




Applied Machine Learning

Decision Trees

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Admin

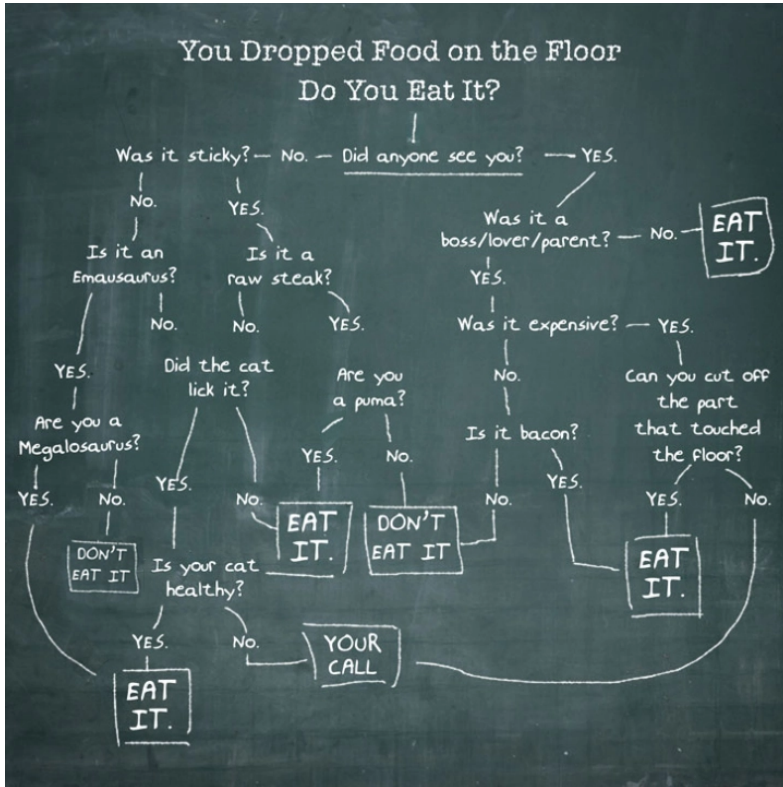
- Remember to do the two quizzes before the add/drop 
 - second one is testing different topics which are building block of next lectures
- Join a study group, and form your project groups (independent of each other) 
- Slack channel is up, feel free to discuss anything course related, and help others with the course materials, do not share your solutions or answers but hints, discussions, collaborations are welcome so that others could reach the correct solutions themselves
- Do not (re)share the course materials, lecture videos, zoom link, etc.
- The first mini-project will be released soon, go to TA lecture hours to be ready for it 
- Any questions?

Learning objectives

Decision trees:

- how does it model the data?
- how to specify the best model using a cost function
- how the cost function is optimized

Decision trees: motivation



pros.

- decision trees are interpretable
- they are not very sensitive to outliers
- do not need data normalization

cons.

- they could easily overfit and are unstable

Notation overview

	<tumorsize, texture, perimeter>	,	<cancer>	
$x^{(1)}$	<18.2,	27.6,	117.5>	, < No >
$x^{(2)}$	<17.9,	10.3,	122.8>	, < No >
$x^{(3)}$	<20.2,	14.3,	111.2>	, < Yes >
\vdots				
$x^{(N)}$	<15.5,	15.2,	135.5>	, < No >

Our datasets consists of N pairs of input vector and corresponding target or label

$$\mathcal{D} = \{(x^{(1)}, y^{(1)}), \dots, (x^{(N)}, y^{(N)})\}$$

we use N to denote the size of the dataset and n for indexing a pair of input, label

x, y denote an input and label pair where

$$x \text{ is a } D\text{-dimensional vector: } x = [x_1, x_2, \dots, x_D]$$

we use D to denote the number of *features* (dimensionality of the input space)

$y \in \{1, \dots, C\}$ for classification problems, we use C for number of classes

$x_d^{(n)}$ $n \in [1 \dots N]$ indexes an instance, row index, e.g. which patient
 $d \in [1 \dots D]$ indexes a feature, column index, e.g. which measurement

e.g. $x_2^{(3)}$

Decision trees: idea

- divide the input space into regions $\mathbb{R}_1, \dots, \mathbb{R}_K$ using a tree structure
- assign a prediction **label** to each region

for classification this is the class label

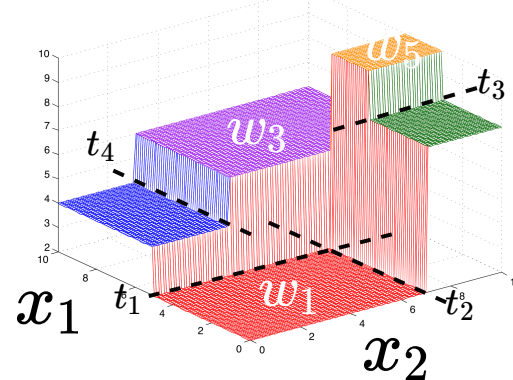
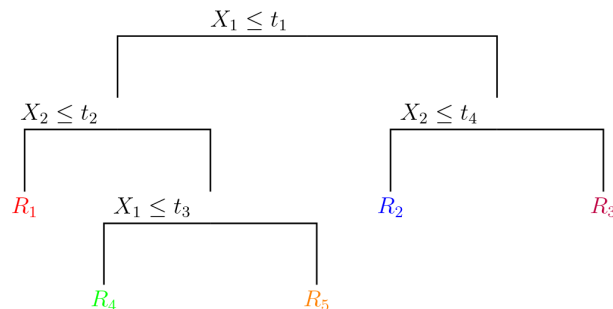
for regression, this is a real scalar or vector

