Machine Learning to Language Model

Topic 01 - Introduction to Machine Learning

Jaihua Yen

https://jaihuayen.github.io/homeweb/

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- Al Models
- Gradient Descent
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- Wrap Up



ARTIFICIAL INTELLIGENCE

A program that can sense, reason, act, and adapt.



MACHINE LEARNING

Algorithms whose performance improve as they are exposed to more data over time.



DEEP LEARNING

Subset of machine learning in which multilayered neural networks learn from vast amount of data.

https://www.globaltechcouncil.org/artificial-intelligence/clearing-the-confusion-ai-vs-machine-learning-vs-deep-learning/

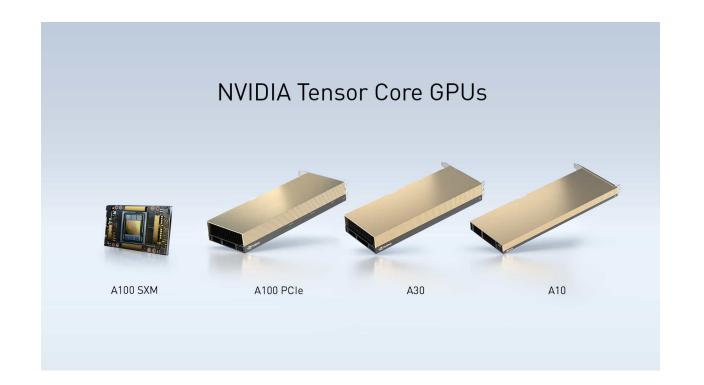
The Era of Al

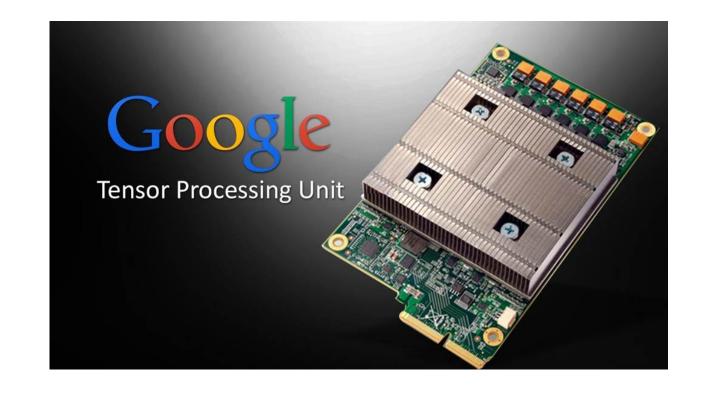
Al could finally be introduced into practice in general tasks!

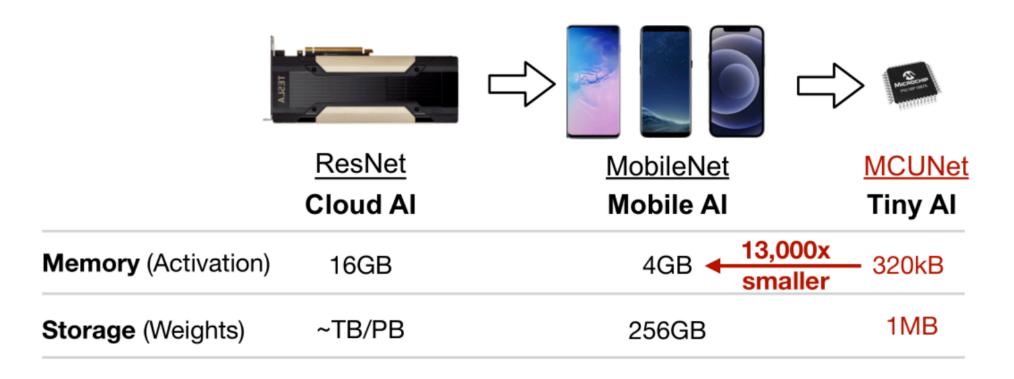
- Tremendous improvement in computational resources.
- Enhancement of model architecture for model efficiency.
- Release open-source large pre-trained general models.
- Development of novel model training algorithms.



