Accelerator Architectures for Machine Learning (AAML)

Lecture 2: Basics of DNN Models

Tsung Tai Yeh
Department of Computer Science
National Yang-Ming Chiao Tung University

Acknowledgements and Disclaimer

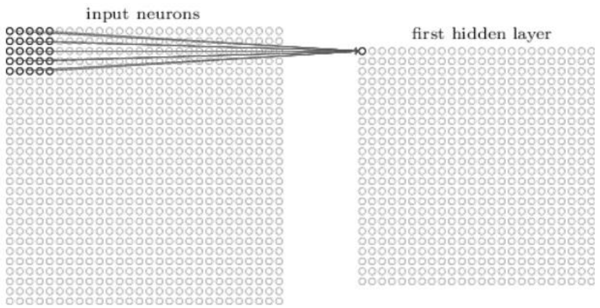
- Slides was developed in the reference with
  Joel Emer, Vivienne Sze, Yu-Hsin Chen, Tien-Ju Yang, ISCA 2019 tutorial
  Efficient Processing of Deep Neural Network, Vivienne Sze, Yu-Hsin Chen, Tien-Ju Yang, Joel Emer, Morgan and Claypool Publisher, 2020
  Yakun Sophia Shao, EE290-2: Hardware for Machine Learning, UC Berkeley, 2020
  CS231n Convolutional Neural Networks for Visual Recognition, Stanford University, 2020

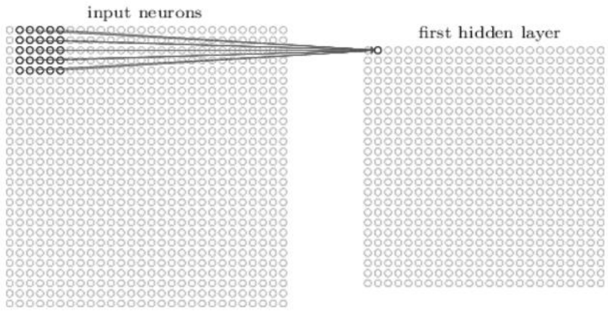
Outline

- Convolution Neural Network
  - Residual network
  - Depthwise convolution
- Transformer Model Architecture
  - Encoder-decoder based model
  - Large Language Models

Deep convolutional neural networks

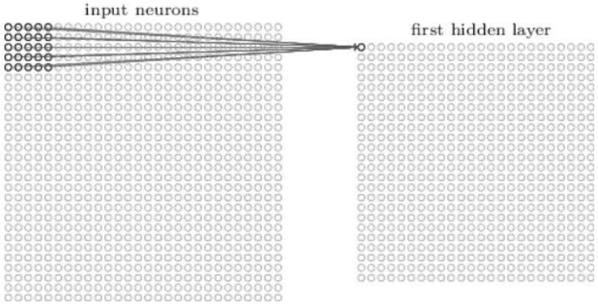
- Each neuron only sees a “**local receptive field**”
  - 5 x 5 grid of neurons in this example
  - The first neuron is looking for feature in the top-left 5x5 corner of the image
  - Combines the 25 inputs with 25 synaptic weights to decide its output
  - The set of 5x5 weights as a “**filter**”

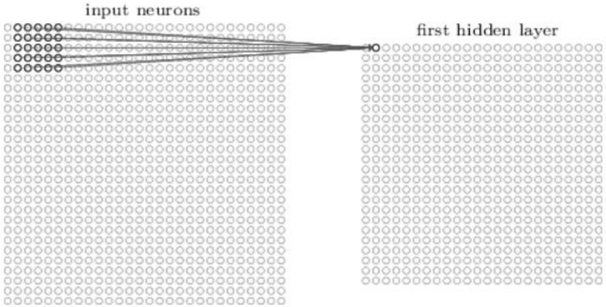




Deep convolutional neural networks

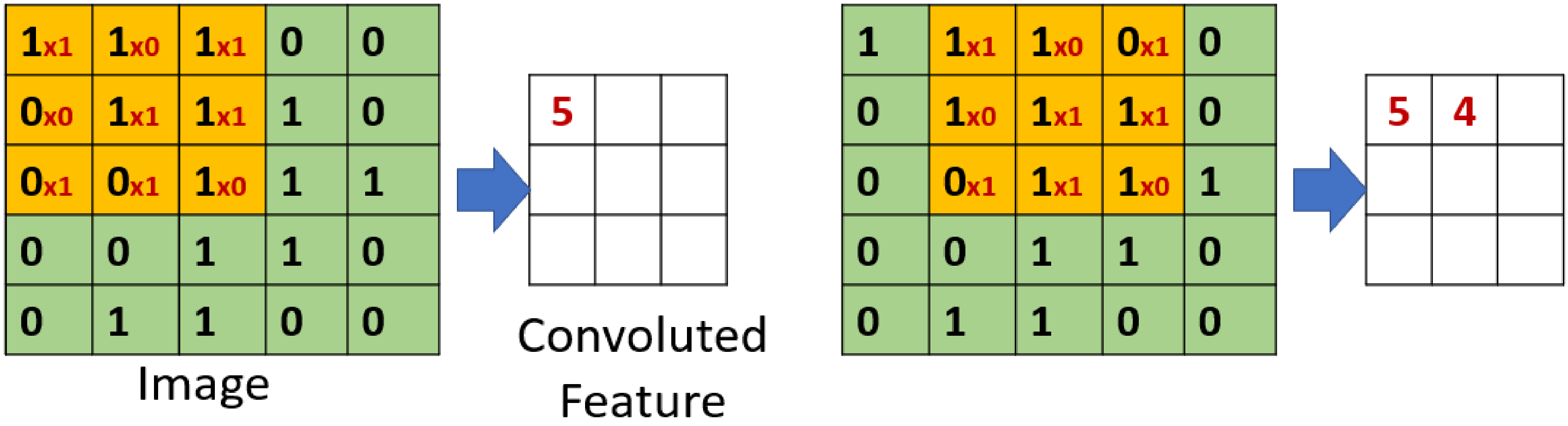
- **Convolution**
  - Applying a 5x5 filter (kernel) to each part of the image
  - All the neurons are sharing the same set of 25 weights (plus bias)
  - Why do we create small size filter ?
    - The small local receptive field and the use of shared weights can help for slow learning rate in early layers of the network





Convolutional Computation Details

- **Convolution**
  - Sliding dot product or cross-correlation
  - Convoluting a 5x5x1 image with a 3x3x1 filter kernel to get a 3x3x1 convoluted feature



CNN Dimension Parameters

- N – Number of **input fmaps**/**output fmaps** (**batch size**)
- C – Number of 2D **input fmaps**/**filters** (**channels**)
- H – Height of **input fmap** (**activations**)
- W – Width of **input fmap** (**activations**)
- R – Height of 2D **filter** (**weights**)
- S – Width of 2D **filter** (**weights**)
- M – Number of 2D **output fmaps** (**channels**)
- F – Width of **output fmap** (**activations**)
- E – Height of **output fmap** (**activations**)

CONV Layer Tensor Computation

Output fmaps (Y) **Bias (B)** **Input fmaps (X)** **Filter weights (W)**

$$Y[n][m][x][y] = Activation(B[m] + \sum_{i=0}^{R-1} \sum_{j=0}^{S-1} \sum_{k=0}^{C-1} X[n][k][Ux+i][Uy+j] \times W[m][k][i][j])$$

$$0 \le n \le N, 0 \le m \le M, 0 \le y \le E, 0 \le x \le F$$

$$E = (H - R + U)/U, F = (W - S + U)/U$$

Shape Parameter	Description
N	fmap batch size
M	# of filters or # of output fmap channels
C	# of input fmap or # of filter channels
U	Convolution stride

CONV Layer Implementation

```
for ( n = 0;   n < N;   n++) {
      for (m = 0;   m < M;   m++) {
           for   (x = 0;   x < F;   x++)       {
                for    ( y = 0;   y < E;   y++)     {
                                   Y[n][m][x][y] = B[m];
                                   for  (  i = 0;   i < R;  i++)     {
                                         for  (  j = 0;  j < S;  j++)      {
                                                    for  (  k = 0;  k < C;  k++) {
                                                           Y[n][m][x][y] += X[n][k][Ux+i][Uy+j] x W[m][k][i][j]
                                                    }
                                         }
                                   }
                                   Y[n][m][x][y] = Activation(Y[n][m][x][y]);
                    }
             }
       }
}
```

For each output fmap value

CONV & Activation

How to run CONV in parallel ?

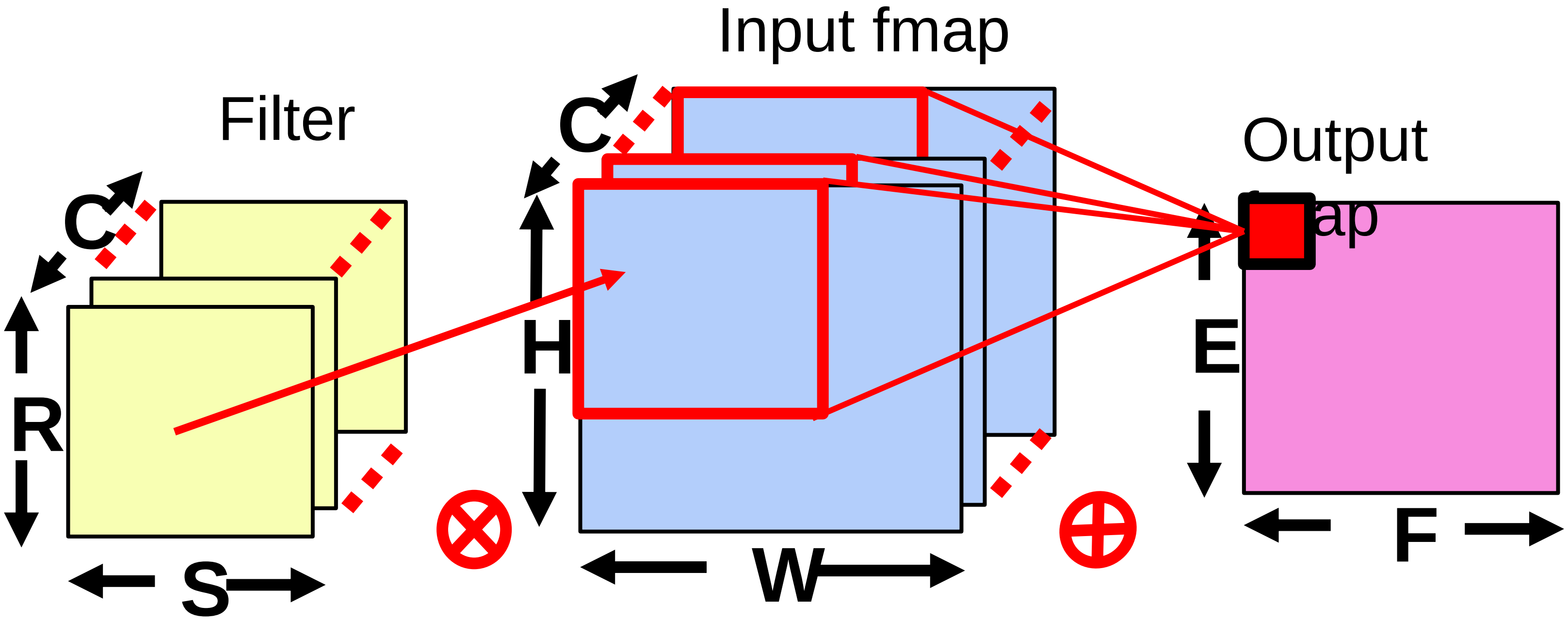
CONV Layer Parallel Implementation

```
Parallel_for ( n = 0;   n < N;   n++) {
    Parallel_for (m = 0;   m < M;   m++) {
        Parallel_for   (x = 0;   x < F;   x++)       {
            Parallel_for    ( y = 0;   y < E;   y++)     {
                    Y[n][m][x][y] = B[m];
                    for  (  i = 0;   i < R;  i++)     {
                        for  (  j = 0;  j < S;  j++)      {
                            for  (  k = 0;  k < C;  k++) {
                                Y[n][m][x][y] += X[n][k][Ux+i][Uy+j] x W[m][k][i][j]
                            }
                        }
                    }
                    Y[n][m][x][y] = Activation(Y[n][m][x][y]);
            }
        }
    }
}
```

