--- Task 1.1---

Dataset Selected: Vasil'chuk, Yurij K; Vasil'chuk, Alla Constantinovna; Budantseva, Nadine A (2023): Stable isotope composition of syngenetic ice wedges, 14C dates of Seyakha yedoma and surrounding sediments, and January air palaeotemperatures for 25-21 cal ka BP in northwestern Siberia. https://doi.pangaea.de/10.1594/PANGAEA.962428

--- Task 1.2---

- Who created the dataset?

The dataset was created by Yurij K Vasil'chuk, Alla Constantinovna Vasil'chuk, and Nadine A Budantseva. It was submitted and proofread by Yurij K Vasil'chuk and Lyubov Bludushkina at the faculty of Geography, department of Geochemistry of Landscapes and Geography of Soils, Lomonosov Moscow State University.

- What do the instances represent?

The instances in the dataset represent the stable isotope composition of syngenetic ice wedges, radiocarbon dates of Seyakha yedoma and surrounding sediments, and reconstructed January air paleotemperatures for 25-21 cal ka BP in northwestern Siberia.

- How was the data acquired?

The specific methods of data acquisition are not detailed in the provided abstract.However, the data likely involves fieldwork for sample collection and laboratory analysis for stable isotope and radiocarbon dating.

- Was any preprocessing/cleaning/labeling of the data done?

The provided abstract does not specify any preprocessing, cleaning, or labeling of the data. This information would be relevant to understand how the raw data was transformed or curated before analysis.

- Has the dataset been used for any tasks already?

Yes, the dataset has been used in research studies, as indicated by the related publications, including the study "AMS 14 C DATING OF SEYAKHA YEDOMA AND JANUARY AIR PALAEOTEMPERATURES FOR 25–21 CAL KA BP BASED ON THE STABLE ISOTOPE COMPOSITIONS OF SYNGENETIC ICE WEDGES" by Vasil'chuk et al.

- Will the dataset be distributed to third parties?

The dataset is publicly available and distributed under the Creative Commons Attribution 4.0 International (CC-BY-4.0) license, which allows for sharing and adaptation by third parties.

- Who will be supporting/hosting/maintaining the dataset?

The dataset is hosted on PANGAEA, a data publisher for earth and environmental science, which also provides curation and maintenance services. The exact details of ongoing support are not specified.

--- Task1.3---

- Has the dataset been used for any tasks already?

This question is relevant as it helps understand the practical applications and validation of the dataset. Knowing that the dataset has been used in published research provides credibility and context for its usage. It indicates the types of scientific analyses of the dataset is suitable. In this case, the dataset's application in studying Late Pleistocene climatic conditions demonstrates its utility in reconstructing historical climate patterns and contributes to broader research in earth and environmental sciences.

Workbook

Use this notebook to complete the exercises throughout the workshop.

Table of Contents

Section 1

Exercise 1.1

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

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/2019_Yellow_Taxi_Trip_Data.csv')
```

Exercise 1.2

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

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/2019_Yellow_Taxi_Trip_Data.csv')

df.shape
```

Out[ ]:
```
(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.

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/2019_Yellow_Taxi_Trip_Data.csv')

df[['fare_amount','tip_amount','tolls_amount','total_amount']].describe()
```

Out[ ]:

	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`).

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/2019_Yellow_Taxi_Trip_Data.csv')

df.loc[df['trip_distance'].idxmax(), ['fare_amount','tip_amount','tolls_amount','total_amount']]
```

Out[ ]:
```
fare_amount      176.0
tip_amount       18.29
tolls_amount      6.12
total_amount    201.21
Name: 8338, dtype: object
```

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.

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/Meteorite_Landings.csv')

df.rename(columns={'mass (g)': 'mass'}, inplace=True)

df.drop(['reclat','reclong'], axis=1, inplace=True)

df.sort_values(['mass'], ascending=False, inplace=True)

df.head()
```

Out[ ]:

	name	id	nametype	recclass	mass	fall	year	GeoLocation
16392	Hoba	11890	Valid	Iron, IVB	60000000.0	Found	01/01/1920 12:00:00 AM	(-19.58333, 17.91667)
5373	Cape York	5262	Valid	Iron, IIIAB	58200000.0	Found	01/01/1818 12:00:00 AM	(76.13333, -64.93333)
5365	Campo del Cielo	5247	Valid	Iron, IAB-MG	50000000.0	Found	12/22/1575 12:00:00 AM	(-27.46667, -60.58333)
5370	Canyon Diablo	5257	Valid	Iron, IAB-MG	30000000.0	Found	01/01/1891 12:00:00 AM	(35.05, -111.03333)
3455	Armanty	2335	Valid	Iron, IIIE	28000000.0	Found	01/01/1898 12:00:00 AM	(47.0, 88.0)

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.)

