

Bias Variance

Prepared By: Dr.Mydhili K Nair, Professor, ISE Dept, RIT
For: Machine Learning Class
Target Audience: Sem 6 Students

Bias



Not animals

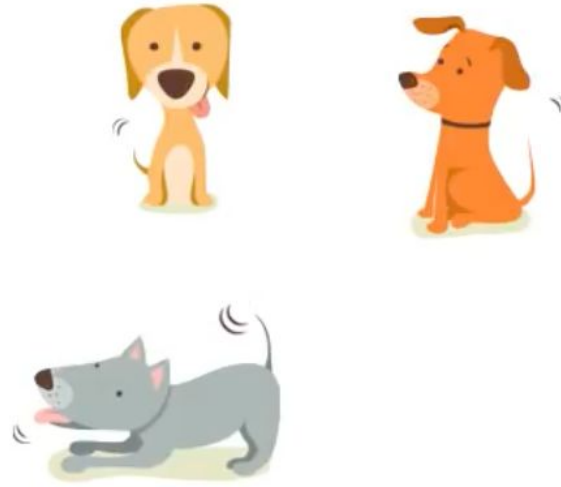


Animals

Our Classification Model is too specific



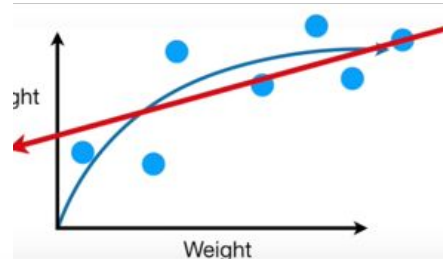
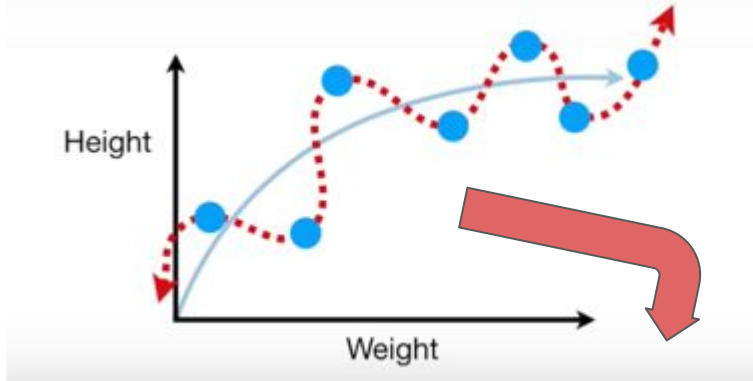
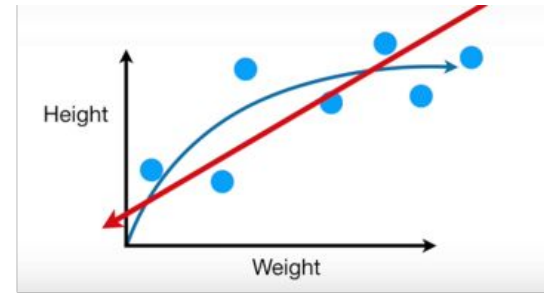
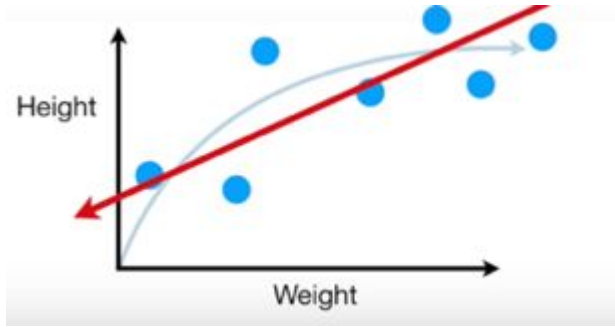
Anything but dogs that are
wagging their tail



Too specific

Dogs that are wagging their tail

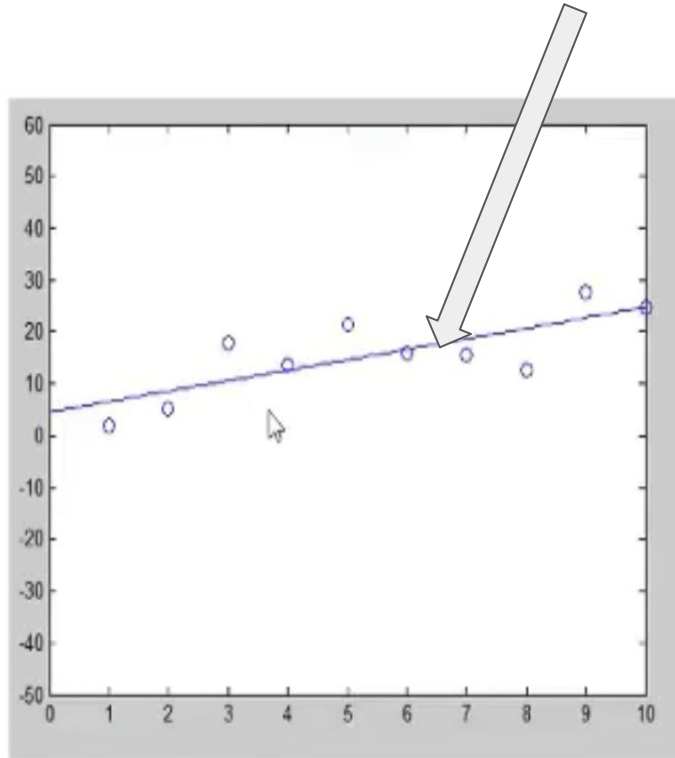
Linear Model: How much ever you vary the “prediction regression line” it will not fit the curve and there will always be a **bias** between actual value and predicted value.



Bias error is completely eliminated. This non-linear model fits the data points perfectly. Zero Bias.

