Exploratory Data Analysis in Python

👋 Welcome to your workspace! Here, you can write and run Python code and add text in Markdown. Below, we've imported the datasets from the course *Exploratory Data Analysis in Python* as DataFrames as well as the packages used in the course. This is your sandbox environment: analyze the course datasets further, take notes, or experiment with code!

Don't know where to start?

Try completing these tasks:

- Begin by calculating the number of rows and columns and displaying the names of columns for each DataFrame. Change any column names for better readability.
- Experiment and compute a correlation matrix for variables in `nsfg`.
- Compute the simple linear regression of `WTKG3` (weight) and `HTM4` (height) in `brfss` (or any other variables you are interested in!). Then, compute the line of best fit and plot it. If the fit doesn't look good, try a non-linear model.

In [ ]:

```
# Importing course packages; you can add more too!
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats
import scipy.interpolate
import statsmodels.formula.api as smf

sns.set_context('talk')

# Importing course datasets as DataFrames
brfss = pd.read_hdf('datasets/brfss.hdf5', 'brfss') # Behavioral Risk Factor Surveillance System (BRFSS)
gss = pd.read_hdf('datasets/gss.hdf5', 'gss') # General Social Survey (GSS)
nsfg = pd.read_hdf('datasets/nsfg.hdf5', 'nsfg') # National Survey of Family Growth (NSFG)

brfss.head() # Display the first five rows
```

Out[ ]:

	SEX	HTM4	WTKG3	INCOME2	_LLCPWT	_AGEG5YR	_VEGESU1	_HTMG10	AGE
96230	2.0	160.0	60.33	8.0	1398.525290	6.0	2.14	150.0	47.0
244920	2.0	163.0	58.97	5.0	84.057503	13.0	3.14	160.0	89.5
57312	2.0	163.0	72.57	8.0	390.248599	5.0	2.64	160.0	42.0
32573	2.0	165.0	74.84	1.0	11566.705300	3.0	1.46	160.0	32.0
355929	2.0	170.0	108.86	3.0	844.485450	3.0	1.81	160.0	32.0

In [ ]:

```
# renaming the column of weight and height:
brfss.rename(columns= {'WTKG3' : 'WEIGHT' , 'HTM4' : 'HEIGHT', 'INCOME2' : 'INCOME'}, inplace=True)

# DIsplaying columns and shape
print("brfss: ")
print(brfss.shape)
print(brfss.columns)
print()
print("gss: ")
print(gss.shape)
print(gss.columns)
print()
print("nsfg: ")
print(nsfg.shape)
print(nsfg.columns)
print()
```

```
brfss:
(100000, 9)
Index(['SEX', 'HEIGHT', 'WEIGHT', 'INCOME', '_LLCPWT', '_AGEG5YR', '_VEGESU1',
       '_HTMG10', 'AGE'],
      dtype='object')

gss:
(62466, 10)
Index(['year', 'age', 'cohort', 'sex', 'race', 'educ', 'realinc', 'gunlaw',
       'grass', 'wtssall'],
      dtype='object')

nsfg:
(9358, 10)
Index(['caseid', 'outcome', 'birthwgt_lb1', 'birthwgt_oz1', 'prglngth',
       'nbrnaliv', 'agecon', 'agepreg', 'hpagelb', 'wgt2013_2015'],
      dtype='object')
```

Expermienting correlation Matrix for National Survey of Growth Family

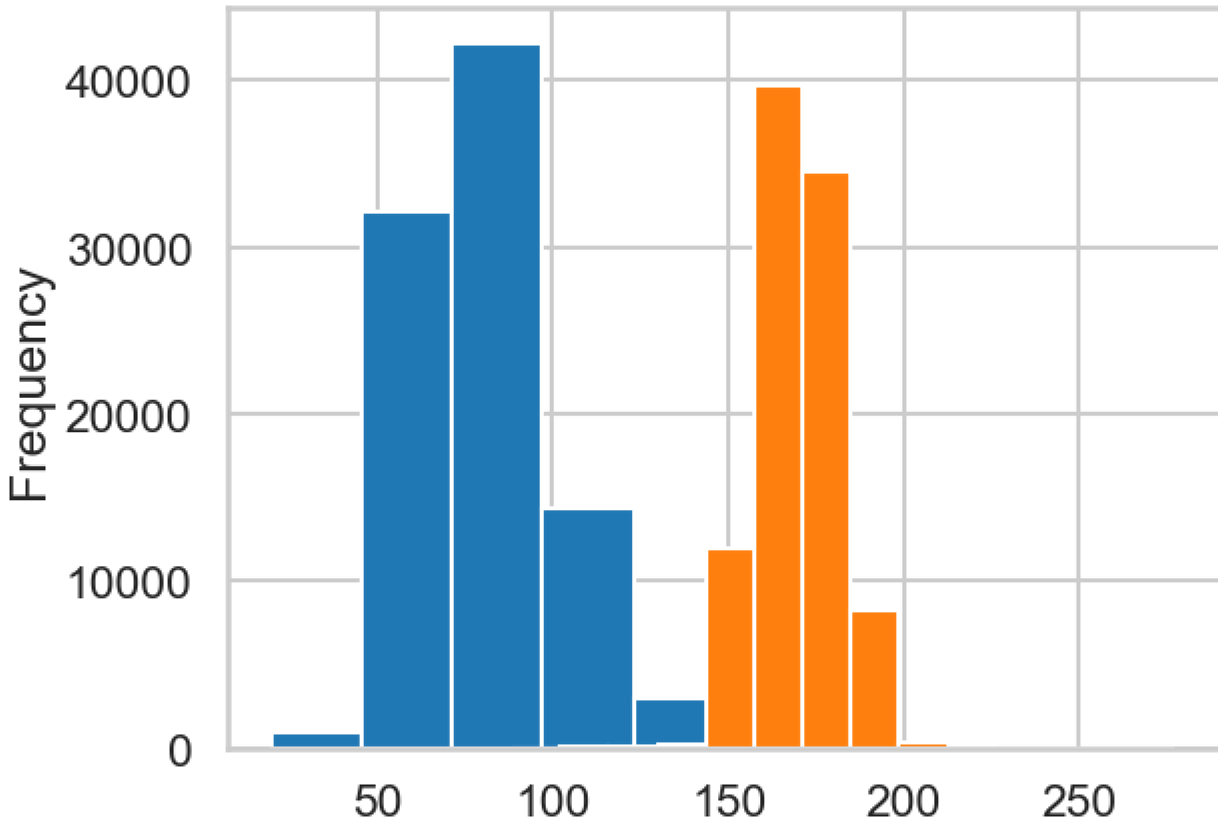
In [ ]:
```
nsfg.corr()
```

Out[ ]:

