Aprendizaje Supervisado 2da Parte

Franco Luque - Matías Marenchino

Agenda

- Repaso
  Aprendizaje Supervisado / SVMs / Ensembles / NNs

- Resolución Laboratorio 1

- Estrategias para Machine Learning

- Caso de Estudio: Clasificación de Texto

Repaso

Motivation

Example 1

- **A credit card company receives applications for new credit cards. Each one has information about an applicant:**
    - salary
    - age
    - marital status
    - Veraz
    - Credit report from BCRA
    - ...
- **Problem: determine if an application should be approved or rejected**

Example 2

- **Problem: classify an email as SPAM or not**

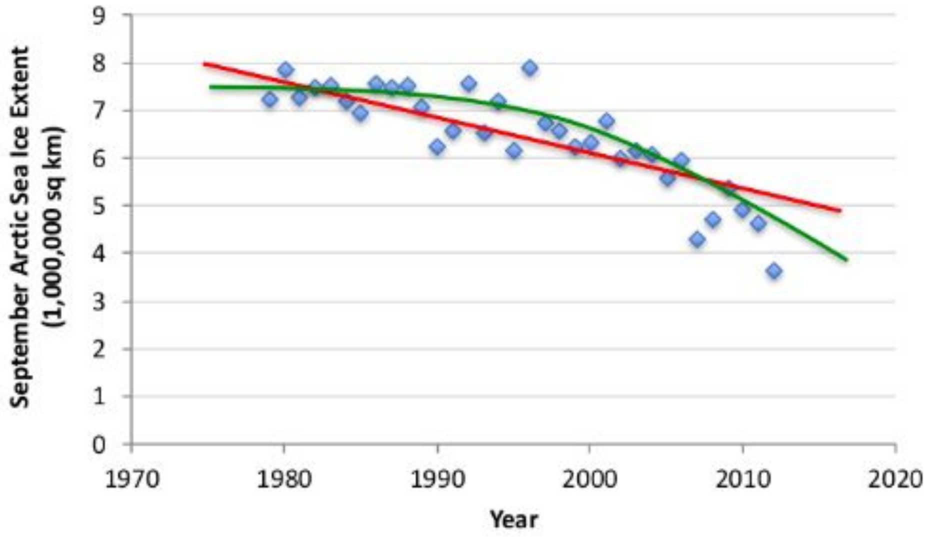
Describing the problem

- **Data:** A set of records (or samples, instances) described by n attributes: A1, A2, … An and each sample is labelled with a class (Like SPAM or NOT) or a "score" (like the credit score)

- **Goal:** To learn a model (or a function) from the data that can be used to predict the labels that the records have (and labels for new unlabelled records)

Aprendizaje supervisado: regresión

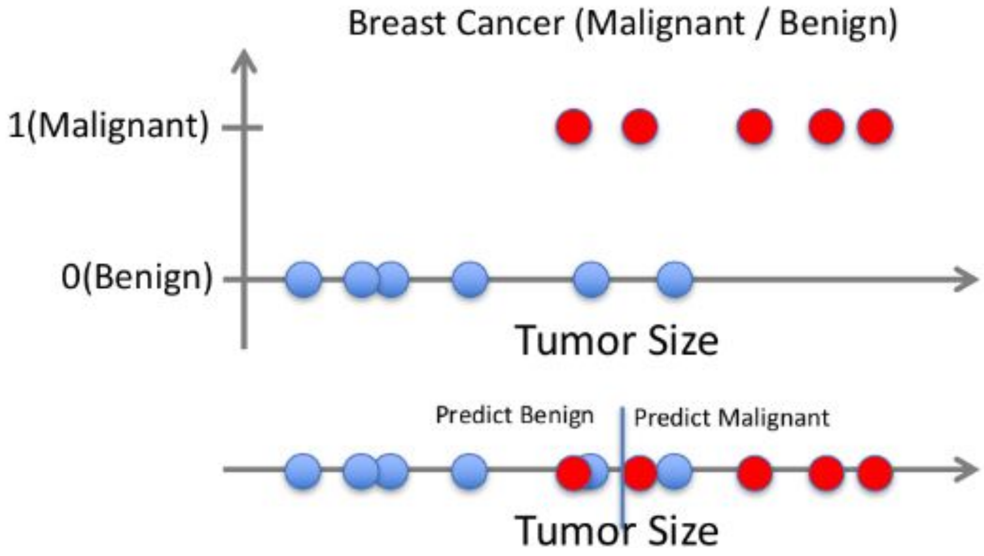
- Dados $(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)$
- Aprender una $f(x)$ que permita predecir y a partir de x
  - Si y está en $\mathbb{R}^n$ $\rightarrow$ **regresión**



Slides from the previous course

Aprendizaje supervisado: clasificación

- Dados $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
- Aprender una $f(x)$ que permita predecir y a partir de x
  - Si y es categórica → **clasificación**



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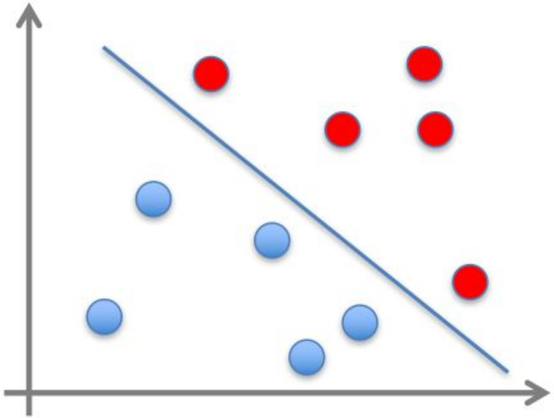
Supervised Learning

