AI200: APPLIED MACHINE LEARNING

SUPPORT VECTOR MACHINE (SVM)

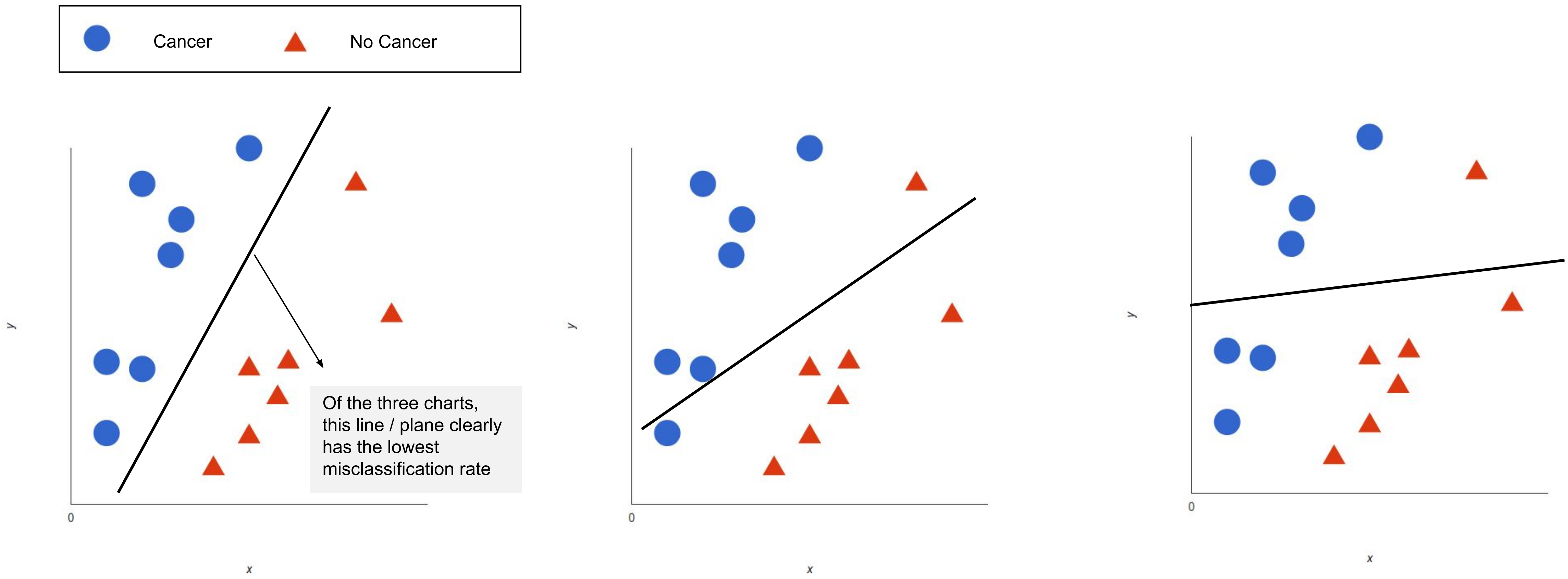
OVERVIEW & LITERATURE OF MACHINE LEARNING

Machine Learning

1. Spectrum of supervision	Supervised Learning		Unsupervised Learning			Reinforcement Learning
2. Types of problems	Regression	Classification	Clustering	Association	Dimensionality Reduction	
3. Types of algorithm / models	Linear regression Polynomial regression Neural Networks Decision Tree Random Forest XGBoost	Logistic Regression KNN Naïve Bayes SVM Neural Networks Decision Tree Random Forest XGBoost	Neural Networks K-Means Hierarchical Clustering Hidden Markov Models Gaussian Mixture	Apriori Algorithm FP-Growth Algorithm Eclat Algorithm	Neural Networks SVD PCA	
4. Types of applications	Forecasting Predictions Process optimization New Insights	Fraud Detection Image Classification Customer Retention Diagnostics	Recommendations Targeted Marketing Customer Segmentation	Market Basket Analysis	Feature Elicitation Structure Discovery Meaningful Compression Big Data Visualisation	Real-time Decisions Game AI Learning Tasks Skill Acquisition Robot Navigation