	caseid	outcome	birthwgt_lb1	birthwgt_oz1	prglngth	nbrnaliv	agecon	agepreg	hpagelb	wgt2013_2015
caseid	1.000000	0.008242	0.031117	0.007099	-0.013421	-0.011034	0.005928	0.005070	-0.004079	-0.010248
outcome	0.008242	1.000000	NaN	NaN	-0.769822	NaN	0.080566	0.013941	NaN	-0.008798
birthwgt_lb1	0.031117	NaN	1.000000	0.033587	0.034431	0.028940	0.000668	0.001307	0.043975	-0.002318
birthwgt_oz1	0.007099	NaN	0.033587	1.000000	0.015756	0.064146	-0.008354	-0.008210	0.021013	0.007592
prglngth	-0.013421	-0.769822	0.034431	0.015756	1.000000	-0.137692	-0.007540	0.050353	-0.025549	0.022063
nbrnaliv	-0.011034	NaN	0.028940	0.064146	-0.137692	1.000000	0.057479	0.056067	0.063696	0.002455
agecon	0.005928	0.080566	0.000668	-0.008354	-0.007540	0.057479	1.000000	0.998897	0.498077	0.088143
agepreg	0.005070	0.013941	0.001307	-0.008210	0.050353	0.056067	0.998897	1.000000	0.497856	0.088440
hpagelb	-0.004079	NaN	0.043975	0.021013	-0.025549	0.063696	0.498077	0.497856	1.000000	0.015616
wgt2013_2015	-0.010248	-0.008798	-0.002318	0.007592	0.022063	0.002455	0.088143	0.088440	0.015616	1.000000

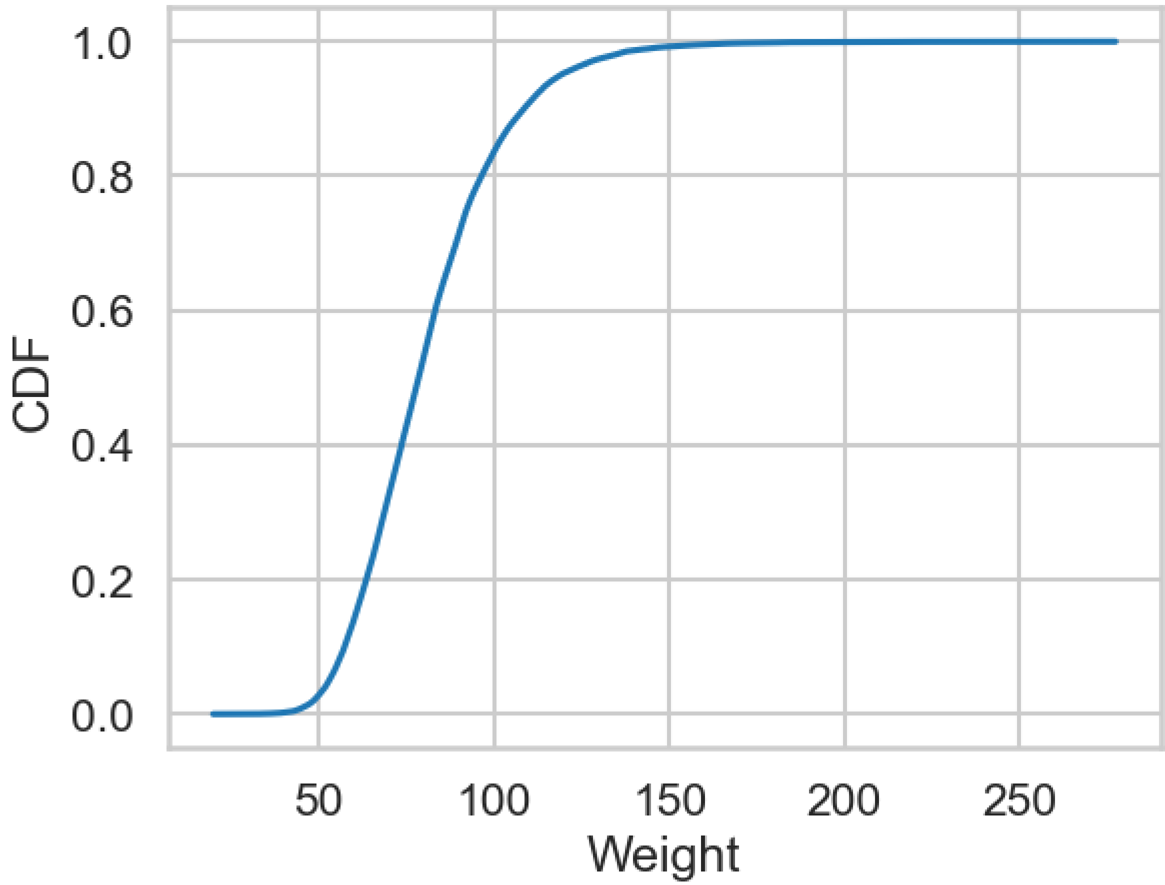
LEts begin to compute the relationship between weight and height, but first we want to look at distributions.

In [ ]:
```
# sns.catplot(y='HEIGHT', data=brfss, kind='count')
brfss['WEIGHT'].plot(kind = 'hist')
plt.hist(brfss['HEIGHT'])
plt.show()
```



