

# Testing and Error Metrics

## Machine Learning

(Largely based on slides from Luis Serrano)

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Institute of Computing (IC/Unicamp)

MC886, August 28, 2019

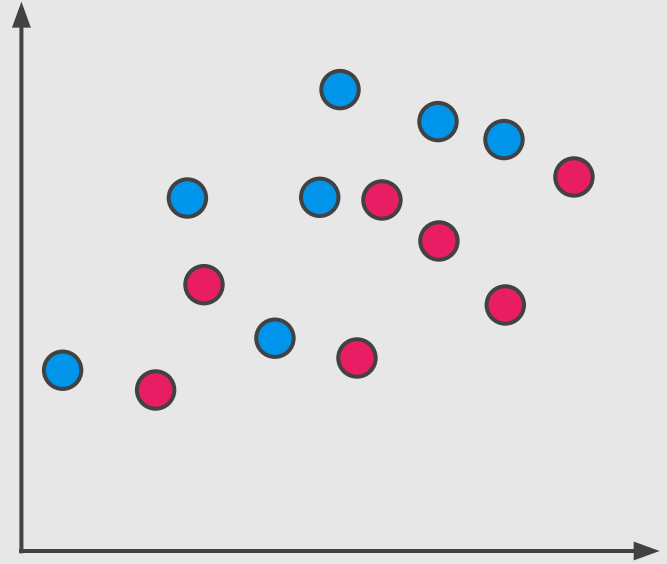
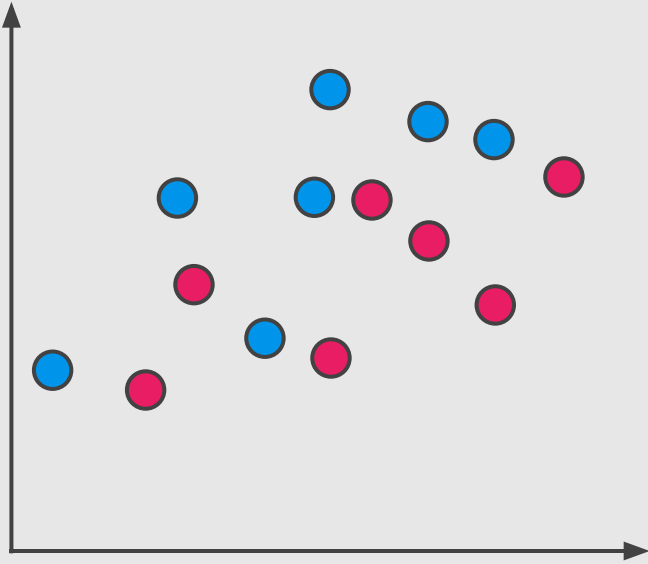
How well is my model doing?

# Today's Agenda

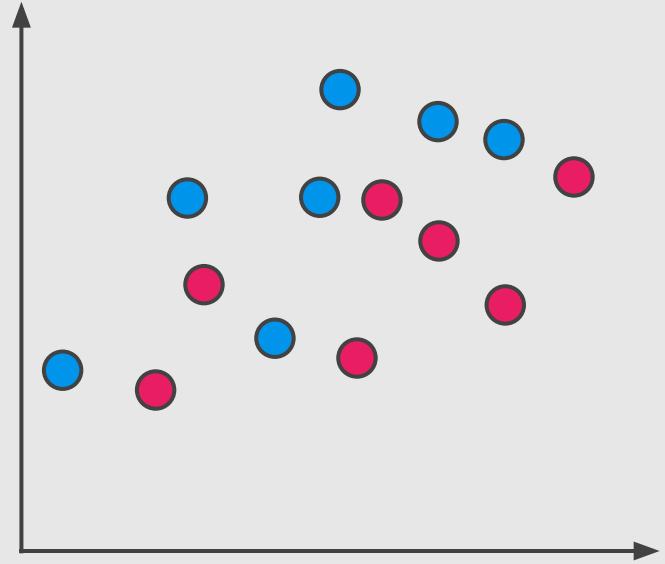
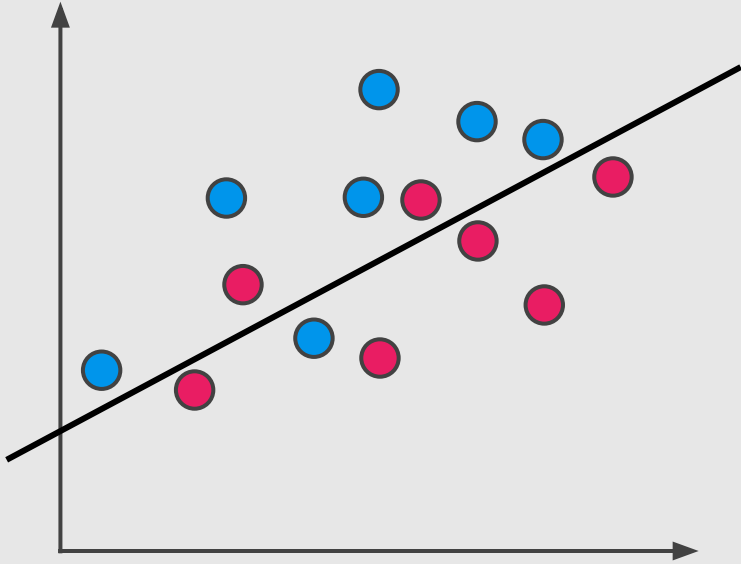
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- Testing and Error Metrics
  - Training, Testing
  - Accuracy
  - Precision
  - Recall
  - F-Score

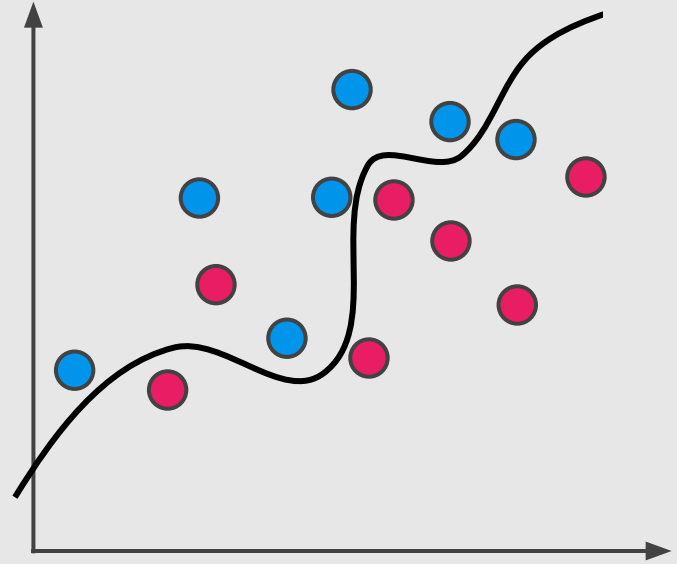
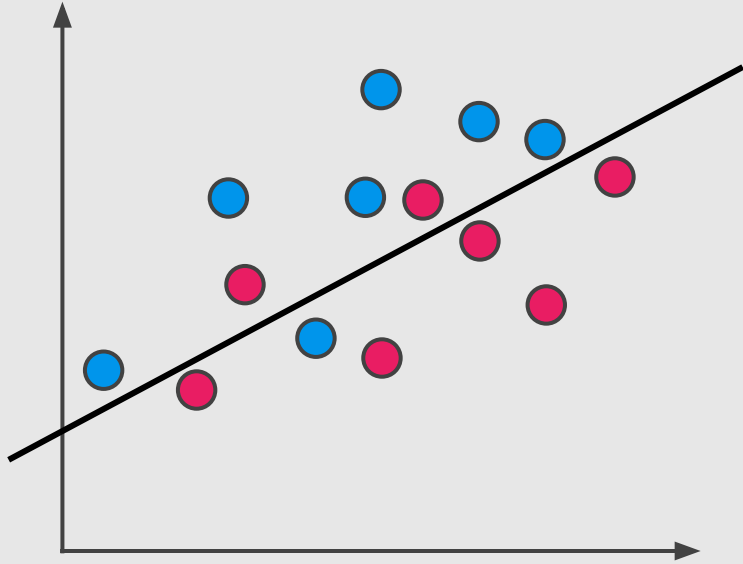
# Which model is better?



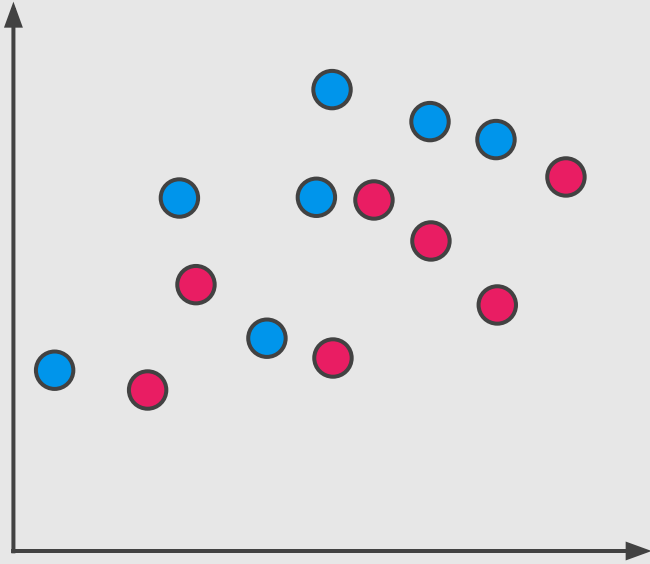
# Which model is better?



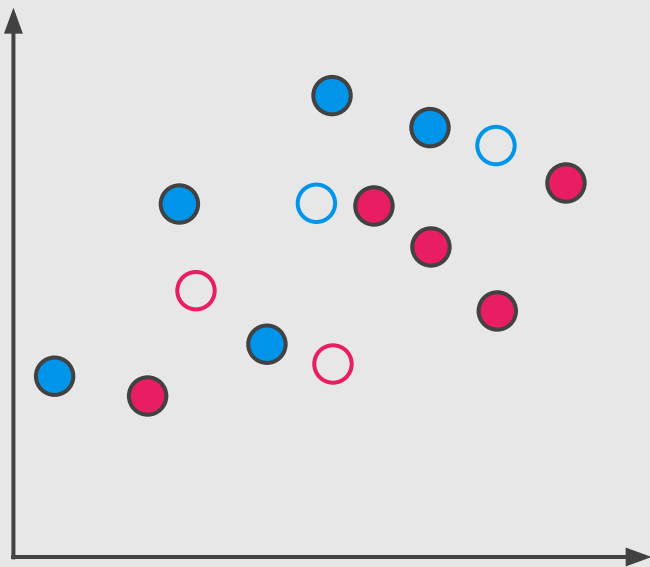
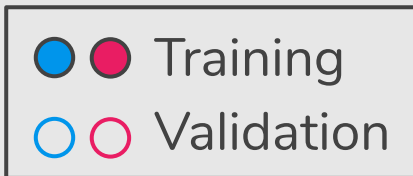
# Which model is better?



# Why validating?

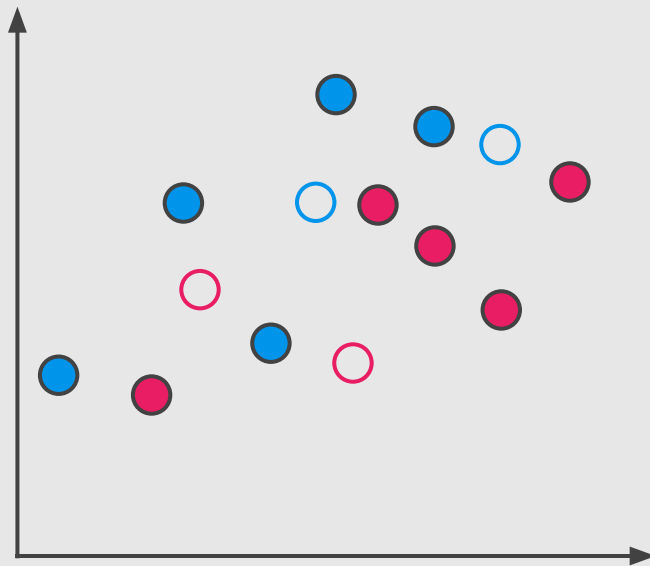
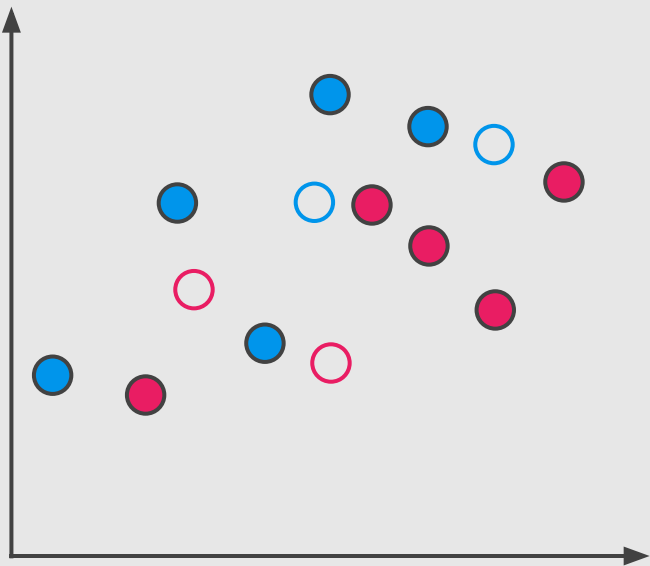
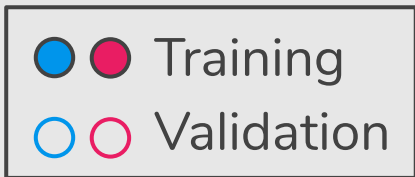


