Lab01

October 8, 2023

[415]:
```
!pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in
/Users/kamil/PycharmProjects/NeuralNetwork/venv/lib/python3.9/site-packages
(0.0.2)
```

[416]:
```
from ucimlrepo import fetch_ucirepo
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

[417]:
```
# fetch dataset
heart_disease = fetch_ucirepo(id=45)

# data (as pandas dataframes)
X = heart_disease.data.features
y = heart_disease.data.targets
```

0.1 Ogólny przegląd danych

Additional Information

This database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to date. The "goal" field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 4. Experiments with the Cleveland database have concentrated on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0).

wartości liczbowe atrybutu num: -0 brak oznak choroby -1,2,3,4 występujące oznaki choroby

[418]:
```
# variable information
variable_info = heart_disease.variables
variable_info
```

[418]:

	name	role	type	demographic	\
0	age	Feature	Integer	Age	
1	sex	Feature	Categorical	Sex	
2	cp	Feature	Categorical	None	
3	trestbps	Feature	Integer	None	
4	chol	Feature	Integer	None	

```
5        fbs  Feature  Categorical        None
6    restecg  Feature  Categorical        None
7    thalach  Feature      Integer        None
8      exang  Feature  Categorical        None
9    oldpeak  Feature      Integer        None
10     slope  Feature  Categorical        None
11        ca  Feature      Integer        None
12      thal  Feature  Categorical        None
13       num   Target      Integer        None

                                        description  units missing_values
0                                              None  years             no
1                                              None   None             no
2                                              None   None             no
3   resting blood pressure (on admission to the ho…  mm Hg            no
4                                 serum cholestoral  mg/dl             no
5                   fasting blood sugar > 120 mg/dl   None             no
6                                              None   None             no
7                       maximum heart rate achieved   None             no
8                           exercise induced angina   None             no
9   ST depression induced by exercise relative to …   None            no
10                                             None   None             no
11  number of major vessels (0-3) colored by flour…   None            yes
12                                             None   None            yes
13                      diagnosis of heart disease   None             no
```

[419]:
```
X
```

[419]:
```
      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0      63    1   1       145   233    1        2      150      0      2.3
1      67    1   4       160   286    0        2      108      1      1.5
2      67    1   4       120   229    0        2      129      1      2.6
3      37    1   3       130   250    0        0      187      0      3.5
4      41    0   2       130   204    0        2      172      0      1.4
..    …  …   ..       …   …  …      …      …    …       …
298    45    1   1       110   264    0        0      132      0      1.2
299    68    1   4       144   193    1        0      141      0      3.4
300    57    1   4       130   131    0        0      115      1      1.2
301    57    0   2       130   236    0        2      174      0      0.0
302    38    1   3       138   175    0        0      173      0      0.0

     slope   ca  thal
0        3  0.0   6.0
1        2  3.0   3.0
2        2  2.0   7.0
3        3  0.0   3.0
4        1  0.0   3.0
```

```
..     …  …   …
298    2  0.0  7.0
299    2  2.0  7.0
300    2  1.0  7.0
301    2  1.0  3.0
302    1  NaN  3.0

[303 rows x 13 columns]
```

[420]:
```
y
```

[420]:
```
     num
0      0
1      2
2      1
3      0
4      0
..   …
298    1
299    2
300    3
301    1
302    0

