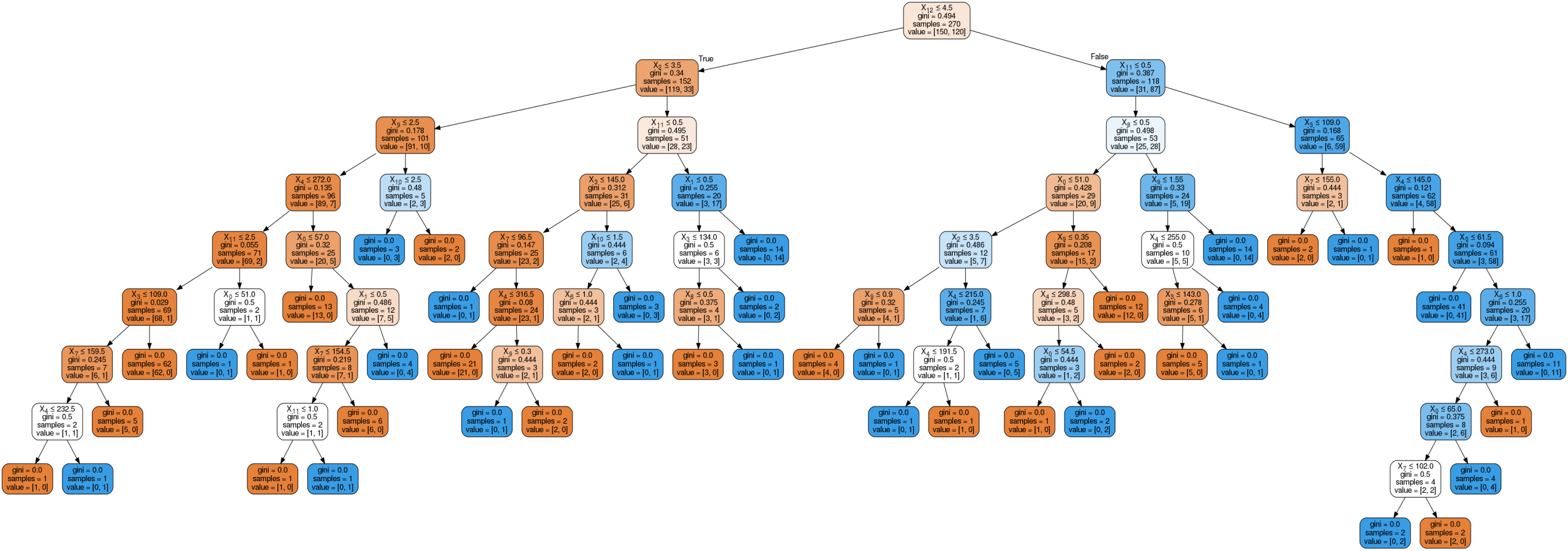
Decision Trees Classifier

Decision Tree Classifier

Heart Dataset (statlog version)
13 features
270 samples



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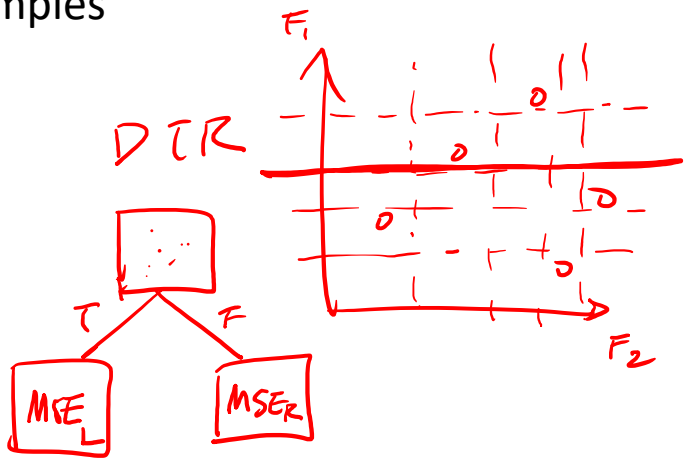
