

```
In [1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

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

```
In [2]: df=pd.read_csv('heart.csv')
df.head()
```

```
Out[2]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	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	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

```
In [3]: df.exang.value_counts()
```

```
Out[3]: 0    204
1     99
Name: exang, dtype: int64
```

```
In [4]: 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
```

In [5]: df.describe()

Out[5]:

	age	sex	cp	trestbps	chol	fbs	restecg	thal
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

In [6]: df.corr()

Out[6]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach
age	1.000000	-0.098447	-0.068653	0.279351	0.213678	0.121308	-0.116211	-0.398522
sex	-0.098447	1.000000	-0.049353	-0.056769	-0.197912	0.045032	-0.058196	-0.044020
cp	-0.068653	-0.049353	1.000000	0.047608	-0.076904	0.094444	0.044421	0.295762
trestbps	0.279351	-0.056769	0.047608	1.000000	0.123174	0.177531	-0.114103	-0.046698
chol	0.213678	-0.197912	-0.076904	0.123174	1.000000	0.013294	-0.151040	-0.009940
fbs	0.121308	0.045032	0.094444	0.177531	0.013294	1.000000	-0.084189	-0.008567
restecg	-0.116211	-0.058196	0.044421	-0.114103	-0.151040	-0.084189	1.000000	0.044123
thalach	-0.398522	-0.044020	0.295762	-0.046698	-0.009940	-0.008567	0.044123	1.000000
exang	0.096801	0.141664	-0.394280	0.067616	0.067023	0.025665	-0.070733	-0.378812
oldpeak	0.210013	0.096093	-0.149230	0.193216	0.053952	0.005747	-0.058770	-0.344187
slope	-0.168814	-0.030711	0.119717	-0.121475	-0.004038	-0.059894	0.093045	0.386784
ca	0.276326	0.118261	-0.181053	0.101389	0.070511	0.137979	-0.072042	-0.213177
thal	0.068001	0.210041	-0.161736	0.062210	0.098803	-0.032019	-0.011981	-0.096439
target	-0.225439	-0.280937	0.433798	-0.144931	-0.085239	-0.028046	0.137230	0.421741

In [7]: `df.cov()`

Out[7]:

	age	sex	cp	trestbps	chol	fbs	restecg	thala
age	82.484558	-0.416661	-0.643499	44.495902	100.585076	0.392433	-0.555013	-82.9033
sex	-0.416661	0.217166	-0.023736	-0.463970	-4.780309	0.007475	-0.014261	-0.4698
cp	-0.643499	-0.023736	1.065132	0.861714	-4.113774	0.034719	0.024108	6.9916
trestbps	44.495902	-0.463970	0.861714	307.586453	111.967215	1.109042	-1.052324	-18.7591
chol	100.585076	-4.780309	-4.113774	111.967215	2686.426748	0.245427	-4.116703	-11.8004
fbs	0.392433	0.007475	0.034719	1.109042	0.245427	0.126877	-0.015769	-0.0698
restecg	-0.555013	-0.014261	0.024108	-1.052324	-4.116703	-0.015769	0.276528	0.5314
thalach	-82.903318	-0.469871	6.991618	-18.759131	-11.800494	-0.069897	0.531462	524.6464
exang	0.413022	0.031014	-0.191168	0.557111	1.631991	0.004295	-0.017474	-4.0762
oldpeak	2.214583	0.051993	-0.178821	3.934486	3.246794	0.002377	-0.035883	-9.1535
slope	-0.944791	-0.008819	0.076137	-1.312832	-0.128964	-0.013147	0.030151	5.4593
ca	2.566356	0.056357	-0.191080	1.818373	3.737252	0.050259	-0.038741	-4.9932
thal	0.378139	0.059930	-0.102201	0.668022	3.135488	-0.006983	-0.003858	-1.3524
target	-1.021343	-0.065307	0.223330	-1.267950	-2.203855	-0.004983	0.035998	4.8187



```
In [8]: df.age.value_counts()
```

```
Out[8]: 58    19
        57    17
        54    16
        59    14
        52    13
        51    12
        62    11
        60    11
        44    11
        56    11
        64    10
        41    10
        63     9
        67     9
        65     8
        43     8
        45     8
        55     8
        42     8
        61     8
        53     8
        46     7
        48     7
        66     7
        50     7
        49     5
        47     5
        70     4
        39     4
        35     4
        68     4
        38     3
        71     3
        40     3
        69     3
        34     2
        37     2
        29     1
        74     1
        76     1
        77     1
        Name: age, dtype: int64
```

```
In [9]: df.sex.value_counts()
```

```
Out[9]: 1    207
        0     96
        Name: sex, dtype: int64
```

```
In [10]: df.cp.value_counts()
```

```
Out[10]: 0    143  
         2     87  
         1     50  
         3     23  
         Name: cp, dtype: int64
```

```
In [11]: pd.crosstab(df.sex,df.cp).T.head()
```

```
Out[11]:
```

sex	0	1
cp		
0	39	104
1	18	32
2	35	52
3	4	19

```
In [12]: pd.crosstab(df.sex,df.age).T.head()
```

