IMPROVING CUSTOMER CHURN PREDICTION THROUGH SEGMENTATION

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Abstract

Customer churn prediction models have been proven to provide companies the ability to determine if a customer will churn based on a variety of factors. However, this space still has room for improvement and this paper aims to determine if a customer churn prediction accuracy can be improved through the use of customer segmentation by cluster groups of customers based on similarities in their buying patterns and company engagement behaviours. Through this process, companies will also gain the ability to better understand which variables lead to a higher churn rate while also being able to use these clusters for ulterior targeted marketing initiatives.

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1 Introduction

In our current era, marketing is very important and companies invest heavily in marketing in order to acquire new users, where a survey found that companies are happy to allocated 57% of their budgets to digital marketing activities and plan to increase this spending by another 16% in 2023[1]. One large issue they face is that after such a large initial investment, they would like to see a ROI (return on investment) and retain their customers over long periods of time to make the initial investment worthwhile. Further, it has also been found that acquiring a new customer is anywhere from 5-25% times more expensive than retaining an existing one[2] and a study[3] found that increasing customer retention rates by just 5% increases profits from anywhere between 25% to 95% . With this in mind, anticipating and understanding customers' intentions to end a relationship is crucial for companies and can be considered a competitive advantage. Additionally, it has been seen that in the e-commerce sector, there is a large disconnect between companies and customers as there are so many options available to the consumer and they have the option of changing their purchasing pattern without informing sellers.

As the ability to predict customer churn already exists, the goal of this paper is to identify if clustering customer data prior to predicting churn will increase the prediction accuracy. The main reasoning behind being able to understand customer churn for a cluster of customers is to identify what patterns can be found for customers who churn from a company as well as those customers who do not churn from a company. Using this customer data and creating clusters of ‘similar customers’ can allow a company to make decisions that will directly impact that cluster. For example, a company can identify customers who are likely to churn due to believing a product is

overpriced and can then send this cluster a promotional offer (i.e. targeted marketing). In this research, customer data is first clustered using segmentation techniques including K-Means, DBSCAN and GMM, and then a customer churn prediction is performed on each cluster. The prediction accuracy of the clustered data is compared against the prediction accuracy over the overall dataset to conclude whether clustering data can improve customer churn prediction accuracy. After feeding customer data into the churn prediction classifier models of Random Forest, MLP and Gradient Boosting, it was seen that the highest accuracy prediction model was the Gradient Boosting Classifier with a testing accuracy of 83%. Comparing this to the segmented customer data that was done using K-Means, DBSCAN and GMM, it was seen that the testing accuracy did indeed improve and combination of segmenting customer data with GMM along with performing a churn prediction with the gradient boosting classifier yielded a testing accuracy of 84%.

2 Literature Review

The overall idea of predicting customer churn has been applied to industries ranging from telecommunications (in order to understand how customers act when in a contractual setting) to B2C and e-commerce (in order to understand how customers act when in a non-contractual setting where turnover is hard to determine). Regardless of the industry, the idea of companies keeping up with one another in a consumer-driven industry where options for a certain product are widespread and accessible to customers has also been explored to determine how companies can stand out to a customer[4]. The conclusion was made that being able to both predict customer churn for either a product or overall company as well as identifying crucial variables that affected a customer's reasoning to churn were of great importance to decrease overall customer churn[6].

2.1 Customer Segmentation Techniques

There are a handful of studies that have explored how segmenting customers through different techniques can either improve or impair customer churn predictions. A research paper that looked to determine how customer segmentation affects customer churn predictions found two main factors need to be considered. The first being that it is crucial to carry out segmentation when considering customer churn and the second being that the prediction model being built requires variables that are highly correlated with churn scores as opposed to just performing a customer churn prediction on overall customer data[6]. So far, this has been done in the context of segmenting customers on time slices in intervals based on the given data, followed by predicting customer churn on the slices, which led to the conclusion that setting up multiple-slices within a given dataset would improve performance in churn prediction[5]. This is a very informative discovery for businesses that collect data and improve their business based on timings, such as for e-commerce websites that look at how long consumers stay on given pages, how long it takes a consumer to actually check out, and how long a time interval there is for a customer to return to the website to buy a product again. However, this is mainly important to B2C and e-commerce businesses, and would not have any impact on banks, telecommunication and B2B companies that are not as focused on time interval data points.

Furthermore, other clustering techniques have also been introduced, including k-means, and the LRFM (length, recency, frequency, monetary) model[9]. Both of these techniques have made great contributions in segmenting customers for the purpose of churn prediction, with k-means being the most popular segmenting technique. However, there has been a missing component in the space as it has not been determined which segmenting technique leads to the best customer churn predictions. In addition to the mentioned three techniques, there are a handful of other clustering techniques which will be explored to determine which works best and leads to the highest accuracy churn prediction. Although k-means is the most commonly used clustering technique, it does have its drawbacks in that the k random initial centroids must be chosen prior to running the model. There are 2 methods that have been used to help determine what the ideal initial value should be. The first being to enumerate K from 2 to 8 and plot the results in order to obtain the relation between the contour coefficient and K in order to determine the number of clusters[6]. The second being to apply the k-means algorithm with different k values and plotting the curves of the SSE and average silhouette coefficient against the number of clusters to analyze the two curves to identify the optimal number of clusters[7]. The optimal number of clusters can then be found by plotting the evaluation measure against the number of clusters and looking for the points in the plot at which a knee, peak or dip forms.

Furthermore, two other models are used for the purpose of clustering large data and these are DBSCAN and GMM. Both are clustering methods revolving around clustering data based on distanced based calculations, but each have their own individual benefits, which are discussed in Section 3.1. The main benefit to both DBSCAN[17] and GMM[16] is that they allow the ability for large to extremely large datasets to form meaningful clusters while reducing the computational effort required for each algorithm. This in turn can allow for more complex datasets to be parsed and iterations to be made for fine tuning without computation power being a concern. Additionally, a paper[8] that looked at both DBSCAN and GMM for the purpose of clusters with tighter boundaries as well as being able to recognize potential outliers better than K-Means, which is also of great value when working with large datasets.

As the use case for each of the clustering models expands beyond just being able to create meaningful clusters and involves being able to use these clusters to improve churn predictions, comparing the models against each other will help to conclude which method truly yields the highest model accuracy. This will also be compared to a scenario where no clustering is done to see how the results vary when a standard churn prediction is performed on an entire dataset.

2.2 Customer Churn Prediction Methods

Customer churn is an important metric that has been thoroughly explored in the data science space. From simple customer churn models involving regression models[11] to more complex machine learning models involving MLPs[17], many methods have been explored to determine what the best fit for predicting customer churn is. Since a variety of methods have been researched already and this is not the target improvement of this paper, I will be using the pre-existing customer churn prediction models with the highest accuracy to determine if the test accuracy of these models improve when the added layer of customer segmentation is introduced.

