MACHINE LEARNING ALGORITHM

Unit-III

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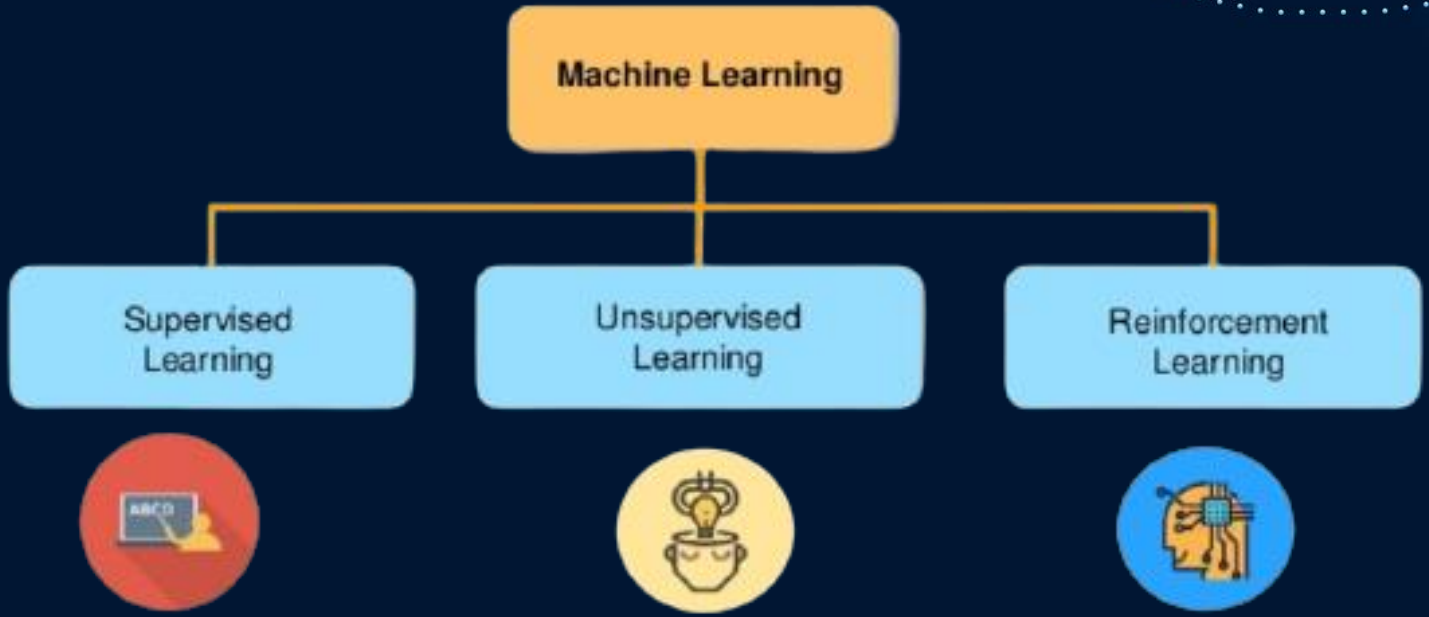
YouTube Channel on Machine Learning Algorithms
https://tinyurl.com/GopalMachineLearningAlgorithms

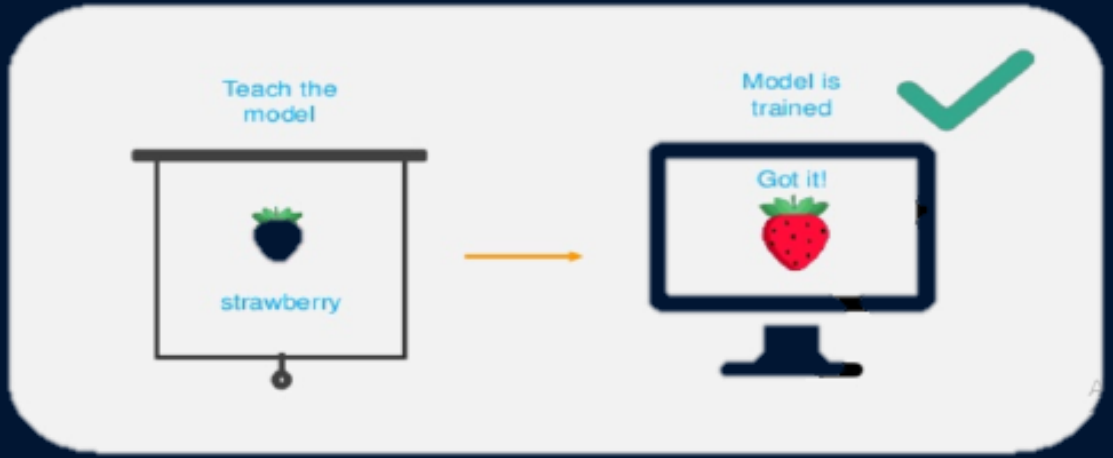
Support Vector Machine



Support Vector Machine

Supervised Learning

Machine learning model learns from the past input data and makes future prediction as output



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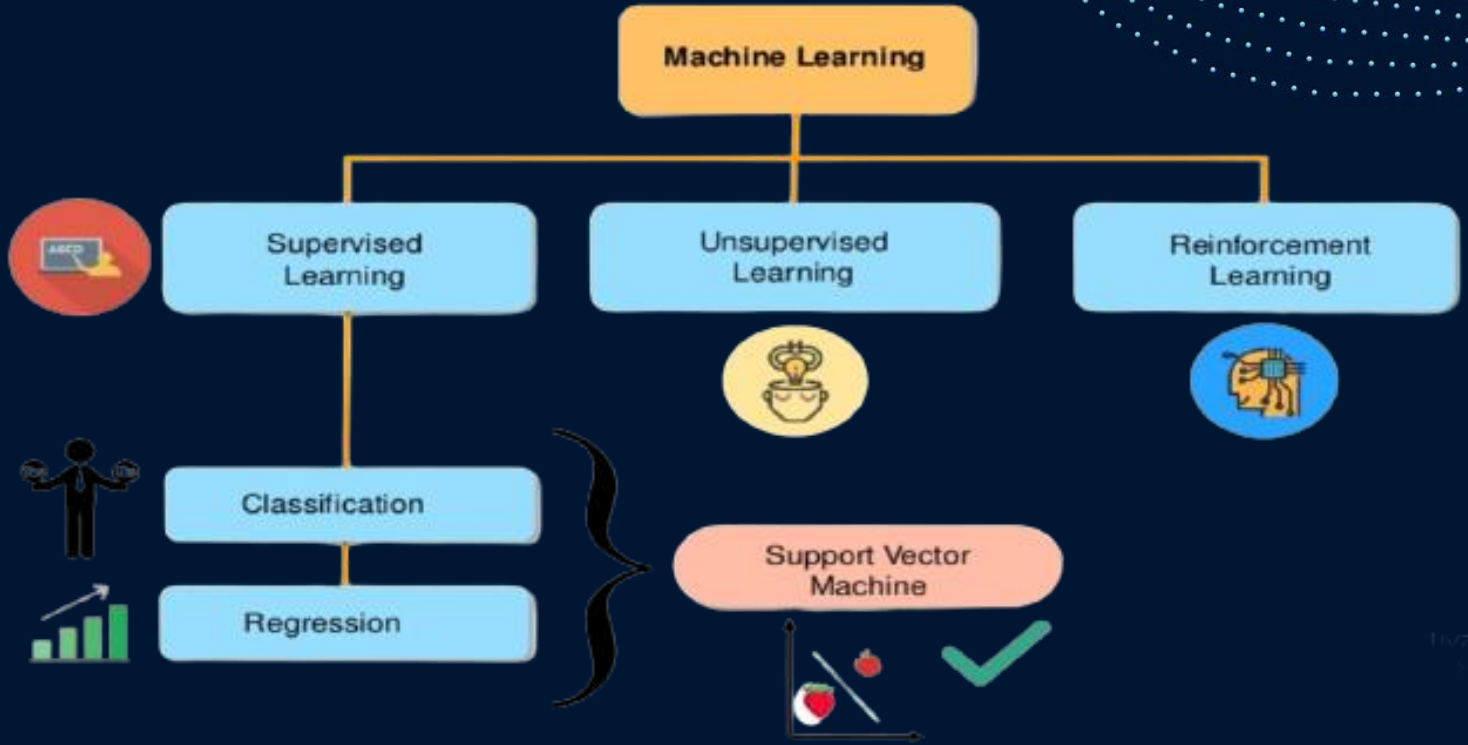

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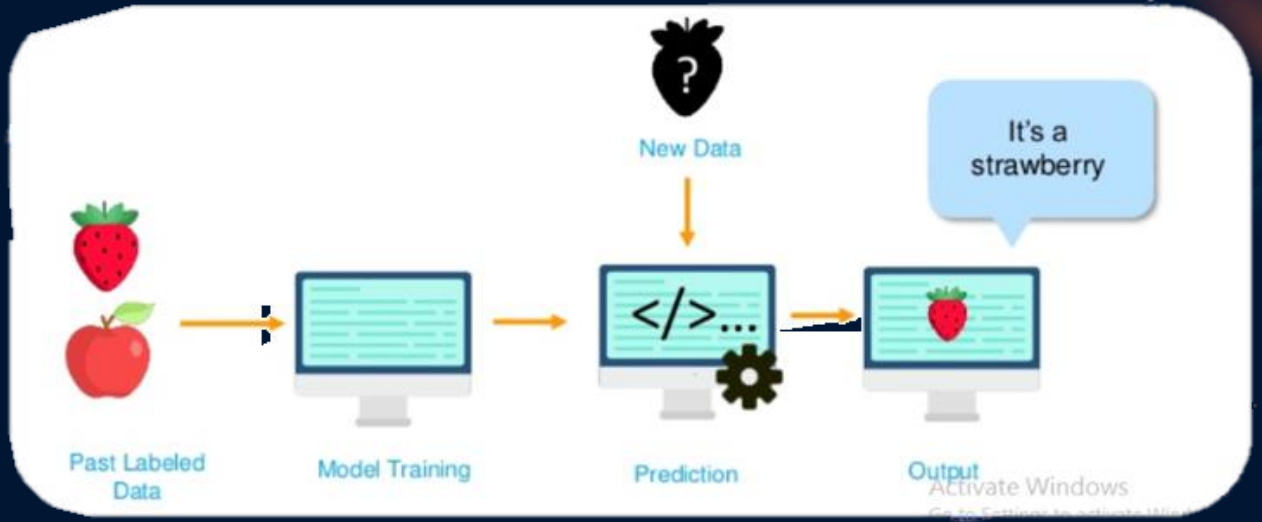

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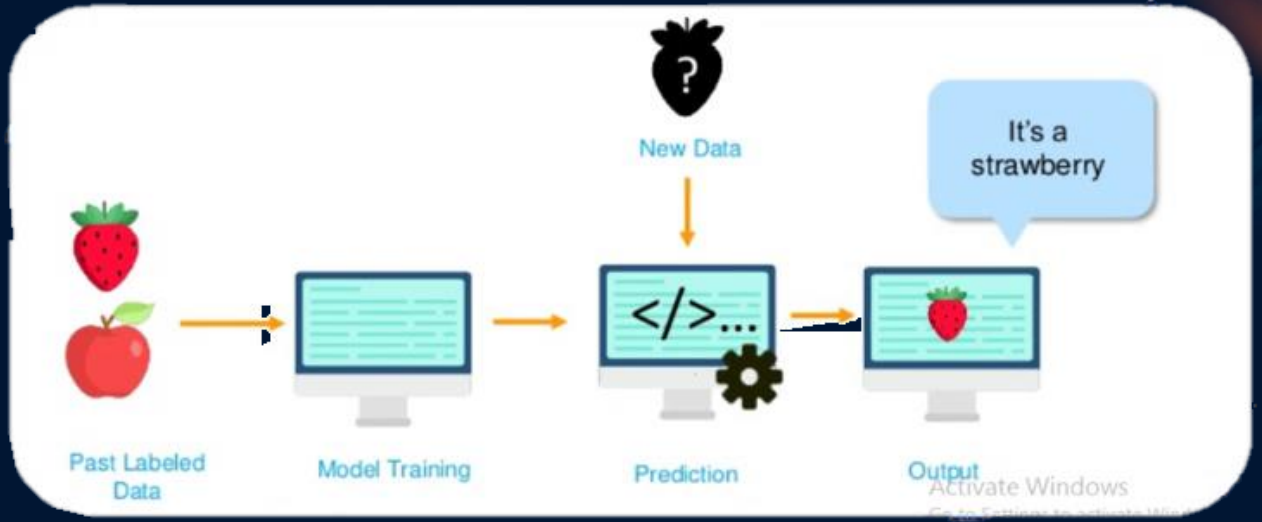
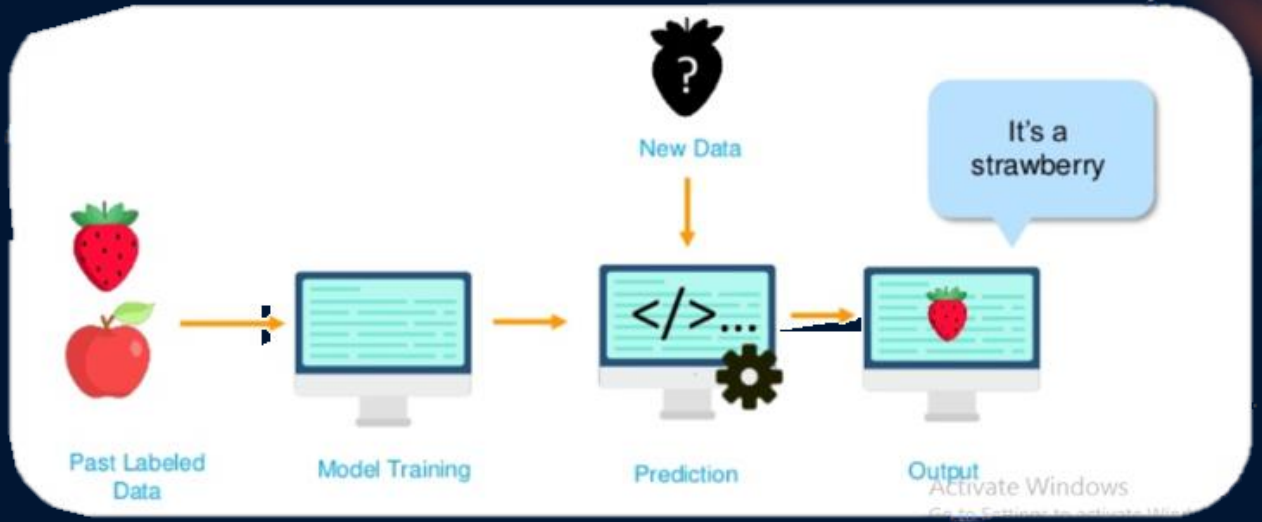


Support Vector Machine

SVM is a supervised learning method that looks at data and sorts it into one of the two categories



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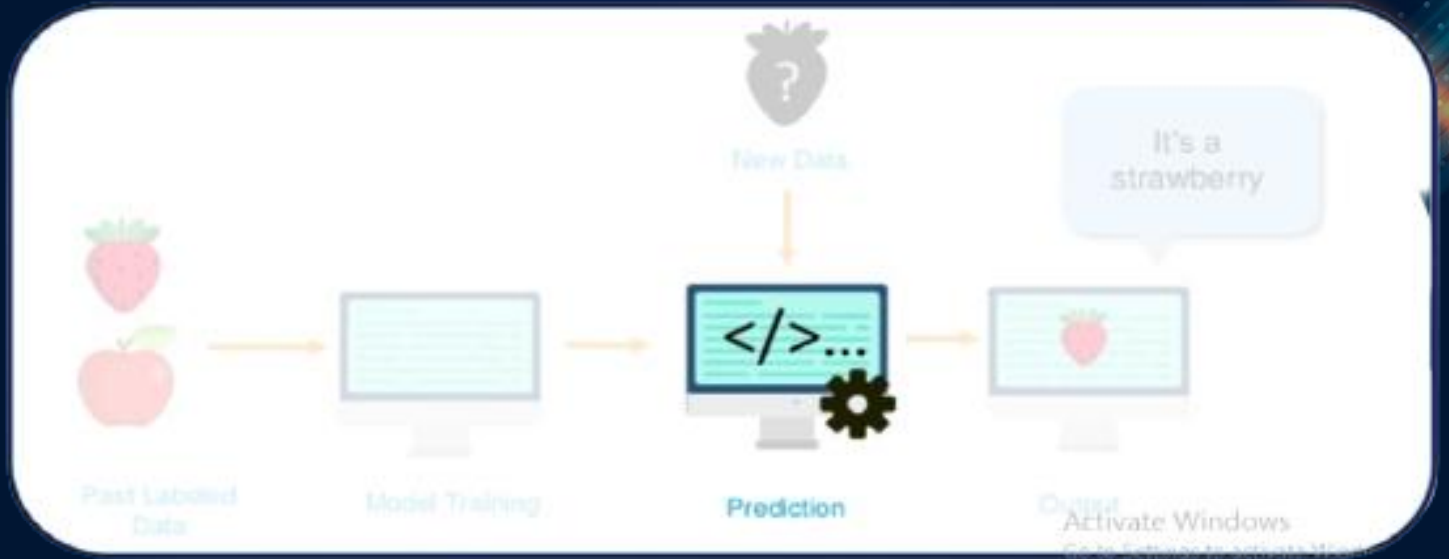

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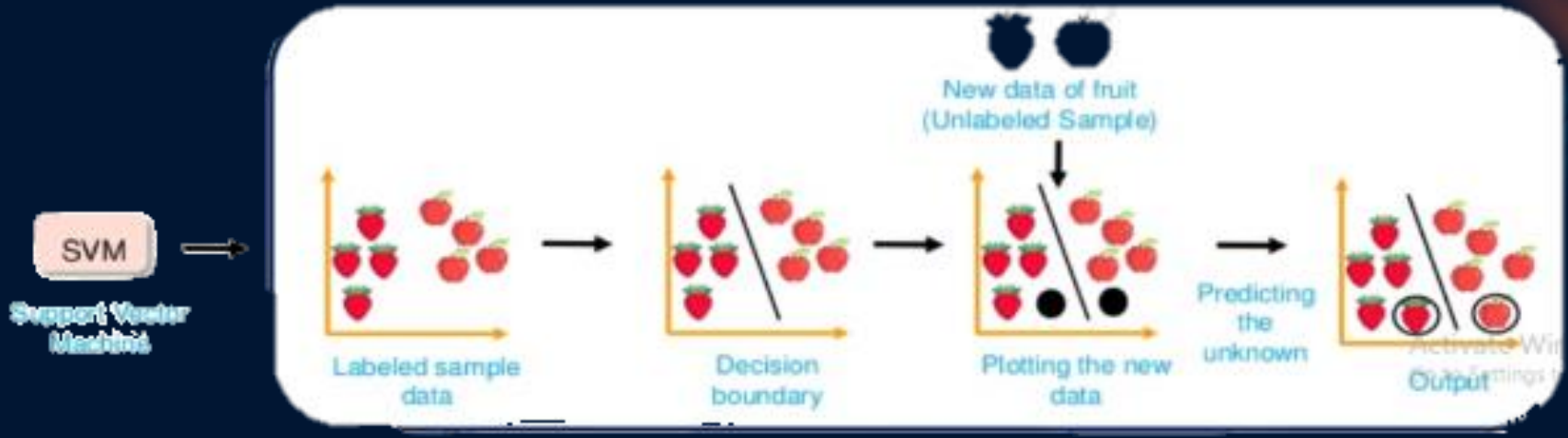

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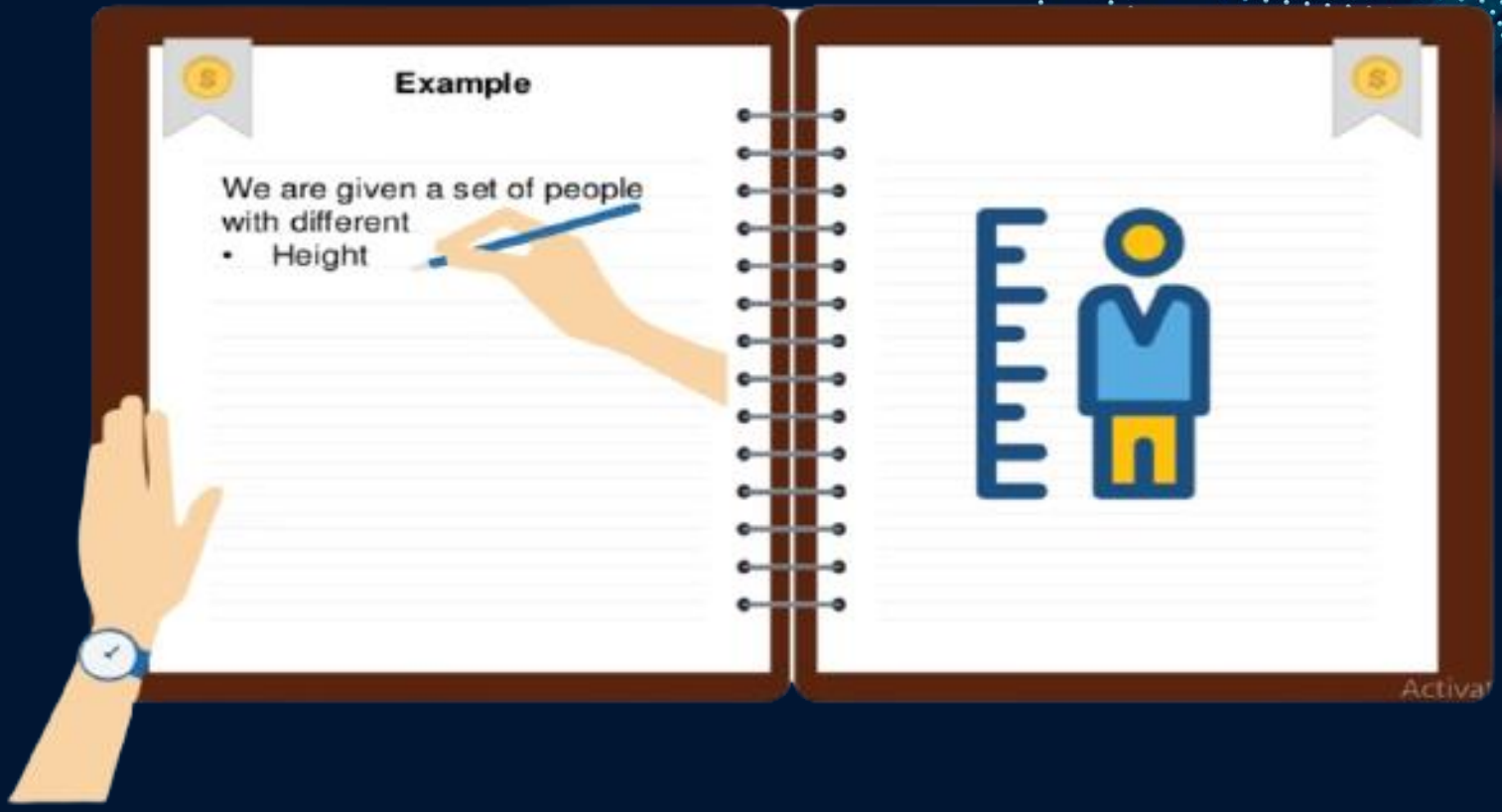

