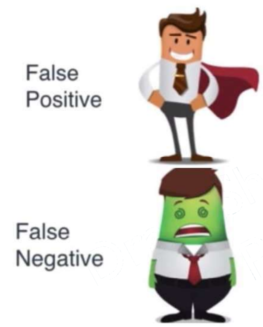


ML Testing and Error Metrics

Testing

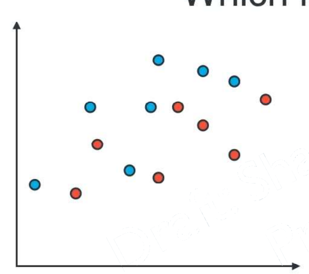
How well is my model doing?

Testing

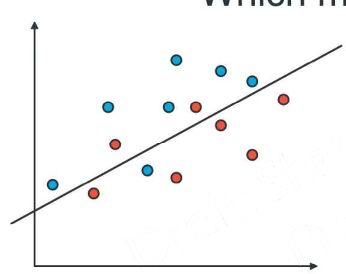
How well is my model doing?

How do I improve it?

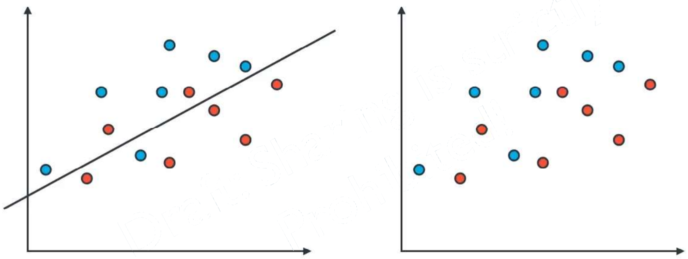
Which model is better



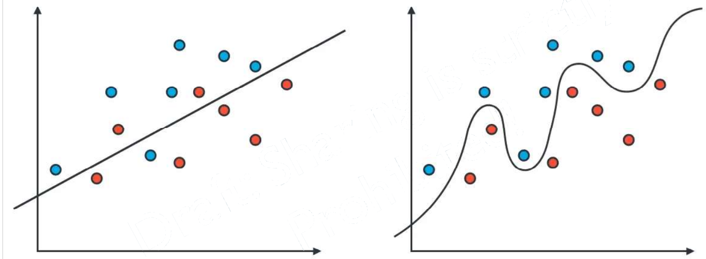
Which model is better



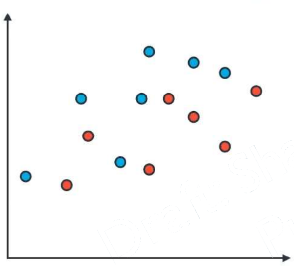
Which model is better



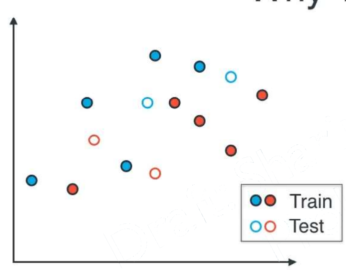
Which model is better



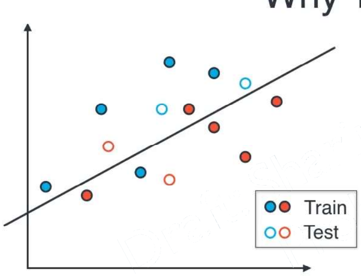
Why Testing?



Why Testing?

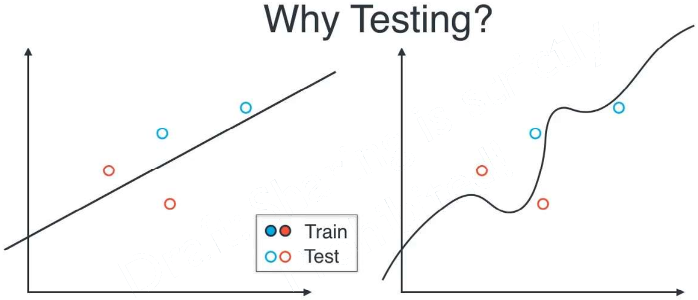


Why Testing?

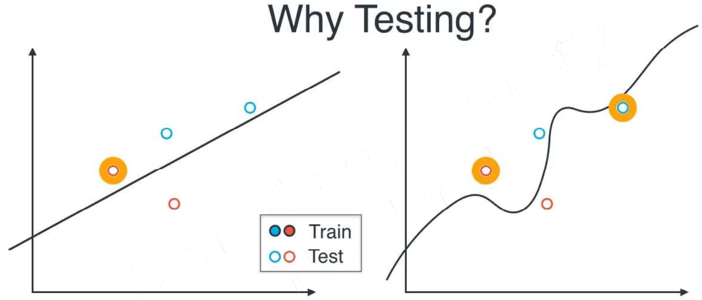


Why Testing?

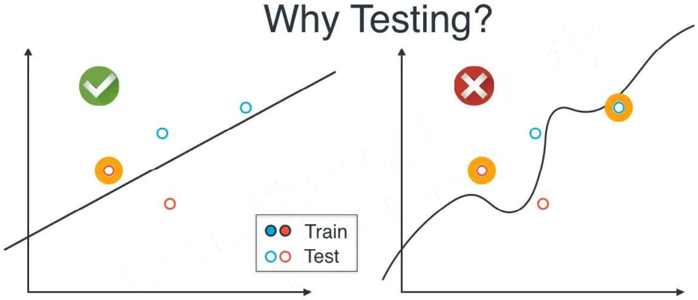
Why Testing?



Why Testing?



Why Testing?

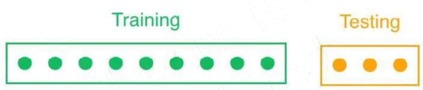


Golden Rule # 1

Golden Rule # 2

Golden Rule # 3

How do we not ‘lose’ the training data?

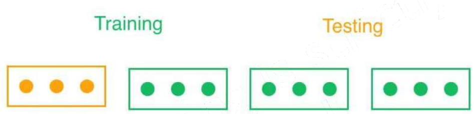


K-Fold Cross Validation

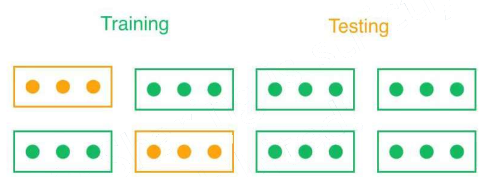
Training

Testing

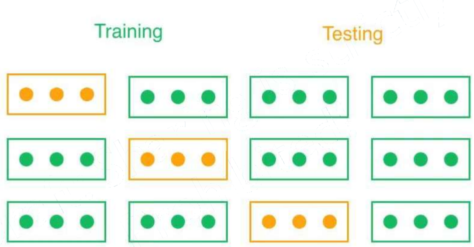
K-Fold Cross Validation



K-Fold Cross Validation

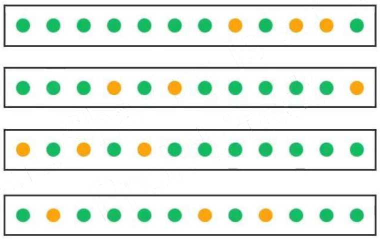


K-Fold Cross Validation



K-Fold Cross Validation

Randomizing in Cross Validation



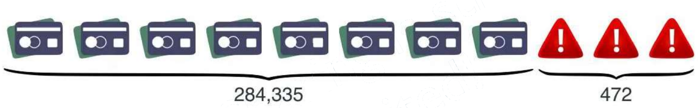
Evaluation Metrics

How well is my model doing?

Credit Card Fraud

Credit Card Fraud

Credit Card Fraud



Credit Card Fraud

Model: All transactions are good.

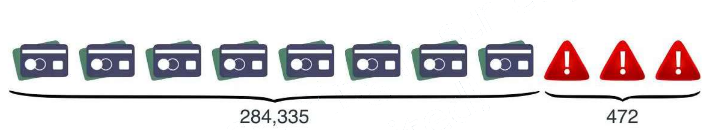
Credit Card Fraud

Model: All transactions are good.

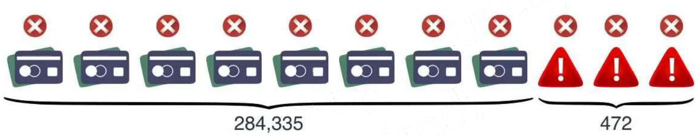
$$\text{Correct} = \frac{284{,}335}{284{,}807} = 99.83\%$$

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

Credit Card Fraud

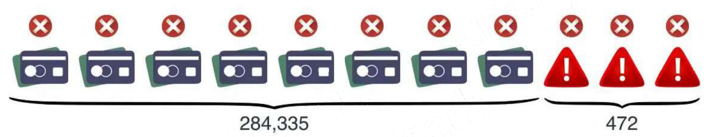


Credit Card Fraud



Model: All transactions are fraudulent.

Credit Card Fraud



Model: All transactions are fraudulent.

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

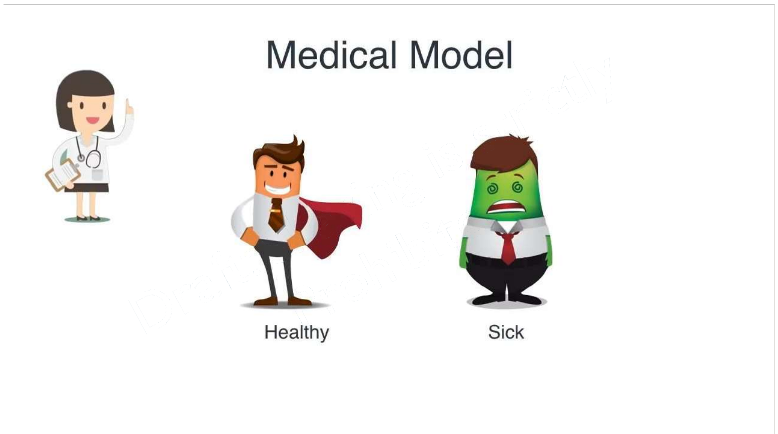
Credit Card Fraud

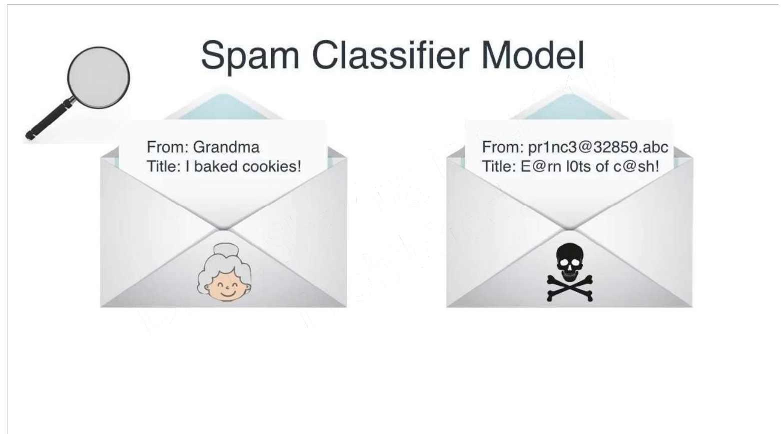
Model: All transactions are fraudulent.