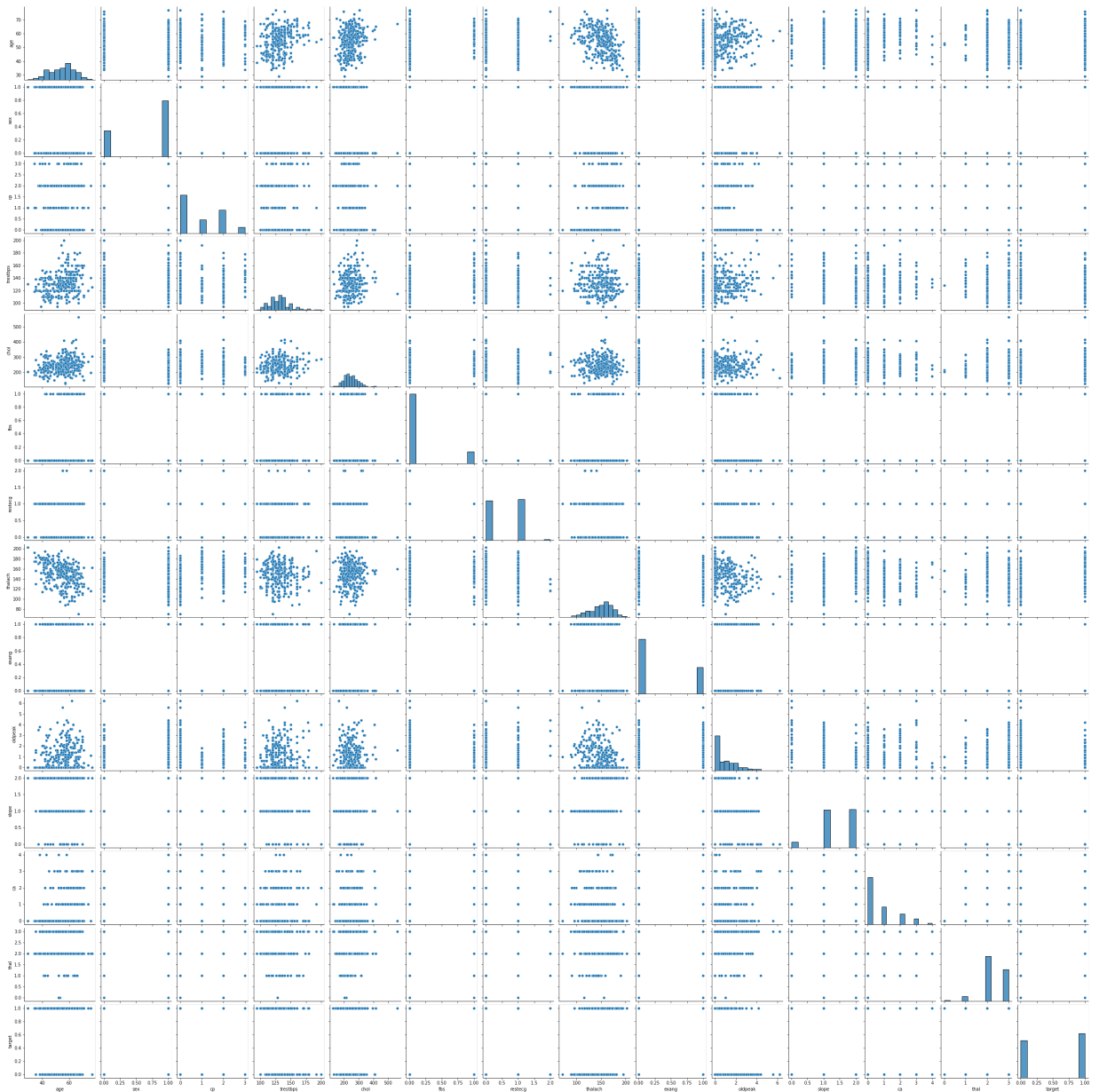
```
Out[12]:
```

sex	0	1
age		
29	0	1
34	1	1
35	1	3
37	1	1
38	0	3

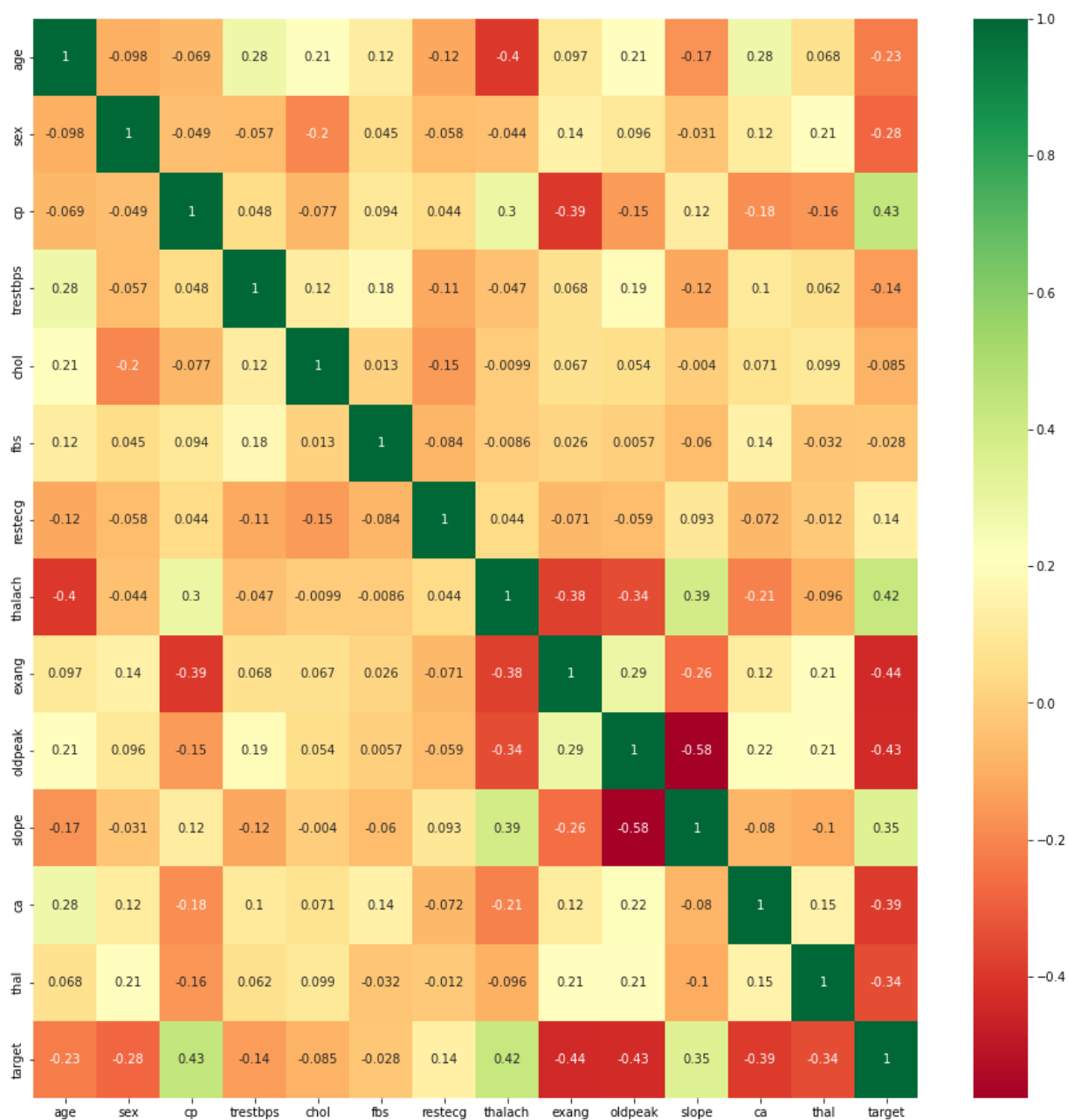
Data Visualization

```
In [13]: sns.pairplot(df)
```

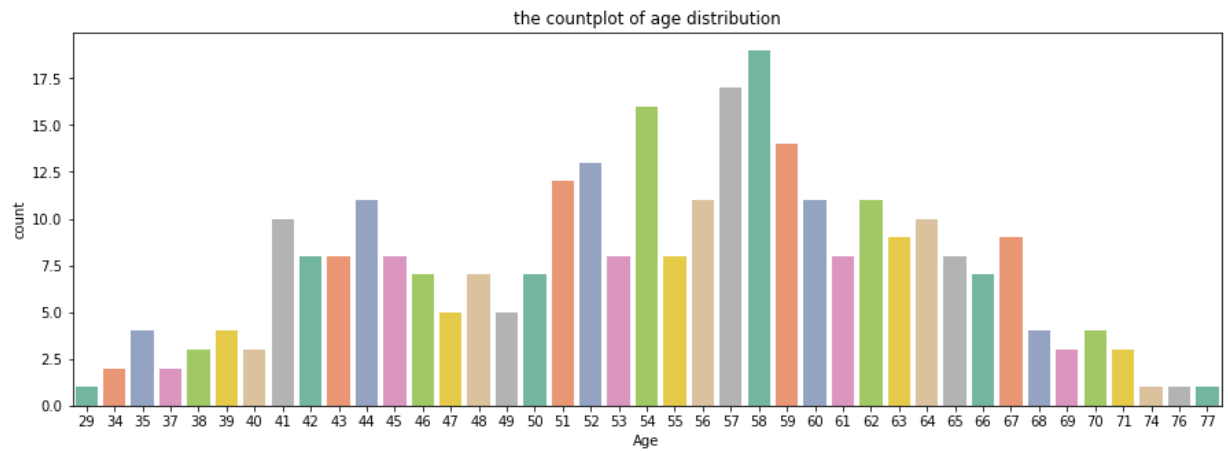
```
Out[13]: <seaborn.axisgrid.PairGrid at 0x22f5b5449a0>
```



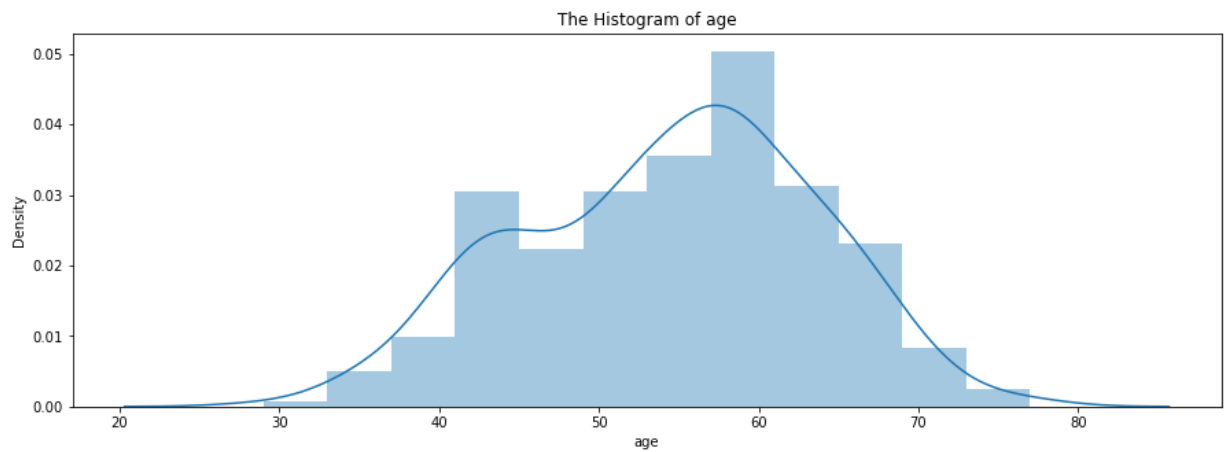
```
In [14]: plt.figure(figsize=(16,16))
sns.heatmap(df.corr(),annot=True,cmap="RdYlGn")
plt.show()
```



