OLA Business Case:

Business Problem Statement:

- Recruiting and retaining drivers is seen by industry watchers as a tough battle for Ola. Churn among drivers is high and it's very easy for drivers to stop working for the service on the fly or jump to Uber depending on the rates.
- As the companies get bigger, the high churn could become a bigger problem. To find new drivers, Ola is casting a wide net, including people who don't have cars for jobs. But this acquisition is really costly. Losing drivers frequently impacts the morale of the organization and acquiring new drivers is more expensive than retaining existing ones.
- You are working as a data scientist with the Analytics Department of Ola, focused on driver team attrition. You are provided with the monthly information for a segment of drivers for 2019 and 2020 and tasked to predict whether a driver will be leaving the company or not based on their attributes like:
  - Demographics (city, age, gender etc.)
  - Tenure information (joining date, Last Date)
  - Historical data regarding the performance of the driver (Quarterly rating, Monthly business acquired, grade, Income)

In [ ]:

```

```

Dataset Columns Information:

- MMMM-YY : Reporting Date (Monthly)
- Driver_ID : Unique id for drivers
- Age : Age of the driver
- Gender : Gender of the driver – Male : 0, Female: 1
- City : City Code of the driver
- Education_Level : Education level – 0 for 10+ ,1 for 12+ ,2 for graduate
- Income : Monthly average Income of the driver
- Date Of Joining : Joining date for the driver
- LastWorkingDate : Last date of working for the driver
- Joining Designation : Designation of the driver at the time of joining
- Grade : Grade of the driver at the time of reporting
- Total Business Value : The total business value acquired by the driver in a month (negative business indicates cancellation/refund or car EMI adjustments)
- Quarterly Rating : Quarterly rating of the driver: 1,2,3,4,5 (higher is better)

In [ ]:

```

```

To Do:

1. Perform basic univariate data analysis about each column of the data and find missing values/outliers
2. Aggregate data in order to remove multiple occurrences of same driver data
3. Perform data preprocessing - Duplicate value check and imputation, missing value check and imputation (using KNN Imputer), outlier treatment, class imbalance treatment, feature engineering (creating features for quarterly rating increase and monthly income increase), target variable creation
4. Find which features contribute the most towards driver churn using EDA (bi-variate analysis) and Hypothesis testing
5. Check correlation among independent variables and how they interact with each other
6. Use Bagging and Boosting models, explain the results, try with Hyperparameter tuning
7. Do model evaluation (Classification Report/ROC-AUC/Precision-Recall)
8. Provide actionable Insights & Recommendations

In [ ]:

Importing required Libraries and Dataset:

In [3]:
```
import calendar
import joblib
import math
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from scipy.stats import spearmanr
import seaborn as sns

from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import lightgbm as lgbm

from sklearn.metrics import (
    classification_report, roc_auc_score,
    roc_curve, f1_score,
    confusion_matrix, ConfusionMatrixDisplay,
    classification_report
)
```

In [4]:
```
import warnings
warnings.filterwarnings('ignore')
pd.set_option('display.max_columns', None)

import matplotlib_inline
matplotlib_inline.backend_inline.set_matplotlib_formats('svg')

from IPython.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
```

In [ ]:

In [1]:
```
!python -m wget https://d2beiqkhq929f0.cloudfront.net/public_assets/assets/000/002/492/original/ola_driver_scaler.csv
```

```
Saved under ola_driver_scaler.csv
```

In [14]:
```
df = pd.read_csv("ola_driver_scaler.csv")
df.drop(columns=['Unnamed: 0'], inplace=True)
df_original = df.copy()
```

In [15]:
```
df.head()
```

Out[15]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
0	01/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	2381060	2
1	02/01/19	1	28.0	0.0	C23	2	57387	24/12/18	NaN	1	1	-665480	2
2	03/01/19	1	28.0	0.0	C23	2	57387	24/12/18	03/11/19	1	1	0	2
3	11/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1
4	12/01/20	2	31.0	0.0	C7	2	67016	11/06/20	NaN	2	2	0	1

In [16]:
```
df.tail()
```

Out[16]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
19099	08/01/20	2788	30.0	0.0	C27	2	70254	06/08/20	NaN	2	2	740280	3
19100	09/01/20	2788	30.0	0.0	C27	2	70254	06/08/20	NaN	2	2	448370	3
19101	10/01/20	2788	30.0	0.0	C27	2	70254	06/08/20	NaN	2	2	0	2
19102	11/01/20	2788	30.0	0.0	C27	2	70254	06/08/20	NaN	2	2	200420	2
19103	12/01/20	2788	30.0	0.0	C27	2	70254	06/08/20	NaN	2	2	411480	2

In [ ]:

Basic Statistical Summary of Dataset:

In [17]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19104 entries, 0 to 19103
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   MMM-YY                19104 non-null  object 
 1   Driver_ID             19104 non-null  int64  
 2   Age                   19043 non-null  float64
 3   Gender                19052 non-null  float64
 4   City                  19104 non-null  object 
 5   Education_Level       19104 non-null  int64  
 6   Income                19104 non-null  int64  
 7   Dateofjoining         19104 non-null  object 
 8   LastWorkingDate       1616 non-null   object 
 9   Joining Designation   19104 non-null  int64  
 10  Grade                 19104 non-null  int64  
 11  Total Business Value  19104 non-null  int64  
 12  Quarterly Rating      19104 non-null  int64  
dtypes: float64(2), int64(7), object(4)
memory usage: 1.9+ MB
```

In [18]:
```
df.describe(include="all")
```

Out[18]:

	MMM-YY	Driver_ID	Age	Gender	City	Education_Level	Income	Dateofjoining	LastWorkingDate	Joining Designation	Grade	Total Business Value	Quarterly Rating
count	19104	19104.000000	19043.000000	19052.000000	19104	19104.000000	19104.000000	19104	1616	19104.000000	19104.000000	1.910400e+04	19104.000000
unique	24	NaN	NaN	NaN	29	NaN	NaN	869	493	NaN	NaN	NaN	NaN
top	01/01/19	NaN	NaN	NaN	C20	NaN	NaN	23/07/15	29/07/20	NaN	NaN	NaN	NaN
freq	1022	NaN	NaN	NaN	1008	NaN	NaN	192	70	NaN	NaN	NaN	NaN
mean	NaN	1415.591133	34.668435	0.418749	NaN	1.021671	65652.025126	NaN	NaN	1.690536	2.252670	5.716621e+05	2.008899
std	NaN	810.705321	6.257912	0.493367	NaN	0.800167	30914.515344	NaN	NaN	0.836984	1.026512	1.128312e+06	1.009832
min	NaN	1.000000	21.000000	0.000000	NaN	0.000000	10747.000000	NaN	NaN	1.000000	1.000000	-6.000000e+06	1.000000
25%	NaN	710.000000	30.000000	0.000000	NaN	0.000000	42383.000000	NaN	NaN	1.000000	1.000000	0.000000e+00	1.000000
50%	NaN	1417.000000	34.000000	0.000000	NaN	1.000000	60087.000000	NaN	NaN	1.000000	2.000000	2.500000e+05	2.000000
75%	NaN	2137.000000	39.000000	1.000000	NaN	2.000000	83969.000000	NaN	NaN	2.000000	3.000000	6.997000e+05	3.000000
max	NaN	2788.000000	58.000000	1.000000	NaN	2.000000	188418.000000	NaN	NaN	5.000000	5.000000	3.374772e+07	4.000000

In [19]:
```
df.columns
```

Out[19]:
```
Index(['MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City', 'Education_Level',
       'Income', 'Dateofjoining', 'LastWorkingDate', 'Joining Designation',
       'Grade', 'Total Business Value', 'Quarterly Rating'],
      dtype='object')
```

In [20]:
```
df.shape
```

Out[20]:
```
(19104, 13)
```

In [ ]:

Checking datatypes of columns in Dataset:

In [22]:
```
df.dtypes
```

Out[22]:
```
MMM-YY                   object
Driver_ID                 int64
Age                     float64
Gender                  float64
City                     object
Education_Level           int64
Income                    int64
Dateofjoining            object
LastWorkingDate          object
Joining Designation       int64
Grade                     int64
Total Business Value      int64
Quarterly Rating          int64
dtype: object
```

In [ ]:

Data Preprocessing:

Updating the names of columns in Dataset:

In [23]:
```
df = df.rename(columns={"Dateofjoining": "Date_Of_Joining",
                        "LastWorkingDate": "Last_Working_Date",
                        "Joining Designation": "Joining_Designation",
                        "Total Business Value": "Total_Business_Value",
                        "Quarterly Rating": "Quarterly_Rating"
                       })
```

In [24]:
```
df.columns
```

Out[24]:
```
Index(['MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City', 'Education_Level',
       'Income', 'Date_Of_Joining', 'Last_Working_Date', 'Joining_Designation',
       'Grade', 'Total_Business_Value', 'Quarterly_Rating'],
      dtype='object')
```

In [ ]:

Data Preprocessing:

Updating the datatypes of specific columns in Dataset:

In [25]:
```
df['MMM-YY'] = pd.to_datetime(df['MMM-YY'], format="%m/%d/%y")
df['Date_Of_Joining'] = pd.to_datetime(df['Date_Of_Joining'], format="%d/%m/%y")
df['Last_Working_Date'] = pd.to_datetime(df['Last_Working_Date'], format="%d/%m/%y")
```

In [ ]:

Unique Values in Columns:

In [26]:
```
df.nunique()
```

Out[26]:
```
MMM-YY                     24
Driver_ID                2381
Age                        36
Gender                      2
City                       29
Education_Level             3
Income                   2383
Date_Of_Joining           869
Last_Working_Date         493
Joining_Designation         5
Grade                       5
Total_Business_Value    10181
Quarterly_Rating            4
dtype: int64
```

In [ ]:

Data Preprocessing:

Duplicate Value Check:

In [28]:
```
def find_duplicate_rows(df):
    duplicate_row_indices = df[df.duplicated(keep=False)].index.tolist()
    if len(duplicate_row_indices) > 0:
        return duplicate_row_indices
    else:
        return "No duplicate rows found in the DataFrame."
```

In [30]:
```
find_duplicate_rows(df)
```

Out[30]:
```
'No duplicate rows found in the DataFrame.'
```

In [29]:
```
def find_duplicate_columns(df):
    duplicate_columns = set()
    for i in range(df.shape[1]):
        col = df.iloc[:,i]
        for j in range(i+1, df.shape[1]):
            if col.equals(df.iloc[:,j]):
                duplicate_columns.add(df.columns[j])
    if len(duplicate_columns) > 0:
        return list(duplicate_columns)
    else:
        return "No duplicate columns found in the DataFrame."
```

In [31]:
```
find_duplicate_columns(df)
```

Out[31]:
```
'No duplicate columns found in the DataFrame.'
```

In [ ]:

Data Preprocessing:

Missing Value Check and Imputation:

In [32]:
```
def find_missing_value_percentage(df):

    missing_df = df.isna().sum()
    missing_df_non_zero = missing_df[missing_df!=0]
    missing_df_non_zero.sort_values(ascending=False, inplace=True)
    missing_df_non_zero_perc = (missing_df_non_zero/df.shape[0]).round(4)*100
    missing_df_non_zero_perc = [
        str(round(x, 2)) + ' %' for x in list(missing_df_non_zero_perc.values)
    ]
    missing_values_final_df = pd.DataFrame({
        'Feature name' : list(missing_df_non_zero.index),
        'Missing value %' : missing_df_non_zero_perc
        }
    )
    print(missing_values_final_df)
```

In [33]:
```
find_missing_value_percentage(df)
```

```
        Feature name Missing value %
0  Last_Working_Date         91.54 %
1                Age          0.32 %
2             Gender          0.27 %
```

There is a very high percentage of missing values in LastworkingDate but that's okay because that's not a feature used in model training, it'll be actually used to create target variable (is_churned)

In [ ]:

Data Preprocessing:

Initial Cleaning, Preprocessing and Aggregation before EDA:

In [35]:
```
df.columns
```

Out[35]:
```
Index(['MMM-YY', 'Driver_ID', 'Age', 'Gender', 'City', 'Education_Level',
       'Income', 'Date_Of_Joining', 'Last_Working_Date', 'Joining_Designation',
       'Grade', 'Total_Business_Value', 'Quarterly_Rating'],
      dtype='object')
```

In [34]:
```
df.sort_values(by=['Driver_ID', 'MMM-YY'], inplace=True)
```

In [36]:
```
dfg = df.groupby('Driver_ID').agg({
    'MMM-YY' : 'count',
    'Age' : 'mean',
    'Gender' : 'mean',
    'City' : 'first',
    'Education_Level' : 'first',
    'Income' : 'unique',
    'Date_Of_Joining' : 'first',
    'Last_Working_Date': 'last',
    'Joining_Designation': 'first',
    'Grade': 'unique',
    'Total_Business_Value': 'unique',
    'Quarterly_Rating': 'unique'
}).reset_index()
```

In [45]:
```
def create_increase_flag(ip_array):
    if len(ip_array)==1:
        return 0
    diff_array = ip_array[1:] - ip_array[:-1]
    diff_array[diff_array == 0] = 0
    diff_array[diff_array > 0] = 1
    diff_array[diff_array < 0] = -1
    return diff_array.mean()


def create_last_tenure_diff(input_array):
    if len(input_array)==1:
        return 0
    return np.sign(input_array[-1] - input_array[-2])


def is_promoted(row):
    diff = row['avg_grade'] - row['Joining_Designation']
    if math.isclose(diff, 0):
        return 0
    elif diff > 0:
        return 1
    return -1
```

In [ ]:

In [38]:
```
dfg.rename(columns={'MMM-YY' : 'num_months'}, inplace=True)
dfg['DOJ_Year'] = dfg['Date_Of_Joining'].dt.year
dfg['DOJ_Month'] = dfg['Date_Of_Joining'].dt.month_name()
dfg['Gender'] = dfg['Gender'].map({0.0 : 'Male', 1.0 : 'Female'})
dfg['Age'] = dfg['Age'].astype('int')
```

In [39]:
```
dfg['avg_income'] = dfg['Income'].apply(np.mean)
dfg['income_increase_flag'] = dfg['Income'].apply(create_increase_flag)
dfg['income_last_tenure_diff'] = dfg['Income'].apply(create_last_tenure_diff).astype('int')
```

In [40]:
```
dfg['avg_grade'] = dfg['Grade'].apply(np.mean)
dfg['grade_increase_flag'] = dfg['Grade'].apply(create_increase_flag)
dfg['grade_last_tenure_diff'] = dfg['Grade'].apply(create_last_tenure_diff)
```

In [41]:
```
dfg['avg_total_business_value'] = dfg['Total_Business_Value'].apply(np.mean)
dfg['total_business_value_increase_flag'] = dfg['Total_Business_Value'].apply(create_increase_flag)
dfg['total_business_value_last_tenure_diff'] = dfg['Total_Business_Value'].apply(create_last_tenure_diff).astype('int')
```

In [42]:
```
dfg['avg_quarterly_rating'] = dfg['Quarterly_Rating'].apply(np.mean)
dfg['quarterly_rating_increase_flag'] = dfg['Quarterly_Rating'].apply(create_increase_flag)
dfg['quarterly_rating_last_tenure_diff'] = dfg['Quarterly_Rating'].apply(create_last_tenure_diff).astype('int')
```

In [46]:
```
dfg['is_promoted'] = dfg.apply(is_promoted, axis=1)
dfg['churned'] = [0]*dfg.shape[0]
dfg.loc[~dfg.Last_Working_Date.isnull(), 'churned'] = 1
```

In [ ]:

In [48]:
```
dfg.drop(
    columns=[
        'Income', 'Grade', 'Total_Business_Value',
        'Quarterly_Rating', 'Last_Working_Date',
        'Driver_ID', 'Date_Of_Joining'
    ],
    inplace=True
)
```

In [51]:
```
dfg['index'] = dfg.index
```

In [52]:
```
dfg.columns
```

Out[52]:
```
Index(['num_months', 'Age', 'Gender', 'City', 'Education_Level',
       'Joining_Designation', 'DOJ_Year', 'DOJ_Month', 'avg_income',
       'income_increase_flag', 'income_last_tenure_diff', 'avg_grade',
       'grade_increase_flag', 'grade_last_tenure_diff',
       'avg_total_business_value', 'total_business_value_increase_flag',
       'total_business_value_last_tenure_diff', 'avg_quarterly_rating',
       'quarterly_rating_increase_flag', 'quarterly_rating_last_tenure_diff',
       'is_promoted', 'churned', 'index'],
      dtype='object')
```

In [53]:
```
dfg.head()
```

Out[53]:

	num_months	Age	Gender	City	Education_Level	Joining_Designation	DOJ_Year	DOJ_Month	avg_income	income_increase_flag	income_last_tenure_diff	avg_grade	grade_increase_flag	grade_last_tenure_diff	avg_
0	3	28	Male	C23	2	1	2018	December	57387.0	0.0	0	1.0	0.0	0	
1	2	31	Male	C7	2	2	2020	June	67016.0	0.0	0	2.0	0.0	0	
2	5	43	Male	C13	2	2	2019	July	65603.0	0.0	0	2.0	0.0	0	
3	3	29	Male	C9	0	1	2019	September	46368.0	0.0	0	1.0	0.0	0	
4	5	31	Female	C11	1	3	2020	July	78728.0	0.0	0	3.0	0.0	0	

In [54]:
```
dfg.tail()
```

Out[54]:

	num_months	Age	Gender	City	Education_Level	Joining_Designation	DOJ_Year	DOJ_Month	avg_income	income_increase_flag	income_last_tenure_diff	avg_grade	grade_increase_flag	grade_last_tenure_diff	a
2376	24	33	Male	C24	0	2	2015	October	82815.0	0.0	0	3.0	0.0	0	
2377	3	34	Female	C9	0	1	2020	August	12105.0	0.0	0	1.0	0.0	0	
2378	9	44	Male	C19	0	2	2018	July	35370.0	0.0	0	2.0	0.0	0	
2379	6	28	Female	C20	2	1	2018	July	69498.0	0.0	0	1.0	0.0	0	
2380	7	29	Male	C27	2	2	2020	August	70254.0	0.0	0	2.0	0.0	0	

In [56]:
```
dfg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2381 entries, 0 to 2380
Data columns (total 23 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   num_months                          2381 non-null   int64  
 1   Age                                 2381 non-null   int32  
 2   Gender                              2381 non-null   object 
 3   City                                2381 non-null   object 
 4   Education_Level                     2381 non-null   int64  
 5   Joining_Designation                 2381 non-null   int64  
 6   DOJ_Year                            2381 non-null   int64  
 7   DOJ_Month                           2381 non-null   object 
 8   avg_income                          2381 non-null   float64
 9   income_increase_flag                2381 non-null   float64
 10  income_last_tenure_diff             2381 non-null   int32  
 11  avg_grade                           2381 non-null   float64
 12  grade_increase_flag                 2381 non-null   float64
 13  grade_last_tenure_diff              2381 non-null   int64  
 14  avg_total_business_value            2381 non-null   float64
 15  total_business_value_increase_flag  2381 non-null   float64
 16  total_business_value_last_tenure_diff 2381 non-null   int32  
 17  avg_quarterly_rating                2381 non-null   float64
 18  quarterly_rating_increase_flag      2381 non-null   float64
 19  quarterly_rating_last_tenure_diff   2381 non-null   int32  
 20  is_promoted                         2381 non-null   int64  
 21  churned                             2381 non-null   int64  
 22  index                               2381 non-null   int64  
dtypes: float64(8), int32(4), int64(8), object(3)
memory usage: 390.8+ KB
```

In [57]:
```
dfg.shape
```

Out[57]:
```
(2381, 23)
```

After aggregation, there are only 2500 rows, hence the dataset size is quite less

In [58]:
```
find_missing_value_percentage(dfg)
```

```
Empty DataFrame
Columns: [Feature name, Missing value %]
Index: []
```

There are no missing values in the new dataset

In [ ]:
```

```

Data Preprocessing:

KNN Imputation:

Note: Missing value imputation technique like KNNImputation is not needed because the aggregation automatically takes care of missing values as well as create new features.

In [59]:
```
dfg.describe()
```

Out[59]:

ase_flag	grade_last_tenure_diff	avg_total_business_value	total_business_value_increase_flag	total_business_value_last_tenure_diff	avg_quarterly_rating	quarterly_rating_increase_flag	quarterly_rating_last_tenure_diff	is_prom
1.000000	2381.000000	2.381000e+03	2381.000000	2381.000000	2381.000000	2381.000000	2381.000000	2381.0
0.018480	0.018480	3.745311e+05	0.122662	-0.019740	1.536679	0.036539	-0.005880	0.1
0.134706	0.134706	4.994292e+05	0.439303	0.836176	0.672356	0.596848	0.681051	0.3
0.000000	0.000000	-2.771060e+05	-1.000000	-1.000000	1.000000	-1.000000	-1.000000	0.0
0.000000	0.000000	0.000000e+00	0.000000	-1.000000	1.000000	0.000000	0.000000	0.0
0.000000	0.000000	2.239375e+05	0.000000	0.000000	1.000000	0.000000	0.000000	0.0
0.000000	0.000000	5.325633e+05	0.250000	1.000000	2.000000	0.000000	0.000000	0.0
1.000000	1.000000	4.333230e+06	1.000000	1.000000	4.000000	1.000000	1.000000	1.0

In [60]:
```
df = dfg.copy()
```

In [ ]:

Exploratory Data Analysis (EDA):

Defining important functions for performing EDA:

In [61]:
```
def display_normalized_value_counts(data, col):
    print(data[col].value_counts(normalize=True).round(4)*100)
```

In [62]:
```
def display_cumulative_value_counts(data, col):
    print((data[col].value_counts(normalize=True).round(4)*100).cumsum())
```

In [63]:
```
def display_countplot(data, col, order=False, order_list=None, rot=False):
    if order:
        order = order_list if order_list else sorted(data[col].astype('int').unique().tolist())
        sns.countplot(data=data, x=col, order=order)
    else:
        sns.countplot(data=data, x=col)
    if rot:
        plt.xticks(rotation=90)
    plt.show()
```

In [162]:
```
def display_countplot_with_hue(data, col_x, col_hue, order_col=None, rot=False):
    if order_col:
        sns.countplot(data=data, x=col_x, hue=col_hue, order=order_col)
    else:
        sns.countplot(data=data, x=col_x, hue=col_hue)
    if rot:
        plt.xticks(rotation=60)
        plt.show()
```

In [65]:
```
def display_countplot_top_k_categories(data, col, k, include_na=False, rot=False):
    if not include_na:
        data=data.loc[((~data[col].isna()) & (data[col]!='NA'))]
    top_k_categories = data[col].value_counts()[:k].index.tolist()
    sns.countplot(data=data.loc[data[col].isin(top_k_categories)], x=col, order=top_k_categories)
    if rot:
        plt.xticks(rotation=45)
    plt.show()
```

In [66]:
```
def display_kde_plot(data, col):
    sns.kdeplot(data=data, x=col)
    plt.grid()
    plt.show()
```

In [67]:
```
def display_kde_plot_with_hue(data, col_x, col_hue, hue_order=None):
    sns.kdeplot(data=data, x=col_x, hue=col_hue, hue_order=hue_order)
    plt.grid()
    plt.show()
```

In [68]:
```
def display_two_kde_plots(data, col1, col2, xlabel=None):
    sns.kdeplot(data=data, x=col1, label=col1)
    sns.kdeplot(data=data, x=col2, label=col2)
    if xlabel:
        plt.xlabel(xlabel)
    plt.legend()
    plt.grid()
    plt.show()
```

In [69]:
```
def display_cdf_plot(data, col):
    sns.ecdfplot(data=data, x=col)
    plt.yticks(np.arange(0, 1.1, 0.1))
    plt.grid()
    plt.show()
```

In [70]:
```
def display_smooth_cdf_plot(data, col, bandwidth=None):
    kde = gaussian_kde(data[col], bw_method=bandwidth)
    x = np.linspace(min(data[col]), max(data[col]), 100)
    cdf = np.cumsum(kde(x))
    cdf = cdf / cdf[-1]
    plt.yticks(np.arange(0, 1.1, 0.1))
    plt.plot(x, cdf)
    plt.grid()
    plt.show()
```

In [71]:
```
def display_box_plot(data, col):
    sns.boxplot(data=data, x=col)
    plt.grid()
    plt.show()
```

In [72]:
```
def display_box_plot_2d(data, col_x, col_y, col_order=None):
    sns.boxplot(data=data, x=col_x, y=col_y, order=col_order)
    plt.grid()
    plt.show()
```

In [73]:
```
def display_two_box_plots(data, col1, col2):
    plt.subplot(211)
    sns.boxplot(data=data, x=col1, color='r')
    plt.subplot(212)
    sns.boxplot(data=data, x=col2, color='b')
    plt.show()
```

In [74]:
```
def display_bar_plot(data, col1, col2, rot=False, grid=True):
    sns.barplot(data=data, x=col1, y=col2)
    if grid:
        plt.grid()
    if rot:
        plt.xticks(rotation=60)
    plt.show()
```

In [75]:
```
def display_scatter_plot(data, col_x, col_y, grid=True):
    sns.scatterplot(data=data, x=col_x, y=col_y)
    if grid:
        plt.grid()
    plt.show()
```

In [76]:
```
def display_pearson_corr_coef(data, x, y):
    print(f"PCC between '{x}' and '{y}' = {np.corrcoef(data[x], data[y]).round(3)[0, 1]}")
```

In [77]:
```
def display_spearman_rank_corr_coef(data, x, y):
    print(f"SRCC between '{x}' and '{y}' = {round(spearmanr(data[x], data[y])[0], 3)}")
```

In [78]:
```
def display_correlation_plot(df):
    sns.heatmap(df.corr(), annot=True, fmt='.2f')
```

In [142]:
```
def display_grouped_value_counts_percentage(df, col, target_col='churned', temp_col='index'):
    df2 = df.groupby([col, target_col]).agg({temp_col : 'count'}).reset_index().rename({temp_col : 'count'}, axis=1)
    dfg_sum = df2.groupby(col).agg({'count' : 'sum'}).reset_index().rename({'count' : 'sum'}, axis=1)
    dff = df2.merge(dfg_sum, on=col)
    dff['percentage']=(dff['count']/dff['sum']).round(4)*100

    return dff.drop(columns=['count', 'sum'])
```

In [ ]:

Univariate Analysis:

In [81]:
```
plt.rcParams["figure.figsize"] = (18,6)
```

In [80]:
```
df.columns
```

Out[80]:
```
Index(['num_months', 'Age', 'Gender', 'City', 'Education_Level',
       'Joining_Designation', 'DOJ_Year', 'DOJ_Month', 'avg_income',
       'income_increase_flag', 'income_last_tenure_diff', 'avg_grade',
       'grade_increase_flag', 'grade_last_tenure_diff',
       'avg_total_business_value', 'total_business_value_increase_flag',
       'total_business_value_last_tenure_diff', 'avg_quarterly_rating',
       'quarterly_rating_increase_flag', 'quarterly_rating_last_tenure_diff',
       'is_promoted', 'churned', 'index'],
      dtype='object')
```

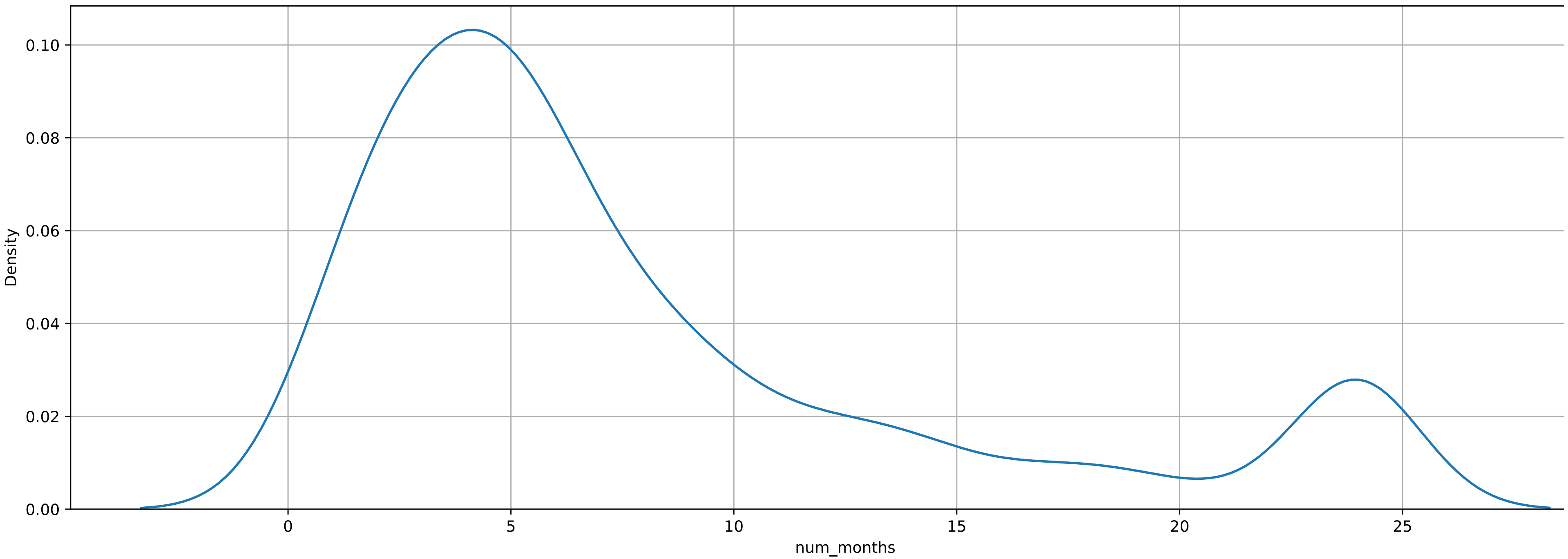
In [ ]:

Number of months spent:

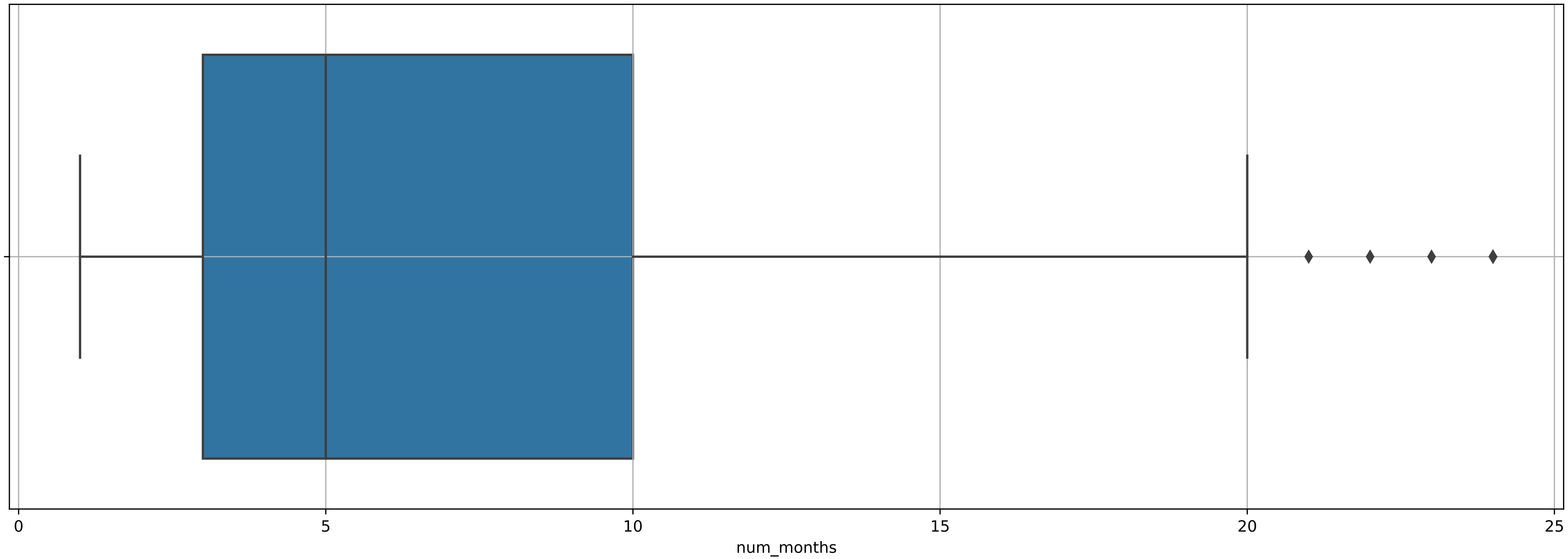
In [82]:
```
df['num_months'].describe()
```

Out[82]:
```
count    2381.00000
mean        8.02352
std         6.78359
min         1.00000
25%         3.00000
50%         5.00000
75%        10.00000
max        24.00000
Name: num_months, dtype: float64
```

In [83]:
```
display_kde_plot(df, 'num_months')
```



In [84]:
```
display_box_plot(df, 'num_months')
```



Tenure is a right skewed distribution with median tenure at about 5 months, it contains outliers on the right side

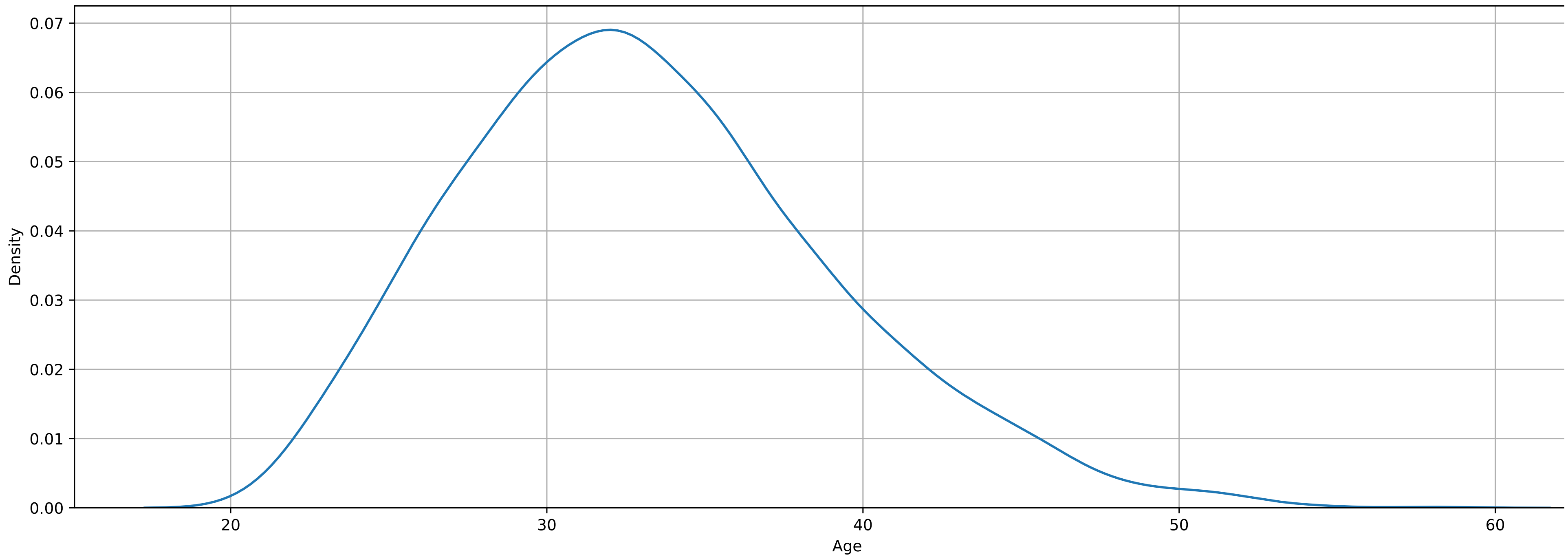
In [ ]:

Age:

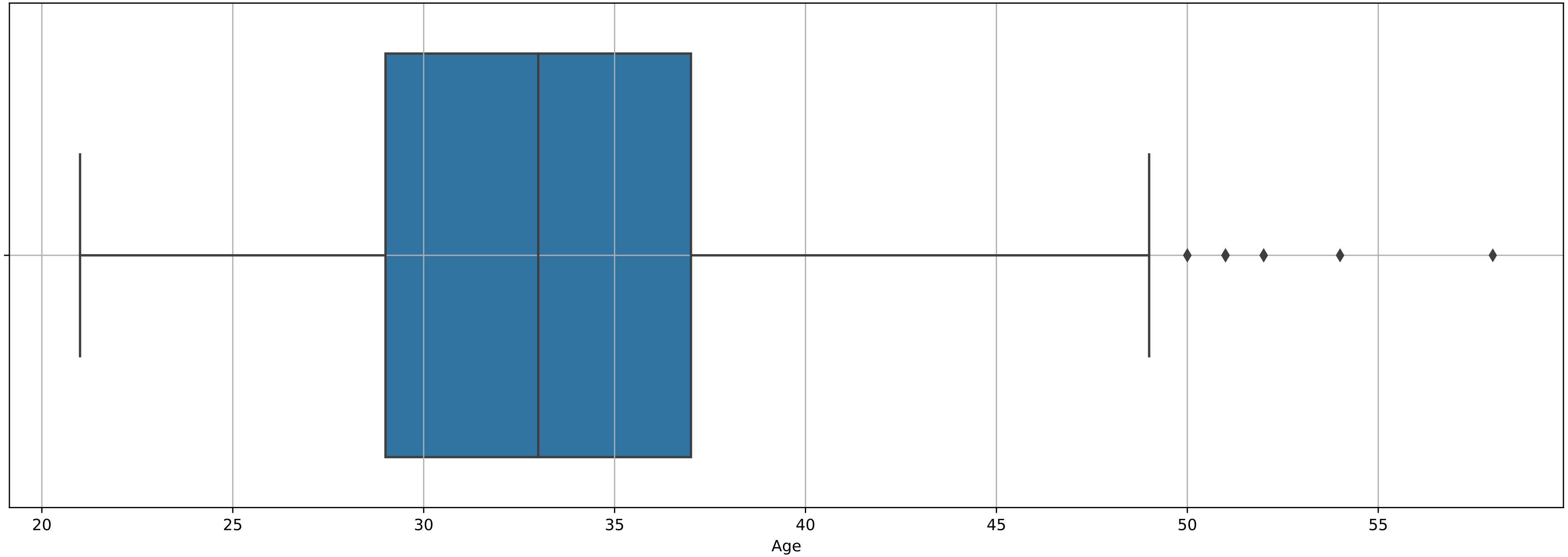
In [85]:
```
df['Age'].describe()
```

Out[85]:
```
count    2381.000000
mean       33.149937
std         5.868427
min        21.000000
25%        29.000000
50%        33.000000
75%        37.000000
max        58.000000
Name: Age, dtype: float64
```

In [86]:
```
display_kde_plot(df, 'Age')
```



In [87]:
```
display_box_plot(df, 'Age')
```



Age is almost a symmetric distribution with some outliers on the RHS and median age is about 33

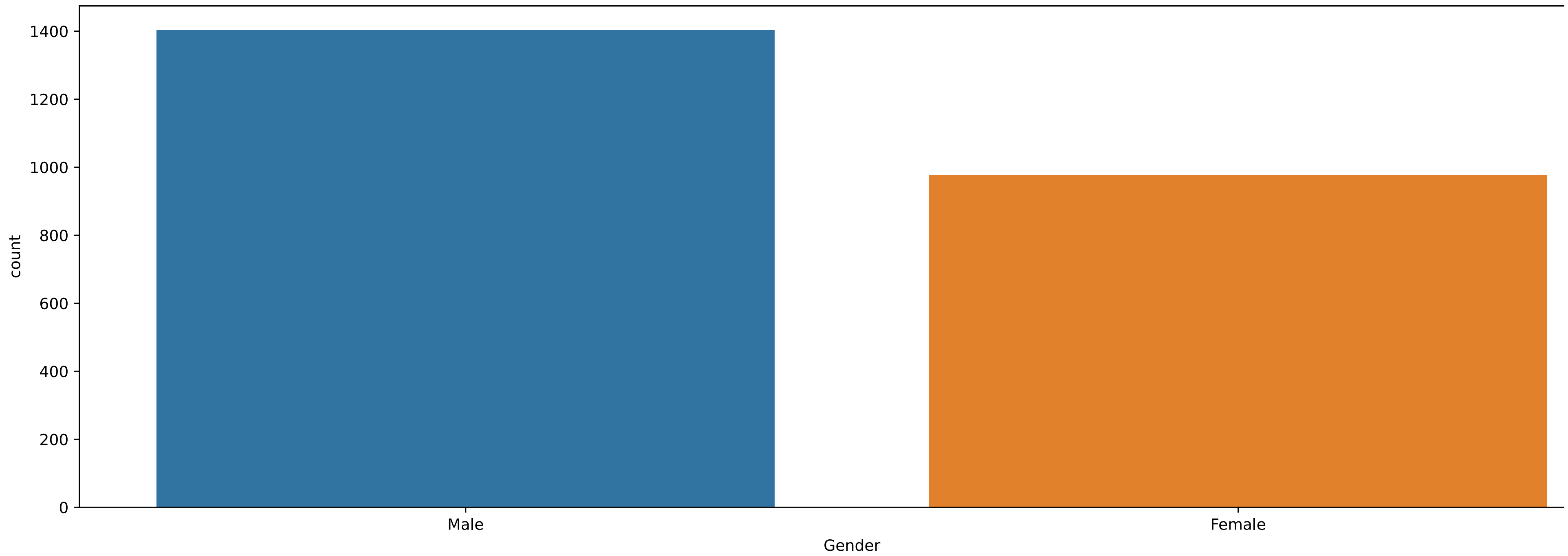
In [ ]:

Gender:

In [89]:
```
display_normalized_value_counts(df, 'Gender')
```