O PyTorch 2.0

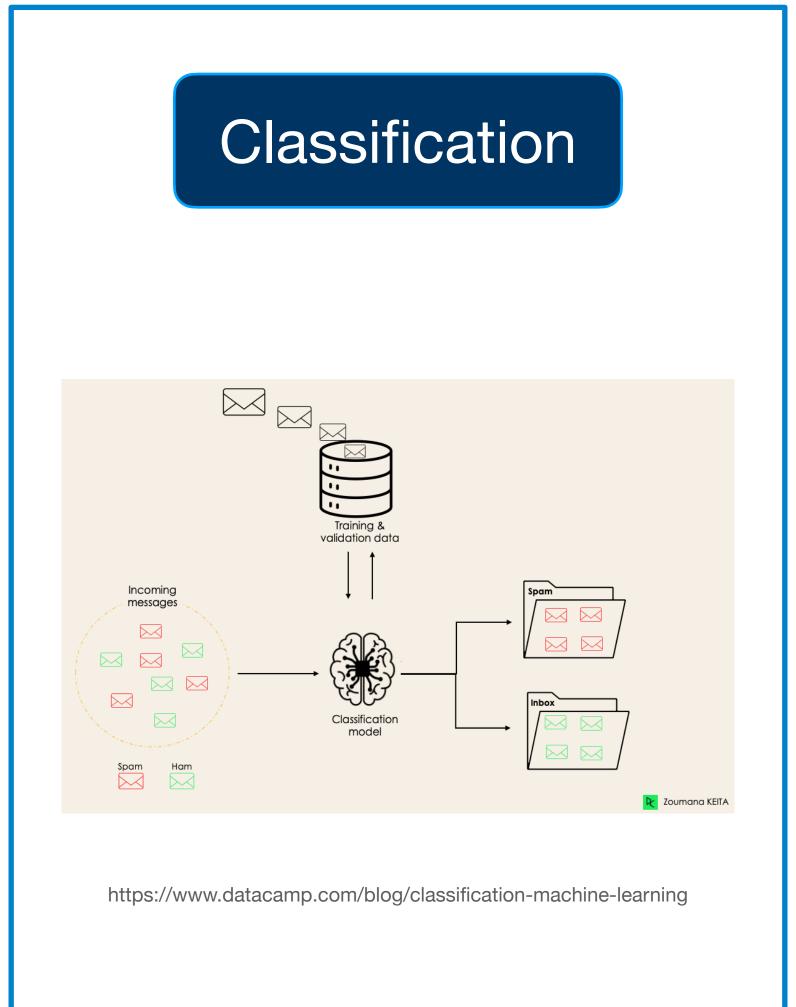


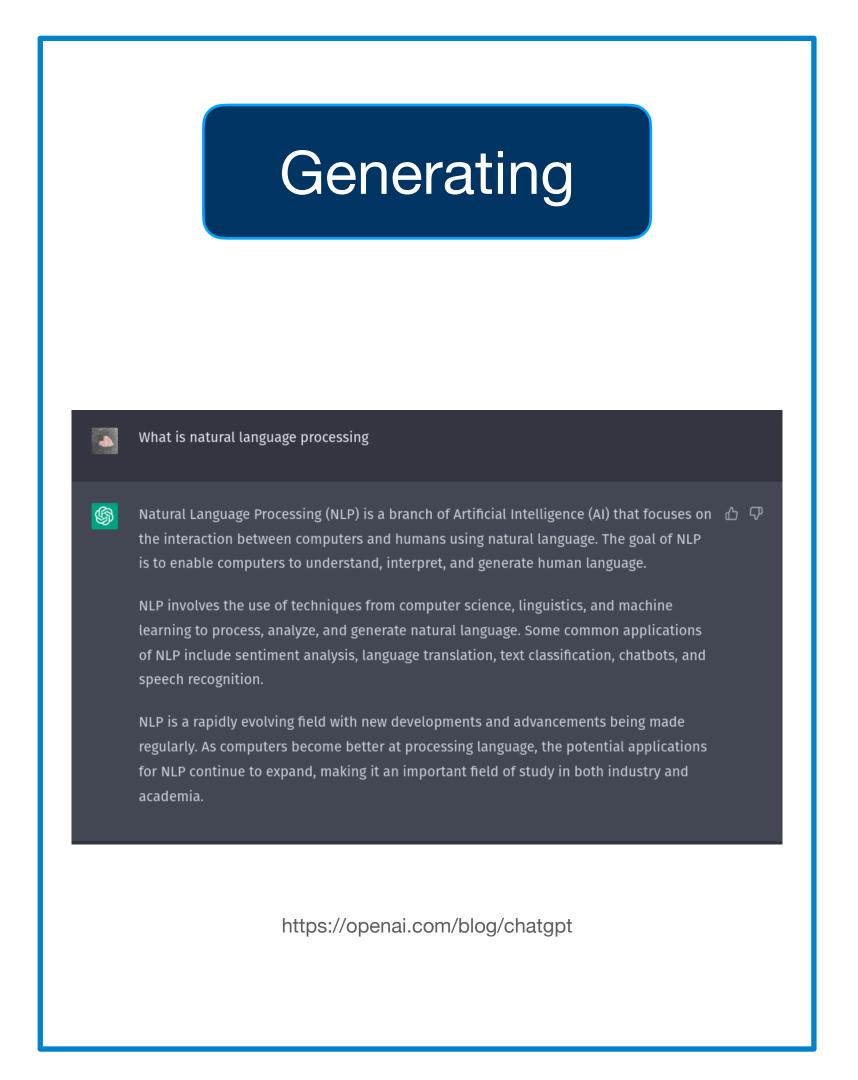




Al models could be used in these tasks:







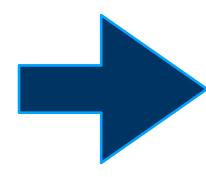
Al models are functions!





The image of dog.