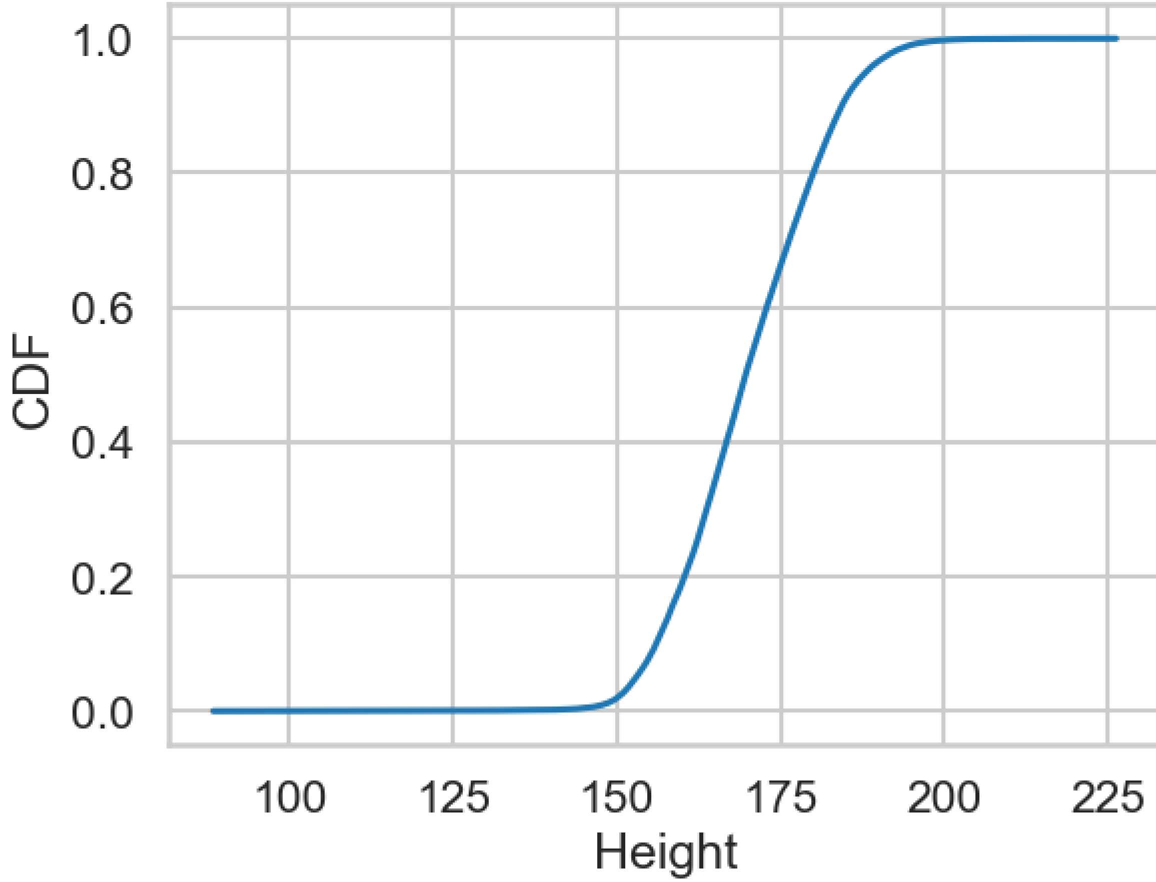
Now if we take a look at cdfs

In [ ]:
```
cdf = brfss['WEIGHT'].value_counts(normalize=True).sort_index().cumsum()
plt.plot(cdf)
plt.xlabel('Weight')
plt.ylabel('CDF')
plt.show()
plt.clf()
```




```
<Figure size 640x480 with 0 Axes>
```

In [ ]:
```
cdf = brfss['HEIGHT'].value_counts(normalize=True).sort_index().cumsum()
plt.plot(cdf)
plt.xlabel('Height')
plt.ylabel('CDF')
plt.show()
plt.clf()
```




```
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```
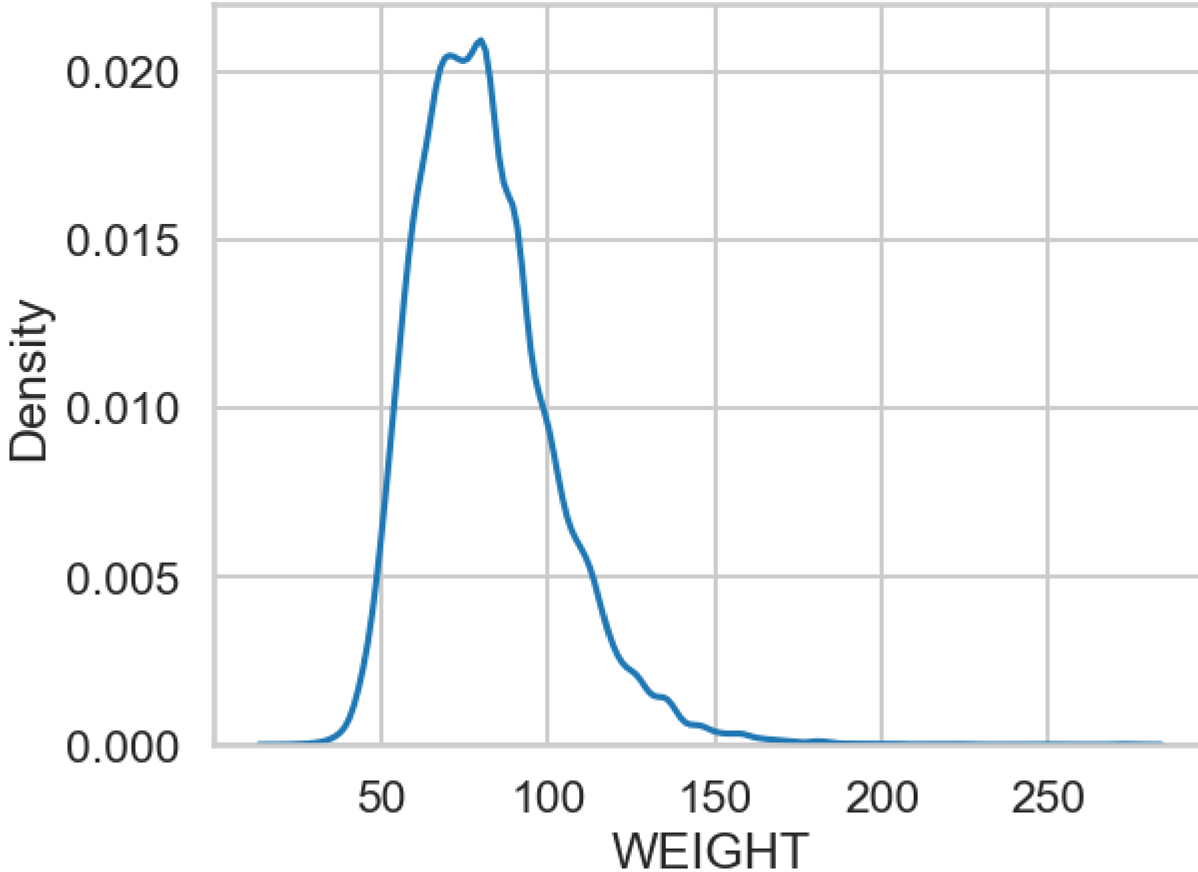
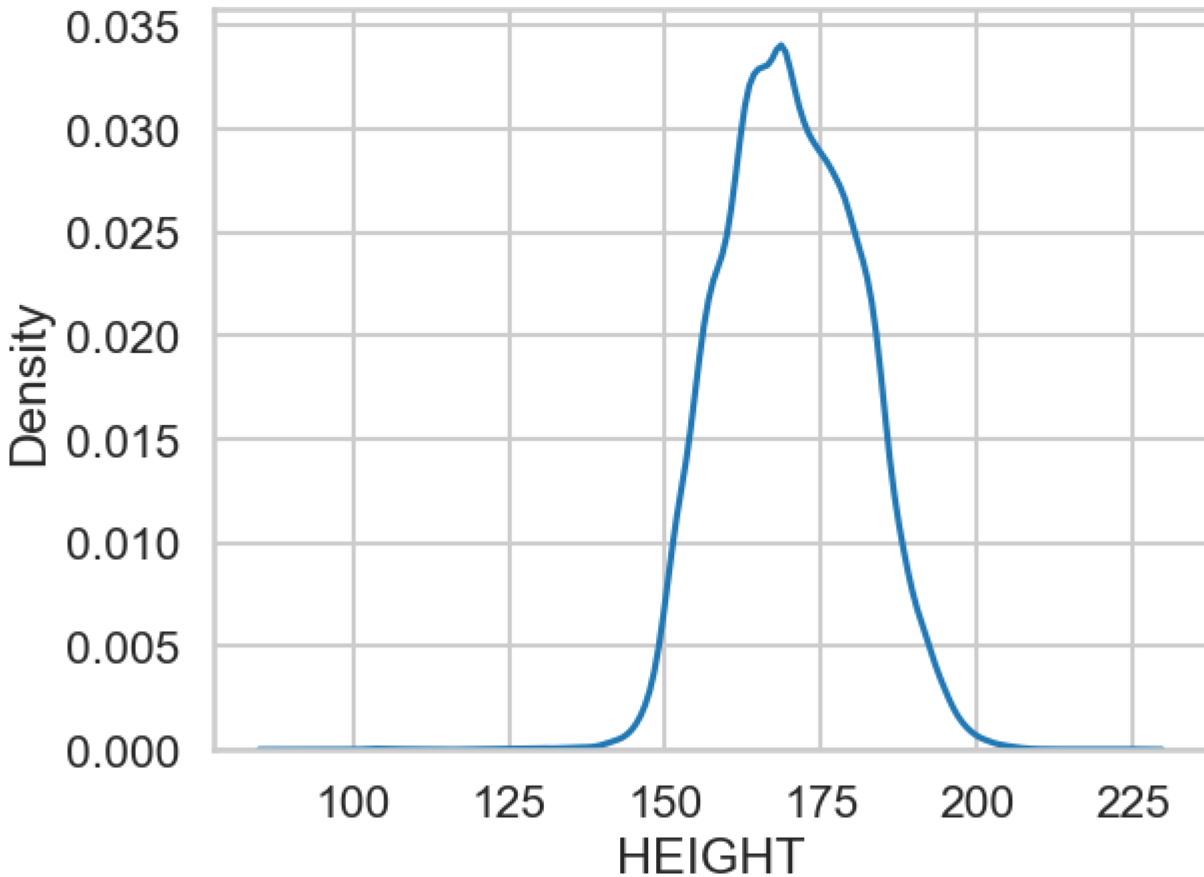

In [ ]:
```
height = brfss[['WEIGHT']].reset_index()
sns.kdeplot(x='WEIGHT', data=height)
plt.show()
plt.clf()
```




