MACHINE LEARNING
SVM
(Support Vector Machine)

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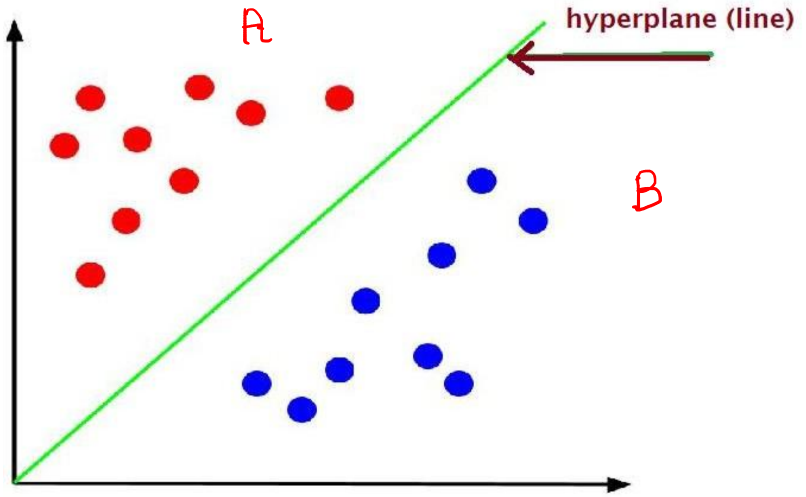
Overview

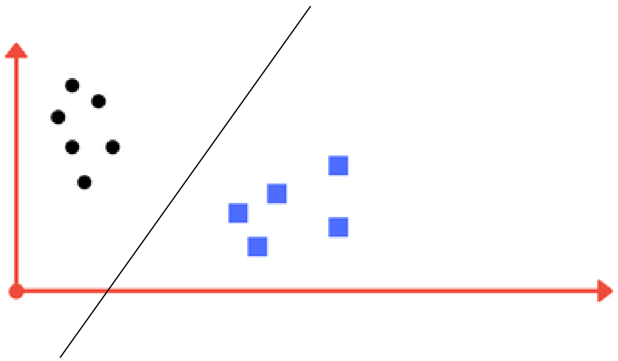
- It is a supervised machine learning algorithm that can be used for both **classification and regression**
- However, it is mostly used in **classification problems**
- The objective of the support vector machine algorithm is to find a **hyperplane** in an N-dimensional space(N — the number of features) that distinctly classifies the data points
- **Hyperplane**: A decision boundary separating different classes in feature space and is represented by the equation $\underset{\text{weight}}{w}\overset{i/p}{x} + \underset{\text{bias}}{b} = 0$ in linear classification.

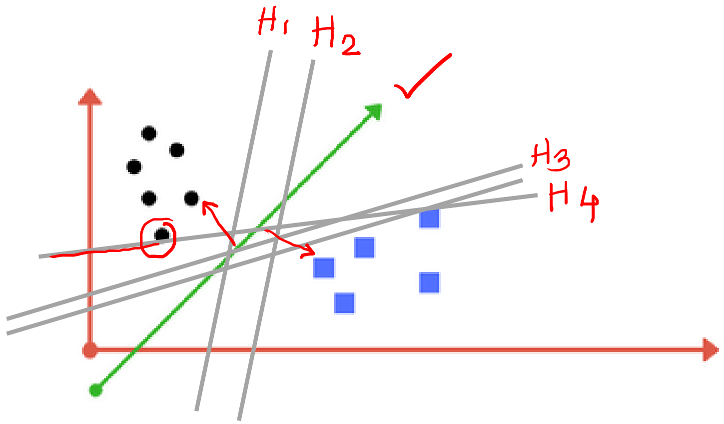


How does it work ?