# Why validating?

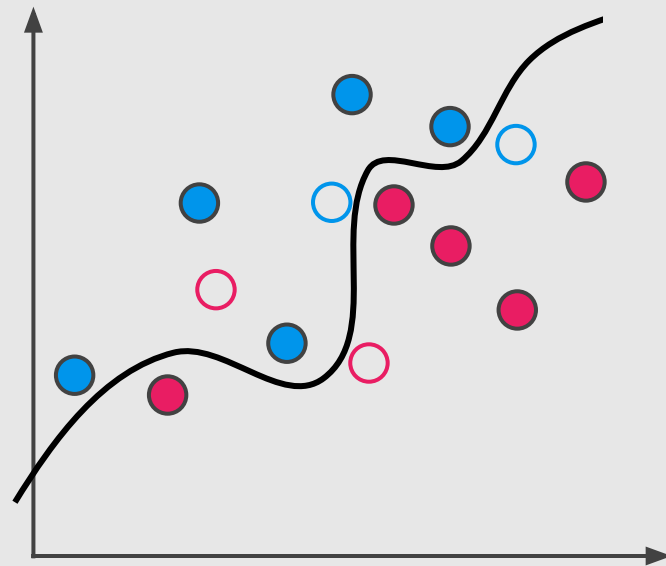
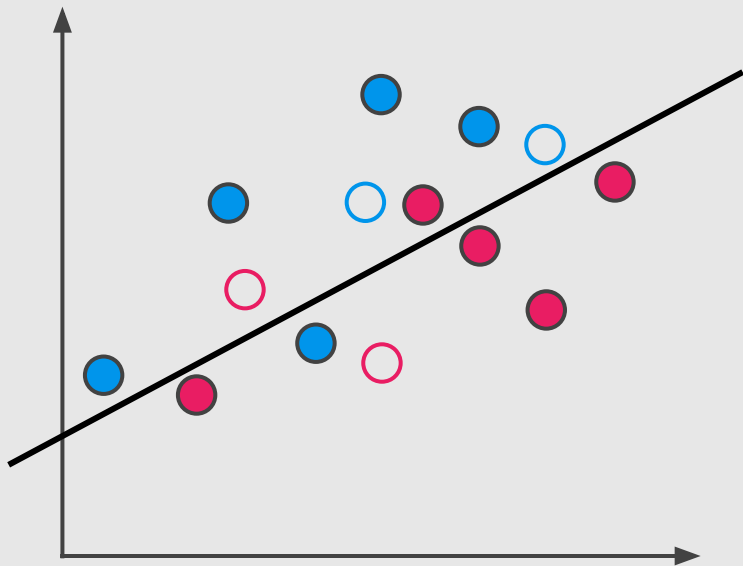
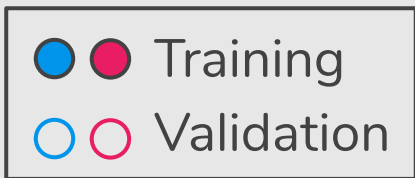




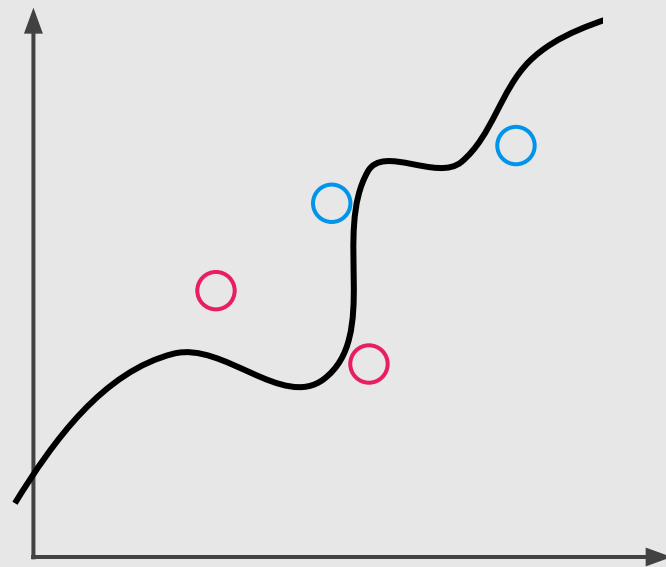
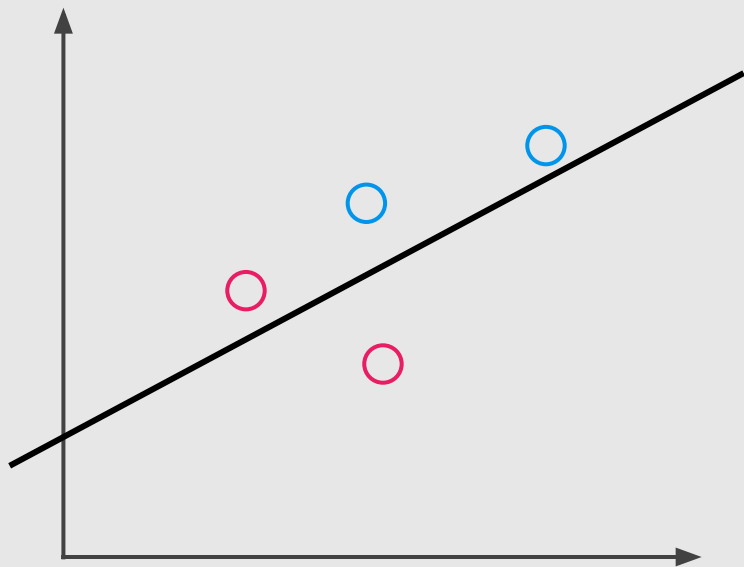
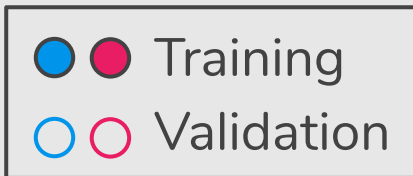
# Why validating?



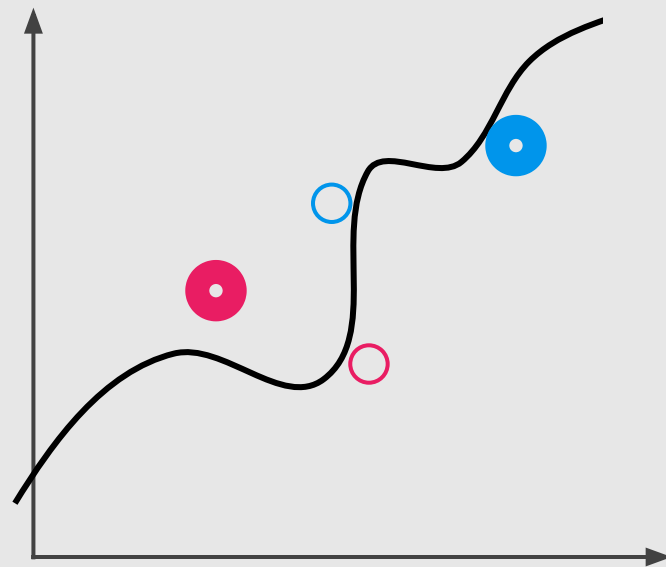
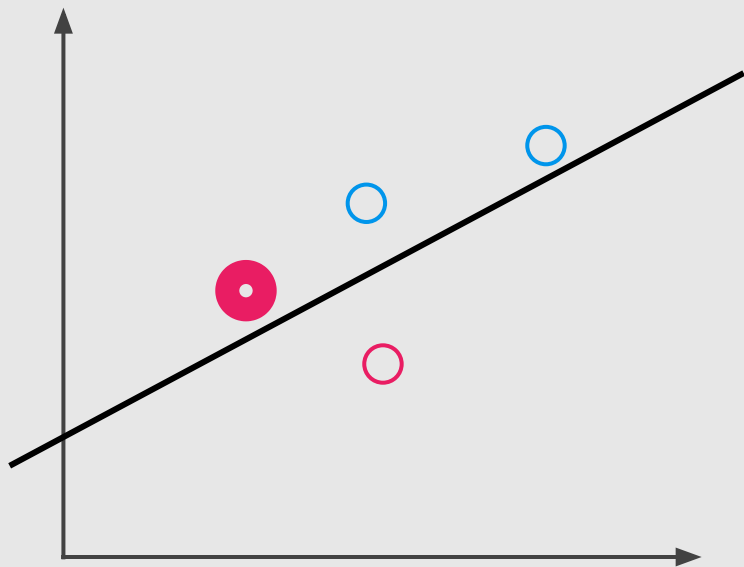
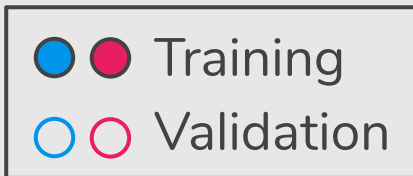
# Why validating?



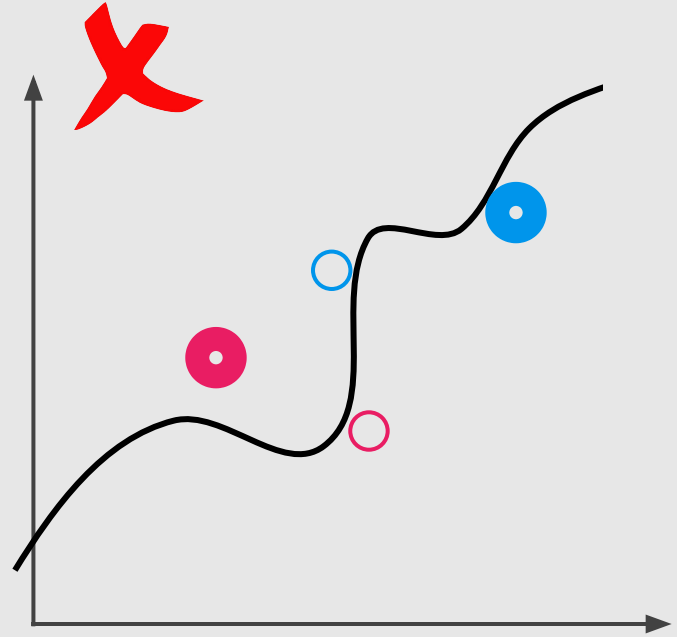
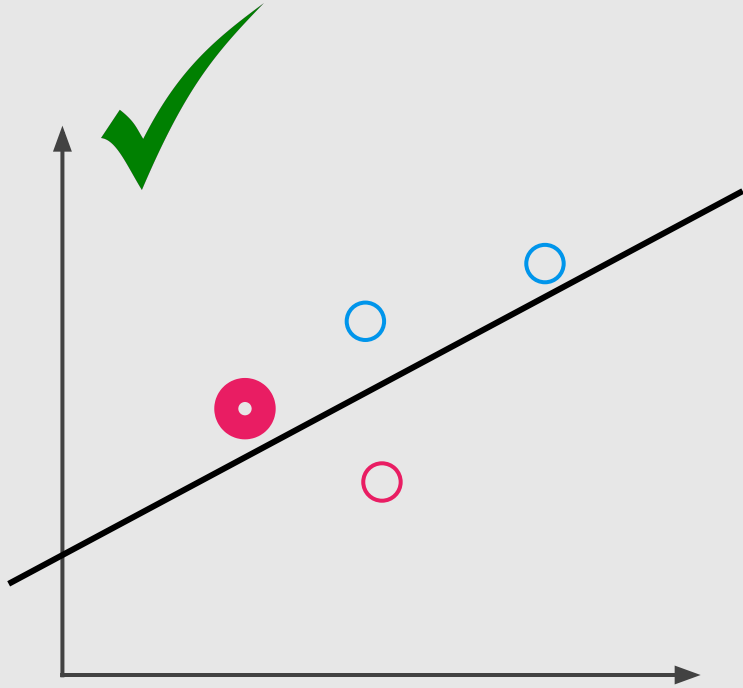
# Why validating?



