

# Classification Accuracy

**Vishal Patel**

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1. Introduction

2. The Data Science Process

**3. Supervised Learning: Classification Accuracy Measures**

4. Unsupervised Learning

5. The Grunt Work

6. Wrap Up

$$X = \begin{pmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1j} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2j} \\ x_{31} & x_{32} & x_{33} & \dots & x_{3j} \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ \cdot & \cdot & \cdot & & \cdot \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nj} \end{pmatrix}$$

$$y = \begin{pmatrix} 1 \\ 1 \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{pmatrix}$$

$$\hat{p} = \begin{pmatrix} 0.29 \\ 0.90 \\ 0.31 \\ \cdot \\ \cdot \\ \cdot \\ 0.47 \end{pmatrix}$$

predict\_proba()

$$\hat{y} = \begin{pmatrix} 0 \\ 1 \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{pmatrix}$$


predict()

True Class (y)	Predicted Probability ( $\hat{p}$ )
+	0.29
+	0.90
-	0.31
-	0.89
+	0.95
+	0.71
-	0.24
+	0.12
-	0.59
-	0.47



True Class (y)	Predicted Probability ( $\hat{p}$ )
+	0.95
+	0.90
-	0.89
+	0.71
-	0.59
-	0.47
-	0.31
+	0.29
-	0.24
+	0.12



True Class (y)	Predicted Probability ( $\hat{p}$ ) 	Predicted Class	True / False?	True Positive	False Positive	True Negative	False Negative
+	0.95	+	True Positive	1	0	0	0
+	0.90	+	True Positive	2	0	0	0
−	0.89	+	False Positive	2	1	0	0
+	0.71	+	True Positive	3	1	0	0
−	0.59	+	False Positive	3	2	0	0
−	0.47	−	True Negative	3	2	1	0
−	0.31	−	True Negative	3	2	2	0
+	0.29	−	False Negative	3	2	2	1
−	0.24	−	True Negative	3	2	3	0
+	0.12	−	False Negative	3	2	3	2

True Class (y)	Predicted Probability ( $\hat{p}$ ) ↓	Predicted Class	True / False?	True Positive	False Positive	True Negative	False Negative
+	0.95	+	True Positive	3	2	3	2
+	0.90	+	True Positive				
-	0.89	+	False Positive				
+	0.71	+	True Positive				
-	0.59	+	False Positive				
-	0.47	-	True Negative				
-	0.31	-	True Negative				
+	0.29	-	False Negative				
-	0.24	-	True Negative				
+	0.12	-	False Negative				

True Class

	Predicted Class	
	+	-
+	<div>True Positive</div> <div>3</div>	<div>False Negative</div> <div>2</div>
-	<div>False Positive</div> <div>2</div>	<div>True Negative</div> <div>3</div>

Confusion matrix

True Class (y)	Predicted Probability ( $\hat{p}$ ) ↓
+	0.95
+	0.90
-	0.89
+	0.71
-	0.59
-	0.47
-	0.31
+	0.29
-	0.24
+	0.12

True Positive	False Positive	True Negative	False Negative
3	2	3	2

ACCURACY

=

$$\frac{\text{TP} + \text{TN}}{\text{Total Population}}$$

$$= \frac{3 + 3}{10} = 60.0\%$$

SENSITIVITY

=

$$\frac{\text{TP}}{\text{Total Positives}}$$

$$= \frac{3}{3 + 2} = 60.0\%$$

RECALL

True Positive Rate

SPECIFICITY

=

$$\frac{\text{TN}}{\text{Total Negatives}}$$

$$= \frac{3}{3 + 2} = 60.0\%$$

True Negative Rate

True Class (y)	Predicted Probability ( $\hat{p}$ ) ↓
+	0.95
+	0.90
-	0.89
+	0.71
-	0.59
-	0.47
-	0.31
+	0.29
-	0.24
+	0.12

True Positive	False Positive	True Negative	False Negative
3	2	3	2

**RECALL** =  $\frac{\text{TP}}{\text{Total Positives}}$  = 60.0%

**PRECISION** =  $\frac{\text{TP}}{\text{Predicted Positives}}$  =  $\frac{3}{3 + 2} = 60.0\%$

**F1 SCORE** =  $\frac{1}{\frac{1}{\text{Recall}} + \frac{1}{\text{Precision}}}$  =  $\frac{1}{\frac{1}{0.6} + \frac{1}{0.6}} = 0.60$



True Class (y)	Predicted Probability ( $\hat{p}$ )	Predicted Class
+	0.95	+
+	0.90	+
-	0.89	+
+	0.71	+
-	0.59	+
-	0.47	-
-	0.31	-
+	0.29	-
-	0.24	-
+	0.12	-

THRESHOLD = 0.5

True Positive	False Positive	True Negative	False Negative
3	2	3	2

Measure	Value
Accuracy	0.60
Sensitivity (Recall)	0.60
Specificity	0.60
Precision	0.60
F1 Score	0.60

True Class (y)	Predicted Probability ( $\hat{p}$ )	Predicted Class
+	0.95	+
+	0.90	+
-	0.89	+
+	0.71	+
-	0.59	-
-	0.47	-
-	0.31	-
+	0.29	-
-	0.24	-
+	0.12	-

THRESHOLD = 0.6

True Positive	False Positive	True Negative	False Negative
3	1	4	2

Measure	Value
Accuracy	0.70
Sensitivity (Recall)	0.60
Specificity	0.80
Precision	0.75
F1 Score	0.67

← PROBABILITY THRESHOLD VALUES →

Measure	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Accuracy	0.50	0.40	0.40	0.50	0.60	0.70	0.70	0.60	0.70
Sensitivity (Recall)	1.00	0.80	0.60	0.60	0.60	0.60	0.60	0.40	0.40
Specificity	--	--	0.20	0.40	0.60	0.80	0.80	0.80	1.00
Precision	0.50	0.44	0.43	0.50	0.60	0.75	0.75	0.67	1.00
F1 Score	0.67	0.57	0.50	0.55	0.60	0.67	0.67	0.50	0.57

- 1 The values depend on the decision boundary.

