Assignment 2 : Exploratory Data Analysis(EDA)

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Course: CAP 5768 Introduction to Data science

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Link of Assignment 2: https://colab.research.google.com/drive/1irgmoPDNrf_r8Hq0Mx907sE1RjMBuYwE?usp=sharing (https://colab.research.google.com/drive/1irgmoPDNrf_r8Hq0Mx907sE1RjMBuYwE?usp=sharing)

In [192]:
```
#Importing required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import pearsonr
import seaborn as sns
%matplotlib inline
```

In [193]:
```
# Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remoun
t, call drive.mount("/content/drive", force_remount=True).
```

Part 1: Salaries

The Python code below will load a dataset containing the salaries and demographic data of more than 1000 employees of a hypothetical company, available in the file salaries.csv, which is a simple comma-separated list of labels and values.

In [194]:
```
#Loading Data frame as df name
#checking on data and variables
df = pd.read_csv('/content/drive/My Drive/salaries.csv')
#head function will give us result of frist 5 row
df.head()
```

Out[194]:

	earn	height	sex	ed	age	race
0	50000.0	74.424439	male	16	45	white
1	60000.0	65.537543	female	16	58	white
2	30000.0	63.629198	female	16	29	white
3	50000.0	63.108562	female	16	91	other
4	51000.0	63.402484	female	17	39	white

In [195]:
```
#tail function will show us 5 last row of dataset
df.tail()
```

Out[195]:

	earn	height	sex	ed	age	race
1187	19000.0	72.165733	male	12	29	white
1188	15000.0	61.135800	female	18	82	white
1189	8000.0	63.664164	female	12	33	white
1190	60000.0	71.925836	male	12	50	white
1191	6000.0	68.368486	male	12	27	white

1.1 Solution

Earn: Yearly salary in USD

Height: person's height in inches

Sex: Person's Gender

ed: Education completed by a Person in years

Age: person's Age

Race: Person's Race(Ethinicity)

In [196]:
```
#shape mean how many rows and columns we have in dataset
print('Data frame of file = ',df.shape)
#count funtion means how many number of count in each variables
print(df.count())
```

```
Data frame of file =  (1192, 6)
earn      1192
height    1192
sex       1192
ed        1192
age       1192
race      1192
dtype: int64
```

In [197]:
```
#using this code we can see missing data
df.isnull().sum()
```

Out[197]:
```
earn      0
height    0
sex       0
ed        0
age       0
race      0
dtype: int64
```

In [198]:
```
#code for describing dataset
df.describe()
```

Out[198]:

	earn	height	ed	age
count	1192.000000	1192.000000	1192.000000	1192.000000
mean	23154.773490	66.915154	13.504195	41.378356
std	19472.296925	3.853968	2.420175	15.867428
min	200.000000	57.503219	3.000000	18.000000
25%	10000.000000	64.009746	12.000000	29.000000
50%	20000.000000	66.451265	13.000000	38.000000
75%	30000.000000	69.848100	16.000000	51.000000
max	200000.000000	77.051282	18.000000	91.000000

In [199]:
```
 # This will give us Index, Datatype and Memory information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1192 entries, 0 to 1191
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   earn    1192 non-null   float64
 1   height  1192 non-null   float64
 2   sex     1192 non-null   object
 3   ed      1192 non-null   int64
 4   age     1192 non-null   int64
 5   race    1192 non-null   object
dtypes: float64(2), int64(2), object(2)
memory usage: 56.0+ KB
```

Summary statistics and correlations Let's explore the dataset by plotting some graphs and displaying summary statistics.

The code below should display:

- Min, max, average, and median salary (global)
- A histogram of salaries
- A scatterplot correlating salaries and years of education
- The (Pearson) correlation coefficient between the two variables.

This should help us get started.

In [200]:
```
print ('salaries mean =',df['earn'].mean())
```

```
salaries mean = 23154.773489932886
```

In [201]:
```
print ('salaries median =',df['earn'].median())
```

```
salaries median = 20000.0
```

In [202]:
```
print ('salaries mode =',df['earn'].mode())
```

```
salaries mode = 0    15000.0
dtype: float64
```

Together we will get all result for salary statistics

In [203]:
```
#salary statistics
salary = np.array(df['earn'])
print("--- Salary statistics ---")
print("Minimum salary (global): ${:6.2f}".format(np.min(salary)))
print("Maximum salary (global): ${:6.2f}".format(np.max(salary)))
print("Average salary (global): ${:6.2f}".format(np.mean(salary)))
print("Median  salary (global): ${:6.2f}".format(np.median(salary)))
```

```
--- Salary statistics ---
Minimum salary (global): $200.00
Maximum salary (global): $200000.00
Average salary (global): $23154.77
Median  salary (global): $20000.00
```

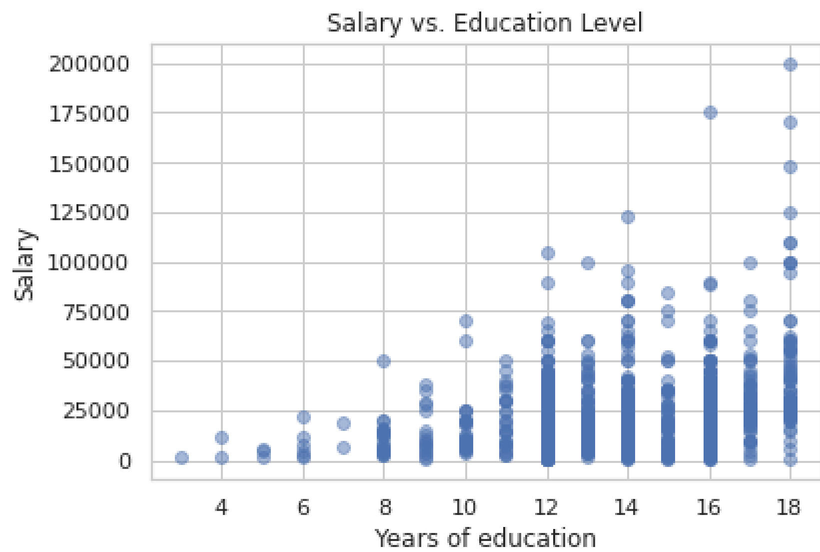
In [204]:
```
#plotting histogram for salary distribution
plt.hist(salary)
plt.title('Salary Distribution')
plt.xlabel('Salary')
plt.ylabel('Number of Range')
plt.show()
```

In [205]:
```
years = np.array(df['ed'])

salary = np.array(df['earn'])
years
```

Out[205]:
```
array([16, 16, 16, ..., 12, 12, 12])
```

A scatterplot correlating salaries and years of education.

In [206]:
```
plt.title('Salary vs. Education Level')
plt.xlabel('Years of education')
plt.ylabel('Salary');
plt.scatter( years,salary, alpha=0.5)
plt.show()
```



The (Pearson) correlation coefficient between the two variables.

In [207]:
```
# Compute Pearson coefficient
corr, _ = pearsonr(salary,years)
print('Correlation coefficient: ',corr)
```

```
Correlation coefficient:  0.3399765246894847
```

The Pearson correlation coefficient (a value between -1 and 1) can be used to summarize the strength of the linear relationship between two data samples.

