Waze Project

Milestone 5 / 5a - Regression analysis: Build a regression model. Evaluate the model

Regression modeling

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

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

This notebook has three parts:

Part 1: EDA & Checking Model Assumptions

Part 2: Model Building, Results, and Evaluation

Part 3: Conclusions, Insights, and Recommendations

Imports and data loading

In [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
```

In [4]:
```
# Load the dataset by running this cell
df = pd.read_csv('https://raw.githubusercontent.com/adacert/waze/main/Synthetic_Waze_Dat
```

Part 1. Explore data with EDA & Checking model assumptions

In [5]:
```
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
```

The label column is missing 700 values

In [6]:
```python
df.head()
```

Out[6]:

	ID	label	sessions	drives	total_sessions	n_days_after_onboarding	total_navigations_fav1	total_navigati
0	0	retained	283	226	296.748273	2276	208	
1	1	retained	133	107	326.896596	1225	19	
2	2	retained	114	95	135.522926	2651	0	
3	3	retained	49	40	67.589221	15	322	
4	4	retained	84	68	168.247020	1562	166	

Remove the ID column since we don't need this information.

In [7]:
```python
df = df.drop('ID', axis=1)
```

Class balance of the dependent (target) variable, `label`.

In [8]:
```python
df['label'].value_counts(normalize=True)
```

Out[8]:
```
retained    0.822645
churned     0.177355
Name: label, dtype: float64
```

In [9]:
```python
df.describe()
```

Out[9]:

	sessions	drives	total_sessions	n_days_after_onboarding	total_navigations_fav1	total_naviga
count	14999.000000	14999.000000	14999.000000	14999.000000	14999.000000	14!
mean	80.633776	67.281152	189.964447	1749.837789	121.605974	
std	80.699065	65.913872	136.405128	1008.513876	148.121544	
min	0.000000	0.000000	0.220211	4.000000	0.000000	
25%	23.000000	20.000000	90.661156	878.000000	9.000000	
50%	56.000000	48.000000	159.568115	1741.000000	71.000000	
75%	112.000000	93.000000	254.192341	2623.500000	178.000000	
max	743.000000	596.000000	1216.154633	3500.000000	1236.000000	

The following columns all seem to have outliers:

sessions, drives, total_sessions, total_navigations_fav1, total_navigations_fav2, driven_km_drives, duration_minutes_drives

The maximum values of all these columns surpass the 75th percentile by multiple standard deviations, suggesting the presence of potential outliers in these variables.

Create features

In [10]:
```
# 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()
```

Out[10]:
```
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.

In [11]:
```
# 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()
```

Out[11]:
```
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`

Creates a new, binary feature called `professional_driver` that is a 1 for users who had 100 or more drives **and** drove on 20+ days in the last month.

Note: The objective is to create a new feature that separates professional drivers from other drivers.

In [12]:
```
# Create `professional_driver` column
df['professional_driver'] = np.where((df['drives'] >= 60) & (df['driving_days'] >= 15),
```

In [13]:
```
# 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
```

Out[13]:

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

The churn rate among professional drivers stands at 7.6%, whereas non-professionals experience a churn rate of 19.9%. This observation appears to contribute a valuable predictive signal to the model.

Preparing variables

In [14]:

```
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
```

In [15]:

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

Impute outliers

Calculate the **95th percentile** of each column and change to this value any value in the column that exceeds it.

In [16]:

```
# 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
```

In [17]:

```
df.describe()
```

Out[17]:

	sessions	drives	total_sessions	n_days_after_onboarding	total_navigations_fav1	total_naviga
count	14299.000000	14299.000000	14299.000000	14299.000000	14299.000000	142
mean	76.539688	63.964683	183.717304	1751.822505	114.562767	
std	67.243178	55.127927	118.720520	1008.663834	124.378550	
min	0.000000	0.000000	0.220211	4.000000	0.000000	

25%	23.000000	20.000000	90.457733	878.500000	10.000000
50%	56.000000	48.000000	158.718571	1749.000000	71.000000
75%	111.000000	93.000000	253.540450	2627.500000	178.000000
max	243.000000	200.000000	455.439492	3500.000000	422.000000

Encode categorical variables

In [18]:

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

Out[18]:

	label	label2
14994	retained	0
14995	retained	0
14996	retained	0
14997	churned	1
14998	retained	0

Checking assumptions

The following are the assumptions for this logistic regression:

- Independent observations
- No extreme outliers
- Little to no multicollinearity among X predictors
- Linear relationship between X and the **logit** of y

Collinearity

In [20]:

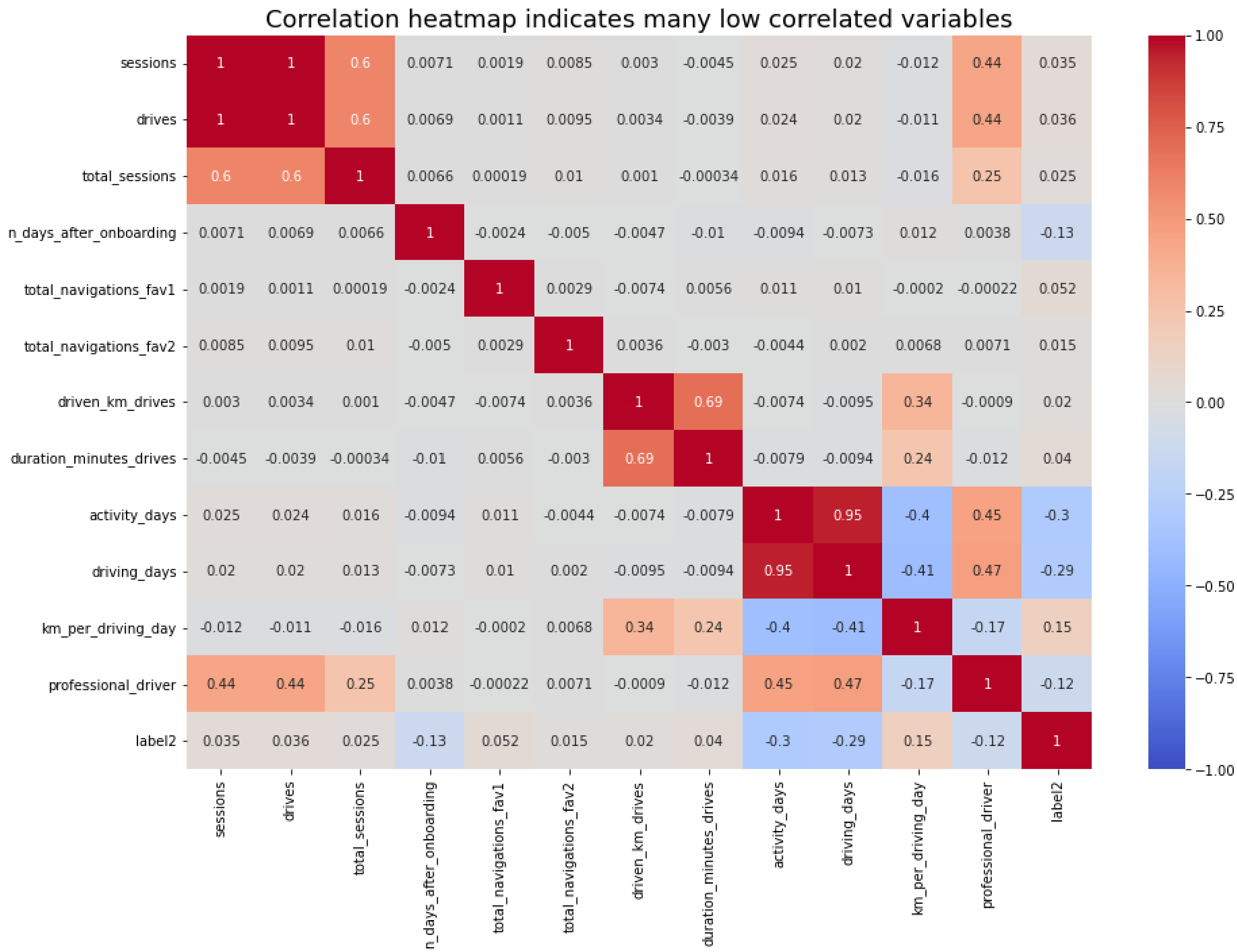
```
# Generate a correlation matrix
df.corr(method='pearson')
```

Out[20]:

	sessions	drives	total_sessions	n_days_after_onboarding	total_navigations_fav1
sessions	1.000000	0.996942	0.597189	0.007101	0.001858
drives	0.996942	1.000000	0.595285	0.006940	0.001058
total_sessions	0.597189	0.595285	1.000000	0.006596	0.000187
n_days_after_onboarding	0.007101	0.006940	0.006596	1.000000	-0.002450
total_navigations_fav1	0.001858	0.001058	0.000187	-0.002450	1.000000
total_navigations_fav2	0.008536	0.009505	0.010371	-0.004968	0.002866
driven_km_drives	0.002996	0.003445	0.001016	-0.004652	-0.007368
duration_minutes_drives	-0.004545	-0.003889	-0.000338	-0.010167	0.005646
activity_days	0.025113	0.024357	0.015755	-0.009418	0.010902
driving_days	0.020294	0.019608	0.012953	-0.007321	0.010419
km_per_driving_day	-0.011569	-0.010989	-0.016167	0.011764	-0.000197

professional_driver	0.443654	0.444425	0.254433	0.003770	-0.000224
label2	0.034911	0.035865	0.024568	-0.129263	0.052322

In [22]:
```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();
```



Variables that are multicollinear with each other?

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

Create dummies

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

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

In [23]:
```python
# Create new `device2` variable
df['device2'] = np.where(df['device']=='Android', 0, 1)
df[['device', 'device2']].tail()
```

Out[23]:

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

Part 2. Model building, Results, and Evaluation

Assign predictor variables and target

In [24]:
```
# Isolate predictor variables
X = df.drop(columns = ['label', 'label2', 'device', 'sessions', 'driving_days'])
```

In [25]:
```
# Isolate target variable
y = df['label2']
```

Split the data

In [26]:
```
# Perform the train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_state=42)
```

In [27]:
```
# Use .head()
X_train.head()
```

Out[27]:

	drives	total_sessions	n_days_after_onboarding	total_navigations_fav1	total_navigations_fav2	driven_kı
152	108	186.192746	3116	243	124	889
11899	2	3.487590	794	114	18	328
10937	139	347.106403	331	4	7	740
669	108	455.439492	2320	11	4	656
8406	10	89.475821	2478	135	0	127

Instantiate a logistic regression model

Add the argument `penalty = None`.

We add `penalty = None` since the predictors are unscaled.

In [30]:
```
model = LogisticRegression(penalty='none', max_iter=400)