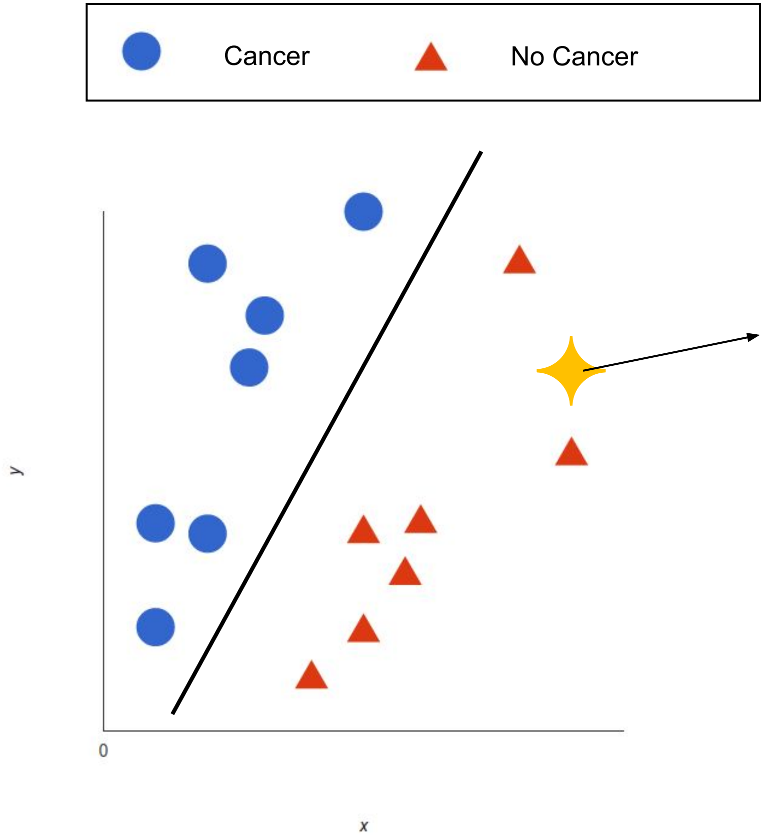
WHAT IS SVM: LAYMAN INTUITION

- The idea behind Support Vector Machine is:
  - We iteratively draw a line / plane and calculate the misclassification rate in each instance
  - The line / plane that has the low misclassification rate is chosen to serve as the classifier



WHAT IS SVM: LAYMAN INTUITION

- The idea behind Support Vector Machine is:
    - When we need to classify the new data point, we just need to see which side of the classifier this data falls on



This new data point is classified as “No Cancer” as it falls on the other side of the SVM classifier.

WHY SHOULD YOU LEARN SVM?

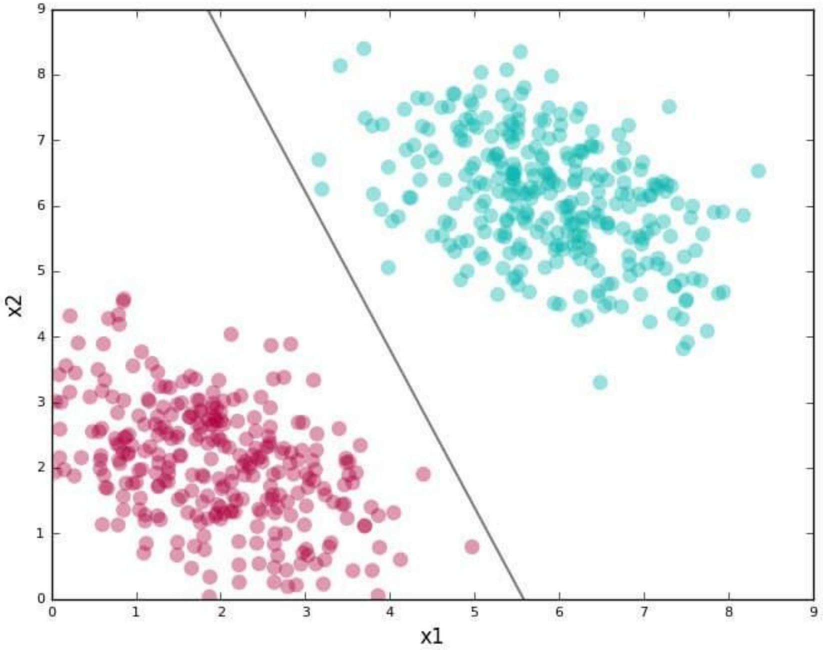
- SVM is a very powerful model that deals well even with non-linear data
- Can be used for both classification and regression problems
- SVM scales well to high dimensional data
- It sounds impressive ☺