$$\text{Model 1: } y = b_0 + b_1x$$

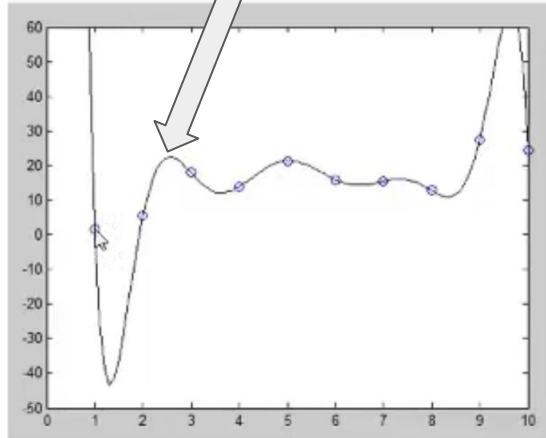
Linear
Model



x	y
1	1.7
2	5.3
3	18.0
4	13.8
5	21.4
6	15.9
7	15.5
8	12.7
9	27.5
10	24.6

$$\text{Model 2: } y = b_0 + b_1x + b_2x^2 + b_3x^3 + \dots + b_9x^9$$

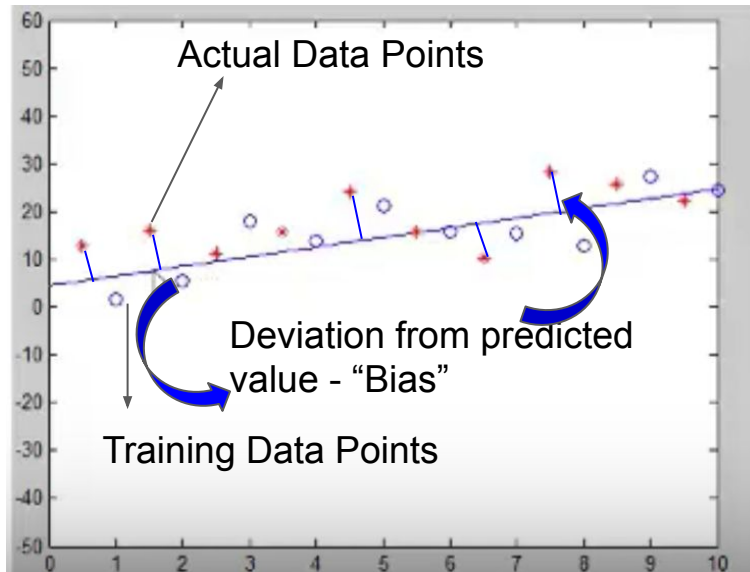
x	x^2		x^9	y
1	1	...	1	1.7
2	4		262144	5.3
3	9		4E+08	18.0
16			7E+10	13.8
25			4E+12	21.4
36			1E+14	15.9
49			2E+15	15.5
64			2E+16	12.7
81			2E+17	27.5
100			1E+18	24.6



9th Order
Polynomial
Model

$$\text{Model 1: } y = b_0 + b_1x$$

Our Classification
Model is too
simple - **HIGH
BIAS**

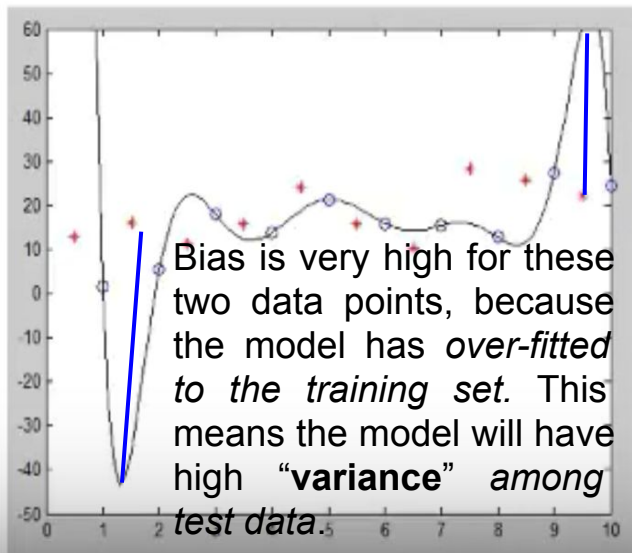


x	y
1	1.7
2	5.3
3	18.0
4	13.8
5	21.4
6	15.9
7	15.5
8	12.7
9	27.5
10	24.6

$$\text{Model 2: } y = b_0 + b_1x + b_2x^2 + b_3x^3 + \cdots + b_9x^9$$

Our
Classification
Model is too
specific -
**HIGH
VARIANCE**

x	x^2		x^9	y
1	1	...	1	1.7
2	4		262144	5.3
3	9		4E+08	18.0
4	16		7E+10	13.8
5	25		4E+12	21.4
6	36		1E+14	15.9
7	49		2E+15	15.5
8	64		2E+16	12.7
9	81		2E+17	27.5
10	100		1E+18	24.6



Error due to bias (underfitting)



Not animals



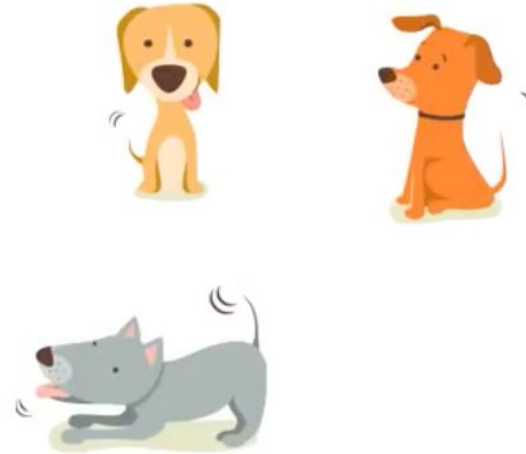
Animals

Too simple

Error due to variance (overfitting)



Anything but dogs that are wagging their tail



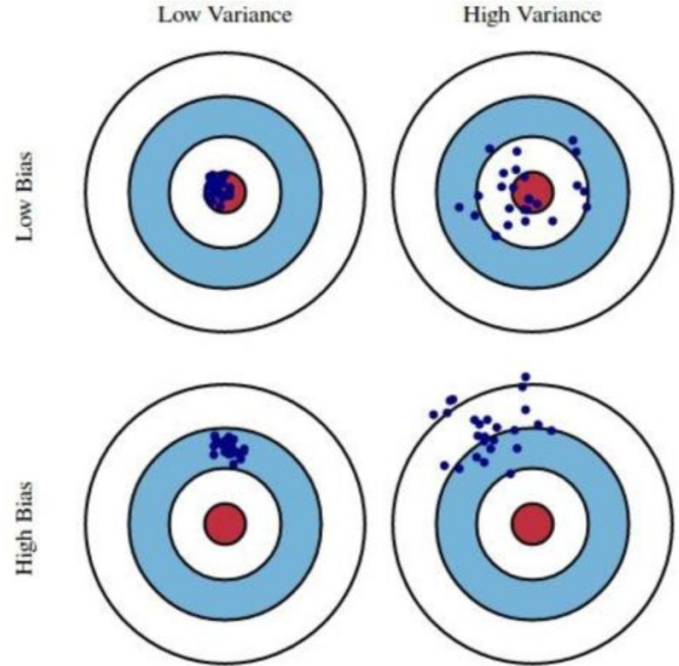
Too specific

Dogs that are wagging their tail

Trade-off between Bias-variance

“Bias is the algorithm’s tendency to consistently learn the wrong thing by not taking into account all the information in the data (underfitting).”

“Variance is the algorithm’s tendency to learn random things irrespective of the real signal by fitting highly flexible models that follow the error/noise in the data too closely (overfitting).”