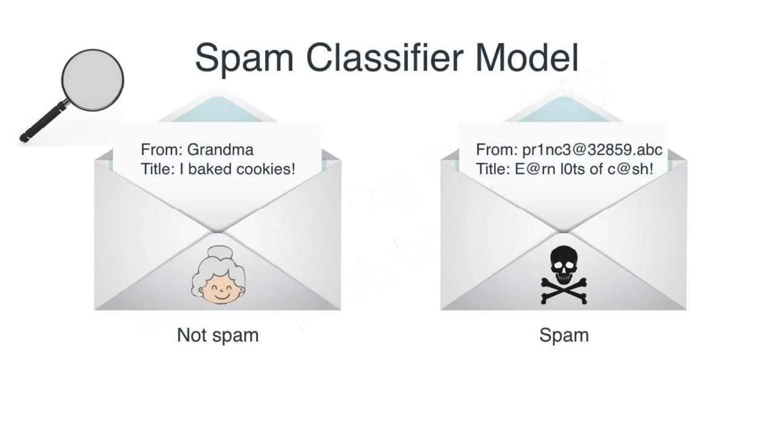
Great! Now I'm catching *all* the bad transactions!

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

Medical Model







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

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

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

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

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

10,000 Patients

Confusion Matrix

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Healthy	800	8000

10,000 Patients

Confusion Matrix

Diagnosis

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

10,000 Patients

Confusion Matrix

Diagnosis

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

10,000 Patients

Confusion Matrix

Diagnosis

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

Confusion Matrix

10,000
Patients

Diagnosis

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

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

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

Confusion Matrix

1,000
e-mails

Folder

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

Confusion Matrix

1,000
e-mails

Folder

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

Confusion Matrix

1,000
e-mails

Folder

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

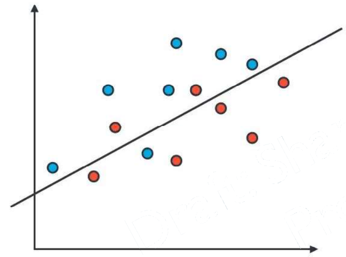
Confusion Matrix

1,000
e-mails

Folder

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

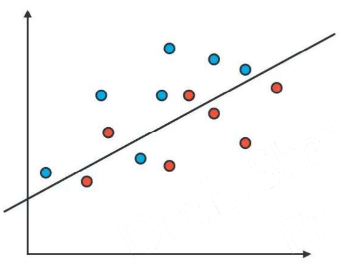
Confusion Matrix



Prediction

Data	Guessed Positive	Guessed Negative
Positive		
Negative		

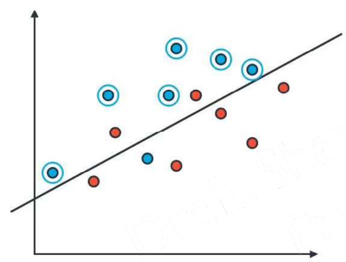
Confusion Matrix



Prediction

Data	Guessed Positive	Guessed Negative
Positive	True positives	
Negative		

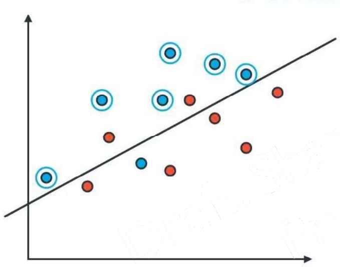
Confusion Matrix



Prediction

Data	Guessed Positive	Guessed Negative
Positive	True positives	
Negative		

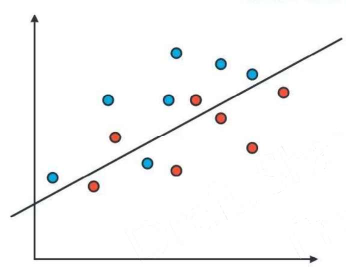
Confusion Matrix



Prediction

Data	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		

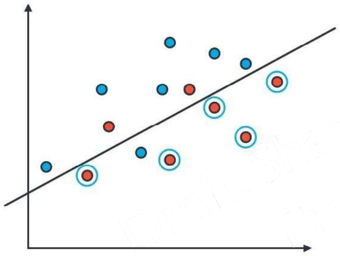
Confusion Matrix



Prediction

Data	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		True Negatives

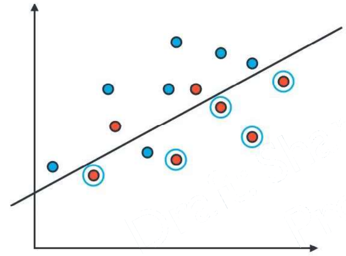
Confusion Matrix



Prediction

Data	Guessed Positive	Guessed Negative
Positive	6 True positives	
Negative		True Negatives

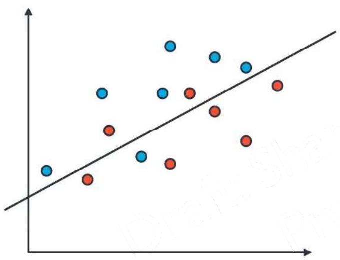
Confusion Matrix



Prediction

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

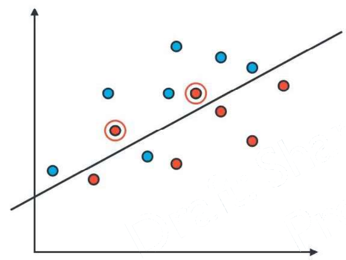
Confusion Matrix



Prediction

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

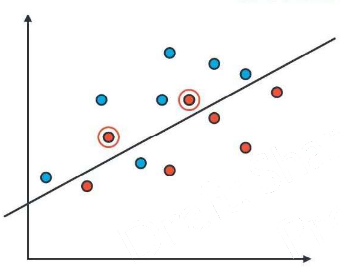
Confusion Matrix



Prediction

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

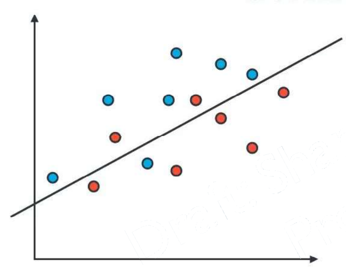
Confusion Matrix



Prediction

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

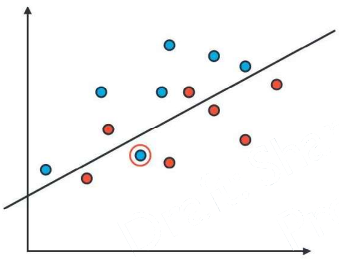
Confusion Matrix



Prediction

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

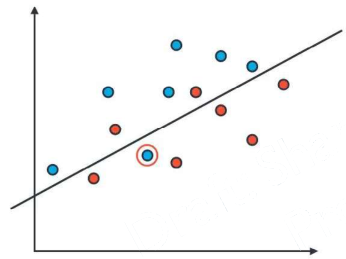
Confusion Matrix



Prediction

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

Confusion Matrix



Prediction

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

Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Healthy	800	8000

Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Healthy	800	8000

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

Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Healthy	800	8000

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

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

Accuracy

Diagnosis

Patients	Diagnosed sick	Diagnosed Healthy
Sick	1000	200
Healthy	800	8000

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

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

Accuracy

Folder

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

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

Accuracy =

Accuracy

Folder

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

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

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

Accuracy

Folder

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

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

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

	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 Positives	False Negatives
Not Spam	False Positives	True Negatives

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

	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

Find all the sick people
Ok if not all are sick

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

EVALUATION METRICS

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

Find all the sick people
Ok if not all are sick

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

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

Find all the sick people
Ok if not all are sick

High Recall

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 Precision

Precision

Diagnosis

Patients		Diagnosed sick	Diagnosed Healthy
	Sick	1000	200 ✖
	Is Healthy	600	9000

Precision

Diagnosis

Patients		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

Diagnosis

Patients		Diagnosed sick	Diagnosed Healthy
	Sick	1000	200 ✖
	Healthy	800	8000

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

Precision

Diagnosis

Patients		Diagnosed sick	Diagnosed Healthy
	Sick	1000	200 ✖
	Healthy	800	8000

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

Folder

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

Precision

Folder

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

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

Precision

Folder

E-mail

	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

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

Precision

Folder

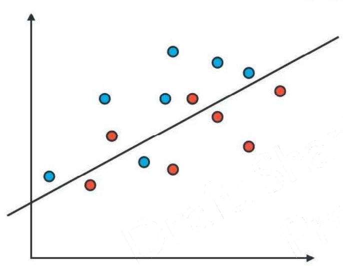
E-mail

	Spam Folder	Inbox
Spam	100	170
Not spam	30	700

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

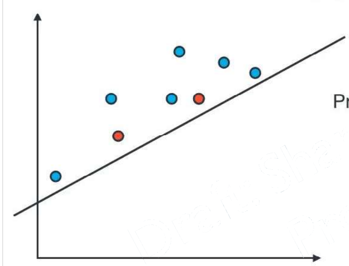
$$\text{Precision} = \frac{100}{100 + 30} = 76.9\%$$

Precision



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

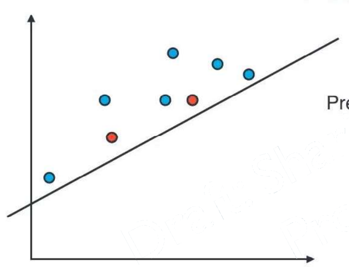
Precision



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?

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

$$= \frac{6}{6 + 2}$$

$$= \frac{6}{8}$$

$$= 75\%$$

Recall

Diagnosis

Patients

	Diagnosed Sick	Diagnosed Healthy
Sick	1000	200
Is Healthy	800	8000

Recall

Diagnosis

Patients	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

Diagnosis

Patients	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

Diagnosis

Patients	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

Folder

E-mail	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

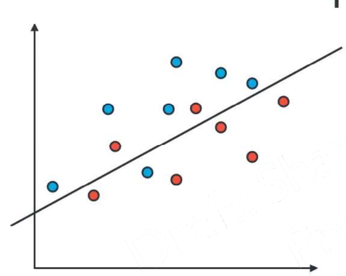
Folder

E-mail	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?

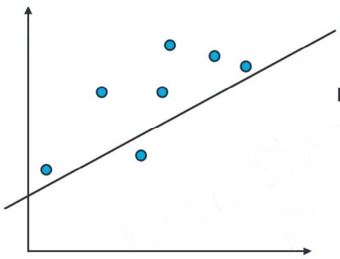
$$\text{Recall} = \frac{100}{100 + 170} = 37\%$$

Recall



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

Recall



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

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False Negatives}} = \frac{6}{6 + 1} = \frac{6}{7} = 85.7\%$$

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%

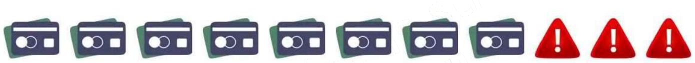
Average = 69.5%

Spam Detector

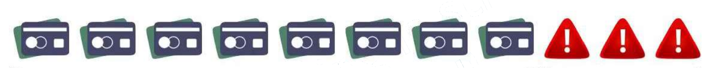
Precision: 76.9%
Recall: 37%

Average = 56.95%

Credit Card Fraud



Credit Card Fraud



284,335

472

Credit Card Fraud

Model: All transactions are good.

