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Analysis of Consumer Behaviour in Food Delivery Platforms

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ABSTRACT

During recent years online food delivery applications like Zomato, Swiggy and others became a routine for many people. Nowadays, it is even easier and more comfortable for the young generation like students ordering food online instead of going out and dining somewhere. Therefore, there has been a generation of a lot of information about people and their behaviour that can help to find patterns and understand the target audience better.

To avoid using someone else's dataset, we developed and distributed our own Google form and obtained 462 responses from actual customers. Thus, we had a chance to get behavioural data and see actual trends in our field. We started working on the task by performing preprocessing and analysing of the received data using Python. We managed to visualize various trends related to expenditure per order, ordering frequency, time, platform preference, etc. Moreover, we developed a machine learning algorithm using Decision Tree classification.

As a result, we found that people preferred moderate expenditures, ordered mostly at night time, and preferred to use Zomato service. Our predictive model reached only approximately 21.7% accuracy and proved the complex nature of humans' decision-making process.

1. Introduction

Food consumption habits have also undergone a significant change in recent years. The rise of food ordering sites such as Zomato and Swiggy has made it easier for people to order food quickly and efficiently. More and more consumers are now resorting to ordering food from their favourite spots online rather than having to physically go there. Data analysis companies can make use of a variety of data that is generated when customers order food online. Proper analysis can offer valuable insight into the consumer's behaviour. In this project, we aimed at determining the factors affecting user choices while ordering food online. Instead of making use of any existing dataset, we chose to collect the data ourselves by conducting a survey.

This project incorporates both data analysis and machine learning techniques to analyse and predict consumer behaviour.

2. Motivation

One of the biggest motivations for conducting such a project was using actual data instead of depending on the online datasets that have been used by many researchers in their studies. Our aims were to gather real answers from real respondents, Sense real behaviour regarding ordering products, construct an entire system starting from gathering data till predicting results.

Using our own form, we gathered the actual responses from the respondents, which made us understand the behaviour of the users.

3. Problem Statement

Even though there is a considerable amount of information available in food delivery services, it can be difficult to draw conclusions from them. The most significant problems encountered includes Identifying the consumer's taste, detecting any tendencies in their orders, determining what application would be preferable to the consumer, Managing inconsistencies in human behaviour.

These problems will be tackled in this project through the analysis of the collected data using machine learning.

4. Objectives

The purpose of this project is to collect real-life data on consumers' food ordering, Analyse consumer preferences and behaviour, look into how often and how much money they spend, examine trends in food ordering apps, create a model for predicting the preferred delivery application.

5. Data Collection

A google form containing questions regarding ordering patterns in relation to food was designed.

This google form was shared with the help of students and general public.

In all, a total number of 462 questionnaires were gathered from this exercise.

The following are some of the questions that were asked in the questionnaire;

- •Age groups
- •Popular fast-food chains
- •Favorite cafes
- •Ordering patterns
- •Offline or online preference
- •Delivery application preference
- •Average bill size
- •Time of ordering

The entire dataset used in this project is entirely created by us

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6. Methodology

The research process is carried out following a pipeline involving data collection, data preprocessing, data analysis, and predictive models.

6.1 Technologies Used

We are using python and machine learning for analysis of the data.

