Capstone Project 3

January 16, 2023

1 Examining Factors Responsible for Heart Attacks

1.1 Objective:

Cardiovascular diseases are the leading cause of death globally. This analysis aims to identify the leading factors of Cardiovascular Diseases, using Logistic Regression model to predict the outcome of the test data.

1.2 Variable Descriptions:

age: age in years **sex:** (1 = male; 0 = female) **cp:** chest pain type * Value 0: typical angina *Value 1: atypical angina* Value 2: non-anginal pain *Value 3: asymptomatic

trestbps: resting blood pressure (in mm Hg) **chol:** serum cholestoral in mg/dl **fbs:** (fasting blood sugar > 120 mg/dl) (1 = true; 0 = false) **restecg:** resting electrocardiographic results - Value 0: normal - Value 1: having ST-T wave abnormality (T wave inversions and/or-elevation or ST depression of > 0.05 mV) - Value 2: showing probable or definite left ventricular hypertrophy by Estes' criteria

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:** thalassemia types: - thal value 0 = Silent carrier - thal value 1 = Mild carrier - thal value 2 = Reverseable carrier - thal value 3 = Fixed defect carrier

target: 0= less chance of heart attack, 1= more chance of heart attack

2 1. Import Modules & Data

[1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')

df = pd.read_excel('heart data.xlsx')
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 has 14 columns and 303 rows (inc header)
- There appears to be no missing values
- All columns contain int64 or float64 datatypes

[2]:
```
df.shape
```

[2]:
```
(303, 14)
```

3 2. Data Wrangling

[3]:
```
# check missing values
df.isnull().sum()
```

[3]:
```
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
```

[4]:
```
# check for duplicates
df.duplicated().any()
```

[4]:
```
True
```

[5]:
```
# drop duplicates and keep first occurance
df.drop_duplicates(keep='first', inplace=True)
df.reset_index(drop=True, inplace=True)
```

[6]:
```
# view top 5 rows
df.head()
```

[6]:
```
   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
```

[7]:
```
# check count of unique values
df.nunique()
```

[7]:
```
age          41
sex           2
cp            4
trestbps     49
chol        152
fbs           2
restecg       3
thalach      91
exang         2
oldpeak      40
slope         3
ca            5
thal          4
target        2
```

```
dtype: int64
```

4 3. Exploratory Data Analysis

4.0.1 Central Tendencies & Data Distribution

[8]:
```
# view statistics of data
df.describe()
```

[8]:

	age	sex	cp	trestbps	chol	fbs
count	302.00000	302.000000	302.000000	302.000000	302.000000	302.000000
mean	54.42053	0.682119	0.963576	131.602649	246.500000	0.149007
std	9.04797	0.466426	1.032044	17.563394	51.753489	0.356686
min	29.00000	0.000000	0.000000	94.000000	126.000000	0.000000
25%	48.00000	0.000000	0.000000	120.000000	211.000000	0.000000
50%	55.50000	1.000000	1.000000	130.000000	240.500000	0.000000
75%	61.00000	1.000000	2.000000	140.000000	274.750000	0.000000
max	77.00000	1.000000	3.000000	200.000000	564.000000	1.000000

	restecg	thalach	exang	oldpeak	slope	ca
count	302.000000	302.000000	302.000000	302.000000	302.000000	302.000000
mean	0.526490	149.569536	0.327815	1.043046	1.397351	0.718543
std	0.526027	22.903527	0.470196	1.161452	0.616274	1.006748
min	0.000000	71.000000	0.000000	0.000000	0.000000	0.000000
25%	0.000000	133.250000	0.000000	0.000000	1.000000	0.000000
50%	1.000000	152.500000	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	302.000000	302.000000
mean	2.314570	0.543046
std	0.613026	0.498970
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

[9]:
```
# modes of df
modes = df.mode(axis=0, dropna=True)
modes
```

[9]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak
0	58.0	1.0	0.0	120.0	197	0.0	1.0	162.0	0.0	0.0
1	NaN	NaN	NaN	NaN	204	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	234	NaN	NaN	NaN	NaN	NaN

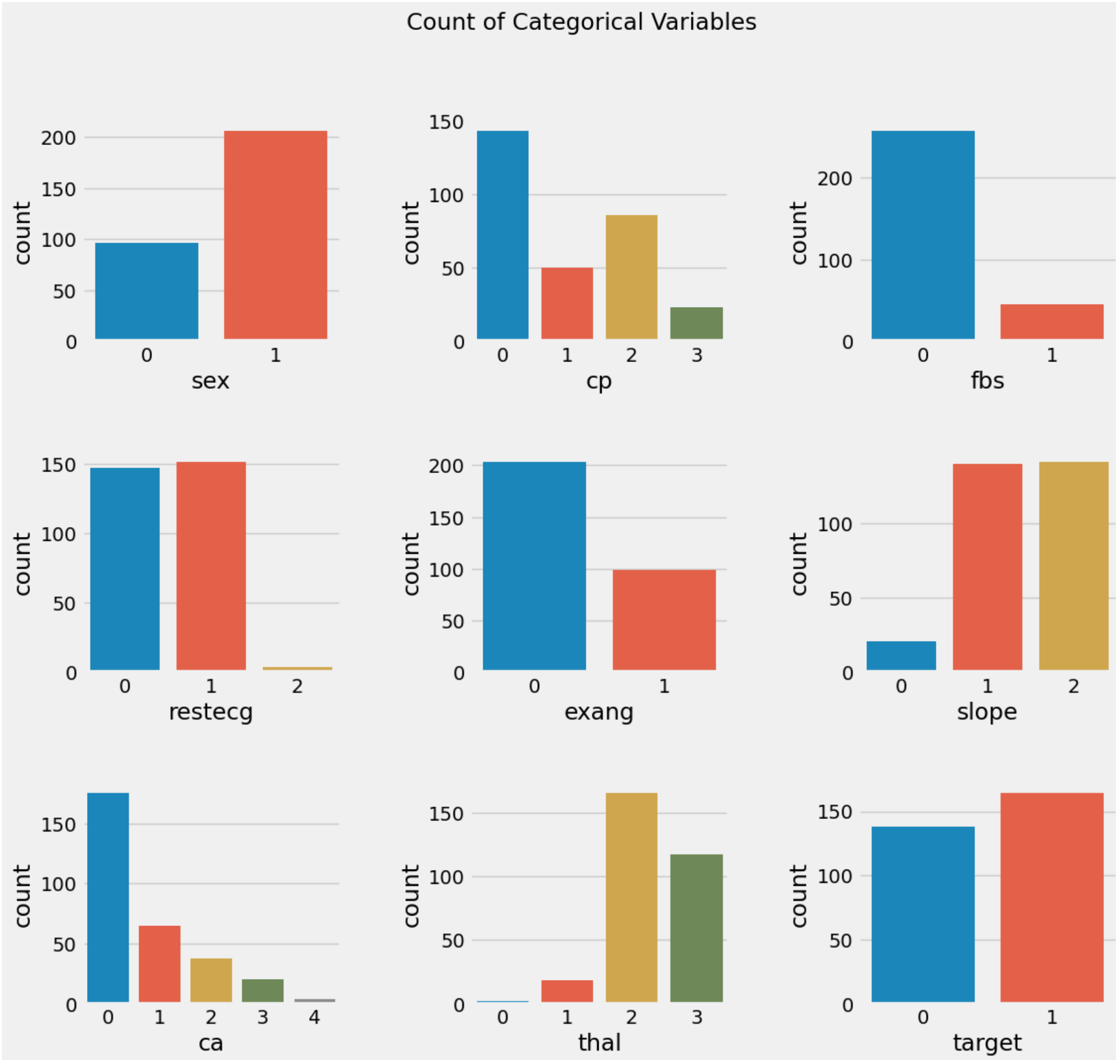
```
   slope   ca  thal  target
0    2.0  0.0   2.0     1.0
1    NaN  NaN   NaN     NaN
2    NaN  NaN   NaN     NaN
```