Credit Card Fraud

Model: All transactions are good.

Precision = 100% Recall = $\frac{0}{472}$ = 0%

Credit Card Fraud

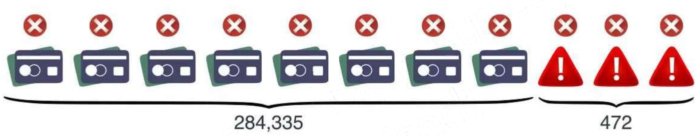
Model: All transactions are good.

Precision = 100% Recall = $\frac{0}{472}$ = 0%

Average = 50%

Credit Card Fraud

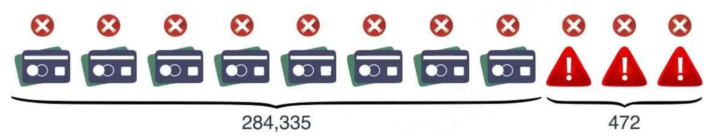
Credit Card Fraud



Model: All transactions are fraudulent.

Precision = $\frac{472}{284{,}807}$ = .016% Recall = $\frac{472}{472}$ = 100%

Credit Card Fraud



Model: All transactions are fraudulent.

Precision = $\frac{472}{284{,}807}$ = .016% Recall = $\frac{472}{472}$ = 100%

Average = 50.008%

Harmonic mean

y

x

Harmonic mean

y

Arithmetic Mean = $\frac{x+y}{2}$

x

Harmonic mean

y

Arithmetic Mean = $\frac{x+y}{2}$

Harmonic Mean = $\frac{2xy}{x+y}$

x

Harmonic mean

y

Precision = 1
Recall = 0
Average = 0.5
Harmonic Mean = 0

Arithmetic Mean = $\frac{x+y}{2}$

Harmonic Mean = $\frac{2xy}{x+y}$

x

Harmonic mean

y

Precision = 1
Recall = 0
Average = 0.5
Harmonic Mean = 0

Arithmetic Mean = $\frac{x+y}{2}$

Precision = 0.2
Recall = 0.8
Average = 0.5
Harmonic Mean = 0.32

Harmonic Mean = $\frac{2xy}{x+y}$

x

Harmonic mean

y

Precision = 1
Recall = 0
Average = 0.5
Harmonic Mean = 0

Arithmetic Mean = $\frac{x+y}{2}$

Precision = 0.2
Recall = 0.8
Average = 0.5
Harmonic Mean = 0.32

Harmonic Mean = $\frac{2xy}{x+y}$

x

~~Arithmetic Mean(Precision, Recall)~~

Harmonic mean

Arithmetic Mean = $\frac{x+y}{2}$

Harmonic Mean = $\frac{2xy}{x+y}$

y

x

Precision = 1
Recall = 0
Average = 0.5
Harmonic Mean = 0

Precision = 0.2
Recall = 0.8
Average = 0.5
Harmonic Mean = 0.32

~~Arithmetic Mean(Precision, Recall)~~
F1 Score = Harmonic Mean(Precision, 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 Score = $\frac{2 \times 55.7 \times 83.3}{55.7 + 83.3}$ = 66.76%

F1 Score

Spam Detector Model

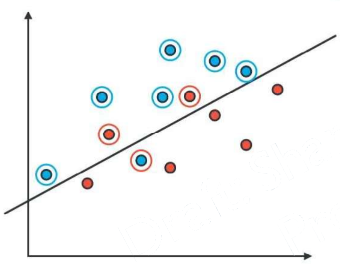
Precision = 76.9%

Recall = 37%

Average = 56.95%

F1 Score = $\frac{2 \times 76.9 \times 37}{76.9 + 37}$ = 49.96%

F1 Score

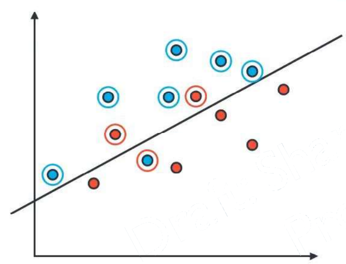


Precision = 75%

Recall = 85.7%

Average = 80.35

F1 Score



Precision = 75%

Recall = 85.7%

Average = 80.35

F1 Score = $\frac{2 \times 75 \times 85.7}{75 + 85.7}$ = 80%

Types of Errors

Types of Errors

Types of Errors

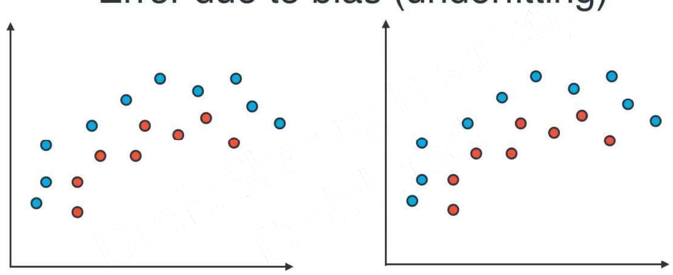
Underfitting

Types of Errors

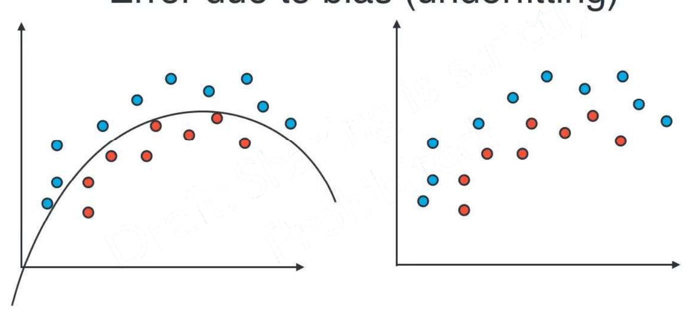
Underfitting

Overfitting

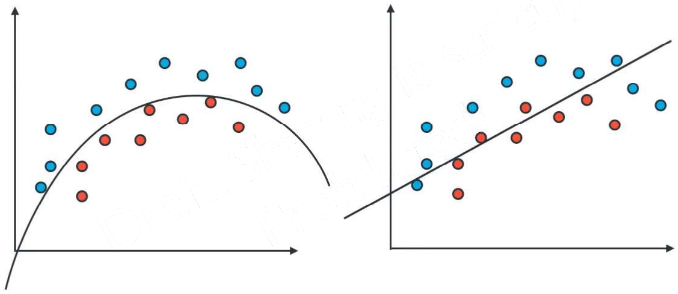
Error due to bias (underfitting)



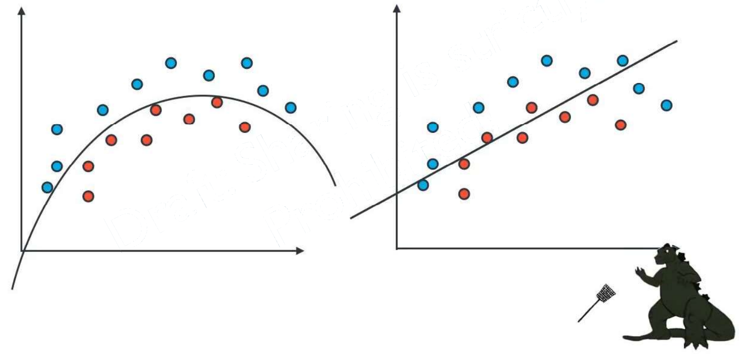
Error due to bias (underfitting)



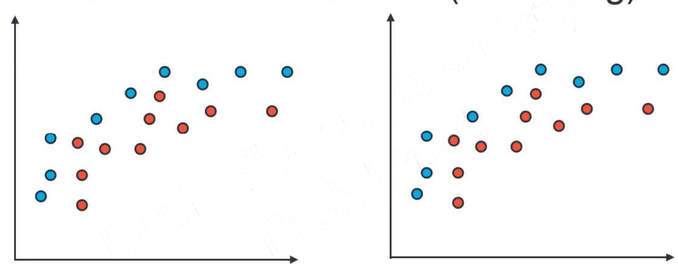
Error due to bias (underfitting)



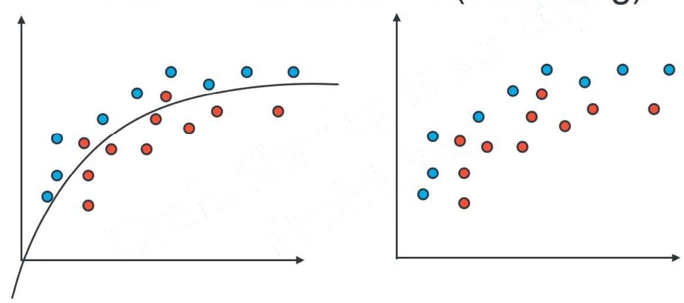
Error due to bias (underfitting)



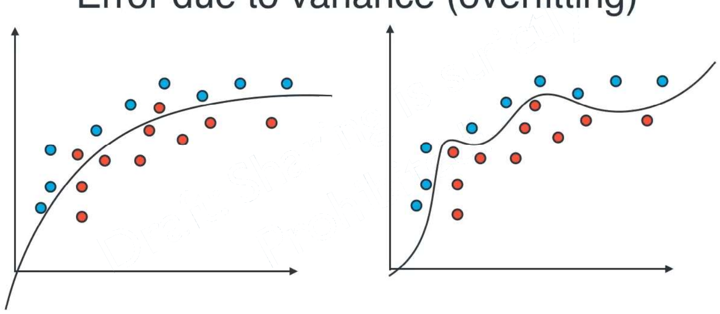
Error due to variance (overfitting)



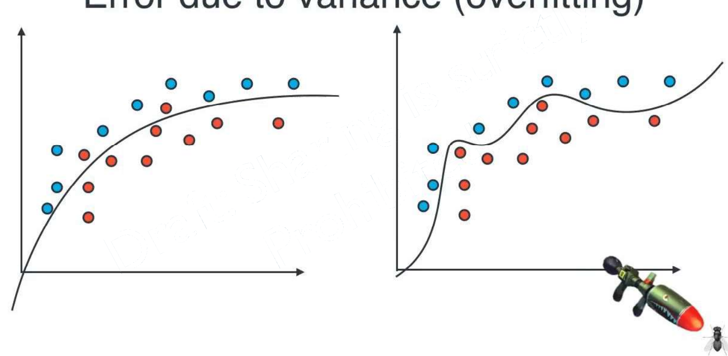
Error due to variance (overfitting)



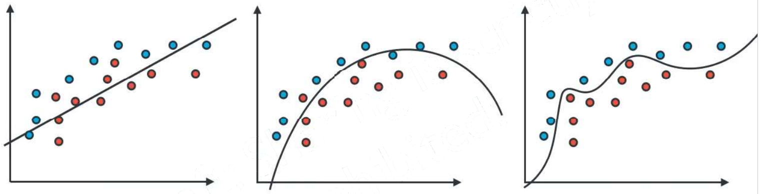
Error due to variance (overfitting)