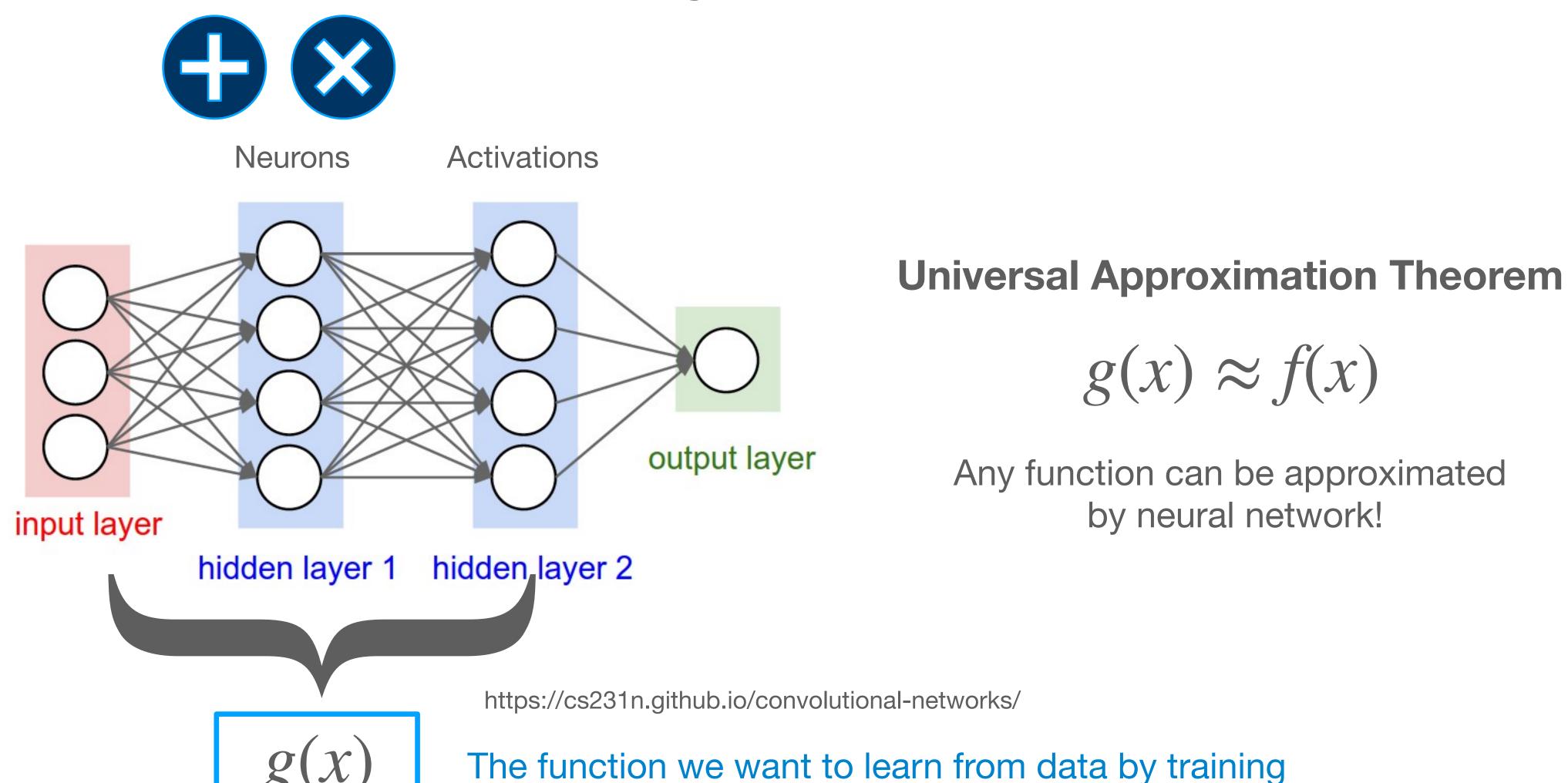
Hello





Translate "你好" in English.

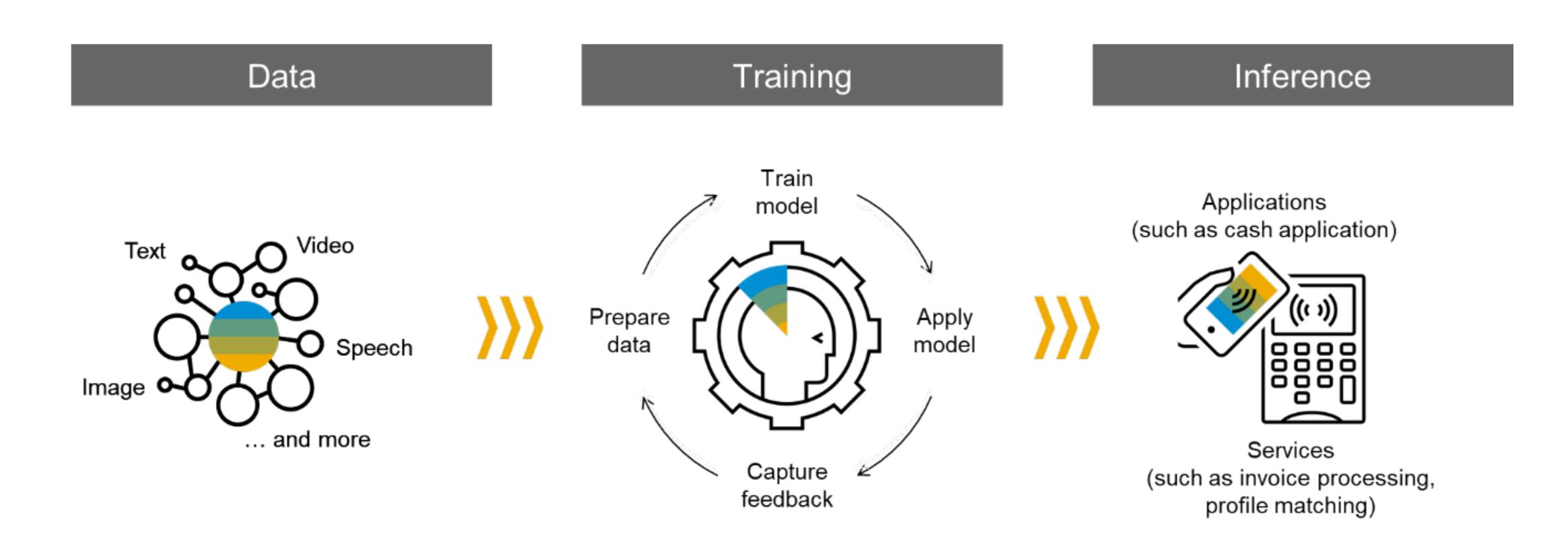
Al models are functions built by <u>neural networks</u>



How to Train Al Models?

Machine Learning

Mathematical Fundations of Model Training

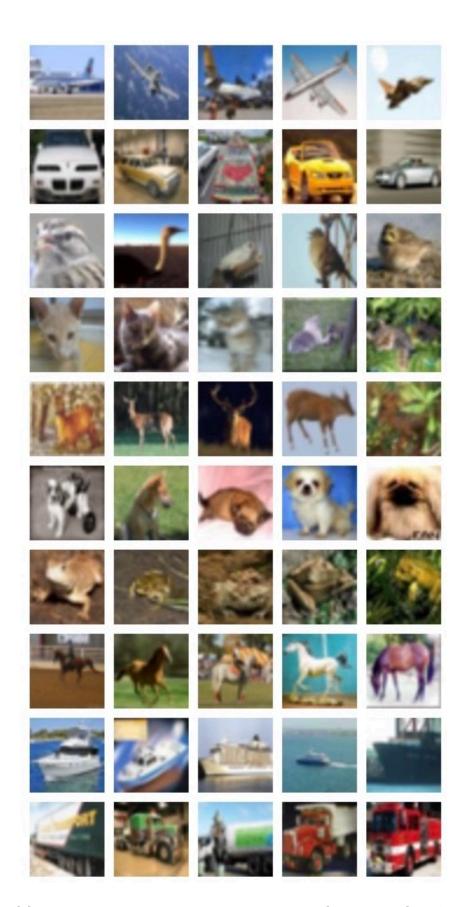


https://blogs.sap.com/2019/04/05/machine-learning-in-sap-strategy/

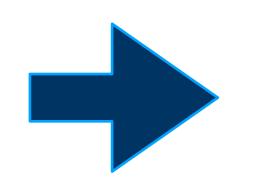
Training Dataset

Given datasets and tags to train Al model.

X









airplane

automobile

bird

cat

deer

dog

frog

horse

ship

truck

Model Training

Cannot perfectly predict the true label in the first time

x g(x) \hat{y} \longleftrightarrow y automobile ship

We want to improve the model output in order to have better performance!

