# Phase-3 Submission

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**Department:** Computer Science and Engineering

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**Github Repository Link:** [Github link]

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## 1. Problem Statement

***"Predicting customer churn using  machine learning to uncover hidden patterns"***

*This project addresses the challenge of **customer churn prediction** in a subscription-based business environment. Churn refers to customers discontinuing the use of a service. Identifying users with a high likelihood of leaving helps businesses take proactive retention actions. This is a **multi-class classification** problem where the model predicts a **churn risk score from 1 to 5**. The solution enables strategic interventions, better marketing targeting, and higher customer lifetime value.*

## 2. Abstract

*The project focuses on predicting the churn risk score of customers in a retail/subscription business using machine learning. Churn impacts business profitability and sustainability, especially in competitive markets. The goal is to analyze customer data, identify patterns that lead to churn, and build a predictive model. After detailed preprocessing and exploratory data analysis, the team engineered relevant features and trained multiple classification models. The best-*

*performing model helps classify customers into risk categories. This aids in enhancing retention efforts and reducing business losses.*

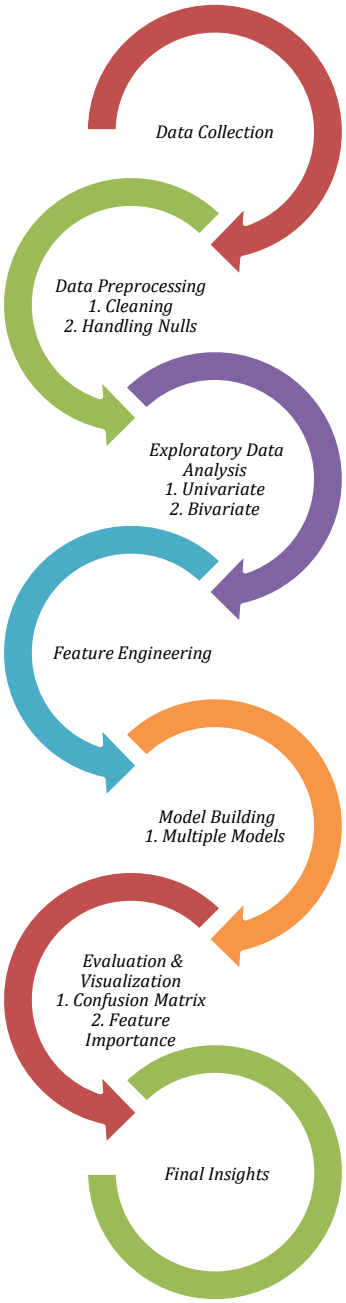
## 3. System Requirements

- ***Hardware:***
  - *Minimum 4 GB RAM*
  - *Intel i3 processor or higher*
- ***Software:***
  - *Python 3.8 or later*
  - *Libraries: pandas, numpy, matplotlib, seaborn, scikit-learn*
  - *IDE: Jupyter Notebook / Google Colab*

## 4. Objectives

- *Predict the **churn risk score (1 to 5)** using customer behavior and profile features.*
- *Identify key factors contributing to high churn risk.*
- *Enable targeted customer retention strategies.*
- *Deliver a model with good predictive performance and practical interpretability.*

## 5. Flowchart of Project Workflow




## 6. Dataset Description

- ***Source:*** *Dataset link*
- ***Type:*** *Synthetic / Private*
- ***Size:*** *36,992 rows × 25 columns*

- ***df.head():***
  *Contains customer demographic and transactional attributes such as:*

- *customer_id, age, region_category, membership_category, avg_time_spent, avg_transaction_value, points_in_wallet, etc.*

```
df.head()
```