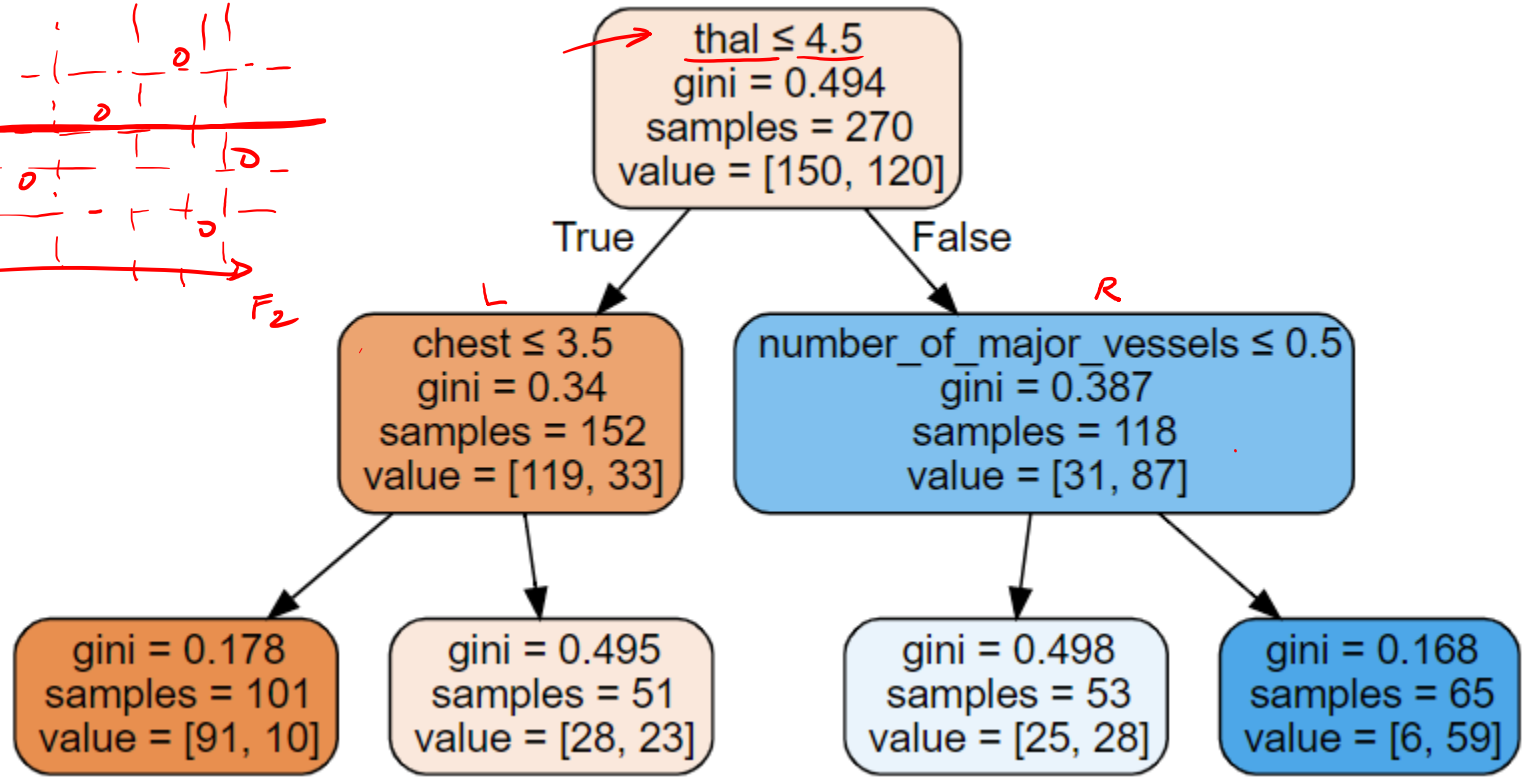




Decision Tree Split Criteria

Regression Tree

MSE (RSS)

$$H(X_m) = \frac{1}{N_m} \sum_{i \in N_m} (y_i - \bar{y}_m)^2$$

MAE

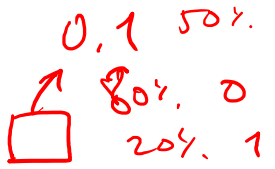
$$H(X_m) = \frac{1}{N_m} \sum_{i \in N_m} |y_i - \bar{y}_m|$$

