Day24_EDA_Hands_On_Practical_On_Heart_Disease

June 16, 2025

Step-by-Step EDA on Heart Disease Dataset

Today we are going to explore the **Heart Disease Dataset** step by step using Python.

We will:

- Load and understand the data
- Explore individual features (Univariate Analysis)
- Explore relationships between features (Bivariate and Multivariate Analysis)
- Handle missing values
- Check data quality using assert statements
- Detect outliers
- Summarize key findings

Heart disease or Cardiovascular disease (CVD) is a class of diseases that involve the heart or blood vessels. CVDs are the leading cause of death globally, accounting for 17.9 million deaths (32.1%) in 2015. While death rates have declined in developed countries since the 1970s, they have increased in developing nations.

This notebook walks through a detailed Exploratory Data Analysis (EDA) of a heart disease dataset, aiming to understand its structure, spot patterns, and prepare the data for further analysis.

What is Exploratory Data Analysis (EDA)?

Exploratory Data Analysis (EDA) is the first and most important step in any data analysis or machine learning project. It helps us understand the dataset, find patterns, detect outliers, and prepare the data for modeling.

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1 Introduction to EDA

When we get a new dataset, we often ask:

- What is the distribution of the data?
- Are there any missing values, outliers, or anomalies?
- What assumptions are present in the dataset?
- Are there any relationships between variables?
- Is the dataset ready for machine learning?
- Which algorithm might work best on this dataset?

The answer to these questions is **EDA**. It gives us a clear picture of the dataset before any modeling.

2 Objectives of EDA

The key goals of EDA are:

1. Understand the distribution of the data.
2. Identify missing values, outliers, or anomalies.
3. Discover relationships between variables.
4. Validate assumptions before modeling.

3 Types of EDA

EDA techniques can be divided in two ways: - **Graphical** vs **Non-Graphical** - **Univariate** vs **Multivariate**

3.1 Univariate Non-Graphical EDA

- Focuses on one variable.
- Uses summary statistics (mean, median, mode, etc.).
- Detects outliers and unusual values.

3.2 Multivariate Non-Graphical EDA

- Compares two or more variables.
- Uses correlation, cross-tabulation, etc.

3.3 Univariate Graphical EDA

- Uses visual tools like histograms, bar plots, pie charts.
- Helps understand individual variable distributions.

3.4 Multivariate Graphical EDA

- Visual tools for variable interactions like:
  - Side-by-side boxplots
  - Scatter plots
  - Heatmaps
  - Pair plots

Now that we understand what EDA is, let's begin the practical analysis by importing the required libraries.

4 Import libraries

[1]:
```
# Import libraries¶
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as st
```

```
%matplotlib inline

sns.set(style="whitegrid")
```

[2]:
```
# ignore warnings

import warnings
warnings.filterwarnings('ignore')
```

I have imported the libraries. The next step is to import the datasets.

5 Import dataset

will import the dataset with the usual pandas read_csv() function which is used to import CSV (Comma Separated Value) files.

[3]:
```
df = pd.read_csv(r'C:\Users\aksha\Downloads\heart.csv')
```

6 Exploratory Data Analysis

6.1 Check shape of the dataset

It is a good idea to first check the shape of the dataset.

[4]:
```
# print the shape
print('The shape of the dataset : ', df.shape)
```

```
The shape of the dataset :  (303, 14)
```

Now, we can see that the dataset contains 303 instances and 14 variables.

6.2 Preview the dataset

[5]:
```
# preview dataset
df.head()
```

[5]:
```
   age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  slope  \
0   63    1   3       145   233    1        0      150      0      2.3      0
1   37    1   2       130   250    0        1      187      0      3.5      0
2   41    0   1       130   204    0        0      172      0      1.4      2
3   56    1   1       120   236    0        1      178      0      0.8      2
4   57    0   0       120   354    0        1      163      1      0.6      2

   ca  thal  target
0   0     1       1
1   0     2       1
2   0     2       1
3   0     2       1
4   0     2       1
```

[6]:
```
df.tail()
```

[6]:
```
     age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
298   57    0   0       140   241    0        1      123      1      0.2
299   45    1   3       110   264    0        1      132      0      1.2
300   68    1   0       144   193    1        1      141      0      3.4
301   57    1   0       130   131    0        1      115      1      1.2
302   57    0   1       130   236    0        0      174      0      0.0

     slope  ca  thal  target
298      1   0     3       0
299      1   0     3       0
300      1   2     3       0
301      1   1     3       0
302      1   1     2       0
```

6.3 View column names

[7]:
```
df.columns
```

[7]:
```
Index(['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach',
       'exang', 'oldpeak', 'slope', 'ca', 'thal', 'target'],
      dtype='object')
```

6.4 Summary of dataset

[8]:
```
# summary of 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   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    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
```

Dataset description

The dataset contains several columns which are as follows -

- age : age in years
- sex : (1 = male; 0 = female)
- cp : chest pain type
- trestbps : resting blood pressure (in mm Hg on admission to the hospital)
- chol : serum cholestoral in mg/dl
- fbs : (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)
- restecg : resting electrocardiographic results
- thalach : maximum heart rate achieved
- exang : exercise induced angina (1 = yes; 0 = no)
- 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 : 3 = normal; 6 = fixed defect; 7 = reversable defect
- target : 1 or 0

The above df.info() command gives us the number of filled values along with the data types of columns.

If we simply want to check the data type of a particular column, we can use the following command.

[9]:
```
df.dtypes
```

[9]:
```
age           int64
sex           int64
cp            int64
trestbps      int64
chol          int64
fbs           int64
restecg       int64
thalach       int64
exang         int64
oldpeak     float64
slope         int64
ca            int64
thal          int64
target        int64
dtype: object
```

6.5 Important Points About the Dataset

Some variables in the dataset are stored as numbers (integers), but they actually represent categories. These should be considered **categorical variables**, not numerical.

Let's look at a few examples:

- **sex**
  - Values: `1 = male`, `0 = female`

  - This is actually a character variable (categorical), but it's stored as `int64`.
- **fbs** *(fasting blood sugar)*
  - Values: `1 = true`, `0 = false`

  - Although it represents true/false, it's stored as `int64`. It should be treated as a categorical variable.
- **exang** *(exercise-induced angina)*
  - Values: `1 = yes`, `0 = no`

  - Again, this is categorical but stored as `int64`.
- **target**
  - Values: `1 = disease`, `0 = no disease`

  - This is the outcome variable and also categorical, but stored as `int64`.

Conclusion:
These variables are encoded using numbers, but they should be treated as **categorical (object)** types during analysis or visualization.

6.6 Statistical properties of dataset

[10]:
```python
# statistical properties of dataset
df.describe()
```

[10]:
```
              age         sex          cp    trestbps        chol         fbs  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean    54.366337    0.683168    0.966997  131.623762  246.264026    0.148515
std      9.082101    0.466011    1.032052   17.538143   51.830751    0.356198
min     29.000000    0.000000    0.000000   94.000000  126.000000    0.000000
25%     47.500000    0.000000    0.000000  120.000000  211.000000    0.000000
50%     55.000000    1.000000    1.000000  130.000000  240.000000    0.000000
75%     61.000000    1.000000    2.000000  140.000000  274.500000    0.000000
max     77.000000    1.000000    3.000000  200.000000  564.000000    1.000000

          restecg     thalach       exang     oldpeak       slope          ca  \
count  303.000000  303.000000  303.000000  303.000000  303.000000  303.000000
mean     0.528053  149.646865    0.326733    1.039604    1.399340    0.729373
std      0.525860   22.905161    0.469794    1.161075    0.616226    1.022606
min      0.000000   71.000000    0.000000    0.000000    0.000000    0.000000
25%      0.000000  133.500000    0.000000    0.000000    1.000000    0.000000
50%      1.000000  153.000000    0.000000    0.800000    1.000000    0.000000
75%      1.000000  166.000000    1.000000    1.600000    2.000000    1.000000
max      2.000000  202.000000    1.000000    6.200000    2.000000    4.000000

             thal      target
```

```
count  303.000000  303.000000
mean     2.313531    0.544554
std      0.612277    0.498835
min      0.000000    0.000000
25%      2.000000    0.000000
50%      2.000000    1.000000
75%      3.000000    1.000000
max      3.000000    1.000000
```

Important Points to Note About `df.describe()`

- The command **`df.describe()`** gives us the **summary statistics** (like mean, std, min, max) of **numerical variables only**. It automatically excludes character (categorical) variables.

To view statistics of only character (object) variables: "'python df.describe(include=['object'])

7 Univariate analysis

Univariate Analysis – Target Variable (Heart Disease)

What is `target`?

The `target` variable indicates whether a patient has heart disease or not:

- `1` → Patient has heart disease (positive)
- `0` → Patient does **not** have heart disease (negative)

7.1 Number of Unique Values

[12]:
```python
df['target'].nunique()
```

[12]: 2

This checks how many distinct values the column contains. Output should be 2.

7.2 View Unique Values

[13]:
```python
df['target'].unique()
# Expected output: array([1, 0])
```

[13]: array([1, 0], dtype=int64)

7.3 Frequency Distribution

Interpretation:

- 165 patients have heart disease (target = 1)
- 138 patients do not have heart disease (target = 0)

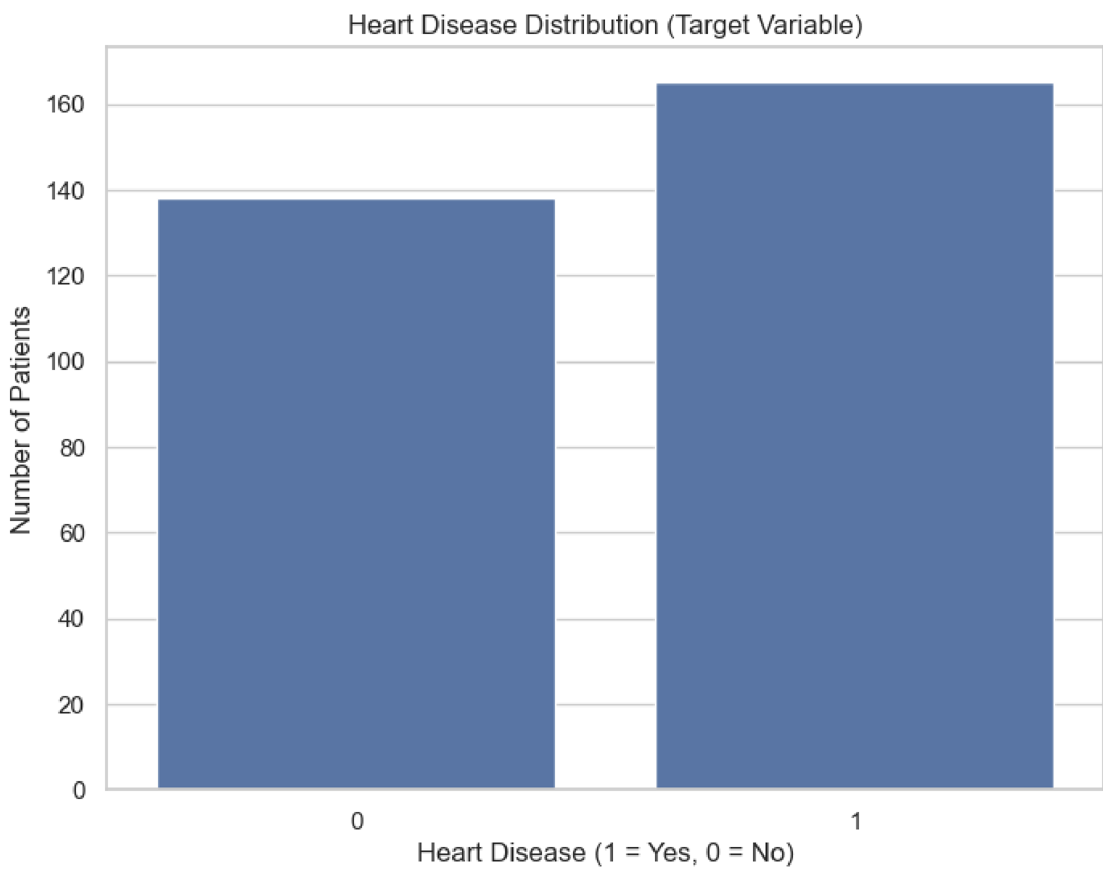
[14]:
```python
df['target'].value_counts()
```

[14]:
```
target
1    165
0    138
Name: count, dtype: int64
```

7.4 Visualize Frequency Distribution

[15]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", data=df)
plt.title("Heart Disease Distribution (Target Variable)")
plt.xlabel("Heart Disease (1 = Yes, 0 = No)")
plt.ylabel("Number of Patients")
plt.show()
```



This confirms:

- 165 patients have heart disease
- 138 do not

Target Variable with Other Features

7.5 Frequency Distribution of Target by Sex

[16]:
```
df.groupby('sex')['target'].value_counts()
```

[16]:
```
sex  target
0    1          72
     0          24
1    0         114
     1          93
Name: count, dtype: int64
```

sex = 1 → Male

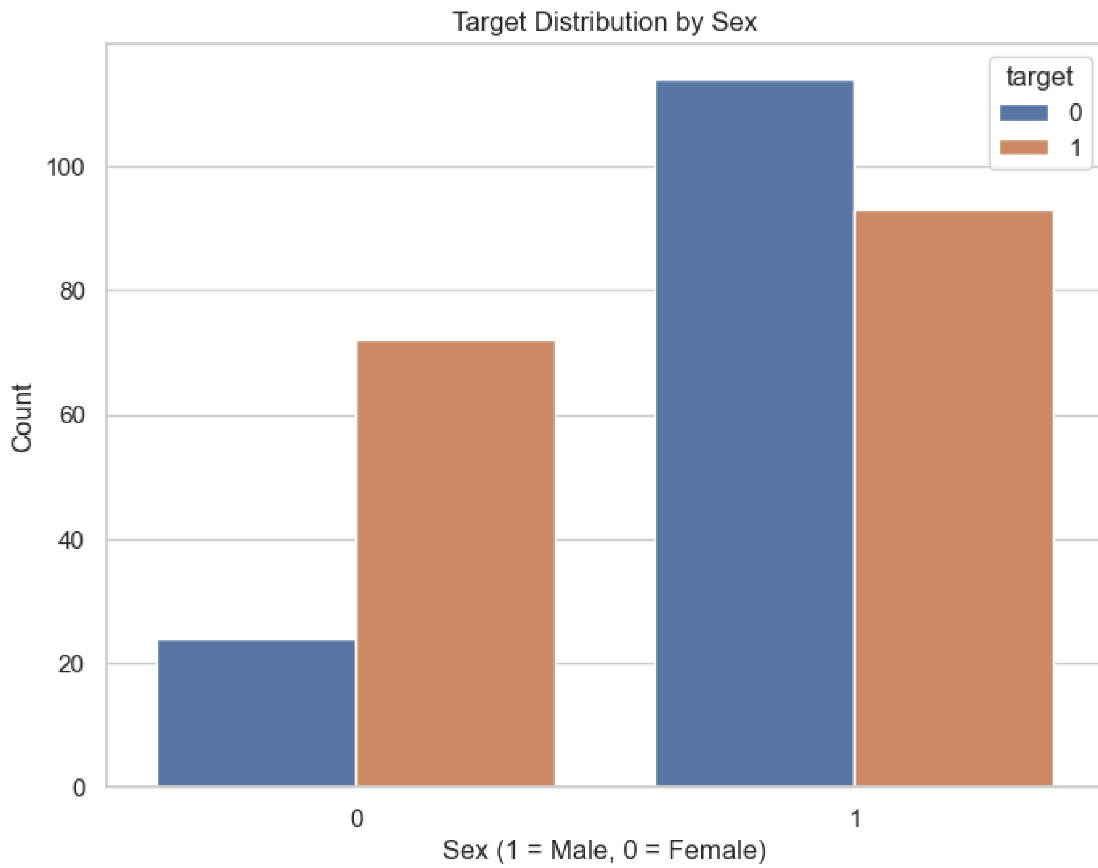
sex = 0 → Female

From data:

- Out of 96 females, 72 have heart disease, 24 do not
- Out of 207 males, 93 have heart disease, 114 do not

7.6 Visualize with Countplot (Sex vs Target)

[17]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="sex", hue="target", data=df)
plt.title("Target Distribution by Sex")
plt.xlabel("Sex (1 = Male, 0 = Female)")
plt.ylabel("Count")
plt.show()
```

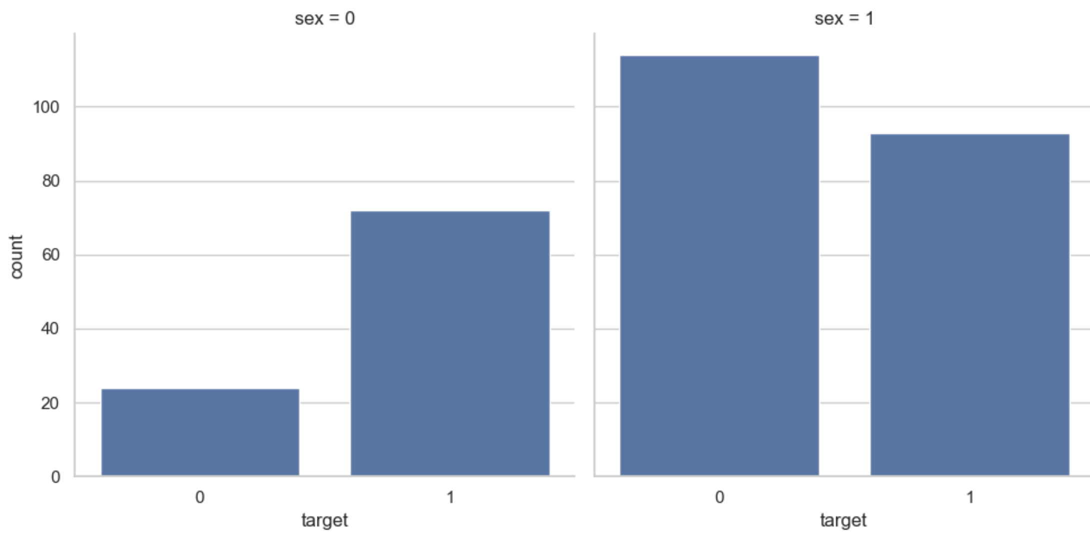


Interpretation:

You can see heart disease distribution across male and female patients.