- x can be multi-dimensional
  - Each dimension corresponds to an attribute



- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

…

Based on example by Andrew Ng

Slides from the previous course

Aprendizaje supervisado

Functions $\mathcal{F}$

$f : \mathcal{X} \to \mathcal{Y}$

Training data

$\{(x_i, y_i) \in \mathcal{X} \times \mathcal{Y}\}$

LEARNING

$$\boxed{\begin{array}{l} \text{find } \hat{f} \in \mathcal{F} \\ \text{s.t. } y_i \approx \hat{f}(x_i) \end{array}}$$

Learning machine

New data

PREDICTION

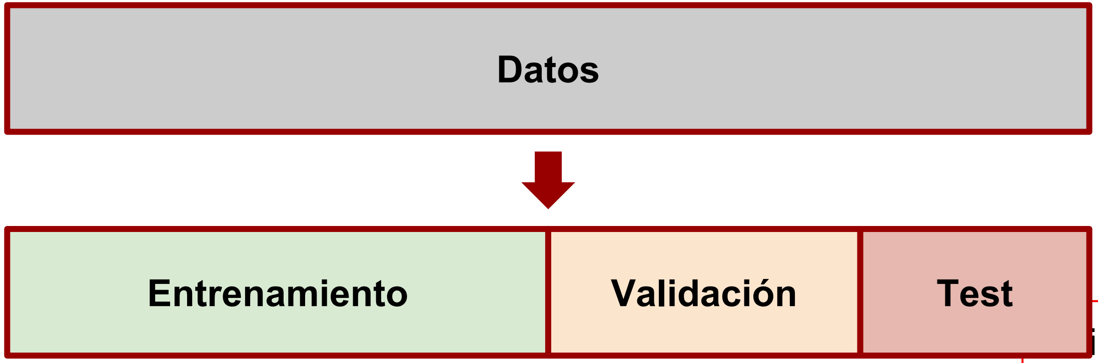
$$\boxed{y = \hat{f}(x)} \Leftarrow \boxed{x}$$

Slides from the previous course

Elección de *hiperparámetros*

Dividir el conjunto total de ejemplos en tres subconjuntos

- **Entrenamiento**: aprendizaje de variables del modelo
- **Validación**: ajuste/elección de hiperparámetros
- **Test**: estimación final de la performance del modelo entrenado (y con hiperparámetros elegidos adecuadamente



