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EXPLORING CONSUMER BEHAVIOUR PATTERNS AND MODELLING CHURN PREDICTION IN THE FOOD DELIVERY SERVICE INDUSTRY: A CASE STUDY

Poh Yee Yang[1], Jun Kit Chaw[2*], Xiang Cheng[3], Mei Choo Ang[4], Mohamad Hidir Mhd Salim[5]

[1] Faculty of Computing and Information Technology, Tunku Abdul Rahman University of Management and Technology, Malaysia.
Email: kevin1997gladys@gmail.com
[2] Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Malaysia
Email: chawjk@ukm.edu.my
[3] Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Malaysia
Email: cxacademic@gmail.com
[4] Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Malaysia
Email: amc@ukm.edu.my
[5] Institute of Visual Informatics, Universiti Kebangsaan Malaysia, Malaysia
Email: mhdhidir@ukm.edu.my
[*] Corresponding Author

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Abstract:

In the current market, businesses are always looking for ways to sustain and maintain their stability. One of the key strategies is to maintain consumer loyalty and create a peak consumer experience. The study focuses on a third-party delivery service that collaborates with restaurants and fast-food stalls, which is finding it increasingly challenging to maintain individual relationships with its growing consumer base. To address this issue, the study uses churn analysis to extract semantic consumer behavioural information from transaction details, restaurant information, and consumer profiles. The churn analysis process involves six stages: forming objectives, data acquisition, data pre-processing, machine learning, data visualization, and data reporting. Datasets were obtained from a food delivery company and pre-processed using various techniques, including data cleaning, data integration, data transformation, and data reduction. During data pre-processing, the churn period was defined, and various machine learning algorithms such as Artificial Neural Network, Support Vector Machine, AdaBoost Classifier, Gradient Boosting Classifier, XGboost Classifier, and Deep Neural Network were used to predict outcomes. The models were evaluated using metrics such as Area Under the Curve, Confusion Matrix, and Receiver Operating Characteristic. The testing of classifiers was performed with varying feature reduction methods. The findings provide valuable insights into the churn analysis process

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and how it can be used to extract semantic consumer behavioural information, which can help improve consumer retention and satisfaction, leading to increased revenue and business growth.

Keywords:

Consumer Behaviour Patterns; Churn Analysis; Machine Learning; Foodservice Industry; Data Visualization

Introduction

Consumer behavior analysis is a flourishing field that has its roots in various disciplines such as psychology, economics, artificial intelligence, sociology, and anthropology (Ross 2022). In today's technologically advanced world, businesses have various channels to reach their consumers, such as social media, advertising campaigns, and direct mailing. This has resulted in a proliferation of similar products and retail services, which can make decision-making complicated for consumers (Dwivedi et al. 2021). It is increasingly challenging for humans to manually interpret or predict consumer purchasing patterns in this complex environment. As a result, consumer behavior analysis has gained popularity in facilitating retailers and companies to understand consumer purchasing decisions and predict future trends.

The aim of this study is to use churn analysis to examine consumer behavior and extract meaningful insights about the food ordering and delivery process. The process involves gathering information from various sources, such as transaction details, consumer profiles and location, and purchasing processes. By analyzing this data, interesting trends and insights can be generated to help businesses make better decisions to improve their operations and services. The study originated from research questions of how the food delivery web application can obtain consumer information without manual observations and how consumer behavioral analysis can be applied in the context of food delivery platform.

The company being studied is a third-party delivery service that collaborates with various restaurants and fast-food establishments. It primarily receives online orders from busy working adults and college students aged 18 to 40 in Kuala Lumpur, Cheras, Ampang, Subang, Sri Petaling, Kepong, Johor Bahru, and Taman Merdeka in Malaysia. At the time of the research, the company had around 18,000 registered users and was processing 8 to 10K transactions per month. Due to the increasing number of consumers, it has become challenging for the company to maintain individual relationships with each customer. Hence, consumer behavior analytics can help them identify trends and patterns in consumer behavior (Awotunde et al. 2023). The data available for analysis is structured and includes consumer transaction details, restaurant information, and consumer profiles.

The study is organized into 5 Sections, next Section 2 provides the related works that focuses on churn analysis and relevant machine learning models. Section 3 covers the process of the proposed method. In Section 4, the performance of our model using different feature reduction techniques is presented in terms of AUC, confusion matrix and ROC, while in Section 5, the conclusion and future work are presented.

