# Prueba_tecnica_DS

April 21, 2022

## 1 Prueba Técnica Data Science

En Los Ángeles existe un sistema compartido de bicicletas que brinda datos anónimos acerca del uso del servicio. La tabla que se proporciona contiene el histórico de viajes que se han realizado desde 2016 y contiene una columna que es de particular interés y que se buscará analizar a más profundidad: Passholder_type. A continuación se presentan las columnas que contiene la tabla:

- trip_id: identificador único para el viaje
- duration: duración del viaje en minutos
- start_time: dia/hora donde en viaje inicia en formato ISO 8601 tiempo local
- end_time: dia/hora donde el viaje termina en formato ISO 8601 tiempo local
- start_station: la estación donde el viaje inició
- start_lat: la latitud de la estación donde el viaje se originó
- start_lon: la longitud de la estación donde el viaje se originó
- end_station: la estación donde el viaje terminó
- end_lat: la latitud de la estación donde terminó el viaje
- end_lon: la longitud de la estación donde terminó el viaje
- bike_id: un entero único que identifica la bicicleta
- plan_duration: número de días que el usuario tendrá el paso. 0 significa un viaje único (Walk-up plan)
- trip_route_category: "Round trip" son viajes que empiezan y terminan en la misma estación
- passholder_type: El nombre del plan de passholder

[335]:
```python
# Librerias para lectura y visualización de datos
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import folium

# Oversampling
from imblearn.over_sampling import SMOTE

# Librerias de Machine learning
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

```
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler, LabelEncoder, StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV,␣
↪StratifiedKFold
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
↪f1_score, confusion_matrix, make_scorer
from xgboost import XGBClassifier
from yellowbrick.cluster import KElbowVisualizer
from sklearn.mixture import GaussianMixture

import joblib
from datetime import datetime
import warnings

warnings.filterwarnings('ignore')
```

[336]:
```
# Lectura de datos
df = pd.read_csv('./train_set.csv')
df.head(3)
```

[336]:
```
     trip_id  duration           start_time             end_time  start_lat  \
0  101750280        35  2018-08-07 11:20:00  2018-08-07 11:55:00  33.748920
1   46560345        32      9/17/2017 17:51      9/17/2017 18:23  34.035679
2  120016336         6  2019-04-22 09:22:00  2019-04-22 09:28:00  34.046070

    start_lon    end_lat     end_lon bike_id  plan_duration  \
0 -118.275192  33.748920 -118.275192   06530            1.0
1 -118.270813  34.047749 -118.243172    6683            0.0
2 -118.233093  34.047749 -118.243172   06710           30.0

  trip_route_category passholder_type  start_station  end_station
0          Round Trip         Walk-up           4127         4127
1             One Way         Walk-up           3057         3062
2             One Way    Monthly Pass           3022         3062
```

## 1.1 EDA

### 1.1.1 Time

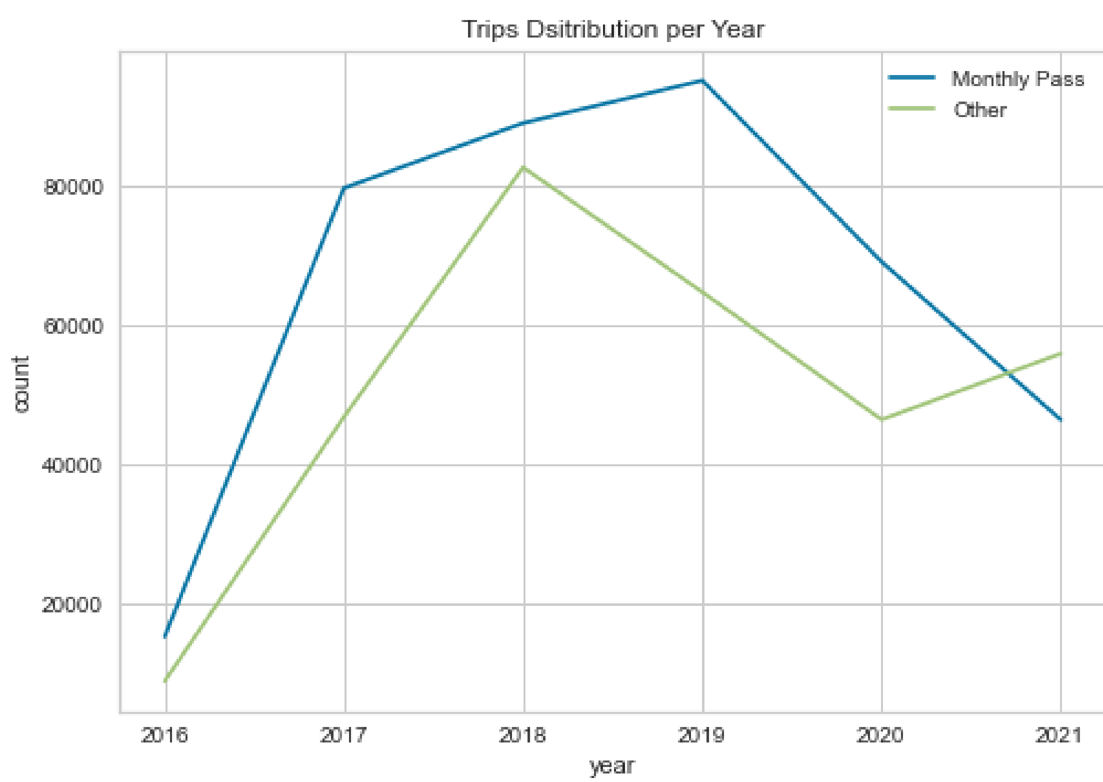
[524]:
```
df_eda = df.copy()
```

[525]:
```
# Transformación de datos tipo fecha
df_eda['start_time'] = pd.to_datetime(df_eda['start_time'])
df_eda['end_time'] = pd.to_datetime(df_eda['end_time'])
```

```
# extracción de año, mes, día de la semana y  hora deldía
df_eda['year'] = df_eda['start_time'].dt.year
df_eda['month'] = df_eda['start_time'].dt.month
df_eda['day_of_week'] = df_eda['start_time'].dt.day_of_week
df_eda['hour_of_day'] = df_eda['start_time'].dt.hour
```

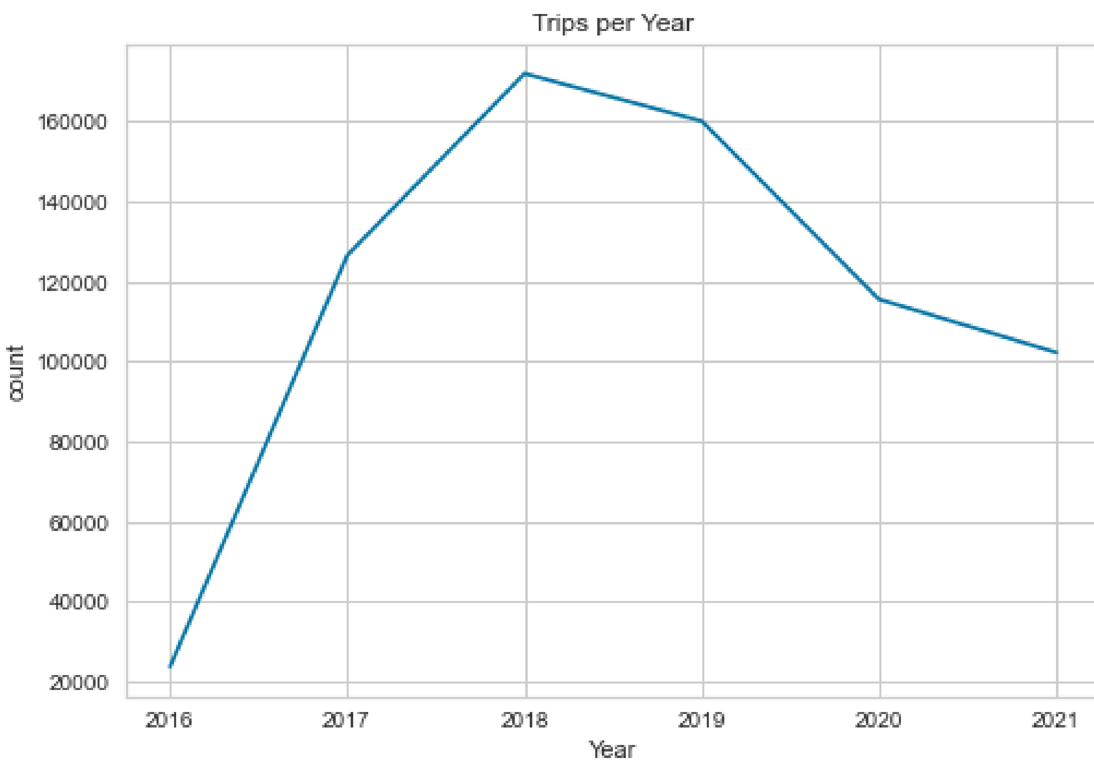
[530]:

```
# Gráfica del uso de bicicletas en el tiempo
trip_per_month_Monthly = df_eda[df_eda['passholder_type'] == 'Monthly Pass'].
 ↪groupby('year')['trip_id'].count().to_frame().reset_index()
trip_per_month_Monthly.columns = ['year', 'count']

trip_per_month_Other = df_eda[df_eda['passholder_type'] != 'Monthly Pass'].
 ↪groupby('year')['trip_id'].count().to_frame().reset_index()
trip_per_month_Other.columns = ['year', 'count']


sns.lineplot(x = 'year', y = 'count', data = trip_per_month_Monthly, label =␣
 ↪'Monthly Pass')
sns.lineplot(x = 'year', y = 'count', data = trip_per_month_Other, label =␣
 ↪'Other')
plt.legend()
plt.title('Trips Dsitribution per Year')
plt.show()
```



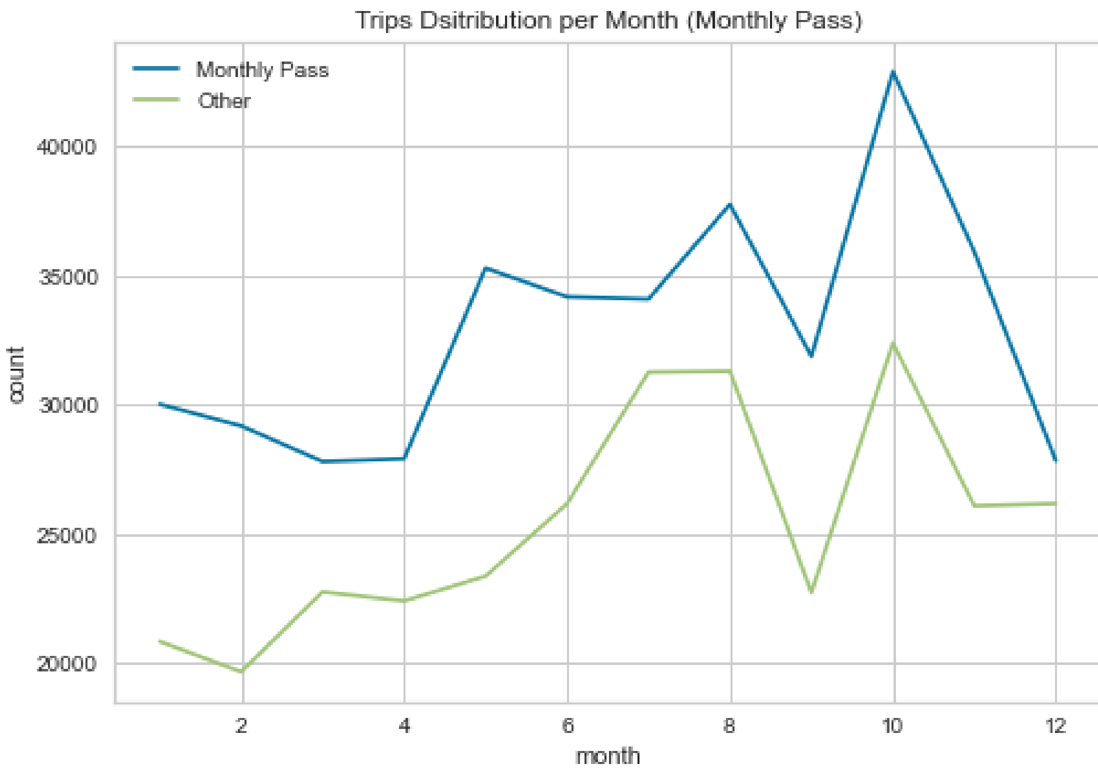
En esta gráfica podemos observar que la tendencia del uso de membresías mensuales ha ido a la baja a apartir del año 2019, contrario a la tendencia alcista que se intuía. Por otro lado, el resto de membresías parecen estar en un periodo alcista. Sin embargo la caída en las subscripciones mensuales ha provocado en general una baja en eluso de bicicletas como se puede apreciar en la gráfica siguiente:

[533]:
```
trips_per_year = df_eda.groupby('year')['trip_id'].count()
plt.plot(trips_per_year)
plt.title('Trips per Year')
plt.xlabel('Year')
plt.ylabel('count')
plt.show()
```




[538]:
```
# Gráfica del uso de bicicletas por mes (Monthly Pass)
trip_per_month_M = df_eda[df_eda['passholder_type'] == 'Monthly Pass'].
 ↪groupby('month')['trip_id'].count().to_frame().reset_index()
trip_per_month_M.columns = ['month', 'count']