Bull's eye diagram

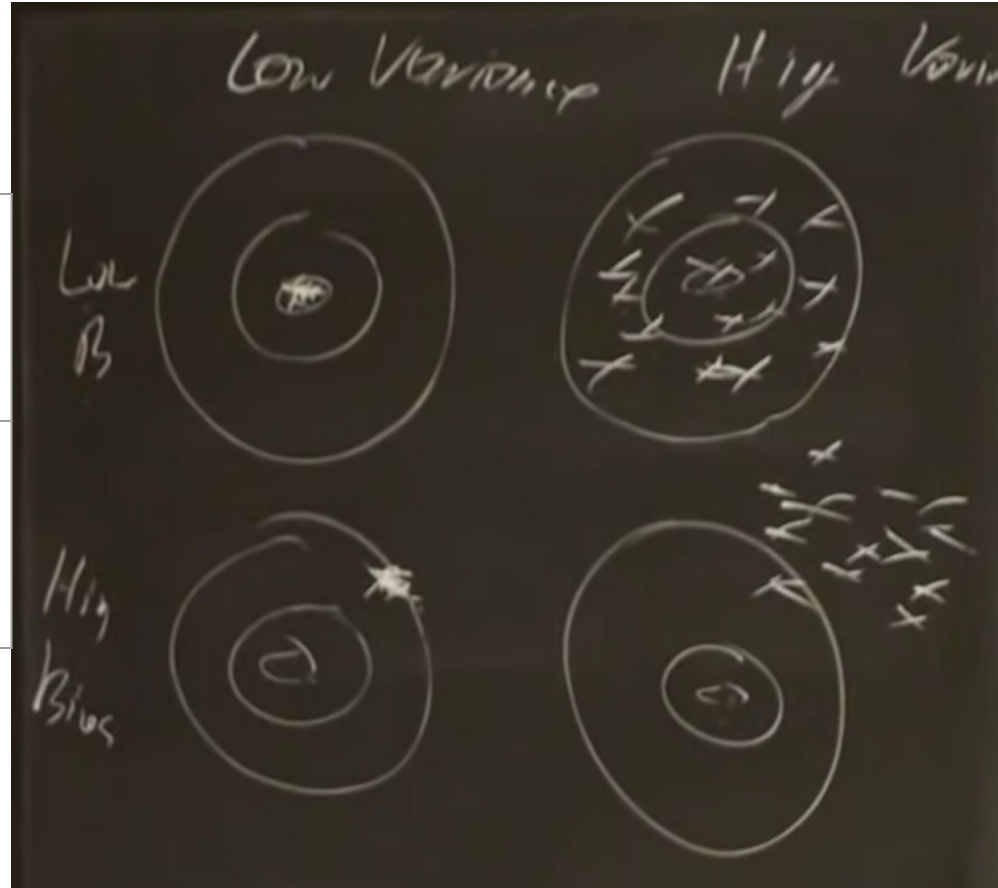
Low Variance

High Variance

**Low
Bias**

**High
Bias**

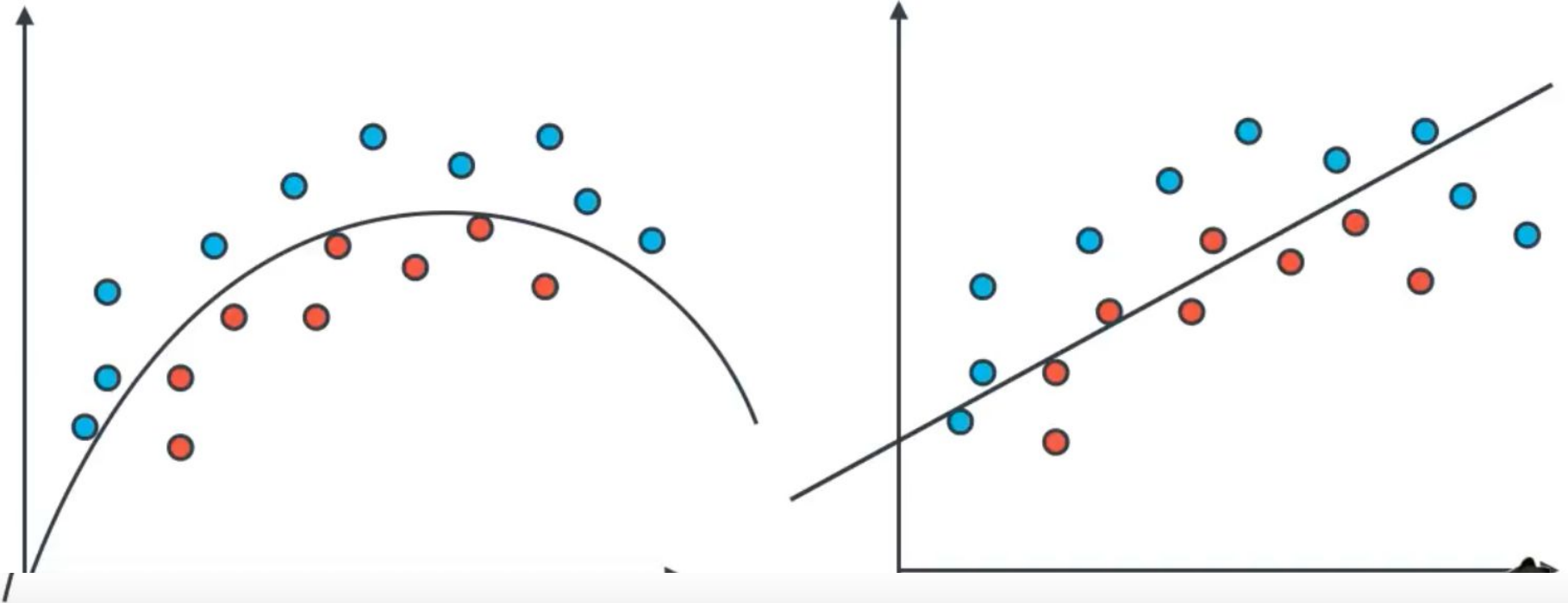
Every
Model
aims at
Low Bias
& *Low
Variance*



