Project 1 - Yellow Taxi's

Find a dataset to use

The dataset chosen was the January 2024 dataset for yellow taxis in New York City. I selected this dataset because I find the US fascinating, with how different it is from the UK. I wanted to see if I could learn something new about the differences. This dataset provided a great opportunity to explore taxi patterns in New York City.

https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

Troubles

Problem: The dataset is a format called parquet, its can't read using read_csv since its a different format

Solution: **Use pip to install Pyarrow or Fast Parquet**. I choose Pyarrow since its more recommended, its said to have better performance and **adpotion**.

Imports

In [ ]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import numpy as np
```

In [ ]:

```
file_path = 'yellow_tripdata_2024-01.parquet'
df = pd.read_parquet(file_path)
```

In [ ]:

```
df.head() # It works
```

Out[ ]:

	VendorID	tpep_pickup_datetime	tpep_dropoff_datetime	passenger_count	trip_distance	Rateco
0	2	2024-01-01 00:57:55	2024-01-01 01:17:43	1.0	1.72	
1	1	2024-01-01 00:03:00	2024-01-01 00:09:36	1.0	1.80	
2	1	2024-01-01 00:17:06	2024-01-01 00:35:01	1.0	4.70	
3	1	2024-01-01 00:36:38	2024-01-01 00:44:56	1.0	1.40	
4	1	2024-01-01 00:46:51	2024-01-01 00:52:57	1.0	0.80	

Slight investigation

In [ ]:

```
df.columns
```

Out[ ]:
```
Index(['VendorID', 'tpep_pickup_datetime', 'tpep_dropoff_datetime',
       'passenger_count', 'trip_distance', 'RatecodeID', 'store_and_fwd_flag',
       'PULocationID', 'DOLocationID', 'payment_type', 'fare_amount', 'extra',
       'mta_tax', 'tip_amount', 'tolls_amount', 'improvement_surcharge',
       'total_amount', 'congestion_surcharge', 'Airport_fee'],
      dtype='object')
```

In [ ]:
```
df.shape
```

Out[ ]:
```
(2964624, 19)
```

In [ ]:
```
# Calculate the number of NaN values in each column
na_counts = df.isna().sum()

# Filter the counts to show only columns with more than 0 NaN values
na_counts_filtered = na_counts[na_counts > 0]

# Display the filtered results
na_counts_filtered

# There's 5 columns to be careful of when working with them.
# Airport_Fee makes sense since not everyone pays one,
# Congestion_surcharge is fine for the same reason

# Passenger_count shouldn't have missing entryies and is something to be considerec
# However its definetly suspicious all 5 columns have the same number of missing er
```

Out[ ]:
```
passenger_count         140162
RatecodeID              140162
store_and_fwd_flag      140162
congestion_surcharge    140162
Airport_fee             140162
dtype: int64
```

Given the large volume of data available (2964624 Rows Nearly 3 Million and 19 Columns), our results are likely to be reliable.

Deciding which columns to drop

Before going further I should decide which columns I would like to investigate first and what questions I want to answer. Doing this now stops me from cleaning data that I will not end up using data so its best to do it now.

First I would like to do General analysis.

- 1) What are the busiest times of day for pickups and drop-offs? (Analyze tpep_pickup_datetime and tpep_dropoff_datetime)

- 2) How does trip distance vary by time of day or day of the week? (tpep_pickup_datetime, trip_distance)

I would like to do more but I will choose more questions later on. So each question will have its own dataset since they need different columns dropped

Busiest times for pickups and drops

We need the columns, 'tpep_pickup_datetime', 'tpep_dropoff_datetime'

In [ ]:
```
df_q1 = df[['tpep_pickup_datetime', 'tpep_dropoff_datetime']].copy()
df_q1.head()

# Copy is VERY IMPORTANT to ensure that df_q1 is a separate object from the origina
# Without .copy(), df_q1 would be a view of the original DataFrame. This means that
# made to df_q1 would also affect the original DataFrame (df) and vice versa. By us
# we create an independent DataFrame that we can modify without impacting the origi
```

Out[ ]:

	tpep_pickup_datetime	tpep_dropoff_datetime
0	2024-01-01 00:57:55	2024-01-01 01:17:43
1	2024-01-01 00:03:00	2024-01-01 00:09:36
2	2024-01-01 00:17:06	2024-01-01 00:35:01
3	2024-01-01 00:36:38	2024-01-01 00:44:56
4	2024-01-01 00:46:51	2024-01-01 00:52:57

In [ ]:
```
df_q1.info()
# The data types for the two columns are both datetime64.
# This appropriate for our question to investigate busiest times
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2964624 entries, 0 to 2964623
Data columns (total 2 columns):
 #   Column                 Dtype
---  ------                 -----
 0   tpep_pickup_datetime   datetime64[us]
 1   tpep_dropoff_datetime  datetime64[us]
dtypes: datetime64[us](2)
memory usage: 45.2 MB
```

Lets count how many pickups occured in each hour across the month. Like which ones where picked at 9 etc.

In [ ]:
```
# Make a row of pick up hours
df_q1["pickup_hour"] = df_q1["tpep_pickup_datetime"].dt.hour
# This line gives an error if "copy()" was not implemented earlier.

