Decision Trees and Random Forests

Outline

- Decision Stump
- Decision Trees
- Random Forest

Decision Stump

- **Idea** to determine the feature and the split threshold that maximizes a certain score
  - Classification score

```
# Compute classification score
score = np.sum(y_pred == y)
```

  - Information gain

```
# Compute information gain
entropyTotal = entropy(y)
p_sat = sat_set.shape[0] / float(N)
p_not = 1. - p_sat
H_sat = entropy(sat_set)
H_not = entropy(not_set)
score = (entropyTotal - p_sat * H_sat -
         p_not * H_not)
```

Decision Stump

- Consider this dataset of 6 samples and 2 features and with target values $\in \{1, 2\}$

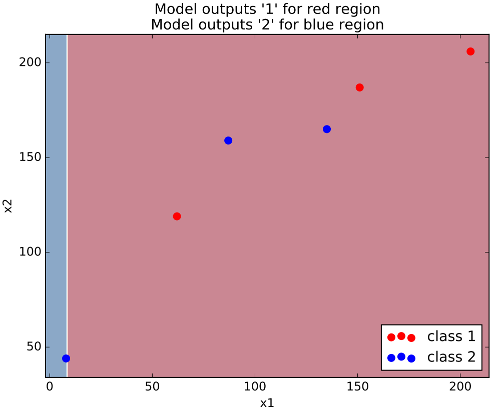
x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