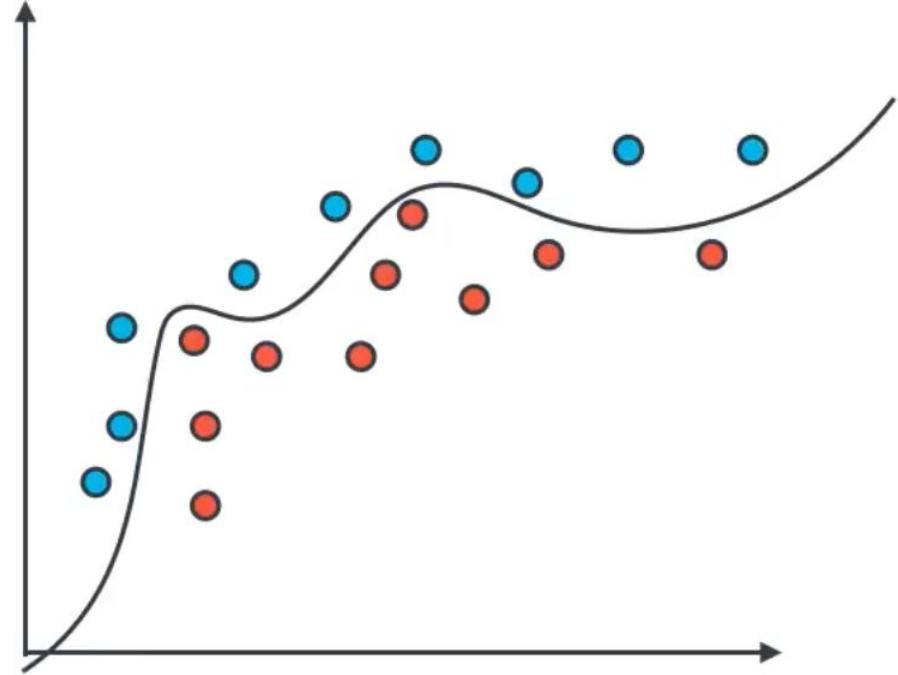
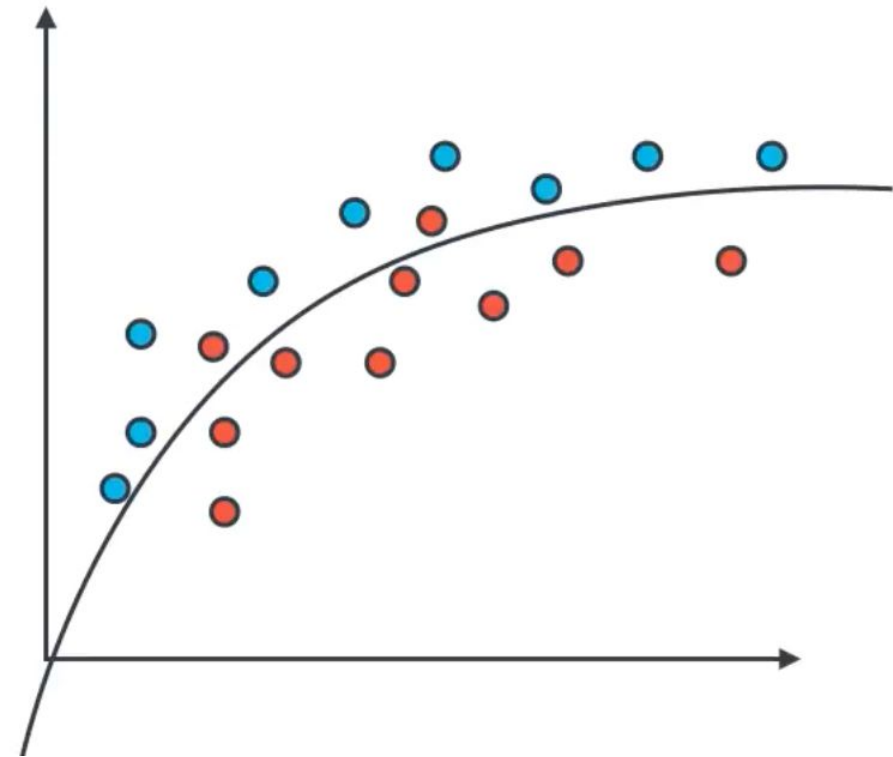
Bias - Variance Tradeoff

Overfitting - Underfitting

Error due to bias (underfitting)



Error due to variance (overfitting)



Overfitting (aka variance):

A model is said to be overfit if it is over trained on the data such that, it even learns the noise from it. An overfit model learns each and every example so perfectly that it misclassifies an unseen/new example. For a model that's overfit, we have a perfect/close to perfect training set score while a poor test/validation score.

Reasons behind overfitting:

1. Using a complex model for a simple problem which picks up the noise from the data. Example: Fitting a neural network to the Iris dataset.
2. Small datasets, as the training set may not be a right representation of the universe.

Source: <https://towardsdatascience.com/learning-curve-to-identify-overfitting-underfitting-problems-133177f38df5>

Underfitting (aka bias):

A model is said to be underfit if it is unable to learn the patterns in the data properly. An underfit model doesn't fully learn each and every example in the dataset. In such cases, we see a low score on both the training set and test/validation set.

Reasons behind underfitting:

1. Using a simple model for a complex problem which doesn't learn all the patterns in the data. Example: Using a logistic regression for image classification
2. The underlying data has no inherent pattern. Example, trying to predict a student's marks with his father's weight.

Source: <https://towardsdatascience.com/learning-curve-to-identify-overfitting-underfitting-problems-133177f38df5>

Tradeoff

High bias
(Underfitting)

Not animals



Animals



Bad on Training set
Bad on Testing set

Just Right

Not dogs



Dogs



Good on Training set
Good on Testing set

High variance
(Overfitting)

