# Decision Trees and Random Forests
# Tutorial 1

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CPSC 340

# 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 $\in \{1, 2\}$

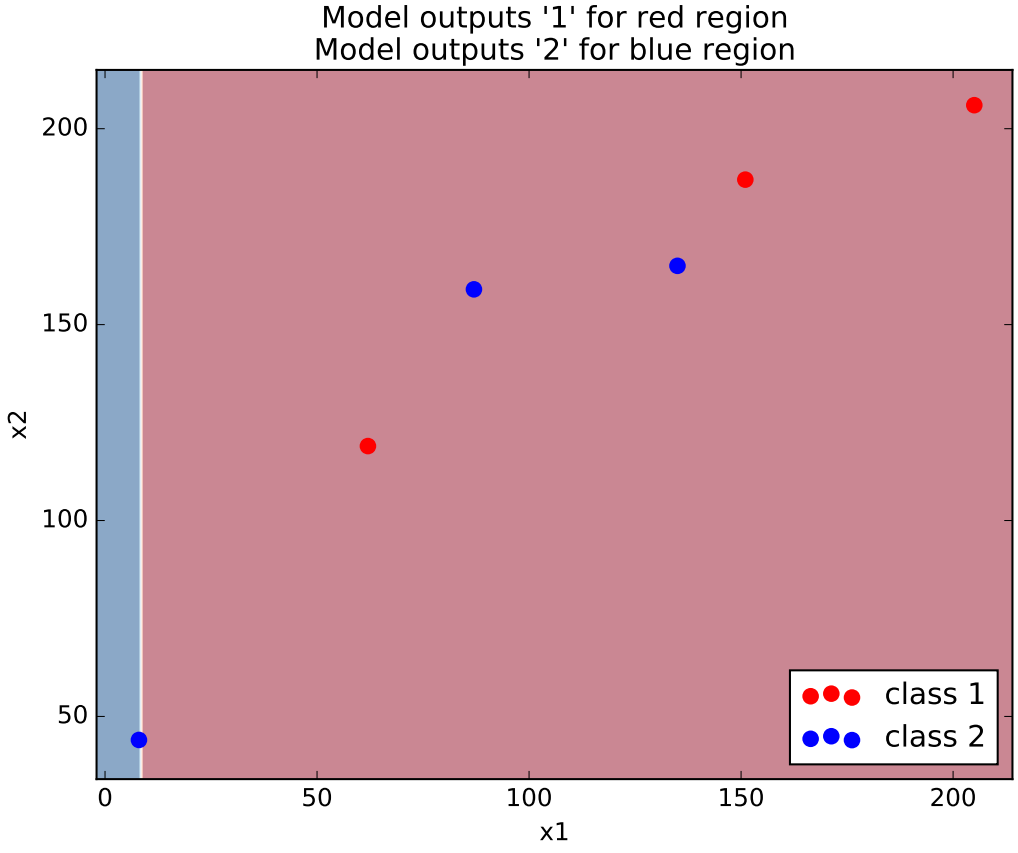
| x1 | x2 | y |
|---|---|---|
| 8 | 44 | 2 |
| 62 | 119 | 1 |
| 87 | 159 | 2 |
| 135 | 165 | 2 |
| 151 | 187 | 1 |
| 205 | 206 | 1 |

