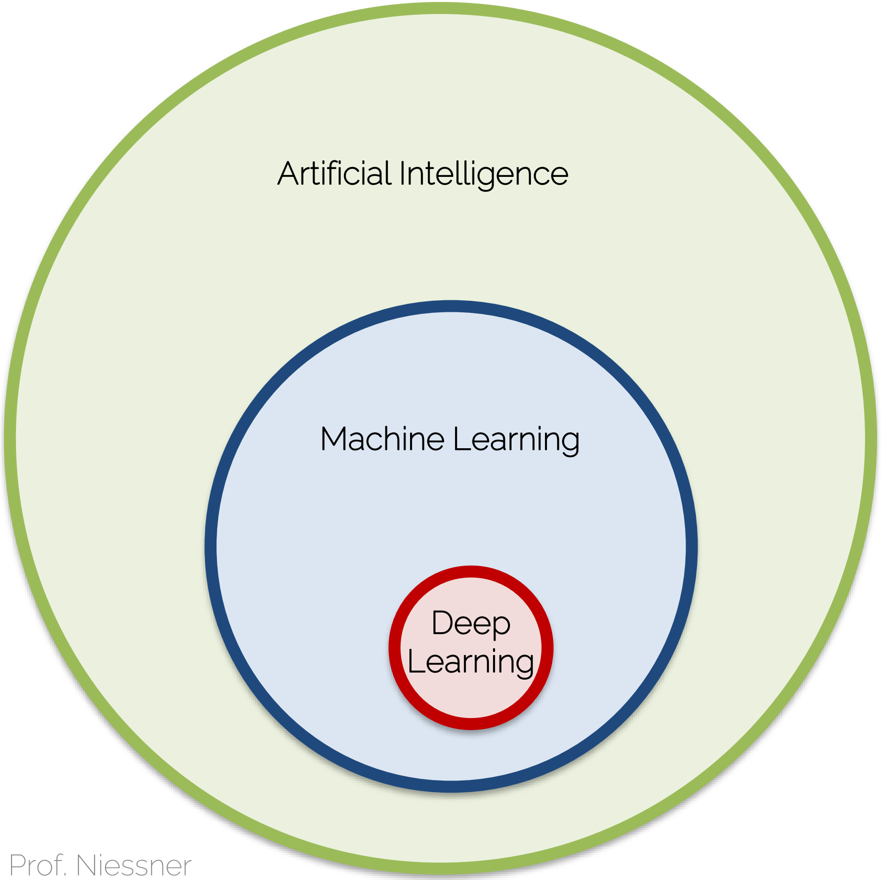
Machine Learning Basics

AI vs ML vs DL

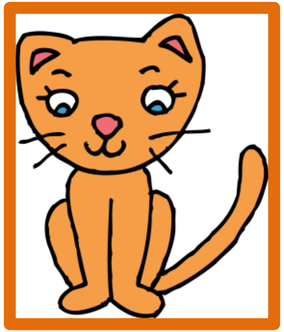


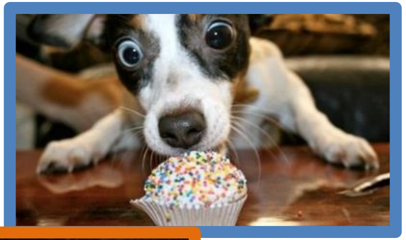
A Simple Task: Image Classification

Image Classification

Task

Image Classification





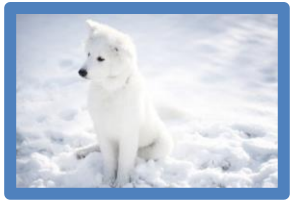


Image Classification

Occlusions

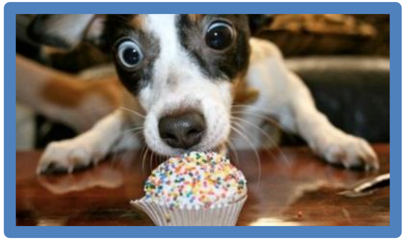
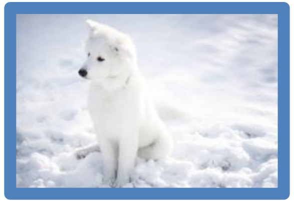
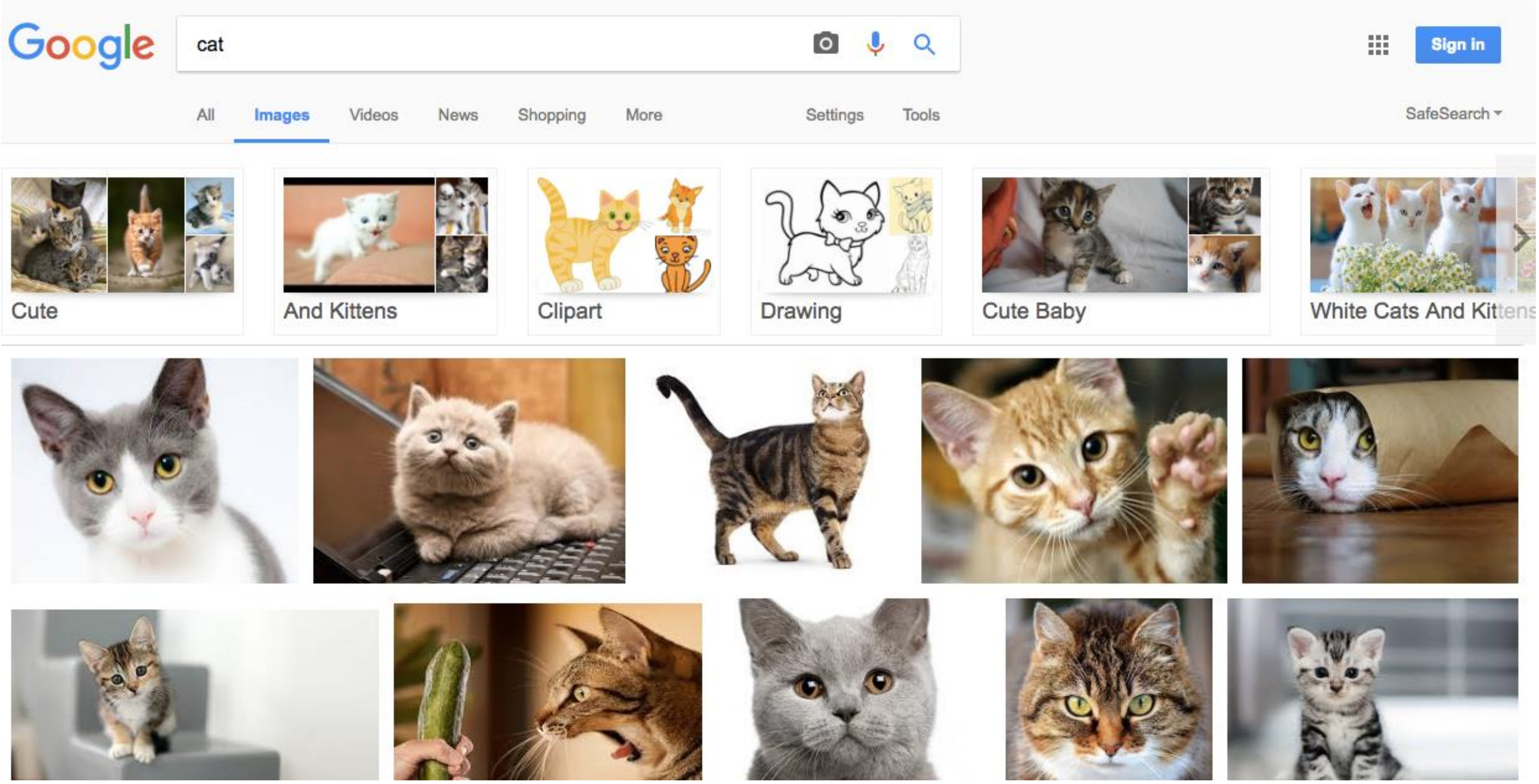


