Machine Learning Basics

Machine Learning

Task

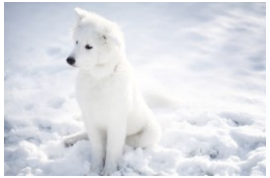
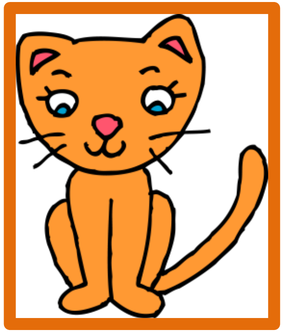
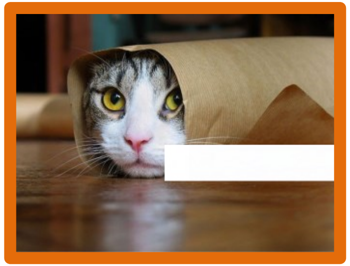
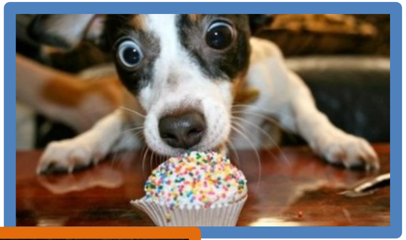
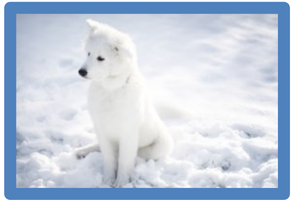
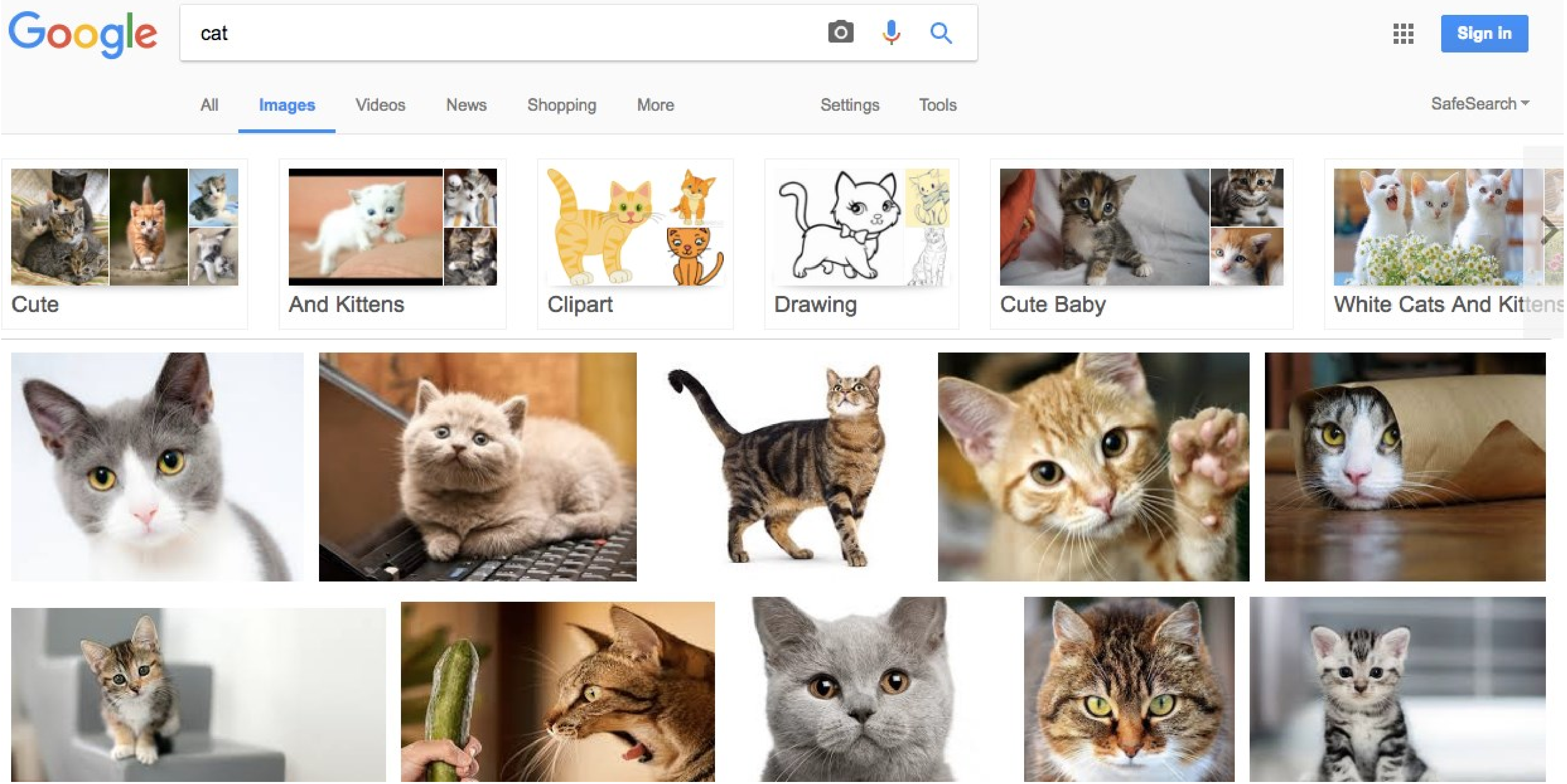


Image Classification



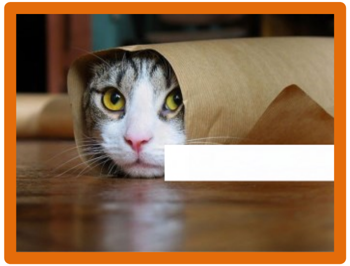


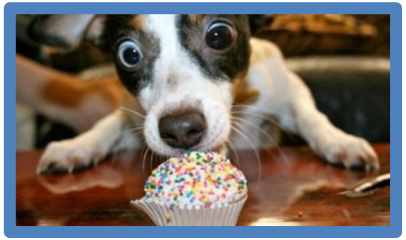
Pose

Illumination

Appearance

Image Classification





Occlusions

Image Classification

Background clutter

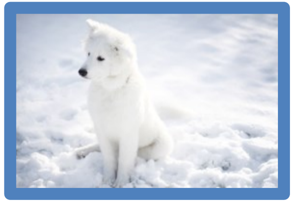
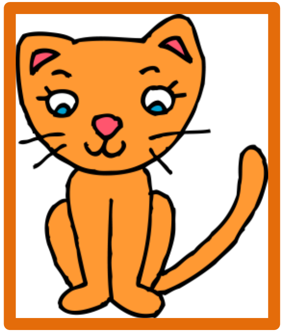


Image Classification



Representation

Machine Learning

- How can we learn to perform image classification?

