Cardiovascular Disease Pediction Project.



Source:

Creators:

- 1. Hungarian Institute of Cardiology. Budapest: Andras Janosi, M.D.
- 2. University Hospital, Zurich, Switzerland: William Steinbrunn, M.D.
- 3. University Hospital, Basel, Switzerland: Matthias Pfisterer, M.D.
- 4. V.A. Medical Center, Long Beach and Cleveland Clinic Foundation: Robert Detrano, M.D., Ph.D.



- According to WHO, Cardiovascular diseases (CVDs) are the number 1 cause of death globally, taking an estimated 17.9 million lives each year, which accounts for 31% of all deaths worlwide.
- More than four out of five CVD deaths are due to heart attacks and strokes, and one third of these deaths occur prematurely in people under 70 years of age.
- CVDs are a group of disorders of the heart and blood vessels and include coronary heart disease, cerebrovascular disease, rheumatic heart disease and other conditions.

It can also be associated with damage to arteries in organs such as the brain, heart, kidneys
and eyes. People with cardiovascular disease or who are at high cardiovascular risk (due to
the existence of one or more risk factors such as hypertension, diabetes, hyperlipidaemia or
already established disease) need early detection and management wherein a machine
learning model can be of great help.

How can we reduce the Heart diseases death rate?

- The early prognosis of cardiovascular diseases can aid in making decisions on lifestyle changes in high risk patients and in turn reduce the complications.
- We Aim to deploy a machine learning model that can predict whether the person may have a
 heart disease or not.

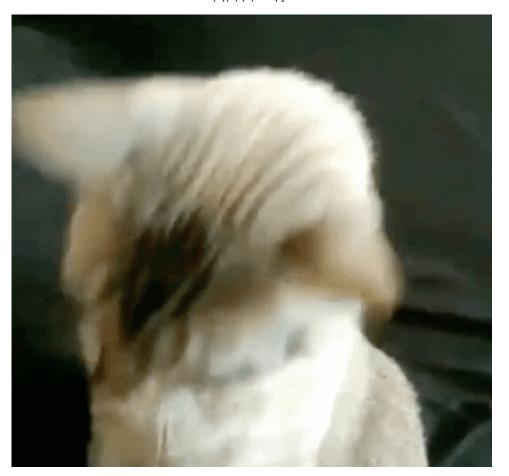
Our Problem

 Predict the presence or absence of cardiovascular disease (CVD) using the patient examination results.

Import Libraries

QEDA:

Let's Explore our data !!!



- Analyze by describing the data

In [3]: # First 5 rows of the dataframe
df.head()

Out[3]:		age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	са	thal	target
	0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
	1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
	2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
	3	56	1	1	120	236	0	1	178	0	8.0	2	0	2	1
	4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

```
In [4]: # Columns of data
df.columns
```

Features:

There are 2 types of input features:

· Objective: factual information;

· Examination: results of medical examination;

sex : 1 = Male , 0=Female

cp : Chest Pain

Angina: Angina is caused when there is not enough oxygen-rich blood flowing to a certain part
of the heart. The arteries of the heart become narrow due to fatty deposits in the artery walls.
The narrowing of arteries means that blood supply to the heart is reduced, causing angina.
Value 0: typical angina || Value 1: atypical angina || Value 2: non-anginal pain || 3:
asymptomatic

threstbps : Resting blood pressure

• (Normal pressure with no exercise)

chol: serum cholestoral in mg/dl

Cholesterol means the blockage for blood supply in the blood vessels

fbs: fasting blood sugar > 120 mg/dl

 (1 = true; 0 = false) blood sugar taken after a long gap between a meal and the test. Typically, it's taken before any meal in the morning.

restecg: resting electrocardiographic results (values 0,1,2)

 ECG values taken while person is on rest which means no exercise and normal functioning of heart is happening

thalach: maximum heart rate achieved

exang: exercise induced angina

(1 = yes; 0 = no) is chest pain while exercising or doing any physical activity.

oldpeak = ST depression induced by exercise relative to rest

- ST Depression is the difference between value of ECG at rest and after exercise.
- An electrocardiogram records the electrical signals in your heart. It's a common and painless
 test used to quickly detect heart problems and monitor your heart's health. Electrocardiograms
 — also called ECGs or EKGs are often done in a doctor's office, a clinic or a hospital room.
 ECG machines are standard equipment in operating rooms and ambulances. Some personal devices, such as smart watches,

slope: the slope of the peak exercise ST segment

Value 0: upsloping — Value 1: flat — Value 2: downsloping

ca: number of major vessels (0-3) colored by flourosopy

 Fluoroscopy is an imaging technique that uses X-rays to obtain real-time moving images of the interior of an object. In its primary application of medical imaging, a fluoroscope (/ 'flʊərəskoʊp/) allows a physician to see the internal structure and function of a patient, so that the pumping action of the heart or the motion of swallowing, for example, can be watched

thal: The Types of thalassemia

• (1,3 = normal; 6 = fixed defect; 7 = reversable defect)

