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CSCE A415
HW #2.2

Problem 2: Logistic Regression

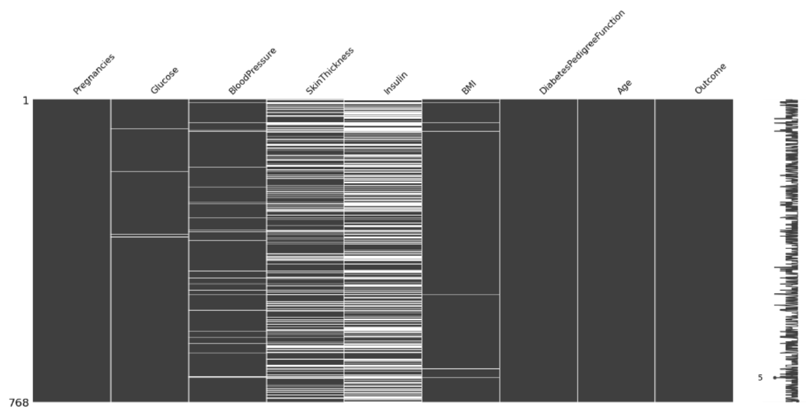
Data Manipulation

I've experimented with three approaches:

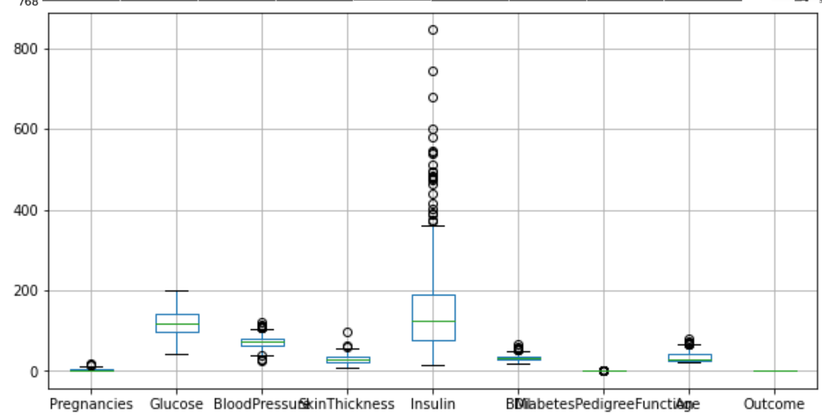
1. Removing **all** missing information and highly correlated attributes.
2. Removing **all** missing information.
3. Using linear regression to fill in **some** missing information.

The following was implemented in all three approaches:

The dataset contains both *NULL* values and *0*'s where information is missing. The *0*'s have been converted to *NULL* for missing-data consistency [5].



Most of the missing information is in the *SkinThickness* and *Insulin* columns [6 - missingno]. There are 44 rows that contain *NULL* values **outside** of those two columns [7]. These rows compose about 5.7% of the dataset and will be dropped [11].

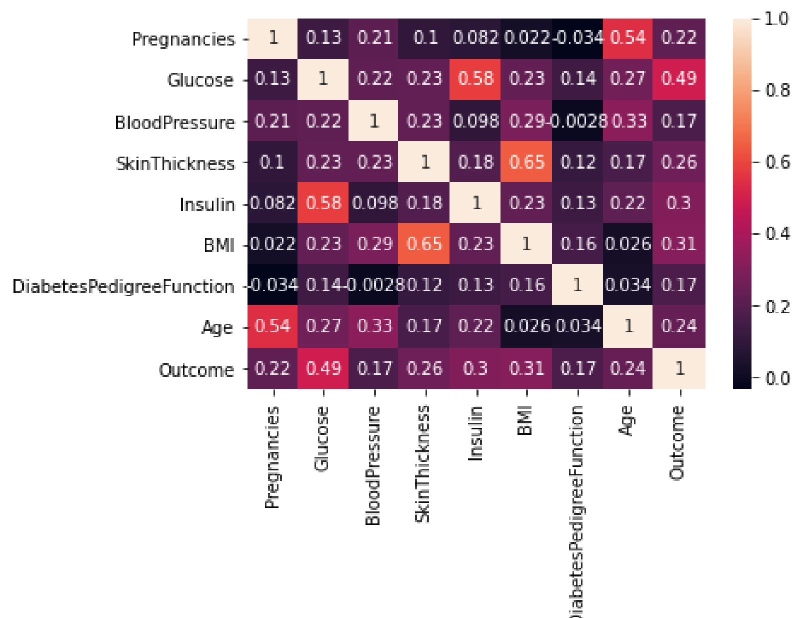


The *Insulin* column shows high variability (large number of outliers [9 - boxplot]) and a high correlation (0.58) with the *Glucose* column [10 - corrMatrix]. Because of this, it is dropped [12].

Approaches #1 & #2:

The remaining missing data is limited to the *SkinThickness* column, which has a high correlation (0.65) with the *BMI* column [10 – corrMatrix]. Because of this, it is also dropped [12].

Approach #1 drops the *Pregnancies* column due to its high correlation (0.54) with the *Age* column [10 – corrMatrix]. I chose to drop *Pregnancies* instead of *Age* because *Age* has a higher correlation with *Outcome*.



Approach #3:

This approach uses linear regression to fill in the missing data in the *SkinThickness* column using the data in the *BMI* column, with which it shares a high correlation. This had the expected effect of increasing the correlation even more, which will probably have a negative impact on the final result.

Testing [15]:

All three approaches were run through a logistic regression model [15]. First, they were fitted and tested against their entire respective datasets (no train/test split) to see the overall accuracy of the logistic regression model. They were then tested using a range of train/test split ratios (50 iterations per split averaged together) to see how each affected the perceived accuracy of each model.

Results [15]:

Having fewer highly correlated attributes in the final model improves the model's overall accuracy, even if only slightly as my models show (0.779 > 0.776 > 0.769). Additionally, the more valid data that's used to train the logistic regression model, the more accurate the model becomes – as seen by the change in accuracy between different train/test ratios. However, using a high train/test ratio may inflate the model's score due to the relatively small test pool. A formal proof would be needed, but I believe training a regression model using all rows of a dataset and then testing the model using the same data (as I did before doing the splits) is a better approach to gauging the overall accuracy of that model.

As a sidenote/afterthought, the linear regression models of this dataset were much better at classifying non-diabetic entries than they were at classifying diabetic entries, with a false positive rate of about 12% and a false negative rate of about 42% [15 – confMatrix].

		Predicted Class	
		Non-Diabetic	Diabetic
Actual Class	Non-Diabetic	420	55
	Diabetic	105	144

Confusion Matrix for an instance of Model #1

```
Score Results

#1
0.7790
Train/Test     Score
90/10          0.7940
80/20          0.7731
70/30          0.7748
60/40          0.7677
50/50          0.7752
40/60          0.7677
30/70          0.7639
20/80          0.7627
10/90          0.7554

#2
0.7762
Train/Test     Score
90/10          0.7825
80/20          0.7756
70/30          0.7659
60/40          0.7679
50/50          0.7674
40/60          0.7695
30/70          0.7668
20/80          0.7630
10/90          0.7540

#3
0.7693
Train/Test     Score
90/10          0.7756
80/20          0.7668
70/30          0.7662
60/40          0.7669
50/50          0.7652
40/60          0.7628
30/70          0.7623
20/80          0.7619
10/90          0.7474
```