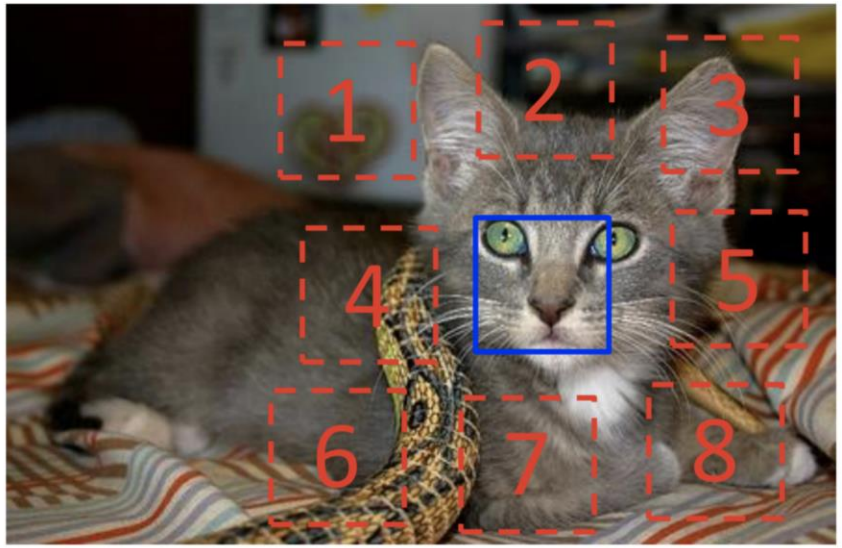
Slide: LeCun

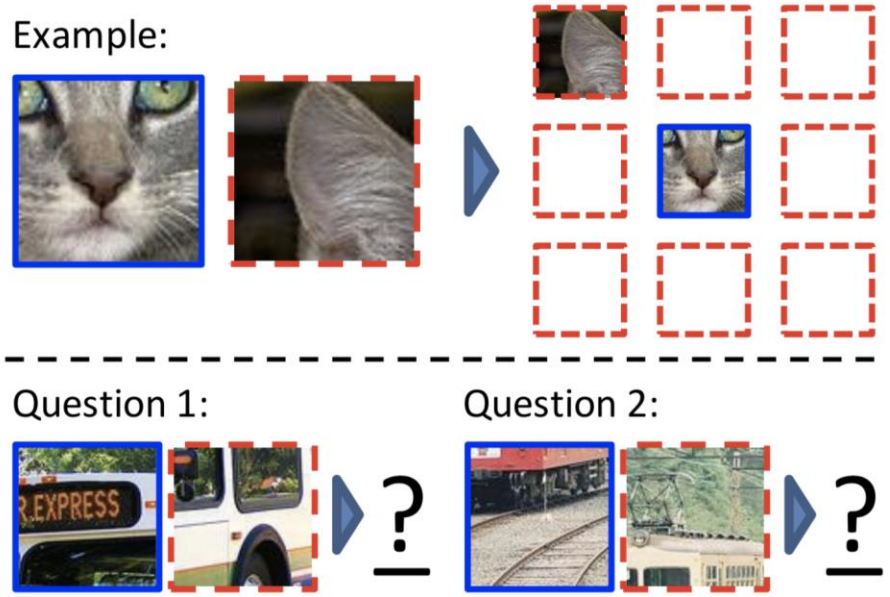
Image: Rotation



- Learn image semantics in the process

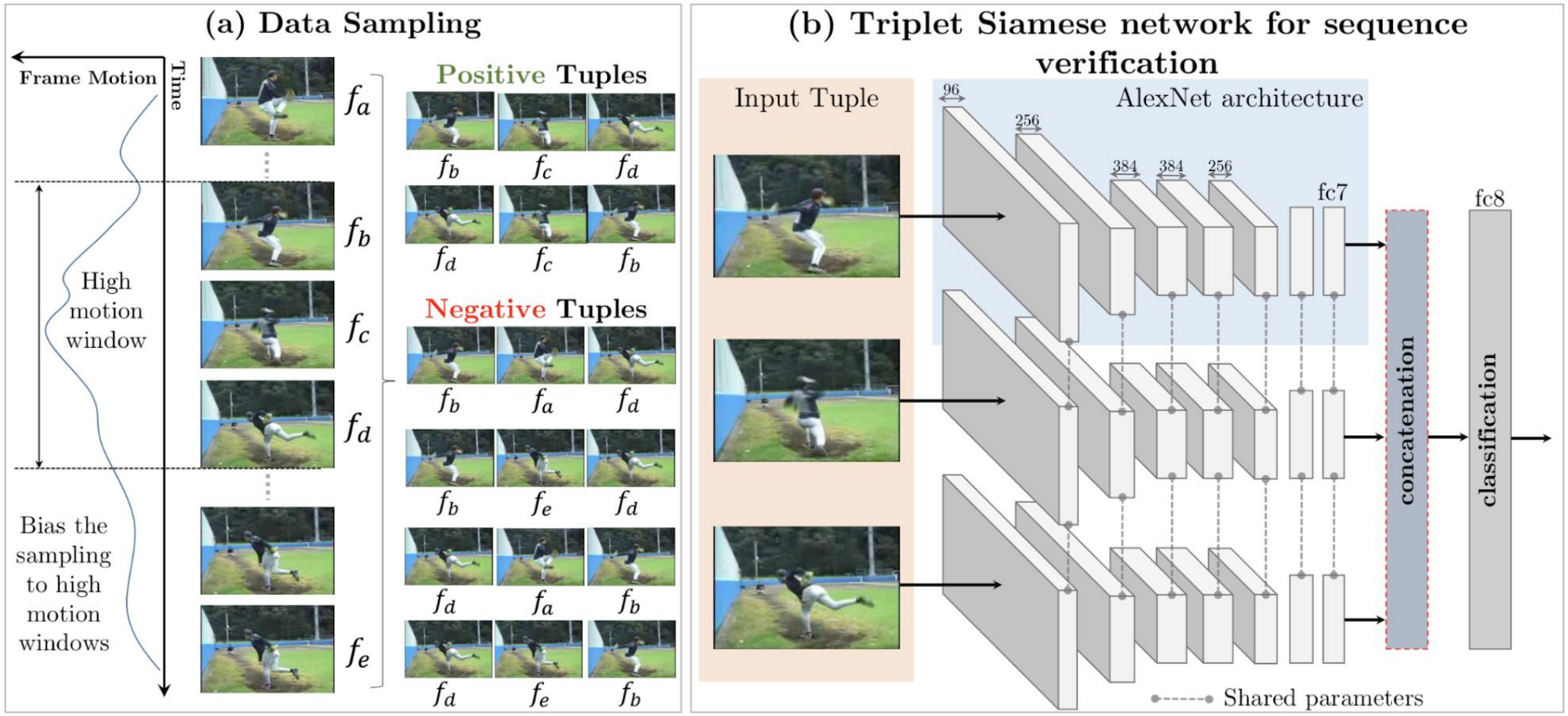
Image: Patch





- Gap between patches is crucial…

Video: Frame Sequence



NLP

- Predict next word of a sentence
  - Language Model

- Predict words within the context window
  - word2vec

Why self-supervision works

- In the process of solving auxiliary tasks, the network learns **representations** of inputs
- that could be utilized to solve downstream tasks