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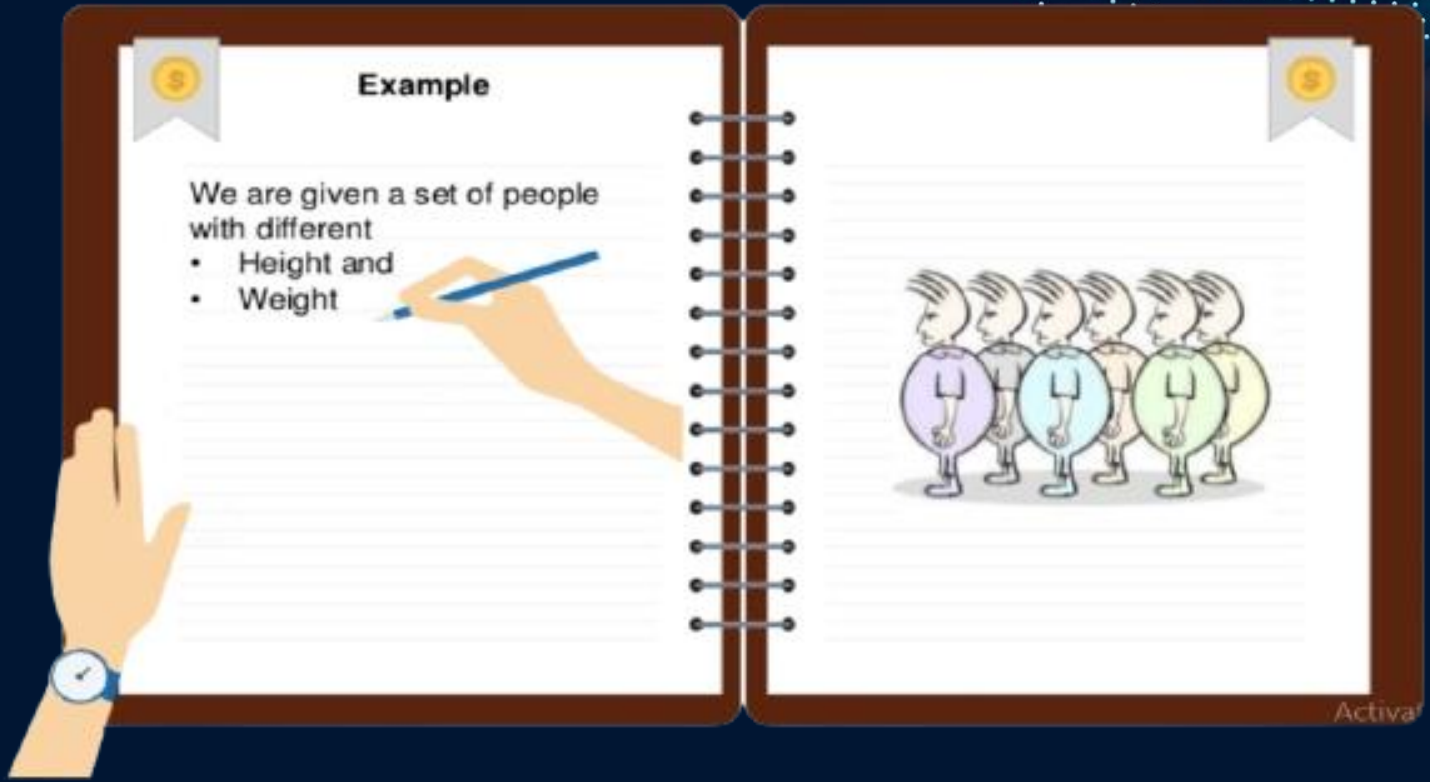

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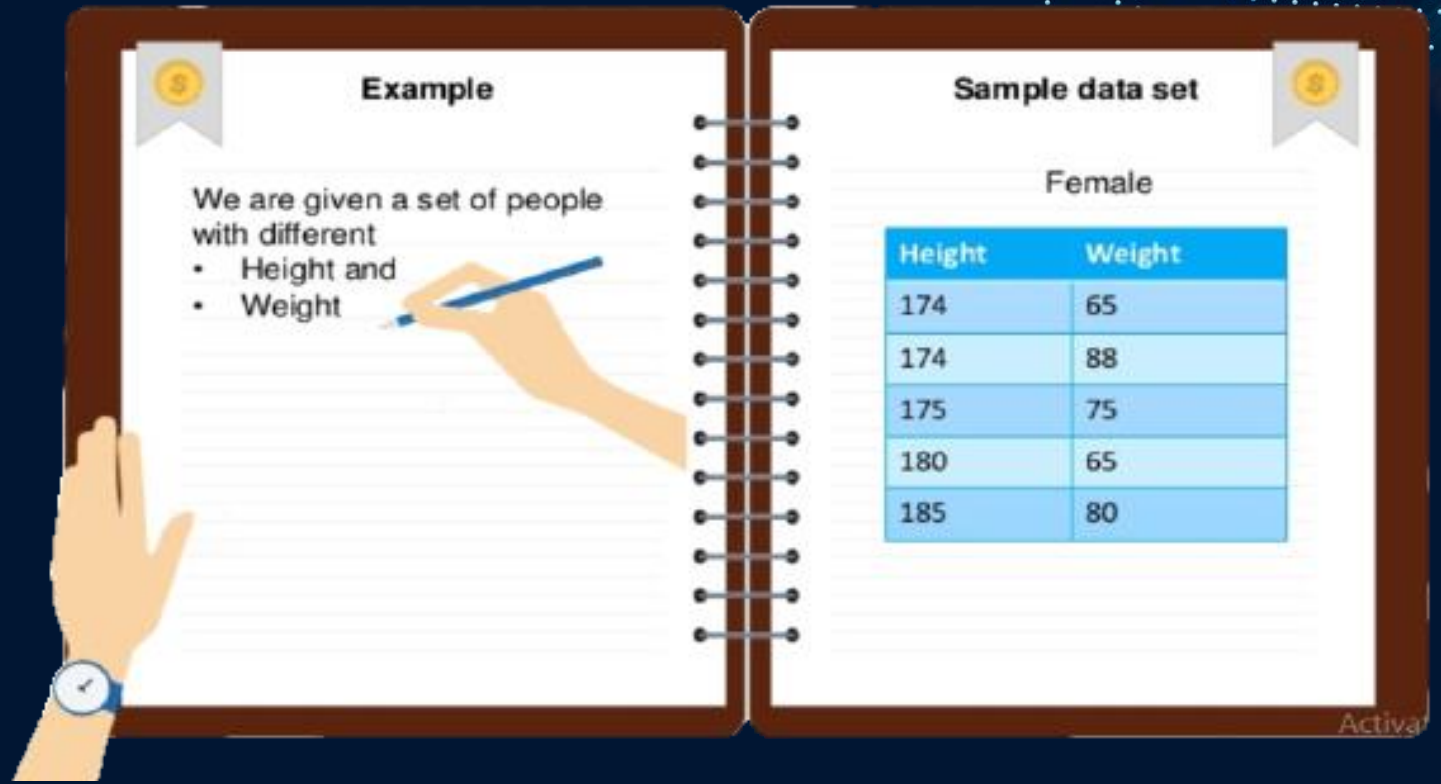

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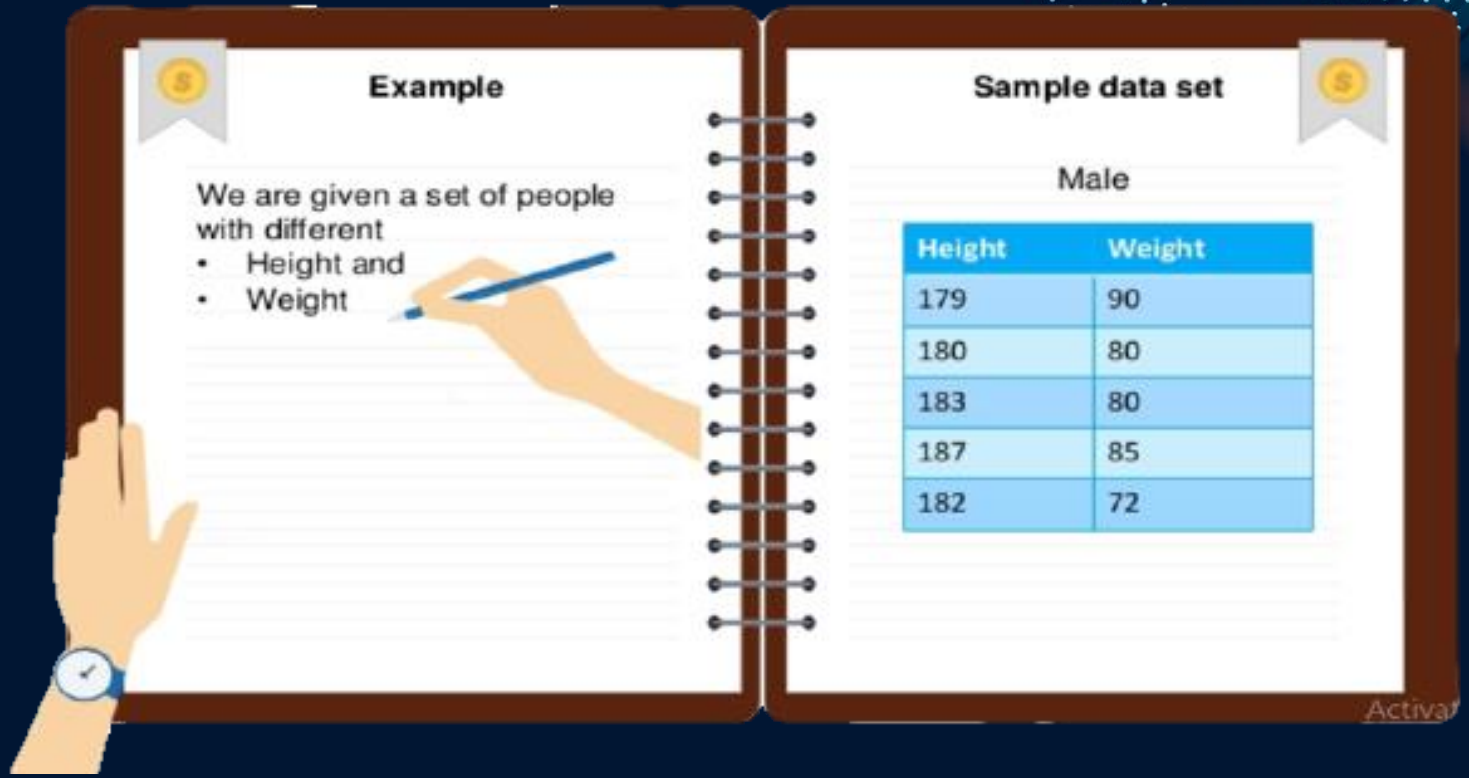

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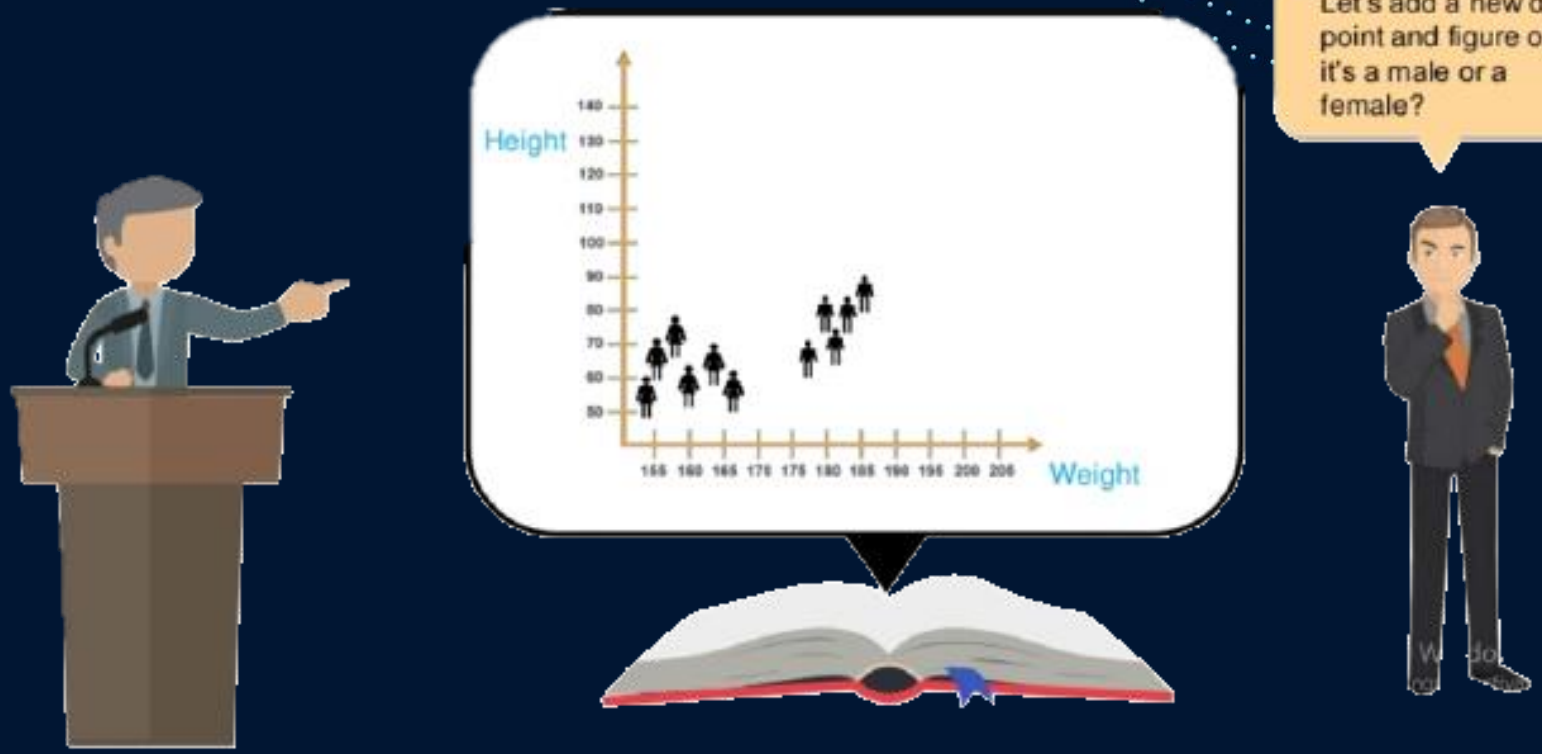

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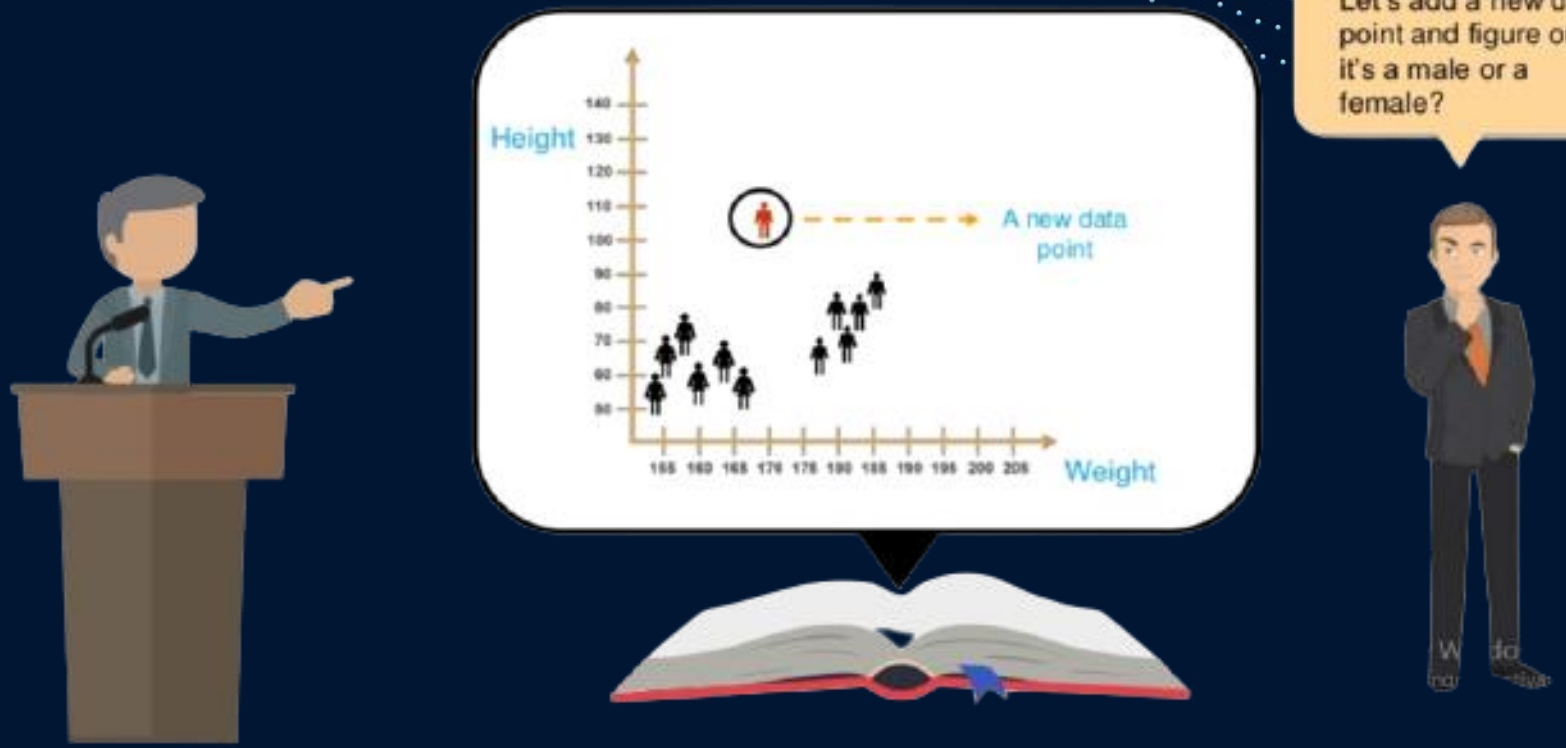

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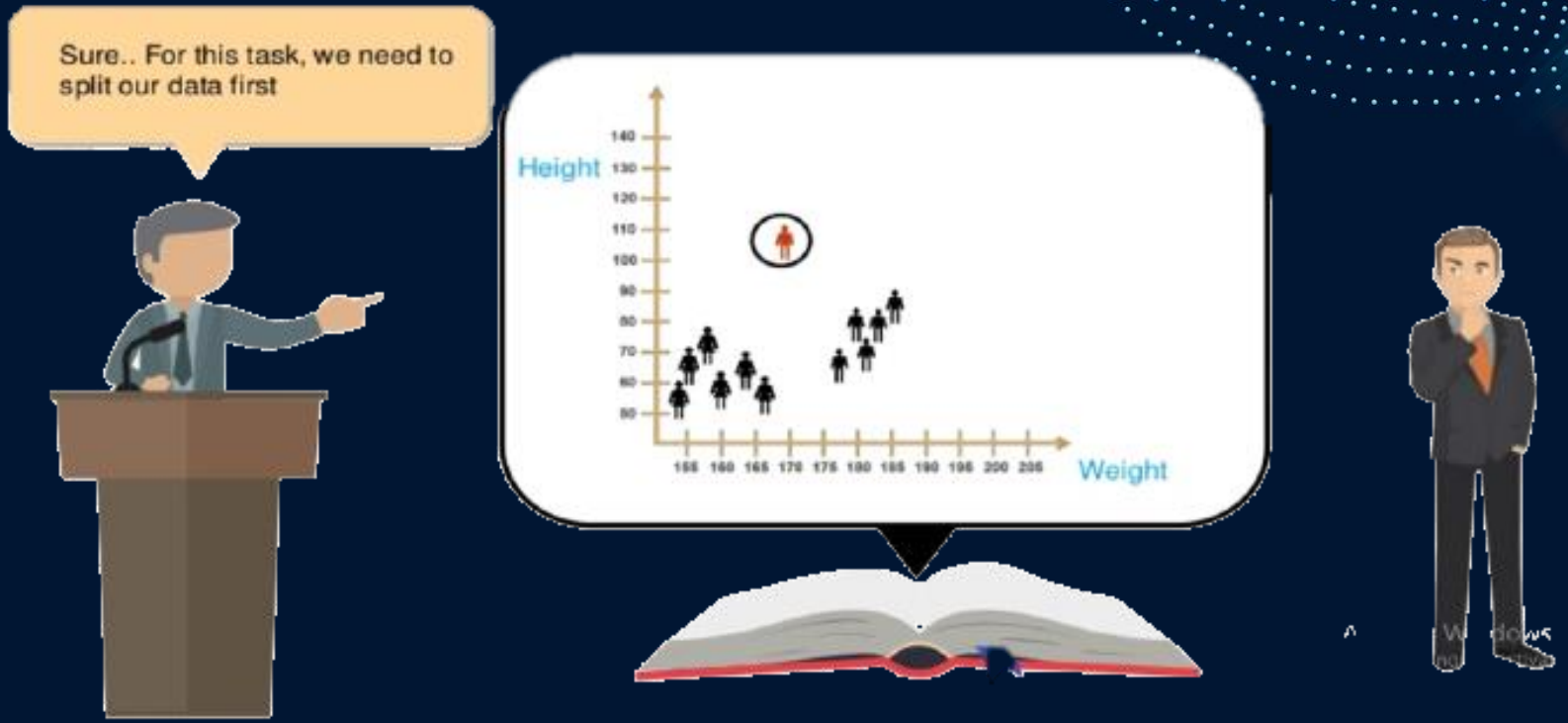

