# Lecture 08 – Classification Models

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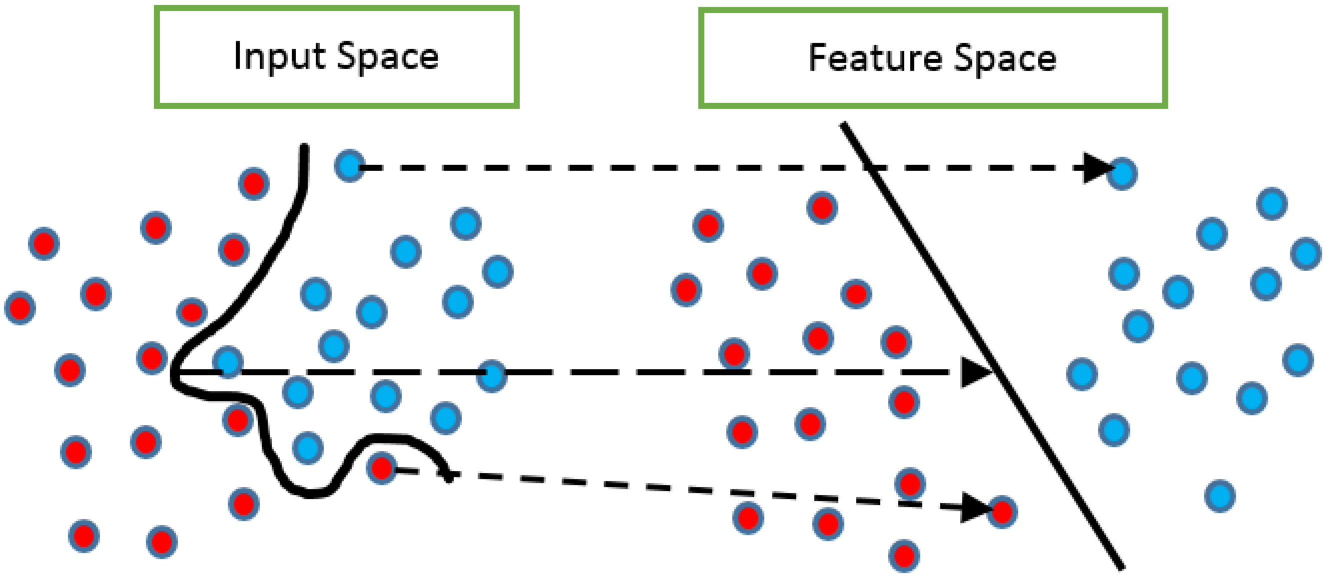
# Topics

- Discussion of Lecture #07
  - Image Descriptors
- Classification Models
  - K-NN, Logistic Regression, Decision Trees Naïve Bayes, SVM and MLP
- Evaluation Metrics
  - Accuracy, Precision, Recall and F1-Score
- Practice

# Problem

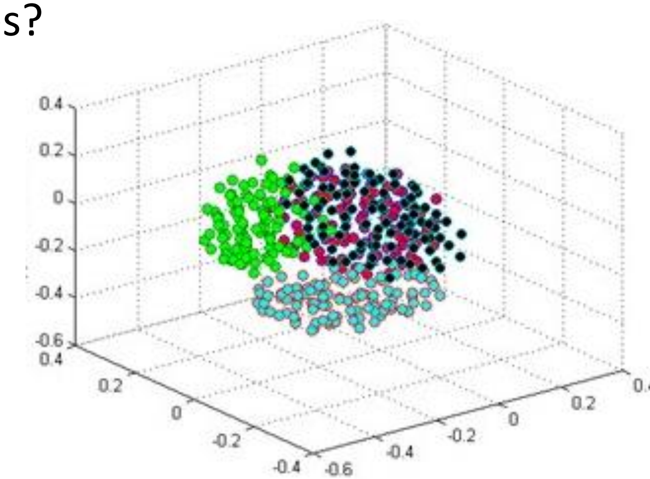
- So far, we have extracted features from data to compute the feature space.



# Problem

- How discriminating are features?

Input Space

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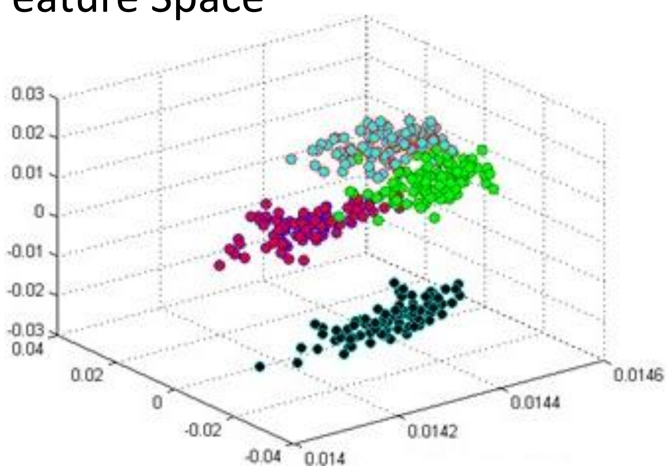
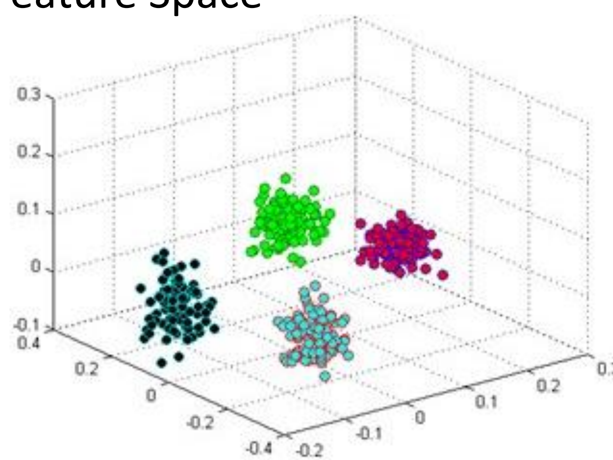
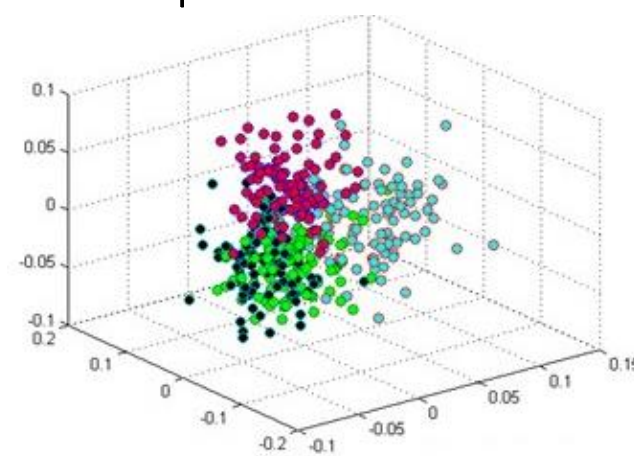
Feature Space’




Feature Space’’

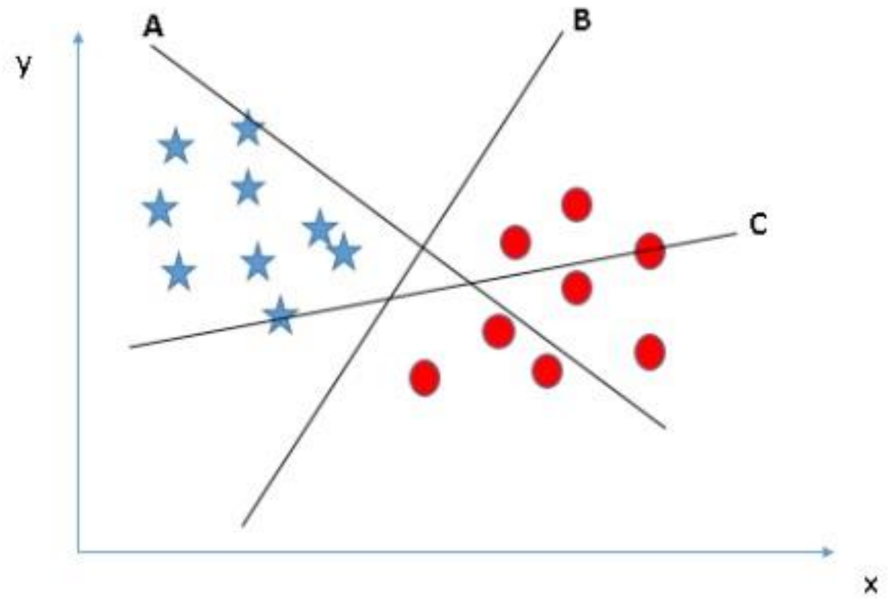



Feature Space ’’’



