

1) Clustering (10%)

a. Is K-medoid more robust to noise (or outliers) than the K-means algorithm?
Explain your answer.

Answer: Yes.

K-means, based on the squared Euclidean distance, $d(x, \mu)^2$, which defined by the following equation: $\mu_i = \mu(C_i) = \operatorname{argmin}_{\mu \in \mathbb{R}^n} \{\sum_{x \in C_i} d(x, \mu)^2\}$, μ_i defines the mean of the centroid of each cluster. The squared distance can be influenced by noises (or outliers) that their distance to the centroid is expected to be bigger than the examples (the main points we would like to cluster).

In contrast to K-mean, K-medoid, based on the differences between the examples, points labeled to be in a cluster and their medoid which this algorithm peaks and changes iteratively according to the L1 distances. Therefore, it is less affected from the noises are mostly far from the points.

b. Prove that for the 1D case ($x \in \mathbb{R}^1$) of K-means, the centroid (μ) which minimizes the term $\sum_{i=1}^m (x_i - \mu)^2$ is the mean of m examples.

b) Proof:

Lets find the μ that minimizes the sum of the squared distance $(d(x, \mu))^2$ in 1D:

$$\frac{d}{d\mu} \sum_{i=1}^m (x_i - \mu)^2 = \sum_{i=1}^m \frac{d}{d\mu} (x_i - \mu)^2 = -2 \sum_{i=1}^m (x_i - \mu)$$
$$= -2 \sum_{i=1}^m x_i + 2m\mu \stackrel{\text{demanding for extremum}}{=} 0$$

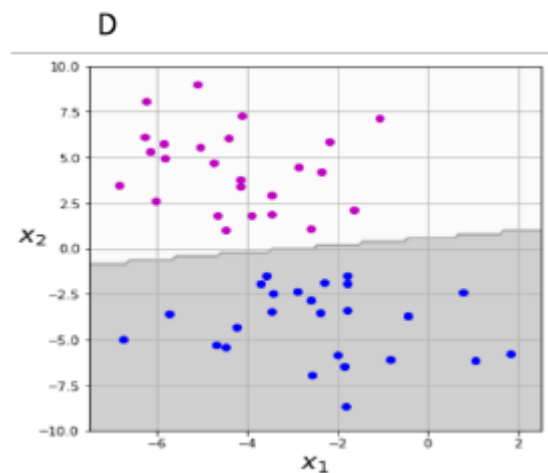
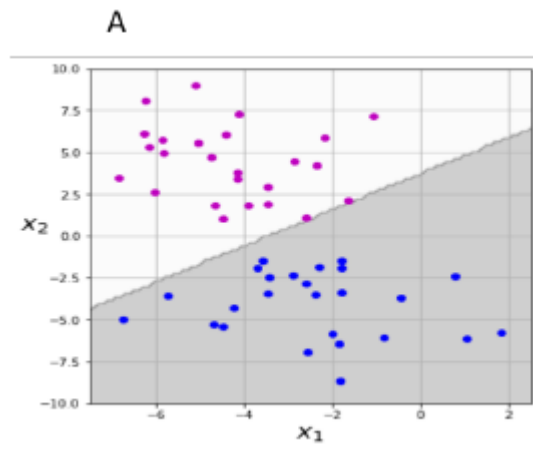
Therefore, $\mu = \frac{1}{m} \sum_{i=1}^m x_i$

Lets check minimum point by the second derivative:

$$\frac{d}{d\mu^2} \left(\sum_{i=1}^m (x_i - \mu)^2 \right) = \frac{d}{d\mu} \left(-2 \sum_{i=1}^m (x_i - \mu) \right) = 2m > 0$$

↓
minimum point

2) SVM (30%)



