1 Exercise 1

1.1 Cross Entropy

$$H(y,g) = -(0 * log(0.25) + 1 * log(0.6) + 0 * log(0.15)) = 0.222$$

1.2 Mean Squared Error Loss

$$MSE(y,g) = \frac{1}{3}(0.25^2 + (-0.4)^2 + 0.15^2) = 0.0817$$

1.3 Hinge Loss

$$SVM(y,j) = max(0, 0.25 - 0.6 + 1) + max(0, 0.15 - 0.6 + 1) = 1.2$$

2 Task A

2.1 Accuracy

$$ACC = \frac{TP + TN}{P + N}$$

, high accuracy of predicting predominant class is easily achieved and misleading. If we have highly unbalanced data the problem of accuracy as a metric is quite apparent: Let's consider an example with medical data: normally only a few patients have a certain disease. If our dataset consists of 200 patients, of which only 8 have cancer, than a classifier which predicts that no patient has cancer would yield 96 percent accuracy; this prediction however would be deadly for the patients. If we also consider false negatives, than we see that in every case of a cancer patient, the classifier predicted no cancer and thus false negatives are 100 percent.The ability to capture misclassifications in a satisfying way is what is lacking in the accuracy metric.

In a multi-class setting, exact matching does not distinguish between partially correct and completely incorrect labelling. The denominator, **P+N** which is equivalent to number of samples(N) is constant. It is thus sensitive to only how many labels correctly identified with respect to N

For a single class C Precision, Recall and $F1$ are defined as follows:

$$F1_c = \frac{2|Precision_c \times Recall_c|}{|Recall_c| + |Precision_c|}$$

The harmonic mean of $Precision_c = \frac{|T_c \cap P_c|}{|T_c|}$ and $Recall_c = \frac{|T_c \cap P_c|}{|P_c|}$

$$Jacc_c = \frac{|T_c \cap P_c|}{|T_c \cup P_c|}$$

which can e rewritten as

$$Jacc_c = \frac{|T_c \cap P_c|}{|P_c| + |T_c| - |T_c \cap P_c|}$$

$$Jacc_c \leq F1_c$$

Jaccard's metric penalizes bad classification more than the F score "https://stats.stackexchange.com/questions/ dice-score-vs-iou"

2.2 Task B

GT Class	#	Freq
B	4	
T	4	
D	4	
C	0	

$Prescision = \frac{1}{n}\sum_{i=1}^{n} \frac{tp}{tp+fp}$ $Recall = \frac{1}{n}\sum_{i=1}^{n} \frac{tp}{tp+fn}$ $Accuracy = \frac{1}{n}\sum_{i=1}^{n} \frac{tp}{tp+tn+fp+fn}$
$J_{acc} = \frac{1}{n}\sum_{i=1}^{n} \frac{tp}{tp+fp+fn}$

Confusion Matrix

$$\text{B}\ \begin{array}{c|c} 2 & 3 \\ \hline 1 & 2 \end{array}\ \text{T}\ \begin{array}{c|c} 3 & 2 \\ \hline 2 & 1 \end{array}\ \text{D}\ \begin{array}{c|c} 1 & 2 \\ \hline 2 & 3 \end{array}\ \text{C}\ \begin{array}{c|c} 0 & 6 \\ \hline 2 & 0 \end{array}$$

	Accuracy	Precision	Recall	Jacc	F1
B	$\frac{5}{8} = 0.63$	$\frac{2}{3} = 0.67$	$\frac{2}{4} = 0.5$	$\frac{2}{5} = 0.4$	$\frac{4}{7}$
T	$\frac{5}{8} = 0.63$	$\frac{3}{5} = 0.6$	$\frac{3}{4} = 0.75$	$\frac{3}{6} = 0.5$	$\frac{2}{3}$
D	$\frac{1}{8} = 0.13$	$\frac{1}{3} = 0.33$	$\frac{1}{4} = 0.25$	$\frac{1}{6} = 0.17$	$\frac{2}{7}$
C	$\frac{0}{8} = 0$	$\frac{0}{2} = 0$	$\frac{0}{2} = 0$	$\frac{0}{2} = 0$	$2\frac{0}{0} = 0$
AvgF					
AvgC					

Mean Computations
class balance:

$$Jacc_{cb} = \frac{1}{4}(0.4 + 0.5 + 0.17 + 0) = 0.27$$

$$Precision_{cb} = \frac{1}{n}\sum_{i=1}^{n} \frac{|T_i \cap P_i|}{|T_i|} = \frac{1}{2}\left(\frac{1}{3} + \frac{4}{7}\right) = 0.4\overline{523809}$$

$$Recall_{cb} = \frac{1}{n}\sum_{i=1}^{n} \frac{|T_i \cap P_i|}{|P_i|} = \frac{1}{2}\left(\frac{1}{2} + \frac{1}{2}\right) = 0.5$$

$$F1_{cb} = \frac{1}{n}\sum_{i=1}^{n} \frac{2|T_i \cap P_i|}{|P_i| + |T_i|} = \frac{1}{3}\left(\frac{4}{7} + \frac{2}{3} + \frac{2}{7}\right) = \frac{32}{63}$$

class frequency:

Because we only have two classes and both have a freq of 0.5 the results are the same as with the class balance.

exact match:

$$ExMatch = \frac{\#correctInstances}{\#instances} = \frac{2}{8} = 0.25$$

Questions

1. Intuitively the Exact Match would be the strictest metric possible. However,it might not be the lowest number: how come?
Because the absolute values of these metrics are not comparable. A value of 1 in the jaccard metric does not mean the same as a $F1$ value of 1

2. Can you compute the global accuracy on this example? Justify your answer.

3. What is the main issue going from multi-class to multi-label setting?
In a multi-class setting a prediction is either correct of not. In a multi-label setting we can have partially correct labels. Under these conditions we need different definition for the metrics.