Introduction to Deep Learning*

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University of Texas at Dallas
Apr 8th, 2019

*This slide is a reconsolidating of materials from the following courses:
MIT 6.S191: Introduction to Deep Learning: introtodeeplearning.com
Stanford CS230: Deep Learning: http://cs230.stanford.edu/

Outline

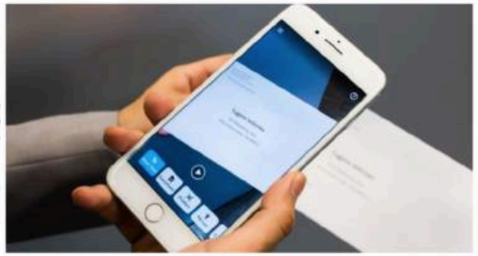
- Motivations of Deep Learning
- Perceptrons and Neural Networks
- Deep Learning in CV
  - CNN
  - GAN
- Deep Learning in NLP
  - RNN

The Rise of Deep Learning

'Deep Voice' Software Can Clone Anyone's Voice With Just 3.7 Seconds of Audio

Using snippets of voices, Baidu's 'Deep Voice' can generate new speech, accents, and tones.

Let There Be Sight: How Deep Learning Is Helping the Blind 'See'



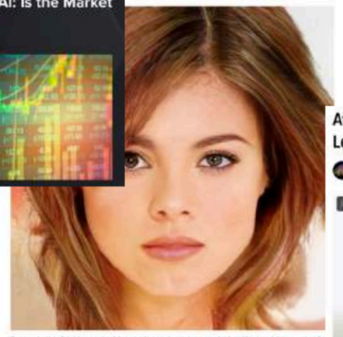
AI Can Help In Predicting Cryptocurrency Value

'Creative' AlphaZero leads way for chess computers and, maybe, science

Former chess world champion Garry Kasparov likes what he sees of computer that could be used to find cures for diseases

How an A.I. 'Cat-and-Mouse Game' Generates Believable Fake Photos

By CADE METZ and KEITH COLLINS JAN. 2, 2018



Stock Predictions Based On AI: Is the Market Truly Predictable?

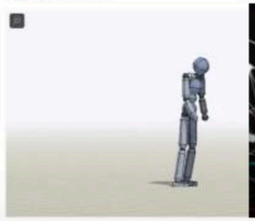
Complex of bacteria-infecting viral proteins modeled in CASP 13. The complex cont that were modeled individually. PROTEIN DATA BANK

Google's DeepMind aces protein folding

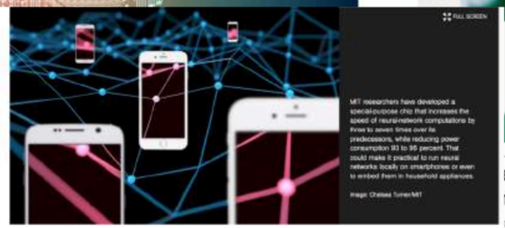
By Robert F. Service | Dec. 6, 2018 , 12:05 PM

To create the final image in this set, the system generated 10 million revisions over 18 days.

After Millions of Trials, These Simulated Humans Learned to Do Perfect Backflips and Cartwheels



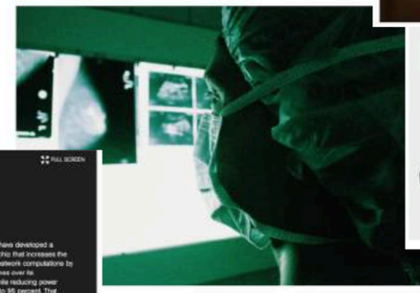
Researchers introduce a deep learning method that converts mono audio recordings into 3D sounds using video scenes

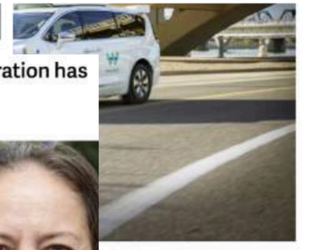


Neural networks everywhere

New chip reduces neural networks' power consumption by up to 95 percent, making them practical for battery-powered devices.

Wed, 01/16/2019 - 8:00am 1 Comment by Kenny Walter - Digital Reporter - @RandDMagazine





e faces show how far AI image generation has nced in just four years

ple on the right aren't real; they're the product of machine learning

Automation And Algorithms: De-Risking Manufacturing With Artificial Intelligence

Sarah Goehrke Contributor

Manufacturing

I focus on the industrialization of additive manufacturing.

TWEET THIS

The two key applications of AI in manufacturing are pricing and manufacturability feedback

What is Deep Learning?

Artificial Intelligence

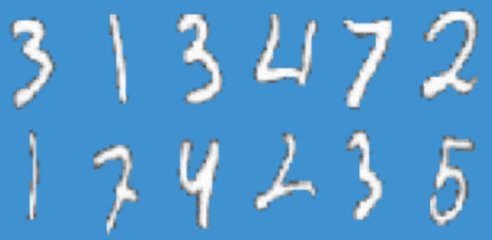
Any technique that enables computers to mimic human behavior

Machine Learning

Ability to learn without explicitly being programmed

Deep Learning

Extract patterns from data using neural networks

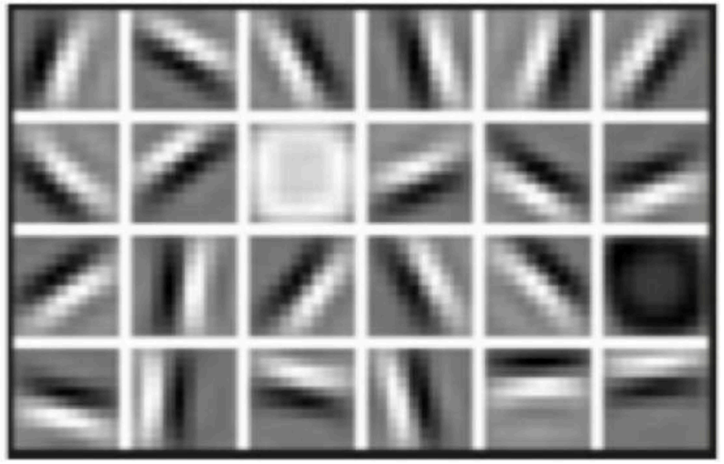


Why Deep Learning?

Hand engineered features are time consuming, brittle and not scalable in practice

Can we learn the **underlying features** directly from data?

Low Level Features



Lines & Edges

Mid Level Features

Eyes & Nose & Ears

High Level Features

Facial Structure

Why Now?

Neural Networks date back decades, so why the resurgence?

1952 Stochastic Gradient Descent

1958 Perceptron
- Learnable Weights

1986 Backpropagation
- Multi-Layer Perceptron

1995 Deep Convolutional NN
- Digit Recognition

1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET

WIKIPEDIA
The Free Encyclopedia

2. Hardware

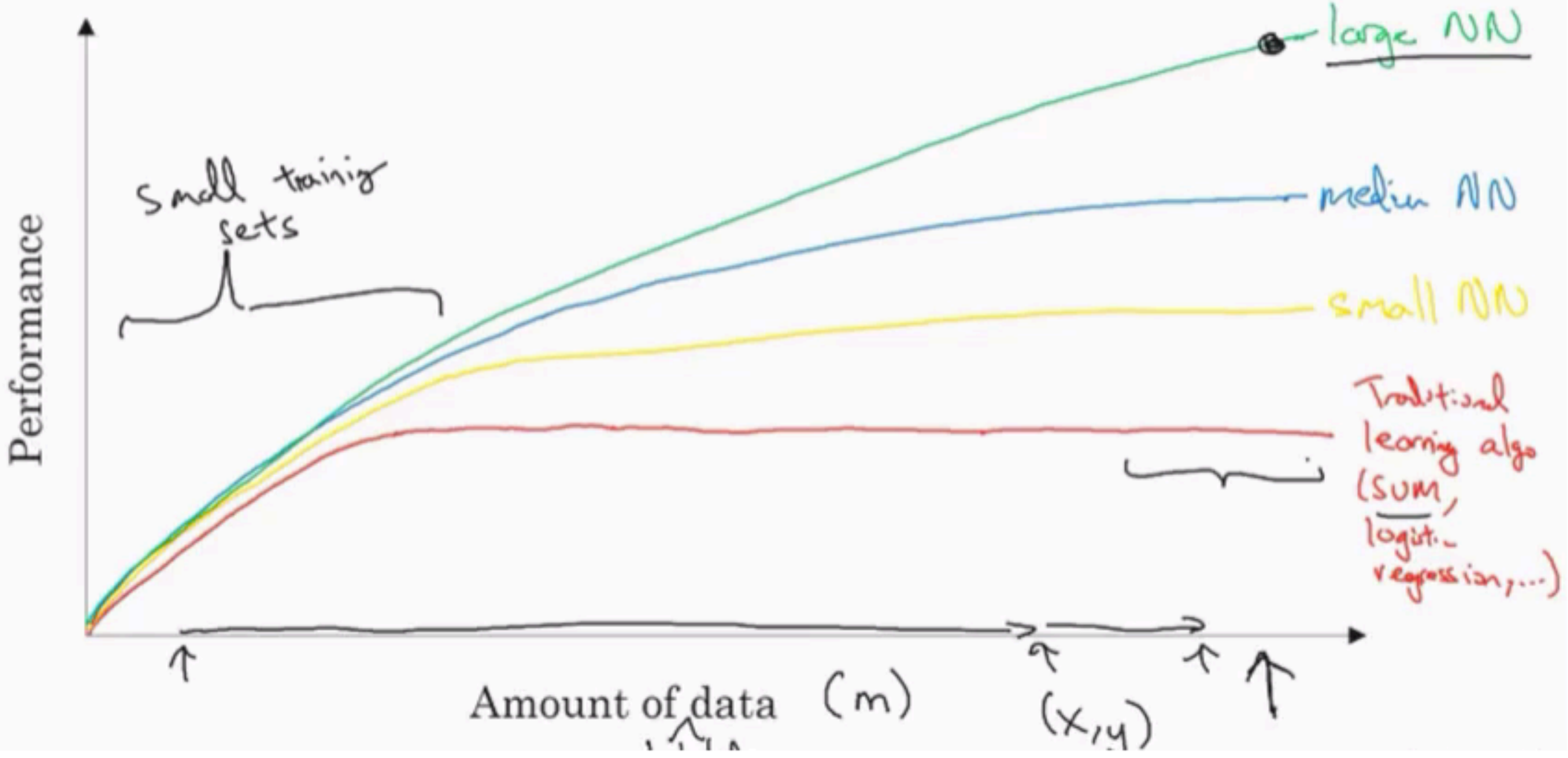
- Graphics Processing Units (GPUs)
- Massively Parallelizable

3. Software

- Improved Techniques
- New Models
- Toolboxes

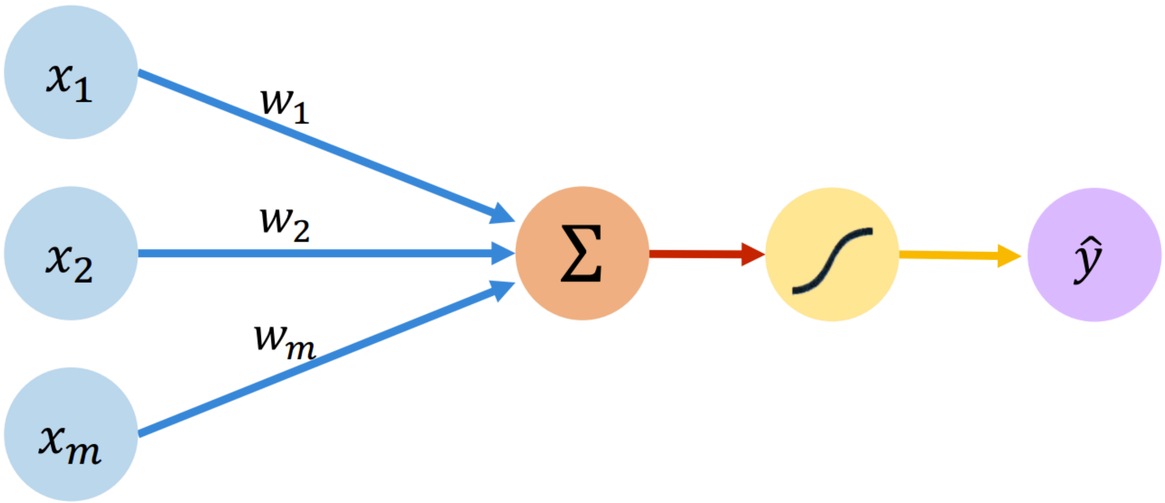
TensorFlow

Scale drives deep learning progress



The Perceptron: Forward Propagation

The structural building block of deep learning



Output

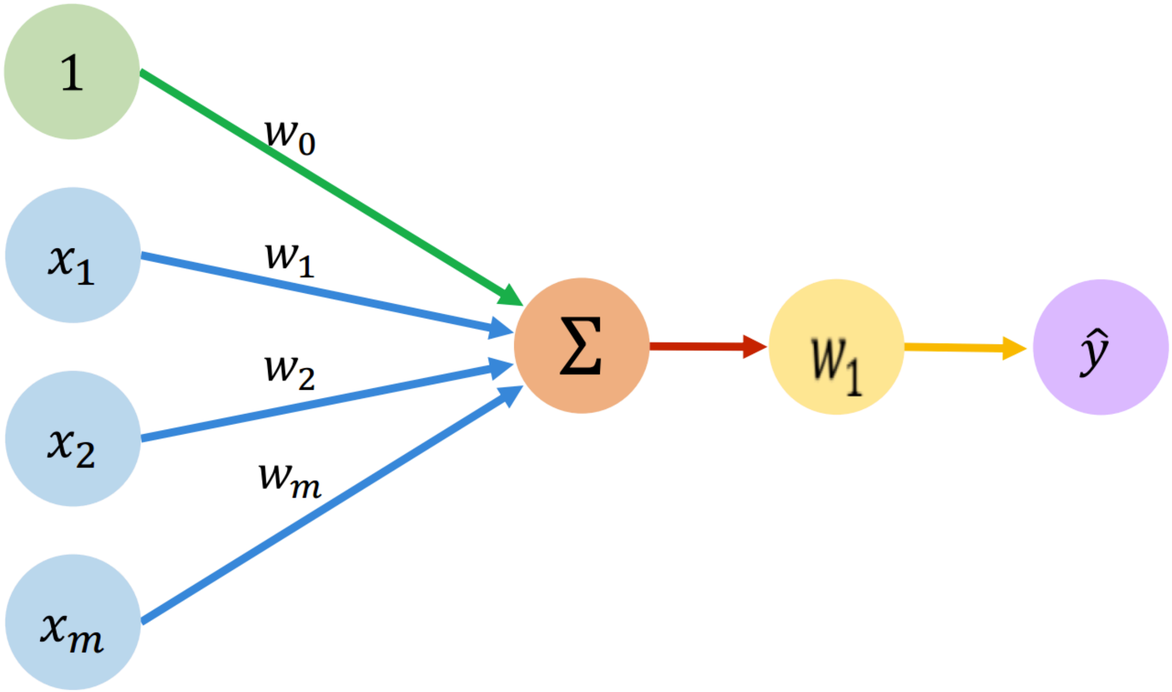
Linear combination of inputs

$$\hat{y} = g\left(\sum_{i=1}^{m} x_i \, w_i\right)$$

Non-linear activation function

Inputs Weights Sum Non-Linearity Output

The Perceptron: Forward Propagation



Inputs Weights Sum Non-Linearity Output

Output

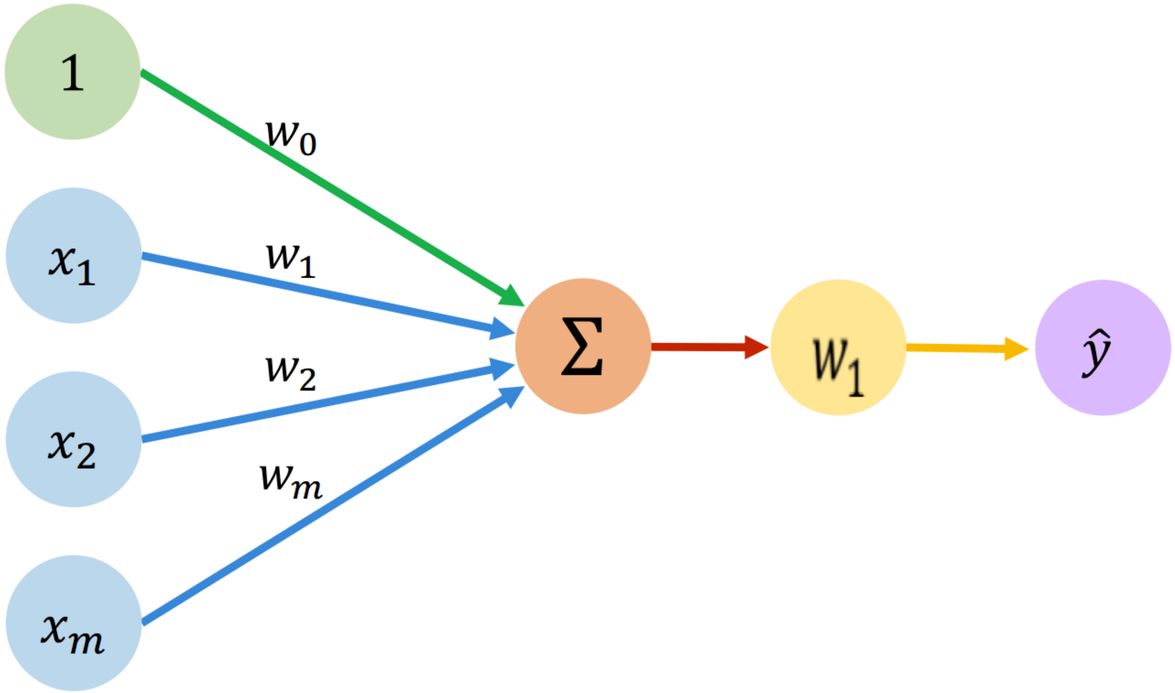
Linear combination of inputs

$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i \, w_i\right)$$

Non-linear activation function

Bias

The Perceptron: Forward Propagation



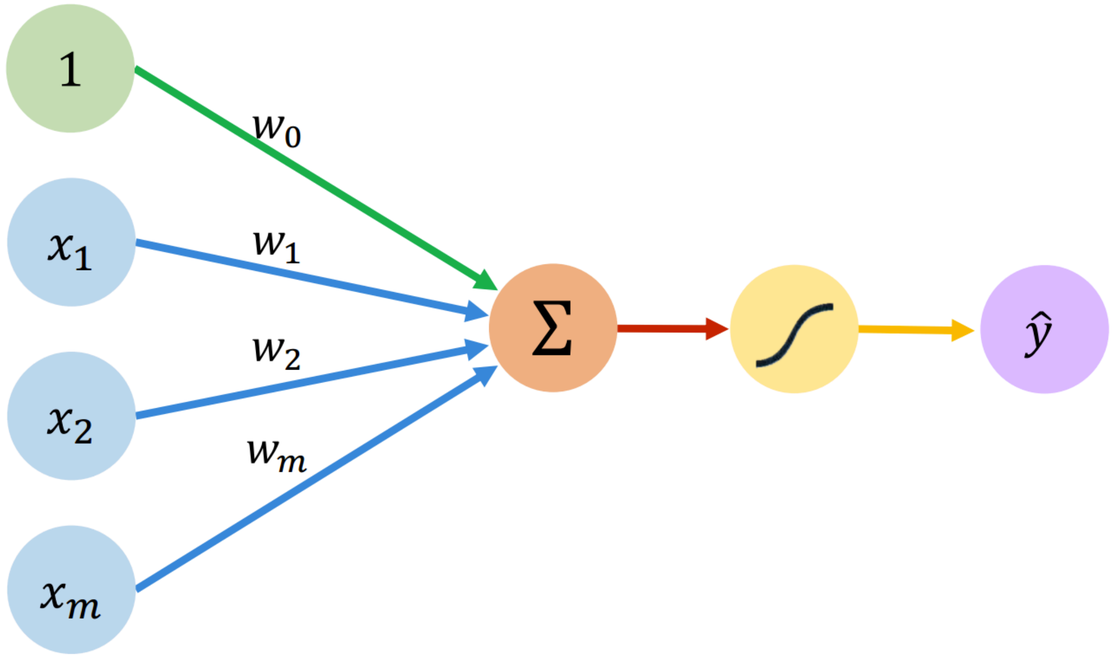
$$\hat{y} = g\left(w_0 + \sum_{i=1}^{m} x_i\, w_i\right)$$

$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W}\right)$$

where: $\boldsymbol{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$ and $\boldsymbol{W} = \begin{bmatrix} w_1 \\ \vdots \\ w_m \end{bmatrix}$

Inputs Weights Sum Non-Linearity Output

The Perceptron: Forward Propagation



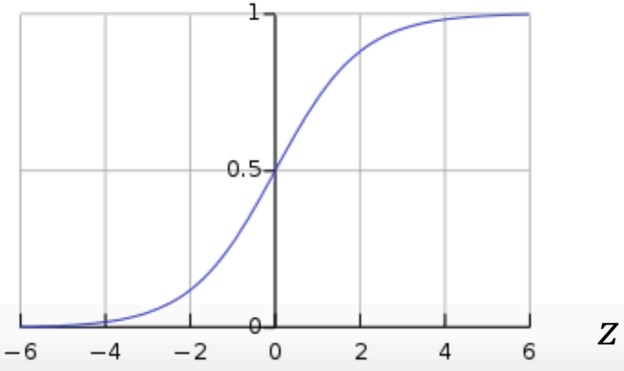
Inputs Weights Sum Non-Linearity Output

Activation Functions

$$\hat{y} = g\left(w_0 + \boldsymbol{X}^T \boldsymbol{W} \right)$$

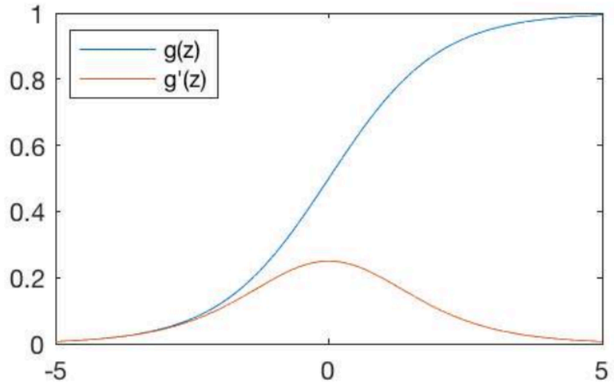
- Example: sigmoid function

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



Common Activation Functions

Sigmoid Function

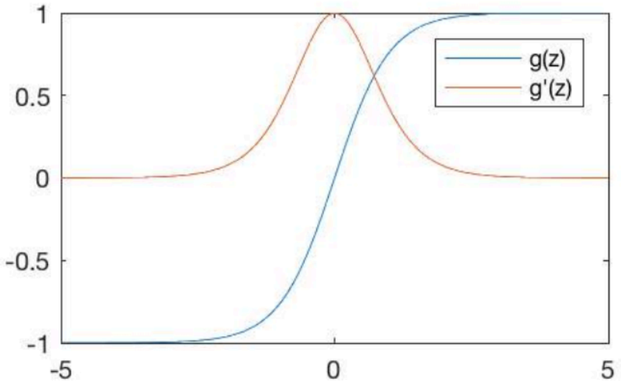


$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

`tf.nn.sigmoid(z)`

Hyperbolic Tangent

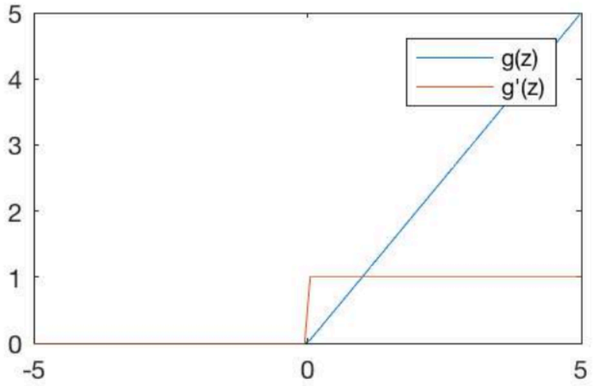


$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

`tf.nn.tanh(z)`

Rectified Linear Unit (ReLU)



