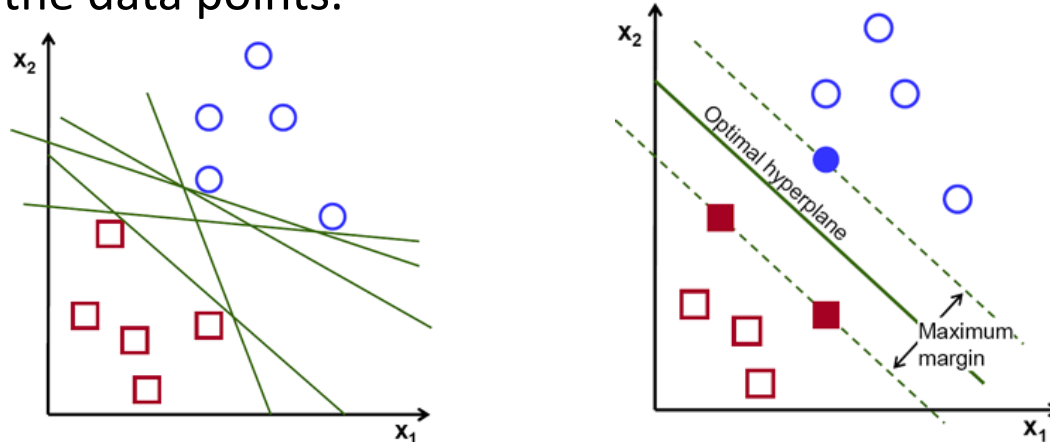


Support Vector Machine (SVM)

SVM

- “Support Vector Machine” (SVM) is a supervised [machine learning algorithm](#) which can be used for both classification or regression challenges.
- 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.

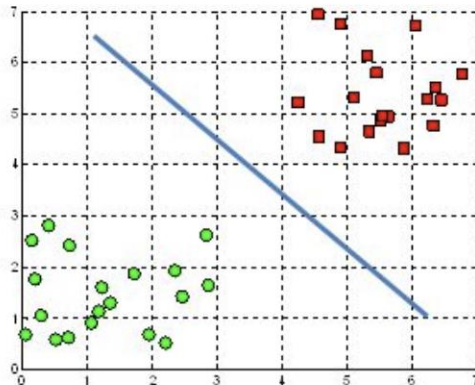


- To separate the two classes of data points, there are many possible hyperplanes that could be chosen.
- Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes.
- Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

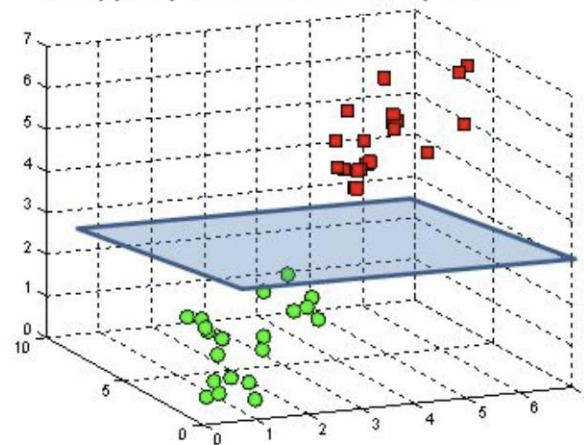
Hyperplanes and Support Vectors

- Hyperplanes are decision boundaries that help classify the data points.
- Data points falling on either side of the hyperplane can be attributed to different classes.
- Also, the dimension of the hyperplane depends upon the number of features.
- If the number of input features is 2, then the hyperplane is just a line.
- If the number of input features is 3, then the hyperplane becomes a two-dimensional plane.
- It becomes difficult to imagine when the number of features exceeds 3.