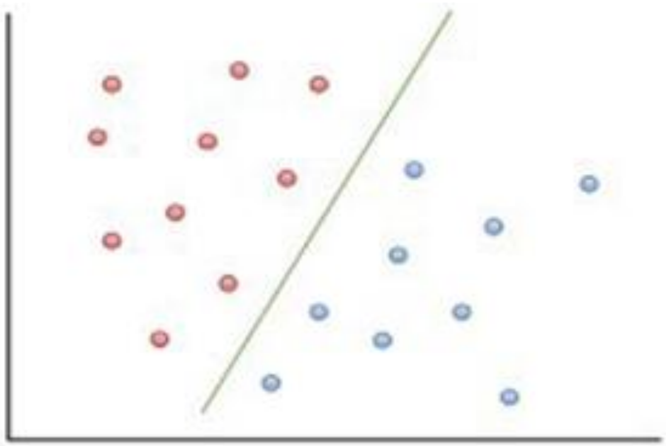
# Problem

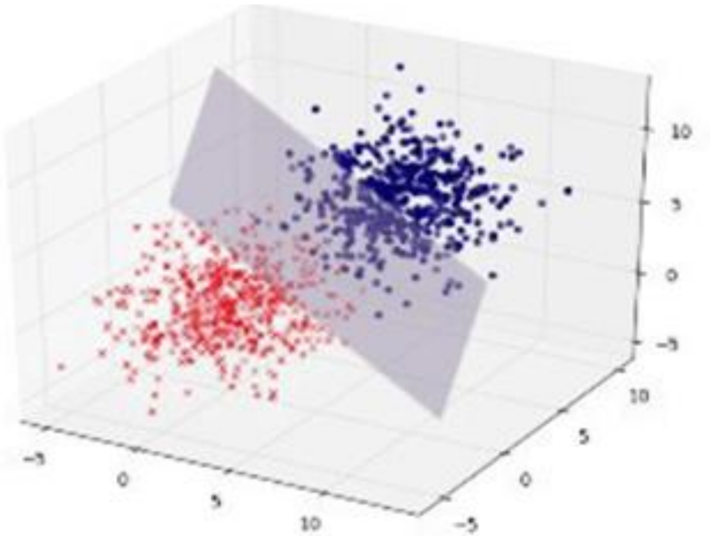
- How to compute the decision boundary?



# Problem

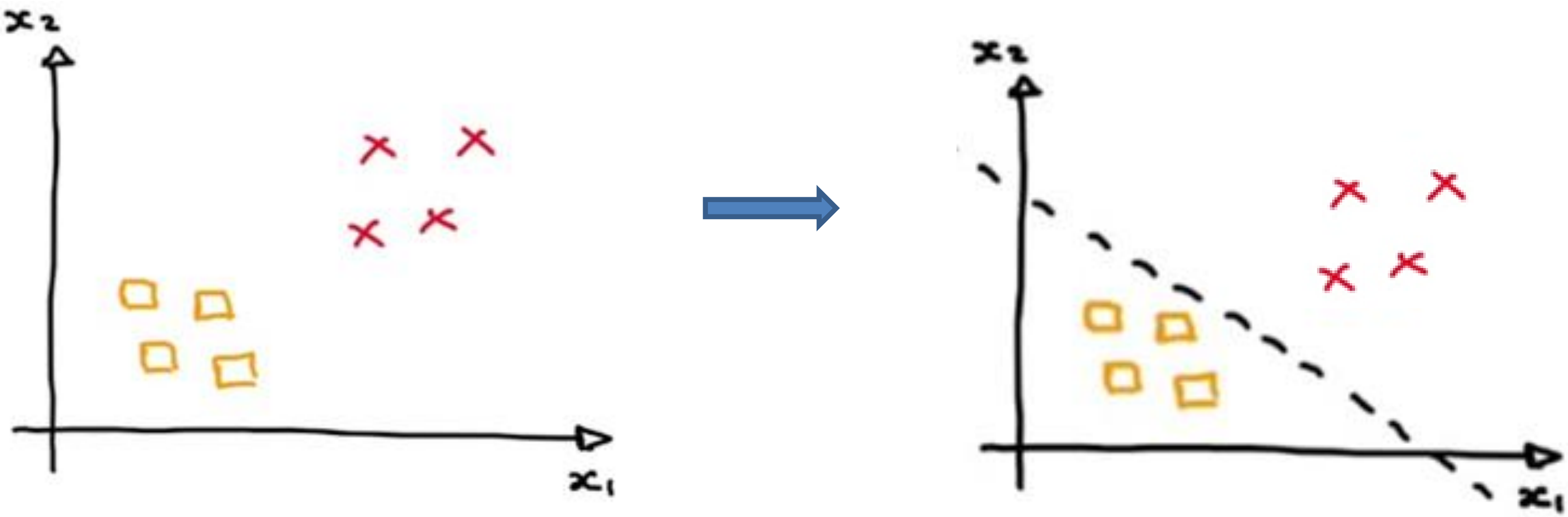
- Hyperplane
  - 2-D, 3-D … N-D (or N-Features)





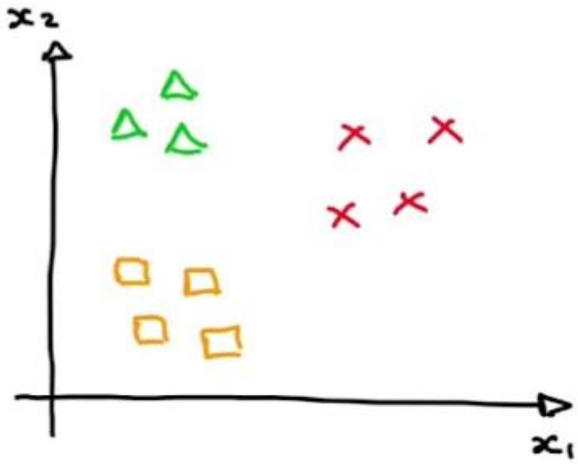
# Problem

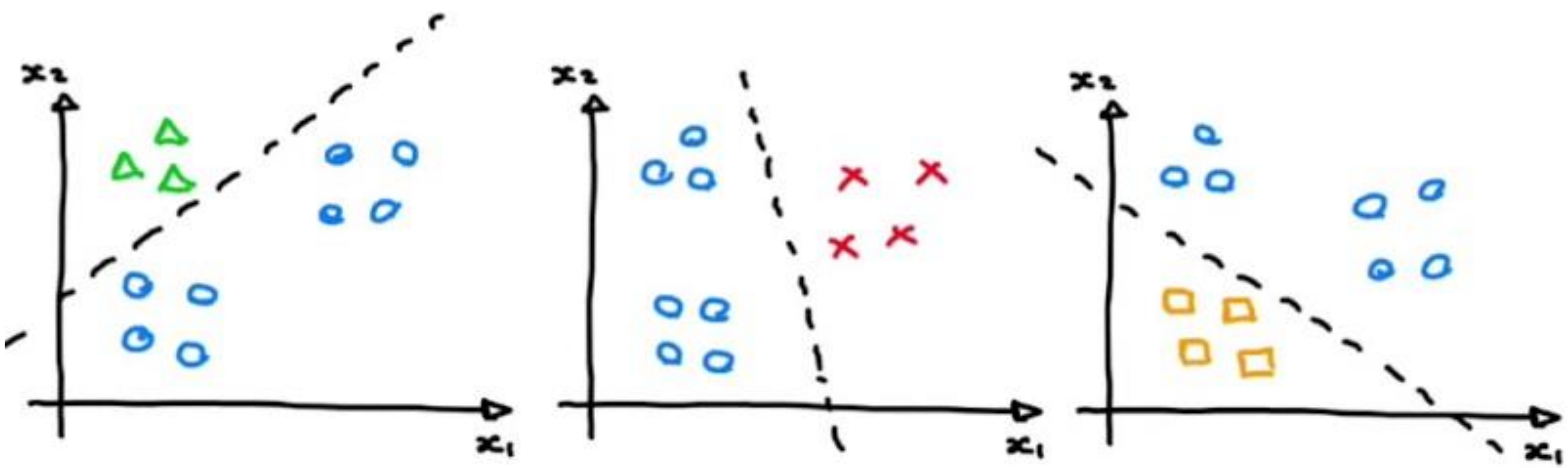
- Binary Classification vs Multi-Class Classification