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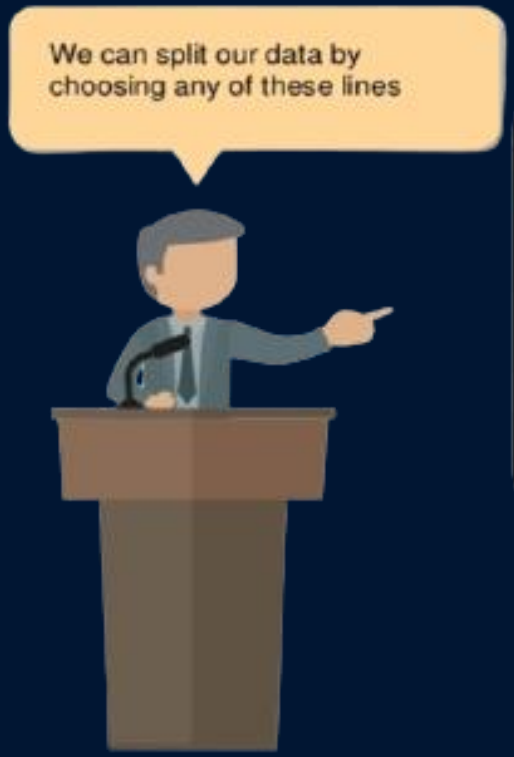

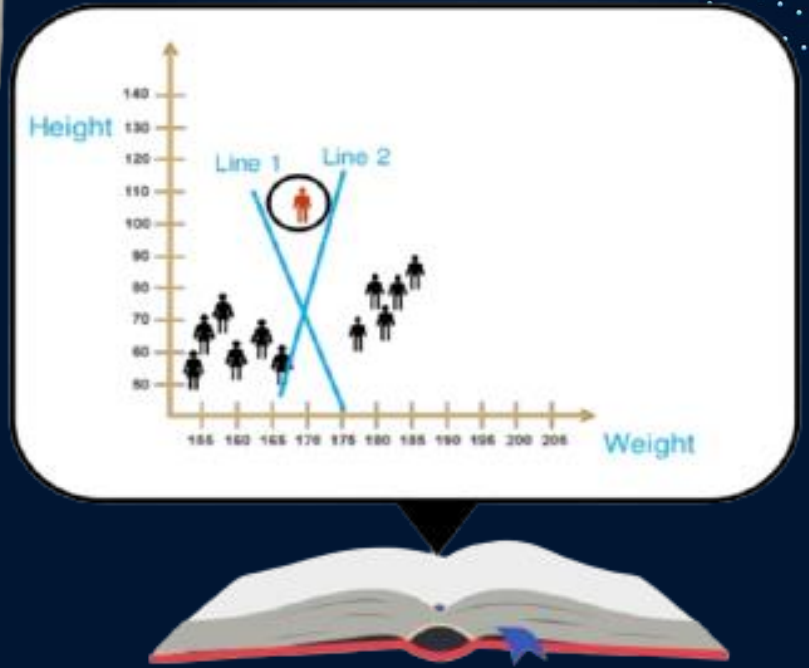

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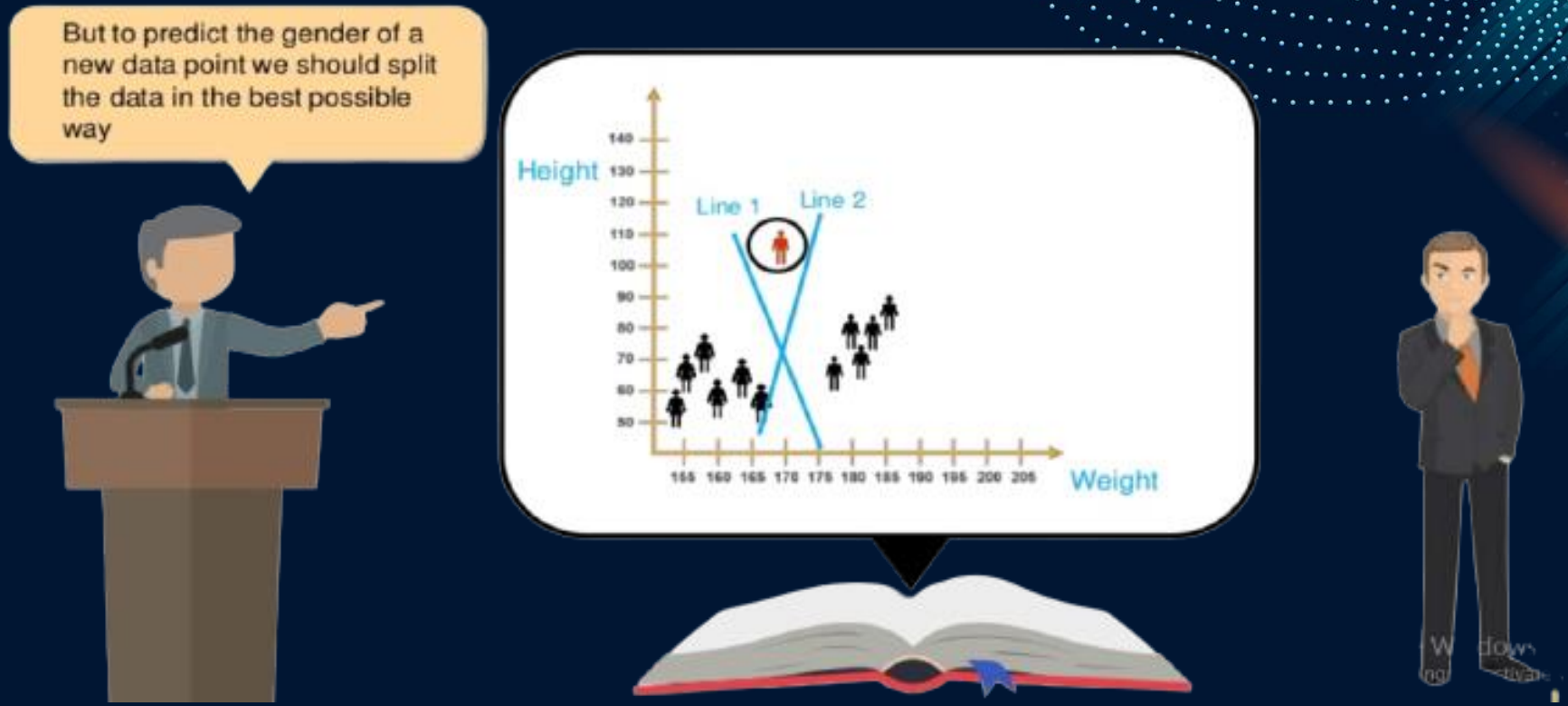

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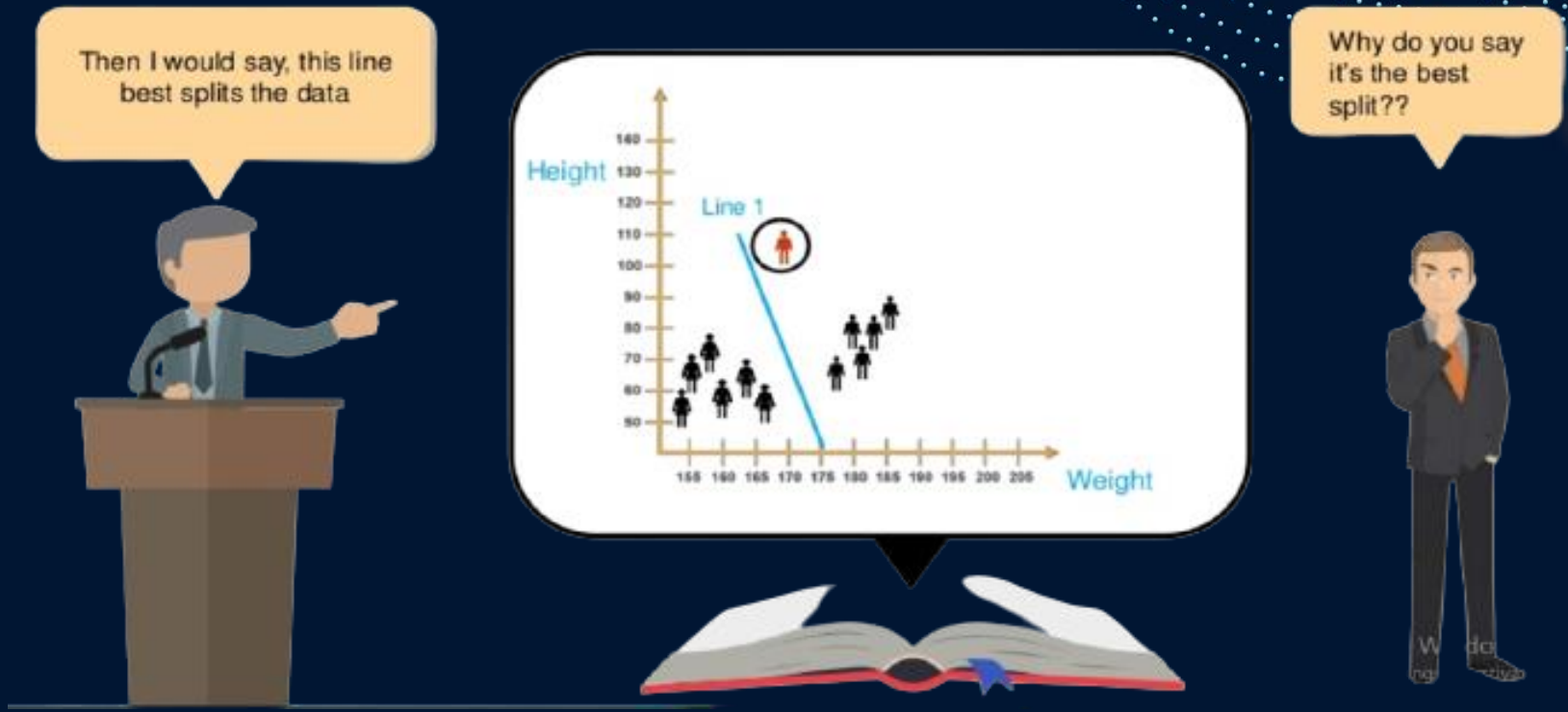

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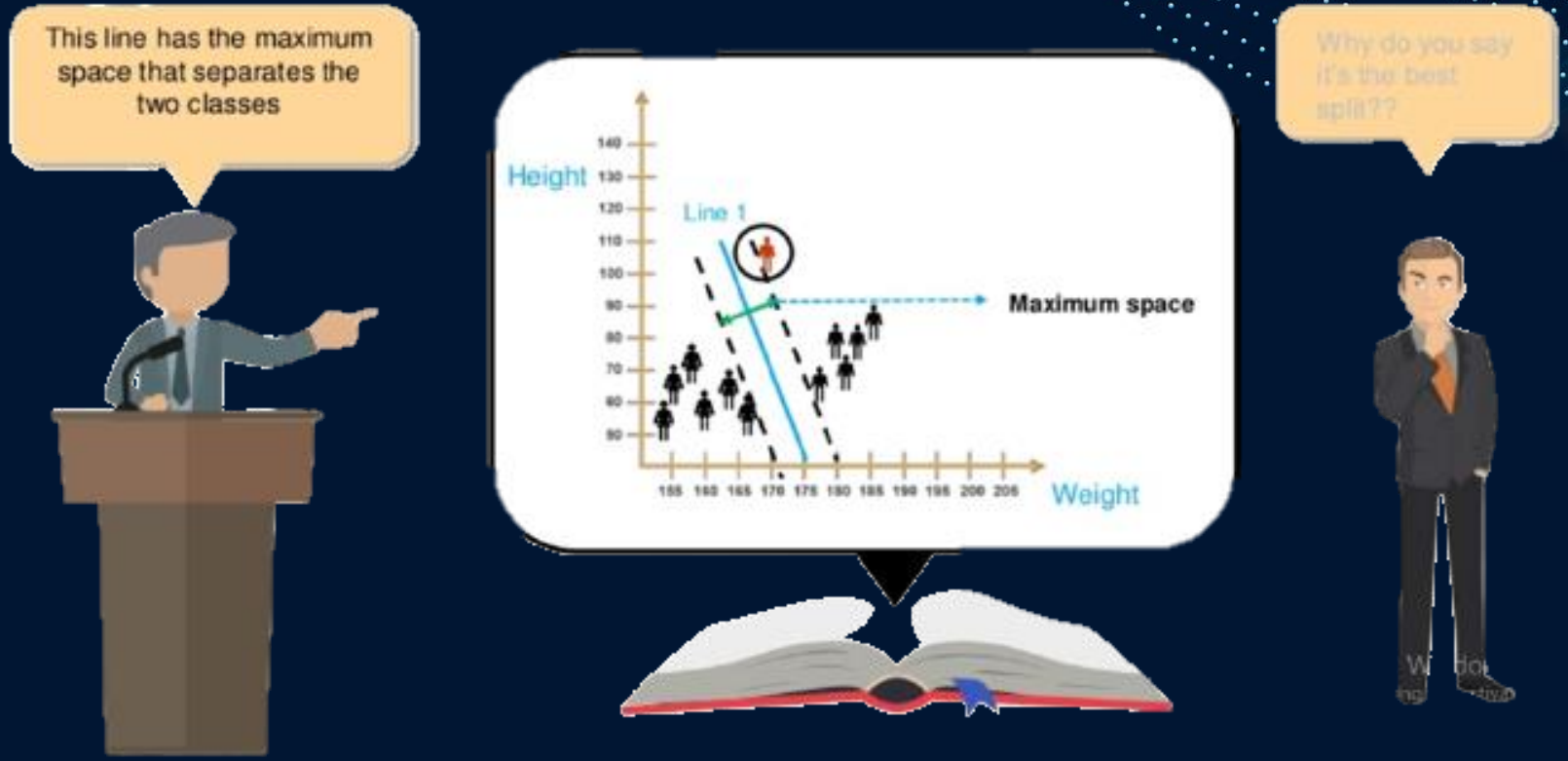

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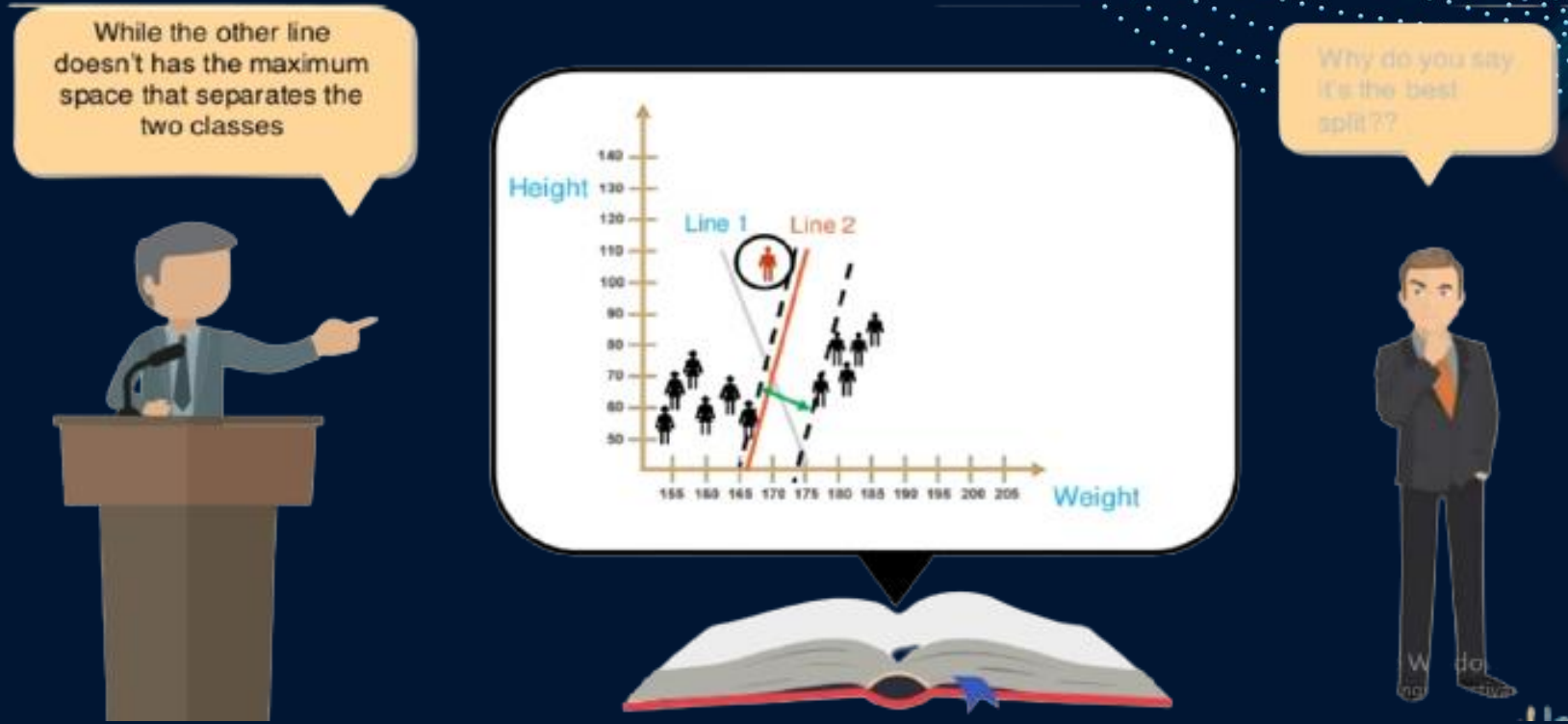

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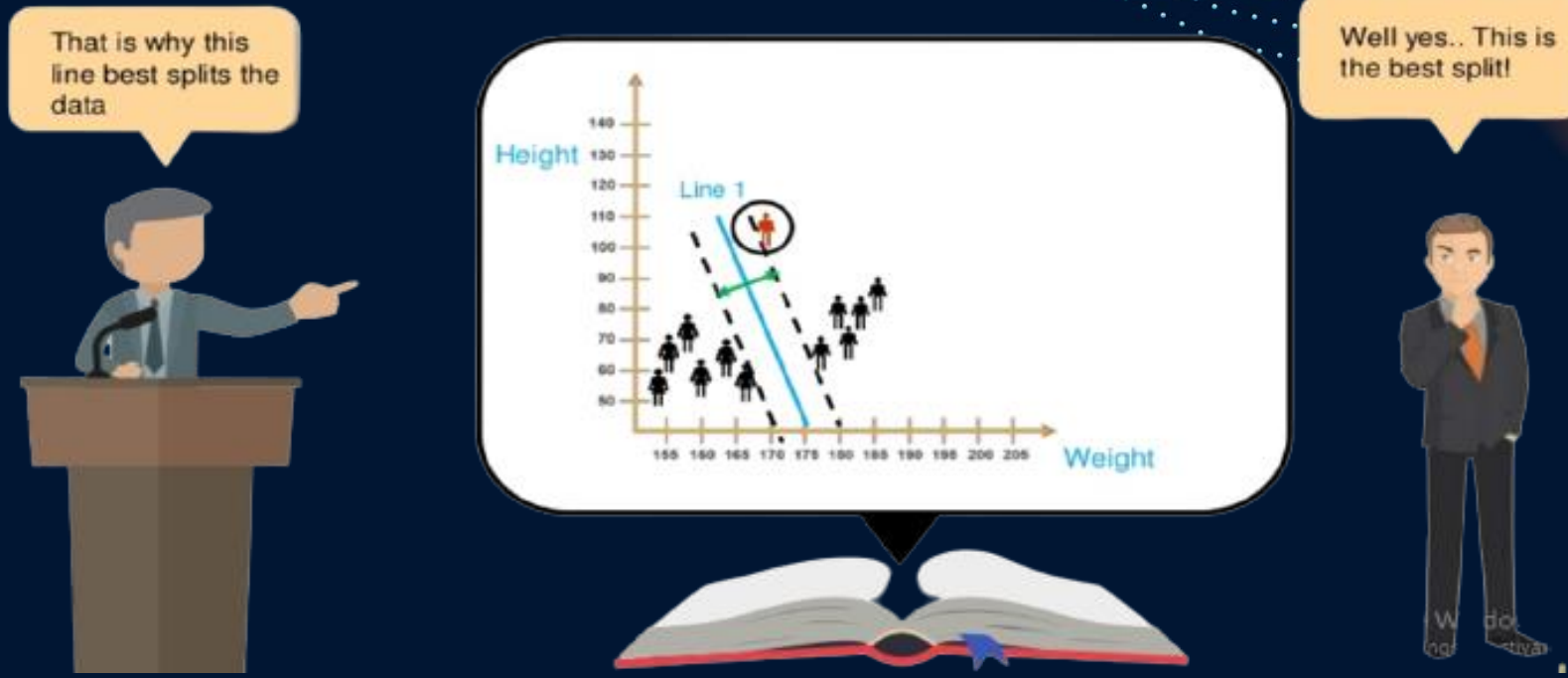