trip_per_month_O = df_eda[df_eda['passholder_type'] != 'Monthly Pass'].
 ↪groupby('month')['trip_id'].count().to_frame().reset_index()
```

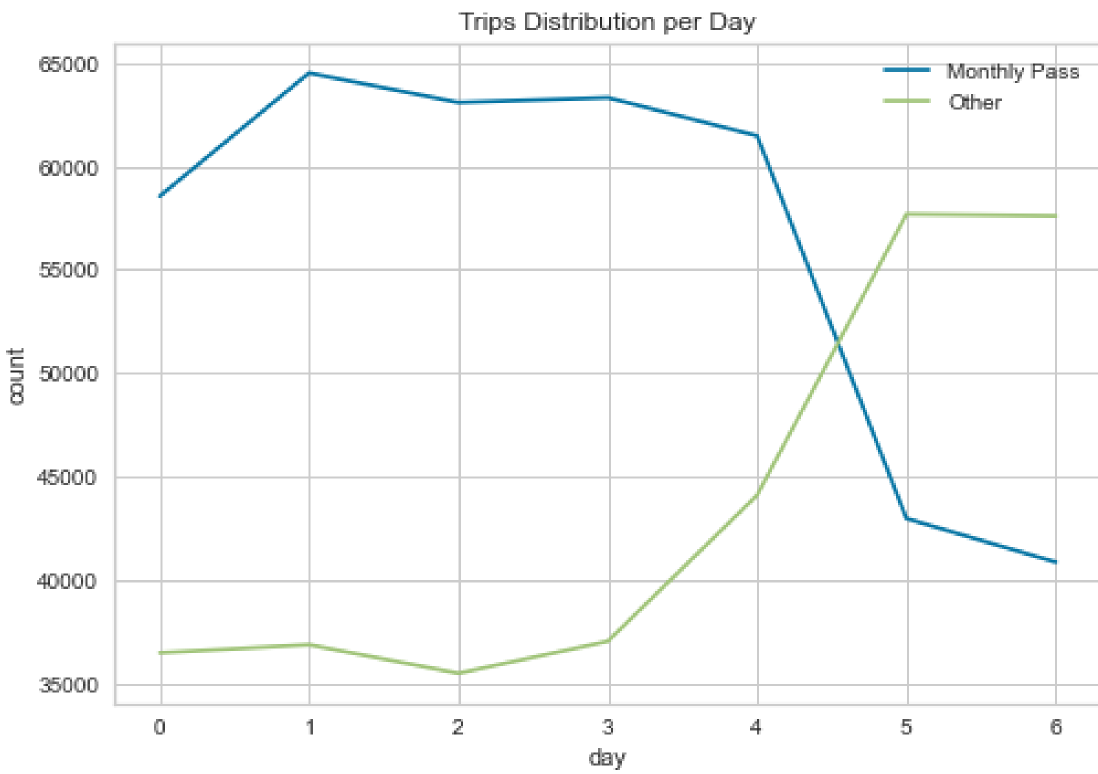
```
trip_per_month_O.columns = ['month', 'count']

sns.lineplot(x = 'month', y = 'count', data = trip_per_month_M, label =␣
↪'Monthly Pass')
sns.lineplot(x = 'month', y = 'count', data = trip_per_month_O, label = 'Other')
plt.legend()
plt.title('Trips Dsitribution per Month (Monthly Pass)')
plt.show()
```




Podemos observar que ambas distribuciones son más o menos similares por lo que podemos intuir que el mes no tiene demasiada influencia en la elección del tipo de membresía. Excepto tal vez por el mes 5 donde vemos una ligera preferencia por aquellos que poseen una membresía mensual.

[540]:
```
# Uso de bicicleta por día de la semana (Monthly)
trip_per_day_M = df_eda[df_eda['passholder_type'] == 'Monthly Pass'].
↪groupby('day_of_week')['trip_id'].count().to_frame().reset_index()
trip_per_day_M.columns = ['day', 'count']

trip_per_day_O = df_eda[df_eda['passholder_type'] != 'Monthly Pass'].
↪groupby('day_of_week')['trip_id'].count().to_frame().reset_index()
trip_per_day_O.columns = ['day', 'count']
```

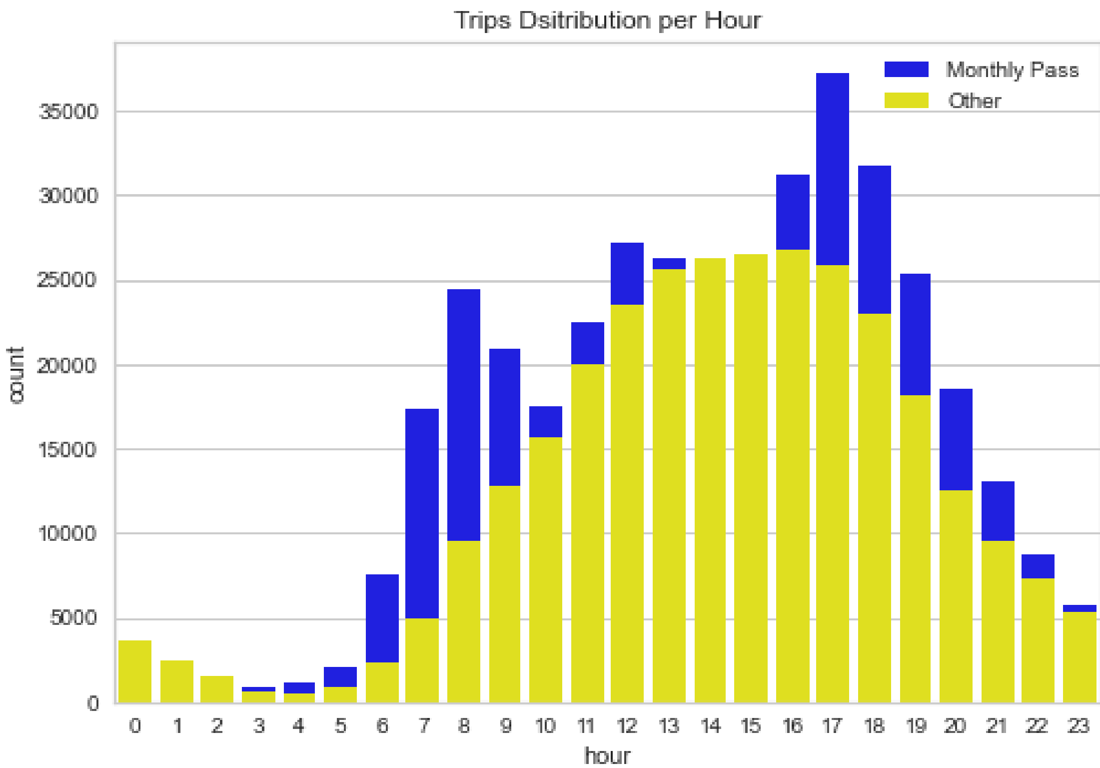
```
sns.lineplot(x = 'day', y = 'count', data = trip_per_day_M, label = 'Monthly␣
↪Pass')
sns.lineplot(x = 'day', y = 'count', data = trip_per_day_O, label = 'Other')
plt.title('Trips Distribution per Day')
plt.show()
```




En este caso si que puede observarse una tendencia en el comportamiento del uso de bicicleta entre aquellos con membresía mensual y los demás, aquellos con membresía mensual tienden a usar la bicicleta entre semana, mientras que aquellos con otro tipo de membresía suelen usarla los fines de semana, tal vez por recreación más que como un medio de transporte usual. Lo que puede sugerir que aquellos con una membresía mensual son personas que usan la bicicleta para transportarse al trabajo o la escuela, más que por diversión.

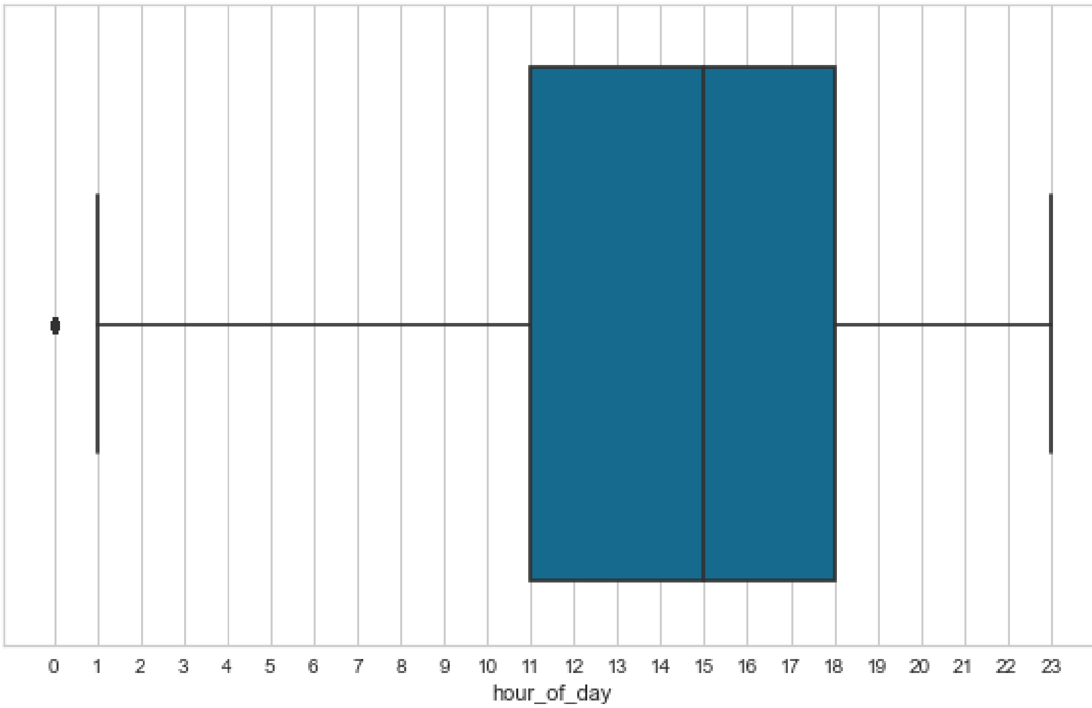
[544]:
```
trip_per_hour_O = df_eda[df_eda['passholder_type'] != 'Monthly Pass'].
↪groupby('hour_of_day')['trip_id'].count().to_frame().reset_index()
trip_per_hour_O.columns = ['hour', 'count']

trip_per_hour_M = df_eda[df_eda['passholder_type'] == 'Monthly Pass'].
↪groupby('hour_of_day')['trip_id'].count().to_frame().reset_index()
trip_per_hour_M.columns = ['hour', 'count']
```