- **Representation Learning**
  - In comparison to **feature engineering**
  - A system automatically discover features (e.g. word embedding)

- ICLR

However

- The self-supervised task is not my objective!
- Self-supervised applications serve as a pre-training method, that captures semantic/context/correlation, learns **generic knowledge**
- Fine-tuning for the downstream tasks
- Which brings to transfer learning, specifically pre-train and fine-tune

Motivation

- Train a network from scratch?
  - Limited data, especially supervised
  - Limited computational resources (maybe u don’t feel it now lol)

- Observation: tasks that are similar in context
  - image classification, HUGE dataset and lots of efforts
  - Image style transfer (e.g. horse 2 zebra)
    - Is there any supervised data at all?
    - Same context: understanding images

Transfer Learning

- Transfer learning is a machine learning method where a model developed for a task is reused as the starting point for a model on a second task.

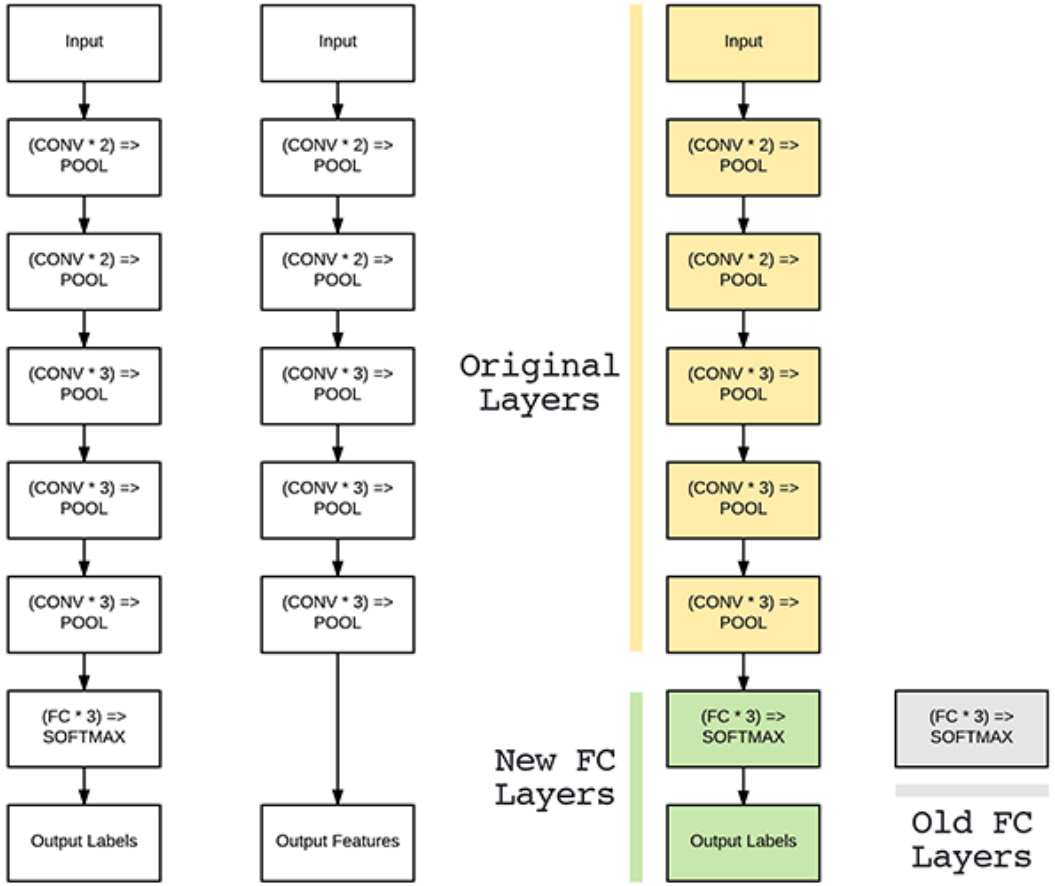
- Often,
  - The first task is rich in data(supervised in CV & self-supervised in NLP)
  - The first model is computationally expensive
  - The second task lacks data or accurate annotation
  - Both tasks are similar in underlying generic knowledge

TL: Feature Extraction Approach

- Extract the data representation from the first approach as the input for the second model, keeps the first model param unchanged
- For instance
  - Word2vec in NLP
- Question: Are features discovered in the first task exactly what we want in solving the second task?