# Why validating?



# Why validating?



Friends don't let friends  
use testing data  
for training

Data

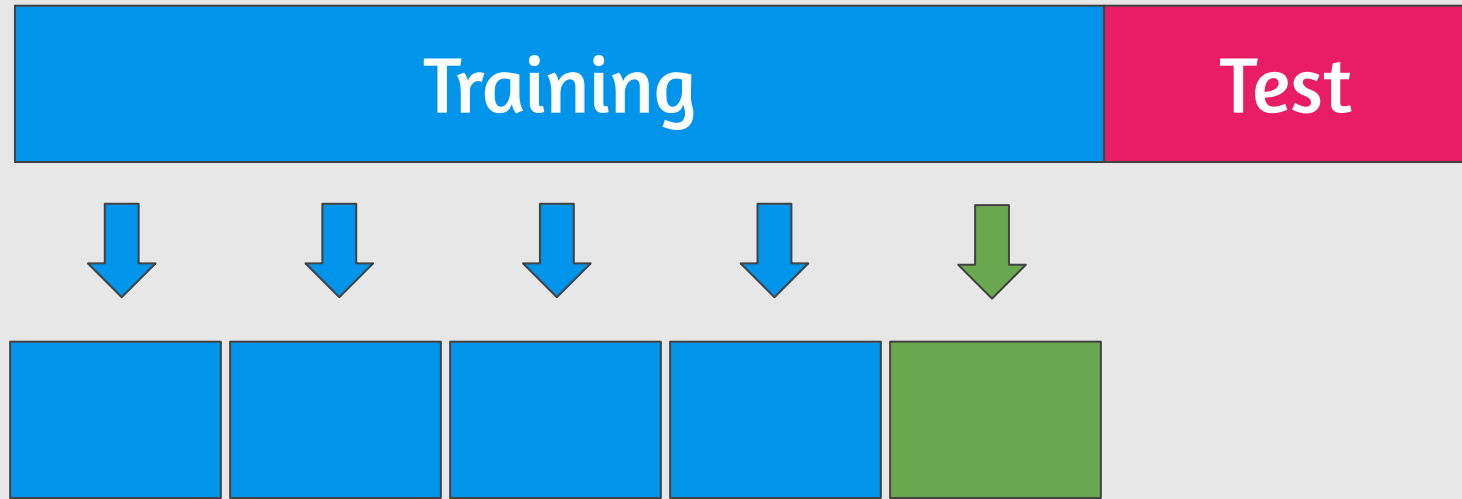


Training Test



Training Validation Test

# k-fold Cross Validation

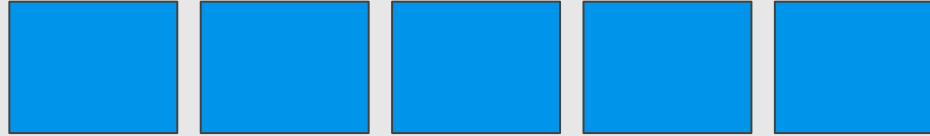




# k-fold Cross Validation



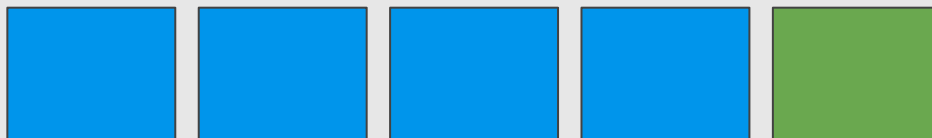
$k = 5$



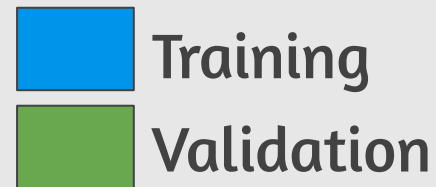
# k-fold Cross Validation



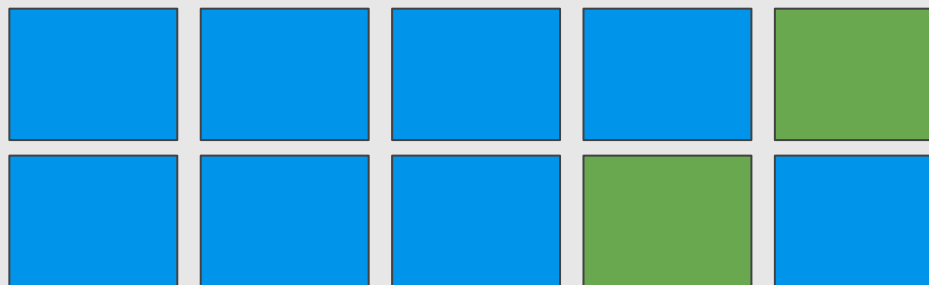
$k = 5$



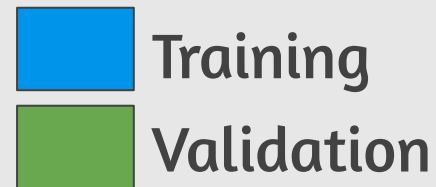
# k-fold Cross Validation



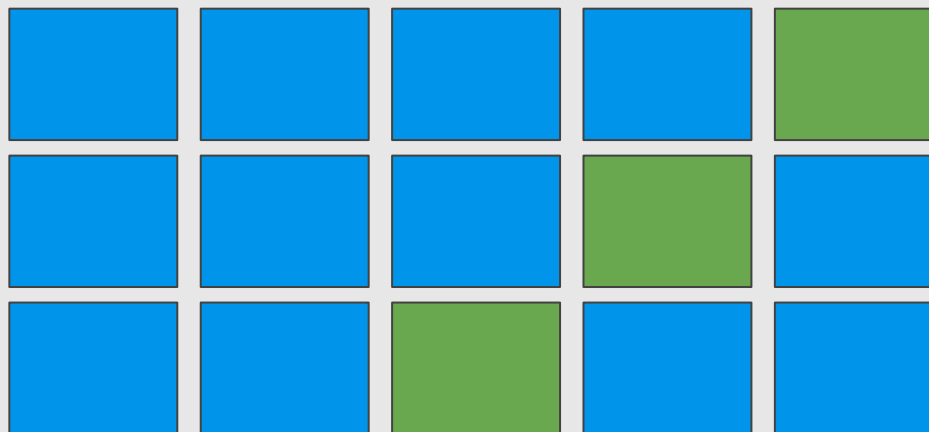
$k = 5$



# k-fold Cross Validation



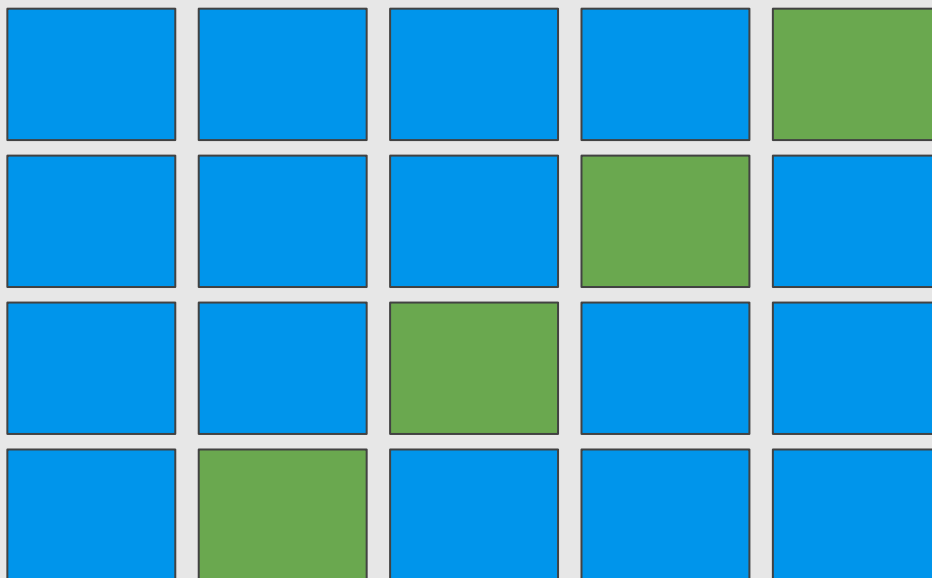
$k = 5$



# k-fold Cross Validation



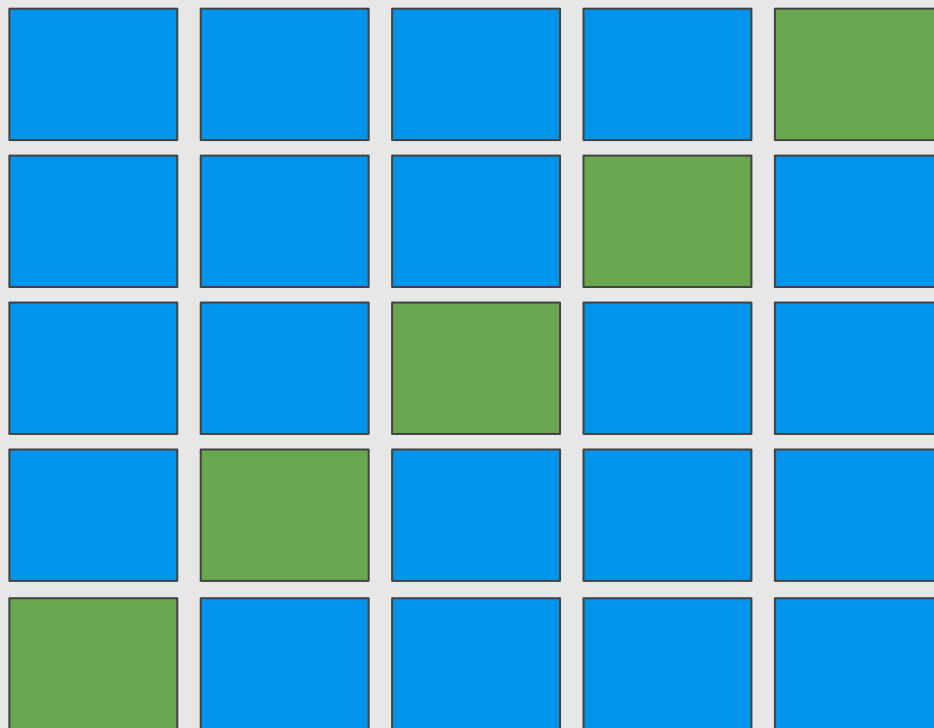
$k = 5$



# k-fold Cross Validation



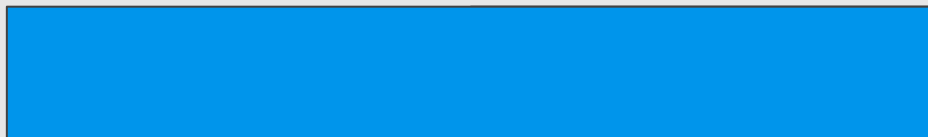
$k = 5$



# $k \times 2$ -fold Cross Validation



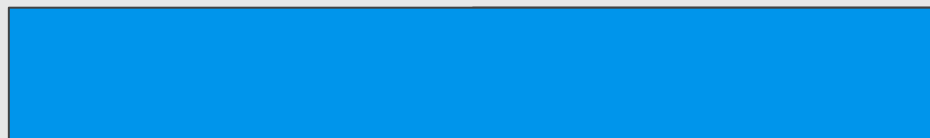
$k = 5$



# $k \times 2$ -fold Cross Validation



$k = 5$





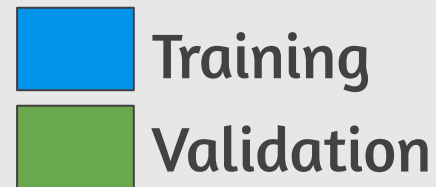
# $k \times 2$ -fold Cross Validation



$k = 5$



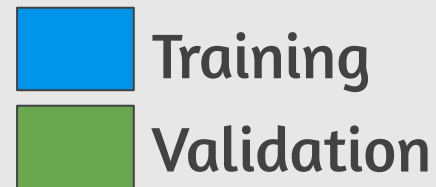
# $k \times 2$ -fold Cross Validation



$k = 5$



# $k \times 2$ -fold Cross Validation



$k = 5$



← randomized

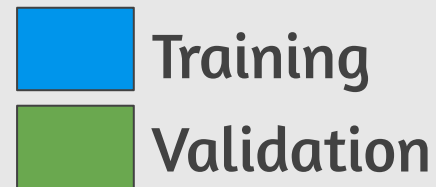
# $k \times 2$ -fold Cross Validation



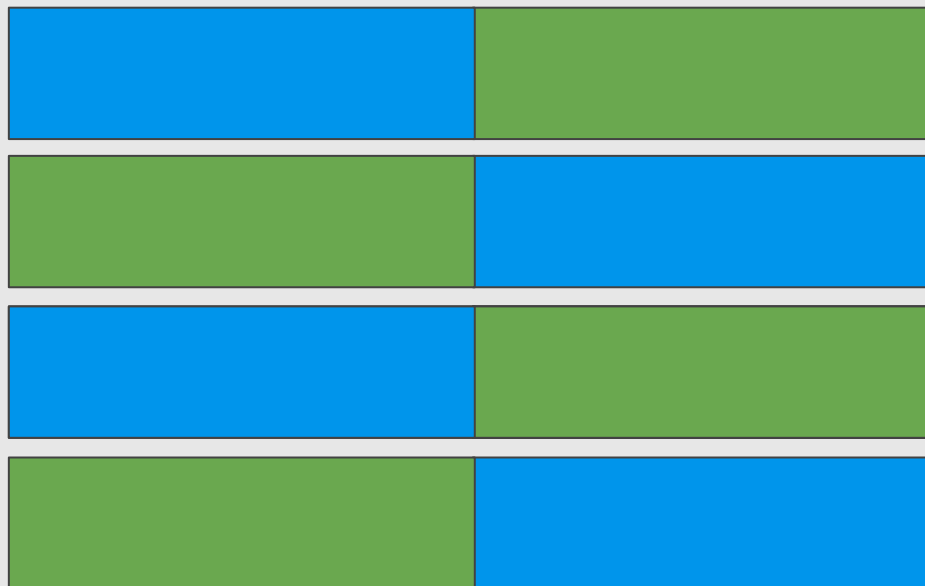
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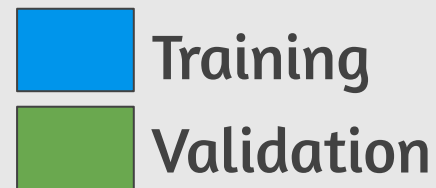
# $k \times 2$ -fold Cross Validation



$k = 5$



# $k \times 2$ -fold Cross Validation



$k = 5$

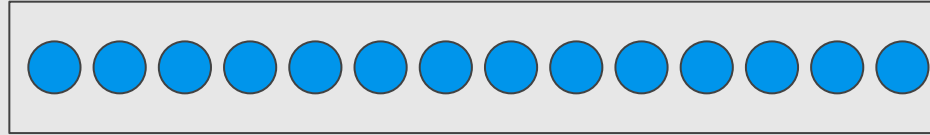


...