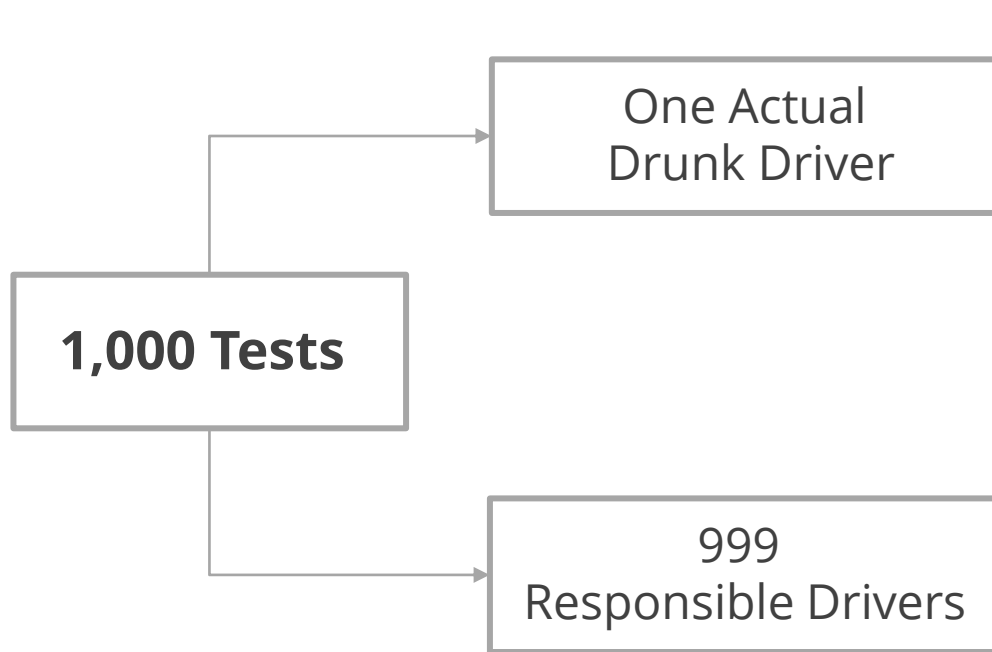
# Breathalyzers

## ASSUMPTIONS:

1. **One in a thousand** drivers is driving drunk.
2. A breathalyzer **never** fails to detect a truly drunk person.
3. However, it displays false drunkenness in **5%** of the cases when the driver is actually sober.
4. A police officer stops a **random** driver and asks her to take the breathalyzer test.
5. The test indicates that the driver **is** drunk.

**What is the probability that the driver is DUI?**

- (a)** 95%      **(b)** 90%      **(c)** 5%      **(d)** 2%



**The test never fails to detect a truly drunk person.**  
Hence, the test result for this person would display drunkenness (aka “positive”).

True Positive	False Positive
1	0

**The tests would show false drunkenness in 5% of these cases.**  
Hence, ~50 of these tests would display drunkenness (aka “positives”).

True Positive	False Positive
0	50

**PRECISION**

=

$$\frac{\text{TP}}{\text{Predicted Positives}}$$

$$= \frac{1 + 0}{1 + 0 + 50 + 0} \approx 2.0\%$$

This is the probability that *one* of the drivers among all drivers who tested positive is actually drunk.

## ALTERNATIVE SCENARIO:



**The test never fails to detect a truly drunk person.**  
Hence, the test result for these drivers would display drunkenness (aka "positives").

True Positive	False Positive
500	0

**The tests would show false drunkenness in 5% of these cases.**  
Hence, 25 test results would display drunkenness (aka "positives").

True Positive	False Positive
0	25

**PRECISION**

=

$$\frac{\text{TP}}{\text{Predicted Positives}}$$

$$= \frac{500}{500 + 25} \approx 95.0\%$$

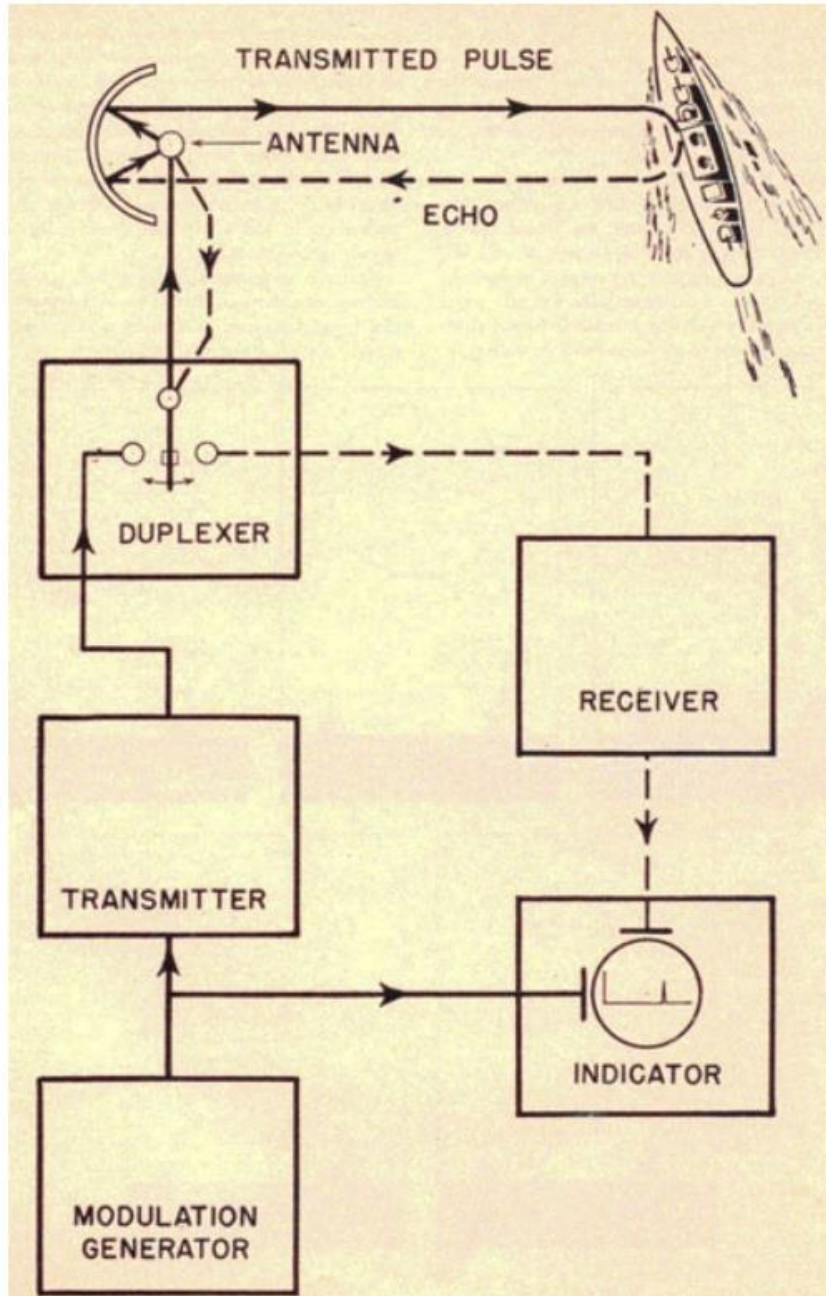
This is the probability that *one* of the drivers among all drivers who tested positive is actually drunk.

