2. Classification evaluation

ROC and precision recall curve (8 pts)

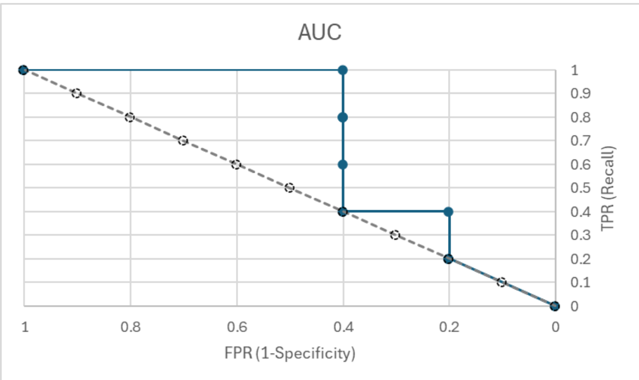
Calculate ROC curve and precision recall curve with the following thresholds: [0,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1] The probabilities are:

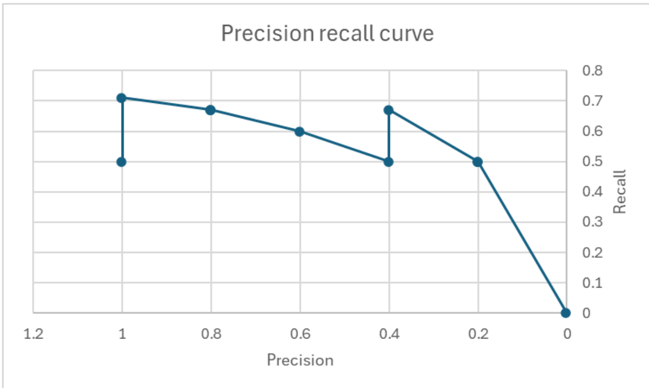
classifier 2	classifier 1	label
1	0.41	1
0.72	0	0
0.99	0	0
0.14	0.73	1
0	0.62	0
0.94	1	1
0.1	1	0
0.77	0.14	1
0.02	0	0
1	0.55	1

$TPR = Recall = \frac{TP}{TP+FN}$ $Precision = \frac{TP}{TP+FP}$ $Specificity = \frac{TN}{TN+FP}$ $FPR = 1 - Specificity$

Classifier 1:

classifier 1	label	0	>0.1	>0.2	>0.3	>0.4	>0.5	>0.6	>0.7	>0.8	>0.9	>1
0.41	1	1	1	1	1	1	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0.73	1	1	1	1	1	1	1	1	1	0	0	0
0.62	0	1	1	1	1	1	1	1	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	0
1	0	1	1	1	1	1	1	1	1	1	1	0
0.14	1	1	1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0.55	1	1	1	1	1	1	1	0	0	0	0	0
TP		5	5	4	4	4	3	2	2	1	1	0
FP		5	2	2	2	2	2	2	1	1	1	0
FN		0	0	1	1	1	2	3	3	4	4	5
TN		0	3	3	3	3	3	3	4	4	4	5
Precision		0.5	0.71	0.67	0.67	0.67	0.6	0.5	0.67	0.5	0.5	0
TPR - Recall		1	1	0.8	0.8	0.8	0.6	0.4	0.4	0.2	0.2	0
Specificity		0	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.8	0.8	1
FPR		1	0.4	0.4	0.4	0.4	0.4	0.4	0.2	0.2	0.2	0

