workbook

November 2, 2024

1 Workbook

Use this notebook to complete the exercises throughout the workshop.

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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.

[2]:
```
import pandas as pd
data = pd.read_csv('2019_Yellow_Taxi_Trip_Data.csv')
data.iloc[0:5]
```

[2]:
```
   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.

[7]:
```python
row_c = data.shape[0]
print("Rows: " + str(row_c))
```

```
Rows: 10000
```

[6]:
```python
col_c = data.shape[1]
print("Columns: " + str(col_c))
```

```
Columns: 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.

[18]:
```python
data[["fare_amount", "tip_amount", "tolls_amount", "total_amount"]].describe()
```

[18]:

	fare_amount	tip_amount	tolls_amount	total_amount
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	15.106313	2.634494	0.623447	22.564659
std	13.954762	3.409800	6.437507	19.209255
min	-52.000000	0.000000	-6.120000	-65.920000
25%	7.000000	0.000000	0.000000	12.375000
50%	10.000000	2.000000	0.000000	16.300000
75%	16.000000	3.250000	0.000000	22.880000
max	176.000000	43.000000	612.000000	671.800000

Exercise 1.4

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

[25]:
```
lt = data.loc[data["trip_distance"].idxmax()]
lt.loc[["fare_amount", "tip_amount", "tolls_amount", "total_amount"]]
```

[25]:
```
fare_amount      176.0
tip_amount       18.29
tolls_amount      6.12
total_amount    201.21
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.

[44]:
```
data = pd.read_csv('Meteorite_Landings.csv') # import data
data.rename(columns={'mass (g)': 'mass'}).drop(['reclat', 'reclong',␣
 ↪'GeoLocation'], axis=1).sort_values(by='mass')
```

[44]:
```
                 name     id nametype      recclass  mass   fall  \
31063  Österplana 050  56149   Relict     Relict OC   0.0  Found
31062  Österplana 049  56148   Relict     Relict OC   0.0  Found
31075  Österplana 062  56161   Relict     Relict OC   0.0  Found
12640            Gove  52859   Relict   Relict iron   0.0  Found
31064  Österplana 051  56150   Relict     Relict OC   0.0  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
31063  01/01/2003 12:00:00 AM
31062  01/01/2012 12:00:00 AM
31075  01/01/2010 12:00:00 AM
12640  01/01/1979 12:00:00 AM
31064  01/01/2006 12:00:00 AM
…                           …
38282  01/01/1931 12:00:00 AM
38283  01/01/1931 12:00:00 AM
38285  01/01/1978 12:00:00 AM
41472  01/01/1979 12:00:00 AM
```

```
45698  01/01/1930 12:00:00 AM

[45716 rows x 7 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.)

[ ]:
```python
# new cell for finding the error in year. It's a bit easier to work with in a␣
↪separate
# cell as the rest of the output doesn't really interest me for now
# first hunch from a previous error I got, when slicing and converting the year␣
↪column:
# there might be a null value. Let's check if there is
data.isnull().values.any() # >>> np.True_ -> there is a null/NaN value preset␣
↪in year, let's find it
data[data['year'].isnull()] # profit.
```

[72]:
```python
data['year'] = pd.to_numeric(data['year'].str.slice(6,10), errors='coerce').
↪astype('Int32')
# astype not necessarily needed, but much prettier than a float value
data['before_1970'] = data['year'] < 1970
data.set_index('id').sort_values(by='id').loc[10036:10041]
#data.set_index('id').sort_values(by='id').loc[45700] checking if NaN is␣
↪propagated as expected
```

```
              name     id nametype                 recclass  mass (g)   fall year  \
0           Aachen      1    Valid                       L5      21.0   Fell  NaN
1           Aarhus      2    Valid                       H6     720.0   Fell  NaN
2             Abee      6    Valid                      EH4  107000.0   Fell  NaN
3         Acapulco     10    Valid              Acapulcoite    1914.0   Fell  NaN
4          Achiras    370    Valid                       L6     780.0   Fell  NaN
…              …      …      …                          …         …      …    …
45711  Zillah 002  31356    Valid                  Eucrite     172.0  Found  NaN
45712      Zinder  30409    Valid  Pallasite, ungrouped      46.0  Found  NaN
45713        Zlin  30410    Valid                       H4       3.3  Found  NaN
45714   Zubkovsky  31357    Valid                       L6    2167.0  Found  NaN
45715  Zulu Queen  30414    Valid                     L3.7     200.0  Found  NaN
```

```
         reclat    reclong            GeoLocation
0      50.77500    6.08333      (50.775, 6.08333)
1      56.18333   10.23333    (56.18333, 10.23333)
2      54.21667 -113.00000     (54.21667, -113.0)
3      16.88333  -99.90000      (16.88333, -99.9)
4     -33.16667  -64.95000     (-33.16667, -64.95)
…           …          …                    …
45711  29.03700   17.01850      (29.037, 17.0185)
45712  13.78333    8.96667     (13.78333, 8.96667)
45713  49.25000   17.66667      (49.25, 17.66667)
45714  49.78917   41.50460     (49.78917, 41.5046)
45715  33.98333 -115.68333  (33.98333, -115.68333)

[45716 rows x 10 columns]
```