- 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 |

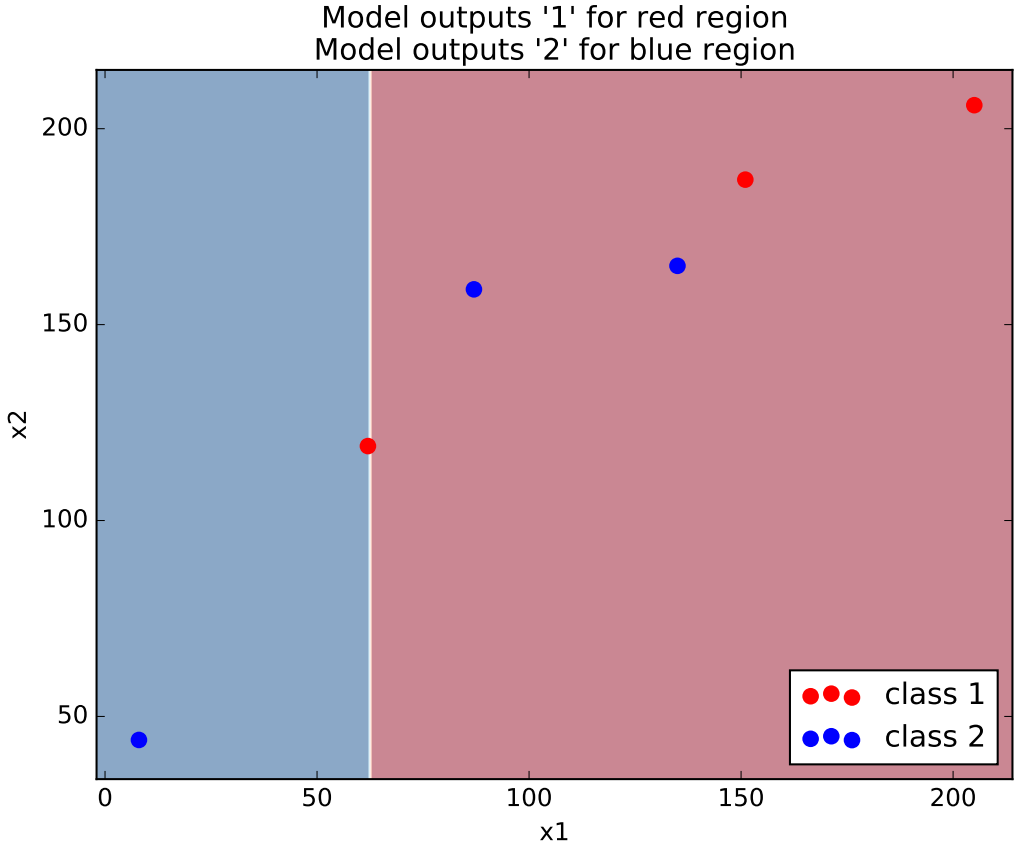



- Classification Score $= 4$

# 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 |

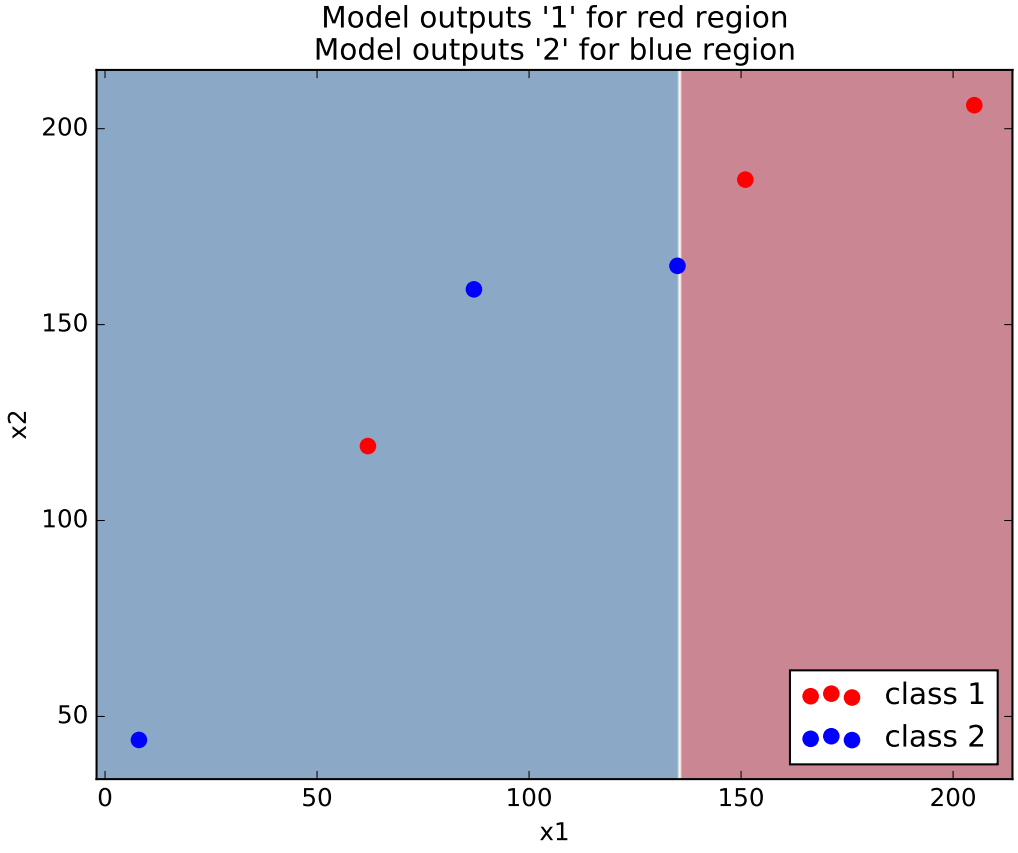



- Classification Score = 4

# 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 |

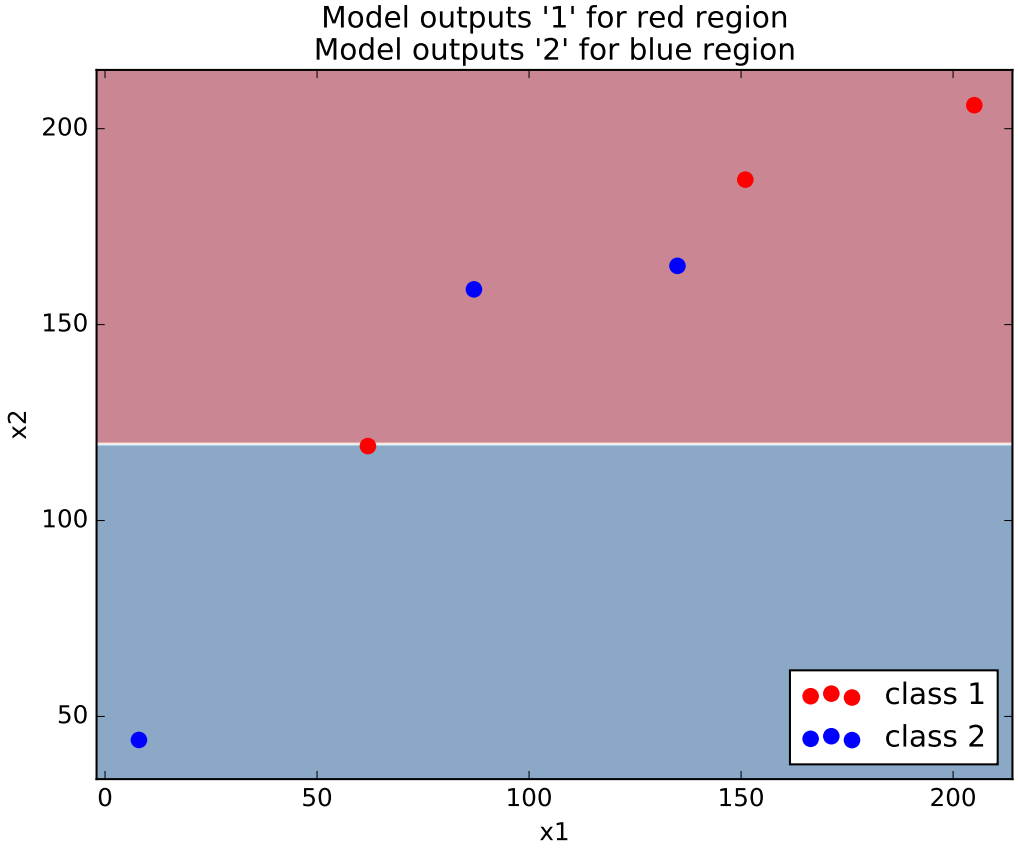



- Classification Score = 5

# 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 |

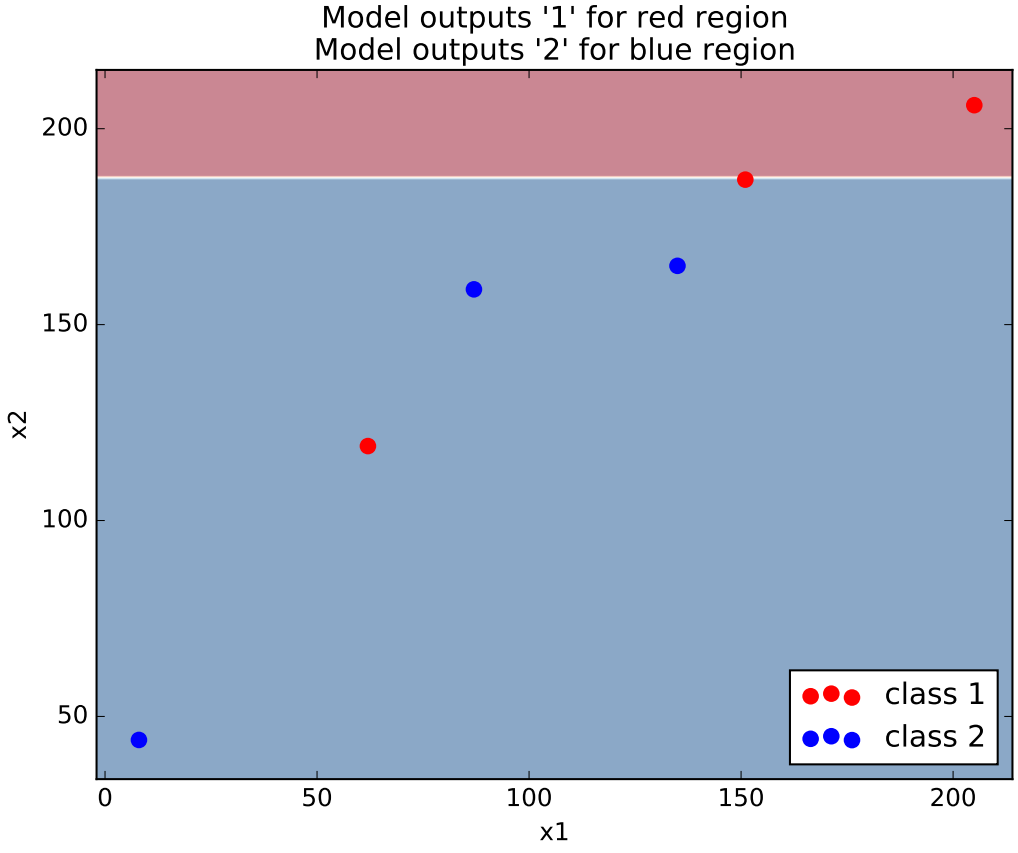



- Classification Score = 3

