

## ML Testing and Error Metrics



Testing

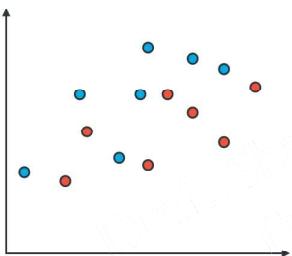
How well is my model doing?

Testing

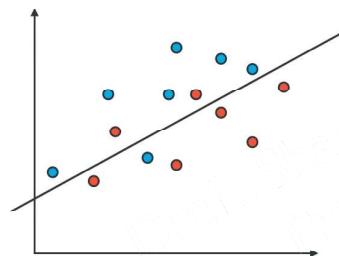
How well is my model doing?

How do I improve it?

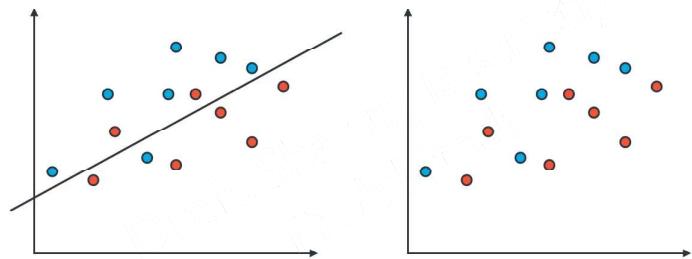
Which model is better



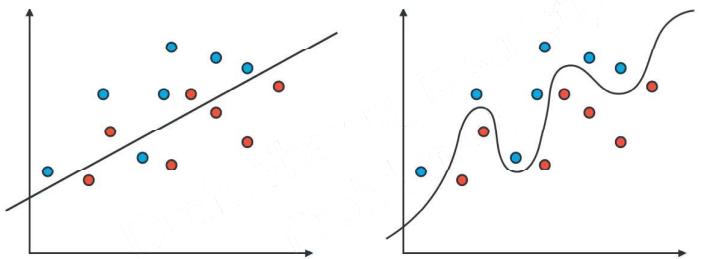
Which model is better



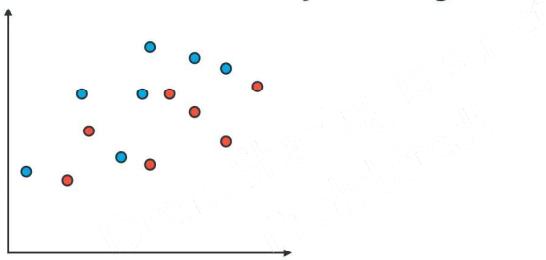
Which model is better



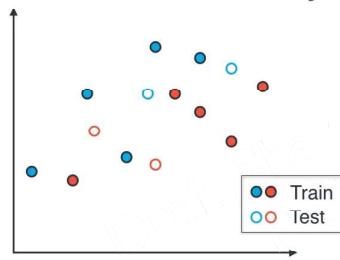
Which model is better



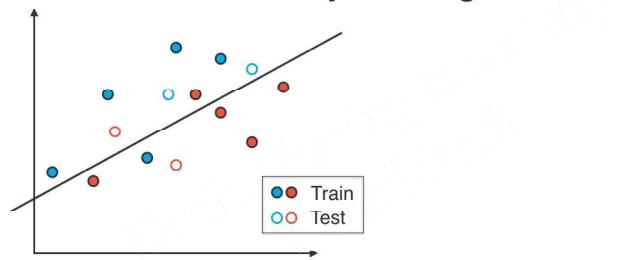
Why Testing?



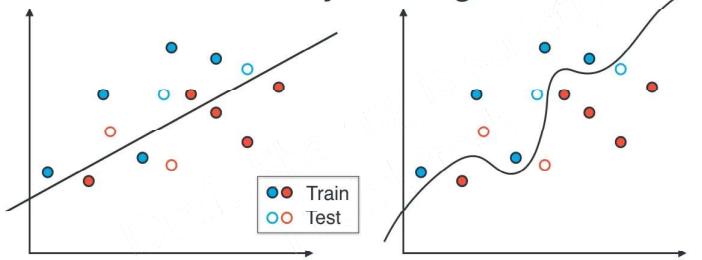
Why Testing?



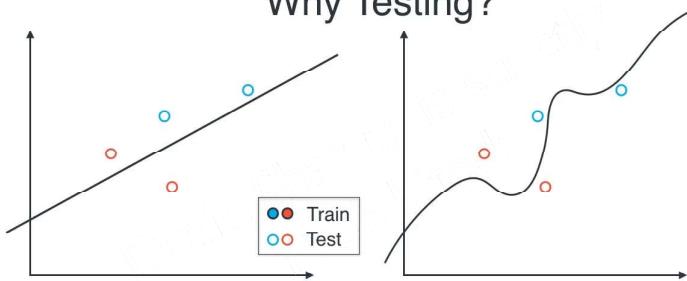
Why Testing?



Why Testing?



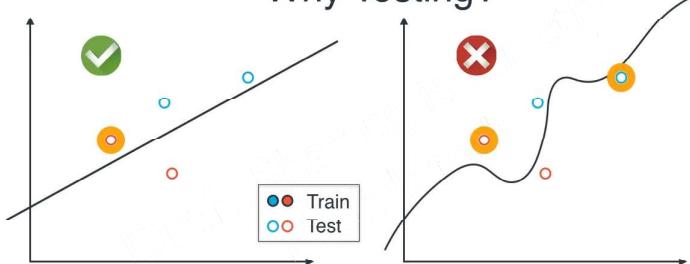
## Why Testing?



## Why Testing?



## Why Testing?



## Golden Rule # 1



## Golden Rule # 2



## Golden Rule # 3



How do we not ‘lose’ the training data?



K-Fold Cross Validation

Training      Testing

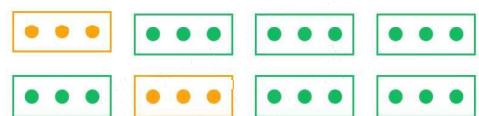


K-Fold Cross Validation

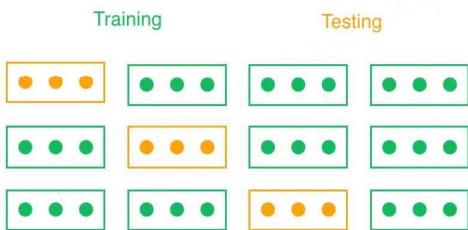


K-Fold Cross Validation

Training      Testing

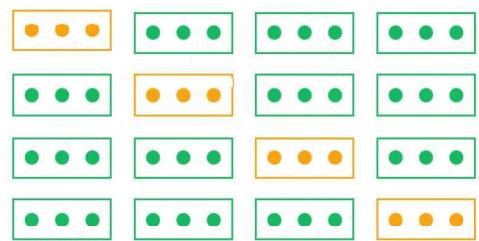


K-Fold Cross Validation

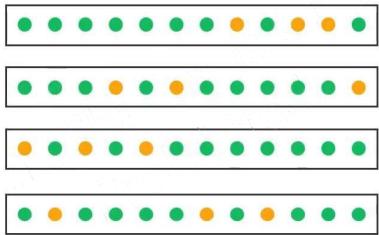


K-Fold Cross Validation

Training      Testing



## Randomizing in Cross Validation



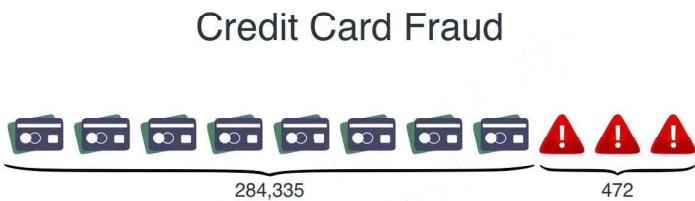
## Evaluation Metrics

How well is my model doing?

## Credit Card Fraud



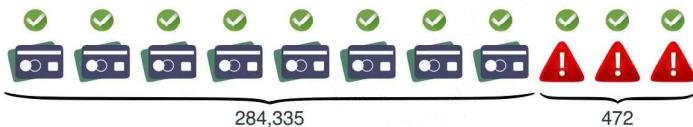
## Credit Card Fraud



## Credit Card Fraud



## Credit Card Fraud

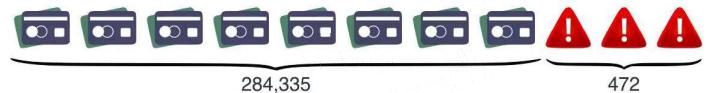


Model: All transactions are good.

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

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

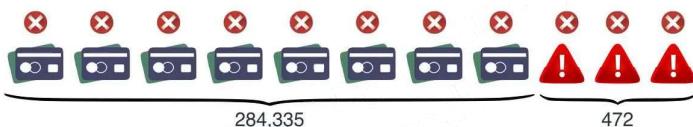
## Credit Card Fraud



284,335

472

## Credit Card Fraud

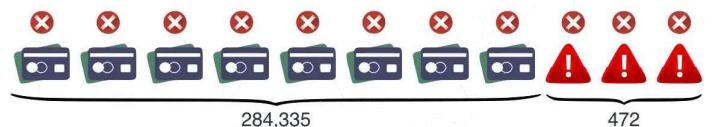


284,335

472

Model: All transactions are fraudulent.

## Credit Card Fraud



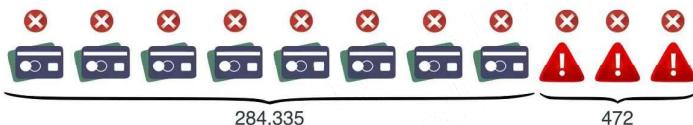
284,335

472

Model: All transactions are fraudulent.

