# DDA6307/CSC6052/MDS6002: Natural Language Processing

香港中文大學（深圳）
The Chinese University of Hong Kong, Shenzhen

## Lecture 4: Deep Learning for NLP

Spring 2024
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School of Data Science

# To recap…

# What is in the previous lecture?

- **n-gram Language Models**
  - What is an n-gram language model?
  - Generating from a language model
  - Evaluating a language model (perplexity)
  - Smoothing: additive, interpolation, discounting
- **Word embeddings**
  - How do we represent words in NLP models?
  - Distributional hypothesis
  - Sparse vs dense vectors
- **Word2vec and other variants**
  - Word2vec
  - How to train this model?
  - Skip-gram with negative sampling (SGNS) and other variants
  - Evaluating word embeddings

# n-gram models

Unigram $$P(w_1, w_2, ...w_n) = \prod_{i=1}^{n} P(w_i)$$ e.g. P(the) P(cat) P(sat)

Bigram $$P(w_1, w_2, ...w_n) = \prod_{i=1}^{n} P(w_i|w_{i-1})$$ e.g. P(the) P(cat | the) P(sat | cat)

and Trigram, 4-gram, and so on.

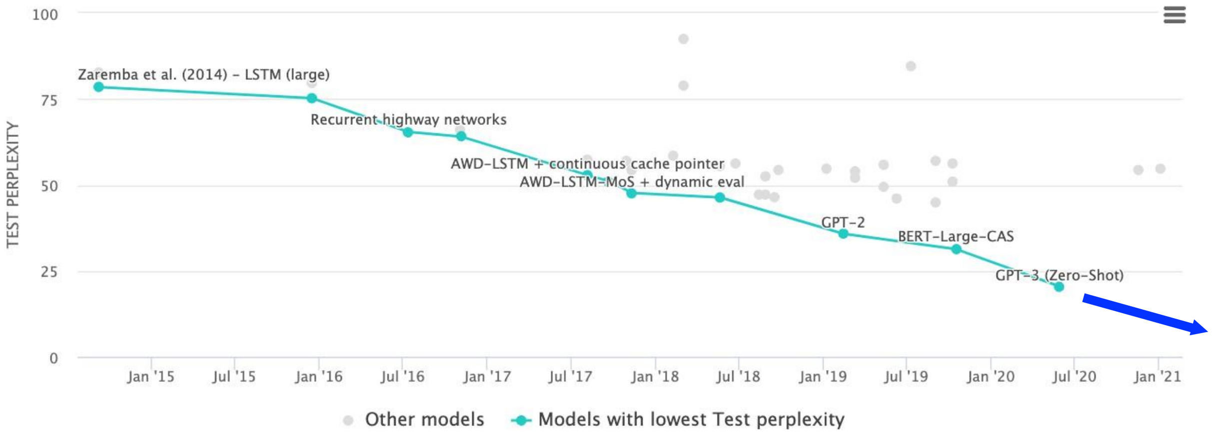
*Larger the n, more accurate and better the language model*
*(but also higher costs)*

*Caveat: Assuming infinite data!*

# Perplexity

Training corpus 38 million words, test corpus 1.5 million words, both **WSJ**

| N-gram Order | Unigram | Bigram | Trigram |
|---|---|---|---|
| Perplexity (test) | 962 | 170 | 109 |




GPT-3 175B:
ppl = 20.5

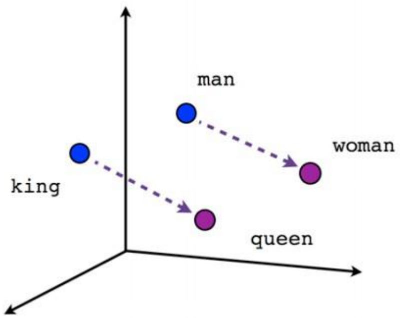
https://paperswithcode.com/sota/language-modelling-on-penn-treebank-word

# Word embeddings

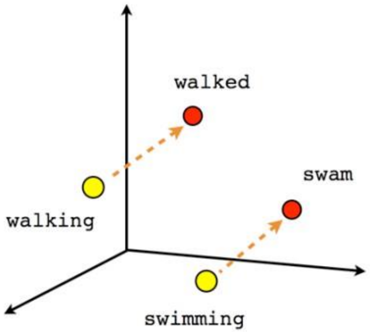
ACL'19 **Towards Understanding Linear Word Analogies**

**Kawin Ethayarajh, David Duvenaud[†], Graeme Hirst**
University of Toronto
[†]Vector Institute
{kawin, duvenaud, gh}@cs.toronto.edu

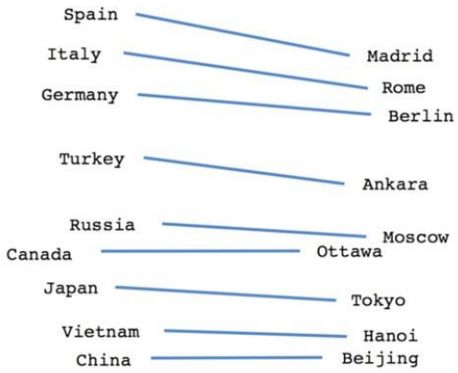
- They have some other nice properties too!




Male-Female




Verb tense




Country-Capital

$$v_{\text{man}} - v_{\text{woman}} \approx v_{\text{king}} - v_{\text{queen}}$$

$$v_{\text{Paris}} - v_{\text{France}} \approx v_{\text{Rome}} - v_{\text{Italy}}$$

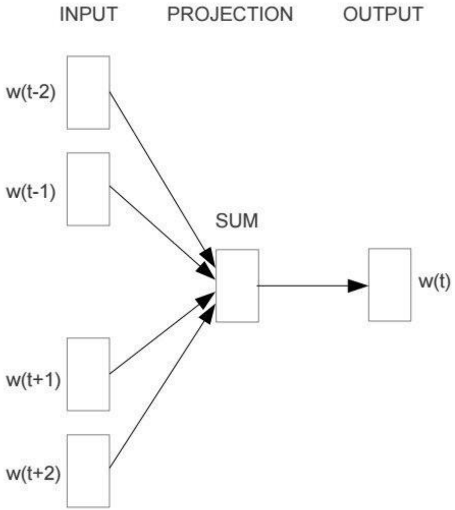
Word analogy test: $a : a^* :: b : b^*$

$$b^* = \arg\max_{w \in V} \cos(e(w), e(a^*) - e(a) + e(b))$$

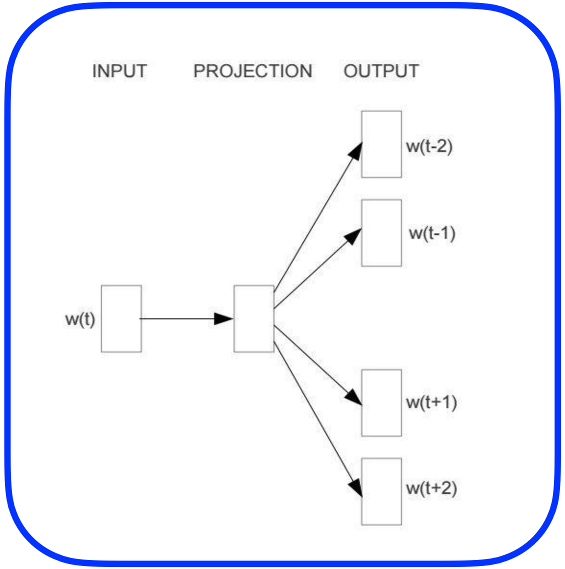
# Word embeddings

- (Mikolov et al 2013a): Efficient Estimation of Word Representations in Vector Space
- (Mikolov et al 2013b): Distributed Representations of Words and Phrases and their Compositionality

Thomas
Mikolov




Continuous Bag of Words
(CBOW)

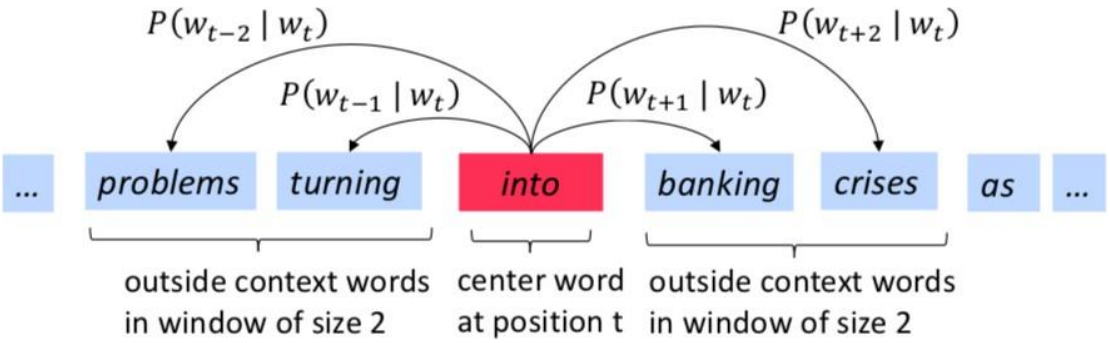



Skip-gram

# Skip-gram

- Assume that we have a large corpus $w_1, w_2, \ldots, w_T \in V$
- **Key idea:** Use each word to **predict** other words in its context
- Context: a fixed window of size 2*m* (m = 2 in the example)

A classification problem!



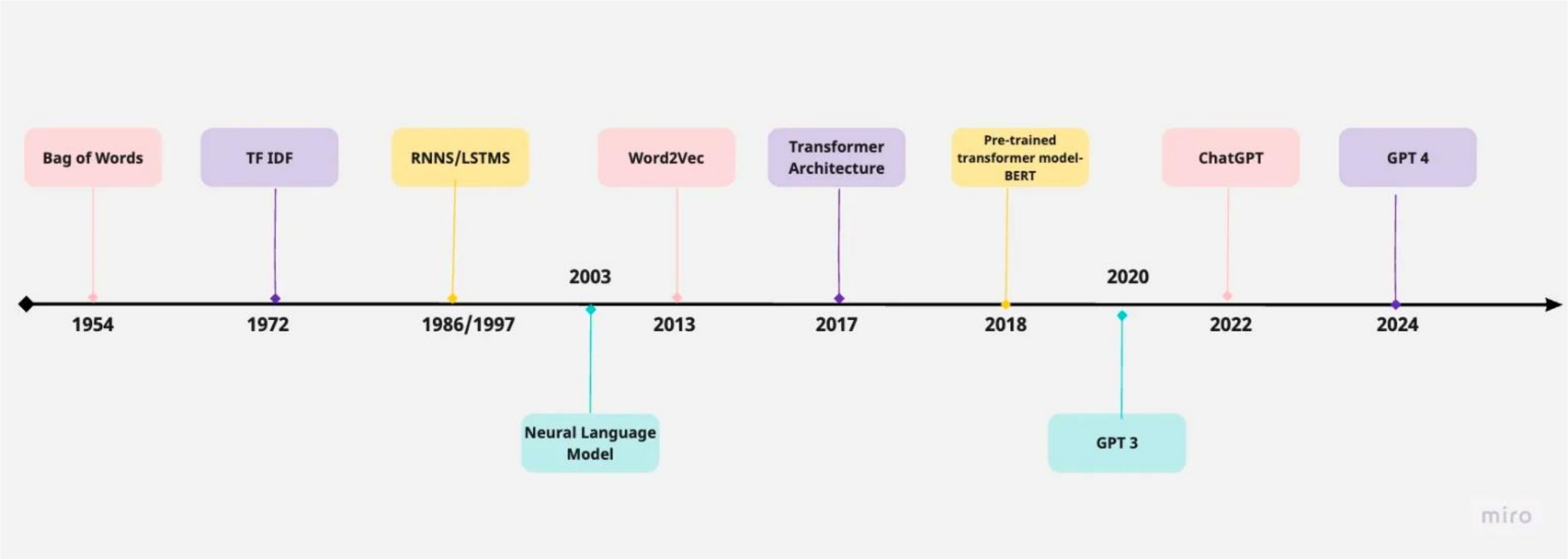

$P(b \mid a)$ = given the center word is a, what is the probability that b is a context word?

$P(\cdot \mid a)$ is a probability distribution defined over V: $\sum_{w \in V} P(w \mid a) = 1$

We are going to define this distribution soon!

# Today’s Lecture– Big Picture

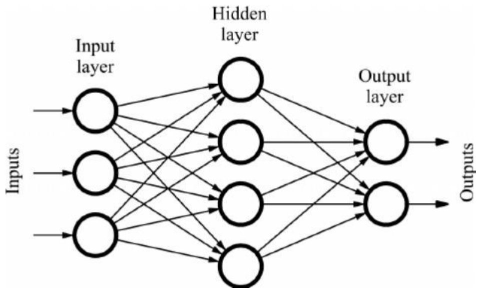
# A brief timeline of the evolution of NLP



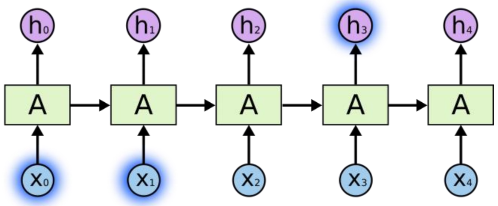

https://medium.com/pal4ai/the-pre-transformer-era-of-nlp-part-1-2103eff9744

# Which neural networks should be used for LLM?

- ✓ Multilayer Perceptron (MLP)
- ✓ Convolutional neural network
- ✓ Recurrent neural network
- ✓ **Transformer**

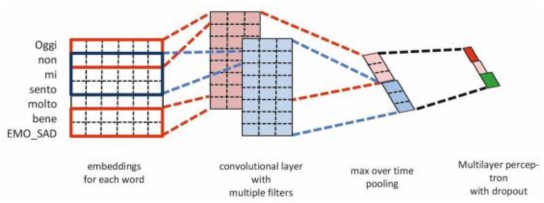



MLP

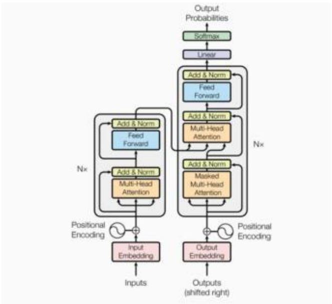



Recurrent NNs

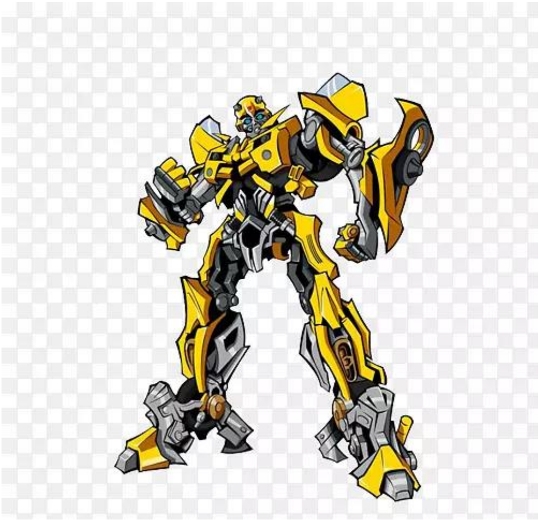
Convolutional NNs




Transformer



# Which Transformer is so powerful?



# Today's lecture

- **MLP**
  +: Strongest inductive bias: if all words are concatenated
  +: Weakest inductive bias: if all words are averaged
  - : The interaction at the token-level is too weak
- CNN & RNN
  +: The interaction at the token-level is slightly better.
    CNN: Bringing the global token-level interaction to the window-level
      - : Make simplifications, its global dependencies are limited
    RNN: An ideal method for processing token sequences
      - : Its recursive nature has the problem of disaster forgetting.
- Transformer
  +: Achieve **global dependence** at the **token-level** by **decoupling** token-level interaction and feature-level abstraction into two components, in **SAN** and **FNN**.

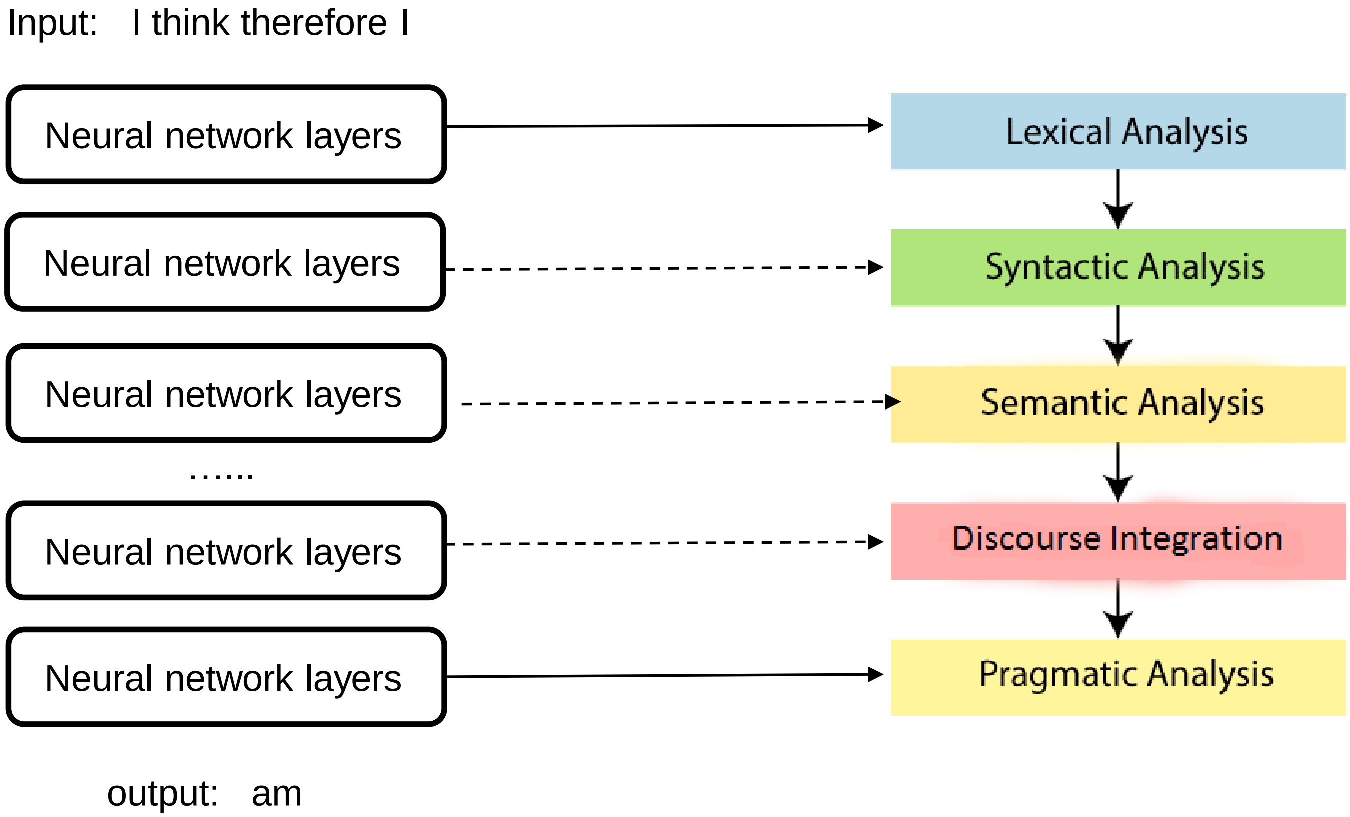
- Scaling law and emergent ability

# Semantic Abstraction and Semantic composition

# What is Semantic abstraction?


Pixel -> texture -> region -> object -> relation -> semantics->

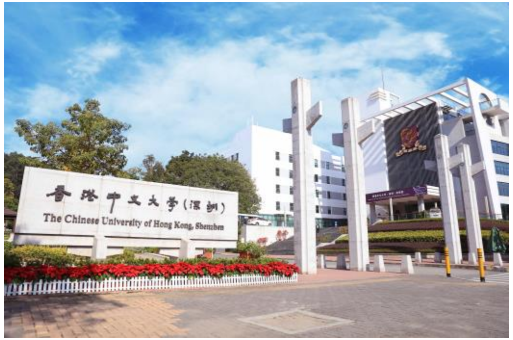
# Higher-level layers deal with higher-degree abstraction



# What is Semantic composition?

Ivory (象牙)

tower (塔)

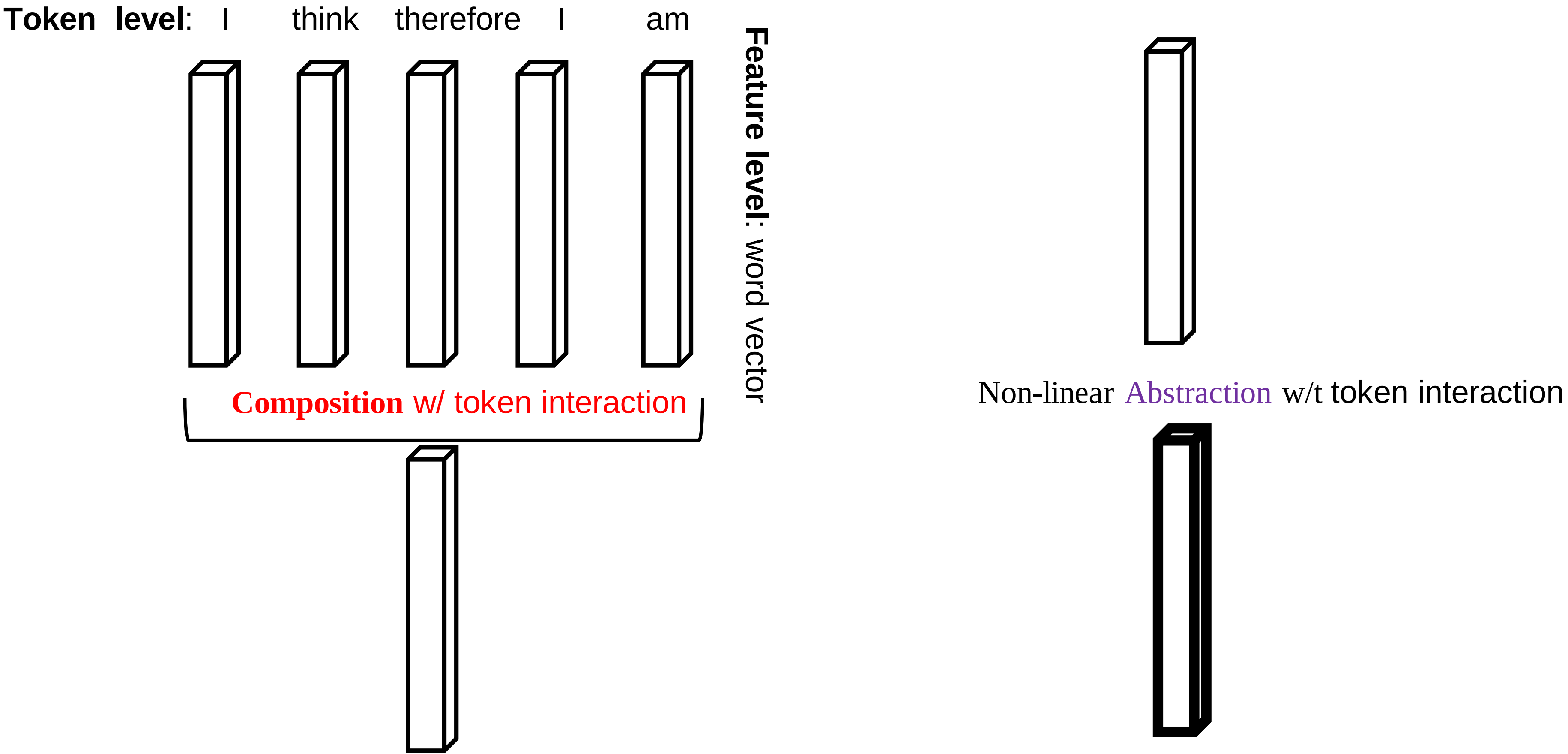



Ivory tower (象牙塔)

Semantic composition is the task of understanding the meaning of text by composing the meanings of the individual words in the text.

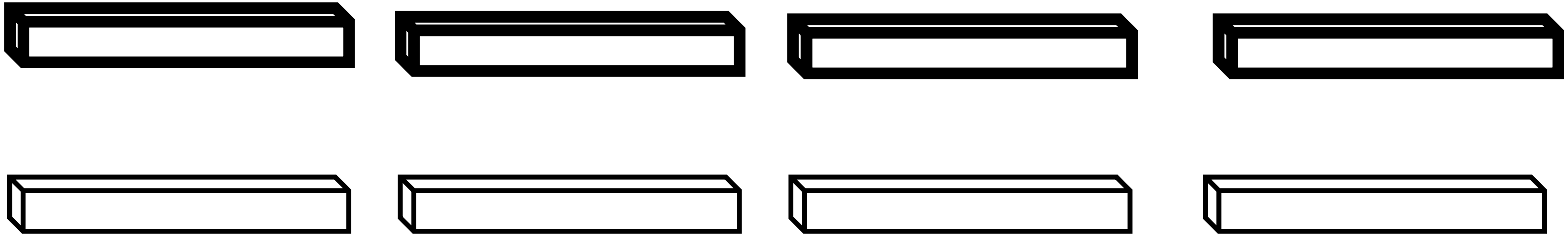
It involves **token interaction**

# Semantic composition vs. Semantic Abstraction



# How to combine composition and Abstraction

**A flatten solution: MLP (e.g. NNLM)**

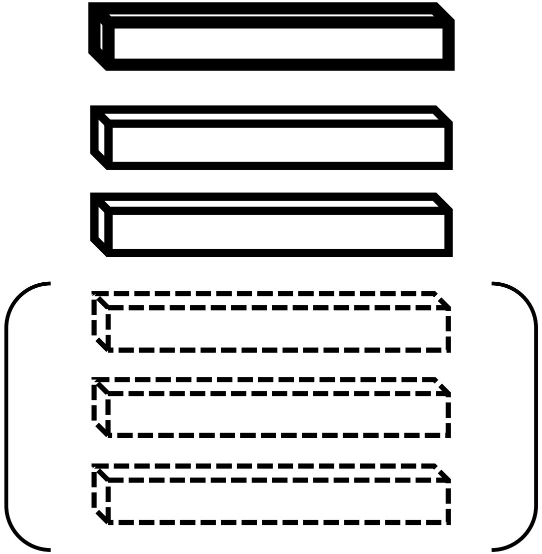


**Complexity:** $O(D^2L^2)$

Yoshua Bengio et.al A Neural Probabilistic Language Model. NIPS 2003

# How to combine composition and Abstraction

**A variant of MLP (**e.g. CBoW**)**



**Remove** token interaction in deeper layers

Mean pooling (token interaction) in the first layer

**Complexity: O($D^2$)**

T Mikolov et.al Efficient Estimation of Word Representations in Vector Space. https://arxiv.org/abs/1301.3781

# Inductive bias of composition

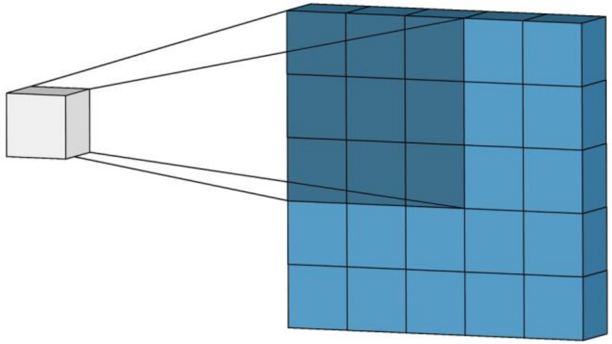
How we believe **tokens should be interacted** as the inductive bias, also considering semantic abstraction simultaneously?

Definition: The inductive bias (a.k.a learning bias) of a learning algorithm is the set of assumptions that a machine learning algorithm makes about the relationship between input variables (features) and output variables (labels) based on the training data.

# Inductive bias of composition

CNN: **local** composition within a window

RNN: **recurrently** compose tokens from left to right or right to left.



# Issues of CNN and RNN

CNN: **local** composition：

How to make long-term token interaction that is longer than the kernal size?