$k$  times =  $k \times 2$  folds

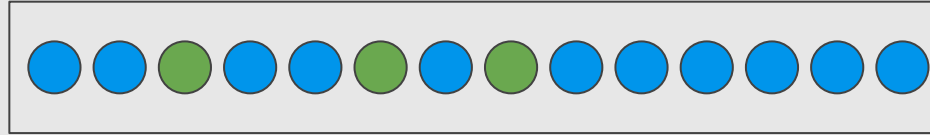
# Randomizing in Cross Validation

- Training
- Validation



# Randomizing in Cross Validation

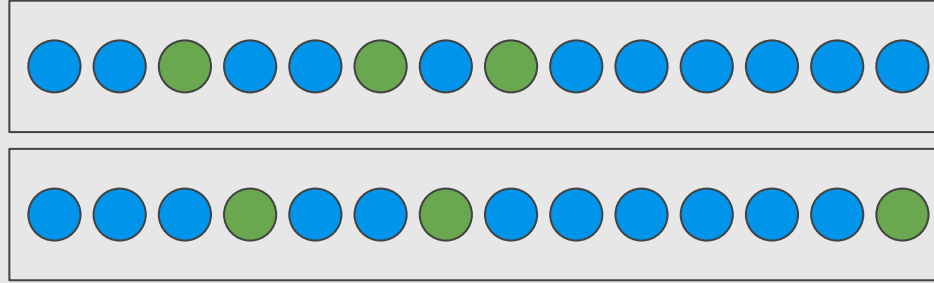
- Training
- Validation





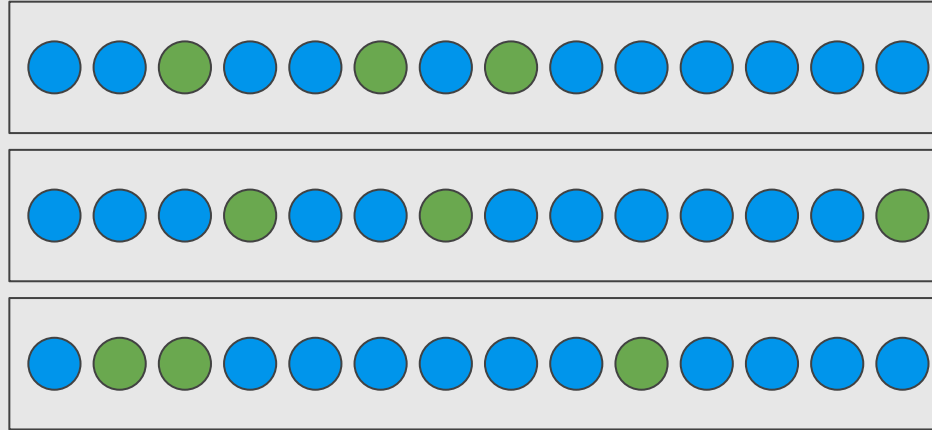
# Randomizing in Cross Validation

- Training
- Validation



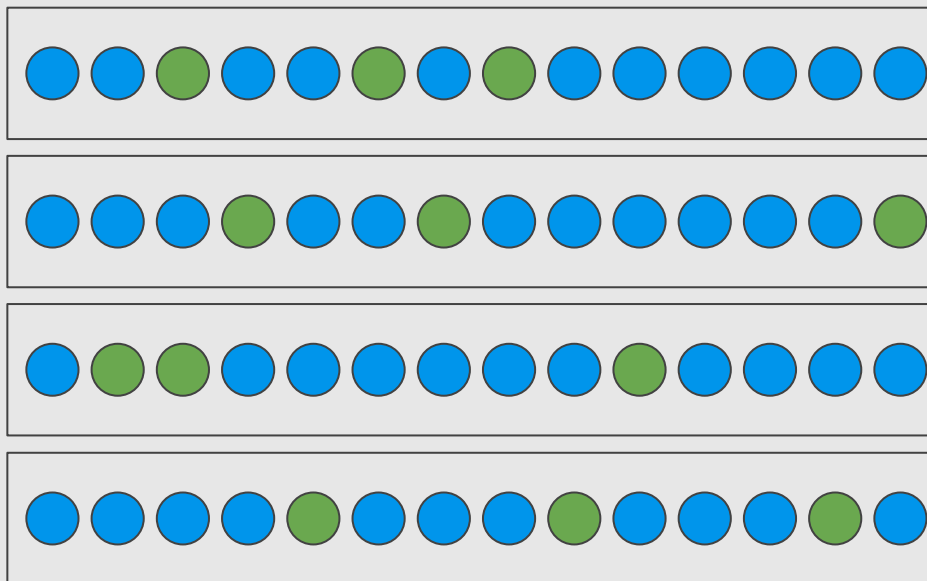
# Randomizing in Cross Validation

- Training
- Validation



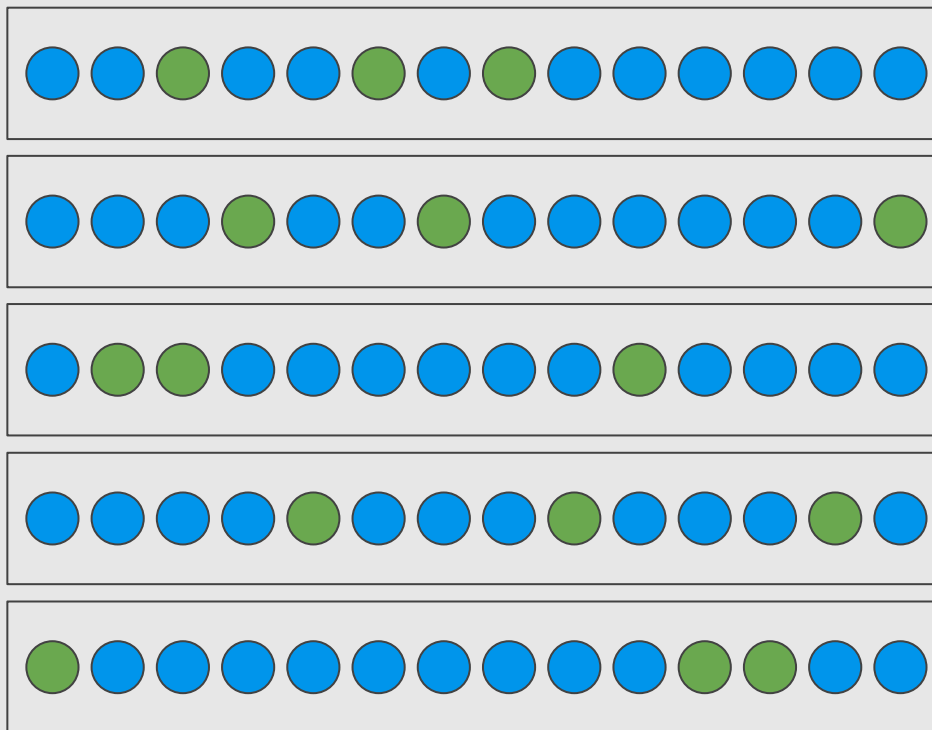
# Randomizing in Cross Validation

- Training
- Validation



# Randomizing in Cross Validation

- Training
- Validation



# MO850A: Tópicos Avançados em Ciência da Computação I — **Scientific Methodology**

Prof. Jacques Wainer (IC/Unicamp)

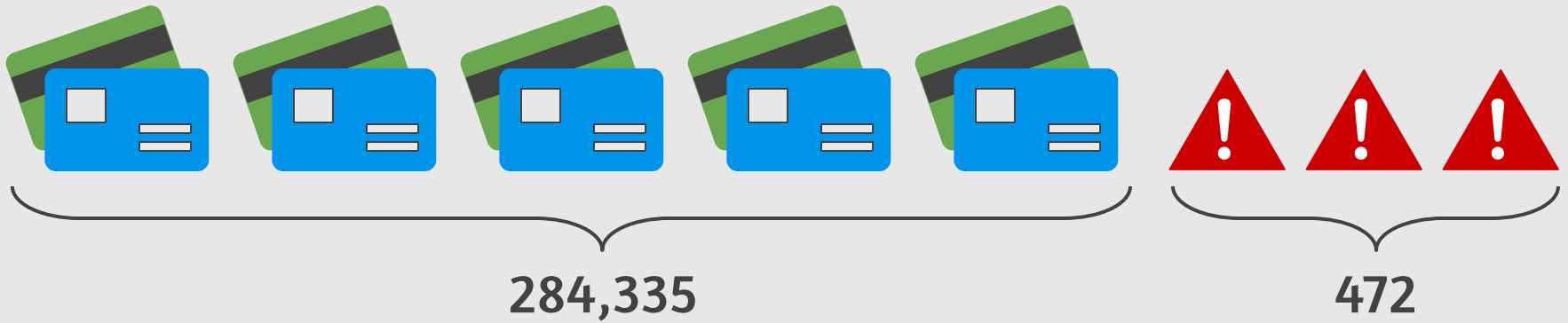
# Evaluation Metrics

How well is my model doing?

# Credit Card Fraud

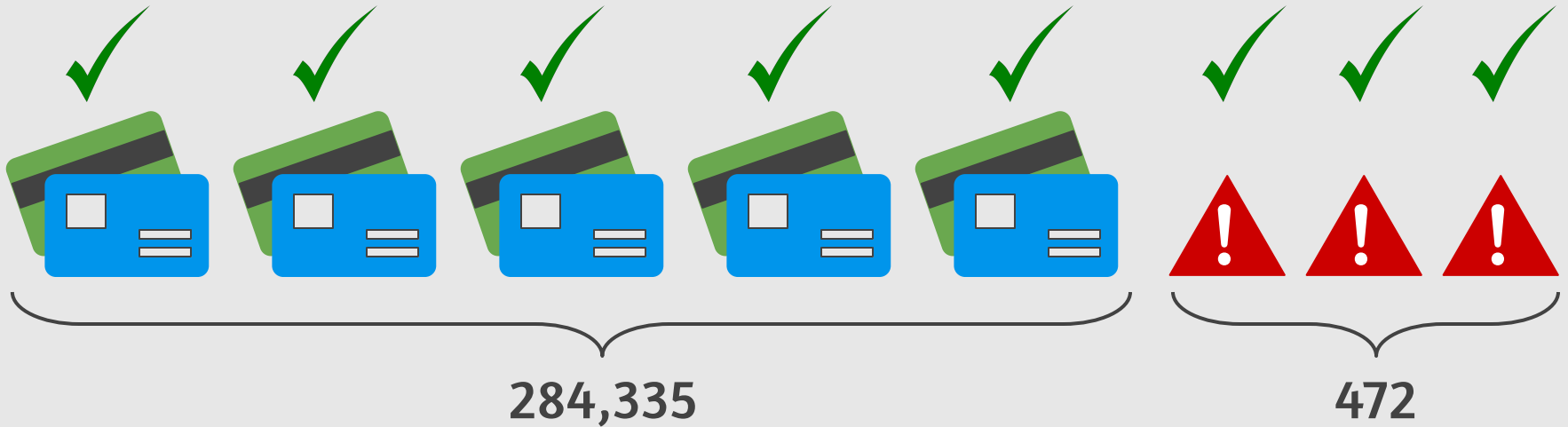


# Credit Card Fraud



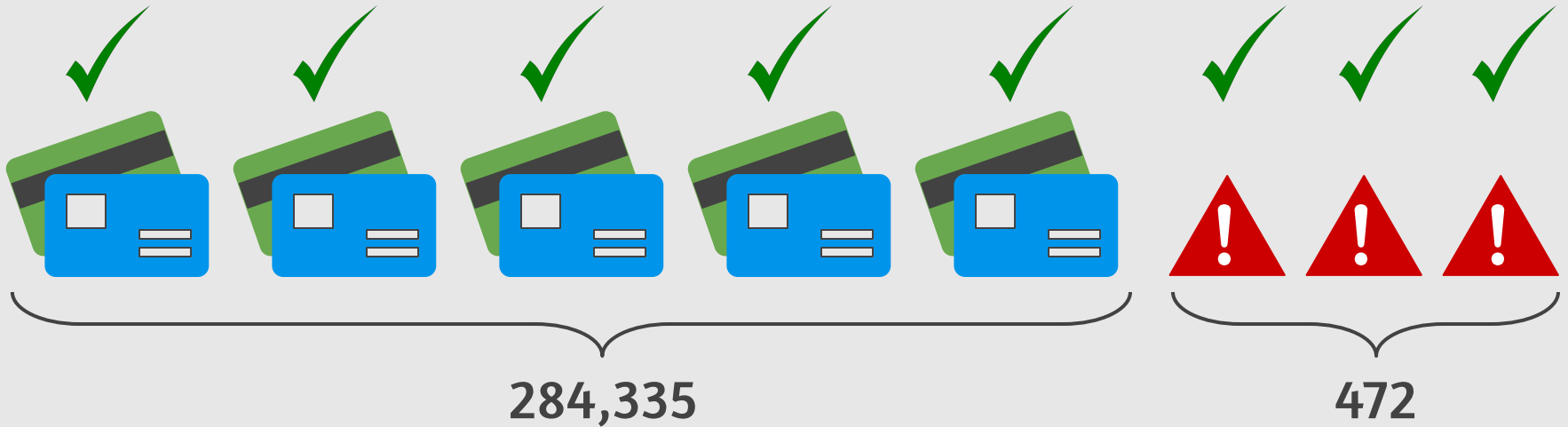


# Credit Card Fraud



Model: All transactions are good.

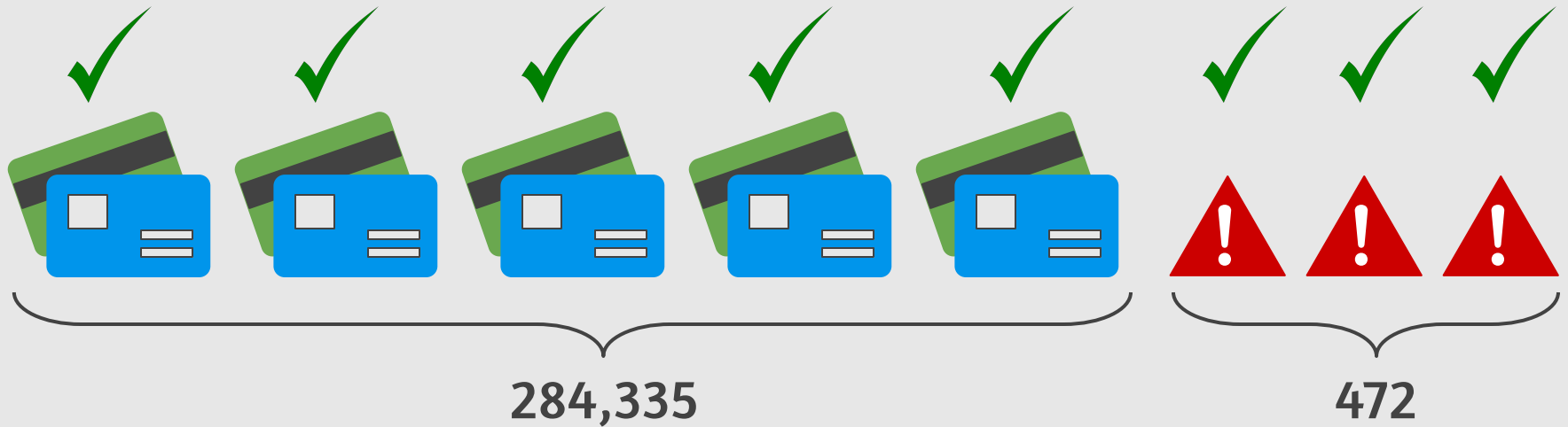
# Credit Card Fraud



Model: All transactions are good.

$$\text{Correct} = \frac{284,335}{284,807} = 99.83\%$$

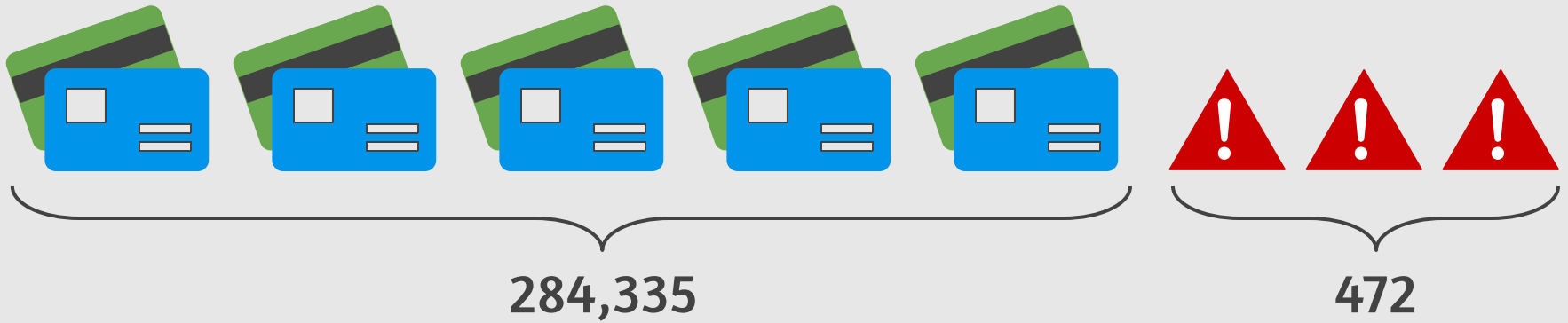
# Credit Card Fraud



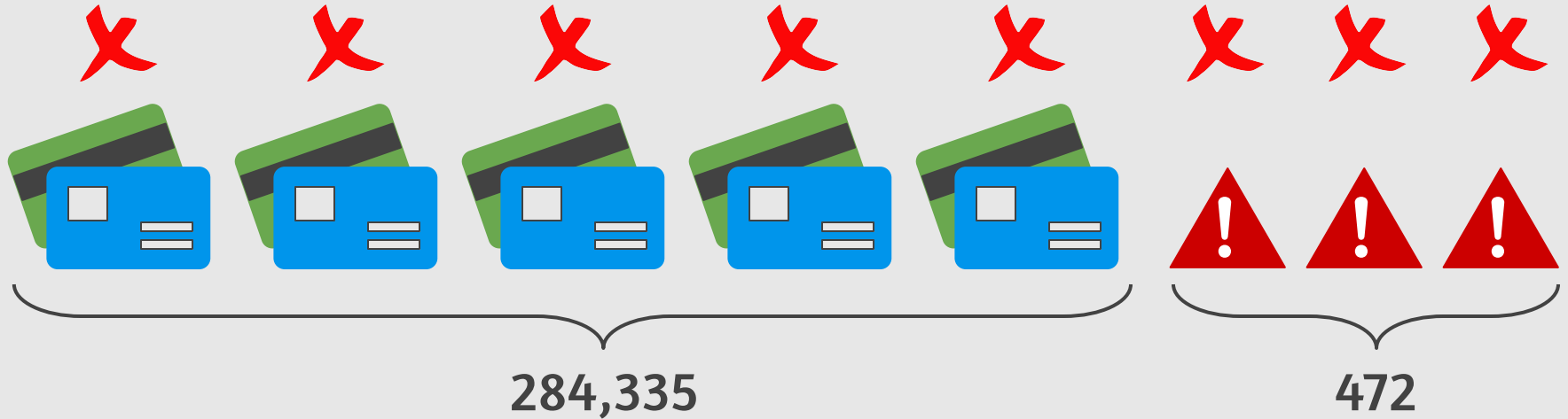
Model: All transactions are good.

Problem: I'm not catching any of the bad ones!