# 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 |

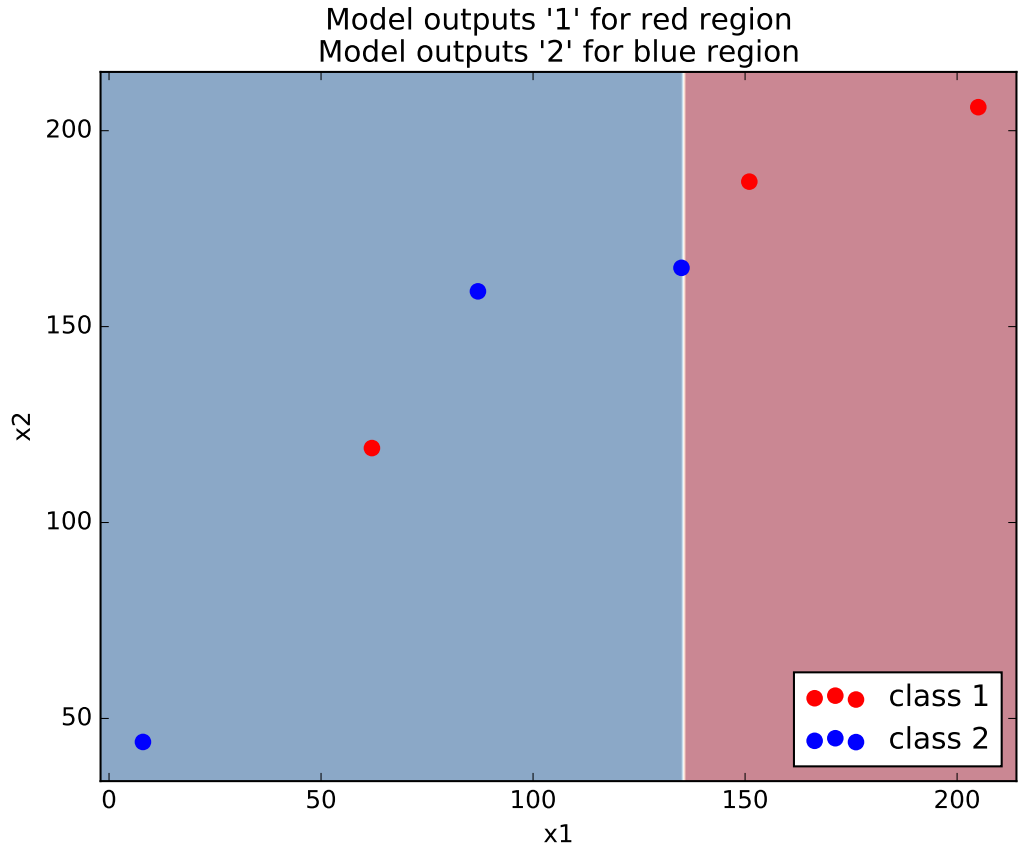



- Classification Score = 4

# Decision Stump - best split

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

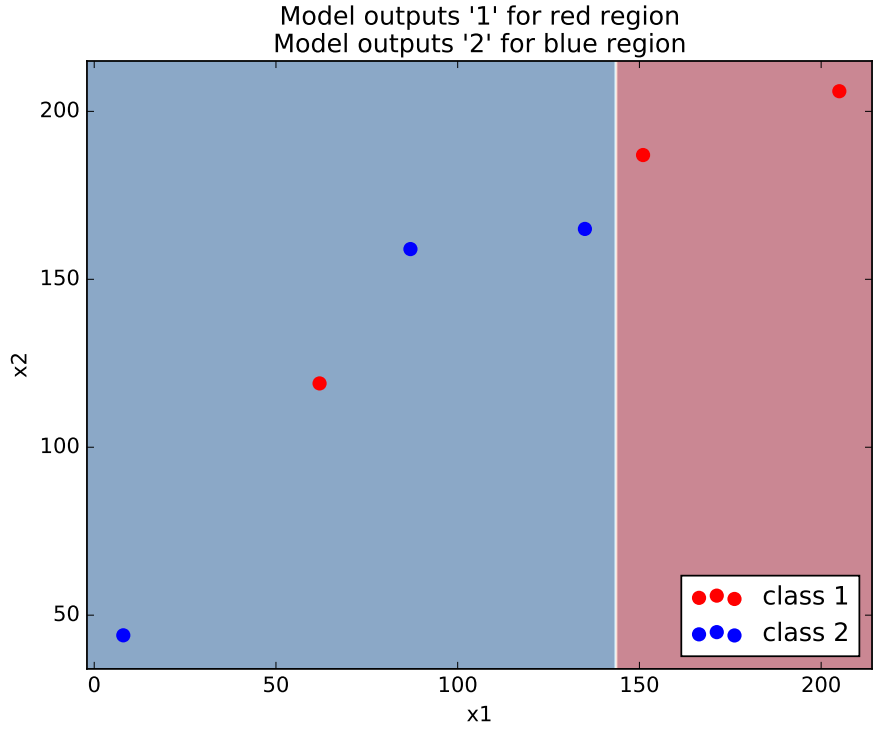
| x1 | x2 | y |
|---|---|---|
| 8 | 44 | 2 |
| 62 | 119 | 1 |
| 87 | 159 | 2 |
| 135 | 165 | 2 |
| 151 | 187 | 1 |
| 205 | 206 | 1 |

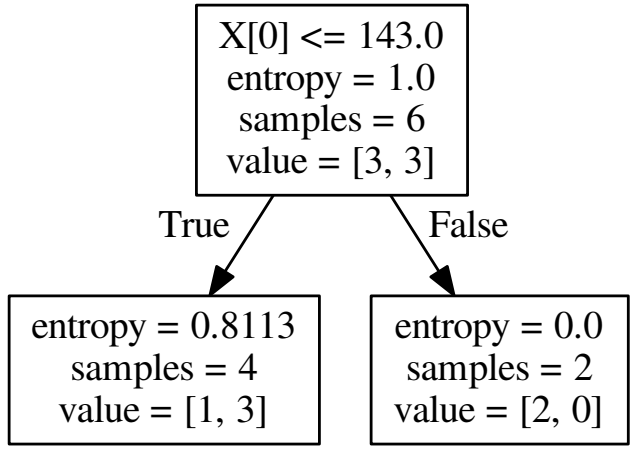



- Classification Score = 5

# Decision Tree

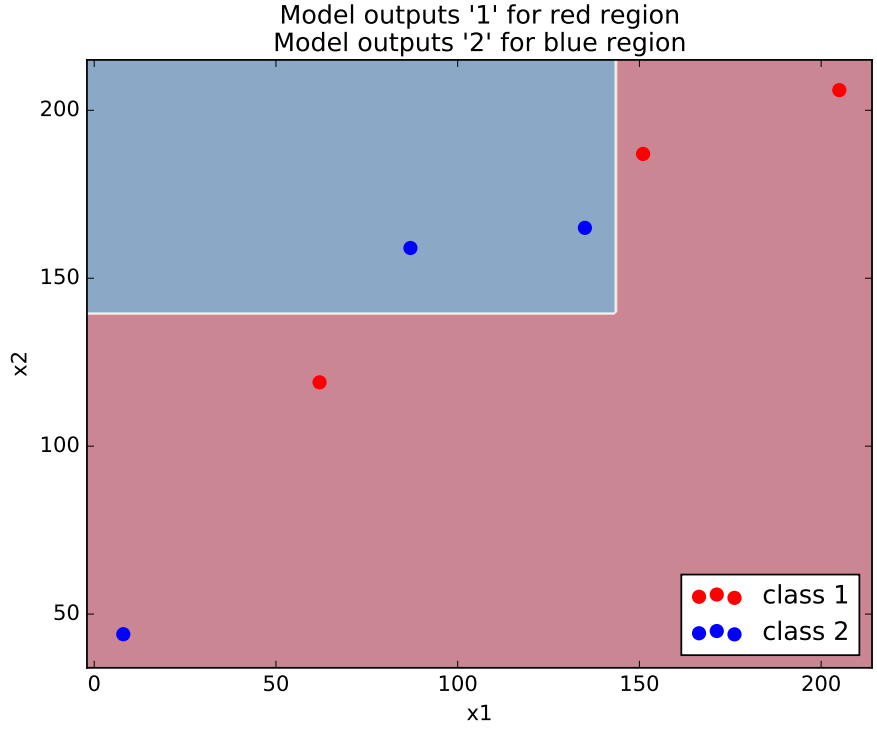
- A decision stump is a decisiont tree with depth 1