Task

Image classification

Experience

Data

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

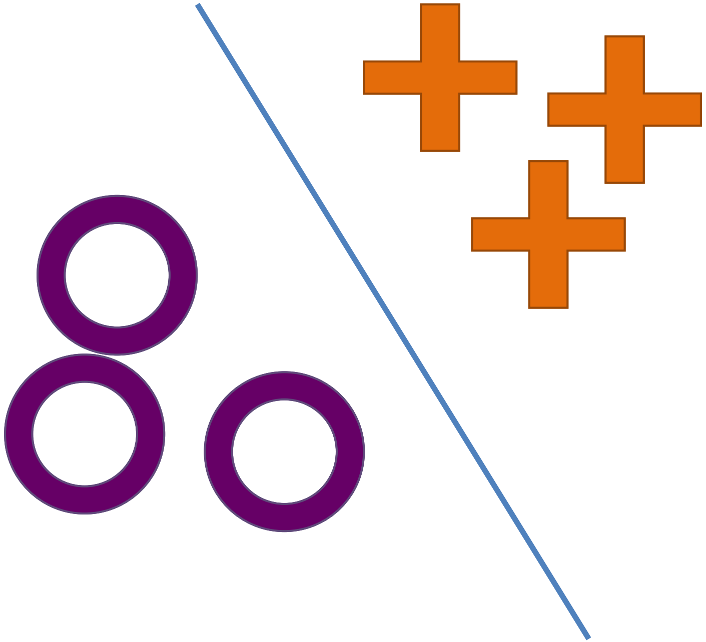
Machine Learning

Unsupervised learning

Supervised learning

Machine Learning

Unsupervised learning

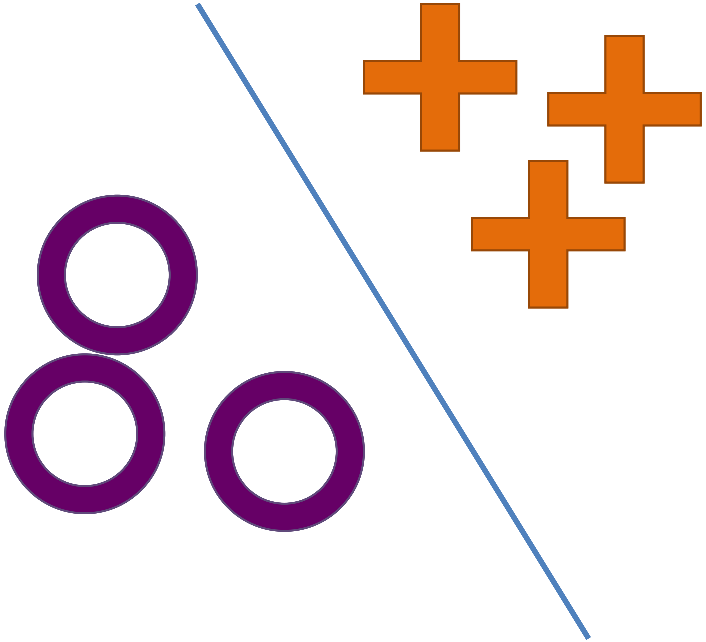


Supervised learning

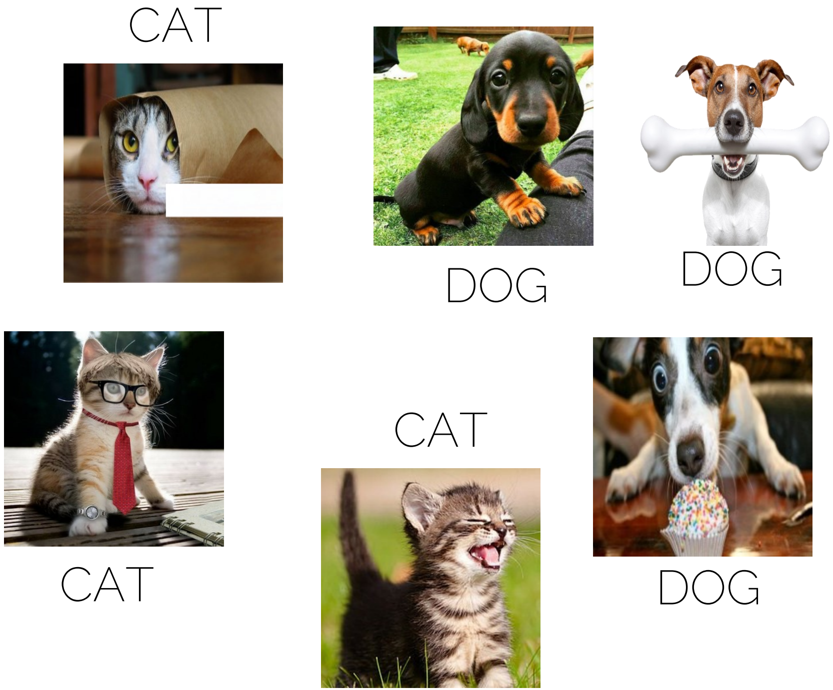
- Labels or target classes

Machine Learning

Unsupervised learning



Supervised learning



Machine Learning

- How can we learn to perform image classification?

U erlying as umption that
trai and te ata come
from t distribution

Machine Learning

- How can we learn to perform image classification?

Task

Image classification

Performance measure

Accuracy

Experience

Data

Machine Learning

Unsupervised learning

Supervised learning

Reinforcement learning

Machine Learning

Unsupervised learning

Supervised learning

Reinforcement learning

Agents ← reward — Environment

Machine Learning

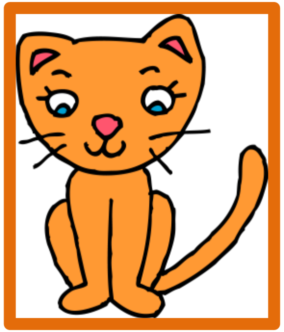
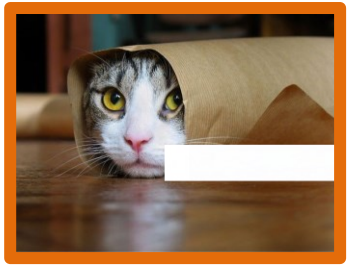
Unsupervised learning