Related Works

There is plenty of similar research out there using consumer behavioral analysis in various types of fields including retail store (Kim, Kim, and Hwang 2020), insurance (Arumugam and

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Bhargavi 2019), banking (He, Hung, and Liu 2023) and healthcare (Schubbe et al. 2020). Churn analysis refers to a technique that predicts the percentage of subscribers who cancel their subscriptions within a given time frame (Tsai and Chen 2010). Many firms adopt this approach to evaluate the value of their consumers, with the aim of retaining or maximizing their profit potential (Ahn et al. 2020). Figure 1 illustrates the six stages involved in churn analysis. Firstly, the process begins with identifying the business problems or objectives. Next, data acquisition is carried out to gather pertinent datasets from the real world, which can be structured, semi-structured, or unstructured. The following stage is data pre-processing, which involves using modern technologies and data tools to clean, integrate, transform, and reduce the collected data.

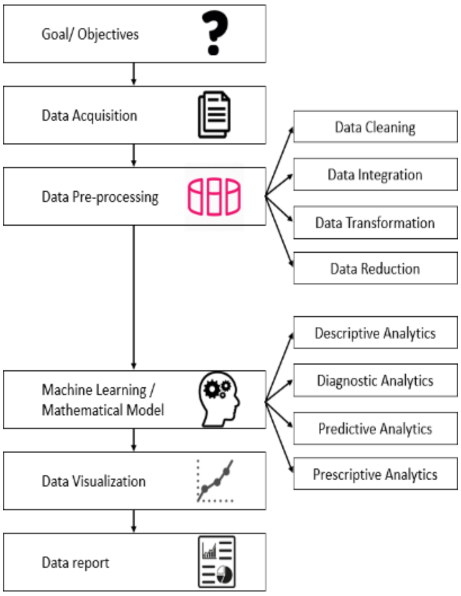

Figure 1: Processes of Churn Analysis

Churn Analysis

Churn analysis has become a widespread practice among businesses, especially as the number of organizations and startups in the market continues to grow, leading to increased competition. Companies have recognized the significance of implementing business strategies to maintain a stable income in the market. These strategies include acquiring new consumers and ensuring the loyalty of existing ones. However, acquiring new consumers can often be more expensive than retaining existing ones, as it involves several expenses such as advertisements, promotions, and credit searches. As a result, preventing consumer churn and retaining existing consumers has become a well-known marketing strategy that is being used across all industries.

Churn analysis enables a company to group consumers based on their likelihood to churn and further subdivide the churners according to their profitability (Ahn et al. 2020). By taking actions to retain the group of consumers that are likely to churn but yield high profits, the company can ensure the maintenance of its overall profits. (Suh 2023). Churn management can be classified into two approaches which are reactive and proactive (Burez and Van den Poel 2007). The reactive approach involves intervening only after a consumer has already decided to churn, while the proactive approach involves identifying consumers with a tendency to churn through continuous churn analysis and offering them incentives before they churn. Studies have shown that the proactive approach has lower incentive costs compared to the reactive approach.

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However, inaccurate churn analysis can lead to wasted resources and ineffective targeting of consumers, rendering both approaches ineffective.

Machine Learning Algorithms

Model training and prediction can be performed using machine learning algorithms, which can be classified as supervised or unsupervised. Several investigations on churn analysis have utilized supervised machine learning techniques, including Decision Trees (DT), Artificial Neural Networks (ANN), and Support Vector Machines (SVM) (Lalwani et al. 2022; Vafeiadis et al. 2015).

DT are tree-like structures consisting of internal nodes, leaf nodes, and branches. They recursively divide the data into smaller partitions. DT are nonparametric, which means that no assumptions are made about the input data (Chermiti 2019) and widely used in churn prediction as well as analysis because they can handle missing values, manage numerical and nonlinear consumer data, and predict future trends in consumer behavior, revenue and sales, and consumer churning probability (Pejić Bach, Pivar, and Jaković 2021).

ANN works by processing input signals and their corresponding weights to generate output signals (Chuntao and Yonghong 2006). It is a popular algorithm for descriptive and predictive data analytics, especially in fitting non-linear functions. In the study on training a churn prediction model for the telecommunications industry, Saha et al. (Saha et al. 2023) found that both ANN and DNN algorithms outperformed other methods in predicting consumer churn for the Indian and Southeast Asian telecom industries, as well as for the American telecom market in a second dataset. In order to enhance the predictive performance of machine learning techniques in consumer churn analysis, researchers have employed feature transformation namely Principal Component Analysis (PCA) before feeding into the machine learning models. With these features, SVM produced higher accuracy, recall, and F1-score than other algorithms such as logit, k-nearest neighbors, naive Bayes, and DT. Although feature transformation can improve the performance of a model, it can also make it difficult to interpret the relationship between the prediction output and the original features. This is because the transformed features exist in a different space, which can complicate the process of understanding the model's results.