```
<Figure size 640x480 with 0 Axes>
```

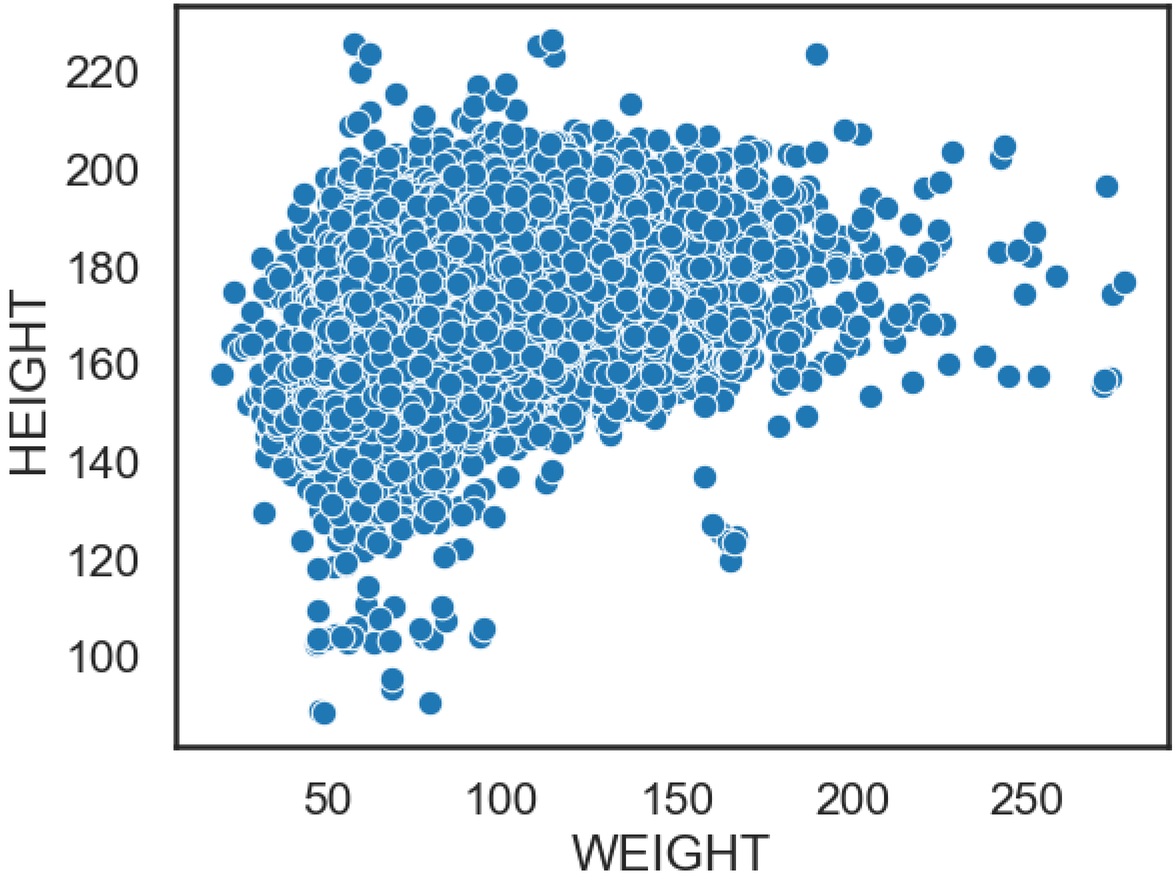
In [ ]:
```
height = brfss[['HEIGHT']].reset_index()
sns.kdeplot(x='HEIGHT', data=height)
plt.show()
plt.clf()
```