```
sns.barplot(x = 'hour', y = 'count', data = trip_per_hour_M, label = 'Monthly␣
 ↪Pass', color = 'blue')
sns.barplot(x = 'hour', y = 'count', data = trip_per_hour_O, label = 'Other',␣
 ↪color = 'yellow')
plt.legend()
plt.title('Trips Dsitribution per Hour')
plt.show()
```




En general se puede apreciar un comportamiento bastante similar en ambas categorías, las personas suelen usar la bicicleta entre las 11 de la mañana y las 6 de la tarde, esto se puede apreciar en la siguiente gráfica.

[347]:
```
plt.figure(figsize = (10, 6))
sns.boxplot(x = 'hour_of_day', data = df_eda)
plt.xticks(list(range(0, 24)))
plt.show()
```




### 1.1.2 Location

[546]:
```
df_eda.describe()
```

[546]:

| | trip_id | duration | start_lat | start_lon |
|---|---|---|---|---|
| count | 7.000000e+05 | 700000.000000 | 694437.000000 | 694437.000000 |
| mean | 1.069468e+08 | 37.084979 | 34.044952 | -118.253849 |
| std | 4.497342e+07 | 125.302510 | 0.325255 | 2.332640 |
| min | 8.369648e+06 | 1.000000 | 33.710979 | -118.495422 |
| 25% | 7.538051e+07 | 7.000000 | 34.037460 | -118.280952 |
| 50% | 1.179410e+08 | 13.000000 | 34.046612 | -118.256980 |
| 75% | 1.404178e+08 | 26.000000 | 34.051941 | -118.247162 |
| max | 1.794831e+08 | 1440.000000 | 55.705528 | 118.238258 |

| | end_lat | end_lon | plan_duration | start_station |
|---|---|---|---|---|
| count | 681426.000000 | 681426.000000 | 699792.000000 | 700000.000000 |
| mean | 34.044175 | -118.259183 | 44.928697 | 3499.720464 |
| std | 0.299721 | 2.129781 | 92.816296 | 615.918795 |
| min | 33.710979 | -118.495422 | 0.000000 | 3000.000000 |
| 25% | 34.037048 | -118.280952 | 1.000000 | 3031.000000 |
| 50% | 34.046520 | -118.256981 | 30.000000 | 3064.000000 |
| 75% | 34.050911 | -118.246422 | 30.000000 | 4214.000000 |
| max | 55.705528 | 37.606541 | 999.000000 | 4594.000000 |

```
       end_station           year          month    day_of_week  \
count  700000.000000  700000.000000  700000.000000  700000.000000
mean     3489.726771    2018.748306       6.773867       3.022640
std       613.040769       1.400052       3.355686       1.983241
min      3000.000000    2016.000000       1.000000       0.000000
25%      3030.000000    2018.000000       4.000000       1.000000
50%      3064.000000    2019.000000       7.000000       3.000000
75%      4214.000000    2020.000000      10.000000       5.000000
max      4594.000000    2021.000000      12.000000       6.000000

         hour_of_day
count  700000.000000
mean       14.127986
std         4.646858
min         0.000000
25%        11.000000
50%        15.000000
75%        18.000000
max        23.000000
```

En lat y lon existen algunas anomalías que pueden ser intercambiados por la información correcta. Y es que en la mayoría de los casos se tiene que la información faltante o incorrecta en cuanto la latitud y longitud, aparece de manera correcta en su contraparte, es decir,si faltan los valores en los puntos iniciales, se puede encontrar la información correcta en el punto final del trayecto.

[547]:
```
df_eda[df_eda['start_station'] == 4496][['start_lat', 'start_lon', 'end_lat',␣
↪'end_lon']].describe()
```

[547]:
```
        start_lat   start_lon     end_lat     end_lon
count  169.000000  169.000000  160.000000  160.000000
mean    53.648009   22.834424   45.112796  -38.457900
std      6.381435   45.816000   10.895048   78.235297
min     33.972980 -118.423943   33.958790 -118.471550
25%     55.705528   37.606541   33.976189 -118.418419
50%     55.705528   37.606541   55.705528   37.606541
75%     55.705528   37.606541   55.705528   37.606541
max     55.705528   37.606541   55.705528   37.606541
```

[548]:
```
df_eda['start_lat'].where(df_eda['start_station'] != 4496, 33.972980, inplace =␣
↪True)
df_eda['start_lon'].where(df_eda['start_station'] != 4496,         -118.423943,␣
↪inplace = True)
df_eda['end_lat'].where(df_eda['end_station'] != 4496, 33.972980, inplace =␣
↪True)
df_eda['end_lon'].where(df_eda['end_station'] != 4496,         -118.423943,␣
↪inplace = True)
```

[549]:
```
df_eda[df_eda['start_station'] == 3039][['start_lat', 'start_lon', 'end_lat',␣
↪'end_lon']].describe()
```

[549]:

| | start_lat | start_lon | end_lat | end_lon |
|---|---|---|---|---|
| count | 64.000000 | 64.000000 | 64.000000 | 64.000000 |
| mean | 34.024502 | -114.696490 | 34.017551 | -118.407443 |
| std | 0.000185 | 29.579016 | 0.016102 | 0.038656 |
| min | 34.024479 | -118.393867 | 33.987381 | -118.472832 |
| 25% | 34.024479 | -118.393867 | 34.024479 | -118.393867 |
| 50% | 34.024479 | -118.393867 | 34.024479 | -118.393867 |
| 75% | 34.024479 | -118.393867 | 34.024479 | -118.393867 |
| max | 34.025959 | 118.238258 | 34.063389 | -118.236160 |

[550]:
```
df_eda['start_lat'].where(df_eda['start_station'] != 3039, 34.024479, inplace =␣
↪True)
df_eda['start_lon'].where(df_eda['start_station'] != 3039,         -118.
↪393867         , inplace = True)
df_eda['end_lat'].where(df_eda['end_station'] != 3039, 34.024479, inplace =␣
↪True)
df_eda['end_lon'].where(df_eda['end_station'] != 3039,         -118.
↪393867         , inplace = True)
```

[551]:
```
df_eda[df_eda['end_lat'].isnull()]['end_station'].unique()
```

[551]: array([3000, 4285, 4286], dtype=int64)

[552]:
```
df_eda[df_eda['start_lat'].isnull()]['start_station'].unique()
```

[552]: array([4285, 4286, 3000], dtype=int64)

[553]:
```
df_eda[df_eda['start_station'] == 3000][['start_lat', 'start_lon', 'end_lat',␣
↪'end_lon']].describe()
```

[553]:

| | start_lat | start_lon | end_lat | end_lon |
|---|---|---|---|---|
| count | 8.000000 | 8.000000 | 706.000000 | 706.000000 |
| mean | 34.025853 | -118.238215 | 34.051884 | -118.307948 |
| std | 0.000023 | 0.000003 | 0.045625 | 0.088880 |
| min | 34.025841 | -118.238220 | 33.958790 | -118.491341 |
| 25% | 34.025841 | -118.238215 | 34.035679 | -118.377068 |
| 50% | 34.025841 | -118.238213 | 34.048401 | -118.258530 |
| 75% | 34.025853 | -118.238213 | 34.053570 | -118.248350 |
| max | 34.025890 | -118.238213 | 34.186569 | -118.129181 |

[554]:
```
df_eda['start_lat'].where(df_eda['start_station'] != 3000, 34.025841, inplace =␣
↪True)
df_eda['start_lon'].where(df_eda['start_station'] != 3000,         -118.238213,␣
↪inplace = True)
```

```
df_eda['end_lat'].where(df_eda['end_station'] != 3000, 34.025841, inplace =␣
↪True)
df_eda['end_lon'].where(df_eda['end_station'] != 3000,         -118.238213,␣
↪inplace = True)
```

[555]:
```
df_eda[df_eda['start_station'] == 4285][['start_lat', 'start_lon', 'end_lat',␣
↪'end_lon']].describe()
```

[555]:

| | start_lat | start_lon | end_lat | end_lon |
|---|---|---|---|---|
| count | 0.0 | 0.0 | 1958.000000 | 1958.000000 |
| mean | NaN | NaN | 34.021756 | -118.440741 |
| std | NaN | NaN | 0.057508 | 0.051618 |
| min | NaN | NaN | 33.958790 | -118.491341 |
| 25% | NaN | NaN | 33.988419 | -118.477448 |
| 50% | NaN | NaN | 33.996239 | -118.468292 |
| 75% | NaN | NaN | 34.023389 | -118.409081 |
| max | NaN | NaN | 34.186569 | -118.238213 |

[556]:
```
df_eda['start_lat'].where(df_eda['start_station'] != 4285, 34.021756, inplace =␣
↪True)
df_eda['start_lon'].where(df_eda['start_station'] != 4285,         -118.440741,␣
↪inplace = True)
df_eda['end_lat'].where(df_eda['end_station'] != 4285, 34.021756, inplace =␣
↪True)
df_eda['end_lon'].where(df_eda['end_station'] != 4285,         -118.440741,␣
↪inplace = True)
```

[557]:
```
df_eda[df_eda['start_station'] == 4286][['start_lat', 'start_lon', 'end_lat',␣
↪'end_lon']].describe()
```

[557]:

| | start_lat | start_lon | end_lat | end_lon |
|---|---|---|---|---|
| count | 0.0 | 0.0 | 658.000000 | 658.000000 |
| mean | NaN | NaN | 34.011992 | -118.453243 |
| std | NaN | NaN | 0.035937 | 0.043585 |
| min | NaN | NaN | 33.958790 | -118.491341 |
| 25% | NaN | NaN | 33.995281 | -118.481552 |
| 50% | NaN | NaN | 34.014309 | -118.471550 |
| 75% | NaN | NaN | 34.021756 | -118.440741 |
| max | NaN | NaN | 34.186569 | -118.238213 |

[558]:
```
df_eda['start_lat'].where(df_eda['start_station'] != 4286, 34.011992, inplace =␣
↪True)
df_eda['start_lon'].where(df_eda['start_station'] != 4286,         -118.453243,␣
↪inplace = True)
df_eda['end_lat'].where(df_eda['end_station'] != 4286, 34.011992, inplace =␣
↪True)
```