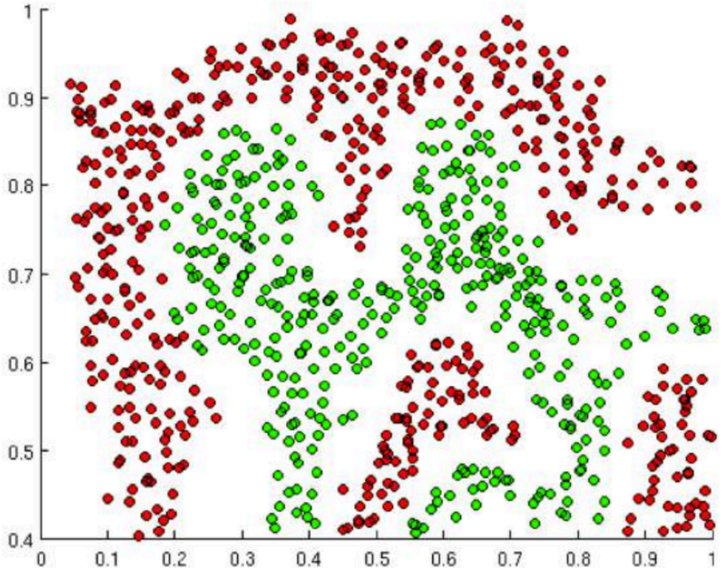
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

`tf.nn.relu(z)`

Importance of Activation Functions

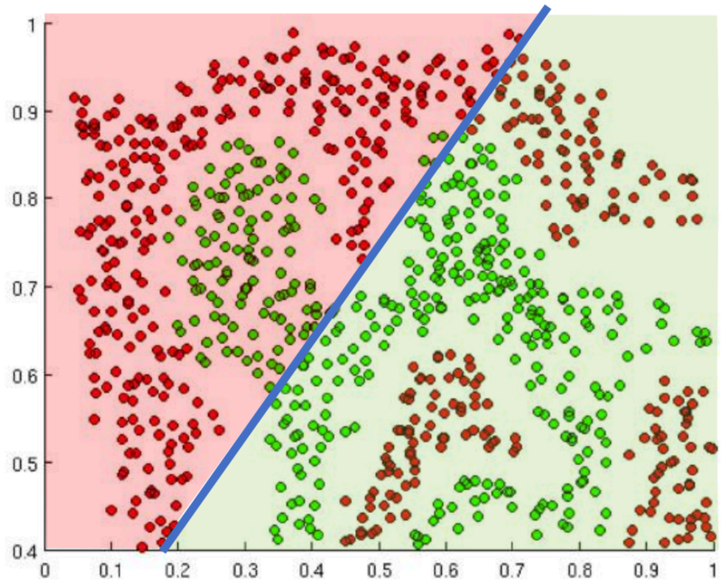
The purpose of activation functions is to ***introduce non-linearities*** *into the network*



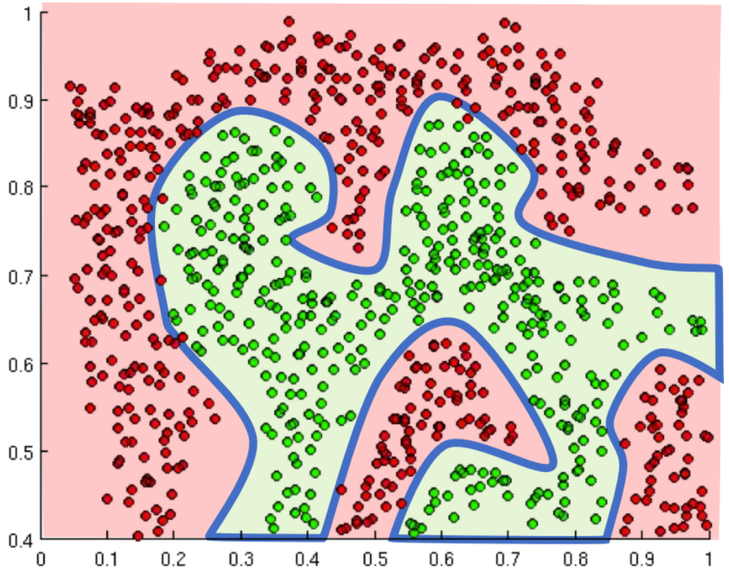
What if we wanted to build a Neural Network to distinguish green vs red points?

Importance of Activation Functions

*The purpose of activation functions is to **introduce non-linearities** into the network*

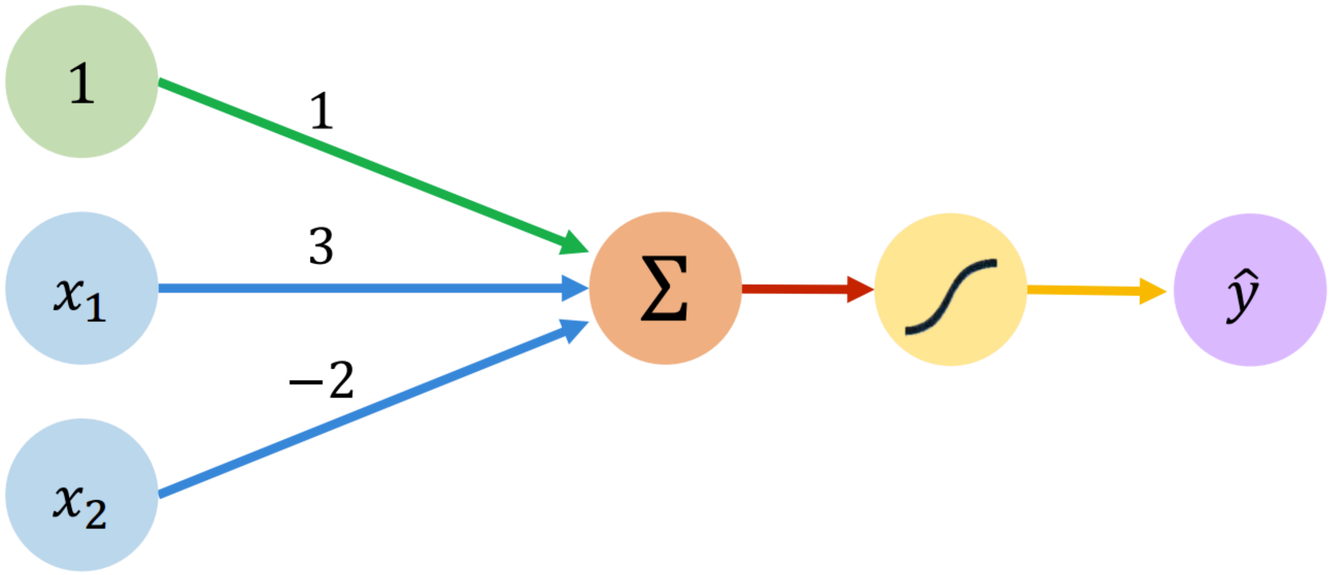


Linear Activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

The Perceptron: Example



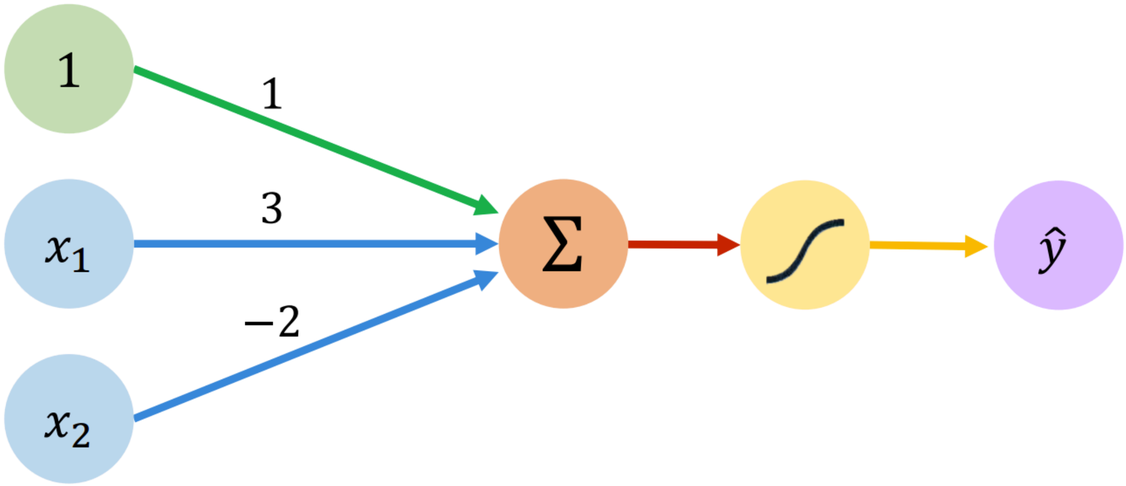
We have: $w_0 = 1$ and $\boldsymbol{W} = \begin{bmatrix} 3 \\ -2 \end{bmatrix}$

$$\hat{y} = g(w_0 + \boldsymbol{X}^T \boldsymbol{W})$$

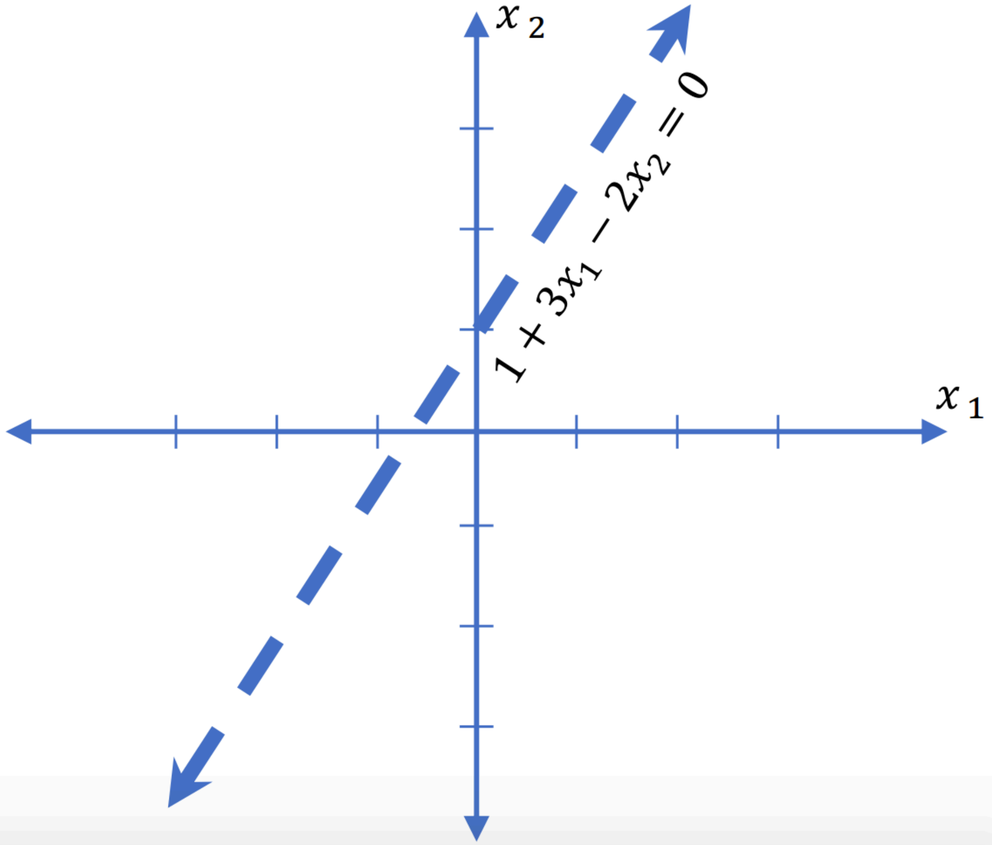
$$= g\left(1 + \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}^T \begin{bmatrix} 3 \\ -2 \end{bmatrix}\right)$$

$$\hat{y} = g(\underbrace{1 + 3x_1 - 2x_2}_{\text{This is just a line in 2D!}})$$

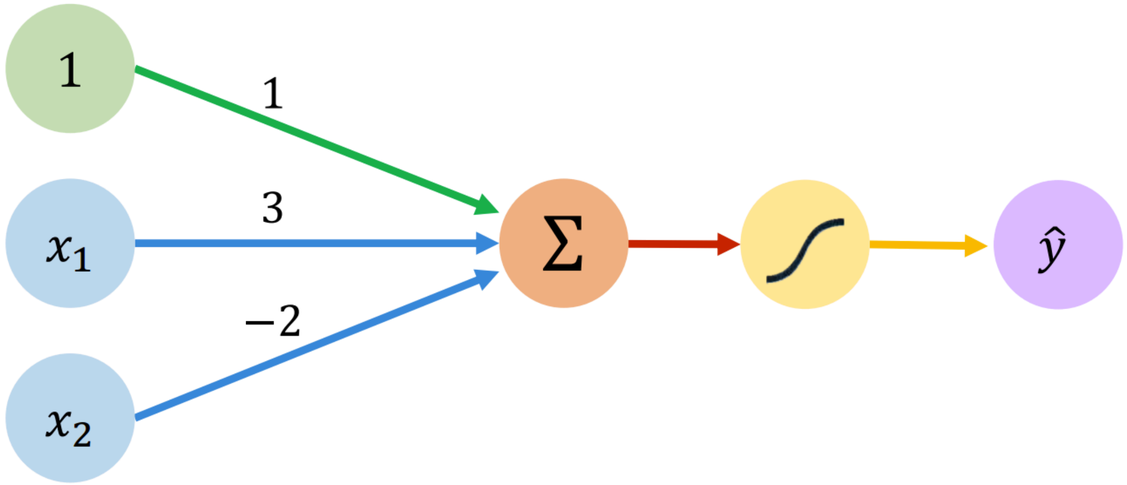
The Perceptron: Example



$$\hat{y} = g(1 + 3x_1 - 2x_2)$$



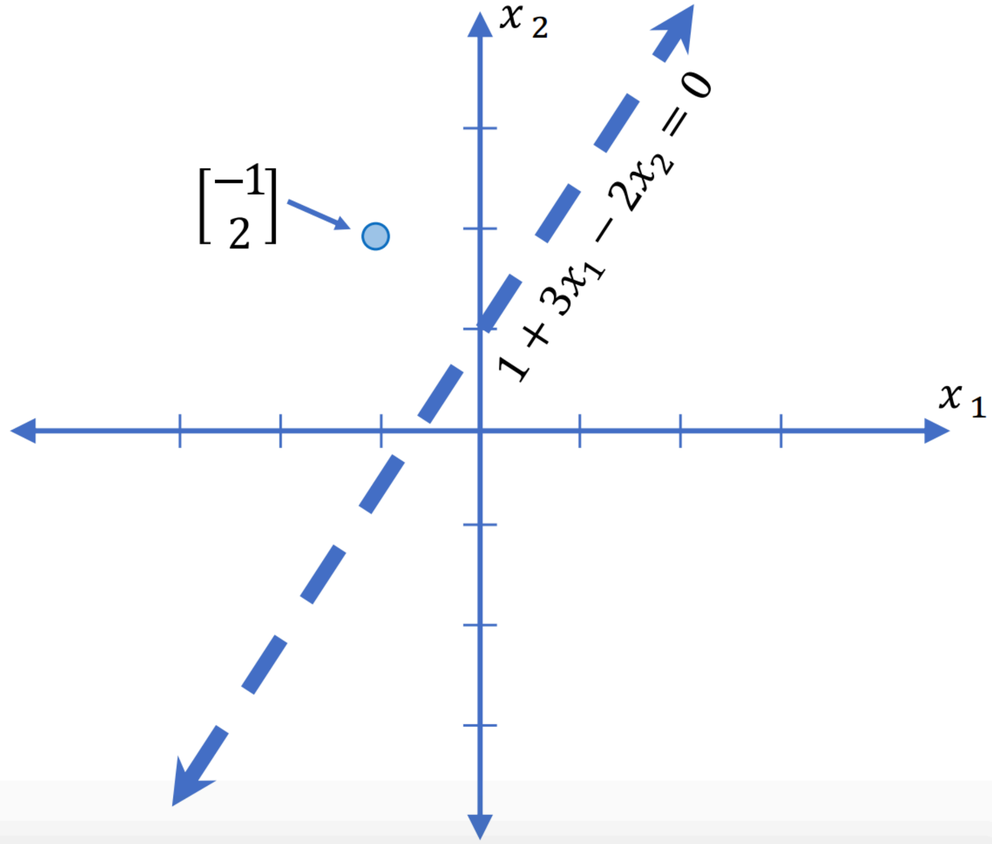
The Perceptron: Example



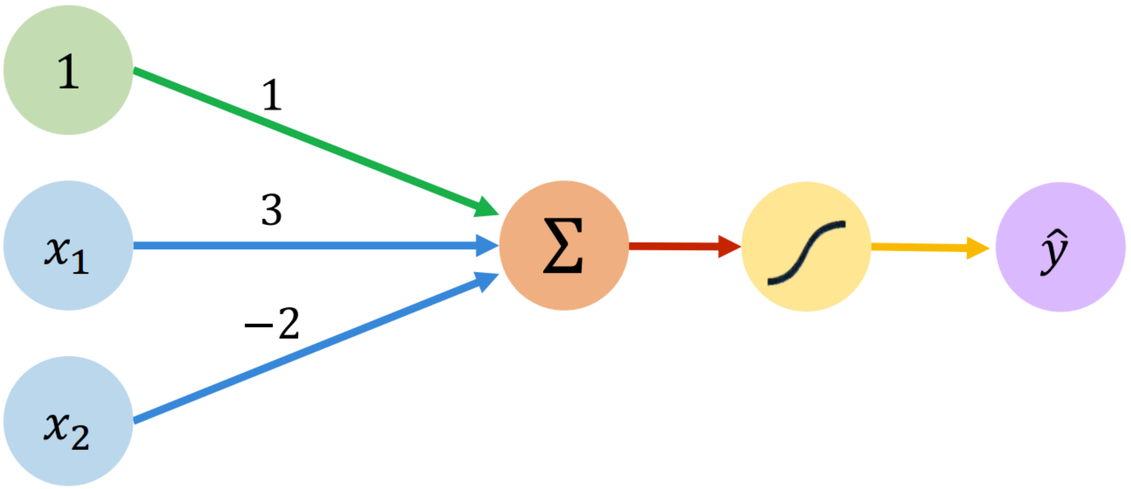
Assume we have input: $\boldsymbol{X} = \begin{bmatrix} -1 \\ 2 \end{bmatrix}$