- SVM separates the classes using hyperplane
- In two dimensional space this hyperplane is a line dividing a plane in two parts where in each class lay in either side
- To separate the two classes of data points, there are many possible hyperplanes that could be chosen
- Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes

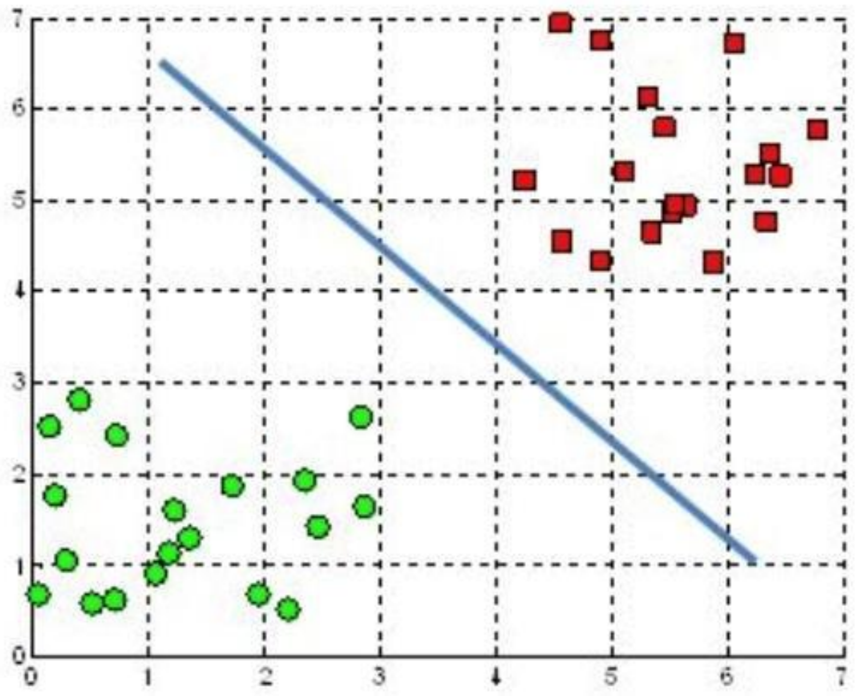
If hyperplane is chosen in this way



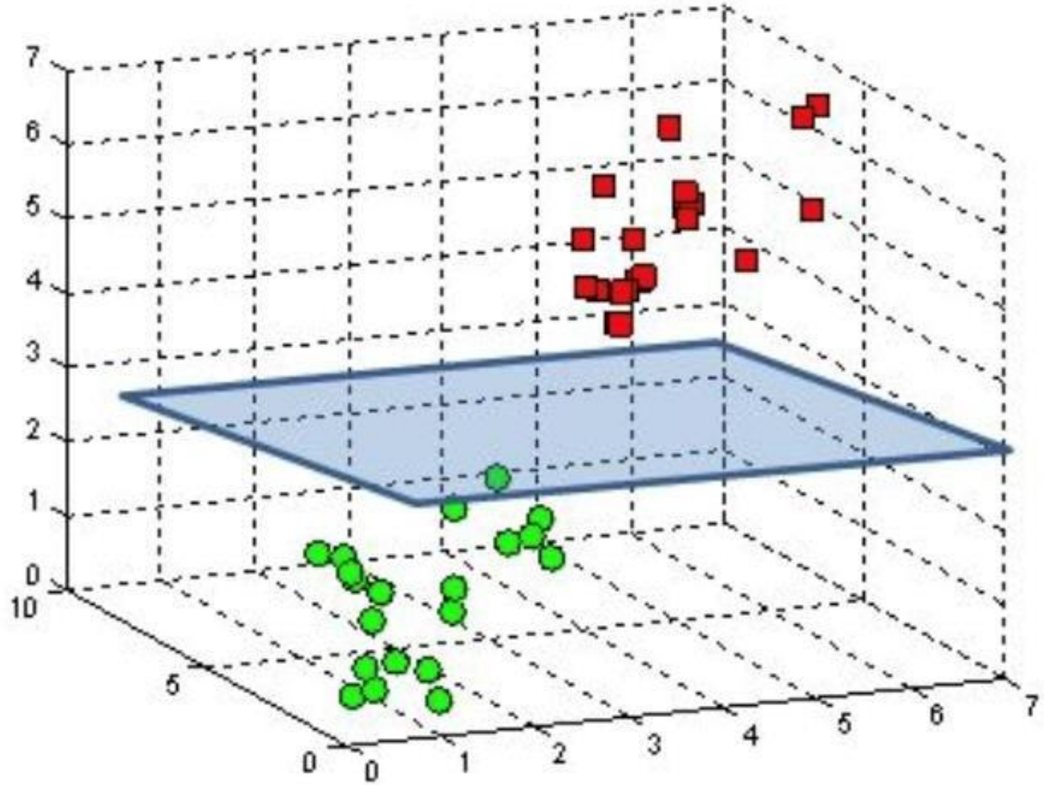


Hyperplane

A hyperplane in $\mathbb{R}^2$ is a line

