Activity_Course 2 Waze project lab

October 25, 2023

1 Waze Project

Course 2 - Get Started with Python

Welcome to the Waze Project!

Your Waze data analytics team is still in the early stages of their user churn project. Previously, you were asked to complete a project proposal by your supervisor, May Santner. You have received notice that your project proposal has been approved and that your team has been given access to Waze's user data. To get clear insights, the user data must be inspected and prepared for the upcoming process of exploratory data analysis (EDA).

A Python notebook has been prepared to guide you through this project. Answer the questions and create an executive summary for the Waze data team.

2 Course 2 End-of-course project: Inspect and analyze data

In this activity, you will examine data provided and prepare it for analysis. This activity will help ensure the information is,

1. Ready to answer questions and yield insights
2. Ready for visualizations
3. Ready for future hypothesis testing and statistical methods

The purpose of this project is to investigate and understand the data provided.

The goal is to use a dataframe contructed within Python, perform a cursory inspection of the provided dataset, and inform team members of your findings.

This activity has three parts:

Part 1: Understand the situation * How can you best prepare to understand and organize the provided information?

Part 2: Understand the data

- Create a pandas dataframe for data learning, future exploratory data analysis (EDA), and statistical activities
- Compile summary information about the data to inform next steps

Part 3: Understand the variables

- Use insights from your examination of the summary data to guide deeper investigation into variables

Follow the instructions and answer the following questions 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 Identify data types and compile summary information

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 stages: Plan, Analyze, Construct, and Execute.

4.1 PACE: Plan

Consider the questions in your PACE Strategy Document and those below to craft your response:

4.1.1 Task 1. Understand the situation

- How can you best prepare to understand and organize the provided driver data?

Begin by exploring your dataset and consider reviewing the Data Dictionary.

==> MY RESPONSE TO THE QUESTION IS HERE

Before working with any dataset, exploring and reviewing the data dictionary are the important steps to better understanding the data structure including column name, data type, and its description. This way will lead us to ensure that we can understand and identify key variables of data for the stakeholders.

4.2 PACE: Analyze

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

4.2.1 Task 2a. Imports and data loading

Start by importing the packages that you will need to load and explore the dataset. Make sure to use the following import statements:

- `import pandas as pd`

- import numpy as np

[1]:
```
# Import packages for data manipulation
### YOUR CODE HERE ###
import pandas as pd
import numpy as np
```

Then, load the dataset into a dataframe. Creating a dataframe will help you conduct data manipulation, exploratory data analysis (EDA), and statistical activities.

Note: As shown in this cell, the dataset has been automatically loaded in for you. You do not need to download the .csv file, or provide more code, in order to access the dataset and proceed with this lab. Please continue with this activity by completing the following instructions.

[2]:
```
# Load dataset into dataframe
df = pd.read_csv('waze_dataset.csv')
```

4.2.2 Task 2b. Summary information

View and inspect summary information about the dataframe by **coding the following:**

1. df.head(10)
2. df.info()

Consider the following questions:

1. When reviewing the `df.head()` output, are there any variables that have missing values?
2. When reviewing the `df.info()` output, what are the data types? How many rows and columns do you have?
3. Does the dataset have any missing values?

[3]:
```
### YOUR CODE HERE ###
df.head(10)
```

[3]:
```
   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
5   5  retained       113     103      279.544437                     2637
6   6  retained         3       2      236.725314                      360
7   7  retained        39      35      176.072845                     2999
8   8  retained        57      46      183.532018                      424
9   9   churned        84      68      244.802115                     2997

   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
5                      0                     0        901.238699
6                    185                    18       5249.172828
7                      0                     0       7892.052468
8                      0                    26       2651.709764
9                     72                     0       6043.460295

   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
5               439.101397             15            11   iPhone
6               726.577205             28            23   iPhone
7              2466.981741             22            20   iPhone
8              1594.342984             25            20  Android
9              2341.838528              7             3   iPhone
```

[4]:
```python
### YOUR CODE HERE ###
df.info()
```

```
<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
```

==> MY RESPONSE TO THE QUESTIONS IS HERE

1. When reviewing the df.head() output, are there any variables that have missing values? In the first 10 observations, the variables had no missing values.
2. When reviewing the df.info() output, what are the data types? How many rows and columns do you have? The "label" and "device" variable is of the object type. The "total_sessions", "driven_km_drives", and "duration_minutes_drives" is of the type float64. The other variables are of the type int64. Overall, there are 14,999 rows and 13 columns.
3. Does the dataset have any missing values? There are 700 missing values in the "label" column as shown in the result above that is 14,299 rows instead of 14,999 rows.