For each output fmap value

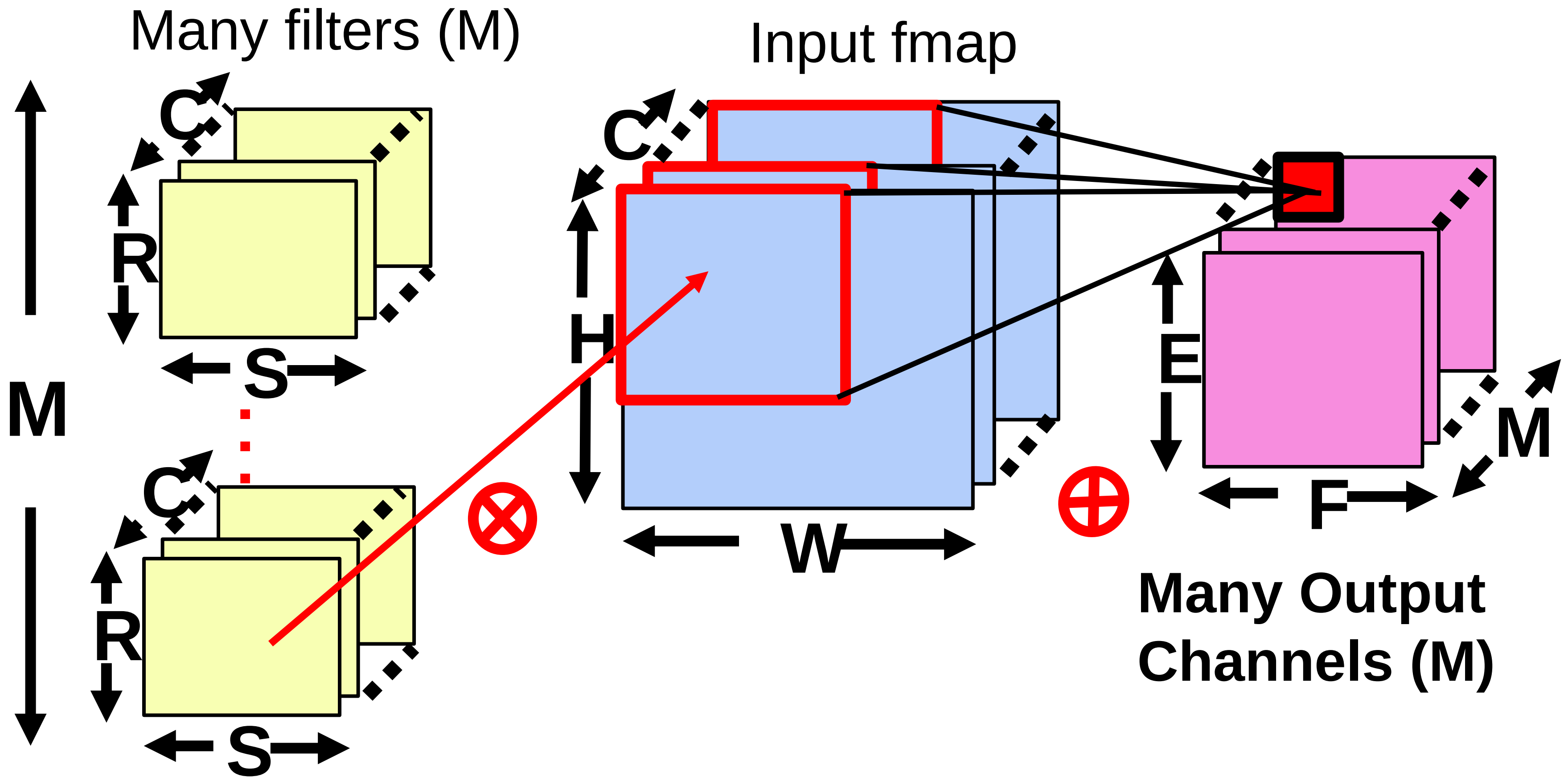
CONV & Activation

Convolution (CONV) Layer

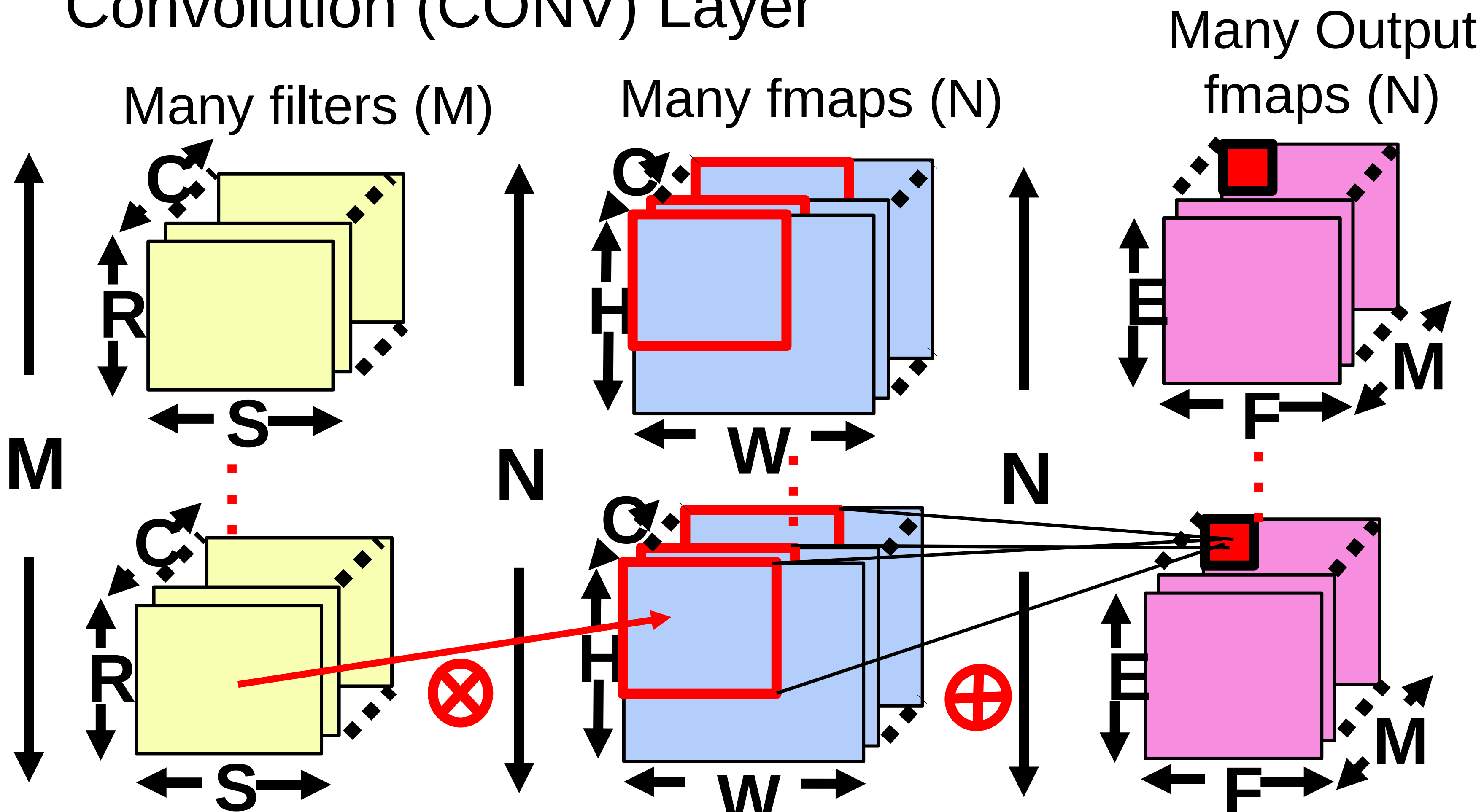


Many Input Channels (C), e.g. RGB in an image

Convolution (CONV) Layer

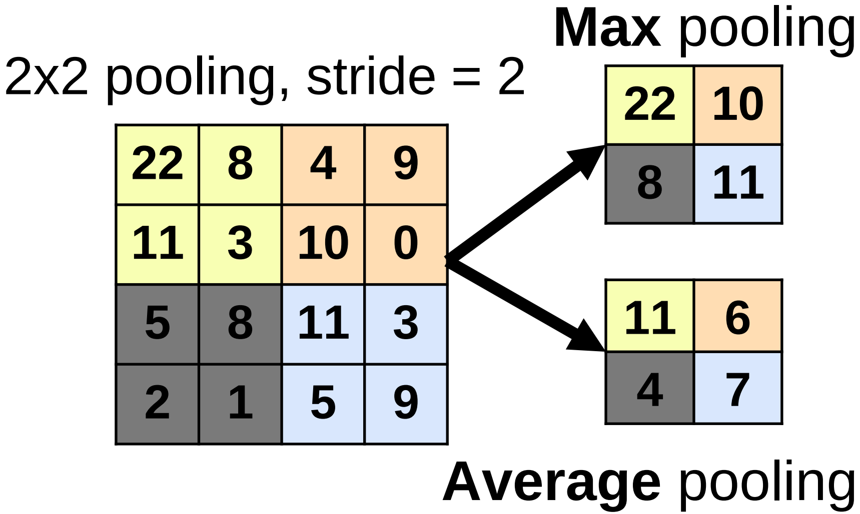


Convolution (CONV) Layer



Pooling

- **Pooling**
  - Once a feature has been found, its's exact location isn't as important as its relative location – help us reduce the parameters
  - Further reduce the network, say reduce 4 neurons into a single one



Input fmap size: W_1 x H_1 x C_1
Spatial extent: **F**
Stride **S**
Output fmap after pooling: W_2 x H_2 X C_2
$W_2 = (W_1 – F) / S + 1$
$H_2 = (H_1 – F) / S + 1$
$C_2 = C_1$

https://cs231n.github.io/convolutional-networks/

POOL Layer Implementation

```
for ( n = 0;   n < N;   n++) {
      for (m = 0;   m < M;   m++) {
           for   (x = 0;   x < F;   x++)      {
                for    ( y = 0;   y < E;   y++)     {
                          max = -Inf
                          for  (  i = 0;   i < R;  i++)     {
                                for  (  j = 0;  j < S;  j++)     {
                                      if  (  X[n][m][Ux+i][Uy+j] > max) {
                                              max = X[n][m][Ux+i][Uy+j];
                                      }
                                 }
                          }
                          Y[n][m][x][y] = max;
                }
           }
      }
}
```

for each pooled value

Find the max in each window

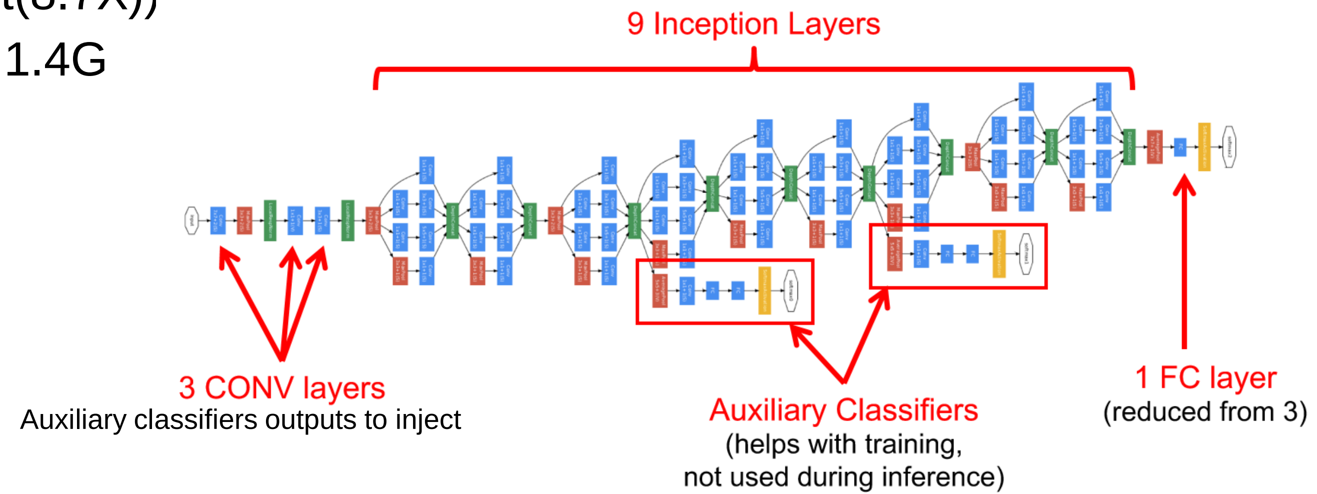
GoogleNet Inception Architecture

- 22 layers
- Fully-Connected Layers: 1
- **Weights: 7.0 M** (< VGG(19.7X) AlexNet(8.7X))
- MACs: 1.4G

ILSCVR14 Winner

GoogleNet is used to classify images

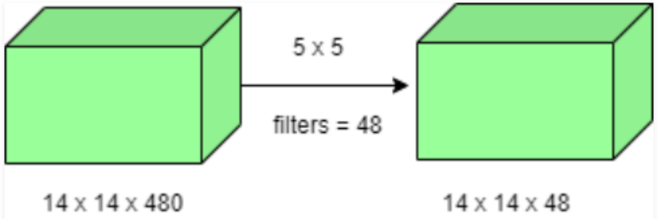
GoogleNet top-5 error rate is 6.67% over VGG 7.3%



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

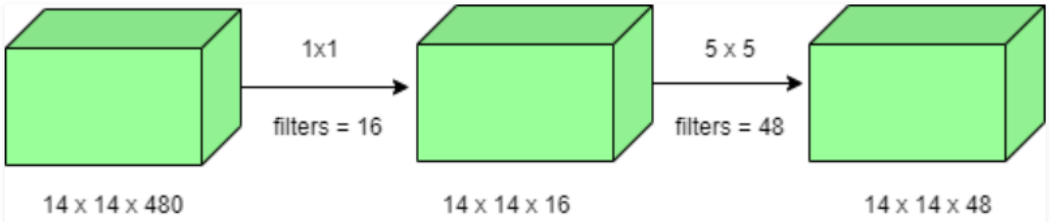
What's New in GoogleNet ?

- **1 x 1 CONV filter (why?)**
  - Decrease the number of parameters (weights and biases)
  - Increase the depth of the network



Case 1: 5x5 filter, # of filter = 48
Total MACs: (14x14x48)x(5x5x480) = **112.9M**

Case 2: 1x1 filter, # of filter = 16 as intermediate
Total MACs: (14x14x16)x(1x1x480) + (14x14x48)x(5x5x16)= **5.3M**



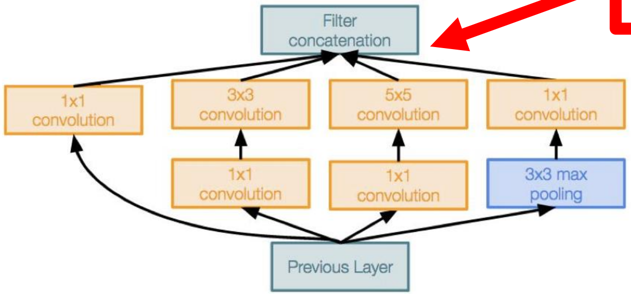
GoogleNet can be trained in a single machine such as (GPU with limit memory space) !!

https://www.geeksforgeeks.org/understanding-googlenet-model-cnn-architecture/

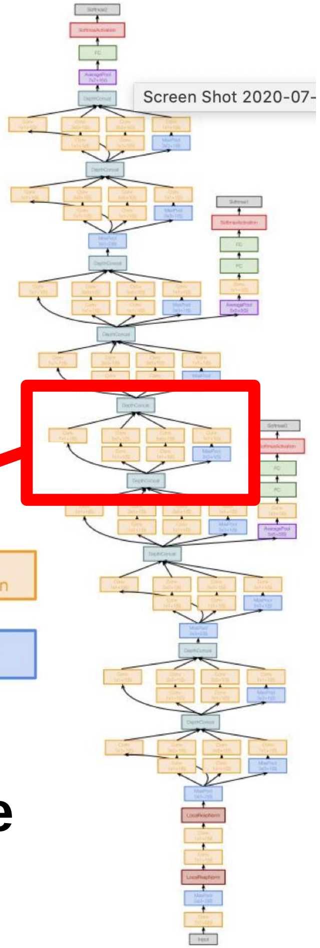
What's New in GoogleNet ?

- **Inception module**
  - A local network topology (network within a network)
  - Stack modules on top of each other
  - Multiple receptive field sizes for CONV (1x1, 3x3, 5x5)
  - Pooling operation (3x3)
  - Depth-wise filter concatenation

What's the problem of inception module?



Inception module



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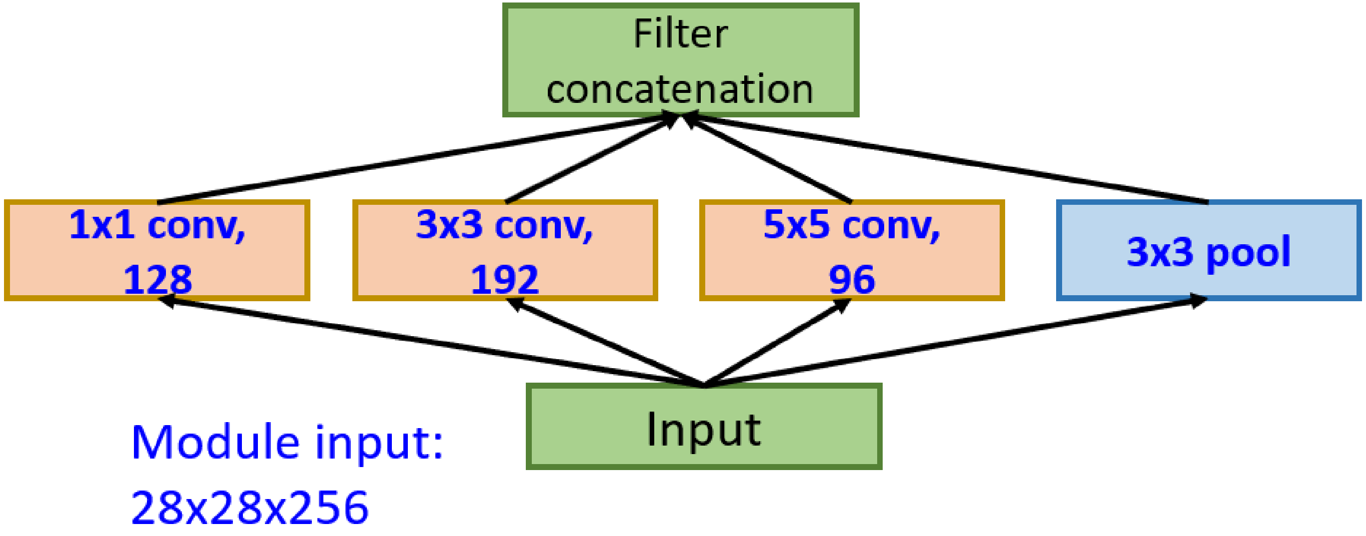
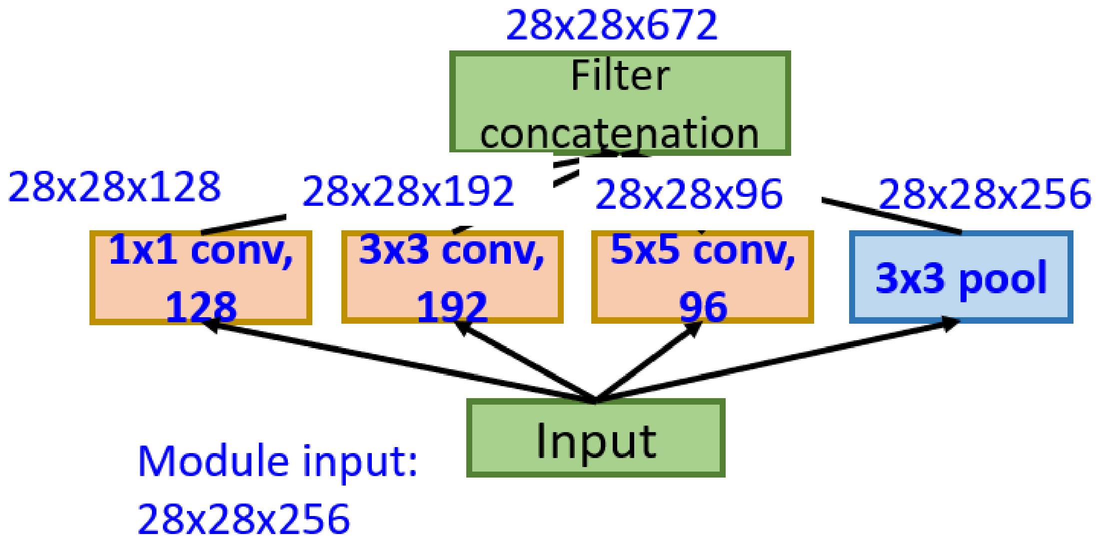
GoogleNet Inception Module Problems?