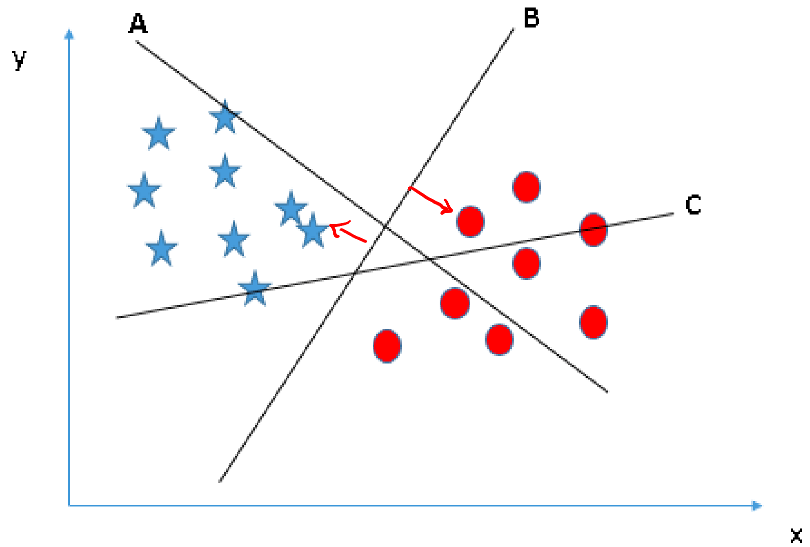


A hyperplane in $\mathbb{R}^3$ is a plane



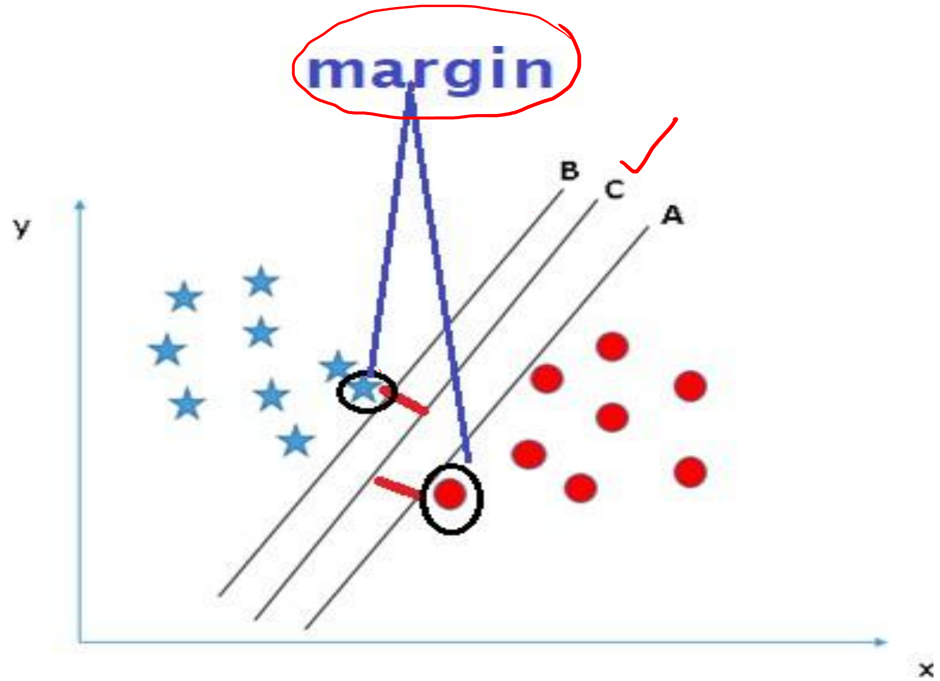
Scenario 1

- Here, we have three hyper-planes (A, B and C)
- Now, identify the right hyper-plane to classify star and circle
- You need to remember a thumb rule to identify the right hyper-plane
  1 - **Select the hyper-plane which segregates the two classes better (No mis-classification)**
2 - In this scenario, **hyper-plane "B" has excellently performed this job**