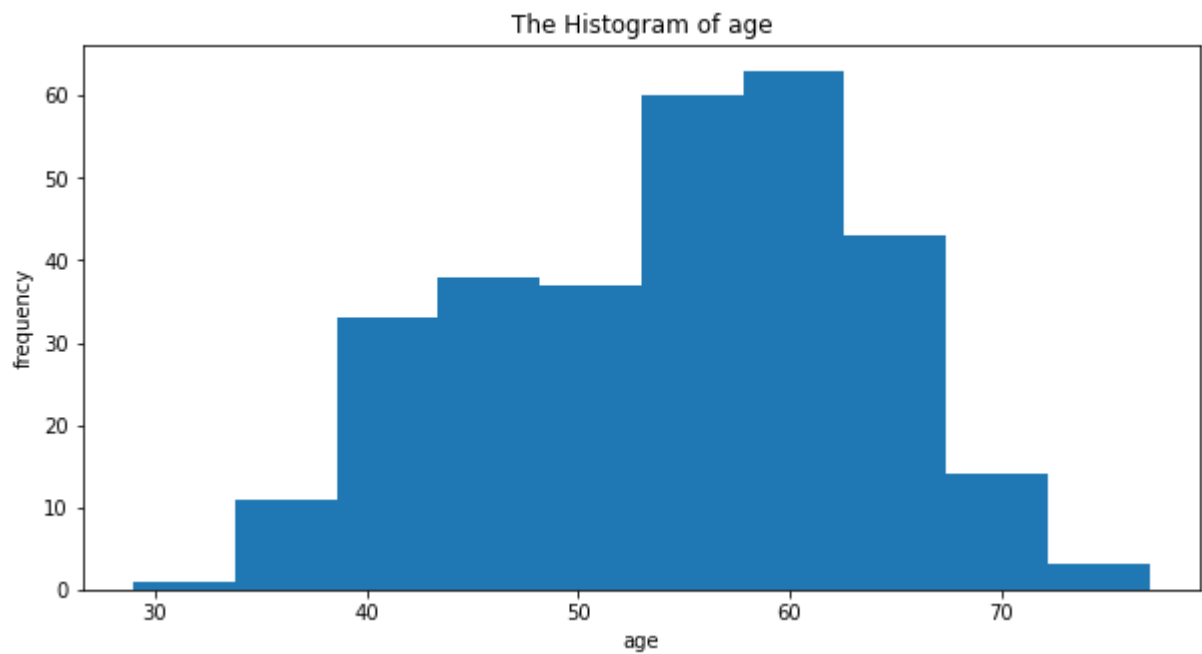
```
In [15]: plt.figure(figsize=(15,5))
sns.countplot(df.age,palette='Set2')
plt.title('the countplot of age distribution')
plt.xlabel('Age')
plt.ylabel('count')
plt.show()
```



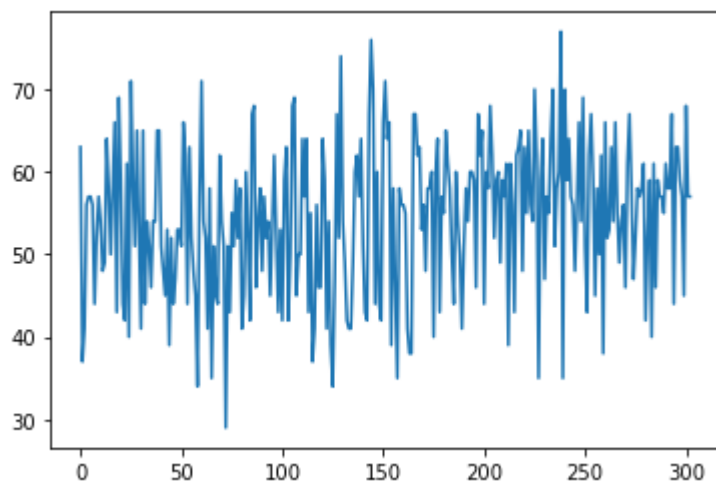
```
In [16]: plt.figure(figsize=(15,5))
sns.distplot(df.age)
plt.title('The Histogram of age')
plt.show()
```



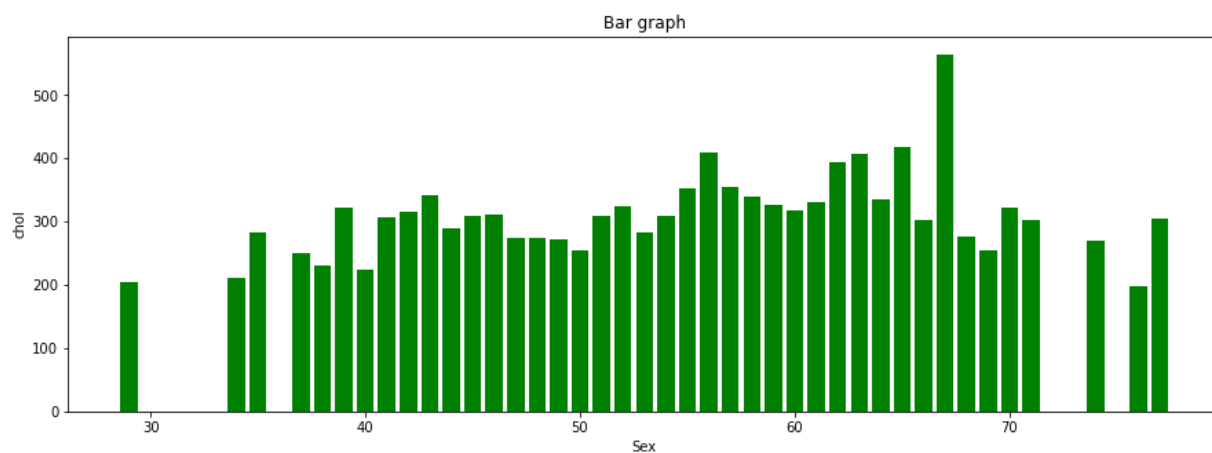

```
In [17]: plt.figure(figsize=(10,5))  
plt.hist(df.age)  
plt.title('The Histogram of age')  
plt.xlabel('age')  
plt.ylabel('frequency')  
plt.show()
```



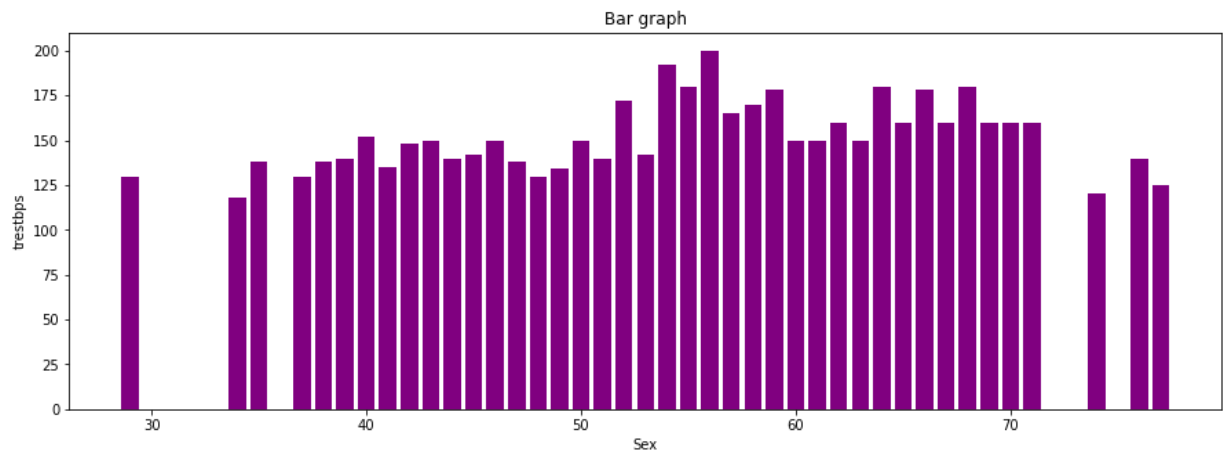
```
In [18]: plt.plot(df.age)
plt.show()
```



