# Statistics I: Technology help — Python

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Description: Python code for an introductory applied statistics course. This is work in progress.

## Module 1: Data and decisions

To import a text file with data in Python, you first have find the path to the file. The data file students.csv used un the example is stored on my web site: https://luc-hens.github.io/students.csv Usually, you will have your data file stored on your computer. In that case you have to give the path to that file, which looks something like:
/Users/luchens/Documents/Data/students.csv
This is for macOS; I think Windows uses backslashes: \ (check).

Note: it is good practive to not have spaces in a csv file. The pandas command read_csv has an option skipinitialspace=True ("Skip spaces after delimiter") but that does not solve all the problems caused by blank spaces in a csv file.

In [43]:
```
import pandas as pd
df = pd.read_csv('https://luc-hens.github.io/students.csv', sep=',', skipi
print(df)
display(df)
```

```
    case     sex  height  weight                  major
0      1  Female     172      63               Business
1      2  Female     170      70  International Affairs
2      3  Female     170      52                  Other
3      4  Female     171      52         Communications
4      5    Male     186      90               Business
5      6    Male     183      79               Business
6      7    Male     170      66         Communications
7      8  Female     169      56               Business
8      9    Male     175      75  International Affairs
9     10  Female     175      65         Communications
10    11    Male     195      94               Business
11    12  Female     176      51  International Affairs
12    13    Male     188      76  International Affairs
13    14    Male     192      82               Business
14    15    Male     172      70  International Affairs
15    16  Female     169      53               Business
16    17  Female     172      52  International Affairs
17    18    Male     178      85               Business
18    19  Female     177      59         Communications
19    20    Male     178      72  International Affairs
20    21  Female     160      54               Business
21    22  Female     175      54  International Affairs
22    23    Male     190      70  International Affairs
23    24    Male     178      85               Business
24    25  Female     163      55               Business
25    26  Female     161      59               Business
26    27  Female     162      44         Communications
```

```
27    28  Female     170      54                   Business
28    29  Female     154      52                   Business
29    30  Female     170      65                   Business
```

| | case | sex | height | weight | major |
|---|---|---|---|---|---|
| **0** | 1 | Female | 172 | 63 | Business |
| **1** | 2 | Female | 170 | 70 | International Affairs |
| **2** | 3 | Female | 170 | 52 | Other |
| **3** | 4 | Female | 171 | 52 | Communications |
| **4** | 5 | Male | 186 | 90 | Business |
| **5** | 6 | Male | 183 | 79 | Business |
| **6** | 7 | Male | 170 | 66 | Communications |
| **7** | 8 | Female | 169 | 56 | Business |
| **8** | 9 | Male | 175 | 75 | International Affairs |
| **9** | 10 | Female | 175 | 65 | Communications |
| **10** | 11 | Male | 195 | 94 | Business |
| **11** | 12 | Female | 176 | 51 | International Affairs |
| **12** | 13 | Male | 188 | 76 | International Affairs |
| **13** | 14 | Male | 192 | 82 | Business |
| **14** | 15 | Male | 172 | 70 | International Affairs |
| **15** | 16 | Female | 169 | 53 | Business |
| **16** | 17 | Female | 172 | 52 | International Affairs |
| **17** | 18 | Male | 178 | 85 | Business |
| **18** | 19 | Female | 177 | 59 | Communications |
| **19** | 20 | Male | 178 | 72 | International Affairs |
| **20** | 21 | Female | 160 | 54 | Business |
| **21** | 22 | Female | 175 | 54 | International Affairs |
| **22** | 23 | Male | 190 | 70 | International Affairs |
| **23** | 24 | Male | 178 | 85 | Business |
| **24** | 25 | Female | 163 | 55 | Business |
| **25** | 26 | Female | 161 | 59 | Business |
| **26** | 27 | Female | 162 | 44 | Communications |
| **27** | 28 | Female | 170 | 54 | Business |
| **28** | 29 | Female | 154 | 52 | Business |
| **29** | 30 | Female | 170 | 65 | Business |

To display just the first couple of lines of the data frame called df:

In [44]:
```
df.head()
```

Out[44]:

| | case | sex | height | weight | major |
|---|---|---|---|---|---|
| **0** | 1 | Female | 172 | 63 | Business |
| **1** | 2 | Female | 170 | 70 | International Affairs |
| **2** | 3 | Female | 170 | 52 | Other |
| **3** | 4 | Female | 171 | 52 | Communications |
| **4** | 5 | Male | 186 | 90 | Business |

To display the last couple of lines of the data frame called df:

In [45]:
```
df.tail()
```

Out[45]:

| | case | sex | height | weight | major |
|---|---|---|---|---|---|
| **25** | 26 | Female | 161 | 59 | Business |
| **26** | 27 | Female | 162 | 44 | Communications |
| **27** | 28 | Female | 170 | 54 | Business |
| **28** | 29 | Female | 154 | 52 | Business |
| **29** | 30 | Female | 170 | 65 | Business |

To display the 10 first lines of the data frame:

In [46]:
```
df.head(10)
```

Out[46]:

| | case | sex | height | weight | major |
|---|---|---|---|---|---|
| **0** | 1 | Female | 172 | 63 | Business |
| **1** | 2 | Female | 170 | 70 | International Affairs |
| **2** | 3 | Female | 170 | 52 | Other |
| **3** | 4 | Female | 171 | 52 | Communications |
| **4** | 5 | Male | 186 | 90 | Business |
| **5** | 6 | Male | 183 | 79 | Business |
| **6** | 7 | Male | 170 | 66 | Communications |
| **7** | 8 | Female | 169 | 56 | Business |
| **8** | 9 | Male | 175 | 75 | International Affairs |
| **9** | 10 | Female | 175 | 65 | Communications |

Show the column names (variable names) (this is useful to check whether there are no blank spaces in the variable names):

In [47]:
```
list(df)
```

Out[47]:
```
['case', 'sex', 'height', 'weight', 'major']
```

Inspect the data types in the dataframe called df:

In [48]:
```
df.dtypes
```

Out[48]:
```
case        int64
sex        object
height      int64
weight      int64
major      object
dtype: object
```

To display just one of the variables:

In [49]:
```
print(df.height)
```

```
0     172
1     170
2     170
3     171
4     186
5     183
6     170
7     169
8     175
9     175
10    195
11    176
12    188
13    192
14    172
15    169
16    172
17    178
18    177
19    178
20    160
21    175
22    190
23    178
24    163
25    161
26    162
27    170
28    154
29    170
Name: height, dtype: int64
```

In [ ]:

# Module 2: Displaying and describing categorical data

## Bar chart and pie chart

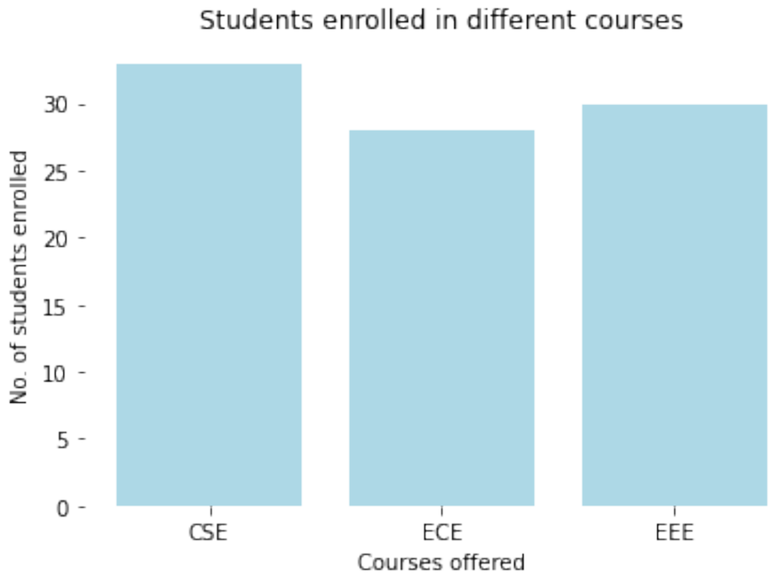
Generate a **bar chart** showing enrolment in three classes with course codes CSE (33 students), ECE (28 students), EEE (30 students):

(Documentation: https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.bar.html)

(Example is taken from https://www.analyticsvidhya.com/blog/2021/08/understanding-bar-plots-in-python-beginners-guide-to-data-visualization/ )