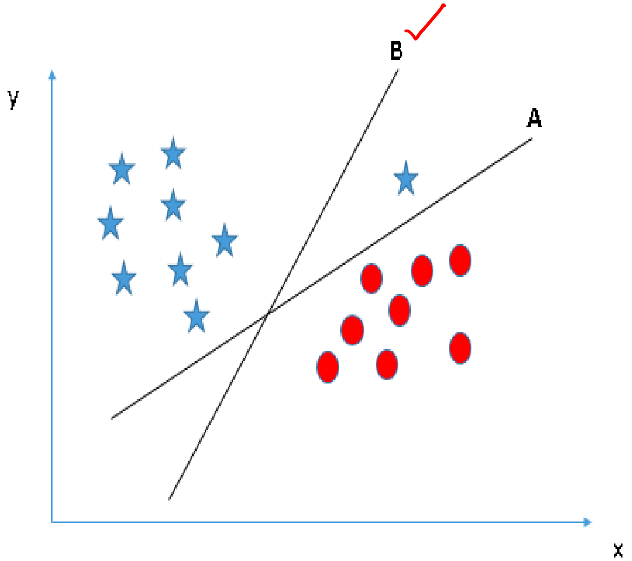
Scenario 2

- Here, we have three hyper-planes (A, B and C) and all are segregating the classes well
- Now, How can we identify the right hyper-plane? C
- Here, maximizing the distances between nearest data point (either class) and hyper-plane will help us to decide the right hyper-plane. This distance is called as **Margin.**

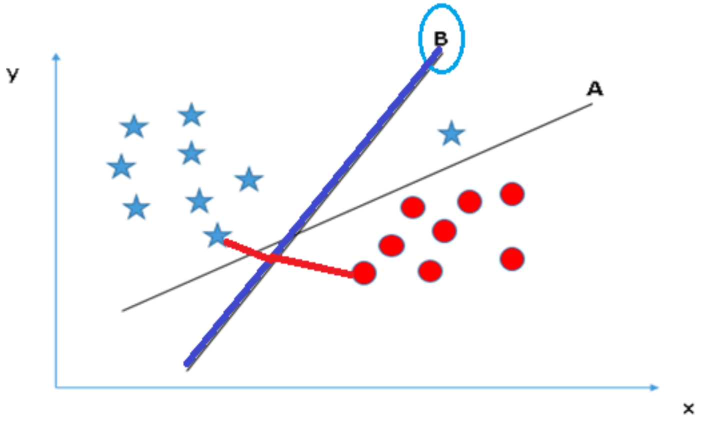


Scenario 3

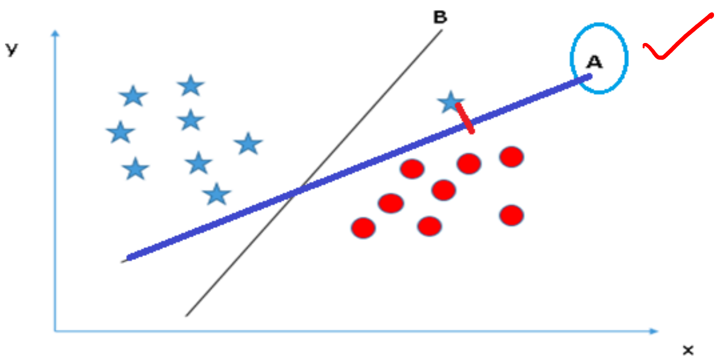
- Use the rules as discussed in previous section to identify the right hyper-plane
- Some of you may have selected the hyper-plane **B** as it has higher margin compared to **A.**
- But, SVM selects the hyper-plane which classifies the classes accurately prior to maximizing margin
- Here, hyper-plane B has a classification error and A has classified all correctly
- Therefore, the right hyper-plane is **A.** (no miss classification)



