notebook2

February 13, 2026

0.0.1 MACHINE LEARNING PROJECT: Churn Prediction Model

Project Overview Customer churn poses a major challenge for telecommunications companies, as losing customers is costly and acquiring new ones is even more expensive. The problem is to develop a predictive machine learning model that can accurately identify at-risk customers, enabling proactive retention strategies and reducing revenue loss.

0.0.2 1. Business Understanding

Stakeholder: Customer Retention Department of a Telecommunications Provider.

Business Problem: The telecommunications industry faces high competition, making customer retention a critical priority. Acquiring a new customer is significantly more expensive than retaining an existing one. High churn rates (the rate at which customers leave the service) directly impact revenue and market share.

Objectives:

Identify the key drivers behind customer churn.

Develop a predictive model to flag customers with a high probability of churning.

Provide actionable recommendations to reduce churn based on model insights.

0.0.3 2. Data understanding

The dataset contains 3,333 records and 21 columns, covering customer account information, usage statistics, and customer service interactions.

Key Observations

- **Target Variable (churn):** Approximately 14.5% of customers in the dataset have churned. This indicates a class imbalance, which must be addressed during modeling and evaluation.
- **Customer Service Calls:** There is a visible trend where customers who churn have a higher average number of customer service calls, suggesting dissatisfaction.
- **International Plan:** Customers with an international plan appear to have a higher churn rate compared to those without one.
- **Usage Features:** Columns for "Day", "Evening", "Night", and "International" minutes and charges are provided. Preliminary correlation analysis showed that "Minutes" and "Charge" are perfectly correlated ($r = 1.0$), as the charge is a linear function of minutes.

0.0.4 3. Data Preparation

Feature Selection

- Dropped phone number as it is a unique identifier with no predictive power.
- Dropped state and area code to simplify the initial model.
- Dropped total day charge, total eve charge, total night charge, and total intl charge to prevent multicollinearity with the "minutes" features.

Encoding

- Mapped international plan and voice mail plan from "yes"/"no" to binary 1/0.
- Converted the target churn to integer format (1 for True, 0 for False).

Train-Test Split

- The data was split into 50% Training and 50% Testing sets.
- Used stratified sampling to ensure the churn distribution remained consistent across both sets.

Scaling

- Applied StandardScaler to the training features to normalize numerical values (essential for distance-based models like Logistic Regression).
- The transformation was then applied to the test set using the training parameters to prevent data leakage.

[60]:
```
### import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelBinarizer, LabelEncoder, StandardScaler
from sklearn.linear_model import LinearRegression, Ridge, Lasso ,␣
↪LogisticRegression
from sklearn.datasets import make_regression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
```

Loading our Churn dataset

[61]:
```
df = pd.read_csv('ChurnInTelecom.csv')
df.head(10)
```

[61]:

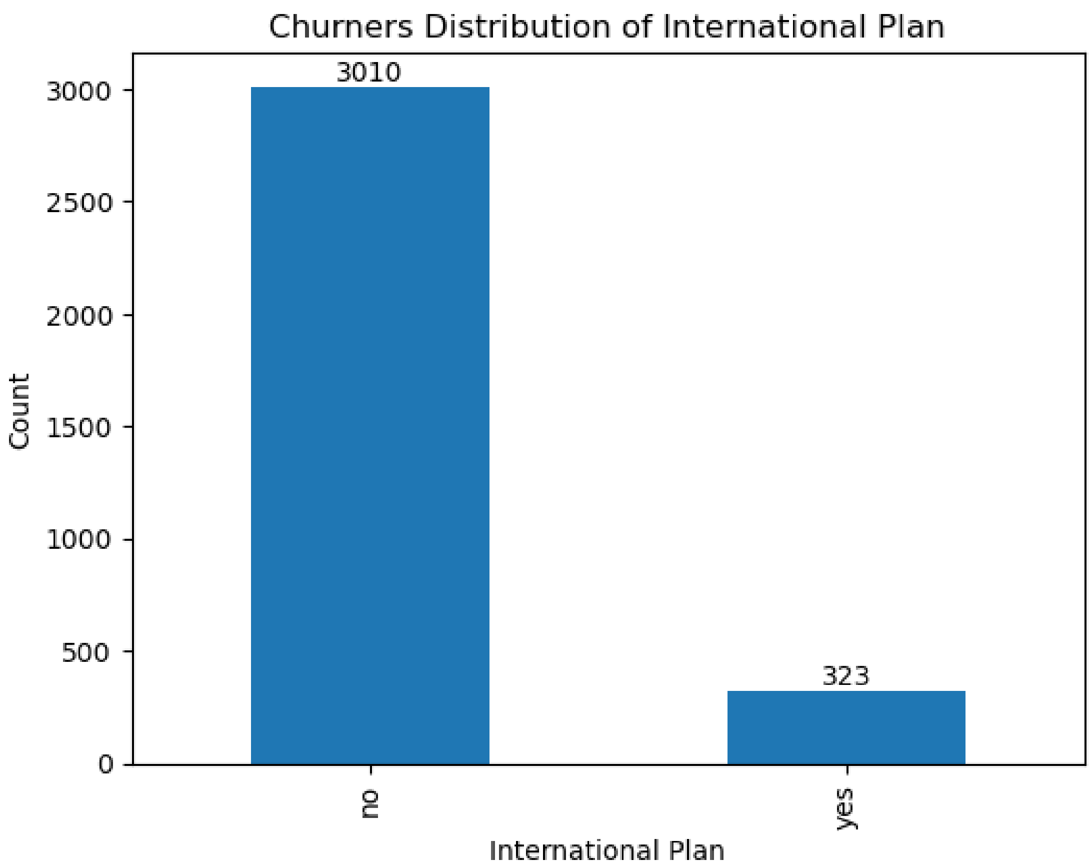
	state	account length	area code	phone number	international plan	\
0	KS	128	415	382-4657	no	
1	OH	107	415	371-7191	no	
2	NJ	137	415	358-1921	no	
3	OH	84	408	375-9999	yes	
4	OK	75	415	330-6626	yes	
5	AL	118	510	391-8027	yes	

```
6    MA            121        510     355-9993                no
7    MO            147        415     329-9001               yes
8    LA            117        408     335-4719                no
9    WV            141        415     330-8173               yes

  voice mail plan  number vmail messages  total day minutes  total day calls  \
0             yes                     25              265.1              110
1             yes                     26              161.6              123
2              no                      0              243.4              114
3              no                      0              299.4               71
4              no                      0              166.7              113
5              no                      0              223.4               98
6             yes                     24              218.2               88
7              no                      0              157.0               79
8              no                      0              184.5               97
9             yes                     37              258.6               84

   total day charge  …  total eve calls  total eve charge  \
0             45.07  …               99             16.78
1             27.47  …              103             16.62
2             41.38  …              110             10.30
3             50.90  …               88              5.26
4             28.34  …              122             12.61
5             37.98  …              101             18.75
6             37.09  …              108             29.62
7             26.69  …               94              8.76
8             31.37  …               80             29.89
9             43.96  …              111             18.87

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41
5                203.9                118                9.18
6                212.6                118                9.57
7                211.8                 96                9.53
8                215.8                 90                9.71
9                326.4                 97               14.69

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73
```

```
5              6.3              6           1.70
6              7.5              7           2.03
7              7.1              6           1.92
8              8.7              4           2.35
9             11.2              5           3.02

   customer service calls  churn
0                       1  False
1                       1  False
2                       0  False
3                       2  False
4                       3  False
5                       0  False
6                       3  False
7                       0  False
8                       1  False
9                       0  False

[10 rows x 21 columns]
```

