Implementation

How do we select the best attribute at each node? For all attributes, we compute the information gain if the dataset is split on that attribute:

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

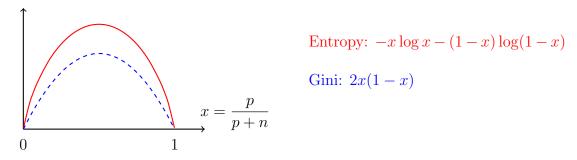
 p_k = Number of positive examples with attribute = k
 n_k = Number of negative examples with attribute = k
 $p = p_0 + p_1$ = Number of positive examples before split
 $n = n_0 + n_1$ = Number of negative examples before split

There are two common ways to measure information.

Entropy:
$$\mathcal{I}(p,n) = -\frac{p}{p+n} \log \frac{p}{p+n} - \frac{n}{p+n} \log \frac{n}{p+n} \quad \text{if } p,n \neq 0$$

$$\mathcal{I}(p,0) = \mathcal{I}(0,n) = 0$$
 Gini impurity:
$$\mathcal{I}(p,n) = \frac{p}{p+n} \left(1 - \frac{p}{p+n}\right) + \frac{n}{p+n} \left(1 - \frac{n}{p+n}\right)$$

We used entropy since it's stated in the specification, but Gini impurity is faster to compute. Both metrics should give similar results since their graphs have a similar shape:



When comparing their graphs, their relative heights do not matter because minimizing a function is equivalent to minimizing any positive multiple of that function.

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. During testing, the relevant cells in the confusion matrix are incremented.

Evaluation

Each cell of the confusion matrix is a total, not an average, over all folds of cross validation.

| Predicted | Actual | | | | | | | |
|-----------|--------|---------|------|-----------|---------|----------|--|--|
| | Anger | Disgust | Fear | Happiness | Sadness | Surprise | | |
| Anger | | | | | | | | |
| Disgust | | | | | | | | |
| Fear | | | | | | | | |
| Happiness | | | | | | | | |
| Sadness | | | | | | | | |
| Surprise | | | | | | | | |

From the confusion matrix above, we can compute these summary statistics:

| | Anger | Disgust | Fear | Happiness | Sadness | Surprise |
|-------------|-------|---------|------|-----------|---------|----------|
| Precision | | | | | | |
| Recall | | | | | | |
| F_1 score | | | | | | |

Miscellaneous

Noisy-Clean Datasets Question

The noisy dataset has lower performance.

 $Ambiguity\ Question$

In case our 6 trees predict that an image depicts more than 1 emotion, we considered the following methods of selecting 1 emotion:

- 1. Pick the first emotion in alphabetical order This is effectively selecting an emotion at random.
- 2. Disable each active unit in turn, and take a majority vote Example:

Pruning Question