Akinwande Alexander's Untitled project Private





Table of Content:

- 1. Introduction
- 2. Loading Libraries and Data
- 3. Understanding the Data
- 4. Data Manipulation
- 5. Data Visualization
- 6. Machine Learning Model Evaluaton and Prediction
- 7. Conclusion

Introduction

What is Customer Churn?

Customer churn is the rate at which customers discontinue their relationship with a company. In telecommunications, this rate is notably high—typically ranging from 15% to 25% annually—due to intense competition and customer preferences for better pricing, service quality, or additional features.

With millions of subscribers, telecom providers cannot realistically apply personalized retention strategies at scale. However, by leveraging data to identify high-risk customers, companies can target retention efforts more effectively. This strategic focus can reduce churn, strengthen customer loyalty, and enhance overall customer lifetime value (CLV).

Churn is more than a metric—it's a critical indicator of business health. Retaining an existing customer is far less expensive than acquiring a new one. Companies that minimize churn benefit from lower acquisition costs, stronger brand loyalty, and higher profitability.

Effective churn reduction depends on early detection. This requires a holistic view of customer behavior across in-store activity, product usage, customer service interactions, digital engagement, and social media trends. By acting on these insights, telecom companies can preserve market share and create a foundation for sustainable growth.

Objectives of This Analysis:

This analysis explores customer churn within a telecom dataset and aims to answer the following questions:

- What percentage of customers have churned versus those who remain active?
- Are there identifiable churn patterns based on gender?
- Does churn vary by the type of service subscribed to?
- Which service types are the most profitable?
- What features and services contribute most significantly to profitability?

Loading Libraries and Data

```
#Importing Libraries
import pandas as pd
import numpy as np
import missingno as msno
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
{\color{red} \textbf{import}} \ \textbf{plotly.graph\_objects} \ {\color{red} \textbf{as}} \ \textbf{go}
from plotly.subplots import make_subplots
import math
import warnings
warnings.filterwarnings('ignore')
{\color{red} \textbf{from}} \  \, \text{sklearn.preprocessing} \  \, {\color{red} \textbf{import}} \  \, \text{StandardScaler}
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from xgboost import XGBClassifier
# from catboost import CatBoostClassifier
from sklearn import metrics
from sklearn.metrics import roc curve
from sklearn.metrics import recall_score, confusion_matrix, precision_score, f1_score, accuracy_score, classification_rep
```

```
#Importing Data
df = pd.read_csv(r'/work/telco.csv')
df.head()
       Customer ID obje...
                           Gender object
                                              Age int64
                                                                  Under 30 object
                                                                                      Senior Citizen ob...
                                                                                                          Married object
                                                                                                                              Dependents object
      8779-QRDMV
                                                                                                          Nο
                                                                                                                              Nο
                           Male
                                                             78
                                                                  Nο
                                                                                      Yes
      7495-00KFY
                           Female
                                                             74
                                                                                      Yes
                                                                  No
                                                                                                          Yes
                                                                                                                              Yes
      1658-BYGOY
                           Male
                                                             71
   3 4598-XLKNJ
                           Female
                                                             78
                                                                  Nο
                                                                                      Yes
                                                                                                          Yes
                                                                                                                              Yes
   4
      4846-WHAFZ
                                                                                                          Yes
                          Female
                                                             80
                                                                  No
                                                                                      Yes
                                                                                                                              Yes
5 rows, 50 cols 10 🗸
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```

• based on the just a quick look at the data, we can see that there's some cleaning is

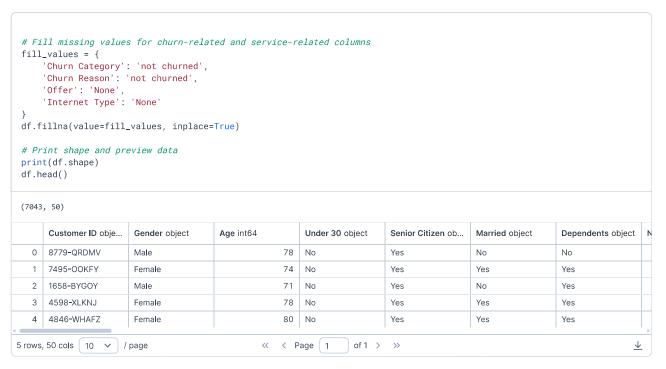
Understanding the Data

