

# 5 ALGORITHMS YOU MUST BE AWARE OF BEFORE GOING TO DEEP LEARNING

FOR A BETTER FUTURE ...

**Ghosh 4 AI**



Ghosh4AI





# Some common challenges

- Classification ( KNN, Decision Trees, Neural Nets, SVM )
- Clustering ( K-Means, Hierarchical, Fuzzy C Means)
- Density Estimation (Gaussian Mixture Models)
- Regression (Linear or Logistic Regression)
- Dimensionality Reduction (PCA, LDA, SVD)

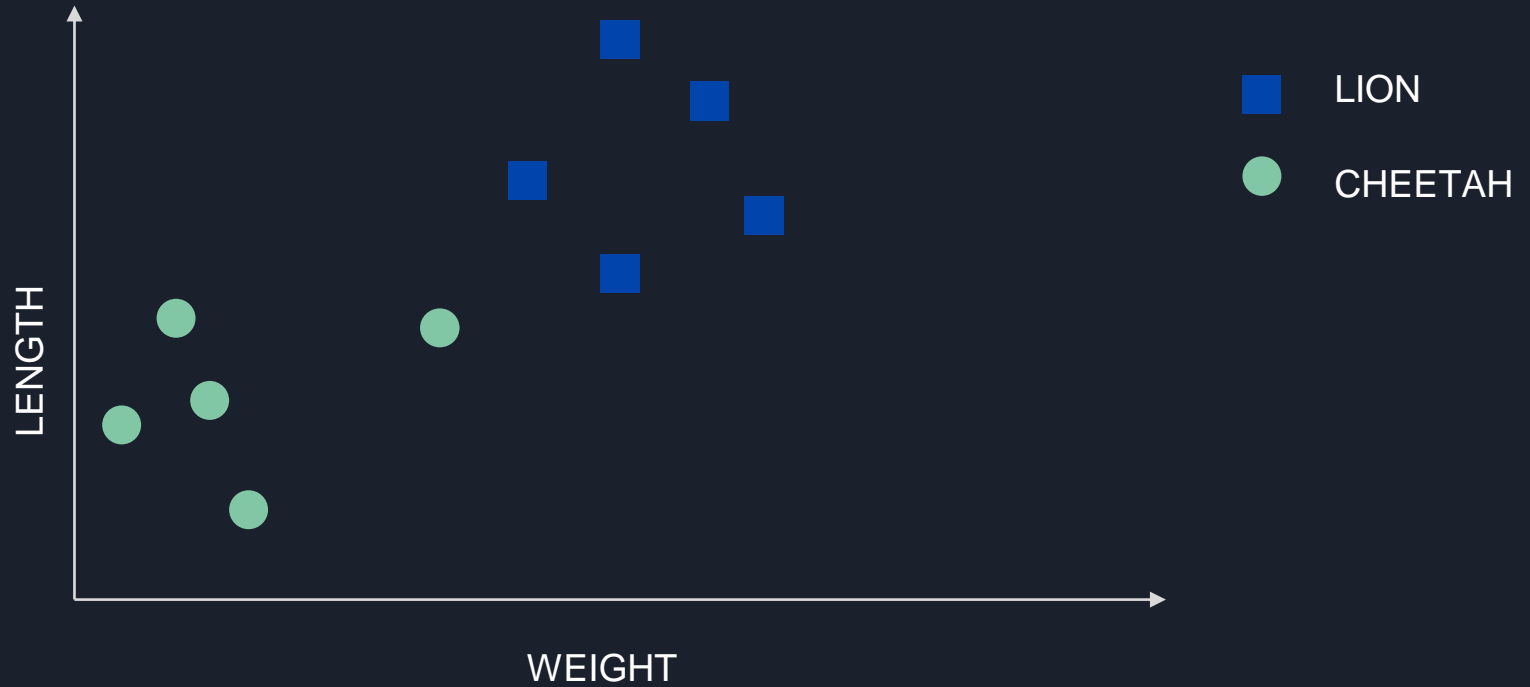
and many more



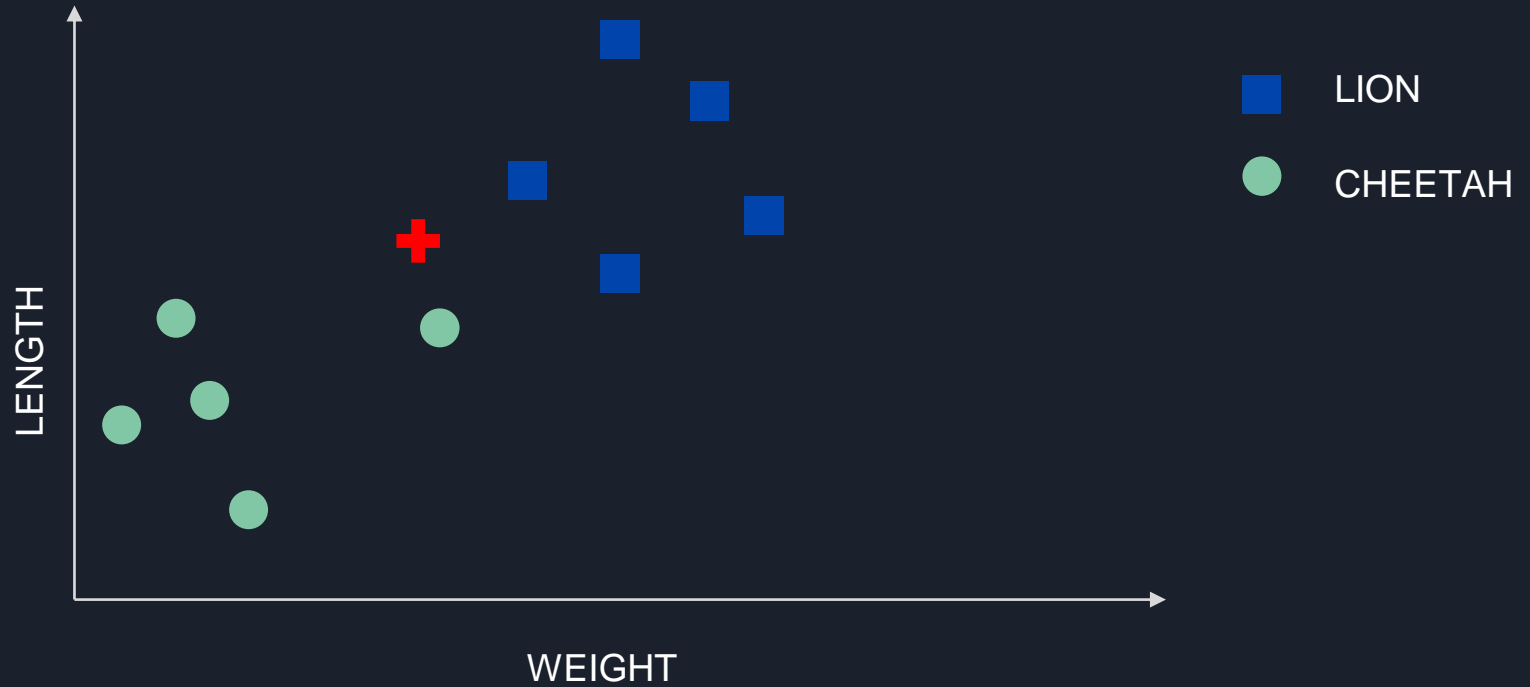
# K-Nearest Neighbor (KNN)



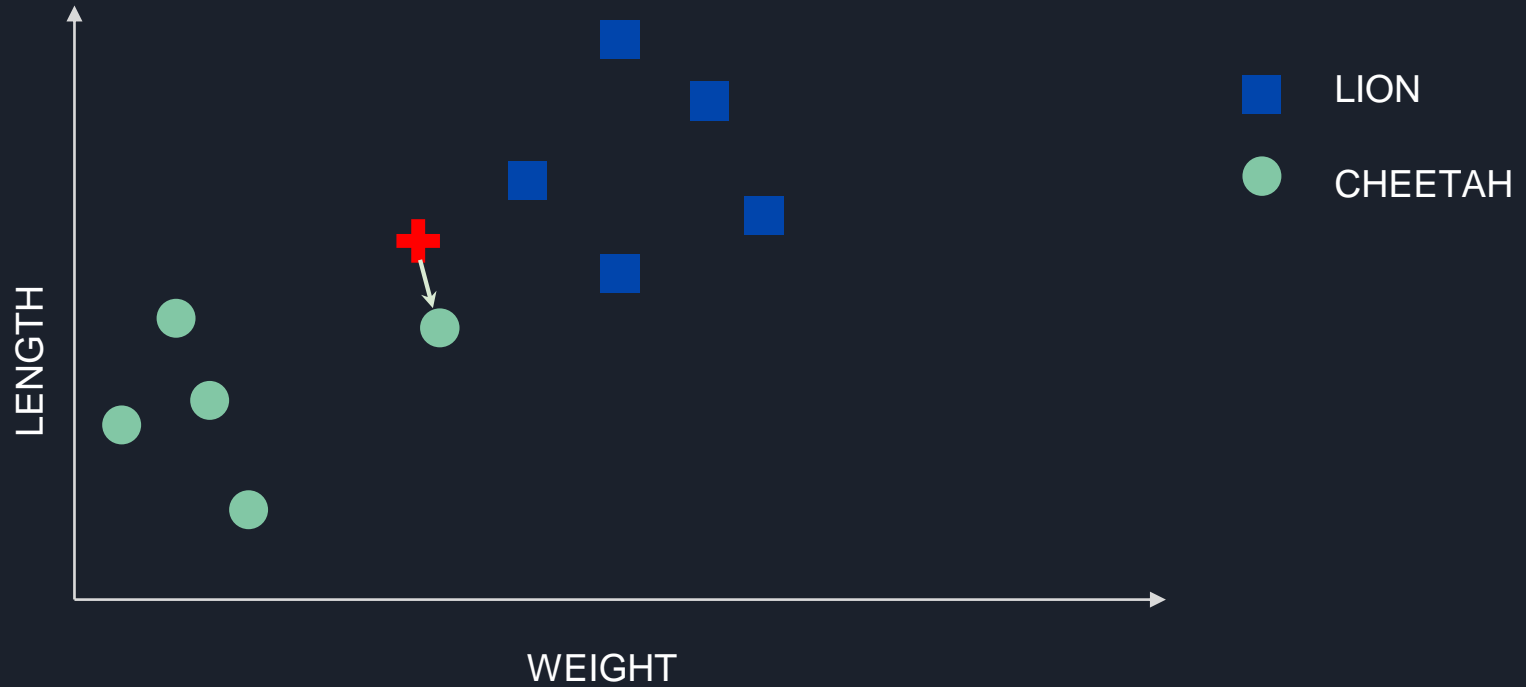
The simplest idea is often the best idea