```
Male      58.97
Female    41.03
Name: Gender, dtype: float64
```

In [90]:
```
display_countplot(df, 'Gender')
```



Ratio of Male:Female in Ola drivers is 60:40 (which is reasonable as Driver profession is a male dominated industry)

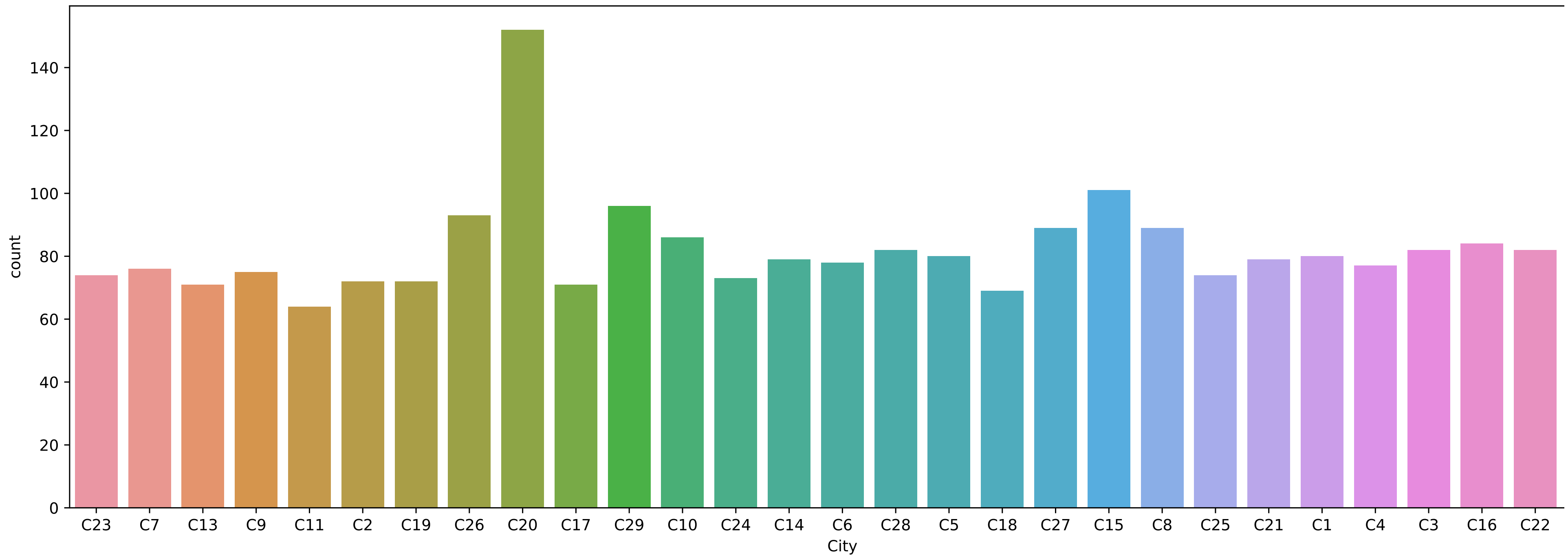
In [ ]:

City:

In [91]:
```
display_normalized_value_counts(df, "City")
```

```
C20    6.38
C15    4.24
C29    4.03
C26    3.91
C8     3.74
C27    3.74
C10    3.61
C16    3.53
C22    3.44
C3     3.44
C28    3.44
C12    3.40
C5     3.36
C1     3.36
C21    3.32
C14    3.32
C6     3.28
C4     3.23
C7     3.19
C9     3.15
C25    3.11
C23    3.11
C24    3.07
C19    3.02
C2     3.02
C17    2.98
C13    2.98
C18    2.90
C11    2.69
Name: City, dtype: float64
```

In [92]:
```
display_countplot(df, 'City')
```



Number of drivers across most cities is almost similar with the exception being C20 which contains approx. 6% of the drivers

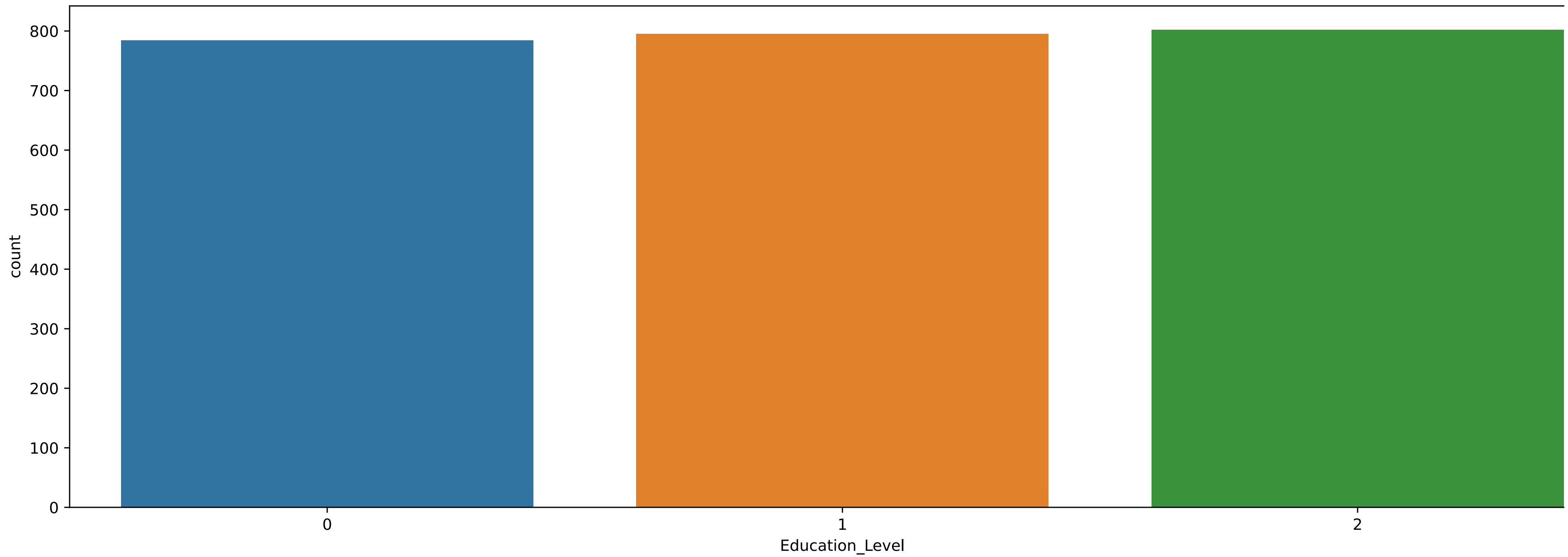
In [ ]:

Education Level:

In [93]:
```
display_normalized_value_counts(df, "Education_Level")
```

```
2    33.68
1    33.39
0    32.93
Name: Education_Level, dtype: float64
```

In [94]:
```
display_countplot(df, 'Education_Level')
```



There are equal proportion of drivers which studied upto 10th, upto 12th and those who are graduates

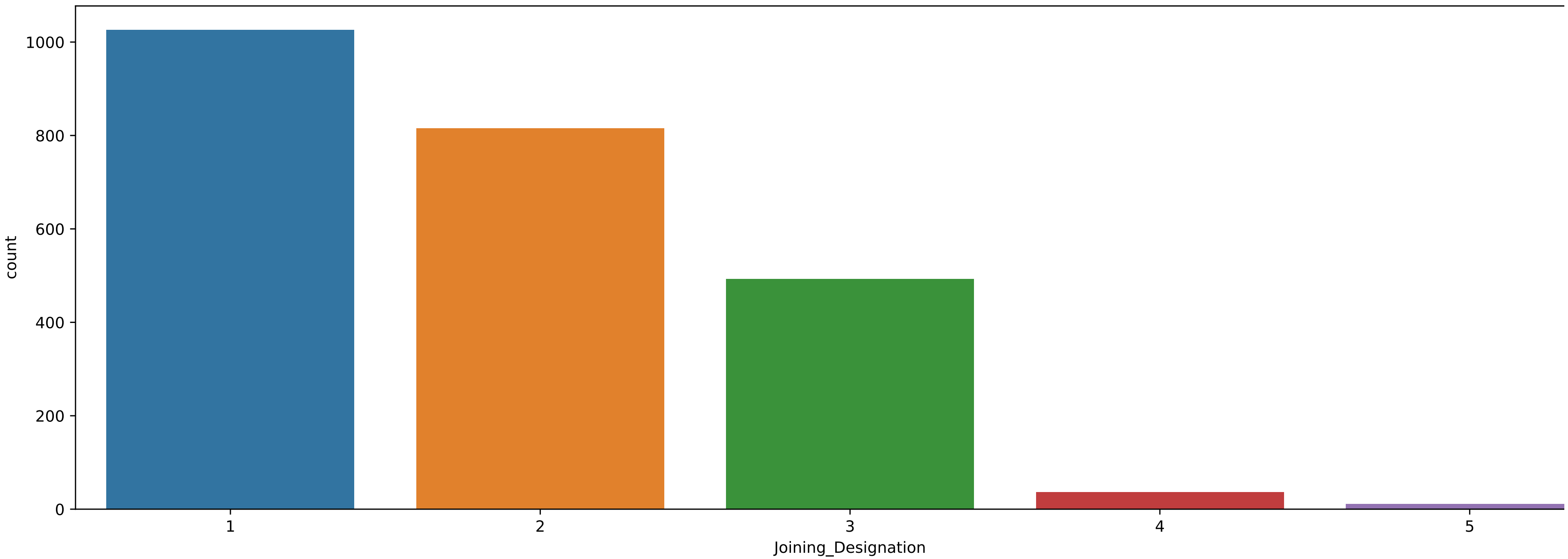
In [ ]:

Joining Designation:

In [95]:
```
display_normalized_value_counts(df, "Joining_Designation")
```

```
1    43.09
2    34.23
3    20.71
4     1.51
5     0.46
Name: Joining_Designation, dtype: float64
```

In [97]:
```
display_countplot(df, 'Joining_Designation')
```



98% of the drivers join at designation 1, 2 or 3 while only 2% join at 4 or 5

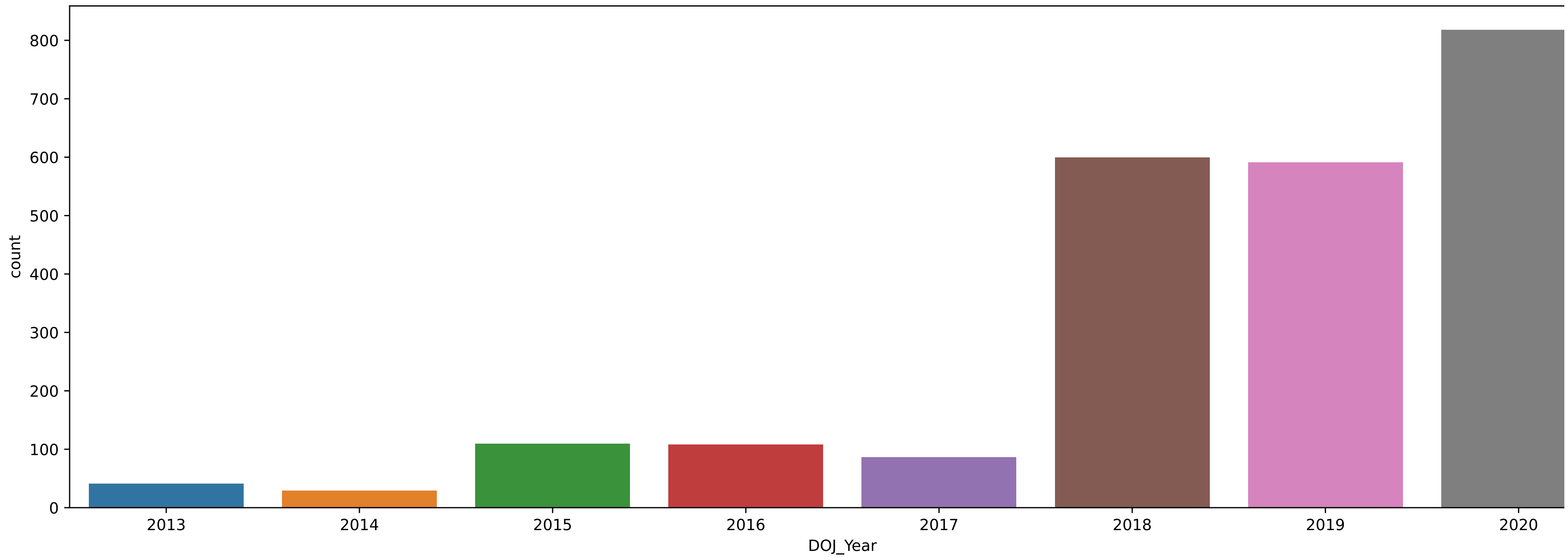
In [ ]:

DOJ Year:

In [98]:
```
display_normalized_value_counts(df, "DOJ_Year")
```

```
2020    34.36
2018    25.16
2019    24.82
2015     4.58
2016     4.54
2017     3.61
2013     1.72
2014     1.22
Name: DOJ_Year, dtype: float64
```

In [99]:
```
display_countplot(df, 'DOJ_Year')
```



85% of the drivers joined in between 2018-2020

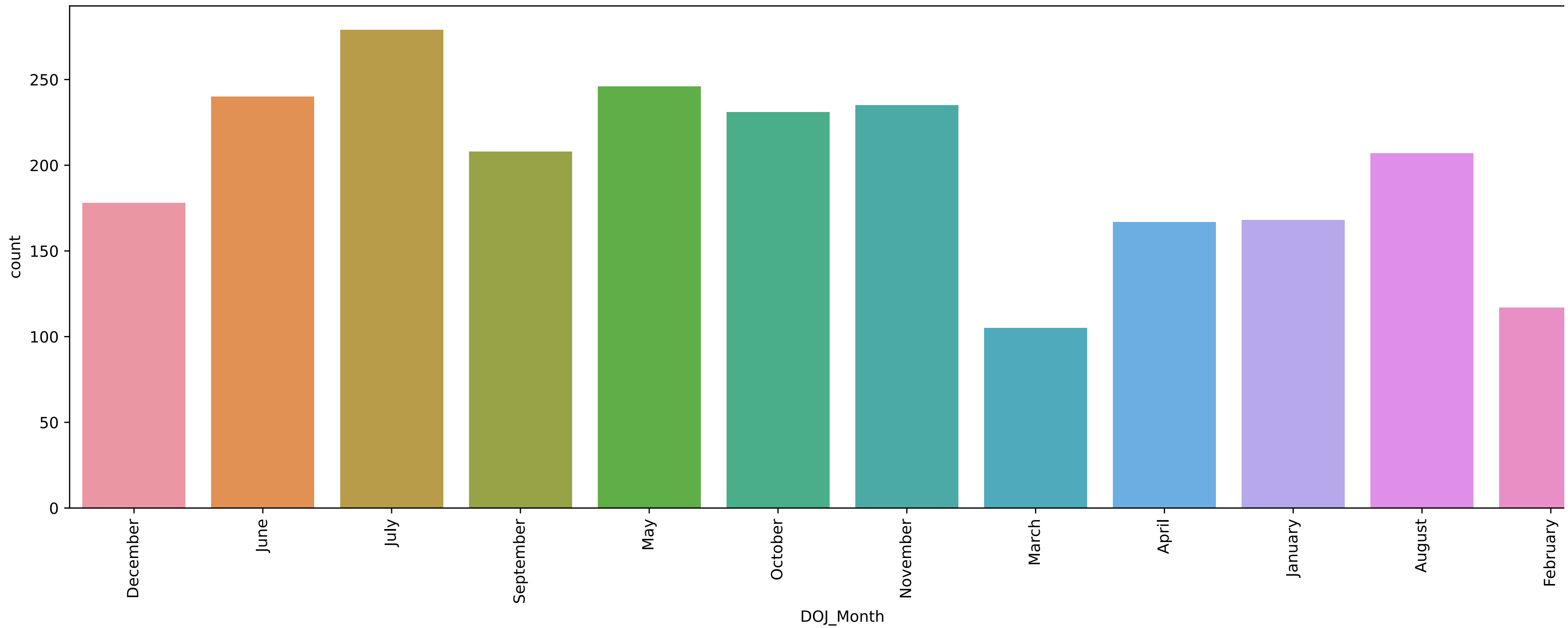
In [ ]:

DOJ Month:

In [100]:
```
display_normalized_value_counts(df, "DOJ_Month")
```

```
July         11.72
May          10.33
June         10.08
November      9.87
October       9.70
September     8.74
August        8.69
December      7.48
January       7.06
April         7.01
February      4.91
March         4.41
Name: DOJ_Month, dtype: float64
```

In [101]:
```
display_countplot(df, 'DOJ_Month', rot=True)
```



Number of people joining is highest in May-July while lowest in Feb-March

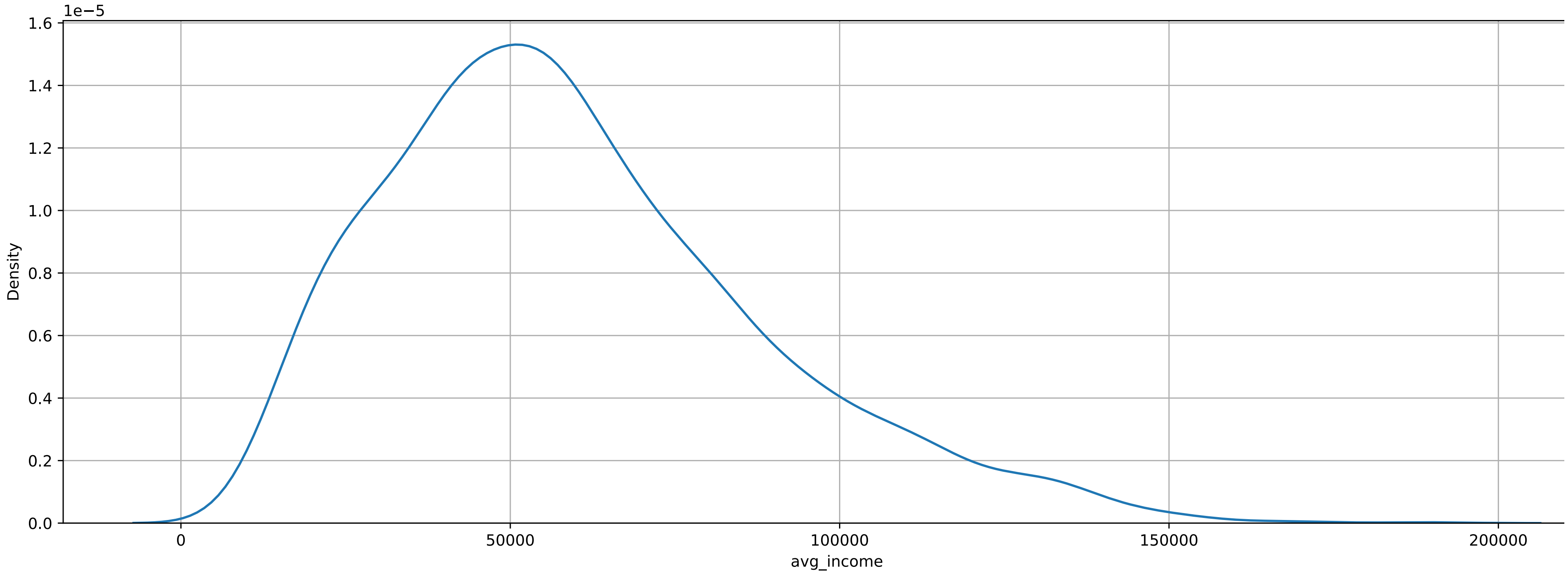
In [ ]:

Average income:

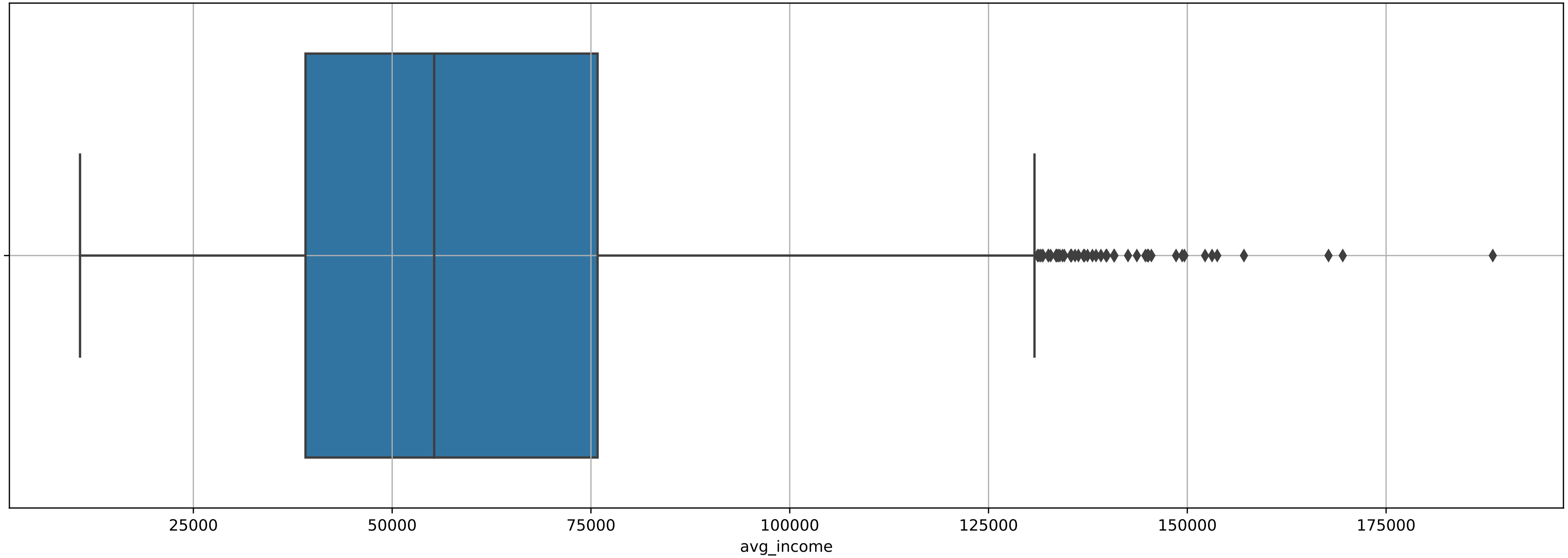
In [102]:
```
df['avg_income'].describe()
```

Out[102]:
```
count      2381.000000
mean      59272.610248
std       28325.327154
min       10747.000000
25%       39104.000000
50%       55285.000000
75%       75835.000000
max      188418.000000
Name: avg_income, dtype: float64
```

In [103]:
```
display_kde_plot(df, 'avg_income')
```



In [104]:
```
display_box_plot(df, 'avg_income')
```



This looks like a right tailed distribution with significant outliers on the RHS, median income is close to 50k

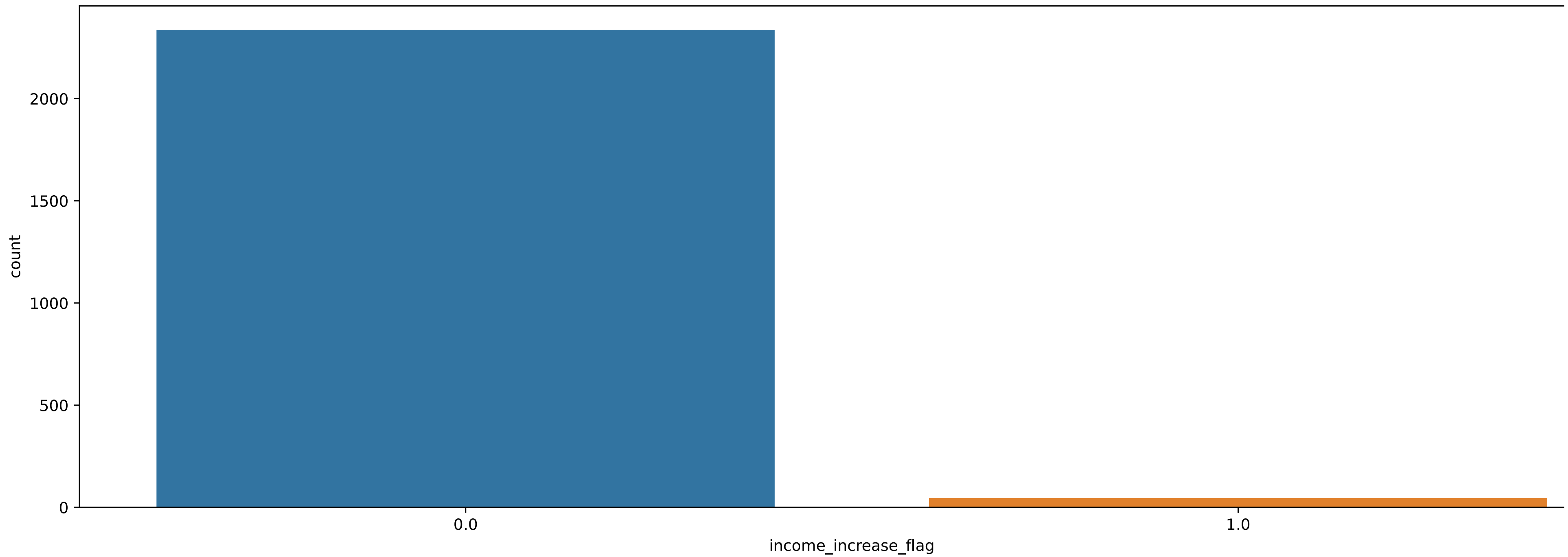
In [ ]:

Income increase flag:

In [105]:
```
display_normalized_value_counts(df, "income_increase_flag")
```

```
0.0    98.15
1.0     1.85
Name: income_increase_flag, dtype: float64
```

In [106]:
```
display_countplot(df, 'income_increase_flag')
```



For 98% of the drivers, income remained the same across their tenure at Ola, while for the rest 2%, income increased

In [ ]:

Income difference between ultimate and penultimate months at OLA:

In [107]:
```
display_normalized_value_counts(df, "income_last_tenure_diff")
```

```
0    98.15
1     1.85
Name: income_last_tenure_diff, dtype: float64
```

It's better to drop this feature as this information is already captured in "income_increase_flag"

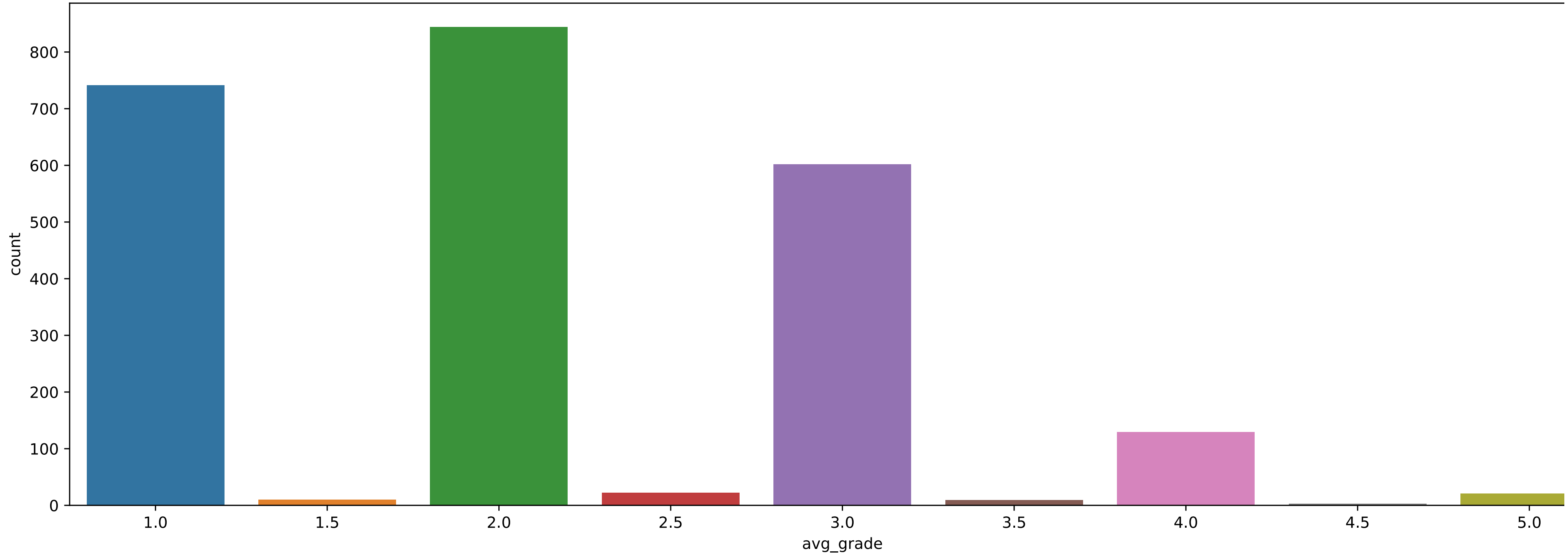
In [ ]:

Average grade:

In [108]:
```
display_normalized_value_counts(df, "avg_grade")
```

```
2.0    35.45
1.0    31.12
3.0    25.28
4.0     5.42
2.5     0.92
5.0     0.88
1.5     0.42
3.5     0.38
4.5     0.13
Name: avg_grade, dtype: float64
```

In [109]:
```
display_countplot(df, 'avg_grade')
```



This distribution is very similar to Joining Grade's distribution

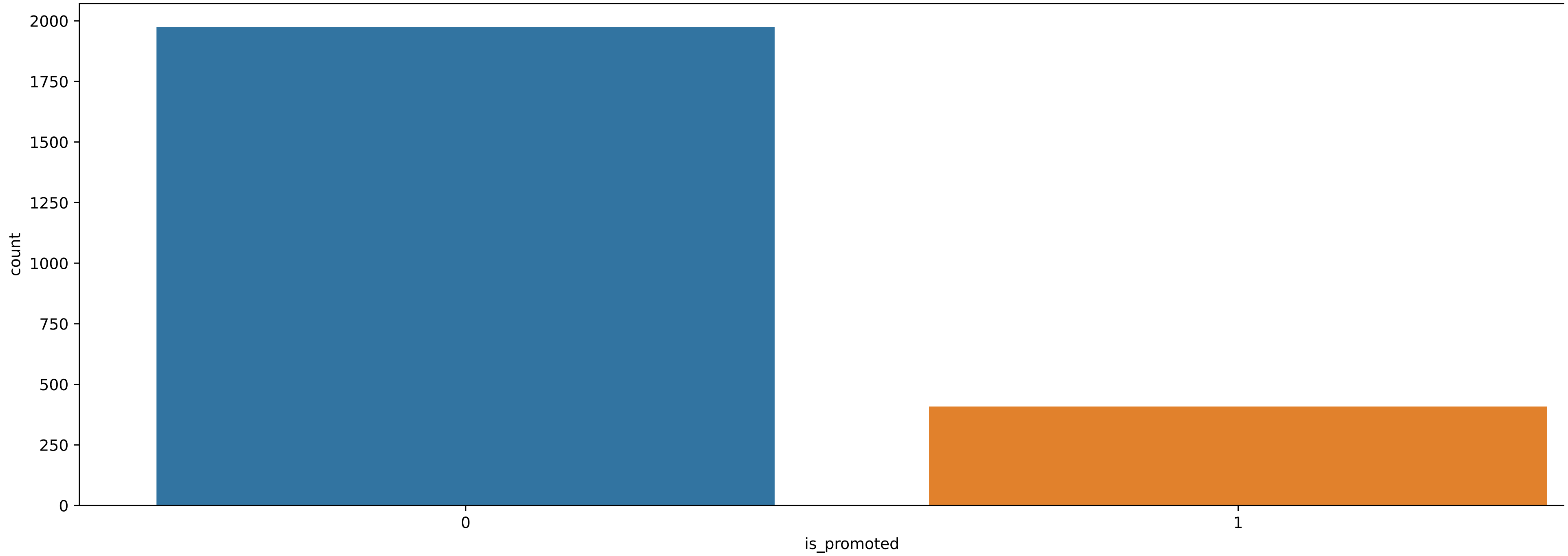
In [ ]:

Is Promoted:

In [110]:
```
display_normalized_value_counts(df, "is_promoted")
```