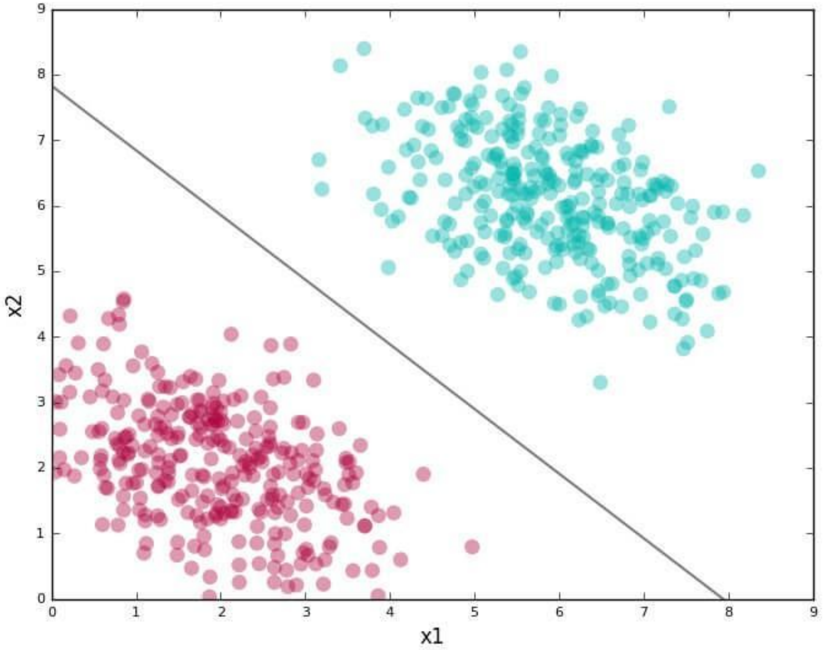
SUPPORT VECTOR MACHINES (SVM)

MECHANISM BEHIND MODEL

MECHANISM BEHIND MODEL: SUPPORT VECTORS

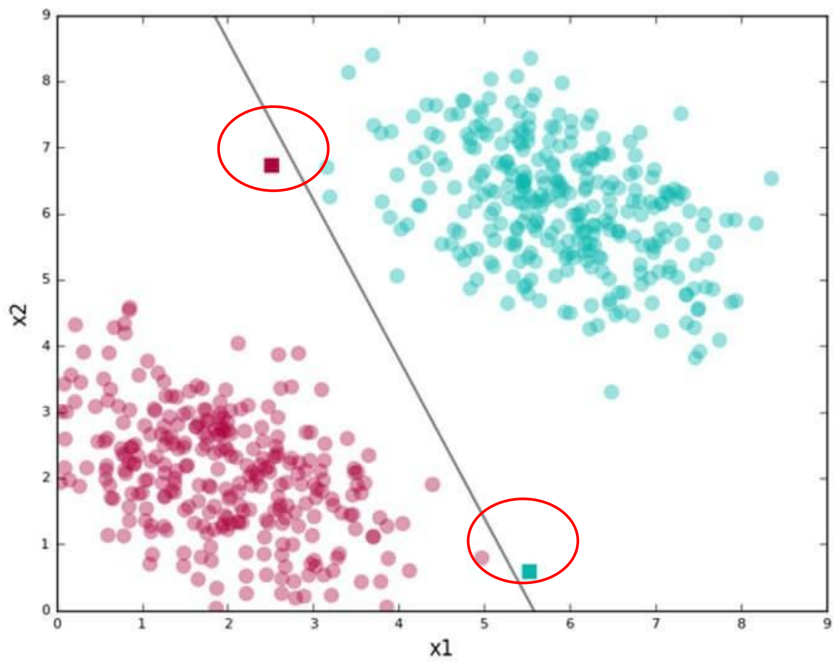
- But surely there are many ways to draw a line/plane such we can perfectly classify our training data?
- In the image below, both lines separate the red and green clusters. Is there a good reason to choose one over another?

