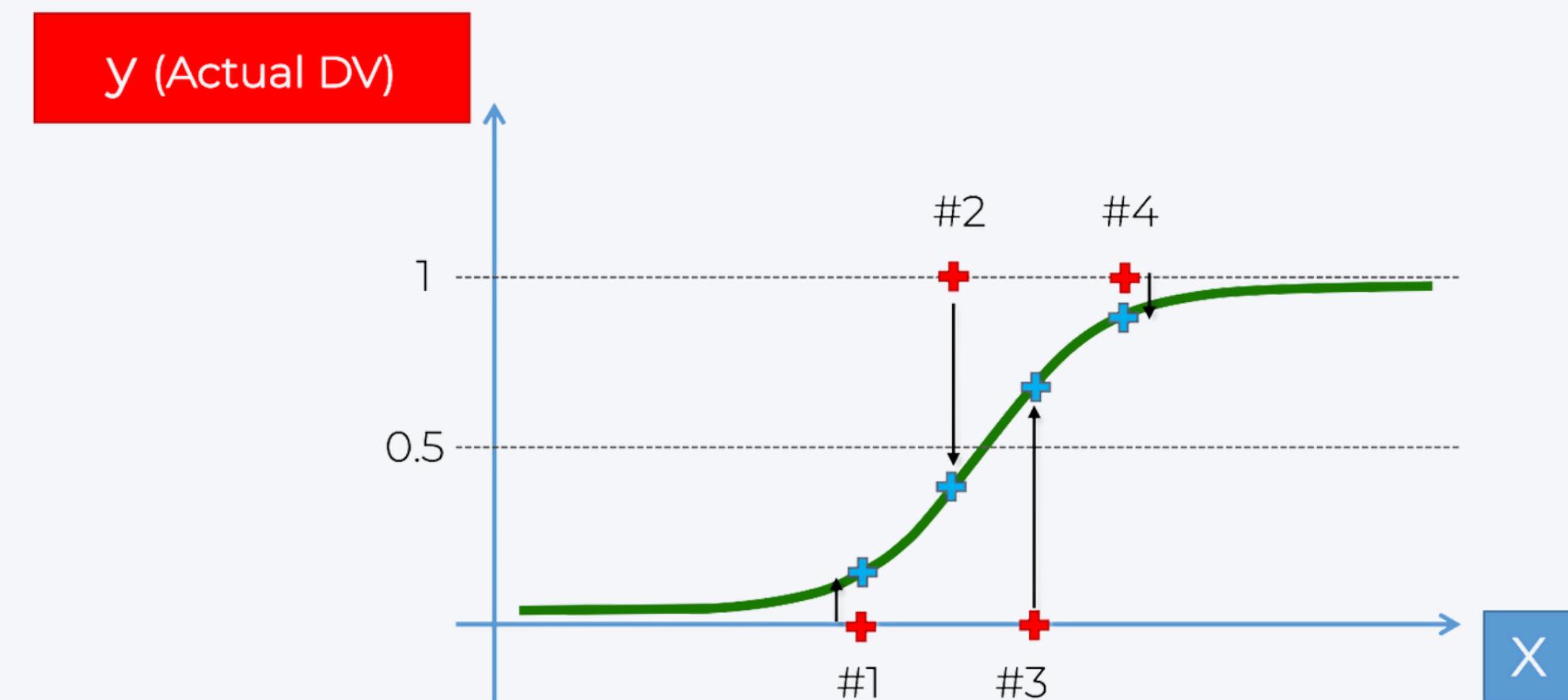