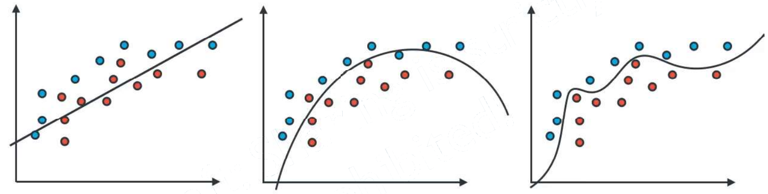
Error due to variance (overfitting)



Model Complexity Graph



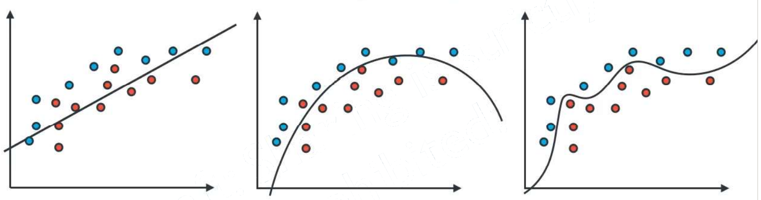
Model Complexity Graph



High Bias

degree = 1

Model Complexity Graph



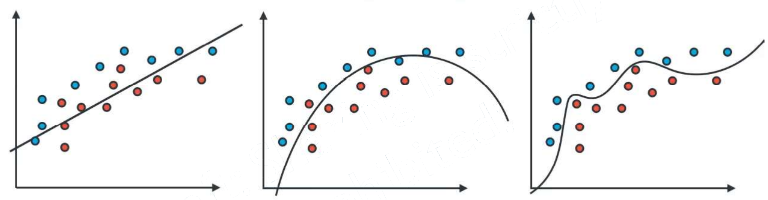
High Bias

degree = 1

High Variance

degree = 6

Model Complexity Graph



High Bias

degree = 1

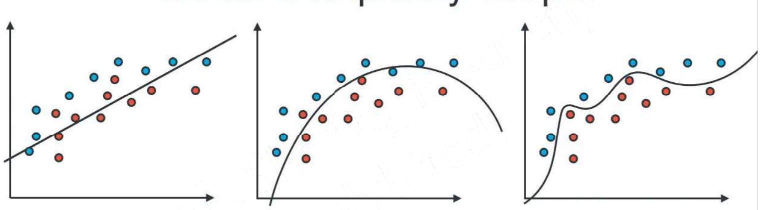
Just Right

degree = 2

High Variance

degree = 6

Model Complexity Graph



High Bias

degree = 1

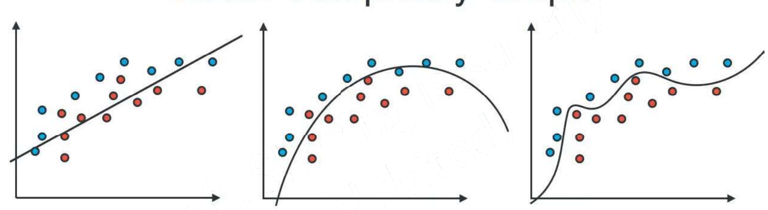
Just Right

degree = 2

High Variance

degree = 6

Model Complexity Graph



High Bias

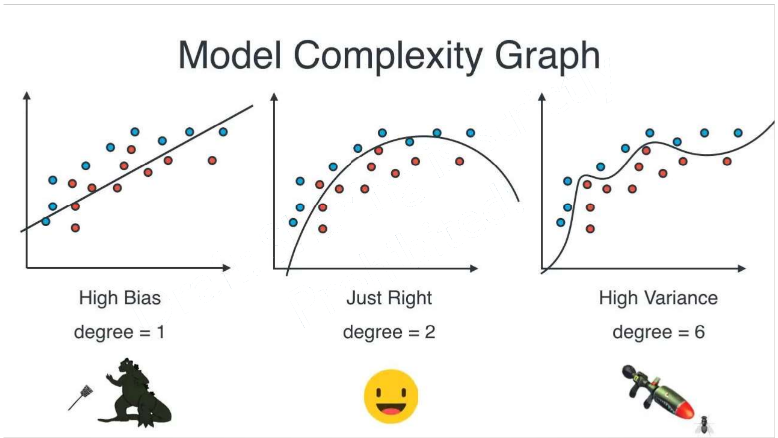
degree = 1

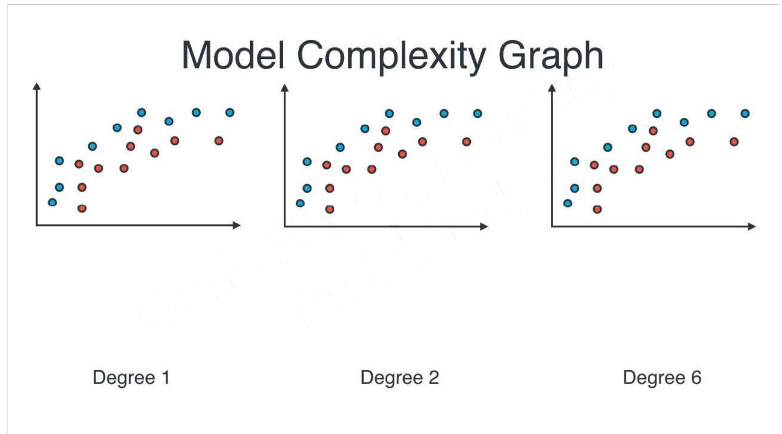
Just Right

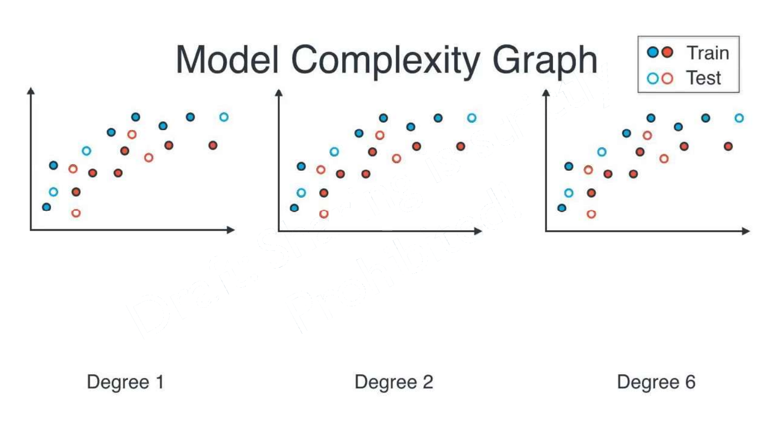
degree = 2

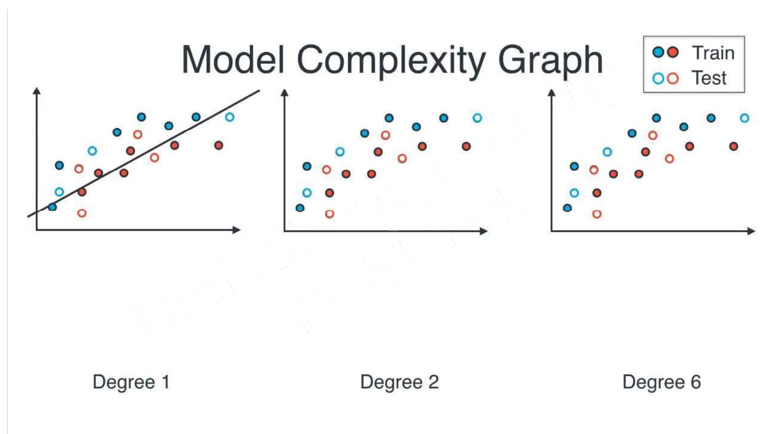
High Variance

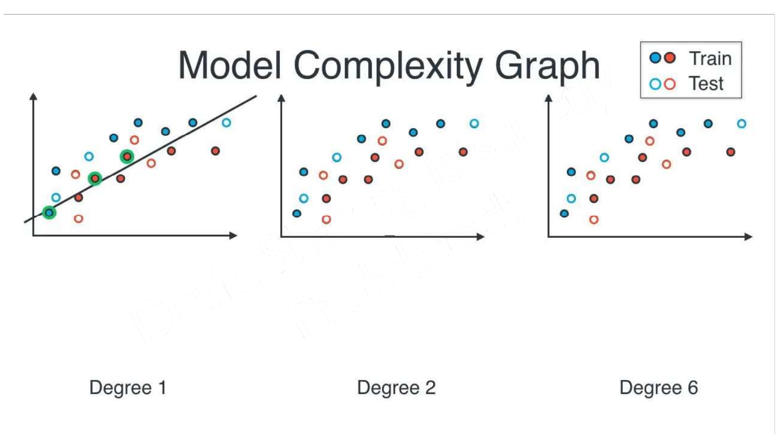
degree = 6

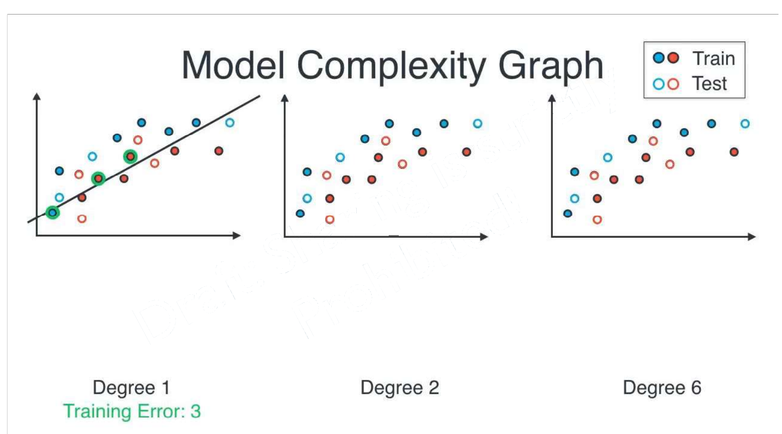

Model Complexity Graph
High Bias
degree = 1
Just Right
degree = 2
High Variance
degree = 6