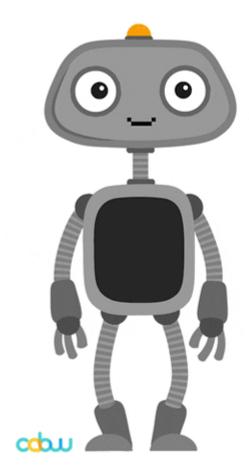
```
In [5]: # Getting some informations about the dataset
        df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 303 entries, 0 to 302
        Data columns (total 14 columns):
             Column
                       Non-Null Count Dtype
                                       ----
         0
                       303 non-null
                                       int64
             age
                       303 non-null
             sex
                                       int64
         1
         2
                       303 non-null
                                       int64
             ср
         3
             trestbps 303 non-null
                                       int64
         4
             chol
                       303 non-null
                                       int64
         5
             fbs
                       303 non-null
                                       int64
         6
                       303 non-null
             restecg
                                       int64
         7
             thalach
                       303 non-null
                                       int64
         8
             exang
                       303 non-null
                                       int64
         9
             oldpeak
                       303 non-null
                                       float64
         10 slope
                       303 non-null
                                       int64
         11
             ca
                       303 non-null
                                       int64
         12
             thal
                       303 non-null
                                       int64
         13 target
                       303 non-null
                                       int64
        dtypes: float64(1), int64(13)
        memory usage: 33.3 KB
In [6]: # Number of rows and columns
        df.shape
Out[6]: (303, 14)
In [7]: df.values
Out[7]: array([[63.,
                                     0.,
                      1., 3., ...,
                                          1.,
                                               1.],
               [37.,
                      1., 2., ...,
                                     0.,
                                          2.,
                                               1.],
               [41.,
                      0.,
                           1., ...,
                                     0.,
                                               1.],
                                          3.,
               [68.,
                      1.,
                           0., ..., 2.,
               [57.,
                      1., 0., ..., 1., 3.,
                                               0.],
                      0., 1., ..., 1., 2.,
               [57.,
```

```
In [8]: | sex = df.sex.values
        restecg = df.restecg.values
        exang = df.exang.values
        slope = df.slope.values
        print("Sex values are : ",set(sex))
        print("Restecg values are : ",set(restecg))
        print("Exang values are : ",set(exang))
        print("Slope values are : ",set(slope))
        Sex values are : {0, 1}
        Restecg values are : {0, 1, 2}
        Exang values are : {0, 1}
        Slope values are : {0, 1, 2}
In [9]: df.apply(lambda x:len(x.unique()))
Out[9]: age
                      41
                      2
        sex
                      4
        ср
        trestbps
                     49
        chol
                     152
        fbs
                      2
        restecg
                      3
        thalach
                      91
                      2
        exang
        oldpeak
                      40
        slope
                       3
                       5
        ca
        thal
                       4
                       2
        target
        dtype: int64
```

- Dealing with Missing Values:

```
In [10]: # Checking for missing values
         df.isna().sum()
Out[10]: age
                      0
                      0
          sex
          ср
          trestbps
                      0
          chol
          fbs
                      0
          restecg
          thalach
                      0
          exang
          oldpeak
                      0
          slope
          ca
          thal
          target
          dtype: int64
```

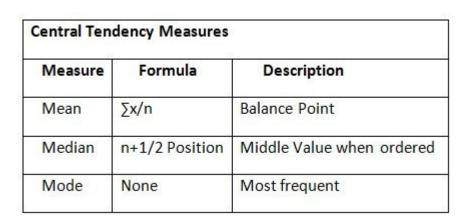
• No missing data, cool! :)



- Does it indicate that the data is really stable? check the outliers or Wrong Data. . .
- First we will need some statistical information...
- Statistical measuers (mean , standard deviation , min , max) :

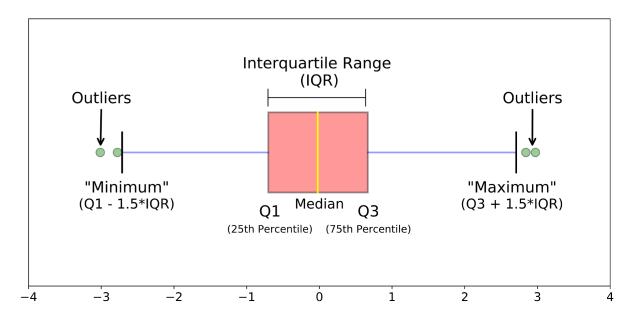
In [11]: display(df.describe())

	age	sex	ср	trestbps	chol	fbs	restecg	tha
count	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.000000	303.00
mean	54.366337	0.683168	0.966997	131.623762	246.264026	0.148515	0.528053	149.64
std	9.082101	0.466011	1.032052	17.538143	51.830751	0.356198	0.525860	22.90
min	29.000000	0.000000	0.000000	94.000000	126.000000	0.000000	0.000000	71.00
25%	47.500000	0.000000	0.000000	120.000000	211.000000	0.000000	0.000000	133.50
50%	55.000000	1.000000	1.000000	130.000000	240.000000	0.000000	1.000000	153.00
75%	61.000000	1.000000	2.000000	140.000000	274.500000	0.000000	1.000000	166.00
max	77.000000	1.000000	3.000000	200.000000	564.000000	1.000000	2.000000	202.00



- Detecting outliers 😈 :

• A box and whisker plot (also called boxplot) shows the five numbers summary of a set of data : minimum , lower quartile , meduium, upper quartile and maximum .