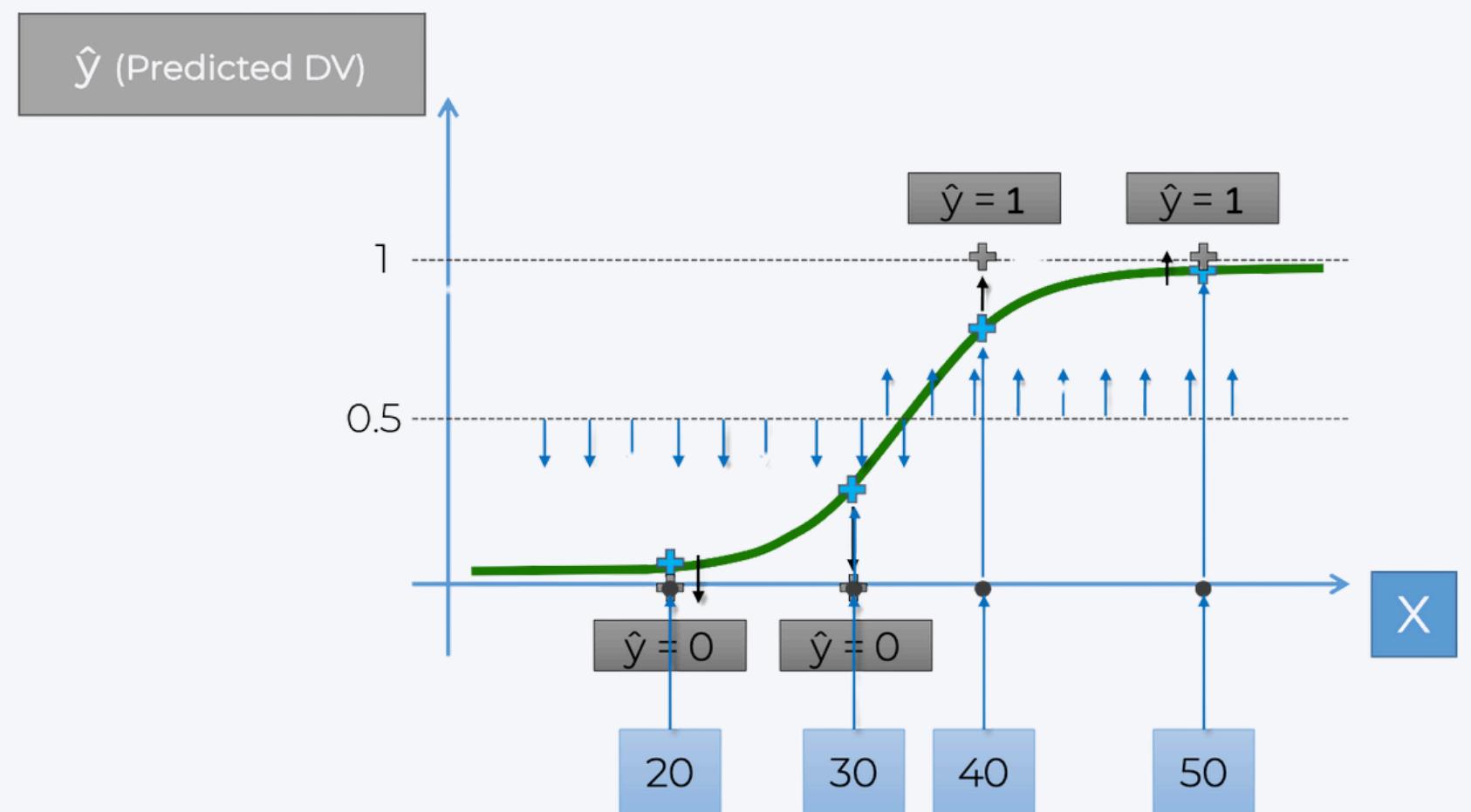


