Data Collection and Storage (SQL)

Project description

You're working as an analyst for Zuber, a new ride-sharing company that's launching in Chicago. Your task is to find patterns in the available information. You want to understand passenger preferences and the impact of external factors on rides. You'll study a database, analyze data from competitors, and test a hypothesis about the impact of weather on ride frequency.

In [1]:
```
#load libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import random as random


from functools import reduce
from math import factorial
from scipy import stats as st
from statistics import mean
from IPython.display import display
from random import sample


pd.set_option('display.max_columns', 500)
```

In [2]:
```
#load all data
company_rides = pd.read_csv('/datasets/project_sql_result_01.csv')
data_dropoff = pd.read_csv('/datasets/project_sql_result_04.csv')
```

Now let's have a look at this data.

In [3]:
```
company_rides.sample(15)
```

Out[3]:

	company_name	trips_amount
30	Setare Inc	230
40	6574 - Babylon Express Inc.	31
44	2092 - 61288 Sbeih Company	27
9	Blue Ribbon Taxi Association Inc.	5953
0	Flash Cab	19558
15	Checker Taxi Affiliation	2216
25	Top Cab Affiliation	978
33	Metro Jet Taxi A	146
29	303 Taxi	250
54	2192 - 73487 Zeymane Corp	14
63	3556 - 36214 RC Andrews Cab	2
18	24 Seven Taxi	1775
45	3011 - 66308 JBL Cab Inc.	25
34	Norshore Cab	127
39	0118 - 42111 Godfrey S. Awir	33

In [4]:
```
company_rides.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64 entries, 0 to 63
Data columns (total 2 columns):
company_name    64 non-null object
trips_amount    64 non-null int64
dtypes: int64(1), object(1)
memory usage: 1.1+ KB
```

In [5]:
```
company_rides.describe(include='all')
```

Out[5]:

	company_name	trips_amount
count	64	64.000000
unique	64	NaN
top	Chicago Taxicab	NaN
freq	1	NaN
mean	NaN	2145.484375
std	NaN	3812.310186
min	NaN	2.000000
25%	NaN	20.750000
50%	NaN	178.500000
75%	NaN	2106.500000
max	NaN	19558.000000

No dublicates found and all formats for this dataset look OK.

In [6]:
```
data_dropoff.sample(15)
```

Out[6]:

	dropoff_location_name	average_trips
9	Sheffield & DePaul	1259.766667
55	Dunning	30.166667
33	Portage Park	119.733333
45	Boystown	53.966667
62	Brighton Park	19.466667
25	Irving Park	296.566667
82	South Deering	7.500000
36	Kenwood	89.366667
43	Mckinley Park	64.033333
1	River North	9523.666667
61	Grand Crossing	22.600000
11	East Village	1212.066667
22	Lincoln Square	356.733333
13	Uptown	849.666667
86	West Elsdon	5.666667

In [7]:
```
data_dropoff.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 94 entries, 0 to 93
Data columns (total 2 columns):
dropoff_location_name    94 non-null object
average_trips            94 non-null float64
dtypes: float64(1), object(1)
memory usage: 1.6+ KB
```

In [8]:
```
data_dropoff.describe(include='all')
```

Out[8]:

	dropoff_location_name	average_trips
count	94	94.000000
unique	94	NaN
top	Streeterville	NaN
freq	1	NaN
mean	NaN	599.953728
std	NaN	1714.591098
min	NaN	1.800000
25%	NaN	14.266667
50%	NaN	52.016667
75%	NaN	298.858333
max	NaN	10727.466667

Same here. No dublicates found and all formats look okay. I already see that there is a huge spread between amount of trips taken to different neighboorhoods.

identify the top 10 neighborhoods in terms of drop-offs and make graph.