- 1 The values depend on the **decision boundary**.
- 2 The values depend on the **class probabilities**.

**We need a measure that is independent of those two factors.**



## RADAR OPERATOR'S MANUAL

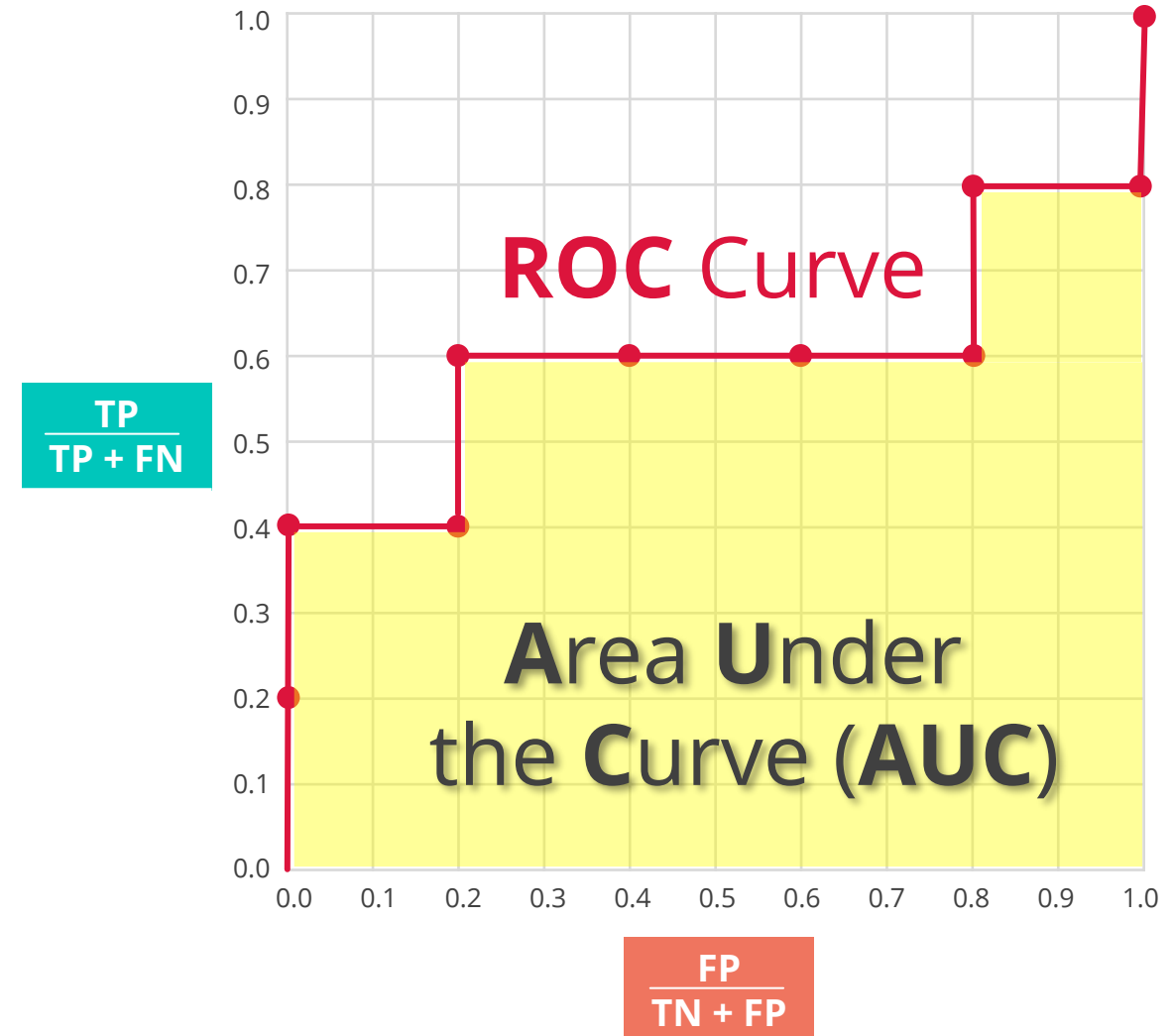


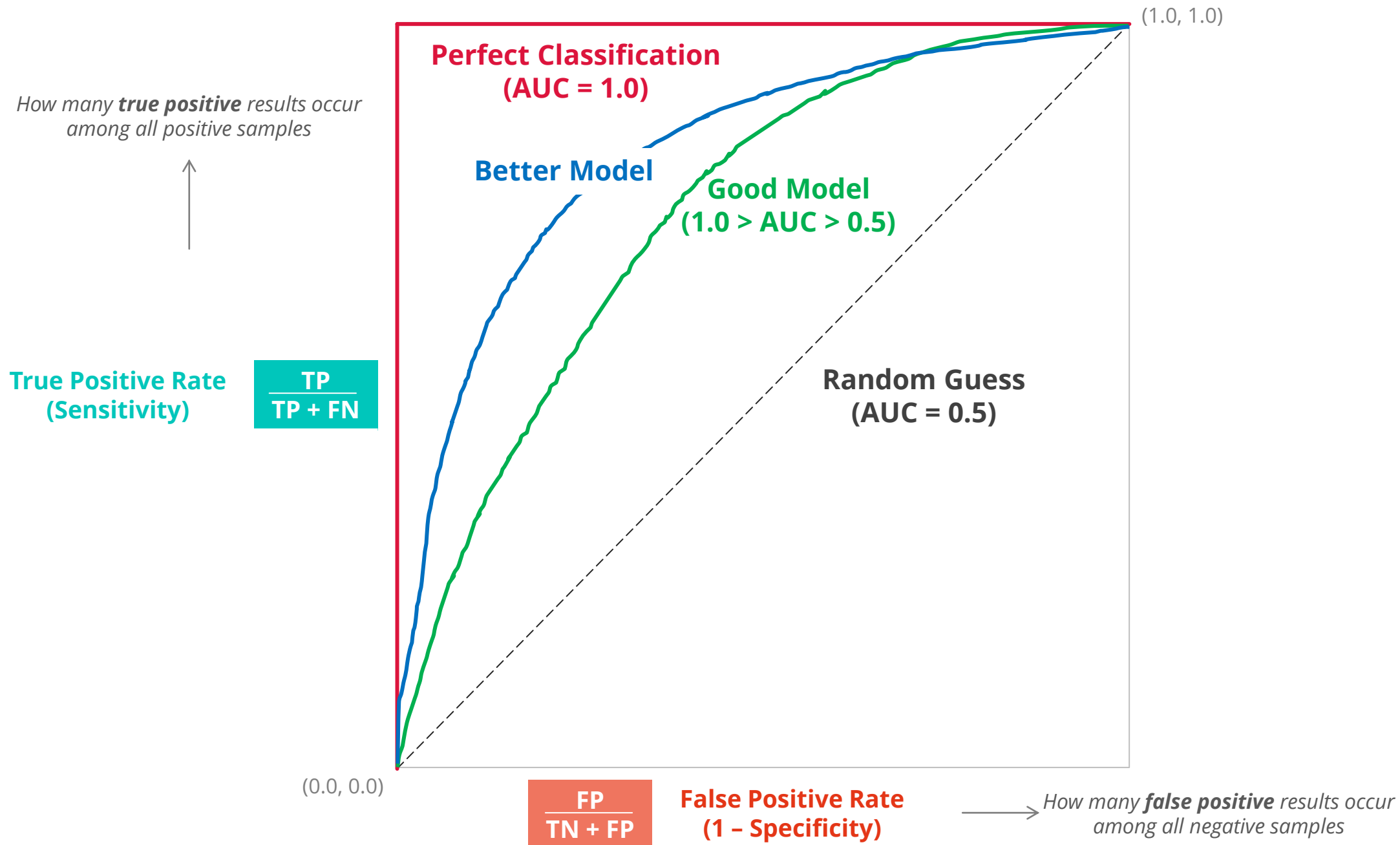
- Following the attack on Pearl Harbor in 1941, the United States army began new research to improve the **predictive accuracy** to correctly detect an enemy aircraft from their radar signals.