- Demonstrate classification scores for several splits

Decision Stump

- Split s.t. $y = 1$ if $x1 > 8$ and $y = 2$ otherwise

x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

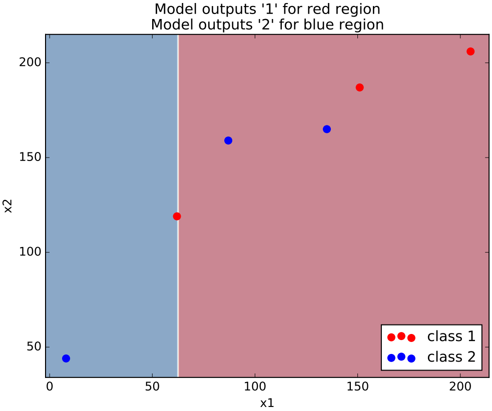


- Classification Score = 4

Decision Stump

- Split s.t. $y = 1$ if $x1 > 62$ and $y = 2$ otherwise

x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

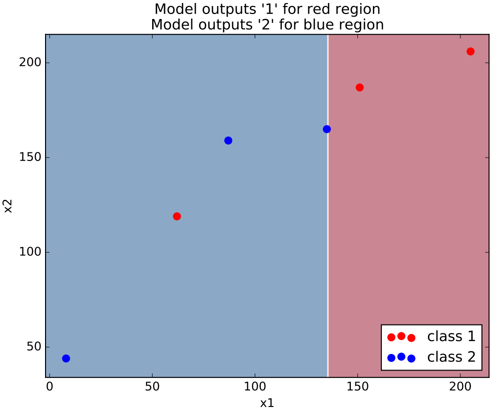


- Classification Score = 3

Decision Stump

- Split s.t. $y = 1$ if $x1 > 135$ and $y = 2$ otherwise

x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

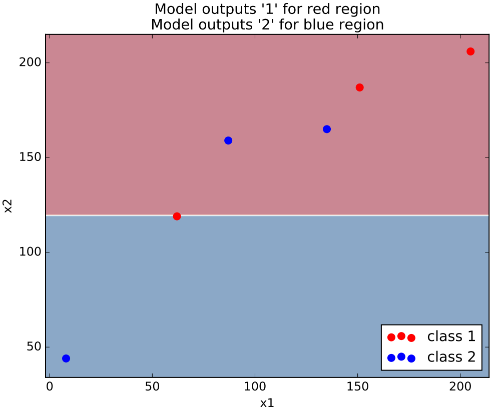


- Classification Score = 5

Decision Stump

- Split s.t. $y = 1$ if $x2 > 119$ and $y = 2$ otherwise

x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

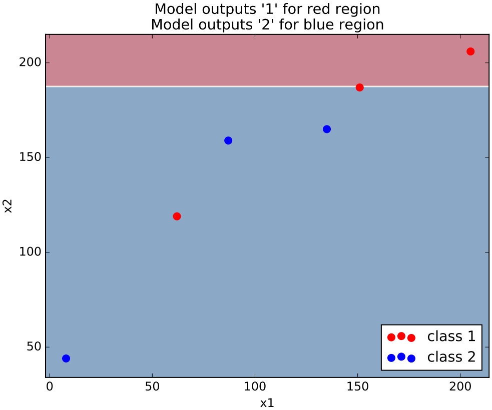


- Classification Score = 3

Decision Stump

- Split s.t. $y = 1$ if $x2 > 187$ and $y = 2$ otherwise

x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

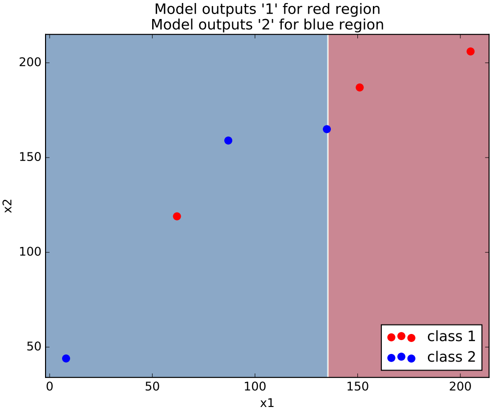


- Classification Score $= 4$

Decision Stump - best split

- Split s.t. $y = 1$ if $x1 > 135$ and $y = 2$ otherwise

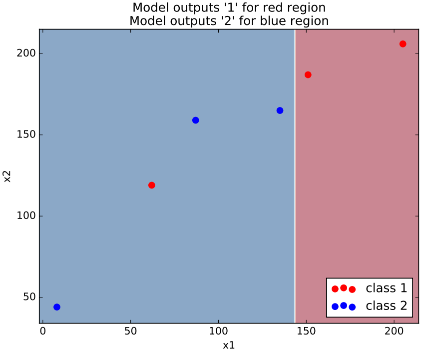
x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

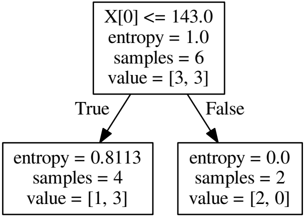


- Classification Score = 5

Decision Tree

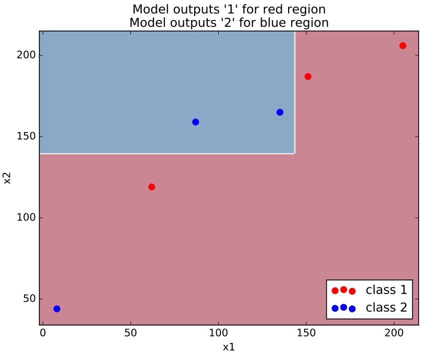
- A decision stump is a decision tree with depth 1

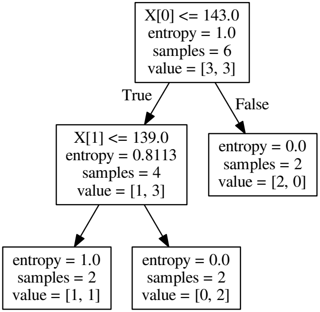




Decision Tree

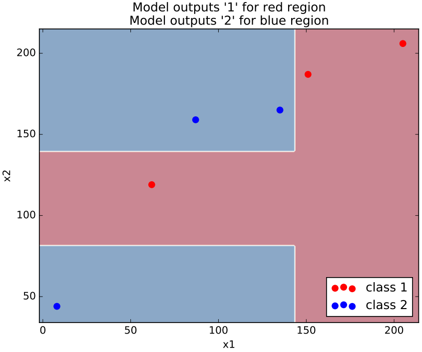
- A decision tree with depth 2

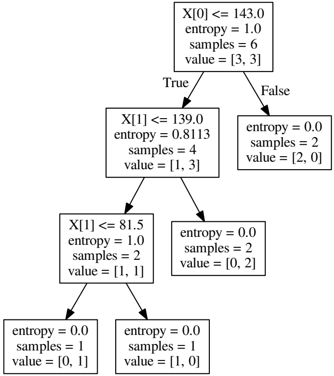




Decision Tree

- A decision stump is a decisiont tree with depth 1





Random Forest - Ensemble learning

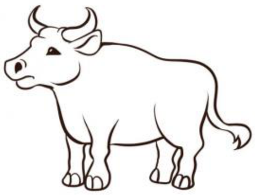
1. Train more than one decision tree on different subsets of the dataset
2. Given a test sample, aggregate the decision tree predictions:
    - then take their mean, max, median, etc.

x1	x2	y
8	44	2
62	119	1
87	159	2
135	165	2
151	187	1
205	206	1

- For example,
    - train first decision tree on samples 1 and 2
    - train second decision tree on samples 2, 3, and 4
    - train third decision tree on samples 4,5, and 6