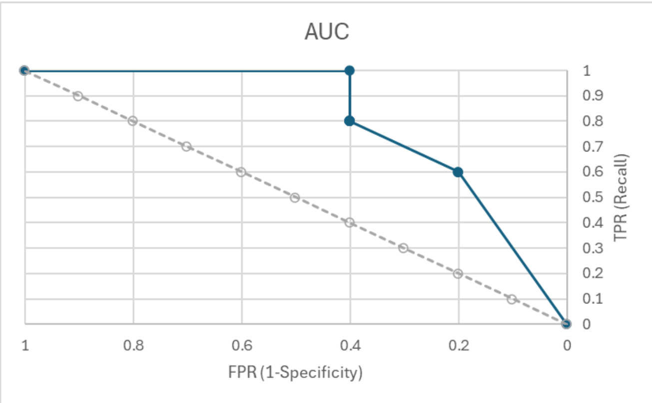


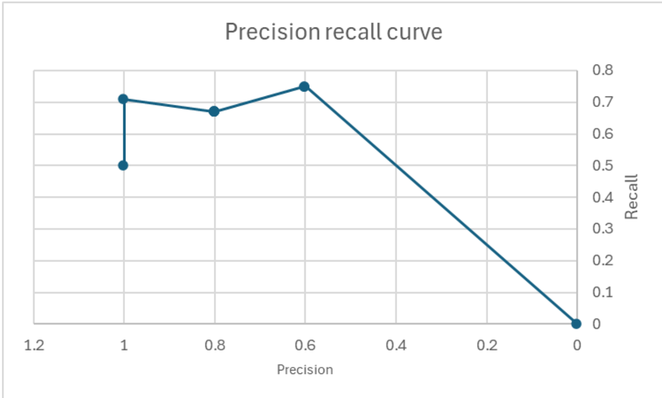


$$\text{Calculate AUC} = \frac{0.2 \cdot 0.2}{2} + 0.2 \cdot 0.4 + 0.6 \cdot 1 = 0.7$$

Classifier 2:

classifier 2	label	0	>0.1	>0.2	>0.3	>0.4	>0.5	>0.6	>0.7	>0.8	>0.9	>1
1	1	1	1	1	1	1	1	1	1	1	1	0
0.72	0	1	1	1	1	1	1	1	1	0	0	0
0.99	0	1	1	1	1	1	1	1	1	1	1	0
0.14	1	1	1	0	0	0	0	0	0	0	0	0
0	0	1	0	0	0	0	0	0	0	0	0	0
0.94	1	1	1	1	1	1	1	1	1	1	1	0
0.1	0	1	0	0	0	0	0	0	0	0	0	0
0.77	1	1	1	1	1	1	1	1	1	0	0	0
0.02	0	1	0	0	0	0	0	0	0	0	0	0
1	1	1	1	1	1	1	1	1	1	1	1	0
TP		5	5	4	4	4	4	4	4	3	3	0
FP		5	2	2	2	2	2	2	2	1	1	0
FN		0	0	1	1	1	1	1	1	2	2	5
TN		0	3	3	3	3	3	3	3	4	4	5
Precision		0.5	0.71	0.67	0.67	0.67	0.67	0.67	0.67	0.75	0.75	0
TPR - Recall		1	1	0.8	0.8	0.8	0.8	0.8	0.8	0.6	0.6	0
Specificity		0	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.8	1
FPR		1	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.2	0.2	0





$$Calculate\ AUC = \frac{0.2 \cdot 0.6}{2} + \frac{(0.8 + 0.6) \cdot 0.2}{2} + 0.6 \cdot 1 = 0.8$$

1.Which model is better based on those graphs?

Classifier 2 is better based on the provided graphs because it has a higher AUC value. A higher AUC generally indicates better model performance, with 1.0 being the perfect score. In this case, the AUC for Classifier 2 suggests that it has a better ability to discriminate between positive and negative instances compared to Classifier 1.

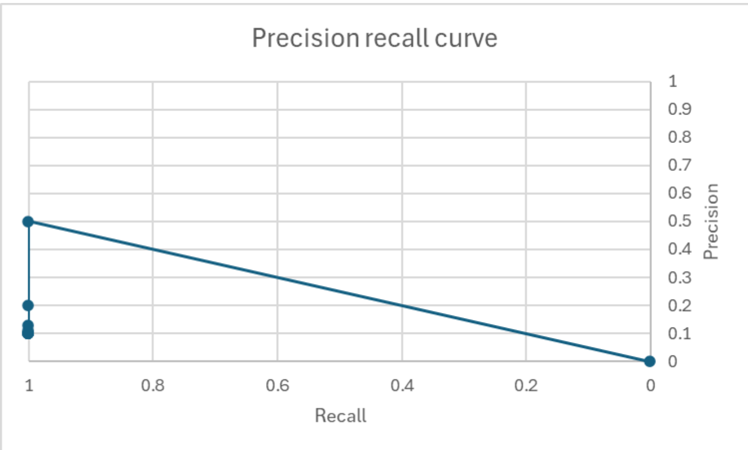
2. If those models predict heart attack, choose a 'one threshold' metric (such as acc, precision, etc..) and explain why it's a suitable metric for this case.