Image Classification

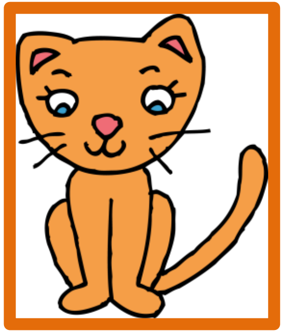
Background clutter





Pose Illumination Appearance

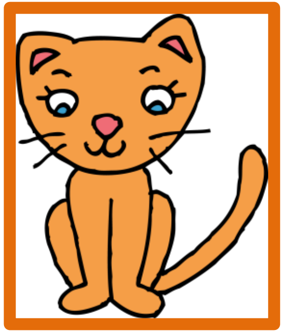
Image Classification



Representation

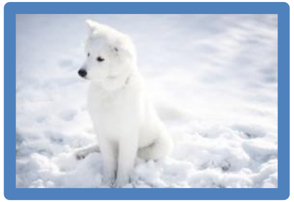
A Simple Classifier

Nearest Neighbor







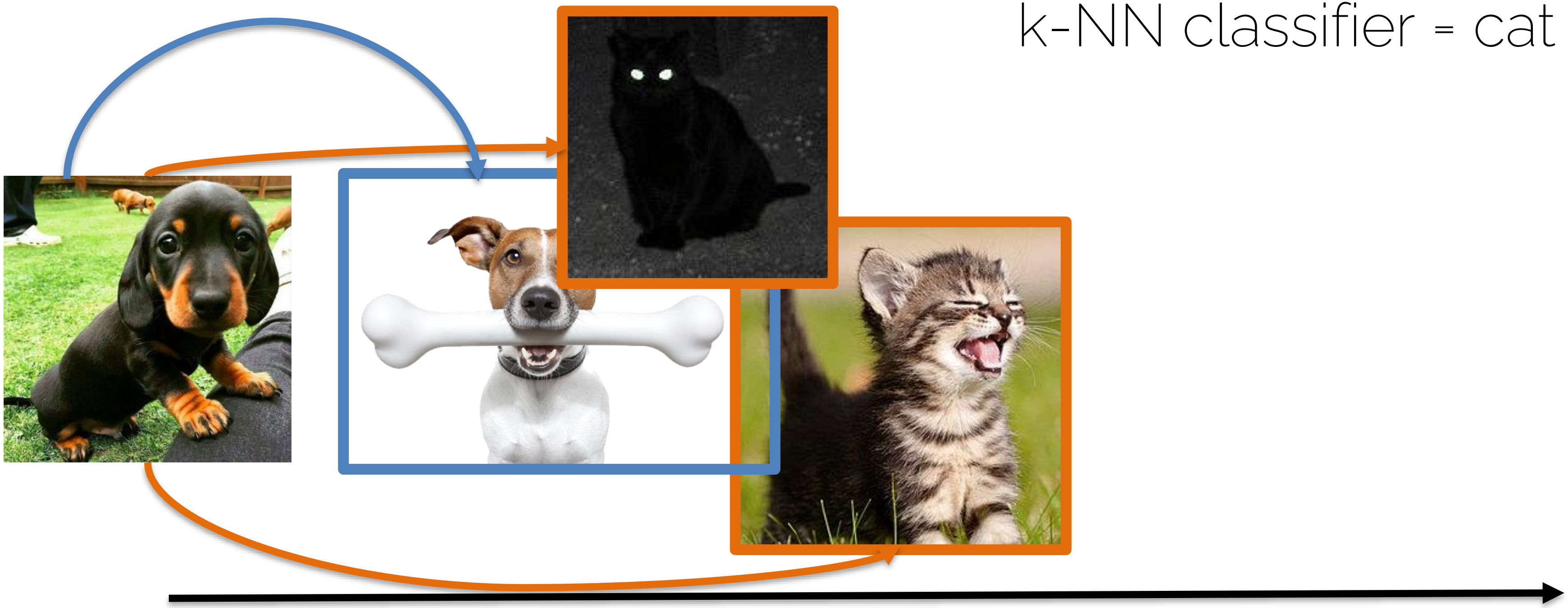

Nearest Neighbor

NN classifier = dog

distance

Nearest Neighbor

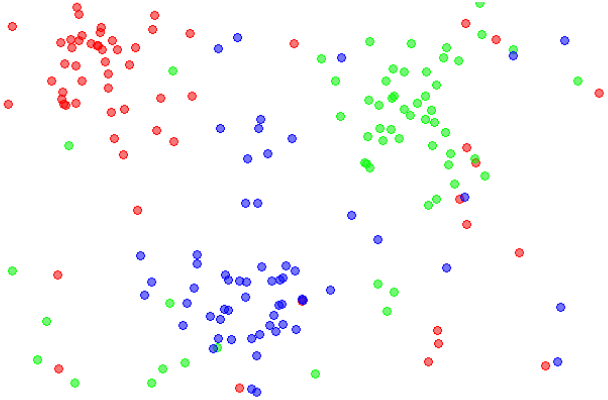
k-NN classifier = cat



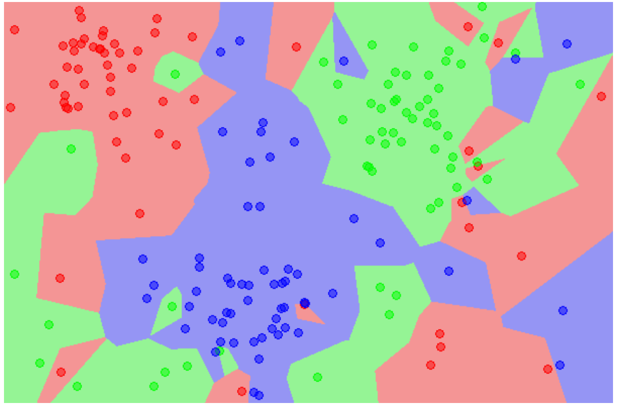
distance

Nearest Neighbor

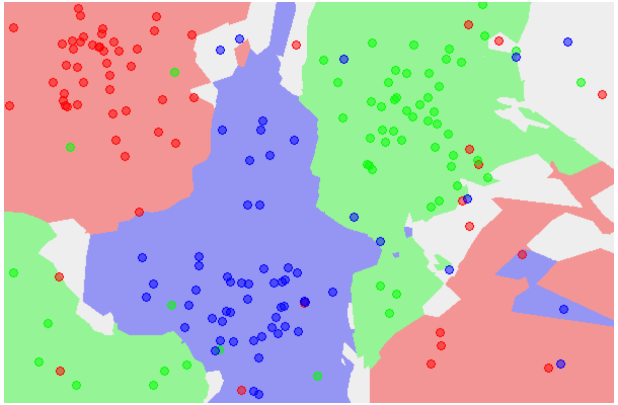
The Data



NN Classifier



5NN Classifier



How does the NN classifier perform on training data?

What classifier is more likely to perform best on test data?

What are we actually learning?

Source: https://commons.wikimedia.org/wiki/File:Data3classes.png

Nearest Neighbor

- Hyperparameters
  - L1 distance : $|x - c|$
  - L2 distance : $||x - c||_2$
  - No. of Neighbors: k

- These parameters are problem dependent.

- How do we choose these hyperparameters?

Machine Learning for Classification

Machine Learning

- How can we learn to perform image classification?

Task

Image classification

Experience

Data

Machine Learning

- $M_\theta(I) = \{\text{DOG}, \text{CAT}\}$

Model

Model Params

Image

Class Label

CAT

DOG

DOG

CAT

CAT

DOG

Machine Learning

- $M_\theta(I) = \{\text{DOG}, \text{CAT}\}$

Model

Model Params

Image

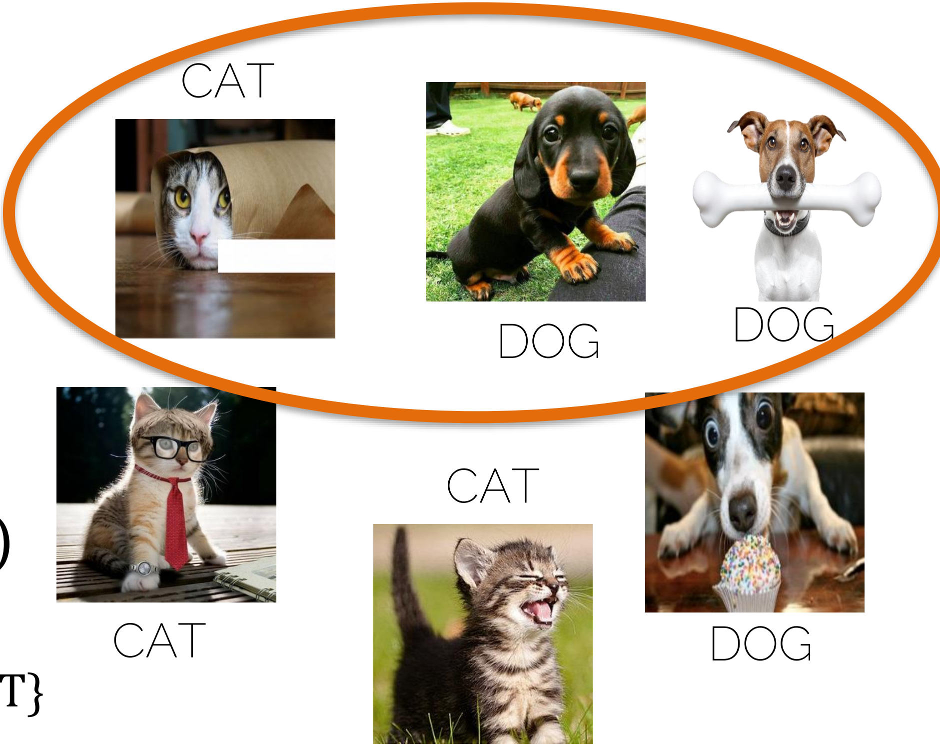
Class Label

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \sum_i \mathrm{D}(M_\theta(I_i) - Y_i)$$