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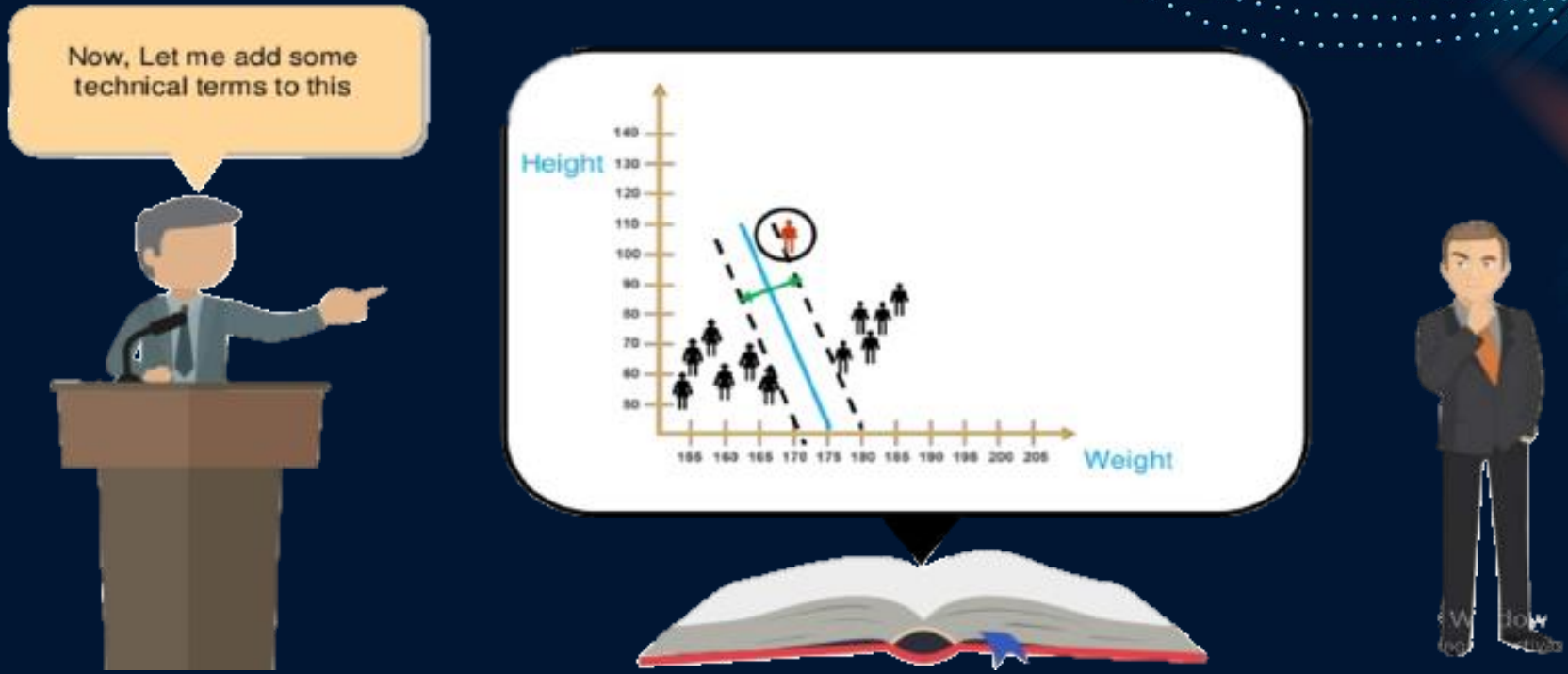

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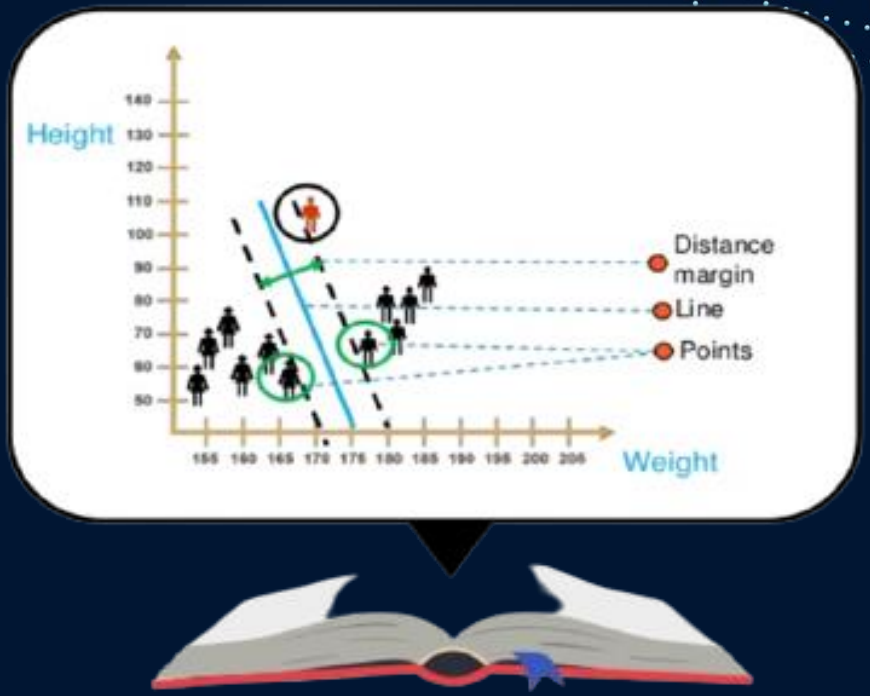


Support Vector Machine

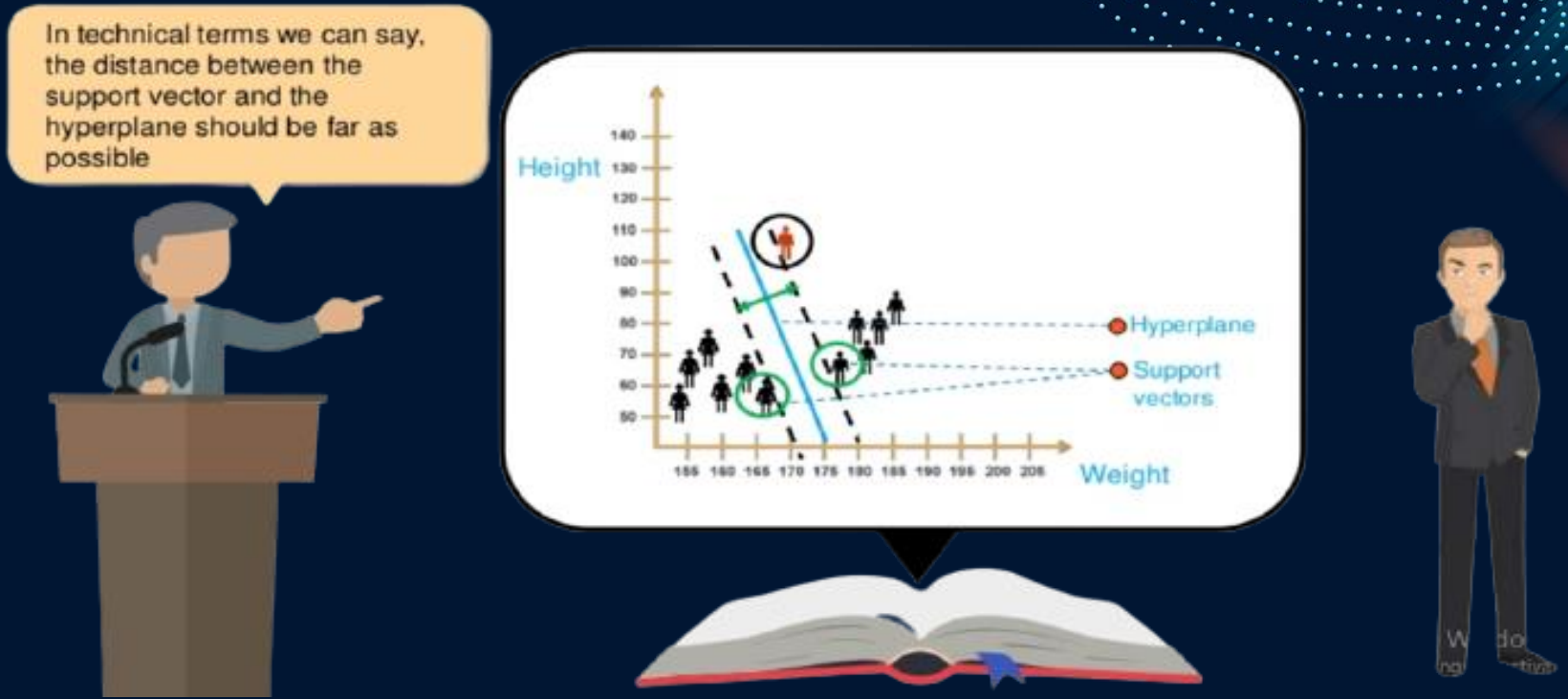
Margin:-

1. Margin is the perpendicular distance between the closest data points and the Hyperplane (on both sides)

2. The best optimised line (hyperplane) with maximum margin is termed as Margin Maximal Hyperplane.

3. The closest points where the margin distance is calculated are considered as the support vectors.
4. Here the hyperplane is a 2d plane drawn parallel to x-axis that is the separator.

Support Vector Machine



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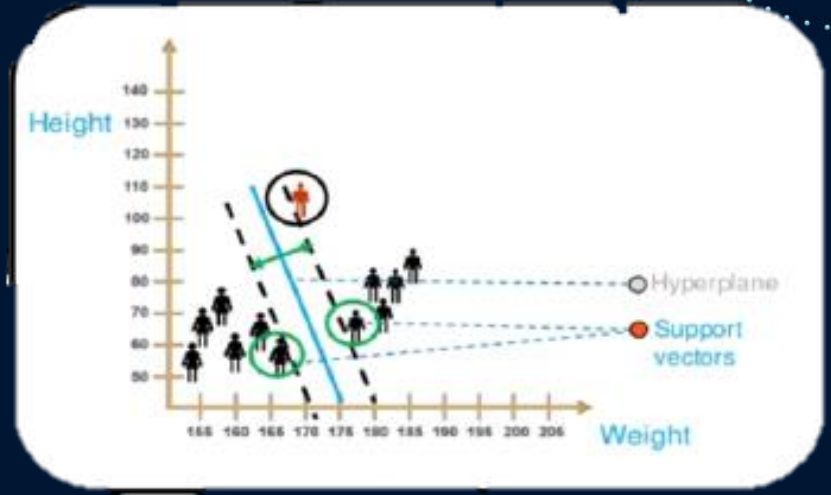

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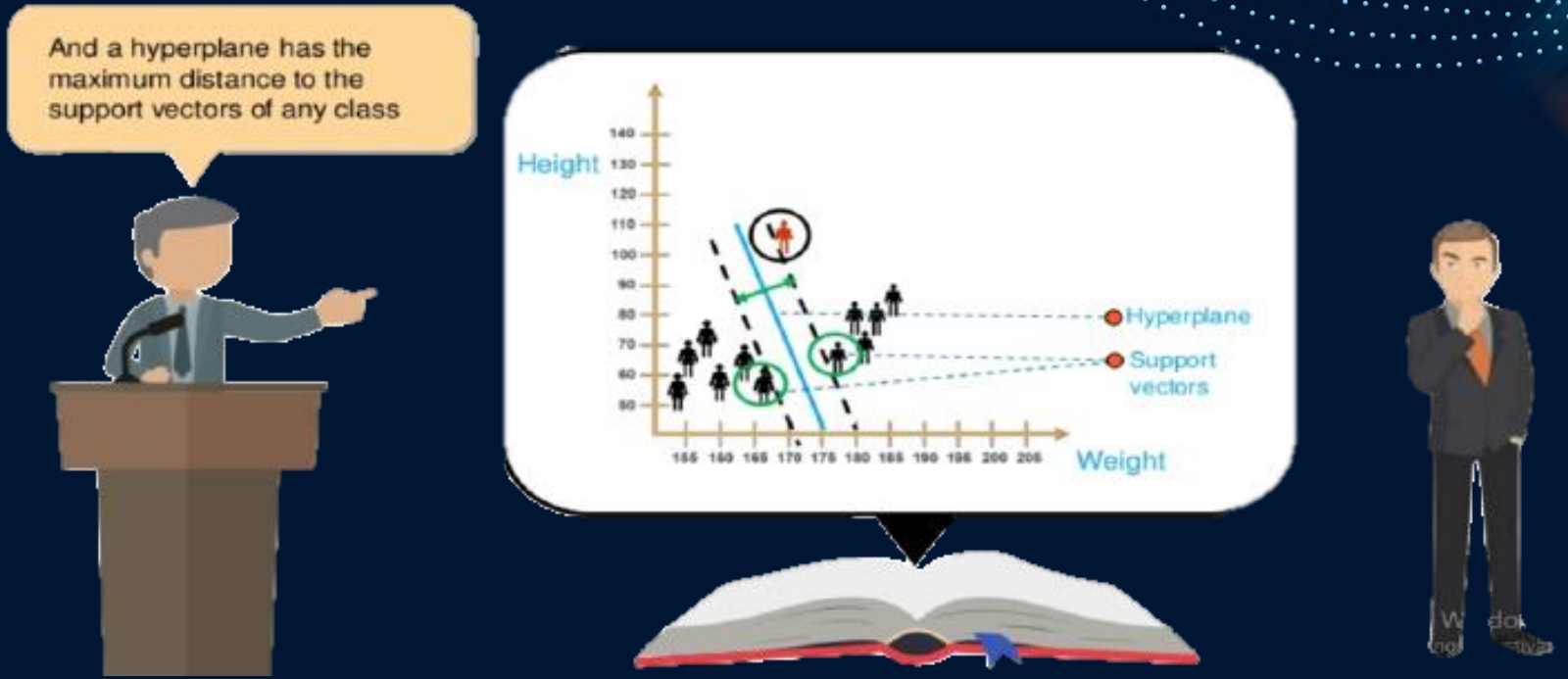

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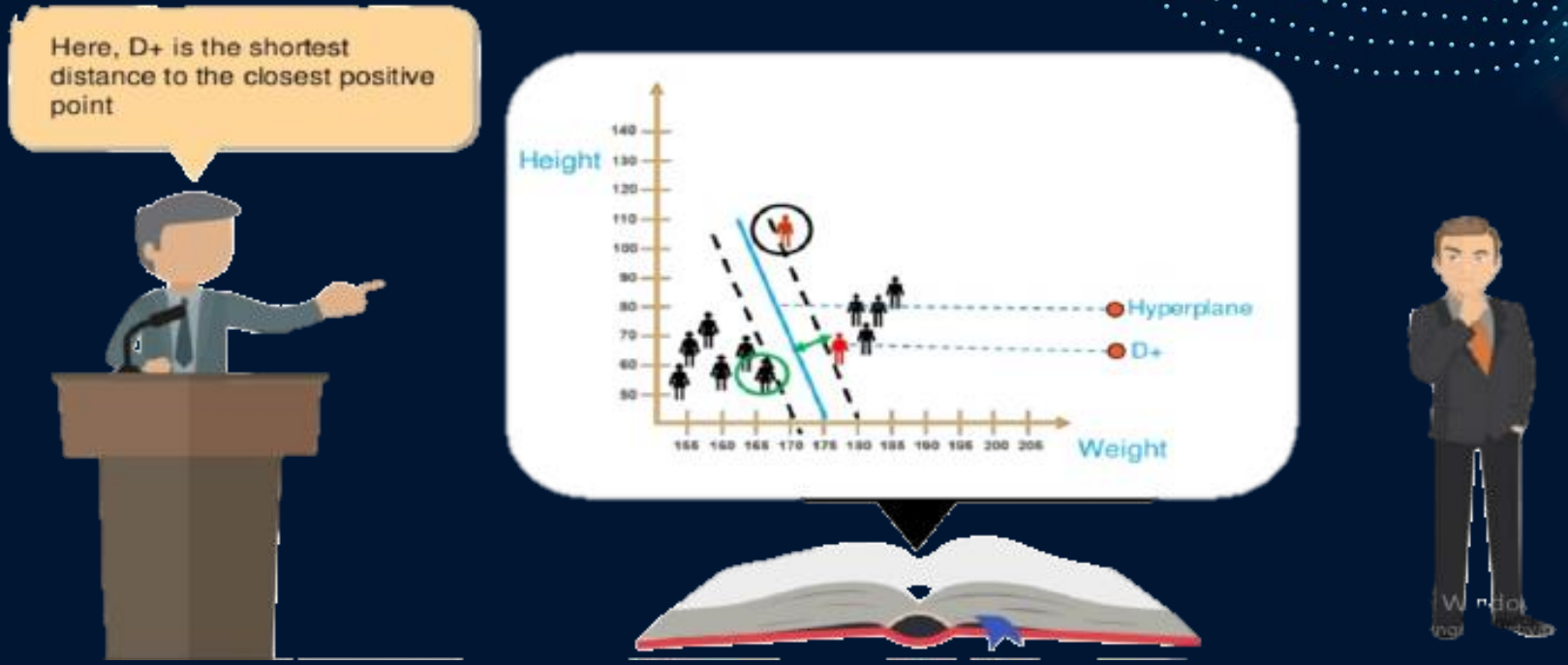

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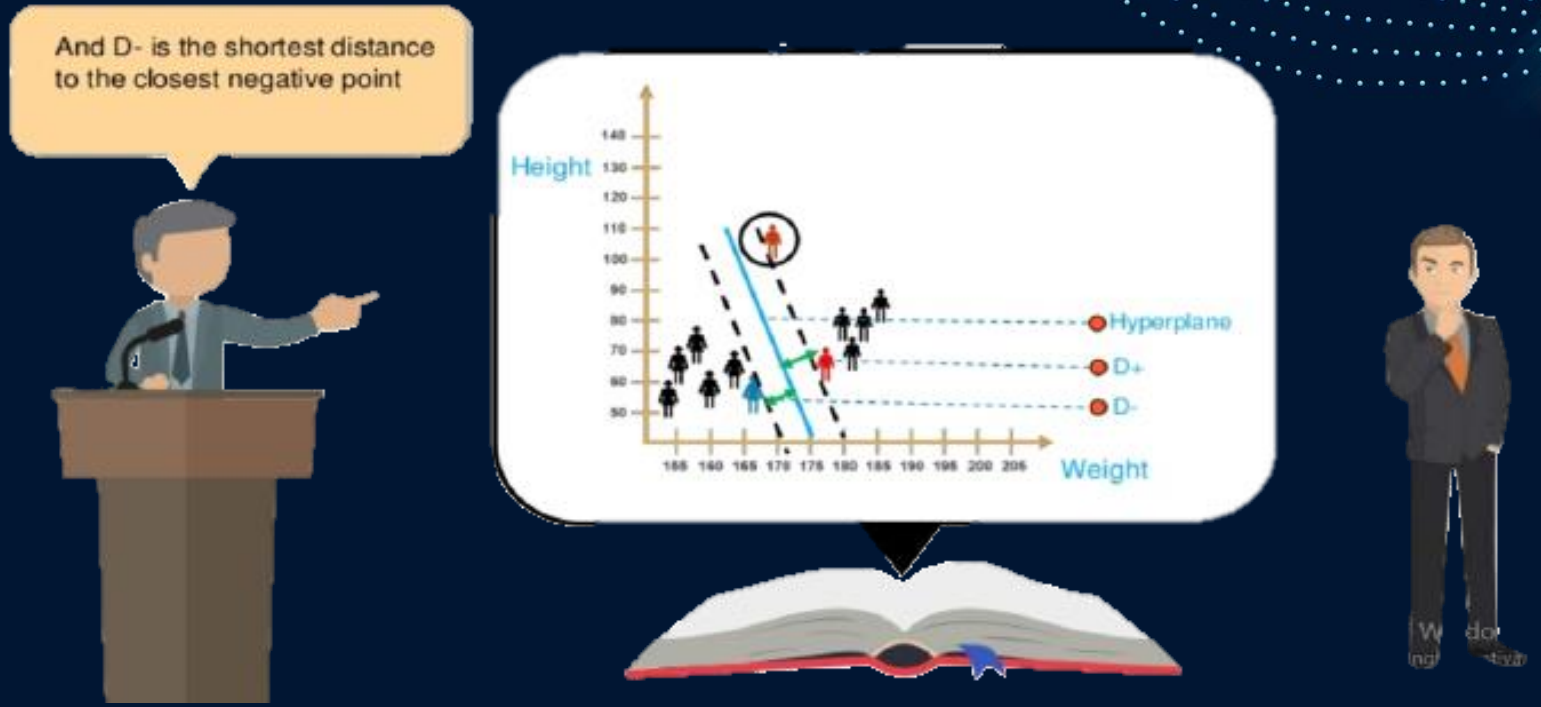