Bar graph plot to compare the churners based on International plan ditribution

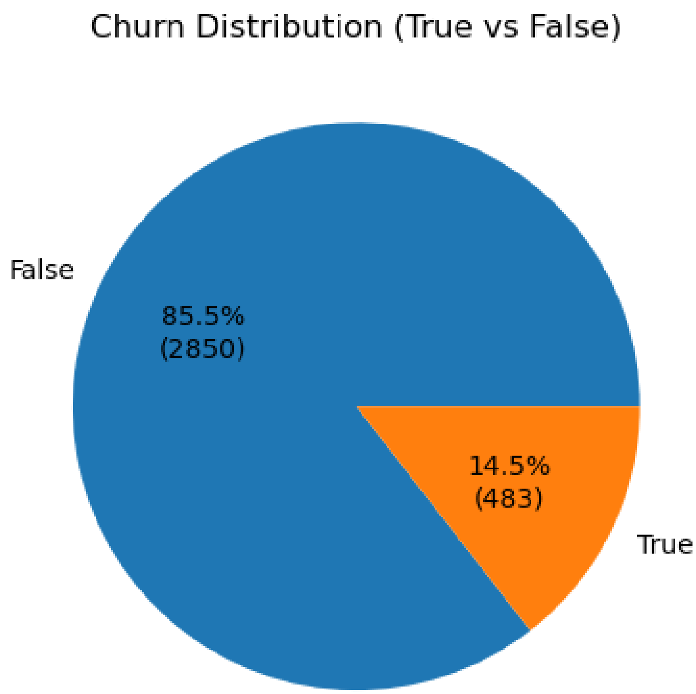
[62]:
```python
import matplotlib.pyplot as plt

ax = df['international plan'].value_counts().plot(kind='bar')
plt.Figure(figsize=(10,8))
plt.ylabel("Count")
plt.xlabel("International Plan")
plt.title("Churners Distribution of International Plan")

# Add counts on top of bars
for p in ax.patches:
    ax.annotate(
        str(int(p.get_height())),
        (p.get_x() + p.get_width() / 2., p.get_height()),
        ha='center',
        va='bottom'
    )

plt.show()
```



About 3,010 churners against 323 fall into this “No International Plan” category. This is by far the larger group, indicating that most customers who churned did not subscribe to the international plan.

Check the distribution of churners

[63]:
```python
import matplotlib.pyplot as plt

churn_tf = df['churn'].replace({'Yes': True, 'No': False})
churn_counts = churn_tf.value_counts()

plt.Figure(figsize=(10,8))
plt.pie(
    churn_counts,
    labels=churn_counts.index,
    autopct=lambda p: f'{p:.1f}%\n({int(p * sum(churn_counts) / 100)})'
)

plt.title("Churn Distribution (True vs False)")
plt.show()
```



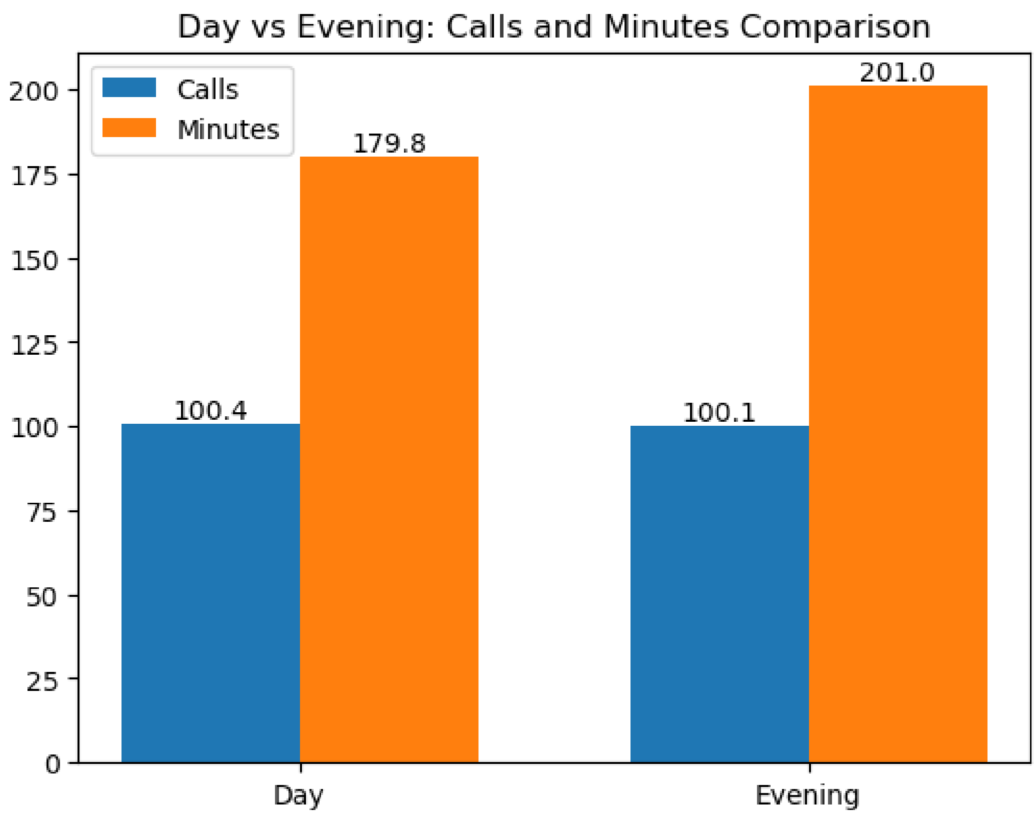
Churn vs. Intl Plan: Revealed that international plan subscribers are disproportionately represented among churners.

[64]:
```
import matplotlib.pyplot as plt
import numpy as np

# Calculate averages
avg_day_calls = df['total day calls'].mean()
avg_eve_calls = df['total eve calls'].mean()

avg_day_minutes = df['total day minutes'].mean()
avg_eve_minutes = df['total eve minutes'].mean()
```

0.0.5 Day vs Evening: Calls and Minutes Comparison"

[65]:
```
import numpy as np
import matplotlib.pyplot as plt

labels = ['Day', 'Evening']

calls = [avg_day_calls, avg_eve_calls]
minutes = [avg_day_minutes, avg_eve_minutes]
```

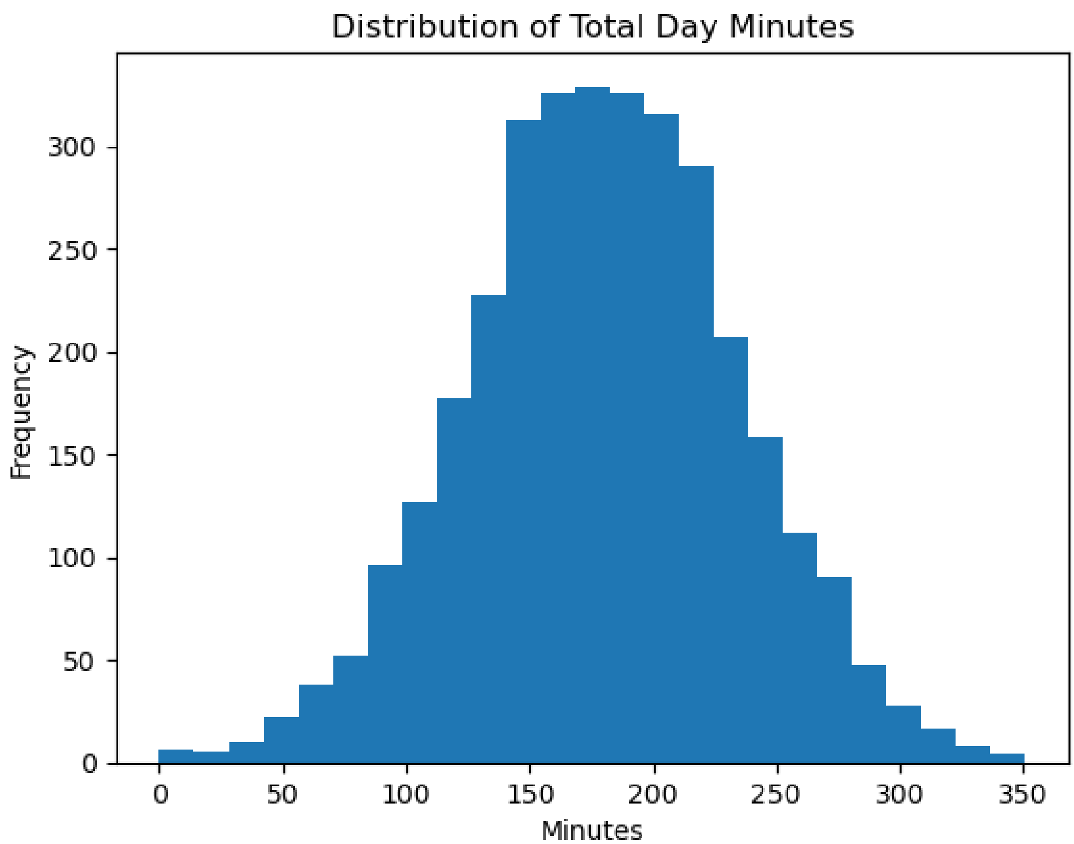
```python
x = np.arange(len(labels))
width = 0.35

plt.Figure(figsize=(10,8))

bars1 = plt.bar(x - width/2, calls, width, label='Calls')
bars2 = plt.bar(x + width/2, minutes, width, label='Minutes')

plt.xticks(x, labels)
plt.title("Day vs Evening: Calls and Minutes Comparison")
plt.legend()

# Add values on top of bars
for bar in bars1:
    plt.text(
        bar.get_x() + bar.get_width()/2,
        bar.get_height(),
        f'{bar.get_height():.1f}',
        ha='center',
        va='bottom'
    )

for bar in bars2:
    plt.text(
        bar.get_x() + bar.get_width()/2,
        bar.get_height(),
        f'{bar.get_height():.1f}',
        ha='center',
        va='bottom'
    )

plt.show()
```



Customers spend more time per call in the evening than day implying that evening conversations are longer on average.