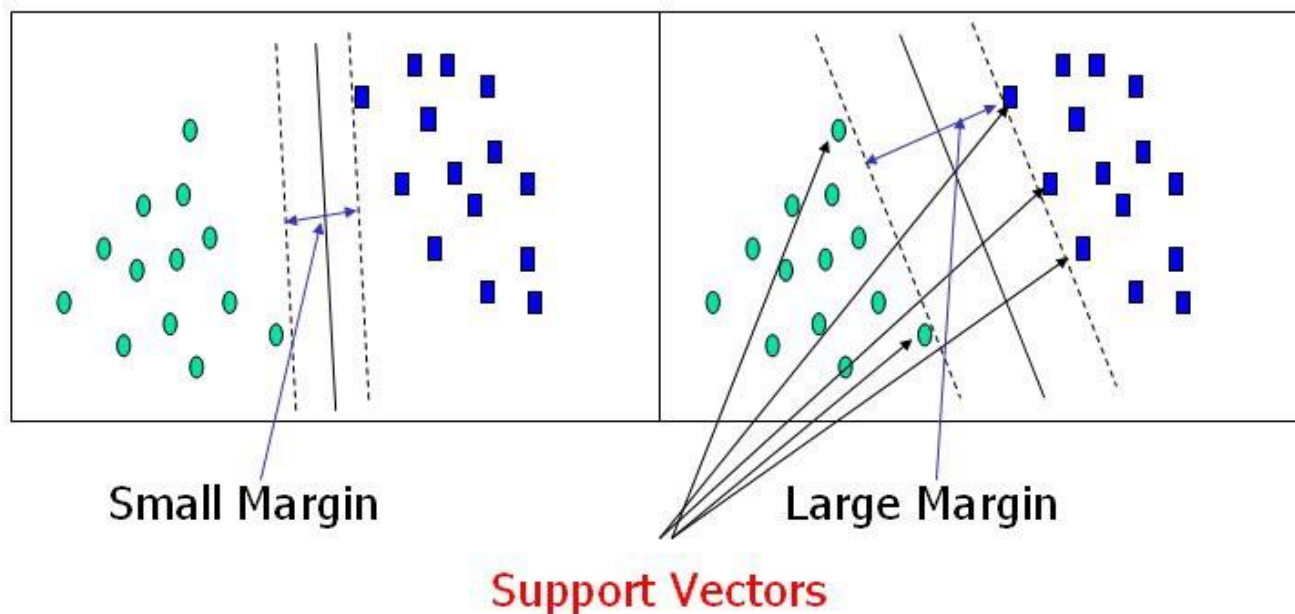
A hyperplane in \mathbb{R}^2 is a line



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

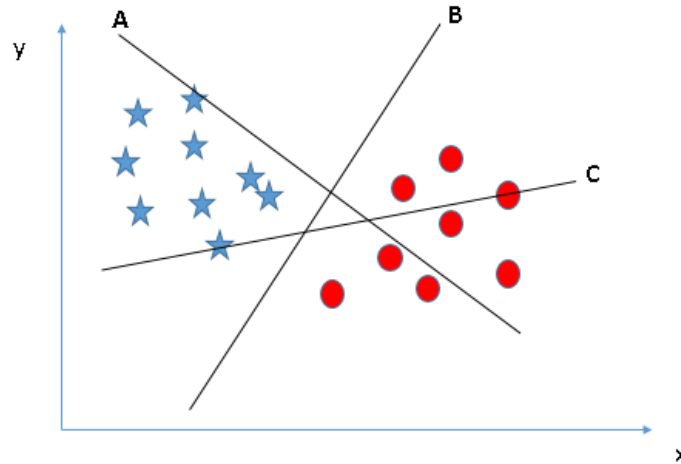


- Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane.
- Using these support vectors, we maximize the margin of the classifier.
- Deleting the support vectors will change the position of the hyperplane.
- These are the points that help us build our SVM.



How does it work?