```
<Figure size 640x480 with 0 Axes>
```

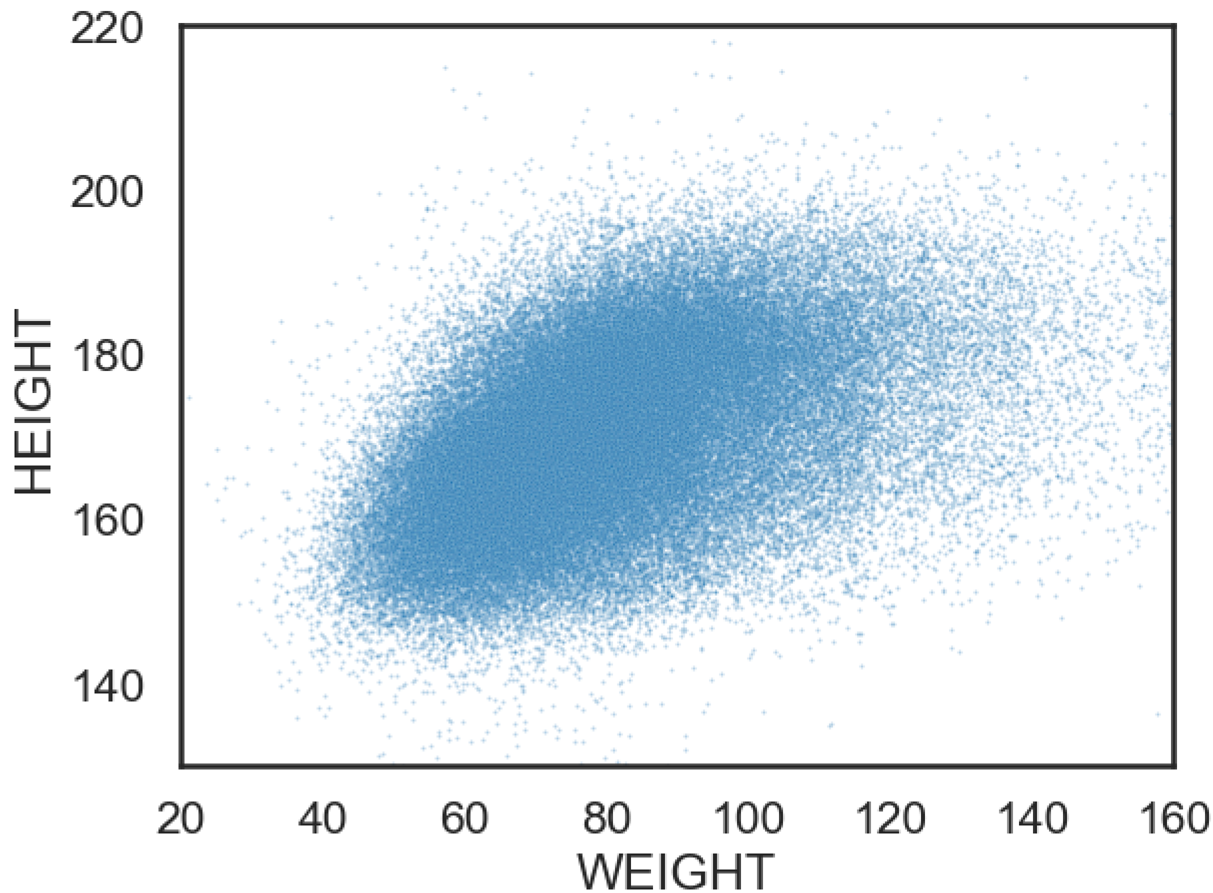
Lets take a look at relationship of weight and height

In [ ]:
```
sns.set_style('white')
sns.scatterplot(x='WEIGHT' , y='HEIGHT', data=brfss)
plt.show()
```



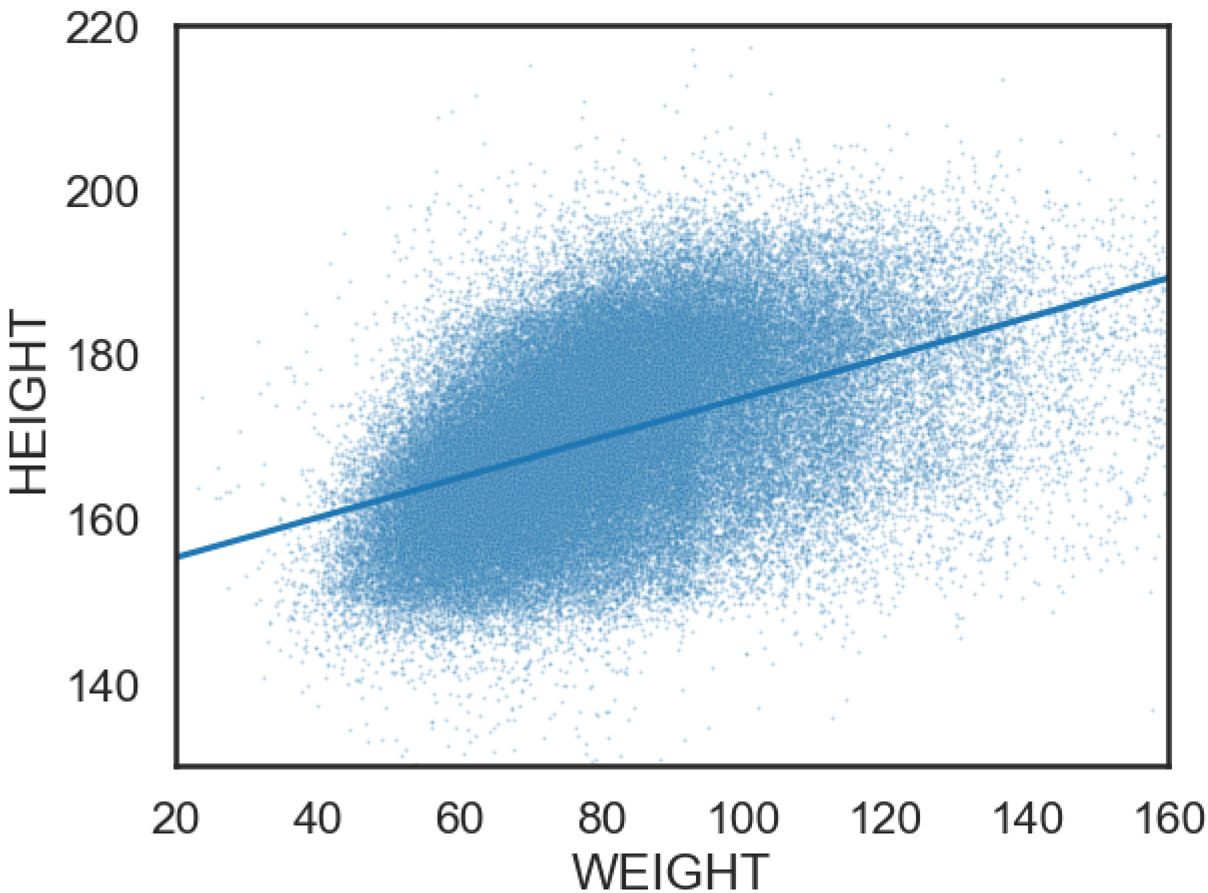
Since it is not visible clearly, so size of marker should be small and let's try juttering

In [ ]:
```
plt.clf()
brfss['WEIGHT'] = brfss['WEIGHT'] + np.random.normal(0, 2, size=len(brfss))
brfss['HEIGHT'] = brfss['HEIGHT'] + np.random.normal(0 , 2 , size=len(brfss))