$$f(x) = \sum_k w_k \mathbb{I}(x \in \mathbb{R}_k)$$

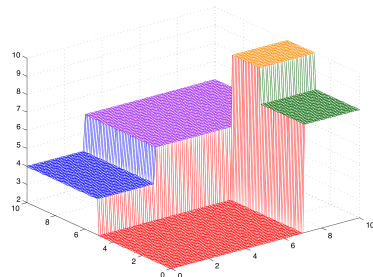
how to build the regions and the tree?

split regions successively based on the value of a single variable called test

each region is a set of conditions $\mathbb{R}_2 = \{x_1 \geq t_1, x_2 \leq t_4\}$



Prediction per region



What constant w_k should we use for prediction in each region \mathbb{R}_k ?

Classification

count the frequency of classes per region,
predict the most frequent label or return
probability $w_k = \text{mode}(y^{(n)} | x^{(n)} \in \mathbb{R}_k)$

Regression

use the mean value of training data-points in
that region $w_k = \text{mean}(y^{(n)} | x^{(n)} \in \mathbb{R}_k)$

example: predicting survival in titanic

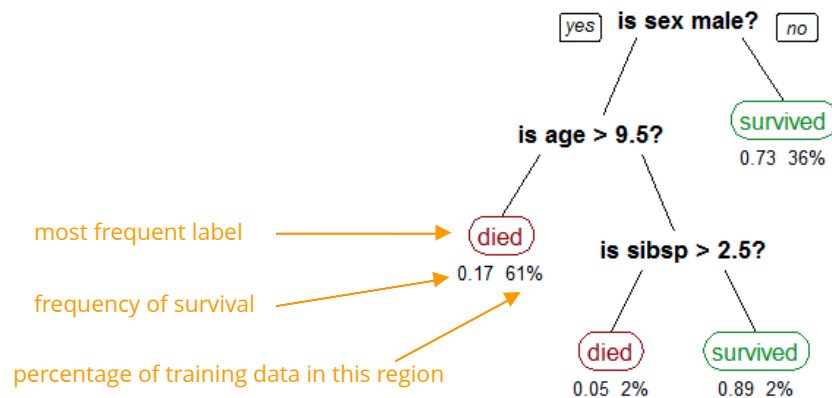
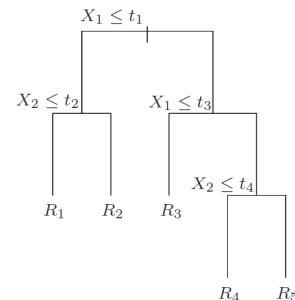


figure from [wiki](#)

Possible tests

next questions: what are all the possible tests? which test do we choose next?



Continuous features

all the values that appear in the dataset can be used to split



Categorical features

if a feature can take C values $x_i \in \{1, \dots, C\}$

convert that feature into C binary features (**one-hot coding**) $x_{i,1}, \dots, x_{i,C} \in \{0, 1\}$

split based on the value of a binary feature

alternatives:

- **multi-way** split: can lead to regions with few datapoints
- binary splits that produce balanced subsets

Food Name	Categorical #	Calories
Apple	1	95
Chicken	2	231
Broccoli	3	50

Apple	Chicken	Broccoli	Calories
1	0	0	95
0	1	0	231
0	0	1	50

one-hot example from [here](#)

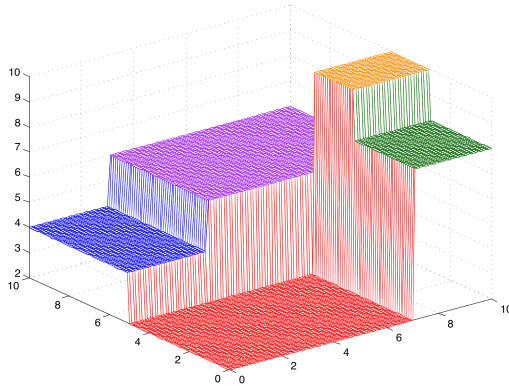
Cost function

Most ML algorithms minimize a cost function or maximize an objective function

find a **decision tree** minimizing the following cost function, this cost function specifies "what is a good decision or regression tree?"