In [50]:

```
import numpy as np
import matplotlib.pyplot as plt
# Dataset generation
data_dict = {'CSE':33, 'ECE':28, 'EEE':30}
courses   = list(data_dict.keys())
values    = list(data_dict.values())
fig = plt.figure()    # add option `figsize = (10, 5)` to control size
#  Bar plot
plt.box(False)                  # get rid of the box
plt.bar(courses, values, color ='lightblue')
plt.xlabel("Courses offered")
plt.ylabel("No. of students enrolled")
plt.title("Students enrolled in different courses")
plt.show()
```

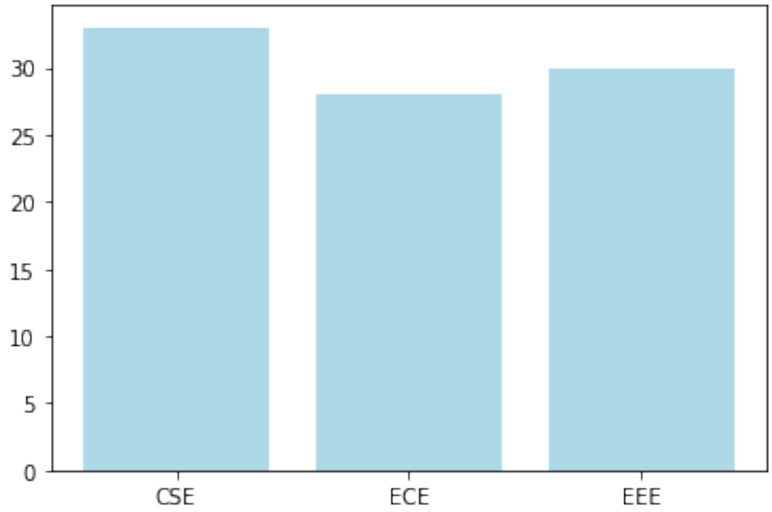



**Save a plot** to a file (.png or .pdf):

In [51]:

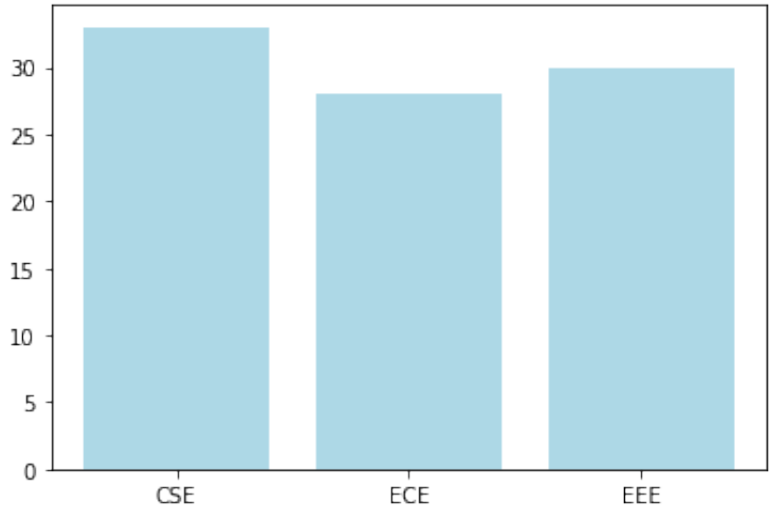
```
fig = plt.figure()
plt.bar(courses, values, color ='lightblue')
fig.savefig('saved_figure-1000dpi.png', dpi = 1000, transparent=True)
# the plot is saved to the current working directory (cwd)
# to find out what the current working directory (cwd) is:
import os
print('The file is saved to the current working directory: ',os.getcwd())
```

```
The file is saved to the current working directory:  /Users/luchens/Documents/jupyter-notebooks
```




To save the plot as a .pdf:

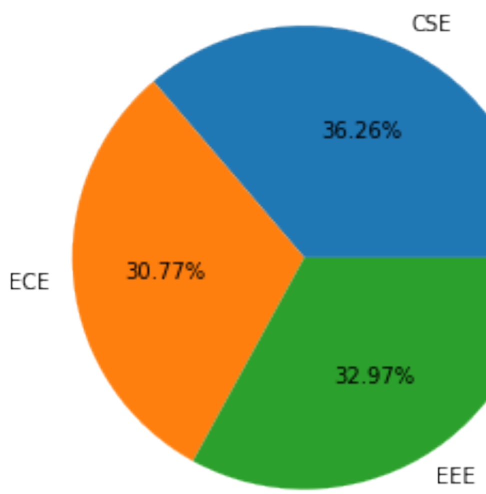
In [52]:
```
fig = plt.figure()
plt.bar(courses, values, color ='lightblue')
fig.savefig('saved_figure-1000dpi.pdf', dpi = 1000, transparent=True)
```




Generate a **pie chart** for the same data (pie charts are usually a poor way to display data):

(documentation: https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.pie.html )

In [53]:
```
import numpy as np
import matplotlib.pyplot as plt
# Dataset generation
data_dict = {'CSE':33, 'ECE':28, 'EEE':30}
courses   = list(data_dict.keys())
values    = list(data_dict.values())
fig = plt.figure(figsize = (10, 5))
# Pie chart:
plt.pie(values, labels=courses,autopct='%1.2f%%')    # option: autopct to sl
plt.show()
```




Generate a bar chart and a pie chart from an imported data set (students.csv):

Use `value_counts()` to count the how many times each of the values of the variable 'sex' in the dataframe 'df' occurs:

In [54]:
```
a = df.sex.value_counts()
print(a)
```

```
Female     18
Male       12
Name: sex, dtype: int64
```

In [55]:
```
a.values
```

Out[55]:
```
array([18, 12])
```

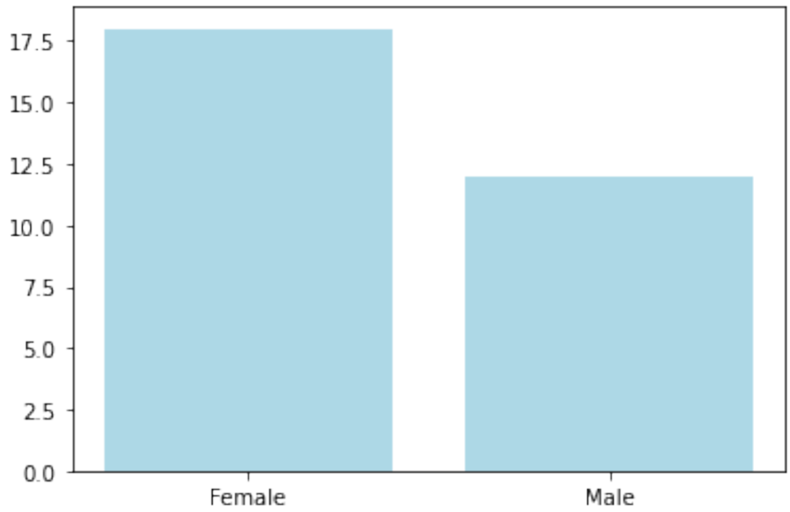
In [56]:
```
a.index
```

Out[56]:
```
Index(['Female', 'Male'], dtype='object')
```

Then use `a` as input for the `bar()` function:

In [57]:
```
plt.bar(a.index, a.values, color ='lightblue')
```

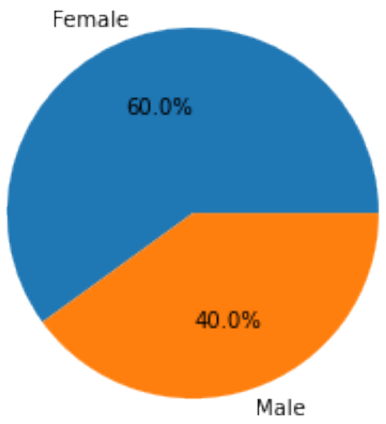
Out[57]:
```
<BarContainer object of 2 artists>
```



Or use `a` as input for the `pie()` function:

In [58]:
```
plt.pie(a.values,labels=a.index,autopct='%1.1f%%')
```

Out[58]:
```
([<matplotlib.patches.Wedge at 0x7ff30aa5c160>,
  <matplotlib.patches.Wedge at 0x7ff30aa5c850>],
 [Text(-0.3399187721714582, 1.046162142464278, 'Female'),
  Text(0.3399188701202255, -1.0461621106387813, 'Male')],
 [Text(-0.18541023936624992, 0.5706338958896061, '60.0%'),
  Text(0.18541029279285026, -0.5706338785302443, '40.0%')])
```




