Exemplar_Course 5 Waze project lab

October 2, 2024

1 Waze Project

Course 5 - Regression analysis: Simplify complex data relationships

Your team is more than halfway through their user churn project. Earlier, you completed a project proposal, used Python to explore and analyze Waze's user data, created data visualizations, and conducted a hypothesis test. Now, leadership wants your team to build a regression model to predict user churn based on a variety of variables.

You check your inbox and discover a new email from Ursula Sayo, Waze's Operations Manager. Ursula asks your team about the details of the regression model. You also notice two follow-up emails from your supervisor, May Santner. The first email is a response to Ursula, and says that the team will build a binomial logistic regression model. In her second email, May asks you to help build the model and prepare an executive summary to share your results.

A notebook was structured and prepared to help you in this project. Please complete the following questions and prepare an executive summary.

2 Course 5 End-of-course project: Regression modeling

In this activity, you will build a binomial logistic regression model. As you have learned, logistic regression helps you estimate the probability of an outcome. For data science professionals, this is a useful skill because it allows you to consider more than one variable against the variable you're measuring against. This opens the door for much more thorough and flexible analysis to be completed.

The purpose of this project is to demostrate knowledge of exploratory data analysis (EDA) and a binomial logistic regression model.

The goal is to build a binomial logistic regression model and evaluate the model's performance.

This activity has three parts:

Part 1: EDA & Checking Model Assumptions * What are some purposes of EDA before constructing a binomial logistic regression model?

Part 2: Model Building and Evaluation * What resources do you find yourself using as you complete this stage?

Part 3: Interpreting Model Results

- What key insights emerged from your model(s)?
- What business recommendations do you propose based on the models built?

Follow the instructions and answer the question below to complete the activity. Then, you will complete an executive summary using the questions listed on the PACE Strategy Document.

Be sure to complete this activity before moving on. The next course item will provide you with a completed exemplar to compare to your own work.

3 Build a regression model

4 PACE stages

Throughout these project notebooks, you'll see references to the problem-solving framework PACE. The following notebook components are labeled with the respective PACE stage: Plan, Analyze, Construct, and Execute.

4.1 PACE: Plan

Consider the questions in your PACE Strategy Document to reflect on the Plan stage.

4.1.1 Task 1. Imports and data loading

Import the data and packages that you've learned are needed for building logistic regression models.

[1]:
```
# Packages for numerics + dataframes
import pandas as pd
import numpy as np

# Packages for visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Packages for Logistic Regression & Confusion Matrix
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score,␣
 ↪precision_score, \
recall_score, f1_score, confusion_matrix, ConfusionMatrixDisplay
from sklearn.linear_model import LogisticRegression
```

Import the dataset.

[2]:
```
# Load the dataset by running this cell
```

```python
df = pd.read_csv('waze_dataset.csv')
```

4.2 PACE: Analyze

Consider the questions in your PACE Strategy Document to reflect on the Analyze stage.

In this stage, consider the following question:

- What are some purposes of EDA before constructing a binomial logistic regression model?

  Outliers and extreme data values can significantly impact logistic regression models. After visualizing data, make a plan for addressing outliers by dropping rows, substituting extreme data with average data, and/or removing data values greater than 3 standard deviations.

  EDA activities also include identifying missing data to help the analyst make decisions on their exclusion or inclusion by substituting values with dataset means, medians, and other similar methods.

  Additionally, it can be useful to create variables by multiplying variables together or calculating the ratio between two variables. For example, in this dataset you can create a drives_sessions_ratio variable by dividing drives by sessions.

4.2.1 Task 2a. Explore data with EDA

Analyze and discover data, looking for correlations, missing data, potential outliers, and/or duplicates.

Start with `shape` and `info()`.

[3]:
```python
print(df.shape)

df.info()
```

```
(14999, 13)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   ID                       14999 non-null  int64
 1   label                    14299 non-null  object
 2   sessions                 14999 non-null  int64
 3   drives                   14999 non-null  int64
 4   total_sessions           14999 non-null  float64
 5   n_days_after_onboarding  14999 non-null  int64
 6   total_navigations_fav1   14999 non-null  int64
 7   total_navigations_fav2   14999 non-null  int64
 8   driven_km_drives         14999 non-null  float64
```

```
 9   duration_minutes_drives  14999 non-null  float64
 10  activity_days            14999 non-null  int64
 11  driving_days             14999 non-null  int64
 12  device                   14999 non-null  object
dtypes: float64(3), int64(8), object(2)
memory usage: 1.5+ MB
```

Question: Are there any missing values in your data?

Yes, the `label` column is missing 700 values.

Use `head()`.

[4]:
```python
df.head()
```

[4]:
```
   ID     label  sessions  drives  total_sessions  n_days_after_onboarding  \
0   0  retained       283     226      296.748273                     2276
1   1  retained       133     107      326.896596                     1225
2   2  retained       114      95      135.522926                     2651
3   3  retained        49      40       67.589221                       15
4   4  retained        84      68      168.247020                     1562

   total_navigations_fav1  total_navigations_fav2  driven_km_drives  \
0                     208                       0       2628.845068
1                      19                      64      13715.920550
2                       0                       0       3059.148818
3                     322                       7        913.591123
4                     166                       5       3950.202008

   duration_minutes_drives  activity_days  driving_days   device
0              1985.775061             28            19  Android
1              3160.472914             13            11   iPhone
2              1610.735904             14             8  Android
3               587.196542              7             3   iPhone
4              1219.555924             27            18  Android
```

Use the `drop()` method to remove the ID column since you don't need this information for your analysis.