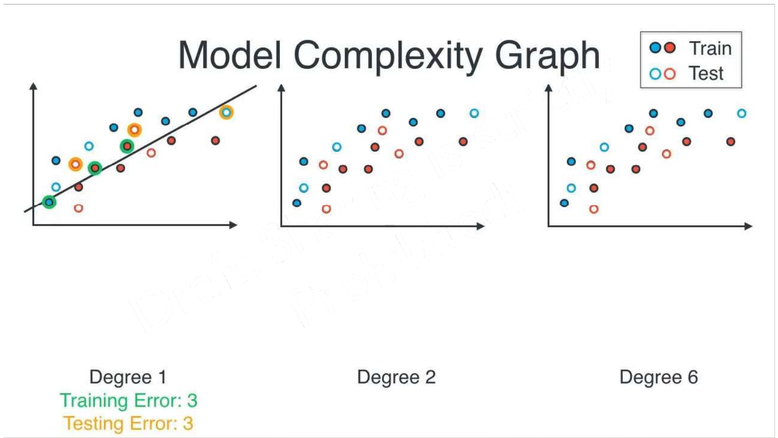

Model Complexity Graph
Degree 1
Degree 2
Degree 6

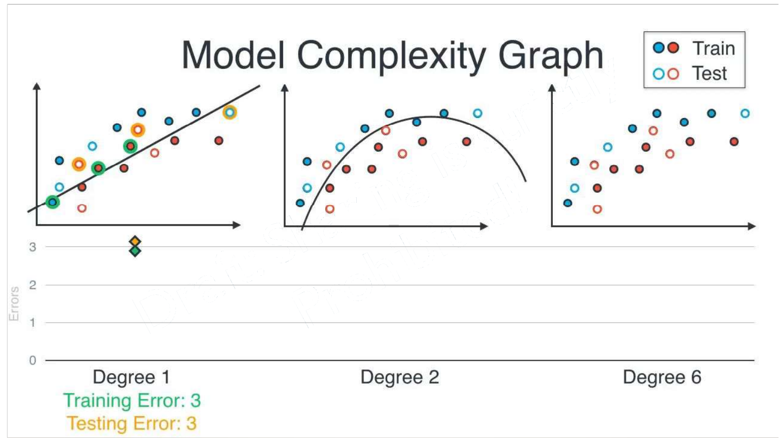

Model Complexity Graph
Train
Test
Degree 1
Degree 2
Degree 6

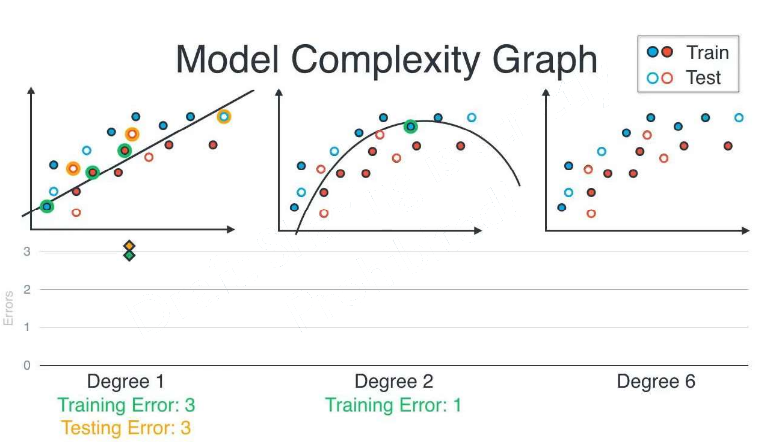

Model Complexity Graph
Train
Test
Degree 1
Degree 2
Degree 6

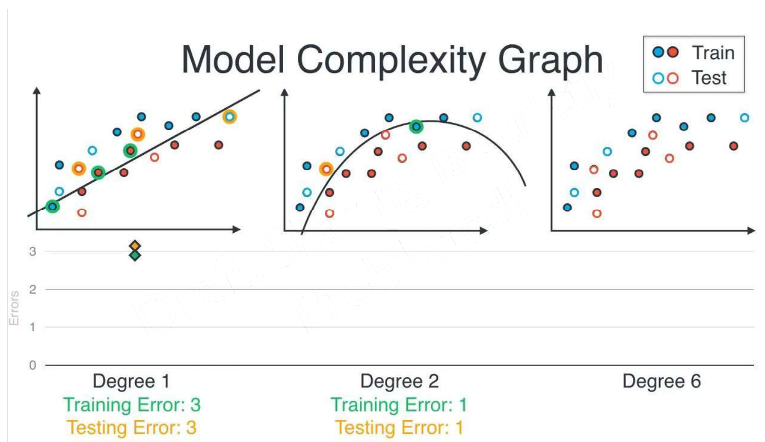

Model Complexity Graph
Train
Test
Degree 1
Degree 2
Degree 6

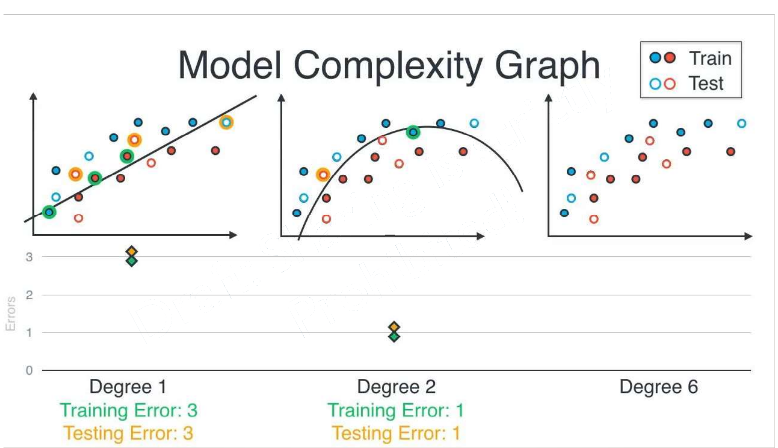

Model Complexity Graph
Train
Test
Degree 1
Training Error: 3
Degree 2
Degree 6

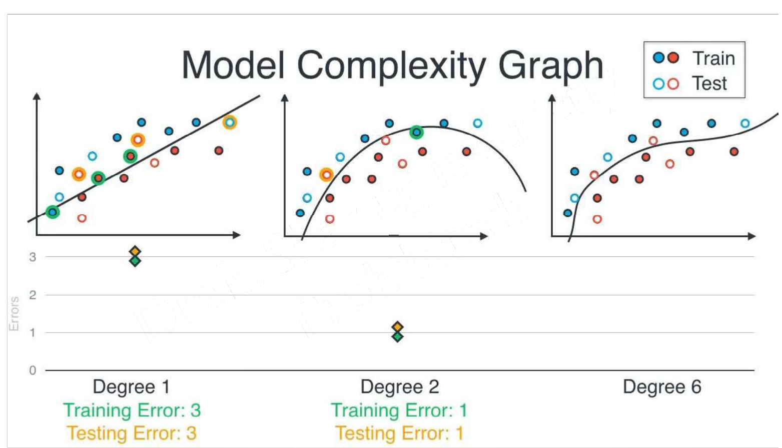

Model Complexity Graph
Train
Test
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Degree 6

