



# Support Vector Machines

---

**Utkarsh Kulshrestha**

Artificial Intelligence Engineer

[kuls.utkarsh1205@gmail.com](mailto:kuls.utkarsh1205@gmail.com)

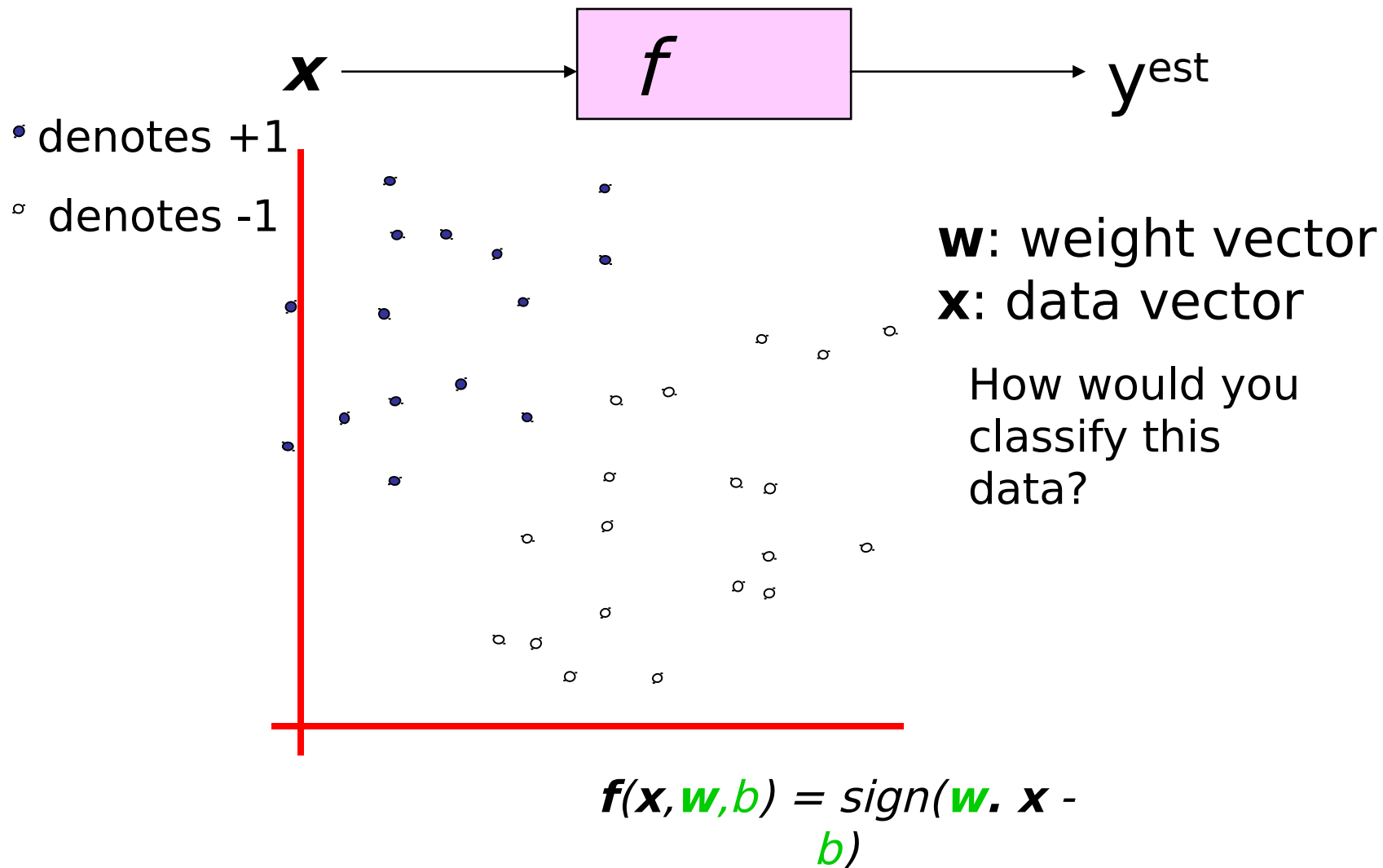


# History of SVM

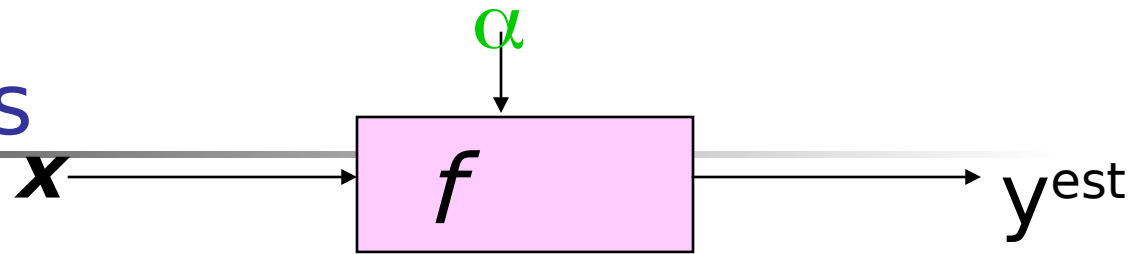
---

- SVM is related to statistical learning theory [3]
- SVM was first introduced in 1992 [1]
- SVM becomes popular because of its success in handwritten digit recognition
  - 1.1% test error rate
- SVM is now regarded as an important example of “kernel methods”, one of the **key area in machine learning**