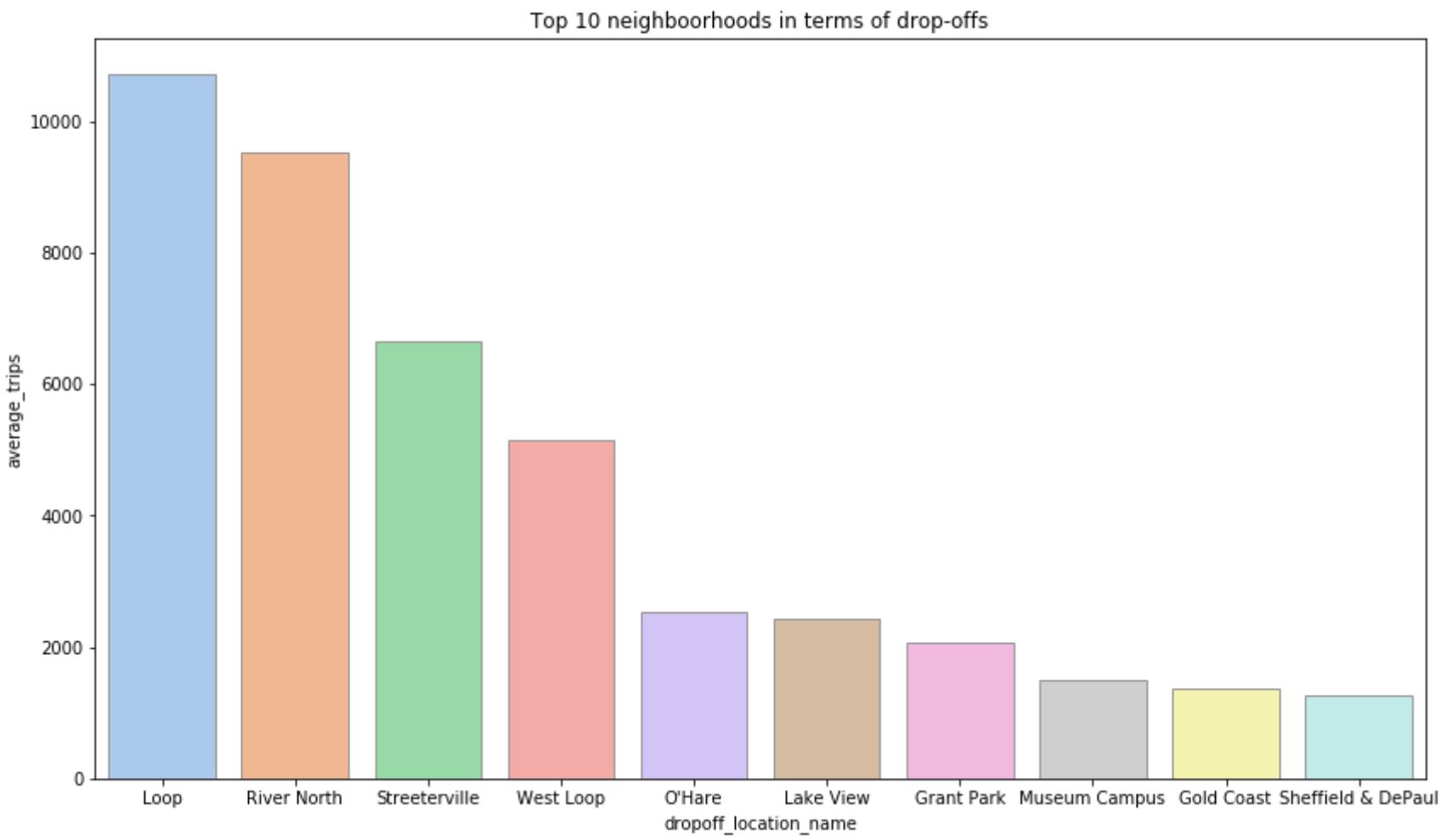
In [9]:
```
top_neighboorhoods=data_dropoff.sort_values(by='average_trips', ascending=False).head(10).round(2)

top_neighboorhoods
```

Out[9]:

	dropoff_location_name	average_trips
0	Loop	10727.47
1	River North	9523.67
2	Streeterville	6664.67
3	West Loop	5163.67
4	O'Hare	2546.90
5	Lake View	2420.97
6	Grant Park	2068.53
7	Museum Campus	1510.00
8	Gold Coast	1364.23
9	Sheffield & DePaul	1259.77

In [10]:
```
fig, ax = plt.subplots(figsize=(14,8))
ax.set_title('Top 10 neighboorhoods in terms of drop-offs')
sns.catplot(data=top_neighboorhoods, x="dropoff_location_name", y='average_trips', kind="bar", palette="pastel",
            edgecolor=".6", ax=ax)
plt.close(2);
```

