W6. Neural Network

Guang Cheng

University of California, Los Angeles

guangcheng@ucla.edu

Week 6

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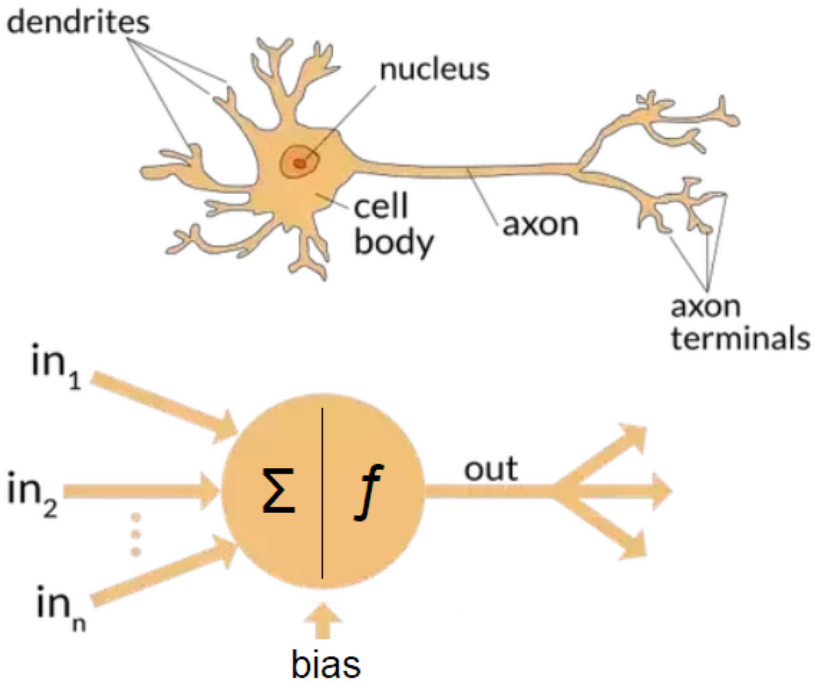
- These nuances require a modeling approach that goes beyond linear combinations – neural networks.

Neurons



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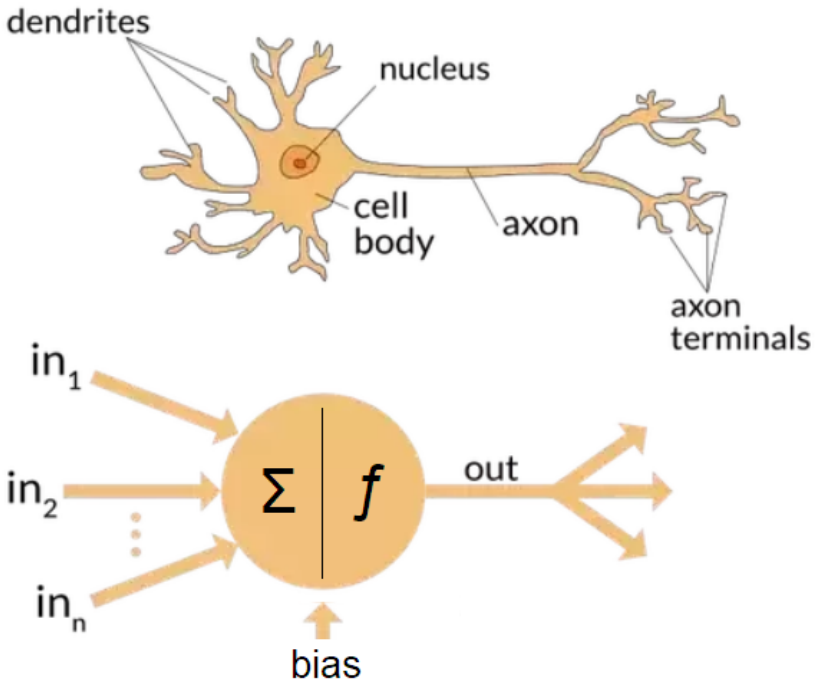

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- **Processing Non-linear Messages:** Through activation, neurons can process complex non-linear pattern and decision boundries.

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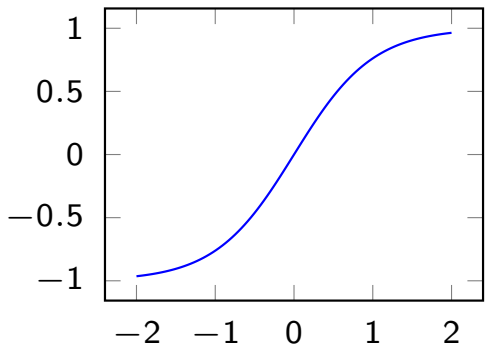
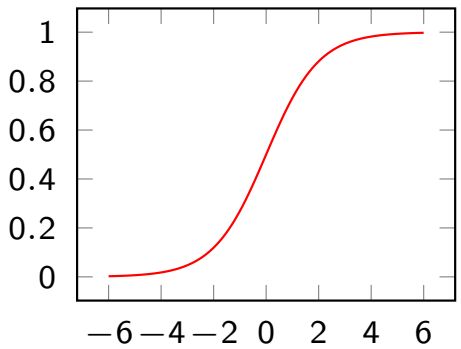
- Popular activation functions $\sigma(\cdot)$:

