Decision Tree Exercises

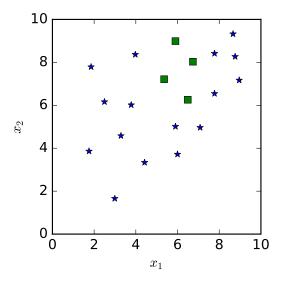
1. Gini Impurity

The goal in building a decision tree is to create the smallest possible tree in which each leaf node contains training data from only one class. In evaluating possible splits, it is useful to have a way of measuring the *purity* of a node. The purity describes how close the node is to containing data from only one class. Gini purity is defined as follows¹:

$$\phi(\mathbf{p}) = \sum_{j} p_j (1 - p_j)$$

Where $\mathbf{p} = (p_1, ..., p_n)$ and each p_i is the fraction of elements from class i. This expresses the fractions of incorrect predictions in the node if the class of each element was predicted by randomly selecting a label according to the distribution of classes in the node. This value will be 0 if all elements are from the same class, and it increases as the mix becomes more uniform.

Calculate the Gini impurity of the following data set:



¹Notation follows: Breiman, Leo. "Technical note: Some properties of splitting criteria." Machine Learning 24.1 (1996): 41-47.

2. Tree Construction

The decision tree construction algorithm proceeds by recursively splitting the training data into increasingly smaller subsets. When splitting a node in the tree we search across all dimensions and all split points to select the split that results in the greatest decrease in impurity. This goodness-of-split value can be expressed as:

$$\Theta(s,t) = \phi(\mathbf{p}) - P_L \phi(\mathbf{p_L}) - P_R \phi(\mathbf{p_R})$$

Where s is a possible split, t is the node and P_L and P_R represent the fraction of elements of nodes that ended up in the left child and right child respectively. Higher values represent better splits.

Execute the recursive tree-construction algorithm on the data above and draw the resulting tree. Calculate the impurity of each node and the goodness-of-split for each split.

3. Classification

Classify the following three points using your decision tree.

- (4, 10)
- (6, 10)
- (6,0)