$$\hat{y} = g\left(1 + (3 * -1) - (2 * 2)\right)$$
$$= g(-6) \approx 0.002$$

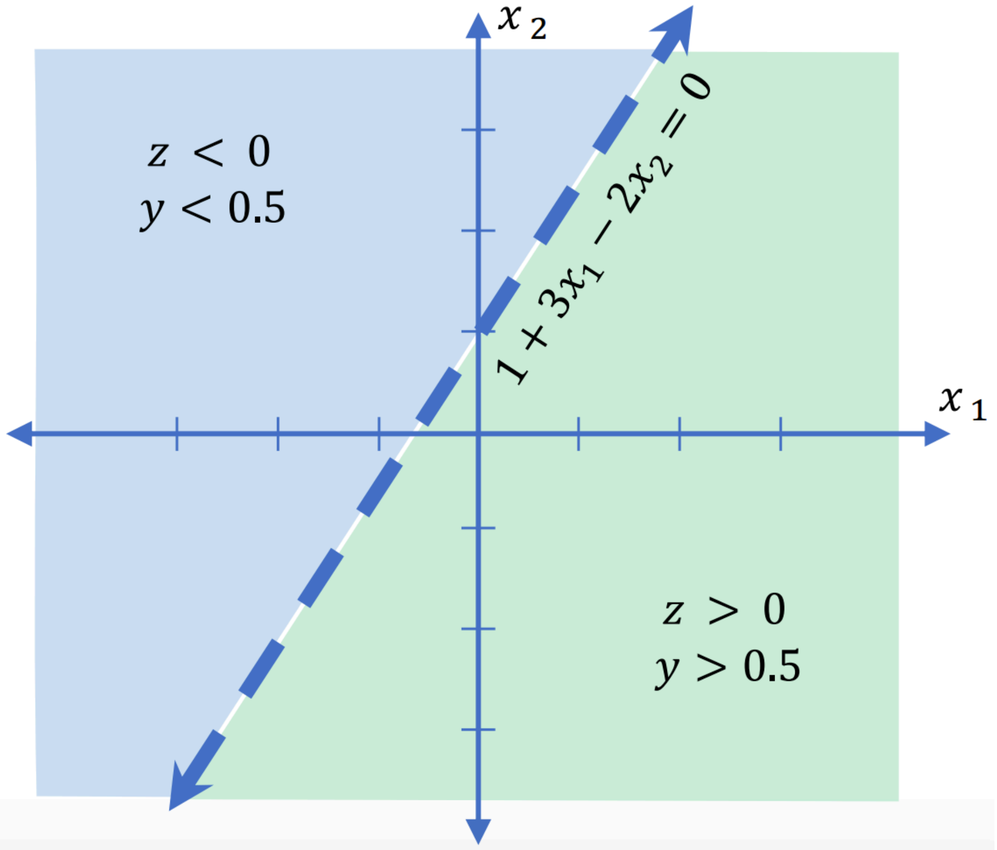
$$\hat{y} = g(1 + 3x_1 - 2x_2)$$



The Perceptron: Example

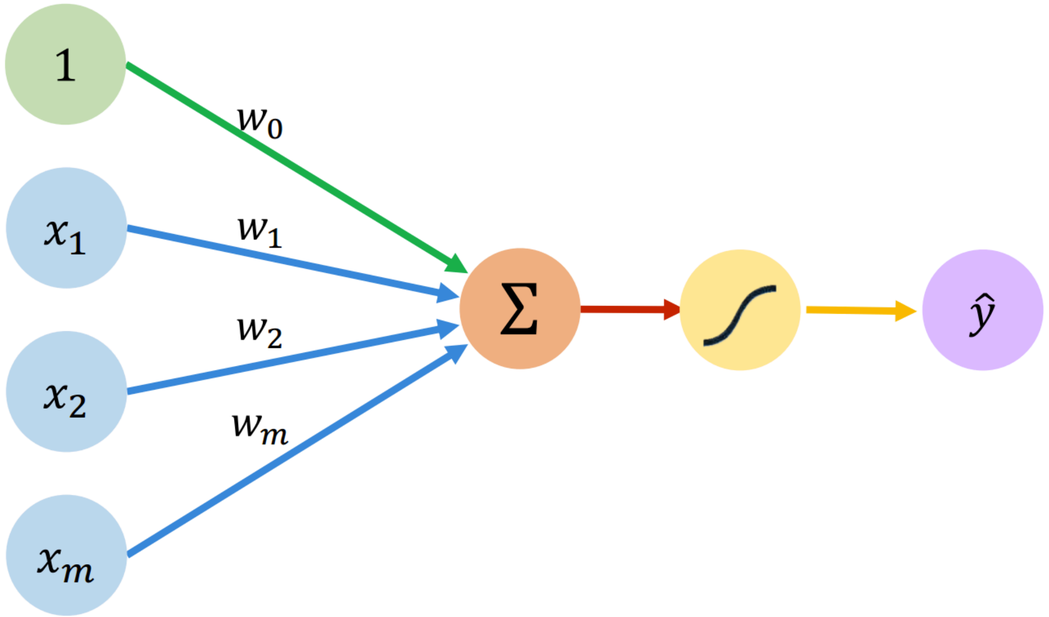


$$\hat{y} = g(1 + 3x_1 - 2x_2)$$



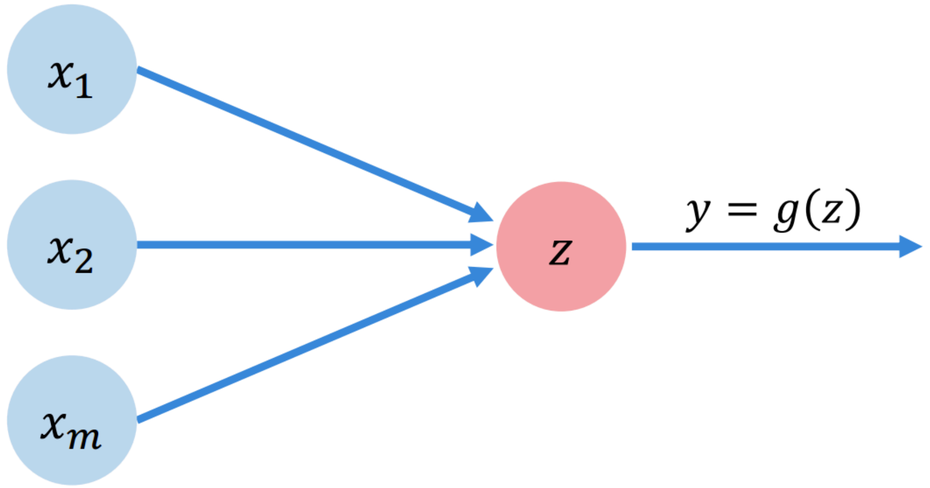
Build Neural Networks with Perceptron

The Perceptron: Simplified



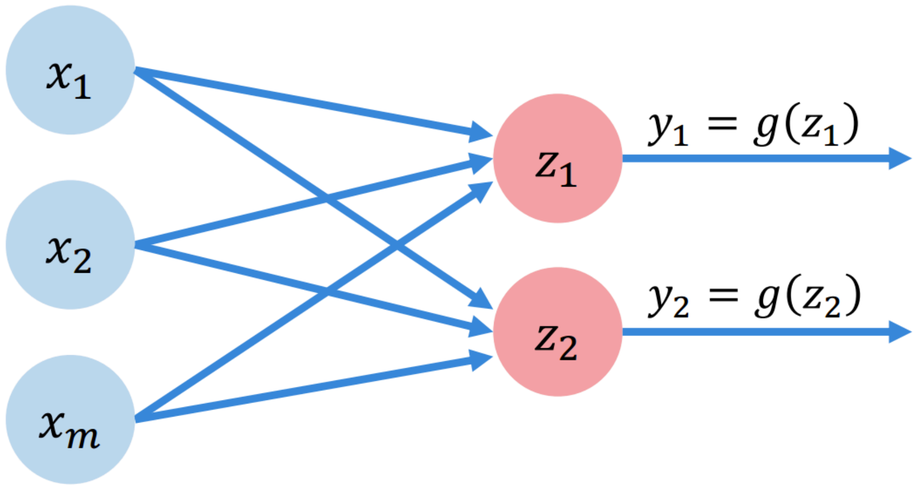
Inputs Weights Sum Non-Linearity Output

The Perceptron: Simplified



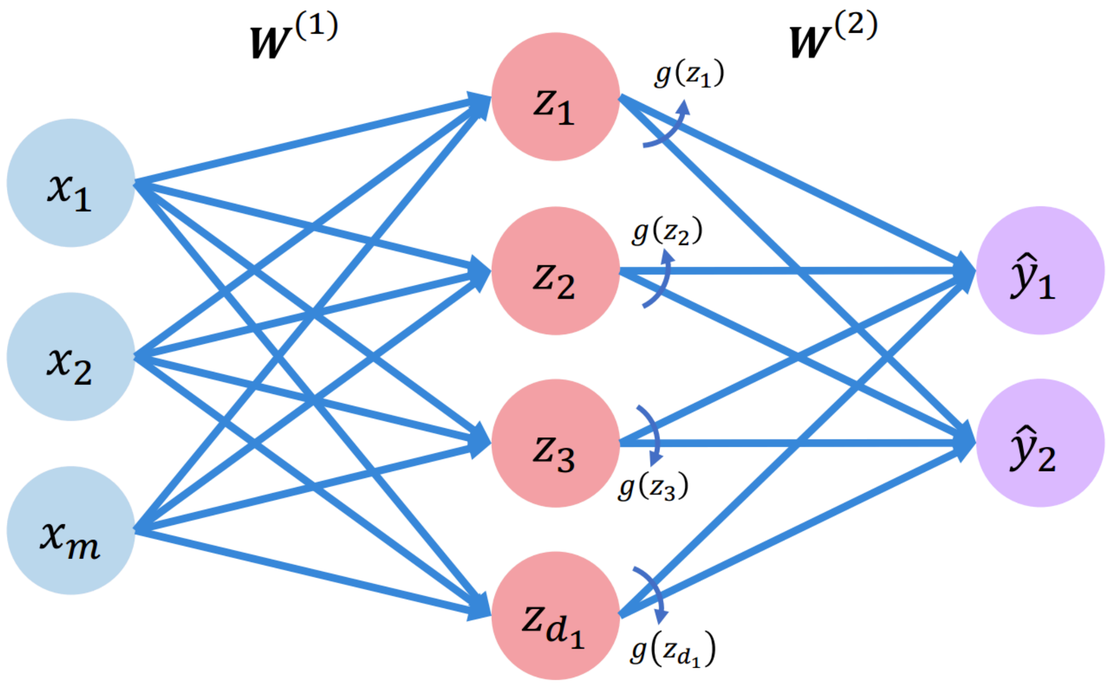
$$z = w_0 + \sum_{j=1}^{m} x_j w_j$$

Multi Output Perceptron



$$z_i = w_{0,i} + \sum_{j=1}^{m} x_j \, w_{j,i}$$

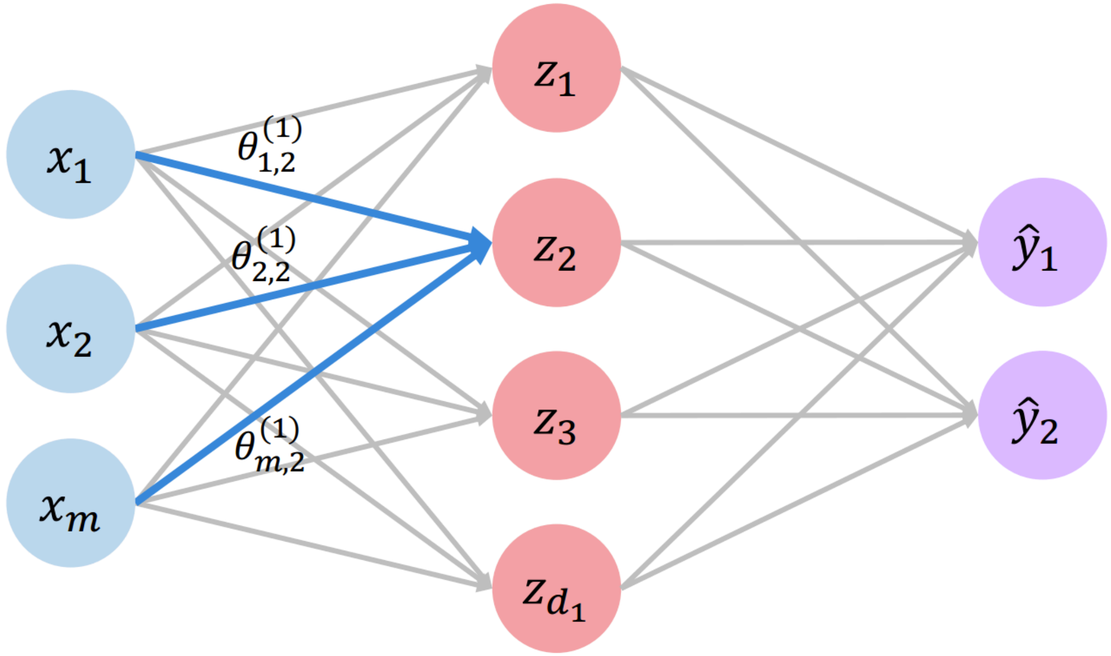
Single Layer Neural Network



Inputs Hidden Final Output

$$z_i = w_{0,i}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,i}^{(1)} \qquad \hat{y}_i = g\left(w_{0,i}^{(2)} + \sum_{j=1}^{d_1} z_j \, w_{j,i}^{(2)} \right)$$

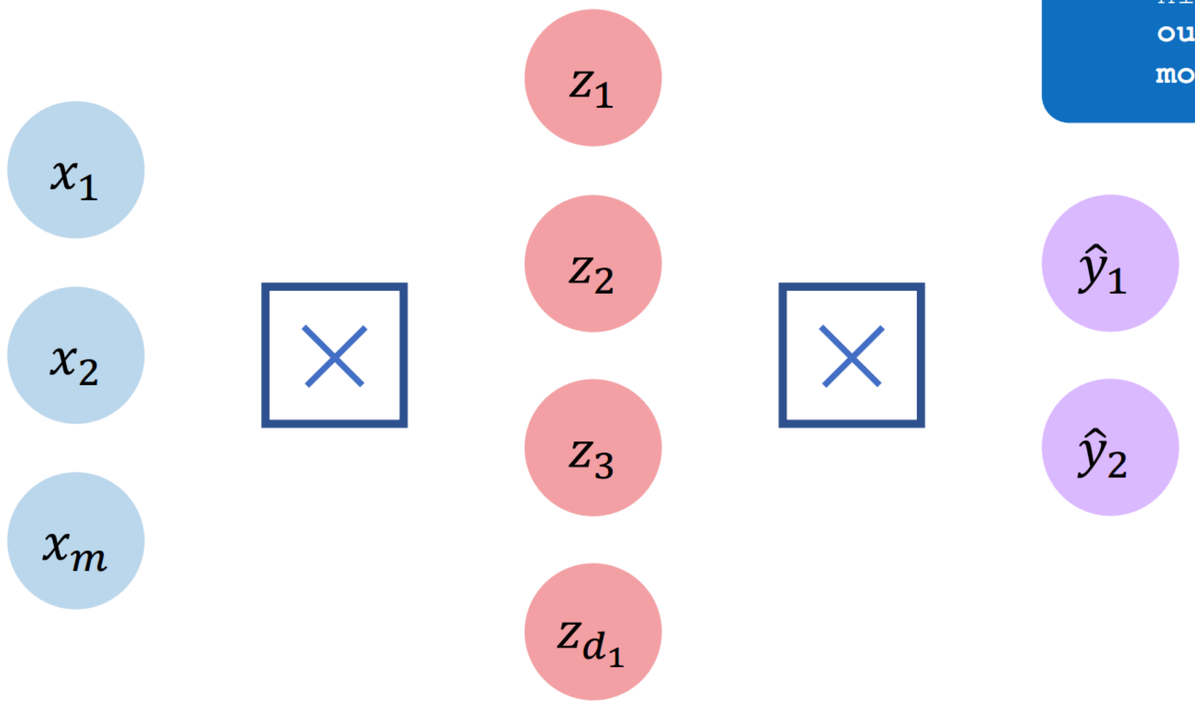
Single Layer Neural Network



$$z_2 = w_{0,2}^{(1)} + \sum_{j=1}^{m} x_j \, w_{j,2}^{(1)}$$

$$= w_{0,2}^{(1)} + x_1 \, w_{1,2}^{(1)} + x_2 \, w_{2,2}^{(1)} + x_m \, w_{m,2}^{(1)}$$

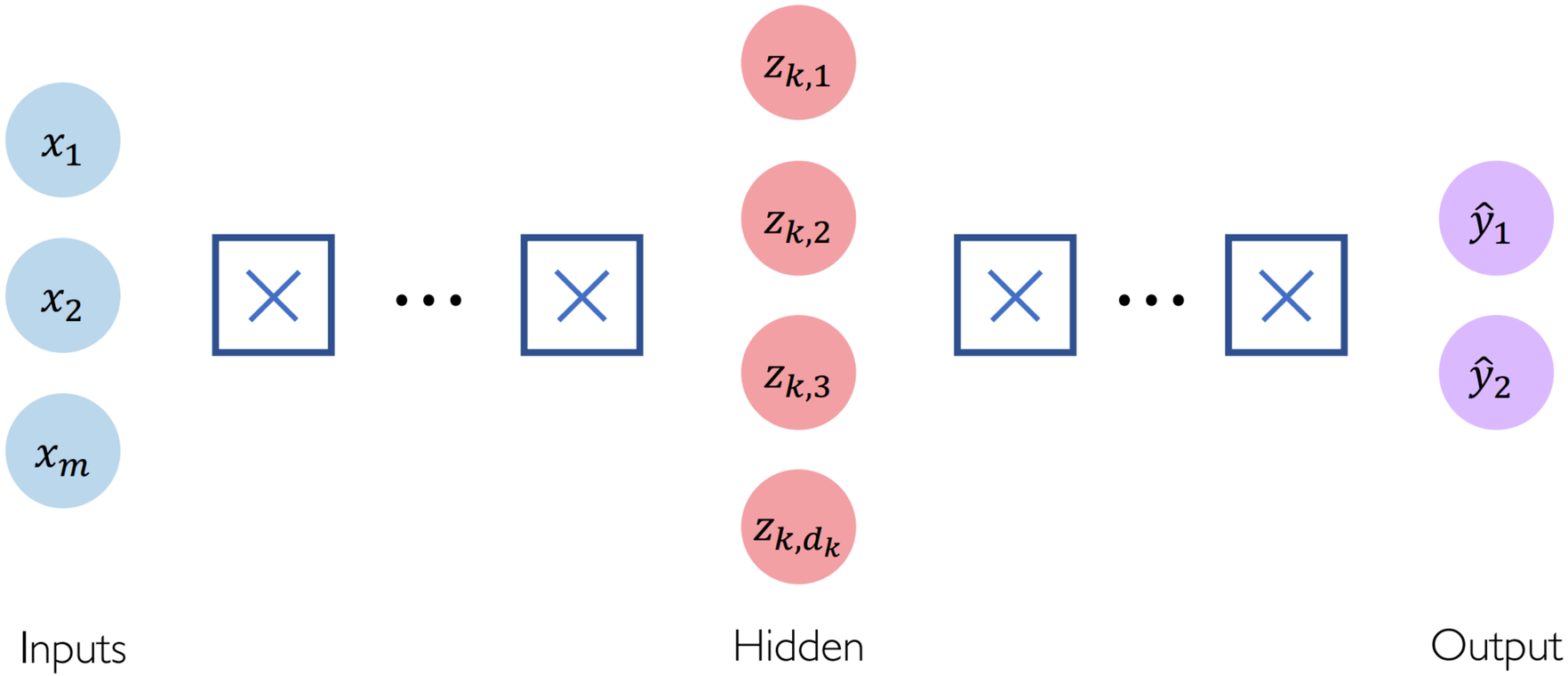
Multi Output Perceptron




```
from tf.keras.layers import *

inputs = Inputs(m)
hidden = Dense(d1)(inputs)
outputs = Dense(2)(hidden)
model = Model(inputs, outputs)
```

Deep Neural Network



$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{d_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

Example Problem

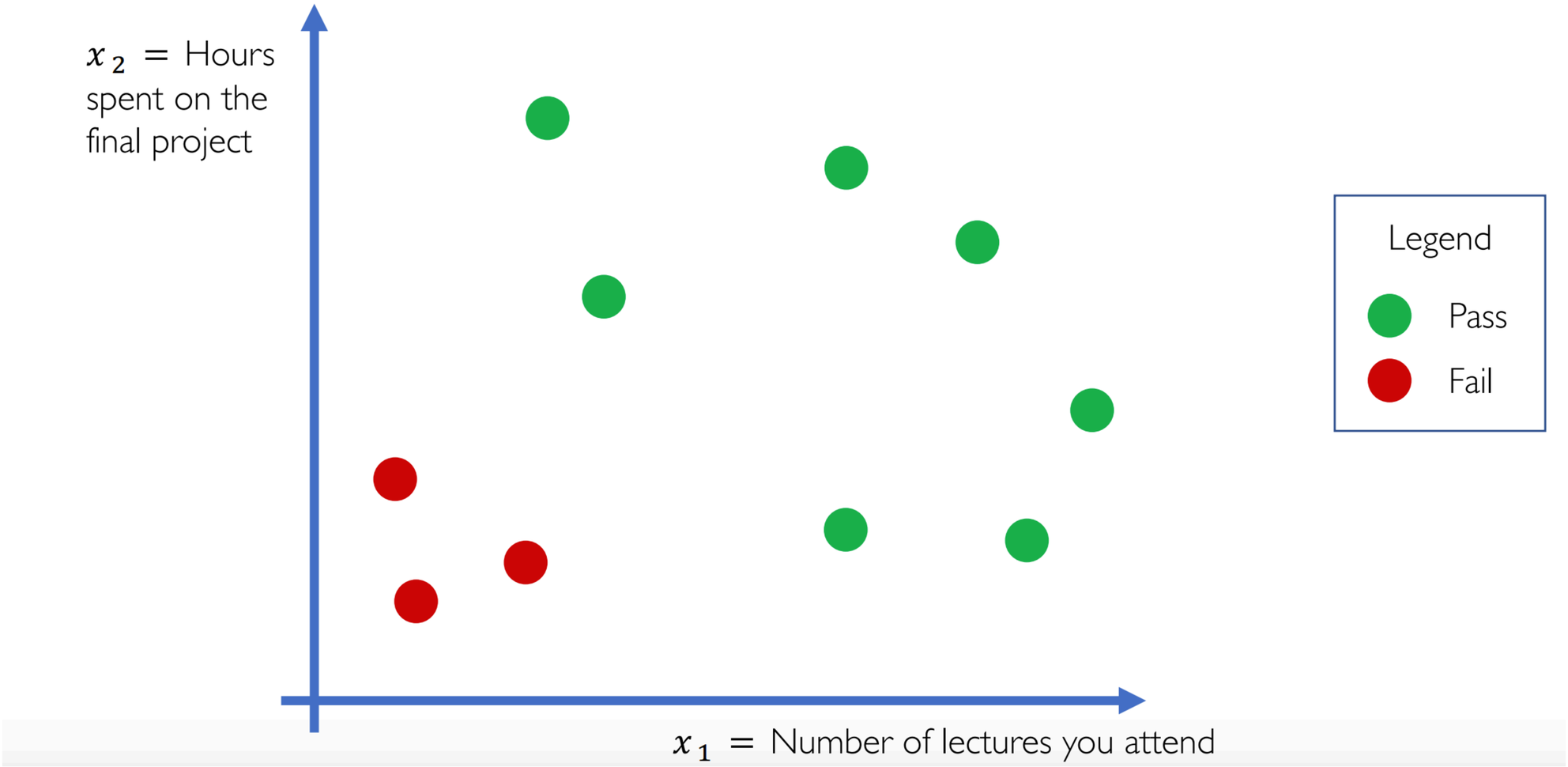
Will I pass this class?

Let's start with a simple two feature model

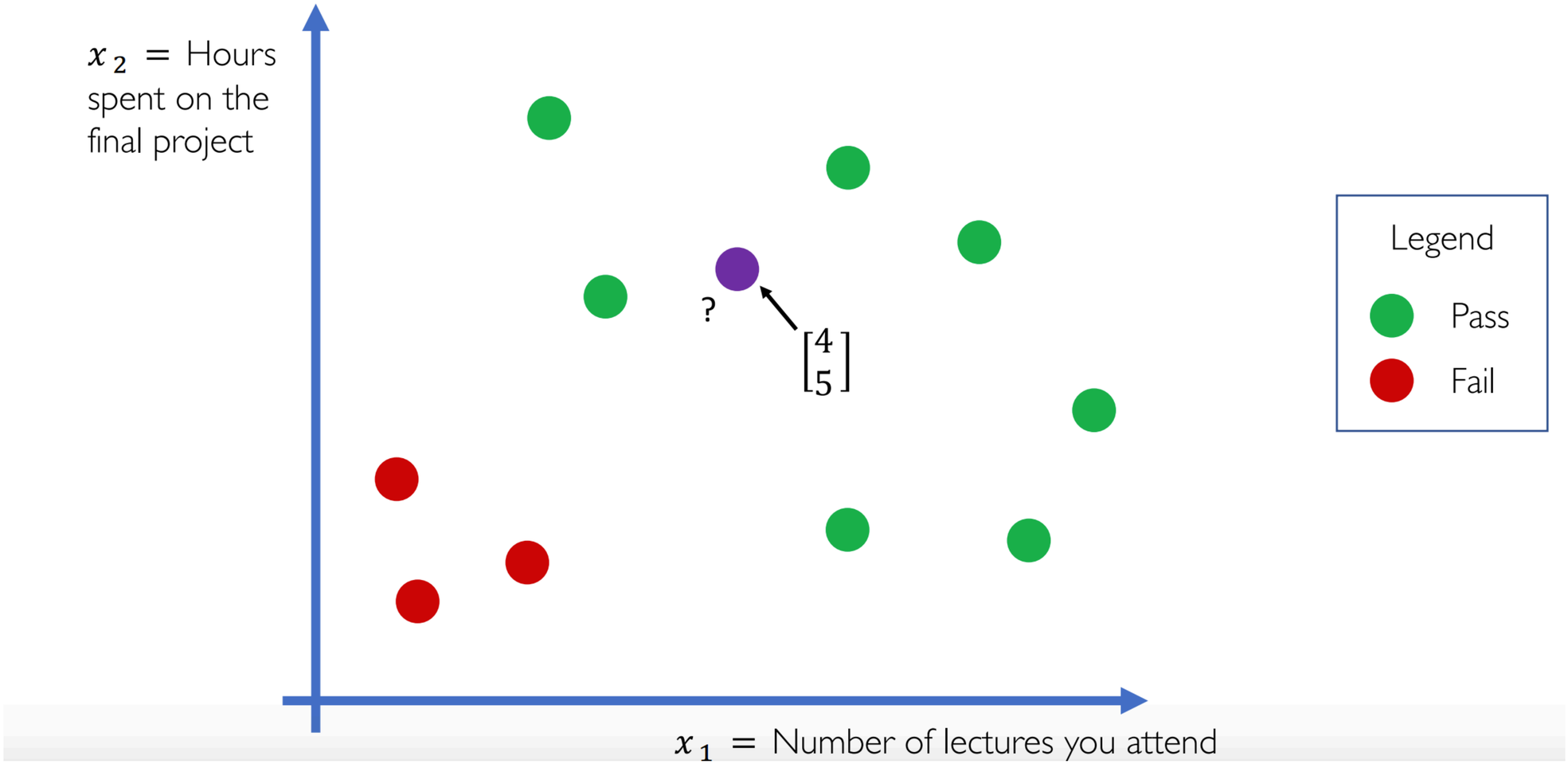
x_1 = Number of lectures you attend

x_2 = Hours spent on the final project

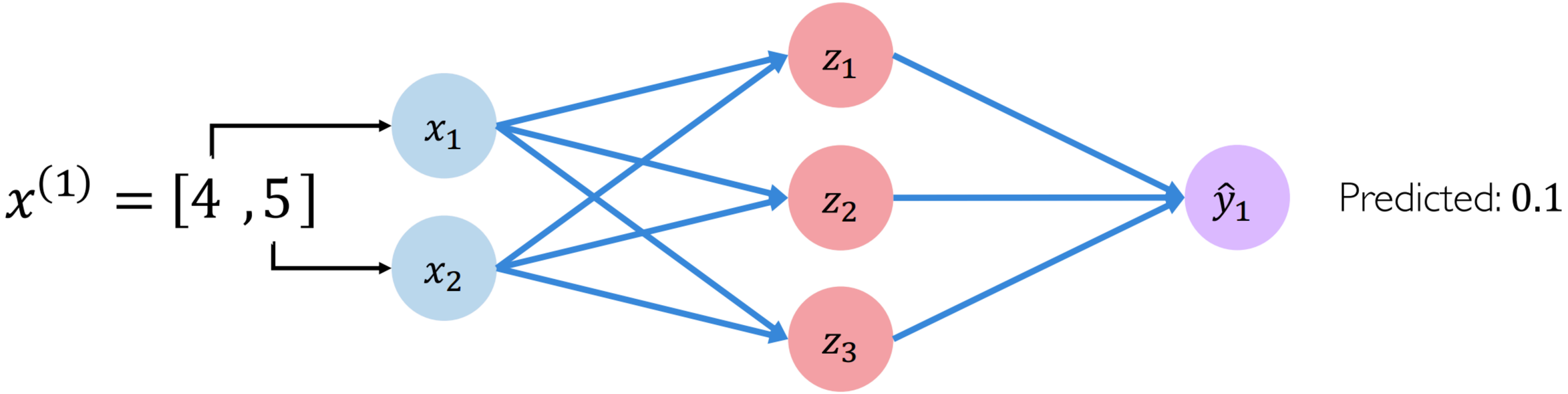
Example Problem: Will I pass this class?