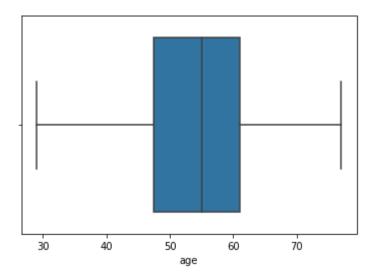
Age outliers :

In [12]: sns.boxplot(df['age'])

C:\ProgramData\Anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWar ning: Pass the following variable as a keyword arg: x. From version 0.12, the o nly valid positional argument will be `data`, and passing other arguments witho ut an explicit keyword will result in an error or misinterpretation.

warnings.warn(

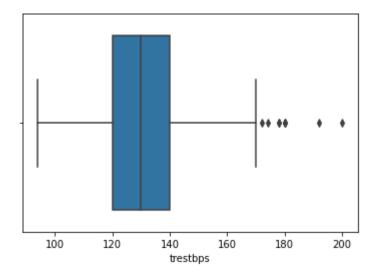
Out[12]: <AxesSubplot:xlabel='age'>



Trestbps outliers:

```
In [13]: sns.boxplot(df['trestbps'])
```





Out[16]: (90.0, 170.0)

In [17]: df[df['trestbps'] > upper_limit]

Out[17]:

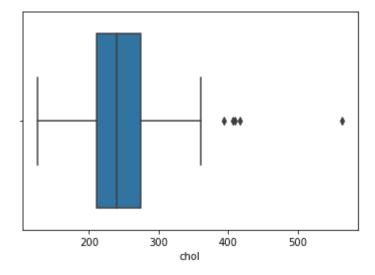
	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	са	thal	target
8	52	1	2	172	199	1	1	162	0	0.5	2	0	3	1
101	59	1	3	178	270	0	0	145	0	4.2	0	0	3	1
110	64	0	0	180	325	0	1	154	1	0.0	2	0	2	1
203	68	1	2	180	274	1	0	150	1	1.6	1	0	3	0
223	56	0	0	200	288	1	0	133	1	4.0	0	2	3	0
241	59	0	0	174	249	0	1	143	1	0.0	1	0	2	0
248	54	1	1	192	283	0	0	195	0	0.0	2	1	3	0
260	66	0	0	178	228	1	1	165	1	1.0	1	2	3	0
266	55	0	0	180	327	0	2	117	1	3.4	1	0	2	0

```
In [18]: df = df[df['trestbps'] <= upper_limit]
In [19]: df.shape
Out[19]: (294, 14)</pre>
```

Chol outliers :

```
In [20]: sns.boxplot(df['chol'])
```

Out[20]: <AxesSubplot:xlabel='chol'>



```
In [21]: # Chot
Q1 = df.chol.quantile(0.25)
Q3 = df.chol.quantile(0.75)
Q1, Q3
```

Out[21]: (211.0, 273.75)

```
In [22]: IQR = Q3 - Q1 IQR
```

Out[22]: 62.75

```
In [23]: lower_limit = Q1 - 1.5*IQR
    upper_limit = Q3 + 1.5*IQR
    lower_limit, upper_limit
```

Out[23]: (116.875, 367.875)

```
In [24]: df[df['chol'] > upper_limit]
```

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	age	sex	ср	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	са	thal	target
28	65	0	2	140	417	1	0	157	0	0.8	2	1	2	1
85	67	0	2	115	564	0	0	160	0	1.6	1	0	3	1
96	62	0	0	140	394	0	0	157	0	1.2	1	0	2	1
220	63	0	0	150	407	0	0	154	0	4.0	1	3	3	0
246	56	0	0	134	409	0	0	150	1	1.9	1	2	3	0

```
In [25]: df = df[df['chol'] < upper_limit]</pre>
```

```
In [26]: df.shape
```

Out[26]: (289, 14)

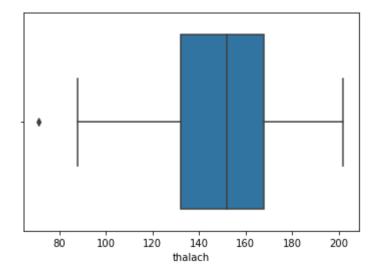
Thalach outliers:

```
In [27]: sns.boxplot(df['thalach'])
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWar ning: Pass the following variable as a keyword arg: x. From version 0.12, the o nly valid positional argument will be `data`, and passing other arguments witho ut an explicit keyword will result in an error or misinterpretation.

warnings.warn(

Out[27]: <AxesSubplot:xlabel='thalach'>



```
In [28]: # Thalach
Q1 = df.thalach.quantile(0.25)
Q3 = df.thalach.quantile(0.75)
Q1, Q3
```

Out[28]: (132.0, 168.0)