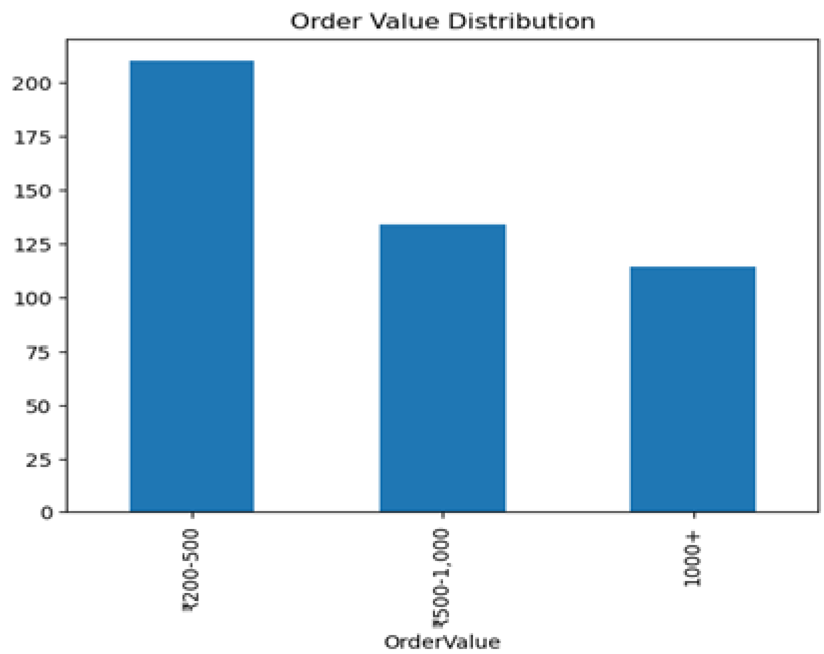
- •Python (programming language)
- •Pandas and NumPy (data handling packages)
- •Matplotlib and Seaborn (visualization libraries)
- •Scikit-learn (machine learning)
- •Jupyter Notebook (development environment)

6.2 Exploratory Data Analysis

The Exploratory Data Analysis (EDA) was conducted to gain insights from the data. Several visualizations were used to effectively analyse the user behaviour.

7. Exploratory Data Analysis

In order to better understand the data, various visualizations were generated to detect any patterns in user behaviour in terms of expenditure, frequency, time, and preferred platforms, which proved beneficial for



gaining insights and forming a good base for analysis.

7.1 Order Value Distribution

Fig. 1. Distribution of Order Value Among Users

It was found out that the majority of the users spent between ₹200-500, whereas there was a small portion of higher spending customers falling under ₹1000 and higher category groups. This suggests that users usually go for cheaper options, implying that price does matter to a certain degree when it comes to food delivery orders.

7.2 Popular Fast-Food Chains

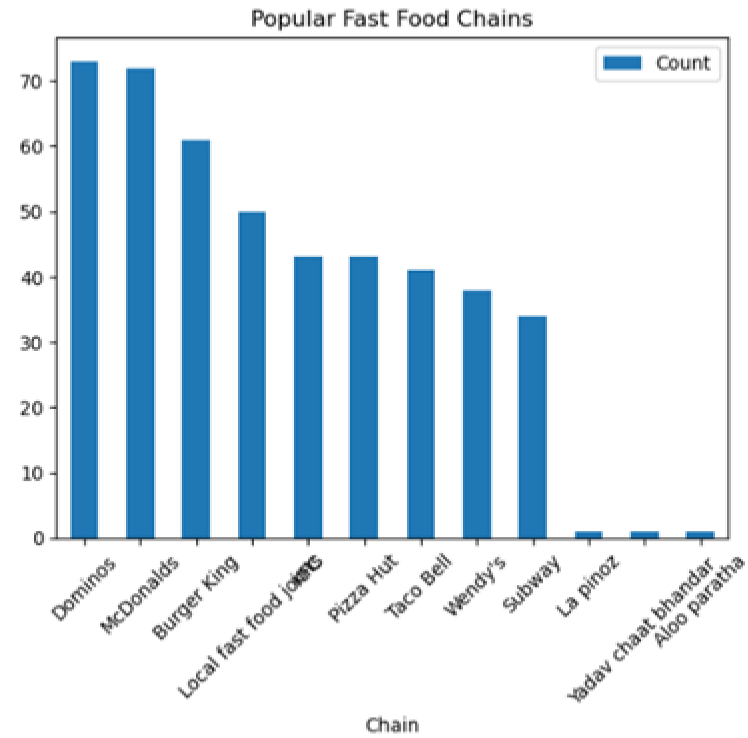


Fig. 2. Preferred Fast Food Chains Among Users

Domino's and McDonald's emerged to be the top choices among the fast-food restaurants, being followed by Burger King and Pizza Hut. The popularity of the local food was also evident from the data collected.