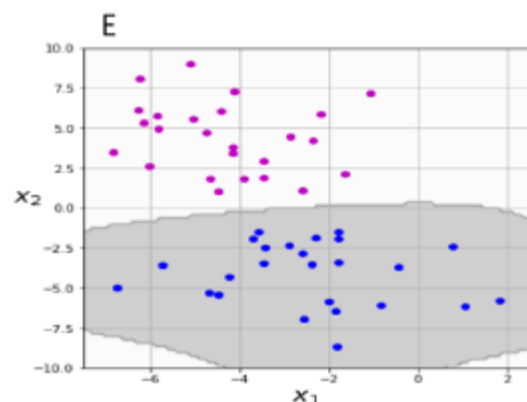
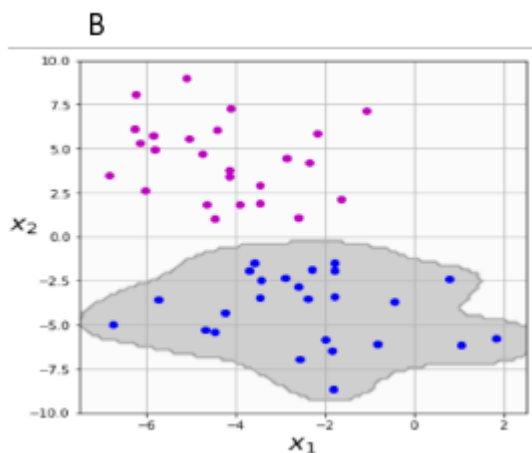
As we can see from the graphs both are linear separable. However, they are different from one another in the margin length.

According to the optimization problem: $\operatorname{argmin}_{w,b} \left\{ C \sum_{i=1}^m \xi_i + \frac{1}{2} \|w\|^2 \right\}$

In order to minimize this expression, we have two values that we have to take in account: The first one, C represents the penalty of misclassification and the second one is the margin, which defined as $\frac{2}{\|w\|}$. Therefore, we have to find a tradeoff between maximizing the margin and minimizing the mistakes. When C is small, misclassification is given less importance and focus more on maximizing the margin, - **option 1**, while, when C is large, the focus is more on avoiding misclassification at the expense of small - **option 2**.

Graph A has higher margin, so smaller C - **option 1**.

Graph D has smaller margin, so higher C - **option 2**.

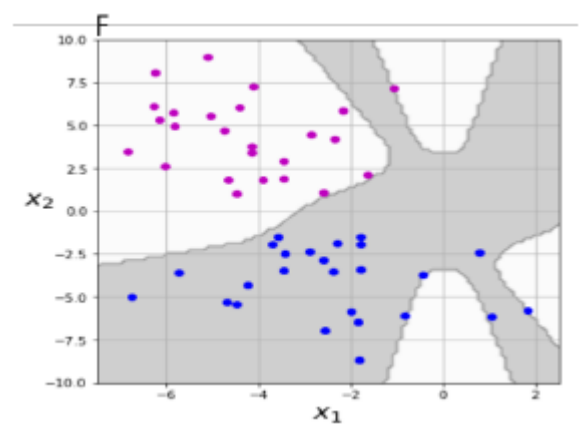
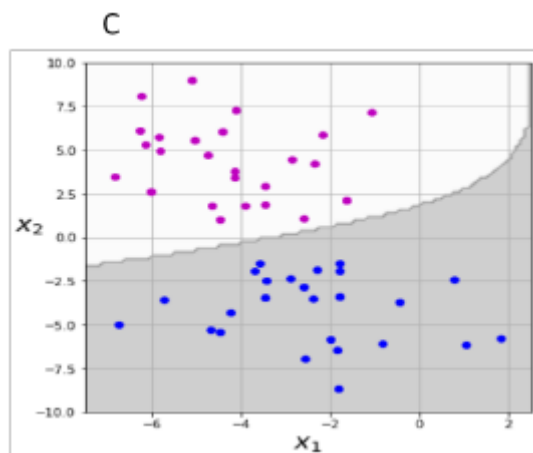


RBF kernel – Radial basis function: $k(\mathbf{x}, \mathbf{z}) = \exp(-\|\mathbf{x} - \mathbf{z}\|^2 / (2\sigma^2))$

$$= \exp(-||x - z||^2 \cdot \gamma) = \exp(-||x - z||^2) \times \exp(-\gamma) \rightarrow \gamma = \frac{1}{\sigma^2}$$

These graphs have the highest correlation one the other, as we can see from their shapes that that **graph E** is bigger than **B** in by factor gamma. Which makes sense because exponent is a monotonic function.