A simplified way to interpret the result is:

- A value of 0 means no correlation
- Values below -0.5 or above 0.5 indicates a notable (negative/positive) correlation

1.2 Your turn! (10-14 points) Write code to:

1. Display the total headcount and the number (and %) of male and female employees. (2 pts)
2. Compute and display the min, max, average, and median salary per gender. (8 pts)
3. (OPTIONAL) Plot meaningful graphs that could provide insight into the gender inequality (if any is present) associated with the salaries in the company. (<= 4 bonus points)

In [208]:
```
#checking on dataset
df
```

Out[208]:

	earn	height	sex	ed	age	race
0	50000.0	74.424439	male	16	45	white
1	60000.0	65.537543	female	16	58	white
2	30000.0	63.629198	female	16	29	white
3	50000.0	63.108562	female	16	91	other
4	51000.0	63.402484	female	17	39	white
...	...	...	...	...	...	...
1187	19000.0	72.165733	male	12	29	white
1188	15000.0	61.135800	female	18	82	white
1189	8000.0	63.664164	female	12	33	white
1190	60000.0	71.925836	male	12	50	white
1191	6000.0	68.368486	male	12	27	white

1192 rows × 6 columns

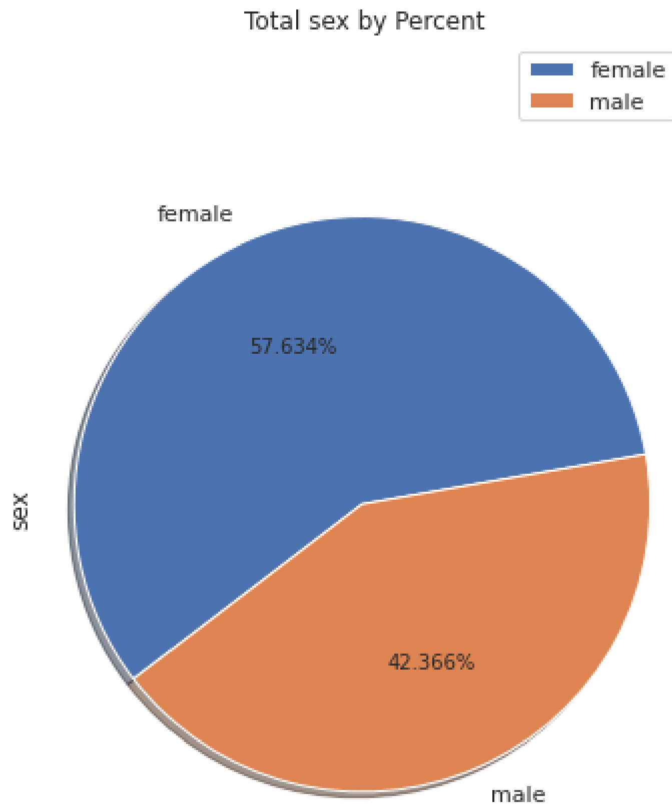
1.2 Solution

1. Display the total headcount and the number (and %) of male and female employees.

In [209]:
```
import numpy as np
female = (df['sex'] == 'female')
male = (df['sex']=='male')
print('Out of  1192 employees')
print ('total count of female : ',sum(female))
print ('total count of male : ',sum(male))
```

```
Out of  1192 employees
total count of female :  687
total count of male :  505
```

In [210]:
```
a = pd.DataFrame(df['sex'].value_counts())
#a.columns=['sex']
plt.rcParams['figure.figsize'] = [5,7]
a.plot(kind='pie', y='sex',autopct='%1.3f%%',startangle=10, shadow = Tru
e)
plt.title('Total sex by Percent')
plt.style.use('ggplot')
plt.axis('equal')
plt.tight_layout()
plt.show()
```



After computing above operation we can see in result the number of headcount or percentage of female is more than number of males.

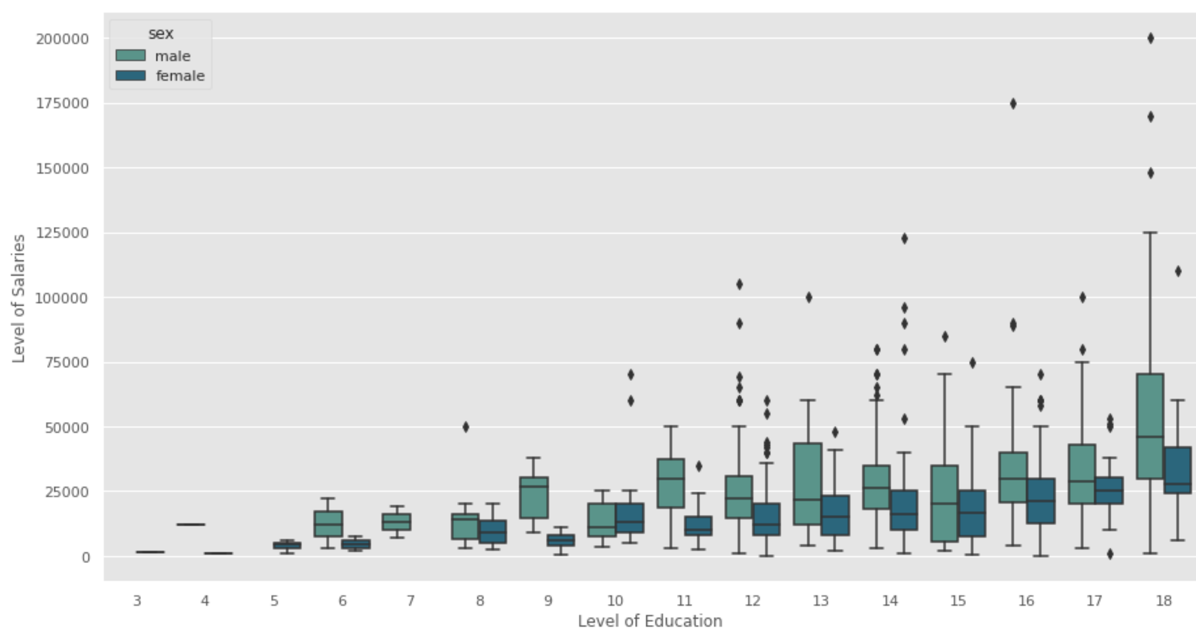
2. Computer and display the min, max, average, and median salary per gender.

In [211]:
```
def salary_statstics(gendre_name, gendre_filter):
    print('\nSalary stats for {} employees'.format(gendre_name))

    s = df[gendre_filter]['earn']
    print('Minimum salary: {:6,.0f}'.format(s.min()))
    print('Maximum salary: {:7,.0f}'.format(s.max()))
    print('Average salary: {:6,.0f}'.format(s.mean()))
    print('Median  salary: {:7,.0f}'.format(s.median()))

salary_statstics('female', female)
salary_statstics('male', male)
```

```
Salary stats for female employees
Minimum salary:    200
Maximum salary: 123,000
Average salary: 18,280
Median  salary:  15,000

Salary stats for male employees
Minimum salary:  1,000
Maximum salary: 200,000
Average salary: 29,786
Median  salary:  25,000
```

3. Plot meaningful graphs that could provide insight into the gender inequality (if any is present) associated with the salaries in the company.

In [212]:
```
g = sns.boxplot(data=df,x='ed', y='earn', hue='sex',palette="crest")
g.figure.set_size_inches(15,8)
plt.xlabel('Level of Education')
plt.ylabel('Level of Salaries')
plt.show()
```



The average salary for female is lower than males average salaries, with level of education males are getting higher than females.