Evaluating classification Model

Evaluating Classification Model

False Positives & False Negatives

When evaluating a classification model, we often deal with prediction errors.



Evaluating Classification Model

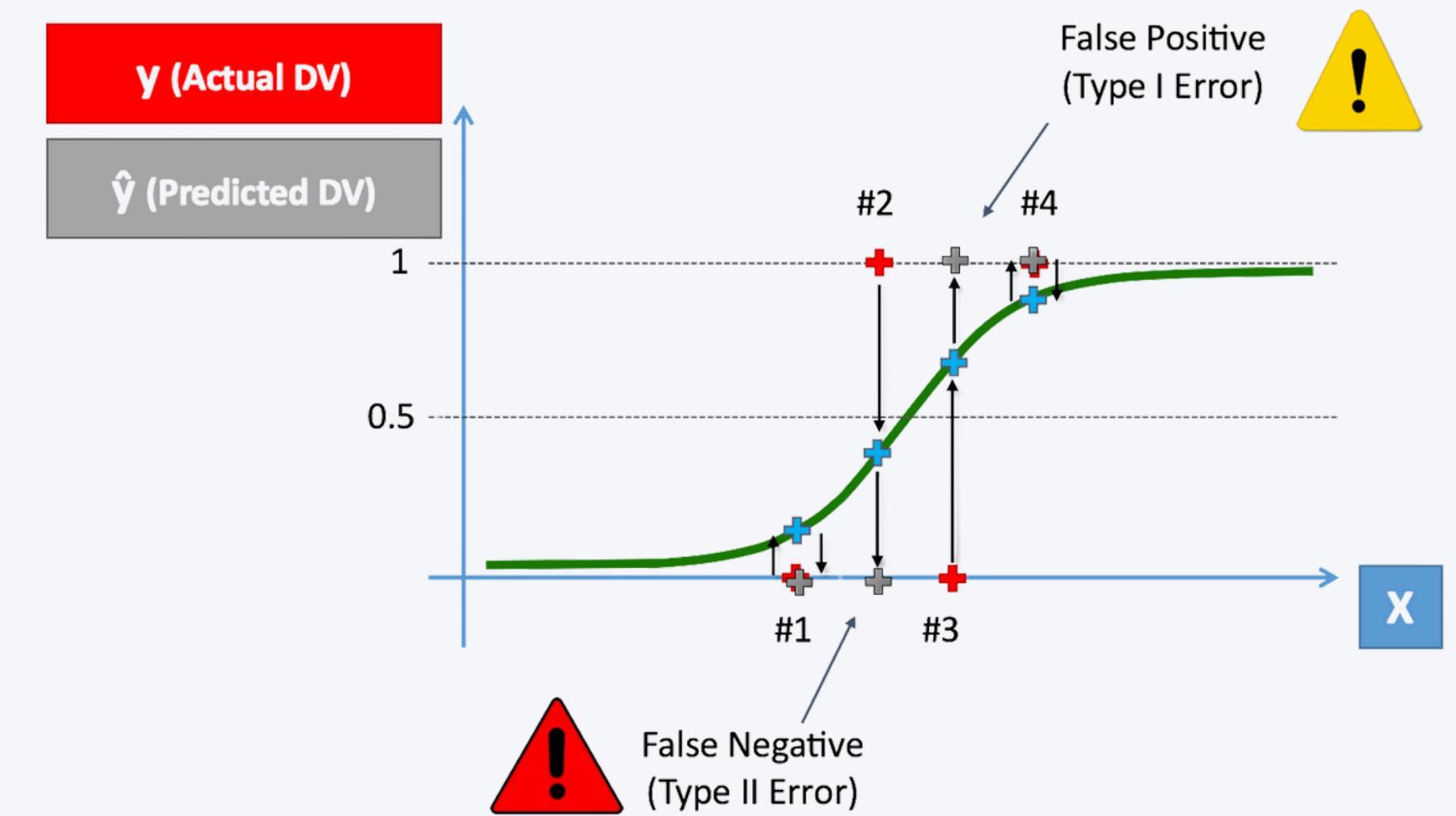
False Positives & False Negatives

False Positives (Type I Error)

- The model incorrectly predicts a positive outcome when the actual outcome is negative.
- Example: A medical test predicts a patient has a disease when they do not.

False Negatives (Type II Error)

- The model incorrectly predicts a negative outcome when the actual outcome is positive.
- Example: A medical test predicts a patient does not have a disease when they actually do.



Evaluating Classification Model

How This Relates to Model Evaluation

- These errors are crucial for measuring model performance.
- A good classification model should minimize both types of errors while maintaining high accuracy.
- Depending on the application, one type of error may be more costly than the other (e.g., in fraud detection, false negatives can be more dangerous).

Evaluating Classification Model

Confusion Matrix & Accuracy

The confusion matrix is a fundamental tool for evaluating classification models.

It provides a summary of prediction results by comparing actual and predicted values.

The main components are:

- **True Positive (TP):** The model correctly predicted the positive class.
- **True Negative (TN):** The model correctly predicted the negative class.
- **False Positive (FP) (Type I Error):** The model incorrectly predicted positive when the actual class was negative.
- **False Negative (FN) (Type II Error):** The model incorrectly predicted negative when the actual class was positive.