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/Meteorite_Landings.csv')
```

```python
df['year']=df['year'].str.slice(start=6, stop=10)

df.dropna(subset = ['year'],inplace = True)

df['year']=df['year'].astype('int64')

df = df.assign(before1970=lambda x: x.year < 1970)

df.set_index('id')

df.sort_index()

between = df.loc[10036:10040]

between.head()
```

Out[ ]:

	name	id	nametype	recclass	mass (g)	fall	year	reclat	reclong	GeoLocation	before1970
10036	Elephant Moraine 90022	8432	Valid	CK5	15.5	Found	1990	-76.28573	156.45721	(-76.28573, 156.45721)	False
10037	Elephant Moraine 90023	8433	Valid	CK5	31.5	Found	1990	-76.27507	156.41038	(-76.27507, 156.41038)	False
10038	Elephant Moraine 90024	8434	Valid	Eucrite-br	22.8	Found	1990	-76.28843	156.47872	(-76.28843, 156.47872)	False
10039	Elephant Moraine 90025	8435	Valid	CK5	45.8	Found	1990	-76.28200	156.39926	(-76.282, 156.39926)	False
10040	Elephant Moraine 90026	8436	Valid	CK5	61.5	Found	1990	-76.29226	156.45353	(-76.29226, 156.45353)	False

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.

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/Meteorite_Landings.csv')

df['year'] = df['year'].str.slice(start=6, stop=10)
df.dropna(subset=['year'], inplace=True)
df['year'] = df['year'].astype('int64')

df_filtered = df.query('2005 <= year <= 2009')

count_df = df_filtered.groupby(['year', 'fall'])['id'].count().unstack()

p95_df = df_filtered.groupby(['year', 'fall'])['mass (g)'].apply(lambda x: x.quantile(0.95)).unstack()

final_df = pd.merge(count_df, p95_df, left_index=True, right_index=True, suffixes=('_count', '_p95_mass'))

final_df.head()
```

Out[ ]:

fall	Fell_count	Found_count	Fell_p95_mass	Found_p95_mass
year				
2005	NaN	875.0	NaN	4500.00
2006	5.0	2451.0	25008.0	1600.50
2007	8.0	1181.0	89675.0	1126.90
2008	9.0	948.0	106000.0	2274.80
2009	5.0	1492.0	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.

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/Meteorite_Landings.csv')

print(df.groupby('fall')['mass (g)'].describe())
```

```
         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.

In [ ]:
```python
import pandas as pd

df = pd.read_csv('../data/2019_Yellow_Taxi_Trip_Data.csv')

df['tpep_dropoff_datetime'] = pd.to_datetime(df['tpep_dropoff_datetime'])

df.set_index('tpep_dropoff_datetime', inplace = True)

df = df.resample('H').agg({'trip_distance': 'sum', 'fare_amount': 'sum', 'tolls_amount': 'sum', 'tip_amount': 'sum'})

print(df.nlargest(5, 'tip_amount'))

#df.head()
```

```
                       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
```

Out[ ]:

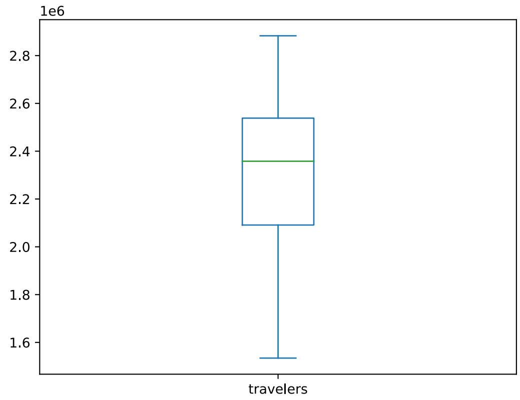
	trip_distance	fare_amount	tolls_amount	tip_amount
tpep_dropoff_datetime				
2019-10-23 07:00:00	0.67	4.5	0.0	0.0
2019-10-23 08:00:00	17.07	62.5	0.0	4.0
2019-10-23 09:00:00	1.58	58.0	0.0	0.0
2019-10-23 10:00:00	0.00	0.0	0.0	0.0
2019-10-23 11:00:00	0.00	0.0	0.0	0.0

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.