```
df_eda['end_lon'].where(df_eda['end_station'] != 4286,         -118.453243,␣
 ↪inplace = True)
```

[559]:
```
df_eda[df_eda['start_lat'].isnull()]['start_station'].unique()
```

[559]:
```
array([], dtype=int64)
```

Por otro lado, hay estaciones que tienen multiples coordenadas como ubicación, para volver uniforme esta información usaremos los valores mínimos tanto de la latitud como de la longitud.

[362]:
```
# Eliminación de multiples coordenadas para algunas estaciones
for i in df_eda['start_station'].unique():
    lat = df_eda[df_eda['start_station'] == i]['start_lat'].min()
    lon =  df_eda[df_eda['start_station'] == i]['start_lon'].min()

    df_eda['start_lat'].where(df_eda['start_station'] != i, lat, inplace = True)
    df_eda['start_lon'].where(df_eda['start_station'] != i,         lon,␣
 ↪inplace = True)
    df_eda['end_lat'].where(df_eda['end_station'] != i, lat, inplace = True)
    df_eda['end_lon'].where(df_eda['end_station'] != i,         lon, inplace =␣
 ↪True)
```

A continuación se encontrarán las estaciones donde parte más gente con una membresía mensual.

[560]:
```
stations0 = list(df_eda['start_station'].unique())
lats = []
lons = []
counts_monthly = []
counts_no_monthly = []

for station in stations0:
    lats.append(df_eda[df_eda['start_station'] == station].iloc[0, 4])
    lons.append(df_eda[df_eda['start_station'] == station].iloc[0, 5])
    counts_monthly.append(df_eda[(df_eda['start_station'] == station) &␣
 ↪(df_eda['passholder_type'] == 'Monthly Pass')]['end_station'].value_counts().
 ↪to_list())
    counts_no_monthly.append(df_eda[(df_eda['start_station'] == station) &␣
 ↪(df_eda['passholder_type'] != 'Monthly Pass')]['end_station'].value_counts().
 ↪to_list())
```

[561]:
```
stations_df0 = pd.DataFrame({
    'lat': lats,
    'lon': lons,
    'station': stations0,
    'count_monthly': counts_monthly,
    'count_no_monthly': counts_no_monthly
})
```

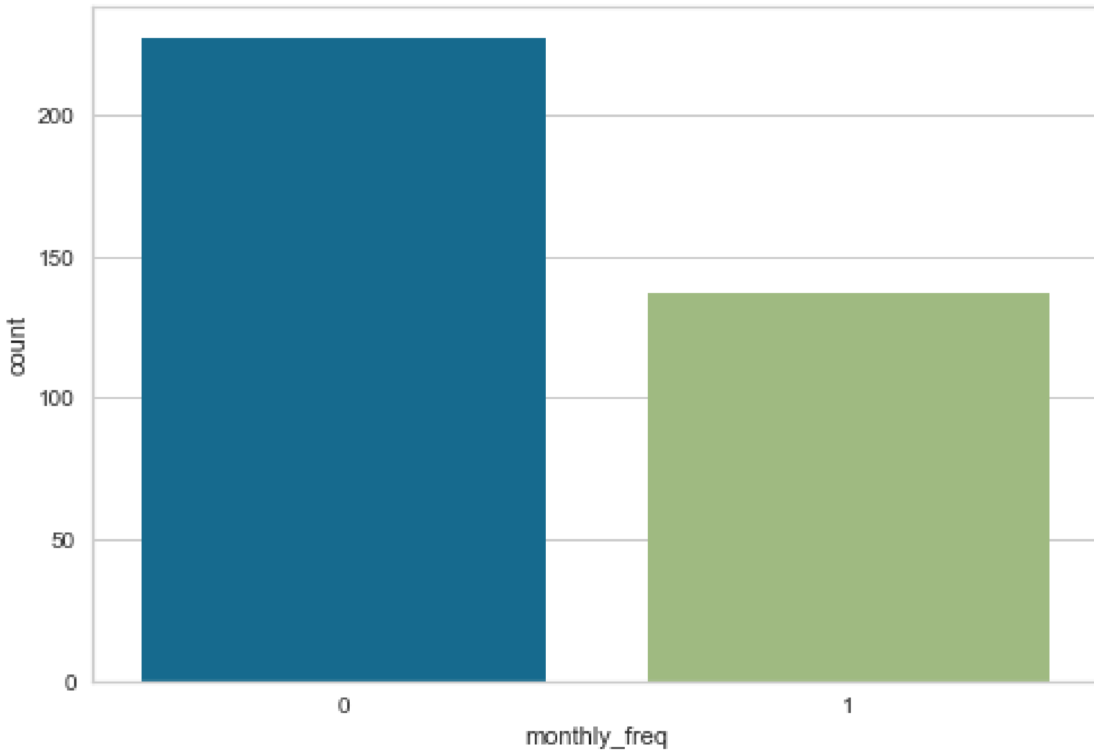
```
stations_df0['count_monthly'] = stations_df0['count_monthly'].apply(lambda x:␣
↪x[0] if len(x) != 0 else 0)
stations_df0['count_no_monthly'] = stations_df0['count_no_monthly'].
↪apply(lambda x: x[0] if len(x) != 0 else 0)
stations_df0['monthly_freq'] = stations_df0['count_monthly'] -␣
↪stations_df0['count_no_monthly']
stations_df0['monthly_freq'] = stations_df0['monthly_freq'].apply(lambda x: 1␣
↪if x > 0 else 0)
stations_df0
```

[561]:

```
           lat         lon  station  count_monthly  count_no_monthly  \
0    33.748920 -118.275192     4127             62                64
1    34.035679 -118.270813     3057            165               147
2    34.046070 -118.233093     3022            475               584
3    34.062580 -118.290092     4304            350               112
4    34.026291 -118.277687     4266            499                97
..         …          …        …              …                 …
359  34.011570 -118.495422     4395              2                 1
360  34.030460 -118.389099     4363              1                 3
361  34.036770 -118.425377     4373              2                 1
362  34.145748 -118.144287     4143              1                 0
363  34.172451 -118.370369     4327              0                 1

     monthly_freq
0               0
1               1
2               0
3               1
4               1
..            …
359             1
360             0
361             1
362             1
363             0

[364 rows x 6 columns]
```

[562]:

```
sns.countplot(x = 'monthly_freq', data = stations_df0)
plt.show()
```




Aquí se puede observar que la personas con una membresía mensual usan una menor cantidad de las estaciones para salir, lo que pude significar que están concentrados en zonas bastante específicas.

[366]:
```
colors = list(stations_df0['monthly_freq'])

for i in range(len(colors)):
    if colors[i] == 1:
        colors[i] = 'blue'
    else:
        colors[i] = 'red'
```

[367]:
```
m = folium.Map(location = [34.025841, -118.238213], zoom_start = 12, tiles =␣
↪"Stamen Terrain")



for i, station in enumerate(stations0):
      folium.Marker( [lats[i], lons[i]],
                  popup = 'Station ' + str(stations0[i]),
                  icon = folium.Icon(color = colors[i])
                  ).add_to(m)
m
```

[367]: <folium.folium.Map at 0x236438e3490>

En el mapa podemos observar que efectivamente los usuarios de membresías diferentes a la mensual, se encuentran completamente dispersos en toda la zona, mientras que aquellos usuarios con membresías mensuales parecieran aglomerarse en ciertos puntos. Estos puntos pueden ser centros educativos o empresas.

[563]:
```
stations = list(df_eda['end_station'].unique())
lats = []
lons = []
counts_monthly = []
counts_no_monthly = []

for station in stations:
    lats.append(df_eda[df_eda['end_station'] == station].iloc[0, 4])
    lons.append(df_eda[df_eda['end_station'] == station].iloc[0, 5])
    counts_monthly.append(df_eda[(df_eda['end_station'] == station) &␣
↪(df_eda['passholder_type'] == 'Monthly Pass')]['end_station'].value_counts().
↪to_list())
    counts_no_monthly.append(df_eda[(df_eda['end_station'] == station) &␣
↪(df_eda['passholder_type'] != 'Monthly Pass')]['end_station'].value_counts().
↪to_list())
```

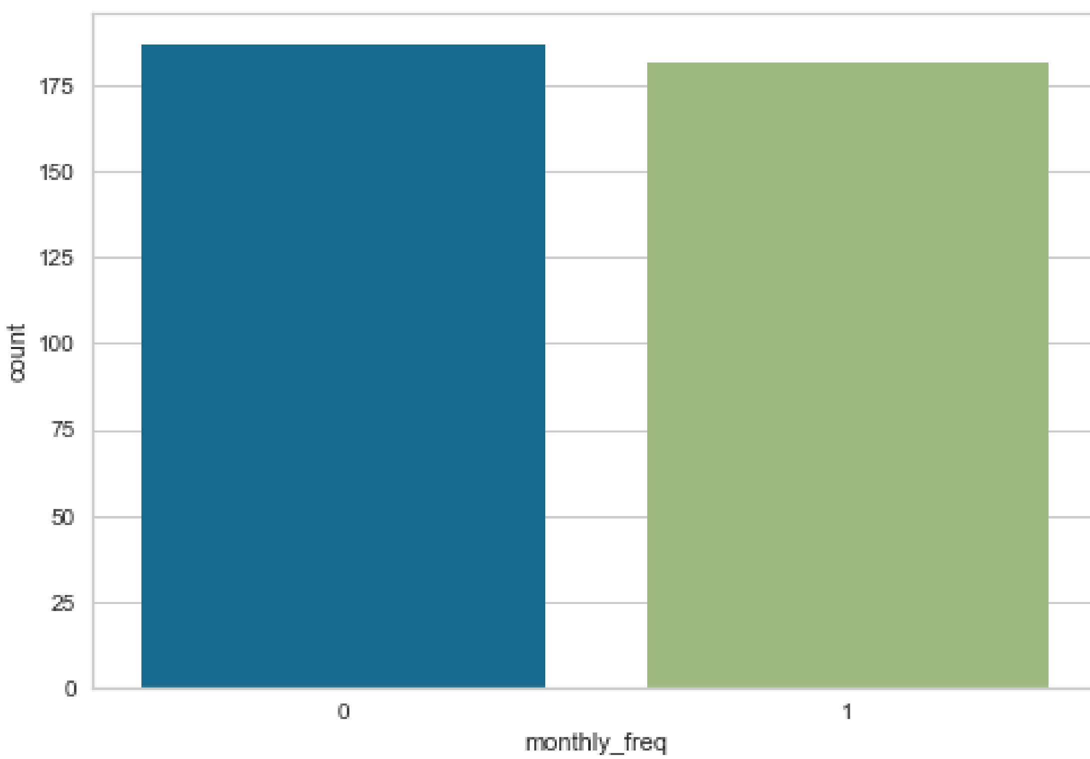
[564]:
```
stations_df = pd.DataFrame({
    'lat': lats,
    'lon': lons,
    'station': stations,
    'count_monthly': counts_monthly,
    'count_no_monthly': counts_no_monthly
})

stations_df['count_monthly'] = stations_df['count_monthly'].apply(lambda x:␣
↪x[0] if len(x) != 0 else 0)
stations_df['count_no_monthly'] = stations_df['count_no_monthly'].apply(lambda␣
↪x: x[0] if len(x) != 0 else 0)
stations_df['monthly_freq'] = stations_df['count_monthly'] -␣
↪stations_df['count_no_monthly']
stations_df['monthly_freq'] = stations_df['monthly_freq'].apply(lambda x: 1 if␣
↪x > 0 else 0)
stations_df
```

[564]:
```
         lat         lon  station  count_monthly  count_no_monthly  \
0  33.748920 -118.275192     4127            110                89
1  34.035679 -118.270813     3062           4475              2047
2  34.062580 -118.290092     4311            755               419
3  34.026291 -118.277687     4443            412               188
4  34.135250 -118.132370     4158            455               316
```

