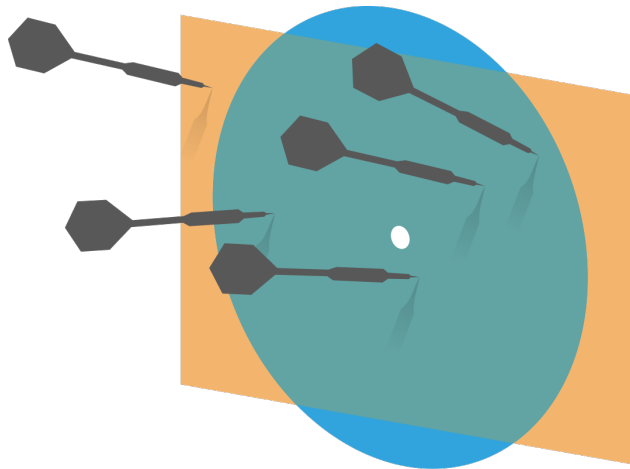


Probability and Statistics for Computer Science



“...many problems are naturally
classification problems” ---Prof.
Forsyth

Credit: wikipedia

Last time

- ✱ Demo of Principal Component Analysis
- ✱ Introduction to classification

Objectives

- ✱ Decision tree (II) }
- ✱ Random forest
- ✱ Support Vector Machine (I)

Classifiers

- ✱ Why do we need classifiers?
prediction patterns
- ✱ What do we use to quantify the performance of a classifier?
efficient
confusion matrix
- ✱ What is the baseline accuracy of a 5-class classifier using 0-1 loss function?
 $\frac{1}{5}$
- ✱ What's validation and cross-validation in classification?

Performance of a multiclass classifier

✧ Assuming there are c classes:

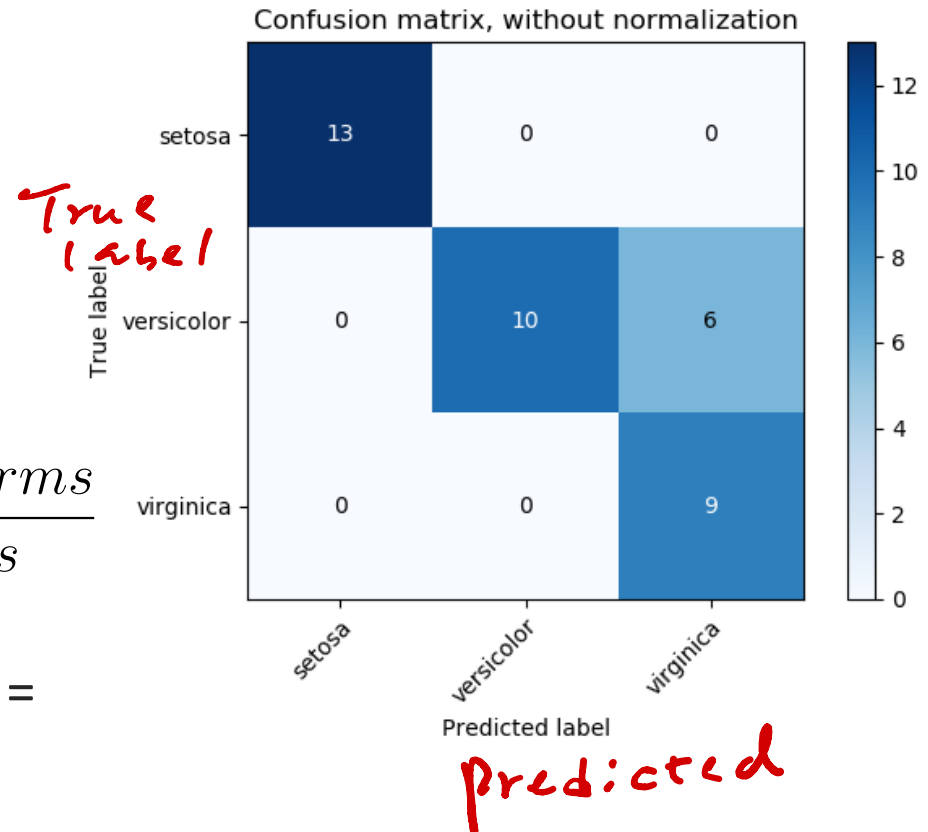
✧ The class confusion matrix is $c \times c$

✧ Under the 0-1 loss function

$$\text{accuracy} = \frac{\text{sum of diagonal terms}}{\text{sum of all terms}}$$

ie. in the right example, accuracy = $32/38=84\%$

✧ The baseline accuracy is $1/c$.



Source: scikit-learn

Cross-validation

Split the data in multiple ways

Training vs. Testing/
validation

randomly

{ "fold"
"leave-one-out"

Purpose ?

Q1. Cross-validation

Cross-validation is a method used to prevent overfitting in classification.