TL: Fine-Tuning Approach

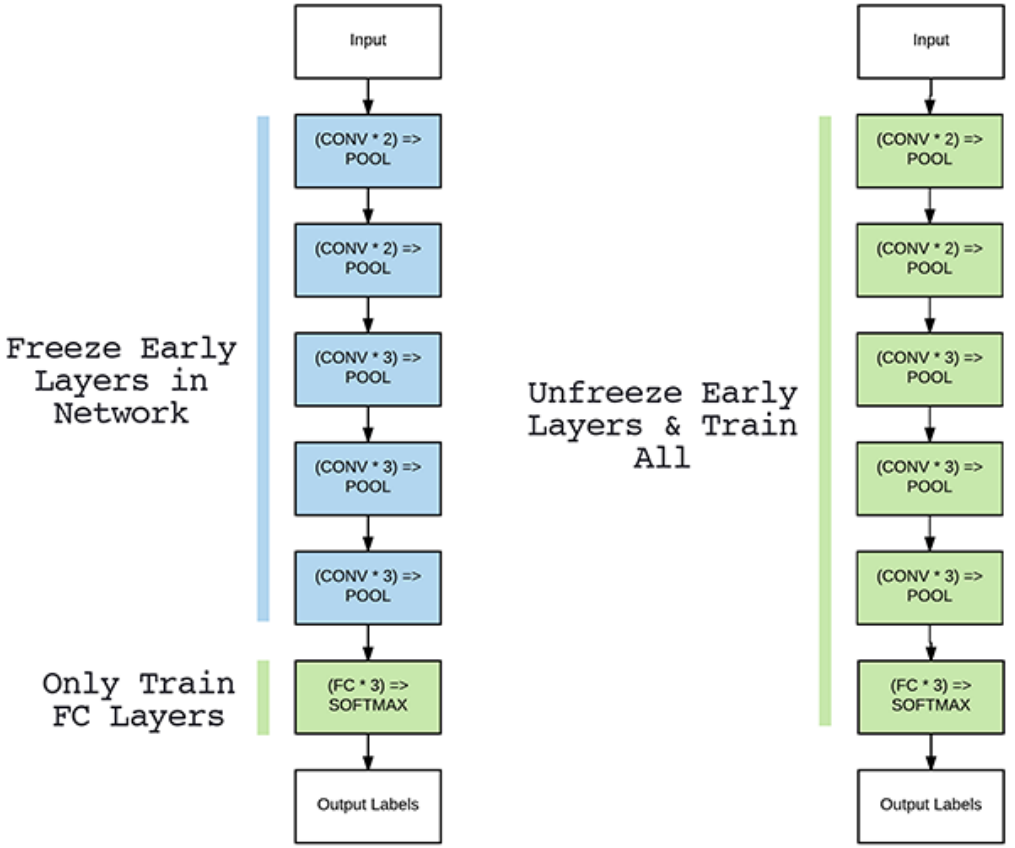
- #1 Architecture Change
- MOST COMMON APPROACH
- **Truncate the last softmax layer**
- **and replace it with a new one**
- Retain orinigal layer's params



TL: Fine-Tuning Approach

- #2 Optimization Scheme: Shallow vs Deep FT

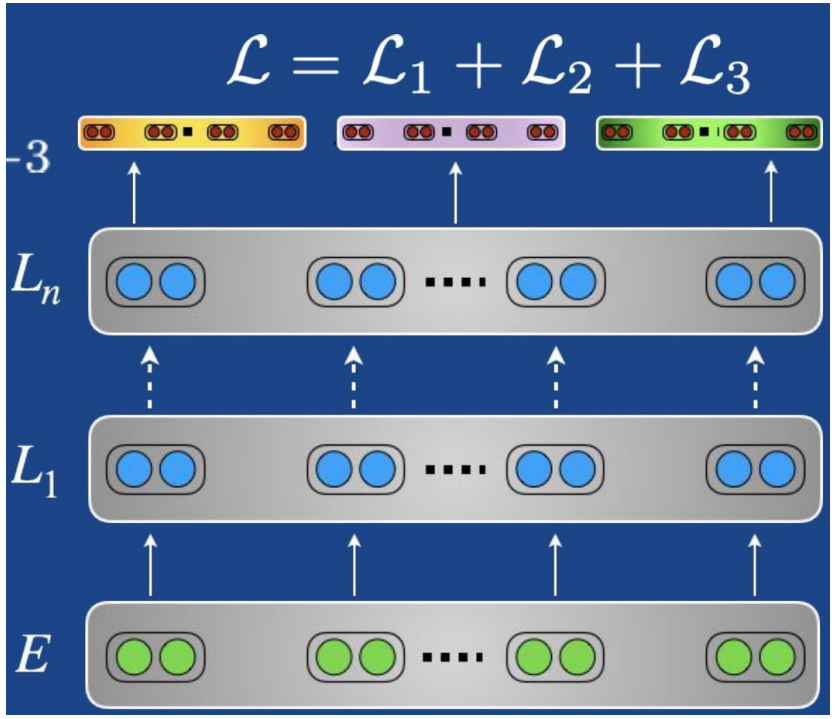
- Tricks in deep FT
  - Reduced learning rate
  - Gradual unfreezing (direction?)
  - Tougher regularization
  - warmup



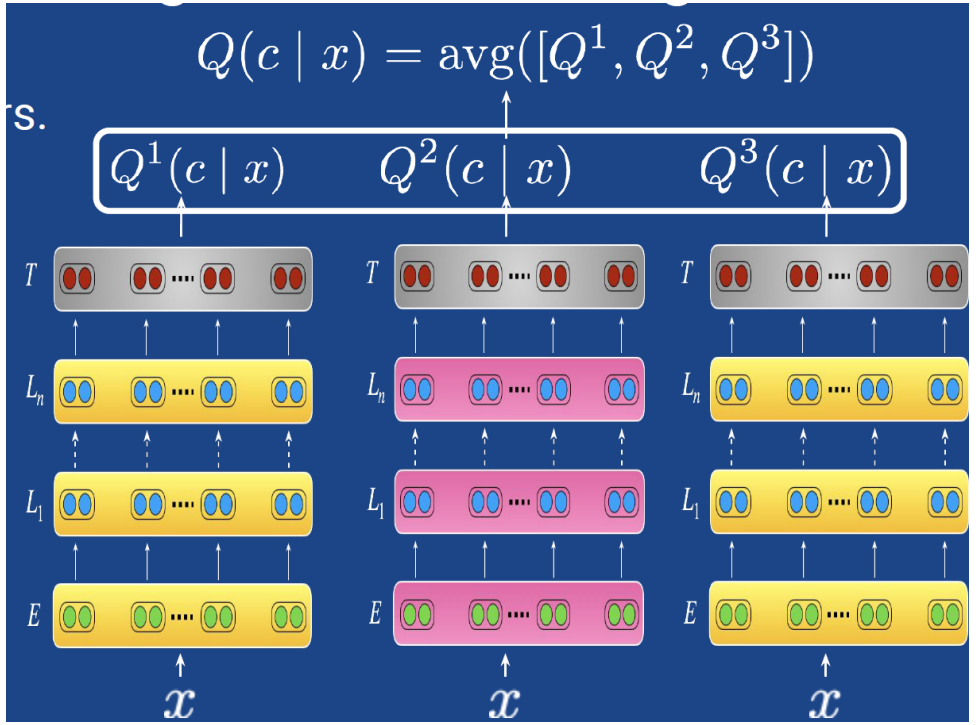
TL: Fine-Tuning Approach

- #3 Getting more signal

- Multi-task fine-tuning



Ensembling



Takeaway till now

- Self-supervised learning
- Transfer learning
- Pre-training
- Fine-tuning

Contents

- Introduction to NLP
- Word Embedding and RNNs
- Attention and Transformers
- Self-supervised Learning
- Pre-trained Language Models