```
In [29]: IQR = Q3 - Q1
          IQR
Out[29]: 36.0
In [30]: lower_limit = Q1 - 1.5*IQR
          upper limit = Q3 + 1.5*IQR
          lower_limit, upper_limit
Out[30]: (78.0, 222.0)
In [31]: |df[df['thalach'] < lower_limit]</pre>
Out[31]:
                   sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca
               age
                                                                                     thal target
           272
                67
                                120
                                     237
                                           0
                                                          71
                                                                        1.0
                                                                               1
                                                                                   0
                                                                                        2
In [32]: | df = df[df['thalach'] > lower_limit]
In [33]: df.shape
Out[33]: (288, 14)
```

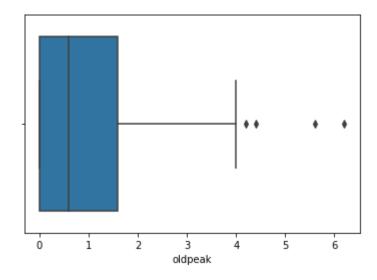
Oldpeak outliers:

```
In [34]: sns.boxplot(df['oldpeak'])
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWar ning: Pass the following variable as a keyword arg: x. From version 0.12, the o nly valid positional argument will be `data`, and passing other arguments witho ut an explicit keyword will result in an error or misinterpretation.

warnings.warn(

Out[34]: <AxesSubplot:xlabel='oldpeak'>



```
In [35]: # Oldpeak
          Q1 = df.oldpeak.quantile(0.25)
          Q3 = df.oldpeak.quantile(0.75)
          Q1, Q3
Out[35]: (0.0, 1.6)
In [36]: IQR = Q3 - Q1
          IQR
Out[36]: 1.6
In [37]: |lower_limit = Q1 - 1.5*IQR
          upper limit = Q3 + 1.5*IQR
          lower_limit, upper_limit
Out[37]: (-2.4000000000000004, 4.0)
In [38]: df[df['oldpeak'] > upper_limit]
Out[38]:
                            trestbps chol fbs
                                               restecg thalach exang oldpeak slope
                age
                    sex
                         ср
                                                                                    ca
                                                                                       thal target
           204
                 62
                          0
                                             0
                                                                                     3
                                                                                          3
                                                                                                 0
                       0
                                 160
                                      164
                                                    0
                                                          145
                                                                   0
                                                                          6.2
                                                                                  0
           221
                 55
                       1
                          0
                                 140
                                      217
                                             0
                                                    1
                                                           111
                                                                   1
                                                                          5.6
                                                                                  0
                                                                                     0
                                                                                          3
                                                                                                 0
           250
                 51
                       1
                          0
                                 140
                                      298
                                             0
                                                    1
                                                          122
                                                                   1
                                                                          4.2
                                                                                     3
                                                                                          3
                                                                                                 0
                                                                                  1
           291
                 58
                       1
                          0
                                 114
                                      318
                                             0
                                                    2
                                                          140
                                                                   0
                                                                          4.4
                                                                                  0
                                                                                     3
                                                                                           1
                                                                                                 0
In [39]: df = df[df['oldpeak'] < upper limit]</pre>
```



Visulization

Distribution of data:

1- Dealing with discreate features using Probability Mass Function:

- A discrete variable is a variable that can only take on a "countable" number of values. If you can count a set of items, then it's a discrete variable.
- In statistics we represent a distribution of discrete variables with PMF's (Probability Mass Functions) and CDF's (Cumulative Distribution Functions).
- A probability mass function (pmf) is a function over the sample space of a discrete random variable X which gives the probability that X is equal to a certain value.
- · We have some discrete fetures such as sex, cp , fps , target.

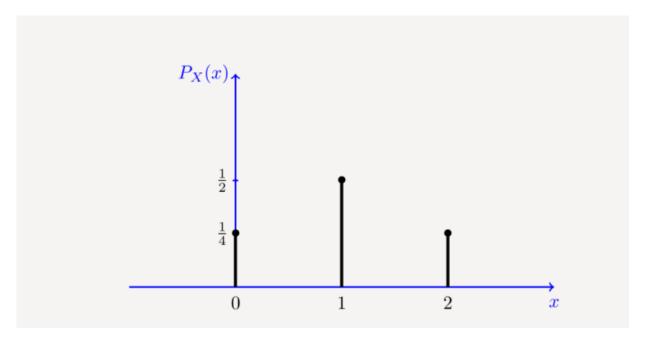
Let X be a discrete random variable on a sample space S. Then the probability mass function f(x) is defined as

$$f(x) = P[X = x].$$

Each probability mass function satisfies the following two conditions:

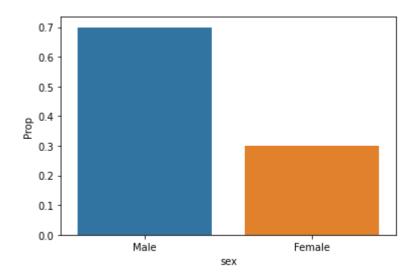
$$\text{(i)} \qquad f(x) \geq 0 \text{ for all } x \in S,$$