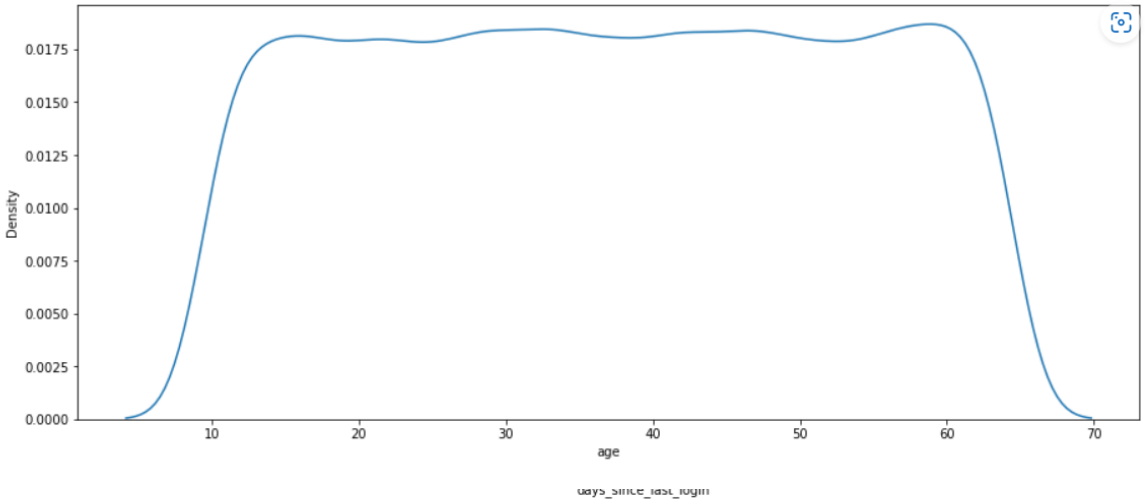
| | customer_id | Name | age | gender | security_no | region_category | membership_category | joining_date | joined_through_referral | referral_id | preferred_offer_types | mediu |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | fffe43004900440036003000300038 00 | Pattie Morrisey | 18 | F | XW0DQ7H | Village | Platinum Membership | 2017-08-17 | No | xxxxxxxx | Gift Vouchers/Coupons | |
| 1 | fffe43004900440032003100300035003700 | Traci Peery | 32 | F | 5K0N3X1 | City | Premium Membership | 2017-08-28 | ? | CID21329 | Gift Vouchers/Coupons | |
| 2 | fffe43004900440031003900320036 00 | Merideth Mcmeen | 44 | F | 1F2TCL3 | Town | No Membership | 2016-11-11 | Yes | CID12313 | Gift Vouchers/Coupons | |
| 3 | fffe43004900440036003000330031003600 | Eufemia Cardwell | 37 | M | VJGJ33N | City | No Membership | 2016-10-29 | Yes | CID3793 | Gift Vouchers/Coupons | |
| 4 | fffe43004900440031003900350030003600 | Meghan Kosak | 31 | F | SVZXCWB | City | No Membership | 2017-09-12 | No | xxxxxxxx | Credit/Debit Card Offers | |