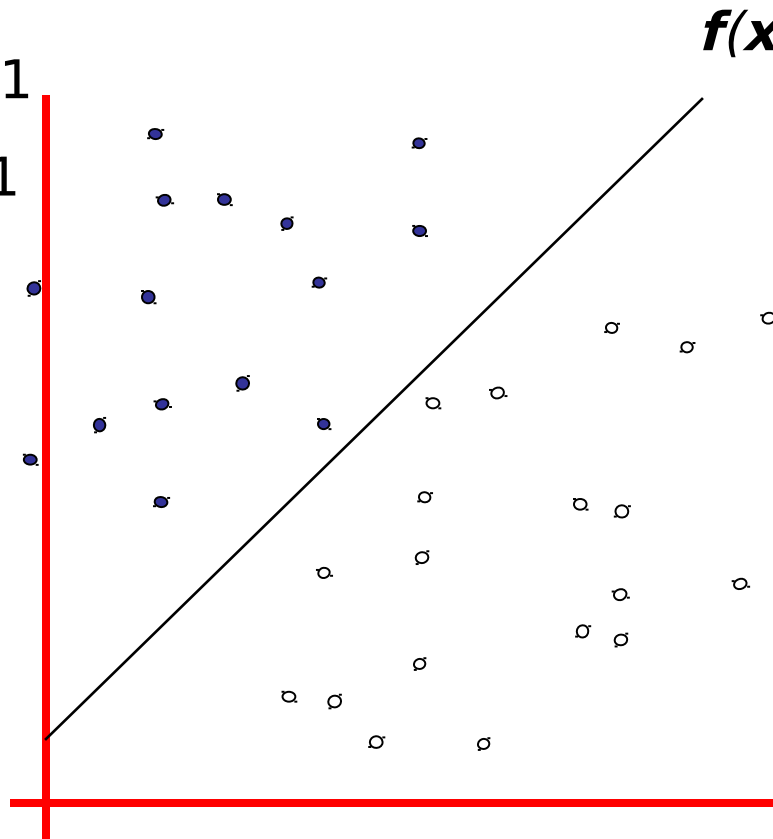
# Linear Classifiers



# Linear Classifiers



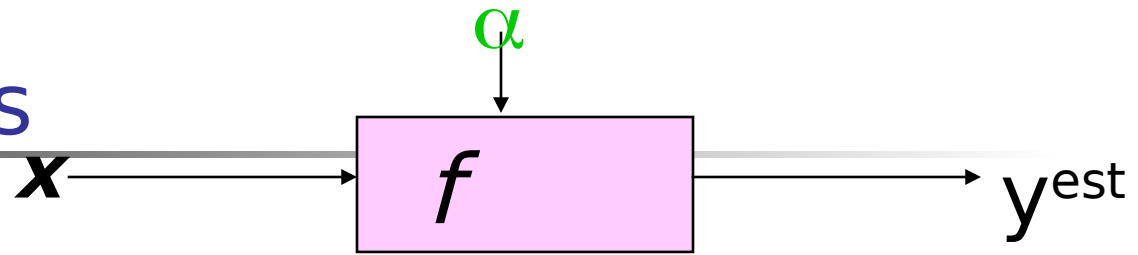
- denotes +1
- denotes -1



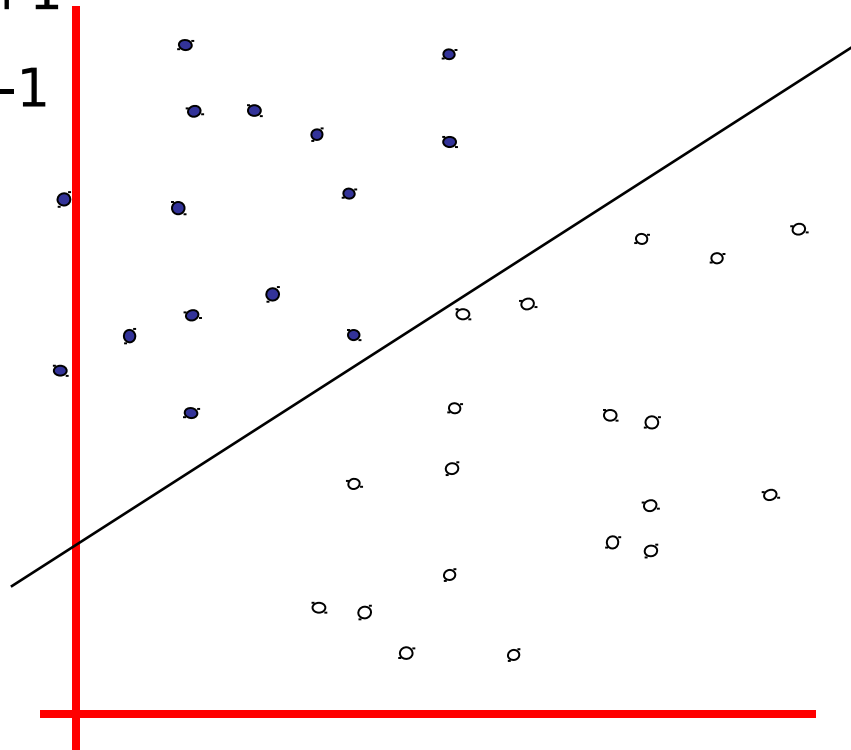
$$f(\mathbf{x}, \mathbf{w}, b) = \text{sign}(\mathbf{w} \cdot \mathbf{x} - b)$$

How would you classify this data?