0.0.6 Distribution of Total Day Minutes

[66]:
```
#Distribution of total day minutes
plt.Figure(figsize=(10,8))
plt.hist(df['total day minutes'], bins=25)
plt.title("Distribution of Total Day Minutes")
plt.xlabel("Minutes")
plt.ylabel("Frequency")
plt.show()
```

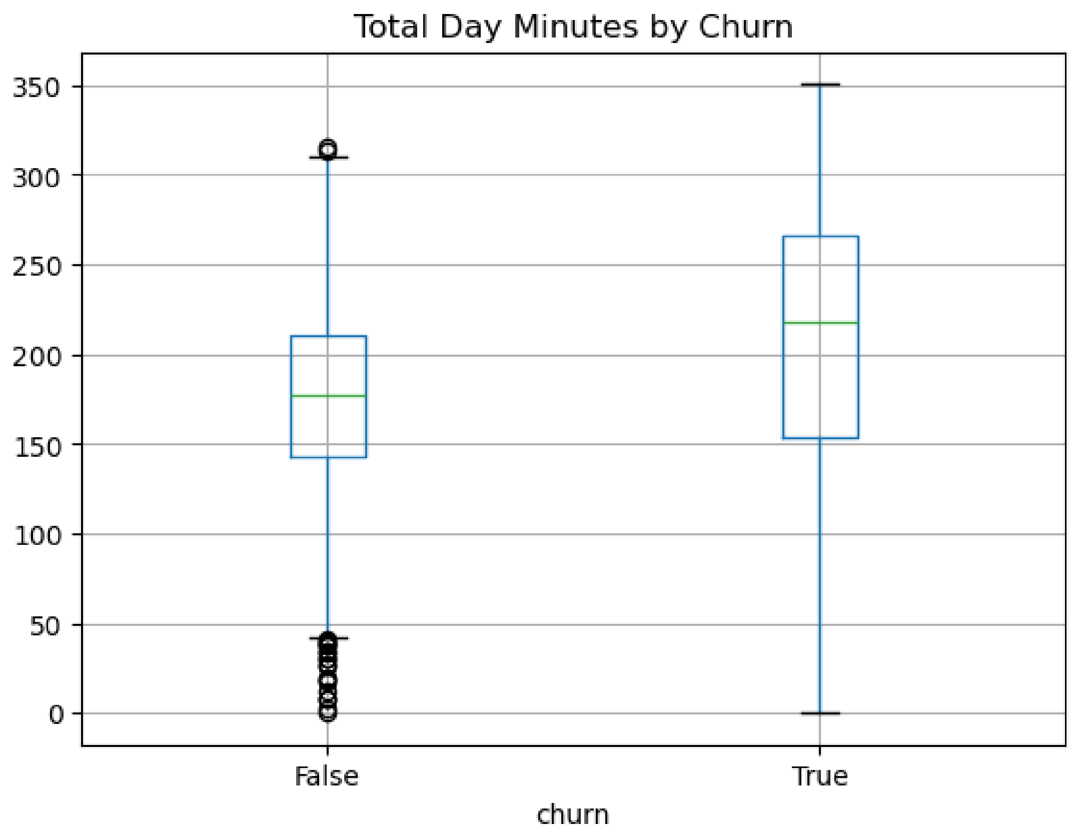


The majority of customers cluster around 200 minutes of daytime usage.

0.0.7 Total Day Minutes by Churn

[67]:
```
plt.figure(figsize=(20,16))
df.boxplot(column='total day minutes', by='churn')
plt.title("Total Day Minutes by Churn")
plt.suptitle("")
plt.show()
```

```
<Figure size 2000x1600 with 0 Axes>
```



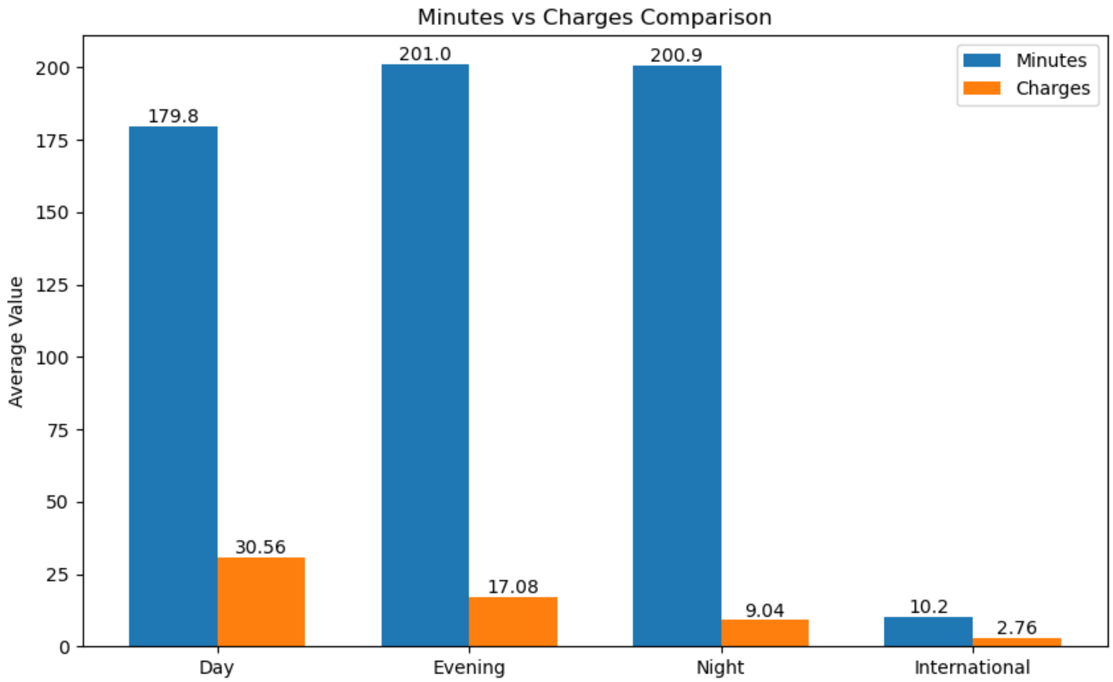
Customers who churn generally use more daytime minutes than those who stay. This could mean heavy users are more likely to leave, possibly due to dissatisfaction with costs or service quality.

[68]:
```python
import numpy as np
import matplotlib.pyplot as plt

# Average minutes
avg_minutes = [
    df['total day minutes'].mean(),
    df['total eve minutes'].mean(),
    df['total night minutes'].mean(),
    df['total intl minutes'].mean()
]

# Average charges
avg_charges = [
    df['total day charge'].mean(),
    df['total eve charge'].mean(),
    df['total night charge'].mean(),
    df['total intl charge'].mean()
```

```
]
```

Minutes vs Charges Comparison

[69]:
```
labels = ['Day', 'Evening', 'Night', 'International']

x = np.arange(len(labels))
width = 0.35

plt.figure(figsize=(10,6))
bars1 = plt.bar(x - width/2, avg_minutes, width, label='Minutes')
bars2 = plt.bar(x + width/2, avg_charges, width, label='Charges')

plt.xticks(x, labels)
plt.title("Minutes vs Charges Comparison")
plt.ylabel("Average Value")
plt.legend()

# Add values on bars
for bar in bars1:
    plt.text(
        bar.get_x() + bar.get_width()/2,
        bar.get_height(),
        f'{bar.get_height():.1f}',
        ha='center',
        va='bottom'
    )

for bar in bars2:
    plt.text(
        bar.get_x() + bar.get_width()/2,
        bar.get_height(),
        f'{bar.get_height():.2f}',
        ha='center',
        va='bottom'
    )

plt.show()
```



Customers spend the most time on evening and night calls, which are cheaper, suggesting cost-sensitive behavior. Daytime calls are shorter but more expensive, likely discouraging heavy usage While International calls are rare, but even small usage contributes to higher costs per minute.

