# ICS635 Homework 4: by Lambert Leong

## Problem 1

Maximizing the conditional likelihood of the data.

$$\mathcal{L}(\mathcal{D}) = p_\theta(y_n|x_n) = \prod_n^N (\hat{y_n})^{y_n}(1-\hat{y_n})^{1-y_n}$$

Maximizing the log-likelihood

$$log\mathcal{L}(\mathcal{D}) = \sum_n^N (\hat{y_n} log(y_n) + (1-y_n) log(1-\hat{y_n}))$$

Minimizing the binary cross-entropy loss

$$L(\mathcal{D}) = -\frac{1}{N}\sum_n^N (\hat{y_n} log(y_n) + (1-y_n) log(1-\hat{y_n}))$$

$$-\frac{1}{N}L(\mathcal{D}) = \sum_n^N (\hat{y_n} log(y_n) + (1-y_n) log(1-\hat{y_n}))$$

Therefore, we can say maximizing the log-likelihood is equivalent to minimizing the binary cross-entropy loss

$$log\mathcal{L}(\mathcal{D}) = -\frac{1}{N}L(\mathcal{D})$$

## Problem 2

1. Sample size is large enough to do a 60%, 20%, 20% split for train, validation, and test.
2. The exact architecture or neural net model is ambiguous.
3. The loss function being optimized is not clear.
4. The exact hyper parameters optimized are not stated.
5. The evaluation method for the competition is unclear(i.e. are they using AUROC, AUPRC, or etc).
6. It seems as though the test set was not used. The individual does not report how the tuned model did on the test set.
7. It is unclear if the individual is first place on the leader board of if they actually won the whole competition.
8. The final optimized parameters are not reported which makes it difficult to reproduce the work.

9. It is not clear what data set was used to train the final model that was submitted. Did the individual use just the model trained on the 80% training data or all the training data?

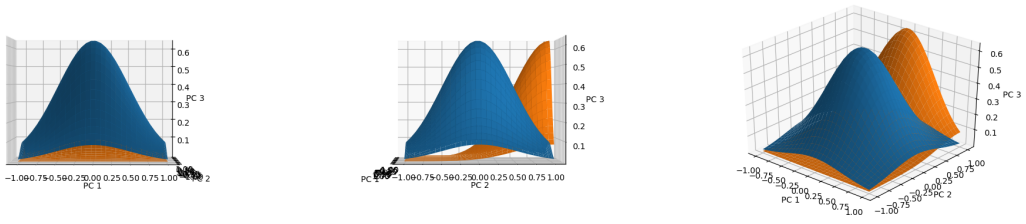
10. The final test set, mentioned in the last line, is ambiguous because it could be referring to the withheld dataset that is used to pick the winners or the final test set(10% of the training) that the individual set aside when he did his data split.

**Problem 3**

1. Centering data affects the principal components if it is calculated via singular value decomposition. However, if one is to compute the principal components by first computing the covariance matrix then centering should not affect principal components.

2. Scaling data can help prevent one principal component explaining the majority of the variance. If the data is not scaled properly, one feature could dominate and influence the axis of maximal variance.

3. Classes will be indistinguishable if the two classes are centered around the same space with respect to the two dimensions or principal components they are plotted in. In other words, if a 2D plot is made using the wrong two components, it could appear that the 2 Gaussians are superimposed on each other which would make them appear indistinguishable. Interchanging one principal component for a third or plotting in a higher dimension will likely show some separability.




(a) view of PC1 vs PC3, Indistinguishable

(b) View of PC2 vs PC3, Class separation visible

(c) 3D plot, Class separation visible

Figure 1: Example of how 2D views can lead to indistinguishable classes

4. If the network is free of any nonlinearities then it is convex. It will be equivalent to plotting the data in principal component space.

**Problem 4**

1. If you have data points on previous days to construct a reasonable posterior, it will be better than flipping a coin.

2. Trusting the oracle can change prediction. If a new Gaussian process is fit with the addition of new data point, it can narrow the range of your prediction; so yes it will affect your models prediction.

3. MAP