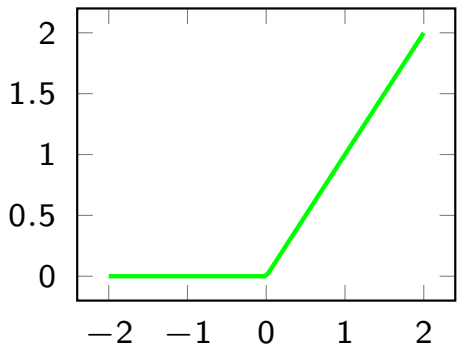
$\tanh(x)$



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



$ReLU(x) = \max(0, x)$



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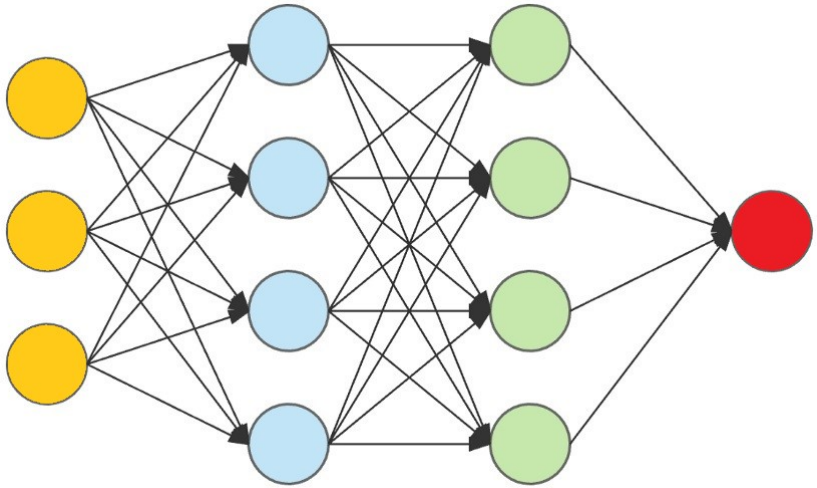
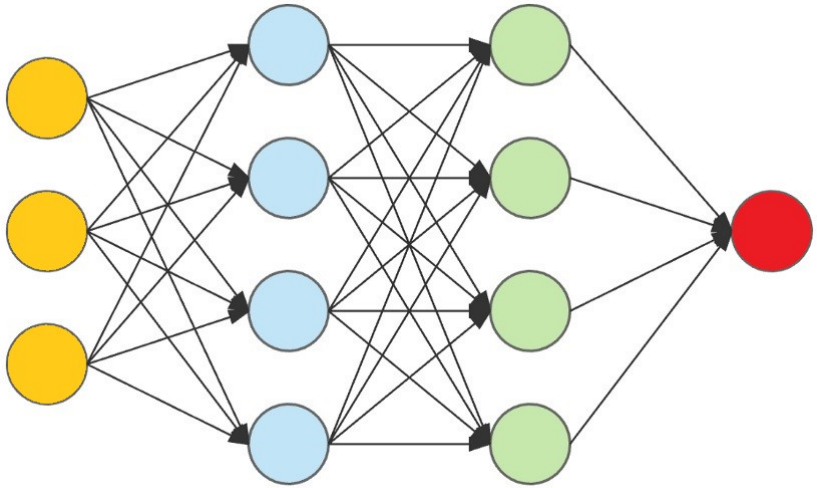
- **Complex Function Implementation:** Through the use of deep architectures, neural networks can implement intricate functions, capturing a wide variety of relationships in data.
- **Constraint Range of Value:** Through activation, output of layers can be constrained to some desired ranges. For example, sigmoid activation limits output to $[0, 1]$, which can represents a probability.
- **No Curse of Dimensionality.**

From Single Neurons to a Network



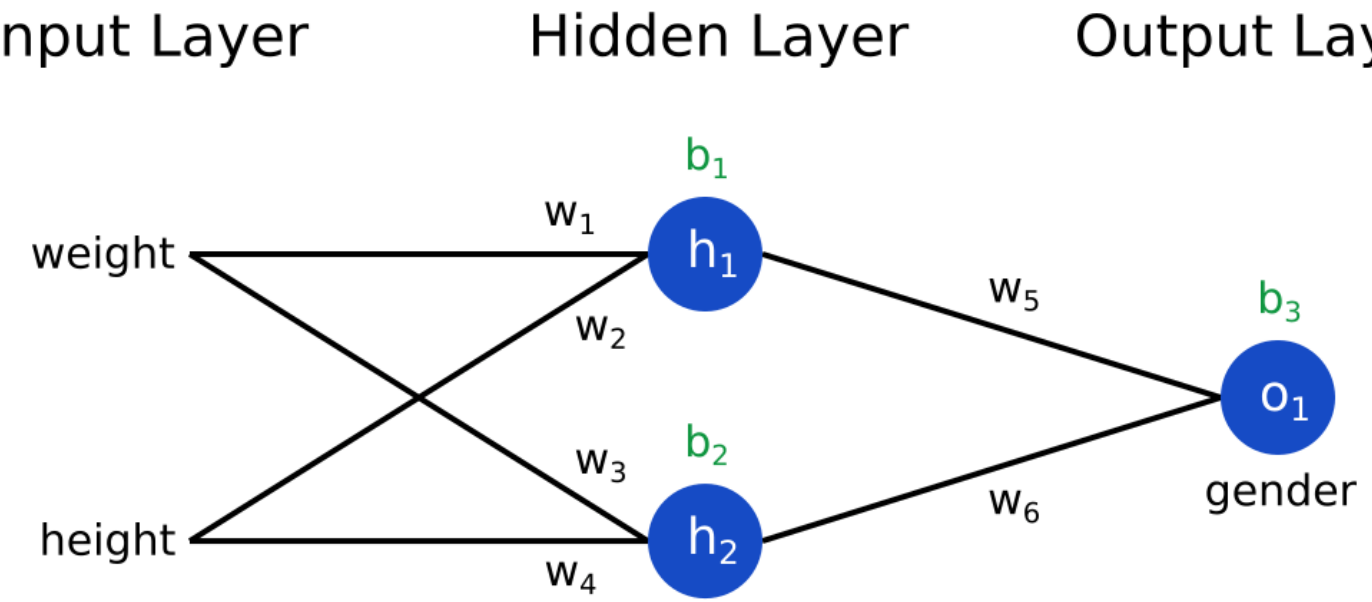
- **Building Blocks:** Each neuron in a neural network acts as a fundamental unit that receives inputs, applies weights to them, and generates an output using an activation function.

From Single Neurons to a Network



- **Building Blocks:** Each neuron in a neural network acts as a fundamental unit that receives inputs, applies weights to them, and generates an output using an activation function.
- **Layered Structure:** Neurons are organized into layers, where the output of one layer are weighted, and serves as the input to the next. This enables the network to model complex relationships through intricate patterns of weights and activations.

Connecting Neurons Into Network



Mathematical Definition: In the example network above, output, y, is calculated as $y = \sigma(w_5 \cdot h_1 + w_6 \cdot h_2 + b_3)$ where $h_1 = \sigma(w_1 \cdot x_1 + w_2 \cdot x_2 + b_1)$ and $h_2 = \sigma(w_3 \cdot x_1 + w_4 \cdot x_2 + b_2)$. Here, x_1 and x_2 are the input features (weight and height), σ denotes an activation function, and b_3 is the bias for the output neuron.