# Now plot the scatter of weight and height and select required scale
fig = sns.scatterplot(y='HEIGHT' , x='WEIGHT', data=brfss, s=2, alpha=0.3)
plt.xlim(20 , 160)
plt.ylim(130 , 220)
plt.show()
```



Developing a Linear Relationship

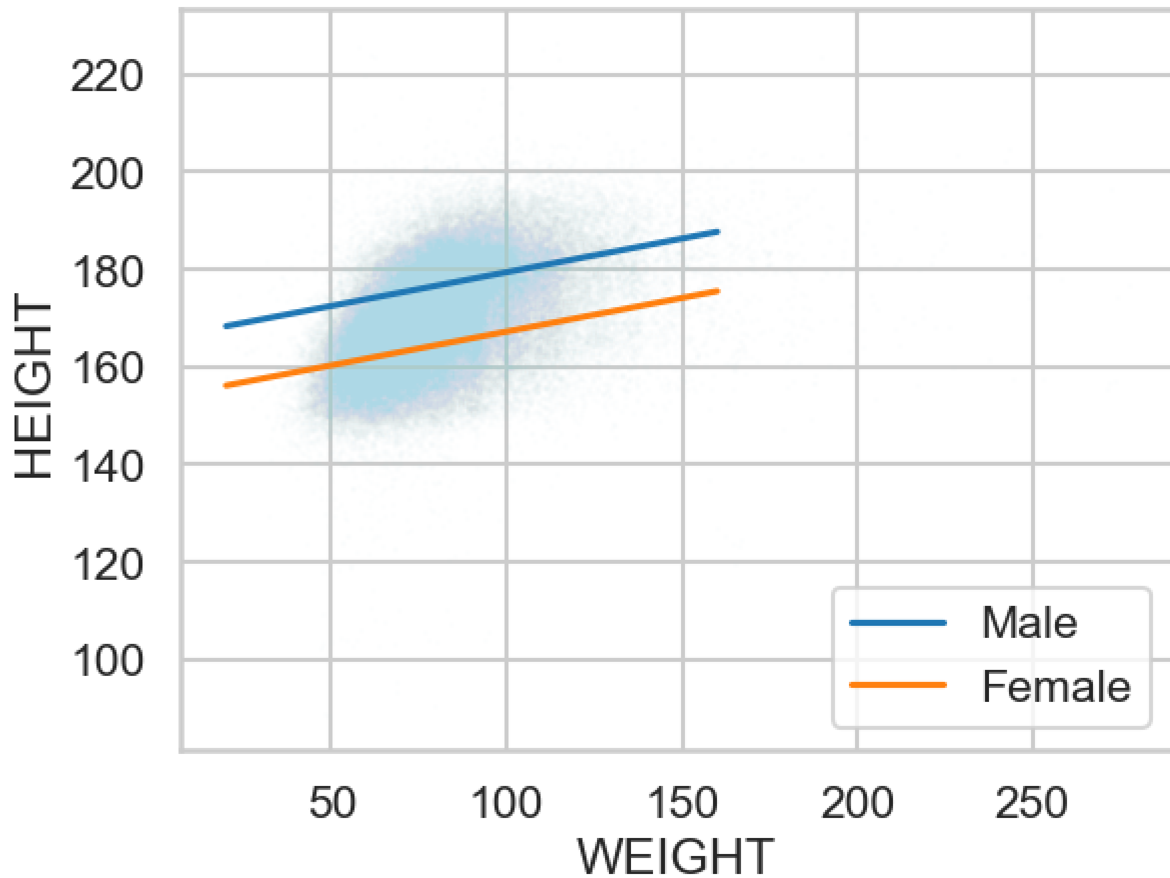
In [ ]:
```
weight = brfss['WEIGHT']
height = brfss['HEIGHT']
model = smf.ols('HEIGHT ~ WEIGHT', data=brfss).fit()
fx = np.array([weight.min(), weight.max()])
fy = model.params['Intercept'] + model.params['WEIGHT'] * fx
plt.plot(fx, fy, '-')
fig = sns.scatterplot(y='HEIGHT' , x='WEIGHT', data=brfss, s=2, alpha=0.3)
plt.xlim(20 , 160)
plt.ylim(130 , 220)
plt.show()
```



Great , we we know that the weight of the person also depends upon the age and the income so lets try exploring it for males and females

In [ ]:
```
from statistics import mode
from turtle import color


brfss['SEX'].replace(2, 0 , inplace=True)