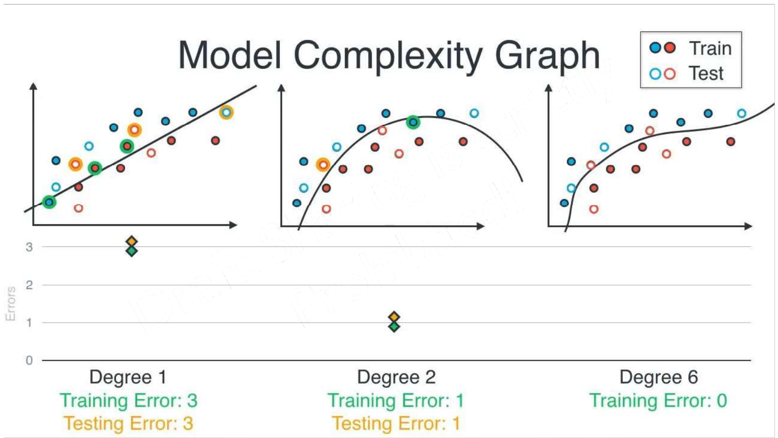

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Degree 6

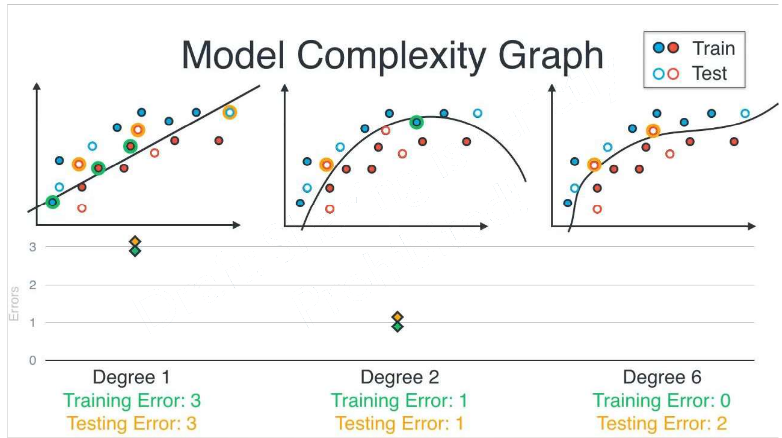

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Degree 6

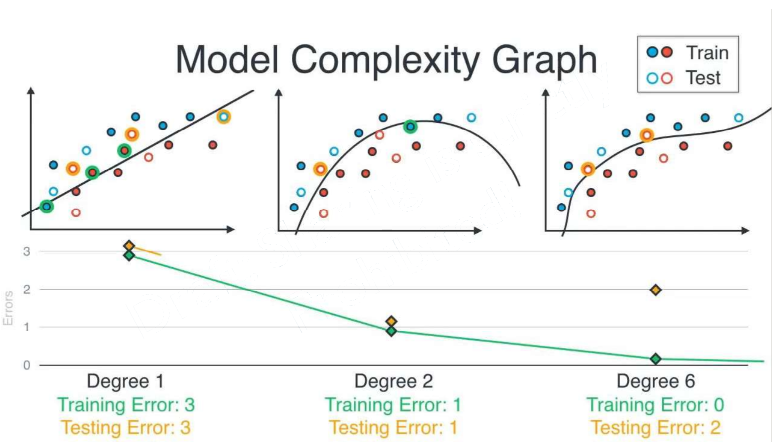

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6

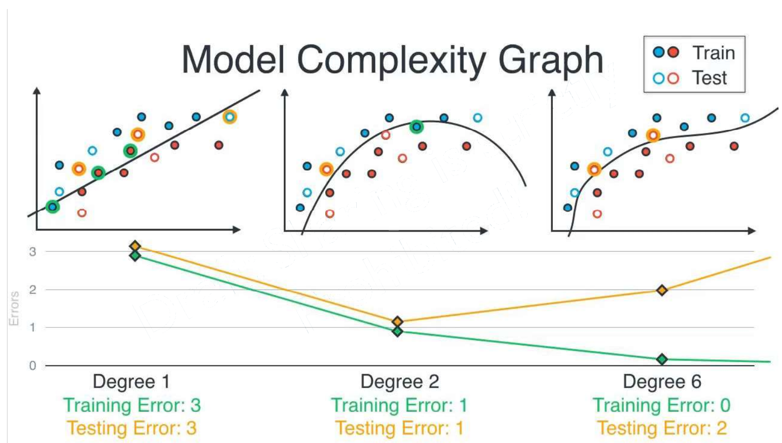

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6

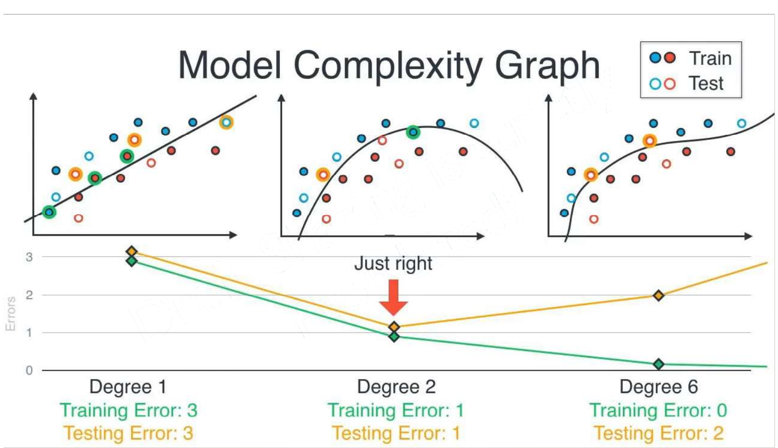

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6

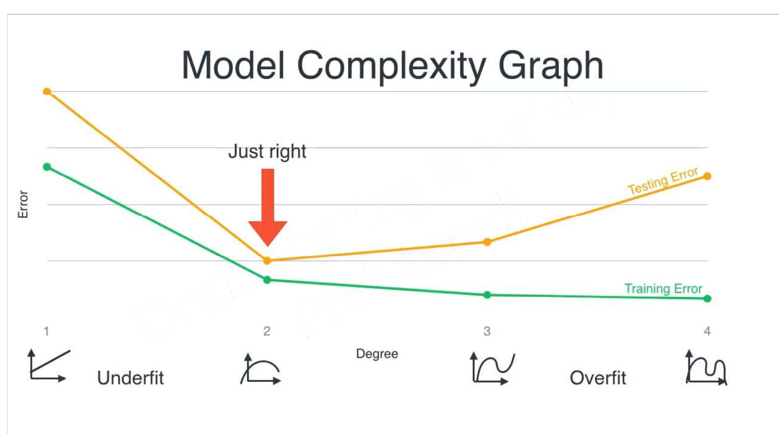

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6
Training Error: 0


Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6
Training Error: 0
Testing Error: 2


Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6
Training Error: 0
Testing Error: 2

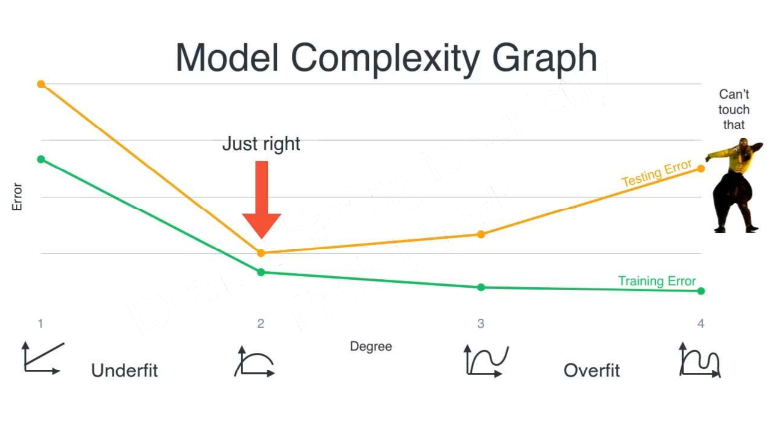

Model Complexity Graph
Train
Test
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6
Training Error: 0
Testing Error: 2

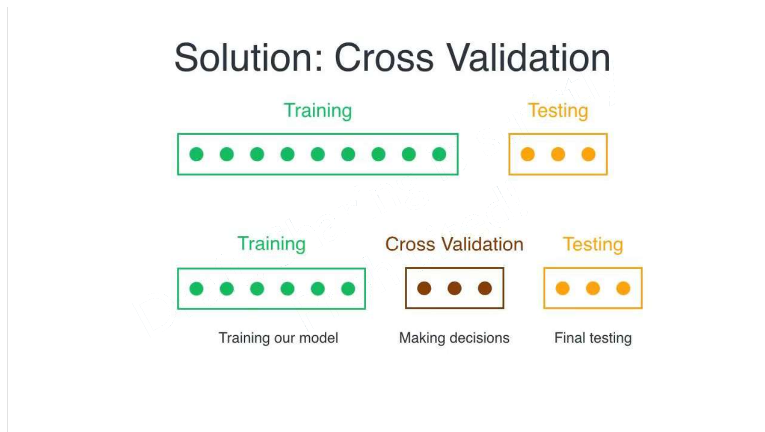

Model Complexity Graph
Train
Test
Just right
Errors
3
2
1
0
Degree 1
Training Error: 3
Testing Error: 3
Degree 2
Training Error: 1
Testing Error: 1
Degree 6
Training Error: 0
Testing Error: 2

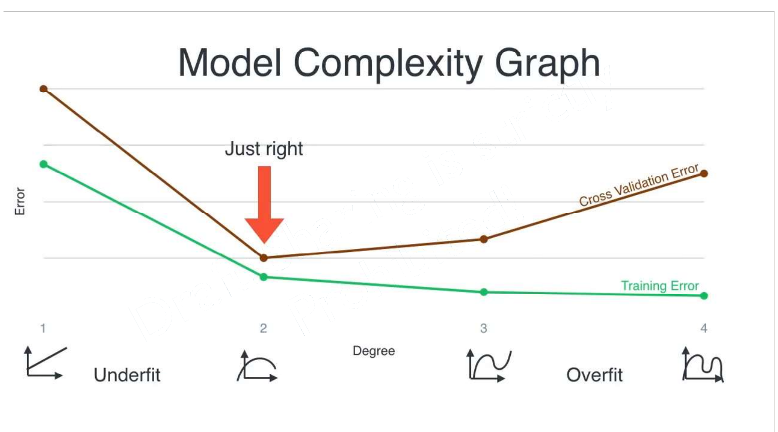

Model Complexity Graph
Just right
Error
Testing Error
Training Error
1
2
3
4
Degree
Underfit
Overfit

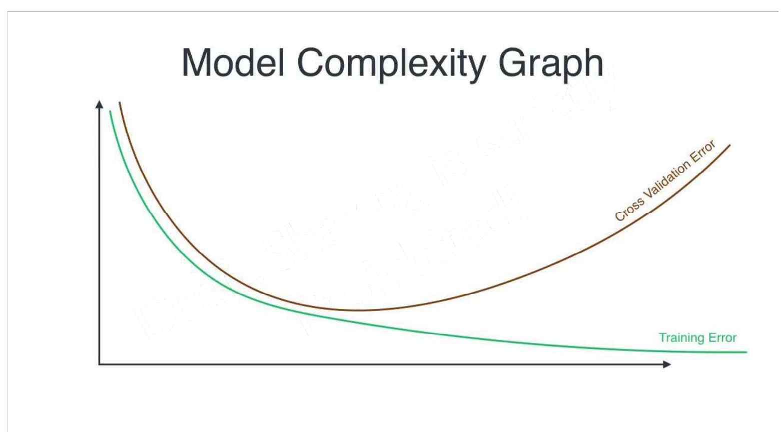

GOLDEN RULE # 1
Thou shalt never
use your testing
data for training
Error
1
4


I'VE MADE A
HUGE MISTAKE
GOLDEN RULE # 1
Thou shalt never
use your testing
data for training
Error
1
4

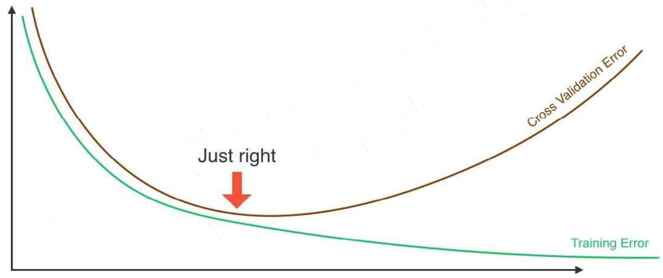

Model Complexity Graph
Can't
touch
that
Just right
Testing Error
Training Error
Error
1
2
3
4
Degree
Underfit
Overfit


Solution: Cross Validation
Training
Testing
Training
Cross Validation
Testing
Training our model
Making decisions
Final testing

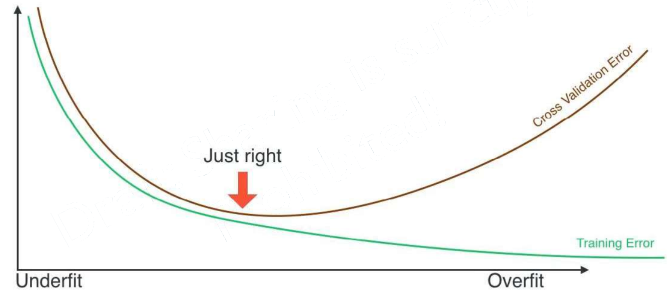

Model Complexity Graph
Just right
Cross Validation Error
Training Error
Error
1
2
3
4
Degree
Underfit
Overfit