# Problem

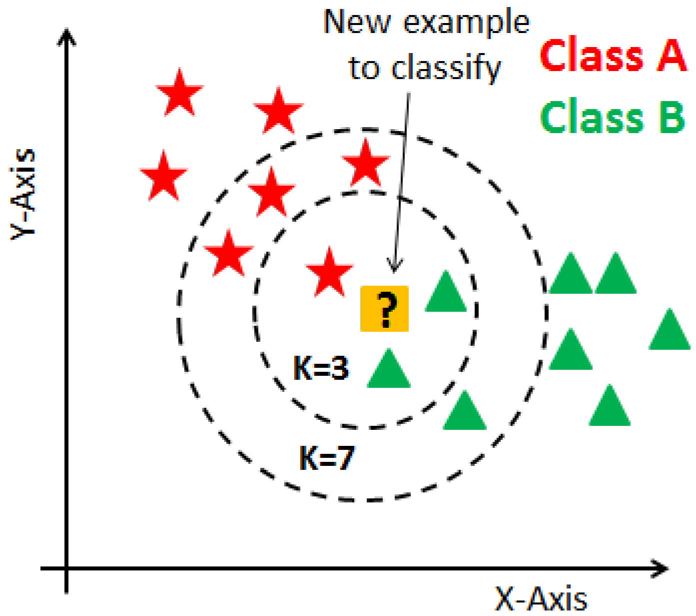
- Binary vs Multi-Class



# Classification Models
# KNN

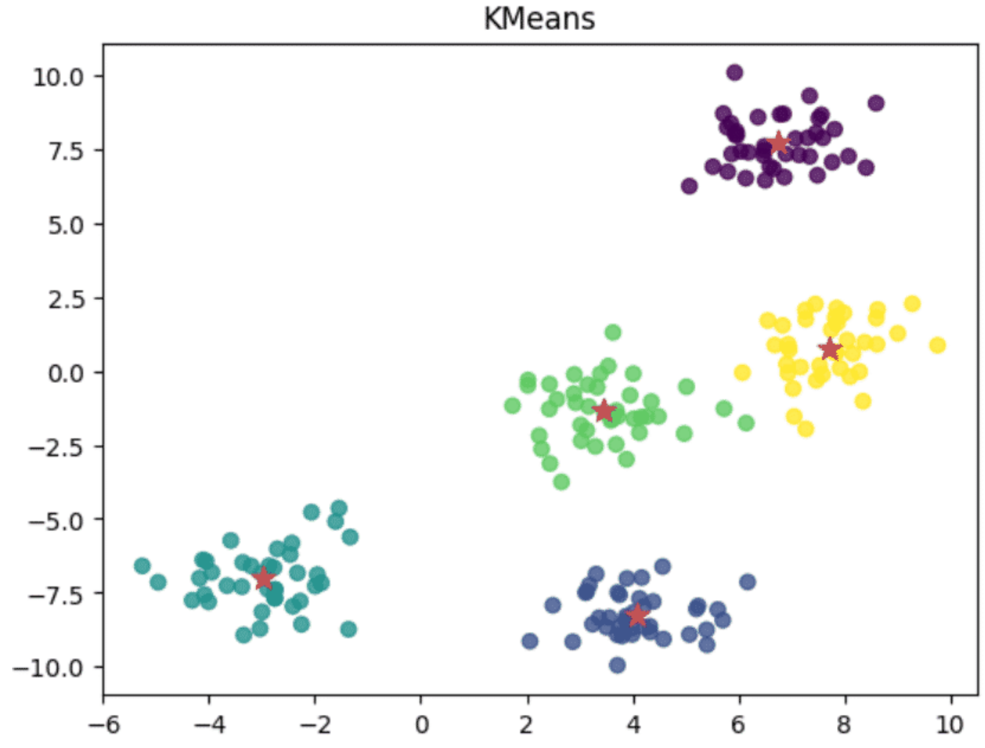
- Computes the similarity in a feature space (Euclidian Distance, Manhattan....)
- The K-Nearest Neighbors determines the class (Majority Vote)
- There is no training step. Compute the distance of the test sample to each training sample




$$d(x,y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2}$$

# Classification Models
# K-Means

- Computes the distance between k-cluster
- The clusters are defined in training step

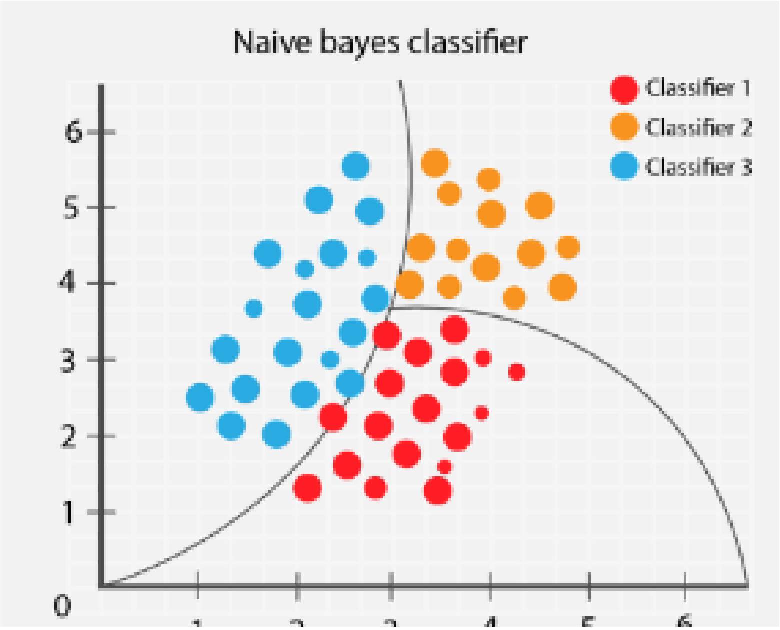


# Classification Models
# Naïve Bayes

- Bayes Theorem
- *A priori vs Posteriori* Probabilities

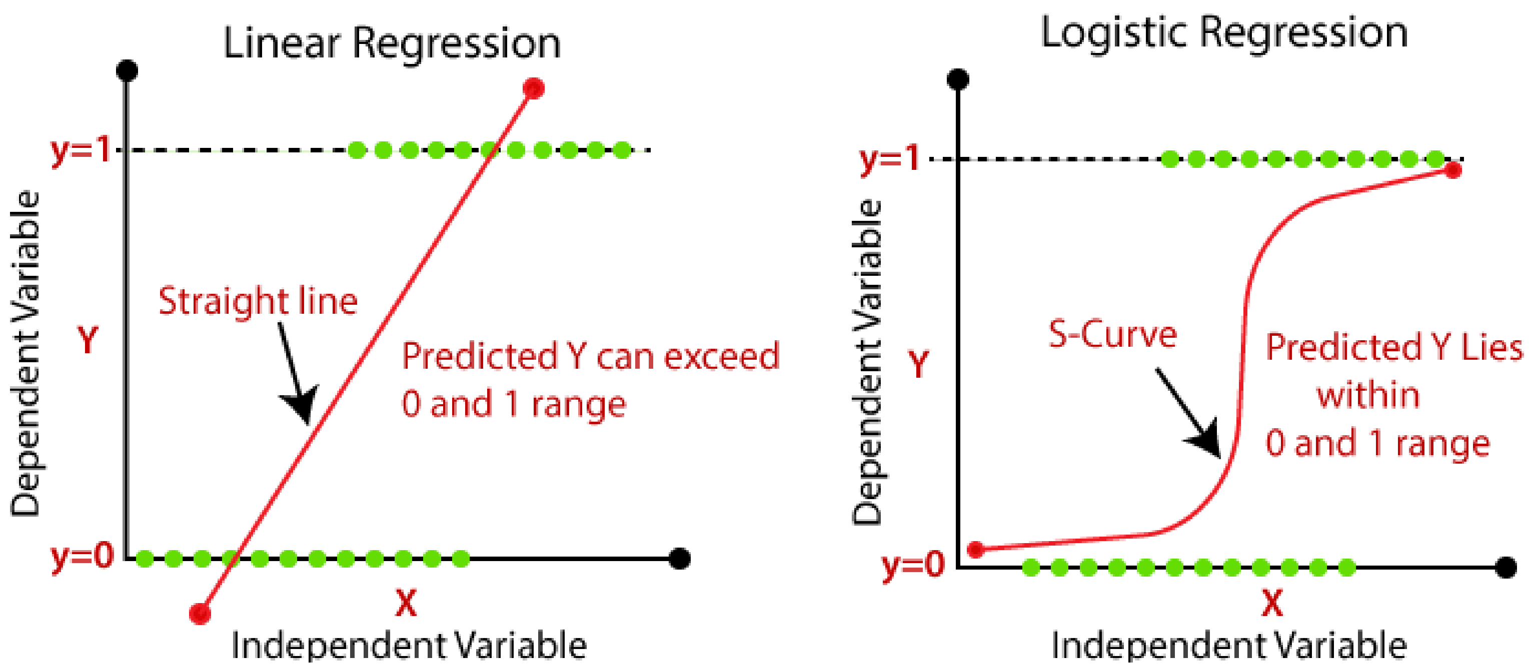
$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