Supervised learning

Reinforcement learning

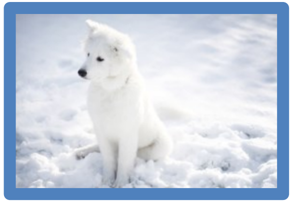
A Simple Classifier

Nearest Neighbor

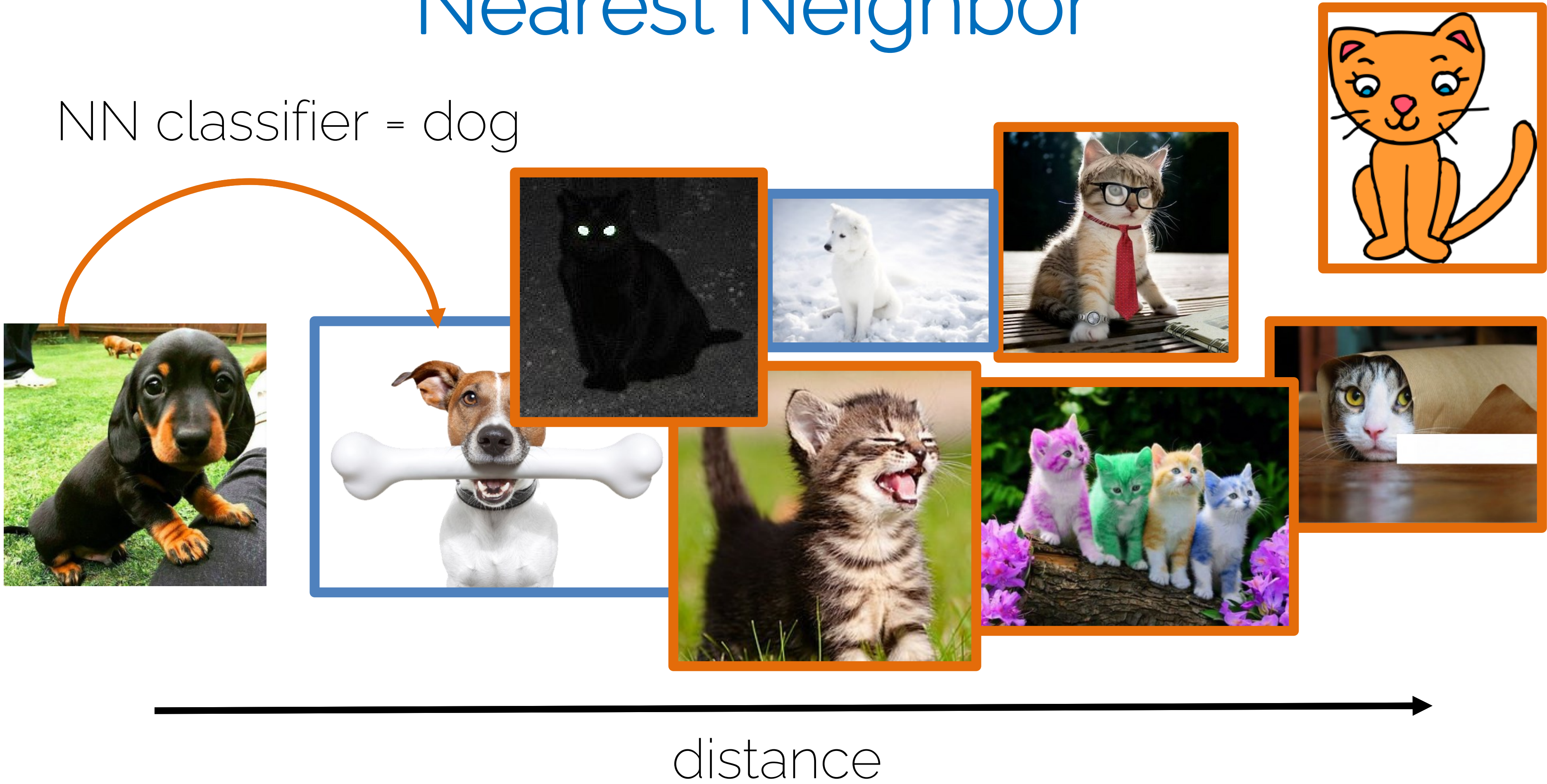







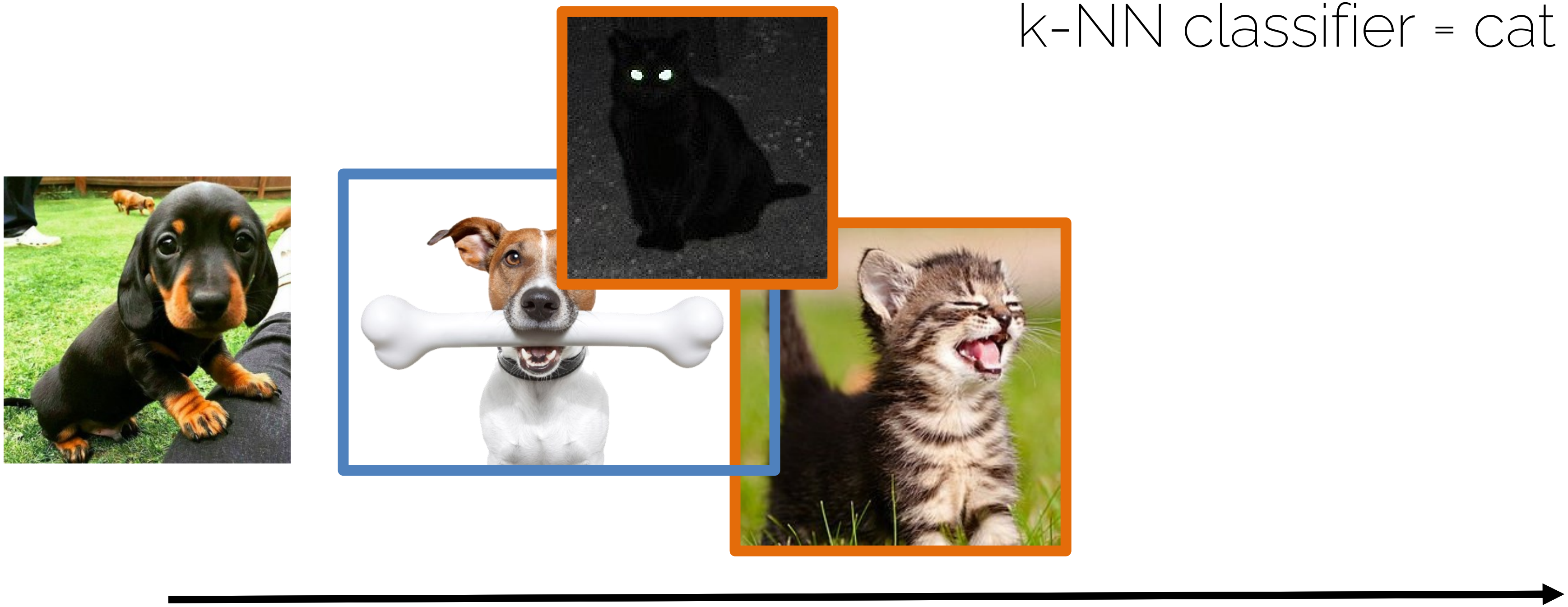



Nearest Neighbor



Nearest Neighbor

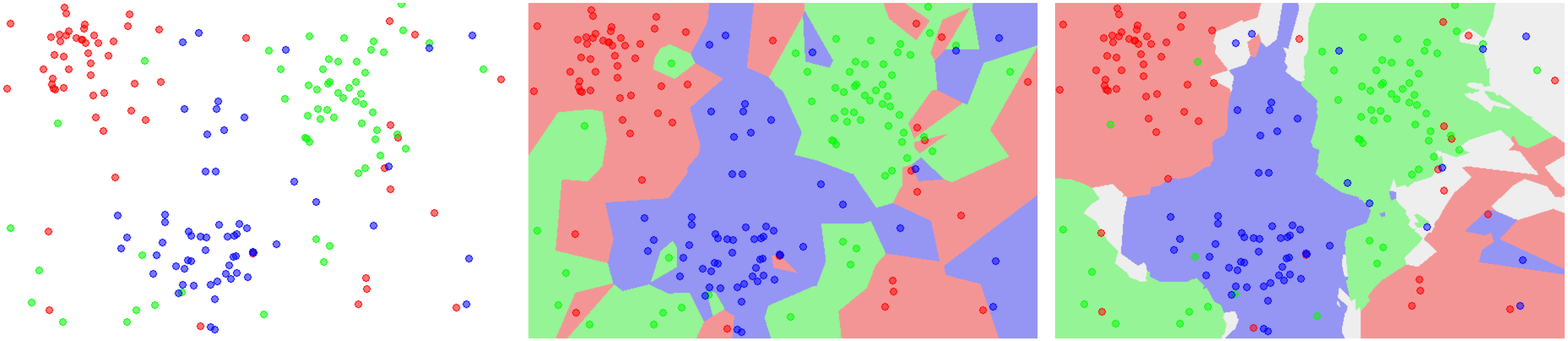
k-NN classifier = cat



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?