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.

[3]:
```
data = pd.read_csv('Meteorite_Landings.csv') # import data
data['year'] = pd.to_numeric(data['year'].str.slice(6,10), errors='coerce').
 ↪astype('Int32')
fd = data[(data['year'] >= 2005) & (data['year'] <= 2009)] # cut rows
fd = fd[['year', 'fall', 'mass (g)']] # cut columns
pt = pd.pivot_table(
    fd,
    columns=['year','fall'],
    values=['mass (g)'],
    aggfunc={'fall': ['count'],
             'mass (g)': [lambda x: x.quantile(0.95)]}
)
pt
```

[3]:
```
year                  2005     2006              2007              2008         \
fall                 Found     Fell   Found      Fell   Found       Fell   Found
fall     count       875.0      5.0  2451.0       8.0  1181.0        9.0   948.0
mass (g) <lambda>   4500.0  25008.0  1600.5   89675.0  1126.9   106000.0  2274.8

year                  2009
fall                  Fell    Found
fall     count         5.0  1492.00
mass (g) <lambda>   8333.4  1397.25
```

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.

[5]:
```
# I'm honestly not sure if the result is correct tbh
data = pd.read_csv('Meteorite_Landings.csv') # import clean data
fd = data[['mass (g)', 'fall']] # cut columns
pt = pd.pivot_table(
    fd,
    columns=['fall'],
    values=['mass (g)'],
    aggfunc={'mass (g)': 'describe'}
)
pt
```

[5]:
```
fall                    Fell         Found
mass (g) 25%    6.860000e+02  6.940000e+00
         50%    2.800000e+03  3.050000e+01
         75%    1.045000e+04  1.780000e+02
         count  1.075000e+03  4.451000e+04
         max    2.300000e+07  6.000000e+07
         mean   4.707072e+04  1.246192e+04
         min    1.000000e-01  0.000000e+00
         std    7.170671e+05  5.711058e+05
```

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.

[6]:
```
data = pd.read_csv('2019_Yellow_Taxi_Trip_Data.csv',        # import data
                parse_dates=['tpep_dropoff_datetime'],      # cast datetime
                index_col=['tpep_dropoff_datetime'])        # set index for␣
 ↪resample
data = data[[
    'trip_distance', 'fare_amount', 'tolls_amount', 'tip_amount'    # cut all␣
 ↪irrelevant rows
   ]].resample('h').sum().nlargest(                                  # resample␣
 ↪hourly, sum relevant columns
       n=5, columns='tip_amount'                                     # find␣
 ↪hours with largest tip amount
       )
data
```

[6]:
```
                       trip_distance  fare_amount  tolls_amount  tip_amount
tpep_dropoff_datetime
2019-10-23 16:00:00         10676.95     67797.76        699.04    12228.64
2019-10-23 17:00:00         16052.83     70131.91       4044.04    12044.03
```