- What is the output size of 1x1 conv, with 128 filters ?



GoogleNet Inception Module Problems?



CONV Ops:

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x192x3x3x256

[5x5 conv, 96] 28x28x96x5x5x256

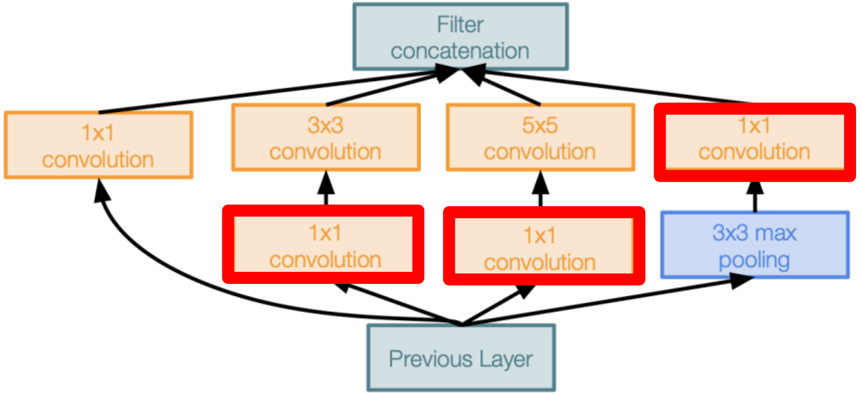
Total: 854 M ops

Very expensive compute

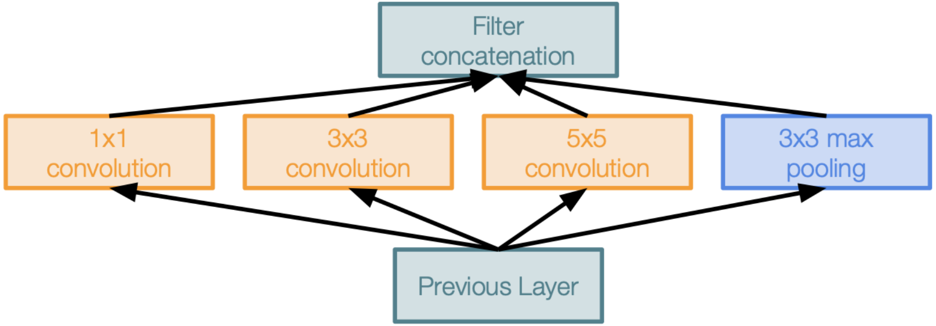
Solution: "bottleneck" layers that use 1x1 convolutions to reduce feature depth

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

Dimension Reduction on GoogleNet



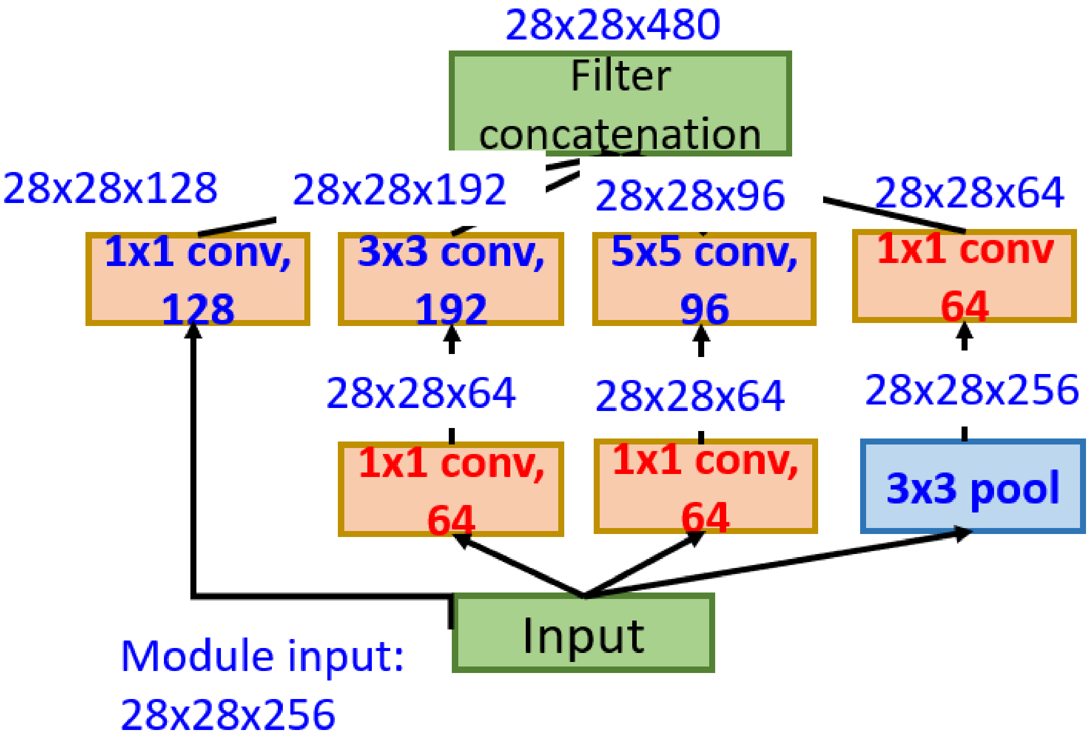
Inception module with **dimension reduction** using **1x1 conv "bottleneck" layers**



Naïve inception module

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

GoogleNet 1x1 Bottleneck Layer Ops



Conv Ops:

[1x1 conv, 64] 28x28x64x1x1x256

[1x1 conv, 64] 28x28x64x1x1x256

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x192x3x3x64

[5x5 conv, 96] 28x28x96x5x5x64

[1x1 conv, 64] 28x28x64x1x1x256

Total: 358 M ops

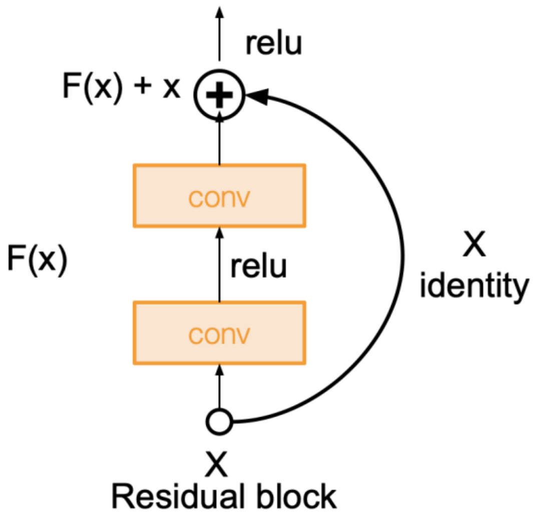
Naïve version has **854M ops**

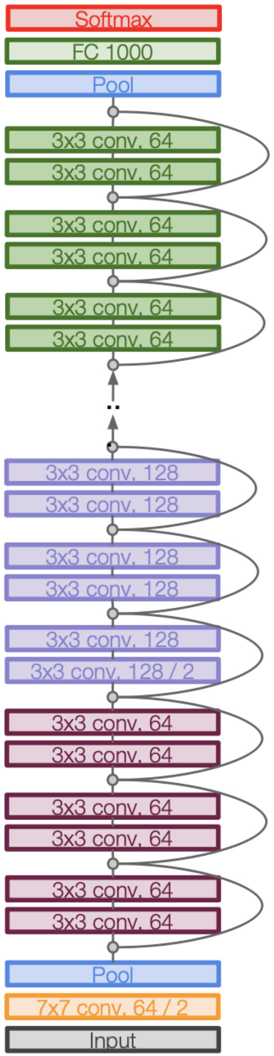
Bottleneck layer can reduce ops using dimension reduction

ResNet Model Overview

- 152-layer model for ImageNet Classification
- ILSVRC'15 winner (3.57% top-5 error)
- Using residual blocks and connections

How to train the data in ULTRA-DEEP network (over 1000 layers)?





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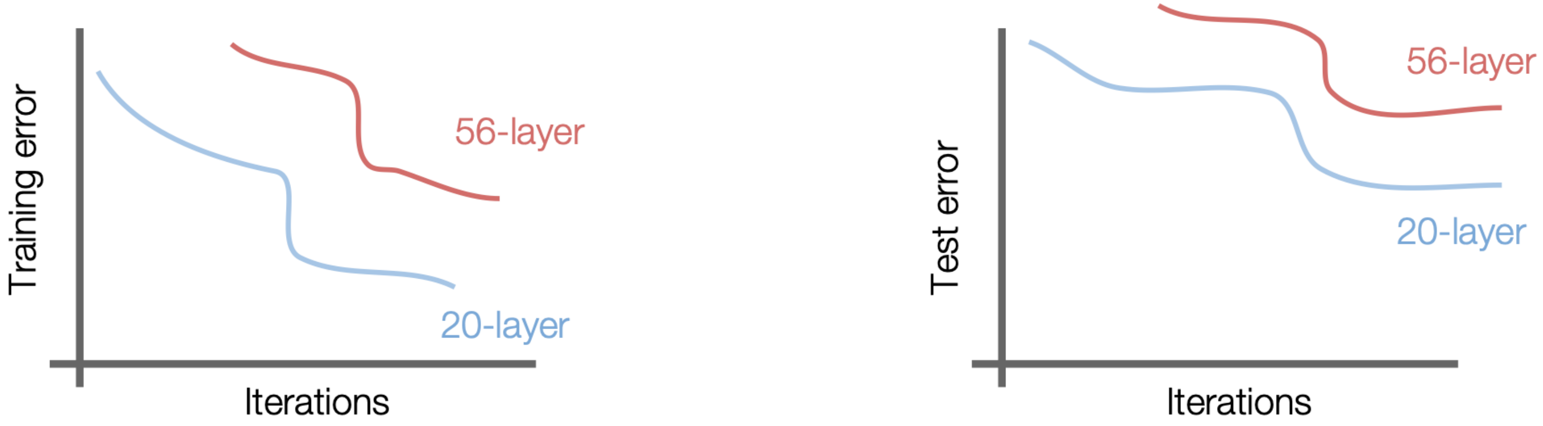
Deep Network Training Problems on ResNet

- Training and test error are increased with the length of networks



What is wrong when increasing the length of networks?
- Deeper model performs worse on both training and test error (overfitting?)

[He et al., 2015]

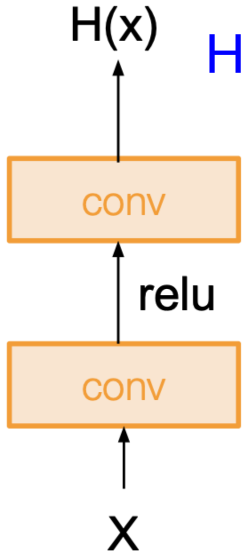
Deep Network Training Problems on ResNet

- Why overfitting isn't the main reason to increase error rate of 56-layer?
- Hypothesis: vanishing gradient raises error rate of ultra-deep networks?
  - Solution: Add layers to fit a residual mapping instead of fitting a desired underlying mapping directly (skipping connection)(What?)

Deep Network Training Problems on ResNet

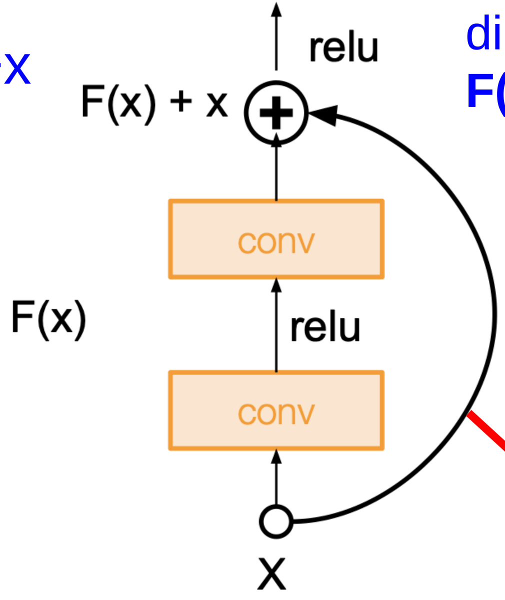
- Solution: Add layers to fit a residual mapping instead of fitting a desired underlying mapping directly

Why not use H(x) directly?