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Support Vector Machines

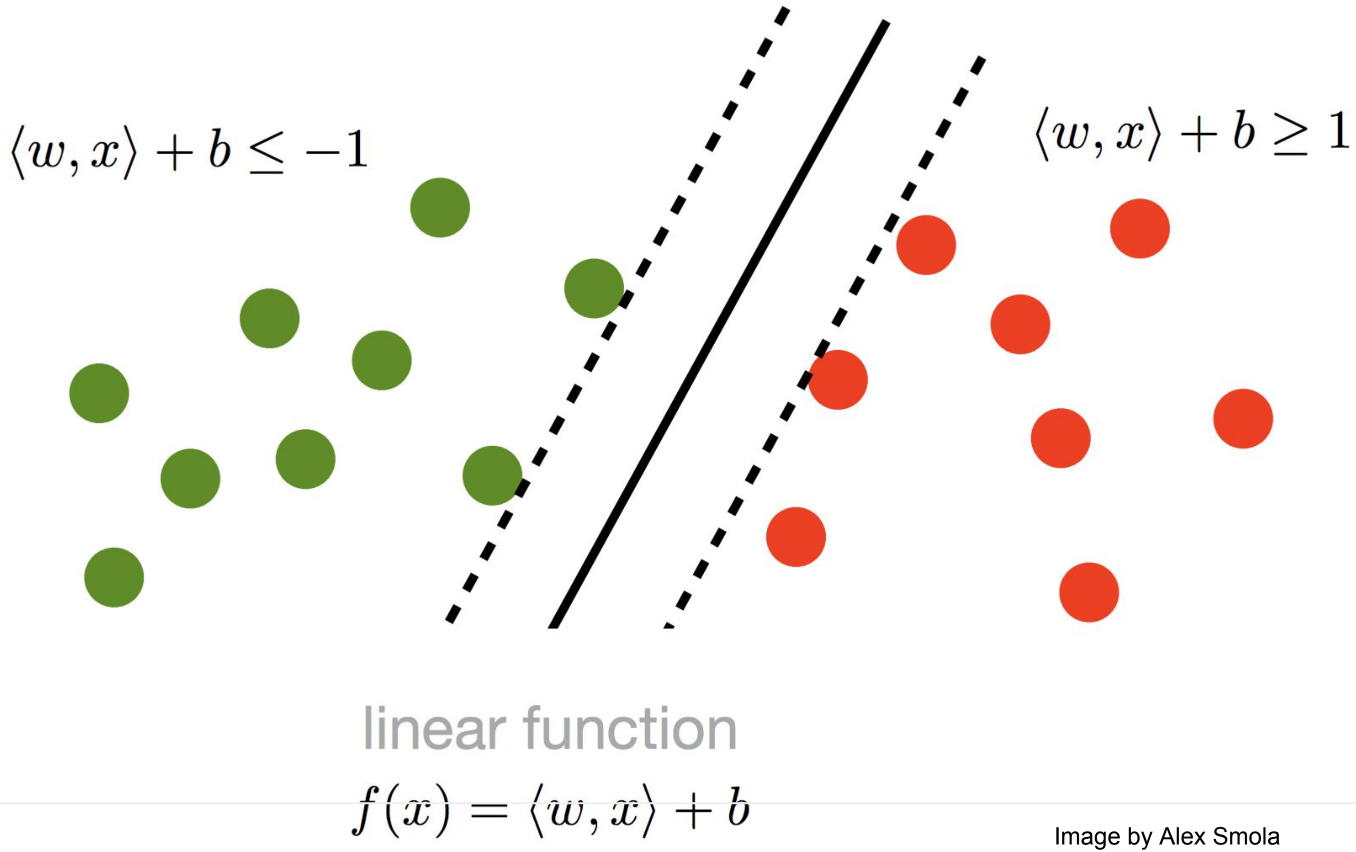


Image by Alex Smola

SVMs: slack variables

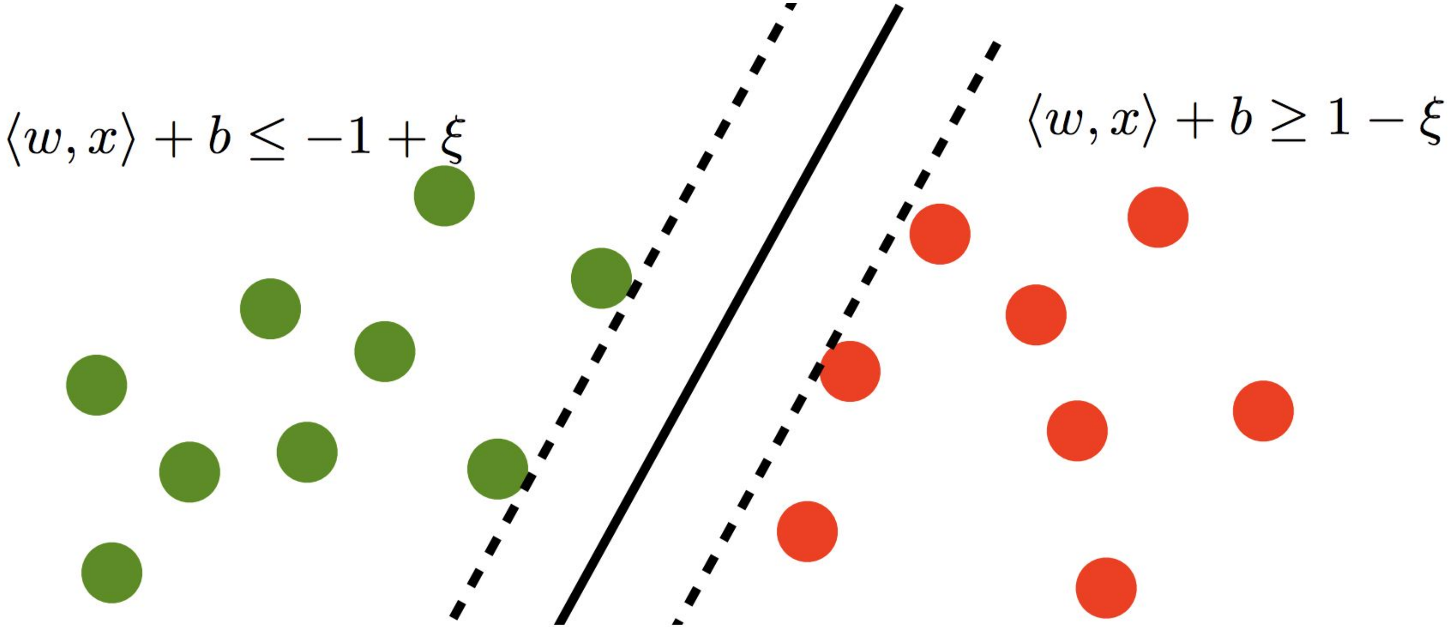
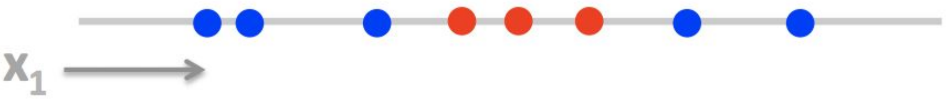
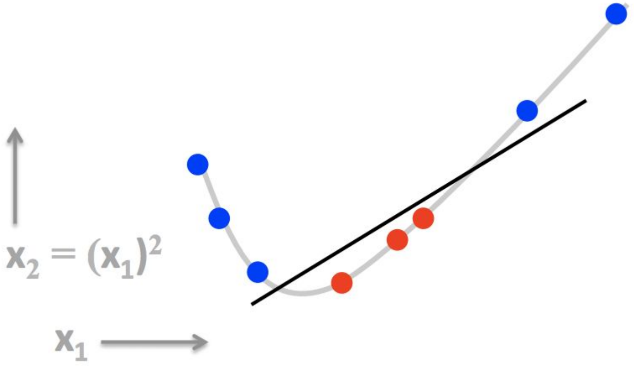


