Heart Disease Dataset

After cleaning the dataset, various attributes will be plotted to show distribution and trends.

This dataset is from 1988, containing 1025 rows and 14 features.

The features are:

Age, sex, **CP** (chest pain type, 4 values), **trestbps** (resting blood pressure), **chol** (serum cholestoral in mg/dl), **fbs** (fasting blood sugar > 120 mg/dl), **restecg** (resting electrocardiographic results, values 0,1,2), **thalach** (maximum heart rate achieved), **exang** (exercise induced angina), **oldpeak** (oldpeak = ST depression induced by exercise relative to rest), **slope** (the slope of the peak exercise ST segment), **ca** (number of major vessels, 0-3 colored by flourosopy), **thal** (0 = normal; 1 = fixed defect; 2 = reversable defect), and **target**.

The dataset can be found at: [https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset]

```
In [1]:
          import numpy as np
          import pandas as pd
          import matplotlib.pyplot as plt
          import seaborn as sns
         data = pd.read_csv('heart.csv')
In [3]:
In [5]: data.head()
Out[5]:
             age sex cp trestbps chol fbs restecg thalach exang oldpeak slope ca thal to
                                                                                              3
          0
              52
                    1
                        0
                                125
                                     212
                                            0
                                                     1
                                                           168
                                                                     0
                                                                             1.0
                                                                                     2
                                                                                         2
          1
              53
                    1
                        0
                               140
                                     203
                                            1
                                                     0
                                                           155
                                                                     1
                                                                             3.1
                                                                                     0
                                                                                         0
                                                                                              3
          2
              70
                    1
                        0
                               145
                                     174
                                            0
                                                     1
                                                           125
                                                                     1
                                                                             2.6
                                                                                     0
                                                                                         0
                                                                                              3
                                                                                              3
          3
              61
                    1
                        0
                                148
                                     203
                                            0
                                                     1
                                                           161
                                                                     0
                                                                            0.0
                                                                                     2
              62
                    0
                        0
                               138
                                     294
                                            1
                                                     1
                                                           106
                                                                     0
                                                                             1.9
                                                                                     1
                                                                                         3
                                                                                              2
          data.shape
In [7]:
          (1025, 14)
Out[7]:
In [16]: data.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1025 entries, 0 to 1024
Data columns (total 14 columns):
Column Non-Null Count Dtype
--- -----

π	COTUIIII	NOII-I	vali count	Deype
0	age	1025	non-null	int64
1	sex	1025	non-null	int64
2	ср	1025	non-null	int64
3	trestbps	1025	non-null	int64
4	chol	1025	non-null	int64
5	fbs	1025	non-null	int64
6	restecg	1025	non-null	int64
7	thalach	1025	non-null	int64
8	exang	1025	non-null	int64
9	oldpeak	1025	non-null	float64
10	slope	1025	non-null	int64
11	ca	1025	non-null	int64
12	thal	1025	non-null	int64
13	target	1025	non-null	int64

dtypes: float64(1), int64(13)

memory usage: 112.2 KB

In [20]: #data.isnull().sum()

In [24]: data.describe().T

Out[24]:

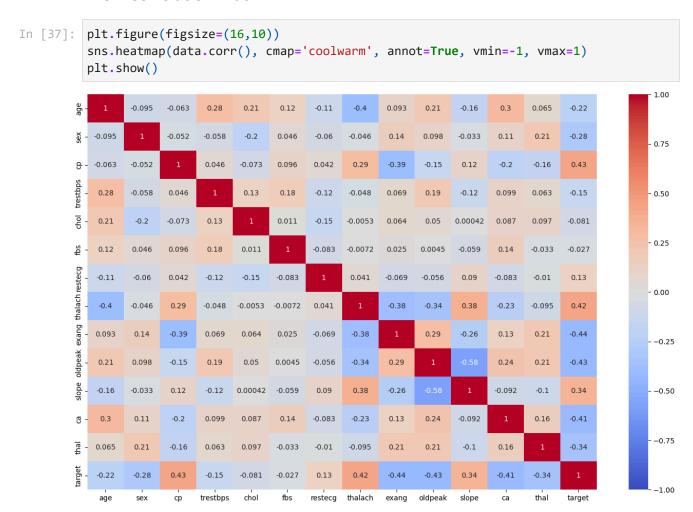
	count	mean	std	min	25%	50%	75%	max
age	1025.0	54.434146	9.072290	29.0	48.0	56.0	61.0	77.0
sex	1025.0	0.695610	0.460373	0.0	0.0	1.0	1.0	1.0
ср	1025.0	0.942439	1.029641	0.0	0.0	1.0	2.0	3.0
trestbps	1025.0	131.611707	17.516718	94.0	120.0	130.0	140.0	200.0
chol	1025.0	246.000000	51.592510	126.0	211.0	240.0	275.0	564.0
fbs	1025.0	0.149268	0.356527	0.0	0.0	0.0	0.0	1.0
restecg	1025.0	0.529756	0.527878	0.0	0.0	1.0	1.0	2.0
thalach	1025.0	149.114146	23.005724	71.0	132.0	152.0	166.0	202.0
exang	1025.0	0.336585	0.472772	0.0	0.0	0.0	1.0	1.0
oldpeak	1025.0	1.071512	1.175053	0.0	0.0	0.8	1.8	6.2
slope	1025.0	1.385366	0.617755	0.0	1.0	1.0	2.0	2.0
ca	1025.0	0.754146	1.030798	0.0	0.0	0.0	1.0	4.0
thal	1025.0	2.323902	0.620660	0.0	2.0	2.0	3.0	3.0
target	1025.0	0.513171	0.500070	0.0	0.0	1.0	1.0	1.0