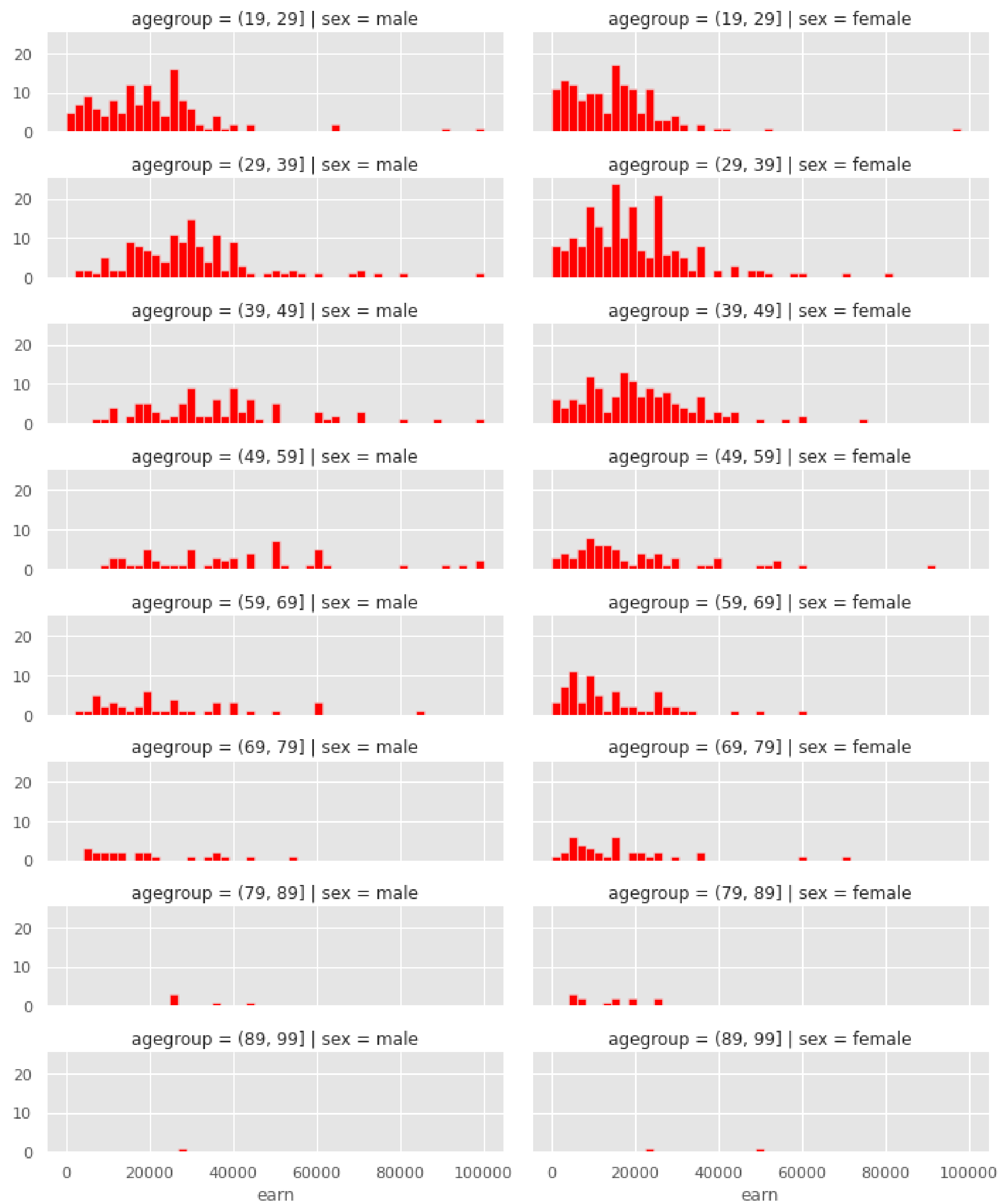
- By analyzing together male and female there is sign of gender discrimination in salaries. However there is missing other most important variables like years of experience. This plot is starting point for data collection.

Since we do not have enough data in dataset, this will use age as a proxy for now.

For that matter, first we will group into ten years each.

In [213]:
```
df['agegroup'] = pd.cut(x=df['age'], bins=[19, 29, 39, 49, 59, 69, 79, 8
9, 99])
bins = np.linspace(np.min(df['earn']), 100000, 50)
g = sns.FacetGrid(df, col='sex', row='agegroup')
g.fig.set_figheight(12)
g.fig.set_figwidth(10)
g.map(plt.hist, 'earn', bins=bins, color='red')
```

Out[213]: <seaborn.axisgrid.FacetGrid at 0x7f0002500c50>



In [214]:
```
#Using Plotly express library
import plotly.express as px
import plotly.graph_objects as go # or plotly.express as px
fig = px.bar(df, x="age", y="earn", color="sex", barmode="group")
fig.for_each_annotation(lambda a: a.update(text=a.text.split("=")[-1]))
fig.show()
fig = go.Figure()
# In coloab I have used following graph is visible Please use Pictures o
f the graph or Follow google colab link
```

The plots shows us that females getting lower values salaries in each group, but the total samples in each category are less to make it conclusive. The main earning in between 22 to 58 years.

Here we have grouped the age and above graph we are keeping 3 parameter together earning, age and sex. In second plot the skewed is right hand and clearly see that red lins as it indicates females and blue for males.

Graph starts from at age of 18 to 91. for males at age of 18 start of salary is 50K and for females just 15K.

Yet, this is not conclusive because we can not conclude results on age parameter, the remaining parameters are also important skills, field of industry etc. Not everybody has same experience at same age. But the one point is clear females are getting lower valued salary.

Signs of inequality

As you can possibly tell by now, this dataset may help us test hypotheses and answer questions related to possible sources of inequality associated with the salary distribution: gender, age, race, etc..

Let's assume, for the sake of argument, that the number of years of education should correlate well with a person's salary (this is clearly a weak argument and the plot and Pearson correlation coefficient computation above suggests that this is not the case) and that other suspiciously high (positive or negative) correlations could be interpreted as a sign of inequality.

Hypotheses H1, H2, H3 At this point, we will formulate 3 different hypotheses that might suggest that the salary distribution is biased by factors such as age, gender, or race:

- H1: Older employees are paid less (i.e., ageism)
- H2: Female employees are paid less (i.e., gender bias)
- H3: Non-whites are paid less (i.e, race bias).

H1 Ageism: older employees are paid less

The hypothesis is that older employees are paid less.

As here we have set a cur of 68 as we test the hypothesis "older than 60 years of age" for this exercise.

Here we are assuming

NOTE: we are assuming years of education should be an indication of salary level.

Step 1: add a column that defines who is "old" for this analsys. This will simplify the remainder of the code.

In [215]:
```
df['old'] = df['age'] > 60
corr1,_ = pearsonr(df['earn'], df['old'])
print('Correlation coefficient: ', corr1)
a = df.groupby('old')
a.agg(np.mean)
```

```
Correlation coefficient:  -0.09108937257262509
```

Out[215]:

	earn	height	ed	age
old				
False	23909.835481	67.116196	13.685828	36.171457
True	18991.617486	65.806674	12.502732	70.087432

In [216]:
```
#creating pairplot for better understanding on correlation
import matplotlib.pyplot as plt
import seaborn as sns
sns.pairplot(df)
plt.show()
```

```
<string>:6: RuntimeWarning:

Converting input from bool to <class 'numpy.uint8'> for compatibility.

<string>:6: RuntimeWarning:

Converting input from bool to <class 'numpy.uint8'> for compatibility.
```

The hypothesis is that older employees are paid less. Th result is very small negative correalation coefficient, which is almost neglible.