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

Nearest Neighbor

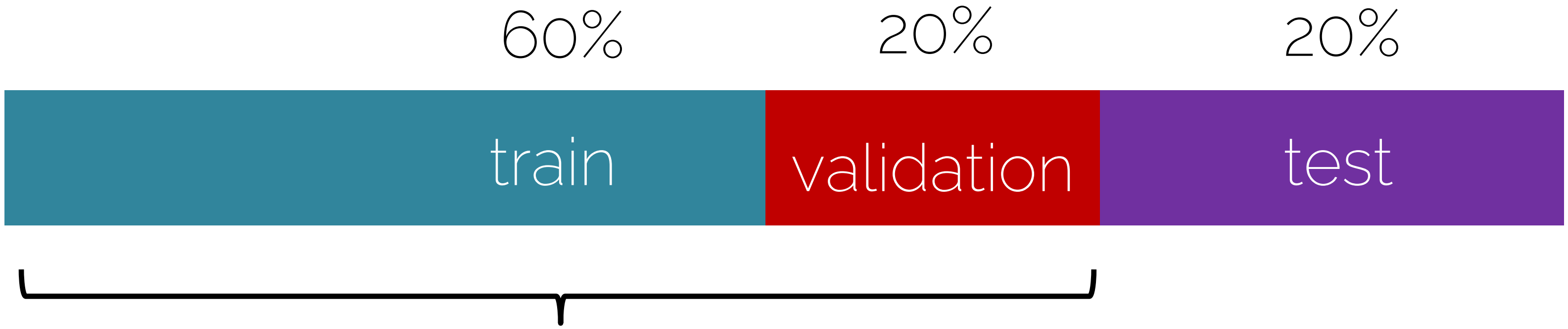
- Hyperparameters
  - L1 distance : $|x - c|$
  - L2 distance : $||x - c||_2$
  - No. of Neighbors: k

- These parameters are problem dependent.

- How do we choose these hyperparameters?

Basic Recipe for Machine Learning

- Split your data



Find your hyperparameters

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

Basic Recipe for Machine Learning

- Split your data

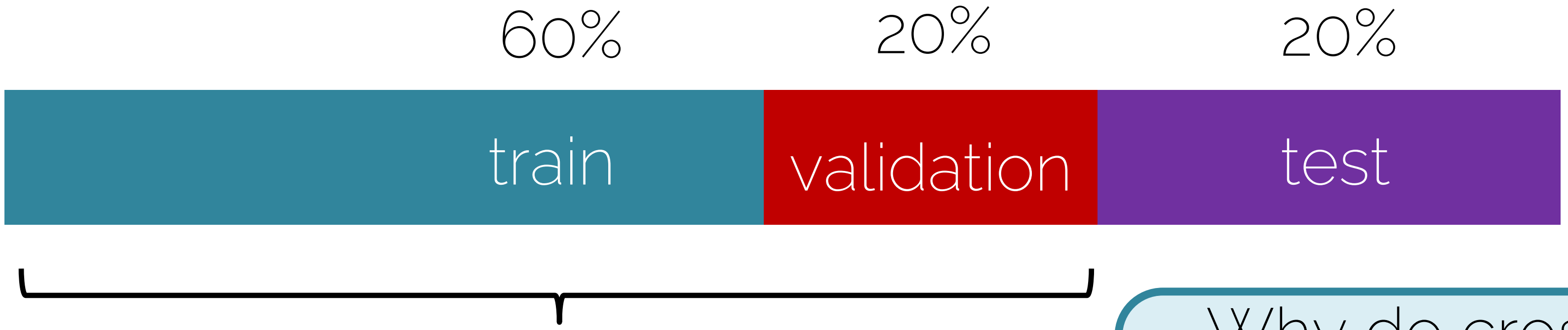
train	validation	test
60%	20%	20%

Test set is only used once!

Cross Validation

Split the **training data** into N folds

Cross Validation



Find your hyperparameters

Why do cross validation?
Why not just train and test?

Cross Validation

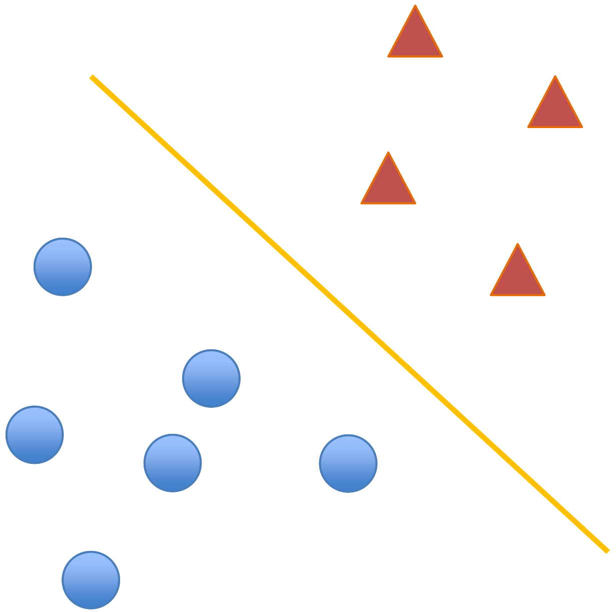
60%	20%	20%
train	validation	test

Test set is only used once!

Why do cross validation? Why not just train and test?

Linear Decision Boundaries

This lecture

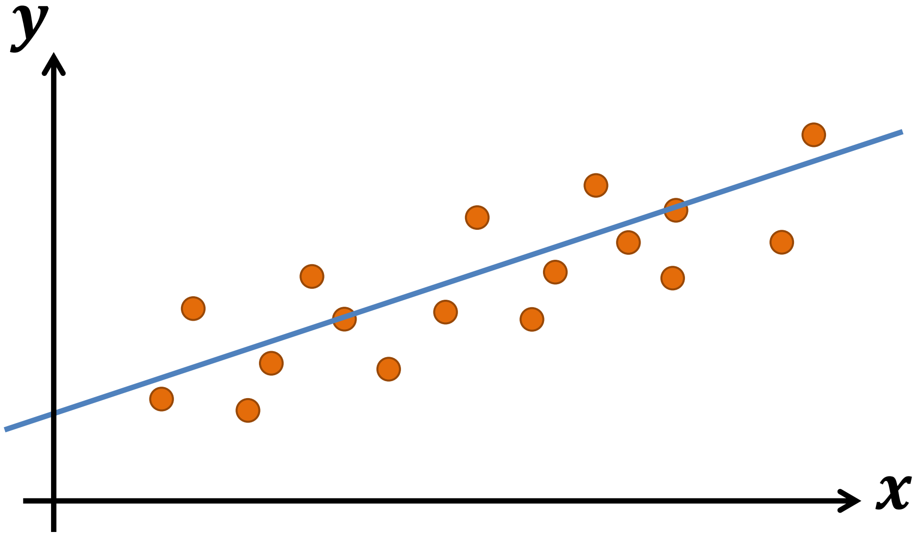


What are the pros and cons for using linear decision boundaries?