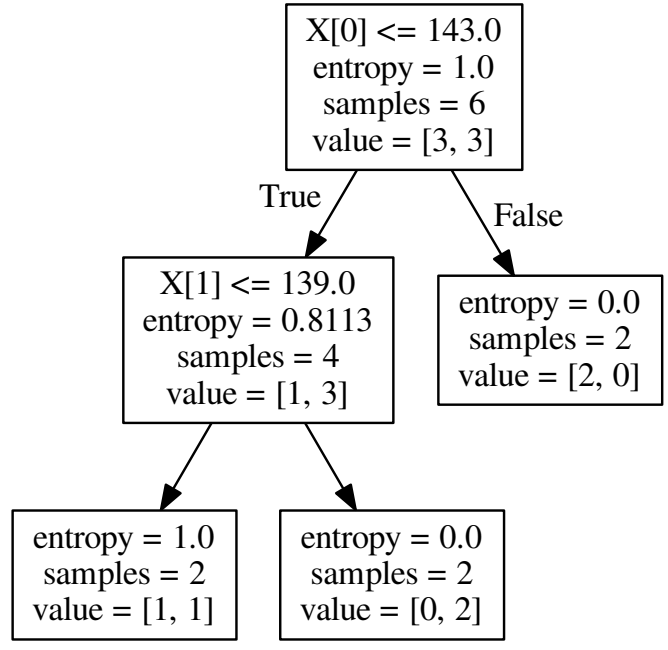


# Decision Tree

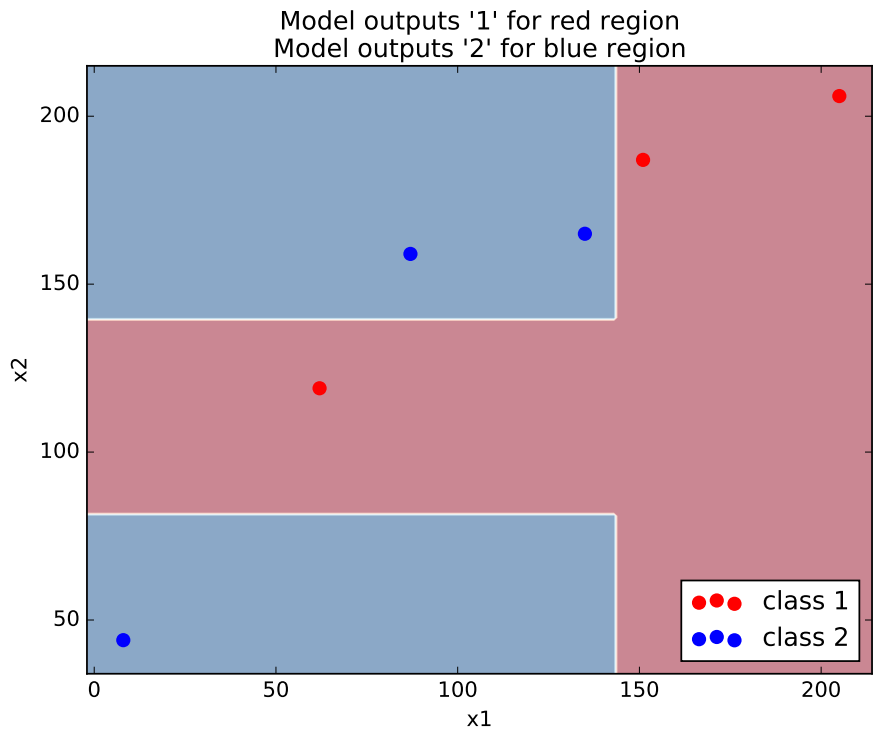
- A decision stump is a decisiont tree with depth 1

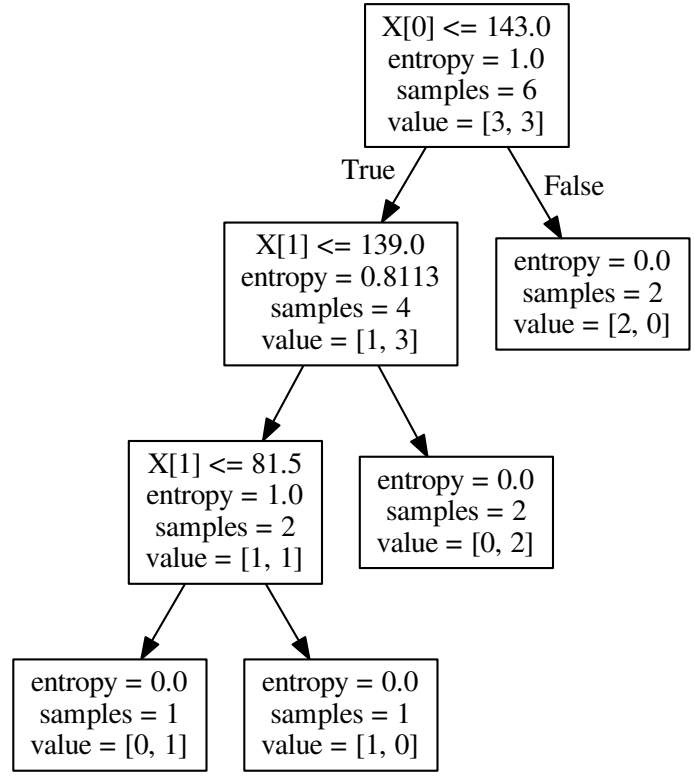


# Decision Tree

- 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, gather the decision tree predictions and

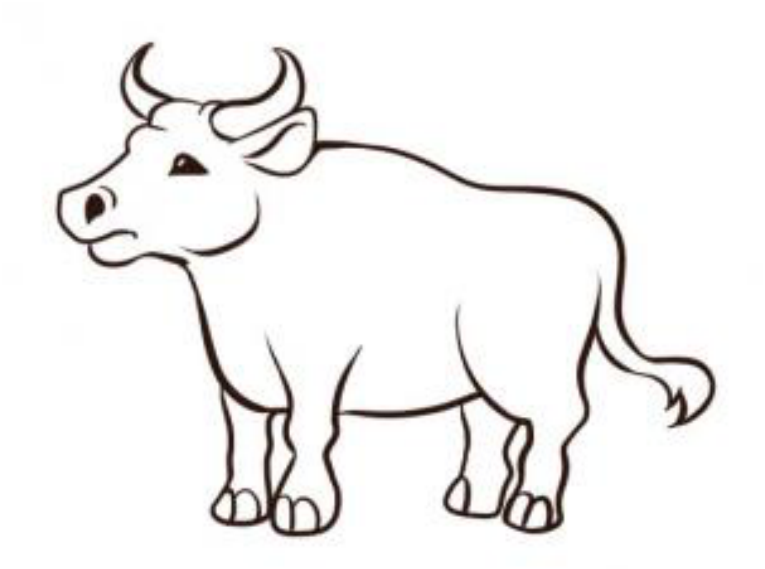
- take their mean, max, median, etc.