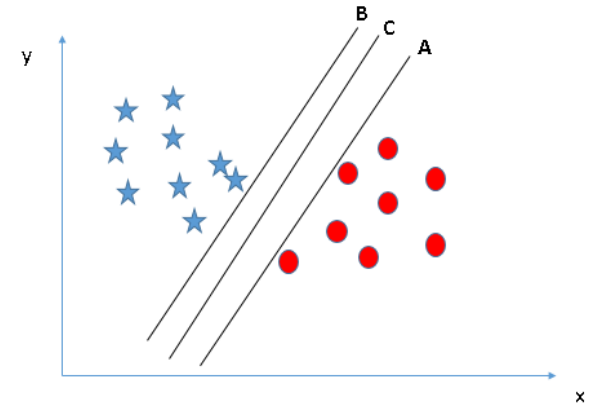
- **Identify the right hyper-plane (Scenario-1):**
 - Here, we have three hyper-planes (A, B and C). Now, identify the right hyper-plane to classify star and circle.



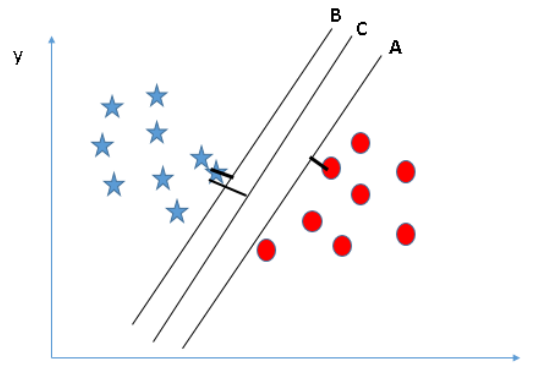
- You need to remember a thumb rule to identify the right hyper-plane: “Select the hyper-plane which segregates the two classes better”. In this scenario, hyper-plane “B” has excellently performed this job.

- **Identify the right hyper-plane (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?

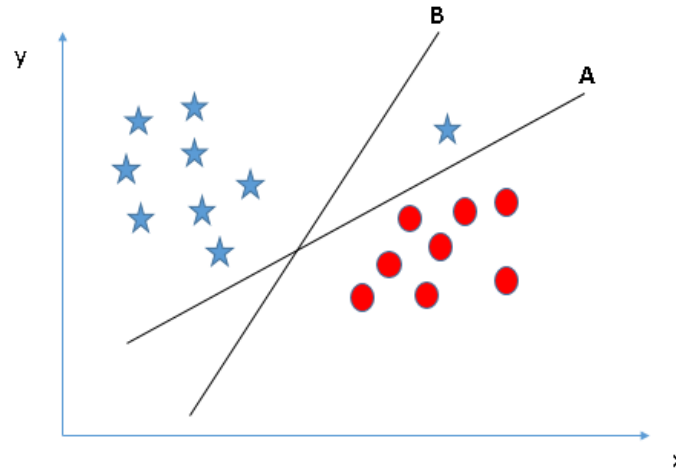


- Here, maximizing the distances between nearest data point (either class) and hyper-plane will help us to decide the right hyper-plane. This distance is called as **Margin**. Let's look at the below snapshot:



- Above, you can see that the margin for hyper-plane C is high as compared to both A and B. Hence, we name the right hyper-plane as C. Another lightning reason for selecting the hyper-plane with higher margin is robustness. If we select a hyper-plane having low margin then there is high chance of miss-classification.

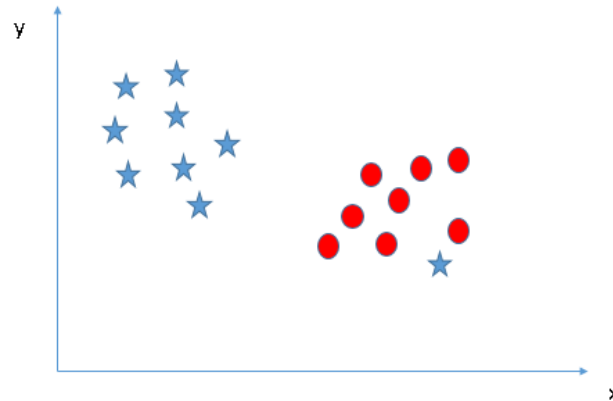
- **Identify the right hyper-plane (Scenario-3):**
 - Hint: Use the rules as discussed in previous section to identify the right hyper-plane.