[10]:
```
# medians of df
medians = df.median()
medians
```

[10]:
```
age          55.5
sex           1.0
cp            1.0
trestbps    130.0
chol        240.5
fbs           0.0
restecg       1.0
thalach     152.5
exang         0.0
oldpeak       0.8
slope         1.0
ca            0.0
thal          2.0
target        1.0
dtype: float64
```

4.0.2 Countplots for Categorical Natured Variables

[11]:
```
plt.style.use('fivethirtyeight')
plt.figure(1, figsize=(12,11))
n =0

for x in ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope', 'ca', 'thal',␣
 ↪'target']:
    n += 1
    plt.subplot(3,3,n)
    plt.subplots_adjust(hspace=0.5, wspace=0.5)
    sns.countplot(data=df, x=x)

plt.suptitle('Count of Categorical Variables')
plt.show()
```



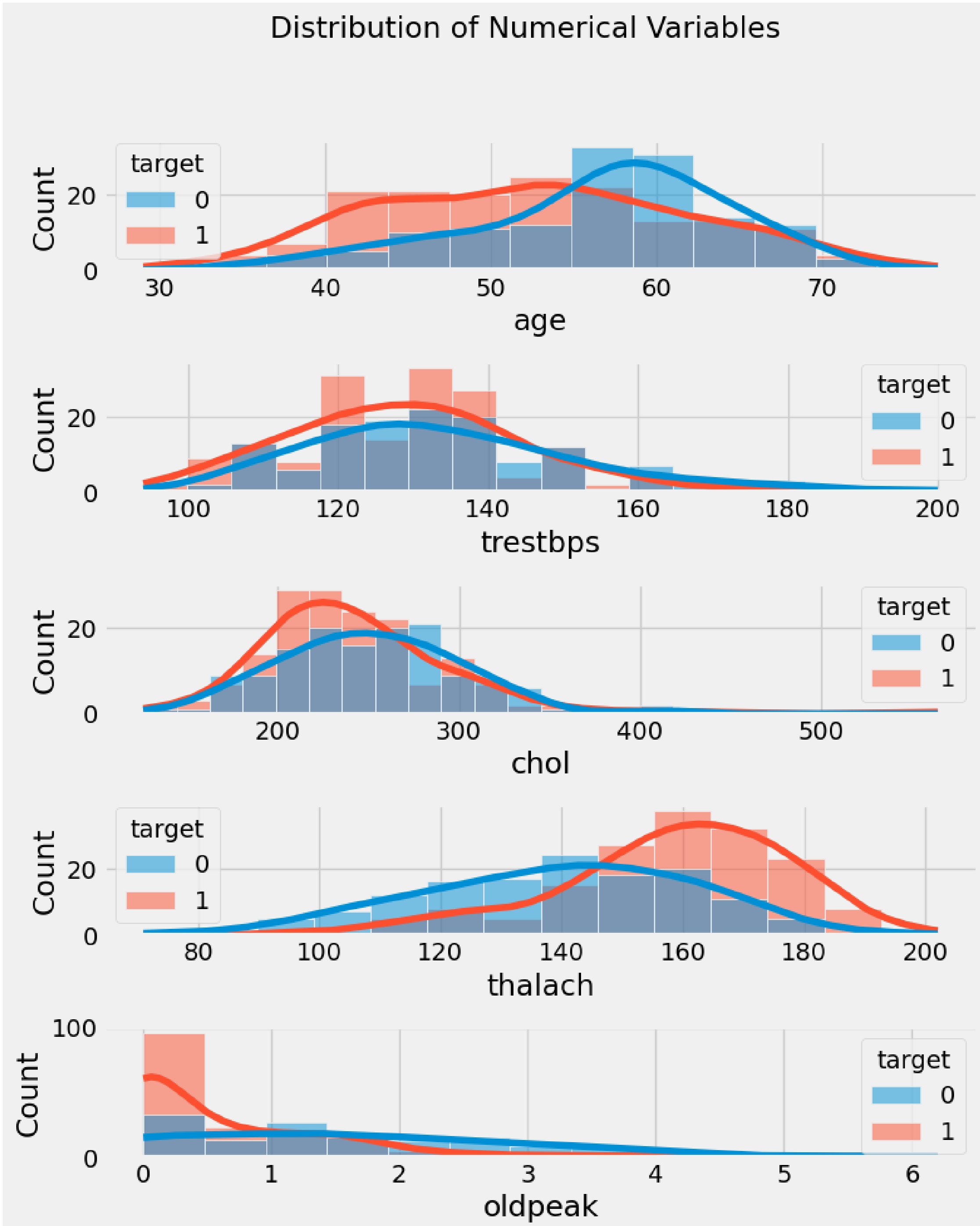
Observations: - There are more Female patients as compared to Male patients - Type 0 cp is most common - fbs (blood fasting sugar) is much likely to be less than 120mg/dl - Results 2 is very rare in restecg. Result 0 and 1 are most common - There are more non-exercise induced anigmas - There are more slope 1 and 2 occurences compared to slope 0 - The most common value of blood vessels is 0, and the least common blood vessel value is 4. This value 4 occurance may be an error, as it has nor been included into the data variable values description - There are more value 1s of 'target', indicating there are more patients with likelihood of CVD in dataset.