# Linear Classifiers



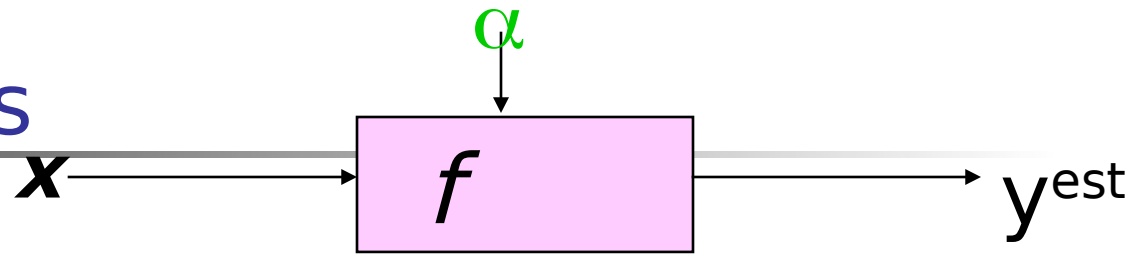
- denotes +1
- denotes -1



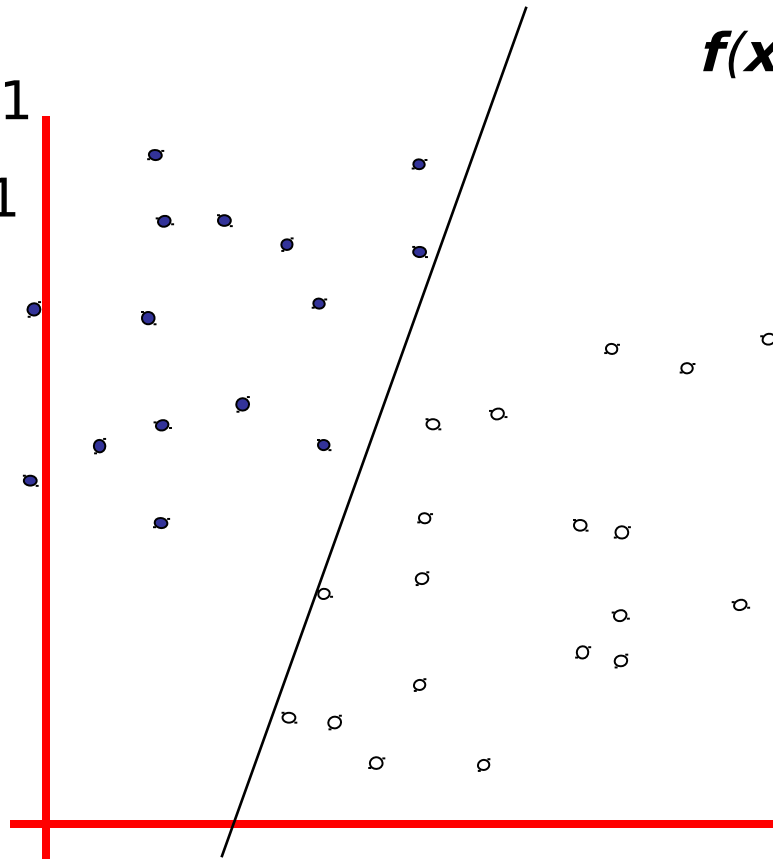
$$f(\mathbf{x}, \mathbf{w}, b) = \text{sign}(\mathbf{w} \cdot \mathbf{x} - b)$$

How would you classify this data?