H2 Gender bias: females are paid less

In [217]:

```
df['#Sex'] = (df['sex'] == 'female').astype(int)
corr, _= pearsonr(df['earn'], df['#Sex'])
print('Correlation coefficient: ', corr)
g = df.groupby('sex')
g.agg(np.mean)
```

```
Correlation coefficient:  -0.2921021854657078
```

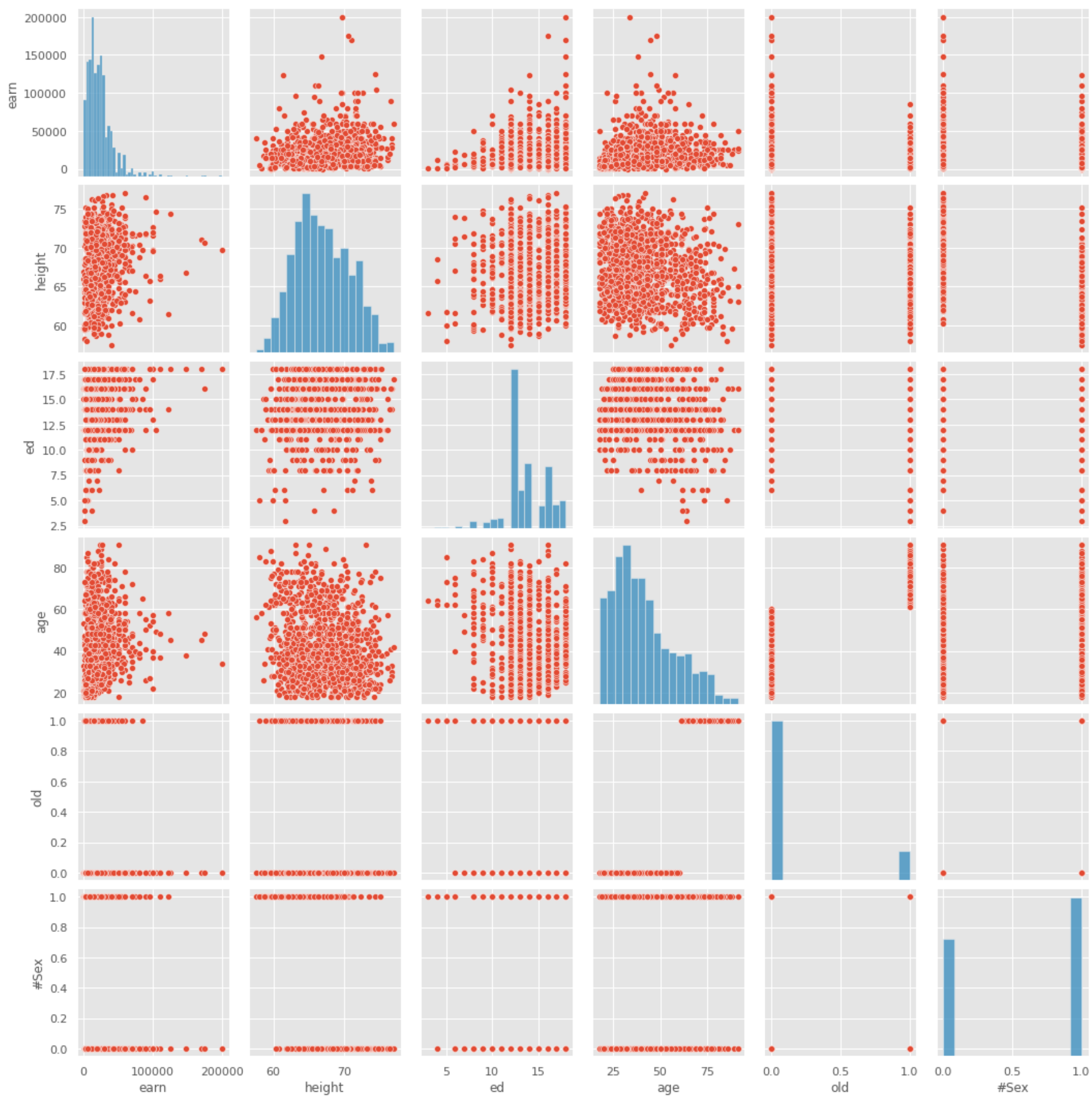
Out[217]:

sex	earn	height	ed	age	old	#Sex
female	18280.195051	64.605603	13.436681	42.259098	0.161572	1.0
male	29786.130693	70.057058	13.596040	40.180198	0.142574	0.0

The table shows that different factors are inside a similar range for male and female. Given that the normal training level is basically the equivalent for the two classifications (we are assuming there is correlation between education and salary) and normal age is additionally about the equivalent, we can infer that we have signs of discrimination.

In [218]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.pairplot(df)
plt.show()
```

```
<string>:6: RuntimeWarning:

Converting input from bool to <class 'numpy.uint8'> for compatibility.

<string>:6: RuntimeWarning:

Converting input from bool to <class 'numpy.uint8'> for compatibility.
```



Conclusion: the information we have demonstrate there might be sign of discrimination. Be that as it may, it is anything but a solid relationship. In view of this outcome, the following activity is gather and investigate other significant components (for example years of experience, hours worked per month, etc.)

H3 Race bias: non-whites are paid less

In [219]:
```
df['non-white'] = (df['race'] != 'white').astype(int)
corr, _ = pearsonr(df['earn'], df['non-white'])
print('Correlation coefficient: ', corr)
g = df.groupby('non-white')
g.agg(np.mean)
```