In using pre-existing customer churn prediction models, the idea is to use a range of models that have high test accuracies. With this in mind, standard machine learning algorithms would be used, as well as ones that are more complex and make use of subsets of machine learning such as neural networks to determine if the combination of each method along with segmentation improves the overall test accuracy. Starting with different standard ML algorithms and their effect on predicting customer churn a paper[11] that looked into LR, KNN, DT, SVM, RF, XGBoost and LightGBM all being used against a customer dataset in order to predict customer churn with the highest accuracy was investigated. A handful of evaluation metrics were used to determine the validity of each model, and the results indicated that LR had the lowest accuracy at 82%, while RF, LightGBM, XGB with the highest accuracy at 89%, 88.95% and 88.88% respectively[11]. With this information, it is decided that both Random Forest and XGB would be used as two of the customer churn prediction methods in this paper as they yielded the highest test accuracy. Next, looking at models that make use of neural networks, a paper [10] that researched the use of MLP for churn predictions found that using an MLP model with customer data yielded a test accuracy of 94% using 6 hidden layers, a momentum of 0.2, learning rate of 0.3 and total epochs of 500. As this test accuracy is even better than that of XGB and Random Forest, MLP would also be used in addition to the two, to determine if accuracy for all 3 models or a specific model increases in combination with the mentioned customer segmentation techniques.

2.3 Evaluation and Validation Metrics

The final and one of the most important steps through this research process is evaluation and validation, which involve using mathematical metrics to quantify the validity of a given model. The overall use case of evaluation metrics from a mathematical standpoint changes depending on the type of classification being done and models being used. For binary classification the most commonly used identifiers involve looking at accuracy, misclassification, precision, recall, and f-score based on the false positive, true positive, true negative, false negative predictions laid out by a model [14]. For rare event classification problems, such as in the case of customer churn, AUC (area under the curve) is the preferred accuracy performance measure to use [15]. As a result, AUC is one of the most common evaluation approaches used in this domain and is essentially equal to the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative one, and is one of the evaluation approaches used in this paper. As explained in another paper, an intuitive interpretation of the AUC is that it provides an estimate of the probability that a randomly chosen instance of class 1 is correctly rated or ranked higher than a randomly selected instance of class 0 (i.e., the probability that a churned is

assigned a higher probability to churn than a non-churner)[16].

3 Methodology and Experiments

As explored in Section 2, the premise of this paper is to first cluster groups of data based on similarities, using common customer segmentation techniques including K-Means, DBSCAN and GMM and towards a customer churn prediction. This will be compared to a simple customer churn prediction without any prior customer segmentation to then determine if segmenting customers prior to performing a churn prediction. Increases accuracy and leads to a better overall prediction on if a customer will churn or not. The segmentation techniques of K-Means, DBSCAN and GMM were all chosen for the benefits mentioned in Section 2.1 in that they are the most common segmentation techniques used, they are able to efficiently cluster data from large to extremely large datasets while using less computational power, and not being influenced or affected highly by outliers in the dataset.

3.1 Segmentation Techniques

The first and possibly most popular segmentation technique is K-Means, which essentially uses the distance between data points as a measure of 'similarity' in order to create clusters. This is done by starting with an arbitrary initialization value K, for the number of clusters that would be formed with the data and this K will be determined using methods discussed in Section 2.1 and serves as the initial centroids. From here, each data point Xn needs to be assigned to its closest cluster centroid Cn, which is done by calculating the distance between Xn and Cn and choosing a cluster associated to each data point where distance between the data point and centroid is minimized. The distance metrics used here is Euclidean distance and can be calculated as $d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$. This is done for each data point for the first iteration, and then the centroids are re-initialized by calculating the average of all data points for each cluster. This is done to determine the new cluster center and mathematically can be represented as $C_i = \frac{1}{|N_i|}\sum x_i$. This process is then repeated multiple times until the points stop moving and each centroid has been centered around a cluster, thus forming the final segmentations. Mini-Batch K-Means works in the same way in terms of determining clusters, however it takes small randomly chosen batches of the dataset for each iteration, which proves to be useful when working with large datasets in order to process data easier. By working with data in batches, each update uses gradient descent and computational power can be heavily decreased.

The second segmentation technique is DBSCAN, which stands for Density-Based Spatial Clustering of Applications with Noise and its main benefit is that it is able to find arbitrarily shaped clusters and cluster with outliers, which is better for real-world applications where data is not as separable and easily clustered. DBSCAN operates with two parameters **eps**, which is the distance that specifies the neighborhoods where two points are considered to be neighbors if the distance between them are less than or equal to the eps parameter. The second parameter is **minPts**, which specifies the minimum number of data points to define a cluster. Using both parameters, points can be classified as core points, border points or outliers, where core points are labeled if there are at least a number of points (specified by minPts) in an area with radius specified by eps. Border points are classified if the point is reachable from a core point and there are less than a number of points (specified by minPts). In Figure 1 below, it can be seen that red points are core points, yellow points are border points and blue points are outliers. In this way, the algorithm starts from a starting point and goes around marking the points as such, and once a cluster formation starts, all points within that neighborhood of the initial point become a part of that cluster. From there, another point is randomly chosen from points that have not been visited and the same procedure is applied to form another cluster and this is repeated until all points have been visited once, thus creating the segmentations.

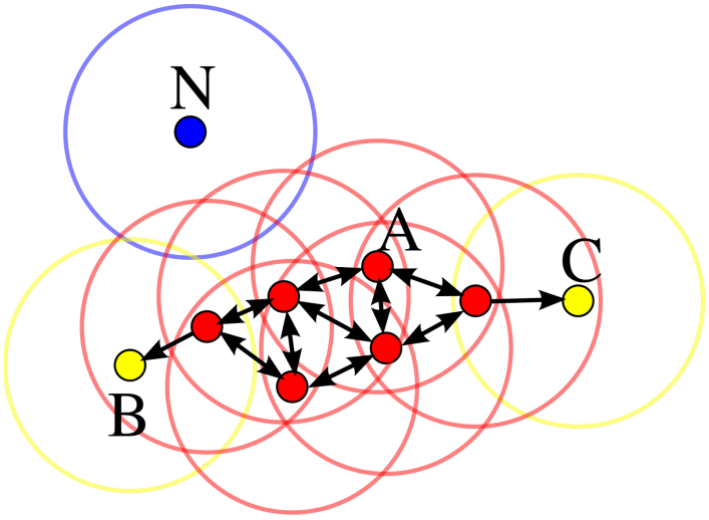


Figure 1 – Illustration of core points, border points and outliers

The final segmentation technique in GMM, which stands for Gaussian Mixture Model and essentially follows the Expectation-Maximization (EM) algorithm, but for data points that follow a Gaussian distribution. The main benefit with GMM is that it does not require circular clusters to be created, but can cluster data in any shape/form and go off the parameters of mean and covariance to describe the shape and position of each cluster. Since the model follow a Gaussian distribution, it can be represented mathematically as $N(x: \mu, \Sigma) = \frac{1}{(2\pi\Sigma)^{1/2}} \exp\left(-\frac{1}{2}(x - \mu)^T \Sigma^{-1}(x - \mu)\right)$ where x is the vector for a single data point, μ is the vector for f the mean for each cluster and Σ represents the covariance matrix between each dimension. In terms of the algorithm itself, it works similarly to K-Means, where a number of clusters K is arbitrarily chosen, and the initial parameters for each centroid are randomly established. The difference comes in the part of forming clusters where the likelihood that the dataset originates within the initial set of clusters with the current mean and covariance parameters is calculated and this likelihood is then maximized by changing the parameters. This step is repeated until the change in the parameters is less than a set amount or until a fixed number of iterations is reached, thus forming the clusters in the necessary oblong clusters.