if,B is selected as hyperplane

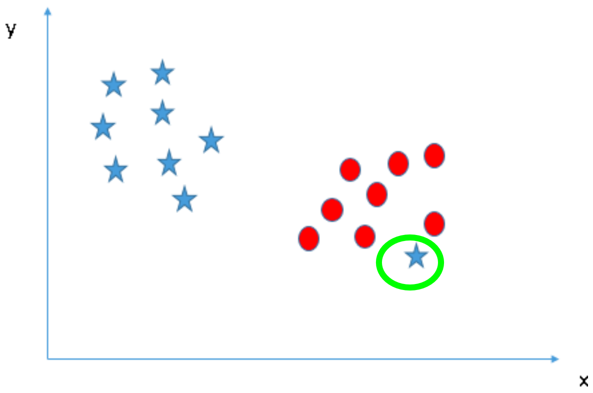


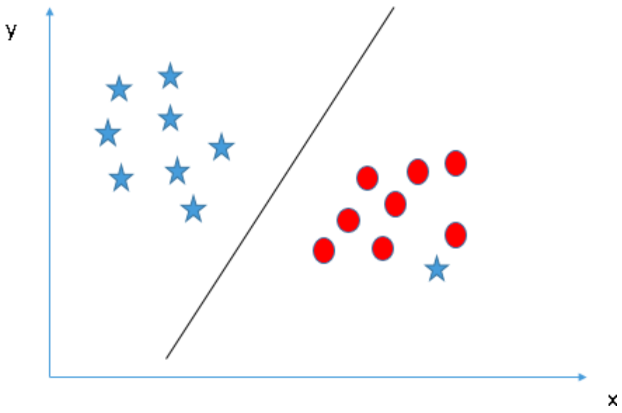
if, A is selected as hyperplane

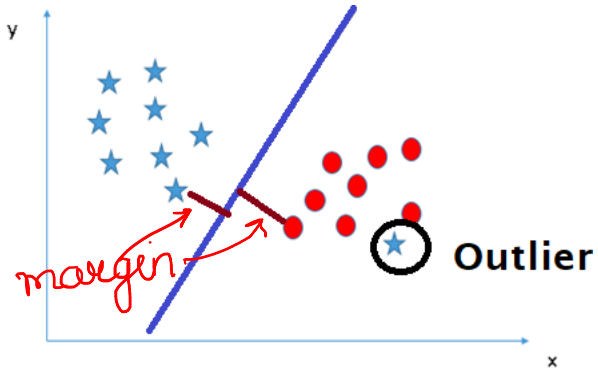


Scenario 4

- Unable to segregate the two classes using a straight line, as one of star lies in the territory of other(circle) class as an outlier
- SVM has a feature to ignore outliers and find the hyper-plane that has maximum margin.
- Hence, we can say, SVM is robust to **outliers.**





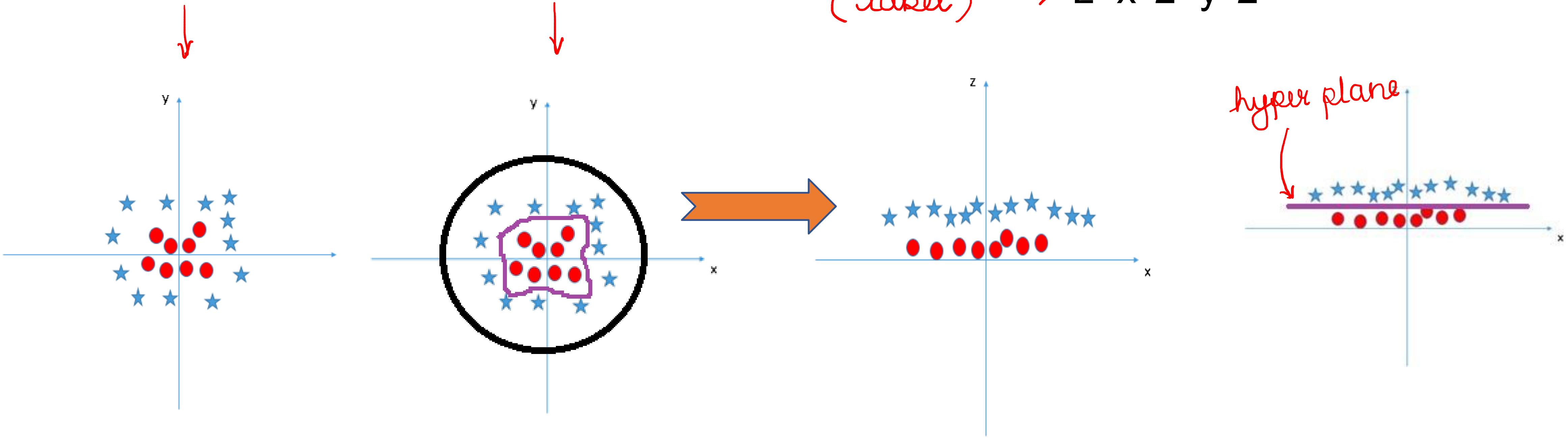


Scenario 5

- In the scenario below, we can't have linear hyper-plane between the two classes

