

Measuring Performance in Classification Models

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Reading Materials

- ▶ Max Kuhn. Chapter 11.

Two outcomes of classification models

- ▶ Predicted Probabilities
- ▶ Class Prediction

Examples

- ▶ Predicting if a passenger in the titanic is survived or not survived
- ▶ The outcome could look like this.

ID	Prob. of Survived	Prediction
1	0.55	Survived
2	0.2	Not Survived
3	0.94	Survived
4	0.63	Survived
5	0.9	Survived
6	0.35	Not Survived
7	0.84	Survived
8	0.38	Not Survived
9	0.01	Not Survived
10	0.68	Survived
11	0.71	Survived
12	0.45	Not Survived





Examples

- ▶ Notice that this model predicts “Survived” for passengers with the probabilities of being greater than 0.5
- ▶ 0.5 is called **cut-off value**.
- ▶ The cut-off value is set by 0.5 by default.
- ▶ The cut-off value can be changed by the modeler.

Confusion Matrices

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

Confusion Matrices

		Actual Values	
		1	0
Predicted Values	1	TRUE POSITIVE  TYPE 1 ERROR	FALSE POSITIVE  TYPE 1 ERROR
	0	FALSE NEGATIVE  TYPE 2 ERROR	TRUE NEGATIVE 

Confusion Matrices - Example

- ▶ “Survived” = “**Positive**”
- ▶ “Not Survived” = “**Negative**”

ID	Prob. of Survived	Prediction	Truth	Evaluation
1	0.55	Survived	Survived	TP
2	0.2	Not Survived	Survived	FN
3	0.94	Survived	Survived	TP
4	0.63	Survived	Not Survived	FP
5	0.9	Survived	Survived	TP
6	0.35	Not Survived	Not Survived	TN
7	0.84	Survived	Not Survived	FP
8	0.38	Not Survived	Not Survived	TN
9	0.01	Not Survived	Not Survived	TN
10	0.68	Survived	Survived	TP
11	0.71	Survived	Survived	TP
12	0.45	Not Survived	Survived	FN

Confusion Matrices

	Predicted Positive	Predicted Negative
Actual Positive	5	2
Actual Negative	2	3

Model evaluation from Confusion Matrices

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$\text{Misclassification Rate} = \frac{FN + FP}{\text{Total}} = \frac{FN + FP}{TN + TP + FN + FP}$$

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP}$$

$$\text{Sensitivity} = \frac{TP}{\text{Actual Positive}} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{\text{Actual Negative}} = \frac{TN}{TN + FP}$$

Model evaluation from Confusion Matrices

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN)
Actual Negative	False Positive (FP)	True Negative (TN)

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} = \frac{2TP}{2TP + FN + FP}$$

Confusion Matrices

	Predicted Positive	Predicted Negative
Actual Positive	TP = 5	FN = 2
Actual Negative	FP = 2	TN = 3

$$\text{Misclassification Rate} = 4/12$$

$$\text{Accuracy} = 8/12$$

$$\text{Sensitivity} = 5/7$$

$$\text{Specificity} = 3/5$$

$$\text{Precision} = 5/7; \text{F1-Score} = 5/7$$

ROC Curves

- ▶ Notice that all of the measures calculated in the last slide are based on the **cut-off 0.5**
- ▶ What if we change the cut-off value, **c** ?

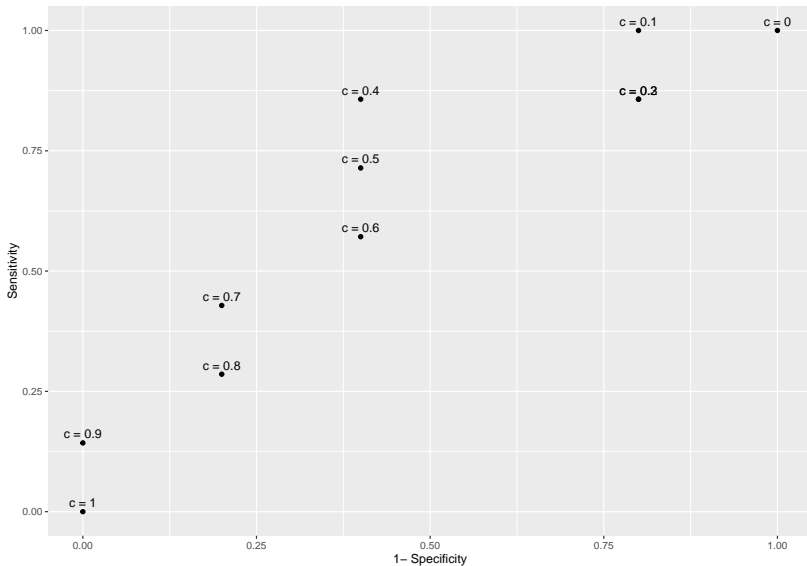
ROC Curves

- What is the best cut-off value?