# Credit Card Fraud

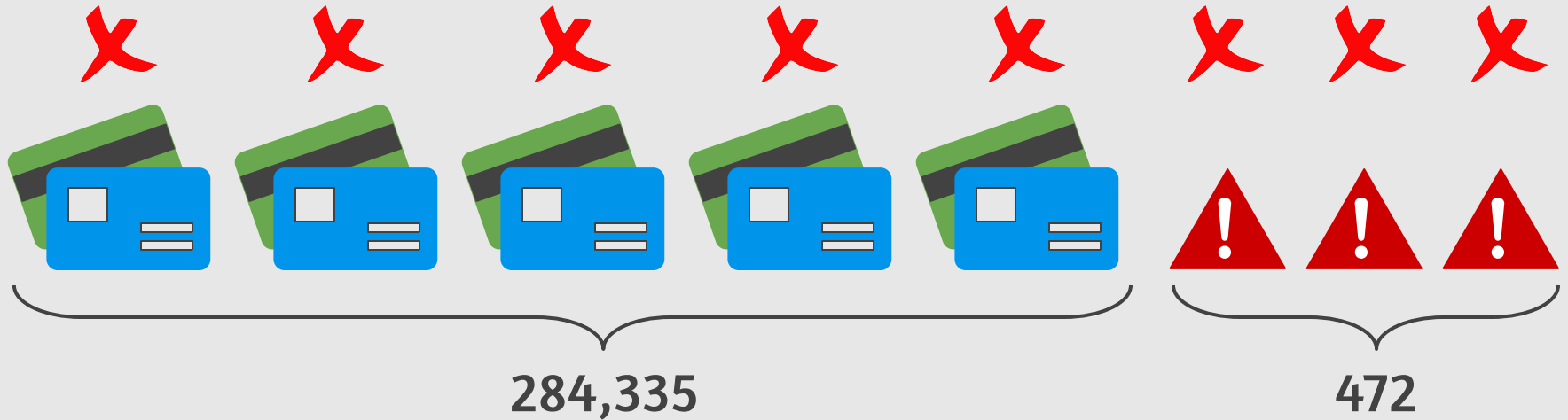


# Credit Card Fraud



Model: All transactions are fraudulent.

# Credit Card Fraud



Model: All transactions are fraudulent.

Problem: I'm accidentally catching all the good ones!

# Medical Model



Health



Sick

# Spam Classifier Model




Not Spam





Spam






# Confusion Matrix Table

	Diagnosed Sick	Diagnosed Healthy
Sick		
Healthy		





# Confusion Matrix Table

	Diagnosed Sick	Diagnosed Healthy
Sick	True Positive 	
Healthy		






# Confusion Matrix Table

	Diagnosed Sick	Diagnosed Healthy
Sick	True Positive 	
Healthy		True Negative 

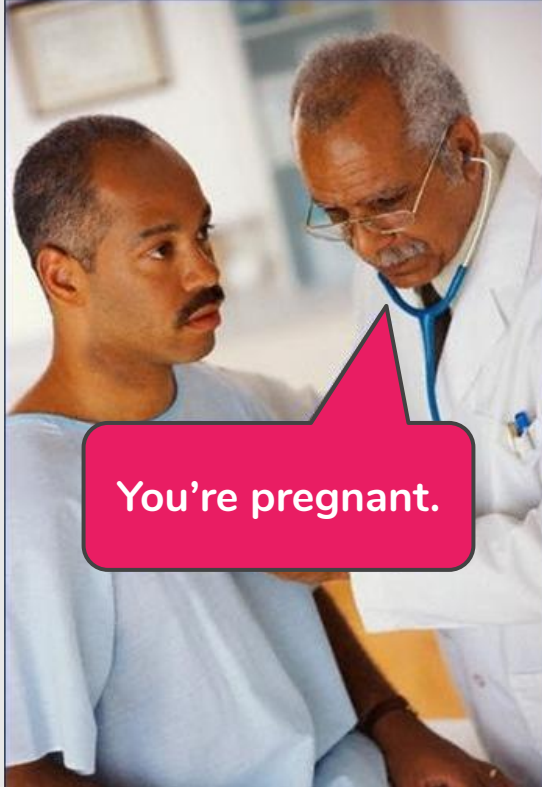
# Confusion Matrix Table

	Diagnosed Sick	Diagnosed Healthy
Sick	True Positive 	False Negative 
Healthy		True Negative 

# Confusion Matrix Table

	Diagnosed Sick	Diagnosed Healthy
Sick	True Positive 	False Negative 
Healthy	False Positive 	True Negative 

## Type I Error (False Positive)



## Type II Error (False Negative)








# Confusion Matrix Table



10,000  
patients

		Diagnosis	
		Diagnosed Sick	Diagnosed Healthy
Patients	Sick	1000	200
	Healthy	800	8000

# Confusion Matrix Table

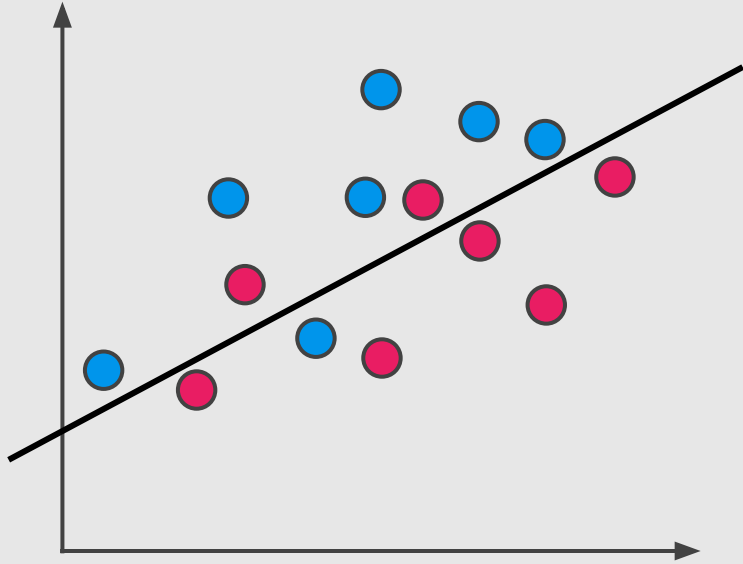
	Sent to Spam Folder	Sent to Inbox
Spam	True Positive 	False Negative 
Not Spam	False Positive 	True Negative 



# Confusion Matrix Table

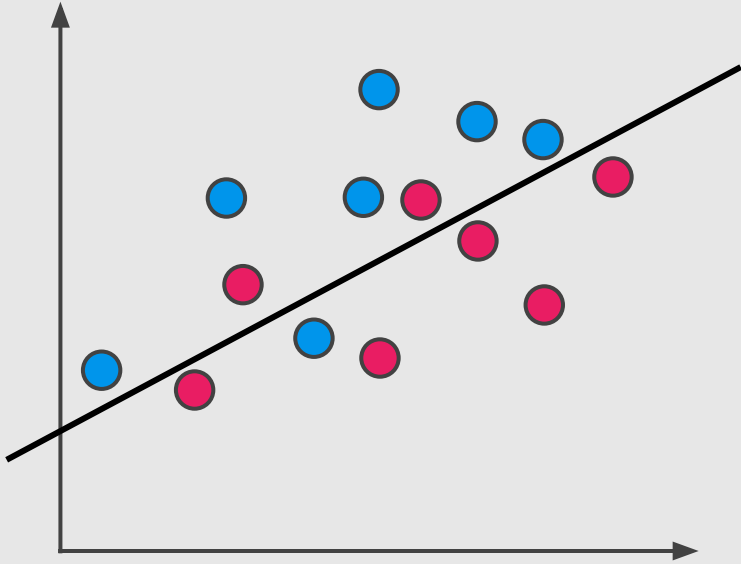
		Folder	
		Spam Folder	Inbox
1,000 emails	Spam	100	170
	Not Spam	30	700

# Confusion Matrix Table



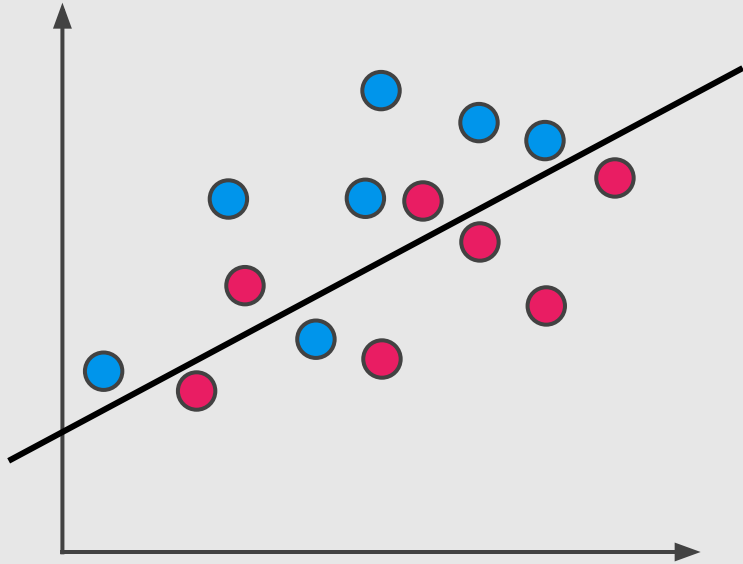
		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive		
	Negative		

# Confusion Matrix Table



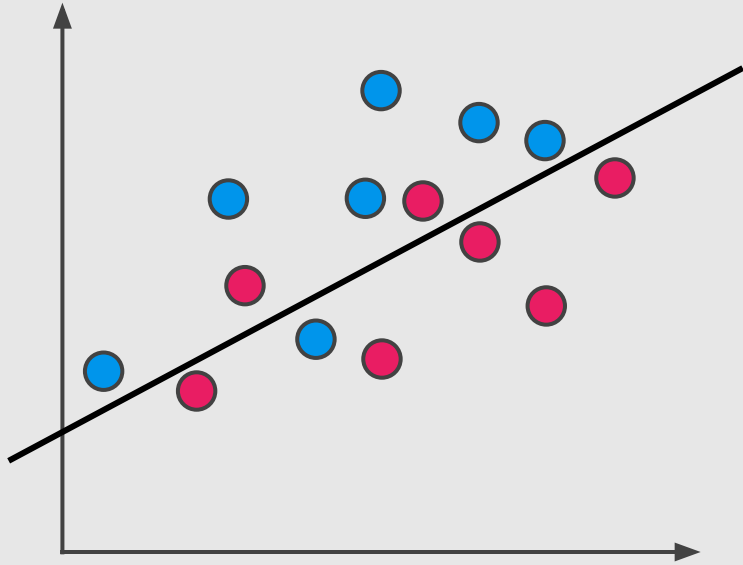
		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive	6 True positives	
	Negative		

# Confusion Matrix Table



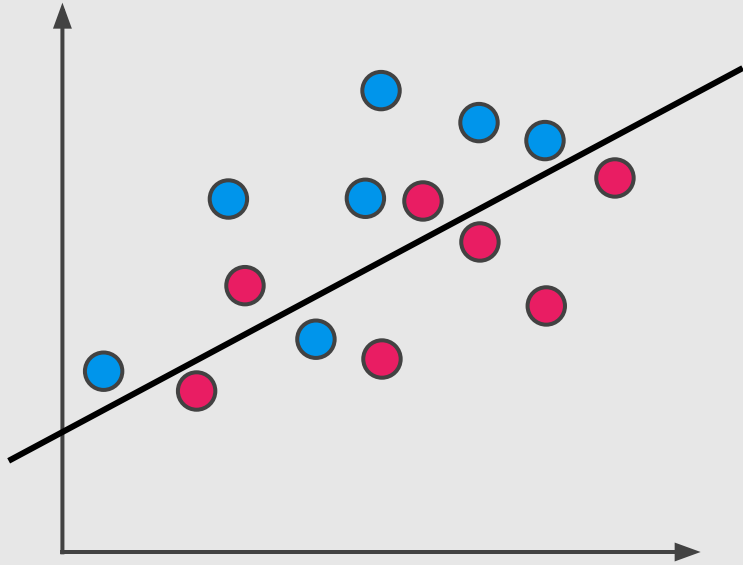
		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive	6 True positives	
	Negative		5 True negatives

# Confusion Matrix Table



		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive	6 True positives	
	Negative	2 False positives	5 True negatives

# Confusion Matrix Table



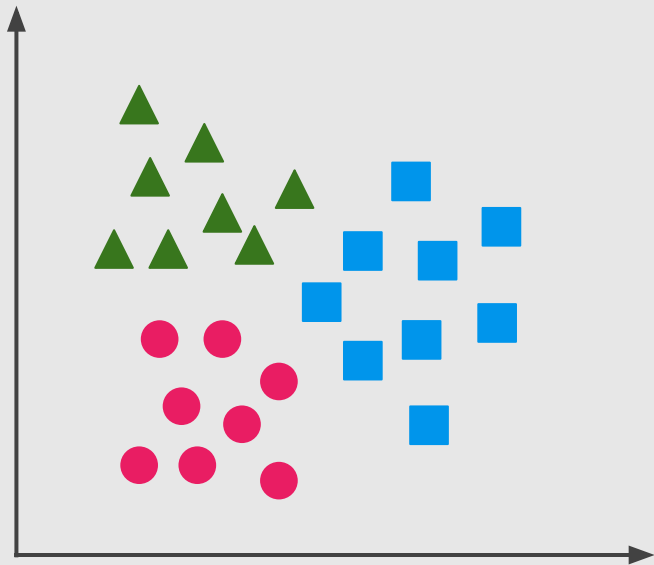
		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive	6 True positives	1 False negative
	Negative	2 False positives	5 True negatives