"Distance" function

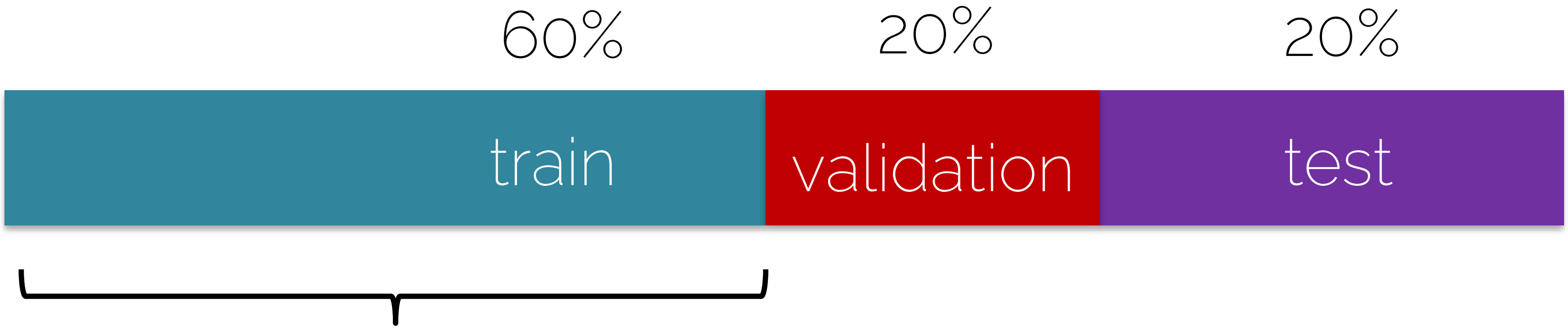
$\{\text{DOG}, \text{CAT}\}$

Given i images with train labels



Basic Recipe for Machine Learning

- Split your data

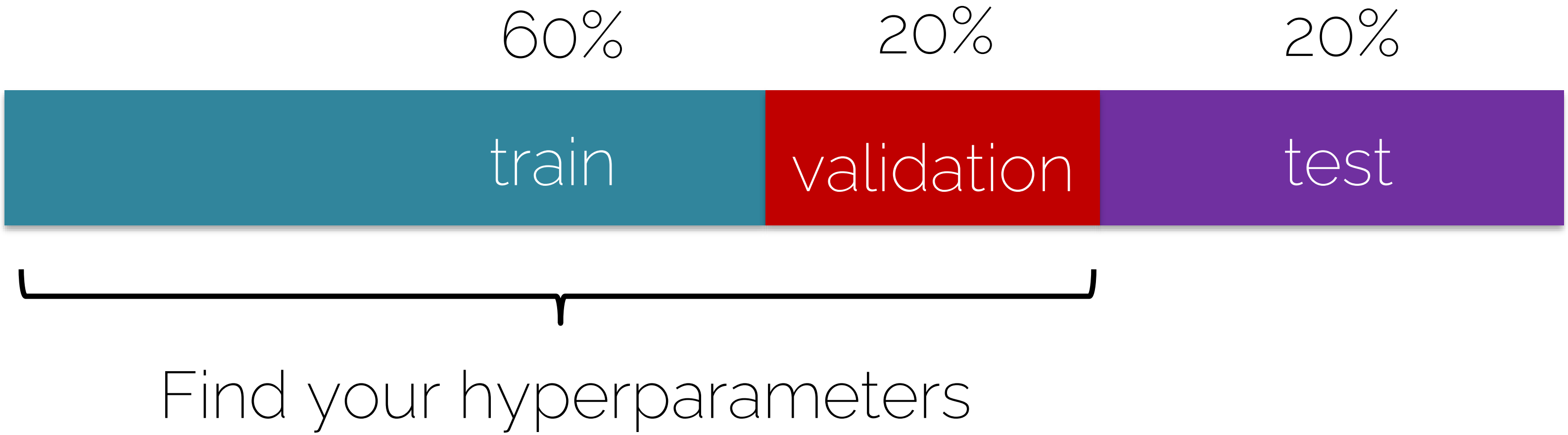


Find model params $\boldsymbol{\theta}$

Other splits are also possible (e.g., 80%/10%/10%)

Basic Recipe for Machine Learning

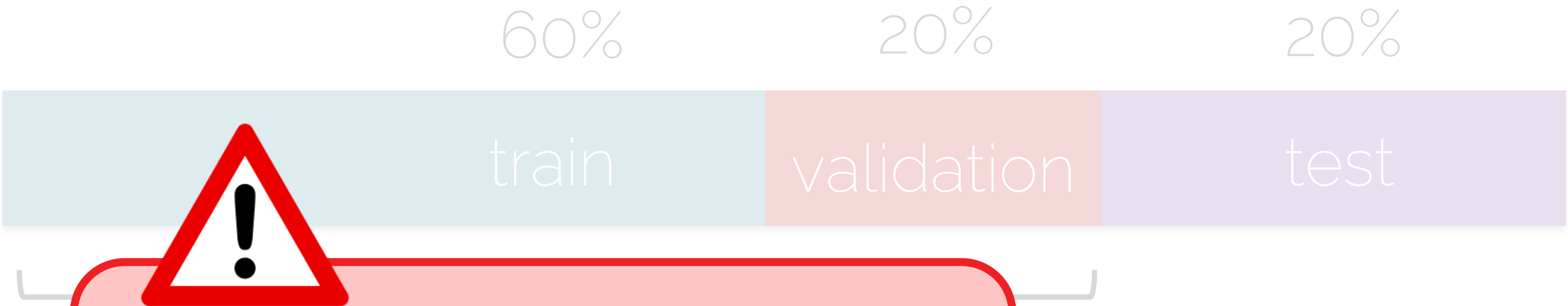
- Split your data



Other splits are also possible (e.g., 80%/10%/10%)

Basic Recipe for Machine Learning

- Split your data



Test set is only used once!

Machine Learning

- How can we learn to perform image classification?

Task

Image classification

Performance measure

Accuracy

Experience

Data

Machine Learning

Unsupervised learning

Supervised learning

- Labels or target classes

Machine Learning

Unsupervised learning

Supervised learning

CAT

DOG

DOG

CAT

CAT

DOG

Machine Learning

Unsupervised learning

- No label or target class
- Find out properties of the structure of the data
- Clustering (k-means, PCA, etc.)