```
..         …          …      …            …              …
364  34.029121 -118.403168     4327            0                1
365  34.011992 -118.453243     4362            0                1
366  34.025860 -118.284103     4468            1                1
367  34.036770 -118.425377     4373            2                1
368  34.145748 -118.144287     4143            1                0

     monthly_freq
0               1
1               1
2               1
3               1
4               1
..            …
364             0
365             0
366             0
367             1
368             1

[369 rows x 6 columns]
```

[566]:

```
sns.countplot(x = 'monthly_freq', data = stations_df)
plt.show()
```



En este caso observamos una cantidad similar para ambas categorías en el caso de las estaciones de llegada, vemos una disminución en las estaciones usadas de llegada por parte del resto de membresías y un aumento en el caso de la membresía mensual. Esto significa que en el primer caso, estos se concentran en lugares específicos al llegar a su destino mientras que se dispersan los poseedores de una membresía mensual.

[567]:
```
colors = list(stations_df['monthly_freq'])

for i in range(len(colors)):
    if colors[i] == 1:
        colors[i] = 'blue'
    else:
        colors[i] = 'red'
```

[568]:
```
m = folium.Map(location = [34.025841, -118.238213], zoom_start = 12, tiles =␣
 ↪"Stamen Terrain")




for i, station in enumerate(stations):
      folium.Marker( [lats[i], lons[i]],
                popup = 'Station ' + str(stations[i]) ,
                icon = folium.Icon(color = colors[i])
                ).add_to(m)
m
```

[568]: <folium.folium.Map at 0x2367334a700>

En este caso no vemos concentraciones específicas de aquellos con membresía mensual, si no que se encuentran dispersos la igual que su contraparte.

Analicemos un poco más, el uso de las estaciones.

## 1.2 Data Cleaning

### 1.2.1 Missing Values

[569]:
```
df_eda.isnull().sum() / len(df) * 100
```

[569]:
```
trip_id                0.000000
duration               0.000000
start_time             0.000000
end_time               0.000000
start_lat              0.000000
start_lon              0.000000
```

```
end_lat                  0.000000
end_lon                  0.000000
bike_id                  0.000000
plan_duration            0.029714
trip_route_category      0.000000
passholder_type          0.368000
start_station            0.000000
end_station              0.000000
year                     0.000000
month                    0.000000
day_of_week              0.000000
hour_of_day              0.000000
dtype: float64
```

[570]:
```
df_eda['passholder_type'].value_counts()
```

[570]:
```
Monthly Pass    394769
Walk-up         212426
One Day Pass     44455
Annual Pass      34092
Flex Pass        11604
Testing             78
Name: passholder_type, dtype: int64
```

Al igual que en el caso de las coordenadas, los valores nulos que se encuentran en la columna *passholder_type* se encuentran correctos en la columna *plan_duration* y viceversa.

[572]:
```
df_eda[df_eda['passholder_type'].isnull()]['plan_duration'].unique()
```

[572]:
```
array([30.])
```

[573]:
```
df_eda['passholder_type'].fillna('Monthly Pass', inplace = True)
```

[574]:
```
df_eda['passholder_type'].value_counts()
```

[574]:
```
Monthly Pass    397345
Walk-up         212426
One Day Pass     44455
Annual Pass      34092
Flex Pass        11604
Testing             78
Name: passholder_type, dtype: int64
```

[575]:
```
df_eda[df_eda['plan_duration'].isnull()]['passholder_type'].unique()
```

[575]:
```
array(['Monthly Pass'], dtype=object)
```

[576]:
```
df_eda['plan_duration'].fillna(30., inplace = True)
```

[577]:
```
df_eda.isnull().sum() / len(df) * 100
```

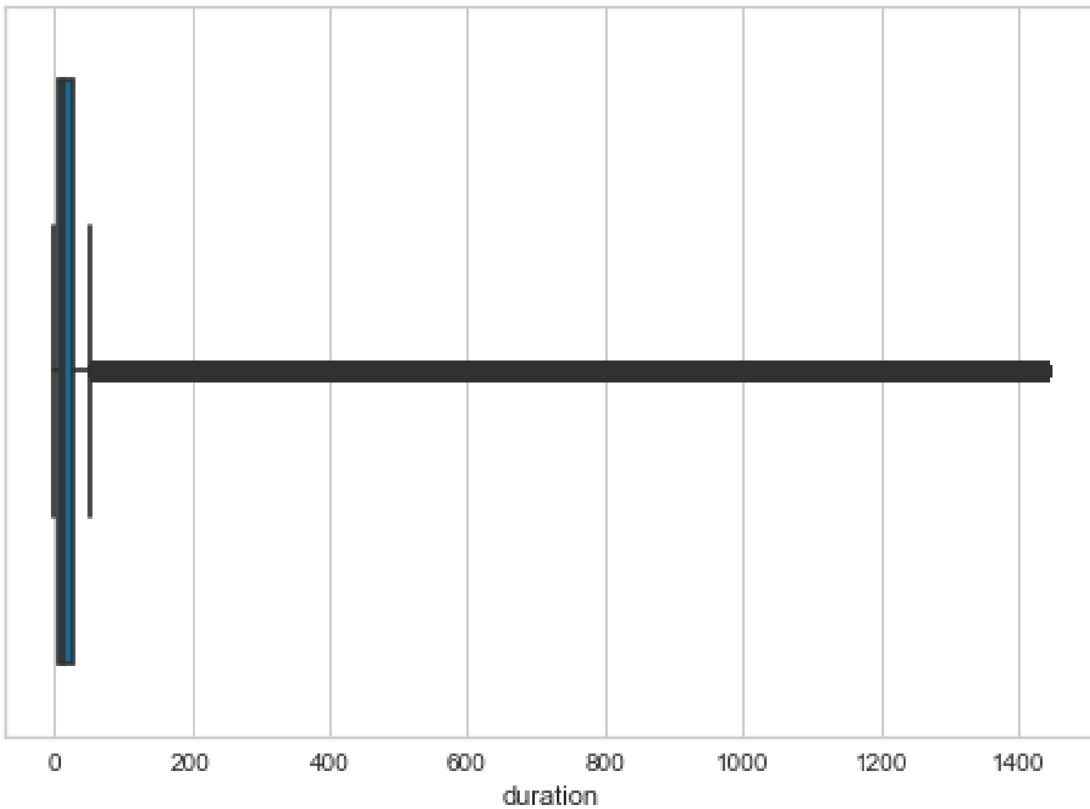
[577]:
```
trip_id                0.0
duration               0.0
start_time             0.0
end_time               0.0
start_lat              0.0
start_lon              0.0
end_lat                0.0
end_lon                0.0
bike_id                0.0
plan_duration          0.0
trip_route_category    0.0
passholder_type        0.0
start_station          0.0
end_station            0.0
year                   0.0
month                  0.0
day_of_week            0.0
hour_of_day            0.0
dtype: float64
```

### 1.2.2 Outliers

[389]:
```
df_eda['duration'].describe()
```

[389]:
```
count    700000.000000
mean         37.084979
std         125.302510
min           1.000000
25%           7.000000
50%          13.000000
75%          26.000000
max        1440.000000
Name: duration, dtype: float64
```

[390]:
```
sns.boxplot( df_eda['duration'] )
plt.show()
```




Existe una gran cantidad de datos atípicos en la variable *duration*, estos serán tratados con el método Quantile-based Flooring.

**Quantile-based Flooring and Capping**

[391]:
```
df_eda['duration'].quantile(0.10) , df_eda['duration'].quantile(0.90)
```

[391]: (4.0, 59.0)

[392]:
```
df_eda['duration'].where(df_eda['duration'] >= 4., 4, inplace = True)
df_eda['duration'].where(df_eda['duration'] <= 59., 59., inplace = True)
```

## 1.3 Data Preparation

A continuación se obtendrá la distancia entre los puntos de salida y llegada a partir de las coordenadas.

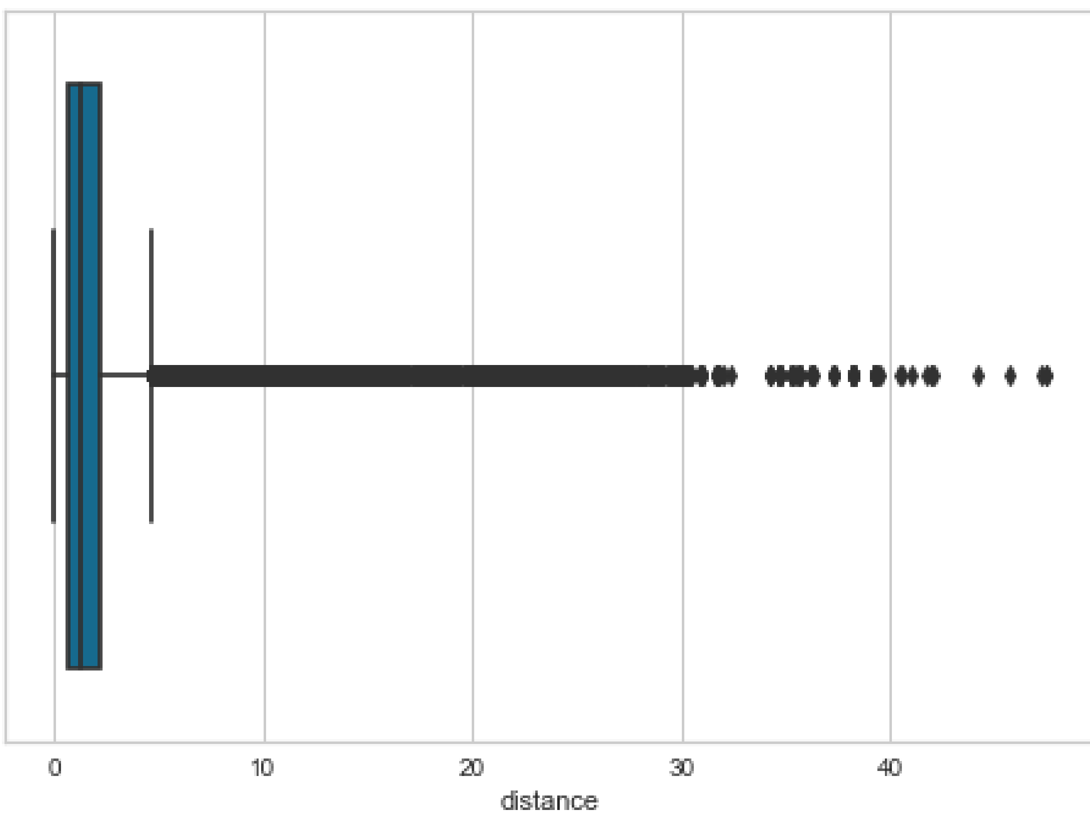
[393]:
```
# Funciones para calcular la distancia entre dos puntos sobre el planeta Tierra
def haversine_array(lat1, lng1, lat2, lng2):
    lat1, lng1, lat2, lng2 = map(np.radians, (lat1, lng1, lat2, lng2))
    AVG_EARTH_RADIUS = 6371  # in km
    lat = lat2 - lat1
```