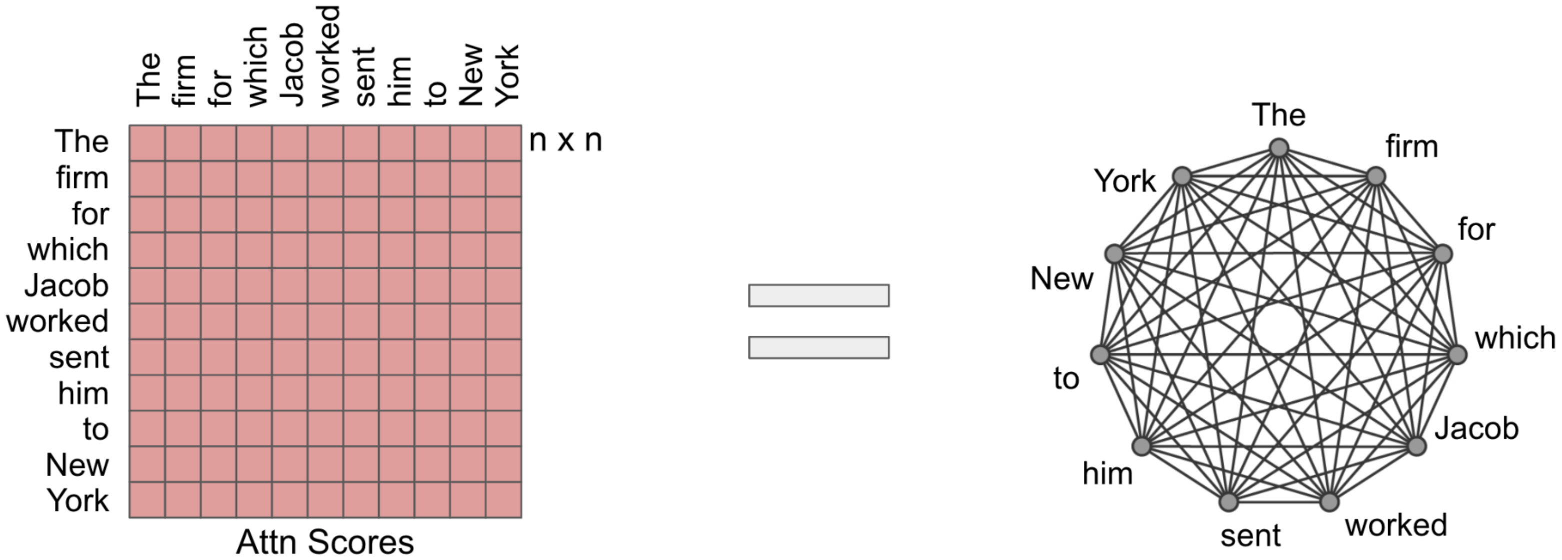
RNN: **recurrent** composition

What if we forget tokens checked 10 timestamp ago?

# How can we freely compose tokens without constraints (weaker inductive bias) ?

The modern deep learning is just using weaker inductive biases and make more data-driven instead of prior-driven.

# Make each token to see every other token



# Efficiency: Decompose abstraction and composition

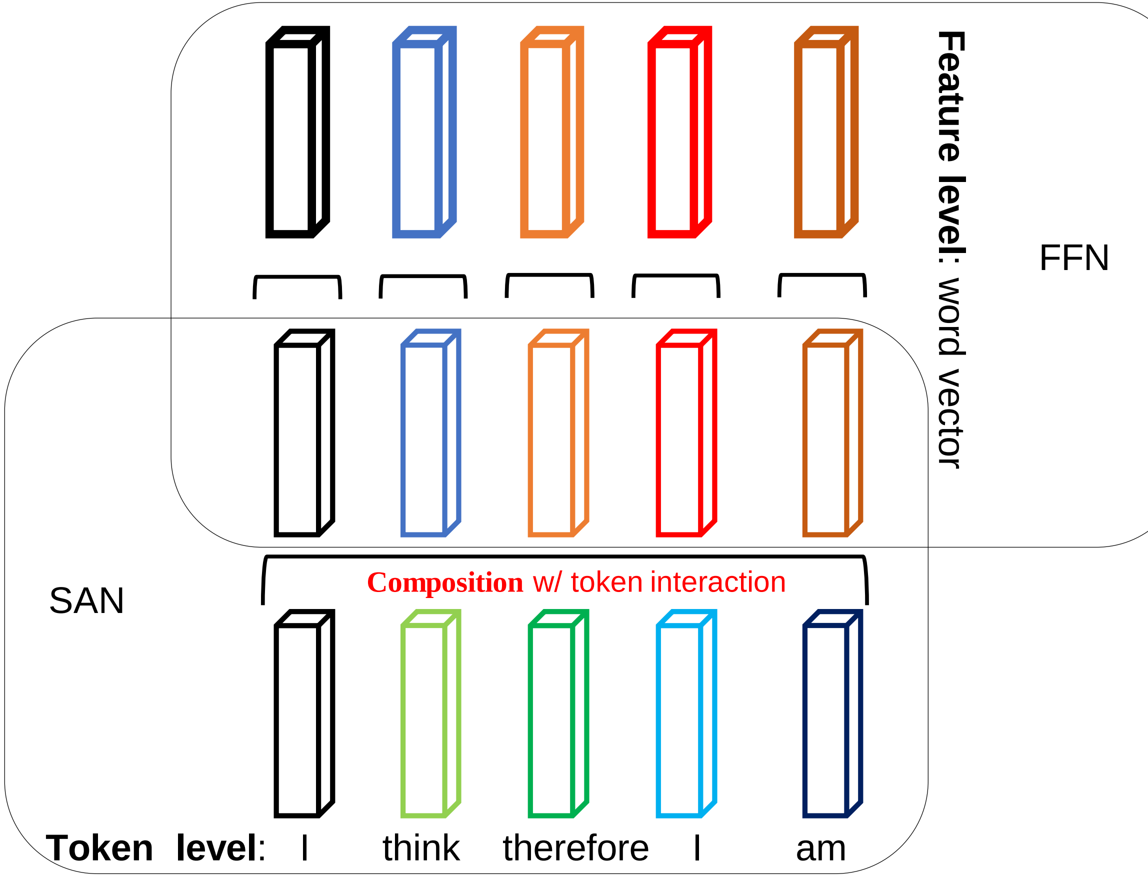
FFN: abstraction

SAN: composition

……

FFN: abstraction

SAN: composition



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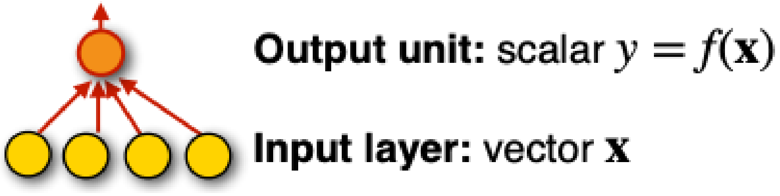
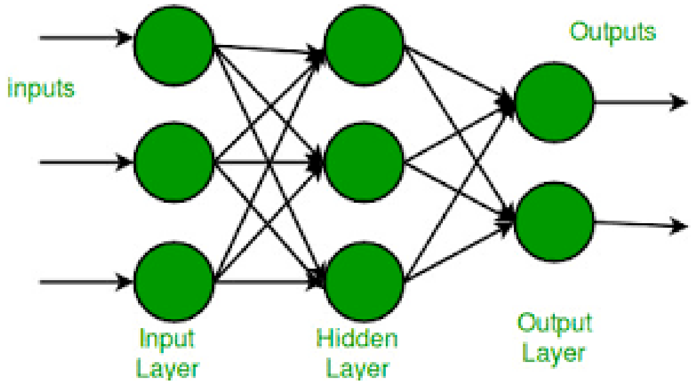
- Scaling law and emergent ability

# Multilayer Perceptron (MLP)

**Definition:** The Multilayer Perceptron (MLP) is a type of artificial neural network (ANN) that consists of multiple layers of interconnected artificial neurons or perceptrons.

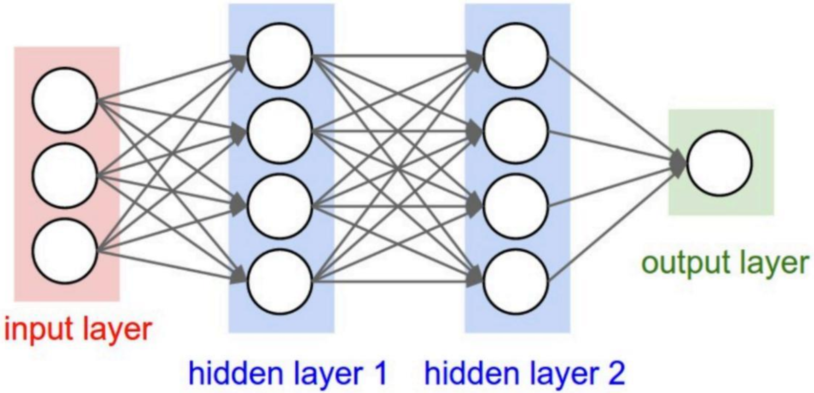
A **perceptron** can be seen as a single neuron (one output unit with a vector or **layer** of input units):



# Feed-forward NNs

- The units are connected with no cycles
- The outputs from units in each layer are passed to units in the next higher layer. No outputs are passed back to lower layers




**Fully-connected (FC) layers:**

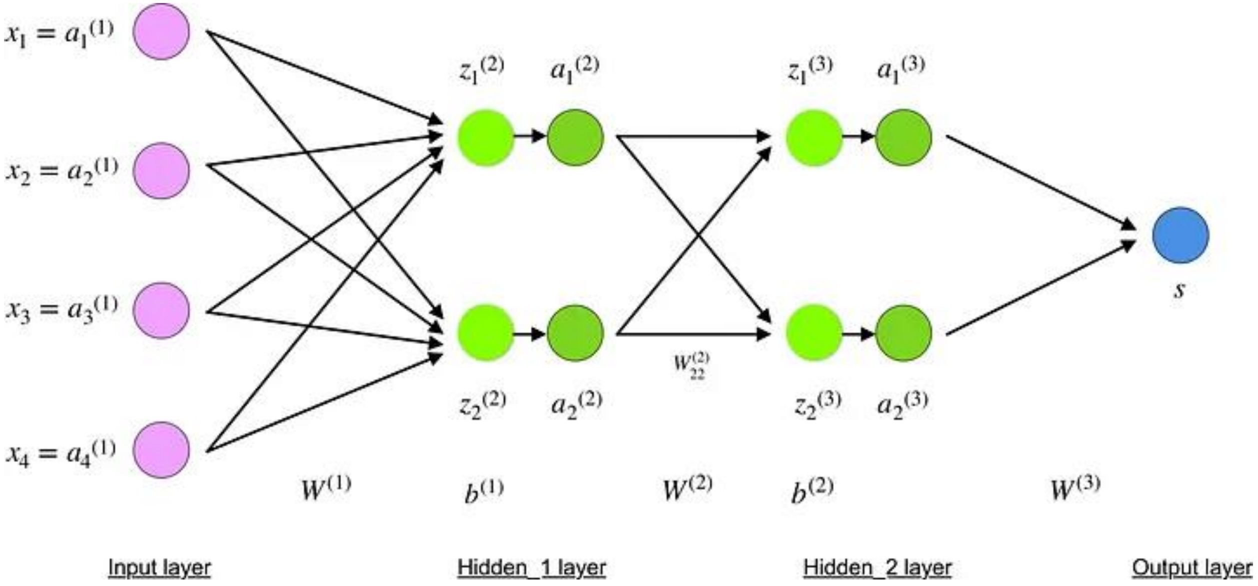
All the units from one layer are fully connected to every unit of the next layer.

```
# forward-pass of a 3-layer neural network:
f = lambda x: 1.0/(1.0 + np.exp(-x)) # activation function (use sigmoid)
x = np.random.randn(3, 1) # random input vector of three numbers (3x1)
h1 = f(np.dot(W1, x) + b1) # calculate first hidden layer activations (4x1)
h2 = f(np.dot(W2, h1) + b2) # calculate second hidden layer activations (4x1)
out = np.dot(W3, h2) + b3 # output neuron (1x1)
```

# Backpropagation

**Definition:**

Backpropagation, short for "backward propagation of errors," is a supervised learning algorithm used for training artificial neural networks, including deep learning models like Multilayer Perceptrons (MLPs).




https://towardsdatascience.com/understanding-backpropagation-algorithm-7bb3aa2f95fd

# Backpropagation: a simple example

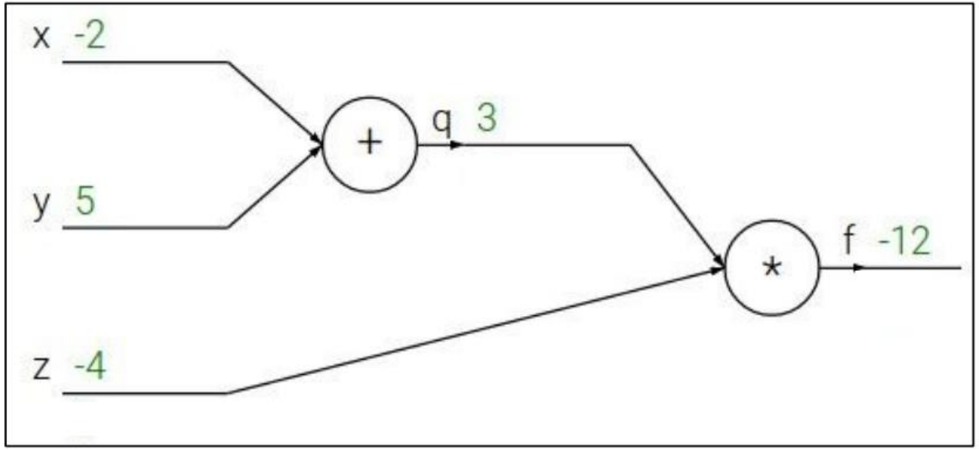
$$f(x, y, z) = (x + y)z$$

e.g. x = -2, y = 5, z = -4

$$q = x + y \qquad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \qquad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



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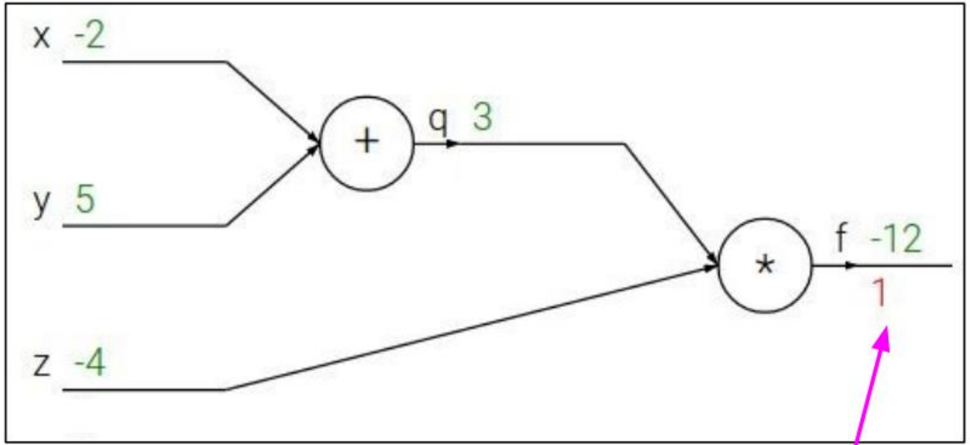


$$\frac{\partial f}{\partial f}$$

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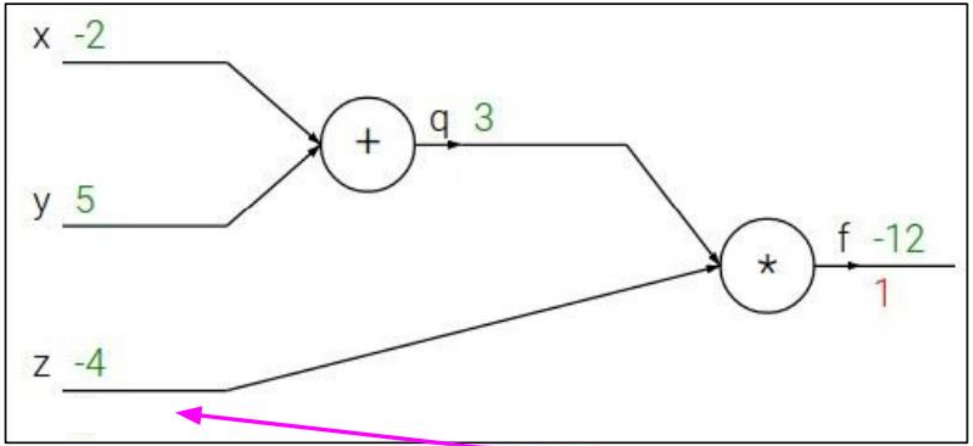


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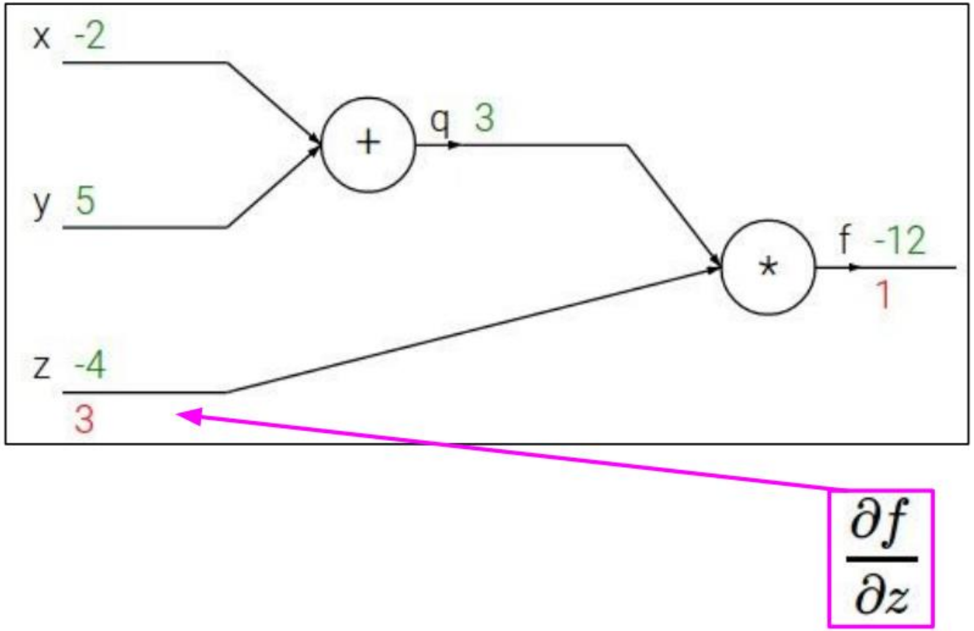

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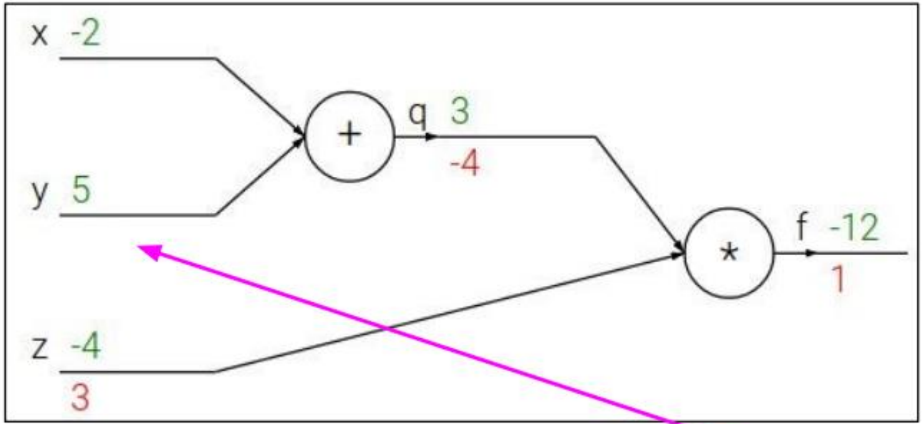


$$\frac{\partial f}{\partial y}$$

Chain rule:

$$\frac{\partial f}{\partial y} = \frac{\partial f}{\partial q} \frac{\partial q}{\partial y}$$

Upstream gradient

Local gradient

# Backpropagation: a simple example

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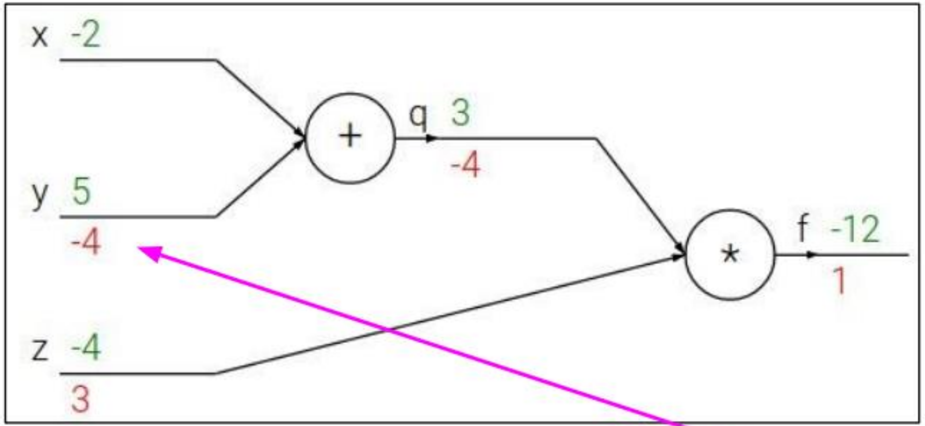


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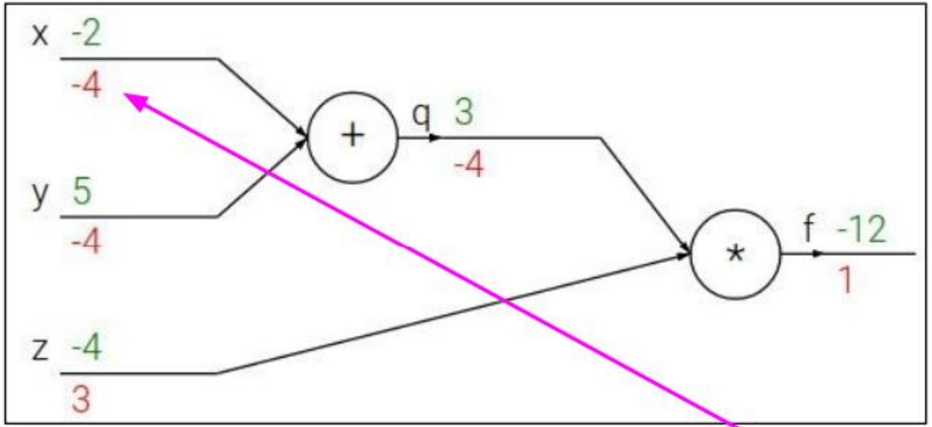


$$\frac{\partial f}{\partial x}$$

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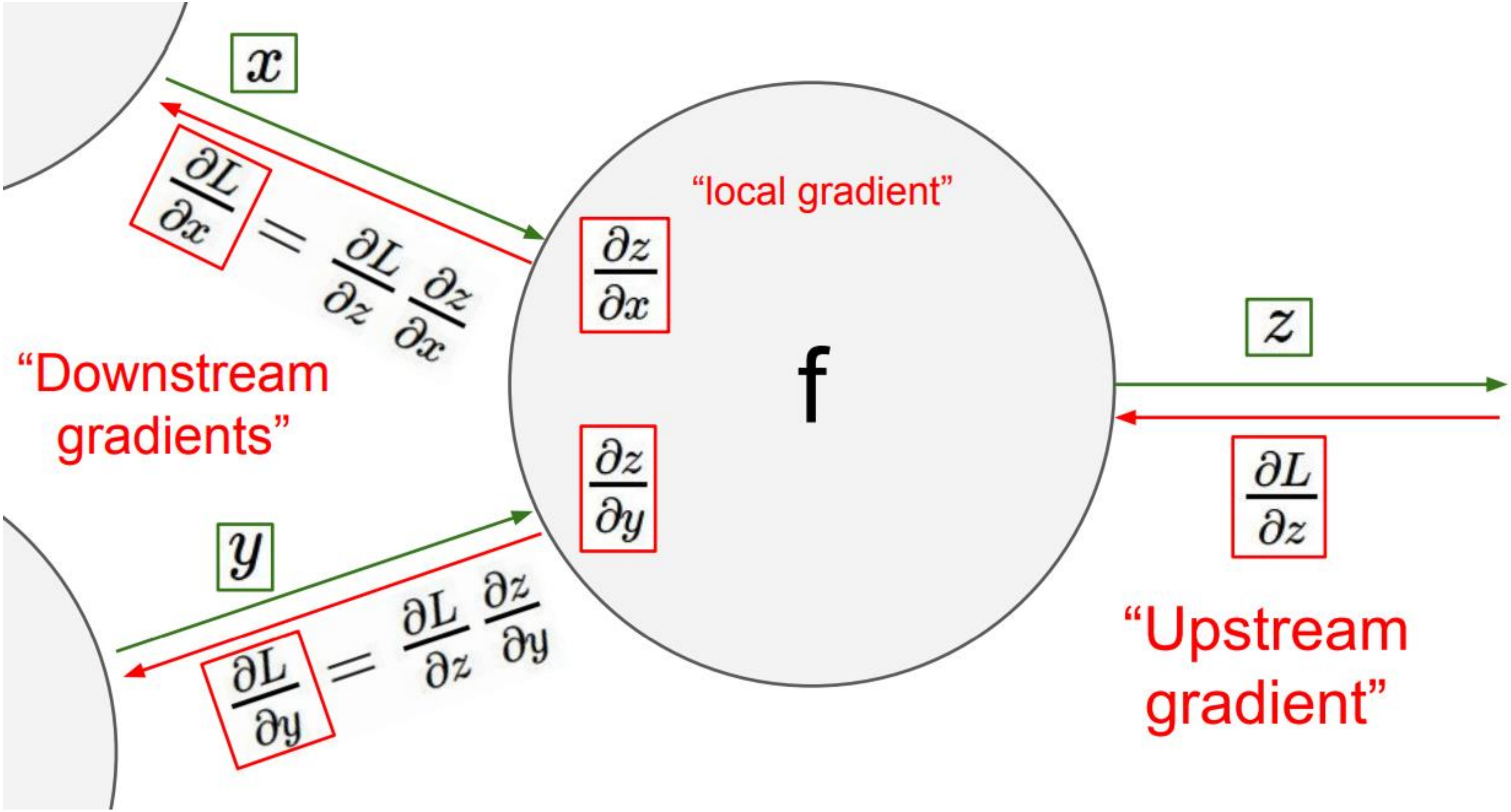
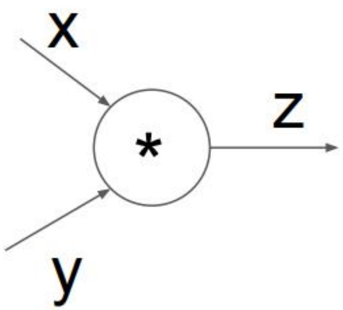
Upstream gradient

Local gradient



$x$
$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial x}$
"local gradient"
$\frac{\partial z}{\partial x}$
$z$
f
"Downstream gradients"
$\frac{\partial z}{\partial y}$
$\frac{\partial L}{\partial z}$
$y$
$\frac{\partial L}{\partial y} = \frac{\partial L}{\partial z}\frac{\partial z}{\partial y}$
"Upstream gradient"

# Modularized implementation: forward / backward API




(x,y,z are scalars)

## Gate / Node / Function object: Actual PyTorch code

```
class Multiply(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x, y):
    ctx.save_for_backward(x, y)
    z = x * y
    return z
  @staticmethod
  def backward(ctx, grad_z):
    x, y = ctx.saved_tensors
    grad_x = y * grad_z   # dz/dx * dL/dz
    grad_y = x * grad_z   # dz/dy * dL/dz
    return grad_x, grad_y
```

Need to cache some values for use in backward

Upstream gradient

Multiply upstream and local gradients

# PyTorch sigmoid layer

```
#ifndef TH_GENERIC_FILE
#define TH_GENERIC_FILE "THNN/generic/Sigmoid.c"
#else

void THNN_(Sigmoid_updateOutput)(
          THNNState *state,
          THTensor *input,
          THTensor *output)
{
  THTensor_(sigmoid)(output, input);
}
```

**Forward**

$$\boxed{\sigma(x) = \frac{1}{1+e^{-x}}}$$

Forward actually defined elsewhere...

```
static void sigmoid_kernel(TensorIterator& iter) {
  AT_DISPATCH_FLOATING_TYPES(iter.dtype(), "sigmoid_cpu", [&]() {
    unary_kernel_vec(
        iter,
        [=](scalar_t a) -> scalar_t { return (1 / (1 + std::exp((-a)))); },
        [=](Vec256<scalar_t> a) {
          a = Vec256<scalar_t>((scalar_t)(0)) - a;
          a = a.exp();
          a = Vec256<scalar_t>((scalar_t)(1)) + a;
          a = a.reciprocal();
```

```
void THNN_(Sigmoid_updateGradInput)(
          THNNState *state,
          THTensor *gradOutput,
          THTensor *gradInput,
          THTensor *output)
{
  THNN_CHECK_NELEMENT(output, gradOutput);
  THTensor_(resizeAs)(gradInput, output);
  TH_TENSOR_APPLY3(scalar_t, gradInput, scalar_t, gradOutput, scalar_t, output,
    scalar_t z = *output_data;
    *gradInput_data = *gradOutput_data * (1. - z) * z;
  );
}

#endif
```

**Backward**

$$\boxed{(1-\sigma(x))\,\sigma(x)}$$

https://github.com/pytorch/pytorch/blob/517c7c98610402e2746586c78987c64c28e024aa/aten/src/THNN/generic/Sigmoid.c

# Feedforward neural language models

**A Neural Probabilistic Language Model** (Bengio et al., 2003)


**Yoshua Bengio** BENGIOY@IRO.UMONTREAL.CA
**Réjean Ducharme** DUCHARME@IRO.UMONTREAL.CA
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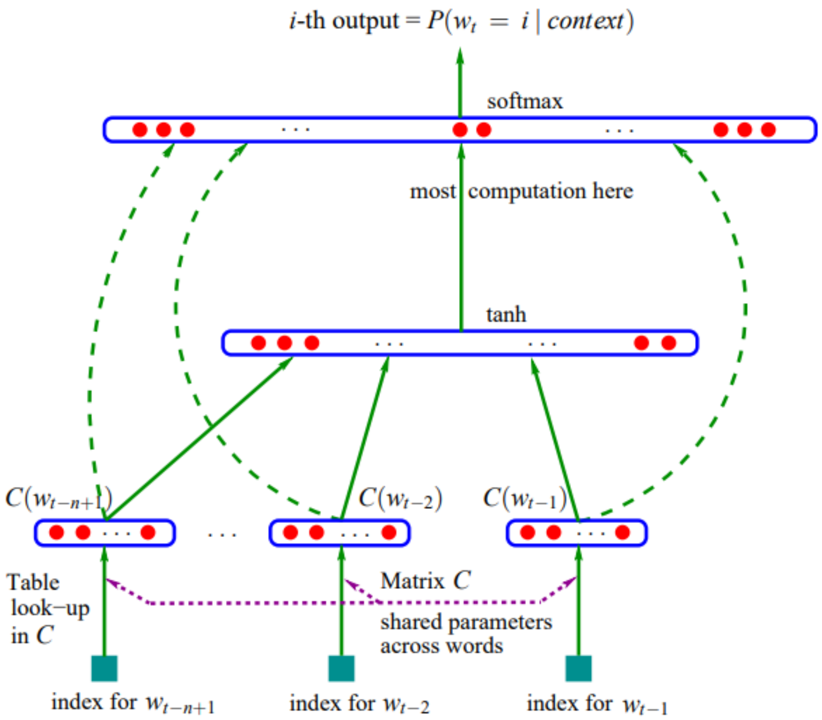
**Yoshua Bengio**

Probabilistic models of sequences: In the 1990s, Bengio combined neural networks with probabilistic models of sequences, such as hidden Markov models. These ideas were incorporated into a system used by AT&T/NCR for reading handwritten checks, were considered a pinnacle of neural network research in the 1990s, and modern deep learning speech recognition systems are extending these concepts.