Classification Tree

Gini

impurity

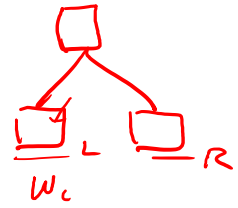
$$H(X_m) = \sum_k p_{mk}(1 - p_{mk})$$



Entropy

uncertainty

$$H(X_m) = -\sum_k p_{mk} \log(p_{mk})$$

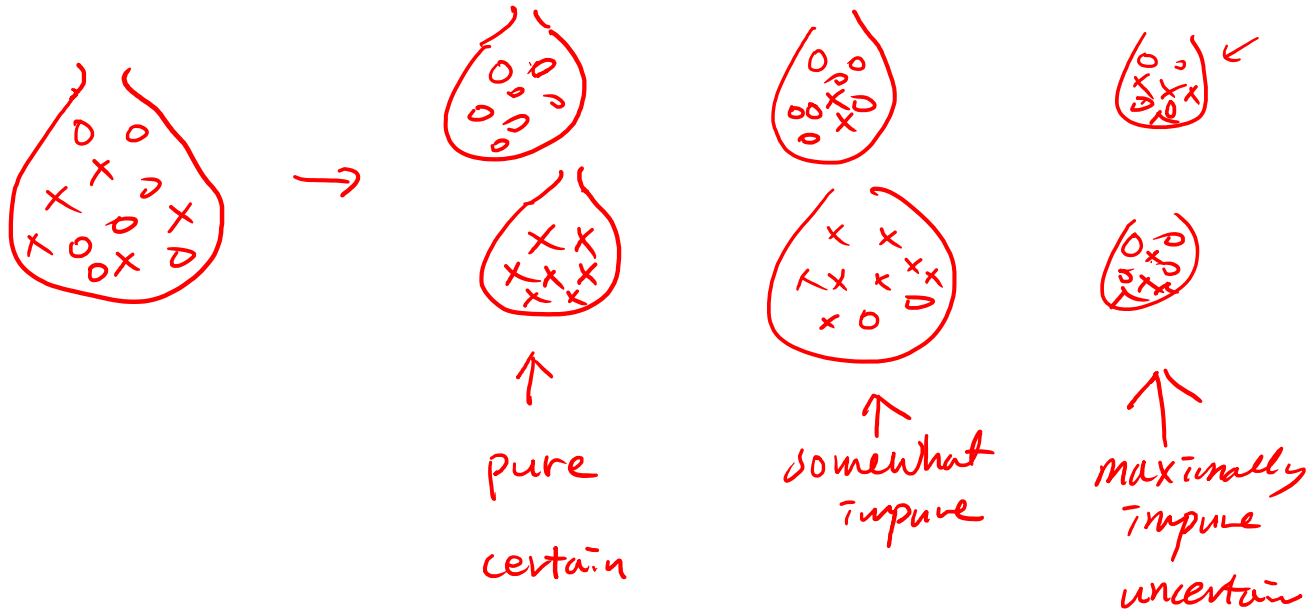


Information Gain = E(parent)-E(children)

