Performance Metrics

Regression

- Mean squared error
- Mean absolute error

Classification

- Accuracy
- Confusion matrix
- Precision
- Recall
- Specificity
- F-measure

Performance metrics for regression

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$$

Mean squared error

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right|$$

Mean absolute error

Accuracy

- Fraction (or percentage) of correct predictions made by a classifier
- Equivalently, probability that a prediction will be correct

acc = correct predictions/total predictions

= 1 - incorrect predictions/total predictions

Advantage:

It can be used for two-class (positive and negative) and multiple class problems

Disadvantage:

Uninformative when classes are unbalanced. Always predicting the majority class yields high accuracy but it's meaningless

Confusion Matrix
2D array of counters describing the behavior of a classifier

Confusion matrix for a classifier on the MNIST dataset

Let c be the confusion matrix

c[i,j] = number of examples of class i classified as class j

Accuracy is given by:

sum(diagonal(c)) / sum(c)

		Predicted Labels									
		0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
	0	987	1	2	0	0	0	2	0	7	1
	1	0	977	7	2	3	2	0	2	6	1
	2	2	3	976	4	4	0	1	4	6	0
	3	0	1	18	951	0	14	0	3	9	4
True Labels	**4**	0	1	2	0	979	0	2	0	3	13
	5	3	0	3	9	5	968	2	0	5	5
	6	1	3	2	0	0	7	982	0	5	0
	7	3	4	3	0	13	0	0	969	0	8
	8	2	6	4	7	3	5	2	3	966	2
	9	1	1	2	6	12	2	0	8	5	963

Confusion Matrix for binary classification (positive vs. negative)

		Prediction	
		0	1
Actual	0	TN	FP
	1	FN	TP

$$
\begin{aligned}
precision &= \frac{TP}{TP + FP} \\
recall &= \frac{TP}{TP + FN} \\
F1 &= \frac{2 \times precision \times recall}{precision + recall} \\
accuracy &= \frac{TP + TN}{TP + FN + TN + FP} \\
specificity &= \frac{TN}{TN + FP}
\end{aligned}
$$

Quiz

Write functions to compute the following performance metrics on the MNIST dataset

- Accuracy
- Confusion matrix
- Precision
- Recall