Ariel University

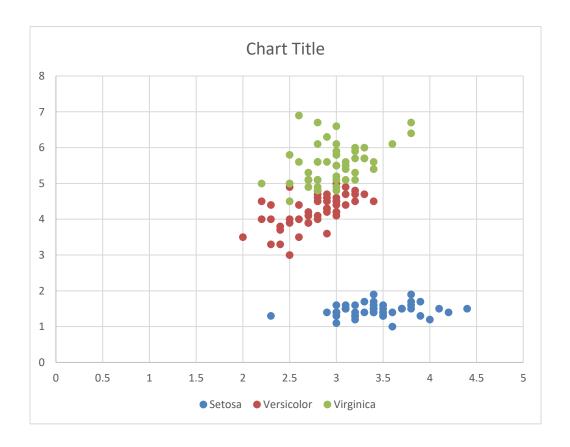
Machine Learning

Homework 2

Problem 1. Class **C** has VC-dimension d. Class **C'** includes all objects that are formed by intersections and unions (in any order) of s objects in **C**. Give an upper bound on the VC-dimension of **C'**.

Note: For the next two problems, hand in code, and also hand in the answers in a <u>separate file</u>, not together with the code.

Problem 2. The famous UCI Iris data set contains information on 150 flowers from three species of iris: Setosa, Versicolor and Virginica. For this assignment we will take only the second and third features for each flower:



Implement the Perceptron algorithm as learned in class on this data set (without normalizing the vectors).

- 1. Run Perceptron on Setosa and Versicolor. What is the final vector? How many mistakes were made by Perceptron? What is the true maximum margin?
- 2. Run Perceptron on Setosa and Virginica. What is the final vector? How many mistakes were made by Percepton? What is the true maximum margin?
- 3. Compare the two results above, and explain how and why they differ.
- 4. What would happen if we ran Perceptron on Versicolor and Virginica?

Problem 3. Now let's take Versicolor and Virginica alone. Each pair of points in this set can define a line that passes through the two points. The set of all such lines is our hypothesis set **H**, that is our set of rules. Implement Adaboost using the above set of rules.

One run of Adaboost is as follows: Split the data randomly into $\frac{1}{2}$ test (T) and $\frac{1}{2}$ train (S). Use the points of S (not T) to define the hypothesis set of lines. Run Adaboost on S to identify the 8 most important lines h_i and their respective weights α_i . For each k=1,...,8, compute the empirical error of the function H_k on the training set, and the true error of H_k on the test set:

$$H_k(x) = sign(\sum_{i=1}^k \alpha_i h_i(x))$$

$$\bar{e}(H_k) = \frac{1}{n} \sum_{x_i \in S} [y_i \neq H_k(x)]$$

$$e(H_k) = \frac{1}{n} \sum_{x_i \in T} [y_i \neq H_k(x)]$$

Execute 100 runs of Adaboost, and report $\bar{e}(H_k)$ and $e(H_k)$ averaged over the 100 runs. Hand in code in python (write at the top which version of python you're using) and printouts of the value of each H_k for each dataset (total: 16 values). Answer the following:

Analyze the behavior of Adaboost on train and test. Do you see any exceptional behavior? Do you see overfitting? Explain.