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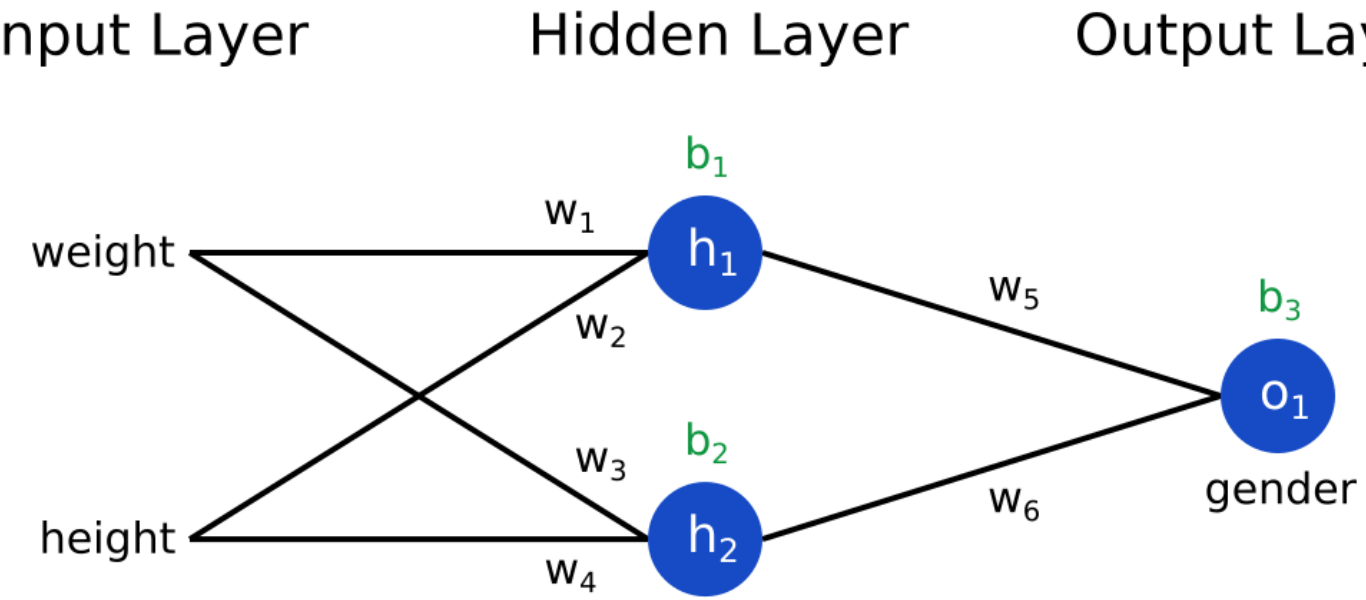

Example Calculation: Given inputs $x_1 = 70$ (weight) and $x_2 = 1.75$ (height), with weights $w_1 = 0.2, w_2 = 0.4, w_3 = -0.5$, $w_4 = 0.3, w_5 = 1, w_6 = -1.5$, and biases $b_1 = 0.1, b_2 = -0.1, b_3 = 0.5$. The hidden layer activations: $h_1 = \sigma(0.2 \cdot 70 + 0.4 \cdot 1.75 + 0.1)$ and $h_2 = \sigma(-0.5 \cdot 70 + 0.3 \cdot 1.75 - 0.1)$. Then $y = \sigma(1 \cdot h_1 - 1.5 \cdot h_2 + 0.5)$.

From Single Neurons to a Network

In-class exercise: Given inputs $x_1 = 20$ (weight) and $x_2 = 3$ (height), with weights $w_1 = -0.2, w_2 = 1, w_3 = -0.5$, $w_4 = 0.3, w_5 = -1, w_6 = 0$, and biases $b_1 = 1, b_2 = -0.2, b_3 = 0.5$. Let σ be the ReLu function. Please calculate hidden nodes h_1, h_2 and final outcome y.

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$h_1 = ReLU(20 * (-0.2) + 3 * 1 + 1) = 0$
$h_2 = ReLU(-0.5 * 20 + 0.3 * 3 - 0.2) = 0$
$y = ReLU(0 + 0 + 0.5) = 0.5.$

Network Definition in Matrix Form

The network computation can be expressed in vector/matrix form as:

$$y = \sigma(\mathbf{W}_2\mathbf{h} + b_3)$$

where

$$\mathbf{h} = \sigma(\mathbf{W}_1\mathbf{x} + \mathbf{b})$$

and

$$\mathbf{W}_1 = \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \end{bmatrix}, \quad \mathbf{W}_2 = \begin{bmatrix} w_5 \\ w_6 \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

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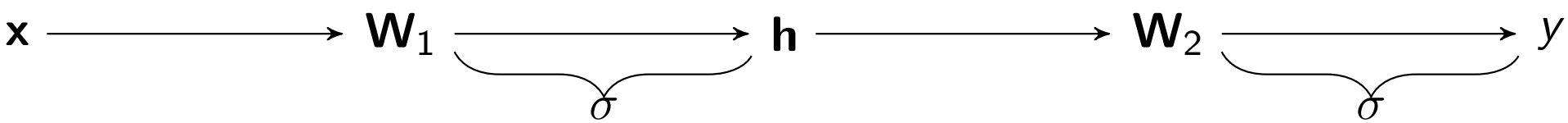

Loss Function

As long as we have data $\{x_i, y_i\}_{i=1}^n$, we can learn the network weights w_j's by minimizing a loss function. Loss functions measures the difference between the network's predictions $\hat{y}$ and the actual target values y.

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Brief intro to "double descent phenomenon"

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- **Deep Learning Capability**: It enables neural networks to learn from complex data and perform tasks like image recognition, language translation (large language model), and playing games (reinforcement learning) at a high level.
- **Scalability**: This method scales well with large neural networks and datasets, which is crucial for modern deep learning applications that involve vast amounts of data and complex models.

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  - Gradient of Loss with respect to w: $(\frac{\partial L}{\partial w} = -0.106)$

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  - Gradient of Loss with respect to w: $(\frac{\partial L}{\partial w} = -0.106)$
- Putting it all together gives us the gradient of the loss with respect to w, which is used to update w in the direction that reduces the loss.

Simple Example of Computing Gradient

- Let's compute the actual numbers for this example, including the gradient.
- For our simplified example, the computations yield the following results:
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- If we have a learning rate α, the weight update rule would be:

$$w_{\text{new}} = w - \alpha \cdot \frac{\partial L}{\partial w},$$

where w is the weight estimate in the previous update.

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- Work out the update w_{next} after setting the learning rate $\alpha = 0.1$.