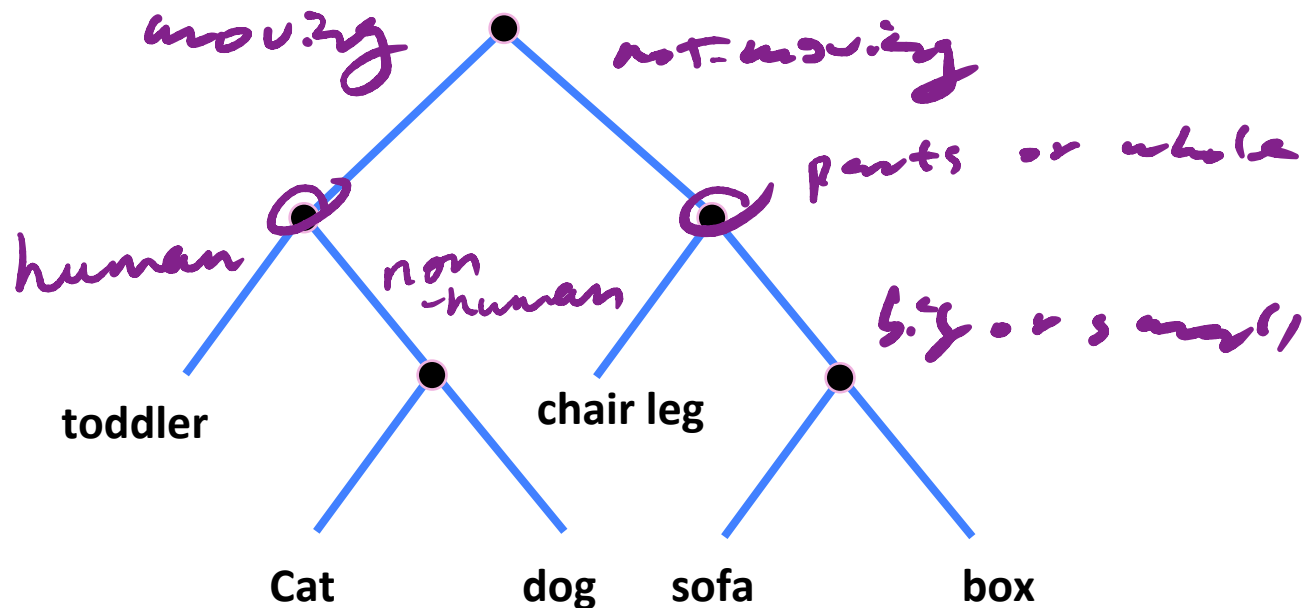


A. TRUE

B. FALSE

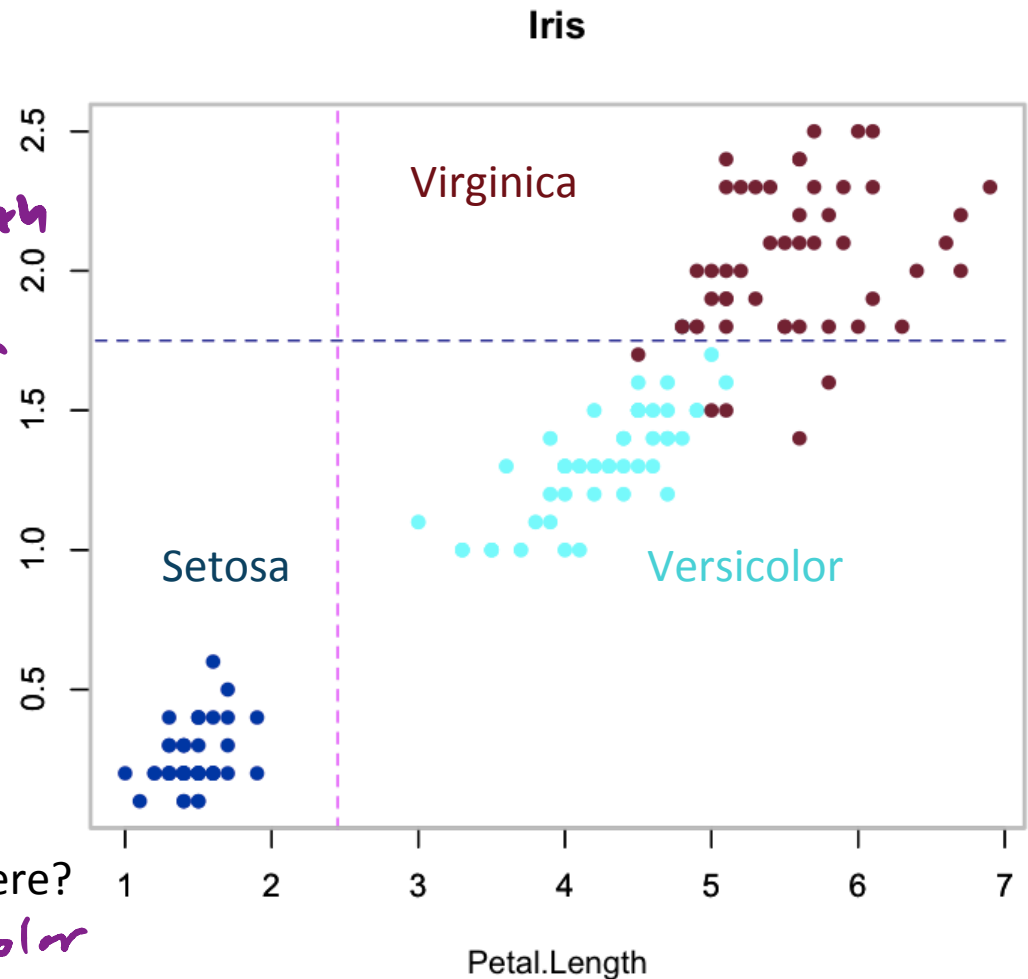
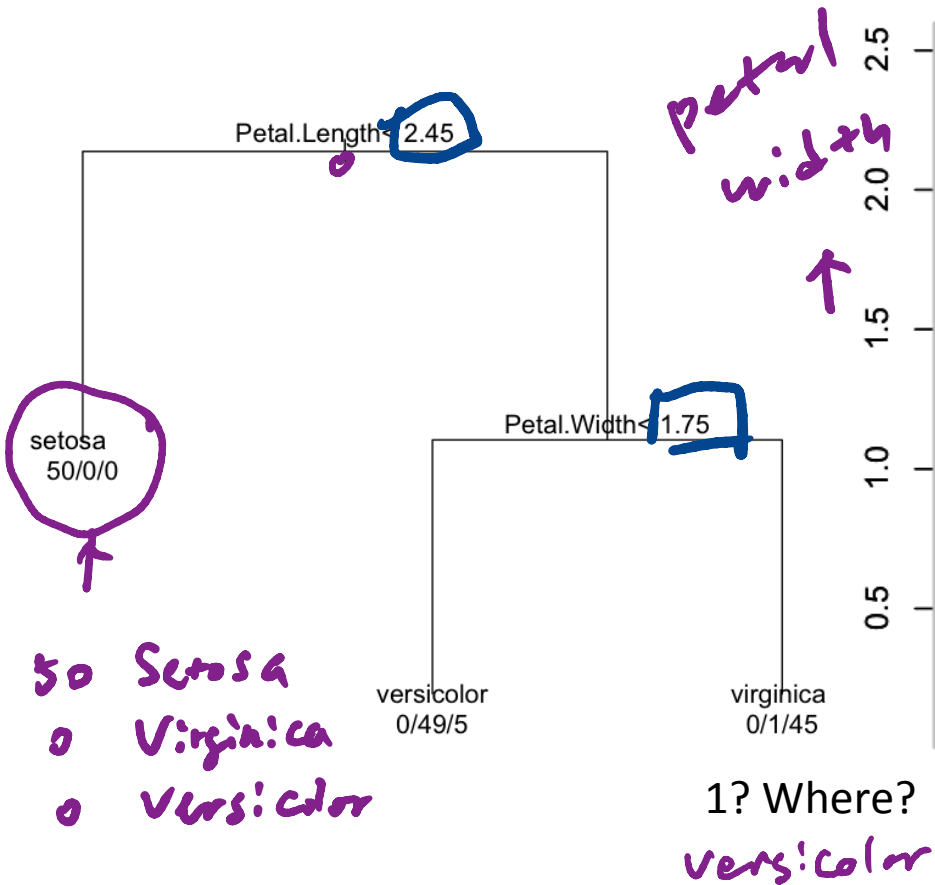
Decision tree: object classification

- ✦ The object classification **decision tree** can classify objects into multiple classes using sequence of simple tests. It will naturally grow into a tree.



Training a decision tree: example

✿ The “Iris” data set

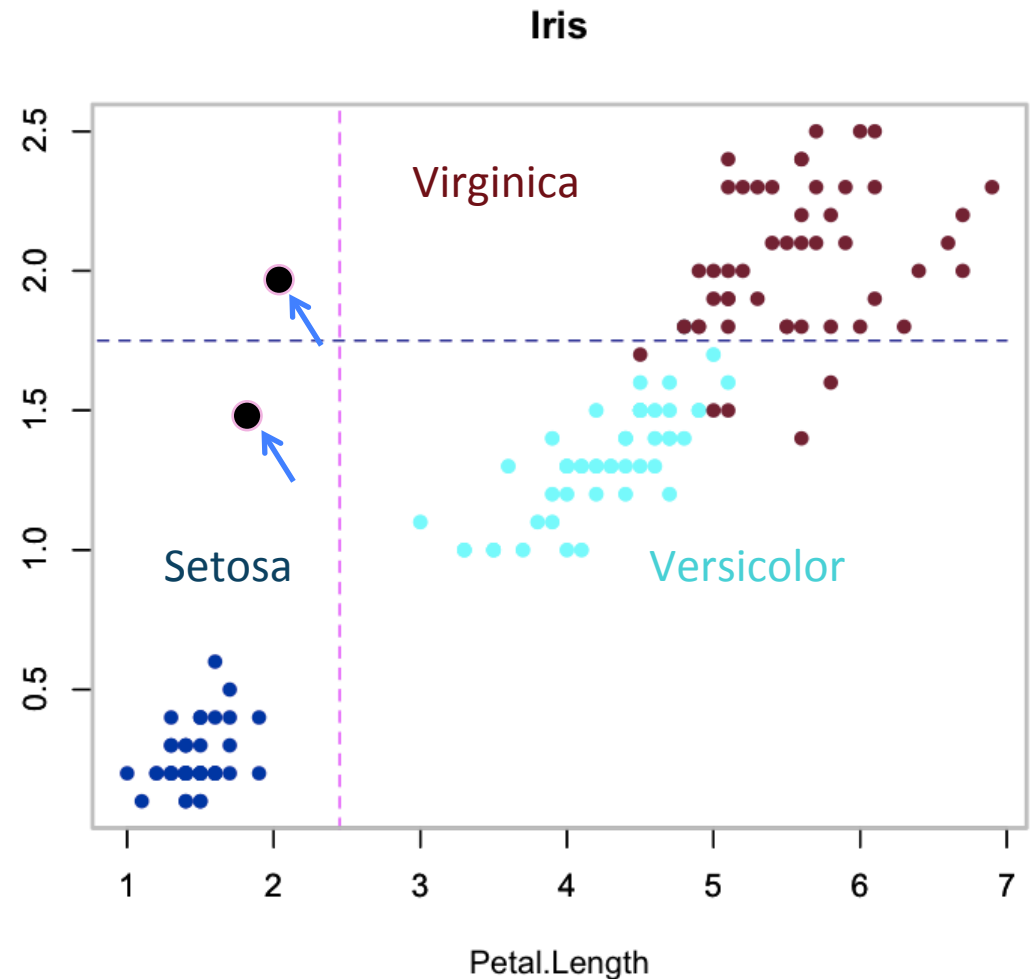
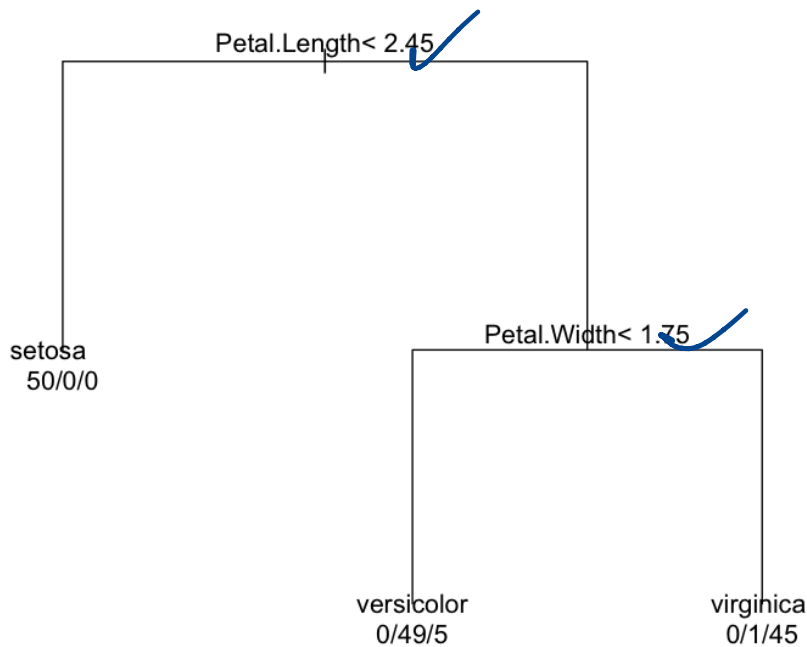