“Original” Layer

H(x) = F(X)+x



“Residual” Block

Instead of fitting H(x) directly, use **residual F(x) = H(x) - x**

Identity mapping
F(x) = x

Shortcut/skip connection

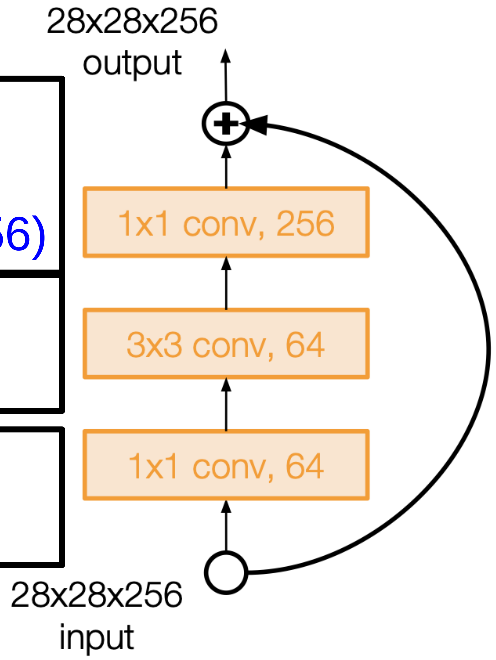
Bottleneck Layer on ResNet

- ResNet50+ also uses "bottleneck" layer to improve efficiency for deep networks (similar to GoogleNet)

1x1 conv, 256 filters projects back to 256 feature maps (28x28x256)

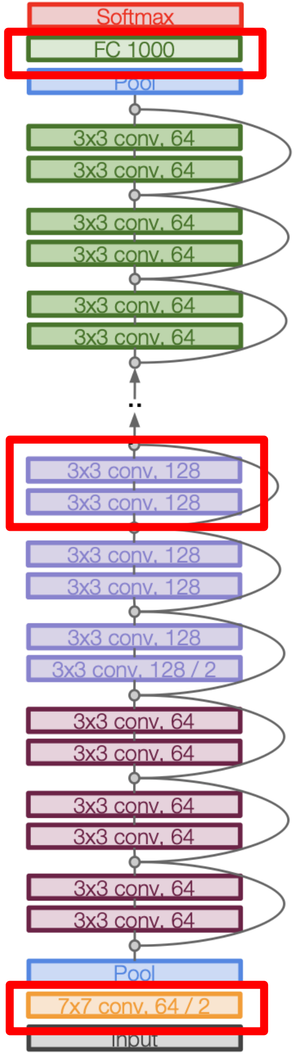
3x3 conv operates over only 64 feature maps

1x1 conv, 64 filters projects to 28x28x64



ResNet Model Details

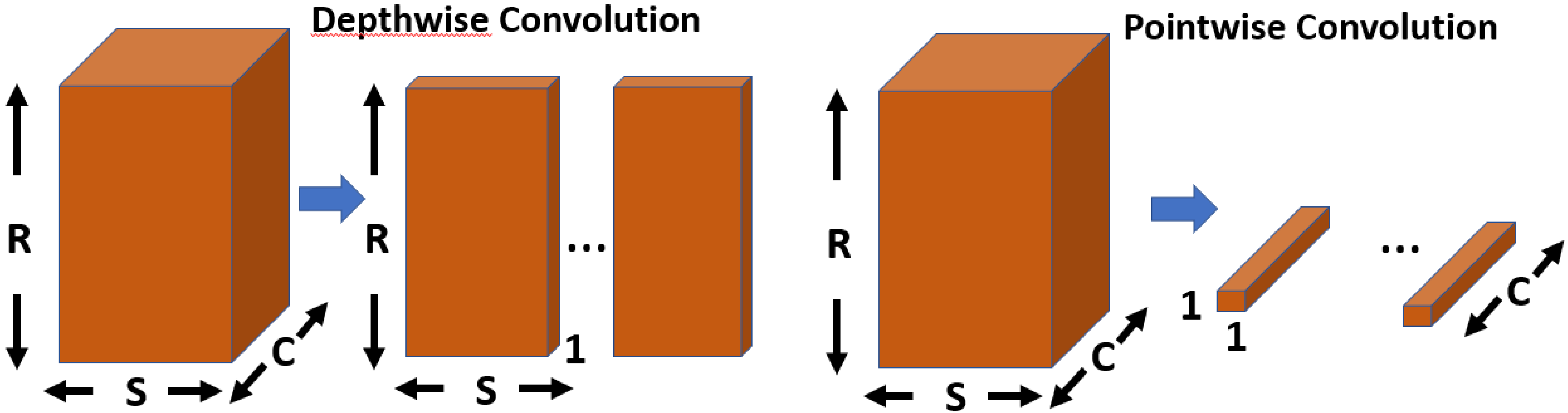
- Full ResNet architecture
  - Stack residual blocks
  - Every residual block has two 3x3 conv layers
  - Periodically, double the number of filters and down-sample using stride 2 (/2 in each dimension)
  - Additional conv layer at the beginning
  - Only FC 1000 to output class
  - Total depths of 34, 50, 101 or 152 layers for ImageNet



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

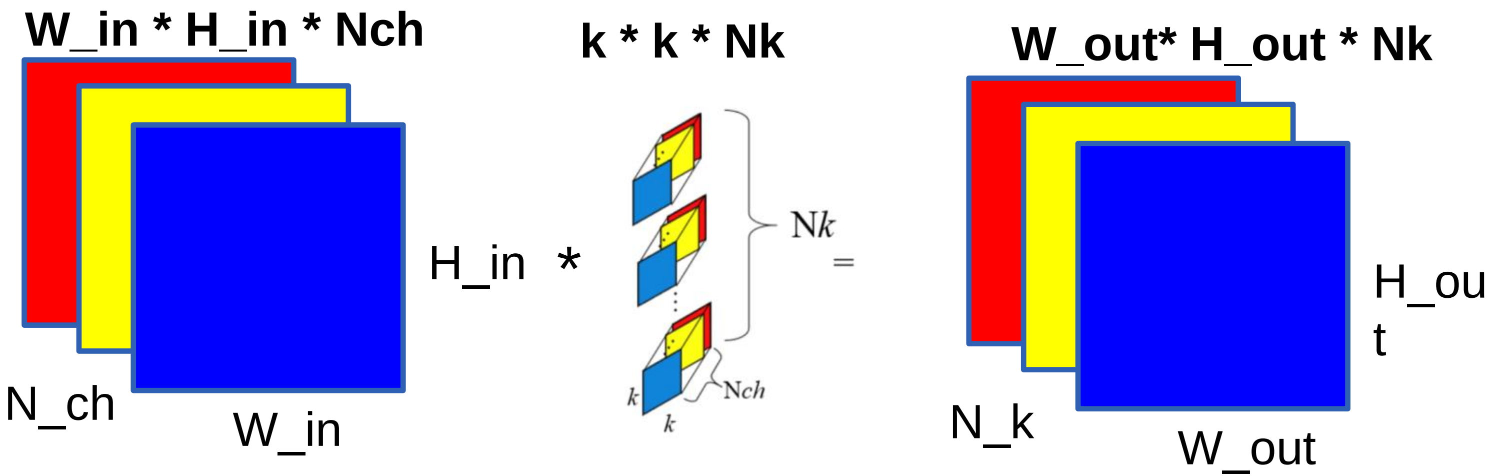
MobileNet v1: Depthwise Separable CONV

- Decouple **cross-channel correlations** and **spatial correlations** in the feature maps
- How to reduce # of parameters? [Andrew et. al. arxiv, 2017]



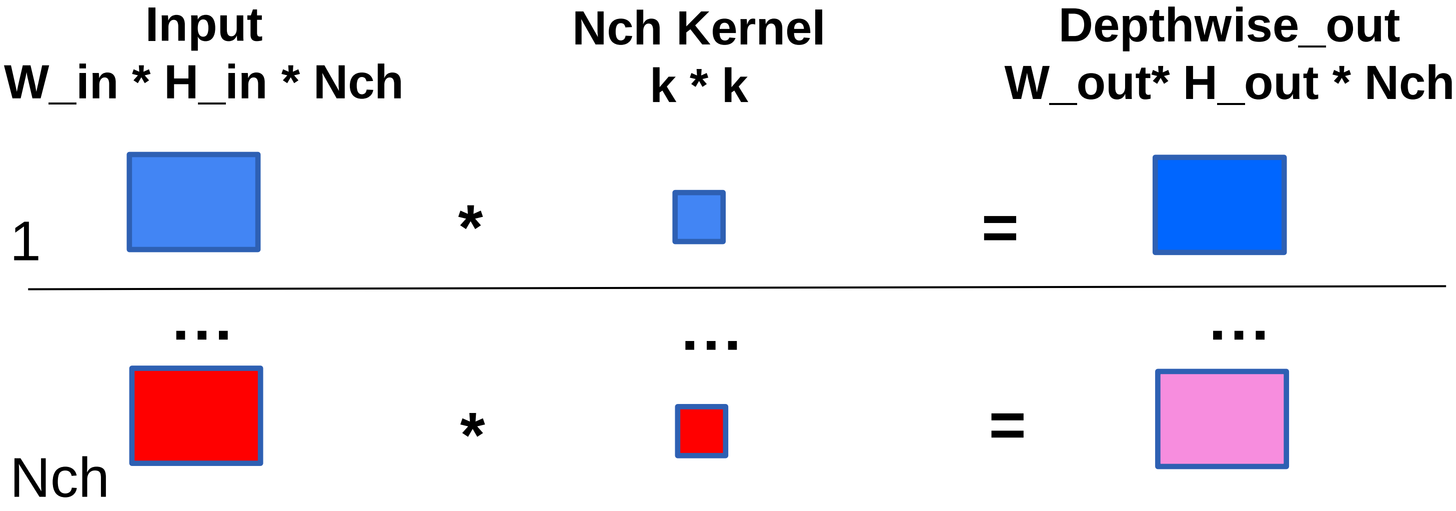
What is Depthwise Separable Convolution ?

- **Purpose**: Reduce the amount of CONV computation
- **Input:** W_in * H_in * Nch (# of channels)
- **Kernel:** k * k * Nk (# of kernels)
- **Output:** W_out * H_out * Nk (# of kernels)



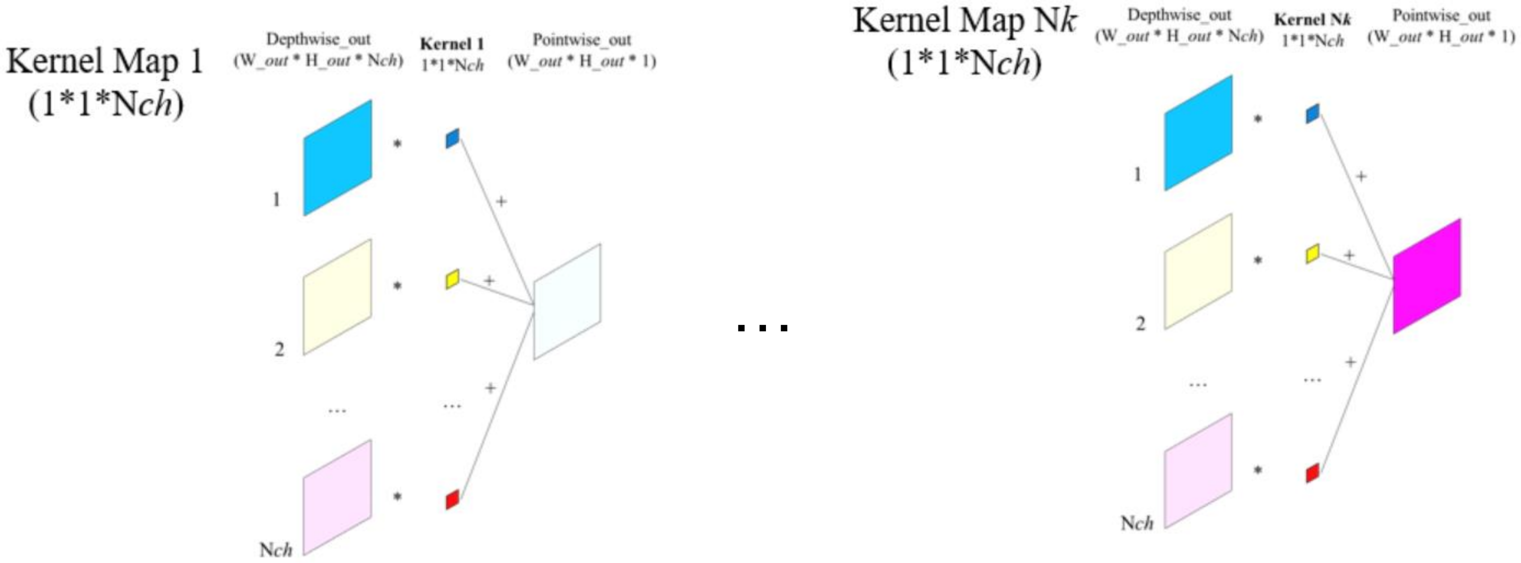
Depthwise Convolution

- Each channel of inputs has a **k * k** kernel
- Separate the convolution of each channel
- **Difference:** Every kernel convolves with all channels in standard CONV



Pointwise Convolution

- The number of kernel: Nk with (1 * 1 * Nch) size
- Do CONV on the outputs of depthwise convolution



Pointwise convolution

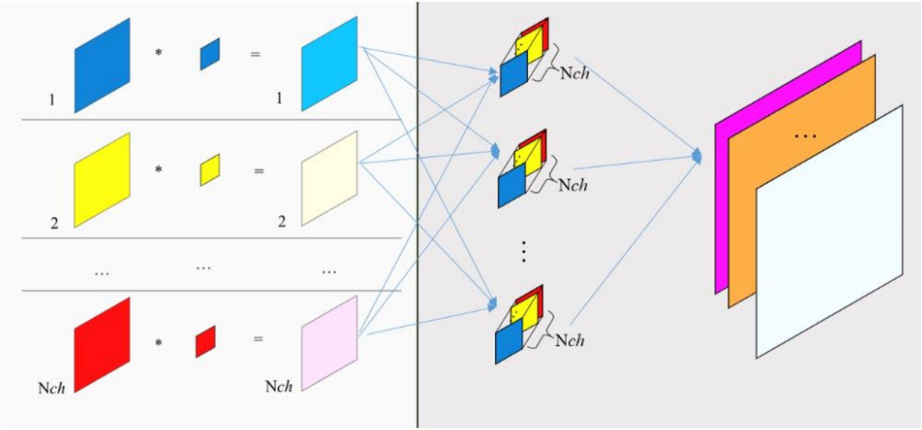
[深度學習-MobileNet (Depthwise separable convolution) | by Tommy Huang | Medium]

Depthwise + Pointwise Convolution

Depthwise convolution
Input: W_in * H_in * Nch
Nch Kernel (k * k)
Output: W_out * H_out * Nch

Pointwise convolution
Input: W_out * H_out * Nch
Nk kernel = (1 * 1 * Nk)
Output = W_out * H_out * Nk

Depthwise convolution **Pointwise convolution**



深度學習-MobileNet (Depthwise separable convolution) | by Tommy Huang | Medium

Depthwise Separable Convolution

- **Standard CONV**
  - Input: W_in * H_in * Nch
  - Kernel: k * k * Nk
  - Output: W_out * H_out * Nk
  - Computation: W_in * H_in * Nch * k * k * Nk
- **Depthwise separable convolution**
  - Depthwise CONV computation: W_in * H_in * Nch * k * k
  - Pointwise CONV computation: Nch * Nk * W_in * H_in

$$\frac{\text{Depthwise separable CONV}}{\text{Standard CONV}} = \frac{W\_in * H\_in * Nch * k * k + Nch * Nk * W\_in * H\_in}{W\_in * H\_in * Nch * k * k * Nk}$$

$$= \frac{1}{Nk} + \frac{1}{K*k}$$

Depthwise Separable Convolution

- Depthwise separable convolution can save more computation when
  - kernel size is large
  - The number of kernel is increased
- Suppose input is 416 * 416 * 50, # of filter is 10, its size is 3 * 3.
- How much computation can be saved by depthwise separable convolution ?
  - 1/10 + 1/9 = 0.22

Takeaway Questions

- What are problems in ultra-deep neural networks ?
  - (A) Over-fitting
  - (B) Gradient vanishing
  - (C) Low training accuracy
- Given a CNN model below, how many channels are in the second layer ?
  - (A) 4
  - (B) 8
  - (C) 16