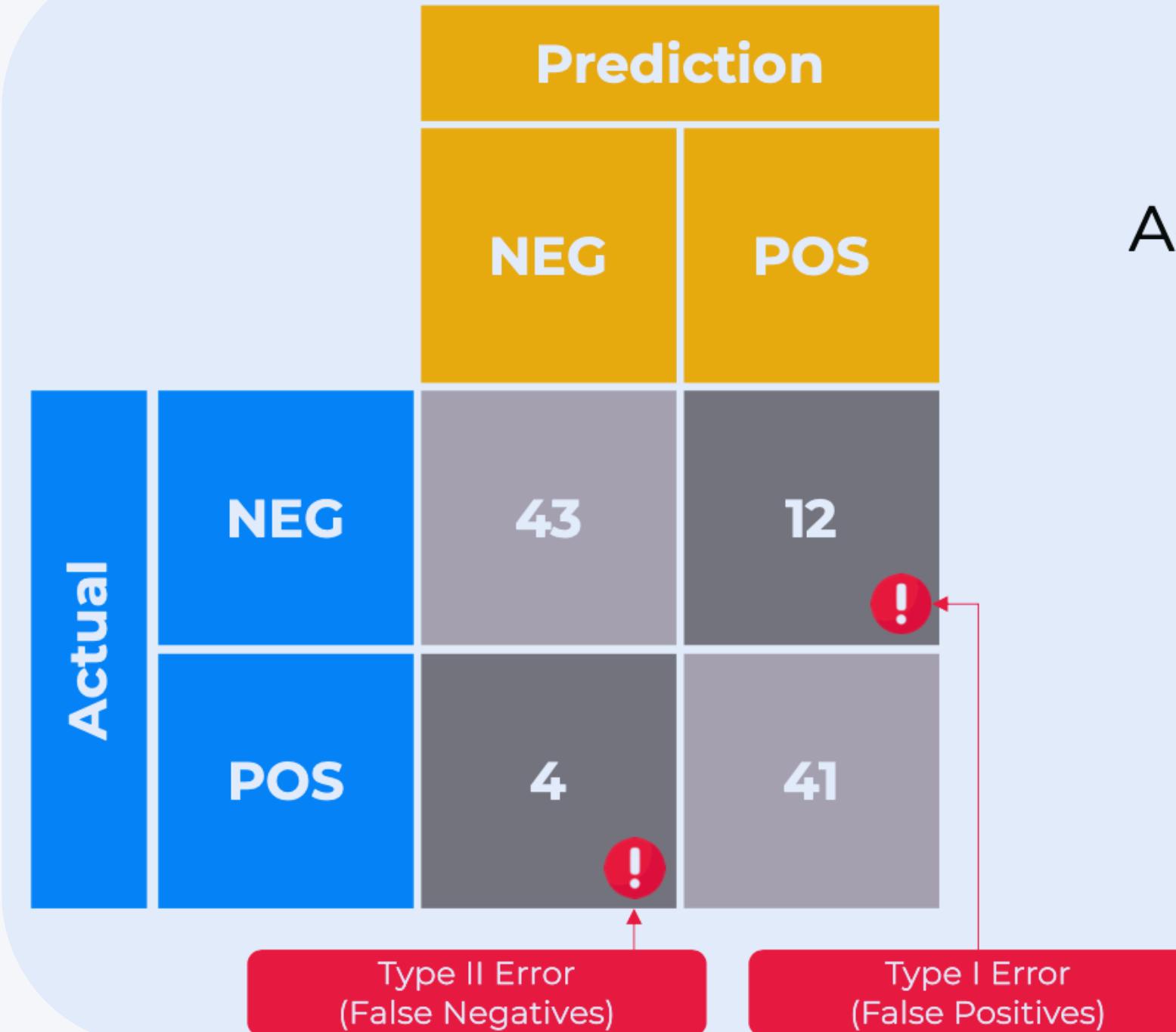
		Prediction	
		NEG	POS
Actual	NEG	TRUE NEG	FALSE POS
	POS	FALSE NEG	TRUE POS

Annotations below the table:

- Type II Error (False Negatives) points to the bottom-left cell (Actual POS, Predicted NEG).
- Type I Error (False Positives) points to the bottom-right cell (Actual NEG, Predicted POS).

Evaluating Classification Model

Confusion Matrix & Accuracy



Accuracy Rate and Error Rate:

$$AR = \frac{Correct}{Total} = \frac{TN + TP}{Total} = \frac{84}{100} = 84\%$$

$$ER = \frac{Incorrect}{Total} = \frac{FP + FN}{Total} = \frac{16}{100} = 16\%$$



Evaluating Classification Model

Precision, Recall, and F1-Score Explanation

Precision (Positive Predictive Value):

Precision measures the accuracy of positive predictions made by the model.

It answers:

"Of all the instances predicted as positive, how many were actually positive?"

High Precision: Few false positives, meaning when the model predicts positive, it is often correct.

Low Precision: Many false positives, meaning the model is often incorrect in predicting positives.

		Prediction	
		NEG	POS
Actual	NEG	TRUE NEG	FALSE POS
	POS	FALSE NEG	TRUE POS

Type II Error (False Negatives) !

Type I Error (False Positives) !

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



Evaluating Classification Model

Precision, Recall, and F1-Score Explanation

Recall (Sensitivity or True Positive Rate):

Recall measures how well the model identifies all actual positive cases.

It answers:

"Of all the actual positive cases, how many did the model correctly identify?"

- **High Recall:** Few false negatives, meaning most actual positives are correctly classified.
- **Low Recall:** Many false negatives, meaning the model misses many actual positives.

		Prediction	
		NEG	POS
Actual	NEG	TRUE NEG	FALSE POS
	POS	FALSE NEG	TRUE POS

Type II Error (False Negatives) Type I Error (False Positives)

$$\text{Recall} = \frac{TP}{TP + FN}$$



Evaluating Classification Model

Precision, Recall, and F1-Score Explanation

F1-Score (Harmonic Mean of Precision & Recall)

The F1-score balances Precision and Recall.

It is useful when we want a single metric that considers both false positives and false negatives.

		Prediction	
		NEG	POS
Actual	NEG	TRUE NEG	FALSE POS
	POS	FALSE NEG	TRUE POS

Type II Error (False Negatives) !

Type I Error (False Positives) !