# Confusion Matrix Table ( $n$ classes)

Class 1: ▲

Class 2: ■

Class 3: ●

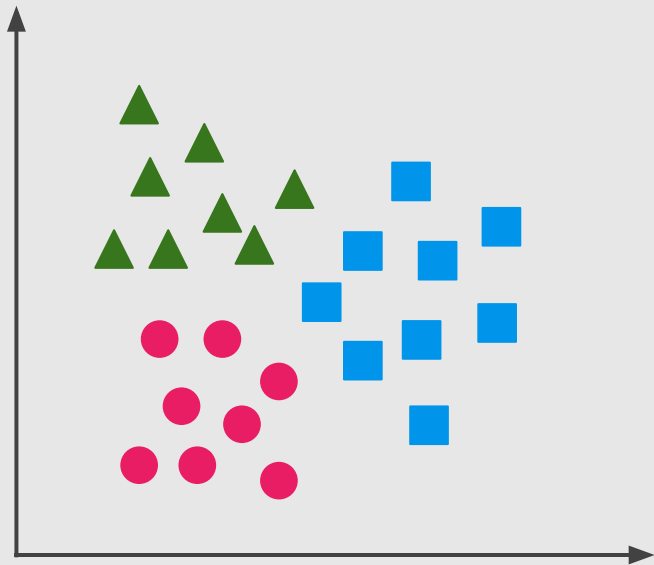


# Confusion Matrix Table ( $n$ classes)

Class 1: ▲

Class 2: ■

Class 3: ●



Predicted Class

	Gussed Class 1	Gussed Class 2	Gussed Class 3
Class 1			
Class 2			
Class 3			

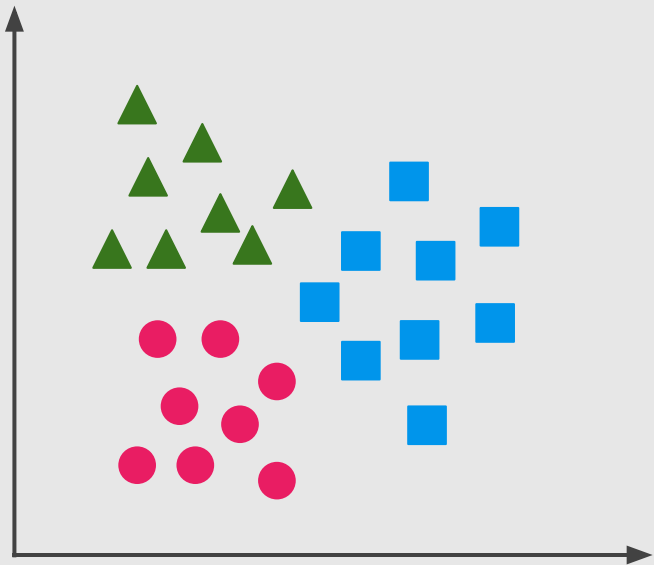


# Confusion Matrix Table ( $n$ classes)

Class 1: ▲

Class 2: ■

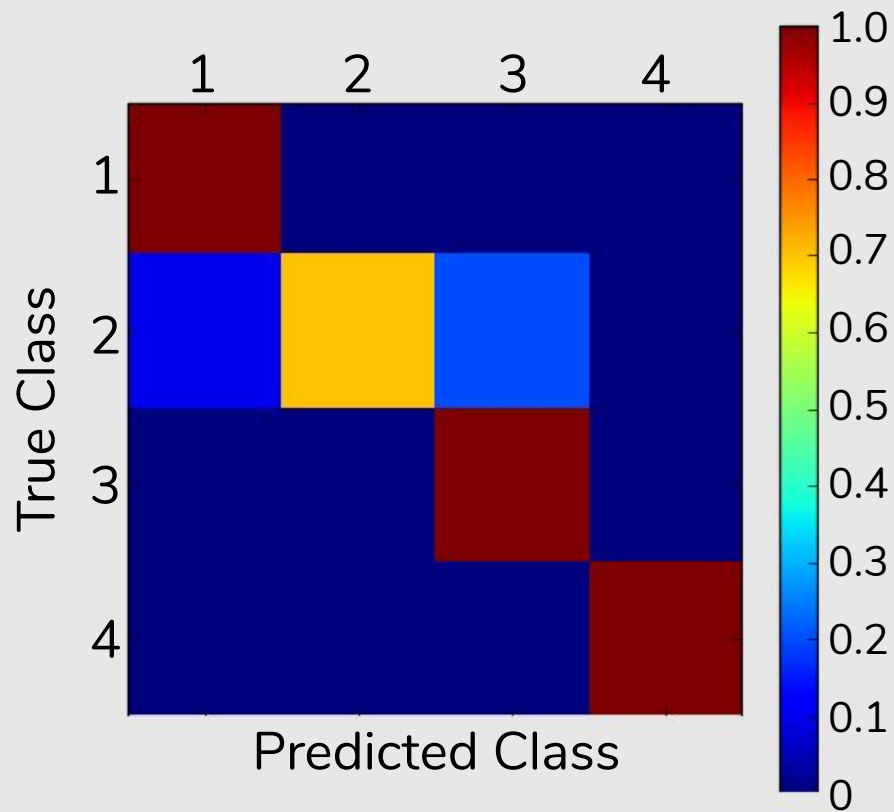
Class 3: ●



Predicted Class

	Gussed Class 1	Gussed Class 2	Gussed Class 3
Class 1	5	2	1
Class 2	3	6	0
Class 3	0	1	7

# Confusion Matrix Table ( $n$ classes)



# Accuracy



## Diagnosis

Patients

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

# Accuracy



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

## Accuracy:

Out of all the **patients**, how many did we classify correctly?

# Accuracy



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

Accuracy:

Out of all the **patients**, how many did we classify correctly?

Accuracy =

$$\frac{1,000 + 8,000}{\quad}$$

Patients

# Accuracy



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000


Accuracy:

Out of all the **patients**, how many did we classify correctly?

Accuracy =

$$\frac{1,000 + 8,000}{10,000} = 90\%$$

# Accuracy




		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700

**Accuracy:**

Out of all the **emails**, how many did we classify correctly?

# Accuracy



		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700

**Accuracy:**

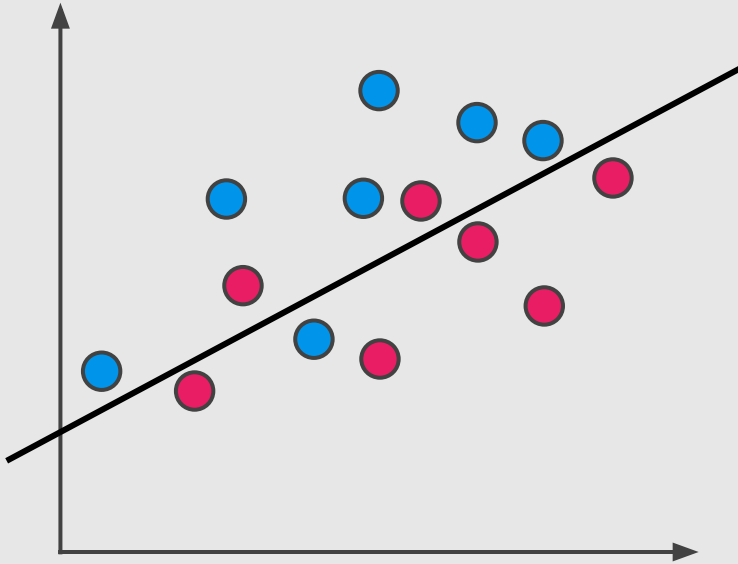
Out of all the **emails**, how many did we classify correctly?

Accuracy =

$$\frac{100 + 700}{1,000} = 80\%$$



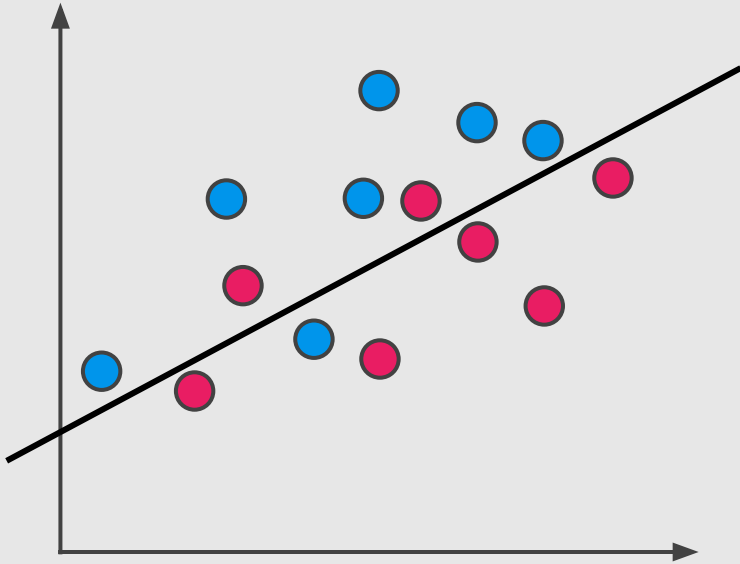
# Accuracy



**Accuracy:**

Out of all the **data**, how many points did we classify correctly?

# Accuracy



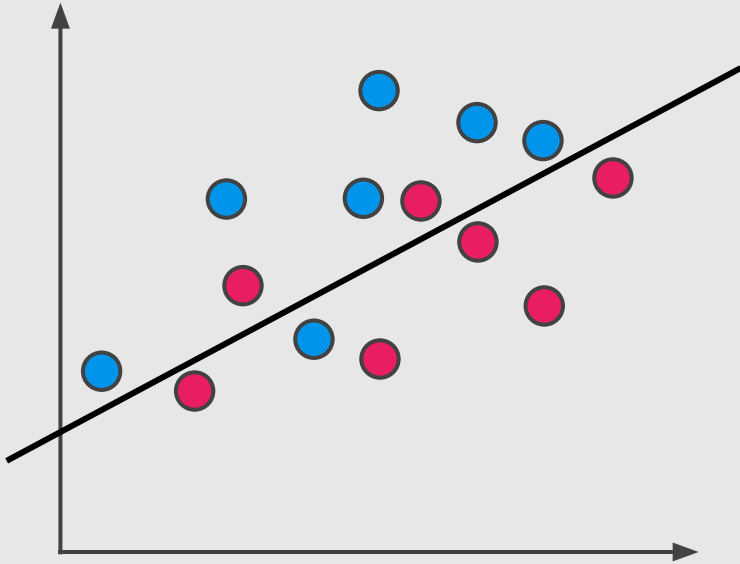
**Accuracy:**

Out of all the **data**, how many points did we classify correctly?

Accuracy =

$$\frac{\text{Correctly Classified Points}}{\text{All points}}$$

# Accuracy



**Accuracy:**


Out of all the **data**, how many points did we classify correctly?

Accuracy =

$$\frac{\text{Correctly Classified Points}}{\text{All points}}$$

$$\frac{11}{11 + 3} = 78.57\%$$

# Accuracy



		Prediction	
		Fraudulent	Not Fraudulent
Transactions	Fraudulent	0	472
	Not Fraudulent	0	284,335

Accuracy:

Out of all the **transactions**, how many did we classify correctly?


Accuracy =

$$\frac{0 + 284,335}{284,807} = 99.83\%$$

# Overall (Normalized) Accuracy


Prediction

Transactions



	Fraudulent	Not Fraudulent
Fraudulent	0	472
Not Fraudulent	0	284,335

# Overall (Normalized) Accuracy




		Prediction	
		Fraudulent	Not Fraudulent
Transactions	Fraudulent	0	472
	Not Fraudulent	0	284,335

Overall Accuracy =

$$\frac{\frac{TP}{TP + FN} + \frac{TN}{TN + FP}}{2} =$$

# Overall (Normalized) Accuracy




		Prediction	
		Fraudulent	Not Fraudulent
Transactions	Fraudulent	0	472
	Not Fraudulent	0	284,335

Overall Accuracy =

$$\frac{\frac{TP}{TP + FN} + \frac{TN}{TN + FP}}{2} =$$
$$\frac{\frac{0}{0 + 472} + \frac{284,335}{284,335 + 0}}{2} =$$

# Overall (Normalized) Accuracy



		Prediction	
		Fraudulent	Not Fraudulent
Transactions	Fraudulent	0	472
	Not Fraudulent	0	284,335


Overall Accuracy =

$$\frac{\frac{TP}{TP + FN} + \frac{TN}{TN + FP}}{2} =$$
$$\frac{\frac{0}{0 + 472} + \frac{284,335}{284,335 + 0}}{2} =$$
$$\frac{0 + 100}{2} = 50\%$$



# Overall (Normalized) Accuracy

Accuracy = 80%



		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700


Overall Accuracy =

$$\frac{\frac{TP}{TP + FN} + \frac{TN}{TN + FP}}{2} =$$
$$\frac{\frac{100}{100 + 170} + \frac{700}{700 + 30}}{2} =$$
$$\frac{37.0 + 95.9}{2} = 66.5\%$$

# Overall (Normalized) Accuracy

Accuracy = 90%






## Diagnosis






	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

Overall Accuracy =

$$\frac{\frac{TP}{TP + FN} + \frac{TN}{TN + FP}}{2} =$$
$$\frac{\frac{1000}{1000 + 200} + \frac{8000}{8000 + 800}}{2} =$$
$$\frac{83.3 + 90.9}{2} = 87.1\%$$

	Diagnosed Sick	Diagnosed Healthy
Sick	True Positive 	False Negative 
Healthy	False Positive 	True Negative 

	Diagnosed Sick	Diagnosed Healthy
Sick		False Negative 
Healthy	False Positive 	



Sent to Spam Folder

Sent to Inbox

Spam

True Positive



False Negative



Not Spam

False Positive



True Negative





Sent to Spam Folder

Sent to Inbox

Spam

False Negative



Not Spam

False Positive



# Evaluation Metrics



Medical Model

False positives ok  
False negatives **NOT** ok



Spam Detector

False positives **NOT** ok  
False negatives ok

# Evaluation Metrics



Medical Model

False positives ok  
False negatives **NOT** ok  
**High Recall**



Spam Detector

False positives **NOT** ok  
False negatives ok  
**High Precision**



# Precision



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

Patients

# Precision



## Diagnosis

		Diagnosis	
		Diagnosed Sick	Diagnosed Healthy
Patients	Sick	1,000	200
	Healthy	800	8,000

## Precision:

Out of all the patients we diagnosed with illness, how many were actually sick?

# Precision



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

## Precision:

Out of all the patients we diagnosed with illness, how many were actually sick?

# Precision



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000


## Precision:

Out of all the patients we diagnosed with illness, how many were actually sick?

Precision =

$$\frac{1,000}{1,000 + 800} = 55.7\%$$

# Precision




		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700

## Precision:

Out of all the emails sent to the spam inbox, how many did were actually spam?

# Precision



		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700

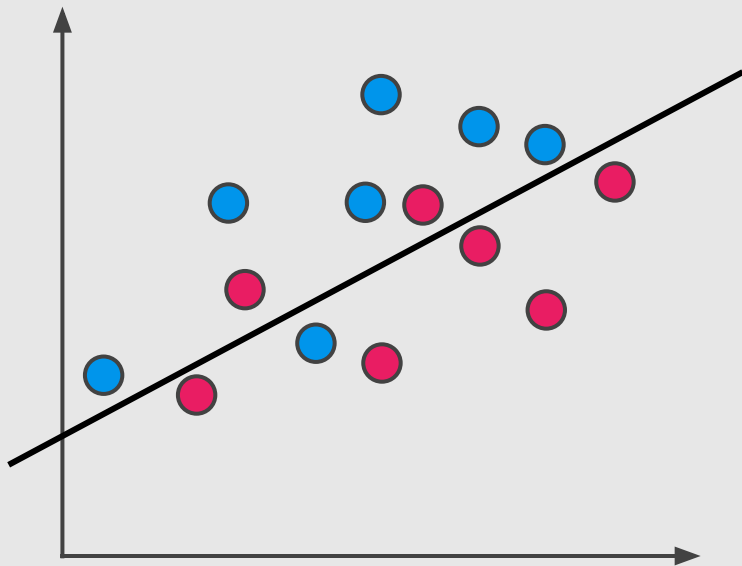
## Precision:

Out of all the emails sent to the spam inbox, how many did were actually spam?