Supervised learning

CAT

DOG

DOG

CAT

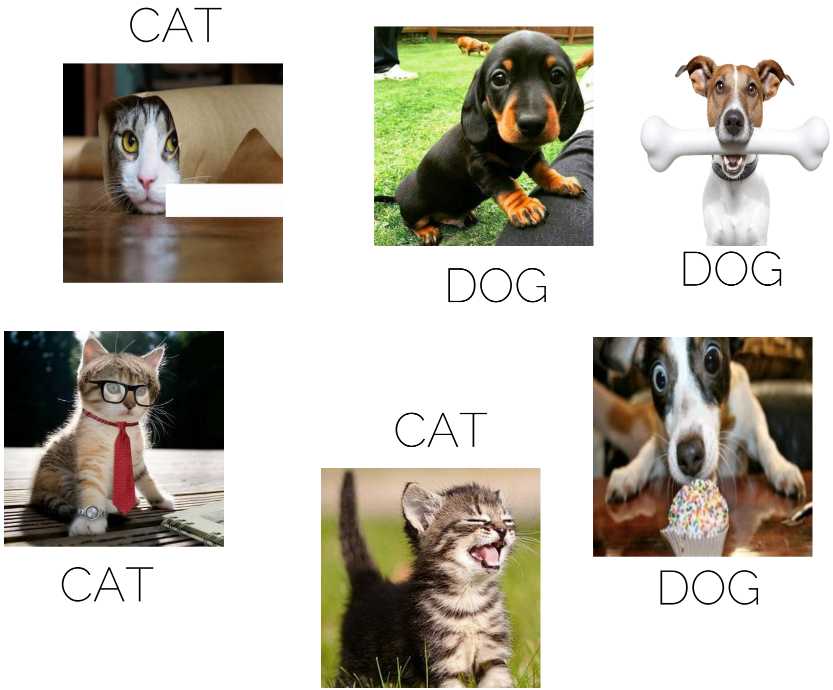
CAT

DOG

Machine Learning

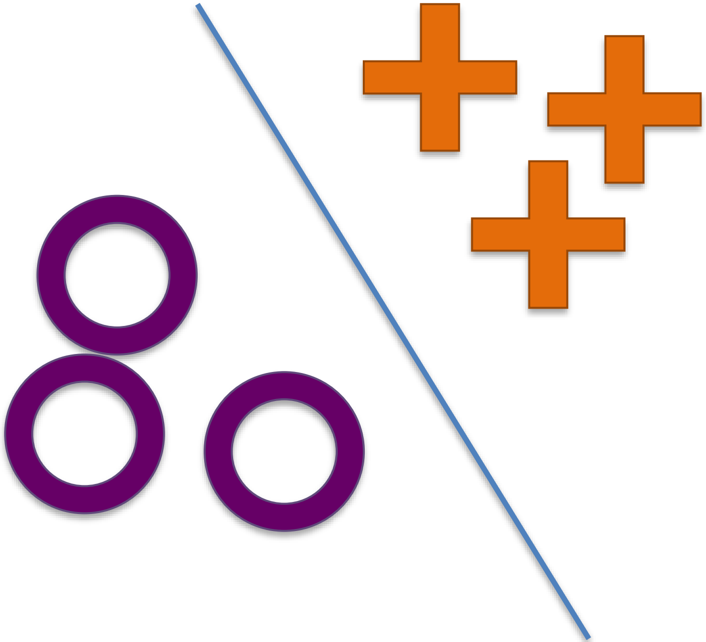
Unsupervised learning

Supervised learning



Machine Learning

Unsupervised learning



Supervised learning

CAT

DOG

DOG

CAT

CAT

DOG

Machine Learning

Unsupervised learning

Supervised learning

Reinforcement learning

Agents —interaction→ Environment

Machine Learning

Unsupervised learning

Supervised learning

Reinforcement learning

Machine Learning

Unsupervised learning

Supervised learning

Reinforcement learning

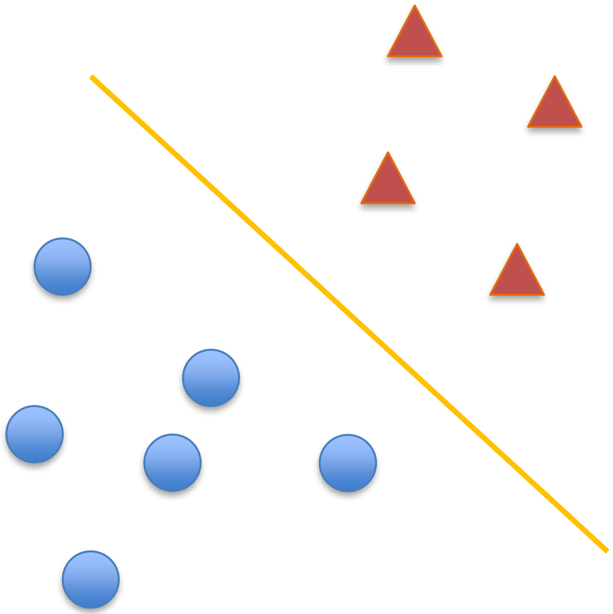
Agents

reward

Environment

Linear Decision Boundaries

Let's start with a simple linear Model!

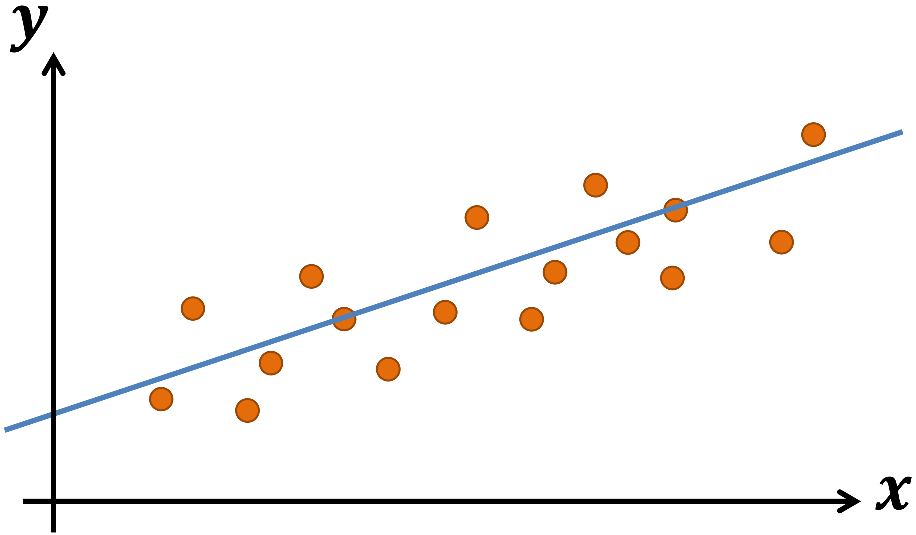


What are the pros and cons for using linear decision boundaries?

Linear Regression

Linear Regression

- Supervised learning
- Find a linear model that explains a target $\boldsymbol{y}$ given inputs $\boldsymbol{x}$



Linear Regression

Training

$\{\boldsymbol{x}_{1:n}, \boldsymbol{y}_{1:n}\}$ → Learner → $\boldsymbol{\theta}$

Data points

Model parameters

Input (e.g., image, measurement)

Labels (e.g., cat/dog)

Linear Regression

Training

can be parameters of a Neural Network

$\{\boldsymbol{x}_{1:n}, \boldsymbol{y}_{1:n}\}$ → **Learner** → $\boldsymbol{\theta}$

Data points — Model parameters

Testing

$x_{n+1}, \boldsymbol{\theta}$ → **Predictor** → $\hat{y}_{n+1}$

Estimation

Linear Prediction

- A linear model is expressed in the form

$$\hat{y}_i = \sum_{j=1}^{d} x_{ij}\theta_j$$

input dimension

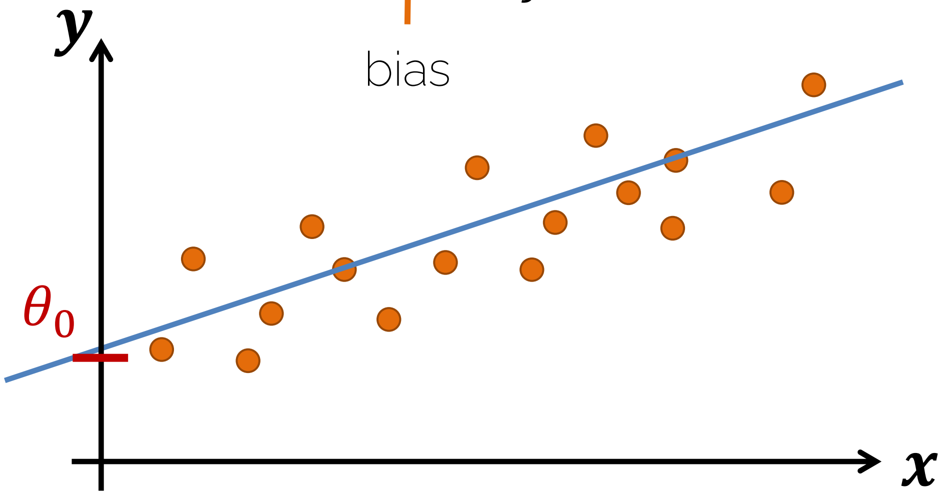
weights (i.e., model parameters)

Input data, features

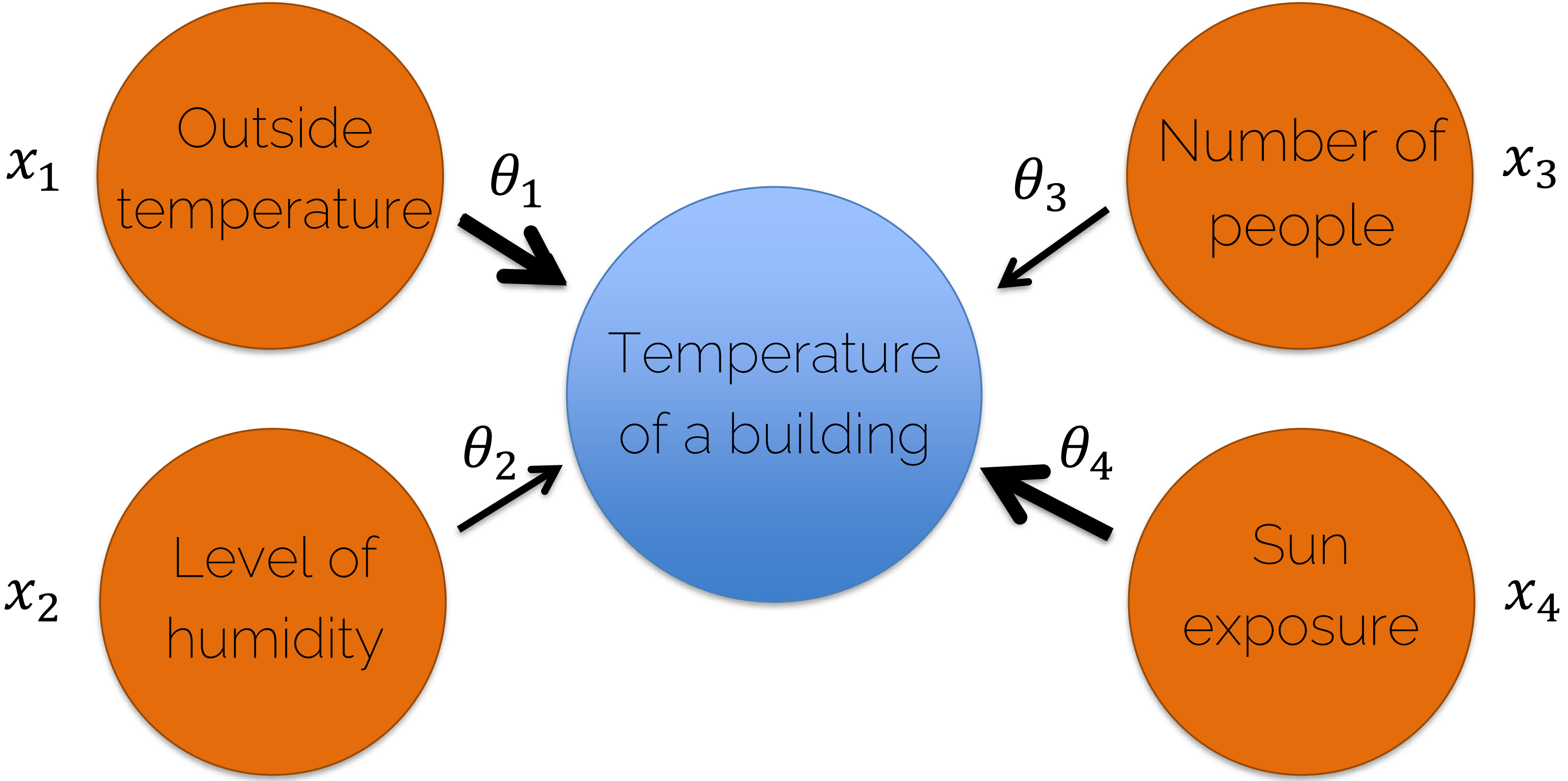
Linear Prediction

- A linear model is expressed in the form

$$\hat{y}_i = \underbrace{\boxed{\theta_0}}_{\text{bias}} + \sum_{j=1}^{d} x_{ij}\theta_j = \theta_0 + x_{i1}\theta_1 + x_{i2}\theta_2 + \cdots + x_{id}\theta_d$$