```
0    82.86
1    17.14
Name: is_promoted, dtype: float64
```

In [111]:
```
display_countplot(df, 'is_promoted')
```



17% of the drivers have witnessed an increase in their grade while 83% remained at the same grade

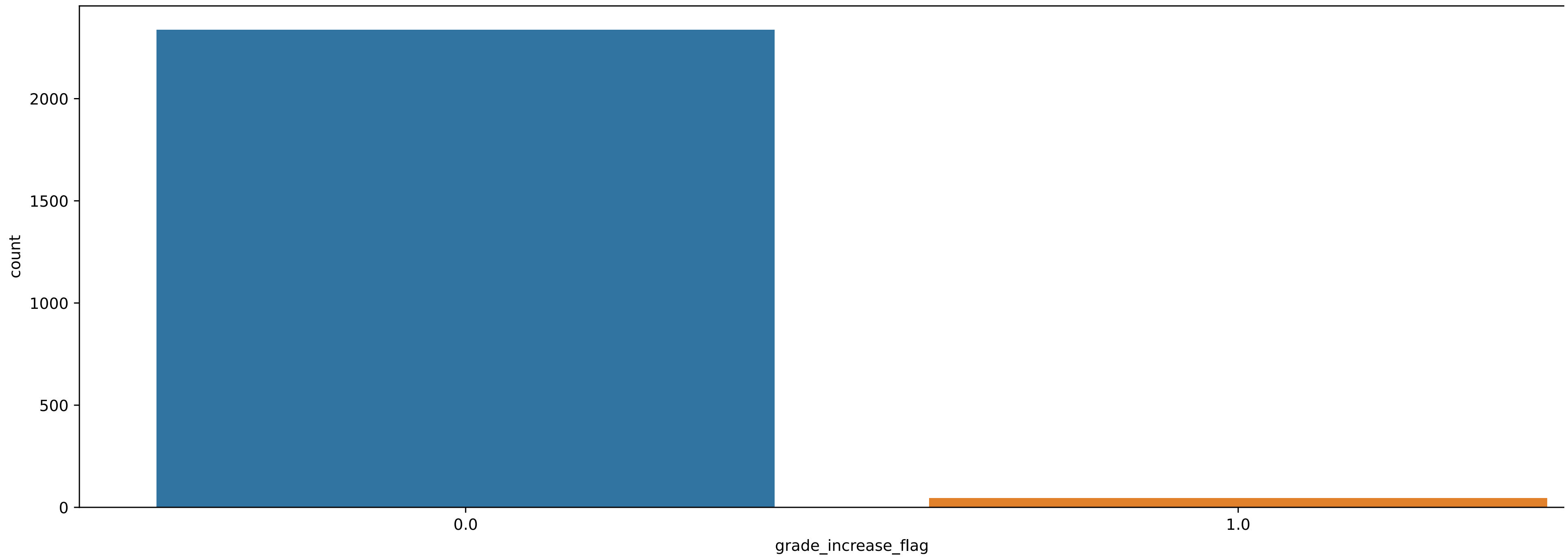
In [ ]:

Grade increase flag:

In [112]:
```
display_normalized_value_counts(df, "grade_increase_flag")
```

```
0.0    98.15
1.0     1.85
Name: grade_increase_flag, dtype: float64
```

In [113]:
```
display_countplot(df, 'grade_increase_flag')
```



About 2% of the people witnessed an increase in their grades during subsequent months at OLA

In [ ]:

Grade difference between ultimate and penultimate months at OLA:

In [114]:
```
display_normalized_value_counts(df, "grade_last_tenure_diff")
```

```
0    98.15
1     1.85
Name: grade_last_tenure_diff, dtype: float64
```

This is the same as 'grade_increase_flag' hence can be dropped

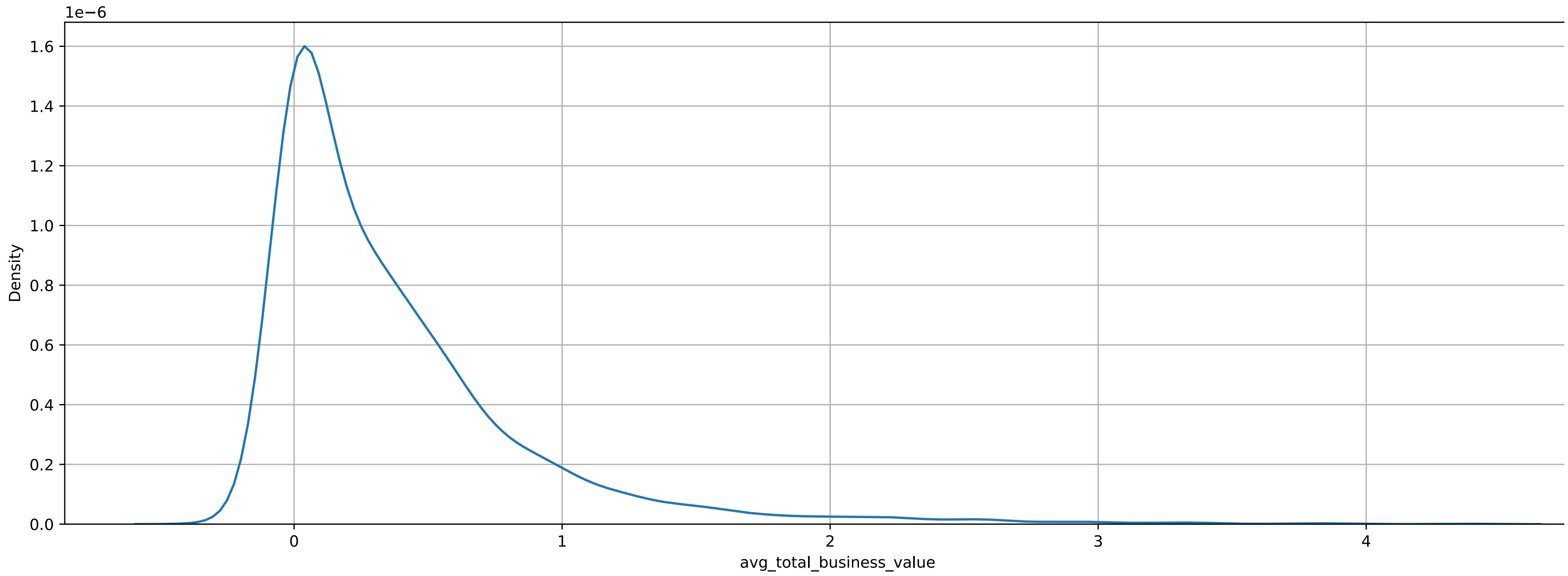
In [ ]:

Average total business value (TBV):

In [116]:
```
df['avg_total_business_value'].describe()
```

Out[116]:
```
count     2.381000e+03
mean      3.745311e+05
std       4.994292e+05
min      -2.771060e+05
25%       0.000000e+00
50%       2.239375e+05
75%       5.325633e+05
max       4.333230e+06
Name: avg_total_business_value, dtype: float64
```

In [117]:
```
display_kde_plot(df, 'avg_total_business_value')
```



This is a clear right tailed distribution containig severe outliers on the RHS (median TBV is about 2.25 Lakhs while max goes upto 43 Lakhs)

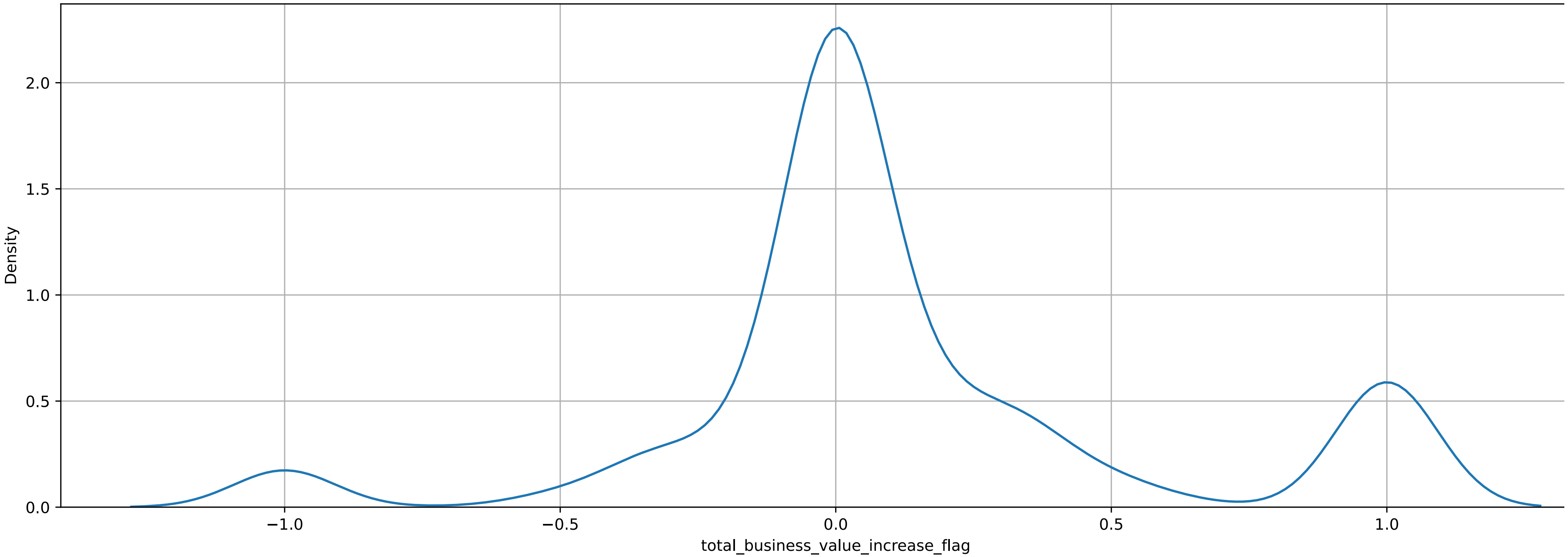
In [ ]:

TBV increase flag:

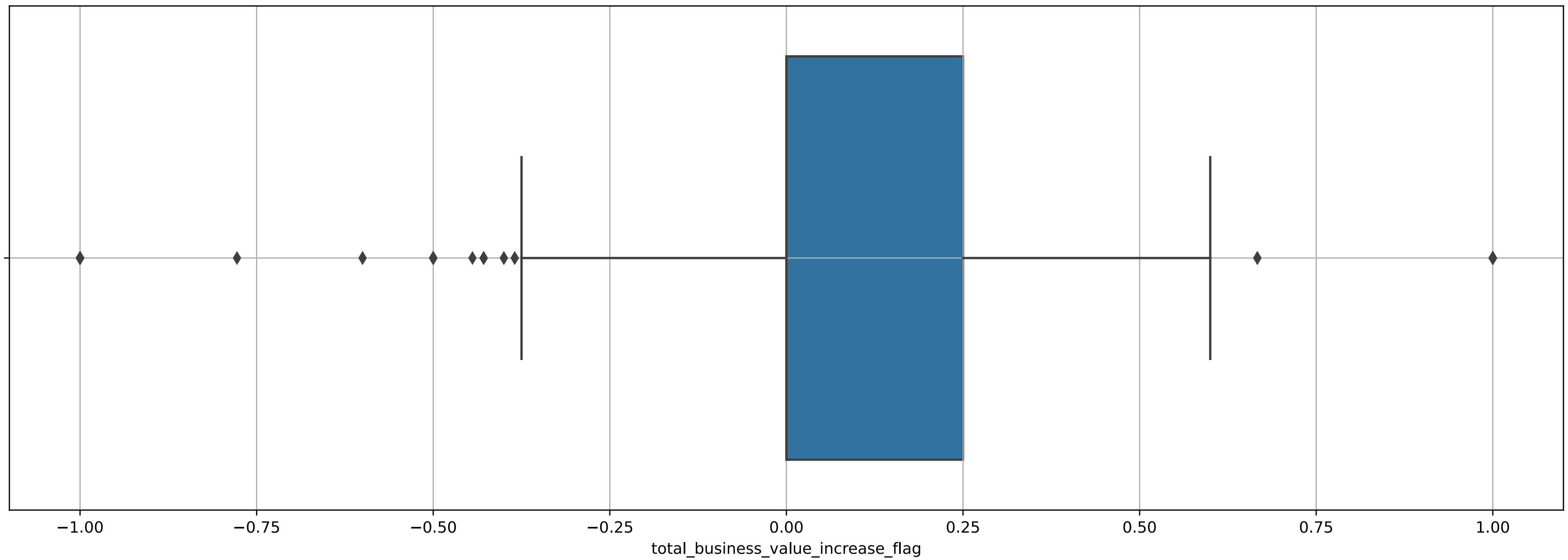
In [118]:
```
df['total_business_value_increase_flag'].describe()
```

Out[118]:
```
count    2381.000000
mean        0.122662
std         0.439303
min        -1.000000
25%         0.000000
50%         0.000000
75%         0.250000
max         1.000000
Name: total_business_value_increase_flag, dtype: float64
```

In [119]:
```
display_kde_plot(df, 'total_business_value_increase_flag')
```



In [120]:
```
display_box_plot(df, 'total_business_value_increase_flag')
```



This looks like an almost symmetric distribution

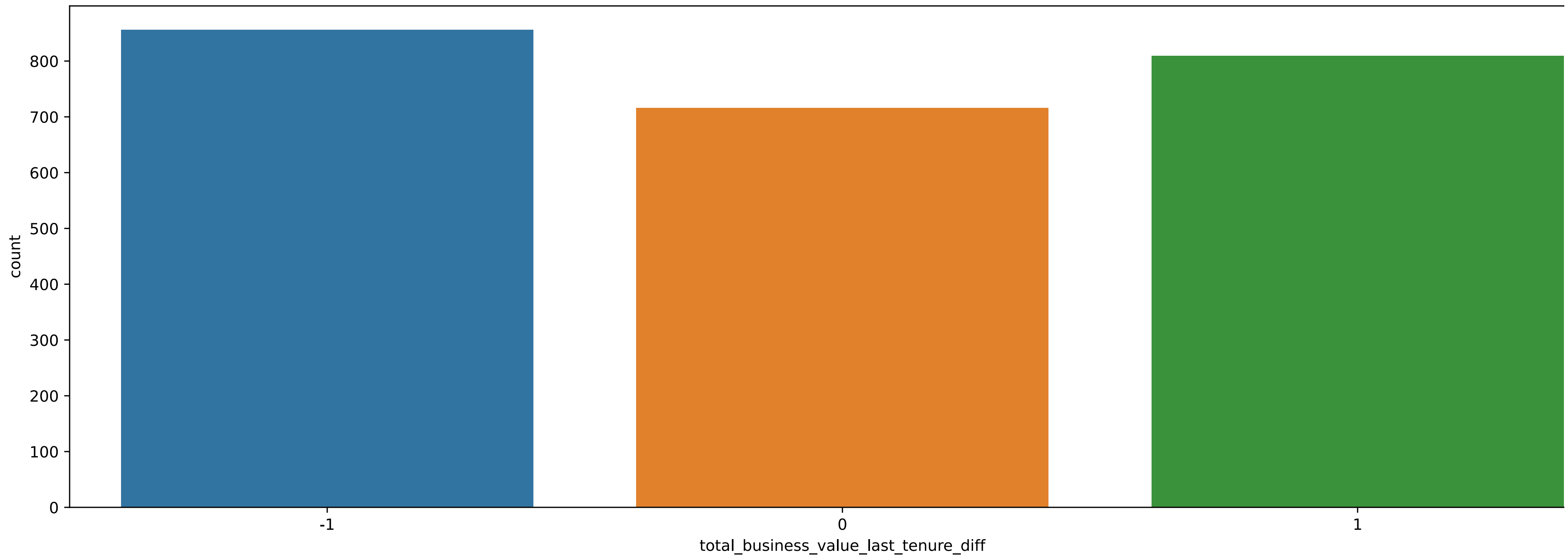
In [ ]:

TBV difference between ultimate and penultimate months at OLA:

In [121]:
```
display_normalized_value_counts(df, "total_business_value_last_tenure_diff")
```

```
-1    35.95
 1    33.98
 0    30.07
Name: total_business_value_last_tenure_diff, dtype: float64
```

In [122]:
```
display_countplot(df, 'total_business_value_last_tenure_diff')
```



The distribution among people who incurred a decreased in TBV, who incurred an increase in TBV and for those whom TBV remained same is approximately the same.

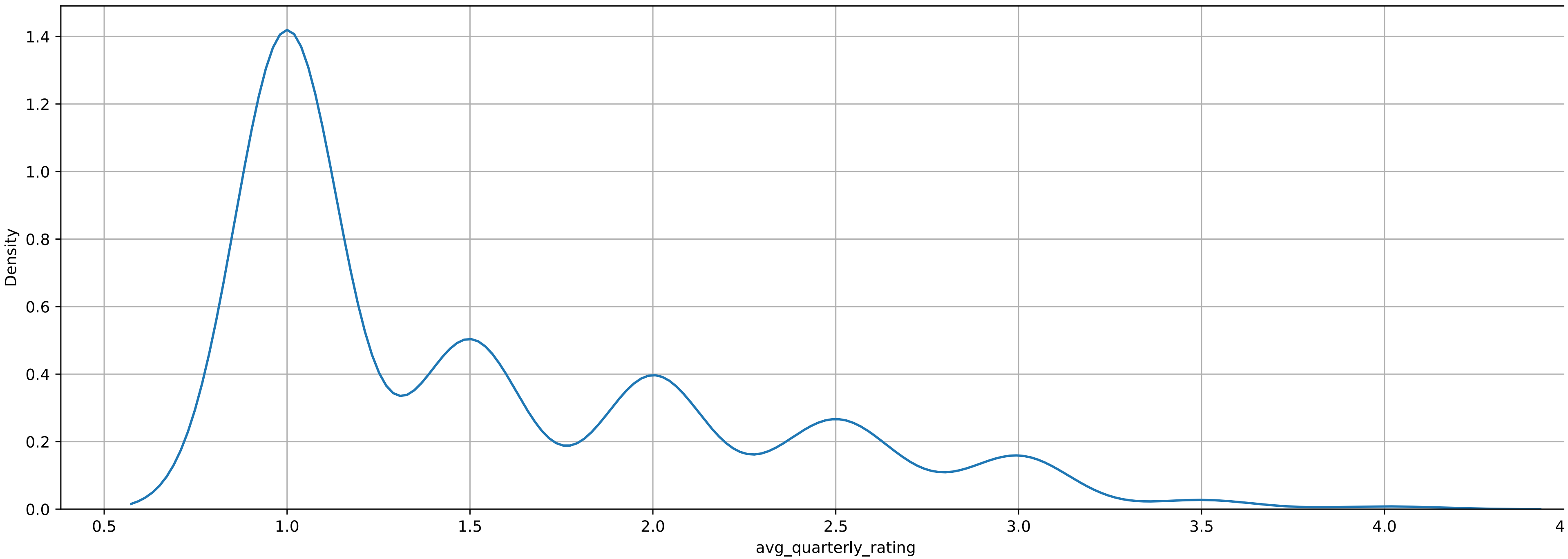
In [ ]:

Average quarterly rating:

In [123]:
```
df['avg_quarterly_rating'].describe()
```

Out[123]:
```
count    2381.000000
mean        1.536679
std         0.672356
min         1.000000
25%         1.000000
50%         1.000000
75%         2.000000
max         4.000000
Name: avg_quarterly_rating, dtype: float64
```

In [124]:
```
display_kde_plot(df, 'avg_quarterly_rating')
```



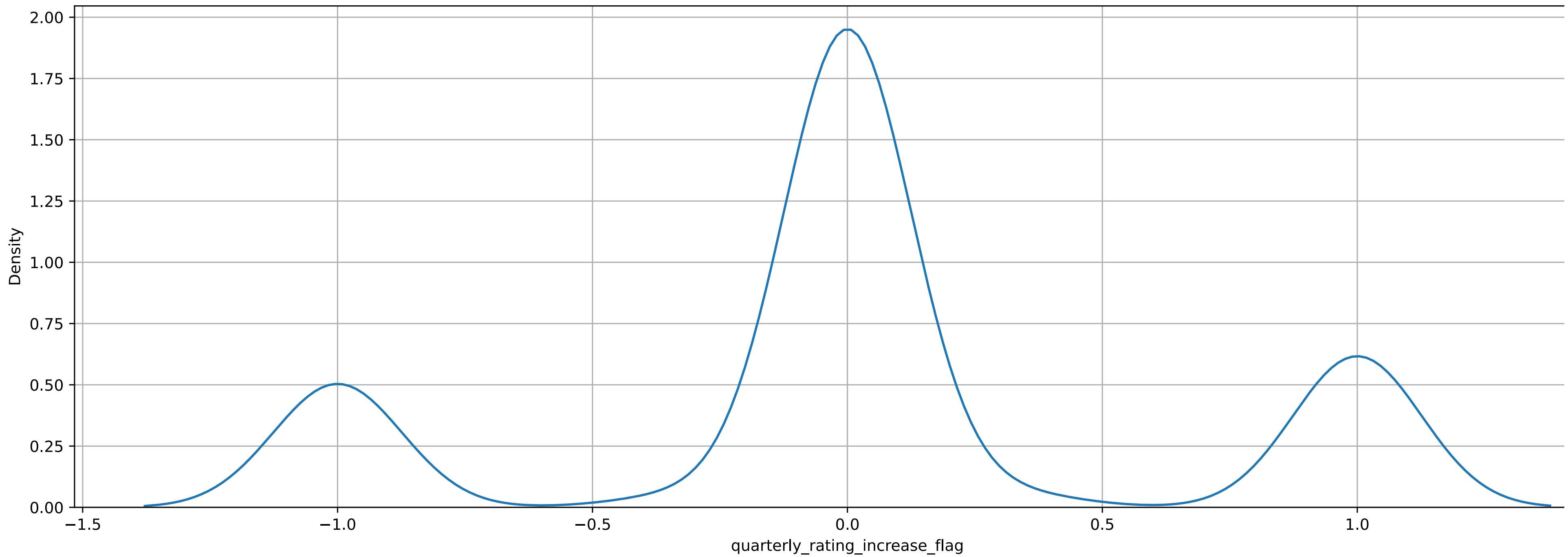
In [ ]:

Quarterly rating increase flag:

In [125]:
```
display_normalized_value_counts(df, "quarterly_rating_increase_flag")
```

```
 0.000000    61.57
 1.000000    19.49
-1.000000    15.92
 0.333333     1.64
-0.333333     1.39
Name: quarterly_rating_increase_flag, dtype: float64
```

In [126]:
```
display_kde_plot(df, 'quarterly_rating_increase_flag')
```



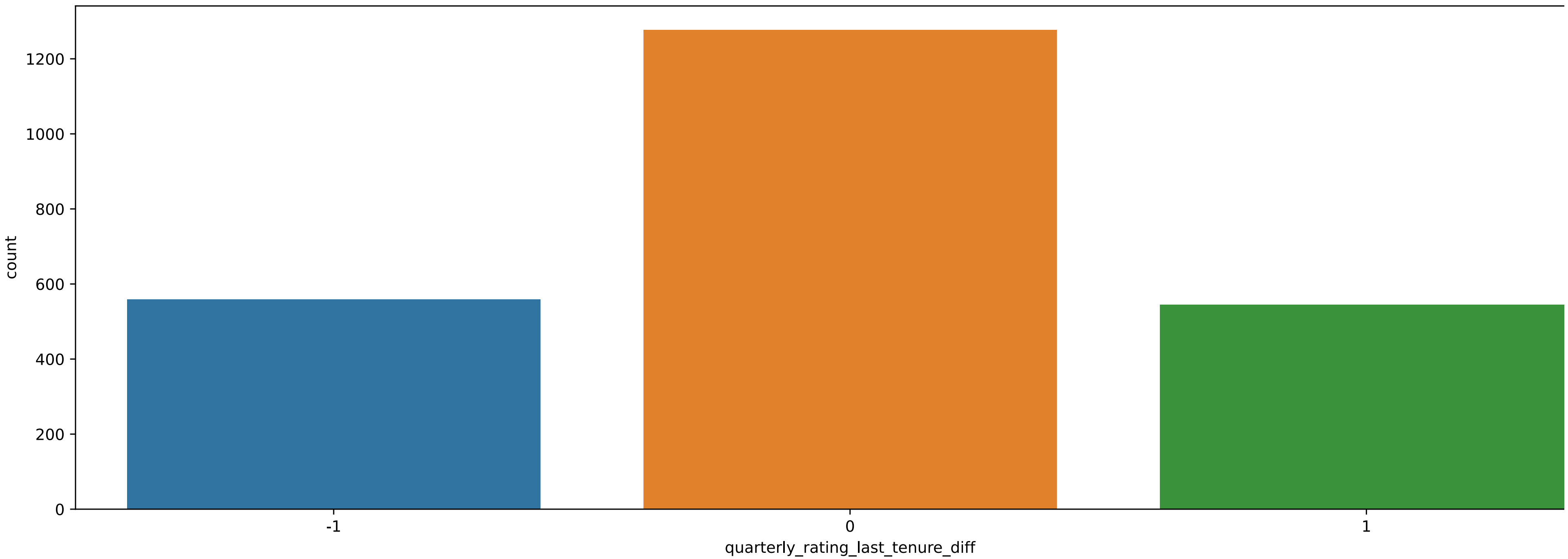
In [ ]:

Quarterly rating difference between ultimate and penultimate months at OLA:

In [127]:
```
display_normalized_value_counts(df, "quarterly_rating_last_tenure_diff")
```

```
 0    53.63
-1    23.48
 1    22.89
Name: quarterly_rating_last_tenure_diff, dtype: float64
```

In [128]:
```
display_countplot(df, 'quarterly_rating_last_tenure_diff')
```



For about 50% of the people, the quarterly rating remained same for the last 2 tenures, for about 25% of the people, quarterly ratings increased and for about 25% of the people, quarterly ratings decreased

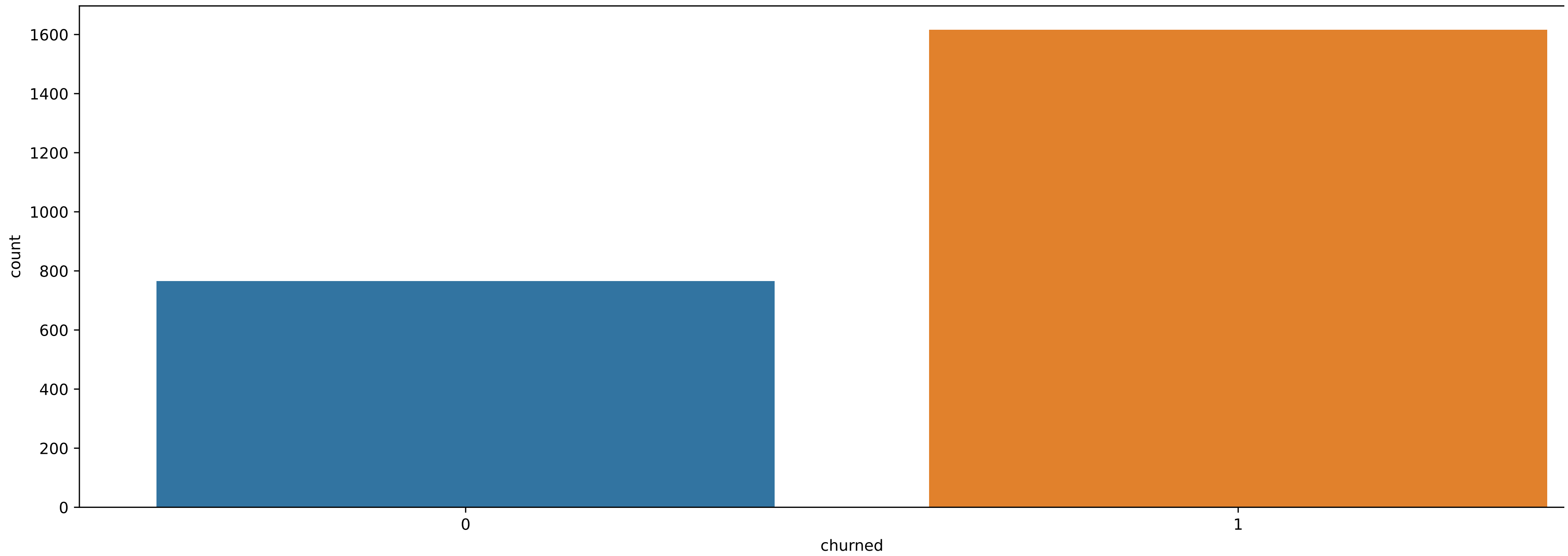
In [ ]:

Is churned ?

In [129]:
```
display_normalized_value_counts(df, "churned")
```

```
1    67.87
0    32.13
Name: churned, dtype: float64
```

In [130]:
```
display_countplot(df, 'churned')
```



The churn rate is very high (68%), only 32% of the drivers did not churn

In [ ]:

Bivariate Analysis:

In [131]:
```
plt.rcParams["figure.figsize"] = (18,6)
```

In [132]:
```
df.columns
```

Out[132]:
```
Index(['num_months', 'Age', 'Gender', 'City', 'Education_Level',
       'Joining_Designation', 'DOJ_Year', 'DOJ_Month', 'avg_income',
       'income_increase_flag', 'income_last_tenure_diff', 'avg_grade',
       'grade_increase_flag', 'grade_last_tenure_diff',
       'avg_total_business_value', 'total_business_value_increase_flag',
       'total_business_value_last_tenure_diff', 'avg_quarterly_rating',
       'quarterly_rating_increase_flag', 'quarterly_rating_last_tenure_diff',
       'is_promoted', 'churned', 'index'],
      dtype='object')
```

In [ ]:

Number of months spent:

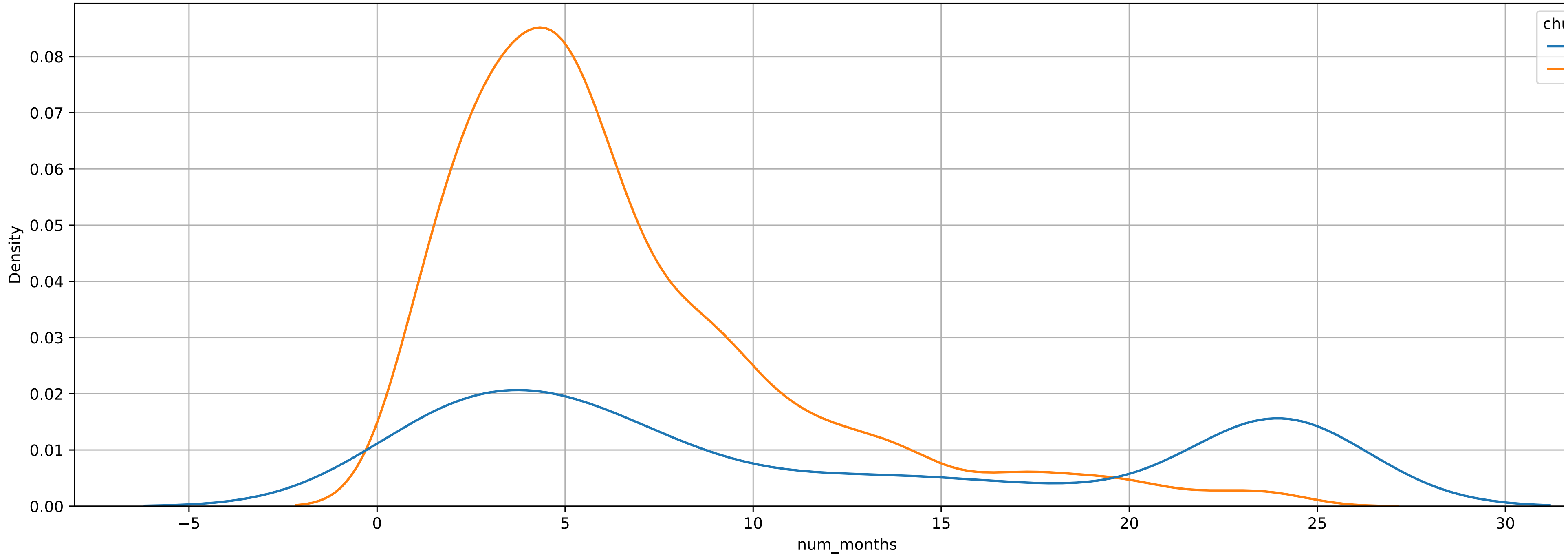
In [133]:
```
display_pearson_corr_coef(df, 'num_months', 'churned')
```

```
PCC between 'num_months' and 'churned' = -0.346
```

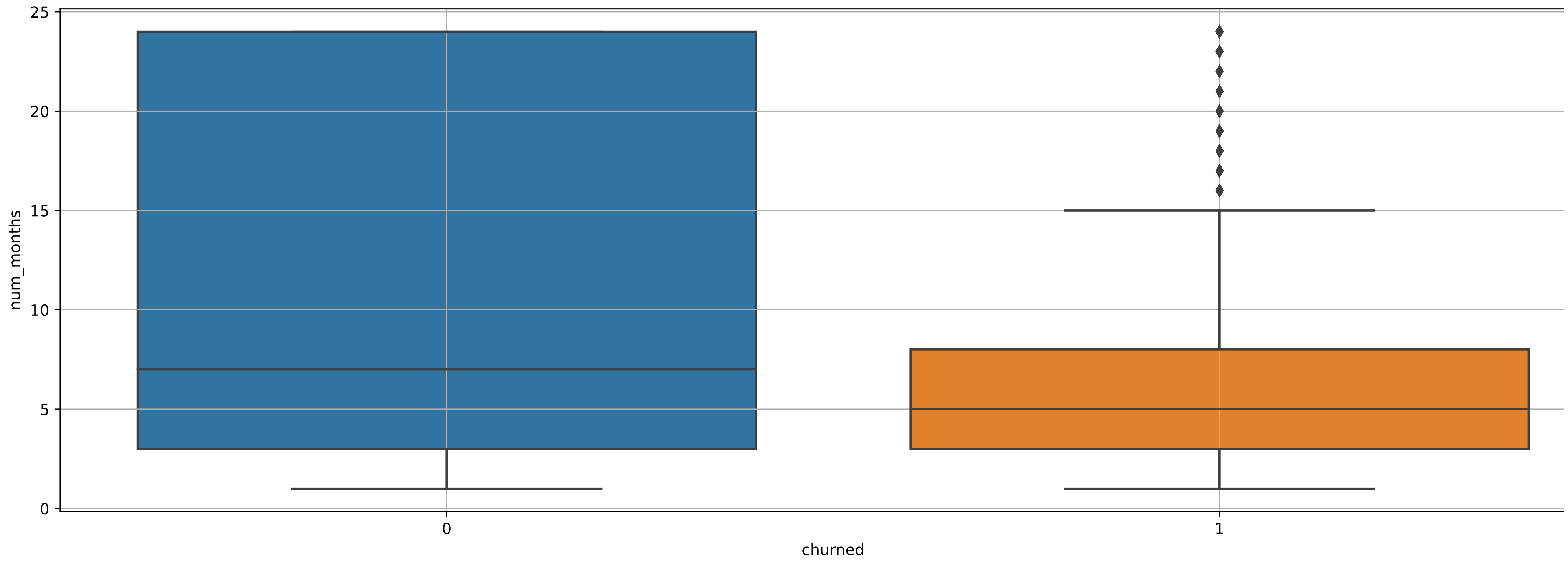
In [134]:
```
display_spearman_rank_corr_coef(df, 'num_months', 'churned')
```