[303 rows x 1 columns]
```

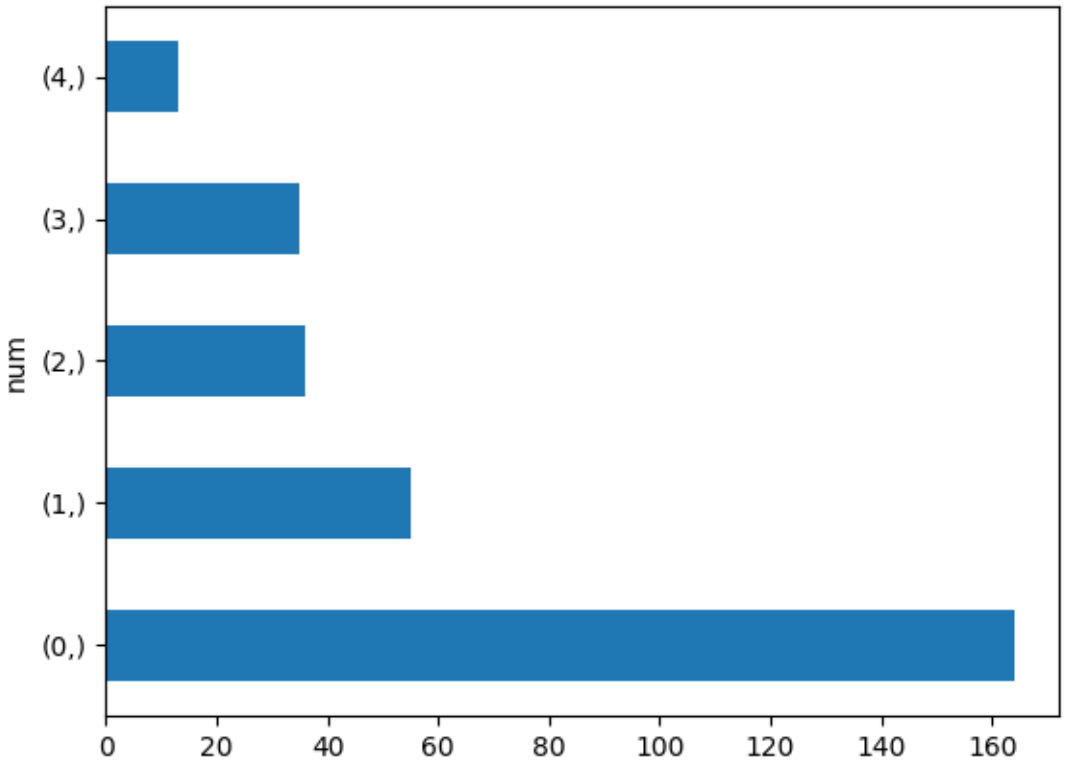
0.2 1.Czy zbiór jest zbalansowany pod względem liczby próbek na klasy?

[421]:
```
y_value_counts = y.value_counts()
y_value_counts
```

[421]:
```
num
0      164
1       55
2       36
3       35
4       13
Name: count, dtype: int64
```

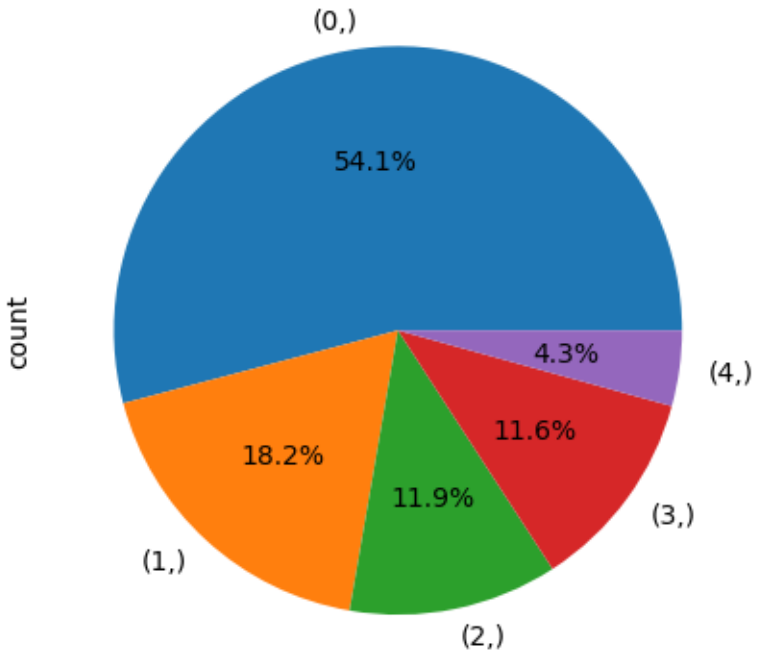
[422]:
```
y_value_counts.plot(kind='barh')
```

[422]:
```
<Axes: ylabel='num'>
```



[423]:
```
y_value_counts.plot(kind='pie', autopct='%1.1f%%')
```

[423]: <Axes: ylabel='count'>



Można zauważyć, że najwięcej przypadków jest dla wartości 0, która stanowi ponad połowę wszystkich wartości, jeśli chodzi o pozostałe, przypadek 1 posiada również duży wkład, 2 i 3 mają prawie taką samą częstotliwość na poziomie ok.12%, przypadek 4 jest najmniej liczny i stanowi niecałe 5%.

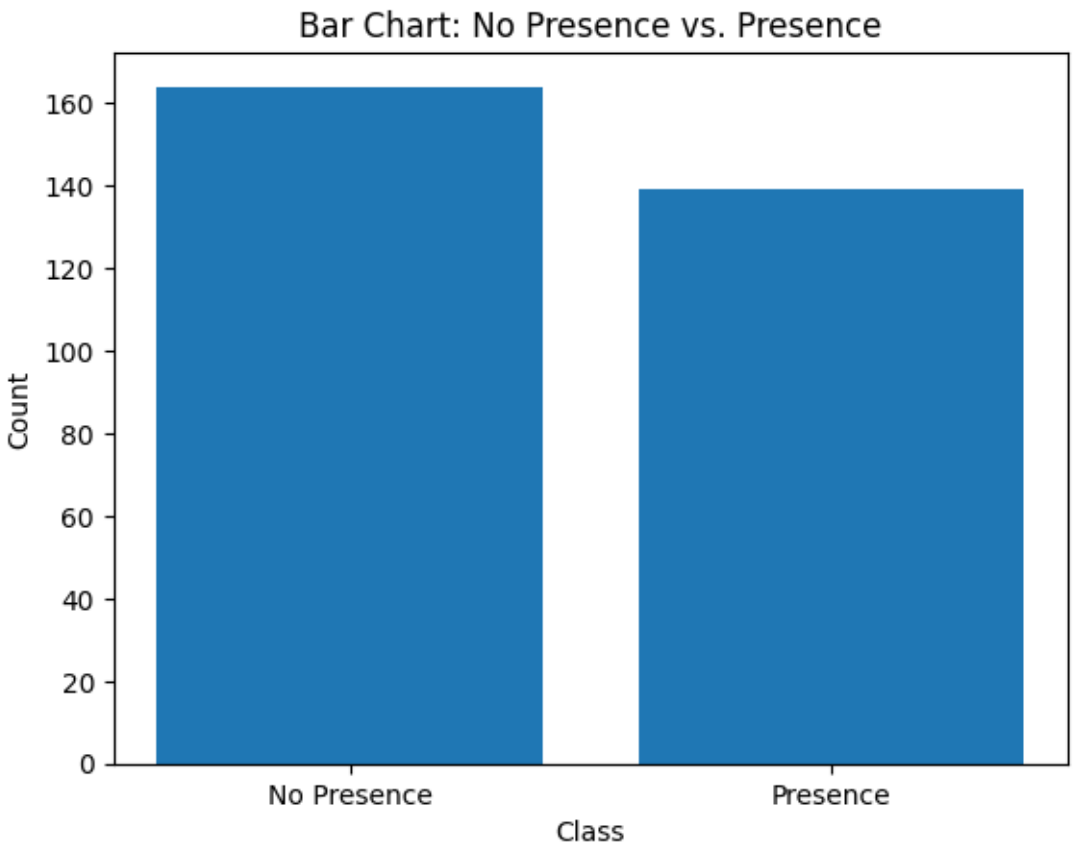
Odpowiedź: Zbiór danych nie jest najlepiej zbalansowany, ponieważ niektóre klasy mają znacznie więcej próbek niż inne.

[424]:
```
no_presence = y[y==0].count().sum()
presence = y[y!=0].count().sum()
presence,no_presence
```

[424]:
```
(139, 164)
```

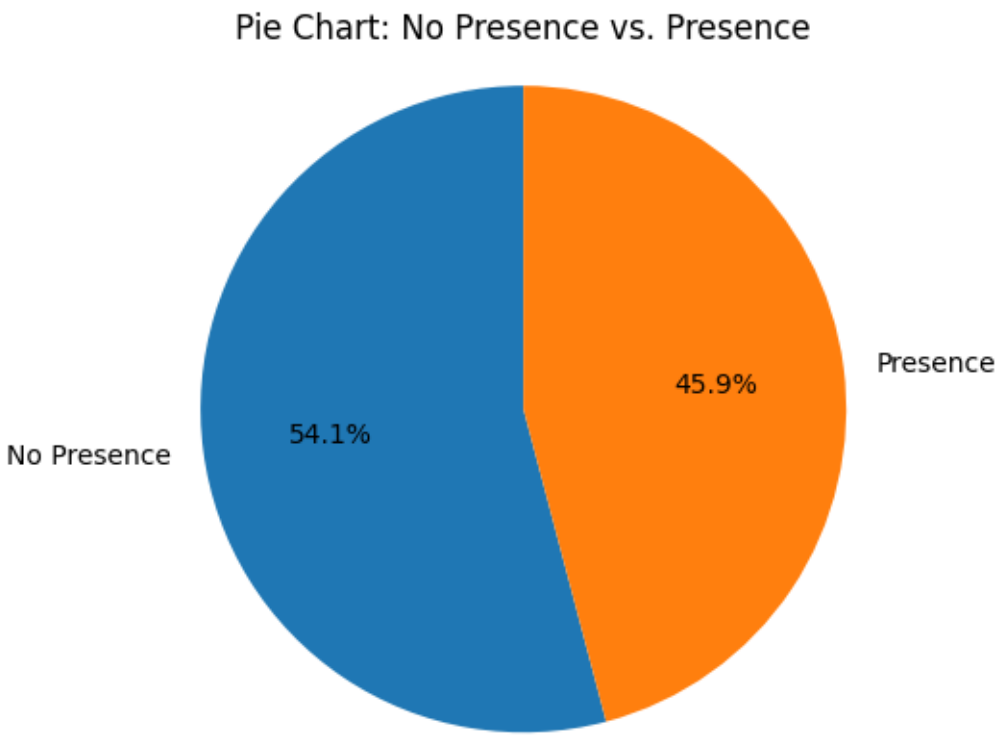
[425]:
```
# Create a bar chart
plt.bar(['No Presence', 'Presence'], [no_presence, presence])
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Bar Chart: No Presence vs. Presence')
```

[425]:
```
Text(0.5, 1.0, 'Bar Chart: No Presence vs. Presence')
```



[426]:
```
labels = ['No Presence', 'Presence']
sizes = [no_presence, presence]
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=90)
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.title('Pie Chart: No Presence vs. Presence')