BERT

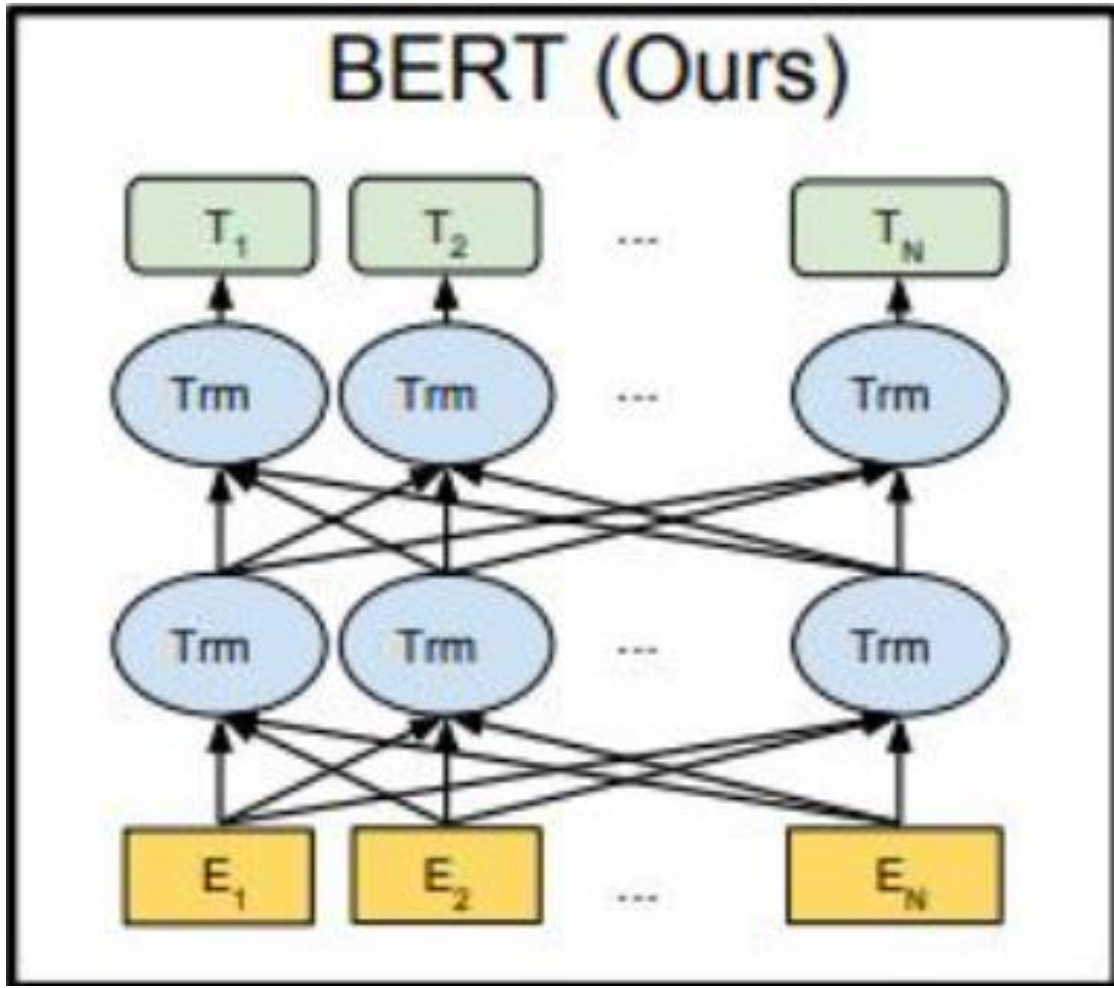
- **B**idirectional **E**ncoder **R**epresentation from **T**ransformers

- After transformers, another shocking breakthrough from Google to the NLP community

- A self-supervised pre-training Language Model
  - Architecture?
  - Self-supervised pre-training tasks?
  - How do I use it in fine-tuning downstream tasks?

BERT Architecture

- Only encoder of transformer
- Bidirectional? Undirectional
  - Read the entire sequence at once
  - The ‘context window’ is total



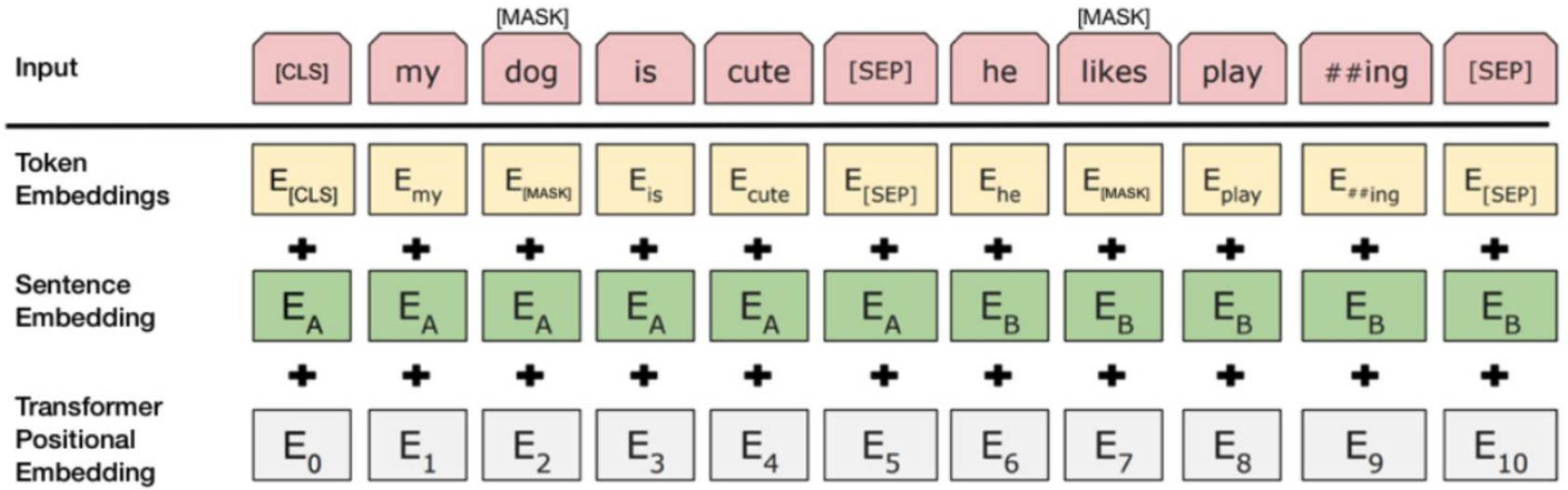
BERT Pre-training Tasks

- #1 Masked Language Model
- Pick 15% tokens and replace with
  - 80% [MASK], 10% random token, 10% the original one
  - Why not all [MASK]? [MASK] is not in fine-tuning process

$$P(w_i|w_1, \ldots, w_{i-1}, w_{i+1}, \ldots, w_n)$$

- #2 Next Sentence Prediction
- Each sequence is a concatenation of two sentences A & B
  - 50% B follows A
  - 50% B is a random sentence in the corpus
  - Binary classification

