

# Classification: Loss function

It would be natural to expect the Average Loss to be Accuracy (fraction of correct predictions).

On a per example basis, the corresponding loss  $\mathcal{L}^{(i)}$  would be either 1 or 0, depending on correctness.

This is not the case.

Recall the mapping of probability to prediction

$$\hat{\mathbf{y}}^{(i)} = \begin{cases} \text{Negative} & \text{if } \hat{p}^{(i)} < 0.5 \\ \text{Positive} & \text{if } \hat{p}^{(i)} \geq 0.5 \end{cases}$$

The prediction for example  $i$  changes only when probability  $\hat{p}^{(i)}$  crosses the threshold.

Suppose the class for example  $i$  is Positive:  $\mathbf{y}^{(i)} = \text{Positive}$ .

- Is our model "better" when  
 $\hat{p}^{(i)} \approx 1$  than when  $\hat{p}^{(i)} = 0.5$   
 $\hat{p}^{(i)} = (.5 - \epsilon)$  than when  $\hat{p}^{(i)} \approx 0$

- The per-example Accuracy is the same in both comparisons
- But a model with probability  $\hat{p}^{(i)}$  closer to 1 for a Positive example  $i$  would seem to better

There is no *degree* or magnitude of inaccuracy

- Two models may have the same Accuracy even though the probabilities of one may be closer to perfect than the other
- In our search for the best  $\Theta$ , Accuracy won't be a guide

In mathematical terms: we want our Loss function be be continuous and differentiable.

Accuracy (and the per-example analog) satisfies neither.

We will introduce Binary Cross Entropy loss to overcome this difficulty.

Think of Binary Cross Entropy as a continuous analog of Accuracy.

# Binary Cross Entropy

Let's encode the Positive labels  $y^{(i)}$  with the number 1 and Negative labels with the number 0. The loss for example  $i$  will be defined as 
$$\text{loss}^{ip}_{\Theta} = \begin{cases}$$

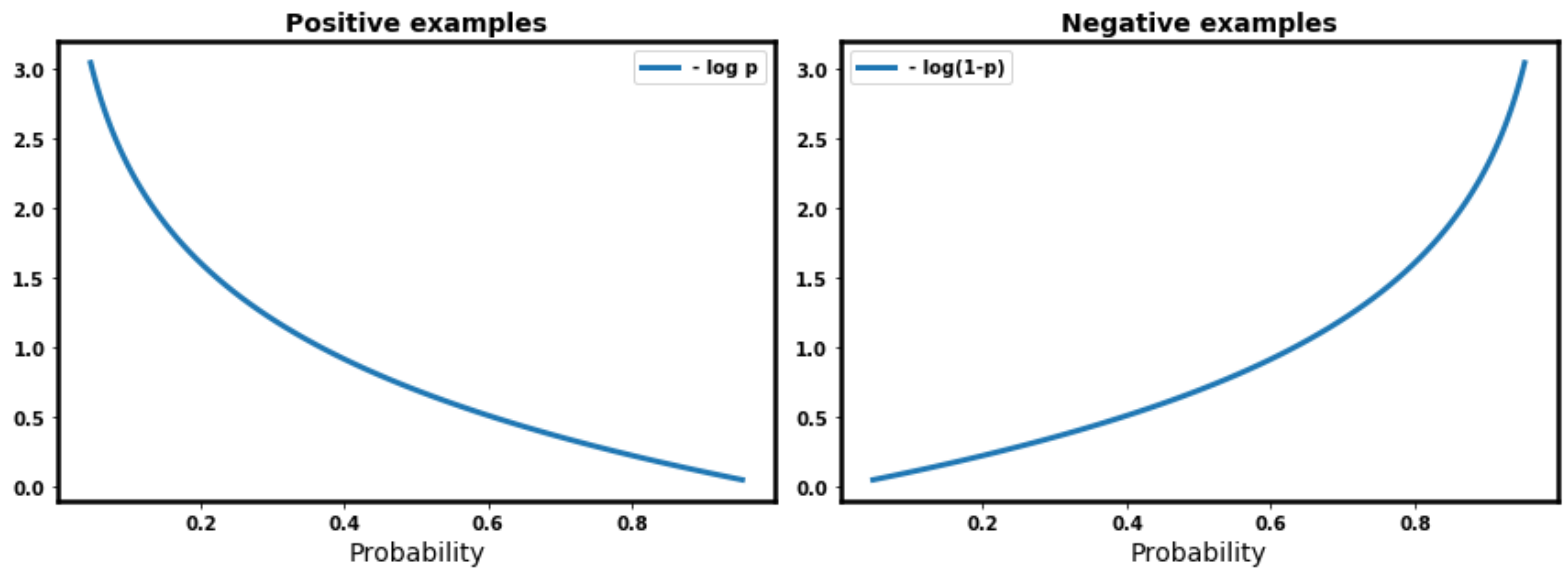
- $\log(\hat{p})$  &  $\text{if } y^{ip} = 1$
- $\log(1-\hat{p})$  &  $\text{if } y^{ip} = 0$   $\end{cases}$