```
display(df.shape)
(7043, 50)
```

```
display(df.dtypes)
Customer ID
                                     object
Gender
                                     object
                                      int64
Aae
Under 30
                                     object
Senior Citizen
                                     object
Married
                                     object
Dependents
                                     object
Number of Dependents
                                      int64
                                     object
Country
                                     object
City
                                     object
Zip Code
                                      int64
Latitude
                                     float64
Longitude
                                    float64
Population
                                      int64
Ouarter
                                     object
Referred a Friend
                                     object
Number of Referrals
                                      int64
Tenure in Months
                                      int64
Offer
                                     object
Phone Service
                                     object
Avg Monthly Long Distance Charges
                                     float64
Multiple Lines
                                     object
Internet Service
                                     object
Internet Type
                                     object
Avg Monthly GB Download
                                     int64
Online Security
                                     object
Online Backup
                                     object
Device Protection Plan
                                     object
Premium Tech Support
                                     object
Streaming TV
                                     object
Streaming Movies
                                     object
```

```
display(df.info())
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 50 columns):
# Column
                                 Non-Null Count Dtype
                               7043 non-null object
0 Customer ID
                                7043 non-null object
1 Gender
                                7043 non-null int64
2 Age
3 Under 30
                               7043 non-null object
                               7043 non-null object
4 Senior Citizen
                                 7043 non-null object
   Dependents
                                 7043 non-null
   Number of Dependents
                               7043 non-null int64
                               7043 non-null object
8 Country
                                7043 non-null object
9 State
10 City
                                7043 non-null object
11 Zip Code
                               7043 non-null int64
12 Latitude
                               7043 non-null float64
13 Longitude
                               7043 non-null float64
                               7043 non-null int64
14 Population
                               7043 non-null object
15 Ouarter
                              7043 non-null object
7043 non-null int64
7043 non-null int64
16 Referred a Friend
17 Number of Referrals
18 Tenure in Months
                                3166 non-null object
19 Offer
                      7043 non-null object
20 Phone Service
21 Avg Monthly Long Distance Charges 7043 non-null float64
22 Multiple Lines
                     7043 non-null object
23 Internet Service
                                 7043 non-null object
24 Internet Type
                                 5517 non-null object
```

```
display(df.isnull().sum())
Customer ID
                                        0
Gender
                                        0
                                        0
Aae
Under 30
Senior Citizen
                                        0
Married
                                        0
Dependents
\hbox{Number of Dependents}
                                        0
Country
City
                                        А
Zip Code
Latitude
                                        0
Longitude
Population
Quarter
                                        0
Referred a Friend
                                        0
Number of Referrals
                                        0
Tenure in Months
                                        А
Offer
                                     3877
Phone Service
                                        0
Avg Monthly Long Distance Charges
Multiple Lines
Internet Service
                                        0
Internet Type
                                     1526
Avg Monthly GB Download
Online Security
                                        0
                                        0
Online Backup
Device Protection Plan
                                        0
Premium Tech Support
                                        0
Streaming TV
                                        0
Streaming Movies
                                        0
```