model.fit(X_train, y_train)
```

Out[30]:
```
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)
```

In [31]:
```
pd.Series(model.coef_[0], index=X.columns)
```

Out[31]:
```
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
```

In [32]:

```python
model.intercept_
```

Out[32]:

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

Check final assumption

Verifies the linear relationship between X and the estimated log odds (known as logits) by making a regplot.

In [33]:

```python
# Get the predicted probabilities of the training data
training_probabilities = model.predict_proba(X_train)
training_probabilities
```

Out[33]:

```
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]])
```

Below creates a dataframe called `logit_data` that is a copy of `df`.

Below also creates a new column called `logit` in the `logit_data` dataframe. The data in this column should represent the logit for each user.

In [34]:

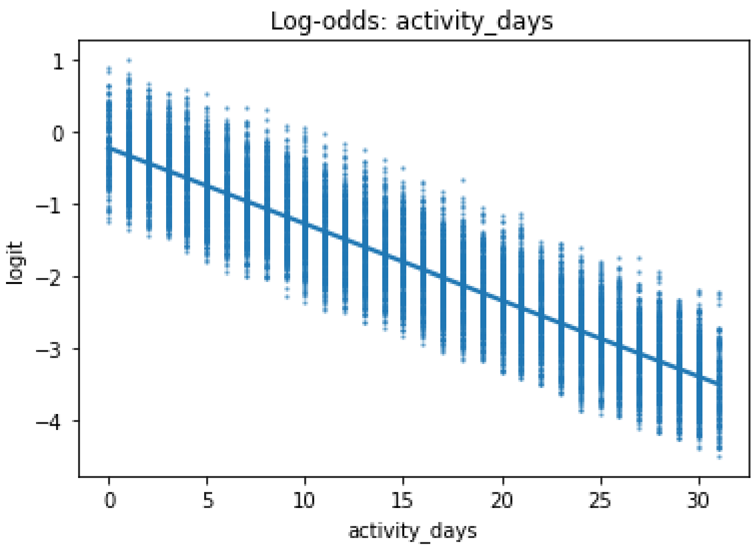
```python
# 1. Copy the `X_train` dataframe and assign to `logit_data`
logit_data = X_train.copy()

# 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]
```

Below creates a dataframe called `logit_data` that is a copy of `df`.

Below also creates a new column called `logit` in the `logit_data` dataframe. The data in this column should represent the logit for each user.

In [35]:

```python
# Plot regplot of `activity_days` log-odds
sns.regplot(x='activity_days', y='logit', data=logit_data, scatter_kws={'s': 2, 'alpha':
plt.title('Log-odds: activity_days');
```



Results and evaluation

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

Below we will make predictions on the test data.

In [36]:
```
# Generate predictions on X_test
y_preds = model.predict(X_test)
```

Accuracy of the model

In [37]:
```
# Score the model (accuracy) on the test data
model.score(X_test, y_test)
```

Out[37]:
```
0.8237762237762237
```

Results shown with a confusion matrix

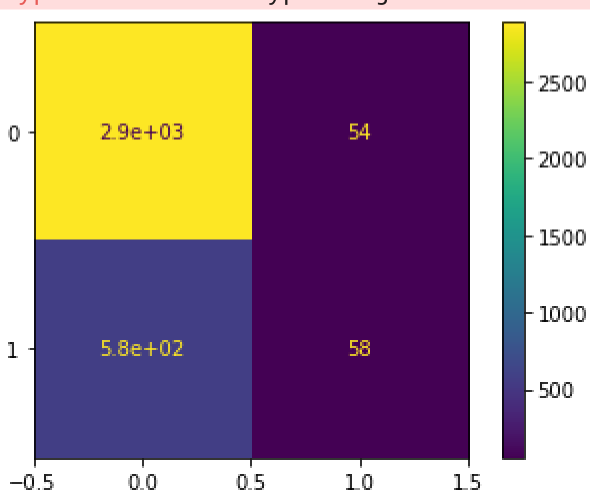
In [53]:
```
cm = confusion_matrix(y_test, y_preds)
```

The below confusion matrix shows an error, but displays correctly.

In [54]:
```
disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=None)
disp.plot()
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-54-5be7a6a26f01> in <module>
      1 disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=None)
----> 2 disp.plot()

/opt/conda/lib/python3.7/site-packages/sklearn/metrics/_plot/confusion_matrix.py in plot
(self, include_values, cmap, xticks_rotation, values_format, ax)
    107                ytickslabels=self.display_labels,
    108                ylabel="True label",
--> 109                xlabel="Predicted label")
    110 
    111         ax.set_ylim((n_classes - 0.5, -0.5))

/opt/conda/lib/python3.7/site-packages/matplotlib/artist.py in set(self, **kwargs)
   1099             sorted(kwargs.items(), reverse=True,
   1100                    key=lambda x: (self._prop_order.get(x[0], 0), x[0])))
```

```
-> 1101             return self.update(props)
   1102
   1103         def findobj(self, match=None, include_self=True):

/opt/conda/lib/python3.7/site-packages/matplotlib/artist.py in update(self, props)
   1004
   1005             with cbook._setattr_cm(self, eventson=False):
-> 1006                 ret = [_update_property(self, k, v) for k, v in props.items()]
   1007
   1008             if len(ret):

/opt/conda/lib/python3.7/site-packages/matplotlib/artist.py in <listcomp>(.0)
   1004
   1005             with cbook._setattr_cm(self, eventson=False):
-> 1006                 ret = [_update_property(self, k, v) for k, v in props.items()]
   1007
   1008             if len(ret):

/opt/conda/lib/python3.7/site-packages/matplotlib/artist.py in _update_property(self, k,
 v)
   1001                         raise AttributeError('{!r} object has no property {!r}'
   1002                                              .format(type(self).__name__, k))
-> 1003                     return func(v)
   1004
   1005             with cbook._setattr_cm(self, eventson=False):

/opt/conda/lib/python3.7/site-packages/matplotlib/axes/_base.py in set_yticklabels(self,
 labels, fontdict, minor, **kwargs)
   3774                 kwargs.update(fontdict)
   3775             return self.yaxis.set_ticklabels(labels,
-> 3776                                              minor=minor, **kwargs)
   3777
   3778         def xaxis_date(self, tz=None):

/opt/conda/lib/python3.7/site-packages/matplotlib/axis.py in set_ticklabels(self, tickla
bels, minor, *args, **kwargs)
   1714                     "3.1; passing them will raise a TypeError in Matplotlib 3.3.")
   1715             get_labels = []
-> 1716             for t in ticklabels:
   1717                 # try calling get_text() to check whether it is Text object
   1718                 # if it is Text, get label content