Linear Regression

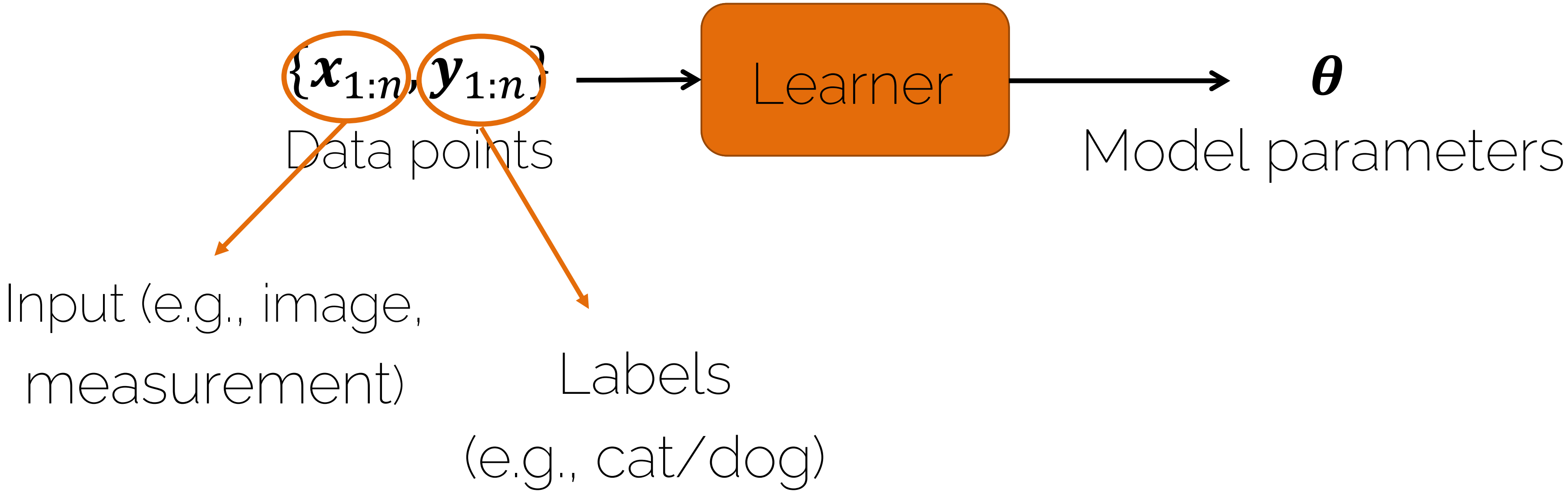
Linear Regression

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



Linear Regression

Training



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

input dimension

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

weights (i.e., model parameters)

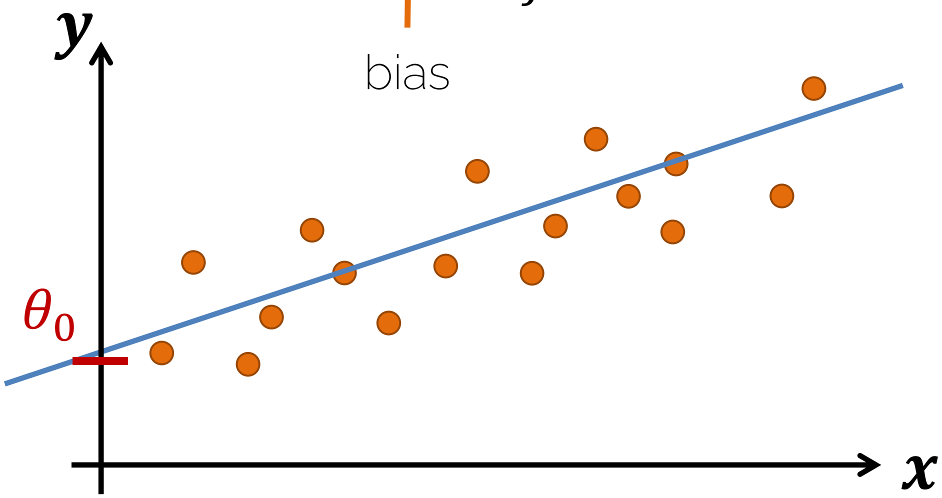
Input data, features

Linear Prediction

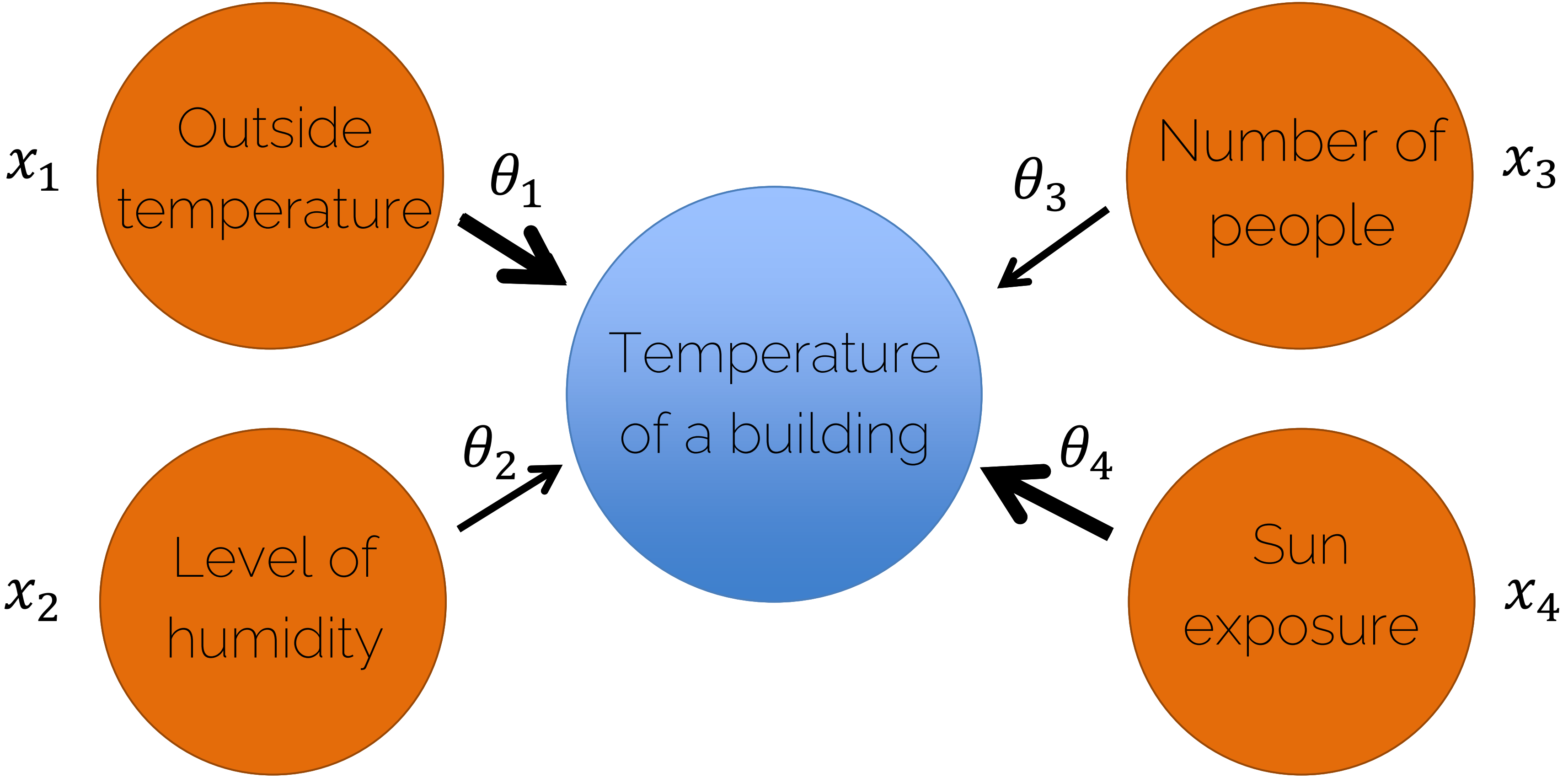
- A linear model is expressed in the form