brfss['WEIGHT2'] = brfss['WEIGHT'] ** 2
brfss['INCOME2'] = brfss['INCOME'] ** 2
brfss['AGE2'] = brfss['AGE'] ** 2
#Compute a multiple Regression
model = smf.ols('HEIGHT ~ WEIGHT + INCOME + INCOME2 + AGE + AGE2 + C(SEX)' , data=brfss).fit()
```

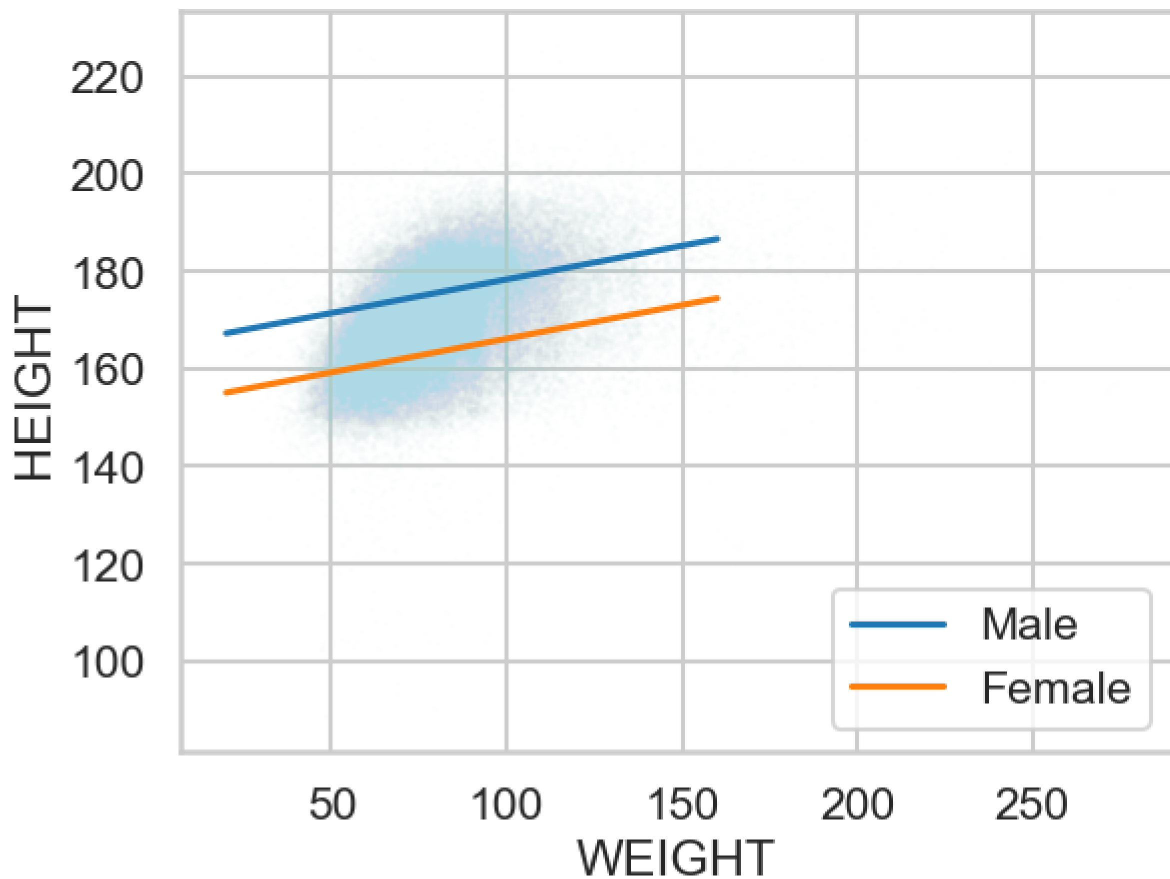
```
#Getting median income
median_income = brfss['INCOME'].mean()

# Developing the dataframe
df = pd.DataFrame()
df['WEIGHT'] = np.linspace(20 , 160)
df['WEIGHT2'] = df['WEIGHT'] ** 2
df['INCOME'] = median_income
df['INCOME2'] = df['INCOME'] ** 2
df['AGE'] = 30
df['AGE2'] = df['AGE'] ** 2

# Generating predictions for male
df['SEX'] = 1
pred_male = model.predict(df)

#Generating predictions for female
df['SEX'] = 0
pred_female = model.predict(df)

sns.set_style('whitegrid')
sns.lineplot(x='WEIGHT', y=pred_male, label='Male', data=df)
sns.lineplot(x='WEIGHT' , y=pred_female, data=df, label="Female")
fig = sns.scatterplot(y='HEIGHT' , x='WEIGHT', data=brfss, s=2, alpha=0.03, color='lightblue')
plt.show()
```



The prediction we generated for male and female for age 30, which is a common age with median income, shows a strong linear relationship and as we can predict, the male will be having more height vs weight on normal income. Let's predict for LOWER INCOME on age 30 keeping constant.

In [ ]:
```
# calling df from previous cell, just updating with the incomes
from operator import mod


twentry_fifth = brfss['INCOME'].quantile(0.25)
df['INCOME'] = twentry_fifth
df['INCOME2'] = df['INCOME']  ** 2