Cut-off Values	Sensitivity	Specificity
$c = 0$	1.0000000	0.0
$c = 0.1$	1.0000000	0.2
$c = 0.2$	0.8571429	0.2
$c = 0.3$	0.8571429	0.2
$c = 0.4$	0.8571429	0.6
$c = 0.5$	0.7142857	0.6
$c = 0.6$	0.5714286	0.6
$c = 0.7$	0.4285714	0.8
$c = 0.8$	0.2857143	0.8
$c = 0.9$	0.1428571	1.0
$c = 1$	0.0000000	1.0

ROC

► **Question:** What is the best cut-off value?



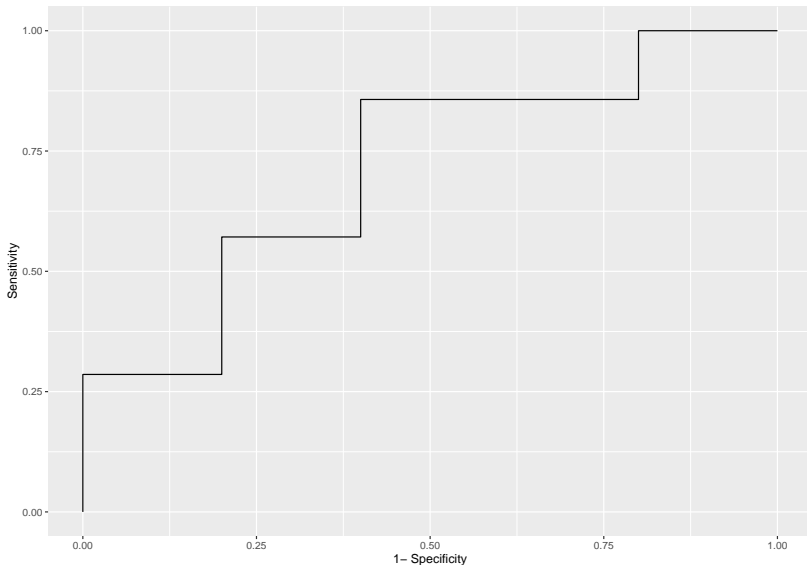
ROC Curve

- ▶ **Question:** What is the best cut-off value?
- ▶ **Answer:** $c = 0.4$ is the best cut-off value

ROC Curve

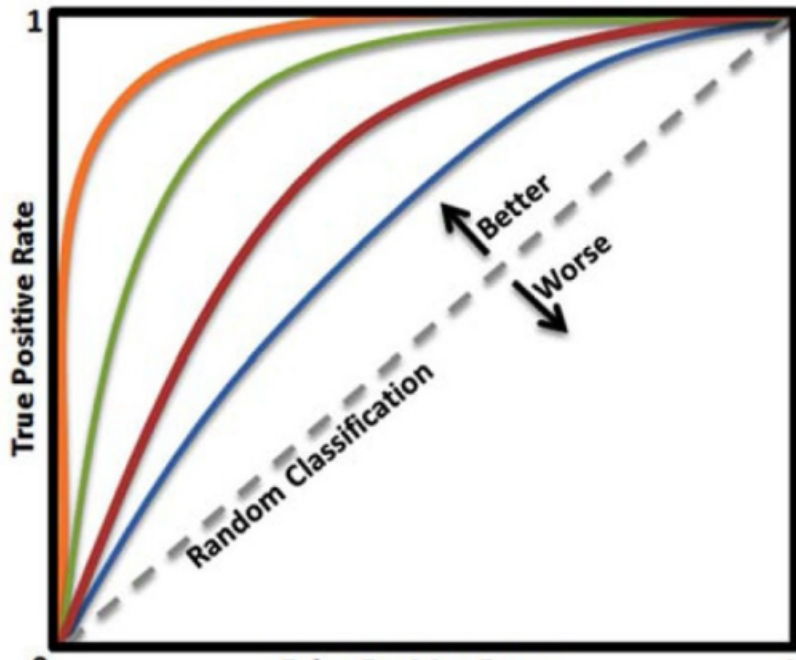
- ▶ Each cut-off value c results a pair of (1-Specificity, Sensitivity) or (TP Rate, FP Rate)
- ▶ The collections of all these pairs/points for all the cut-off values is the Receiver operating characteristic Curve (ROC Curve)