7.3 Delivery Platform Usage

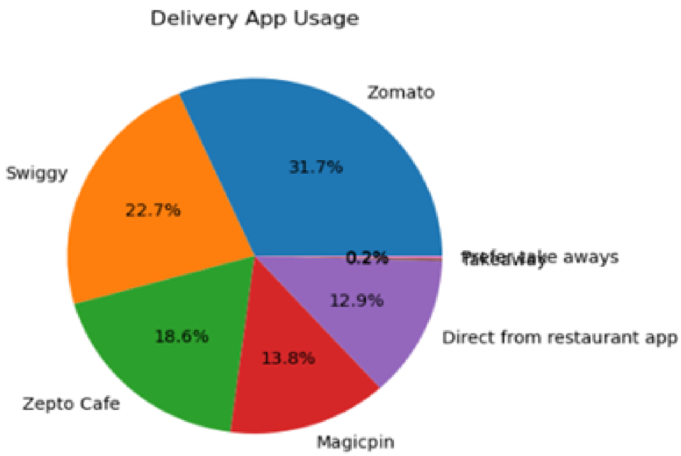


Fig. 3. Distribution of Delivery Platform Usage

It was seen that Zomato was the most popular platform, followed by Swiggy. Other platforms did not have very high usage.

7.4 Eating Frequency

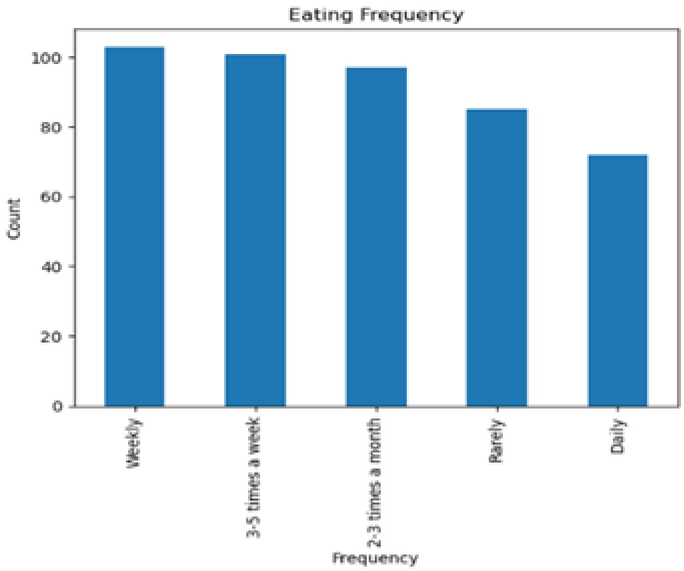


Fig. 4. Frequency of Food Ordering

Weekly or even multiple-time orders per week seemed to be the trend here, rather than making daily orders for food.

7.5 Time of Ordering

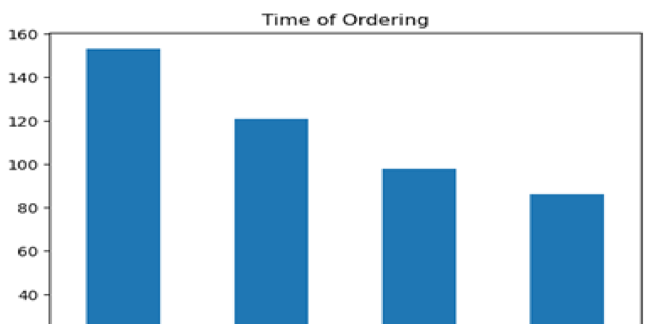


Fig. 5. Preferred Time for Food Ordering

It was observed that nighttime was the preferred time for ordering food followed by evening snacks. It is interesting to note that morning hours for ordering food was the least popular, which could indicate that people prefer ordering food during their leisure time.