7.7 Alternate Visualization – Side-by-Side Columns

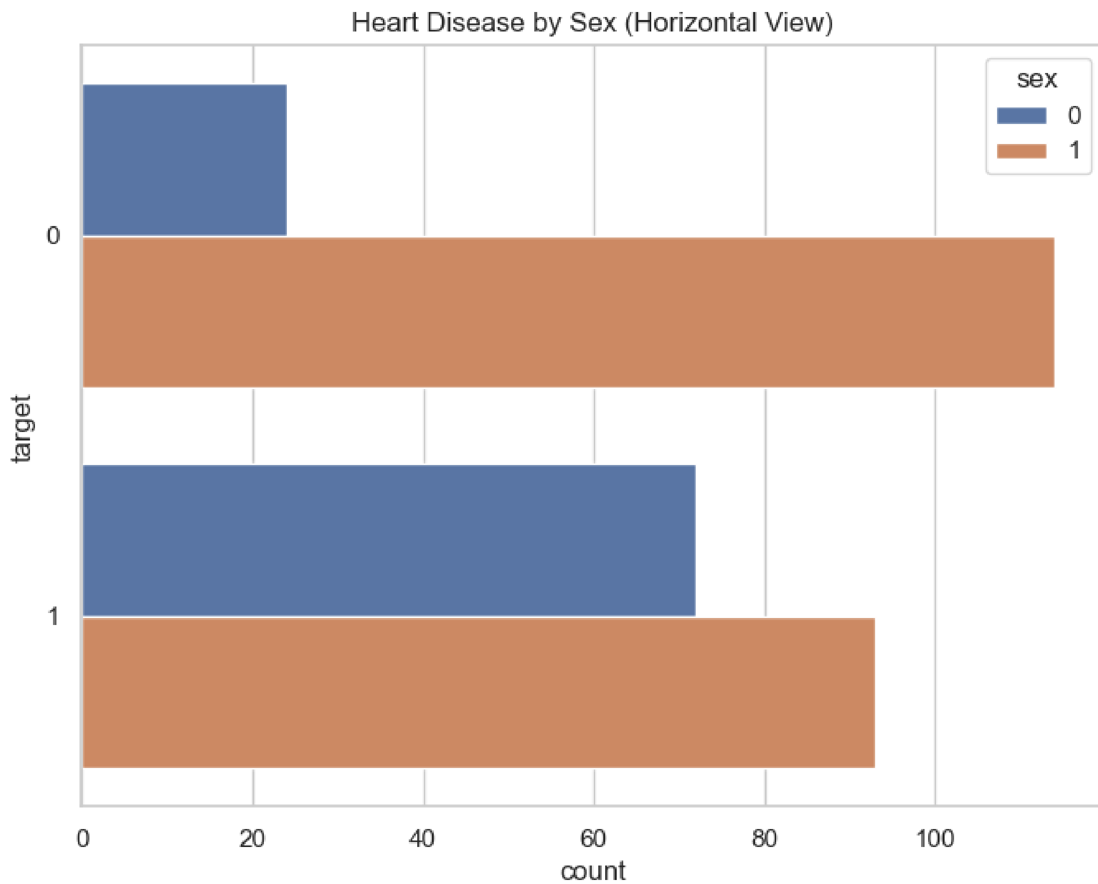
[20]:
```
ax = sns.catplot(x="target", col="sex", data=df, kind="count", height=5,␣
↪aspect=1)
plt.show()
```



Easier to interpret with clear separation for male and female.

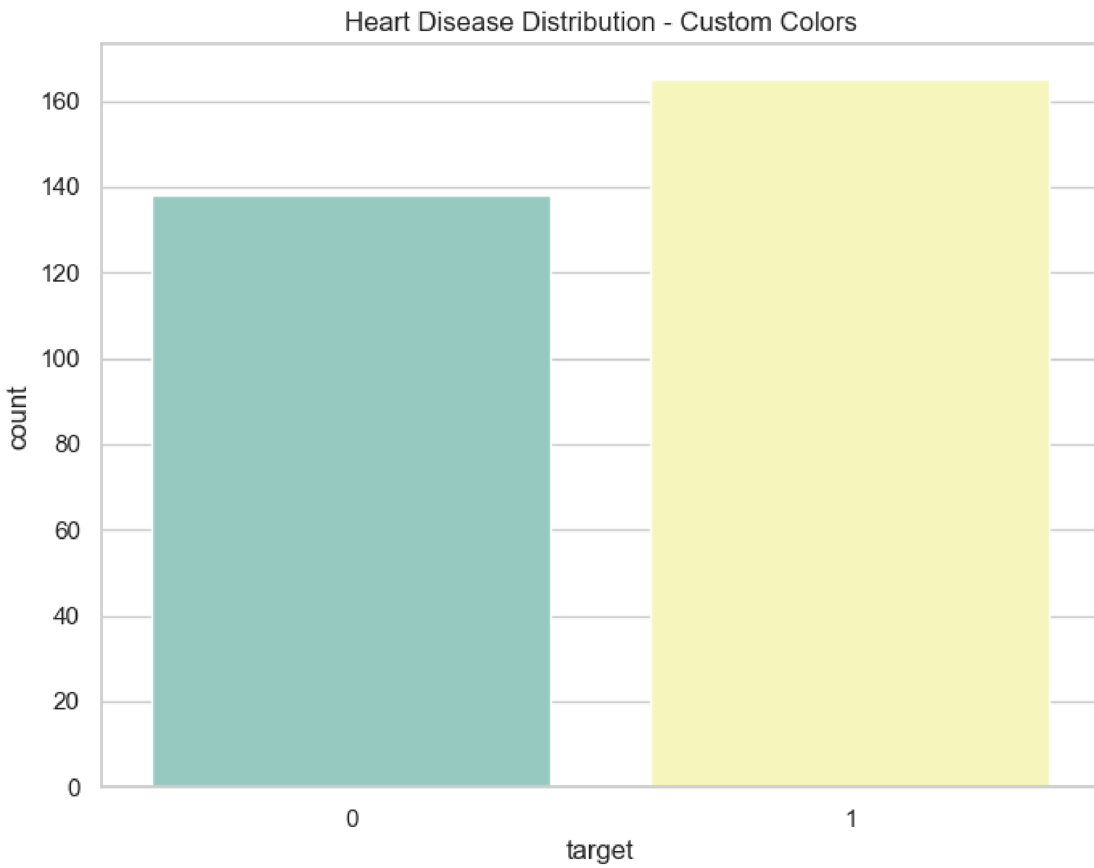
7.8 Horizontal Bars

[21]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(y="target", hue="sex", data=df)
plt.title("Heart Disease by Sex (Horizontal View)")
plt.show()
```



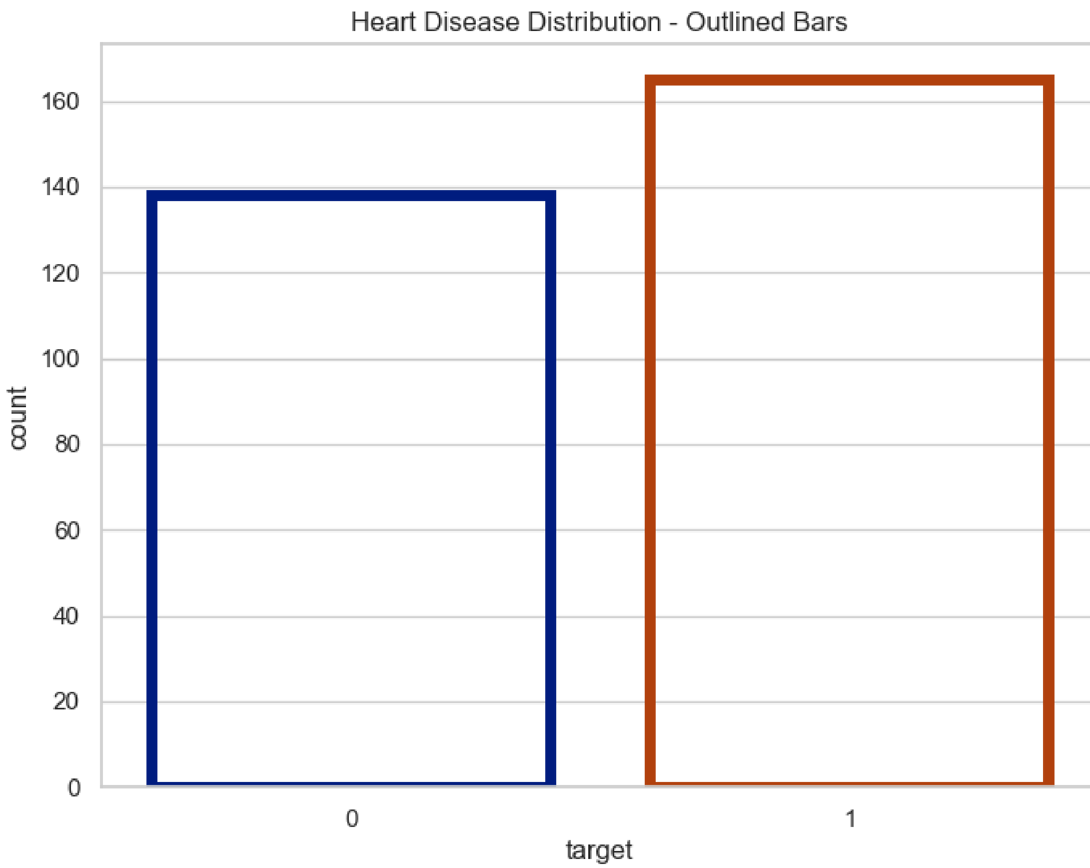
7.9 Use Different Color Palette

[22]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", data=df, palette="Set3")
plt.title("Heart Disease Distribution - Custom Colors")
plt.show()
```



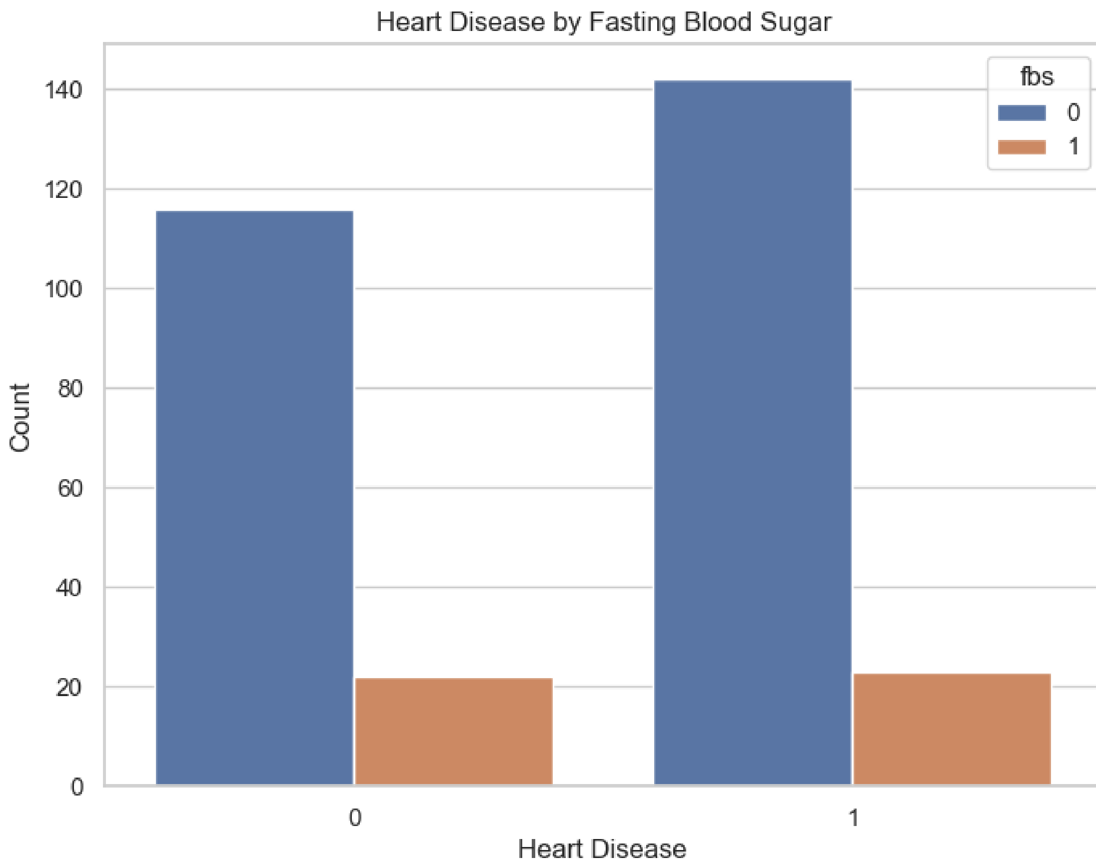
7.10 Stylish Edge with plt.bar look

[23]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(
    x="target",
    data=df,
    facecolor=(0, 0, 0, 0),
    linewidth=5,
    edgecolor=sns.color_palette("dark", 3)
)
plt.title("Heart Disease Distribution - Outlined Bars")
plt.show()
```



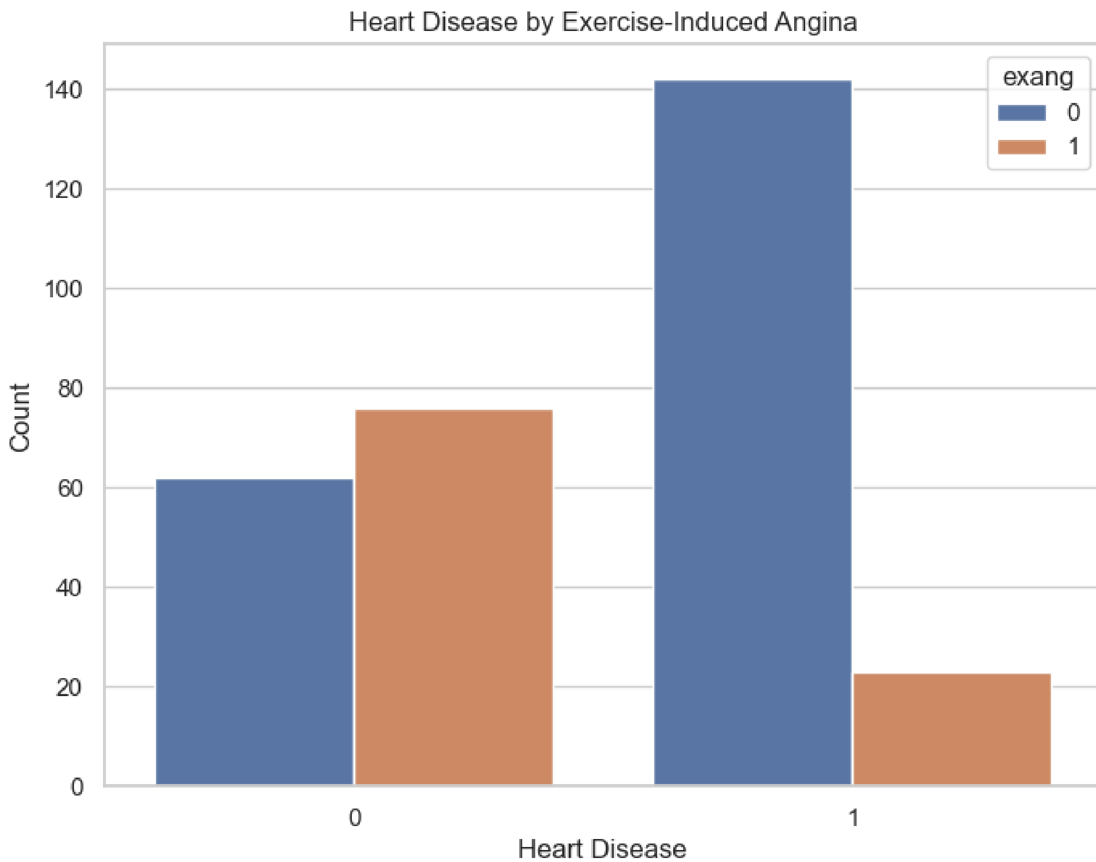
7.11 Target Distribution vs fbs (Fasting Blood Sugar)

[24]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", hue="fbs", data=df)
plt.title("Heart Disease by Fasting Blood Sugar")
plt.xlabel("Heart Disease")
plt.ylabel("Count")
plt.show()
```