# For male
df['SEX'] = 1
```

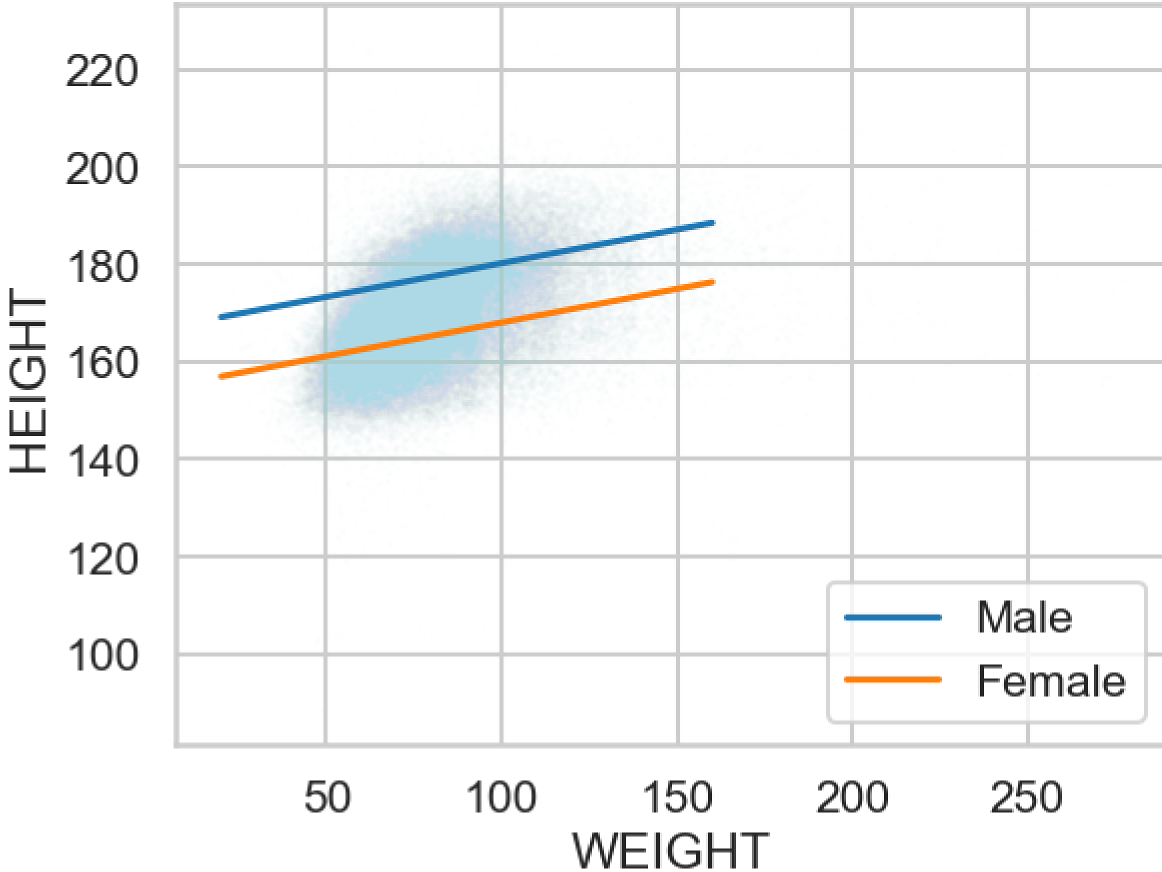
```
pred_male = model.predict(df)

#For female
df['SEX'] = 0
pred_female = model.predict(df)

sns.lineplot(x='WEIGHT' , y=pred_male, data=df, label='Male')
sns.lineplot(x='WEIGHT' , y=pred_female, data=df, label='Female')
fig = sns.scatterplot(y='HEIGHT' , x='WEIGHT', data=brfss, s=2, alpha=0.03, color='lightblue')
```



We have constantly getting a strong linear relationship, let's try with HIGHER INCOME. Usually age of 50 have higher incomes, so we will put it into action and predict a model for higher incomes with age 50.

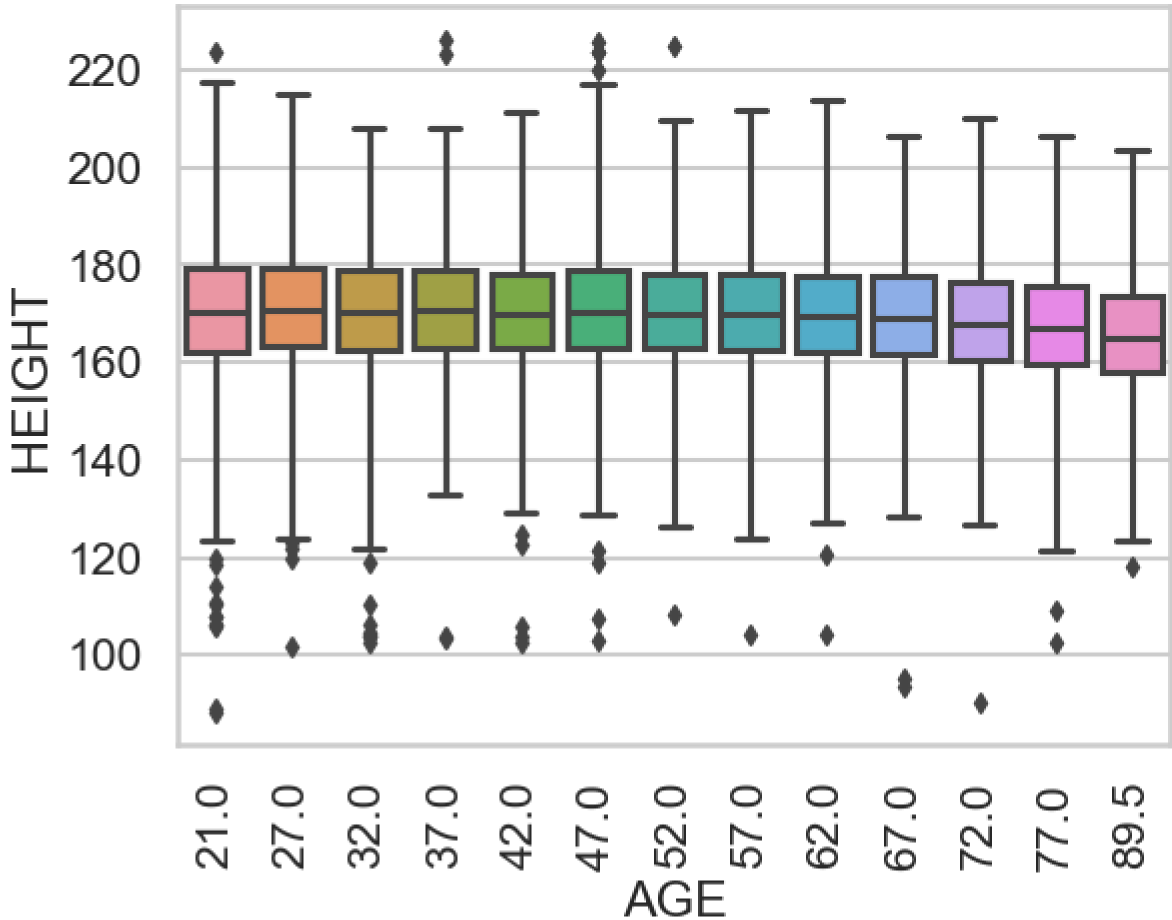
In [ ]:
```
# calling df from previous cell, just updating with the incomes
from operator import mod
```

```
twentry_fifth = brfss['INCOME'].quantile(0.75)
df['INCOME'] = twentry_fifth
df['INCOME2'] = df['INCOME']  ** 2
df['AGE'] = 50
df['AGE2'] = df['AGE'] ** 2

# For male
df['SEX'] = 1
pred_male = model.predict(df)

#For female
df['SEX'] = 0
pred_female = model.predict(df)

sns.lineplot(x='WEIGHT' , y=pred_male, data=df, label='Male')
sns.lineplot(x='WEIGHT' , y=pred_female, data=df, label='Female')
fig = sns.scatterplot(y='HEIGHT' , x='WEIGHT', data=brfss, s=2, alpha=0.03, color='lightblue')
```



We have seen for higher incomes also, these models show that only age and weight are the factor for Heights, Height depends upon a litte decreasing age with strong increasing weight. We can verify the results by boxplot of height vs age.

In [ ]:
```
sns.boxplot(x='AGE', y='HEIGHT', data=brfss, whis=2.5)
plt.xticks(rotation=90)
plt.show()
```



Hope you like and enjoy the presentation.