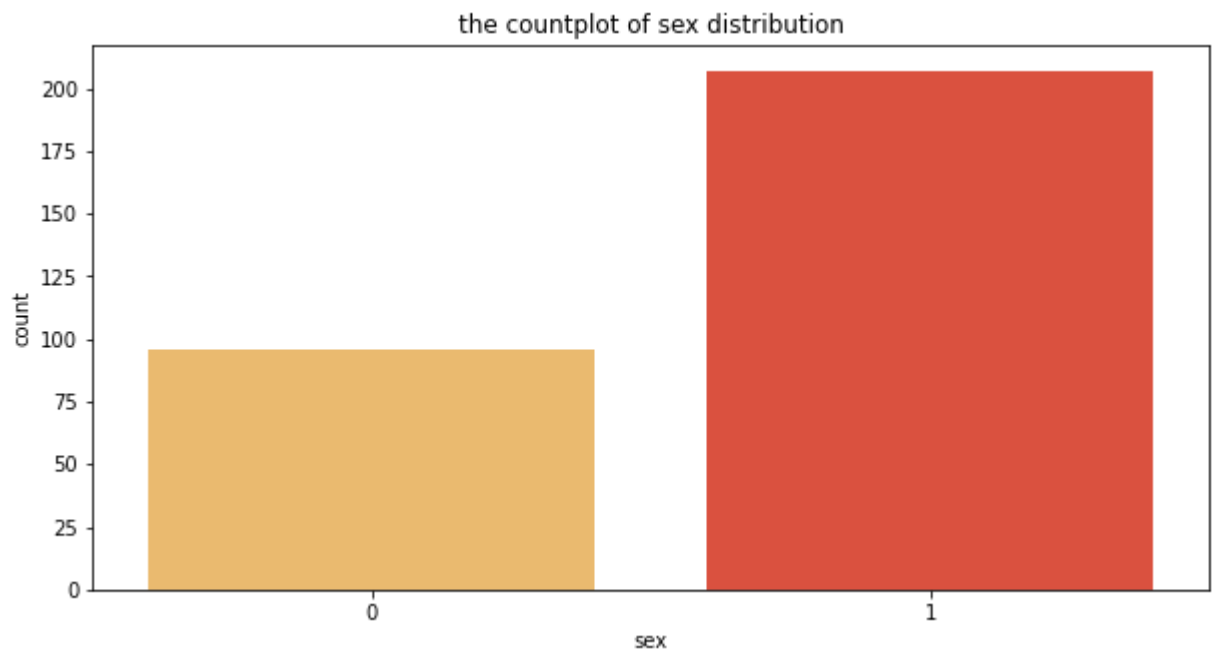
```
In [19]: plt.figure(figsize=(15,5))
plt.bar(df.age,df.chol,color='green')
plt.xlabel('Sex')
plt.ylabel('chol')
plt.title('Bar graph')
plt.show()
```



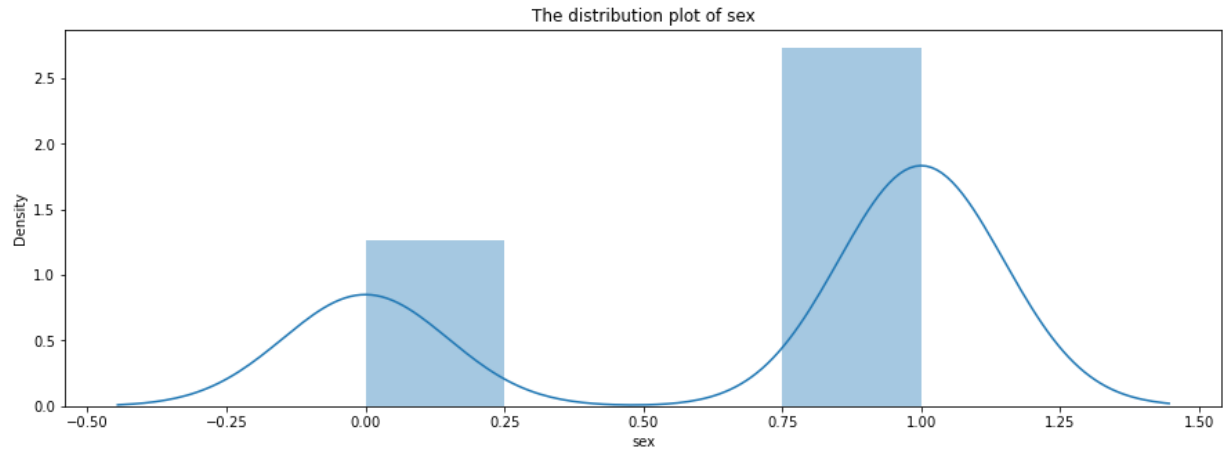
```
In [20]: plt.figure(figsize=(15,5))
plt.bar(df.age,df.trestbps,color='purple')
plt.xlabel('Sex')
plt.ylabel('trestbps')
plt.title('Bar graph')
plt.show()
```



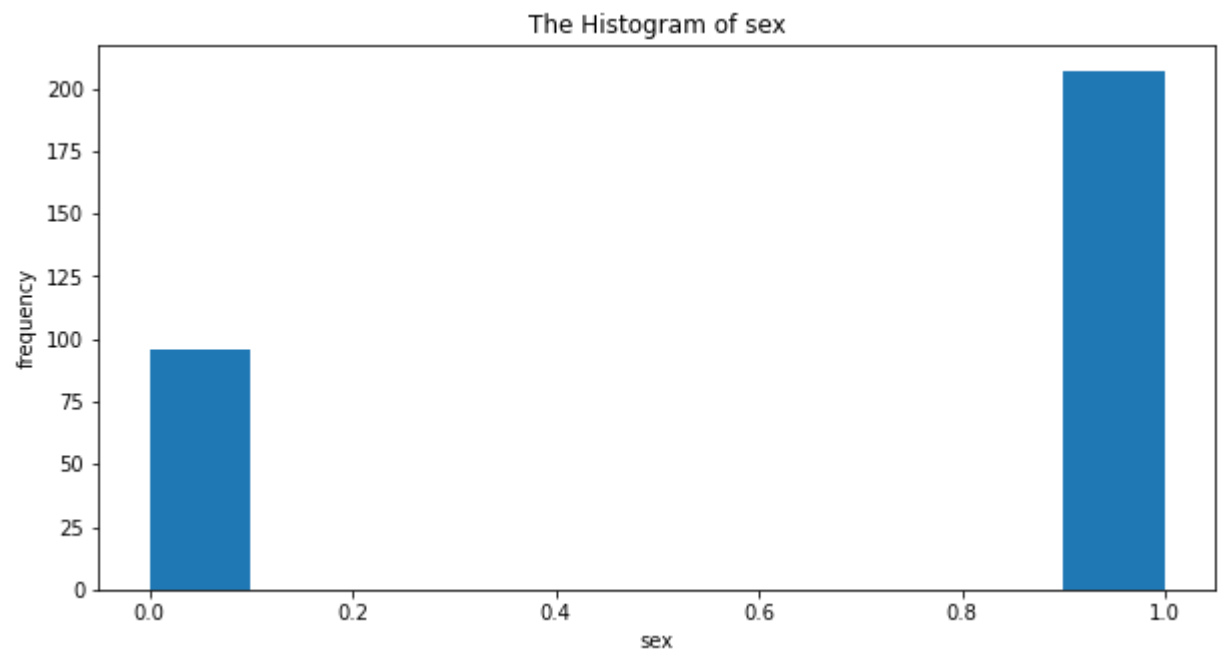
```
In [21]: plt.figure(figsize=(10,5))
sns.countplot(df.sex,palette='YlOrRd')
plt.title('the countplot of sex distribution')
plt.show()
```