regression cost

first calculate cost per region \mathbb{R}_k



we predict $w_k = \text{mean}(y^{(n)} | x^{(n)} \in \mathbb{R}_k)$ for region \mathbb{R}_k

mean squared error (MSE)

$$\text{cost}(\mathbb{R}_k, \mathcal{D}) = \frac{1}{N_k} \sum_{x^{(n)} \in \mathbb{R}_k} (y^{(n)} - w_k)^2$$

number of instances in region k truth prediction

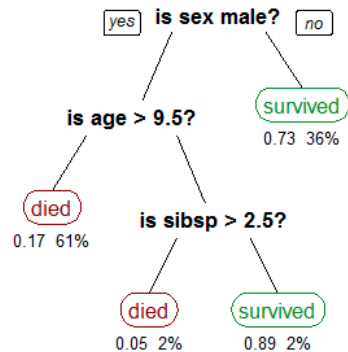
total cost is the normalized sum over all regions $\text{cost}(\mathcal{D}) = \sum_k \frac{N_k}{N} \text{cost}(\mathbb{R}_k, \mathcal{D})$

Cost function

find a **decision tree** minimizing the following cost function, this cost function specifies "what is a good decision or regression tree?"

classification cost

again, calculate the cost per region \mathbb{R}_k



for each region we predict the most frequent label $w_k = \text{mode}(y^{(n)} | x^{(n)} \in \mathbb{R}_k)$

misclassification rate

$$\text{cost}(\mathbb{R}_k, \mathcal{D}) = \frac{1}{N_k} \sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} \neq w_k)$$

number of instances in region k truth prediction

total cost is the normalized sum $\text{cost}(\mathcal{D}) = \sum_k \frac{N_k}{N} \text{cost}(\mathbb{R}_k, \mathcal{D})$

Cost function

find a **decision tree** minimizing the following cost function, this cost function specifies "what is a good decision or regression tree?"

total cost is the normalized sum $\text{cost}(\mathcal{D}) = \sum_k \frac{N_k}{N} \text{cost}(\mathbb{R}_k, \mathcal{D})$

problem

it is sometimes possible to build a tree with **zero cost**:

build a large tree with each instance having its own region (*overfitting!*)

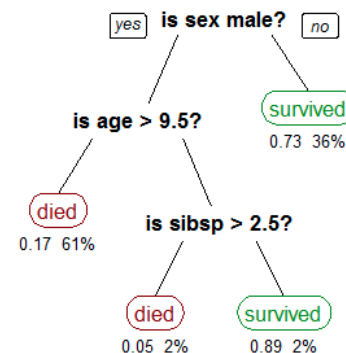
example

use features such as height, eye color etc, to make perfect prediction on training data

solution

find a decision tree with at most **K tests** minimizing the cost function

K tests = K internal node in our binary tree = K+1 leaves (regions)



Search space

K+1 regions

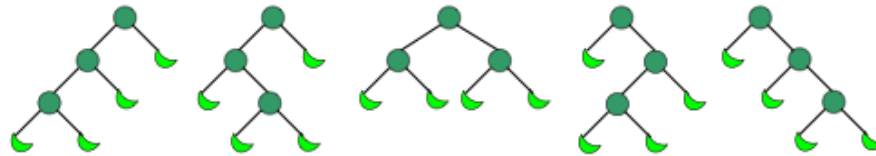
objective: find a decision tree with **K tests** minimizing the cost function

the number of full binary trees with K+1 leaves (regions \mathbb{R}_k) is the **Catalan number**

$$\frac{1}{K+1} \binom{2K}{K}$$

exponential in K

1, 1, 2, **5**, 14, 42, 132, 429, 1430, 4862, 16796, 58786, 208012, 742900, 2674440, 9694845, 35357670, 129644790, 477638700, 1767263190, 6564120420, 24466267020, 91482563640, 343059613650, 1289904147324, 4861946401452



we also have a choice of feature x_d for each of K internal node D^K

moreover, for each feature different choices of splitting

bottom line: finding optimal decision tree is an **NP-hard** combinatorial optimization problem

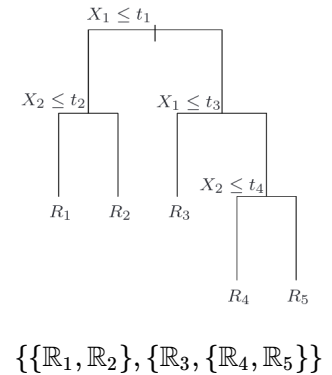
Greedy heuristic

finding the **optimal** tree is too difficult, instead use a greedy heuristic to find a **good** tree
recursively split the regions based on a **greedy choice of the next test**
end the recursion if not **worth-splitting**

```
function fit-tree( $\mathbb{R}_{\text{node}}$ ,  $\mathcal{D}$ , depth)

   $\mathbb{R}_{\text{left}}, \mathbb{R}_{\text{right}}$  = greedy-test ( $\mathbb{R}_{\text{node}}$ ,  $\mathcal{D}$  )
  if not worth-splitting(depth,  $\mathbb{R}_{\text{left}}, \mathbb{R}_{\text{right}}$  )
    return  $\mathbb{R}_{\text{node}}$ 
  else
    left-set = fit-tree( $\mathbb{R}_{\text{left}}$ ,  $\mathcal{D}$ , depth+1)
    right-set = fit-tree( $\mathbb{R}_{\text{right}}$ ,  $\mathcal{D}$ , depth+1)
    return {left-set, right-set}
```