Great! Now I'm catching *all* the bad transactions!

## Credit Card Fraud



284,335

472

Model: All transactions are fraudulent.

Great! Now I'm catching *all* the bad transactions!

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

## Medical Model



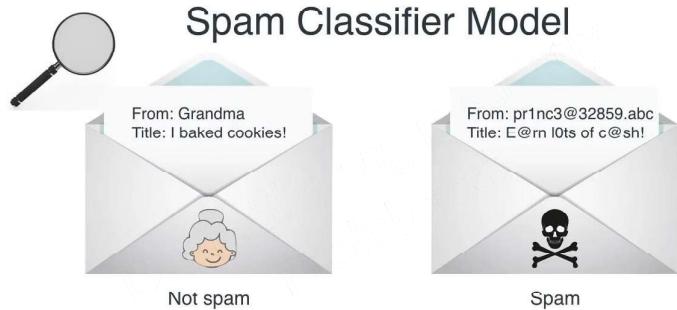
## Medical Model



## Spam Classifier Model



## Spam Classifier Model



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

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

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

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

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

Confusion Matrix

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

Confusion Matrix

Patients	Diagnosis	
	Diagnosed sick	Diagnosed healthy
Sick	1000 True positives	200
Healthy	800	8000

Confusion Matrix

Patients	Diagnosis	
	Diagnosed sick	Diagnosed healthy
Sick	1000 True positives	200 False Negatives
Healthy	800	8000

Confusion Matrix

Patients	Diagnosis	
	Diagnosed sick	Diagnosed healthy
Sick	1000 True positives	200 False Negatives
Healthy	800 False Positives	8000



10,000  
Patients

## Confusion Matrix

		Diagnosis	
		Diagnosed sick	Diagnosed Healthy
Patients	Sick	1000 True positives	200 False Negatives
	Healthy	800 False Positives	8000 True Negatives

	Sent to Spam Folder		Sent to Inbox	
	Spam	Not Spam	Spam	Not Spam
True Positives				
False Negatives				



	Sent to Spam Folder		Sent to Inbox	
	Spam	Not Spam	Spam	Not Spam
True Positives				
False Negatives				



1,000  
e-mails

## Confusion Matrix

		Folder	
		Spam Folder	Inbox
E-mail	Spam	100 True positives	170
	Not spam	30	700



1,000  
e-mails

## Confusion Matrix

		Folder	
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E-mail	Spam	100 True positives	170 False Negatives
	Not spam	30	700



1,000  
e-mails

## Confusion Matrix

		Folder	
		Spam Folder	Inbox
E-mail	Spam	100 True positives	170 False Negatives
	Not spam	30 False Positives	700

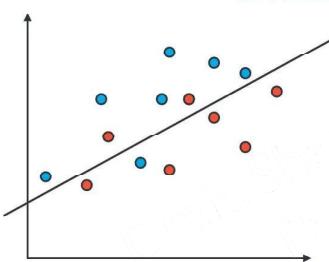
## Confusion Matrix



1,000  
e-mails

Folder		
	Spam Folder	Inbox
Spam	100 True positives	170 False Negatives
Not spam	30 False Positives	700 True Negatives

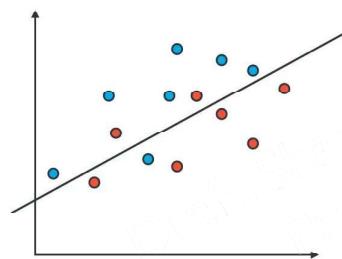
## Confusion Matrix



Prediction

Prediction		
	Guessed Positive	Guessed Negative
Positive		
Negative		

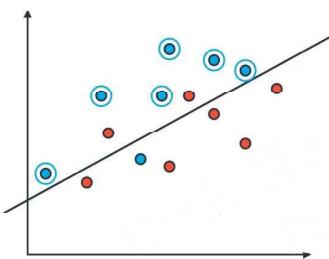
## Confusion Matrix



Prediction

Prediction		
	Guessed Positive	Guessed Negative
Positive	True positives	
Negative		

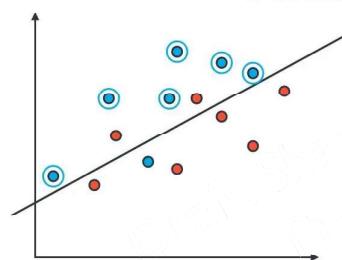
## Confusion Matrix



Prediction

Prediction		
	Guessed Positive	Guessed Negative
Positive	True positives	
Negative		

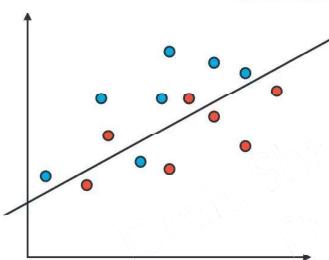
## Confusion Matrix



Prediction

Prediction		
	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		

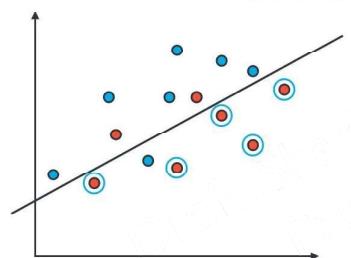
## Confusion Matrix



Prediction

Prediction		
	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		True Negatives

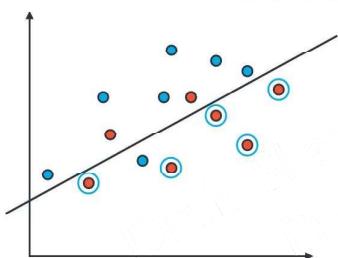
### Confusion Matrix



Prediction

	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		True Negatives

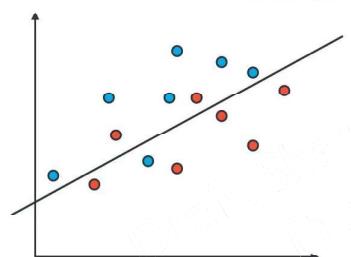
### Confusion Matrix



Prediction

	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		5 True Negatives

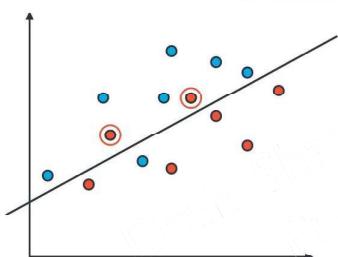
### Confusion Matrix



Prediction

	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative	False Positives	5 True Negatives

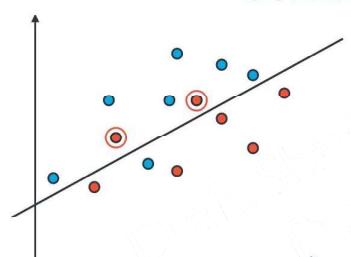
### Confusion Matrix



Prediction

	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative	False Positives	5 True Negatives

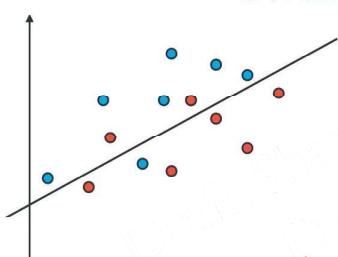
### Confusion Matrix



Prediction

	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative	2 False Positives	5 True Negatives

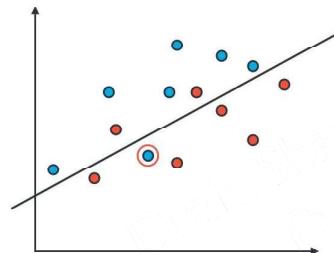
### Confusion Matrix



Prediction

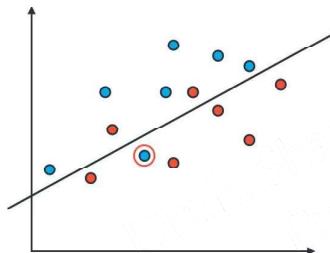
	Guessed Positive	Guessed Negative
Positive	6 True positives	False Negatives
Negative	2 False Positives	5 True Negatives

## Confusion Matrix



		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive	6 True positives	False Negatives
	Negative	2 False Positives	5 True Negatives

## Confusion Matrix



		Prediction	
		Guessed Positive	Guessed Negative
Data	Positive	6 True positives	1 False Negatives
	Negative	2 False Positives	5 True Negatives



## Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
	Sick	1000
Healthy	800	8000



## Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
	Sick	1000
Healthy	800	8000

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



## Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
	Sick	1000
Healthy	800	8000



## Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
	Sick	1000
Healthy	800	8000

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

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

$$\text{Accuracy} = \frac{1,000 + 8,000}{10,000}$$

$$\text{Accuracy} = \frac{1,000 + 8,000}{10,000}$$

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



## Accuracy

E-mail	Folder	
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

Accuracy: Out of all the e-mails, how many did we classify correctly?

$$\text{Accuracy} =$$



## Accuracy

E-mail	Folder	
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

Accuracy: Out of all the e-mails, how many did we classify correctly?

$$\text{Accuracy} = \frac{100 + 700}{1000}$$



## Accuracy

E-mail	Folder	
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

Accuracy: Out of all the e-mails, how many did we classify correctly?

$$\text{Accuracy} = \frac{100 + 700}{1000} = 80\%$$

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



## Accuracy

		Diagnosed Sick	Diagnosed Healthy
			
		Sick	Healthy
		False Negative 	
		False Positive 	



## Accuracy

		Sent to Spam Folder	Sent to Inbox
			
		Spam	Not Spam
		True Positives 	False Negatives 
		False Positives 	True Negatives 

	Sent to Spam Folder	Sent to Inbox
Spam		False Negatives 
Not Spam	False Positives 	

## 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



Spam Detector  
False positives **NOT** ok  
False negatives ok

## EVALUATION METRICS



Medical Model  
False positives ok  
False negatives **NOT** ok



Spam Detector  
False positives **NOT** ok  
False negatives ok

Find all the sick people  
Ok if not all are sick

You don't necessarily need to find all spam  
But they better all be spam

## EVALUATION METRICS



Medical Model  
False positives ok  
False negatives **NOT** ok



Spam Detector  
False positives **NOT** ok  
False negatives ok

You don't necessarily need to find all spam  
But they better all be spam

High Recall

High Precision



## Precision

Patients

Diagnosis		
	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Is Healthy	600	9000



## Precision

Patients

Diagnosis		
	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Is Healthy	600	9000

Precision: Out of the patients we diagnosed with an illness, how many did we classify correctly?