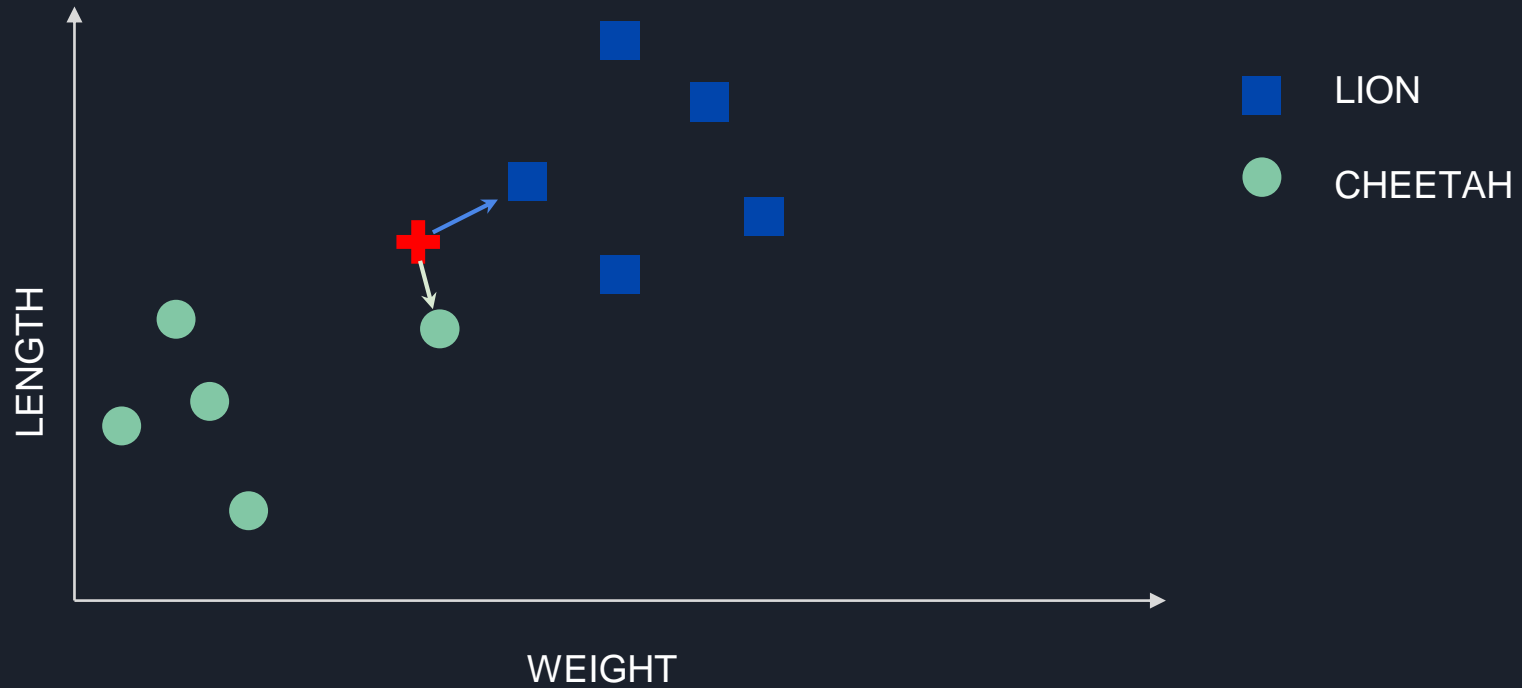
The simplest idea is often the best idea



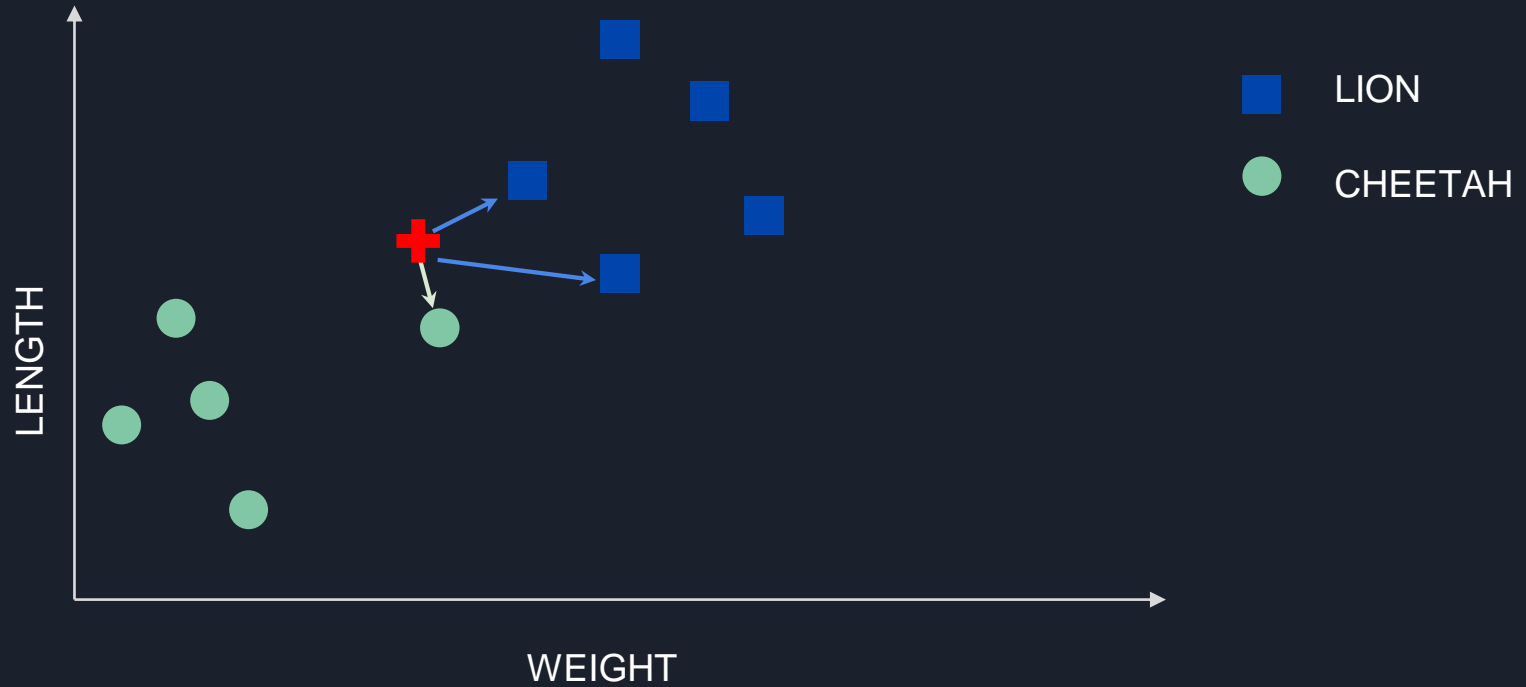
# The simplest idea



# Ambiguity



# More neighbours... Better predictions





# Further References

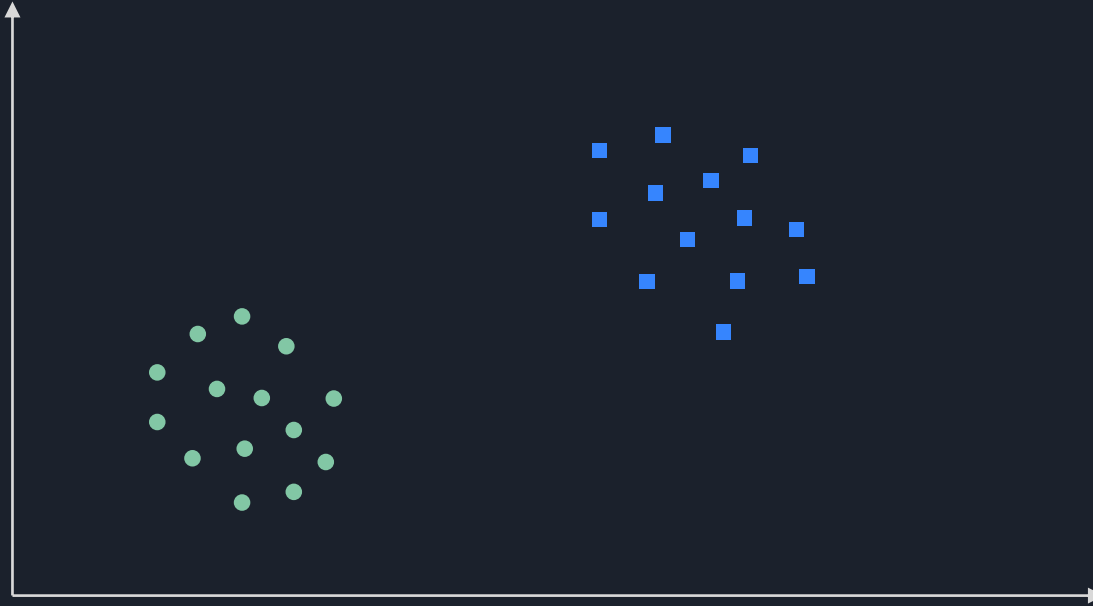
- Wikipedia - [k-nearest neighbors algorithm](#) - Wikipedia
- Blogs :
  - [Introduction to KNN, K-Nearest Neighbors : Simplified](#) - Analytics Vidhya
  - [A Quick Introduction to K-Nearest Neighbors Algorithm](#) - Medium
  - [K-Nearest Neighbours](#) - GeeksforGeeks
- Demo :
  - <http://vision.stanford.edu/teaching/cs231n-demos/knn/>
- API
  - [sklearn.neighbors.KNeighborsClassifier](#) — scikit-learn 0.19.2
  - [k-nearest neighbor classification](#) - MATLAB
  - [Weka 3 - Data Mining with Open Source Machine Learning Software](#)
- Books :
  - Machine Learning – T. Mitchell
  - Pattern Recognition and Machine Learning – C.M. Bishop
- Related Papers
  - [K-nearest neighbour](#)
  - [A fuzzy k-nearest neighbor algorithm](#)
  - [The distance-weighted k-nearest-neighbor rule](#)
  - [When is “nearest neighbor” meaningful?](#)



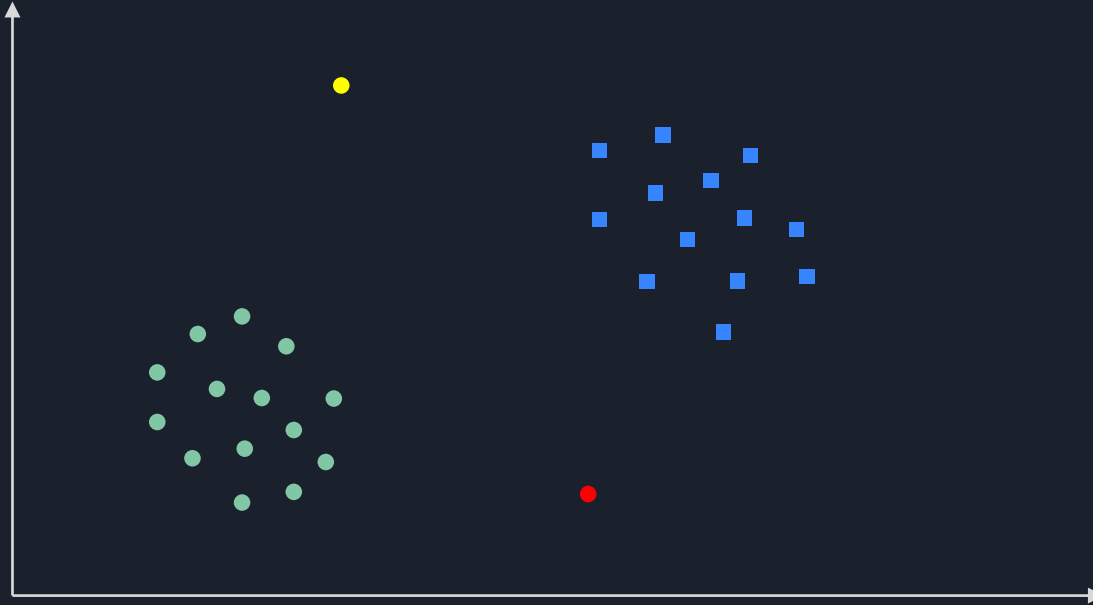
# K-Means Clustering



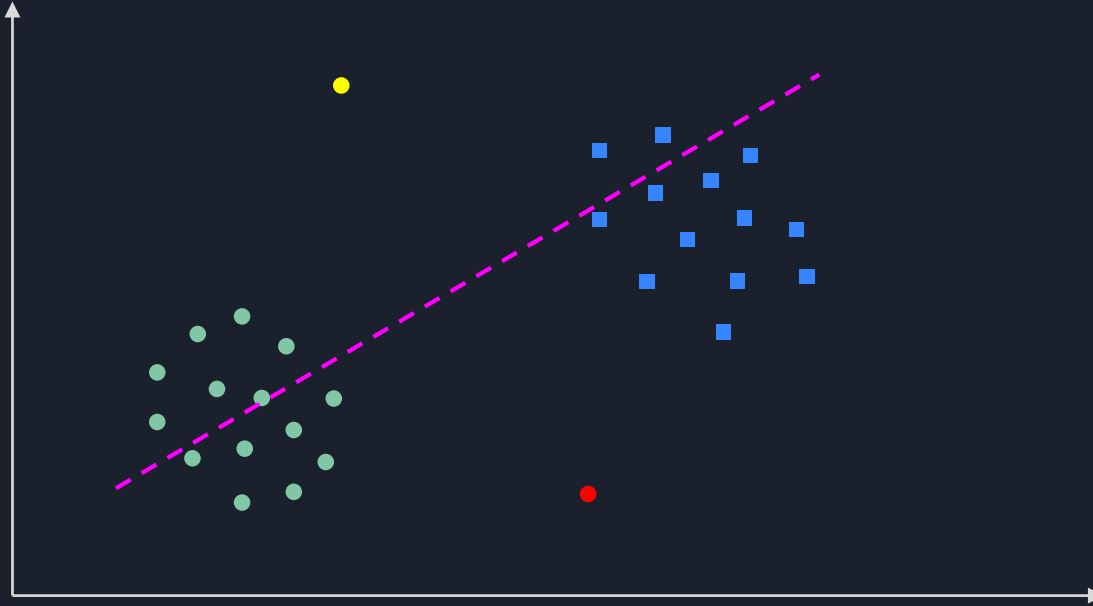
# Clustering : Dividing samples into groups