```

[426]:
```
Text(0.5, 1.0, 'Pie Chart: No Presence vs. Presence')
```



Jeśli jednak pójść dalej i zobaczyć na wartości atrybutu num w perspektywie - ‘ma objawy’ ‘nie ma objawow’, rozkład będzie bardziej zbalansowany.

0.3 2. Jakie są średnie i odchylenia cech liczbowych?

[427]:
```
numeric_variables = variable_info[(variable_info['type']=='Integer') &␣
↪(variable_info['name']!='num')]['name']
numeric_variables
```

[427]:
```
0          age
3     trestbps
4         chol
7      thalach
9      oldpeak
11          ca
Name: name, dtype: object
```

[428]:
```
X[numeric_variables].describe().loc[['mean','std']]
```

[428]:

	age	trestbps	chol	thalach	oldpeak	ca
mean	54.438944	131.689769	246.693069	149.607261	1.039604	0.672241
std	9.038662	17.599748	51.776918	22.875003	1.161075	0.937438

0.4 3. Dla cech liczbowych: czy ich rozkład jest w przybliżeniu normalny?

[429]:
```
from scipy import stats
```

[430]:
```
numeric_df = X[numeric_variables]
numeric_df
```

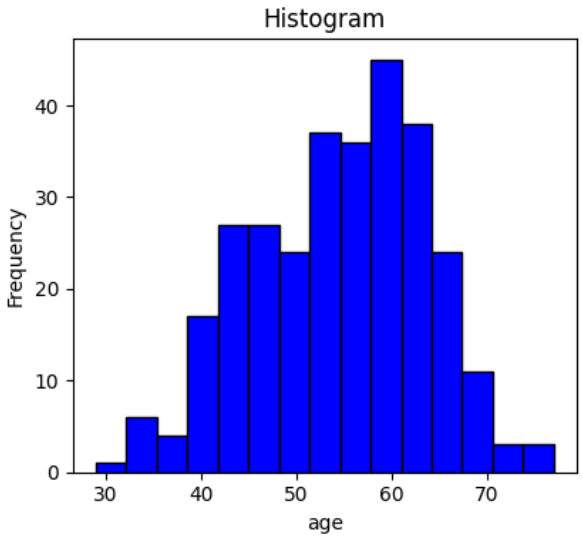
[430]:

	age	trestbps	chol	thalach	oldpeak	ca
0	63	145	233	150	2.3	0.0
1	67	160	286	108	1.5	3.0
2	67	120	229	129	2.6	2.0
3	37	130	250	187	3.5	0.0
4	41	130	204	172	1.4	0.0
..	…	…	…	…	…	…
298	45	110	264	132	1.2	0.0
299	68	144	193	141	3.4	2.0
300	57	130	131	115	1.2	1.0
301	57	130	236	174	0.0	1.0
302	38	138	175	173	0.0	NaN

[303 rows x 6 columns]

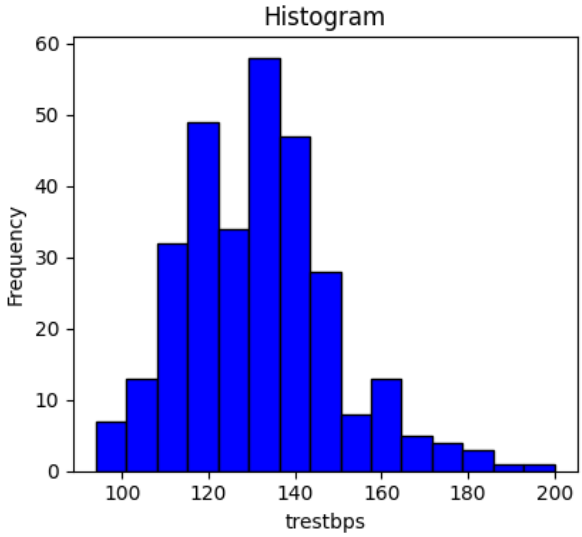
[431]:
```
# Perform the Shapiro-Wilk test and create histograms for each attribute
for column in numeric_df.columns:
    # Shapiro-Wilk test
    p_value = stats.shapiro(numeric_df[column])[1]