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Evaluating Classification Model

Precision, Recall, and F1-Score Explanation

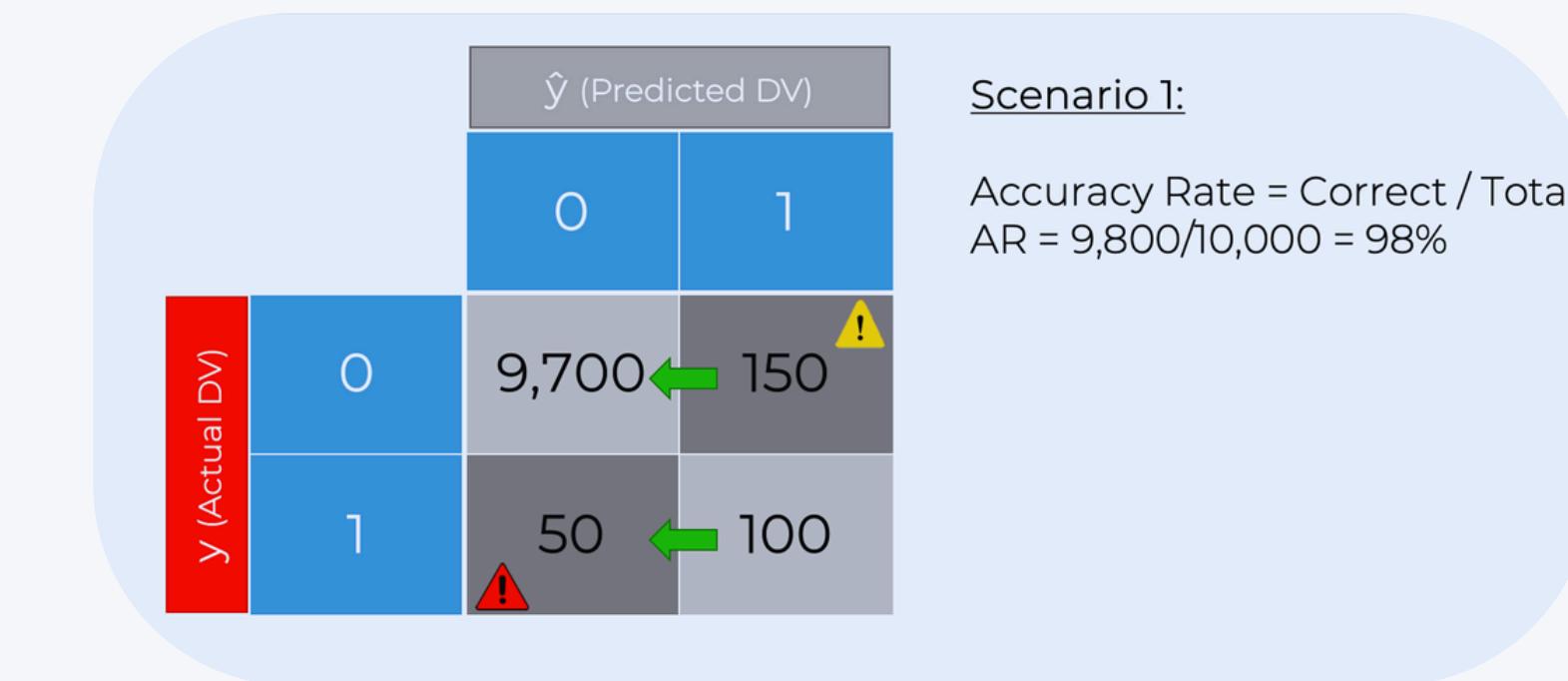
Key Insights:

- ✓ Precision is important when false positives are costly (e.g., spam detection, where incorrectly flagging an important email is bad).
- ✓ Recall is important when false negatives are costly (e.g., medical diagnoses, where missing a disease is dangerous).
- ✓ F1-Score is a balanced metric, especially useful when the dataset is imbalanced.

Evaluating Classification Model

Accuracy Paradox - Scenario 1

- Here is a confusion matrix with two classes (0 and 1).
- The model achieves 98% accuracy, but it highlights a critical issue: **imbalanced data**.



- While most negative cases (0s) are correctly predicted (9,700), the model fails to correctly classify a significant number of positive cases (50 false negatives).

Accuracy alone does not tell the full story of model performance, especially in imbalanced datasets.

Evaluating Classification Model

Accuracy Paradox - Scenario #2

- The model slightly improves, increasing accuracy to 98.5%, but it completely ignores class 1 (no correct positive predictions).
- This highlights the accuracy paradox, where accuracy increases while performance for an important class worsens.