The difference between the true label and predicted label

Loss Function

Measurement of model performance

The difference between the true label and predicted label





y

automobile







 $[0,0.4,0,0,0,0,0,0,0,0,0,0] \quad [0,0,0,0,0,0,0,0,0,1,0]$

Loss function (Cross Entropy Loss)

$$L = -\sum_{i=1}^{n} y_i \log \hat{y}_i$$

$$y_i = 1$$
 The higher the predicted probability the lower the loss you will get

$$y_i = 0$$
 The whole term will be 0 so it doesn't matter

Loss Function

Measurement of model performance

The difference between the true label and predicted label





y

automobile







 $[0,0.4,0,0,0,0,0,0,0,0,0] \quad [0,0,0,0,0,0,0,0,0,1,0]$

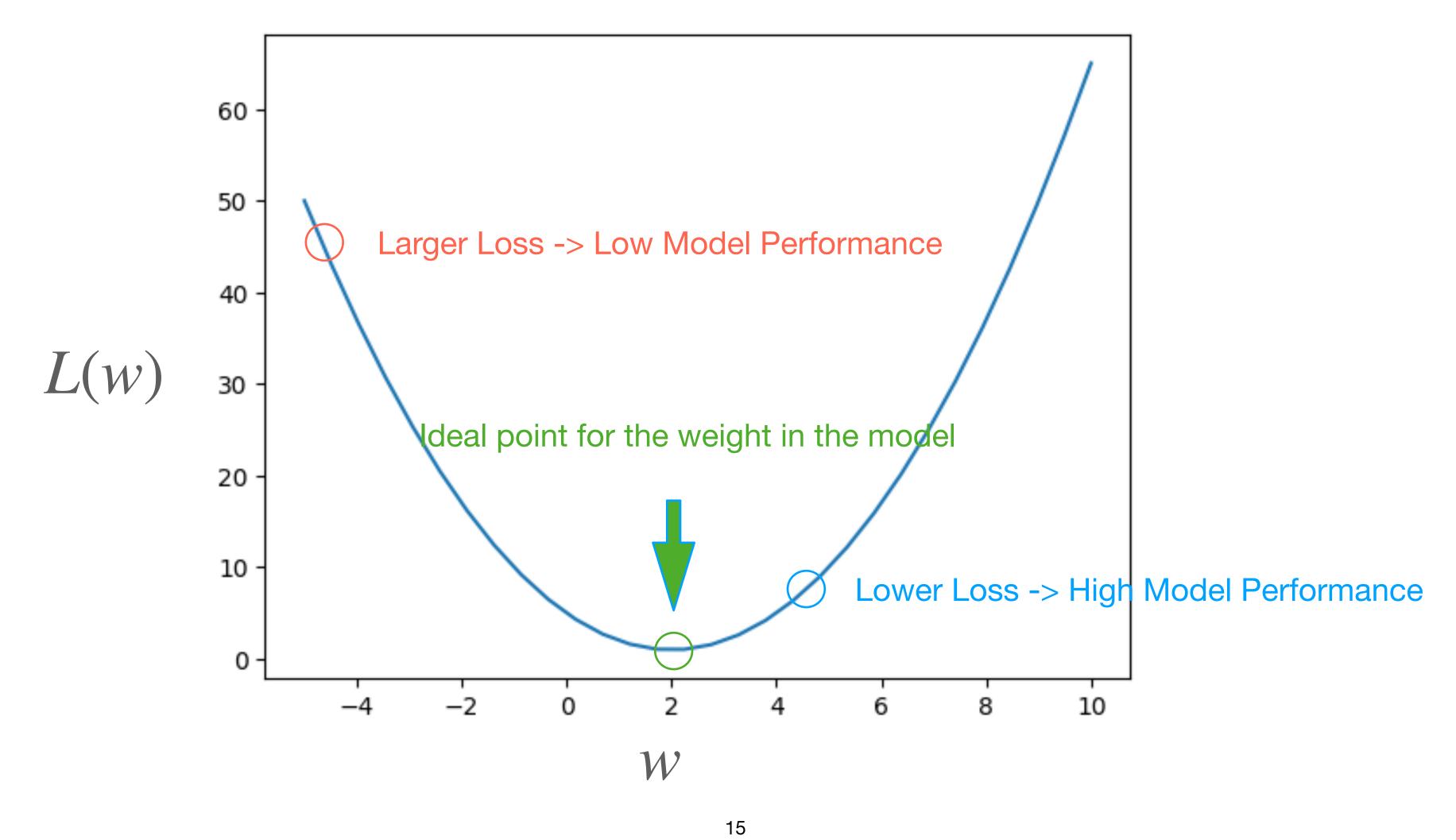
Loss function (Cross Entropy Loss)