Decision Tree Split Criteria

Gini

$$H(X_m) = \sum_k p_{mk}(1 - p_{mk})$$

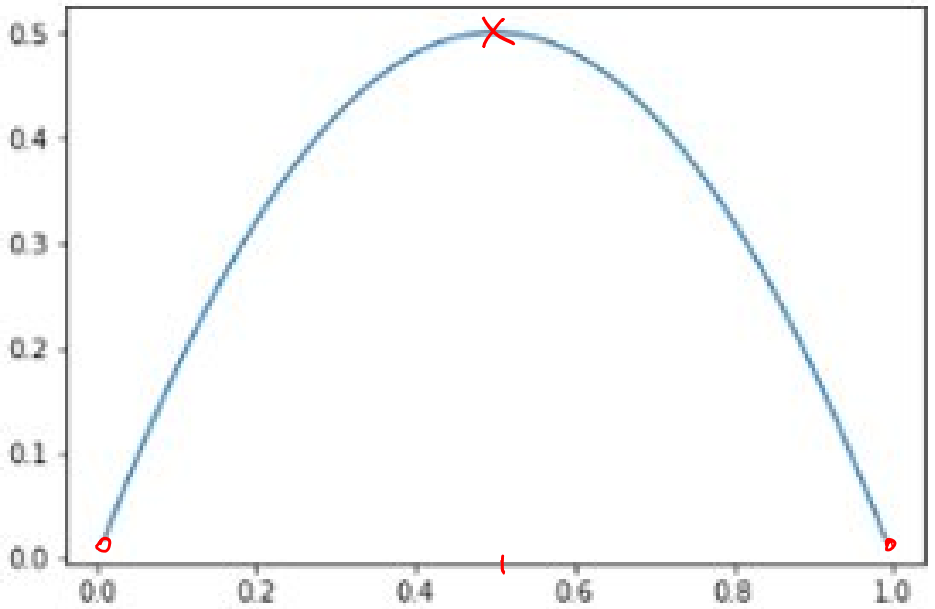


Entropy

$$H(X_m) = -\sum_k p_{mk} \log(p_{mk})$$

Split criterion- Gini index

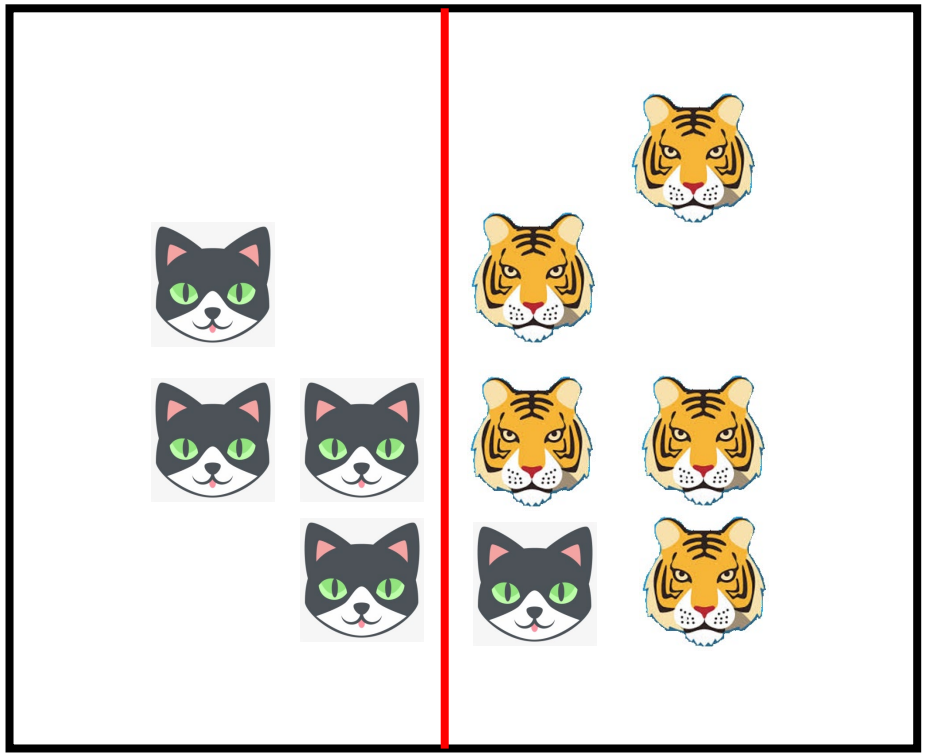
```
a = np.arange(0.01,1,0.01)
plt.plot(a,2*a*(1-a));
```



$$H(X_m) = \sum_k p_{mk}(1 - p_{mk})$$

What is the Gini of this box?