Linear Prediction



Linear Prediction

$$\begin{bmatrix} \boxed{\hat{y}_1} \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = \theta_0 + \begin{bmatrix} \boxed{x_{11} \quad \cdots \quad x_{1d}} \\ x_{21} \quad \cdots \quad x_{2d} \\ \vdots \quad \ddots \quad \vdots \\ x_{n1} \quad \cdots \quad x_{nd} \end{bmatrix} \cdot \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_d \end{bmatrix}$$

$$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} 1 & x_{11} & \cdots & x_{1d} \\ 1 & x_{21} & \cdots & x_{2d} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{nd} \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_d \end{bmatrix} \quad \Rightarrow \quad \hat{\mathbf{y}} = \mathbf{X}\boldsymbol{\theta}$$

Linear Prediction

$$\hat{\mathbf{y}} = \mathbf{X}\boldsymbol{\theta}$$

Input features

(one sample has $\boldsymbol{d}$ features)

Prediction

$$\begin{bmatrix} \boxed{\hat{y}_1} \\ \hat{y}_2 \\ \vdots \\ \hat{y}_n \end{bmatrix} = \begin{bmatrix} 1 & \boxed{x_{11} \quad \cdots \quad x_{1d}} \\ 1 & x_{21} \quad \cdots \quad x_{2d} \\ \vdots & \vdots \quad \ddots \quad \vdots \\ 1 & x_{n1} \quad \cdots \quad x_{nd} \end{bmatrix} \begin{bmatrix} \theta_0 \\ \theta_1 \\ \vdots \\ \theta_d \end{bmatrix}$$

Model parameters

($\boldsymbol{d}$ weights and $\mathbf{1}$ bias)

Linear Prediction

Temperature of the building

$$\begin{bmatrix}\hat{y}_1\\ \hat{y}_2\end{bmatrix} = \begin{array}{c} \begin{array}{ccccc}\text{Bias} & \text{Outside temperature} & \text{Humidity} & \text{Number people} & \text{Sun exposure (\%)}\end{array} \\ \begin{bmatrix}1 & 25 & 50 & 2 & 50\\ 1 & -10 & 50 & 0 & 10\end{bmatrix}\end{array} \cdot \begin{array}{c}\text{MODEL}\\ \begin{bmatrix}0.2\\ 0.64\\ \boxed{0}\\ \boxed{1}\\ \boxed{0.14}\end{bmatrix}\end{array}$$

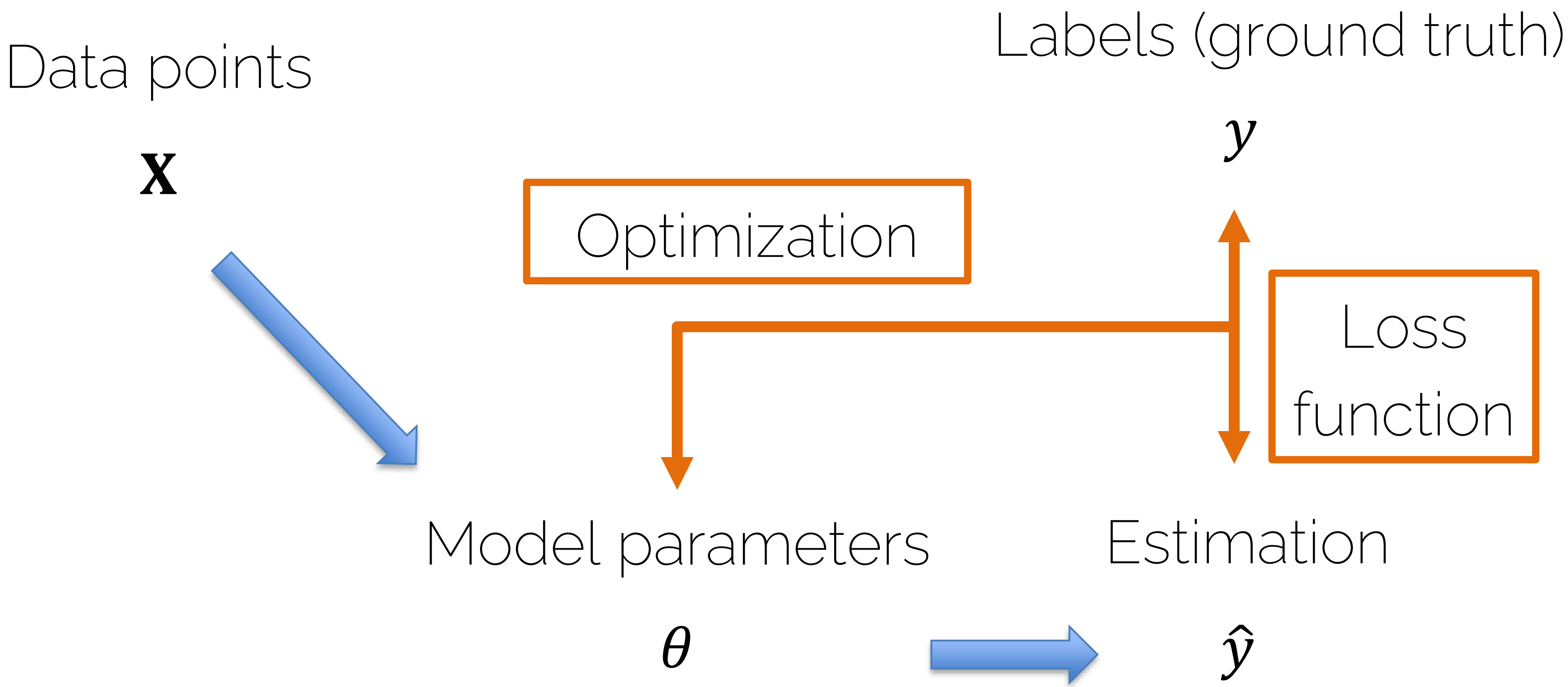
Linear Prediction

Temperature of the building

$$\begin{bmatrix}\hat{y}_1\\ \hat{y}_2\end{bmatrix} = \begin{array}{c}\begin{array}{ccccc}\text{Bias} & \text{Outside temperature} & \text{Humidity} & \text{Number people} & \text{Sun exposure (\%)}\end{array}\\ \begin{bmatrix}1 & 25 & 50 & 2 & 50\\ 1 & -10 & 50 & 0 & 10\end{bmatrix}\end{array} \cdot \begin{array}{c}\text{MODEL}\\ \begin{bmatrix}0.2\\ 0.64\\ 0\\ 1\\ 0.14\end{bmatrix}\end{array}$$

How do we obtain the model?

How to Obtain the Model?

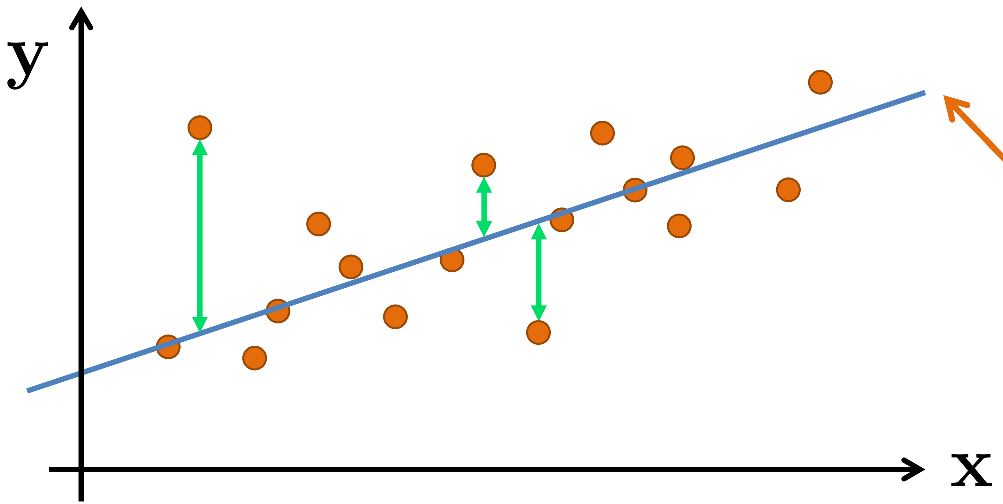


How to Obtain the Model?

- **Loss function:** measures how good my estimation is (how good my model is) and tells the optimization method how to make it better.