```
df.shape
df.dtypes
df.info()
df.isnull().sum()
df.head()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 50 columns):
 # Column
                                   Non-Null Count Dtype
---
    -----
                                   -----
 0
    Customer ID
                                   7043 non-null object
 1
    Gender
                                   7043 non-null object
 2
                                   7043 non-null
    Age
 3
                                   7043 non-null object
 4
    Senior Citizen
                                   7043 non-null object
                                 7043 non-null object
 5
    Married
                                 7043 non-null object
 6 Dependents
    Number of Dependents
                                7043 non-null int64
 8 Country
                                 7043 non-null object
 9 State
                                  7043 non-null object
 10 City
                                   7043 non-null object
                                   7043 non-null int64
 11 Zip Code
                                   7043 non-null float64
 12 Latitude
 13 Longitude
                                   7043 non-null
                                                 float64
 14 Population
                                   7043 non-null
                                                 int64
 15 Quarter
                                   7043 non-null
 16 Referred a Friend
                                   7043 non-null
                                                 object
 17 Number of Referrals
                                 7043 non-null
                                                 int64
 18 Tenure in Months
                                 7043 non-null int64
 19 Offer
                                 7043 non-null object
 20 Phone Service
                                 7043 non-null object
 21 Avg Monthly Long Distance Charges 7043 non-null float64
 22 Multiple Lines
                                  7043 non-null object
                                   7043 non-null object
 23 Internet Service
 24 Internet Tyne
                                 7043 non-null object
      Customer ID obje... Gender object
                                        Age int64
                                                         Under 30 object
                                                                           Senior Citizen ob...
                                                                                            Married object
                                                                                                             Dependents object
  0 8779-QRDMV
                       Male
                                                     78
                                                         No
                                                                           Yes
                                                                                            No
                                                                                                             No
      7495-OOKFY
                       Female
                                                     74
                                                         No
                                                                           Yes
                                                                                            Yes
                                                                                                             Yes
  2 1658-BYGOY
                       Male
                                                     71
                                                         No
                                                                           Yes
                                                                                            No
                                                                                                             Yes
  3 4598-XLKNJ
                       Female
                                                         No
                                                                           Yes
                                                                                            Yes
                                                                                                             Yes
                                                     78
  4 4846-WHAFZ
                       Female
                                                     80
                                                                                            Yes
                                                                                                             Yes
                                                         No
                                                                          Yes
5 rows, 50 cols 10 🗸 / page
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                                                                                                                            \overline{\psi}
```

df.nunique() 7043 Customer ID Gender 2 62 Aae Under 30 Senior Citizen 2 2 Married Dependents Number of Dependents 10 1 Country 1106 City Zip Code 1626 Latitude 1626 1625 Longitude Population 1569 Quarter 1 Referred a Friend Number of Referrals
Tenure in Months 2 12 72 Offer 6 Phone Service 2 Avg Monthly Long Distance Charges 3584 Multiple Lines 2 Internet Service Internet Type Avg Monthly GB Download 50
Online Security 2 Online Backup 2 Device Protection Plan 2 Premium Tech Support Streaming TV Streaming Movies

The data set includes information about:

- Customers who left within the last month the column is called Churn
- Services that each customer has signed up for phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information how long they've been a customer, contract, payment method, paperless billing, monthly charges, and total charges
- Demographic info about customers gender, age range, and if they have partners and dependents
- · Based on the checking the data; there are no null values found,

Data Manipulation

50%

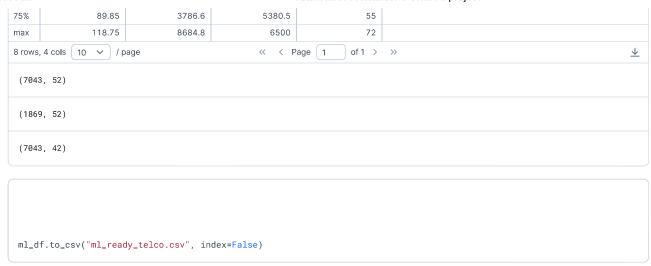
70.35

1394.55