7.12 Target Distribution vs exang (Exercise-Induced Angina)

[25]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="target", hue="exang", data=df)
plt.title("Heart Disease by Exercise-Induced Angina")
plt.xlabel("Heart Disease")
plt.ylabel("Count")
plt.show()
```



Summary of Univariate Findings

- target is our key variable indicating heart disease (1 = Yes, 0 = No)
- 165 patients have heart disease
- 138 patients do not have heart disease
- Among 96 females:
  - 72 have heart disease
  - 24 do not
- Among 207 males:
  - 93 have heart disease
  - 114 do not
- We also explored heart disease patterns by fbs and exang.

8 Bivariate Analysis – Correlation with Target

8.1 Estimate Correlation Coefficients

We will calculate Pearson's correlation coefficient between all numeric features using:

[26]:
```
correlation = df.corr()
```

[27]:
```
correlation
```

[27]:
```
               age       sex        cp  trestbps      chol       fbs  \
age       1.000000 -0.098447 -0.068653  0.279351  0.213678  0.121308
sex      -0.098447  1.000000 -0.049353 -0.056769 -0.197912  0.045032
cp       -0.068653 -0.049353  1.000000  0.047608 -0.076904  0.094444
trestbps  0.279351 -0.056769  0.047608  1.000000  0.123174  0.177531
chol      0.213678 -0.197912 -0.076904  0.123174  1.000000  0.013294
fbs       0.121308  0.045032  0.094444  0.177531  0.013294  1.000000
restecg  -0.116211 -0.058196  0.044421 -0.114103 -0.151040 -0.084189
thalach  -0.398522 -0.044020  0.295762 -0.046698 -0.009940 -0.008567
exang     0.096801  0.141664 -0.394280  0.067616  0.067023  0.025665
oldpeak   0.210013  0.096093 -0.149230  0.193216  0.053952  0.005747
slope    -0.168814 -0.030711  0.119717 -0.121475 -0.004038 -0.059894
ca        0.276326  0.118261 -0.181053  0.101389  0.070511  0.137979
thal      0.068001  0.210041 -0.161736  0.062210  0.098803 -0.032019
target   -0.225439 -0.280937  0.433798 -0.144931 -0.085239 -0.028046

           restecg   thalach     exang   oldpeak     slope        ca  \
age      -0.116211 -0.398522  0.096801  0.210013 -0.168814  0.276326
sex      -0.058196 -0.044020  0.141664  0.096093 -0.030711  0.118261
cp        0.044421  0.295762 -0.394280 -0.149230  0.119717 -0.181053
trestbps -0.114103 -0.046698  0.067616  0.193216 -0.121475  0.101389
chol     -0.151040 -0.009940  0.067023  0.053952 -0.004038  0.070511
fbs      -0.084189 -0.008567  0.025665  0.005747 -0.059894  0.137979
restecg   1.000000  0.044123 -0.070733 -0.058770  0.093045 -0.072042
thalach   0.044123  1.000000 -0.378812 -0.344187  0.386784 -0.213177
exang    -0.070733 -0.378812  1.000000  0.288223 -0.257748  0.115739
oldpeak  -0.058770 -0.344187  0.288223  1.000000 -0.577537  0.222682
slope     0.093045  0.386784 -0.257748 -0.577537  1.000000 -0.080155
ca       -0.072042 -0.213177  0.115739  0.222682 -0.080155  1.000000
thal     -0.011981 -0.096439  0.206754  0.210244 -0.104764  0.151832
target    0.137230  0.421741 -0.436757 -0.430696  0.345877 -0.391724

              thal    target
age       0.068001 -0.225439
sex       0.210041 -0.280937
cp       -0.161736  0.433798
trestbps  0.062210 -0.144931
chol      0.098803 -0.085239
```

```
fbs       -0.032019 -0.028046
restecg   -0.011981  0.137230
thalach   -0.096439  0.421741
exang      0.206754 -0.436757
oldpeak    0.210244 -0.430696
slope     -0.104764  0.345877
ca         0.151832 -0.391724
thal       1.000000 -0.344029
target    -0.344029  1.000000
```

8.2 Correlation with Target

Let's view how other features correlate with the target variable:

[28]:
```
correlation['target'].sort_values(ascending=False)
```

[28]:
```
target      1.000000
cp          0.433798
thalach     0.421741
slope       0.345877
restecg     0.137230
fbs        -0.028046
chol       -0.085239
trestbps   -0.144931
age        -0.225439
sex        -0.280937
thal       -0.344029
ca         -0.391724
oldpeak    -0.430696
exang      -0.436757
Name: target, dtype: float64
```

Interpretation of Correlation Coefficient

- +1 → Strong positive correlation
- 0 → No correlation
- -1 → Strong negative correlation

Findings:

- No variable has a strong positive or negative correlation with target.
- cp (chest pain type) and thalach (maximum heart rate) show mild positive correlation.
- fbs (fasting blood sugar) shows no correlation.

8.3 Analysis of cp (Chest Pain Type)

8.3.1 Check Unique Values

[29]:
```
df['cp'].nunique()
```

[29]:
```
4
```

8.3.2 Frequency Distribution

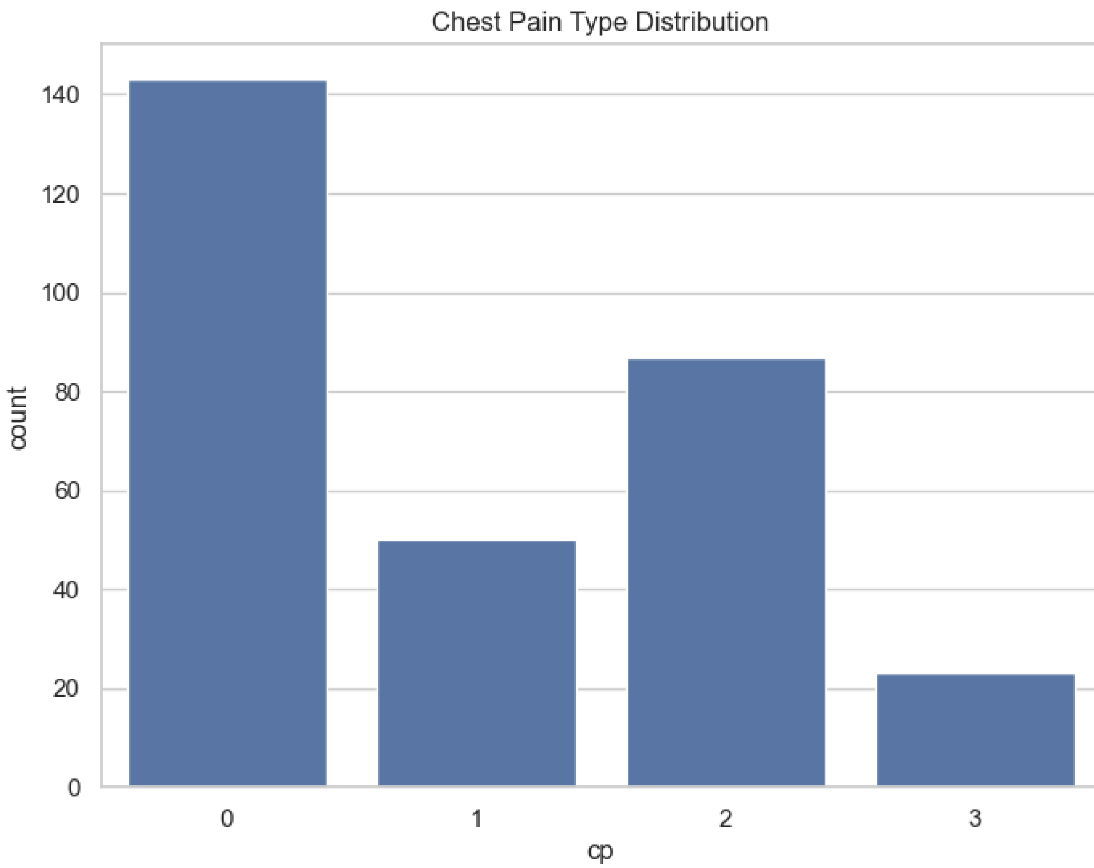
[30]:
```
df['cp'].value_counts()
```

[30]:
```
cp
0    143
2     87
1     50
3     23
Name: count, dtype: int64
```

Values: 0, 1, 2, 3 → Different types of chest pain

8.3.3 Visualize cp Distribution

[31]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="cp", data=df)
plt.title("Chest Pain Type Distribution")
plt.show()
```



8.3.4 target vs cp

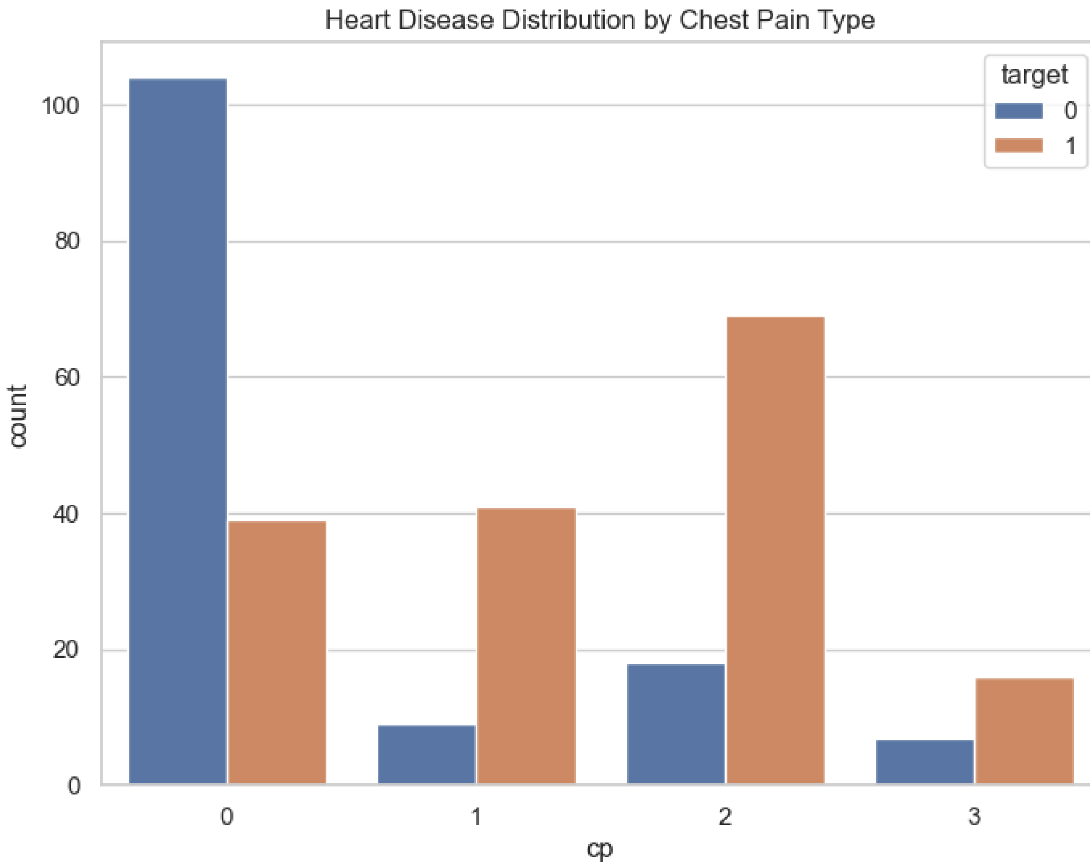
[32]:
```
df.groupby('cp')['target'].value_counts()
```

[32]:
```
cp  target
0   0         104
    1          39
1   1          41
    0           9
2   1          69
    0          18
3   1          16
    0           7
Name: count, dtype: int64
```

This groups heart disease presence across different chest pain types.

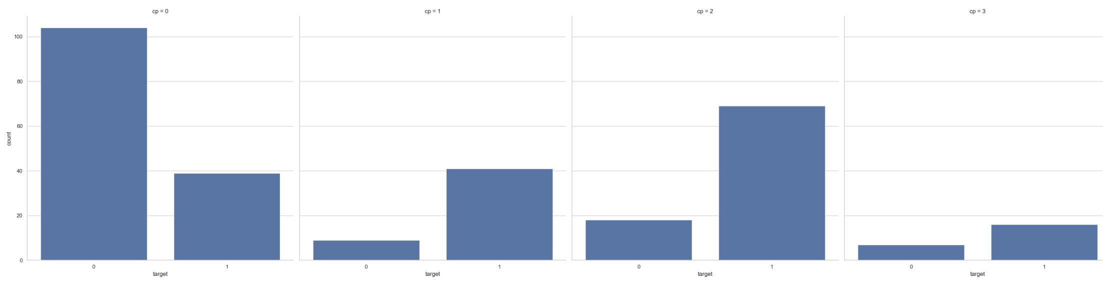
8.3.5 Visualize target by cp

[33]:
```
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.countplot(x="cp", hue="target", data=df)
plt.title("Heart Disease Distribution by Chest Pain Type")
plt.show()
```



8.3.6 Alternate: target vs cp – Column Format

[37]:
```
ax = sns.catplot(x="target", col="cp", data=df, kind="count", height=8,␣
↪aspect=1)
plt.show()
```



8.4 Analysis of thalach (Max Heart Rate)

8.4.1 Unique Values

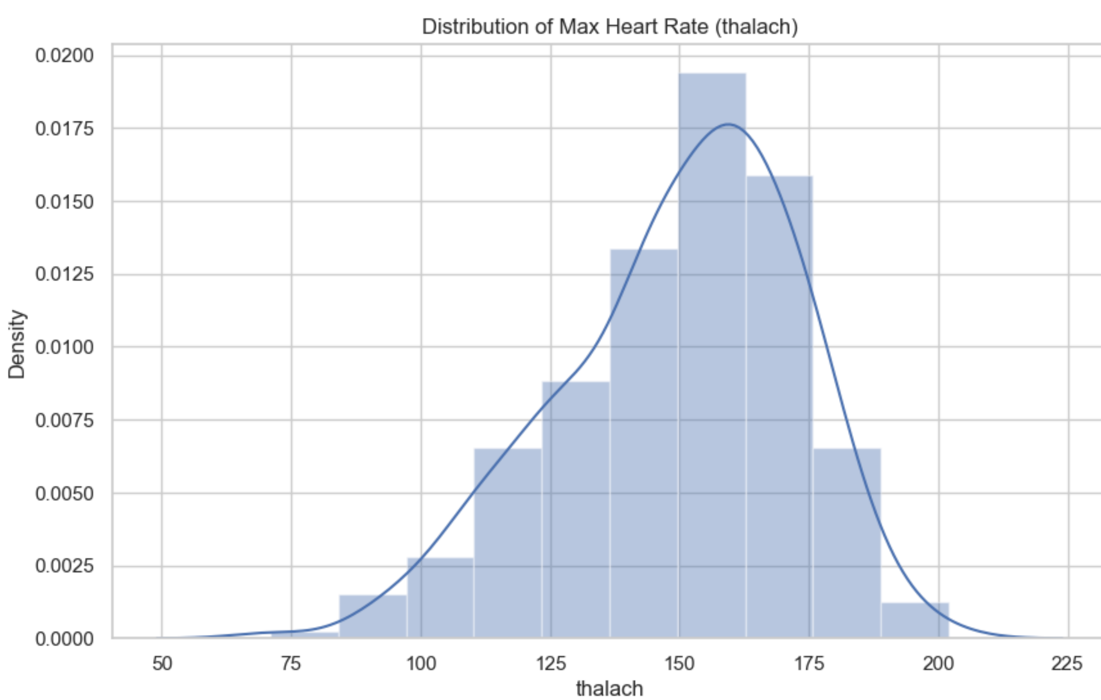
[38]:
```
df['thalach'].nunique()
```

[38]: 91

Output: 91 (Continuous numeric feature)