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- Let's do the final calculation.

$$(1.2 - 0.713)^2/2 = 0.12.$$

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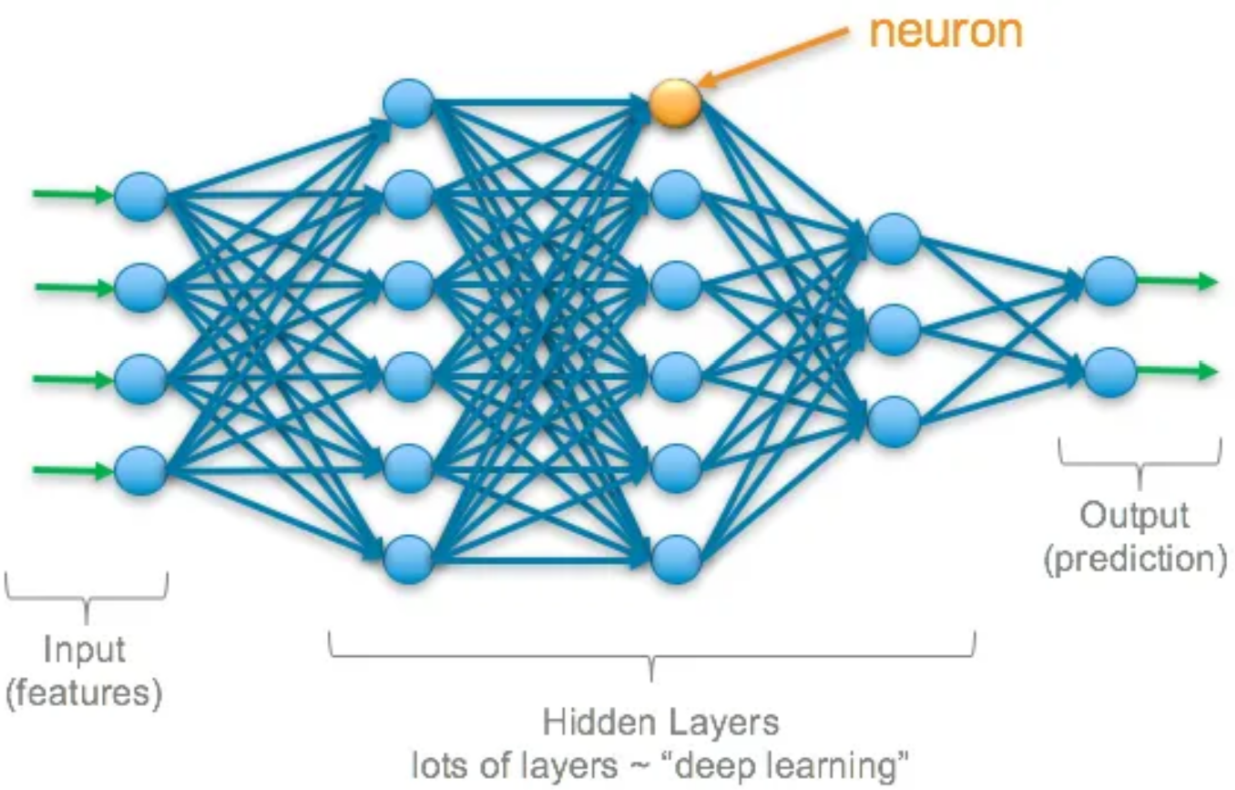
- Our previous examples are 1-hidden layer (fully connected) neural networks, i.e., shallow neural networks.

Layers in Deep Neural Networks



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- Form of raw data: pixel in image data; tokenization in text data; embedding of tabular data.

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- **Hidden Layers**: Layers between the input and output layers. There can be many hidden layers in a DNN, and they are where most of the computation takes place. Each hidden layer transforms its input data into a slightly more abstract and composite representation. The network can have different types of hidden layers, including:

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  - **Recurrent Layers**: Used for processing sequential data, where the output from previous steps is fed back into the model to predict the outcome of a sequence. This is particularly useful in language modeling and time series analysis.

Layers in Deep Neural Networks

- **Output Layer**: The final layer that produces the output of the model. The design of the output layer depends on the specific task (e.g., regression, classification). For classification tasks, the output layer often uses a softmax function to generate probabilities for each class.

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- How to improve the traditional neural networks ?
- Use Recurrent Neural Networks!

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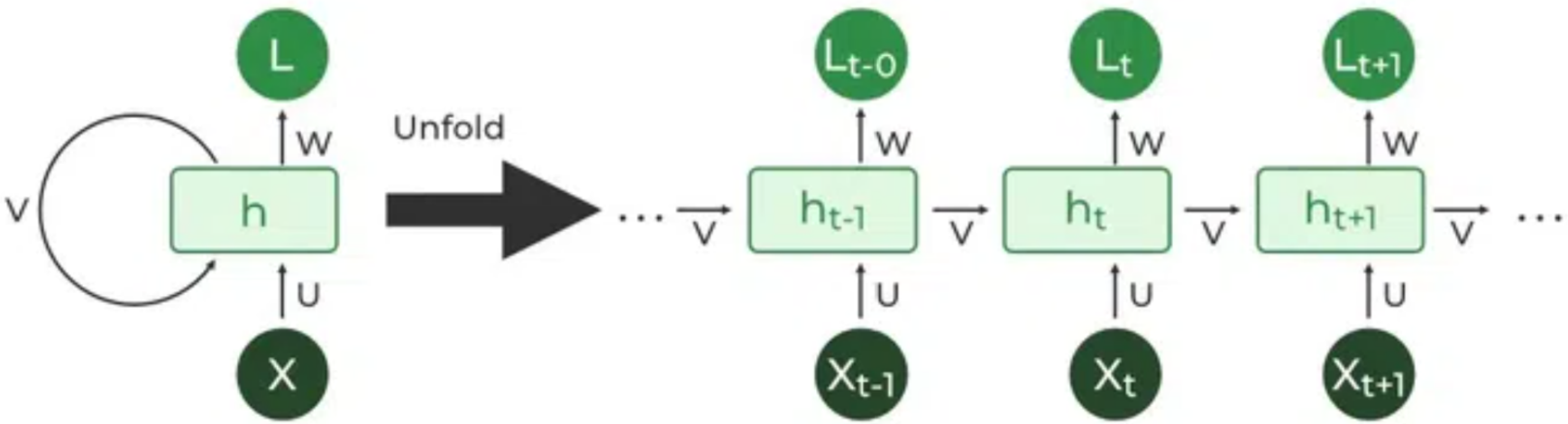
- The main and most important feature of RNN is its Hidden state, which remembers some information about a sequence. The state is also referred to as Memory State since it remembers the previous input to the network.
- It uses the same parameters for each input as it performs the same task on all the inputs or hidden layers to produce the output. This reduces the complexity of parameters, unlike other neural networks.

The schematic diagram of RNN



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- These parameters are updated using Back propagation.

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  - Gradient vanishing and exploding problems.
  - Training an RNN is a very difficult task.
  - It cannot process very long sequences if using tanh or relu as an activation function.

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- How to deal with Long-Term Dependencies, Vanishing and Exploding Gradients in RNN ?