Not dogs who wag
their tail

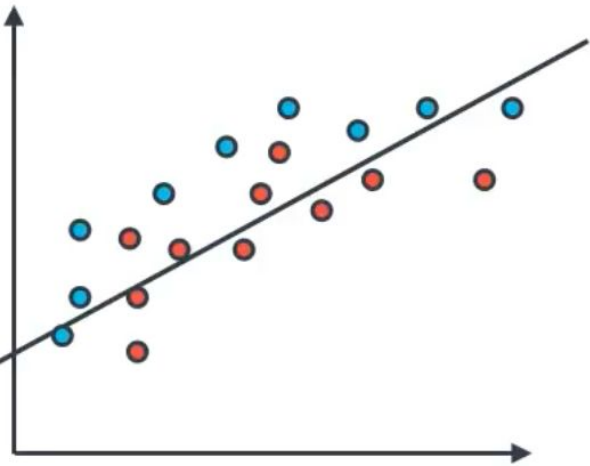


Dogs who wag
their tail

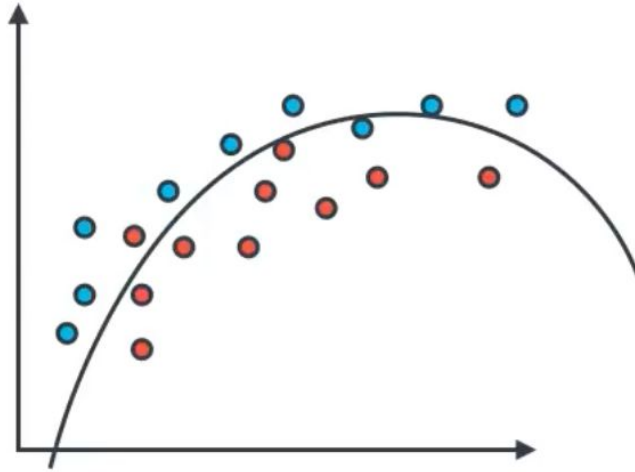


Great on Training set
Bad on Testing set

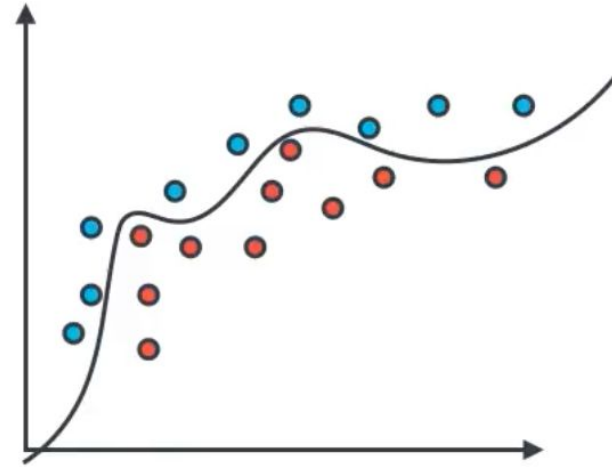
Model Complexity Graph



High Bias
degree = 1