final decision tree in the form of nested list of regions



Choosing tests

the split is **greedy** because it looks one step ahead
this may not lead to the lowest overall cost

```
function greedy-test (  $\mathbb{R}_{\text{node}}, \mathcal{D}$  )  
    best-cost = inf  
    for each feature  $d \in \{1, \dots, D\}$  and each possible test  
        split  $\mathbb{R}_{\text{node}}$  into  $\mathbb{R}_{\text{left}}, \mathbb{R}_{\text{right}}$  based on the test  
        split-cost =  $\frac{N_{\text{left}}}{N_{\text{node}}} \text{cost}(\mathbb{R}_{\text{left}}, \mathcal{D}) + \frac{N_{\text{right}}}{N_{\text{node}}} \text{cost}(\mathbb{R}_{\text{right}}, \mathcal{D})$   
        if split-cost < best-cost:  
            best-cost = split-cost  
             $\mathbb{R}_{\text{left}}^* = \mathbb{R}_{\text{left}}$   
             $\mathbb{R}_{\text{right}}^* = \mathbb{R}_{\text{right}}$   
  
    return  $\mathbb{R}_{\text{left}}^*, \mathbb{R}_{\text{right}}^*$ 
```

Stopping the recursion

worth-splitting subroutine

if we stop when \mathbb{R}_{node} has zero cost, we may overfit

heuristics for stopping the splitting:

- reached a desired depth
- number of examples in \mathbb{R}_{left} or $\mathbb{R}_{\text{right}}$ is too small
- w_k is a good approximation, the cost is small enough
- reduction in cost by splitting is small

$$\text{cost}(\mathbb{R}_{\text{node}}, \mathcal{D}) = \left(\frac{N_{\text{left}}}{N_{\text{node}}} \text{cost}(\mathbb{R}_{\text{left}}, \mathcal{D}) + \frac{N_{\text{right}}}{N_{\text{node}}} \text{cost}(\mathbb{R}_{\text{right}}, \mathcal{D}) \right)$$

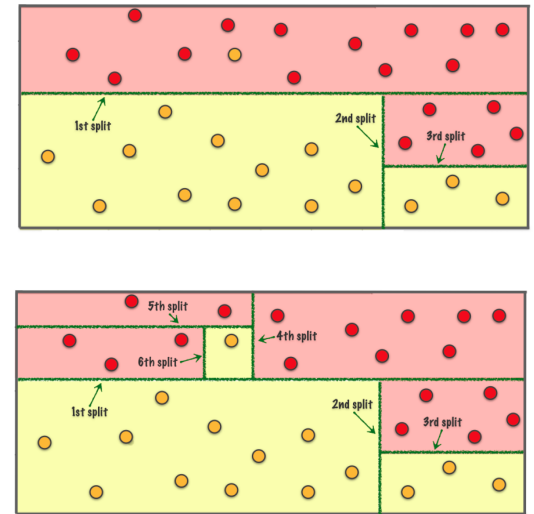


image credit: <https://alanjeffares.wordpress.com/tutorials/decision-tree/>

revisiting the classification cost

ideally we want to optimize the misclassification rate

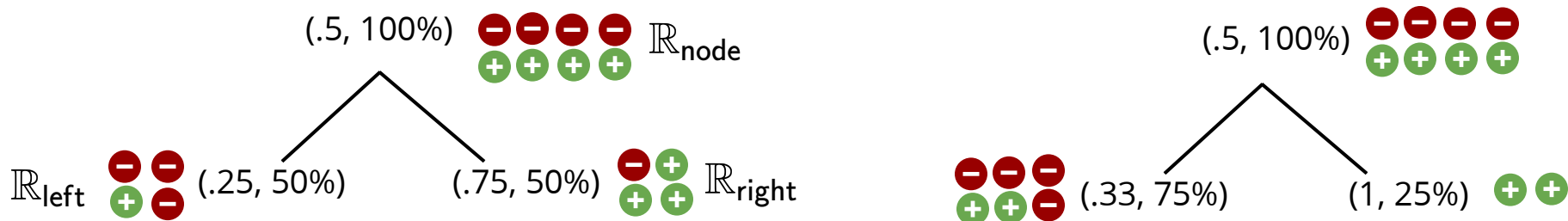
$$\text{cost}(\mathbb{R}_k, \mathcal{D}) = \frac{1}{N_k} \sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} \neq w_k)$$

this may not be the optimal cost for *each step of greedy heuristic*

example

both splits have the same misclassification rate (2/8)

$$\text{cost}(\mathcal{D}) = \frac{1}{N} \sum_k \sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} \neq w_k)$$



however the second split *may be* preferable because one region does not need further splitting

idea: use a measure for homogeneity of labels in regions

Entropy: a measure of the *unpredictability*

The most basic concept in the field of **Information Theory**

entropy is the **expected amount of information** in observing a random variable y

note that it is common to use capital letters for random variables (here for consistency we use lower-case)

$$H(y) = - \sum_{c=1}^C p(y=c) \log p(y=c) \quad \text{averaged on all its possible outcomes}$$