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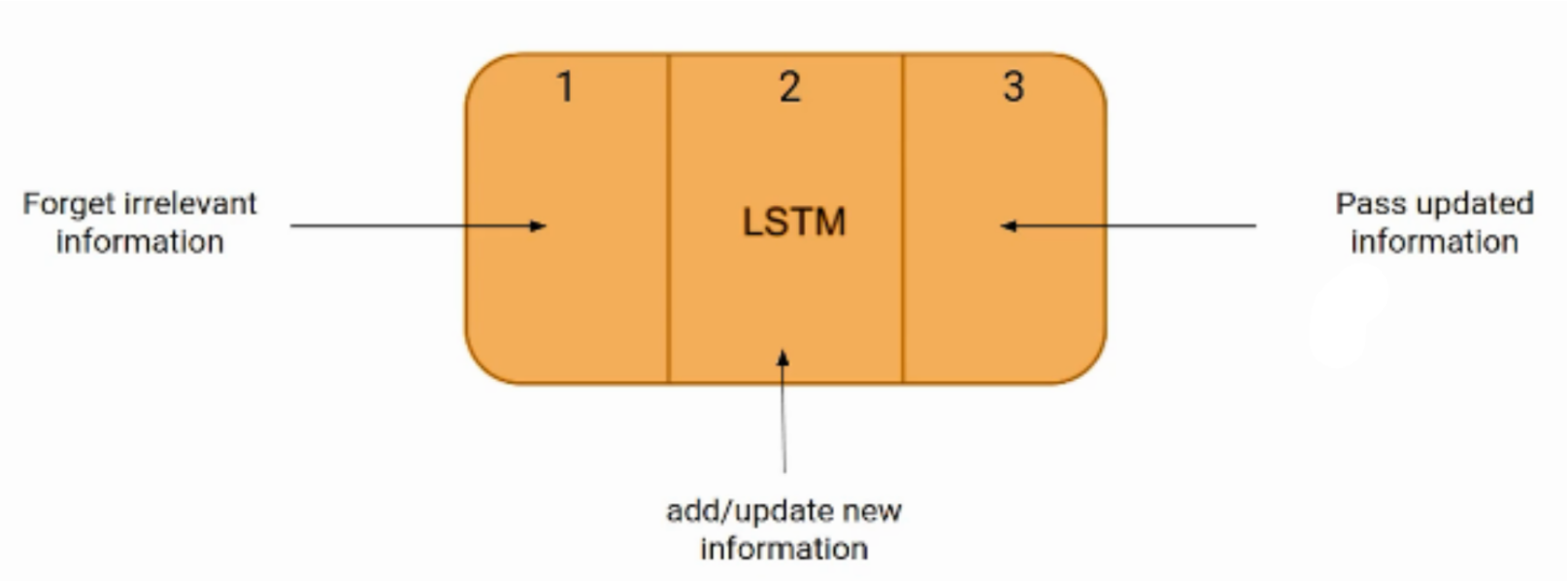
- Unlike traditional neural networks, LSTM incorporates feedback connections, allowing it to process entire sequences of data, not just individual data points. This makes it highly effective in understanding and predicting patterns in sequential data like time series, text, and speech.

LSTM architecture

- At a high level, LSTM works very much like an RNN cell. Here is the internal functioning of the LSTM network. The LSTM network architecture consists of three parts, as shown in the image below, and each part performs an individual function.



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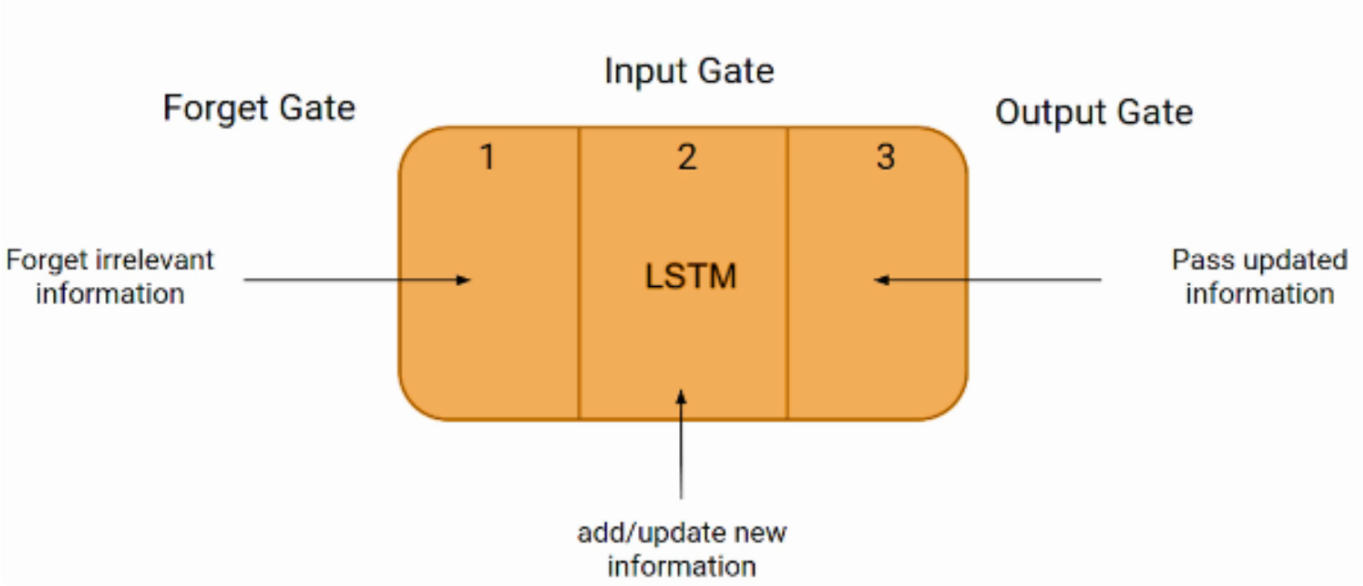
- The first part chooses whether the information coming from the previous timestamp is to be remembered or is irrelevant and can be forgotten.
- In the second part, the cell tries to learn new information from the input to this cell.
- At last, in the third part, the cell passes the updated information from the current timestamp to the next timestamp. This one cycle of LSTM is considered a single-time step.