| 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

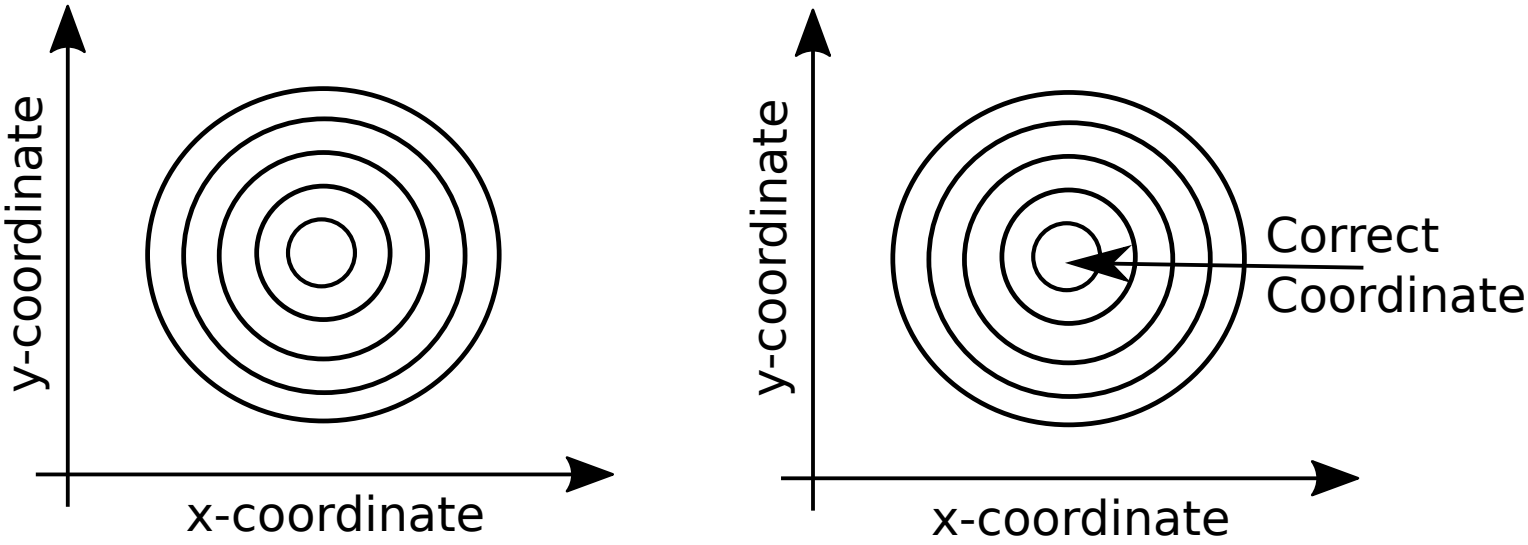
# Ensemble learning - example 1

- 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
- However, if measurement errors are uncorrelated
  - wrong perceptions get averaged out