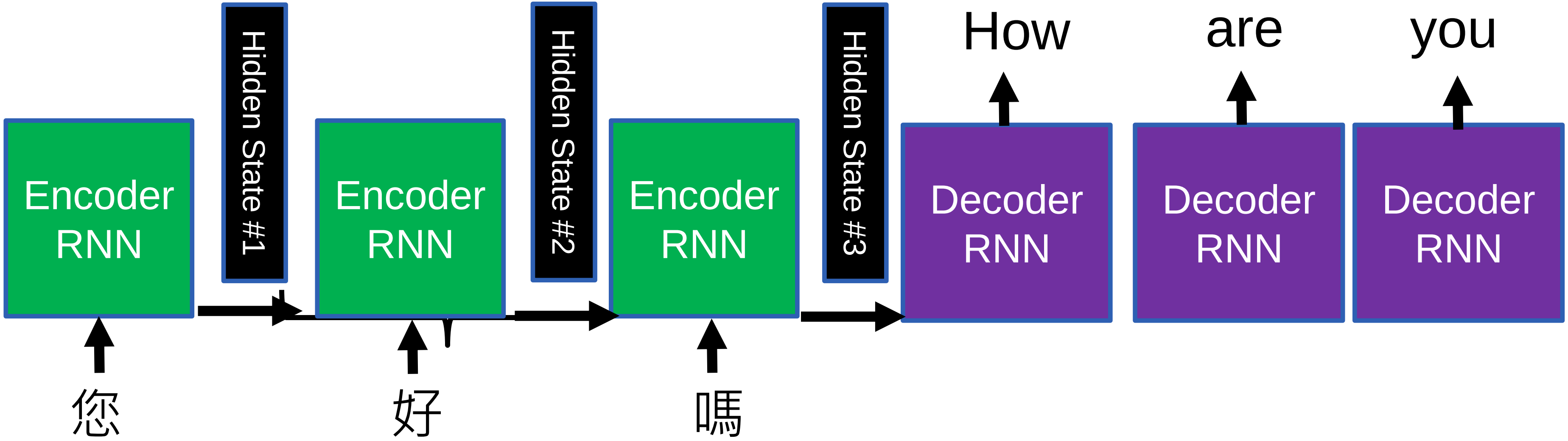
	Input size	# of filter	Filter size	# of channel
Layer1	12 x 12	4	3x3	64
Layer2	12 x 12	16	3x3	

Takeaway Questions

- A standard CONV layer
  - Input: W_in * H_in * Nch = (32 * 32 * 16)
  - Kernel: k * k * Nk = (3 * 3 * 8)
  - Computation: W_in * H_in * Nch * k * k * Nk = (32 * 32 * 16 * 3 * 3 * 8)
- What is the amount of computation that is carried out by **depthwise separable convolution ?**
  - (A) (32 * 32 * 16 * 3 * 3) + (3 * 8 * 8)
  - (B) (32 * 32 * 3 * 3 * 8) + (16 * 3 * 3)
  - (C) (32 * 32 * 16 * 3 * 3) + (16 * 8 * 32 * 32)

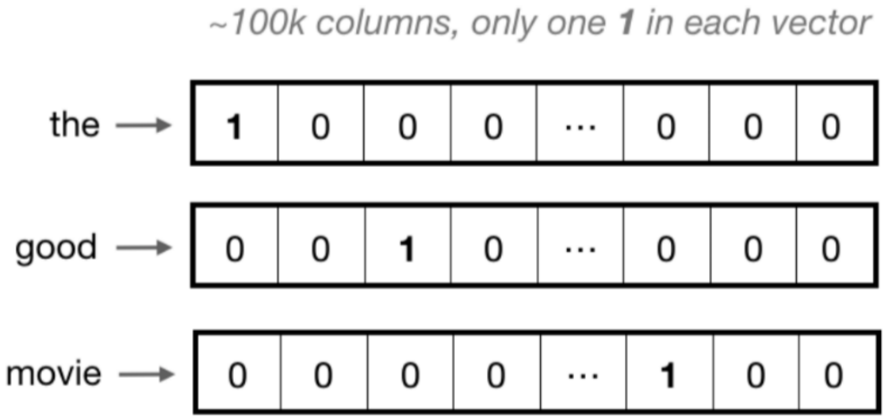
Classical Sequence-to-Sequence Model

- Pass the last hidden state of the encoding stage
- Decoder uses this last hidden state to do the prediction



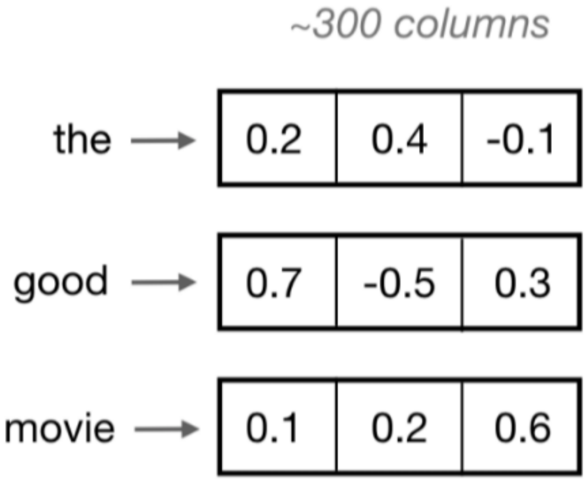
Word Representation

- **One-Hot Encoding**
  - Representing each word as a vector that has as many values in it
  - Each column in a vector is one possible word in a vocabulary
  - Problem
    - In large vocabularies, these vectors can get very long
    - Contain all 0's except for one value
    - Sparse representation



Word Representation

- **Word Embedding**
  - Map the word index to a continuous word embedding through a look-up table
  - Popular pre-trained word embeddings
    - Word2Vec, GloVe



Positional Encoding (PE)

- **Positional encoding (PE)**
  - Information to each word about its position in the sentence
  - **Unique** encoding for each word’s position in a sentence
  - Distance between any two positions is **consistent** across sentences with different lengths
  - Encode words by using **sin(), cos()** with different frequencies
  - **Deterministic** and **generalize** to longer sentences

$$\vec{p_t}^{(i)} = f(t)^{(i)} := \begin{cases} \sin(\omega_k . t), & \text{if } i = 2k \\ \cos(\omega_k . t), & \text{if } i = 2k+1 \end{cases} \qquad \omega_k = \frac{1}{10000^{2k/d}}$$

Positional Encoding (PE)

- Arguments
  - L: maximum # of possible positions
  - d_{model}: dimension of the embeddings
  - n: can be set to any value
  - k: position
  - i: dimension

$$pos(k) = \begin{bmatrix} \sin \omega_1 \cdot k \\ \cos \omega_1 \cdot k \\ \\ \sin \omega_2 \cdot k \\ \cos \omega_2 \cdot k \\ \\ \vdots \\ \sin \omega_{d_{model}/2} \cdot k \\ \cos \omega_{d_{model}/2} \cdot k \end{bmatrix}_{d_{model}} \quad \text{, where } \omega_i = 10000^{\frac{2i}{d_{model}}}$$

- For each $k = 0$ to $L - 1$
  - For each $i = 0$ to $\frac{d_{model}}{2}$
    - $PE_{(k,2i)} = \sin(\frac{k}{n^{\frac{2i}{d_{model}}}})$
    - $PE_{(k,2i+1)} = \cos(\frac{k}{n^{\frac{2i}{d_{model}}}})$

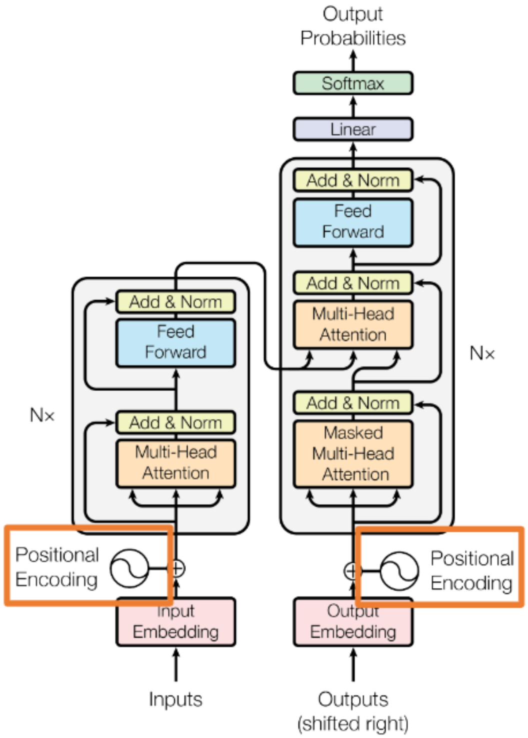
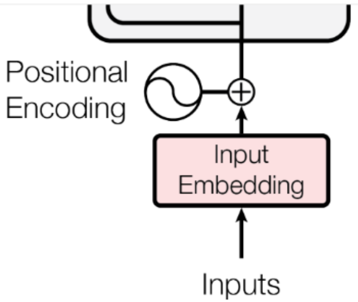
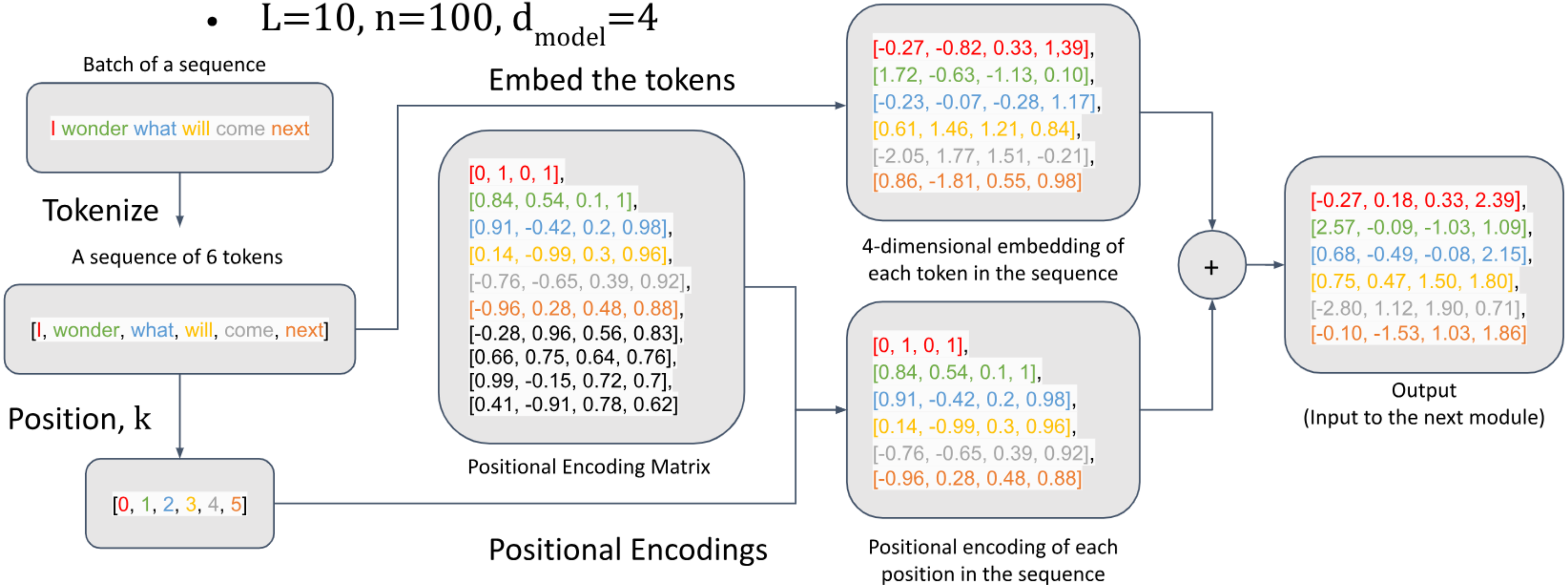


Figure 1: The Transformer - model architecture.

Positional Encoding (PE)

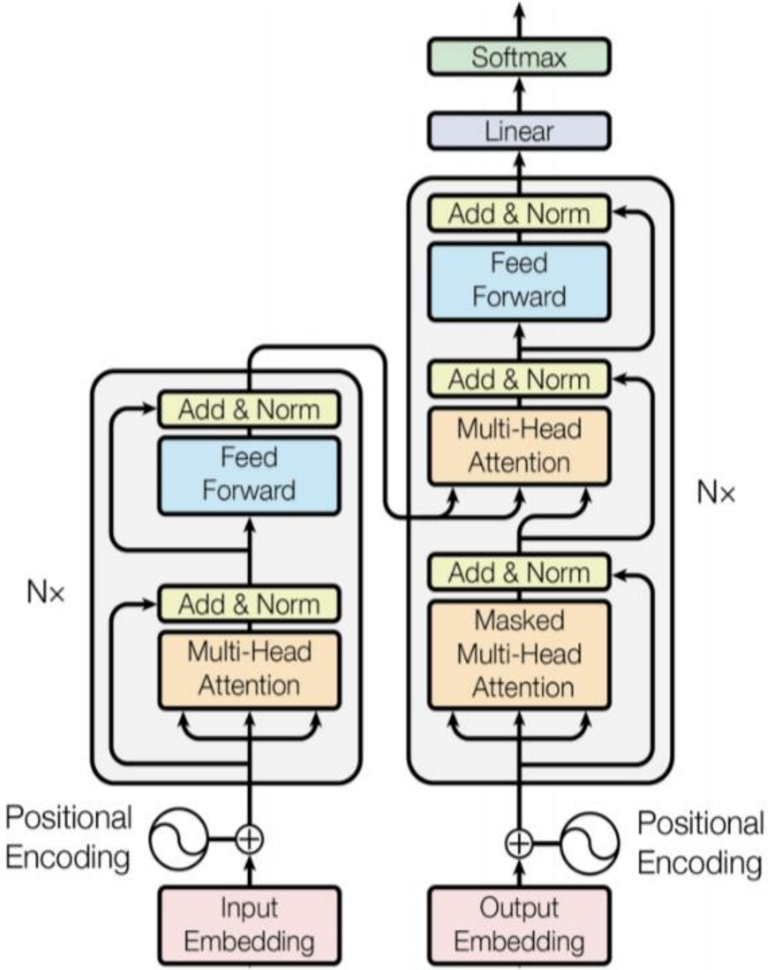


- Arguments
  - L=10, n=100, d_{model}=4



Transformer Model Architecture

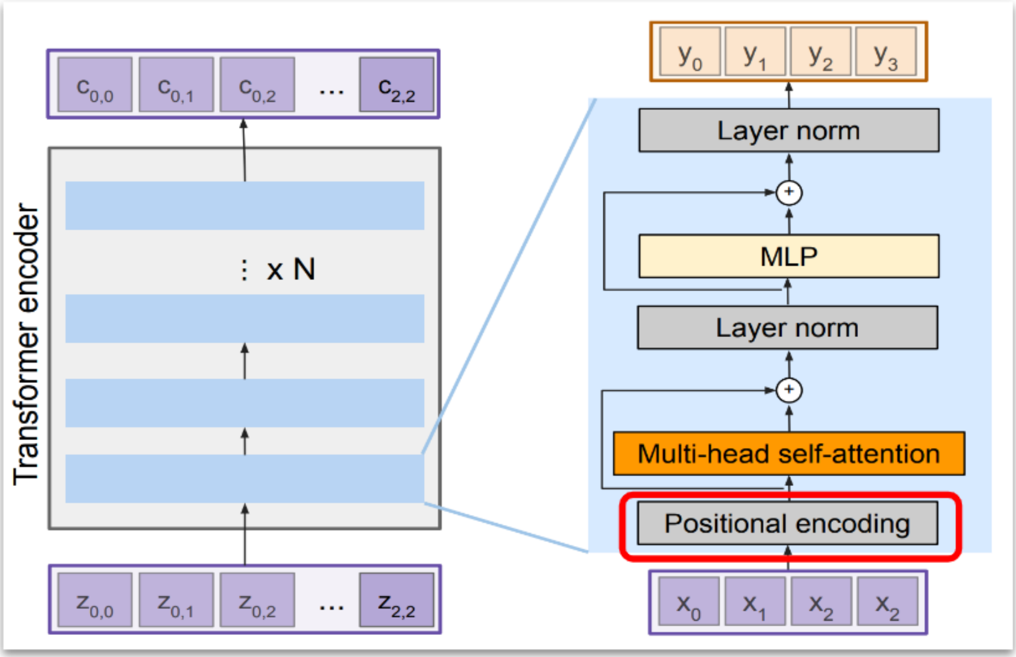
- Each **encoder** block has two sub-layers
  - Multi-head self-attention
  - A position-wise fully connected feed-forward
- Each **decoder** block has an additional third sub-layer
  - The third is a masked multi-head attention over the output of the encoder stack
- A **residual connection** is added around each of the two sub-layers
- The decoder yields the output sequence of symbols one element at a time



https://web.stanford.edu/class/cs224n/slides/cs224n-2020-lecture10-QA.pdf
Vaswani et al. 2017 https://arxiv.org/pdf/1706.03762.pdf

