

# Machine Learning PSET 5

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## Problem 1

1.

$$P(Y = -) = \frac{9}{21} = \frac{3}{7}; P(Y = +) = \frac{12}{21} = \frac{4}{7}$$

$$H(Y) = - \sum_{y \in Y} p(y) \log_2 p(y) = -\frac{3}{7} * \log_2 \frac{3}{7} - \frac{4}{7} * \log_2 \frac{4}{7} = 0.985$$

2.

$$H(Y|X = x) = - \sum_{y \in Y} p(y|x) \log_2 p(y|x)$$

$P(Y = y X_1 = x)$	$X_1 = T$	$X_1 = F$
$y = +$	7/8	5/13
$y = -$	1/8	8/13

$$H(Y|X_1 = T) = -\frac{7}{8} * \log_2 \frac{7}{8} - \frac{1}{8} \log_2 \frac{1}{8} = 0.5436$$

$$H(Y|X_1 = F) = -\frac{5}{13} * \log_2 \frac{5}{13} - \frac{8}{13} \log_2 \frac{8}{13} = 0.9612$$

Same Process as above we can get.

$P(Y = y X_2 = x)$	$X_2 = T$	$X_2 = F$
$y = +$	7/10	5/11
$y = -$	3/10	6/11
$P(Y X_2 = x)$	0.8813	0.9940

The distribution of X are

	T	F
$P(X_1 = x)$	8/21	13/21
$P(X_2 = x)$	10/21	11/21

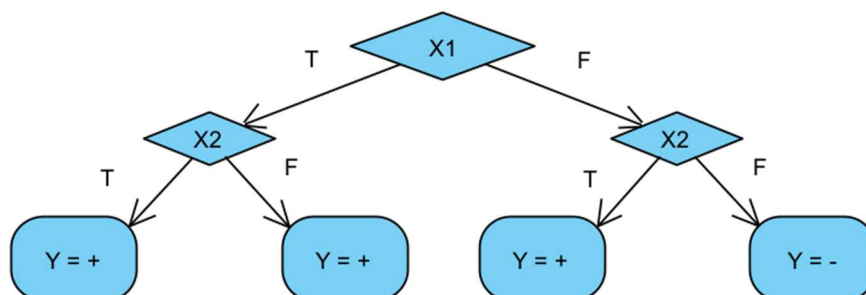
$$H(Y|X) = \sum_{x \in X} p(x) H(Y|X = x)$$

$$H(Y|X_1) = 0.8021; H(Y|X_2) = 0.9403$$

$$IG(X_1) \equiv H(Y) - H(Y|X_1) = 0.985 - 0.8021 = 0.1829$$

$$IG(X_2) \equiv H(Y) - H(Y|X_2) = 0.985 - 0.9403 = 0.0447$$

3. From the first section, the first node is  $X_1$  because it has the highest information gain.  
The second node is  $X_2$ .



## Problem 2

### Preprocessing

This data set contains discrete and continuous variables. I scale all continuous variables into  $[-1, 1]$ . Discrete variables are 'Type1' and 'Type2'. They are transformed into One-Hot code which involves creating a binary column for each unique value in a categorical variable. For an example, 'Type1=Grass' transformed to a new variable 'Type1\_Grass = 1'. This method is useful because the categories have no inherent order.

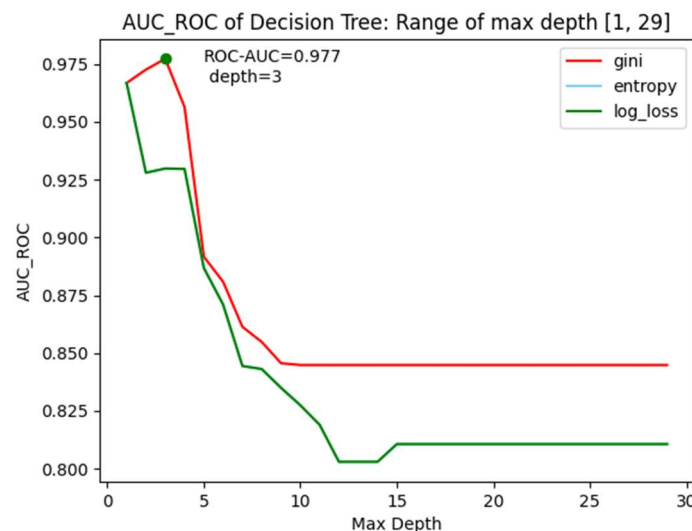
### Method of Evaluation

This is a classification problem with 65 positive (Legendary = True) sample and 735 negative sample. This means samples in this dataset is not balanced. If a model predicts all sample

into negative, it will have  $\frac{735}{800} = 91.875\%$  of accuracy. Therefore, Area Under ROC Curve

(AUC-ROC) is a better index for evaluation. The ROC curve plots the true positive rate against the false positive rate for different threshold values, and the AUC-ROC measures the area under this curve. The AUC-ROC value ranges between 0 and 1, where 0.5 represents random guessing, and 1 represents a perfect model. I'm using cross validation score to get average AUC-ROC score.

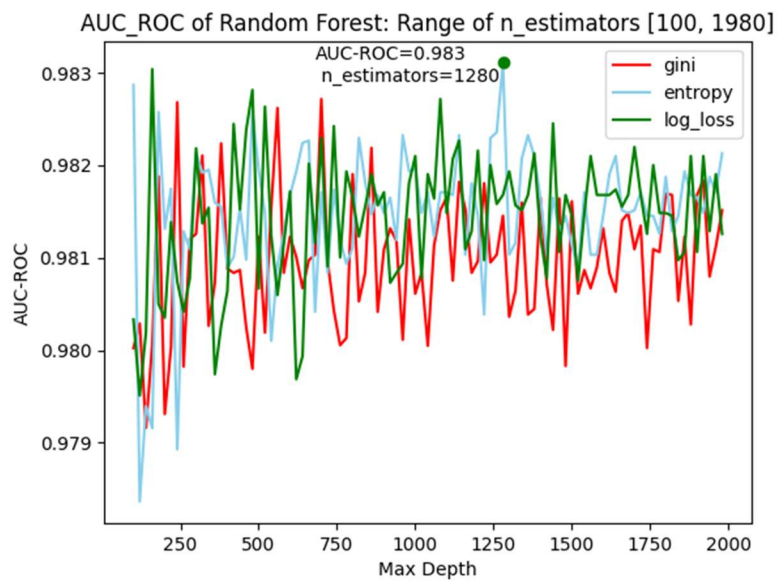
### Model Performance



This figure is the AUC-ROC of decision tree model in different max depth and criterion (function to measure the quality of a split). The decision tree reaches the highest AUC-ROC at depth=3. Before that point, the model is underfitting since there are not enough nodes in the tree to discriminate samples. After that model is over fitting, that fit too closely to the training data and become less generalizable. The importance of features are.

Feature	Importance
Total	0.9748525020726886
Sp. Atk	0.02514749792731145
Other	0.0

Therefore, the best indicator in decision tree model is Total.



Random Forest have higher over-all AUC-ROC than decision tree. The highest AUC-ROC is 0.983 when it has 1280 decision tree as base estimator.