```
    lng = lng2 - lng1
    d = np.sin(lat * 0.5) ** 2 + np.cos(lat1) * np.cos(lat2) * np.sin(lng * 0.
 ↪5) ** 2
    h = 2 * AVG_EARTH_RADIUS * np.arcsin(np.sqrt(d))
    return h

def dummy_manhattan_distance(lat1, lng1, lat2, lng2):
    a = haversine_array(lat1, lng1, lat1, lng2)
    b = haversine_array(lat1, lng1, lat2, lng1)
    return a + b
```

[582]:
```
lat_lon_df = df_eda[['start_lat', 'start_lon', 'end_lat', 'end_lon']]
lat_lon_df = lat_lon_df.assign(distance = lambda row:␣
 ↪dummy_manhattan_distance(row['start_lat'], row['start_lon'], row['end_lat'],␣
 ↪row['end_lon']) )
```

[583]:
```
df_eda['distance'] = lat_lon_df['distance']
```

[584]:
```
sns.boxplot( df_eda['distance'] )
plt.show()
```



Observamos una gran cantidad de puntos atípicos que serán tratados igual que antes.

[585]:
```
df_eda['distance'].quantile(0.10) , df_eda['distance'].quantile(0.90)
```

[585]: (0.0, 3.618447068172667)

[586]:
```
df_eda['distance'].where(df_eda['distance'] <= 3.7, 3.7, inplace = True)
```

Obtendremos dos variables categorícas a partir de las variables númericas *distance* y *duration*.

[587]:
```
def distance(x):
    if x <= 0.3:
        return 'short'
    elif x > 0.3 and x <= 2:
        return 'medium'
    else:
        return 'large'

# categoría de distance
df_eda['distance_cat'] = df_eda['distance'].apply(distance)
```

[588]:
```
# Categoría de duration
df_eda['duration_cat'] = df_eda['duration'].apply(lambda x: 'little' if x <= 20␣
↪else 'much')
```

[590]:
```
# Variables que se transformarán a categoricas
categories = ['trip_route_category', 'passholder_type', 'year', 'day_of_week' ,␣
↪'distance_cat', 'duration_cat',  'month']

# Variables que se eliminarán del modelo
to_drop = ['trip_id', 'start_time', 'end_time', 'start_lat', 'start_lon',␣
↪'end_lat', 'end_lon', 'bike_id','start_station', 'end_station',␣
↪'plan_duration']
```

[591]:
```
for cat in categories:
    df_eda[cat] = df_eda[cat].astype('category')
```

[592]:
```
df_eda.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700000 entries, 0 to 699999
Data columns (total 21 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   trip_id              700000 non-null  int64
 1   duration             700000 non-null  int64
 2   start_time           700000 non-null  datetime64[ns]
 3   end_time             700000 non-null  datetime64[ns]
 4   start_lat            700000 non-null  float64
```

```
 5   start_lon            700000 non-null  float64
 6   end_lat              700000 non-null  float64
 7   end_lon              700000 non-null  float64
 8   bike_id              700000 non-null  object
 9   plan_duration        700000 non-null  float64
 10  trip_route_category  700000 non-null  category
 11  passholder_type      700000 non-null  category
 12  start_station        700000 non-null  int64
 13  end_station          700000 non-null  int64
 14  year                 700000 non-null  category
 15  month                700000 non-null  category
 16  day_of_week          700000 non-null  category
 17  hour_of_day          700000 non-null  int64
 18  distance             700000 non-null  float64
 19  distance_cat         700000 non-null  category
 20  duration_cat         700000 non-null  category
dtypes: category(7), datetime64[ns](2), float64(6), int64(5), object(1)
memory usage: 79.4+ MB
```

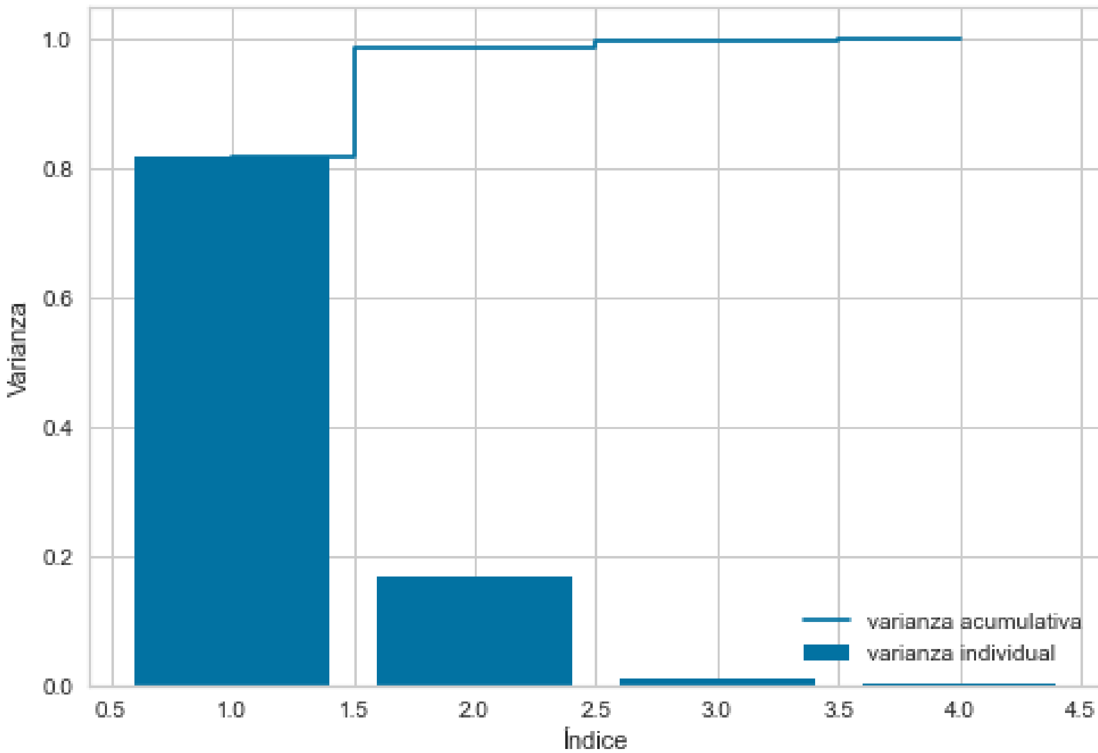
[593]:
```
# Creación de dataset para el modelo predictivo
df_model = df_eda.drop(to_drop, axis = 1)
```

[594]:
```
df_model.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700000 entries, 0 to 699999
Data columns (total 10 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   duration             700000 non-null  int64
 1   trip_route_category  700000 non-null  category
 2   passholder_type      700000 non-null  category
 3   year                 700000 non-null  category
 4   month                700000 non-null  category
 5   day_of_week          700000 non-null  category
 6   hour_of_day          700000 non-null  int64
 7   distance             700000 non-null  float64
 8   distance_cat         700000 non-null  category
 9   duration_cat         700000 non-null  category
dtypes: category(7), float64(1), int64(2)
memory usage: 20.7 MB
```

[595]:
```
# Debido a que las coordenadas geográficas contienen una gran cantidad de␣
 ↪ruido, procederemos a transformarlas mediante PCA
coords = df_eda[['start_lat', 'start_lon', 'end_lat', 'end_lon']]

cov_mat = np.cov(coords.T)
eigen_vals, eigen_vecs = np.linalg.eig(cov_mat)
```

```
tot = sum(eigen_vals)
var_exp = [ev / tot for ev in sorted(eigen_vals, reverse = True)]
cum_var_exp = np.cumsum(var_exp)
plt.bar(range(1, 5), var_exp, label = 'varianza individual', align = 'center')
plt.step(range(1, 5), cum_var_exp, where = 'mid', label = 'varianza␣
↪acumulativa')
plt.xlabel('Índice')
plt.ylabel('Varianza')
plt.legend(loc = 'best')
plt.show()
```




En la gráfica podemos observar que tres componentes serían suficientes, pues contendrían casi el 100% de la información, sin embargo, queremos dejarlo de la misma dimensionalidad, por lo que seleccionaremos 4.

[596]:
```
pca_geo = PCA(n_components = 4, random_state = 42)
coords = pca_geo.fit_transform(coords)
```

[597]:
```
df_model['geo_1'] = coords[:, 0]
df_model['geo_2'] = coords[:, 1]
df_model['geo_3'] = coords[:, 2]
df_model['geo_4'] = coords[:, 3]
```

[599]:
```
df_model.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700000 entries, 0 to 699999
Data columns (total 14 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   duration             700000 non-null  int64
 1   trip_route_category  700000 non-null  category
 2   passholder_type      700000 non-null  category
 3   year                 700000 non-null  category
 4   month                700000 non-null  category
 5   day_of_week          700000 non-null  category
 6   hour_of_day          700000 non-null  int64
 7   distance             700000 non-null  float64
 8   distance_cat         700000 non-null  category
 9   duration_cat         700000 non-null  category
 10  geo_1                700000 non-null  float64
 11  geo_2                700000 non-null  float64
 12  geo_3                700000 non-null  float64
 13  geo_4                700000 non-null  float64
dtypes: category(7), float64(5), int64(2)
memory usage: 42.1 MB
```

[604]:
```
# Transformaremos la variable target mediante un etiquetado
le = LabelEncoder()
le.fit(df_model['passholder_type'])
df_model['passholder_type_cat'] =  le.transform( df_model['passholder_type'])
```

[605]:
```
df_model['passholder_type_cat'].unique()
```

[605]:
```
array([5, 2, 3, 0, 1, 4])
```

[415]:
```
le.inverse_transform([5, 2, 3, 0, 1, 4])
```

[415]:
```
array(['Walk-up', 'Monthly Pass', 'One Day Pass', 'Annual Pass',
       'Flex Pass', 'Testing'], dtype=object)
```

La categoria de nuestro interés es la assignada como etiqueta 2.

[606]:
```
# Obtención de variables Dummies de las variables categóricas
df_model_dummies = df_model.drop(['passholder_type'], axis = 1)
df_model_dummies = pd.get_dummies(df_model_dummies, drop_first = True)
```

[607]:
```
df_model_dummies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 700000 entries, 0 to 699999
Data columns (total 34 columns):
```

```
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   duration                        700000 non-null  int64
 1   hour_of_day                     700000 non-null  int64
 2   distance                        700000 non-null  float64
 3   geo_1                           700000 non-null  float64
 4   geo_2                           700000 non-null  float64
 5   geo_3                           700000 non-null  float64
 6   geo_4                           700000 non-null  float64
 7   passholder_type_cat             700000 non-null  int32
 8   trip_route_category_Round Trip  700000 non-null  uint8
 9   year_2017                       700000 non-null  uint8
 10  year_2018                       700000 non-null  uint8
 11  year_2019                       700000 non-null  uint8
 12  year_2020                       700000 non-null  uint8
 13  year_2021                       700000 non-null  uint8
 14  month_2                         700000 non-null  uint8
 15  month_3                         700000 non-null  uint8
 16  month_4                         700000 non-null  uint8
 17  month_5                         700000 non-null  uint8
 18  month_6                         700000 non-null  uint8
 19  month_7                         700000 non-null  uint8
 20  month_8                         700000 non-null  uint8
 21  month_9                         700000 non-null  uint8
 22  month_10                        700000 non-null  uint8
 23  month_11                        700000 non-null  uint8
 24  month_12                        700000 non-null  uint8
 25  day_of_week_1                   700000 non-null  uint8
 26  day_of_week_2                   700000 non-null  uint8
 27  day_of_week_3                   700000 non-null  uint8
 28  day_of_week_4                   700000 non-null  uint8
 29  day_of_week_5                   700000 non-null  uint8
 30  day_of_week_6                   700000 non-null  uint8
 31  distance_cat_medium             700000 non-null  uint8
 32  distance_cat_short              700000 non-null  uint8
 33  duration_cat_much               700000 non-null  uint8
dtypes: float64(5), int32(1), int64(2), uint8(26)
memory usage: 57.4 MB
```

[608]:
```python
# Escritura de los datos
df_model_dummies.to_csv('./df_model_dummies.csv')
print('File Saved')
```