# Linear Classifiers



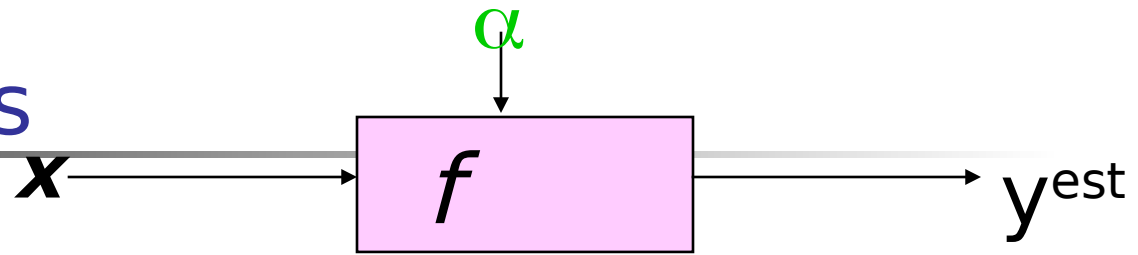
- denotes +1
- denotes -1



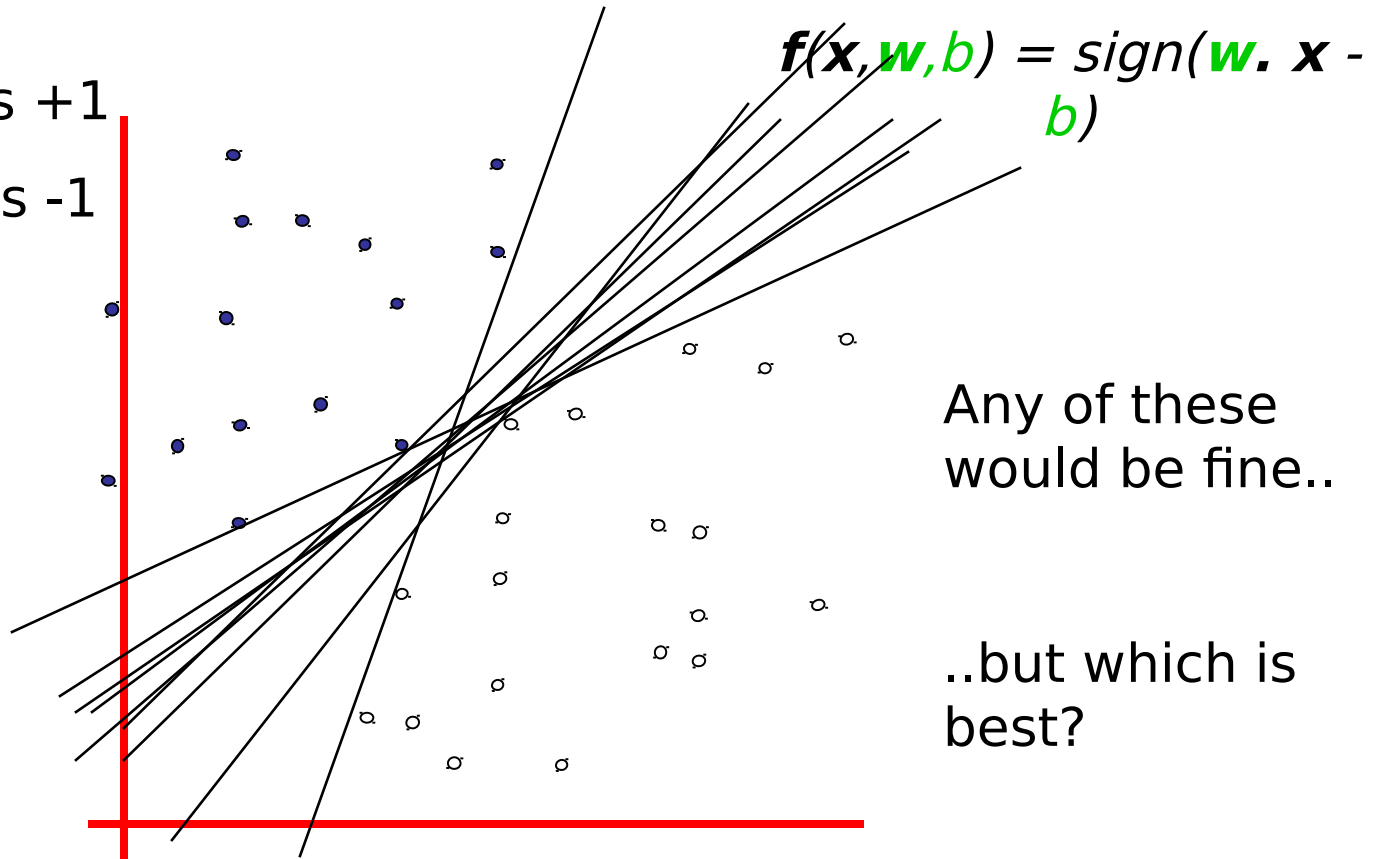
$$f(\mathbf{x}, \mathbf{w}, b) = \text{sign}(\mathbf{w} \cdot \mathbf{x} - b)$$

How would you classify this data?

# Linear Classifiers



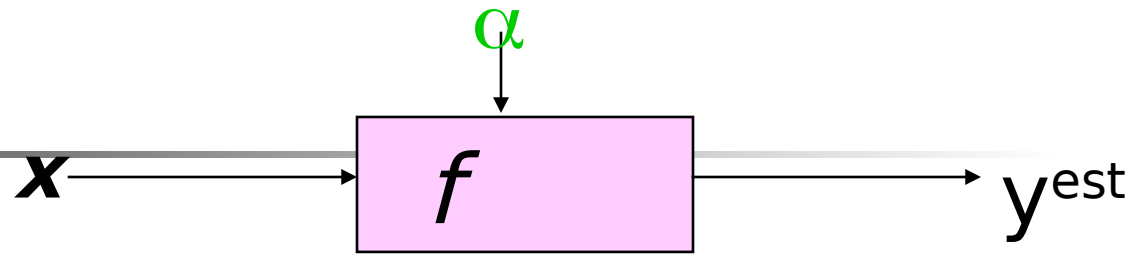
- denotes +1
- denotes -1



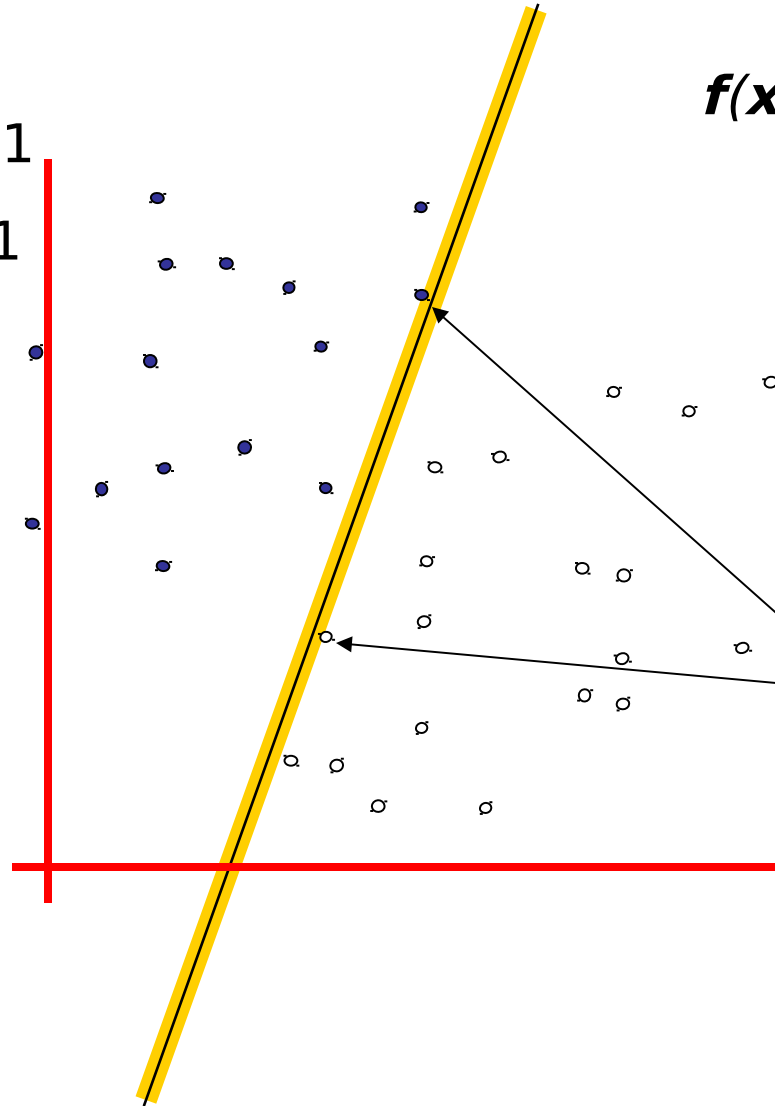
Any of these  
would be fine..

