



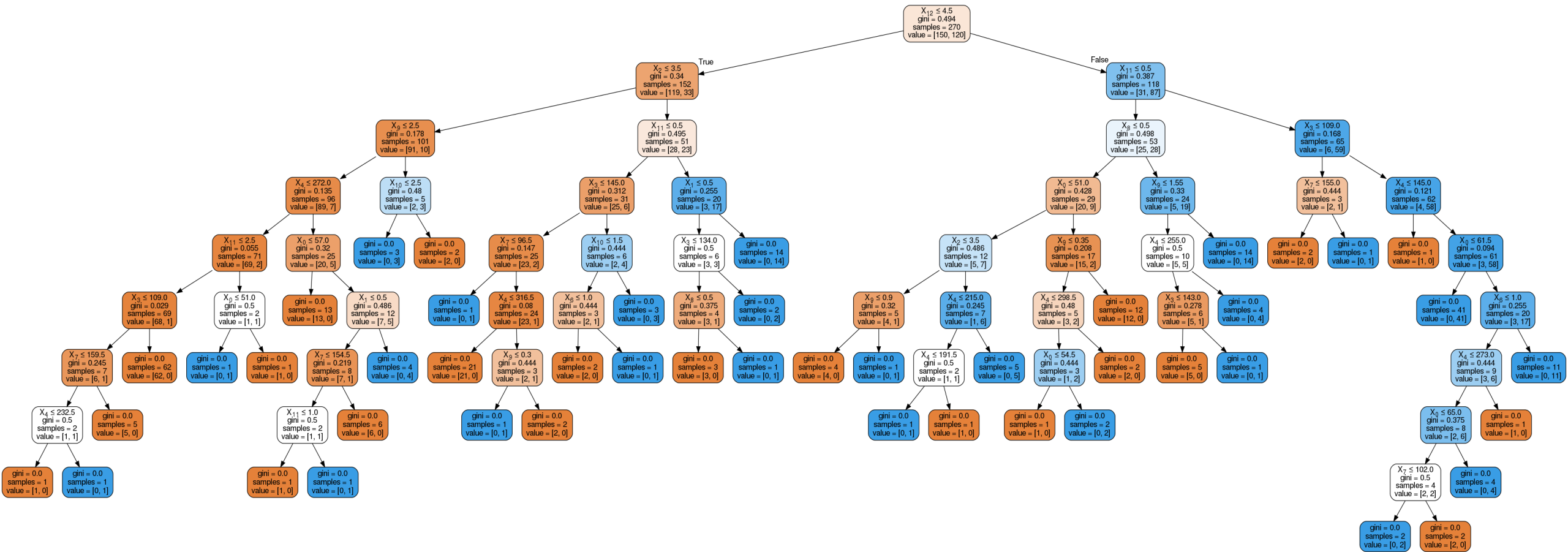
Decision Trees Classifier

Decision Tree Classifier

Heart Dataset (statlog version)