Transformer Model Architecture

- Transformer encoder



img src: [Stanford CS 231n]

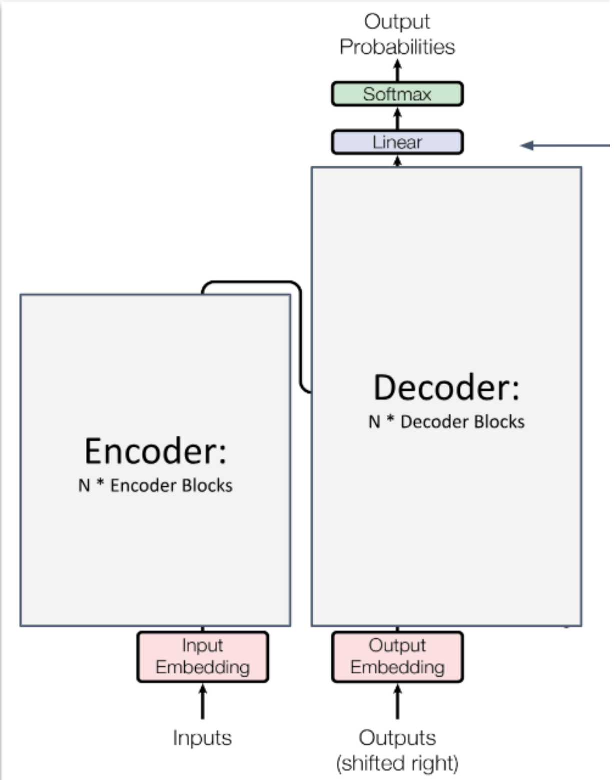
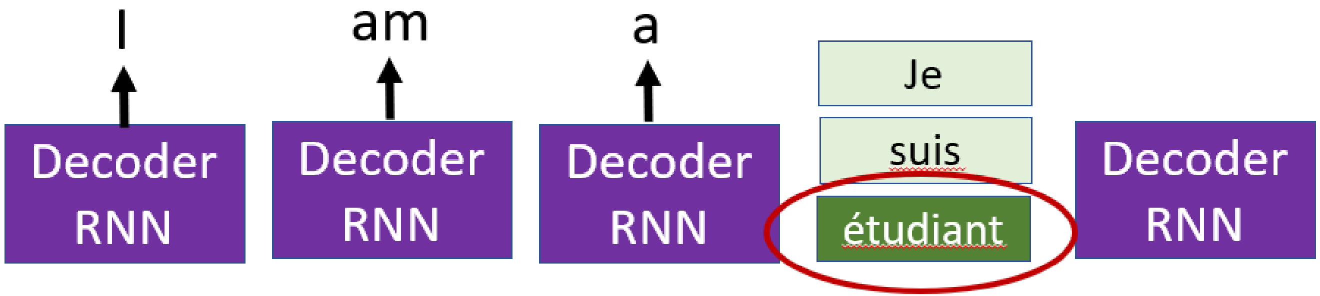


Figure 1: The Transformer - model architecture.

Bottleneck of Sequence-to-Sequence Model

- It is challenging for the model to deal with long sentences
- **Attention**
  - The encoder passes all the hidden states to the decoder
  - The attention enables the decoder to focus on the word before it generates the English translation
  - This ability amplifies the signal from the relevant part of the input sentence



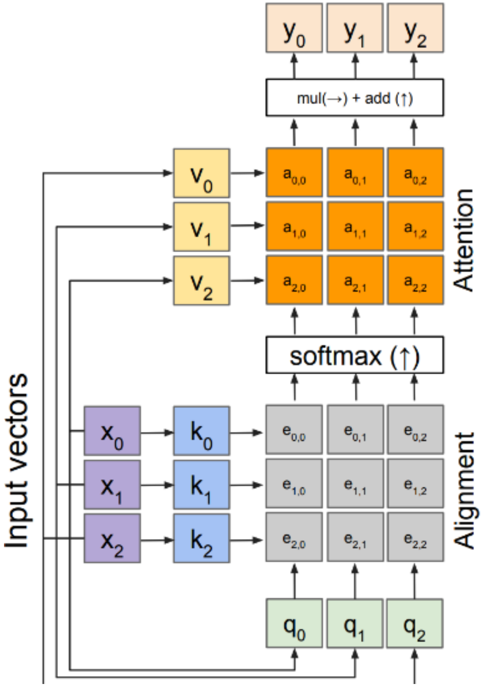
Transformer Model Architecture

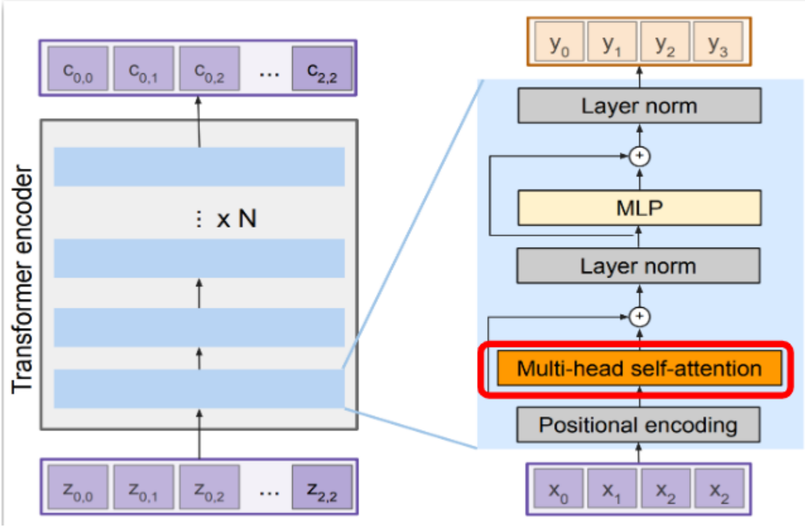
- $Q = \mathbf{X} \cdot W^Q$
- $K = \mathbf{X} \cdot W^K$
- $V = \mathbf{X} \cdot W^V$

Q: query
K: key
V: value

- Encoder – Multi-head self-attention

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

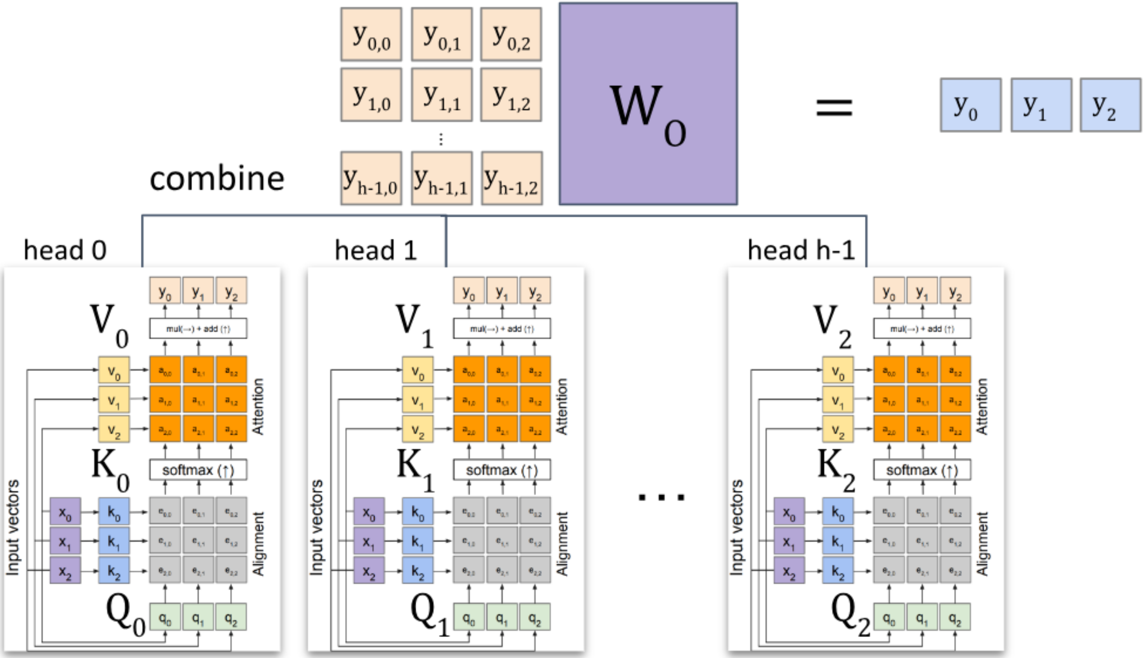




Transformer Model Architecture

- $Q_i = \mathbf{X} \cdot W^Q_i$
- $K_i = \mathbf{X} \cdot W^K_i$
- $V_i = \mathbf{X} \cdot W^V_i$

- Encoder – Multi-head self-attention

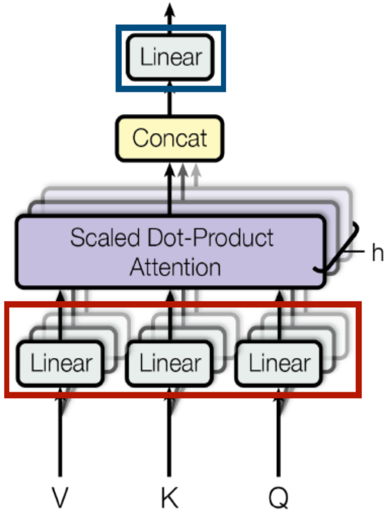


Multi-head Self-attention

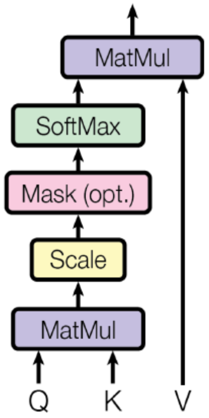
Multi-Head Self-Attention (MHSA)

- **Project** Q, K, and V with h **different** learned linear projections
- Perform the **scaled dot-product attention** function on each of Q, K, V **in parallel**
- **Concatenate** the output values
- **Project** the output values again, resulting in the final values

$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head_1}, \ldots, \mathrm{head_h})\boxed{W^O}$$
$$\text{where } \mathrm{head_i} = \mathrm{Attention}(Q\boxed{W_i^Q}, K\boxed{W_i^K}, V\boxed{W_i^V})$$



Scaled Dot-Product Attention

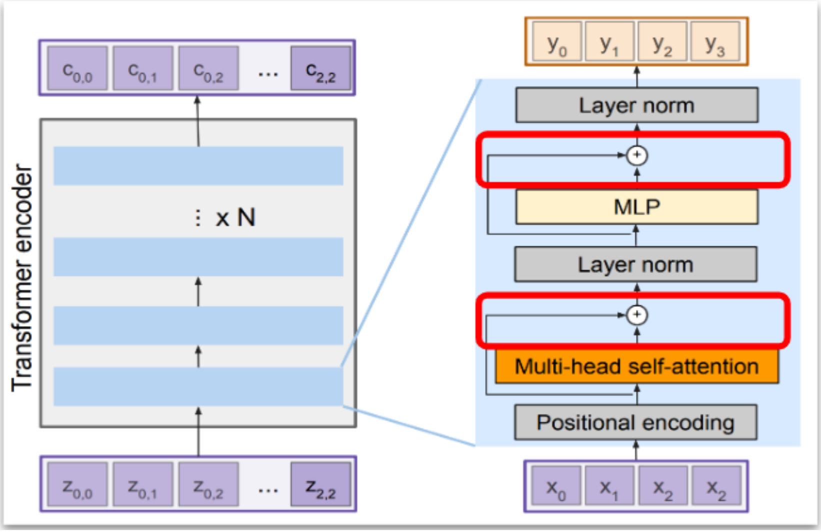


$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Transformer Model Architecture

- Encoder – Residual connection
  - Address exploding/vanishing gradients
  - Equation
    - F(x): output of previous layer
    - x: input of previous layer

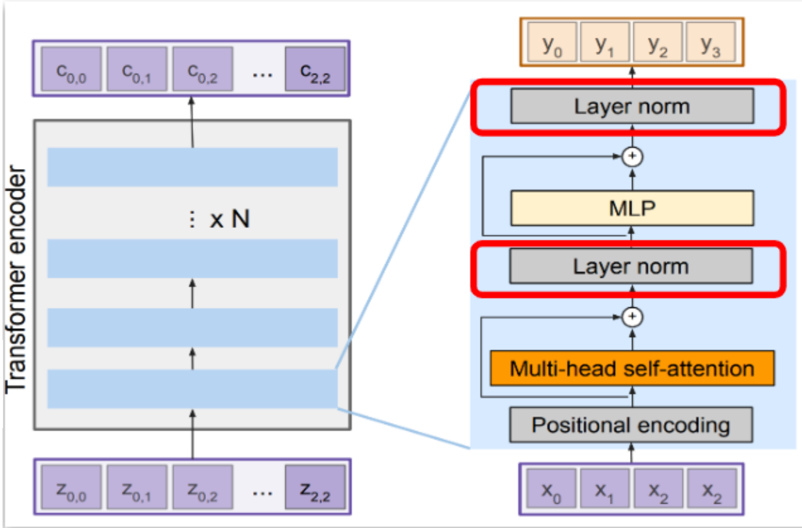
$$y = x + F(x)$$



Transformer Model Architecture

- Encoder – Layer normalization
  - For each input vector x = (x1 ..Xm)
    - Calculate Mean, variance
    - Normalize the vector x
      - Small ε -> avoid dividing 0
    - Scale and shift

γ, β are learnable parameters



$$\mu = \frac{\sum_i x_i}{m}$$

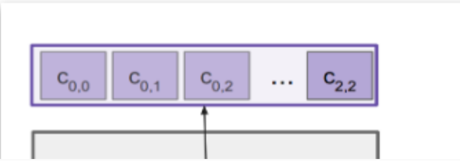
$$\sigma^2 = \frac{\sum_i (x_i - \mu)^2}{m}$$

$$\widehat{x_i} = \frac{(x_i - \mu)}{\sqrt{\sigma^2 + \varepsilon}}$$

$$y_i = \gamma \widehat{x_i} + \beta$$

Transformer Model Architecture

- Encoder – Feed Forward Network
  - Contains 2 linear transformations and 1 ReLU