(ii)
$$\sum_{x \in S} f(x) = 1$$



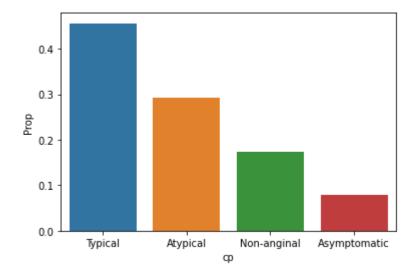
```
In [40]: x = df['sex']
x = pd.DataFrame(x.value_counts())  # Make a new Data Frame for ( gender , val
length = len(df['sex'])  # Total numbers of people (sex gender)
data = pd.DataFrame(x)
data.columns = ["Counts"]  # Rename the coulmn from Sex to Counts
data["Prop"] = data["Counts"]/ length  # Make a new column for probability for ed
sex = ["Male", "Female"]
data['sex'] = sex
sns.barplot(data["sex"],data["Prop"])
```

Out[40]: <AxesSubplot:xlabel='sex', ylabel='Prop'>



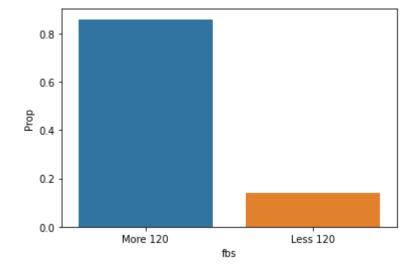
```
In [41]: x = df['cp']
x = pd.DataFrame(x.value_counts()) #Make a new Data Frame for ( gender , value collength = len(df['cp']) # Total numbers of people (sex gender)
data = pd.DataFrame(x)
data.columns = ["Counts"] # Rename the coulmn from Sex to Counts
data["Prop"] = data["Counts"]/ length # Make a new column for probability for ed
cp = ["Typical", "Atypical", "Non-anginal", "Asymptomatic"]
data['cp'] = cp
sns.barplot(data["cp"],data["Prop"])
```

Out[41]: <AxesSubplot:xlabel='cp', ylabel='Prop'>



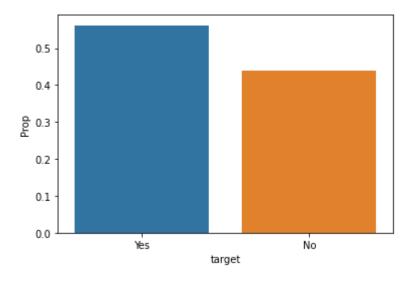
```
In [42]: x = df['fbs']
x = pd.DataFrame(x.value_counts())
length = len(df['fbs'])
data = pd.DataFrame(x)
data.columns = ["Counts"]
data["Prop"] = data["Counts"]/ length
fbs = ["More 120","Less 120"]
data['fbs'] = fbs
sns.barplot(data["fbs"],data["Prop"])
```

Out[42]: <AxesSubplot:xlabel='fbs', ylabel='Prop'>



```
In [43]: x = df['target']
x = pd.DataFrame(x.value_counts())  #Make a new Data Frame for ( gender , val
length = len(df['target'])  # Total numbers of people (sex gender)
data = pd.DataFrame(x)
data.columns = ["Counts"]  # Rename the coulmn from Sex to Counts
data["Prop"] = data["Counts"]/ length  # Make a new column for probability for e
target = ["Yes","No"]
data['target'] = target
sns.barplot(data["target"],data["Prop"])
```

Out[43]: <AxesSubplot:xlabel='target', ylabel='Prop'>

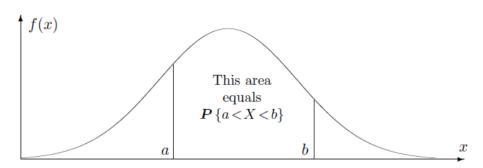


· Ohhh! Our Problem looks balanced!!

2- Dealing with Continious features using Probability Denisty Function :

- A continuous variable takes on an "uncountable" number of values. An example of a continuous variable is length. Length can be measured to an arbitrary degree and is therefore continuous.
- In statistics We represent distributions of continuous variables with PDF's (Probability Density Functions) and CDF's.
- Probability density function (PDF) is a statistical expression that defines a probability distribution (the likelihood of an outcome) for a discrete random variable (e.g., a stock or ETF) as opposed to a continuous random variable.
- We have some continious features such as age, trestbps, chol, oldpeak.

$$\int_a^b f(x) dx = F(b) - F(a) = P\{a < X < b\}$$



```
In [44]: fig, ax = plt.subplots(2,2, figsize=(12,10))
    sns.distplot(df.age, bins = 20, ax=ax[0,0])
    sns.distplot(df.trestbps, bins = 20, ax=ax[0,1])
    sns.distplot(df.chol, bins = 20, ax=ax[1,0])
    sns.distplot(df.oldpeak, bins = 20, ax=ax[1,1])
```

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Futur eWarning: `distplot` is a deprecated function and will be removed in a future v ersion. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram s).

warnings.warn(msg, FutureWarning)

C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Futur eWarning: `distplot` is a deprecated function and will be removed in a future v ersion. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram s).

warnings.warn(msg, FutureWarning)

