1

November 23, 2023

1 Workbook

Use this notebook to complete the exercises throughout the workshop.

Table of Contents

1.0.1 Section 1

Exercise 1.1

Create a DataFrame by reading in the `2019_Yellow_Taxi_Trip_Data.csv` file. Examine the first 5 rows.

[ ]:
```
import pandas as pd
df = pd.read_csv("2019_Yellow_Taxi_Trip_Data.csv")
df[:5]
```

[ ]:
```
   vendorid     tpep_pickup_datetime    tpep_dropoff_datetime  \
0         2  2019-10-23T16:39:42.000  2019-10-23T17:14:10.000
1         1  2019-10-23T16:32:08.000  2019-10-23T16:45:26.000
2         2  2019-10-23T16:08:44.000  2019-10-23T16:21:11.000
3         2  2019-10-23T16:22:44.000  2019-10-23T16:43:26.000
4         2  2019-10-23T16:45:11.000  2019-10-23T16:58:49.000

   passenger_count  trip_distance  ratecodeid store_and_fwd_flag  \
0                1           7.93           1                  N
1                1           2.00           1                  N
2                1           1.36           1                  N
3                1           1.00           1                  N
4                1           1.96           1                  N

   pulocationid  dolocationid  payment_type  fare_amount  extra  mta_tax  \
0           138           170             1         29.5    1.0      0.5
1            11            26             1         10.5    1.0      0.5
```

```
2          163          162            1          9.5    1.0       0.5
3          170          163            1         13.0    1.0       0.5
4          163          236            1         10.5    1.0       0.5

   tip_amount  tolls_amount  improvement_surcharge  total_amount  \
0        7.98          6.12                    0.3         47.90
1        0.00          0.00                    0.3         12.30
2        2.00          0.00                    0.3         15.80
3        4.32          0.00                    0.3         21.62
4        0.50          0.00                    0.3         15.30

   congestion_surcharge
0                   2.5
1                   0.0
2                   2.5
3                   2.5
4                   2.5
```

Exercise 1.2

Find the dimensions (number of rows and number of columns) in the data.

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

[ ]:
```
(10000, 18)
```

Exercise 1.3

Using the data in the `2019_Yellow_Taxi_Trip_Data.csv` file, calculate summary statistics for the `fare_amount`, `tip_amount`, `tolls_amount`, and `total_amount` columns.

[ ]:
```
df[["fare_amount", "tip_amount", "tolls_amount", "total_amount"]].sum()
```

[ ]:
```
fare_amount     151063.13
tip_amount       26344.94
tolls_amount      6234.47
total_amount    225646.59
dtype: float64
```

Exercise 1.4

Isolate the `fare_amount`, `tip_amount`, `tolls_amount`, and `total_amount` for the longest trip by distance (`trip_distance`).

[ ]:
```
df.iloc[df["trip_distance"].idxmax(axis=0)][["fare_amount", "tip_amount",␣
 ↪"tolls_amount", "total_amount", "trip_distance"]]
```

[ ]:
```
fare_amount       176.0
tip_amount        18.29
```

```
tolls_amount        6.12
total_amount      201.21
trip_distance      38.11
Name: 8338, dtype: object
```

1.0.2 Section 2

Exercise 2.1

Read in the meteorite data from the `Meteorite_Landings.csv` file, rename the `mass (g)` column to `mass`, and drop all the latitude and longitude columns. Sort the result by mass in descending order.

[ ]:
```
df2 = pd.read_csv("Meteorite_Landings.csv").rename(columns={"mass (g)":
↪"mass"}).drop(columns=["reclat", "reclong"]).sort_values(by=["mass"],
↪ascending=[False])
df2
```

[ ]:
```
                  name     id nametype      recclass        mass   fall  \
16392             Hoba  11890    Valid     Iron, IVB  60000000.0  Found
5373         Cape York   5262    Valid   Iron, IIIAB  58200000.0  Found
5365    Campo del Cielo   5247    Valid  Iron, IAB-MG  50000000.0  Found
5370     Canyon Diablo   5257    Valid  Iron, IAB-MG  30000000.0  Found
3455           Armanty   2335    Valid    Iron, IIIE  28000000.0  Found
…                  …     …       …            …           …      …
38282    Wei-hui-fu (a)  24231    Valid          Iron         NaN  Found
38283    Wei-hui-fu (b)  24232    Valid          Iron         NaN  Found
38285           Weiyuan  24233    Valid  Mesosiderite         NaN  Found
41472     Yamato 792768  28117    Valid           CM2         NaN  Found
45698     Zapata County  30393    Valid          Iron         NaN  Found

                         year            GeoLocation
16392  01/01/1920 12:00:00 AM   (-19.58333, 17.91667)
5373   01/01/1818 12:00:00 AM   (76.13333, -64.93333)
5365   12/22/1575 12:00:00 AM  (-27.46667, -60.58333)
5370   01/01/1891 12:00:00 AM     (35.05, -111.03333)
3455   01/01/1898 12:00:00 AM            (47.0, 88.0)
…                         …                      …
38282  01/01/1931 12:00:00 AM                    NaN
38283  01/01/1931 12:00:00 AM                    NaN
38285  01/01/1978 12:00:00 AM   (35.26667, 104.31667)
41472  01/01/1979 12:00:00 AM      (-71.5, 35.66667)
45698  01/01/1930 12:00:00 AM           (27.0, -99.0)

[45716 rows x 8 columns]
```

