

Google Analytics Transaction Prediction

1. Introduction to Data

The Google Merchandise Store, or GStore, is where Google swag is sold. This data set involves customer data information for previous users and customers. The data includes device information, geographical information, trafficking, timing, and more.

2. Problem to Solve

A very small percentage of users make purchases and produce the revenue for a business. The problem is how to appropriately budget and allocate money for marketing purposes. Through the course of this project, the data will be analyzed to predicted whether a user will complete a transaction. If predicted accurately, marketing can focus budgets on the features of importance in hopes of increasing customers and revenue.

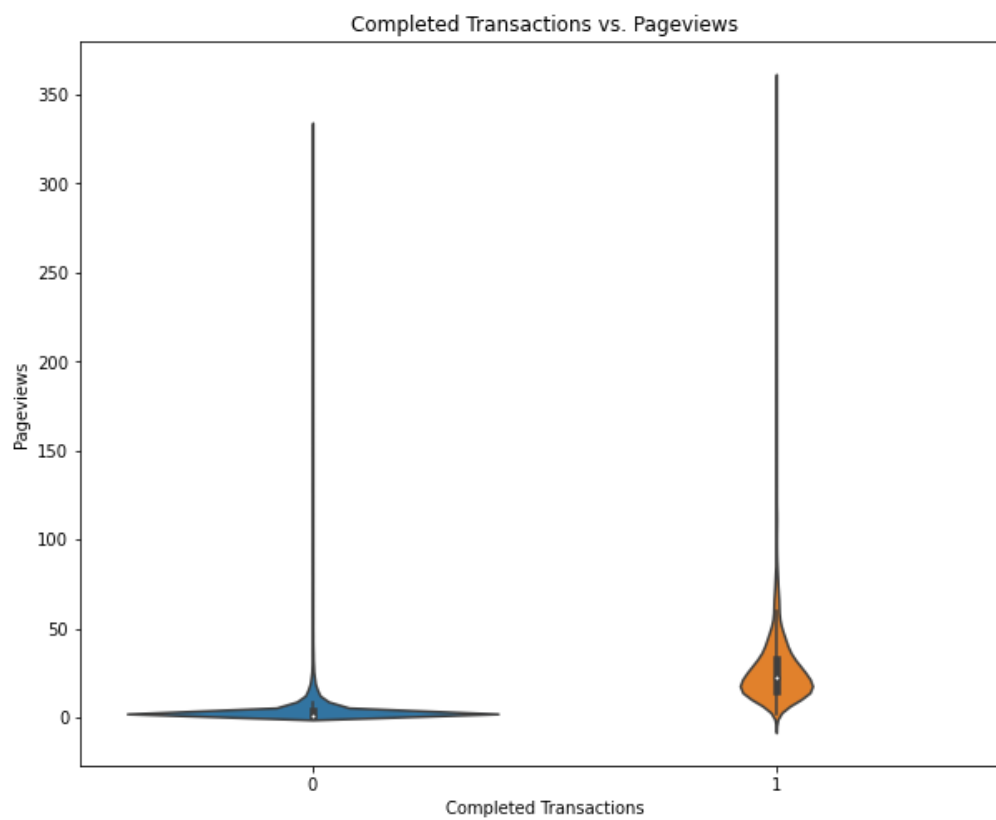
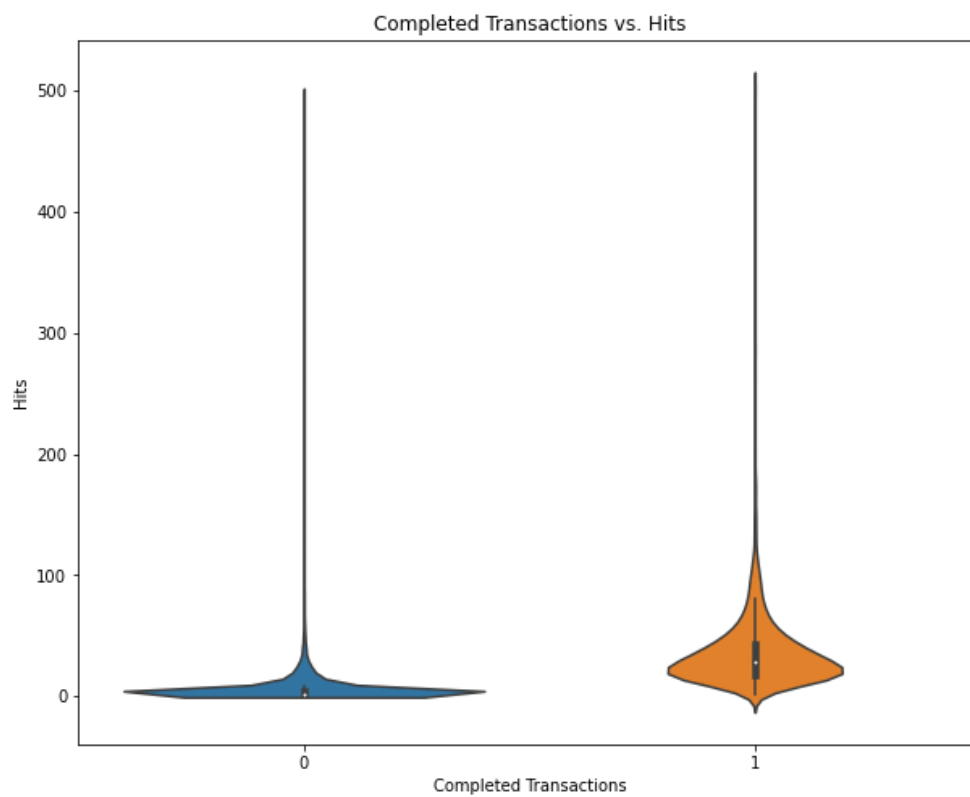
3. Data Cleaning