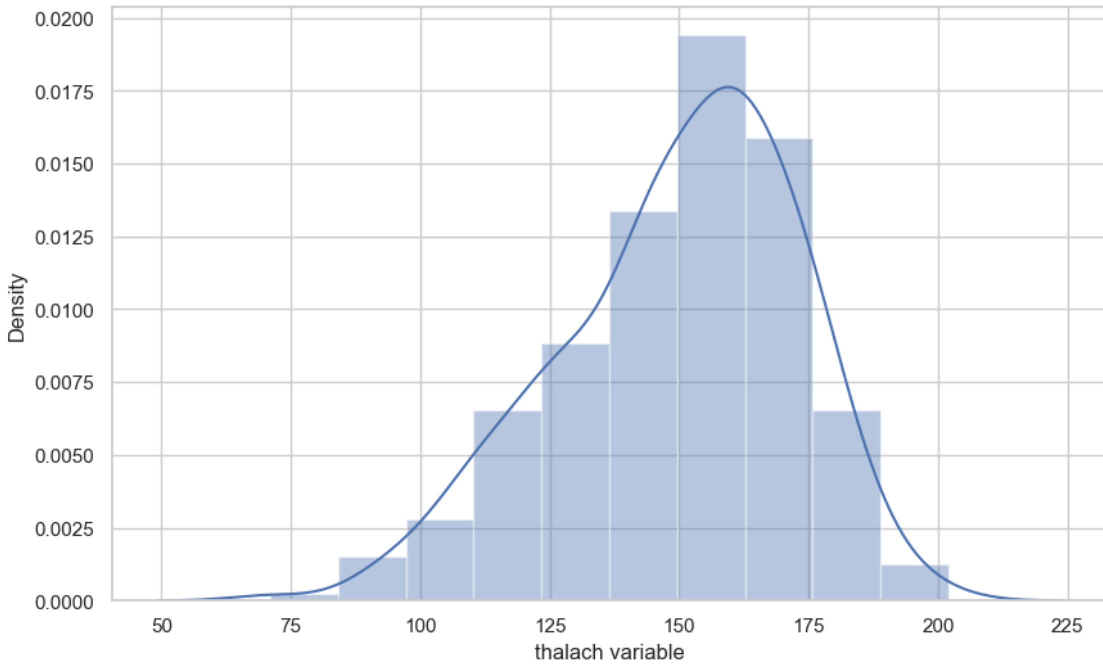
8.4.2 Visualize Distribution (Histogram + KDE)

[39]:
```
f, ax = plt.subplots(figsize=(10, 6))
x = df['thalach']
ax = sns.distplot(x, bins=10)
plt.title("Distribution of Max Heart Rate (thalach)")
plt.show()
```



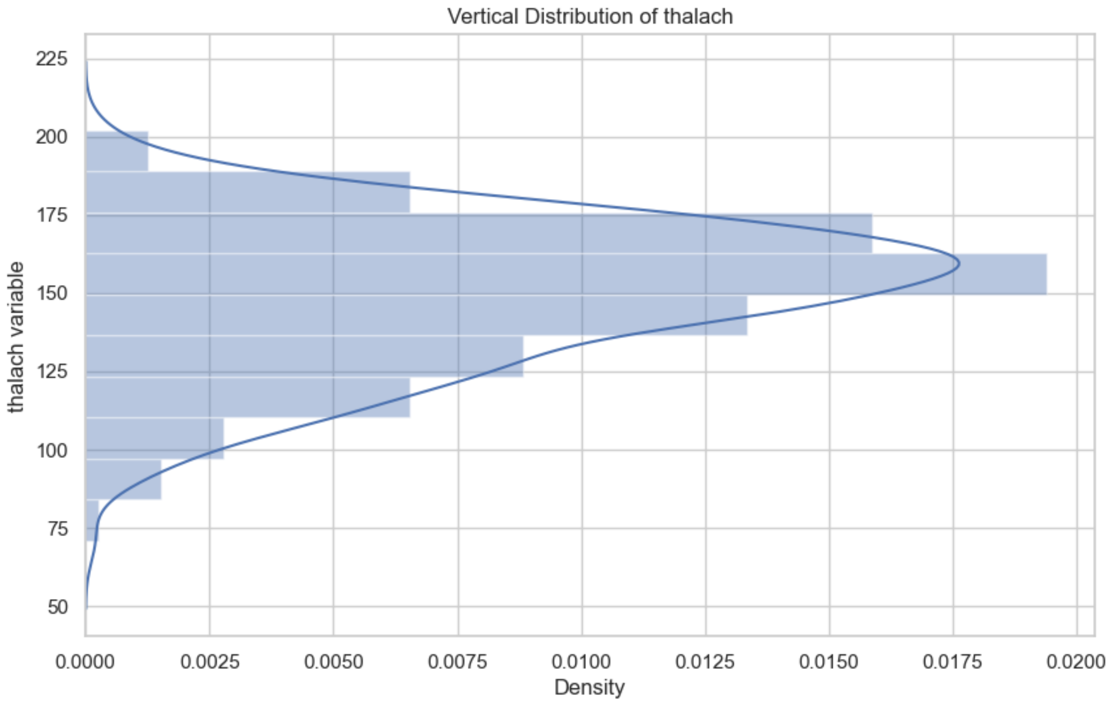
8.4.3 Pandas Series Label

[40]:
```
f, ax = plt.subplots(figsize=(10, 6))
x = pd.Series(df['thalach'], name="thalach variable")
ax = sns.distplot(x, bins=10)
plt.show()
```



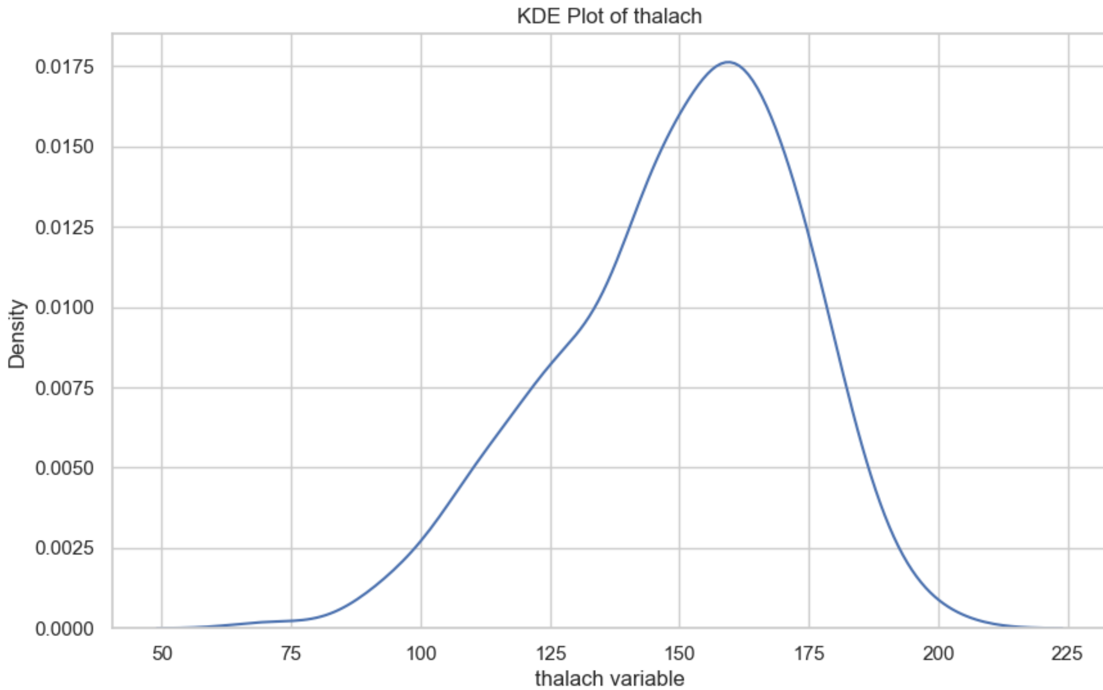
8.4.4 Vertical Histogram

[41]:
```
f, ax = plt.subplots(figsize=(10, 6))
ax = sns.distplot(x, bins=10, vertical=True)
plt.title("Vertical Distribution of thalach")
plt.show()
```



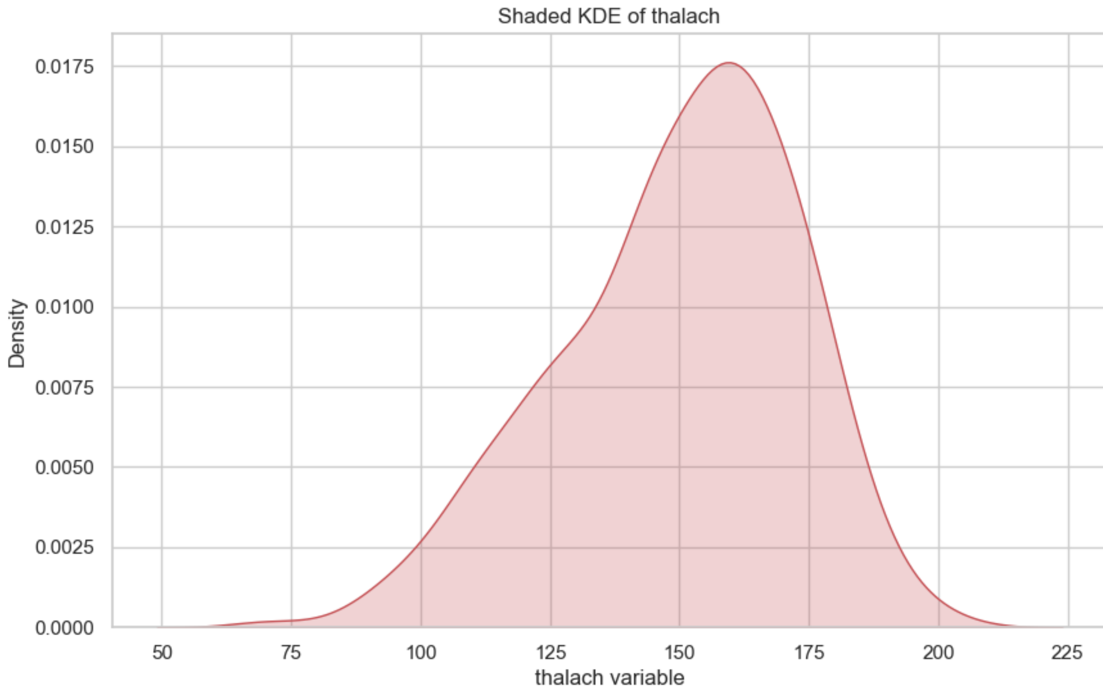
8.4.5 KDE Plot (Smooth Curve)

[42]:
```
f, ax = plt.subplots(figsize=(10, 6))
ax = sns.kdeplot(x)
plt.title("KDE Plot of thalach")
plt.show()
```



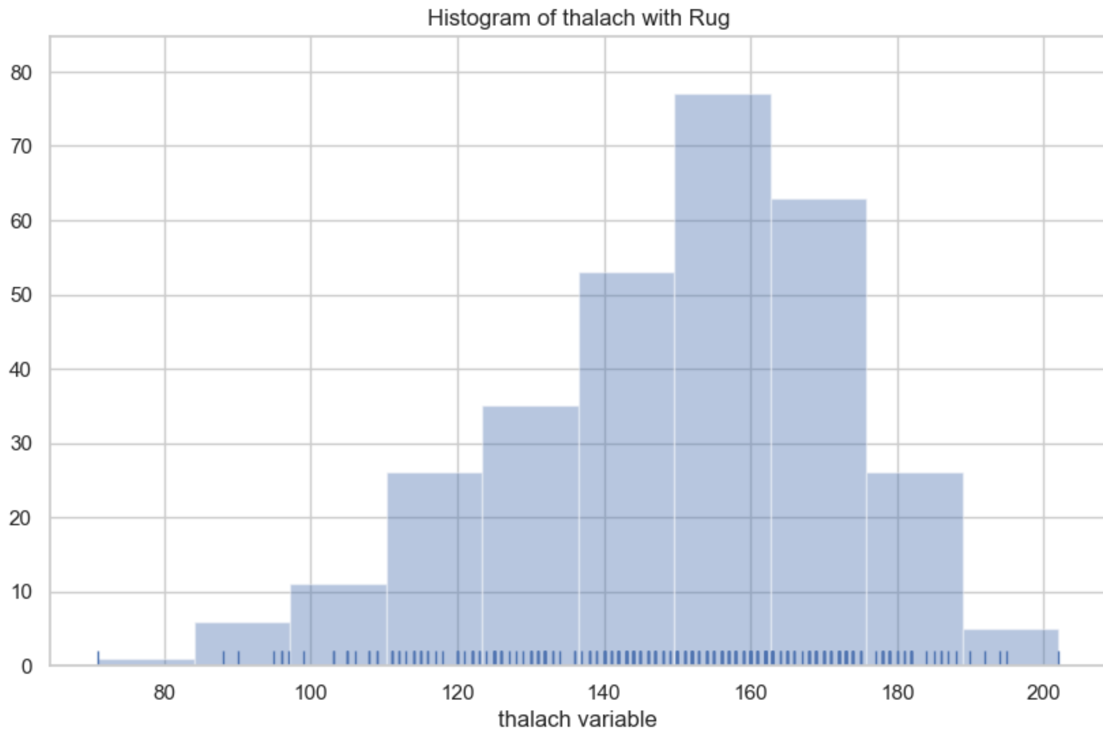
8.4.6 Shaded KDE Plot

[43]:
```
f, ax = plt.subplots(figsize=(10, 6))
ax = sns.kdeplot(x, shade=True, color='r')
plt.title("Shaded KDE of thalach")
plt.show()
```



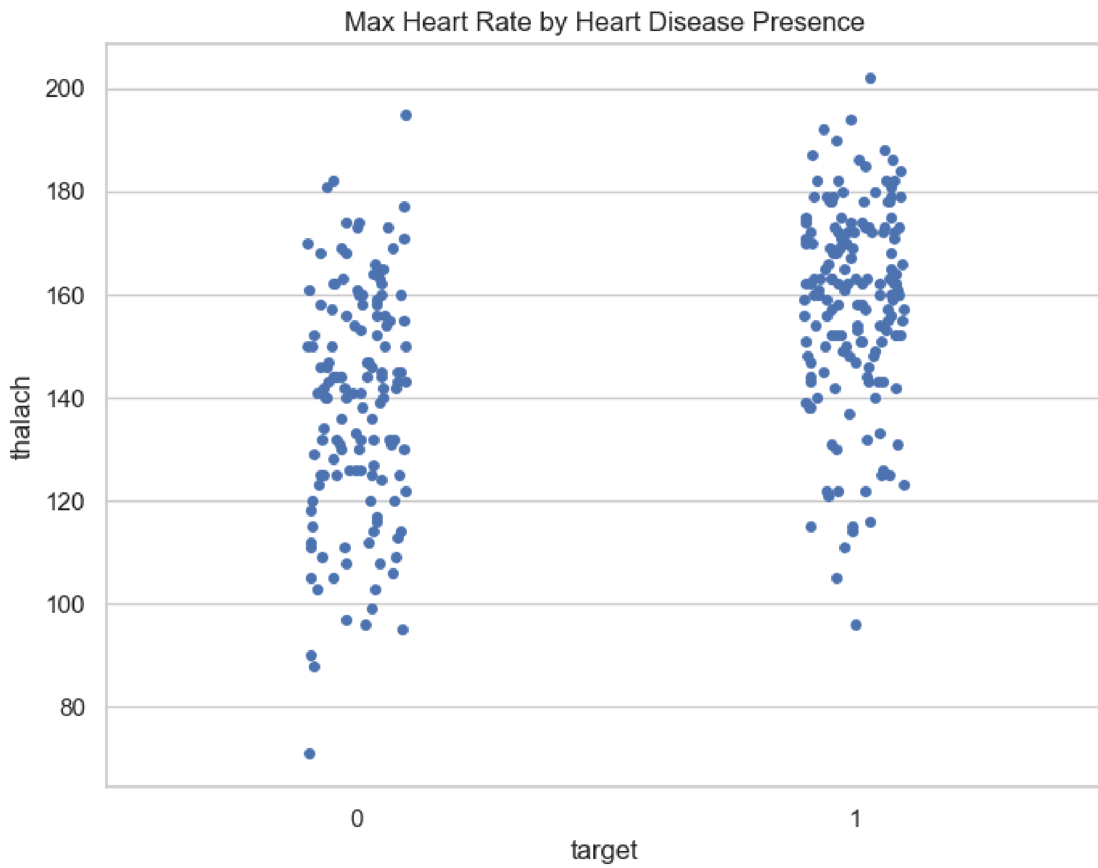
8.4.7 Histogram (No KDE, With Rug)

[44]:
```
f, ax = plt.subplots(figsize=(10, 6))
ax = sns.distplot(x, kde=False, rug=True, bins=10)
plt.title("Histogram of thalach with Rug")
plt.show()
```