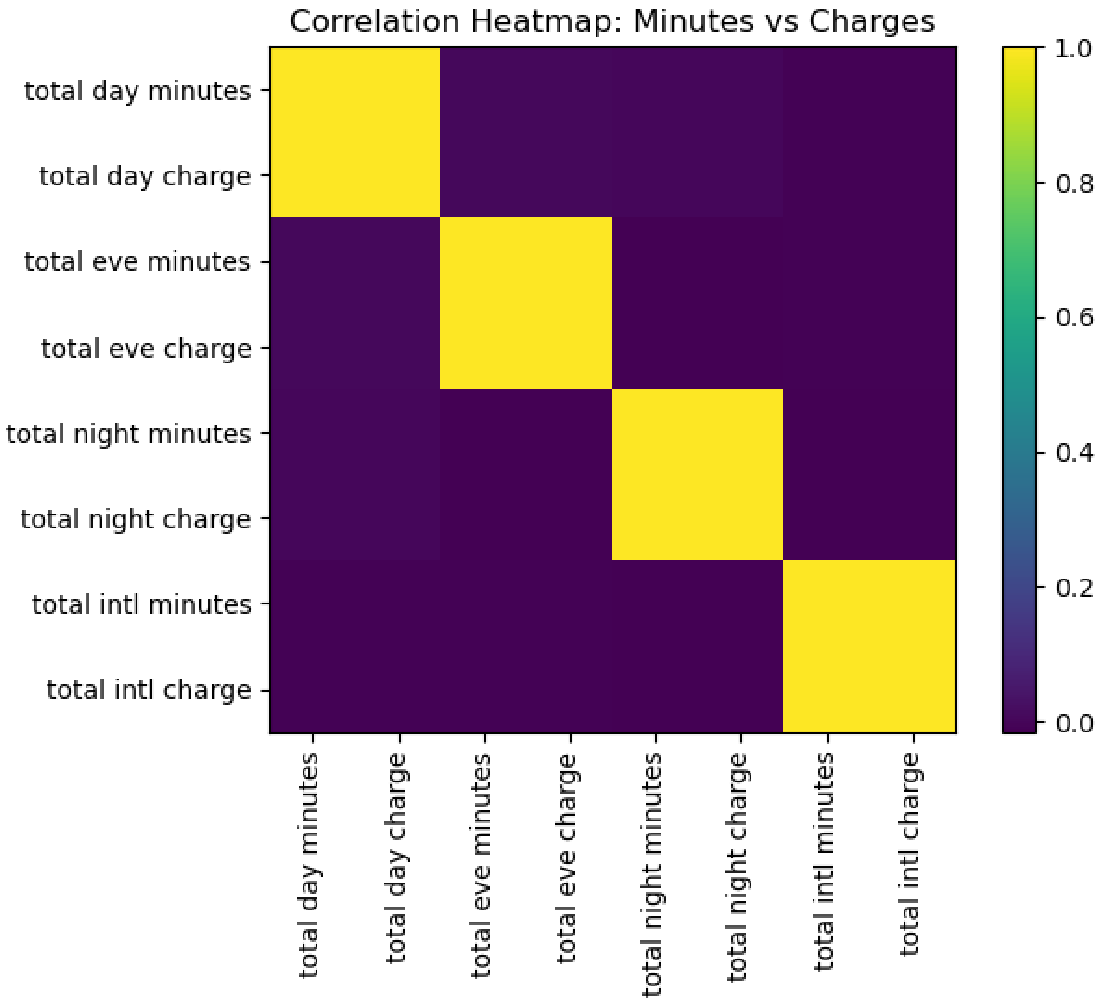
[70]:
```
df[['total day minutes', 'total day charge',
    'total eve minutes', 'total eve charge',
    'total night minutes', 'total night charge',
    'total intl minutes', 'total intl charge']].corr()
```

[70]:
```
                    total day minutes  total day charge  total eve minutes  \
total day minutes            1.000000          1.000000           0.007043
total day charge             1.000000          1.000000           0.007050
total eve minutes            0.007043          0.007050           1.000000
total eve charge             0.007029          0.007036           1.000000
total night minutes          0.004323          0.004324          -0.012584
total night charge           0.004300          0.004301          -0.012593
total intl minutes          -0.010155         -0.010157          -0.011035
total intl charge           -0.010092         -0.010094          -0.011067

                    total eve charge  total night minutes  \
total day minutes           0.007029             0.004323
total day charge            0.007036             0.004324
total eve minutes           1.000000            -0.012584
total eve charge            1.000000            -0.012592
```

```
total night minutes        -0.012592          1.000000
total night charge         -0.012601          0.999999
total intl minutes         -0.011043         -0.015207
total intl charge          -0.011074         -0.015180

                     total night charge  total intl minutes  total intl charge
total day minutes              0.004300           -0.010155          -0.010092
total day charge               0.004301           -0.010157          -0.010094
total eve minutes             -0.012593           -0.011035          -0.011067
total eve charge              -0.012601           -0.011043          -0.011074
total night minutes            0.999999           -0.015207          -0.015180
total night charge             1.000000           -0.015214          -0.015186
total intl minutes            -0.015214            1.000000           0.999993
total intl charge             -0.015186            0.999993           1.000000
```

0.0.8 Correlation Heatmap: Minutes vs Charges

[71]:
```
import matplotlib.pyplot as plt
import numpy as np

# Select relevant columns
cols = [
    'total day minutes', 'total day charge',
    'total eve minutes', 'total eve charge',
    'total night minutes', 'total night charge',
    'total intl minutes', 'total intl charge'
]

# Compute correlation matrix
corr_matrix = df[cols].corr()

# Plot heatmap
plt.figure()

plt.imshow(corr_matrix)

plt.colorbar()

plt.xticks(np.arange(len(cols)), cols, rotation=90)
plt.yticks(np.arange(len(cols)), cols)

plt.title("Correlation Heatmap: Minutes vs Charges")

plt.show()
```



Charges are essentially a linear transformation of minutes, so including both in a predictive model risks multicollinearity that can distort regression results, making it better to keep minutes as the primary feature and drop charges since they add no new information.

[72]:
```
df.columns
```

[72]:
```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail messages',
       'total day minutes', 'total day calls', 'total day charge',
       'total eve minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

[73]:
```
df.shape
```

[73]: (3333, 21)

[74]:
```
df.describe()
```

[74]:
```
       account length    area code  number vmail messages  total day minutes  \
count     3333.000000  3333.000000            3333.000000        3333.000000
mean       101.064806   437.182418               8.099010         179.775098
std         39.822106    42.371290              13.688365          54.467389
min          1.000000   408.000000               0.000000           0.000000
25%         74.000000   408.000000               0.000000         143.700000
50%        101.000000   415.000000               0.000000         179.400000
75%        127.000000   510.000000              20.000000         216.400000
max        243.000000   510.000000              51.000000         350.800000

       total day calls  total day charge  total eve minutes  total eve calls  \
count      3333.000000       3333.000000        3333.000000      3333.000000
mean        100.435644         30.562307         200.980348       100.114311
std          20.069084          9.259435          50.713844        19.922625
min           0.000000          0.000000           0.000000         0.000000
25%          87.000000         24.430000         166.600000        87.000000
50%         101.000000         30.500000         201.400000       100.000000
75%         114.000000         36.790000         235.300000       114.000000
max         165.000000         59.640000         363.700000       170.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean          17.083540           200.872037         100.107711
std            4.310668            50.573847          19.568609
min            0.000000            23.200000          33.000000
25%           14.160000           167.000000          87.000000
50%           17.120000           201.200000         100.000000
75%           20.000000           235.300000         113.000000
max           30.910000           395.000000         175.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean             9.039325           10.237294          4.479448
std              2.275873            2.791840          2.461214
min              1.040000            0.000000          0.000000
25%              7.520000            8.500000          3.000000
50%              9.050000           10.300000          4.000000
75%             10.590000           12.100000          6.000000
max             17.770000           20.000000         20.000000