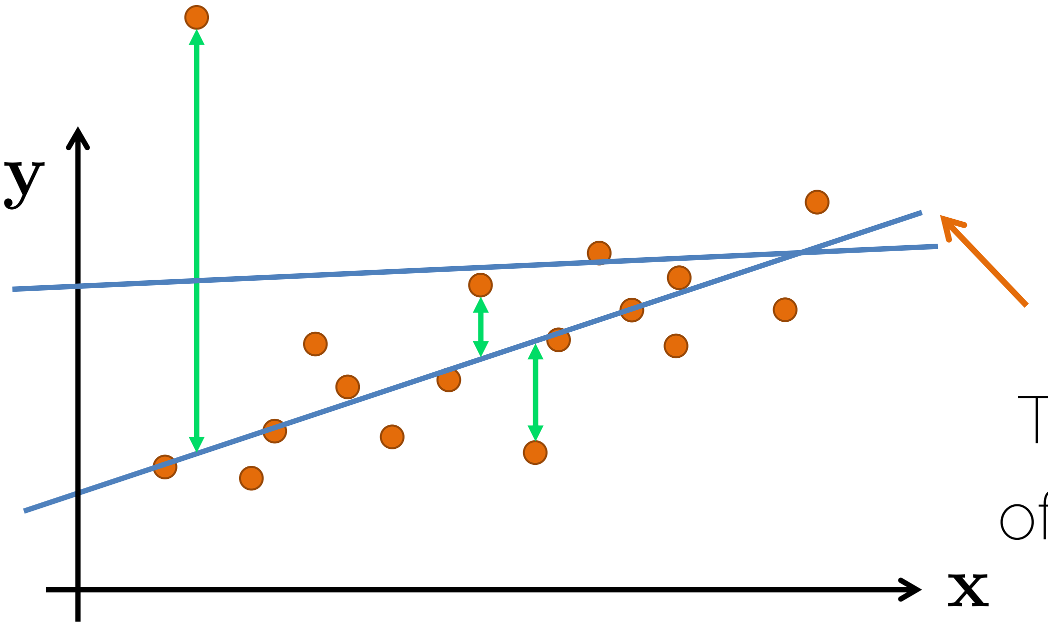
- **Optimization:** changes the model in order to improve the loss function (i.e., to improve my estimation).

Linear Regression: Loss Function



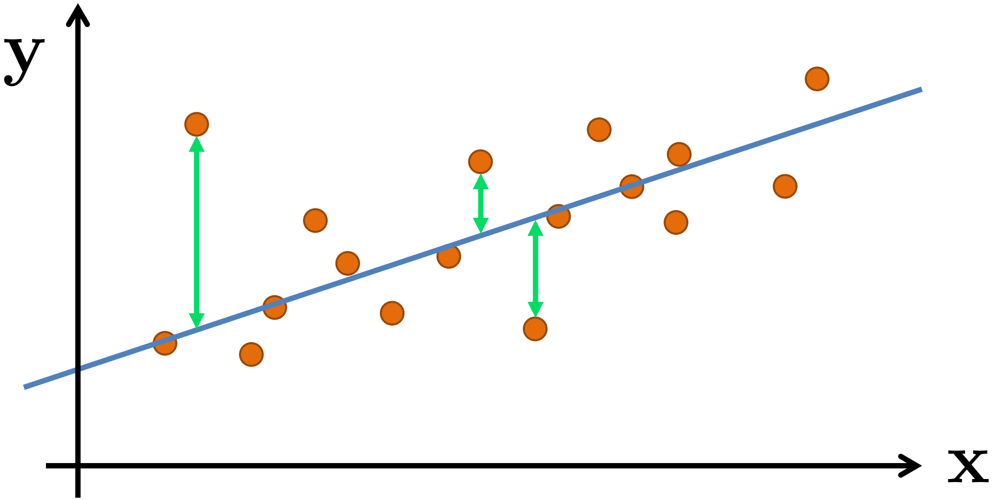
Prediction:
Temperature
of the building

Linear Regression: Loss Function



Prediction:
Temperature
of the building

Linear Regression: Loss Function



Minimizing

$$J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

Objective function
Energy
Cost function

Optimization: Linear Least Squares

- Linear least squares: an approach to fit a linear model to the data

$$\min_{\theta} \; J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

- Convex problem, there exists a closed-form solution that is unique.

Optimization: Linear Least Squares

$$\min_{\boldsymbol{\theta}} \; J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{x}_i\boldsymbol{\theta} - y_i)^2$$

n training samples

The estimation comes from the linear model

Optimization: Linear Least Squares

$$\min_{\boldsymbol{\theta}} \; J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{x}_i\boldsymbol{\theta} - y_i)^2$$

$$\min_{\boldsymbol{\theta}} \; J(\boldsymbol{\theta}) = (\mathbf{X}\boldsymbol{\theta} - \boldsymbol{y})^T(\mathbf{X}\boldsymbol{\theta} - \boldsymbol{y})$$

Matrix notation

$\boldsymbol{n}$ training samples, each input vector has size $\boldsymbol{d}$

$\boldsymbol{n}$ labels

Optimization: Linear Least Squares

$$\min_{\boldsymbol{\theta}} \ J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \ = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{x}_i\boldsymbol{\theta} - y_i)^2$$

$$\min_{\boldsymbol{\theta}} \ J(\boldsymbol{\theta}) = (\mathbf{X}\boldsymbol{\theta} - \boldsymbol{y})^T(\mathbf{X}\boldsymbol{\theta} - \boldsymbol{y})$$

Matrix notation

More on matrix notation in the next exercise session

Optimization: Linear Least Squares

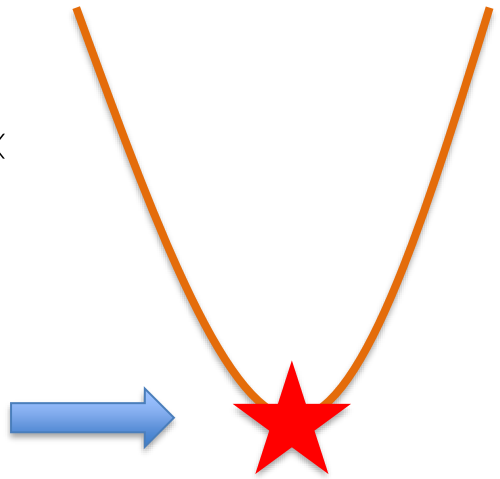
$$\min_{\boldsymbol{\theta}} \; J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \; = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{x}_i\boldsymbol{\theta} - y_i)^2$$

$$\min_{\boldsymbol{\theta}} \; J(\boldsymbol{\theta}) = (\mathbf{X}\boldsymbol{\theta} - \boldsymbol{y})^T(\mathbf{X}\boldsymbol{\theta} - \boldsymbol{y})$$

$$\frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = 0$$

Convex

Optimum



Optimization

Details in the exercise session!

$$\frac{\partial J(\theta)}{\partial \theta} = 2\mathbf{X}^T\mathbf{X}\boldsymbol{\theta} - 2\mathbf{X}^T\mathbf{y} = 0$$

$$\theta = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}$$

We have found an analytical solution to a convex problem

Inputs: Outside temperature, number of people, …

True output: Temperature of the building

Is this the best Estimate?

- Least squares estimate

$$J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2$$

Maximum Likelihood

Maximum Likelihood Estimate

$p_{data}(\mathbf{y}|\mathbf{X})$ True underlying distribution

$p_{model}(\mathbf{y}|\mathbf{X}, \boldsymbol{\theta})$ Parametric family of distributions

Controlled by parameter(s)

Maximum Likelihood Estimate

- A method of estimating the parameters of a statistical model given observations,

$$p_{model}(\mathbf{y}|\mathbf{X}, \boldsymbol{\theta})$$

Observations from $p_{data}(\mathbf{y}|\mathbf{X})$

Maximum Likelihood Estimate

- A method of estimating the parameters of a statistical model given observations, by finding the parameter values that **maximize the likelihood** of making the observations given the parameters.

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \; p_{model}(\mathbf{y}|\mathbf{X}, \boldsymbol{\theta})$$

Maximum Likelihood Estimate

- MLE assumes that the training samples are **independent** and **generated by the same probability distribution**

$$p_{model}(\mathbf{y}|\mathbf{X}, \boldsymbol{\theta}) = \prod_{i=1}^{n} p_{model}(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

"i.i.d." assumption

Maximum Likelihood Estimate

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \boxed{\prod_{i=1}^{n}} p_{model}(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \boxed{\sum_{i=1}^{n} \log} \, p_{model}(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

Logarithmic property $\log ab = \log a + \log b$

Back to Linear Regression

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \sum_{i=1}^{n} \log \boxed{p_{model}(y_i|\mathbf{x}_i, \boldsymbol{\theta})}$$

What shape does our probability distribution have?

Back to Linear Regression

$$p(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

What shape does our probability distribution have?

