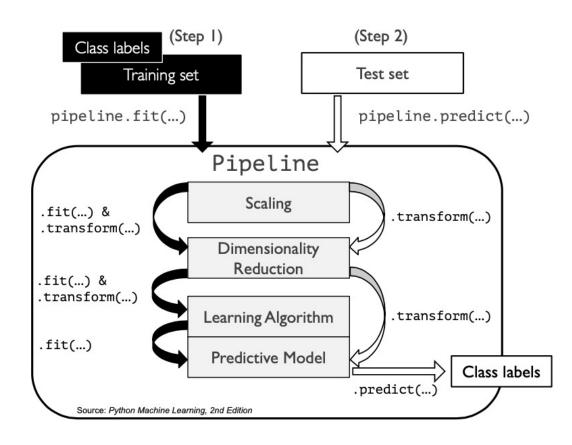
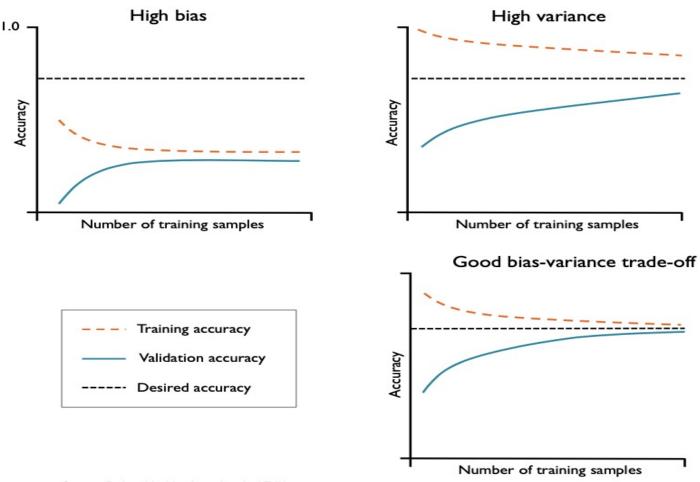
Model Evaluation

Model Evaluation



Bias – Variance Trade-off



Source: Python Machine Learning, 2nd Edition

2x2 Confusion Matrix

Predicted class

$$\begin{array}{c|c} P & N \\ \hline True & False \\ Positives & (FN) \\ \hline \textbf{Actual} & \\ \textbf{Class} & False \\ N & Positives \\ (FP) & True \\ Negatives \\ Negatives \\ (TN) & \\ \end{array}$$

$$ERR = \frac{FP + FN}{FP + FN + TP + TN} = 1 - ACC \tag{1}$$

$$ACC = \frac{TP + TN}{FP + FN + TP + TN} = 1 - ERR \tag{2}$$

Confusion Matrix for Multi-Class Settings

Predicted Labels

		Class 0	Class 1	Class 2
True Labels	Class 0	T(0,0)		
	Class 1		T(1,1)	
	Class 2			T(2,2)

Confusions matrices are traditionally for binary class problems but we can easily generalize it to multi-class settings

False Positive Rate and False Negative Rate

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN} \tag{3}$$

$$TPR = \frac{TP}{P} = \frac{TP}{FN + TP} \tag{4}$$

Precision, Recall, and F1 Score

$$PRE = \frac{TP}{TP + FP} \tag{5}$$

$$REC = TPR = \frac{TP}{P} = \frac{TP}{FN + TP} \tag{6}$$

$$F_1 = 2 \cdot \frac{PRE \cdot REC}{PRE + REC} \tag{7}$$

Sensitivity and Specificity

$$SEN = TPR = REC = \frac{TP}{P} = \frac{TP}{FN + TP}$$
 (8)

$$SPC = TNR = \frac{TN}{N} = \frac{TN}{FP + TN} \tag{9}$$

Sensitivity measures the recovery rate of the Positives and complimentary, the Specificity measures the recovery rate of the Negatives.

Balanced Accuracy / Average Per-Class Accuracy

Predicted Labels

Class 0 Class 1 Class 2

Class 0 T(0,0)

Class 1 T(1,1)

Class 2

 $ACC = \frac{T}{n}$

True Labels

Predicted Labels

		Class 0	Class 1	Class 2
Labels	Class 0	3	0	0
an I	Class 1	7	50	12
	Class 2	0	0	18