Image by Alex Smola

SVMs: Kernels





Images by Alex Ihler

Multiclass SVMs

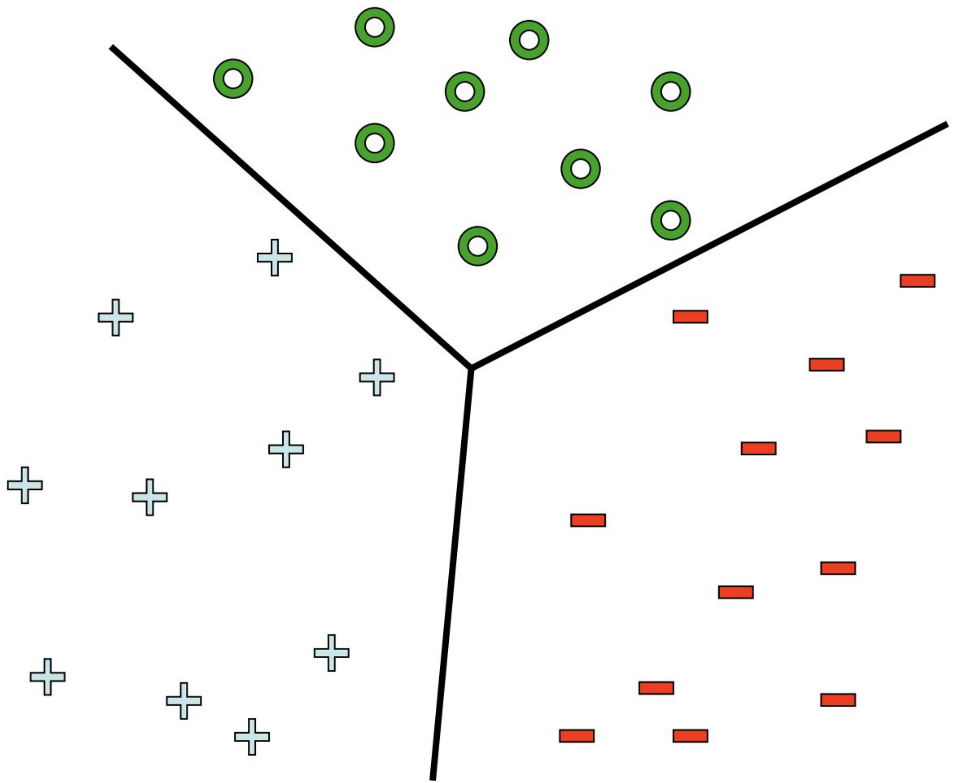


Image by David Sontag

Multiclass SVMs: one vs the rest

- **Training:** For M classes:

  construct a hyperplane between class k and the other M − 1 classes => M SVMs

- **Classification:** make M predictions (one for each SVMs) and find out the one getting more hits into its positive region.

Decision Trees (review)

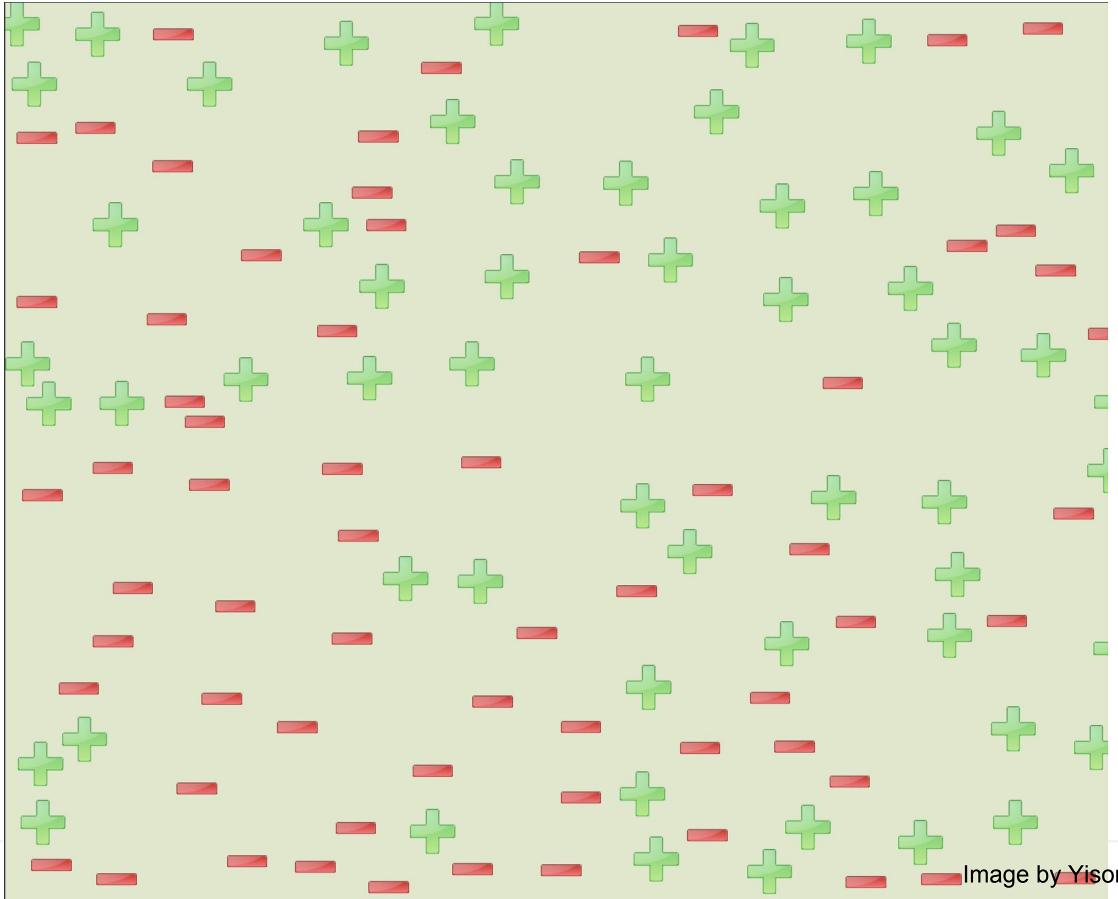


Image by Yisong Yue

Decision Trees (review)

Image by Yisong Yue

Ensemble Learning

- Generate a set of "learners" that, when combined, have higher accuracy.
- Assuming we have three learners: L1, L2, L3
- The predictions from them may differ
- What would we do? Who do we trust?
  - Believe the model that we know is best?
  - Go with the majority?