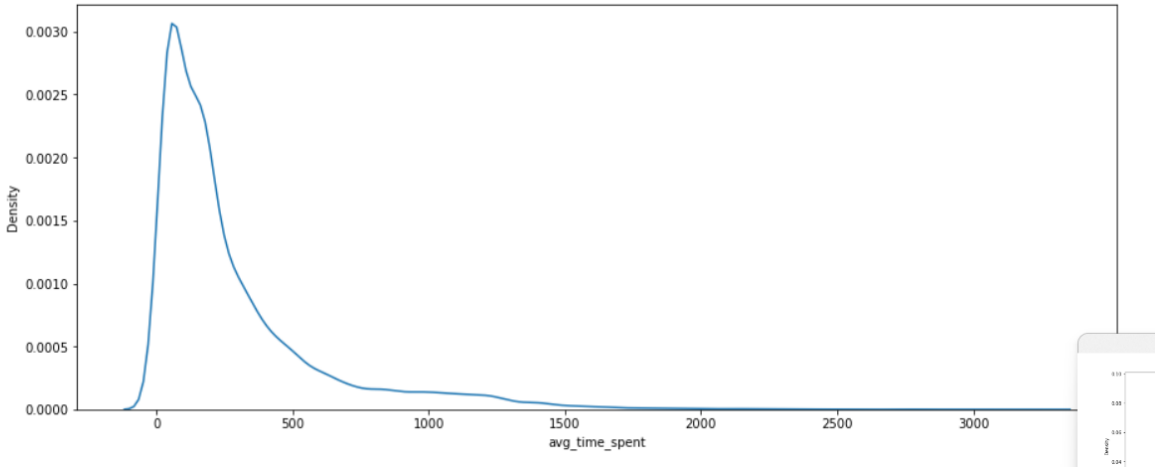
## 7. Data Preprocessing

- ***Missing Values:***
  - *region_category and points_in_wallet were imputed with **median**.*
- ***Error Handling:***
  - *Incorrect churn risk values (-1) corrected using **lambda functions**.*
- ***Dropped Columns:***
  - *customer_id, name, security_no, referral_id, and avg_frequency_login_days (due to irrelevance or poor data quality).*
- ***Type Conversion:***
  - *Converted joining_date and last_visit_time to **datetime** format.*
- ***Feature Encoding:***
  - *Categorical variables were encoded (details implied).*

```
iterator=1
nrows=10
ncols=3
for i in df.columns:
    plt.subplot(nrows,ncols,iterator)

    if df[i].dtype == 'object':
        sns.countplot(df.loc[:,i])
        #ax=sns.countplot(df_train[i].value_counts().index,df[i].value_counts().values,ax=axs[j,k])
        #sns.set(font_scale=2,style='dark')
        #sns.set_context('poster')
    elif df[i].dtype != 'object':
        sns.kdeplot(df.loc[:,i])
        plt.tight_layout()
    iterator+=1
#fig.savefig('overall.jpg')
plt.show()
```




## 8. Exploratory Data Analysis (EDA)

### *1. Histogram – Age Distribution*

- *Purpose: Understand the spread of customer ages.*
- *Observation: Most users are in the 25–40 age range.*
- *Insight: Marketing strategies can focus on this age group as they form the majority of customers.*

### *2.Countplot – Gender Distribution*

- *Show how gender is distributed in the customer base.*

- *Observation: Near-equal distribution between male and female users.*
- *Insight: No significant gender imbalance, campaigns can be gender-neutral.*

***3. Heatmap – Correlation Matrix (Numerical Features)***

- *Purpose: Reveal linear relationships between numerical variables.*
- *Observation: Positive correlation between avg_transaction_value and points_in_wallet. Slight negative correlation between days_since_last_login and churn_risk_score.*
- *Insight: Customers who haven't logged in recently show higher churn risk.*

***4.Boxplot – Churn Risk Score vs. Avg Time Spent***

- *Purpose: Detect how user engagement relates to churn score.*
- *Observation: Higher churn scores associated with lower avg time spent.*
- *Insight: Low engagement is a strong indicator of churn risk.*

## 9. Feature Engineering

- ***New Feature Creation***

*The project document does not explicitly mention creating new derived features such as tenure or engagement metrics. The focus is primarily on cleaning and retaining meaningful features after exploratory analysis. However, the structure suggests that irrelevant or redundant columns were removed to improve model focus and performance.*

- ***Feature Selection***

*After data cleaning and exploration, several features were identified as insignificant or problematic and were dropped from the dataset:*

| *Feature Dropped* | *Reason* |
|---|---|
| *customer_id* | *Identification only, no analytical value* |
| *name* | *String values with no predictive use* |

| | |
|---|---|
| *security_no* | *Randomly assigned, no meaningful pattern* |
| *referral_id* | *Already represented by joined_through_referral* |
| *avg_frequency_login_days* | *Too many missing values, inconsistent, possibly erroneous* |