The Proposed Method

This study consists of four main modules: Load datasets, data pre-processing, machine learning, and reporting. The program initially loaded various datasets in Excel format and transformed them into arrays, which were then referred to by program variables. To prepare the data for further analysis, various data preprocessing methods such as data cleaning, data integration, data transformation, and data reduction were applied to eliminate any irregularities and noise from the data. Subsequently, different machine learning algorithms were utilized to train a prediction model on the dataset. Each algorithm's performance was evaluated to identify the most suitable one for the project. Finally, all the outcomes were plotted on graphs, charts, or tables for a better understanding of the results. Based on the processes depicted in Figure 1, we designed our methodology as shown in Figure 2.

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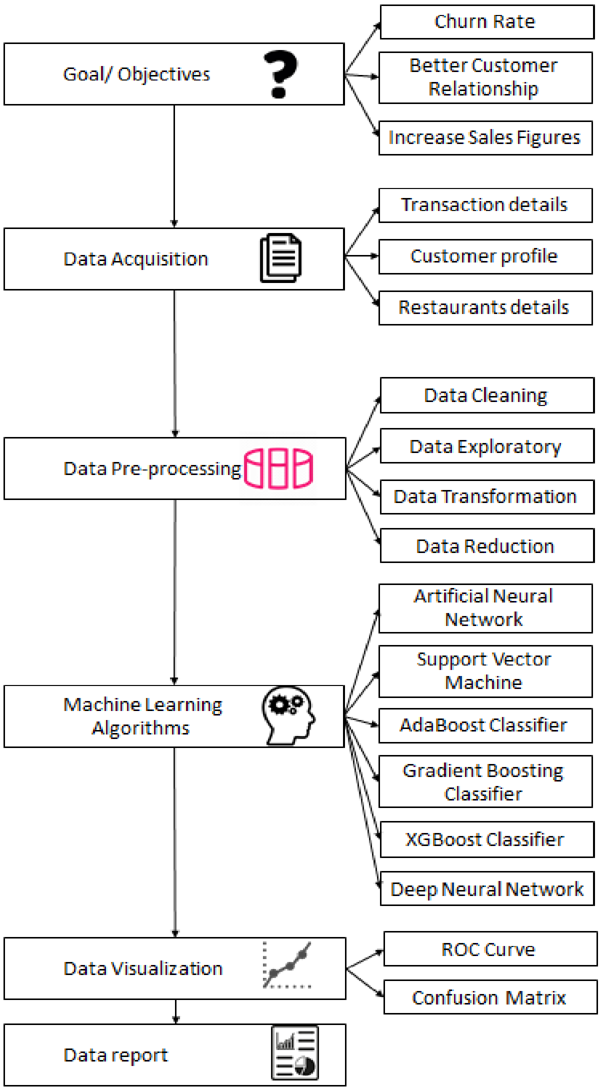

Figure 2: Churn Analysis for the Acquired Food Delivery Dataset

Data Preprocessing

The data preprocessing phase was divided into four parts, which were data cleaning, data integration, data transformation, and data reduction. Various algorithms were utilized to carry out these tasks effectively. During the initial stage of data preprocessing, the raw data was categorized into three types: numerical, categorical, and ordinal. Numerical data were features that could be represented using numerical values, while categorical data were attributes that had no numerical significance, such as gender and nationality. Ordinal data were features that were expressed in a qualitative manner but could be ranked, ordered, or scaled. To prepare the categorical and ordinal data for analysis, they were label encoded. For example, the gender attribute with the values 'male' and 'female' were transformed into '0' and '1' respectively.

Next, the target variable, referred to as the 'Churner' column, was established, where a value of '1' represents customers who churn, while '0' denotes those who do not. Through analysis of the dataset spanning six months, the optimal churn period was identified to be approximately 21 days or 3 weeks. This implies that any consumer who does not use the company's services

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for more than 21 days is considered a churner. Extra columns, such as the days between transactions and the delivery distance in kilometers, were also defined for more efficient analysis, calculated from the latitude and longitude provided in the datasets.

To ensure optimal input datasets for the predictive models, missing values were avoided. Several approaches are available to handle missing data, such as removing rows with missing values. However, this approach may result in data loss and introduce potential biases to the datasets. Hence, we utilized imputation technique to handle missing values by substituting them with other values such as mean, median or mode of the dataset.