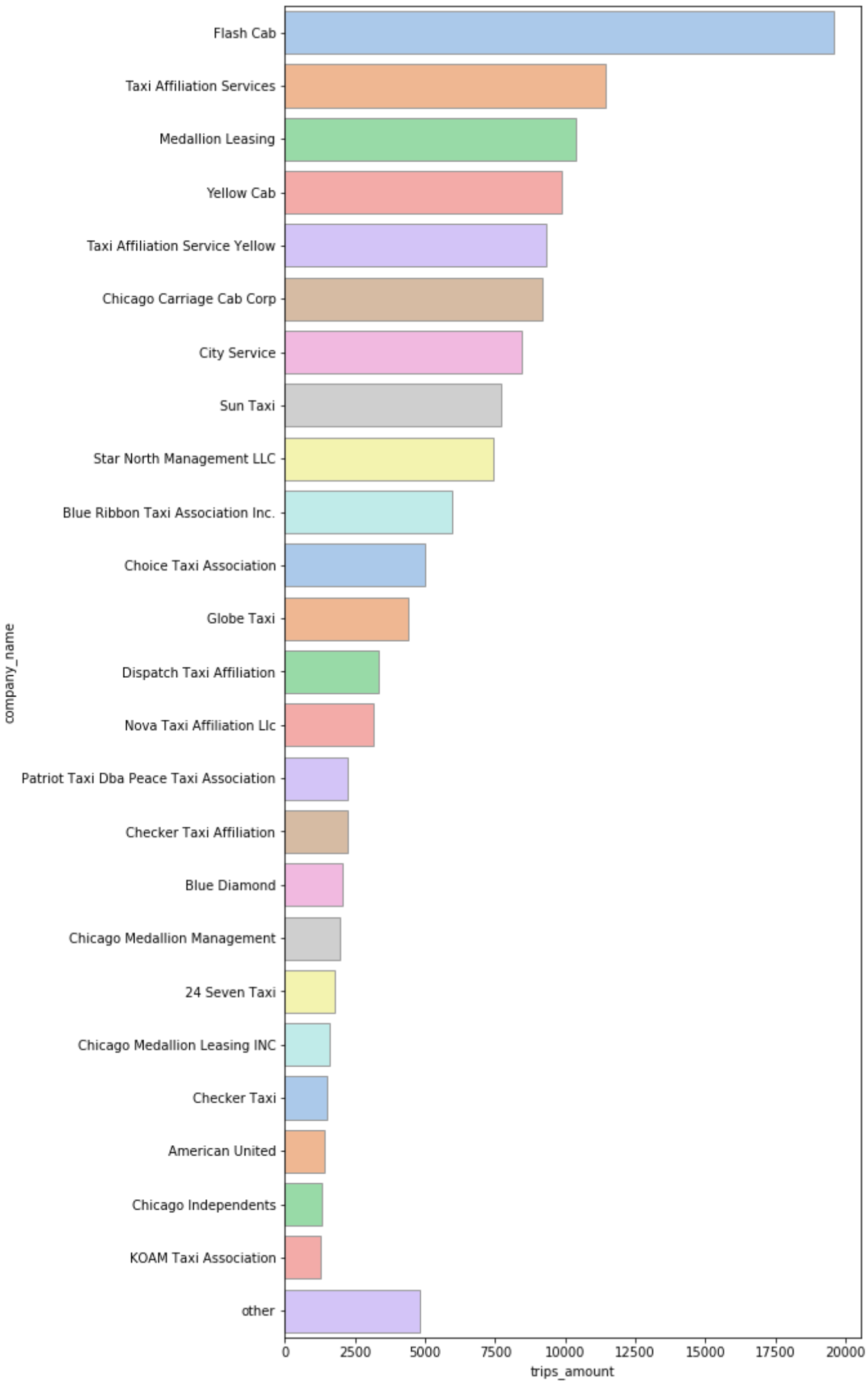


This plot shows us that the 4 most popular neighbourhoods are much more popular than other ones. Loop neighboorhood gets almost 10 times more dropoffs than Sheffield & DePaul.

Make graph for taxi companies and number of rides.

In [11]:
```
#group all companies that have less than 1100 trips to other
df = (company_rides.query('trips_amount >=1100')
            .append(pd.Series(['other',company_rides.query('trips_amount<1100').trips_amount.sum()],
                              index = ['company_name','trips_amount']), ignore_index=True))

fig, ax1 = plt.subplots(figsize=(8,19))
ax.set_title('Trips amounts for different companies')
sns.catplot(data=df, y="company_name", x='trips_amount', kind="bar", palette="pastel", edgecolor=".6",
            ax=ax1)
plt.close(2);
```



From this data I see that Flash cab is a definite leader with a much higher amount of rides than their competitors. And also the market is mostly rulled by big companies, small companies even combined don't give comparabile amount of rides to bigger ones.