$$ACC = \frac{3 + 50 + 18}{90} \approx 0.79$$

$$APCACC = \frac{83/90 + 71/90 + 78/90}{3} \approx 0.86$$

Balanced Accuracy / Average Per-Class Accuracy

Predicted Labels

True Labels

	Class 0	Neg Class	
Class 0	3	0	
Neg Class	7	80	

Predicted Labels

rue Labels

	Class 1	Neg Class
Class 1	50	19
Neg Class	0	21

Predicted Labels

True Labels

	Class 2	Neg Class
Class 2	18	0
Neg Class	12	60

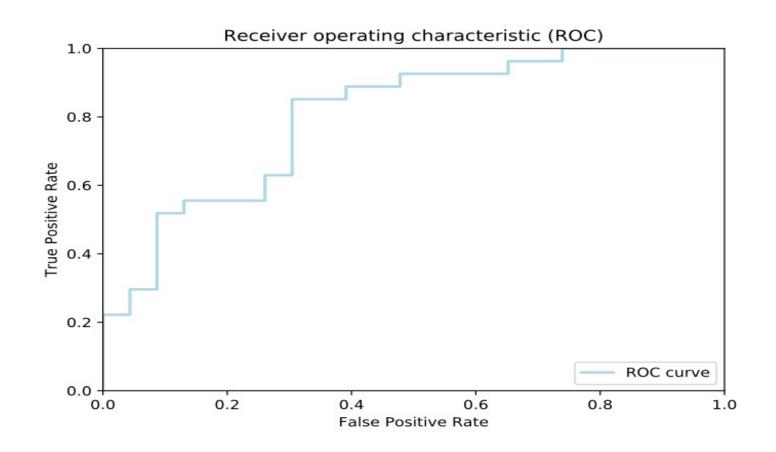
Predicted Labels

	Class 0	Class 1	Class 2
Class 0	3	0	0
Class 1	7	50	12
Class 2	0	0	18
	Class 1	Class 0 3 Class 1 7	Class 1 7 50

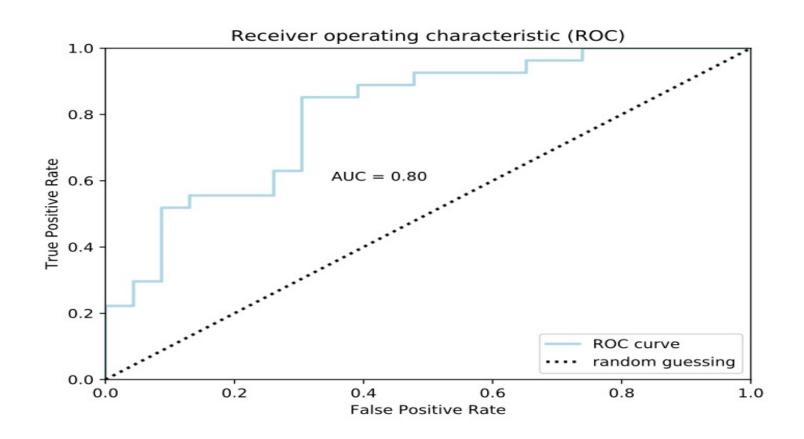
$$APC\ ACC = \frac{83/90 + 71/90 + 78/90}{3} \approx 0.86$$

Receiver Operating Characteristic curve (ROC curve)

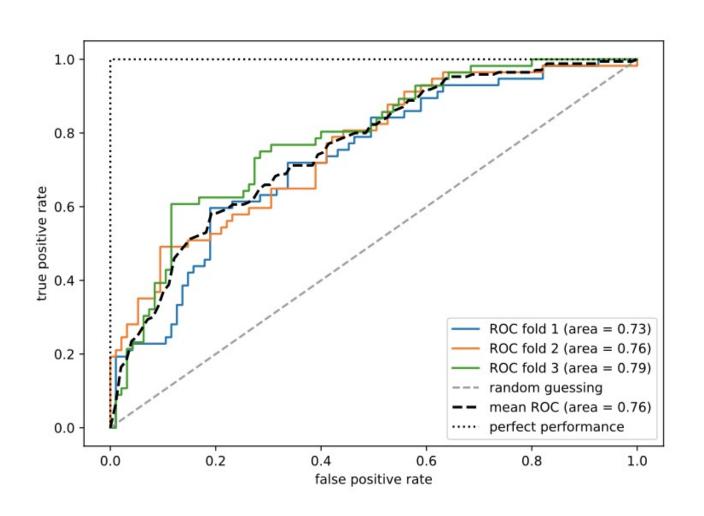
- Trade-off between True Positive Rate and False Positive Rate
- ROC can be plotted by changing the prediction threshold
- ROC term comes from "Radar Receiver Operators" (analysis of radar [RAdio Direction And Ranging] images)



ROC Area Under the Curve (AUC)



ROC and k-Fold Cross-Validation



Macro and Micro Averaging

$$PRE_{micro} = \frac{TP_1 + \dots + TP_c}{TP_1 + \dots + TP_c + FP_1 + \dots + FP_c}$$

$$PRE_{macro} = \frac{PRE_1 + \dots + PRE_c}{c}$$

Micro-averaging is useful if we want to weight each instance or prediction equally, whereas macro-averaging weights all classes equally to evaluate the overall performance of a classifier with regard to the most frequent class labels.