Training a decision tree

- ✱ Choose a dimension/feature and a split
- ✱ Split the training Data into left- and right-child subsets D_l and D_r
left *right*
- ✱ Repeat the two steps above recursively on each child
- ✱ Stop the recursion based on some conditions
- ✱ Label the leaves with class labels

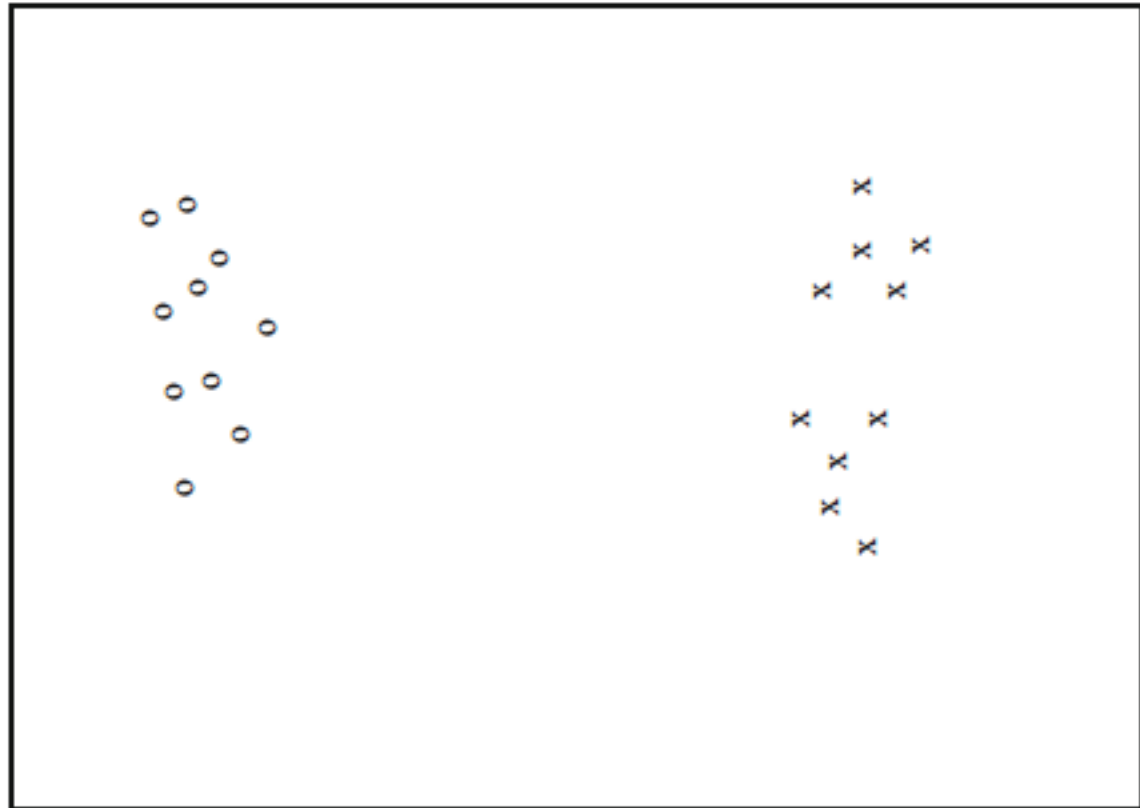
Classifying with a decision tree: example

✿ The “Iris” data set



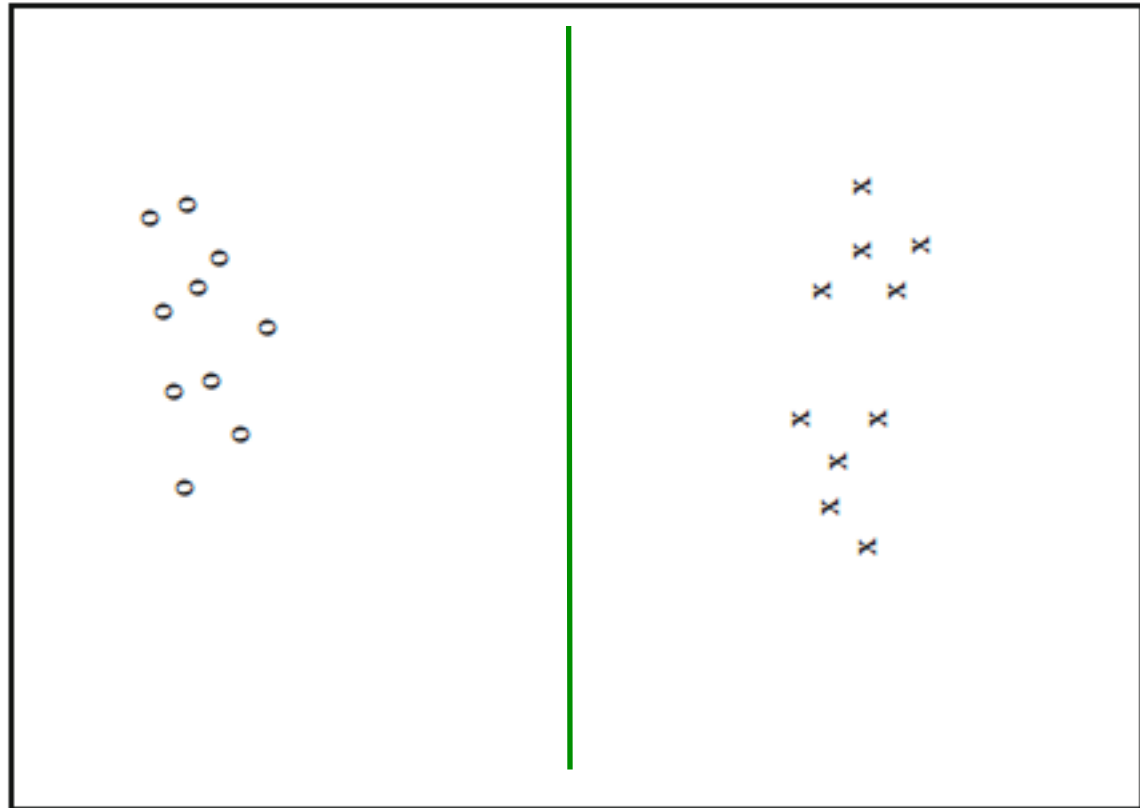
Choosing a split

- ✱ An informative split makes the subsets more concentrated and reduces uncertainty about class labels