```
Out[26]: 723
```

```
In [28]: data = data.drop_duplicates()
   data.shape
```

Out[28]: (302, 14)

View Correlation Matrix



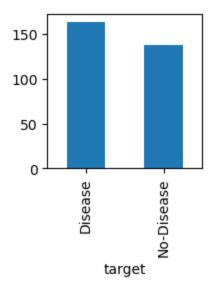
Insights from Correlation Matrix

Name: proportion, dtype: float64

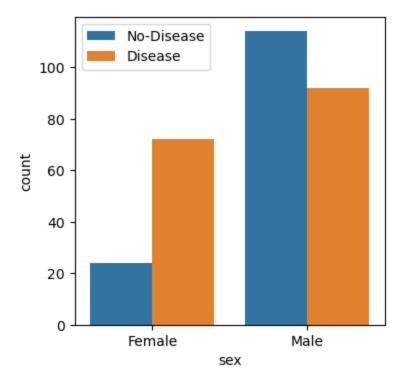
- Chest pain, maximum heart rate, and slope have high correlation with the target.
- Exercise induced angina, oldpeak, ca, and thal negatively correlate wiht the target.

Is the dataset balanced in terms of positive and negative labels?

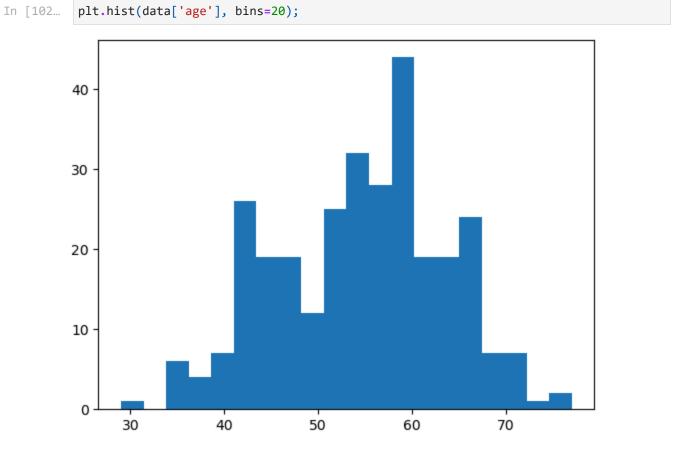
```
In [118... data.target.value_counts().plot(kind='bar', figsize=(2,2))
    plt.xticks([0,1], ['Disease', 'No-Disease'])
    plt.xlabel('target');
```



Do male or female have more heart disease?



Check age distribution.

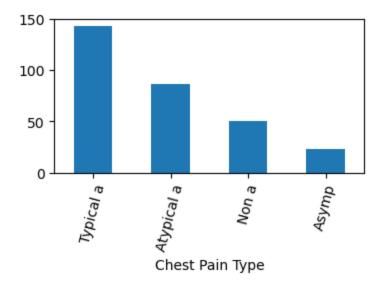


In []: #sns.distplot(data['age'], bins=20)
#plt.show()

Check chest pain type:

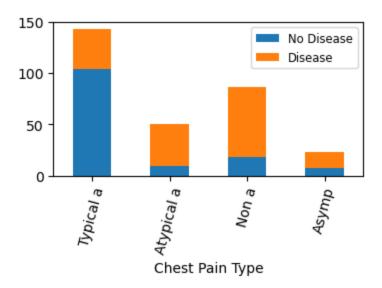
- 0: typeical angina
- 1: atypical angina
- 2: non-anginal pain
- 3: asymptomatic

