Implementation

We select the best attribute at each node by computing its information gain, which is the decrease in entropy of the dataset after it has been split on that attribute.

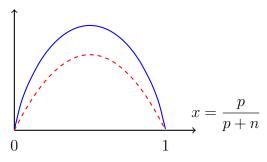
Gain(Attribute) =
$$I(p,n) - \left[\frac{p_0 + n_0}{p+n} I(p_0,n_0) + \frac{p_1 + n_1}{p+n} I(p_1,n_1)\right]$$

 $p = \text{Number of positive examples before split}$
 $n = \text{Number of negative examples before split}$
 $p_k = \text{Number of positive examples with attribute} = k$
 $n_k = \text{Number of negative examples with attribute} = k$
 $I(p,n) = -\frac{p}{p+n} \log \frac{p}{p+n} - \frac{n}{p+n} \log \frac{n}{p+n}$

We could have used another information metric such as the Gini impurity:

$$I(p,n) = \frac{p}{p+n} \left(1 - \frac{p}{p+n} \right) + \frac{n}{p+n} \left(1 - \frac{n}{p+n} \right)$$

which should give similar results to entropy since their graphs have a similar shape:



Entropy: $-x \log x - (1-x) \log(1-x)$

Gini: 2x(1-x)

To evaluate our decision tree, we performed cross validation as follows:

- 1. Shuffle the dataset and split it into K = 10 parts
- 2. For each $k \in \{1, \dots, K\}$ we train the decision tree on the dataset **excluding** part k and then test the decision tree on part k.

Evaluation

Confusion matrix:

	Anger	Disgust	Fear	Happiness	Sadness	Surprise
Anger						
Disgust						
Fear						
Happiness						
Sadness						
Surprise						

Precision

Recall

 F_1 score

Miscellaneous

 $Noisy ext{-}Clean\ Datasets\ Question$

The noisy dataset has lower performance.

 $Ambiguity\ Question$

 $Pruning\ Question$