Ensemble Learning

- **An ensemble model is a model that is a combination of several different models**
- **Usually, an ensemble is more accurate than all its constituent models**
- **Why?**
    - **Intuition:** "two know more than one"

Ensemble Learning. First approach: Voting

- Given n classifiers m1, m2, … mn
- Consider a new classifier M that, given a datum x, M computes m1(x), m2(x), …, counts the predictions and returns the most predicted class
- How well would M work?

Bagging

- Let D be the dataset
- Repeat k times:
  - Create D' from D by randomly selecting |D| instances of D with replacement
  - Learn a new model m
- Return a model that selects the most frequent prediction among m1, …, mk predictions

Bagging

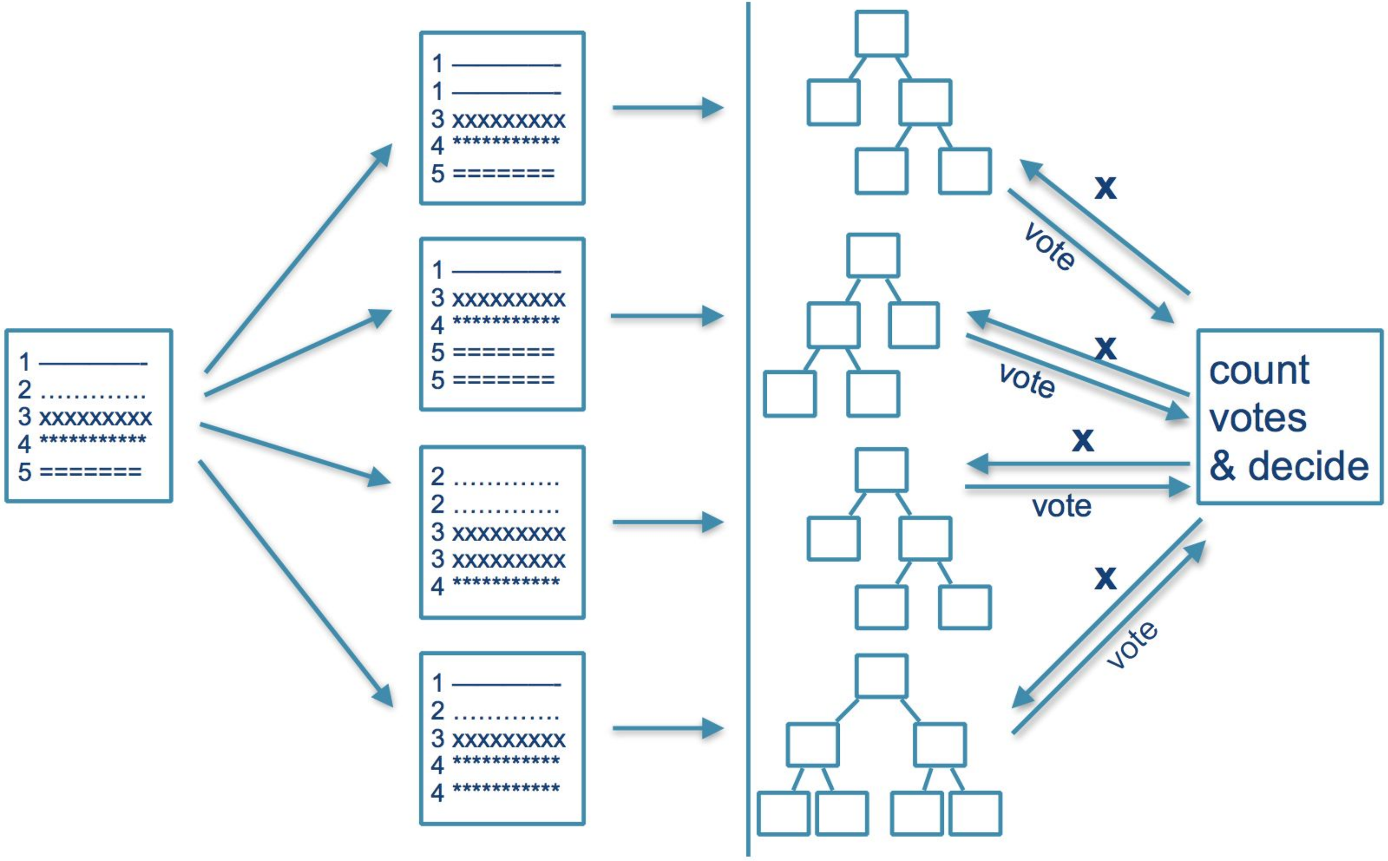


Image by Hendrik Blockeel

Bagging for Decision Trees

- Bagging generally works well for unstable learners
  - A learner is unstable if small changes in the dataset can give very different resulting models
  - It turns out that decision tree learners are indeed unstable
- Disadvantage: learning k trees is k times as expensive as learning one tree

Random Forests

- **Like bagging, with one improvement**
  - **For trees, ALL the features are considered to create a split node (inner node)**
  - **For random forests, at each node consider only M randomly chosen attributes (not all)**
  - **Usually take** $M = \sqrt{\text{number of attributes}}$