## Contingency table

To create a contingency table use `pandas.crosstab(index, columns)`. For an example see: https://www.statology.org/contingency-table-python/ Here is how to create a contingency table for the categorical variables (sex, major) from the students data file stored in the datraframe called df:

In [59]:
```
import pandas as pd
pd.crosstab(index=df['major'], columns=df['sex'],margins=True)
```

Out[59]:

| sex | Female | Male | All |
|---|---|---|---|
| **major** | | | |
| **Business** | 9 | 6 | 15 |
| **Communications** | 4 | 1 | 5 |
| **International Affairs** | 4 | 5 | 9 |
| **Other** | 1 | 0 | 1 |
| **All** | 18 | 12 | 30 |

To express all frequencies as relative frequencies, divide by number of observations:

In [60]:
```
n = len(df)     # number of observations
pd.crosstab(index=df['major'], columns=df['sex'],margins=True)/n
```

Out[60]:

| sex | Female | Male | All |
|---|---|---|---|
| **major** | | | |
| **Business** | 0.300000 | 0.200000 | 0.500000 |
| **Communications** | 0.133333 | 0.033333 | 0.166667 |
| **International Affairs** | 0.133333 | 0.166667 | 0.300000 |
| **Other** | 0.033333 | 0.000000 | 0.033333 |
| **All** | 0.600000 | 0.400000 | 1.000000 |

... and multiply by 100 (percent) to get percentages:

In [61]:
```
100*pd.crosstab(index=df['major'], columns=df['sex'],margins=True)/n
```

Out[61]:

| sex | Female | Male | All |
|---|---|---|---|
| **major** | | | |
| **Business** | 30.000000 | 20.000000 | 50.000000 |
| **Communications** | 13.333333 | 3.333333 | 16.666667 |
| **International Affairs** | 13.333333 | 16.666667 | 30.000000 |
| **Other** | 3.333333 | 0.000000 | 3.333333 |
| **All** | 60.000000 | 40.000000 | 100.000000 |

Summary statistics (qualitative variables only):

In [62]:
```
df.describe(include=['object'])
```

Out[62]:

| | sex | major |
|---|---|---|
| **count** | 30 | 30 |
| **unique** | 2 | 4 |
| **top** | Female | Business |
| **freq** | 18 | 15 |

Summary statistics of one categorical variable (in this case: sex)

In [63]:
```
df['sex'].describe()
```

Out[63]:
```
count         30
unique         2
top       Female
freq          18
Name: sex, dtype: object
```

# Module 3: Displaying and describing quantitative variables

## Descriptive statistics (mean, median, standard deviation,...)

Summary statistics (all variables) using the `describe()` function from pandas:

In [64]:
```
df.describe(include='all')
```

Out[64]:

| | case | sex | height | weight | major |
|---|---|---|---|---|---|
| **count** | 30.000000 | 30 | 30.000000 | 30.000000 | 30 |
| **unique** | NaN | 2 | NaN | NaN | 4 |
| **top** | NaN | Female | NaN | NaN | Business |
| **freq** | NaN | 18 | NaN | NaN | 15 |
| **mean** | 15.500000 | NaN | 174.033333 | 65.133333 | NaN |
| **std** | 8.803408 | NaN | 9.625696 | 13.356474 | NaN |
| **min** | 1.000000 | NaN | 154.000000 | 44.000000 | NaN |
| **25%** | 8.250000 | NaN | 170.000000 | 54.000000 | NaN |
| **50%** | 15.500000 | NaN | 172.000000 | 64.000000 | NaN |
| **75%** | 22.750000 | NaN | 178.000000 | 74.250000 | NaN |
| **max** | 30.000000 | NaN | 195.000000 | 94.000000 | NaN |

Summary statistics of one variable (in this case: height) using the `describe()` function from pandas

In [65]:
```
df['height'].describe()
```

Out[65]:
```
count     30.000000
mean     174.033333
std        9.625696
min      154.000000
25%      170.000000
50%      172.000000
75%      178.000000
max      195.000000
Name: height, dtype: float64
```

Summary statistics (quantitative variables only) using the `describe()` function from pandas:

In [66]:
```
df.describe()
```

Out[66]:

| | case | height | weight |
|---|---|---|---|
| **count** | 30.000000 | 30.000000 | 30.000000 |
| **mean** | 15.500000 | 174.033333 | 65.133333 |
| **std** | 8.803408 | 9.625696 | 13.356474 |
| **min** | 1.000000 | 154.000000 | 44.000000 |
| **25%** | 8.250000 | 170.000000 | 54.000000 |
| **50%** | 15.500000 | 172.000000 | 64.000000 |
| **75%** | 22.750000 | 178.000000 | 74.250000 |
| **max** | 30.000000 | 195.000000 | 94.000000 |

**Mean** and **standard deviation** of one of the variables ('height') from the 'df' dataframe:

In [67]:
```
import pandas as pd
df.height.mean()                              # height.mean() does not work: Name
```

Out[67]: 174.03333333333333

In [68]:
```
df.height.std()
```

Out[68]: 9.625695974240289

Other descriptive statistics:

In [69]:
```
df.height.median()    # simularly: min() ; max() ; sum() ; count() ; quanti
```

Out[69]: 172.0

In [70]:
```
df.height.quantile(q=0.50)    # the 50th percentile is the same as the media
```

Out[70]: 172.0

In [71]:
```
df.height.quantile(q=0.25)   # the 25th percentile (the first quartile)
```

Out[71]: 170.0

In [72]:
```
df.height.quantile(q=0.75)   # the 75th percentile (the third quartile)
```

Out[72]: 178.0

In [73]:
```
df.height.quantile(q=0.75)-df.height.quantile(q=0.25) # the interquartile r
```

Out[73]: 8.0

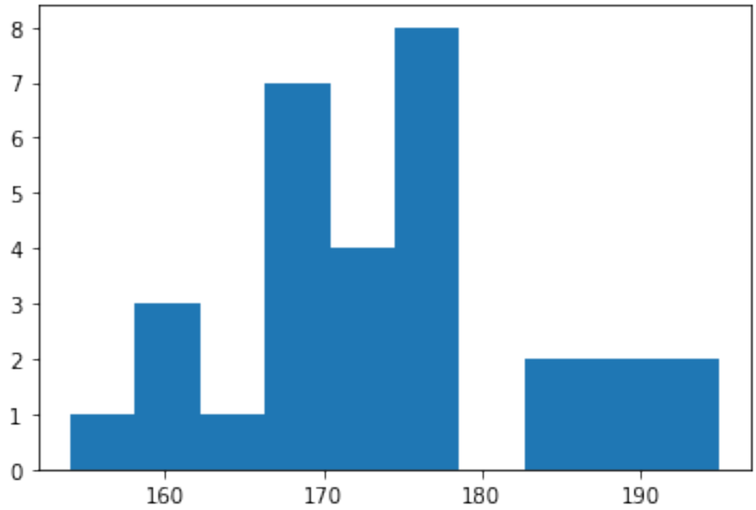
## Histogram

To draw a **histogram** use `hist()` from the `maplotlib.pyplot` package.

**Frequency histogram** (vertical axis shows counts, absolute frequencies):

In [74]:
```
import matplotlib.pyplot as plt
plt.hist(df.height)    # the default is a frequency histogram: vertical axi
```

Out[74]:
```
(array([1., 3., 1., 7., 4., 8., 0., 2., 2., 2.]),
 array([154. , 158.1, 162.2, 166.3, 170.4, 174.5, 178.6, 182.7, 186.8,
        190.9, 195. ]),
 <BarContainer object of 10 artists>)
```

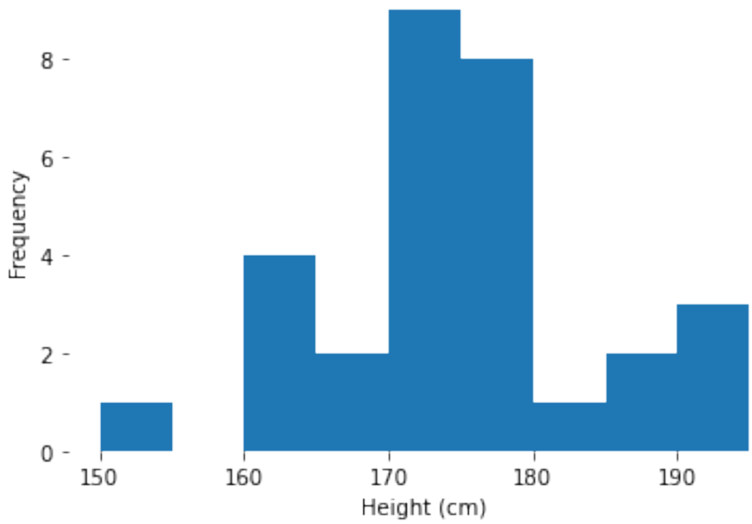



In the output, the first array gives gives the counts (absolute frequencies) for each of the classes (bins). The second array gives the edges of the bins ( https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.hist.html).