$$L = -\sum_{i=1}^{n} y_i \log \hat{y}_i$$
$$= -\sum_{i=1}^{n} y_i \log g(x_i)$$

$$L(w) \triangleq -\sum_{i=1}^{\infty} y_i \log(wx_i)$$

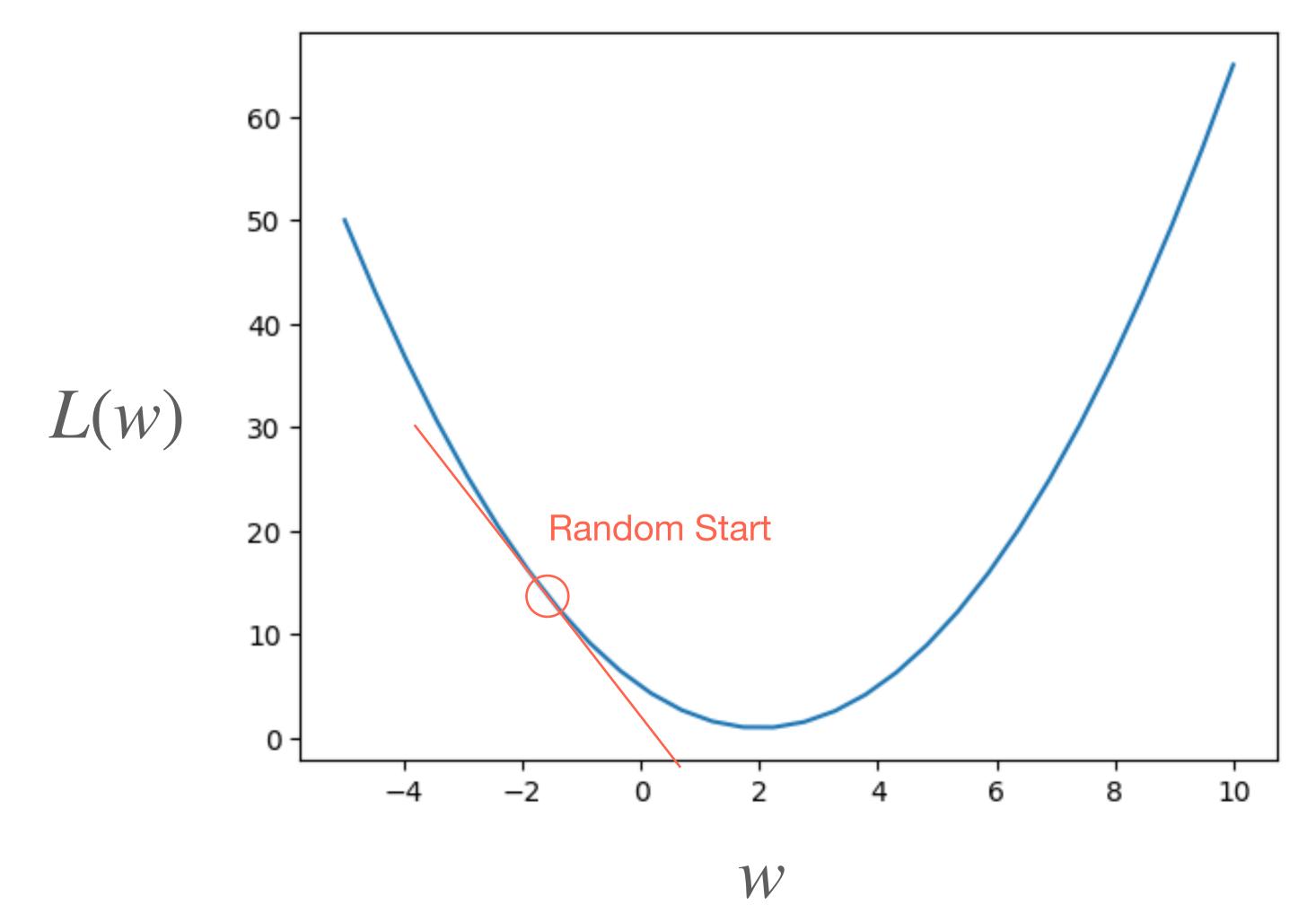
Loss Function

Measurement of model performance



Training Procedure

Start for Random Initialization of Weight



Intuition:

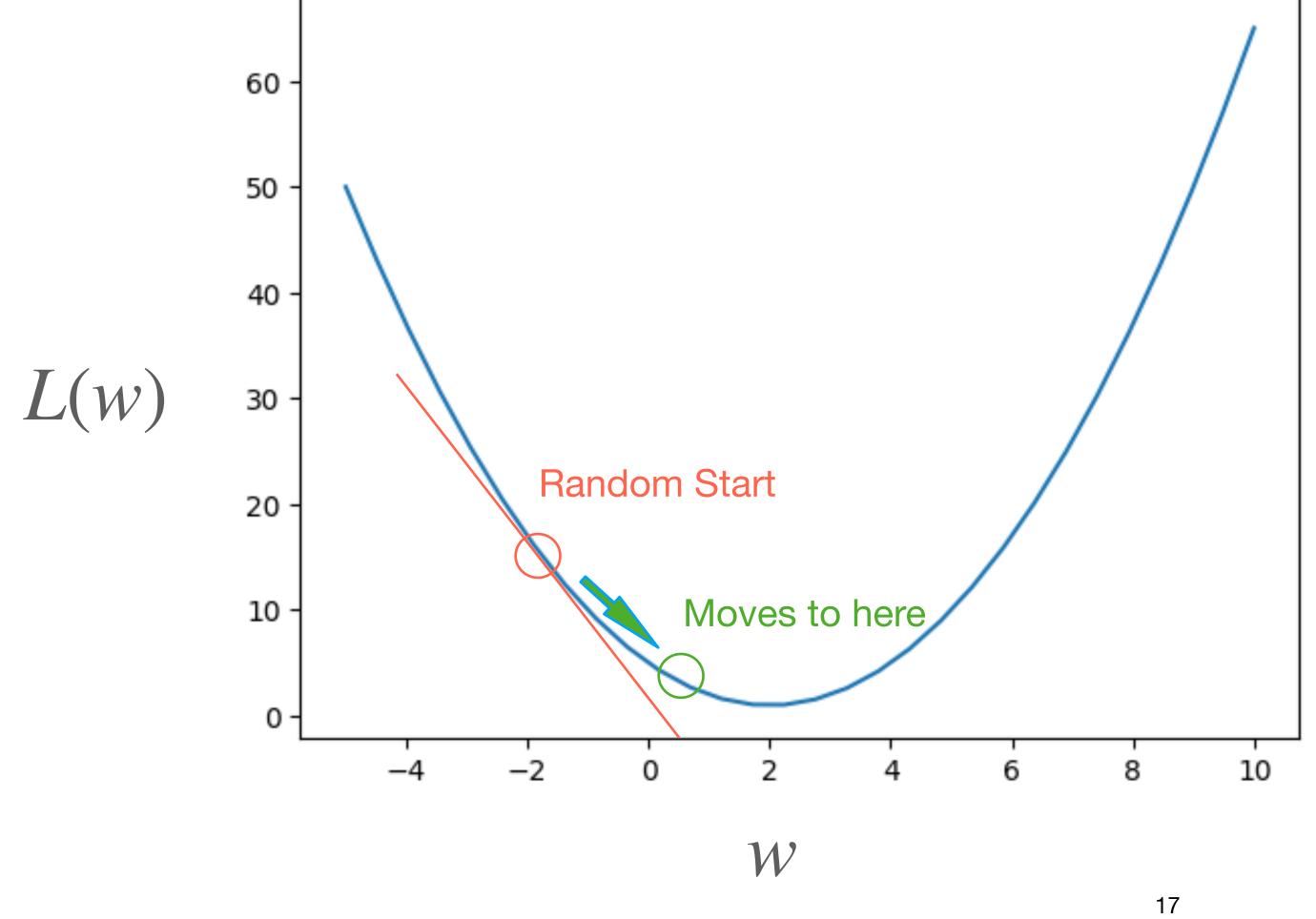
Walk to the lower point of the loss function