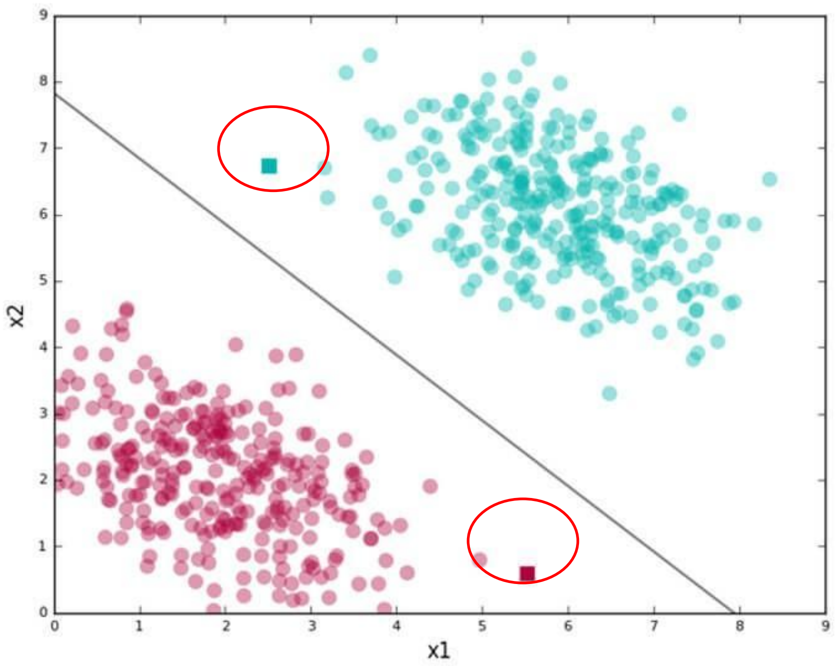




MECHANISM BEHIND MODEL: SUPPORT VECTORS

- Remember that the worth of a classifier is not in how well it separates the training data. We eventually want it to classify yet-unseen data points. As such, we want to choose a line that captures the general pattern in the training data, so that it does well on the test data.
- The first line is a bit skewed. Its lower half runs too close to the red cluster, and in its upper half it runs too close to the green cluster. If it sees a test point that's a little farther out from the clusters, it will likely get the label wrong.
- The second line maximizes distance from both the clusters while getting the training data separation right. By being right in the middle of the two clusters, it gives the data distributions for each class some wiggle room so to speak, and thus generalizes well on test data.