```
File Saved
```

[2]:
```python
# Lectura de los datos, en caso de ser necesario
# df_model_dummies = pd.read_csv('./df_model_dummies.csv')
# df_model_dummies.drop('Unnamed: 0', axis = 1, inplace = True)
```

```
# print('File Opened')
```

[622]:
```
# Las columnas iniciales consideradas para el modelo son:
features = df_model_dummies.drop('passholder_type_cat', axis = 1).columns
features
```

[622]:
```
Index(['duration', 'hour_of_day', 'distance', 'geo_1', 'geo_2', 'geo_3',
       'geo_4', 'trip_route_category_Round Trip', 'year_2017', 'year_2018',
       'year_2019', 'year_2020', 'year_2021', 'month_2', 'month_3', 'month_4',
       'month_5', 'month_6', 'month_7', 'month_8', 'month_9', 'month_10',
       'month_11', 'month_12', 'day_of_week_1', 'day_of_week_2',
       'day_of_week_3', 'day_of_week_4', 'day_of_week_5', 'day_of_week_6',
       'distance_cat_medium', 'distance_cat_short', 'duration_cat_much'],
      dtype='object')
```

[623]:
```
X = df_model_dummies.drop('passholder_type_cat', axis = 1).values
y = df_model_dummies['passholder_type_cat'] # La variable target será␣
↪passholder_type_cat es decir, passholder_type transformada a etiqueta
```

[624]:
```
X.shape, y.shape
```

[624]:
```
((700000, 33), (700000,))
```

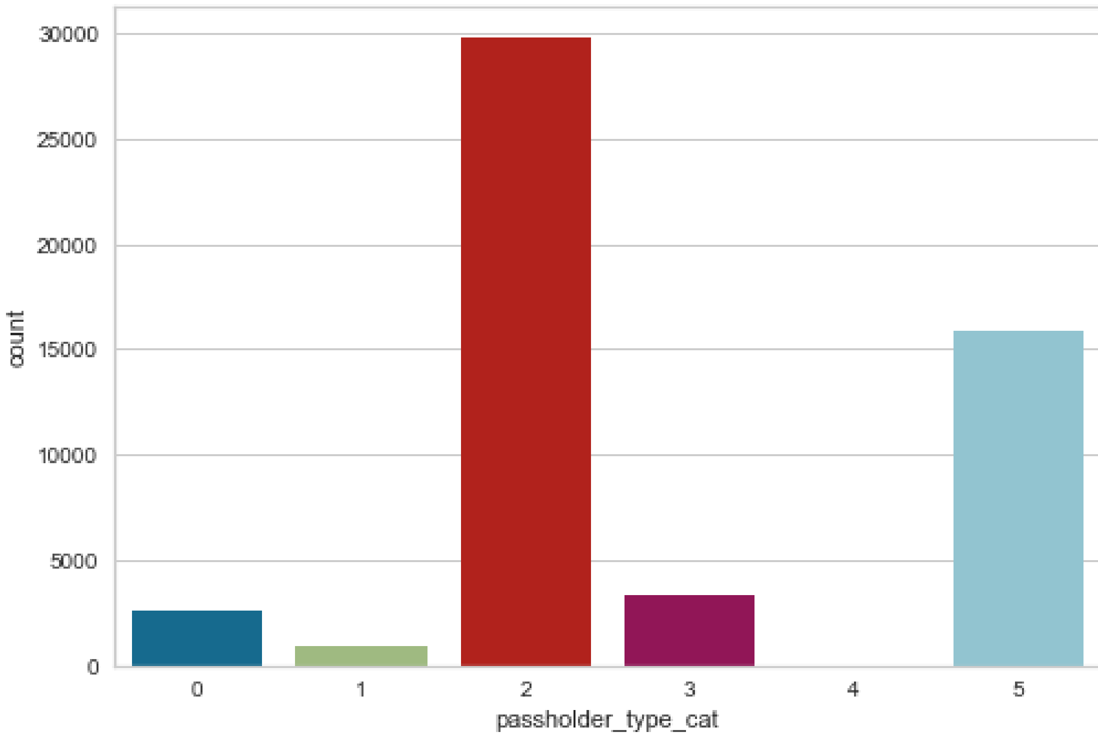
Dado que se tiene una gran cantidad de información seleccionaremos una muestra de manera aleatoria para entrenar nuestro modelo, el resto servirá para hacer una simulación y medir la eficiencia del modelo en datos que nunca ha visto.

[625]:
```
X_simulation, X_new, y_simulation, y_new = train_test_split(X, y, test_size = 0.
↪075, stratify = y, random_state = 42)
```

[626]:
```
X_simulation.shape, X_new.shape
```

[626]:
```
((647500, 33), (52500, 33))
```

[627]:
```
sns.countplot(y_new)
plt.show()
```




Claramente hay una desbalanceo en las categorías, por lo que utilizaremos una técnica de oversampling.

[628]:
```
%%time
smote = SMOTE(random_state = 42, n_jobs = -1)
X_over, y_over = smote.fit_resample(X_new, y_new)
```

```
Wall time: 7.18 s
```

[629]:
```
X_over.shape
```

[629]:
```
(178806, 33)
```

## 1.4 Feature Selection

[630]:
```
X_train, X_test, y_train, y_test = train_test_split(X_over, y_over, test_size =␣
 ↪0.3, stratify = y_over)
```

Dado que se crearon muchas variables puede existir redundancia en ellas, para evitarlo usaremos una técnica de selección de variables iterativa, mediante RandomForest.

[631]:
```
%%time
rfe = RFE(RandomForestClassifier(random_state = 42), n_features_to_select = 28)
rfe.fit(X_train, y_train)
print('Features Selected')
```

```
Features Selected
Wall time: 3min 35s
```

[632]:
```python
# Guardamos el modelo
joblib.dump(rfe, './MODELS/selection.pkl')
print('Model Saved')
```

```
Model Saved
```

[8]:
```python
# Lectura del modelo en caso de ser necesario
# rfe = joblib.load('./MODELS/selection.pkl')
```

[633]:
```python
X_train_rfe = rfe.transform(X_train)
X_test_rfe = rfe.transform(X_test)
```

[716]:
```python
selected_features = []
for i in range(X_over.shape[1]):
    if rfe.support_[i]:
        print(features[i])
        selected_features.append(features[i])
```

```
duration
hour_of_day
distance
geo_1
geo_2
geo_3
geo_4
trip_route_category_Round Trip
year_2017
year_2018
year_2019
year_2020
year_2021
month_3
month_4
month_5
month_6
month_10
month_12
day_of_week_1
day_of_week_2
day_of_week_3
day_of_week_4
day_of_week_5
day_of_week_6
distance_cat_medium
distance_cat_short
duration_cat_much
```

Observamos que las variables númericas que se crearon, fueron consideradas importantes dentro del modelo, sin embargo se eliminaron algunas categóricas creadas como variables dummies.

## 1.5 Modeling

### 1.5.1 Baseline

[635]:
```
%%time
print(datetime.now().time())

lr = LogisticRegression(max_iter = 10000)
lr.fit(X_train_rfe, y_train)
y_pred = lr.predict(X_test_rfe)
accuracy_score(y_test,y_pred)
```

```
11:28:11.454793
Wall time: 10min 15s
Parser   : 108 ms
```

[635]:
```
0.6090749785615749
```

Es un score relativamente malo, y fué un tiempo bastante largo, por lo que se probarán métodos ensemble.

### 1.5.2 Advanced Models

[636]:
```
%%time
print(datetime.now().time())

rf = RandomForestClassifier(random_state = 42)
rf.fit(X_train_rfe, y_train)
y_pred = rf.predict(X_test_rfe)
rf.score(X_test_rfe, y_test)
```

```
11:39:16.566280
Wall time: 39.7 s
```

[636]:
```
0.8785839454159055
```

[ ]:
```
%%time
print(datetime.now().time())

gb = GradientBoostingClassifier()
gb.fit(X_train_rfe, y_train)
y_pred = gb.predict(X_test_rfe)
gb.score(X_test_rfe, y_test)
```

[639]:
```
%%time
print(datetime.now().time())

```

```
xgb = XGBClassifier(eval_metric = 'logloss')
xgb.fit(X_train_rfe, y_train)
y_pred = xgb.predict(X_test_rfe)
xgb.score(X_test_rfe, y_test)
```

```
11:45:53.877577
Wall time: 41.6 s
```

[639]: 0.8427165280936579

### 1.5.3 Hyperparameters

[640]:
```
params1 = {
        'max_depth':range(5, 14, 2),
         'min_child_weight':[6, 7]
        }
```

[641]:
```
%%time
print(datetime.now().time())

grid = GridSearchCV(estimator = XGBClassifier(eval_metric = 'logloss'),
                param_grid = params1,
                scoring = 'accuracy',
                cv = 10,
                verbose = 4)

grid.fit(X_train_rfe, y_train)
```

```
11:47:14.178929
Fitting 10 folds for each of 10 candidates, totalling 100 fits
[CV 1/10] END ..max_depth=5, min_child_weight=6;, score=0.825 total time=  33.0s
[CV 2/10] END ..max_depth=5, min_child_weight=6;, score=0.827 total time=  34.9s
[CV 3/10] END ..max_depth=5, min_child_weight=6;, score=0.830 total time=  33.9s
[CV 4/10] END ..max_depth=5, min_child_weight=6;, score=0.821 total time=  33.4s
[CV 5/10] END ..max_depth=5, min_child_weight=6;, score=0.823 total time=  34.0s
[CV 6/10] END ..max_depth=5, min_child_weight=6;, score=0.822 total time=  33.9s
[CV 7/10] END ..max_depth=5, min_child_weight=6;, score=0.827 total time=  34.1s
[CV 8/10] END ..max_depth=5, min_child_weight=6;, score=0.820 total time=  39.0s
[CV 9/10] END ..max_depth=5, min_child_weight=6;, score=0.826 total time=  38.6s
[CV 10/10] END .max_depth=5, min_child_weight=6;, score=0.823 total time=  33.7s
[CV 1/10] END ..max_depth=5, min_child_weight=7;, score=0.819 total time=  34.2s
[CV 2/10] END ..max_depth=5, min_child_weight=7;, score=0.827 total time=  34.3s
[CV 3/10] END ..max_depth=5, min_child_weight=7;, score=0.831 total time=  34.3s
[CV 4/10] END ..max_depth=5, min_child_weight=7;, score=0.821 total time=  34.5s
[CV 5/10] END ..max_depth=5, min_child_weight=7;, score=0.822 total time=  33.8s
[CV 6/10] END ..max_depth=5, min_child_weight=7;, score=0.822 total time=  34.4s
[CV 7/10] END ..max_depth=5, min_child_weight=7;, score=0.824 total time=  33.7s
[CV 8/10] END ..max_depth=5, min_child_weight=7;, score=0.823 total time=  36.4s
```