..but which is  
best?

# Classifier Margin



- denotes +1
- denotes -1



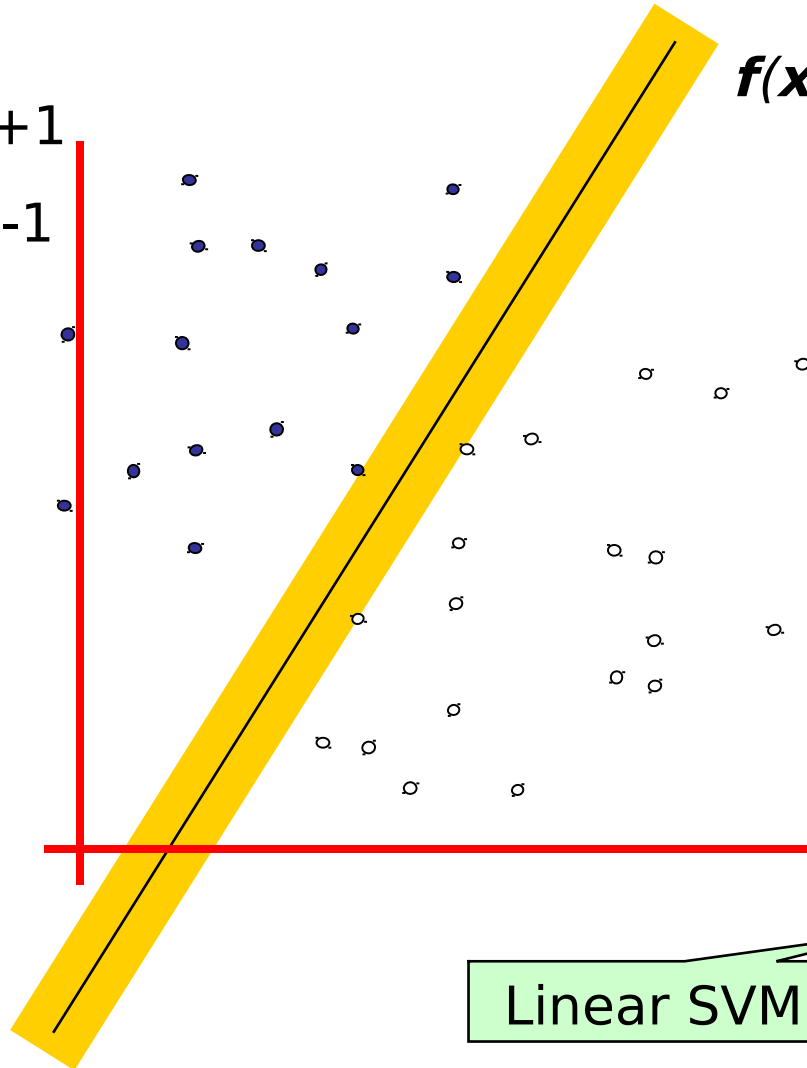
$$f(\mathbf{x}, \mathbf{w}, b) = \text{sign}(\mathbf{w} \cdot \mathbf{x} - b)$$

Define the **margin** of a linear classifier as the width that the boundary could be increased by **before hitting a datapoint**.



# Maximum Margin

- denotes +1
- denotes -1



$$f(\mathbf{x}, \mathbf{w}, b) = \text{sign}(\mathbf{w} \cdot \mathbf{x} - b)$$

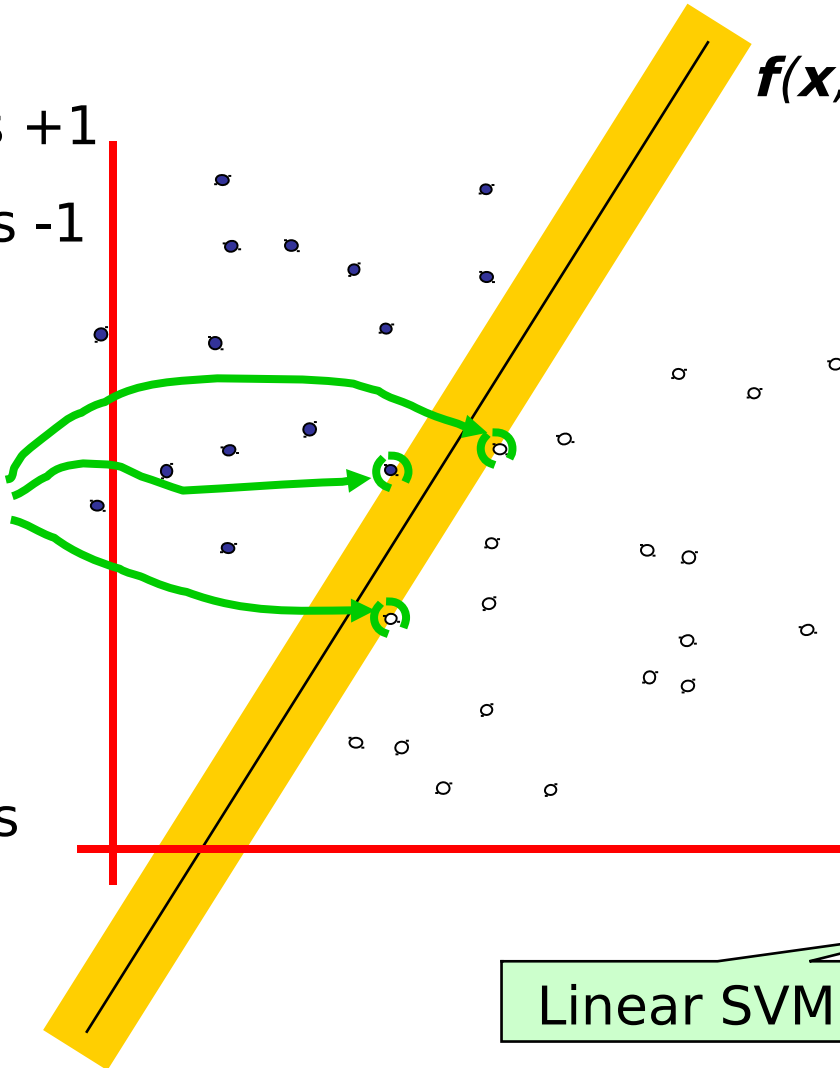
The **maximum margin linear classifier** is the linear classifier with the, um, maximum margin.