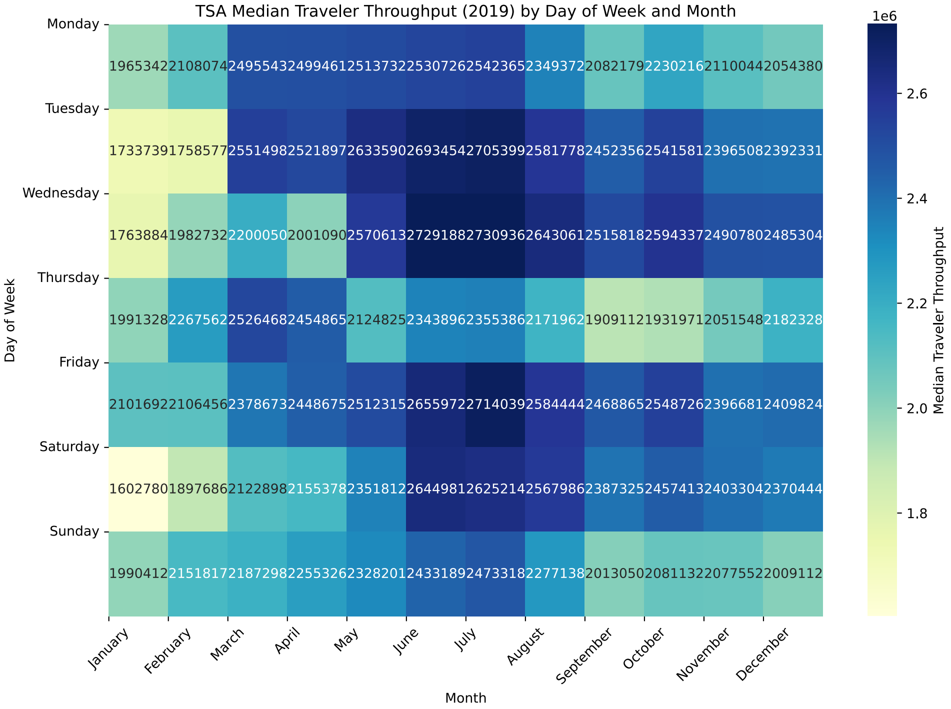
In [ ]:
```
import pandas as pd
import matplotlib_inline
from utils import mpl_svg_config

matplotlib_inline.backend_inline.set_matplotlib_formats(
    'svg',
    **mpl_svg_config('section-3')

)

df = pd.read_csv('../data/tsa_melted_holiday_travel.csv',parse_dates=True, index_col='date')

box2019 = df.query('year == 2019').travelers.plot(kind='box')

#box2020 = df.query('year == 2020').travelers.plot(kind='box')

#box2021 = df.query('year == 2021').travelers.plot(kind='box')
```



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.

In [ ]:
```
import pandas as pd
import matplotlib_inline
from utils import mpl_svg_config
import matplotlib.pyplot as plt
import seaborn as sns

matplotlib_inline.backend_inline.set_matplotlib_formats(
    'svg', # output images using SVG format
    **mpl_svg_config('section-3') # optional: configure metadata

)



# Load the TSA traveler throughput data
df = pd.read_csv('../data/tsa_melted_holiday_travel.csv', parse_dates=True, index_col='date')

# Extract year, month, and day of week from the 'date' column
df['Year'] = df.index.year
df['Month'] = df.index.month
df['DayOfWeek'] = df.index.dayofweek

df_2019 = df[df['Year'] == 2019]

pivot_table = pd.pivot_table(df_2019, values='travelers', index='DayOfWeek', columns='Month', aggfunc='median')

month_order = ['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', 'October', 'November', 'December']
day_order = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']

plt.figure(figsize=(12, 8))
sns.heatmap(pivot_table, cmap='YlGnBu', annot=True, fmt=".0f", cbar_kws={'label': 'Median Traveler Throughput'})
plt.title('TSA Median Traveler Throughput (2019) by Day of Week and Month')
plt.xlabel('Month')
plt.ylabel('Day of Week')

plt.xticks(ticks=range(12), labels=month_order, rotation=45)
plt.yticks(ticks=range(7), labels=day_order, rotation=0)

plt.show()
```