    # Create a histogram
    plt.figure(figsize=(8, 4))
    plt.subplot(1, 2, 1)
    plt.hist(numeric_df[column], bins=15, color='blue', edgecolor='black')
    plt.xlabel(column)
    plt.ylabel('Frequency')
    plt.title('Histogram')

    # Check normality based on p-value
    plt.subplot(1, 2, 2)
    if p_value > 0.05:
        plt.text(0.1, 0.5, f'p-value: {p_value:.4f}\nProbably Normal',␣
↪fontsize=12)
    else:
        plt.text(0.1, 0.5, f'p-value: {p_value:.4f}\nNot Normal', fontsize=12,␣
↪color='red')
    plt.axis('off')
    plt.title('Shapiro-Wilk Test')

    plt.tight_layout()
```

```
plt.show()
```



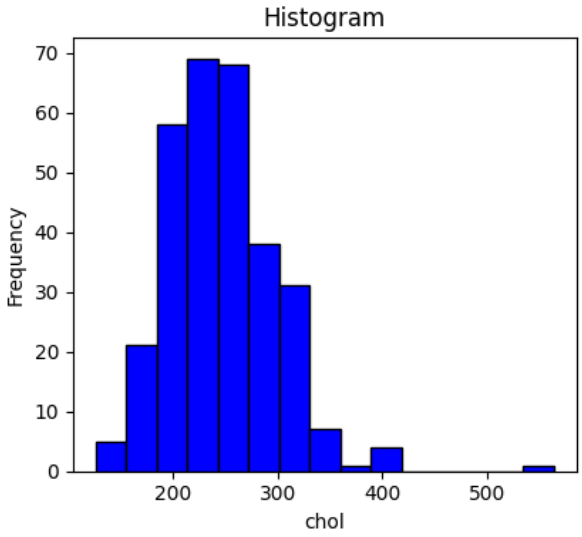
Shapiro-Wilk Test