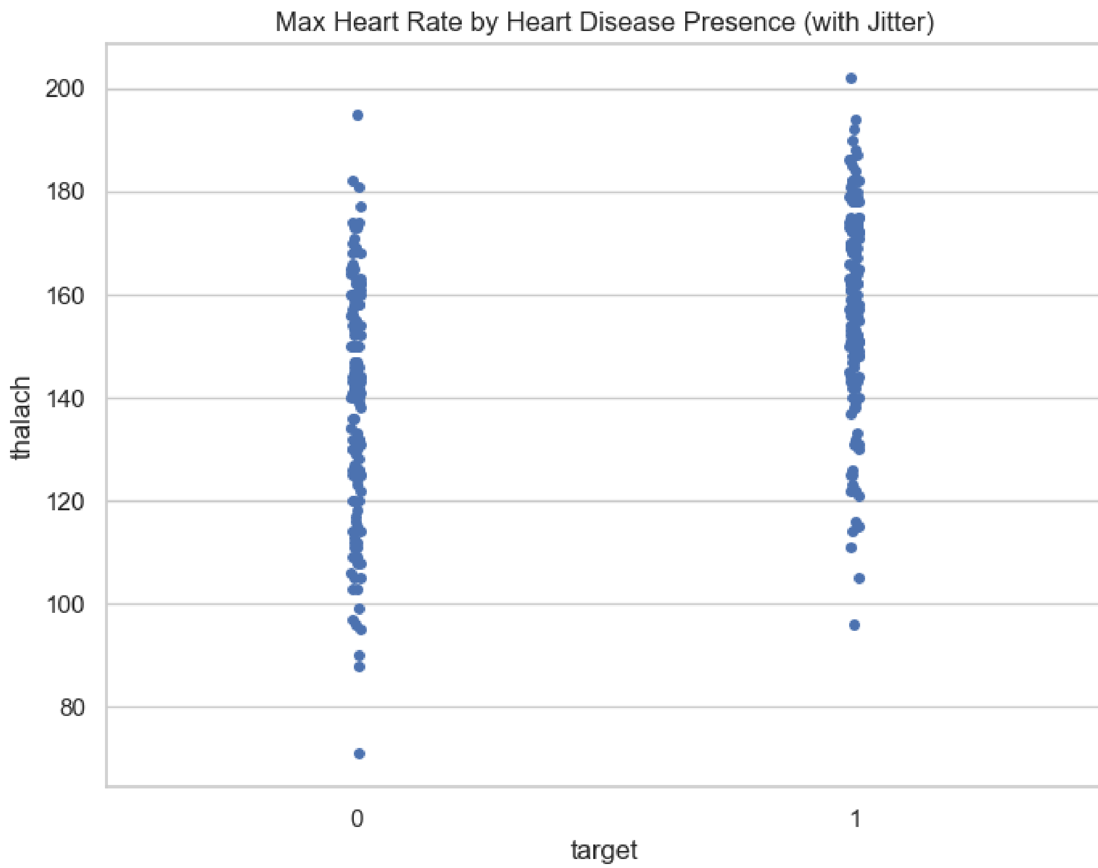
8.4.8 thalach vs target – Strip Plot

[45]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="target", y="thalach", data=df)
plt.title("Max Heart Rate by Heart Disease Presence")
plt.show()
```



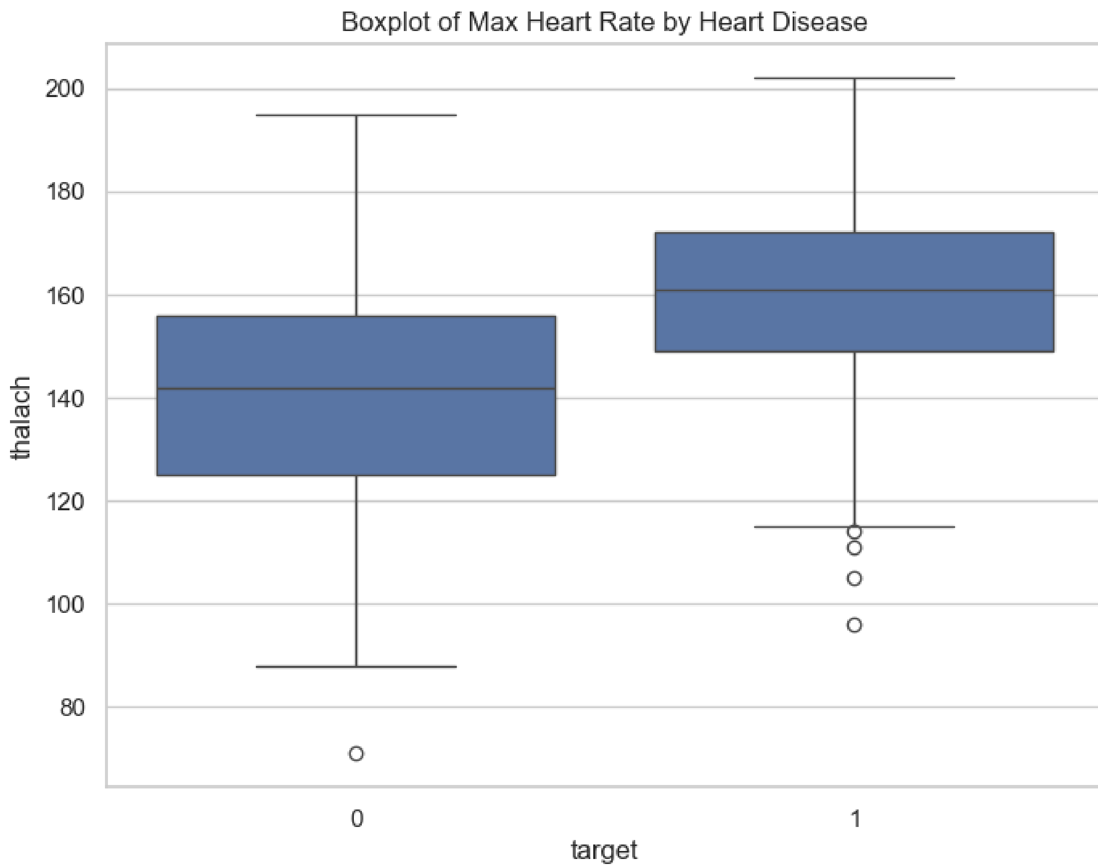
8.4.9 Strip Plot with Jitter

[46]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="target", y="thalach", data=df, jitter=0.01)
plt.title("Max Heart Rate by Heart Disease Presence (with Jitter)")
plt.show()
```