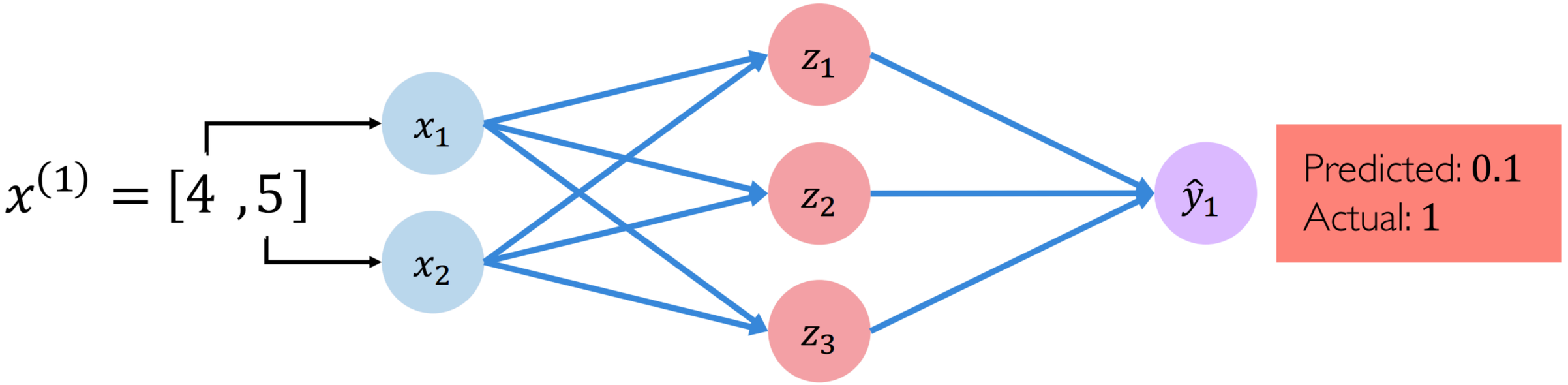
Example Problem: Will I pass this class?



Example Problem: Will I pass this class?

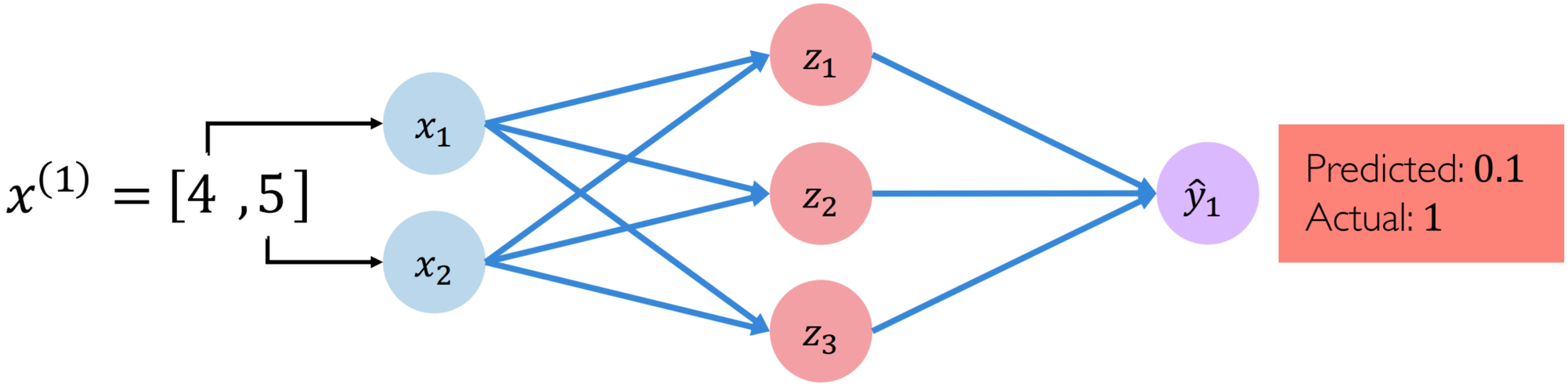


Example Problem: Will I pass this class?



Quantifying Loss

*The **loss** of our network measures the cost incurred from incorrect predictions*



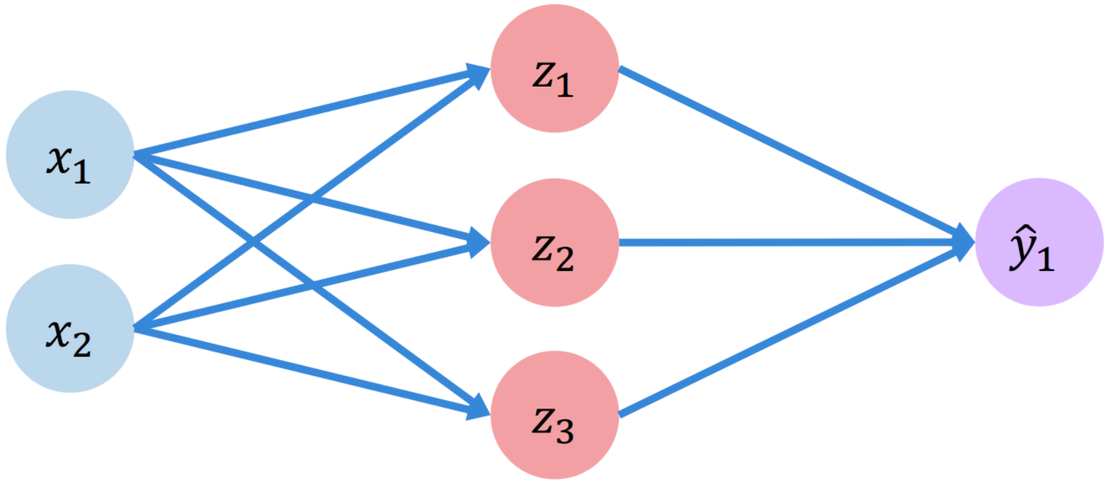
$$\mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

Empirical Loss

*The **empirical loss** measures the total loss over our entire dataset*

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$$f(x) = \begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix} \qquad y = \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix}$$

$$\boldsymbol{J}(\boldsymbol{W}) = \frac{1}{n}\sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

Predicted Actual

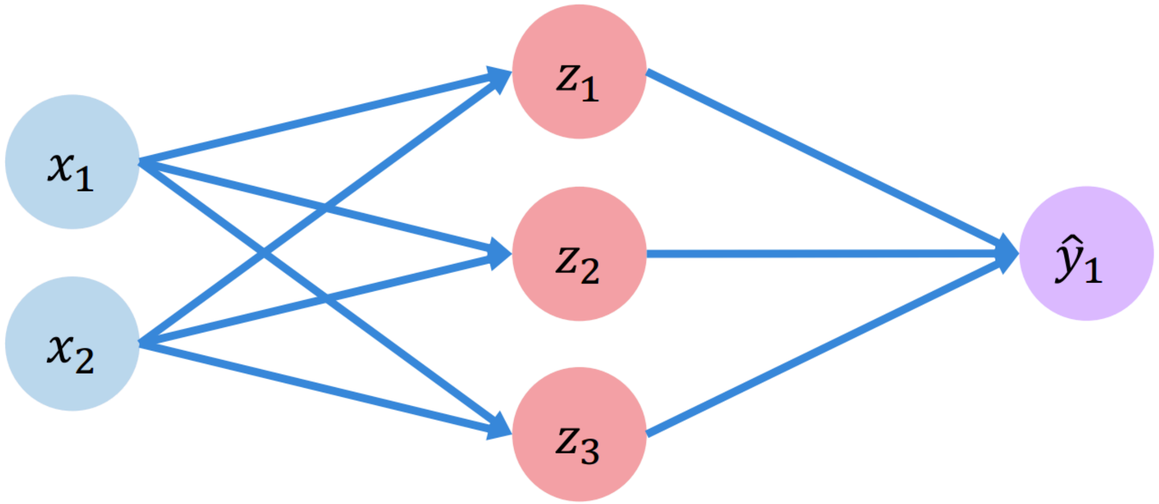
Also known as:

- Objective function
- Cost function
- Empirical Risk

Binary Cross Entropy Loss

Cross entropy loss *can be used with models that output a probability between 0 and 1*

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$f(x)$

$$\begin{bmatrix} 0.1 \\ 0.8 \\ 0.6 \\ \vdots \end{bmatrix}$$

y

$$\begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix}$$

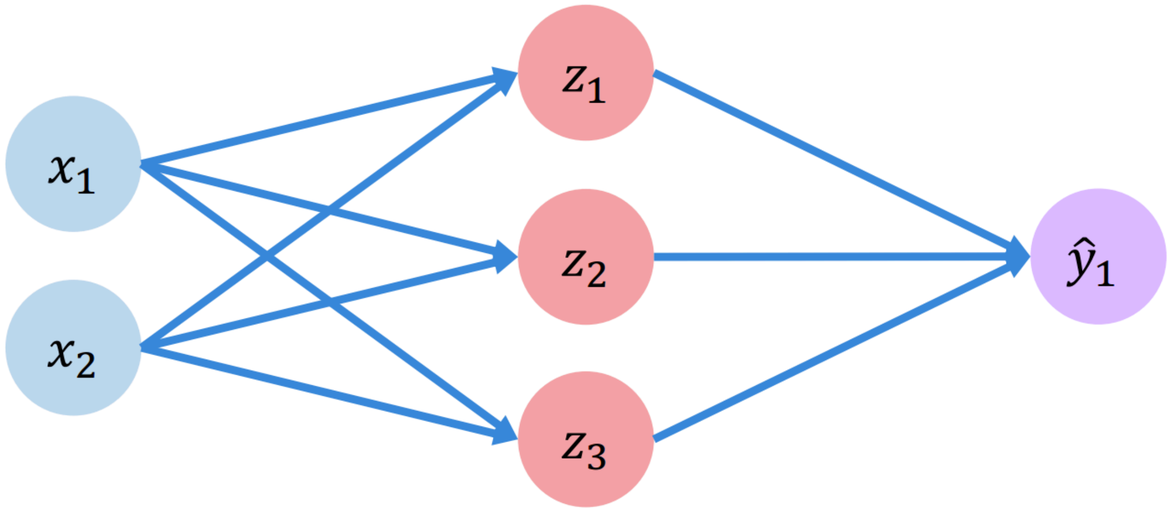
$$\boldsymbol{J(W)} = \frac{1}{n}\sum_{i=1}^{n} y^{(i)} \log\left(f\left(x^{(i)}; \boldsymbol{W}\right)\right) + (1 - y^{(i)}) \log\left(1 - f\left(x^{(i)}; \boldsymbol{W}\right)\right)$$

Actual Predicted Actual Predicted

Mean Squared Error Loss

Mean squared error loss *can be used with regression models that output continuous real numbers*

$$\boldsymbol{X} = \begin{bmatrix} 4, & 5 \\ 2, & 1 \\ 5, & 8 \\ \vdots & \vdots \end{bmatrix}$$



$$\boldsymbol{J(W)} = \frac{1}{n}\sum_{i=1}^{n}\left(y^{(i)} - f\left(x^{(i)}; \boldsymbol{W}\right)\right)^2$$

Actual Predicted

$f(x)$ y

$$\begin{bmatrix} 30 \\ 80 \\ 85 \\ \vdots \end{bmatrix} \quad \begin{bmatrix} 90 \\ 20 \\ 95 \\ \vdots \end{bmatrix}$$

Final Grades (percentage)

Loss Optimization

We want to find the network weights that ***achieve the lowest loss***

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} J(\boldsymbol{W})$$

Loss Optimization

We want to find the network weights that ***achieve the lowest loss***

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} \mathcal{L}\left(f\left(x^{(i)}; \boldsymbol{W}\right), y^{(i)}\right)$$

$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} J(\boldsymbol{W})$$

Remember:

$$\boldsymbol{W} = \left\{\boldsymbol{W}^{(0)}, \boldsymbol{W}^{(1)}, \dots\right\}$$

Gradient Descent

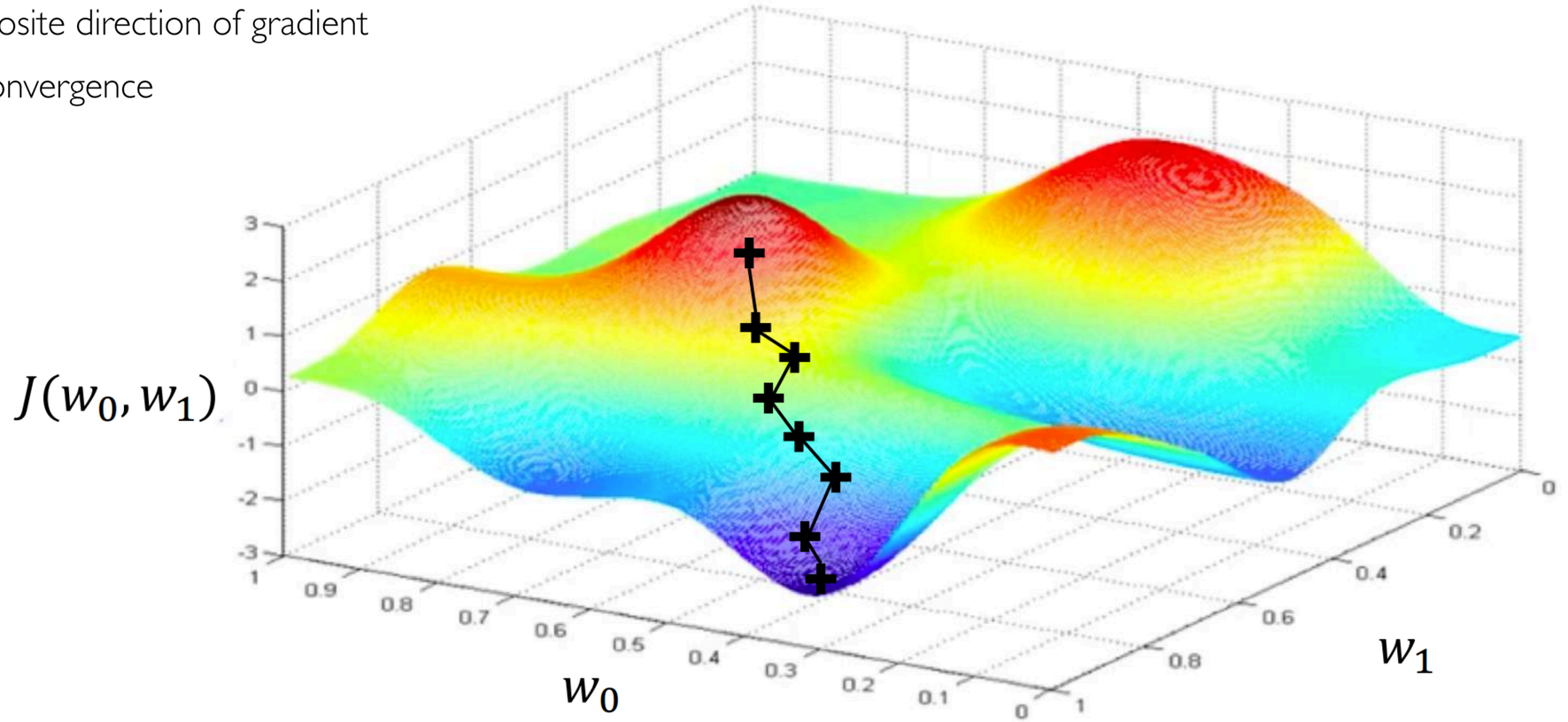
$$\boldsymbol{W}^* = \underset{\boldsymbol{W}}{\operatorname{argmin}} J(\boldsymbol{W})$$

Randomly pick an initial (w_0, w_1)

Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$

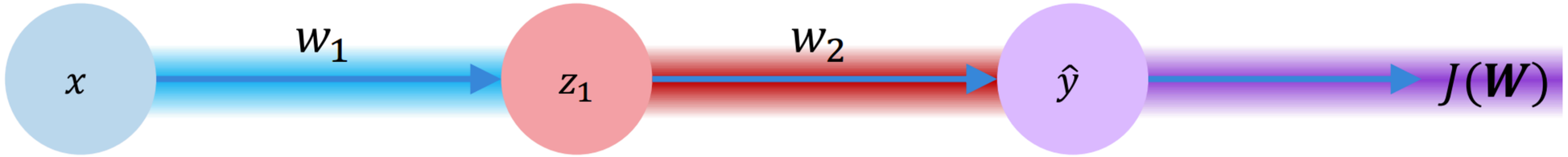
Take small step in opposite direction of gradient

Repeat until convergence



Remember:
Our loss is a function of the network weights!

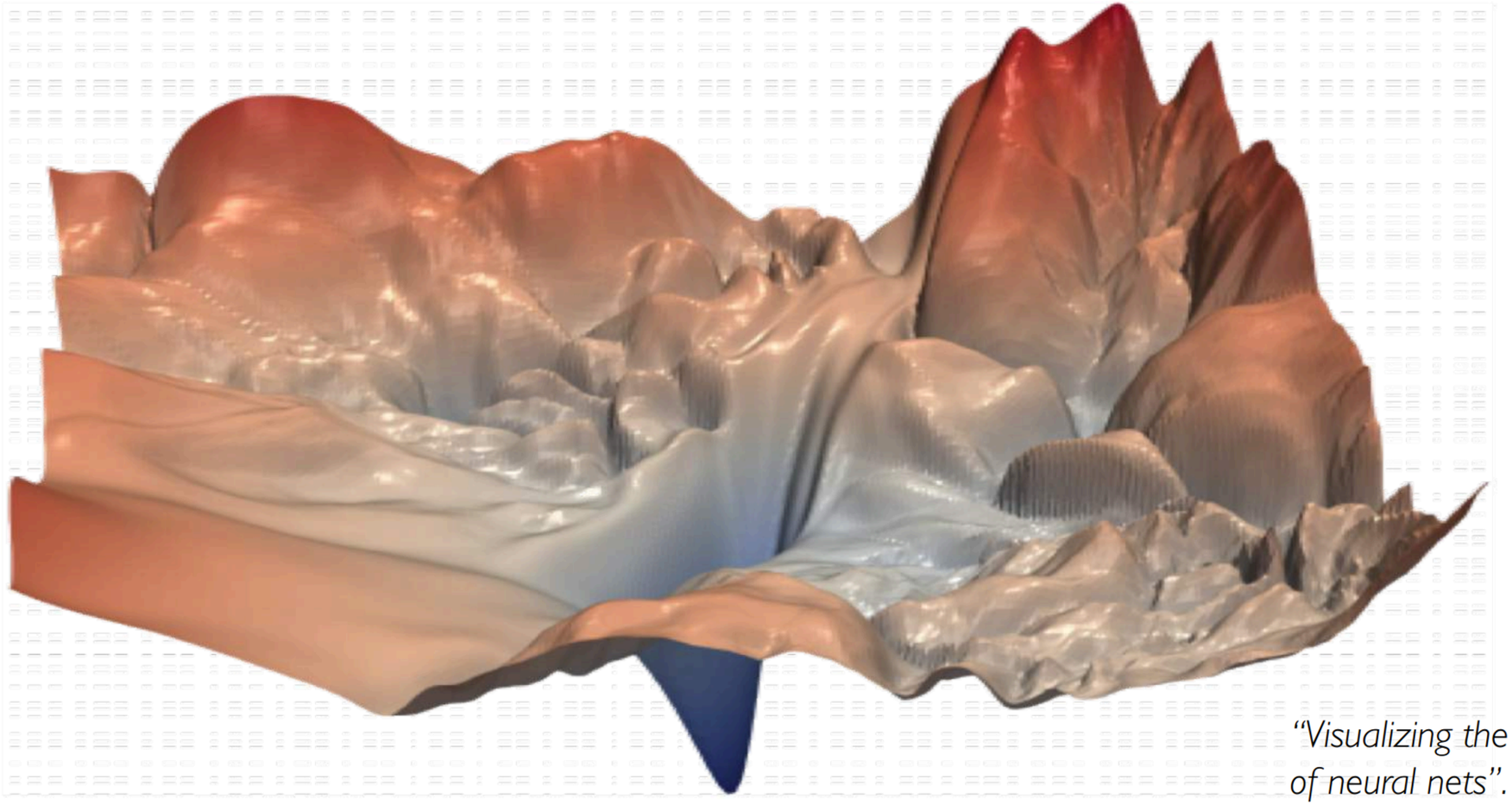
Computing Gradients: Backpropagation



$$\frac{\partial J(\boldsymbol{W})}{\partial w_1} = \frac{\partial J(\boldsymbol{W})}{\partial \hat{y}} * \frac{\partial \hat{y}}{\partial z_1} * \frac{\partial z_1}{\partial w_1}$$

Repeat this for ***every weight in the network*** *using gradients from later layers*

Training Neural Networks is Difficult

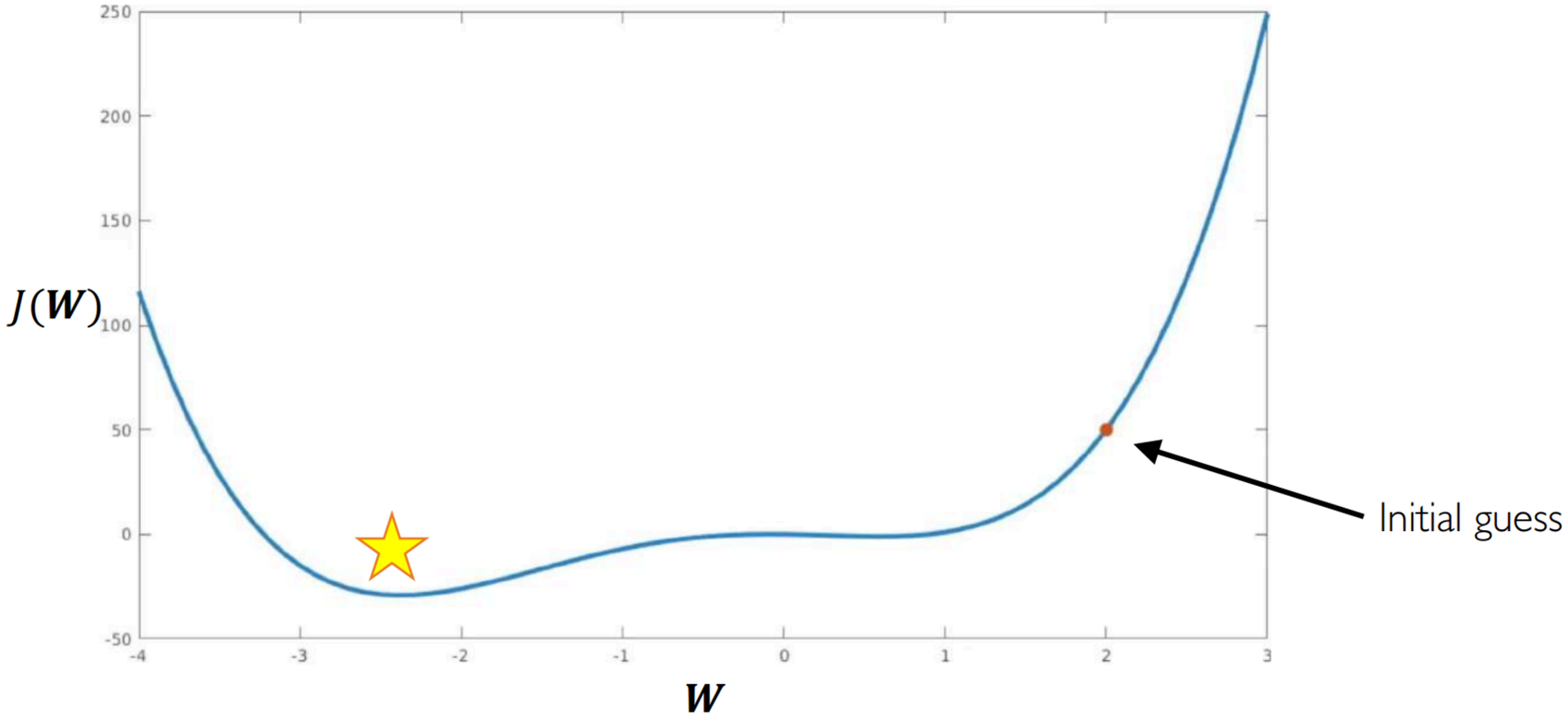


"Visualizing the loss landscape of neural nets". Dec 2017.