Sanity Check:

[12]:
```
# replacing value 4 'ca' to the nearest value 3, to adhere to variable
↪despcription values

df.ca = df['ca'].replace('4','3')
```

4.1 Distribution of Numerical Varaibles

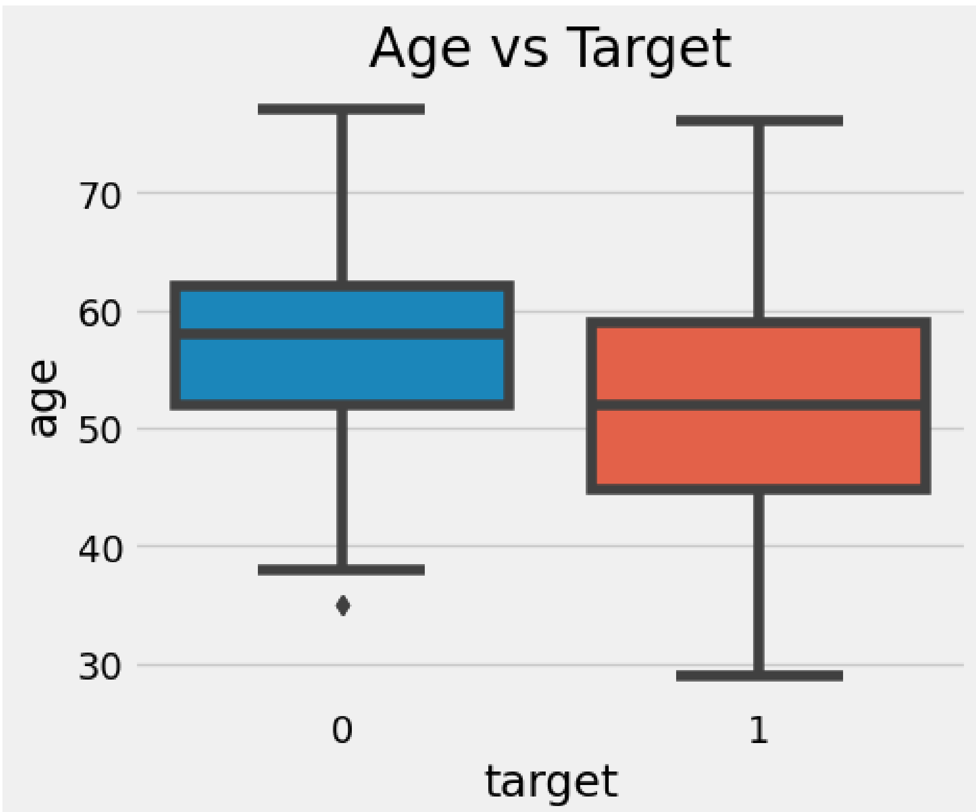
[13]:
```
plt.style.use('fast')
plt.figure(1, figsize=(8,10))
n =0

for x in ['age','trestbps','chol','thalach','oldpeak']:
    n += 1
    plt.subplot(5,1,n)
    plt.subplots_adjust(hspace=0.7, wspace=0.5)
    sns.histplot(data=df, x=x, kde=True, hue='target')

plt.suptitle('Distribution of Numerical Variables')
plt.show()
```



Observations: - Patient age is concentrated around 45 and 65 range, peaking at late 50s - Blood pressure is concentrated on the 120 -149 mark - Chloesterol serum is denser in the 200 - 280 range - The most common max heart rate achieved value is 160

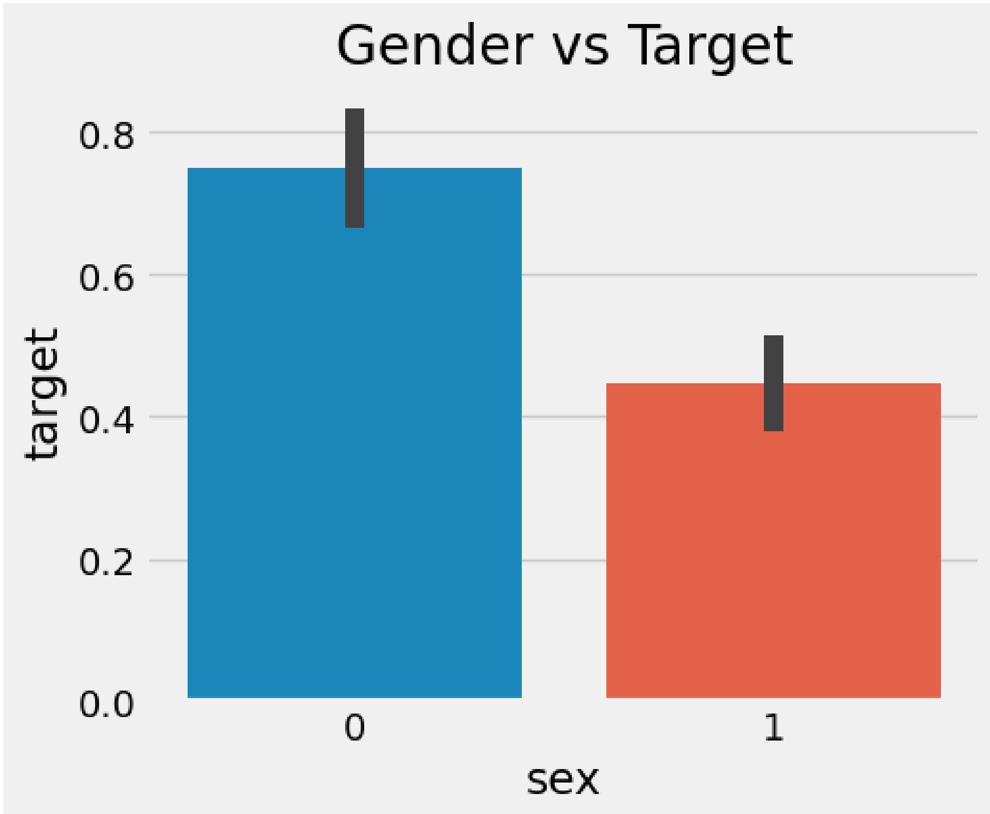
4.1.1 Bivariate Analysis

[14]:
```
# age vs target
plt.style.use('fivethirtyeight')
plt.figure(figsize=(5,4))
sns.boxplot(df, x='target', y='age')
plt.title('Age vs Target')
plt.show()
```