8.4.10 Boxplot – thalach vs target

[47]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x="target", y="thalach", data=df)
plt.title("Boxplot of Max Heart Rate by Heart Disease")
plt.show()
```



Interpretation:

People with target = 1 (heart disease) tend to have higher max heart rate

than those with target = 0.

Findings of Bivariate Analysis

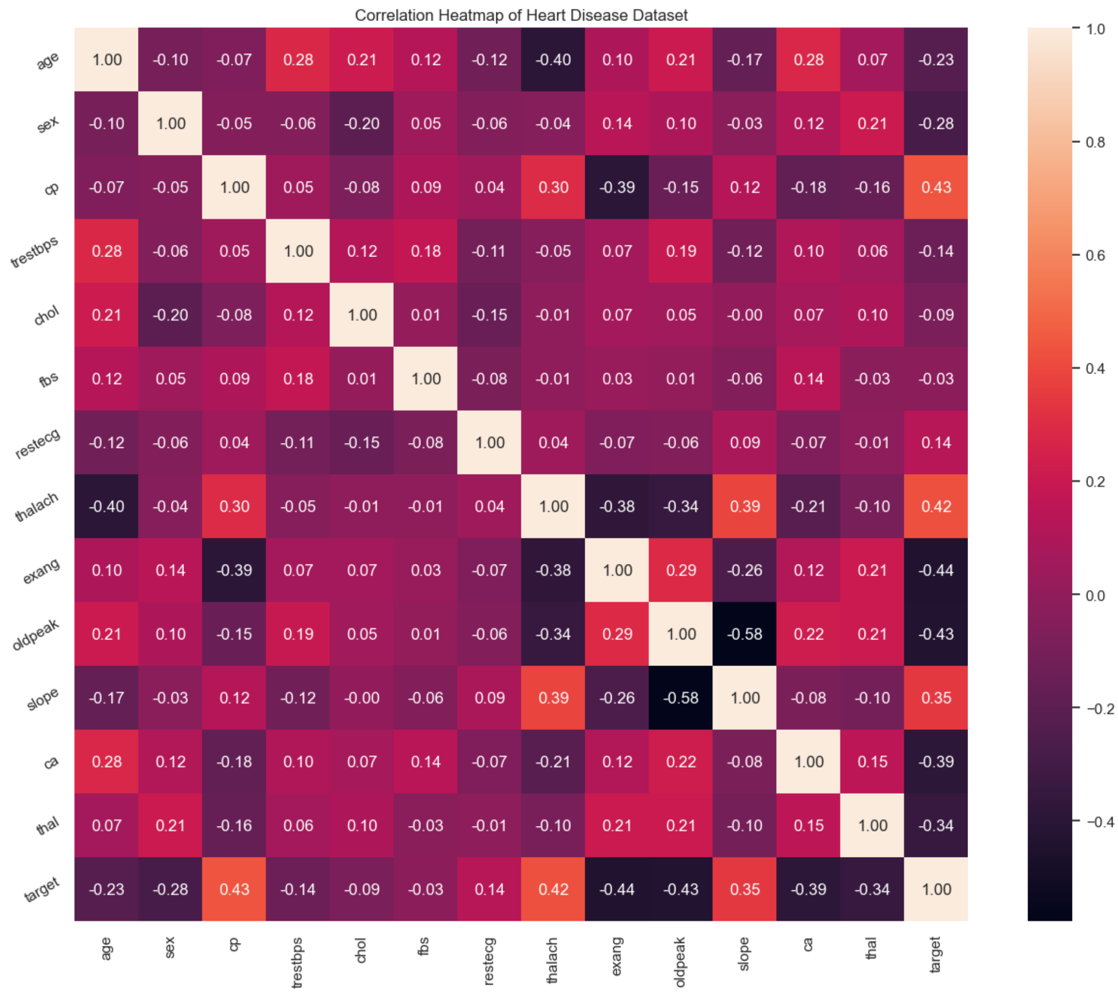
- No features have a strong correlation (either positive or negative) with target.
- cp and thalach show mild positive correlation with heart disease.
- No correlation observed between fbs and target.
- thalach distribution is slightly negatively skewed.
- Patients with heart disease (target = 1) tend to have higher thalach compared to those without heart disease.
- The relationship between chest pain type (cp) and heart disease is clearly visible with categorical plots.

9 Multivariate Analysis

The objective of multivariate analysis is to **discover hidden patterns and relationships** between multiple variables in the dataset.

9.1 Correlation Heatmap

[48]:
```
plt.figure(figsize=(16,12))
plt.title('Correlation Heatmap of Heart Disease Dataset')
a = sns.heatmap(correlation, square=True, annot=True, fmt='.2f',␣
 ↪linecolor='white')
a.set_xticklabels(a.get_xticklabels(), rotation=90)
a.set_yticklabels(a.get_yticklabels(), rotation=30)
plt.show()
```



Interpretation

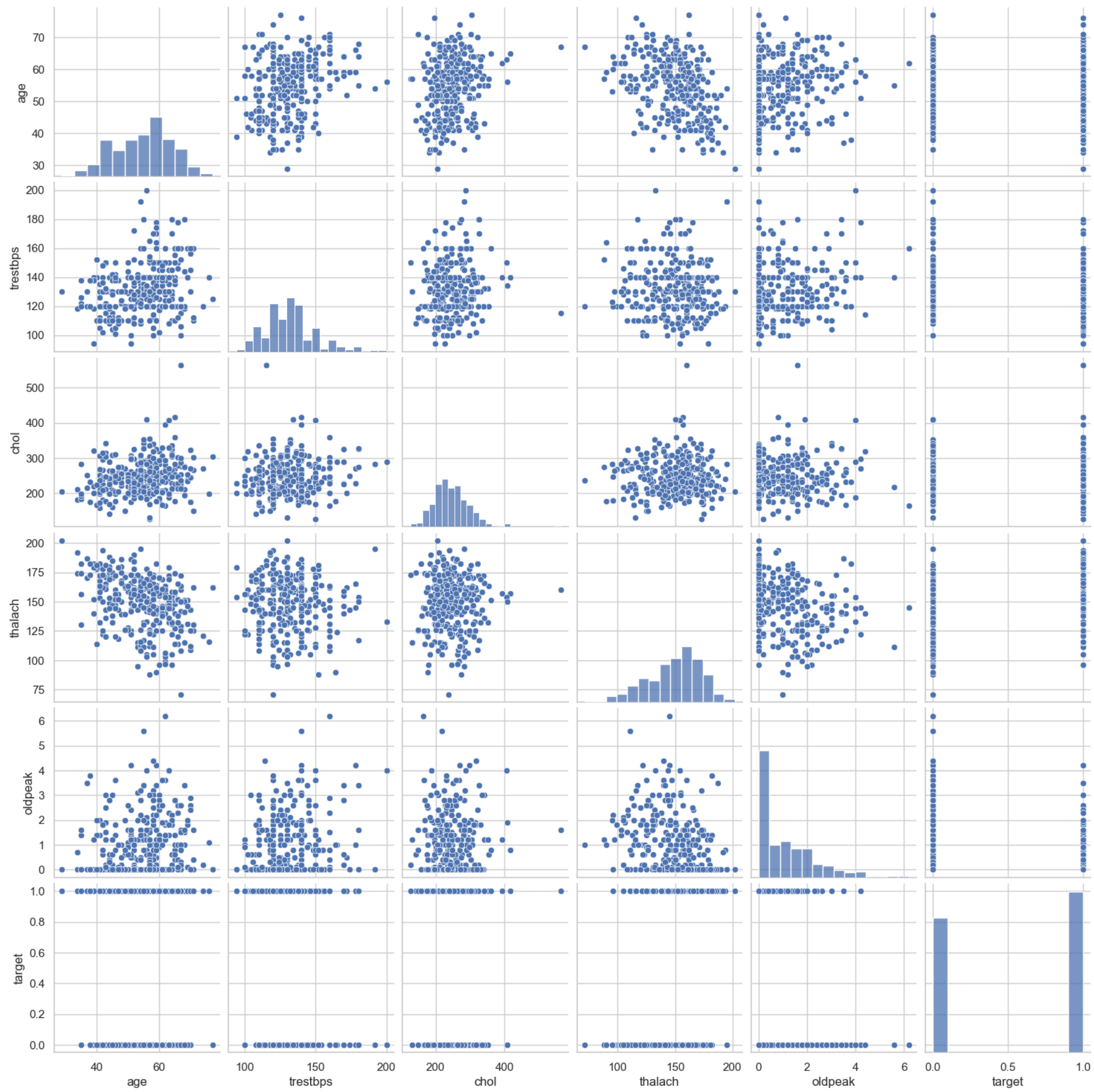
From the heatmap:

- target & cp → Mild positive correlation (0.43)
- target & thalach → Mild positive correlation (0.42)
- target & slope → Weak positive correlation (0.35)
- target & exang → Mild negative correlation (-0.44)
- target & oldpeak → Mild negative correlation (-0.43)
- target & ca → Weak negative correlation (-0.39)
- target & thal → Weak negative correlation (-0.34)

9.2 Pair Plot

Define Numerical Variables

[49]:
```
num_var = ['age', 'trestbps', 'chol', 'thalach', 'oldpeak', 'target']
sns.pairplot(df[num_var], kind='scatter', diag_kind='hist')
plt.show()
```



We compare interactions among numeric variables and their relationship with target. Helps identify linear or non-linear trends, clusters, and outliers.

9.3 In-Depth Variable Relationships

9.3.1 Analysis: age Distribution

Unique Values & Summary

[51]:
```
df['age'].nunique()
```

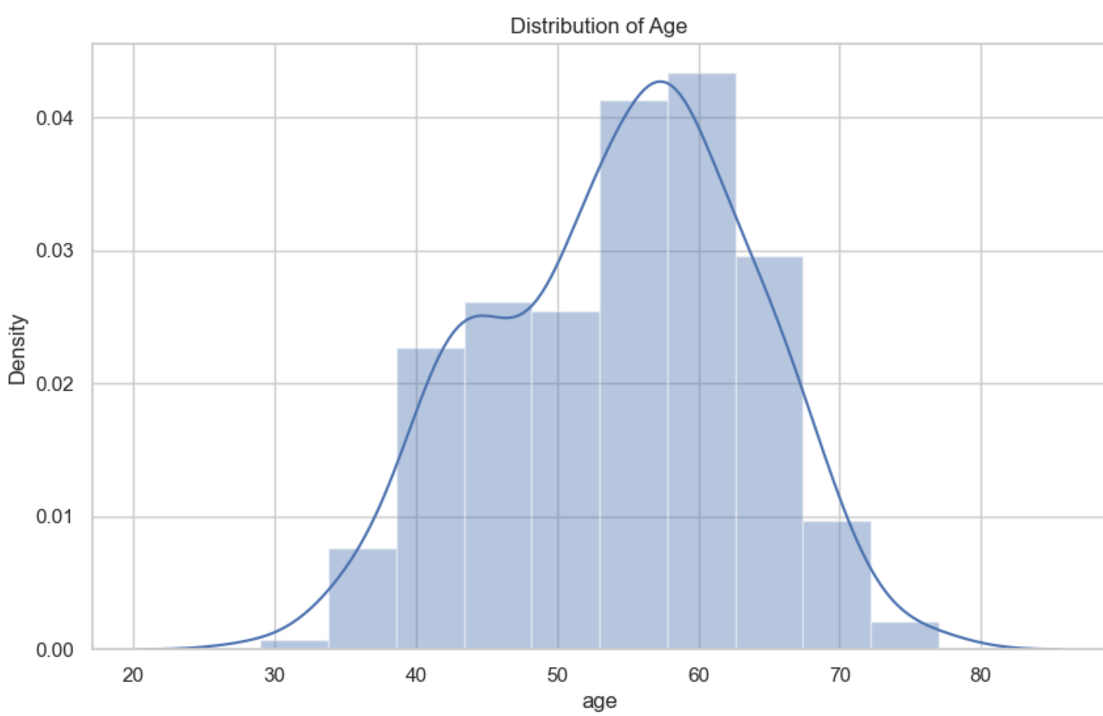
[51]:
```
41
```

[52]:
```
df['age'].describe()
```

[52]:
```
count    303.000000
mean      54.366337
std        9.082101
min       29.000000
25%       47.500000
50%       55.000000
75%       61.000000
max       77.000000
Name: age, dtype: float64
```

9.3.2 Distribution Plot

[53]:
```python
f, ax = plt.subplots(figsize=(10,6))
x = df['age']
ax = sns.distplot(x, bins=10)
plt.title("Distribution of Age")
plt.show()
```

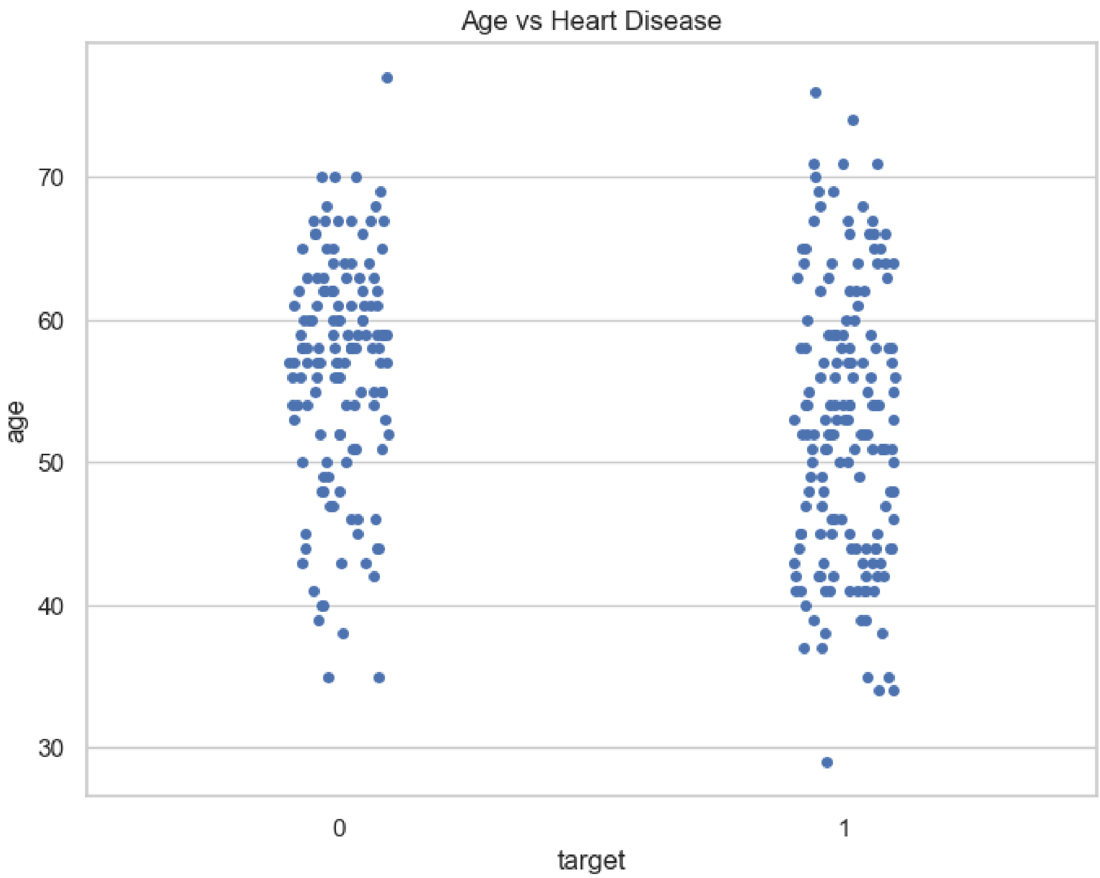


Interpretation:

- Age is approximately normally distributed
- Mean age   54.37 years
- Range: 29 to 77 years

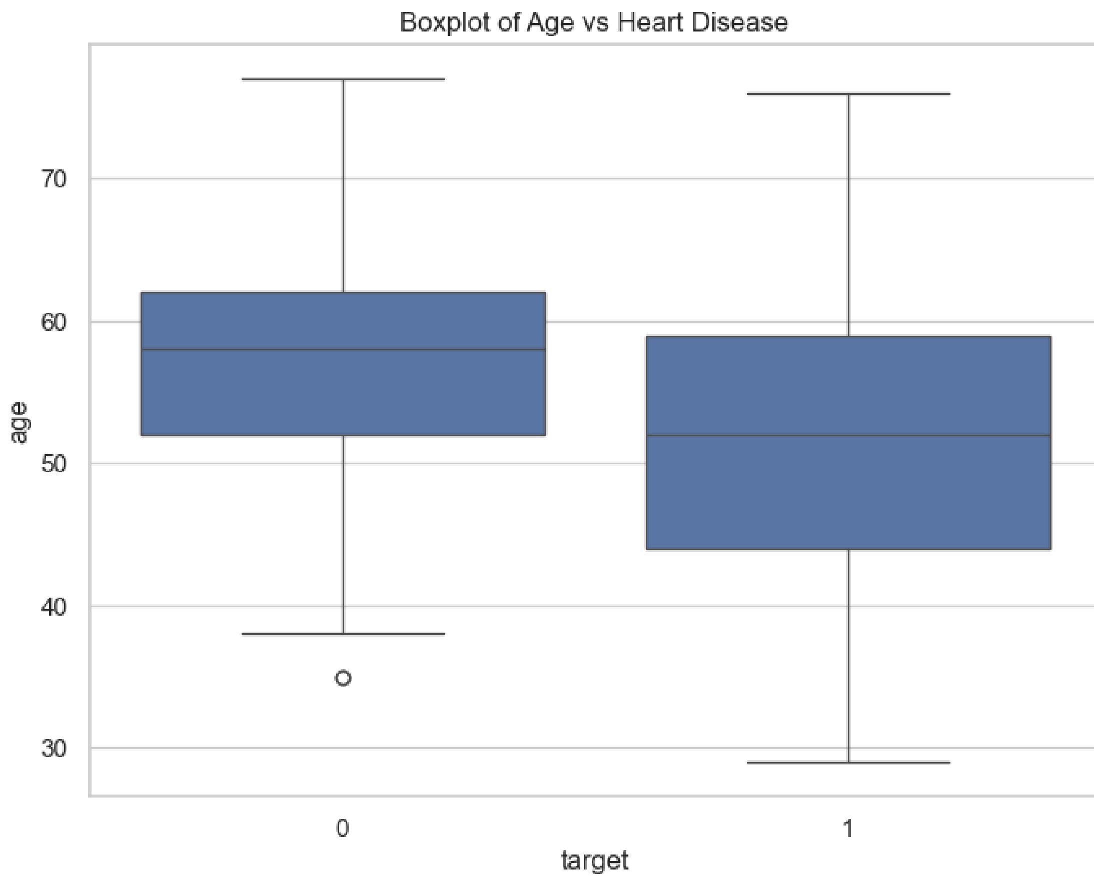
9.3.3 Age vs Target

[54]:
```
# stripplot
f, ax = plt.subplots(figsize=(8, 6))
sns.stripplot(x="target", y="age", data=df)
plt.title("Age vs Heart Disease")
plt.show()
```



Interpretation: People with and without heart disease have comparable age ranges.

[55]:
```
# Boxplot
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x="target", y="age", data=df)
plt.title("Boxplot of Age vs Heart Disease")
plt.show()
```

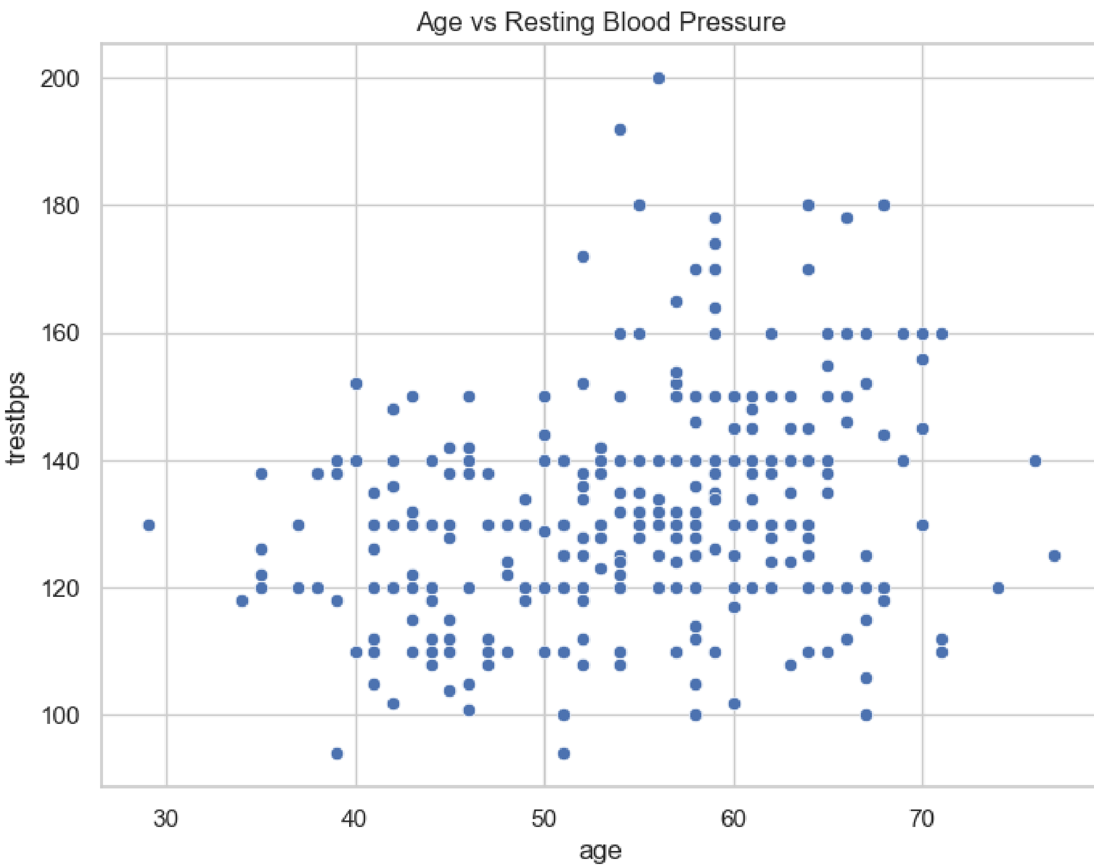


Interpretation:

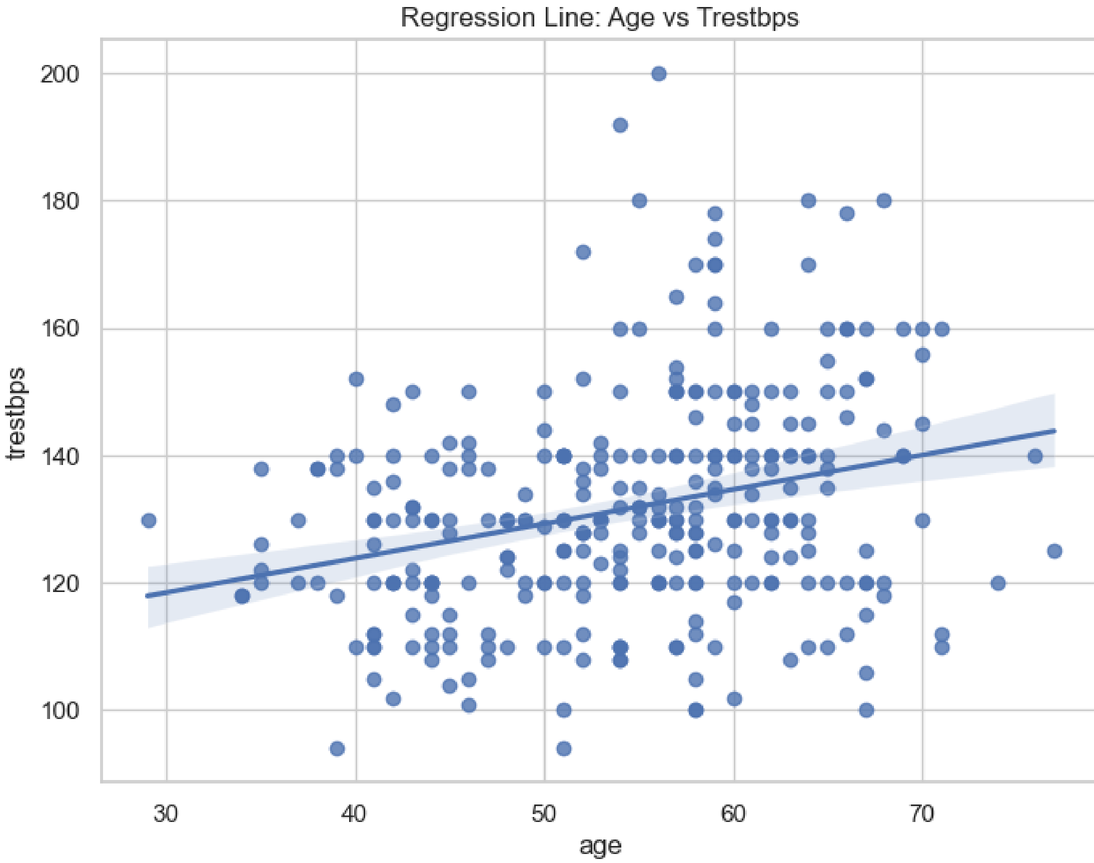
- People with heart disease tend to have a lower average age
- Spread of age is higher in people with heart disease

9.3.4 Age vs Trestbps (Resting BP)

[56]:
```
# Scatter Plot
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.scatterplot(x="age", y="trestbps", data=df)
plt.title("Age vs Resting Blood Pressure")
plt.show()
```



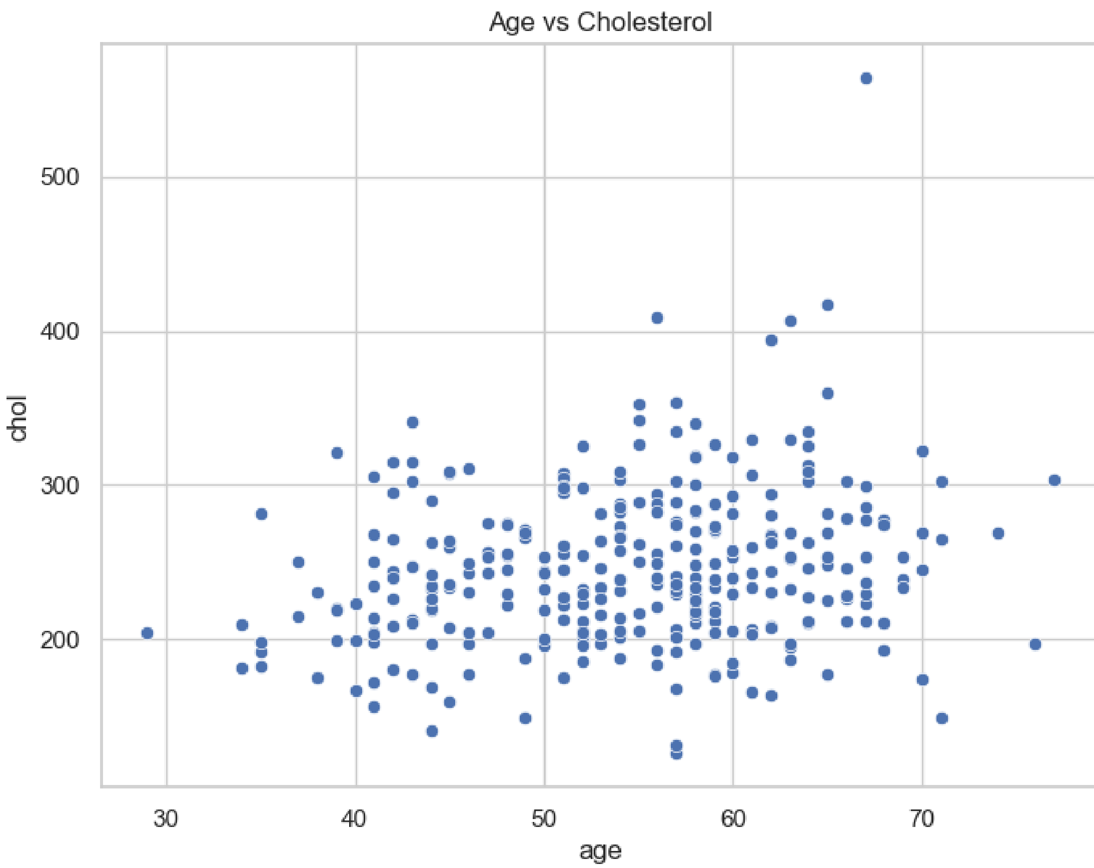
[57]:
```python
# With Regression Line
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.regplot(x="age", y="trestbps", data=df)
plt.title("Regression Line: Age vs Trestbps")
plt.show()
```



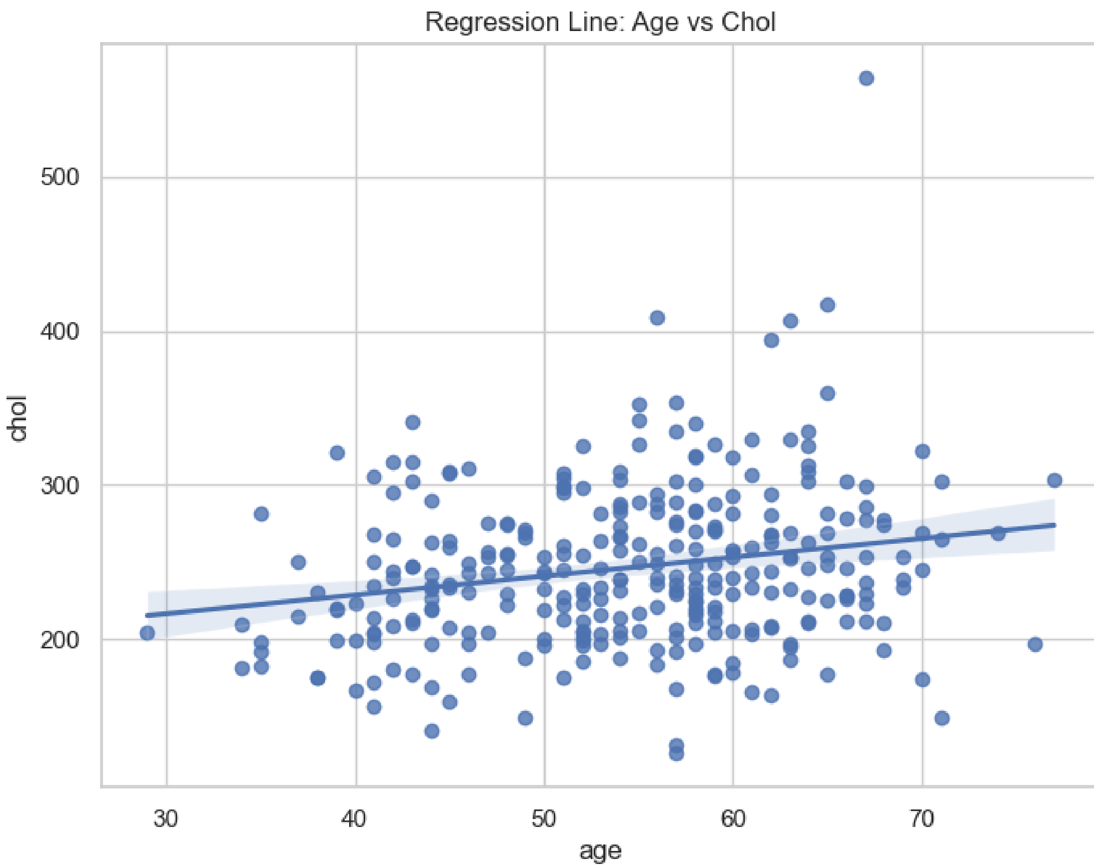
Interpretation: No meaningful correlation between age and resting blood pressure.

9.4 Age vs Chol (Cholesterol)

[58]:
```
# Scatter Plot
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.scatterplot(x="age", y="chol", data=df)
plt.title("Age vs Cholesterol")
plt.show()
```



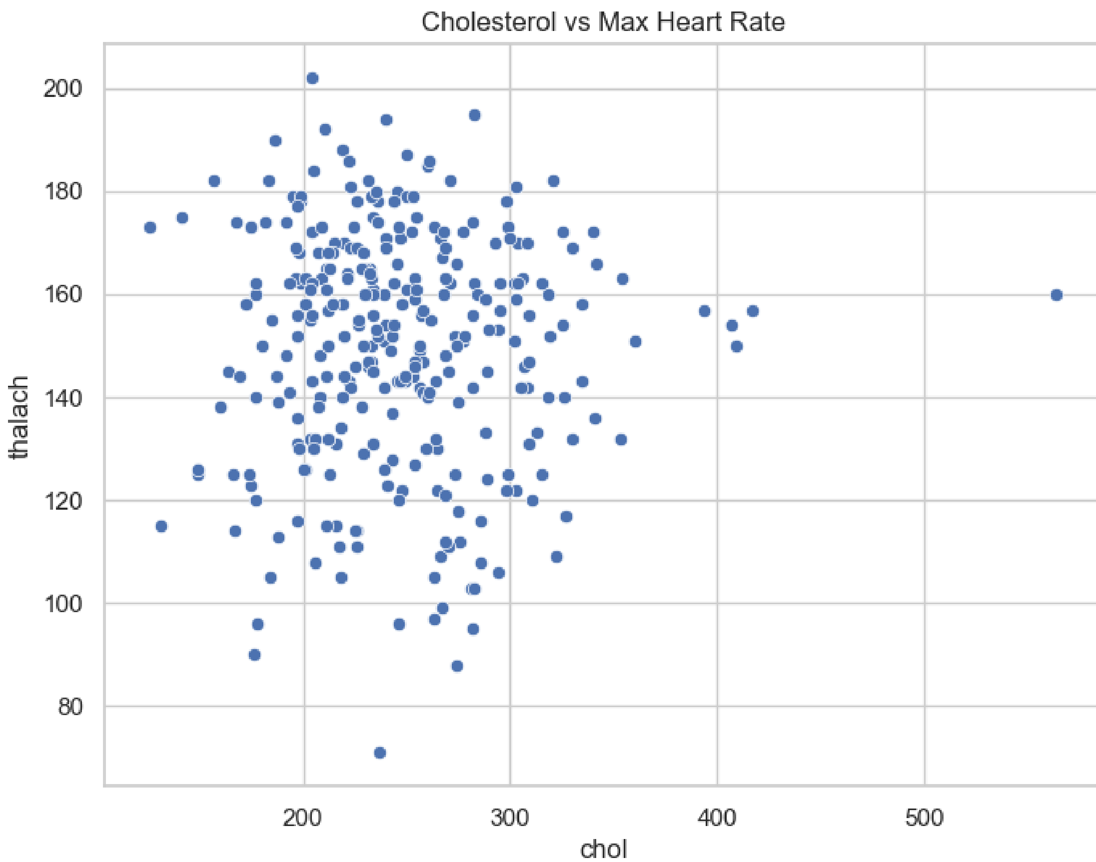