Exercise 2.2

Using the meteorite data from the `Meteorite_Landings.csv` file, update the `year` column to only contain the year, convert it to a numeric data type, and create a new column indicating whether the meteorite was observed falling before 1970. Set the index to the `id` column and extract all the rows with IDs between 10,036 and 10,040 (inclusive) with `loc[]`. **Hint 1**: Use `year.str.slice()` to grab a substring.

Hint 2: Make sure to sort the index before using `loc[]` to select the range.

Bonus: There's a data entry error in the `year` column. Can you find it? (Don't spend too much time on this.)

[ ]:

```
cleanedDf = df2.copy()
cleanedDf['year'] = cleanedDf['year'].apply(lambda x: int(x[6:11]) if␣
↪isinstance(x, str) else x)
# cleanedDf['year'] = cleanedDf['year'].map(lambda x: x[6:11],␣
↪na_action='ignore')
cleanedDf['before_1970'] = cleanedDf['year'].map(lambda y: y < 1970)
cleanedDf.set_index('id', inplace=True)

rows = cleanedDf.loc[(cleanedDf.index >= 10036) & (cleanedDf.index <= 10040)]
contains_non_string = df2.apply(lambda x: x.name if not isinstance(x['year'],␣
↪str) else None, axis=1).dropna()
contains_non_string
rows
```

[ ]:

```
            name nametype          recclass      mass   fall    year  \
id
10039  Ensisheim    Valid               LL6  127000.0   Fell  1491.0
10038     Enshi     Valid                H5    8000.0   Fell  1974.0
10037      Enon     Valid  Iron, ungrouped     763.0  Found  1883.0
10036    Enigma     Valid                H4      94.0  Found  1967.0

                  GeoLocation  before_1970
id
10039       (47.86667, 7.35)         True
10038          (30.3, 109.5)        False
10037     (39.86667, -83.95)         True
10036  (31.33333, -82.31667)         True
```

Exercise 2.3

Using the meteorite data from the `Meteorite_Landings.csv` file, create a pivot table that shows both the number of meteorites and the 95th percentile of meteorite mass for those that were found versus observed falling per year from 2005 through 2009 (inclusive). Hint: Be sure to convert the `year` column to a number as we did in the previous exercise.

[ ]:

```
```

```
dfConverted = df2.copy()
dfConverted['year'] = dfConverted['year'].apply(lambda x: x[6:11] if␣
 ↪isinstance(x, str) else x)
dfConverted['year'] = pd.to_numeric(dfConverted['year'], errors='coerce')
dfConverted = dfConverted[(dfConverted['year'] >= 2005) & (dfConverted['year']␣
 ↪<= 2009)]

dfConverted

pivot_table = pd.pivot_table(dfConverted,
                              values=['mass'],
                              index=['year'],
                              columns=['fall'],
                              aggfunc={'mass': ['count', ('95%-Quantil', lambda␣
 ↪x: pd.Series.quantile(x, q=0.95))]}, fill_value=0)

# pivot_table.columns = ['fall_count_found', 'fall_count_observed',␣
 ↪'95th_percentile_found', '95th_percentile_observed']


pivot_table
```

[ ]:

```
                 mass
        95%-Quantil          count
fall           Fell    Found  Fell Found
year
2005.0          0.0  4500.00     0   874
2006.0      25008.0  1600.50     5  2450
2007.0      89675.0  1126.90     8  1181
2008.0     106000.0  2274.80     9   948
2009.0       8333.4  1397.25     5  1492
```

Exercise 2.4

Using the meteorite data from the `Meteorite_Landings.csv` file, compare summary statistics of the mass column for the meteorites that were found versus observed falling.