High-dimensional word embeddings and attention: In 2000, Bengio authored the landmark paper, "A Neural Probabilistic Language Model," that introduced high-dimension word embeddings as a representation of word meaning. Bengio's insights had a huge and lasting impact on natural language processing tasks including language translation, question answering, and visual question answering. His group also introduced a form of attention mechanism which led to breakthroughs in machine translation and form a key component of sequential processing with deep learning.

Generative adversarial networks: Since 2010, Bengio's papers on generative deep learning, in particular the Generative Adversarial Networks (GANs) developed with Ian Goodfellow, have spawned a revolution in computer vision and computer graphics. In one fascinating application of this work, computers can actually create original images, reminiscent of the creativity that is considered a hallmark of human intelligence.

https://awards.acm.org/about/2018-turing




A Neural Probabilistic Language Model (Bengio et al., 2003)

# Feedforward neural language models

**A Neural Probabilistic Language Model** (Bengio et al., 2003)

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Key idea: Instead of estimating raw probabilities, let's use a **neural network** to fit the **probabilistic distribution of language**!

$$P(w \mid \text{I am a good}) \quad P(w \mid \text{I am a great})$$

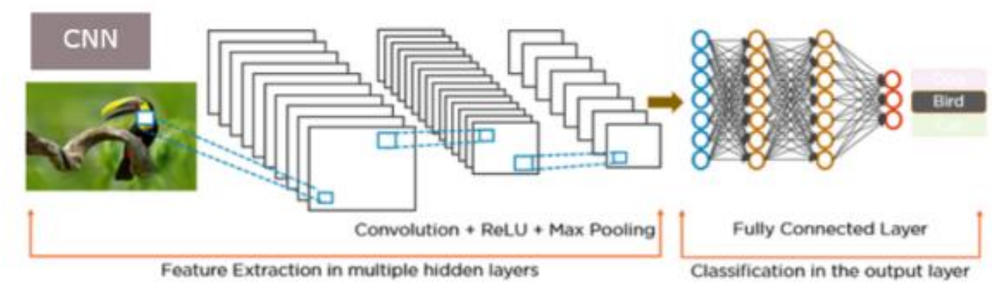
**Key ingredient**: word embeddings $\quad \mathbf{e(good)} \approx \mathbf{e(great)}$

Hope: this would give us similar distributions for similar contexts!

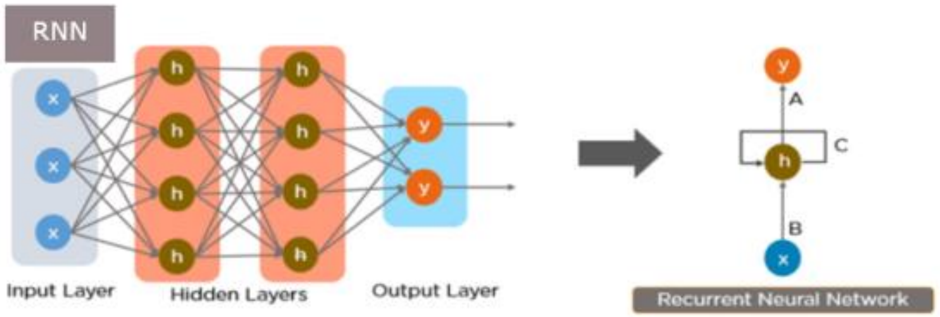
# CNN&RNN

- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)

**Convolutional Neural Network**




**Recurrent Neural Network**



# Today's lecture

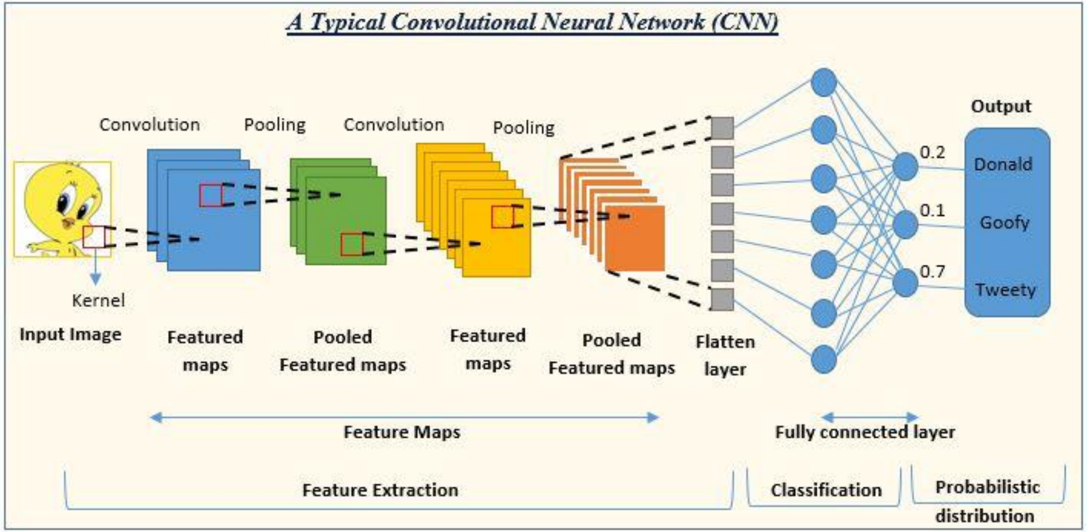
- MLP
  +: Strongest inductive bias: if all words are concated
  +: Weakest inductive bias: if all words are averaged
  - : The interaction at the token-level is too weak
- **CNN & RNN**
  +: The interaction at the token-level is slightly better.
  CNN: Bringing the global token-level interaction to the window-level
  - : Make simplifications, its global dependencies are limited
  RNN: An ideal method for processing token sequences
  - : Its recursive nature has the problem of disaster forgetting.
- Transformer
  +: Achieve **global dependence** at the **token-level** by **decoupling** token-level interaction and feature-level abstraction into two components, in **SAN** and **FNN**.

- Scaling law and emergent ability

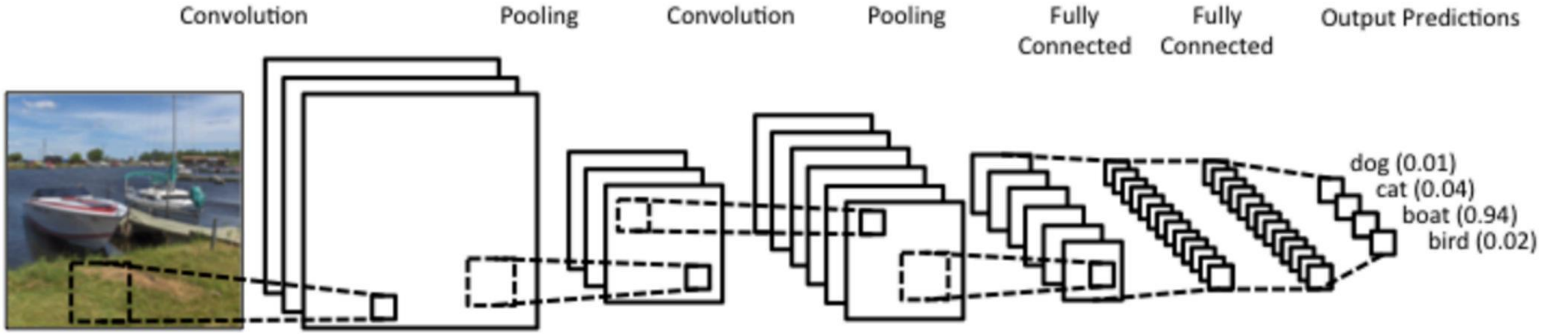
# CNN

## Convolutional Neural Network

- What is CNN?
- Motivation: Image Processing
- Key Components
  - \- Convolutional Layers
  - \- Pooling Layers
  - \- Fully Connected Layers
- Hierarchical Feature Extraction

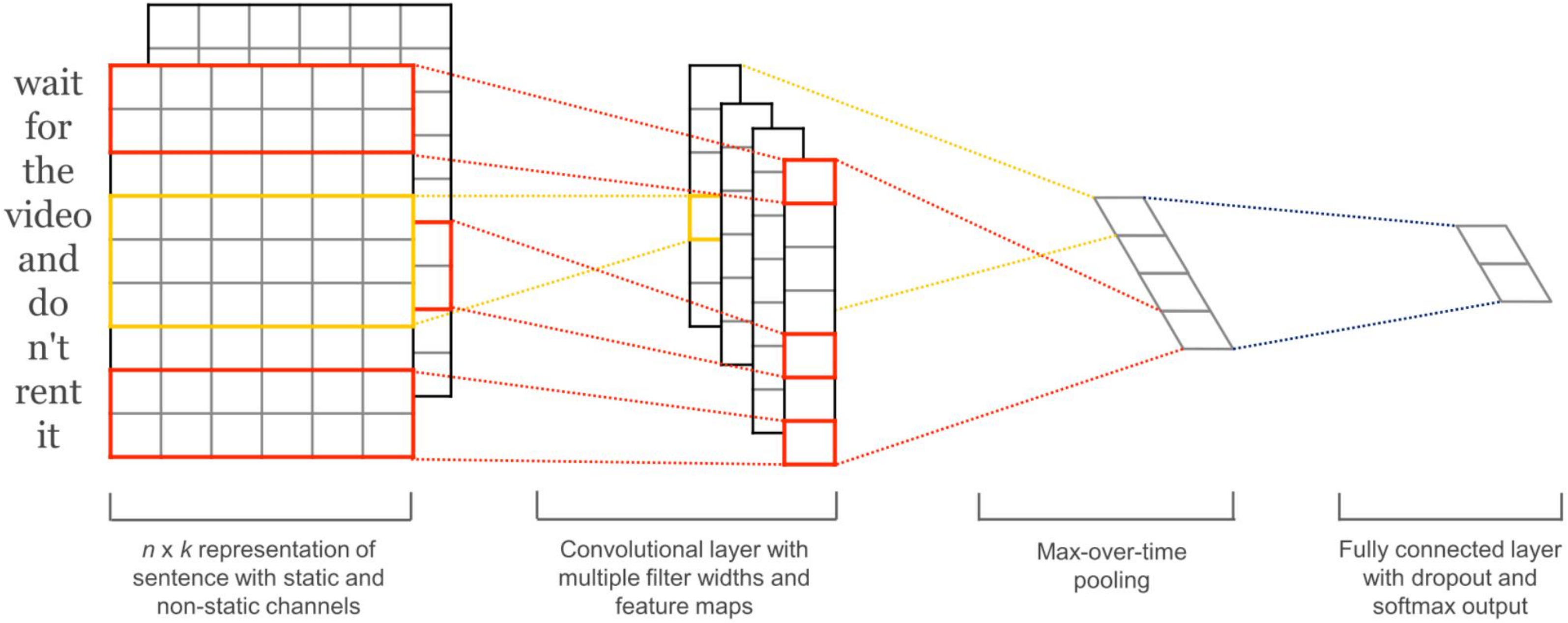


# Convolutional NNs in image classification



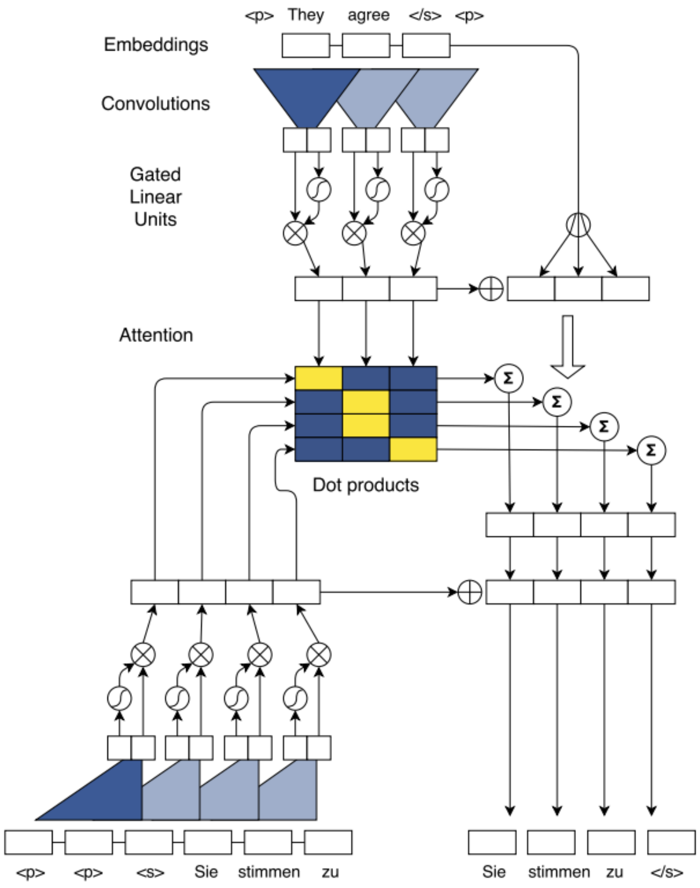

Key components: 1) convolution; 2) pooling; 3) multiple channels (feature maps)

# Convolutional NNs for text classification




(Kim 2014): Convolutional Neural Networks for Sentence Classification

# Convolutional Sequence to Sequence Learning

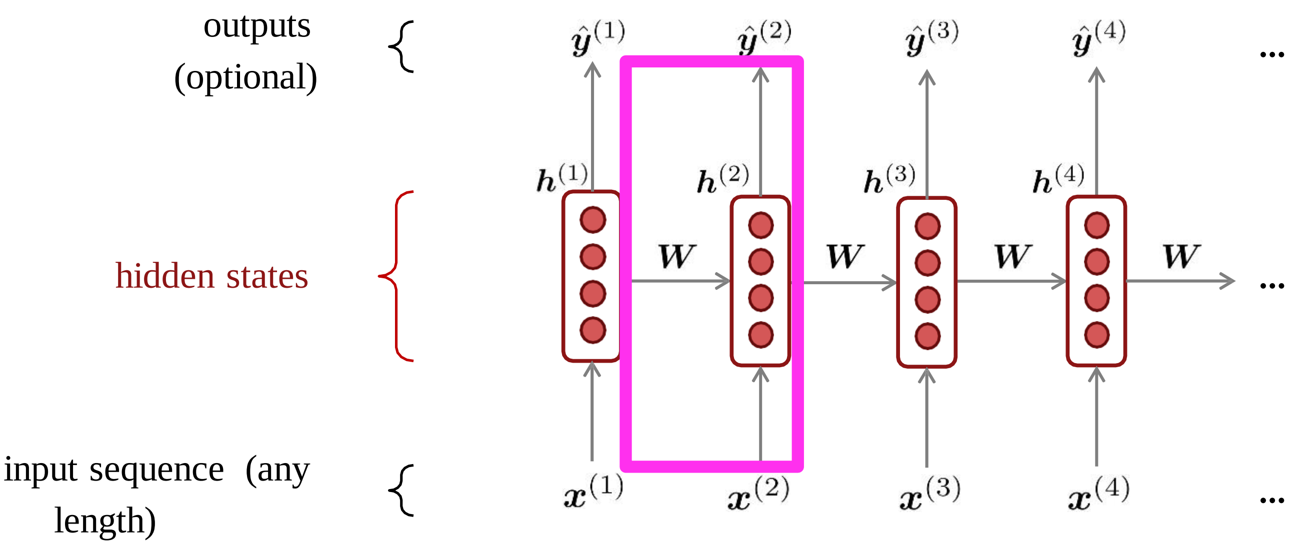



- Encoder and decoder are simple blocks of convolution operation followed by nonlinearity on fixed size of input.
- Introduce a concept of order preservation as a positional vectors p = (p_1,p_2 ...,p_m). In combination of both input elements are represented as E = (e_1=w_1+p_1, e_2=w_2+p_2, ....,e_m=w_m+p_m).
- Adds a linear mapping to project between the embedding size f and the convolution outputs that are size 2d.
- Computes a distribution over the T possible next target elements y_i+1 by transforming the top decoder output h_i_l via a linear layer with weights and bias.

https://browse.arxiv.org/pdf/1705.03122.pdf

# RNN
## Recurrent Neural Network

**Core idea:** Apply the same weights $W$ *repeatedly*



# A Simple RNN Language Model

$\hat{\boldsymbol{y}}^{(4)} = P(\boldsymbol{x}^{(5)} | \text{the students opened their})$

output distribution

$\hat{\boldsymbol{y}}^{(t)} = \text{softmax}\left(\boldsymbol{U}\boldsymbol{h}^{(t)} + \boldsymbol{b}_2\right) \in \mathbb{R}^{|V|}$

hidden states

$\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h\boldsymbol{h}^{(t-1)} + \boldsymbol{W}_e\boldsymbol{e}^{(t)} + \boldsymbol{b}_1\right)$

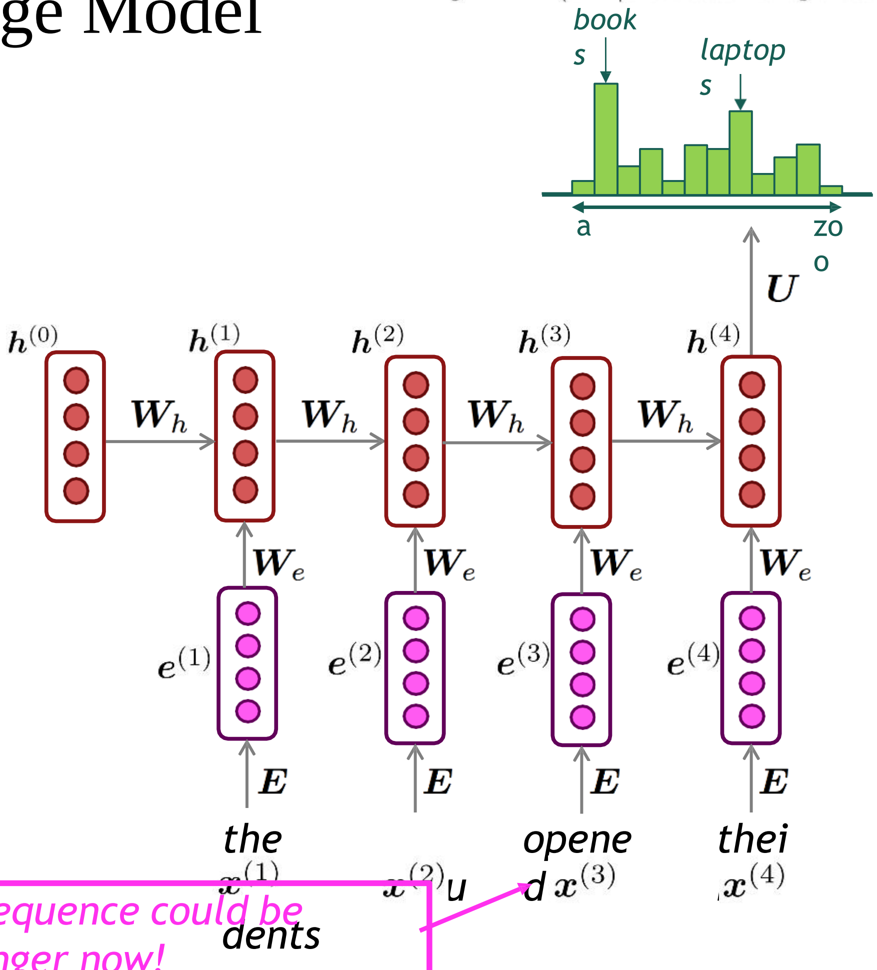
$\boldsymbol{h}^{(0)}$ is the initial hidden state

word embeddings

$\boldsymbol{e}^{(t)} = \boldsymbol{E}\boldsymbol{x}^{(t)}$

words / one-hot vectors

$\boldsymbol{x}^{(t)} \in \mathbb{R}^{|V|}$




***Note**: this input sequence could be much longer now!*

# RNN Language Models

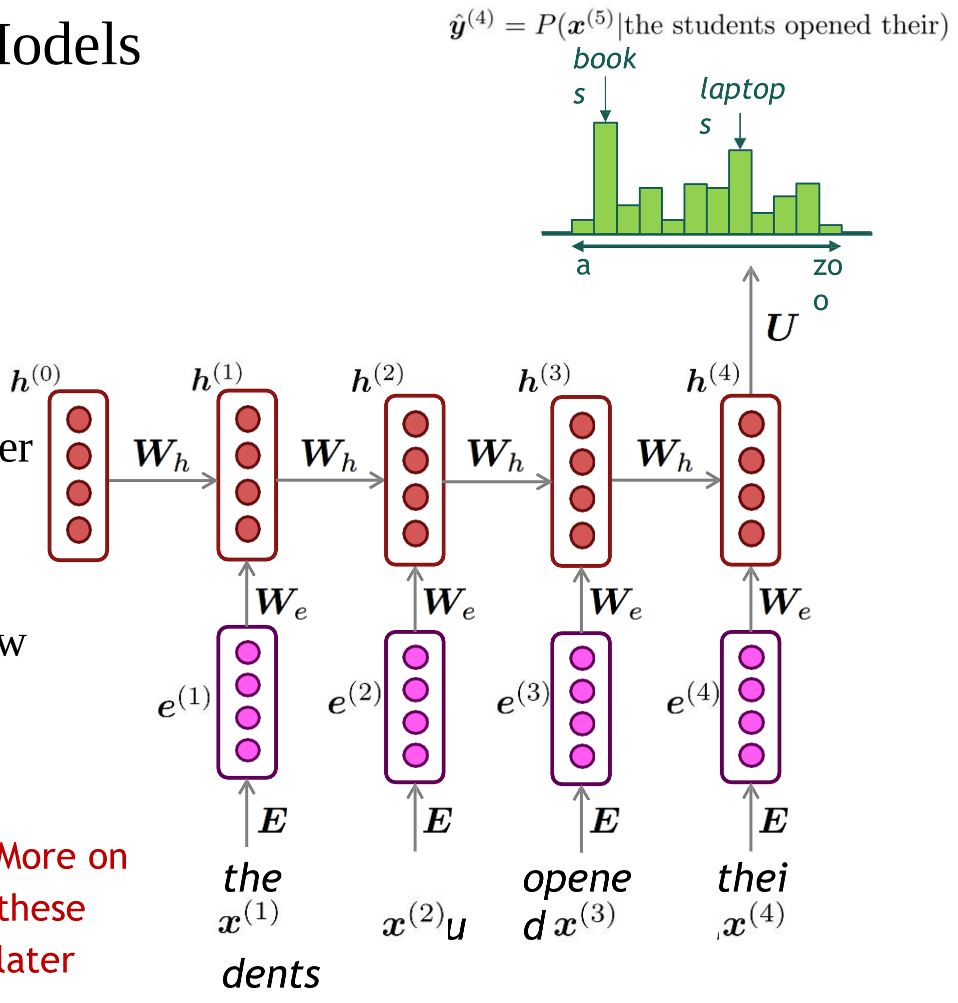
RNN **Advantages**:

- Can process any length input
- Computation for step $t$ can (in theory) use information from many steps back
- Model size doesn't increase for longer input context
- Same weights applied on every timestep, so there is symmetry in how inputs are processed.