3.2 Churn Prediction Techniques

Upon completing a customer segmentation using the above methods, the next step would be to use these segments to create a churn prediction. This is done using Random Forest, MLP and XGBoost in order to determine if there are any differences in accuracy between the two prediction techniques and to identify which prediction technique performs better both with and without a segmented dataset. The main reason for choosing each of these 3 churn prediction methods as outlined in Section 2.2, is their ability to accurately predict customer churn with test accuracies higher than any other machine learning classifier models.

Random Forest is a branch of decision trees, and essentially builds a union of decision trees that are merged together and trained with a bagging method to obtain an accurate prediction. In the sense of decision trees, each data point is evaluated against a certain condition amongst a set of criteria, and depending on the outcome of each check, the data point is routed through the tree to the next checkpoint. The criteria is identified during training by the algorithm, which creates the tree based on the training data set variable values. This decision making and branching occurs until the algorithm reaches either the maximum tree depth (i.e., has gone through all the variables in the tree), or when no further split is possible. As mentioned before, where random forest differs is that it adds additional randomness to the model by training the decision tree on multiple datasets which are all overlapping subsets of the original dataset (i.e., the same data is sampled multiple times). This process is known as bagging where a random sample of data in a training set is selected with replacement.

MLP or multilayer perceptron's are machine learning models that make use of neural networks to generate a set of outputs based on a given set of inputs. AS MLPs are multilayered, they consist of input nodes, output nodes and multiple hidden layers that allow for processing and scaling data in order to train a network and arrive at one output when given multiple inputs. As an MLP is fully connected, each node of each layer is connected to every node in the succeeding layers by an associated weight value. In order to determine these weight values, MLPs make use of backpropagation, which is essentially a training process that requires taking the error rate between each node from the input node to the output node, and feeding the loss do re-calculate the error rate in a backward manner from the output node to the input node while fine tuning the weights of each layer in order to minimize the error.

XGBoost or Extreme Gradient Boosting is able to accurately make stronger predictions by combining the estimates of a set of simpler, weaker models. It uses a combination of both Gradient Boosting and Decision Trees where weights are assigned to all independent variables which are then fed into a decision tree which outputs a prediction. The weight of the variables which are classified as 'wrong prediction' by the tree is increased and these variables are fed to the subsequent decision tree. In this manner, each predictor can be compared against one another to produce a weighted average which results in an accurate and higher accuracy model. In terms of gradient boosting, gradient descent algorithm is used to minimize the loss when adding new models. XGBoost would minimize a regularized objective function, L1 and L2, which combines a loss function based on the target-predicted output and a penalty term for model complexity. The training would then iteratively add new trees that predict the error term for prior trees, which are then all combined to come to a final prediction.

3.3 Experiments

Now that the baseline of what each model is and how they will be implemented has been established, experiments can begin to be carried out in order to better understand how customer segmentation can be used to make more accurate churn predictions.

3.3.1 Dataset

The dataset used for this paper comes courtesy of an online data challenge[18], consisting of data from a website as well as 20 variables of collected data for each individual customer who has held a membership on the website before. The dataset also offers a churn risk score variable ranging from 1 to 5, where 5 is most likely to churn. In order to better understand the variables in the dataset and what data cleaning needed to be done, some exploratory data analysis was done. The variables in the customer dataset can be seen in Table 1 with the first 7 being numerical variables, and the rest being categorical.

Variable	Variable Type
days_since_last_login	numerical - int
avg_time_spent	numerical - int
avg_transaction_value	numerical - int
avg_frequency_login_days	numerical - int
points_in_wallet	numerical - int
churn_risk_score	numerical - int
age	numerical - int
gender	categorical - object
region_category	categorical - object
membership_category	categorical - object
joined_through_referral	categorical - object
preferred_offer_types	categorical - object
medium_of_operation	categorical - object
Internet_option	categorical - object
used_special_discount	categorical - object
offer_application_preference	categorical - object
past_complaint	categorical - object
complaint_status	categorical - object
feedback	categorical - object

Table 1 – List of Variables with Variable Type

When looking at the categorical variables, there were a few observations that could be made. The first, which can be seen in Figure 2 for the number of males and females based on churn risk score, is that the dataset was overall balanced, which meant that no imputations would need to be done other than on the target variable (churn_risk_score) in order to balance the dataset. Additionally, based on the 'Feedback' variable that can be seen in Figure 3 below, the majority of feedback that was given was negative and we can also see that those points always lead to a higher churn risk score (4-5), while the feedback that was positive lead to a lower churn risk score (between 1-3) . Lastly, based on the 'Membership Type' variable that can be seen in Figure 4 below, it can be seen that those customers with a higher tier membership type end up with a lower churn risk score, while those with a more standard or no membership end up with a higher churn risk score. Based on this, from a high level it can be noted that these variables should be taken into consideration and can be considered more important for the skew that is created when the target variable is involved. Next taking a look at numerical variables, a correlation plot was used to see if there are any numerical variables highly correlated with churn risk score, which can be seen in Figure 5 below. It can be seen that no variable is highly correlated with churn risk score, with 'points_in_wallet' and 'avg_transaction_value' displaying the highest correlation with a negative correlation of -0.29. Based on this, it can be noted that those two variables may be numerical variables of high importance as they are the highest correlated variables with the target variable.