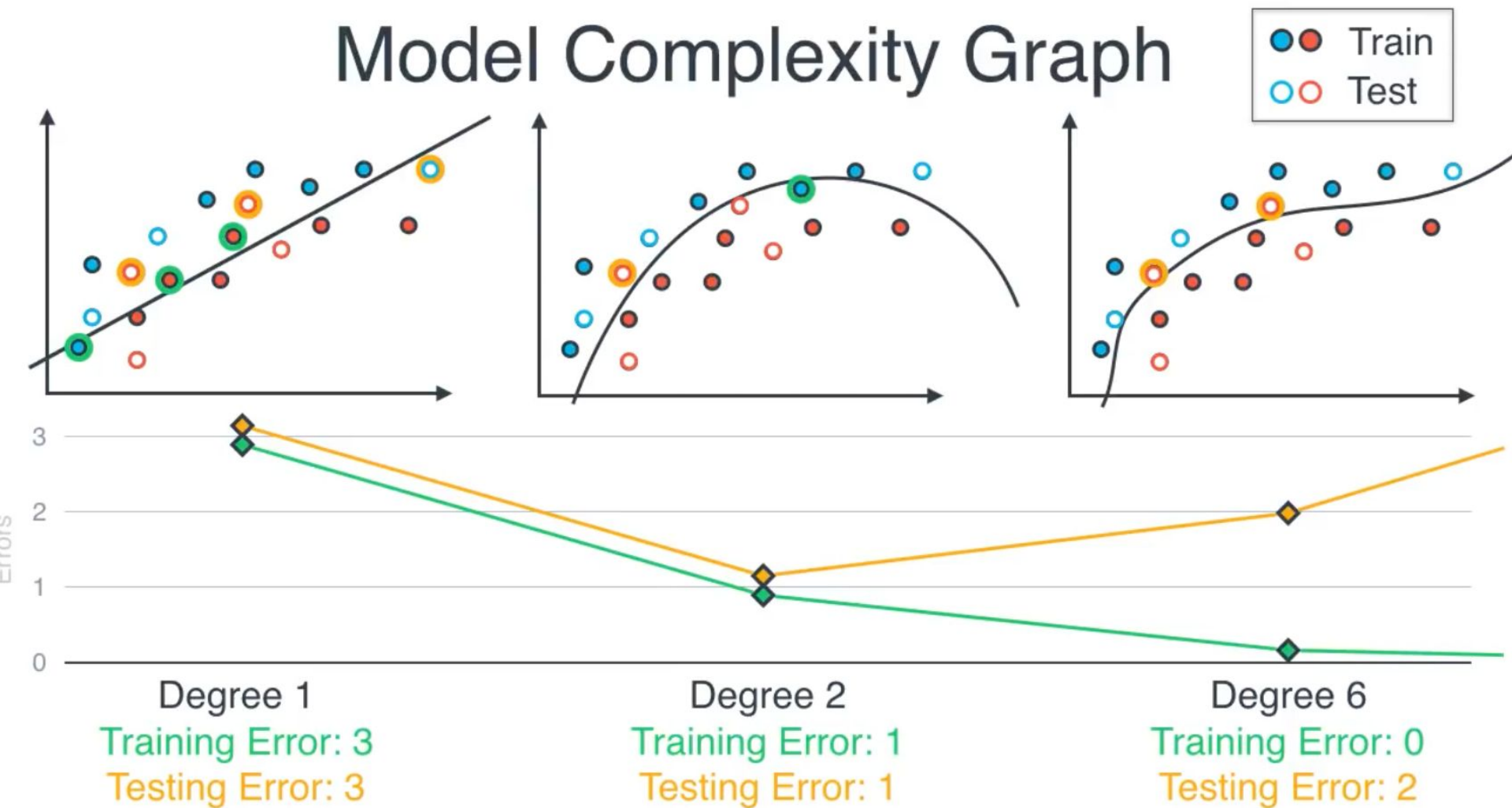


Just Right
degree = 2



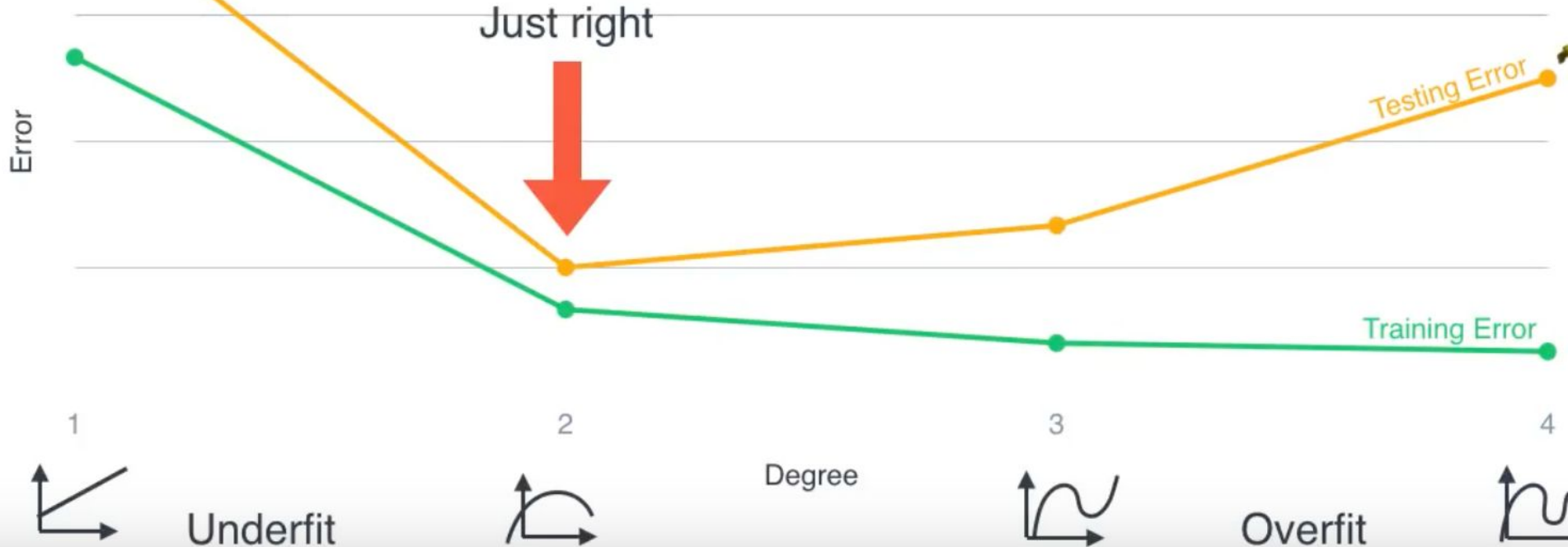
High Variance
degree = 6

Model Complexity Graph



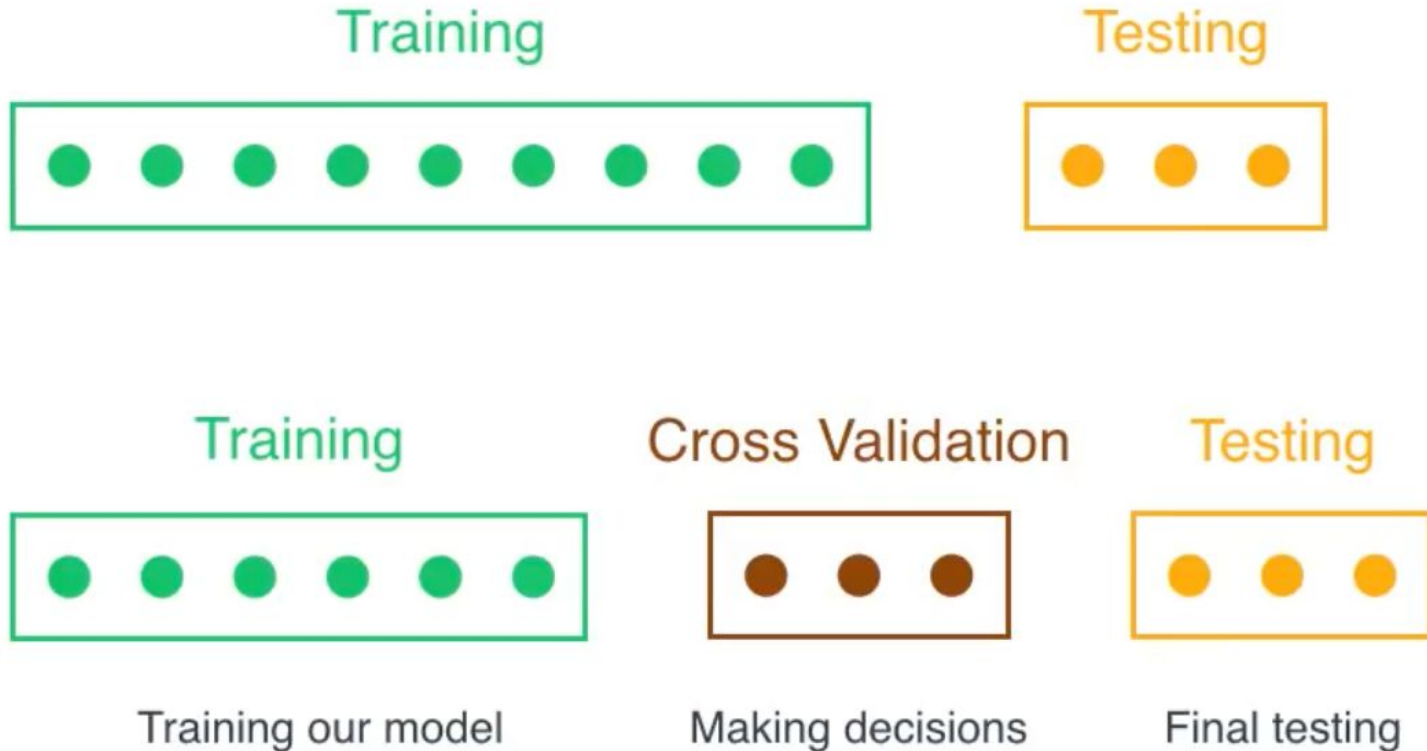
Model Complexity Graph

You should never use your **testing data for training**!!!