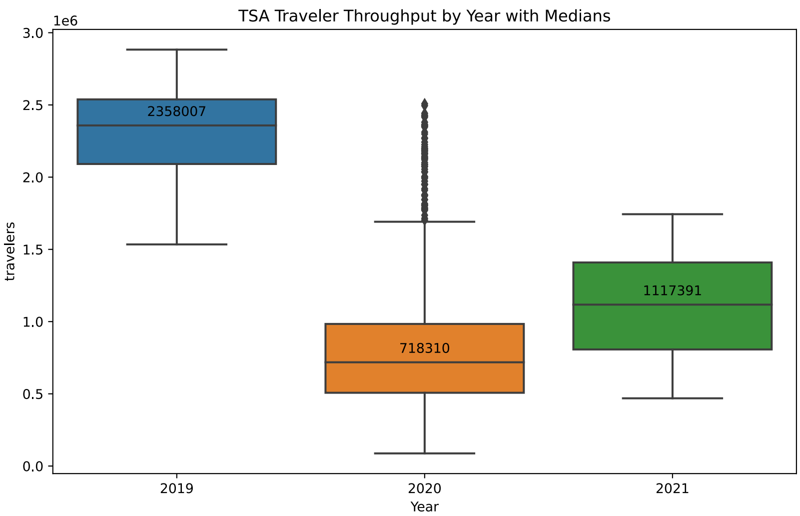


Exercise 3.3

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.

In [ ]:

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('../data/tsa_melted_holiday_travel.csv')

df['date'] = pd.to_datetime(df['date'])

df['Year'] = df['date'].dt.year

plt.figure(figsize=(10, 6))
ax = sns.boxplot(x='Year', y='travelers', data=df)

medians = df.groupby(['Year'])['travelers'].median()

for x_tick, (year, median) in enumerate(medians.items()):
    ax.annotate(f'{median:.0f}', xy=(x_tick, median),
                xytext=(0,5),
                textcoords='offset points',
                ha='center', va='bottom')

plt.title('TSA Traveler Throughput by Year with Medians')
plt.show()
```



In [ ]:

Data Bias: Fairness Gerrymandering

In this exercise you will slip into the role of data scientists that are requested as data experts for a judicial dispute. The scenario in dispute is as follows:

A woman of color applied for a job at the company *MajorEngine*, but got rejected. She suspects that she got turned down for racist and sexist reasons, *i.e.* because she is a woman of color. *MajorEngine* refutes this claim and provides employment records in court in order to disprove the claims.

In [ ]:
```python
import pandas as pd
import matplotlib.pyplot as plt

# load the data from the file 'hiring_records_MajorEngine.csv' and inspect the first rows with the pandas function 'head'
# TODO: Your code goes here

df = pd.read_csv('hiring_records_MajorEngine.csv')

df.head()
```

Out[ ]:

	gender	race
0	male	white
1	female	white
2	female	white
3	male	white
4	male	hispanic

Task 1

Slip into the role of a data scientist hired by *MajorEngine* in order to show that based on the employment records

(a) the company has no racist hiring policy, and

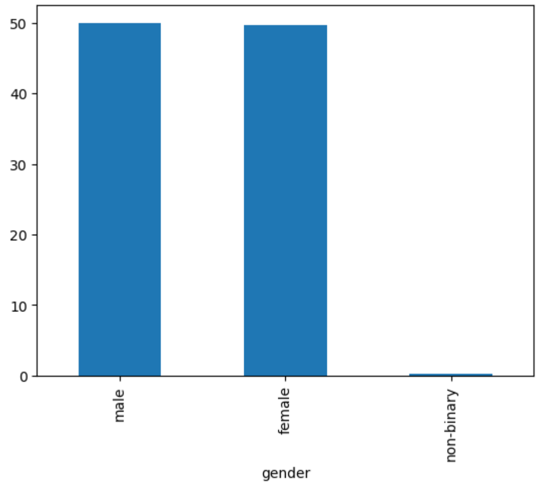
(b) has no strongly sexist hiring policy. Note that according to the 2020 U.S. census, the perfect, expected percentage of white employees would be 61.6%.

Use bar charts to convey your findings to a lay person and write a comment that explains your figure in favor of *MajorEngine*.

Hint: While exploring the dataset, look at the ratio of white employees vs. non-white employees, and the ratio of male employees vs. non-male employees. It can also be useful to create a plot of the ideal distribution as comparison.

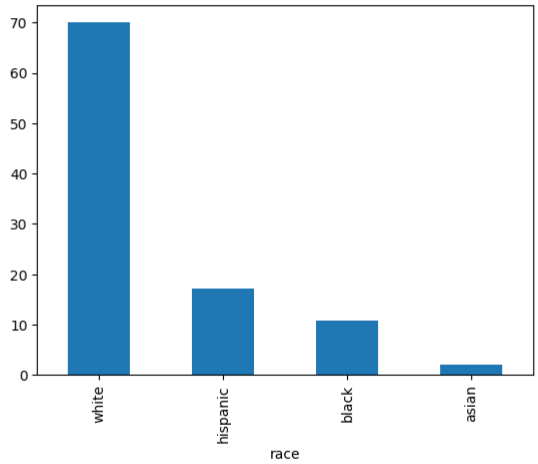
In [ ]:
```python
# Part (a): show that MajorEngine has no strongly racist hiring policy

