Mondragon Unibertsitatea

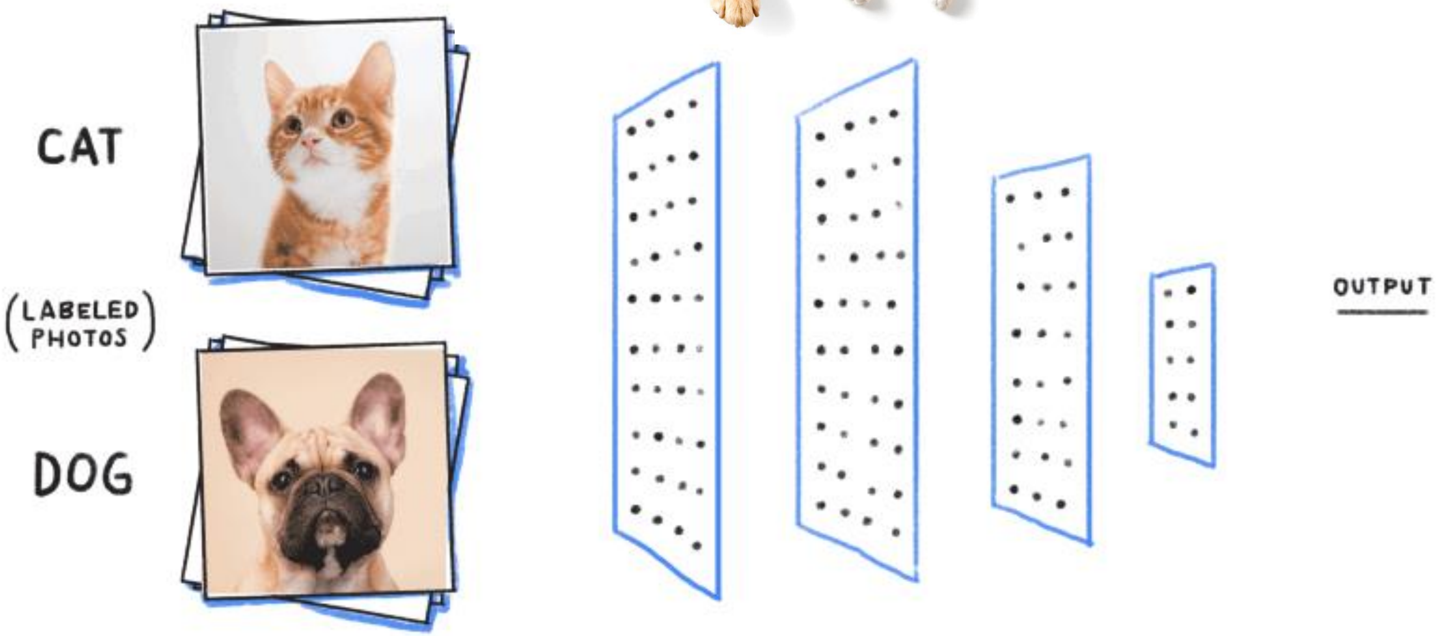
Escuela Politécnica Superior

Classification

Classification

Source: Towards Data Science

Classification



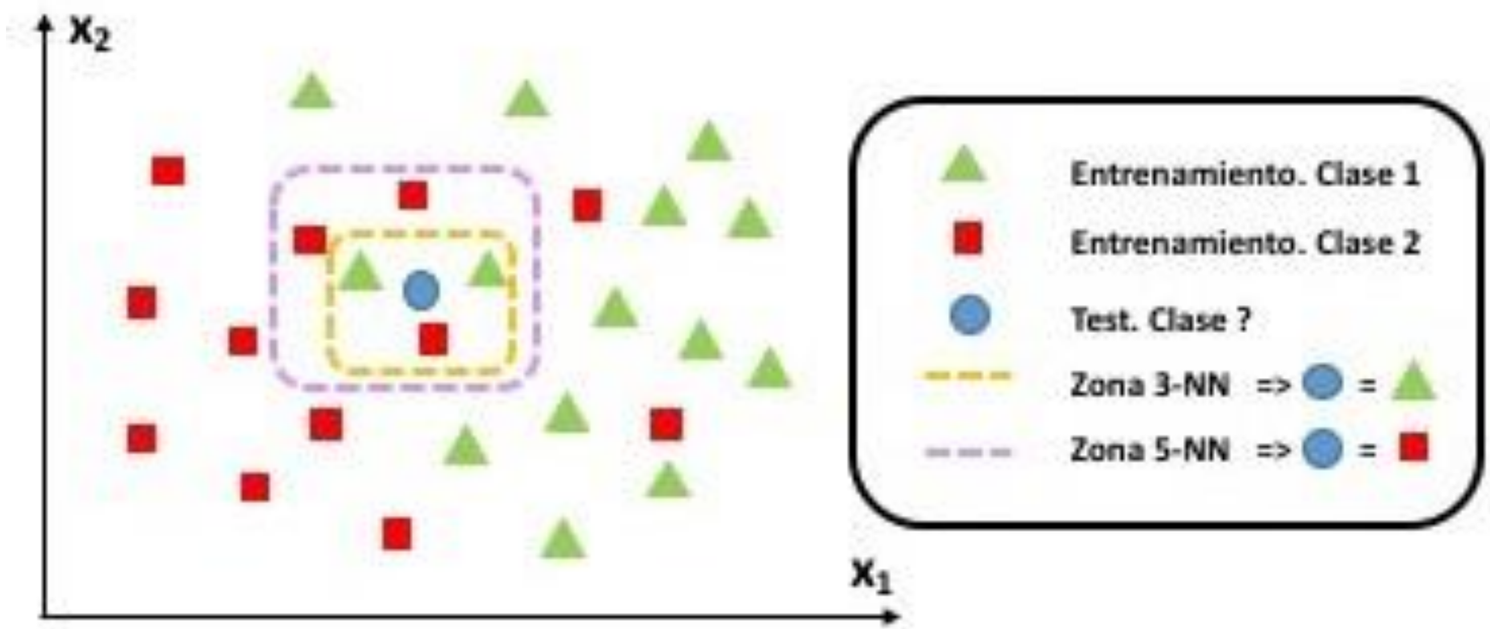
Input Data

Mathematical Model

Class Prediction

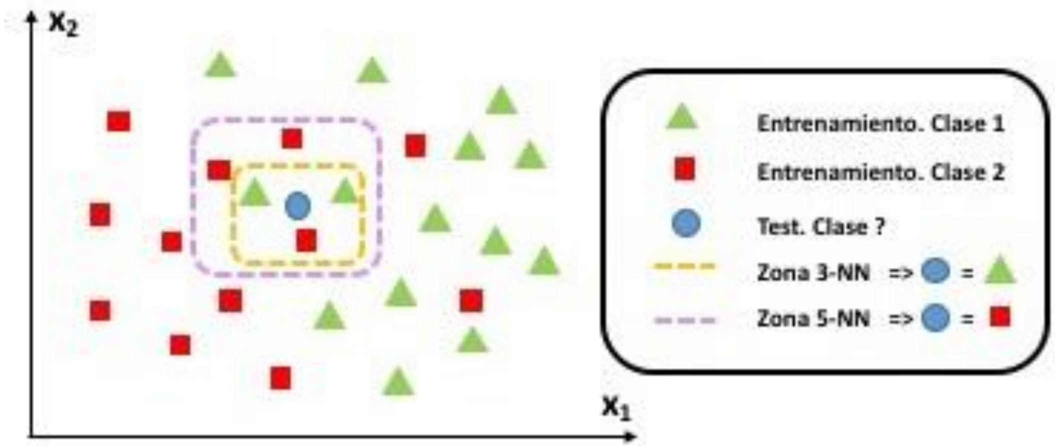
Source: Towards Data Science

K-Nearest Neighbors



K-Nearest Neighbors

- Given a training set and a sample, for which we want to obtain a prediction



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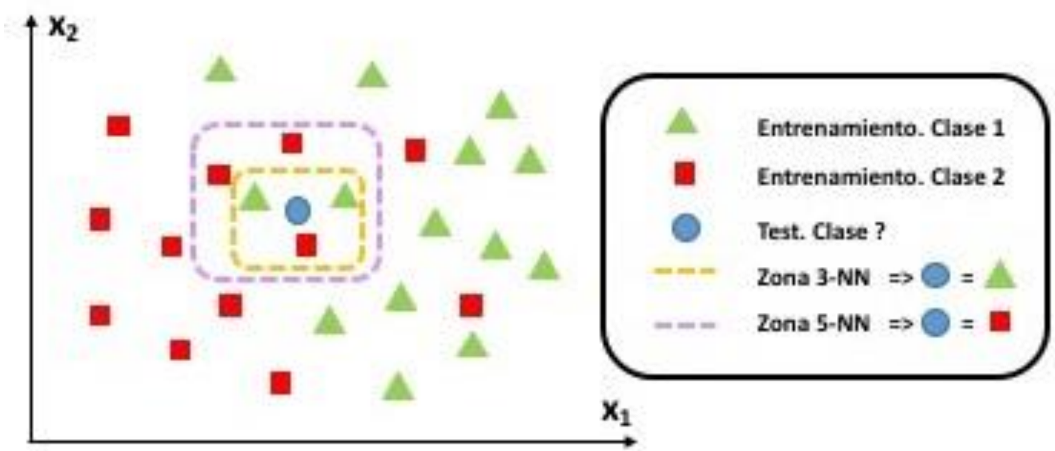

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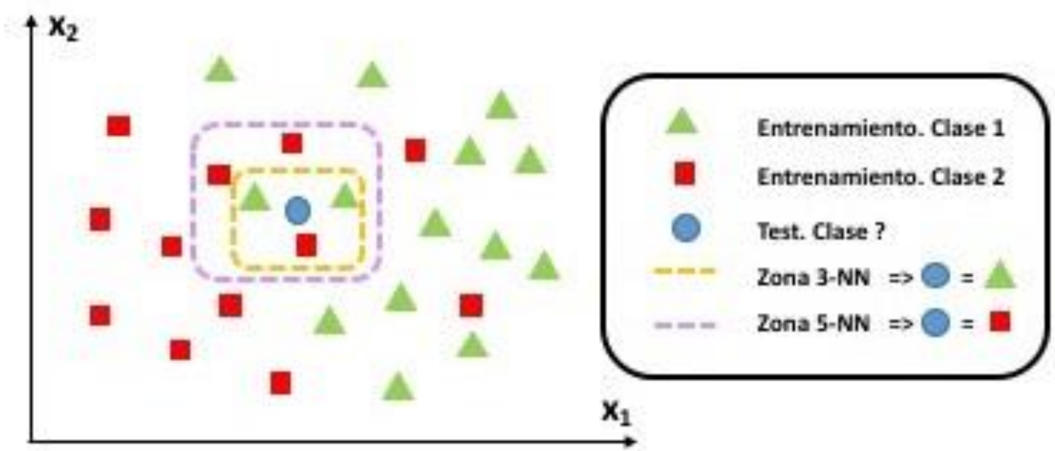

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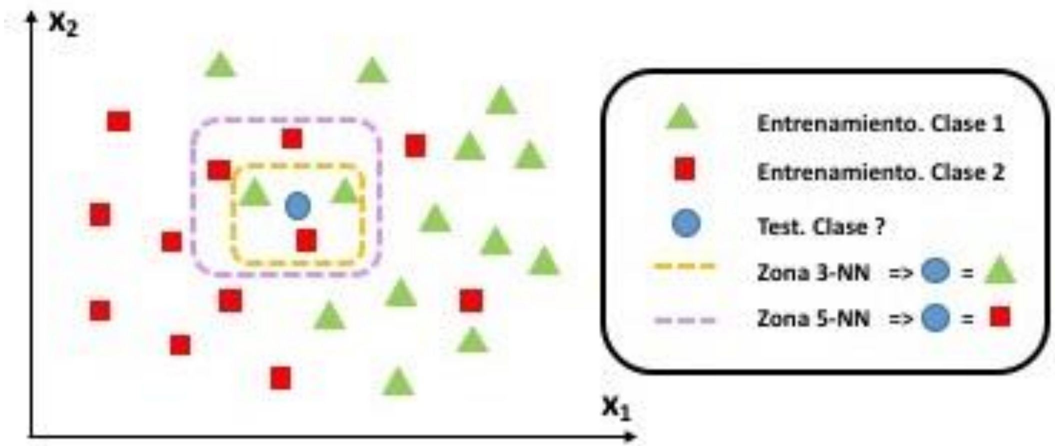

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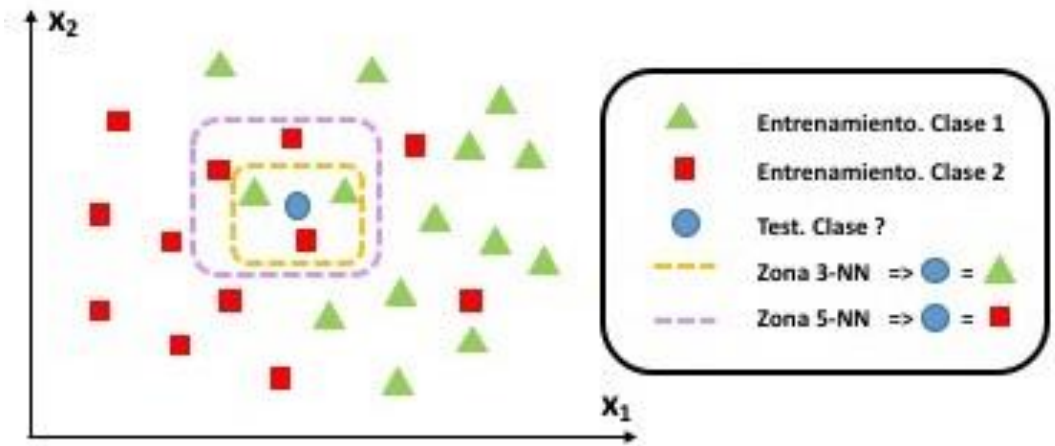