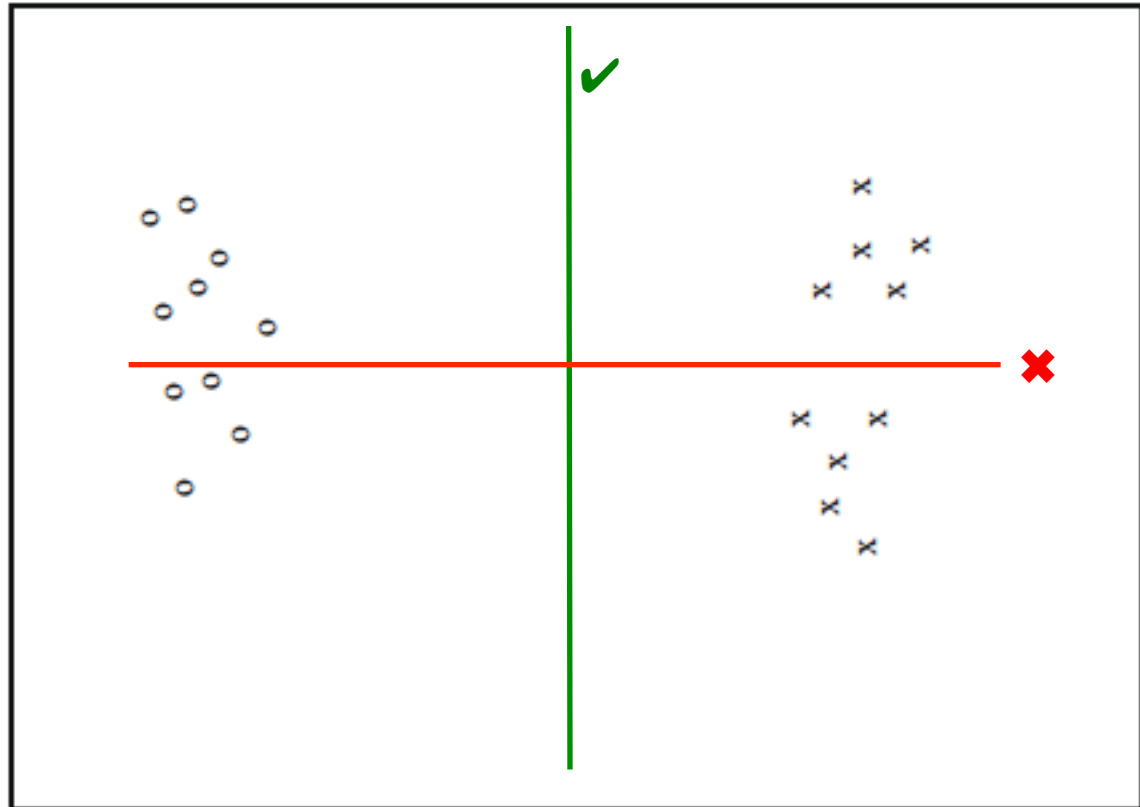
Choosing a split

- ✱ An informative split makes the subsets more concentrated and reduces uncertainty about class labels

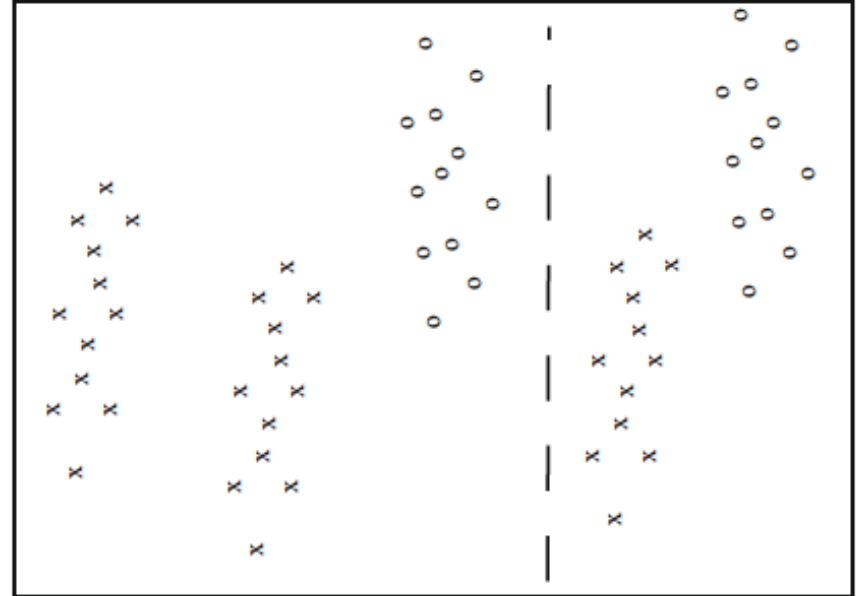
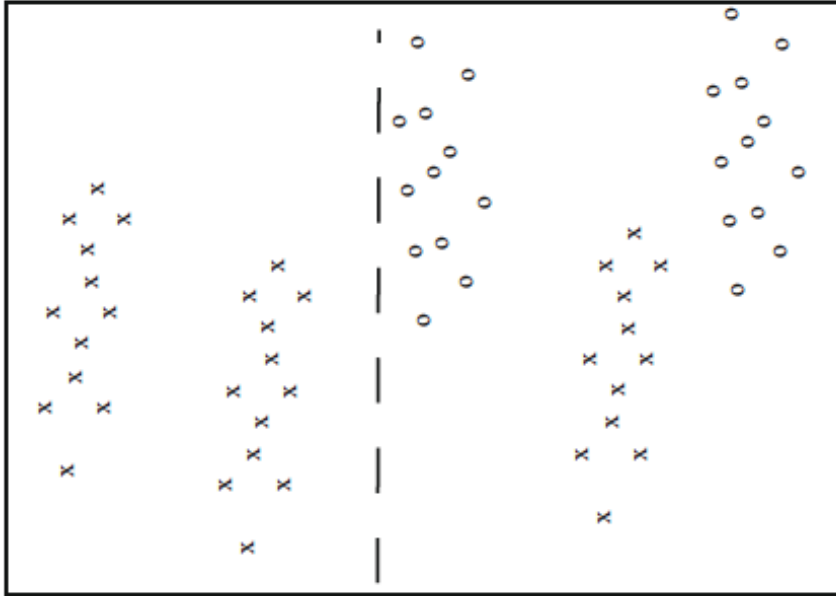


Choosing a split

- ✱ An informative split makes the subsets more concentrated and reduces uncertainty about class labels

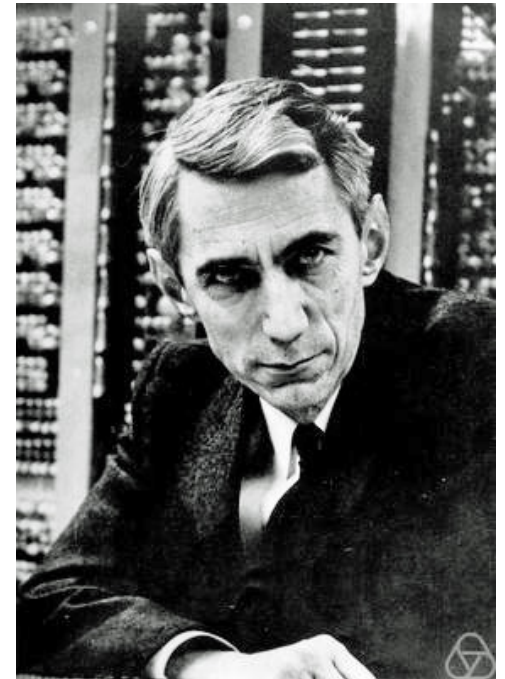


Which is more informative?



Quantifying uncertainty using entropy

- ✱ We can measure uncertainty as the number of bits of information needed to distinguish between classes in a dataset (first introduced by Claude Shannon)
 - ✱ We need $\log_2 2 = 1$ bit to distinguish 2 equal classes
 - ✱ We need $\log_2 4 = 2$ bit to distinguish 4 equal classes



Claude Shannon (1916-2001)

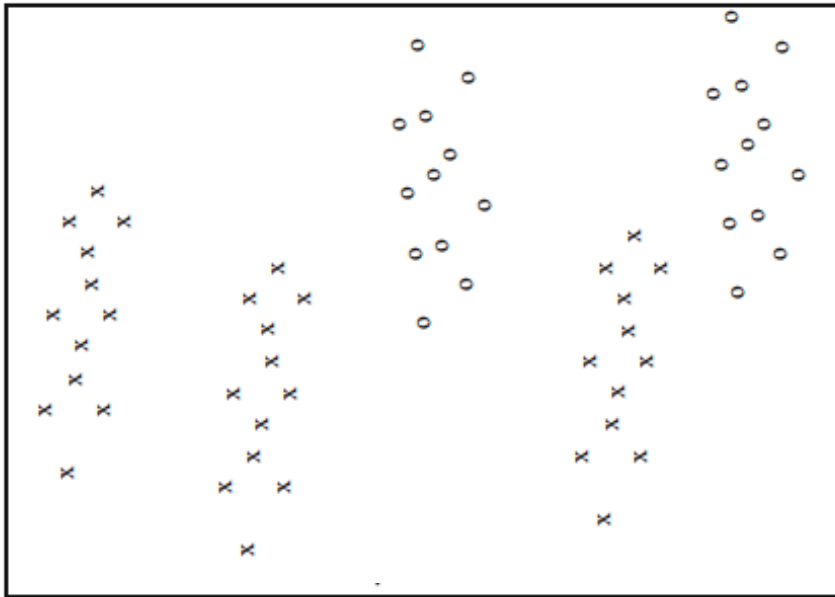
Quantifying uncertainty using entropy

- ✱ **Entropy** (Shannon entropy) is the measure of uncertainty for a general distribution
 - ✱ If class i contains a fraction $P(i)$ of the data, we need $\log_2 \frac{1}{P(i)}$ bits for that class
 - ✱ The entropy $H(D)$ of a dataset is defined as the **weighted mean** of entropy for every class:

$$H(D) = \sum_{i=1}^c P(i) \log_2 \frac{1}{P(i)}$$
$$= \sum_{i=1}^c -P(i) \log_2 P(i)$$