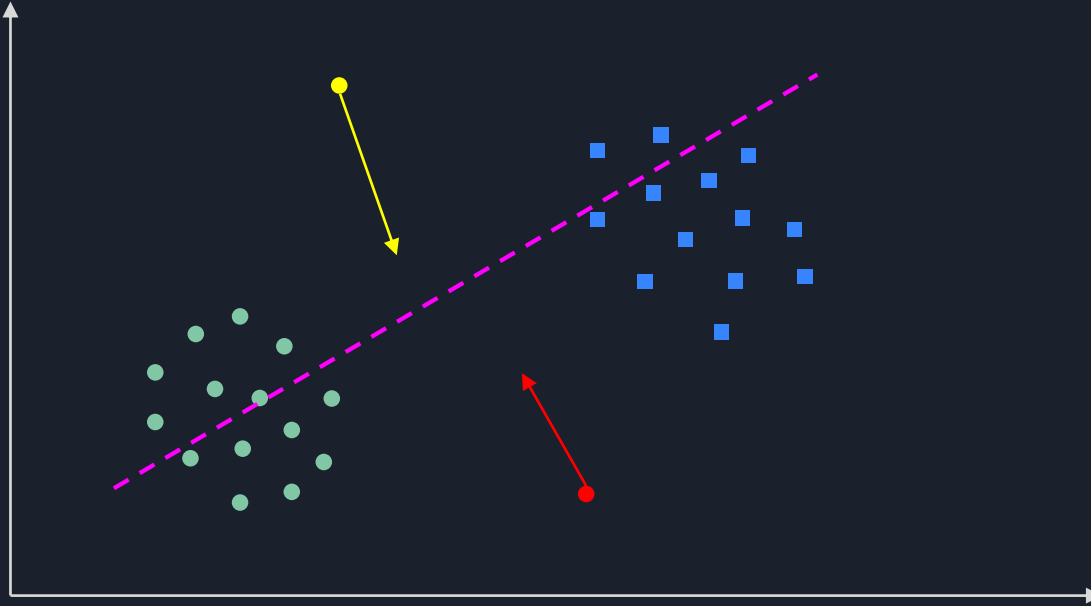
2 classes 2 means



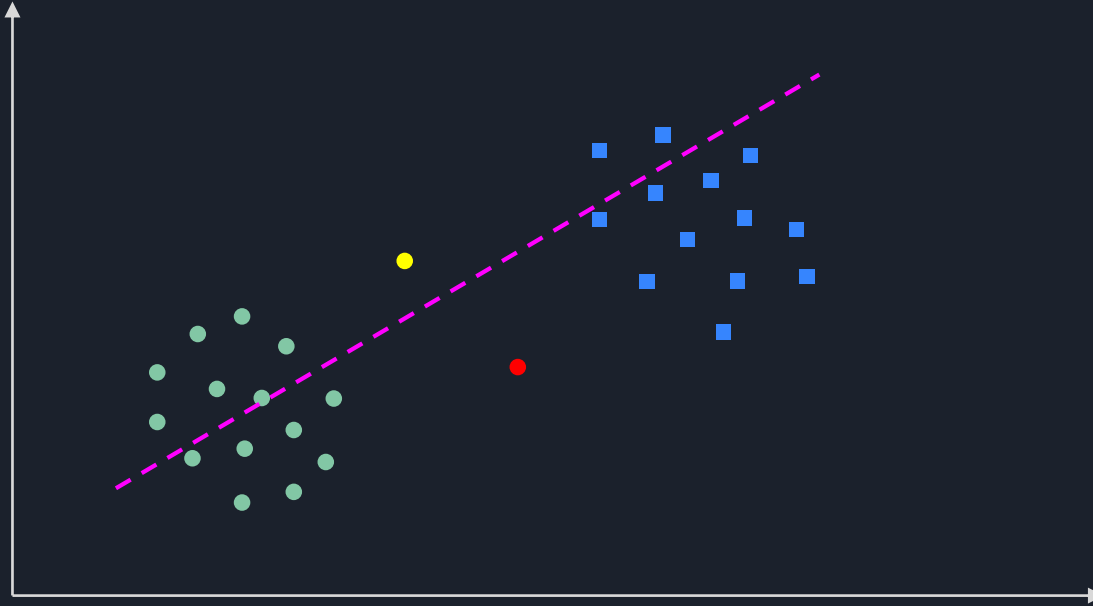
# Who belongs to whom



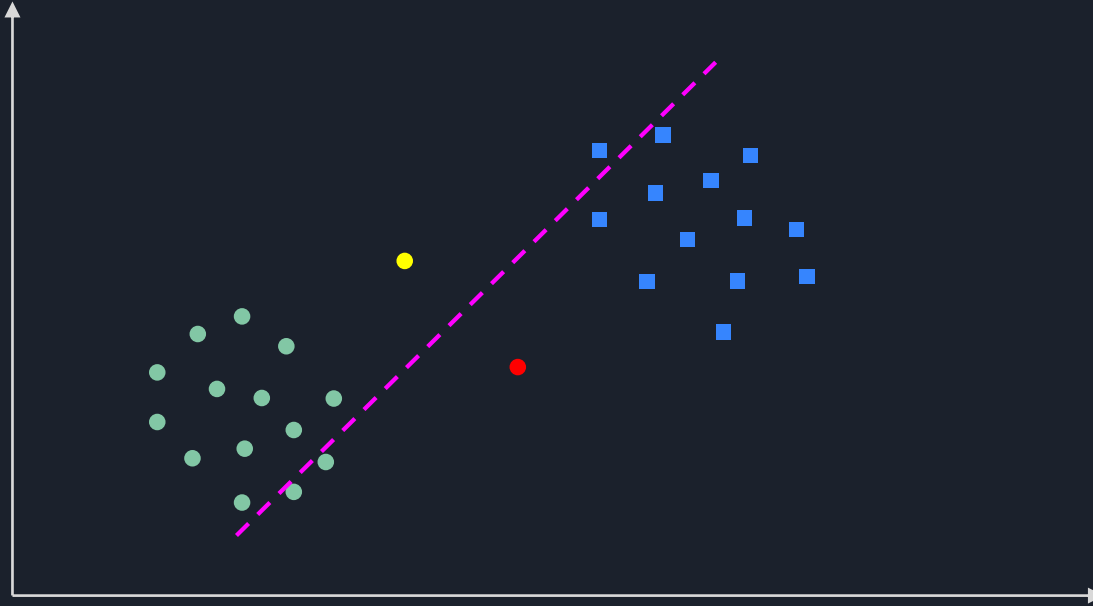
Means need to move to the centre of their members