4.2.3 Task 2c. Null values and summary statistics

Compare the summary statistics of the 700 rows that are missing labels with summary statistics of the rows that are not missing any values.

Question: Is there a discernible difference between the two populations?

[5]:
```
# Isolate rows with null values
### YOUR CODE HERE ###
null_df = df[df['label'].isnull()]

# Display summary stats of rows with null values
### YOUR CODE HERE ###
null_df.describe()
```

[5]:
```
                 ID    sessions      drives  total_sessions  \
count    700.000000  700.000000  700.000000      700.000000
mean    7405.584286   80.837143   67.798571      198.483348
std     4306.900234   79.987440   65.271926      140.561715
min       77.000000    0.000000    0.000000        5.582648
25%     3744.500000   23.000000   20.000000       94.056340
50%     7443.000000   56.000000   47.500000      177.255925
75%    11007.000000  112.250000   94.000000      266.058022
max    14993.000000  556.000000  445.000000     1076.879741

       n_days_after_onboarding  total_navigations_fav1  \
count               700.000000              700.000000
mean               1709.295714              118.717143
std                1005.306562              156.308140
min                  16.000000                0.000000
25%                 869.000000                4.000000
50%                1650.500000               62.500000
75%                2508.750000              169.250000
max                3498.000000             1096.000000

       total_navigations_fav2  driven_km_drives  duration_minutes_drives  \
count              700.000000        700.000000               700.000000
mean                30.371429       3935.967029              1795.123358
```

```
std          46.306984      2443.107121          1419.242246
min           0.000000       290.119811            66.588493
25%           0.000000      2119.344818           779.009271
50%          10.000000      3421.156721          1414.966279
75%          43.000000      5166.097373          2443.955404
max         352.000000     15135.391280          9746.253023

       activity_days  driving_days
count     700.000000    700.000000
mean       15.382857     12.125714
std         8.772714      7.626373
min         0.000000      0.000000
25%         8.000000      6.000000
50%        15.000000     12.000000
75%        23.000000     18.000000
max        31.000000     30.000000
```

[6]:
```python
# Isolate rows without null values
### YOUR CODE HERE ###
notnull_df = df[~df['label'].isnull()]

# Display summary stats of rows without null values
### YOUR CODE HERE ###
notnull_df.describe()
```

[6]:
```
                 ID      sessions        drives  total_sessions  \
count  14299.000000  14299.000000  14299.000000    14299.000000
mean    7503.573117     80.623820     67.255822      189.547409
std     4331.207621     80.736502     65.947295      136.189764
min        0.000000      0.000000      0.000000        0.220211
25%     3749.500000     23.000000     20.000000       90.457733
50%     7504.000000     56.000000     48.000000      158.718571
75%    11257.500000    111.000000     93.000000      253.540450
max    14998.000000    743.000000    596.000000     1216.154633

       n_days_after_onboarding  total_navigations_fav1  \
count             14299.000000            14299.000000
mean               1751.822505              121.747395
std                1008.663834              147.713428
min                   4.000000                0.000000
25%                 878.500000               10.000000
50%                1749.000000               71.000000
75%                2627.500000              178.000000
max                3500.000000             1236.000000

       total_navigations_fav2  driven_km_drives  duration_minutes_drives  \
count            14299.000000      14299.000000             14299.000000
```

```
mean        29.638296      4044.401535           1864.199794
std         45.350890      2504.977970           1448.005047
min          0.000000        60.441250             18.282082
25%          0.000000      2217.319909            840.181344
50%          9.000000      3496.545617           1479.394387
75%         43.000000      5299.972162           2466.928876
max        415.000000     21183.401890          15851.727160

       activity_days  driving_days
count   14299.000000  14299.000000
mean       15.544653     12.182530
std         9.016088      7.833835
min         0.000000      0.000000
25%         8.000000      5.000000
50%        16.000000     12.000000
75%        23.000000     19.000000
max        31.000000     30.000000
```

==> MY RESPONSE TO THE QUESTION IS HERE

After comparing summary statistics of minimum, maximum, average, and position between two groups, the observations with missing retention labels with those that aren't missing any values, show that there is nothing outstanding. The means and standard deviations are quite consistent between the two groups.