- Variants

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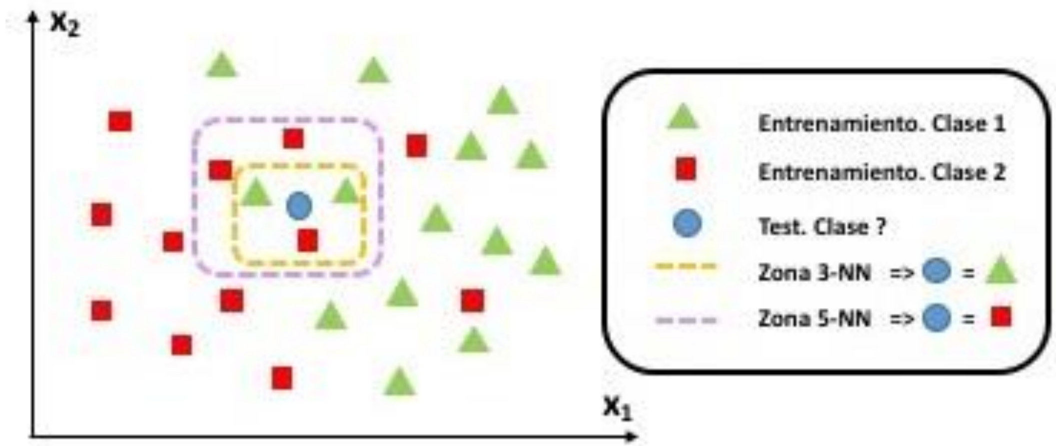

- Variants:
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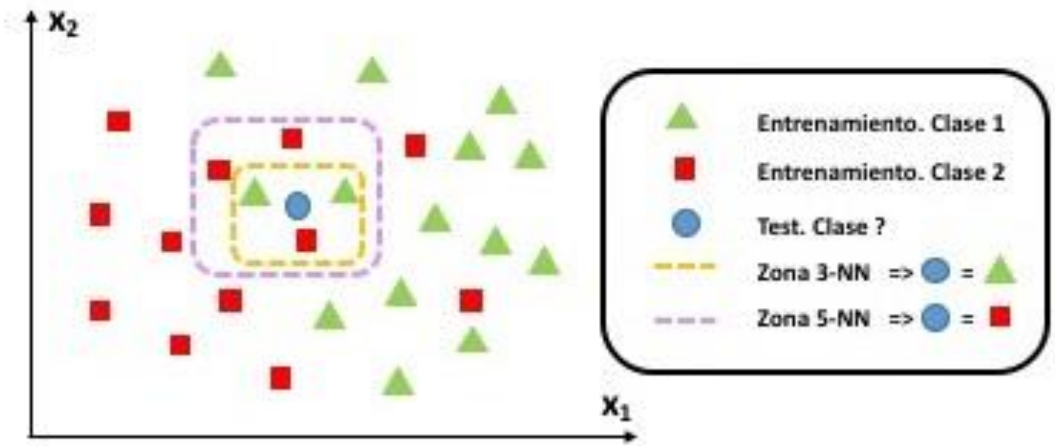

- Variants:
  - Use a weighted mean, which weights are inversely proportional to the distance
  - Without prefixing K, choose a threshold for defining the neighborhood (radius) and consider as neighbors all training samples that are not further than that radius

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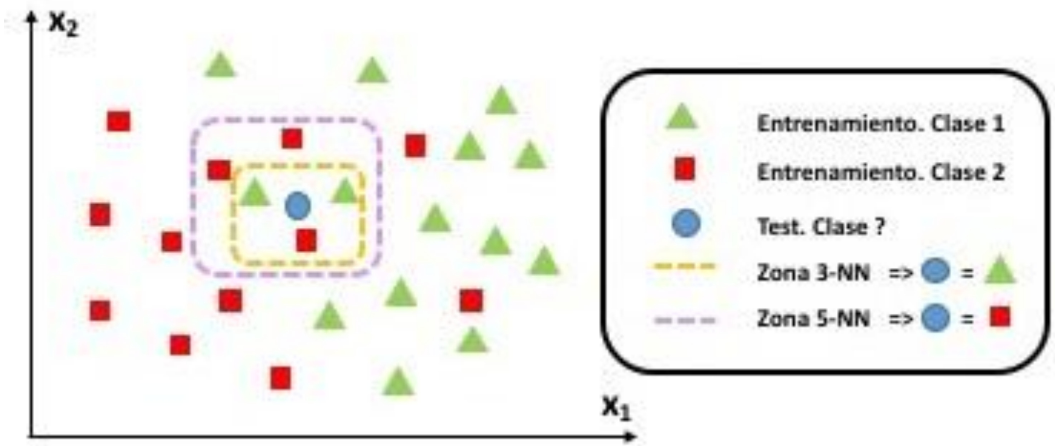

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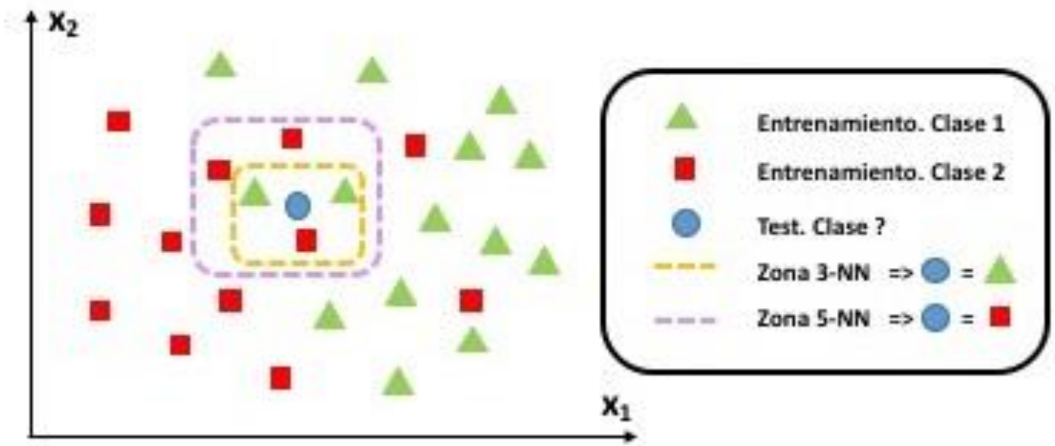

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  - Use a weighted mean, which weights are inversely proportional to the distance
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- **Prefixing K** is a tricky task to solve
- We must design an strategy for **breaking ties**

Decision trees

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- Decision Trees (C4.5)
  - They can handle both continuous and descrete variables
  - They are highly interpretable if the number of variables is not much high
  - They can suffer from *overfitting* (adapt too much to the training data loosing extrapolation power to unseen data)

Tiempo	Temp.	Humedad	Viento	Jugar golf
Lluvia	Calor	Alta	Suave	No
Lluvia	Calor	Alta	Fuerte	No
Cubierto	Calor	Alta	Suave	Sí
Soleado	Templado	Alta	Suave	Sí
Soleado	Frío	Normal	Suave	Sí
Soleado	Frío	Normal	Fuerte	No
Cubierto	Frío	Normal	Fuerte	Sí
Lluvia	Templado	Alta	Suave	No
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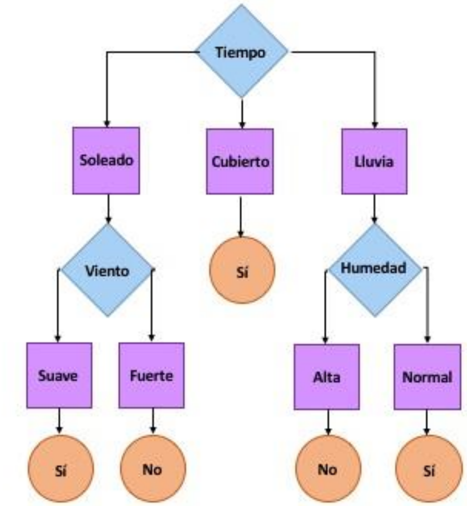

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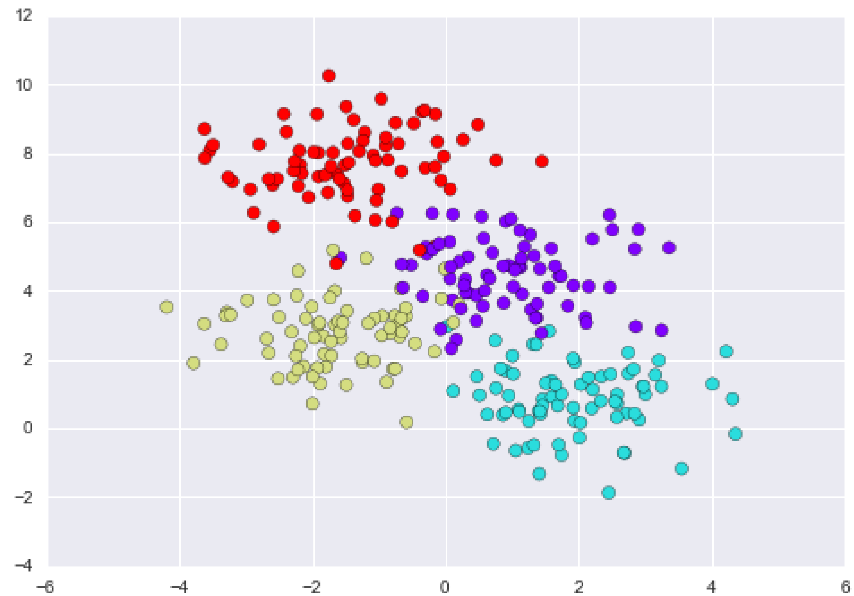

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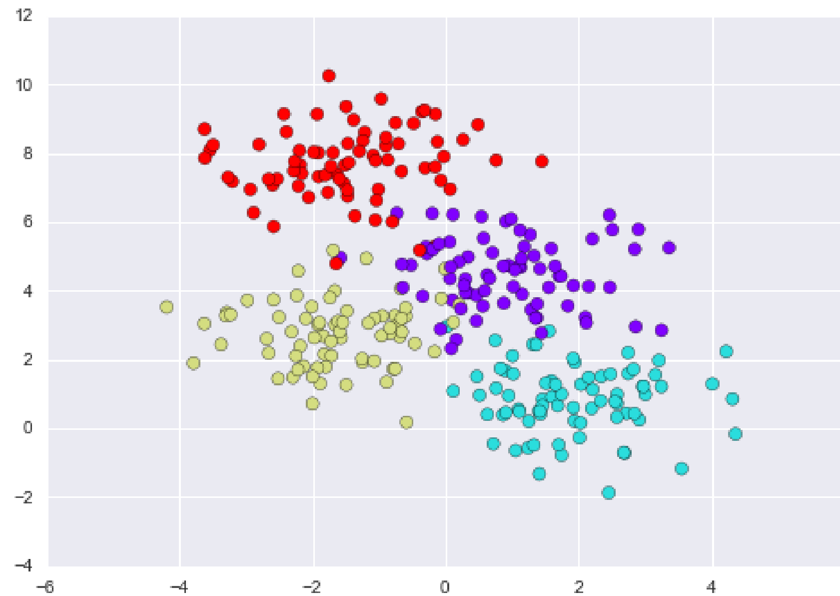

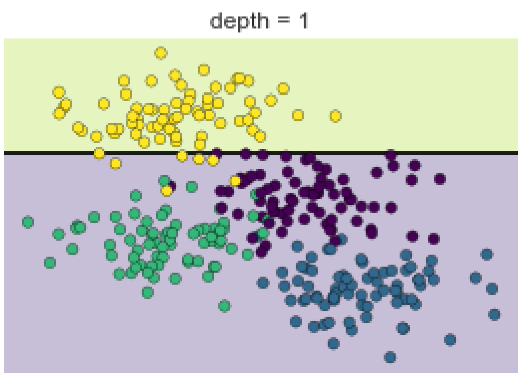

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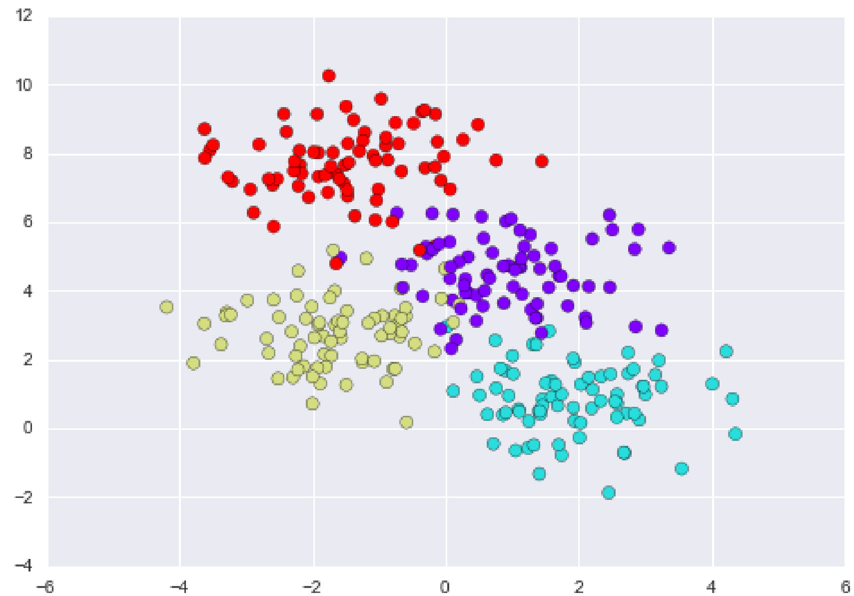