Entropy: before the split

$$p(x) = \frac{3}{5} \quad p(o) = \frac{2}{5}$$



$$H(D) = -\frac{3}{5} \log_2 \frac{3}{5} - \frac{2}{5} \log_2 \frac{2}{5}$$
$$= 0.971 \text{ bits}$$

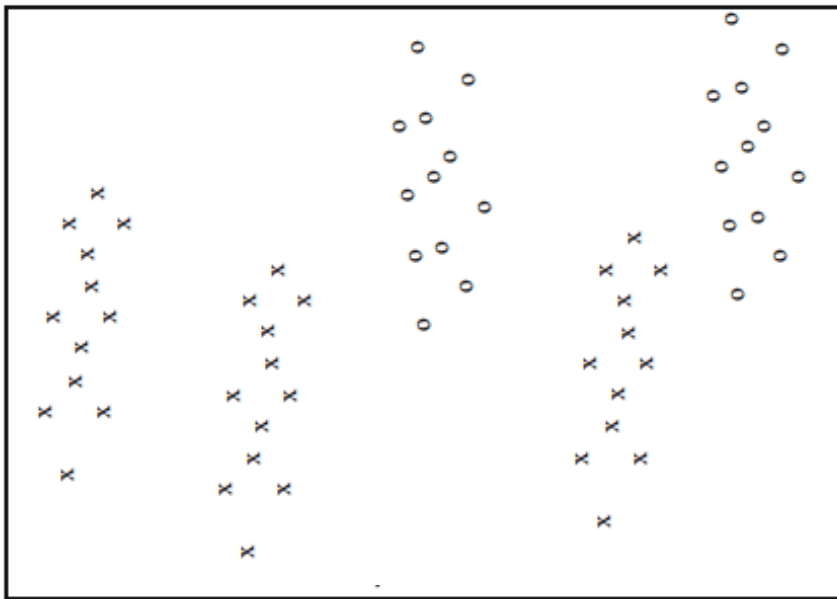


$$H(D_L) = ?$$

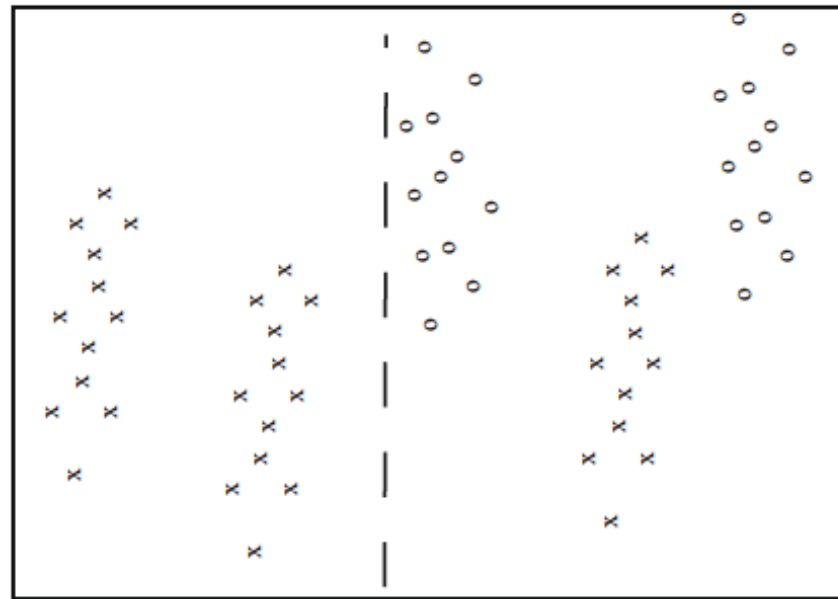
$$H(D_R) = ?$$

Entropy: examples

$$p(x) = 1$$

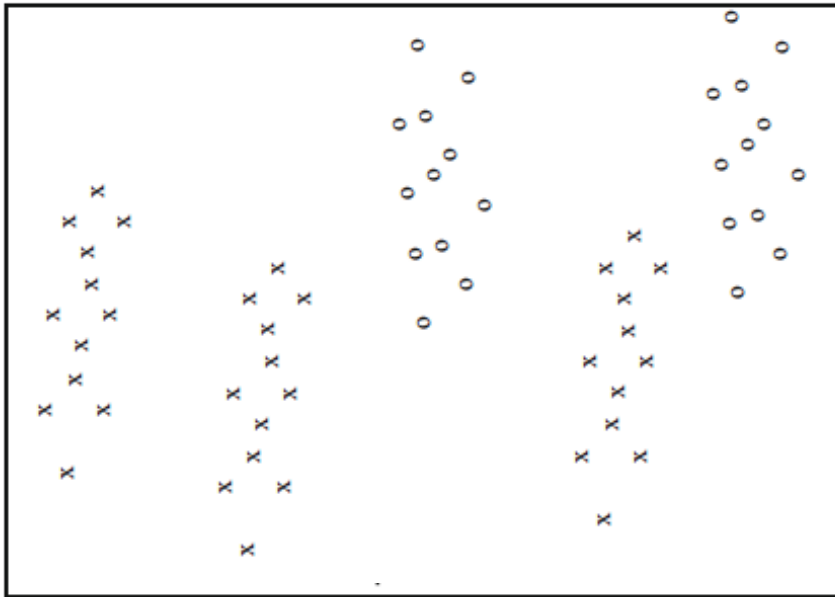


$$H(D) = -\frac{3}{5} \log_2 \frac{3}{5} - \frac{2}{5} \log_2 \frac{2}{5}$$
$$= 0.971 \text{ bits}$$



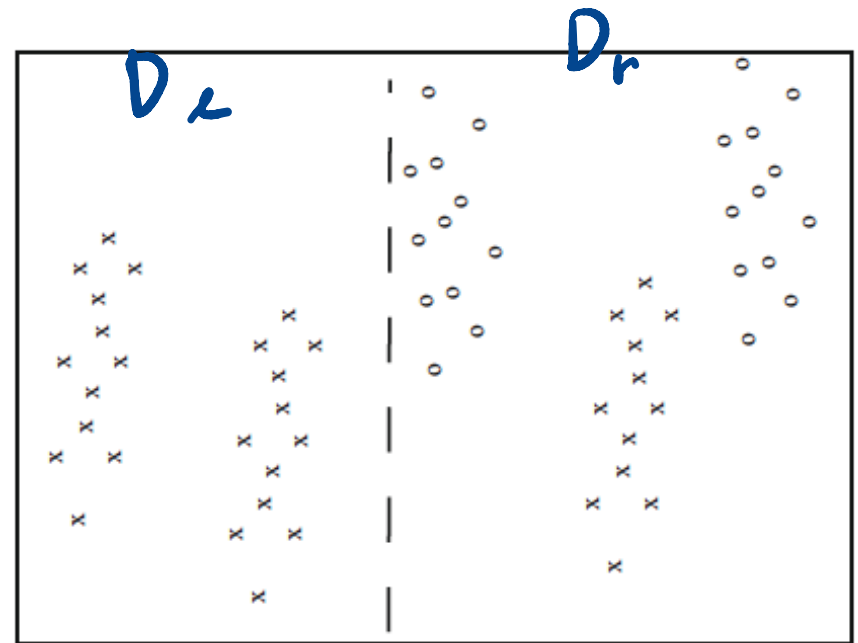
$$H(D_1) = -1 \log_2 1 = 0 \text{ bits}$$

