Learning Coursework: Task 1 report

April 9, 2020

1.2 - Correlation matrix interpretation

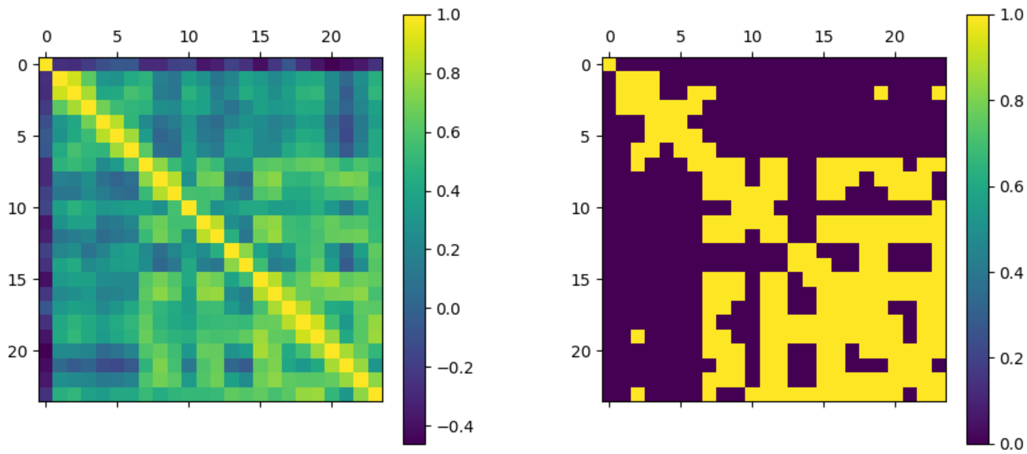

Figure 1: Covariance matrix heatmaps - the full one and one with an applied step function (1 if > 0.5, -1 if < 0.5, 0 otherwise)

Negative correlations

As we can see on Figure 1, the only feature that is negatively correlated with others is the feature with index 0 (dark blue bars on the upper and left edges of the matrix). These are weak negative correlations, as they are bounded below by about -0.4.

Positive correlations

As we can see in the second plot on Figure 1, there are many features with high positive correlations (> 0.5, seen in yellow). We can observe two clusters of features that are mostly correlated with each other - features $[1, 6]$ and features $[7, 23]$ (the rectangles that contain all the pairs of features within these intervals are mostly yellow).

1.3

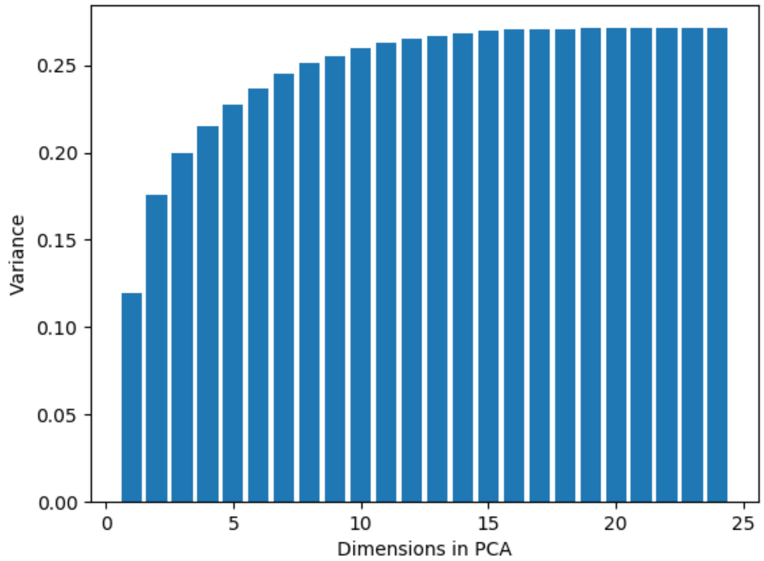

Figure 2: **Task 1.3b - Cumulative variance graph**; it can be seen that the marginal gain is decreasing with each new dimension