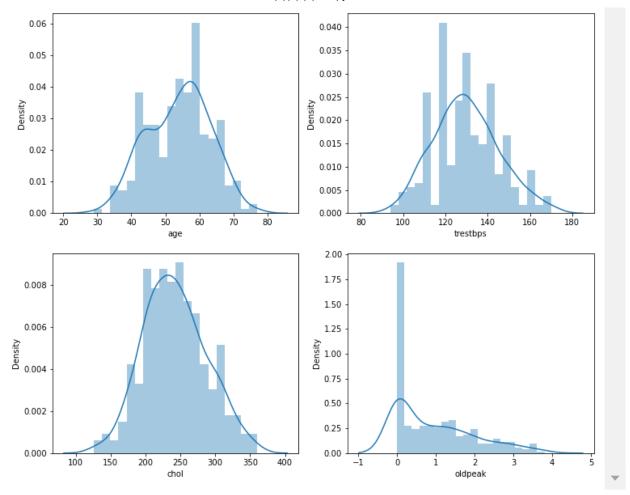
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: Futur eWarning: `distplot` is a deprecated function and will be removed in a future v ersion. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram s).

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warnings.warn(msg, FutureWarning)

Out[44]: <AxesSubplot:xlabel='oldpeak', ylabel='Density'>



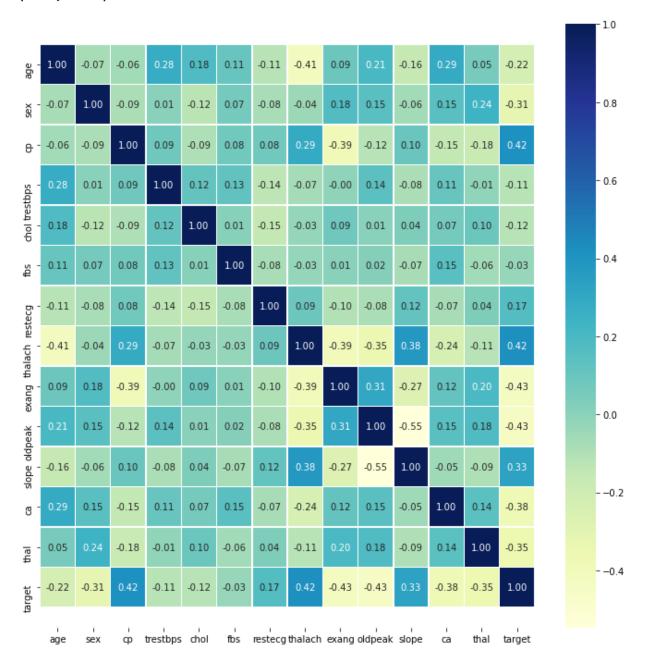
Other Visulizations:



Correlation Matrix:

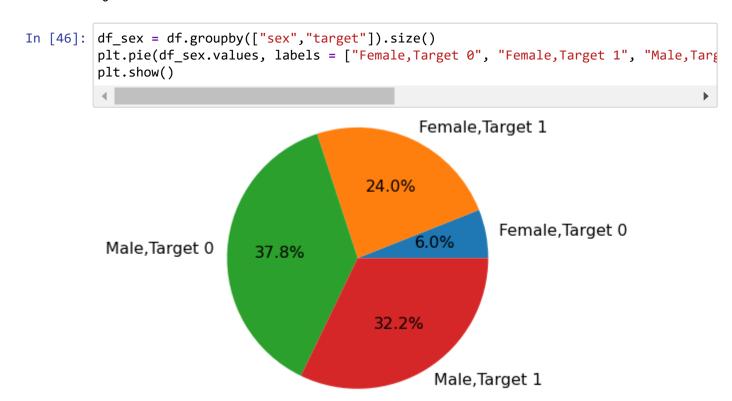
• In probability theory and statistics, a covariance matrix is a square matrix giving the covariance between each pair of elements of a given random vector.

Out[45]: (14.5, -0.5)



- fbs and chol are the lowest correlated with the target variable.
- All other variables have a significant correlation with the target variable.

Gender vs Target:



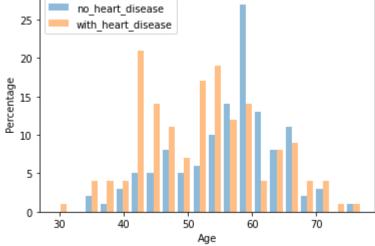
Conclusion:

• **A** The ratio of male has heart disease is 30.7%, a little bit higher than female.

Age vs Target:



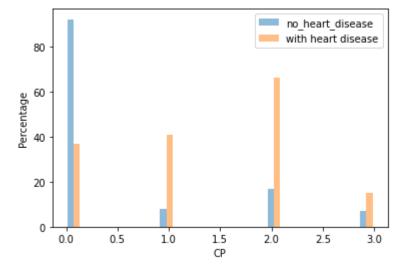
```
In [47]: plt.hist([df[df.target==0].age, df[df.target==1].age], bins = 20, alpha = 0.5, laplt.xlabel("Age")
plt.ylabel("Percentage")
plt.legend()
plt.show()
```



• A The ratio get higher over the age of forty. That is, people who is over forty is under high risk of heart disease.