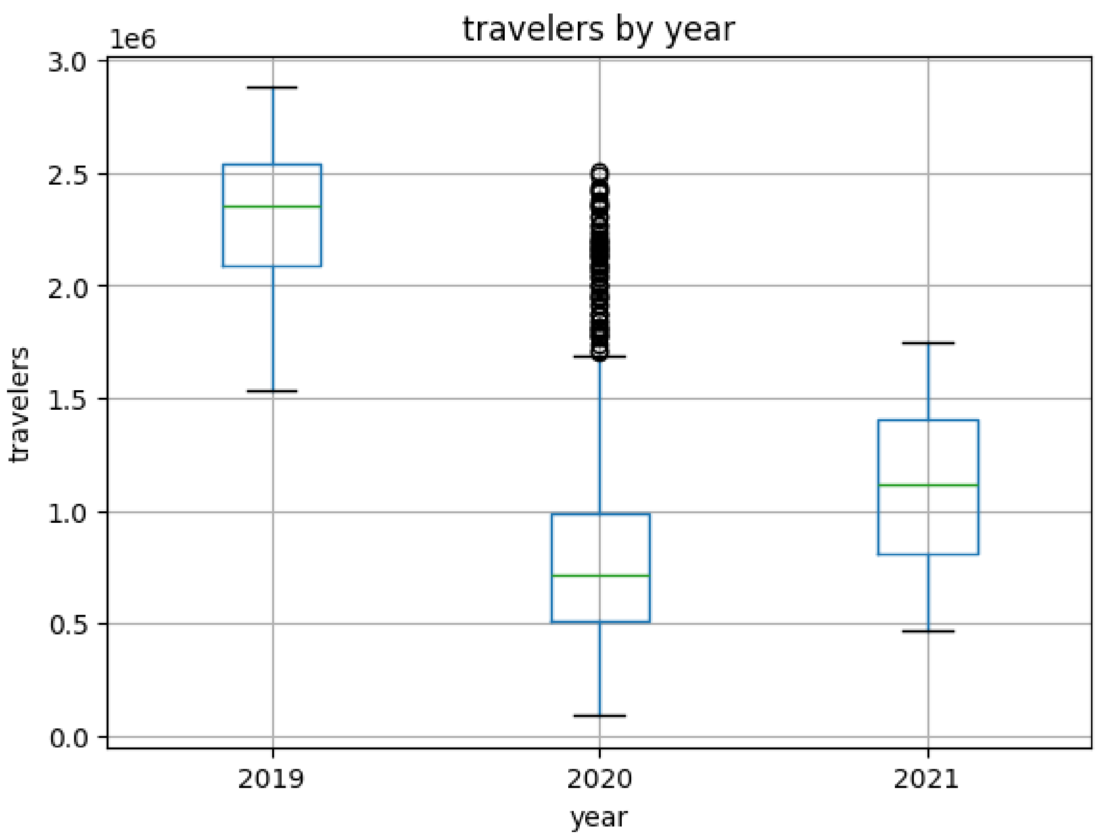
```
2019-10-23 18:00:00          3104.56      11565.56       1454.67      1907.64
2019-10-23 15:00:00            14.34        213.50          0.00        51.75
2019-10-23 19:00:00            98.59        268.00         24.48        25.74
```

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.

[7]:
```python
import matplotlib.pyplot as plt                          # import for␣
 ↪customization
data = pd.read_csv('tsa_melted_holiday_travel.csv')      # import data
data.boxplot(column='travelers', by='year')              # generate boxplot
plt.title('travelers by year')                           # change title because␣
 ↪the default title sucks
plt.suptitle('')                                         # hide the shitty␣
 ↪default title
plt.ylabel('travelers')                                  # add y label
plt.show()                                               # show plt changes
```



