Credit Card Fraud Detection with Machine Learning

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Abstract

The following report summarizes the approach to tackling the issue within imbalanced dataset when it comes to applying classification methods. The problem was solved by applying the Synthetic Minority Oversampling Technique (SMOTE) to the imbalanced dataset prior to training it on desired classification models, which in this case are Random Forest and Neural Network. The results achieved were much more meaningful after SMOTE was applied to the dataset.

Keywords*: Credit Card Fraud. Machine Learning. SMOTE. Random Forest. Neural Network.*

Introduction

The two main research questions are:

- How to overcome the imbalance nature of the dataset, also efficiently and accurately classify whether a transaction is fraudulent or not?
- What variables are deemed important when it comes to classifying fraudulent activities?

The Dataset

The selected dataset was acquired from Kaggle and contained 6,362,620 rows by 11 columns. The dataset was however generated by the Paysim Simulator, thus does not actually contain real transactions. Due to the confidentiality restrictions, it was not possible to acquire data of real transactions. However, the simulator uses aggregated

data to generate samples that closely resemble the normal operation of transactions and injects malicious behavior for later evaluation on the performance of fraud detection methods.

The data contains a total of 11 columns such as:

- **Step**: maps a unit of time in the real world. For example, 1 step is 1 hour of time.
- **Type**: types of transaction, i.e.: Cash In/Out, Debit, Payment and Transfer.
- **Amount**: amount per transaction.
- **nameOrig**: name of the person who started the transaction.
- **OldbalanceOrg**: initial balance before the transaction.
- **NewbalanceOrg**: new balance after the transaction.
- **nameDest**: the recipient of the transaction. The labels that start with “C” indicate a Customer, whereas a starting “M” means Merchant.
- **oldBalanceDest**: initial balance of the recipient before the transaction.
- **newBalanceDest**: new balance of the recipient after the transaction.
- **isFraud**: the target variable. The indication of whether the activity is fraudulent or not (dichotomous).
- **isFlaggedFraud**: whether the transaction was flagged as fraud.

The dataset contains 6,354,407 fraudulent activities to only 8,213 non-frauds. Thus, only 0.12% of all transactions are fraudulent. Obviously, this limits the credibility of the overall accuracy achieved from any classification algorithm. In other words, the overall accuracy could still be high even if the model fails to detect fraudulent transactions simply due to the significant discrepancy of the labels distribution.

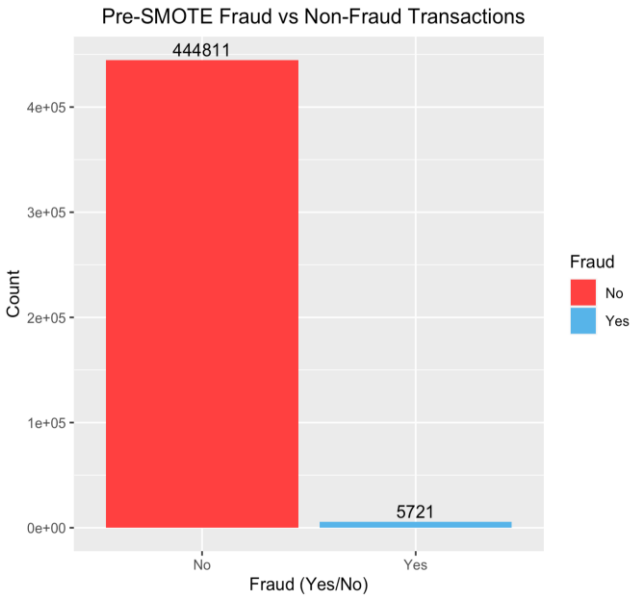
Data Pre-Processing

Fortunately, the dataset contains no NA's, thus no sample imputation or omission was needed. In terms of features selection, "Step", "nameOrig, "isFlaggedFraud" and "old and new BalanceDest" were omitted from the model. The reasoning behind this decision was "Step" does not provide any meaningful interpretation to the data. If anything, it provides some context on how each simulation relates to the real world, which is not necessary if we were to have data from the real world. Including all the names of the people who started the transactions would just be counterproductive as it will lead to overfitting in the models. Although there were technically no NA's in the data, there was a large amount of unavailable data for the "old" and "new" balanceDest columns that was marked as 0's. Lastly, "isFlaggedFraud" is non-essential as all values in the column are 0, meaning none of the activities were flagged at all. In addition, for the purpose of mitigate the computation expense, the training data was slightly modified. All fraudulent accounts were reserved but they are accompanied by only 10% of the non-fraud activities. Thus, resulting in a training dataset consisted of 444,811 non-fraud to 5721 fraud samples (still only 1.2% are frauds).