Gini: $H(X_m) = \sum_k p_{mk}(1 - p_{mk})$



D

0.5

$\frac{1}{2} \cdot (\frac{1}{2}) + \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{2}$

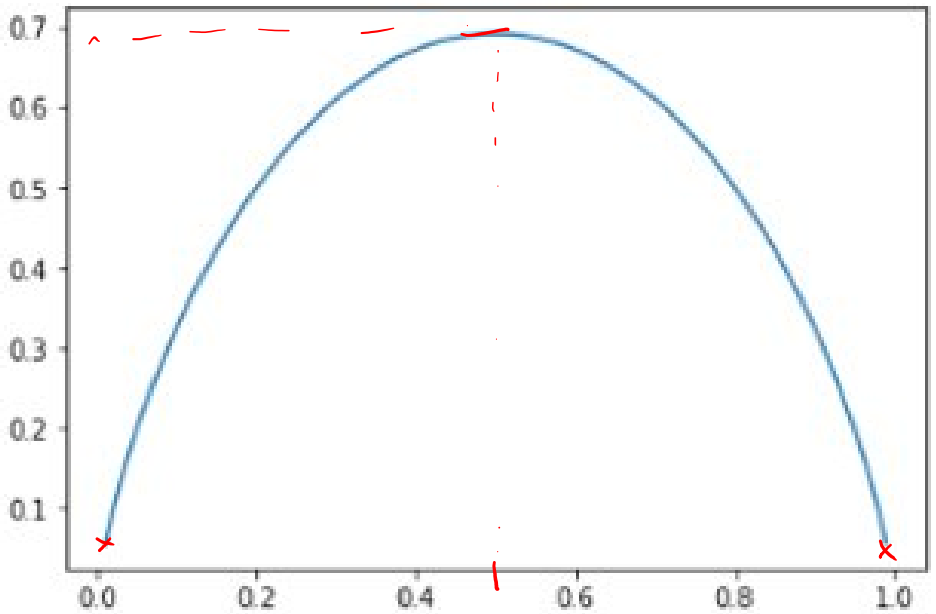
$P_c = \frac{1}{6}$

$P_t = 5/6$

$\frac{1}{6} \cdot \frac{5}{6} + \frac{5}{6} \frac{1}{6} = \frac{5}{18}$

Split criterion- Entropy

```
a = np.arange(0.01,1,0.01)
plt.plot(a,-a*np.log(a)-(1-a)*np.log(1-a));
```



$\log_2$ $\log_{10}$ $\log$

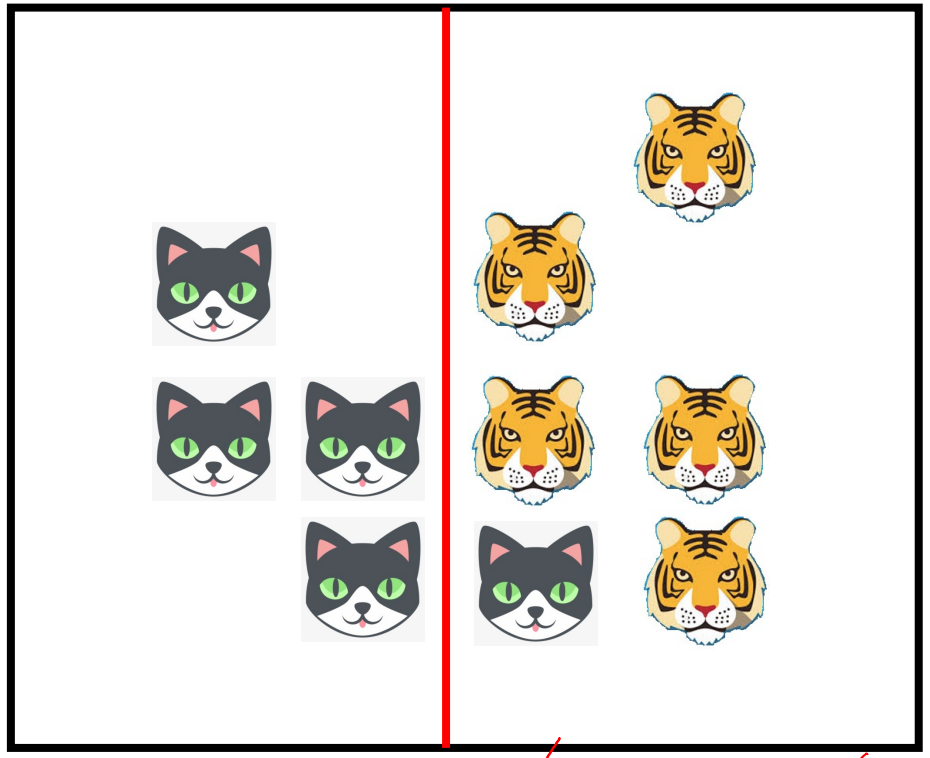
$$H(X_m) = -\sum_k p_{mk} \log(p_{mk})$$