[5]:
```python
df = df.drop('ID', axis=1)
```

Now, check the class balance of the dependent (target) variable, `label`.

[6]:
```python
df['label'].value_counts(normalize=True)
```

[6]:
```
retained    0.822645
churned     0.177355
Name: label, dtype: float64
```

Call `describe()` on the data.

[7]:
```
df.describe()
```

[7]:

	sessions	drives	total_sessions	n_days_after_onboarding
count	14999.000000	14999.000000	14999.000000	14999.000000
mean	80.633776	67.281152	189.964447	1749.837789
std	80.699065	65.913872	136.405128	1008.513876
min	0.000000	0.000000	0.220211	4.000000
25%	23.000000	20.000000	90.661156	878.000000
50%	56.000000	48.000000	159.568115	1741.000000
75%	112.000000	93.000000	254.192341	2623.500000
max	743.000000	596.000000	1216.154633	3500.000000

	total_navigations_fav1	total_navigations_fav2	driven_km_drives
count	14999.000000	14999.000000	14999.000000
mean	121.605974	29.672512	4039.340921
std	148.121544	45.394651	2502.149334
min	0.000000	0.000000	60.441250
25%	9.000000	0.000000	2212.600607
50%	71.000000	9.000000	3493.858085
75%	178.000000	43.000000	5289.861262
max	1236.000000	415.000000	21183.401890

	duration_minutes_drives	activity_days	driving_days
count	14999.000000	14999.000000	14999.000000
mean	1860.976012	15.537102	12.179879
std	1446.702288	9.004655	7.824036
min	18.282082	0.000000	0.000000
25%	835.996260	8.000000	5.000000
50%	1478.249859	16.000000	12.000000
75%	2464.362632	23.000000	19.000000
max	15851.727160	31.000000	30.000000

Question: Are there any variables that could potentially have outliers just by assessing at the quartile values, standard deviation, and max values?

> *Yes, the following columns all seem to have outliers:* * `sessions` * `drives` * `total_sessions` * `total_navigations_fav1` * `total_navigations_fav2` * `driven_km_drives` * `duration_minutes_drives`
>
> *All of these columns have max values that are multiple standard deviations above the 75th percentile. This could indicate outliers in these variables.*

4.2.2 Task 2b. Create features

Create features that may be of interest to the stakeholder and/or that are needed to address the business scenario/problem.

km_per_driving_day You know from earlier EDA that churn rate correlates with distance driven per driving day in the last month. It might be helpful to engineer a feature that captures this information.

1. Create a new column in `df` called `km_per_driving_day`, which represents the mean distance driven per driving day for each user.
2. Call the `describe()` method on the new column.

[8]:
```
# 1. Create `km_per_driving_day` column
df['km_per_driving_day'] = df['driven_km_drives'] / df['driving_days']

# 2. Call `describe()` on the new column
df['km_per_driving_day'].describe()
```

[8]:
```
count    1.499900e+04
mean              inf
std               NaN
min      3.022063e+00
25%      1.672804e+02
50%      3.231459e+02
75%      7.579257e+02
max               inf
Name: km_per_driving_day, dtype: float64
```

Note that some values are infinite. This is the result of there being values of zero in the `driving_days` column. Pandas imputes a value of infinity in the corresponding rows of the new column because division by zero is undefined.

1. Convert these values from infinity to zero. You can use `np.inf` to refer to a value of infinity.
2. Call `describe()` on the `km_per_driving_day` column to verify that it worked.

[9]:
```
# 1. Convert infinite values to zero
df.loc[df['km_per_driving_day']==np.inf, 'km_per_driving_day'] = 0

# 2. Confirm that it worked
df['km_per_driving_day'].describe()
```

[9]:
```
count    14999.000000
mean       578.963113
std       1030.094384
min          0.000000
25%        136.238895
50%        272.889272
75%        558.686918
max      15420.234110
Name: km_per_driving_day, dtype: float64
```

professional_driver Create a new, binary feature called `professional_driver` that is a 1 for users who had 60 or more drives **and** drove on 15+ days in the last month.

Note: The objective is to create a new feature that separates professional drivers from other drivers. In this scenario, domain knowledge and intuition are used to determine these deciding thresholds, but ultimately they are arbitrary.

To create this column, use the `np.where()` function. This function accepts as arguments: 1. A condition 2. What to return when the condition is true 3. What to return when the condition is false

```
Example:
x = [1, 2, 3]
x = np.where(x > 2, 100, 0)
x
array([  0,   0, 100])
```

[10]:
```
# Create `professional_driver` column
df['professional_driver'] = np.where((df['drives'] >= 60) & (df['driving_days']␣
↪>= 15), 1, 0)
```

Perform a quick inspection of the new variable.

1. Check the count of professional drivers and non-professionals
2. Within each class (professional and non-professional) calculate the churn rate

[11]:
```
# 1. Check count of professionals and non-professionals
print(df['professional_driver'].value_counts())

# 2. Check in-class churn rate
df.groupby(['professional_driver'])['label'].value_counts(normalize=True)
```

```
0    12405
1     2594
Name: professional_driver, dtype: int64
```

[11]:
```
professional_driver  label
0                    retained    0.801202
                     churned     0.198798
1                    retained    0.924437
                     churned     0.075563
Name: label, dtype: float64
```

The churn rate for professional drivers is 7.6%, while the churn rate for non-professionals is 19.9%. This seems like it could add predictive signal to the model.