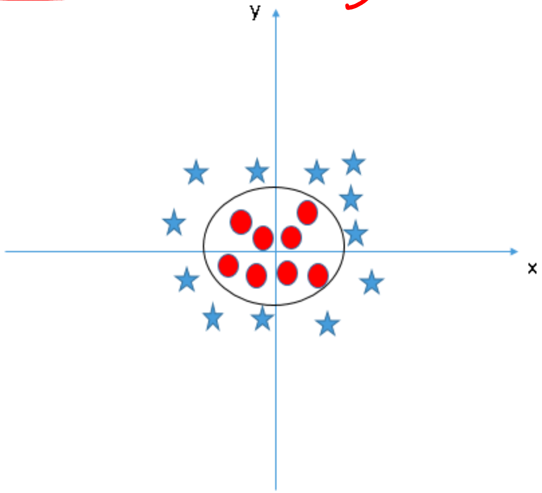
- SVM solves this problem by introducing **kernel**

(label) $z=x^2+y^2$



Scenario 5

- Points to consider are:
  $z = x^2 + y^2$
  - All values for z would be positive always because z is the squared sum of both x and y
  - In the original plot, red circles appear close to the origin of x and y axes, leading to lower value of z and star relatively away from the origin result to higher value of z.
- In SVM, it is easy to have a linear hyper-plane between these two classes, but for such scenarios, SVM uses a trick called as **Kernel**.
- These are functions which takes low dimensional input space and transform it to a higher dimensional space, i.e. it converts non separable problem to separable problem
- It is mostly useful in non-linear separation problem
- Simply put, it does some extremely complex data transformations, then find out the process to separate the data based on the labels or outputs you've defined.



Tuning Parameters - Kernels

- The learning of the hyperplane in linear SVM is done by transforming the problem using some linear algebra.
- This is where the kernel plays role.
- **Kernel**: A function that maps data to a higher-dimensional space enabling SVM to handle non-linearly separable data.

Hard Margin: A maximum-margin hyperplane that perfectly separates the data without misclassifications.

outlier

Soft Margin: Allows some misclassifications by introducing slack variables, balancing margin maximization and misclassification penalties when data is not perfectly separable.

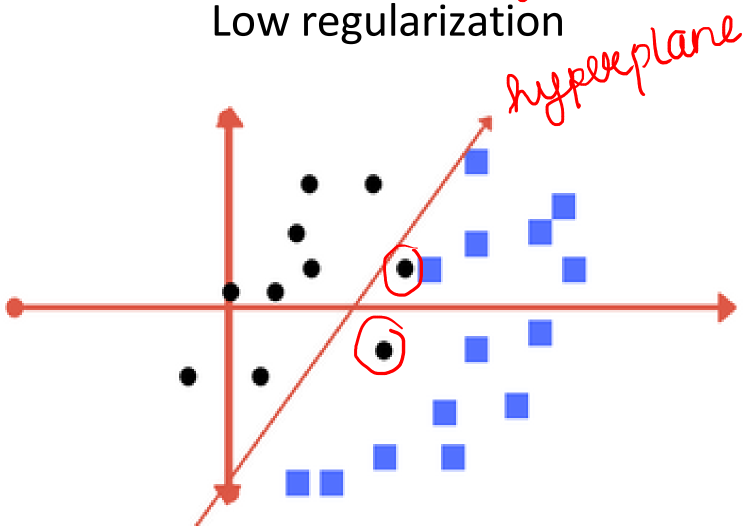
outlier

Tuning Parameters - Regularization

- The Regularization parameter tells the SVM optimization how much you want to avoid misclassifying each training example
- For large values of C, the optimization will choose a smaller-margin hyperplane if that hyperplane does a better job of getting all the training points classified correctly
- Conversely, a very small value of C will cause the optimizer to look for a larger-margin separating hyperplane, even if that hyperplane misclassifies more points