Back to Linear Regression

$$p(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

Gaussian Noise

Mean

Assuming $y_i = \mathbf{x}_i\boldsymbol{\theta} + \sigma_i$ with $\sigma_i \sim \mathcal{N}(0, \sigma^2)$

Gaussian:

$$p(y_i) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{-\frac{1}{2\sigma^2}(y_i-\mu)^2}$$

$$y_i \sim \mathcal{N}(\mu, \sigma^2)$$

Back to Linear Regression

$$p(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

Mean

Gaussian Noise

Assuming $y_i = \mathbf{x}_i\boldsymbol{\theta} + \sigma_i$ with $\sigma_i \sim \mathcal{N}(0, \sigma^2)$

$$\longrightarrow \quad y_i \sim \mathcal{N}(\mathbf{x}_i\boldsymbol{\theta}, \sigma^2)$$

Gaussian:

$$p(y_i) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{-\frac{1}{2\sigma^2}(y_i-\mu)^2}$$

$$y_i \sim \mathcal{N}(\mu, \sigma^2)$$

Back to Linear Regression

$$p(y_i|\mathbf{x}_i, \boldsymbol{\theta}) = ?$$

Gaussian Noise

Mean

Assuming $y_i = \mathbf{x}_i\boldsymbol{\theta} + \sigma_i$ with $\sigma_i \sim \mathcal{N}(0, \sigma^2)$

$$\longrightarrow \quad y_i \sim \mathcal{N}(\mathbf{x}_i\boldsymbol{\theta}, \sigma^2)$$

Gaussian:

$$p(y_i) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{-\frac{1}{2\sigma^2}(y_i - \mu)^2}$$

$$y_i \sim \mathcal{N}(\mu, \sigma^2)$$

Back to Linear Regression

$$p(y_i|\mathbf{x}_i, \boldsymbol{\theta}) = (2\pi\sigma^2)^{-1/2} e^{-\frac{1}{2\sigma^2}(y_i - \mathbf{x}_i\boldsymbol{\theta})^2}$$

Assuming $y_i = \mathbf{x}_i\boldsymbol{\theta} + \sigma_i$ with $\sigma_i \sim \mathcal{N}(0, \sigma^2)$

$$\longrightarrow \quad y_i \sim \mathcal{N}(\mathbf{x}_i\boldsymbol{\theta}, \sigma^2)$$

Gaussian:

$$p(y_i) = \frac{1}{\sqrt{(2\pi\sigma^2)}} e^{-\frac{1}{2\sigma^2}(y_i - \mu)^2} \qquad y_i \sim \mathcal{N}(\mu, \sigma^2)$$

Back to Linear Regression

$$p(y_i|\mathbf{x}_i, \boldsymbol{\theta}) = (2\pi\sigma^2)^{-1/2} e^{-\frac{1}{2\sigma^2}(y_i - \mathbf{x}_i\boldsymbol{\theta})^2}$$

Original optimization problem

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \sum_{i=1}^{n} \log p_{model}(y_i|\mathbf{x}_i, \boldsymbol{\theta})$$

Back to Linear Regression

$$\sum_{i=1}^{n} \log \left[(2\pi\sigma^2)^{-\frac{1}{2}} e^{-\frac{1}{2\sigma^2}(y_i - \boldsymbol{x}_i\boldsymbol{\theta})^2} \right]$$

Canceling $\mathbf{log}$ and $\boldsymbol{e}$

$$\sum_{i=1}^{n} -\frac{1}{2} \log\ (2\pi\sigma^2) + \sum_{i=1}^{n} \left(-\frac{1}{2\sigma^2} \right) (y_i - \boldsymbol{x}_i\boldsymbol{\theta})^2$$

Matrix notation

$$-\frac{n}{2} \log(2\pi\sigma^2)\ - \frac{1}{2\sigma^2} (\boldsymbol{y} - \boldsymbol{X\theta})^T (\boldsymbol{y} - \boldsymbol{X\theta})$$

Back to Linear Regression

$$\theta_{ML} = \arg\max_{\theta} \boxed{\sum_{i=1}^{n} \log p_{model}(y_i|\mathbf{x}_i, \boldsymbol{\theta})}$$

$$-\frac{n}{2}\log(2\pi\sigma^2) - \frac{1}{2\sigma^2}(\mathbf{y} - \mathbf{X}\boldsymbol{\theta})^T(\mathbf{y} - \mathbf{X}\boldsymbol{\theta})$$

$$\frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = 0$$

$$\boldsymbol{\theta} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\mathbf{y}$$

Details in the exercise session!

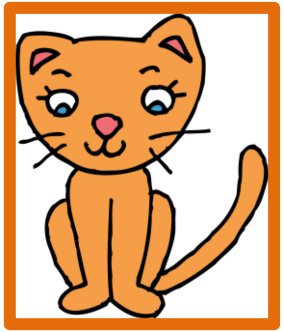
How can we find the estimate of theta?

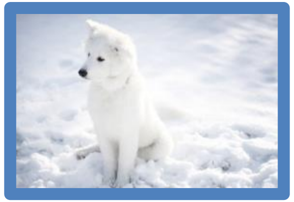
Linear Regression

- Maximum Likelihood Estimate (MLE) corresponds to the Least Squares Estimate (given the assumptions)

- Introduced the concepts of loss function and optimization to obtain the best model for regression

Image Classification



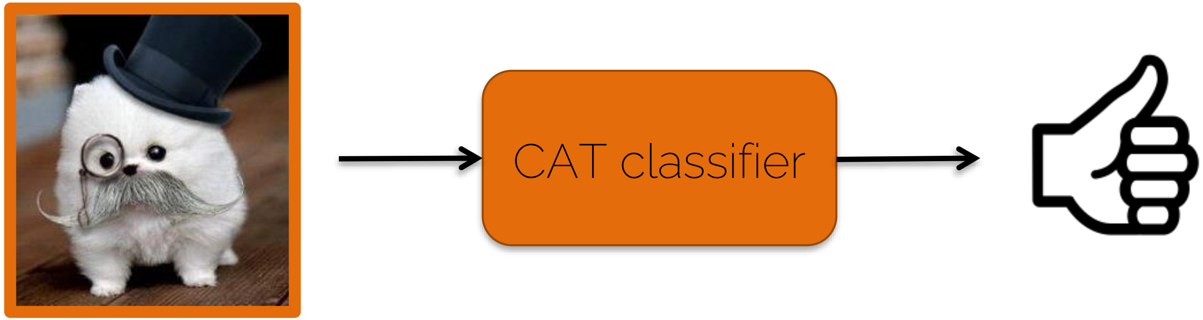


Regression vs Classification

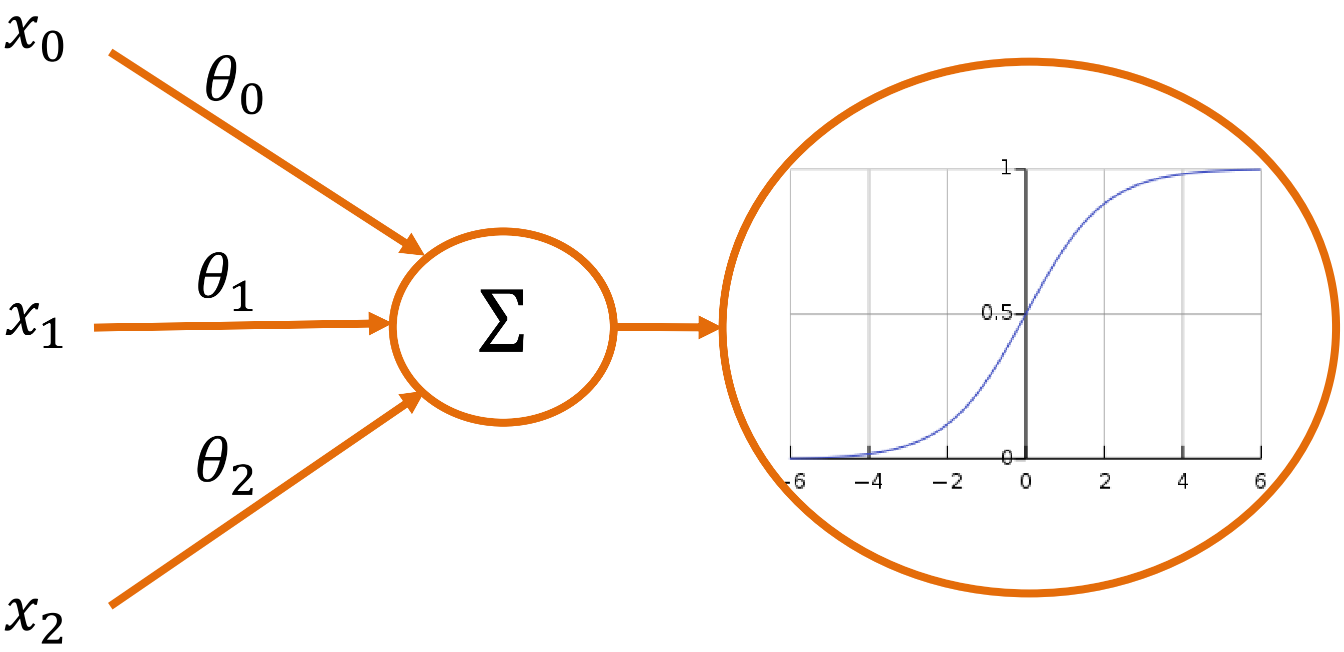
- Regression: predict a continuous output value (e.g., temperature of a room)

- Classification: predict a discrete value
  - Binary classification: output is either 0 or 1
  - Multi-class classification: set of N classes

