

HW 3 - Cancer and Diabetes analysis

ECGR 5105 - Summer 2024

Joshua Ayers

SID: 801083470

Professor: Vinit Katariya

Github: https://github.com/Jayers0/HW3_ECGR5105

Problem 1:

I implemented logistic regression on the diabetes dataset that I had loaded into a pandas dataframe. For this assignment I shifted from my previous functional programming paradigm to use classes both because I have not had experience in dedicated OOP in python but also because I would like to use the classes created to make a simple ML framework of my own.

In my log regression class I implemented L2 regularization though I didn't use it for this problem.

Results:

Accuracy: 0.7338

Precision: 0.6250

Recall: 0.6364

F1 Score: 0.6306

Problem 2:

Invoking the class defined in problem 1, I defined 2 models on with L2 regularization and loaded the data. I had issues with getting this to work until I analyzed the data and found that there were 2 issues:

1. The malignant and benign data was defined as a char rather than an int or a bool and thus would cause issues with the classifier
2. There was an extra column defined at the end of the csv that was loading a column of NaN values

To fix these issues I removed the extra column by directly modifying the dataset by removing the extra comma and I used a lambda function to replace M and B with 1 or 0 respectively

Sub-Problem 1 Results:

Accuracy (L2): 0.9912

Precision (L2): 1.0000

Recall (L2): 0.9767

F1 Score (L2): 0.9882

Sub problem 2 Results:

Accuracy (L2): 0.9912

Precision (L2): 1.0000

Recall (L2): 0.9767

F1 Score (L2): 0.9882

In this case I am very suspicious of the performance. In problem 1 the predictive metrics were substantially lower. Because there was substantially more data this may have allowed closer results. However if this was the case I would be very surprised. I believe that there must be some other issue. Regardless whatever caused this issue obfuscated the performance difference between the L2 regularized and the non-regularized models. However I can say that in this case the abundance of data allowed the model to train to be much more precise.

Problem 3:

In the same way as problem 1 I defined a naive bayesian model class this class. Refer to the graphs produced for performance metrics.

Problem 4:

As before I defined a PCA class designed to allow principle component analysis. It is notable that this class was much much less performant than the other classes taking over 1 min to train on the data whereas the previous functions took only a second or less to train. This is probably a result of the exponential growth of the permutation of relations as one increases dimensions in PCA.

The performance results of this model were quite good. Staying steady at just under 100% precision, accuracy and recall and F1.

Refer to the graphs produced for performance metrics.

Problem 5:

It seems as though this problem is asking me to repeat problem 2. Log reg beats every other model on the cancer dataset however I think that is an erroneous result. Otherwise PCA

outperforms bayesian but not to a degree that would make it more usefull given its high compute load.