Get rid of the box, add labels to the axes, and let the bins start at 150, 155, 160,...:

In [75]:
```
import matplotlib.pyplot as plt
plt.box(False)                # get rid of the box
plt.xlabel('Height (cm)')     # add label on x-axis
plt.ylabel('Frequency')       # add label on x-axis
plt.hist(df.height,bins=[150,155,160,165,170,175,180,185,190,195])
```

Out[75]:
```
(array([1., 0., 4., 2., 9., 8., 1., 2., 3.]),
 array([150, 155, 160, 165, 170, 175, 180, 185, 190, 195]),
 <BarContainer object of 9 artists>)
```




**Relative frequency histogram** (vertical axis shows relative frequencies):

In [76]:
```
df.height.size   # size gives the number of observations of the variable hei
```

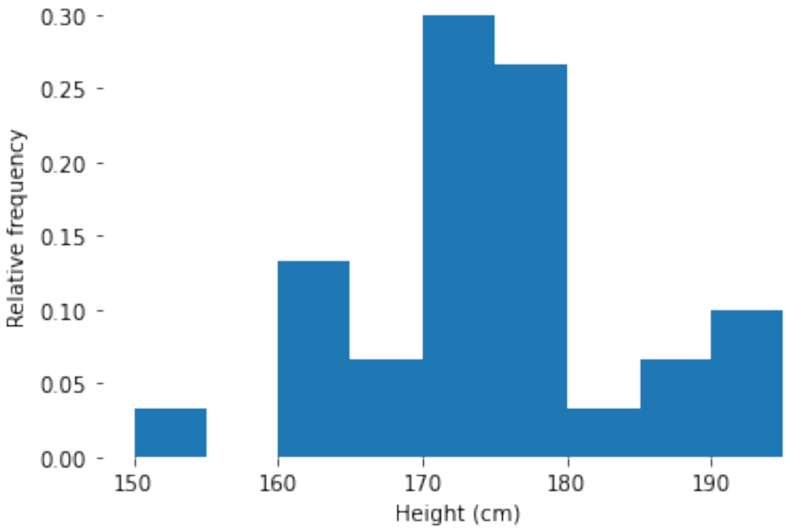
Out[76]: 30

In [77]:

```
import matplotlib.pyplot as plt
import numpy as np
plt.box(False)                   # get rid of the box
plt.xlabel('Height (cm)')        # add label on x-axis
plt.ylabel('Relative frequency')      # add label on x-axis
plt.hist(df.height, weights=np.zeros_like(df.height) + 1. / df.height.size,
         bins=[150,155,160,165,170,175,180,185,190,195])
```

Out[77]:

```
(array([0.03333333, 0.        , 0.13333333, 0.06666667, 0.3       ,
        0.26666667, 0.03333333, 0.06666667, 0.1       ]),
 array([150, 155, 160, 165, 170, 175, 180, 185, 190, 195]),
 <BarContainer object of 9 artists>)
```



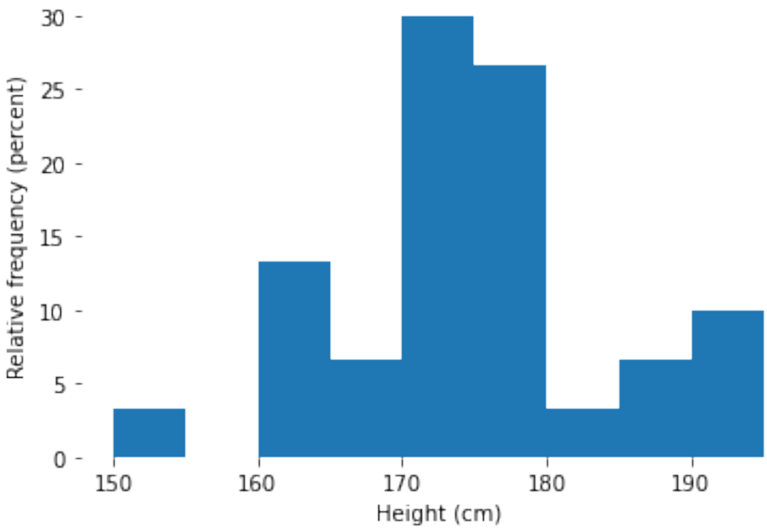

In the output, the first array gives gives the relative frequencies for each of the classes (bins). The second array gives the edges of the bins ( https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.hist.html).

To get a relative frequency histogram with relative frequencies expressed as percentages, multiply the weights by 100:

In [78]:

```
import matplotlib.pyplot as plt
import numpy as np
df.height.size  # size gives the number of observations of the variable he
plt.box(False)                   # get rid of the box
plt.xlabel('Height (cm)')        # add label on x-axis
plt.ylabel('Relative frequency (percent)')      # add label on x-axis
plt.hist(df.height, weights=100*(np.zeros_like(df.height) + 1. / df.height.
         bins=[150,155,160,165,170,175,180,185,190,195])
```

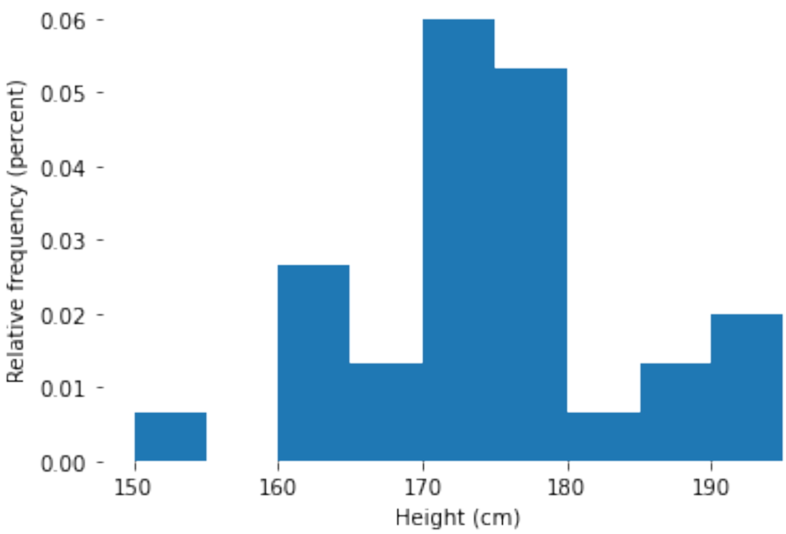
Out[78]:
```
(array([ 3.33333333,  0.        , 13.33333333,  6.66666667, 30.        ,
        26.66666667,  3.33333333,  6.66666667, 10.        ]),
 array([150, 155, 160, 165, 170, 175, 180, 185, 190, 195]),
 <BarContainer object of 9 artists>)
```




**Density histogram** (vertical axis shows densities):

In [79]:
```
import matplotlib.pyplot as plt
df.height.size  # size gives the number of observations of the variable hei
plt.box(False)             # get rid of the box
plt.xlabel('Height (cm)')  # add label on x-axis
plt.ylabel('Relative frequency (percent)')      # add label on x-axis
plt.hist(df.height, density=True, bins=[150,155,160,165,170,175,180,185,190
```

Out[79]:
```
(array([0.00666667, 0.        , 0.02666667, 0.01333333, 0.06      ,
        0.05333333, 0.00666667, 0.01333333, 0.02      ]),
 array([150, 155, 160, 165, 170, 175, 180, 185, 190, 195]),
 <BarContainer object of 9 artists>)
```



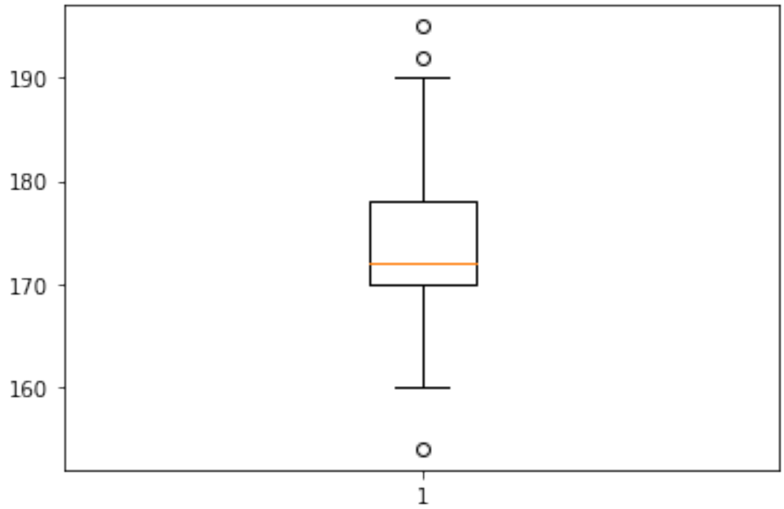

In the output, the first array gives gives the densities for each of the classes (bins). The second array gives the edges of the bins ( https://matplotlib.org/stable/api/_as_gen/matplotlib.pyplot.hist.html).