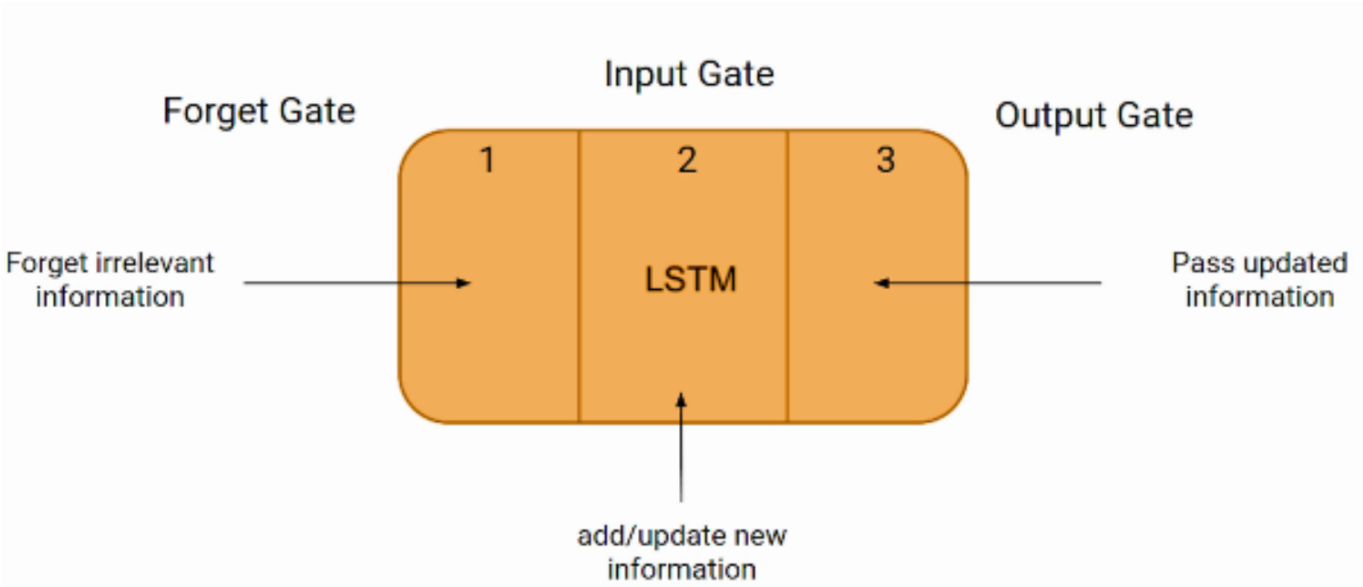
The Logic Behind LSTM

- These three parts of an LSTM unit are known as gates. They control the flow of information in and out of the memory cell or lstm cell.



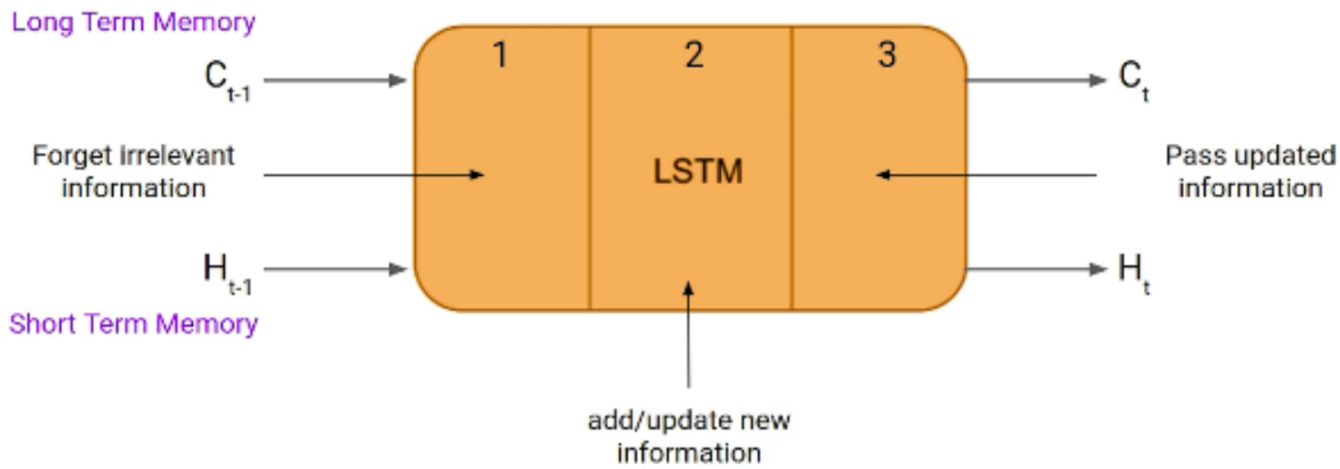
The Logic Behind LSTM

- These three parts of an LSTM unit are known as gates. They control the flow of information in and out of the memory cell or lstm cell.
- The first gate is called **Forget gate**, the second gate is known as the **Input gate**, and the last one is the **Output gate**.



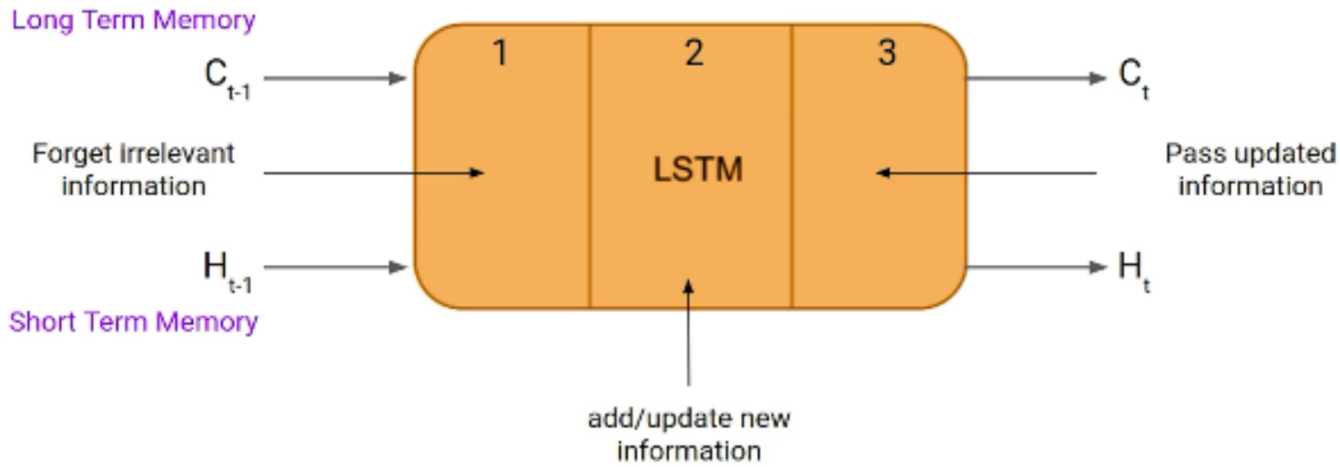
The Logic Behind LSTM

- An LSTM has a hidden state where H_{t-1} represents the hidden state of the previous timestamp and H_t is the hidden state of the current timestamp.