Model Training and Prediction

After the data has been preprocessed, it was then fed into various machine learning algorithms for model training and prediction. The machine learning algorithms used were ANN, SVM, AdaBoost Classifier (AB), Gradient Boosting Classifier (GBC), XGboost Classifier (XGB) and DNN. After results were obtained, Area under Receiver Operating Characteristics Curve (AUC) Curve and Confusion Matrix were constructed to evaluate each machine learning algorithm used.

Results and Discussion

This section presents the exploratory data analytics (EDA) that produces the final dataset for training the machine learning models and the models' comparative analysis.

EDA

After conducting EDA, we have uncovered several findings and insights concerning the dataset. To begin with, as illustrated in Figure 3, the dataset contains more non-churners than churners, which is beneficial for the business. Nevertheless, the percentage of churners is relatively significant as it nearly reaches 50% in this instance, implying that measures are required to prevent a further increase in churn rates.

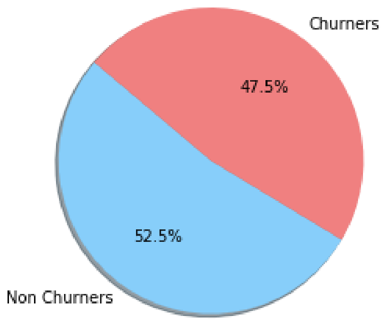

Figure 3: Pie Chart of Churner vs Non-Churner

A heatmap as shown in Figure 4 represents the correlation between the columns in the dataset using the Pearson correlation coefficient (PCC). The analysis revealed a relatively high correlation value of 0.63 between Average Spending and Average Item Ordered Per Transaction, which is a typical scenario where increased items ordered per transaction results in more spending. The second highest correlation value of 0.28 was found between Total Number Of Comments and Total Number of Transactions, indicating that users tend to write more comments as the number of transactions they make increases.

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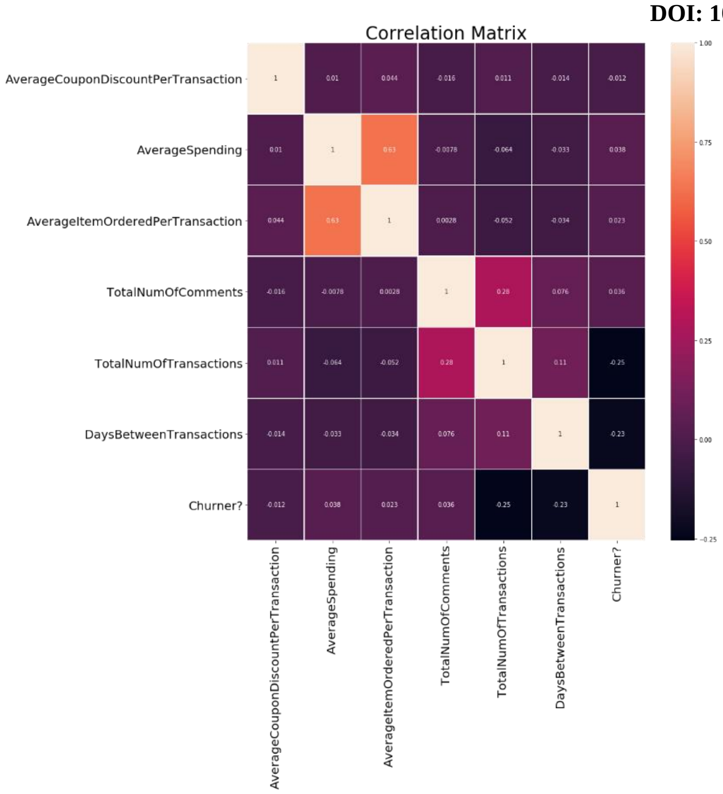

Figure 4: Heatmap Representing the Correlation Between Columns in Dataset

Figure 5 illustrates the Total Number of Transactions (top) and the Average Coupon Discount per Transaction (bottom) for different cities. Kuala Lumpur city has the highest number of transactions and redeemed the largest amount of coupon discounts, as shown in the figure. Furthermore, it is observed that the number of non-churners (represented by the blue bars) decreased in all cities, while the number of churners increased in some cities. This suggests that the more a user utilizes coupons for discounts, the higher the likelihood that the user will churn. For example, users who depend heavily on coupons might be more price-sensitive and change to other food delivery service that offers better deals.