Exploratory Data Analysis

The data is divided into a 70-30 training-testing split. As mentioned above, the pre-SMOTE training data contains about ~450k samples (Figure 1). 5721 of which are non-frauds which account for about 1.2% of all transactions. Despite the slight modification, the training data remains heavily imbalanced thus SMOTE will be required in order to achieve good accuracy and precision.

Figure 1



Looking at Figure 2, with outliers removed, we can see that most transactions are done on a smaller scale. The distribution of transaction amount is heavily skewed to the left. Intuitively, this makes sense because every day commercial purchases and other use of money are rarely done on a six, seven figure scale.

Figure 2

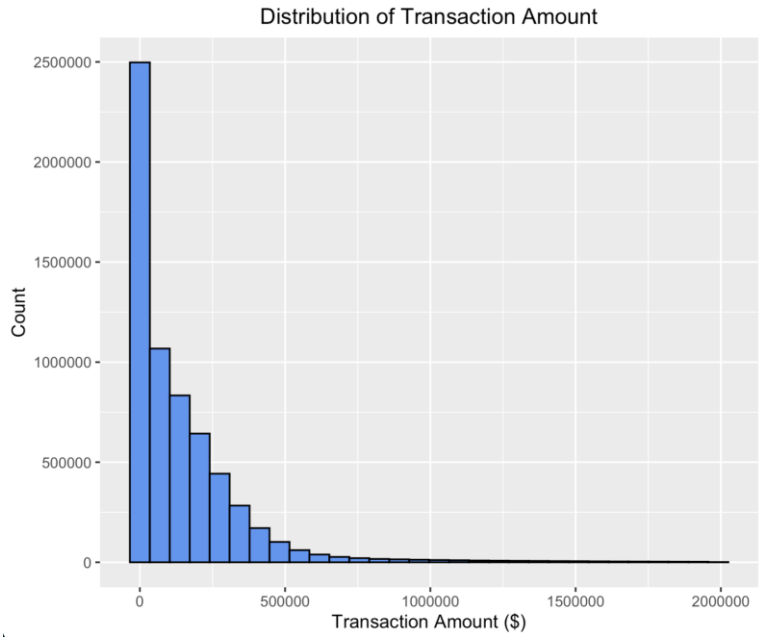
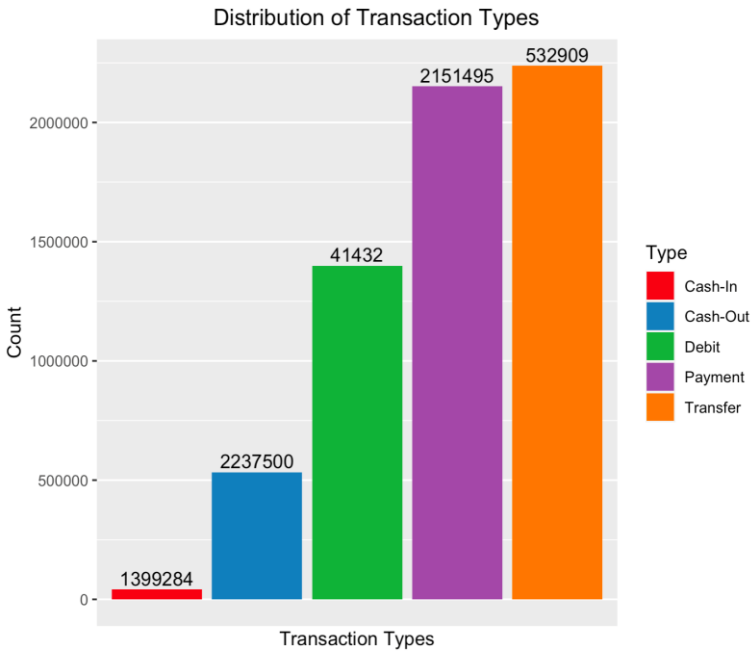


Figure 3

Figure 3 provides an insight to the distribution of transaction types. Transfers and forms of payment dominate the dataset as transactions done with debit come in third. It is interesting to see the discrepancy between recorded transactions of cash-in vs. cash-out. However, this could also be the result of my modification random sampling.