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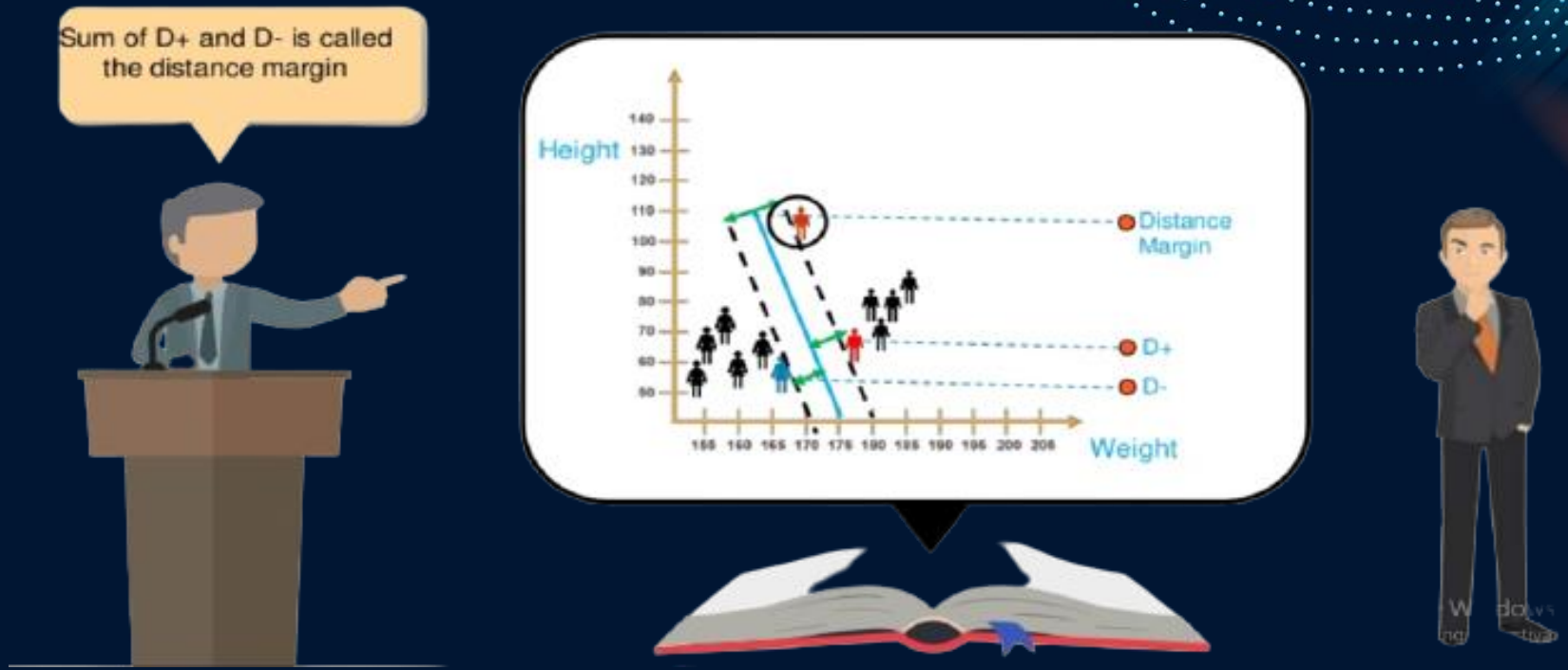

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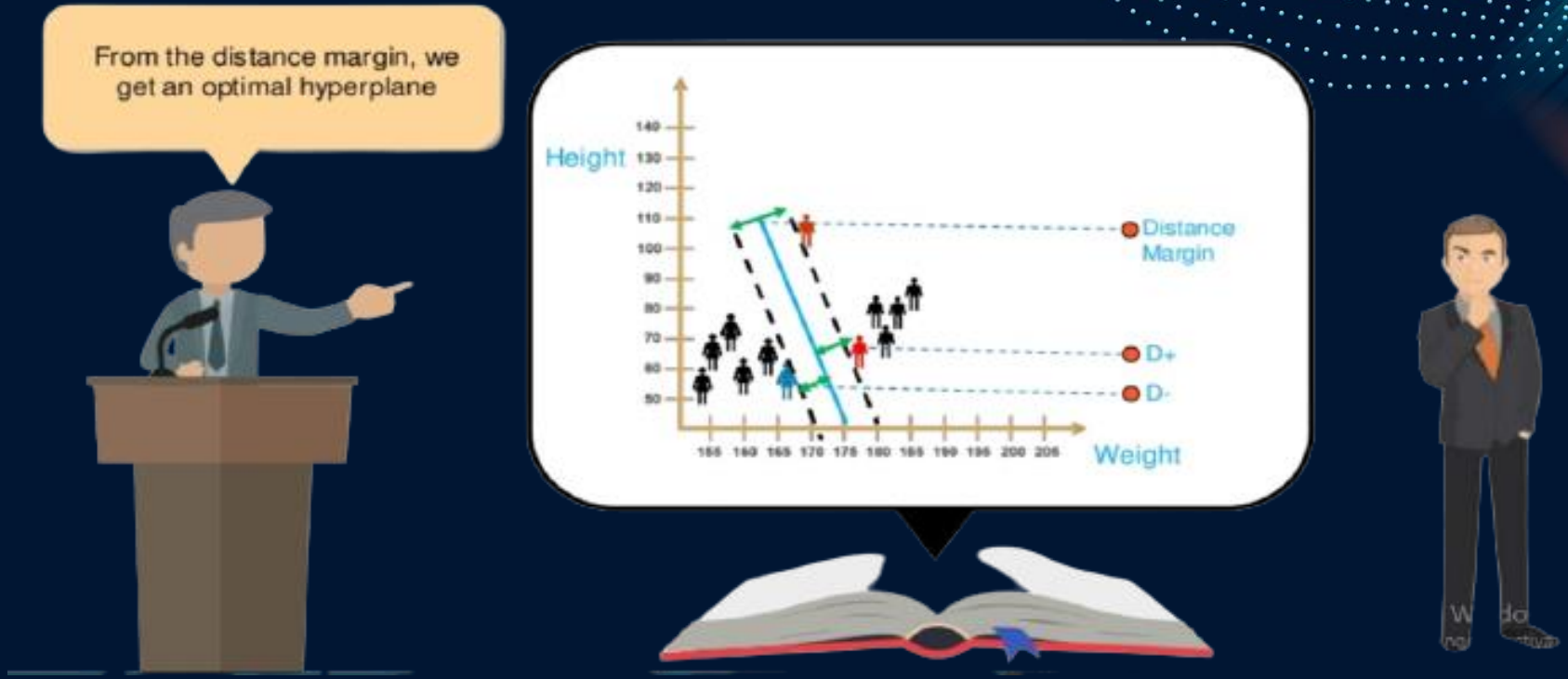

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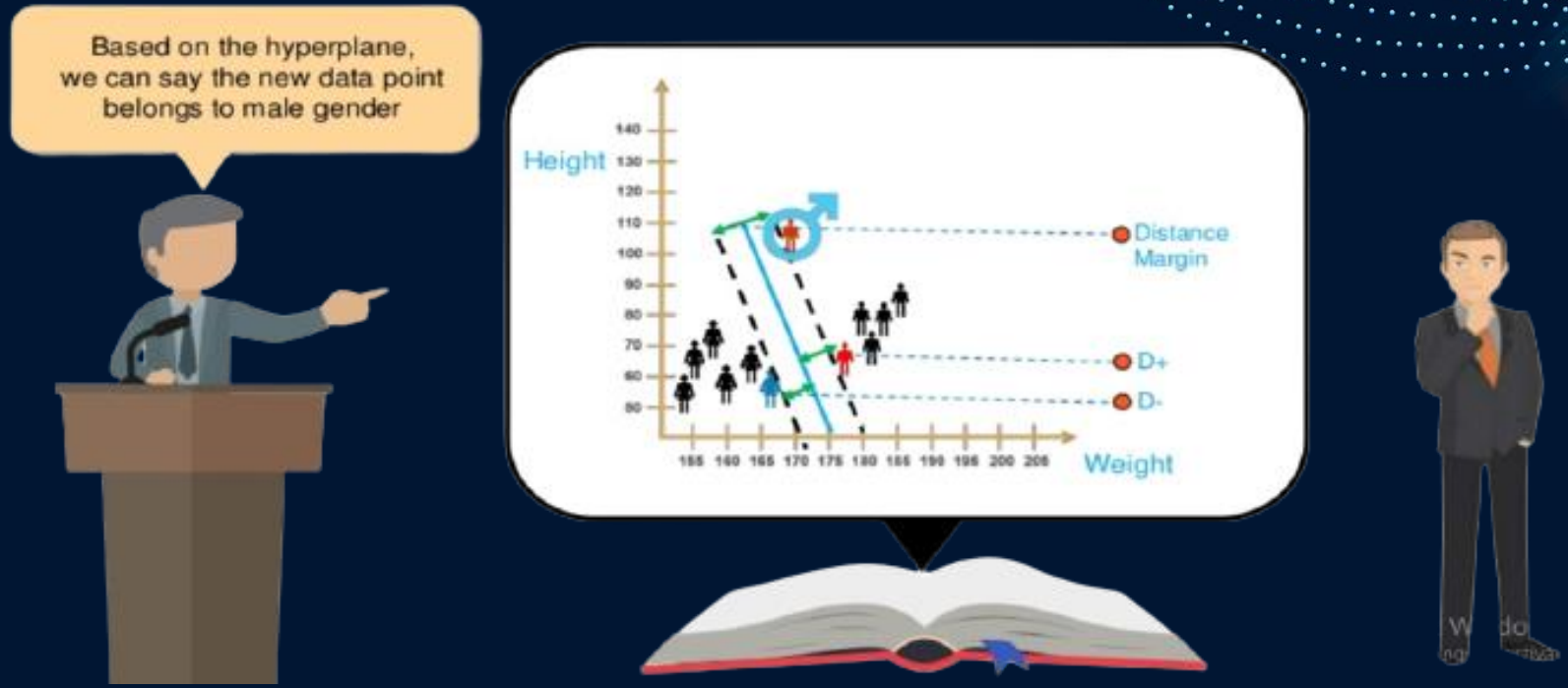

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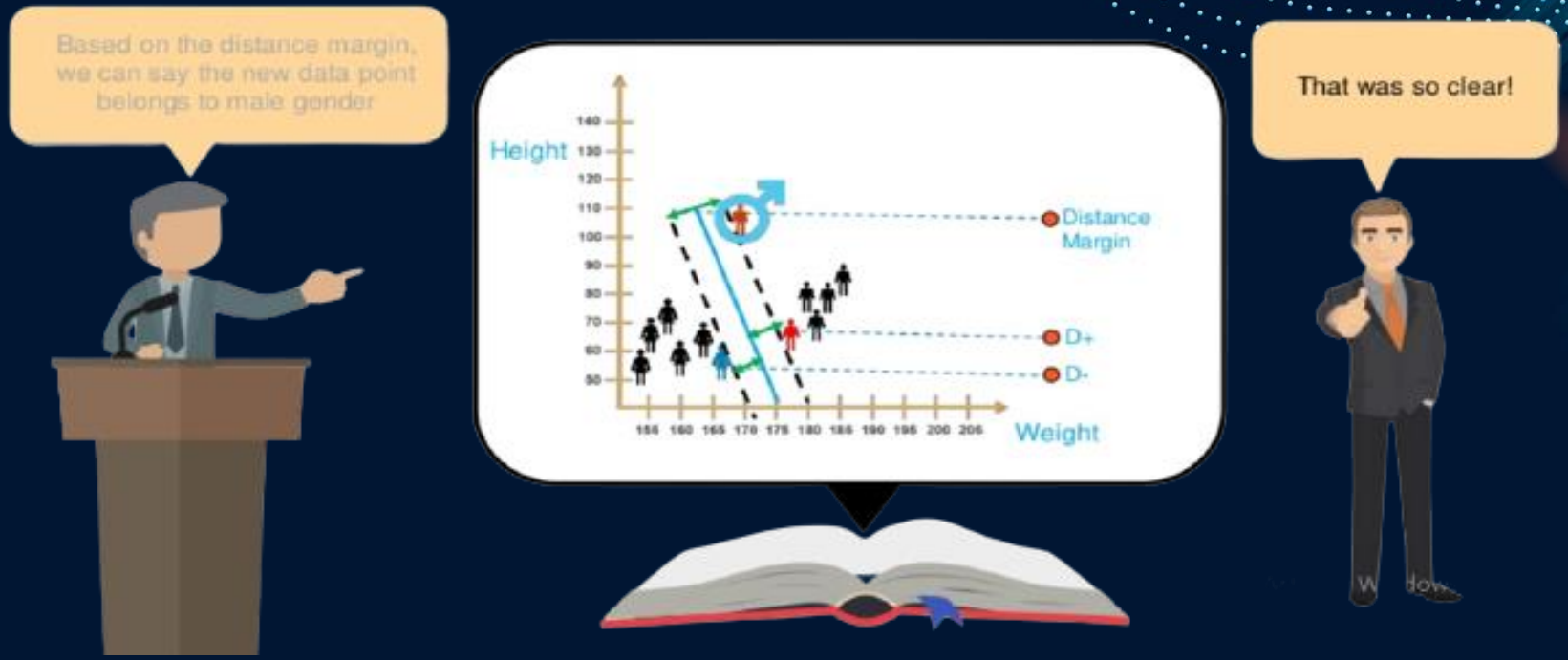
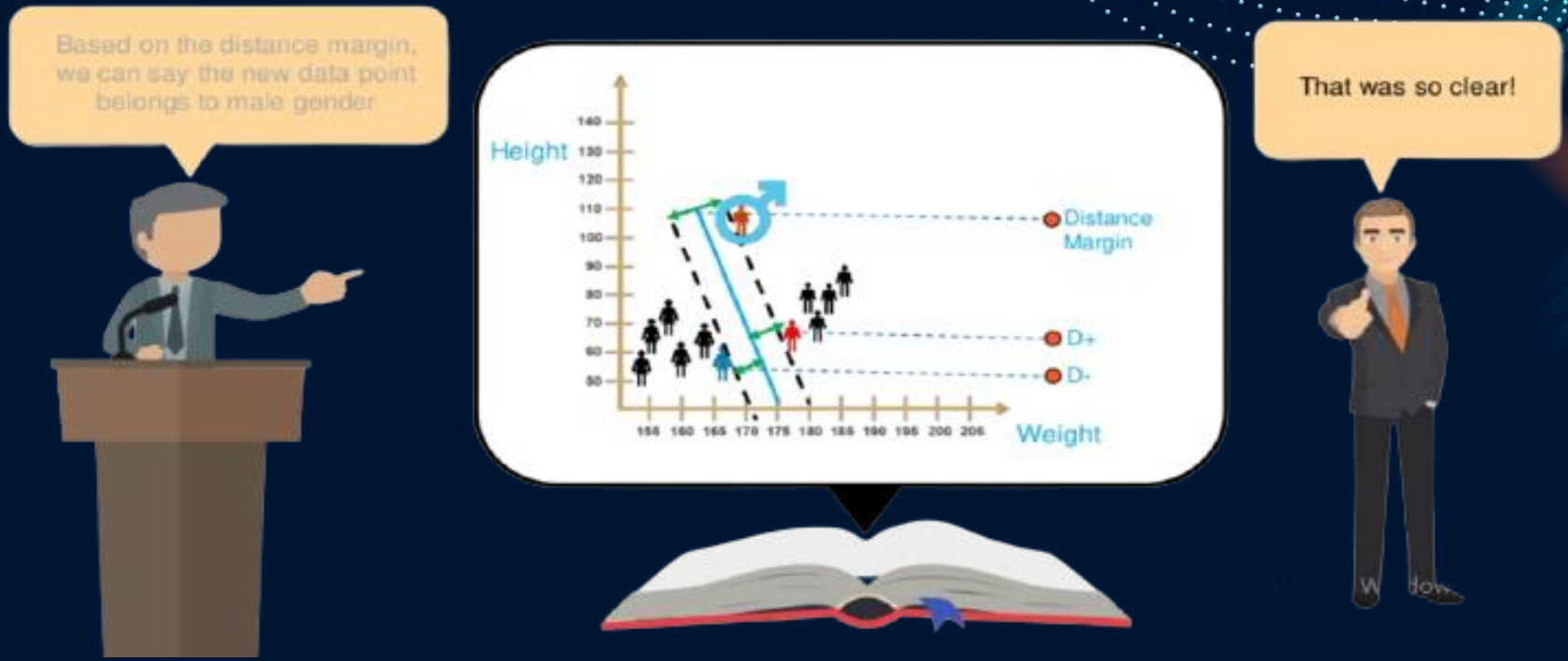


What is Support Vector Machine



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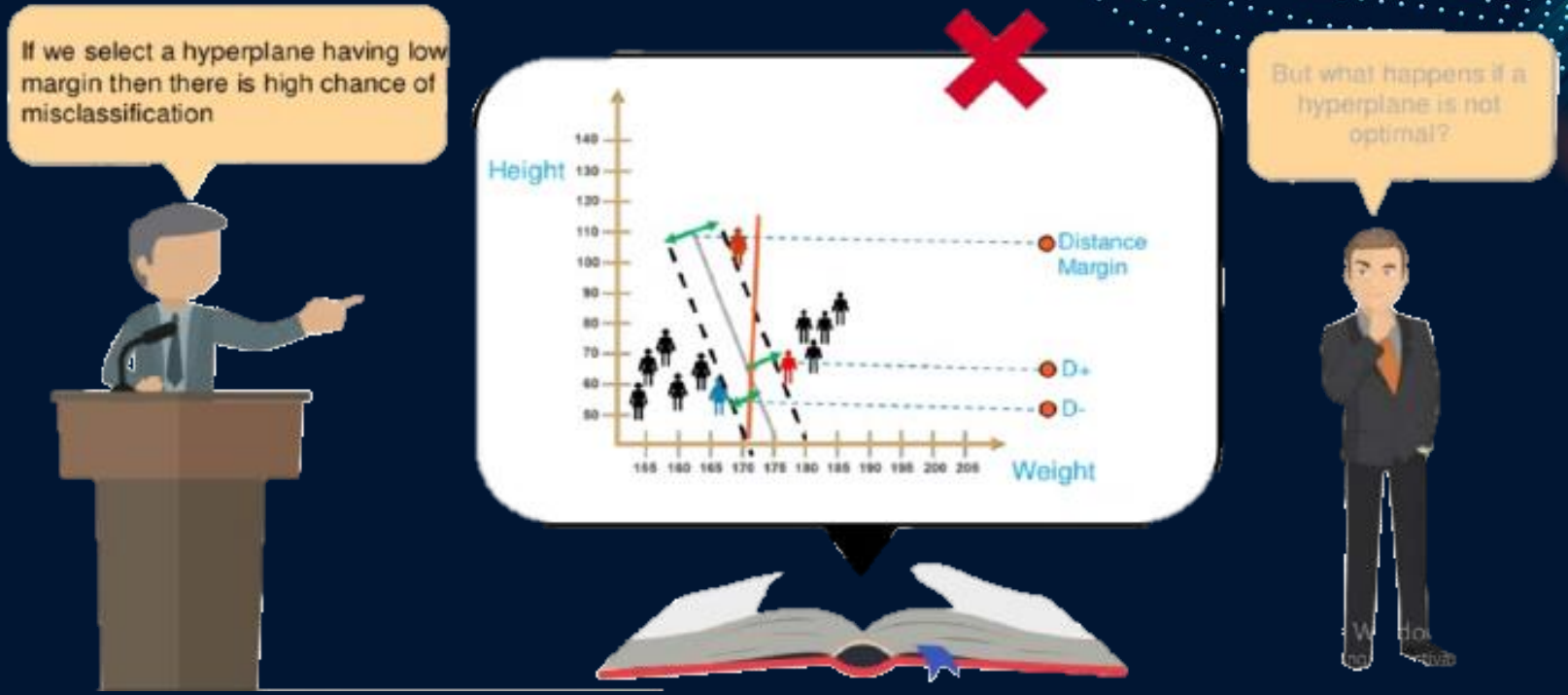