```
[59]: # With Regression Line
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.regplot(x="age", y="chol", data=df)
plt.title("Regression Line: Age vs Chol")
plt.show()
```



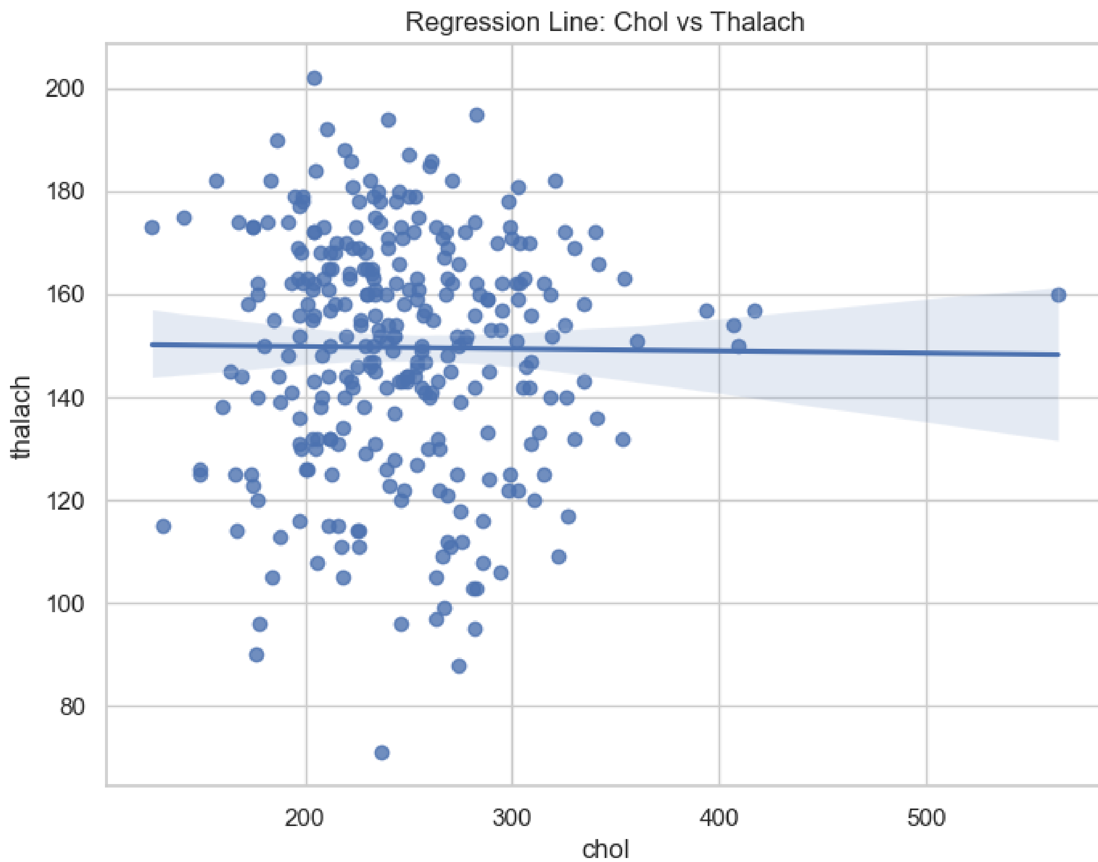
Interpretation: Slight positive correlation between age and cholesterol.

9.5 Chol vs Thalach

[60]:
```
# Scatter Plot
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.scatterplot(x="chol", y="thalach", data=df)
plt.title("Cholesterol vs Max Heart Rate")
plt.show()
```



[61]:
```
# With Regression Line
f, ax = plt.subplots(figsize=(8, 6))
ax = sns.regplot(x="chol", y="thalach", data=df)
plt.title("Regression Line: Chol vs Thalach")
plt.show()
```



Interpretation: No visible correlation between cholesterol and max heart rate.

Summary of Multivariate Analysis

This table summarizes the strength and direction of relationships between key variables based on the multivariate analysis conducted above.

Relationship	Correlation	Description
`target` & `cp`	+0.43	Mild positive correlation
`target` & `thalach`	+0.42	Mild positive correlation
`target` & `slope`	+0.35	Weak positive correlation
`target` & `exang`	-0.44	Mild negative correlation
`target` & `oldpeak`	-0.43	Mild negative correlation
`target` & `ca`	-0.39	Weak negative correlation
`target` & `thal`	-0.34	Weak negative correlation
`age` & `chol`	~+0.1	Slight positive trend
`chol` & `thalach`	~0	No correlation
`age` & `trestbps`	~0	No correlation

[ ]:
```
# Dealing with Missing Values
```

- In **Pandas**, missing data is represented by two values:
  - **`None`**: A Python singleton object used to indicate missing data.
  - **`NaN`**: Stands for *Not a Number*, a special floating-point value used across data systems.
- Pandas provides multiple ways to **detect and handle** missing values.

9.6 Pandas `isnull()` and `notnull()` Functions

- `isnull()` → Returns `True` if a value is missing (NaN/None), else `False`.
- `notnull()` → Returns `True` if a value is **not** missing.

These functions are essential for filtering or cleaning datasets containing incomplete data.

9.7 Useful Commands to Detect Missing Values

Command	Purpose
`df.isnull()`	Checks each cell → `True` if missing, else `False`.
`df.isnull().sum()`	Returns count of missing values in **each column**.
`df.isnull().sum().sum()`	Total missing values in the **entire DataFrame**.
`df.isnull().mean()`	Returns **percentage** of missing values per column.
`df.isnull().any()`	Shows which columns have **any** missing values (`True`/`False`).
`df.isnull().any().any()`	Returns single `True`/`False` → does any column have missing values?
`df.isnull().values.any()`	Same as above → returns `True` if **any** missing value exists.
`df.isnull().values.sum()`	Gives the **total count** of missing values in the dataset.

9.8 Check for Missing Values in Our Dataset

[62]:
```
# Check missing values per column
df.isnull().sum()
```

[62]:
```
age         0
sex         0
cp          0
trestbps    0
chol        0
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
ca          0
thal        0
target      0
dtype: int64
```

Interpretation: The output confirms that there are no missing values in our dataset.

10 Check with assert Statement

To ensure **data integrity**, we must confirm that:

- There are **no missing values** in the dataset.
- There are **no unexpected 0s or negative values**, depending on context.

Using `assert` statements helps us **programmatically validate assumptions** in the dataset. If the condition is `True`, it does nothing. If `False`, it raises an `AssertionError`.

Understanding `assert`

“‘python assert 1 == 1 # Does nothing (passes silently)

assert 1 == 2 # Raises AssertionError

10.1 Check : No Missing Values

[63]:
```
assert pd.notnull(df).all().all()
```

This statement checks that no NaN or None values exist in the entire DataFrame.

10.2 Check : All Values Are Greater Than or Equal to 0

[64]:
```
assert (df >= 0).all().all()
```

This checks that no negative values exist in the dataset.

Interpretation The above assert statements did not throw any error, which confirms that:

- There are no missing values in the dataset.
- All values are greater than or equal to 0.

11 Outlier Detection

We will use **boxplots** to visually detect outliers in the **continuous numerical variables**:

Variables: - `age` - `trestbps` (Resting Blood Pressure) - `chol` (Serum Cholesterol) - `thalach` (Maximum Heart Rate Achieved) - `oldpeak` (ST depression)

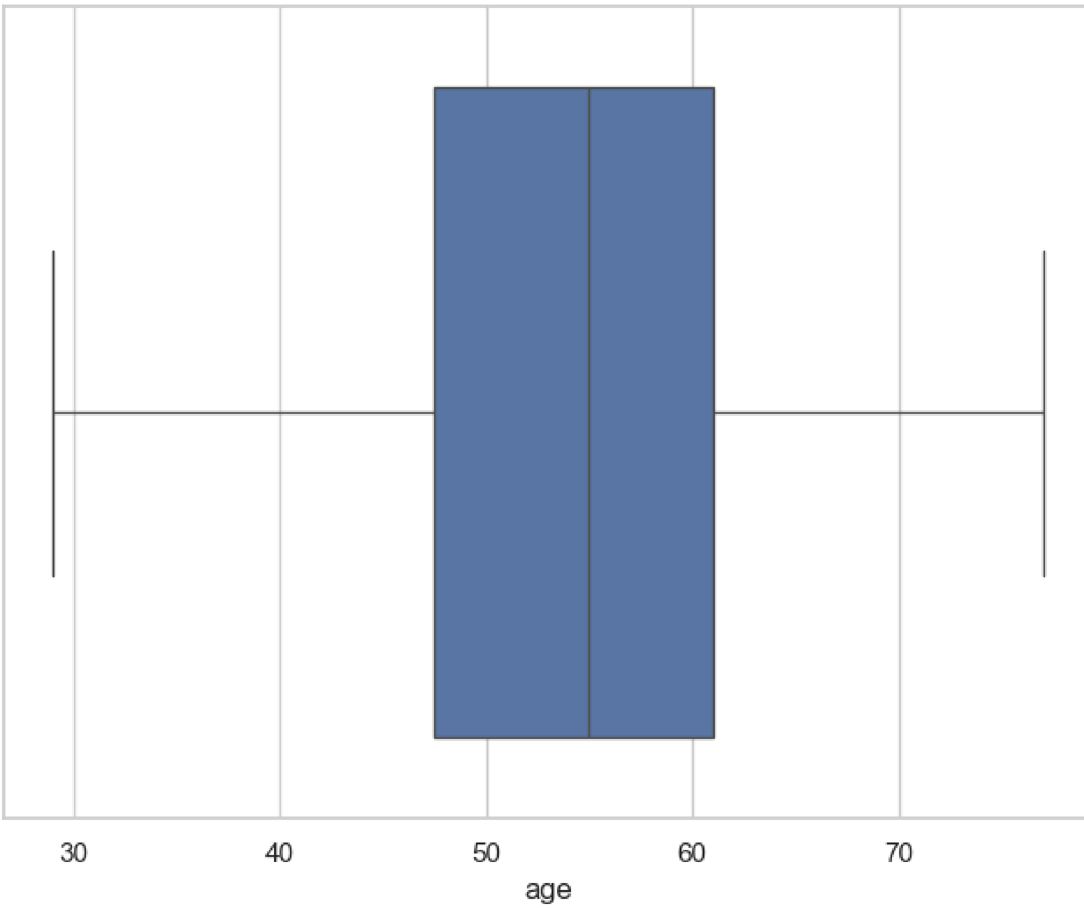
11.1 `age` Variable

[65]:
```
df['age'].describe()
```

[65]:
```
count    303.000000
mean      54.366337
std        9.082101
min       29.000000
25%       47.500000
50%       55.000000
75%       61.000000
max       77.000000
```