Precision =

$$\frac{100}{100 + 30} = 76.9\%$$

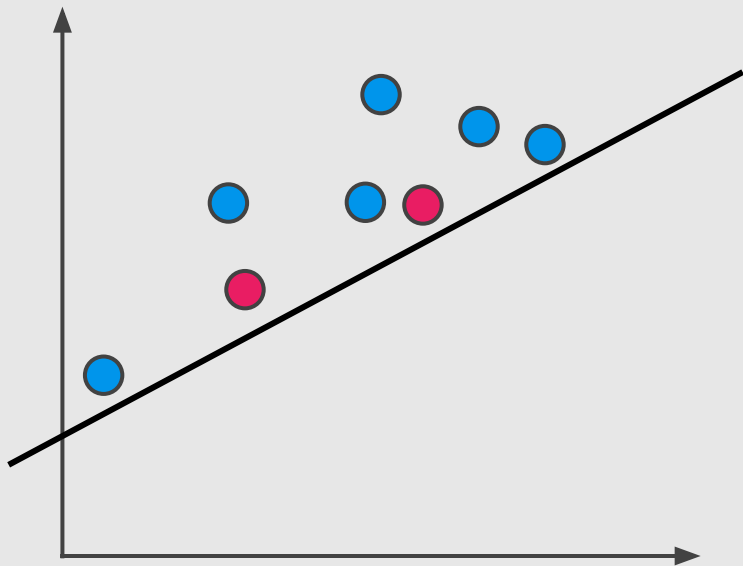
# Precision



## Precision:

Out of all the points we've predicted to be positive, how many are correct?

# Precision

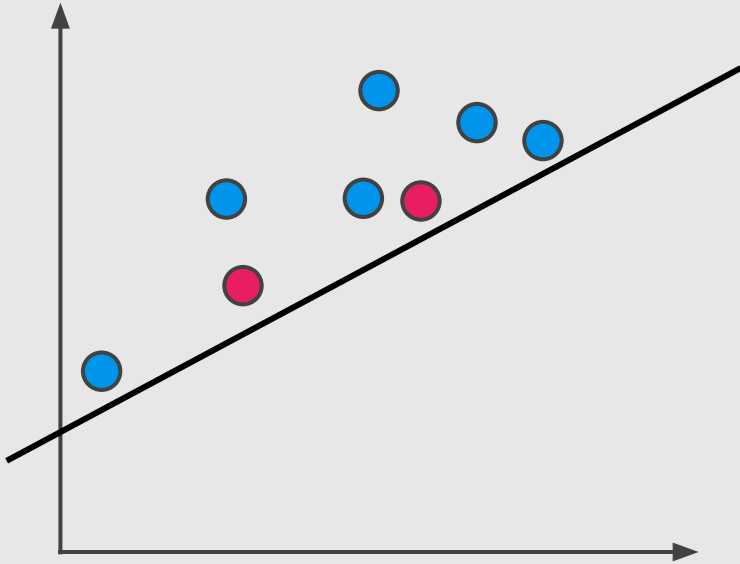


## Precision:

Out of all the points we've predicted to be positive, how many are correct?



# Precision



**Precision:**

Out of all the points we've predicted to be positive, how many are correct?

Precision =

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

# Recall



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

Patients

# Recall



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

Patients

## Recall:

Out of all the sick patients, how many did we correctly diagnose as sick?

# Recall



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000

## Recall:

Out of all the sick patients, how many did we correctly diagnose as sick?

Patients

# Recall



## Diagnosis

	Diagnosed Sick	Diagnosed Healthy
Sick	1,000	200
Healthy	800	8,000


## Recall:

Out of all the sick patients, how many did we correctly diagnose as sick?

Recall =

$$\frac{1,000}{1,000 + 200} = 83.3\%$$

# Recall




		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700

## Recall:

Out of all the spam emails, how many were correctly sent to the spam folder?

# Recall



		Folder	
		Spam Folder	Inbox
Email	Spam	100	170
	Not Spam	30	700

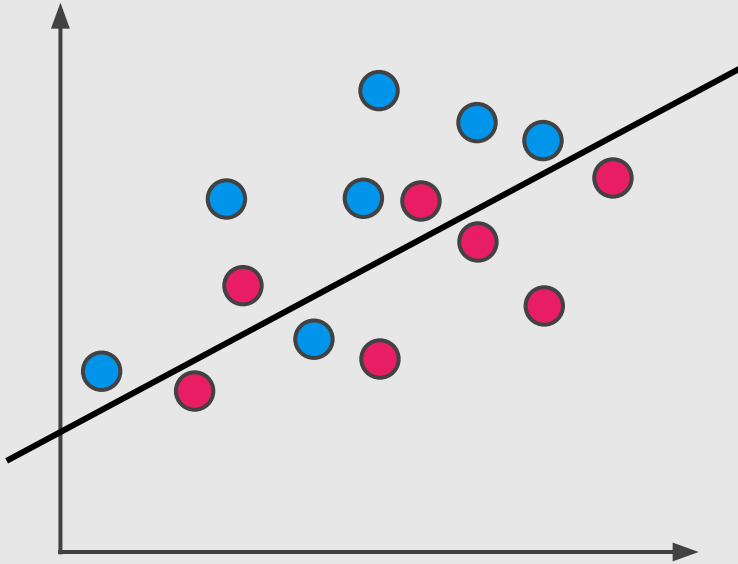
## Recall:

Out of all the spam emails, how many were correctly sent to the spam folder?

Recall =

$$\frac{100}{100 + 170} = 37\%$$

# Recall

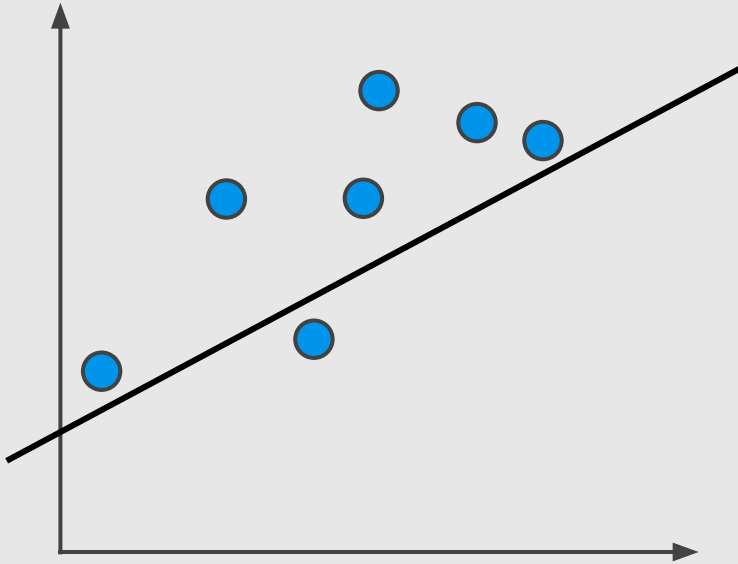


## Recall:

Out of all the points labelled positive, how many did we correctly predict?



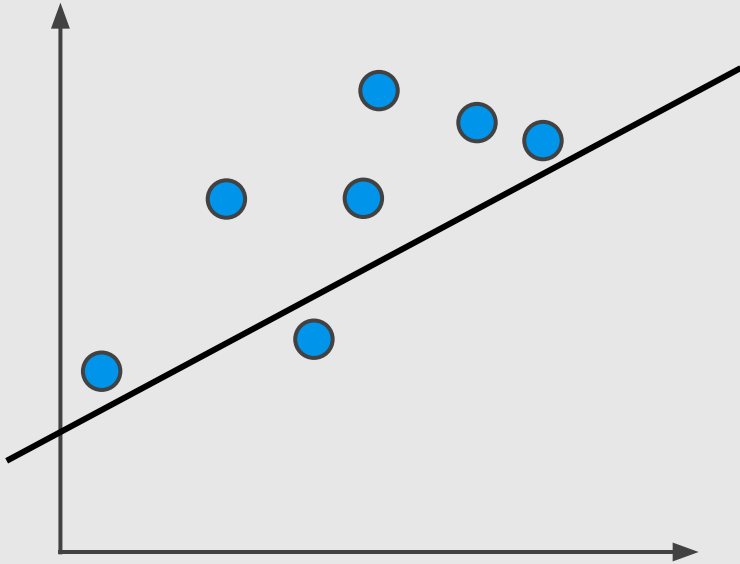
# Recall



## Recall:

Out of all the points labelled positive, how many did we correctly predict?

# Recall



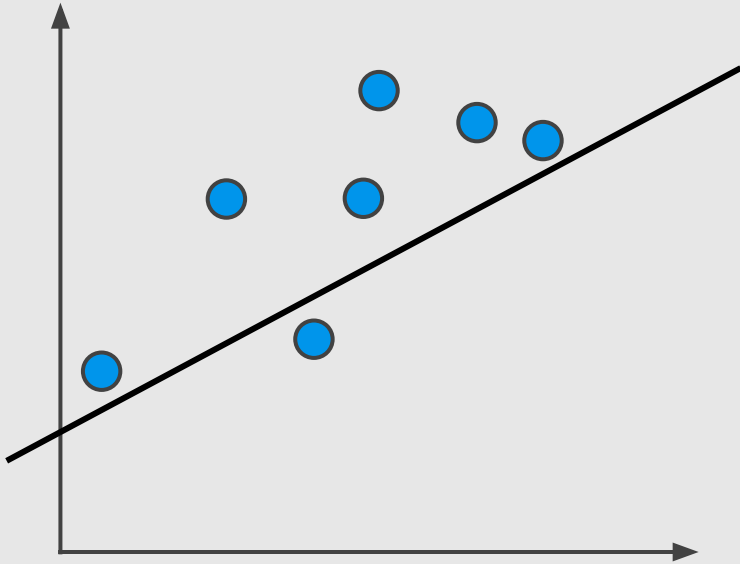
## Recall:

Out of all the points labelled positive, how many did we correctly predict?

Recall =

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

# Recall



## Recall:

Out of all the points labelled positive, how many did we correctly predict?

Recall =

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\frac{6}{6 + 1} = 85.7\%$$

# Precision and Recall



Medical Model

Precision: 55.7%

**Recall: 83.3%**



Spam Detector

**Precision: 76.9%**

Recall: 37%

# One Score?



Medical Model

Precision: 55.7%

**Recall: 83.3%**

Average = 69.5%



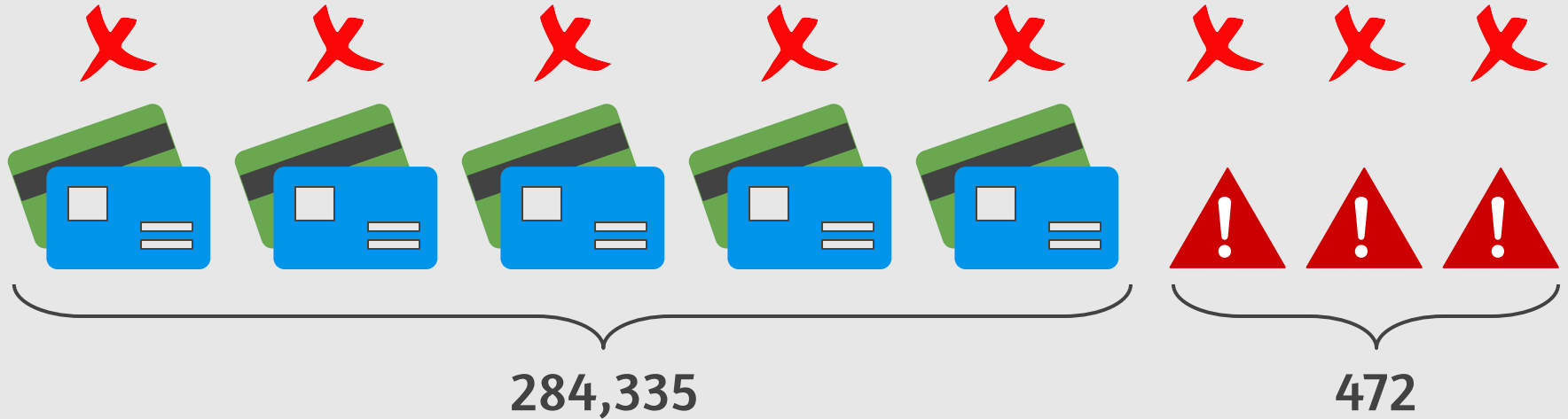
Spam Detector

**Precision: 76.9%**

Recall: 37%

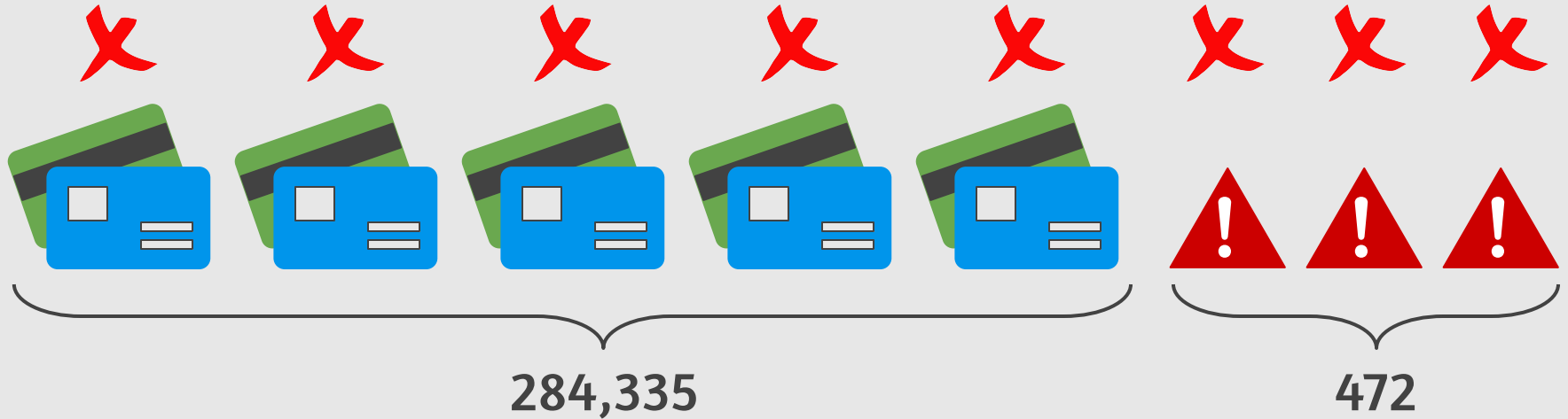
Average = 56.9%

# Credit Card Fraud



Model: All transactions are fraudulent.