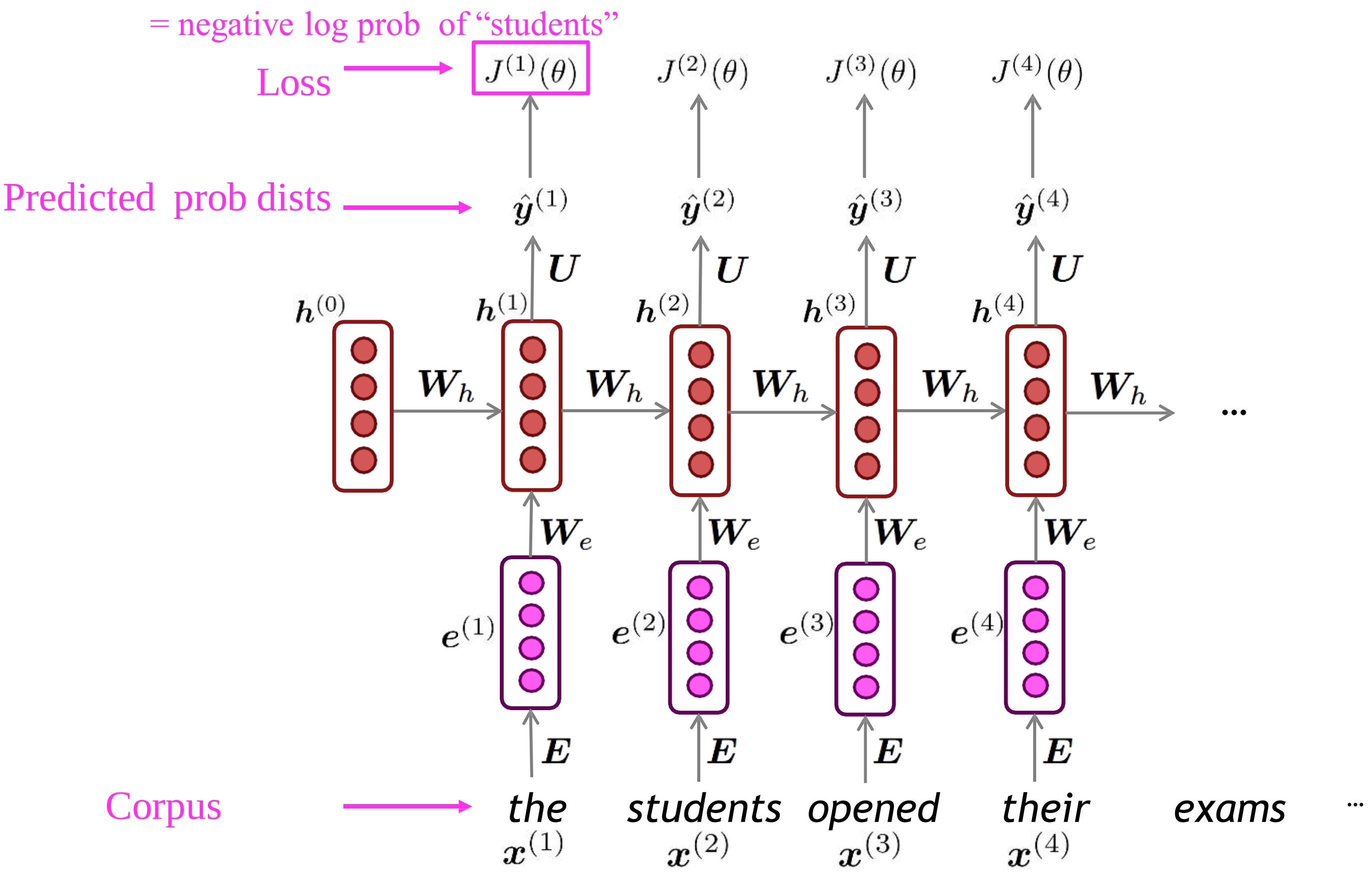
RNN **Disadvantages**:

- Recurrent computation is slow
- In practice, difficult to access information from many steps back

More on these later

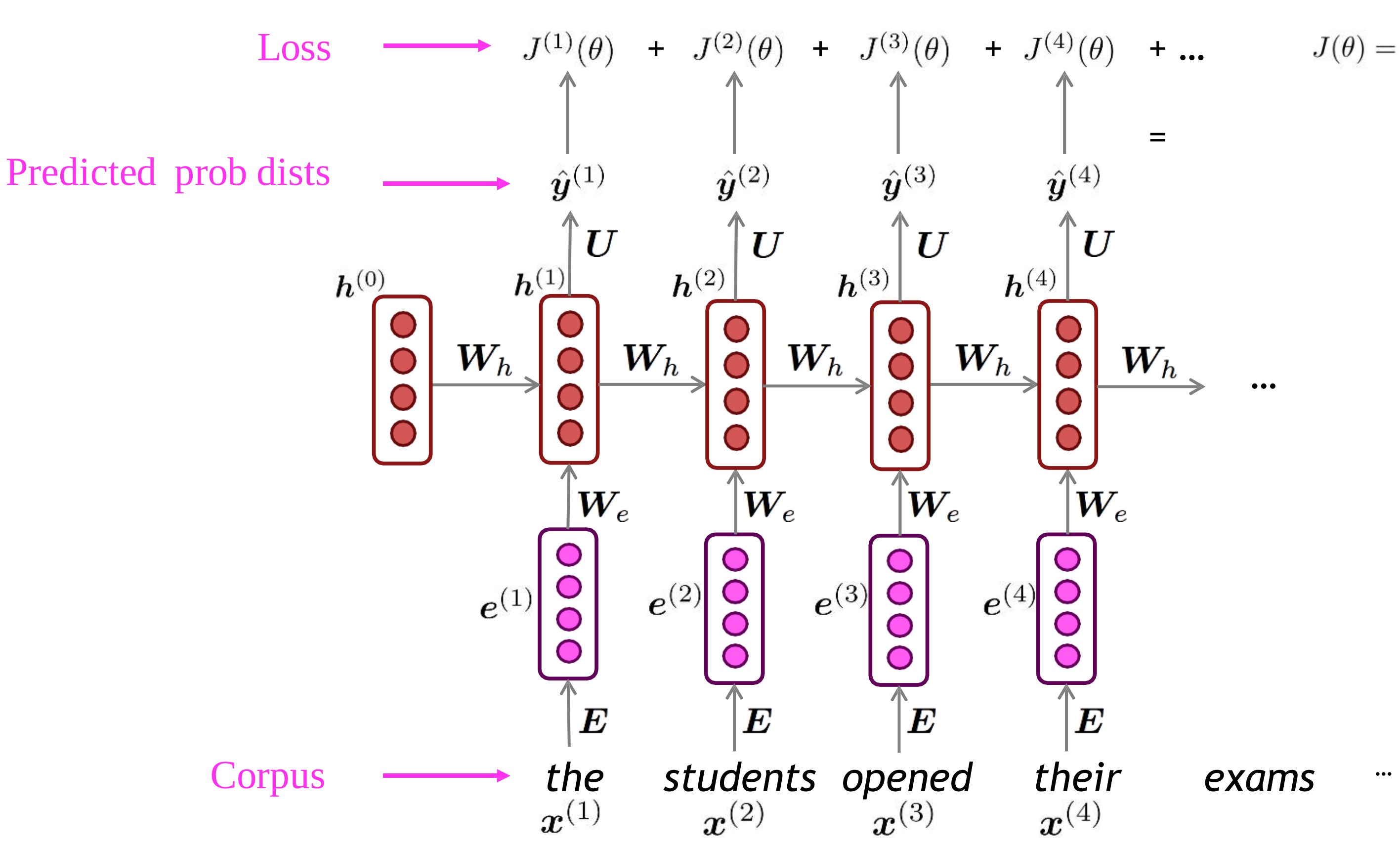


# Training an RNN Language Model



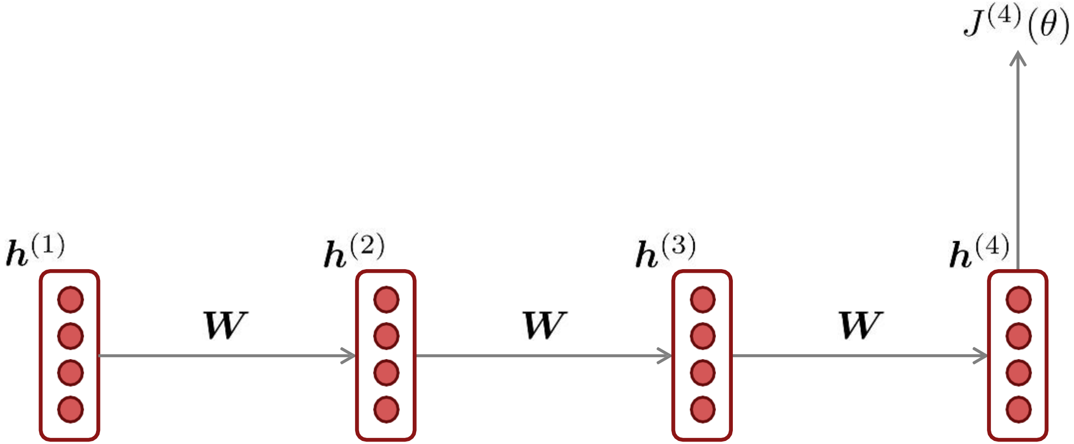
# Training an RNN Language Model

"Teacher forcing"

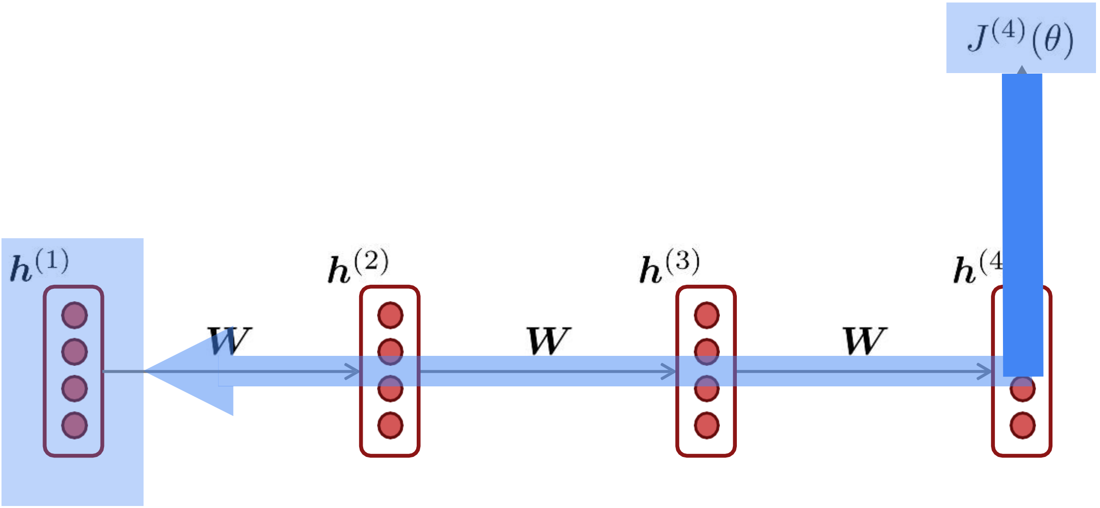



$$J(\theta) = \frac{1}{T}\sum_{t=1}^{T} J^{(t)}(\theta)$$

# Problems with RNNs: Vanishing and Exploding Gradients

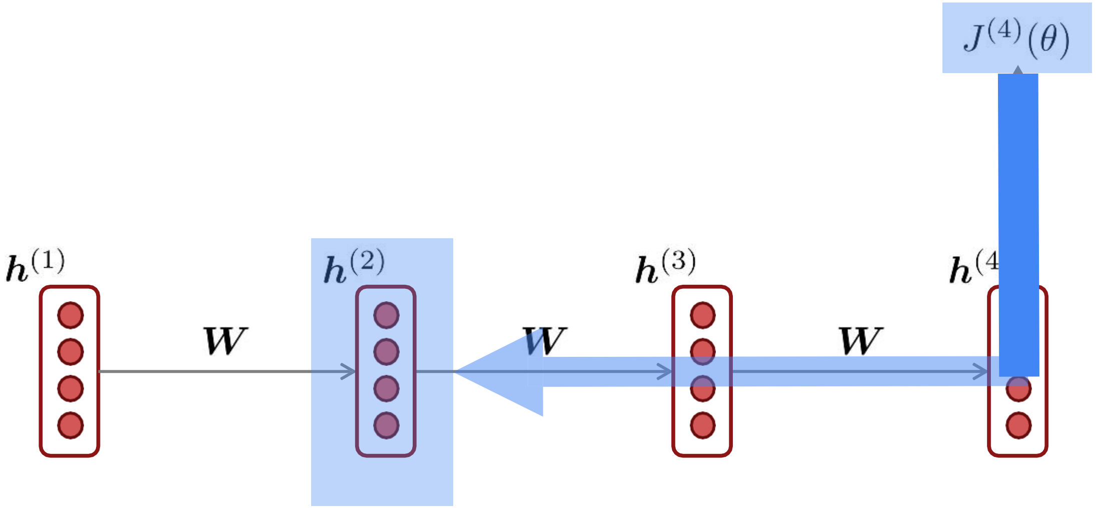


# Vanishing gradient intuition




$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \ ?$$

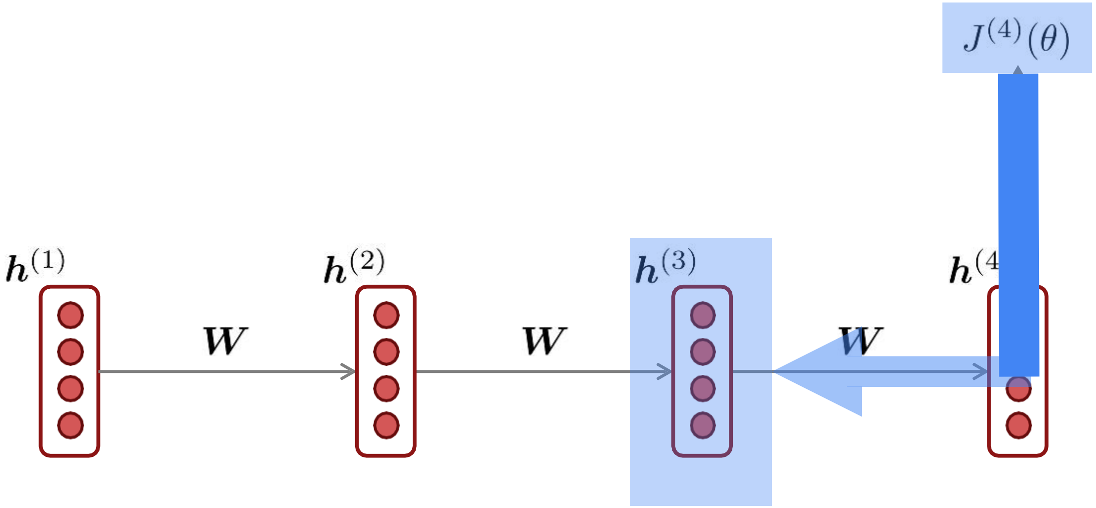
# Vanishing gradient intuition




$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(2)}}$$

chain rule!

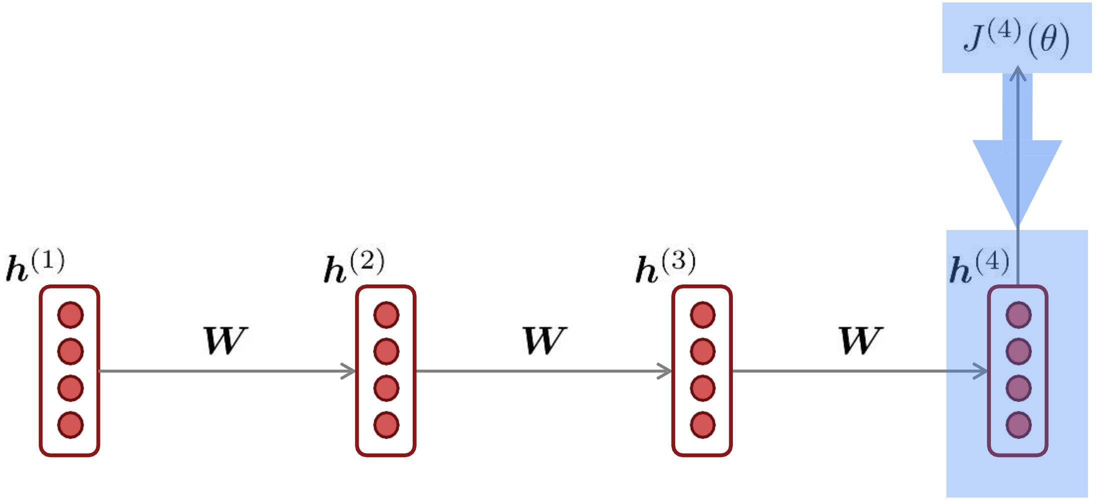
# Vanishing gradient intuition




$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}} \times \qquad \frac{\partial \boldsymbol{h}^{(3)}}{\partial \boldsymbol{h}^{(2)}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(3)}}$$

chain rule!

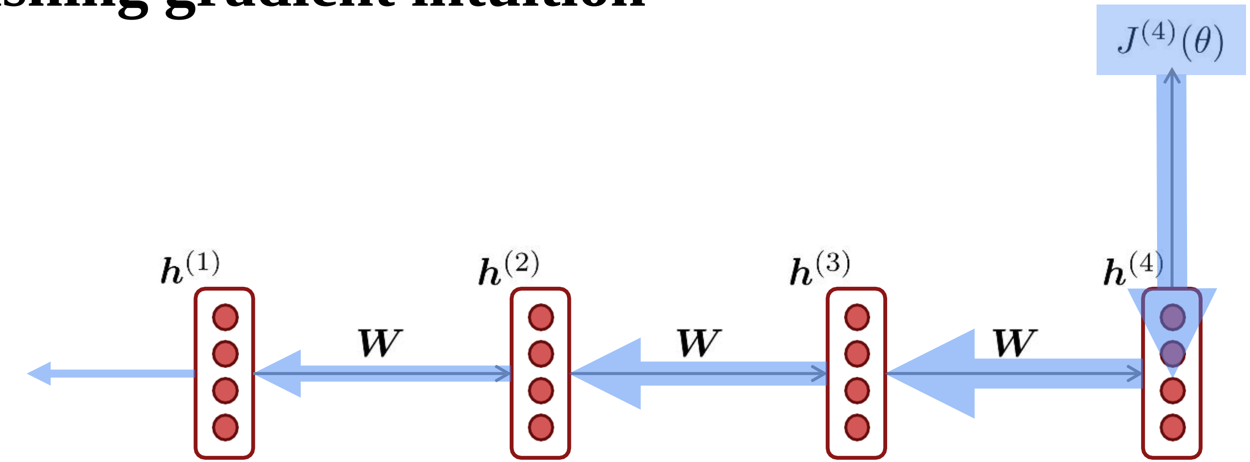
# Vanishing gradient intuition




$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}} \times \frac{\partial \boldsymbol{h}^{(3)}}{\partial \boldsymbol{h}^{(2)}} \times \frac{\partial \boldsymbol{h}^{(4)}}{\partial \boldsymbol{h}^{(3)}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(4)}}$$

chain rule!

# Vanishing gradient intuition




$$\frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(1)}} = \boxed{\frac{\partial \boldsymbol{h}^{(2)}}{\partial \boldsymbol{h}^{(1)}}} \times \boxed{\frac{\partial \boldsymbol{h}^{(3)}}{\partial \boldsymbol{h}^{(2)}}} \times \boxed{\frac{\partial \boldsymbol{h}^{(4)}}{\partial \boldsymbol{h}^{(3)}}} \times \frac{\partial J^{(4)}}{\partial \boldsymbol{h}^{(4)}}$$

What happens if these are small?

**Vanishing gradient problem:**
When these are small, the gradient signal gets smaller and smaller as it backpropagates further

# Transformer

- **Encoder**
- **Decoder**
- **Self-attention**
- **Multi-head self-attention**
- **Positional Encoding**

# Today’s lecture

- MLP
  +: Strongest inductive bias: if all words are concated
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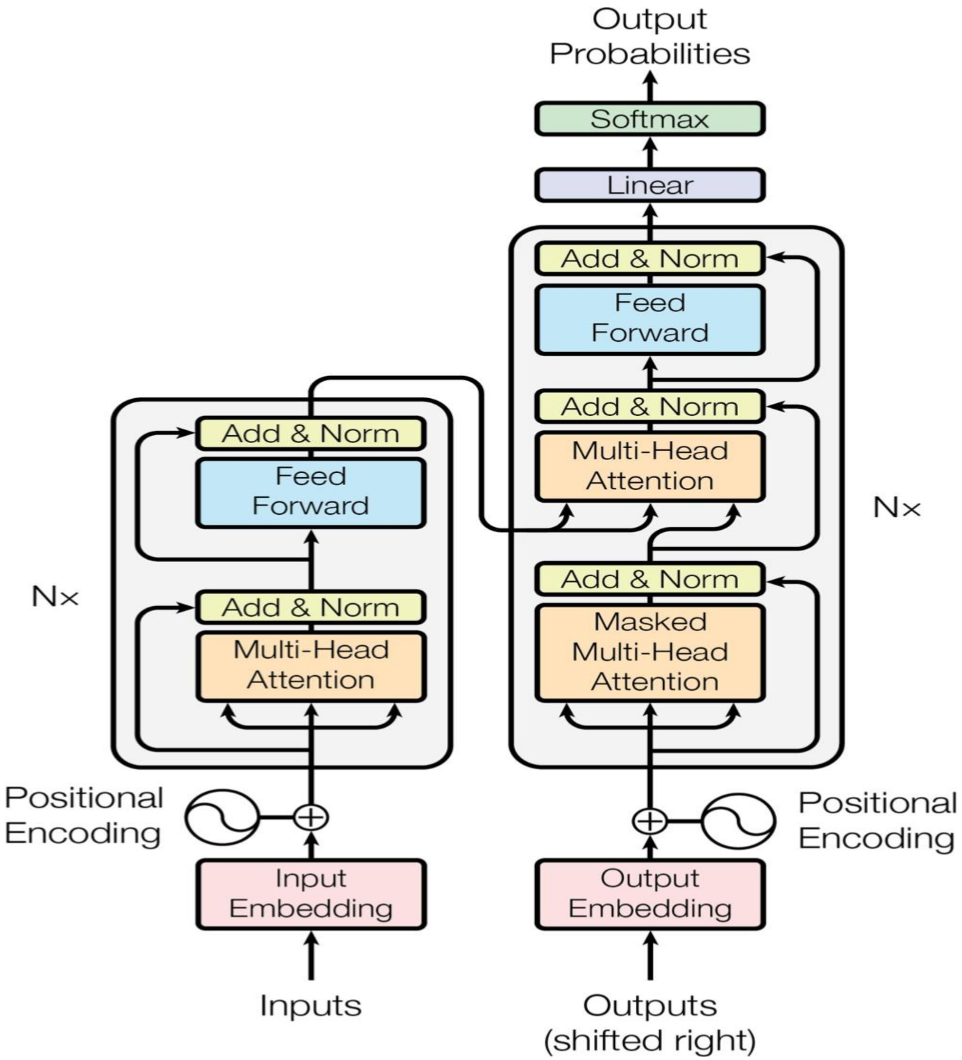
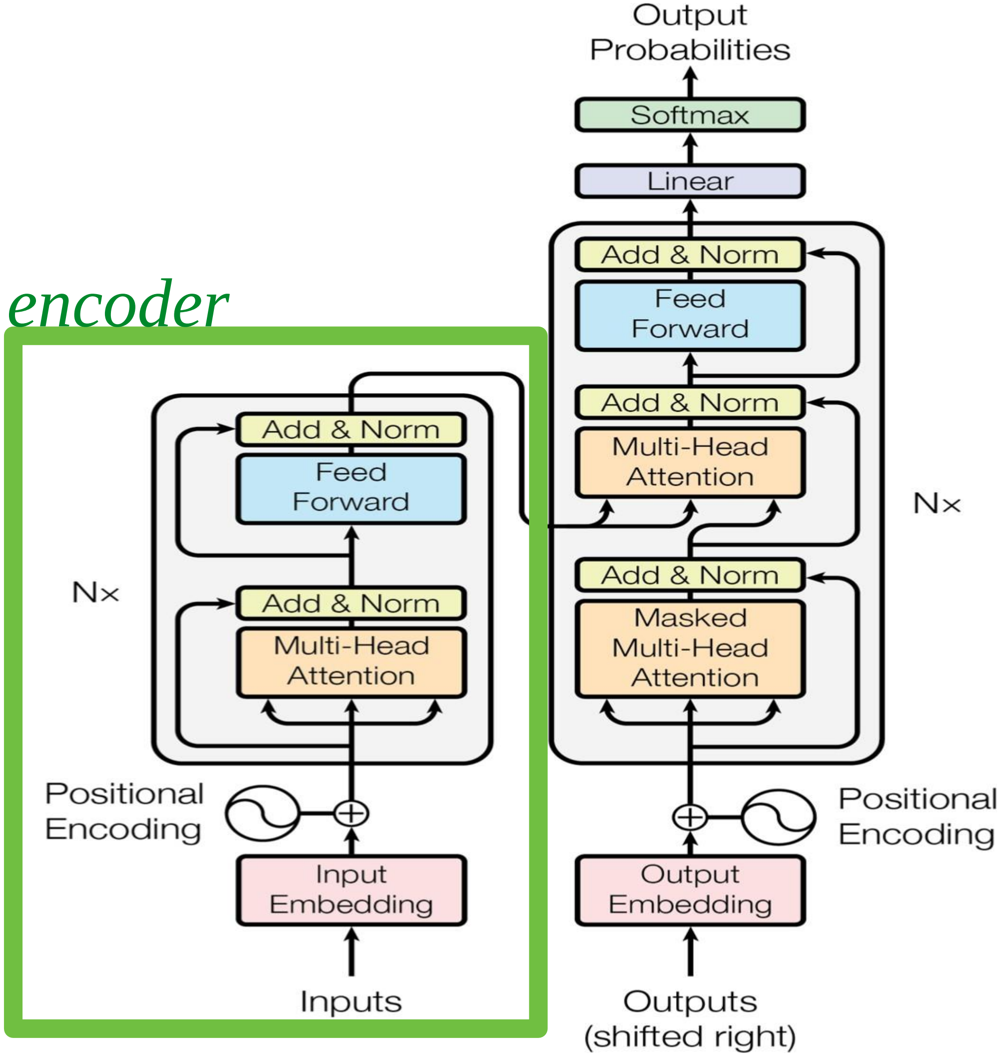
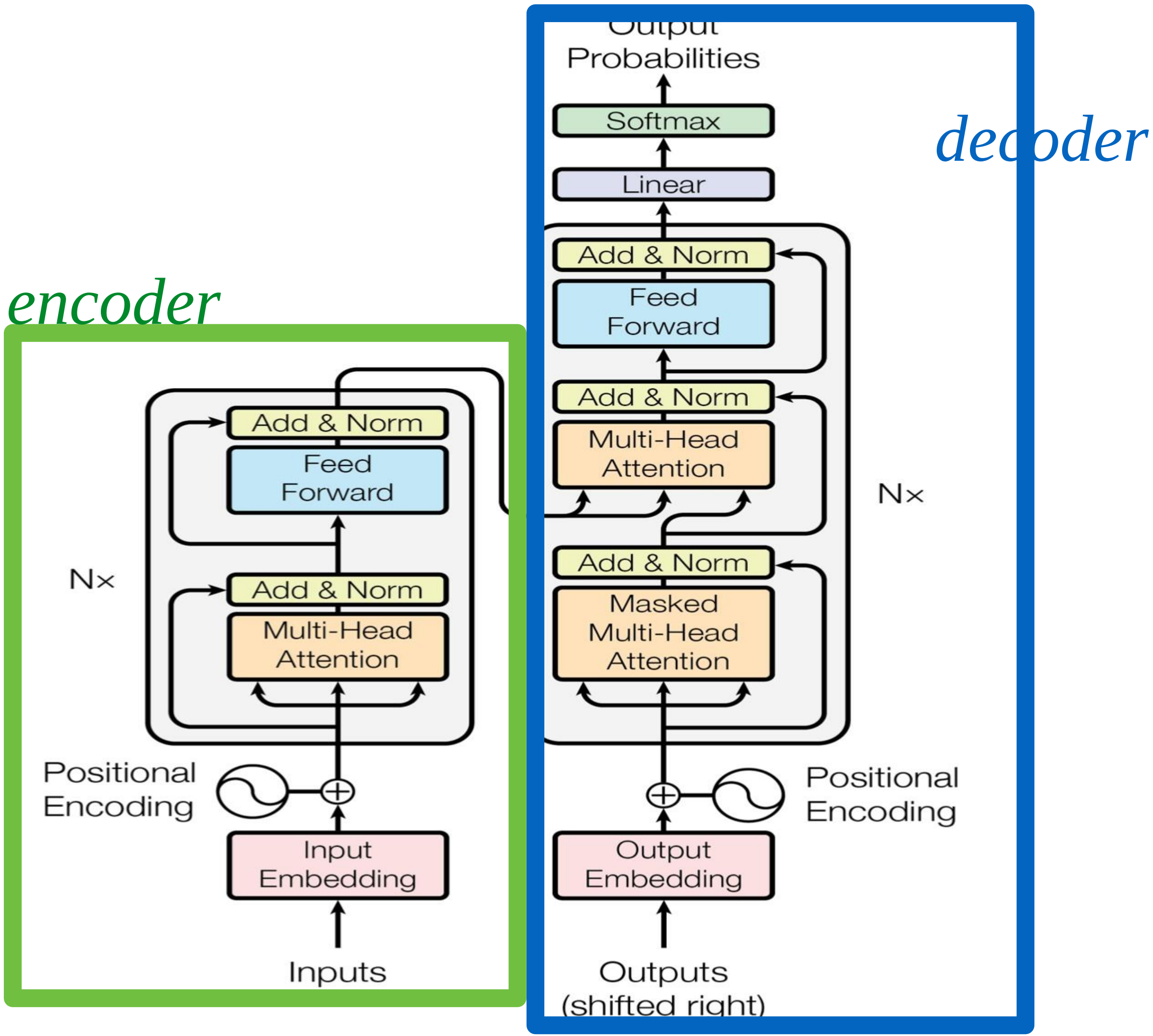
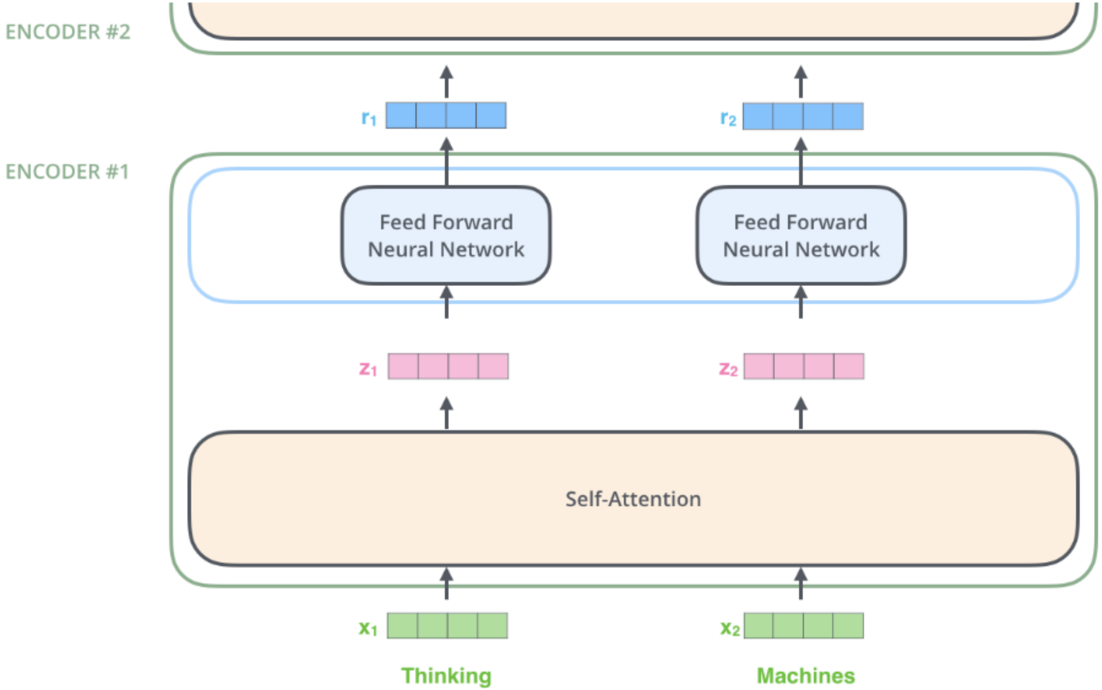
- Scaling law and emergent ability


Output
Probabilities
Softmax
Linear
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Add & Norm
Masked
Multi-Head
Attention
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Positional
Encoding
Positional
Encoding
Input
Embedding
Output
Embedding
Inputs
Outputs
(shifted right)


encoder
Output Probabilities
Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Add & Norm
Masked Multi-Head Attention
Add & Norm
Feed Forward
Nx
Add & Norm
Multi-Head Attention
Positional Encoding
Input Embedding
Inputs
Positional Encoding
Output Embedding
Outputs (shifted right)



encoder
decoder
Output
Probabilities
Softmax
Linear
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Add & Norm
Masked
Multi-Head
Attention
Nx
Positional
Encoding
Output
Embedding
Outputs
(shifted right)
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Positional
Encoding
Input
Embedding
Inputs

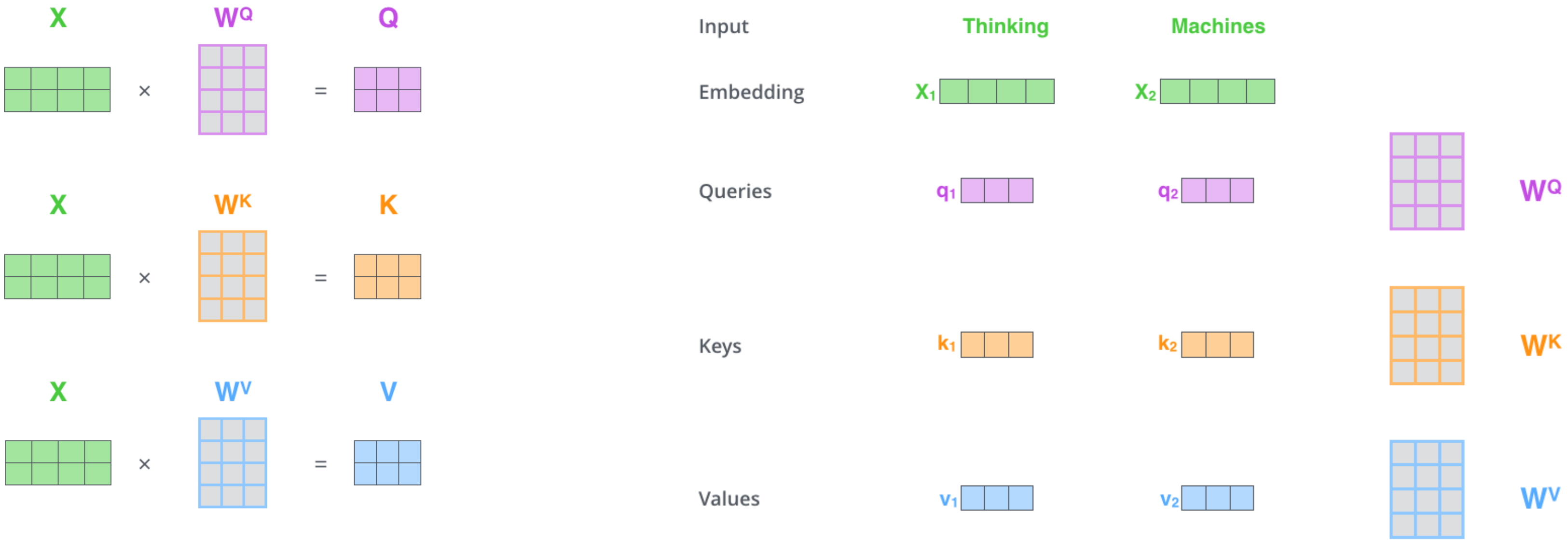



The word at each position passes through a self-attention process. Then, they each pass through a feed-forward neural network -- the exact same network with each vector flowing through it separately.