		\hat{y} (Predicted DV)	
		0	1
y (Actual DV)	0	9,850 	0 
	1	150 	0 

Scenario 1:

Accuracy Rate = Correct / Total
 $AR = 9,800/10,000 = 98\%$

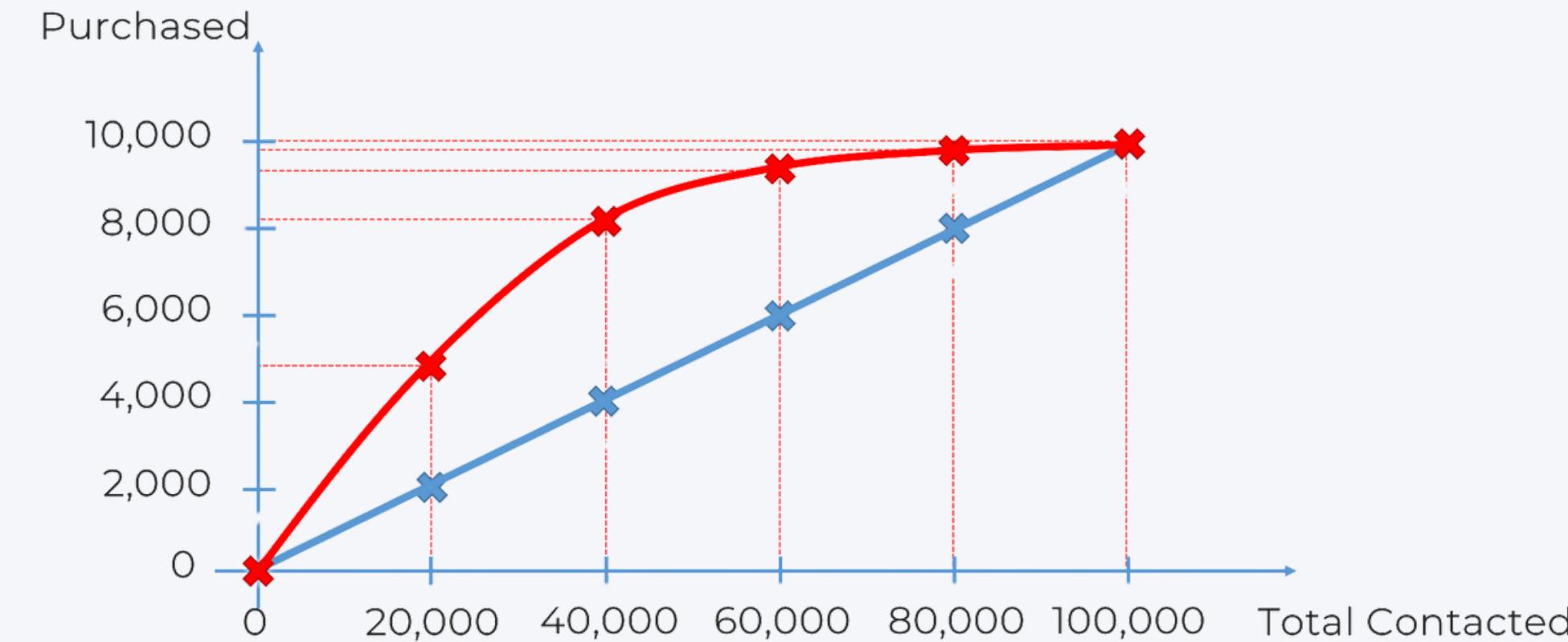
Scenario 2:

Accuracy Rate = Correct / Total
 $AR = 9,850/10,000 = 98.5\% $

A high accuracy does not necessarily mean the model is good. Other metrics like precision and recall must be considered.

CAP (Cumulative Accuracy Profile) - Introduction

- CAP is a visualization technique to evaluate classification models.