$$\text{Posterior} = \frac{\text{prior x likelihood}}{\text{evidence}}$$



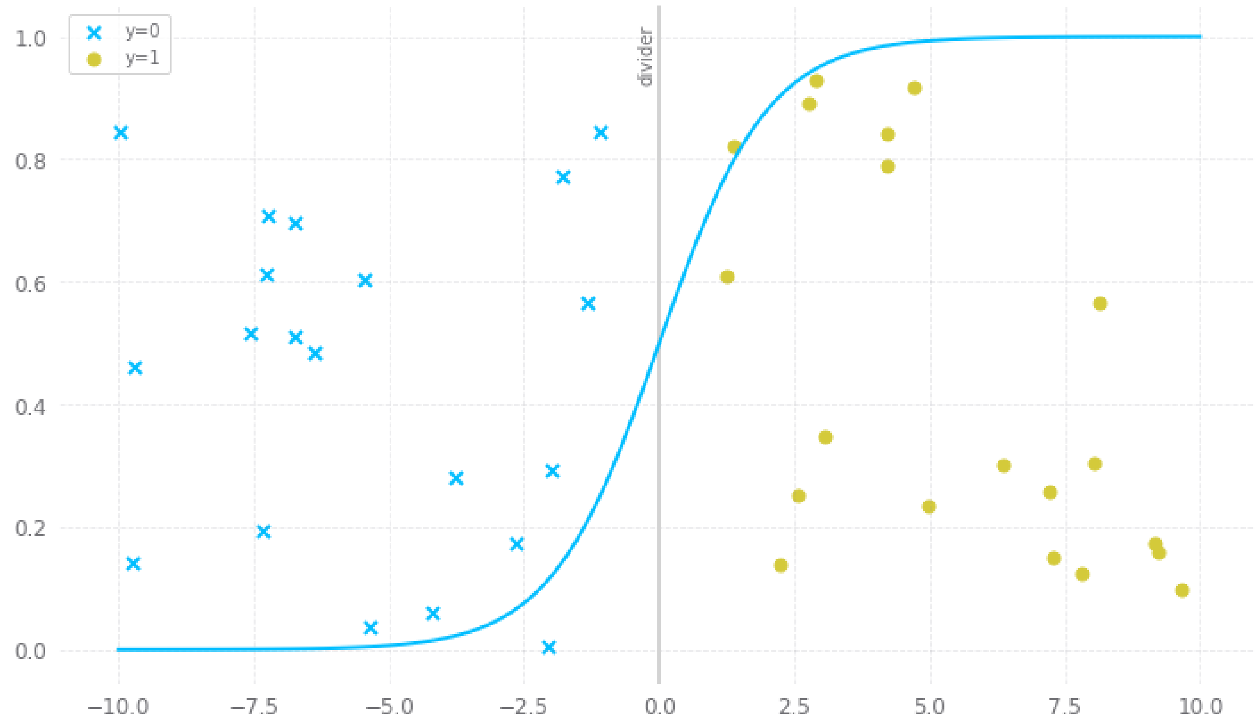
# Classification Models
# Logistic Regression

- Linear vs Logistic



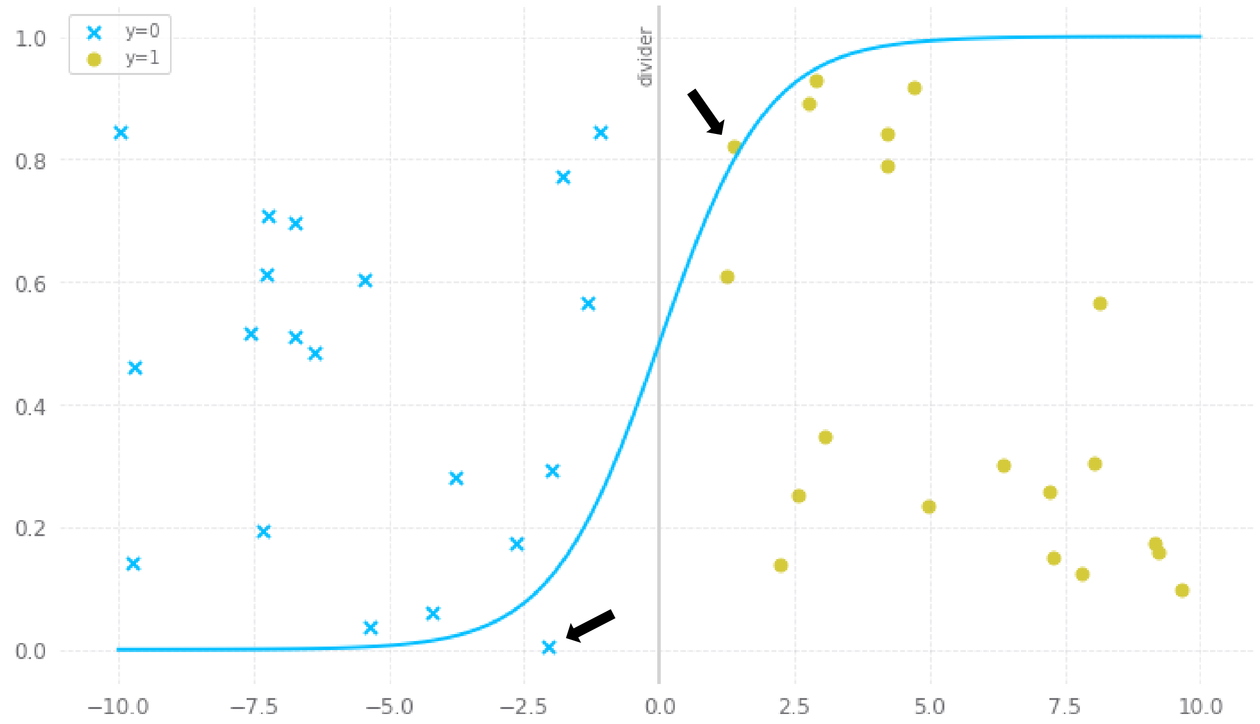
# Classification Models
# Logistic Regression (LR)