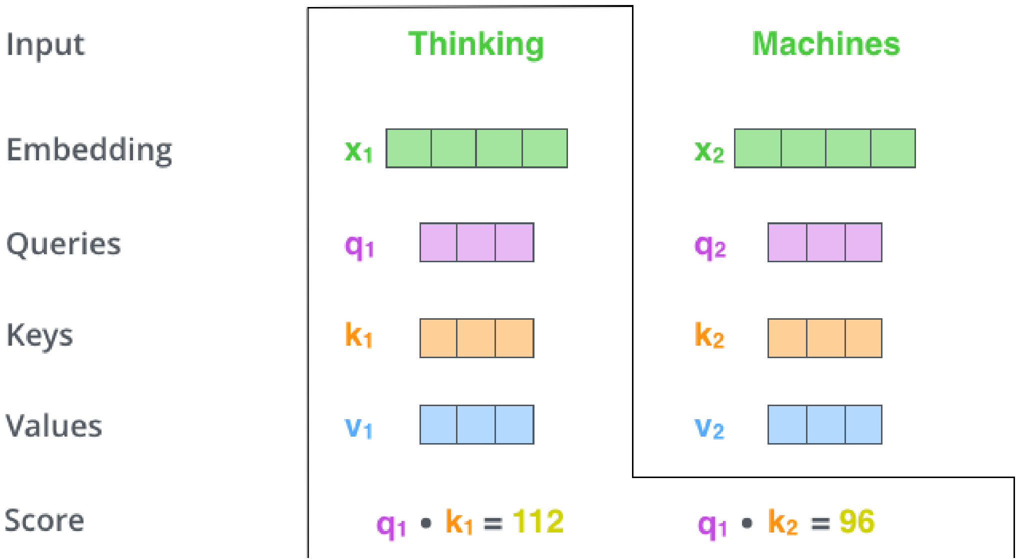
Token abstraction

Between-token interaction

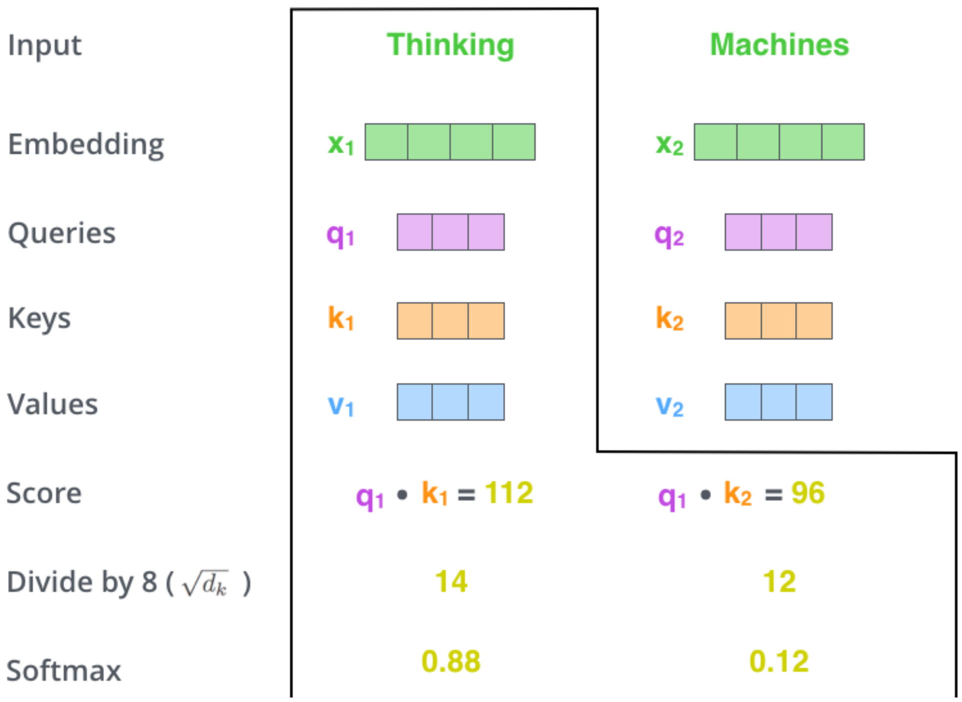
https://jalammar.github.io/illustrated-transformer/




Multi-faced token representation (QKV)

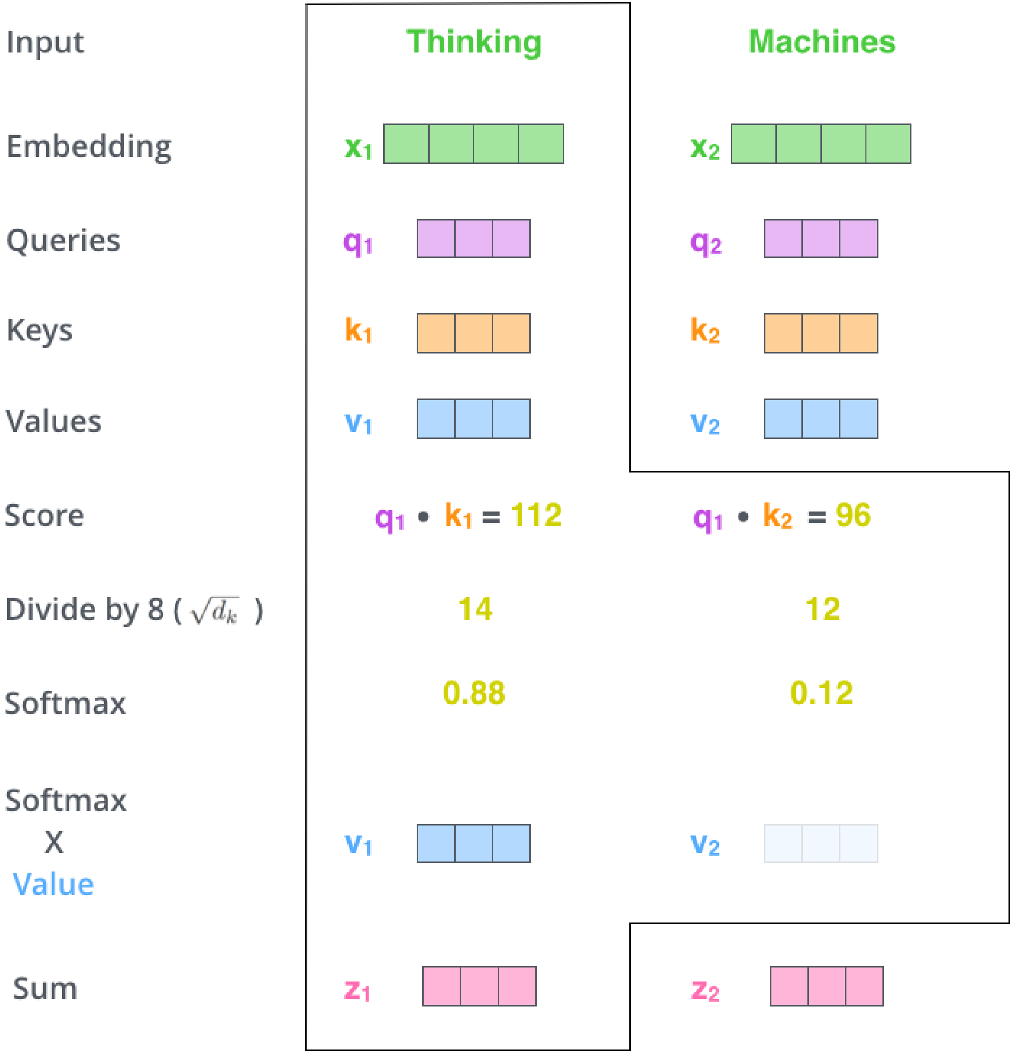



**Key-value** interaction between tokens



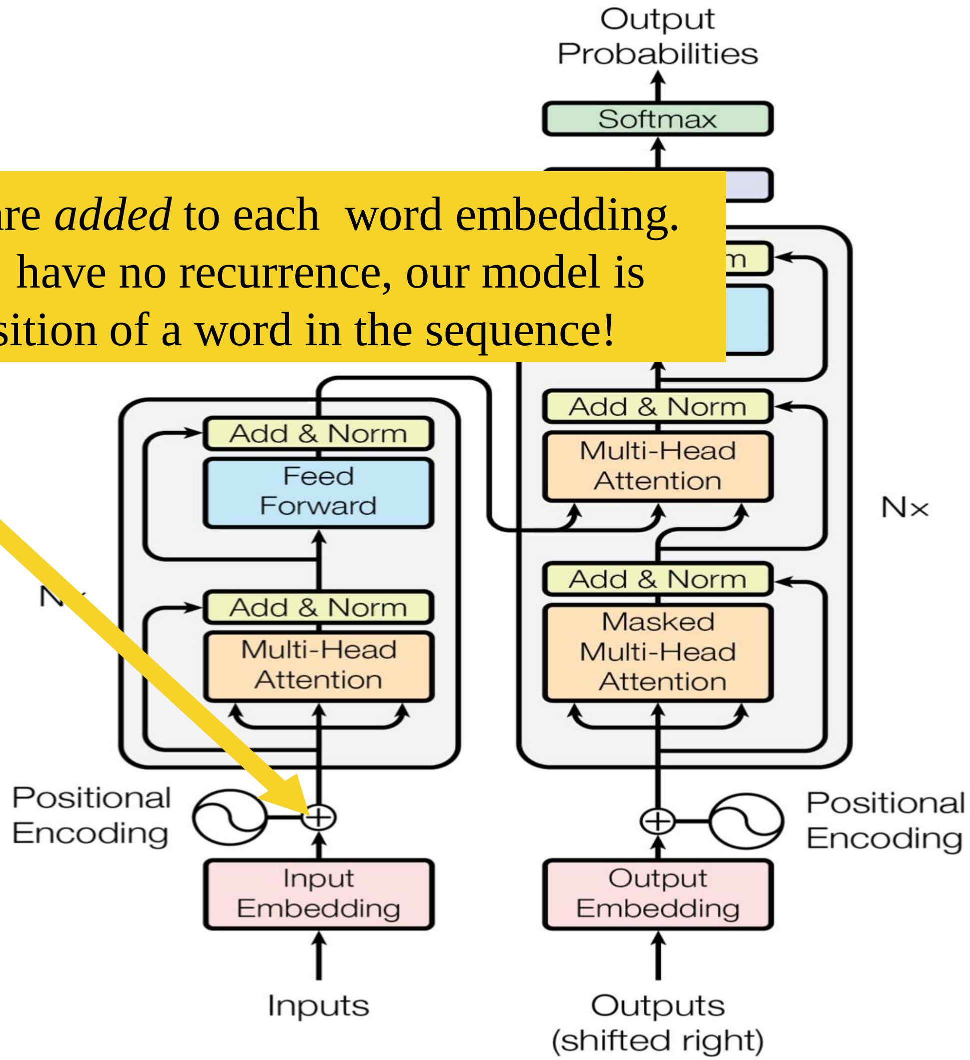

**Normalize** the **Key-value** interaction as attention (a probability distribution)

p.s. why softmax makes a probability distribution?

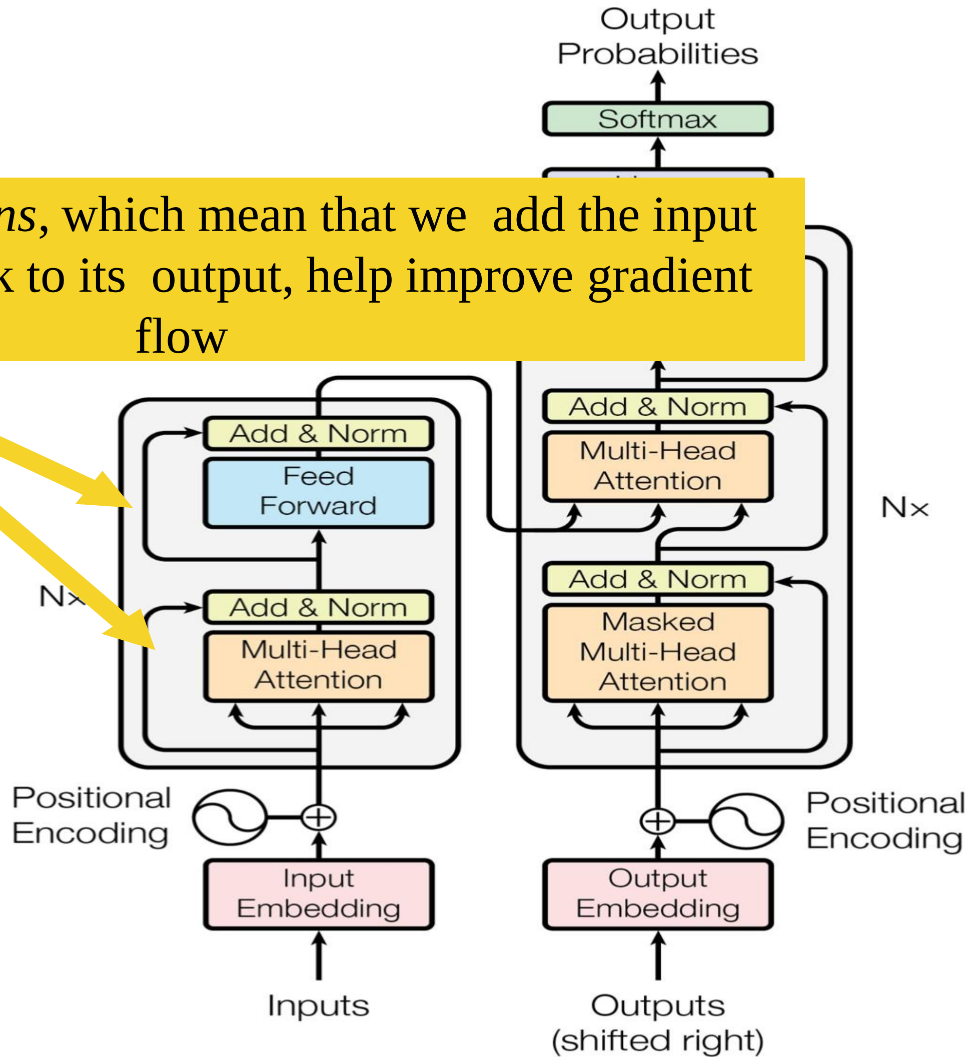


Input
Thinking
Machines
Embedding
$x_1$
$x_2$
Queries
$q_1$
$q_2$
Keys
$k_1$
$k_2$
Values
$v_1$
$v_2$
Score
$q_1 \cdot k_1 = 112$
$q_1 \cdot k_2 = 96$
Divide by 8 ( $\sqrt{d_k}$ )
14
12
Softmax
0.88
0.12
Softmax X Value
$v_1$
$v_2$
Sum
$z_1$
$z_2$

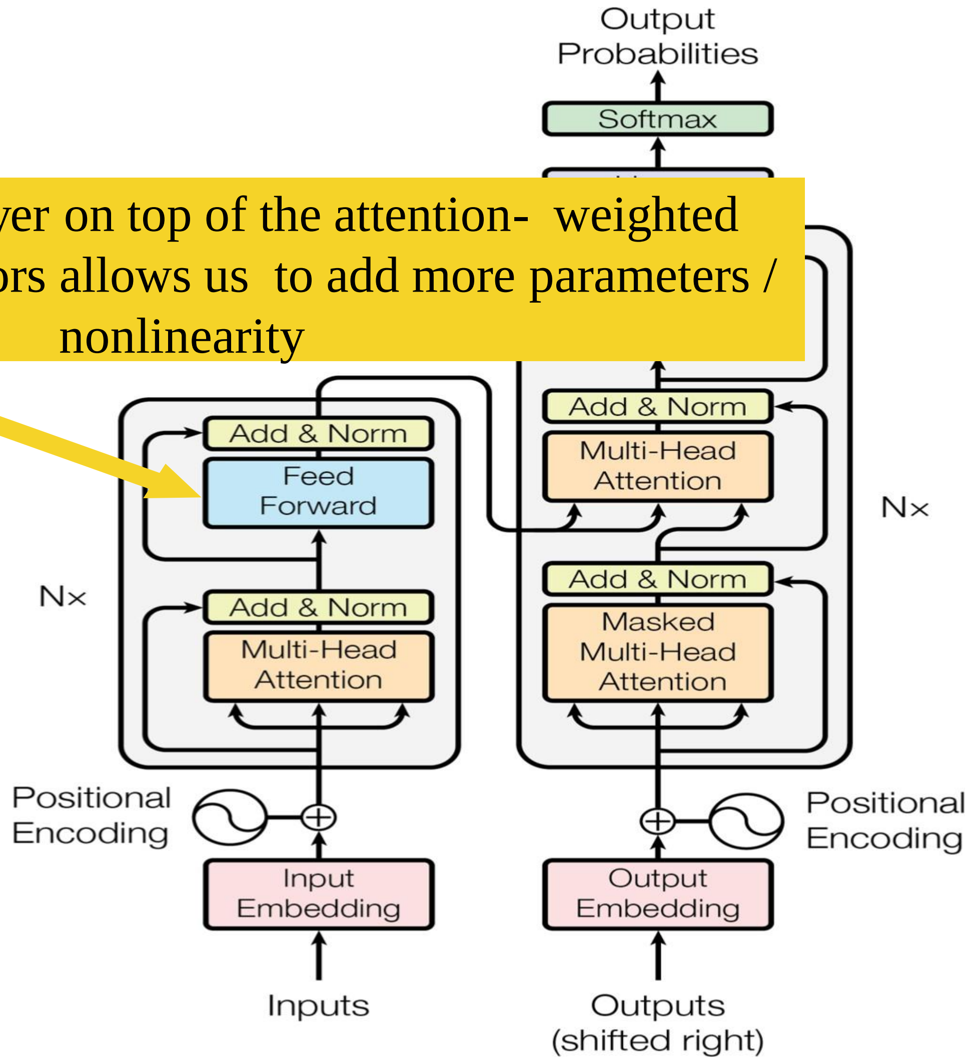
Position embeddings are *added* to each word embedding. Otherwise, since we have no recurrence, our model is unaware of the position of a word in the sequence!



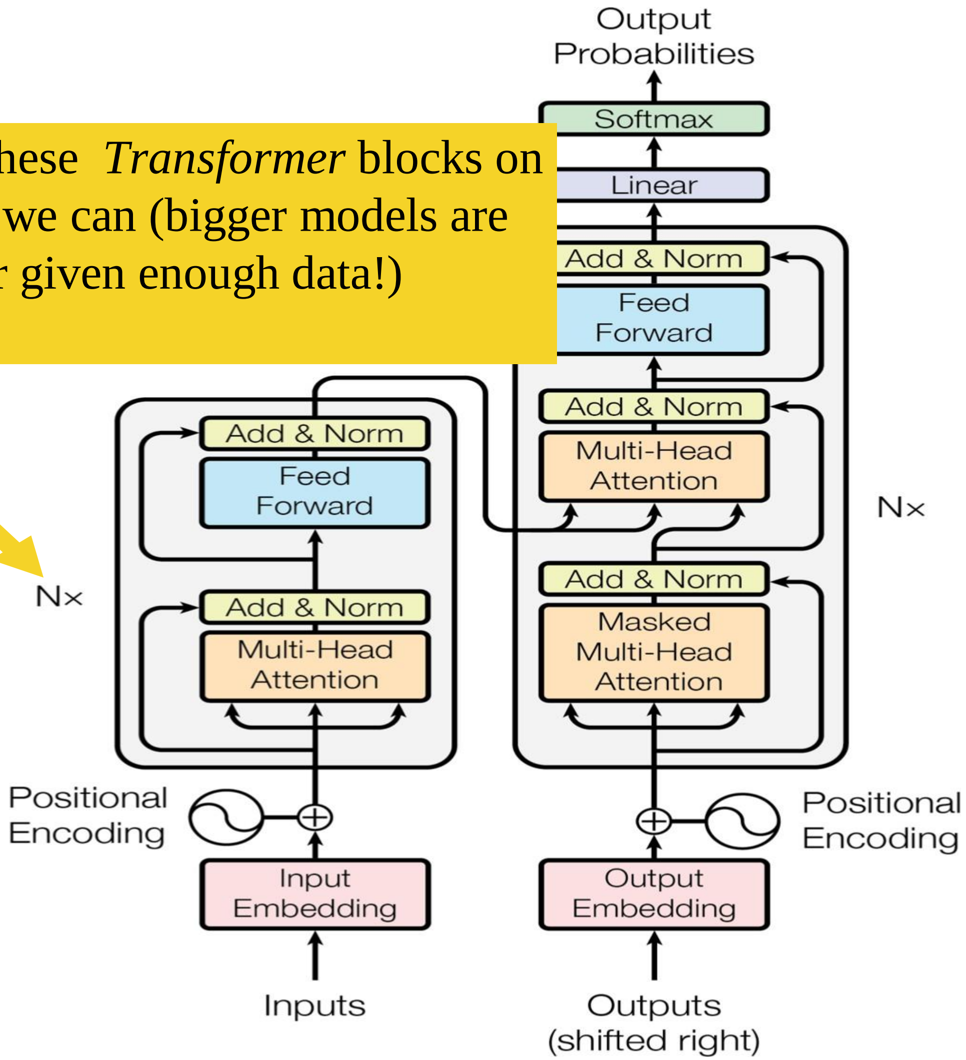
*Residual connections*, which mean that we add the input to a particular block to its output, help improve gradient flow



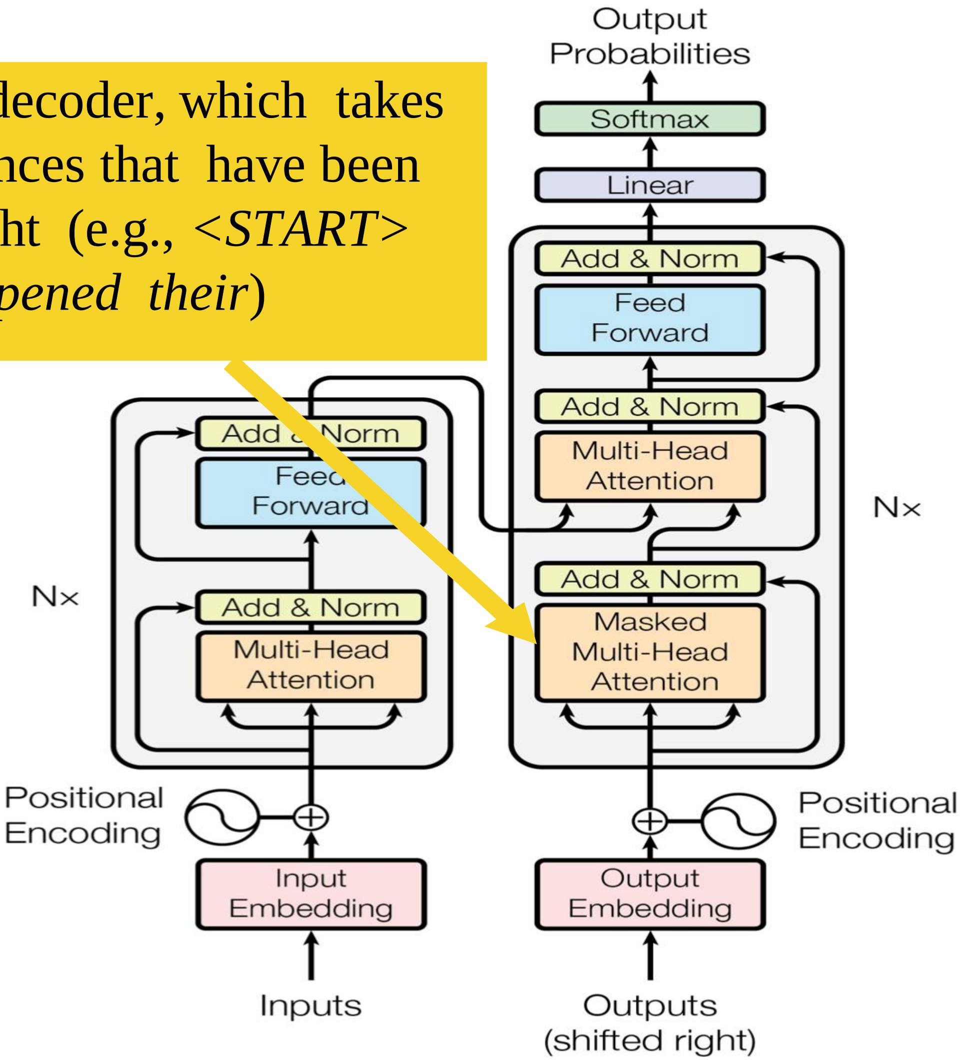
A feed-forward layer on top of the attention- weighted averaged value vectors allows us to add more parameters / nonlinearity



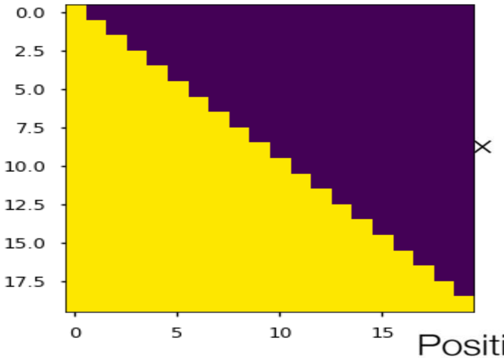
We stack as many of these *Transformer* blocks on top of each other as we can (bigger models are generally better given enough data!)