df_q1.head()
```

Out[ ]:

	tpep_pickup_datetime	tpep_dropoff_datetime	pickup_hour
0	2024-01-01 00:57:55	2024-01-01 01:17:43	0
1	2024-01-01 00:03:00	2024-01-01 00:09:36	0
2	2024-01-01 00:17:06	2024-01-01 00:35:01	0
3	2024-01-01 00:36:38	2024-01-01 00:44:56	0
4	2024-01-01 00:46:51	2024-01-01 00:52:57	0

In [ ]:
```
# Group by the hour and count the occurrences
hourly_pickup_counts = df_q1['pickup_hour'].value_counts().sort_index()

# Convert the Series to a DataFrame so we can see 2 columns
hourly_pickup_counts_df = hourly_pickup_counts.reset_index()
# Reset index turns the index of unique values into a column, thus into a df too.
```

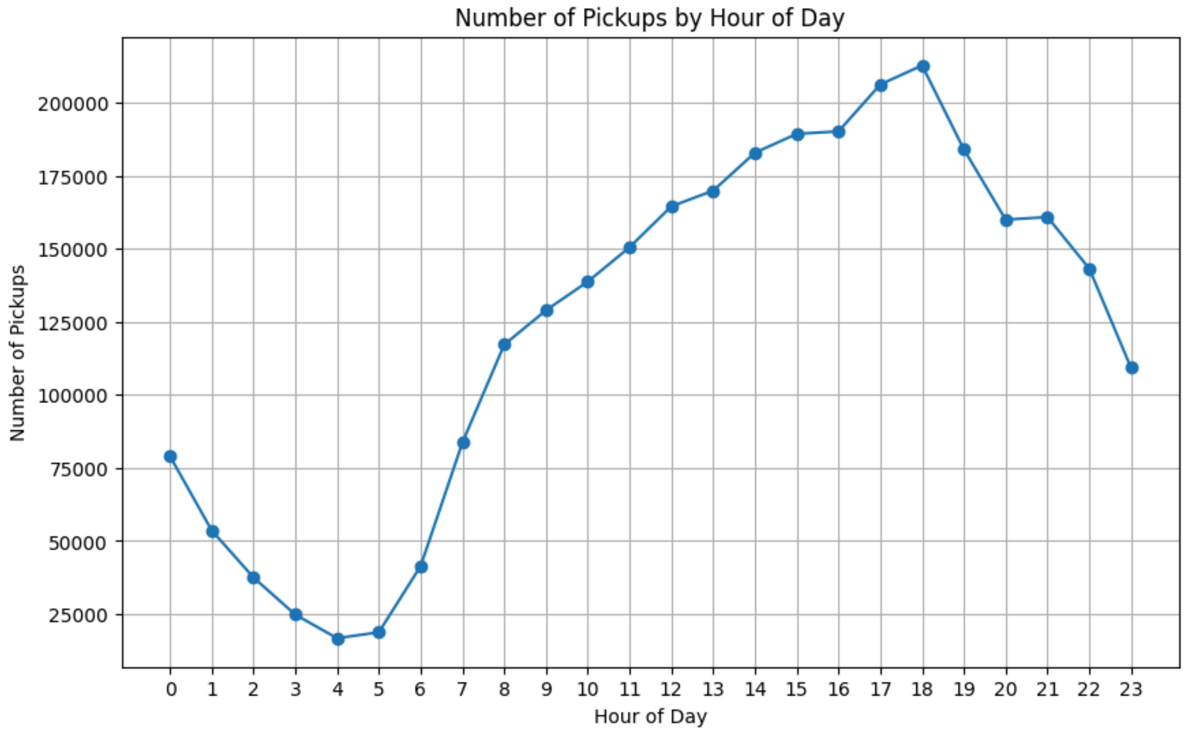
```
# Name the new column
hourly_pickup_counts_df.columns = ['Hour', 'Pickup_Count']

print(hourly_pickup_counts_df)
```

```
    Hour  Pickup_Count
0      0         79094
1      1         53627
2      2         37517
3      3         24811
4      4         16742
5      5         18764
6      6         41429
7      7         83719
8      8        117209
9      9        128970
10    10        138778
11    11        150542
12    12        164559
13    13        169903
14    14        182898
15    15        189359
16    16        190201
17    17        206257
18    18        212788
19    19        184032
20    20        159989
21    21        160888
22    22        143261
23    23        109287
```

In [ ]:

```
# Plot the data
plt.figure(figsize=(10, 6))
plt.plot(hourly_pickup_counts.index, hourly_pickup_counts.values, marker='o')
plt.title('Number of Pickups by Hour of Day')
plt.xlabel('Hour of Day')
plt.ylabel('Number of Pickups')
plt.xticks(range(0, 24))  # Ensure x-axis shows each hour from 0 to 23
plt.grid(True)
plt.show()
```



We can see that the lowest number of pickups occured during 4-5 AM. The highest at 4-5 PM

This pattern is quite symmetrical.

How does trip distance vary across day of the week?

I also need to check for events during the month of January that could lead to anomalies.

In [ ]:
```
df_q2 = df[["tpep_pickup_datetime", "trip_distance"]].copy()
df_q2.head()
```

Out[ ]:

	tpep_pickup_datetime	trip_distance
0	2024-01-01 00:57:55	1.72
1	2024-01-01 00:03:00	1.80
2	2024-01-01 00:17:06	4.70
3	2024-01-01 00:36:38	1.40
4	2024-01-01 00:46:51	0.80

In [ ]:
```
df_q2['day_of_week'] = df_q2['tpep_pickup_datetime'].dt.day_name()
df_q2.head()
```

Out[ ]:

	tpep_pickup_datetime	trip_distance	day_of_week
0	2024-01-01 00:57:55	1.72	Monday
1	2024-01-01 00:03:00	1.80	Monday
2	2024-01-01 00:17:06	4.70	Monday
3	2024-01-01 00:36:38	1.40	Monday
4	2024-01-01 00:46:51	0.80	Monday

In [ ]:

```
df_q2["day_of_week"].value_counts().sort_values(ascending=False)
```

Out[ ]:

```
day_of_week
Wednesday    495032
Tuesday      463664
Thursday     428593
Saturday     421158
Friday       408588
Monday       408277
Sunday       339312
Name: count, dtype: int64
```

Although the results suggest that wednesday is the day with the most work during January with the highest count this is not true.

The reasons for this is that Monday, Tuesday and Wednesday all had 5 days during the month whilist the others had 4 so this is unfair.

To make it fair we need to divide the results for each column appropriately.

In [ ]:

```
print(495032/5)
# A figure used to check if division below worked.
```

```
99006.4
```

In [ ]:

```
# Get the count of each day
day_counts = df_q2["day_of_week"].value_counts()

# Define division factors
division_factors = {'Monday': 5, 'Tuesday': 5, 'Wednesday': 5, 'Thursday': 4, 'Fric

# Apply the division based on the division factors
adjusted_counts = day_counts.map(lambda count: count / division_factors.get(day_cou

# Sort the adjusted counts from largest to smallest
sorted_adjusted_counts = adjusted_counts.sort_values(ascending=False)