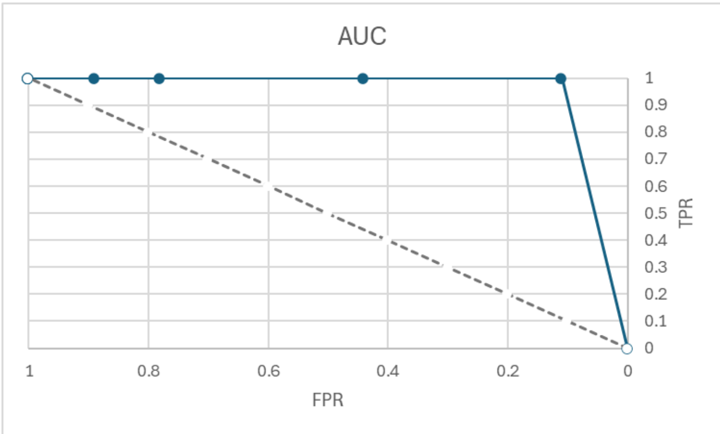
If the models are designed for predicting heart attacks, the chosen 'one threshold' metric will be Recall. Recall assesses the capability of the model to correctly identify individuals at risk of a heart attack among all those who may experience one.
In the context of heart attack prediction, recall becomes particularly relevant as it emphasizes the importance of minimizing false negatives. False negatives, where the model fails to predict a person at risk of a heart attack, can have serious consequences. Therefore, by prioritizing recall, we aim to enhance the model's ability to recognize and correctly classify individuals who are truly at risk, contributing to a more effective and reliable predictive system for heart attacks.

Curves differences (7 pts)

Create a new table with two columns: 'label' and 'predictions'. Fill the table with 10 rows of values representing binary labels and corresponding predicted probabilities. Ensure that the values chosen for the predictions are deliberately selected to make the ROC curve and precision-recall curve look different - which means that according to one curve the model is good, and according to the second one it's bad. After filling the table, draw both the ROC curve and precision-recall curve using the provided data. Explain the values that you chose and the reason for the change.

predictions	label	>0	>0.1	>0.2	>0.3	>0.4	>0.5	>0.6	>0.7	>0.8	>0.9	>1
0.91	1	1	1	1	1	1	1	1	1	1	1	0
0.84	0	1	1	1	1	1	1	1	1	1	0	0
0.98	0	1	1	1	1	1	1	1	1	1	1	0
0.78	0	1	1	1	1	1	1	1	1	0	0	0
0.88	0	1	1	1	1	1	1	1	1	1	0	0
0.82	0	1	1	1	1	1	1	1	1	1	0	0
0.74	0	1	1	1	1	1	1	1	1	0	0	0
0.7	0	1	1	1	1	1	1	1	0	0	0	0
0.8	0	1	1	1	1	1	1	1	1	0	0	0
0.6	0	1	1	1	1	1	1	0	0	0	0	0
TP		1	1	1	1	1	1	1	1	1	1	0
FP		9	9	9	9	9	9	8	7	4	1	0
FN		0	0	0	0	0	0	0	0	0	0	1
TN		0	0	0	0	0	0	1	2	5	8	9
Precision		0.1	0.1	0.1	0.1	0.1	0.1	0.11	0.13	0.2	0.5	0
TPR - Recall		1	1	1	1	1	1	1	1	1	1	0
Specificity		0	0	0	0	0	0	0.11	0.22	0.56	0.89	1
FPR		1	1	1	1	1	1	0.89	0.78	0.44	0.11	0





$$Efficient\ Area\ Computation\ for\ AUC - ROC = \frac{0.11 \cdot 1}{2} + 0.89 \cdot 1 = 0.945$$

$$Efficient\ Area\ Computation\ for\ Precision - Recall\ Curves = \frac{0.5 \cdot 1}{2} = 0.25$$

AUC-ROC yields a favorable value of 0.945, indicative of strong model performance, as it signifies a high true positive rate compared to false positive rate. However, the recall precision curve's score of 0.25 indicates suboptimal performance.

AUC-ROC highlights the model's robustness in distinguishing between classes, whereas the recall-precision curve reflects a deficiency in precision at certain recall levels, suggesting potential model refinement needs.