```
Correlation coefficient:  -0.0825210949221862
```

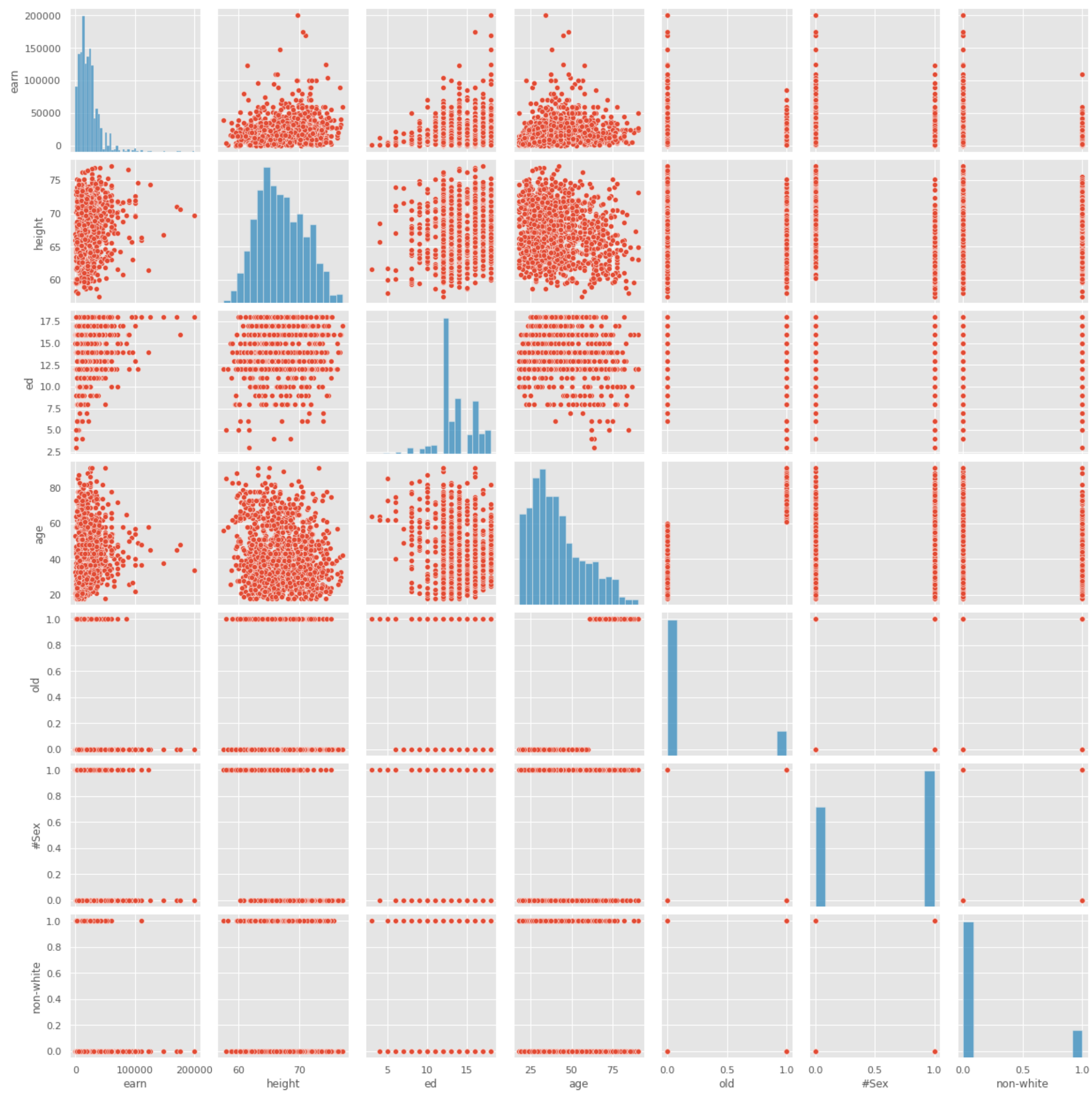
Out[219]:

non-white	earn	height	ed	age	old	#Sex
0	23882.469161	67.055796	13.551062	41.736097	0.156724	0.574317
1	19609.497537	66.229958	13.275862	39.635468	0.137931	0.586207

The result is very negligible for race biased.

In [220]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.pairplot(df)
plt.show()
```

```
<string>:6: RuntimeWarning:

Converting input from bool to <class 'numpy.uint8'> for compatibility.

<string>:6: RuntimeWarning:

Converting input from bool to <class 'numpy.uint8'> for compatibility.
```



In conclusion nothing comes highlighted that could point out discrimination.

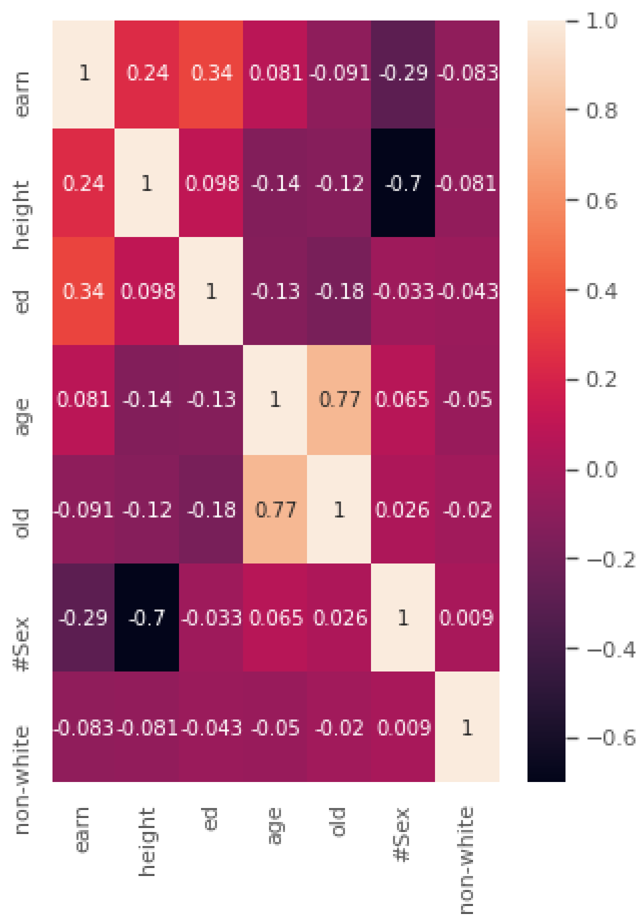
The following tables shows us all H1,H2 and H3 hypotheses results together.

In [221]:
```
df.corr()
```

Out[221]:

	earn	height	ed	age	old	#Sex	non-white
earn	1.000000	0.241848	0.339977	0.081003	-0.091089	-0.292102	-0.082521
height	0.241848	1.000000	0.098408	-0.136515	-0.122541	-0.699253	-0.080582
ed	0.339977	0.098408	1.000000	-0.132069	-0.176299	-0.032551	-0.042762
age	0.081003	-0.136515	-0.132069	1.000000	0.770859	0.064767	-0.049785
old	-0.091089	-0.122541	-0.176299	0.770859	1.000000	0.026041	-0.019596
#Sex	-0.292102	-0.699253	-0.032551	0.064767	0.026041	1.000000	0.009044
non-white	-0.082521	-0.080582	-0.042762	-0.049785	-0.019596	0.009044	1.000000

In [222]:
```
corrMatrix = df.corr()
sns.heatmap(corrMatrix, annot=True)
plt.show()
```



Part 2: Fuel consumption

'

The Python code below will load a dataset containing fuel consumption data for ~400 vehicles produced in the 1970s and the 1980s along with some characteristic information associated with each model.

Here, displacement refers to a vehicle's engine size and the fuel efficiency is measured in miles per gallon (mpg).

See: [https://archive.ics.uci.edu/ml/datasets/Auto+MPG (https://archive.ics.uci.edu/ml/datasets/Auto+MPG)](https://archive.ics.uci.edu/ml/datasets/Auto+MPG) for additional information.

In [223]:
```
sns.set(style='ticks', palette='Set2')
%matplotlib inline
```

In [224]:
```
data = pd.read_csv("http://archive.ics.uci.edu/ml/machine-learning-datab
ases/auto-mpg/auto-mpg.data-original",
                     delim_whitespace = True, header=None,
                     names = ['mpg', 'cylinders', 'displacement', 'horsepo
wer', 'weight', 'acceleration',
                              'model', 'origin', 'car_name'])
print(data.shape)
```

```
(406, 9)
```

In [225]:
```
#here we have dropped missing data
data.dropna(inplace=True)
print(data.shape)
```

```
(392, 9)
```

In [226]:
```
data.head()
```

Out[226]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
0	18.0	8.0	307.0	130.0	3504.0	12.0	70.0	1.0	chevrolet chevelle malibu
1	15.0	8.0	350.0	165.0	3693.0	11.5	70.0	1.0	buick skylark 320
2	18.0	8.0	318.0	150.0	3436.0	11.0	70.0	1.0	plymouth satellite
3	16.0	8.0	304.0	150.0	3433.0	12.0	70.0	1.0	amc rebel sst
4	17.0	8.0	302.0	140.0	3449.0	10.5	70.0	1.0	ford torino

2.1 Your turn! (10-12 points)

Write code to:

- Count the number of 3- and 5-cylinder vehicles in the dataset, display the count, and discard those entries (rows). (6 pts)
- Compute and display the min, max, and average fuel consumption (in mpg) for 4-, 6-, and 8-cylinder vehicles. (4 pts)
- (OPTIONAL) Display the name of the most and least fuel efficient vehicles in the dataset (<= 2 points)

Solution

1. Three- and five-cylinder cars

- Count the number of 3- and 5-cylinder vehicles in the dataset, display the count, and discard those entries (rows).