CP vs Target:

```
In [48]: plt.hist([df[df.target==0].cp, df[df.target==1].cp], bins = 20, alpha = 0.5, labe
plt.xlabel("CP")
plt.ylabel("Percentage")
plt.legend()
plt.show()
```



• \triangle cp {Chest Pain} : People with cp equl to 1, 2, 3 are more likely to have heart disease than people with cp equal to 0.

Trestbps vs Target:



```
In [49]: plt.hist([df[df.target==0].trestbps, df[df.target==1].trestbps], bins = 20, alpha
plt.xlabel("trestbps")
plt.ylabel("percentage")
plt.legend()
plt.show()

**Top heart_disease
with heart disease

**Top heart_disease
**Top heart
```

100

110

120

130

trestbps

140

• 1 The ideal blood pressure should be lower than 120 mmHg. Whether the patients have heart disease or not, over 50% patients have higher blood pressure.

150

160

170

Chol vs Target:

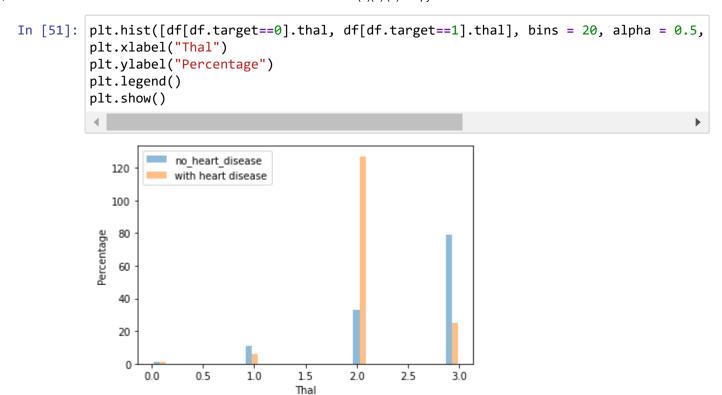
```
plt.hist([df[df.target==0].chol, df[df.target==1].chol], bins = 20, alpha = 0.5,
plt.xlabel("Chol")
plt.ylabel("Percentage")
plt.legend()
plt.show()
                                             no_heart_disease
   17.5
                                             with heart disease
   15.0
   12.5
 Percentage
   10.0
    7.5
     5.0
     2.5
    0.0
              150
                        200
                                  250
                                             300
                                                       350
```

Chol

Conclusion:

 Also, amounts of people having heart disease are over 200mg/dl of chol. According to the research, the normal value of chol should be lower than 200mg/dl.

Thal vs Target:



• People with thal value equal to 2 (fixed defect: used to be defect but ok now) are more likely to have heart disease.

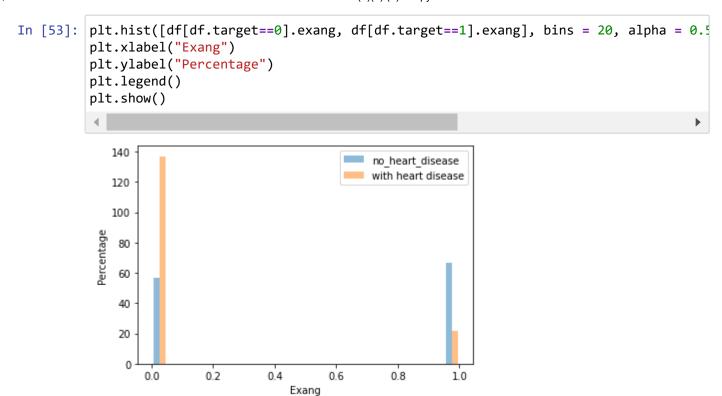
Slope vs Target:



• People with slope value equal to 2 (Downslopins: signs of unhealthy heart) are more likely to have heart disease than people with slope value equal to 0 (Upsloping: better heart rate with excercise) or 1 (Flatsloping: minimal change (typical healthy heart)).

Exang vs Target:

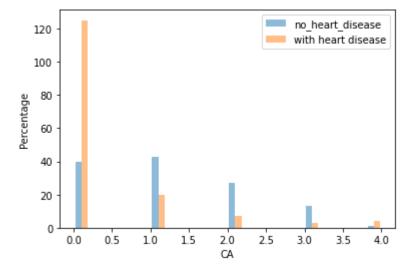




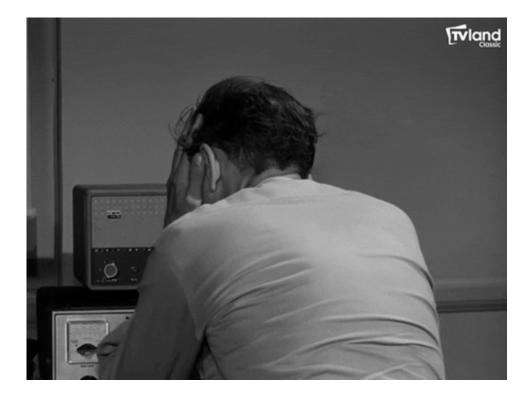
• People with value 0 (No ==> exercice induced angina) have heart disease more than people with value 1 (Yes ==> exercice induced angina)

CA vs Target:

```
In [54]: plt.hist([df[df.target==0].ca, df[df.target==1].ca], bins = 20, alpha = 0.5, labe
plt.xlabel("CA")
plt.ylabel("Percentage")
plt.legend()
plt.show()
```



• A The more blood movement the better so people with ca equal to 0 are more likely to have heart disease.