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

bias



Linear Prediction



Linear Prediction

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

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

bias

Linear Prediction

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

Prediction

Input features

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

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

Model parameters

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

Linear Prediction

Temperature of the building

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

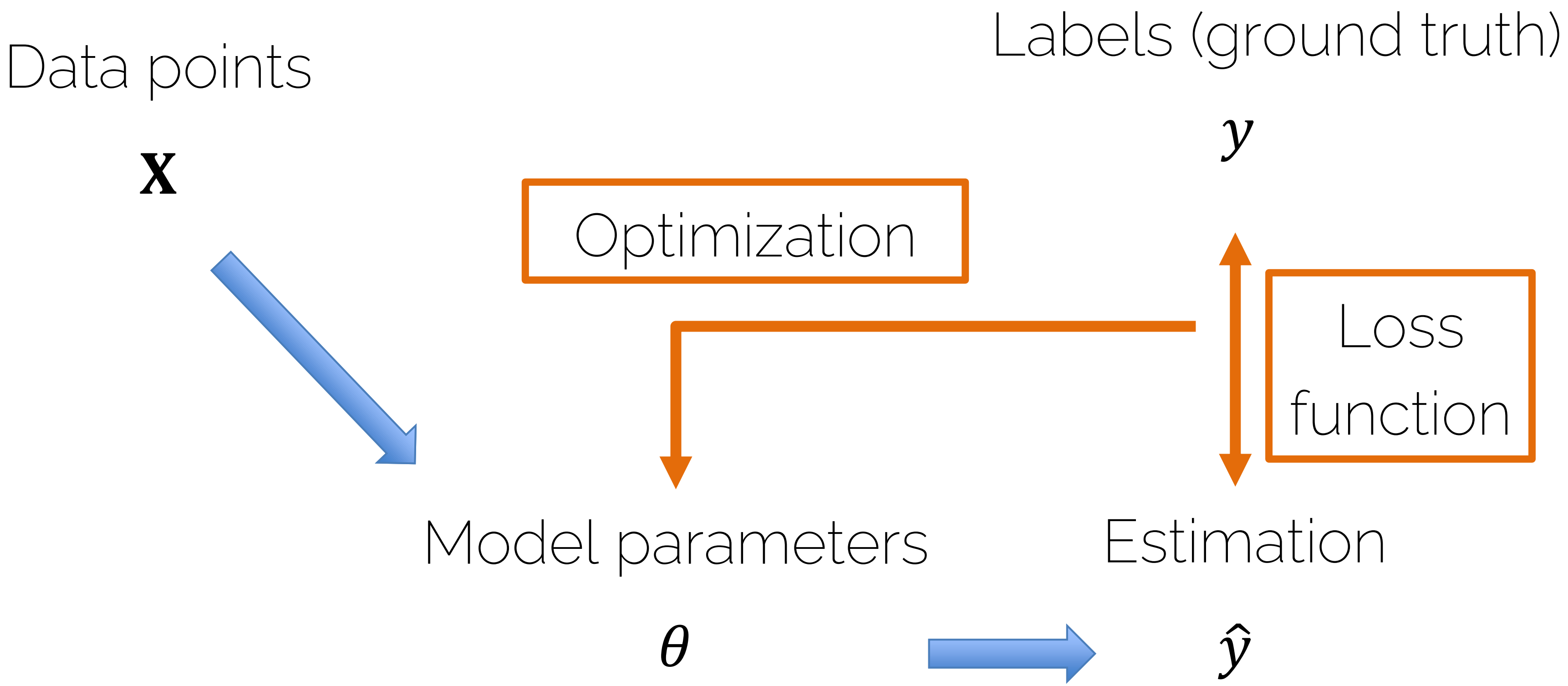
Linear Prediction

How do we obtain the model?

Temperature of the building

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

How to Obtain the Model?

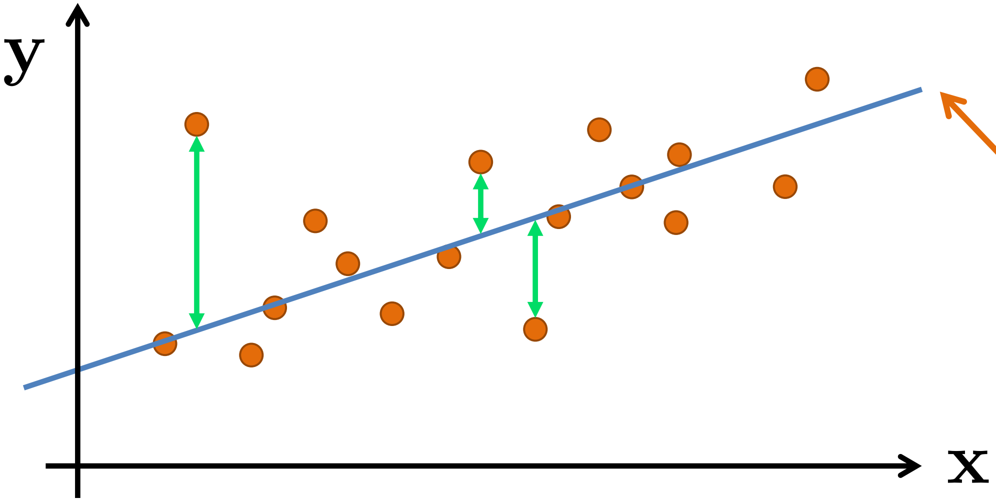


How to Obtain the Model?

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

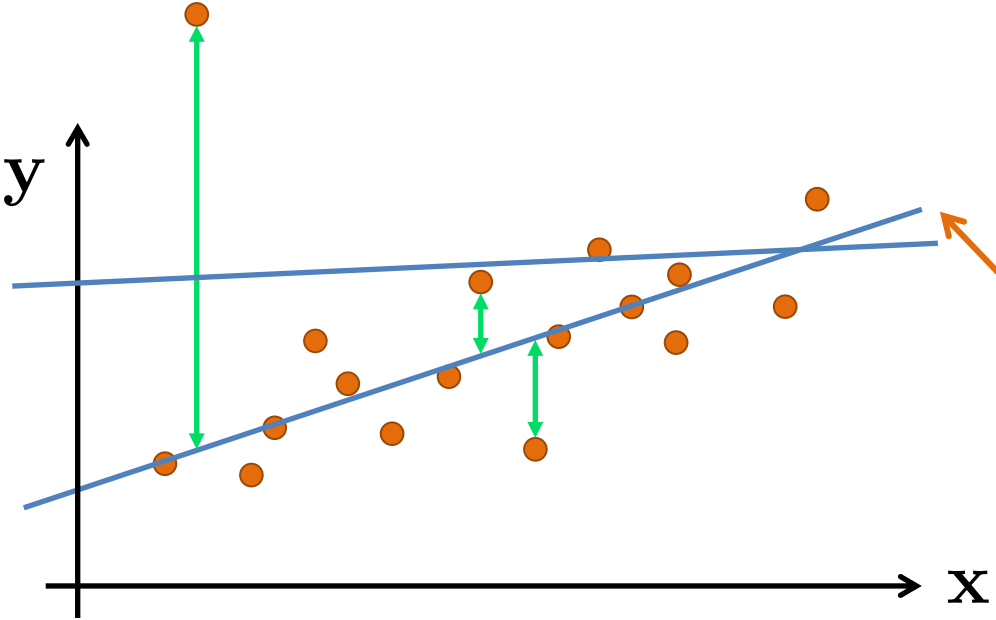
- **Optimization:** changes the model in order to improve the loss function (i.e., to improve my estimation).