In [227]:
```
import numpy as np
cylinder_3 = (data['cylinders'] == 3)
cylinder_5 = (data['cylinders'] == 5)
print ('total count of cylinder_3 : ',sum(cylinder_3))
print ('total count of cylinder_5 : ',sum(cylinder_5))
```

```
total count of cylinder_3 :  4
total count of cylinder_5 :  3
```

In [228]:
```
df1 = data[data.cylinders != 3]
df1
```

Out[228]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
0	18.0	8.0	307.0	130.0	3504.0	12.0	70.0	1.0	chevrolet chevelle malibu
1	15.0	8.0	350.0	165.0	3693.0	11.5	70.0	1.0	buick skylark 320
2	18.0	8.0	318.0	150.0	3436.0	11.0	70.0	1.0	plymouth satellite
3	16.0	8.0	304.0	150.0	3433.0	12.0	70.0	1.0	amc rebel sst
4	17.0	8.0	302.0	140.0	3449.0	10.5	70.0	1.0	ford torino
...	...	...	...	...	...	...	...	...	...
401	27.0	4.0	140.0	86.0	2790.0	15.6	82.0	1.0	ford mustang gl
402	44.0	4.0	97.0	52.0	2130.0	24.6	82.0	2.0	vw pickup
403	32.0	4.0	135.0	84.0	2295.0	11.6	82.0	1.0	dodge rampage
404	28.0	4.0	120.0	79.0	2625.0	18.6	82.0	1.0	ford ranger
405	31.0	4.0	119.0	82.0	2720.0	19.4	82.0	1.0	chevy s-10

388 rows × 9 columns

In [229]:
```
df2 = df1[df1.cylinders != 5]
df2
```

Out[229]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
0	18.0	8.0	307.0	130.0	3504.0	12.0	70.0	1.0	chevrolet chevelle malibu
1	15.0	8.0	350.0	165.0	3693.0	11.5	70.0	1.0	buick skylark 320
2	18.0	8.0	318.0	150.0	3436.0	11.0	70.0	1.0	plymouth satellite
3	16.0	8.0	304.0	150.0	3433.0	12.0	70.0	1.0	amc rebel sst
4	17.0	8.0	302.0	140.0	3449.0	10.5	70.0	1.0	ford torino
...	...	...	...	...	...	...	...	...	...
401	27.0	4.0	140.0	86.0	2790.0	15.6	82.0	1.0	ford mustang gl
402	44.0	4.0	97.0	52.0	2130.0	24.6	82.0	2.0	vw pickup
403	32.0	4.0	135.0	84.0	2295.0	11.6	82.0	1.0	dodge rampage
404	28.0	4.0	120.0	79.0	2625.0	18.6	82.0	1.0	ford ranger
405	31.0	4.0	119.0	82.0	2720.0	19.4	82.0	1.0	chevy s-10

385 rows × 9 columns

2. Min, max, average fuel consumption by number of cylinders

In [230]:
```
cars = df2.groupby('cylinders')
cars.agg([min, max, np.mean])['mpg']
```

Out[230]:

	min	max	mean
cylinders			
4.0	18.0	46.6	29.283920
6.0	15.0	38.0	19.973494
8.0	9.0	26.6	14.963107

3. Most and least fuel efficient vehicles

In [231]:
```
def car_names(cn):
  cn.join(str(i) for i in cn['car_name'])
  return

cn = df2
cn[cn['mpg']== cn['mpg'].max()]
```

Out[231]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
329	46.6	4.0	86.0	65.0	2110.0	17.9	80.0	3.0	mazda glc

Mazada glc is most efficient fuel car

In [232]:
```
cn[cn['mpg']== cn['mpg'].min()]
```

Out[232]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
34	9.0	8.0	304.0	193.0	4732.0	18.5	70.0	1.0	hi 1200d

hi 1200d is least efficient fuel car

Hypotheses and questions

This dataset may help us test hypotheses and answer questions related to fuel consumption.

To get started: Which features of a vehicle correlate best with its mpg -- displacement, weight, or horsepower?

2.2. Your turn! (24 points)

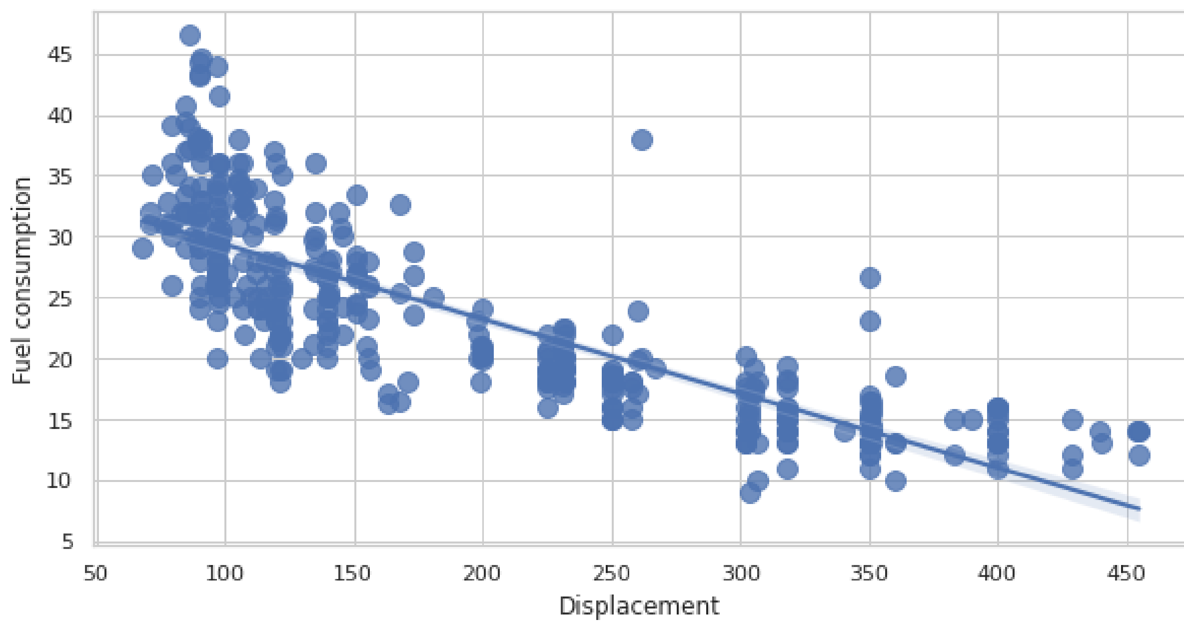
Write Python code to plot the relationship between (8 pts each):