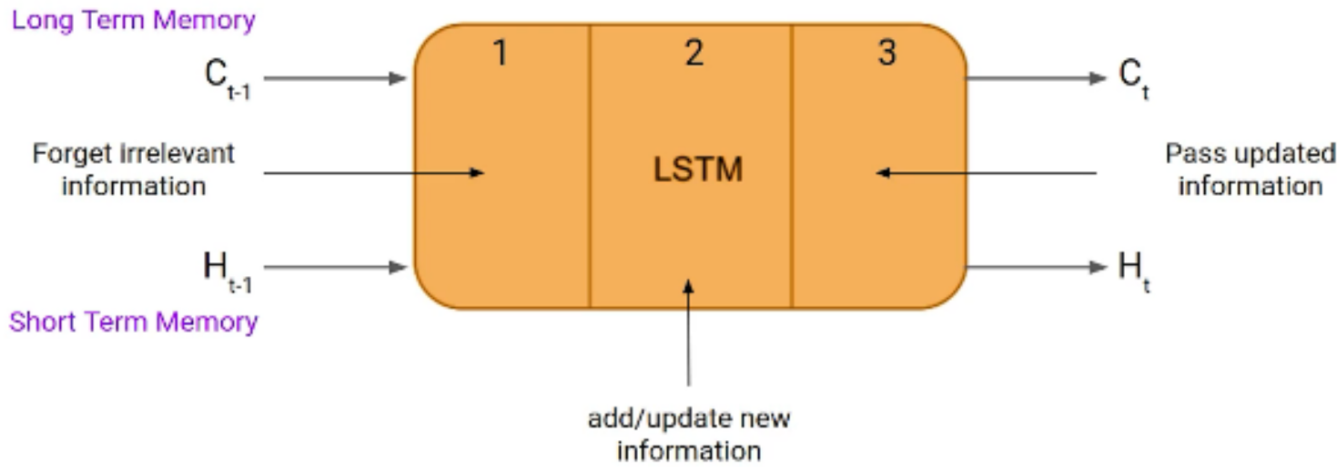
The Logic Behind LSTM

- An LSTM has a hidden state where H_{t-1} represents the hidden state of the previous timestamp and H_t is the hidden state of the current timestamp.
- Additionally, LSTM has a cell state represented by C_{t-1} and C_t for the previous and current timestamps, respectively.



The Logic Behind LSTM

- An LSTM has a hidden state where H_{t-1} represents the hidden state of the previous timestamp and H_t is the hidden state of the current timestamp.
- Additionally, LSTM has a cell state represented by C_{t-1} and C_t for the previous and current timestamps, respectively.
- Here the hidden state is known as Short term memory, and the cell state is known as Long term memory. Refer to the following image.



Forget gate

- The forget gate decides which information should be thrown away or kept. It looks at the current input x_t and the previous hidden state h_{t-1}, and outputs a number between 0 and 1 for each number in the cell state C_{t-1}. A value of 0 means "completely forget this" while a value of 1 means "completely retain this."

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- The forget gate's decision is made using the following formula:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where W_f are the weights, b_f is the bias term for the forget gate, and σ denotes the sigmoid function, ensuring the output is between 0 and 1.

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- It operates in two steps: First, a sigmoid layer decides which values will be updated, and then a tanh layer creates a vector of new candidate values, $\widetilde{C}_t$, that could be added to the state.
- The formula for updating the cell state is:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$

$$\widetilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

where i_t is the output of the input gate, determining which values to update, and $\widetilde{C}_t$ is the vector of candidate values.

A more popular NN architecture to deal with sequence data ?

- Use Transformers !

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com

Noam Shazeer* Google Brain noam@google.com

Niki Parmar* Google Research nikip@google.com

Jakob Uszkoreit* Google Research usz@google.com

Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu

Łukasz Kaiser* Google Brain lukaszkaiser@google.com

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

"ImageNet Moment for Natural Language Processing"

Pretraining:
Download a lot of text from the internet

Train a giant Transformer model for language modeling

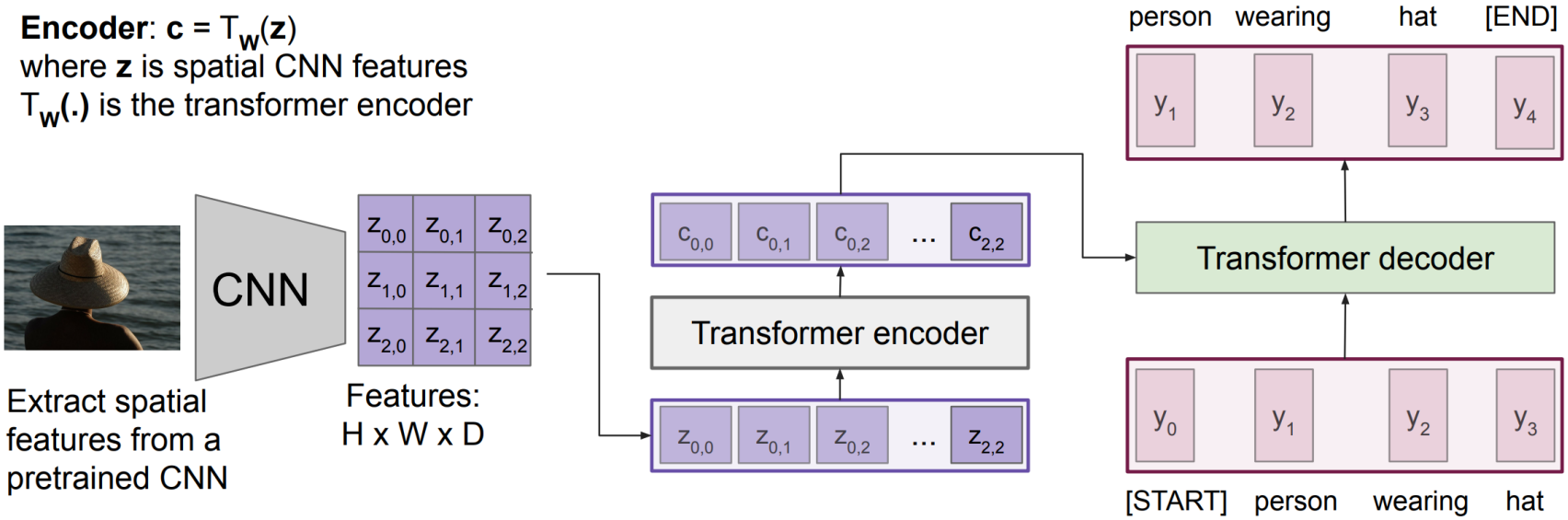
Finetuning:
Fine-tune the Transformer on your own NLP task