Note the negative signs:

- The term being negated is a Utility (which we want to maximize)

A plot will give us some intuition.

```
In [4]: svmh.plot_log_p(x_axis="Probability")
```



- For Positive examples: the loss approaches 0 as the predicted probability approaches the correct value (1).
- For Negative examples: the loss approaches 0 as the predicted probability approaches the correct value (0).

In a Deep Dive (after the introduction of a bit of math) we will gain a greater appreciation it's meaning.

For now: be content that Binary Cross Entropy seems to have the right slope and asymptotic behavior.



Because only one of  $\mathbf{y}^{(i)}$  and  $(1 - \mathbf{y}^{(i)})$  is non zero, we can re-write the two-case statement into a single expression

$$\mathcal{L}_{\Theta}^{(i)} = - \left( \mathbf{y}^{(i)} * \log(\hat{p}^{(i)}) + (1 - \mathbf{y}^{(i)}) * \log(1 - \hat{p}^{(i)}) \right)$$

This expression is referred to as *Binary Cross Entropy*; it and the multi-class version will become quite familiar going forward.

The Loss for the entire training set is simply the average (across examples) of the Loss for the example

$$\mathcal{L}_{\Theta} = \frac{1}{m} \sum_{i=1}^m \mathcal{L}_{\Theta}^{(i)}$$

# Loss function for Multinomial Classification: Cross Entropy

A Multinomial Classifier (when categories/classes  $||C|| > 2$ ) can be created from multiple Binary Classifiers

- Create a separate Binary Classifier for each  $c \in C$
- The classifier for category  $c$  attempts to classify
  - Each example with target category of  $c$  as Positive
  - All other examples as Negative
- Combine the  $||C||$  classifiers to produce a vector  $\hat{p}$  of length  $||C||$ 
  - normalize across  $c \in C$  to sum to 1
  - $\hat{p}_c$  denotes the normalized value for category  $c$ 
    - **Notation abuse:** subscripts should be integers, not categories

Both the target  $\mathbf{y}$  and the prediction  $\hat{\mathbf{p}}$  are represented as vectors of length  $||C||$

- We write  $\mathbf{y}_c, \hat{p}_c$  to denote the element of the vector corresponding to category  $c$
- Each vector can be interpreted as a probability distribution, e.g.

$$\forall c \in C : \mathbf{y}_c \geq 0$$

$$\sum_{c \in C} \mathbf{y}_c = 1$$

- $\mathbf{y}$  was created with One Hot Encoding (OHE), so properties satisfied by construction
- $\hat{p}_c$  satisfies the properties by virtue of the normalization of the predictions of the  $||C||$  binary classifiers

With  $\mathbf{y}, \hat{\mathbf{p}}$  encoded as vectors, per example Binary Cross Entropy can be generalized to  $\|C\| \geq 2$  categories:

$$\mathcal{L}_{\Theta}^{(i)} = - \sum_{c=1}^{\|C\|} \left( \mathbf{y}_c^{(i)} * \log(\hat{\mathbf{p}}_c^{(i)}) \right)$$

This is the multinomial analog of Binary Cross Entropy and is called **Cross Entropy**.

Cross Entropy can be interpreted as a measure of the "distance" between distributions  $\mathbf{y}$  and  $\hat{p}$

- Minimized when they are identical
- We will use Cross Entropy in the future both as a Loss function and a way of comparing probability distributions

In [5]: `print("Done")`

Done