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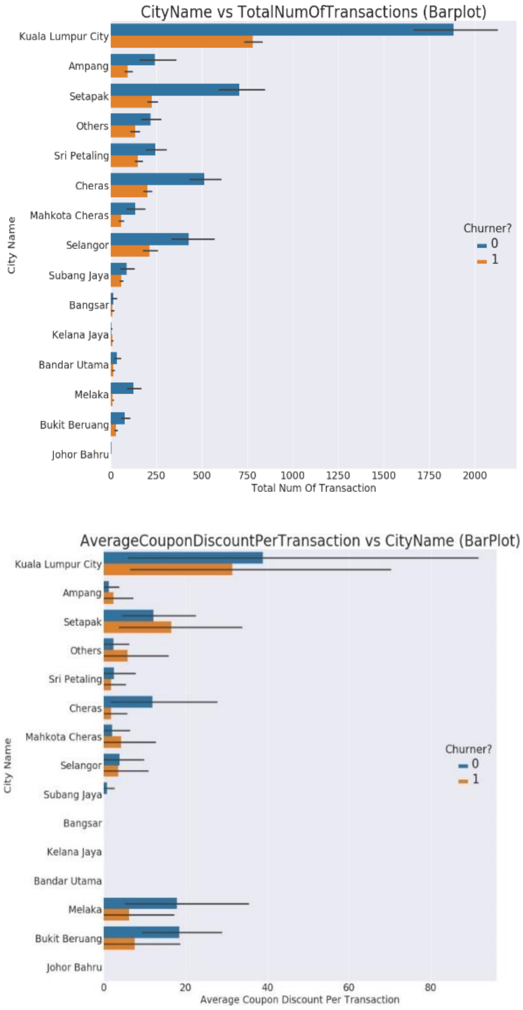

Figure 5: Bar Plot Representing City VS Total Number of Transactions (Top) and Average Coupon Discounted Per Transaction (Bottom)

The bar plot in Figure 6 displays the Transaction Counts for each day from February to March 2018.

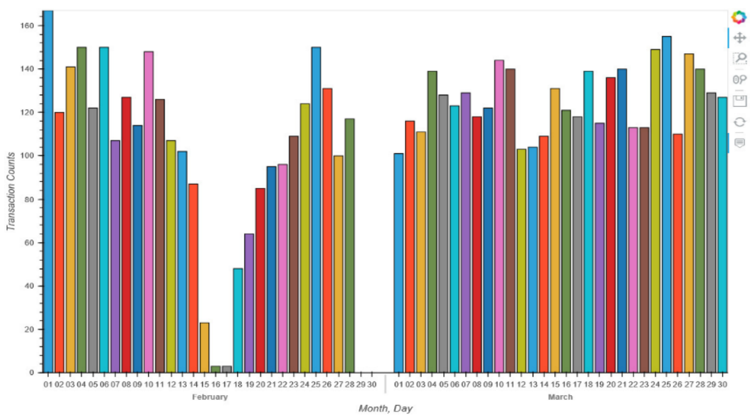

Figure 6: Bar Plot Representing the Transaction Counts on Each Day within February and March 2018

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The figure is noteworthy as there is a sharp drop and rise in transactions between the 10th and 25th of February 2018. This can be attributed to the Chinese New Year (CNY) festivities that fall on the 16th and 17th of February, with the 15th of February being the New Year's Eve. During these periods, families, especially those of Chinese descent, tend to dine out at Chinese restaurants and purchase traditional CNY foods. Therefore, to increase sales during these periods, the food delivery company can collaborate with these restaurants to provide consumers with the convenience of enjoying their seasonal cuisines without having to leave their homes.

Figure 7 depicts the number of churners in different cities and the corresponding staff members responsible for the customers. The figure reveals that a particular staff member with the ID ‘5a5768bb6186fb032cdb66fe’ working in Kuala Lumpur City has a significantly higher rate of churners.