## Precision

Patients

Diagnosis		
	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Is healthy	800	9000

Precision: Out of the patients we diagnosed with an illness, how many did we classify correctly?



## Precision

Patients

Diagnosis		
	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Is healthy	800	9000

Precision: Out of the patients we diagnosed with an illness, how many did we classify correctly?

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



## Precision

E-mail

Folder		
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700



## Precision

E-mail

Folder		
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

Precision: Out of all the e-mails sent to the spam inbox, how many were actually spam?



## Precision

E-mail	Folder	Spam Folder	Inbox
Spam	100	170	
Not spam	30	700	

Precision: Out of all the e-mails sent to the spam inbox, how many were actually spam?



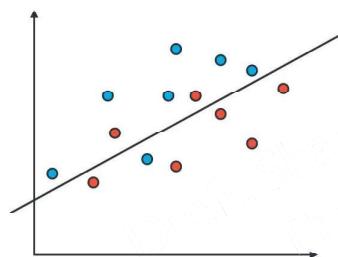
## Precision

E-mail	Folder	Spam Folder	Inbox
Spam	100	170	
Not spam	30	700	

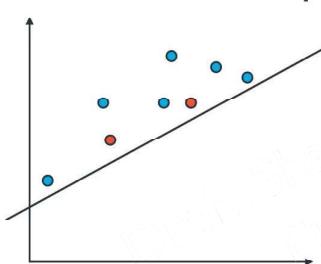
Precision: Out of all the e-mails sent to the spam inbox, how many were actually spam?

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

## Precision



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

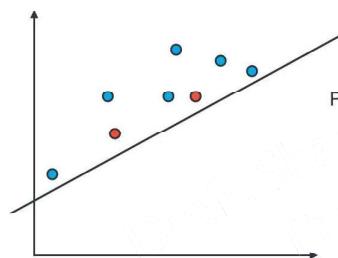


## Precision

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

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False Positives}}$$

## Precision



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

$$\begin{aligned} \text{Precision} &= \frac{\text{True positives}}{\text{True positives} + \text{False Positives}} \\ &= \frac{6}{6 + 2} \\ &= \frac{6}{8} \\ &= 75\% \end{aligned}$$



## Recall

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



## Recall

Patients

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

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



## Recall

Patients

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

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



## Recall

Patients

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

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

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



## Recall

E-mail

Folder		
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

Recall: Out of the all the spam e-mails, how many were correctly sent to the spam folder?



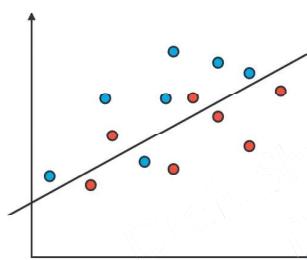
## Recall

E-mail

Folder		
	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

Recall: Out of the all the spam e-mails, how many were correctly sent to the spam folder?

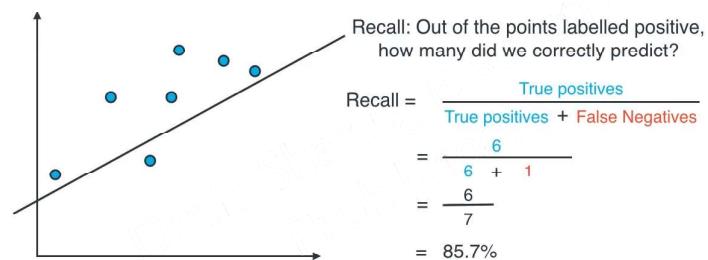
$$\text{Recall} = \frac{100}{100 + 170} = 37\%$$



## Recall

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

## Recall



## Precision and Recall



Medical Model

Precision: 55.7%  
Recall: 83.3%



Spam Detector  
Precision: 76.9%  
Recall: 37%

## Precision and Recall



Medical Model  
Precision: 55.7%  
Recall: 83.3%



One score?



Spam Detector  
**Precision: 76.9%**  
Recall: 37%

## F1 Score



Medical Model

Precision: 55.7%  
Recall: 83.3%



Spam Detector  
**Precision: 76.9%**  
Recall: 37%

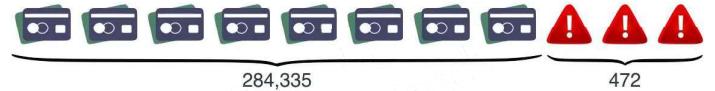
Average = 69.5%

Average = 56.95%

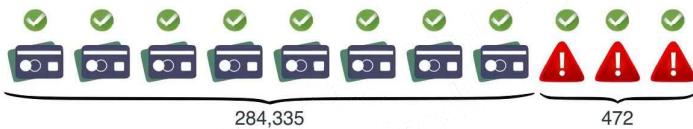
## Credit Card Fraud



## Credit Card Fraud



## Credit Card Fraud



Model: All transactions are good.

## Credit Card Fraud

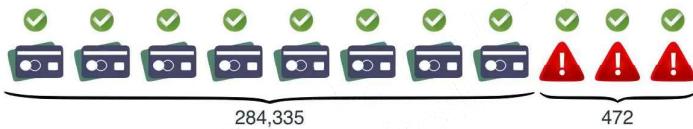


Model: All transactions are good.

$$\text{Precision} = 100\%$$

$$\text{Recall} = \frac{0}{472} = 0\%$$

## Credit Card Fraud



Model: All transactions are good.

$$\text{Precision} = 100\%$$

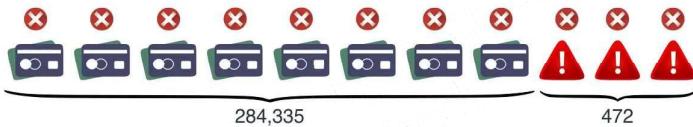
$$\text{Recall} = \frac{0}{472} = 0\%$$

$$\text{Average} = 50\%$$

## Credit Card Fraud



## Credit Card Fraud



Model: All transactions are fraudulent.

$$\text{Precision} = \frac{472}{284,807} = .016\%$$

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

## Credit Card Fraud



Model: All transactions are fraudulent.

$$\text{Precision} = \frac{472}{284,807} = .016\%$$

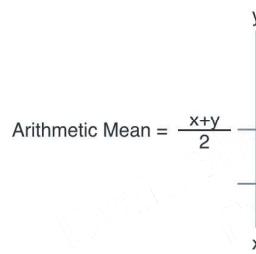
$$\text{Recall} = \frac{472}{472} = 100\%$$

$$\text{Average} = 50.008\%$$

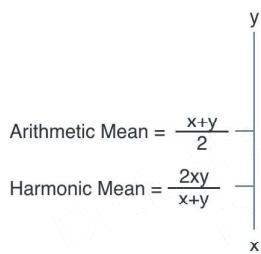
## Harmonic mean



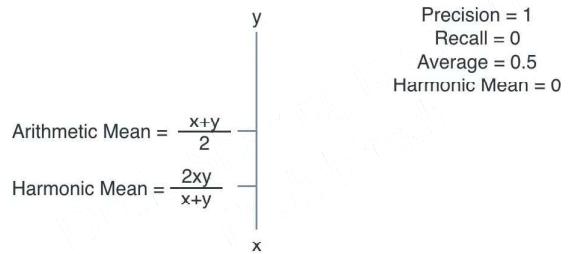
## Harmonic mean



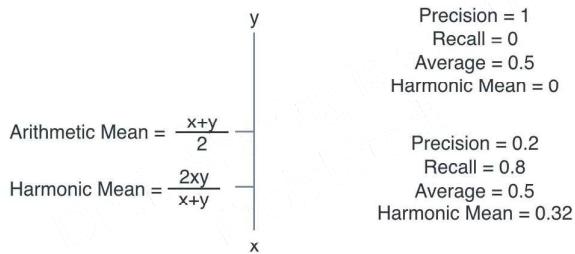
## Harmonic mean



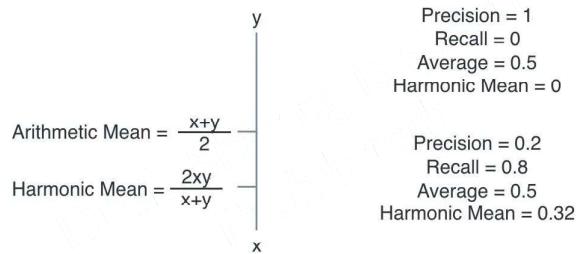
## Harmonic mean



## Harmonic mean



## Harmonic mean



~~— Arithmetic Mean(Precision, Recall) —~~

## Harmonic mean

$$\begin{array}{l} y \\ | \\ \text{Arithmetic Mean} = \frac{x+y}{2} \\ | \\ \text{Harmonic Mean} = \frac{2xy}{x+y} \\ | \\ x \end{array}$$

$$\begin{array}{l} \text{Precision} = 1 \\ \text{Recall} = 0 \\ \text{Average} = 0.5 \\ \text{Harmonic Mean} = 0 \\ \\ \text{Precision} = 0.2 \\ \text{Recall} = 0.8 \\ \text{Average} = 0.5 \\ \text{Harmonic Mean} = 0.32 \end{array}$$