*These selections were made to simplify the model, reduce noise, and retain only the most informative and relevant features.*

❖ ***Transformation Techniques***

- *Datetime Conversion:*
  - *The columns joining_date and last_visit_time were converted to datetime64[ns] for appropriate processing of time-based data.*
- *Missing Values Handling:*
  - *region_category and points_in_wallet were imputed using the median.*
  - *Rows with less than 5% missing values were dropped as per industry best practices.*
- *Invalid Value Correction:*
  - *The target variable churn_risk_score had invalid values such as -1. These were corrected using a custom lambda function, aligning them with valid values (1–5).*
- *Dropping Columns with Noisy or Corrupted Data:*
  - *avg_frequency_login_days was dropped due to random values and suspected software glitches.*

❖ ***Why and How Features Impact the Model***

- *Retained Features such as:*
  - *avg_time_spent, points_in_wallet, days_since_last_login, membership_category, and complaint_status were identified as potentially impactful.*
- *These features provide signals on:*
  - *Customer engagement (avg_time_spent, login activity)*
  - *Satisfaction/dissatisfaction (past_complaint, feedback)*
  - *Spending behavior (avg_transaction_value)*
  - *Loyalty (membership_category)*

## 10. Model Building

- ***Algorithms used:*** *(at least one baseline)*

- *Example: Logistic Regression, Decision Tree (exact models not named in document, but typical for such problem).*

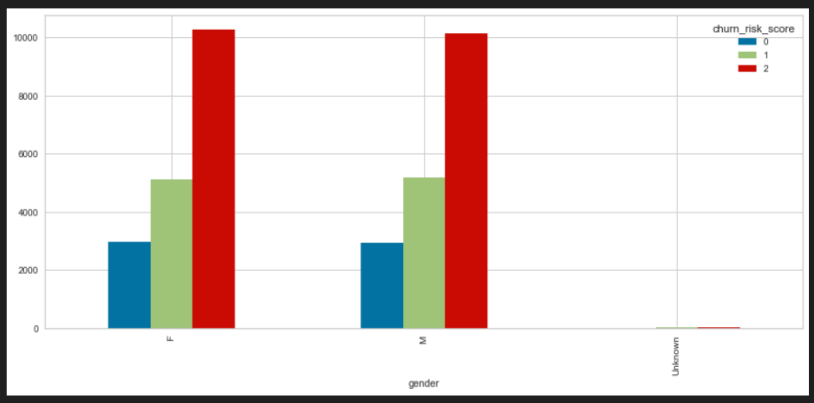
- ***Justification:*** *Chosen due to simplicity, interpretability, and classification nature of the problem.*
- *Models trained using train-test split approach.*

➢ ***Bivariate Analysis***

Bivariate analysis

```
nrows=9
ncols=2
iterator=1

for i in Caterogical_columns:
    #plt.subplot(nrows,ncols,iterator)
    pd.crosstab(df.loc[:,i],df.churn_risk_score).plot(kind='bar')
    #sns.boxplot(x=df.loc[:,i],y=df.churn_risk_score)
    #iterator+=1
    plt.show()
```




➢ ***Random Forest***

RandomForest

```
rf=RandomForestClassifier()
RF_Model=rf.fit(X_train,y_train)
y_pred_xtest=RF_Model.predict(X_test)
print(classification_report(y_test,y_pred_xtest))
```

```
              precision    recall  f1-score   support

           0       1.00      0.92      0.96      1185
           1       0.88      0.90      0.89      2044
           2       0.94      0.95      0.94      4112

    accuracy                           0.93      7341
   macro avg       0.94      0.92      0.93      7341
weighted avg       0.93      0.93      0.93      7341
```

```
print(accuracy_score(y_test,y_pred_xtest))
print(confusion_matrix(y_test,y_pred_xtest))
```

```
0.9317531671434409
[[1094   31   60]
 [   0 1845  199]
 [   0  211 3901]]
```