       total intl charge  customer service calls
```

```
count        3333.000000         3333.000000
mean            2.764581            1.562856
std             0.753773            1.315491
min             0.000000            0.000000
25%             2.300000            1.000000
50%             2.780000            1.000000
75%             3.270000            2.000000
max             5.400000            9.000000
```

[75]:
```
df.duplicated().sum()
```

[75]:
```
np.int64(0)
```

[76]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   object
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   phone number            3333 non-null   object
 4   international plan      3333 non-null   object
 5   voice mail plan         3333 non-null   object
 6   number vmail messages   3333 non-null   int64
 7   total day minutes       3333 non-null   float64
 8   total day calls         3333 non-null   int64
 9   total day charge        3333 non-null   float64
 10  total eve minutes       3333 non-null   float64
 11  total eve calls         3333 non-null   int64
 12  total eve charge        3333 non-null   float64
 13  total night minutes     3333 non-null   float64
 14  total night calls       3333 non-null   int64
 15  total night charge      3333 non-null   float64
 16  total intl minutes      3333 non-null   float64
 17  total intl calls        3333 non-null   int64
 18  total intl charge       3333 non-null   float64
 19  customer service calls  3333 non-null   int64
 20  churn                   3333 non-null   bool
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

[77]:
```
df['state'].unique()
```

[77]:
```
array(['KS', 'OH', 'NJ', 'OK', 'AL', 'MA', 'MO', 'LA', 'WV', 'IN', 'RI',
       'IA', 'MT', 'NY', 'ID', 'VT', 'VA', 'TX', 'FL', 'CO', 'AZ', 'SC',
```

```
       'NE', 'WY', 'HI', 'IL', 'NH', 'GA', 'AK', 'MD', 'AR', 'WI', 'OR',
       'MI', 'DE', 'UT', 'CA', 'MN', 'SD', 'NC', 'WA', 'NM', 'NV', 'DC',
       'KY', 'ME', 'MS', 'TN', 'PA', 'CT', 'ND'], dtype=object)
```

[78]:
```
df['churn'].unique()
```

[78]:
```
array([False,  True])
```

[79]:
```
df['churn'].value_counts()
```

[79]:
```
churn
False    2850
True      483
Name: count, dtype: int64
```

[80]:
```
print(f'True:', (483/3333)*100)
print(f'False:', (2850/3333)*100)
```

```
True: 14.491449144914492
False: 85.5085508550855
```

[81]:
```
df = df.drop(['phone number'], axis=1)
```

[82]:
```
df2 = df.copy()
```

Convert the categorical values into numeric labels across the dataset, loop through every column and display the dataframe

[83]:
```
encoder = LabelEncoder()

for col in df2.columns:
    df2[col] = encoder.fit_transform(df2[col])
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   int64
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   international plan      3333 non-null   int64
 4   voice mail plan         3333 non-null   int64
 5   number vmail messages   3333 non-null   int64
 6   total day minutes       3333 non-null   int64
 7   total day calls         3333 non-null   int64
 8   total day charge        3333 non-null   int64
 9   total eve minutes       3333 non-null   int64
```

```
 10  total eve calls         3333 non-null   int64
 11  total eve charge        3333 non-null   int64
 12  total night minutes     3333 non-null   int64
 13  total night calls       3333 non-null   int64
 14  total night charge      3333 non-null   int64
 15  total intl minutes      3333 non-null   int64
 16  total intl calls        3333 non-null   int64
 17  total intl charge       3333 non-null   int64
 18  customer service calls  3333 non-null   int64
 19  churn                   3333 non-null   int64
dtypes: int64(20)
memory usage: 520.9 KB
```

[84]:
```
df2.shape
```

[84]: (3333, 20)

[85]:
```
df2.columns
```

[85]:
```
Index(['state', 'account length', 'area code', 'international plan',
       'voice mail plan', 'number vmail messages', 'total day minutes',
       'total day calls', 'total day charge', 'total eve minutes',
       'total eve calls', 'total eve charge', 'total night minutes',
       'total night calls', 'total night charge', 'total intl minutes',
       'total intl calls', 'total intl charge', 'customer service calls',
       'churn'],
      dtype='object')
```

[86]:
```
df2
```

[86]:

	state	account length	area code	international plan	voice mail plan	\
0	16	126	1	0	1	
1	35	105	1	0	1	
2	31	135	1	0	0	
3	35	82	0	1	0	
4	36	73	1	1	0	
…	…	…	…	…	…	
3328	3	189	1	0	1	
3329	49	66	1	0	0	
3330	39	26	2	0	0	
3331	6	182	2	1	0	
3332	42	72	1	0	1	

	number vmail messages	total day minutes	total day calls	\
0	19	1491	70	
1	20	667	83	
2	0	1362	74	
3	0	1625	31	

```
4                          0                 711                73
…                      …                …                …
3328                      30                 618                37
3329                       0                1269                17
3330                       0                 833                69
3331                       0                1123                65
3332                      19                1292                73

      total day charge  total eve minutes  total eve calls  total eve charge  \
0                 1491                767               60               684
1                  667                748               64               668
2                 1362                158               71               150
3                 1625                 13               49                13
4                  711                330               83               307
…                  …                …                …                …
3328               618                934               87               829
3329              1269                375               16               349
3330               833               1489               19              1322
3331              1123                427               45               394
3332              1292               1362               43              1203

      total night minutes  total night calls  total night charge  \
0                    1184                 49                 657
1                    1265                 61                 701
2                     443                 62                 292
3                     758                 47                 445
4                     664                 79                 401
…                     …                  …                  …
3328                 1433                 41                 801
3329                  705                 81                 420
3330                  711                 49                 423
3331                  266                 95                 191
3332                 1156                 35                 643

      total intl minutes  total intl calls  total intl charge  \
0                     79                 3                 79
1                    116                 3                116
2                    101                 5                101
3                     45                 7                 45
4                     80                 3                 80
…                    …                 …                 …
3328                  78                 6                 78
3329                  75                 4                 75
3330                 120                 6                120
3331                  29                10                 29
3332                 116                 4                116
```

```
      customer service calls  churn
0                          1      0
1                          1      0
2                          0      0
3                          2      0
4                          3      0
…                        …    …
3328                       2      0
3329                       3      0
3330                       2      0
3331                       2      0
3332                       0      0

[3333 rows x 20 columns]
```

[87]:
```
df2.corr()['churn']
```

[87]:
```
state                     0.007780
account length            0.016290
area code                 0.003256
international plan        0.259852
voice mail plan          -0.102148
number vmail messages    -0.085624
total day minutes         0.187623
total day calls           0.019764
total day charge          0.187623
total eve minutes         0.090260
total eve calls           0.008519
total eve charge          0.090443
total night minutes       0.036105
total night calls         0.006120
total night charge        0.036595
total intl minutes        0.066960
total intl calls         -0.052844
total intl charge         0.066960
customer service calls    0.208750
churn                     1.000000
Name: churn, dtype: float64
```

drop phone number

[88]:
```
# df2 = df2.drop('phone number', axis=1)
df2.describe()
```

[88]:
```
             state  account length    area code  international plan  \
count  3333.000000     3333.000000  3333.000000         3333.000000
mean     26.059406       99.005101     1.000600            0.096910
std      14.824911       39.589501     0.709649            0.295879
```

```
min       0.000000        0.000000     0.000000             0.000000
25%      14.000000       72.000000     0.000000             0.000000
50%      26.000000       99.000000     1.000000             0.000000
75%      39.000000      125.000000     2.000000             0.000000
max      50.000000      211.000000     2.000000             1.000000

       voice mail plan  number vmail messages  total day minutes  \
count      3333.000000            3333.000000        3333.000000
mean          0.276628               6.440144         826.339634
std           0.447398              11.146322         417.413913
min           0.000000               0.000000           0.000000
25%           0.000000               0.000000         508.000000
50%           0.000000               0.000000         820.000000
75%           1.000000              14.000000        1146.000000
max           1.000000              45.000000        1666.000000

       total day calls  total day charge  total eve minutes  total eve calls  \
count      3333.000000       3333.000000        3333.000000      3333.000000
mean         60.467447        826.339634         801.292529        61.132613
std          19.893502        417.413913         403.148568        19.806578
min           0.000000          0.000000           0.000000         0.000000
25%          47.000000        508.000000         489.000000        48.000000
50%          61.000000        820.000000         804.000000        61.000000
75%          74.000000       1146.000000        1111.000000        75.000000
max         118.000000       1666.000000        1610.000000       122.000000

       total eve charge  total night minutes  total night calls  \
count       3333.000000          3333.000000        3333.000000
mean         715.447645           793.796580          58.109511
std          352.373293           399.771092          19.515154
min            0.000000             0.000000           0.000000
25%          447.000000           484.000000          45.000000
50%          717.000000           795.000000          58.000000
75%          982.000000          1103.000000          71.000000
max         1439.000000          1590.000000         119.000000