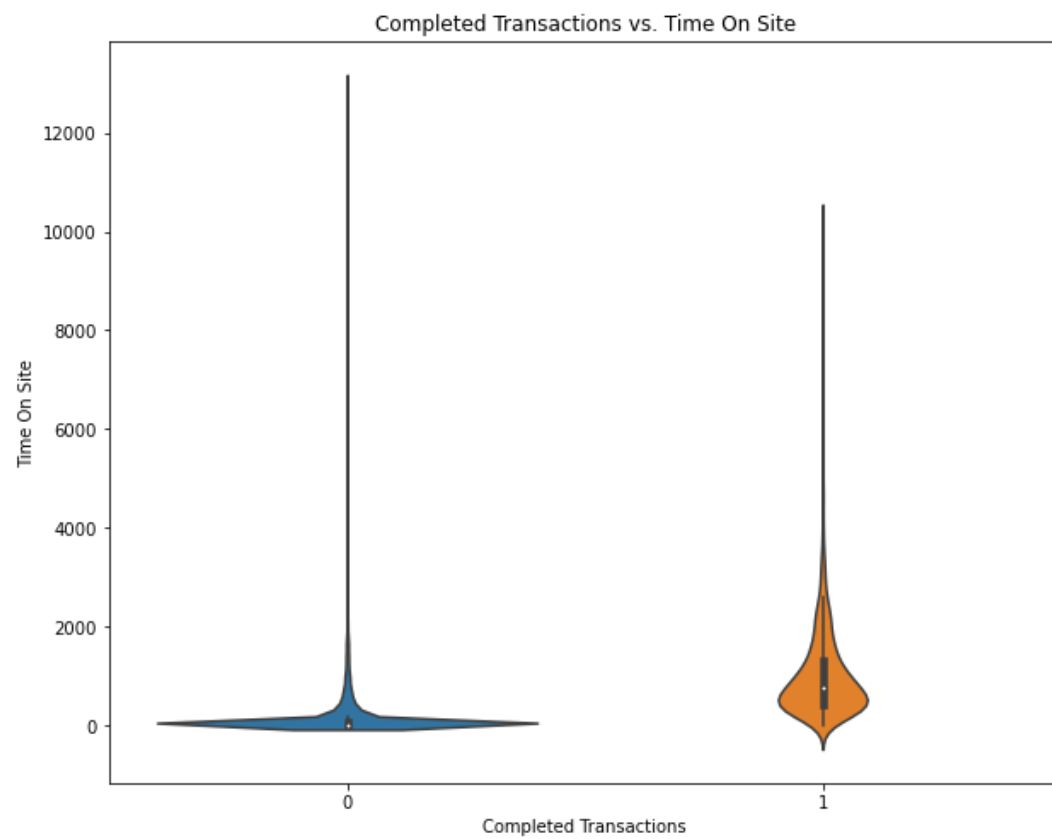
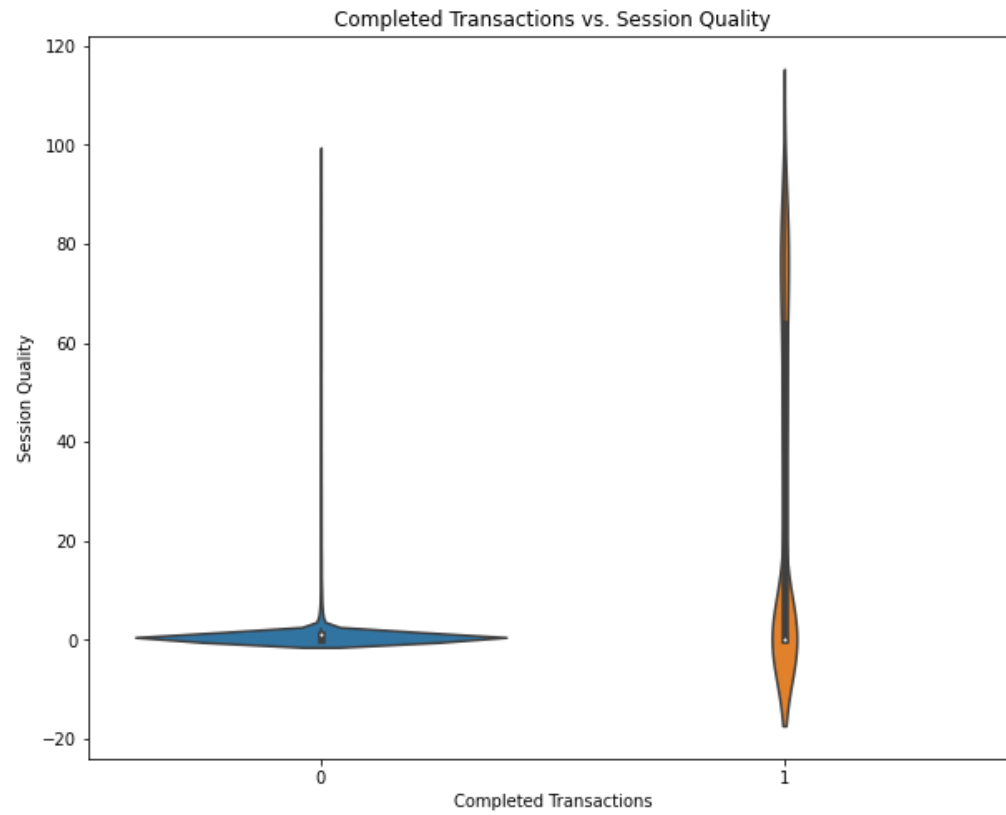
In the data cleaning process, I followed the following steps:

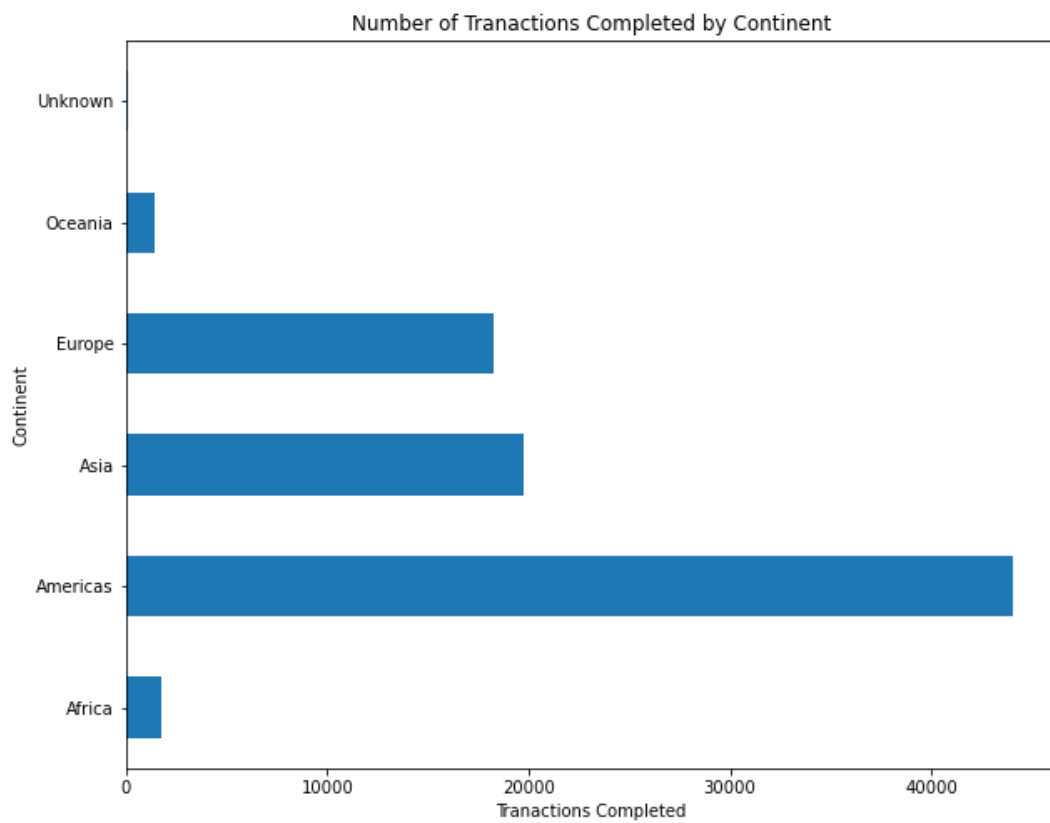
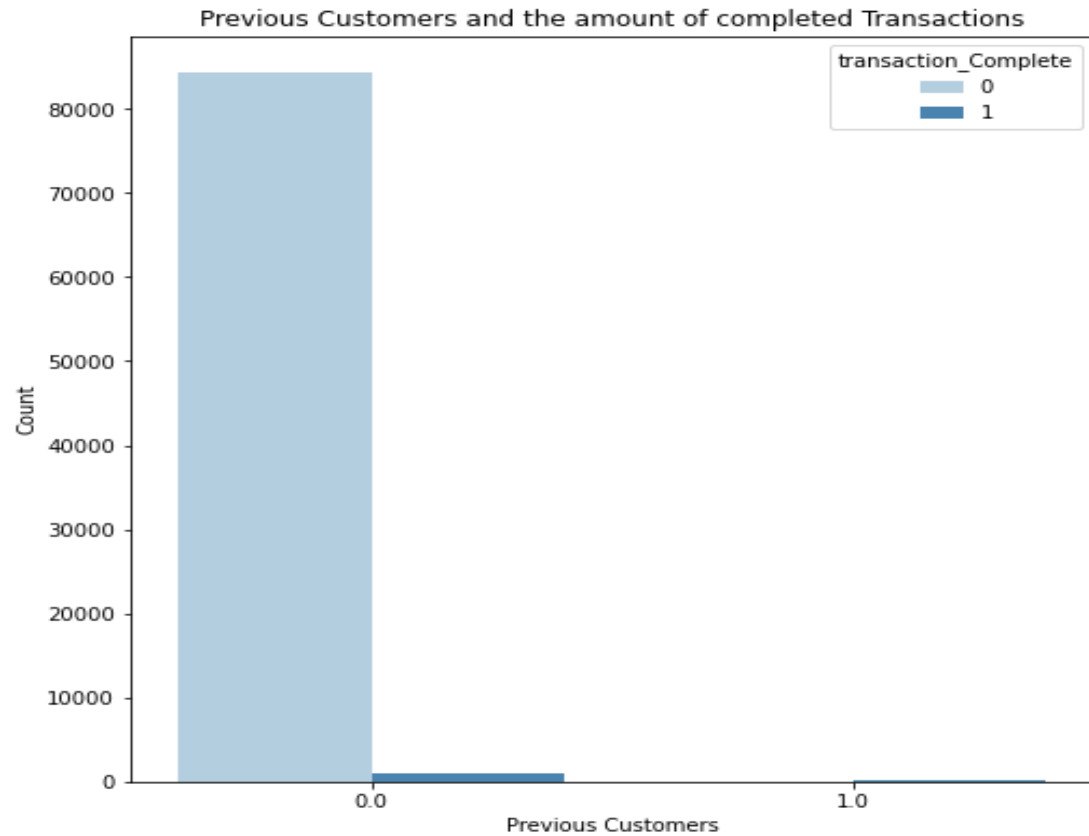
1. There were 4 json columns. The first step I took was to use json normalize to expanding those columns.
2. Some columns given did not have any information in this data set. Those columns were dropped.
3. Formatting issues were address, such as multiple notations for 'Unknown'.
4. Day, month, year, and weekday columns were created.
5. A previous customer column was created based on a customer's previous transactions.
6. Our target feature was created. We are predicting if a user will complete a transaction.