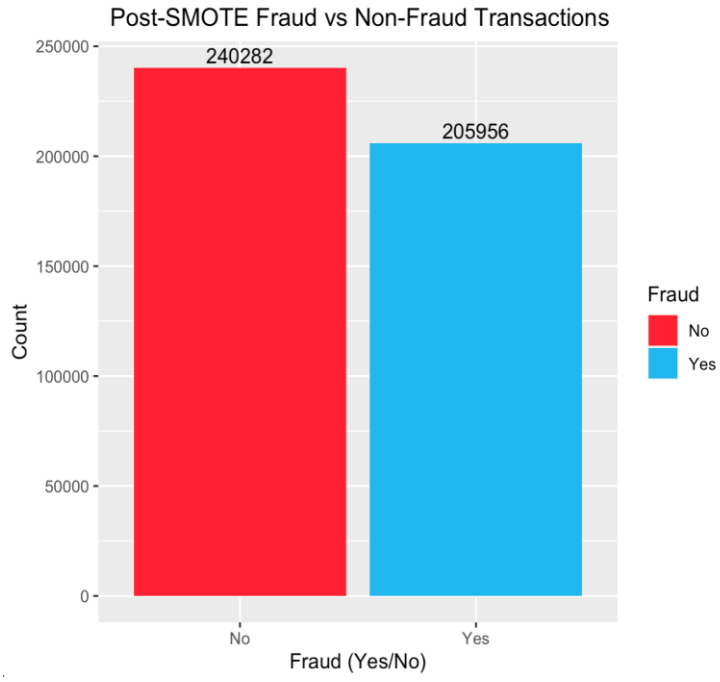


Synthetic Minority Oversampling Technique (SMOTE)

Figure 4

SMOTE is a popular solution to solving the discrepancy issue in imbalanced data. Using SMOTE, we were able to synthetically generate new samples by observing the characteristics of the minority set. SMOTE grants the target variable a nice 55-45 ratio, thus creating a much more balanced dataset ready for classification (see Figure 3).

The new training set now contains ~440k samples, ~205k of which are now frauds.

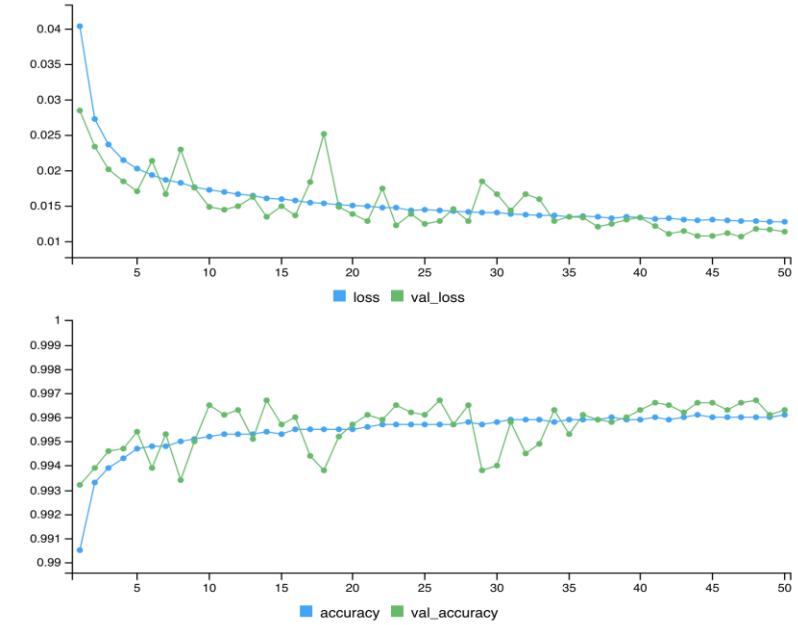


Classification Models

Neural Network (Keras)

