Name	Formula	Direction	Range	Description
Performance measures for regression				
Mean Squared Error (MSE)	$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \left( y^{(i)} - \hat{y}^{(i)} \right)^2$	min	$[0,\infty)$	Mean of the squared distances between the target variable $y$ and the predicted target $\hat{y}$ .
Mean Absolute Error (MAE)	$rac{1}{n_{ ext{test}}}\sum_{i=1}^{n_{ ext{test}}}\left y^{(i)}-\hat{y}^{(i)} ight $	min	$[0,\infty)$	More robust than MSE, since it is less influenced by large errors.
$R^2$	$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \left  y^{(i)} - \hat{y}^{(i)} \right  \\ 1 - \frac{\sum_{i=1}^{n_{\text{test}}} \left( y^{(i)} - \hat{y}^{(i)} \right)^2}{\sum_{i=1}^{n_{\text{test}}} \left( y^{(i)} - \bar{y} \right)^2}$	max	$(-\infty,1]$	Compare the sum of squared errors (SSE) of the model to a constant baseline model.
Performance measures for classification based on class labels				
Accuracy (ACC)	$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \mathbb{I}_{\left\{y^{(i)} = \hat{y}^{(i)}\right\}}$	max	[0, 1]	Proportion of correctly classified observations.
Balanced Accuracy (BA)	$\frac{1}{g} \sum_{k=1}^{g} \frac{1}{n_{\text{test } k}} \sum_{y^{(i)}: y^{(i)} = k} \mathbb{I}_{\{y^{(i)} = \hat{y}^{(i)}\}}$	$\max$	[0, 1]	Variant of the accuracy that accounts for imbalanced classes.
Classification Error (CE)	$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \mathbb{I}_{\left\{y^{(i)} \neq \hat{y}^{(i)}\right\}}$	min	[0, 1]	CE = 1 - ACC is the proportion of incorrect predictions.
ROC measures	$\begin{array}{l} \underset{t \in \operatorname{sg}}{\operatorname{trest}} g = 1 & \left\{ y^{(i)} - y^{(i)} \right\} \\ \frac{1}{g} \sum_{k=1}^{g} \frac{1}{n_{\operatorname{test},k}} \sum_{y^{(i)}:y^{(i)} = k} \mathbb{I}_{\left\{y^{(i)} = \hat{y}^{(i)}\right\}} \\ \frac{1}{n_{\operatorname{test}}} \sum_{i=1}^{n_{\operatorname{test}}} \mathbb{I}_{\left\{y^{(i)} \neq \hat{y}^{(i)}\right\}} \\ \operatorname{TPR} = \frac{\operatorname{TP}}{\operatorname{TP+FN}} \end{array}$	max	[0, 1]	True Positive Rate: how many observations of the positive class 1 are predicted as 1?
	$FPR = \frac{FP}{TN + FP}$	min	[0, 1]	False Positive Rate: how many observations of the negative class 0 are falsely predicted as 1?
	$TNR = \frac{TN}{TN + FP}$	max	[0, 1]	True Negative Rate: how many observations of the negative class 0 are predicted as 0?
	$FNR = \frac{FN}{TP + FN}$	min	[0, 1]	False Negative Rate: how many observations of the positive class 1 were falsely predicted as 0?
	$egin{aligned}  ext{PPV} &= rac{ ext{TP}}{ ext{TP} +  ext{FP}} \  ext{NPV} &= rac{ ext{TN}}{ ext{FN} +  ext{TN}} \ 2rac{ ext{PPV-TPR}}{ ext{PPV+TPR}} \end{aligned}$	max	[0, 1]	Positive Predictive Value: how likely is a predicted 1 a true 1?
	$NPV = \frac{TN}{FN + TN}$	$\max$	[0, 1]	Negative Predictive Value: how likely is a predicted 0 a true 0?
$F_1$	$2\frac{\text{PPV-TPR}}{\text{PPV+TPR}}$	max	[0, 1]	$F_1$ is the harmonic mean of PPV and TPR. Especially useful for imbalanced classes.
Cost measure	$\sum_{i=1}^{n_{\text{test}}} C(y^{(i)}, \hat{y}^{(i)})$	min	$[0,\infty)$	Cost of incorrect predictions based on a (usually non-negative) cost matrix $C \in \mathbb{R}^{g,g}$ .
Performance measures for classification based on class probabilities				
Brier Score (BS)	$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \sum_{k=1}^{g} \left( \hat{\pi}_k(\mathbf{x}^{(i)}) - \sigma_k(y^{(i)}) \right)^2$	min	[0, 1]	Measures squared distances of probabilities from the one-hot encoded class labels.
Log-Loss (LL)	$\frac{1}{n_{\text{test}}} \sum_{i=1}^{n_{\text{test}}} \left( -\sum_{k=1}^{g} \sigma_k(y^{(i)}) \log(\hat{\pi}_k(\mathbf{x}^{(i)})) \right)$	min	$[0,\infty)$	A.k.a. Bernoulli, binomial or cross-entropy loss
AUC	, and the second of the second	max	[0,1]	Area under the ROC curve.

 $<sup>\</sup>hat{y}^{(i)}$  denotes the predicted label for observation  $\mathbf{x}^{(i)}$ . ACC, BA, CE, BS, and LL can be used for multi-class classification with g classes. For AUC, multiclass extensions exist as well. The notation  $\mathbb{I}_{\{\cdot\}}$  denotes the indicator function.  $\sigma_k(y) = \mathbb{I}_{\{y=k\}}$  is 1 if y is class k, 0 otherwise (multi-class one-hot encoding).  $n_{\text{test},k}$  is the number of observations in the test set with class k.  $\hat{\pi}_k(\mathbf{x})$  is the estimated probability for observation  $\mathbf{x}^{(i)}$  of belonging to class k. TP is the number of true positives (observations of class 1 with predicted class 1), FP is the number of false positives (observations of class 0 with predicted class 1), TN is the number of true negatives (observations of class 0 with predicted class 0), and FN is the number of false negatives (observations of class 1 with predicted class 0).

Table 1: Popular performance measures used for ML, assuming an arbitrary test set of size  $n_{\text{test}}$ .