Gamma is a parameter that represents the fitting to the training data. As the higher gamma is **option 6** the classification fits more to the training. Therefore, **graph B** fits more to the training set – **option 6**, whereas Graph E has less fitting to the data - **option 5**.

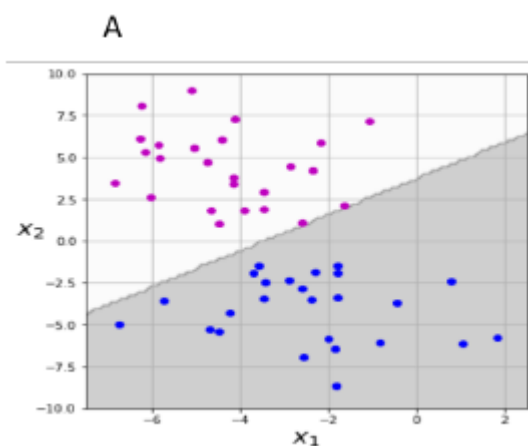


The two left options are the graphs above, so they have polynomial kernels.

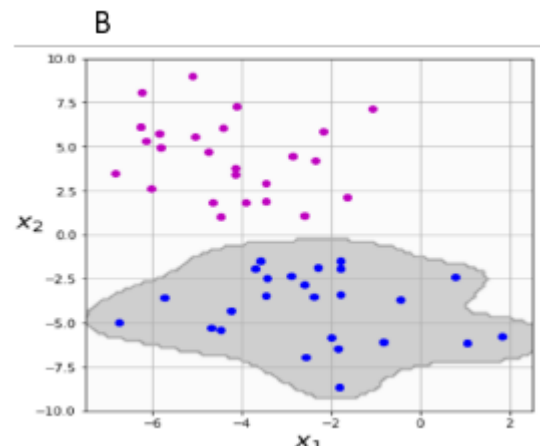
As we can see the **graph C** fits less to the training than **graph F**.

As high the polynomial's order is the complexity of the problem is higher and the graph fits more to the training points – **option 4**, on the contrary to lower polynomial's order – **option 3**

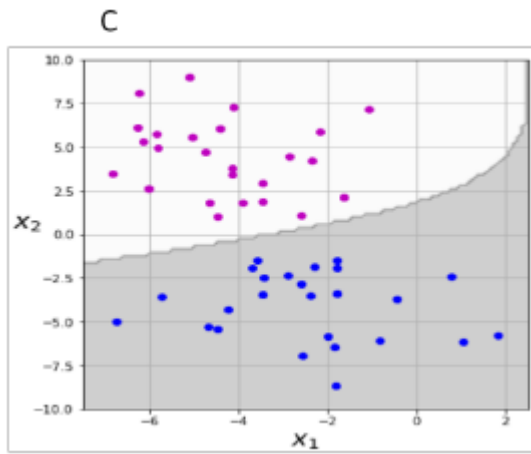
Summary of my matchings:



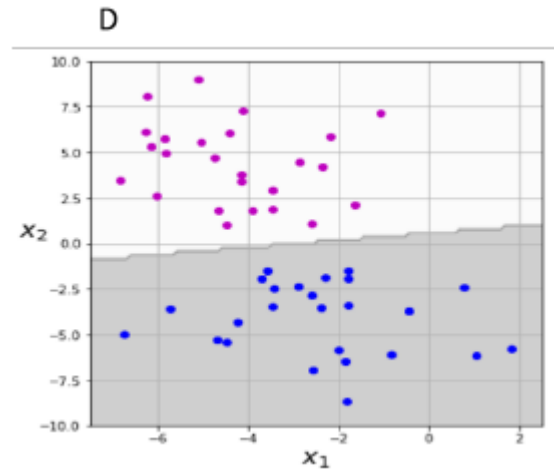
1. Linear kernel with $C = 0.01$.