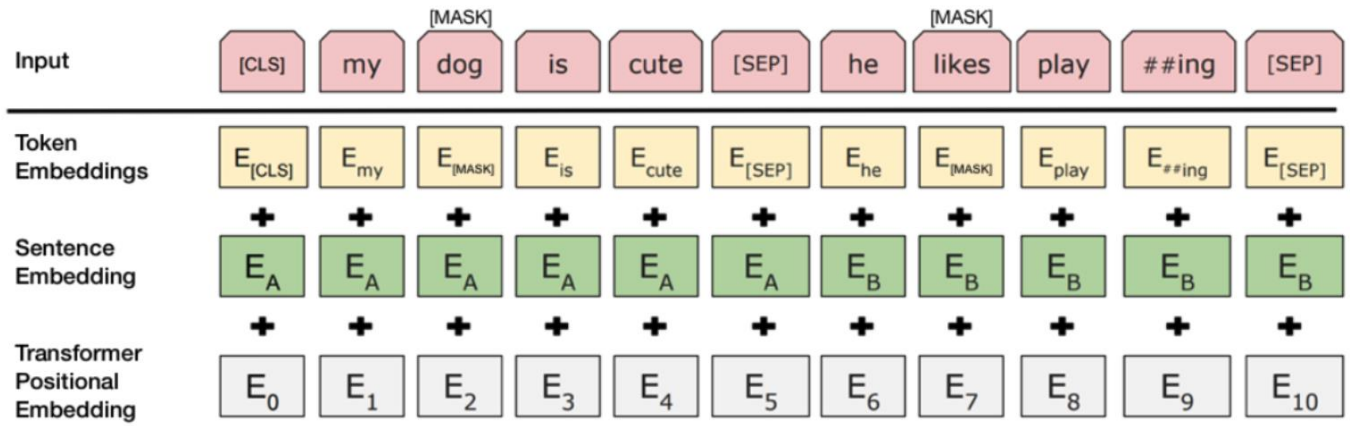
Joint Pre-training Input

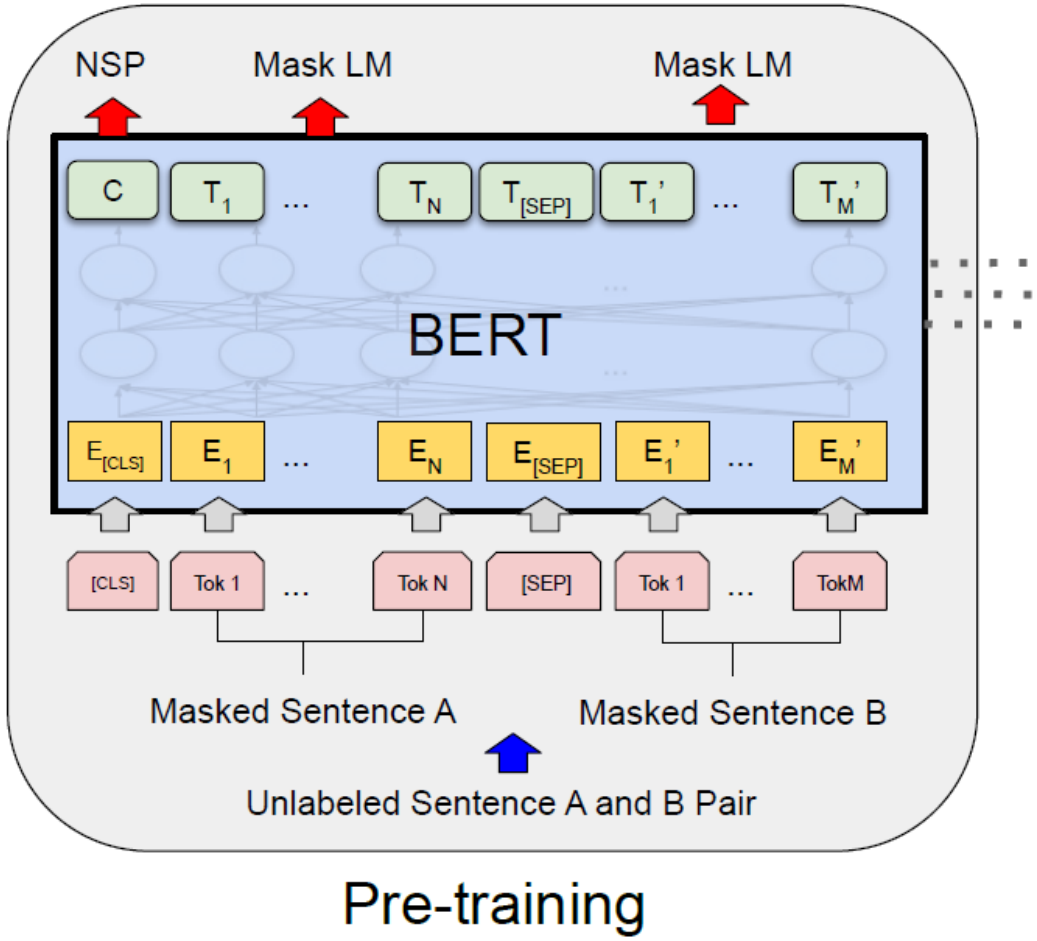


- [CLS]: prompter for next sentence prediction task
- [SEP]: sentence separater
- [MASK]: this word is masked due to Masked LM task