- Logistic Boundary



# Classification Models
# Logistic Regression (LR)

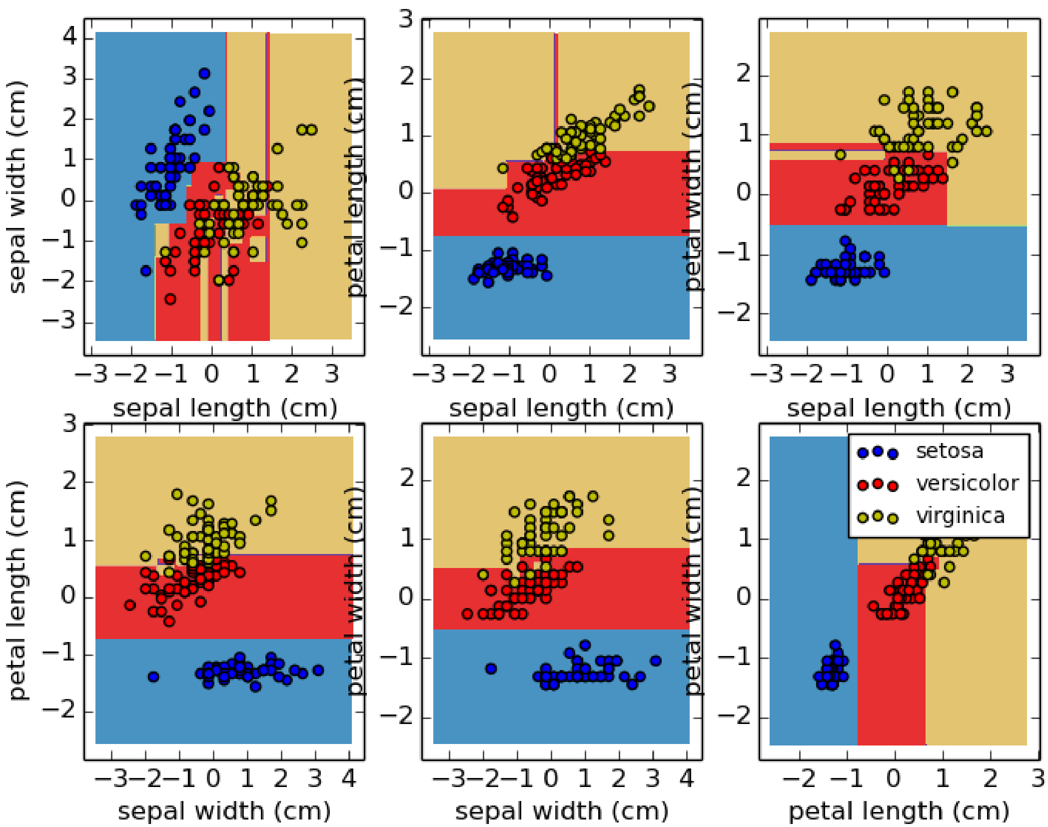
- Logistic Boundary

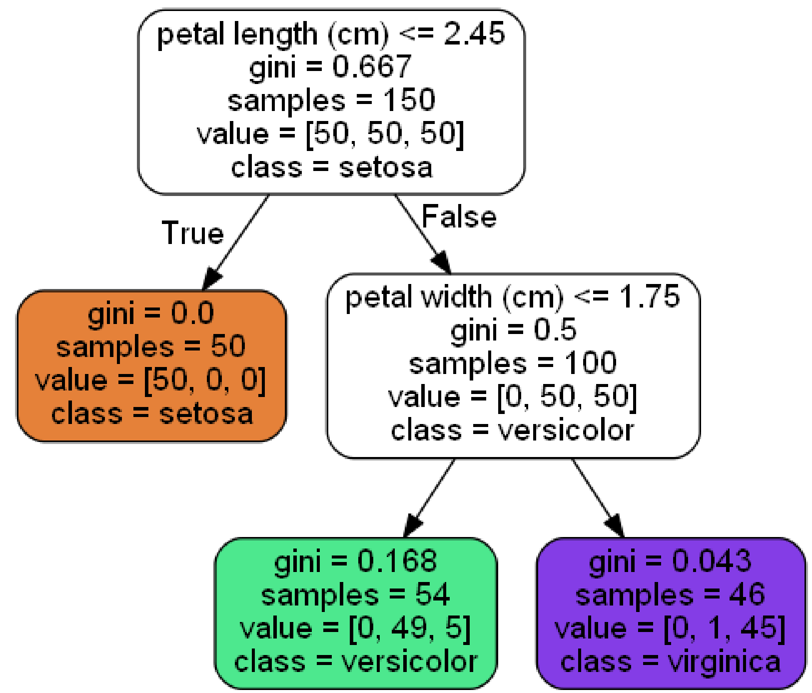


# Classification Models
# Decision Tree

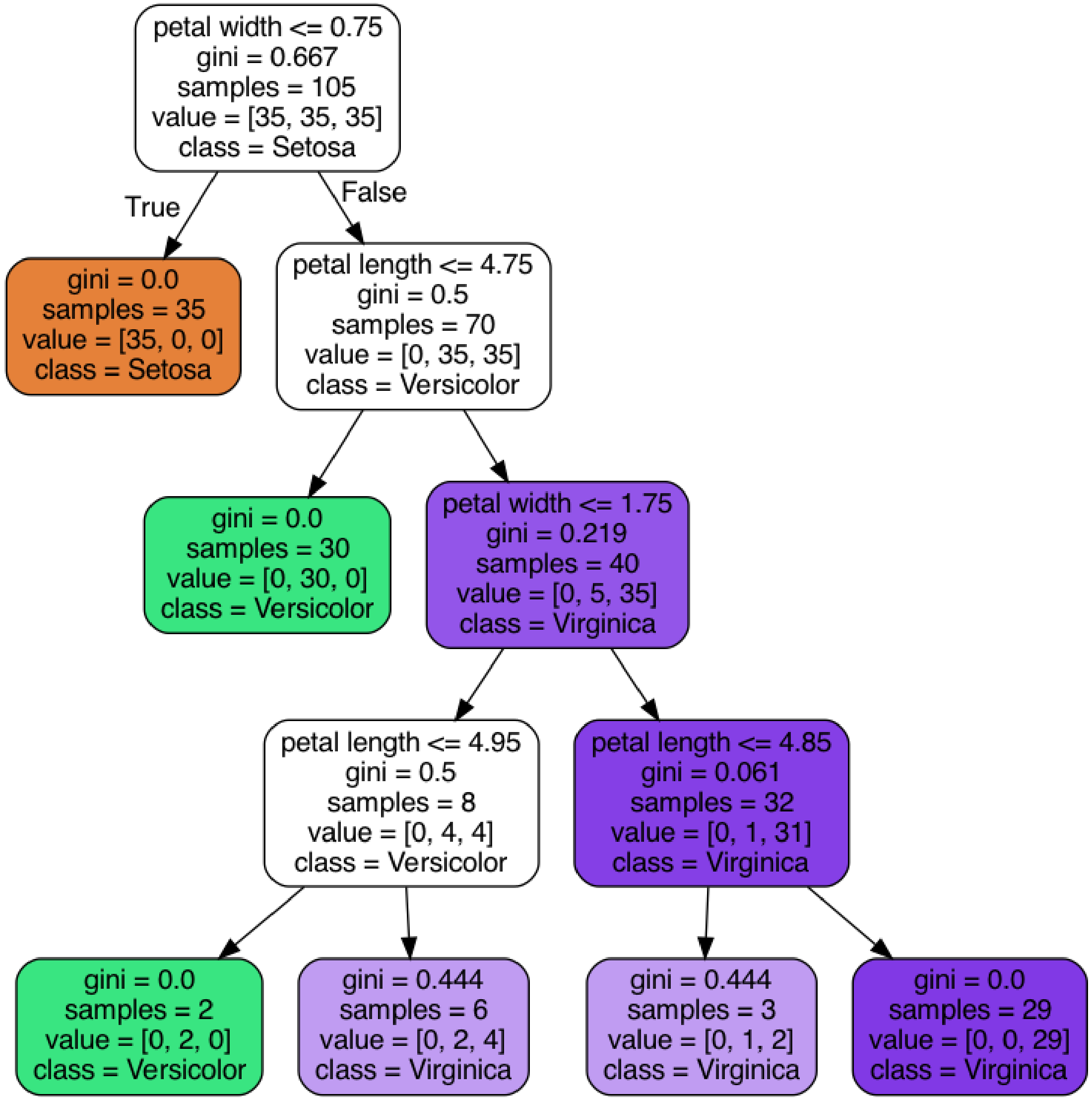
- Creates decision rules from the data features

Decision surface of a decision tree using paired features



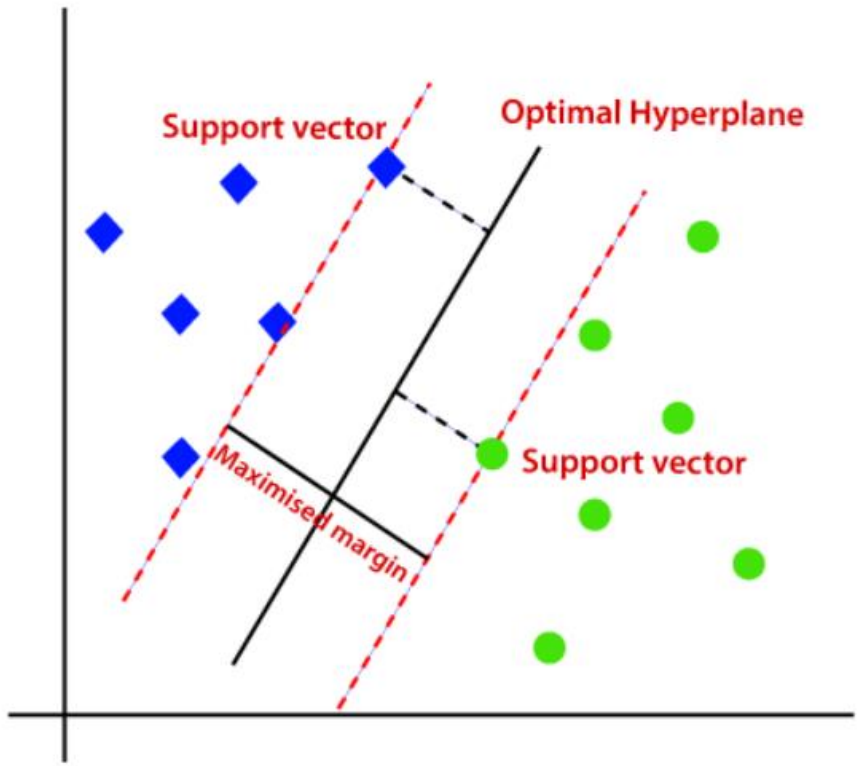



# Classification Models
# Decision Tree



# Classification Models
# Support Vector Machine (SVM)

- The support vectors determine the decision boundary



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# Support Vector Machine (SVM)