Model Complexity Graph
Cross Validation Error
Training Error

Model Complexity Graph



Model Complexity Graph



Summary

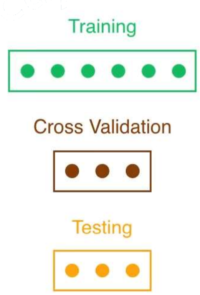
Training data: Train a bunch of models

Summary

Training data: Train a bunch of models

Cross validation data: Pick the best one of the models

Training a Logistic Regression Model



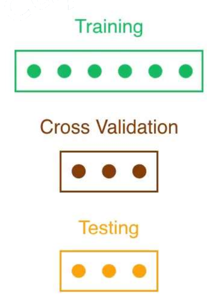
Training a Logistic Regression Model

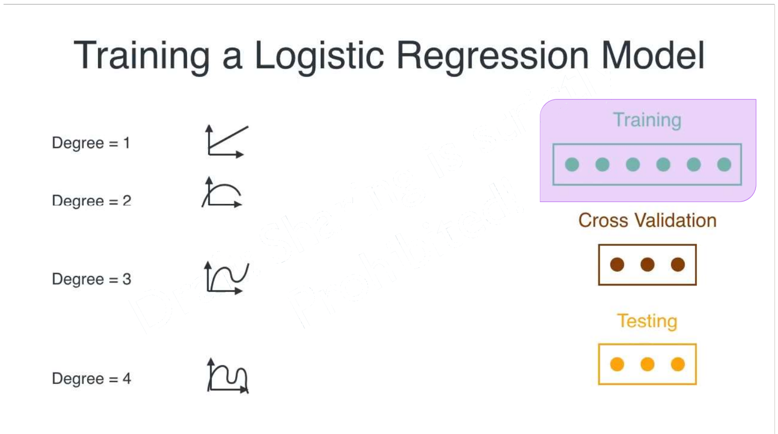
Degree = 1

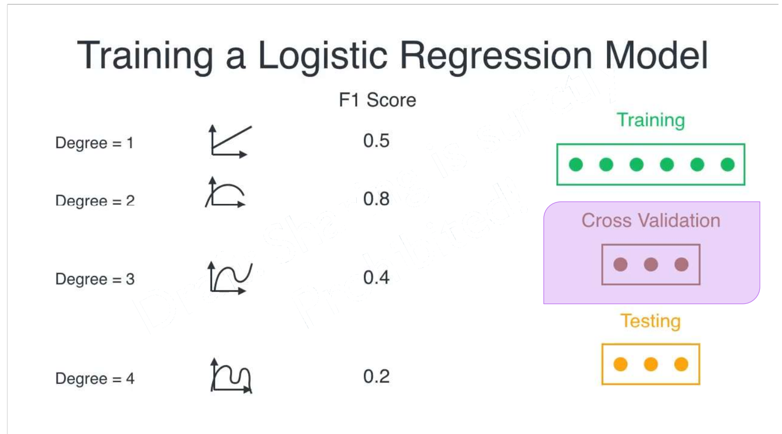
Degree = 2

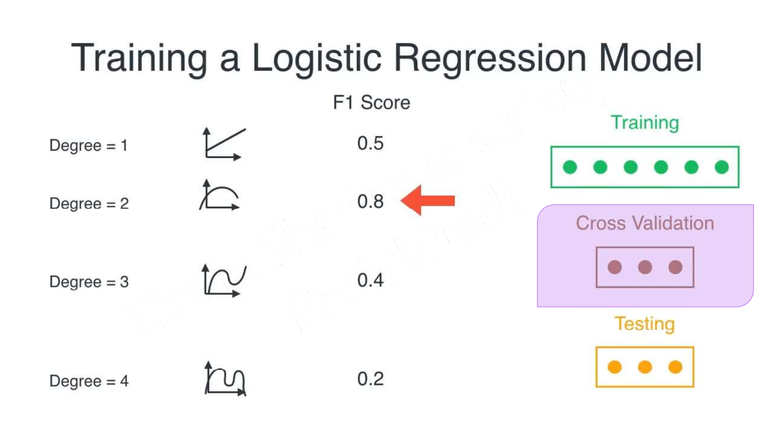
Degree = 3

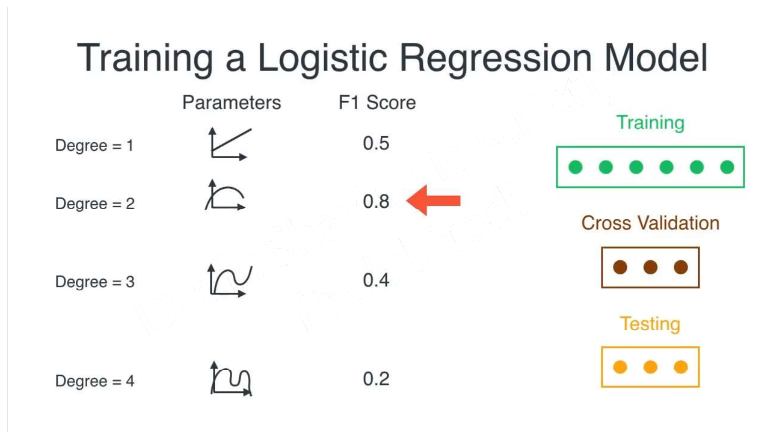
Degree = 4

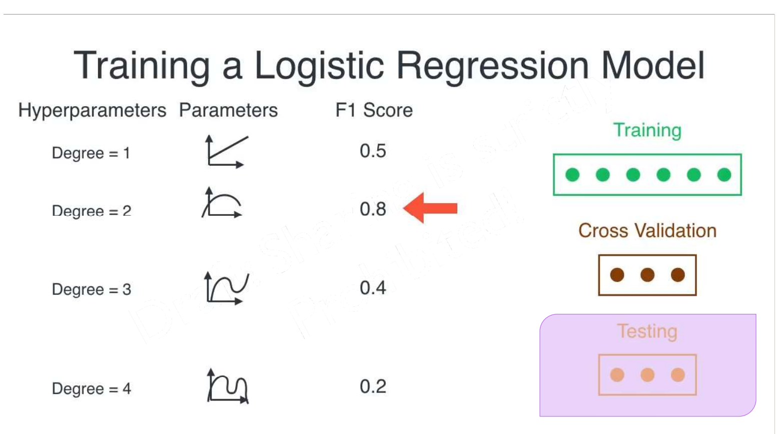


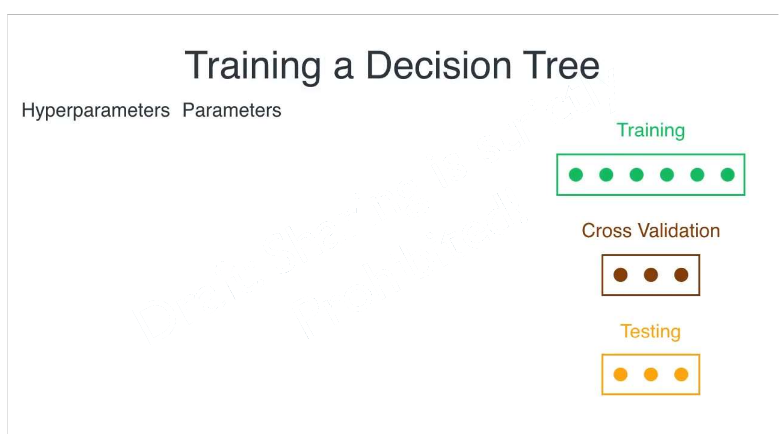

Training a Logistic Regression Model
Degree = 1
Degree = 2
Degree = 3
Degree = 4
Training
Cross Validation
Testing

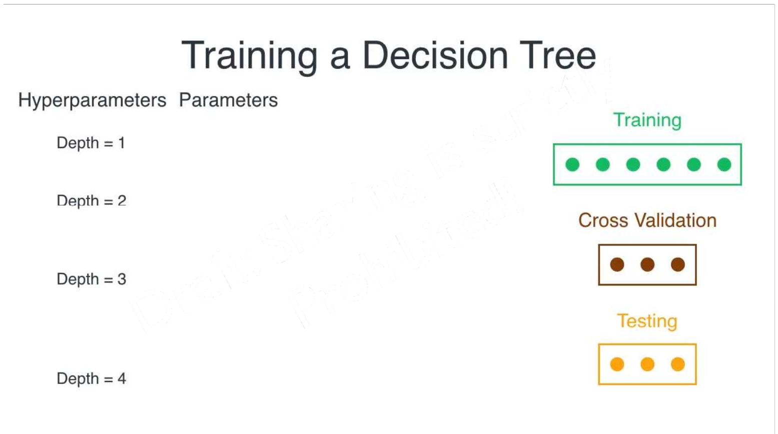

Training a Logistic Regression Model
F1 Score
Degree = 1
0.5
Degree = 2
0.8
Degree = 3
0.4
Degree = 4
0.2
Training
Cross Validation
Testing


Training a Logistic Regression Model
F1 Score
Degree = 1
0.5
Degree = 2
0.8
Degree = 3
0.4
Degree = 4
0.2
Training
Cross Validation
Testing


Training a Logistic Regression Model
Parameters
F1 Score
Degree = 1
0.5
Degree = 2
0.8
Degree = 3
0.4
Degree = 4
0.2
Training
Cross Validation
Testing


Training a Logistic Regression Model
Hyperparameters
Parameters
F1 Score
Degree = 1
0.5
Degree = 2
0.8
Degree = 3
0.4
Degree = 4
0.2
Training
Cross Validation
Testing


Training a Decision Tree
Hyperparameters
Parameters
Training
Cross Validation
Testing