Setting the Learning Rate

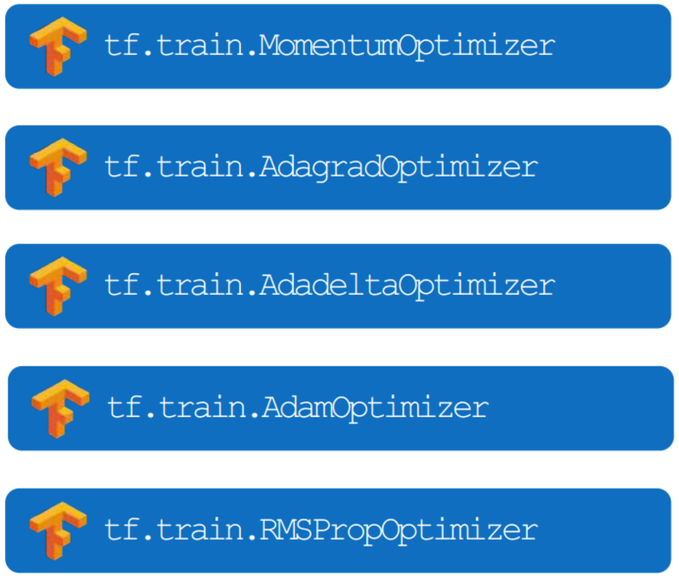
Stable learning rates *converge smoothly and avoid local minima*

Large learning rates *overshoot, become unstable and diverge*



Adaptive Learning Rate Algorithms

- Momentum
- Adagrad
- Adadelta
- Adam
- RMSProp



Qian et al. "On the momentum term in gradient descent learning algorithms." 1999.

Duchi et al. "Adaptive Subgradient Methods for Online Learning and Stochastic Optimization." 2011.

Zeiler et al. "ADADELTA: An Adaptive Learning Rate Method." 2012.

Kingma et al. "Adam: A Method for Stochastic Optimization." 2014.

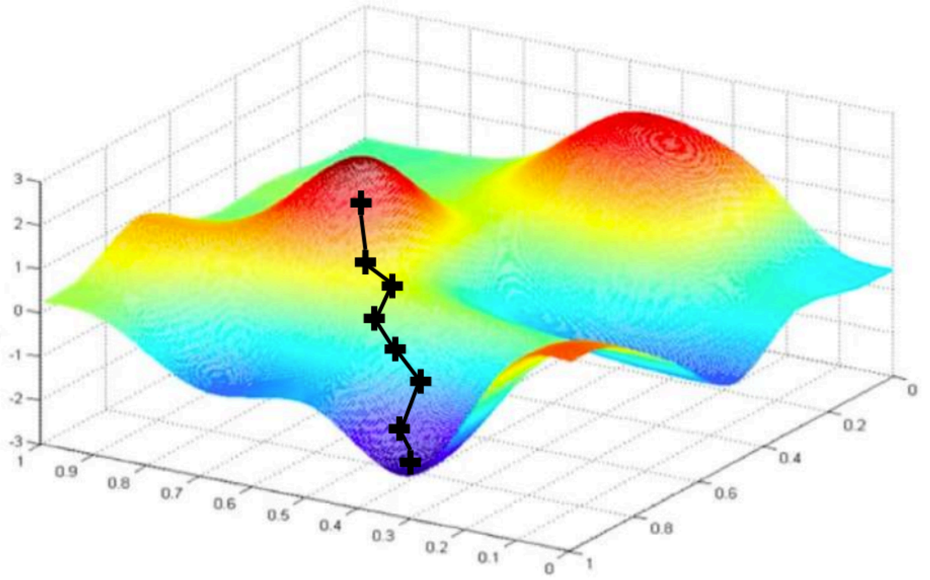
Additional details: http://ruder.io/optimizing-gradient-descent/

Gradient Descent

Algorithm

1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient, $\frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
4. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Return weights

Can be very computational to compute!

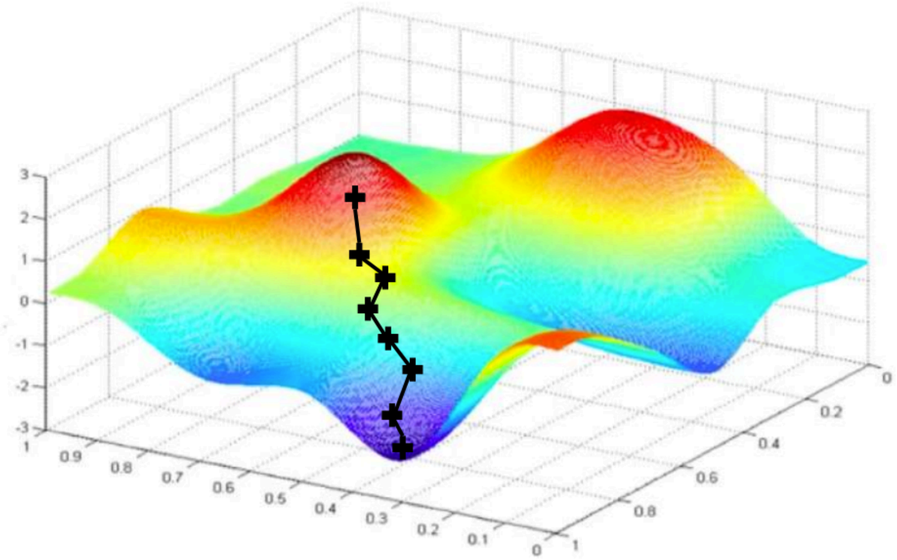


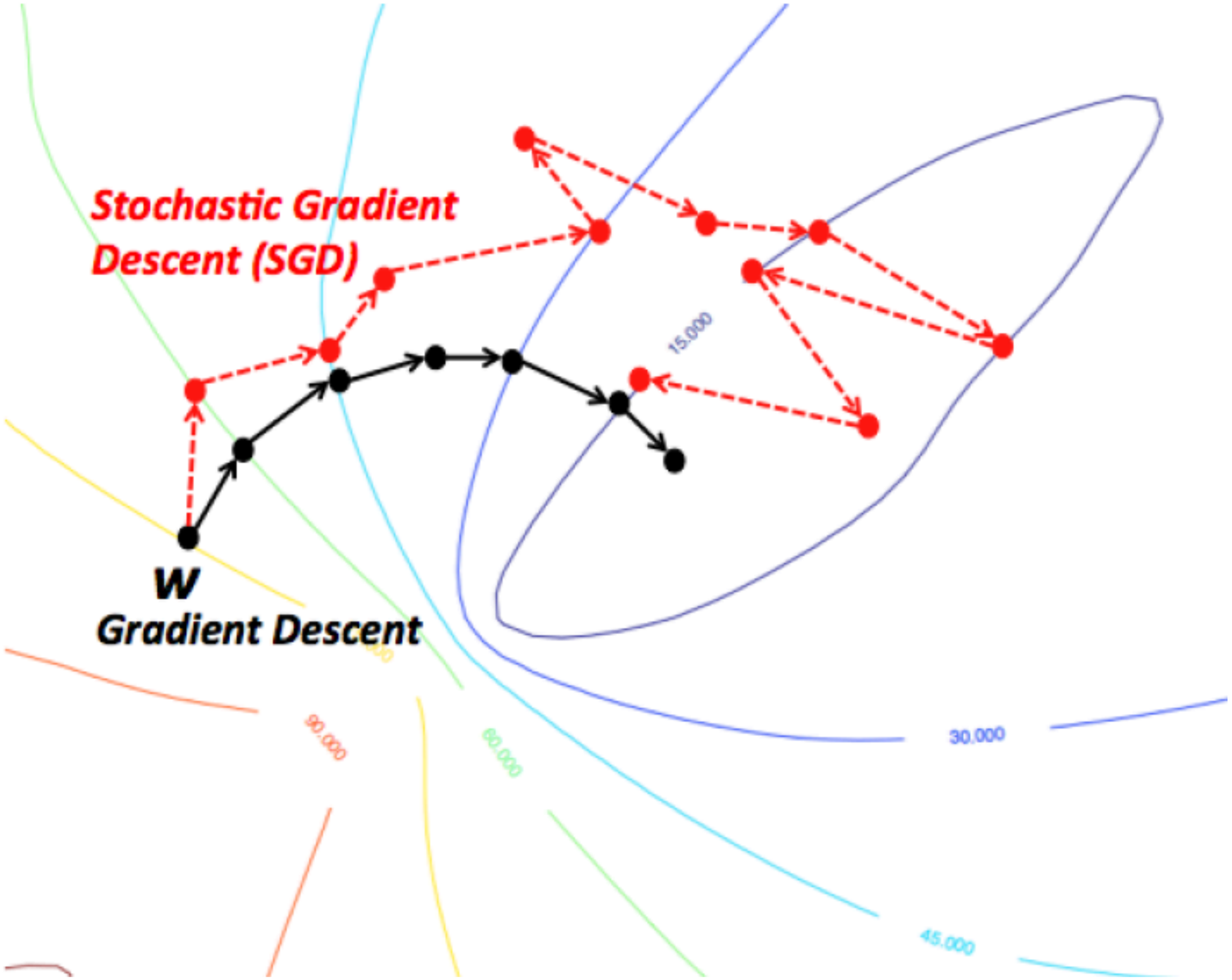
Stochastic Gradient Descent

Algorithm

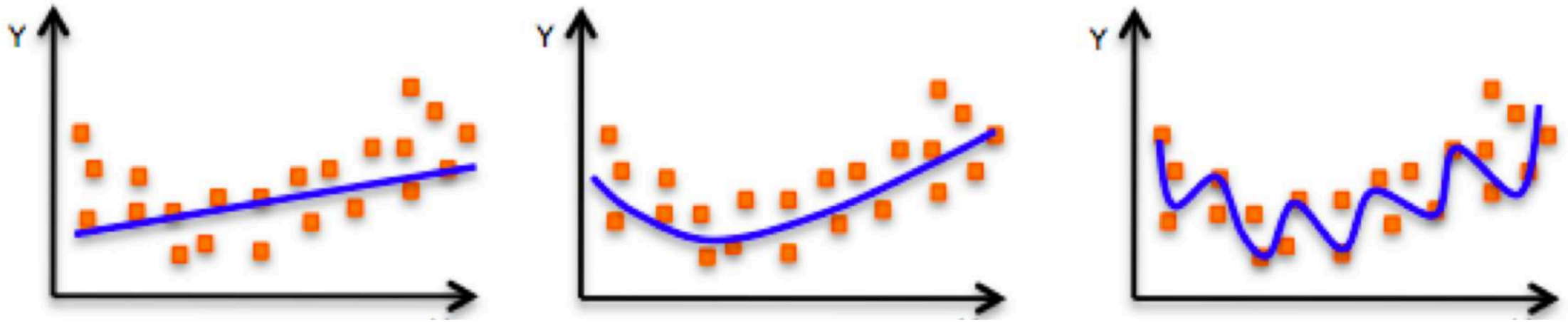
1. Initialize weights randomly $\sim \mathcal{N}(0, \sigma^2)$
2. Loop until convergence:
3. Pick single data point $\boldsymbol{i}$
4. Compute gradient, $\frac{\partial J_i(\boldsymbol{W})}{\partial \boldsymbol{W}}$
5. Update weights, $\boldsymbol{W} \leftarrow \boldsymbol{W} - \eta \frac{\partial J(\boldsymbol{W})}{\partial \boldsymbol{W}}$
6. Return weights

Easy to compute but **very noisy** (stochastic)!




Stochastic Gradient
Descent (SGD)
W
Gradient Descent
15.000
30.000
45.000
60.000
90.000

The Problem of Overfitting



Underfitting
Model does not have capacity to fully learn the data

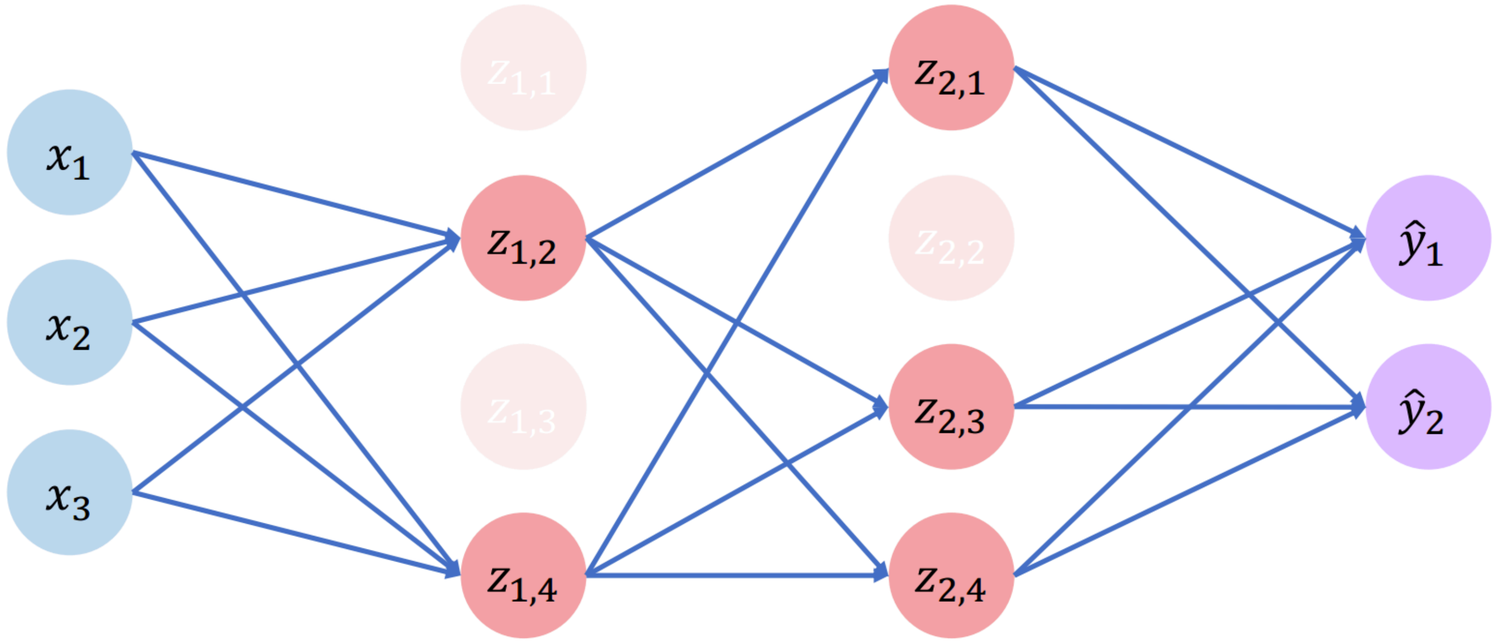
Ideal fit

Overfitting
Too complex, extra parameters, does not generalize well

Regularization 1: Dropout

- During training, randomly set some activations to 0
  - Typically 'drop' 50% of activations in layer
  - Forces network to not rely on any 1 node

`tf.keras.layers.Dropout(p=0.5)`



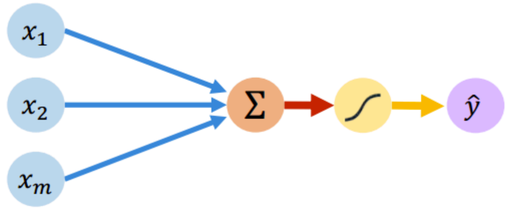
Regularization 2: Early Stopping

- Stop training before we have a chance to overfit

Core Foundation Review

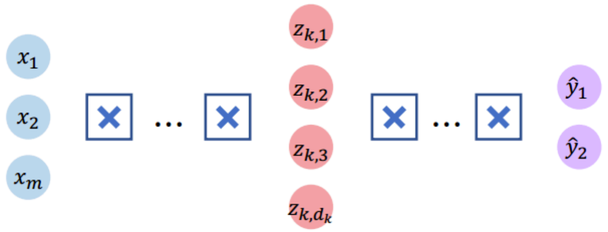
The Perceptron

- Structural building blocks
- Nonlinear activation functions



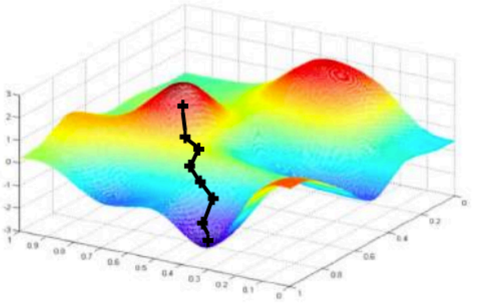
Neural Networks

- Stacking Perceptrons to form neural networks
- Optimization through backpropagation



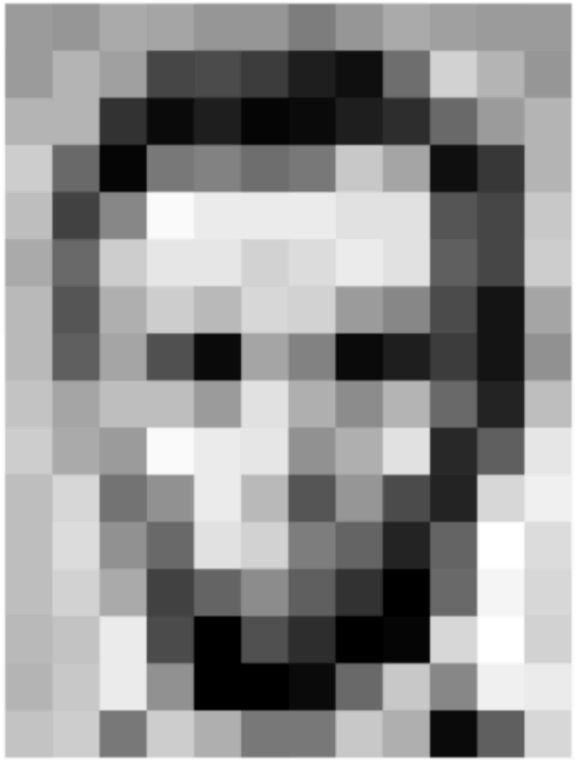
Training in Practice

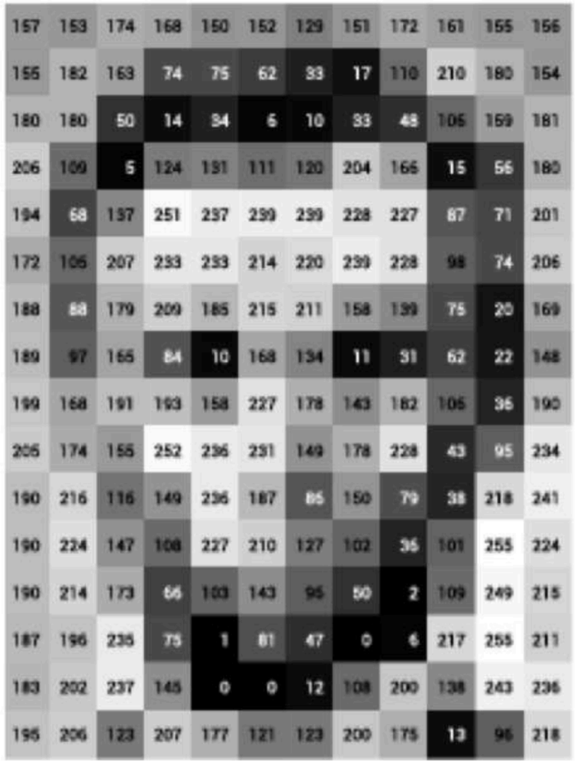
- Adaptive learning
- Batching
- Regularization



Computer Vision

Images are Numbers



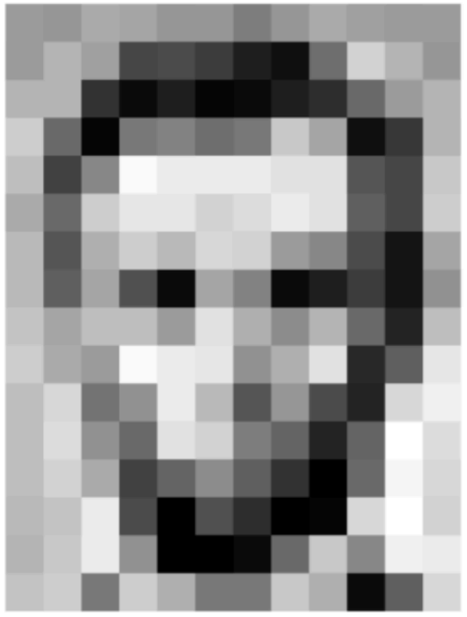


What the computer sees

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Tasks in Computer Vision



Input Image

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Pixel Representation

classification

Lincoln	0.8
Washington	0.1
Jefferson	0.05
Obama	0.05

- **Regression**: output variable takes continuous value
- **Classification**: output variable takes class label. Can produce probability of belonging to a particular class