- They needed **a new measure** to assess various **radar receiver operators** on their ability to discriminate signal (e.g., enemy aircraft) from noise (e.g., flocks of birds).
- This is a **binary classification** problem!

**Receiver Operating Characteristic**  
**ROC Curve**

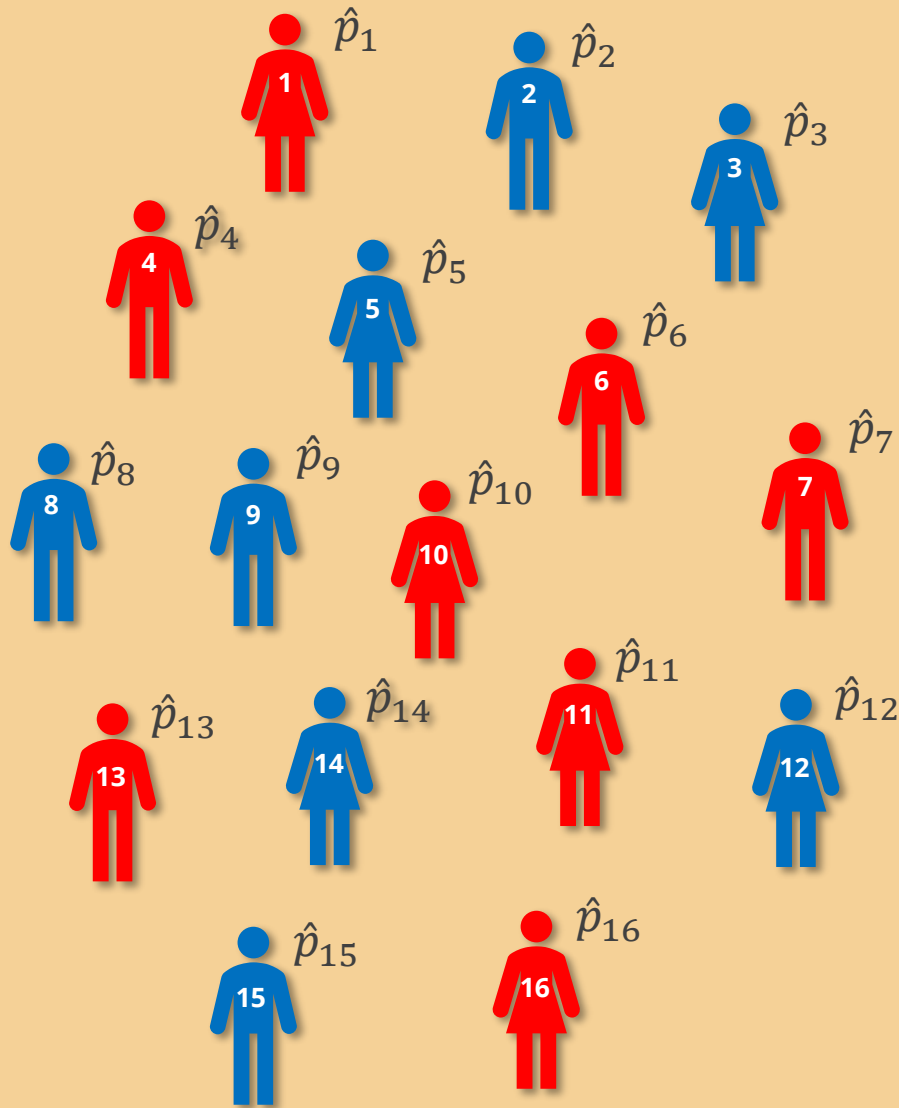
# ROC Curve

True Class (y)	Predicted Probability ( $\hat{p}$ )	$\frac{TP}{TP + FN}$	$\frac{FP}{TN + FP}$
+	0.95	0.2	0.0
+	0.90	0.4	0.0
-	0.89	0.4	0.2
+	0.71	0.6	0.2
-	0.59	0.6	0.4
-	0.47	0.6	0.6
-	0.31	0.6	0.8
+	0.29	0.8	0.8
-	0.24	0.8	1.0
+	0.12	1.0	1.0