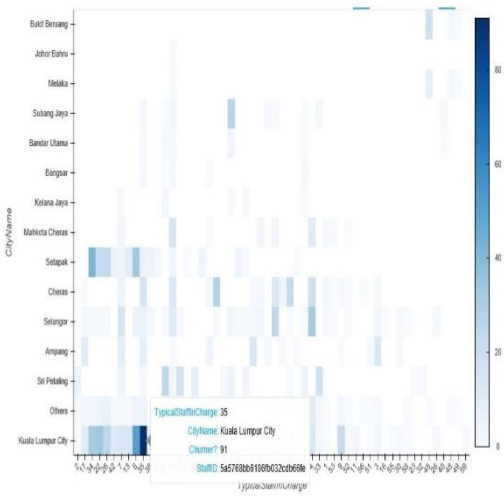

Figure 7: Heatmap Representing City(y-axis) vs Staff In Charge(x-axis) vs Number of Churners (Colour Opacity)

Figure 8 presents a bar chart showcasing the transaction counts, total spendings, and total discounts across different cities. The color-coded segments of the bars denote the count of churners and non-churners. It is noteworthy that the city of Johor exhibits a low volume of transactions but a considerably high total expenditure. Notably, Johor has no churners at present as the company's business operations have recently expanded in this region from the time the data was collected. Additionally, this visual aid allows for a comparison of spending patterns and churn statistics among the different cities.

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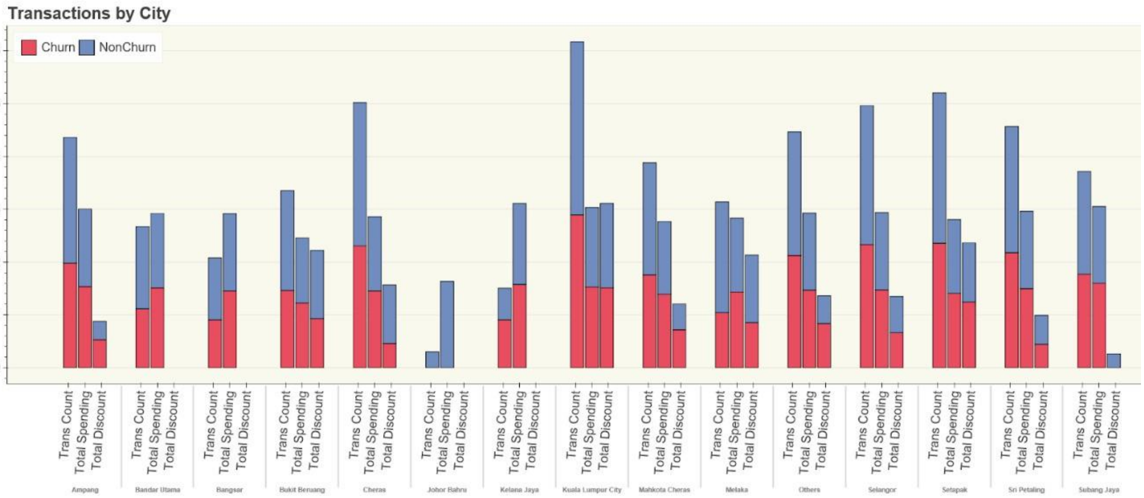

Figure 8: Bar Chart Representing the Transaction Counts, Total Spendings and Total Discounts in Various Cities

Figure 9 shows a Google map plot featuring circular points with various colors representing the coordinates of restaurants, churners, and non-churners, along with a purple line indicating the delivery displacement path. The map highlights that most users tend to purchase food from shops located closer to their location, although some consumers placed orders from a relatively farther distance. Notably, it can be observed that consumers who ordered from a greater distance had a higher likelihood of churning. This could be attributed to a variety of factors, including poor food quality caused by longer delivery times, higher delivery fees, and issues such as sauce spills, cold food, and misplaced toppings during the delivery process.

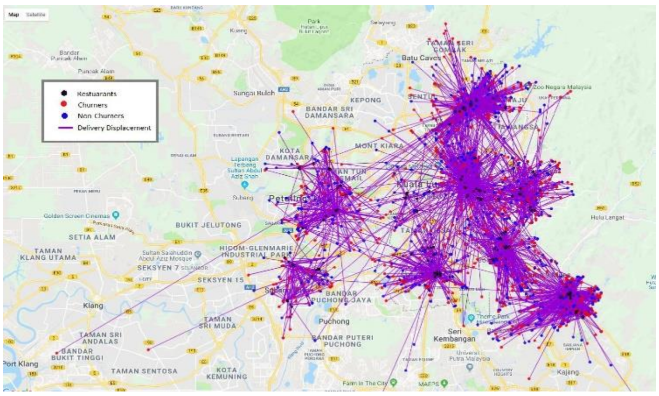

Figure 9: Google Map Plot

Based on the various findings and insights obtained from the dataset, there are some recommendations and solutions that can be suggested. Firstly, regular coupon discounts with a deadline can be provided to encourage users to order more and increase their loyalty towards the service. Secondly, the company can collaborate with restaurants that provide seasonal cuisines during special seasons such as Chinese New Year to increase sales and consumer convenience. Thirdly, a feedback system can be established for consumers to comment on and rate each staff member, which can help improve the quality of service provided by the staff. Finally, to avoid bad food conditions during long-distance deliveries, the company can provide

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extra warm and tight containers to store the food. By implementing these solutions, the company can increase user satisfaction, loyalty and reduce the rate of churn.
After EDA, the features selected for model training are shown in Table 1.