Step 5. Testing hypotheses (Python)

Test the hypothesis:

"The average duration of rides from the Loop to O'Hare International Airport changes on rainy Saturdays."

In [12]:
```
# import new dataframe
data = pd.read_csv('/datasets/project_sql_result_07.csv')
#look at sample
data.sample(15)
```

Out[12]:

	start_ts	weather_conditions	duration_seconds
62	2017-11-11 06:00:00	Good	1260.0
932	2017-11-04 12:00:00	Good	3180.0
495	2017-11-18 16:00:00	Bad	2940.0
347	2017-11-11 17:00:00	Good	2460.0
1021	2017-11-11 10:00:00	Good	1330.0
207	2017-11-11 08:00:00	Good	1200.0
408	2017-11-11 11:00:00	Good	1320.0
921	2017-11-04 17:00:00	Bad	2518.0
886	2017-11-11 18:00:00	Good	1978.0
147	2017-11-04 16:00:00	Bad	3180.0
830	2017-11-11 08:00:00	Good	1440.0
861	2017-11-04 16:00:00	Bad	2760.0
514	2017-11-11 15:00:00	Good	2800.0
988	2017-11-11 08:00:00	Good	1392.0
961	2017-11-11 14:00:00	Good	2491.0

In [13]:
```
#convert date to datetime
data['start_ts']=pd.to_datetime(data.start_ts, format='%Y-%m-%d %H:%M:%S')
```

In [14]:
```
#Check what days of week are in the dataframe
data.start_ts.dt.dayofweek.value_counts()
```

Out[14]:
```
5    1068
Name: start_ts, dtype: int64
```

Seems like all the days in the dataframe are saturday, which is good for us, because that's all we need. Now let's create two lists: one with data for rainy saturdays, one with data for other saturdays. But firstly let's check amount of rainy days compaired to sunny ones.