$-\log p(y=c)$ is the amount of **information** in observing value c

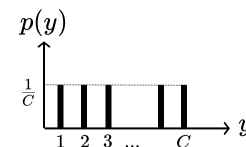
$$I(y=c) = \log\left(\frac{1}{p(y=c)}\right) = -\log(p(y=c))$$

zero information if $p(c)=1$

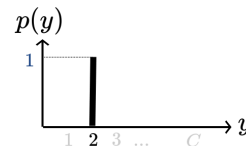
less probable events are more informative $p(c) < p(c') \Rightarrow -\log p(c) > -\log p(c')$

information from two independent events is additive $-\log(p(c)q(d)) = -\log p(c) - \log q(d)$

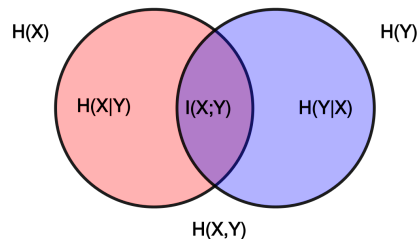
a uniform distribution has the highest entropy $H(y) = - \sum_{c=1}^C \frac{1}{C} \log \frac{1}{C} = \log C$



a deterministic random variable has the lowest entropy $H(y) = -1 \log(1) = 0$



Mutual information



for two random variables t, y , their **mutual information** is

the amount of information t conveys about y

change in the entropy of y after observing the value of t

how much knowing t reduces uncertainty about y

$$I(t, y) = H(y) - H(y|t)$$

conditional entropy $\sum_{l=1}^L p(t=l)H(y|t=l)$ uncertainty we have in y after seeing t

$$= \sum_l \sum_c p(y=c, t=l) \log \frac{p(y=c, t=l)}{p(y=c)p(t=l)} \quad \text{this is symmetric wrt } y \text{ and } t$$

$$= H(t) - H(t|y) = I(y, t)$$

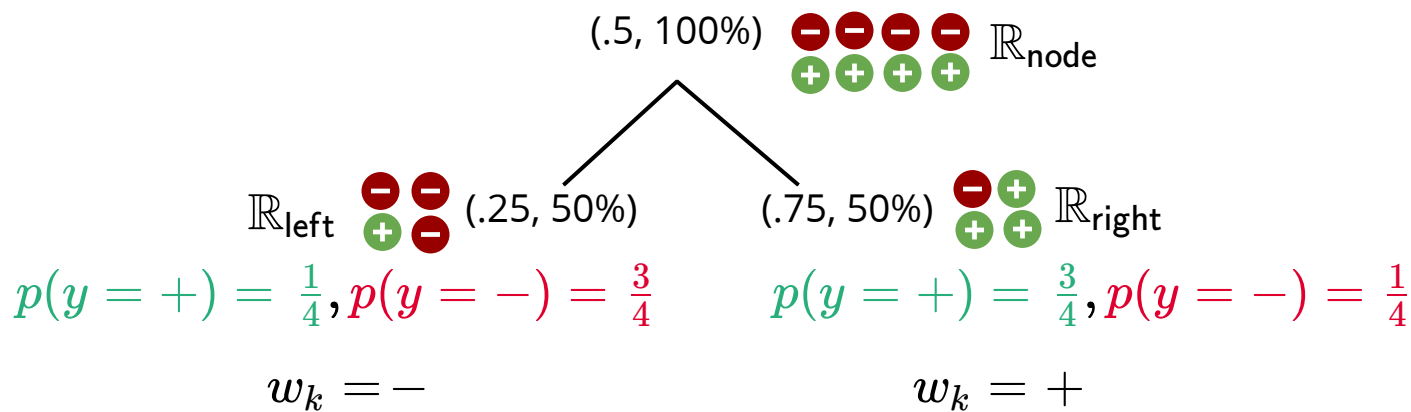
mutual information is always positive and zero only if y and t are independent