1. Fuel consumption and displacement (engine size)
2. Fuel consumption and weight
3. Fuel consumption and horsepower (HP)

Solution

1. **Fuel consumption and displacement (engine size)**

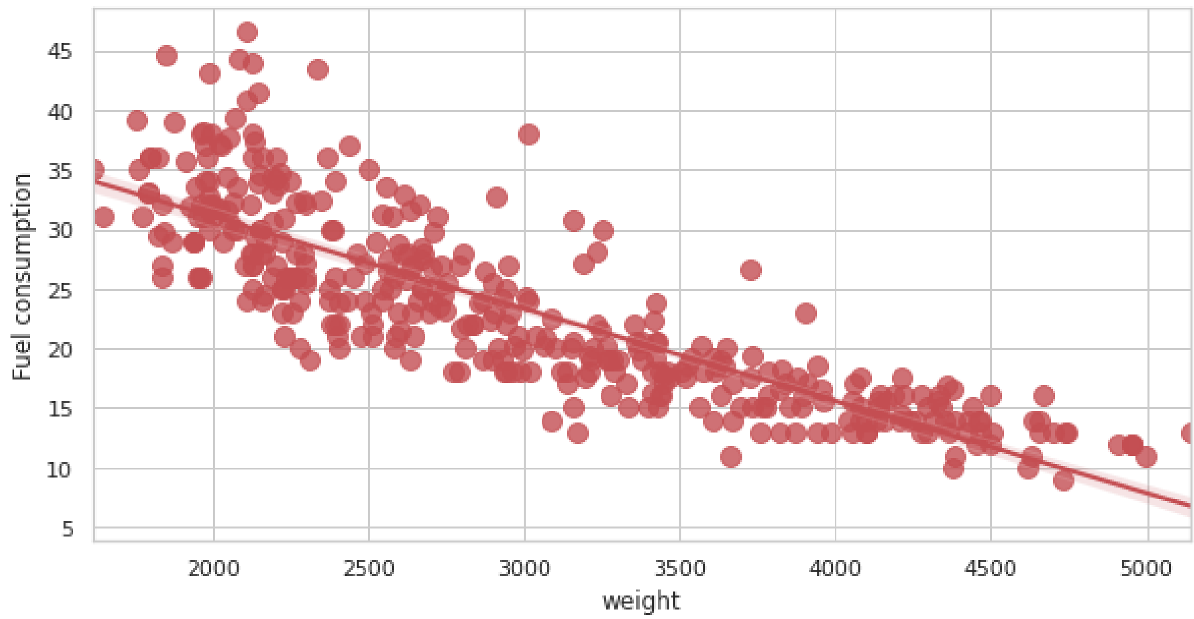
In [233]:
```
#importing library and seting theme for color
import seaborn as sns; sns.set_theme(color_codes=True)
#style
sns.set_style('whitegrid')
#size of plot
plt.figure(figsize=(10,5))
#Regression plot x,y, dataset name, x_jitter to clear noise in data
sns.regplot(x='displacement', y='mpg', data = df2,scatter_kws ={'s':100
},x_jitter=.1)
#labels
plt.xlabel('Displacement')
plt.ylabel('Fuel consumption')
plt.show()
```



In the result there is negative correlation between fuel consumption and displacement.

2. Fuel consumption and weight

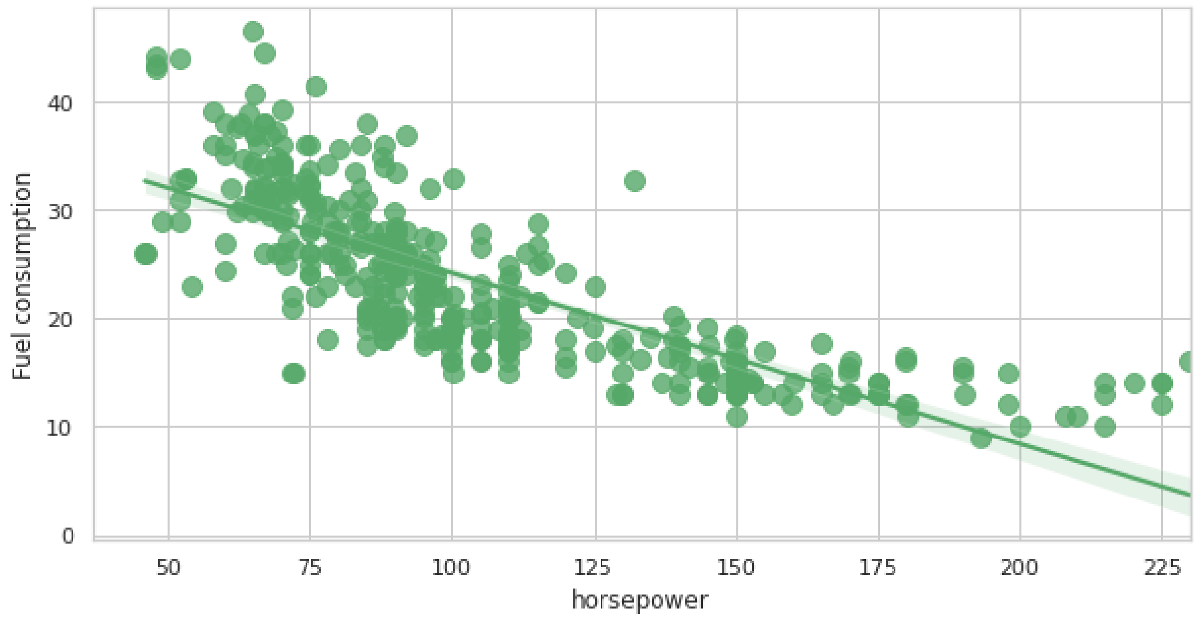
In [234]:
```
#importing library and seting theme for color
import seaborn as sns; sns.set_theme(color_codes=True)
#style
sns.set_style('whitegrid')
#size of plot
plt.figure(figsize=(10,5))
#Regression plot x,y, dataset name, x_jitter to clear noise in data
sns.regplot(x='weight', y='mpg', data = df2,scatter_kws ={'s':100},x_jit
ter=.1,color = 'r')
#labels
plt.xlabel('weight')
plt.ylabel('Fuel consumption')
plt.show()
```



In the above result there is negative correlation between fuel consumption and weight. The graph is linear