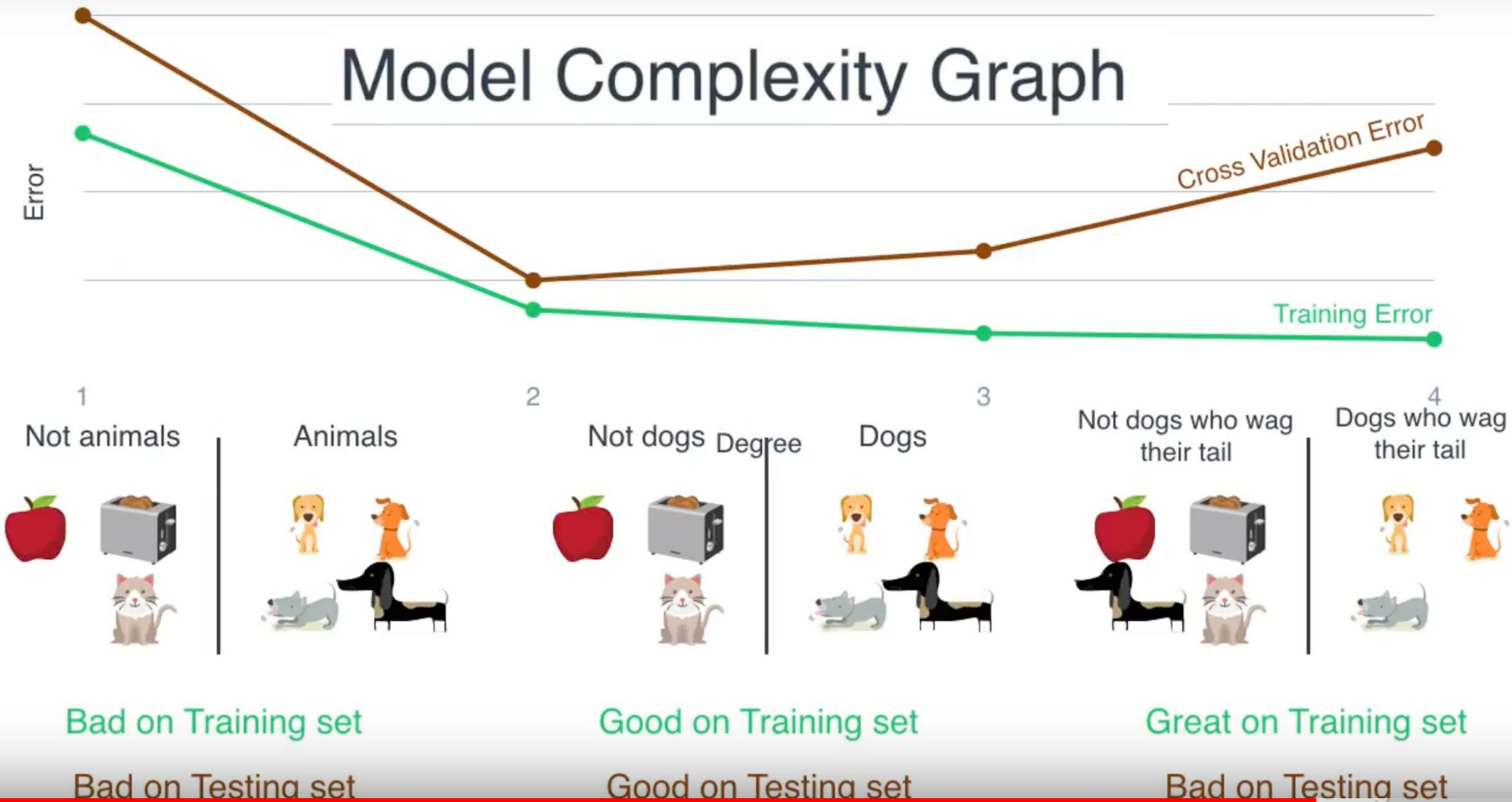


Training - Testing - Validation Datasets

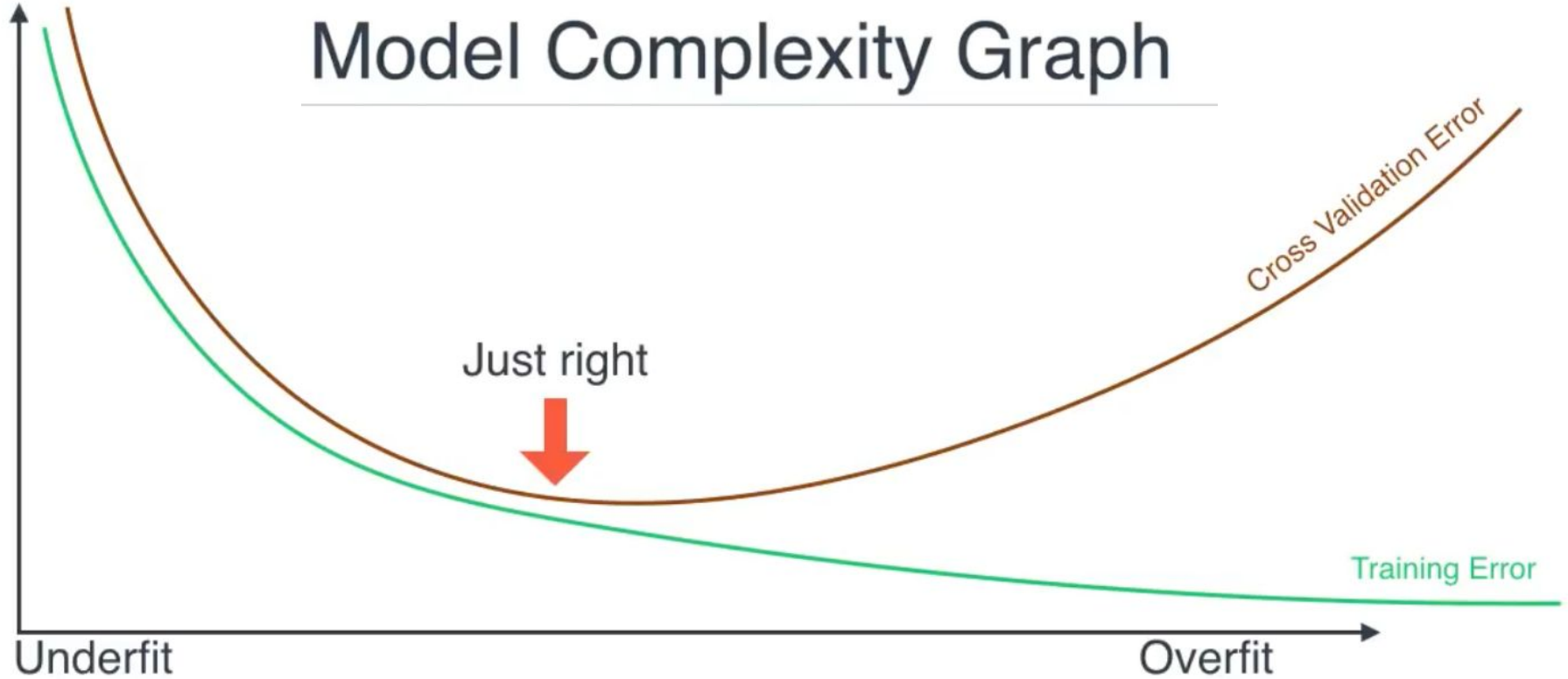
Solution: Cross Validation



Model Complexity Graph



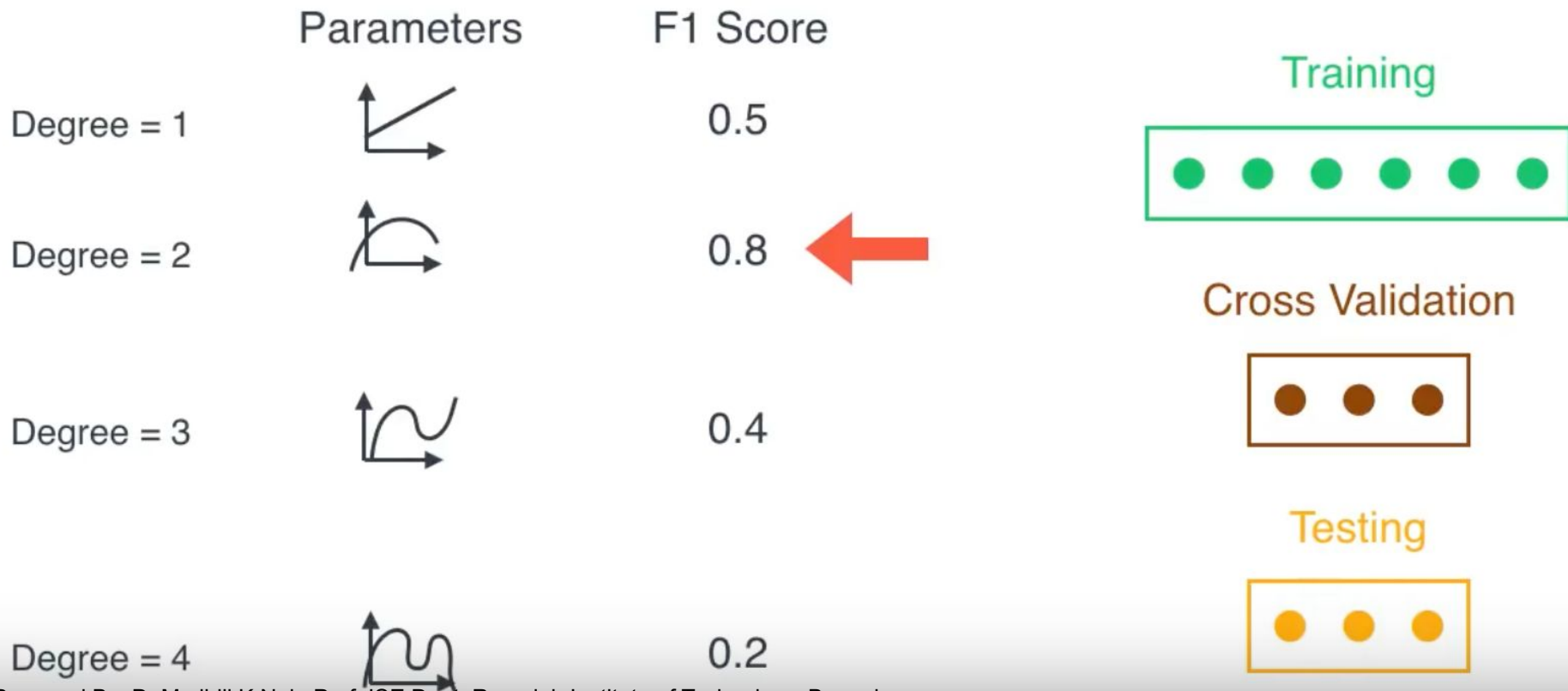
Model Complexity Graph



Training a Decision Tree



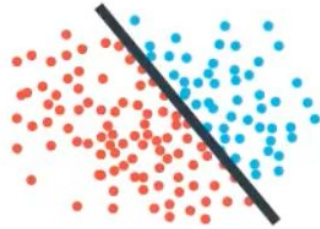
Training a Logistic Regression Model



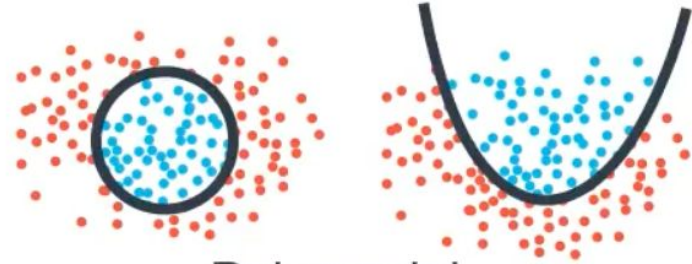
Training a Support Vector Machine

Hyperparameters

Kernel

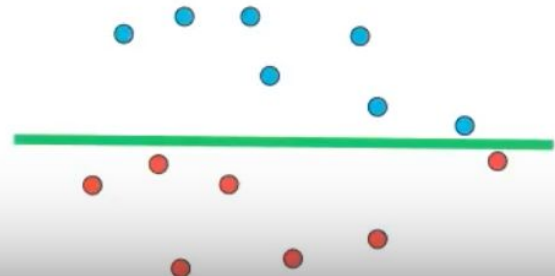
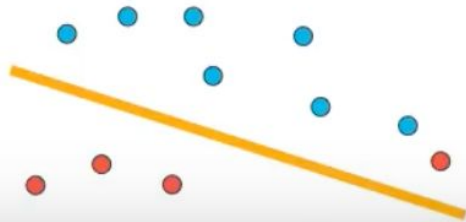


Linear



Polynomial