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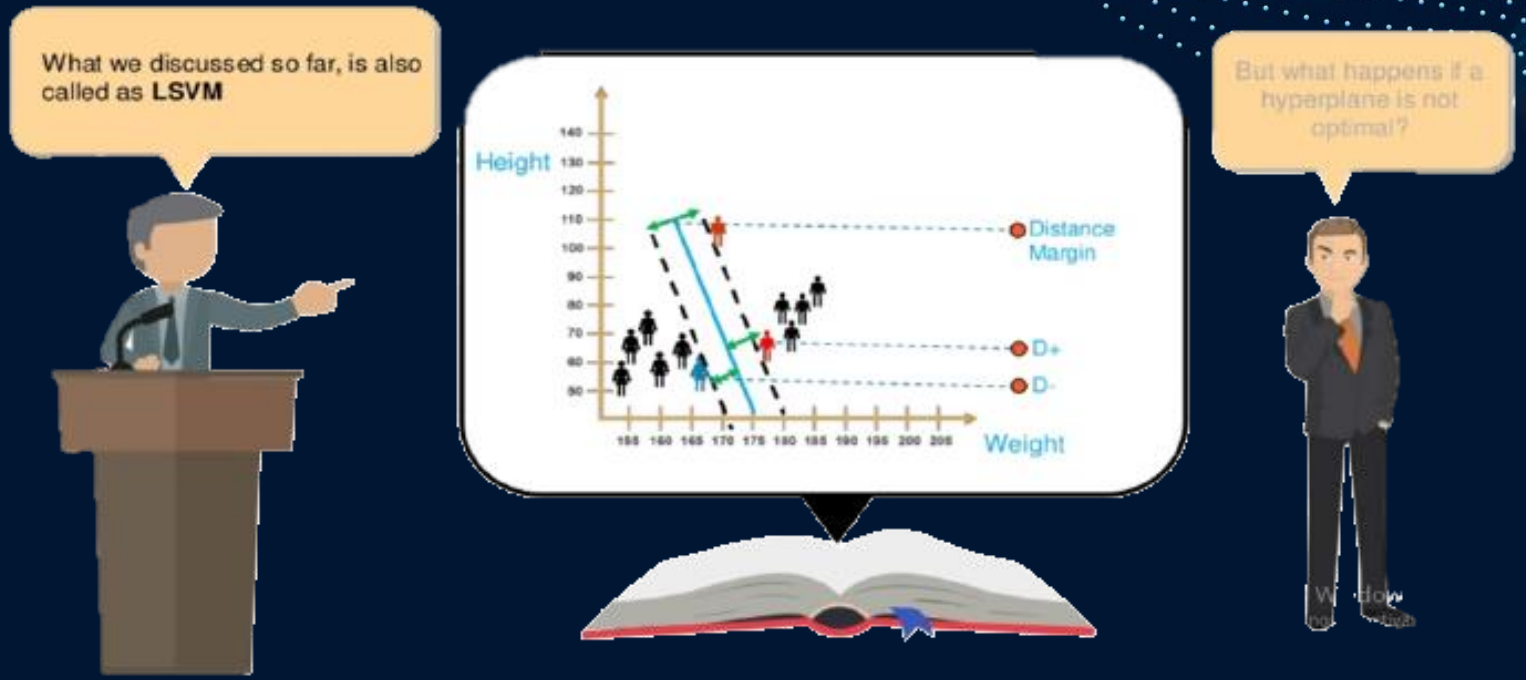
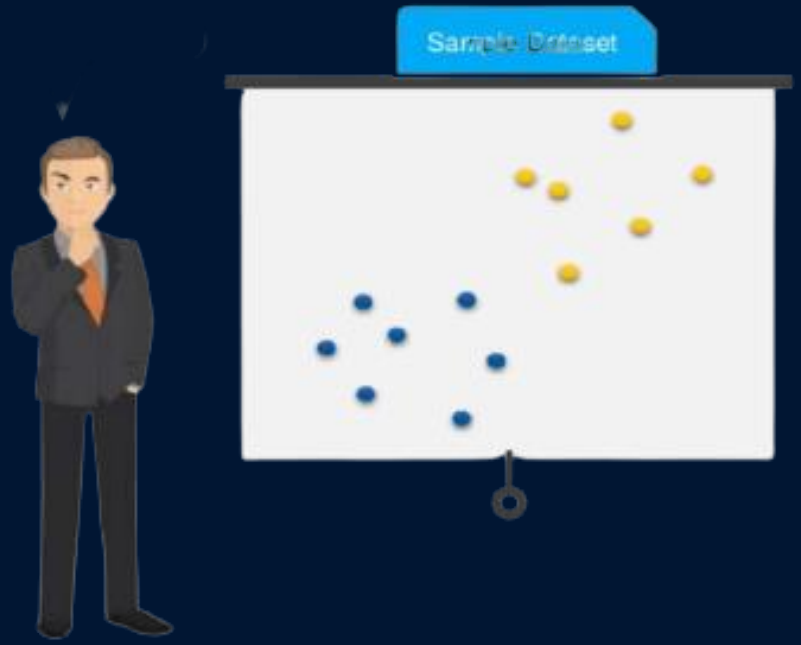


Understanding Support Vector Machine



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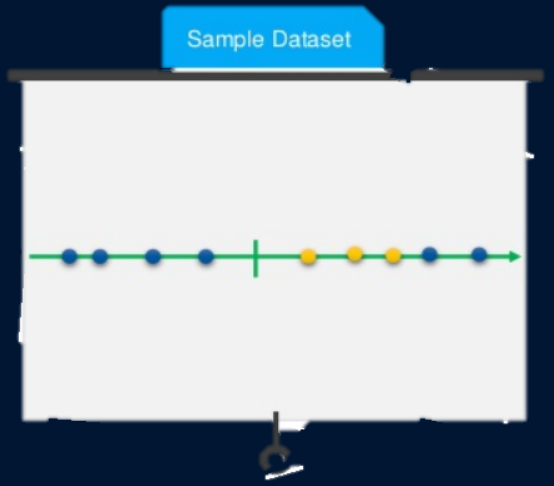

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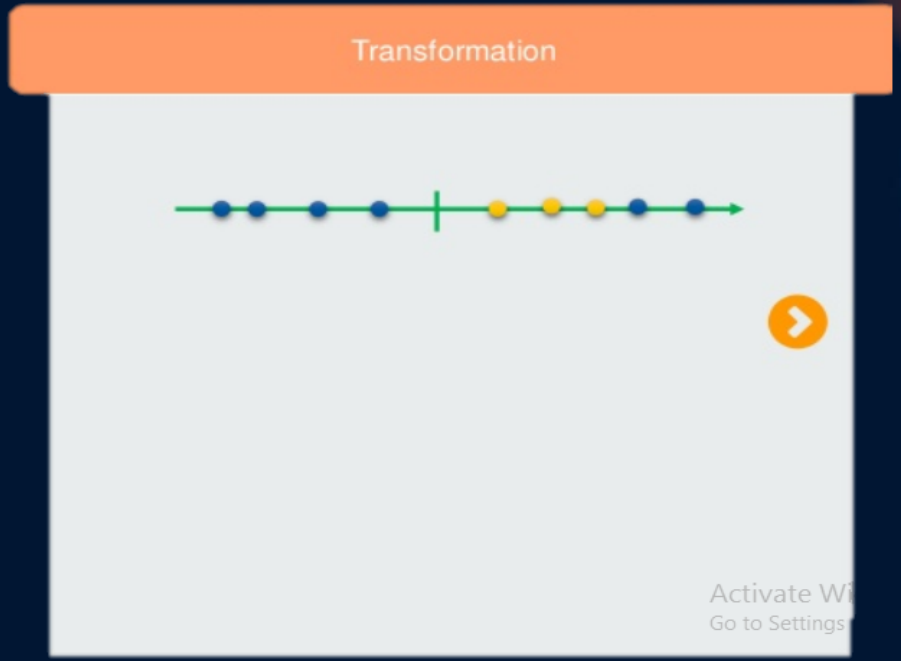

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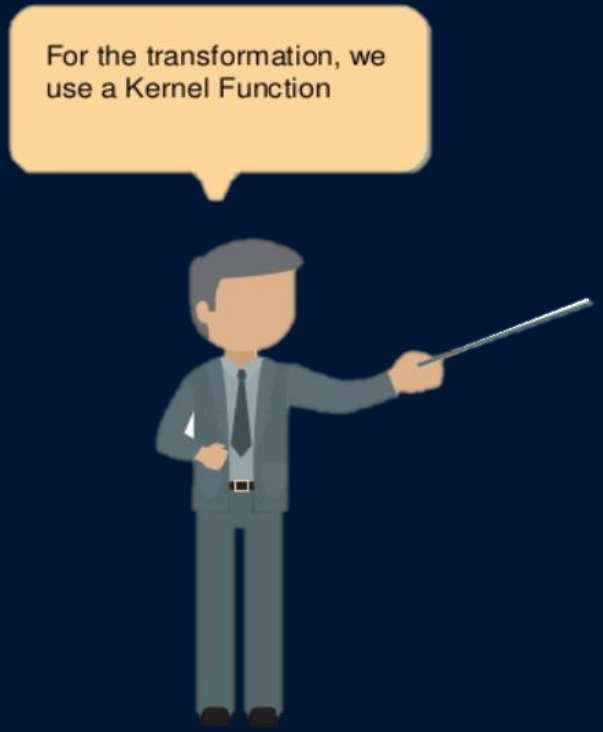
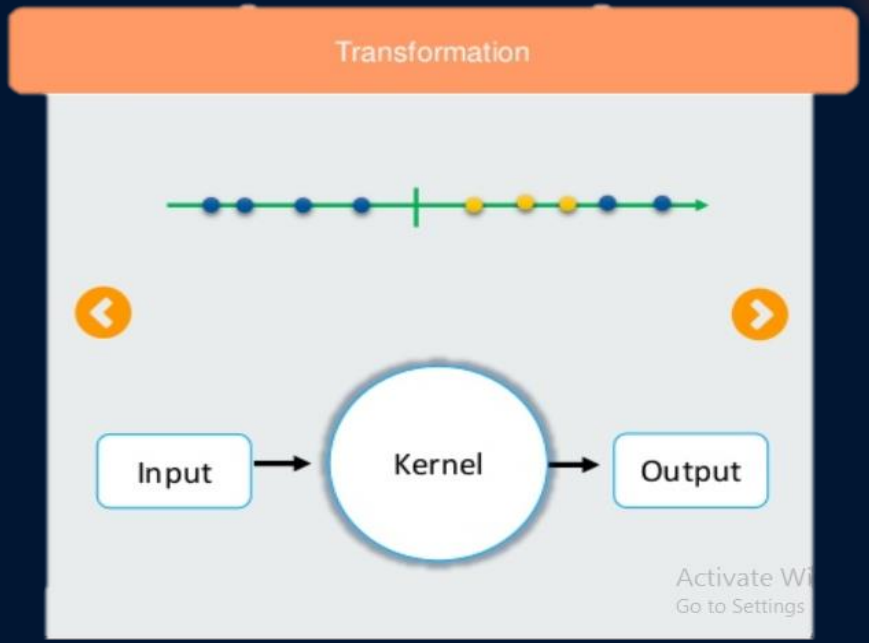




Kernel Function

- Mathematical functions for transforming data
- using some linear algebra
- Different SVM algorithms use different types of kernel functions

Kernel Function: Example

$K(x, y) = \langle f(x), f(y) \rangle$

Kernel function dot product of n- dimensional inputs

Understanding Support Vector Machine

Mathematical representation

$x = (x1, x2, x3); y = (y1, y2, y3)$

$f(x) = (x1x1, x1x2, x1x3, x2x1, x2x2, x2x3, x3x1, x3x2, x3x3)$

$f(y) = (y1y1, y1y2, y1y3, y2y1, y2y2, y2y3, y3y1, y3y2, y3y3)$

$K(x, y) = (<x, y>)^2$

$x = (1, 2, 3)$

$y = (4, 5, 6)$

$f(x) = (1, 2, 3, 2, 4, 6, 3, 6, 9)$

$f(y) = (16, 20, 24, 20, 25, 30, 24, 30, 36)$

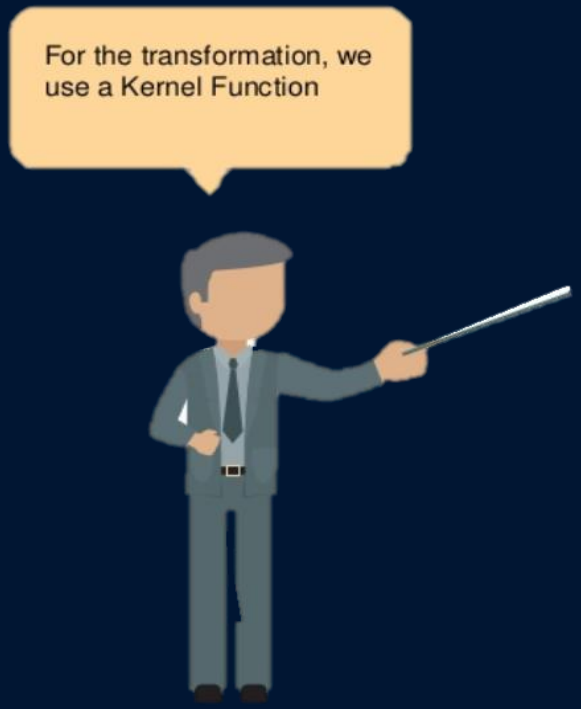
$<f(x), f(y)> = 16 + 40 + 72 + 40 + 100 + 180 + 72 + 180 + 324 = 1024$

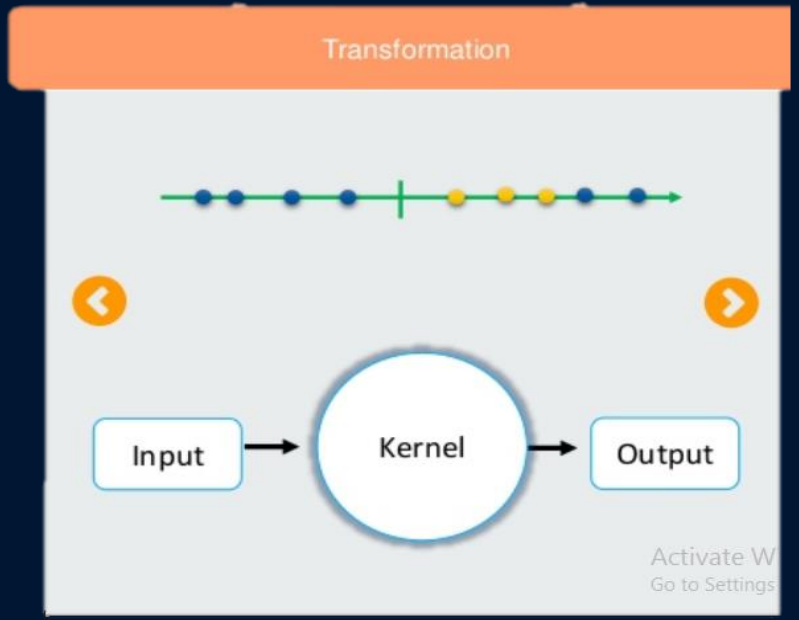
$K(x, y) = (4 + 10 + 18)^2 = 1024$ ----> Kernel function

Various kernels available

1. Linear kernel
2. Non - linear kernel
3. Radial basis function (RBF)
4. Sigmoid
5. Polynomial
6. Exponential

Understanding Support Vector Machine





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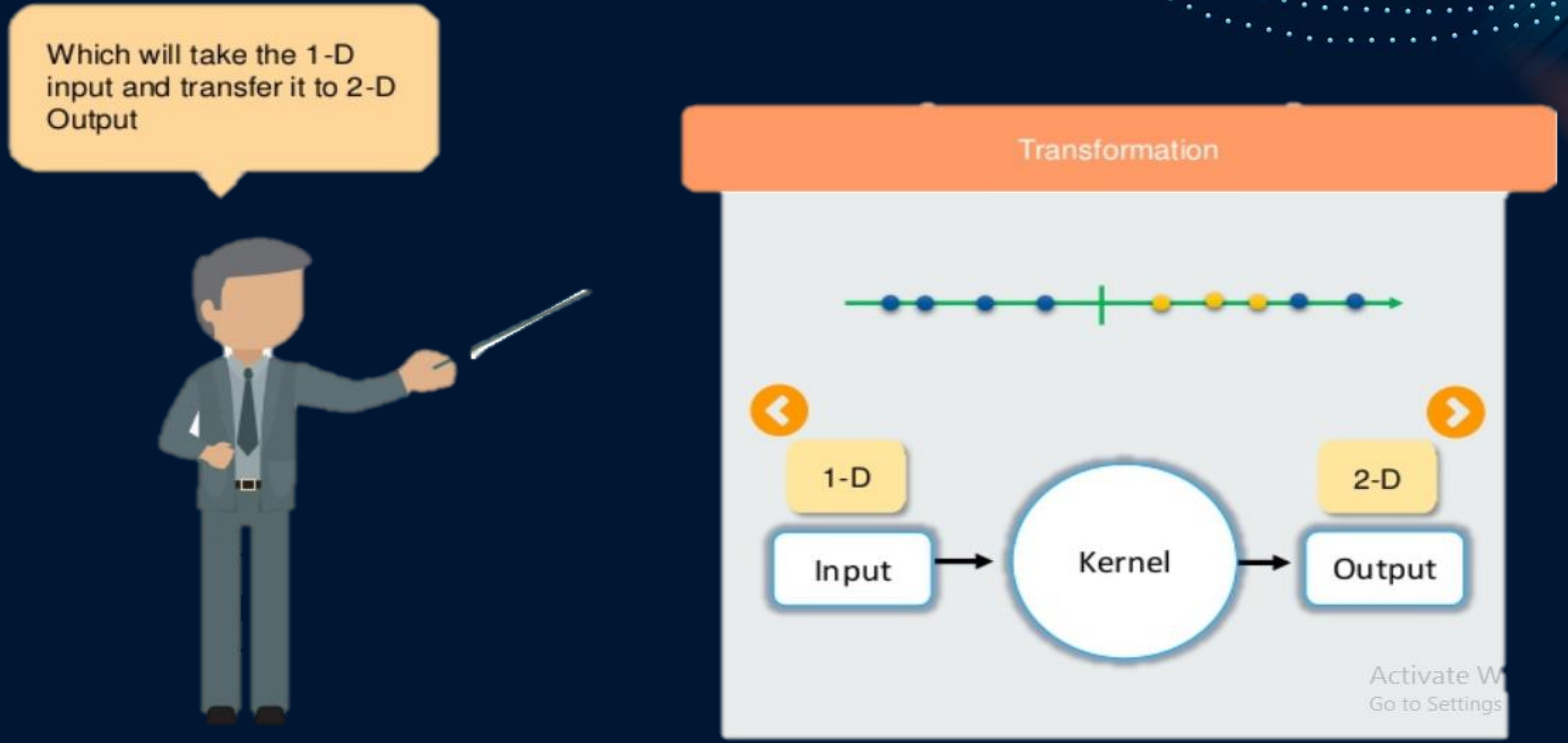

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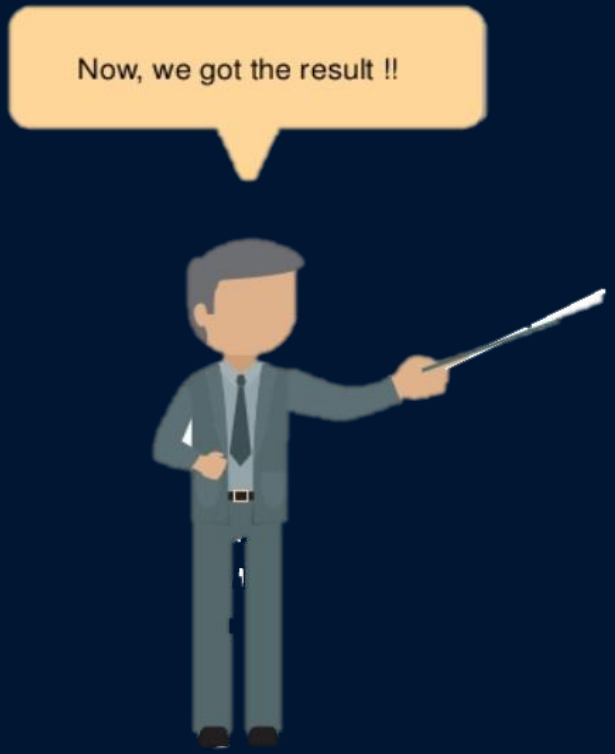

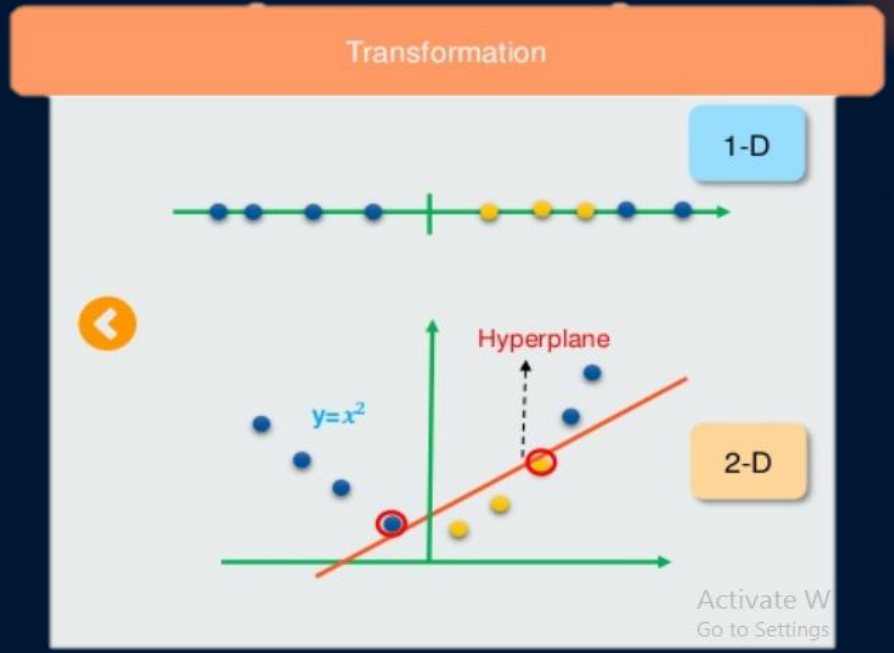

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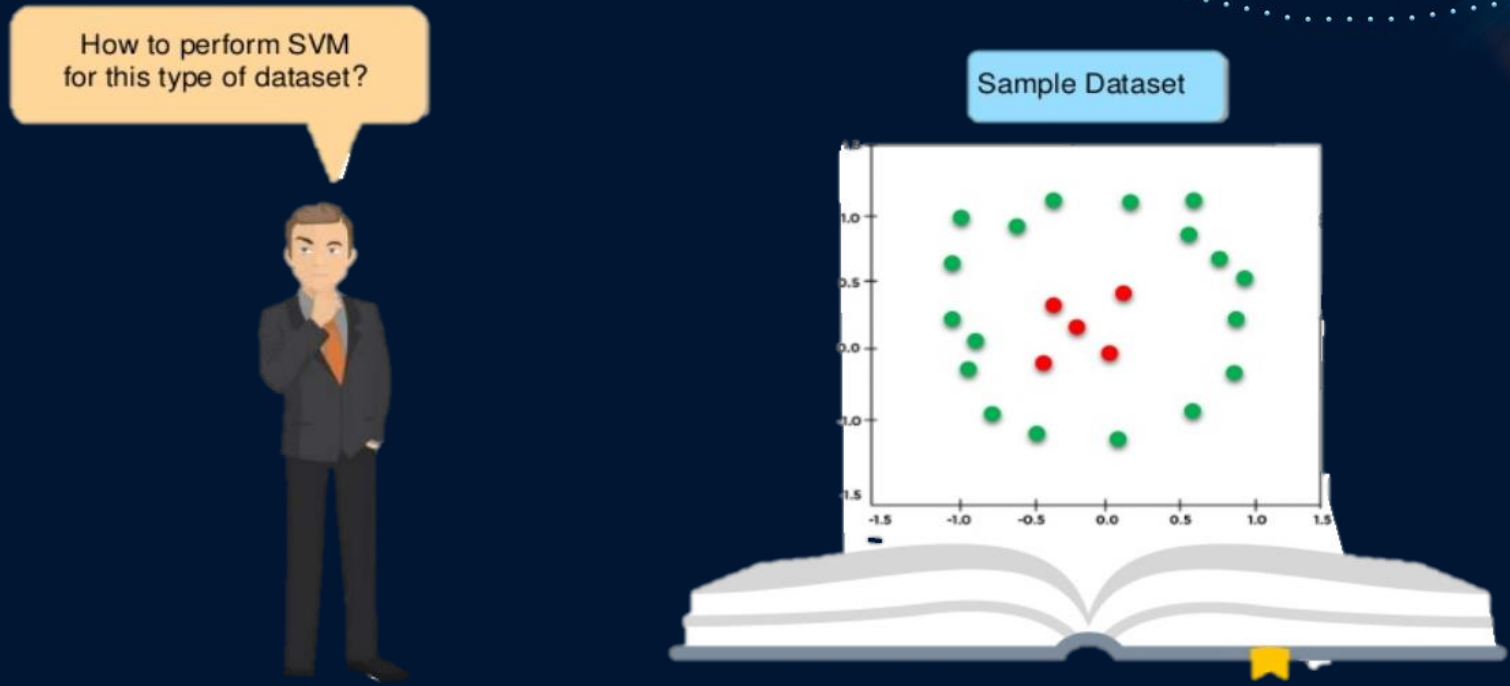