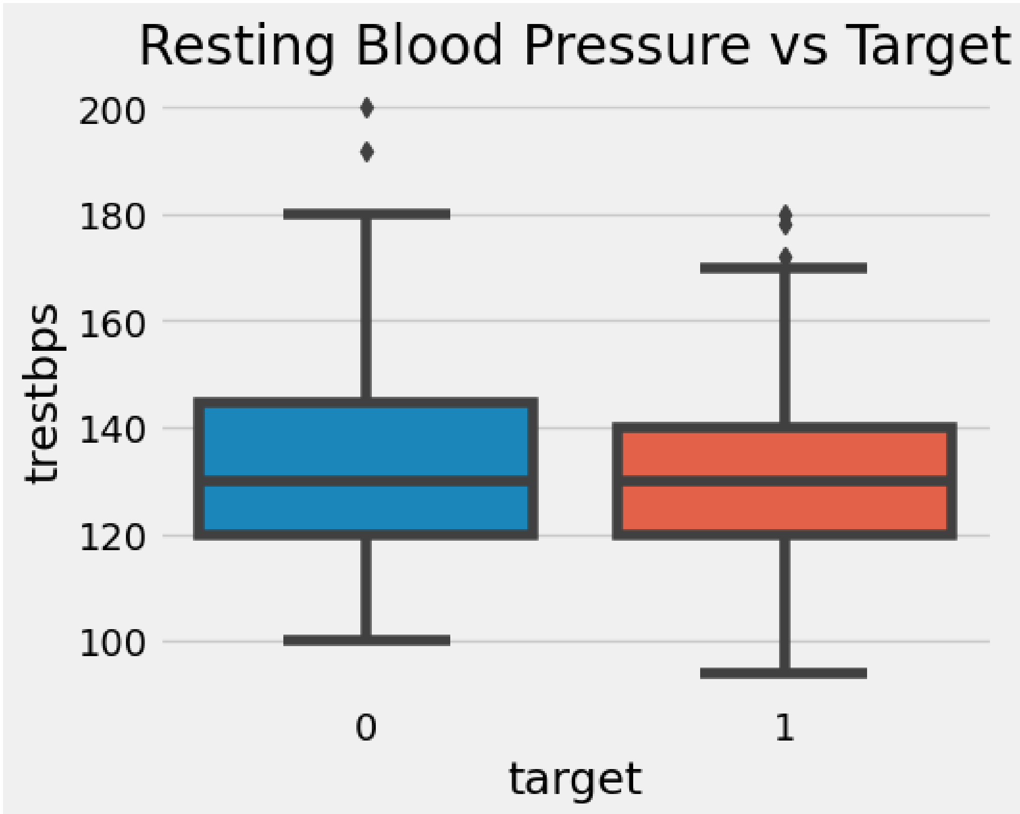
- **More chances of heart attacks occuring in the 45-60 age range**

[15]:
```
# gender vs target
plt.style.use('fivethirtyeight')
plt.figure(figsize=(5,4))
sns.barplot(df, x='sex', y='target')
plt.title('Gender vs Target')
plt.show()
```



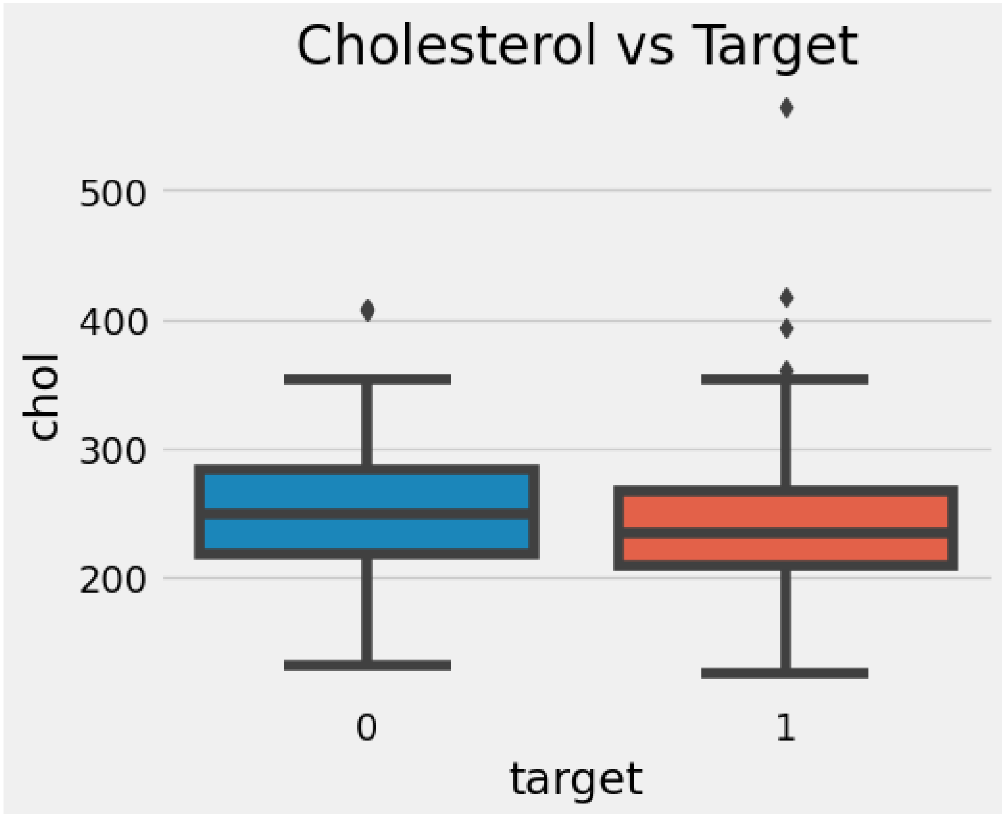
- **Male patients are more likely to get a heart attack**
- Female patients sit in the middle of target measurement

[16]:
```
# trestbps vs target
plt.style.use('fivethirtyeight')
plt.figure(figsize=(5,4))
sns.boxplot(df, x='target', y='trestbps')
plt.title('Resting Blood Pressure vs Target')
plt.show()
```