Random Forests

Common Steps

- Build a random forest considering M attributes
- Predict the value of "Out-of-bag" samples using the random forest
- Estimate the accuracy
- Determine the optimal M (hyperparameter)

Random Forests

- **Random Forests is one of the most efficient and most accurate learning methods to date (2008)** (Caruana+: An empirical evaluation of supervised learning in high dimensions. ICML 2008)
- **Easy to use with little parameter tuning**
- **Easy to debug, but, compared with Decision Trees, the model is less interpretable**

Boosting

- **Bagging goal:** fit large trees to resampled versions of the training data, and classify by majority vote

- **Boosting:** fit large or small trees to "**reweighted**" versions of the training data and classify by **weighted** majority vote

Boosting

- **Each model, defines the features that the next model will focus on**
- **Uses bootstrapping like bagging, but here we weight each sample of data**
  - **Some samples will be used more frequently**
- **Process:**
  - Given a model, track the samples that are more "erroneous" and give them heavier weights (considered to be data that have more complexity and requires more steps)
  - Given a model, track the error rate so that better models are given more weights

Neural Networks Warm-up

Logistic Regression Review

Given x, we would like to find $\hat{y} = P(y = 1|x)$

What is the easiest way to transform x?

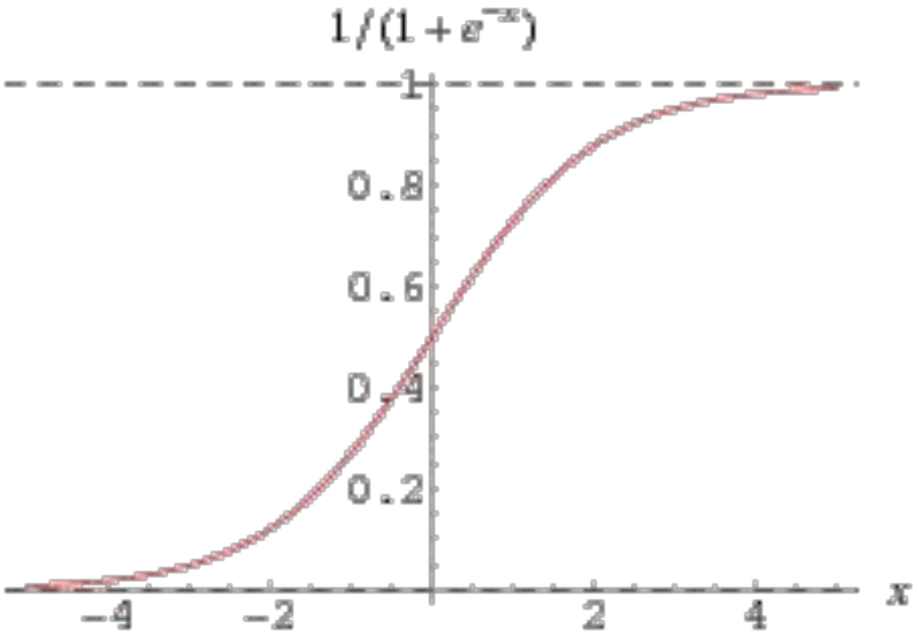
$$\hat{y} = w^T x + b$$

But we would like ŷ to be a probability: $0 \leq \hat{y} \leq 1$

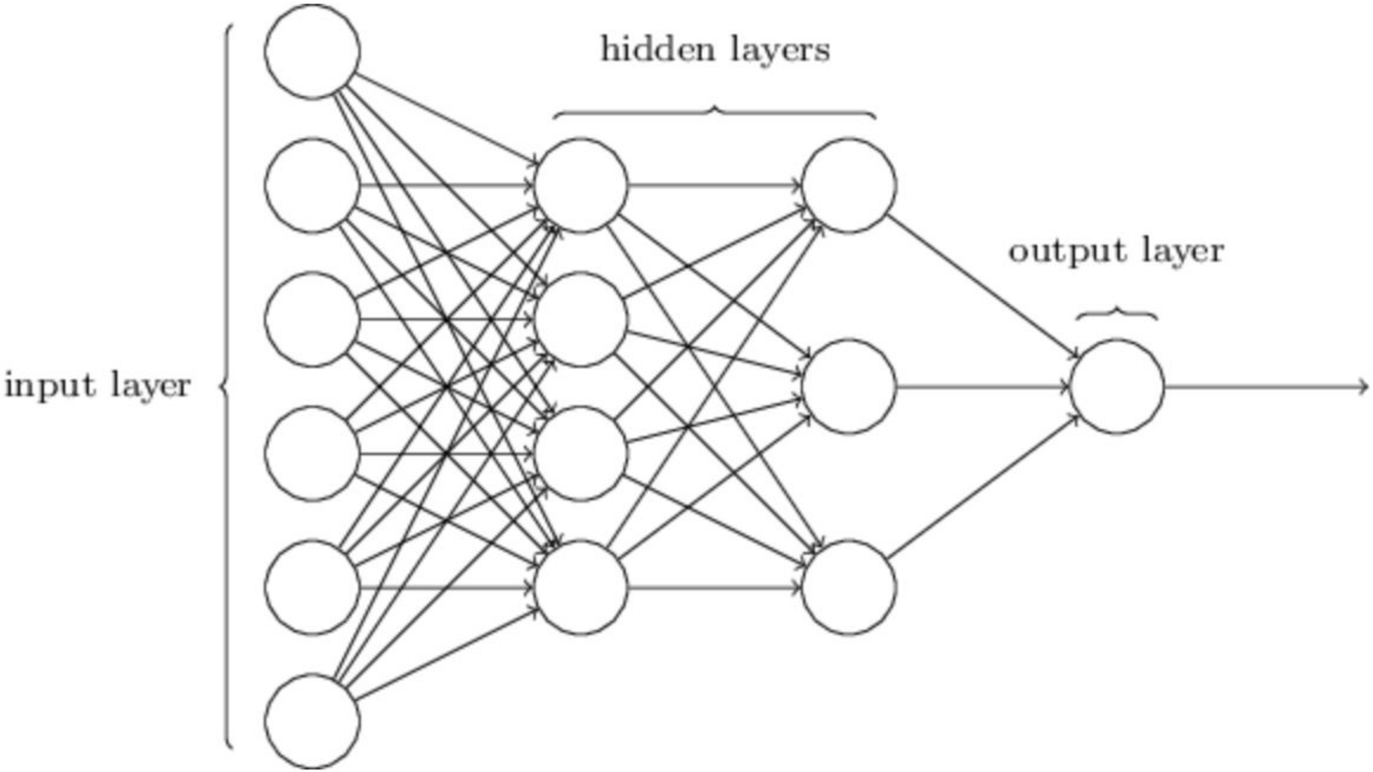
Neural Networks Warm-up

Sigmoid function

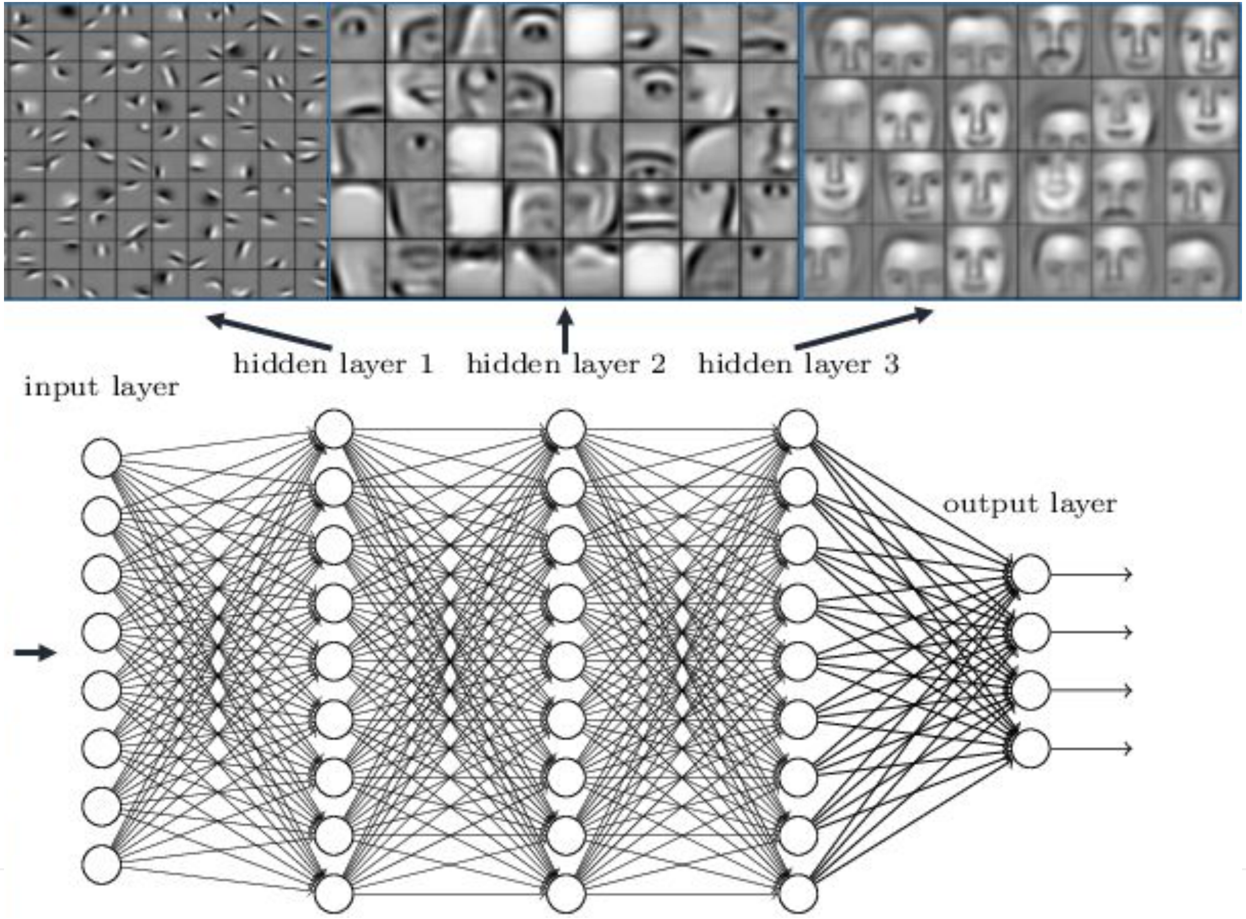
$$f(x) = \frac{1}{1+\exp(-x)}$$



Neural Networks



Deep Neural Networks



Deep Neural Networks

How to split the data?

- Train / Test / Validation

- Now?
  - Too much data (> 10.000.000 samples)

Make sure your train/ test / validation come from the same distribution

Deep Neural Networks

Rule of thumb to deal with bias/variance?