This is the simplest kind of SVM (Called an LSVM)

# Maximum Margin

- denotes +1
- denotes -1

Support Vectors are those datapoints that the margin pushes up against

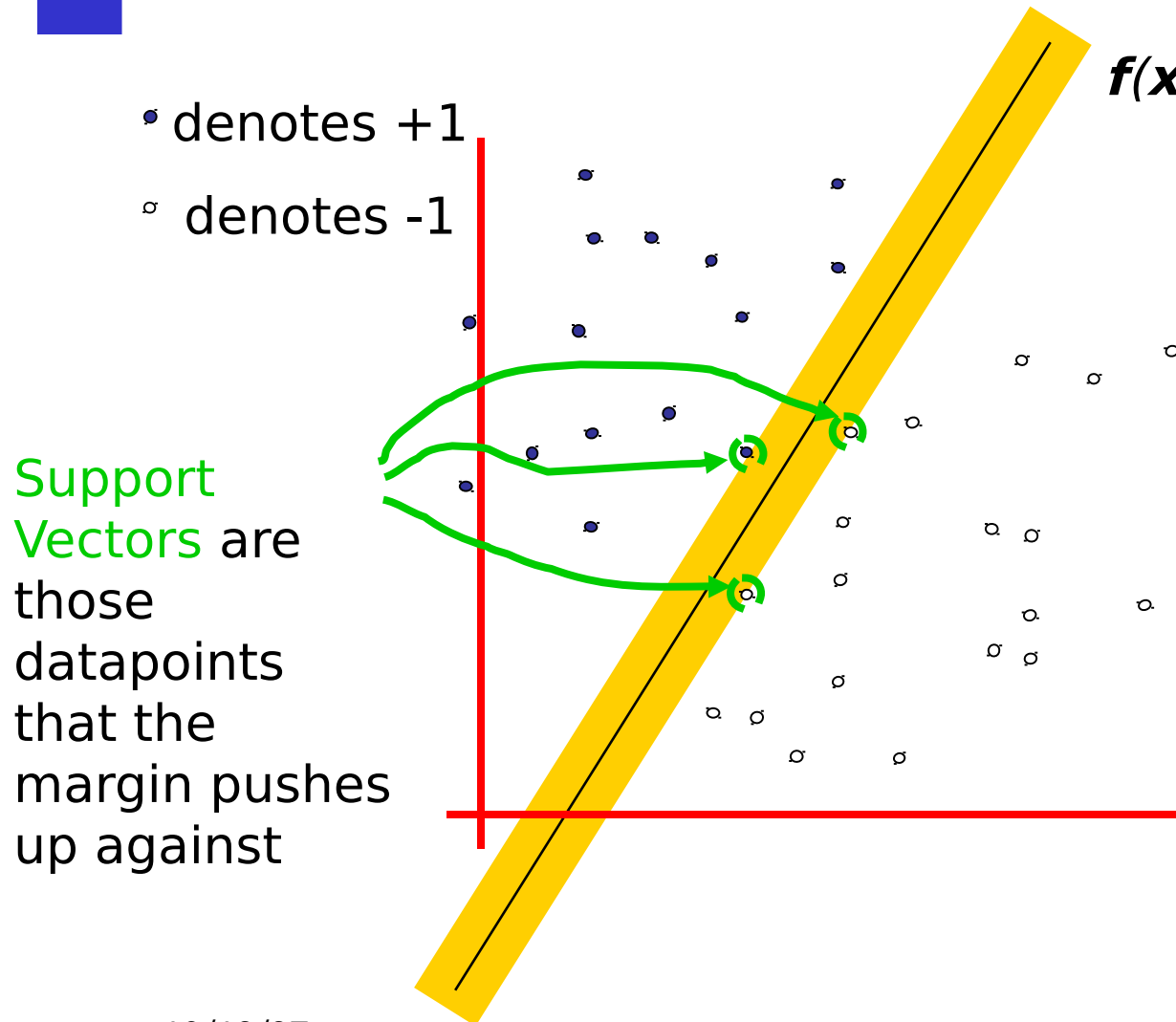


$$f(\mathbf{x}, \mathbf{w}, b) = \text{sign}(\mathbf{w} \cdot \mathbf{x} + b)$$

The **maximum margin linear classifier** is the linear classifier with the, um, maximum margin.