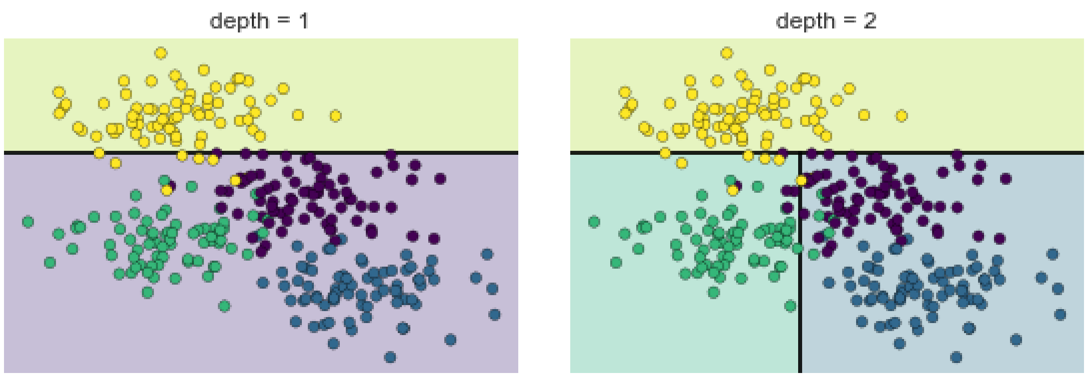

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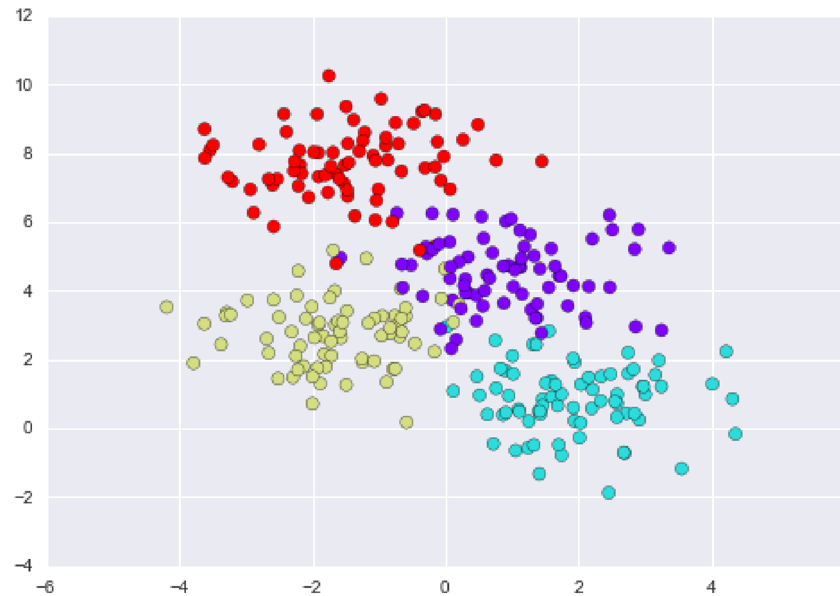
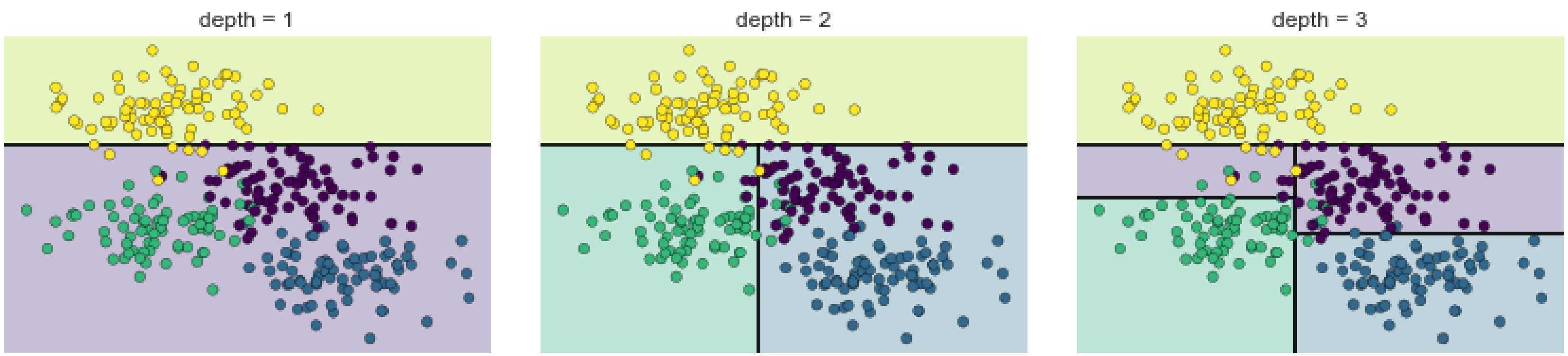
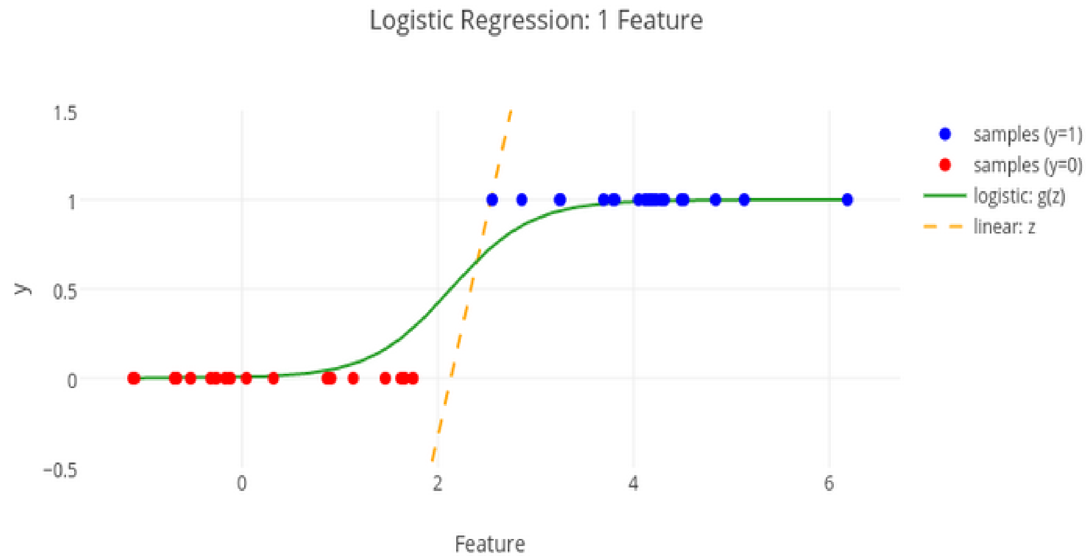




Logistic regression

- Logit function

$$p(X) = \frac{e^{(\beta_0+\beta_1 X)}}{1+e^{(\beta_0+\beta_1 X)}}$$



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  - y = 0, towards the left
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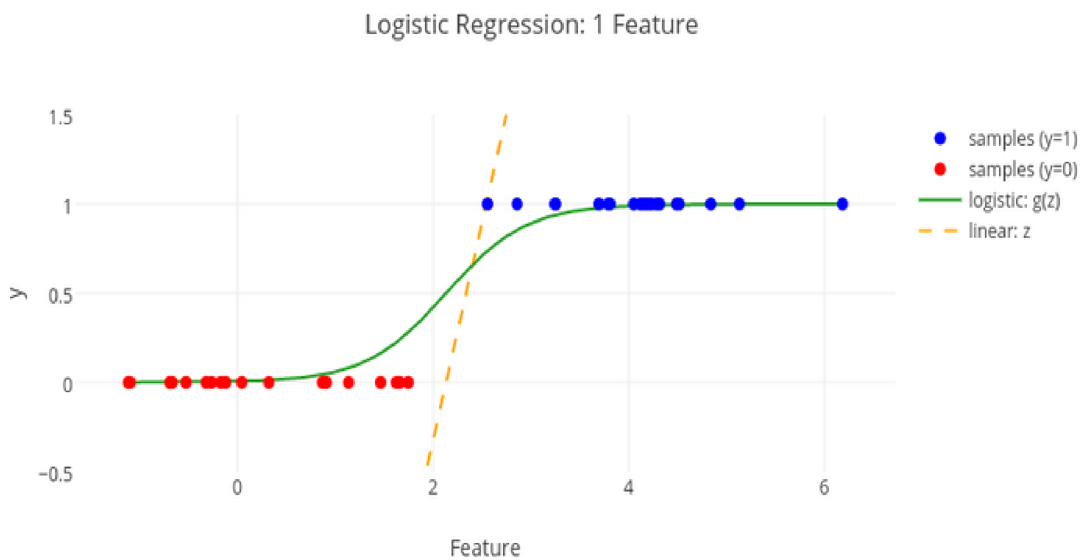

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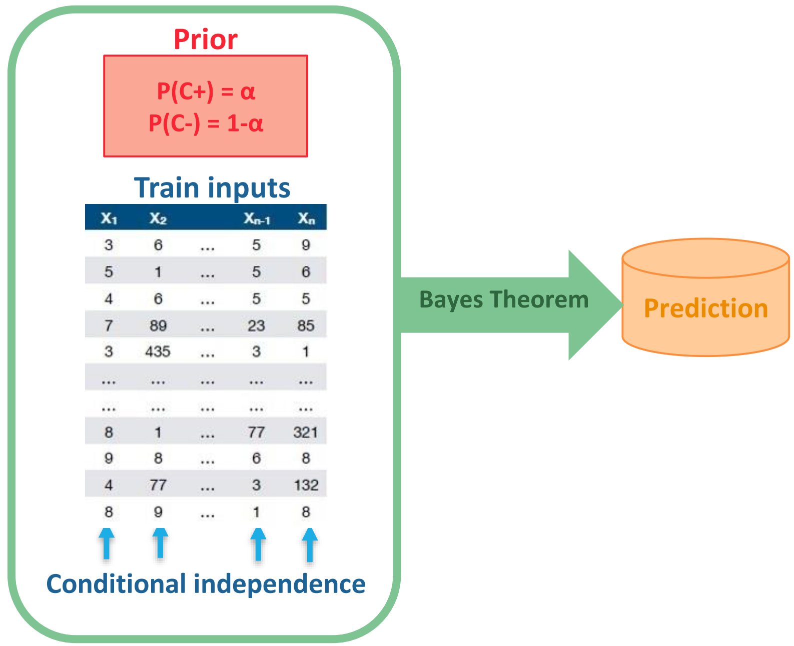
- It estimates classes probabilities

- It is not recommendable for multiclass classification, i.e. not binary

Naïve Bayes



X_1	X_2		X_{n-1}	X_n
3	6	...	5	9
5	1	...	5	6
4	6	...	5	5
7	89	...	23	85
3	435	...	3	1
...	...	...	...	...
...	...	...	...	...
8	1	...	77	321
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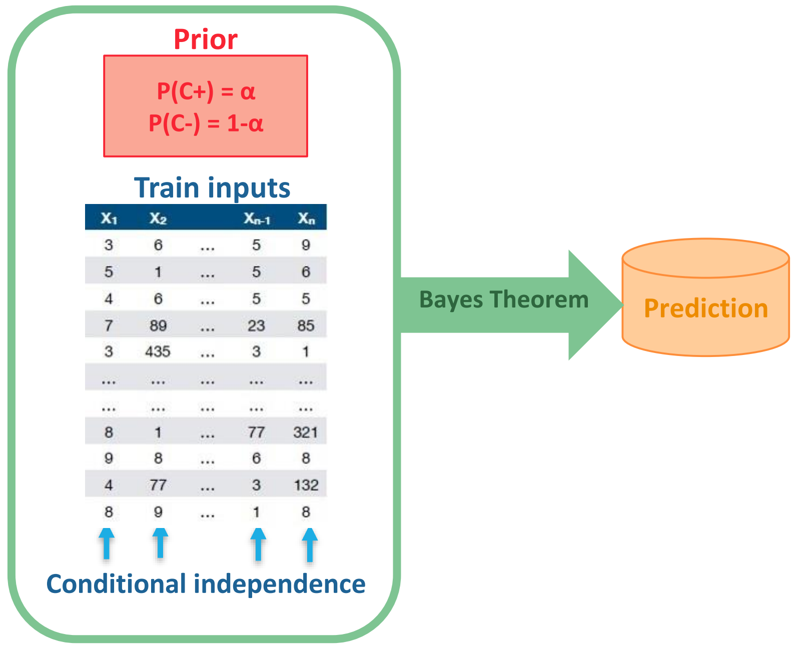
Naïve Bayes

We need to calculate

$$p(C|X_1,\ldots,X_n)$$



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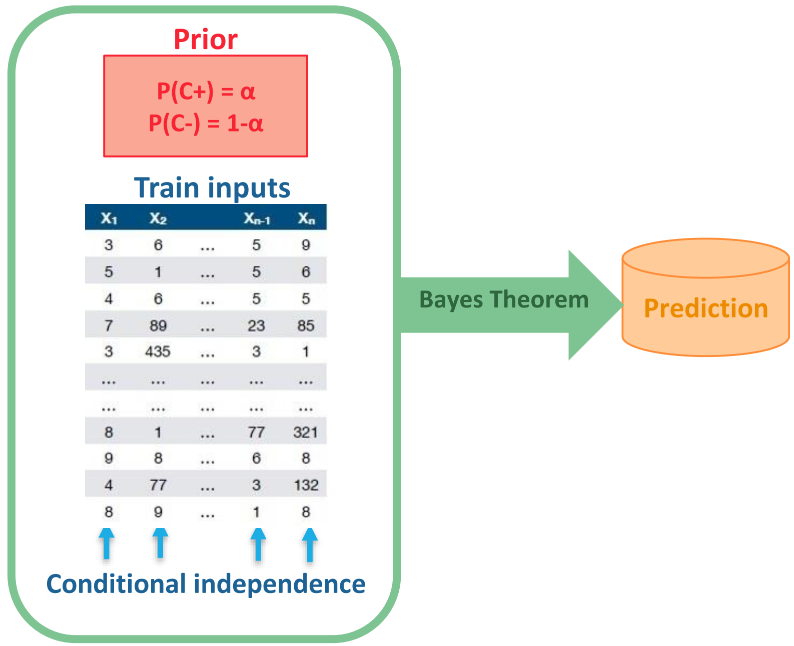