```
In [114... data['cp'].value_counts().plot(kind= 'bar', figsize=(4,2))
    plt.xticks([0,1,2,3], ['Typical a', 'Atypical a', 'Non a', 'Asymp'])
    plt.xticks(rotation=75)
    plt.xlabel('Chest Pain Type')
    plt.show()
```



```
In [173... pain_disease = data.groupby('cp')['target'].value_counts().unstack()

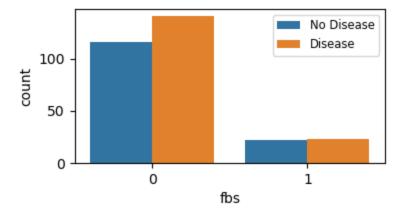
pain_disease.plot(kind='bar', stacked=True, figsize=(4,2))
plt.xticks([0,1,2,3], ['Typical a', 'Atypical a', 'Non a', 'Asymp'])
plt.xticks(rotation=75)
plt.xlabel('Chest Pain Type')
plt.legend(labels=['No Disease', 'Disease'], fontsize='small')
plt.show()
```



In [146... #sns.countplot(x='cp', hue='target', data=data)

Show fasting blood sugar distribution according to target variable

```
In [175... plt.figure(figsize=(4,2))
    sns.countplot(x='fbs', hue='target', data=data)
    plt.legend(['No Disease', 'Disease'], fontsize='small')
    plt.show()
```

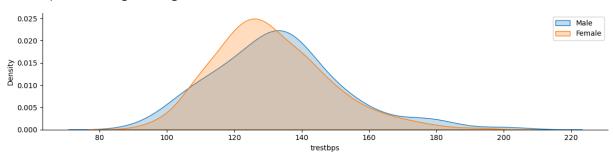


Compare resting blood pressure of the two genders.

```
In [184... g=sns.FacetGrid(data, hue='sex', aspect=4)
    g.map(sns.kdeplot, 'trestbps', shade=True)
    plt.legend(labels=['Male', 'Female'])
```

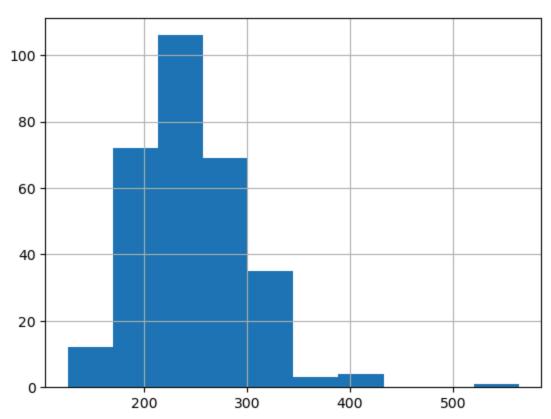
C:\Users\maria\anaconda3\Lib\site-packages\seaborn\axisgrid.py:854: FutureWarning:
 `shade` is now deprecated in favor of `fill`; setting `fill=True`.
 This will become an error in seaborn v0.14.0; please update your code.
 func(*plot_args, **plot_kwargs)
C:\Users\maria\anaconda3\Lib\site-packages\seaborn\axisgrid.py:854: FutureWarning:
 `shade` is now deprecated in favor of `fill`; setting `fill=True`.
 This will become an error in seaborn v0.14.0; please update your code.
 func(*plot_args, **plot_kwargs)

Out[184... <matplotlib.legend.Legend at 0x1e8e3a6b770>



In [186... data['chol'].hist()

Out[186... <Axes: >



Plot Continuous variables

Instead of manually inpsecting each column, we can write the following code:

```
In [192...
           categorical_v = []
           continuous_v = []
           for column in data.columns:
               if data[column].nunique() <= 10:</pre>
                    categorical_v.append(column)
               else:
                    continuous_v.append(column)
In [194...
          categorical_v
           ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal', 'target']
Out[194...
In [196...
          continuous_v
           ['age', 'trestbps', 'chol', 'thalach', 'oldpeak']
Out[196...
In [208...
           data.hist(continuous_v, figsize=(16,8))
           #plt.tight_layout()
           plt.show()
         20
                               chol
         150
         125
         100
  In [ ]:
```