

Chapter 9

Classification Continued





Classification Algorithms

- Dozens of algorithms exist and a lot of them have many variations
- The algorithms can be *classified* into 4 categories
 - Distance-based algorithms
 - Probability-based algorithms
 - **Search-based algorithms**
 - Decision Tree
 - **Optimization-based algorithms**
 - Support Vector Machine

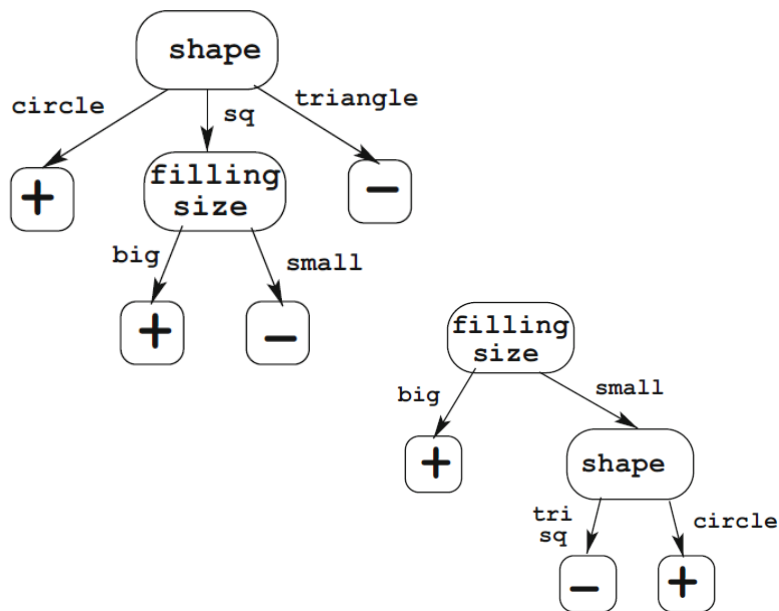


Decision Tree

What is it?

- A technique to create easily interpretable flowchart-like models
- The new (classifiable) object starts at the root node
- At each node, the object travels down based on the value of **one** of it's attribute
- The problem space is *split* by the node along the axis of the attribute
- Leaf nodes are output nodes, at each leaf node we have an assigned output value

Example



Example	crust size	shape	filling size	Class
<i>e1</i>	big	circle	small	pos
<i>e2</i>	small	circle	small	pos
<i>e3</i>	big	square	small	neg
<i>e4</i>	big	triangle	small	neg
<i>e5</i>	big	square	big	pos
<i>e6</i>	small	square	small	neg
<i>e7</i>	small	square	big	pos
<i>e8</i>	big	circle	big	pos



Decision Tree Induction

High level algorithm overview

Let T be the training set.

$grow(T)$:

- (1) Find the attribute, at , that contributes the maximum information about the class labels.
 - (2) Divide T into subsets, T_i , each characterized by a different value of at .
 - (3) For each T_i :
If all examples in T_i belong to the same class, then create a leaf labeled with this class; otherwise, apply the same procedure recursively to each training subset:
 $grow(T_i)$.
-



Decision Tree

■ Pros

- Its simple and interpretable as flowchart or a set of rules
- Very robust: Can handle outliers and missing values, no need to normalize, does not care about attribute correlation (all thanks to handling one attribute at a node)

■ Cons

- Fails at complex models where attribute interrelations are important
- Can only split along an axis
- Only able to learn $x_i \leq a$ rules, where x_i is a predictive attribute and a is a constant

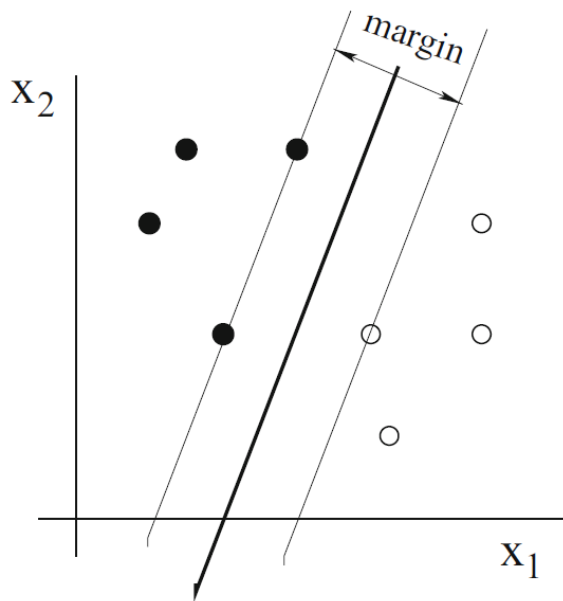


Support Vector Machine

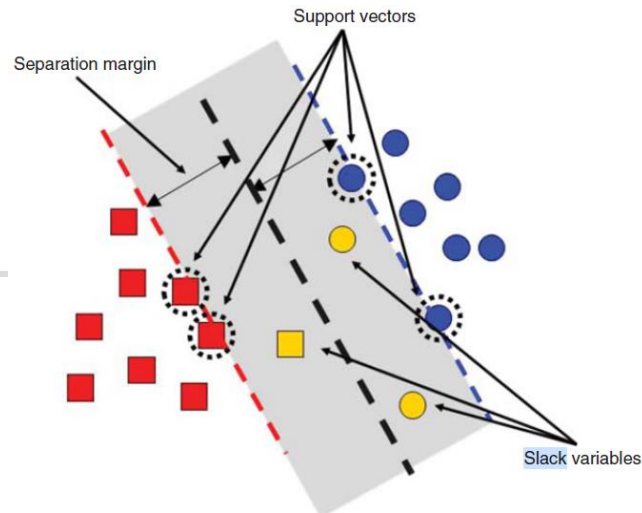
What is it?