Image captioning using transformers

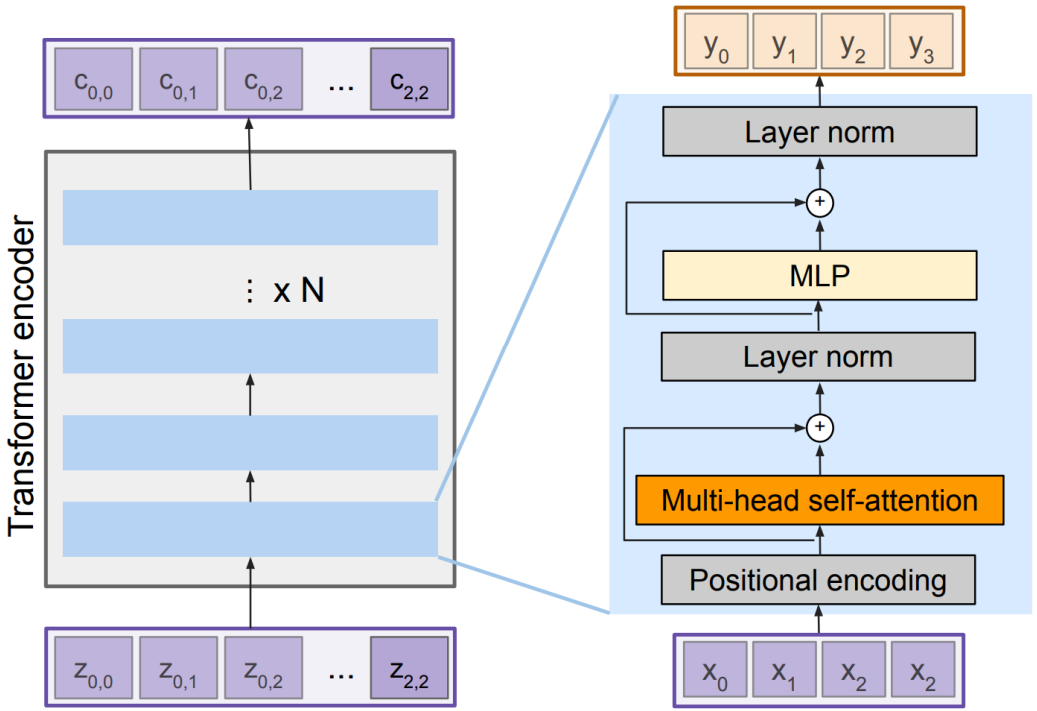
Input: Image **I**
Output: Sequence $\mathbf{y} = y_1, y_2, \ldots, y_T$

Encoder: $\mathbf{c} = T_W(\mathbf{z})$
where **z** is spatial CNN features
$T_W(.)$ is the transformer encoder

Decoder: $y_t = T_D(\mathbf{y}_{0:t-1}, \mathbf{c})$
where $T_D(.)$ is the transformer decoder



The Transformer encoder block



Transformer Encoder Block:

Inputs: Set of vectors **x**
Outputs: Set of vectors **y**

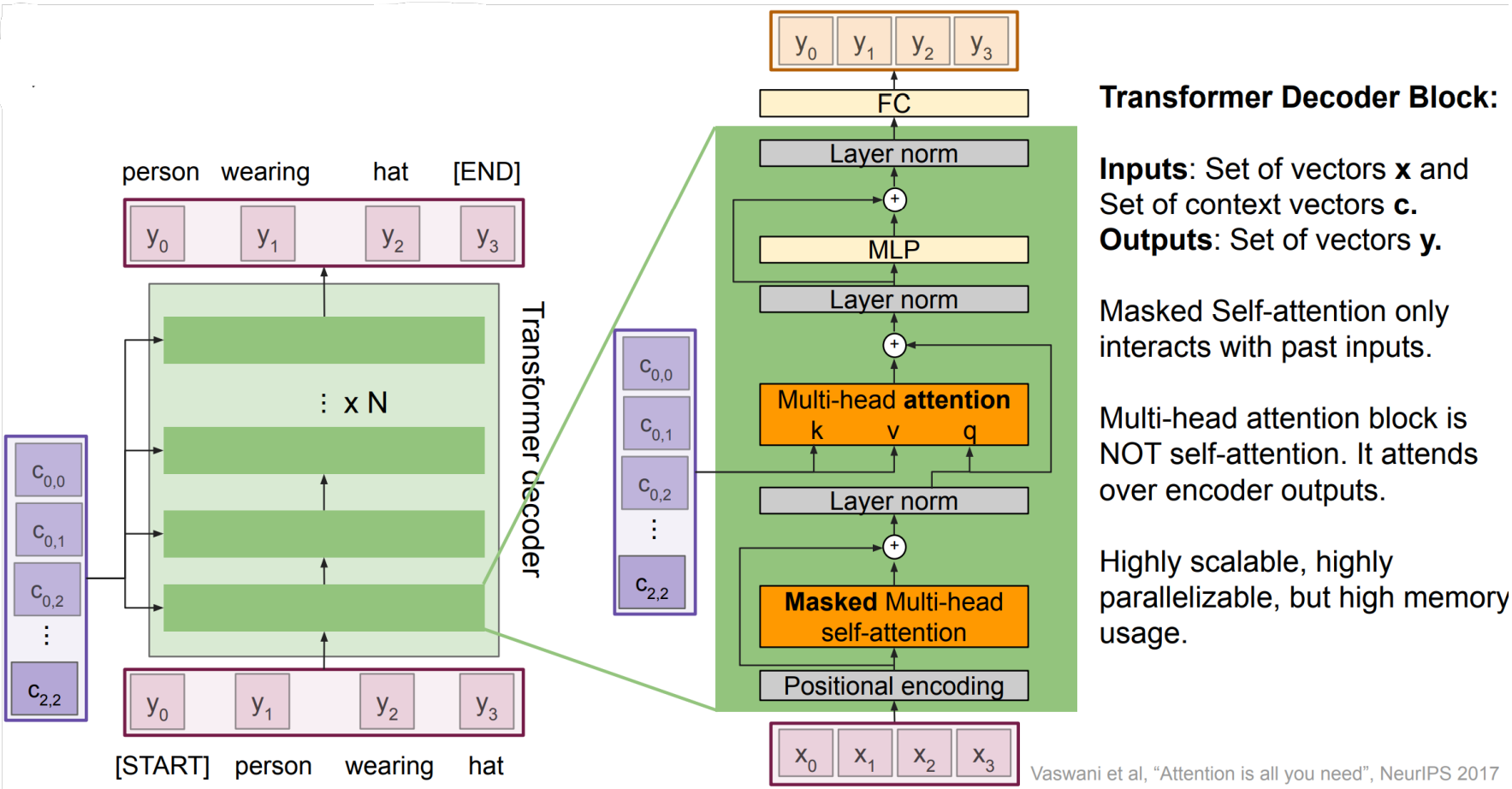
Self-attention is the only interaction between vectors.

Layer norm and MLP operate independently per vector.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, "Attention is all you need", NeurIPS 2017

The Transformer decoder block



Transformer Decoder Block:

Inputs: Set of vectors **x** and Set of context vectors **c.**
Outputs: Set of vectors **y.**

Masked Self-attention only interacts with past inputs.

Multi-head attention block is NOT self-attention. It attends over encoder outputs.

Highly scalable, highly parallelizable, but high memory usage.

Vaswani et al, "Attention is all you need", NeurIPS 2017

Image captioning using ONLY transformers

- Transformers from pixels to language