Linear Regression: Loss Function



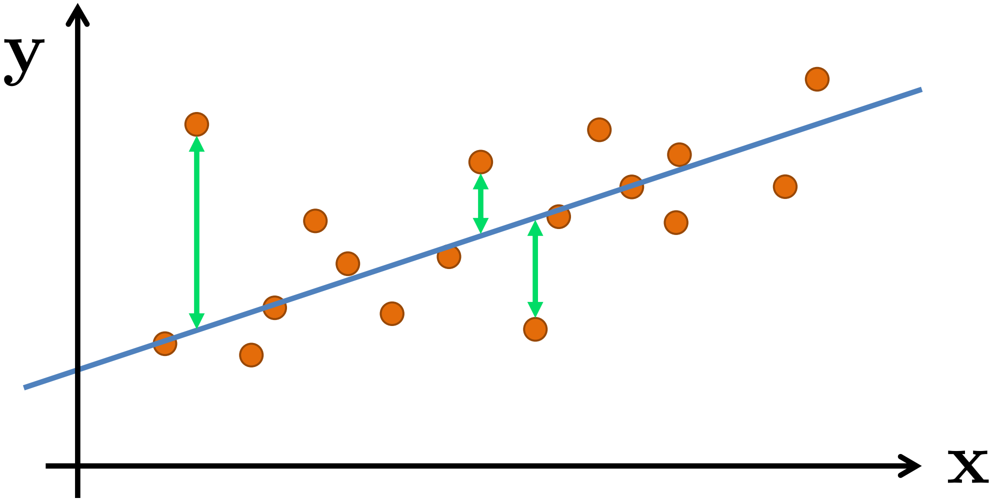
Prediction:
Temperature
of the building

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

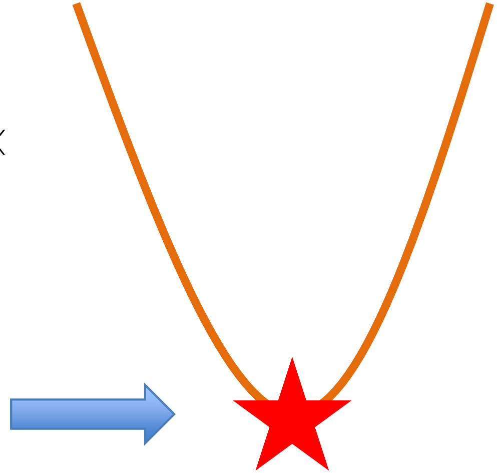
$$\min_{\boldsymbol{\theta}} \; J(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \; = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{x}_i\boldsymbol{\theta} - y_i)^2$$

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

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

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 / Normal distribution

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

mean

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

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

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

mean

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

mean

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

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

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

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

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

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

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

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

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

Details in the exercise session!

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

How can we find the estimate of theta?

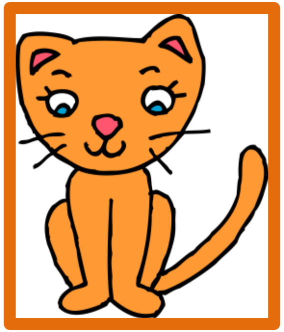
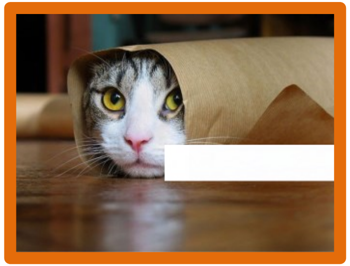
$$\boldsymbol{\theta} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\mathbf{y}$$

Linear Regression

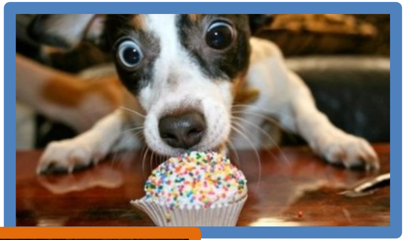
- Maximum Likelihood Estimate (MLE) corresponds to the Least Squares Estimate (given the assumptions)

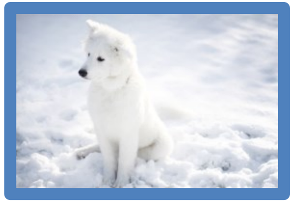
- Introduced the concepts of loss function and optimization to obtain the best model for regression

Image Classification



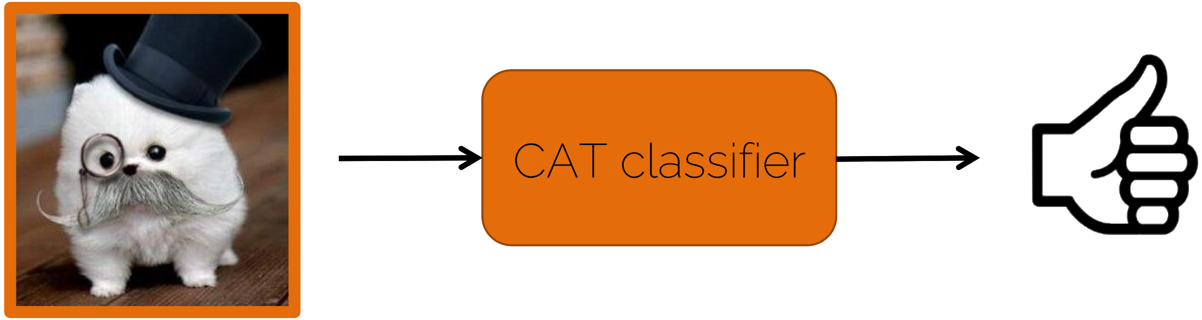



Regression vs Classification

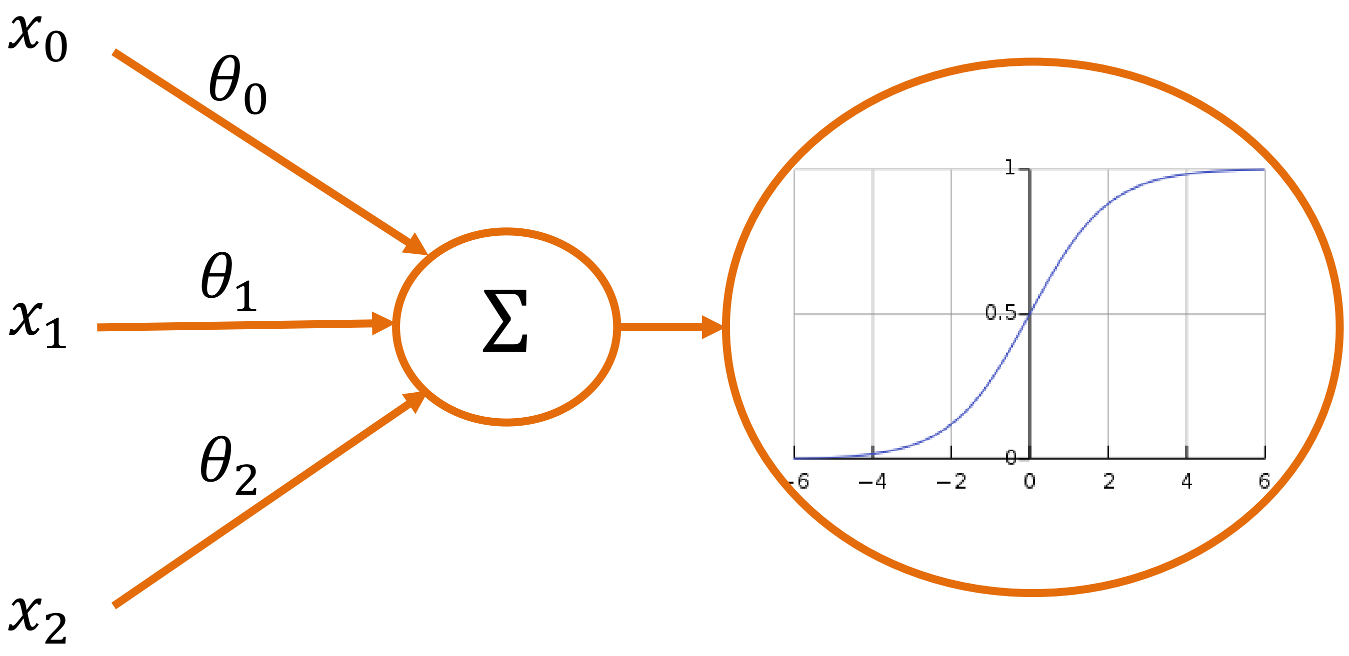
- Regression: predict a continuous output value (e.g., temperature of a room)