p-value: 0.0061
Not Normal



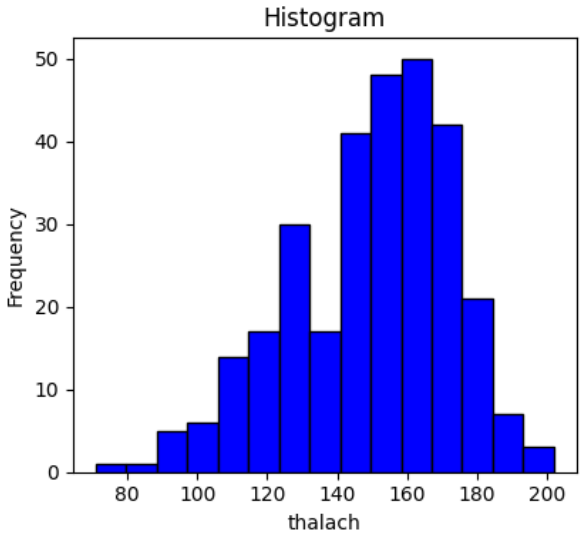
Shapiro-Wilk Test

p-value: 0.0000
Not Normal



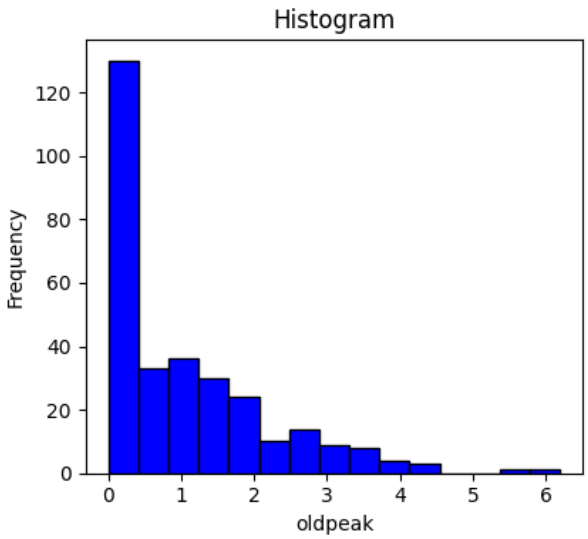
Shapiro-Wilk Test

p-value: 0.0000
Not Normal



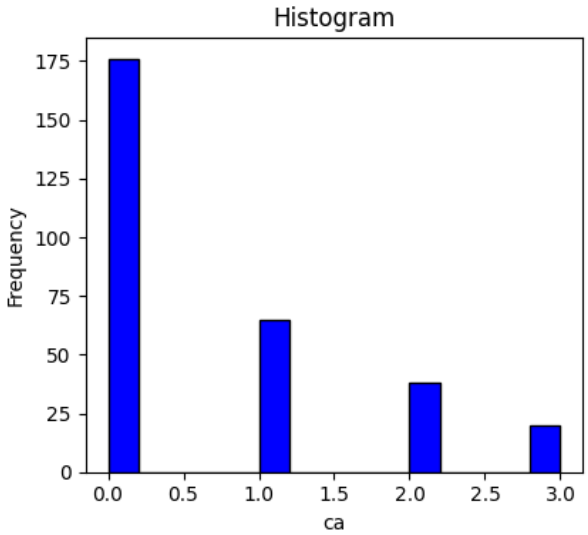
Shapiro-Wilk Test

p-value: 0.0001
Not Normal



Shapiro-Wilk Test

p-value: 0.0000
Not Normal



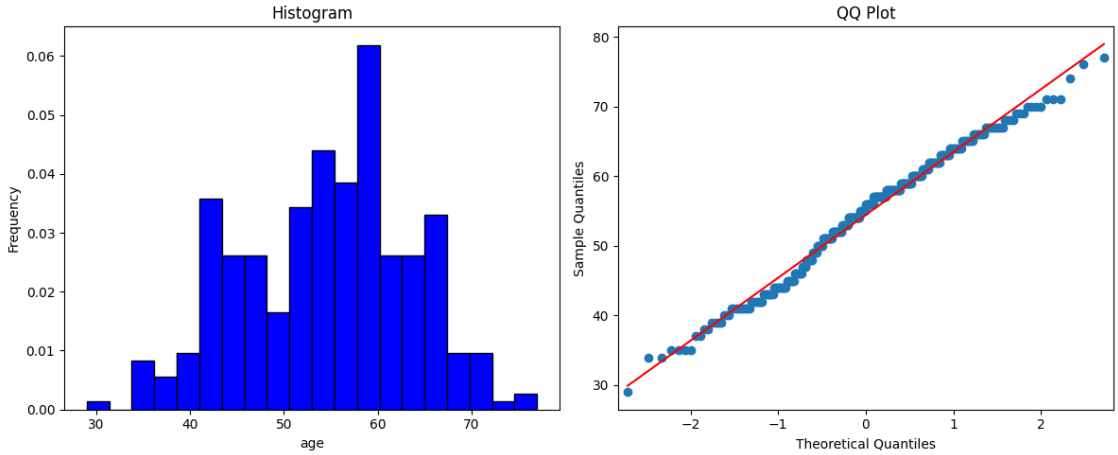
Shapiro-Wilk Test

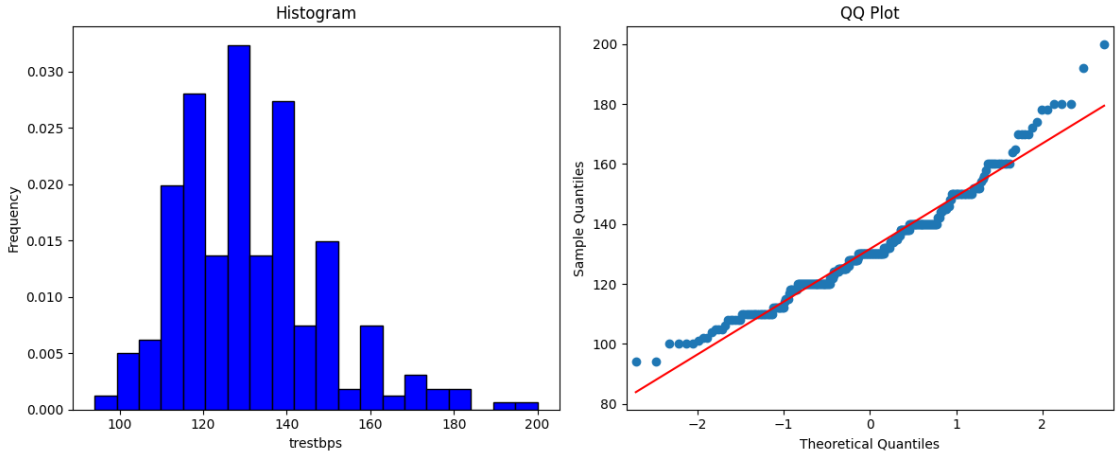
p-value: 1.0000
Probably Normal

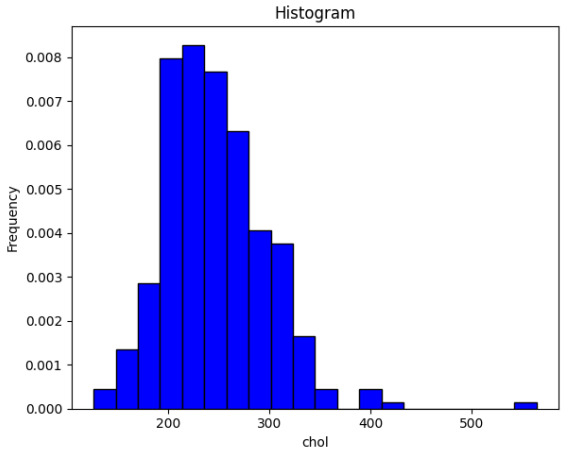
[432]:
```
import statsmodels.api as sm
```

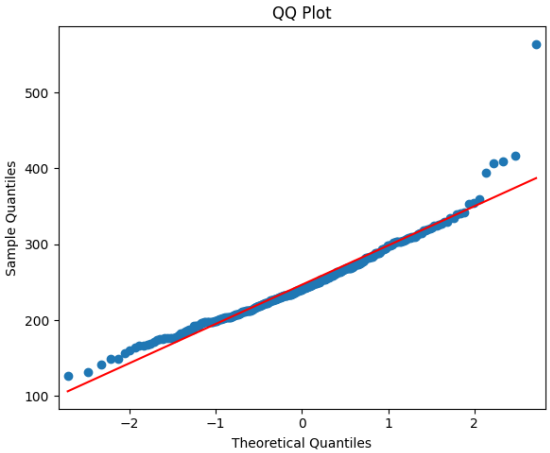
[433]:
```
# Set the number of bins for histograms
num_bins = 20