Means have moved and samples need to decide again

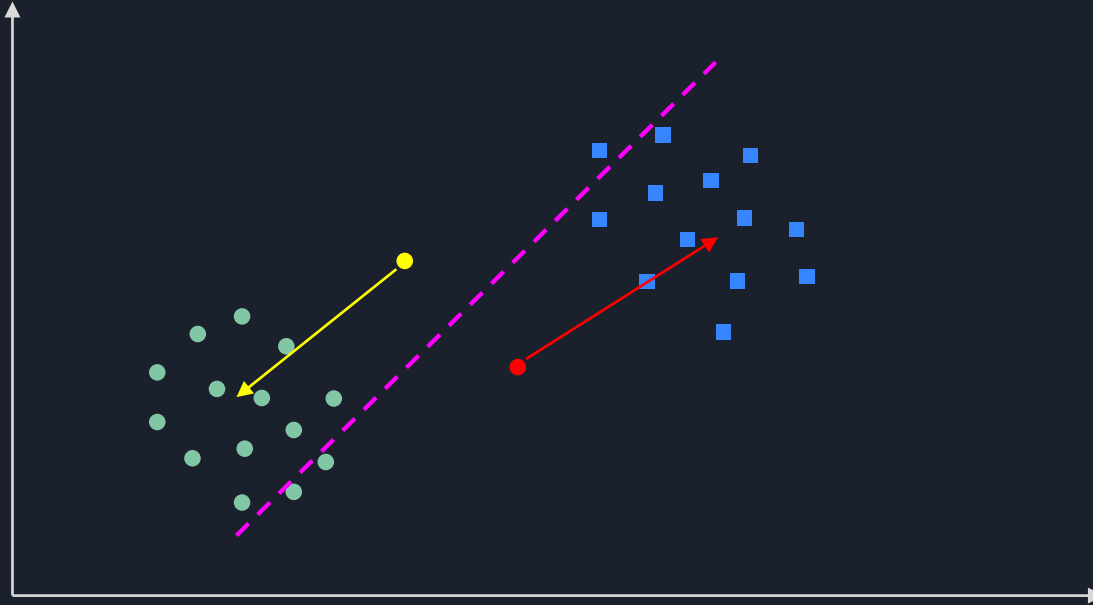


# Switching sides

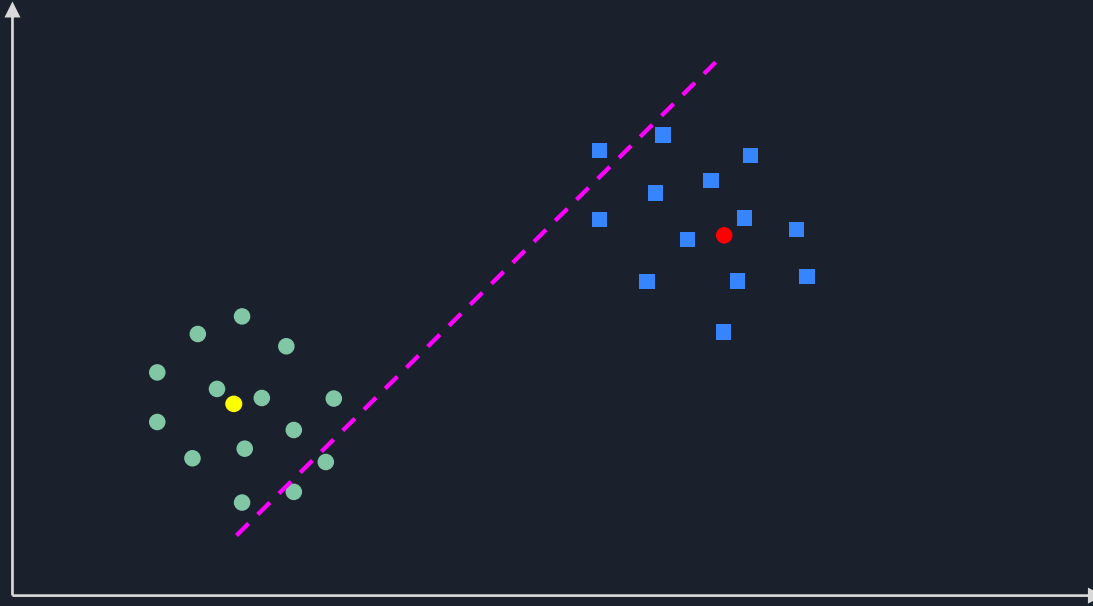




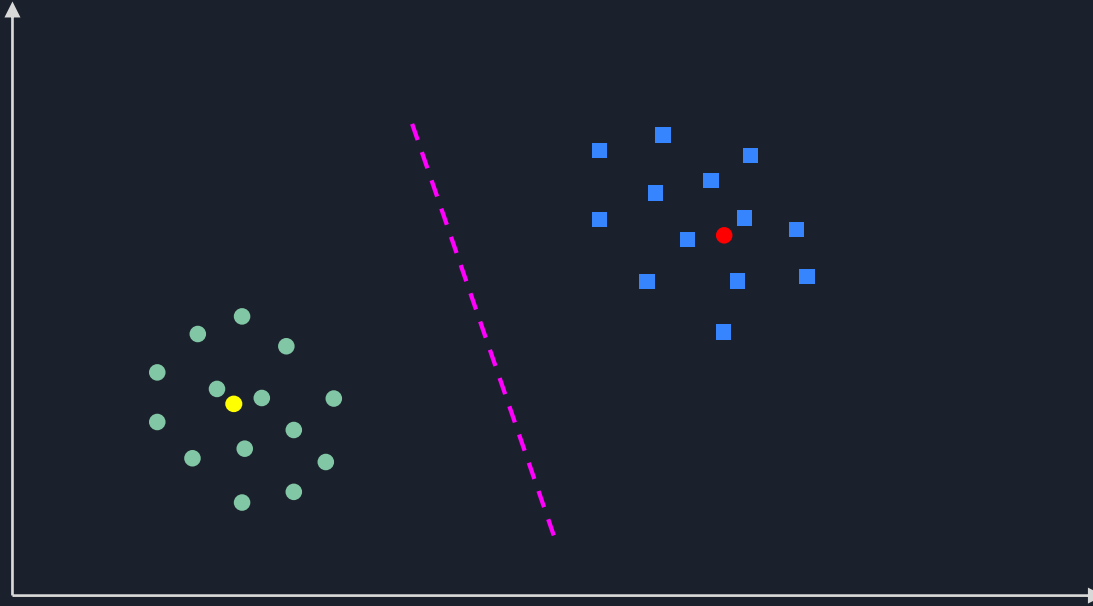
Mean needs to move again



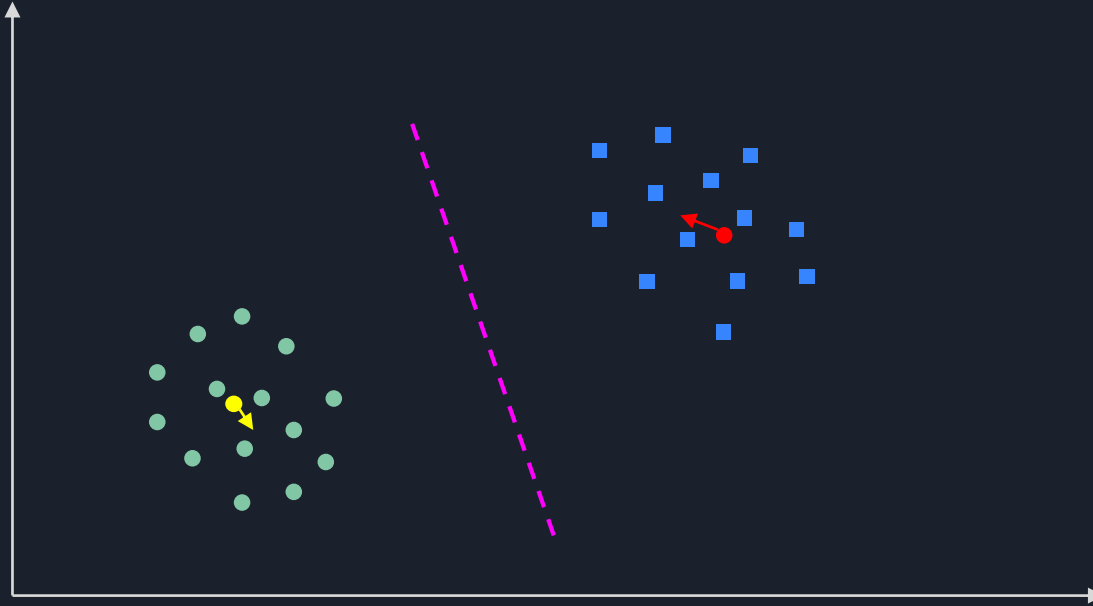
Samples decide again



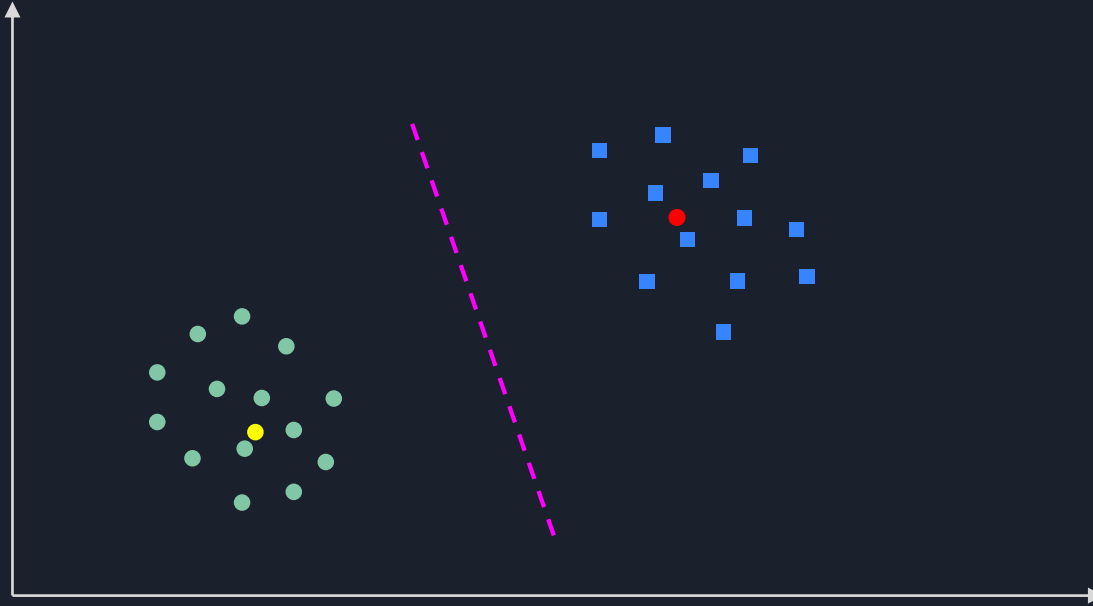
# Switching sides



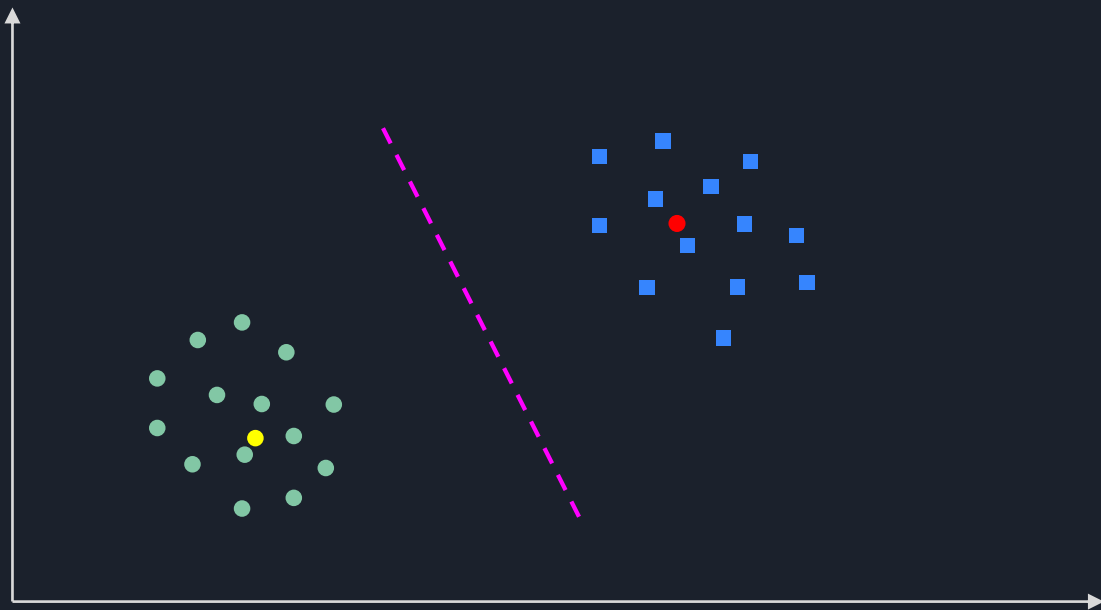
Means move again



Samples need to decide again .. But ...



No need to switch anymore





# Further References

- Wikipedia - [k-means clustering](#) - Wikipedia
- Blogs :
  - [Introduction to K-means Clustering](#) - DataScience.com
  - [Clustering using K-means algorithm](#) – Towards Data Science
  - [K means Clustering](#) - Introduction - GeeksforGeeks
- Demo :
  - <http://web.stanford.edu/class/ee103/visualizations/kmeans/kmeans.html>
- API
  - [sklearn.cluster.KMeans](#) — scikit-learn 0.19.2
  - [k-means clustering](#) – MATLAB
  - [Weka 3](#) - Data Mining with Open Source Machine Learning Software
- Books :
  - Pattern Recognition and Machine Learning – C.M. Bishop
- Related Papers
  - [An efficient \*\*k-means clustering\*\* algorithm](#)
  - [Refining Initial Points for \*\*K-Means Clustering\*\*](#)
  - [An efficient \*\*k-means clustering\*\* algorithm: Analysis and implementation](#)
  - [A \*\*k-means clustering\*\* algorithm](#)