```
SRCC between 'num_months' and 'churned' = -0.204
```

In [135]:
```
display_kde_plot_with_hue(df, 'num_months', 'churned')
```



In [136]:
```
display_box_plot_2d(df, 'churned', 'num_months')
```



Although there's a weak correlation but still we can say that churned drivers spend less amount of time at the company as compared to non churned drivers and hence this seems like an important feature

In [ ]:

Age:

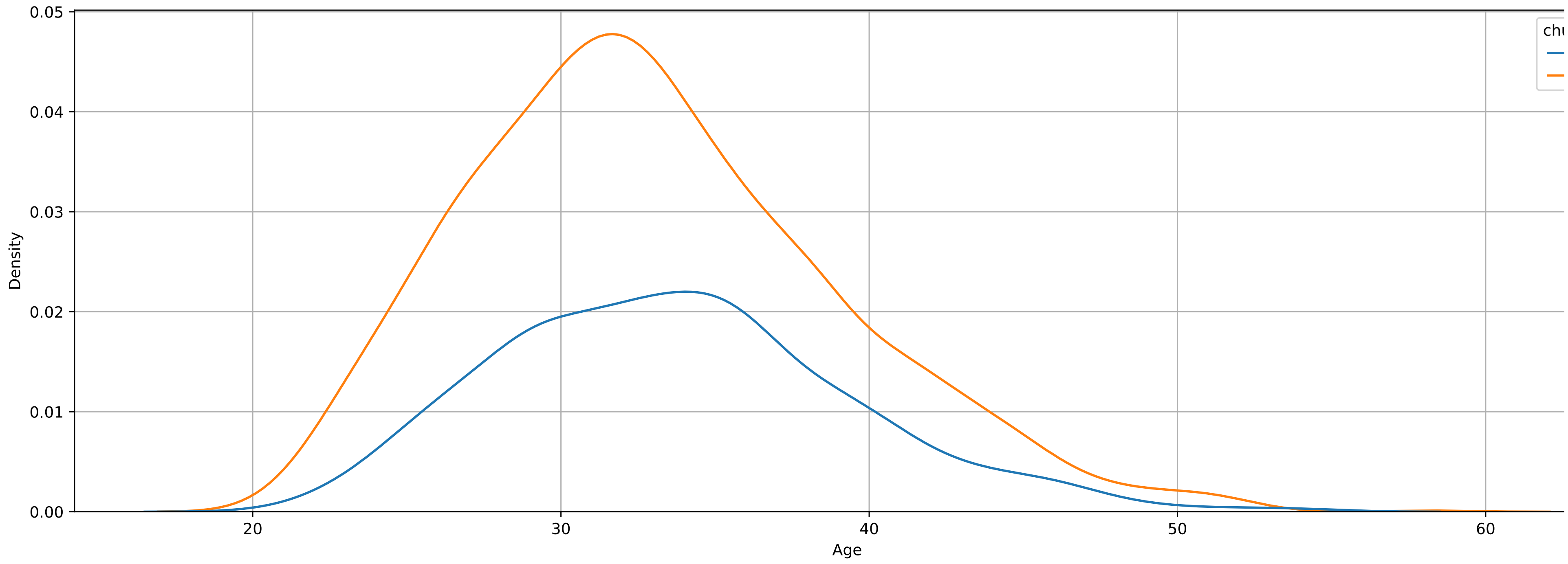
In [137]:
```
display_pearson_corr_coef(df, 'Age', 'churned')
```

```
PCC between 'Age' and 'churned' = -0.056
```

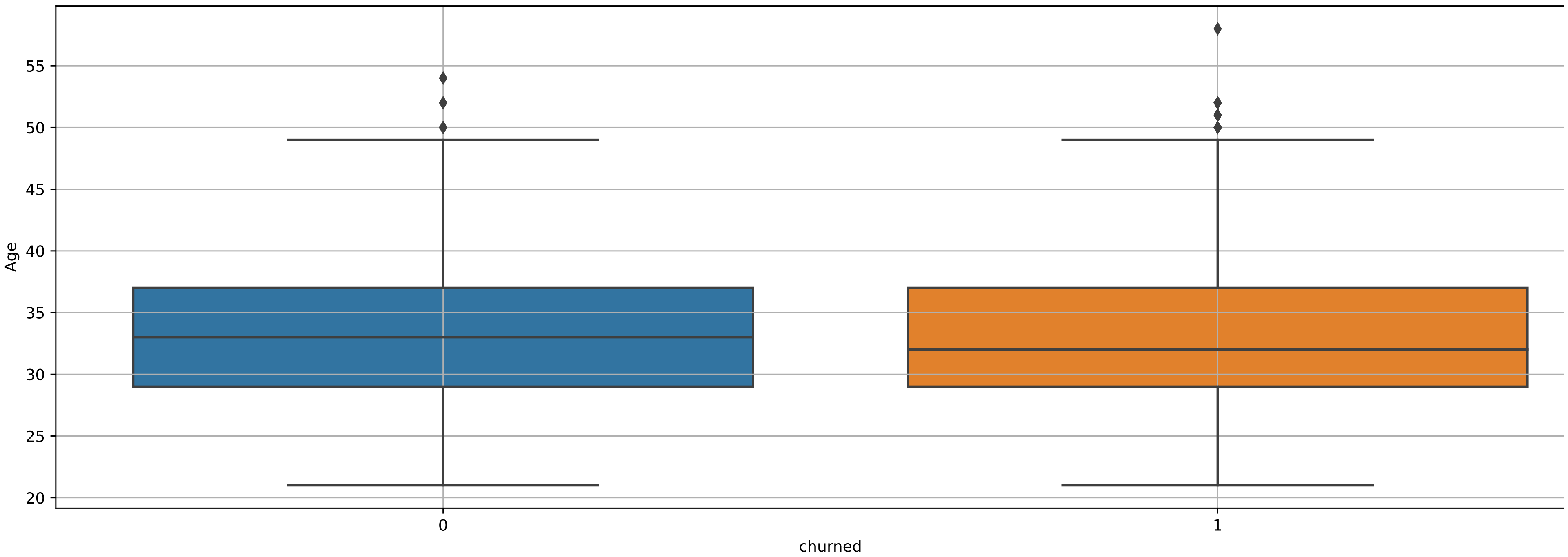
In [138]:
```
display_spearman_rank_corr_coef(df, 'Age', 'churned')
```

```
SRCC between 'Age' and 'churned' = -0.065
```

In [139]:
```
display_kde_plot_with_hue(df, 'Age', 'churned')
```



In [140]:
```
display_box_plot_2d(df, 'churned', 'Age')
```



The plots are almost overlapping, this does not seem like an important feature

In [ ]:

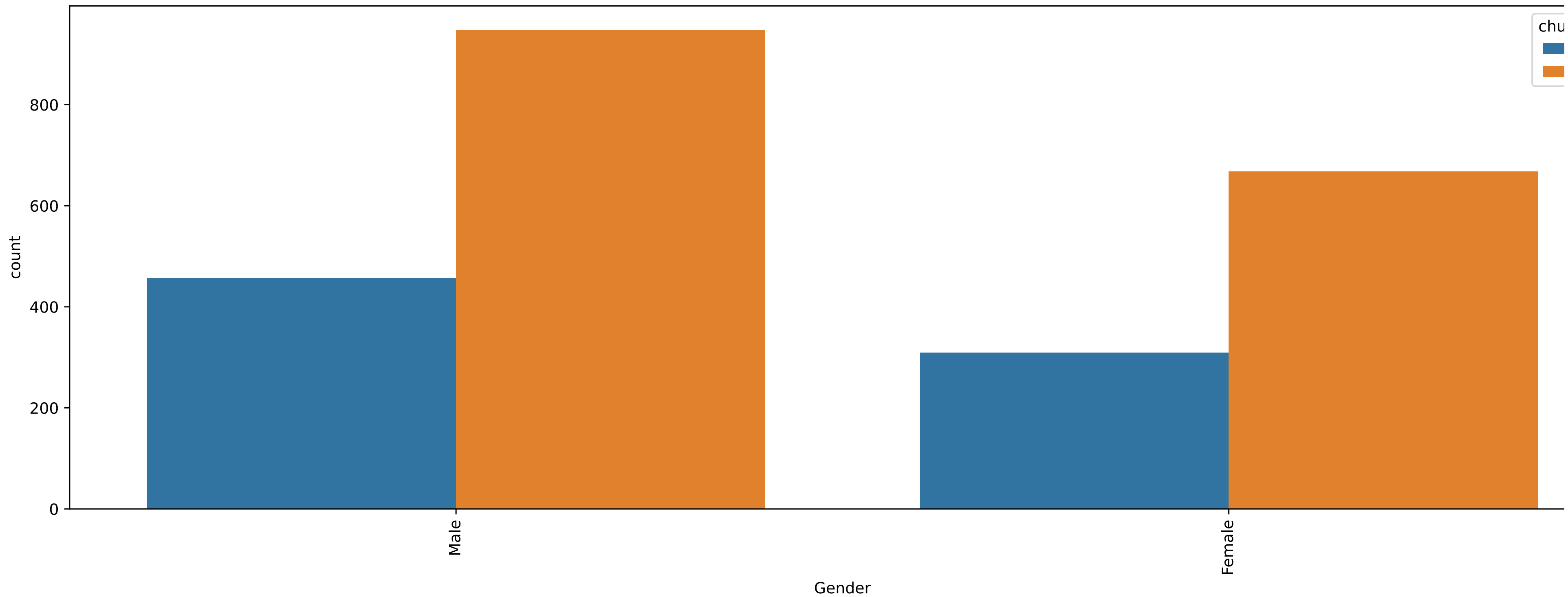
Gender:

In [143]:
```
display_grouped_value_counts_percentage(df, 'Gender')
```

Out[143]:

	Gender	churned	percentage
0	Female	0	31.63
1	Female	1	68.37
2	Male	0	32.48
3	Male	1	67.52

In [144]:
```
display_countplot_with_hue(df, 'Gender', 'churned',)
```



The ratio of churned:non churned is almost the same across both genders, this does not seem as an important feature

In [ ]:

City:

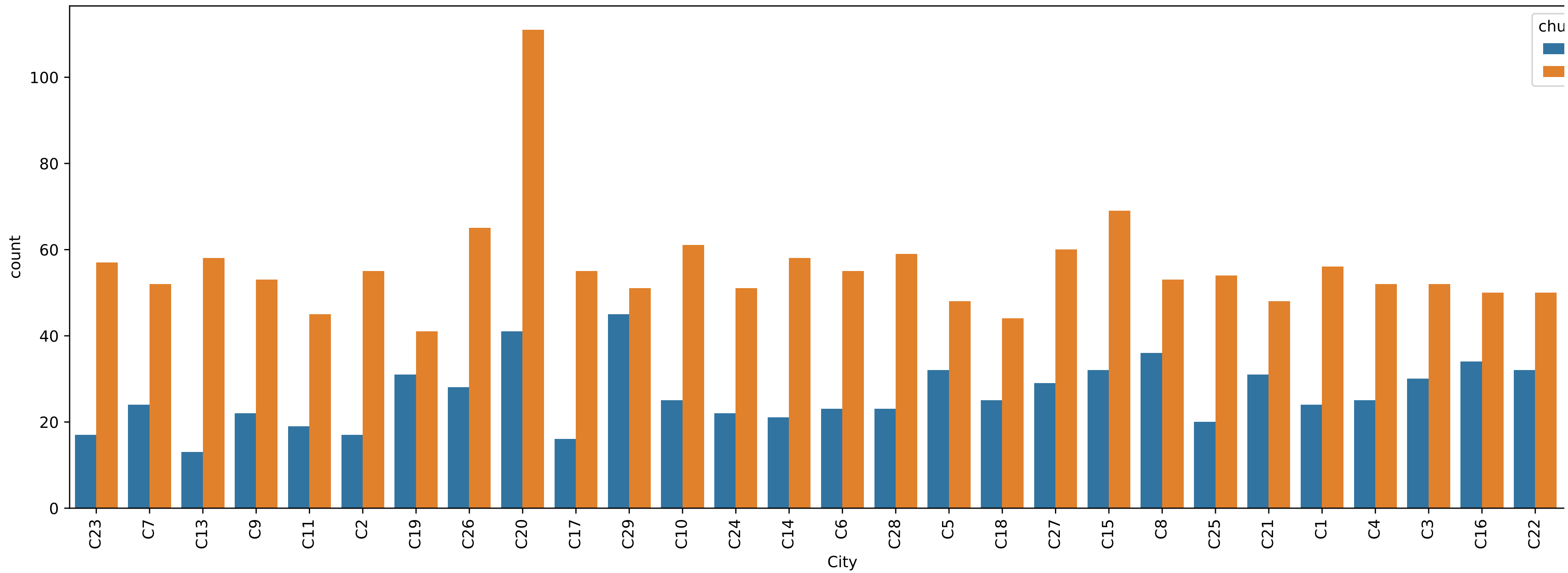
In [145]:
```
display_grouped_value_counts_percentage(df, 'City')
```

Out[145]:

	City	churned	percentage
0	C1	0	30.00
1	C1	1	70.00
2	C10	0	29.07
3	C10	1	70.93
4	C11	0	29.69
5	C11	1	70.31
6	C12	0	34.57
7	C12	1	65.43
8	C13	0	18.31
9	C13	1	81.69
10	C14	0	26.58
11	C14	1	73.42
12	C15	0	31.68
13	C15	1	68.32
14	C16	0	40.48
15	C16	1	59.52
16	C17	0	22.54
17	C17	1	77.46
18	C18	0	36.23
19	C18	1	63.77
20	C19	0	43.06
21	C19	1	56.94
22	C2	0	23.61
23	C2	1	76.39
24	C20	0	26.97
25	C20	1	73.03
26	C21	0	39.24
27	C21	1	60.76
28	C22	0	39.02
29	C22	1	60.98
30	C23	0	22.97
31	C23	1	77.03
32	C24	0	30.14
33	C24	1	69.86
34	C25	0	27.03
35	C25	1	72.97
36	C26	0	30.11

	City	churned	percentage
37	C26	1	69.89
38	C27	0	32.58
39	C27	1	67.42
40	C28	0	28.05
41	C28	1	71.95
42	C29	0	46.88
43	C29	1	53.12
44	C3	0	36.59
45	C3	1	63.41
46	C4	0	32.47
47	C4	1	67.53
48	C5	0	40.00
49	C5	1	60.00
50	C6	0	29.49
51	C6	1	70.51
52	C7	0	31.58
53	C7	1	68.42
54	C8	0	40.45
55	C8	1	59.55
56	C9	0	29.33
57	C9	1	70.67

In [146]:
```
display_countplot_with_hue(df, 'City', 'churned')
```



There is variation among churn rate across different cities, this is definitely an important feature

In [ ]:

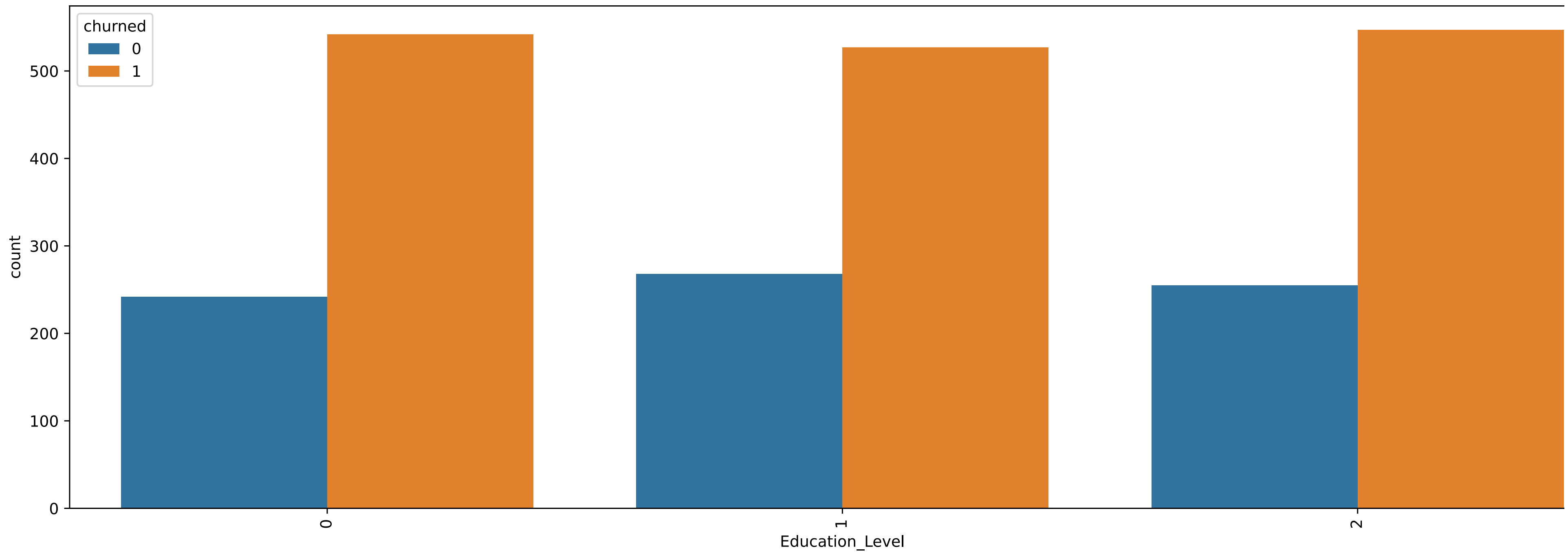
Education Level:

In [147]:
```
display_grouped_value_counts_percentage(df, 'Education_Level')
```

Out[147]:

	Education_Level	churned	percentage
0	0	0	30.87
1	0	1	69.13
2	1	0	33.71
3	1	1	66.29
4	2	0	31.80
5	2	1	68.20

In [148]:
```
display_countplot_with_hue(df, 'Education_Level', 'churned')
```



Churn rate is almost the same across different education levels, this does not seem like an important feature

In [ ]:

Joining Designation:

In [150]:
```
df['Joining_Designation'].value_counts()
```

Out[150]:
```
1    1026
2     815
3     493
4      36
5      11
Name: Joining_Designation, dtype: int64
```

In [153]:
```
display_normalized_value_counts(df, "Joining_Designation")
```

```
1    43.09
2    34.23
3    20.71
4     1.51
5     0.46
Name: Joining_Designation, dtype: float64
```

In [155]:
```
display_grouped_value_counts_percentage(df, 'Joining_Designation')
```

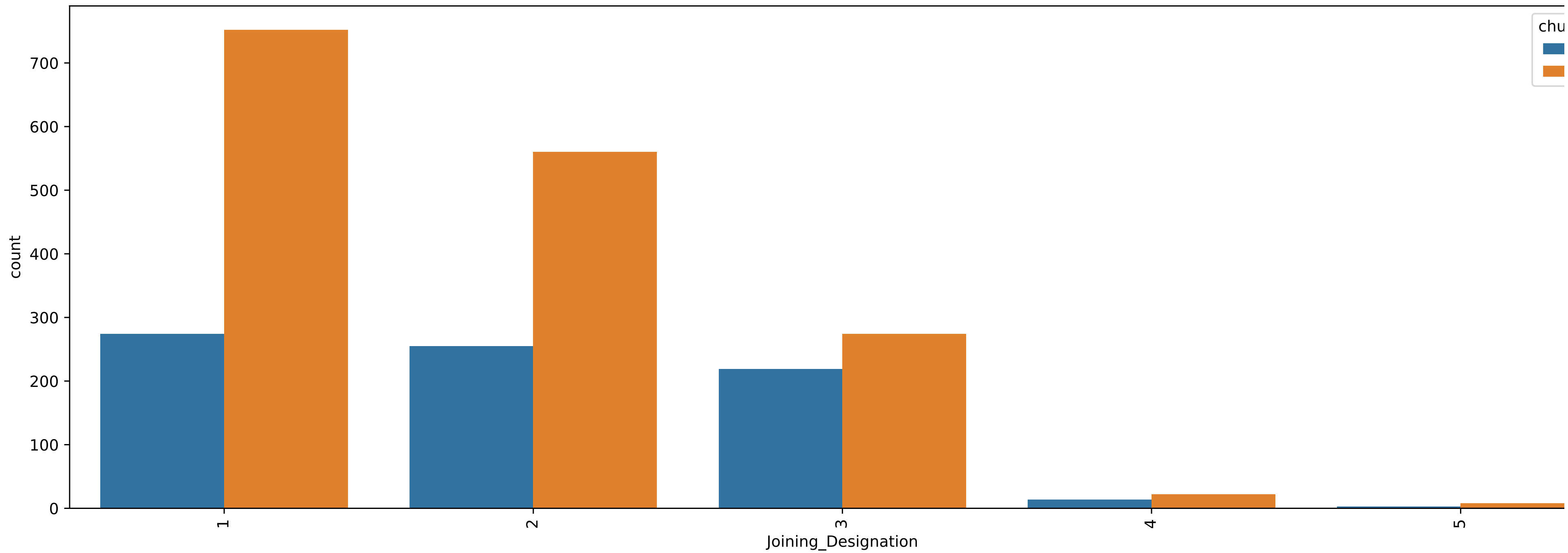
Out[155]:

	Joining_Designation	churned	percentage
0	1	0	26.71
1	1	1	73.29
2	2	0	31.29
3	2	1	68.71
4	3	0	44.42
5	3	1	55.58
6	4	0	38.89
7	4	1	61.11
8	5	0	27.27
9	5	1	72.73

In [156]:
```
display_pearson_corr_coef(df, 'Joining_Designation', 'churned')
```

```
PCC between 'Joining_Designation' and 'churned' = -0.128
```

In [157]:
```
display_countplot_with_hue(df, 'Joining_Designation', 'churned')
```



Churn rate generally decreases as we go up the designation (designations 4 and 5 have less datapoints so they can be outliers also)

In [ ]:
```

```

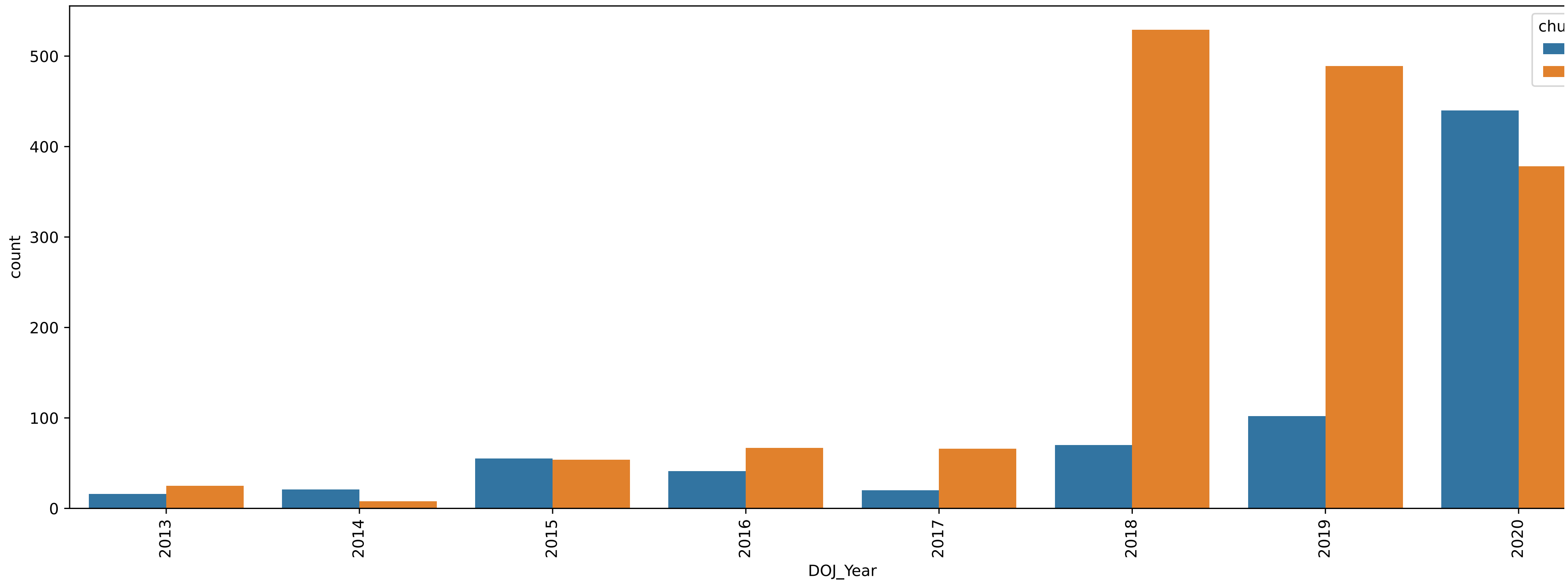
DOJ Year:

In [158]:
```
display_grouped_value_counts_percentage(df, 'DOJ_Year')
```

Out[158]:

	DOJ_Year	churned	percentage
0	2013	0	39.02
1	2013	1	60.98
2	2014	0	72.41
3	2014	1	27.59
4	2015	0	50.46
5	2015	1	49.54
6	2016	0	37.96
7	2016	1	62.04
8	2017	0	23.26
9	2017	1	76.74
10	2018	0	11.69
11	2018	1	88.31
12	2019	0	17.26
13	2019	1	82.74
14	2020	0	53.79
15	2020	1	46.21

In [159]:
```
display_countplot_with_hue(df, 'DOJ_Year', 'churned')
```



There is significant variation among Year of Joining, hence seems an important feature

In [ ]:

DOJ Month:

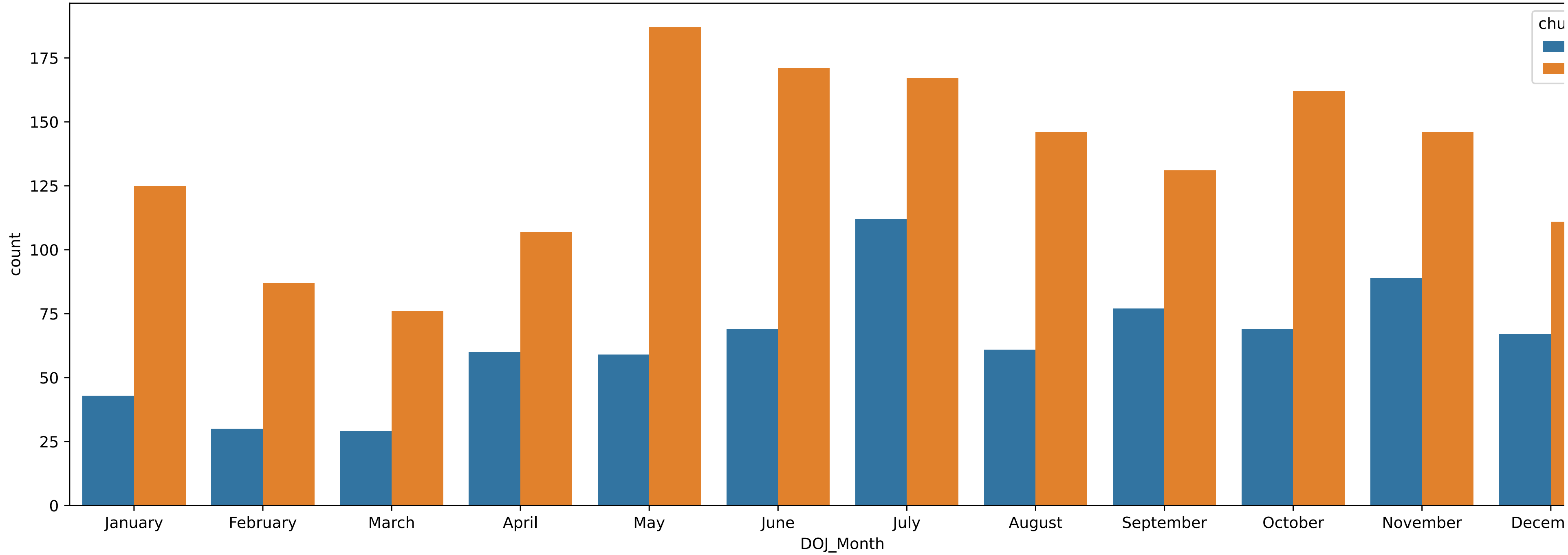
In [160]:
```
dfg_month = display_grouped_value_counts_percentage(df, 'DOJ_Month')
dfg_month['numerical_month'] = dfg_month['DOJ_Month'].apply(lambda x: list(calendar.month_name).index(x))
dfg_month.sort_values(by=['numerical_month', 'churned'], inplace=True)
dfg_month = dfg_month.drop(columns=['numerical_month']).reset_index(drop=True)

dfg_month
```

Out[160]:

	DOJ_Month	churned	percentage
0	January	0	25.60
1	January	1	74.40
2	February	0	25.64
3	February	1	74.36
4	March	0	27.62
5	March	1	72.38
6	April	0	35.93
7	April	1	64.07
8	May	0	23.98
9	May	1	76.02
10	June	0	28.75
11	June	1	71.25
12	July	0	40.14
13	July	1	59.86
14	August	0	29.47
15	August	1	70.53
16	September	0	37.02
17	September	1	62.98
18	October	0	29.87
19	October	1	70.13
20	November	0	37.87
21	November	1	62.13
22	December	0	37.64
23	December	1	62.36

In [163]:
```
display_countplot_with_hue(
    df, 'DOJ_Month', 'churned',
    order_col=list(calendar.month_name)[1:]
)
```

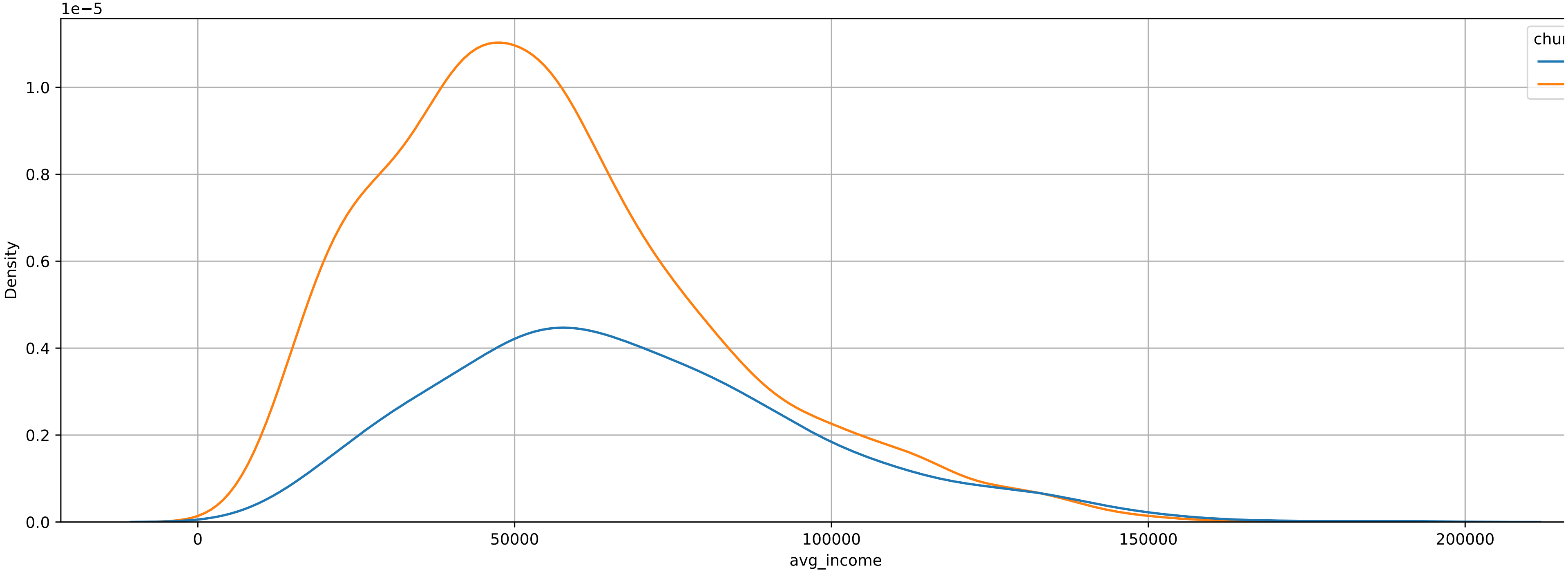


There seems variation in the churn rate based on the Joining month, this seems an important feature

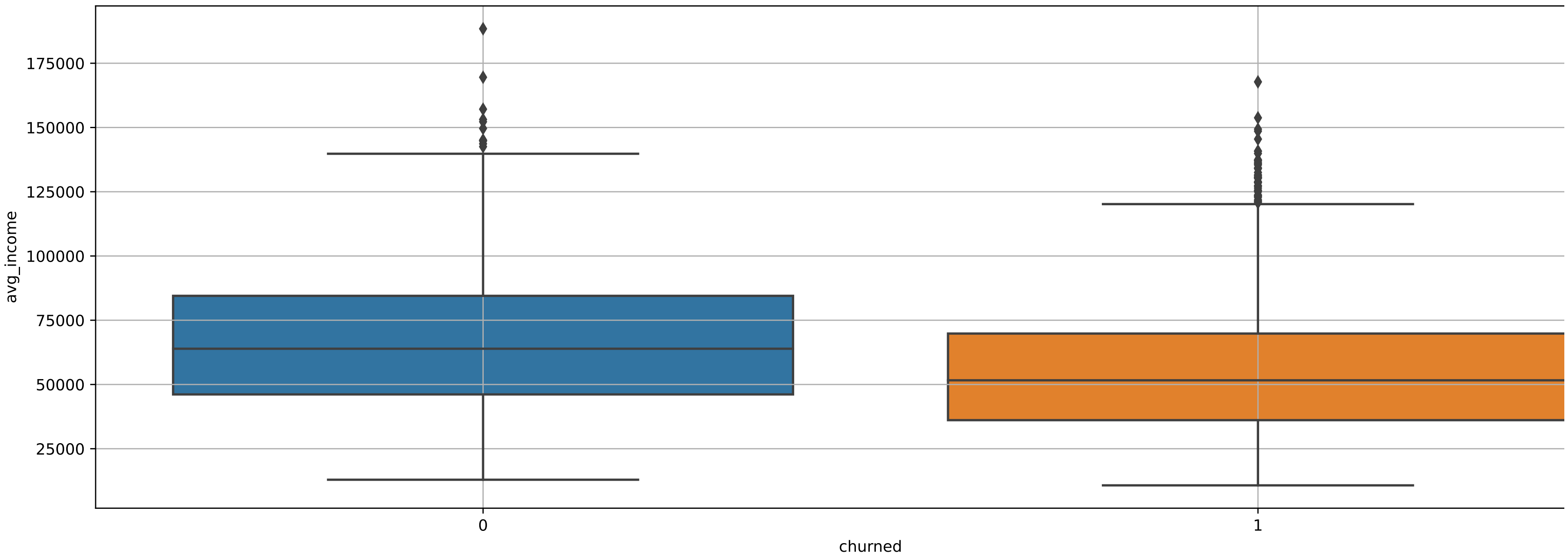
In [ ]:

Average income:

In [164]:
```
display_kde_plot_with_hue(df, 'avg_income', 'churned')
```



In [165]:
```
display_box_plot_2d(df, 'churned', 'avg_income')
```



Average income of churned drivers is slighly less as compared to non churned drivers

In [ ]:

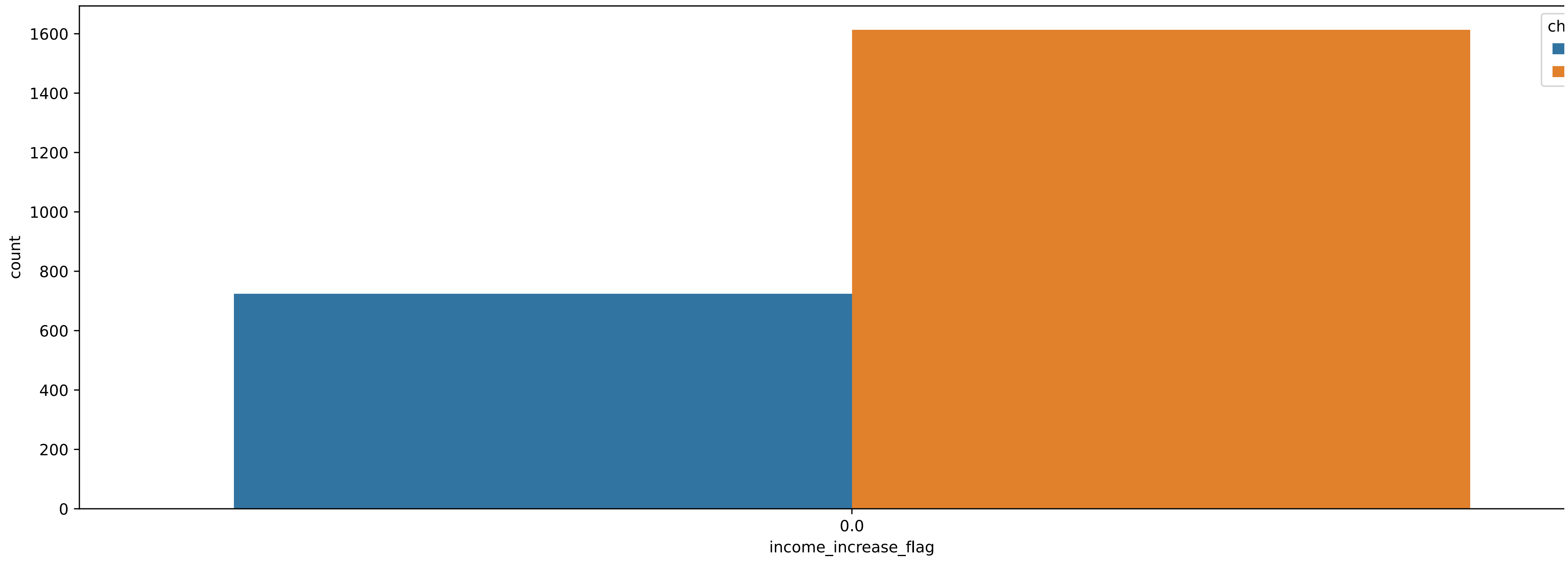
Income increase flag:

In [166]:
```
display_grouped_value_counts_percentage(df, 'income_increase_flag')
```

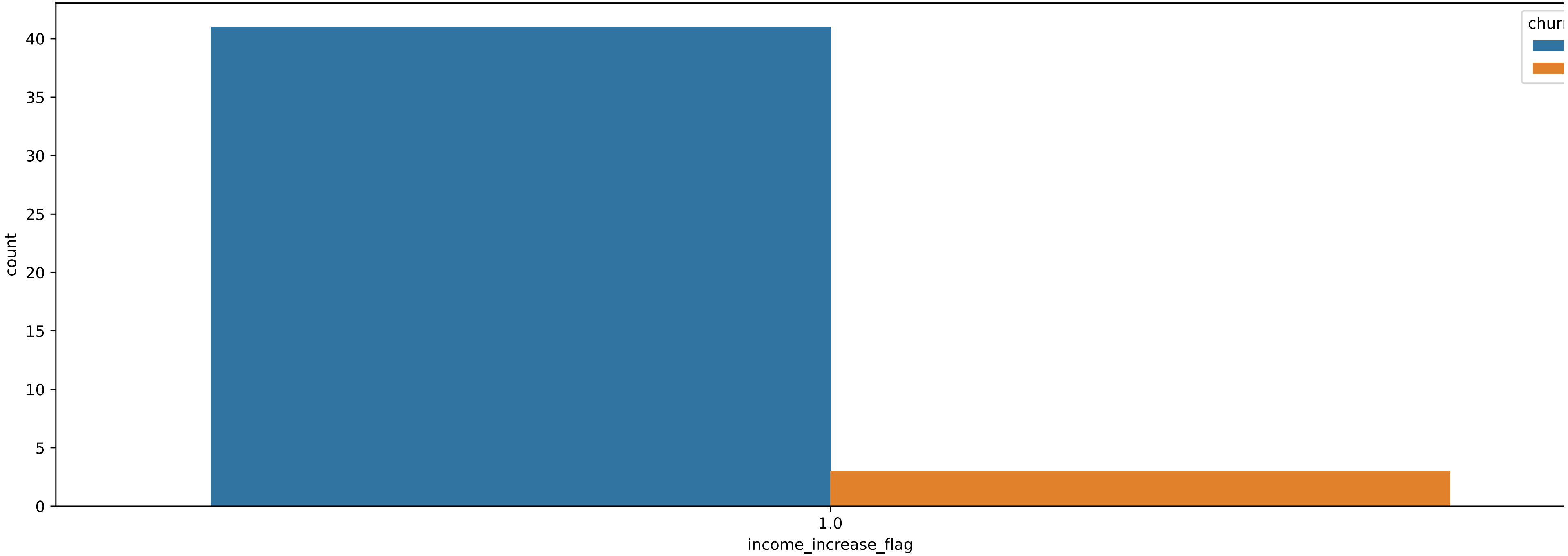
Out[166]:

	income_increase_flag	churned	percentage
0	0.0	0	30.98
1	0.0	1	69.02
2	1.0	0	93.18
3	1.0	1	6.82

In [167]:
```
display_countplot_with_hue(df[df['income_increase_flag']==0],'income_increase_flag', 'churned')
```



In [168]:
```
display_countplot_with_hue(df[df['income_increase_flag']==1],'income_increase_flag', 'churned')
```



The churn rate is very low (7%) when income_increase_flag = 1 as compared to 70% rate when income_increase_flag = 0

In [ ]:

Average grade:

In [169]:
```
display_grouped_value_counts_percentage(df, 'avg_grade')
```

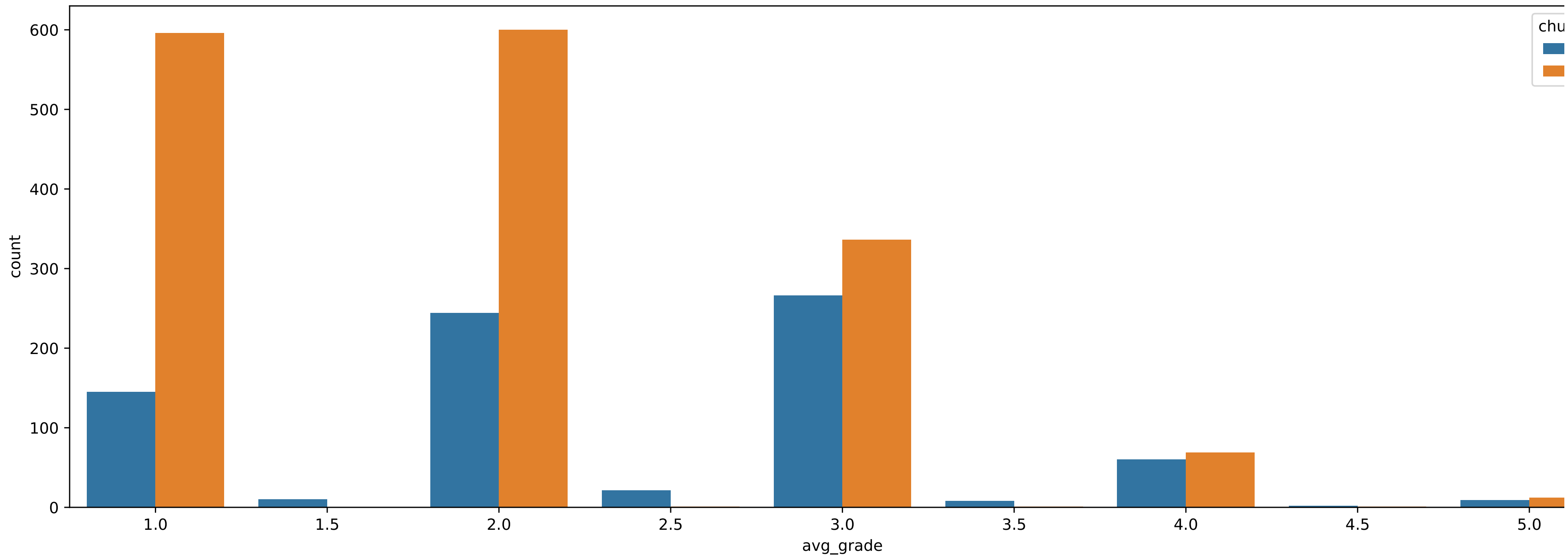
Out[169]:

	avg_grade	churned	percentage
0	1.0	0	19.57
1	1.0	1	80.43
2	1.5	0	100.00
3	2.0	0	28.91
4	2.0	1	71.09
5	2.5	0	95.45
6	2.5	1	4.55
7	3.0	0	44.19
8	3.0	1	55.81
9	3.5	0	88.89
10	3.5	1	11.11
11	4.0	0	46.51
12	4.0	1	53.49
13	4.5	0	66.67
14	4.5	1	33.33
15	5.0	0	42.86
16	5.0	1	57.14

In [170]:
```
display_pearson_corr_coef(df, 'avg_grade', 'churned')
```