13 features

270 samples

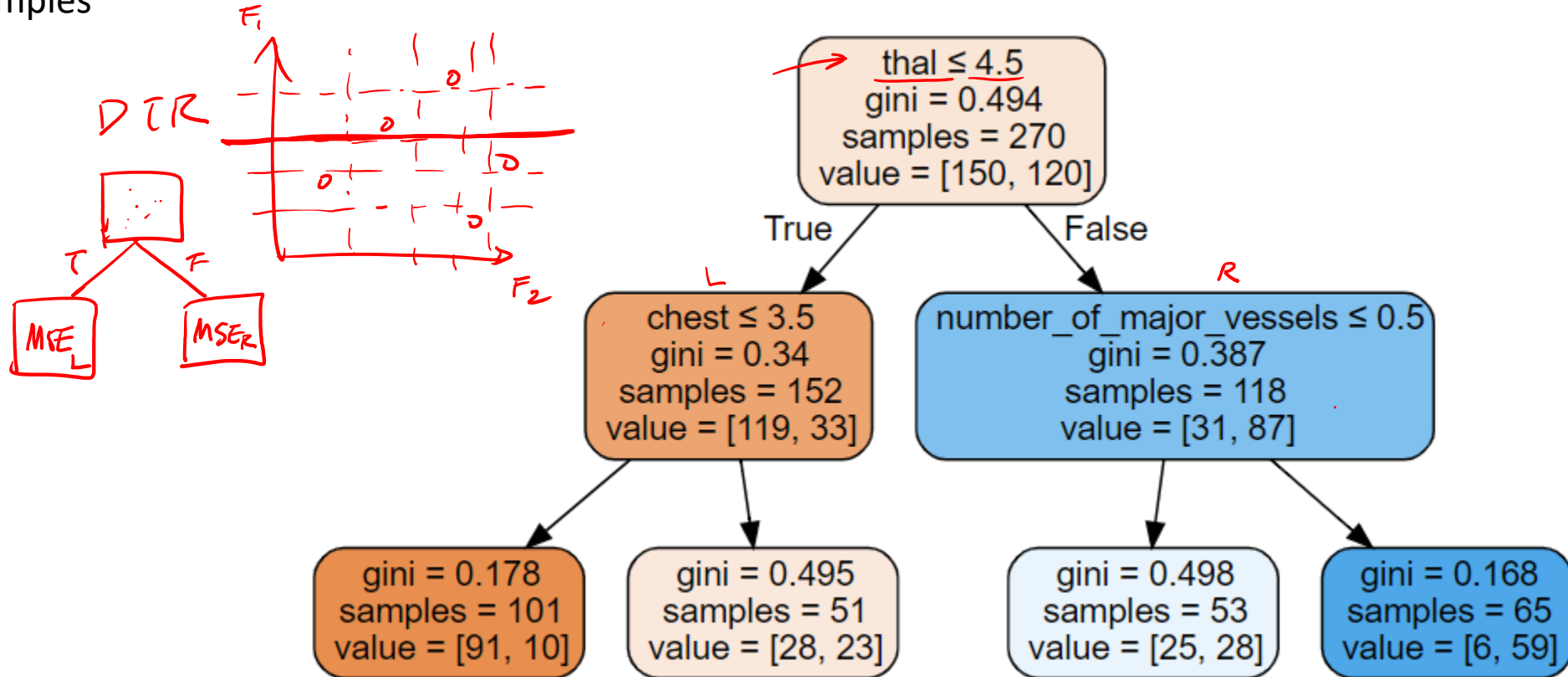


Decision Tree Classifier

Heart Dataset (statlog version)

13 features

270 samples



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

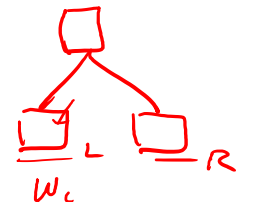
Gini

$$H(X_m) = \sum_k \underbrace{p_{mk}(1 - p_{mk})}_{\text{impurity}}$$

Entropy *uncertainty*

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

0, 1 50%.
80% 0
20% 1

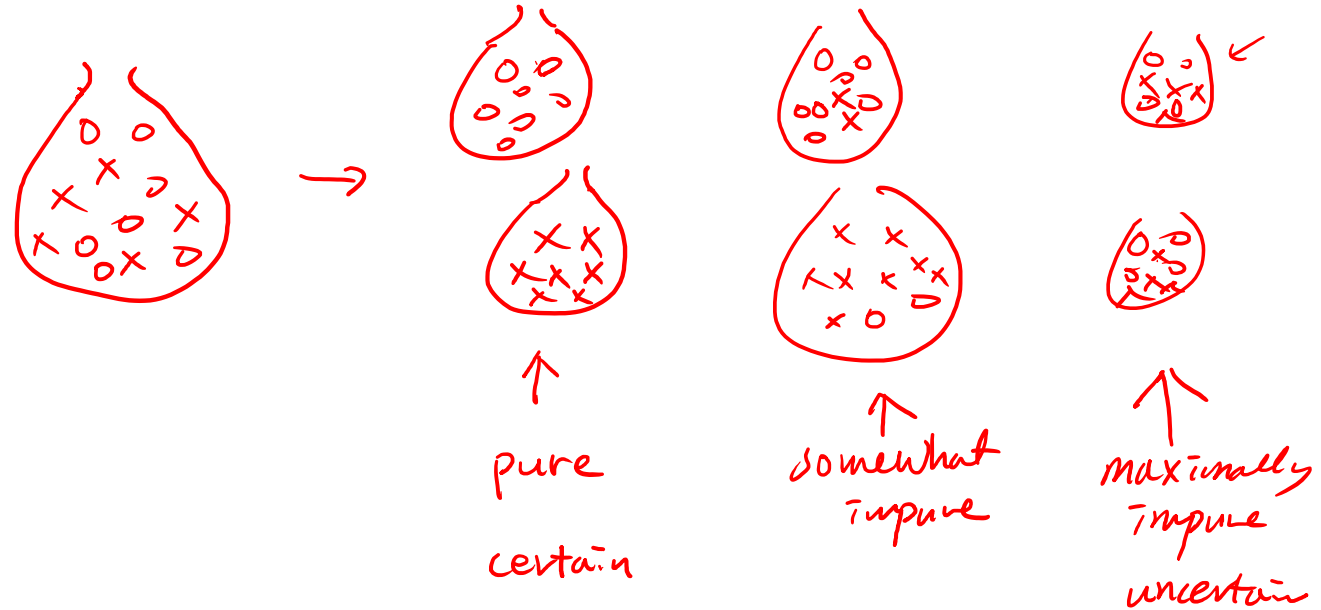


Information Gain = E(parent)-E(children)