The first classification model attempted is a neural network using the Keras interface. The neural network was chosen due to its nature to learn well if given sufficient data (~440k+ of training data). The network is made up of 8 total layers, including the input and output layers. The output layer uses Softmax as its activation function since we are doing classification. LeakyRELU and Hyperbolic Tan (Tanh) are sprinkled through the rest of the layers, one of which contained a dropout rate of 0.1. A variety of combinations of activation functions were tested for this neural network including the popular Sigmoid and RELU functions. RELU was found not to be very effective even though it was much less computationally expensive when compared to Tanh or Sigmoid. Tanh was chosen over Sigmoid because Tanh provides stronger gradients and its ability to overcome certain issues the Sigmoid function cannot. After many trials, it was evident that the network performed best when dominated by Tanh. The neural network uses Stochastic Gradient Descent as its optimizer and Binary Cross Entropy as its loss function since we are doing binary classifications. Lastly, the network uses a 70-30 validation split and has 50 total epochs.

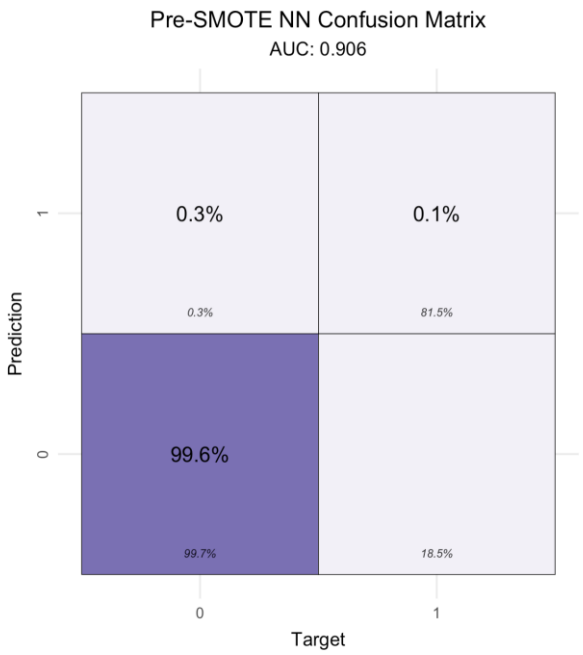
Figure 5. Pre-SMOTE NN



The constructed neural network will be used to train on both pre-SMOTE and post-SMOTE data with identical parameters. Figure 4 displays how the first network performs throughout 50 epochs. Both the model's training and validation accuracies were able to stabilize almost instantaneously. Both accuracies started above 0.99 and never dipped below that mark after the first epoch. However, we should take the accuracy with a grain of salt. This should not come as a surprise as the network does not have to work hard to learn as it is training on a heavily imbalanced dataset after all.

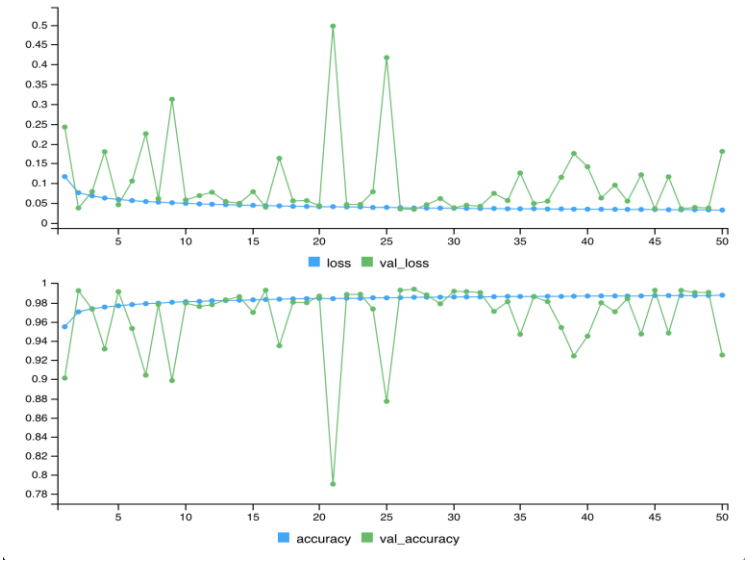
With the limitation of the accuracy metric, we tested the network on the testing set and analyzed the resulting confusion matrix for a higher-level analysis. Figure 5 is the confusion matrix acquired after testing the network on unseen data.