```
# Step-by-step data manipulation and feature engineering
 import numpy as np
 import pandas as pd
 # 1. Define Yes/No conversion function
 def yes_no_to_bool(val):
     if pd.isna(val):
         return np.nan
     return str(val).strip().lower() == 'yes'
 # 2. Convert 'Yes'/'No' and similar to boolean
 yes_no_columns = [
     'Under 30', 'Senior Citizen', 'Married', 'Dependents', 'Referred a Friend', 'Phone Service', 'Multiple Lines', 'Online Security', 'Online Backup',
     'Device Protection Plan', 'Premium Tech Support', 'Streaming TV',
     'Streaming Movies', 'Streaming Music', 'Unlimited Data', 'Paperless Billing'
 1
 df[yes_no_columns] = df[yes_no_columns].applymap(yes_no_to_bool)
 # 3. Create feature: Total number of add-on services subscribed
 addon_services = [
     'Online Security', 'Online Backup', 'Device Protection Plan',
     'Premium Tech Support', 'Streaming TV', 'Streaming Movies', 'Streaming Music'
 df['Total Addon Services'] = df[addon_services].sum(axis=1)
 # 4. Create 'Tenure in Years' by binning 'Tenure in Months'
 df['Tenure in Years'] = pd.cut(
     df['Tenure in Months'],
     bins=range(0, 73, 12),
     labels=range(1, 7)
 # 5. Filter churned customers
 churned_df = df[df['Churn Label'] == 'Yes']
 # 6. Summary statistics (selected numerical features)
 summary_stats = df[['Monthly Charge', 'Total Charges', 'CLTV', 'Tenure in Months']].describe()
 # 7. Prepare cleaned dataset for ML
 ml_df = df.drop(columns=[
     'Customer ID', 'Country', 'State', 'City', 'Zip Code', 'Latitude', 'Longitude', 'Churn Reason', 'Churn Category', 'Quarter'
 ])
 # Convert object columns to categorical and handle missing values
 for col in ml_df.select_dtypes(include='object').columns:
    ml_df[col] = ml_df[col].astype('category')
     if 'None' not in ml_df[col].cat.categories:
         ml_df[col] = ml_df[col].cat.add_categories('None')
     ml_df[col] = ml_df[col].fillna('None')
 # 8. Final info summary
 cleaned_shape = df.shape
 churned_shape = churned_df.shape
 ml_ready_shape = ml_df.shape
 # Show outputs
 display(summary_stats, cleaned_shape, churned_shape, ml_ready_shape)
      Monthly Charge f...
                        Total Charges flo...
                                          CLTV float64
                                                            Tenure in Months f.
                                                     7043
cou...
                 7043
                                   7043
                                                                       7043
                            2280.381264
                                              4400.295755
           64.76169246
                                                                  32.386767
me...
           30.0900471
                            2266.220462
                                              1183.057152
std
                                                                24.54206101
min
                 18.25
                                    18.8
                                                     2003
                                                                          1
                  35.5
                                 400.15
                                                     3469
25%
                                                                          9
```

29

4527



Transformations:

- 1. Converted Yes/No columns to boolean (True/False)
- 2. Engineered Feature: Total Addon Services (sum of optional services)
- 3. Filtered churned customers → 1,869 out of 7,043
- 4. Generated Summary Stats (e.g., Monthly Charge avg = ~\$64.76)
- 5. Prepared ML-ready dataset:
 - · Removed ID/location columns
 - Handled missing values
 - · Cast object fields to categorical

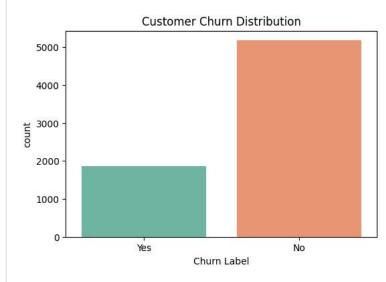
Summary:

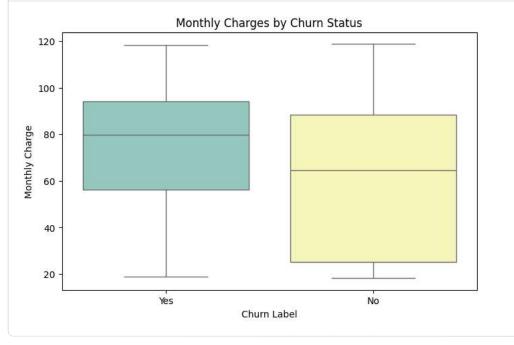
- Original shape: (7043, 50)
- Churned subset: (1869, 52)
- ML-ready shape: (7043, 42)

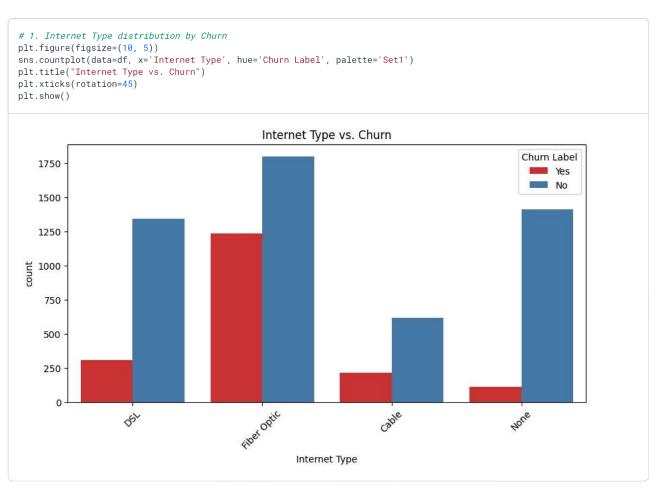
Data Visualization

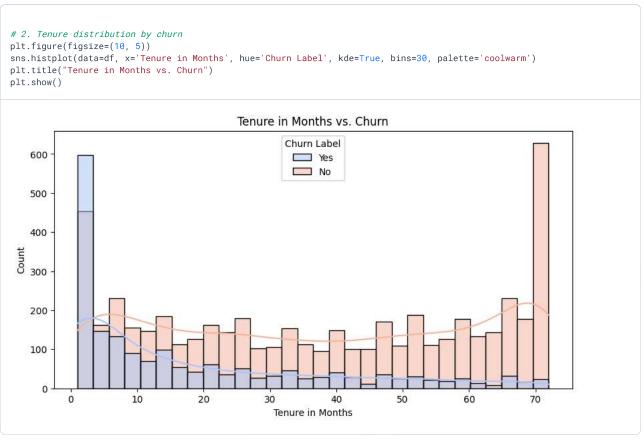
```
# Visualization: Churn distribution
plt.figure(figsize=(6, 4))
sns.countplot(data=df, x='Churn Label', palette='Set2')
plt.title("Customer Churn Distribution")
plt.show()