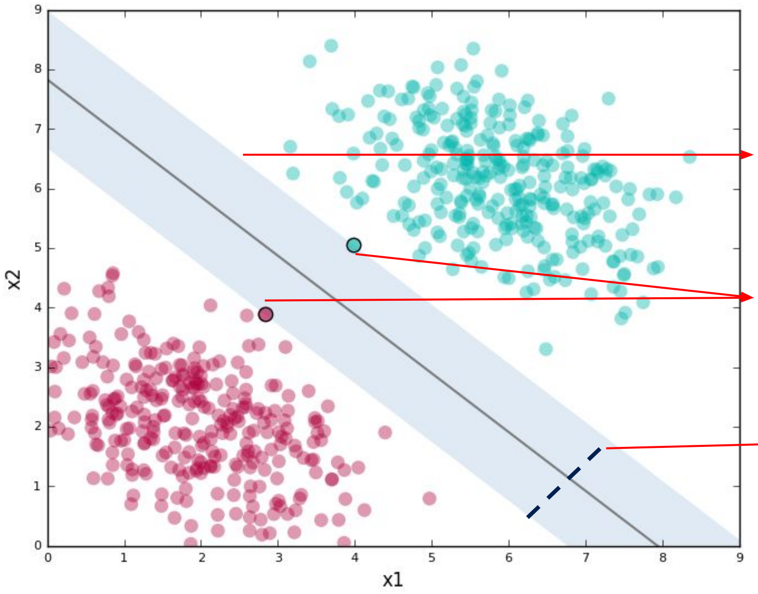
MECHANISM BEHIND MODEL: SUPPORT VECTORS

- SVMs try to find the second kind of line. We selected the better classifier visually, but we need to define the underlying philosophy a bit more precisely to apply it in the general case. Here's a simplified version of what SVMs do:

    1. Find lines that correctly classify the training data
    2. Among all such lines, pick the one that has the greatest distance to the points closest to it.

- The closest points that identify this line are known as support vectors. And the region they define around the line is known as the margin.

- Here's the second line shown with the support vectors: points with black edges (there are two of them) and the margin (the shaded region).



Lines which is adjacent to the support vectors

These points are known as **support vectors**

The distance between 2 margins are known as **maximum margin**

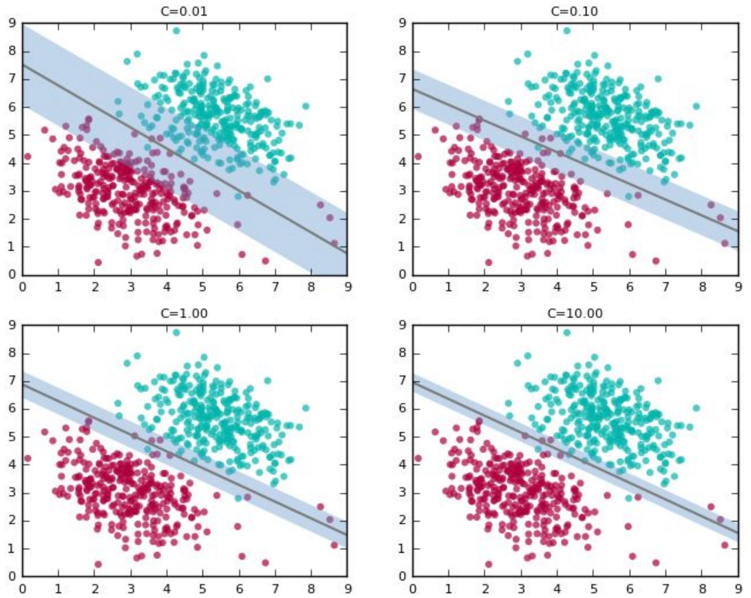
MECHANISM BEHIND MODEL: C VALUE

- Earlier, we looked at the easy case of perfectly linearly separable data. However real-world data is typically messy. You will almost always have a few instances that a linear classifier can't get right.

- Clearly, if we are using a linear classifier, we are never going to be able to perfectly separate the labels. How do SVMs deal with this:

- They allow you to specify how many errors you are willing to accept. You can provide a parameter called "C" to your SVM; this allows you to dictate the tradeoff between:
  1. Having a wide margin.
  2. Correctly classifying training data. A higher value of C implies you want lesser errors on the training data.