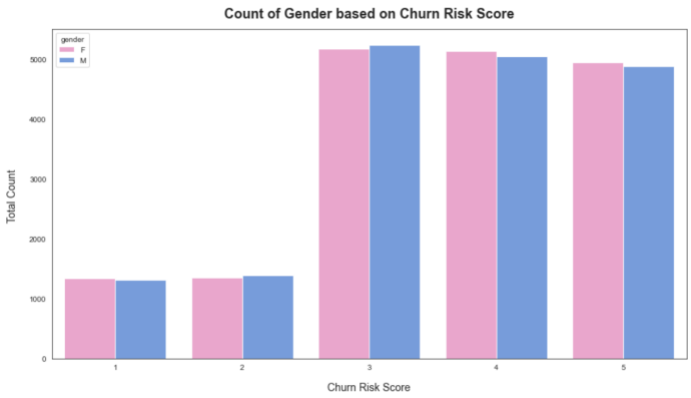


Figure 2 – Count of Gender based on Churn Risk Score

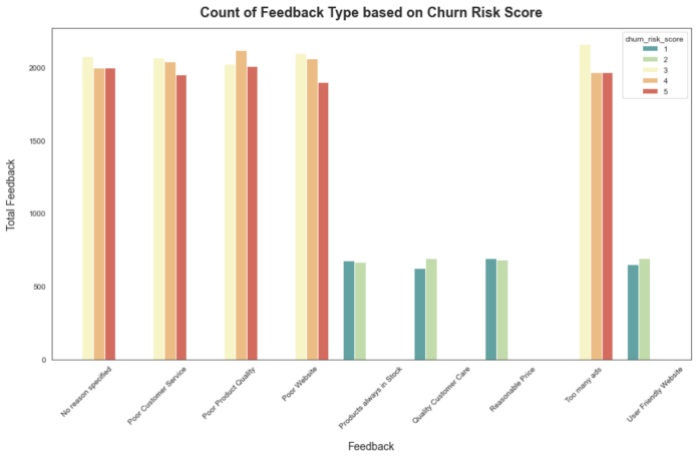


Figure 3 – Count of Feedback Type based on Churn Risk Score

Figure 4 – Count of Membership Type based on Churn Score

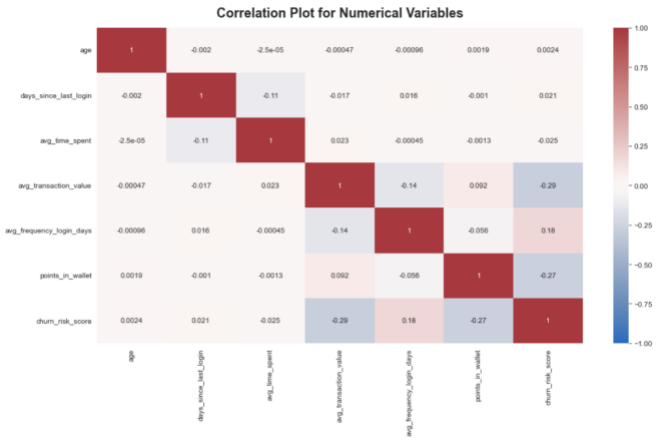


Figure 5 – Correlation Plot for Numerical Variables

3.3.2 Data Preprocessing

Prior to doing any actual modeling with the data, the preliminary step of pre-processing the data has to be done in order to have a clean dataset that can produce valuable insights when plugged into a model. Starting with imputing values, there were many columns that either contained 'Unknown', '?', 'Error', or erroneous negative values that didn't align with the variable. For the categorical variables 'gender', 'joined_through_referral', 'referral_id', 'medium_of_operation, 'days_since_last_login', each of the improper values were replaced with NaN and then the mode was taken and imputed for each of these variables. Based on research, it was found that mode was best for imputing categorical variables with a small number of unique values, which applied to this dataset. Next, for the numerical variables 'days_since_last_login', 'avg_time_spent', 'points_in_wallet', 'avg_frequency_login_days', all erroneous and negative values were replaced with NaN and KNN imputation was done using sklearn's KNNImputer() method, which was found to be the preferred imputation method for numerical variables. To do so, a distance, k, is specified from the missing values, which are then predicted based on the mean of the neighbors. From here, some minor clean-up was done including adding a year variable based on the joining_date variable as well as taking out any negative churn risk (churn_risk_score of -1) from the dataset since this can be considered invalid data and cannot be imputed.

3.3.3 Outliers, Feature Importance & Balancing

Ideally when feeding data into a model, outliers would be minimized, the important features would be highlighted, and the target variable would be balanced in order for more accurate predictions to be made as the algorithms being used require classification data to have an equal number of observations for each class. Based on Figure x below, all the numerical variables were observed using a boxplot in order to understand the distribution for each variable and determine which variables had outlier values. Looking at Figure 6, it can be seen that the numerical variables avg_transaction_value, points_in_wallet, avg_time_spent, avg_frequency_login_days all have outliers, and most outliers occur past the maximum of the boxplot. To handle these outliers, all the data points which are either less than Q1 - 1.5 * IQR or greater than Q3 + 1.5 * IQR, are removed from the dataset. IQR or interquartile range is simply the difference between quantile 3 and quantile 1, and the resulting boxplot after removing the outliers can be seen in Figure 7, where it can be seen that the total number of outliers has significantly decreased.