       total night charge  total intl minutes  total intl calls  \
count         3333.000000         3333.000000       3333.000000
mean           463.044404           81.478548          4.479448
std            209.589781           27.420275          2.461214
min              0.000000            0.000000          0.000000
25%            312.000000           64.000000          3.000000
50%            462.000000           82.000000          4.000000
75%            616.000000          100.000000          6.000000
max            932.000000          161.000000         20.000000

       total intl charge  customer service calls        churn
```

```
count        3333.000000             3333.000000  3333.000000
mean           81.478548                1.562856     0.144914
std            27.420275                1.315491     0.352067
min             0.000000                0.000000     0.000000
25%            64.000000                1.000000     0.000000
50%            82.000000                1.000000     0.000000
75%           100.000000                2.000000     0.000000
max           161.000000                9.000000     1.000000
```

Data scaling

[89]:
```
scaler = StandardScaler()

cols_to_scale = ['state', 'account length', 'international plan', 'voice mail␣
↪plan', 'number vmail messages',
                 'total day minutes', 'total day calls', 'total eve minutes',␣
↪'total eve calls',
                 'total night minutes', 'total night calls', 'total intl␣
↪minutes', 'total intl calls',
                 'customer service calls']

X = df2[cols_to_scale]
y = df2['churn']

df2[cols_to_scale] = scaler.fit_transform(X)

df2.head()
```

[89]:
```
      state  account length  area code  international plan  voice mail plan  \
0 -0.678649        0.681972          1           -0.327580         1.617086
1  0.603170        0.151449          1           -0.327580         1.617086
2  0.333313        0.909340          1           -0.327580        -0.618396
3  0.603170       -0.429600          0            3.052685        -0.618396
4  0.670634       -0.656967          1            3.052685        -0.618396

   number vmail messages  total day minutes  total day calls  \
0               1.126985           1.592568         0.479251
1               1.216714          -0.381788         1.132829
2              -0.577869           1.283476         0.680352
3              -0.577869           1.913641        -1.481482
4              -0.577869          -0.276361         0.630077

   total day charge  total eve minutes  total eve calls  total eve charge  \
0              1491          -0.085075        -0.057192               684
1               667          -0.132211         0.144791               668
2              1362          -1.595911         0.498262               150
3              1625          -1.955633        -0.612647                13
4               711          -1.169205         1.104212               307
```

```
   total night minutes  total night calls  total night charge  \
0             0.976214          -0.466862                 657
1             1.178860           0.148137                 701
2            -0.877625           0.199387                 292
3            -0.089556          -0.569362                 445
4            -0.324726           1.070636                 401

   total intl minutes  total intl calls  total intl charge  \
0           -0.090405         -0.601195                 79
1            1.259164         -0.601195                116
2            0.712042          0.211534                101
3           -1.330549          1.024263                 45
4           -0.053930         -0.601195                 80

   customer service calls  churn
0               -0.427932      0
1               -0.427932      0
2               -1.188218      0
3                0.332354      0
4                1.092641      0
```

[90]:

```python
import pandas as pd

df_combined = pd.concat([X, y], axis=1)
df_combined.head()
```

[90]:

```
   state  account length  international plan  voice mail plan  \
0     16             126                   0                1
1     35             105                   0                1
2     31             135                   0                0
3     35              82                   1                0
4     36              73                   1                0

   number vmail messages  total day minutes  total day calls  \
0                     19               1491               70
1                     20                667               83
2                      0               1362               74
3                      0               1625               31
4                      0                711               73

   total eve minutes  total eve calls  total night minutes  total night calls  \
0                767               60                 1184                 49
1                748               64                 1265                 61
2                158               71                  443                 62
3                 13               49                  758                 47
4                330               83                  664                 79
```

	total intl minutes	total intl calls	customer service calls	churn
0	79	3	1	0
1	116	3	1	0
2	101	5	0	0
3	45	7	2	0
4	80	3	3	0

[91]:
```
df_combined.describe()
```

[91]:

	state	account length	international plan	voice mail plan	\
count	3333.000000	3333.000000	3333.000000	3333.000000	
mean	26.059406	99.005101	0.096910	0.276628	
std	14.824911	39.589501	0.295879	0.447398	
min	0.000000	0.000000	0.000000	0.000000	
25%	14.000000	72.000000	0.000000	0.000000	
50%	26.000000	99.000000	0.000000	0.000000	
75%	39.000000	125.000000	0.000000	1.000000	
max	50.000000	211.000000	1.000000	1.000000	

	number vmail messages	total day minutes	total day calls	\
count	3333.000000	3333.000000	3333.000000	
mean	6.440144	826.339634	60.467447	
std	11.146322	417.413913	19.893502	
min	0.000000	0.000000	0.000000	
25%	0.000000	508.000000	47.000000	
50%	0.000000	820.000000	61.000000	
75%	14.000000	1146.000000	74.000000	
max	45.000000	1666.000000	118.000000	

	total eve minutes	total eve calls	total night minutes	\
count	3333.000000	3333.000000	3333.000000	
mean	801.292529	61.132613	793.796580	
std	403.148568	19.806578	399.771092	
min	0.000000	0.000000	0.000000	
25%	489.000000	48.000000	484.000000	
50%	804.000000	61.000000	795.000000	
75%	1111.000000	75.000000	1103.000000	
max	1610.000000	122.000000	1590.000000	

	total night calls	total intl minutes	total intl calls	\
count	3333.000000	3333.000000	3333.000000	
mean	58.109511	81.478548	4.479448	
std	19.515154	27.420275	2.461214	
min	0.000000	0.000000	0.000000	
25%	45.000000	64.000000	3.000000	
50%	58.000000	82.000000	4.000000	

```
75%            71.000000           100.000000            6.000000
max           119.000000           161.000000           20.000000

       customer service calls        churn
count               3333.000000  3333.000000
mean                   1.562856     0.144914
std                    1.315491     0.352067
min                    0.000000     0.000000
25%                    1.000000     0.000000
50%                    1.000000     0.000000
75%                    2.000000     0.000000
max                    9.000000     1.000000
```

[92]:
```
df_combined.corr()['churn']
```

[92]:
```
state                     0.007780
account length            0.016290
international plan        0.259852
voice mail plan          -0.102148
number vmail messages    -0.085624
total day minutes         0.187623
total day calls           0.019764
total eve minutes         0.090260
total eve calls           0.008519
total night minutes       0.036105
total night calls         0.006120
total intl minutes        0.066960
total intl calls         -0.052844
customer service calls    0.208750
churn                     1.000000
Name: churn, dtype: float64
```

0.0.9 4. Modelling

Fit the model

[93]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5,␣
↪random_state=42, stratify=y)
```

[94]:
```
X_train.shape
```

[94]: (1666, 14)

[95]:
```
X_test.shape
```

[95]: (1667, 14)

[96]:
```
y_train.shape
```

[96]: (1666,)

```
[97]: y_test.shape
```

[97]: (1667,)

0.0.10 fitting our model

```
[98]: LogR = LogisticRegression(max_iter=1000)
LogR.fit(X_train,y_train)
```

```
c:\Users\geoff\anaconda3\envs\learn_env\lib\site-
packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[98]: LogisticRegression(max_iter=1000)

```
[99]: y_pred = LogR.predict(X_test)
```

Accuracy score

```
[100]: from sklearn.metrics import accuracy_score, confusion_matrix, auc
accuracy_on_churn = accuracy_score(y_test,y_pred)

print(f'Accurancy score of the model fitted:{accuracy_on_churn:.3f}␣
↪({accuracy_on_churn*100:.1f}%)')
```