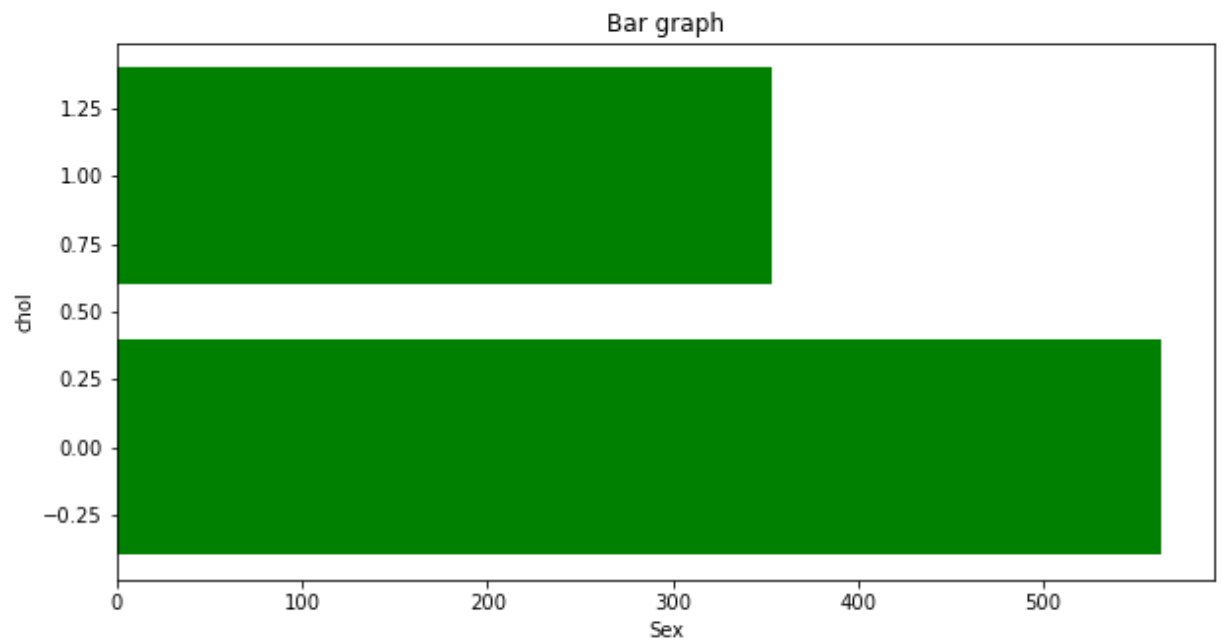
```
In [22]: plt.figure(figsize=(15,5))
sns.distplot(df.sex)
plt.title('The distribution plot of sex')
plt.show()
```



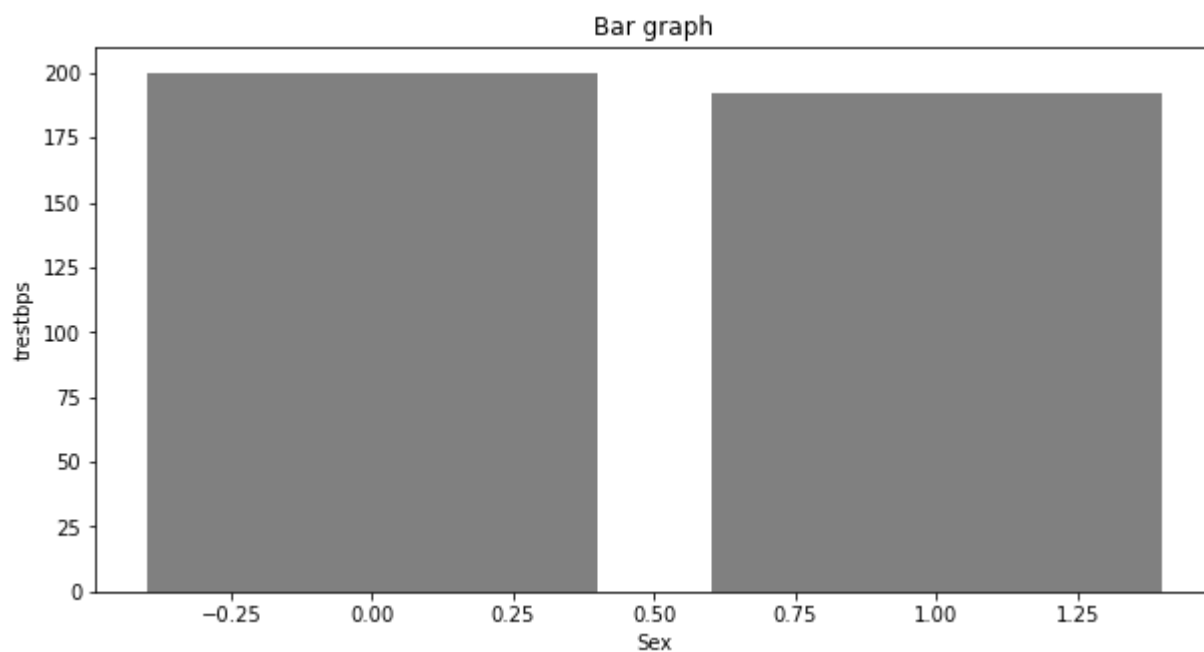
```
In [23]: plt.figure(figsize=(10,5))
plt.hist(df.sex)
plt.title('The Histogram of sex')
plt.xlabel('sex')
plt.ylabel('frequency')
plt.show()
```



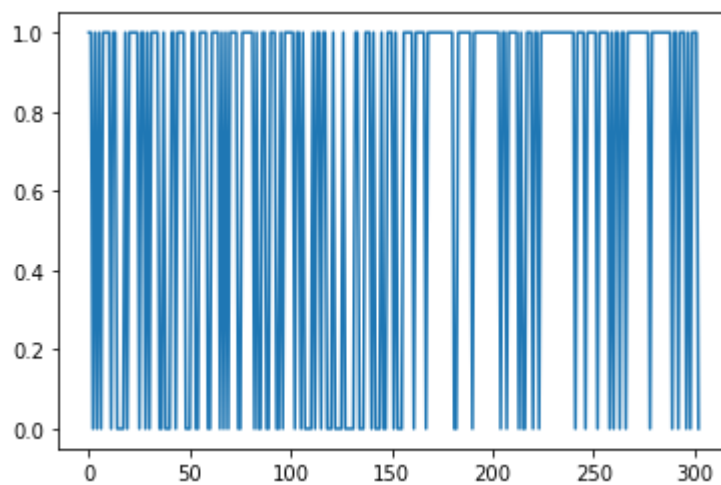
```
In [24]: plt.figure(figsize=(10,5))  
plt.barh(df.sex,df.chol,color='green')  
plt.xlabel('Sex')  
plt.ylabel('chol')  
plt.title('Bar graph')  
plt.show()
```



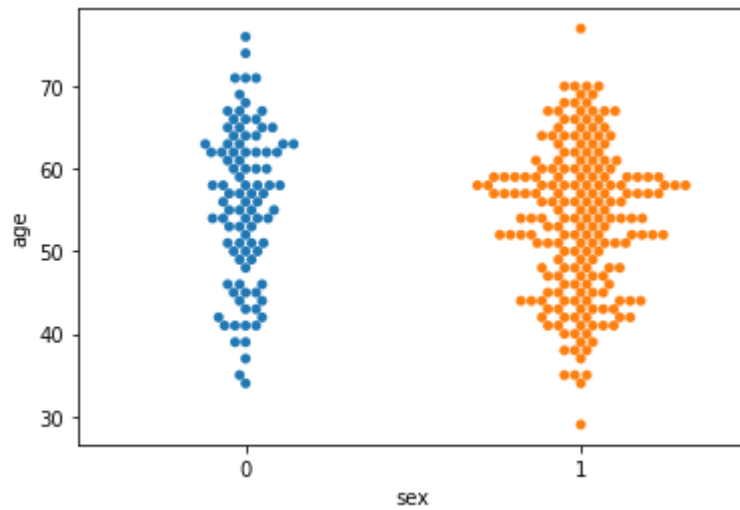
```
In [25]: plt.figure(figsize=(10,5))
plt.bar(df.sex,df.trestbps,color='grey')
plt.xlabel('Sex')
plt.ylabel('trestbps')
plt.title('Bar graph')
plt.show()
```