In mathematical language: Find the direction where the loss will decrease i.e. Slope < 0

$$Slope = \frac{L(w+h) - L(w)}{h}$$

$$\frac{dL}{dw} = \lim_{h \to 0} \frac{L(w+h) - L(w)}{h}$$

A Approach to lower the function value



learning rate
$$w_t = w_{t-1} - r \frac{dL}{dw_{t-1}}$$

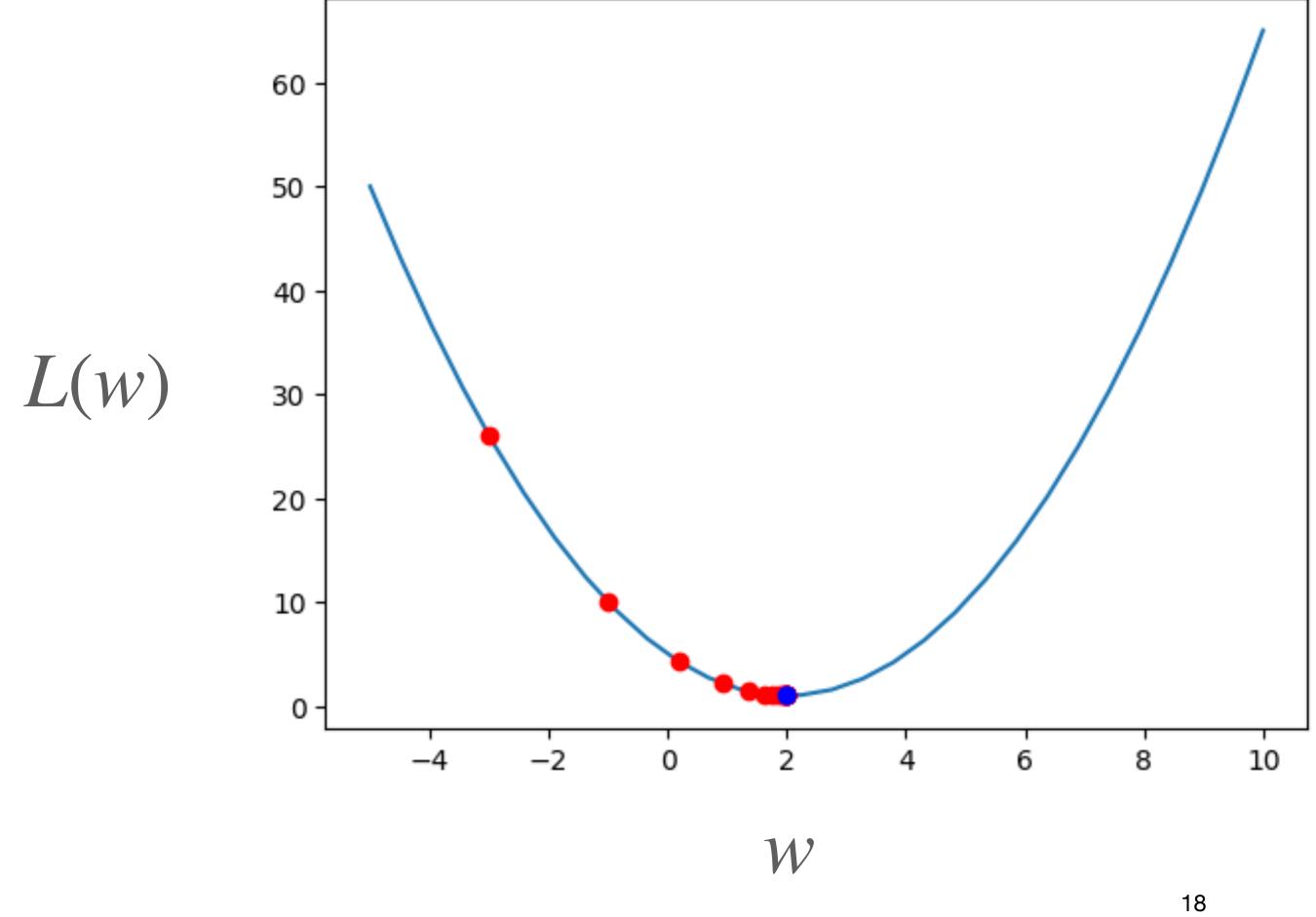
If < 0, this term will be < 0 and w increases If > 0, this term will be > 0 and w decreases

The procedure continues until some given threshold

$$|L(w_t) - L(w_{t-1})| < \epsilon$$

or given update steps t

A Approach to lower the function value



learning rate
$$w_t = w_{t-1} - r$$

$$\frac{dL}{dw_{t-1}}$$

If < 0, this term will be < 0 and w increases If > 0, this term will be > 0 and w decreases

The procedure continues until some given threshold

$$|L(w_t) - L(w_{t-1})| < \epsilon$$

or given update steps t

A High-Dimension Overview

L(x, y, z)2.00 1.75 1.50 1.25 Z 1.00 0.75 0.50 0.25 0.00 1.00 0.75 0.50 0.25 0.00 -0.25 -0.50 -0.75 -1.00 1.00 Update the three parameters at the same time!

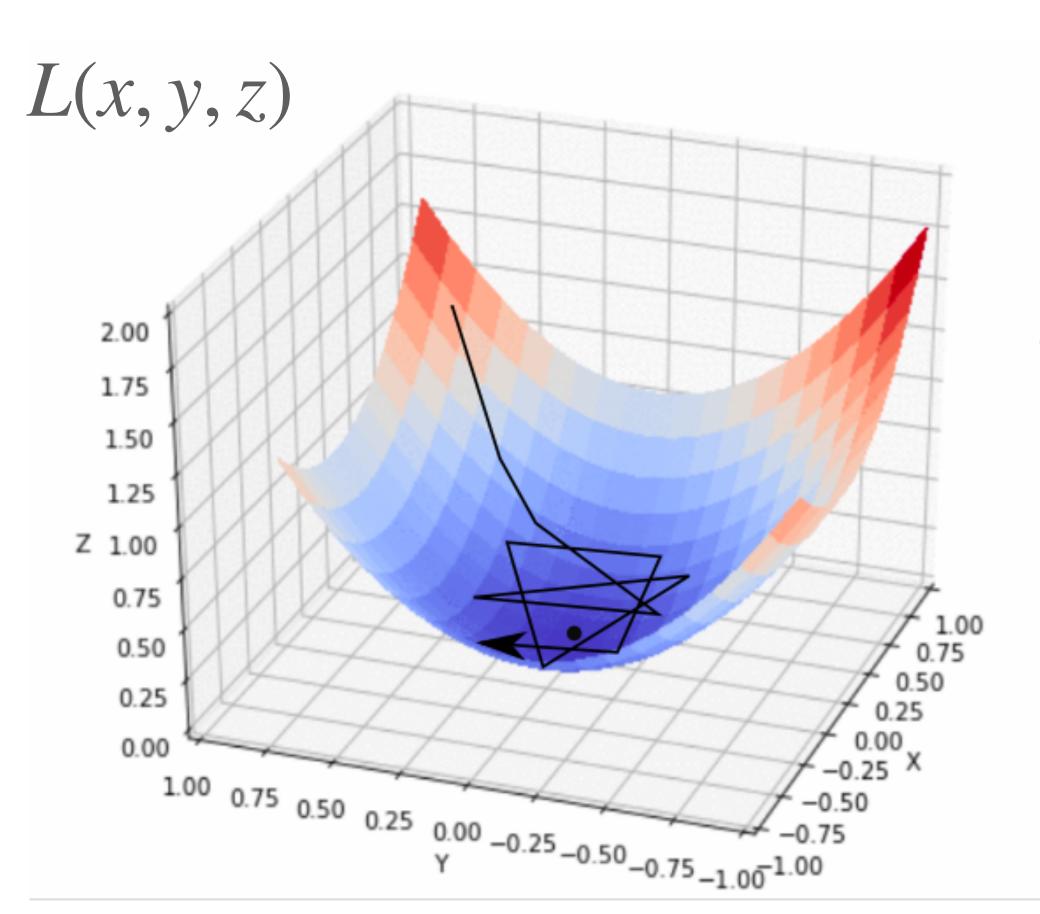
$$x_{t} = x_{t-1} - r \frac{\partial L(x, y, z)}{\partial x_{t-1}}$$