Classification cost: **example**

we care about the empirical distribution of labels in each region $p_k(y = c) = \frac{\sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} = c)}{N_k}$

misclassification cost $\text{cost}(\mathbb{R}_k, \mathcal{D}) = \frac{1}{N_k} \sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} \neq w_k) = 1 - p_k(w_k)$

the most probable class $w_k = \arg \max_c p_k(c)$



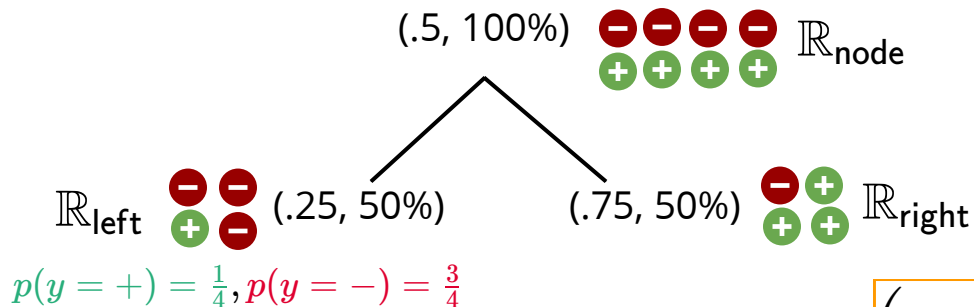
misclassification cost = $\frac{4}{8} \cdot \frac{1}{4} + \frac{4}{8} \cdot \frac{1}{4} = \frac{1}{4}$

Entropy for classification cost: **example**

we care about the empirical distribution of labels in each region $p_k(y = c) = \frac{\sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} = c)}{N_k}$

misclassification cost $\text{cost}(\mathbb{R}_k, \mathcal{D}) = \frac{1}{N_k} \sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} \neq w_k) = 1 - p_k(w_k)$
 the most probable class $w_k = \arg \max_c p_k(c)$

entropy cost $\text{cost}(\mathbb{R}_k, \mathcal{D}) = H(y) = - \sum_{c=1}^C p(y = c) \log p(y = c)$ choose the split with the lowest entropy



misclassification cost

$$\frac{4}{8} \cdot \frac{1}{4} + \frac{4}{8} \cdot \frac{1}{4} = \frac{1}{4}$$

entropy cost

$$\frac{4}{8} \left(-\frac{1}{4} \log\left(\frac{1}{4}\right) - \frac{3}{4} \log\left(\frac{3}{4}\right) \right) + \frac{4}{8} \left(-\frac{1}{4} \log\left(\frac{1}{4}\right) - \frac{3}{4} \log\left(\frac{3}{4}\right) \right)$$

$$\text{cost}(\mathcal{D}) = \sum_k \frac{N_k}{N} \text{cost}(\mathbb{R}_k, \mathcal{D})$$

Entropy for classification cost: **example**



misclassification cost


$$\frac{4}{8} \cdot \frac{1}{4} + \frac{4}{8} \cdot \frac{1}{4} = \frac{1}{4}$$

the same costs

$$\frac{6}{8} \cdot \frac{1}{3} + \frac{2}{8} \cdot \frac{0}{2} = \frac{1}{4}$$

entropy cost (using base 2 logarithm)

$$\frac{4}{8} \left(-\frac{1}{4} \log\left(\frac{1}{4}\right) - \frac{3}{4} \log\left(\frac{3}{4}\right) \right) + \frac{4}{8} \left(-\frac{1}{4} \log\left(\frac{1}{4}\right) - \frac{3}{4} \log\left(\frac{3}{4}\right) \right) \approx .81$$



$$\frac{6}{8} \left(-\frac{1}{3} \log\left(\frac{1}{3}\right) - \frac{2}{3} \log\left(\frac{2}{3}\right) \right) + \frac{2}{8} \cdot 0 \approx .68$$

lower cost split

Entropy for classification cost

we care about the empirical distribution of labels in each region $p_k(y = c) = \frac{\sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} = c)}{N_k}$

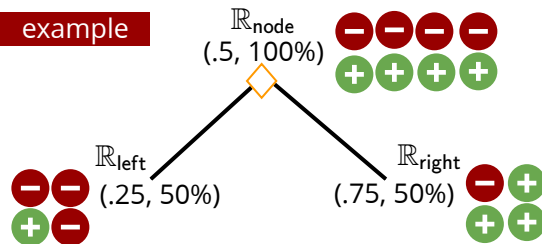
entropy cost $\text{cost}(\mathbb{R}_k, \mathcal{D}) = H(y)$ choose the split with the lowest entropy

change in the cost becomes the **mutual information** between the test and labels

$$\begin{aligned} \text{cost}(\mathbb{R}_{\text{node}}, \mathcal{D}) &= \left(\frac{N_{\text{left}}}{N_{\text{node}}} \text{cost}(\mathbb{R}_{\text{left}}, \mathcal{D}) + \frac{N_{\text{right}}}{N_{\text{node}}} \text{cost}(\mathbb{R}_{\text{right}}, \mathcal{D}) \right) & I(t, y) &= H(y) - H(y|t) \\ &= H(y) - \left(\underbrace{p(x_d \geq t)H(y|x_d \geq t)} + \underbrace{p(x_d < t)H(y|x_d < t)} \right) = I(y, x > t) & & \sum_{l=1}^L p(t = l)H(y|t = l) \end{aligned}$$

this means by using entropy as our cost, we are choosing the test which is **maximally informative** about labels

example



$$\begin{aligned} I(y, \diamond) &= H(y) - \left(p(\diamond)H(y|\diamond) + p(!\diamond)H(y|!\diamond) \right) \\ &= 1 - 0.81 \end{aligned}$$