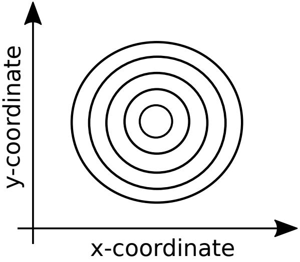
Ensemble learning - example 1

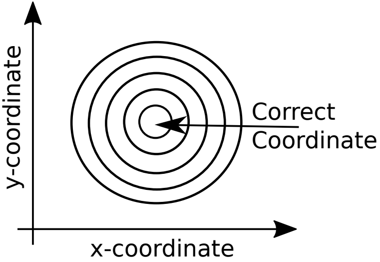
- On a farmer's fair, 800 people volunteered to estimate the **weight** of an ox
- Galton reported 1,197 lb which is the average of the crowd's answers
  - The true value was 1,198 lbs
- Some people would overshoot or undershoot the ox's weight estimate
  - The mean helps in averaging out the errors due to overestimates and underestimates
- If measurement errors are uncorrelated
  - wrong perceptions get averaged out



Ensemble learning - example 2

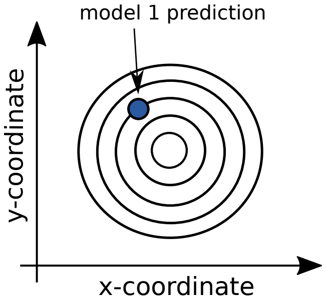
- Predict coordinate of a GPS device

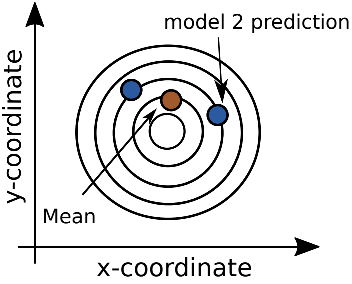




Ensemble learning - example 2

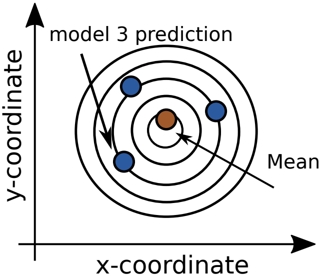
- Predict coordinate of a GPS device using the average of 2 model predictions

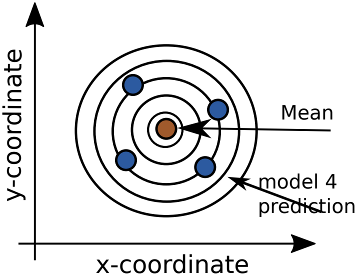




Ensemble learning - example 2

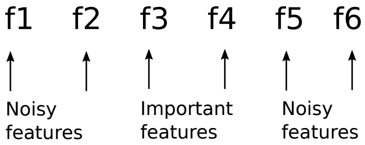
- Predict coordinate of a GPS device using the average of 4 model predictions





Ensemble learning - Intuition

- Say we are trying to predict the health of a patient



- Important Features (just an example):
  - **f3** is blood pressure
  - **f4** is sugar level
- Noisy Features (just an example):
  - **f1** is the height of your backyard tree
  - **f2** is the number of appliances you have

Ensemble learning - Health prediction

- The models highlight which features are thought to be **important** for predicting health

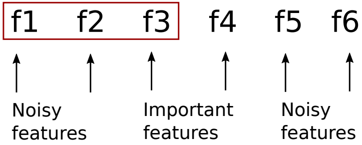


Figure 2: First model (Red)

- Important Features (just an example):
  - **f3** is blood pressure
  - **f4** is sugar level
- Noisy Features (just an example):
  - **f1** is the height of your backyard tree
  - **f2** is the number of appliances you have

Ensemble learning - Health prediction

- The models highlight which features are thought to be **important** for predicting health

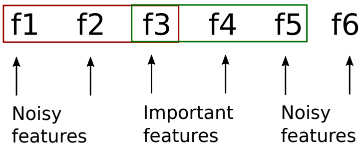


Figure 3: First model (Red) - Second model (Green)

- Important Features (just an example):
  - **f3** is blood pressure
  - **f4** is sugar level
- Noisy Features (just an example):
  - **f1** is the height of your backyard tree
  - **f2** is the number of appliances you have

Ensemble learning - Health prediction

- The models highlight which features are thought to be **important** for predicting health

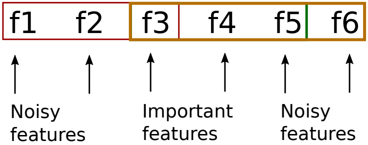


Figure 4: First model (Red) - Second model (Green) - Third model (Yellow)