# Iterate through each column and create histograms and QQ plots
for column in numeric_df.columns:
    # Create a figure with subplots (histogram and QQ plot)
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 5))
```

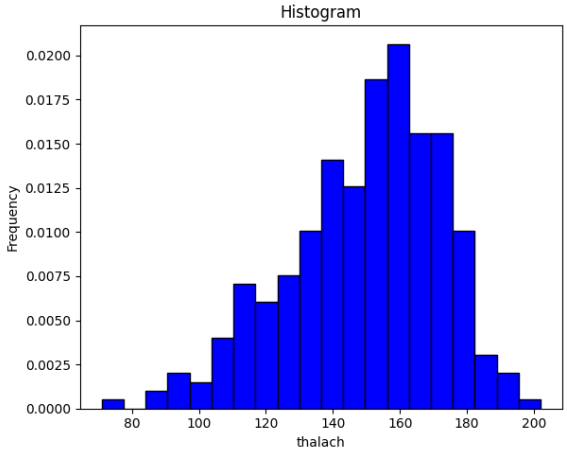
```
    # Create a histogram
    ax1.hist(numeric_df[column], bins=num_bins, color='blue',␣
↪edgecolor='black', density=True)
    ax1.set_xlabel(column)
    ax1.set_ylabel('Frequency')
    ax1.set_title('Histogram')

    # Create a QQ plot for the transformed data
    sm.qqplot(numeric_df[column], line='s', ax=ax2)
    ax2.set_title('QQ Plot')