Joint Pre-training

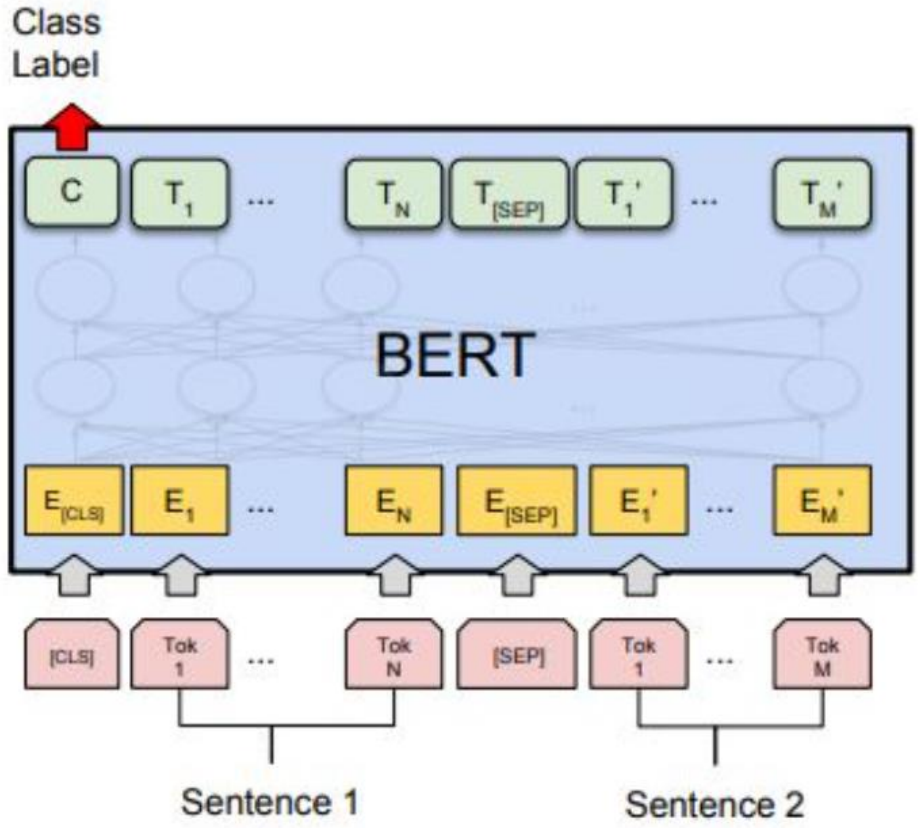
- Next sentence prediction
  - Softmax @ [CLS] token
- Masked Language Model
  - Softmax @ any [MASK] token



