Confusion Matrix

	p' (Predicted)	n' (Predicted)
p (Actual)	True Positive	False Negative
n (Actual)	False Positive	True Negative

Figure:

The Confusion Matrix

The confusion matrix indicates that there were four true negative predictions, three true positive predictions, two false negative predictions, and one false positive prediction. Confusion matrices become more useful in multi-class problems, in which it can be difficult to determine the most frequent types of errors.

Accuracy
Accuracy measures a fraction of the classifier's predictions that are correct.

Accuracy

- However, accuracy is not an informative metric if the proportions of the classes are skewed in the population.
- For example, a classifier that predicts whether or not credit card transactions are fraudulent may be more sensitive to false negatives than to false positives.
- To promote customer satisfaction, the credit card company may prefer to risk verifying legitimate transactions than risk ignoring a fraudulent transaction.

Accuracy

- Because most transactions are legitimate, accuracy is not an appropriate metric for this problem.
- A classifier that always predicts that transactions are legitimate could have a high accuracy score, but would not be useful.
- For these reasons, classifiers are often evaluated using two additional measures called precision and recall.

Precision and Recall

- Recall from Chapter 1, The Fundamentals of Machine Learning, that precision is the fraction of positive predictions that are correct.
- For instance, in our SMS spam classifier, precision is the fraction of messages classified as spam that are actually spam.
- Precision is given by the following ratio:

$$P = \frac{TP}{TP + FP}$$

Recall

- called sensitivity in medical domains, recall is the fraction of the truly positive instances that the classifier recognizes. A recall score of one indicates that the classifier did not make any false negative predictions.
- For our SMS spam classifier, recall is the fraction of spam messages that were truly classified as spam. Recall is calculated with the following ratio:

$$\text{Recall} = \frac{tp}{tp + fn}$$

Precision and Recall

- Individually, precision and recall are seldom informative; they are both incomplete views of a classifier's performance.
- Both precision and recall can fail to distinguish classifiers that perform well from certain types of classifiers that perform poorly.
- A trivial classifier could easily achieve a perfect recall score by predicting positive for every instance.

Precision and Recall

- For example, assume that a test set contains ten positive examples and ten negative examples.
- A classifier that predicts positive for every example will achieve a recall of one, as follows:

$$10 \quad 1 \quad 10 \quad 0 \quad R = = +$$

- A classifier that predicts negative for every example, or that makes only false positive and true negative predictions, will achieve a recall score of zero.
- Similarly, a classifier that predicts that only a single instance is positive and happens to be correct will achieve perfect precision.