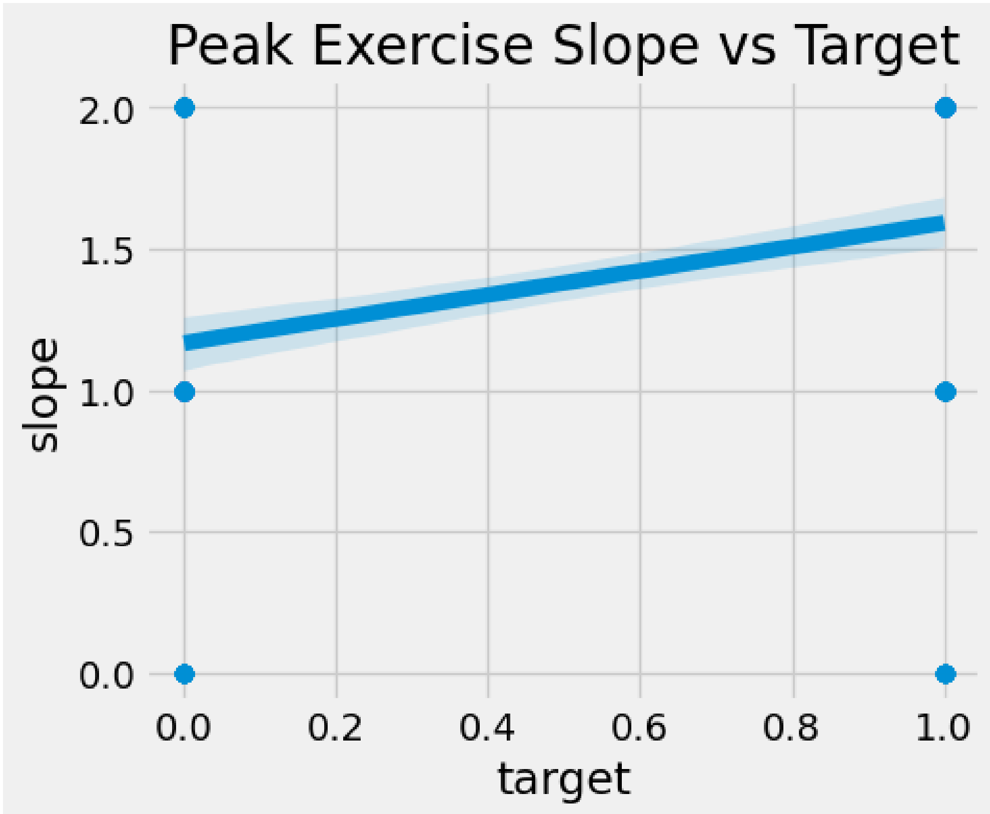
- More chances of a heart attack are seen in the resting blood pressure range of 120 and 140 mark

[17]:
```
# chol vs target
plt.style.use('fivethirtyeight')
plt.figure(figsize=(5,4))
sns.boxplot(df, x='target', y='chol')
plt.title('Cholesterol vs Target')
plt.show()
```



- Cholesterol values for targets appear almost the same.
- Outliers of more chance of heart attack is more prominent

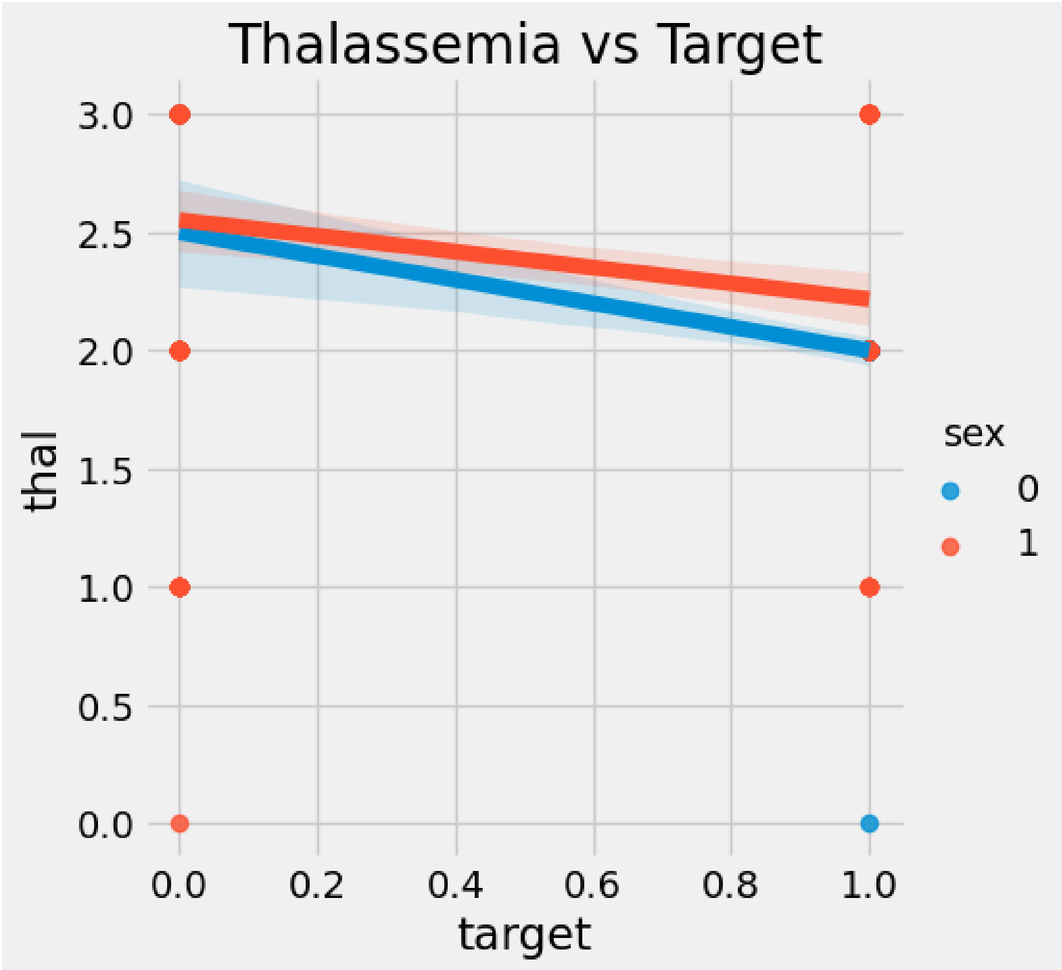
[18]:
```
# slope vs target
plt.style.use('fivethirtyeight')
plt.figure(figsize=(5,4))
sns.regplot(df, x='target', y='slope')
plt.title('Peak Exercise Slope vs Target')
plt.show()
```



- There is a positive trend between slope and cp.
- **This indicates the higher the slope of peak exercise, the more likely the CVD occurs**