Entropy: examples



$$H(D) = -\frac{3}{5} \log_2 \frac{3}{5} - \frac{2}{5} \log_2 \frac{2}{5}$$

$$= 0.971 \text{ bits}$$



$$H(D_l) = -1 \log_2 1 = 0 \text{ bits}$$

$$H(D_r) = -\frac{1}{3} \log_2 \frac{1}{3} - \frac{2}{3} \log_2 \frac{2}{3}$$

$$= 0.918 \text{ bits}$$

Information gain of a split

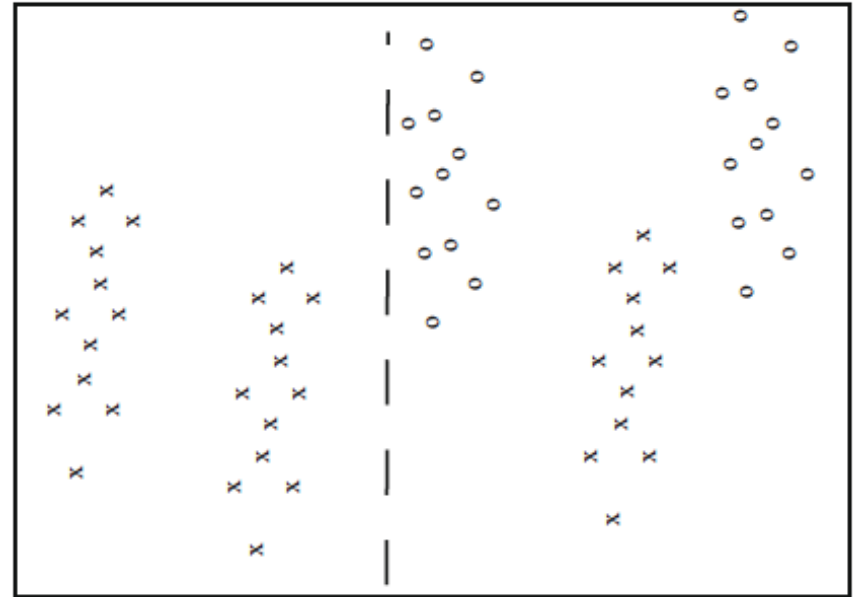
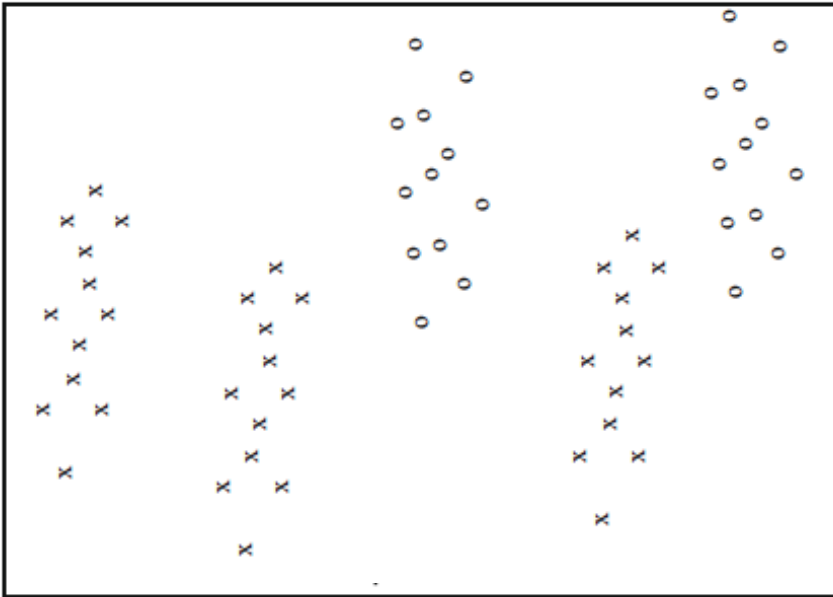
- ✱ The information gain of a split is the amount of entropy that was reduced on average after the split

$$I = H(D) - \left(\frac{N_{Dl}}{N_D} H(D_l) + \frac{N_{Dr}}{N_D} H(D_r) \right)$$

✱ where

- ✱ N_D is the number of items in the dataset D
- ✱ N_{Dl} is the number of items in the left-child dataset D_l
- ✱ N_{Dr} is the number of items in the right-child dataset D_r

Information gain: examples

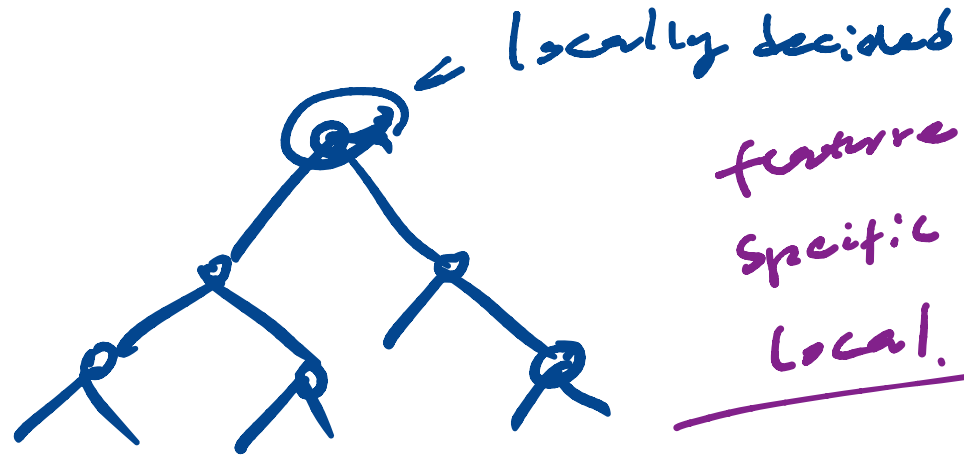


$$\begin{aligned} I &= H(D) - \left(\frac{N_{Dl}}{N_D} H(D_l) + \frac{N_{Dr}}{N_D} H(D_r) \right) \\ &= 0.971 - \left(\frac{24}{60} \times 0 + \frac{36}{60} \times 0.918 \right) \\ &= 0.420 \text{ bits} \end{aligned}$$

Q. Is the splitting method global optimum?

A. Yes

B. No



How to choose a dimension and split

- ✱ If there are d dimensions, choose approximately \sqrt{d} of them as candidates at random
- ✱ For each candidate, find the split that maximizes the information gain
- ✱ Choose the best overall dimension and split
- ✱ Note that splitting can be generalized to categorical features for which there is no natural ordering of the data

When to stop growing the decision tree?

- ✱ Growing the tree too deep can lead to overfitting to the training data
- ✱ Stop recursion on a data subset if any of the following occurs:
 - ✱ All items in the data subset are in the same class
 - ✱ The data subset becomes smaller than a predetermined size
 - ✱ A predetermined maximum tree depth has been reached.

How to label the leaves of a decision tree

- ✱ A leaf will usually have a data subset containing many class labels
- ✱ Choose the class that has the most items in the subset
hard
- ✱ Alternatively, label the leaf with the number it contains in each class for a probabilistic “soft” classification.

c_1 c_2 c_3 *leaf node*



Pros and Cons of a decision tree

- ✱ Pros: Intuitive. easy to implement.
low cost → fast
Discrete vs Cont: RV.
Decision boundary
- ✱ Cons: Not so accurate
overfitting.

Training, evaluation and classification

- ✱ Build the random forest by training each decision tree on a random subset with replacement from the training data and subset of features are also randomly selected--- “Bagging”
- ✱ Evaluate the random forest by testing on its out-of-bag items
- ✱ Classify by merging the classifications of individual decision trees
 - ✱ By simple vote
 - ✱ Or by adding soft classifications together and then take a vote



An example of bagging

Drawing random samples from our training set with replacement. E.g., if our training set consists of 7 training samples, our bootstrap samples (here: $n=7$) can look as follows, where C_1, C_2, \dots, C_m shall symbolize the decision tree classifiers.

$d=9$

random
select
3 out of 9
features

Sample indices	Bagging Round 1	Bagging Round 2	...	Bagging Round M
1	2	7		
2	2	3		
3	1	2		
4	3	1		
5	4	1		
6	7	7		
7	2	1		

C_1

C_2

Pros and Cons of Random forest

- ✱ Pros: *More accurate usually
less likely to be overfitting.*
- ✱ Cons: *relative longer, more cost in
computing*

Q2. Do you think random forest will always outperform simple decision tree?

A. Yes

B. No

unrelated
trees
by using
different
subsets of d
 $d = 3$

Considerations in choosing a classifier

- ✱ When solving a classification problem, it is good to try several techniques.
- ✱ Criteria to consider in choosing the classifier include
 - * Accuracy
 - * Speed } training for the model
 } classification given new data
 - * flexibility (variety of data, small vs big)
 - * Interpretation
 - * scaling effect.