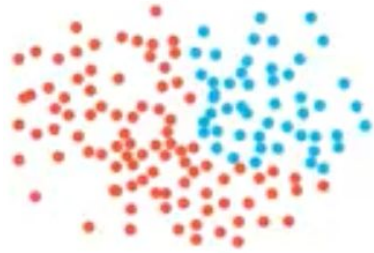
γ



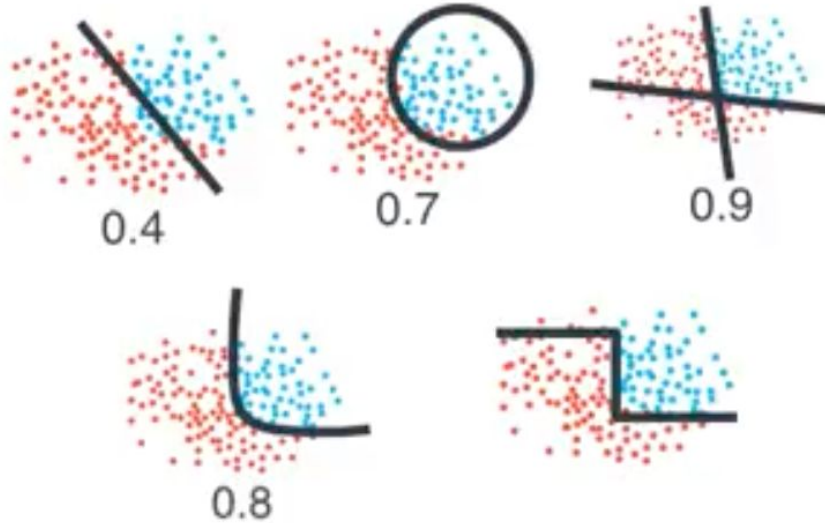
Parameters and Hyperparameters

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

How to use machine learning



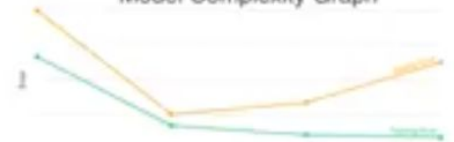
Data



Algorithms



Model Complexity Graph



Metrics

Source:

1. **Bias Variance Dichotomy:**

<https://www.youtube.com/watch?v=DtZ3NaPNBNE&feature=youtu.be>

2. **Train-Test-Validate Dataset:**

<https://www.youtube.com/watch?v=e2vurxnd124&feature=youtu.be>

3. **(Song)Stat Quest - Bias Variance** : <https://youtu.be/EuBBz3bl-aA>