- A technique allowing us to create good generalizing models that separate the problem space
- Unlike logistic regression the model clearly decides the class label instead of probabilistic result
- Unlike Neural Networks we find the most optimal solution to split the data by finding the line that maximizes the margin with respect to the support vectors
- Introduces the **kernel trick** to transform data into linearly separable representation

Support Vector Machine



from *An Introduction to Machine Learning* by Miroslav Kubat



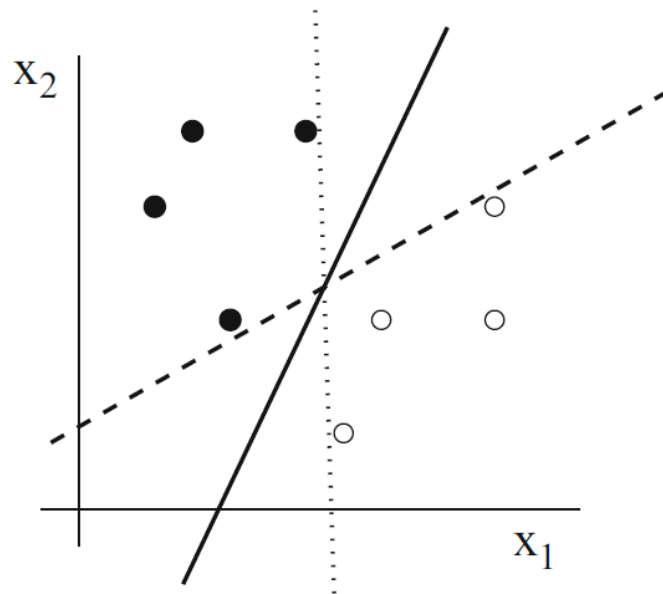
from *A General Introduction to Data Analytics* by by João Moreira et al.

Illustration

- The thick line is the class separator, the thin lines are the support vectors for each class
- The class separator is the best fit for maximizing margin size
- We can allow some *slack variables* inside the margin zone to increase margin size

Support Vector Machine

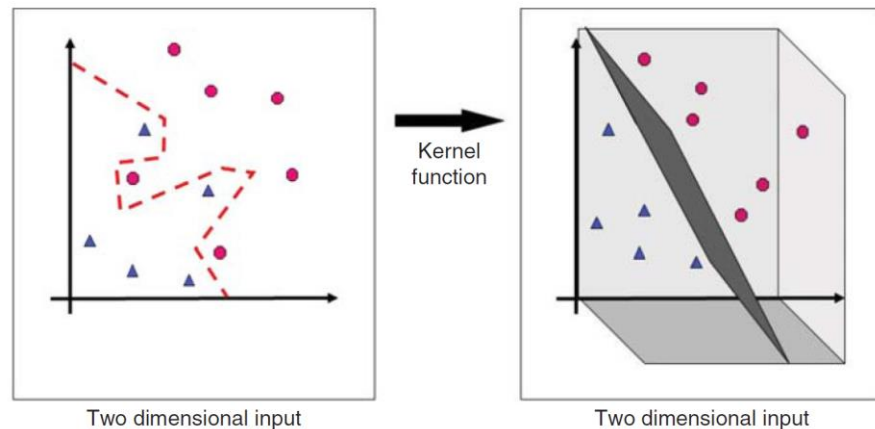
- Out of the many possible separators SVM will find the most optimal one
- Greater margin means better generalized model



Support Vector Machine

Kernel function

- A technique to increase dimensionality in order to transform a non-linear problem into a linear one
- There are also more advanced kernels that can solve non-linear problems these are Radial Basis Function (RBF) and Polynomial kernel



from *A General Introduction to Data Analytics* by by João Moreira et al.



Support Vector Machine

■ **Pros**

- Not random, same results achieved between runs (deterministic)
- Good performance in many problems
- Good theoretical foundations

■ **Cons**

- Very sensitive to hyperparameter values
- Sensitive to outliers, magnitude difference between variables (needs normalization)
- Training time grows at least quadratically with increased training samples



References, Literature, further reading

- Chapter 6 of *Introduction to Machine Learning* by Miroslav Kubat
- <https://towardsdatascience.com/understanding-support-vector-machine-part-1-lagrange-multipliers-5c24a52ffc5e>
- <https://towardsdatascience.com/understanding-support-vector-machine-part-2-kernel-trick-mercers-theorem-e1e6848c6c4d>
- Further methods and comparison https://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html
- <https://www.deeplearningbook.org/contents/ml.html>



Questions?