7.6 Age Distribution

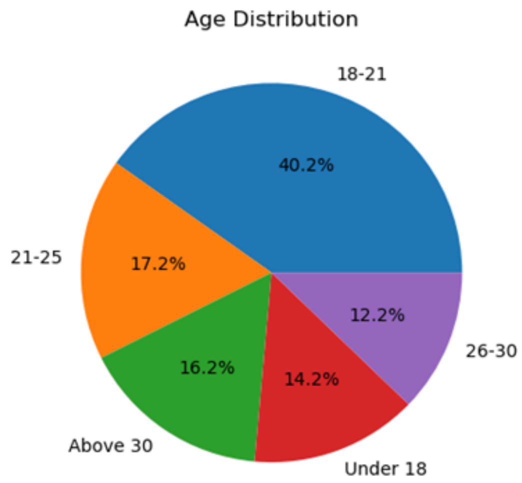


Fig. 7.6. Distribution of Users by Age Group

Most of the respondents were between the age group 18-21 years, which clearly indicates that young users constitute the primary target audience for the platform.

7.7 Age vs Frequency Relationship

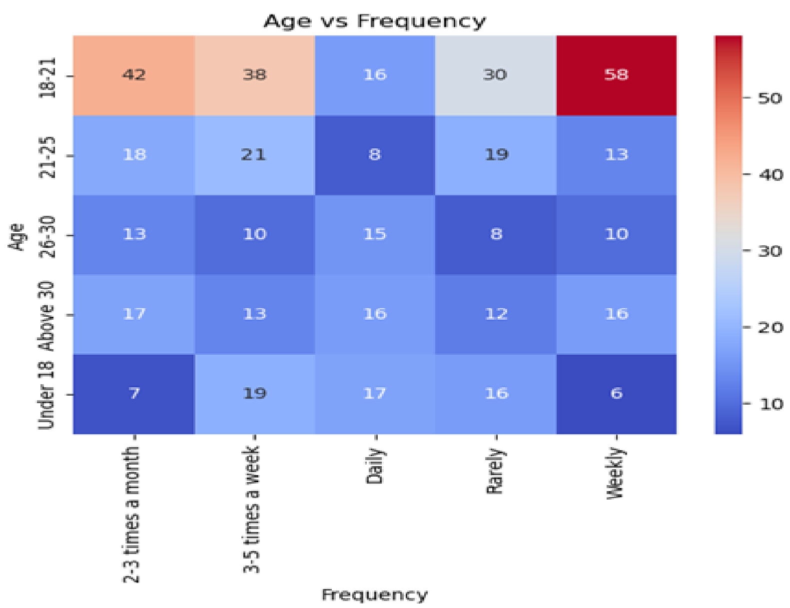


Fig. 7. Relationship Between Age Group and Ordering Frequency

It was observed that there was a high ordering frequency amongst users who belonged to the age group 18-21 years, whereas users above 21 years made lesser orders.

7.8 Summary of Observations

To conclude, it can be stated that the users prefer to spend moderately, place orders once a week, and make orders predominantly during night hours. Also, the target audience consists of young users, and some platforms have a dominant presence in the market.

8. Machine Learning Model

In an attempt to further the analysis to make predictions based on the descriptive statistics, a machine learning model was applied to find out the delivery platform that a user would prefer according to their characteristics and behaviour.

8.1 Problem Formulation

It can be considered a problem of multi-class classification, where the goal is to predict the choice of delivery platform by a user. The input features include age categories, preferred food chain(s), preferred cafe(s), how often the person orders food, whether he/she chooses home delivery or collection himself/herself, the amount of money spent on average, and the time of making the order. The output feature is preferred delivery platform.

8.2 Data Encoding

Given that the data set contains only categorical features, label encoding was applied in order to encode the features using labels. It means that all categories got a unique number.

8.3 Train-Test Split

In this case, the data were split into train and test sets in order to assess the performance of the model. Around 80 percent of the data were used to train the model, while the remaining 20 percent of the data served as a test set.