~~Arithmetic Mean(Precision, Recall)~~  
 $F1\text{ Score} = \text{Harmonic Mean}(\text{Precision}, \text{Recall})$

## F1 Score



Medical Model

Precision = 55.7%  
 Recall = 83.3%  
 Average = 69.5%

## F1 Score



Medical Model

Precision = 55.7%  
 Recall = 83.3%  
 Average = 69.5%  
 $F1\text{ Score} = \frac{2 \times 55.7 \times 83.3}{55.7 + 83.3} = 66.76\%$

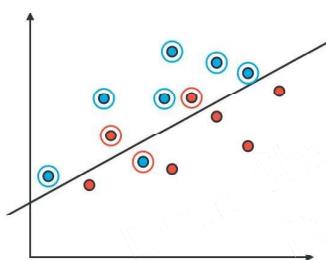
## F1 Score



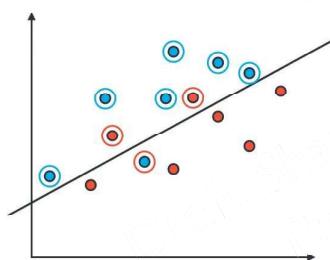
Spam Detector Model

Precision = 76.9%  
 Recall = 37%  
 Average = 56.95%  
 $F1\text{ Score} = \frac{2 \times 76.9 \times 37}{76.9 + 37} = 49.96\%$

## F1 Score



Precision = 75%  
 Recall = 85.7%  
 Average = 80.35



Precision = 75%  
 Recall = 85.7%  
 Average = 80.35  
 $F1\text{ Score} = \frac{2 \times 75 \times 85.7}{75 + 85.7} = 80\%$

Types of Errors



Types of Errors



Types of Errors



Underfitting

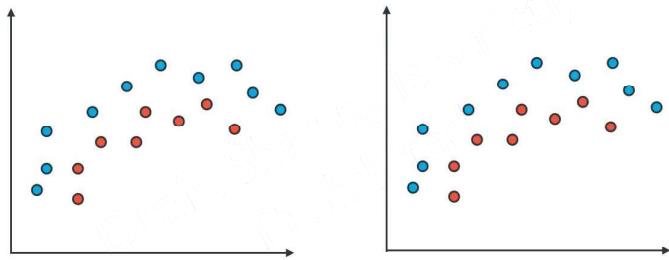


Types of Errors

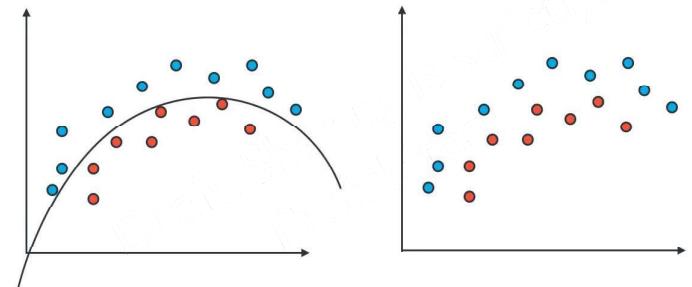


Overfitting

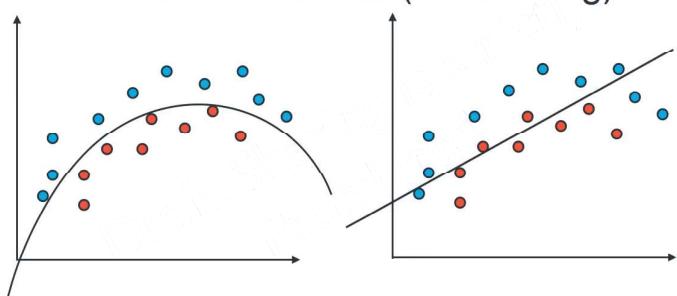
Error due to bias (underfitting)



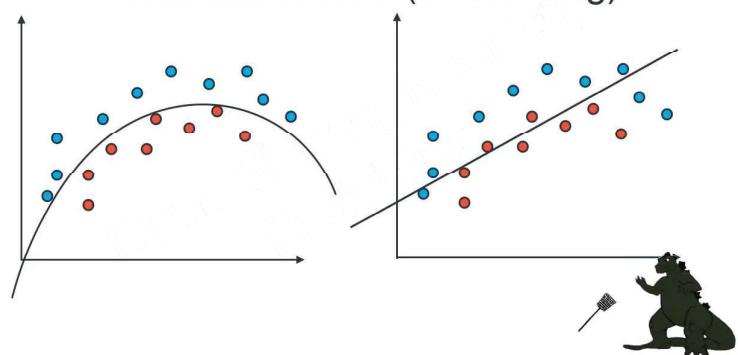
Error due to bias (underfitting)



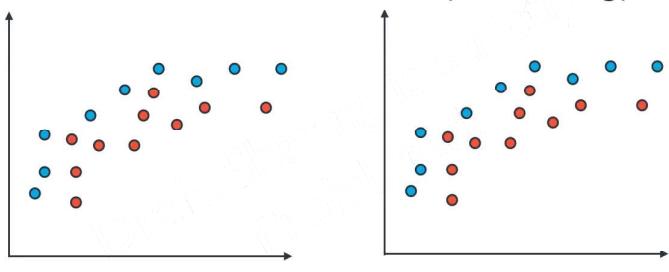
Error due to bias (underfitting)



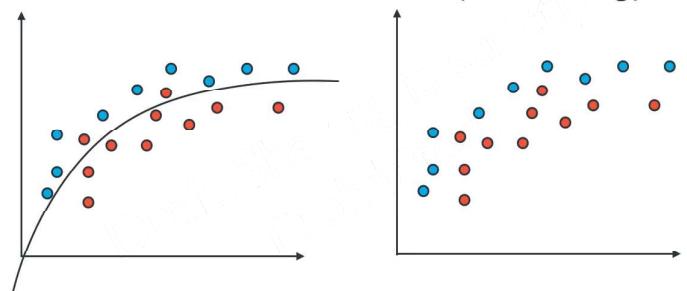
Error due to bias (underfitting)



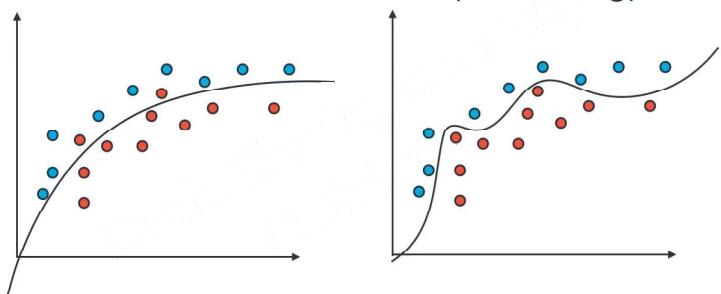
Error due to variance (overfitting)



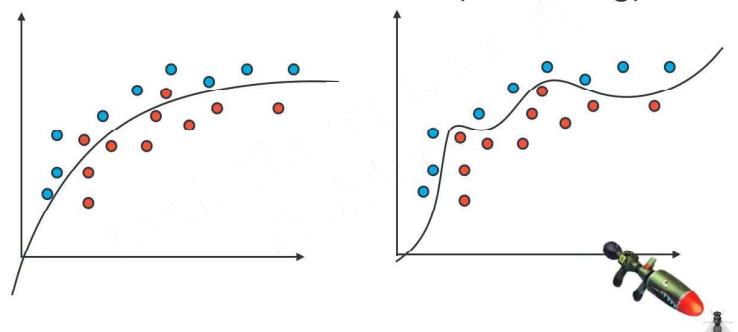
Error due to variance (overfitting)



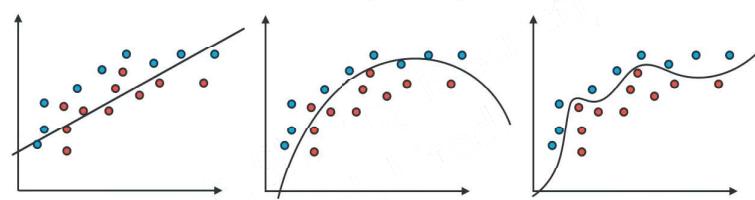
Error due to variance (overfitting)



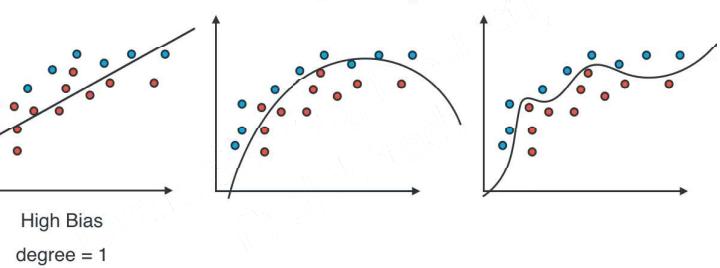
Error due to variance (overfitting)