## Box plot

Use `boxplot()` from `matplotlib` :

In [80]:
```
import matplotlib.pyplot as plt
plt.boxplot(df.height)
```

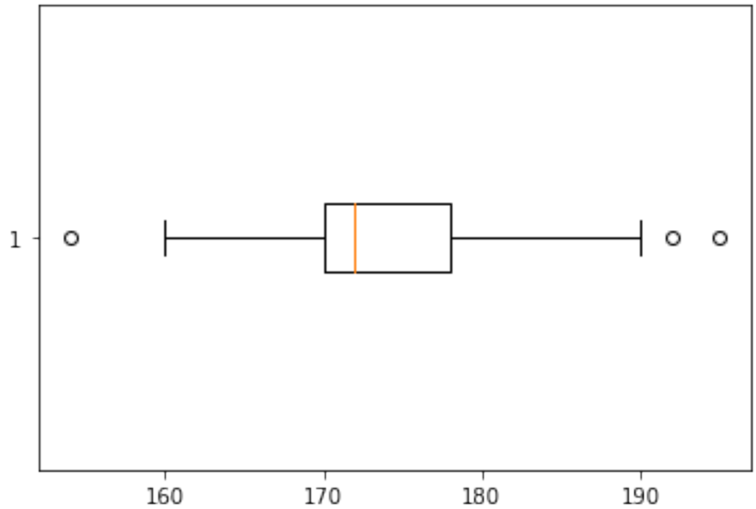
Out[80]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7ff2f8f4d7c0>,
  <matplotlib.lines.Line2D at 0x7ff2f8f4db20>],
 'caps': [<matplotlib.lines.Line2D at 0x7ff2f8f4de80>,
  <matplotlib.lines.Line2D at 0x7ff2f8f58220>],
 'boxes': [<matplotlib.lines.Line2D at 0x7ff2f8f4d460>],
 'medians': [<matplotlib.lines.Line2D at 0x7ff2f8f58580>],
 'fliers': [<matplotlib.lines.Line2D at 0x7ff2f8f588e0>],
 'means': []}
```




Rotate the boxplot to get a horizontal orientation:

In [81]:
```
import matplotlib.pyplot as plt
plt.boxplot(df.height,vert=False)
```

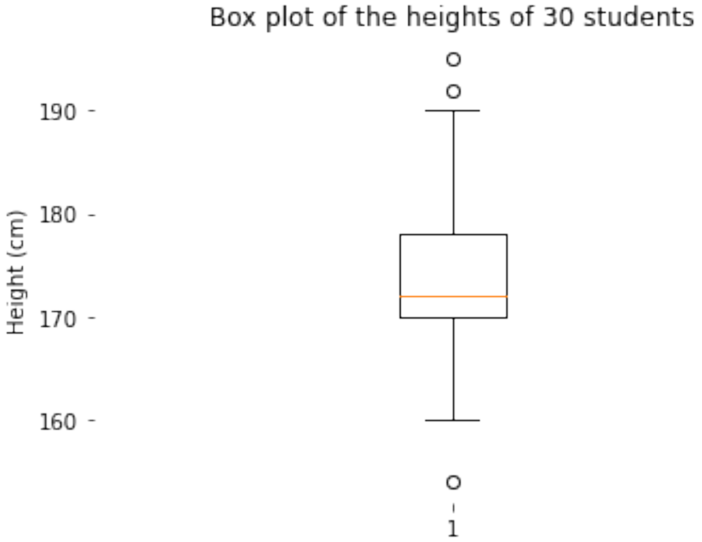
Out[81]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7ff2f9006370>,
  <matplotlib.lines.Line2D at 0x7ff2f90066d0>],
 'caps': [<matplotlib.lines.Line2D at 0x7ff2f9006a30>,
  <matplotlib.lines.Line2D at 0x7ff2f9006d90>],
 'boxes': [<matplotlib.lines.Line2D at 0x7ff2f8f99fd0>],
 'medians': [<matplotlib.lines.Line2D at 0x7ff2f9012130>],
 'fliers': [<matplotlib.lines.Line2D at 0x7ff2f9012490>],
 'means': []}
```




Make the box plot prettier (get rid of the box, label the axes, add title) (still to fix: get rid of the "1" label):

In [82]:
```
import matplotlib.pyplot as plt
plt.box(False)                # get rid of the box
plt.title("Box plot of the heights of 30 students") # add title
plt.xlabel("")  # I want to get rid of the 1 on the x-axis
plt.ylabel("Height (cm)")  # add label to y-axis
plt.boxplot(df.height)
```