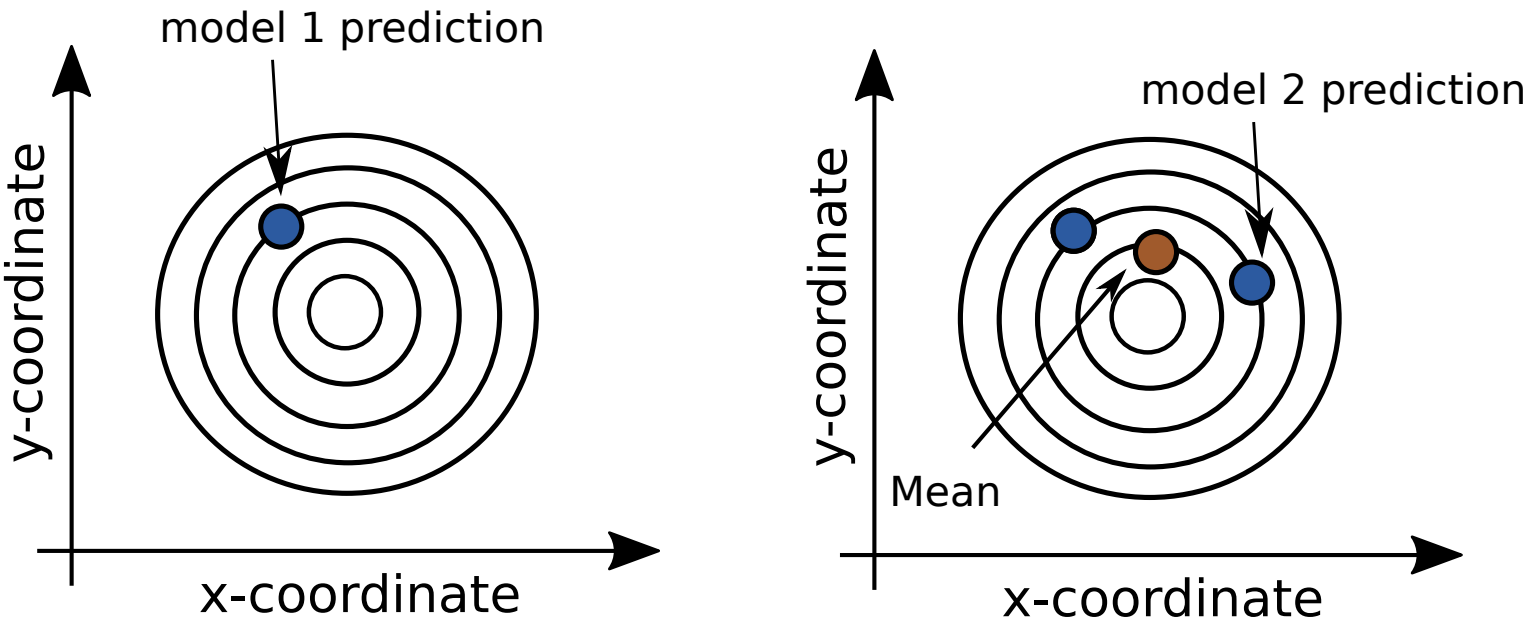
# Ensemble learning - example 2

- Predict coordinate of a GPS device



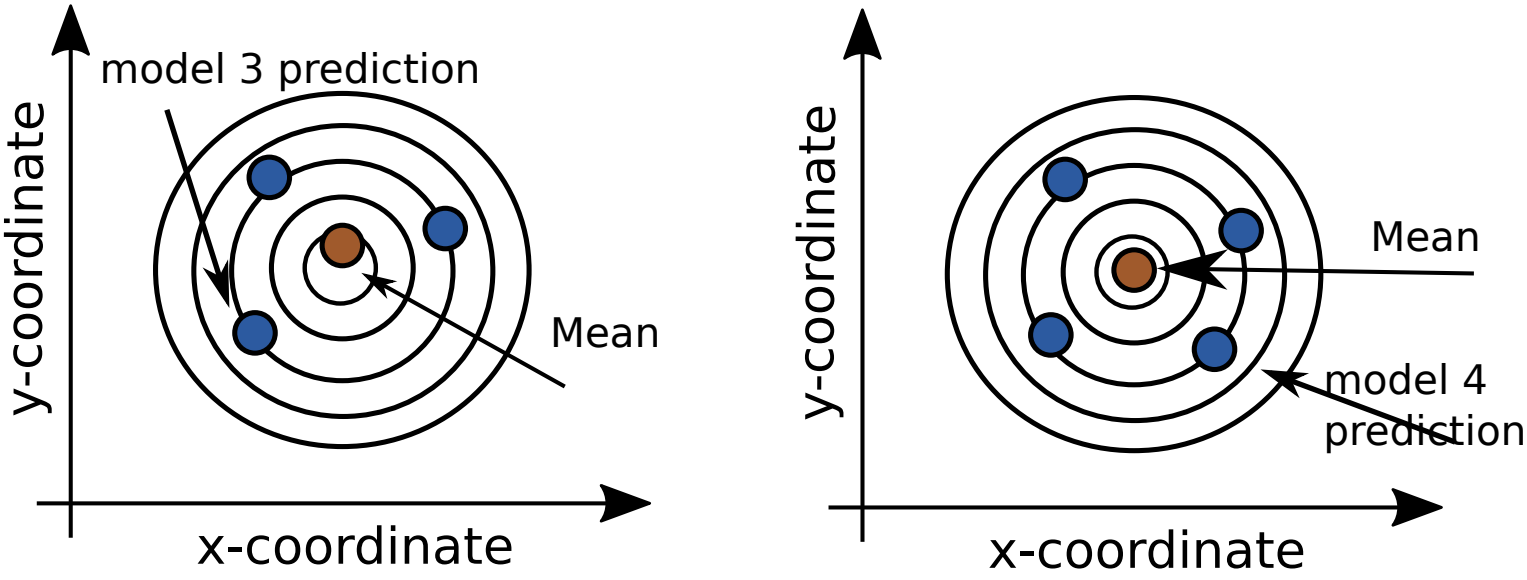
# Ensemble learning - example 2

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



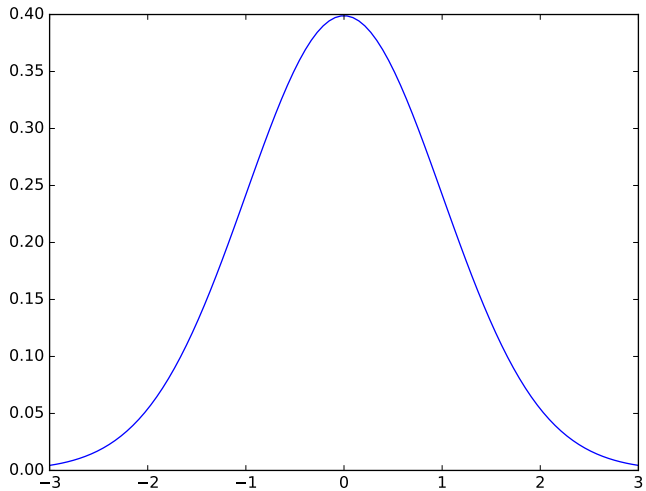
# Ensemble learning - example 2

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



# Ensemble learning - why does it work ?

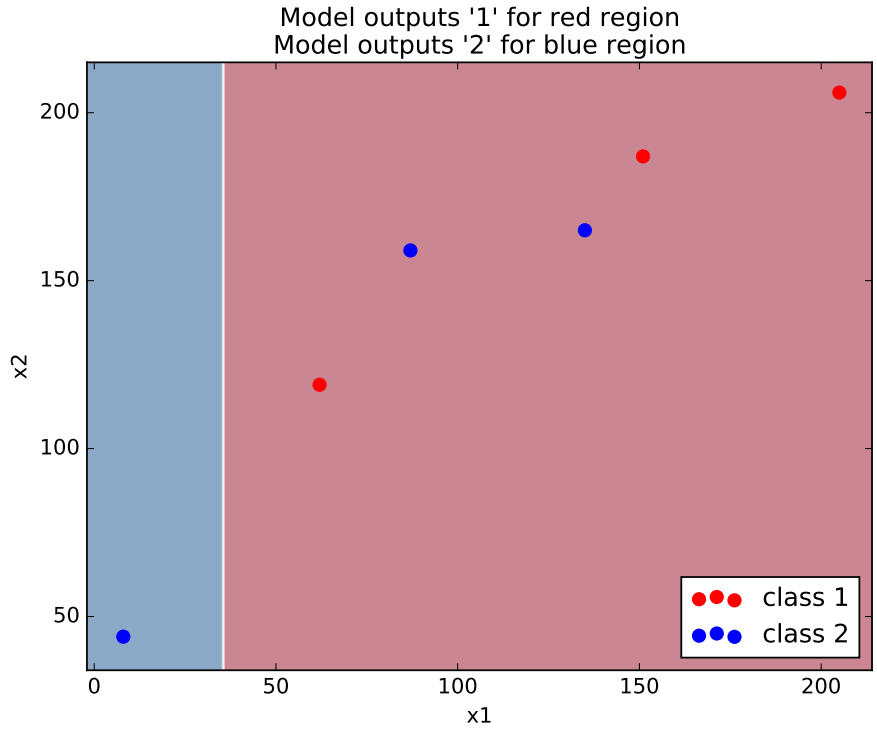
- The more samples and guesses you get the more likely their mean is the true value
- Central limit theorem - as the number of guesses goes to infinity, you approach a normal distribution




- For example, the probability that a trained model predicts a value that is two standard deviations away from the value is 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



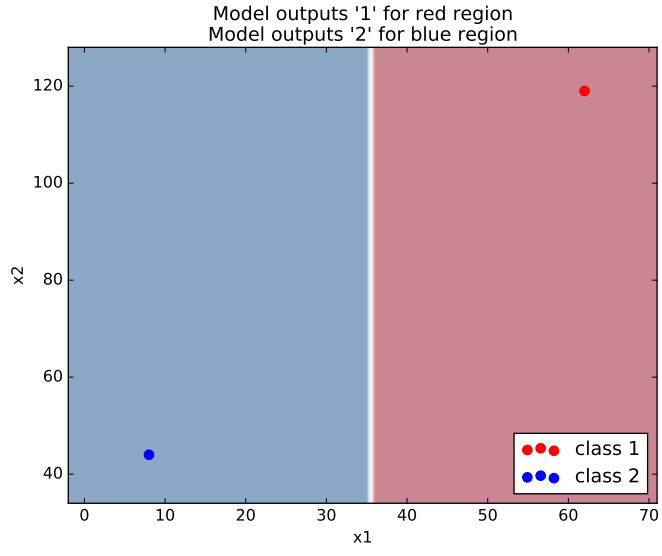
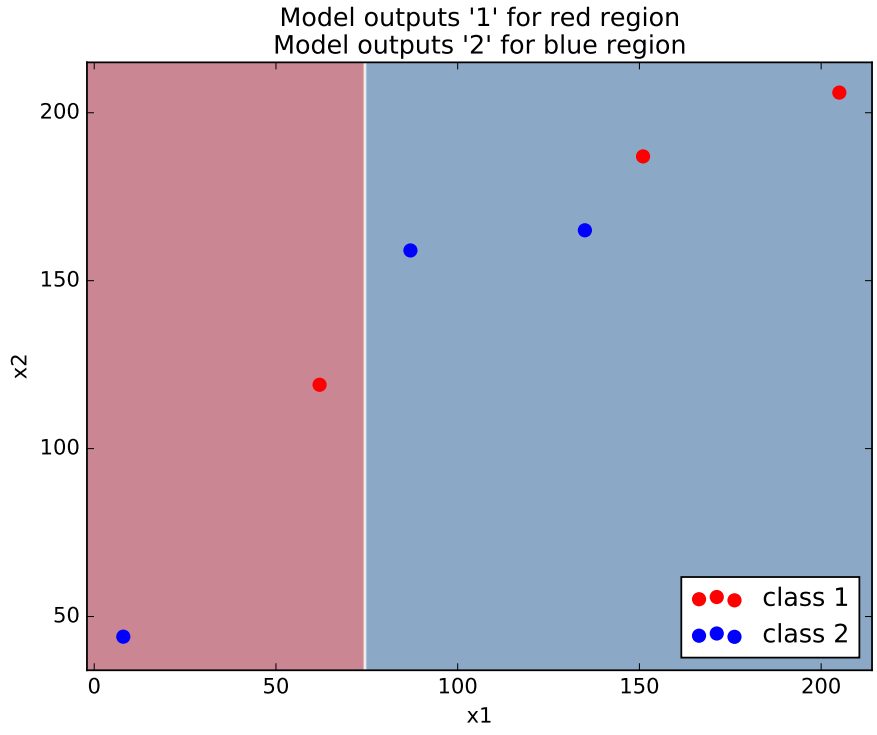