4. Exploratory Data Analysis

In the process of exploring the data, some of the features stood out as being possibly important to whether a user completes a transaction. The visuals below explore those features compared to our target variable of transactions complete.







5. Modeling Approach

Before I began modeling, I created a label encoder for categorical data. Then, I had to address the issue of vastly different amounts of transactions completed or not completed. To correct this, I oversampled the minority, transactions completed. Next, I created 5 different models with hyperparameter tuning. The following chart is the resulting scores from each of the models.

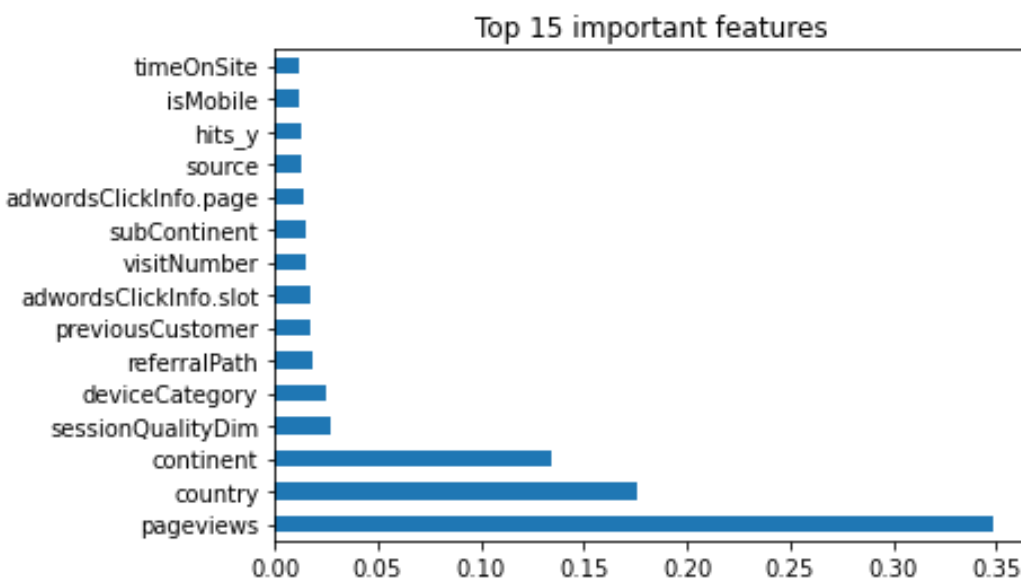
	Model	Accuracy Score	Precision Score	Recall Score	F1 Score
0	Logistic Regression	0.938484	0.943643	0.932572	0.938075
1	Decision Tree Classifier	0.975587	0.956024	0.996998	0.976081
2	Random Forest Classifier	0.962917	0.942692	0.985701	0.963717
3	MultinomialNB	0.812552	0.798723	0.835322	0.816613
4	XGBClassifier	0.994356	0.988829	1.000000	0.994383

6. Findings

The following model and hyperparameters were chosen to be the best model.

```
XGBClassifier(base_score=0.5, booster='gbtree', class_weight=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=0.8, gamma=0.5, gpu_id=-1,
              importance_type='gain', interaction_constraints='', learning_rate=0.1,
              max_delta_step=0, max_depth=20, min_child_weight=1, missing=nan,
              monotone_constraints=(), n_estimators=100, n_jobs=8,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=0.8, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

The features of importance were investigated. Here is the result:



7. Use of Findings

Based on the finding, the top five features deviceCategory, sessionQualityDim, Continent, Country, and pageviews. Marketing teams should focus their budgets to increase customers based on these features.

8. Further Research

With further research, I would investigate to results of combining some of the columns. This could potentially create some new features of importance and help make more accurate models.