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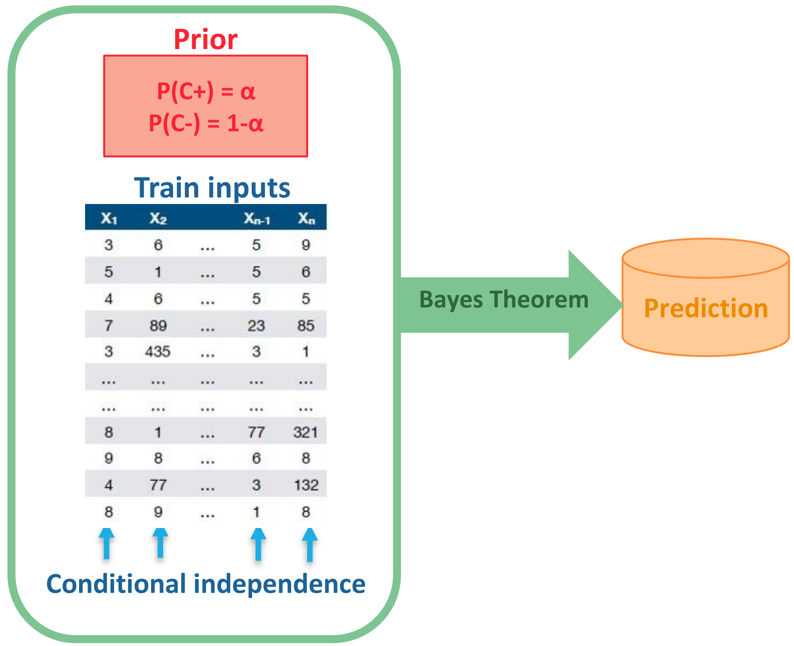

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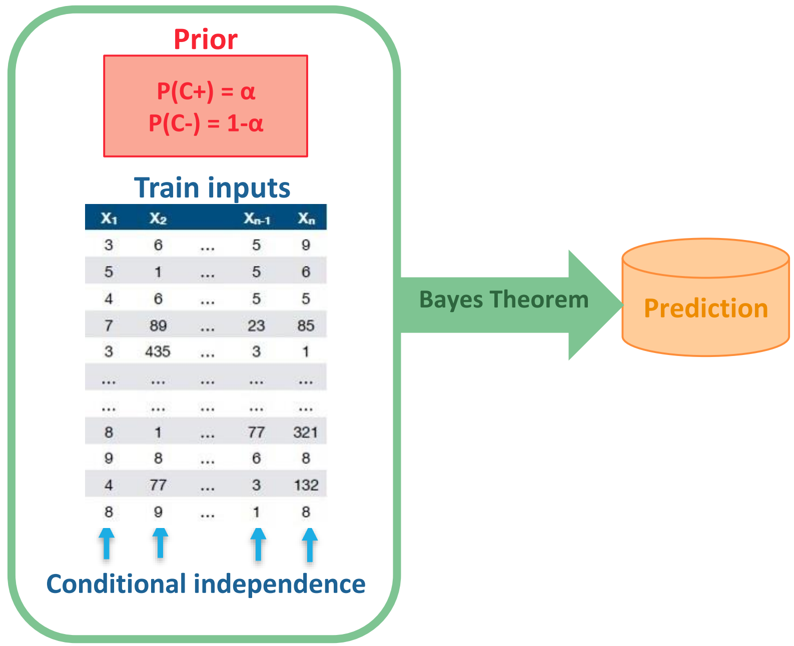

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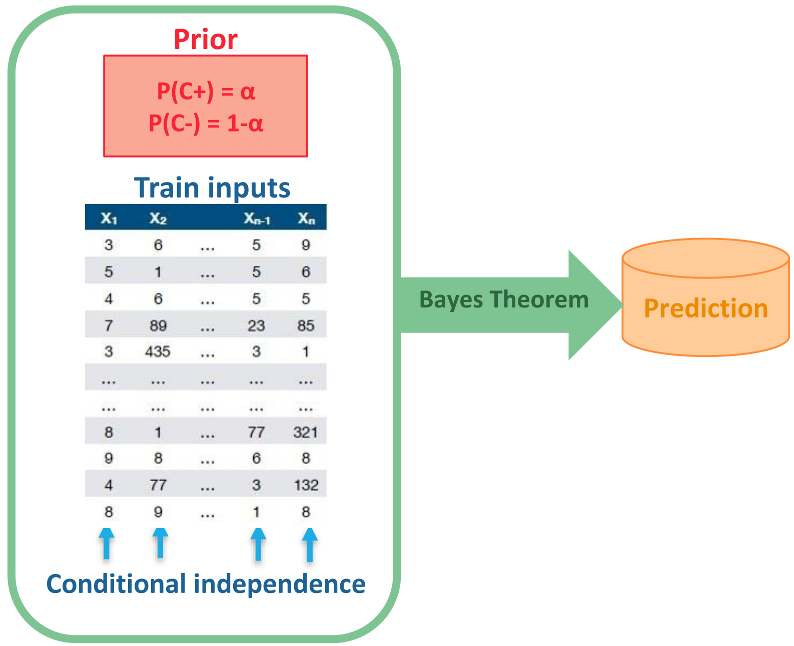

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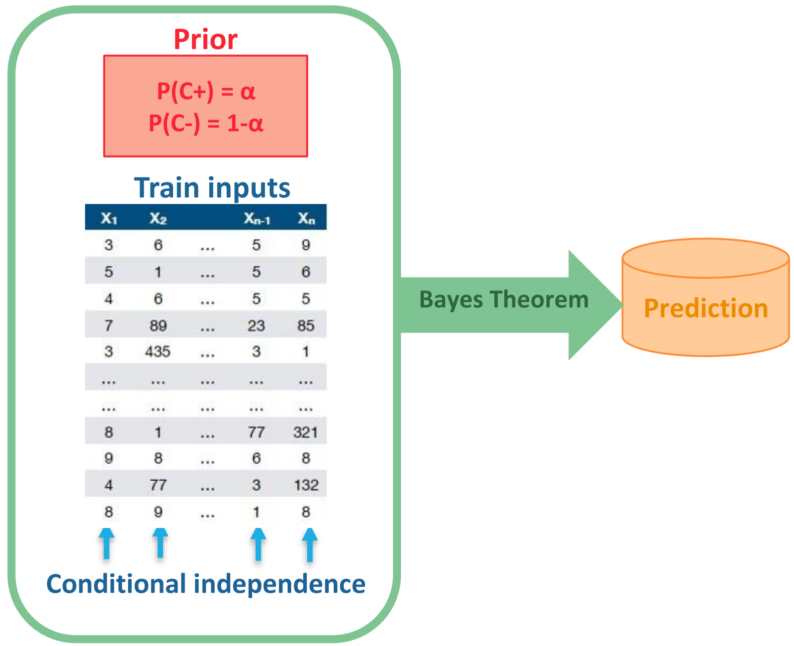

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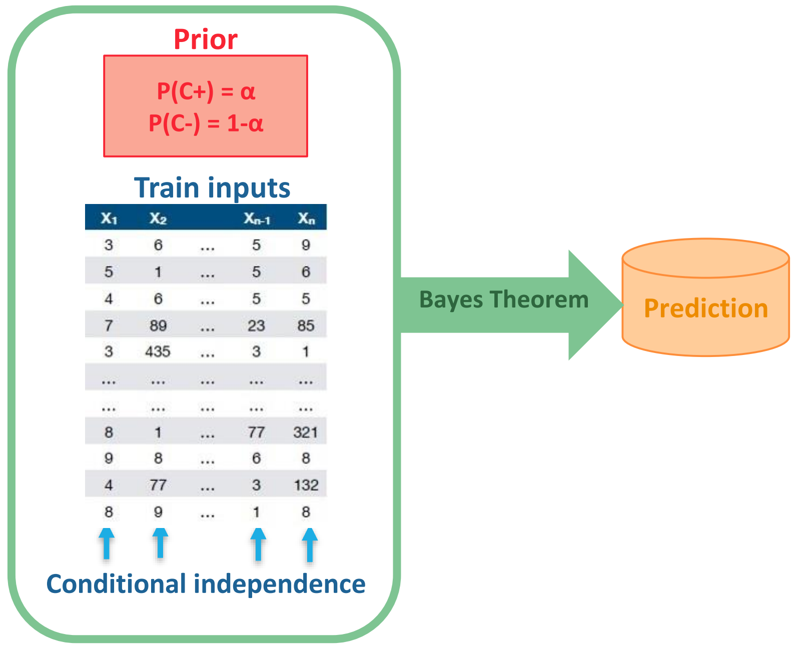

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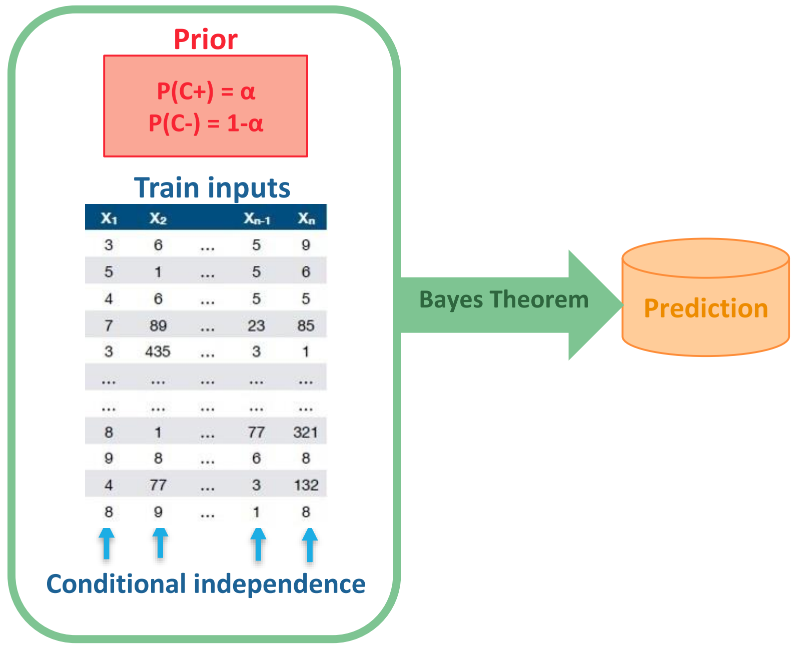

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Sample data

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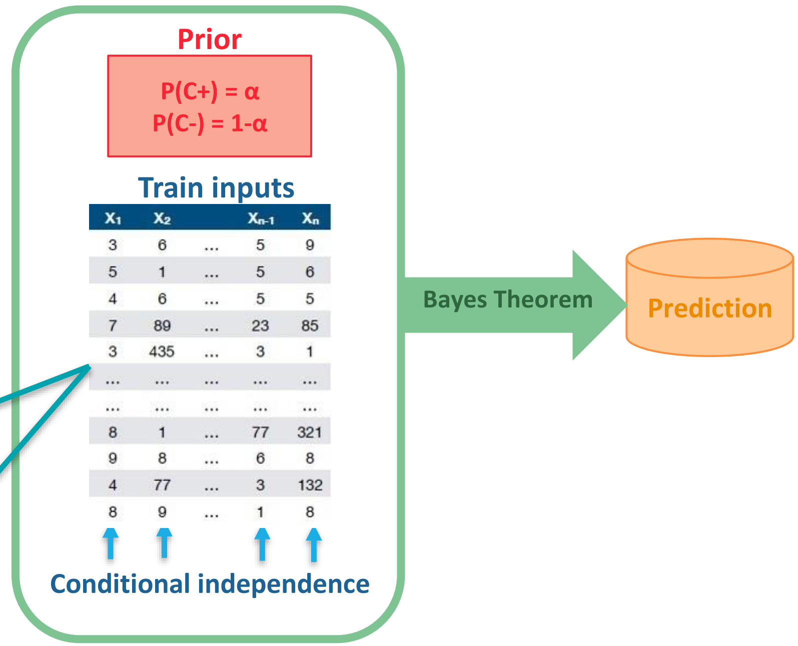

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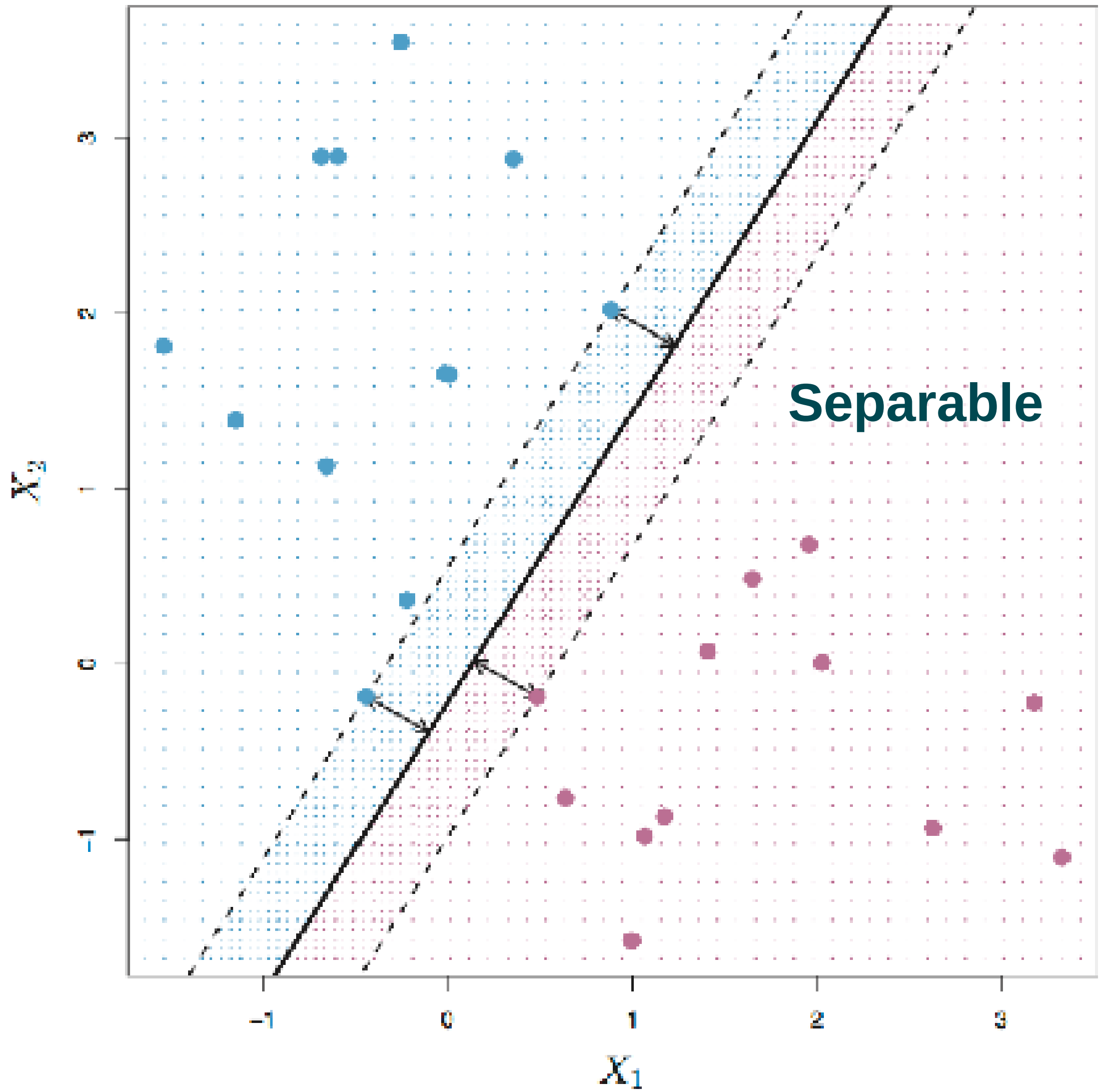
7	89	...	23	85
3	435	...	3	1
...	...	...	...	...
...	...	...	...	...
8	1	...	77	321
9	8	...	6	8
4	77	...	3	132
8	9	...	1	8