$\hat{p}$  = Probability of being a Republican



**Actual  
Republican**

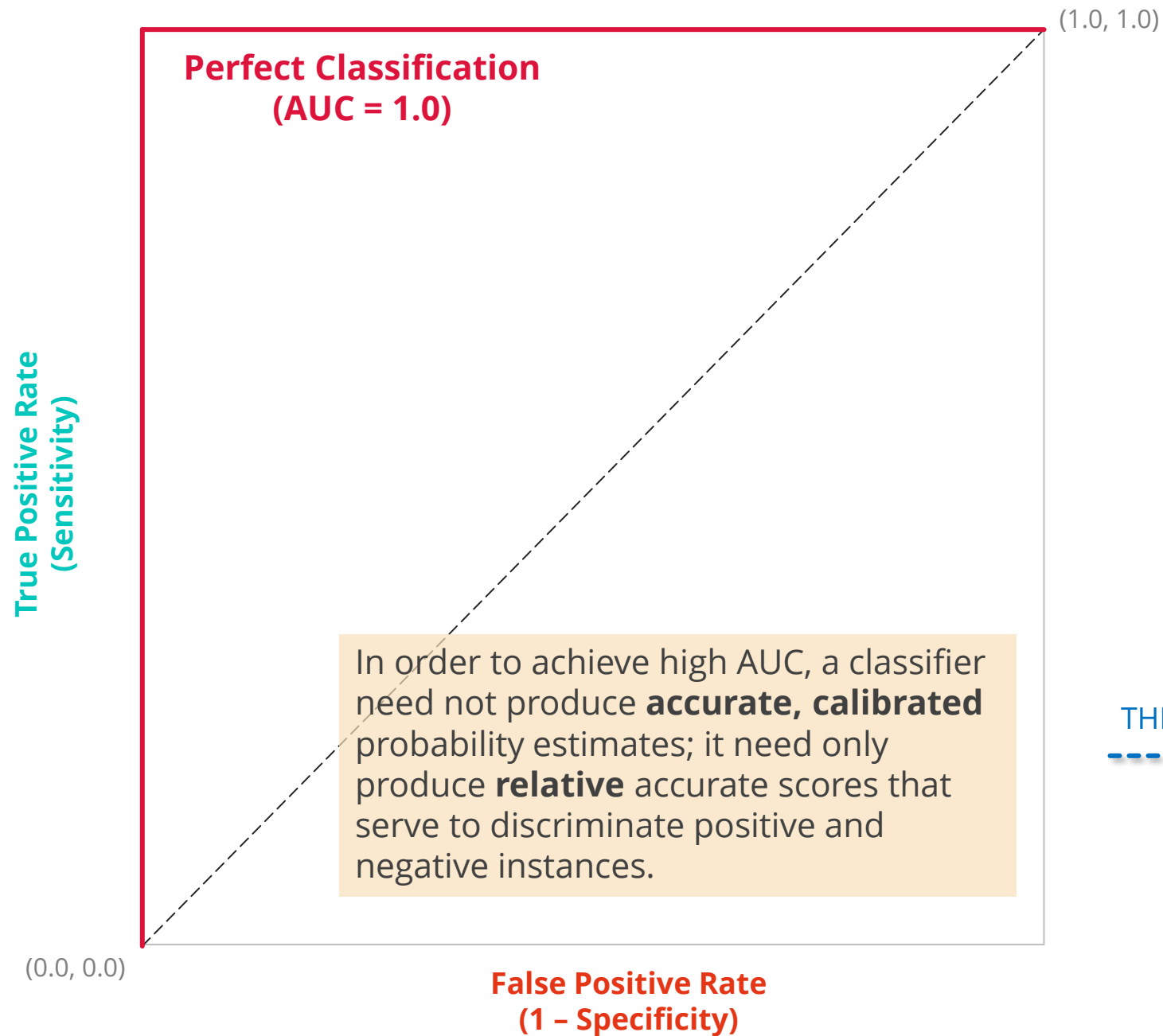
**Actual  
Democrat**

(Both randomly selected)

What is the **probability**  
that  $\hat{p}_4$  is greater than  $\hat{p}_{14}$ ?



**AUC**



ACCURACY = 80%!

THRESHOLD = 0.5

$y$	$\hat{p}$	$\hat{y}$
1	0.99999	1
1	0.99999	1
1	0.99993	1
1	0.99986	1
1	0.99964	1
1	0.99955	1
0	0.68139	1
0	0.50961	1
0	0.48880	0
0	0.44951	0

	MODEL A	MODEL B
True Class (y)	Predicted Probability ( $\hat{p}$ )	Predicted Probability ( $\hat{p}$ )
+	0.29 (-) ✖	0.11 (-) ✖
+	0.90 (+)	0.90 (+)
-	0.31 (-)	0.31 (-)
-	0.89 (+) ✖	0.98 (+) ✖
+	0.95 (+)	0.95 (+)
+	0.71 (+)	0.71 (+)
-	0.24 (-)	0.24 (-)
+	0.12 (-) ✖	0.02 (-) ✖
-	0.59 (+) ✖	0.90 (+) ✖
-	0.47 (-)	0.47 (-)

	MODEL A	MODEL B
True Class (y)	Predicted Probability ( $\hat{p}$ )	Predicted Probability ( $\hat{p}$ )
+	0.29 (-)	0.11 (-)
-	0.89 (+)	0.98 (+)
+	0.12 (-)	0.02 (-)
-	0.59 (+)	0.91 (+)

Equivocally  
wrong

Emphatically  
wrong

Which model is better?