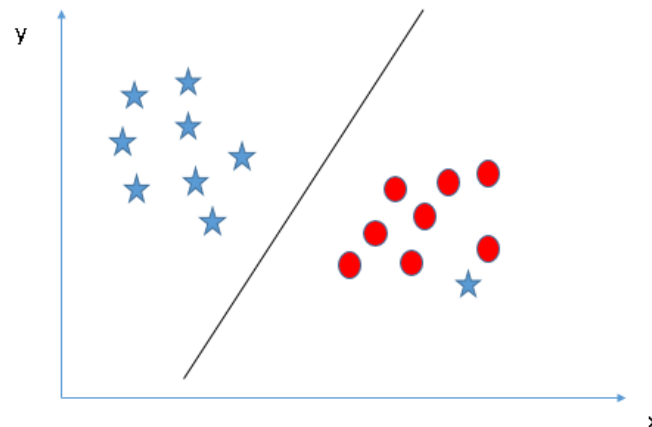
- Some of you may have selected the hyper-plane **B** as it has higher margin compared to **A**. But, here is the catch, SVM selects the hyper-plane which classifies the classes accurately prior to maximizing margin. Here, hyper-plane B has a classification error and A has classified all correctly. Therefore, the right hyper-plane is **A**.

- **Can we classify two classes (Scenario-4)?:**

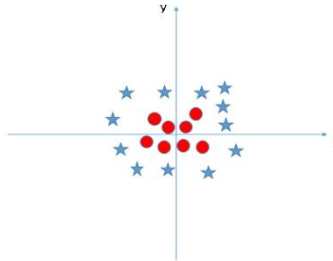
- Below, I am unable to segregate the two classes using a straight line, as one of the stars lies in the territory of other(circle) class as an outlier.



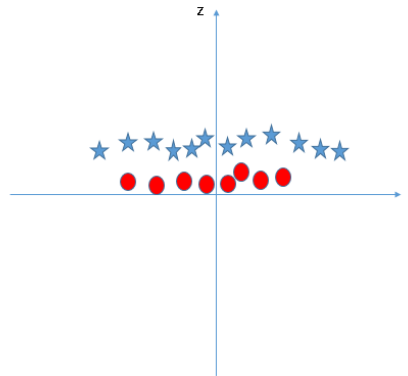
- As I have already mentioned, one star at other end is like an outlier for star class. The SVM algorithm has a feature to ignore outliers and find the hyper-plane that has the maximum margin. Hence, we can say, SVM classification is robust to outliers.



- **Find the hyper-plane to segregate to classes (Scenario-5):**
 - In the scenario below, we can't have linear hyper-plane between the two classes, so how does SVM classify these two classes? Till now, we have only looked at the linear hyper-plane.



- SVM can solve this problem. Easily! It solves this problem by introducing additional feature. Here, we will add a new feature $z = x^2 + y^2$. Now, let's plot the data points on axis x and z:



- In above plot, points to consider are:
 - 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 the SVM classifier, it is easy to have a linear hyper-plane between these two classes.
- But, another burning question which arises is, should we need to add this feature manually to have a hyper-plane.
- No, the SVM algorithm has a technique called the [kernel](#) trick.
- The SVM kernel is a function that takes low dimensional input space and transforms it to a higher dimensional space i.e. it converts not separable problem to separable problem.
- It is mostly useful in non-linear separation problem.
- Different Kernels in SVM:
 - Linear
 - Polynomial
 - Radial Basis Function
- Simply put, it does some extremely complex data transformations, then finds out the process to separate the data based on the labels or outputs you've defined.

Program: implement SVM on iris
dataset

Thanks