Support Vector Machines



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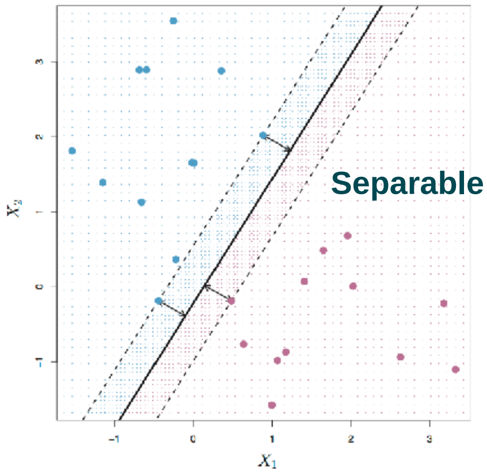

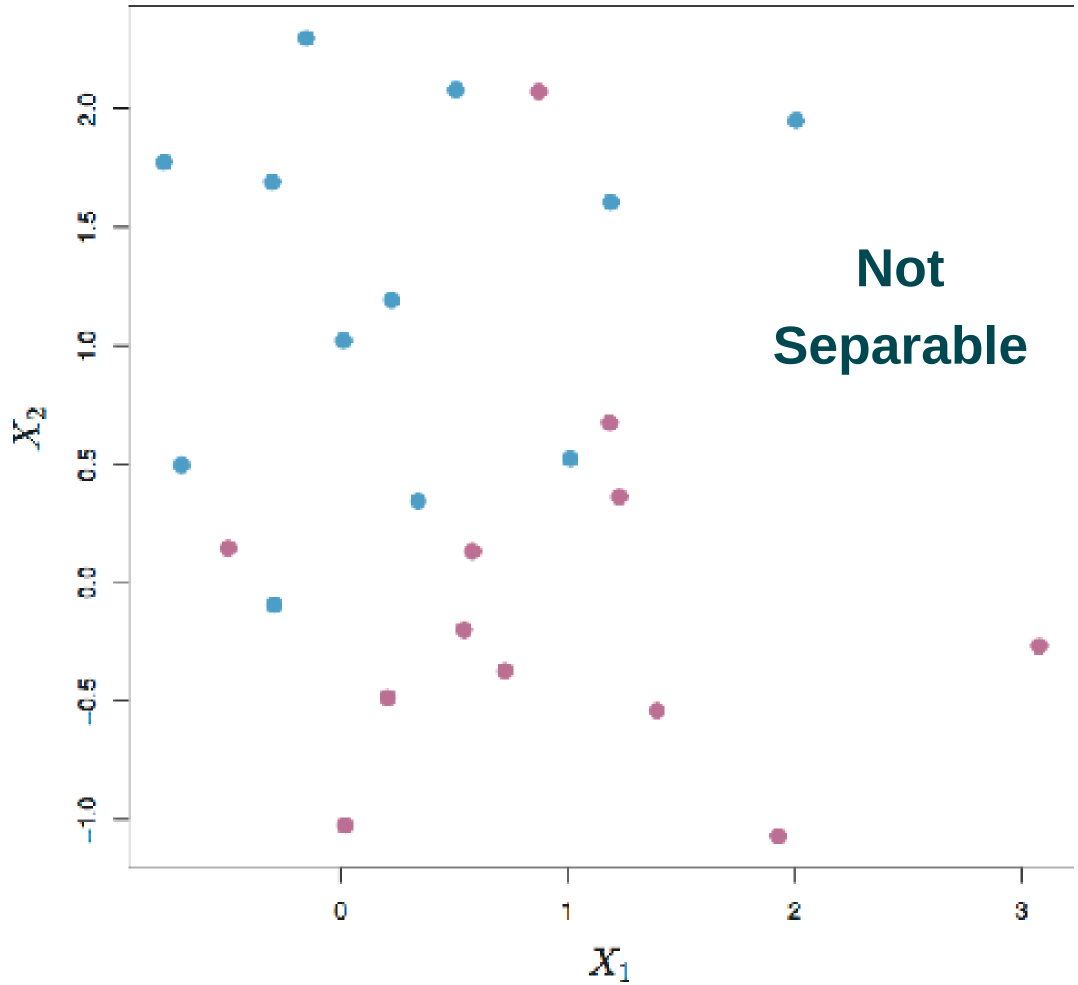

Support Vector Machines

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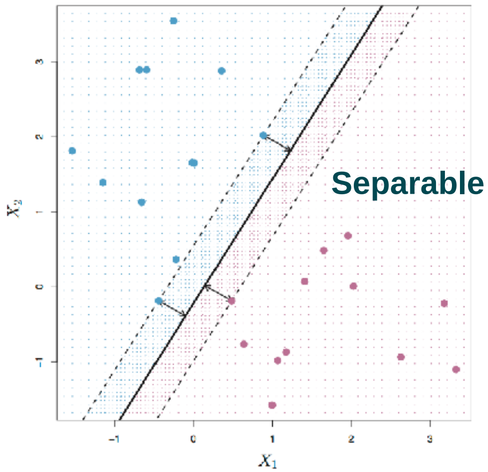

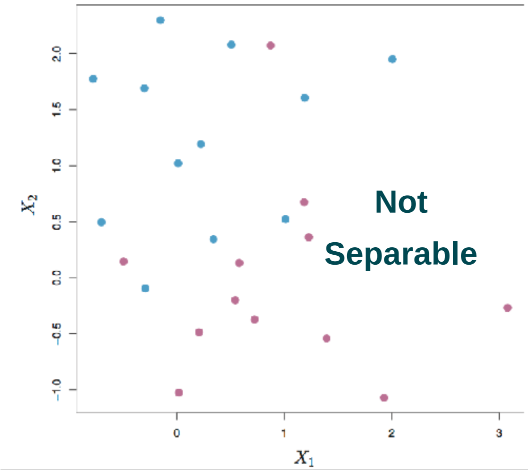

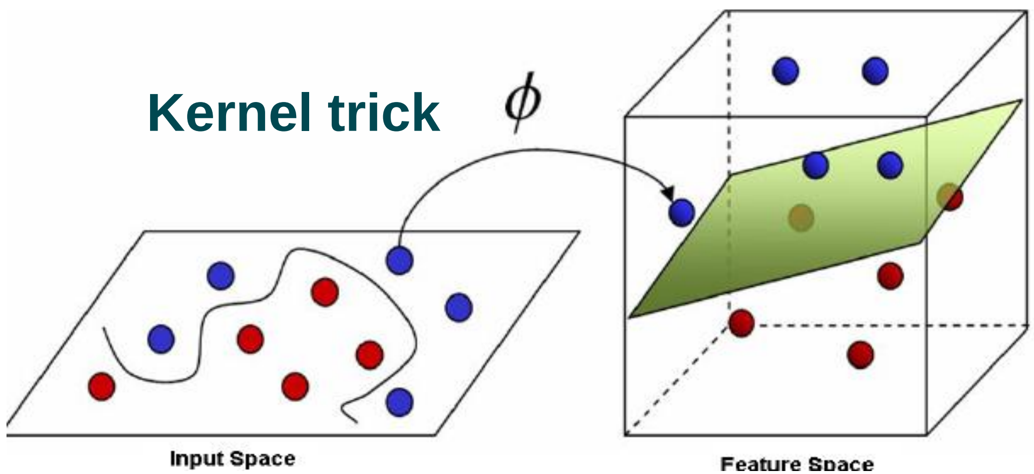

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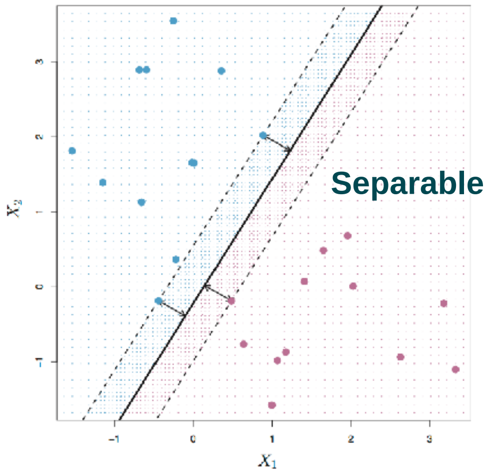

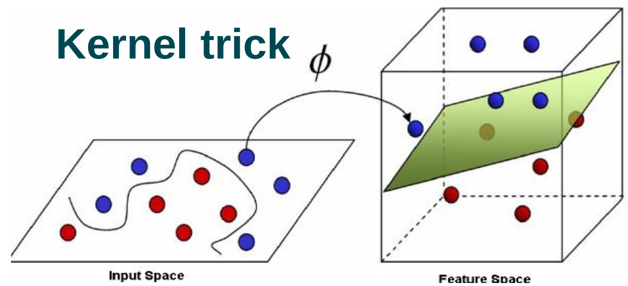

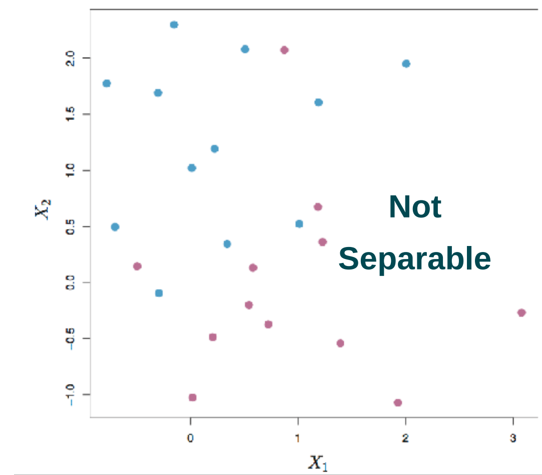

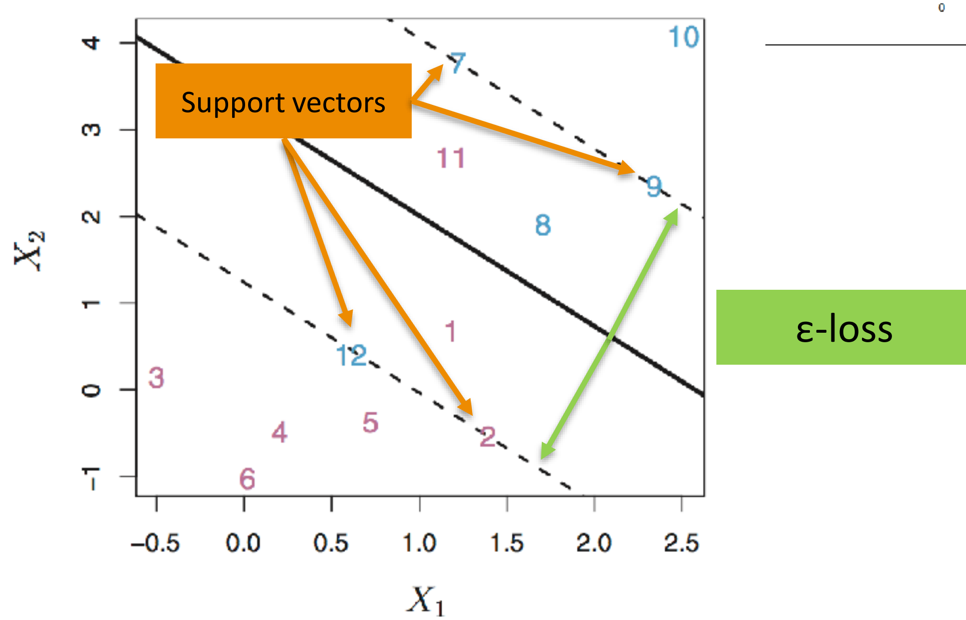

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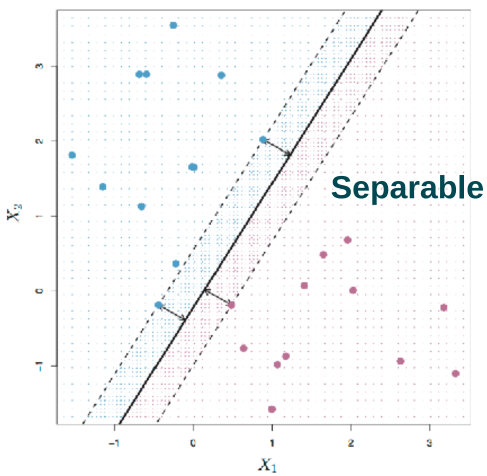
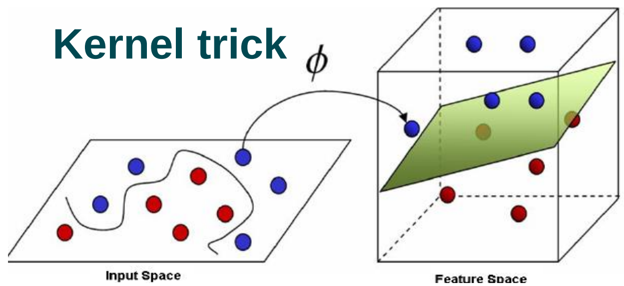
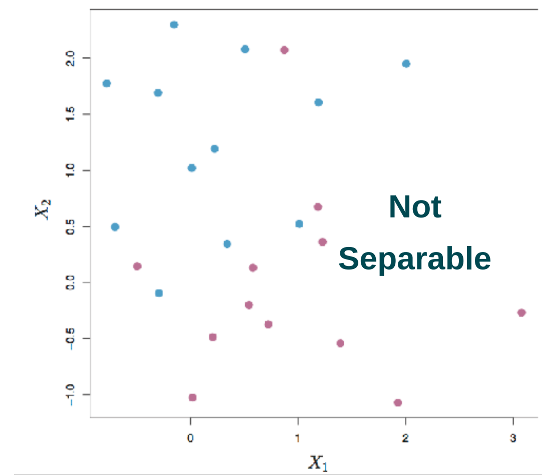