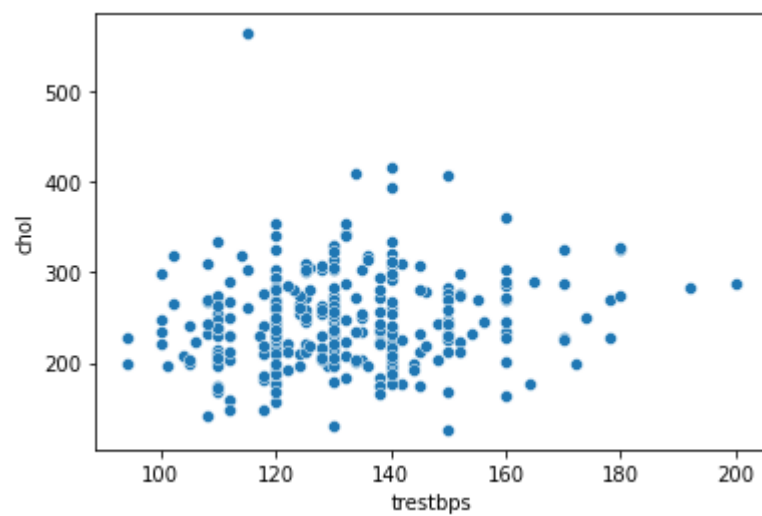
```
In [26]: plt.plot(df.sex)
plt.show()
```



```
In [27]: sns.swarmplot(df.sex,df.age)
plt.xlabel('sex')
plt.ylabel('age')
plt.show()
```



```
In [28]: sns.scatterplot(df.trestbps,df.chol)
plt.show()
```



```
In [1]: gender_size = df.groupby('sex').size()
plt.pie(gender_size, startangle=150, explode=[0.005,0], autopct='% 1.1f %%', shadow
plt.title('Pie chart for Employee sex')
plt.legend(title="sex")
plt.show()
```

```
-----
NameError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_8036\4286359145.py in <module>
----> 1 gender_size = df.groupby('insured_sex').size()
      2 plt.pie(gender_size, startangle=150, explode=[0.005,0], autopct='% 1.1f
      3 %%', shadow=False, labels=['Female', 'Male'])
      4 plt.title('Pie chart for Employee sex')
      5 plt.legend(title="sex")
      6 plt.show()
```

NameError: name 'df' is not defined

Feature engineering

```
In [30]: df['age_category'] = ['youth' if 29<=age<=35
                                else 'adult'
                                if 36<=age<=45
                                else 'old'
                                if 46<=age<=77
                                else None
                                for age in list(df.age.values)]
```

```
In [31]: df.age_category.value_counts()
```

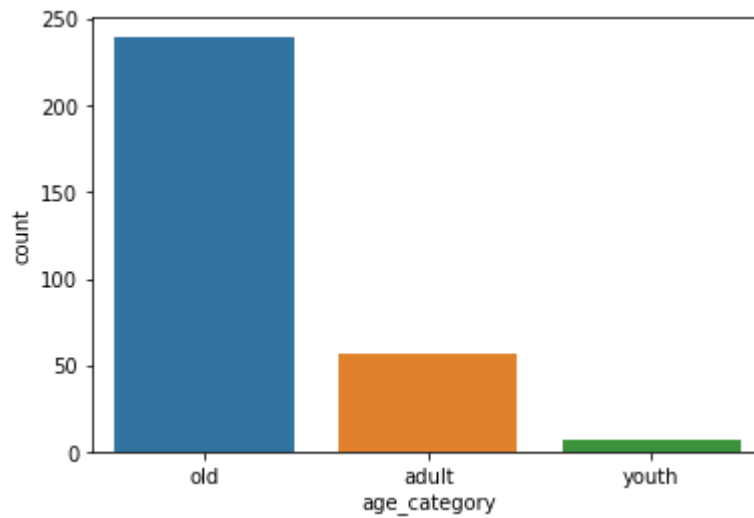
```
Out[31]: old      239
adult    57
youth     7
Name: age_category, dtype: int64
```

```
In [32]: pd.crosstab(df['target'], df['age_category'])
```

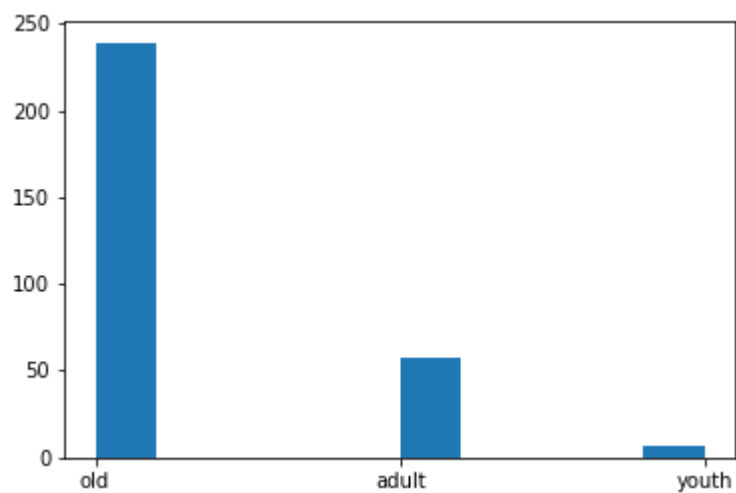
```
Out[32]:
```

	age_category	adult	old	youth
target				
0		14	122	2
1		43	117	5


```
In [33]: sns.countplot(df.age_category)  
plt.show()
```

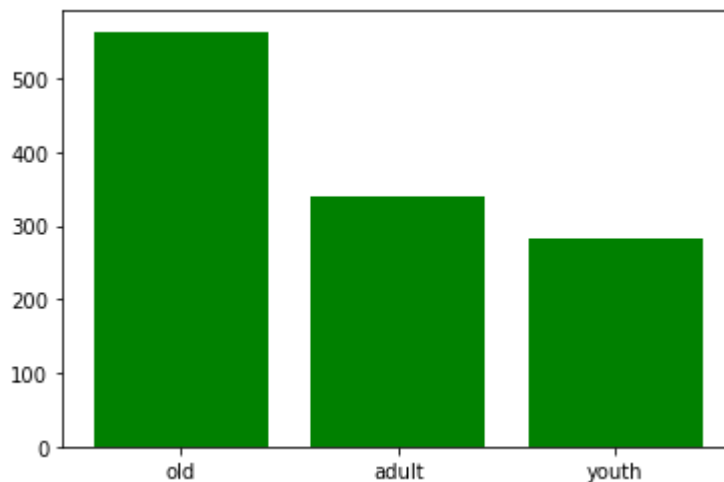


```
In [34]: plt.hist(df.age_category)  
plt.show()
```

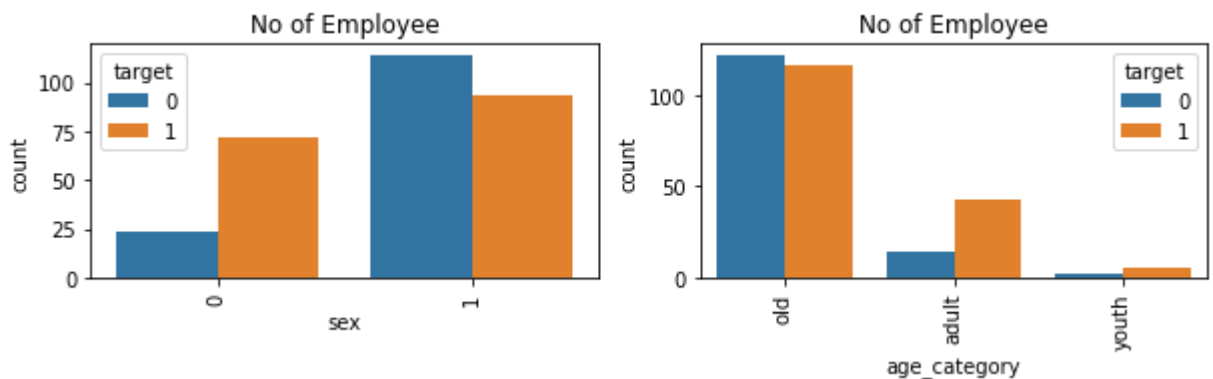


```
In [35]: plt.bar(df.age_category,df.chol,color='green')
```