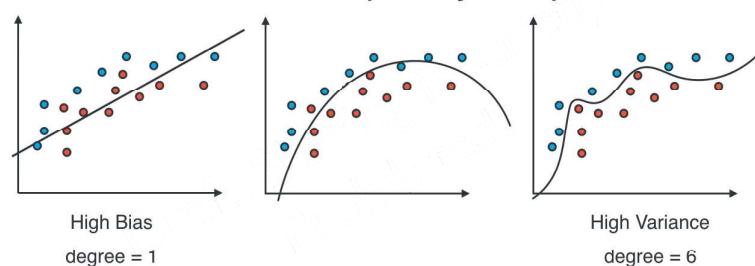
### Model Complexity Graph



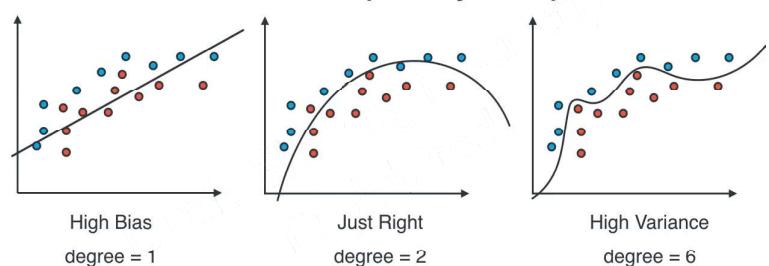
### Model Complexity Graph



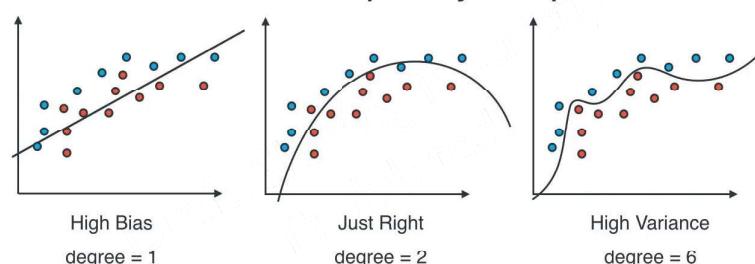
### Model Complexity Graph



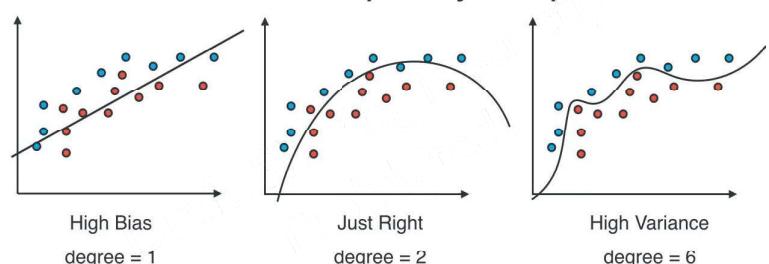
### Model Complexity Graph



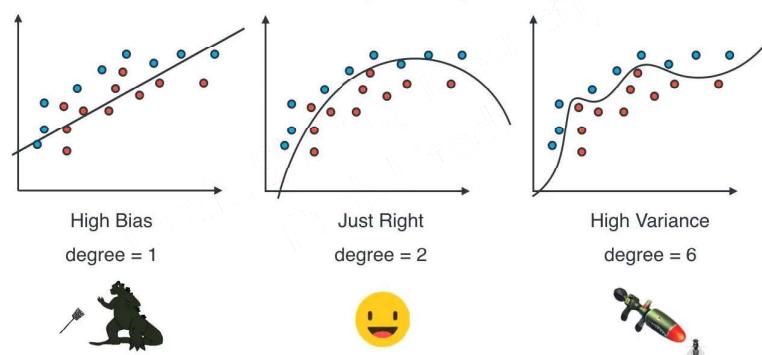
### Model Complexity Graph



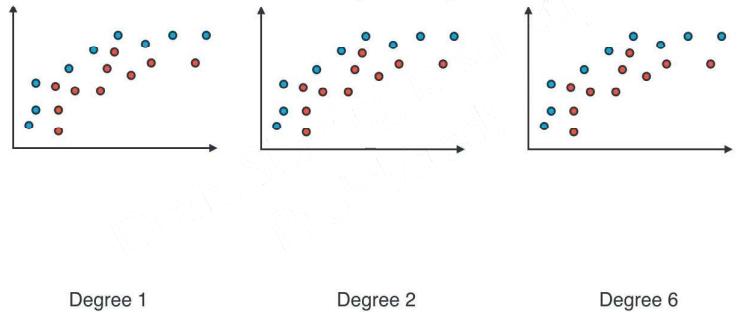
### Model Complexity Graph



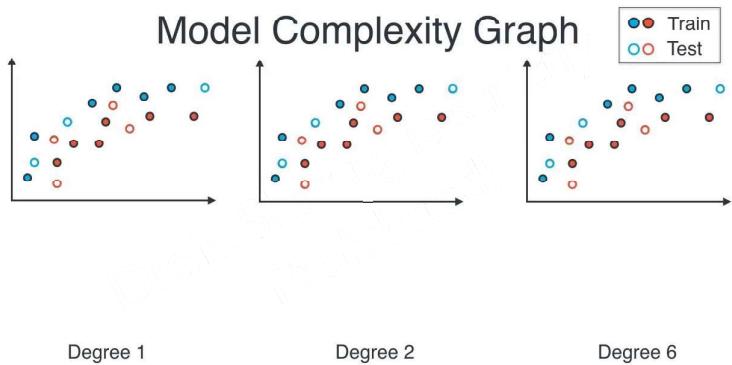
### Model Complexity Graph



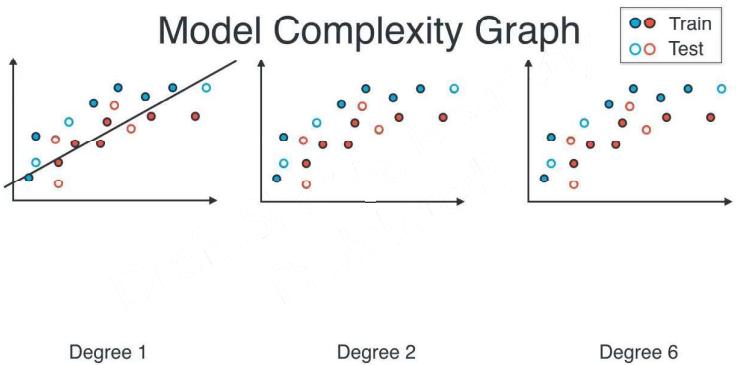
### Model Complexity Graph



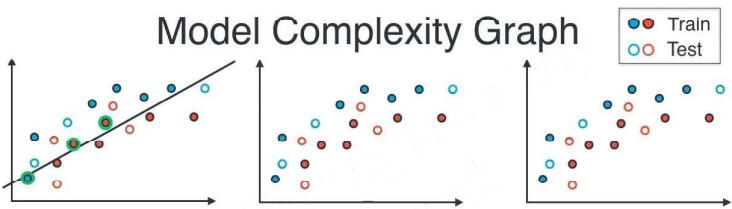
### Model Complexity Graph



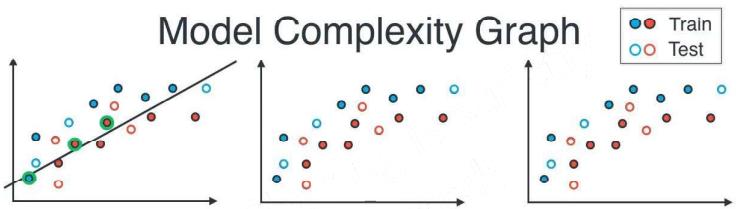
### Model Complexity Graph



### Model Complexity Graph



### Model Complexity Graph



Degree 1

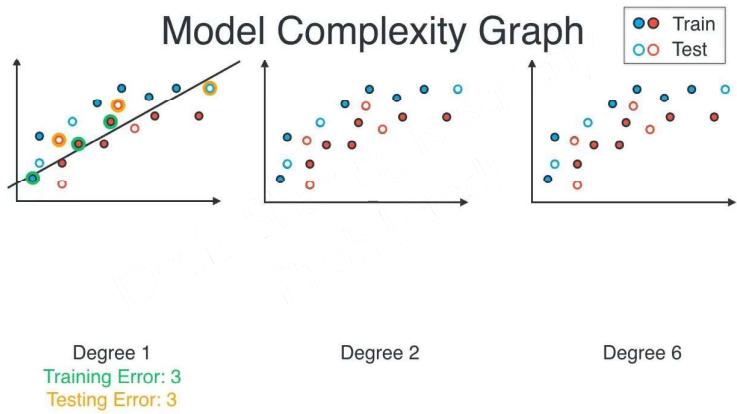
Degree 2

Degree 6

Training Error: 3

Degree 6

### Model Complexity Graph

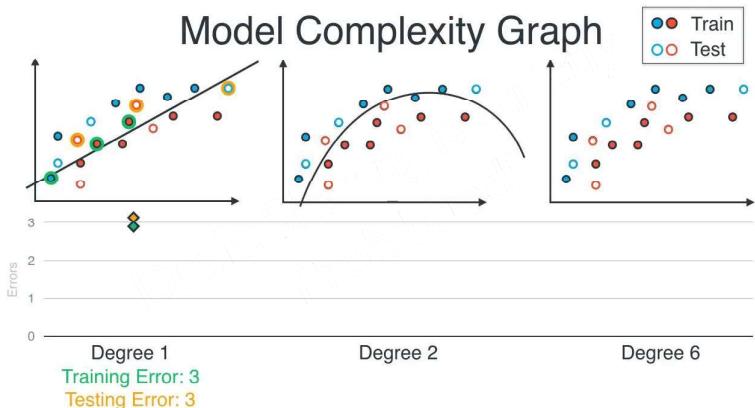