# TODO: Your code goes here

import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('hiring_records_MajorEngine.csv')

gender_count = df['gender'].value_counts(normalize=True)*100

gender_count.plot(kind='bar')
```

Out[ ]: <Axes: xlabel='gender'>



In [ ]:
```python
# Part (b): Show that MajorEngine has no sexist hiring policy

# TODO: Your code goes here

import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv('hiring_records_MajorEngine.csv')

race_count = df['race'].value_counts(normalize=True)*100

race_count.plot(kind='bar')
```

Out[ ]: <Axes: xlabel='race'>



Task 2

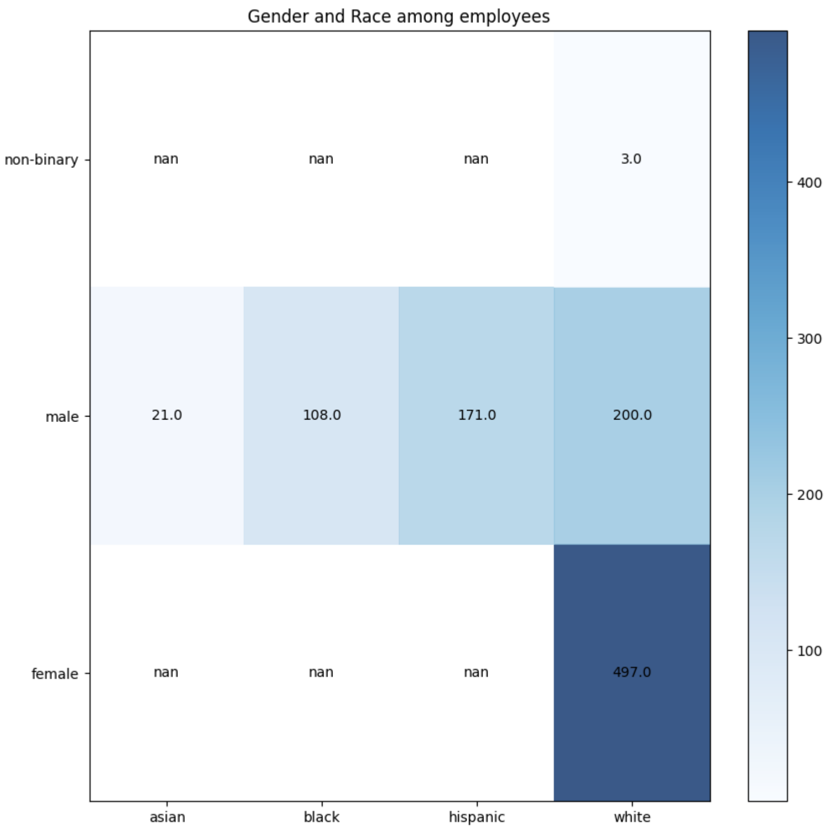
Slip into the role of a data scientist that works pro bono in order to demonstrate that *MajorEngine* has exhibited a bias in the past and thus is likely to have treated the woman of color unfairly.

Use a confusion matrix to convey your findings to a lay person.

Hint: While superficially, the argumentation form task 1 may seem sound, you have the sneaking suspicion that you should look at the two attributes 'race' and 'gender' in combination instead of separately.

Second hint: You may create a makeshift confusion matrix by creating another pandas dataframe of the four intersectional values and renaming columns and index.

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

df = pd.read_csv('hiring_records_MajorEngine.csv')

count_df = df.groupby(['gender', 'race']).size().reset_index(name='count')

pivot_df = count_df.pivot(index='gender', columns='race', values='count')

plt.figure(figsize=(10, 10))
plt.title('Gender and Race among employees')
heatmap = plt.pcolor(pivot_df, cmap=plt.cm.Blues, alpha=0.8)

plt.xticks(np.arange(0.5, len(pivot_df.columns), 1), pivot_df.columns)
plt.yticks(np.arange(0.5, len(pivot_df.index), 1), pivot_df.index)

for race_idx, race in enumerate(pivot_df.columns):
    for gender_idx, gender in enumerate(pivot_df.index):
        count = pivot_df.loc[gender, race]
        plt.text(race_idx + 0.5, gender_idx + 0.5, count, ha='center', va='center', color='black')

plt.colorbar(heatmap)
plt.show()
```



Side note: The court case and its arguments are based on a true story. The provided data is obviously made up in order to paint a clearer picture for pedagogic reasons.