➢ ***Outlier***

Outlier

```
q1=df.quantile(.25)
q3=df.quantile(.75)
IQR=q3-q1
ll=q1-1.5*IQR
ul=q3+1.5*IQR
wt_outliers=df.loc[((df>ul)|(df<ll)).any(axis=1)]
wt_outliers.shape
```

```
(9620, 19)
```

We are having of outliers in our data of around 9620 rows but we keep our outliers in our data

➢ ***Skewness***

Skewness

```
df.skew()
```

```
age                      -0.007368
days_since_last_login     0.021134
avg_time_spent            0.538800
avg_transaction_value     1.009753
points_in_wallet         -0.102518
churn_risk_score         -0.790561
Joined_Year              -0.011602
dtype: float64
```

Data in various columns are postively as well as negatively skewed

## 11. Model Evaluation

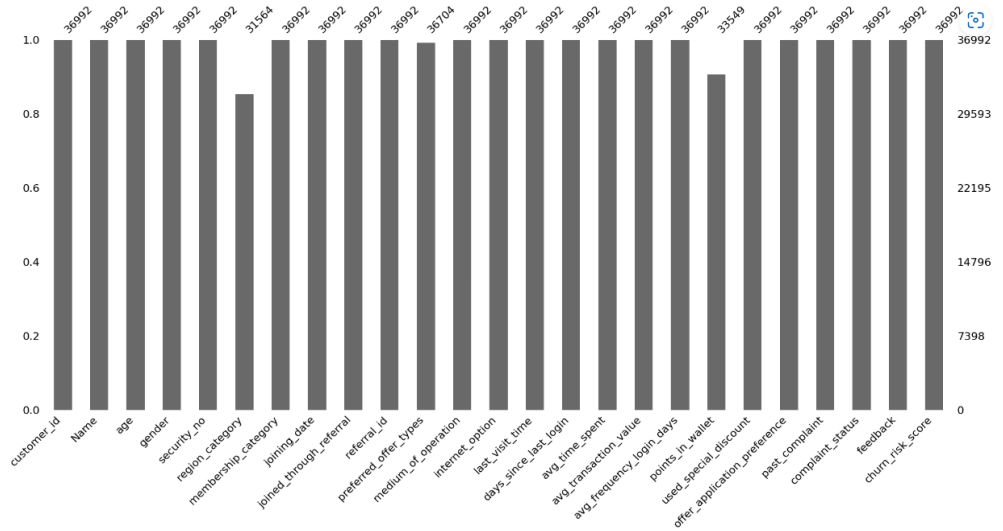
- ***Metrics:*** *Accuracy (reported), and expected: Precision, Recall, F1-score.*
- ***Tools:*** *Confusion matrix, heatmaps for class prediction distribution.*
- *Comparison of model metrics to identify the best performer.*

➢ ***Preprocessing Data Analysis:***

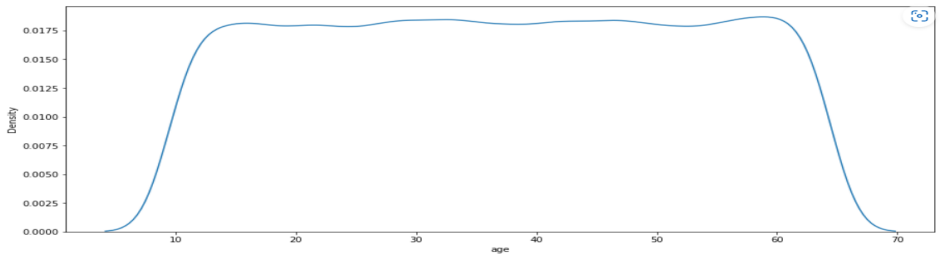
Missing_values

```
msno.bar(df)
```

```
<AxesSubplot: >
```