[19]:
```
# thal vs target
plt.style.use('fivethirtyeight')
plt.figure(figsize=(5,4))
sns.lmplot(df, x='target', y="thal", hue='sex')
plt.title('Thalassemia vs Target')
plt.show()
```

```
<Figure size 500x400 with 0 Axes>
```



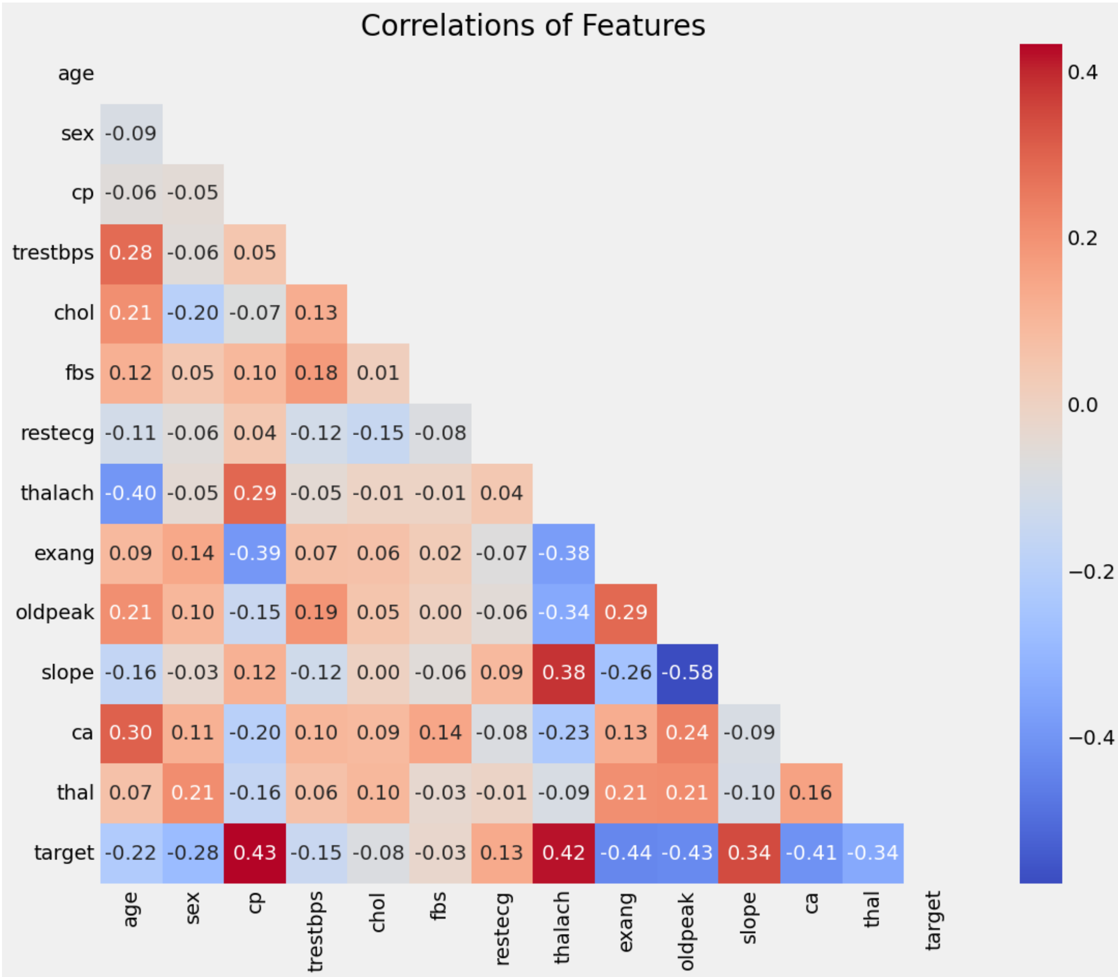
- Thalassemia has a moderately negative relationship to target.
- The correlation between thal and target is -0.34
- **The higher value (in severity) of thal, the more likely the occurance of CVD.** This observation applies to both genders. >Additonal variable description corrections need to be applied for 'thal' column as follows: > thal value 0 = Silent carrier > thal value 1 = Mild carrier > thanl value 2 = Reverseable carrier > thal value 3 = Fixed defect carrier

4.1.2 Correlations of Variables:

Understanding the relationships between features

[20]:
```
# view correlations of features with heatmap

plt.figure(figsize=(12,10))
df_corr = df.corr()
mask = np.triu(np.ones_like(df_corr))
sns.heatmap(df_corr, cmap='coolwarm', annot=True, mask=mask, fmt='.2f')
plt.title('Correlations of Features')
```