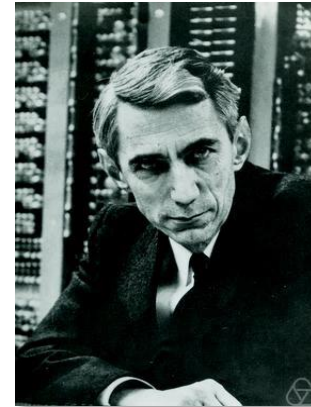
# Log Loss / Cross-entropy Loss

$$\text{logLoss} = -\frac{1}{N} \sum_{i=1}^N (y_i (\log(\hat{p}_i)) + (1 - y_i) \log(1 - \hat{p}_i))$$

If  $y_i = 1$  and  $\hat{p}_i$  is high  $\rightarrow$  Good!

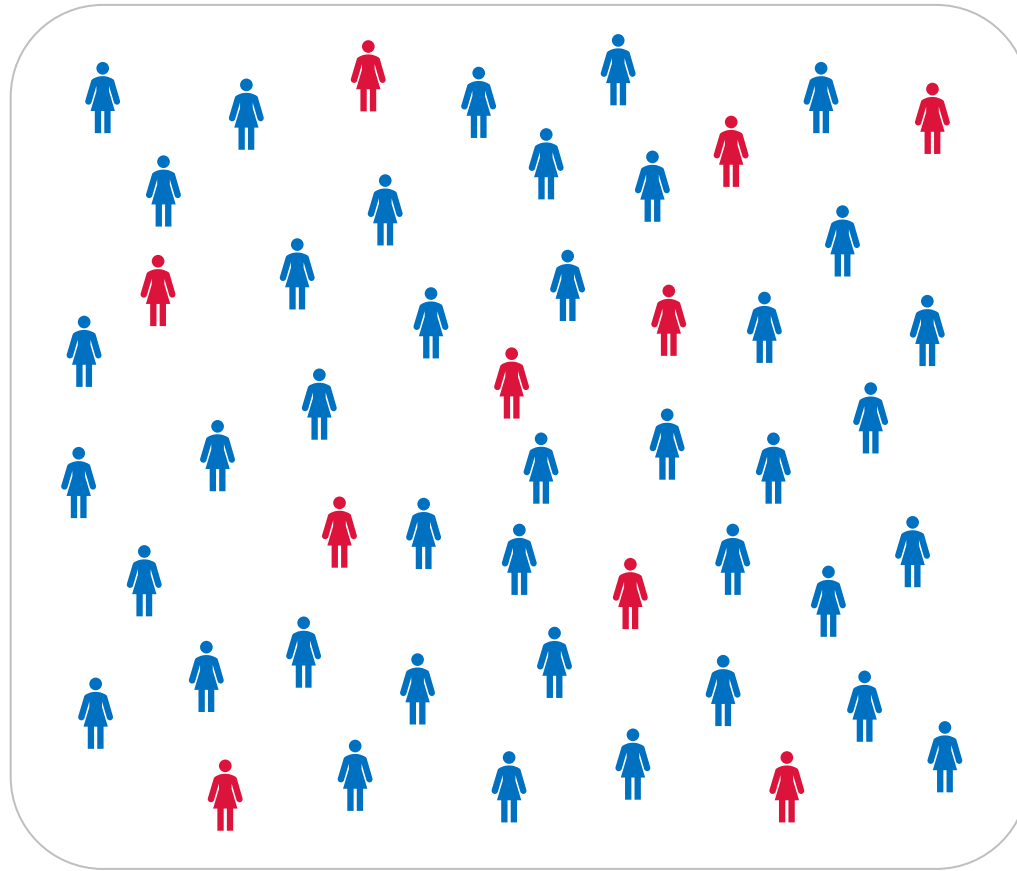
If  $y_i = 0$  and  $\hat{p}_i$  is low  $\rightarrow$  Good!

$$H(p, q) = - \sum_i p_i \log q_i$$



# Model Lift and Gain





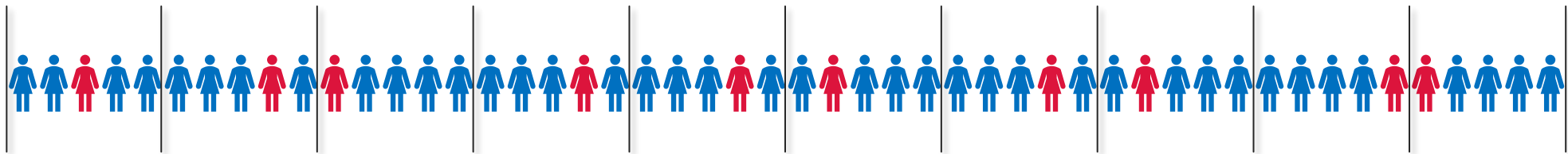
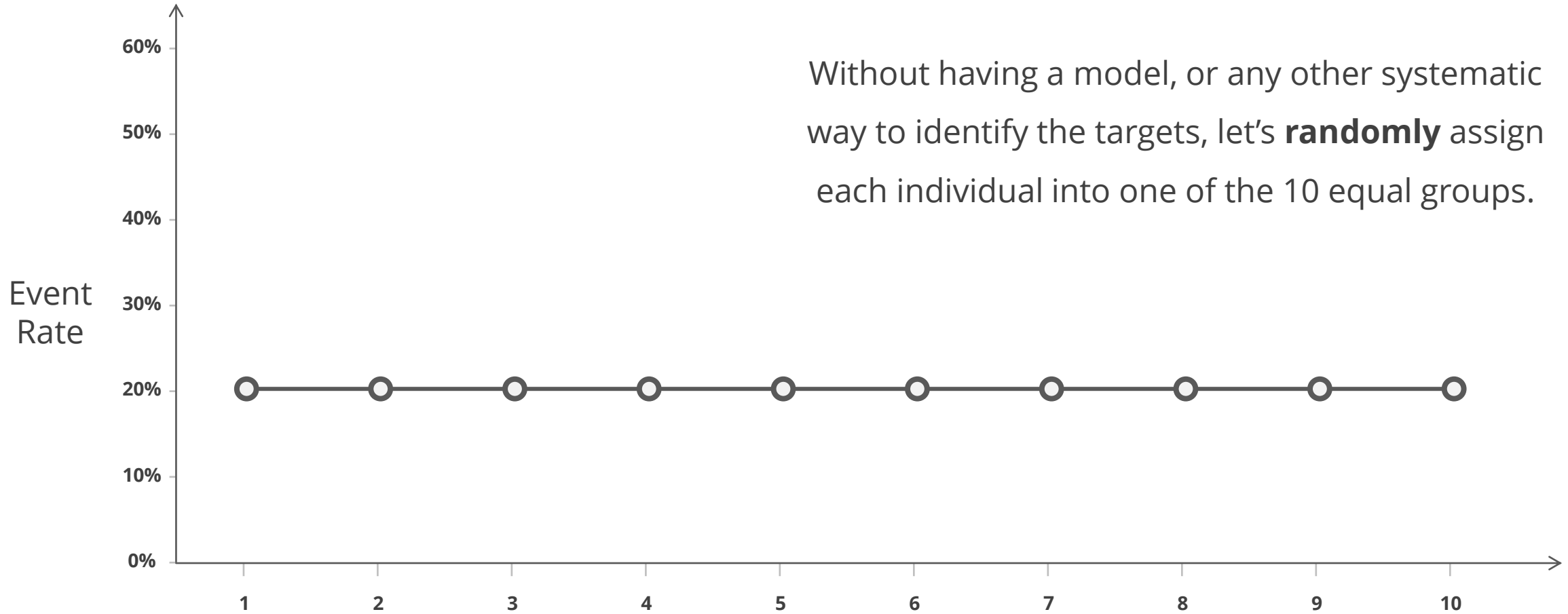
$N = 50$