Table 1: Features in The Final Dataset Used and Their Respective Descriptions

Features	Descriptions
AverageDeliveryDistance(km)	Average of all delivery distances from all delivery orders of the consumer
AverageSpending	Average spendings of the consumer
Rated?	True or False, whether the consumer rated the food delivery service?
Registered?	True or False, whether the consumer registered as a member of the food delivery service?
TotalNumOfComments	The total number of times the consumer provided comments while ordering food
TotalNumOfTransactions	The total number of orders made by the consumer
DaysBetweenTransactions	The number of days between the two most recent transactions
TypicalStaffInCharge	The staff member who served the consumer the most (using mode)
TypicalDeliverySchedule	The usual delivery schedule chosen by the consumer, such as "ASAP", "Later", or "Now"
TypicalShopID	The ID of the restaurant where the consumer placed the most orders
DaysOfWeek	The days of the week when the consumer usually places orders (Monday, Tuesday, etc.)

Machine Learning Models Evaluation

To improve the machine learning performance, it is crucial to identify the discriminative features that can effectively classify consumers into churners and non-churners. However, different feature reduction methods can have varying effects on the performance of different machine learning algorithms, either positively or negatively (Georganos et al. 2018). Hence, the aim of this study is to identify the optimal combination of feature reduction techniques that can generate the highest AUC across all classifiers tested. The training and testing were performed using a ratio of 0.83:0.17, while all datasets underwent standardization prior to the experiments using the same steps.

Table 2 displays the various machine learning classifiers utilized during the testing, training, and prediction phases using different python modules.

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Table 2: Classifiers Used for Model Training and Prediction

Classifiers	Module used
ANN	sklearn.neural_network
SVM	sklearn.svm
AB	sklearn.ensemble
GBC	sklearn.ensemble
XGB	xgboost
DNN	tensorflow.estimator

Table 3 shows the methods employed in this study to decrease the dimensionality. They were tested for the classifiers listed in Table 2.

Table 3: Methods for Decreasing Dimensionality

Methods for increasing or decreasing dimensionality	Module
Kernel PCA (PCA)	sklearn.decomposition.KernelPCA
Feature Agglomeration (FA)	sklearn.cluster.FeatureAgglomeration
Variance Threshold (VT)	sklearn.feature_selection.VarianceThreshold
Gradient Boosting Classifier and Select from Model (GBM)	sklearn.ensemble.GradientBoostingClassifier sklearn.feature_selection.SelectFromModel

Table 4 shows the AUC scores of each classifier along with the time taken for model training and prediction with and without dimensionality reduction for the dataset before training. The results indicate that most of the methods did not improve the performance of the classifiers, with some even showing a decrease in performance. However, the use of VT as a feature reduction method led to an AUC score of 0.83 for GBC, which was the only combination that showed an improvement. Furthermore, this combination required less time to process as the number of features was reduced by one compared to the original program without any feature reduction method. Figure 10 depicts the corresponding ROC curve of classifiers with VT as the feature reduction method.

Table 4: Models vs Methods Used for Decreasing Dimensionality

AUC	PCA	VT	GBM	FA
ANN	0.78	0.77	0.74	0.68
SVM	0.73	0.77	0.74	0.68
AB	0.76	0.81	0.78	0.67
GMB	0.77	**0.83**	0.79	0.67
XGB	0.53	0.82	0.80	0.67
DNN	0.77	0.78	0.76	0.68
Time Taken (seconds)	1495.48	**29.39**	34.63	23.81
Number of features	1108	**10**	6	2

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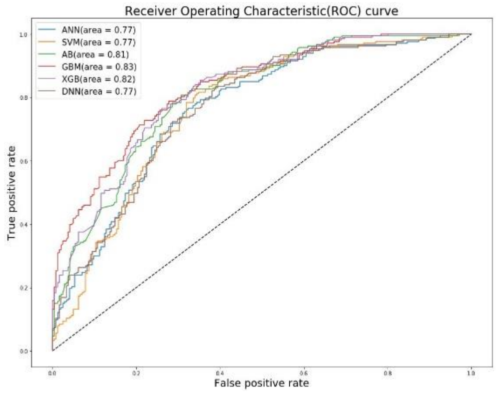

Figure 10: ROC Curve

Besides AUC and ROC, the models were also evaluated by constructing a confusion matrix which consist of 4 parts which are the numbers of True Negative, False Negative, True Positive and False Positive. The confusion matrix is shown in Figure 11.