In [15]:
```
data.weather_conditions.value_counts()
```

Out[15]:
```
Good    888
Bad     180
Name: weather_conditions, dtype: int64
```

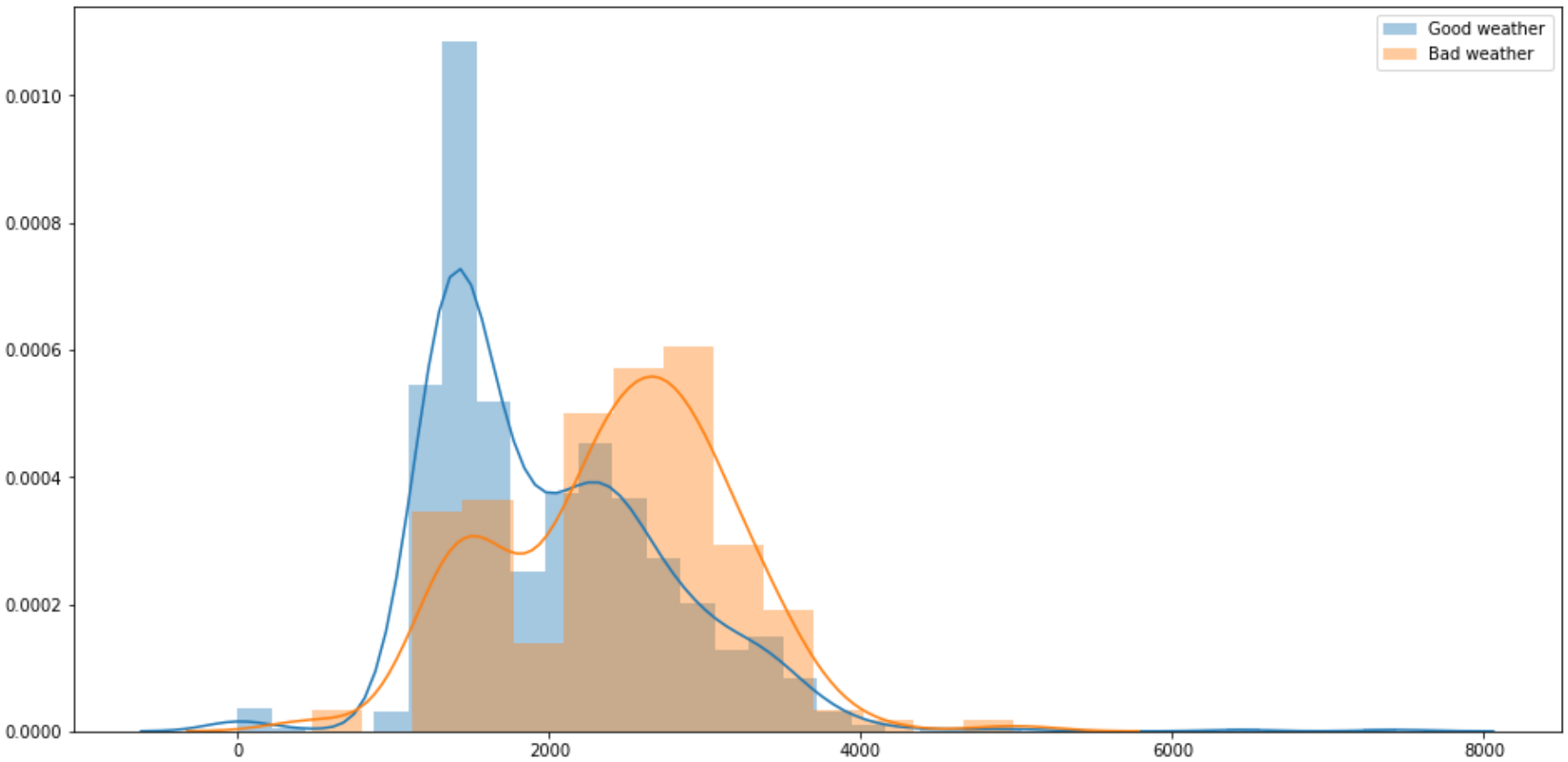
In [16]:
```
bad_weather = data.query('weather_conditions == "Bad"')['duration_seconds'].dropna().tolist()
good_weather = data.query('weather_conditions == "Good"')['duration_seconds'].dropna().tolist()
```

In [17]:
```
#check how does the data look
fig, ax = plt.subplots(figsize=(16,8))
sns.distplot(good_weather, label='Good weather');
sns.distplot(bad_weather, label='Bad weather');
plt.legend();

print ("Amount of values for good weather:", len(good_weather))
print ("Amount of values for bad weather:", len(bad_weather))

print ('Variance of ride length for good weather: {:.2f}'.format(np.var(good_weather)))
print ('Variance of ride length for bad weather: {:.2f}'.format(np.var(bad_weather)))
print ('Average ride length for good weather: {:.2f}'.format(mean(good_weather)))
print ('Average ride length for bad weather: {:.2f}'.format(mean(bad_weather)))
```

```
Amount of values for good weather: 888
Amount of values for bad weather: 180
Variance of ride length for good weather: 575732.93
Variance of ride length for bad weather: 517403.56
Average ride length for good weather: 1999.68
Average ride length for bad weather: 2427.21
```



There are much more good weather days in the dataset than rainy ones. To test a theory we are going to need equal samples. Therefore I will take a random sample with length values for data with good weather.

In [18]:
```
good_weather = random.sample(good_weather, len(bad_weather))
```

We can already see that these samples don't have quite normal distribution, and also even based on the graphs they are pretty different. Here A-B test is not the best tool to use for testing, but unfortunatly we don't know how to do other tests, therefore I will use it.

Now I need to form a Null hypothesis. Null hypothesis should be positive, therefore here right null hypothesis will be:

"The average duration of rides from the Loop to O'Hare International Airport is the same on rainy Saturdays as it is on not rainy saturdays"

In [19]:
```
alpha = .05 # critical statistical significance level
                        # if the p-value is less than alpha, we reject the hypothesis



results = st.ttest_ind(
    good_weather,
    bad_weather, equal_var = False)

print('p-value: {:.8f}'.format(results.pvalue))

if results.pvalue < alpha:
        print("We reject the null hypothesis")
else:
        print("We can't reject the null hypothesis")
```

```
p-value: 0.00000020
We reject the null hypothesis
```

Conclusion

Based on out test I can say thet the average duration of rides from the Loop to O'Hare International Airport on rainy Saturdays is not the same as average duration of rides on sunny Saturdays.