[ ]:

```
dfCompare = df2.copy()
grouped = dfCompare.groupby('fall')['mass'].describe(include='all')
grouped
```

[ ]:

```
          count          mean            std  min     25%     50%      75%  \
fall
Fell     1075.0  47070.715023  717067.125826  0.1  686.00  2800.0  10450.0
Found   44510.0  12461.922983  571105.752311  0.0    6.94    30.5    178.0

              max
```

```
fall
Fell    23000000.0
Found   60000000.0
```

Exercise 2.5

Using the taxi trip data in the `2019_Yellow_Taxi_Trip_Data.csv` file, resample the data to an hourly frequency based on the dropoff time. Calculate the total `trip_distance`, `fare_amount`, `tolls_amount`, and `tip_amount`, then find the 5 hours with the most tips.

[ ]:
```
df4 = pd.read_csv("2019_Yellow_Taxi_Trip_Data.csv",␣
 ↪parse_dates=['tpep_dropoff_datetime'])
df4 = df4.assign(hour=lambda x: x["tpep_dropoff_datetime"].dt.strftime('%H'))\
    .filter(["hour", "trip_distance", "fare_amount", "tolls_amount",␣
 ↪"tip_amount"])

grouped = df4.groupby("hour").sum()
grouped.sort_values(by=["tip_amount"], ascending=False).filter(["tip_amount"]).
 ↪head(5)
```

[ ]:
```
      tip_amount
hour
16      12249.32
17      12044.03
18       1907.64
15         75.10
19         25.74
```

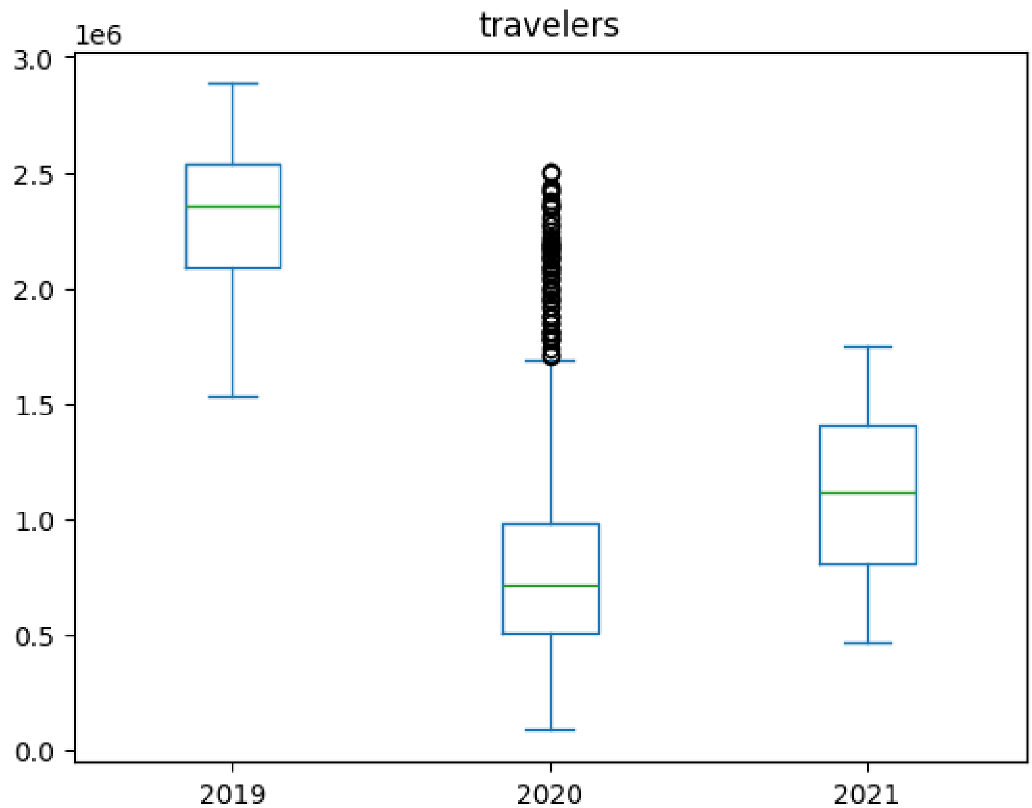
1.0.3 Section 3

Exercise 3.1

Using the TSA traveler throughput data in the `tsa_melted_holiday_travel.csv` file, create box plots for traveler throughput for each year in the data. Hint: Pass `kind='box'` into the `plot()` method to generate box plots.

[ ]:
```
dfTsa = pd.read_csv("tsa_melted_holiday_travel.csv", parse_dates=True)
dfTsa.plot(kind='box', column=["travelers"], by=["year"])
# dfTsa.boxplot(column=["travelers"], by=["year"], kind='box')
```

[ ]:
```
travelers    Axes(0.125,0.11;0.775x0.77)
dtype: object
```



Exercise 3.2

Using the TSA traveler throughput data in the `tsa_melted_holiday_travel.csv` file, create a heatmap that shows the 2019 TSA median traveler throughput by day of week and month.