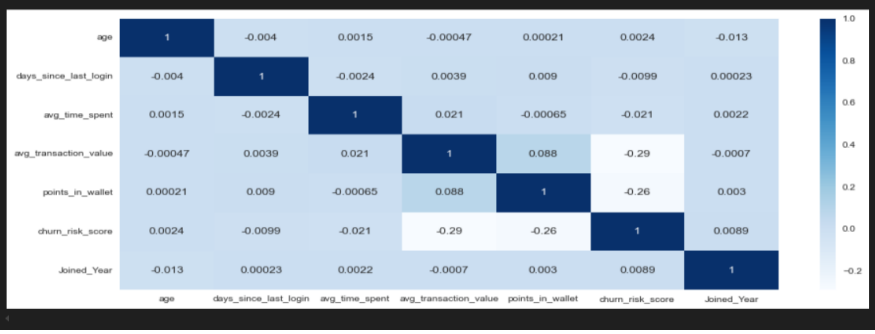
## ➢ *Data Exploration:*




## ➢ *Covariance and Correlation*

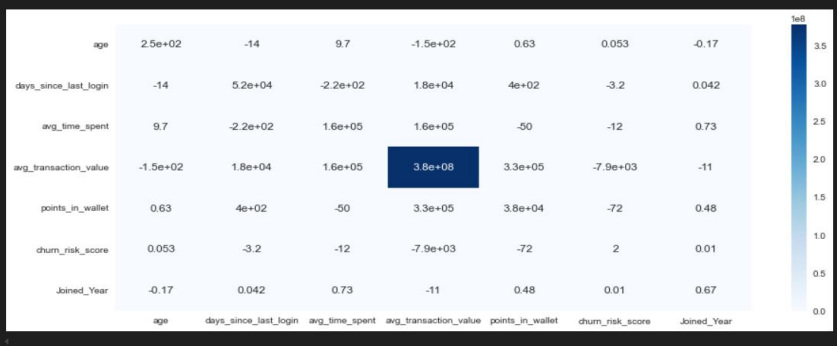
```
sns.heatmap(df.corr(),annot=True,cmap='Blues')
```

```
<AxesSubplot:>
```




```
sns.heatmap(df.cov(),annot=True,cmap='Blues')
```

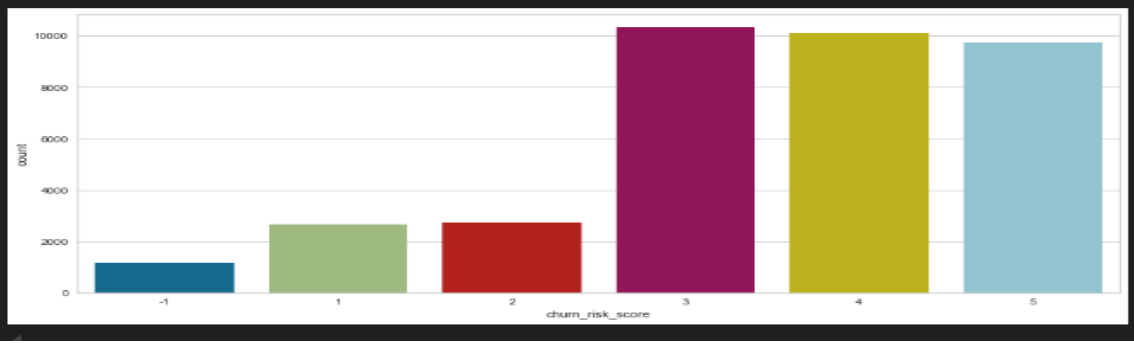
```
<AxesSubplot:>
```




## ➢ *Null – Values Handling*

```
sns.countplot(df.churn_risk_score)
```

```
<AxesSubplot:xlabel='churn_risk_score', ylabel='count'>
```