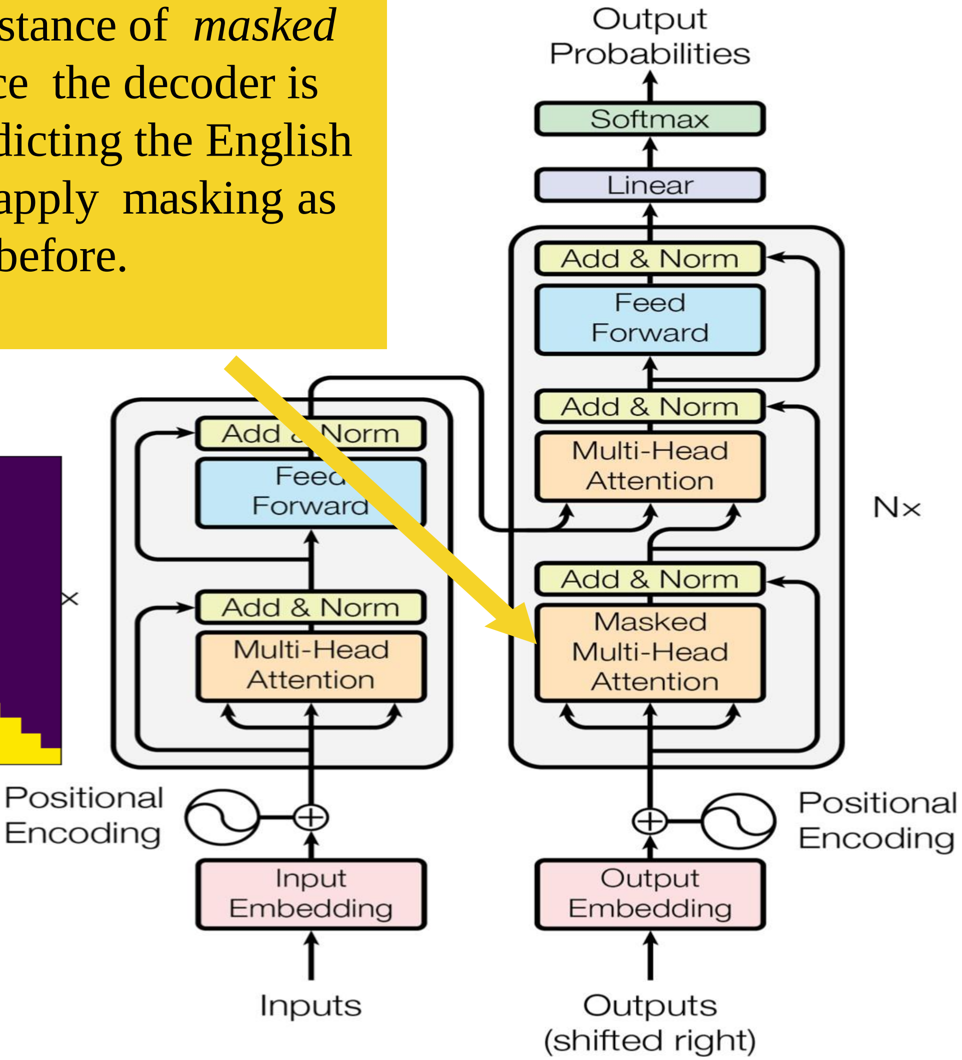


Moving onto the decoder, which takes in English sequences that have been shifted to the right (e.g., *<START> schools opened their*)



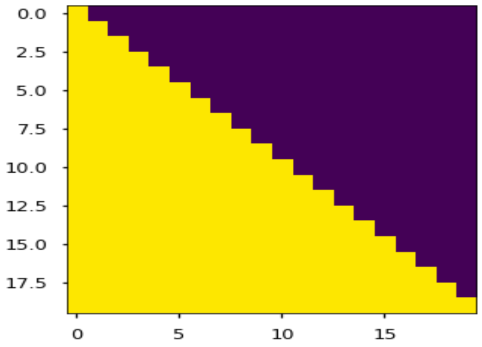
We first have an instance of *masked self attention*. Since the decoder is responsible for predicting the English words, we need to apply masking as we saw before.

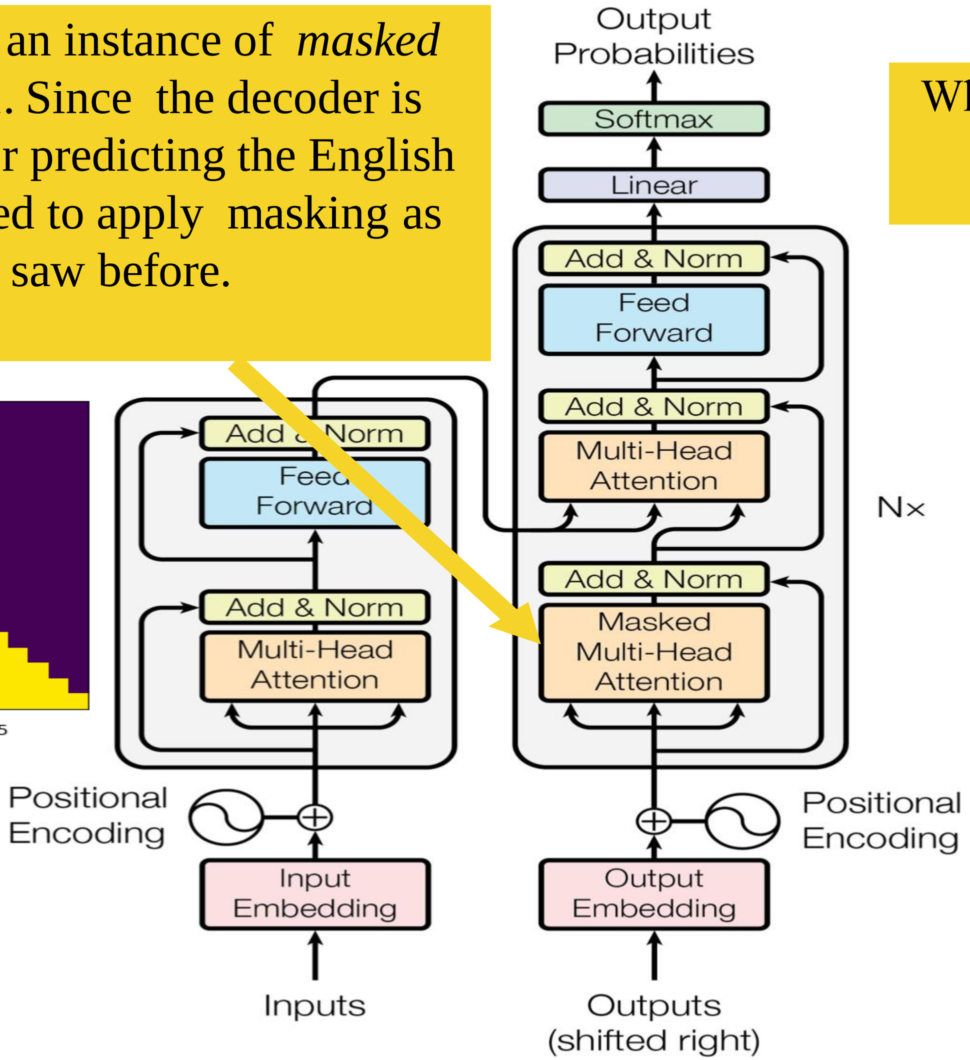


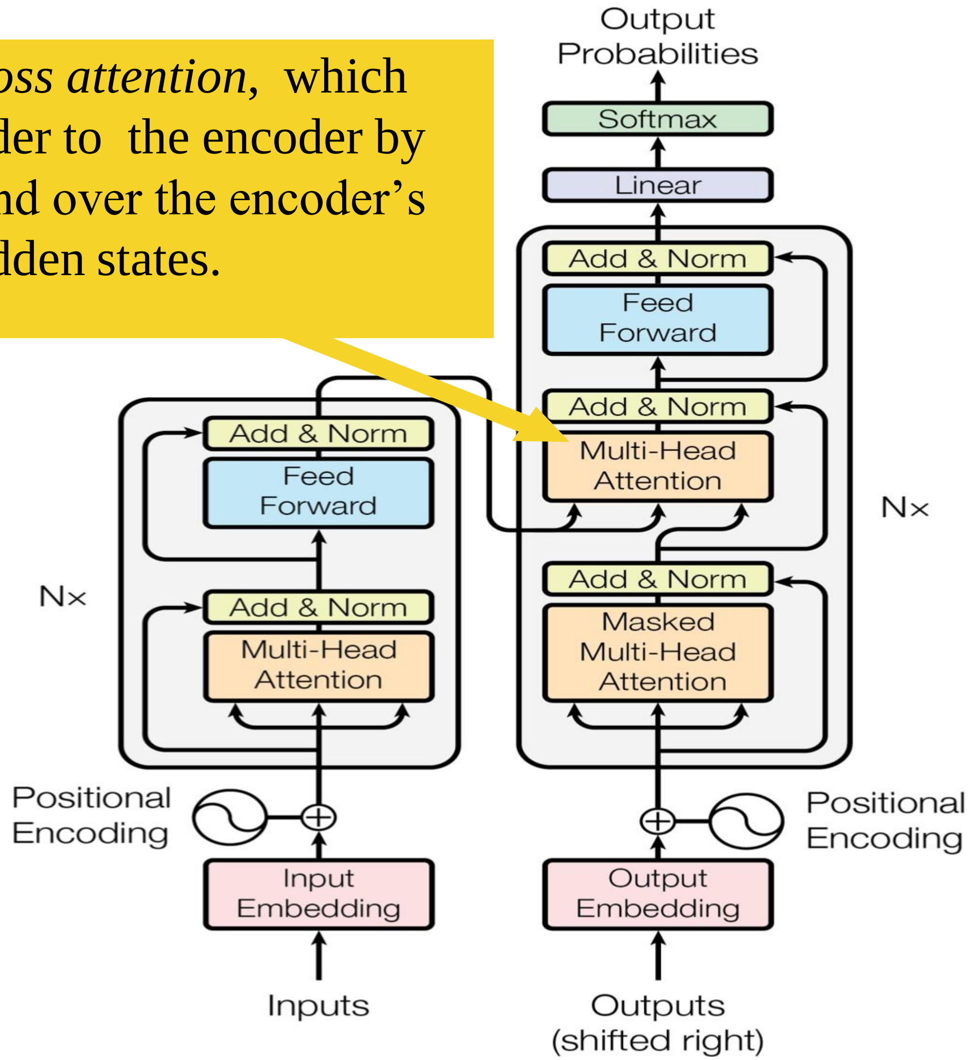
We first have an instance of *masked self attention*. Since the decoder is responsible for predicting the English words, we need to apply masking as we saw before.

Why don't we do masked self-attention in the encoder?

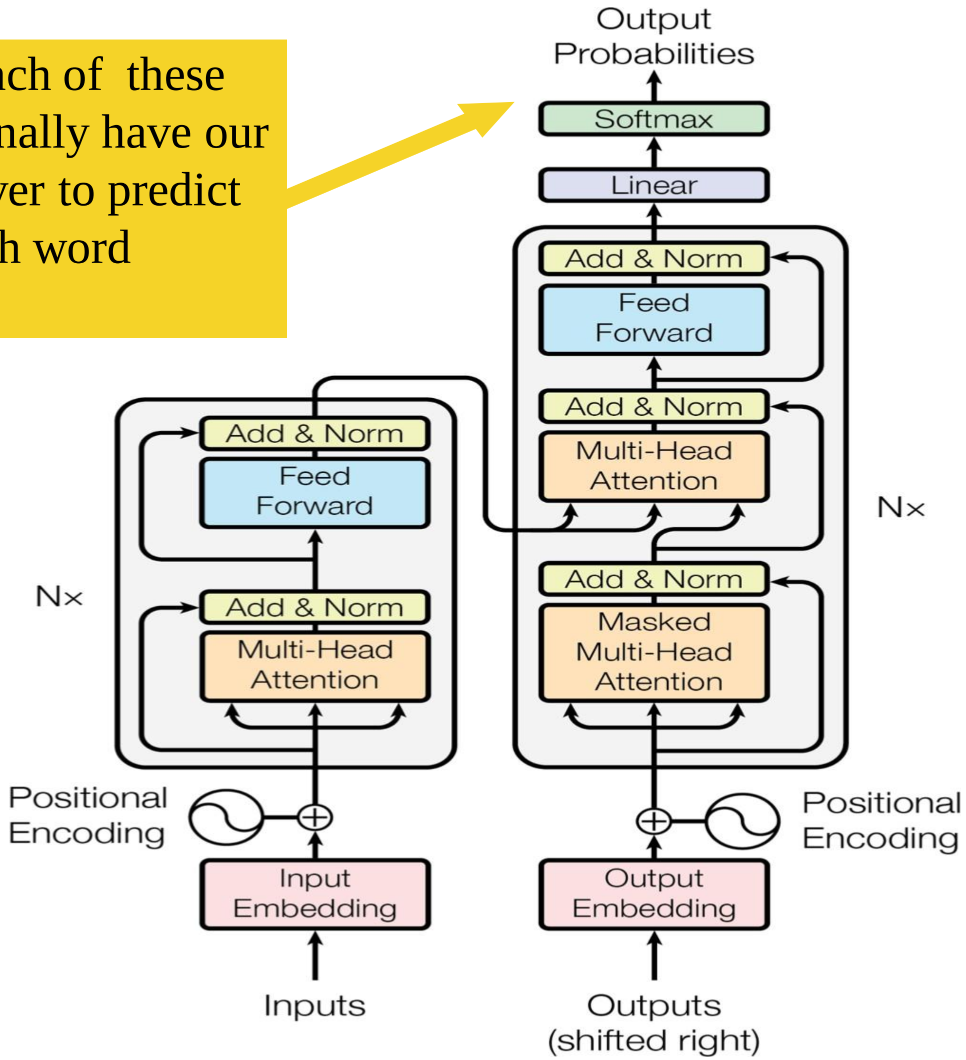


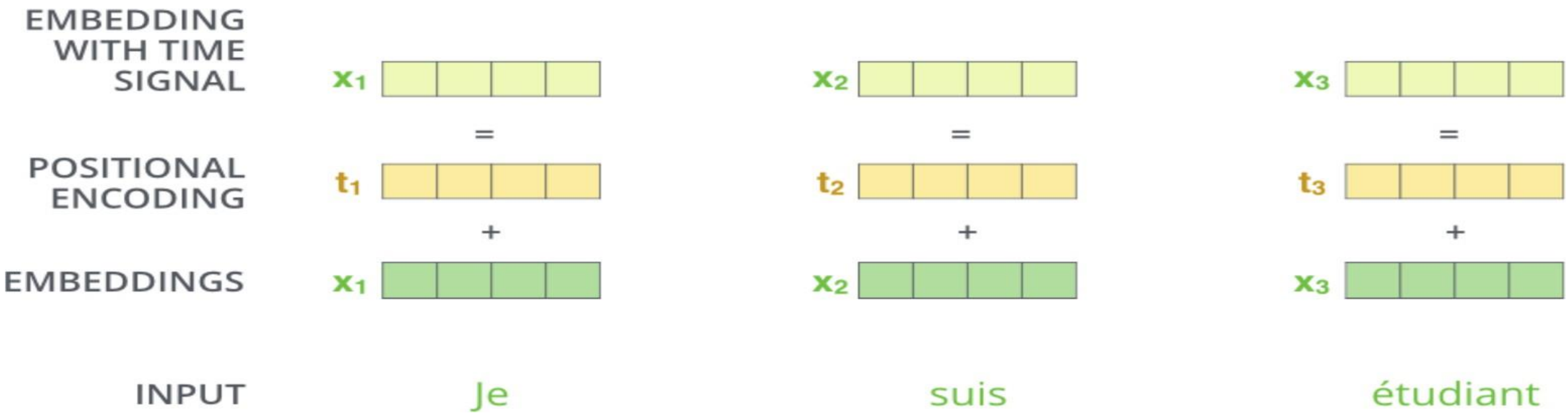
Now, we have *cross attention*, which connects the decoder to the encoder by enabling it to attend over the encoder's final hidden states.



After stacking a bunch of these decoder blocks, we finally have our familiar Softmax layer to predict the next English word



# Positional encoding



# Intuitive example

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 0 : | 0 | 0 | 0 | 0 | 8 : | 1 | 0 | 0 | 0 |
| 1 : | 0 | 0 | 0 | 1 | 9 : | 1 | 0 | 0 | 1 |
| 2 : | 0 | 0 | 1 | 0 | 10 : | 1 | 0 | 1 | 0 |
| 3 : | 0 | 0 | 1 | 1 | 11 : | 1 | 0 | 1 | 1 |
| 4 : | 0 | 1 | 0 | 0 | 12 : | 1 | 1 | 0 | 0 |
| 5 : | 0 | 1 | 0 | 1 | 13 : | 1 | 1 | 0 | 1 |
| 6 : | 0 | 1 | 1 | 0 | 14 : | 1 | 1 | 1 | 0 |
| 7 : | 0 | 1 | 1 | 1 | 15 : | 1 | 1 | 1 | 1 |

https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

# Transformer positional encoding

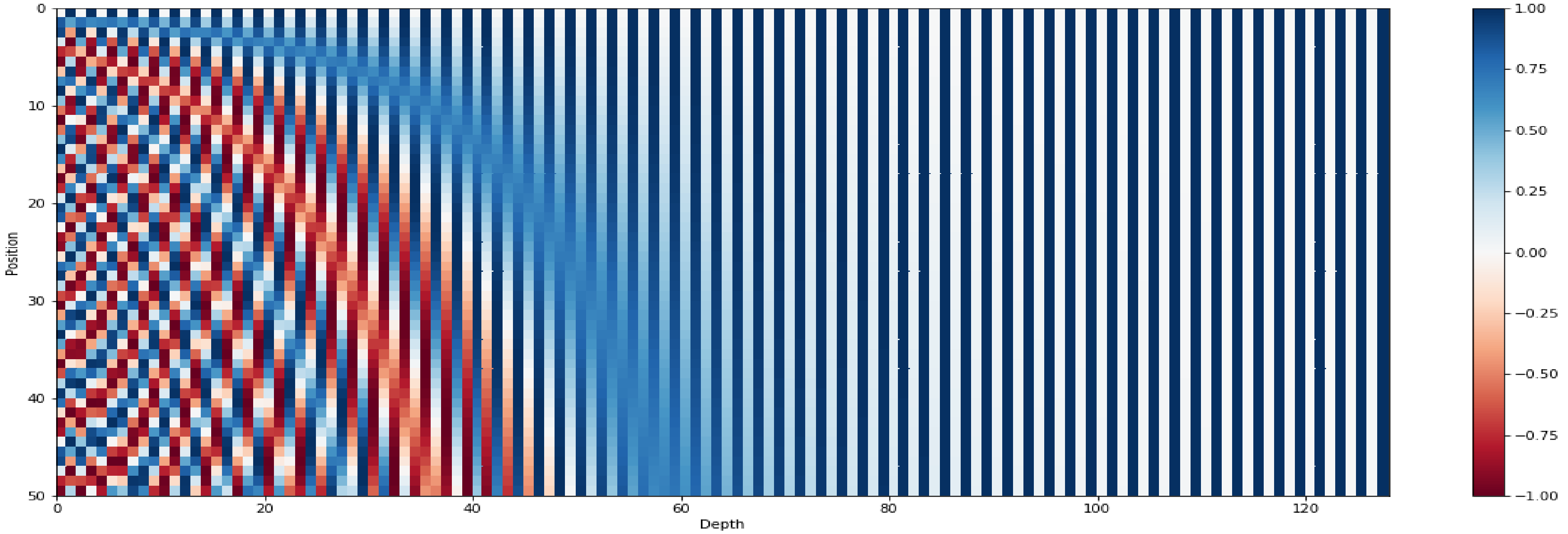
$$PE_{(pos,2i)} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

$$PE_{(pos,2i+1)} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right)$$

Positional encoding is a 512d vector
*i* = a particular dimension of this vector
*pos* = dimension of the word
*d_model* = 512

# What does this look like?

*(each row is the pos. emb. of a 50-word sentence)*



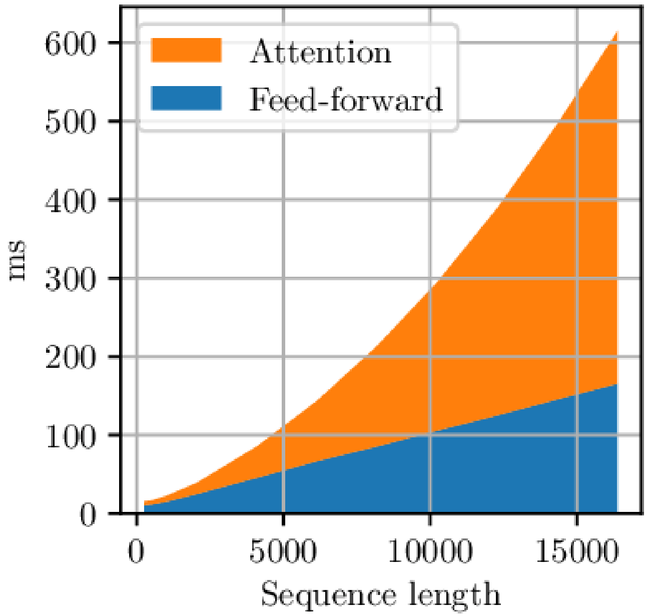

https://kazemnejad.com/blog/transformer_architecture_positional_encoding/

# More on new-Transformer

# What would we like to fix about the Transformer?

**Quadratic compute in self-attention (today):**

- Computing all pairs of interactions means our computation grows quadratically with the sequence length!
- For recurrent models, it only grew linearly!



# Quadratic computation as a function of sequence length

- One of the benefits of self-attention over recurrence was that it's highly parallelizable.
- However, its total number of operations grows as $O(n^2 d)$, where $n$ is the sequence length, and $d$ is the dimensionality.

$$XQ \quad K^\top X^\top = XQK^\top X^\top \in \mathbb{R}^{n\times n}$$

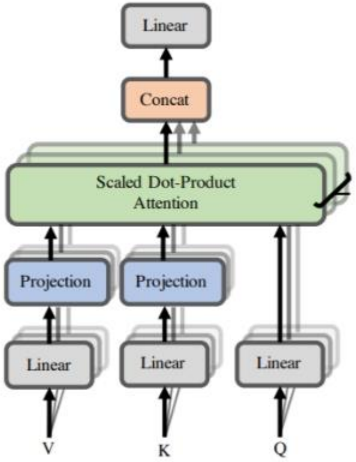
Need to compute all pairs of interactions! $O(n^2 d)$

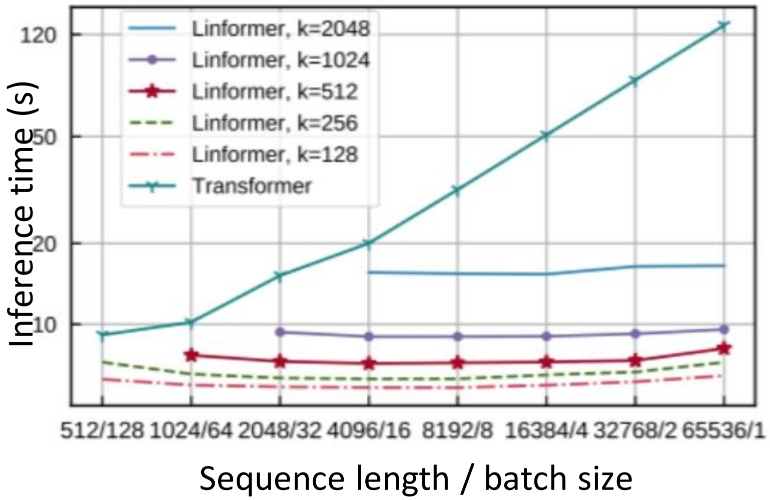
- Think of $d$ as around $\mathbf{1,000}$ (though for large language models it's much larger!).
  - So, for a single (shortish) sentence, $n \leq 30; n^2 \leq \mathbf{900}$.
  - In practice, we set a bound like $n = 512$.
  - **But what if we'd like $\boldsymbol{n} \geq \mathbf{50,000}$?** For example, to work on long documents?

# Work on improving on quadratic self-attention cost

Considerable recent work has gone into the question, *Can we build models like Transformers without paying the all-pairs self-attention cost?*
For example, **Linformer** [Wang et al., 2020]

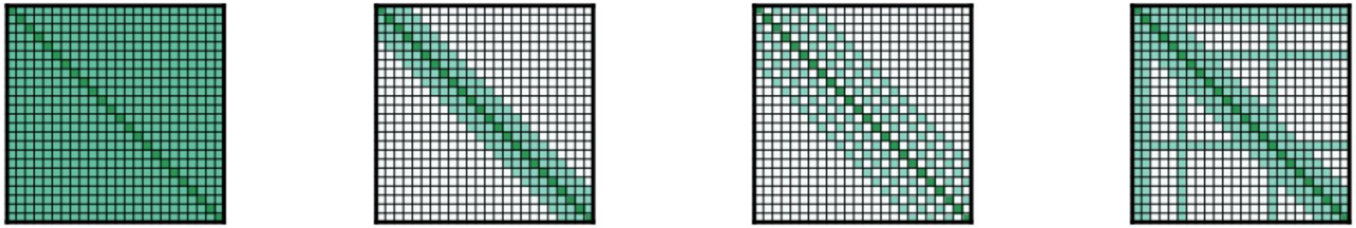
**Key Idea:**
- Linformer introduces a novel concept called "compressed" or "linearized" self-attention.
- Instead of computing attention scores for all pairs of input elements, it employs linear projections to reduce the complexity.



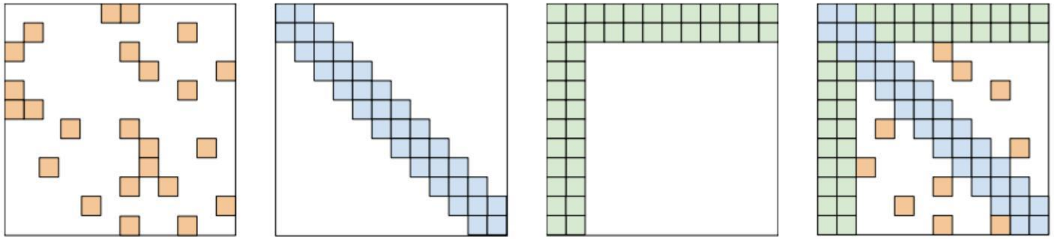
# Example: Longformer / Big Bird

Key idea: use sparse attention patterns!



(a) Full $n^2$ attention (b) Sliding window attention (c) Dilated sliding window (d) Global+sliding window

(Beltagy et al., 2020): Longformer: The Long-Document Transformer



(a) Random attention (b) Window attention (c) Global Attention (d) BIGBIRD

(Zaheer et al., 2021): Big Bird: Transformers for Longer

# Do we even need to remove the quadratic cost of attention?

- **As Transformers Scale Up:** When Transformers are scaled to larger sizes, an increasingly significant portion of computational resources is allocated to tasks outside of the self-attention mechanism, despite its quadratic computational cost.
- **Current Practice:** In practice, nearly all large Transformer-based language models continue to rely on the traditional quadratic-cost attention mechanism that has been presented.
- **Challenges with Cost-Efficiency:** Alternative, more computationally efficient methods often do not perform as effectively when applied at a large scale.
- **Exploring Cheaper Alternatives:** Is there value in exploring cost-efficient alternatives to self-attention, or could we unlock the potential for significantly improved models with much longer contextual information (e.g., >100k tokens) if we find the right approach?

# Do Transformer Modifications Transfer?

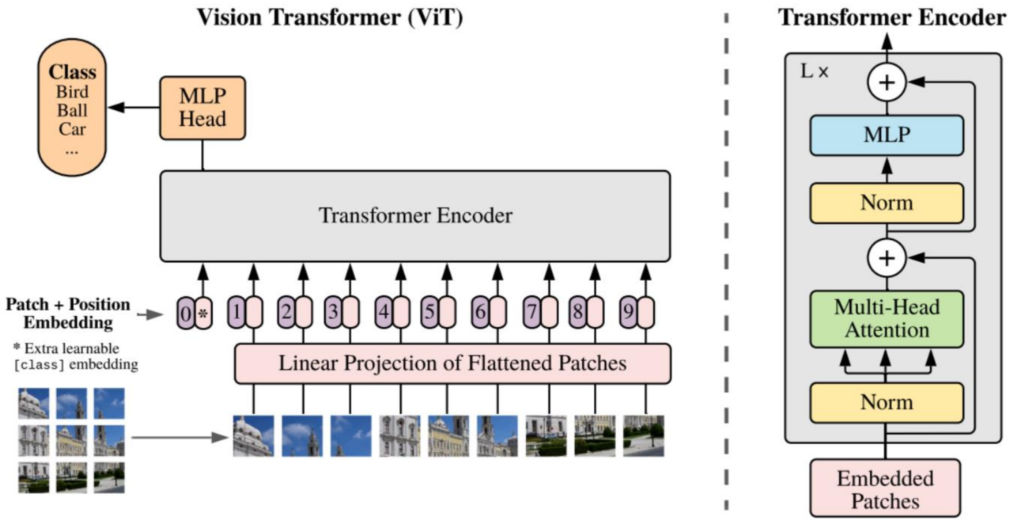
- "Surprisingly, we find that most modifications do not meaningfully improve performance."