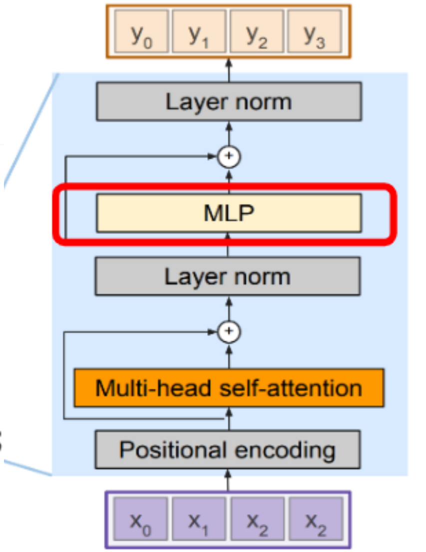


$$FFN(x) = ReLU(W_1 x + b_1)W_2 + b_2$$
$$= \max(0, W_1 x + b_1)W_2 + b_2$$

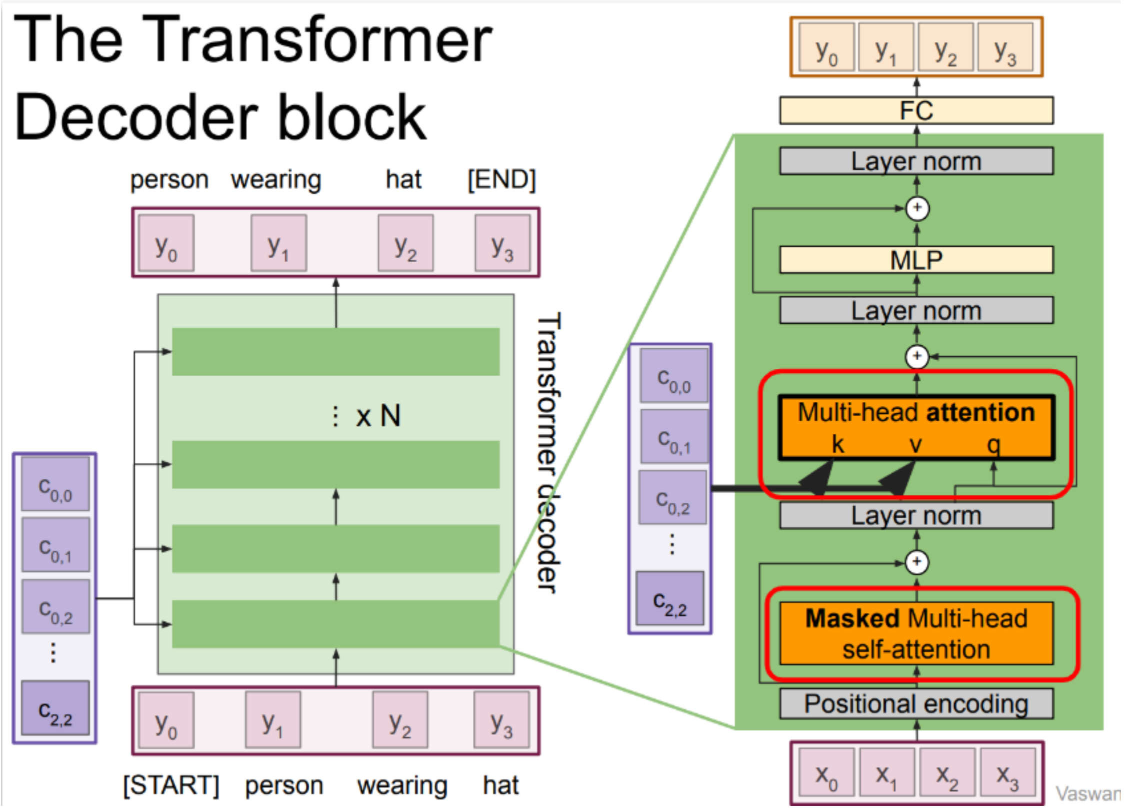
x: output of the previous layer

$W_{1(d_{model} \times d_{ff})}, W_{2(d_{ff} \times d_{model})}$: weight matrices for the two linear layers

b_1, b_2: biases for the two linear layers

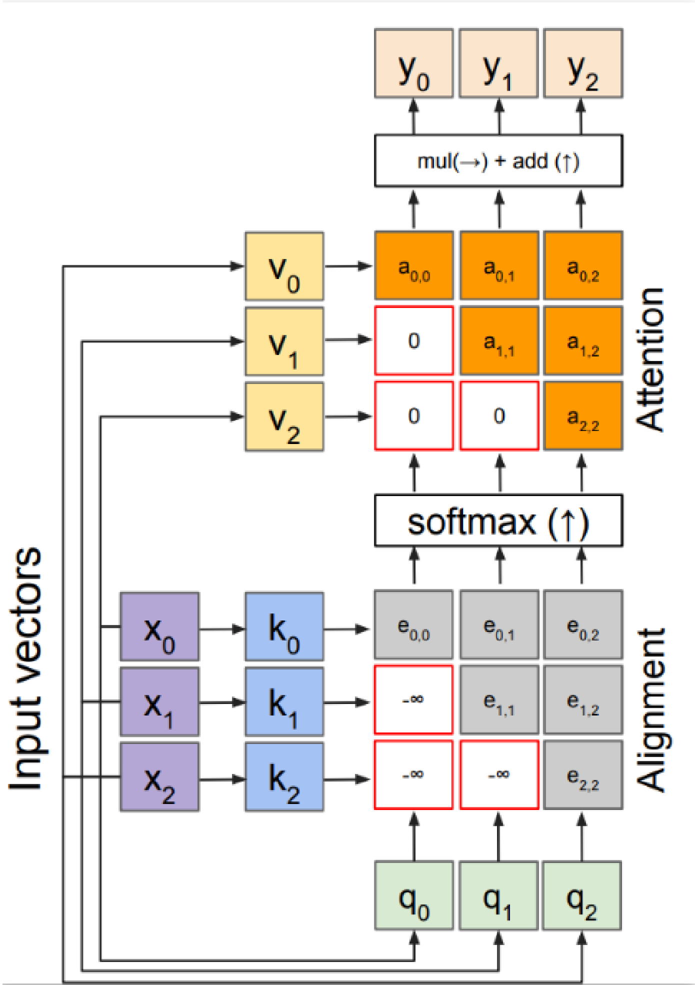


Transformer Model Architecture

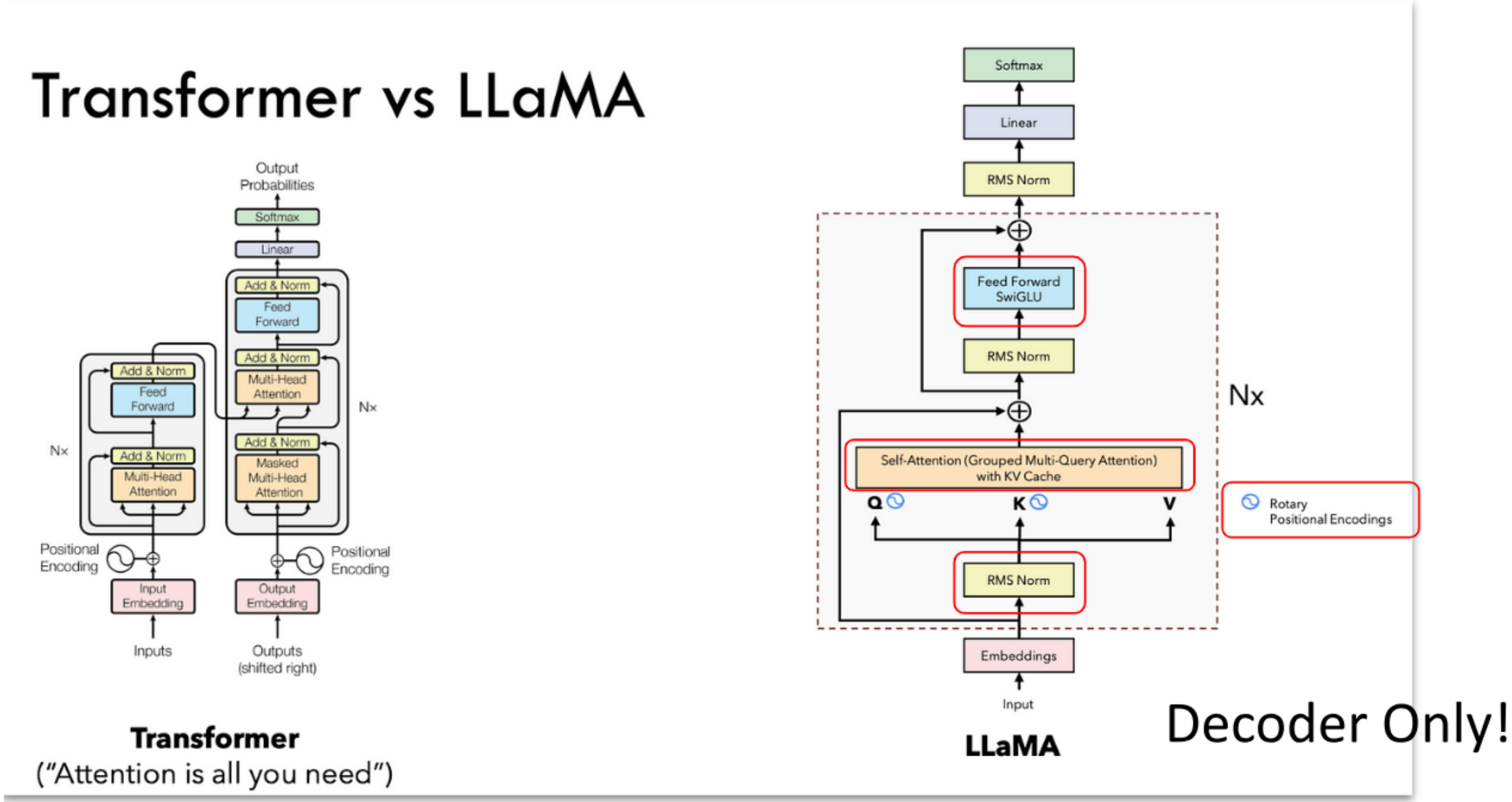


Transformer Model Architecture

- Decoder – Mask self-attention
  - The output of a certain position can only depend on the words on the previous positions
  - Set alignment scores of successive position to negative infinity



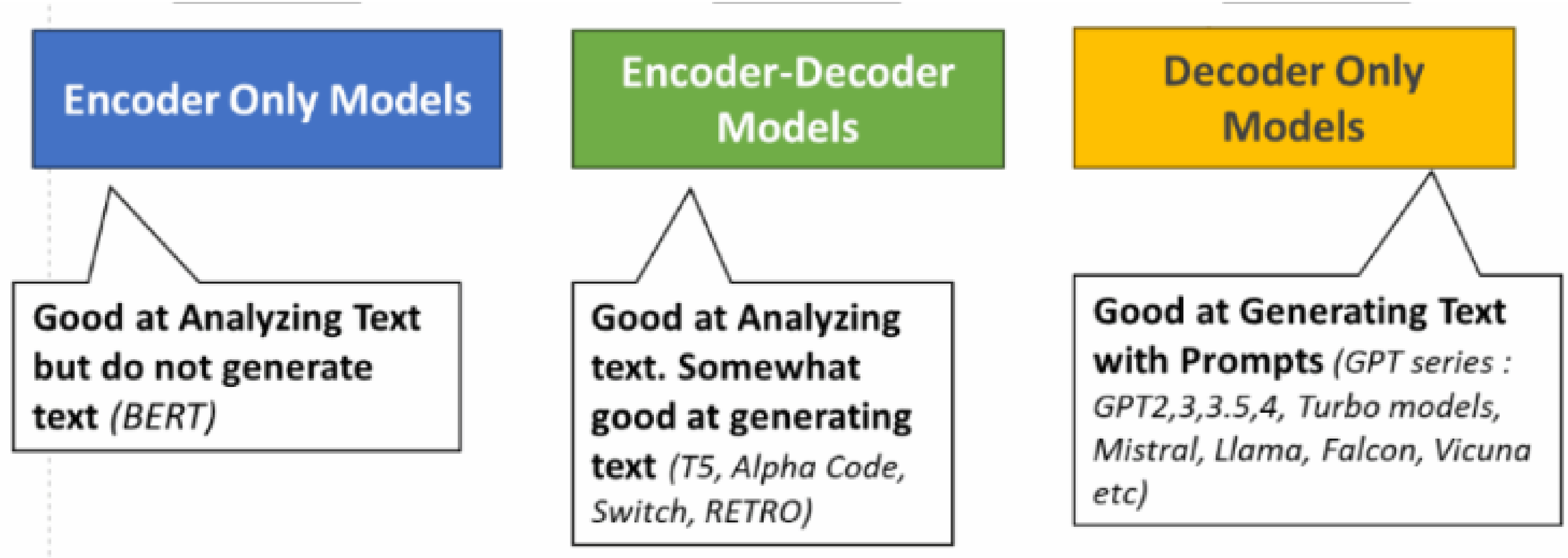
LLaMA Model Architecture



img src: medium @ccibeekeoc42

LLaMA Model Architecture

- Why LLaMA is decoder-only model?



https://www.53ai.com/news/qianyanjishu/1539.html

LLaMA Model Architecture

- Difference between Transformer and LLaMA
  - Decoder-only model
  - Pre-Norm (root mean square (RMS) norm)
  - Rotary positional embedding (RoPE)
  - KV cache
  - Grouped multi query attention
  - SwiGLU activation function rather than ReLU in FFN

LLaMA Model Architecture

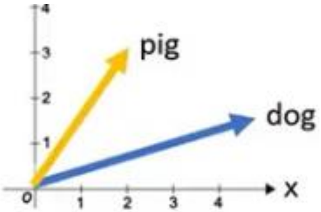
- Rotary positional embedding (RoPE)
  - Combine absolute and relative encoding
    - Absolute positional embedding
      - Assigns a unique vector to each position and doesn't scale well to capture relative position
    - Relative embeddings
      - Focuses on the distance between tokens
      - Enhance the model's understanding of token relationship
  - Rotational mechanism
    - Each position in the sequence is represented by a rotation in the embedding space

LLaMA Model Architecture

- Rotary positional embedding (RoPE)
  - RoPE applies a rotation to the word vector
  - The equation incorporates a rotation matrix that rotates a vector by an angle of Mθ, where M is the absolute position in the sentence.
  - This rotation is applied to the query and key vectors in the self-attention

$$f_{\{q,k\}}(\boldsymbol{x}_m, m) = \begin{pmatrix} \cos m\theta & -\sin m\theta \\ \sin m\theta & \cos m\theta \end{pmatrix} \begin{pmatrix} W^{(11)}_{\{q,k\}} & W^{(12)}_{\{q,k\}} \\ W^{(21)}_{\{q,k\}} & W^{(22)}_{\{q,k\}} \end{pmatrix} \begin{pmatrix} x^{(1)}_m \\ x^{(2)}_m \end{pmatrix}$$

The **pig** chased the **dog**



LLaMA Model Architecture

- Root Mean Square (RMS) normalization
  - Calculate the RMS of the input vectors rather than the mean and variance
  - Efficient normalization
    - No subtracting mean before squaring
    - No shifting in implementation

$$\mathrm{RMS}(x) = \sqrt{\frac{1}{m}\sum_i x_i^{\,2}}$$

$$\widehat{x_i} = \frac{x_i}{\mathrm{RMS}(x)+\varepsilon}$$

$$y_i = \gamma \widehat{x_i}$$

$$\mu = \frac{\sum_i x_i}{m}$$

$$\sigma^2 = \frac{\sum_i (x_i - \mu)^2}{m}$$

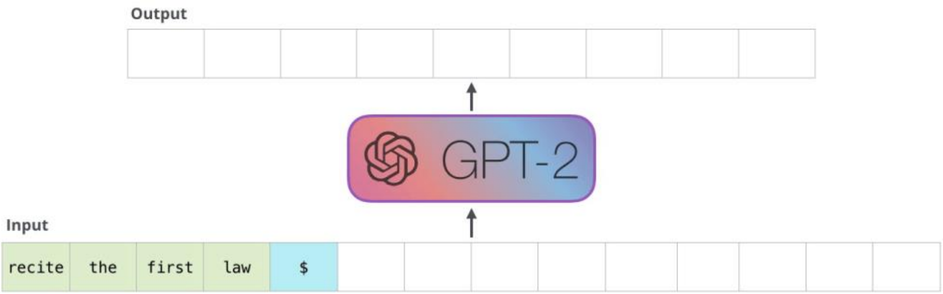
$$\widehat{x_i} = \frac{(x_i - \mu)}{\sqrt{\sigma^2 + \varepsilon}}$$