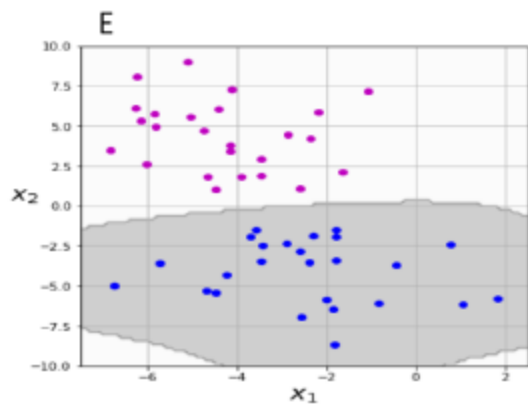
6. RBF kernel with $\gamma = 1$.



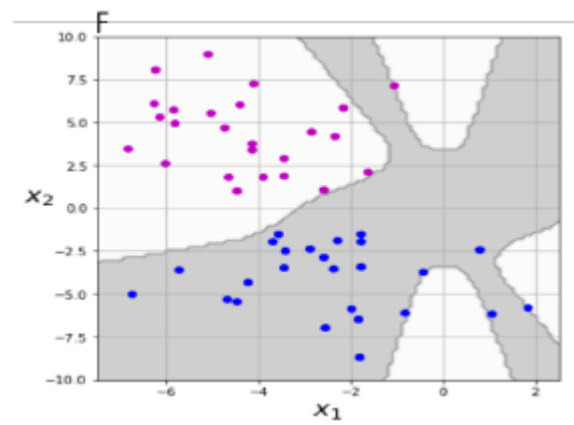
3. 2nd order polynomial kernel.



2. Linear kernel with $C = 1$.



5. RBF kernel with $\gamma = 0.2$.



4. 10th order polynomial kernel.

3) Capability of generalization (20%)

a. What is the scientific term of the balance that Einstein meant to in machine learning aspect?

Answer: The balance in machine learning is the way that the dataset, like in science the real life, is divided to different classes. The balance of the data helps us to consider the reliability of the accuracy of the model. If the different labels are divided equally on the training set, it means that the dataset is balanced. But like the real life it is common that our model is not divided equally, for instance in cases of binary classification that classified patients with different diseases. So we have to apply some method to overcome the imbalanced dataset like using metric performance measures that can give more insight into the accuracy of the model than traditional classification accuracy: Confusion Matrix, F1 Score, ROC Curves, ext.

b. How does each of the terms ($2p$, $2\ln(\hat{L})$) in AIC affect the terms of the balance you defined in (a)?

$$\rightarrow AIC = 2p - 2\ln(\hat{L})$$

Answer: $2p$ - p is the total numbers of parameters, as much as p is smaller the model is easier to analyze, low complexity rather than high-dimensional model with large numbers of parameters which can lead to overfitting. When p is small AIC is small as well, the dimension of the model is small which means high bias and low variance, while high p means high variance and small bias. However, if the p is too small the model can face with misclassification.

The likelihood \hat{L} indicates the goodness fit of a class to the model, $2\ln(\hat{L})$ is a number is the probability that estimates p . Therefore, if \hat{L} is high, according to the equation, AIC decreases.

The balance that I defined in (a) can be represented by a trade-off between bias and variance, (p) in resulting estimators (\hat{L})

c. What are the two options that are likely to happen if this balance was violated?

Answer:

- 1) If we increase the number of parameters p , it can lead to overfitting, and add complexity to the classification that takes a more time and money.
- 2) If we decrease the number of parameters p , it can lead to underfitting, that means we won't have enough parameters for classification.

d. What are we aiming for with the AIC? Should it be high or low? Explain.

Answer: AIC is a mathematical method which evaluates how well a model fits the data. The best model is the one that has minimum AIC among all the other ones.

The best-fit model according to AIC is the one that has the greatest amount of variation that means highest likelihood (\hat{L}) using the fewest possible parameters (p) which indicates also the parsimony of the model.