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 cuff-off value is set by 0.5 by default.
- The cut-off value can be changed by the modeler.

Confusion Matrices

we only talk about binary classification. → positive

→ Negative

	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

0

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 (TP)	2 (FN)
Actual Negative	2 (FP)	3 (TN)

perfect confusion matrix

	TP =	FN = 0
	FP = 0	TN =

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)

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

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

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

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

Covid 19 test

1000 people $\rightarrow$ 10 positive

1000 people $\rightarrow$ 990 negative

Truth

Design a covid test always predict negative.

what is the accuracy of this test on the above 1000 people:

$$\text{Accuracy} = \frac{990}{1000} = 99\%$$

$$\text{Sensitivity} = \frac{0}{10} = 0\%$$

	Predicted P	Predicted N
Actual P	0	10
Actual N	0	990

Test 2

1	9
0	990

precision $= \frac{1}{1} = 100\%$

Sen $= \frac{1}{10}$

Accuracy $= \frac{991}{1000} = 99.1\%$

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)

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

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

$\Rightarrow$

$$\frac{1}{\text{F1-score}} = \frac{\frac{1}{\text{precision}} + \frac{1}{\text{sens}}}{2}$$

(Harmonic means of precision and sens)

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

default

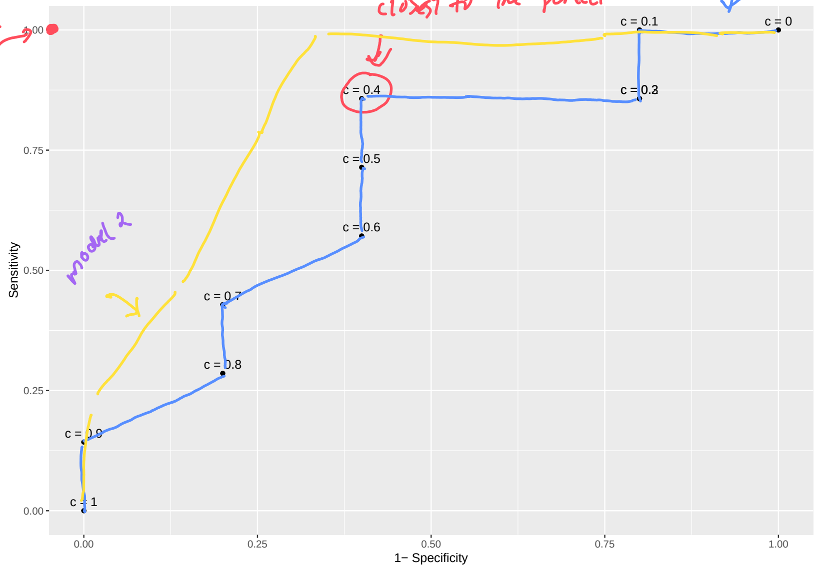
ROC

for model 1

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

perfect model

closest to the perfect model



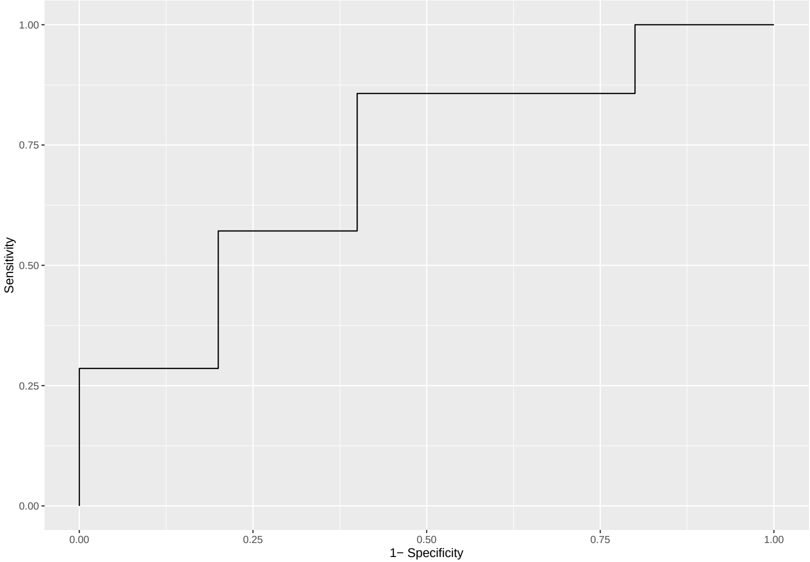
ROC Curve

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

ROC Curve

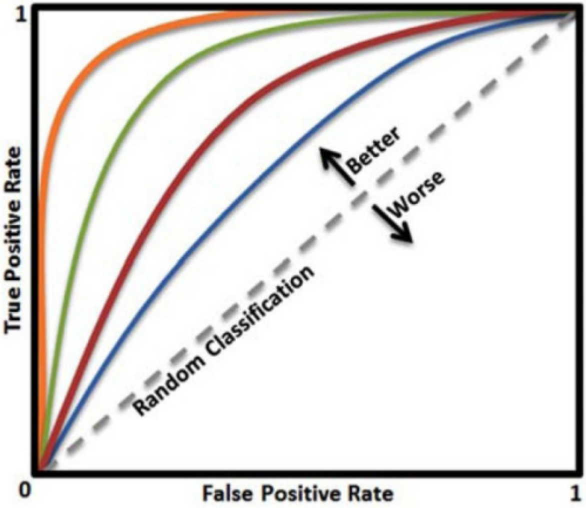
- Each cut-off value **c** results a pair of (1-Specificity, Sensitivity) or (TP Rate, FP Rate)
- The collections of all these pairs/points for all the cut-off values is the Receiver operating characteristic Curve (ROC Curve)

ROC Curve of the example model



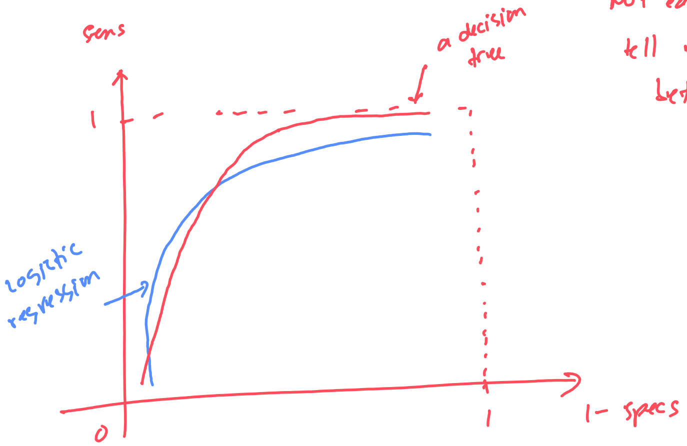
- The curve is not very smooth because the data is very small
- With bigger data, the ROC curve will be very "smooth"

ROC Curve



visually you can tell which model is better.

not easy to visually tell which model is better.

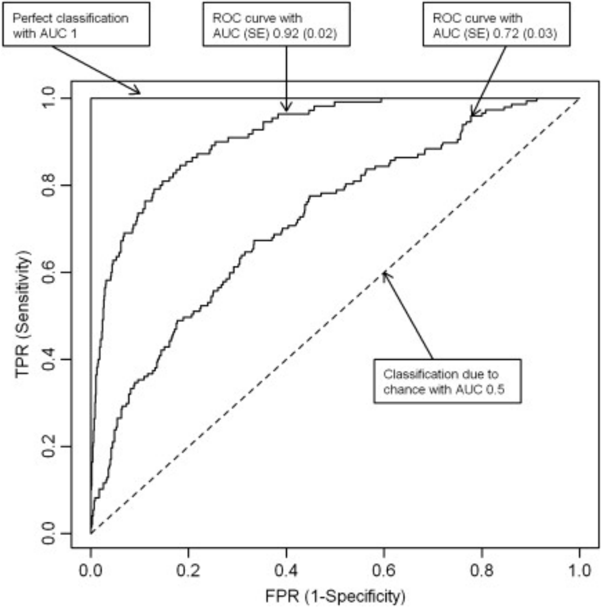


we measure the area under the ROC. The bigger the area the better the ROC. The area is called ROC Index or AUC (Area under curve)