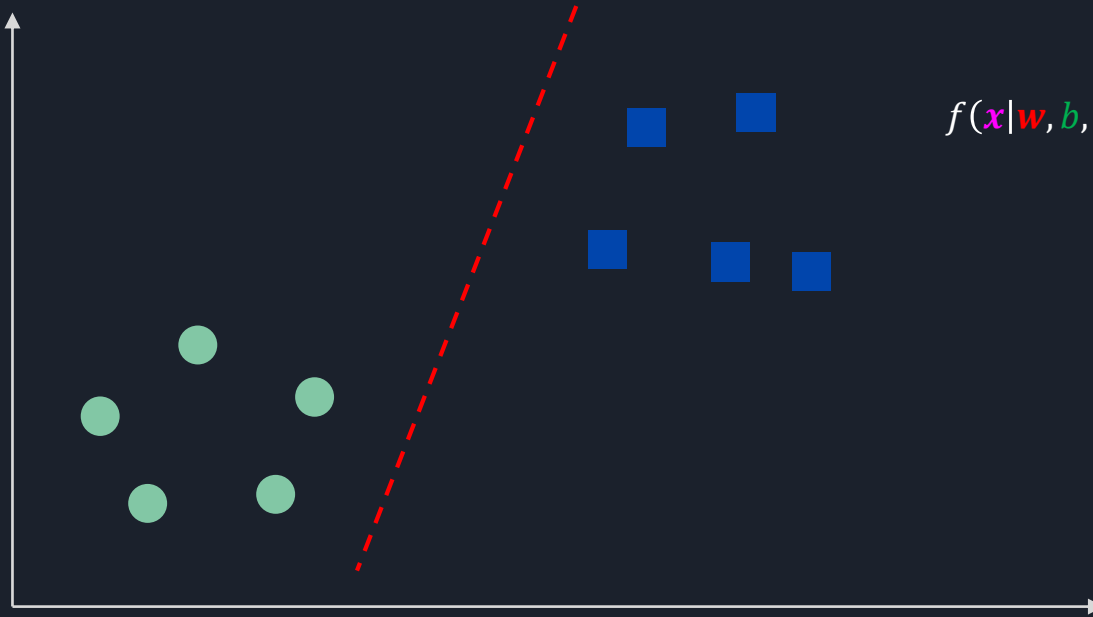


# Support Vector Machines (SVM)





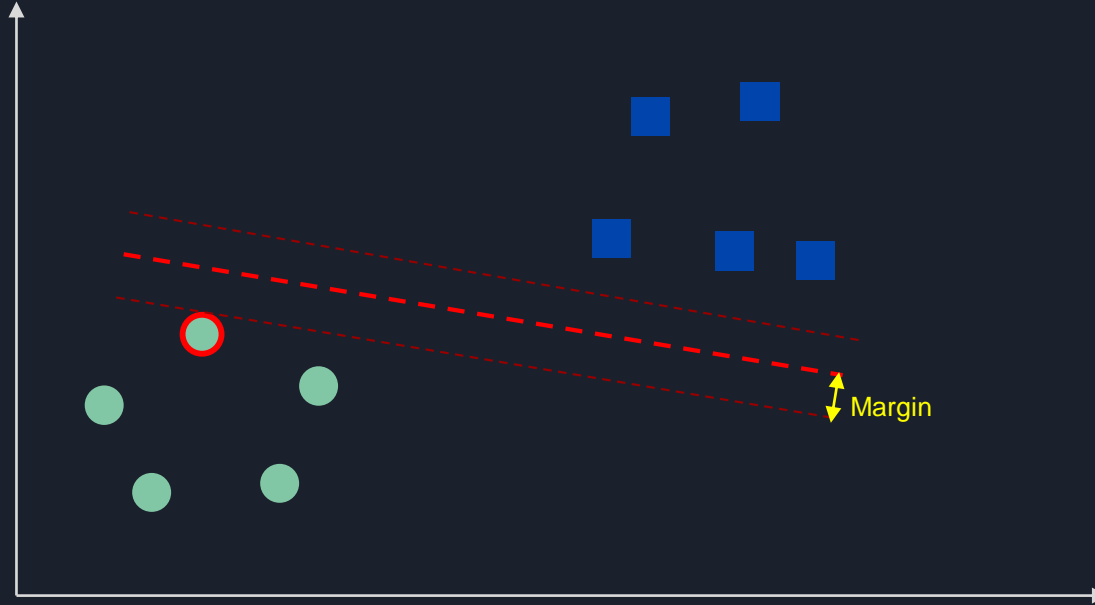
It all comes down to drawing a straight line



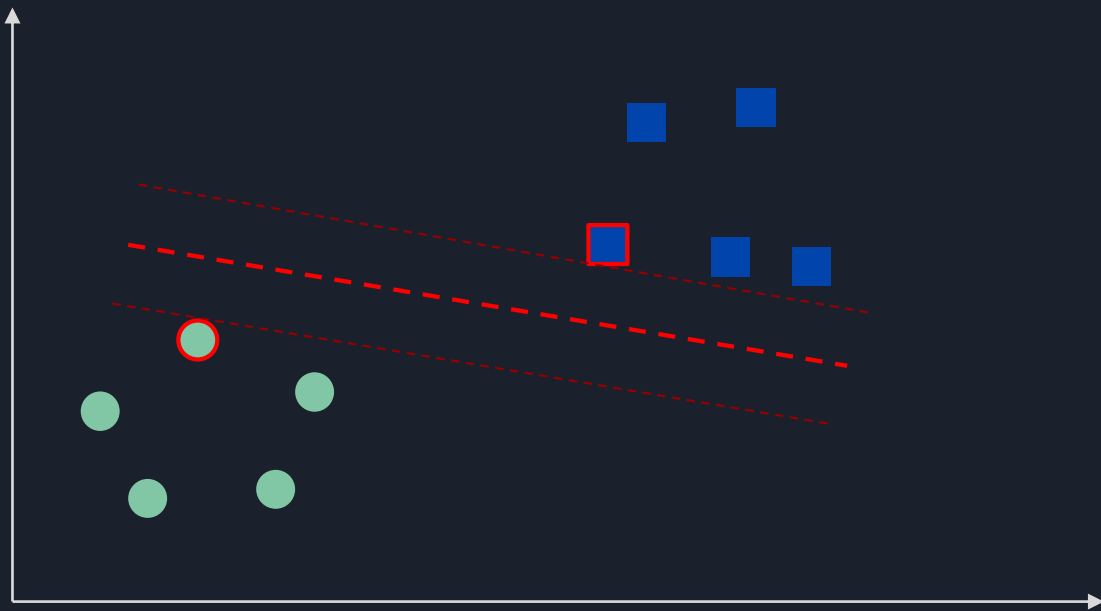
$$f(x|w, b, \phi) = w^T \phi(x) + b$$



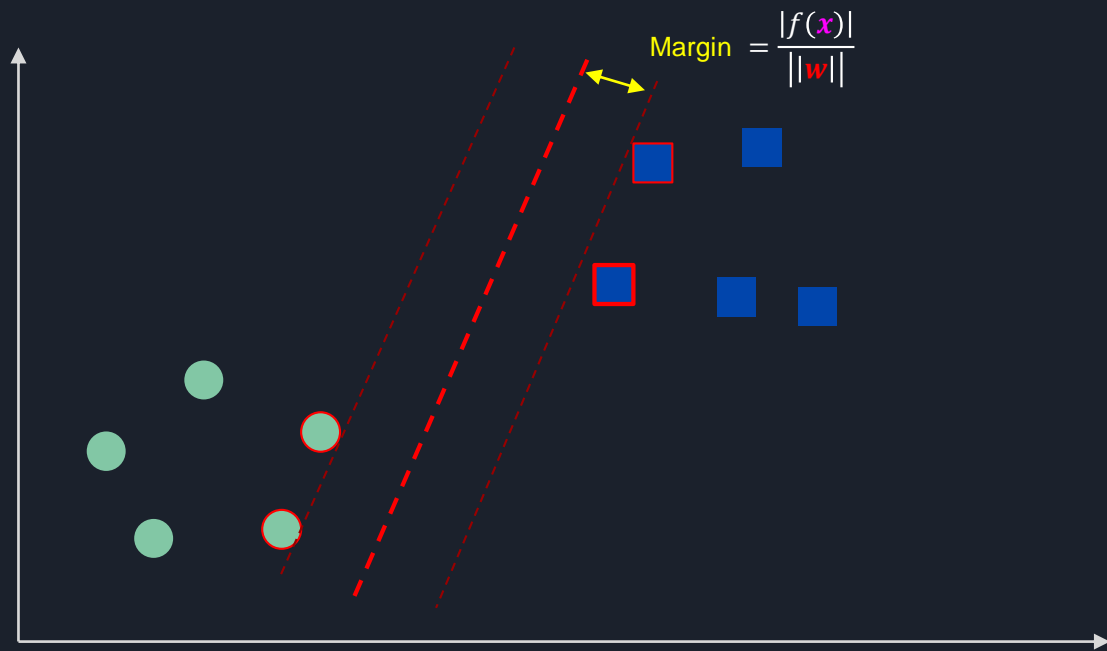
But where to position the line



But lots of options



But lots of options





# A little bit of maths and voila

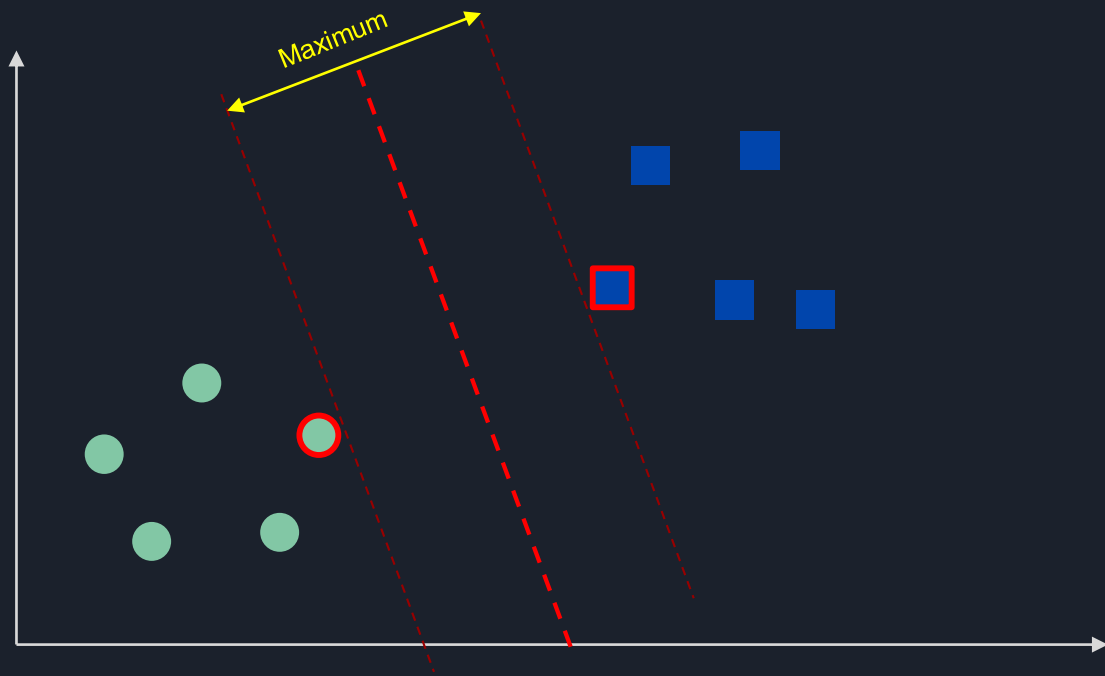
$$\frac{|f(x)|}{||\mathbf{w}||} = \frac{|\mathbf{w}^T \mathbf{x} + b|}{||\mathbf{w}||}$$
$$= \frac{|\kappa \mathbf{w}^T \mathbf{x} + \kappa b|}{||\kappa \mathbf{w}||}$$

Set  $\kappa$  such a way so that  $f(x)$  is 1 or -1  
for the points closest to the line.  
Then Maximum margin can be obtained by

$$\arg \max_w \frac{1}{||\mathbf{w}||}$$

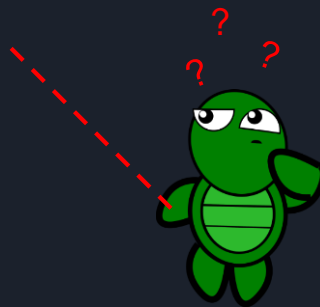
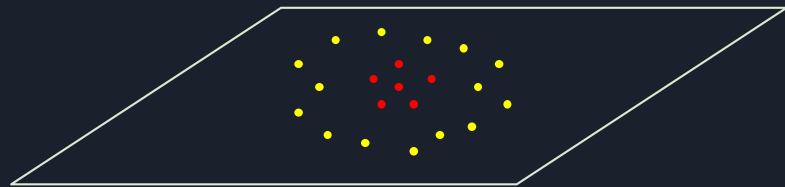


Fat is not always bad...