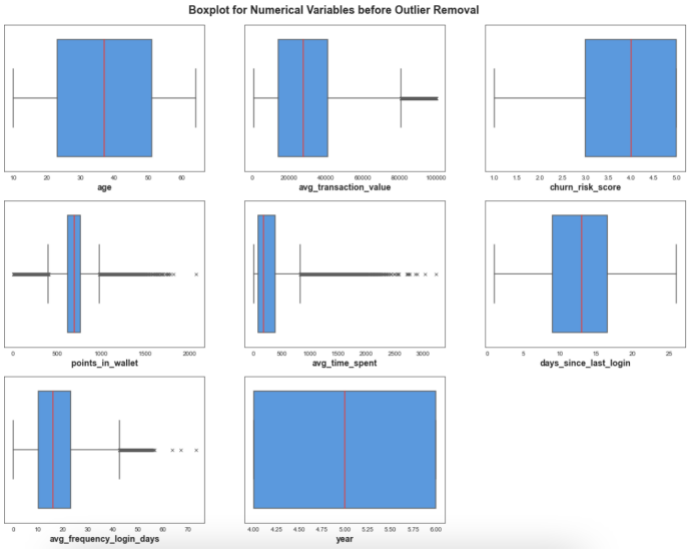


Figure 6 – Boxplot for variables before outlier removal

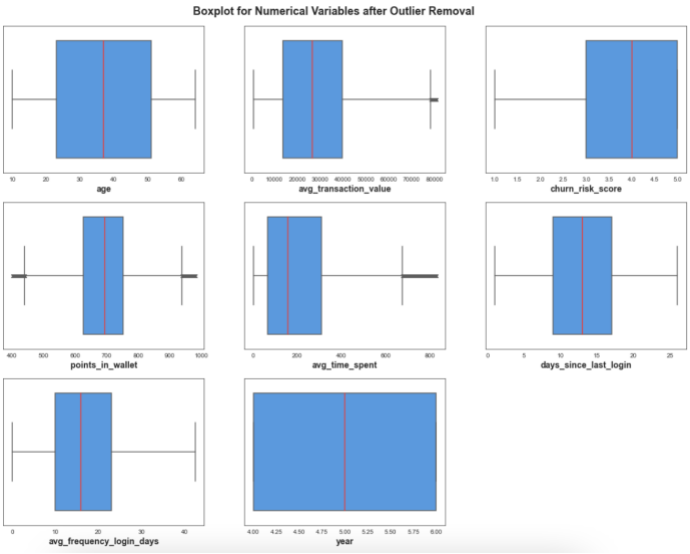


Figure 7 – Boxplot for variables after outlier removal

Looking at the value counts of the target label, it can be see that for each of the churn risk scores (1, 2, 3, 4, 5), they are severely imbalanced where the churn risk scores of 1 and 2 only have a count of ~ 2700 data points whereas the churn risk scores of 3, 4, 5 all have over 10,000 data points. To handle this oversampling will be used where a minority class is specified and oversampling is done to either duplicate data points in the minority class or synthesize new data points from existing data points in the minority class. Specifically, the SMOTE or Synthetic Minority Oversampling Technique is used, which balances the class distribution by randomly increasing the minority class data points by replicating them**).** This is done using SMOTE() method as part of the imblearn package, which takes the values of a dataset as input where the dataset contains the numerical features as well as dummies for each of the categorical features. Upon doing this, the RobustScaler() method is used from the sklearn package in order to re-scale the dataset and remove any additional outliers that have been generated through the SMOTE process.

Finally, identifying the important features of the dataset is crucial in order to understand which features/variables will have a larger effect on both the clustering and churn prediction models, and in turn selecting a subset of variables for the training that will lead to both improved efficiency and effectiveness of the predictive model. To form this subset for both models we use the pre-existing conclusions generated in Section 3.3.1 as well as the RandomForestClassifier() method from the sklearn package. This function essentially fits an X_train and Y_train variable that are developed by taking a train/test split based on setting the features and target variables as well as the random state. This model can then be visualized using a simple bar plot through matplotlib and the resulting plot can be seen in Figure 8 below. Based on this plot, it can be seen that the variables that are scored/ranked as the highest importance in relation to churn_risk_score are points_in_wallet, avg_transaction_value, membership_category_Basic Membership, membership_category_No Membership, avg_frequency_login_days, avg_time_spent, days_since_last_login, and each of the membership categories. Based on this, we can conclude that these variables will contribute most to a customer exiting/churning from the company's services as well as to creating meaningful customer segmentations with the data and so a new and final dataset is formed for the rest of this research with these variables used.

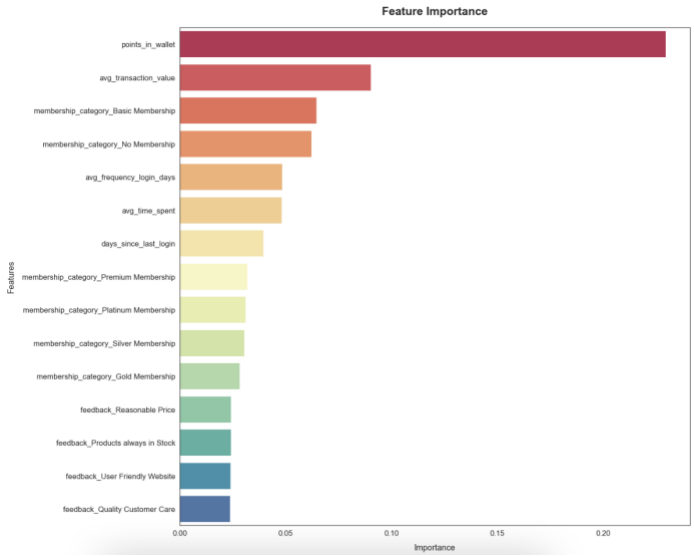


Figure 8 – Feature Importance using RF Classifer

3.3.4 Model Building - Segmentation

For the segmentation piece, K-Means, DBSCAn and GMM are used as discussed in Section 3.1. There are two-fold pre-processing steps necessary for each method, which is the same for each method. The first fold is to standardize all the columns of the dataset, which essentially removes the pre-existing mean and scales each feature/variable to unit variance. The purpose of this is so that each variable has equal contribution to its effect on model fitting and to avoid any biases being created through the prediction process and can be done using the StandardScaler() function provided by sklearn.preprocessing. The second fold is to feed and fit the scaled features into a PCA model, in order to model the data in a smaller subset of variables that can actually be analyzed and visualized throughout the process and come up with insights of actual importance. Within this subset, the data is also retained while also keeping the data as linearly separable as possible in order to form clusters. This process is done using the PCA model from sklearn.decomposition and involves setting an arbitrary number of components (in this case 5), and fitting the newly created scaled features dataset along the range of components. The resulting plot of variance % for each PCA feature can be seen in figure 9, and it can be seen that the highest variance of features are in 0, 1 and 2, and so these will be fed into each segmentation model.

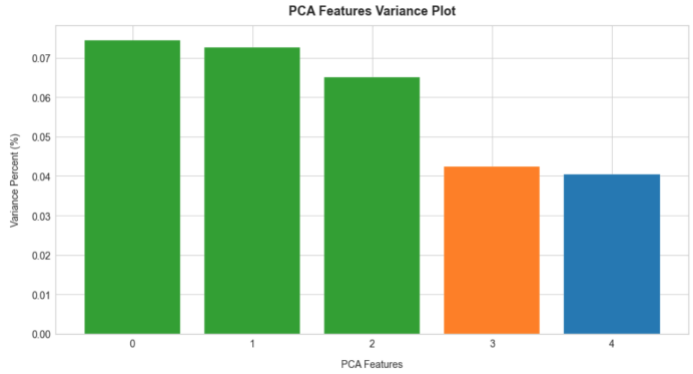


Figure 9 –Plot of PCA Features Variance %

Starting with K-Means, the first step would be to understand what value of k to use for the k-means model, and this can be done by observing the elbow score for each K, where the idea is to choose a K value located at the 'elbow joint' index of the plot. Using the KElbowVisualizer function from the yellowbrick package, the k range is set as between 1 to 50, and the PCA features are fit to the model. The resulting plot can be seen in Figure 10, where the 'elbow joint' can be seen at K = 6, which would be the number of clusters specified in the KMeans model for this data. A second metric used to evaluate the effectiveness of the KMeans algorithm is also employed which is silhouette score from the sklearn.metrics package. After the PCA data is fit to the KMeans model with 6 clusters and an arbitrary set random_state, the silhouette score is evaluated using the Euclidean distances. The silhouette score essentially outlines how similar samples within a cluster are to each other, thus describing how efficient the clusters actually are. Values for silhouette score range between -1 to 1 and the closer the score is to 1, the more dense and well-separated a cluster is distinguished to be. The clusters are then appended to the initial dataset in order to further group the dataset by each cluster.