ROC Curve of the example model

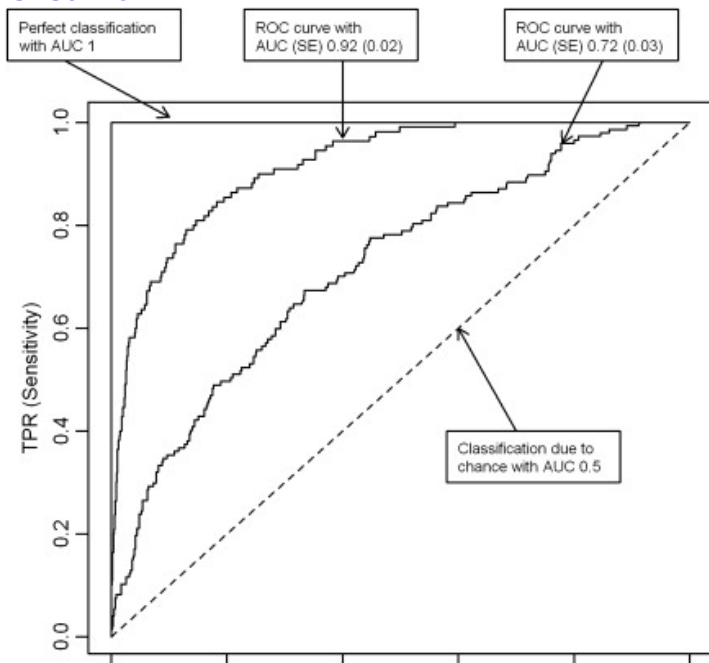


- ▶ The curve is not very smooth because the data is very small
- ▶ With bigger data, the ROC curve will be very “smooth”

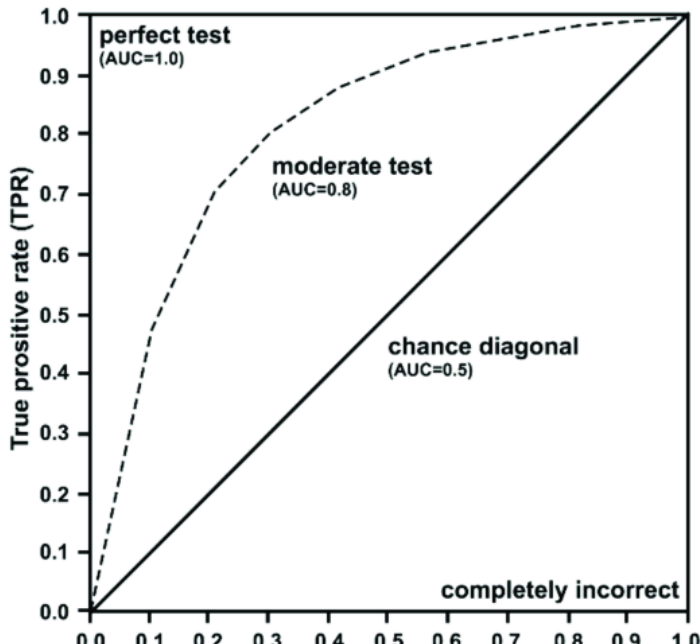
ROC Curve



ROC Curve



ROC Curve



ROC Index

- ▶ ROC Index is the area under the ROC Curve

ROC Index - Area Under the Curve (AUC)

- ▶ The closer the AUC to 1 the better the model
- ▶ The closer the AUC to $1/2$ the worse the model
- ▶ Model with $AUC = 1/2$ is as good as a random guess or guessing by tossing a coin
- ▶ **Question:** What if the AUC less than $1/2$? Are models with AUC less than $1/2$ **useless**?

Another Question

- ▶ **Question:** Is the model with the misclassification rate of 100% the most **useless** model?

Answer

- ▶ **Question:** Is the model with the misclassification rate of 100% an useless model?
- ▶ *Answer:* No, by flipping the predictions of the models, one gets the **perfect model** with 0 misclassification rate.

Back to the Question

- ▶ **Question:** What if the AUC less than $1/2$? Are models with AUC less than $1/2$ **useless**?
- ▶ **Answer:** Model with AUC less than $1/2$ could be made to be better by flipping the predictions (if the model predicts positive, flip it to predict negative)

Cumulative Lift

- ▶ In the dataset, the ratio of “Survived” is $7/12 = 58.33\%$
- ▶ This mean that if we pick **randomly** a passenger in the this group, the chance of picking a “Survived” passenger is 58.33%
- ▶ **Question:** If we want to pick a “Survived” passenger, is there a better way than pick randomly?

Cumulative Lift

- ▶ **Question:** If we want to pick a “Survived” passenger, is there a better way than pick randomly?
- ▶ **Answer:** Yes, we should pick the one with the highest predicted probability.