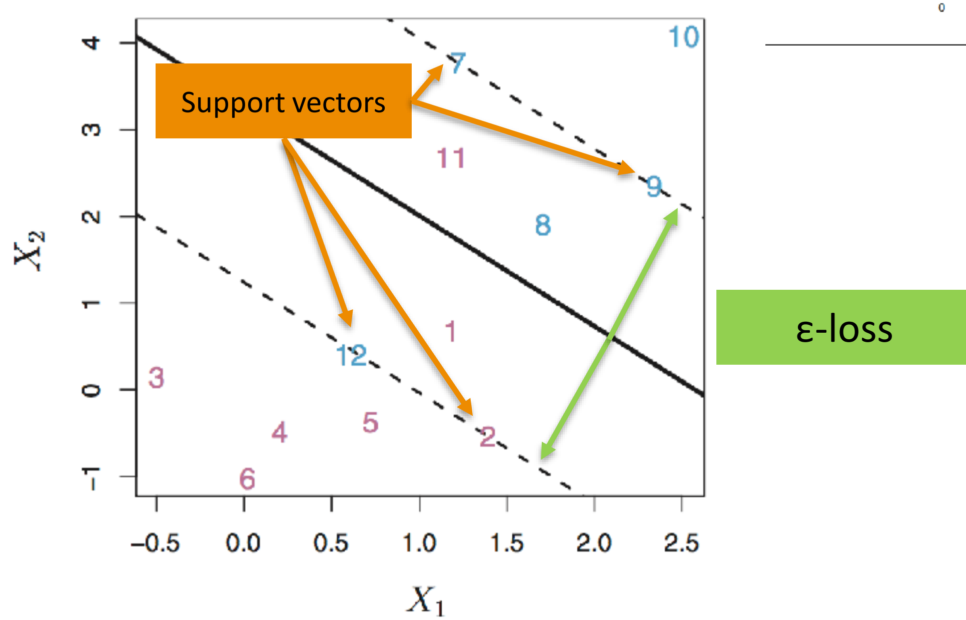


$$\arg \max_{\beta_0,\beta_1,\ldots,\beta_n} M$$

$$\text{subject to} \sum_{j=1}^{n} \beta_j^2 = 1,$$

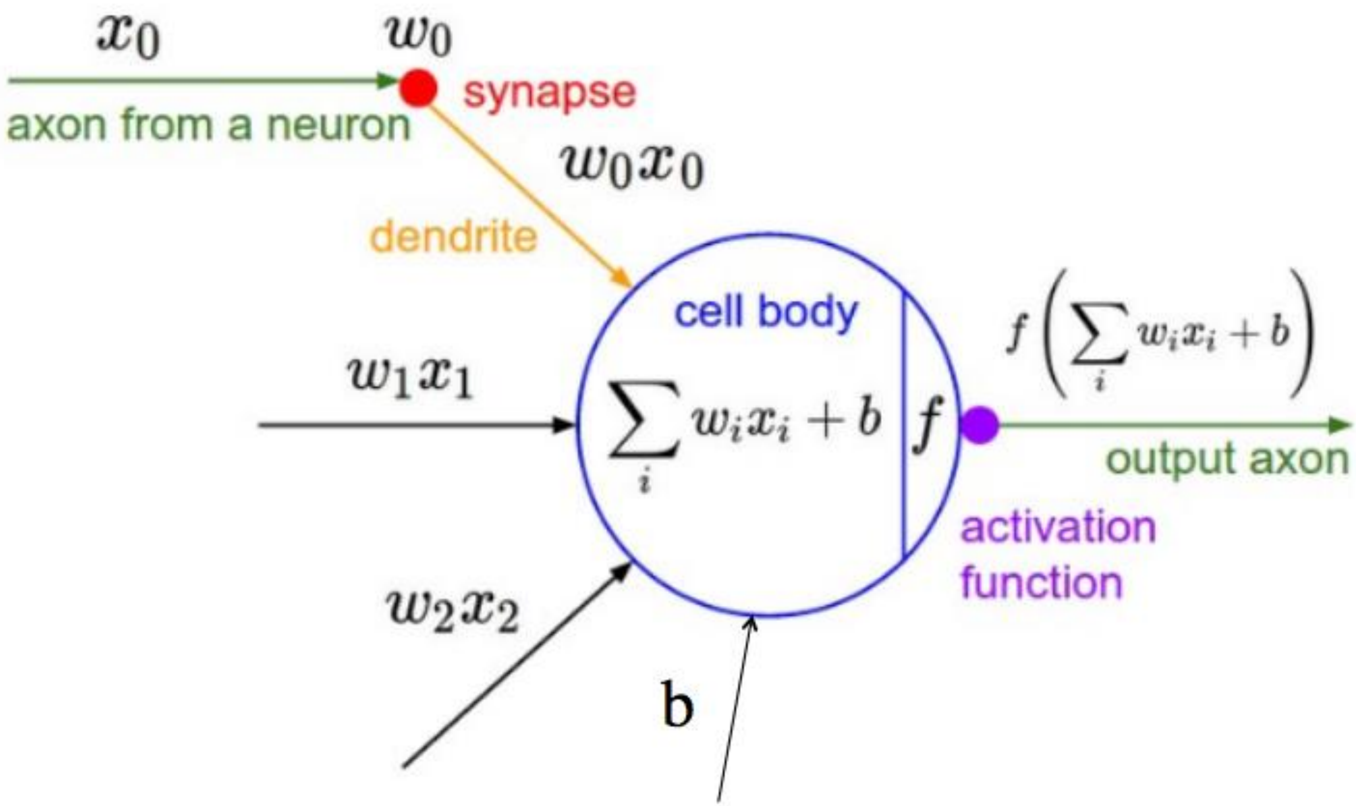
$$y_i * (\beta_0 + \sum_j X_{ij}\beta_{ij}) \geq M(1 - \epsilon_i),$$

$$\epsilon_i \geq 0, \sum_i \epsilon_i \leq C$$



Neural networks

- Neuron



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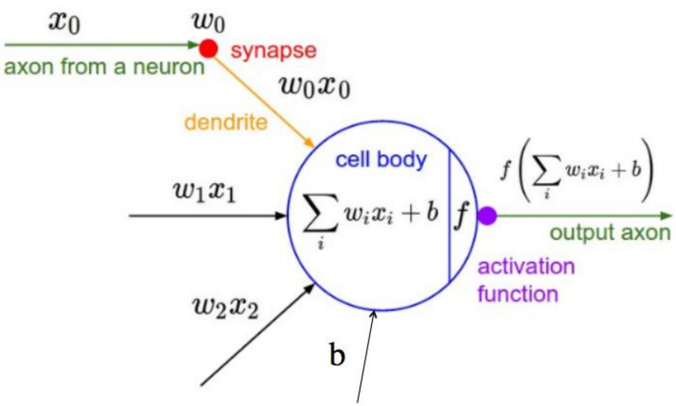
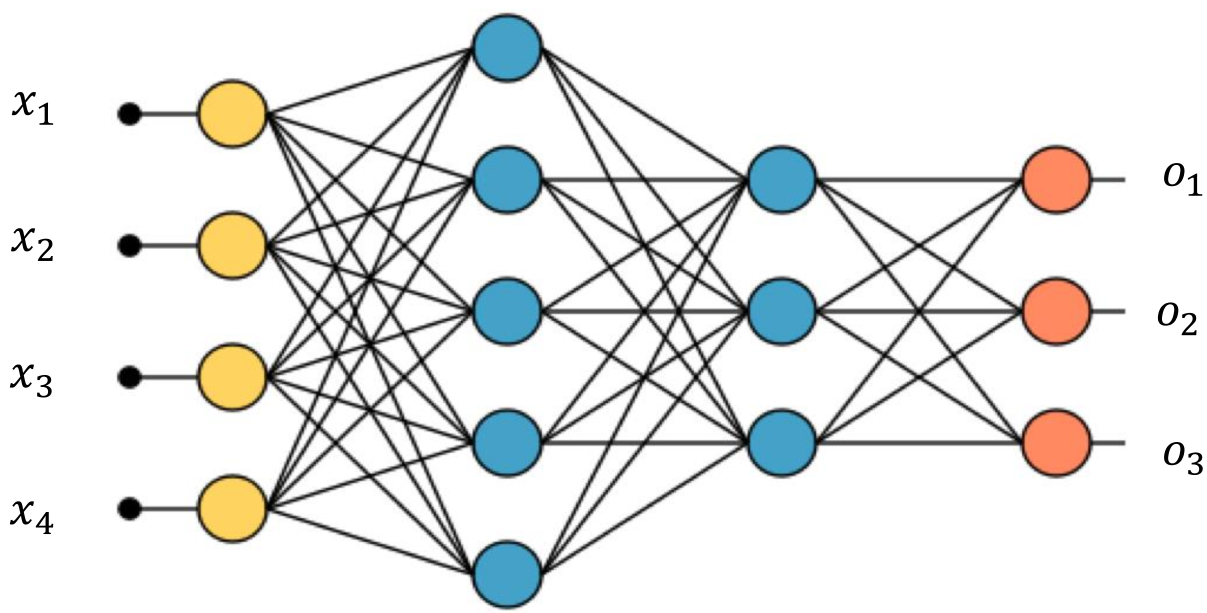


- Neural Network



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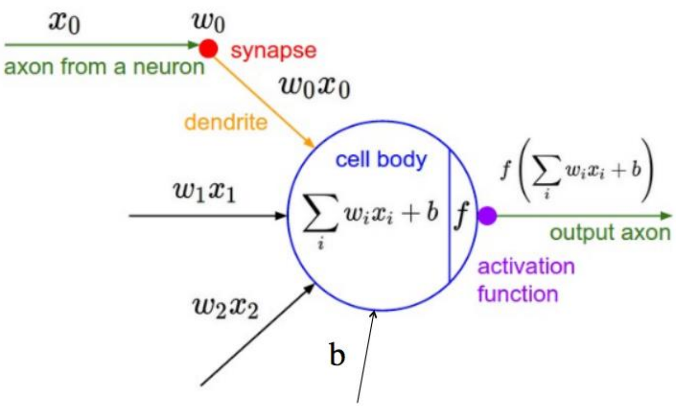

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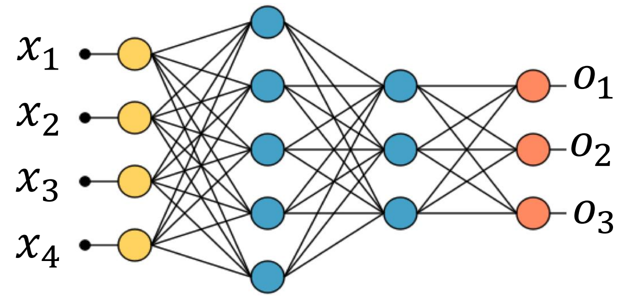

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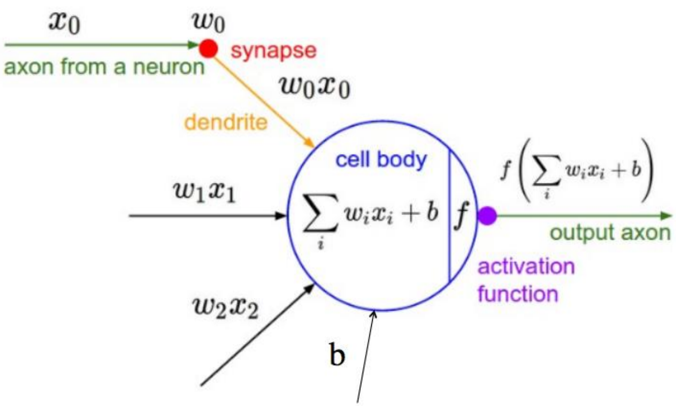

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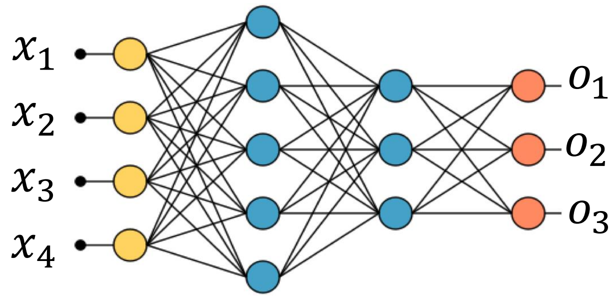