```
PCC between 'avg_grade' and 'churned' = -0.215
```

In [171]:
```
display_countplot_with_hue(df, 'avg_grade', 'churned')
```



There seems variation in the avg_grade with churn rate (churn rate decreases as average grade increases), this seems an important feature

In [ ]:

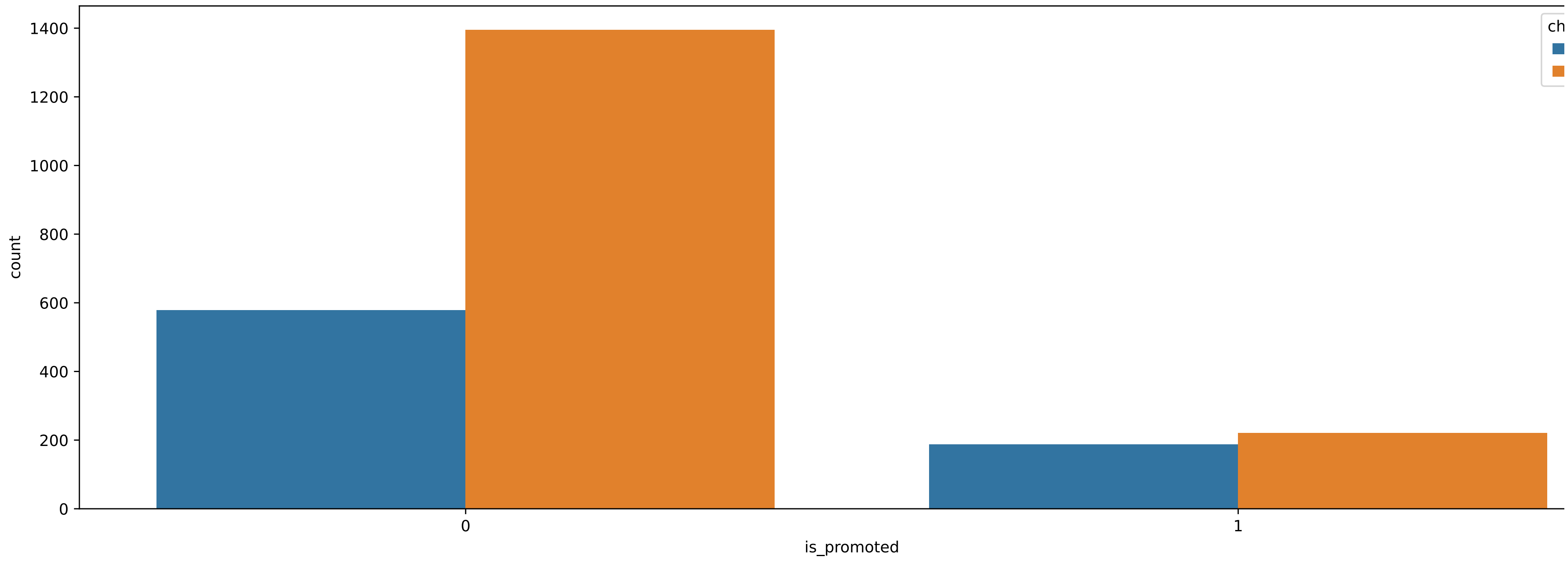
Is Promoted ?

In [172]:
```
display_grouped_value_counts_percentage(df, 'is_promoted')
```

Out[172]:

	is_promoted	churned	percentage
0	0	0	29.30
1	0	1	70.70
2	1	0	45.83
3	1	1	54.17

In [173]:
```
display_countplot_with_hue(df, 'is_promoted', 'churned')
```



Churned rate is significantly lower when the driver has been promoted during his tenure at OLA

In [ ]:

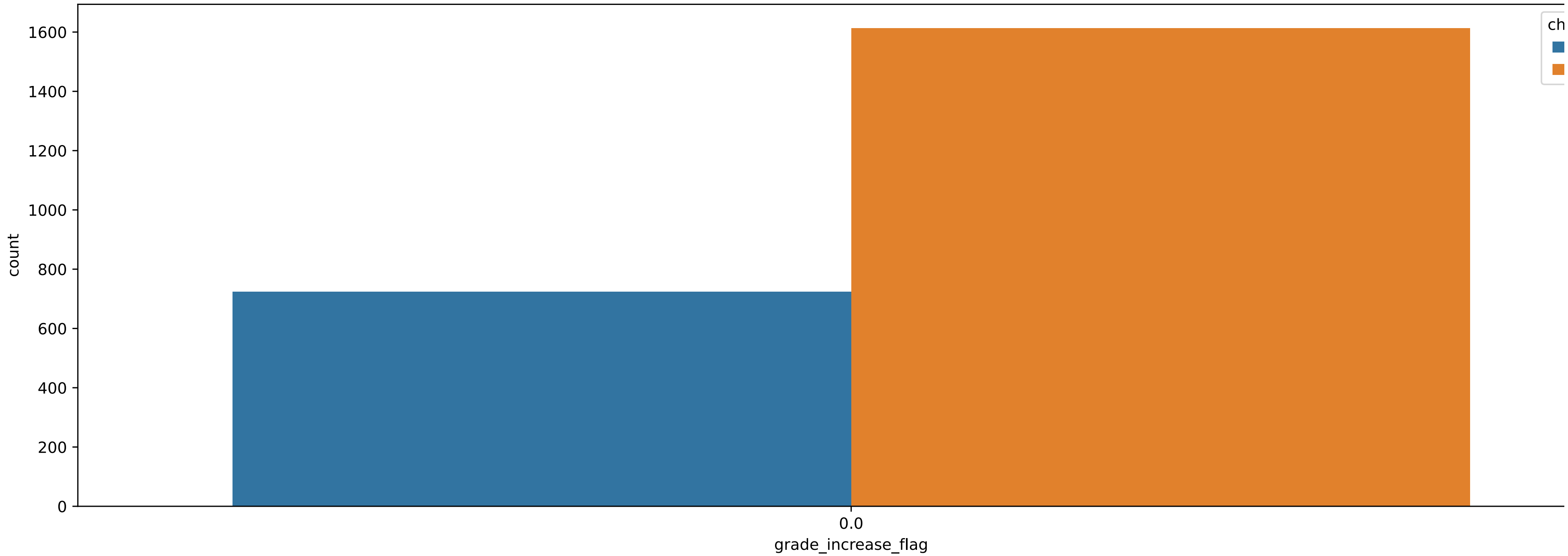
Grade increase flag:

In [174]:
```
display_grouped_value_counts_percentage(df, 'grade_increase_flag')
```

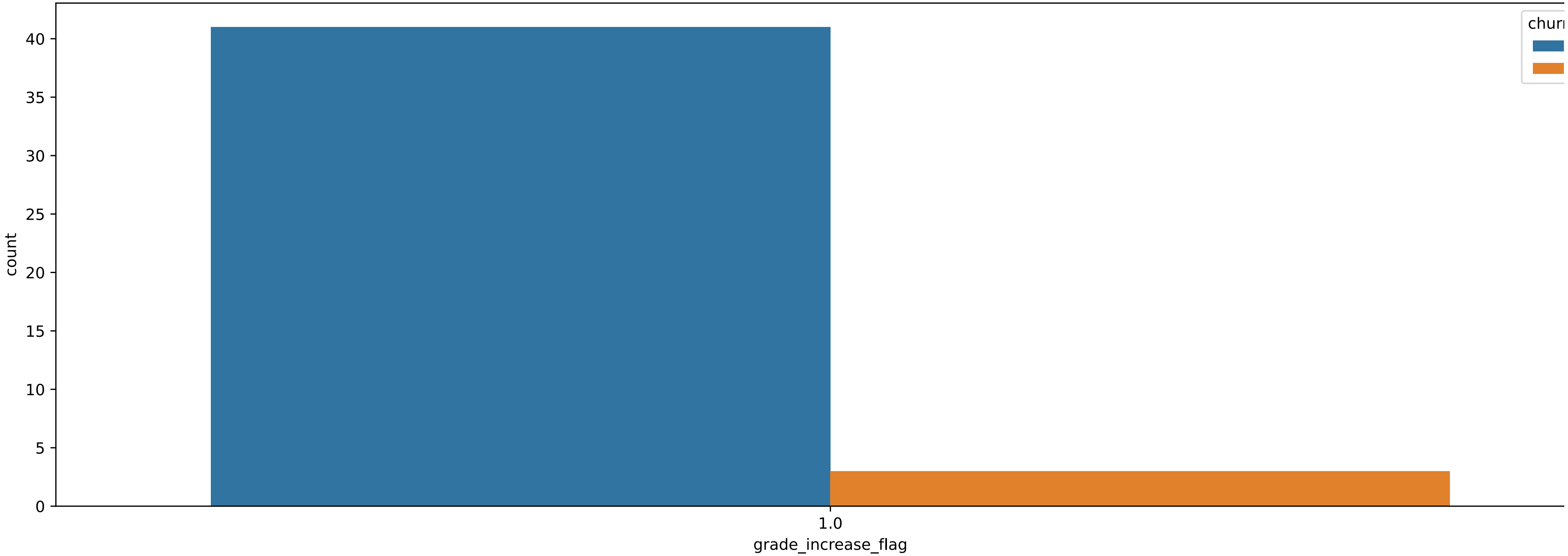
Out[174]:

	grade_increase_flag	churned	percentage
0	0.0	0	30.98
1	0.0	1	69.02
2	1.0	0	93.18
3	1.0	1	6.82

In [175]:
```
display_countplot_with_hue(df[df['grade_increase_flag']==0],'grade_increase_flag', 'churned')
```



In [176]:
```
display_countplot_with_hue(df[df['grade_increase_flag']==1],'grade_increase_flag', 'churned')
```



The churn rate is very low (7%) when grade_increase_flag = 1 as compared to 70% rate when grade_increase_flag = 0

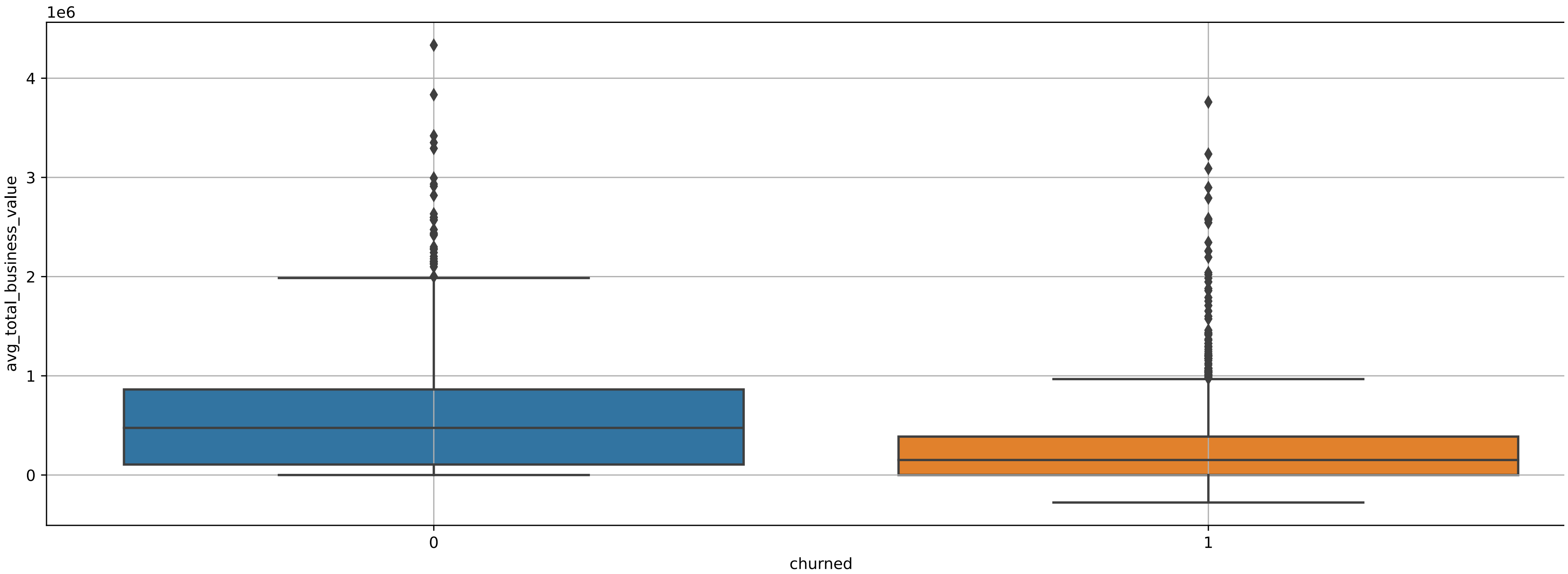
In [ ]:

Average total business value (TBV):

In [177]:
```
display_pearson_corr_coef(df, 'avg_total_business_value', 'churned')
```

```
PCC between 'avg_total_business_value' and 'churned' = -0.308
```

In [178]:
```
display_box_plot_2d(df, 'churned', 'avg_total_business_value')
```



Average total business value is significantly less for churned drivers (negative correlation also indicates the same), hence this seems an important feature

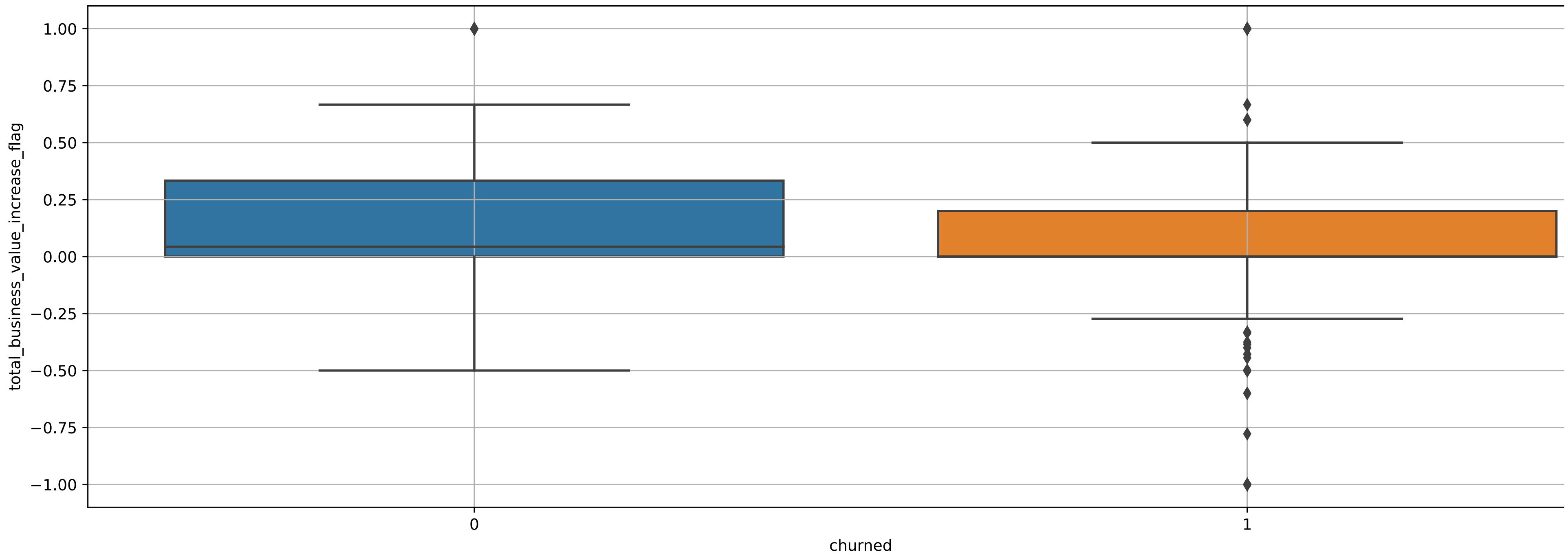
In [ ]:

TBV increase flag:

In [179]:
```
display_pearson_corr_coef(df, 'total_business_value_increase_flag', 'churned')
```

```
PCC between 'total_business_value_increase_flag' and 'churned' = -0.132
```

In [180]:
```
display_box_plot_2d(df, 'churned', 'total_business_value_increase_flag')
```



There's slight difference but it doesn't seem to be significant

In [ ]:

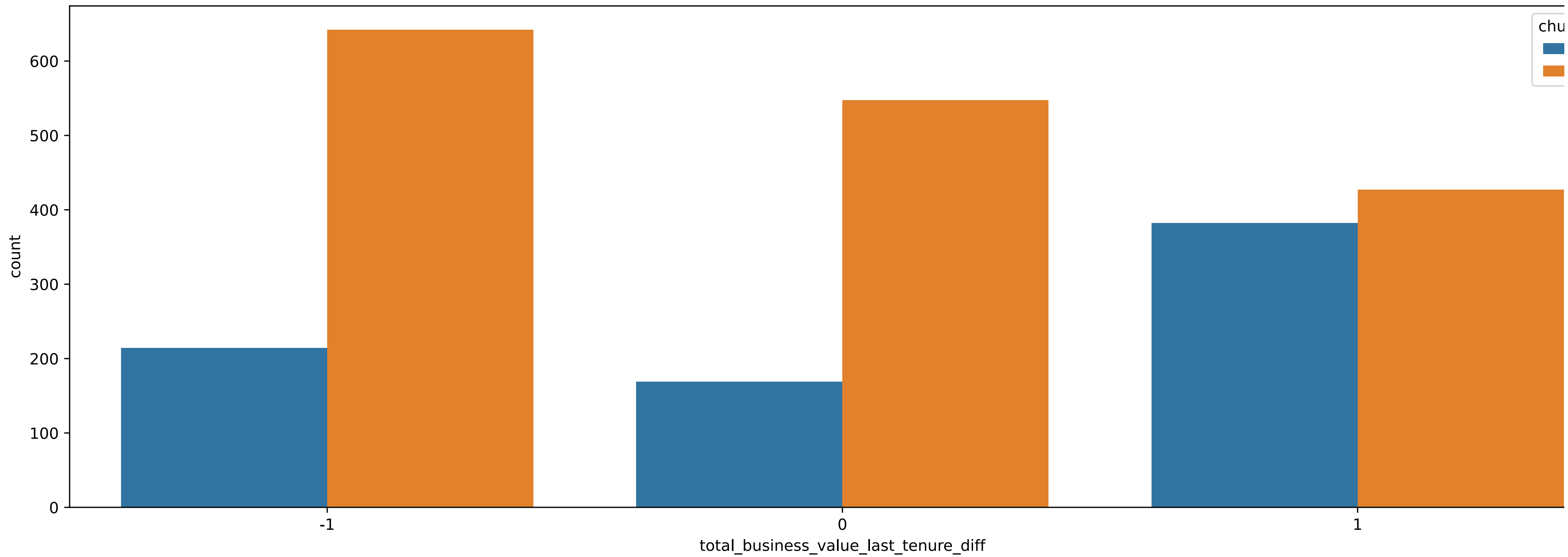
TBV difference between ultimate and penultimate months at OLA:

In [181]:
```
display_grouped_value_counts_percentage(df, 'total_business_value_last_tenure_diff')
```

Out[181]:

	total_business_value_last_tenure_diff	churned	percentage
0	-1	0	25.00
1	-1	1	75.00
2	0	0	23.60
3	0	1	76.40
4	1	0	47.22
5	1	1	52.78

In [182]:
```
display_countplot_with_hue(df, 'total_business_value_last_tenure_diff', 'churned')
```



Churn rate is significantly lower when TBV has increased in the last month as compared to the previous month, this seems an important feature

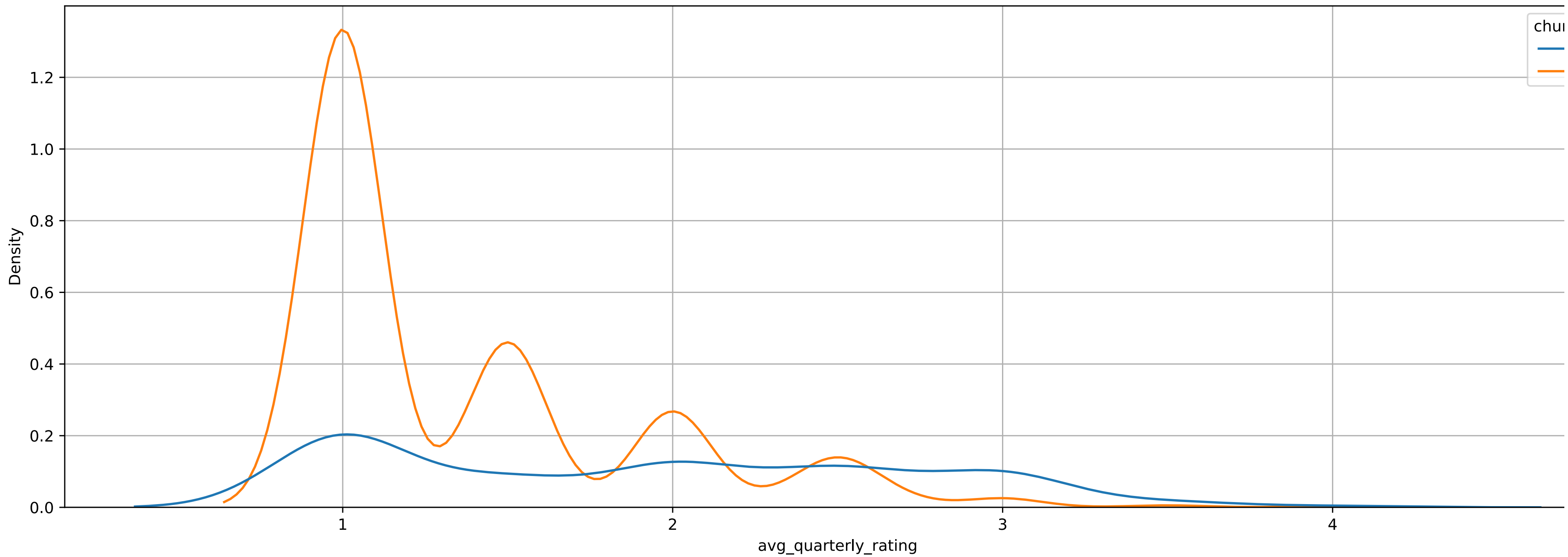
In [ ]:

Average quarterly rating:

In [183]:
```
display_pearson_corr_coef(df, 'avg_quarterly_rating', 'churned')
```

```
PCC between 'avg_quarterly_rating' and 'churned' = -0.376
```

In [184]:
```
display_kde_plot_with_hue(df, 'avg_quarterly_rating', 'churned')
```



Negative correlation indicates that as average quarterly ratings increase, churn rate decreases

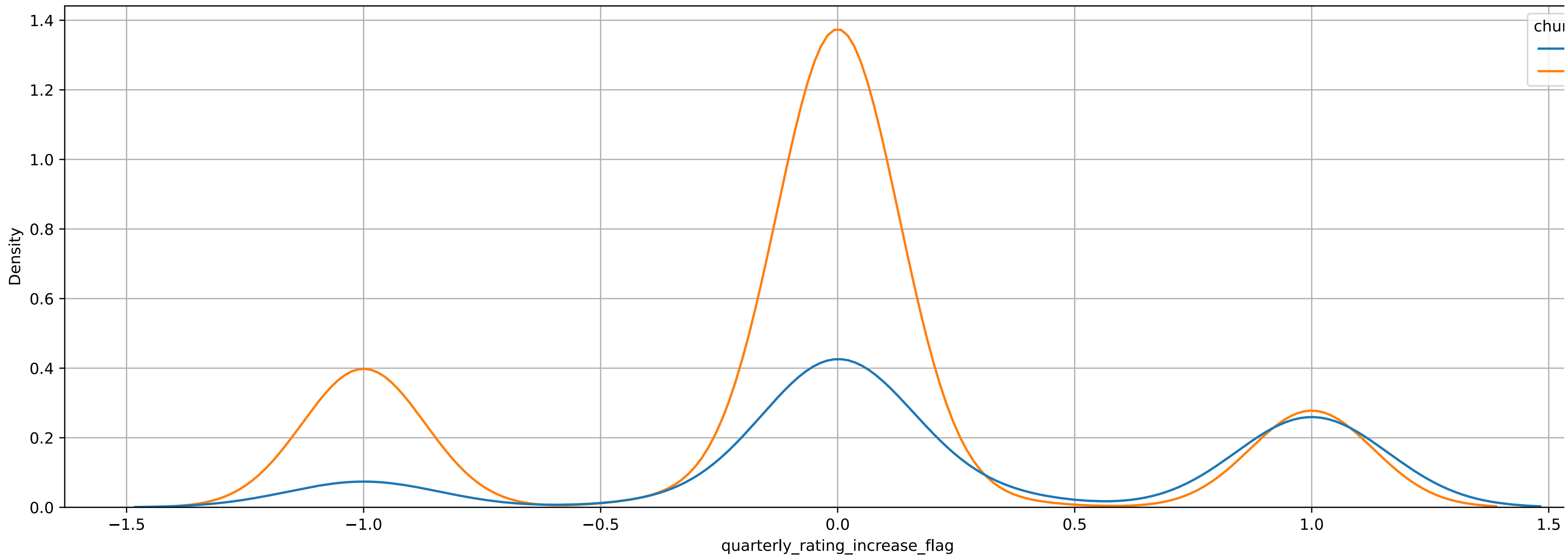
In [ ]:

Quarterly rating increase flag:

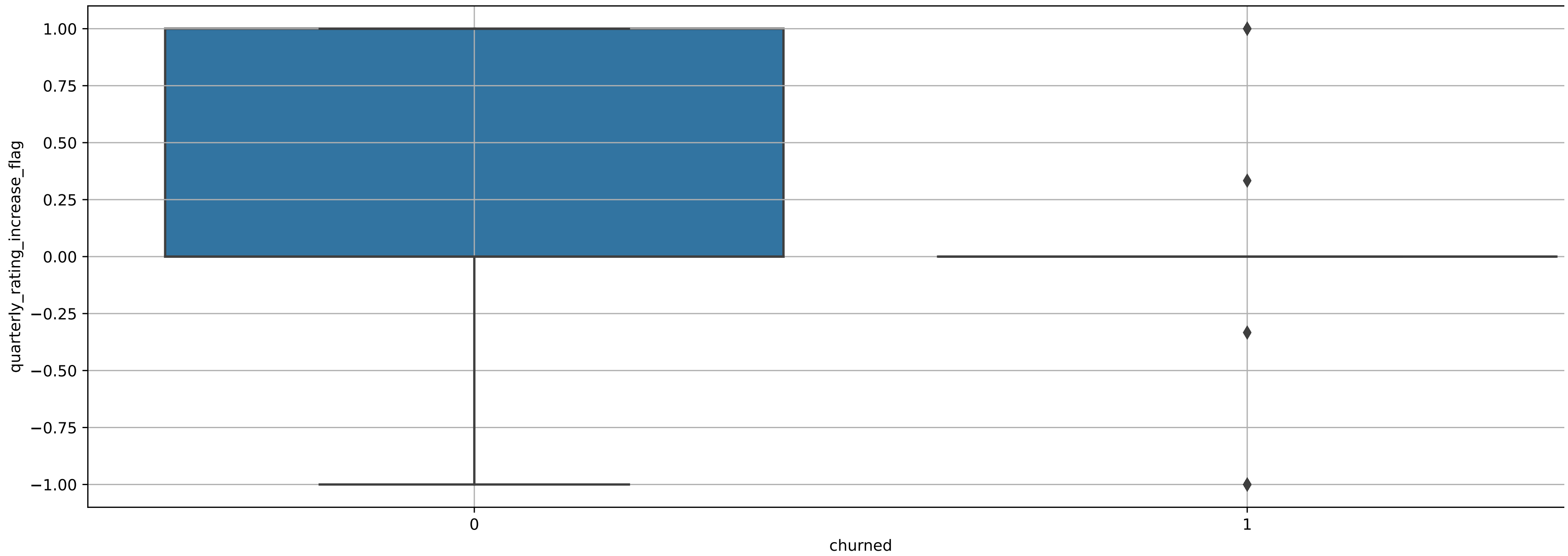
In [185]:
```
display_spearman_rank_corr_coef(df, 'quarterly_rating_increase_flag', 'churned')
```