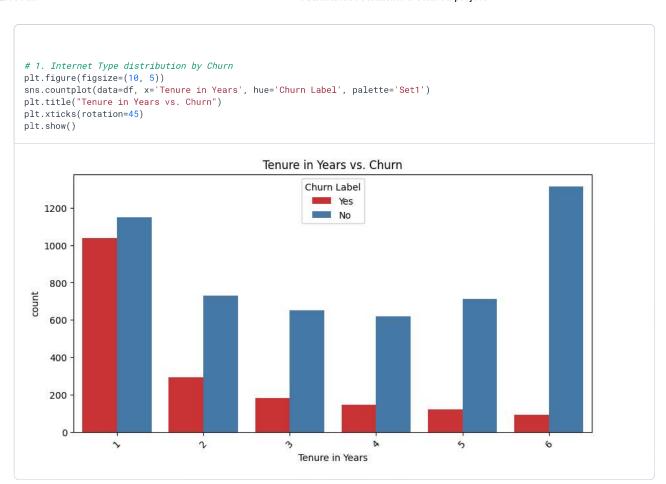
# Visualization: Monthly Charges by Churn
plt.figure(figsize=(8, 5))
sns.boxplot(data=df, x='Churn Label', y='Monthly Charge', palette='Set3')
plt.title("Monthly Charges by Churn Status")
plt.show()
```



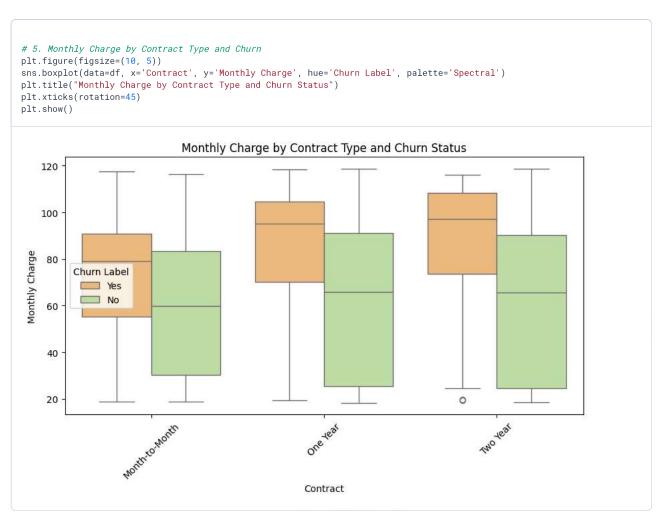


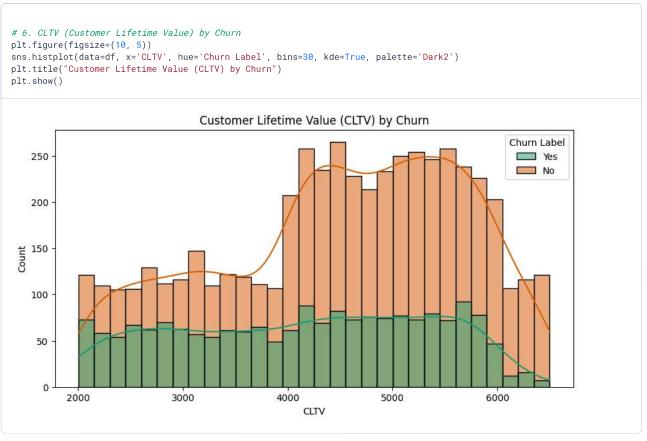






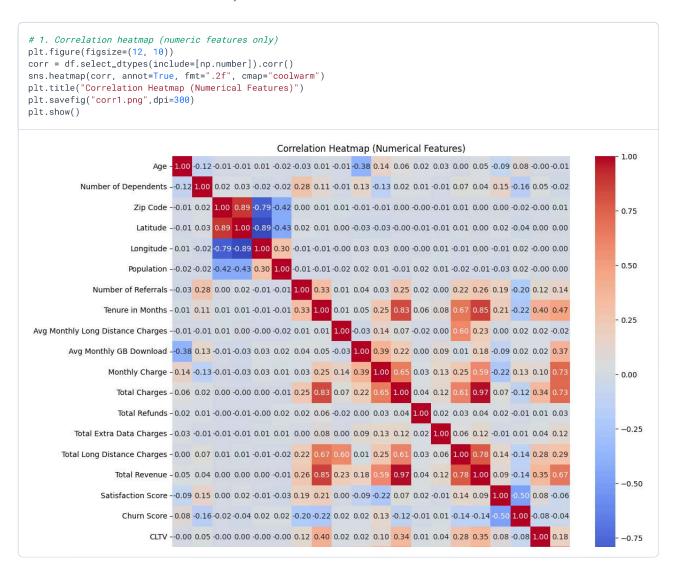






Visual Insights:

- 1. Internet Type vs. Churn:
 - Customers with Fiber Optic internet churn more often than those with DSL or None.
- 2. Tenure vs. Churn:
 - Churned customers typically have shorter tenure (often < 20 months).
- 3. Add-On Services vs. Churn:
 - Those who churn tend to have fewer additional services.
- 4. Contract Type and Monthly Charges:
 - o Month-to-month customers have higher churn, while Two Year contract holders are more stable and have lower churn.
- 5. Customer Lifetime Value (CLTV):
 - · Customers with lower CLTV are more likely to churn.



Correlation Heatmap:

- * Monthly Charge correlates with CLTV and number of Add-On Services.
- * Tenure also strongly affects CLTV, as expected.