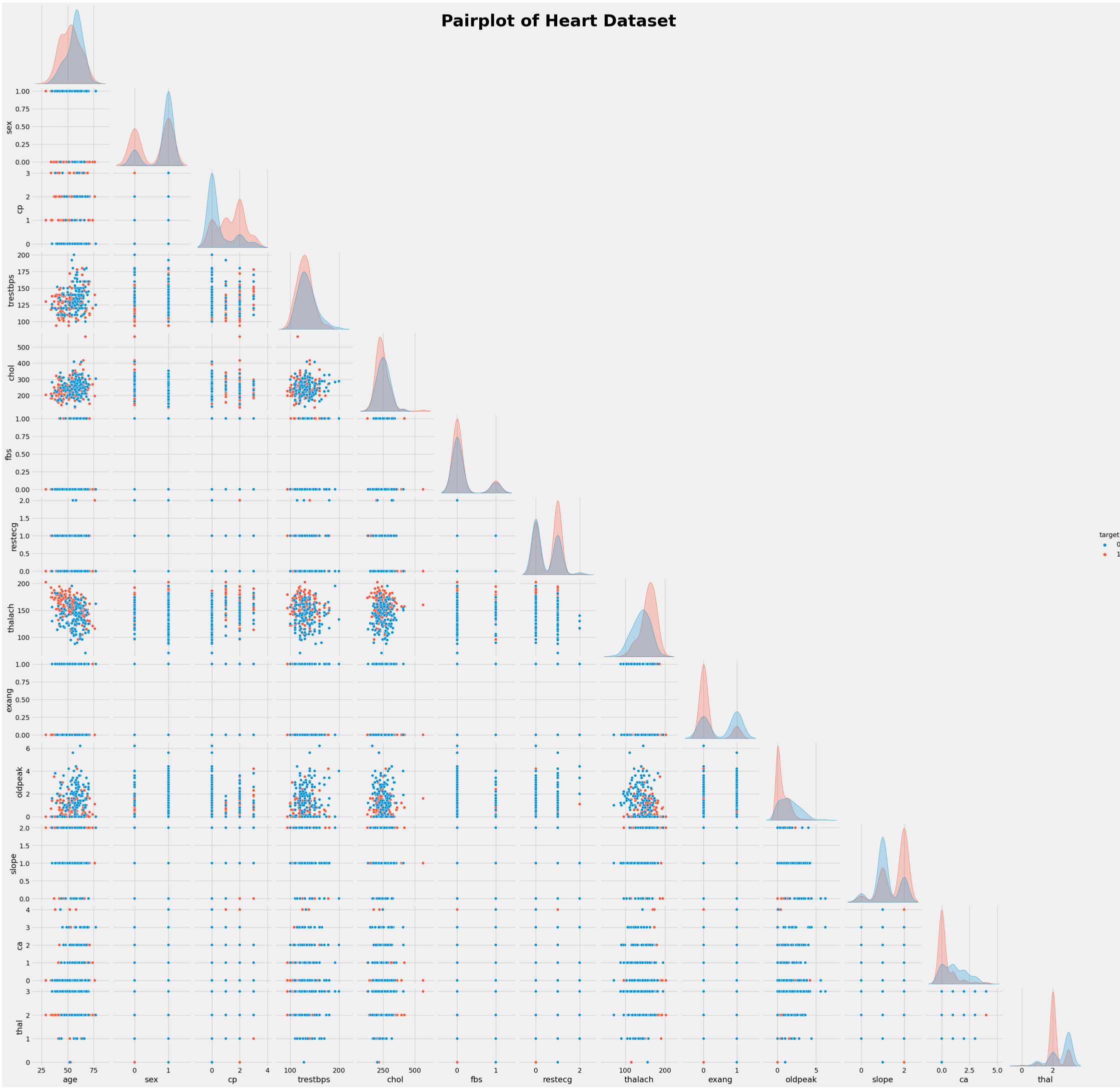
```
plt.show()
```



Observations: - **'target' is positively correlated to 'cp', 'thalach', 'slope', by 0.43, 0.42 and 0.34 respectively. This may indicate that the higher the value of 'cp', 'thalach' and 'slope', the more likely the occurence of an heart attack.** - There is a negative correlation -0.58 between 'slope' and 'oldpeak' - 'target' has negative correlations with ''exang', 'oldpeak', and 'ca' by -0.44, -0.43 and -0.41, respcetively. - 'thalach' has negative correlations with 'exang' and 'oldpeak', of -0.38 and -0.34 respectively - 'exang' and 'oldpeak' have a correlation of 0.29 - 'oldpeak' and 'ca' have acorrelation of 0.24

4.2 Pairplot of All Features

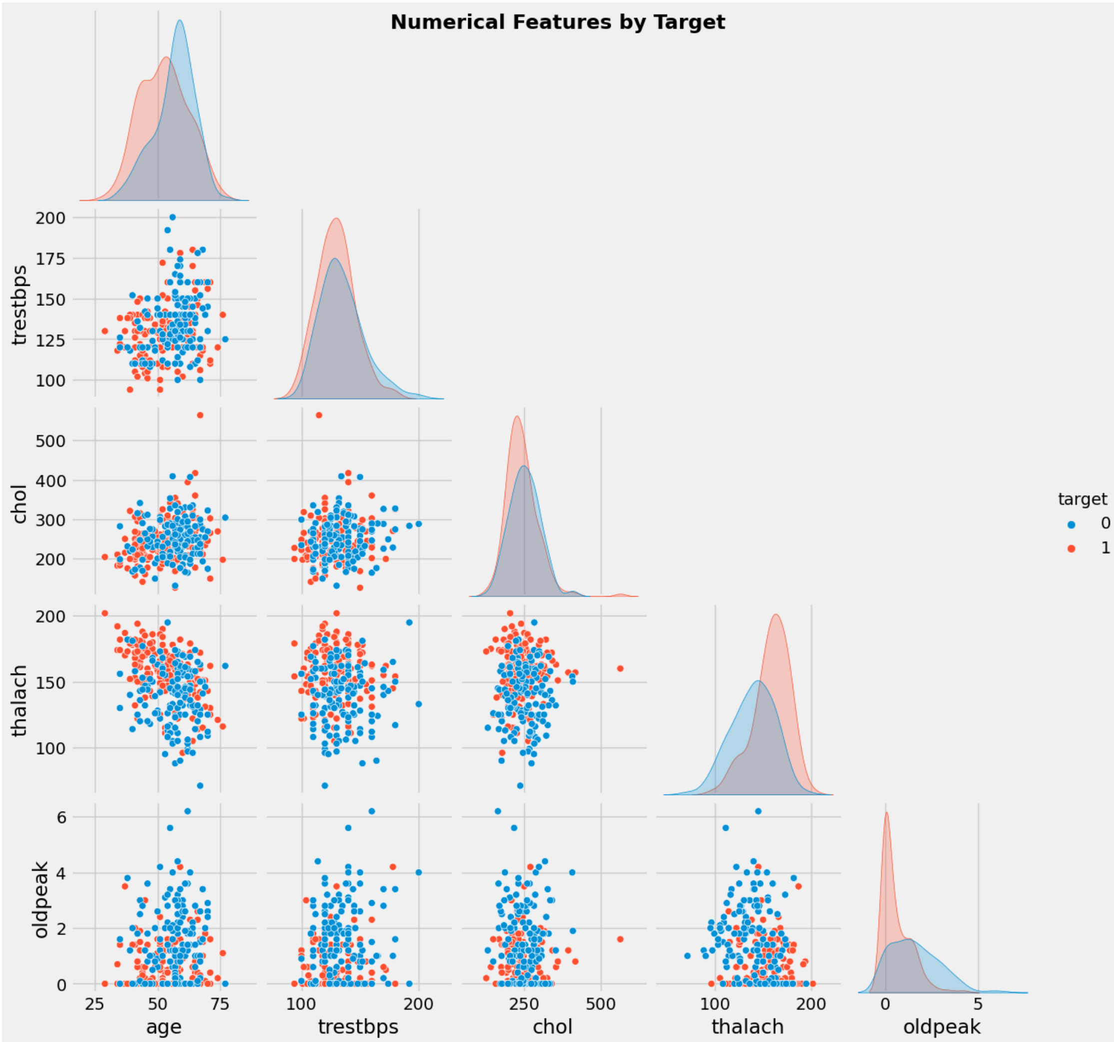
[21]:
```
# pairplot of entire df
plt.style.use('fast')
sns.pairplot(df, hue='target', corner=True)
plt.suptitle('Pairplot of Heart Dataset', fontsize='35', fontweight='heavy')
plt.show()
```