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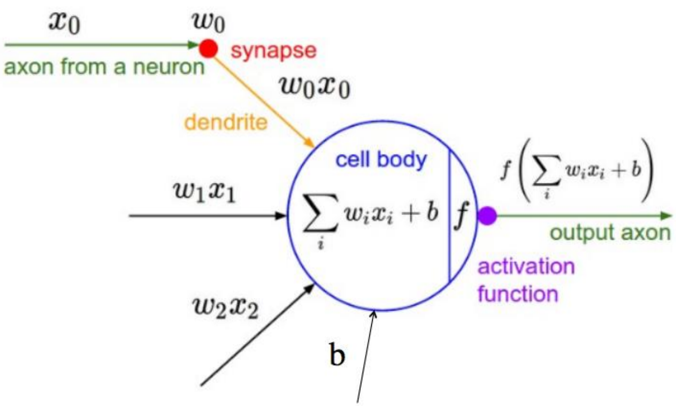

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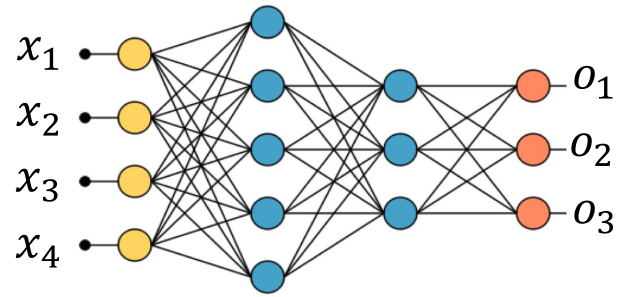

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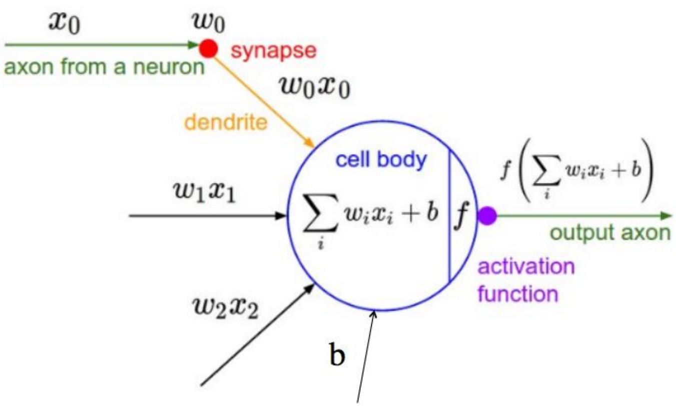

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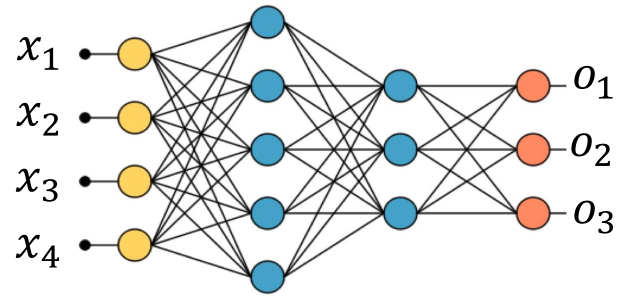

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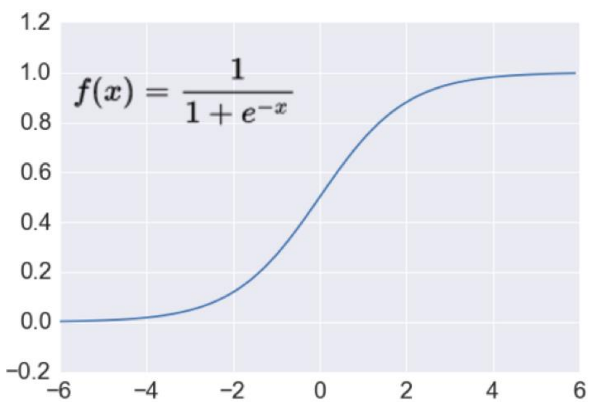
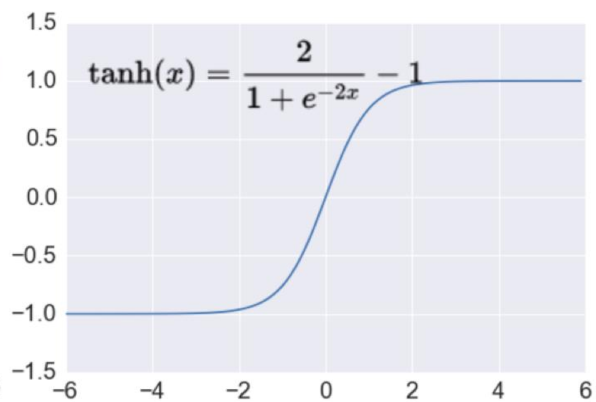
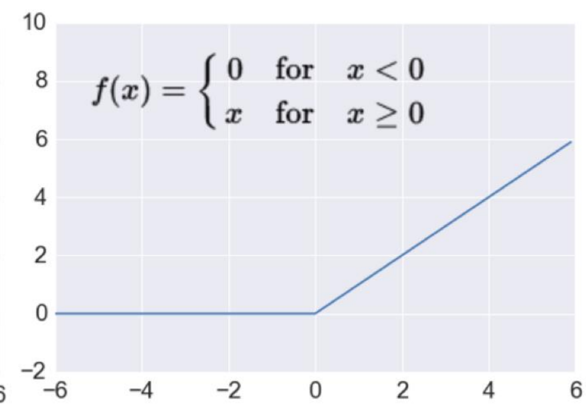


Sigmoid



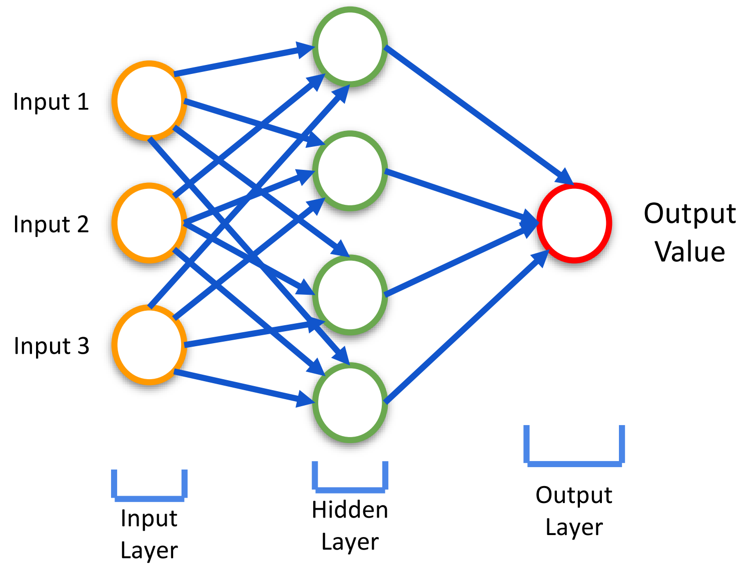
Hyperbolic tangent



ReLu

Neural networks

- Shallow Learning



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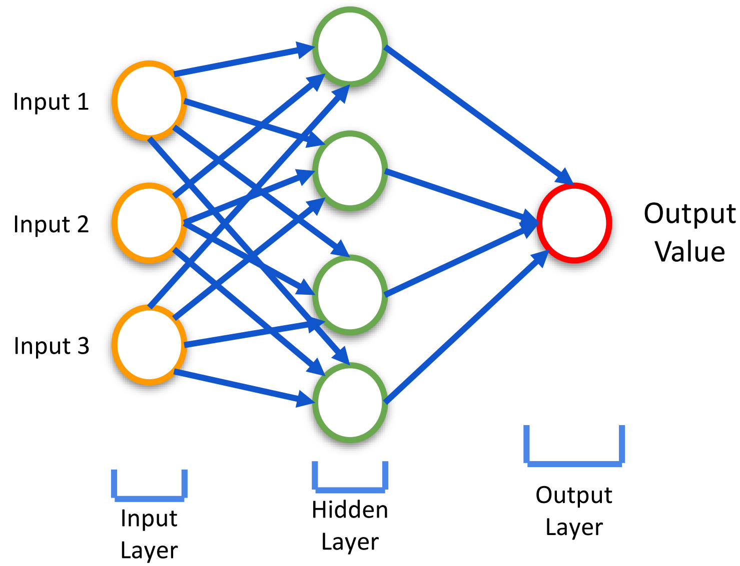
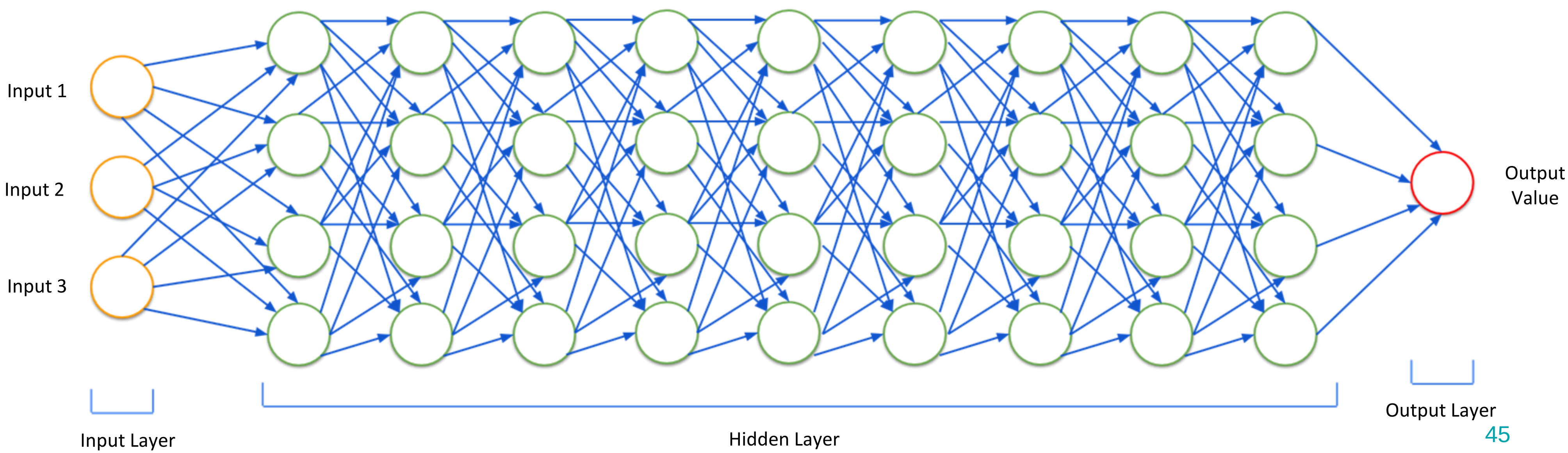


- Deep Learning



Ensemble learning

- Combination of several predictions for a given paradigm

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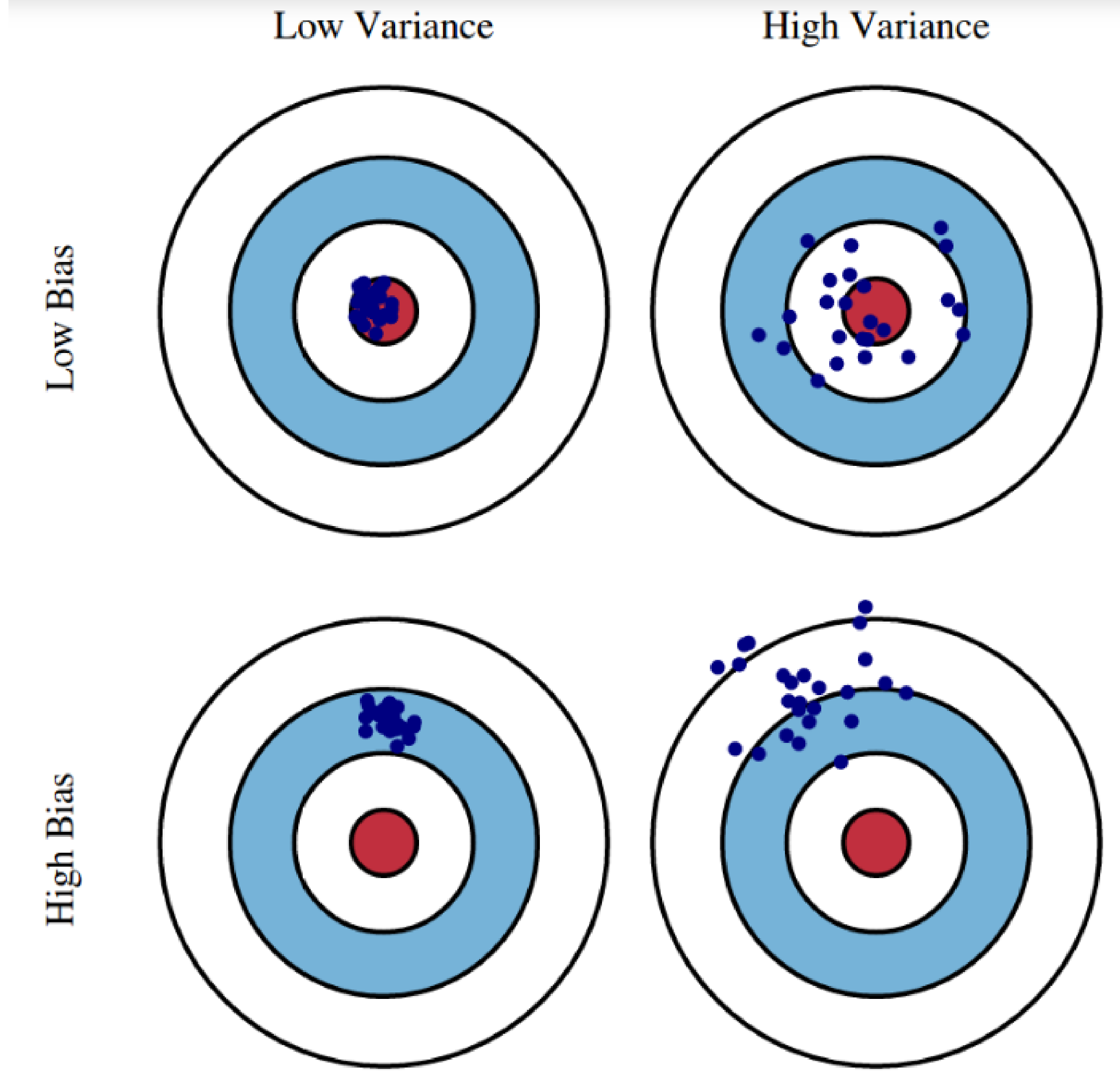

Boosting & AdaBoost

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- It is a boosting algorithm in which the sequential aggregation of weak learners is guided by an **adaptive process**
- Such process considers the error of each weak learner on each sample in order to **adapt the weights for the weak learners** to be aggregated, so that **the overall error decreases as much as possible**.