```
# Plot bar charts (histograms) for numerical columns to show distribution
num_cols = df.select_dtypes(include=['int64', 'float64']).columns
n = len(num\_cols)
cols = 3
rows = math.ceil(n / cols)
plt.figure(figsize=(5 * cols, 4 * rows))
for i, col in enumerate(num_cols):
     plt.subplot(rows, cols, i + 1)
     plt.hist(df[col].dropna(), bins=20, color='skyblue', edgecolor='black')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel("Frequency")
plt.tight_layout()
plt.show()
                                                                                                                     Zip Code
                                                                Number of Dependents
                         Age
   500
                                                  5000
                                                                                                  600
   400
                                                  4000
                                                                                                  500
                                                  3000
                                                  2000
                                                                                                 200
   100
                                                  1000
                                                                                                  100
                         50
Age
                                                                                                     90000 91000 92000 93000 94000 95000 96000
                                                                 Number of Dependents
                                                                                                                     Zip Code
                       Latitude
                                                                     Longitude
                                                                                                                    Population
   1200
                                                  800
                                                                                                 2000
   1000
                                                  600
                                                                                                 1500
   800
                                                Hedne 400
   600
                                                                                               F 1000
    400
                                                  200
                                                                                                  500
                                                                                          -114
                                                       -124
                                                              -122
                                                                     -120
                                                                            -118
                                                                                   -116
                                                                                                                        60000
                                                                                                                     Population
                  Number of Referrals
                                                                  Tenure in Months
                                                                                                          Avg Monthly Long Distance Charges
   4000
                                                  1200
   3500
                                                                                                 800
                                                  1000
   3000
2500
                                                                                                  600
                                                  800
                                                ncy
                                                                                                ncy
```