This is the simplest kind of SVM (Called an LSVM)

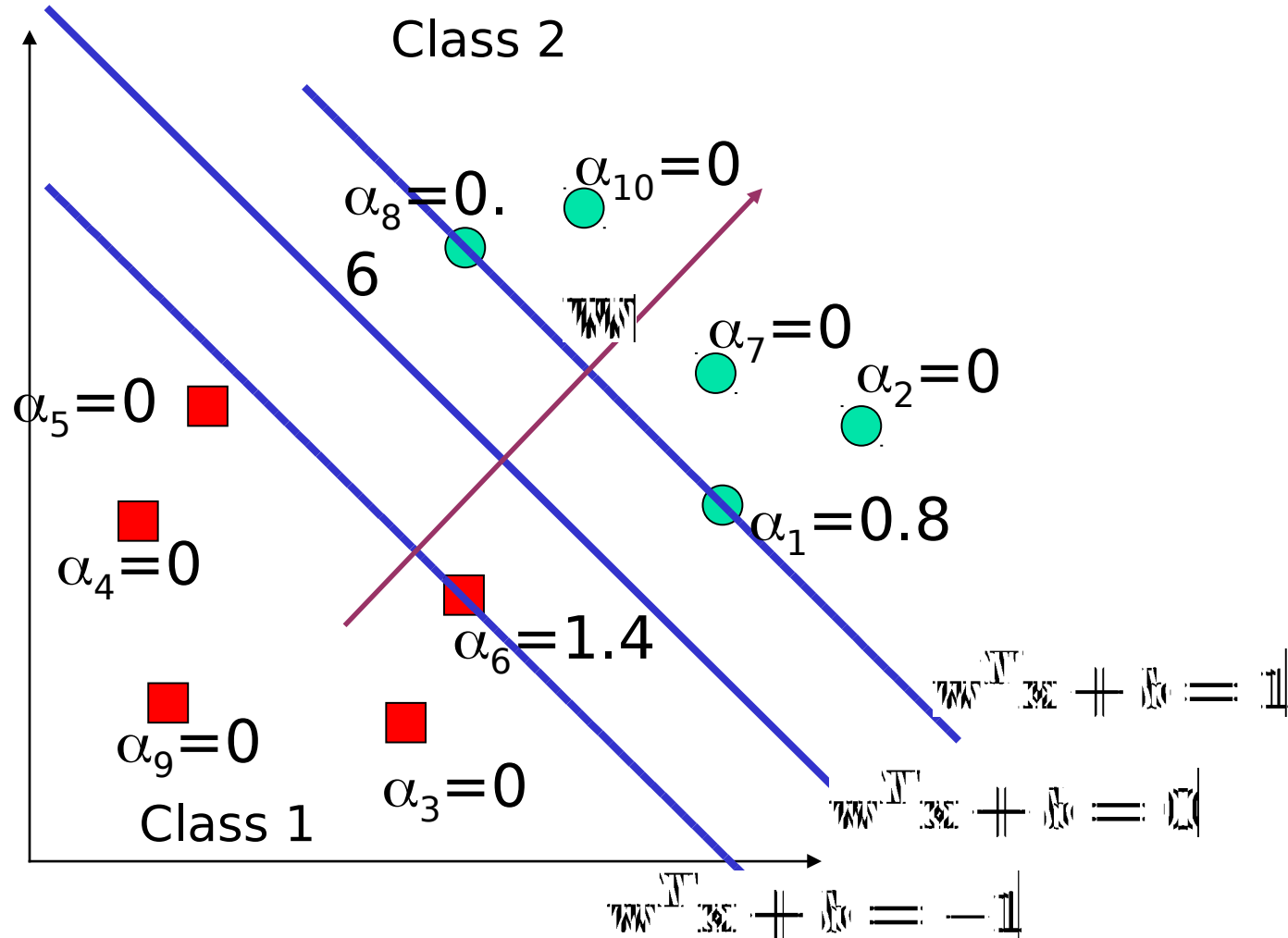
# Why Maximum Margin?



The **maximum margin linear classifier** is the linear classifier with the, um, maximum margin.

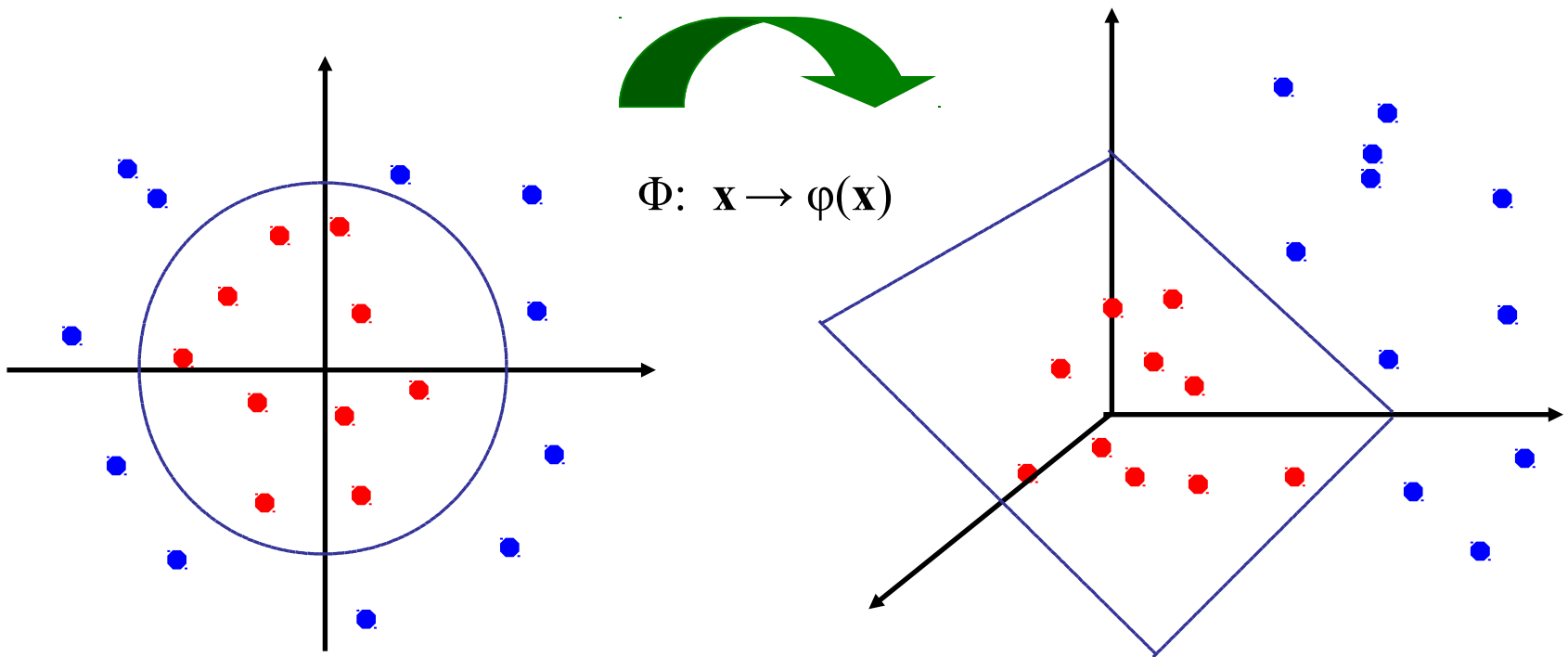
This is the simplest kind of SVM (Called an LSVM)