- Important Features (just an example):
  - **f3** is blood pressure
  - **f4** is sugar level
- Noisy Features (just an example):
  - **f1** is the height of your backyard tree
  - **f2** is the number of appliances you have

Ensemble learning - Health prediction

- The models highlight which features are thought to be **important** for predicting health

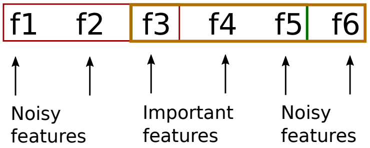


Figure 5: First model (Red) - Second model (Green) - Third model (Yellow)

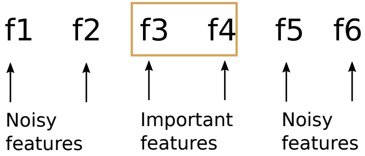
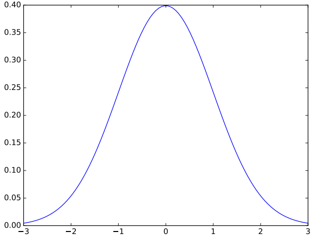


Figure 6: Models' intersection on what features are important

Ensemble learning - why does it work ?

- Central limit theorem - as the number of guesses goes to infinity, you approach a normal distribution
  - The more samples and guesses you get the more likely their mean is the true value



- The probability that a trained model predicts a value that is two standard deviations away from the true value might be low
- But your models are as good as your data
  - Still, it is the most popular technique to boost prediction scores in data science competitions

Random Forests

- Train a decision tree on different subsets of the dataset
- Consider the following trained decision trees

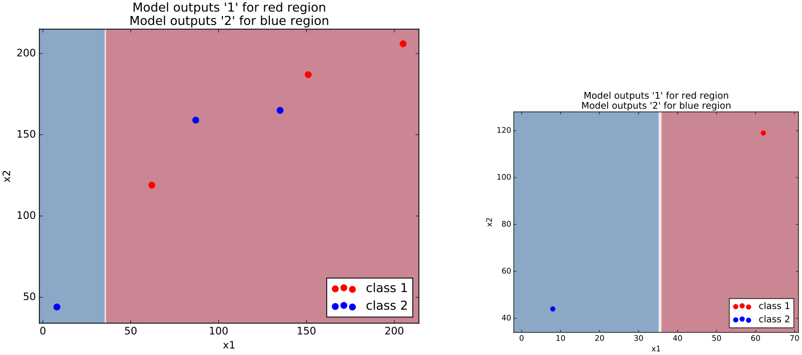


Figure 7: Decision Tree 1 - samples $\{1, 2\}$

Random Forests

- Train a decision tree on different subsets of the dataset
- Consider the following trained decision trees

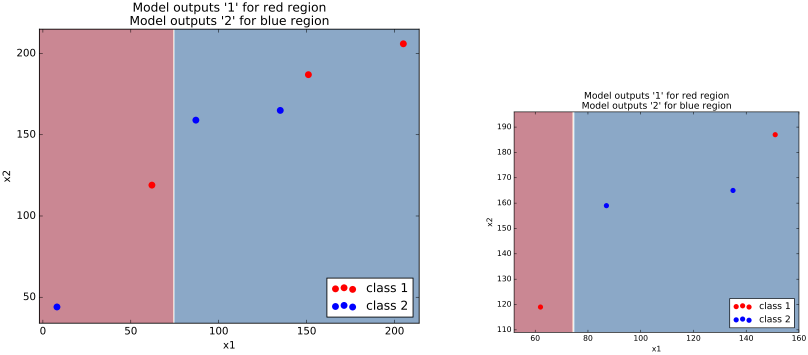


Figure 8: Decision Tree 2 - samples $\{2, 3, 4, 5\}$

Random Forests

- Train a decision tree on different subsets of the dataset
- Consider the following trained decision trees