```
SRCC between 'quarterly_rating_increase_flag' and 'churned' = -0.237
```

In [186]:
```
display_kde_plot_with_hue(df, 'quarterly_rating_increase_flag', 'churned')
```



In [187]:
```
display_box_plot_2d(df, 'churned', 'quarterly_rating_increase_flag')
```



As quarterly ratings increase, churn rate decreases however the plot doesn't look stable.

In [ ]:

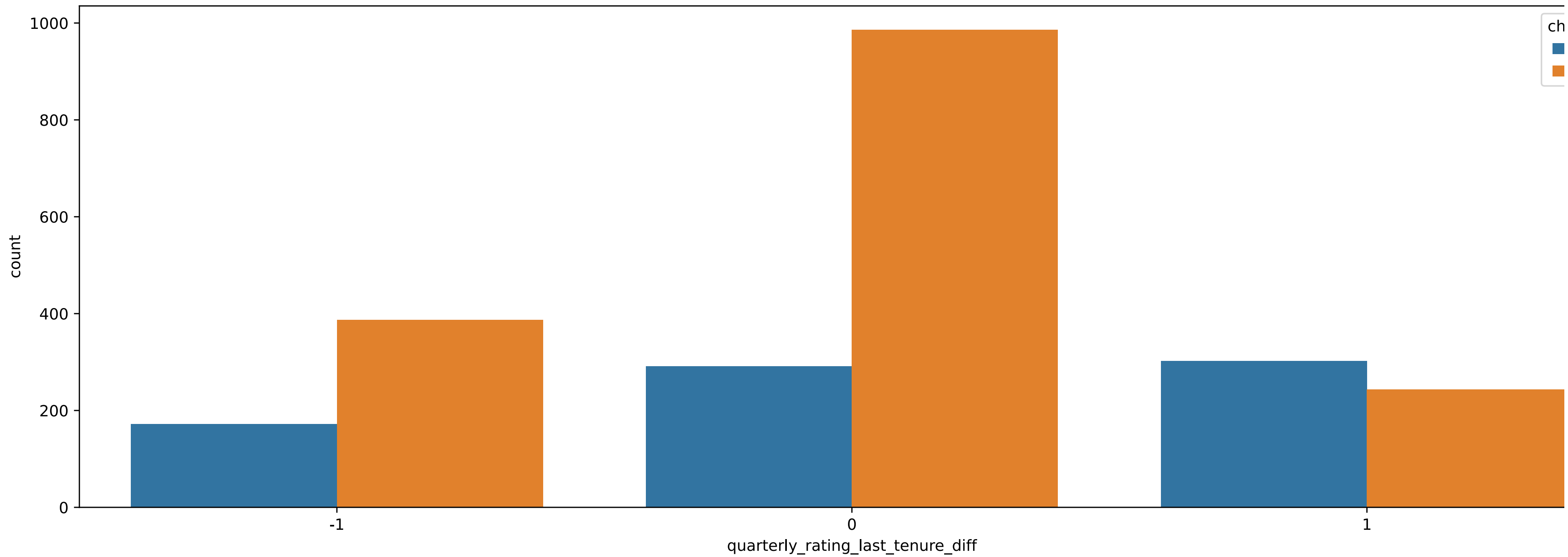
Quarterly rating difference between ultimate and penultimate months at OLA:

In [188]:
```
display_grouped_value_counts_percentage(df, 'quarterly_rating_last_tenure_diff')
```

Out[188]:

	quarterly_rating_last_tenure_diff	churned	percentage
0	-1	0	30.77
1	-1	1	69.23
2	0	0	22.79
3	0	1	77.21
4	1	0	55.41
5	1	1	44.59

In [189]:
```
display_countplot_with_hue(df, 'quarterly_rating_last_tenure_diff', 'churned')
```



The churn rate is significantly lower when the quarterly rating has increased over the last month, hence this seems an important feature

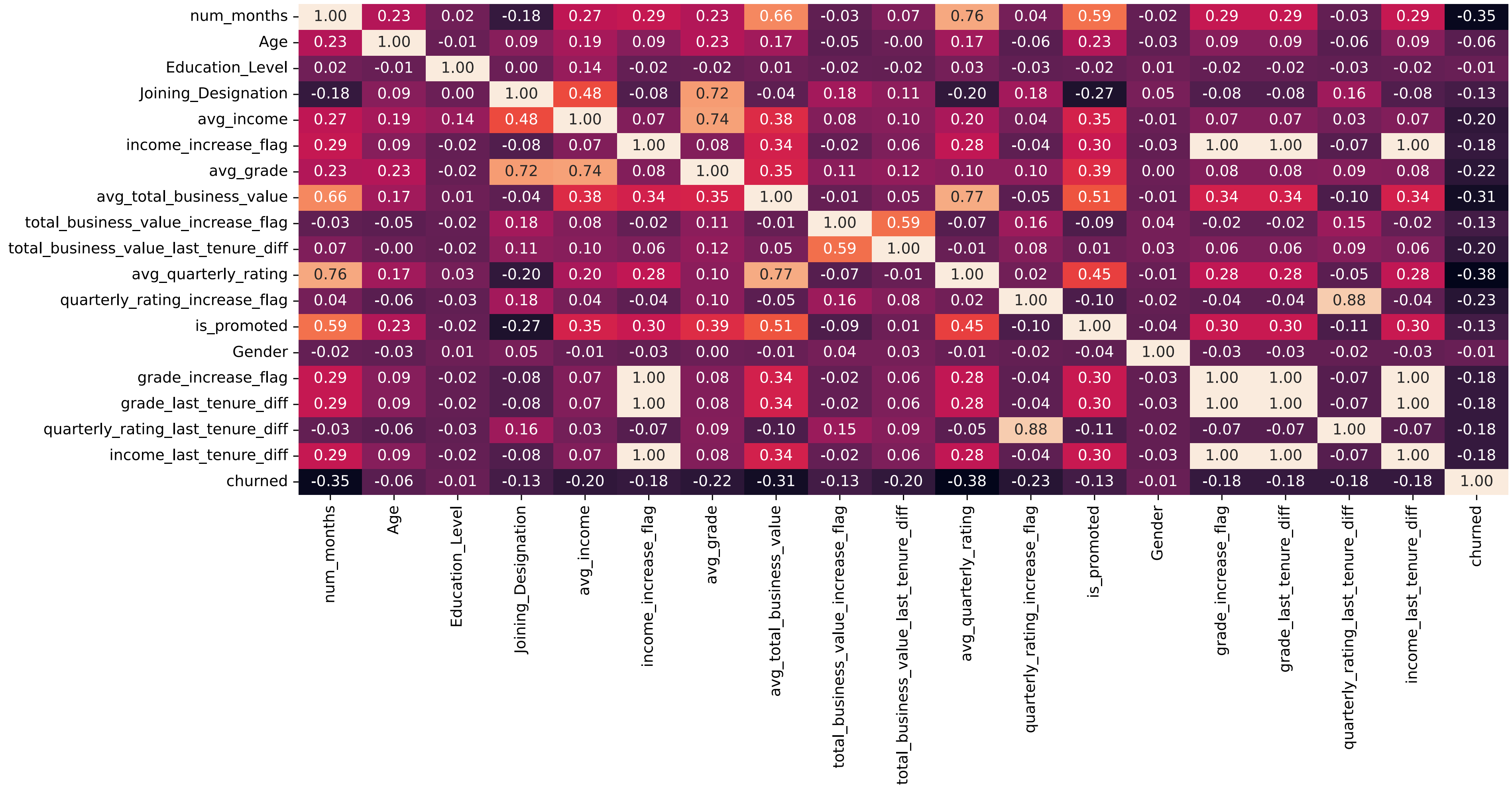
In [ ]:

Correlation Heatmap:

In [191]:
```
corr_df = df[[
    'num_months', 'Age', 'Education_Level', 'Joining_Designation', 'avg_income',
    'income_increase_flag', 'avg_grade', 'avg_total_business_value', 'total_business_value_increase_flag',
    'total_business_value_last_tenure_diff', 'avg_quarterly_rating', 'quarterly_rating_increase_flag',
    'is_promoted', 'Gender', 'grade_increase_flag', 'grade_last_tenure_diff',
    'quarterly_rating_last_tenure_diff', 'income_last_tenure_diff', 'churned'
]]

corr_df['Gender'] = corr_df['Gender'].map({'Female' : 0, 'Male' : 1})
```

In [192]:
```
display_correlation_plot(corr_df)
```



Key Observations:

1. The more months the driver spends at Ola, lower is the churn rate
2. Higher the avg quarterly rating, lower is the churn rate
3. Higher the avg business value, lower is the churn rate
4. Most of the increase_flag and last_tenure_diff variables have high correlation among themselves so we can drop some of these
5. Age, Education level and Gender have very less correlation with churn and hence can be dropped

In [ ]:

Data Preprocessing:

[Train | Cross Validation | Test] Split:

Dropping irrelevant columns (based on EDA)

In [193]:
```
X = df.drop(
        columns=[
            'grade_increase_flag',
            'grade_last_tenure_diff',
            'quarterly_rating_last_tenure_diff',
            'income_last_tenure_diff',
            'Age',
            'Education_Level',
            'Gender',
            'index',
            'churned'
        ]
    )

Y = df['churned']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.15, stratify=Y, random_state=42)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.15, stratify=y_train, random_state=42)
```

In [194]:
```
print(f"X_train shape: {X_train.shape}")
print(f"X_cv shape: {X_cv.shape}")
print(f"X_test shape: {X_test.shape}")
```

```
X_train shape: (1719, 14)
X_cv shape: (304, 14)
X_test shape: (358, 14)
```

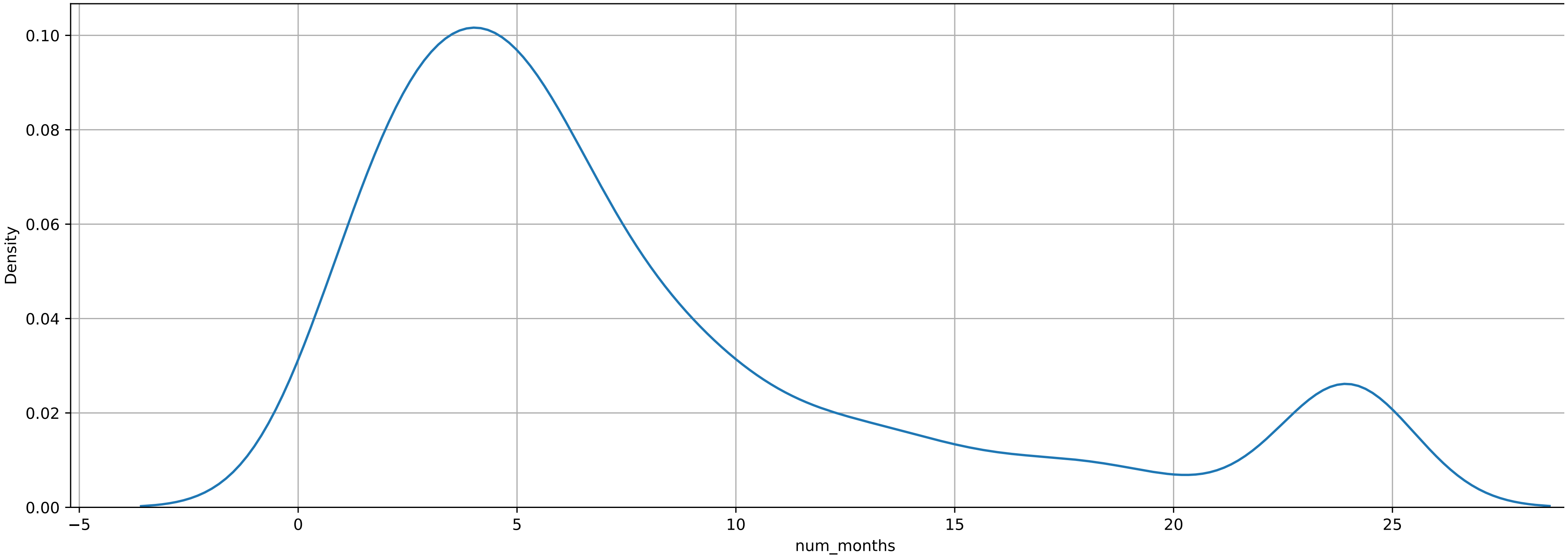
In [ ]:

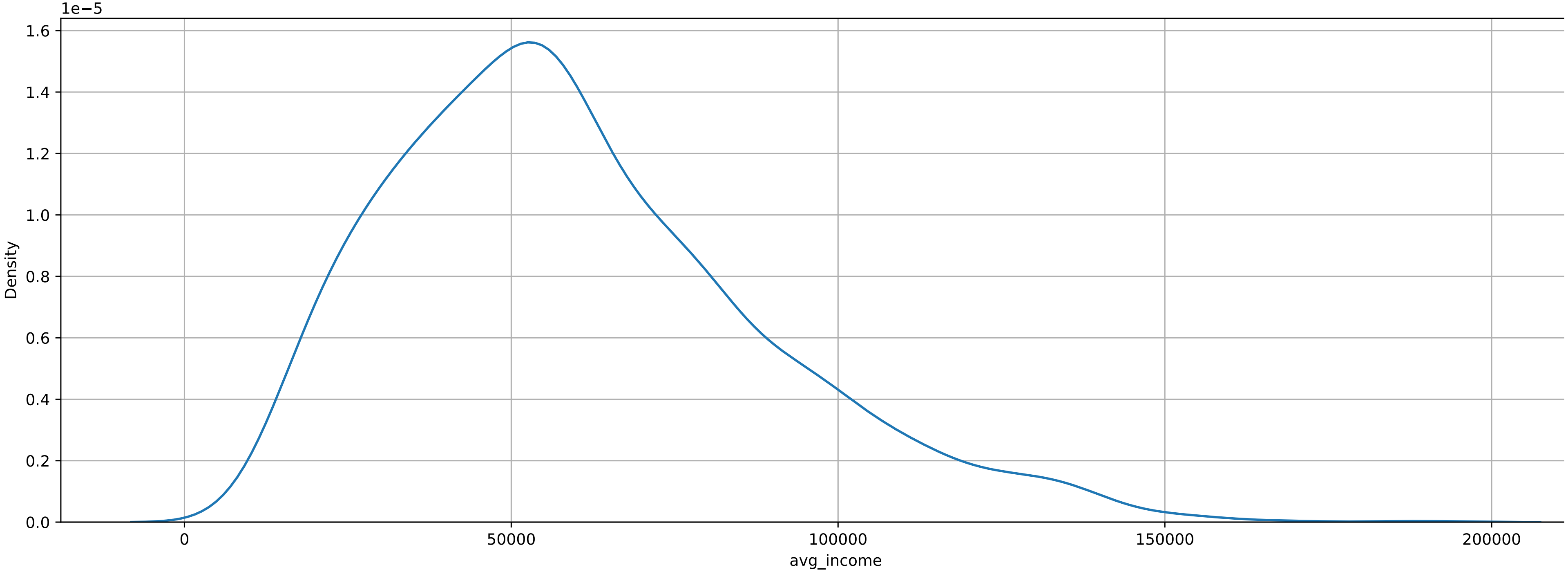
Data Preprocessing:

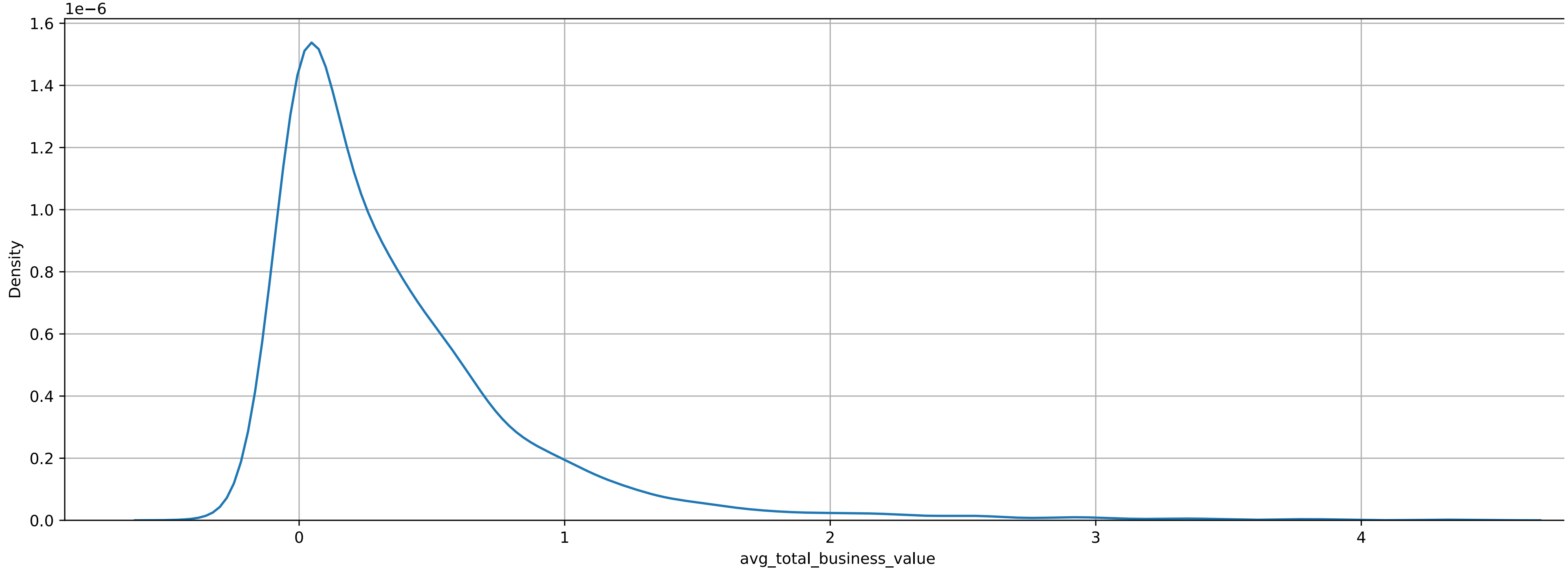
Done by capping the minimum value to Q1 - 1.5 * IQR and capping the maximum value to Q3 + 1.5 * IQR

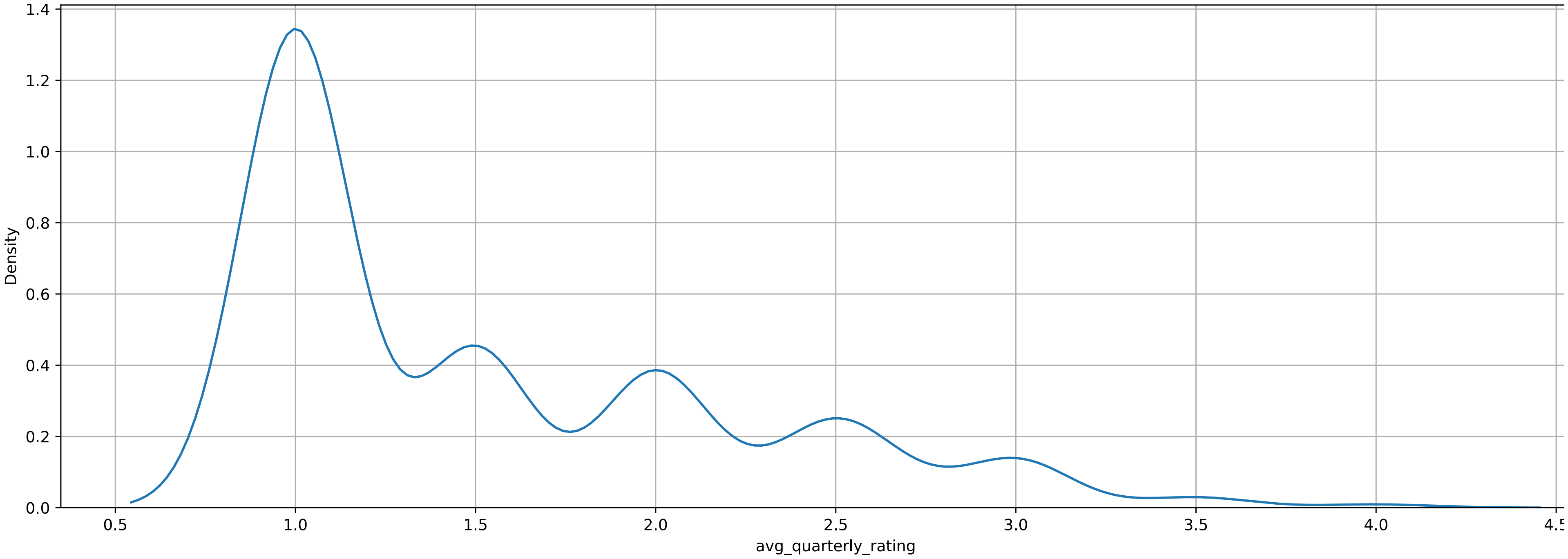
Before outlier handling:

In [198]:
```
for col in ['num_months', 'avg_income', 'avg_total_business_value', 'avg_quarterly_rating']:
    display_kde_plot(X_train, col)
```




1e−5
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Density
0
50000
100000
150000
200000
avg_income


1e−6
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Density
0
1
2
3
4
avg_total_business_value

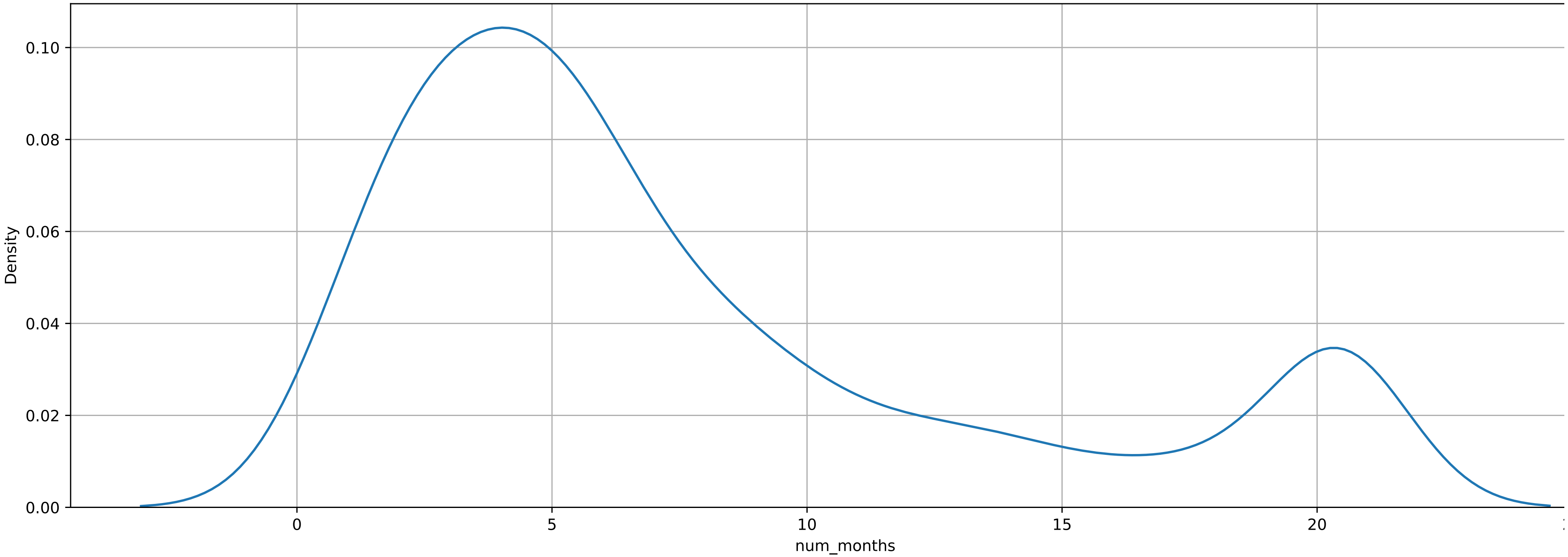


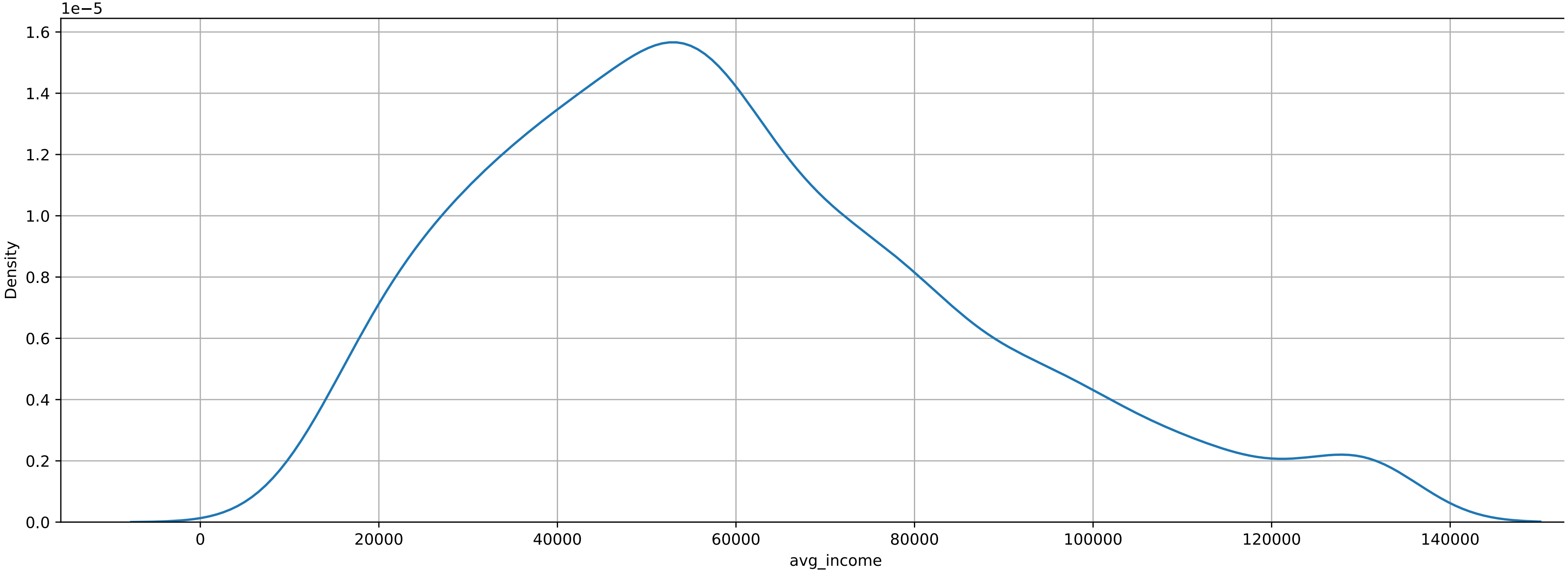
Performing outlier handling:

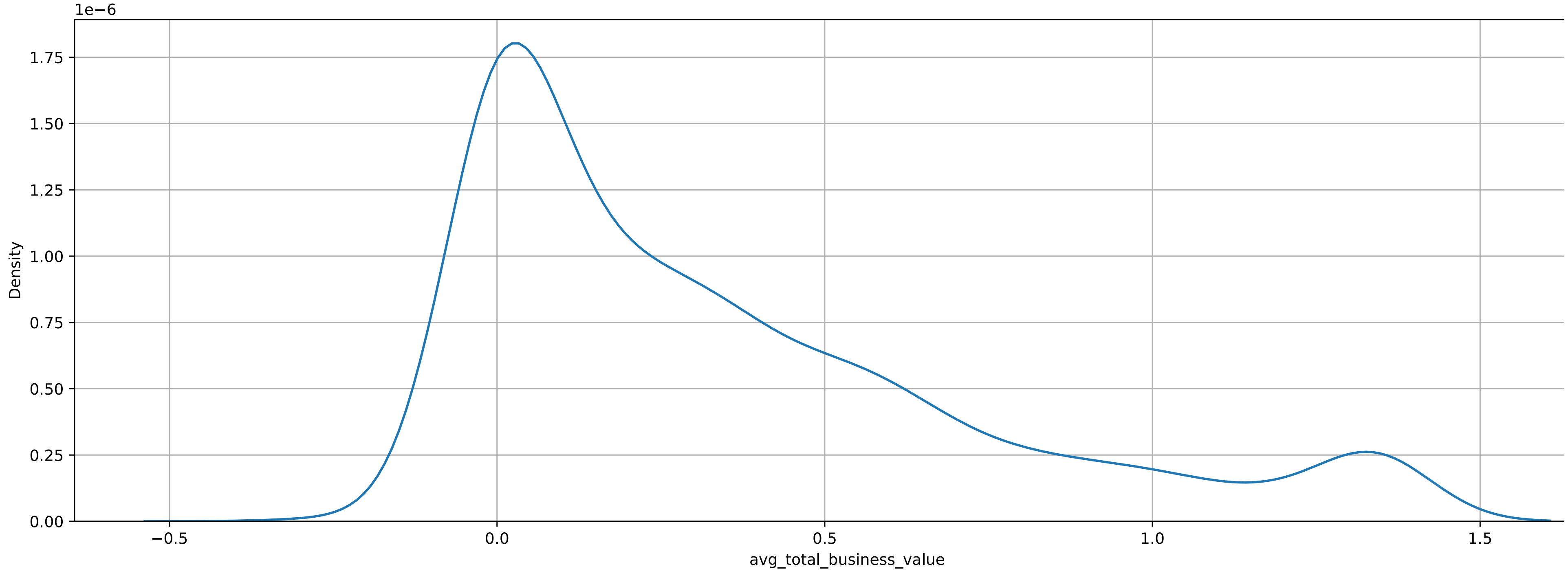
In [199]:
```
for col in ['num_months', 'avg_income', 'avg_total_business_value', 'avg_quarterly_rating']:
    q1 = np.percentile(X_train[col], 25)
    q3 = np.percentile(X_train[col], 75)
    min_clip_value = q1-1.5*(q3-q1)
    max_clip_value = q3+1.5*(q3-q1)
    X_train[col] = np.clip(X_train[col], min_clip_value, max_clip_value)
    X_cv[col] = np.clip(X_cv[col], min_clip_value, max_clip_value)
    X_test[col] = np.clip(X_test[col], min_clip_value, max_clip_value)
```

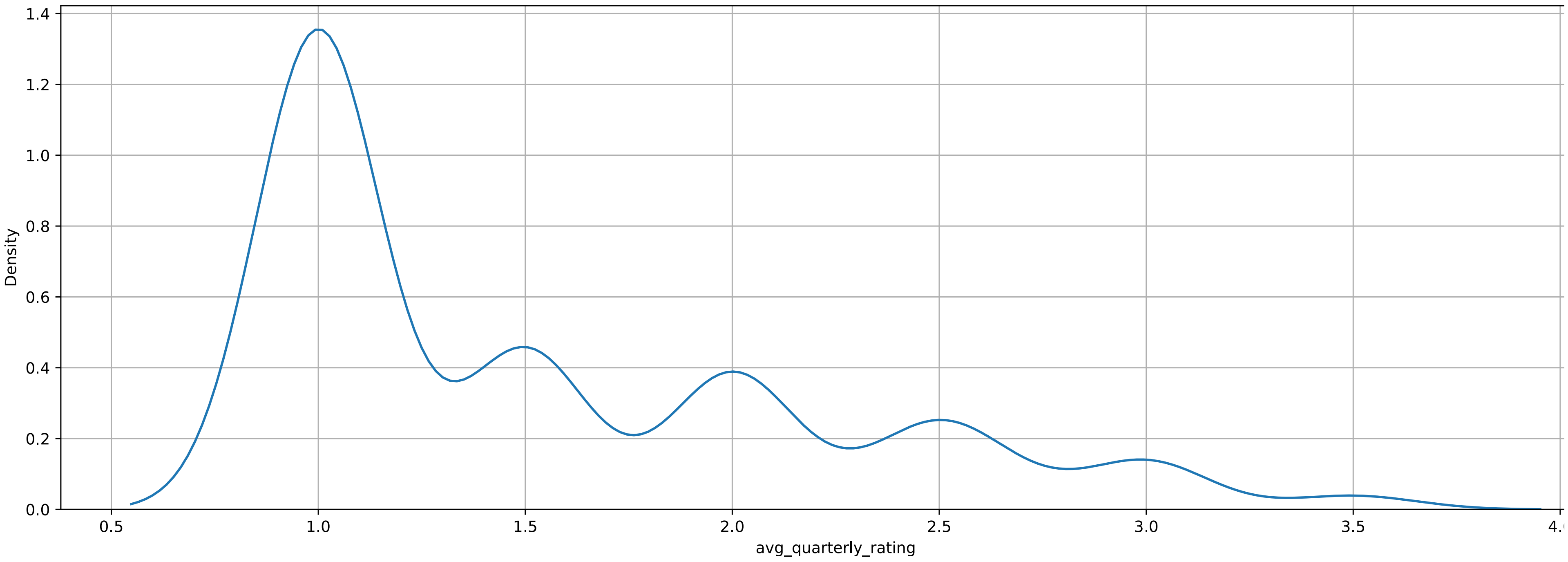
After outlier handling:

In [200]:
```
for col in ['num_months', 'avg_income', 'avg_total_business_value', 'avg_quarterly_rating']:
    display_kde_plot(X_train, col)
```




1e−5
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Density
0
20000
40000
60000
80000
100000
120000
140000
avg_income


1e−6
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Density
−0.5
0.0
0.5
1.0
1.5
avg_total_business_value



In [ ]:

Data Preprocessing:

Feature Engineering:

In this BCS Dataset Standardization is not required since we're building tree based models but for categorical features we will perform One Hot Encoding (OHE)

In [ ]:

One Hot Encoding:

In [201]:
```
cate_cols = ['City', 'DOJ_Year', 'DOJ_Month', 'is_promoted']
```

In [202]:
```
ohe = OneHotEncoder()
ohe.fit(X_train[cate_cols])
feature_names = ohe.get_feature_names_out(cate_cols)

train_encoded = ohe.transform(X_train[cate_cols]).toarray()
train_encoded = pd.DataFrame(train_encoded, columns=feature_names).astype(int)
X_train_encoded = pd.concat([X_train.reset_index(drop=True), train_encoded], axis=1)
X_train_encoded.drop(cate_cols, axis=1, inplace=True)

cv_encoded = ohe.transform(X_cv[cate_cols]).toarray()
cv_encoded = pd.DataFrame(cv_encoded,columns=feature_names).astype(int)
X_cv_encoded = pd.concat([X_cv.reset_index(drop=True), cv_encoded], axis=1)
X_cv_encoded.drop(cate_cols, axis=1, inplace=True)

test_encoded = ohe.transform(X_test[cate_cols]).toarray()
test_encoded = pd.DataFrame(test_encoded, columns=feature_names).astype(int)
X_test_encoded = pd.concat([X_test.reset_index(drop=True), test_encoded], axis=1)
X_test_encoded.drop(cate_cols, axis=1, inplace=True)
```

In [203]:
```
print(X_train_encoded.shape)
print(X_cv_encoded.shape)
print(X_test_encoded.shape)
```