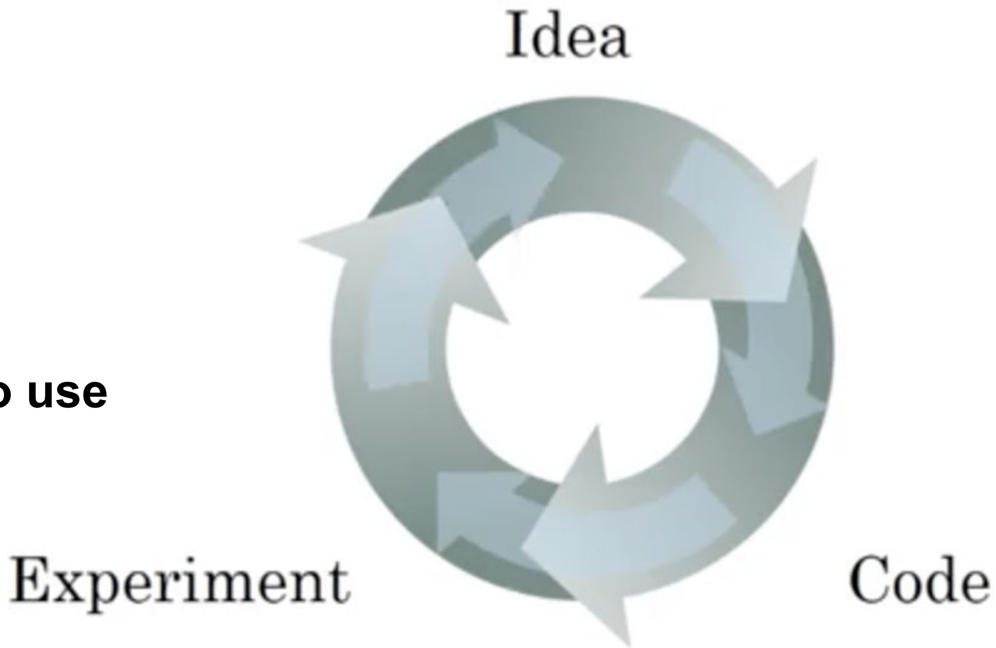
- **High Bias:**
  - **Bigger Network**
  - **Different Network Architecture**

- **High Variance:**
  - **More data**
  - **Regularization**
  - **Different Network Architecture**

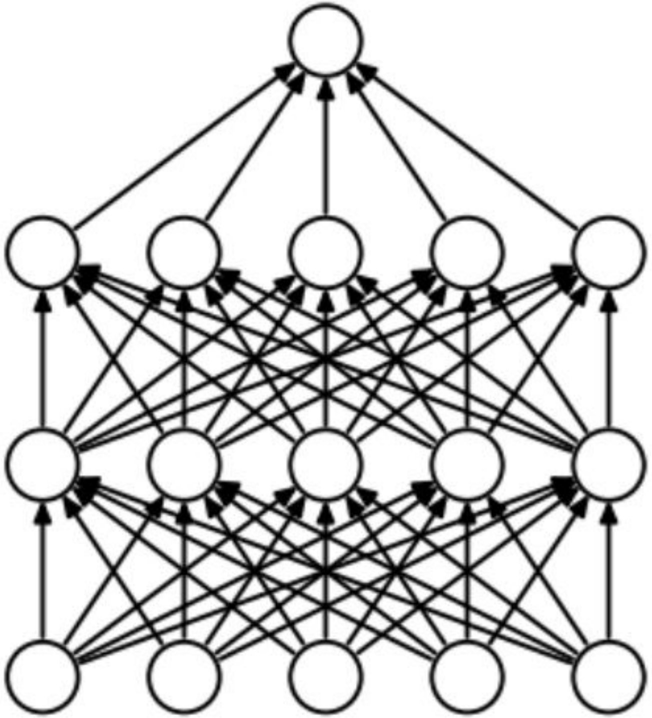
Neural Networks

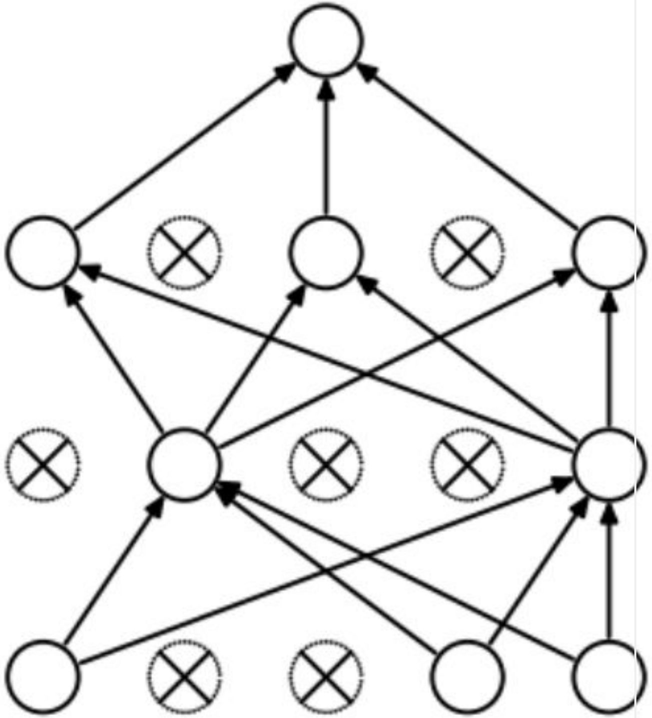
How to decide the size?

- **# hidden layers**
- **# hidden units**
- **What activation function to use**



Neural Networks Dropout


(a) Standard Neural Net


(b) After applying dropout.