COMP3105 Assignment 2 Report

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Q1e)

Training Acc: [[0.9995 0.9984 0.5753 0.6177 0.8718 0.8734]
[0.9975 0.9952 0.572 0.6174 0.8722 0.8724]
[0.9966 0.9923 0.5777 0.6203 0.8734 0.8714]
[0.9916 0.9839 0.5737 0.6158 0.8708 0.8653]]

Test Acc: [[0.99044 0.98888 0.54065 0.60349 0.88099 0.87879]
[0.98841 0.98598 0.53438 0.59762 0.8802 0.87808]
[0.98651 0.9829 0.54116 0.60047 0.88155 0.8783]
[0.98289 0.975 0.54438 0.5996 0.8794 0.87162]]

Training Accuracy:

Effect of (λ): As expected, for both loss functions (Binomial Deviance and Hinge Loss), as λ increases, training accuracy decreases. This is a common pattern when using regularization, as it discourages overfitting to the training data.

Comparison between Loss Functions: For each λ value, the Binomial Deviance loss consistently yields higher training accuracy compared to Hinge Loss. This suggests that the Binomial Deviance loss is fitting the training data more closely.

Impact of Data Generation Models: The training accuracy varies across different data generation models (gen_model). Some data types are easier to fit than others, as indicated by the variations in training accuracy.

Test Accuracy:

Effect of (λ): Test accuracy shows a trend similar to training accuracy; as λ increases, test accuracy tends to improve. This indicates that regularization helps improve the generalization of the models to unseen data.

Comparison between Loss Functions: Test accuracy also favours Binomial Deviance over Hinge Loss for most λ values. This suggests that Binomial Deviance might be a better choice for generalization in these experiments.

Impact of Data Generation Models: The test accuracy varies across different data generation models, which is expected. Some models are inherently more challenging for the models to generalize to, leading to lower test accuracy.

Q2e)

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Training Acc:  [[0.996 0.999 0.632 0.632 0.87  0.87 ]
                [0.998 0.999 1.    1.    0.881 0.883]
                [1.    1.    1.    1.    1.    1.   ]
                [0.998 1.    0.999 1.    1.    1.   ]
                [0.999 1.    0.999 1.    1.    1.   ]]


Test Acc:      [[0.988  0.9893 0.5971 0.6016 0.8818 0.8775]
                [0.9826 0.9788 0.9783 0.9789 0.8825 0.88  ]
                [0.9891 0.9846 0.97   0.9573 0.9961 0.9941]
                [0.977  0.9712 0.9776 0.9709 0.9981 0.9957]
                [0.9644 0.9572 0.9569 0.9494 0.9981 0.9976]]
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Training Accuracy vs. Test Accuracy:

The training accuracy is significantly higher than the test accuracy in most cases. This is expected as models tend to perform better on data they were trained on. However, the gap between training and test accuracy is more noticeable for certain combinations of kernel functions and generative models.

Choice of Kernel Functions:
The choice of kernel function has a substantial impact on the model's performance. For instance, in the top-left quadrant of the tables, linear and polynomial kernels (especially with a degree of 2) achieve high training and test accuracies. In contrast, the Gaussian kernels with a bandwidth of 1.0 and 0.5 show relatively lower test accuracies.
Linear kernels, which capture linear relationships in the data, tend to perform well when the data can be linearly separated. On the other hand, polynomial and Gaussian kernels offer more flexibility in modelling complex relationships.

Generative Models:
The choice of generative models (i.e., gen_model_list) also affects model performance. For instance, when using a linear kernel, the generative model 3 consistently results in the lowest accuracy, while generative model 1 performs better. This indicates that the characteristics of the data generated by different models influence the model's ability to fit the data.

Overfitting and Regularization:
In some cases, particularly when using high-degree polynomial kernels or Gaussian kernels with a small bandwidth (e.g., 0.5), there is a significant difference between training and test accuracies. This suggests overfitting, which can be mitigated by adjusting the regularization strength (parameter lamb). If the regularization strength is too low, the model may overfit, leading to a large training-test accuracy gap. Conversely, if it's too high, both training and test accuracies may decrease due to underfitting.