Cumulative Lift

Order	Predicted Probabilities	True Values
1	0.94	1
2	0.90	1
3	0.84	0
4	0.71	1
5	0.68	1
6	0.63	0
7	0.55	1
8	0.45	1
9	0.38	0
10	0.35	0
11	0.20	1
12	0.01	0

- ▶ Pick randomly, “success rate” is 58.33%
- ▶ Pick the top 1, success rate is $1/1 = 100\%$
- ▶ We say, at $1/12 = 8.33\%$, the model lift is $100/58.33 = 1.71$

Cumulative Lift

Order	Predicted Probabilities	True Values
1	0.94	1
2	0.90	1
3	0.84	0
4	0.71	1
5	0.68	1
6	0.63	0
7	0.55	1
8	0.45	1
9	0.38	0
10	0.35	0
11	0.20	1
12	0.01	0

- ▶ Pick randomly, “success rate” is 58.33%
- ▶ Pick the top 2, success rate is $2/2 = 100\%$
- ▶ We say, at $2/12 = 16.67\%$, the model lift is $100/58.33 = 1.71$

Cumulative Lift

Order	Predicted Probabilities	True Values
1	0.94	1
2	0.90	1
3	0.84	0
4	0.71	1
5	0.68	1
6	0.63	0
7	0.55	1
8	0.45	1
9	0.38	0
10	0.35	0
11	0.20	1
12	0.01	0

- ▶ Pick randomly, “success rate” is 58.33%
- ▶ Pick the top 2, success rate is $2/2 = 100\%$
- ▶ We say, at $2/12 = 16.67\%$, the model lift is $100/58.33 = 1.71$

Cumulative Lift

Order	Predicted Probabilities	True Values
1	0.94	1
2	0.90	1
3	0.84	0
4	0.71	1
5	0.68	1
6	0.63	0
7	0.55	1
8	0.45	1
9	0.38	0
10	0.35	0
11	0.20	1
12	0.01	0

- ▶ Pick randomly, “success rate” is 58.33%
- ▶ Pick the top 3, success rate is $2/3 = 66.66\%$
- ▶ We say, at $3/12 = 25\%$, the model lift is $66.66/58.33 = 1.14$

Cumulative Lift

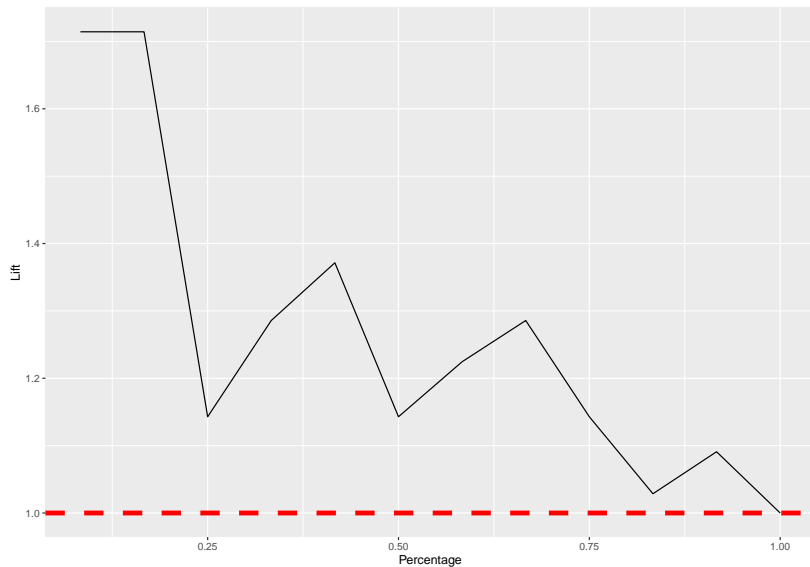
Order	Predicted Probabilities	True Values
1	0.94	1
2	0.90	1
3	0.84	0
4	0.71	1
5	0.68	1
6	0.63	0
7	0.55	1
8	0.45	1
9	0.38	0
10	0.35	0
11	0.20	1
12	0.01	0

- ▶ Pick randomly, “success rate” is 58.33%
- ▶ Pick the top 4, success rate is $3/4 = 75\%$
- ▶ We say, at $4/12 = 25\%$, the model lift is $75/58.33 = 1.28$

Cumulative Lift

Percentage	Lift
0.0833333	1.714286
0.1666667	1.714286
0.2500000	1.142857
0.3333333	1.285714
0.4166667	1.371429
0.5000000	1.142857
0.5833333	1.224490
0.6666667	1.285714
0.7500000	1.142857
0.8333333	1.028571
0.9166667	1.090909
1.0000000	1.000000

Cumulative Lift



Cumulative % Response

Percentage	Percent_Response
0.0833333	1.0000000
0.1666667	1.0000000
0.2500000	0.6666667
0.3333333	0.7500000
0.4166667	0.8000000
0.5000000	0.6666667
0.5833333	0.7142857
0.6666667	0.7500000
0.7500000	0.6666667
0.8333333	0.6000000
0.9166667	0.6363636
1.0000000	0.5833333

Cumulative % Response