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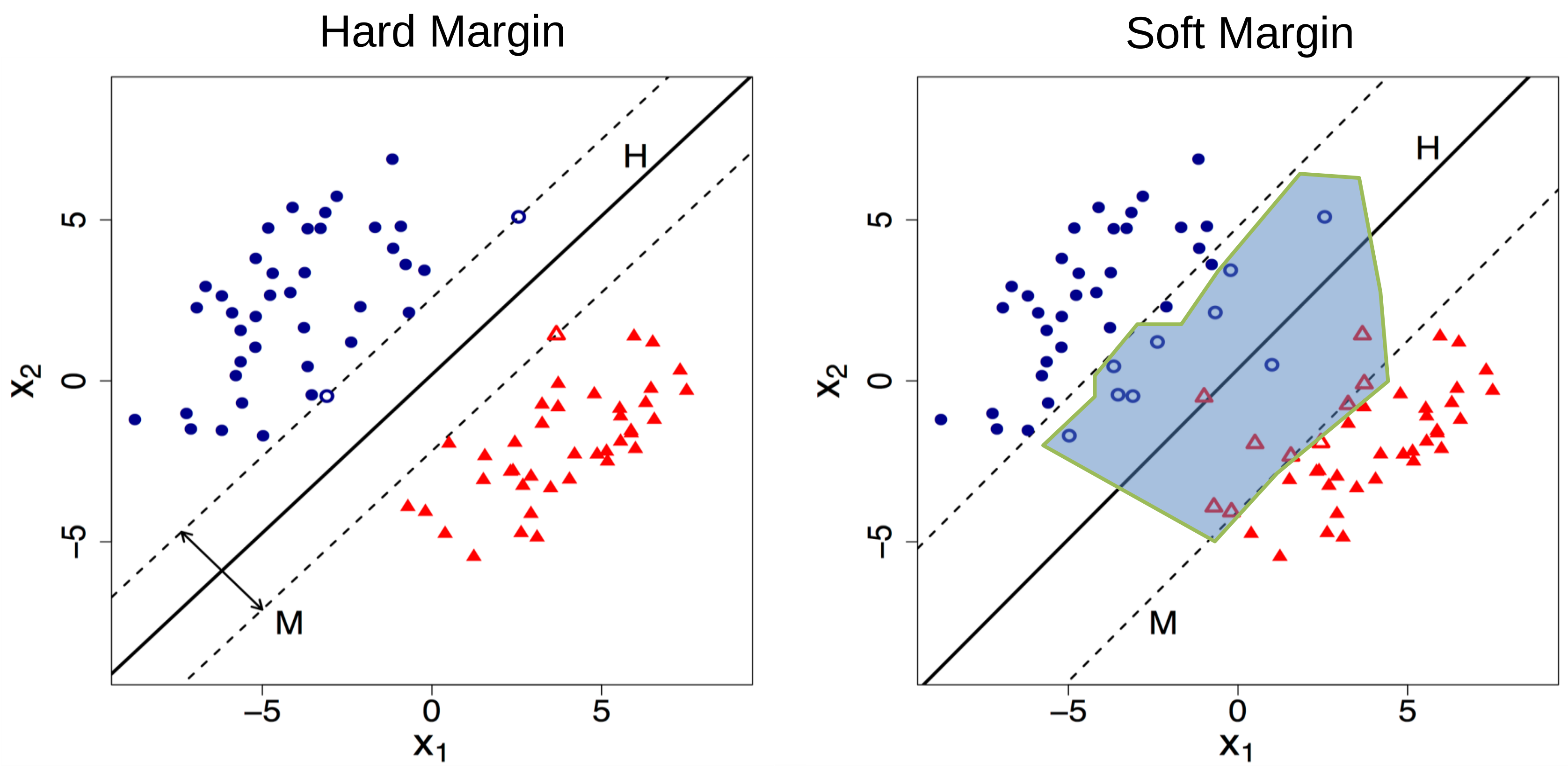
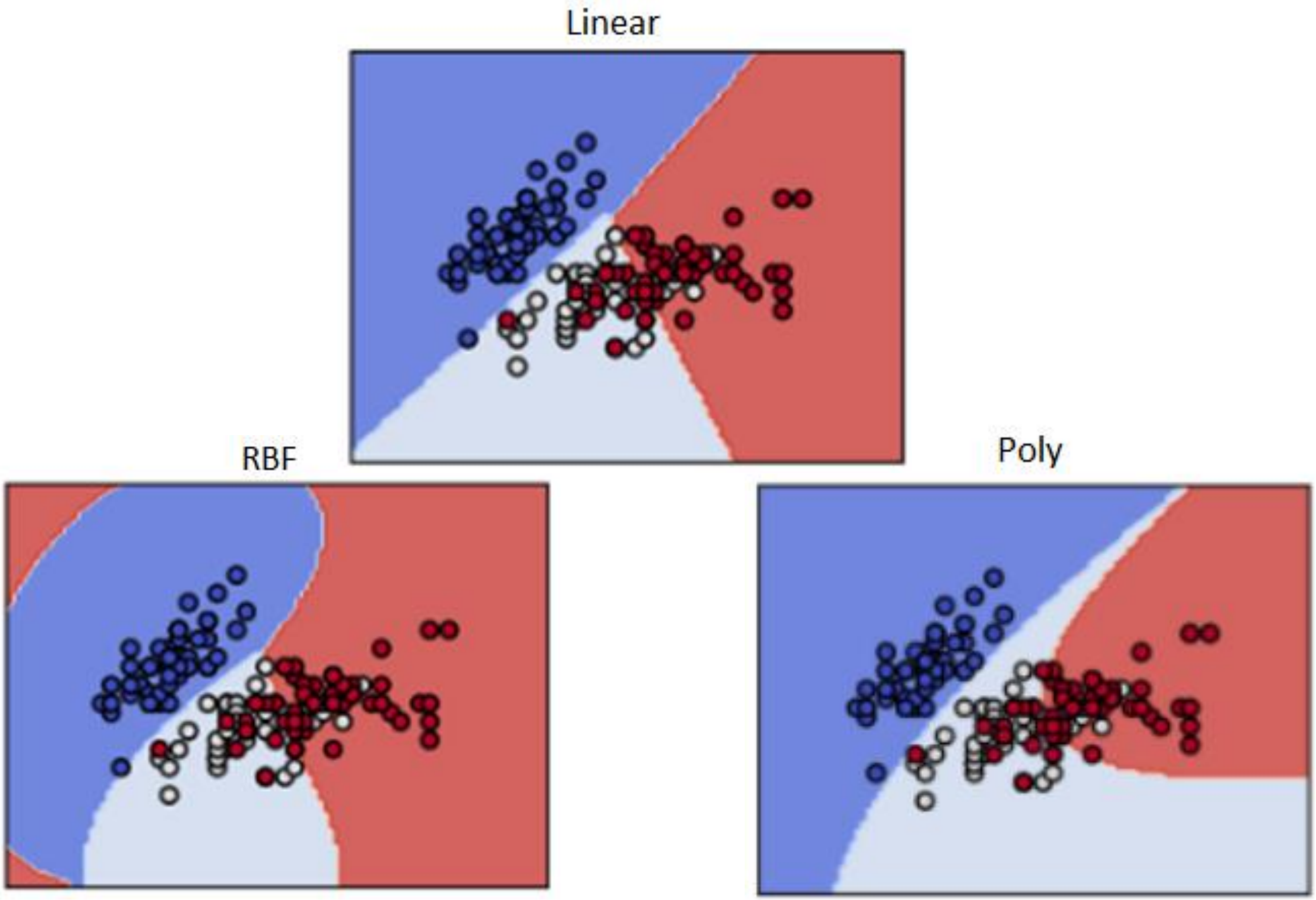