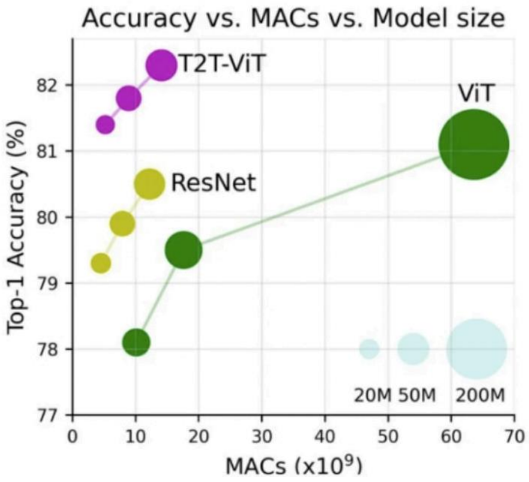
| Model | Params | Ops | Step/s | Early loss | Final loss | SGLUE | XSum | WebQ | WMT EnDe |
|---|---|---|---|---|---|---|---|---|---|
| Vanilla Transformer | 223M | 11.1T | 3.50 | 2.182 ± 0.005 | 1.838 | 71.66 | 17.78 | 23.02 | 26.62 |
| GeLU | 223M | 11.1T | 3.58 | 2.179 ± 0.003 | 1.838 | **75.79** | **17.86** | **25.13** | 26.47 |
| Swish | 223M | 11.1T | 3.62 | 2.186 ± 0.003 | 1.847 | **73.77** | 17.74 | **24.34** | **26.75** |
| ELU | 223M | 11.1T | 3.56 | 2.270 ± 0.007 | 1.932 | 67.83 | 16.73 | 23.02 | 26.08 |
| GLU | 223M | 11.1T | 3.59 | 2.174 ± 0.003 | **1.814** | **74.20** | **17.42** | 24.34 | **27.12** |
| GeGLU | 223M | 11.1T | 3.55 | 2.130 ± 0.006 | **1.792** | **75.96** | **18.27** | **24.87** | **26.87** |
| ReGLU | 223M | 11.1T | 3.57 | 2.145 ± 0.004 | **1.803** | **76.17** | **18.36** | **24.87** | **27.02** |
| SeLU | 223M | 11.1T | 3.55 | 2.315 ± 0.004 | 1.948 | 68.76 | 16.76 | 22.75 | 25.99 |
| SwiGLU | 223M | 11.1T | 3.53 | 2.127 ± 0.003 | **1.789** | **76.00** | **18.20** | **24.34** | **27.02** |
| LiGLU | 223M | 11.1T | 3.59 | 2.149 ± 0.005 | **1.798** | **75.34** | **17.97** | **24.34** | 26.53 |
| Sigmoid | 223M | 11.1T | 3.63 | 2.291 ± 0.019 | 1.867 | **74.31** | 17.51 | 23.02 | 26.30 |
| Softplus | 223M | 11.1T | 3.47 | 2.207 ± 0.011 | 1.850 | **72.45** | 17.65 | **24.34** | **26.89** |
| RMS Norm | 223M | 11.1T | 3.68 | 2.167 ± 0.008 | **1.821** | **75.45** | **17.94** | **24.07** | **27.14** |
| Rezero | 223M | 11.1T | 3.51 | 2.262 ± 0.003 | 1.939 | 61.69 | 15.64 | 20.90 | 26.37 |
| Rezero + LayerNorm | 223M | 11.1T | 3.26 | 2.223 ± 0.006 | 1.858 | 70.42 | 17.58 | 23.02 | 26.29 |
| Rezero + RMS Norm | 223M | 11.1T | 3.34 | 2.221 ± 0.009 | 1.875 | 70.33 | 17.32 | 23.02 | 26.19 |
| Fixup | 223M | 11.1T | 2.95 | 2.382 ± 0.012 | 2.067 | 58.56 | 14.42 | 23.02 | 26.31 |
| 24 layers, $d_{ff} = 1536$, $H = 6$ | 224M | 11.1T | 3.33 | 2.200 ± 0.007 | 1.843 | **74.89** | 17.75 | **25.13** | **26.89** |
| 18 layers, $d_{ff} = 2048$, $H = 8$ | 223M | 11.1T | 3.38 | 2.185 ± 0.005 | **1.831** | **76.45** | 16.83 | **24.34** | **27.10** |
| 8 layers, $d_{ff} = 4608$, $H = 18$ | 223M | 11.1T | 3.69 | 2.190 ± 0.005 | 1.847 | **74.58** | 17.69 | **23.28** | **26.85** |
| 6 layers, $d_{ff} = 6144$, $H = 24$ | 223M | 11.1T | 3.70 | 2.201 ± 0.010 | 1.857 | **73.55** | 17.59 | **24.60** | **26.66** |
| Block sharing | 65M | 11.1T | 3.91 | 2.497 ± 0.037 | 2.164 | 64.50 | 14.53 | 21.96 | 25.48 |
| + Factorized embeddings | 45M | 9.4T | 4.21 | 2.631 ± 0.305 | 2.183 | 60.84 | 14.00 | 19.84 | 25.27 |
| + Factorized & shared embeddings | 20M | 9.1T | 4.37 | 2.907 ± 0.313 | 2.385 | 53.95 | 11.37 | 19.84 | 25.19 |
| Encoder only block sharing | 170M | 11.1T | 3.68 | 2.298 ± 0.023 | 1.929 | 69.60 | 16.23 | 23.02 | 26.23 |
| Decoder only block sharing | 144M | 11.1T | 3.70 | 2.352 ± 0.029 | 2.082 | 67.93 | 16.13 | **23.81** | 26.08 |
| Factorized Embedding | 227M | 9.4T | 3.80 | 2.208 ± 0.006 | 1.855 | 70.41 | 15.92 | 22.75 | 26.50 |
| Factorized & shared embeddings | 202M | 9.1T | 3.92 | 2.320 ± 0.010 | 1.952 | 68.69 | 16.33 | 22.22 | 26.44 |
| Tied encoder/decoder input embeddings | 248M | 11.1T | 3.55 | 2.192 ± 0.002 | 1.840 | **71.70** | 17.72 | **24.34** | 26.49 |
| Tied decoder input and output embeddings | 248M | 11.1T | 3.57 | 2.187 ± 0.007 | **1.827** | **74.86** | 17.74 | **24.87** | **26.67** |
| Untied embeddings | 273M | 11.1T | 3.53 | 2.195 ± 0.005 | **1.834** | **72.99** | 17.58 | **23.28** | 26.48 |
| Adaptive input embeddings | 204M | 9.2T | 3.55 | 2.250 ± 0.002 | 1.899 | 66.57 | 16.21 | **24.07** | **26.66** |
| Adaptive softmax | 204M | 9.2T | 3.60 | 2.364 ± 0.005 | 1.982 | **72.91** | 16.67 | 21.16 | 25.56 |
| Adaptive softmax without projection | 223M | 10.8T | 3.43 | 2.229 ± 0.009 | 1.914 | **71.82** | 17.10 | 23.02 | 25.72 |
| Mixture of softmaxes | 232M | 16.3T | 2.24 | 2.227 ± 0.017 | **1.821** | **76.77** | 17.62 | 22.75 | **26.82** |
| Transparent attention | 223M | 11.1T | 3.33 | 2.181 ± 0.014 | 1.874 | 54.31 | 10.40 | 21.16 | **26.80** |
| Dynamic convolution | 257M | 11.8T | 2.65 | 2.403 ± 0.009 | 2.047 | 58.30 | 12.67 | 21.16 | 17.03 |
| Lightweight convolution | 224M | 10.4T | 4.07 | 2.370 ± 0.010 | 1.989 | 63.07 | 14.86 | 23.02 | 24.73 |
| Evolved Transformer | 217M | 9.9T | 3.09 | 2.220 ± 0.003 | 1.863 | **73.67** | 10.76 | **24.07** | 26.58 |
| Synthesizer (dense) | 224M | 11.4T | 3.47 | 2.334 ± 0.021 | 1.962 | 61.03 | 14.27 | 16.14 | **26.63** |
| Synthesizer (dense plus) | 243M | 12.6T | 3.22 | 2.191 ± 0.010 | 1.840 | **73.98** | 16.96 | **23.81** | **26.71** |
| Synthesizer (dense plus alpha) | 243M | 12.6T | 3.01 | 2.180 ± 0.007 | **1.828** | **74.25** | 17.02 | **23.28** | 26.61 |
| Synthesizer (factorized) | 207M | 10.1T | 3.94 | 2.341 ± 0.017 | 1.968 | 62.78 | 15.39 | **23.55** | 26.42 |
| Synthesizer (random) | 254M | 10.1T | 4.08 | 2.326 ± 0.012 | 2.009 | 54.27 | 10.35 | 19.56 | 26.44 |
| Synthesizer (random plus) | 292M | 12.0T | 3.63 | 2.189 ± 0.004 | 1.842 | **73.32** | 17.04 | **24.87** | 26.43 |
| Synthesizer (random plus alpha) | 292M | 12.0T | 3.42 | 2.186 ± 0.007 | **1.828** | **75.24** | 17.08 | **24.08** | 26.39 |
| Universal Transformer | 84M | 40.0T | 0.88 | 2.406 ± 0.036 | 2.053 | 70.13 | 14.09 | 19.05 | 23.91 |
| Mixture of experts | 648M | 11.7T | 3.20 | 2.148 ± 0.006 | **1.785** | **74.55** | **18.13** | **24.08** | **26.94** |
| Switch Transformer | 1100M | 11.7T | 3.18 | 2.135 ± 0.007 | **1.758** | **75.38** | **18.02** | **26.19** | **26.81** |
| Funnel Transformer | 223M | 1.9T | 4.30 | 2.288 ± 0.008 | 1.918 | 67.34 | 16.26 | 22.75 | 23.20 |
| Weighted Transformer | 280M | 71.0T | 0.59 | 2.378 ± 0.021 | 1.989 | 69.04 | 16.98 | 23.02 | 26.30 |
| Product key memory | 421M | 386.6T | 0.25 | 2.155 ± 0.003 | **1.798** | **75.16** | 17.04 | **23.55** | **26.73** |

## Do Transformer Modifications Transfer Across Implementations and Applications?


Sharan Narang* Hyung Won Chung Yi Tay William Fedus
Thibault Fevry† Michael Matena† Karishma Malkan† Noah Fiedel
Noam Shazeer Zhenzhong Lan† Yanqi Zhou Wei Li
Nan Ding Jake Marcus Adam Roberts Colin Raffel†

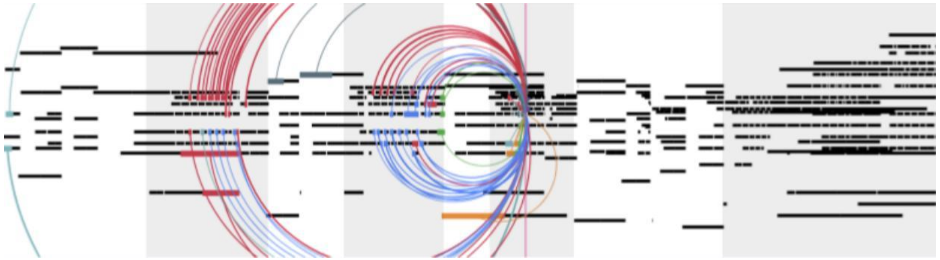
# Vision Transformer (ViT)

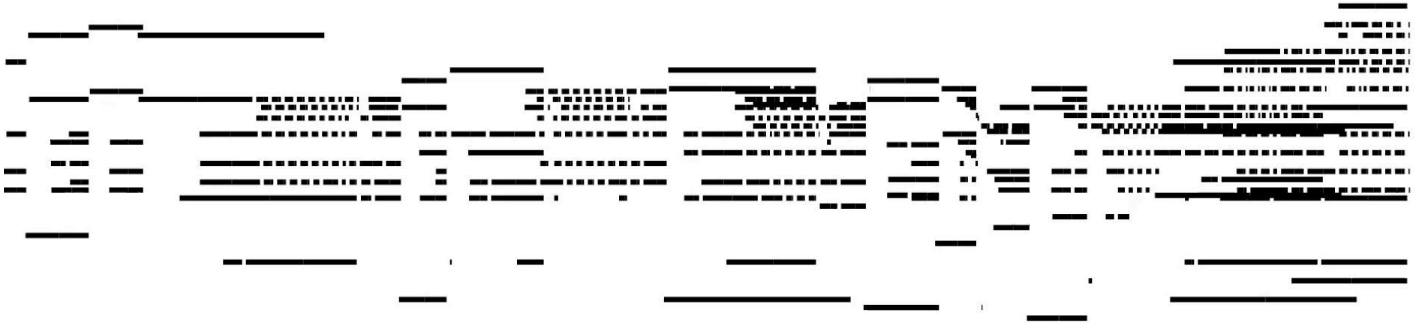



(Dosovitskiy et al., 2021): An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

# Music Transformer





https://magenta.tensorflow.org/music-transformer

(Huang et al., 2018): Music Transformer: Generating Music with Long-Term Structure

# Why transformer

# Why Pretraining + Transformers

- 1.Because transformers are more efficient?

Transformers are shower comparing to LSTM with same amount parameters

Credits from 杨植麟, Recurrent AI

# Why Pretraining + Transformers

- 1.Because transformers are more efficient?

Transformers are shower comparing to LSTM with same amount parameters

- 2. Because transformers are better on machine translation?

RNNs and CNNs are equally good in machine translations

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Transformers are shower comparing to LSTM with same amount parameters

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RNNs and CNNs are equally good in machine translations

- 3. Because transformers use nothing but attention?

So what?

# Why Pretraining + Transformers

- 1.Because transformers are more efficient?

Transformers are shower comparing to LSTM with same amount parameters

- 2. Because transformers are better on machine translation?

RNNs and CNNs are equally good in machine translations

- 3. Because transformers use nothing but attention?

So what?

- 4. Because transformers learns contextualised word embeddings?

RNN also can learn contextualised word embeddings

# Why Pretraining + Transformers

- ❖ **Capacity**: The model has sufficient expressive capabilities
- ❖ **Optimization**: Can optimize and obtain better solutions in a huge expression space
- ❖ **Generalization**: Better solutions can generalize on test data

"Exploring the Limits of Language Modeling
Jozefowicz et al 2016

**LSTM-8192-1024, 1.8 billion params, ppl 30.6**
**LSTM-8192-2048, 3.3 billion params, ppl 32.2**

Dai, Yang et al 2016
**Transformer-XL Base, 0.46 billion params, ppl 23.5**
**Transformer-XL Large, 0.8 billion params, ppl 21.8**

**ppl=perplexity, the lower the better**

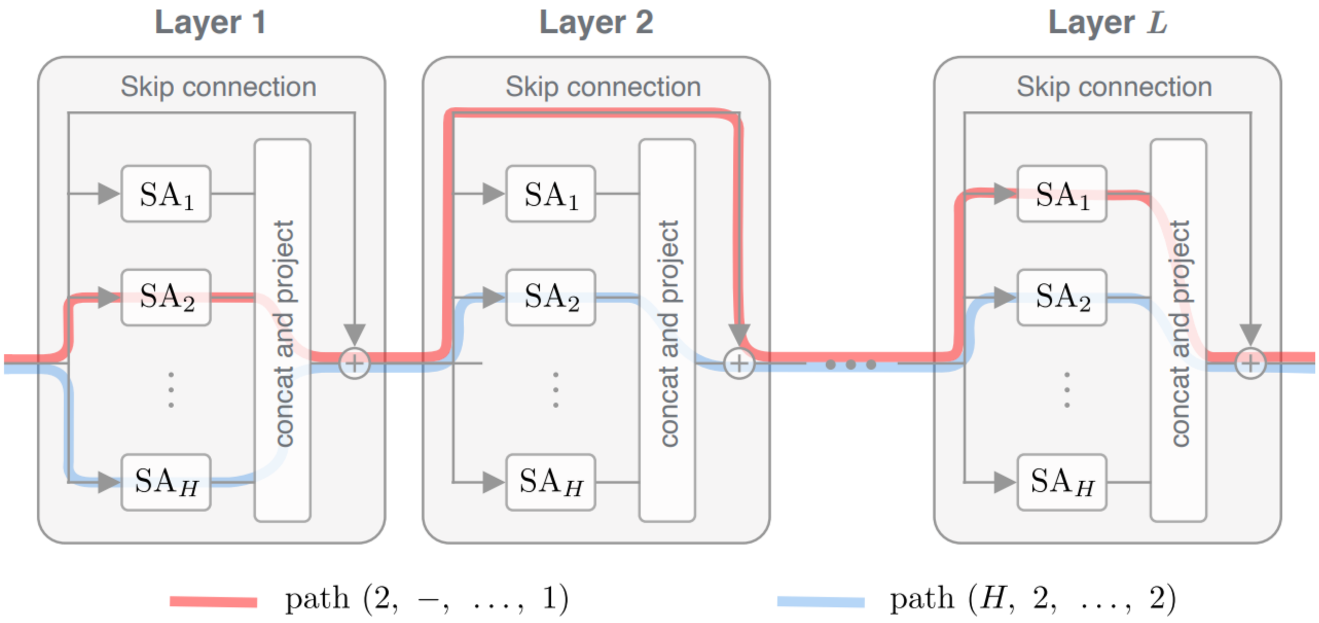
Scalability: Transformers scale much better with more parameters

# Deep understanding of transformer

What if

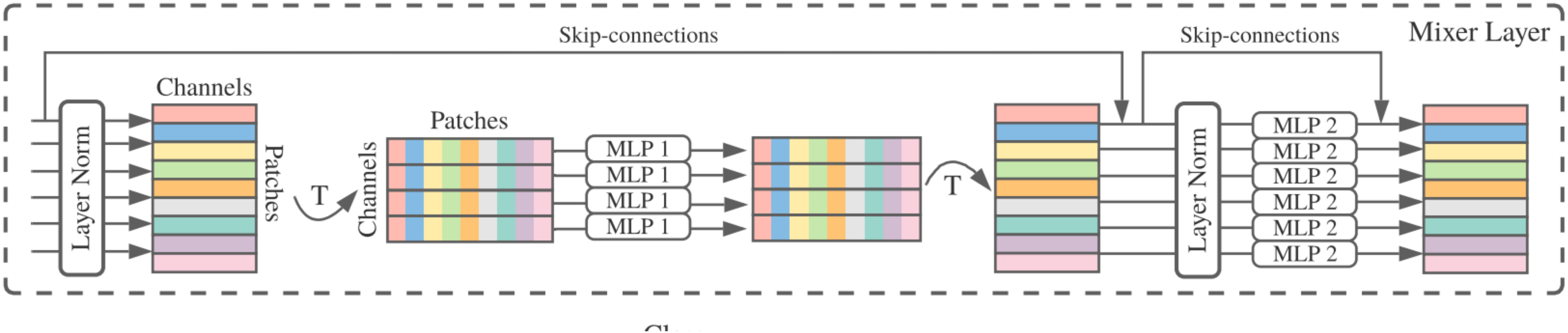
- ✓ removing SAN
- ✓ removing FFN
- ✓ removing PE
- ✓ and many others?

# Without FFN, pure SAN




Y Dong, JB Cordonnier, A Loukas. Attention is not all you need: Pure attention loses rank doubly exponentially with depth. https://browse.arxiv.org/pdf/2103.03404.pdf

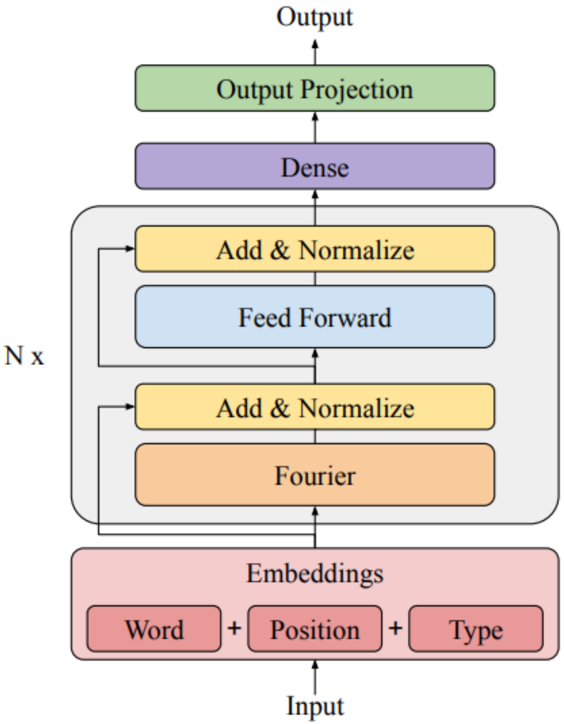
# Without SAN, pure FNN




At least it works for computer vision.

Ilya Tolstikhin et.al MLP-Mixer: An all-MLP Architecture for Vision https://browse.arxiv.org/pdf/2105.01601.pdf

# Replace SAN with fourier




- ❖ Highlight the potential of linear units as a drop-in replacement for the attention mechanism in text classification tasks.
- ❖ FNet will be effective as a lightweight

James Lee-Thorp, Joshua Ainslie, Ilya Eckstein, Santiago Ontanon .
FNet: Mixing Tokens with Fourier Transforms. NAACL 2022

# How to place FFN and SAN

sfsfsfsfsfsfsfsfsfsfsfsfsfsf

(a) Interleaved Transformer

sssssssfsfsfsfsfsfsfsfffffff

(b) Sandwich Transformer

Figure 1: A transformer model (a) is composed of interleaved self-attention (green) and feedforward (purple) sublayers. Our sandwich transformer (b), a reordering of the transformer sublayers, performs better on language modeling. Input flows from left to right.

| **Model** | **PPL** |
|---|---|
| fsfsfffsffsfsssffsfssfssssffsffs | 20.74 |
| sfssffsffffssssfsfffsfsffsfssssf | 20.64 |
| fsffssffssssffsssssffsfssfsfffff | 20.33 |
| fsffffffsssfssffsfssffsfsssffsss | 20.27 |
| fssffffffsfsssfffssssfffssssffss | 19.98 |
| sssfssfsffffssfsfsfsssffsfsfffsf | 19.92 |
| fffsfsssfsffsfsffsffsssssffssffs | 19.69 |
| fffsffssffsssfssfsssfffffsfsssfs | 19.54 |
| sfsfsfsfsfsfsfsfsfsfsfsfsfsfsfsf | **19.13** |
| fsffssfssfffssssfffsssffffsfssfs | 19.08 |
| sfsffssssffssffffsssffsssfsffsff | 18.90 |
| sfsfsfsfsfsfsfsfsfsfsfsfsfsfsfsf | **18.83** |
| sssssssffsffsfsfsffffsfffsfssffs | 18.83 |
| sffsfsffsfsssffssfssssssfffffffs | 18.77 |
| sssfssffsfssfsffsfffssffsfsffssf | 18.68 |
| fffsssssfffsfssssffsfsfsfssffsff | 18.64 |
| sfffsssfsfssfsssssfssfffffsfffsf | 18.61 |
| ssffssfssssffffffssffsssfsffssff | 18.60 |
| fsfsssssfsfsfffffsfffsffssffssss | 18.55 |
| sfsfsfsfsfsfsfsfsfsfsfsfsfsfsfsf | **18.54** |
| sfsfsfsfsfsfsfsfsfsfsfsfsfsfsfsf | **18.49** |
| fsfsssssfsfffssfsffsfsfsfsffffss | 18.38 |
| sfssffsfsfsffsssssfffsssfffsffsf | 18.28 |
| sfsfsfsfsfsfsfsfsfsfsfsfsfsfsfsf | **18.25** |
| sfsfssfsssffsfsfsfsffffssffsfssf | 18.19 |

Ofir Press, Noah A. Smith, Omer Levy. Improving Transformer Models by Reordering their Sublayers.
https://browse.arxiv.org/pdf/1911.03864.pdf

# What will happen if the position embedding model is removed?

Table 3: Experiments on GLUE. The evaluation metrics are following the official GLUE benchmark (Wang et al., 2018). The best performance of each task is bold.

| PEs | single sentence CoLA acc | single sentence SST-2 acc | sentence pair MNLI acc | sentence pair MRPC F1 | sentence pair QNLI acc | sentence pair QQP F1 | sentence pair RTE acc | sentence pair STS-B spear. cor. | sentence pair WNLI acc | mean ± std |
|---|---|---|---|---|---|---|---|---|---|---|
| BERT without PE | 39.0 | 86.5 | 80.1 | 86.2 | 83.7 | 86.5 | 63.0 | 87.4 | 33.8 | 76.6 ± 0.41 |
| fully learnable (BERT-style) APE | 60.2 | **93.0** | 84.8 | 89.4 | 88.7 | 87.8 | **65.1** | **88.6** | 37.5 | 82.2 ± 0.30 |
| fixed sin. APE | 57.1 | 92.6 | 84.3 | 89.0 | 88.1 | 87.5 | 58.4 | 86.9 | 45.1 | 80.5 ± 0.71 |
| learnable sin. APE | 56.0 | 92.8 | 84.8 | 88.7 | 88.5 | 87.7 | 59.1 | 87.0 | 40.8 | 80.6 ± 0.29 |
| fully-learnable RPE | 58.9 | 92.6 | 84.9 | **90.5** | 88.9 | **88.1** | 60.8 | 88.6 | 50.4 | 81.7 ± 0.31 |
| fixed sin. RPE | 60.4 | 92.2 | 84.8 | 89.5 | 88.8 | 88.0 | 62.9 | 88.1 | 45.1 | 81.8 ± 0.53 |
| learnable sin. RPE | 60.3 | 92.6 | **85.2** | 90.3 | **89.1** | **88.1** | 63.5 | 88.3 | 49.9 | 82.2 ± 0.40 |
| fully learnable APE + fully-learnable RPE | 59.8 | 92.8 | 85.1 | 89.6 | 88.6 | 87.8 | 62.5 | 88.3 | **51.5** | 81.8 ± 0.17 |
| fully learnable APE + fixed sin. RPE | 59.2 | 92.4 | 84.8 | 89.9 | 88.8 | 87.9 | 61.0 | 88.3 | 48.2 | 81.5 ± 0.20 |
| fully learnable APE+ learnable sin. RPE | **61.1** | 92.8 | **85.2** | **90.5** | 89.5 | 87.9 | **65.1** | 88.2 | 49.6 | **82.5** ± 0.44 |
| learnable sin. APE + fully-learnable RPE | 57.2 | 92.7 | 84.8 | 88.9 | 88.5 | 87.8 | 58.6 | 88.0 | 51.3 | 80.8 ± 0.44 |
| learnable sin. APE + fixed sin. RPE | 57.6 | 92.6 | 84.5 | 88.8 | 88.6 | 87.6 | 63.1 | 87.4 | 48.7 | 81.3 ± 0.43 |
| learnable sin. APE + learnable sin. RPE | 57.7 | 92.7 | 85.0 | 89.6 | 88.7 | 87.8 | 62.3 | 87.5 | 50.1 | 81.4 ± 0.33 |

Benyou Wang, Lifeng Shang, Christina Lioma, Xin Jiang, Hao Yang, Qun Liu, Jakob Grue Simonsen. On Position Embeddings in BERT. https://openreview.net/pdf?id=onxoVA9FxMw

# Improvements for Norm

## DeepNet - 1000 layer Transformers

A new normalization function (DEEPNORM) is introduced
[replacing it is not Layer Norm! Instead, modify it similarly to:

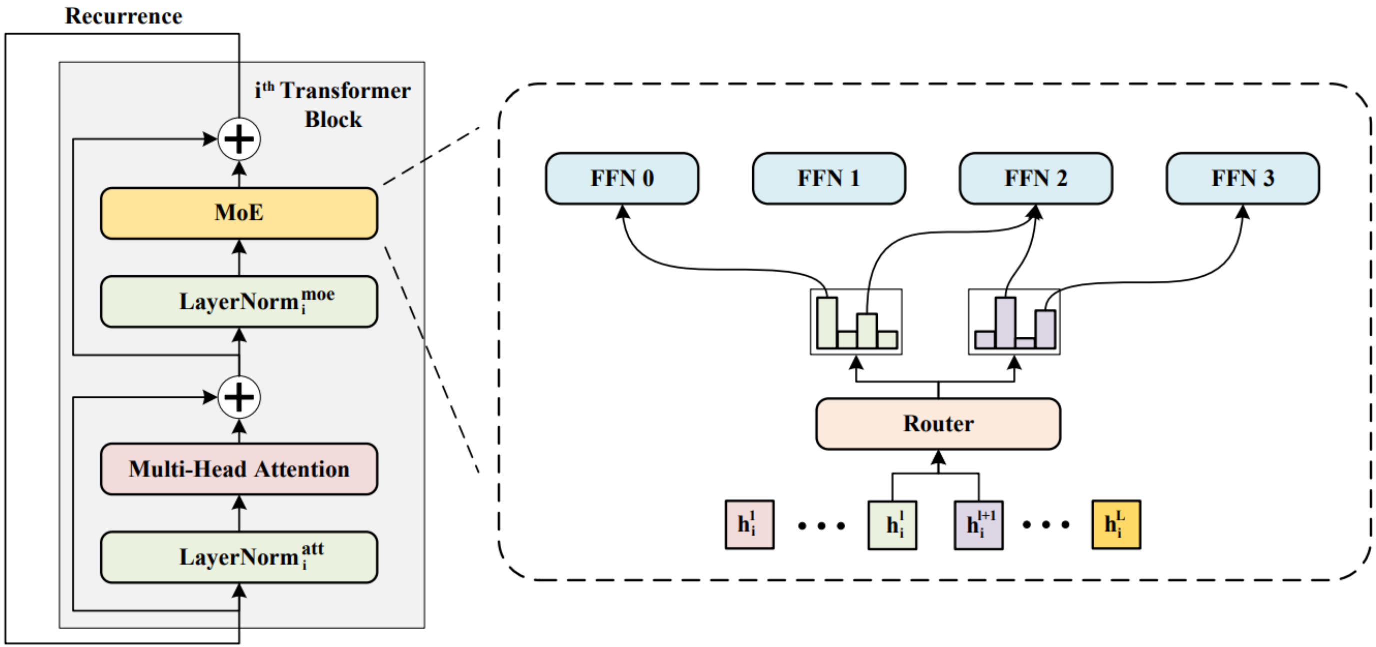
**layernorm (x + f(x)) ---> layernorm(x*alpha + f(x)).**

The proposed method combines the advantages of both schools, namely the good performance of Post-LN and the stable training of Pre-LN, making DEEPNORM the preferred alternative.