$$y_t = y_{t-1} - r \frac{\partial L(x, y, z)}{\partial y_{t-1}}$$

$$z_{t} = z_{t-1} - r \frac{\partial L(x, y, z)}{\partial z_{t-1}}$$

https://blog.paperspace.com/intro-to-optimization-in-deep-learning-gradient-descent/

A High-Dimension Overview



$$\boldsymbol{w} = [x, y, z]$$

$$w_t = w_{t-1} - n\nabla L(x, y, z)$$

This is called gradient, which makes this method called gradient descent!

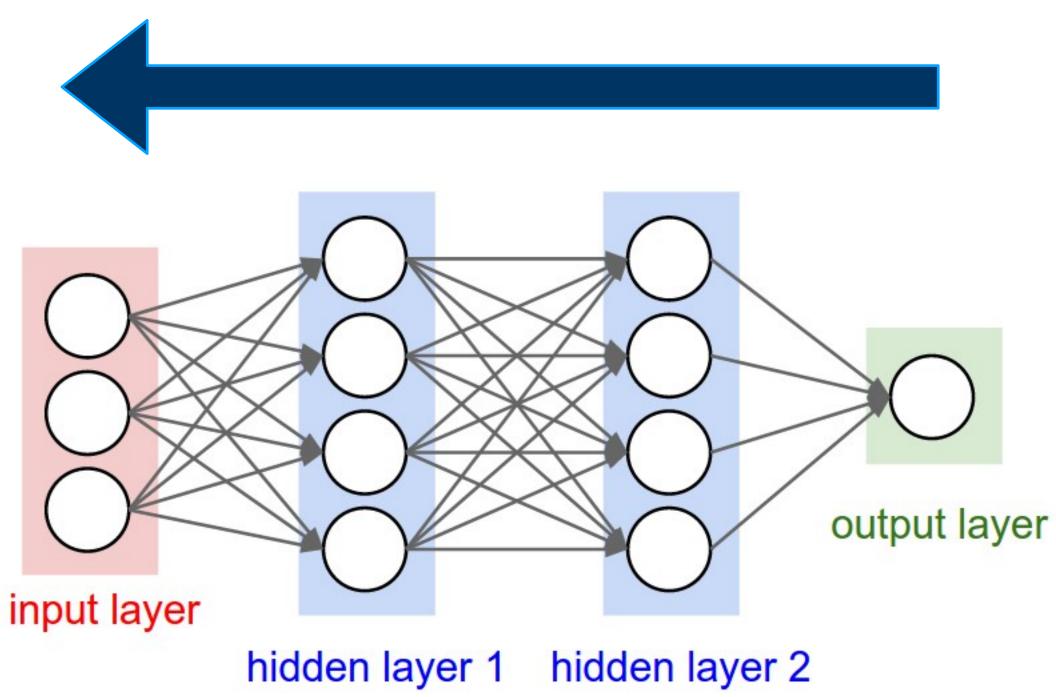
$$\begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix} = \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ z_{t-1} \end{bmatrix} - r \begin{bmatrix} \frac{\partial L}{x_{t-1}} \\ \frac{\partial L}{y_{t-1}} \\ \frac{\partial L}{z_{t-1}} \end{bmatrix}$$

https://blog.paperspace.com/intro-to-optimization-in-deep-learning-gradient-descent/

Backpropogation

A High-Dimension Overview

Use loss to update the weights in backward order



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

$$\boldsymbol{w} = [x, y, z]$$

$$w_t = w_{t-1} - r \nabla L(x, y, z)$$

$$\begin{bmatrix} x_t \\ y_t \\ z_t \end{bmatrix} = \begin{bmatrix} x_{t-1} \\ y_{t-1} \\ z_{t-1} \end{bmatrix} - r \begin{bmatrix} \frac{\partial L}{x_{t-1}} \\ \frac{\partial L}{y_{t-1}} \\ \frac{\partial L}{z_{t-1}} \end{bmatrix}$$

Let's do this in Colab!

Demo

A Very Simple Language Model

- We only predict the next word based on the previous word.
- · Model the predicted probability of a certain word based on a given word.

$$P(c_i | c_{i-1})$$

 c_i is the word in the i position.