Decision Tree Split Criteria

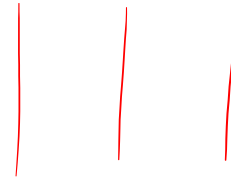
Gini

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



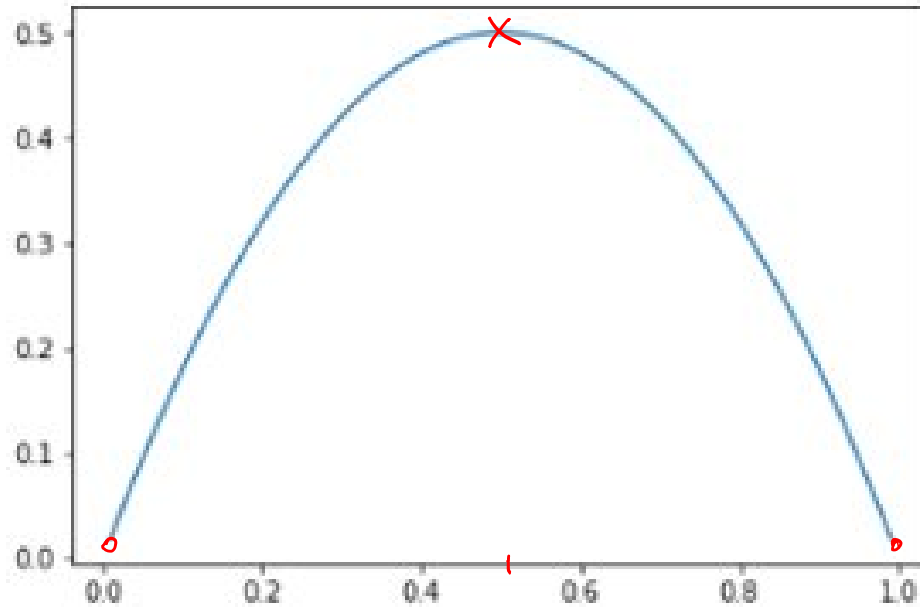
Entropy

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



Split criterion- Gini index

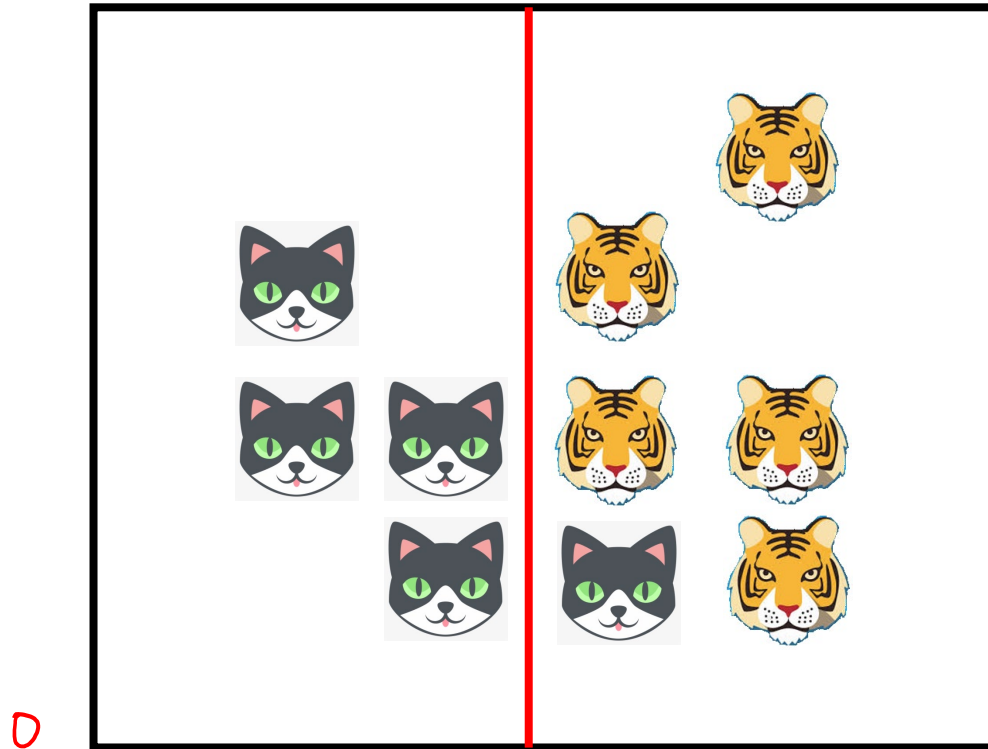
```
a = np.arange(0.01, 1, 0.01)  
plt.plot(a, 2*a*(1-a));
```



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

What is the Gini of this box?