Targets / Events = 10

Non-events = 40

Event Rate = 20%

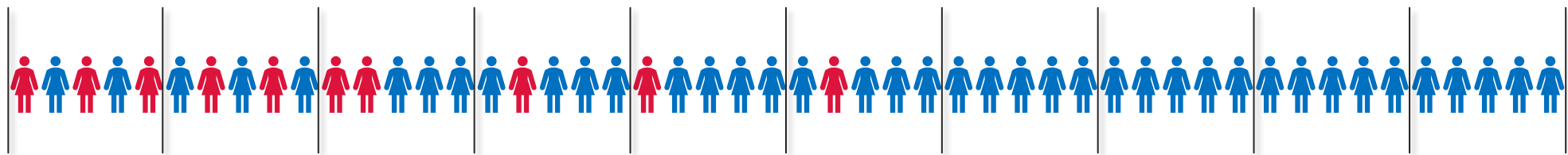
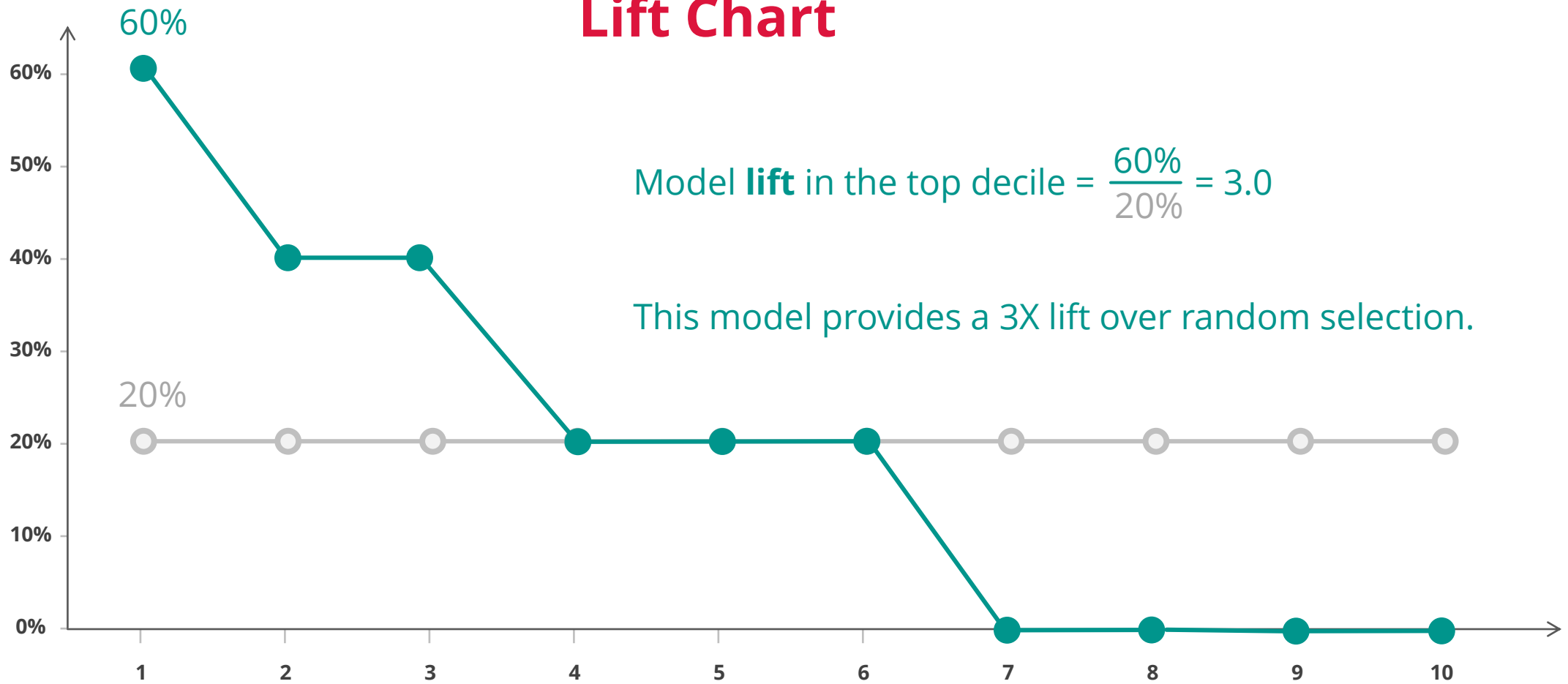
Without having a model, or any other systematic way to identify the targets, let's **randomly** assign each individual into one of the 10 equal groups.