4.3 PACE: Construct

After analysis and deriving variables with close relationships, it is time to begin constructing the model. Consider the questions in your PACE Strategy Document to reflect on the Construct stage.

In this stage, consider the following question:

- Why did you select the X variables you did?

  Initially, columns were dropped based on high multicollinearity. Later, variable selection can be fine-tuned by running and rerunning models to look at changes in accuracy, recall, and precision. Initial variable selection was based on the business objective and insights from prior EDA.

4.3.1 Task 3a. Preparing variables

Call `info()` on the dataframe to check the data type of the `label` variable and to verify if there are any missing values.

[12]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14999 entries, 0 to 14998
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   label                    14299 non-null  object
 1   sessions                 14999 non-null  int64
 2   drives                   14999 non-null  int64
 3   total_sessions           14999 non-null  float64
 4   n_days_after_onboarding  14999 non-null  int64
 5   total_navigations_fav1   14999 non-null  int64
 6   total_navigations_fav2   14999 non-null  int64
 7   driven_km_drives         14999 non-null  float64
 8   duration_minutes_drives  14999 non-null  float64
 9   activity_days            14999 non-null  int64
 10  driving_days             14999 non-null  int64
 11  device                   14999 non-null  object
 12  km_per_driving_day       14999 non-null  float64
 13  professional_driver      14999 non-null  int64
dtypes: float64(4), int64(8), object(2)
memory usage: 1.6+ MB
```

Because you know from previous EDA that there is no evidence of a non-random cause of the 700 missing values in the `label` column, and because these observations comprise less than 5% of the data, use the `dropna()` method to drop the rows that are missing this data.

[13]:
```
# Drop rows with missing data in `label` column
df = df.dropna(subset=['label'])
```

Impute outliers You rarely want to drop outliers, and generally will not do so unless there is a clear reason for it (e.g., typographic errors).

At times outliers can be changed to the **median, mean, 95th percentile, etc.**

Previously, you determined that seven of the variables had clear signs of containing outliers:

- `sessions`
- `drives`
- `total_sessions`
- `total_navigations_fav1`
- `total_navigations_fav2`
- `driven_km_drives`
- `duration_minutes_drives`

For this analysis, impute the outlying values for these columns. Calculate the **95th percentile** of each column and change to this value any value in the column that exceeds it.

[14]:
```
# Impute outliers
for column in ['sessions', 'drives', 'total_sessions', 'total_navigations_fav1',
               'total_navigations_fav2', 'driven_km_drives',␣
 ↪'duration_minutes_drives']:
    threshold = df[column].quantile(0.95)
    df.loc[df[column] > threshold, column] = threshold
```

Call `describe()`.

[15]:
```
df.describe()
```

[15]:
```
            sessions        drives  total_sessions  n_days_after_onboarding  \
count   14299.000000  14299.000000    14299.000000             14299.000000
mean       76.539688     63.964683      183.717304              1751.822505
std        67.243178     55.127927      118.720520              1008.663834
min         0.000000      0.000000        0.220211                 4.000000
25%        23.000000     20.000000       90.457733               878.500000
50%        56.000000     48.000000      158.718571              1749.000000
75%       111.000000     93.000000      253.540450              2627.500000
max       243.000000    200.000000      455.439492              3500.000000

       total_navigations_fav1  total_navigations_fav2  driven_km_drives  \
count            14299.000000            14299.000000      14299.000000
mean               114.562767               27.187216       3944.558631
std                124.378550               36.715302       2218.358258
min                  0.000000                0.000000         60.441250
25%                 10.000000                0.000000       2217.319909
50%                 71.000000                9.000000       3496.545617
75%                178.000000               43.000000       5299.972162
max                422.000000              124.000000       8898.716275

       duration_minutes_drives  activity_days  driving_days  \
```

```
count            14299.000000   14299.000000  14299.000000
mean              1792.911210      15.544653     12.182530
std               1224.329759       9.016088      7.833835
min                 18.282082       0.000000      0.000000
25%                840.181344       8.000000      5.000000
50%               1479.394387      16.000000     12.000000
75%               2466.928876      23.000000     19.000000
max               4668.180092      31.000000     30.000000

       km_per_driving_day  professional_driver
count        14299.000000         14299.000000
mean           581.942399             0.173998
std           1038.254509             0.379121
min              0.000000             0.000000
25%            136.168003             0.000000
50%            273.301012             0.000000
75%            558.018761             0.000000
max          15420.234110             1.000000
```

Encode categorical variables Change the data type of the `label` column to be binary. This change is needed to train a logistic regression model.

Assign a `0` for all `retained` users.

Assign a `1` for all `churned` users.

Save this variable as `label2` as to not overwrite the original `label` variable.

Note: There are many ways to do this. Consider using `np.where()` as you did earlier in this notebook.

[16]:
```
# Create binary `label2` column
df['label2'] = np.where(df['label']=='churned', 1, 0)
df[['label', 'label2']].tail()
```

[16]:
```
          label  label2
14994  retained       0
14995  retained       0
14996  retained       0
14997   churned       1
14998  retained       0
```

4.3.2 Task 3b. Determine whether assumptions have been met

The following are the assumptions for logistic regression:

- Independent observations (This refers to how the data was collected.)
- No extreme outliers

- Little to no multicollinearity among X predictors
- Linear relationship between X and the **logit** of y

For the first assumption, you can assume that observations are independent for this project.

The second assumption has already been addressed.

The last assumption will be verified after modeling.

Note: In practice, modeling assumptions are often violated, and depending on the specifics of your use case and the severity of the violation, it might not affect your model much at all or it will result in a failed model.

Collinearity Check the correlation among predictor variables. First, generate a correlation matrix.

[17]:
```python
# Generate a correlation matrix
df.corr(method='pearson')
```

[17]:
```
                         sessions    drives  total_sessions  \
sessions                 1.000000  0.996942        0.597189
drives                   0.996942  1.000000        0.595285
total_sessions           0.597189  0.595285        1.000000
n_days_after_onboarding  0.007101  0.006940        0.006596
total_navigations_fav1   0.001858  0.001058        0.000187
total_navigations_fav2   0.008536  0.009505        0.010371
driven_km_drives         0.002996  0.003445        0.001016
duration_minutes_drives -0.004545 -0.003889       -0.000338
activity_days            0.025113  0.024357        0.015755
driving_days             0.020294  0.019608        0.012953
km_per_driving_day      -0.011569 -0.010989       -0.016167
professional_driver      0.443654  0.444425        0.254433
label2                   0.034911  0.035865        0.024568