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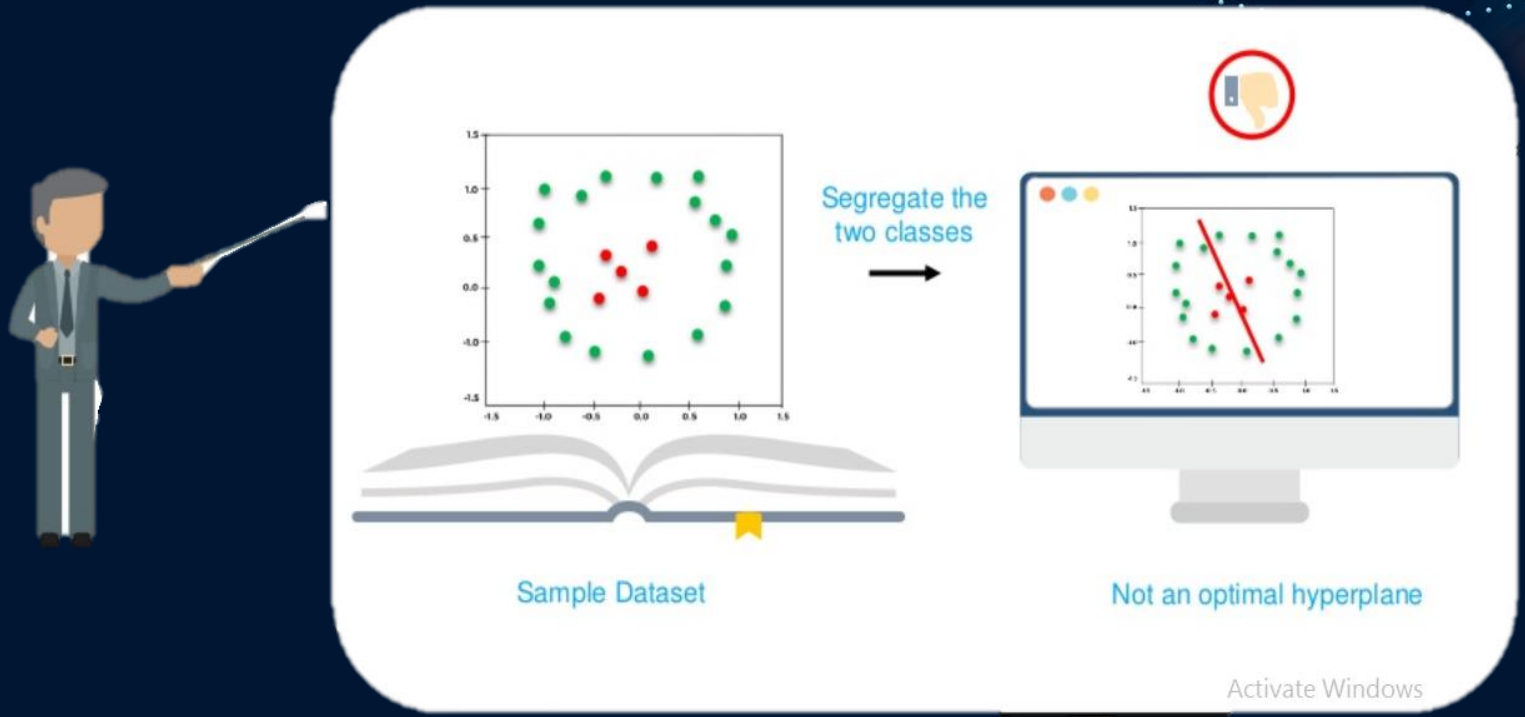
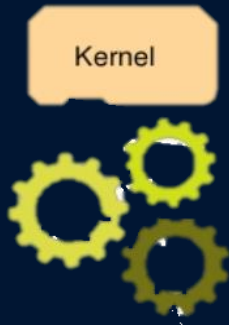
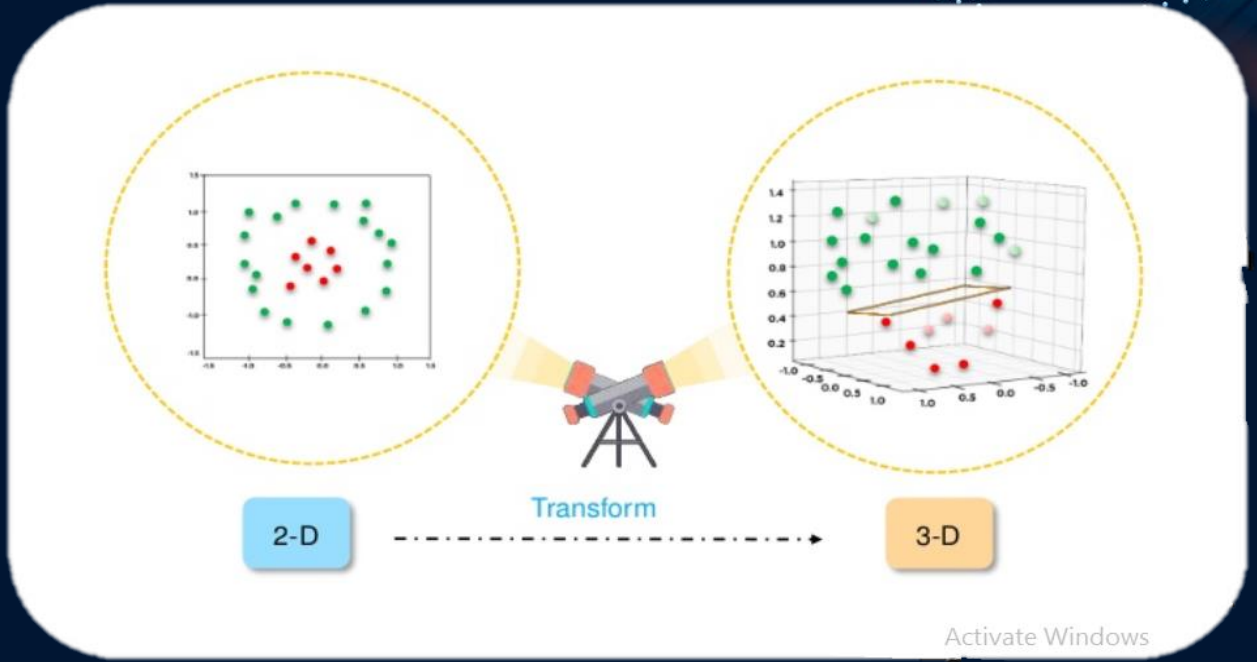
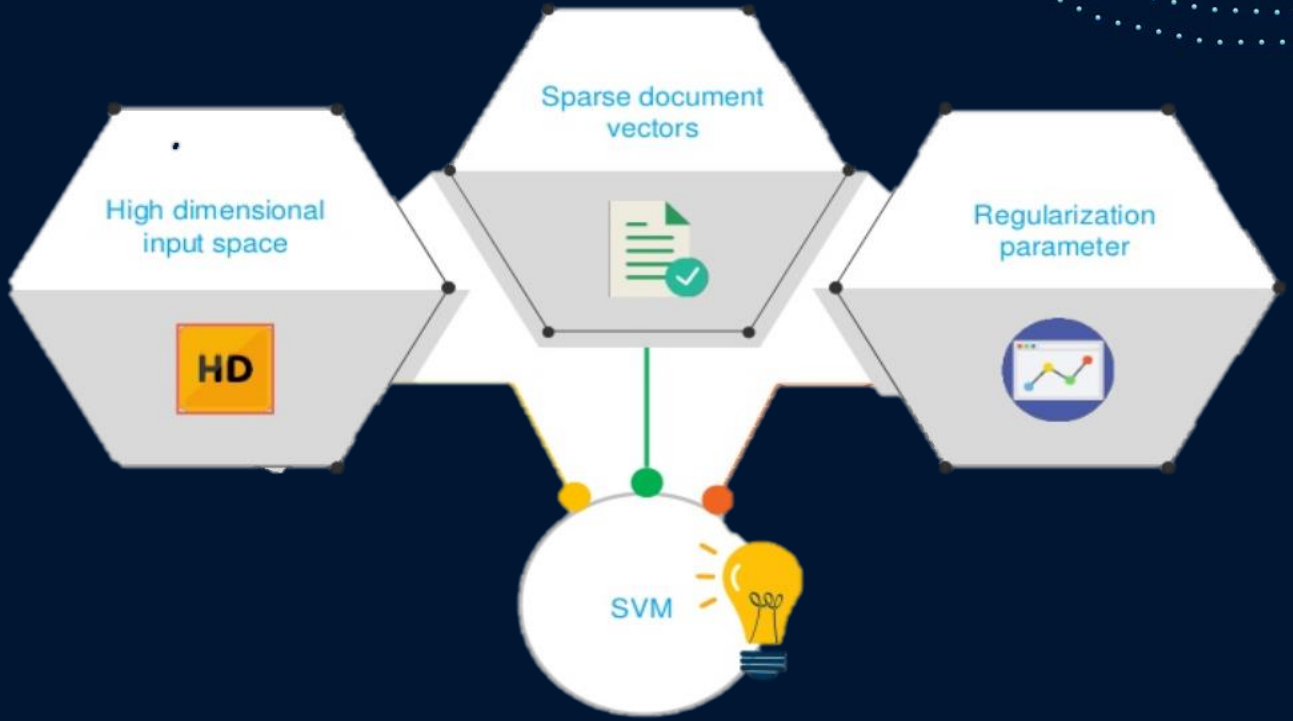


Understanding Support Vector Machine

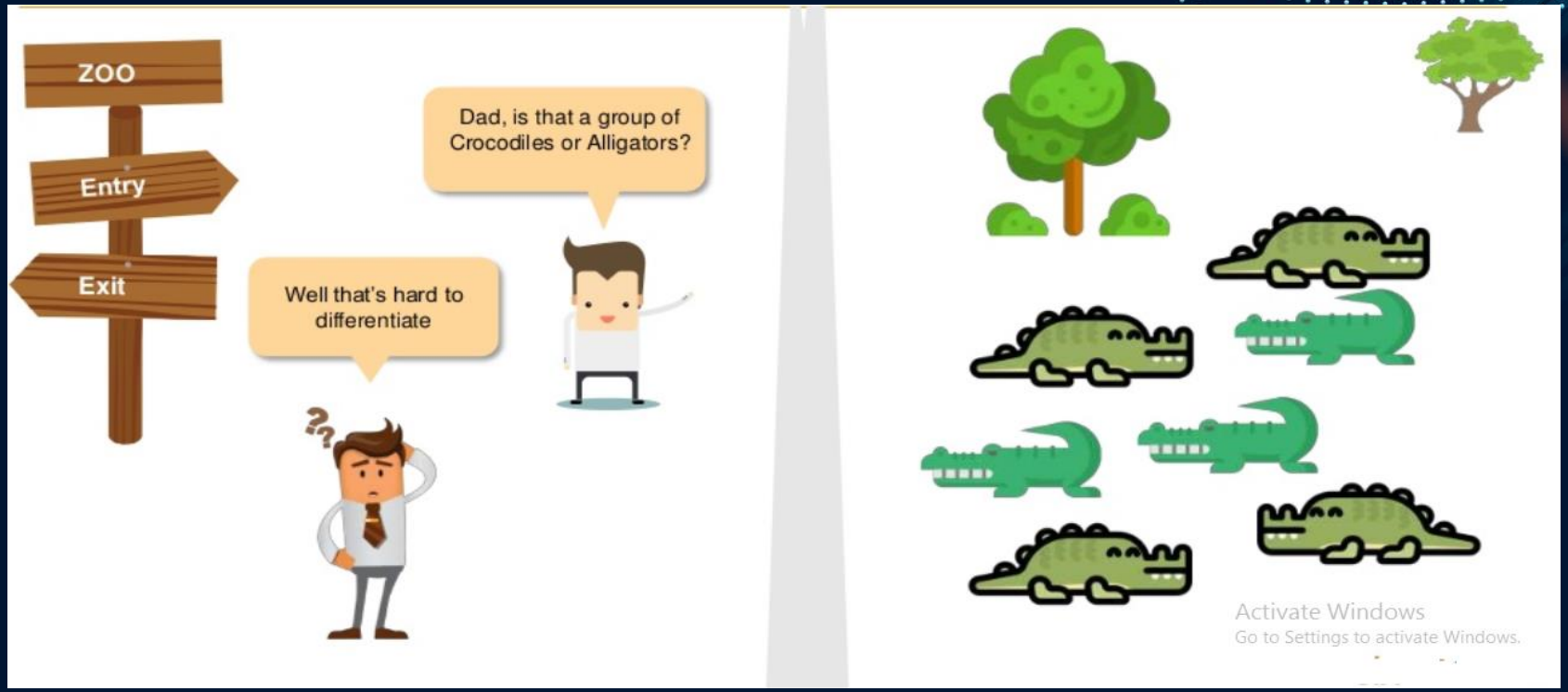




Advantages of Support Vector Machine

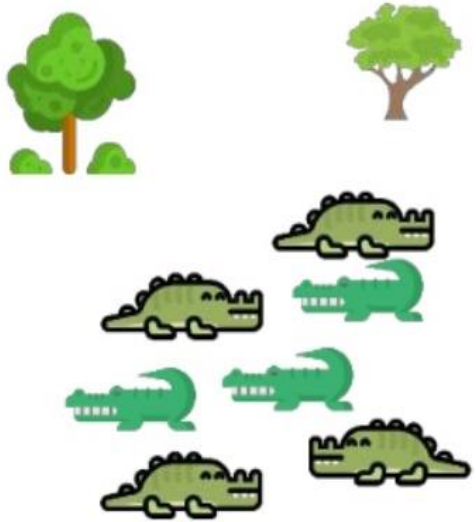


Use Case – Problem Statement

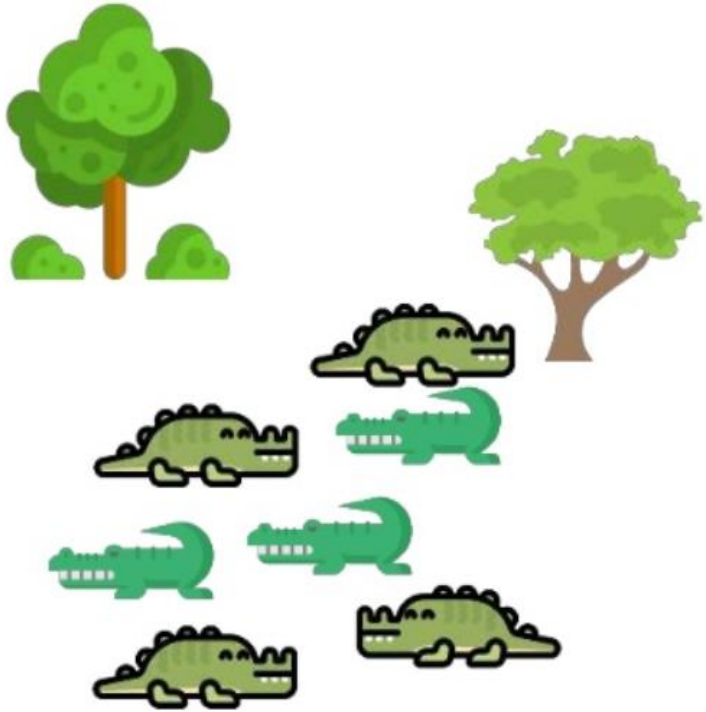


Use Case – Problem Statement

Difference		
		
Size	• Crocodiles are larger in size	• Alligators are smaller in size
Snout Width	• Crocodiles have narrow snout	• Alligators have wider snout



Use Case – Problem Statement



Support Vector Machine: Part 2

- The Support Vector Machine is a supervised learning algorithm mostly used for classification but it can be used also for regression.
- The main idea is that based on the labeled data (training data) the algorithm tries to find the optimal hyperplane which can be used to classify new data points.
- In two dimensions the hyperplane is a simple line.

Support Vector Machine: Part 2

- Usually a learning algorithm tries to learn the most common characteristics (what differentiates one class from another) of a class and the classification is based on those representative characteristics learnt (so classification is based on differences between classes).
- The SVM works in the other way around. It finds the most similar examples between classes. Those will be the support vectors.

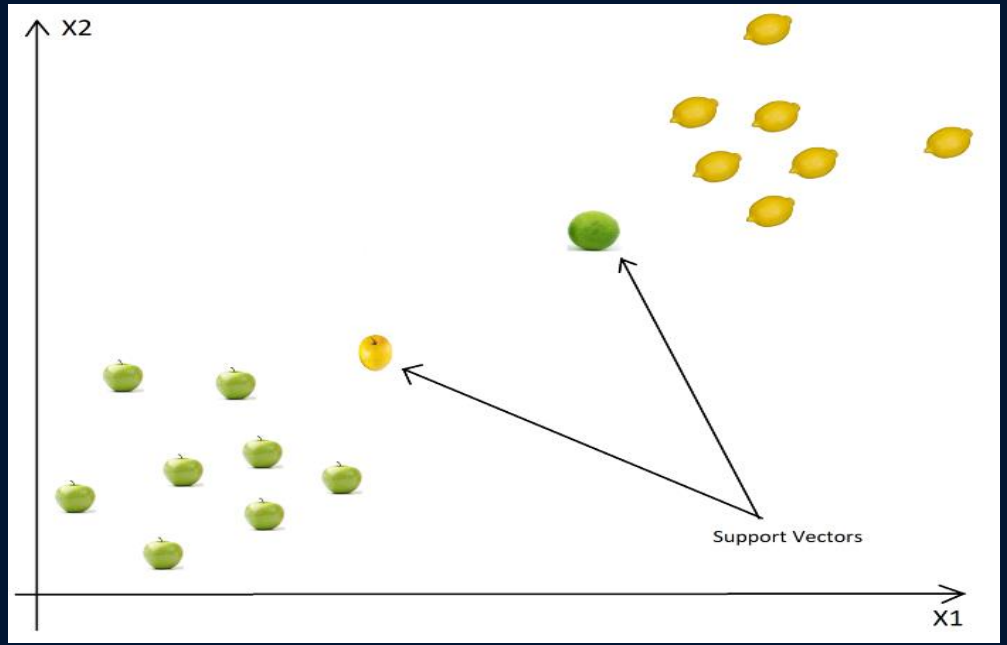
Support Vector Machine: Part 2

An example

- lets consider two classes, apples and lemons.
- Other algorithms will learn the most evident, most representative characteristics of apples and lemons, like apples are green and rounded while lemons are yellow and have elliptic form.
- In contrast, SVM will search for apples that are very similar to lemons, for example apples which are yellow and have elliptic form. This will be a support vector.
- The other support vector will be a lemon similar to an apple (green and rounded).
- So other algorithms learns the differences while SVM learns similarities.