High Level Feature Detection

Let's identify key features in each image category

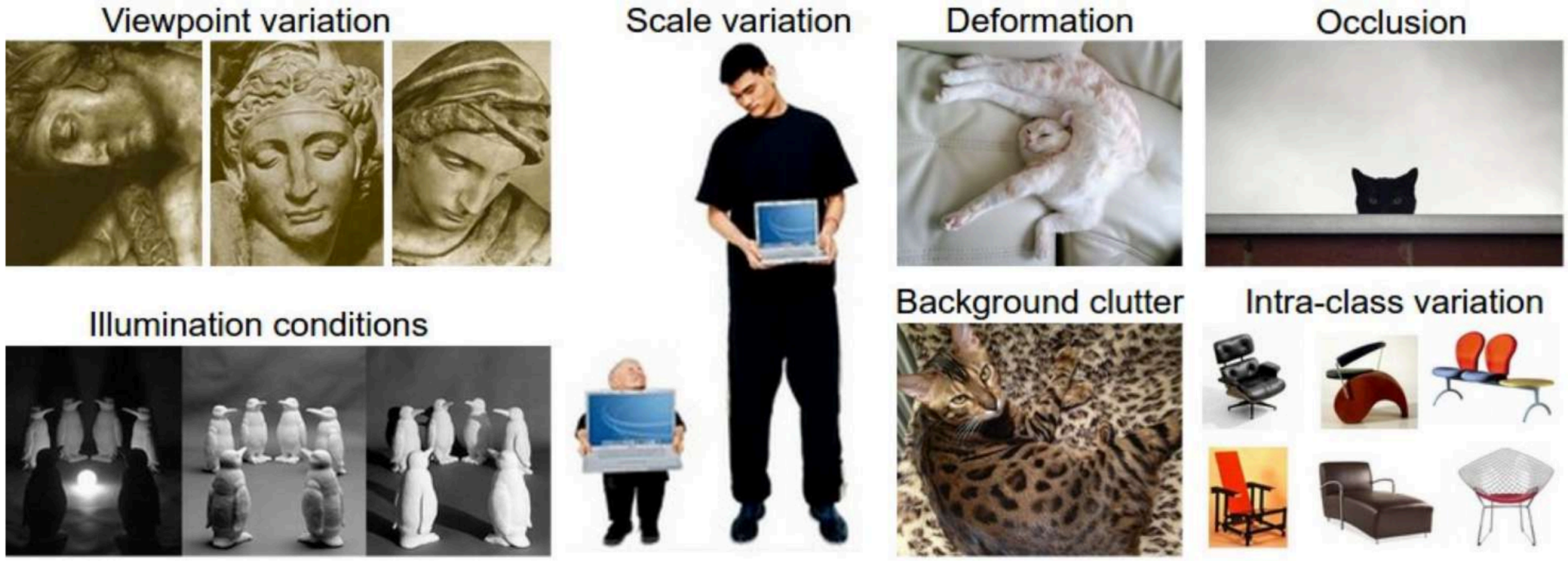
Nose,
Eyes,
Mouth

Wheels,
License Plate,
Headlights

Door,
Windows,
Steps

Manual Feature Extraction

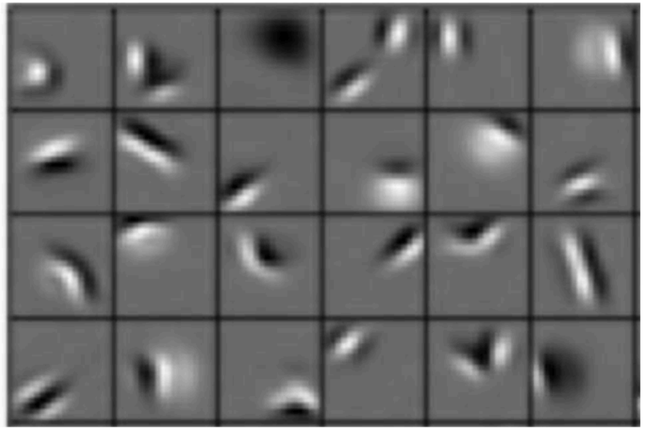
Domain knowledge → Define features → Detect features to classify



Learning Feature Representations

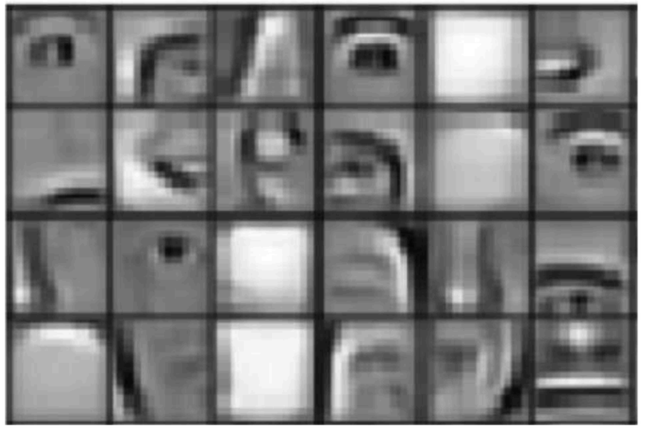
Can we learn a **hierarchy of features** directly from the data instead of hand engineering?

Low level features



Edges, dark spots

Mid level features



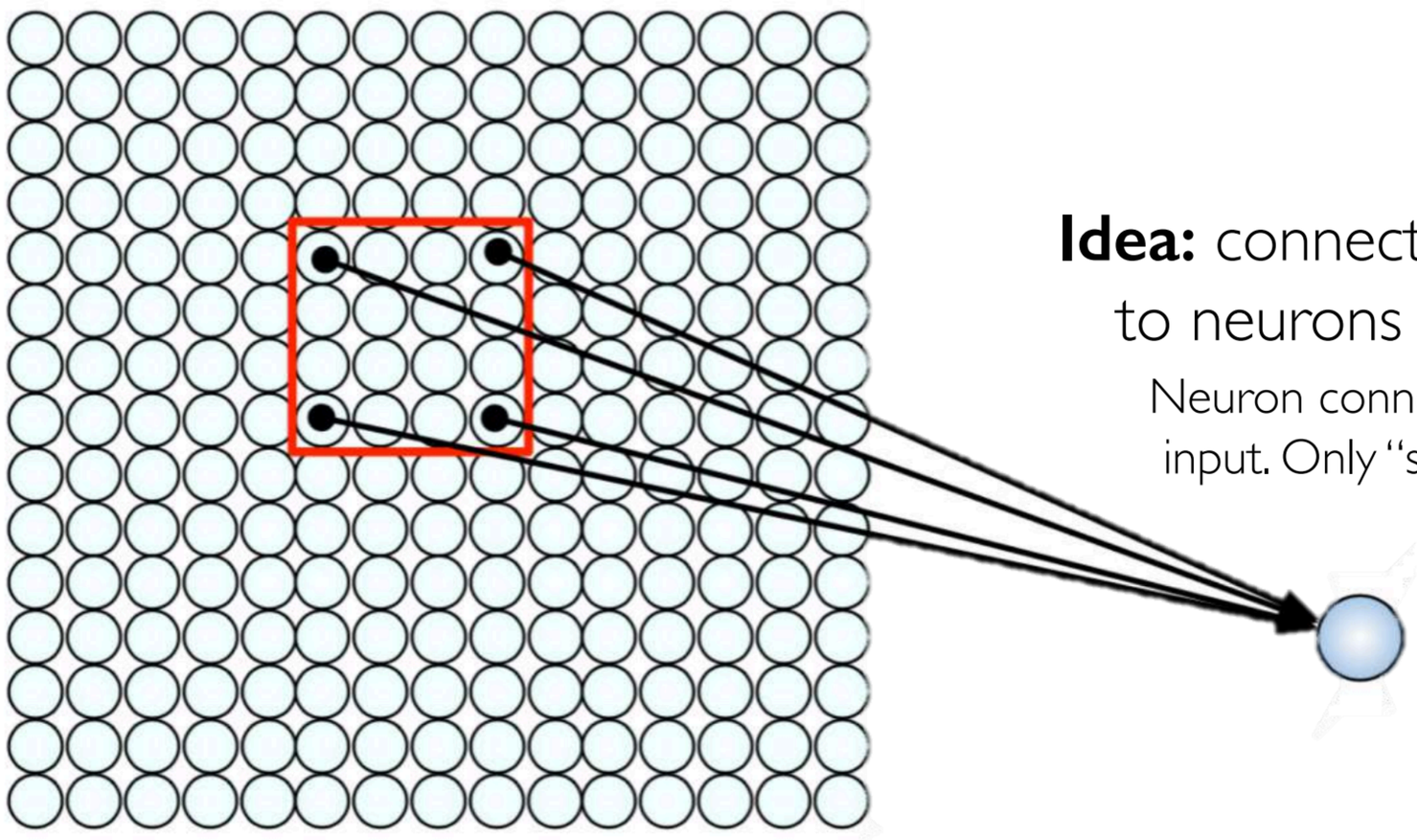
Eyes, ears, nose

High level features

Facial structure

Using Spatial Structure

Input: 2D image.
Array of pixel values



Idea: connect patches of input to neurons in hidden layer.

Neuron connected to region of input. Only "sees" these values.

Producing Feature Maps

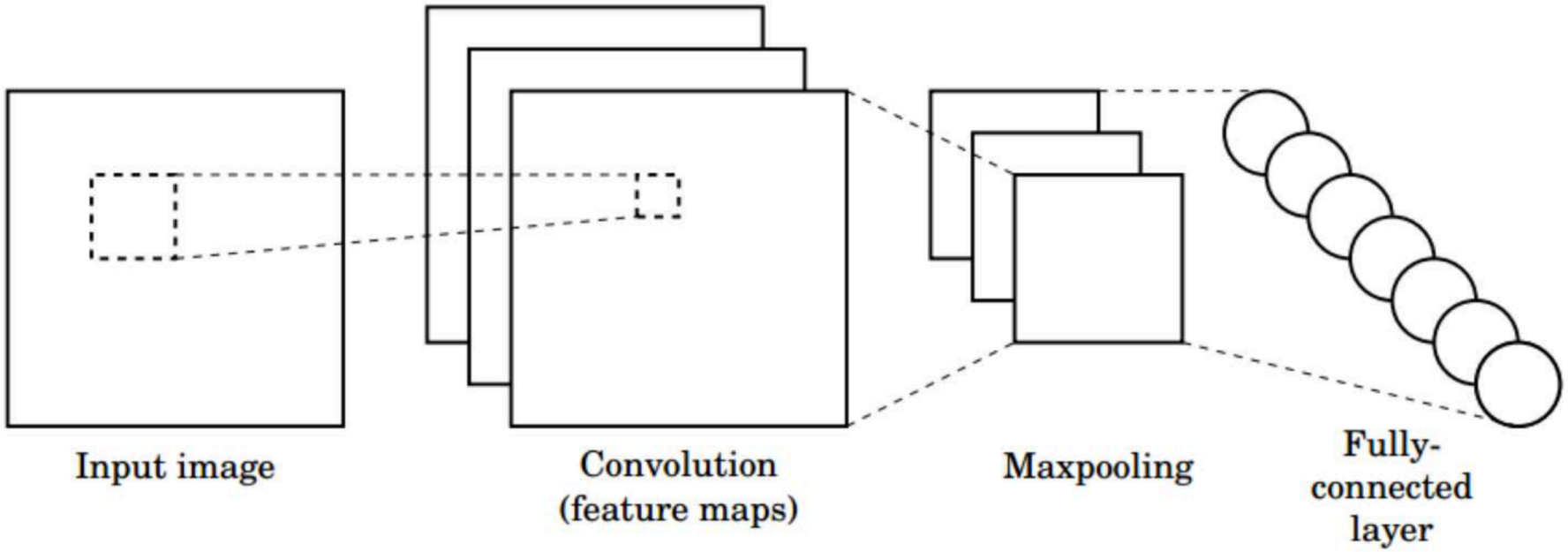
Original

Sharpen

Edge Detect

"Strong" Edge Detect

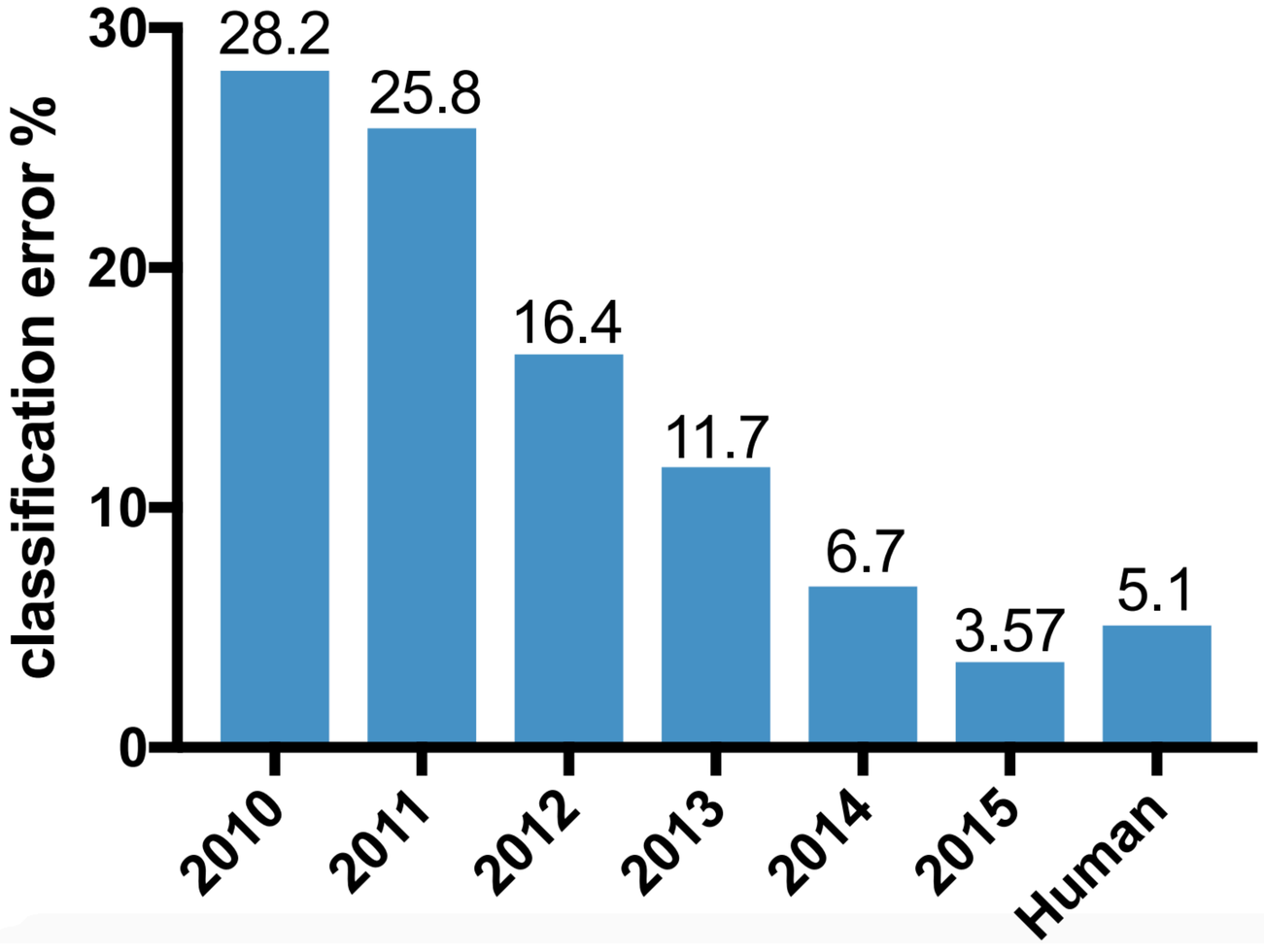
CNNs for Classification



1. **Convolution**: Apply filters with learned weights to generate feature maps.
2. **Non-linearity**: Often ReLU.
3. **Pooling**: Downsampling operation on each feature map.

Train model with image data.
Learn weights of filters in convolutional layers.

ImageNet Challenge: Classification Task



2012: AlexNet. First CNN to win.
- 8 layers, 61 million parameters

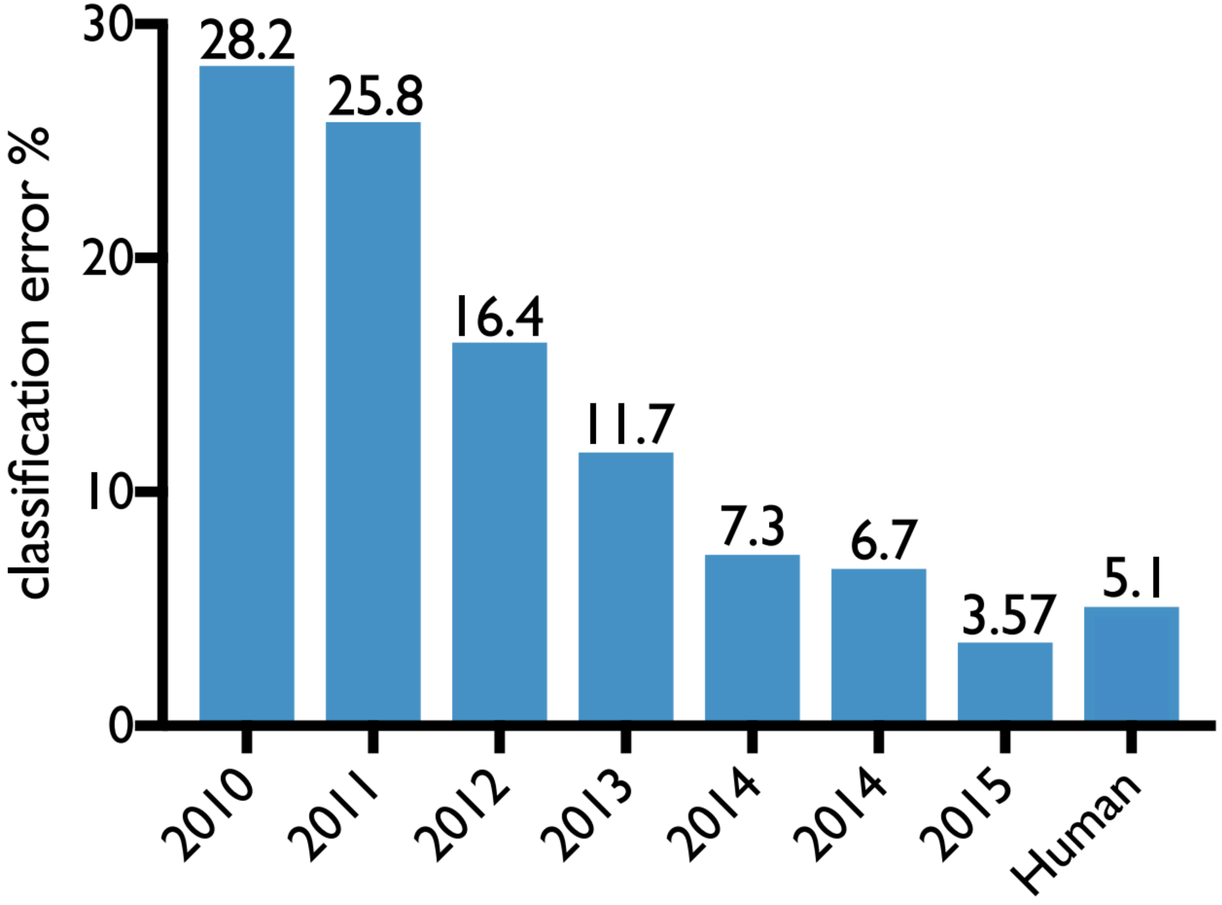
2013: ZFNet
- 8 layers, more filters

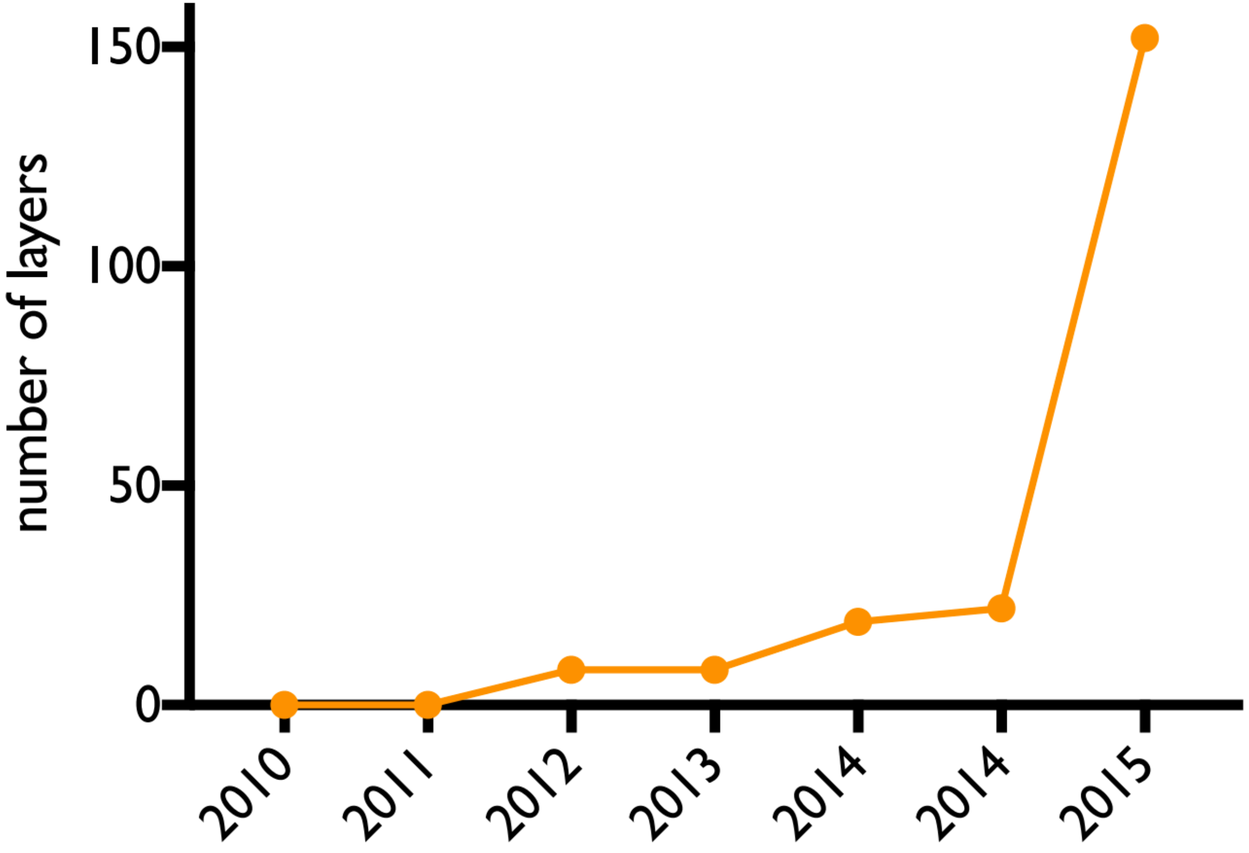
2014: VGG
- 19 layers

2014: GoogLeNet
- "Inception" modules
- 22 layers, 5million parameters

2015: ResNet
- 152 layers

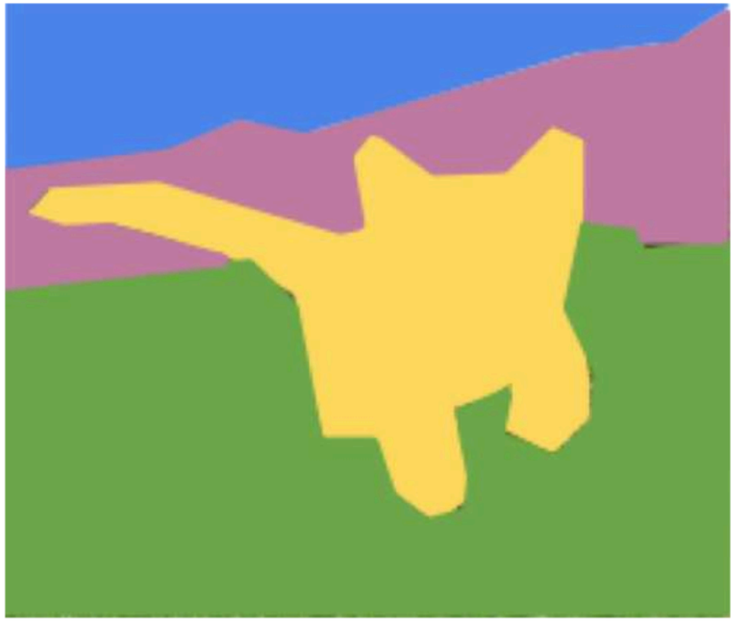
ImageNet Challenge: Classification Task





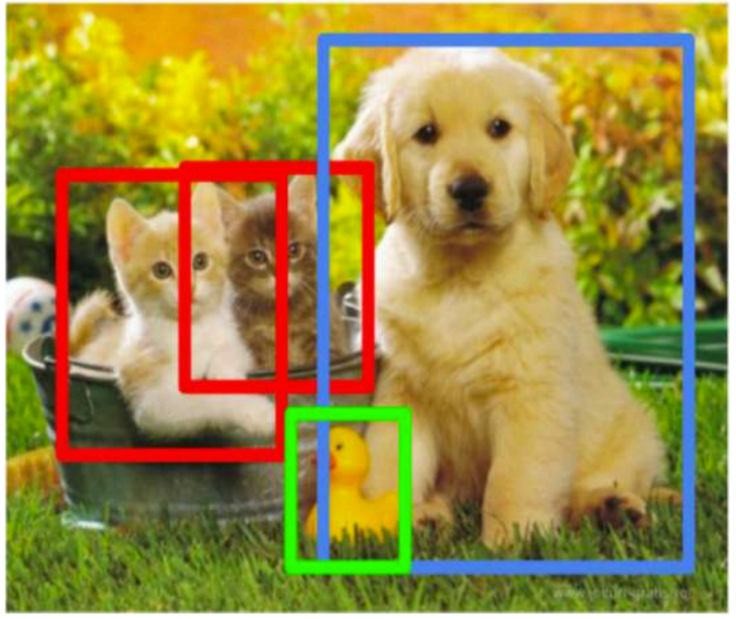
Beyond Classification

Semantic Segmentation



CAT

Object Detection



CAT, DOG, DUCK

Image Captioning

The cat is in the grass.