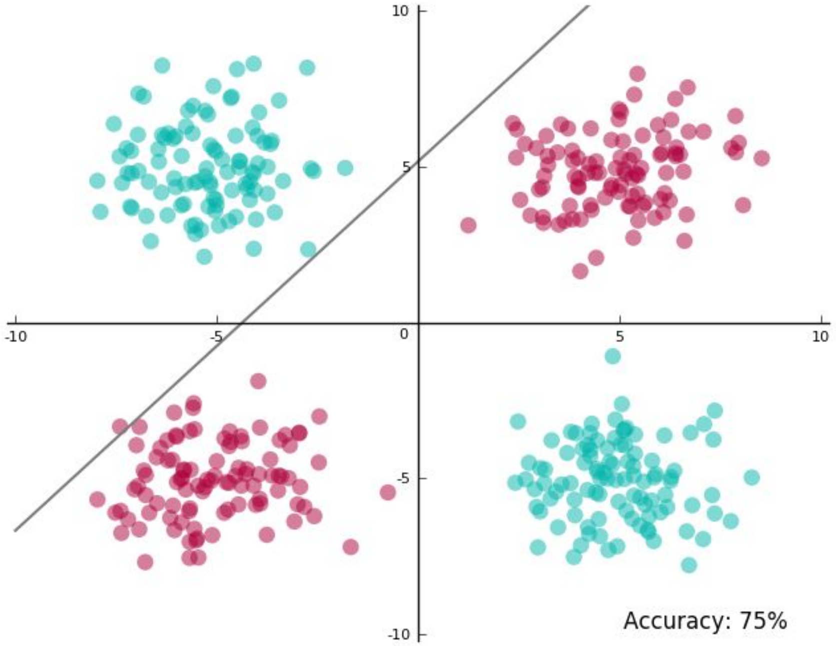
- It bears repeating that this is a tradeoff. You get better classification of training data at the expense of a wide margin.



The following plots show how the classifier and the margin vary as we increase the value of C. We will explore this through code and Sklearn later on.

MECHANISM BEHIND MODEL: KERNEL TRICK

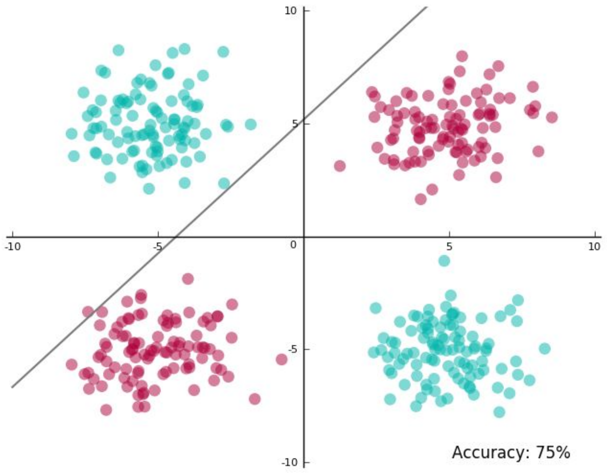
- Now what if your data is non-linear like our image below?
  - We can essentially apply kernel trick. This involves applying mathematical functions such as polynomial functions to elevate the data to a higher dimensionality where it becomes easier to draw the plane
  - There are many kernel types, but these are the popular ones:
    - Polynomial Kernel
    - Radial Basis Function Kernel
    - Sigmoid Kernel



Here you can see that no matter how we cut the data points, we are always going to end up with very high misclassification rates

MECHANISM BEHIND MODEL: KERNEL TRICK

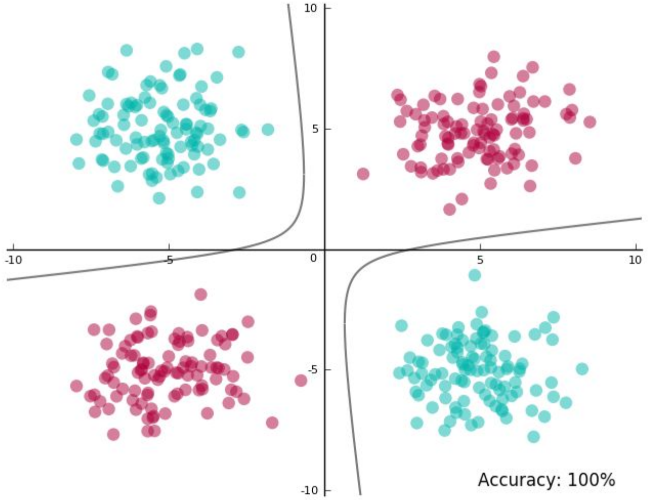
- Let's apply kernel trick to our data!



Apply kernel trick to elevate the data to a high dimensionality

Now do you see a space where you can slip a plane?