ROC Curve

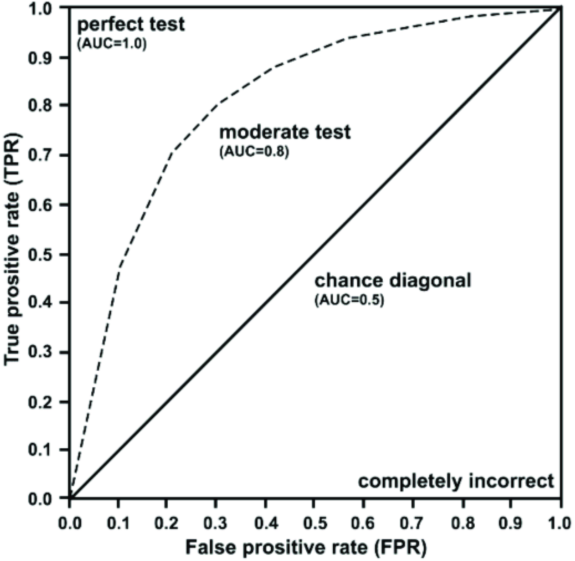
- The closer the curve to the point (0,1) the better the model
- The best cut-off value is at the point closest to (0,1)
- (0,1) is the **perfect point**, resulting 0 misclassification model.
- At (0,0) the model predicts everything positive
- At (1,1) the model predicts everything negative
- The ROC of the random guess model is the diagonal

ROC Curve



- AUC = Area Under the (ROC) Curve

ROC Curve



perfect test
(AUC=1.0)
moderate test
(AUC=0.8)
chance diagonal
(AUC=0.5)
completely incorrect
True prositive rate (TPR)
False prositive rate (FPR)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

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 positve, 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 predictied 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

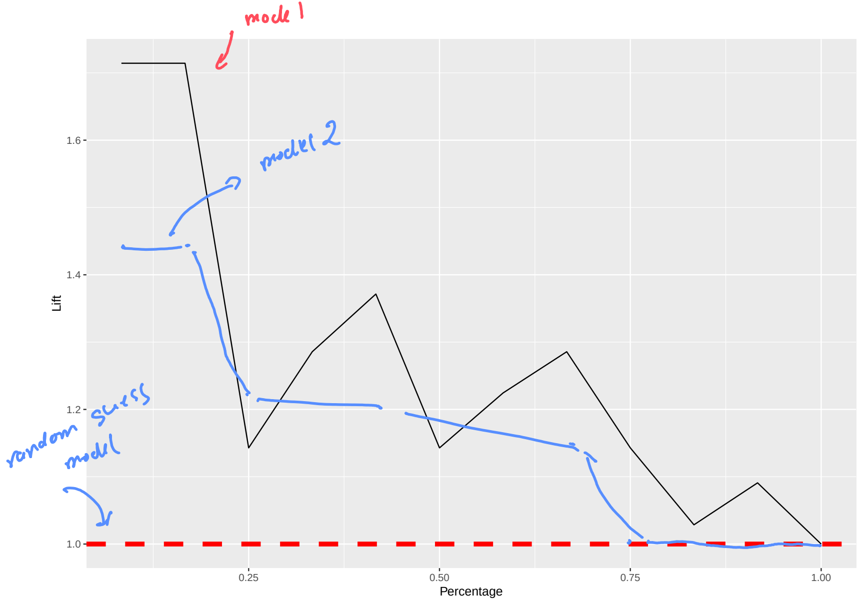
Order	Predicted Probabilities	True Values
1	0.94	1
2	0.90	1
3	0.84	0
4	0.71	1
5	0.68	1
6	0.63	0
7	0.55	1
8	0.45	1
9	0.38	0
10	0.35	0
11	0.20	1
12	0.01	0

- 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