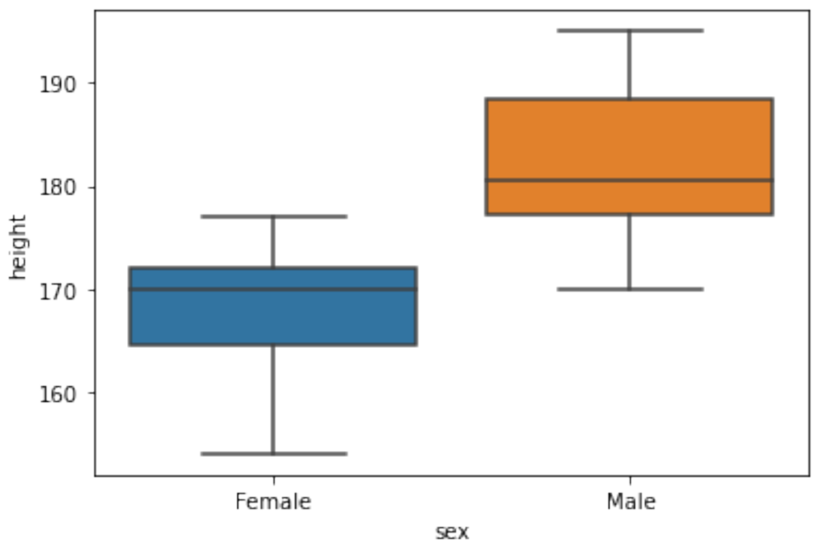
Out[82]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x7ff2e8a184f0>,
  <matplotlib.lines.Line2D at 0x7ff2e8a18850>],
 'caps': [<matplotlib.lines.Line2D at 0x7ff2e8a18bb0>,
  <matplotlib.lines.Line2D at 0x7ff2e8a18eb0>],
 'boxes': [<matplotlib.lines.Line2D at 0x7ff2e8a18190>],
 'medians': [<matplotlib.lines.Line2D at 0x7ff2e8a221f0>],
 'fliers': [<matplotlib.lines.Line2D at 0x7ff2e8a22550>],
 'means': []}
```




To compare the heights of men and women, use **side-by-side boxplots** (from the `seaborn` package):

In [83]:
```
import seaborn as sns
sns.boxplot(data=df,x="sex",y='height')
```

Out[83]: `<AxesSubplot:xlabel='sex', ylabel='height'>`




In [84]:
```
df.sex.count()
```

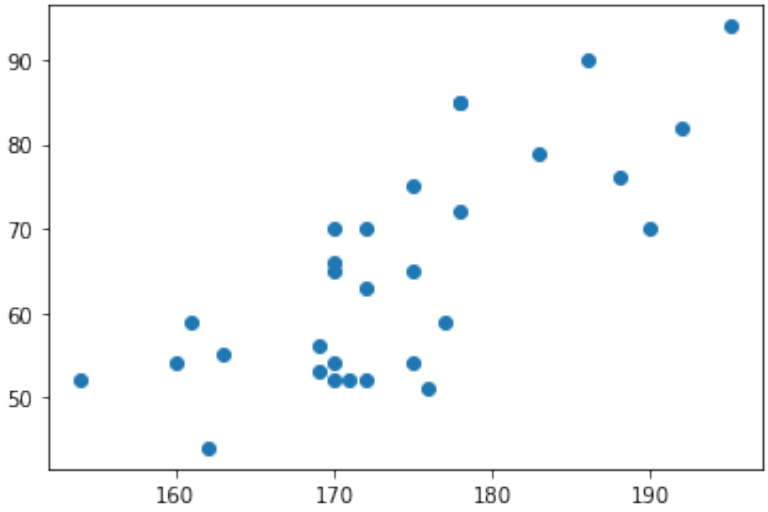
Out[84]: 30

## Module 4: Correlation and Regression

Make a **scatter plot** of heights (horizontal axis) and weights (vertical axis) using `scatter()` from `matplotlib.pyplot` :

In [85]:
```
import numpy as np
import matplotlib.pyplot as plt
plt.scatter(df.height,df.weight)
```

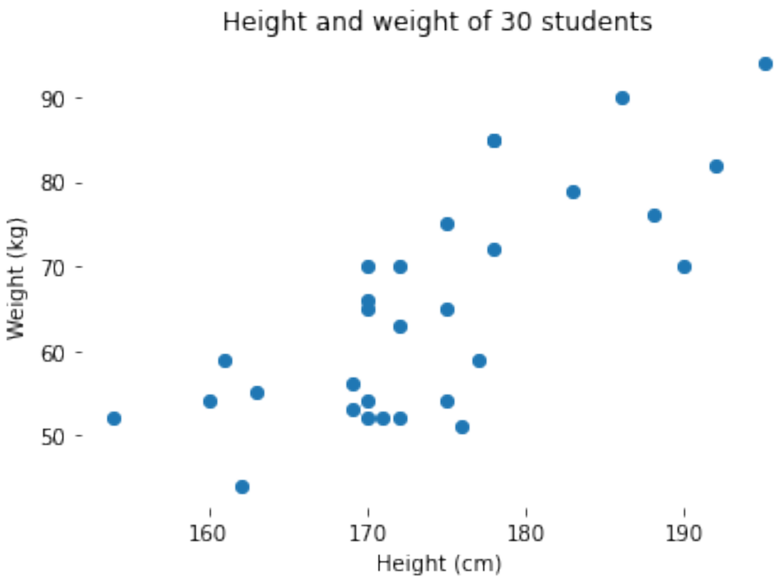
Out[85]: <matplotlib.collections.PathCollection at 0x7ff2f912b7f0>




Make the scatter plot prettier (get rid of the box, add labels to the axes):

In [86]:
```
plt.box(False)                  # get rid of the box
plt.title("Height and weight of 30 students") # add title
plt.xlabel("Height (cm)")  # add label to x-axis
plt.ylabel("Weight (kg)")  # add label to y-axis
plt.scatter(df.height,df.weight)
```

Out[86]: <matplotlib.collections.PathCollection at 0x7ff2e8a61460>




Correlation coefficient:

In [87]:
```
# correlation matrix between all quantitative variables of a data frame:
df.corr()
```

Out[87]:

| | case | height | weight |
|---|---|---|---|
| **case** | 1.000000 | -0.320457 | -0.254260 |
| **height** | -0.320457 | 1.000000 | 0.752567 |
| **weight** | -0.254260 | 0.752567 | 1.000000 |

To get *one* of the correlation coefficients, first convert to matrix:

In [88]:
```
import numpy as np
corr_matrix = np.array(df.corr())
print(corr_matrix)
```

```
[[ 1.         -0.32045686 -0.25426022]
 [-0.32045686  1.          0.75256681]
 [-0.25426022  0.75256681  1.        ]]
```

In [89]:
```
# extract the correlation between height and weight (caution: rows and colu
corr_matrix[1][2]
```

Out[89]:
```
0.7525668130284301
```

In [90]:
```
# correlation between height and weight (directly, without computing the co
df.height.corr(df.weight)
```

Out[90]:
```
0.7525668130284301
```

Find the **line of best fit** using statsmodels:

In [91]:
```
import statsmodels.api as sms
import statsmodels.formula.api as smf
# Fit regression model:
results = smf.ols('df.weight ~ df.height', data=df).fit()
# Inspect the results:
print(results.summary())
```

```
                            OLS Regression Results                            
==============================================================================
===
Dep. Variable:              df.weight   R-squared:                       0.
566
Model:                            OLS   Adj. R-squared:                  0.
551
Method:                 Least Squares   F-statistic:                     36
.57
Date:                Mon, 20 Dec 2021   Prob (F-statistic):            1.61e
-06
Time:                        17:35:56   Log-Likelihood:                 -107
.29
No. Observations:                  30   AIC:                             21
8.6
Df Residuals:                      28   BIC:                             22
1.4
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
===
                 coef    std err          t      P>|t|      [0.025      0.9
75]
------------------------------------------------------------------------------
---
Intercept   -116.6011     30.097     -3.874      0.001    -178.252     -54.
951
df.height      1.0443      0.173      6.047      0.000       0.691       1.
398
==============================================================================
===
Omnibus:                        2.804   Durbin-Watson:                   2.
486
Prob(Omnibus):                  0.246   Jarque-Bera (JB):                1.
333
Skew:                           0.007   Prob(JB):                        0.
514
Kurtosis:                       1.968   Cond. No.                      3.21e
+03
==============================================================================
===

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corr
ectly specified.
[2] The condition number is large, 3.21e+03. This might indicate that there
are
strong multicollinearity or other numerical problems.
```

To get just the coefficients:

In [92]:
```
results.params
```

Out[92]:
```
Intercept   -116.601087
df.height      1.044251
dtype: float64
```

To get the first coefficient (intercept):

In [93]:
```
results.params[0]
```

Out[93]:
```
-116.6010867272883
```

To get the second coefficient (slope coefficient):

In [94]:
```
results.params[1]
```

Out[94]: 1.044250641987867

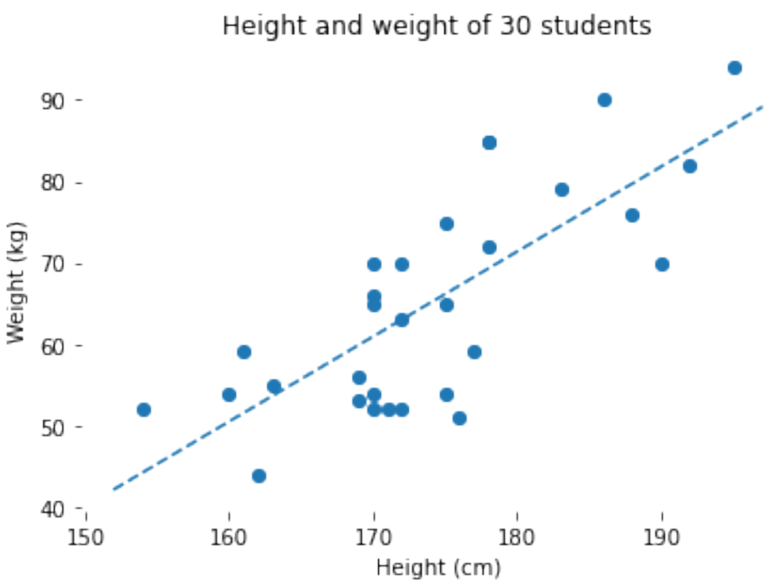
To get the t-values of the coefficients:

In [95]:
```
results.tvalues
```

Out[95]:
```
Intercept   -3.874200
df.height    6.047248
dtype: float64
```

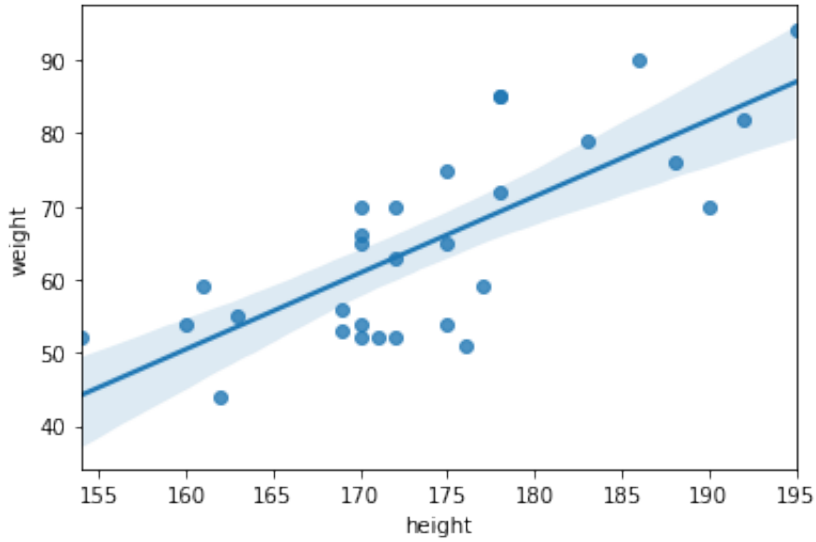
Add line of best fit to the scatter plot (see: https://stackoverflow.com/questions/7941226/how-to-add-line-based-on-slope-and-intercept-in-matplotlib):

In [96]:
```
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as sms
import statsmodels.formula.api as smf