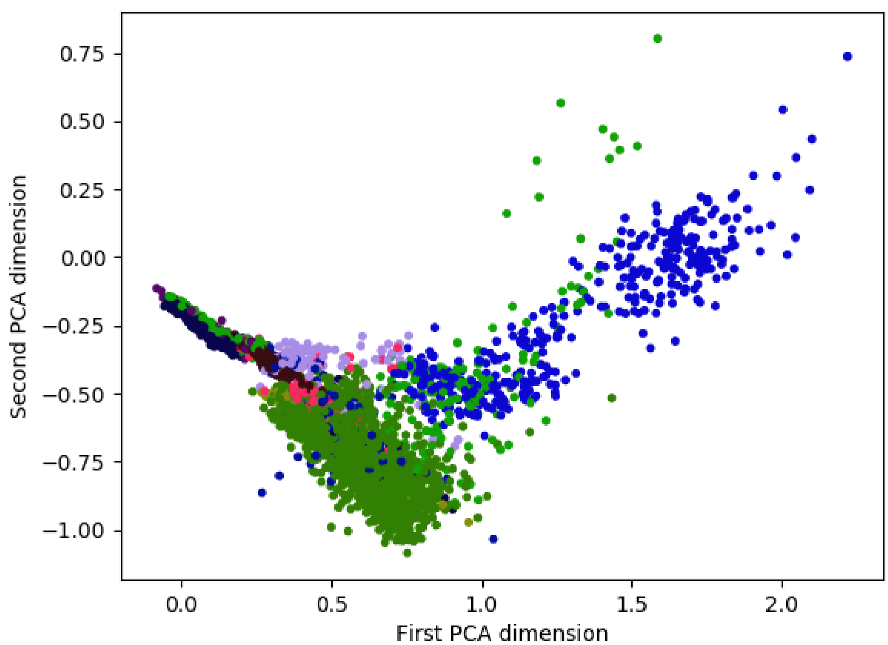

Figure 3: **Task 1.3c - 2D-PCA plane**; labels have unique colours assigned

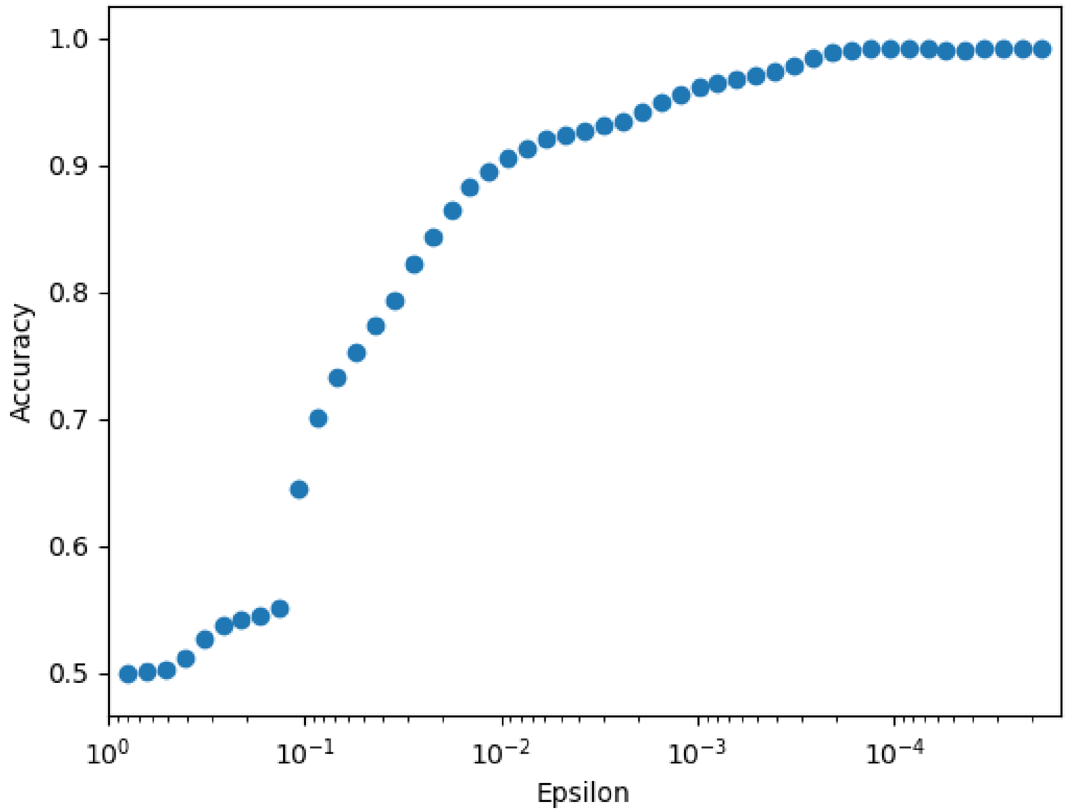

Figure 4: **1.5 - Impact of the epsilon on accuracy**; logarithmically scaled x-axis

1.4b - Accuracy vs Covariance Matrix Type

For the dataset given, epsilon = 0.01 and Kfolds = 5, the accuracies are given in the following table:

CovKind	*Full*	*Diagonal*	*Shared*
Accuracy	90.101%	83.028%	88.271 %

1.5 - Regularisation parameter analysis

Intuitively, we would expect the accuracy to drop when taking bigger epsilons, as this makes the approximation of the covariance matrix worse. Figure 4 confirms that; the accuracy increases when we take smaller epsilons. What is more, the plot becomes nearly flat for $x < 10^{-4}$, so there is no benefit from taking smaller epsilons than that.