Hongyu Wang, Shuming Ma, Li Dong, Shaohan Huang, Dongdong Zhang, Furu Wei. DeepNet: Scaling Transformers to 1,000 Layers. https://browse.arxiv.org/pdf/2203.00555.pdf

# Should the model be deeper or wider?

Go Wider Instead of Deeper




- WideNet first compresses trainable parameters along with depth by parameter-sharing across transformer blocks
- Each expert requires enough tokens to train.

Fuzhao Xue, Ziji Shi, Futao Wei, Yuxuan Lou, Yong Liu, Yang You. **Go Wider Instead of Deeper. https://arxiv.org/abs/2107.11817**

# Acknowledgement


- Princeton COS 484: Natural Language Processing. Contextualized Word Embeddings. Fall 2019
- CS447: Natural Language Processing. Language Models. *http://courses.engr.illinois.edu/cs447*
- *http://cs231n.stanford.edu/*
- *https://medium.com/@gautam.karmakar/summary-seq2seq-model-using-convolutional-neural-network-b1eb100fb4c4*
- Transformers and sequence- to-sequence learning. CS 685, Fall 2021. Mohit Iyyer. College of Information and Computer Sciences. University of Massachusetts Amherst. https://people.cs.umass.edu/~miyyer/cs685_f21/slides/05-transformers.pdf

# Scaling law？

# Scaling Law for Neural Language Models

Performance depends strongly on scale! We keep getting better performance as we scale the model, data, and compute up!

## Scaling Laws for Neural Language Models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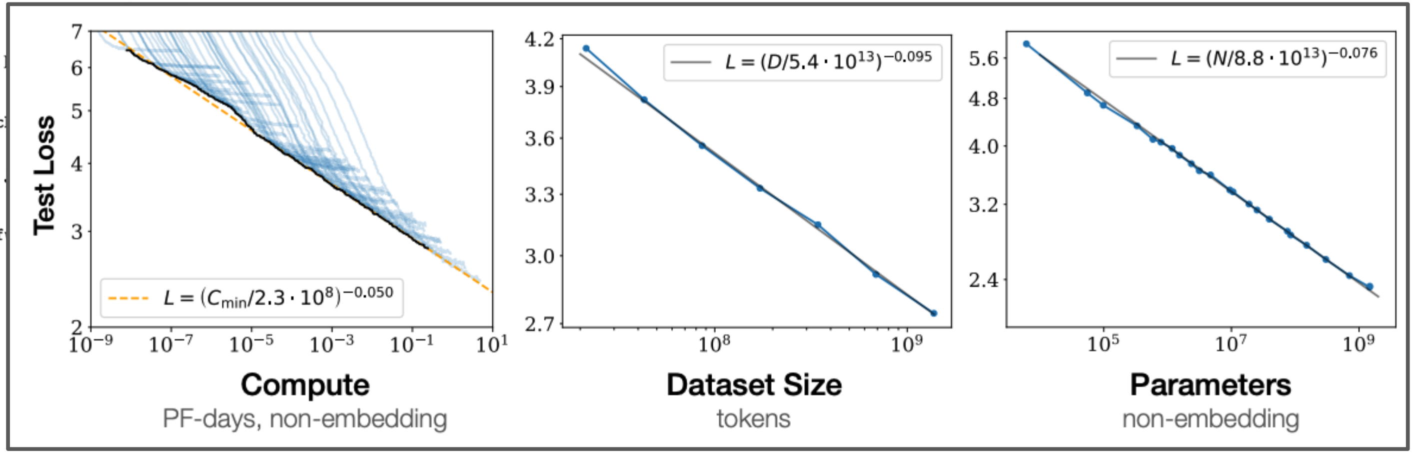
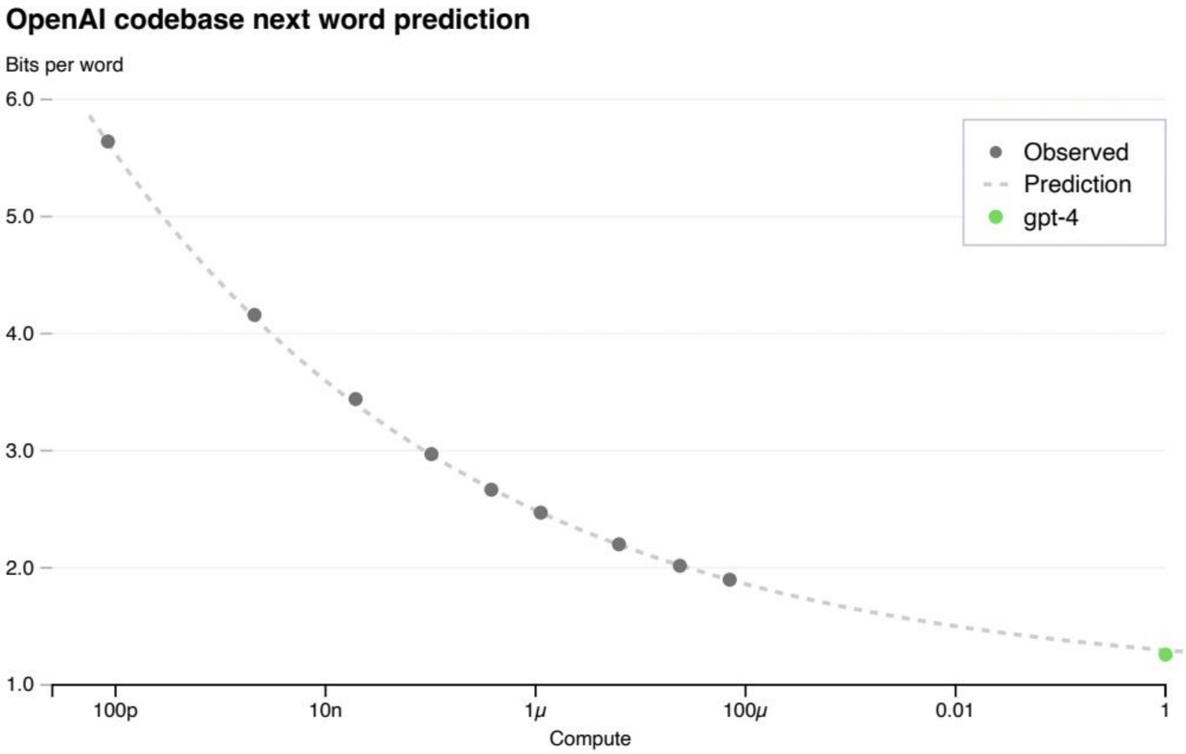




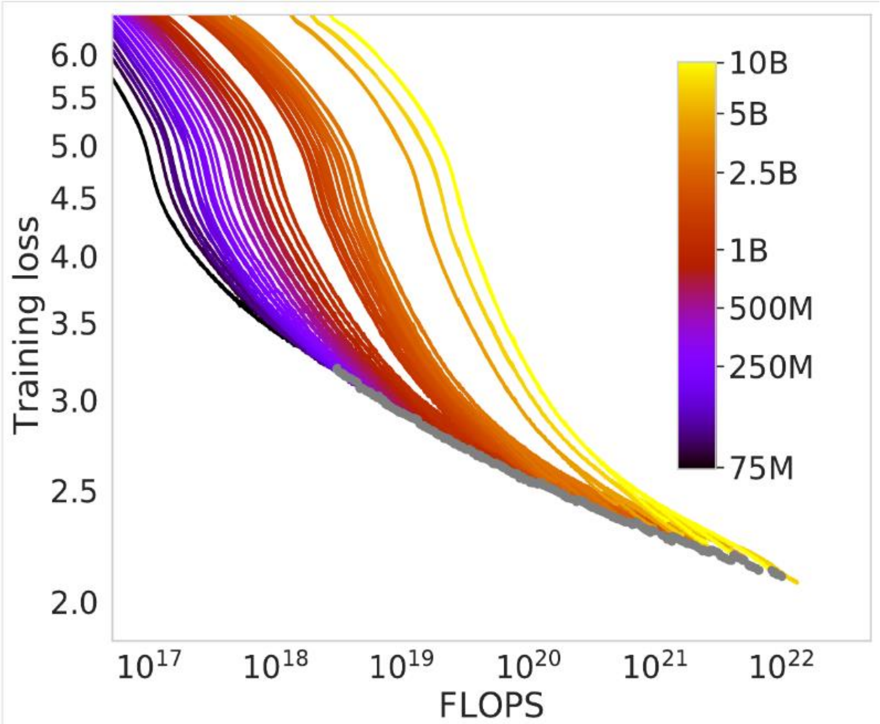
Emergent abilities of large language models (TMLR '22).
J. Wei, Y. Tay, R. Bommasani, C. Raffel, B. Zoph, S. Borgeaud, D. Yogatama, M. Bosma, D. Zhou, D. Metzler, E. Chi, T. Hashimoto, O. Vinyals, P. Liang, J. Dean, & W. Fedus.

# Scaling laws




*GPT-4 Technical Report, OpenAI (2023)*

# Challenge to scaling law: Chinchilla’s Death



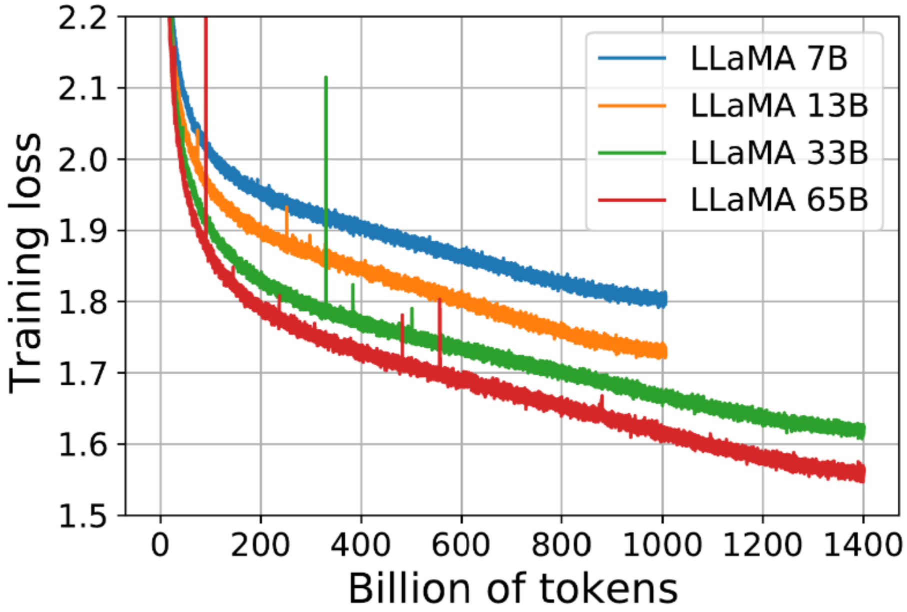

Smaller models eventually reach the limit of their capacity for knowledge, and their learning slows, while that of a larger model, with a larger capacity, will overtake them and reach better performance past a given amount of training time.

While estimating how to get the best bang during training, OpenAI & DeepMind attempted to draw the Pareto frontier.

https://espadrine.github.io/blog/posts/chinchilla-s-death.html

# Challenge to scaling law: Chinchilla's Death

## Can Chinchillas picture a Llama's sights?




- ❖ Each curve first plummets in a **power law**,
- ❖ and then seemingly enters a **nearly-linear** decrease in loss (corresponding to a fairly constant rate of knowledge acquisition).
- ❖ At the very tip of the curve, they all break this line by **flattening** slightly.

- ❖ This should consider the cosine LR schedule.

https://espadrine.github.io/blog/posts/chinchilla-s-death.html

# Challenge to scaling law: Chinchilla's Death

## Can Chinchillas picture a Llama's sights?


Let's picture instead a race: All those models start at the same time, and we want to know which one crosses the finish line first.

In other words, when throwing a fixed amount of compute at the training, who learns the most in that time?

**the 7B enters a near-linear regime, with a steep downward trend, and seems on its way to maybe overpass the 13B again?**

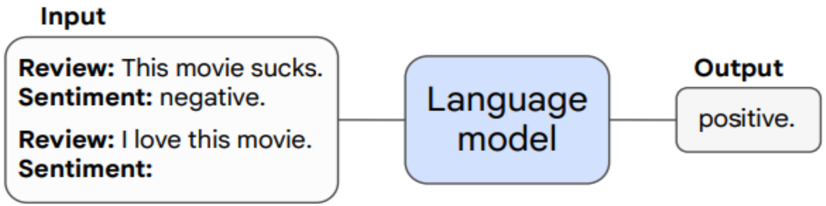
https://espadrine.github.io/blog/posts/chinchilla-s-death.html

# Emergent ability？

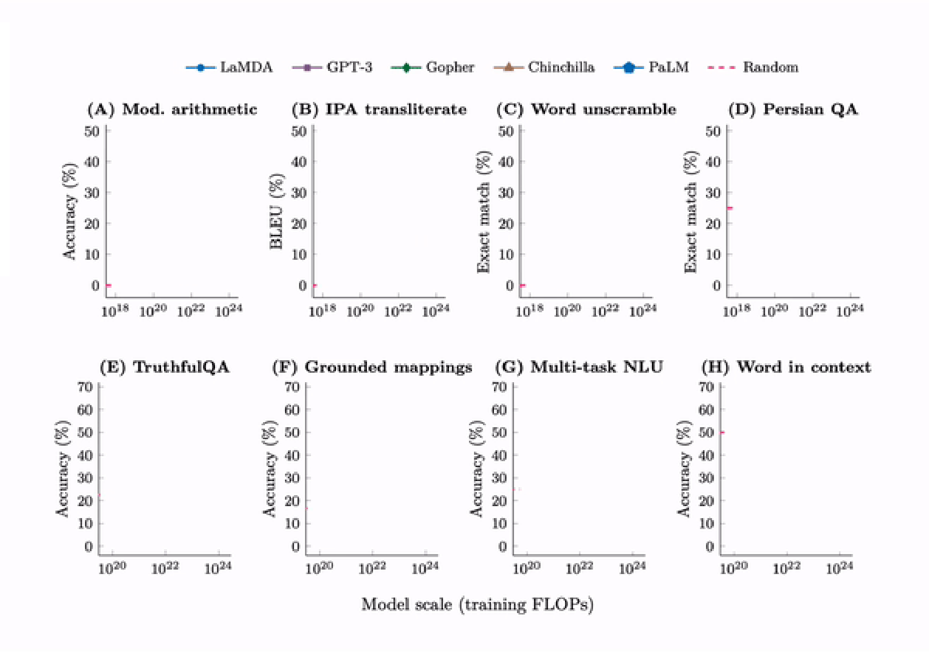
# **Emergent properties in LLMs**:

Some ability of LM is not present in smaller models but is present in larger models

## Emergent Capability: Few-shot prompting

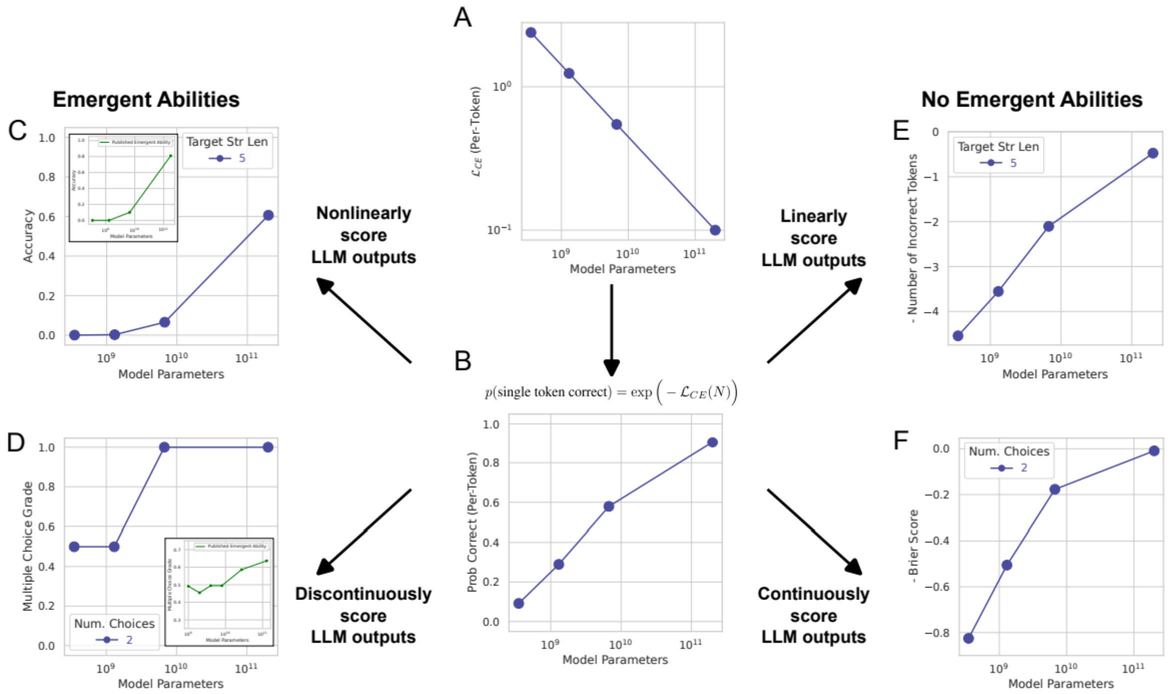



*> A few-shot prompted task is emergent if it achieves random accuracy for small models and above-random accuracy for large models.*




https://docs.google.com/presentation/d/1yzbmYB5E7G8lY2-KzhmArmPYwwl7o7CUST1xRZDUu1Y/edit?resourcekey=0-6_TnUMoK WCk_FN2BiPxmbw#slide=id.g1fc34b3ac18_0_27

# Emergent capabilities may be a consequence of metric choice




It seems that emergent ability of a model only occurs if the measure of per-token error rate of any model is scaled **non-linearly or discontinuously**.

Rylan Schaeffer, Brando Miranda, and Sanmi Koyejo. Are Emergent Abilities of Large Language Models a Mirage? https://browse.arxiv.org/pdf/2304.15004.pdf

# DDA6307/CSC6052/MDS6002: Natural Language Processing

香港中文大學（深圳）
The Chinese University of Hong Kong, Shenzhen

## Tutorial:
## Basic NLP practical tutorial

CHEN, Junying
223040263@link.cuhk.edu.cn

# DDA6307/CSC6052/MDS6002: Natural Language Processing

香港中文大學(深圳)
The Chinese University of Hong Kong, Shenzhen

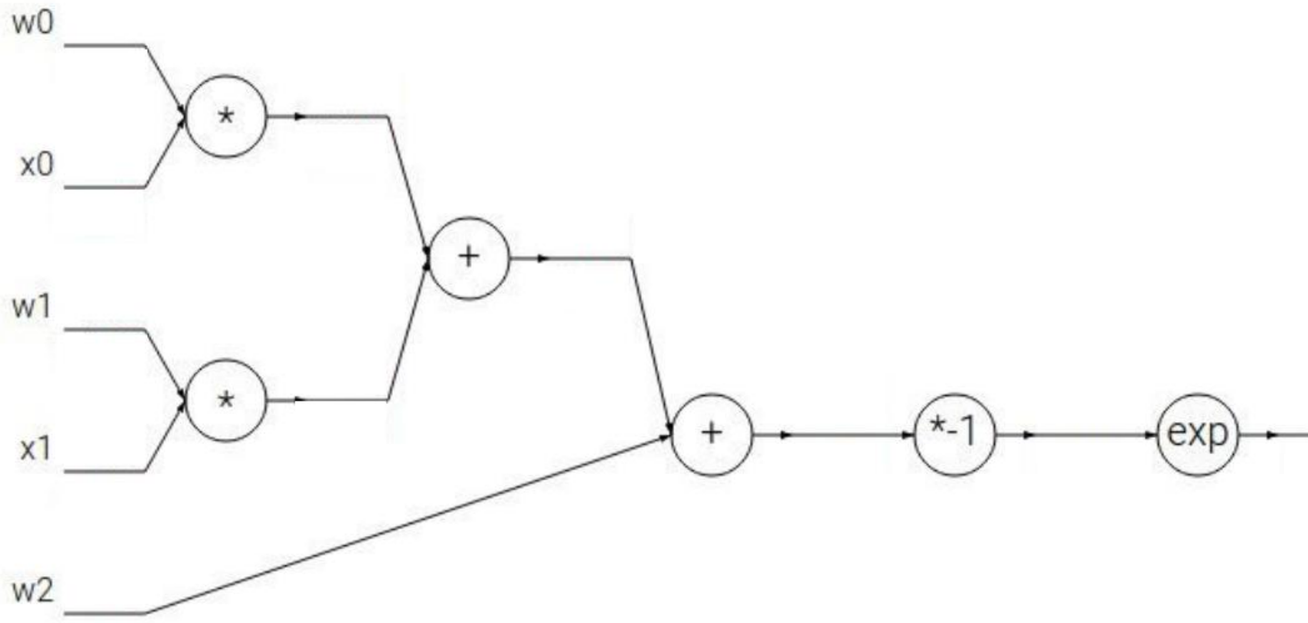
## Tutorial:
## Derivation of Backpropagation in Neural Network

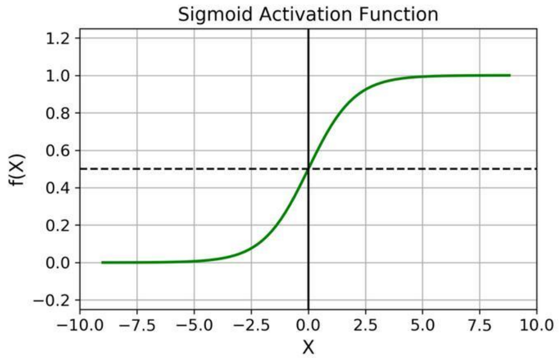
YU, Fei
222043013@link.cuhk.edu.cn

Another example
learned by yourself.

# Another example

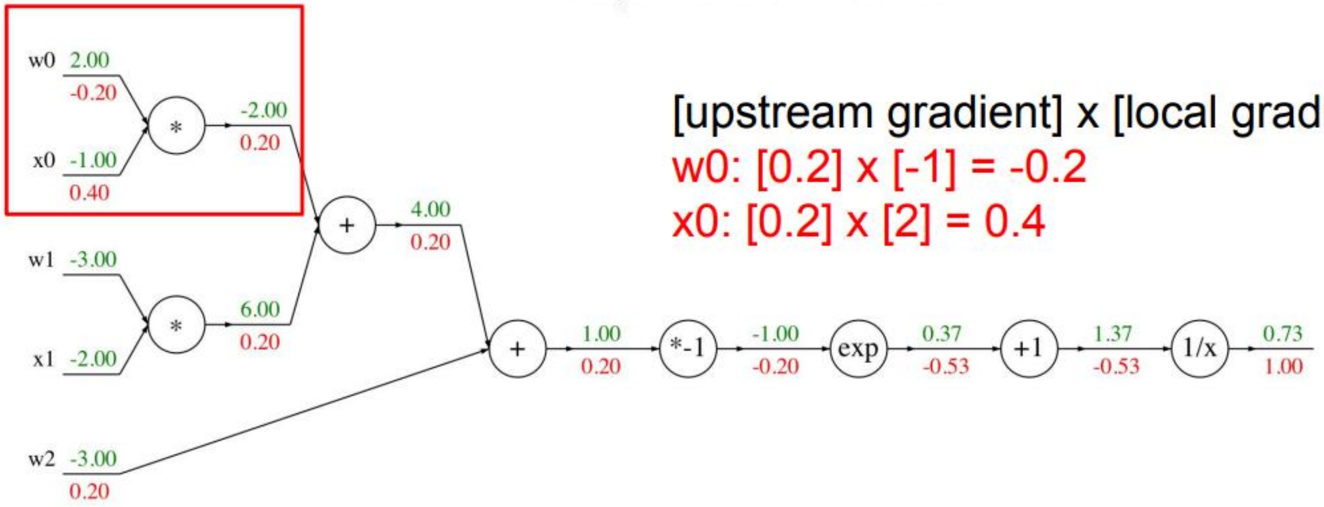
$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$



# Another example

$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$




[upstream gradient] x [local gradient]

w0: [0.2] x [-1] = -0.2

x0: [0.2] x [2] = 0.4

$$f(x) = e^x \quad \rightarrow \quad \frac{df}{dx} = e^x \qquad\qquad f(x) = \frac{1}{x} \quad \rightarrow \quad \frac{df}{dx} = -1/x^2$$

$$f_a(x) = ax \quad \rightarrow \quad \frac{df}{dx} = a \qquad\qquad f_c(x) = c + x \quad \rightarrow \quad \frac{df}{dx} = 1$$

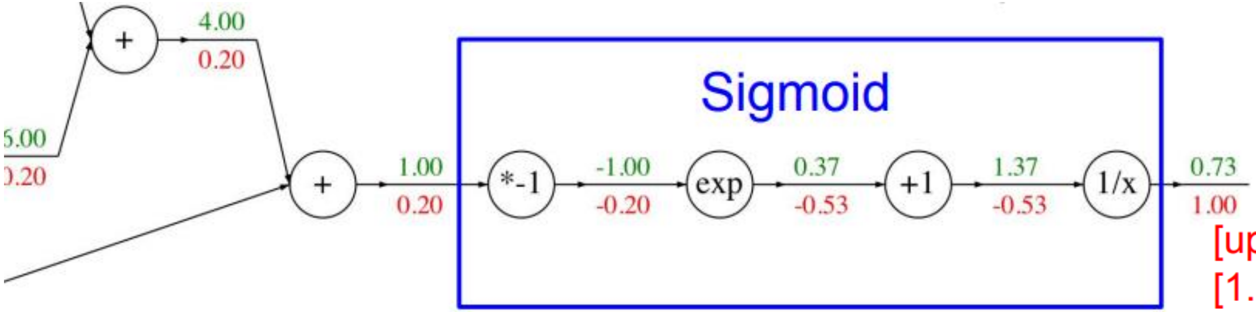
# Another example

$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

Sigmoid function

$$\boxed{\sigma(x) = \frac{1}{1+e^{-x}}}$$

Computational graph representation may not be unique. Choose one where local gradients at each node can be easily expressed!




[upstream gradient] x [local gradient]

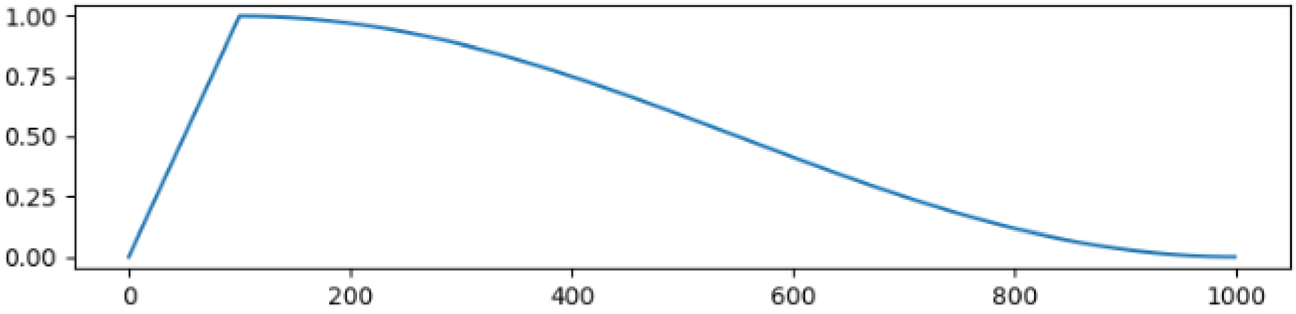
[1.00] x [(1 - 0.73) (0.73)] = 0.2

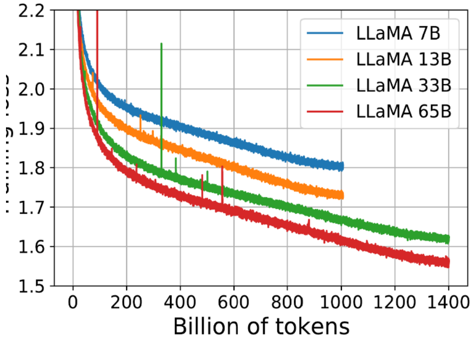
Sigmoid local gradient:

$$\frac{d\sigma(x)}{dx} = \frac{e^{-x}}{(1+e^{-x})^2} = \left(\frac{1+e^{-x}-1}{1+e^{-x}}\right)\left(\frac{1}{1+e^{-x}}\right) = (1-\sigma(x))\,\sigma(x)$$

# Challenge to scaling law: Chinchilla's Death

## Can Chinchillas picture a Llama's sights?




The slowdown in learning is an artefact of cosine schedule. The model does not necessarily cease to have the capacity to learn at the same near-linear rate!

https://espadrine.github.io/blog/posts/chinchilla-s-death.html