# Fit regression model:
results = smf.ols('df.weight ~ df.height', data=df).fit()

def abline(slope, intercept):
    """Plot a line from slope and intercept"""
    axes = plt.gca()
    x_vals = np.array(axes.get_xlim())
    y_vals = intercept + slope * x_vals
    plt.plot(x_vals, y_vals, '--')

plt.box(False)                # get rid of the box
plt.title("Height and weight of 30 students") # add title
plt.xlabel("Height (cm)")  # add label to x-axis
plt.ylabel("Weight (kg)")  # add label to y-axis
plt.scatter(df.height,df.weight)
abline(results.params[1],results.params[0])      # add line y=a*x+b  (a = s
```



The seaborn package has more advanced ways to display data. Add a **line of best fit** to the scatter plot using the seaborn package:

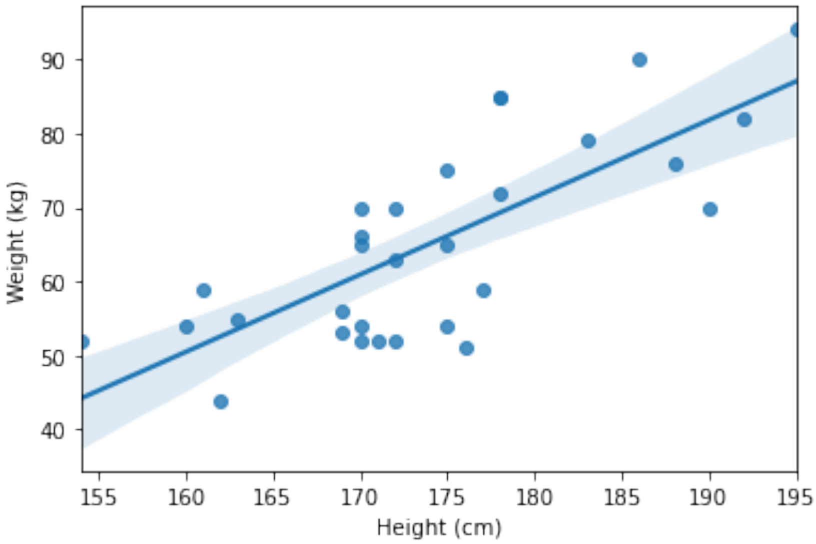
In [97]:
```
import seaborn as sns   # regplot: regression plot
sns.regplot(x=df.height,y=df.weight, data=df)
plt.show()
```




Label the axes:

In [98]:
```
x, y = pd.Series(df.height, name="Height (cm)"), pd.Series(df.weight, name=
sns.regplot(x=x,y=y, data=df)
```

Out[98]:
```
<AxesSubplot:xlabel='Height (cm)', ylabel='Weight (kg)'>
```




# Module 5: Randomness and Probability

# Module 6: Random variables and probability models

Calculate **binomial probability** (*k* = number of successes, *n* = number of trials, *p* = probability of success) ( `pmf` stands for: probability mass function—like pdf but for a discrete random variable):

In [99]:
```
# calculate binomial probability (k= number of successes, n = number of tri
from scipy.stats import binom
binom.pmf(k=10, n=12, p=0.6)    # pmf: probability mass function (like pdf b
```

Out[99]: 0.06385228185599987

Calculate cumulative binomial probability:

In [100…
```
from scipy.stats import binom
binom.cdf(k=10, n=12, p=0.6)
```

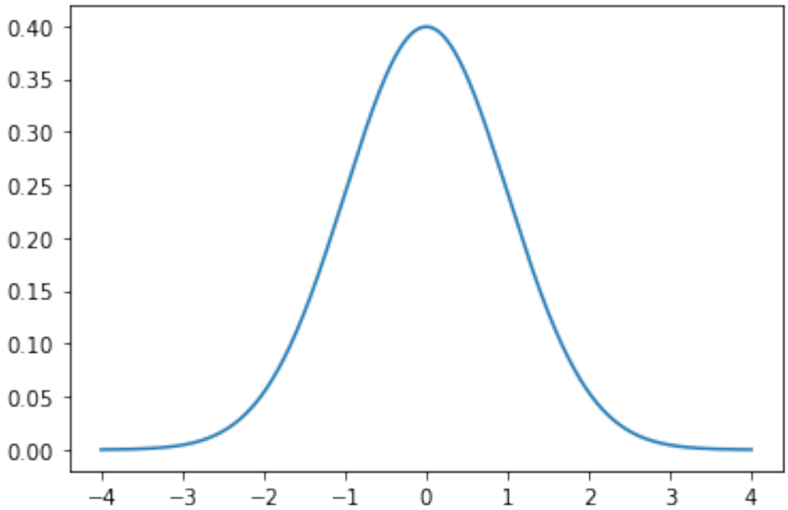
Out[100… 0.980408958976

# Module 7: The Normal distribution

Plot the **probability density function** (pdf) of the normal curve (https://www.statology.org/plot-normal-distribution-python/):

In [101…
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
# x-axis ranges from -4 and 4 with .001 steps:
x = np.arange(-4, 4, 0.001)

# plot normal distribution with mean 0 and standard deviation 1
plt.plot(x, norm.pdf(x, 0, 1))
```

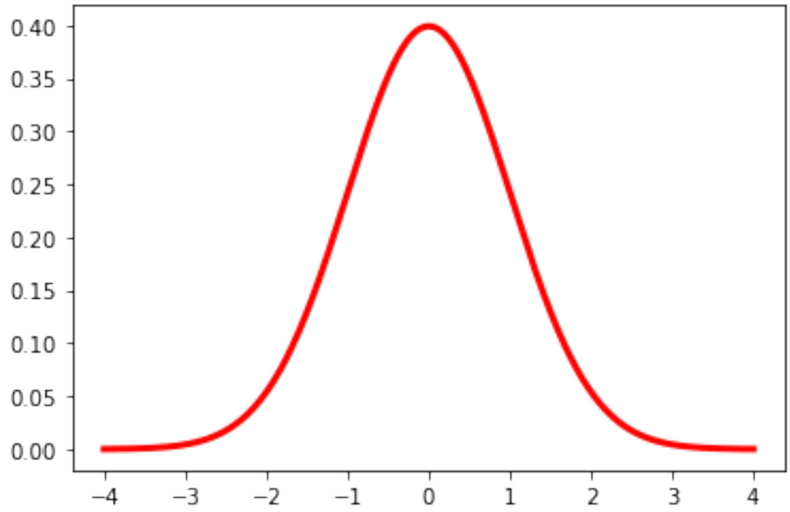
Out[101… [<matplotlib.lines.Line2D at 0x7ff2e8af6f40>]




Change color, linewidth:

In [102…
```
plt.plot(x, norm.pdf(x, 0, 1), color='red', linewidth=3)
```

Out[102… [<matplotlib.lines.Line2D at 0x7ff2f9277580>]




## Area under normal curve:

To find an area under the normal curve, use the **cumulative density function** (cdf) of the normal distribution. (documentation: see: https://docs.scipy.org/doc/scipy/reference/stats.html)