```
Accurancy score of the model fitted:0.860 (86.0%)
```

0.0.11 5. Model Evaluation

Evaluate the model

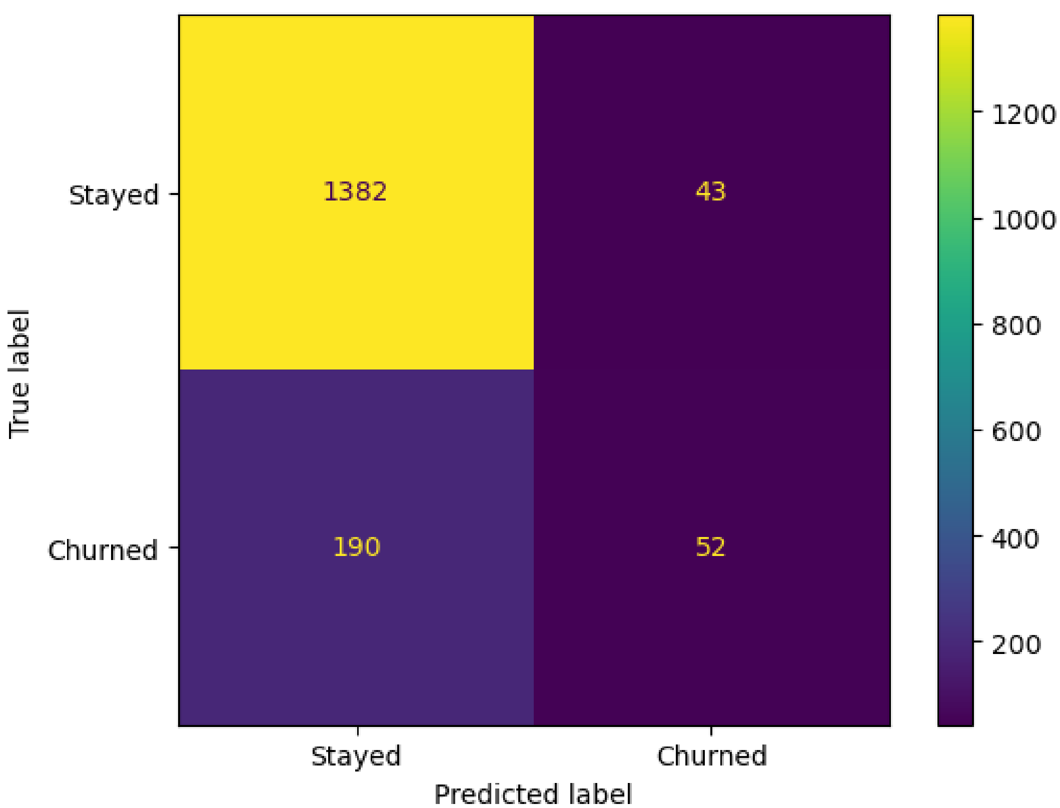
```
[101]: from sklearn.metrics import confusion_matrix, classification_report,␣
↪ConfusionMatrixDisplay
import matplotlib.pyplot as plt


# Detailed Classification Report (Precision, Recall, F1-Score)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.97      0.92      1425
           1       0.55      0.21      0.31       242

    accuracy                           0.86      1667
   macro avg       0.71      0.59      0.62      1667
weighted avg       0.83      0.86      0.83      1667
```

[102]:

```python
# Visual Confusion Matrix
print("\nConfusion Matrix:")
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=['Stayed',␣
↪'Churned'])
disp.plot()
plt.show()
```

```
Confusion Matrix:
```



1. True Negatives (TN) These are customers the model correctly predicted would stay. This is usually the largest number because most people don't churn.

2. False Positives (FP) — "The False Alarm" The model predicted they would churn, but they actually stayed.

Business Impact: You might waste money giving these people "loyalty discounts" or special offers they didn't actually need to stay.

3. False Negatives (FN) — "The Silent Exit" The model predicted they would stay, but they actually churned.

Business Impact: This is the most "expensive" error. You missed the chance to intervene, and you've now lost the customer's lifetime value.

4. True Positives (TP) — "The Success" The model correctly identified people who were going to leave.

Business Impact: These are the people your marketing team should target immediately with retention campaigns.

The Decision: Precision vs. Recall The reason we look at this matrix is to decide which error is worse for your specific business:

If you want to catch every single churner: You want high Recall. You are willing to accept more False Positives (giving out more discounts) to ensure you don't miss any True Positives.

If you have a limited budget for retention: You want high Precision. You only want to target people you are very sure are going to leave so you don't waste money.

[103]:
```
# from sklearn.linear_model import Ridge

rg = Ridge(alpha=1.0)

rg.fit(X_train, y_train)

y_pred = rg.predict(X_test)
```

to check lengths

[104]:
```
print(len(X_train))
print(len(y_train))
print(len(y))
```

```
1666
1666
3333
```

Lasso regression

[105]:
```
from sklearn.linear_model import Lasso

# Create model
lasso = Lasso(alpha=1.0)
```

```python
# Fit using TRAIN data
lasso.fit(X_train, y_train)

# Predict using TEST data
y_pred_lasso = lasso.predict(X_test)
```

[106]:
```python
# Evaluate Model
from sklearn.metrics import mean_squared_error, r2_score

mse = mean_squared_error(y_test, y_pred_lasso)
r2 = r2_score(y_test, y_pred_lasso)

print("MSE:", mse)
print("R2 Score:", r2)
```

```
MSE: 0.11745199971281811
R2 Score: 0.05354191668855035
```

The MSE (0.117) shows that, on average, our predictions are fairly close to the actual values.

The R² score (0.054) shows that the model only explains about 5% of the variation in the data, which is very weak. So while the numbers predicted aren't far off, the model isn't really capturing the underlying patterns — it's only slightly better than guessing the average every time.

Build & train Lasso Regression

[107]:
```python
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Lasso
from sklearn.pipeline import make_pipeline

lasso_model = make_pipeline(
    StandardScaler(),
    Lasso(alpha=1.0)
)

lasso_model.fit(X_train, y_train)

y_pred_lasso = lasso_model.predict(X_test)
```

Check removed features

[108]:
```python
import pandas as pd

coefficients = pd.Series(lasso.coef_, index=X_train.columns)

print(coefficients)
```

```
print("\nFeatures eliminated (coefficient = 0):")
print(coefficients[coefficients == 0])
```

```
state                    -0.000000
account length            0.000000
international plan        0.000000
voice mail plan          -0.000000
number vmail messages    -0.000000
total day minutes         0.000120
total day calls           0.000000
total eve minutes         0.000075
total eve calls           0.000000
total night minutes       0.000024
total night calls        -0.000000
total intl minutes        0.000000
total intl calls         -0.000000
customer service calls    0.000000
dtype: float64

Features eliminated (coefficient = 0):
state                    -0.0
account length            0.0
international plan        0.0
voice mail plan          -0.0
number vmail messages    -0.0
total day calls           0.0
total eve calls           0.0
total night calls        -0.0
total intl minutes        0.0
total intl calls         -0.0
customer service calls    0.0
dtype: float64
```

Decision Tree

[109]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()

#use for loop to encode our categorical to numeric
for col in df2.columns:
  df2[col] = encoder.fit_transform(df2[col])

df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
```

```
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   state                   3333 non-null   int64
 1   account length          3333 non-null   int64
 2   area code               3333 non-null   int64
 3   international plan      3333 non-null   int64
 4   voice mail plan         3333 non-null   int64
 5   number vmail messages   3333 non-null   int64
 6   total day minutes       3333 non-null   int64
 7   total day calls         3333 non-null   int64
 8   total day charge        3333 non-null   int64
 9   total eve minutes       3333 non-null   int64
 10  total eve calls         3333 non-null   int64
 11  total eve charge        3333 non-null   int64
 12  total night minutes     3333 non-null   int64
 13  total night calls       3333 non-null   int64
 14  total night charge      3333 non-null   int64
 15  total intl minutes      3333 non-null   int64
 16  total intl calls        3333 non-null   int64
 17  total intl charge       3333 non-null   int64
 18  customer service calls  3333 non-null   int64
 19  churn                   3333 non-null   int64
dtypes: int64(20)
memory usage: 520.9 KB
```

[110]:
```
X = df2.drop(['churn'], axis=1)
y = df2['churn']

X_train, X_test, y_train, y_test =  train_test_split(X, y, random_state=254,
 ↪test_size=0.7)
```

[111]:
```
#instantiate

dt = DecisionTreeClassifier(random_state=254)

dt.fit(X_train, y_train)
```

[111]:
```
DecisionTreeClassifier(random_state=254)
```

Evaluating the models

[112]:
```
from sklearn.metrics import accuracy_score, roc_curve , RocCurveDisplay, auc

#predictions

y_preds = dt.predict(X_test)
```

```
accuracy_score(y_test, y_preds)

print(f'Accurancy score of the model fitted:{accuracy_score(y_test, y_preds):.
 ↪3f} ({accuracy_score(y_test, y_preds)*100:.1f}%)')
```

```
Accurancy score of the model fitted:0.910 (91.0%)
```