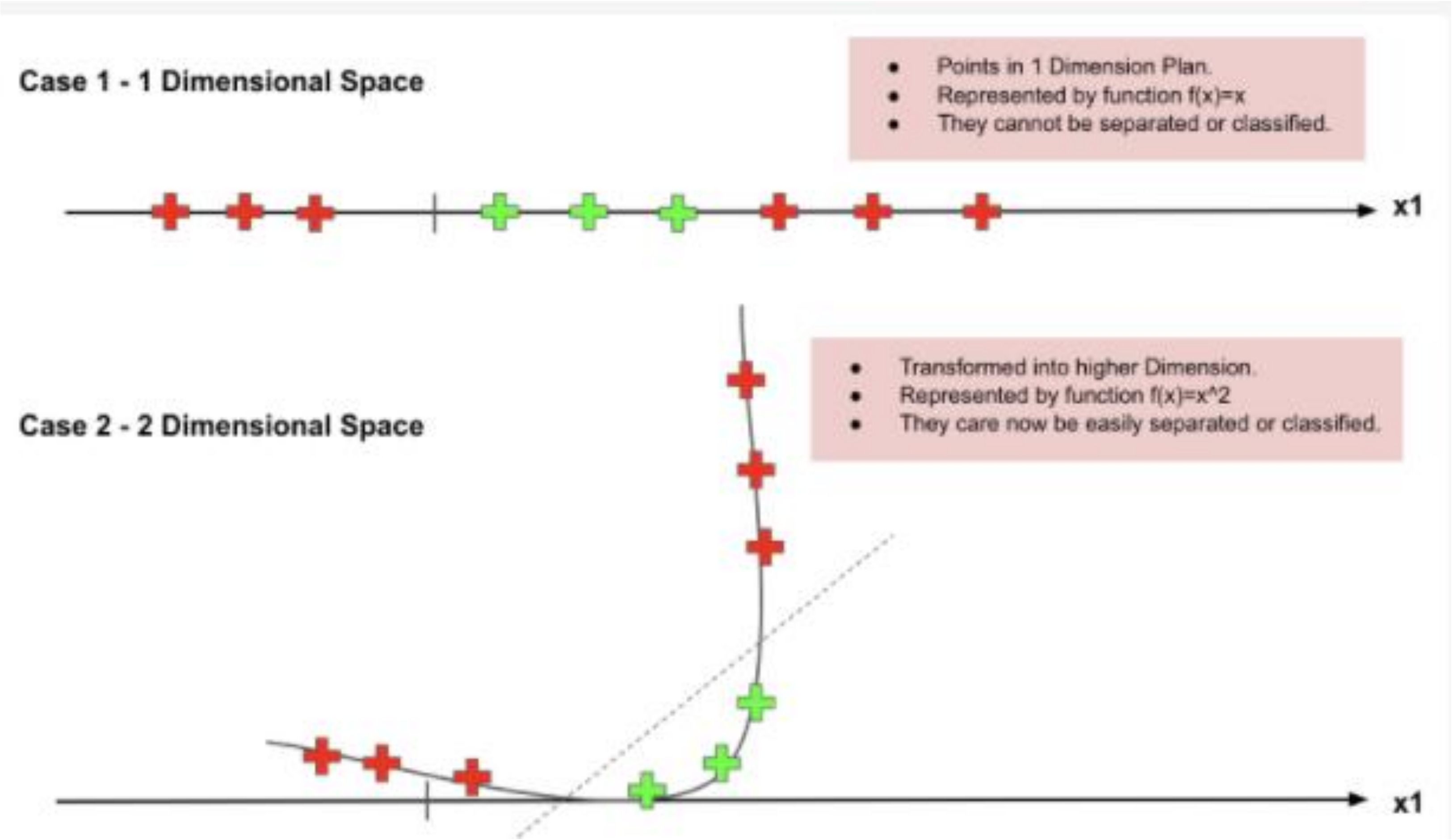
# Classification Models
# Support Vector Machine (SVM)

- Kernels



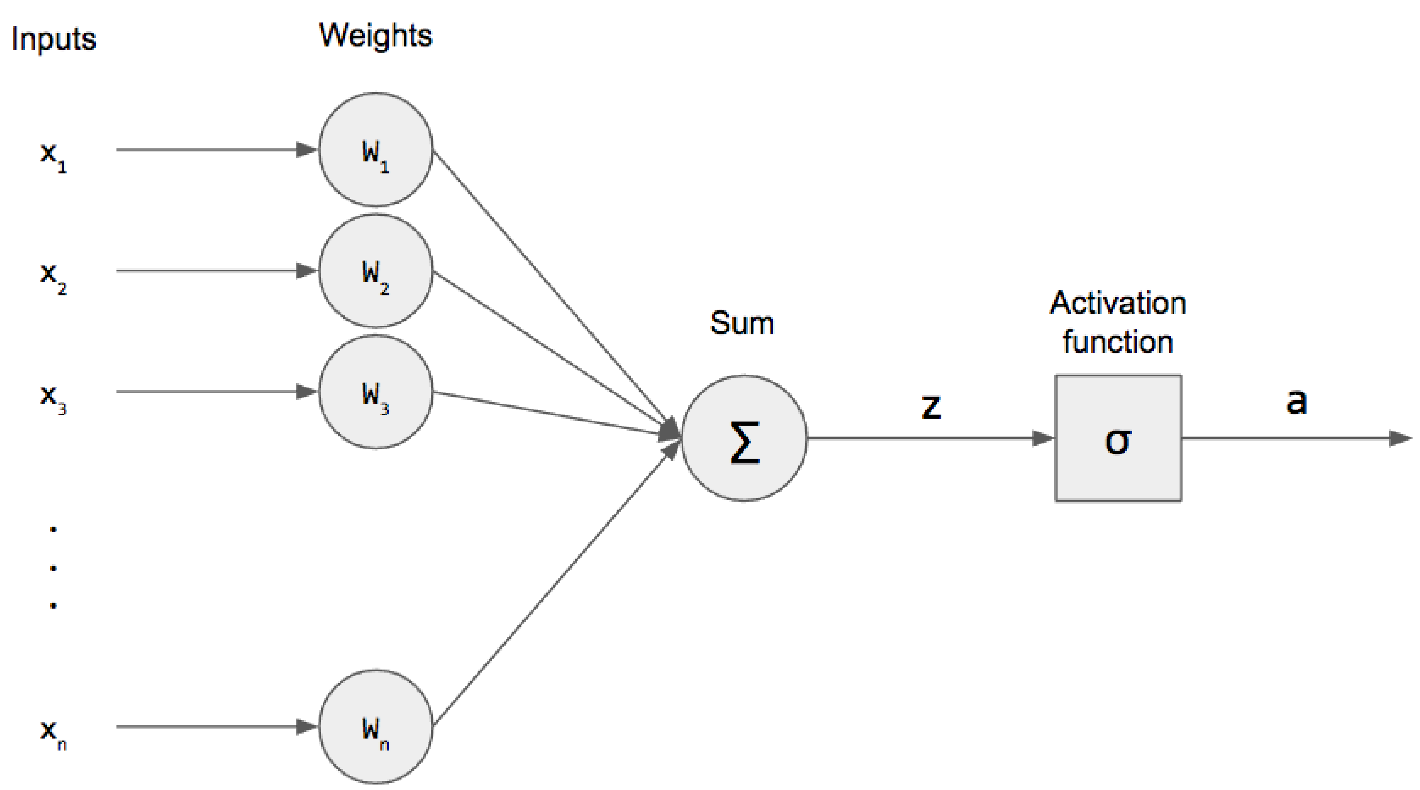
# Classification Models
# Support Vector Machine (SVM)

- Kernel Trick



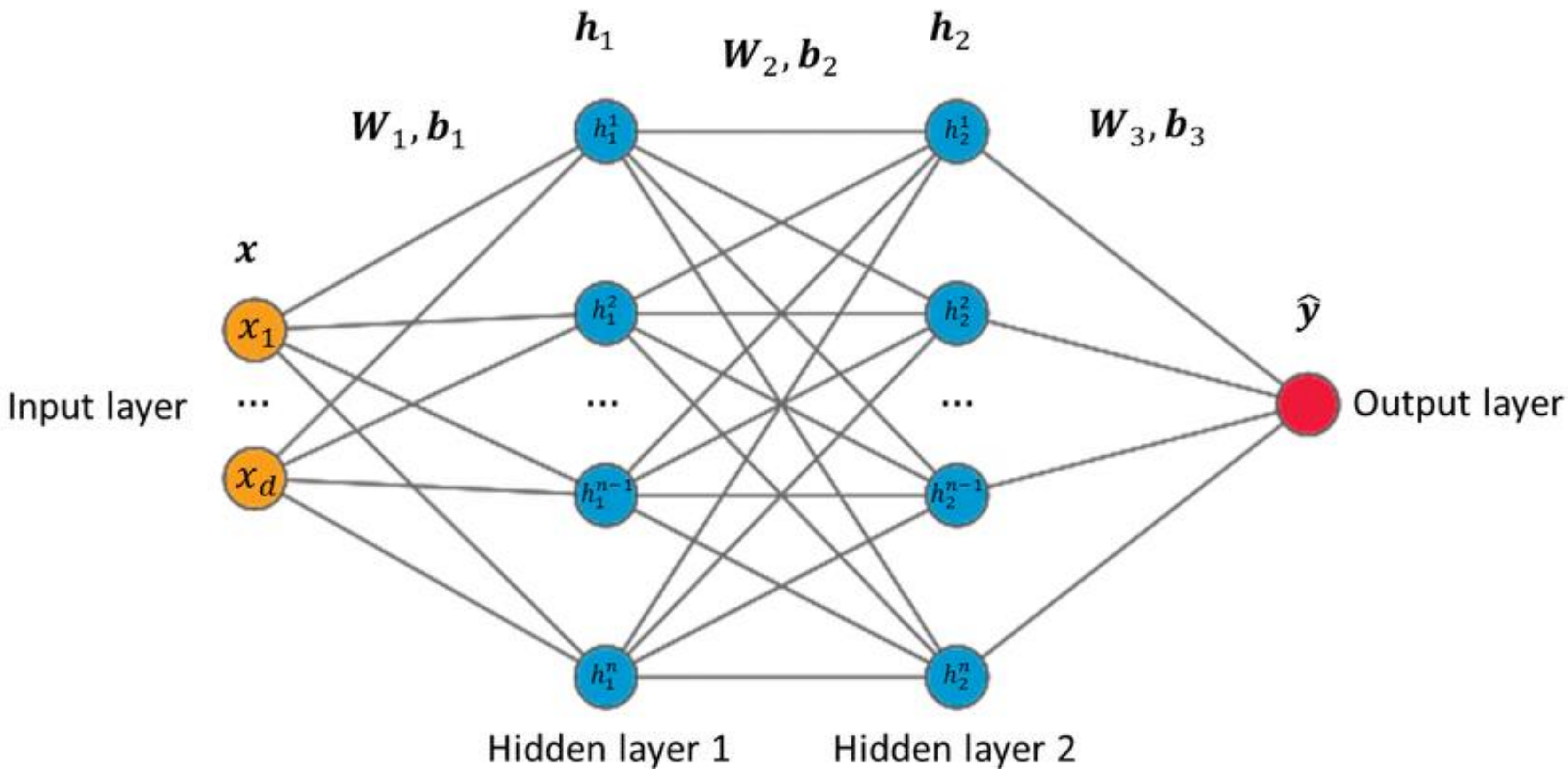
# Classification Models
# Multi-Layer Perceptron