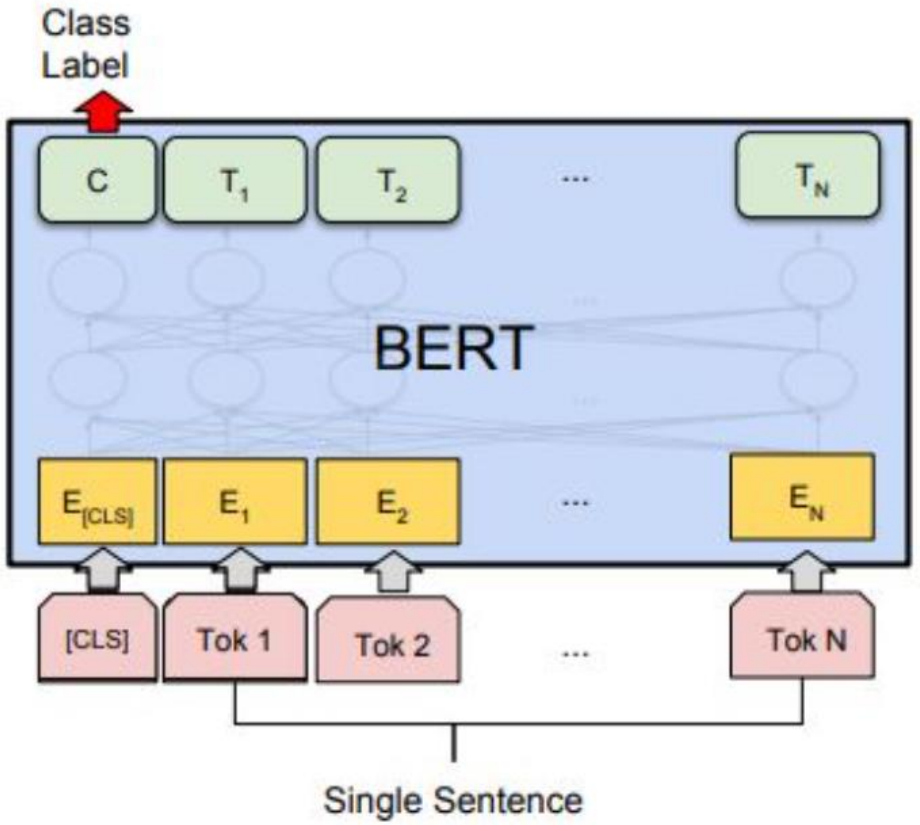


Pre-training

Fine-tuning on Downstream NLP Tasks

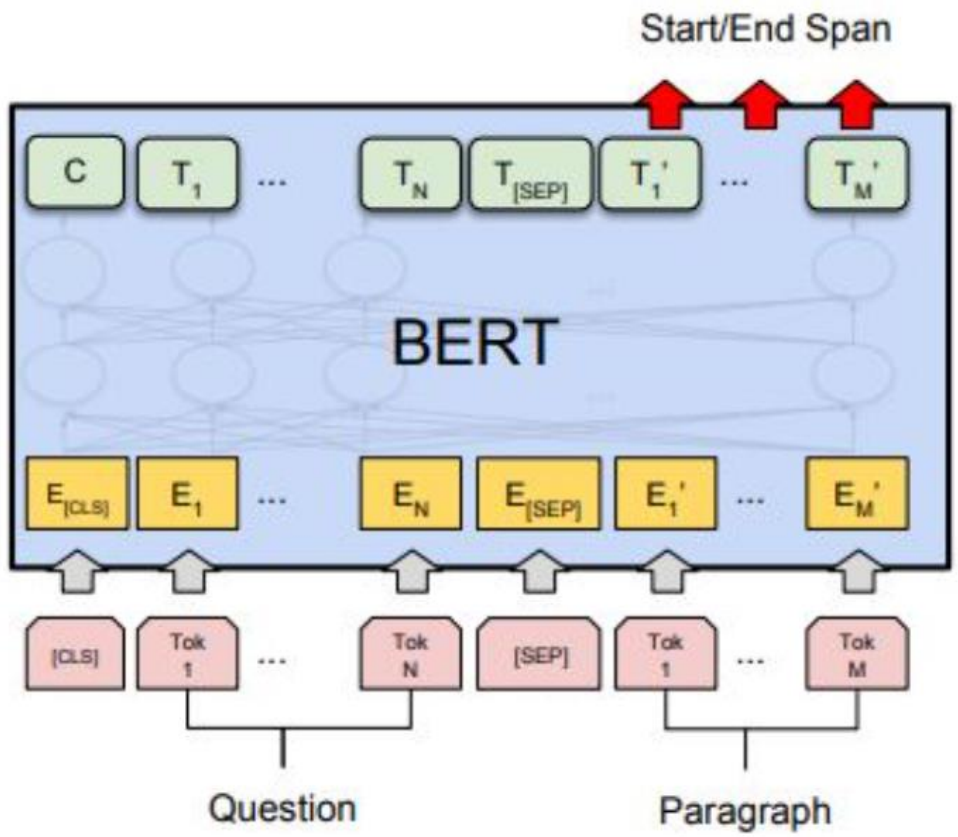


(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

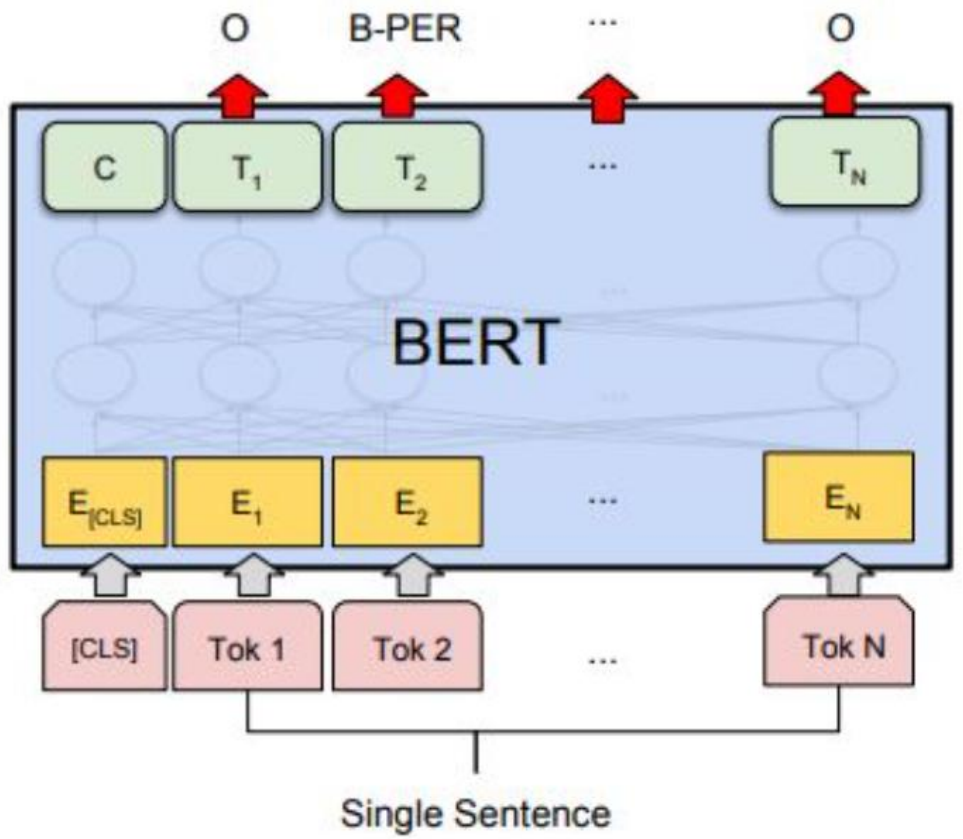


(b) Single Sentence Classification Tasks: SST-2, CoLA

Fine-tuning on Downstream NLP Tasks



(c) Question Answering Tasks:
SQuAD v1.1



(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

BERT Contributions

- #1 A deep model could also succeed in NLP

- #2 Representation Learning will be ubiquitous in NLP
  - Word2vec: one word, one embedding
  - BERT & more: context-aware embedding

- #3 Pre-training & Fine-tuning schema is substantiated
  - In fact, use pre-trained models whenever u can!

RoBERTa

- Robustly Optimized BERT Pre-training Approach
  - Shorter pre-train time, better downstream performance

- Change #1: Remove Next Sentence Prediction
  - Better performance on downstream tasks
- Change #2: Bigger batch sizes & longer sequences
  - Augment parallelization & end-task acc
- Change #3: Dynamically change [MASK] strategy
  - Re[MASK] every 4 epochs, 10 different [MASK]ed seqs in 40 epochs

GPT-3

- “Language Models are Few-shot Learners” by OpenAI
- 175 billion parameters, 12million $ for pre-training once

- Outperforms on Cloze, Q&A, Translation, Coreference Resolution, Reasoning, Reading Comprehension, Standard Test,…

- Few-shot, one-shot & zero-shot nature further substantiates the efficacy of pre-training to capture generic knowledge in text

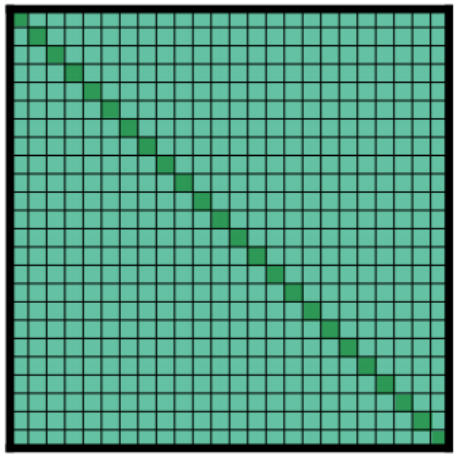
Summary

- Self-supervised Learning
  - Learn to predict part of itself using the rest
- Pre-training & Fine-tuning
  - Pre-train captures generic knowledge, fine-tune for downstream
  - Architecture, Optimization tricks & More Signal
- BERT
  - Architertuce, Pre-Training Tasks, how to pre-train and fine-tune
- RoBERTa & GPT-3

More Advanced LM

LM: LongFormer 1/5

- Full self-attention is O(n^2)

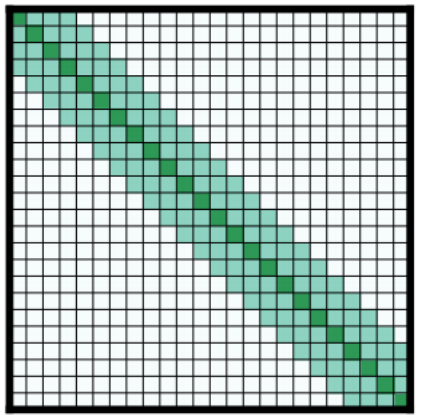


(a) Full n^2 attention

- Computationally expensive
- Only global semantics

- Idea: sparsify the attention map
- Note: A attends to B = query A includes B as key & value