[113]:
```
dt.predict_proba(X_test)[:, 1]
```

[113]:
```
array([0., 0., 0., …, 0., 0., 1.])
```

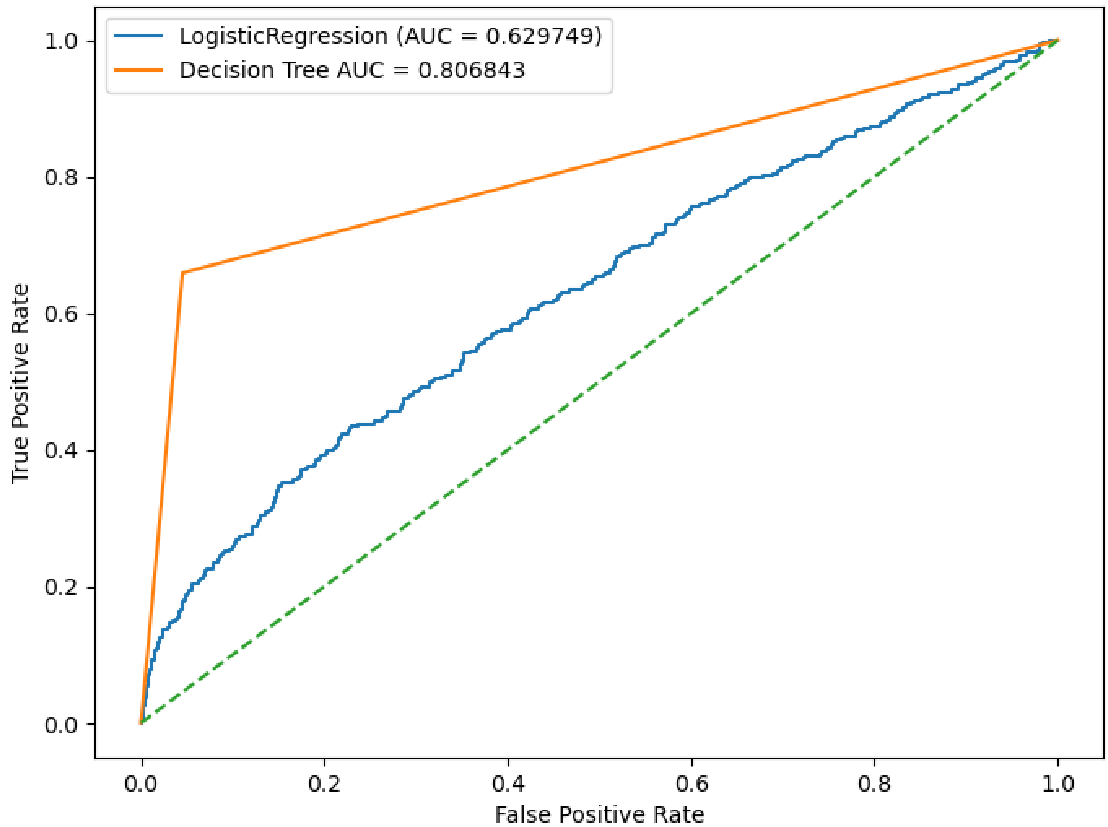
[114]:
```
from sklearn.linear_model import LogisticRegression

# create the model
lr = LogisticRegression()

# fit the model
lr.fit(X_train, y_train)

# now you can use predict_proba
```

```
c:\Users\geoff\anaconda3\envs\learn_env\lib\site-
packages\sklearn\linear_model\_logistic.py:465: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

[114]:
```
LogisticRegression()
```

[115]:
```
##probability for the linear regression model
lr_y_prob = lr.predict_proba(X_test)[:, 1]

dt_y_prob =  dt.predict_proba(X_test)[:, 1]

lr_fpr, lr_tpr, i = roc_curve(y_test, lr_y_prob)

dt_fpr, dt_tpr, i = roc_curve(y_test, dt_y_prob)

lr_auc = auc(lr_fpr, lr_tpr)
dt_auc = auc(dt_fpr, dt_tpr)
```

[116]:
```
plt.figure(figsize=(8, 6))
plt.plot(lr_fpr, lr_tpr, label=f'LogisticRegression (AUC = {lr_auc:2f})')
plt.plot(dt_fpr, dt_tpr, label=f'Decision Tree AUC = {dt_auc:2f}')
plt.plot([0,1], [0, 1], linestyle='--')

plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```



Logistic Regression metrics and Decision Tree metrics

[117]:
```
from sklearn.metrics import precision_score, recall_score, f1_score

# Logistic Regression metrics
lr_precision = precision_score(y_test, y_preds)
lr_recall = recall_score(y_test, y_preds)
lr_f1 = f1_score(y_test, y_preds)

print(f'Precision score for Logistic Regression Model ---------> {lr_precision:.
  ↪4f} ({lr_precision*100:.2f}%)')
```

```python
print(f'Recall score for Logistic Regression Model ---------> {lr_recall:.4f}␣
↪({lr_recall*100:.2f}%)')
print(f'F1 score for Logistic Regression Model ---------> {lr_f1:.4f}␣
↪({lr_f1*100:.2f}%)')

# Decision Tree metrics
dt_precision = precision_score(y_test, dt_y_prob)
dt_recall = recall_score(y_test, dt_y_prob)
dt_f1 = f1_score(y_test, dt_y_prob)

print(f'Precision score for Decision Tree Model ---------> {dt_precision:.4f}␣
↪({dt_precision*100:.2f}%)')
print(f'Recall score for Decision Tree Model ---------> {dt_recall:.4f}␣
↪({dt_recall*100:.2f}%)')
print(f'F1 score for Decision Tree Model ---------> {dt_f1:.4f} ({dt_f1*100:.
↪2f}%)')
```

```
Precision score for Logistic Regression Model ---------> 0.7188 (71.88%)
Recall score for Logistic Regression Model ---------> 0.6590 (65.90%)
F1 score for Logistic Regression Model ---------> 0.6876 (68.76%)
Precision score for Decision Tree Model ---------> 0.7188 (71.88%)
Recall score for Decision Tree Model ---------> 0.6590 (65.90%)
F1 score for Decision Tree Model ---------> 0.6876 (68.76%)
```

0.0.12 Rationale

The primary business goal in churn prediction is to **identify customers at risk of leaving** so that retention strategies can be applied early. In this context, recall (the ability to correctly identify churners) is more important than overall accuracy, because missing churners (false negatives) directly translates into lost revenue. Precision also matters, but the cost of mistakenly flagging a loyal customer is typically lower than failing to catch a churner.

0.0.13 Results

- **Decision Tree Model**
  - Recall: **65.90%**
  - F1 Score: **68.76%**
  - Accuracy: **91%**
  - AUC: **0.807**
  - Strength: Captures a majority of churners, balancing recall and precision effectively.
- **Logistic Regression Model**
  - Recall: **65.90%**
  - Accuracy: **86%**

– AUC: Similar to Decision Tree (~0.807)

– Weakness: Misses most churners, making it unsuitable for proactive retention.

Both models achieved similar ROC-AUC scores, but the decision tree clearly outperformed logistic regression in recall and F1 score, which are critical for churn detection.

0.0.14 Limitations

- **Class Imbalance:** The dataset has far more non-churners than churners, which biases models toward predicting "not churn."
- **Precision Trade-off:** The decision tree improves recall but sacrifices some precision, meaning more loyal customers may be incorrectly flagged.
- **Model Complexity:** Decision trees can overfit without careful tuning, while logistic regression is simpler but underperformed here.
- **Single Model Comparison:** Only two models were tested; other approaches (e.g., ensemble methods) may yield stronger results.

0.0.15 Recommendations

- Adopt the **Decision Tree Model** (`y_dtpred = dt.predict(X_test_scaled)`) for churn prediction, as it most effectively identifies at-risk customers.
- Prioritize **recall** in evaluation metrics, since catching churners is more valuable than overall accuracy.
- Explore **ensemble methods** (Random Forest, Gradient Boosting) to further improve recall while balancing precision.
- Consider **resampling techniques** (SMOTE, class weights) to address class imbalance and strengthen minority class detection.
- Continuously monitor model performance and retrain with updated customer data to maintain accuracy over time.

Conclusion
The decision tree model is the best fit for this churn project. Its superior recall ensures fewer churners are missed, aligning directly with the business goal of early intervention and customer retention. While logistic regression is simpler, it fails to capture churn effectively. Future improvements should focus on ensemble methods and balancing precision-recall, but for now, the decision tree provides the strongest foundation for churn prediction.