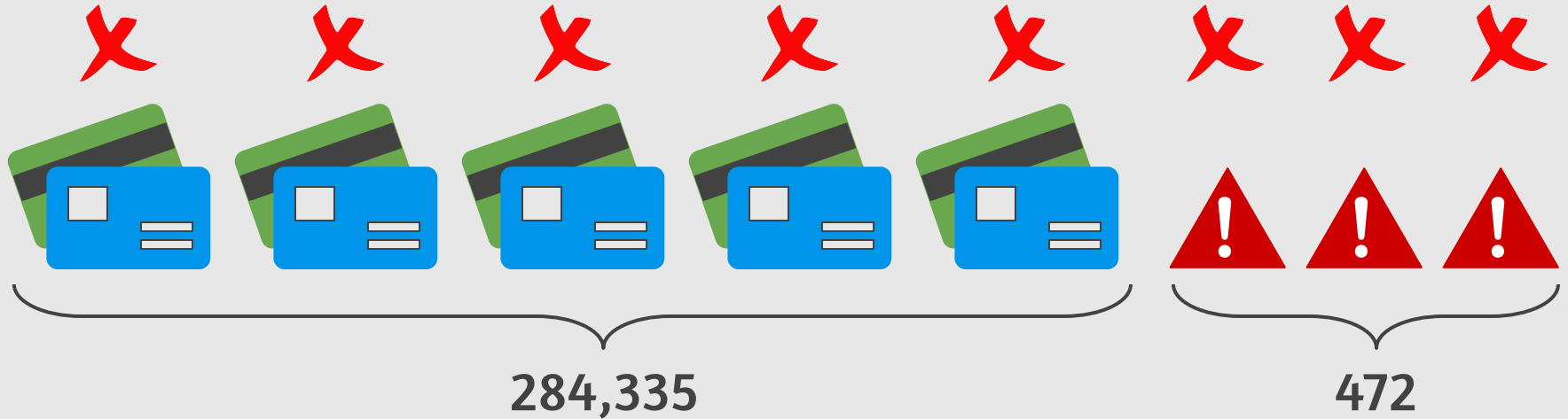
# Credit Card Fraud



Model: All transactions are fraudulent.

$$\text{Precision} = \frac{472}{284,807} = 0.016\%$$

# Credit Card Fraud



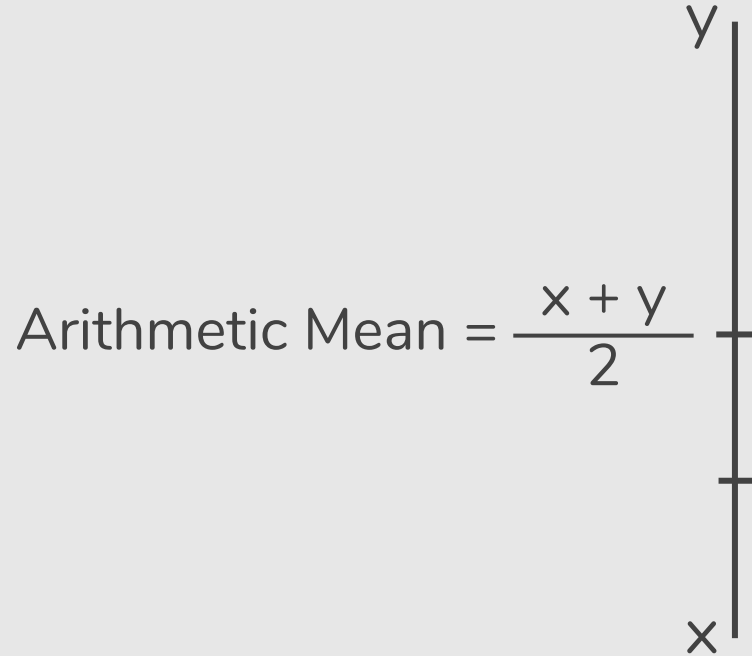
Model: All transactions are fraudulent.

$$\text{Precision} = \frac{472}{284,807} = 0.016\%$$

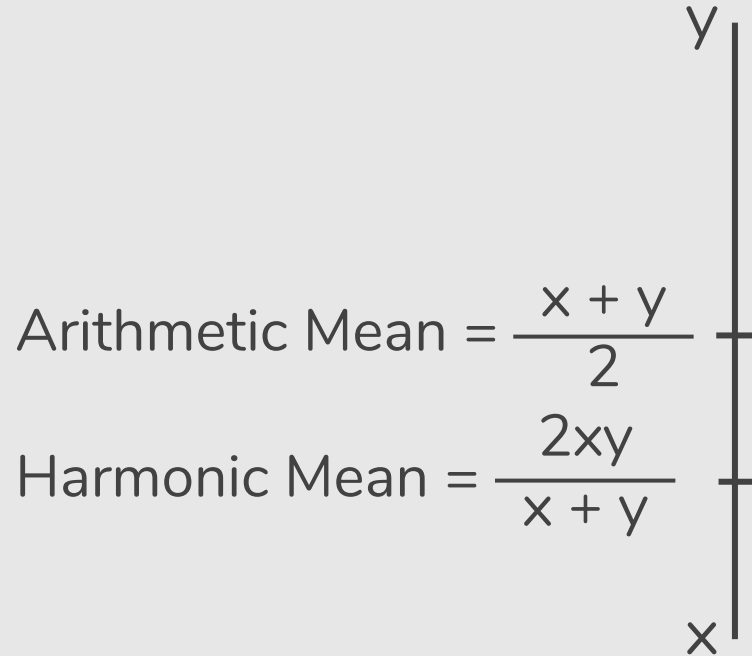
$$\text{Recall} = \frac{472}{472} = 100\%$$



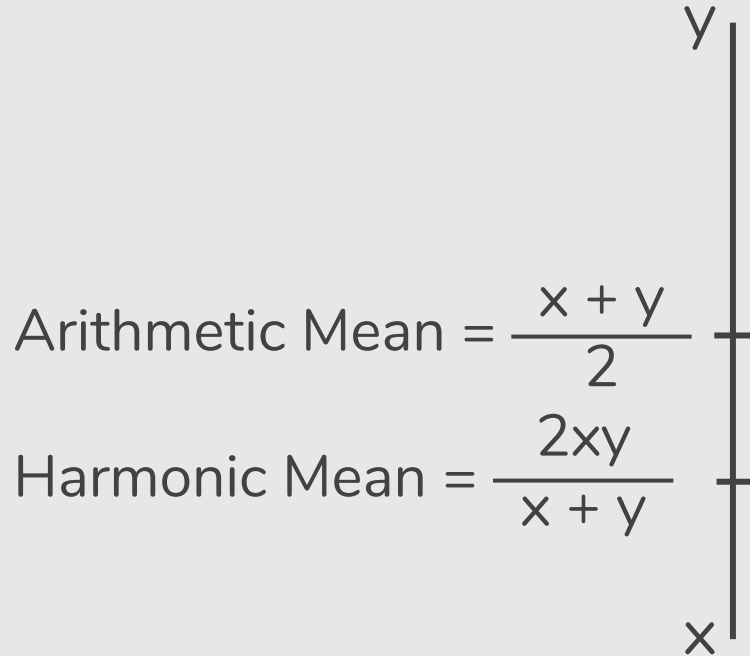
# Harmonic Mean



# Harmonic Mean



# Harmonic Mean



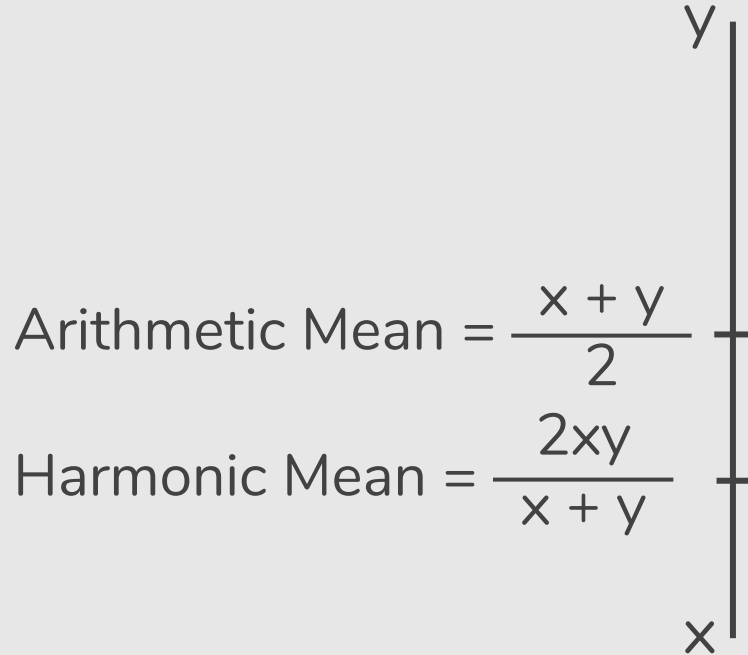
Precision: 1

Recall: 0

Average = 0.5

Harmonic Mean = 0

# Harmonic Mean



Precision: 1

Recall: 0

Average = 0.5

Harmonic Mean = 0

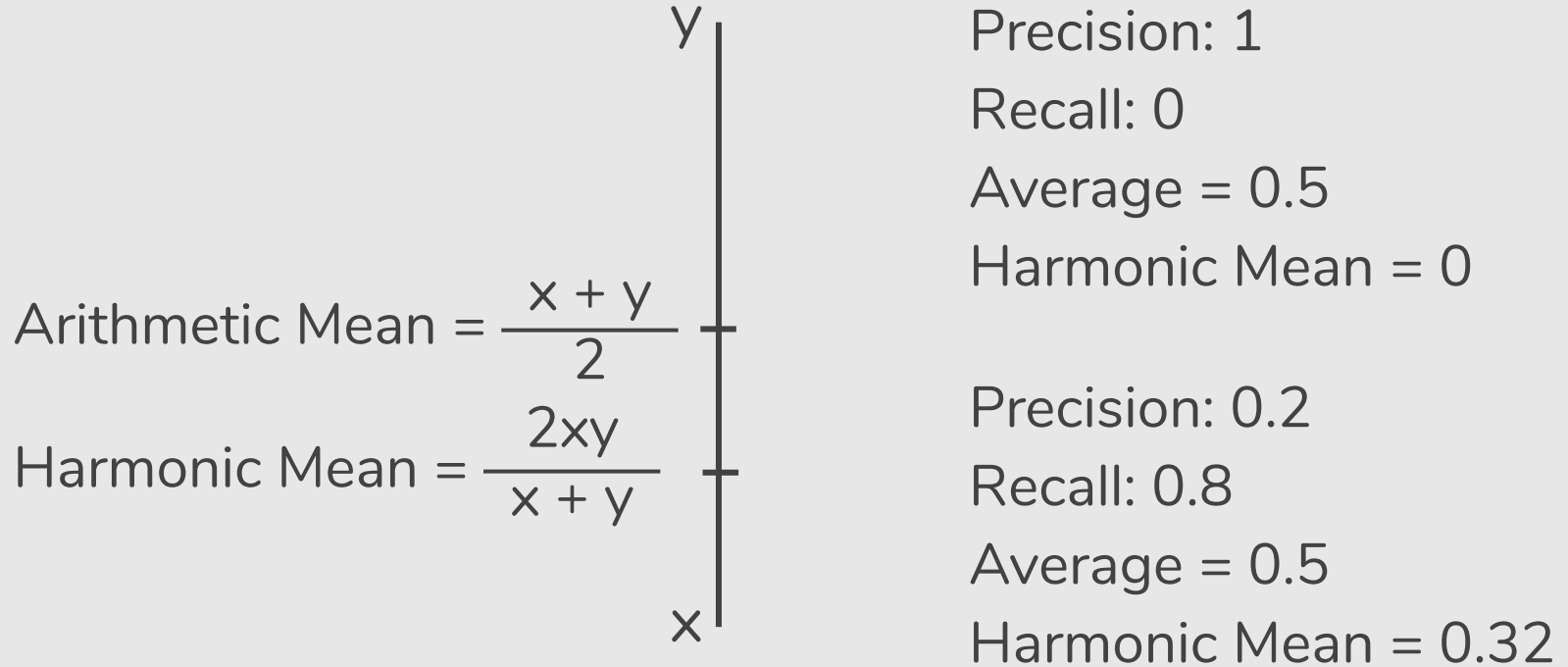
Precision: 0.2

Recall: 0.8

Average = 0.5

Harmonic Mean = 0.32

# Harmonic Mean



F1 Score = Harmonic Mean (Precision, Recall)

# F1 Score



Medical Model

Precision: 55.7%

Recall: 83.3%

Average = 69.5%

F1 Score = 66.8%

# F1 Score



Spam Detector

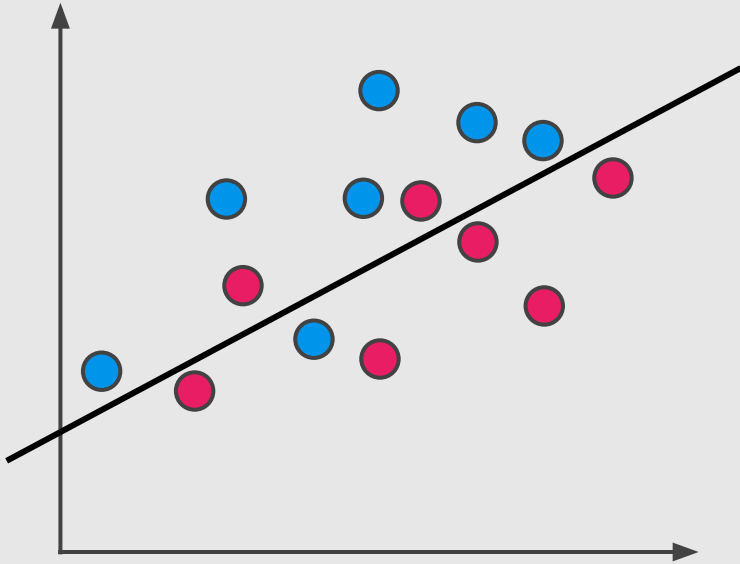
Precision: 76.9%

Recall: 37%

Average = 56.9%

F1 Score = 50.0%

# F1 Score



Precision: 75%

Recall: 85.7%

Average = 80.3%

F1 Score = 80%



# $F_\beta$ Score

# $F_\beta$ Score



Precision



Recall

# $F_\beta$ Score



Precision

F0.5 Score

F1 Score

F2 Score

Recall



# $F_\beta$ Score



Precision

F0.5 Score



F1 Score

F2 Score



Recall

# $F_\beta$ Score



Precision

F0.5 Score

F1 Score

F2 Score

F10 Score



Recall

# $F_\beta$ Score



Precision

F0.5 Score

F1 Score

F2 Score

F10 Score



Recall

# $F_\beta$ Score

F1 Score = Harmonic Mean (Precision, Recall)

# $F_\beta$ Score

F1 Score = Harmonic Mean (Precision, Recall)

$$H = \frac{n}{\frac{1}{x_1} + \frac{1}{x_2} + \dots + \frac{1}{x_n}}$$



# $F_\beta$ Score

F1 Score = Harmonic Mean (Precision, Recall)

$$H = \frac{n}{\frac{1}{x_1} + \frac{1}{x_2} + \dots + \frac{1}{x_n}}$$

$$F_1 = 2 \frac{1}{\frac{1}{\text{recall}} + \frac{1}{\text{precision}}} = 2 \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

## $F_\beta$ Score

$$F_1 = 2 \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

$$F_\beta = (1 + \beta^2) \frac{\text{precision} \cdot \text{recall}}{(\beta^2 \cdot \text{precision}) + \text{recall}}$$

# References

— — —

- [https://en.wikipedia.org/wiki/Precision\\_and\\_recall](https://en.wikipedia.org/wiki/Precision_and_recall)
- [https://en.wikipedia.org/wiki/Binary\\_classification](https://en.wikipedia.org/wiki/Binary_classification)
- [https://en.wikipedia.org/wiki/F1\\_score](https://en.wikipedia.org/wiki/F1_score)
- <https://www.quora.com/What-is-an-intuitive-explanation-of-F-score>
- “Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms”, Neural Computation, p. 1895-1923, 1998  
<https://www.mitpressjournals.org/doi/10.1162/089976698300017197>

## Machine Learning Courses

- Luis Serrano: <https://www.youtube.com/watch?v=aDW44NPhNw0>