Modeling

feature selection

```
In [300]: | from sklearn.ensemble import ExtraTreesRegressor
In [301]: x = df.iloc[:, :-1]
           y = df.iloc[:,-1]
In [302]: model = ExtraTreesRegressor()
           feat_imp = model.fit(x, y)
           feat imp.feature importances
           imp = pd.Series(feat_imp.feature_importances_, index = x.columns)
           imp.nlargest(14).plot(kind = 'barh')
Out[302]: <AxesSubplot:>
               fbs
               sex
            restecg
            trestbps
              slope
               chol
            thalach
               age
            oldpeak
             exang
               thal
                ca
                ф
                                           0.10
                                                0.12
                                                     0.14
                 0.00
                      0.02
                           0.04
                                 0.06
                                      0.08
                                                           0.16
In [303]: | x = np.array(df[['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thala
                   'exang', 'oldpeak', 'slope', 'ca', 'thal']])
           y = np.array(df['target'])
In [304]:
          model = ExtraTreesClassifier()
           model.fit(x, y)
           print(model.feature importances )
           [0.07019788 0.06127766 0.12780186 0.06368515 0.06120136 0.02112841
            0.03363597 0.08791796 0.09404421 0.09198112 0.06144244 0.11963547
            0.1060505 ]
```

knn

```
In [305]: knn = KNeighborsClassifier(n neighbors=5)
          knn.fit(x,y)
Out[305]: KNeighborsClassifier()
In [306]: | x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=.4, random_state=5)
In [307]: | confusion matrix(y test,knn.predict(x test))
Out[307]: array([[34, 19],
                  [ 9, 52]], dtype=int64)
In [308]: df.columns
Out[308]: Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
                  'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
                 dtype='object')
In [309]: |print(knn.score(x train,y train))
          print(knn.score(x_test,y_test))
          0.7514792899408284
          0.7543859649122807
In [310]: prediction lr=knn.predict(x test)
          print('\n clasification report:\n', classification_report(y_test,prediction_lr))
           clasification report:
                          precision
                                       recall f1-score
                                                           support
                              0.79
                                        0.64
                                                   0.71
                                                               53
                      0
                      1
                              0.73
                                        0.85
                                                   0.79
                                                               61
                                                   0.75
                                                              114
               accuracy
                                                   0.75
             macro avg
                              0.76
                                        0.75
                                                              114
          weighted avg
                              0.76
                                        0.75
                                                   0.75
                                                              114
```

logestic regression

```
In [311]: classifier = LogisticRegression(solver='lbfgs',random_state=0)
```

```
In [312]: classifier.fit(x train, y train)
          C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:76
          3: ConvergenceWarning: lbfgs failed to converge (status=1):
          STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
          Increase the number of iterations (max iter) or scale the data as shown in:
              https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
          learn.org/stable/modules/preprocessing.html)
          Please also refer to the documentation for alternative solver options:
              https://scikit-learn.org/stable/modules/linear model.html#logistic-regressi
          on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
          on)
            n iter i = check optimize result(
Out[312]: LogisticRegression(random state=0)
In [313]: | print(classifier.score(x train,y train))
          print(classifier.score(x_test,y_test))
          0.8698224852071006
          0.8508771929824561
In [314]: prediction lr=classifier.predict(x test)
          print('\n clasification report:\n', classification_report(y_test,prediction_lr))
          print('
           clasification report:
                         precision
                                       recall f1-score
                                                          support
                             0.93
                                        0.74
                                                  0.82
                                                              53
                     0
                     1
                             0.81
                                        0.95
                                                  0.87
                                                              61
                                                  0.85
                                                             114
              accuracy
             macro avg
                             0.87
                                        0.84
                                                  0.85
                                                             114
          weighted avg
                             0.86
                                        0.85
                                                  0.85
                                                             114
```

Random Forest classifier

```
In [315]: from sklearn.ensemble import RandomForestClassifier
    from sklearn.model_selection import cross_val_score
    rf_tuned = RandomForestClassifier()
In [316]: rf_tuned = rf_tuned.fit(x,y)
```

```
In [323]: cross val score(rf tuned, x, y, cv = 10).mean()
Out[323]: 0.8442118226600985
In [324]: | print(rf tuned.score(x train,y train))
          print(rf_tuned.score(x_test,y_test))
          1.0
          1.0
In [325]: prediction_lr=rf_tuned.predict(x_test)
          print('____
          print('\n clasification report:\n', classification_report(y_test,prediction_lr))
          print('
                                            ')
           clasification report:
                         precision
                                       recall f1-score
                                                          support
                              1.00
                                        1.00
                     0
                                                  1.00
                                                              53
                                        1.00
                     1
                              1.00
                                                  1.00
                                                              61
              accuracy
                                                  1.00
                                                             114
             macro avg
                              1.00
                                        1.00
                                                  1.00
                                                             114
          weighted avg
                              1.00
                                                  1.00
                                                             114
                                        1.00
```

svm

0.9339622641509434
0.8028169014084507