Degree 1  
Training Error: 3  
Testing Error: 3

Degree 2

Degree 6

### Model Complexity Graph

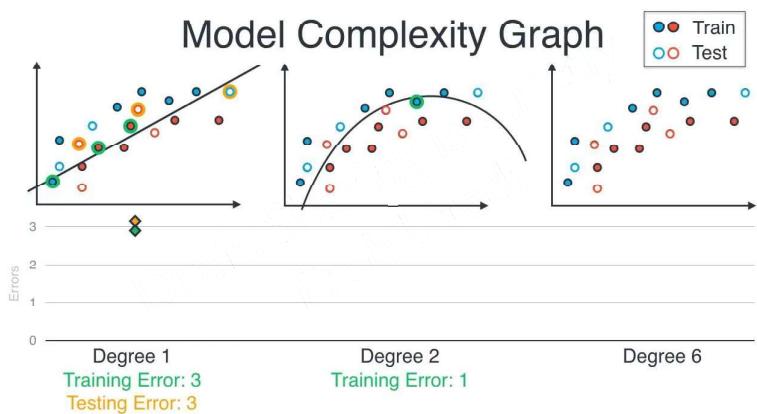


Degree 1  
Training Error: 3  
Testing Error: 3

Degree 2

Degree 6

### Model Complexity Graph

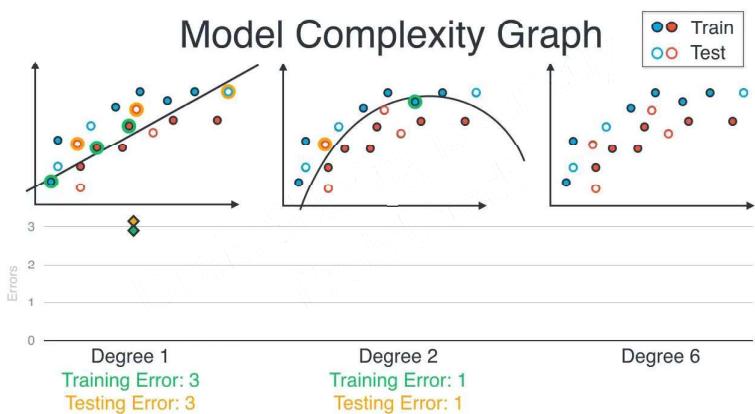


Degree 1  
Training Error: 3  
Testing Error: 3

Degree 2  
Training Error: 1

Degree 6

### Model Complexity Graph

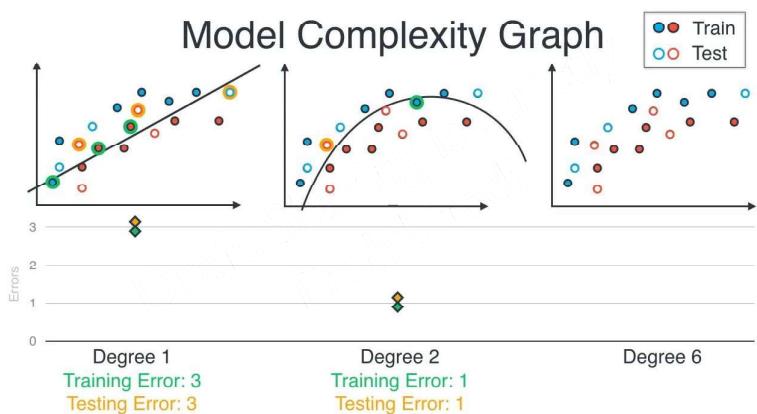


Degree 1  
Training Error: 3  
Testing Error: 3

Degree 2  
Training Error: 1  
Testing Error: 1

Degree 6

### Model Complexity Graph

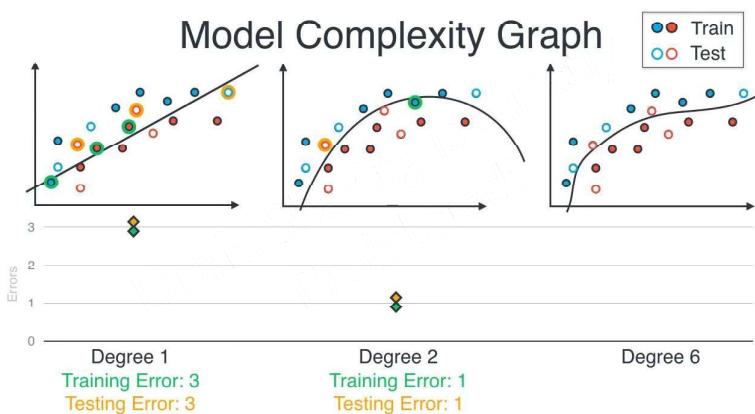


Degree 1  
Training Error: 3  
Testing Error: 3

Degree 2  
Training Error: 1  
Testing Error: 1

Degree 6

### Model Complexity Graph

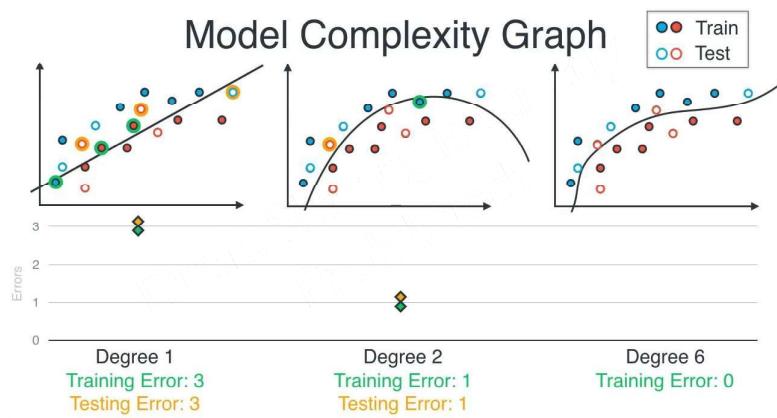


Degree 1  
Training Error: 3  
Testing Error: 3

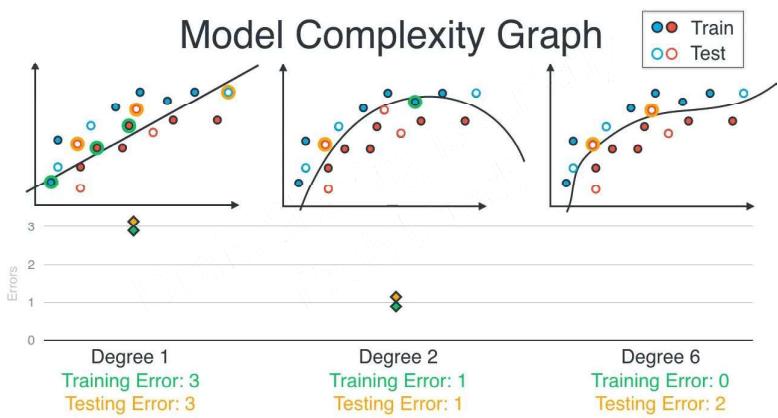
Degree 2  
Training Error: 1  
Testing Error: 1