Support Vector Machine (SVM) overview

- * The Decision boundary and function of a Support Vector Machine
- * Loss function (cost function in the book)
- * Training
- * Validation
- * Extension to multiclass classification

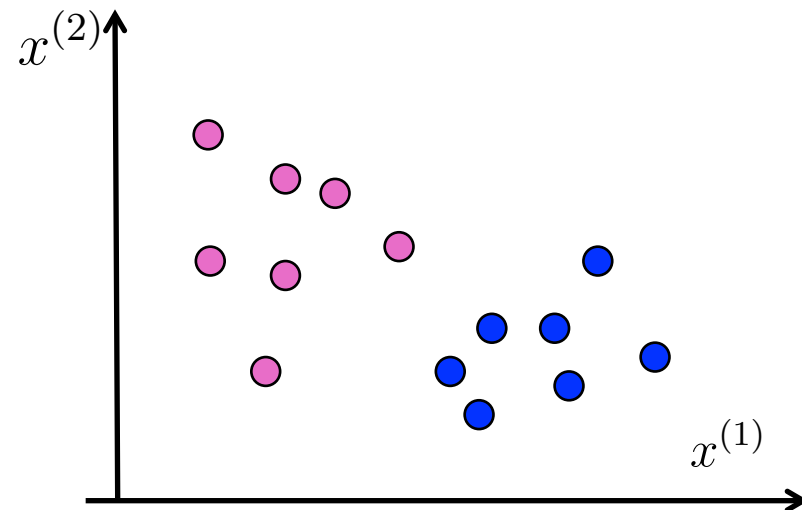
+1
-1

SVM problem formulation

- ✱ At first we assume a binary classification problem
- ✱ The training set consists of N items
 - ✱ Feature vectors x_i of dimension d
 - ✱ Corresponding class labels $y_i \in \{\pm 1\}$

- ✱ We can picture the training data as a d-dimensional scatter plot with colored labels

$x^{(1)}$
 $x^{(2)}$
 $x^{(d)}$



Decision boundary of SVM

✱ SVM uses a hyperplane as its **decision boundary**

✱ The decision boundary is:

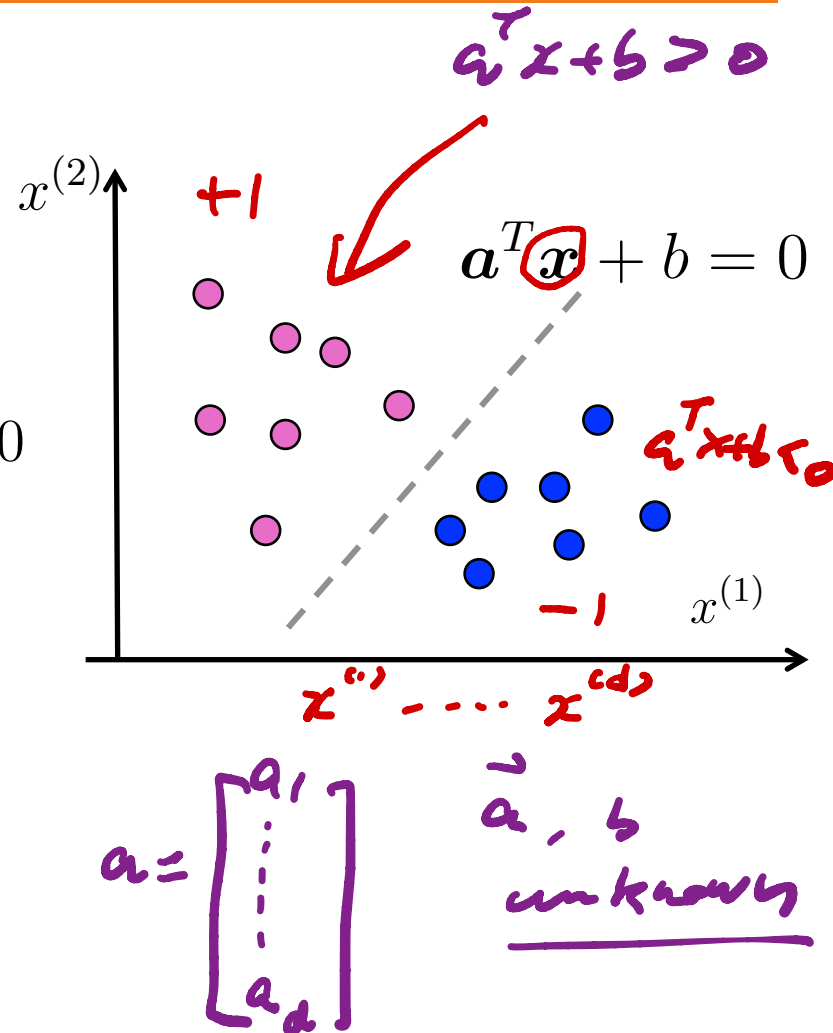
$$a_1x^{(1)} + a_2x^{(2)} + \dots + a_dx^{(d)} + b = 0$$

✱ In vector notation, the hyperplane can be written as:

$$a^T x + b = 0$$

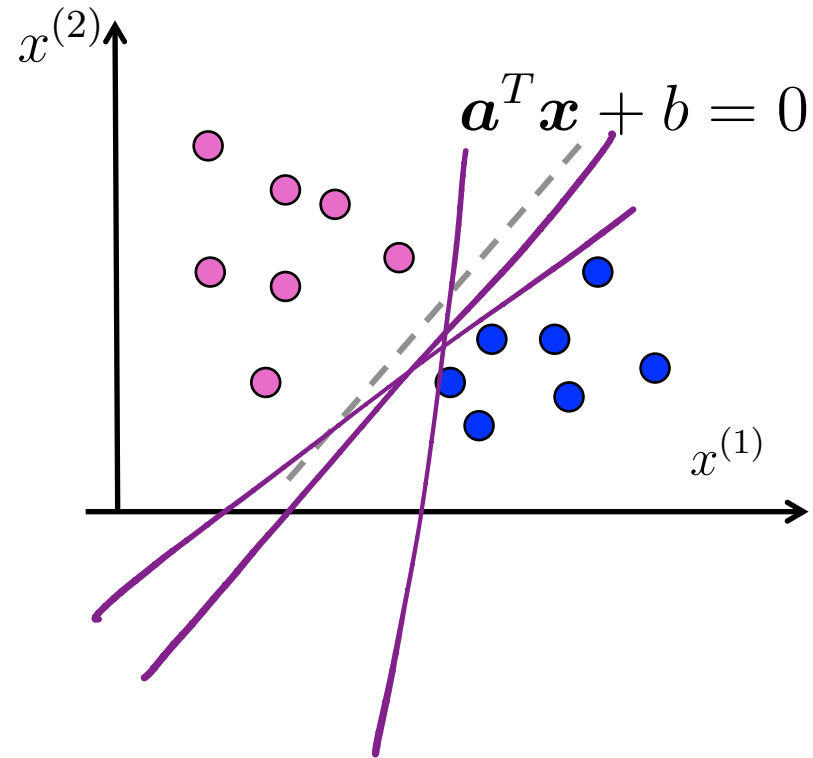
S:gnr($a^T x + b$)

↑



Q3. How many solutions can we have for the decision boundary?

- A. One
- B. Several
- C. Infinite



Classification function of SVM

- ✱ SVM assigns a class label to a feature vector according to the following rule:

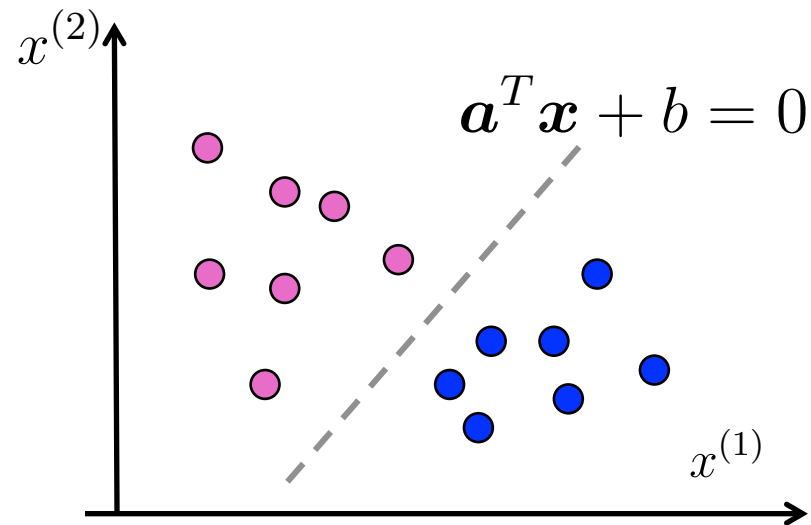
$$+1 \text{ if } \mathbf{a}^T \mathbf{x}_i + b \geq 0$$

$$-1 \text{ if } \mathbf{a}^T \mathbf{x}_i + b < 0$$

- ✱ In other words, the classification function is: $\text{sign}(\mathbf{a}^T \mathbf{x}_i + b)$

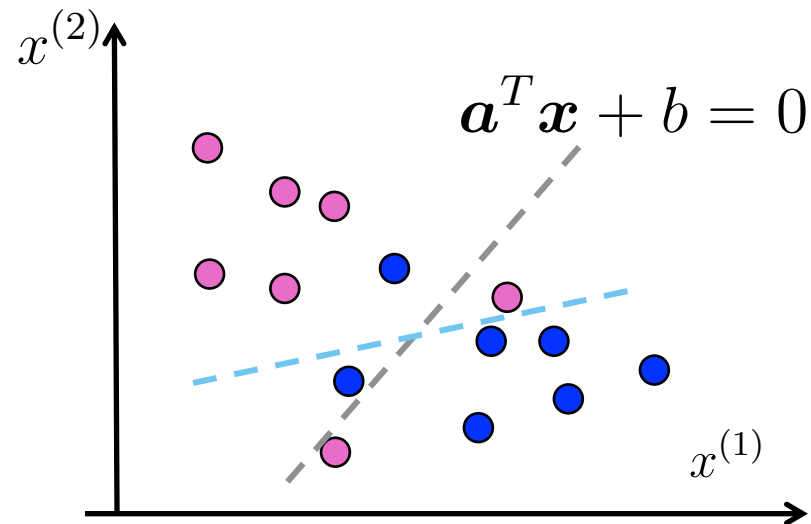
- ✱ Note that

- ✱ If $|\mathbf{a}^T \mathbf{x}_i + b|$ is small, then \mathbf{x}_i was close to the decision boundary
- ✱ If $|\mathbf{a}^T \mathbf{x}_i + b|$ is large, then \mathbf{x}_i was far from the decision boundary



What if there is no clean cut boundary?