Figure 6

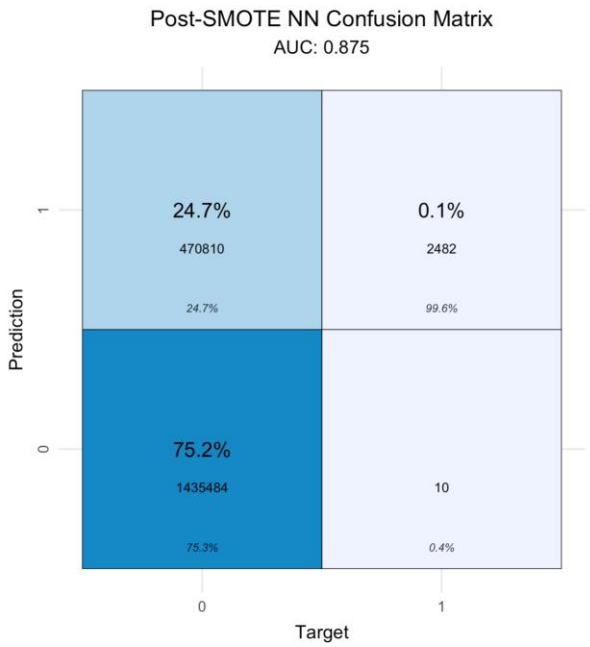


To avoid any confusion (no pun-intended), the smaller percentages represent the classification rates, whereas the larger numbers represent the distribution of the classifications. As we can see, the neural network had no trouble classifying the non-fraud activities; it achieved a 99.7% sensitivity. Surprisingly, its specificity was 81.5% which was terrific given the nature of the imbalanced labels.

Figure 7. Post-SMOTE NN



As we run the same neural network through the new post-SMOTE training data, it is evident that the validation accuracy struggles to converge and the model is having a harder time learning the new labels. Despite the training accuracy's immediate convergence, the validation accuracy seems to fluctuate until after the ~26th epoch, where it showed some signs of stabilization. Although it could be concerning to see the volatile showings of validation accuracy, this may be a classic case of bias-variance tradeoff in machine learning.



The AUC slightly dropped to 0.875 from 0.906. The specificity significantly increased to 99.6%, a big climb from 81.5%. However, this near-perfection specificity came at a cost of sensitivity. The true positive rate dropped by nearly 25% as we witness a rise in the false negative rate. The post-SMOTE neural network is much more careful and more paranoid than the previous. This issue will require further investigation and parameters tuning. As of now, given the context of the problem, which is to accurately identify fraudulent transactions, this may be an unideal tradeoff we can afford. The two networks individually took about 24 minutes per run.

Random Forest

The Random Forest model requires less work to construct and achieved significantly better results for both training datasets. The model builds a maximum of 50 trees and uses only 2 variables per tree to evaluate. The algorithm is much less computationally expensive than the neural network. Each run time was approximately 4-5 minutes and perform significantly better. Both testing runs were able to achieve a near-perfection true positive rate. The difference lies in their specificities; the model trained on the Pre-SMOTE data only achieved a 77% specificity whereas the latter model was able to obtain a staggering true negative rate of 98.8%. See Figure 8.1 and 8.2 for more details.

Shown below are the confusion matrices for the Pre-SMOTE and Post-SMOTE testing runs:

Figure 8.1

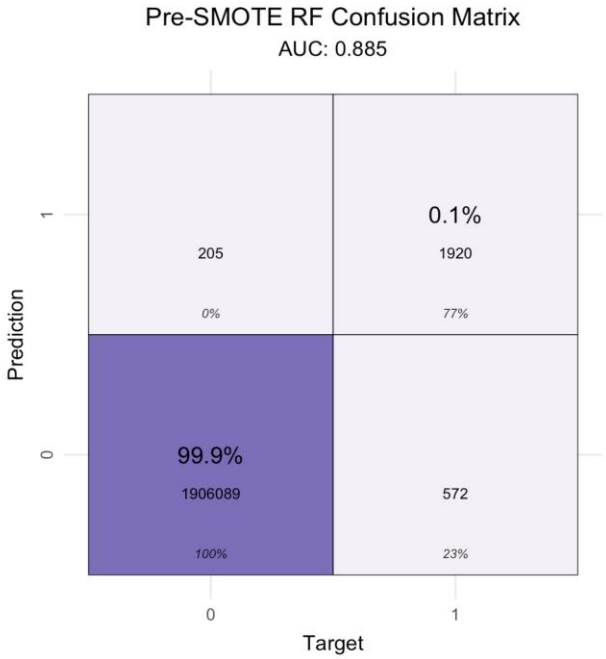
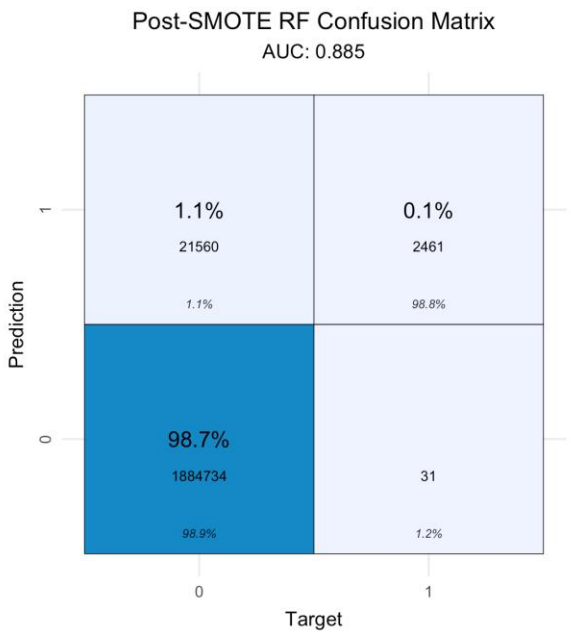
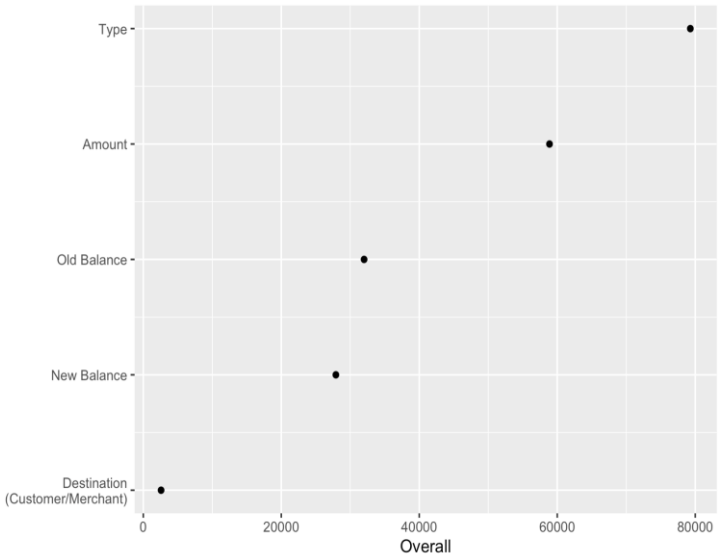


Figure 8.2



Lastly, we were able to gain insights on the importance of each predictor variable using the built-in “varImp” function of R’s “randomForest” package. The result is measured by the Mean Decrease in Accuracy and ranks the “Type” of transaction (transfers, debit, payment, etc.) as the most important variable for classification. Coming in 2nd is the amount per transaction and followed by the old & new balance of the account.



Conclusion

Revisiting the proposed research questions, for the 1st, we can conclude that at the current scale, a combination of Random Forest and SMOTE does an excellent job in classifying the target variables. Although the non-SMOTE imbalanced dataset still achieved respectable classification rates, the post-SMOTE data proves to be exceptionally superior, having a near-perfect sensitivity and specificity.

With Random Forest, we were also able to extract the most important predictors for detecting fraud transactions, which answers the 2nd proposed research question. The Mean Decrease in Accuracy shows that when attempting to flag the transaction, it is imperative to pay attention to its Type and Amount.

Future investigation could be to explore the sustainability of the Random Forest model. Despite its remarkable classification rate, I am interested to see how its precision, accuracy as well as efficiency scales as the dataset scales. Keep in mind that the training data was only a small subset of the original data. In addition, I am curious to analyze the inner workings of the neural network and see whether the network can perform better with some parameters tuning. Given a larger dataset (perhaps the original dataset), could the neural network be the more efficient and versatile classification algorithm for this specific problem? Knowing the nature of neural networks, I do expect this to be the case, but this hypothesis will be up for investigation.