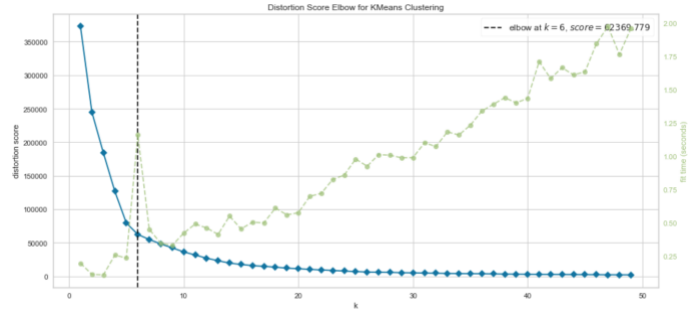


Figure 10 – K Means Elbow plot using KElbowVisualizer

Looking at Figure 11 below, it can be seen what values are assigned to each cluster. For example, Cluster 5 contains data points with the highest avg_transaction_value, points_in_wallet, positive customer feedback, and the lowest avg_frequency_login_days, churn_risk_score, and negative customer feedback. With this in mind, Cluster 5 would be of most value in identifying factors for low churn customers. In contrast, Cluster 1 contains data points with the highest avg_frequency_login_days, churn_risk_score, negative customer feedback and the lowest avg_time_spent, avg_transaction_value, points_in_wallet and positive customer feedback, and this cluster would be of most value in identifying factors or high churn customers.

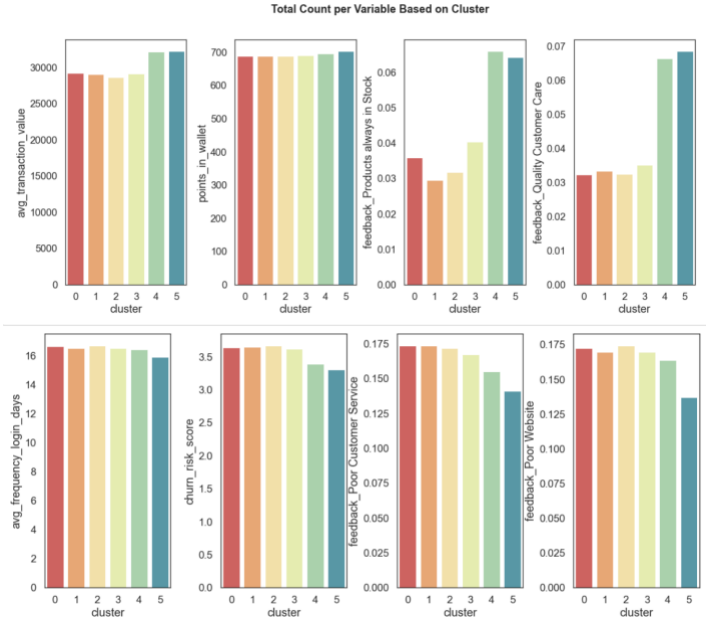


Figure 11 – Plot of clusters based on KMeans segmentation

After appending the clusters to the initial training dataset (seen in Table 2), the dataset is then grouped into separate subsets of datasets based on the cluster number (i.e., cluster 0 would be one dataset, cluster 1 would be another, etc.) and the grouped dataset would then go through the SMOTE balancing method and churn prediction process outlined in sections 3.3.3 and 3.3.5 to understand if clustering customer data using KMeans prior to performing a churn prediction improves the accuracy or not.

feedback_No reason specified	feedback_Poor Customer Service	feedback_Poor Product Quality	feedback_Poor Website	feedback_Products always in Stock	feedback_Quality Customer Care	feedback_Reasonable Price	feedback_Too many ads	feedback_User Friendly Website	cluster
0	0	0	0	1	0	0	0	0	5
0	0	0	0	0	1	0	0	0	2
0	0	0	1	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0

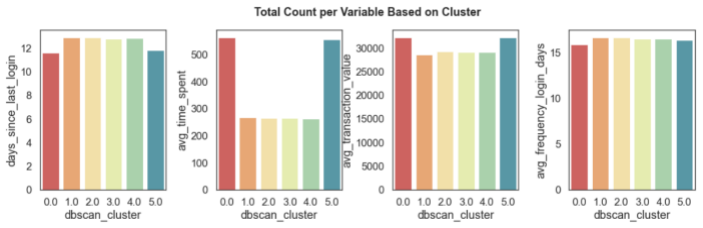
Table 2 – Clusters from KMeans appended to dataset

Next, DBSCAN is employed using the DBSCAN() model from sklearn.cluster package. This model requires only 2 parameters being eps and min_samples where eps defines the neighborhood of a point, x and min_samples is the minimum number of points in a neighborhood needed in order to form a dense region. In order to determine what values to use for these parameters, the NearestNeighbors function is used from the sklearn.neighbors package, which essentially involves fitting the PCA data to the model and calculating the distance and index between each data point. Then sorting and plotting the results in descending order allows for the same 'elbow joint' technique employed for KMeans to be used in order to determine the 'elbow joint' point, which is used for eps. Doing this yields an eps of 0.8 and a min_samples of 9, which are input into the model and fit in order to create a new set of clusters. This set is then appended to the initial training dataset as dbscan_cluster and looking at Table 3 below, it can be seen that the clusters assigned to each row based on KMeans differs from the assignment of clusters by DBSCAN.

eedback_Poor Customer Service	feedback_Poor Product Quality	feedback_Poor Website	feedback_Products always in Stock	feedback_Quality Customer Care	feedback_Reasonable Price	feedback_Too many ads	feedback_User Friendly Website	cluster	dbscan_cluster
0	0	0	1	0	0	0	0	5	0
0	0	0	0	1	0	0	0	2	1
0	0	1	0	0	0	0	0	0	2
0	0	1	0	0	0	0	0	0	2
0	0	1	0	0	0	0	0	0	2

Table 3 – Clusters from DBSCAN appended to dataset

Furthermore, looking at figure 12 below, we can once again see how the clusters are chosen where the separation is not as exaggerated and the distribution is a little more even however, cluster 0 contains the values with the highest avg_time_spent, avg_transaction_value, points_in_wallet, and positive feedback with the lowest days_since_last_login, churn_risk_score and negative customer reviews. Finally, the dataset is then grouped into separate subsets of datasets based on the cluster number and the grouped dataset would then go through the SMOTE balancing method and churn prediction process outlined in sections 3.3.3 and section 3.3.5 to understand if clustering customer data using KMeans prior to performing a churn prediction improves the accuracy or not.



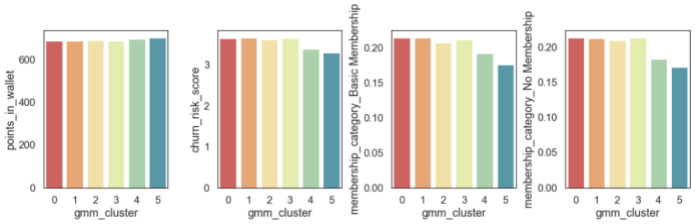


Figure 12 – Plot of clusters based on DBSCAN segmentation

Lastly, GMM is employed using the GaussianMixture function from the sklearn.mixture package, which requires parameters n_components, covariance_type, max_iter and random_state to be identified. Both max_iter and random_state are arbitrary values and max_iter is set to a large number (in this case 2000), while random_state is arbitrarily set to 5. To determine both n_components and covariance_type, a for loop is used to iterate through the PCA data, for the covariance types of full, tied, diag, spherical and number of clusters ranging 1 to 15. For each iteration, the silhouette score and Davies Bouldin score are calculated with the objective to have the highest silhouette score as well as the lowest Davies Bouldin score. After running the for loop, the values are sorted in descending order based on silhouette score, resulting in the most optimal covariance type to be spherical, and the number of clusters to be 6, which yield a silhouette score of 0.865 and Davies Bouldin score of 0.213. The results of this sorting can be seen in Table 4 below.