Degree 6

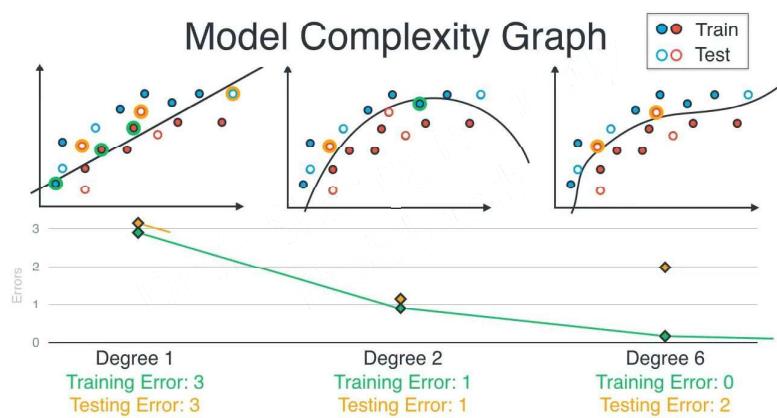
### Model Complexity Graph



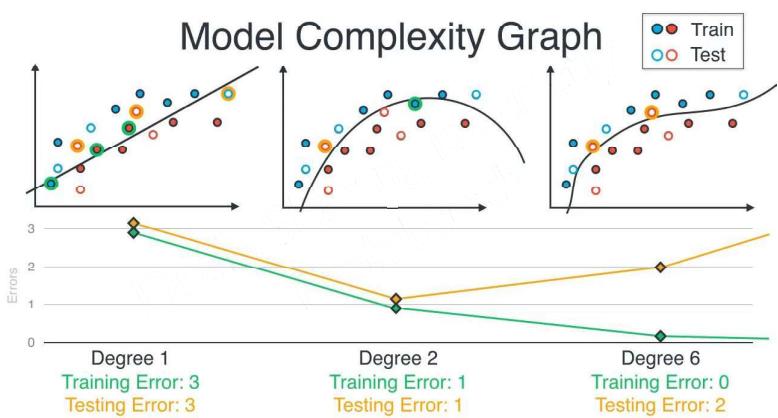
### Model Complexity Graph



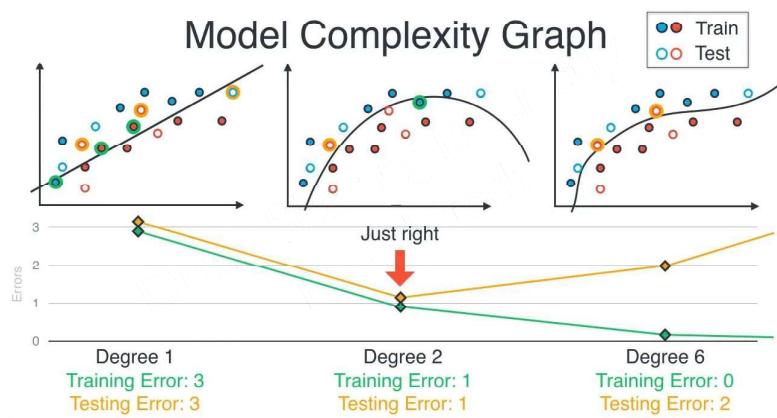
### Model Complexity Graph



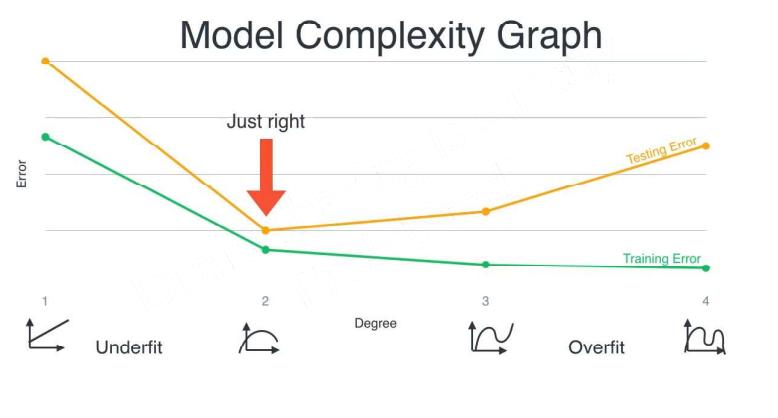
### Model Complexity Graph

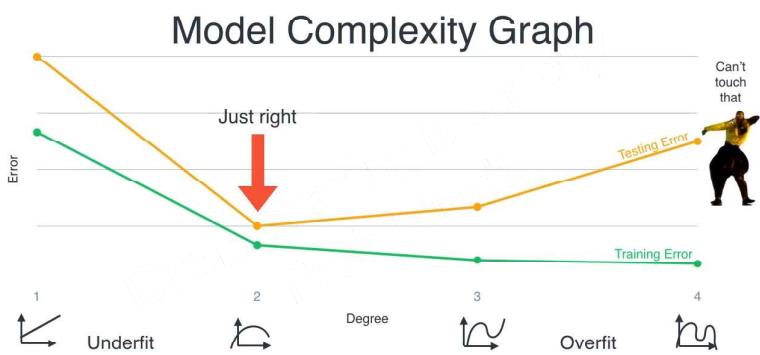


### Model Complexity Graph

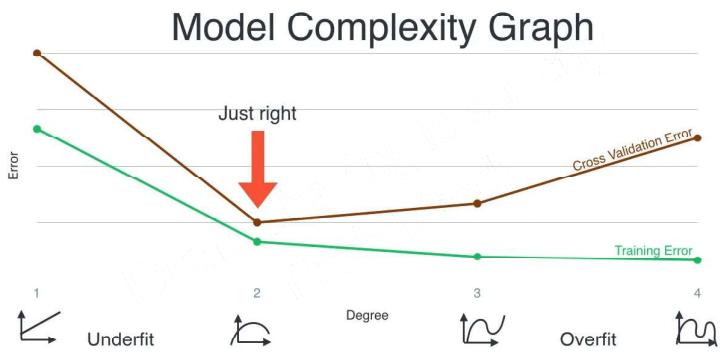
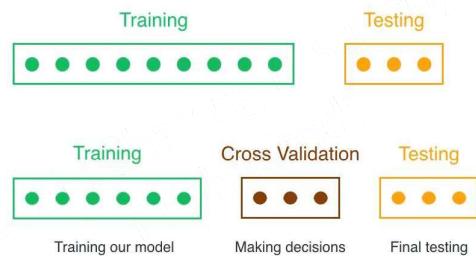


### Model Complexity Graph

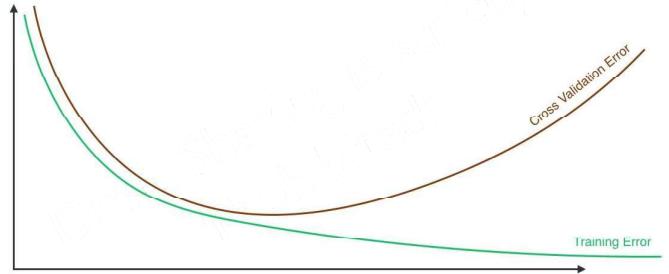




### Solution: Cross Validation



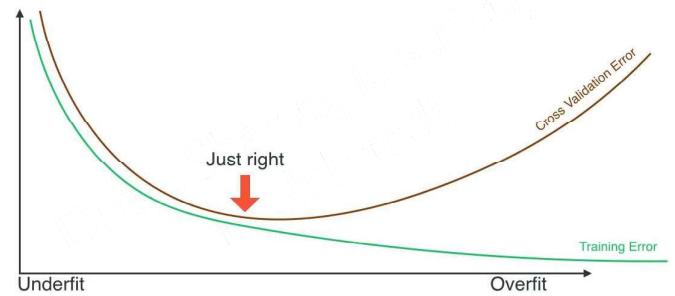
### Model Complexity Graph



## Model Complexity Graph



## Model Complexity Graph



## Summary

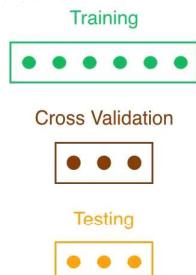
Training data: Train a bunch of models

## Summary

Training data: Train a bunch of models

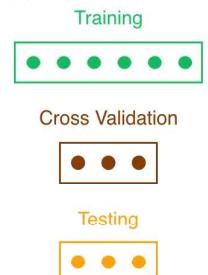
Cross validation data: Pick the best one of the models

## Training a Logistic Regression Model

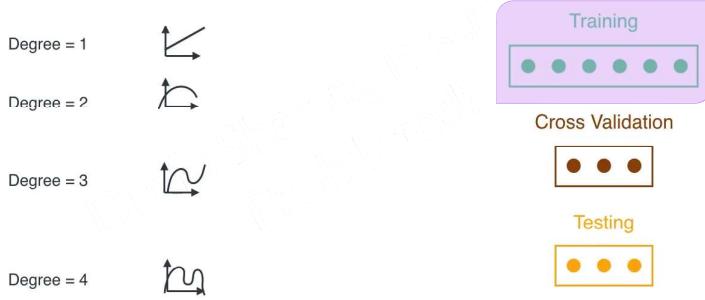


## Training a Logistic Regression Model

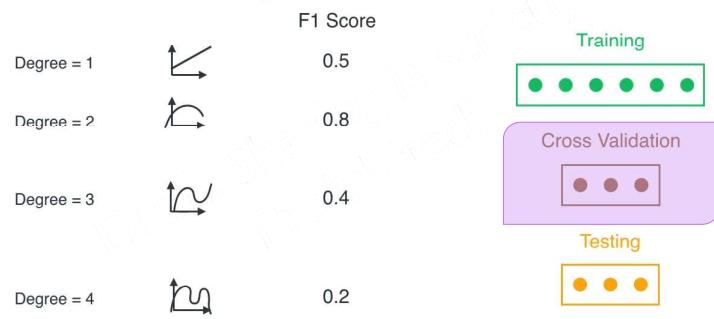
- Degree = 1
- Degree = 2
- Degree = 3
- Degree = 4