Support Vector Machine: Part 2

Visualize the example above in 2D, we will have something like this:

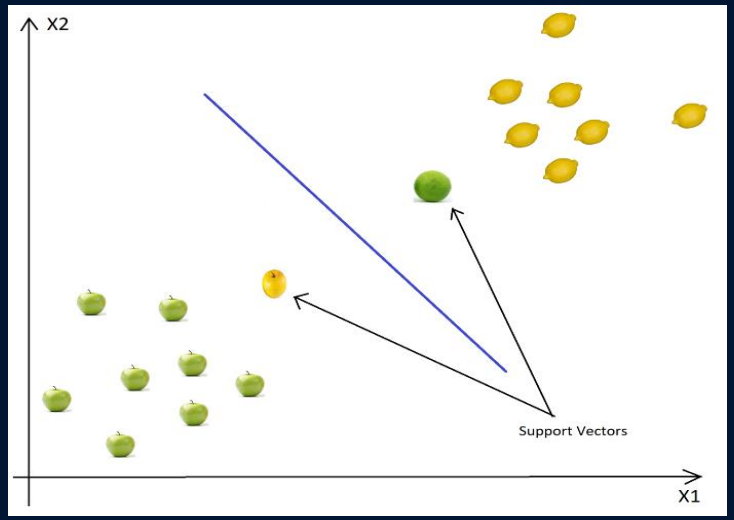


Support Vector Machine: Part 2

- As we go from left to right, all the examples will be classified as apples until we reach the yellow apple.
- From this point, the confidence that a new example is an apple drops while the lemon class confidence increases.
- When the lemon class confidence becomes greater than the apple class confidence, the new examples will be classified as lemons (somewhere between the yellow apple and the green lemon).

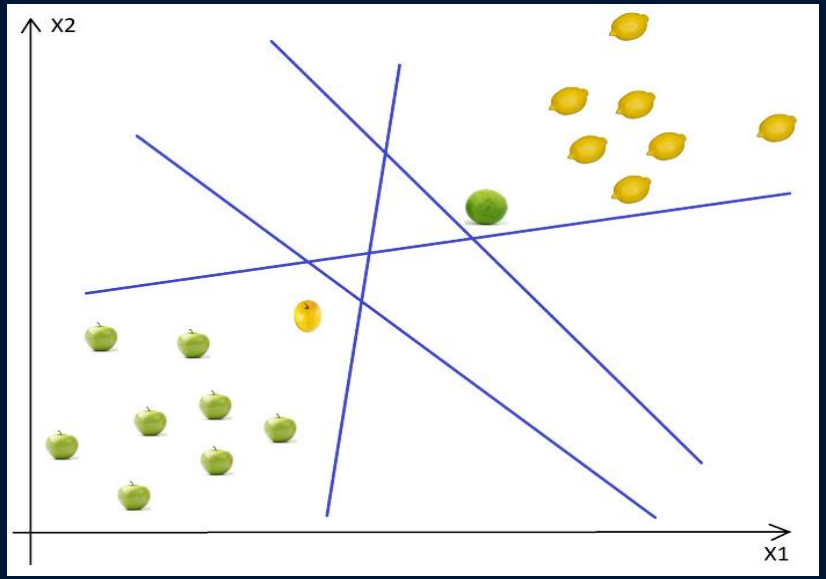
Support Vector Machine: Part 2

- Based on these support vectors, the algorithm tries to find the best hyperplane that separates the classes.
- In 2D the hyperplane is a line, so it would look like this:



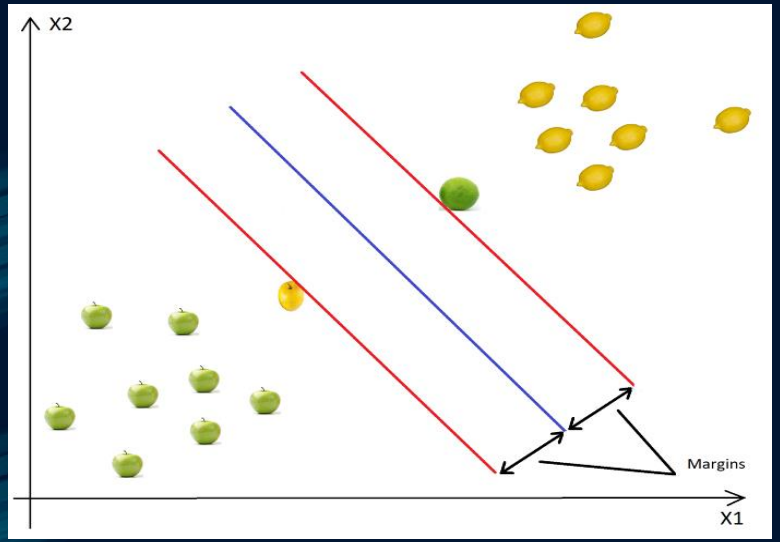
Support Vector Machine: Part 2

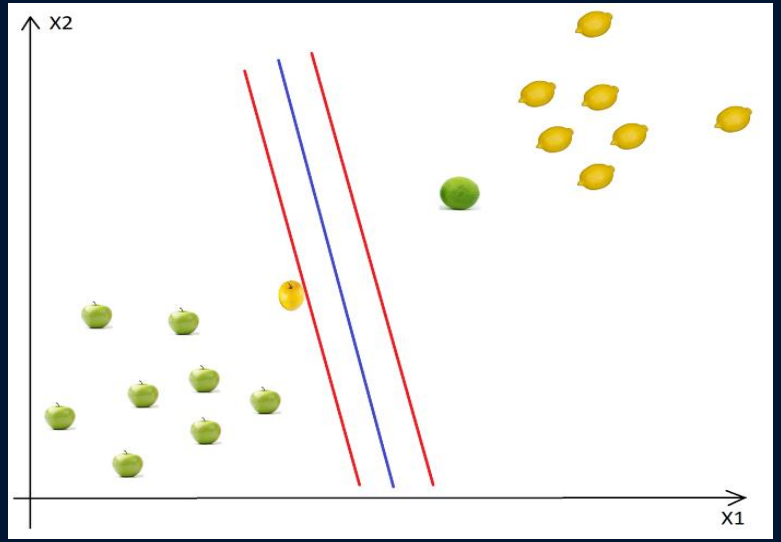
- why did I draw the blue boundary like in the picture above? I could also draw boundaries like this:



Support Vector Machine: Part 2

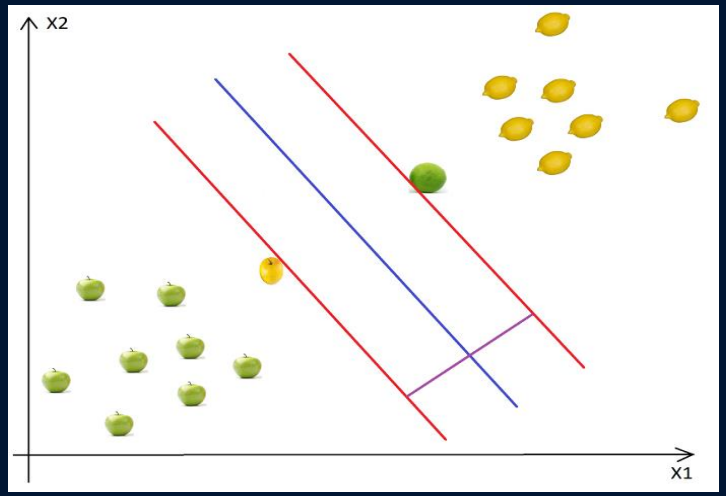
- if we compare the picture Left with the picture Right , we can easily observe, that the first is the optimal hyperplane (line) and the second is a sub-optimal solution, because the margin is far shorter.





Support Vector Machine: Part 2

- Because we want to maximize the margins taking in consideration all the classes, instead of using one margin for each class.
- we use a “global” margin, which takes in consideration all the classes. This margin would look like the purple line in the following picture:



Support Vector Machine: Part 2

- support vectors are data points that defines the position and the margin of the hyperplane.
- We call them “support” vectors, because these are the representative data points of the classes, if we move one of them, the position and/or the margin will change.
- Moving other data points won’t have effect over the margin or the position of the hyperplane.

Support Vector Machine: Part 2

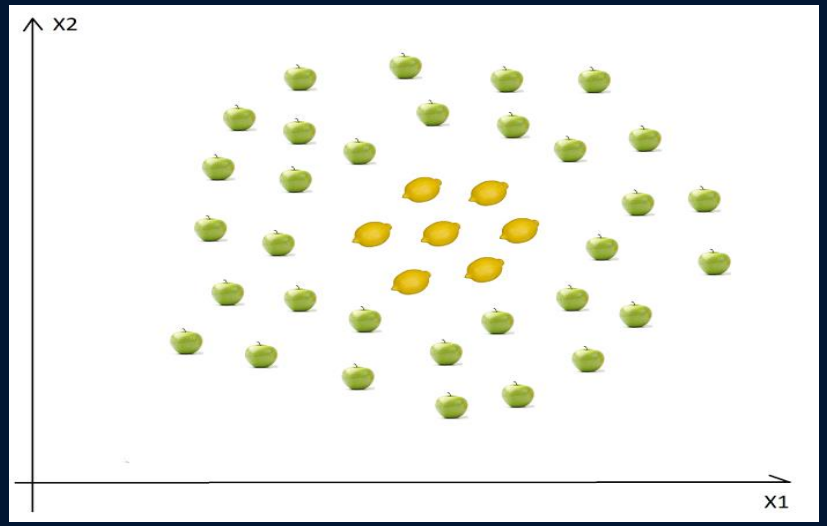
- The basic steps of the SVM are:
- select two hyperplanes (in 2D) which separates the data with no points between them (red lines)

- maximize their distance (the margin)

- the average line (here the line half way between the two red lines) will be the decision boundary

Support Vector Machine: Part 3

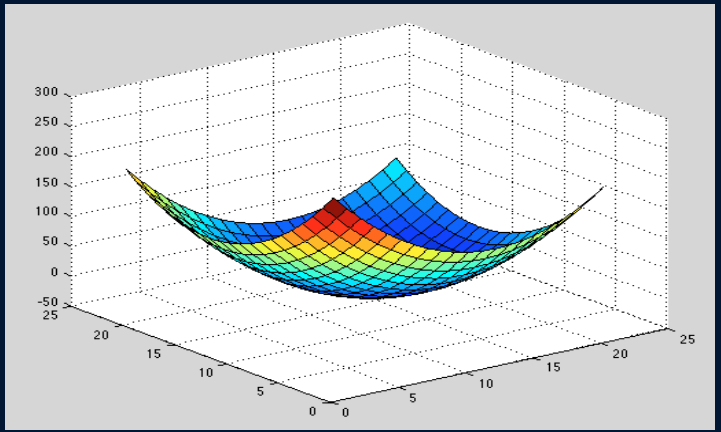
SVM for Non-Linear Data Sets



In this case we cannot find a straight line to separate apples from lemons. So how can we solve this problem. We will use the Kernel Trick!

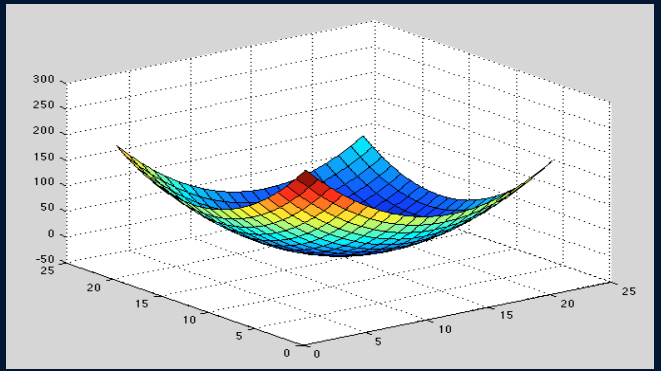
Support Vector Machine: Part 3

- Mapping from 2D to 3D
- let's assume that we add another dimension called X3. Another important transformation is that in the new dimension the points are organized using this formula $x1^2 + x2^2$.
- If we plot the plane defined by the $x^2 + y^2$ formula, we will get something like this:



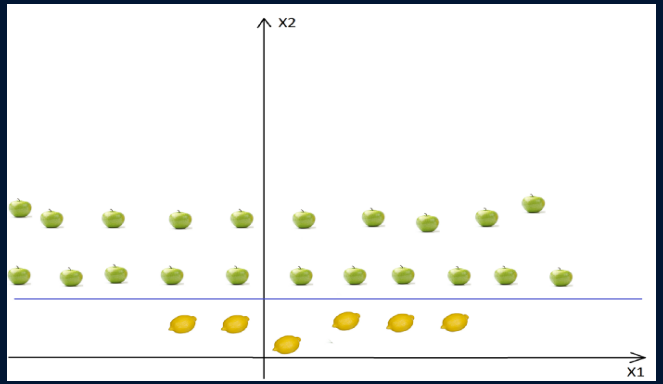
Support Vector Machine: Part 3

- Now we have to map the apples and lemons (which are just simple points) to this new space. Think about it carefully, what did we do? We just used a transformation in which we added levels based on distance.
- If you are in the origin, then the points will be on the lowest level. As we move away from the origin, it means that we are climbing the hill (moving from the center of the plane towards the margins) so the level of the points will be higher.



Support Vector Machine: Part 3

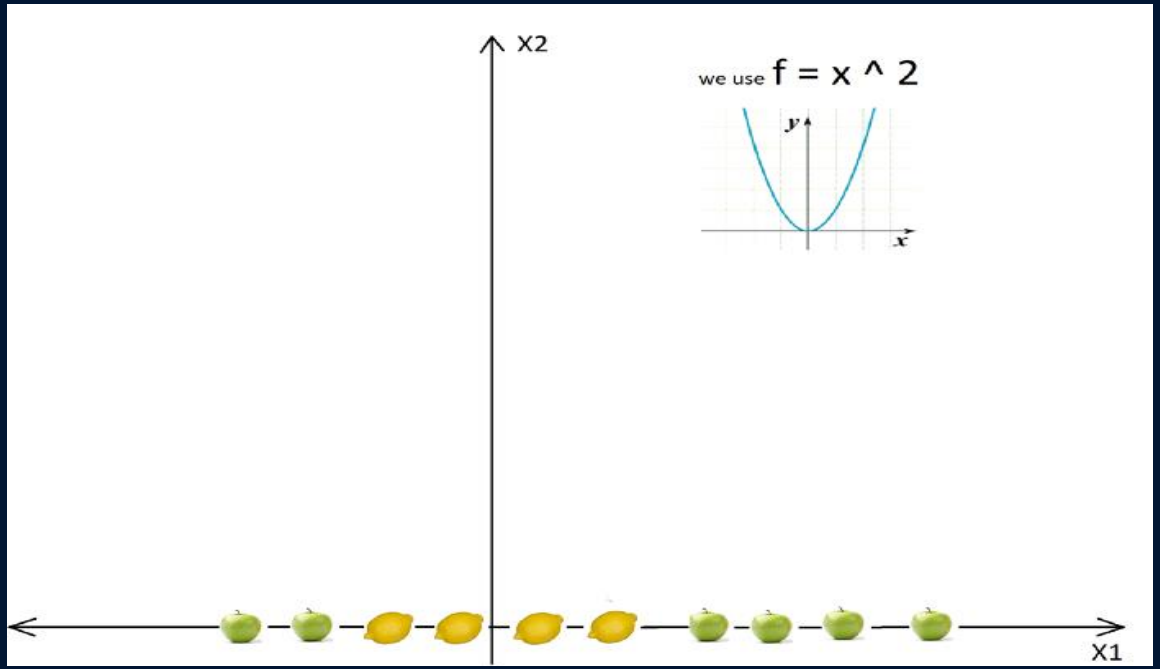
- Now if we consider that the origin is the lemon from the center, we will have something like this:



- Now we can easily separate the two classes. These transformations are called **kernels**. Popular kernels are: **Polynomial Kernel, Gaussian Kernel, Radial Basis Function (RBF), Laplace RBF Kernel, Sigmoid Kernel, Anove RBF Kernel**, etc.

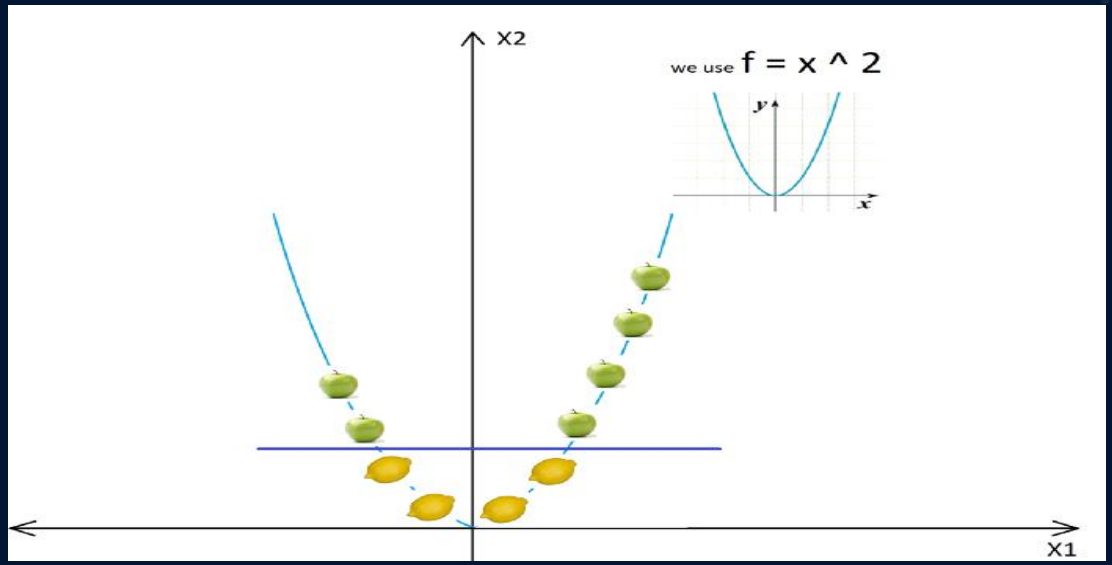
Support Vector Machine: Part 3

- Mapping from 1D to 2D
- Another, easier example in 2D would be:



Support Vector Machine: Part 3

After using the kernel and after all the transformations we will get:

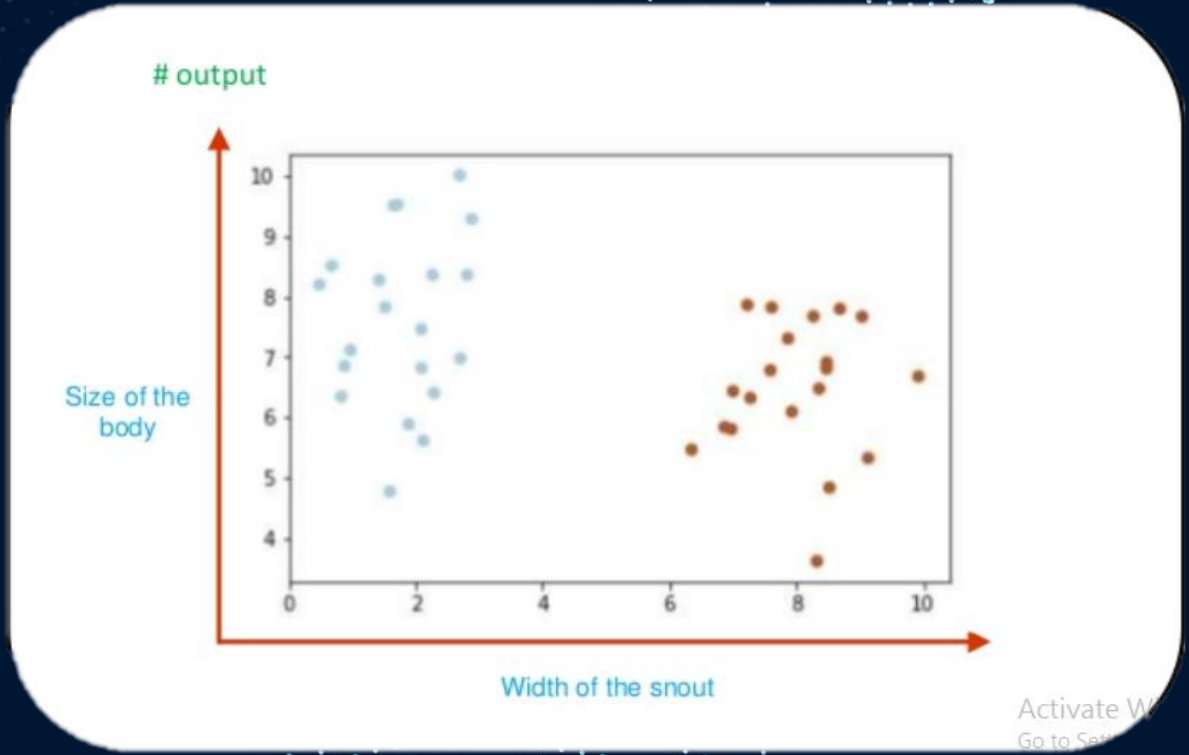


So after the transformation, we can easily delimit the two classes using just a single line

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.datasets.samples_generator import make_blobs
# we create 40 separable points
X, y = make_blobs(n_samples=40, centers=2, random_state=20)

# fit the model, don't regularize for illustration purposes
clf = svm.SVC(kernel='linear', C=1000)
clf.fit(X, y)

plt.scatter(X[:, 0], X[:, 1], c=y, s=30, cmap=plt.cm.Paired)
```



```
# fit the model, don't regularize for illustration purposes
clf = svm.SVC(kernel='linear', C=1000)
clf.fit(X, y)

plt.scatter(X[:, 0], X[:, 1], c=y, s=30,cmap=plt.cm.Paired)
plt.show

# plot the decision function
ax = plt.gca()
xlim = ax.get_xlim()
ylim = ax.get_ylim()

# create grid to evaluate model
xx = np.linspace(xlim[0], xlim[1], 30)
yy = np.linspace(ylim[0], ylim[1], 30)
YY, XX = np.meshgrid(yy, xx)
xy = np.vstack([XX.ravel(), YY.ravel()]).T
Z = clf.decision_function(xy).reshape(XX.shape)
```

Thank You!