- ✱ Some boundaries are better than others for the training data
- ✱ Some boundaries are likely more robust for run-time data
- ✱ We need a quantitative measure to decide about the boundary
- ✱ The **loss function** can help decide if one boundary is better than others



Loss function 1

- ✱ For any given feature vector \mathbf{x}_i with class label $y_i \in \{\pm 1\}$, we want

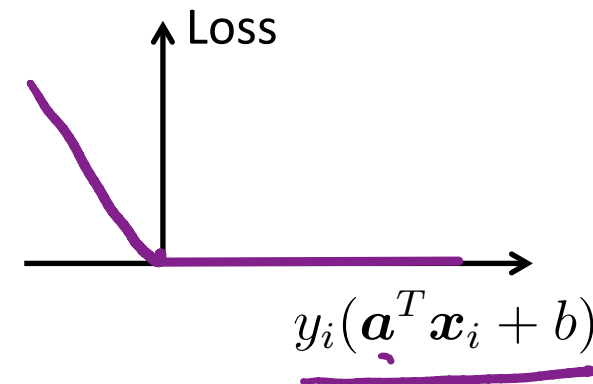
- ✱ Zero loss if \mathbf{x}_i is classified correctly $\text{sign}(\mathbf{a}^T \mathbf{x}_i + b) = y_i$
- ✱ Positive loss if \mathbf{x}_i is misclassified $\text{sign}(\mathbf{a}^T \mathbf{x}_i + b) \neq y_i$
- ✱ If \mathbf{x}_i is misclassified, more loss is assigned if it's further away from the boundary

- ✱ This loss function 1 meets the criteria above:

$$\max(0, -y_i(\mathbf{a}^T \mathbf{x}_i + b))$$

- ✱ Training error cost

$$S(\mathbf{a}, b) = \frac{1}{N} \sum_{i=1}^N \max(0, -y_i(\mathbf{a}^T \mathbf{x}_i + b))$$



Q4. What's the value of this function ?

$$\max(0, -y_i(\mathbf{a}^T \mathbf{x}_i + b)) \quad \text{if} \quad \text{sign}(\mathbf{a}^T \mathbf{x}_i + b) = y_i$$

- A. 0.
- B. others.

Q5. What's the value of this function ?

$$\max(0, -y_i(\mathbf{a}^T \mathbf{x}_i + b)) \quad \text{if } \text{sign}(\mathbf{a}^T \mathbf{x}_i + b) \neq y_i$$

A. 0.

B. A value greater than or equal to 0.

The problem with loss function 1

- ✱ Loss function 1 does not distinguish between the following decision boundaries if they both classify \mathbf{x}_i correctly.
 - ✱ One passes the two classes closely
 - ✱ One that passes with a wider margin
- ✱ But leaving a larger margin gives robustness for run-time data- **the large margin principle**

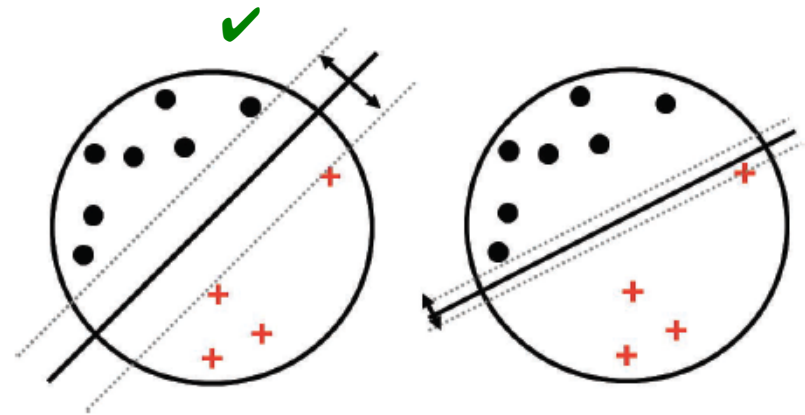



Figure 14.11 Illustration of the large margin principle. Left: a separating hyper-plane with large margin. Right: a separating hyper-plane with small margin.

Q6. Wondering what does “support vector” mean?

- A. Yes.
- B. No.

 Support vectors are those data points in the training data that uniquely define the decision boundary

Q7. SVM classification is faster than decision tree in terms of time complexity

- A. TRUE.
- B. FALSE.

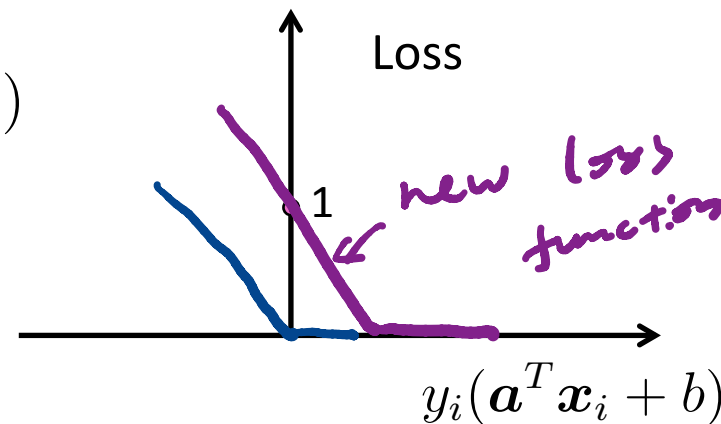
Loss function 2: the hinge loss

- ✱ We want to impose a small positive loss if \mathbf{x}_i is correctly classified but close to the boundary
- ✱ The **hinge loss** function meets the criteria above:

$$\max(0, 1 - y_i(\mathbf{a}^T \mathbf{x}_i + b))$$

- ✱ Training error cost

$$S(\mathbf{a}, b) = \frac{1}{N} \sum_{i=1}^N \max(0, 1 - y_i(\mathbf{a}^T \mathbf{x}_i + b))$$



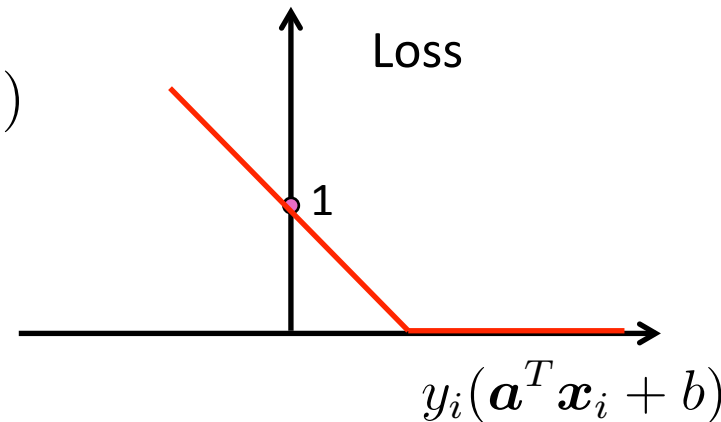
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- ✱ Training error cost

$$S(\mathbf{a}, b) = \frac{1}{N} \sum_{i=1}^N \max(0, 1 - y_i(\mathbf{a}^T \mathbf{x}_i + b))$$



The problem with loss function 2

- ✱ Loss function 2 favors decision boundaries that have large $\|\mathbf{a}\|$ because increasing $\|\mathbf{a}\|$ can zero out the loss for a correctly classified \mathbf{x}_i near the boundary.
- ✱ But large $\|\mathbf{a}\|$ makes the classification function $\text{sign}(\mathbf{a}^T \mathbf{x}_i + b)$ extremely sensitive to small changes in \mathbf{x}_i and make it less robust to run-time data.
- ✱ So small $\|\mathbf{a}\|$ is better.

Assignments

- ✱ Read Chapter 11 of the textbook
- ✱ Next time: SVM-regularization,
Stochastic descent

Additional References

- ✱ Robert V. Hogg, Elliot A. Tanis and Dale L. Zimmerman. “Probability and Statistical Inference”
- ✱ Morris H. Degroot and Mark J. Schervish
"Probability and Statistics"
- ✱ Kelvin Murphy, “Machine learning, A Probabilistic perspective”

See you next time

*See
You!*