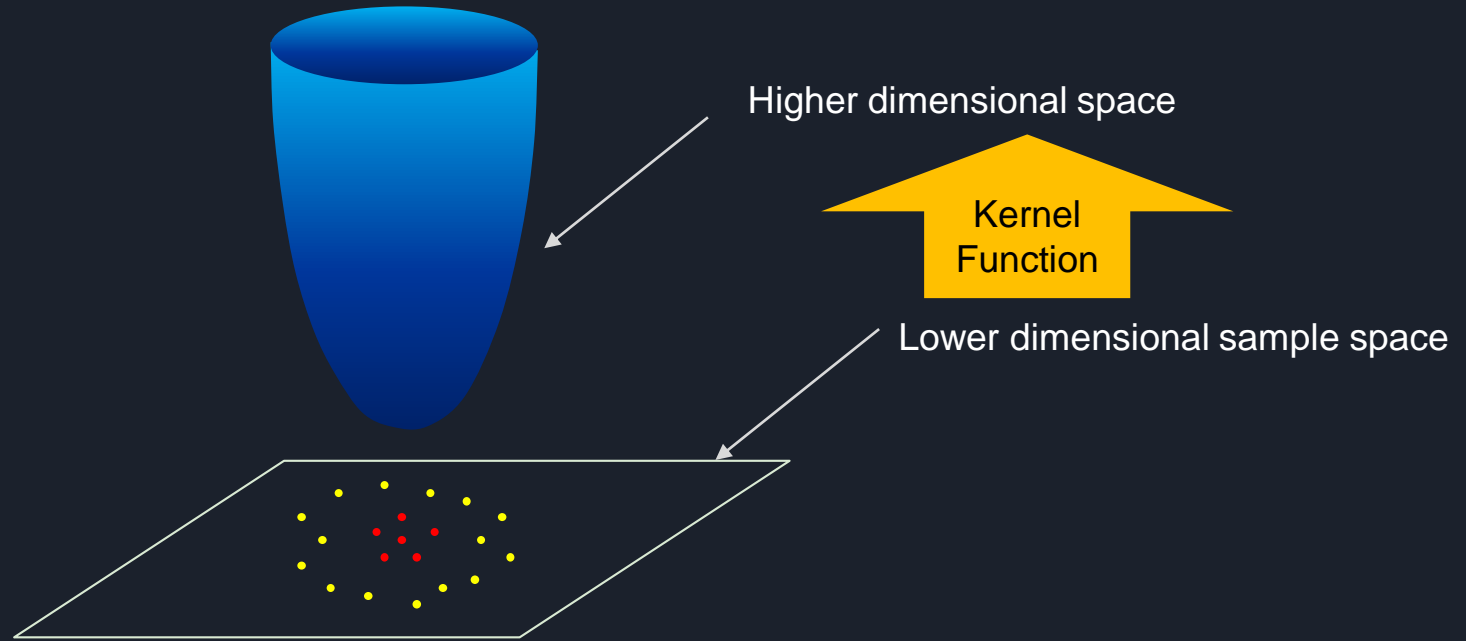




# Is a straight line enough ?

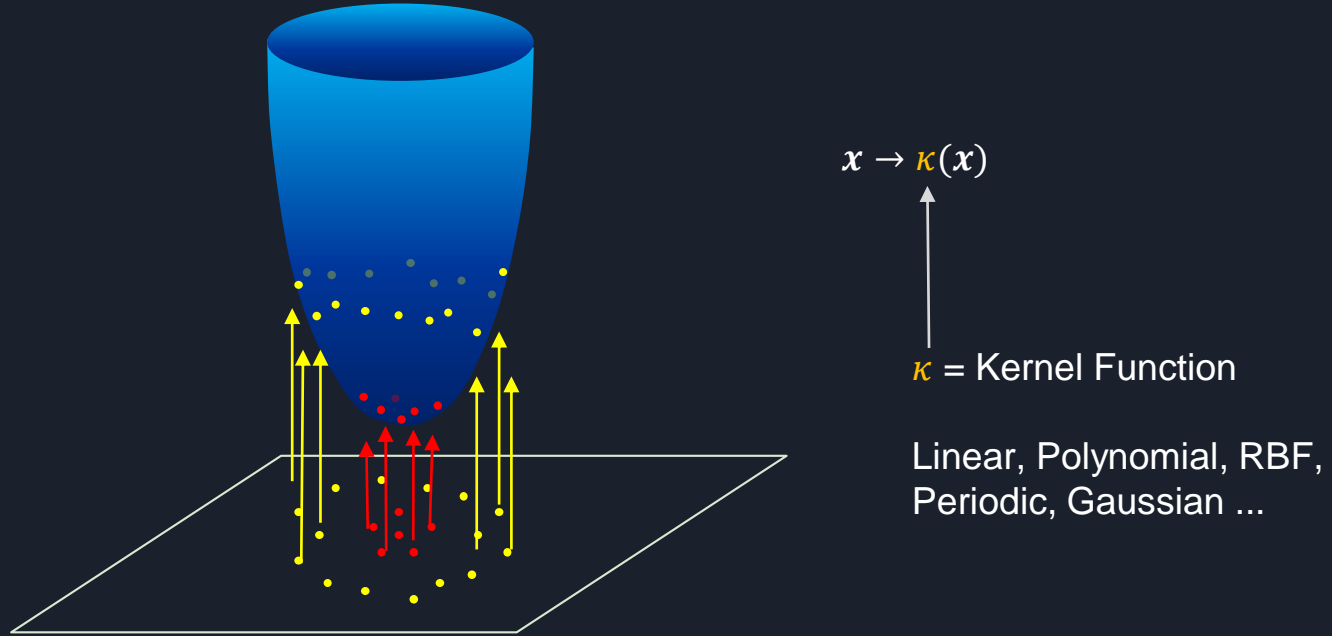


Not in this dimension.. We need more dimensions...

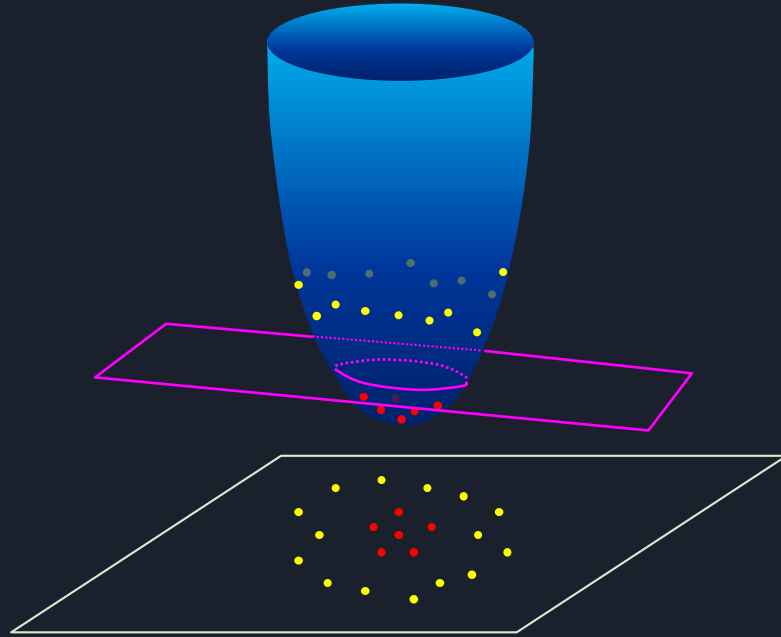




# Map values to higher dimensional space



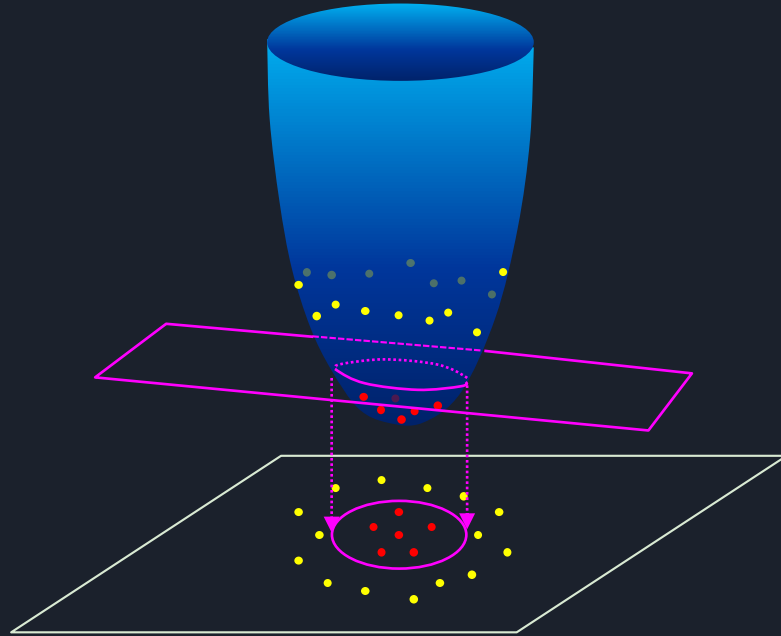
Create a hyperplane in the higher dimension



$$f(\mathbf{x}|\mathbf{w}, b, \kappa) = \mathbf{w}^T \kappa(\mathbf{x}) + b$$



Map values back to the lower dimensional space



$$g(\mathbf{x}) = \kappa^{-1}(f(\mathbf{x}))$$



# Further References

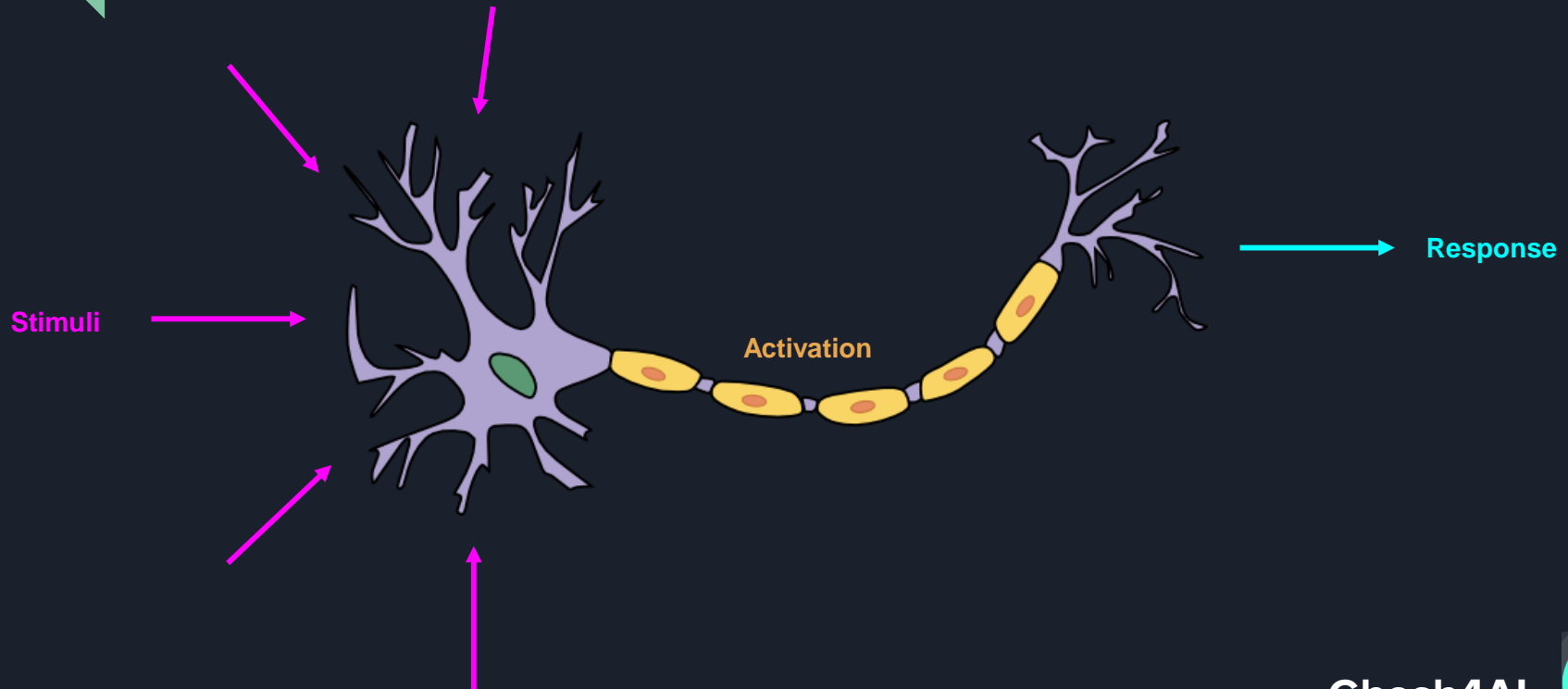
- Wikipedia - [Support vector machine - Wikipedia](#)
- Blogs :
  - [Understanding Support Vector Machine algorithm from examples](#)
  - [Chapter 2 : SVM \(Support Vector Machine\) — Theory](#)
  - [Support Vector Machines for Machine Learning](#)
- API
  - [Support Vector Machines — scikit-learn 0.19.2](#)
  - [Support Vector Machines for Binary Classification – MATLAB](#)
  - [Weka 3 - Data Mining with Open Source Machine Learning Software](#)
  - [LIBSVM -- A Library for Support Vector Machines](#)
- Books :
  - Pattern Recognition and Machine Learning – C.M. Bishop
  - Learning with kernels - Bernhard Schölkopf
- Related Papers
  - [Support vector machines](#)
  - [Measuring the VC-dimension of a learning machine](#)