```
(1719, 61)
(304, 61)
(358, 61)
```

In [ ]:

Model Building:

Evaluation Metric:

- Finding out drivers who are more likely to be churned is more important as compared to finding drivers who might not be churned, so in this case, a particular class is more important than the other (class 1: churned) and hence we can choose F1 Score as the right metric which optimizes both Precision and Recall for the "Churned" class

Helper Functions:

In [204]:
```
def plot_roc_curve_and_display_auc_roc_score(y_true, y_prob, dataset_name):
    fpr, tpr, _ = roc_curve(y_true, y_prob)
    plt.plot(fpr, tpr)
    plt.title(f'{dataset_name} ROC Curve')
    plt.xlabel('FPR')
    plt.ylabel('TPR')
    plt.grid()
    plt.show()
    print(f"{dataset_name} AUC ROC Score = {roc_auc_score(y_true, y_prob).round(3)}")
```

In [205]:
```
def print_classification_report(y_true, y_pred, target_names = ['Retained', 'Churned']):
    print(
        classification_report(
            y_true, y_pred,
            target_names=target_names
        )
    )
```

In [ ]:

Baseline Model : Decision Tree:

In [206]:
```
parameters = {
    'criterion' : ['gini', 'entropy'],
    'max_depth' : [3, 5, 7, 9, 11],
    'class_weight' : [None, 'balanced'],
    'max_features' : ['sqrt', None]
}

dt = DecisionTreeClassifier()
clf = GridSearchCV(
    estimator = dt,
    param_grid = parameters,
    scoring = 'f1'
)

clf.fit(X_train_encoded, y_train)
```

Out[206]:
```
GridSearchCV(estimator=DecisionTreeClassifier(),
             param_grid={'class_weight': [None, 'balanced'],
                         'criterion': ['gini', 'entropy'],
                         'max_depth': [3, 5, 7, 9, 11],
                         'max_features': ['sqrt', None]},
             scoring='f1')
```

In [207]:
```
best_est = clf.best_estimator_
clf.best_params_
```

Out[207]:
```
{'class_weight': None,
 'criterion': 'gini',
 'max_depth': 7,
 'max_features': None}
```

In [ ]:

Predictions:

In [208]:
```
y_train_pred = best_est.predict(X_train_encoded)
y_cv_pred = best_est.predict(X_cv_encoded)
y_test_pred = best_est.predict(X_test_encoded)

y_train_pred_proba = best_est.predict_proba(X_train_encoded)[:, 1]
y_cv_pred_proba = best_est.predict_proba(X_cv_encoded)[:, 1]
y_test_pred_proba = best_est.predict_proba(X_test_encoded)[:, 1]
```

In [ ]:

F1 Score:

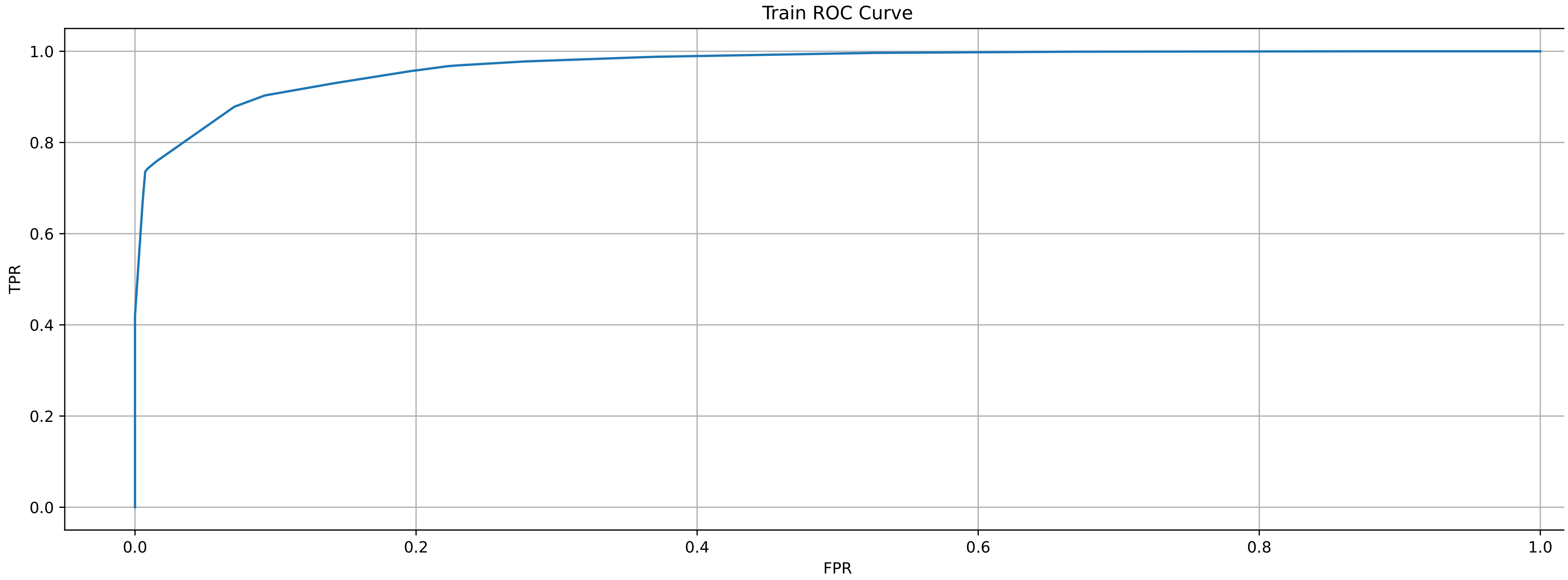
In [209]:
```
print(f'Train F1 Score = {f1_score(y_train, y_train_pred).round(3)}')
print(f'CV F1 Score = {f1_score(y_cv, y_cv_pred).round(3)}')
print(f'Test F1 Score = {f1_score(y_test, y_test_pred).round(3)}')
```

```
Train F1 Score = 0.933
CV F1 Score = 0.91
Test F1 Score = 0.891
```

In [ ]:

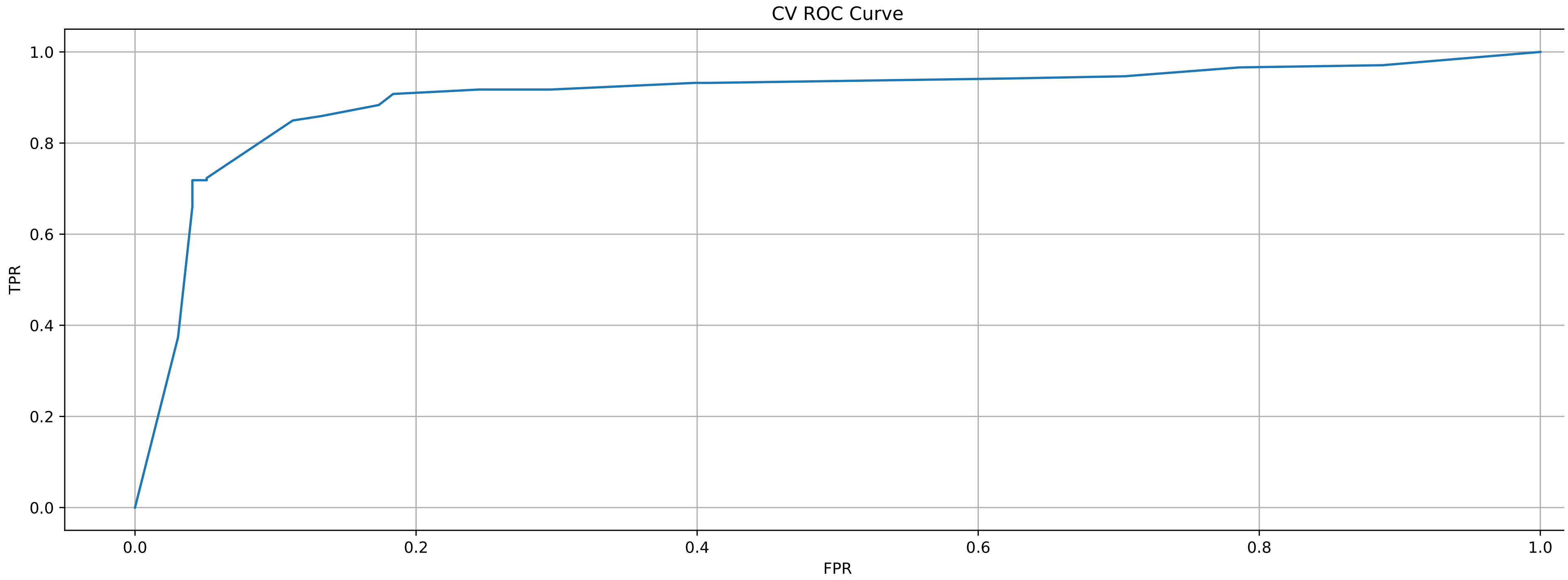
AUC-ROC Score:

In [210]:
```
plot_roc_curve_and_display_auc_roc_score(y_train, y_train_pred_proba, 'Train')
```



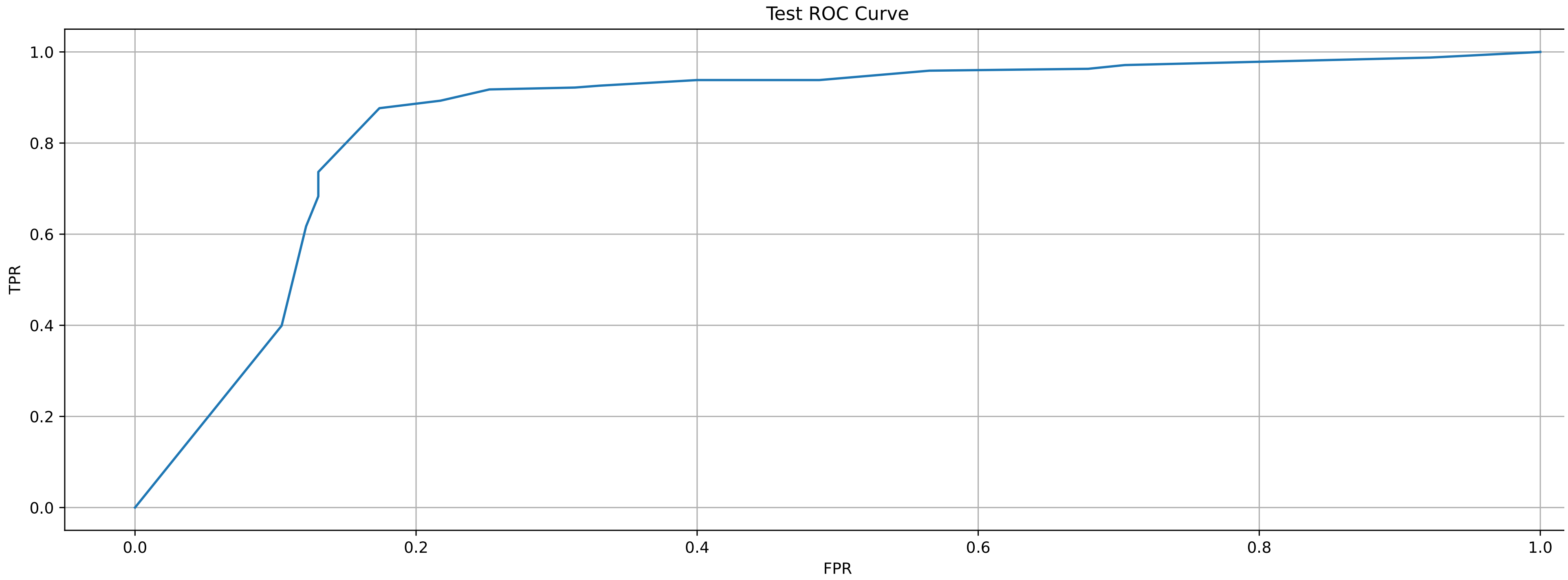

```
Train AUC ROC Score = 0.97
```

In [211]:
```
plot_roc_curve_and_display_auc_roc_score(y_cv, y_cv_pred_proba, 'CV')
```




```
CV AUC ROC Score = 0.901
```

In [212]:
```
plot_roc_curve_and_display_auc_roc_score(y_test, y_test_pred_proba, 'Test')
```




```
Test AUC ROC Score = 0.858
```

In [ ]:

Classification Report:

In [213]:
```
print_classification_report(y_train, y_train_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.90      0.81      0.85       552
     Churned       0.91      0.96      0.93      1167

    accuracy                           0.91      1719
   macro avg       0.90      0.88      0.89      1719
weighted avg       0.91      0.91      0.91      1719
```

In [214]:
```
print_classification_report(y_cv, y_cv_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.81      0.82      0.81        98
     Churned       0.91      0.91      0.91       206

    accuracy                           0.88       304
   macro avg       0.86      0.86      0.86       304
weighted avg       0.88      0.88      0.88       304
```

In [215]:
```
print_classification_report(y_test, y_test_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.81      0.69      0.74       115
     Churned       0.86      0.92      0.89       243

    accuracy                           0.85       358
   macro avg       0.83      0.80      0.82       358
weighted avg       0.84      0.85      0.84       358
```

Baseline model is giving a F1 Score of 0.89 on the test set which is quite good, but Ensemble models are significantly stronger than DT, so these should give better score.

In [ ]:

Bagging (RandomForest Classifier):

In [216]:
```
parameters = {
    'n_estimators' : [100, 200, 300, 400],
    'max_depth' : [7, 9, 11, 13],
    'max_samples' : [0.25, 0.5, 0.75, 1],
    'max_features' : [0.25, 0.5, 0.75, 'sqrt', None],
}

rf = RandomForestClassifier(random_state=42, n_jobs=-1)
clf = GridSearchCV(
    estimator = rf,
    param_grid = parameters,
    scoring = 'f1',
    n_jobs=-1,
    cv=3,
    verbose=1
)

clf.fit(X_train_encoded, y_train)
```

```
Fitting 3 folds for each of 320 candidates, totalling 960 fits
```

Out[216]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(n_jobs=-1, random_state=21),
             n_jobs=-1,
             param_grid={'max_depth': [7, 9, 11, 13],
                         'max_features': [0.25, 0.5, 0.75, 'sqrt', None],
                         'max_samples': [0.25, 0.5, 0.75, 1],
                         'n_estimators': [100, 200, 300, 400]},
             scoring='f1', verbose=1)
```

In [217]:
```
best_est = clf.best_estimator_
clf.best_params_
```

Out[217]:
```
{'max_depth': 11,
 'max_features': 0.5,
 'max_samples': 0.75,
 'n_estimators': 100}
```

In [ ]:

Predictions:

In [218]:
```
y_train_pred = best_est.predict(X_train_encoded)
y_cv_pred = best_est.predict(X_cv_encoded)
y_test_pred = best_est.predict(X_test_encoded)

y_train_pred_proba = best_est.predict_proba(X_train_encoded)[:, 1]
y_cv_pred_proba = best_est.predict_proba(X_cv_encoded)[:, 1]
y_test_pred_proba = best_est.predict_proba(X_test_encoded)[:, 1]
```

In [ ]:

F1 Score:

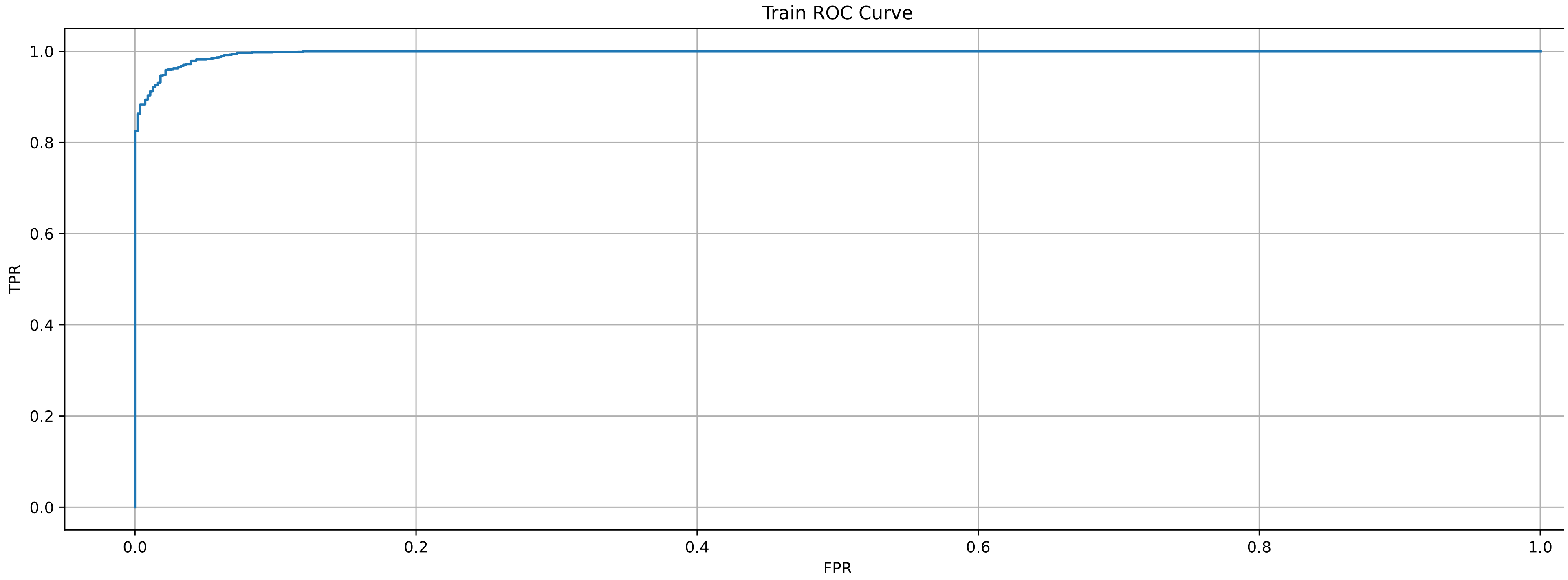
In [219]:
```
print(f'Train F1 Score = {f1_score(y_train, y_train_pred).round(3)}')
print(f'CV F1 Score = {f1_score(y_cv, y_cv_pred).round(3)}')
print(f'Test F1 Score = {f1_score(y_test, y_test_pred).round(3)}')
```

```
Train F1 Score = 0.979
CV F1 Score = 0.916
Test F1 Score = 0.928
```

In [ ]:

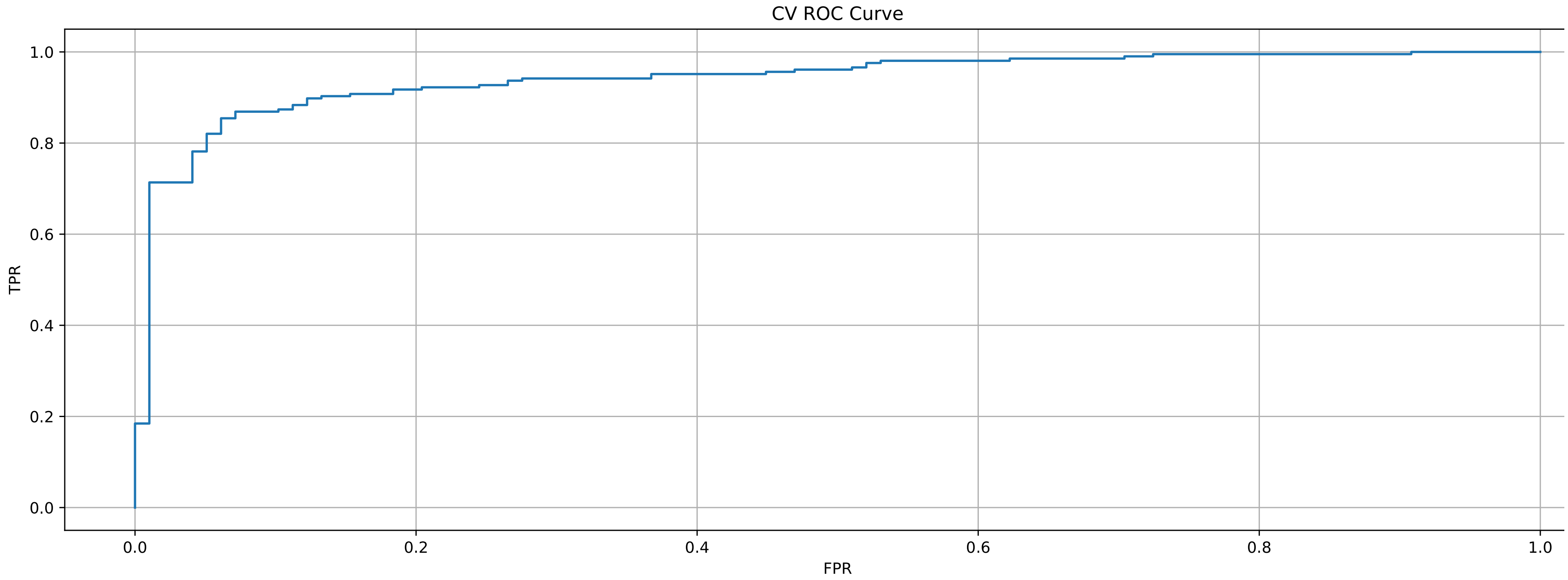
AUC-ROC Score:

In [220]:
```
plot_roc_curve_and_display_auc_roc_score(y_train, y_train_pred_proba, 'Train')
```



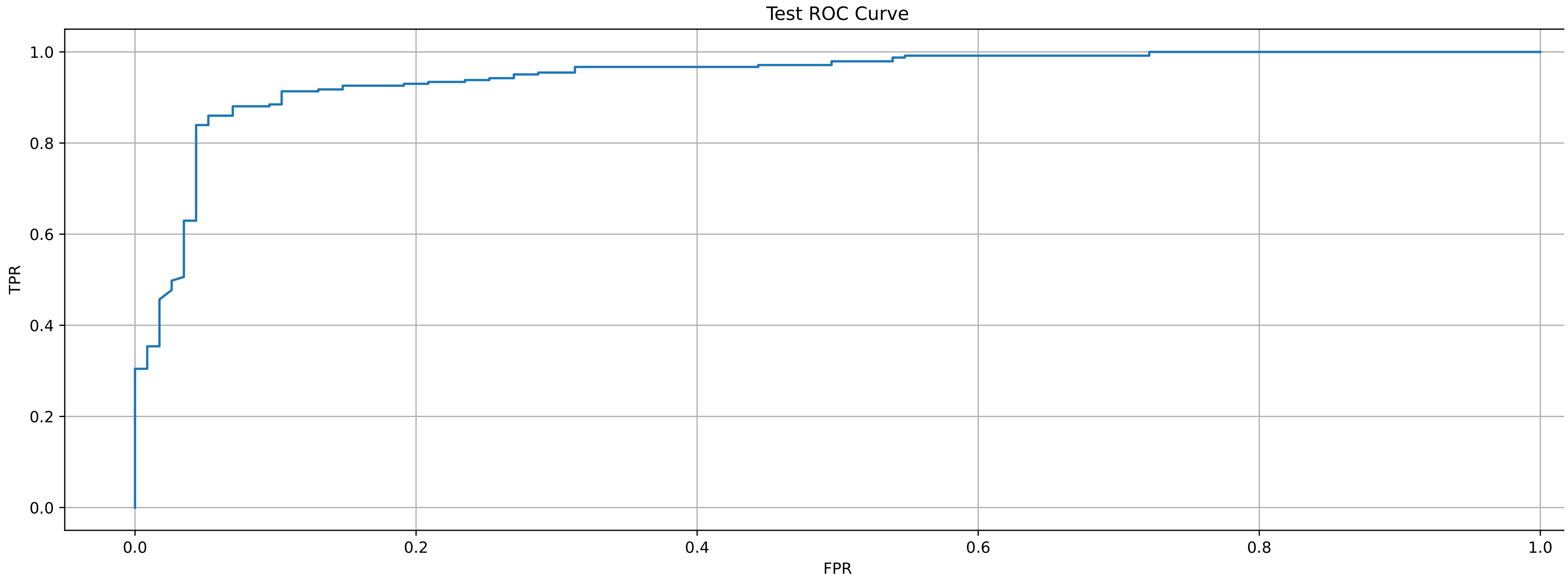

```
Train AUC ROC Score = 0.997
```

In [221]:
```
plot_roc_curve_and_display_auc_roc_score(y_cv, y_cv_pred_proba, 'CV')
```




```
CV AUC ROC Score = 0.942
```

In [222]:
```
plot_roc_curve_and_display_auc_roc_score(y_test, y_test_pred_proba, 'Test')
```




```
Test AUC ROC Score = 0.946
```

In [ ]:

Classification Report:

In [223]:
```
print_classification_report(y_train, y_train_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.97      0.94      0.95       552
     Churned       0.97      0.99      0.98      1167

    accuracy                           0.97      1719
   macro avg       0.97      0.96      0.97      1719
weighted avg       0.97      0.97      0.97      1719
```

In [224]:
```
print_classification_report(y_cv, y_cv_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.81      0.86      0.83        98
     Churned       0.93      0.90      0.92       206

    accuracy                           0.89       304
   macro avg       0.87      0.88      0.87       304
weighted avg       0.89      0.89      0.89       304
```

In [225]:
```
print_classification_report(y_test, y_test_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.84      0.85      0.85       115
     Churned       0.93      0.93      0.93       243

    accuracy                           0.90       358
   macro avg       0.89      0.89      0.89       358
weighted avg       0.90      0.90      0.90       358
```

RandomForest Model Test Score (0.93) is better than DT model but it's slightly overfitting

In [ ]:

Boosting (LightGBM):

In [226]:
```
parameters = {
    'n_estimators' : [100, 200, 300, 400, 500],
    'max_depth' : [1,3,5,7],
    'learning_rate' : [0.025, 0.05, 0.1, 0.2],
    'subsample' : [0.2, 0.4, 0.6, 0.8, 1],
    'colsample_bytree' : [0.2, 0.4, 0.6, 0.8, 1],
}

lgbm_model = lgbm.LGBMClassifier(random_state=42, n_jobs=-1)
clf = GridSearchCV(
    estimator = lgbm_model,
    param_grid= parameters,
    scoring = 'f1',
    n_jobs=-1,
    cv=3,
    verbose=2
)

clf.fit(X_train_encoded, y_train)
```

```
Fitting 3 folds for each of 2000 candidates, totalling 6000 fits
```

Out[226]:
```
GridSearchCV(cv=3, estimator=LGBMClassifier(random_state=42), n_jobs=-1,
             param_grid={'colsample_bytree': [0.2, 0.4, 0.6, 0.8, 1],
                         'learning_rate': [0.025, 0.05, 0.1, 0.2],
                         'max_depth': [1, 3, 5, 7],
                         'n_estimators': [100, 200, 300, 400, 500],
                         'subsample': [0.2, 0.4, 0.6, 0.8, 1]},
             scoring='f1', verbose=2)
```

In [227]:
```
best_est = clf.best_estimator_
clf.best_params_
```

Out[227]:
```
{'colsample_bytree': 0.4,
 'learning_rate': 0.025,
 'max_depth': 7,
 'n_estimators': 400,
 'subsample': 0.2}
```

In [ ]:

Predictions:

In [228]:
```
y_train_pred = best_est.predict(X_train_encoded)
y_cv_pred = best_est.predict(X_cv_encoded)
y_test_pred = best_est.predict(X_test_encoded)

y_train_pred_proba = best_est.predict_proba(X_train_encoded)[:, 1]
y_cv_pred_proba = best_est.predict_proba(X_cv_encoded)[:, 1]
y_test_pred_proba = best_est.predict_proba(X_test_encoded)[:, 1]
```

In [ ]:

F1 Score:

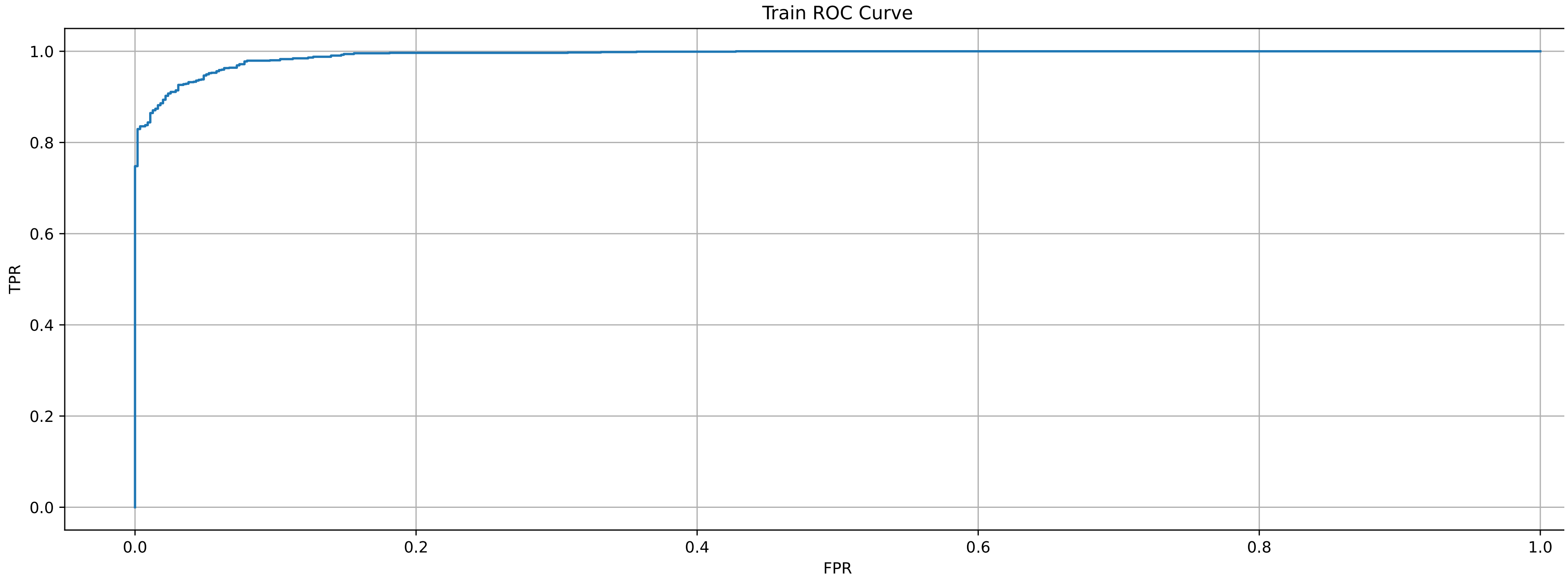
In [229]:
```
print(f'Train F1 Score = {f1_score(y_train, y_train_pred).round(3)}')
print(f'CV F1 Score = {f1_score(y_cv, y_cv_pred).round(3)}')
print(f'Test F1 Score = {f1_score(y_test, y_test_pred).round(3)}')
```

```
Train F1 Score = 0.968
CV F1 Score = 0.917
Test F1 Score = 0.913
```

In [ ]:

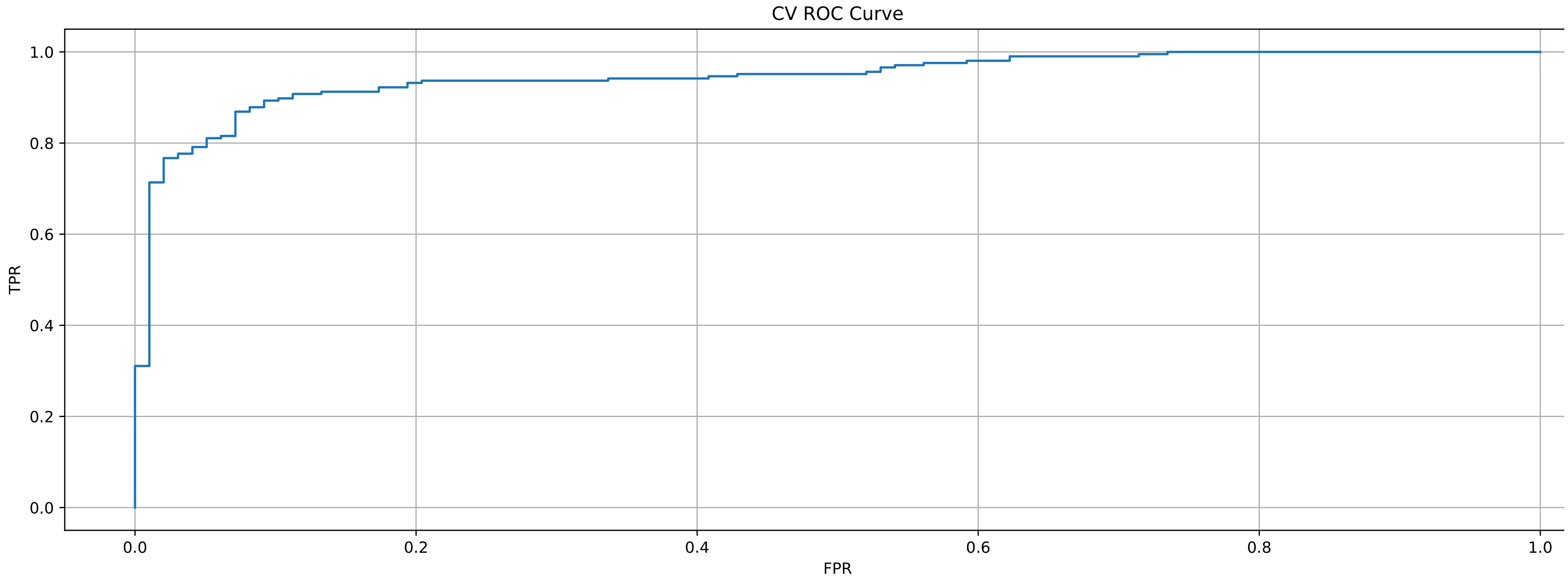
AUC-ROC Score:

In [230]:
```
plot_roc_curve_and_display_auc_roc_score(y_train, y_train_pred_proba, 'Train')
```



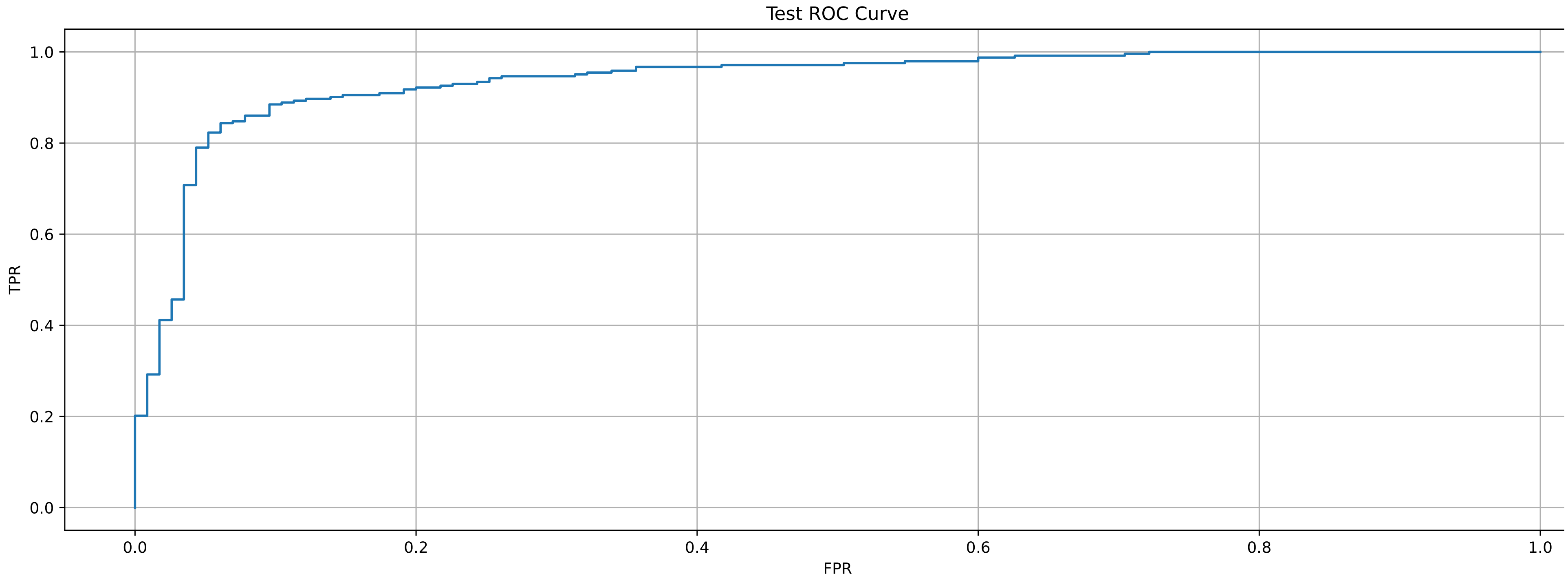

```
Train AUC ROC Score = 0.992
```

In [231]:
```
plot_roc_curve_and_display_auc_roc_score(y_cv, y_cv_pred_proba, 'CV')
```




```
CV AUC ROC Score = 0.945
```

In [232]:
```
plot_roc_curve_and_display_auc_roc_score(y_test, y_test_pred_proba, 'Test')
```




```
Test AUC ROC Score = 0.939
```

The AUC is pretty high for all the ROC curves but since the original data is imbalanced, AUC-ROC is not a right metric

In [ ]:

Classification Report:

In [233]:
```
print_classification_report(y_train, y_train_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.94      0.93      0.93       552
     Churned       0.97      0.97      0.97      1167

    accuracy                           0.96      1719
   macro avg       0.95      0.95      0.95      1719
weighted avg       0.96      0.96      0.96      1719
```

In [234]:
```
print_classification_report(y_cv, y_cv_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.82      0.84      0.83        98
     Churned       0.92      0.91      0.92       206

    accuracy                           0.89       304
   macro avg       0.87      0.87      0.87       304
weighted avg       0.89      0.89      0.89       304
```

In [235]:
```
print_classification_report(y_test, y_test_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.84      0.77      0.81       115
     Churned       0.90      0.93      0.91       243

    accuracy                           0.88       358
   macro avg       0.87      0.85      0.86       358
weighted avg       0.88      0.88      0.88       358
```

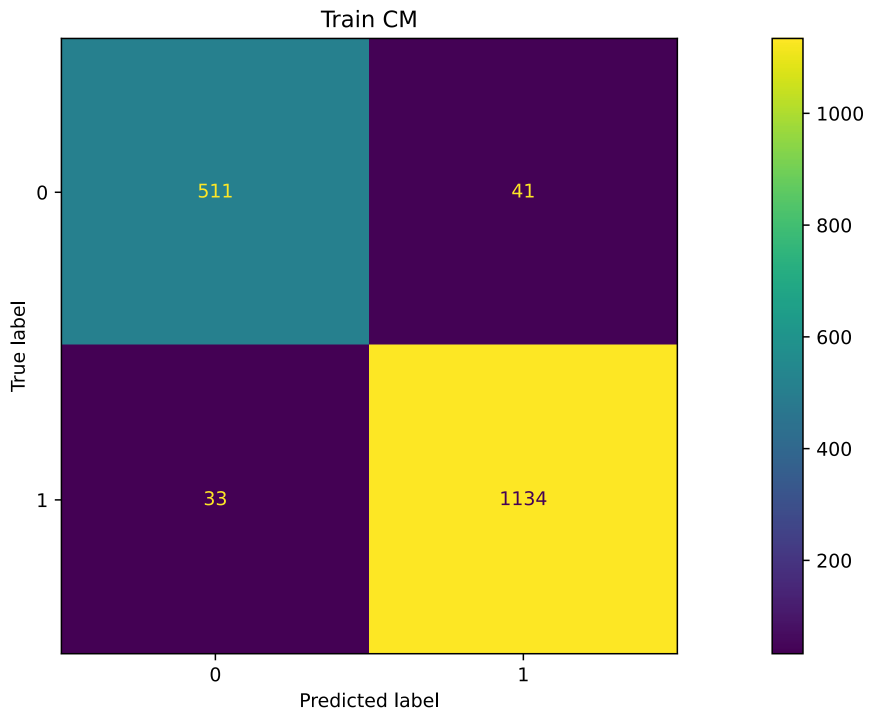
GBDT Model Test Score (0.91) is better than DT model but worse than RF model but it's not overfitting, so given a choice between the three, GBDT is the best.