In [103…

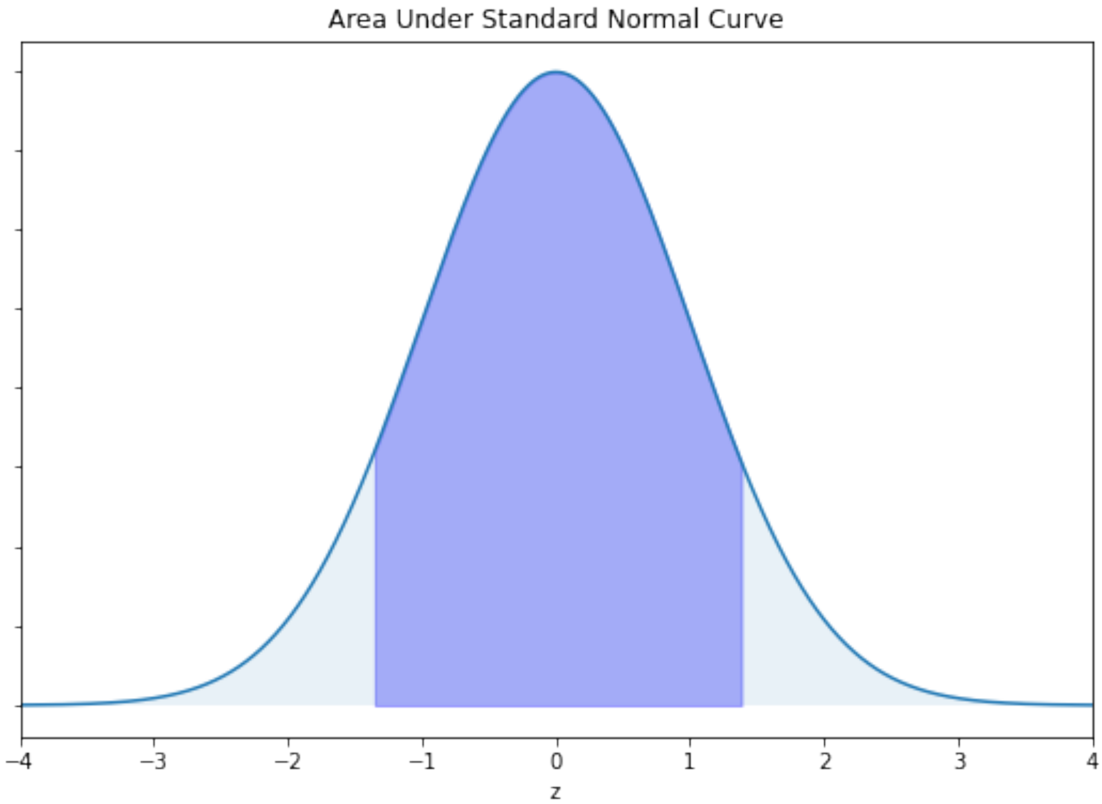
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
mu    = 0     # mean               (for the standard normal distribution, t
sigma = 1     # standard deviation (for the standard normal distribution, t
x1 = -1.96    # lower boundary
x2 = 1.96   # lower boundary
# area under normal curve between x1 and x2:
area = norm.cdf(x2, loc=mu, scale=sigma)-norm.cdf(x1, loc=mu, scale=sigma)
print('The area under the normal curve is', area)
```

```
The area under the normal curve is 0.950004209703559
```

To **plot** the area under the normal curve (see: https://pythonforundergradengineers.com/plotting-normal-curve-with-python.html)

In [104…

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
# define constants
mu = 998.8 # mean
sigma = 73.10  # standard deviation
x1 = 900    # lower boundary
x2 = 1100   # lower boundary
# calculate the standardized values:
z1 = ( x1 - mu )/ sigma
z2 = ( x2 - mu) / sigma
x = np.arange(z1, z2, 0.001) # range of x in spec
x_all = np.arange(-10, 10, 0.001) # entire range of x, both in and out of s
# for standard normal distribution, mean = 0, stddev = 1:
y = norm.pdf(x,0,1)
y2 = norm.pdf(x_all,0,1)
###
# build the plot
fig, ax = plt.subplots(figsize=(9,6))
ax.plot(x_all,y2)
ax.fill_between(x,y,0, alpha=0.3, color='b')
ax.fill_between(x_all,y2,0, alpha=0.1)
ax.set_xlim([-4,4])
ax.set_xlabel('z')
ax.set_yticklabels([])
ax.set_title('Area Under Standard Normal Curve')
plt.savefig('normal_curve.png', dpi=72, bbox_inches='tight')
plt.show()

# area under normal curve between x1 and x2:
area = norm.cdf(x2, loc=mu, scale=sigma)-norm.cdf(x1, loc=mu, scale=sigma)
print('The area under the normal curve is', area)
```




```
The area under the normal curve is 0.8286268028320297
```

## Other continuous distributions

Uniform distribution
(https://docs.scipy.org/doc/scipy/reference/generated/scipy.stats.uniform.html):

In [105…

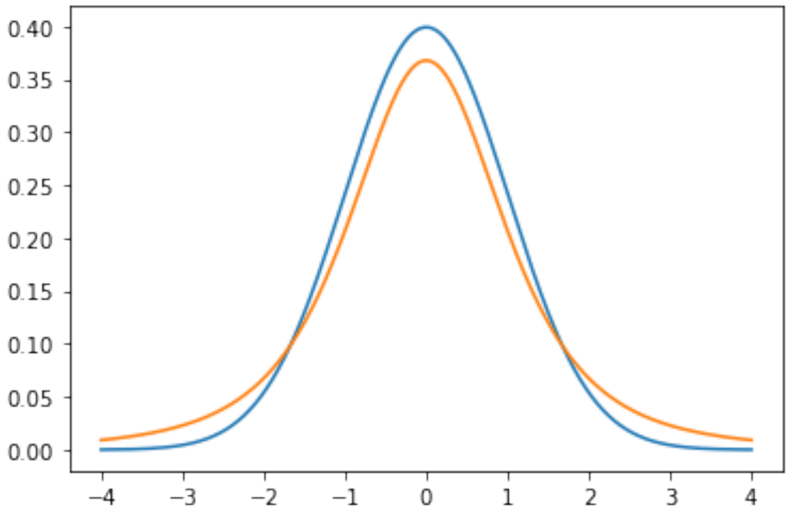
```
from scipy.stats import uniform
# In the standard form, the distribution is uniform on [0, 1].
# Using the parameters loc and scale, one obtains the uniform distribution
uniform.cdf(0.9)
```

Out[105… 0.9

Student *t* distribution (covered in Statistics II)

In [106…

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import t
# x-axis ranges from -4 and 4 with .001 steps:
x = np.arange(-4, 4, 0.001)
plt.figure()
plt.plot(x, norm.pdf(x,0,1 ))     # plot the standard normal curve as a benc
plt.plot(x, t.pdf(x, 3))         # the second argument is the degrees of fre
plt.show()
```




**Still to add:** plotting Student *t* distributions with different degrees of freedom and compare with standard normal distribution (see Haslwanter (2016), p. 110); an animation in which degrees of freedom increase; an interactive diagram in which user can change degrees of freedom; areas under *t* distribution.

# Module 9: Sampling Distributions and Confidence Intervals for Proportions

To find the **confidence interval for a proportion**:
(https://www.statsmodels.org/dev/generated/statsmodels.stats.proportion.proportion_confint

In [107…

```
310 / 1126     # sample proportion = number of successes / number of trials

import statsmodels.api as sm
from statsmodels.stats.proportion import proportion_confint   # Function fo

proportion_confint(count=310,         # count= number of successes
                   nobs=1126,         # nobs = number of trials
                   alpha=(1 - 0.95)) # alpha =  1 - confidence level
```

Out[107…

```
(0.24922129423231776, 0.30140037539468045)
```

# Module 10: Sampling Distributions and Confidence Intervals for Means

To find the **confidence interval for a mean** (in this case: the mean height of all students in the dataframe df):

In [108…

```
import numpy as np
import scipy.stats as stats

degrees_of_freedom    = len(df)-1            # degrees of freedom = sample s
sample_mean           = np.mean(df.height)  # sample mean
sample_standard_error = stats.sem(df.height)   # sample standard error of m

# create confidence interval for the population mean:
stats.t.interval(alpha=0.05, df=degrees_of_freedom, loc=sample_mean, scale=
```

Out[108…

```
(173.9221744669485, 174.14449219971817)
```

# Statistics II: Hypothesis tests

**Still to add:** Hypothesis tests (covered in Statistics II).

# Interacting with the operating system (changing current working directory etc.)

The `os` package allows you to interact with the operating system using Python code.

The **current working directory** (cwd) is where Python will look for input (such as data files) and where it will store output (such as .png or .pdf figures and tables with results). To find out what the current working directory of Python is:

In [109…

```
import os
print(os.getcwd())
```

```
/Users/luchens/Documents/jupyter-notebooks
```

If you want to change the current working directory, use the chdir command of the os package to do so. Here is how to change the current working directory (the expression in quotes is the path to the new working directory — it will be a different path for you, of course):

In [110…

```
os.chdir('/Users/luchens/Documents/Data/')
print(os.getcwd())
```

```
/Users/luchens/Documents/Data
```

To display the files and directories in the working directory, use `os.listdir()`