Training a Decision Tree
Hyperparameters
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Depth = 1
Depth = 2
Depth = 3
Depth = 4
Training
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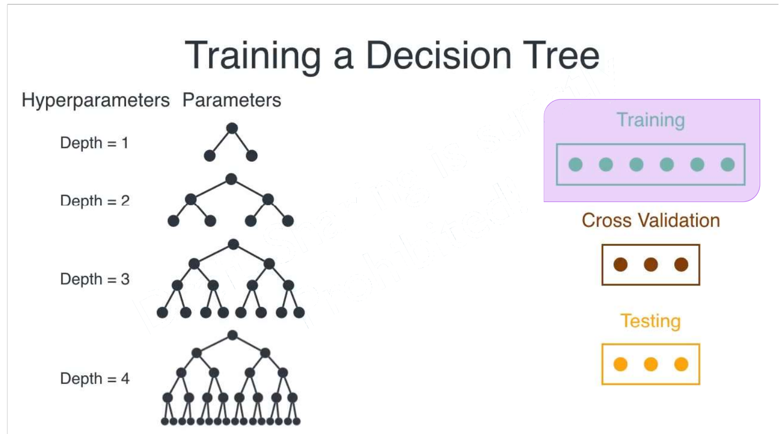
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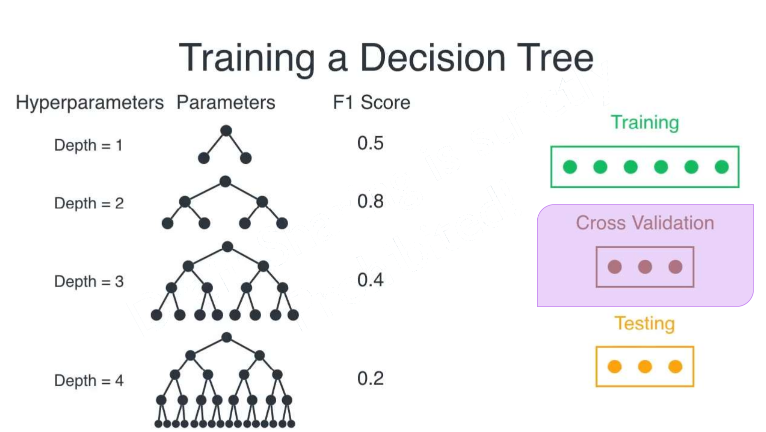
Training a Decision Tree
Hyperparameters
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F1 Score
Depth = 1
0.5
Depth = 2
0.8
Depth = 3
0.4
Depth = 4
0.2
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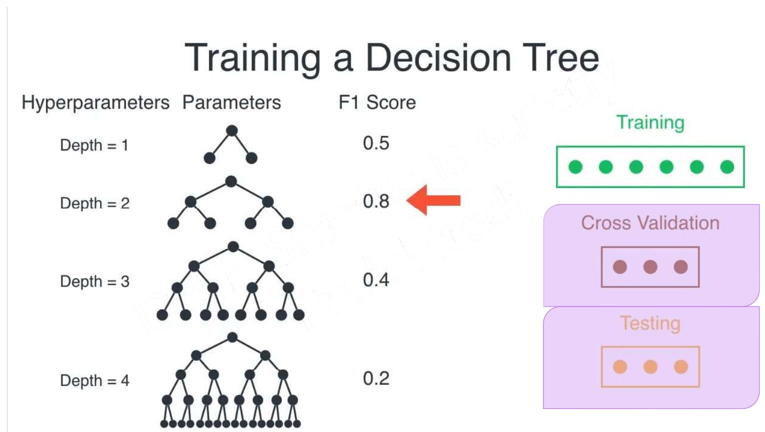
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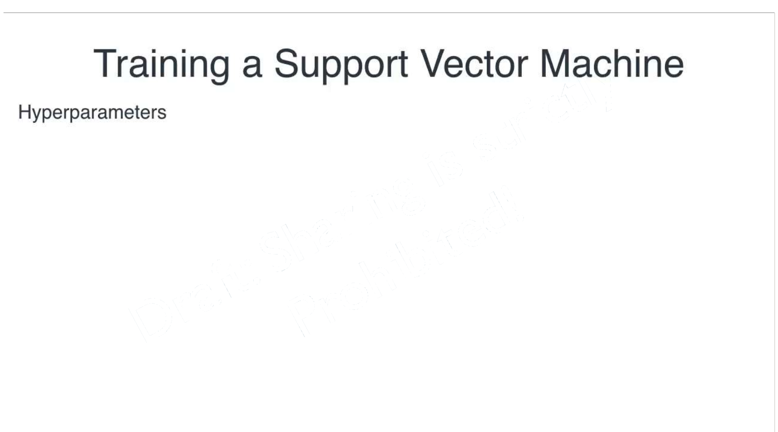
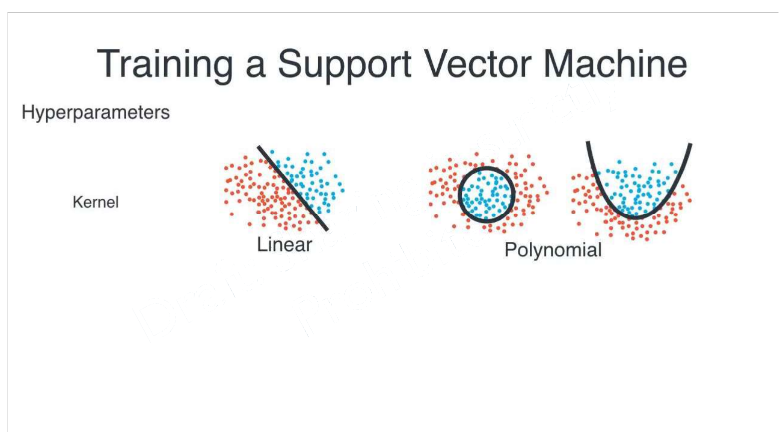
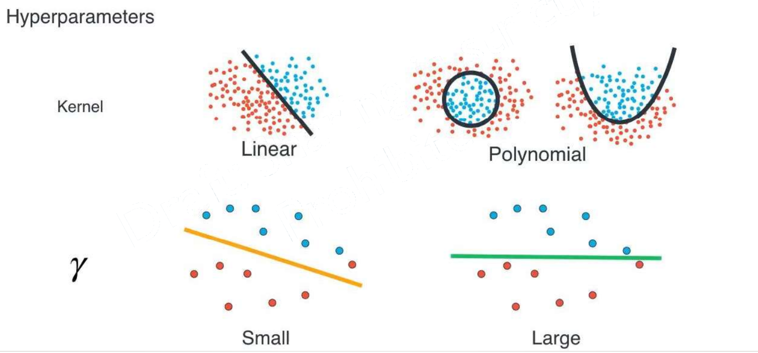
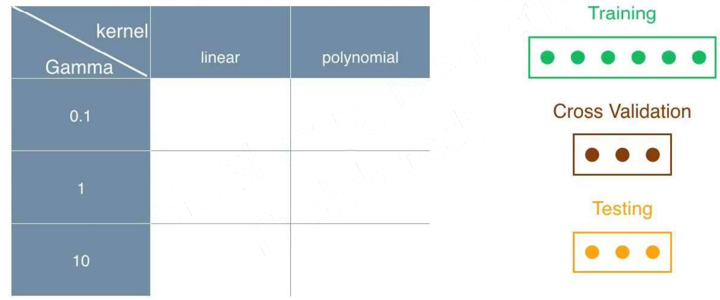

Training a Support Vector Machine
Hyperparameters


Training a Support Vector Machine
Hyperparameters
Kernel
Linear
Polynomial

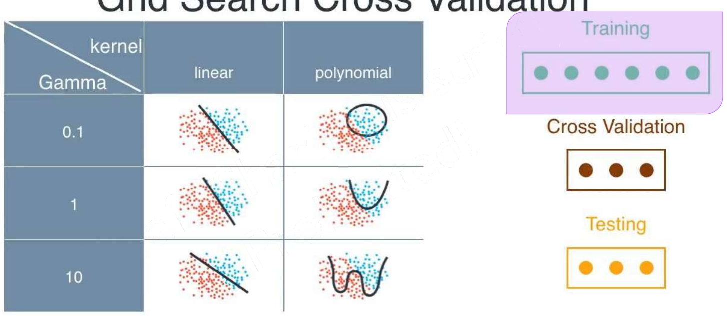
Training a Support Vector Machine



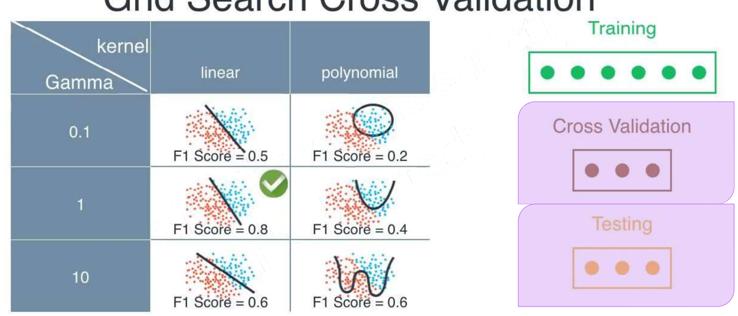
Grid Search Cross Validation



Grid Search Cross Validation



Grid Search Cross Validation



Parameters and Hyperparameters

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Algorithm	Parameters	Hyperparameters
Random Forest	Features Thresholds	Number of trees Depth

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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

How to solve a problem

Problem

How to solve a problem

Problem

Tools

How to solve a problem

How to solve a problem

Measure each tool's performance
Pick the best tool

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Measure each tool's performance
Pick the best tool

How to use machine learning

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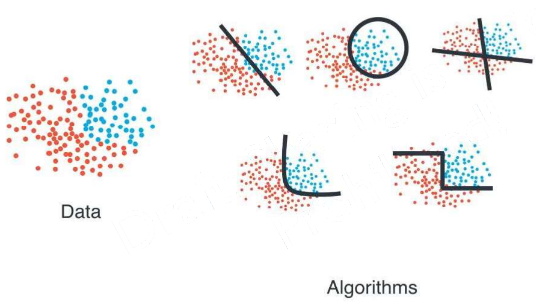
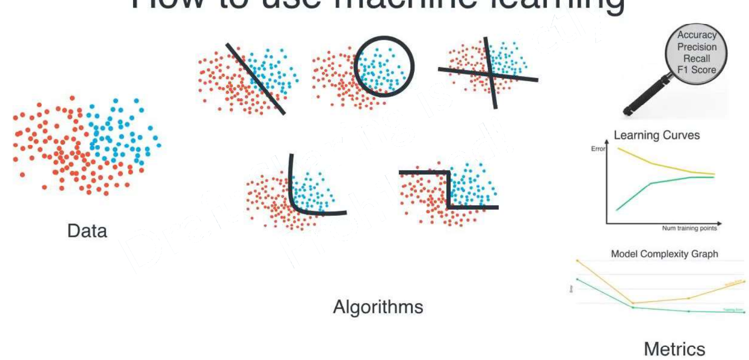
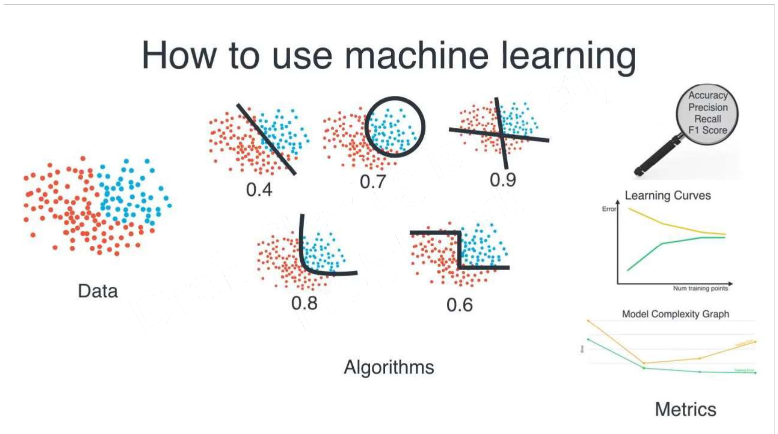
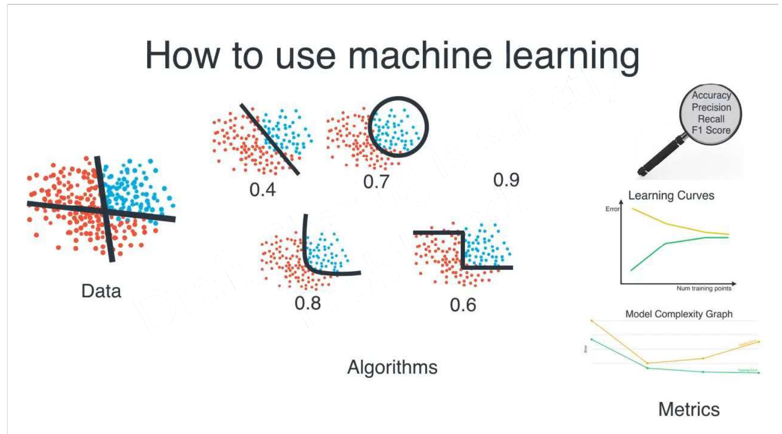


How to use machine learning




How to use machine learning
Accuracy
Precision
Recall
F1 Score
0.4
0.7
0.9
Learning Curves
Error
Num training points
Data
0.8
0.6
Model Complexity Graph
Algorithms
Metrics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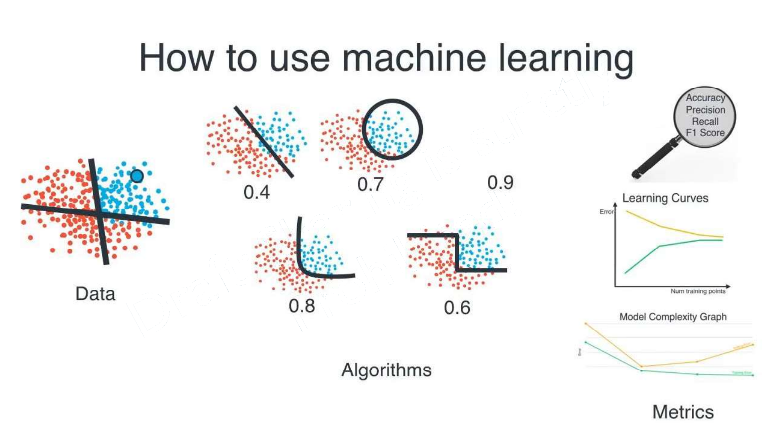
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THANK YOU!