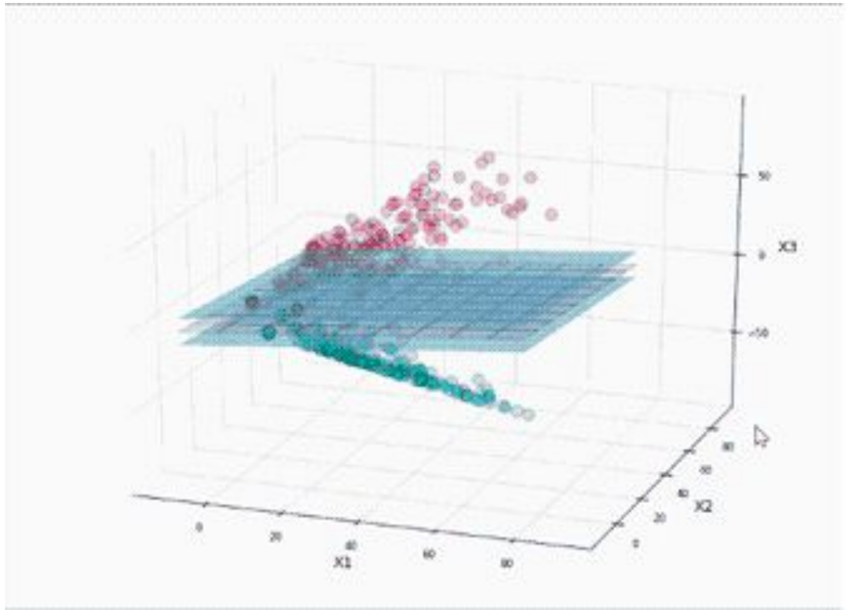
Map back the plane found in high dimensionality to the original dimensionality

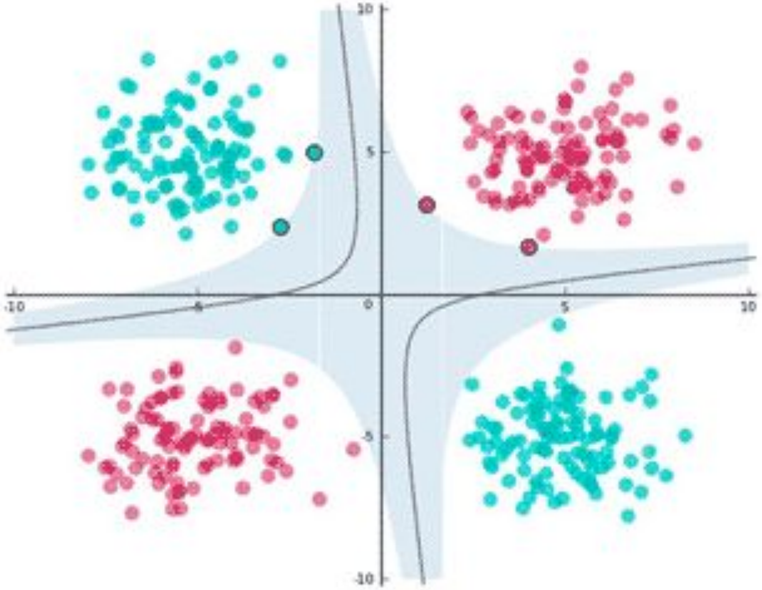


MECHANISM BEHIND MODEL: KERNEL TRICK (FUN FACT)

- When you map it back to the original space, the separating boundary is not a line anymore. This is also true for the margin and support vectors. As far as our visual intuition goes, they make sense in the projected space.

- Take a look at what they look like in the projected space, and then in the original space. The 3D margin is the region (not shaded to avoid visual clutter) between the planes above and below the separating hyperplane





ADDITIONAL RESOURCES

- **Here are some other additional videos on SVM:**
  - https://www.youtube.com/watch?v=Y6RRHw9uN9o
  - https://www.youtube.com/watch?time_continue=2&v=3liCbRZPrZA&feature=emb_title