- Here we give an example of a sentence:
- <s> Al could finally be introduced into practice in general tasks <e>

A Very Simple Language Model

<s> Al could finally be introduced into practice in general tasks <e>

$$c_{i-1}$$
 c_{i}

<S>

A Very Simple Language Model

<s> Al could finally be introduced into practice in general tasks <e>

 C_{i-1} C_i

Al could

A Very Simple Language Model

<s> Al could finally be introduced into practice in general tasks <e>

$$c_{i-1}$$
 c_i

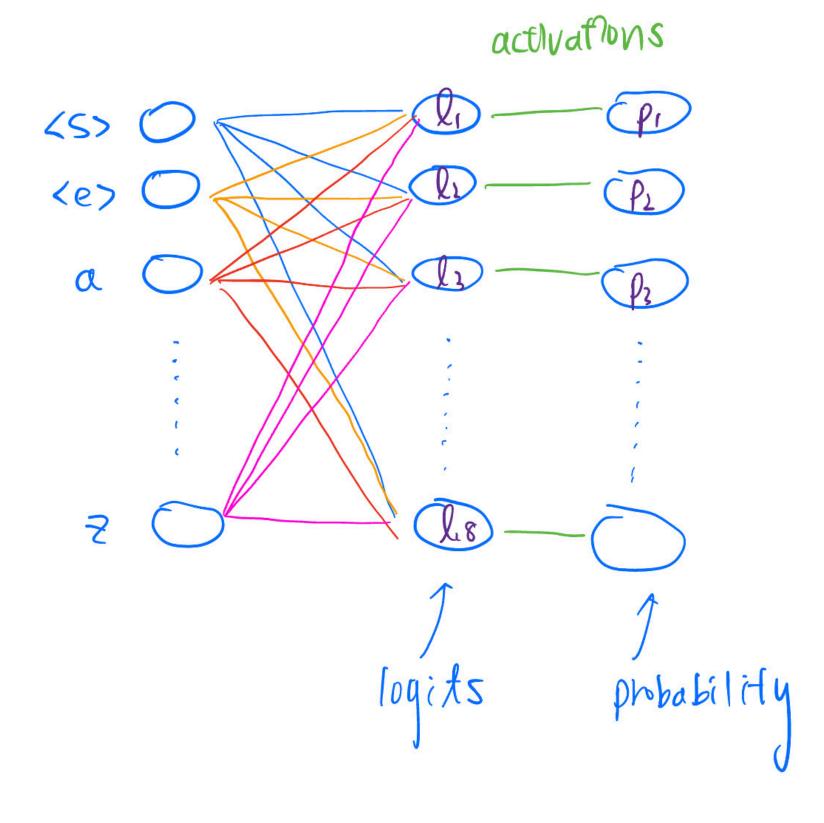
One-hot Encoding

A Very Simple Language Model

We want to train the following neural network

$$v_{\langle s\rangle} = \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$v_{\langle z\rangle} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 1 \end{bmatrix}$$



$$D_{i} = \frac{e^{li}}{\sum_{i=1}^{28} e^{li}}$$

Let's also do this in Colab!

Questions

- What if having too large/small learning rate (r)?
- What if we cannot cover all the cases so that some conditional probability is zero?
- What if we also consider the penalty of the loss of predicting the class that does not contain the ground truth label?

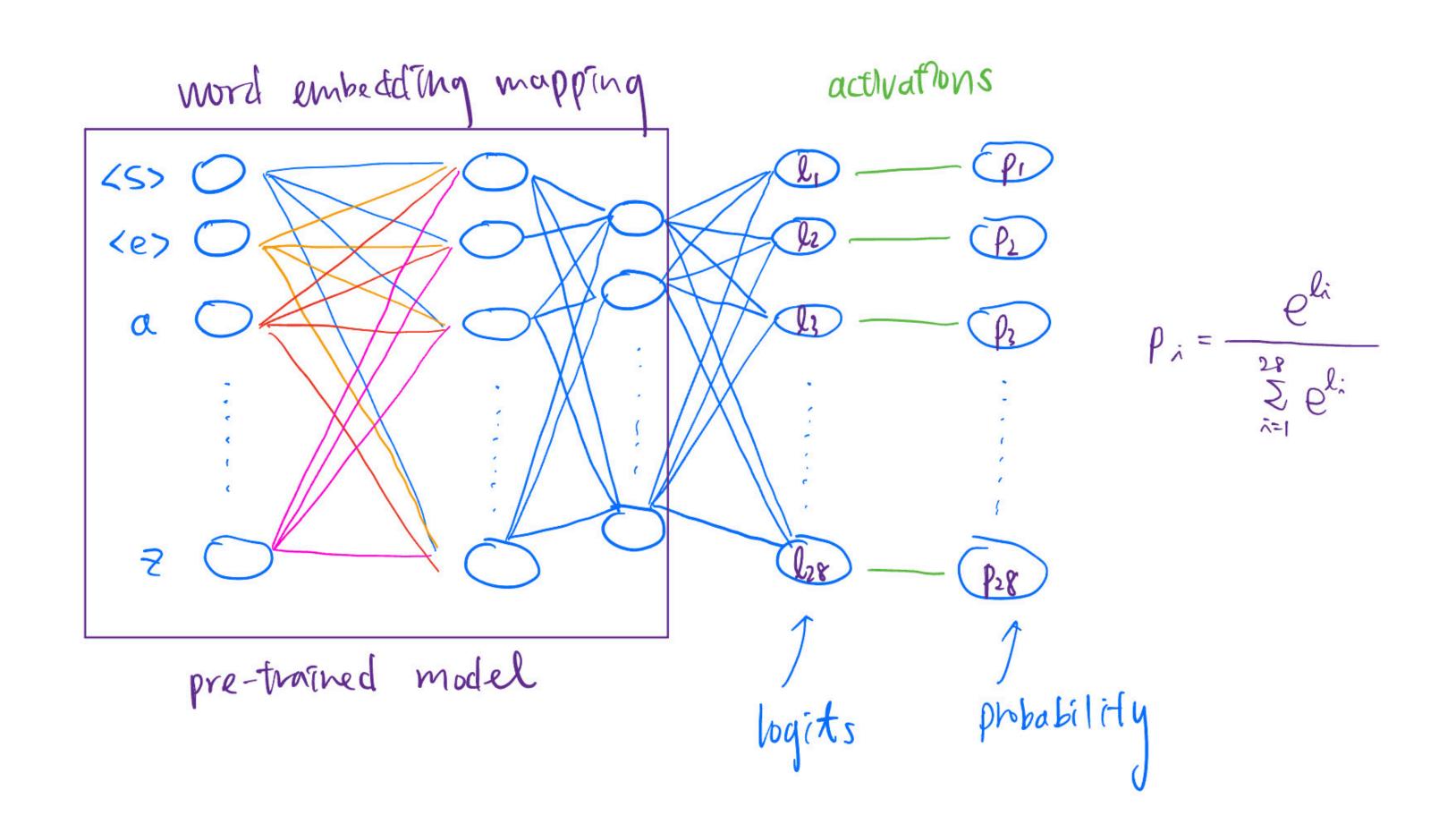
Wrap Up

What We Have Gone Through

- Applications in machine learning
- Training a machine learning model
- Gradient descent
- Bi-gram language model

What's Next

- Deep Neural Network
- Word Embedding
- Transfer Learning



Q&A