Which face is fake?

Supervised vs unsupervised learning

Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn function to map
$x \rightarrow y$

Examples: Classification, regression, object detection, semantic segmentation, etc.

Unsupervised Learning

Data: x
x is data, no labels!

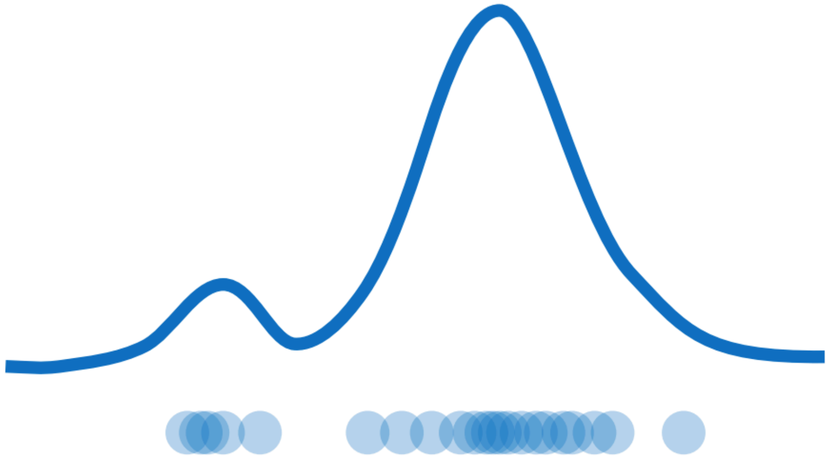
Goal: Learn some *hidden* or *underlying structure* of the data

Examples: Clustering, feature or dimensionality reduction, etc.

Generative modeling

Goal: Take as input training samples from some distribution and learn a model that represents that distribution

Density Estimation

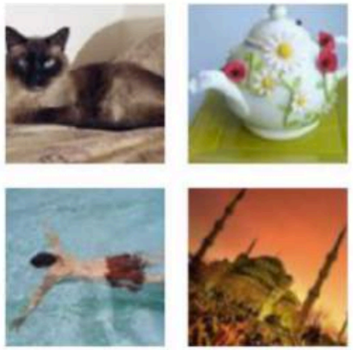


samples

Sample Generation

Input samples

Training data ~ $P_{data}(x)$



Generated samples

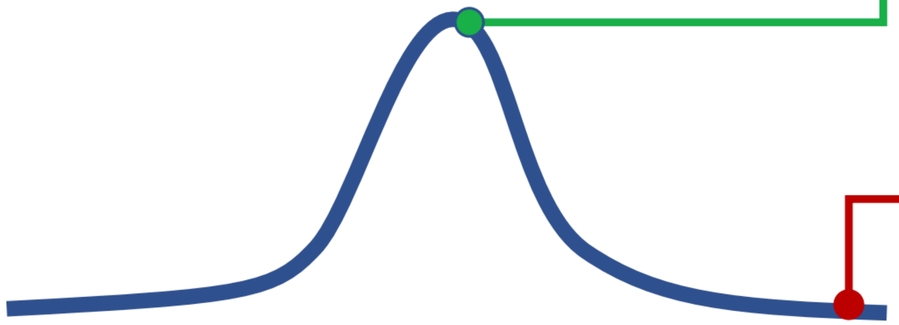
Generated ~ $P_{model}(x)$

Why generative models? Outlier detection

- **Problem:** How can we detect when we encounter something new or rare?
- **Strategy:** Leverage generative models, detect outliers in the distribution
- Use outliers during training to improve even more!

95% of Driving Data:
(1) sunny, (2) highway, (3) straight road

Detect outliers to avoid unpredictable behavior when training



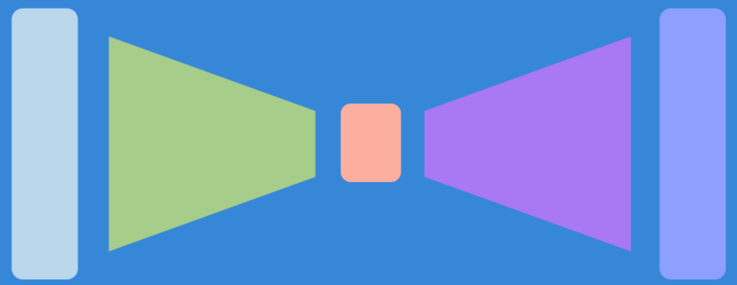
Edge Cases

Harsh Weather

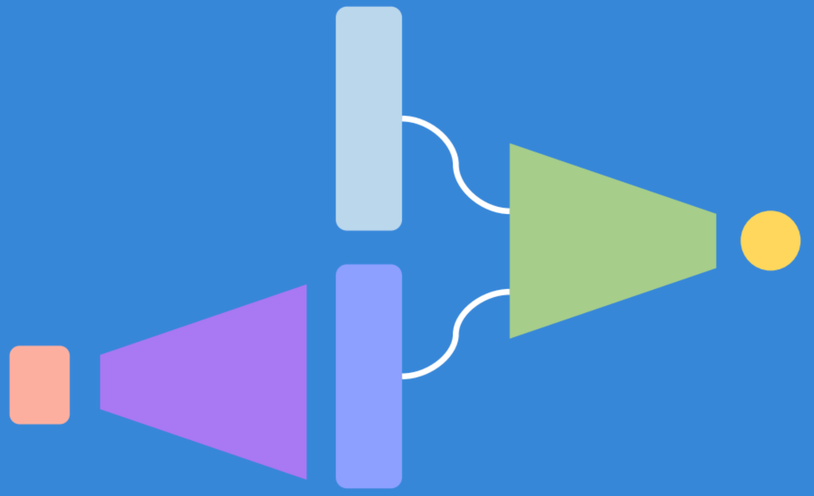
Pedestrians

Latent variable models

Autoencoders and Variational Autoencoders (VAEs)



Generative Adversarial Networks (GANs)



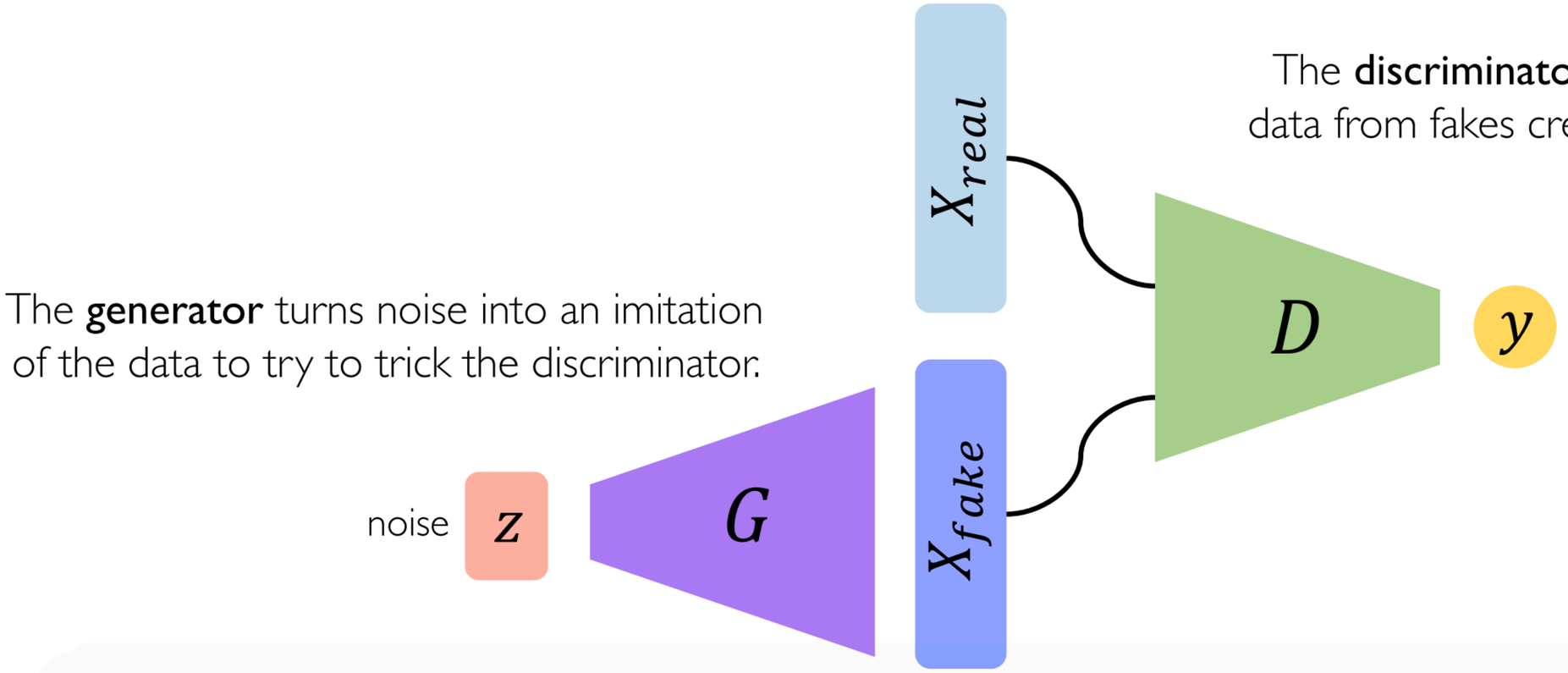
We will discuss this

Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are a way to make a generative model by having two neural networks compete with each other.

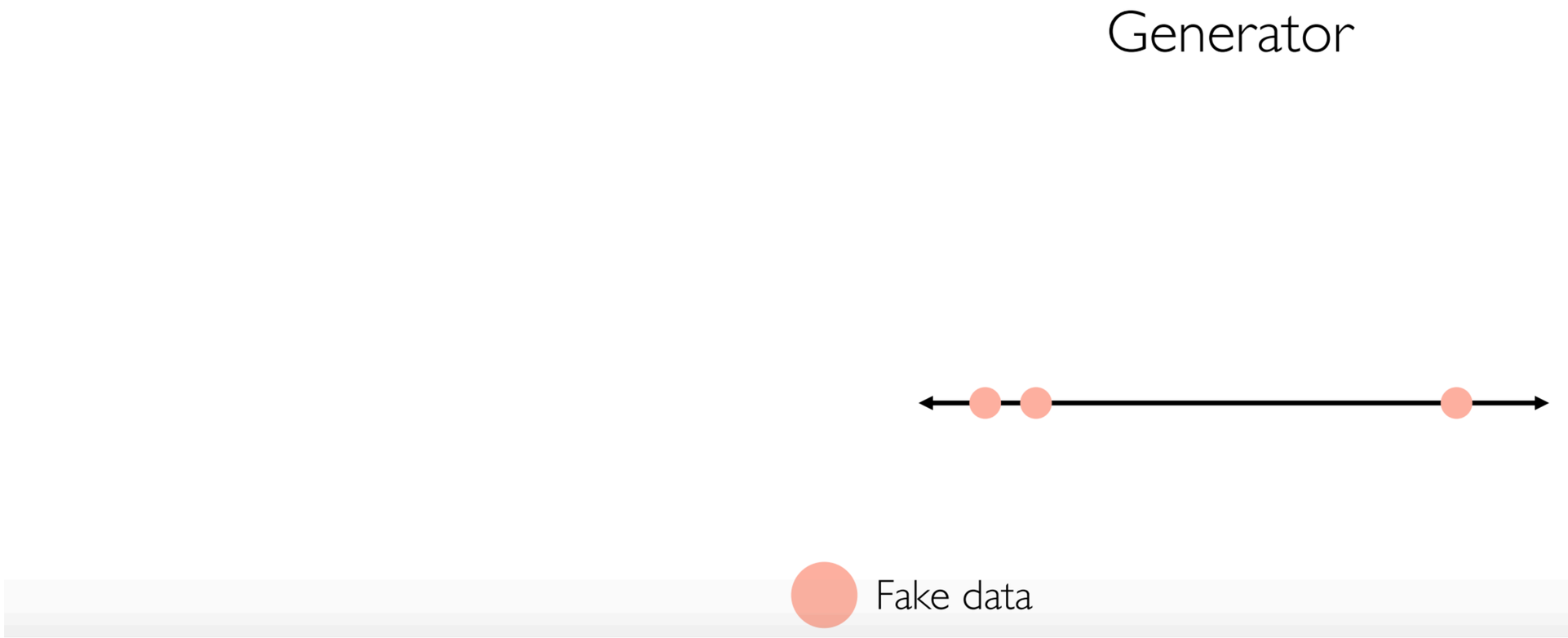
The **discriminator** tries to identify real data from fakes created by the generator.

The **generator** turns noise into an imitation of the data to try to trick the discriminator.



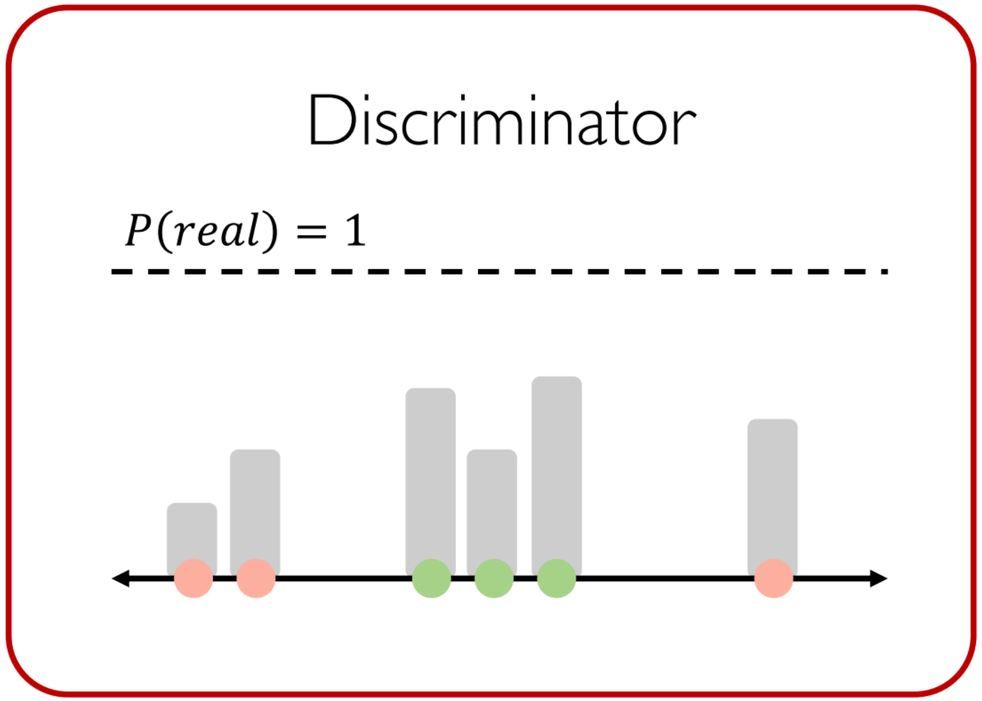
Intuition behind GANs

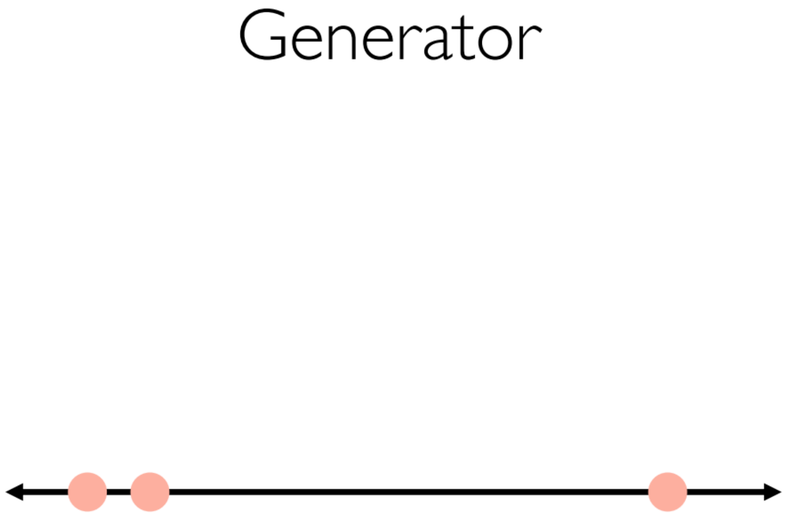
Generator starts from noise to try to create an imitation of the data.



Intuition behind GANs

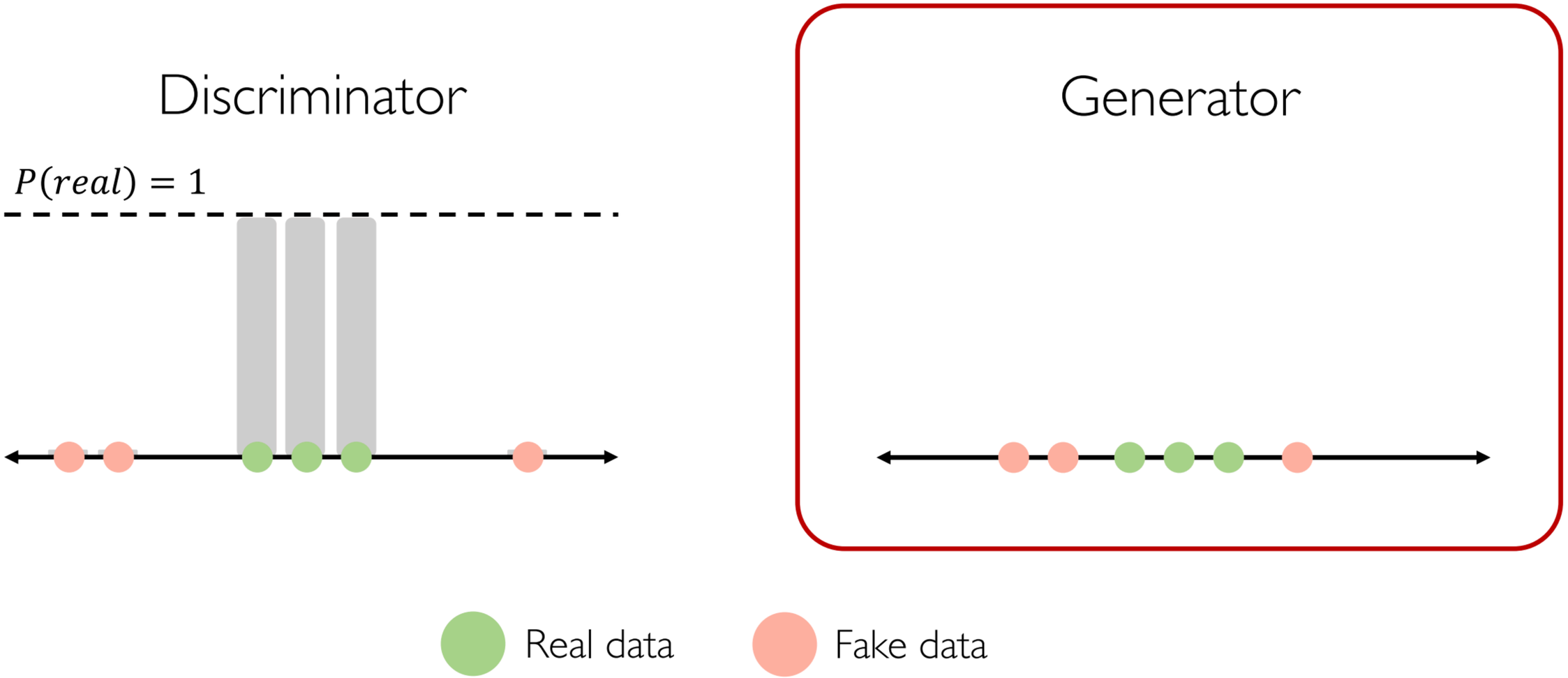
Discriminator tries to predict what's real and what's fake.





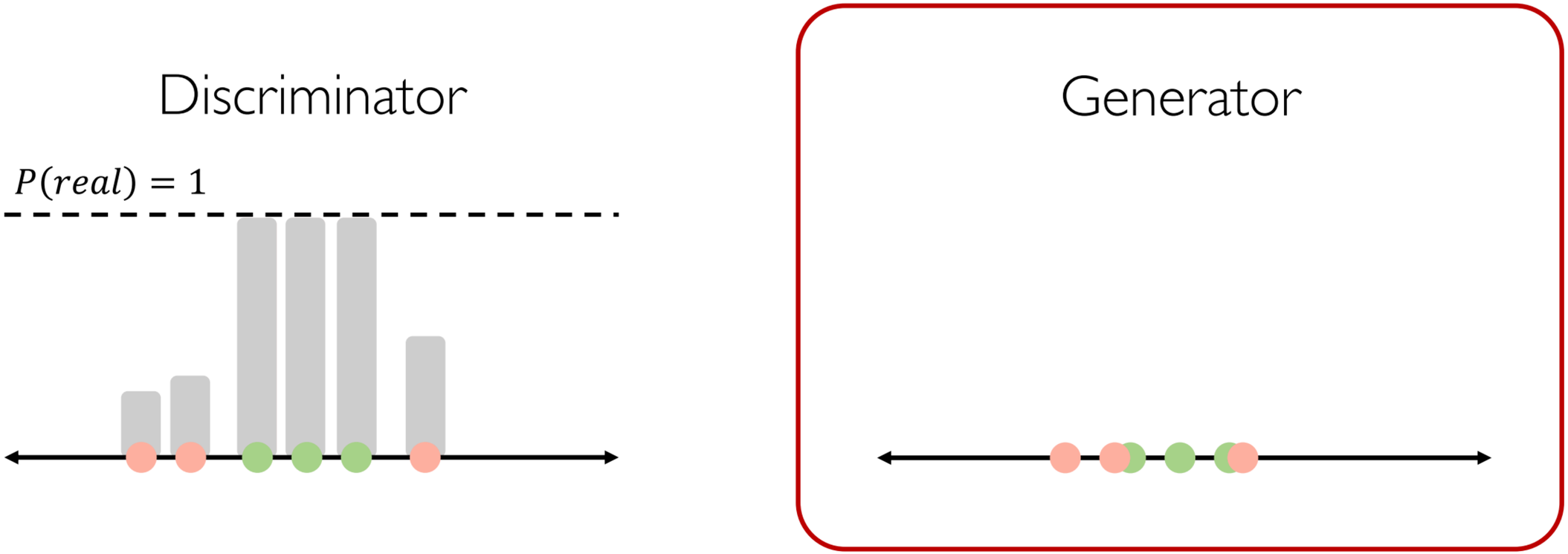
Real data Fake data

Generator tries to improve its imitation of the data.