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



0.5

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

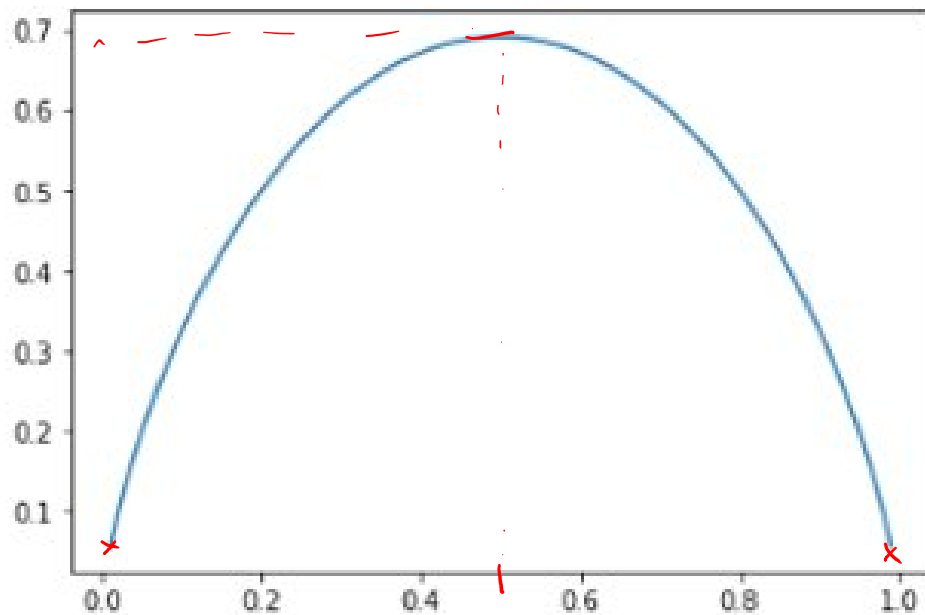
$$p_c = \frac{1}{6}$$

$$p_t = \frac{5}{6}$$

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

Split criterion- Entropy

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



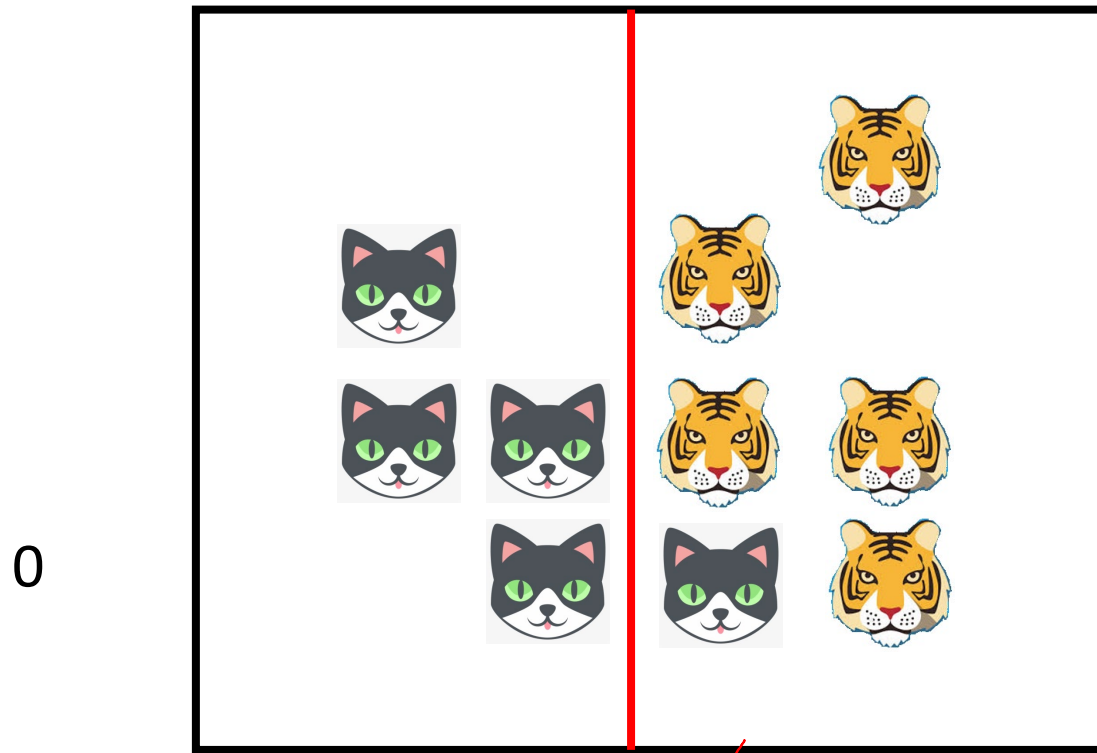
$$H(X_m) = - \sum_k p_{mk} \log(p_{mk})$$