                         n_days_after_onboarding  total_navigations_fav1  \
sessions                                0.007101                0.001858
drives                                  0.006940                0.001058
total_sessions                          0.006596                0.000187
n_days_after_onboarding                 1.000000               -0.002450
total_navigations_fav1                 -0.002450                1.000000
total_navigations_fav2                 -0.004968                0.002866
driven_km_drives                       -0.004652               -0.007368
duration_minutes_drives                -0.010167                0.005646
activity_days                          -0.009418                0.010902
driving_days                           -0.007321                0.010419
km_per_driving_day                      0.011764               -0.000197
professional_driver                     0.003770               -0.000224
label2                                 -0.129263                0.052322
```

	total_navigations_fav2	driven_km_drives
sessions	0.008536	0.002996
drives	0.009505	0.003445
total_sessions	0.010371	0.001016
n_days_after_onboarding	-0.004968	-0.004652
total_navigations_fav1	0.002866	-0.007368
total_navigations_fav2	1.000000	0.003559
driven_km_drives	0.003559	1.000000
duration_minutes_drives	-0.003009	0.690515
activity_days	-0.004425	-0.007441
driving_days	0.002000	-0.009549
km_per_driving_day	0.006751	0.344811
professional_driver	0.007126	-0.000904
label2	0.015032	0.019767

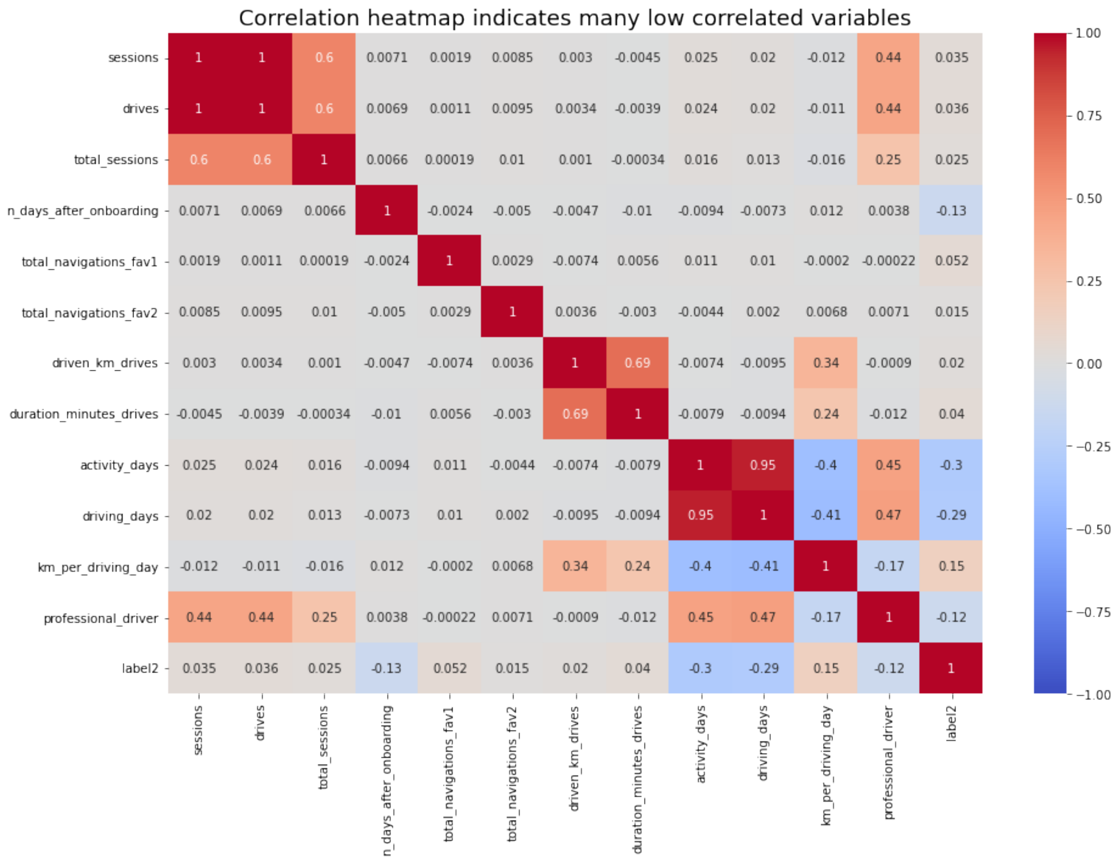
	duration_minutes_drives	activity_days	driving_days
sessions	-0.004545	0.025113	0.020294
drives	-0.003889	0.024357	0.019608
total_sessions	-0.000338	0.015755	0.012953
n_days_after_onboarding	-0.010167	-0.009418	-0.007321
total_navigations_fav1	0.005646	0.010902	0.010419
total_navigations_fav2	-0.003009	-0.004425	0.002000
driven_km_drives	0.690515	-0.007441	-0.009549
duration_minutes_drives	1.000000	-0.007895	-0.009425
activity_days	-0.007895	1.000000	0.947687
driving_days	-0.009425	0.947687	1.000000
km_per_driving_day	0.239627	-0.397433	-0.407917
professional_driver	-0.012128	0.453825	0.469776
label2	0.040407	-0.303851	-0.294259

	km_per_driving_day	professional_driver	label2
sessions	-0.011569	0.443654	0.034911
drives	-0.010989	0.444425	0.035865
total_sessions	-0.016167	0.254433	0.024568
n_days_after_onboarding	0.011764	0.003770	-0.129263
total_navigations_fav1	-0.000197	-0.000224	0.052322
total_navigations_fav2	0.006751	0.007126	0.015032
driven_km_drives	0.344811	-0.000904	0.019767
duration_minutes_drives	0.239627	-0.012128	0.040407
activity_days	-0.397433	0.453825	-0.303851
driving_days	-0.407917	0.469776	-0.294259
km_per_driving_day	1.000000	-0.165966	0.148583
professional_driver	-0.165966	1.000000	-0.122312
label2	0.148583	-0.122312	1.000000

Now, plot a correlation heatmap.

[18]:

```python
# Plot correlation heatmap
plt.figure(figsize=(15,10))
sns.heatmap(df.corr(method='pearson'), vmin=-1, vmax=1, annot=True, cmap='coolwarm')
plt.title('Correlation heatmap indicates many low correlated variables',
          fontsize=18)
plt.show();
```



If there are predictor variables that have a Pearson correlation coefficient value greater than the **absolute value of 0.7**, these variables are strongly multicollinear. Therefore, only one of these variables should be used in your model.

Note: 0.7 is an arbitrary threshold. Some industries may use 0.6, 0.8, etc.

Question: Which variables are multicollinear with each other?

- *`sessions` and `drives`: 1.0*
- *`driving_days` and `activity_days`: 0.95*

4.3.3 Task 3c. Create dummies (if necessary)

If you have selected `device` as an X variable, you will need to create dummy variables since this variable is categorical.

In cases with many categorical variables, you can use pandas built-in `pd.get_dummies()`, or you can use scikit-learn's `OneHotEncoder()` function.

Note: Variables with many categories should only be dummied if absolutely necessary. Each category will result in a coefficient for your model which can lead to overfitting.

Because this dataset only has one remaining categorical feature (`device`), it's not necessary to use one of these special functions. You can just implement the transformation directly.

Create a new, binary column called `device2` that encodes user devices as follows:

- `Android -> 0`
- `iPhone -> 1`

[19]:
```
# Create new `device2` variable
df['device2'] = np.where(df['device']=='Android', 0, 1)
df[['device', 'device2']].tail()
```

[19]:

	device	device2
14994	iPhone	1
14995	Android	0
14996	iPhone	1
14997	iPhone	1
14998	iPhone	1

4.3.4 Task 3d. Model building

Assign predictor variables and target To build your model you need to determine what X variables you want to include in your model to predict your target—`label2`.

Drop the following variables and assign the results to `X`:

- `label` (this is the target)
- `label2` (this is the target)
- `device` (this is the non-binary-encoded categorical variable)
- `sessions` (this had high multicollinearity)
- `driving_days` (this had high multicollinearity)

Note: Notice that `sessions` and `driving_days` were selected to be dropped, rather than `drives` and `activity_days`. The reason for this is that the features that were kept for modeling had slightly stronger correlations with the target variable than the features that were dropped.

[20]:
```
# Isolate predictor variables
X = df.drop(columns = ['label', 'label2', 'device', 'sessions', 'driving_days'])
```

Now, isolate the dependent (target) variable. Assign it to a variable called `y`.

[21]:
```python
# Isolate target variable
y = df['label2']
```

Split the data Use scikit-learn's `train_test_split()` function to perform a train/test split on your data using the X and y variables you assigned above.

Note 1: It is important to do a train test to obtain accurate predictions. You always want to fit your model on your training set and evaluate your model on your test set to avoid data leakage.

Note 2: Because the target class is imbalanced (82% retained vs. 18% churned), you want to make sure that you don't get an unlucky split that over- or under-represents the frequency of the minority class. Set the function's `stratify` parameter to `y` to ensure that the minority class appears in both train and test sets in the same proportion that it does in the overall dataset.

[22]:
```python
# Perform the train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,␣
↪random_state=42)
```

[23]:
```python
# Use .head()
X_train.head()
```

[23]:
```
       drives  total_sessions  n_days_after_onboarding  \
152       108      186.192746                     3116
11899       2        3.487590                      794
10937     139      347.106403                      331
669       108      455.439492                     2320
8406       10       89.475821                     2478

       total_navigations_fav1  total_navigations_fav2  driven_km_drives  \
152                       243                     124       8898.716275
11899                     114                      18       3286.545691
10937                       4                       7       7400.838975
669                        11                       4       6566.424830
8406                      135                       0       1271.248661

       duration_minutes_drives  activity_days  km_per_driving_day  \
152                4668.180092             24          612.305861
11899              1780.902733              5         3286.545691
10937              2349.305267             15          616.736581
669                4558.459870             18          410.401552
8406                938.711572             27           74.779333

       professional_driver  device2
152                      1        1
11899                    0        1
10937                    0        0
669                      1        1
```