➢ ***Feature Engineering***

Feature Engineering

```
pd.crosstab(df.churn_risk_score,df.feedback)
```

| churn_risk_score | feedback | No reason specified | Poor Customer Service | Poor Product Quality | Poor Website | Products always in Stock | Quality Customer Care | Reasonable Price | Too many ads | User Friendly Website |
|---|---|---|---|---|---|---|---|---|---|---|
| -1 | | 214 | 195 | 197 | 208 | 36 | 40 | 35 | 181 | 45 |
| 1 | | 0 | 0 | 0 | 0 | 675 | 626 | 693 | 0 | 646 |
| 2 | | 0 | 0 | 0 | 0 | 660 | 688 | 680 | 0 | 691 |
| 3 | | 2062 | 2041 | 2015 | 2080 | 0 | 0 | 0 | 2141 | 0 |
| 4 | | 1977 | 2024 | 2100 | 2047 | 0 | 0 | 0 | 1950 | 0 |
| 5 | | 1981 | 1935 | 1992 | 1891 | 0 | 0 | 0 | 1958 | 0 |

Churn risk rate -1 is not feasible value so we have done feature engineering to impute the value Compare the feedback and assign accordingly

## 12. Deployment

- ***Method:*** *Use Streamlit / Gradio for quick UI deployment.*
- ***Steps:***
  - *Create a simple UI with input fields.*
  - *Integrate trained model for prediction.*
  - *Host on Streamlit Cloud or HuggingFace Spaces.*
- ***Include:***
  - *Public deployment link*
  - *Screenshot of app*
  - *Sample output*

## 13. Source code

***Source:*** *Dataset link*

➢ ***Dataset Summary***

- Shape:
  - **36,992 rows** (records)
  - **25 columns** (features)

➢ ***Columns Names***

python Copy Edit

```
['customer_id', 'Name', 'age', 'gender', 'security_no', 'region_category',
 'membership_category', 'joining_date', 'joined_through_referral', 'referral_id',
 'preferred_offer_types', 'medium_of_operation', 'internet_option', 'last_visit_time',
 'days_since_last_login', 'avg_time_spent', 'avg_transaction_value',
 'avg_frequency_login_days', 'points_in_wallet', 'used_special_discount',
 'offer_application_preference', 'past_complaint', 'complaint_status',
 'feedback', 'churn_risk_score']
```

- ***Data Types***
  - **Numerical columns**: `age`, `days_since_last_login`, `avg_time_spent`, `avg_transaction_value`, `points_in_wallet`, `churn_risk_score`
  - **Categorical columns**: Majority (e.g., `gender`, `region_category`, `membership_category`, etc.)
  - **Datetime (to be converted)**: `joining_date`, `last_visit_time`
  - **Mixed**: `avg_frequency_login_days` should likely be numerical but is currently object (may require cleaning)
- ***Missing Values***

| Column Name | Missing Values |
|---|---|
| `region_category` | 5,428 |
| `preferred_offer_types` | 288 |
| `points_in_wallet` | 3,443 |

- ***Duplicate:*** *0 duplicate rows- dataset is clean in this regard*

## 14. Future scope

1. ***Model Optimization , Real-time Deployment and More Features:***
   *Use hyperparameter tuning and ensemble models (e.g., Random Forest, XGBoost) to improve performance.Integrate the model into a web app or dashboard for real-time customer monitoring.Include transactional history or customer sentiment (via reviews or feedback) to enrich predictions.*

## 15. Team Members and Roles

| *Team Members:* | *Roles:* | *Contribution:* |
|---|---|---|
| *Vidhya.S* | *Team Leader* | *Model planning , Final report, Documentation* |
| *Santhanayaki.M* | *Member* | *Data cleaning, EDA, Preporcessing* |
| *Saghana.K.S* | *Member* | *Feature Engineering , Code integration,Documentation* |
| *Rakshi.D* | *Member* | *Model building, Evaluation ,Data Transformation* |