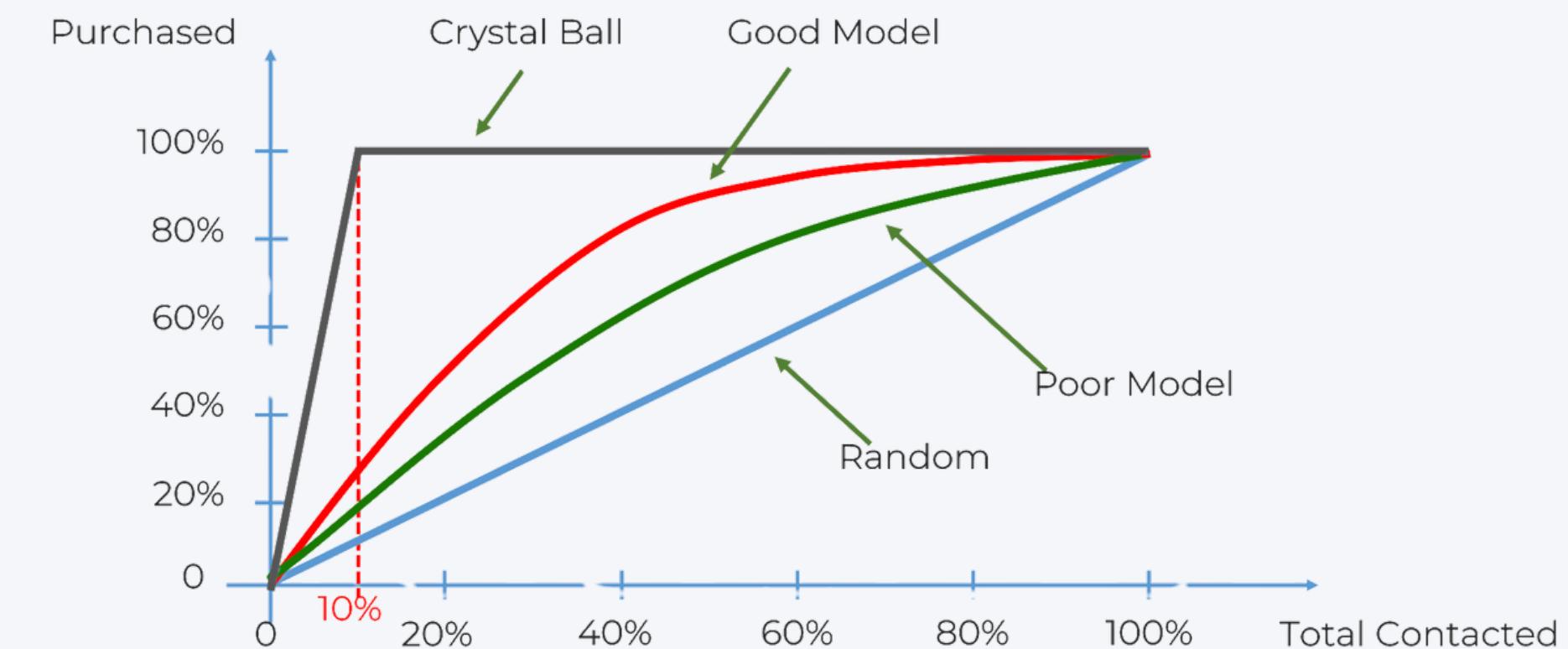
- The x-axis represents total contacted (e.g., customers, patients, etc.), and the y-axis represents the positive outcomes (e.g., purchases, disease detection).
- The red curve shows the model's performance, while the blue diagonal represents random selection.
- **A steeper curve indicates a better model.**

Evaluating Classification Model

CAP Curves - Performance Comparison

Compares different models:

- **Crystal Ball:** A perfect model (ideal case).
- **Good Model:** A practical, effective model.
- **Random Model:** A model that performs no better than random guessing.



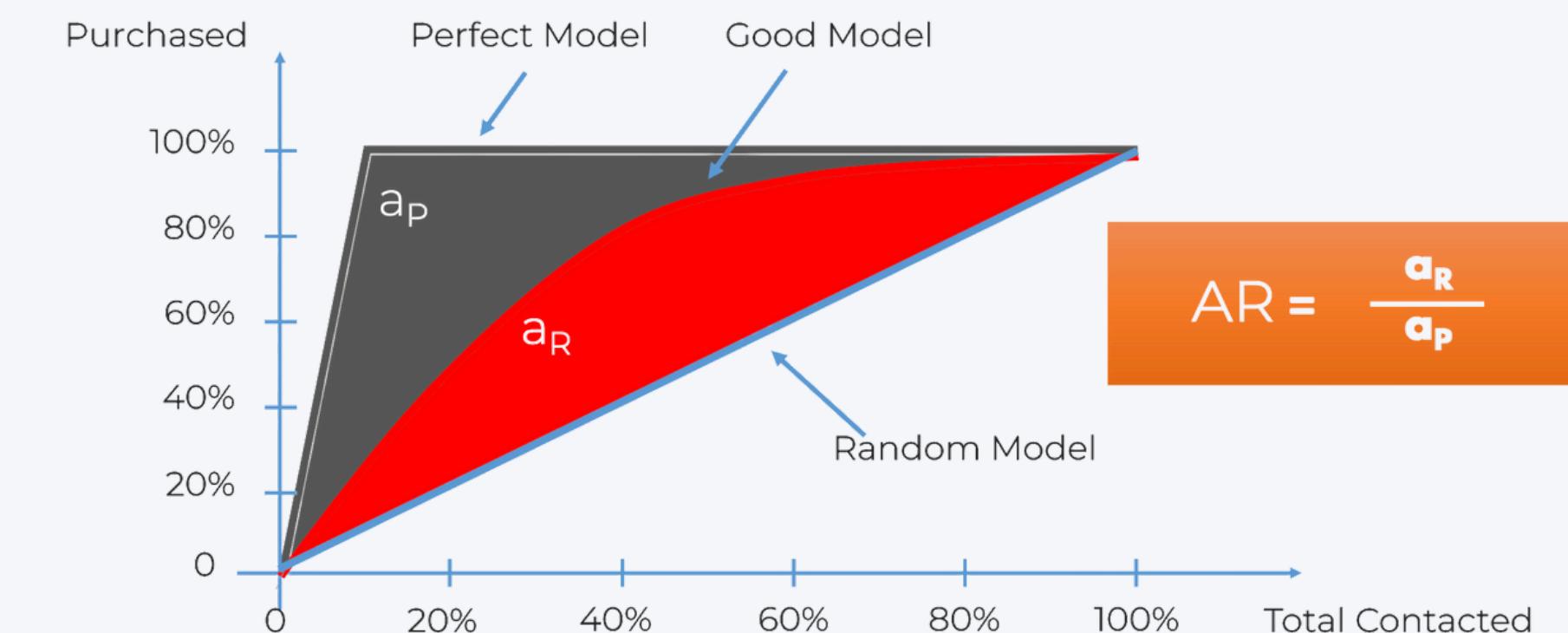
The closer the curve is to the perfect model, the better the classifier.