Figure 2: Decision Tree 2 - samples $\{1, 2\}$

# Random Forests

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



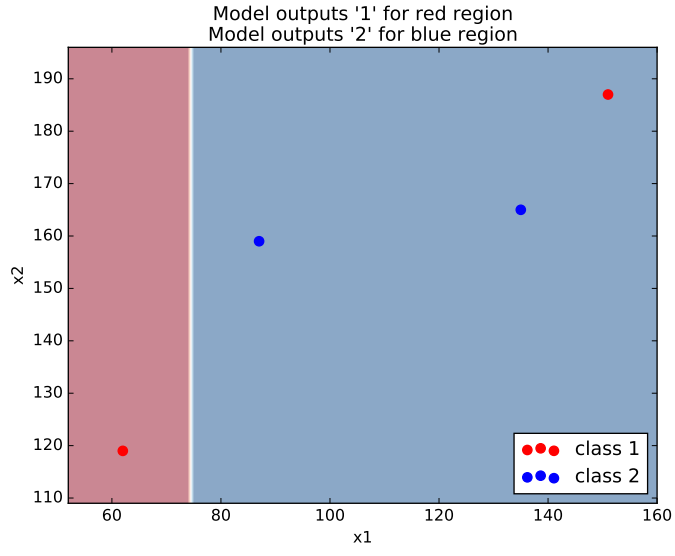
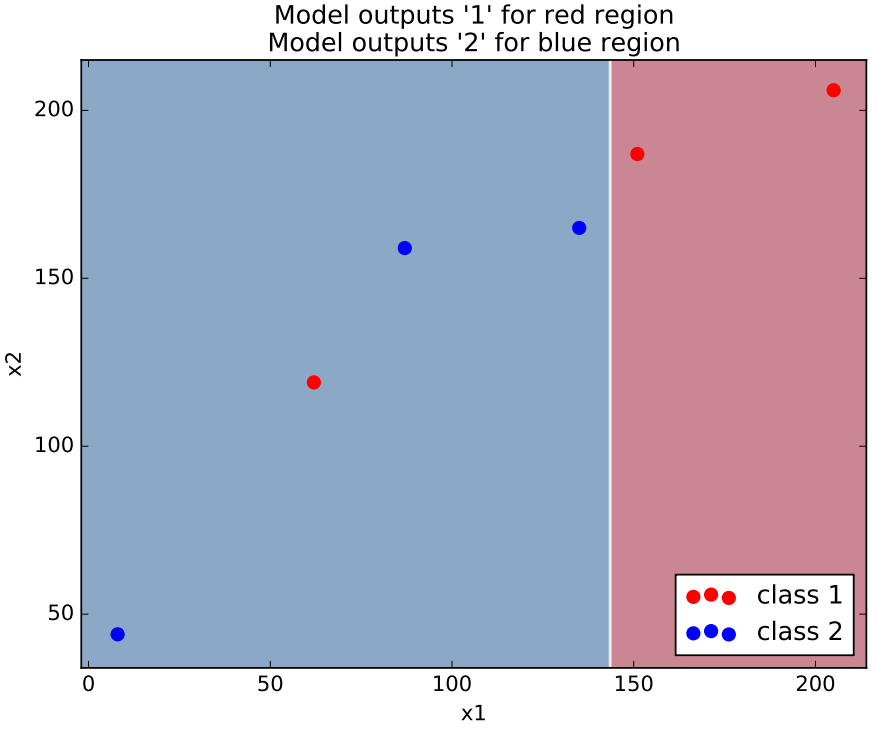




Figure 3: Decision Tree 2 - samples $\{1, 2, 3, 4\}$

# Random Forests

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



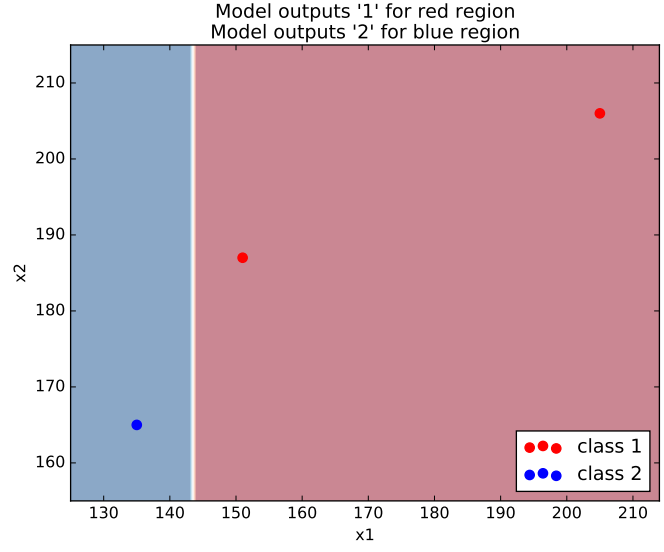
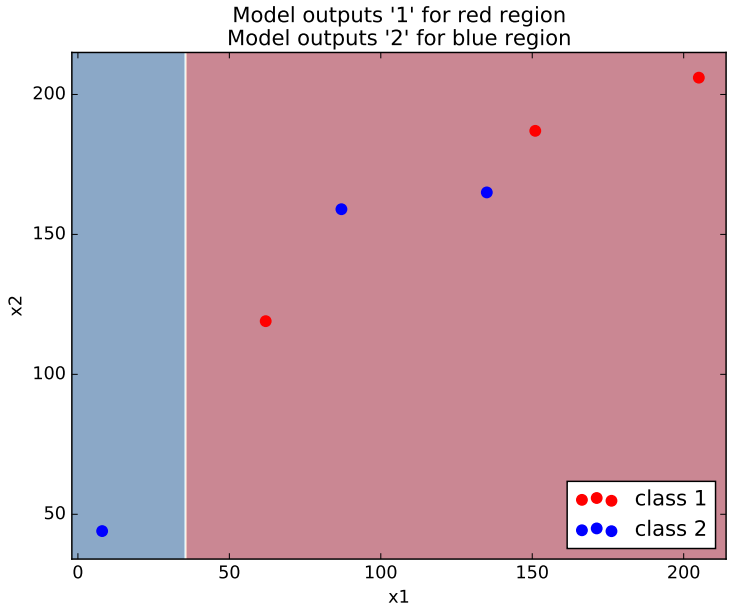
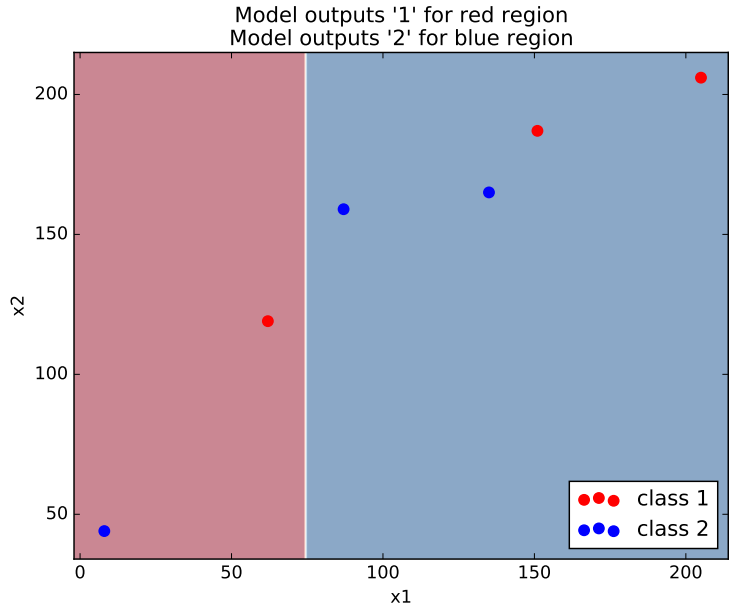
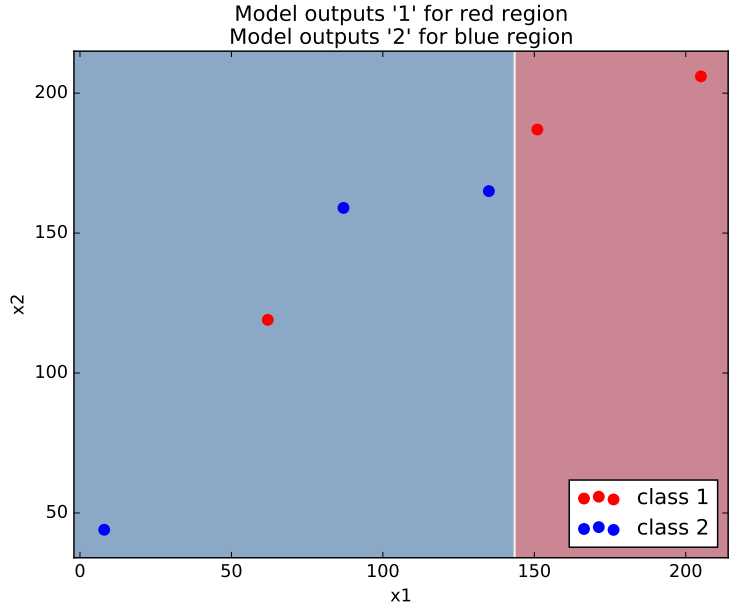