# A Geometrical Interpretation



# Non-linear SVMs: Feature spaces

**General idea:** the original input space can always be mapped to some higher-dimensional feature space where the training set is separable:





# Choosing the Kernel Function

---

- Probably the most tricky part of using SVM.
  - Polynomial Kernel – Non-Linear Data Classification
  - Radial or RBF Kernel – Non-Linear Data Classification
  - Linear Kernel – Linear Data Classification



# Choosing the C Parameter Value

---

C is a regularization parameter that controls the trade off between the achieving a low training error and a low testing error that is the ability to generalize your classifier to unseen data.

In simple terms, C represents the width of the margin for classification purpose.

Higher C = Lesser Width

Lower C = Higher Width

The Optimal value of C lies in between which needs to be calculated on the basis of model accuracy.



# Choosing the Gamma Parameter

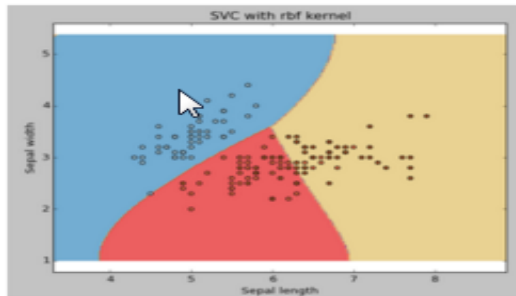
---

- Intuitively, the gamma parameter defines how far the influence of a single training example reaches, with low values meaning 'far' and high values meaning 'close'. The gamma parameters can be seen as the inverse of the radius of influence of samples selected by the model as support vectors.
- Optimal Value of gamma needs to be included otherwise Model can run into over fitting

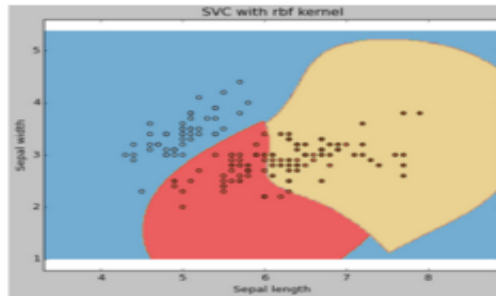


# Effect of C & Gamma

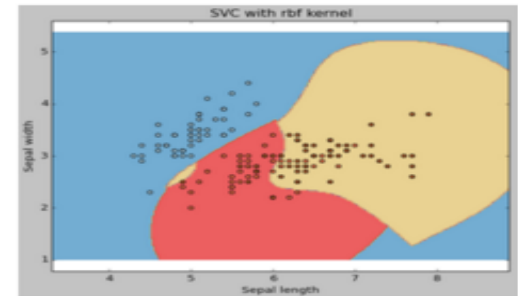
**c = 1**



**C = 100**

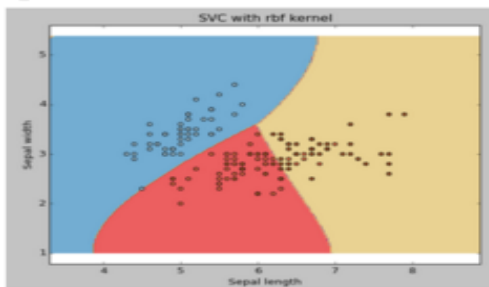


**c = 1000**

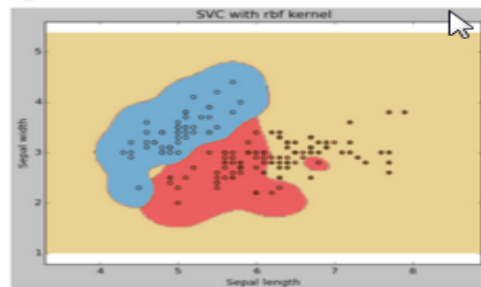


```
svc = svm.SVC(kernel='rbf', C=1,gamma=0).fit(X, y)
```

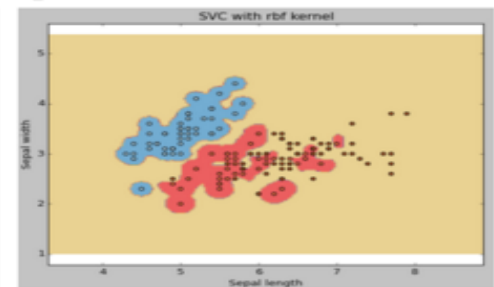
**gamma = 0**



**gamma = 10**



**gamma = 100**





# Summary: Steps for Classification

---

- Select the kernel function to use
- Select the Gamma Parameter to be used.
- Select the parameter of the kernel function and the value of  $C$ 
  - You can use the values suggested by the SVM software, or you can set apart a validation set to determine the values of the parameter



---

Thank You !!!