- 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



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

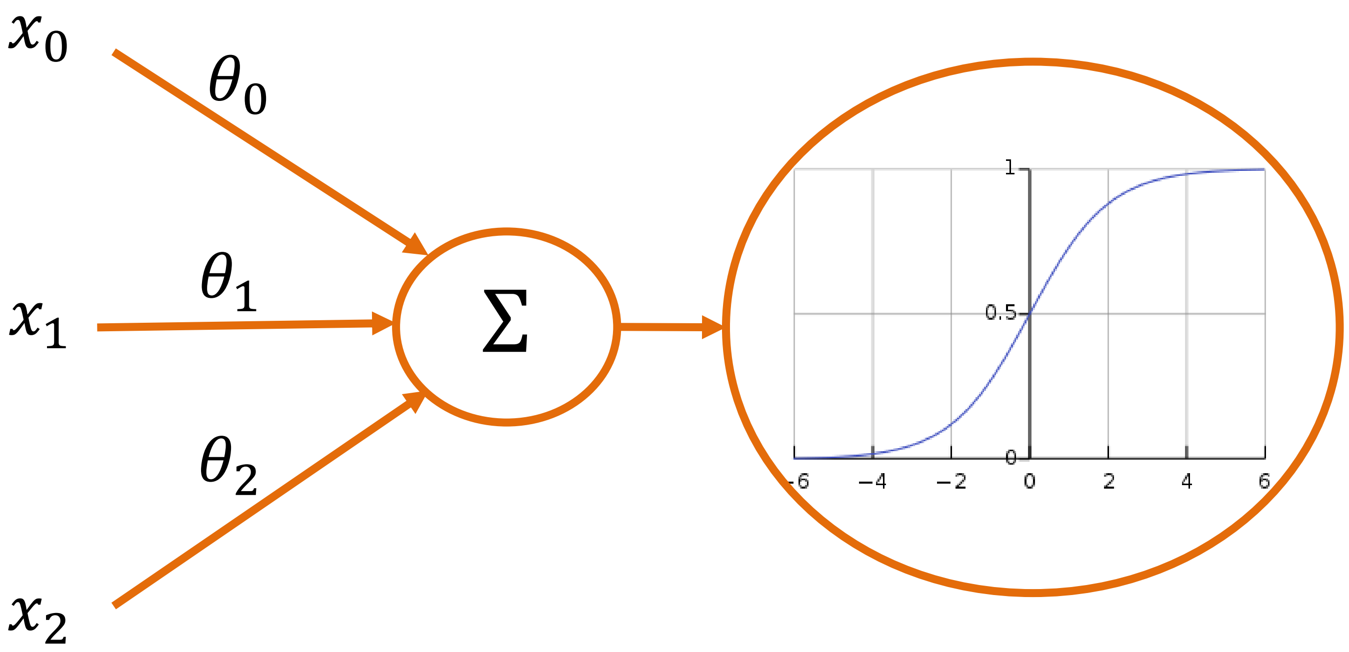
1

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

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

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

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

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

Maximize!

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

Logistic Regression: Loss Function

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

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

We want $\log \hat{y}_i$ large; since logarithm is a monotonically increasing function, we also want 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

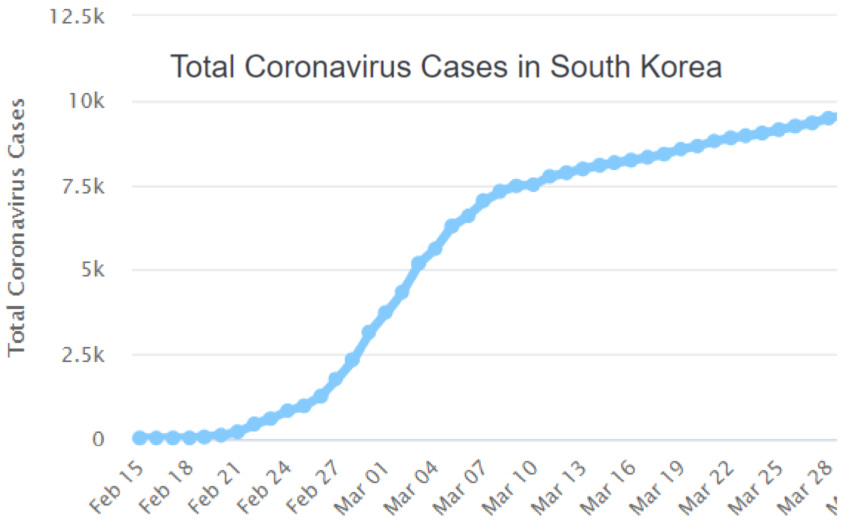
- We can learn from experience

  -> 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

Many Examples of Logistic Regression

- Coronavirus models behave like logistic regressions
  - Exponential spread at beginning
  - Plateaus when certain portion of pop. is infected/immune



https://www.worldometers.info/coronavirus

Many Examples of Logistic Regression

- Coronavirus models behave like logistic regressions
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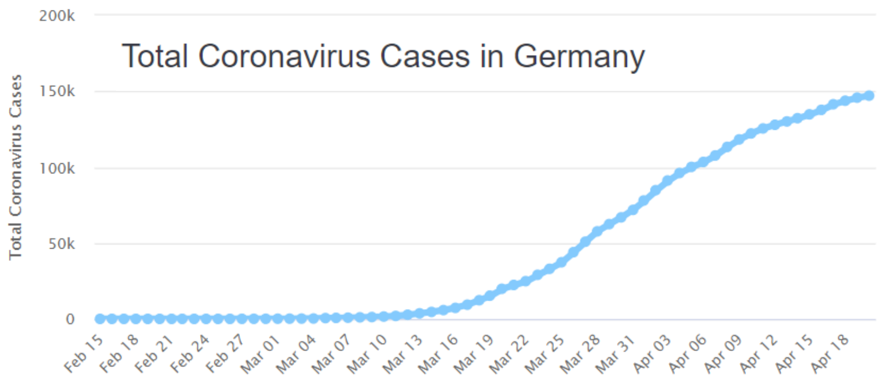

Think about good features:
- Total population
- Population density
- Implementation of Measures
- Reasonable government ☺ ?
- Etc. (many more of course)

https://www.worldometers.info/coronavirus

The Model Matters

- Each case requires different models; linear vs logistic

- Many models:
  - #coronavirus_infections cannot be > #total_population
  - Munich housing prizes seem exponential though
    - No hard upper bound -> prizes can always grow!

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 ☺