    plt.tight_layout()
    plt.show()
```

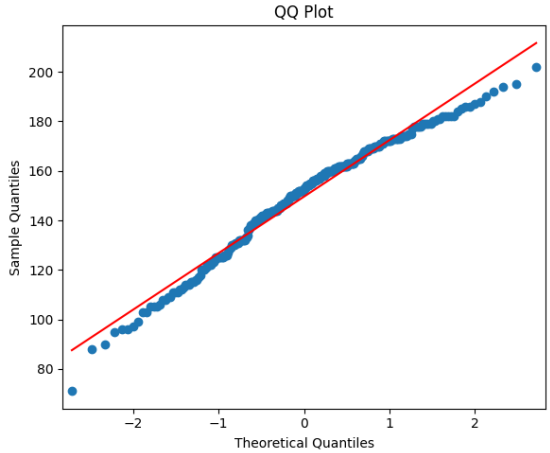


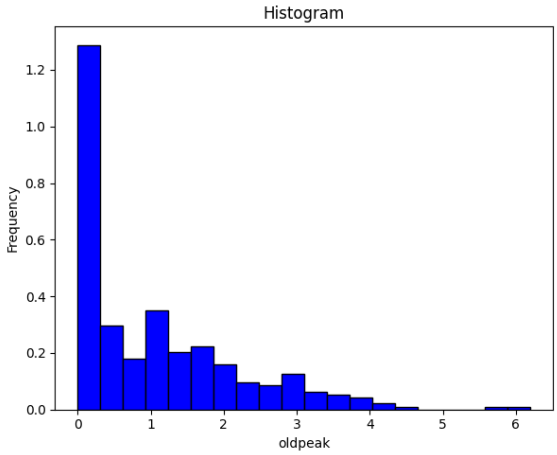


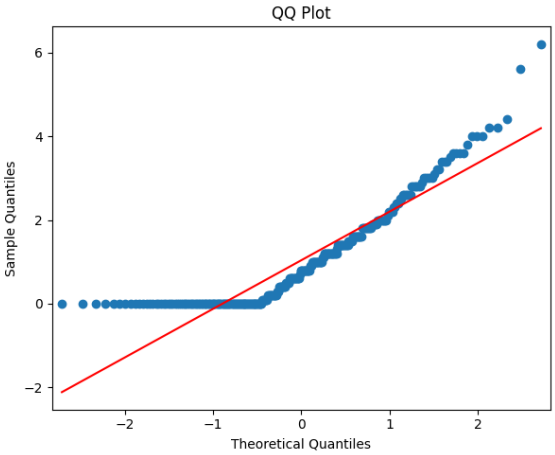

Histogram
Frequency
chol

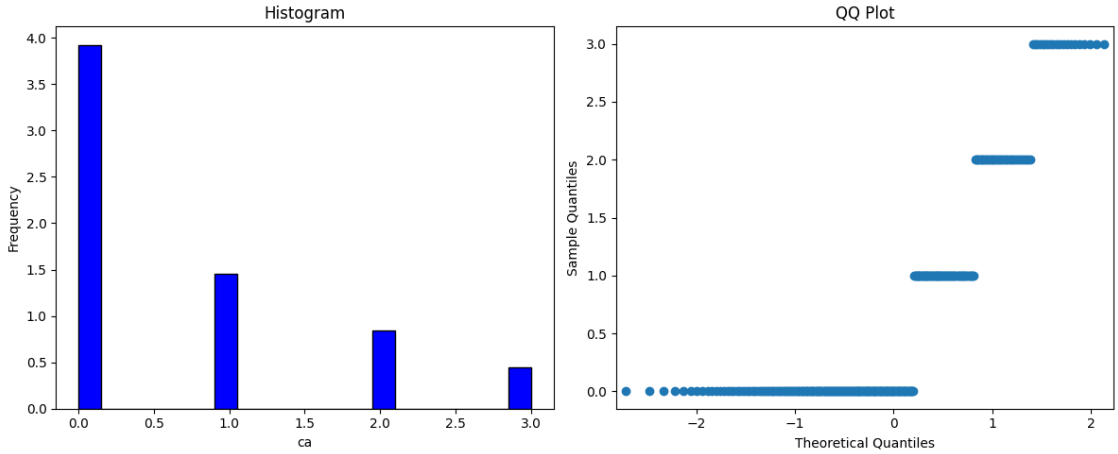

QQ Plot
Sample Quantiles
Theoretical Quantiles


Histogram
Frequency
thalach


QQ Plot
Sample Quantiles
Theoretical Quantiles


Histogram
Frequency
oldpeak


QQ Plot
Sample Quantiles
Theoretical Quantiles



Badając te kwestię postanowiłem sprawdzić najpierw testem Shapiro-Wilka, czy wartości są rozdystrybuowane w sposób normalny, jednak patrząc na histogramy danych i wyniki testu postanowiłem sprawdzić czy dane są w 'przybliżeniu' rozdystrybuowane w sposób normalny, więc postanowiłem sprawdzić mniej restrykcyjnym testem. Wykres kwantylowy (qqplot). Można z tego wyciągnąć, że atrybuty: - thalach - chol - age

mają rozkład podobny do normalnego.