Gini index

another cost for selecting the *test* in classification

misclassification (error) rate

$$\text{cost}(\mathbb{R}_k, \mathcal{D}) = \frac{1}{N_k} \sum_{x^{(n)} \in \mathbb{R}_k} \mathbb{I}(y^{(n)} \neq w_k) = 1 - p(w_k)$$

entropy

$$\text{cost}(\mathbb{R}_k, \mathcal{D}) = H(y)$$

Gini index

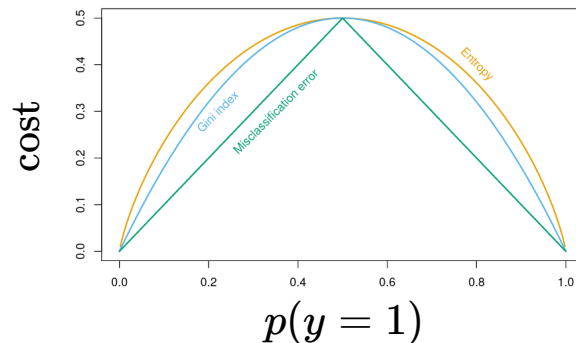
it is the expected error rate

$$\text{cost}(\mathbb{R}_k, \mathcal{D}) = \sum_{c=1}^C p(c)(1 - p(c))$$

probability of class c probability of error

$$= \sum_{c=1}^C p(c) - \sum_{c=1}^C p(c)^2 = 1 - \sum_{c=1}^C p(c)^2$$

comparison of costs of a node when we have 2 classes



C=2

$$1 - \max(p, 1 - p)$$

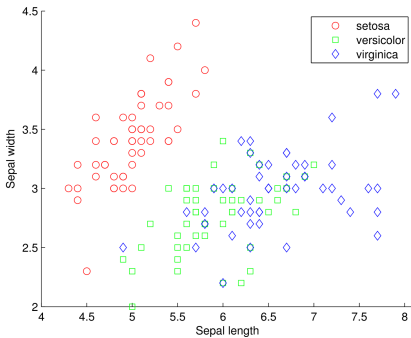
$$-p \log p - (1 - p) \log(1 - p)$$

$$2p(1 - p)$$

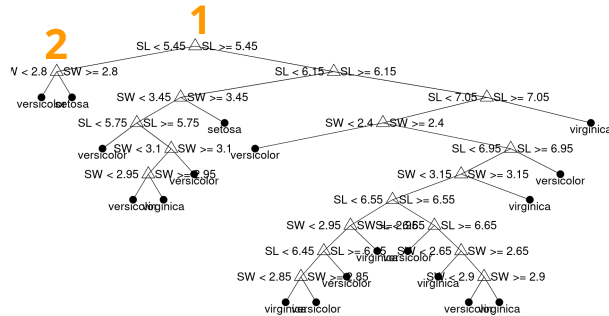
entropy & gini very similar and both favour pure nodes

Decision tree example decision tree for Iris dataset

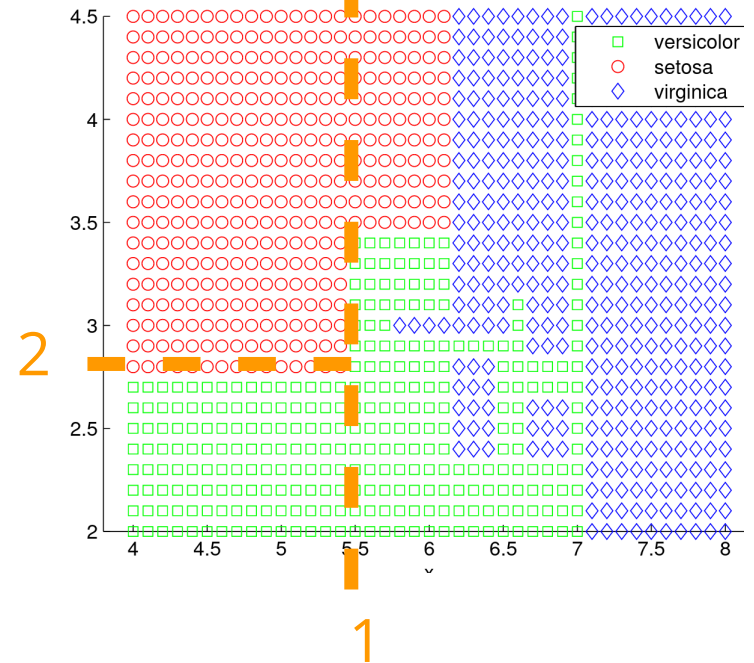
dataset (D=2)



decision tree



decision boundaries



decision boundaries suggest overfitting

confirmed using a validation set

training accuracy ~ 85%

validation accuracy ~ 70%

Decision tree: **overfitting**

a decision tree can fit any **Boolean function** (binary classification with binary features)

example: of decision tree representation of a boolean function (D=3)