10 equal groups, aka **deciles**

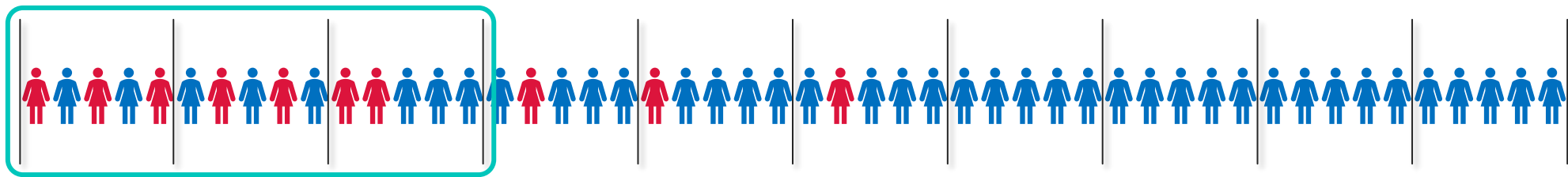
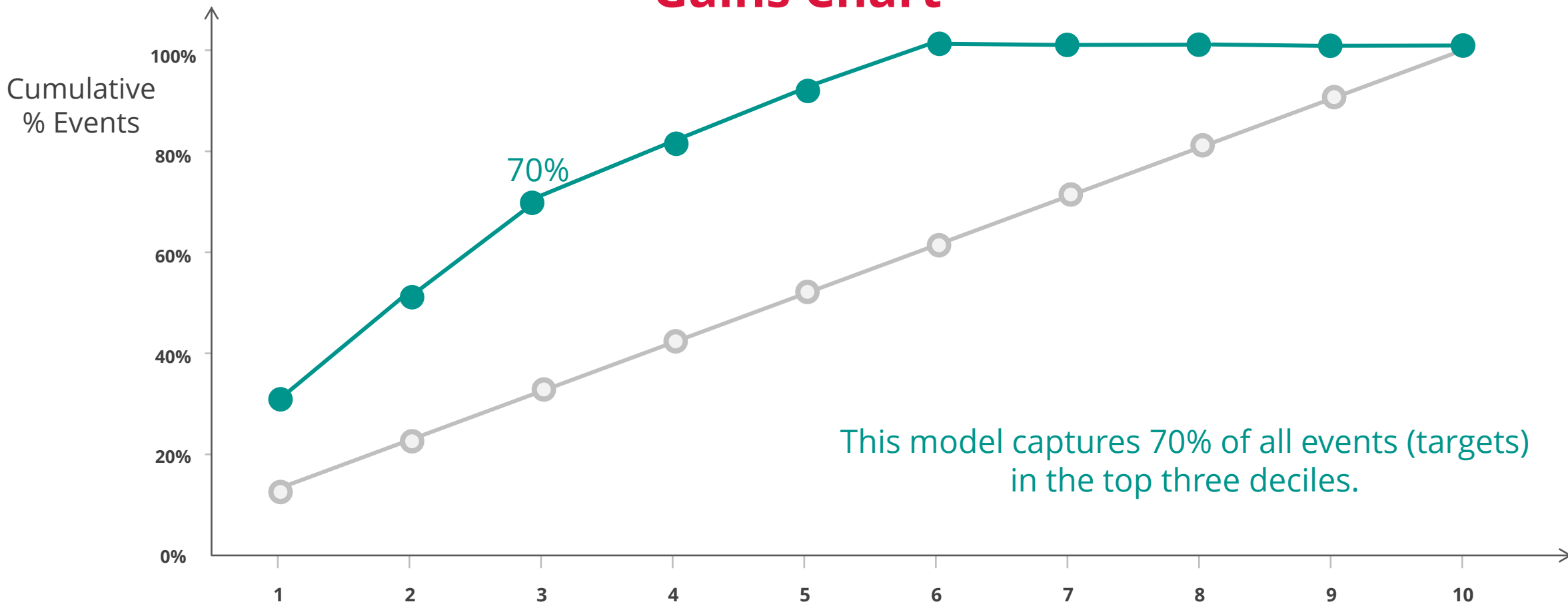
# Lift Chart

Event  
Rate



← High Probability      Ranked according to **predicted probabilities** (from a model)      Low Probability →

# Gains Chart



← High Probability

Ranked according to predicted probabilities (from a model)

Low Probability →

When a measure becomes a target,  
it ceases to be a good measure.

Goodhart's law

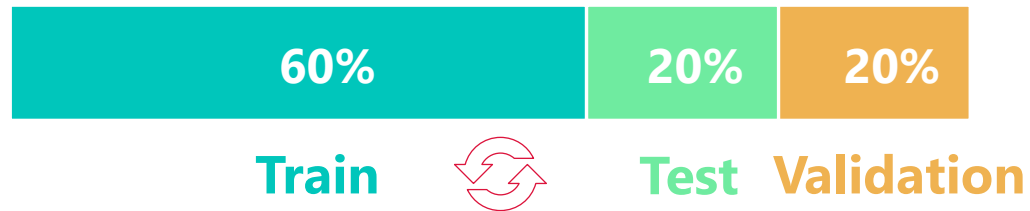


# Tri-fold Partitioning

1. Split the modeling dataset into three random partitions: **train**, **test**, and **validation**.
  - a) There are no hard and fast rules about the proportions of those three partitions.  
Suggested proportions are: 60/20/20, 60/30/10, 70/15/15, 70/20/10, or equal split.
  - b) If the sample size is small, two-fold partitioning or  $k$ -fold cross-validation can be used.
2. **Fit** (train) your models on the **training** set.
3. **Assess** the model accuracy, using one or more metrics, on the **test** set.
  - a) Choose metrics that align with the business objectives.
4. Repeat steps 2 and 3 to **refine** your models, e.g., tune hyper-parameters, select a smaller set of predictors.
5. **Select** the best model based on its performance on the **test** set.
6. Once the model is finalized, **measure** the accuracy of the final model using the **validation** (aka the 'hold-out') set.

# *k*-fold Cross Validation

## Tri-fold Partitioning



Final  
Model Performance  
Summary

## *k*-fold Partitioning