```
Name: age, dtype: float64
```

[66]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x=df["age"])
plt.show()
```



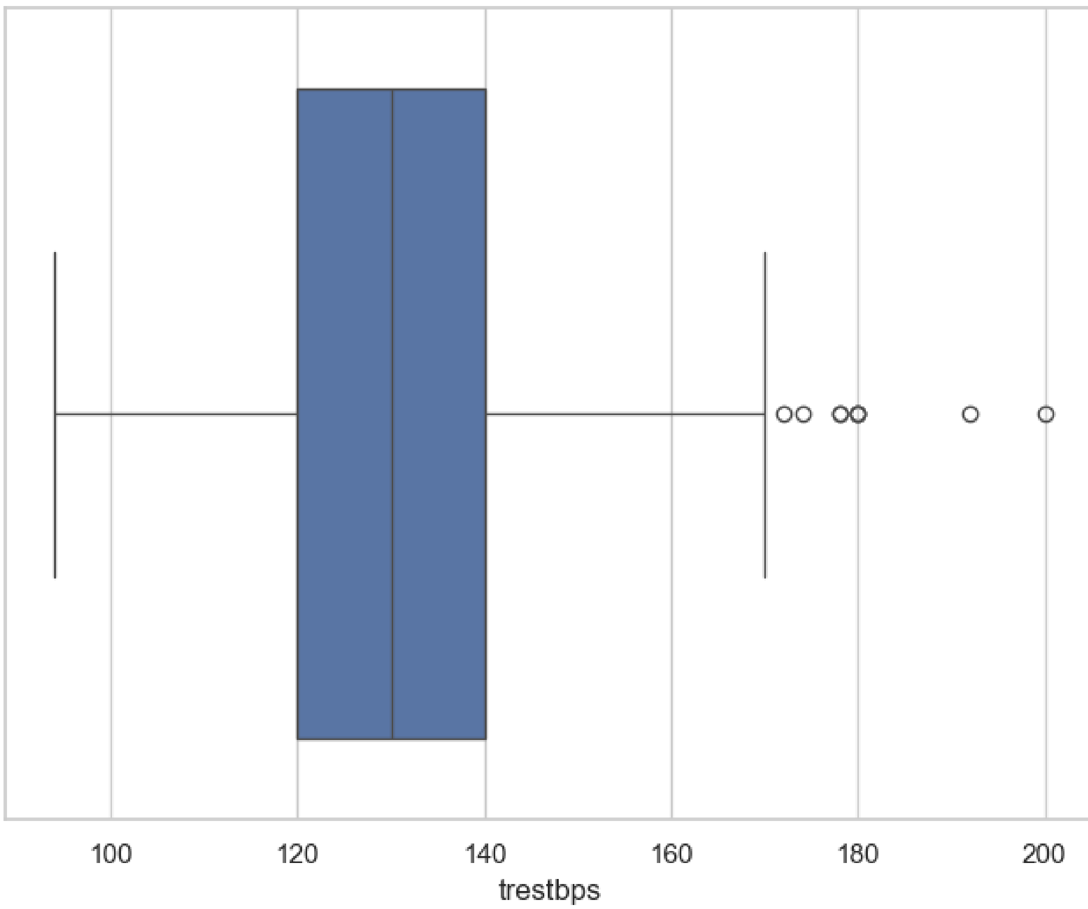
11.2 trestbps Variable

[67]:
```
df['trestbps'].describe()
```

[67]:
```
count    303.000000
mean     131.623762
std       17.538143
min       94.000000
25%      120.000000
50%      130.000000
75%      140.000000
max      200.000000
```

```
Name: trestbps, dtype: float64
```

[68]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x=df["trestbps"])
plt.show()
```



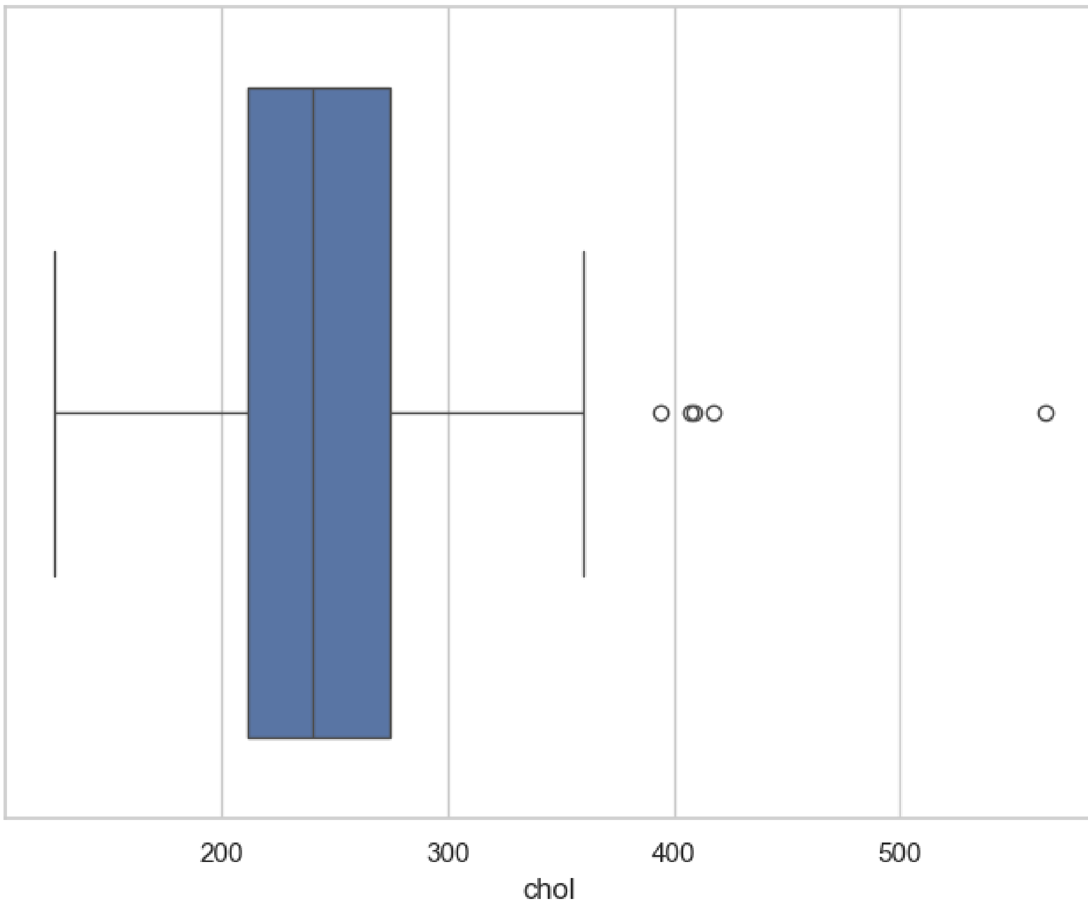
11.3 chol Variable

[69]:
```
df['chol'].describe()
```

[69]:
```
count    303.000000
mean     246.264026
std       51.830751
min      126.000000
25%      211.000000
50%      240.000000
75%      274.500000
max      564.000000
```

```
Name: chol, dtype: float64
```

[70]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x=df["chol"])
plt.show()
```



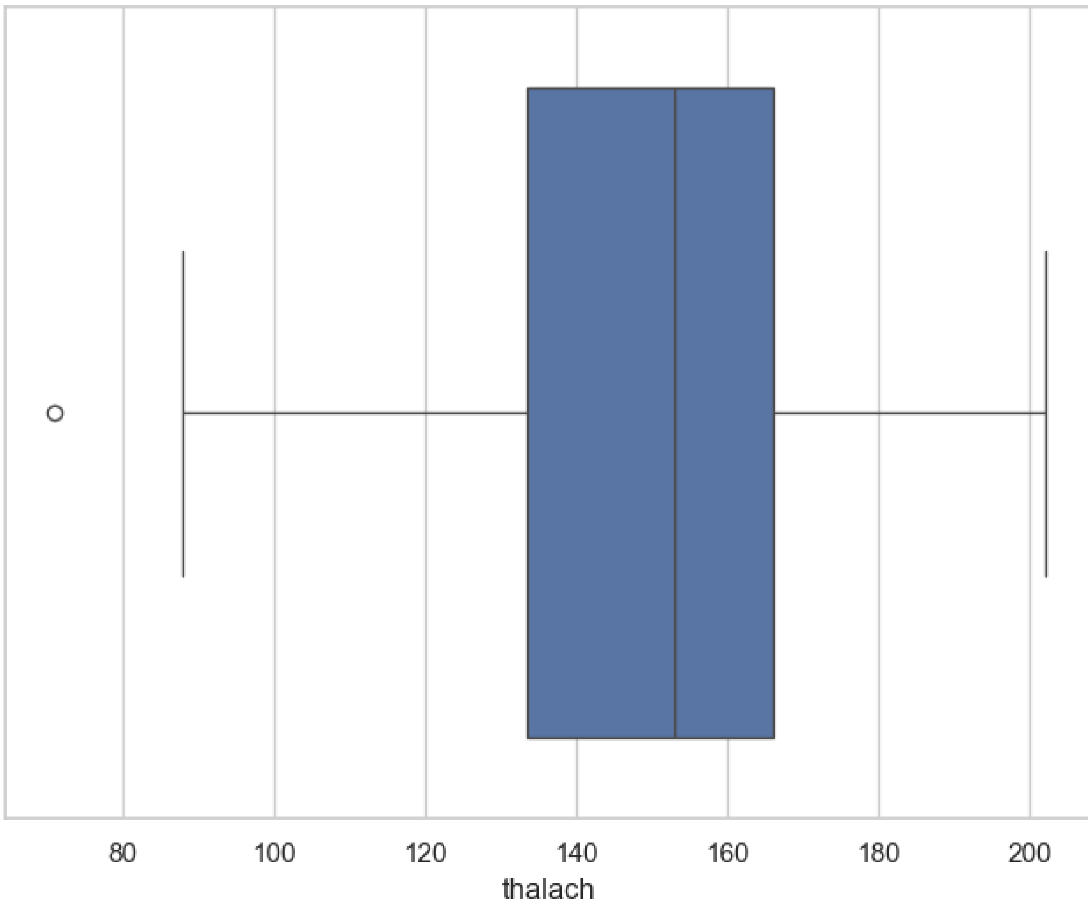
11.4 thalach Variable

[71]:
```
df['thalach'].describe()
```

[71]:
```
count    303.000000
mean     149.646865
std       22.905161
min       71.000000
25%      133.500000
50%      153.000000
75%      166.000000
max      202.000000
```

Name: thalach, dtype: float64

[72]:
```
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x=df["thalach"])
plt.show()
```



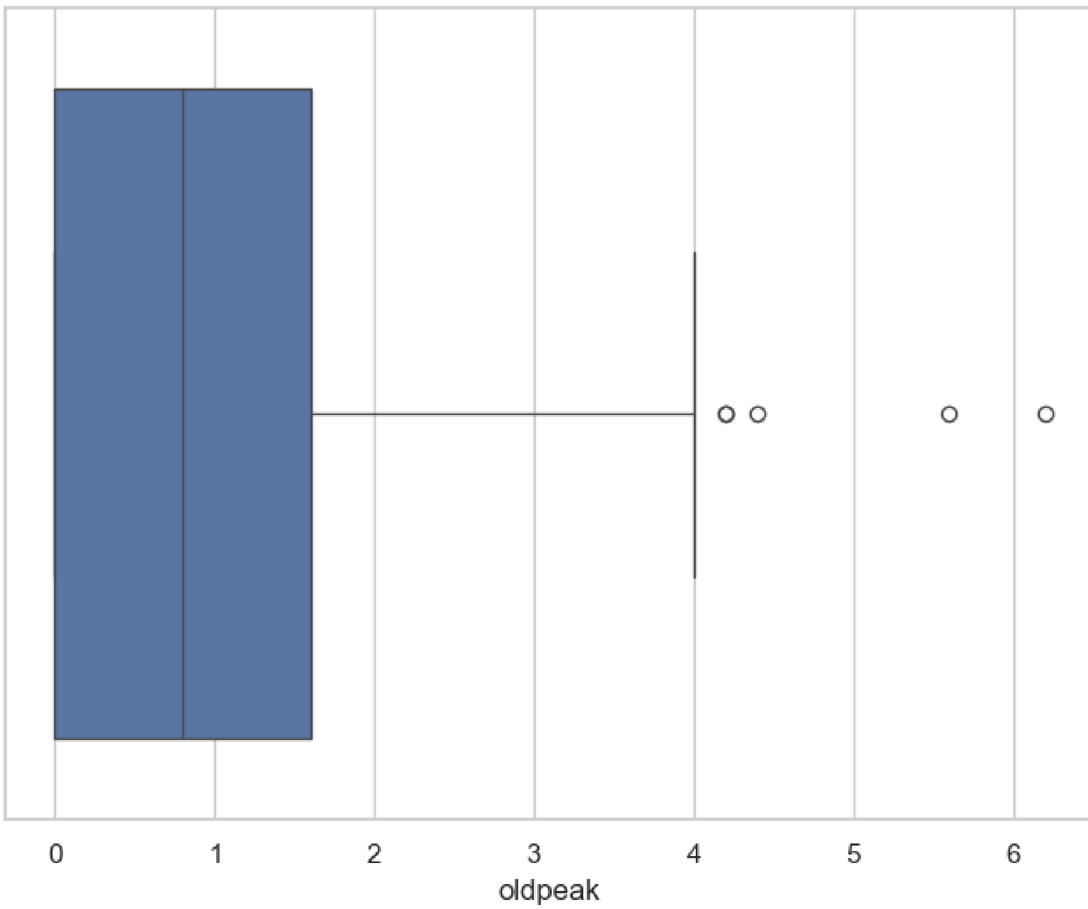
11.5 oldpeak Variable

[73]:
```
df['oldpeak'].describe()
```

[73]:
```
count    303.000000
mean       1.039604
std        1.161075
min        0.000000
25%        0.000000
50%        0.800000
75%        1.600000
max        6.200000
```

```
Name: oldpeak, dtype: float64
```

[74]:
```python
f, ax = plt.subplots(figsize=(8, 6))
sns.boxplot(x=df["oldpeak"])
plt.show()
```



Summary of Outlier Detection

- **age**
  No outliers found.
- **trestbps (Resting Blood Pressure)**
  Outliers on the higher side.
- **chol (Cholesterol)**
  Outliers on the higher side.
- **thalach (Maximum Heart Rate Achieved)**
  One outlier on the lower side.
- **oldpeak (ST Depression)**

Outliers on the higher side.

Note: Variables with outliers may need further investigation or handling.

12 Conclusion

So, friends, our **EDA journey** has come to an end.

In this notebook, we explored the **Heart Disease dataset** and applied many of the strategies from the book *Think Stats – Exploratory Data Analysis in Python* by **Allen B. Downey**.

Key Highlights: - Focused on the **target variable** and analyzed its behavior. - Investigated its interactions with other features using **univariate**, **bivariate**, and **multivariate** analysis. - Used various visualizations like histograms, boxplots, scatter plots, and heatmaps. - Detected and interpreted **missing values** using `isnull()` functions. - Used **assertions** to validate data integrity. - Performed **outlier detection** and summarized key findings.

I hope you enjoyed this kernel and found it helpful on your data analysis journey.

Thank you!