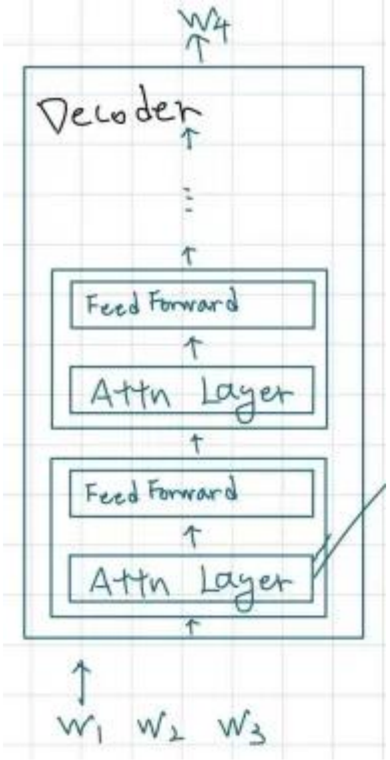
$$y_i = \gamma \widehat{x_i} + \beta$$

Layer norm

LLaMA Model Architecture

- LLM decoder
  - The decoder works in an auto-regressive fashion
    - Given an input, the model predict the next token
    - Taking the combined input in the next step

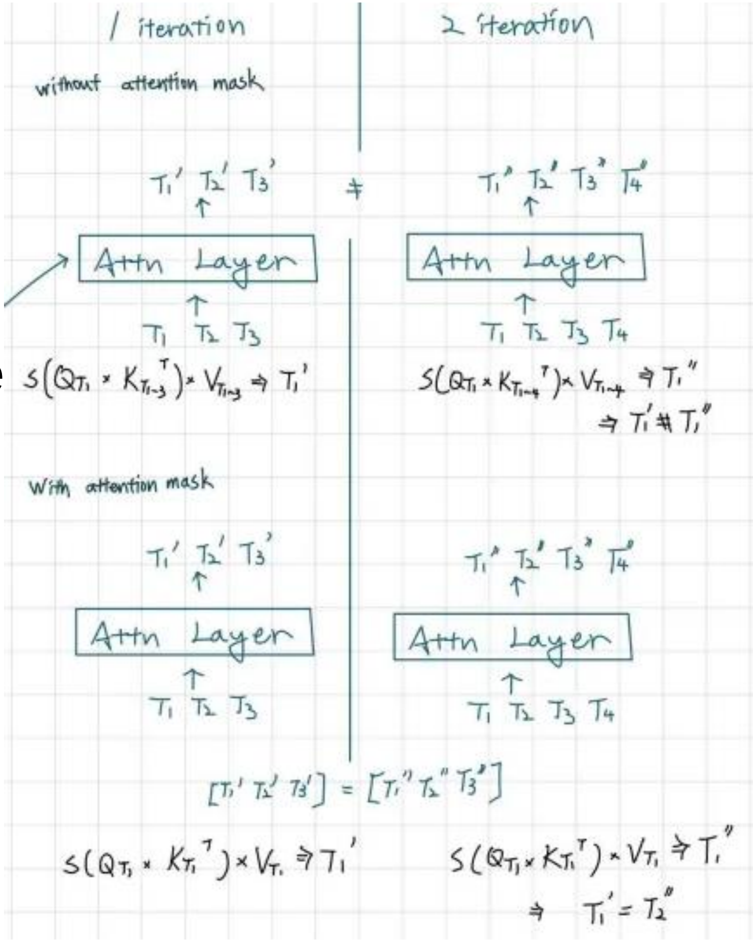




https://medium.com/@joaolages/kv-caching-explained-276520203249

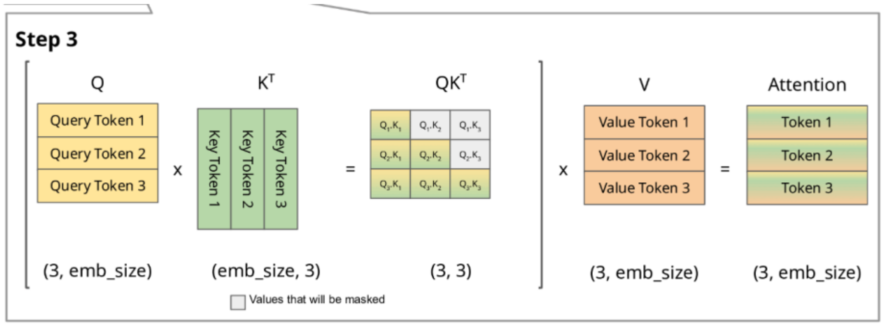
LLaMA Model Architecture

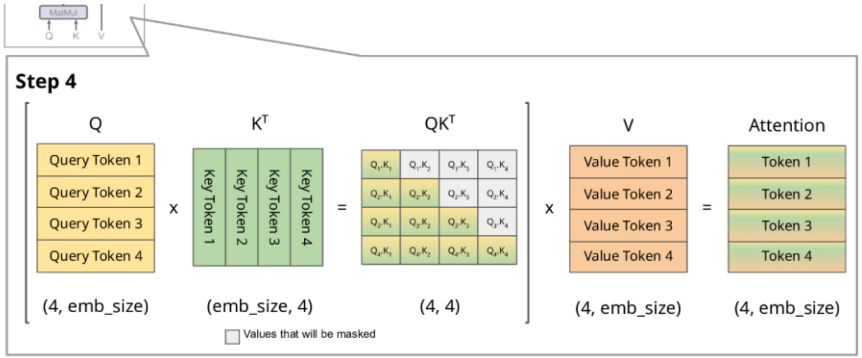
- Sequence mask (<u>in decoder</u>)
  - The decoder cannot see the message in the coming future
  - Use the mask to enable the decoder to only rely on the previous outputs to do the inference → training the decoder



LLaMA Model Architecture

- The scaled dot-product attention
  - The attention of a token only depends on its preceding tokens
  - At each generation step we are recalculating the same previous token attention, when we actually just want to calculate the attention for the new token

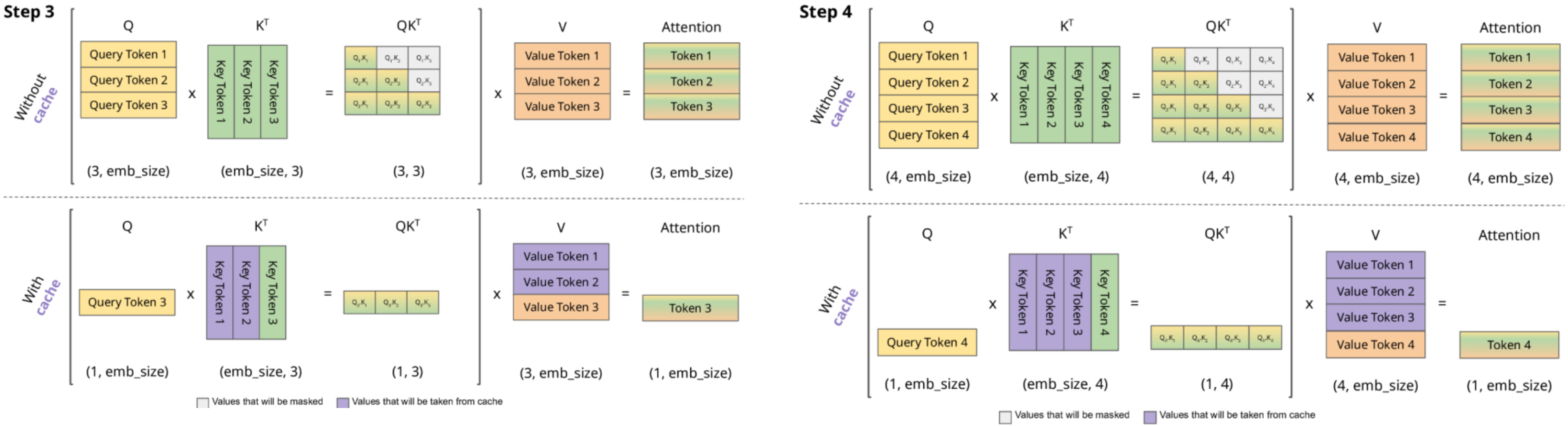




https://medium.com/@joaolages/kv-caching-explained-276520203249

LLaMA Model Architecture

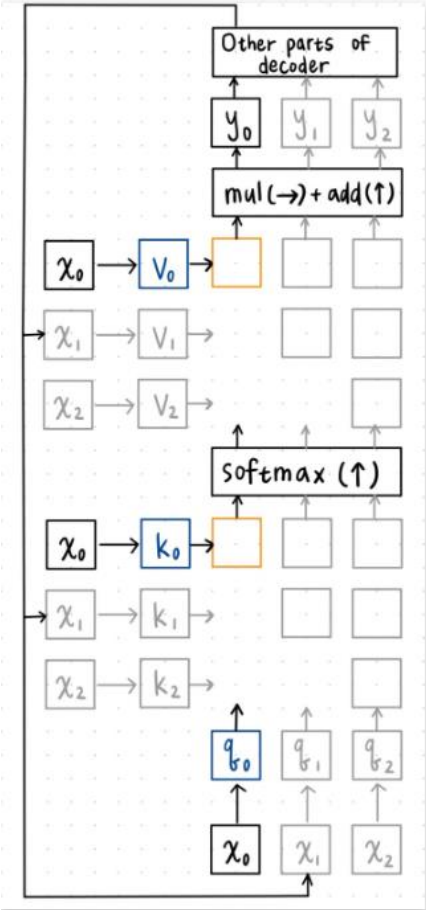
- Key-Value (KV) cache
  - By caching the previous Keys and Values, we can focus on only calculating the attention for the new token.



https://medium.com/@joaolages/kv-caching-explained-276520203249

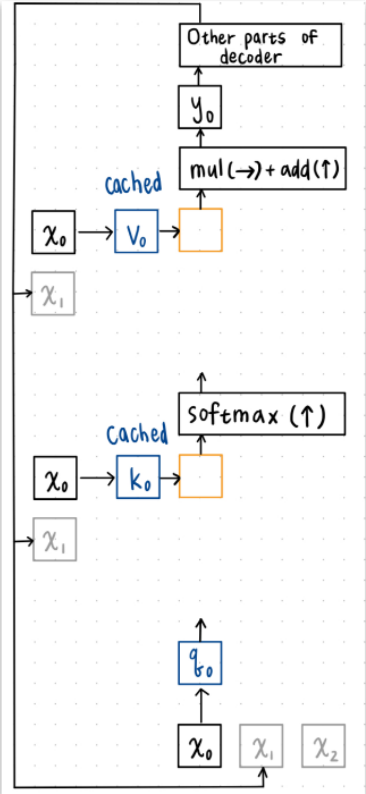
LLaMA Model Architecture

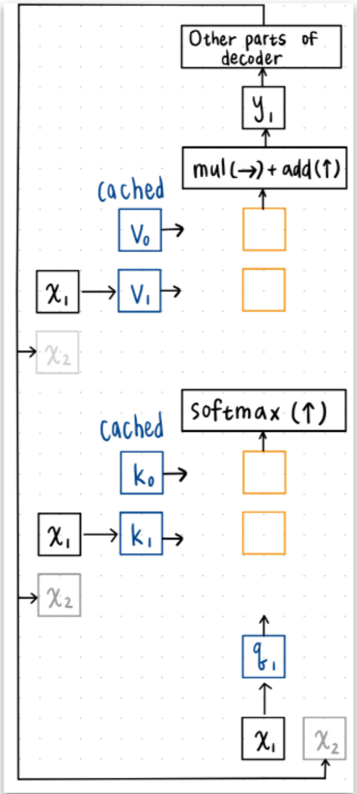
- Key-Value (KV) cache
  - LLM models can generate only one token at a time
  - Each new prediction is dependent on the previous context
    - To predict token number 1000 in the generation, you need information from the previous 999 tokens
  - Optimize the sequential generation process by storing previous calculations to reuse in subsequent tokens, so they don't need to be computed again.

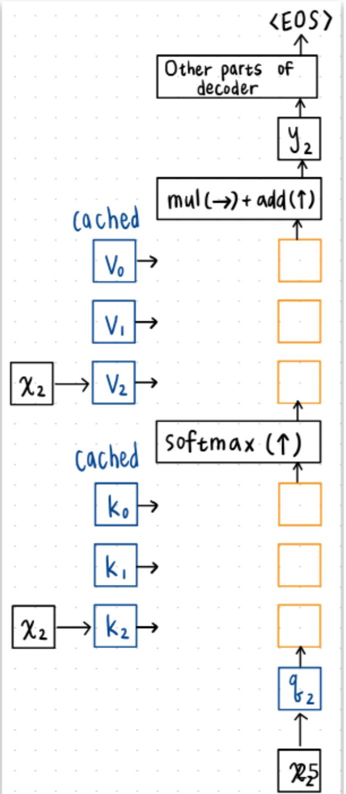


LLaMA Model Architecture

- KV cache







LLaMA Model Architecture

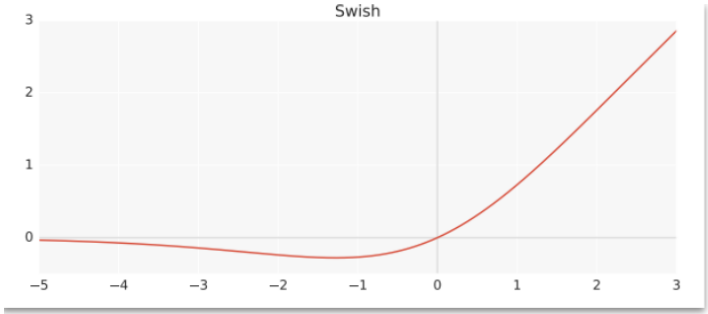
- Key-Value (KV) cache
  - The matrices obtained with KV caching are way smaller, which leads to faster matrix multiplications
  - The downside of the KV cache is
    - When the length of sequences is becoming long
    - Needs the large memory to cache the Key and Value states

LLaMA Model Architecture

- SwiGLU (Swish and Gated Linear Unit)
  - LLU such as PALM and LLAMA use SwiGLU in FFN rather than the usual ReLU -> SwiGLU tackles minus value better than ReLU

$$\mathrm{FFN}_{SwiGLU}(x, W, V, W_2) = (Swish_1(xW) \otimes xV)W_2,$$

$$\text{where } Swish_\beta(x) = x \cdot sigmoid(\beta x) = \frac{x}{1+e^{-\beta x}}$$



img src: medium@neuralnets

Takeaway Questions

- What’s problem the “Attention” aiming to solve?
  - (A) Gradient vanishing
  - (B) Message passing in the long sequence of data
  - (C) Over-fitting
- What are benefits of the “Transformer” ?
  - (A) Large hidden layer
  - (B) The amount of computation is small
  - (C) More data parallelism

Takeaway Questions

- How does the “self-attention” help the encoder?
    - (A) Looking at other works in the input sentence
    - (B) Memorizing the more messages within a network
    - (C) Focus on a specific word