Logistic Regression



Sigmoid for Binary Predictions



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

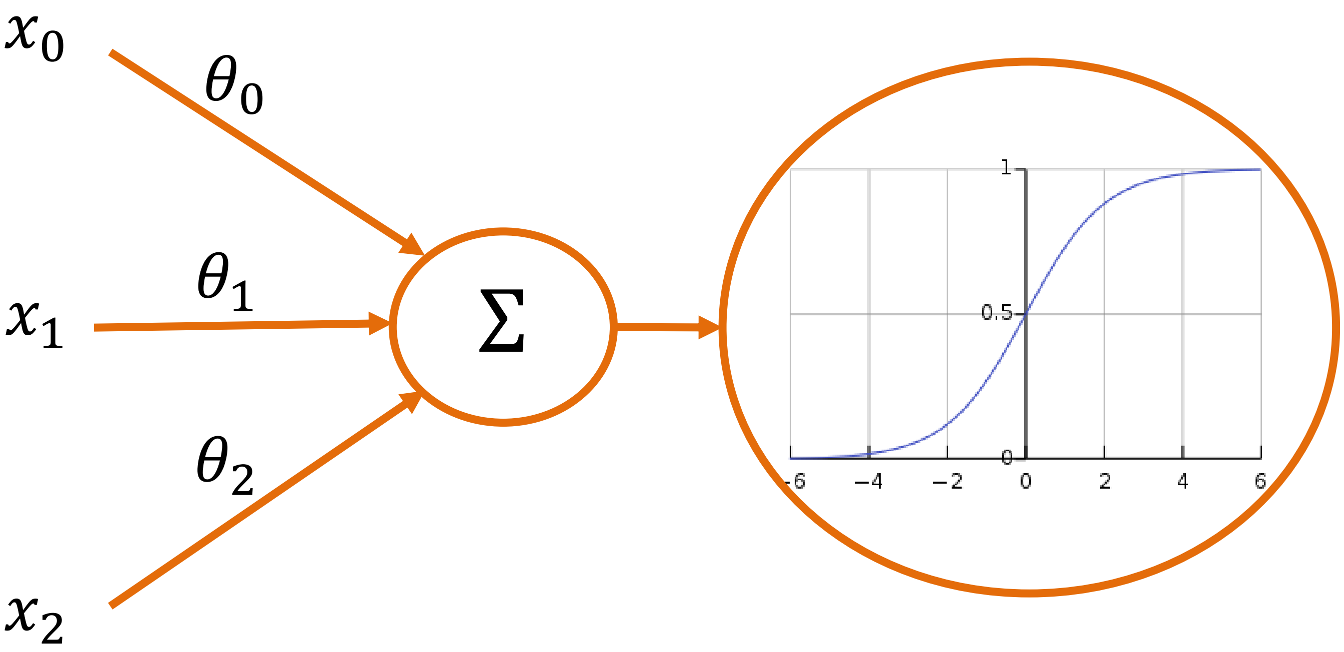
1

Can be interpreted as a probability

0

$$p(y_i = 1|\mathbf{x}_i, \boldsymbol{\theta})$$

Spoiler Alert: 1-Layer Neural Network



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

1

Can be interpreted as a probability

0

$$p(y_i = 1 | \mathbf{x}_i, \boldsymbol{\theta})$$

Logistic Regression

- Probability of a binary output

$$\hat{\mathbf{y}} = p(\mathbf{y} = 1|\mathbf{X}, \boldsymbol{\theta}) = \prod_{i=1}^{n} p(y_i = 1|\mathbf{x}_i, \boldsymbol{\theta})$$

The prediction of our sigmoid

$$\hat{y}_i = \sigma(\mathbf{x}_i\boldsymbol{\theta})$$

Logistic Regression

- Probability of a binary output

$$\hat{\mathbf{y}} = p(\mathbf{y} = 1|\mathbf{X}, \boldsymbol{\theta}) = \prod_{i=1}^{n} p(y_i = 1|\mathbf{x}_i, \boldsymbol{\theta})$$

Bernoulli trial

Model for coins

$$p(z|\phi) = \phi^z (1 - \phi)^{1-z} = \begin{cases} \phi \quad , & \text{if} \quad z = 1 \\ 1 - \phi, & \text{if} \quad z = 0 \end{cases}$$

The prediction of our sigmoid

Logistic Regression

- Probability of a binary output

$$\hat{\mathbf{y}} = p(\mathbf{y} = 1|\mathbf{X}, \boldsymbol{\theta}) = \prod_{i=1}^{n} p(y_i = 1|\mathbf{x}_i, \boldsymbol{\theta})$$

Model for coins

$$\hat{\mathbf{y}} = \prod_{i=1}^{n} \hat{y}_i^{y_i}(1 - \hat{y}_i)^{(1-y_i)}$$

Prediction of the Sigmoid: continuous

True labels: 0 or 1

Logistic Regression: Loss Function

- Probability of a binary output

$$p(\mathrm{y}|\mathbf{X},\boldsymbol{\theta}) = \hat{\mathbf{y}} = \prod_{i=1}^{n} \hat{y}_i^{y_i}(1-\hat{y}_i)^{(1-y_i)}$$

- Maximum Likelihood Estimate

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \log p(\mathrm{y}|\mathbf{X},\boldsymbol{\theta})$$

Logistic Regression: Loss Function

$$p(\mathrm{y}|\mathbf{X},\boldsymbol{\theta}) = \hat{\mathbf{y}} = \boxed{\prod_{i=1}^{n}} \hat{y}_i^{\,y_i}(1-\hat{y}_i)^{(1-y_i)}$$

$$\boxed{\sum_{i=1}^{n} \log} \left(\hat{y}_i^{\,y_i}(1-\hat{y}_i)^{(1-y_i)}\right)$$

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

Logistic Regression: Loss Function

$$\mathcal{L}(\hat{y}_i, y_i) = \boxed{-}[y_i \log \hat{y}_i + \cancel{(1-y_i)\log(1-\hat{y}_i)}]$$

Maximize likelihood by minimizing the loss function

$$y_i = 1 \longrightarrow \mathcal{L}(\hat{y}_i, 1) = -\log \hat{y}_i$$

Maximize!

$$\boldsymbol{\theta}_{\boldsymbol{ML}} = \arg\max_{\boldsymbol{\theta}} \log p(\mathrm{y}|\mathbf{X}, \boldsymbol{\theta})$$

Logistic Regression: Loss Function

$$\mathcal{L}(\hat{y}_i, y_i) = -[y_i \log \hat{y}_i + \cancel{(1 - y_i) \log(1 - \hat{y}_i)}]$$

$$y_i = 1 \longrightarrow \mathcal{L}(\hat{y}_i, 1) = -\log \hat{y}_i$$

To minimize $\mathcal{L}(\hat{y}_i, y_i)$, we want $\mathbf{log}\, \hat{y}_i$ large; since logarithm is a monotonically increasing function, we want a large $\hat{y}_i$.

($\mathbf{1}$ is the largest value our model's estimate can take!)

Logistic Regression: Loss Function

$$\mathcal{L}(\hat{y}_i, y_i) = -[\cancel{y_i \log \hat{y}_i} + (1 - y_i)\log(1 - \hat{y}_i)]$$

$$y_i = 1 \longrightarrow \mathcal{L}(\hat{y}_i, 1) = -\log \hat{y}_i$$

$$y_i = 0 \longrightarrow \mathcal{L}(\hat{y}_i, 0) = -\log(1 - \hat{y}_i)$$

We want $\mathbf{log(1 - \hat{y}_i)}$ large; so we want $\hat{y}_i$ to be small

($\mathbf{0}$ is the smallest value our model's estimate can take!)

Logistic Regression: Loss Function

$$\mathcal{L}(\hat{y}_i, y_i) = -[y_i \log \hat{y}_i + (1 - y_i) \log(1 - \hat{y}_i)]$$

Referred to as *binary cross-entropy* loss (BCE)

- Related to the multi-class loss you will see in this course (also called *softmax loss*)

Logistic Regression: Optimization

- Loss function

$$\mathcal{L}(\hat{y}_i, y_i) = -[y_i \log \hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i)]$$

- Cost function

$$C(\theta) = -\frac{1}{n}\sum_{i=1}^{n}\mathcal{L}(\hat{y}_i, y_i)$$

Minimization

$$\hat{y}_i = \sigma(\mathbf{x}_i\boldsymbol{\theta})$$

$$= -\frac{1}{n}\sum_{i=1}^{n} y_i \log \hat{y}_i + (1 - y_i)\log(1 - \hat{y}_i)$$

Logistic Regression: Optimization

- No closed-form solution
- Make use of an iterative method → gradient descent

Gradient descent – later on!

Why Machine Learning so Cool

- We can learn from experience

  -> Intelligence, certain ability to infer the future!

- Even linear models are often pretty good for complex phenomena: e.g., weather:
  - Linear combination of day-time, day-year etc. is often pretty good

Next Lectures

- Next exercise session: Math Recap II

- Next Lecture: Lecture 3:
  - Jumping towards our first Neural Networks and Computational Graphs

References for further Reading

- Cross validation:
  - https://medium.com/@zstern/k-fold-cross-validation-explained-5aeba90ebb3
  - https://towardsdatascience.com/train-test-split-and-cross-validation-in-python-80b61beca4b6

- General Machine Learning book:
  - Pattern Recognition and Machine Learning. C. Bishop.

See you next week ☺