# Print the sorted adjusted counts
print(sorted_adjusted_counts)
```

```
day_of_week
Thursday     107148.25
Saturday     105289.50
Friday       102147.00
Wednesday     99006.40
Tuesday       92732.80
Sunday        84828.00
Monday        81655.40
Name: count, dtype: float64
```

We can see clearly that wednesday was in act not the day with the most activity but instead it was wednesday. Dividing reasonably has changed are results and made them more correct on which days are the most busy.

In [ ]:
```
df_q2.groupby('day_of_week')['trip_distance'].mean()
```

Out[ ]:
```
day_of_week
Friday       3.603720
Monday       3.680769
Saturday     3.313225
Sunday       3.805528
Thursday     3.473969
Tuesday      4.149548
Wednesday    3.540238
Name: trip_distance, dtype: float64
```

People travel further by taxi on tuesdays.

More Questions

Can I analyse location or are they all unique? (Unique returns unique values, nunique returns the number)

In [ ]:
```
df.shape
```

Out[ ]:
```
(2964624, 19)
```

In [ ]:
```
df["PULocationID"].nunique()
```

Out[ ]:
```
260
```

In [ ]:
```
df["PULocationID"].unique()
```

Out[ ]:
```
array([186, 140, 236,  79, 211, 148, 138, 246, 161, 113, 107, 158,  68,
        90, 132, 164, 237, 141, 263,   4, 238, 239, 233, 162, 262, 137,
       142, 229, 163, 234, 114, 232, 249,  43, 143,  48, 170,  50, 151,
        13,  66,  24, 144,  88, 166, 261,  75,  70,  42, 256, 209, 231,
       222,  87, 224, 265,  14, 125,  63,   7, 264,  41,  12,  74, 116,
       226, 244, 100,  40, 255, 216, 190, 215,  80,  52, 127, 169, 145,
        65,  25, 131, 260,  45,  78, 112, 181, 194,  33, 242,  93,  49,
       152,  83,  97, 136,  18,  20, 106, 243,  17, 146,  39, 223,  82,
       168, 126,  61,  47, 159, 189,  36, 179, 198,  77, 202, 188, 129,
       230,  89, 123, 228, 195, 225,  55,  95,  81, 247, 177,  37, 153,
       173,   6,  19, 157, 196,  69,  94, 217,  34, 193, 227, 251,  92,
        85, 197,  10, 117,  22,   9,  28, 248,  91, 178, 111, 165,  32,
         1,  72, 119,  62,  21,  86,  76, 130,  35,  64, 235, 205, 207,
       180, 135, 121, 134, 219, 212, 160,  67,  56, 257, 258, 124, 108,
       241, 167, 254, 250, 218, 252, 200, 182,  51, 128, 149,  26, 154,
       174,  71,  96,  60, 175, 253,  38, 203,  73, 139, 183, 201,  98,
         3, 122,  29, 210, 213, 208, 171,  23, 220, 192,  16, 155, 191,
        11, 133, 259, 150, 147,   8, 185, 240,  53,  54, 102,  31,  46,
        15,   2,  44, 101,  59, 156, 118, 176,  30, 184, 172, 120,  84,
        57,  27, 187,  58, 105, 221, 206, 199, 245, 214, 115, 204, 109],
      dtype=int32)
```

I have found a CSV that turns the ID given into, "Borough","Zone","service_zone".

Importing CSV

In [ ]:
```
location_df = pd.read_csv("taxi_zone_lookup.csv")
location_df.head()
```

Out[ ]:

	LocationID	Borough	Zone	service_zone
0	1	EWR	Newark Airport	EWR
1	2	Queens	Jamaica Bay	Boro Zone
2	3	Bronx	Allerton/Pelham Gardens	Boro Zone
3	4	Manhattan	Alphabet City	Yellow Zone
4	5	Staten Island	Arden Heights	Boro Zone

In [ ]:
```
location_df.tail()
```

Out[ ]:

	LocationID	Borough	Zone	service_zone
260	261	Manhattan	World Trade Center	Yellow Zone
261	262	Manhattan	Yorkville East	Yellow Zone
262	263	Manhattan	Yorkville West	Yellow Zone
263	264	Unknown	NaN	NaN
264	265	NaN	Outside of NYC	NaN

263 IS UNKNOWN 264 IS OUTSIDE OF NEW YORK CITY

This table is for where people are picked up.

Question: How frequently are airport fees applied to trips, and which locations are most affected?

In [ ]:
```
#df_q2.groupby('day_of_week')['trip_distance']
```

In [ ]:
```
df_q3 = df[["Airport_fee", "PULocationID", "DOLocationID"]].copy()
df_q3.head()
```

Out[ ]:

	Airport_fee	PULocationID	DOLocationID
0	0.0	186	79
1	0.0	140	236
2	0.0	236	79
3	0.0	79	211
4	0.0	211	148

In [ ]:
```
df_q3['is_airport_fee'] = np.where(df_q3['Airport_fee'] > 0, 'yes', 'no')
df_q3.head()
```

Out[ ]:

	Airport_fee	PULocationID	DOLocationID	is_airport_fee
0	0.0	186	79	no
1	0.0	140	236	no
2	0.0	236	79	no
3	0.0	79	211	no
4	0.0	211	148	no

In [ ]:

```
df_q3["is_airport_fee"].value_counts()
# Counts unique values
```

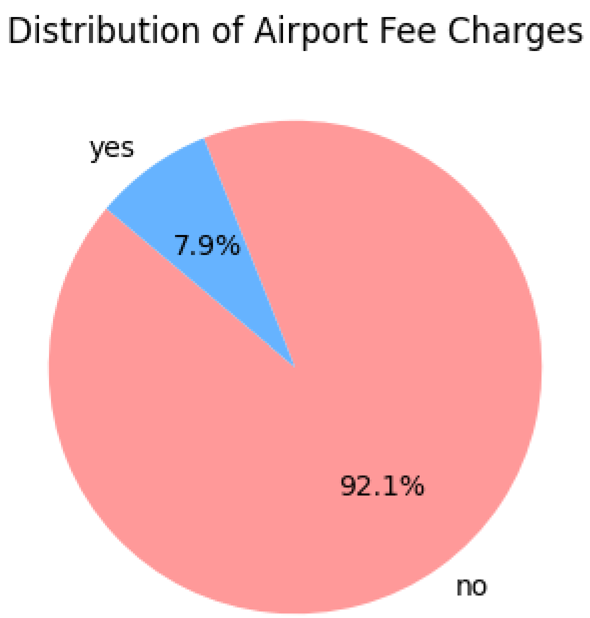
Out[ ]:

```
is_airport_fee
no     2731872
yes     232752
Name: count, dtype: int64
```

In [ ]:

```
fee_counts = df_q3["is_airport_fee"].value_counts()

# Create a pie chart
plt.figure(figsize=(4, 4))
plt.pie(fee_counts, labels=fee_counts.index, autopct='%1.1f%%', startangle=140, col
plt.title('Distribution of Airport Fee Charges')
plt.show()
```



I want to investigate which Borough's airport fee's where most frequent in.

In [ ]:

```
df_q3_5 = df_q3.copy() # DONT RERUN THIS
df_q3 = df_q3.merge(location_df, left_on='PULocationID', right_on='LocationID', how
```

In [ ]:

```
df_q3.head()
```

Out[ ]:

	Airport_fee	PULocationID	DOLocationID	is_airport_fee	LocationID	Borough	Zone
0	0.0	186	79	no	186	Manhattan	Penn Station/Madison Sq West
1	0.0	140	236	no	140	Manhattan	Lenox Hill East
2	0.0	236	79	no	236	Manhattan	Upper East Side North
3	0.0	79	211	no	79	Manhattan	East Village
4	0.0	211	148	no	211	Manhattan	SoHo

In [ ]:

```
# Filter by yes
df_airport_fee_yes = df_q3[df_q3['is_airport_fee'] == 'yes']
```

In [ ]:

```
df_airport_fee_yes["Borough"].value_counts()
# Queens has the highest airport fees leaving.
```

Out[ ]:

```
Borough
Queens           232263
Manhattan           244
Unknown             204
Brooklyn             28
Staten Island         1
Bronx                 1
Name: count, dtype: int64
```

In [ ]:

```
df_q4 = df_q3_5.merge(location_df, left_on="DOLocationID", right_on='LocationID', h
df_q4.head()
```

Out[ ]:

	Airport_fee	PULocationID	DOLocationID	is_airport_fee	LocationID	Borough	Zone	service
0	0.0	186	79	no	79	Manhattan	East Village	Yellow
1	0.0	140	236	no	236	Manhattan	Upper East Side North	Yellow
2	0.0	236	79	no	79	Manhattan	East Village	Yellow
3	0.0	79	211	no	211	Manhattan	SoHo	Yellow
4	0.0	211	148	no	148	Manhattan	Lower East Side	Yellow

In [ ]:

```
# Filter by yes
df_airport_fee_yes_DO = df_q4[df_q4['is_airport_fee'] == 'yes']

df_airport_fee_yes_DO["Borough"].value_counts()
# Queens has the highest airport fees leaving.
```

Out[ ]:
```
Borough
Manhattan        136613
Queens            46068
Brooklyn          36756
Bronx              5144
Unknown             535
Staten Island       320
EWR                 305
Name: count, dtype: int64
```

Conclusion

Throughout this project, I gained valuable insights and skills, particularly regarding taxi patterns in New York City. Here are the key takeaways:

- Peak Times: Taxis are busiest between 4-5 PM and least busy between 4-5 AM.
- Airport Fees:
  - Most passengers paying airport fees and getting picked up are from Queens.
  - Most passengers paying airport fees and being dropped off are headed to Manhattan.
- Busy Days: Thursday is the busiest day for taxi drivers, indicating it’s an optimal day for finding taxi work.

Additionally, I learned about more efficient file formats for large datasets, such as Parquet files, which can be more effective than CSV files.