Evaluating Classification Model

CAP Analysis - Model Evaluation

- AR (Accuracy Ratio) Calculation:
 - $AR = a_R / a_P$, where:
 - a_R is the area under the model's curve.
 - a_P is the area under the perfect model's curve.

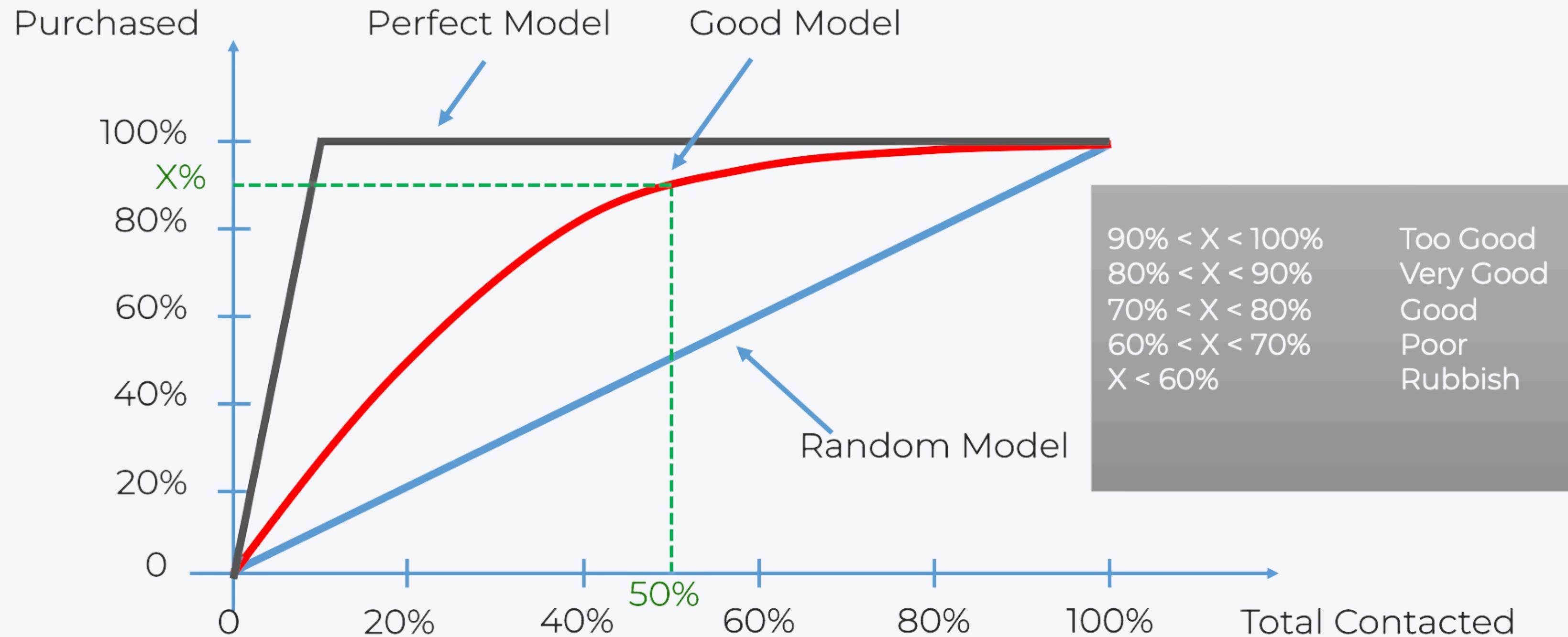
A higher AR value means a better model.



AP analysis provides a quantitative measure of model quality.

Evaluating Classification Model

CAP Analysis - Model Evaluation



Hands-On Code

Evaluating Classification Model