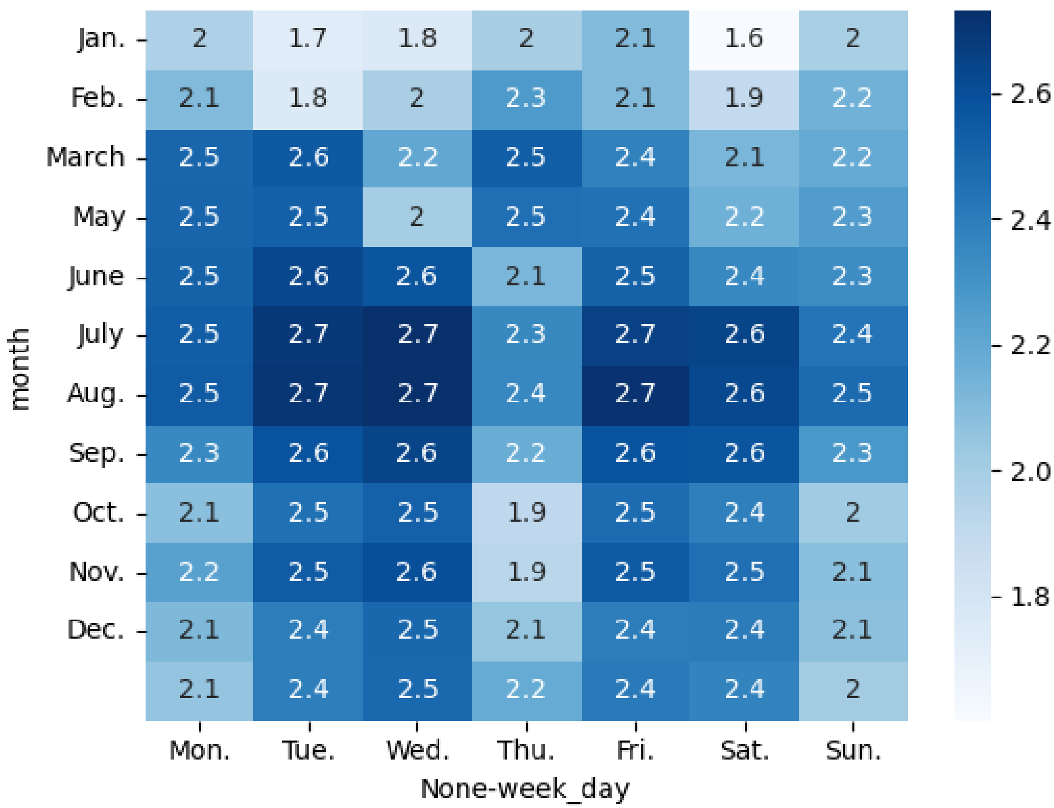
[ ]:
```
import seaborn as sns

working = pd.read_csv("tsa_melted_holiday_travel.csv", parse_dates=True)
# working.set_index('date', inplace=True) # unsere Idee, funktioniert aber nicht
working = pd.read_csv(
        'tsa_melted_holiday_travel.csv',
        parse_dates=True, index_col='date') # aus dem Internet, funktioniert.␣
 ↪Warum bzw. wo der Unterschied zu uns liegt, ist nicht ganz klar.

year2019 = working.loc['2019']
year2019 = year2019.assign(week_day=lambda x: x.index.dayofweek + 1, month=␣
 ↪lambda x: x.index.month)
year2019_pivot = year2019.pivot_table(
                                        values=['travelers'],
                                        index=['month'],
```

```
                                        columns=['week_day'], aggfunc='median'
)
sns.heatmap(data=year2019_pivot / 1e6,
            cmap='Blues',
            annot=True,
            xticklabels=["Mon.", "Tue.", "Wed.", "Thu.", "Fri.", "Sat.", "Sun.
↪"],
            yticklabels=["Jan.", "Feb.", "March", "May", "June", "July", "Aug.
↪", "Sep.", "Oct.", "Nov.", "Dec."])
```

[ ]: <Axes: xlabel='None-week_day', ylabel='month'>



Exercise 3.3

Annotate the medians in the box plot from *Exercise 3.1*. Hint: The x coordinates will be 1, 2, and 3 for 2019, 2020, and 2021, respectively. Alternatively, to avoid hardcoding values, you can use the `Axes.get_xticklabels()` method, in which case you should look at the documentation for the `Text` class.

[ ]:
```
dfTsa = pd.read_csv("tsa_melted_holiday_travel.csv", parse_dates=True)
plot = dfTsa.boxplot(column=["travelers"], by=["year"], return_type=None)
```

```
type(plot)
# plot.get_xticklabels()
```

[ ]: matplotlib.axes._axes.Axes