TypeError: 'NoneType' object is not iterable
```



Precision

In [55]:

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

Out[55]: 0.5178571428571429

Recall

In [56]:
```
# Calculate recall manually
recall = cm[1,1] / (cm[1, 0] + cm[1, 1])
recall
```

Out[56]: 0.0914826498422713

Classification Report

In [57]:
```
# 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
```

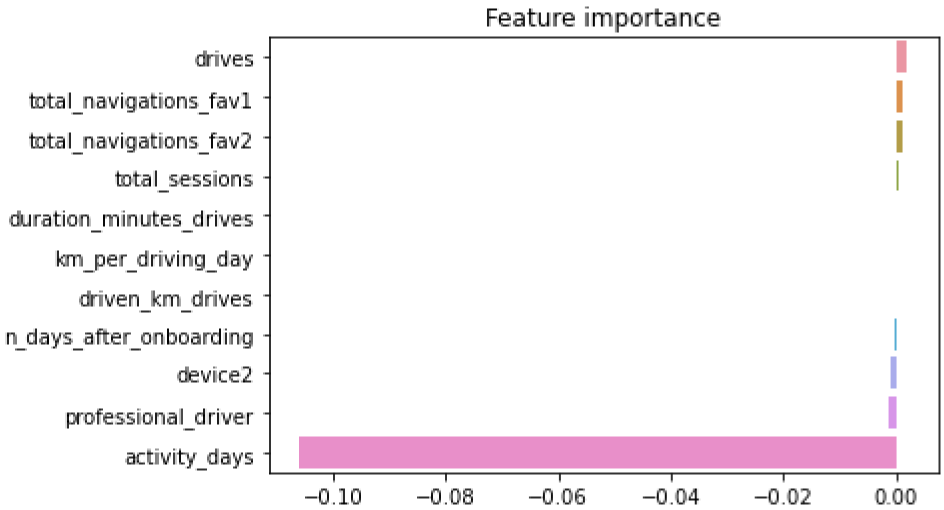
Although the model demonstrates reasonable precision, its recall is extremely low, indicating a high number of false negative predictions. Consequently, it fails to identify and capture users who are likely to churn.

Visual representation of the importance of the model's features

In [58]:
```
# 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
```

Out[58]:
```
[('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)]
```

In [59]:
```
# 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');
```



Part 3: Conclusions, Insights, and Recommendations

Variables that most influenced the model's prediction:

- Among all the features in the model, "activity_days" emerged as the most significant one, exhibiting a negative correlation with user churn. This finding is not unexpected since "activity_days" is highly correlated with "driving_days," which was already identified during the exploratory data analysis (EDA) to have a negative correlation with churn.

Variables expected to be stronger predictors than they were:

- During the exploratory data analysis (EDA), it was observed that the user churn rate rose in conjunction with increasing values in "km_per_driving_day." The correlation heatmap in this notebook further confirmed this observation, indicating that this variable exhibited the highest positive correlation with churn among all the predictor variables, surpassing others by a significant margin. Surprisingly, in the model, "km_per_driving_day" ranked as the second-least important variable.

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

- In a multiple logistic regression model, the presence of feature interactions can lead to relationships that may appear counterintuitive. This phenomenon represents both a strength and a weakness of predictive models. On one hand, capturing these interactions enhances the predictive capabilities of the model. On the other hand, it complicates the model's interpretability, making it more challenging to explain the underlying relationships.

Is it recommended that Waze use this model?

- The usefulness of the model depends on its intended purpose. If the model is employed to inform critical business decisions, its performance may not be sufficiently strong, particularly evident from its low recall score. However, if the model is primarily utilized to guide further exploratory efforts and provide insights, it can still offer value in that context.

Steps that can be taken to improve this model:

- By leveraging domain knowledge, it is possible to engineer new features aimed at improving predictive signal. In the context of this model, one of the engineered features, namely "professional_driver," emerged as the third-most influential predictor. Additionally, scaling the predictor variables and reconstructing the model using different combinations of predictors can be beneficial in minimizing noise stemming from unpromising features.

Additional features that would be needed to help improve the model:

- It would be beneficial to possess drive-level specifics for individual users, such as drive times and geographic locations. Furthermore, obtaining more detailed information regarding how users engage with the app would likely provide valuable insights. For instance, understanding the frequency at which they report or confirm road hazard alerts. Finally, having knowledge of the monthly count of distinct starting and ending locations inputted by each driver could offer valuable additional information.