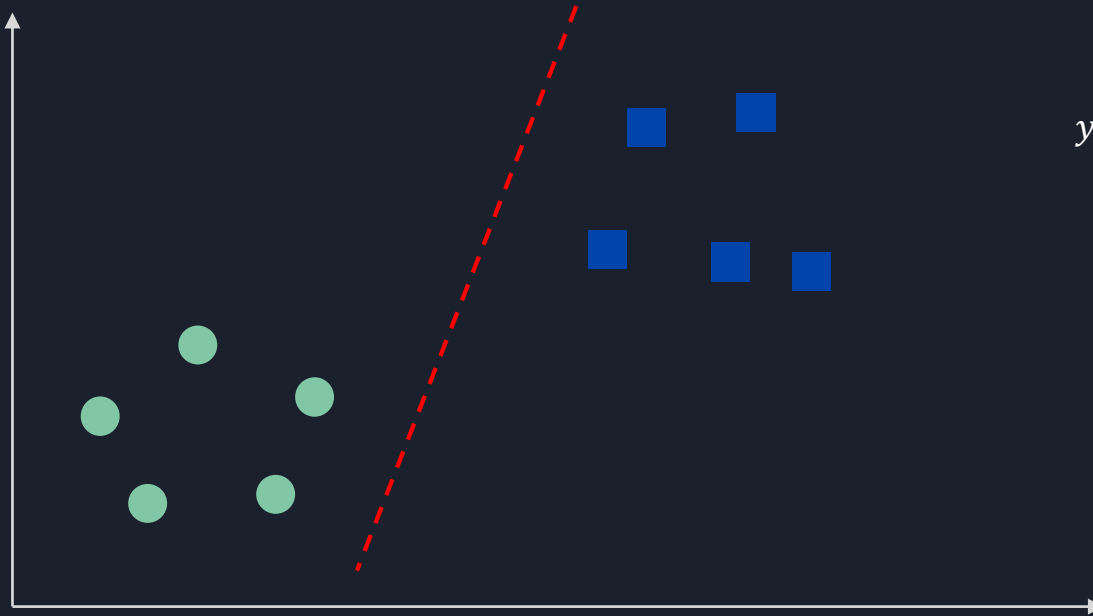
# Multilayer Perceptrons (MLP)



# The real neuron



# Decision as a straight line



$$y = \mathbf{w}^T \mathbf{x} + b$$

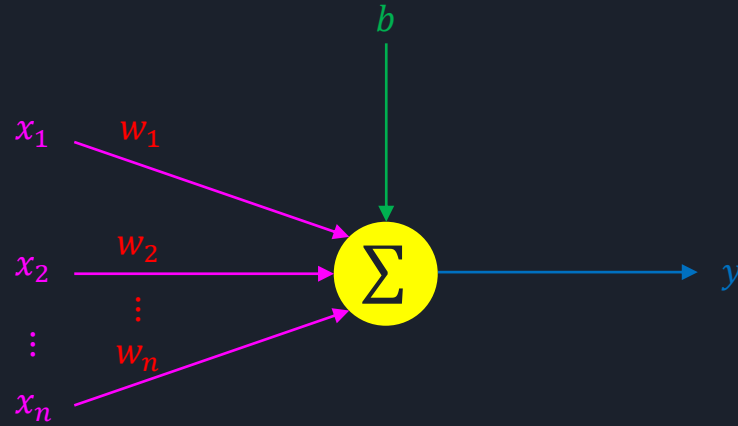


# The straight line

$$y = \mathbf{w}^T \mathbf{x} + b$$

$$y = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} [x_1 \ x_2 \ \dots \ x_n] + b$$

$$y = \sum_i^n w_i x_i + b$$





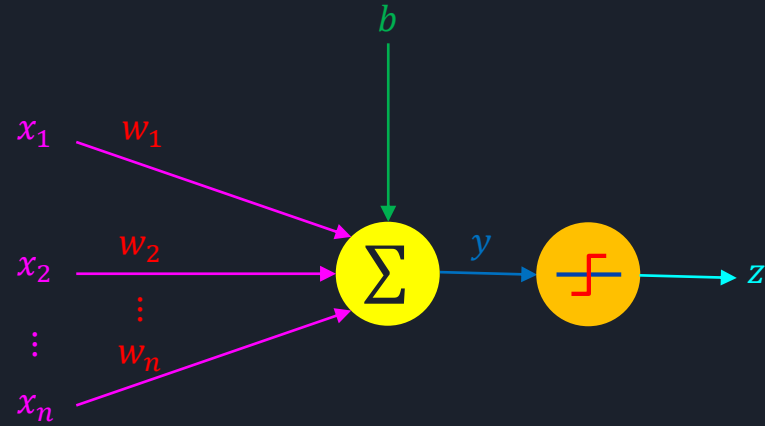
# The artificial Neuron making decisions

$$y = \mathbf{w}^T \mathbf{x} + b$$

$$y = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} [x_1 \ x_2 \ \dots \ x_n] + b$$

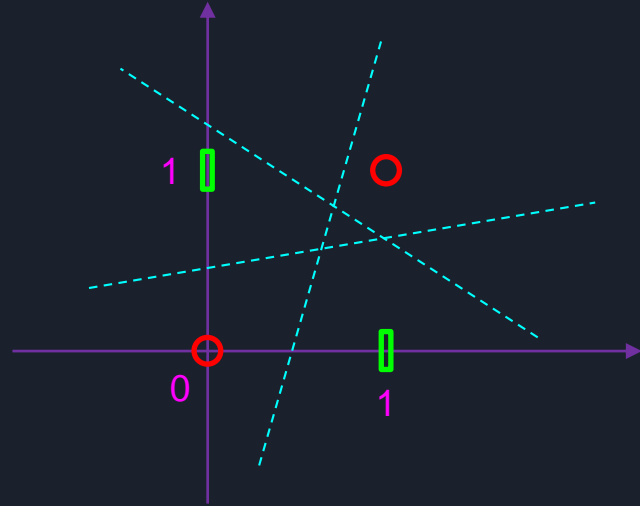
$$y = \sum_i^n w_i x_i + b$$

$$z = \text{sign} \left( \sum_i^n w_i x_i + b \right)$$



# Is a straight line enough ?

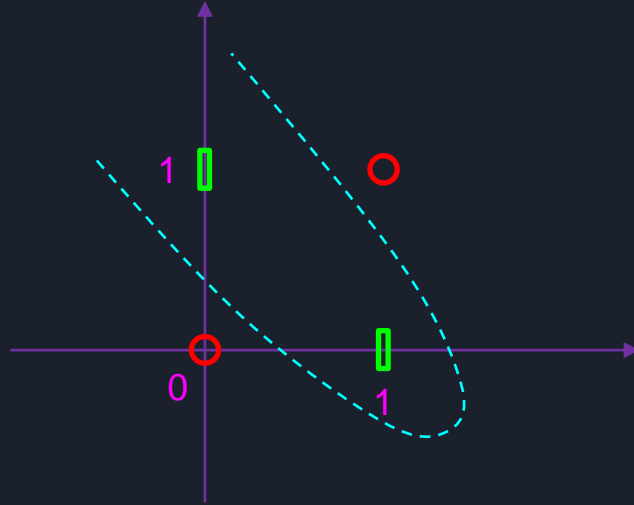
$$z = \text{sign}(w^T x + b)$$



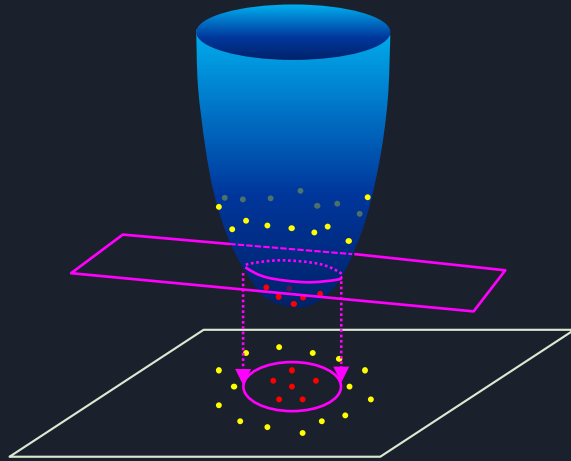
# Bend the line

$$z = f_{NL}(w^T x + b)$$

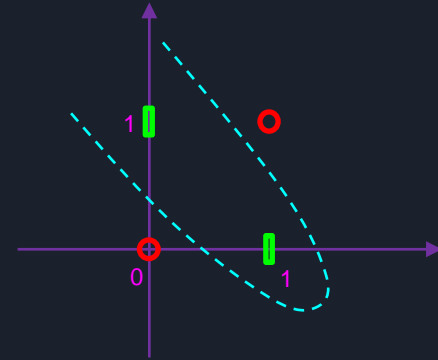
Non Linear Function



# SVM vs Neural Networks



$$z = w^T \phi(x) + b$$

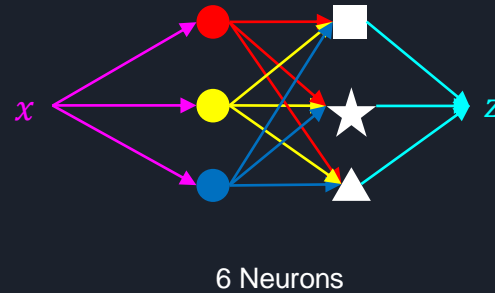
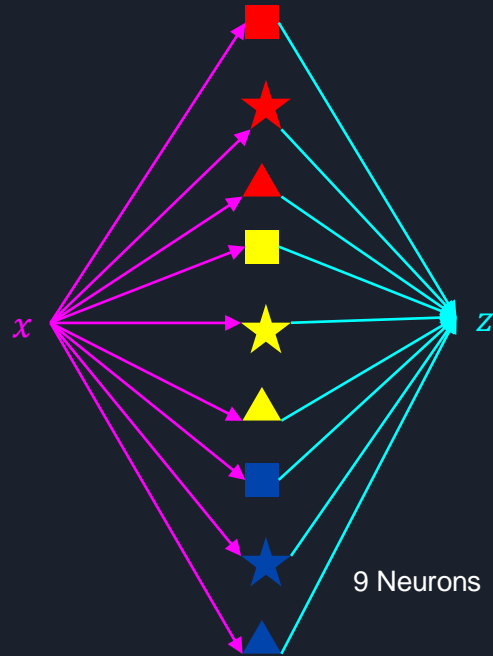