3. Fuel consumption and horsepower (HP)

In [235]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(10,5))
sns.regplot(x='horsepower', y='mpg', data = df2,scatter_kws ={'s':100},x
_jitter=.1, color = 'g')
plt.xlabel('horsepower')
plt.ylabel('Fuel consumption')
plt.show()
```



There is correlation between horsepower and fuel consumption but line is linear and it shows negative correlation.

In conclusion of the relationship between horsepower and fuel consumption that may not be liner in all ranges because at the right side of sample points are far from line. It is appear in above graph,and the cluster of samples more tend below the linear regression line. In this case we need more data for accurate results. With haveing this result most of part the relationship is linear.

Hypotheses H4 and H5

At this point, we will formulate two hypotheses that should be confirmed or refuted based on the data:

- H4: fuel efficiency improved over the years represented in this dataset (i.e., 1970 through 1982).
- H5: Japanese cars (within the same time frame) are more fuel efficient than American or European ones.

2.3 Your turn! (20-26 points)

Write Python code to produce (box)plots that should provide good answers to the hypotheses H4 and H5 above (and some text to explain whether they were confirmed or not).

Weight: 20 pts, i.e., 10 pts per hypothesis. Up to 6 bonus points for insightful additional hypotheses, code, and/or comments.

Hint:

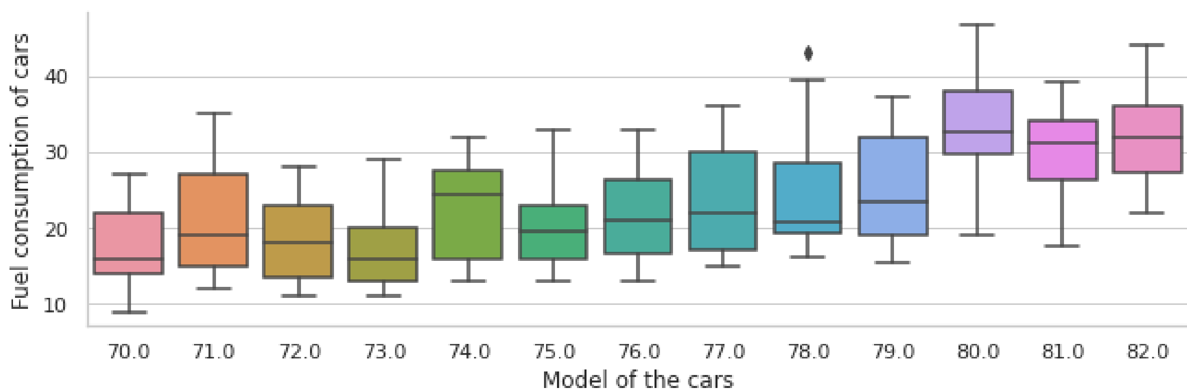
data['Country_code'] = data.origin.replace([1,2,3],['USA','Europe','Japan'])

Solution

H4: fuel efficiency improved over the years represented in this dataset (i.e., 1970 through 1982).

In [236]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(8,5))
sns.catplot(data=df2,x='model',y='mpg',kind='box',height=3, aspect=3)
plt.xlabel('Model of the cars')
plt.ylabel('Fuel consumption of cars')
plt.show()
```

```
<Figure size 576x360 with 0 Axes>
```



The above graphs shows us that the car got more efficient by the time pass over years.The last quarter of models goes up as well.

The recent years cars are more efficient than the last few years of cars.

H5: Japanese cars (within the same time frame) are more fuel efficient than American or European ones.

In [237]:
```
car1= data.copy()
car1['Country_code'] = df2.origin.replace([1,2,3],['USA','Europe','Japa
n'])
car1
```

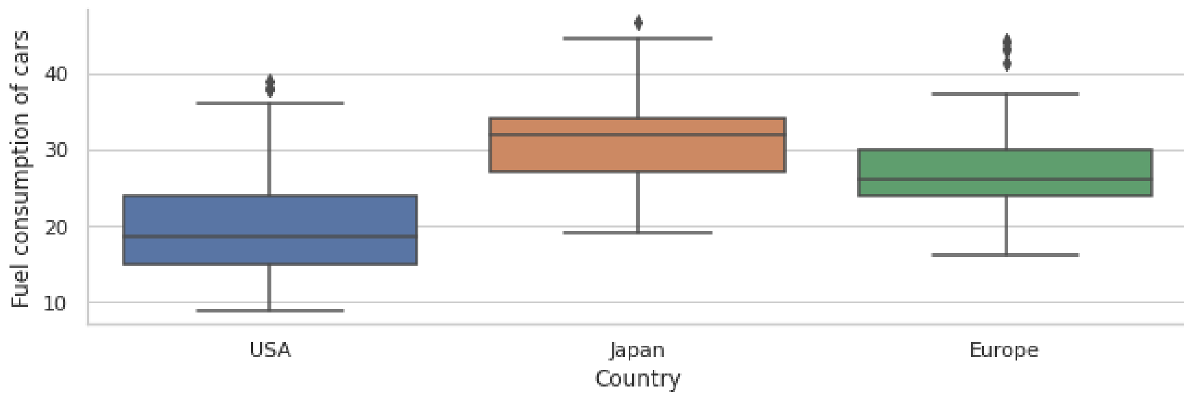
Out[237]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model	origin	car_name
0	18.0	8.0	307.0	130.0	3504.0	12.0	70.0	1.0	chevrolet chevelle malibu
1	15.0	8.0	350.0	165.0	3693.0	11.5	70.0	1.0	buick skylark 320
2	18.0	8.0	318.0	150.0	3436.0	11.0	70.0	1.0	plymouth satellite
3	16.0	8.0	304.0	150.0	3433.0	12.0	70.0	1.0	amc rebel sst
4	17.0	8.0	302.0	140.0	3449.0	10.5	70.0	1.0	ford torino
...	...	...	...	...	...	...	...	...	...
401	27.0	4.0	140.0	86.0	2790.0	15.6	82.0	1.0	ford mustang gl
402	44.0	4.0	97.0	52.0	2130.0	24.6	82.0	2.0	vw pickup
403	32.0	4.0	135.0	84.0	2295.0	11.6	82.0	1.0	dodge rampage
404	28.0	4.0	120.0	79.0	2625.0	18.6	82.0	1.0	ford ranger
405	31.0	4.0	119.0	82.0	2720.0	19.4	82.0	1.0	chevy s-10

392 rows × 10 columns

In [238]:
```
sns.set_style('whitegrid')
plt.figure(figsize=(8,5))
sns.catplot(data=car1,x='Country_code',y='mpg',kind='box',height=3, aspe
ct=3)
plt.xlabel('Country')
plt.ylabel('Fuel consumption of cars')
plt.show()
```

```
<Figure size 576x360 with 0 Axes>
```



The above graphs shows us that in Japanese cars are most efficient fuel consumption than USA and Europe. In boxplot it also shows in general most efficient as shown in the quartiles.

Conclusions (16 points)

Write your conclusions and make sure to address the issues below:

- What have you learned from this assignment?
- Which parts were the most fun, time-consuming, enlightening, tedious?
- What would you do if you had an additional week to work on this?

Solution

What have you learned from this assignment?

- I have learned about google colab funtion, specifically to mount drive to google colab.
- Loading dataset, cleaning of data, hypothesis testing, ploting different plots with using most of inner funtion,creating define funtion and class.
- learned about pandas, numpy, seaborne, matplotlib libraries and lost of operations to create meaning graphs and efficient results.
- Learned heatmaps and pairplot is easy way to get correlation with using function corr()
- how to drop specific row with small line of code
- conceptual I have learned that how to create simple linear regression plot to test hypothesis in simple way.

Which parts were the most fun, time-consuming, enlightening, tedious?

Fun part :

1. playing with multiple format of plots
2. changing their funtions and colors
3. learning how to make regression plot in seaborn
4. learning how to clean data and aggregate data

time-consuming :

- To plot readble format graphs with multiple categories

enlightening

- The power of plotting tools libraries and drroping specific data in one line code

tedious

- Nothing

What would you do if you had an additional week to work on this?

- In addtional I will make more better graphs with color coding and size of the graph
- Try to get more insight from car and salary data such as education and age variable comparion with sex Group and try more different ways .
- Mostly I will focus on to create efficient Defined functions and different methods to get results with simple line of codes.

In [238]:

```
```