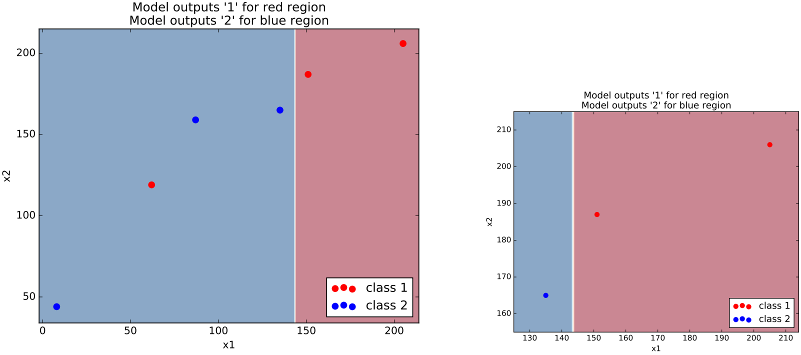
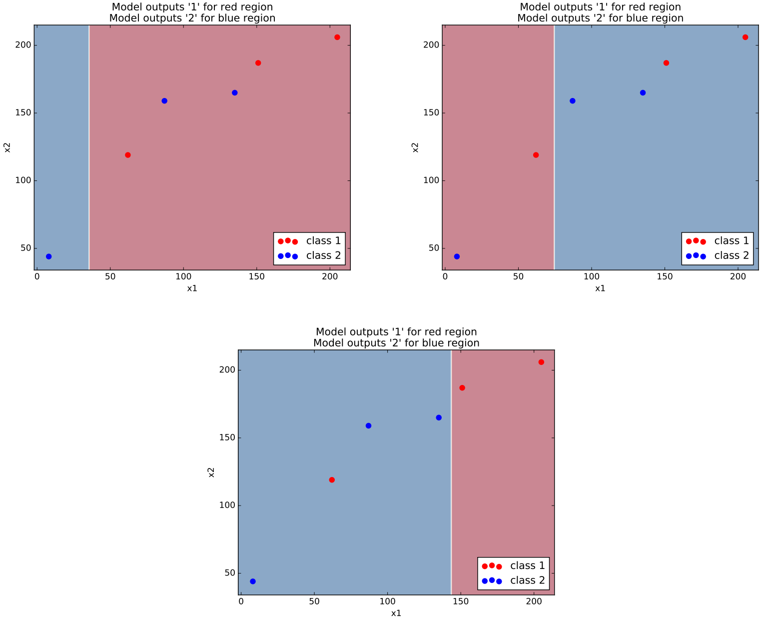
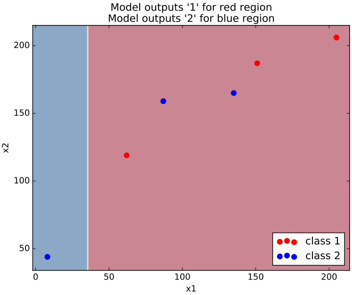


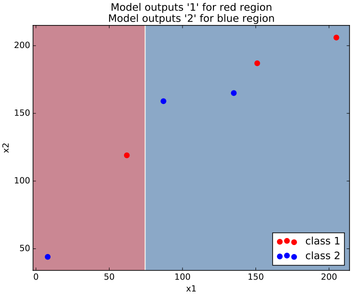
Figure 9: Decision Tree 3 - samples {4,5,6}

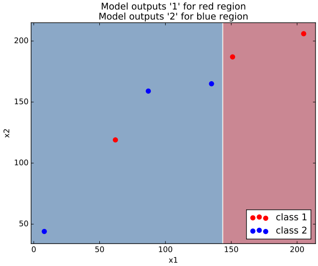
Random Forests - 3 decision trees



What is the result of taking the maximum of the 3 decision model predictions ?

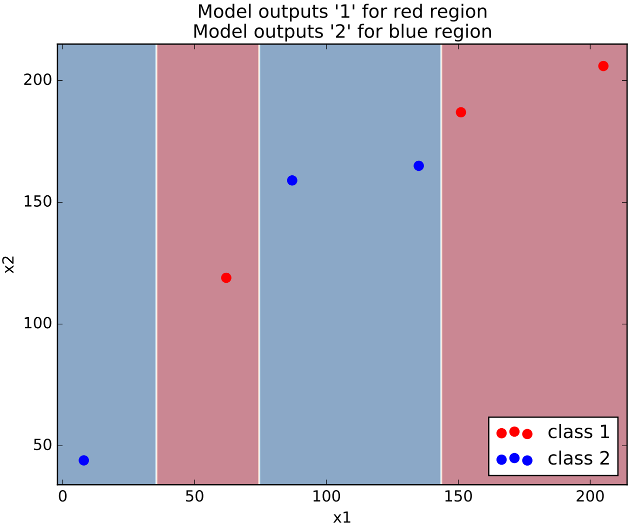






Random Forests - 3 decision trees

- Result of taking the maximum of the 3 decision model predictions



Conclusion

- Decision stump
  - Find the best split value (or threshold) for the best split variable (or feature)
  - The best split is one that maximizes a certain score, such as classification score
- Decision Tree
  - A decision tree is a tree of decision stumps
  - Stop splitting when depth is reached or the score is maximized (classification error $= 0$)
- Random Forests
  - Train several decision trees on different subsets of the dataset
  - Take and process the ensemble of predictions to predict the target value of a test sample