```
8406                          0         1
```

Use scikit-learn to instantiate a logistic regression model. Add the argument `penalty = None`.

It is important to add `penalty = 'none'` since your predictors are unscaled.

Refer to scikit-learn's logistic regression documentation for more information.

Fit the model on `X_train` and `y_train`.

[24]:
```python
model = LogisticRegression(penalty='none', max_iter=400)

model.fit(X_train, y_train)
```

[24]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=400,
                   multi_class='auto', n_jobs=None, penalty='none',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Call the `.coef_` attribute on the model to get the coefficients of each variable. The coefficients are in order of how the variables are listed in the dataset. Remember that the coefficients represent the change in the **log odds** of the target variable for **every one unit increase in X**.

If you want, create a series whose index is the column names and whose values are the coefficients in `model.coef_`.

[25]:
```python
pd.Series(model.coef_[0], index=X.columns)
```

[25]:
```
drives                     0.001913
total_sessions             0.000327
n_days_after_onboarding   -0.000406
total_navigations_fav1     0.001232
total_navigations_fav2     0.000931
driven_km_drives          -0.000015
duration_minutes_drives    0.000109
activity_days             -0.106032
km_per_driving_day         0.000018
professional_driver       -0.001529
device2                   -0.001041
dtype: float64
```

Call the model's `intercept_` attribute to get the intercept of the model.

[26]:
```python
model.intercept_
```

[26]:
```
array([-0.00170675])
```

Check final assumption Verify the linear relationship between X and the estimated log odds (known as logits) by making a regplot.

Call the model's `predict_proba()` method to generate the probability of response for each sample in the training data. (The training data is the argument to the method.) Assign the result to a variable called `training_probabilities`. This results in a 2-D array where each row represents a user in `X_train`. The first column is the probability of the user not churning, and the second column is the probability of the user churning.

[27]:
```
# Get the predicted probabilities of the training data
training_probabilities = model.predict_proba(X_train)
training_probabilities
```

[27]:
```
array([[0.93963483, 0.06036517],
       [0.61967304, 0.38032696],
       [0.76463181, 0.23536819],
       …,
       [0.91909641, 0.08090359],
       [0.85092112, 0.14907888],
       [0.93516293, 0.06483707]])
```

In logistic regression, the relationship between a predictor variable and the dependent variable does not need to be linear, however, the log-odds (a.k.a., logit) of the dependent variable with respect to the predictor variable should be linear. Here is the formula for calculating log-odds, where p is the probability of response:

$$logit(p) = ln(\frac{p}{1-p})$$

1. Create a dataframe called `logit_data` that is a copy of `df`.
2. Create a new column called `logit` in the `logit_data` dataframe. The data in this column should represent the logit for each user.

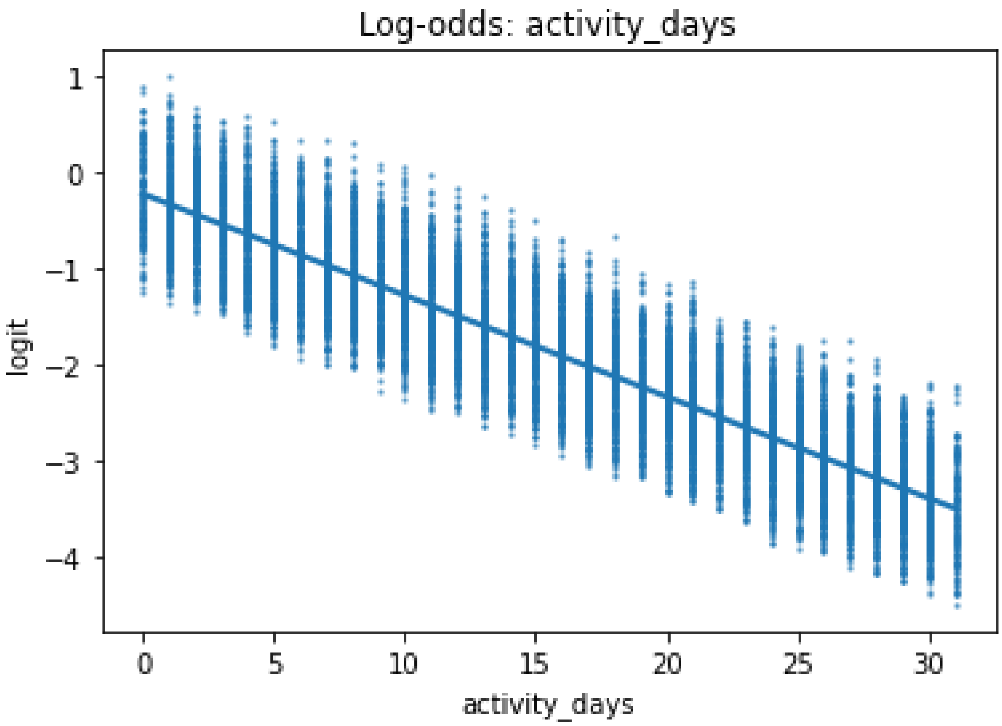
[28]:
```
# 1. Copy the `X_train` dataframe and assign to `logit_data`
logit_data = X_train.copy()