4.2.4 Task 2d. Null values - device counts

Next, check the two populations with respect to the `device` variable.

Question: How many iPhone users had null values and how many Android users had null values?

[7]:
```
# Get count of null values by device
### YOUR CODE HERE ###
null_df['device'].value_counts()
```

[7]:
```
iPhone     447
Android    253
Name: device, dtype: int64
```

==> MY RESPONSE TO THE QUESTION IS HERE

There were 447 of iPhone users and 253 of Android users from 700 rows that contained null values.

Now, of the rows with null values, calculate the percentage with each device—Android and iPhone. You can do this directly with the `value_counts()` function.

[8]:
```
# Calculate % of iPhone nulls and Android nulls
### YOUR CODE HERE ###
```

```
null_df['device'].value_counts(normalize=True) #normalize (default False):␣
↪Return proportions rather than frequencies
```

[8]:
```
iPhone     0.638571
Android    0.361429
Name: device, dtype: float64
```

How does this compare to the device ratio in the full dataset?

[9]:
```
# Calculate % of iPhone users and Android users in full dataset
### YOUR CODE HERE ###
df['device'].value_counts(normalize=True)
```

[9]:
```
iPhone     0.644843
Android    0.355157
Name: device, dtype: float64
```

The percentage of missing values by each device is consistent with their representation in the data overall.

There is nothing to suggest a non-random cause of the missing data.

Examine the counts and percentages of users who churned vs. those who were retained. How many of each group are represented in the data?

[10]:
```
# Calculate counts of churned vs. retained
### YOUR CODE HERE ###
print(df['label'].value_counts())
print("\n")
print(df['label'].value_counts(normalize=True))
```

```
retained    11763
churned      2536
Name: label, dtype: int64


retained    0.822645
churned     0.177355
Name: label, dtype: float64
```

This dataset contains 82% retained users and 18% churned users.

Next, compare the medians of each variable for churned and retained users. The reason for calculating the median and not the mean is that you don't want outliers to unduly affect the portrayal of a typical user. Notice, for example, that the maximum value in the `driven_km_drives` column is 21,183 km. That's more than half the circumference of the earth!

[11]:
```
# Calculate median values of all columns for churned and retained users
### YOUR CODE HERE ###
df.groupby('label').median()
```

[11]:
```
              ID  sessions  drives  total_sessions  n_days_after_onboarding  \
label
churned   7477.5      59.0    50.0      164.339042                   1321.0
retained  7509.0      56.0    47.0      157.586756                   1843.0

          total_navigations_fav1  total_navigations_fav2  driven_km_drives  \
label
churned                     84.5                    11.0       3652.655666
retained                    68.0                     9.0       3464.684614

          duration_minutes_drives  activity_days  driving_days
label
churned               1607.183785            8.0           6.0
retained              1458.046141           17.0          14.0
```

This offers an interesting snapshot of the two groups, churned vs. retained:

Users who churned averaged ~3 more drives in the last month than retained users, but retained users used the app on over twice as many days as churned users in the same time period.

The median churned user drove ~200 more kilometers and 2.5 more hours during the last month than the median retained user.

It seems that churned users had more drives in fewer days, and their trips were farther and longer in duration. Perhaps this is suggestive of a user profile. Continue exploring!

Calculate the median kilometers per drive in the last month for both retained and churned users.

[12]:
```python
# Group data by `label` and calculate the medians
### YOUR CODE HERE ###
medians_by_label = df.groupby('label').median()
# Divide the median distance by median number of drives
### YOUR CODE HERE ###
print('The median kilometers per drive:')
medians_by_label['driven_km_drives'] / medians_by_label['drives']
```

```
The median kilometers per drive:
```

[12]:
```
label
churned     73.053113
retained    73.716694
dtype: float64
```

The median user from both groups drove ~73 km/drive. How many kilometers per driving day was this?