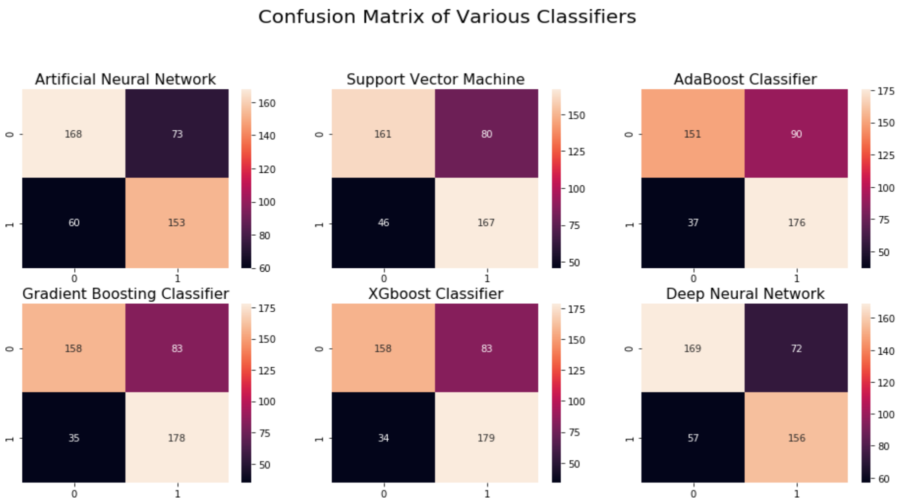

Figure 11: Confusion Matrix

Firstly, there is undoubtedly a trade-off between accuracy and the time required for models to run. Models with higher accuracy often take longer to process. Additionally, the choice of feature extraction method can have significant undesired effect on the performance of classifiers. This is likely due to issues with dimensions, overfitting, and noise induced by unsuitable feature extraction methods. For example, all the feature reduction methods namely PCA, FA and GBC have brought negative impact to nearly all of the machine learning algorithms. Except for VT that was able to improve the AUC of GBM. By removing features with low variance, which frequently contain little information and can introduce noise to the data, VT can improve the performance of GBC and avoid overfitting (Pudjihartono et al. 2022).

To revisit our main argument, targeted marketing efforts can increase the company's sales. In the context of a food delivery service, consumer behaviour analytics can unearth a wealth of actionable insights. For instance, by closely examining purchase patterns, we can discern that customers tend to place larger orders over the weekends. This discovery suggests an opportunity to implement weekend-specific promotions to capitalize on this trend and boost sales during those times. Moreover, churn prediction models can help identify customers at high risk of leaving the platform. Armed with this knowledge, businesses can develop personalized retention strategies, resulting in a tangible reduction in churn rates. By scrutinizing the data, we can gain valuable insights into customers' product preferences. For instance, our analysis may reveal that the 18-24 age group leans towards healthier food options such as salads and smoothies. This information prompts us to consider expanding our menu offerings in this category, catering more effectively to this demographic. Additionally, analysis of customer feedback can pinpoint areas of improvement. If comments consistently highlight dissatisfaction with delivery times, optimizing delivery time reliability becomes a priority to enhance overall customer satisfaction and loyalty. Understanding that customer delivery time preferences is critical, the data may reveal that the majority of customers prefer 'ASAP' delivery. With this insight, we can optimize our delivery routing and staffing during peak 'ASAP' demand hours to reduce delivery times.

Conclusion

Churn analysis is a useful tool that businesses may employ to distinguish churner and non-churner among the consumers. It could be very useful, as the company can provide different approaches of advertising to different groups. In our case study, we have identified several key findings such as the distribution of users, number of transactions, and the factors that contribute to churn. This could help the industrial partner that contributes the real-data for this study to strengthen the consumer retention strategies. For future work, integrating the churn analysis program with the company's database and server can automate the process, and big data warehousing and mining techniques can be used to process larger sets of data more efficiently. Additionally, as the data recorded by the company may change, it is important to develop a program that can handle different types of datasets. By implementing these improvements, the company can stay ahead of the competitors.

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