```
[CV 9/10] END ..max_depth=5, min_child_weight=7;, score=0.826 total time=  33.8s
[CV 10/10] END .max_depth=5, min_child_weight=7;, score=0.823 total time=  36.5s
[CV 1/10] END ..max_depth=7, min_child_weight=6;, score=0.852 total time=  49.2s
[CV 2/10] END ..max_depth=7, min_child_weight=6;, score=0.857 total time= 1.0min
[CV 3/10] END ..max_depth=7, min_child_weight=6;, score=0.859 total time=  53.0s
[CV 4/10] END ..max_depth=7, min_child_weight=6;, score=0.851 total time=  59.2s
[CV 5/10] END ..max_depth=7, min_child_weight=6;, score=0.854 total time= 1.4min
[CV 6/10] END ..max_depth=7, min_child_weight=6;, score=0.850 total time= 1.2min
[CV 7/10] END ..max_depth=7, min_child_weight=6;, score=0.853 total time=  53.2s
[CV 8/10] END ..max_depth=7, min_child_weight=6;, score=0.850 total time=  56.0s
[CV 9/10] END ..max_depth=7, min_child_weight=6;, score=0.853 total time=  56.4s
[CV 10/10] END .max_depth=7, min_child_weight=6;, score=0.854 total time=  46.2s
[CV 1/10] END ..max_depth=7, min_child_weight=7;, score=0.849 total time=  47.4s
[CV 2/10] END ..max_depth=7, min_child_weight=7;, score=0.858 total time=  46.0s
[CV 3/10] END ..max_depth=7, min_child_weight=7;, score=0.860 total time=  46.7s
[CV 4/10] END ..max_depth=7, min_child_weight=7;, score=0.849 total time=  59.1s
[CV 5/10] END ..max_depth=7, min_child_weight=7;, score=0.851 total time=  51.4s
[CV 6/10] END ..max_depth=7, min_child_weight=7;, score=0.847 total time=  45.2s
[CV 7/10] END ..max_depth=7, min_child_weight=7;, score=0.853 total time=  45.3s
[CV 8/10] END ..max_depth=7, min_child_weight=7;, score=0.852 total time=  45.1s
[CV 9/10] END ..max_depth=7, min_child_weight=7;, score=0.854 total time=  45.8s
[CV 10/10] END .max_depth=7, min_child_weight=7;, score=0.853 total time=  45.5s
[CV 1/10] END ..max_depth=9, min_child_weight=6;, score=0.866 total time= 1.0min
[CV 2/10] END ..max_depth=9, min_child_weight=6;, score=0.874 total time=  58.9s
[CV 3/10] END ..max_depth=9, min_child_weight=6;, score=0.876 total time= 1.1min
[CV 4/10] END ..max_depth=9, min_child_weight=6;, score=0.867 total time=  59.0s
[CV 5/10] END ..max_depth=9, min_child_weight=6;, score=0.872 total time= 1.1min
[CV 6/10] END ..max_depth=9, min_child_weight=6;, score=0.866 total time= 1.0min
[CV 7/10] END ..max_depth=9, min_child_weight=6;, score=0.871 total time=  58.1s
[CV 8/10] END ..max_depth=9, min_child_weight=6;, score=0.872 total time=  58.2s
[CV 9/10] END ..max_depth=9, min_child_weight=6;, score=0.871 total time=  57.5s
[CV 10/10] END .max_depth=9, min_child_weight=6;, score=0.869 total time=  58.2s
[CV 1/10] END ..max_depth=9, min_child_weight=7;, score=0.866 total time=  59.2s
[CV 2/10] END ..max_depth=9, min_child_weight=7;, score=0.872 total time=  58.3s
[CV 3/10] END ..max_depth=9, min_child_weight=7;, score=0.873 total time=  58.2s
[CV 4/10] END ..max_depth=9, min_child_weight=7;, score=0.867 total time=  58.8s
[CV 5/10] END ..max_depth=9, min_child_weight=7;, score=0.871 total time= 1.0min
[CV 6/10] END ..max_depth=9, min_child_weight=7;, score=0.864 total time= 1.1min
[CV 7/10] END ..max_depth=9, min_child_weight=7;, score=0.870 total time=  57.6s
[CV 8/10] END ..max_depth=9, min_child_weight=7;, score=0.868 total time=  58.2s
[CV 9/10] END ..max_depth=9, min_child_weight=7;, score=0.872 total time=  59.5s
[CV 10/10] END .max_depth=9, min_child_weight=7;, score=0.868 total time=  57.4s
[CV 1/10] END .max_depth=11, min_child_weight=6;, score=0.878 total time= 1.2min
[CV 2/10] END .max_depth=11, min_child_weight=6;, score=0.882 total time= 1.2min
[CV 3/10] END .max_depth=11, min_child_weight=6;, score=0.881 total time= 1.2min
[CV 4/10] END .max_depth=11, min_child_weight=6;, score=0.877 total time= 1.2min
[CV 5/10] END .max_depth=11, min_child_weight=6;, score=0.879 total time= 1.3min
[CV 6/10] END .max_depth=11, min_child_weight=6;, score=0.876 total time= 1.2min
```

```
[CV 7/10] END .max_depth=11, min_child_weight=6;, score=0.878 total time= 1.2min
[CV 8/10] END .max_depth=11, min_child_weight=6;, score=0.879 total time= 1.2min
[CV 9/10] END .max_depth=11, min_child_weight=6;, score=0.879 total time= 1.2min
[CV 10/10] END max_depth=11, min_child_weight=6;, score=0.882 total time= 1.2min
[CV 1/10] END .max_depth=11, min_child_weight=7;, score=0.875 total time= 1.2min
[CV 2/10] END .max_depth=11, min_child_weight=7;, score=0.886 total time= 1.2min
[CV 3/10] END .max_depth=11, min_child_weight=7;, score=0.884 total time= 1.4min
[CV 4/10] END .max_depth=11, min_child_weight=7;, score=0.875 total time= 1.2min
[CV 5/10] END .max_depth=11, min_child_weight=7;, score=0.877 total time= 1.2min
[CV 6/10] END .max_depth=11, min_child_weight=7;, score=0.877 total time= 1.2min
[CV 7/10] END .max_depth=11, min_child_weight=7;, score=0.879 total time= 1.2min
[CV 8/10] END .max_depth=11, min_child_weight=7;, score=0.875 total time= 1.2min
[CV 9/10] END .max_depth=11, min_child_weight=7;, score=0.877 total time= 1.2min
[CV 10/10] END max_depth=11, min_child_weight=7;, score=0.879 total time= 1.2min
[CV 1/10] END .max_depth=13, min_child_weight=6;, score=0.884 total time= 1.6min
[CV 2/10] END .max_depth=13, min_child_weight=6;, score=0.886 total time= 1.4min
[CV 3/10] END .max_depth=13, min_child_weight=6;, score=0.887 total time= 1.4min
[CV 4/10] END .max_depth=13, min_child_weight=6;, score=0.880 total time= 2.0min
[CV 5/10] END .max_depth=13, min_child_weight=6;, score=0.882 total time= 1.7min
[CV 6/10] END .max_depth=13, min_child_weight=6;, score=0.879 total time= 1.4min
[CV 7/10] END .max_depth=13, min_child_weight=6;, score=0.884 total time= 1.4min
[CV 8/10] END .max_depth=13, min_child_weight=6;, score=0.880 total time= 1.5min
[CV 9/10] END .max_depth=13, min_child_weight=6;, score=0.882 total time= 1.4min
[CV 10/10] END max_depth=13, min_child_weight=6;, score=0.886 total time= 1.4min
[CV 1/10] END .max_depth=13, min_child_weight=7;, score=0.881 total time= 1.5min
[CV 2/10] END .max_depth=13, min_child_weight=7;, score=0.886 total time= 1.5min
[CV 3/10] END .max_depth=13, min_child_weight=7;, score=0.886 total time= 1.4min
[CV 4/10] END .max_depth=13, min_child_weight=7;, score=0.879 total time= 1.4min
[CV 5/10] END .max_depth=13, min_child_weight=7;, score=0.883 total time= 1.5min
[CV 6/10] END .max_depth=13, min_child_weight=7;, score=0.880 total time= 1.3min
[CV 7/10] END .max_depth=13, min_child_weight=7;, score=0.881 total time= 1.4min
[CV 8/10] END .max_depth=13, min_child_weight=7;, score=0.881 total time= 1.4min
[CV 9/10] END .max_depth=13, min_child_weight=7;, score=0.880 total time= 1.4min
[CV 10/10] END max_depth=13, min_child_weight=7;, score=0.885 total time= 1.4min
Wall time: 1h 44min 38s
Parser   : 174 ms
```

[641]:
```
GridSearchCV(cv=10,
             estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     enable_categorical=False,
                                     eval_metric='logloss', gamma=None,
                                     gpu_id=None, importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=None, max_delta_step=None,
```

```
                                     max_depth=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs=None,
                                     num_parallel_tree=None, predictor=None,
                                     random_state=None, reg_alpha=None,
                                     reg_lambda=None, scale_pos_weight=None,
                                     subsample=None, tree_method=None,
                                     validate_parameters=None, verbosity=None),
             param_grid={'max_depth': range(5, 14, 2),
                         'min_child_weight': [6, 7]},
             scoring='accuracy', verbose=4)
```

[642]:
```
grid.best_params_
```

[642]:
```
{'max_depth': 13, 'min_child_weight': 6}
```

[643]:
```
clf = grid.best_estimator_
```

[644]:
```
joblib.dump(clf, './MODELS/classifier.pkl')
```

[644]:
```
['./MODELS/classifier.pkl']
```

[114]:
```
clf = joblib.load('./MODELS/classifier.pkl')
```

[645]:
```
clf.score(X_test_rfe, y_test)
```

[645]:
```
0.8881659893367138
```

[646]:
```
clf
```

[646]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              eval_metric='logloss', gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.300000012,
              max_delta_step=0, max_depth=13, min_child_weight=6, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=8,
              num_parallel_tree=1, objective='multi:softprob', predictor='auto',
              random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=None,
              subsample=1, tree_method='exact', validate_parameters=1,
              verbosity=None)
```

### 1.5.4 Model Evaluation

**Stratified k-fold CV**

[649]:
```
kfold = StratifiedKFold(n_splits=10, shuffle=True,
                        random_state=42).split(X_test_rfe,y_test)
```

[651]:
```
scores = []

for k, (train,test) in enumerate(kfold):
    clf.fit(X_test_rfe[train], np.array(y_test)[train])
    score = clf.score(X_test_rfe[test], np.array(y_test)[test])
    scores.append(score)

    print("Fold #{}, Tamaño:{}, Acc:{}".format(k+1,
                                          np.bincount(np.array(y_test)[train]),
                                              score))

print("Mean Acc CV: {} +/- {}".format(np.mean(scores), np.std(scores)))
```

```
Fold #1, Tamaño:[8047 8046 8046 8046 8046 8046], Acc:0.8430568499534017
Fold #2, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8542132736763609
Fold #3, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8473154362416108
Fold #4, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8540268456375839
Fold #5, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8581282624906786
Fold #6, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8435868754660701
Fold #7, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8489932885906041
Fold #8, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8465697240865027
Fold #9, Tamaño:[8047 8046 8046 8046 8046 8047], Acc:0.8463832960477256
Mean Acc CV: 0.849141539132282 +/- 0.004896783593324223
```

**Simulation set** A continuación pondremos a prueba el modelo seleccionado sobre el resto de las filas no usadas en el entrenamiento.

[652]:
```
X_simulation.shape
```

[652]:
```
(647500, 33)
```

[656]:
```
X_simulation_rfe = rfe.transform(X_simulation)
```

[657]:
```
y_pred = clf.predict(X_simulation_rfe)
```

[658]:
```
accuracy_score(y_simulation, y_pred)
```

[658]:
```
0.6689590733590733
```

Definitivamente es un modelo que puede mejorarse, cosiderando la creación de nuevos features mediante la ubicación. También es un modelo que puede ser mejorado mediante la colección de más datos, considerando cuestiones demográficas, por ejemplo o incluso socieconómicas del usuario. Otra manera de mejorar el score es intentando probar modelos con herramientas de big data como PySpark o con un mayor poder computacional que permita tomar un conjunto de entrenamiento mucho más grande.