log₂ log₁₀ log

Split criterion- Information gain

Information Gain = Reduction in Entropy

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

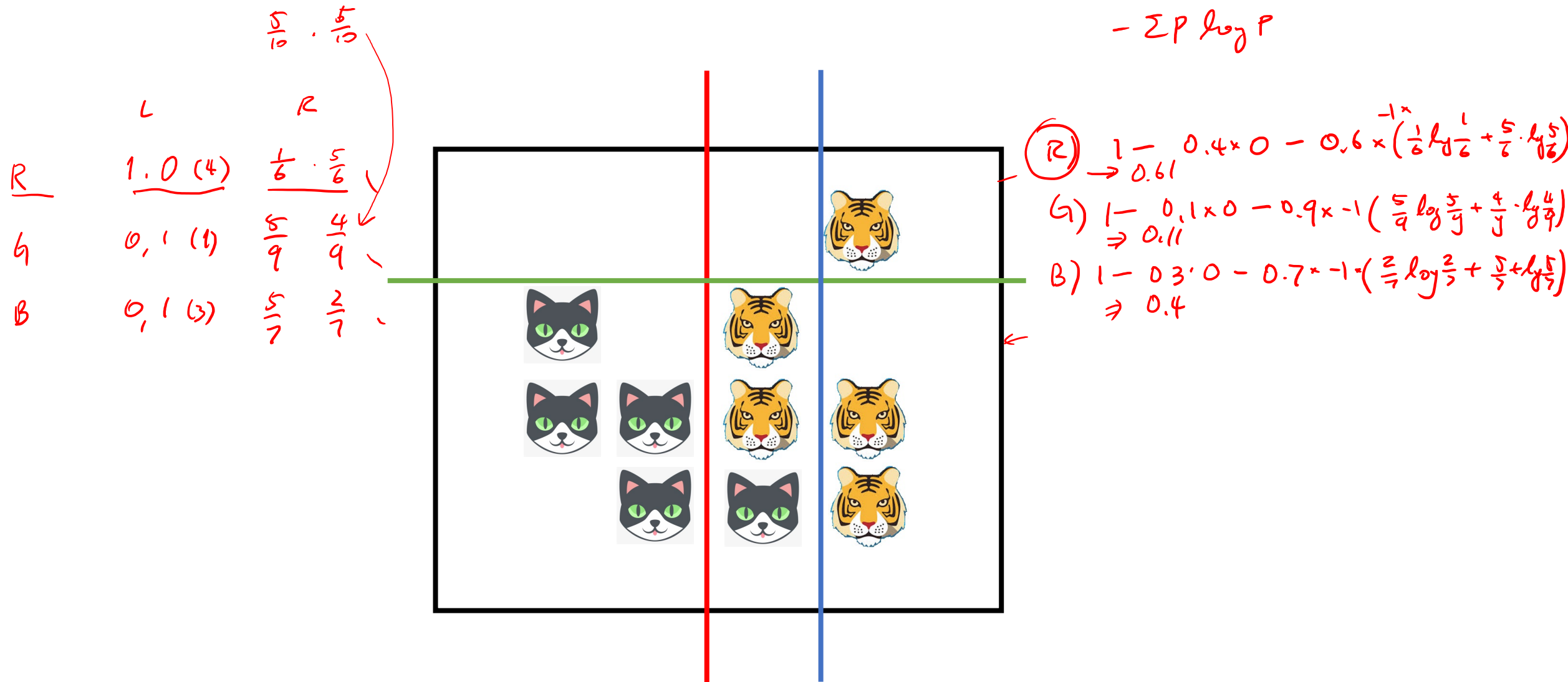


$$- \sum_i P_i \log P_i$$

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

$$\text{Information Gain} = 1 - 0.4 * 0 - 0.6 * 0.65 = 0.61$$

Which split gives the maximum information gain?



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Classification Tree

Gini

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

Entropy

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

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