[13]:
```python
# Divide the median distance by median number of driving days
### YOUR CODE HERE ###
print('The median kilometers per driving day:')
medians_by_label['driven_km_drives'] / medians_by_label['driving_days']
```

```
The median kilometers per driving day:
```

```
[13]: label
churned     608.775944
retained    247.477472
dtype: float64
```

Now, calculate the median number of drives per driving day for each group.

```
[14]: # Divide the median number of drives by median number of driving days
### YOUR CODE HERE ###
print('The median drives per driving day:')
medians_by_label['drives'] / medians_by_label['driving_days']
```

```
The median drives per driving day:
```

```
[14]: label
churned     8.333333
retained    3.357143
dtype: float64
```

The median user who churned drove 608 kilometers each day they drove last month, which is almost 250% the per-drive-day distance of retained users. The median churned user had a similarly disproporionate number of drives per drive day compared to retained users.

It is clear from these figures that, regardless of whether a user churned or not, the users represented in this data are serious drivers! It would probably be safe to assume that this data does not represent typical drivers at large. Perhaps the data—and in particular the sample of churned users—contains a high proportion of long-haul truckers.

In consideration of how much these users drive, it would be worthwhile to recommend to Waze that they gather more data on these super-drivers. It's possible that the reason for their driving so much is also the reason why the Waze app does not meet their specific set of needs, which may differ from the needs of a more typical driver, such as a commuter.

Finally, examine whether there is an imbalance in how many users churned by device type.

Begin by getting the overall counts of each device type for each group, churned and retained.

```
[15]: # For each label, calculate the number of Android users and iPhone users
### YOUR CODE HERE ###
df.groupby(['label', 'device']).size() # size(): size property returns the␣
 ↪number of elements in the DataFrame
```

```
[15]: label     device
churned   Android     891
          iPhone     1645
retained  Android    4183
          iPhone     7580
dtype: int64
```

Now, within each group, churned and retained, calculate what percent was Android and what percent was iPhone.

[16]:
```
# For each label, calculate the percentage of Android users and iPhone users
### YOUR CODE HERE ###
df.groupby('label')['device'].value_counts(normalize=True)
```

[16]:
```
label     device
churned   iPhone     0.648659
          Android    0.351341
retained  iPhone     0.644393
          Android    0.355607
Name: device, dtype: float64
```

The ratio of iPhone users and Android users is consistent between the churned group and the retained group, and those ratios are both consistent with the ratio found in the overall dataset.

4.3 PACE: Construct

Note: The Construct stage does not apply to this workflow. The PACE framework can be adapted to fit the specific requirements of any project.

4.4 PACE: Execute

Consider the questions in your PACE Strategy Document and those below to craft your response:

4.4.1 Task 3. Conclusion

Recall that your supervisor, May Santer, asked you to share your findings with the data team in an executive summary. Consider the following questions as you prepare to write your 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:

==> MY RESPONSE TO THE QUESTION IS HERE

1. Did the data contain any missing values? How many, and which variables were affected? Was there a pattern to the missing data?

ANSWER_1: The dataset has 700 missing values only in the label column and there was no pattern of the missing values.

2. What is a benefit of using the median value of a sample instead of the mean?

ANSWER_2: One benefit of using the median instead of the mean is that it is less sensitive to outliers.

3. Did your investigation give rise to further questions that you would like to explore or ask the Waze team about?

ANSWER_3: Yes, because during examined the median user in each aspect, I found that the median user who churned drove 608 kilometers each day they drove last month, which is almost 250% of the per-drive-day distance of retained users. It would be very helpful to know how these data were collected due to strange behavior of the churned users.

4. What percentage of the users in the dataset were Android users and what percentage were iPhone users?

ANSWER_4: In both churned and retained group, they had a similar trend of the amount of users in each device group, Android users were approximately to 36% of the total users and iPhone users were close to 64% of the total users.

5. What were some distinguishing characteristics of users who churned vs. users who were retained?

ANSWER_5: Churned users drove farther and longer than retained users.

6. Was there an appreciable difference in churn rate between iPhone users vs. Android users?

ANSWER_6: Like answer to question 4th, they had a similar trend of the amount of users in each device group. So, there was no evidence that churn correlated with device.

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.