Bagging

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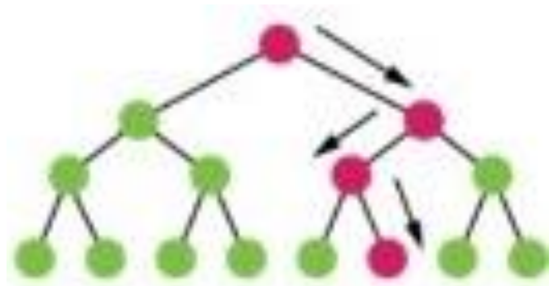
- More recently, new approaches arised, such as **Gradient Boosting classifiers**, being **Extreme Gradient Boosting** (XGBoost) the new ML rockstar

Random Forests

- Ensemble learning for decision trees



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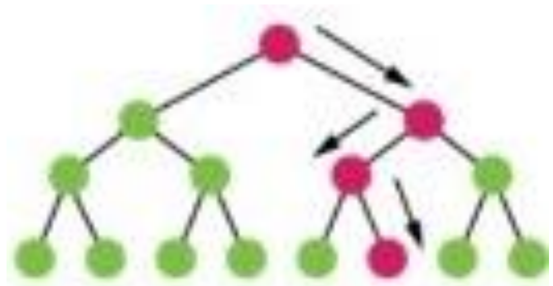

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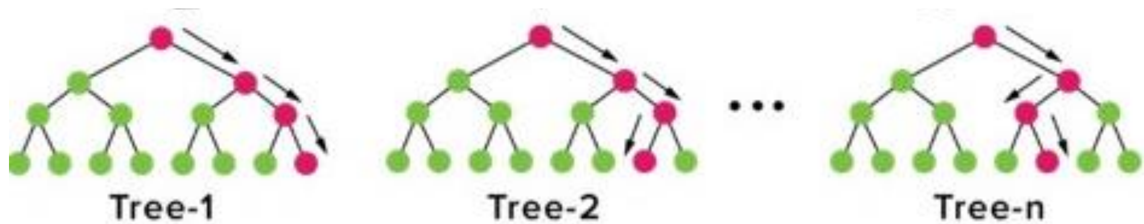

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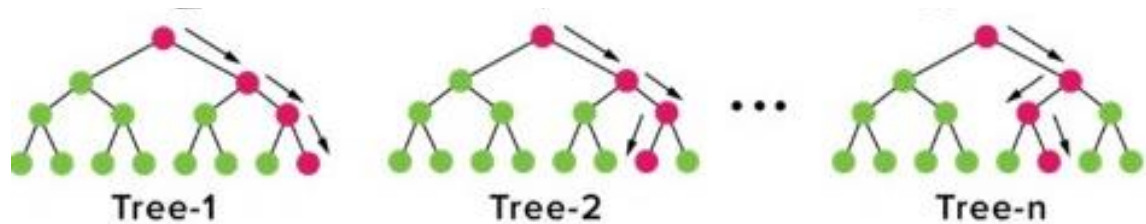

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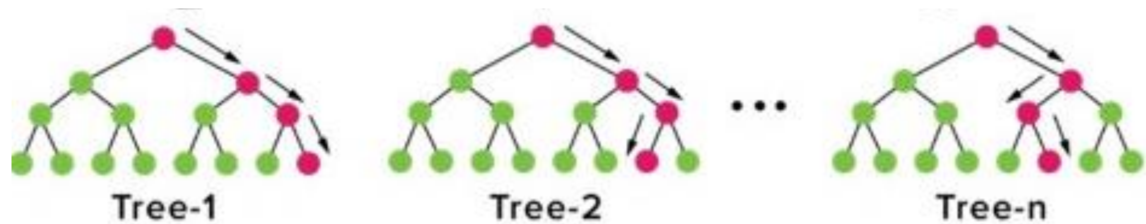

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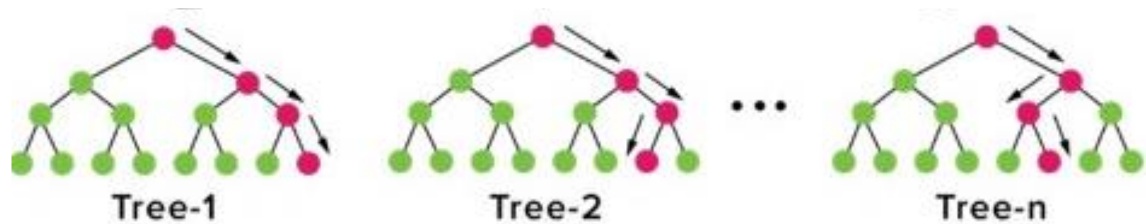

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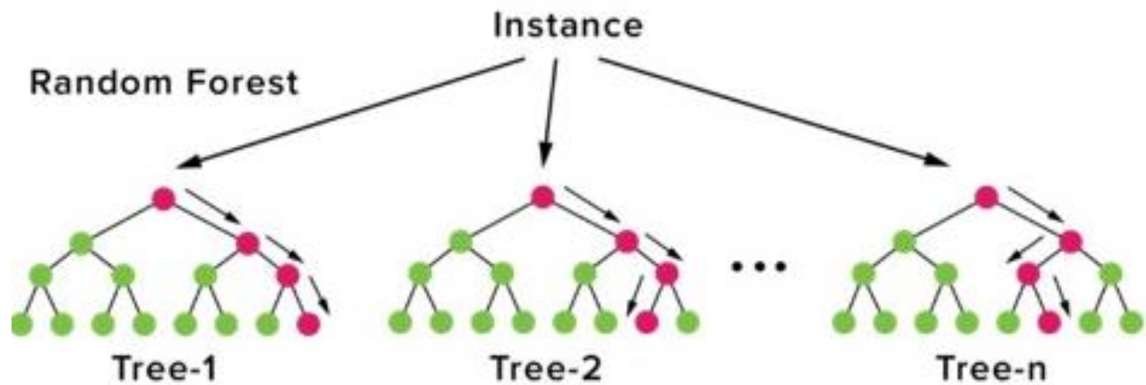

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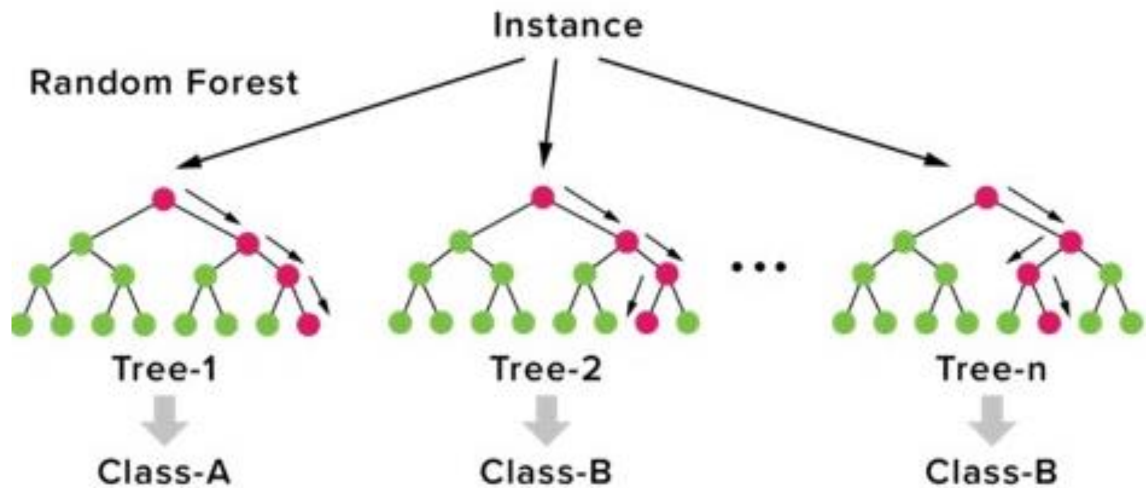

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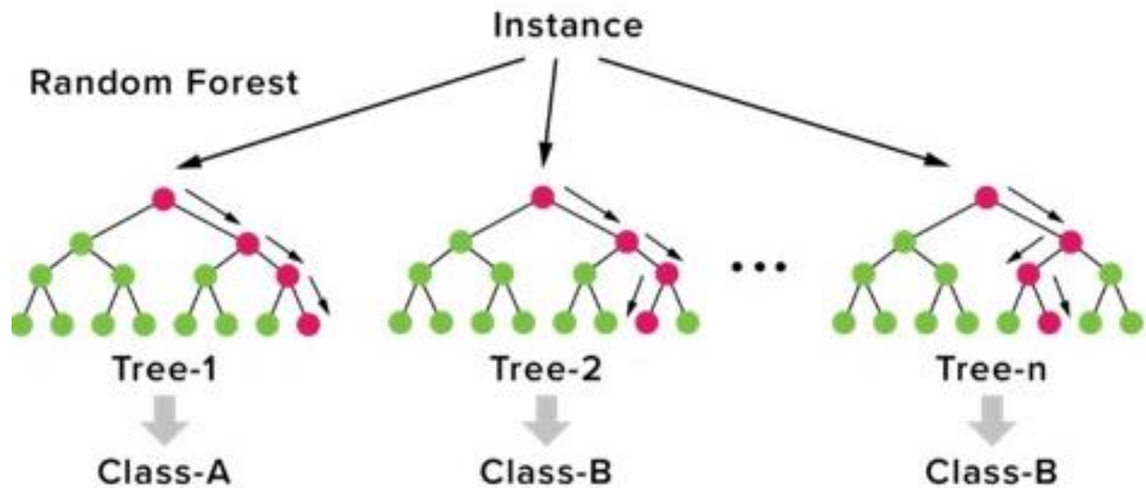

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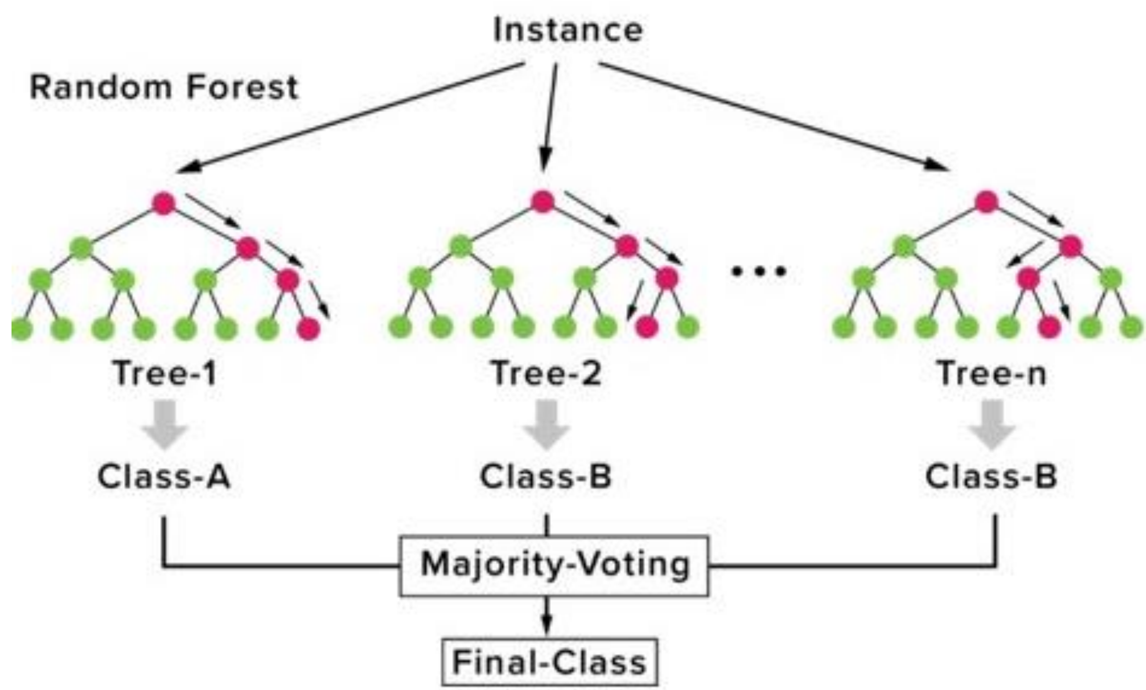

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Iris-versicolor	0.0 %	88.7 %	6.4 %	50
Iris-virginica	0.0 %	11.3 %	93.6 %	50
Σ	50	53	47	150

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Iris-versicolor	0.0 %	88.7 %	6.4 %	50
Iris-virginica	0.0 %	11.3 %	93.6 %	50
Σ	50	53	47	150

- All scores are usable by means of 2 possible simplifications:

Validation

- We must distinguish binary from multiclass classification
- All classification metrics seen in FAA are valid for the binary case
- Only a few are directly applicable to multiclass situations

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- In both cases, numerical scores are **aggregated by averaging**

Python functions

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Algoritmo	Entorno	Función
K-Nearest Neighbors	Scikit-learn	KNeighborsClassifier
Decision tree	Scikit-learn	DecisionTreeClassifier
Logistic Regression	Scikit-learn	LogisticRegression
Naïve Bayes	Scikit-learn	GaussianNB MultinomialNB ComplementNB BernoulliNB
Support Vector Machines	Scikit-learn	SVC NuSVC LinearSVC
Neural Networks	Scikit-learn	MLPClassifier
AdaBoost	Scikit-learn	AdaBoostClassifier
Bagging	Scikit-learn	BaggingClassifier
Random Forests	Scikit-learn	RandomForestClassifier
Gradient Boosting	Scikit-learn	GradientBoostingClassifier HistGradientBoostingClassifier

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Eskerrik asko

Muchas gracias

Thank you

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