# 2. Create a new `logit` column in the `logit_data` df
logit_data['logit'] = [np.log(prob[1] / prob[0]) for prob in␣
 ↪training_probabilities]
```

Plot a regplot where the x-axis represents an independent variable and the y-axis represents the log-odds of the predicted probabilities.

In an exhaustive analysis, this would be plotted for each continuous or discrete predictor variable. Here we show only `activity_days`.

[29]:
```
# Plot regplot of `activity_days` log-odds
sns.regplot(x='activity_days', y='logit', data=logit_data, scatter_kws={'s': 2,␣
 ↪'alpha': 0.5})
plt.title('Log-odds: activity_days');
```



4.4 PACE: Execute

Consider the questions in your PACE Strategy Document to reflect on the Execute stage.

4.4.1 Task 4a. Results and evaluation

If the logistic assumptions are met, the model results can be appropriately interpreted.

Use the code block below to make predictions on the test data.

[30]:
```
# Generate predictions on X_test
y_preds = model.predict(X_test)
```

Now, use the `score()` method on the model with `X_test` and `y_test` as its two arguments. The default score in scikit-learn is **accuracy**. What is the accuracy of your model?

Consider: Is accuracy the best metric to use to evaluate this model?

[31]:
```
# Score the model (accuracy) on the test data
model.score(X_test, y_test)
```

[31]: 0.8237762237762237

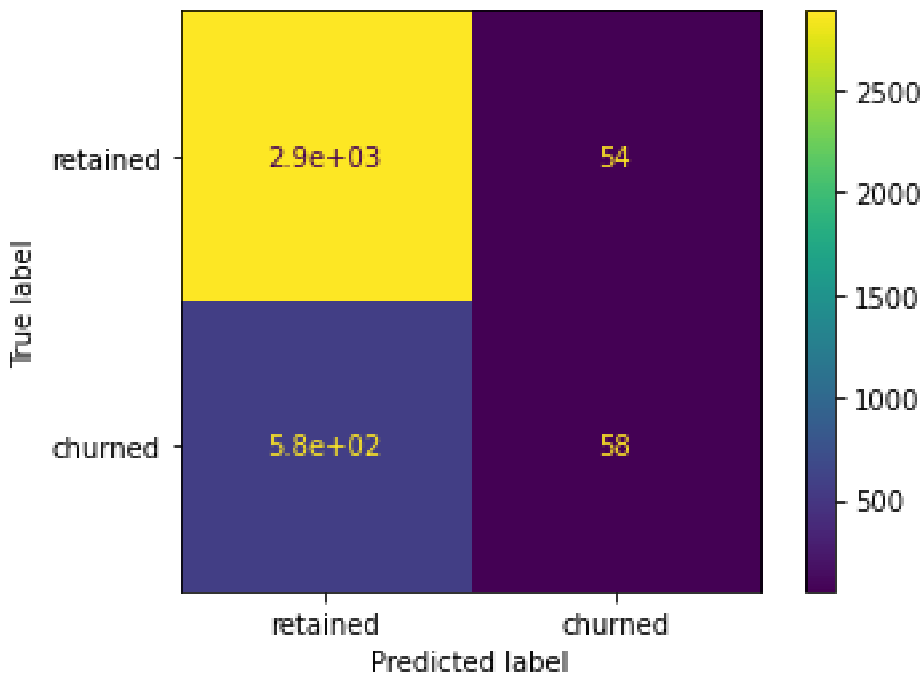
4.4.2 Task 4b. Show results with a confusion matrix

Use the `confusion_matrix` function to obtain a confusion matrix. Use `y_test` and `y_preds` as arguments.

[32]:
```
cm = confusion_matrix(y_test, y_preds)
```

Next, use the `ConfusionMatrixDisplay()` function to display the confusion matrix from the above cell, passing the confusion matrix you just created as its argument.

[33]:
```
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
                              display_labels=['retained', 'churned'],
                              )
disp.plot();
```



You can use the confusion matrix to compute precision and recall manually. You can also use scikit-learn's `classification_report()` function to generate a table from `y_test` and `y_preds`.

[34]:
```
# Calculate precision manually
precision = cm[1,1] / (cm[0, 1] + cm[1, 1])
precision
```

[34]: 0.5178571428571429

[35]:
```python
# Calculate recall manually
recall = cm[1,1] / (cm[1, 0] + cm[1, 1])
recall
```

[35]:
```
0.0914826498422713
```

[36]:
```python
# Create a classification report
target_labels = ['retained', 'churned']
print(classification_report(y_test, y_preds, target_names=target_labels))
```