	Covariance type	Number of Clusters	Silhouette Score	Davies Bouldin Score
34	spherical	6	0.865113	0.213851
24	diag	6	0.865113	0.213851
4	full	6	0.865113	0.213851
14	tied	6	0.865113	0.213851
13	tied	5	0.839559	0.215501
3	full	5	0.839559	0.215501
33	spherical	5	0.839559	0.215501
23	diag	5	0.839559	0.215501
35	spherical	7	0.827277	0.266869
5	full	7	0.827211	0.265882

Table 4 – Resulting Silhouette and Davies Bouldin Scores

These parameters are then fed through the GaussianMixture model with the PCA data fitted to it, and the new set of GMM clustered are produced and appended to the original training dataset. Looking at Table 5 below, it can once again see that the GMM clusters assigned to each row is different from that of KMeans and DBSCAN.

feedback_Poor Product Quality	feedback_Poor Website	feedback_Products always in Stock	feedback_Quality Customer Care	feedback_Reasonable Price	feedback_Too many ads	feedback_User Friendly Website	cluster	dbscan_cluster	gmm_cluster
0	0	1	0	0	0	0	5	0	5
0	0	0	1	0	0	0	2	1	3
0	1	0	0	0	0	0	0	2	0
0	1	0	0	0	0	0	0	2	0
0	1	0	0	0	0	0	0	2	0

Table 5 – Clusters from GMM appended to dataset

Looking at Figure 13 below, it can also be seen that the created clusters are once again not as exaggerated and are slightly more normally distributed, similarly to DBSCAN. For the final time, the dataset is then grouped into separate subsets of datasets based on the cluster number and the grouped dataset would then go through the SMOTE balancing method and churn prediction process outlined in sections 3.3.3 and section 3.3.5 to understand if clustering customer data using KMeans prior to performing a churn prediction improves the accuracy or not.

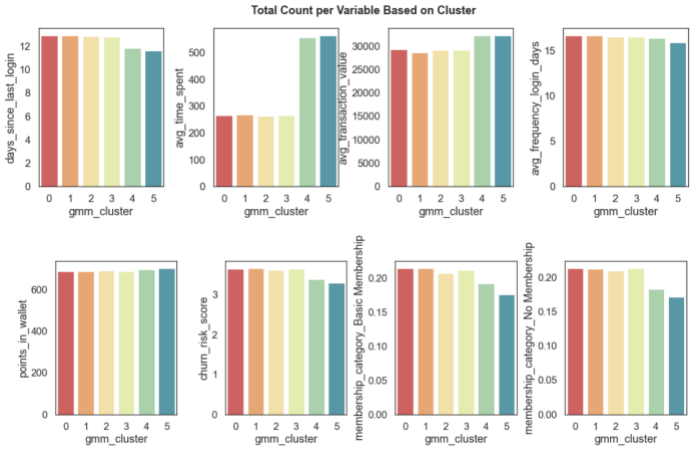


Figure 13 – Plot of clusters based on GMM segmentation

3.3.5 Model Building – Churn Prediction

For the churn prediction, 3 methods are to be used which are Random Forest Classifier, MLP Classifier, and a Gradient Boosting Classifier. To start, the data was split as 70% towards the training set, and 30% towards the testing set. Starting with the Random Forest Classifier, an arbitrary high value is set for n_estimators (in this case 100) , which specifies the number of trees in the forest of the model as well as max_depth which is the number of splits that each decision tree is allowed to make. Setting this value too low leads to the model underfitting the data and setting it too high leads to the model overfitting the data. The general values used for max_depth are 3, 5, or 7, but as this dataset is quite large, a higher value of 25 was chosen as the value for this parameter. Using both parameters, the x_train and

y_train specified in the split are fed into the RandomForestClassifier model from sklearn and a y_prediction is created for each x_test instance. Next, the MLP classifier is utilized where the number of hidden layers and nodes needs to be specified under hidden_layer_sizes. The general rule of thumb of datasets with large dimensions/features is to use 3-5 hidden layers and with this in mind, 3 hidden layers are chosen. To determine the number of nodes in each layer, the general equation used is sqrt(input layers nodes * output layer nodes), and as each subsequent layer requires a decreased number of nodes in order to identify the target class, the nodes selected are 120, 95 and 70. The parameters of x_train and y_train are now fed into the MLPClassifier model from sklearn a y_prediction is created for each x_test instance. Finally a gradient boosting classifier is used with 4 different parameters specified. The first two are n_estimators and max_depth, which are kept the same as in random forest for uniform results. The other two parameters are min_sample_leaf and min_samples_split, which define the minimum observations required in a terminal leaf and the minimum observations required in a node to be considered for splitting. Using cross validation, these are tuned in order to be set to 4 and 5. Once again, both the x_train and y_train parameters are fed into the GradientBoostingClassifier model from sklearn and a y_prediction is created for each x_test instance.

3.3.6 Model Evaluation

For each churn prediction method, a classification report is generated based on the y_test and y_prediction variables as well as a f1 score which is an evaluation metric that measures a model's accuracy by combining the precision and recall scores of a model. Both are generated using the sklearn.metrics package, and are then compared against each other for each churn prediction model to compare the train accuracy, test accuracy and test f1-score in order to determine which model performs best in terms of test accuracy. This metric would be the main evaluation metric in understanding which model performs best and in combination with both the segmented and non-segmented datasets, would help come to a conclusion about which combination of segmentation method and churn prediction method yield the highest test accuracy, and thus would be most useful in improving customer churn predictions.