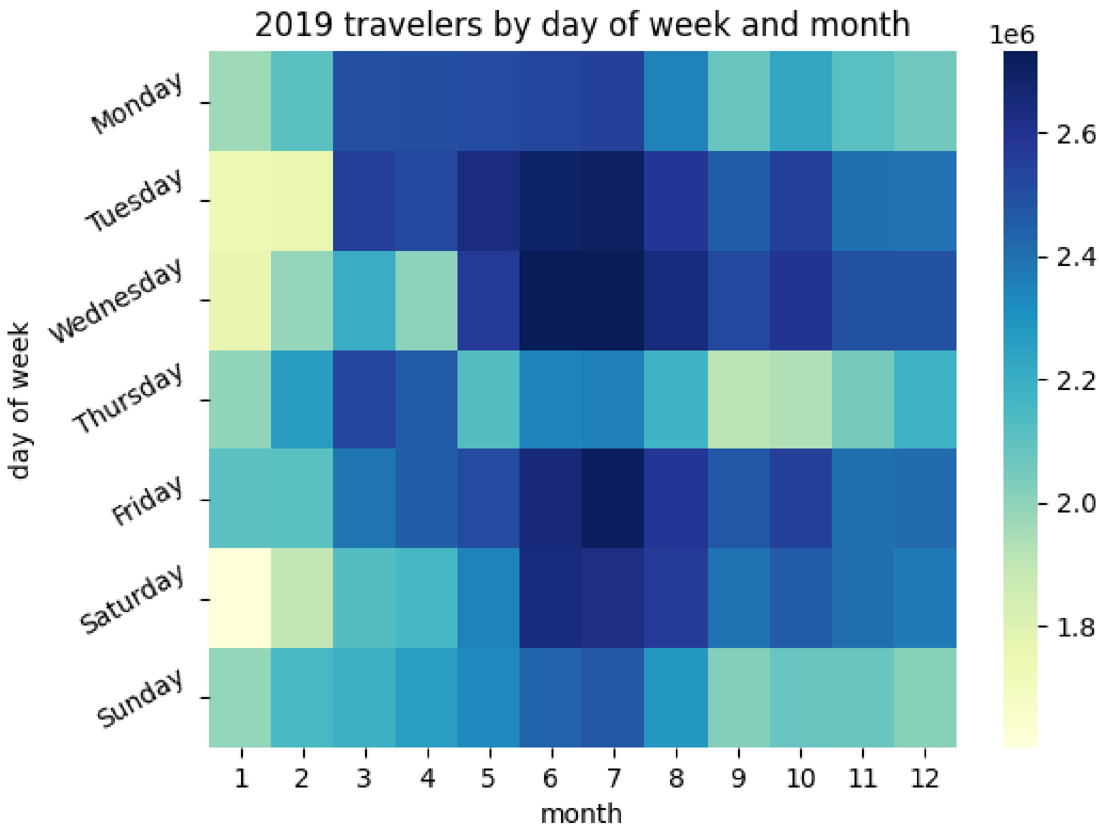
Exercise 3.2

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.

[8]:
```
import seaborn as sns                                        # use seaborn for␣
 ↪heatmap 'cause it's pretty
import matplotlib.pyplot as plt                              # plt for labels and␣
 ↪such
data = pd.read_csv('tsa_melted_holiday_travel.csv')          # import data
data['date'] = pd.to_datetime(data['date'])                  # convert to date-time
data = data[(data['year'] == 2019)]
data['dow'] = data['date'].dt.day_name()                     # get day names
data['month'] = data['date'].dt.month                        # get months

# create pivot table to calculate relevant data
pt = data.pivot_table(
    values='travelers',
    index='dow',
    columns='month',
    aggfunc='median'
)
# reindex in correct order of day of the week
pt = pt.reindex(['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',␣
 ↪'Saturday', 'Sunday'])
# generate heatmap using seaborn (and pretty colors)
sns.heatmap(pt, cmap='YlGnBu')

# make stuff make sense with    labels
plt.title('2019 travelers by day of week and month')
plt.ylabel('day of week')
plt.yticks(rotation=30)
plt.show()
```



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.

[9]:
```
import matplotlib.pyplot as plt
import pandas as pd
data = pd.read_csv('tsa_melted_holiday_travel.csv')

# well I didn't need to annotate the years in 3.1, because I used boxplot()␣
↪instead of plot
# for ease of use.
# So I did it again, using plot, but made life easier for me by creating a␣
↪pivot table first.
# Again, there's no need for separate plots or subplot-schenanigans because of␣
↪groupby. Personally
# I find it much easier to use this way, instead of creating separate plots␣
↪(which of course would
```

```
# be very easy, just plot over groupby, change the labels and use plt to make
 ↪the plots a bit easier to read)
# but why would I want to write so many lines of code for the same thing?
 ↪Anyway, I digress.

pt = data.pivot(columns='year', values='travelers')      # create pivot table
medians = pt.median()                                    # get a list of medians
plot = pt.plot(kind='box')                               # plot
for i, median in enumerate(medians):                     # annotate the medians
    plot.annotate(f'{median:.0f}', xy=(i+1.35, median),
                  ha='center', va='center', fontsize=8)

# plt for prettiness.
plt.title('travelers over year')
plt.suptitle('')
plt.ylabel('travelers')
plt.xlabel('year')
plt.show()
```