- Perceptron



# Classification Models
# Multi-Layer Perceptron

- Multi-Layer Perceptron (MLP)

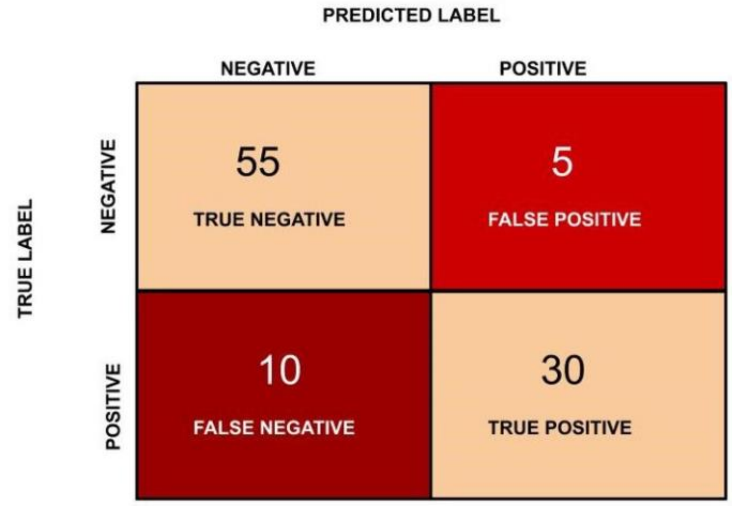


# Evaluation Metrics

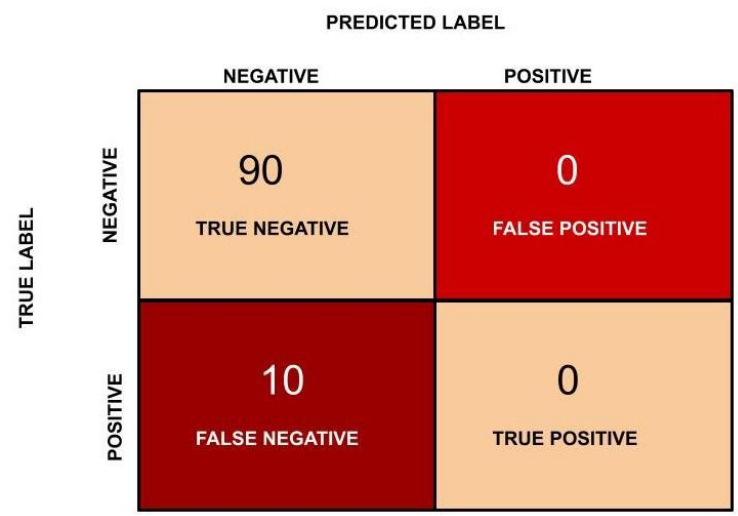
- Accuracy:
  - **Correctly classified** instances over **total** instances

$$Accuracy = \frac{TN + TP}{TN + FP + TP + FN}$$

  - (55 + 30)/(55 + 5 + 30 + 10 ) = 0.850




- What is the problem with accuracy?
  - Imbalanced Data
    - Acc: 90% (90/100)
    - Error TP: 100% (10/10)

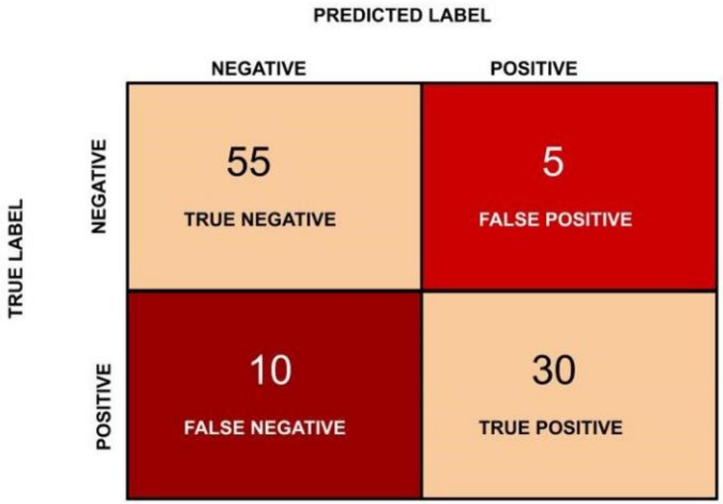


# Evaluation Metrics

- Precision:
  - Correctly **positive classified instances** over **positive predictions**

$$Precision = \frac{TP}{TP + FP}$$

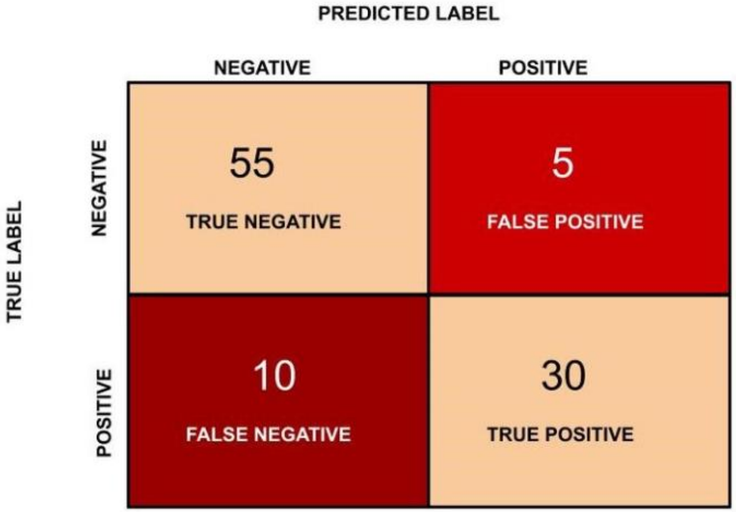
  - 30/(30+ 5) = 0.857




- Recall
  - Correctly **positive classified instances** over **positive instances** (A.K.A Sensitivity or TP Rate)

$$Recall = \frac{TP}{TP + FN}$$

  - 30/(30+ 10) = 0.750

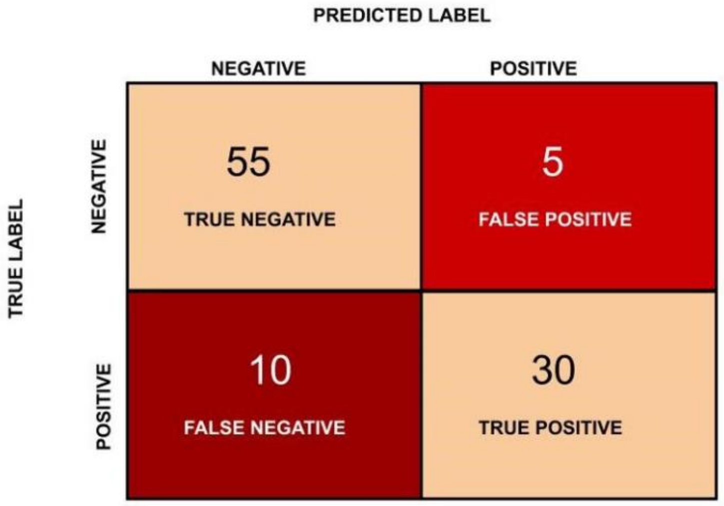


# Evaluation Metrics

- F1-SCORE:
  - Harmonic Mean(*) of precision and recall rates

$$F1\ Score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

  - 2* ( 0.857 * 0.75)/(0.857 + 0.75) = 0.799




- Final Remarks
  - Accuracy: 0.850
  - F1-Score: 0.799
    - Precision: 0.857
    - Recall: 0.750

(*) The harmonic mean is a method that gives less weightage to larger single values and more weightage to smaller values

# Let’s Code!

- [Lecture 08 - Image Classification.ipynb [LINK]]