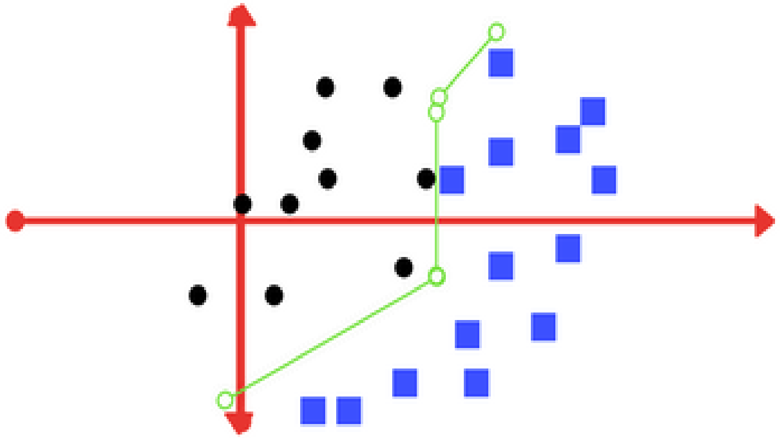
low value of C

Low regularization



large value of C

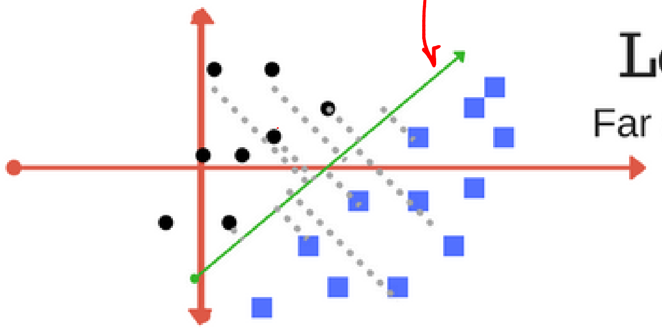
High regularization



Tuning Parameters - Gamma

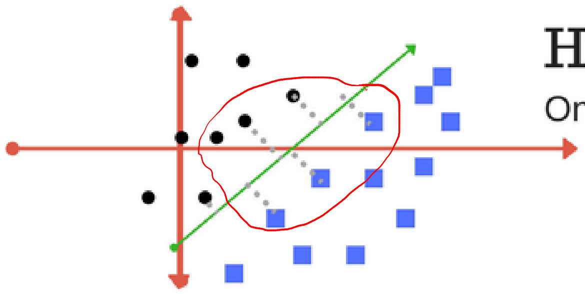
- The gamma parameter defines how far the influence of a single training example reaches, with low values meaning 'far' and high values meaning 'close'
- In other words
  - With low gamma, points far away from plausible separation line are considered in calculation for the separation line
  - Where as high gamma means the points close to plausible line are considered in calculation.

hyper plane



Low Gamma

Far away points are also considered.

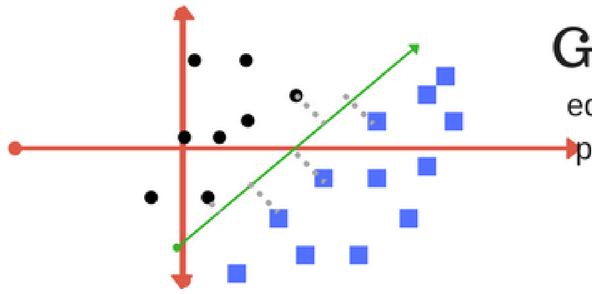


High Gamma

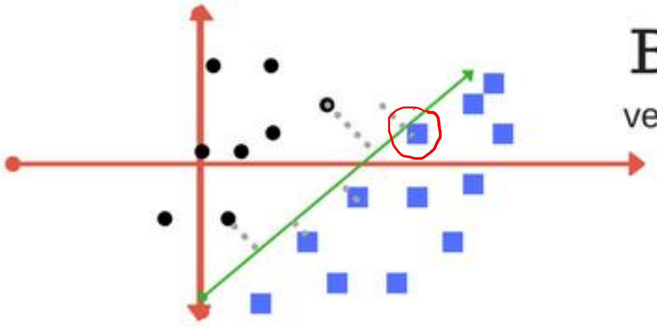
Only nearby points are considered.

Tuning Parameters - Margin

- A margin is a separation of line to the closest class points
- A good margin is one where this separation is larger for both the classes



Good margin
equidistant as as far as possible for both side.



Bad margin
very close to blue class.

Thank You!!