$$z = f_{NL}(w^T x + b)$$

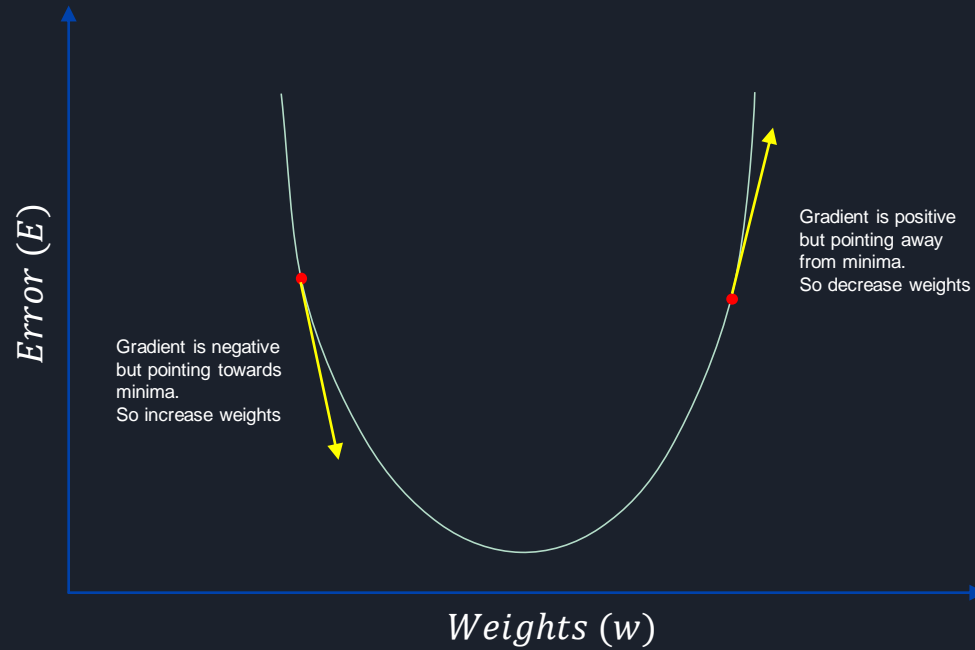


# Stack them up...

Colours = { red, yellow, blue }, Shapes = { Square, Triangle and Star }



# The gradient



# How to calculate weights ?

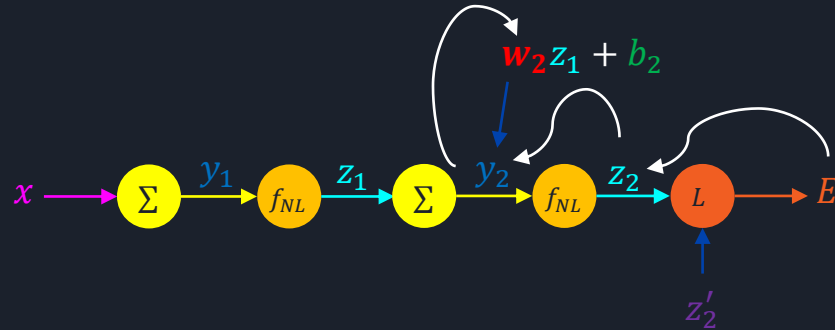
$$\mathbf{w} = \mathbf{w} - \eta \frac{dE}{d\mathbf{w}}$$

Change in error  
with respect to  
change in weights

$$E = L(z_{\text{observed}}, z_{\text{actual}})$$



# Derivative to chain of partial derivatives



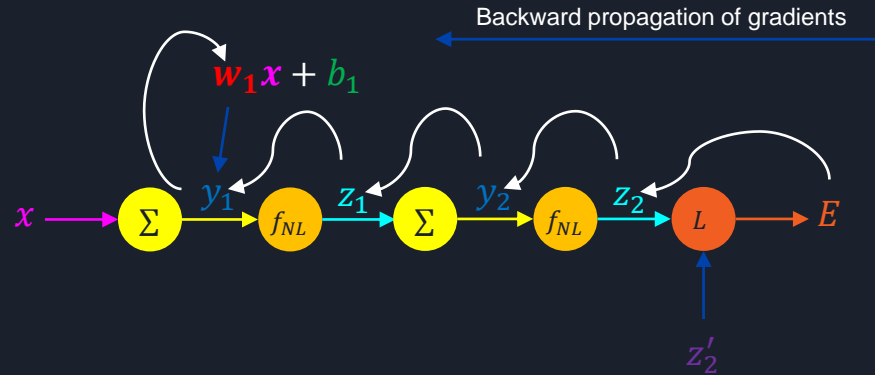
$$E = L(z_2, z'_2)$$

$$\frac{dE}{dw_2} = \frac{\delta E}{\delta z_2} \cdot \frac{\delta z_2}{\delta y_2} \cdot \frac{\delta y_2}{\delta w_2}$$





# Backpropagation through multiple layers



$$E = L(z_2, z'_2)$$

$$\frac{dE}{dw_1} = \frac{\delta E}{\delta z_2} \cdot \frac{\delta z_2}{\delta y_2} \cdot \frac{\delta y_2}{\delta z_1} \cdot \frac{\delta z_1}{\delta y_1} \cdot \frac{\delta y_1}{\delta w_1}$$





# Further References

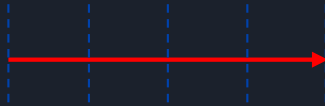
- [Wikipedia -Artificial neural network - Wikipedia](#)
- Blogs :
  - [Neural networks and deep learning](#)
  - [How to build your own Neural Network from scratch in Python](#)
  - [What is a neural network? - Introduction to deep learning](#)
- Demo :
  - [A Neural Network Playground](#)
  - [Neural Network demo — Preset: Binary Classifier for XOR](#)
- API
  - [Neural network models \(supervised\) — scikit-learn 0.19.2](#)
  - [Neural Network Toolbox - MATLAB – MathWorks](#)
  - [Weka 3 - Data Mining with Open Source Machine Learning Software](#)
  - [TensorFlow](#)
  - [PyTorch](#)
- Books :
  - Pattern Recognition and Machine Learning – C.M. Bishop
  - Neural networks- Simon S. Haykin
- Related Papers
  - [Learning internal representations by error propagation](#)
  - [The perceptron: a probabilistic model for information storage and organization in the brain.](#)
  - [A learning algorithm for continually running fully recurrent neural networks](#)
  - [30 years of adaptive neural networks](#)



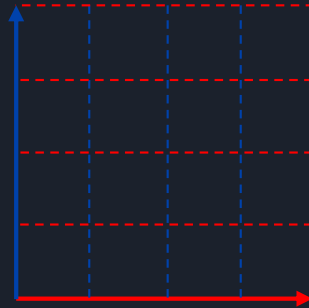
# Principal Component Analysis (PCA)



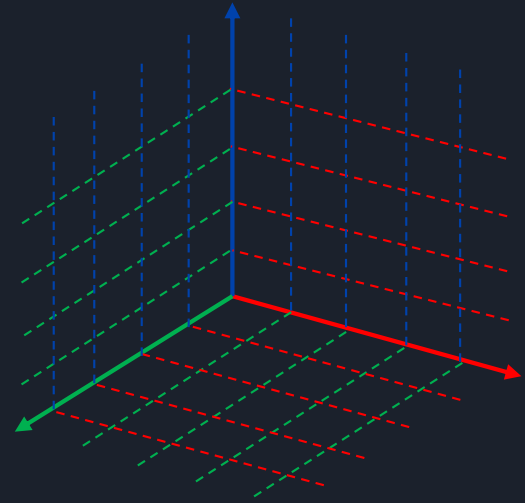
# The curse of dimensionality



4 regions



16 regions

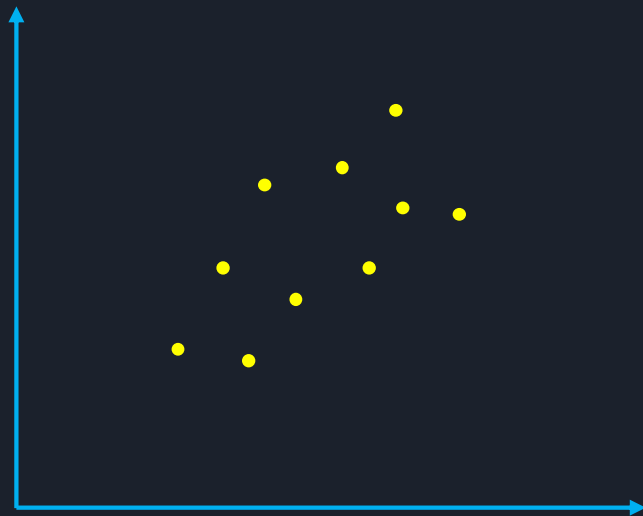


64 regions



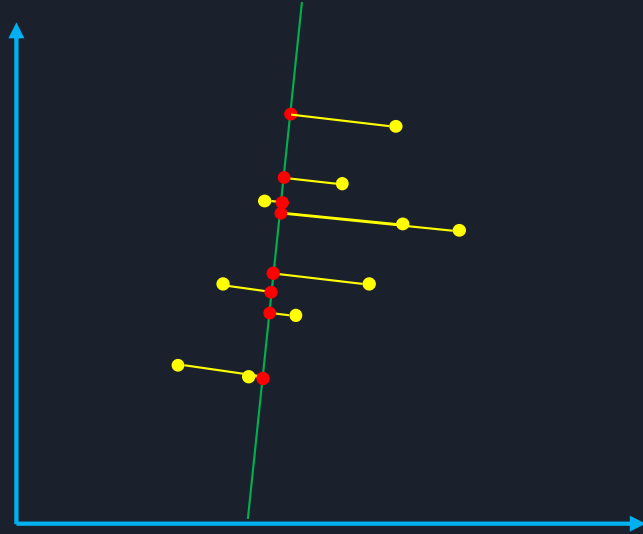


# 2 dimensions to represent sample space

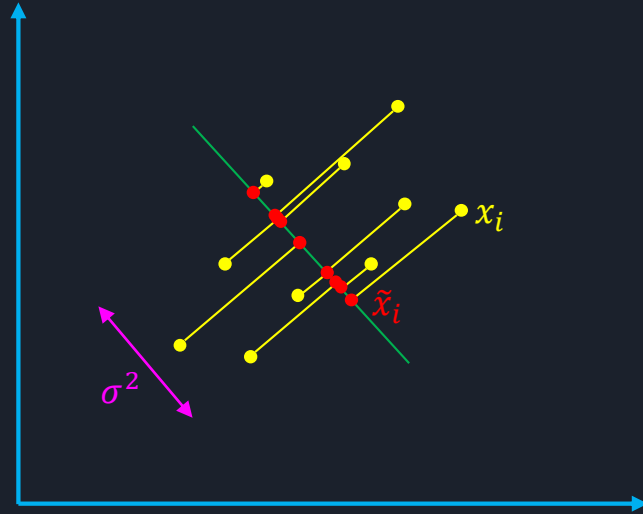




Mapping from 2 dimension to a single dimension.



We want the samples to be distinct in the new dimension... so, more variance

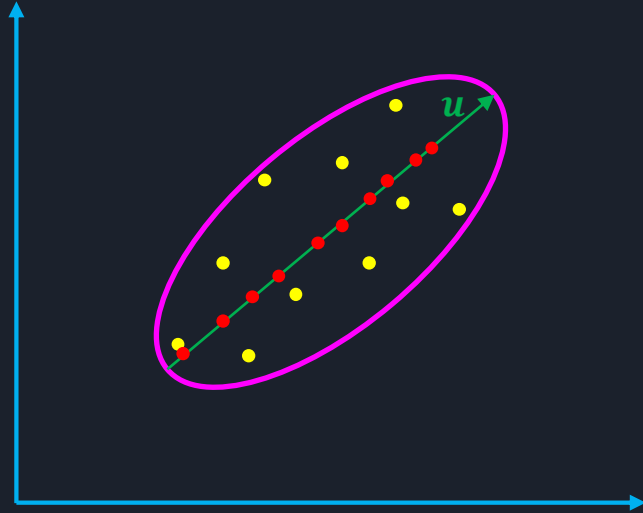


Goal :

- Maximize  $\sigma^2$  or
- Minimize  $\sum_i (x_i - \tilde{x}_i)^2$ .



# Along the major axis of an ellipse



$u$  is the eigen vector corresponding to the largest eigen value





# Further References

- Wikipedia -[Principal component analysis](#) - Wikipedia
- Blogs :
  - [A One-Stop Shop for Principal Component Analysis – Towards Data Science](#)
  - [Understanding Principal Component Analysis – Rishav Kumar - Medium](#)
  - [Practical Guide to Principal Component Analysis \(PCA\) in R & Python](#)
- Demo :
  - <http://setosa.io/ev/principal-component-analysis/>
- API
  - [sklearn.decomposition.PCA — scikit-learn 0.19.2](#)
  - [Principal component analysis \(PCA\) on data - MATLAB princomp](#)
  - [Weka 3 - Data Mining with Open Source Machine Learning Software](#)
- Books :
  - Pattern Recognition and Machine Learning – C.M. Bishop
  - [Principal components analysis – GH Dunteman](#)
- Related Papers
  - [Principal component analysis](#)