In [ ]:

Confusion Matrix:

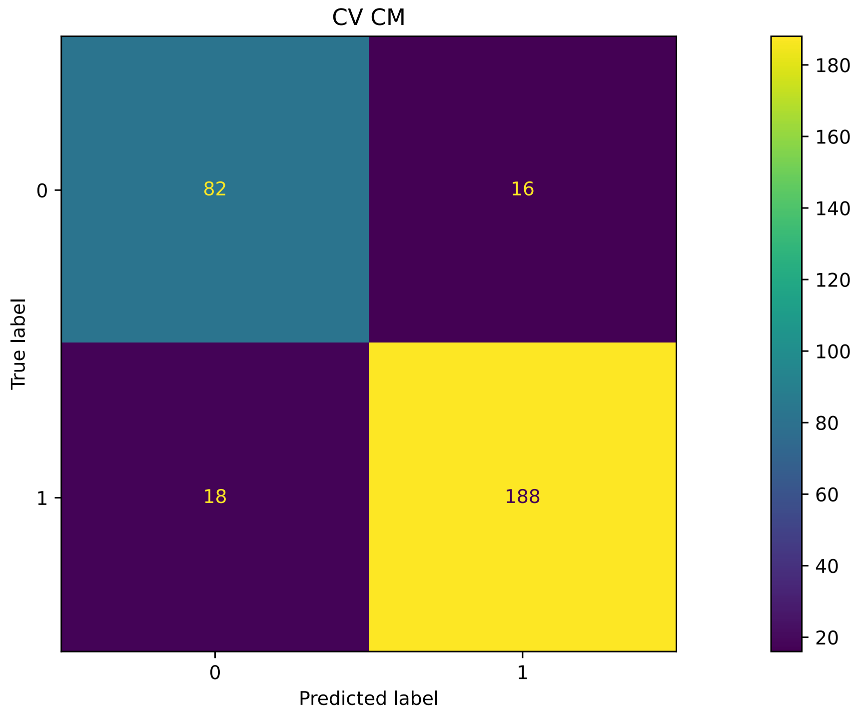
In [236]:
```
# Retained = 0
# Churned = 1

conf_matrix = confusion_matrix(y_train, y_train_pred)
ConfusionMatrixDisplay(conf_matrix).plot()
plt.title("Train CM")
plt.show()
```



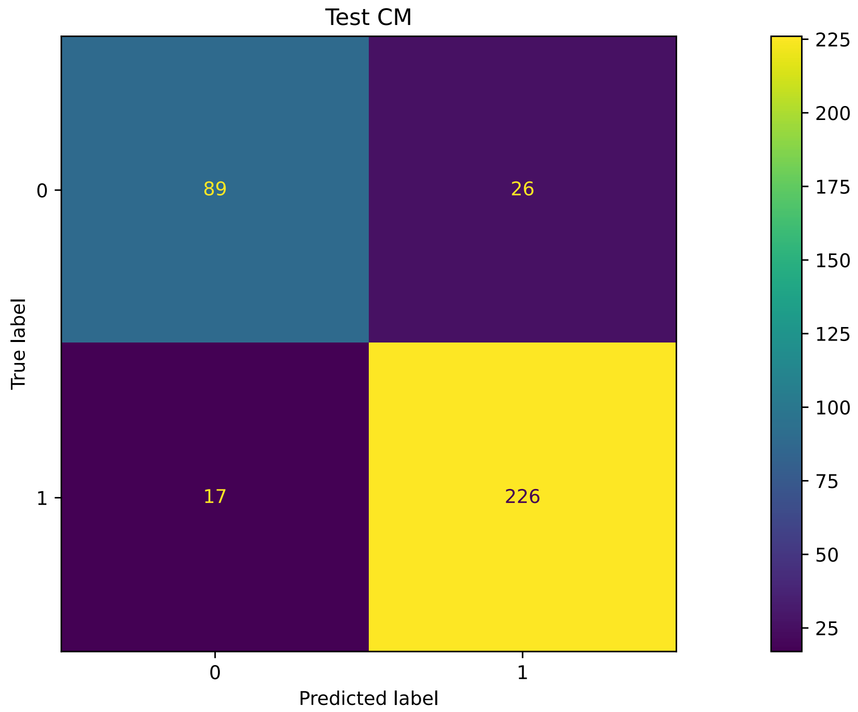
In [237]:
```
# Retained = 0
# Churned = 1

conf_matrix = confusion_matrix(y_cv, y_cv_pred)
ConfusionMatrixDisplay(conf_matrix).plot()
plt.title("CV CM")
plt.show()
```



In [238]:
```
# Retained = 0
# Churned = 1

conf_matrix = confusion_matrix(y_test, y_test_pred)
ConfusionMatrixDisplay(conf_matrix).plot()
plt.title("Test CM")
plt.show()
```



In [ ]:

Treating class imbalance:

Let's train the best model we got using class_weights='balanced' parameter and check the performance

In [239]:
```
lgbm_model = lgbm.LGBMClassifier(
    colsample_bytree = 0.4,
    learning_rate = 0.025,
    max_depth = 3,
    n_estimators = 300,
    subsample = 0.2,
    class_weight='balanced',
    random_state=42,
    n_jobs=-1
)

lgbm_model.fit(X_train_encoded, y_train)
```

Out[239]:
```
LGBMClassifier(class_weight='balanced', colsample_bytree=0.4,
               learning_rate=0.025, max_depth=3, n_estimators=300,
               random_state=42, subsample=0.2)
```

In [ ]:

Predictions:

In [240]:
```
y_train_pred = lgbm_model.predict(X_train_encoded)
y_cv_pred = lgbm_model.predict(X_cv_encoded)
y_test_pred = lgbm_model.predict(X_test_encoded)

y_train_pred_proba = lgbm_model.predict_proba(X_train_encoded)[:, 1]
y_cv_pred_proba = lgbm_model.predict_proba(X_cv_encoded)[:, 1]
y_test_pred_proba = lgbm_model.predict_proba(X_test_encoded)[:, 1]
```

In [ ]:

F1 Score:

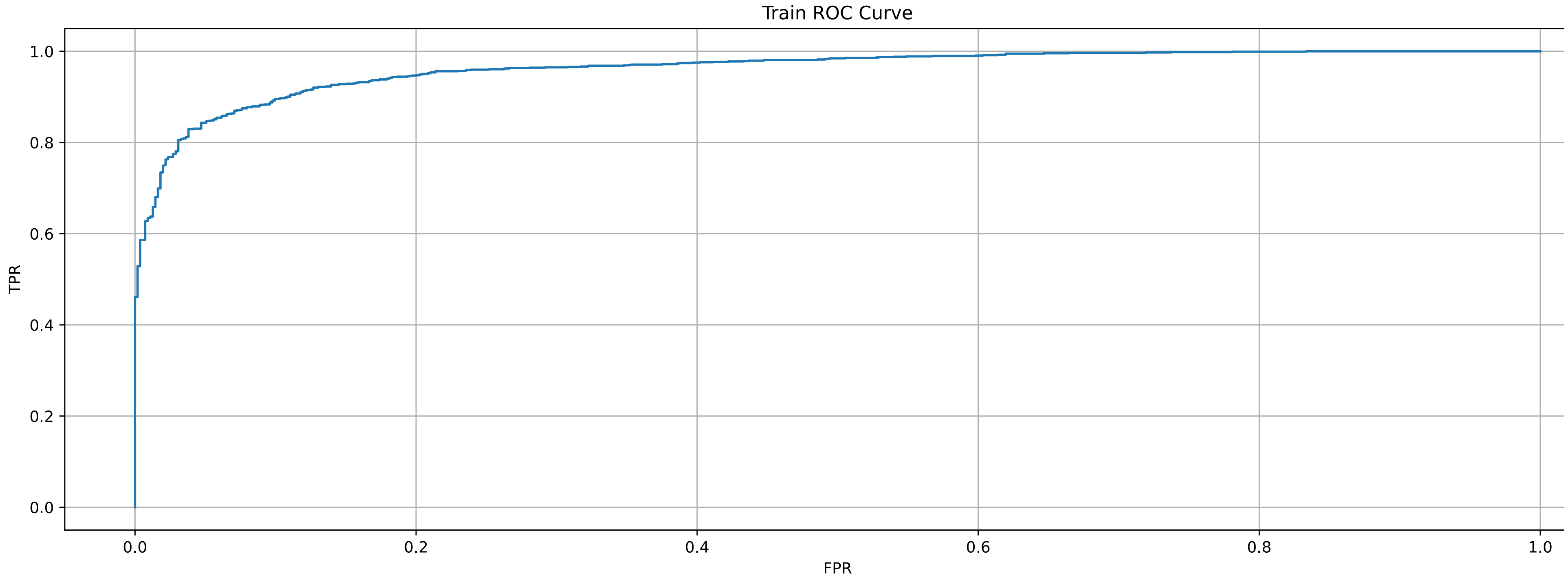
In [241]:
```
print(f'Train F1 Score = {f1_score(y_train, y_train_pred).round(3)}')
print(f'CV F1 Score = {f1_score(y_cv, y_cv_pred).round(3)}')
print(f'Test F1 Score = {f1_score(y_test, y_test_pred).round(3)}')
```

```
Train F1 Score = 0.905
CV F1 Score = 0.899
Test F1 Score = 0.915
```

In [ ]:

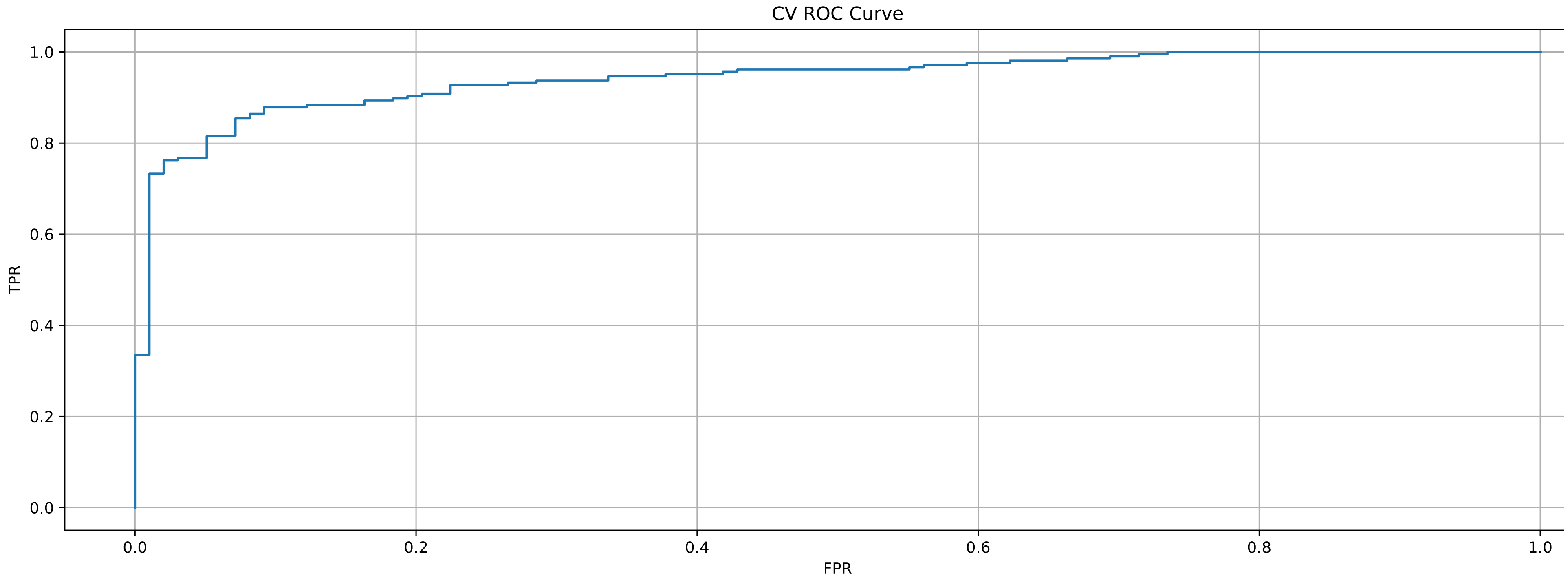
AUC-ROC Score:

In [242]:
```
plot_roc_curve_and_display_auc_roc_score(y_train, y_train_pred_proba, 'Train')
```



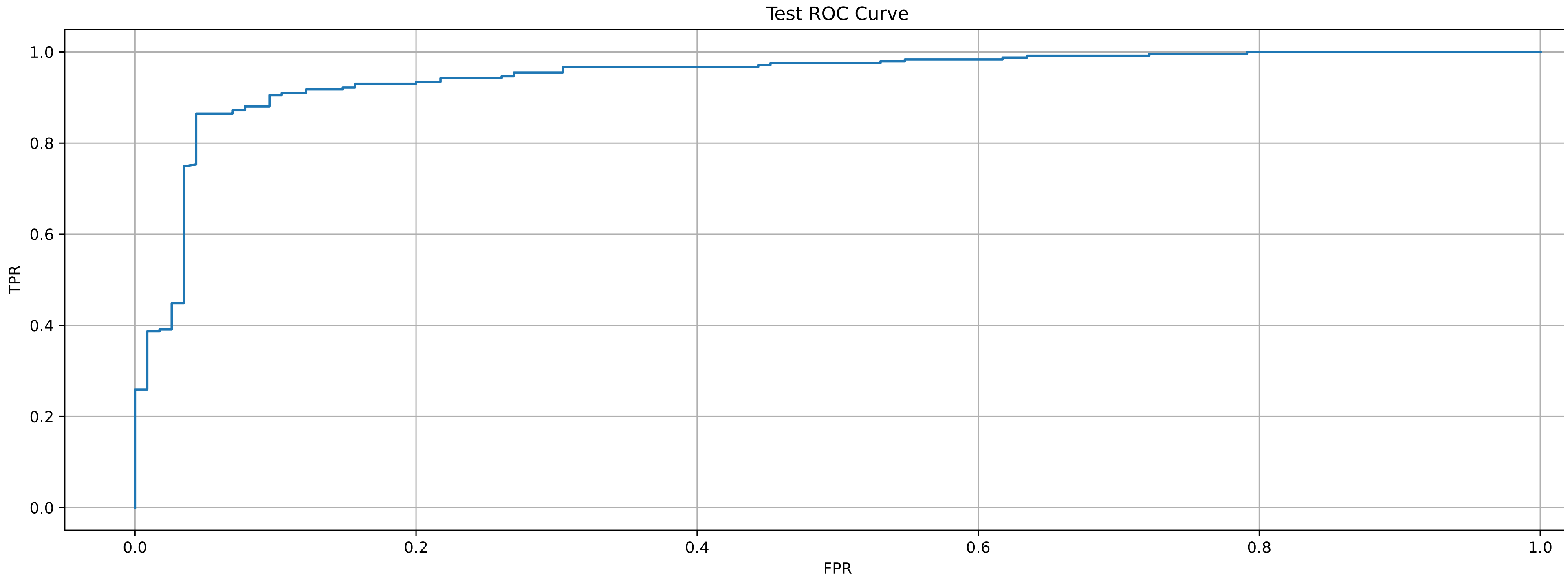

```
Train AUC ROC Score = 0.962
```

In [243]:
```
plot_roc_curve_and_display_auc_roc_score(y_cv, y_cv_pred_proba, 'CV')
```




```
CV AUC ROC Score = 0.942
```

In [244]:
```
plot_roc_curve_and_display_auc_roc_score(y_test, y_test_pred_proba, 'Test')
```




```
Test AUC ROC Score = 0.946
```

In [ ]:

Classification Report:

In [245]:
```
print_classification_report(y_train, y_train_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.75      0.94      0.83       552
     Churned       0.97      0.85      0.90      1167

    accuracy                           0.88      1719
   macro avg       0.86      0.90      0.87      1719
weighted avg       0.90      0.88      0.88      1719
```

In [246]:
```
print_classification_report(y_train, y_train_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.75      0.94      0.83       552
     Churned       0.97      0.85      0.90      1167

    accuracy                           0.88      1719
   macro avg       0.86      0.90      0.87      1719
weighted avg       0.90      0.88      0.88      1719
```

In [247]:
```
print_classification_report(y_test, y_test_pred)
```

```
              precision    recall  f1-score   support

    Retained       0.77      0.95      0.85       115
     Churned       0.97      0.86      0.92       243

    accuracy                           0.89       358
   macro avg       0.87      0.91      0.88       358
weighted avg       0.91      0.89      0.89       358
```

After balancing, recall on the "retained" class has improved significantly and performance on "churned" class has also slightly increased, so it's better if we choose the model with class balancing

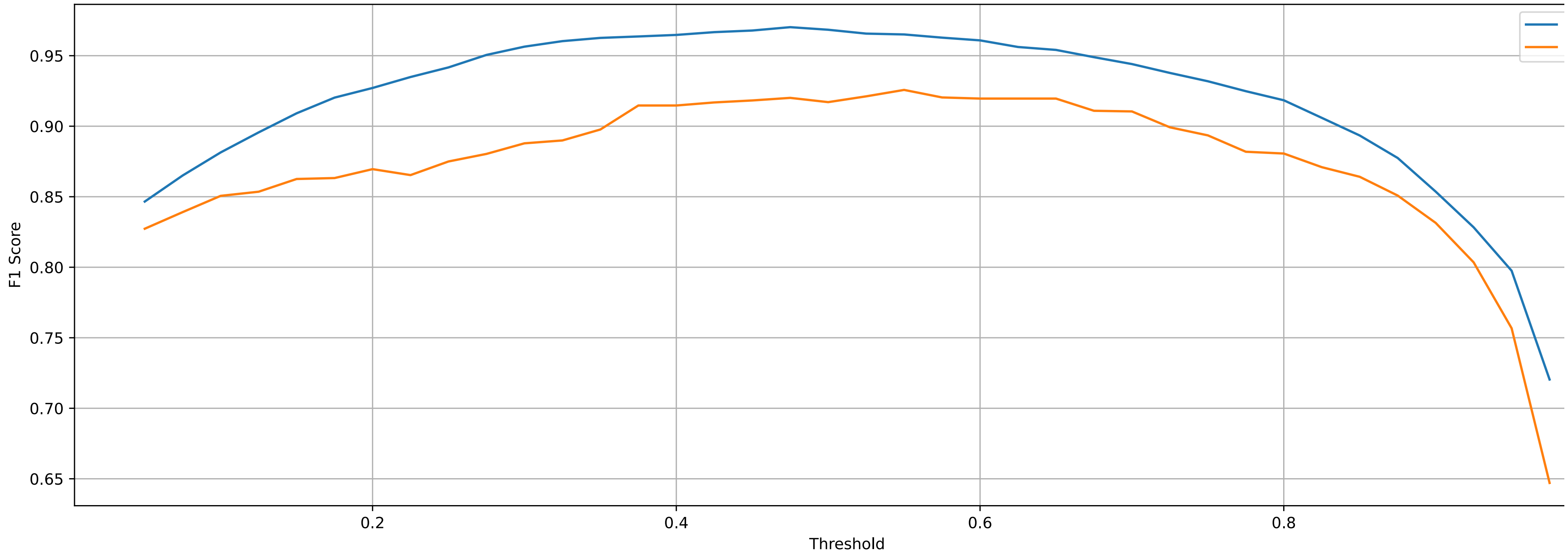
In [ ]:

Finding Best Threshold for classification:

In [248]:
```
predicted_proba_train = best_est.predict_proba(X_train_encoded)
predicted_proba_cv = best_est.predict_proba(X_cv_encoded)
train_f1_scores = []
cv_f1_scores = []
thresholds = np.arange(0.05, 1, 0.025)

for threshold in thresholds:
    train_preds = (predicted_proba_train[:,1] >= threshold).astype('int')
    cv_preds = (predicted_proba_cv[:,1] >= threshold).astype('int')
    trainF1Score = f1_score(y_train, train_preds)
    cvF1Score = f1_score(y_cv, cv_preds)
    train_f1_scores.append(trainF1Score)
    cv_f1_scores.append(cvF1Score)
```

In [250]:
```
plt.rcParams["figure.figsize"] = (18,6)
plt.plot(thresholds, train_f1_scores, label='Train')
plt.plot(thresholds, cv_f1_scores, label='CV')
plt.xlabel('Threshold')
plt.ylabel('F1 Score')
plt.grid()
plt.legend()
plt.show()
```



In [251]:
```
best_threshold_idx = np.argmax(cv_f1_scores)
best_threshold = thresholds[best_threshold_idx]

predicted_proba_test = best_est.predict_proba(X_test_encoded)
test_preds = (predicted_proba_test[:,1] >= best_threshold).astype('int')

print(f"Best threshold = {best_threshold.round(3)} \nTrain F1 Score = {train_f1_scores[best_threshold_idx].round(3)} \nCV F1 Score = {cv_f1_scores[best_threshold_idx].round(3)}
```

```
Best threshold = 0.55
Train F1 Score = 0.965
CV F1 Score = 0.926
Test F1 Score = 0.911
```

The best model has a F1 Score of 0.91 which is decent enough and it's also not overfitting

In [ ]:

Saving the best model:

In [252]:
```
joblib.dump(best_est, 'best_model.joblib')
```

Out[252]:
```
['best_model.joblib']
```

In [ ]:

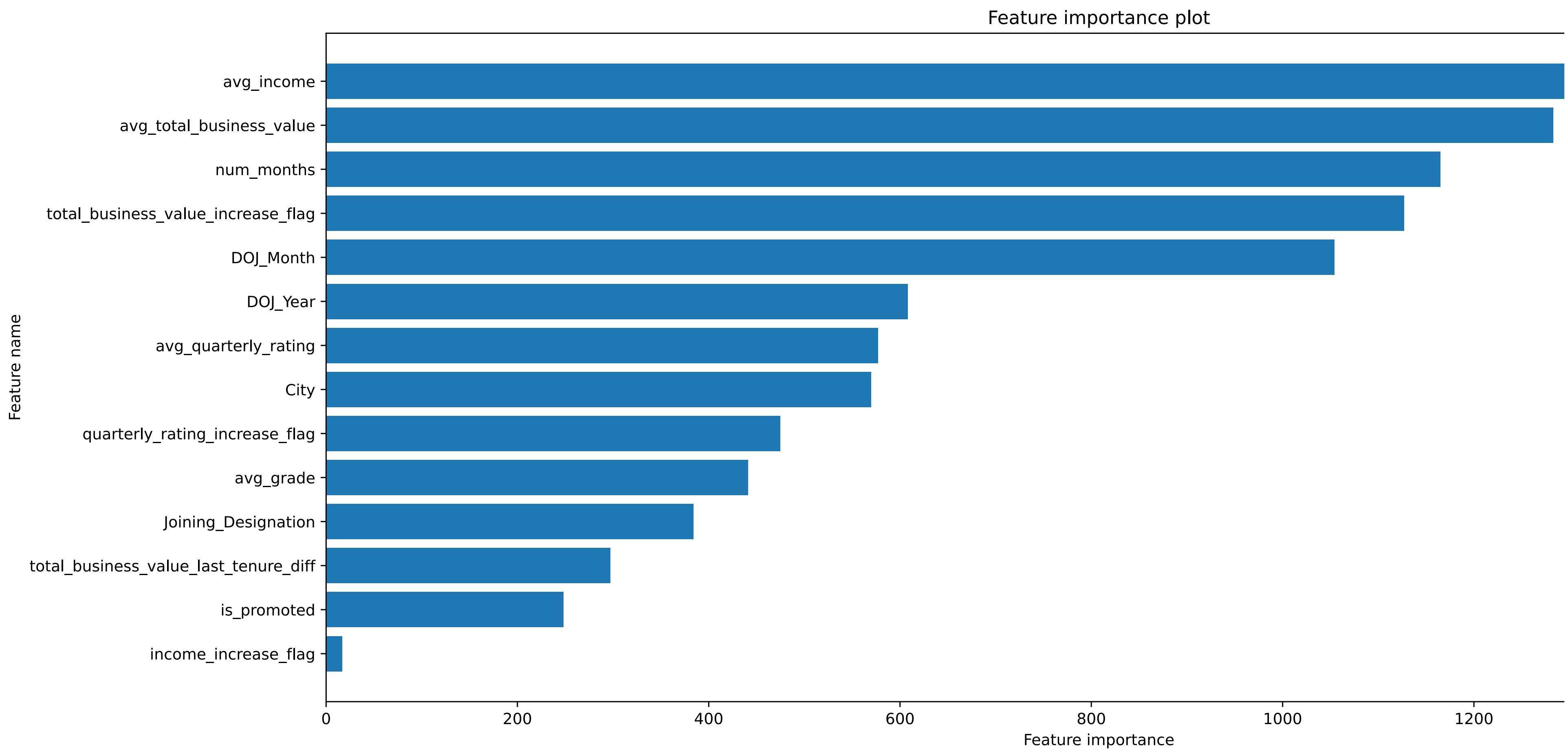
Feature importance:

In [253]:
```
def plot_top_feature_importances(model):
    plt.rcParams["figure.figsize"] = (18,8)

    fnames = list(model.feature_name_)
    fimps = list(model.feature_importances_)
    fname_imp_dict = dict(zip(fnames, fimps))
    fname_imp_dict = dict(sorted(fname_imp_dict.items(), key=lambda x: x[1], reverse=True))
    df_fname_dict = pd.DataFrame(fname_imp_dict.items(), columns=['fname', 'fimp'])
    df_fname_dict.loc[df_fname_dict.fname.str.startswith('DOJ_Year'), 'fname'] = 'DOJ_Year'
    df_fname_dict.loc[df_fname_dict.fname.str.startswith('DOJ_Month'), 'fname'] = 'DOJ_Month'
    df_fname_dict.loc[df_fname_dict.fname.str.startswith('City'), 'fname'] = 'City'
    df_fname_dict.loc[df_fname_dict.fname.str.startswith('is_promoted'), 'fname'] = 'is_promoted'
    df_fname_dict = df_fname_dict.groupby('fname').agg({'fimp' : 'sum'}).reset_index()
    df_fname_dict.sort_values(by='fimp', ascending=False, inplace=True)
    f_names = list(df_fname_dict['fname'].values)
    f_values = list(df_fname_dict['fimp'].values)

    plt.barh(f_names, f_values)
    plt.gca().invert_yaxis()
    plt.title("Feature importance plot")
    plt.xlabel("Feature importance")
    plt.ylabel("Feature name")
    plt.show()
```

In [254]:
```
plot_top_feature_importances(best_est)
```



The top 5 most important features for predicting is_churned are: avg_income , avg_total_business_value , num_months , total_business_value_increase_flag , DOJ_Month

In [ ]:

Error Analysis:

Recreating the original DataFrame:

In [255]:
```
X_total = pd.concat([X_train_encoded, X_cv_encoded, X_test_encoded]).reset_index(drop=True)

y_total = pd.concat([y_train, y_cv, y_test]).reset_index(drop=True)
y_pred = best_est.predict(X_total)
y_pred_proba = best_est.predict_proba(X_total)[:, 1]
df_total = X_total.copy()
df_total['is_churned_true'] = y_total
df_total['is_churned_pred'] = y_pred
df_total['is_churned_pred_proba'] = y_pred_proba

df_orig_cols = pd.DataFrame(
    ohe.inverse_transform(
        df_total.iloc[:, 10:61]
    ),
    columns=['City', 'DOJ_Year', 'DOJ_Month', 'is_promoted']
)

df_orig = pd.concat(
    [
        df_total.iloc[:, :10],
        df_orig_cols,
        df_total.iloc[:, 61:]
    ],
    axis=1
)
```

In [256]:
```
df_orig.head()
```

Out[256]:

	num_months	Joining_Designation	avg_income	income_increase_flag	avg_grade	avg_total_business_value	total_business_value_increase_flag	total_business_value_last_tenure_diff	avg_quarterly_rating	quarterly_rating
0	6.0	3	92079.0	0.0	3.0	7.632000e+04	1.000000	1	1.0	
1	7.0	3	131472.0	0.0	3.0	2.810500e+05	0.333333	1	1.5	
2	20.5	1	129596.5	1.0	3.5	1.345574e+06	-0.043478	1	3.0	
3	6.0	1	21792.0	0.0	1.0	1.123900e+05	1.000000	1	1.0	
4	5.0	3	82822.0	0.0	3.0	4.750000e+05	1.000000	1	1.5	

In [257]:
```
df_orig.tail()
```

Out[257]:

	num_months	Joining_Designation	avg_income	income_increase_flag	avg_grade	avg_total_business_value	total_business_value_increase_flag	total_business_value_last_tenure_diff	avg_quarterly_rating	quarterly_ra
2376	1.0	1	45278.0	0.0	1.0	0.000000	0.000000	0	1.000000	
2377	3.0	2	21412.0	0.0	2.0	0.000000	0.000000	0	1.000000	
2378	14.0	1	23094.0	0.0	1.0	761058.461538	0.500000	1	2.666667	
2379	11.0	1	30860.0	0.0	2.0	360536.000000	0.111111	-1	2.000000	
2380	3.0	2	55344.0	0.0	2.0	0.000000	0.000000	0	1.000000	

In [ ]:

Analyzing the Errors:

In [258]:
```
error_df = df_orig.loc[df_orig['is_churned_pred']!=df_orig['is_churned_true']]

def get_per_point_logloss(row):
    y = row['is_churned_true']
    p = row['is_churned_pred_proba']
    if y:
        return -np.log(p)
    return -np.log(1-p)

error_df['log_loss'] = error_df.apply(get_per_point_logloss, axis=1)
error_df.sort_values(by=['log_loss'], ascending=False, inplace=True)
```

In [259]:
```
print(f"False Positive % : {round(error_df[(error_df['is_churned_true']==0)&(error_df['is_churned_pred']==1)].shape[0]/error_df.shape[0]*100, 3)}")
print(f"False Negative % : {round(error_df[(error_df['is_churned_true']==1)&(error_df['is_churned_pred']==0)].shape[0]/error_df.shape[0]*100, 3)}")
```

```
False Positive % : 54.967
False Negative % : 45.033
```

In [261]:
```
error_df.head(10)
```

Out[261]:

	num_months	Joining_Designation	avg_income	income_increase_flag	avg_grade	avg_total_business_value	total_business_value_increase_flag	total_business_value_last_tenure_diff	avg_quarterly_rating	quarterly_ra
2330	15.0	1	43969.0	0.0	1.0	4.200400e+05	-0.090909	-1	2.000000	
2296	9.0	2	112424.0	0.0	4.0	7.912067e+05	-0.250000	-1	1.500000	
2003	5.0	3	67685.0	0.0	3.0	0.000000e+00	0.000000	0	1.000000	
2340	5.0	2	59481.0	0.0	2.0	0.000000e+00	0.000000	0	1.000000	
2036	4.0	1	24291.0	0.0	1.0	0.000000e+00	0.000000	0	1.000000	
2139	20.5	1	56611.0	0.0	2.0	6.102084e+05	0.222222	1	2.500000	
2160	8.0	3	61912.0	0.0	3.0	1.206325e+06	0.200000	-1	2.666667	
2237	3.0	2	29719.0	0.0	2.0	0.000000e+00	0.000000	0	1.000000	
1879	5.0	3	102175.0	0.0	3.0	5.119100e+05	1.000000	1	1.500000	
2198	20.5	1	109652.0	0.0	3.0	5.610273e+05	0.047619	-1	2.000000	

Key Observations:

1. The datapoints with the highest log loss are FP, many of these have avg TBV as 0, hence the model inferred them as being churned, this could be an error in collecting data so Ola should be more cautious while collecting data
2. Most of these have joined the company in year 2019 which has one of the highest churn rate and hence model is classifying these as "churned"
3. Most of these have very low average quarterly rating hence model is thinking of these as "churned" drivers

In [ ]:
```

```

Insights and Recommendations:

Insights:

- Exploratory Data Analysis (EDA):

1. Year of joining of driver is an important factor in determining the probability of being churned, year 2014 and 2020 have low churn rate where as 2018 and 2019 have very high churn rate
2. Average income of churned drivers is slighly less as compared to non churned drivers
3. The churn rate is significantly low when the driver's income has increased over his/her tenure at OLA
4. Churned rate is significantly lower when the driver has been promoted during his tenure at OLA
5. Average total business value is significantly less for churned drivers
6. As the number of months spent at OLA increases, the probability of driver being churned decreases
7. Age, gender and education level don't have significant effect on the probability of driver being churned
8. After training the model, it was found that, Year of joining the company, Month of joining the company, number of months spent at OLA, total average business value generated by the driver and average quarterly rating of the driver are the 5 most important features
9. The model has a very high precision for churned drivers which means if the model says someone will be churned, he'll definitely be churned while it has high recall for retained drivers which means it's able to correctly remember the actual retained drivers
10. Driver's city is an important factor in determining the probability of being churned, cities like C13, C17, C2 have higher than average churn rate while cities like C12, C16, C19, C21, C22 have lower than average churn rate

11. Churn rate generally decreases as we go up the designation (designations 4 and 5 have less datapoints so they can be outliers also)
12. Churn rate is significantly lower when TBV has increased in the last month as compared to the previous month, this seems an important feature
13. As average quarterly ratings increases, churn rate decreases
14. The churn rate is significantly lower when the quarterly rating has increased over the last month
15. Average income, Average TBV and Average quarterly rating have significant outliers on the higher end

- Final Model:

   1. Best threshold = 0.55
   2. Train F1 Score = 0.965
   3. CV F1 Score = 0.926
   4. Test F1 Score = 0.911

Recommendations:

1. If a driver's Total Business Value is constantly decreasing over the months, he's most likely to be churned, OLA should talk to the drivers to find the reason for this decrease in TBV
2. OLA should pay close attention to newly joined drivers as churn rate is highest among them, some incentives can be given to these drivers to retain them, once they spend enough time at OLA, probability of being churned decreases significantly
3. OLA should give regular increments in pay/grade to drivers as the churn rate decreases significantly when drivers receive increase in pay/grade
4. Some cities like C13, C17, C2 have higher than average churn rate, the reason for this should be investigated, it could be because competitive firms are paying higher or probably because there aren't many customers here so that drivers can recover the base cost, after investigating the reasons, proper corrective measures should be taken for their rectification
5. OLA should pay close attention to driver's average quarterly ratings as those with low quarterly ratings tend to churn more, the reason for low ratings can be due to their unprofessional behaviour with customers and since quarterly ratings directly impact incentives and future rides, the drivers churn, so OLA should pay attention in educating the drivers to behave properly with customers and be on time, not cancel the ride unccessarily etc
6. OLA should be pay close attention to drivers joining on designation 1 and 2 as the churn rate is max. among these, the probable reason is low pay at OLA and higher pay at other competitive firms, the pay scale should be corrected for these drivers if it's lower than other competitive firms.

In [ ]: