# Splitting Datasets One Feature at a Time: Decision Trees

Harvey Alférez, Ph.D.

#### Introduction

branch

Spam; don't read

read immediately

Sending email address is The decision myEmployer.com decision block tree is one of the False True most commonly **Email body** Email to read contains the used when bored word hockey classification False True techniques. **Email from friends;** 

terminal block.

### Introduction (Cont.)

- The kNN algorithm does a great job of classifying, but it didn't lead to any major insights about the data.
- One of the best things about decision trees is that humans can easily understand the data!

### Introduction (Cont.)

- The decision tree does a great job of distilling data into knowledge.
  - With this, you can take a set of unfamiliar data and extract a set of rules.
    - The machine learning will take place as the machine creates these rules from the dataset.
  - The results obtained by using decision trees are often comparable to those from a **human expert** with decades of experience in a given field!

#### Tree Construction

#### CreateBranch() - Recursive

```
Check if every item in the dataset is in the same class:

If so return the class label

Else

find the best feature to split the data

split the dataset

create a branch node

for each split

call createBranch and add the result to the branch node

return branch node
```

#### General approach to decision trees

- 1. Collect: Any method.
- 2. Prepare: This tree-building algorithm works only on nominal values, so any continuous values will need to be quantized.
- 3. Analyze: Any method. You should visually inspect the tree after it is built.
- 4. Train: Construct a tree data structure.
- 5. Test: Calculate the error rate with the learned tree.
- 6. Use: This can be used in any supervised learning task. Often, trees are used to better understand the data.

We're also going to split on one and only one feature at a time. If our training set has 20 features, how do we choose which one to use first?

	Can survive without coming to surface?	Has flippers?	Fish?
1	Yes	Yes	Yes
2	Yes	Yes	Yes
3	Yes	No	No
4	No	Yes	No
5	No	Yes	No

2 Features

2 Classes

- For our classifier algorithm to work, you need to:
  - Measure the entropy (expected value of information)
  - Split the dataset
  - Measure the entropy on the split sets
  - See if splitting was the right thing to do
- You'll do this for all of the features to determine the best feature to split on.

- 1. Measure the Entropy
  - We choose to split our dataset in a way that makes our unorganized data more organized.
    - One way to organize this messiness is to measure the information.
      - Using information theory, you can measure the information before and after the split.

- 1. Measure the Entropy (Cont.)
  - The change in information before and after the split is known as the information gain.
    - When you know how to calculate the information gain, you can split your data across every feature to see which split gives you the highest information gain.
      - The split with the highest information gain is your best option.

- 1. Measure the Entropy (Cont.)
  - In trees.py:

#### 1. Measure the Entropy (Cont.)

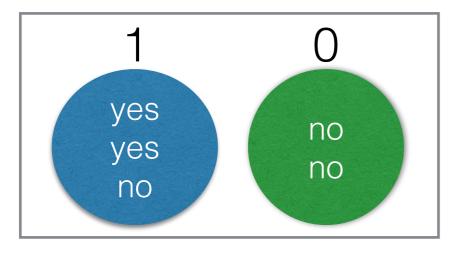
```
>>> import trees
>>> myDat,labels=trees.createDataSet()
>>> myDat
[[1, 1, 'yes'], [1, 1, 'yes'], [1, 0, 'no'], [0, 1, 'no'], [0,
1, 'no']]
>>> trees.calcShannonEnt(myDat)
0.97095059445466858
```

- 1. Measure the Entropy (Cont.)
  - The higher the entropy, the more mixed up the data is:

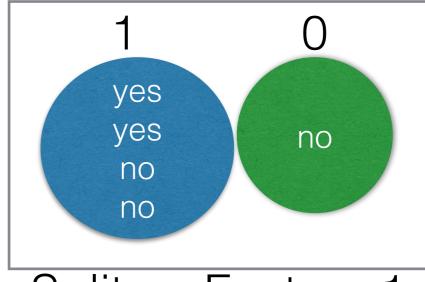
```
>>> myDat[0][-1]
>>> myDat[0][-1]='maybe'
>>> myDat
[[1, 1, 'maybe'], [1, 1, 'yes'], [1, 0, 'no'], [0, 1, 'no'], [0, 1, 'no']]
>>> trees.calcShannonEnt(myDat)
1.3709505944546687
```

 2. Split the Dataset (Shannon Entropy is calculated in the whole dataset before and after splitting)

```
>>> reload(trees)
<module 'trees' from 'trees.py'>
>>> myDat,labels=trees.createDataSet()
>>> trees.chooseBestFeatureToSplit(myDat)
0
>>> myDat
[[1, 1, 'yes'], [1, 1, 'yes'], [1, 0, 'no'], [0, 1, 'no'], [0, 1, 'no']]
```



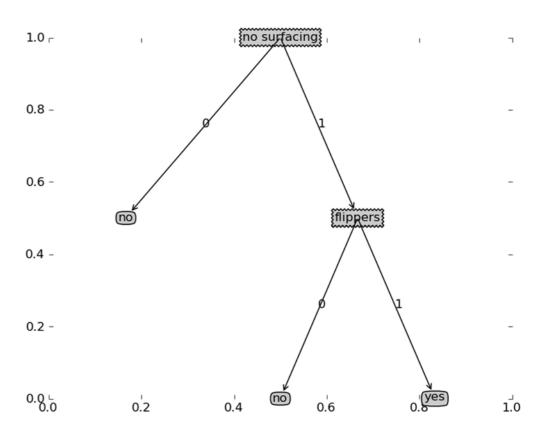
Split on Feature 0



Split on Feature 1

#### 3. Recursively Building the Tree

```
>>> reload(trees)
<module 'trees' from 'trees.pyc'>
>>> myDat,labels=trees.createDataSet()
>>> myTree = trees.createTree(myDat,labels)
>>> myTree
{'no surfacing': {0: 'no', 1: {'flippers': {0: 'no', 1: 'yes'}}}}
```



# Test: Using the Tree for Classification

```
>>> myDat, labels=trees.createDataSet()
>>> labels
['no surfacing', 'flippers']
>>> myTree=treePlotter.retrieveTree (0)
>>> myTree
{'no surfacing': {0: 'no', 1: {'flippers': {0: 'no', 1: 'yes'}}}}
>>> trees.classify(myTree,labels,[1,0])
         'no'
                                                               no surfacing
                                               1.0 _
>>> trees.classify(myTree,labels,[1,1])
         'yes'
                                               0.8 -
 import treePlotter
 treePlotter.createPlot(myTree)
                                               0.6 -
                                               0.4 -
                                               0.2 -
                                               0.0 _
```

# Using Decision Trees to Predict Contact Lens Type

- The Lenses dataset3 is one of the most famous datasets.
- It's a number of observations based on patients' eye conditions and the type of contact lenses the doctor prescribed.
- The classes are hard, soft, and no contact lenses.

# Using Decision Trees to Predict Contact Lens Type (Cont.)

 You can load the data by typing the following into your Python shell:

# Using Decision Trees to Predict Contact Lens Type (Cont.)