Split criterion- Information gain

Information Gain = Reduction in Entropy

$$-\left(\frac{1}{2}\log_2\frac{1}{2}+\frac{1}{2}\log_2\frac{1}{2}\right)=1$$

$$-\sum_i P_i \log P_i$$

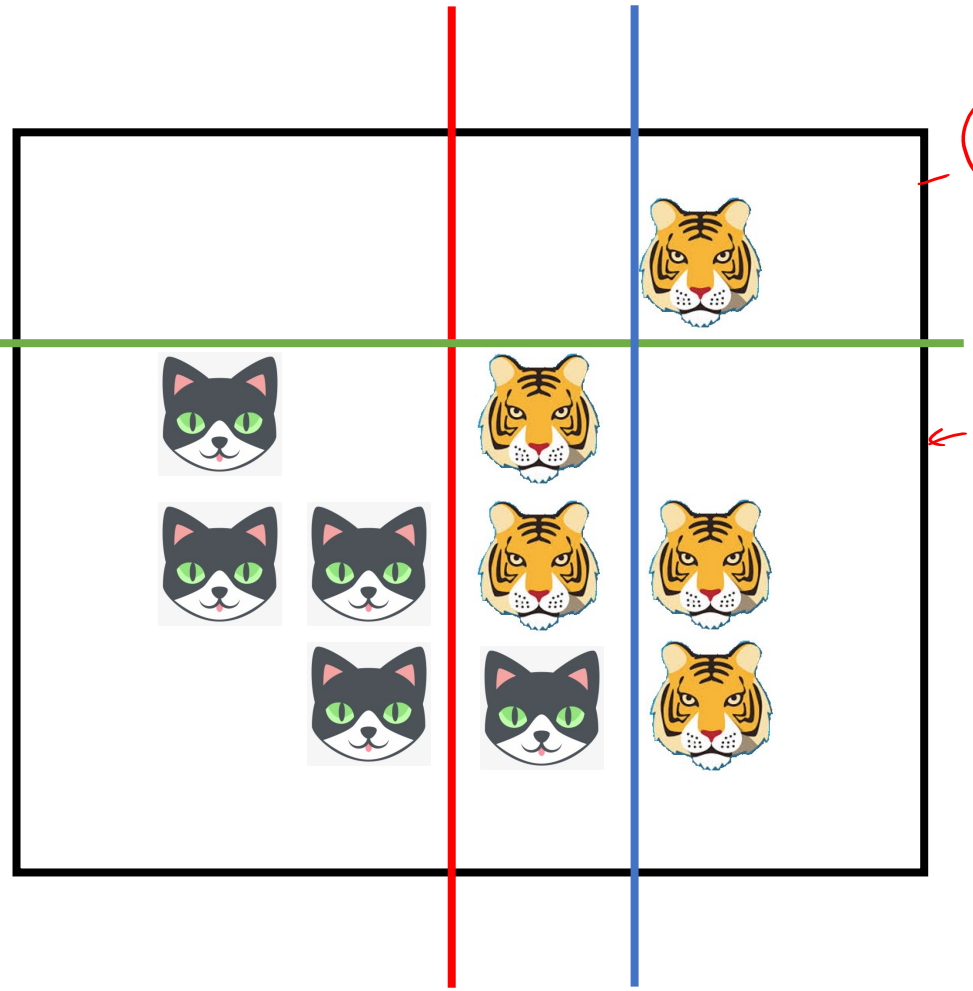


0

$$-\left(\frac{1}{6}\log_2\frac{1}{6}+\frac{5}{6}\log_2\frac{5}{6}\right)=0.65$$

Information Gain = 1 - 0.4*0 - 0.6*0.65 = 0.61

Which split gives the maximum information gain?



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