4.2.1 Pairplot of Numerical Features by Target

[22]:
```
num_data = ['age','trestbps','chol','thalach','oldpeak', 'target']
```

[23]:
```
# Numerical Features
plt.style.use('fast')
sns.pairplot(df[num_data], hue='target', corner=True)
plt.suptitle('Numerical Features by Target', fontsize='17', fontweight='heavy')
plt.show()
```




```
[24]: df.to_excel('cleaneddata.xlsx')
```

5 4. Model Development: Logistic Regression

5.0.1 i. Import Modelling Modules

```
[25]: # import modelling modules
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score
```

5.0.2 ii. Select Features for Analysis

[26]:
```
# declare feature selection:
# trestbps, chol, fbs and restecg will be dropped due to their very low␣
↪correlation values to target

x = df.drop(columns=['trestbps', 'chol', 'fbs', 'restecg', 'target'])
y = df['target']
```

5.0.3 iii. Assess Indicator Variables

[27]:
```
# confirm features are already encoded as per the variable description
print(df.apply(lambda col: col.unique()))
```

```
age         [63, 37, 41, 56, 57, 44, 52, 54, 48, 49, 64, 5…
sex                                                   [1, 0]
cp                                              [3, 2, 1, 0]
trestbps    [145, 130, 120, 140, 172, 150, 110, 135, 160, …
chol        [233, 250, 204, 236, 354, 192, 294, 263, 199, …
fbs                                                   [1, 0]
restecg                                            [0, 1, 2]
thalach     [150, 187, 172, 178, 163, 148, 153, 173, 162, …
exang                                                 [0, 1]
oldpeak     [2.3, 3.5, 1.4, 0.8, 0.6, 0.4, 1.3, 0.0, 0.5, …
slope                                              [0, 2, 1]
ca                                           [0, 2, 1, 3, 4]
thal                                            [1, 2, 3, 0]
target                                                [1, 0]
dtype: object
```

5.0.4 iv. Split data into Training & Test Sets

[28]:
```
# split the dataset into training and test set

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.3,␣
↪random_state=42)
print('Shape of Training & Testing Datasets:')
print("Train_x :",x_train.shape)
print("Test_x :",x_test.shape)
print("Train_y :",y_train.shape)
print("Test_y :",y_test.shape)
```

```
Shape of Training & Testing Datasets:
Train_x : (211, 9)
Test_x : (91, 9)
Train_y : (211,)
Test_y : (91,)
```

5.0.5 v. Feature Scaling with StandardScaler

[29]:
```
# scale independant features only
# dependent variable is already valued at 0-1
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
```

5.0.6 vi. Fit Logistic Regression to Training Set

[30]:
```
# fit trainining set into logreg object
logreg = LogisticRegression(random_state=0)
logreg.fit(x_train, y_train)
```

[30]:
```
LogisticRegression(random_state=0)
```

5.0.7 vii. Predict with Test set

[31]:
```
predict = logreg.predict(x_test)

# predicted values
predict
```

[31]:
```
array([0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0,
       0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1,
       1, 0, 1], dtype=int64)
```

5.0.8 viii. Check Accuracy

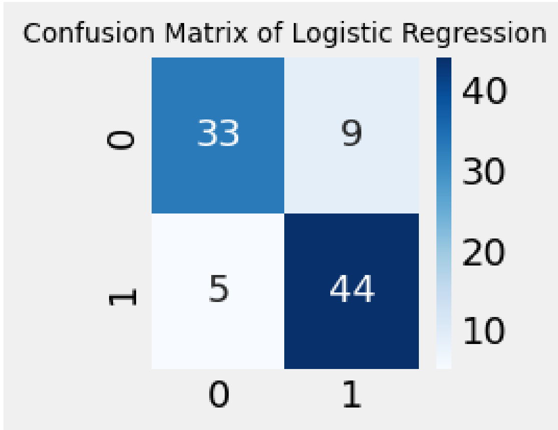
[32]:
```
print('Logistic Regression Accuracy Score is:', accuracy_score(y_test,␣
 ↪predict)*100, '%')
```

```
Logistic Regression Accuracy Score is: 84.61538461538461 %
```

5.0.9 ix. Fit Confusion Matrix into Test Set

[33]:
```
# fit confusion matrix into test set
conf_matrix = confusion_matrix(y_test, predict)
```

[34]:
```
# visualise confusion matrix
plt.figure(figsize=(2,2))
sns.heatmap(conf_matrix, annot=True, cmap='Blues')
plt.title('Confusion Matrix of Logistic Regression', fontsize='10')
plt.show()
```



5.0.10 x. Model Performance

[35]:
```
# Calculating False Positives (FP), False Negatives (FN), True Positives (TP) &
↪True Negatives (TN)

def model_performance(conf_matrix):

    FP = conf_matrix.sum(axis=0) - np.diag(conf_matrix)
    FN = conf_matrix.sum(axis=1) - np.diag(conf_matrix)
    TP = np.diag(conf_matrix)
    TN = conf_matrix.sum() - (FP + FN + TP)

    # Recall or true positive rate
    TPR = TP/(TP+FN)
    print ("The Recall (True Positive rate) per class is: ",TPR)


    # Precision or positive predictive value
    PPV = TP/(TP+FP)
    print ("The Precision per class is: ",PPV)

    # Overall accuracy
    ACC = (TP+TN)/(TP+FP+FN+TN)
    print ("The Accuracy of each class is", ACC)
    print("")

    ##Total averages :
    print ("The average Recall is: ",TPR.sum()/2)
    print ("The average Precision is: ",PPV.sum()/2)
    print ("The average Accuracy is", ACC.sum()/2)
```

Model Performance: Recall, Precision and Accuracy

[36]:
```
model_performance(conf_matrix)
```

```
The Recall (True Positive rate) per class is:  [0.78571429 0.89795918]
The Precision per class is:  [0.86842105 0.83018868]
The Accuracy of each class is [0.84615385 0.84615385]

The average Recall is:  0.8418367346938775
The average Precision is:  0.849304865938431
The average Accuracy is 0.8461538461538461
```

6 5. Tableau Dashboard

Tableau Dashboard Link: https://public.tableau.com/views/HeartAttackFactors_16738268795260/Dashboard
US&publish=yes&:display_count=n&:origin=viz_share_link