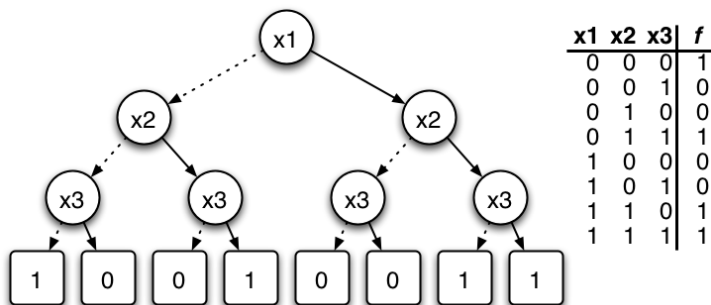


image from: https://www.wikiwand.com/en/Binary_decision_diagram

there are 2^{2^D} such functions, why?

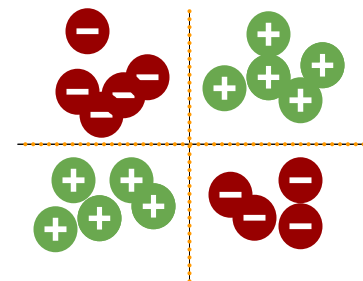
decision tree can perfectly fit our training data

How to solve the problem of overfitting in large decision trees?

idea 1. grow a small tree



problem: substantial reduction in cost may happen after a few steps
by stopping early we cannot know this



example

cost drops after the second node 13 . 2

Decision tree: overfitting & pruning

idea 2.

grow a large tree and then prune it
 greedily turn an internal node into a leaf node
 choice is based on the lowest increase in the cost
 repeat this until left with the root node
 pick the best among the above models using a validation set

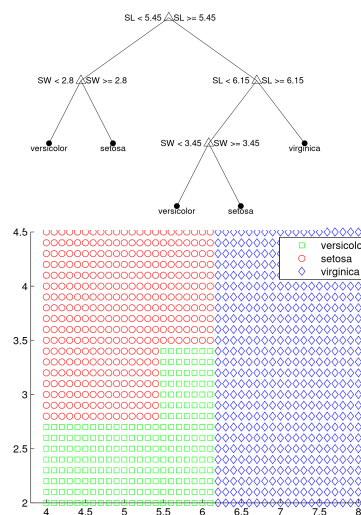
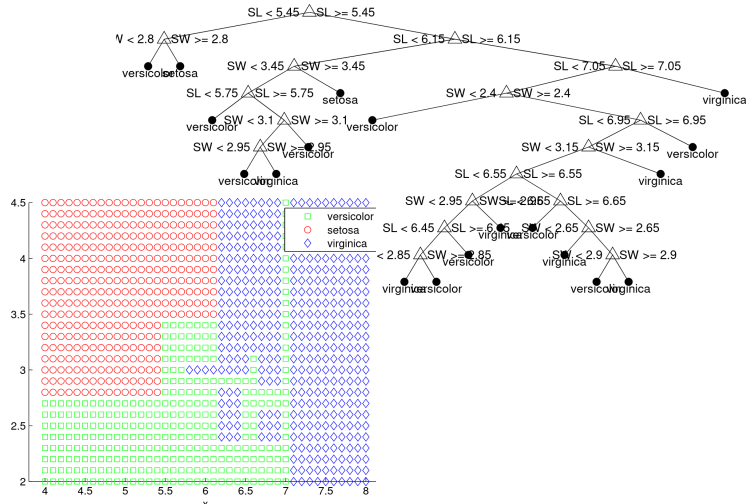
idea 3.

random forests (later!)

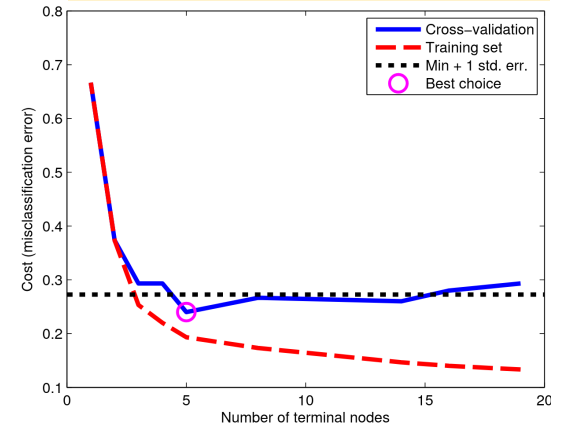
example

before pruning

after pruning



cross-validation is used to pick the best size



Summary

- model: divide the input into axis-aligned regions
- cost: for regression and classification
- optimization:
 - NP-hard
 - use greedy heuristic
- adjust the cost for the heuristic
 - using entropy (relation to mutual information maximization)
 - using Gini index
- there are variations on decision tree heuristics
 - what we discussed in called *Classification and Regression Trees (CART)*
- Compared to KNN, robust to scaling and noise, fast predictions, more interpretable