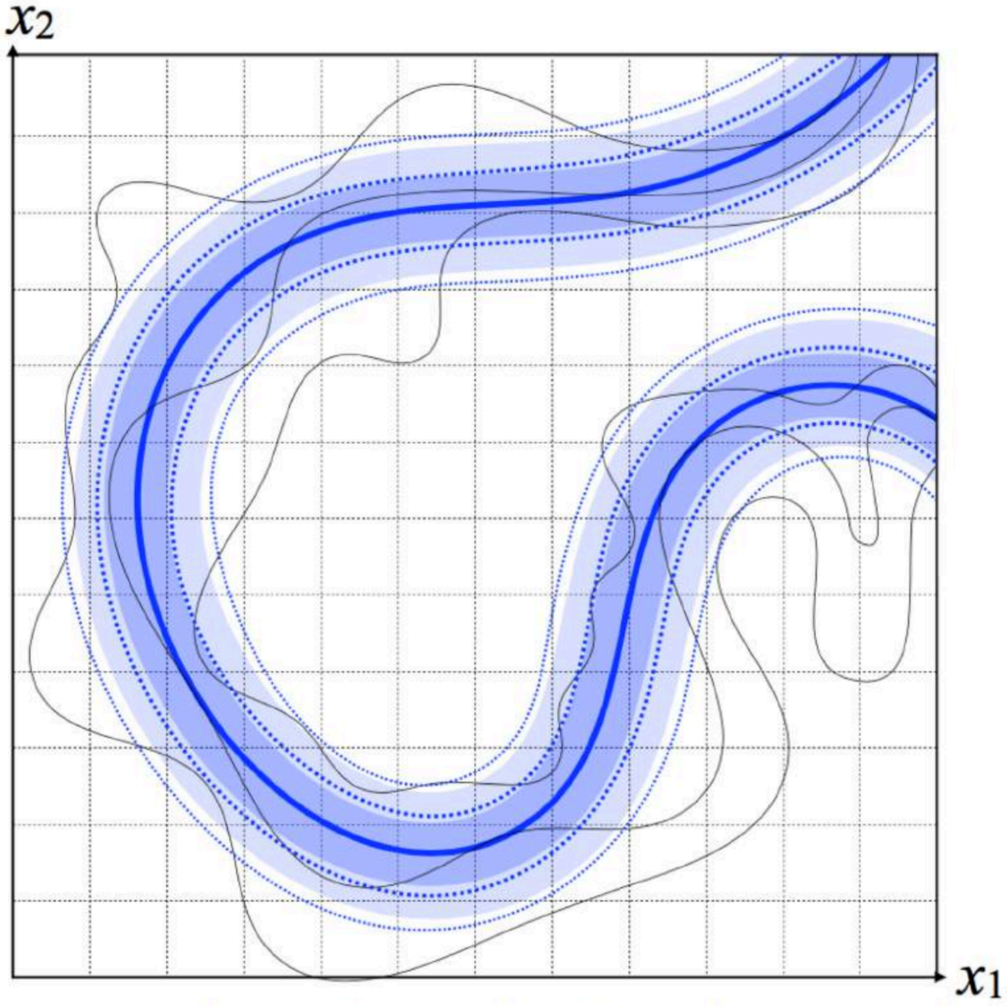


Intuition behind GANs

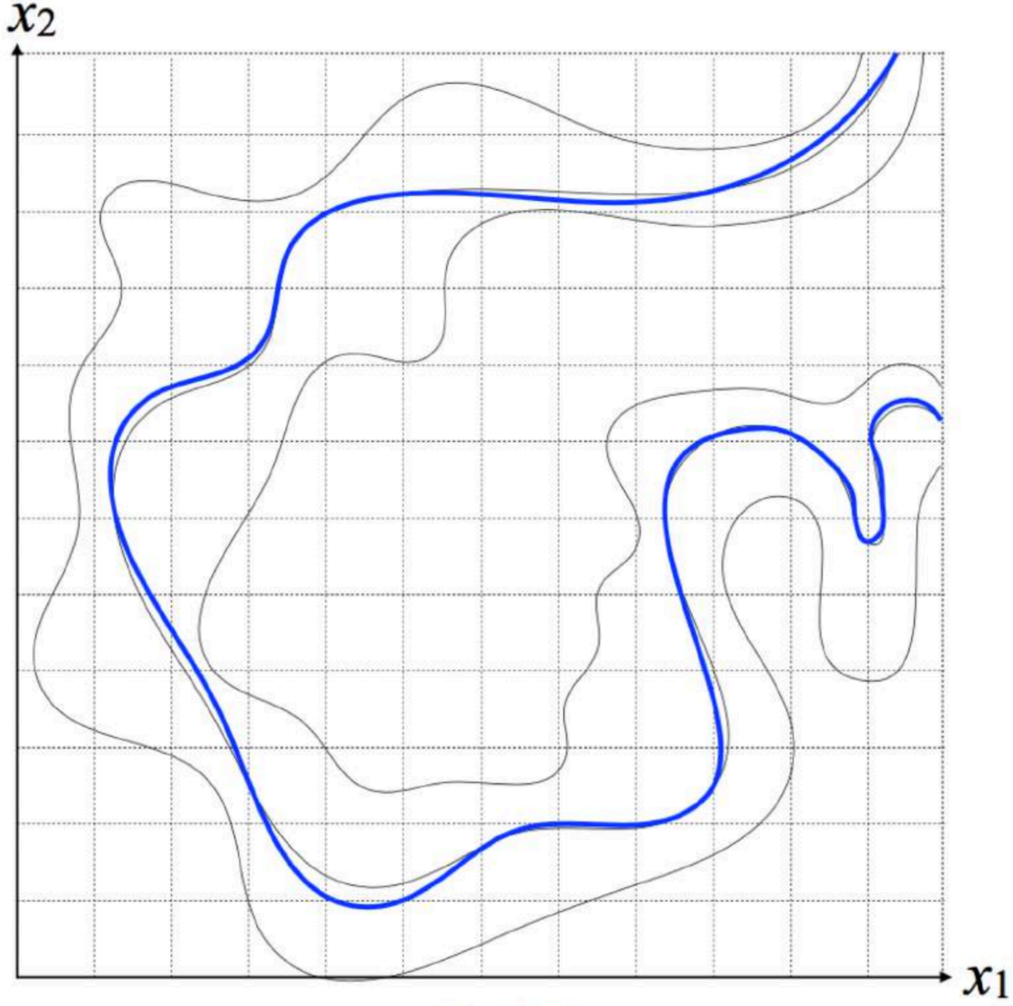
Generator tries to improve its imitation of the data.



Why GANs?



more traditional max-likelihood approach

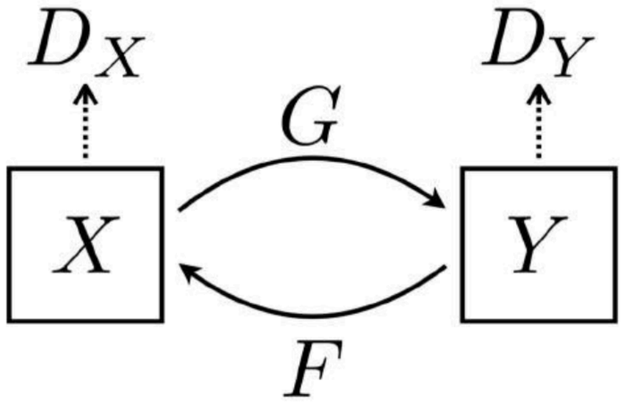


GAN

Style-based transfer: results

CycleGAN: domain transformation

CycleGAN learns transformations across domains with unpaired data.



NLP

A sequence modeling problem: predict the next word

"This morning I took my cat for a walk."

Idea #1: use a fixed window

"This morning I took my cat for a walk."

given these two words

predict the next word

One-hot feature encoding: tells us what each word is

[1 0 0 0 0 0 1 0 0 0]

for a

prediction

Idea #2: use entire sequence as set of counts

"This morning I took my cat for a"

"bag of words"

[0 1 0 0 1 0 0 ... 0 0 1 1 0 0 0 1]

prediction

Idea #3: use a really big fixed window

"This morning I took my cat for a walk."

given these words

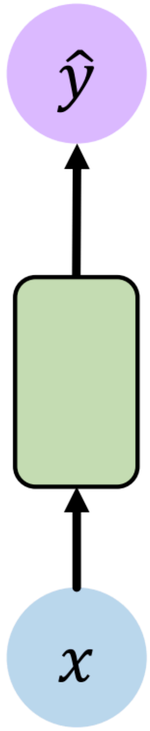
predict the next word

[1 0 0 0 0 0 0 0 0 1 0 0 1 0 0 0 1 0 0 0 0 0 0 1 0 ...]

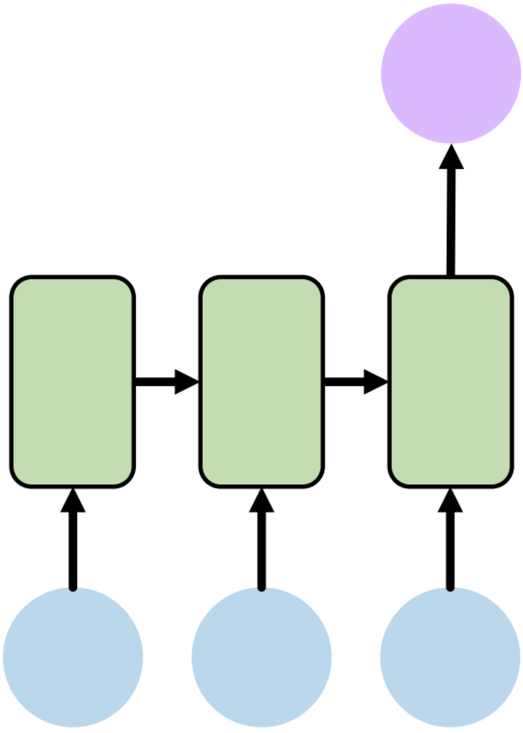
morning I took this cat

prediction

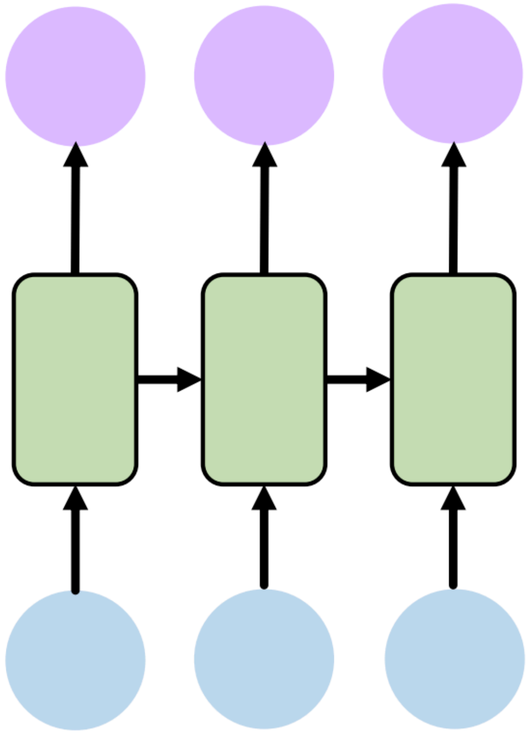
Recurrent neural networks: sequence modeling



One to One
"Vanilla" neural network

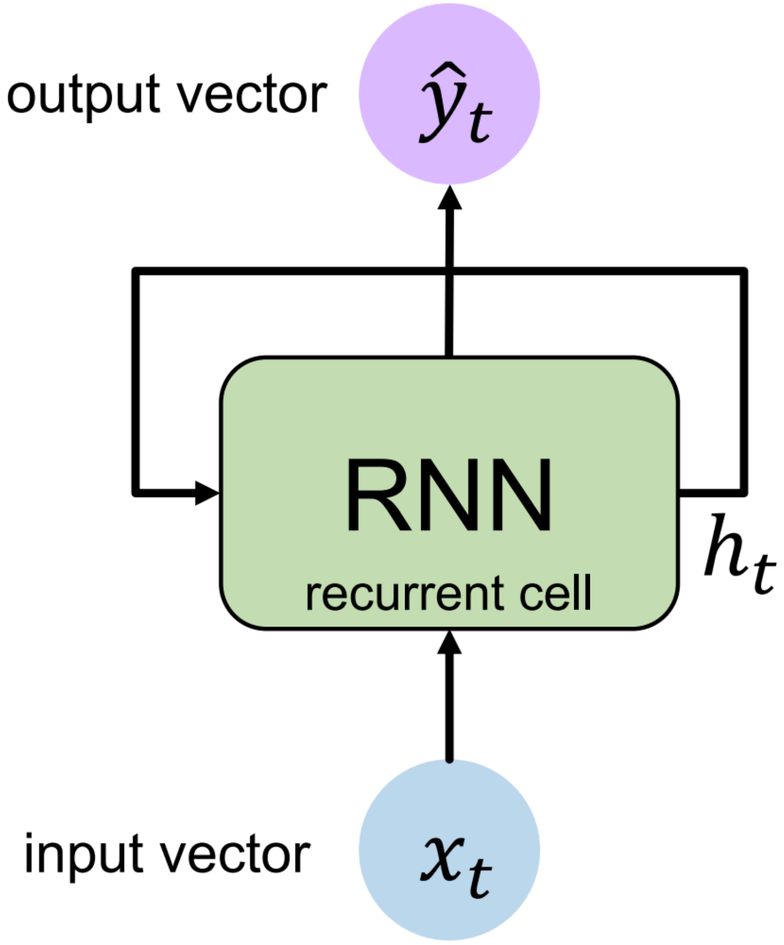


Many to One
Sentiment Classification



Many to Many
Music Generation

A recurrent neural network (RNN)



Apply a **recurrence relation** at every time step to process a sequence:

$$h_t = f_W(h_{t-1}, x_t)$$

new state

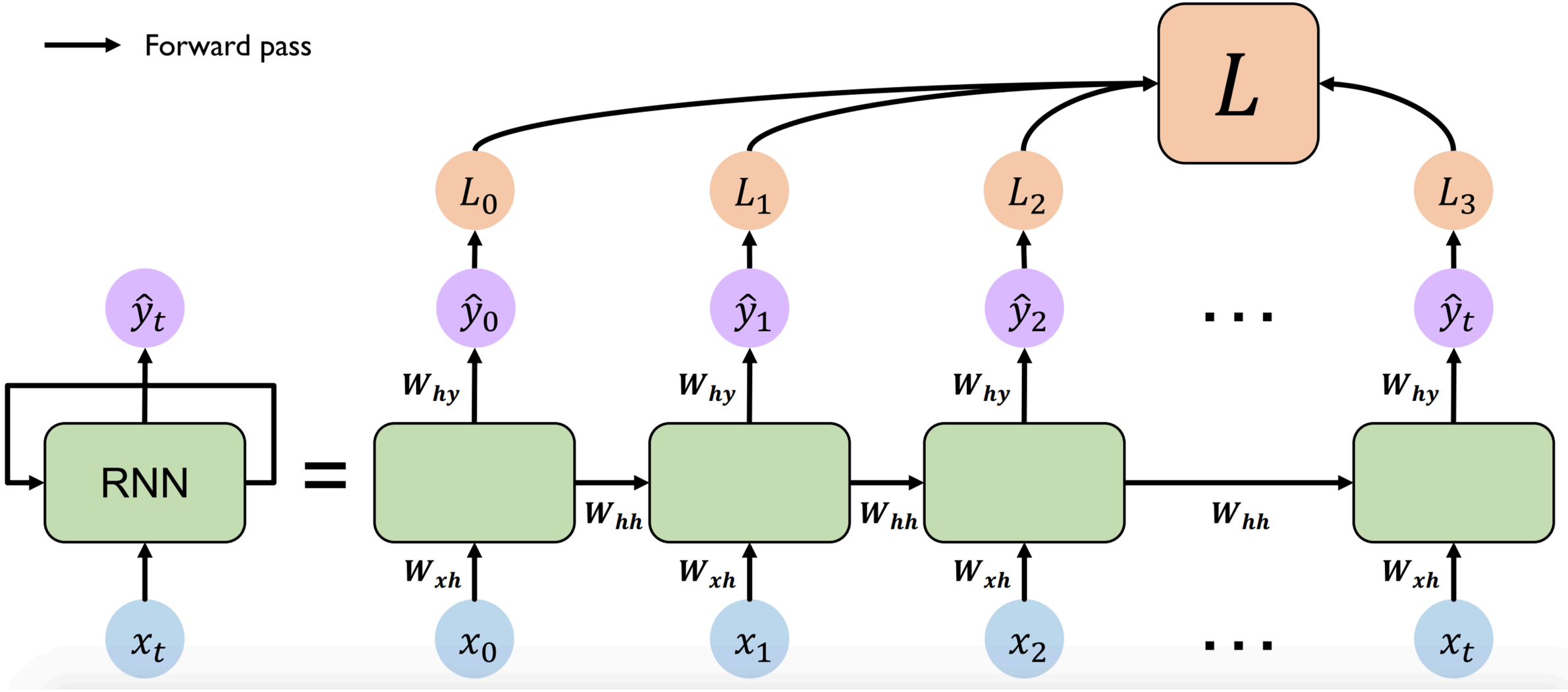
function parameterized by W

old state

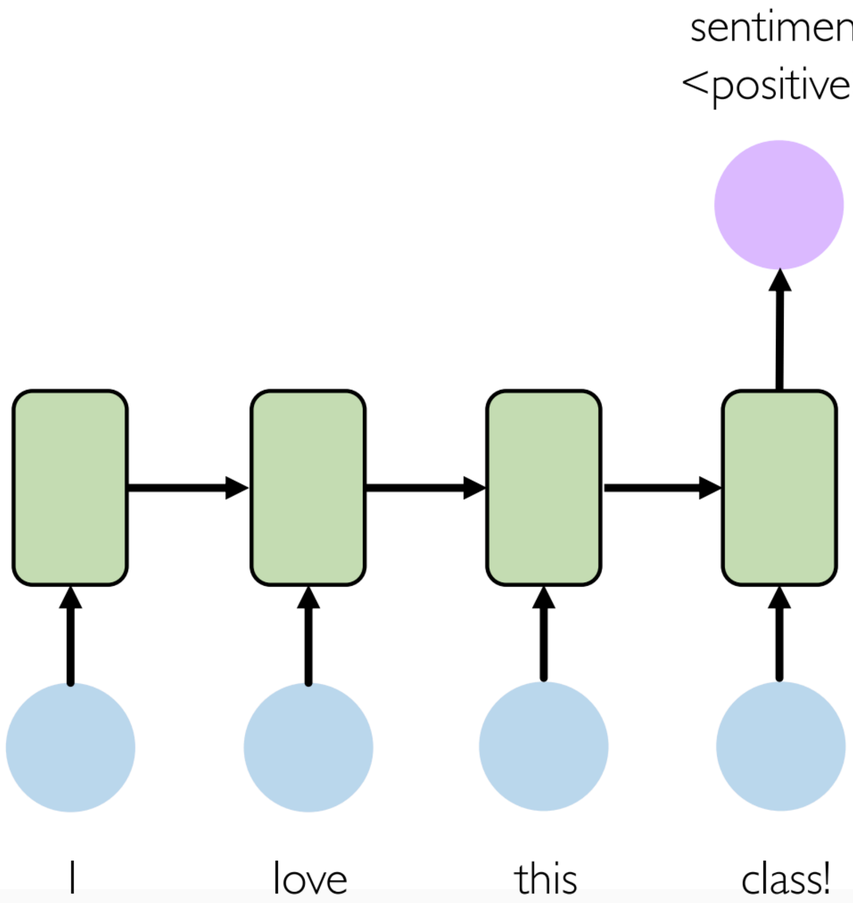
input vector at time step *t*

Note: the same function and set of parameters are used at every time step

RNNs: computational graph across time



Example task: sentiment classification

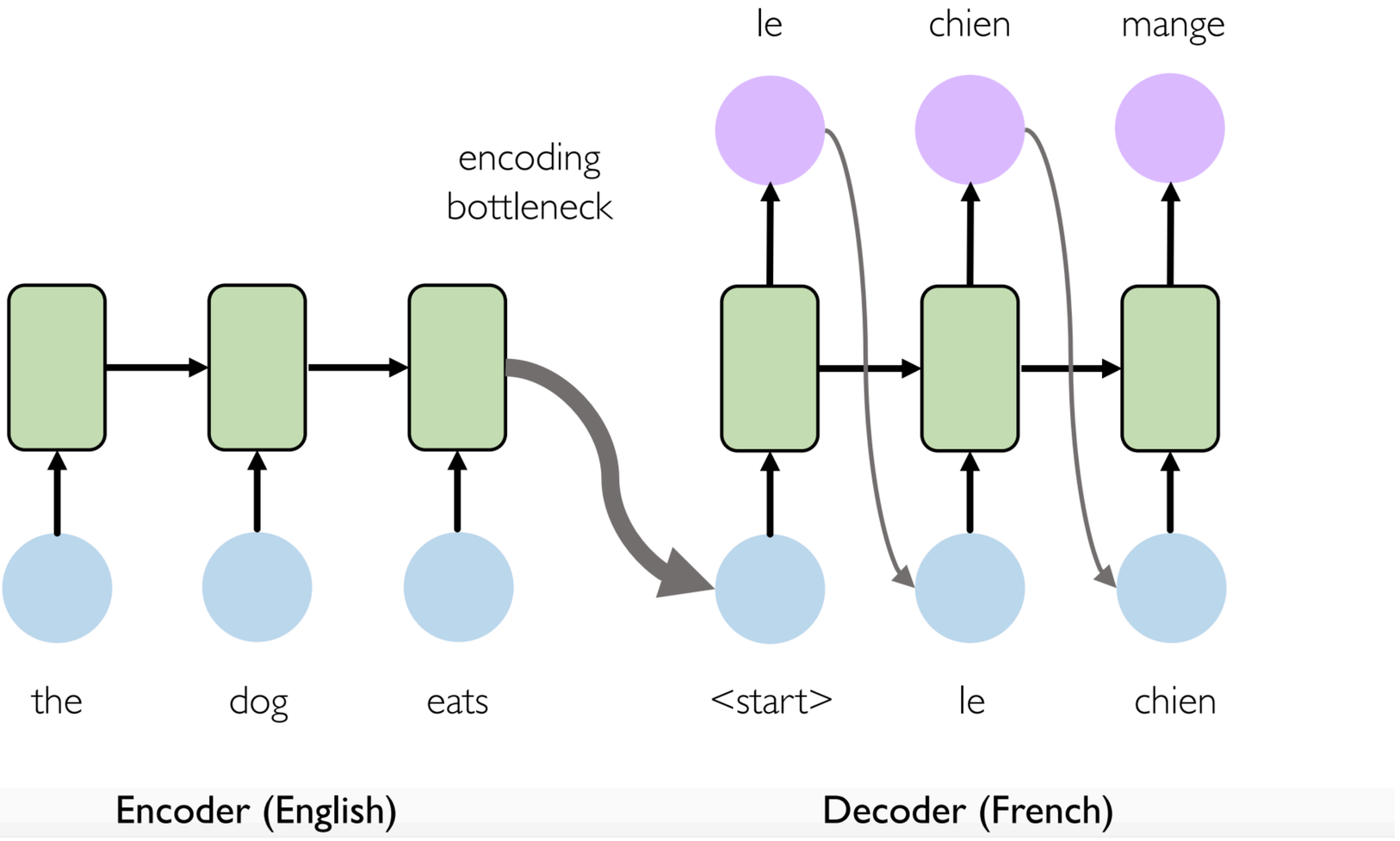


Input: sequence of words

Output: probability of having positive sentiment

```
loss = tf.nn.softmax_cross_entropy_with_logits(
    labels=model.y, logits=model.pred
)
```

Example task: machine translation



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Stanford CS230: Deep Learning: http://cs230.stanford.edu/