```
              precision    recall  f1-score   support

    retained       0.83      0.98      0.90      2941
     churned       0.52      0.09      0.16       634

    accuracy                           0.82      3575
   macro avg       0.68      0.54      0.53      3575
weighted avg       0.78      0.82      0.77      3575
```

Note: The model has mediocre precision and very low recall, which means that it makes a lot of false negative predictions and fails to capture users who will churn.

4.4.3 BONUS

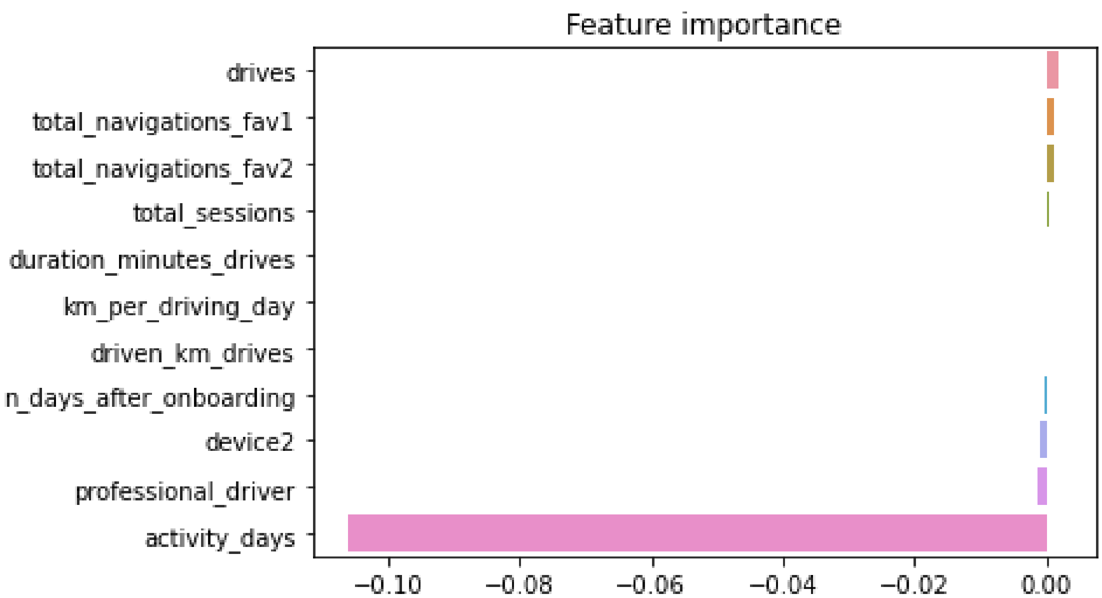
Generate a bar graph of the model's coefficients for a visual representation of the importance of the model's features.

[37]:
```python
# Create a list of (column_name, coefficient) tuples
feature_importance = list(zip(X_train.columns, model.coef_[0]))

# Sort the list by coefficient value
feature_importance = sorted(feature_importance, key=lambda x: x[1],␣
↪reverse=True)
feature_importance
```

[37]:
```
[('drives', 0.001913369447769776),
 ('total_navigations_fav1', 0.001231754741616306),
 ('total_navigations_fav2', 0.0009314786513814626),
 ('total_sessions', 0.00032707088819142904),
 ('duration_minutes_drives', 0.00010909343558951453),
 ('km_per_driving_day', 1.8223094015325207e-05),
 ('driven_km_drives', -1.4860453424647997e-05),
 ('n_days_after_onboarding', -0.00040647763730561445),
 ('device2', -0.0010412175209008018),
 ('professional_driver', -0.0015285041567402024),
 ('activity_days', -0.10603196504385491)]
```

```
[38]: # Plot the feature importances
import seaborn as sns
sns.barplot(x=[x[1] for x in feature_importance],
            y=[x[0] for x in feature_importance],
            orient='h')
plt.title('Feature importance');
```



4.4.4 Task 4c. Conclusion

Now that you've built your regression model, the next step is to share your findings with the Waze leadership team. Consider the following questions as you prepare to write your executive summary. Think about key points you may want to share with the team, and what information is most relevant to the user churn project.

Questions:

1. What variable most influenced the model's prediction? How? Was this surprising?

   `activity_days` was by far the most important feature in the model. It had a negative correlation with user churn. This was not surprising, as this variable was very strongly correlated with `driving_days`, which was known from EDA to have a negative correlation with churn.

2. Were there any variables that you expected to be stronger predictors than they were?

   Yes. In previous EDA, user churn rate increased as the values in `km_per_driving_day` increased. The correlation heatmap here in this notebook revealed this variable to have the strongest positive correlation with churn of any of the predictor variables by a relatively large margin. In the model, it was the second-least-important variable.

3. Why might a variable you thought to be important not be important in the model?

   In a multiple logistic regression model, features can interact with each other and these interactions can result in seemingly counterintuitive relationships. This is both a strength and a weakness of predictive models, as capturing these interactions typically makes a model more predictive while at the same time making the model more difficult to explain.

4. Would you recommend that Waze use this model? Why or why not?

   It depends. What would the model be used for? If it's used to drive consequential business decisions, then no. The model is not a strong enough predictor, as made clear by its poor recall score. However, if the model is only being used to guide further exploratory efforts, then it can have value.

5. What could you do to improve this model?

   New features could be engineered to try to generate better predictive signal, as they often do if you have domain knowledge. In the case of this model, one of the engineered features (`professional_driver`) was the third-most-predictive predictor. It could also be helpful to scale the predictor variables, and/or to reconstruct the model with different combinations of predictor variables to reduce noise from unpredictive features.

6. What additional features would you like to have to help improve the model?

   It would be helpful to have drive-level information for each user (such as drive times, geographic locations, etc.). It would probably also be helpful to have more granular data to know how users interact with the app. For example, how often do they report or confirm road hazard alerts? Finally, it could be helpful to know the monthly count of unique starting and ending locations each driver inputs.

Congratulations! You've completed this lab. However, you may not notice a green check mark next to this item on Coursera's platform. Please continue your progress regardless of the check mark. Just click on the "save" icon at the top of this notebook to ensure your work has been logged.