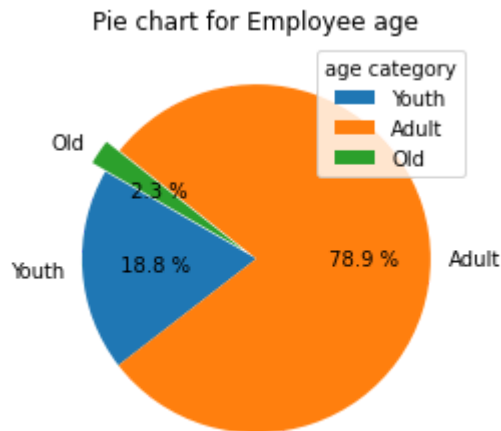
```
Out[35]: <BarContainer object of 303 artists>
```



```
In [36]: features= ['sex', 'age_category']  
fig= plt.subplots(figsize= (10,15))  
  
for i,j in enumerate(features):  
    plt.subplot(4,2, i+1)  
    plt.subplots_adjust(hspace=1.0)  
    sns.countplot(x=j, data=df , hue= "target")  
    plt.xticks(rotation= 90)  
    plt.title("No of Employee")
```



```
In [37]: age_size = df.groupby('age_category').size()
plt.pie(age_size, startangle=150, explode=[0,0,0.09], autopct='% 1.1f %%', shadow=f
plt.title('Pie chart for Employee age')
plt.legend(title="age category")
plt.show()
```



Data preprocessing

```
In [38]: from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df.age_category=le.fit_transform(df.age_category)
```

```
In [39]: df.age_category.value_counts()
```

```
Out[39]: 1    239
         0     57
         2      7
         Name: age_category, dtype: int64
```

```
In [40]: dataset = pd.get_dummies(df, columns = ['sex', 'cp', 'fbs', 'restecg', 'exang', 'slope_2'])
dataset.head()
```

```
Out[40]:
```

	age	trestbps	chol	thalach	oldpeak	target	age_category	sex_0	sex_1	cp_0	...	slope_2	...
0	63	145	233	150	2.3	1	1	0	1	0	...	0	...
1	37	130	250	187	3.5	1	0	0	1	0	...	0	...
2	41	130	204	172	1.4	1	0	1	0	0	...	1	...
3	56	120	236	178	0.8	1	1	0	1	0	...	1	...
4	57	120	354	163	0.6	1	1	1	0	1	...	1	...

5 rows × 32 columns



Model Building

```
In [41]: x=df.drop('target',axis=1)
y=df.target
```

```
In [42]: x.head()
```

```
Out[42]:
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	age_category
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	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1



```
In [43]: y.head()
```

```
Out[43]: 0    1
1    1
2    1
3    1
4    1
Name: target, dtype: int64
```

```
In [44]: from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
x=scaler.fit_transform(x)
```

```
In [45]: from sklearn.model_selection import train_test_split,cross_val_score
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=0)
```

```
In [46]: from sklearn.metrics import accuracy_score,precision_score,recall_score,f1_score,
```

```
In [47]: # Fitting Naive Bayes to the Training set
from sklearn.naive_bayes import GaussianNB
nb_classifier = GaussianNB()
nb_classifier.fit(x_train, y_train)
```

```
Out[47]: GaussianNB()
```

```
In [48]: nb_pred=nb_classifier.predict(x_test)
nb_pred
```

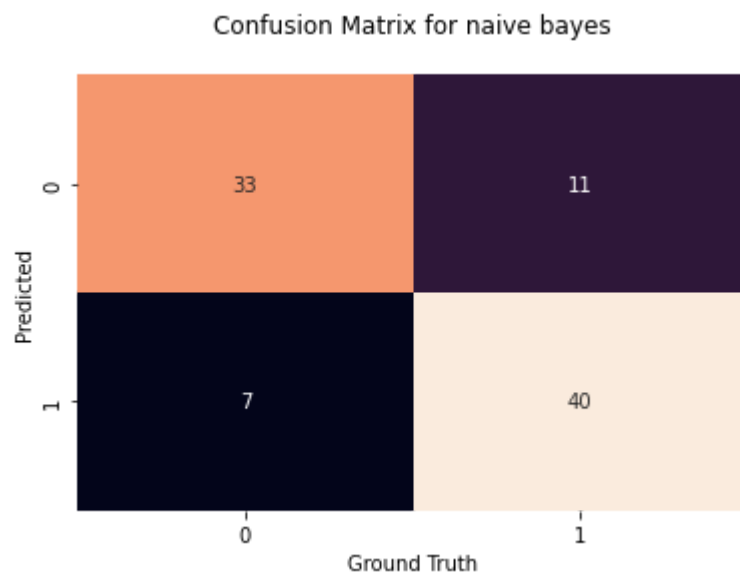
```
Out[48]: array([0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1,
                0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 0,
                1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1,
                0, 0, 0], dtype=int64)
```

```
In [49]: print('Score: ',nb_classifier.score(x_test,y_test))
print('accuracy score: ',accuracy_score(y_test,nb_pred))
print('precision score: ',precision_score(y_test,nb_pred))
print('recall score: ',recall_score(y_test,nb_pred))
```

```
Score:  0.8021978021978022
accuracy score:  0.8021978021978022
precision score:  0.7843137254901961
recall score:  0.851063829787234
```

```
In [50]: def display_confusion_matrix(test,pred,model_name = ''):
    confmatrix= confusion_matrix(test, pred)
    ax = plt.subplot()
    sns.heatmap(confmatrix, annot=True, ax=ax, cbar=False)
    plt.title('Confusion Matrix for '+str(model_name) + '\n')
    ax.set_xlabel('Ground Truth')
    ax.set_ylabel('Predicted')
    ax.xaxis.set_ticklabels(['0','1'])
    ax.yaxis.set_ticklabels(['0','1'])
    plt.show()
```

```
In [51]: display_confusion_matrix(y_test,nb_pred, 'naive bayes')
```



```
In [52]: pd.Series(y_test).value_counts()
```

```
Out[52]: 1    47  
         0    44  
         Name: target, dtype: int64
```

```
In [53]: # Fitting Logistic Regression to the Training set  
         from sklearn.svm import SVC  
         sv_classifier = SVC()  
         sv_classifier.fit(x_train, y_train)
```

```
Out[53]: SVC()
```

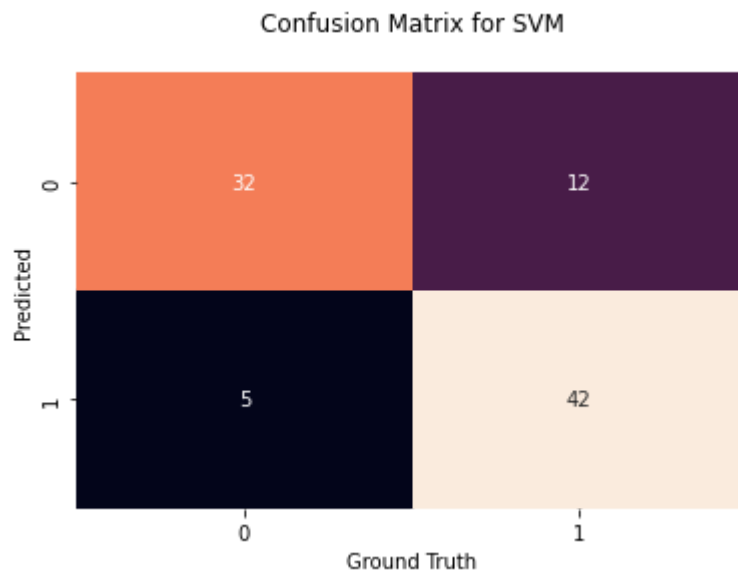
```
In [54]: sv_pred=sv_classifier.predict(x_test)
```