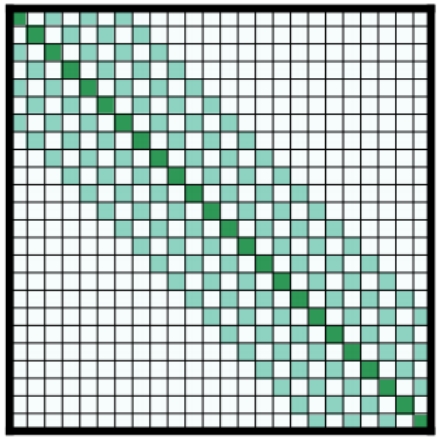
LM: LongFormer 2/5



(b) Sliding window attention

- **Sliding window attention**
- Fixed window size *w*, each token attends to *w/2* left & right
- Complexity: O(n * w)
- With *l* layers of transformer, the top-most layer has a receptive field of *l* * *w*, modeling local and global semantics progressively

LM: LongFormer 3/5



(c) Dilated sliding window

- **Dilated Sliding Window**

- Complexity: O(n * w)
- Receptive Field: O(*l * d * w*), with stride d

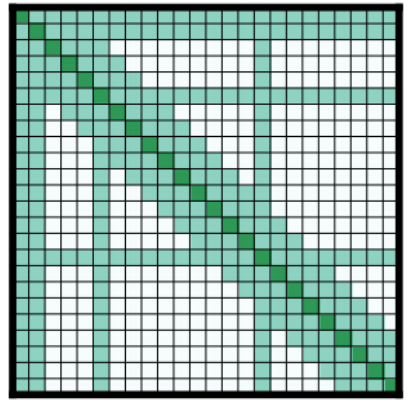
- Combine multi-head attention with different *d, w* settings

LM: LongFormer 4/5

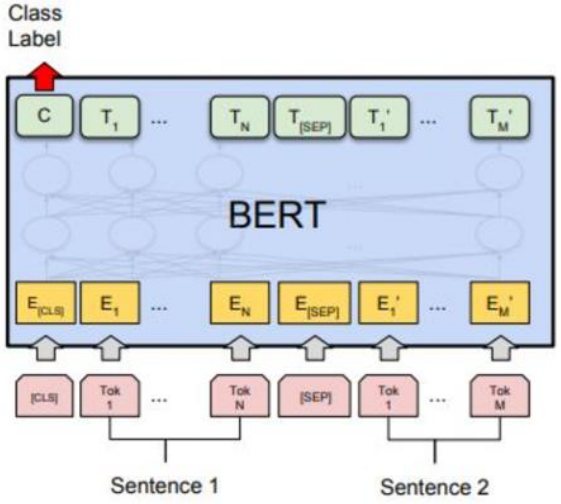
- **Global + Sliding Window Attention**

- A global token if
  - Attend to all other tokens
  - Attended by all other tokens

- e.g. [CLS] in BERT text classification



(d) Global+sliding window



(a) Sentence Pair Classification Tasks: MNLI, QQP, QNLI, STS-B, MRPC, RTE, SWAG

3	Longformer (single)	AI2	March 2020	81.9

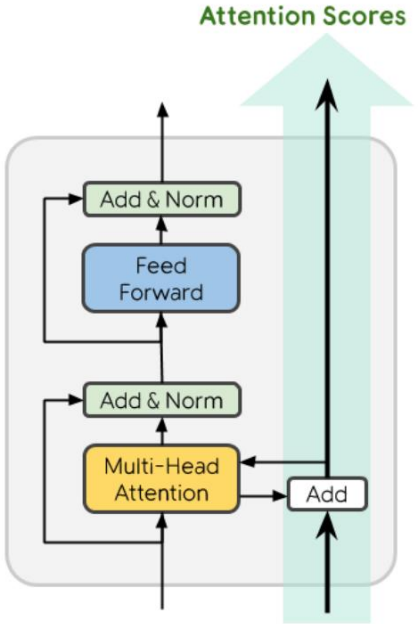
LM: LongFormer 5/5

- Pre-training tasks
  - Masked Language Model
- Issues
  - Inherit RoBERTa parameters checkpoint
  - Frozen weights @ lower levels
- Evaluation
  - Many NLP tasks, Wikihop being one of it

LM: RealFormer 1/2

- Insanely simple: residual connection
- *Prev*, pre-softmax attention scores in the last layer of transformer

$$\text{ResidualMultiHead}\,(Q, K, V, Prev) = \text{Concat}\,(head_1, ..., head_h)\,W^O$$



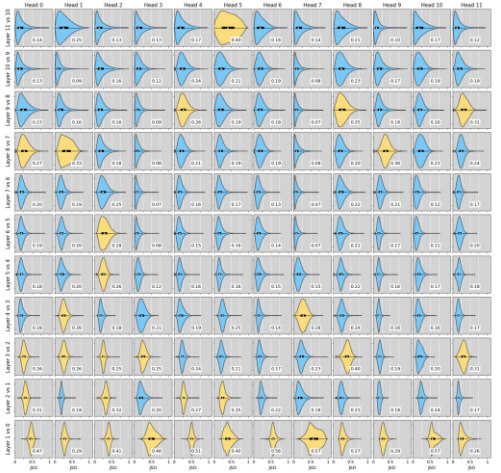
where $head_i = \text{ResidualAttention}\,(QW_i^Q, KW_i^K, VW_i^V, Prev_i)$ and $Prev_i$ is the slice of

$$\text{ResidualAttention}\,(Q', K', V', Prev') = \text{Softmax}\,(\frac{Q'K'^T}{\sqrt{d_k}} + Prev')\,V'. \quad (5)$$

Finally, new attention scores $\frac{Q'K'^T}{\sqrt{d_k}} + Prev'$ are passed over to the next layer.

LM: RealFormer 2/2

- It is a way of regularization, since it encourages attention heads in layer L resemble those in layer L-1
- Observation
  - Sparser attention at the top (meaning…)
  - Lower variance across layers
- Evaluation
  - Many NLP tasks, with Wikihop as one



1	RealFormer-large (single)	[anonymized]	January 2021	84.4

Project

- Reproduce results of the paper
  - “BotRGCN: Twitter Bot Detection with Relational Graph Convolutional Networks”

- Huggingface transformers github, pipeline, for NLP part
- Torch geometric for GNN part
- The template.py framework

- Please seek https://github.com/BunsenFeng/BotRGCN for reference.

Thx for Attention

Shangbin Feng, Xi'an Jiaotong University

wind_binteng@stu.xjtu.edu.cn

October 7, 2021