8.4 Model Selection

The Decision Tree Classifier was chosen as a suitable model in this case because it is a simple and easily interpretable algorithm. This particular model can handle categorical data very well and is appropriate for multi-class classification tasks. Also, its tree structure makes it easy to comprehend the decisions.

8.5 Model Training

The process of training the model included introducing the training data to the model and letting it recognize patterns in the data and relationships between features and the target variable.

8.6 Prediction and Evaluation

The predictive model was applied to the test set.

TABLE 1: Model Performance

Metric	Value
Model Used	Decision Tree
Accuracy	~21.7%
Problem Type	Multi-class Classification

TABLE 2: Classification Report

Class	Precision	Recall	F1-score
Zomato	0.06	0.08	0.07
Swiggy	0.50	0.25	0.33
Zepto Cafe	0.20	0.26	0.23
Magicpin	0.11	0.20	0.14

9. Results and Discussion

9.1 Evaluation of Model Performance

The accuracy of the model was calculated to be around 21.7%. Even though this number may seem quite low, one should understand it from the point of view of the task being analysed. The process of predicting consumer behaviour can be described as rather complicated because of the wide range of possible outcomes.

9.2 Factors Affecting Accuracy

There were several factors that affected the accuracy of the model. First of all, there were multiple output classes, which made it harder to perform the classification. Also, the feature set used to build the model was narrow, and it lacked important parameters, like discounts, delivery time, location, and customer's opinions about the platform. Moreover, consumers' decisions are very unstable.

9.3 Importance of the Results

Even though the accuracy rate was low, the results are quite useful. They allow concluding that the prediction of consumer behaviour and preferences can be done despite the fact that the process is complicated. Besides, the results can be used as a basis for further analysis and improvements.

9.4 Connection between ML and EDA Results

The results provided by the machine learning algorithm correspond to the findings revealed during the exploratory data analysis. The variance in the predictions is in line with the irregularity in the dataset. There are no dominating features in terms of deciding which platform to use.

10. Applications

There are many practical uses of the results of this research within the food delivery market. These may include the possibility for businesses to learn more about their clientele and develop an appropriate strategy. First of all, it is possible to conduct customer segmentation based on spending patterns and order frequency. Another aspect that is worth considering is creating targeted advertisements based on user behaviour and preferences. Moreover, one should not overlook the possibility of introducing personalized recommendations based on certain criteria. This may prove helpful for the optimization of certain platform features for greater user convenience and business success.

11. Limitations

Despite offering valuable insights, however, there are some shortcomings associated with the research. First, although the dataset is big enough to enable statistical computations, it is quite modest, having 462 entries. Also, the number of attributes used in the algorithm is limited, with many practical considerations affecting users' behaviour left out. Moreover, the entire database comprises categorical data only, potentially constraining the analysis. The applied machine learning algorithm is also quite basic without any optimization techniques for parameters to improve the accuracy. Finally, due to the lack of up-to-date information, the investigation captures just one static aspect of consumers' behaviour rather than dynamic changes over time.

12. Future Scope

There are various ways in which this research can be further expanded in order to derive more insightful findings. One possible way could be utilizing machine learning models that are more sophisticated than KNN and logistic regression, such as Random Forest, Gradient Boosting, and XGBoost. Increasing the sample size through the collection of more data would help make the results more reliable and consistent. Further work can also include including more factors that impact consumer decisions, such as the geographical location of users, price differences, availability of discounts, and delivery duration. The construction of a recommendation engine that suggests food services based on the behaviour of users is also another potential approach that could be explored.

13. Conclusion

In this research paper, an in-depth examination of consumer behaviour in the food delivery sector is conducted using firsthand data gathered directly from consumers.

Through the integration of data collection, data visualization, and machine learning, the study detects the essential characteristics of user purchasing behaviour, order frequency, and platform activity. Real-world data increases the validity of the analysis and results.

While achieving intermediate accuracy in predictions, the model demonstrates the underlying complexity of human behaviour and the necessity of employing more sophisticated methods of analysis.

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