```
In [55]: print('Score: ',sv_classifier.score(x_test,y_test))
print('accuracy score: ',accuracy_score(y_test,sv_pred))
print('precision score: ',precision_score(y_test,sv_pred))
print('recall score: ',recall_score(y_test,sv_pred))
print('f1 score: ',f1_score(y_test,sv_pred))
print('\n')
print('classification report: ',classification_report(y_test,sv_pred))
```

Score: 0.8131868131868132
 accuracy score: 0.8131868131868132
 precision score: 0.7777777777777778
 recall score: 0.8936170212765957
 f1 score: 0.8316831683168316

classification report:		precision	recall	f1-score	support
0	0.86	0.73	0.79	44	
1	0.78	0.89	0.83	47	
accuracy			0.81	91	
macro avg	0.82	0.81	0.81	91	
weighted avg	0.82	0.81	0.81	91	

```
In [56]: display_confusion_matrix(y_test,sv_pred, 'SVM')
```



```
In [57]: # Fitting Random Forest Classification to the Training set
from sklearn.ensemble import RandomForestClassifier
rfc_classifier = RandomForestClassifier()
rfc_classifier.fit(x_train, y_train)
```

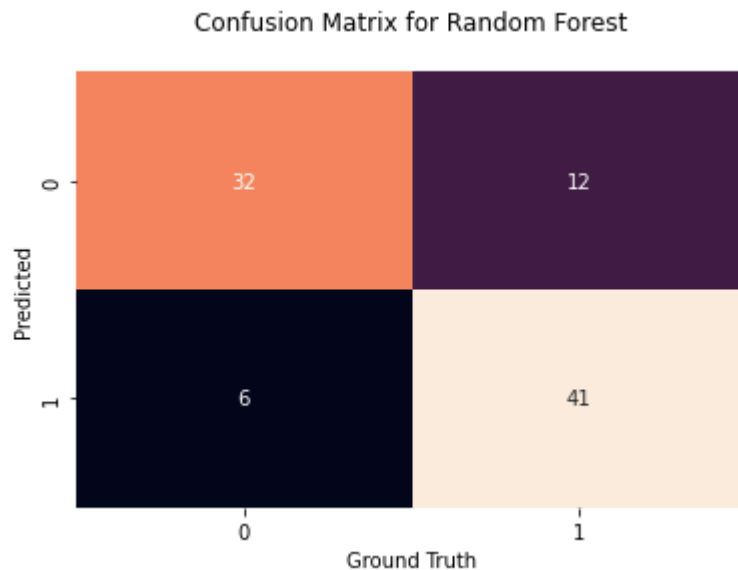
```
Out[57]: RandomForestClassifier()
```

```
In [58]: rfc_pred=rfc_classifier.predict(x_test)
```

```
In [59]: print('Score: ',rfc_classifier.score(x_test,y_test))
print('accuracy score: ',accuracy_score(y_test,rfc_pred))
print('precision score: ',precision_score(y_test,rfc_pred))
print('recall score: ',recall_score(y_test,rfc_pred))
```

```
Score: 0.8021978021978022
accuracy score: 0.8021978021978022
precision score: 0.7735849056603774
recall score: 0.8723404255319149
```

```
In [60]: display_confusion_matrix(y_test,rfc_pred, 'Random Forest')
```



```
In [61]: from sklearn.neighbors import KNeighborsClassifier

knn_classifier = KNeighborsClassifier(n_neighbors=5)
knn_classifier.fit(x_train, y_train)
```

```
Out[61]: KNeighborsClassifier()
```

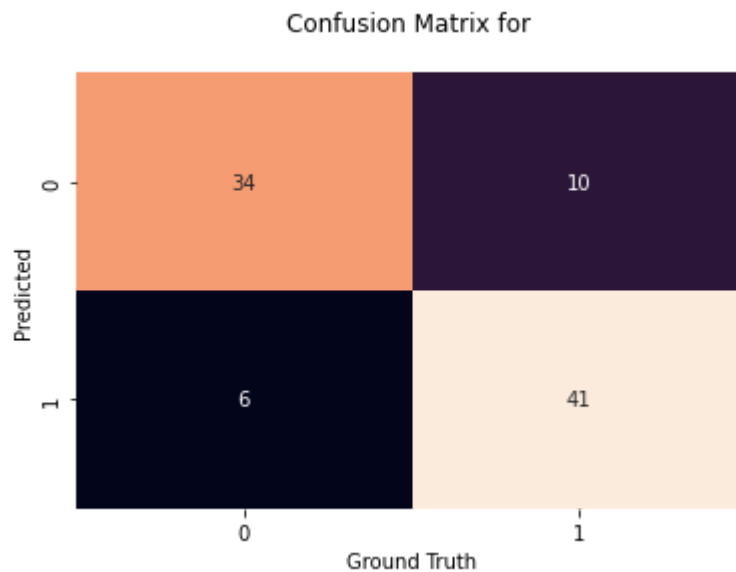
```
In [62]: knn_pred=knn_classifier.predict(x_test)
```

```
In [63]: print('Score: ',rfc_classifier.score(x_test,y_test))
print('accuracy score: ',accuracy_score(y_test,knn_pred))
print('precision score: ',precision_score(y_test,knn_pred))
print('recall score: ',recall_score(y_test,knn_pred))
```

```
Score: 0.8021978021978022
accuracy score: 0.8241758241758241
precision score: 0.803921568627451
recall score: 0.8723404255319149
```



```
In [64]: display_confusion_matrix(y_test,knn_pred)
```



```
In [65]: from xgboost import XGBClassifier  
xgb=XGBClassifier()  
xgb.fit(x_train,y_train)
```

[14:38:39] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.

```
Out[65]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,  
                      colsample_bynode=1, colsample_bytree=1, enable_categorical=False,  
                      gamma=0, gpu_id=-1, importance_type=None,  
                      interaction_constraints='', learning_rate=0.300000012,  
                      max_delta_step=0, max_depth=6, min_child_weight=1, missing=nan,  
                      monotone_constraints=(), n_estimators=100, n_jobs=4,  
                      num_parallel_tree=1, predictor='auto', random_state=0,  
                      reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,  
                      tree_method='exact', validate_parameters=1, verbosity=None)
```

```
In [66]: xgb_pred=xgb.predict(x_test)
```

```
In [67]: print('Score: ',xgb.score(x_test,y_test))
print('accuracy score: ',accuracy_score(y_test,xgb_pred))
print('precision score: ',precision_score(y_test,xgb_pred))
print('recall score: ',recall_score(y_test,xgb_pred))
```

```
Score: 0.8021978021978022
accuracy score: 0.8021978021978022
precision score: 0.7735849056603774
recall score: 0.8723404255319149
```

```
In [68]: from catboost import CatBoostClassifier
cat=CatBoostClassifier()
cat.fit(x_train,y_train)
```

```
-----
ModuleNotFoundError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_9816\4008524781.py in <module>
----> 1 from catboost import CatBoostClassifier
      2 cat=CatBoostClassifier()
      3 cat.fit(x_train,y_train)
```

ModuleNotFoundError: No module named 'catboost'

```
In [76]: cat_pred=cat.predict(x_test)
```

```
In [77]: print('Score: ',cat.score(x_test,y_test))
print('accuracy score: ',accuracy_score(y_test,cat_pred))
print('precision score: ',precision_score(y_test,cat_pred))
print('recall score: ',recall_score(y_test,cat_pred))
```

```
Score: 0.8241758241758241
accuracy score: 0.8241758241758241
precision score: 0.7924528301886793
recall score: 0.8936170212765957
```

```
In [69]: import pickle
```

```
In [72]: pkl_model=open('rfheart.pkl','wb')
pickle.dump(rfc_classifier,pkl_model)
```

```
In [73]: model=pickle.load(open('heart.pkl','rb'))
print(model.predict([[63,1,3,145,233,1,0,150,0,2.3,0,0,1,1]]))

[0]
```

```
In [74]: sv_model=open('svheart.pkl','wb')
pickle.dump(sv_classifier,sv_model)
```

```
In [75]: model=pickle.load(open('svheart.pkl','rb'))
print(model.predict([[63,1,3,145,233,1,0,150,0,2.3,0,0,1,1]]))

[1]
```

```
In [70]: xg_model=open('xheart.pkl','wb')  
         pickle.dump(xgb,xg_model)
```

```
In [75]: kn_model=open('knheart.pkl','wb')  
         pickle.dump(knn_classifier,kn_model)
```

```
In [ ]:
```