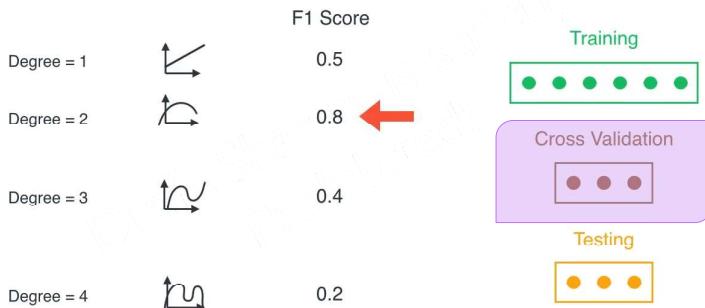
## Training a Logistic Regression Model



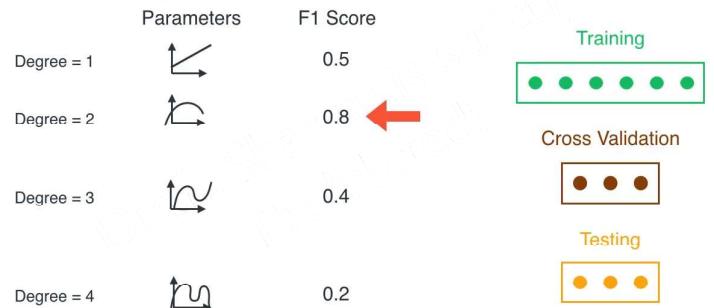
## Training a Logistic Regression Model



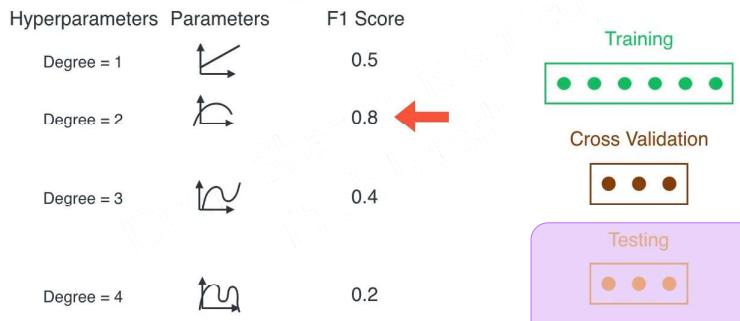
## Training a Logistic Regression Model



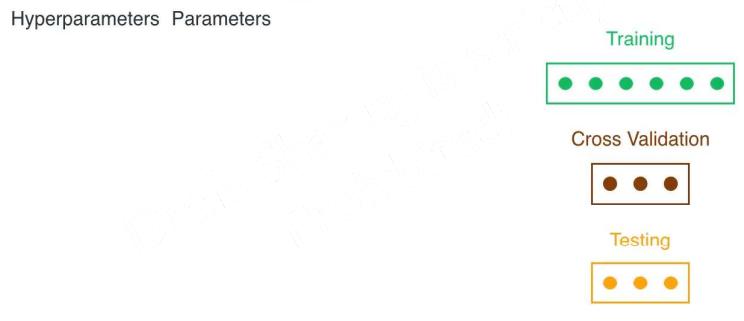
## Training a Logistic Regression Model



## Training a Logistic Regression Model



## Training a Decision Tree



## Training a Decision Tree

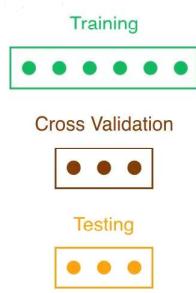
Hyperparameters Parameters

Depth = 1

Depth = 2

Depth = 3

Depth = 4



## Training a Decision Tree

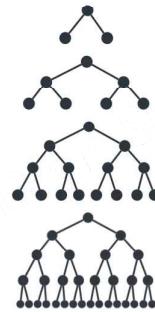
Hyperparameters Parameters

Depth = 1

Depth = 2

Depth = 3

Depth = 4

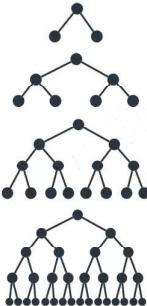


## Training a Decision Tree

Hyperparameters Parameters

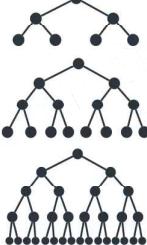
F1 Score

Depth = 1



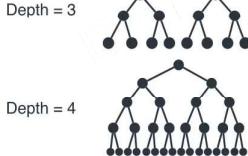
0.5

Depth = 2



0.8

Depth = 3

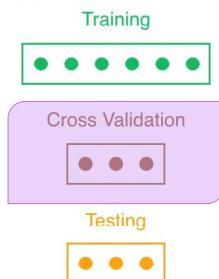


0.4

Depth = 4



0.2

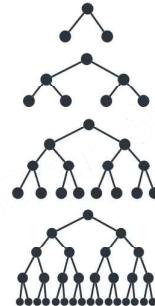


## Training a Decision Tree

Hyperparameters Parameters

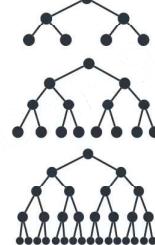
F1 Score

Depth = 1



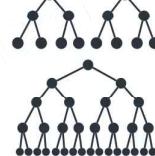
0.5

Depth = 2



0.8

Depth = 3

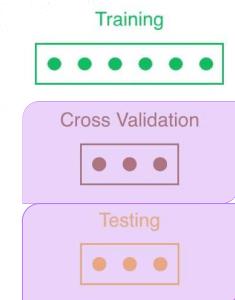


0.4

Depth = 4



0.2



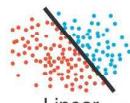
## Training a Support Vector Machine

Hyperparameters

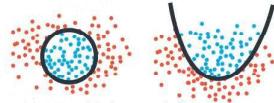
## Training a Support Vector Machine

Hyperparameters

Kernel



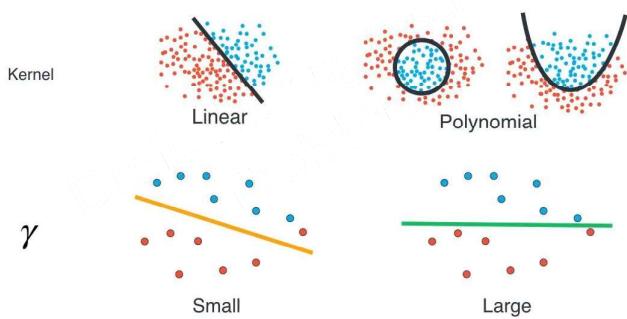
Linear



Polynomial

## Training a Support Vector Machine

Hyperparameters



## Grid Search Cross Validation

kernel \ Gamma	linear	polynomial
0.1		
1		
10		

Legend:

- Training:** Green dots in a row.
- Cross Validation:** Brown dots in a row.
- Testing:** Orange dots in a row.

## Grid Search Cross Validation

kernel \ Gamma	linear	polynomial
0.1		
1		
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Legend:

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## Parameters and Hyperparameters

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Algorithm	Parameters	Hyperparameters
Random Forest	Features Thresholds	Number of trees Depth

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## Parameters and Hyperparameters

Algorithm	Parameters	Hyperparameters
Random Forest	Features Thresholds	Number of trees Depth
Logistic Regression	Coefficients of the polynomial	Degree of the polynomial
Support Vector Machines	Coefficients	Kernel Gamma C
Neural Networks	Coefficients	Number of layers Size of layers Activation function

## How to solve a problem



Problem



Problem



Tools

## How to solve a problem

## How to solve a problem

## How to solve a problem



## How to solve a problem



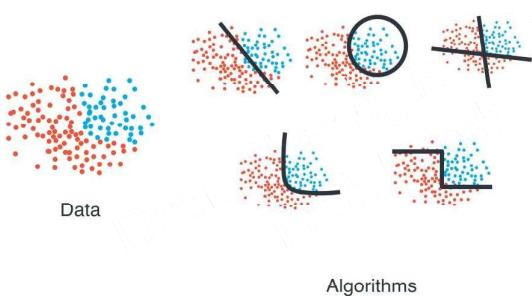
## How to solve a problem



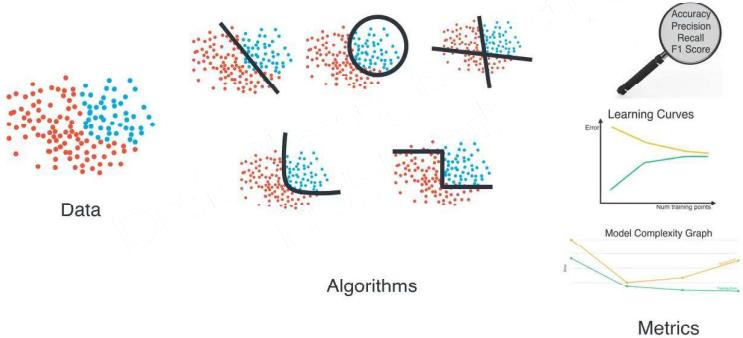
## How to use machine learning



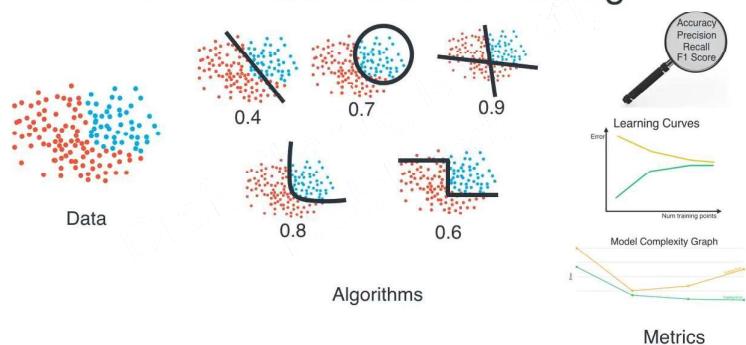
## How to use machine learning



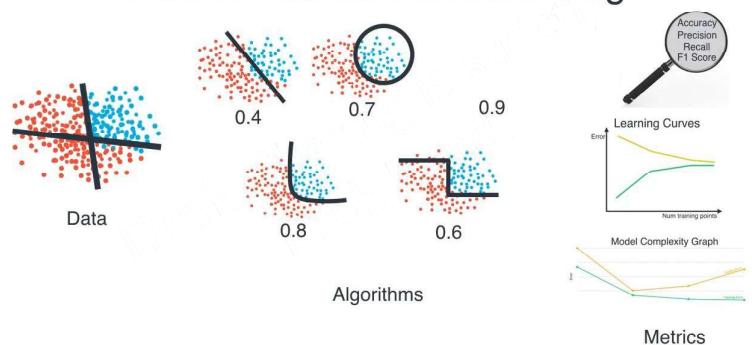
## How to use machine learning



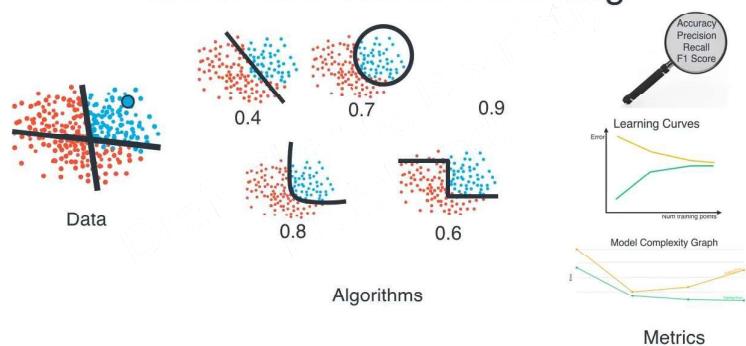
## How to use machine learning



## How to use machine learning



## How to use machine learning



THANK YOU!