Figure 4: Decision Tree 3 - samples {4,5,6}

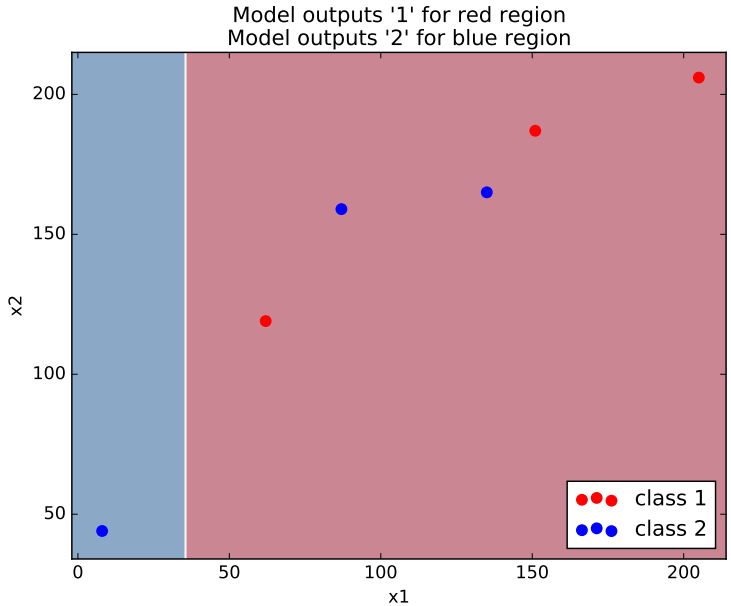
# Random Forests - 3 decision trees

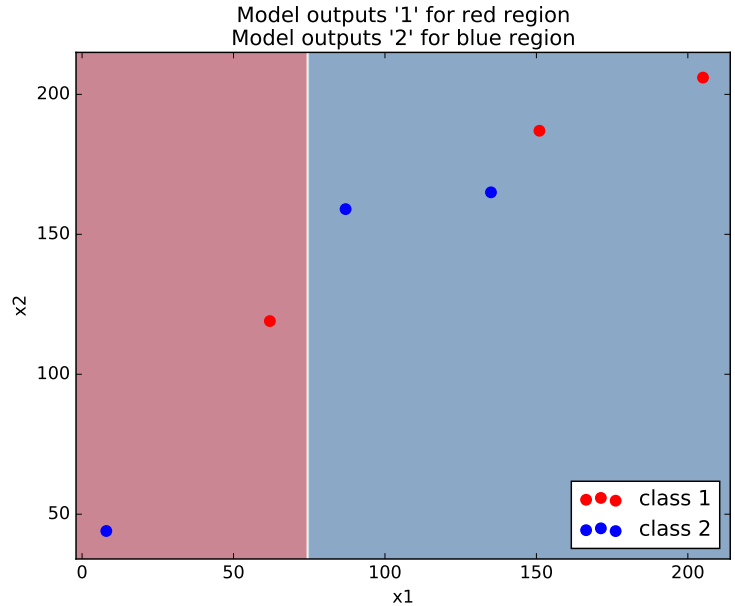


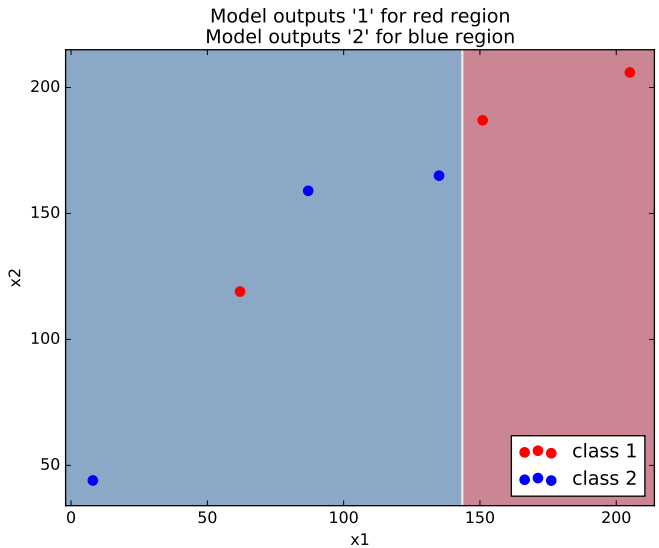



# What is the result of taking the maximum of the 3 decision model predictions ?

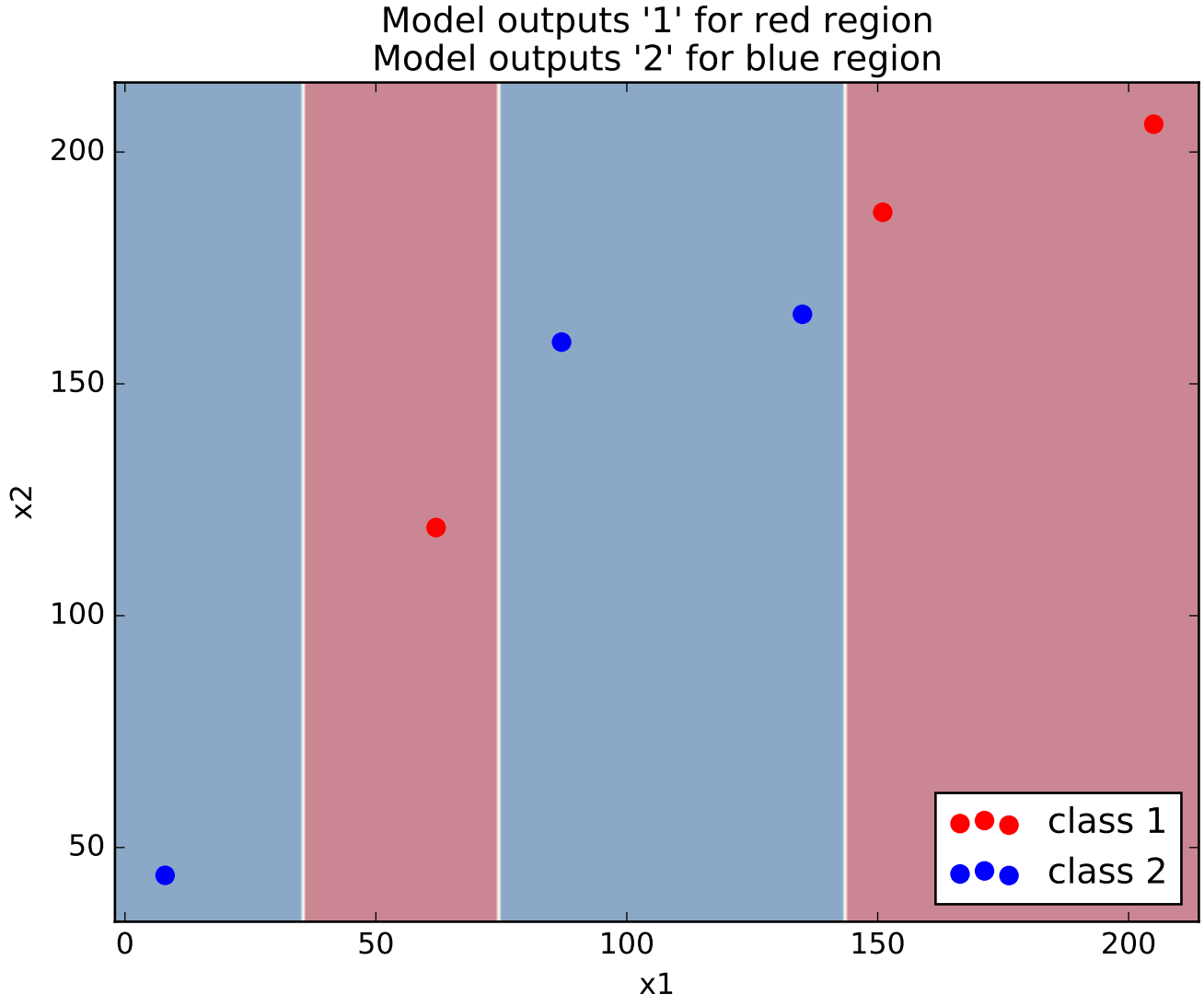


# Random Forests - 3 decision trees

- 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