4 Results

4.1 Churn Prediction – No Segmentation

For the first churn prediction, no segmentation was done in order to build a baseline for what the outcome of a standard churn prediction would be with no segmentation of customer data involved. Looking at table 6 below, an example of how the classification report prints the results of the random forest classifiers prediction over 5 iterations can be seen where the final accuracy was 0.82 with an f1 score of 0.815. A final table with the test accuracies and test f1 scores based on each of the prediction models is then created and can be seen in table 7 below. It can be seen that MLP classifier prediction had a final test accuracy of 0.81 with an f1 score of 0.808, while the gradient boosting classifier prediction had a final accuracy of 0.83 with an f1 score of 0.833. Comparing all 3 results below, it can be seen that Gradient Boosting is the ideal and most accurate model for predicting customer churn without any segmentation involved.

	precision	recall	f1-score	support
1	0.86	0.91	0.89	3072
2	0.91	0.86	0.88	3145
3	0.89	0.93	0.91	3175
4	0.75	0.51	0.61	3138
5	0.71	0.90	0.79	3106
accuracy			0.82	15636
macro avg	0.82	0.82	0.82	15636
weighted avg	0.82	0.82	0.82	15636

0.8153817403030639

Table 6 – Classification Report based on churn prediction

	Model	Train Accuracy	Test Accuracy	Test f1-Score
0	Random Forest	1.000000	0.822077	0.815382
1	MLP	0.987282	0.809350	0.808776
2	Gradient Boosting	1.000000	0.835252	0.833922

Table 7 – Testing Accuracy for each given Model

4.2 Churn Prediction with K-Means

Upon completion of all setup of the KMeans model in Section 3.3.4, the silhouette score is calculated and a value of 0.865 is obtained, which confirms that the model was deployed in a manner in which the clusters are of actual value. After running all 3 classifier prediction models on each individual cluster, the weighted average

between all clusters is taken and a final table of each of the test accuracies and test f1-scores is created and can be seen in Table 8 below. Based on table 8, it can be seen that the Random Forest classifier prediction had a final test accuracy of 0.83 with a f1 score of 0.82, the MLP classifier prediction had a final test accuracy of 0.74 with a f1 score of 0.746, while the gradient boosting classifier prediction had a final accuracy of 0.81 with a f1 score of 0.1. Comparing all 3 results below, it can be seen that when using K-means to cluster customer data prior to doing a segmentation, the test accuracy of random forest is the only one that improves, while the accuracy of MLP and Gradient Boosting both drops. The test accuracy of Random Forest increased by 1% and is comparable to that of gradient boosting when there is no segmentation. It can be concluded that KMeans in combination with Random Forest will yield the best results for predicting customer churn.

	Model	Train Accuracy	Test Accuracy	Test f1-Score
0	Random Forest	1.000000	0.834734	0.827650
1	MLP	1.000000	0.746499	0.746744
2	Gradient Boosting	1.000000	0.810924	0.811102

Table 8 – Testing Accuracy for models based on KMeans

4.3 Churn Prediction with DBSCAN

Upon completion of all setup of the DBSCAN model in Section 3.3.4, all 3 classifier prediction models are run and the results can be seen in table 9 below. It can be seen that the Random Forest classifier prediction had a final test accuracy of 0.837 with a f1 score of 0.83, the MLP classifier prediction had a final test accuracy of 0.81 with an f1 score of 0.808, while the gradient boosting classifier prediction had a final accuracy of 0.836 with an f1 score of 0.837. Comparing all 3 results below, it can be seen that when using DBSCAN to cluster customer data prior to doing a segmentation, the test accuracy of all 3 models actually increases by ~ 1% and all 3 models produce a higher test accuracy than K Means clustering. Out of the 3 models, it can be seen that Random Forest is the best by a slim margin and it can be concluded that DBSCAN in combination with Random Forest will yield the best results for predicting customer churn.

	Model	Train Accuracy	Test Accuracy	Test f1-Score
0	Random Forest	1.000000	0.837528	0.832767
1	MLP	0.976630	0.810123	0.808123
2	Gradient Boosting	1.000000	0.836969	0.837145

Table 9 – Testing Accuracy for models based on DBSCAN

4.4 Churn Prediction with GMM

Upon completion of all setup of the GMM model in Section 3.3.4, all 3 classifier prediction models are run and the results can be seen in table 10 below. It can be seen that the Random Forest classifier prediction had a final test accuracy of 0.836 with a f1 score of 0.831, the MLP classifier prediction had a final test accuracy of 0.336 with a f1 score of 0.246, while the gradient boosting classifier prediction had a final accuracy of 0.844 with an f1 score of 0.845. Comparing all 3 results below, it can be seen that when using GMM to cluster customer data prior to doing a segmentation, the test accuracy of both Random Forest and Gradient Boosting increases by ~ 1% while MLP has significantly dropped and can be deemed unusable in this scenario. Out of the 3 models, it can be seen that Gradient Boosting performs the best throughout the entire report and gradient boosting in combination with GMM will yield the best results for predicting customer churn! The confusion matrix can be seen below in Figure 14, where the predicted vs actual labels are displayed for each churn risk score.

	Model	Train Accuracy	Test Accuracy	Test f1-Score
0	Random Forest	1.000000	0.836552	0.831481
1	MLP	0.343097	0.336408	0.246829
2	Gradient Boosting	1.000000	0.844912	0.845513

Table 10 – Testing Accuracy for models based on GMM

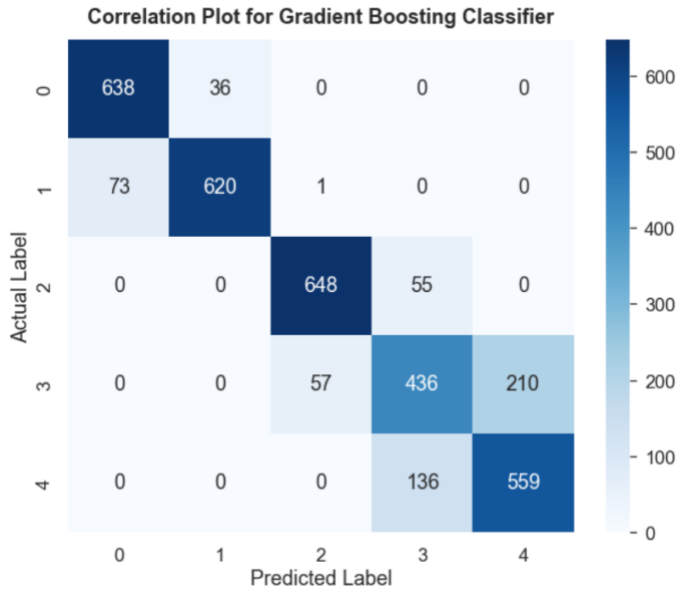


Figure 14 – Correlation Plot for Gradient Boosting with GMM

5 Conclusions and Future Work

After going through the process of testing each combination of customer segmentation techniques along with each churn prediction technique, it can be seen that the combination of GMM with gradient boosting is the most accurate and effective method producing a test accuracy of 84%. It can also be concluded that churn predictions for customer data can be improved by segmenting customer data prior to performing the churn prediction. Although the results are marginal, a 1-2% increase in accuracy can go a long way over a large dataset in order for companies with a larger database of customers to make better decisions. It can also be seen that clustering customers into groups of similarity can allow companies to get a better understanding of what factors are either deterring or positively impacting customers to churn or not churn from using their product.

In terms of future work, although the results are promising, there is still room for improvement as the churn prediction models can still be tweaked and improved. Through more research and iterative work, improving all 3 classifier models (Random Forest, MLP and Gradient Boosting) through parameter tuning could lead to even better accuracy than what was displayed in this report.

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