0.5 4. Dla cech kategorycznych: czy rozkład jest w przybliżeniu równomierny?

[434]:
```
categorical_variables = variable_info[(variable_info['type']=='Categorical')]['name']
categorical_variables
```

[434]:
```
1         sex
2          cp
5         fbs
6     restecg
8       exang
10      slope
12       thal
Name: name, dtype: object
```

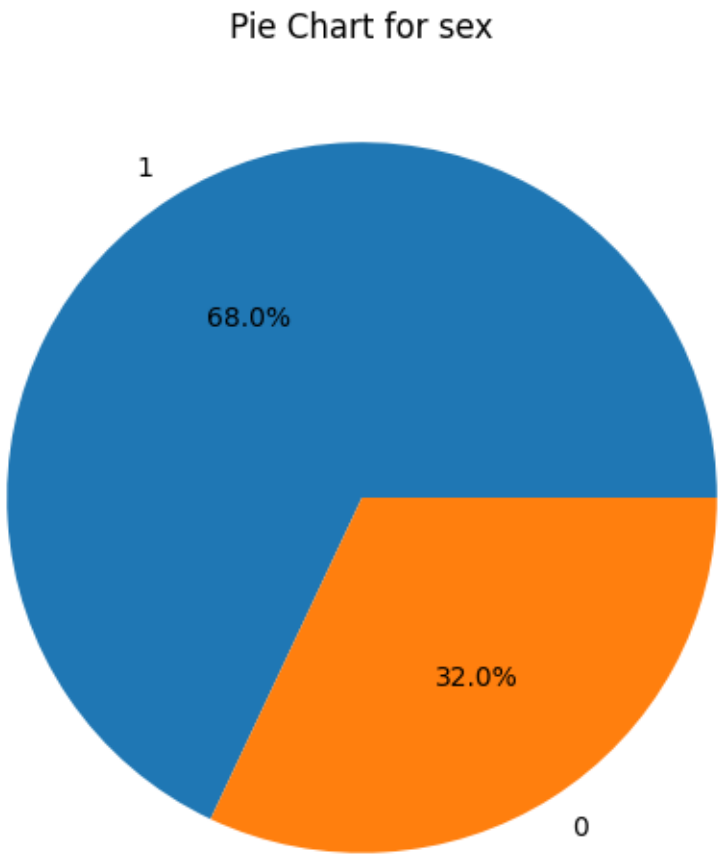
[435]:
```
categorical_df = X[categorical_variables]
categorical_df
```

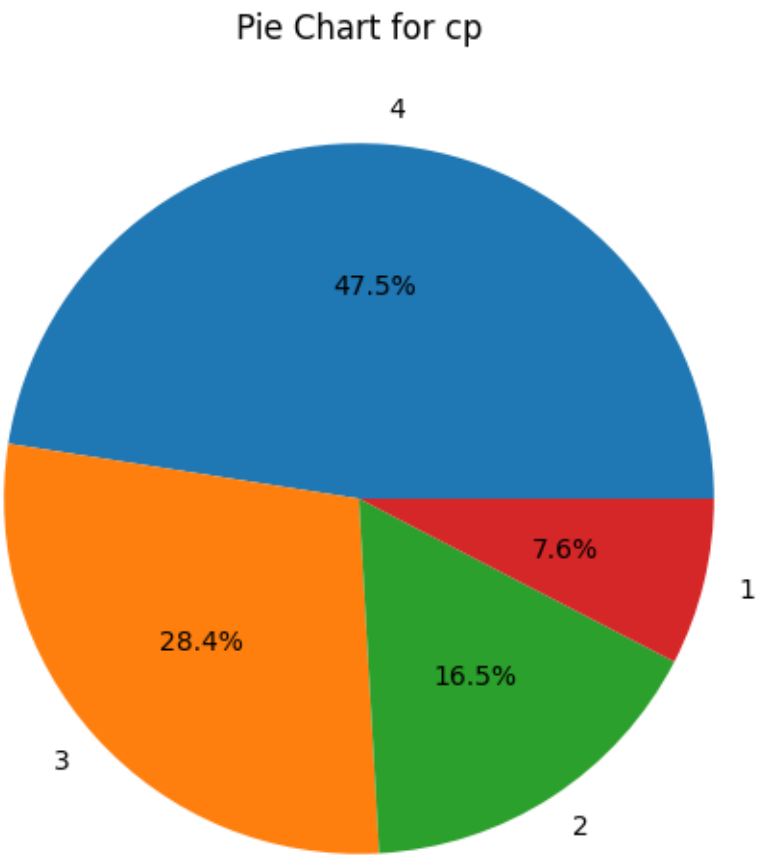
[435]:

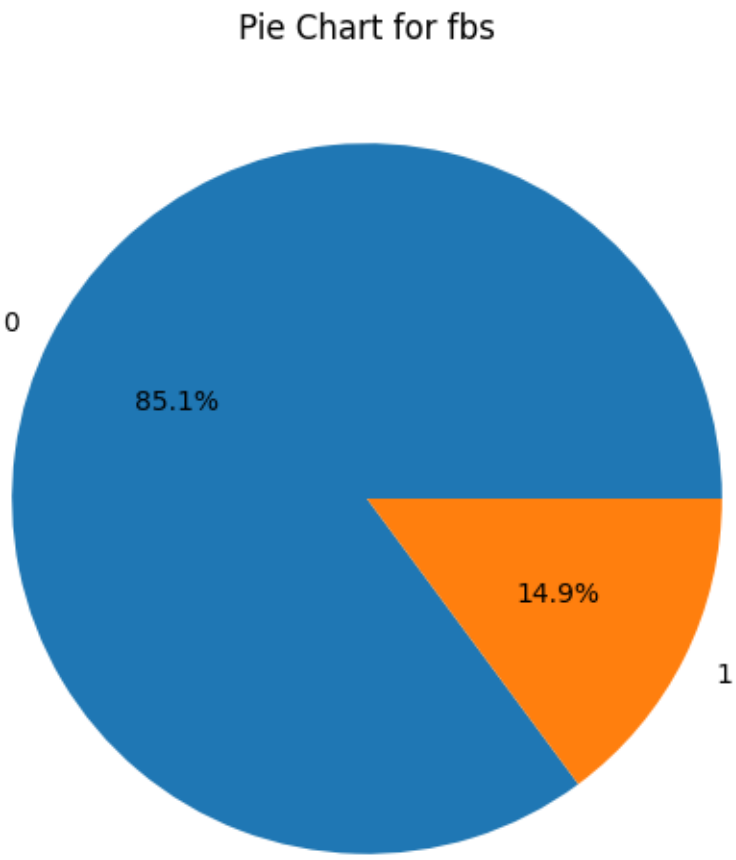
	sex	cp	fbs	restecg	exang	slope	thal
0	1	1	1	2	0	3	6.0
1	1	4	0	2	1	2	3.0
2	1	4	0	2	1	2	7.0
3	1	3	0	0	0	3	3.0
4	0	2	0	2	0	1	3.0

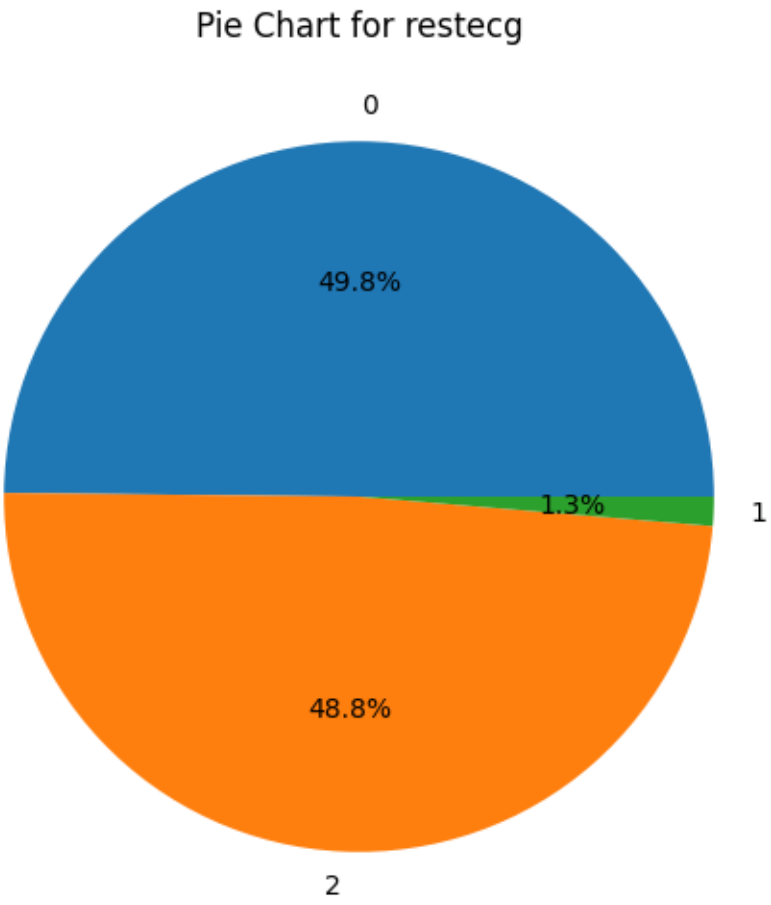
```
..   …  ..  …      …    …    …   …
298   1   1   0       0      0      2   7.0
299   1   4   1       0      0      2   7.0
300   1   4   0       0      1      2   7.0
301   0   2   0       2      0      2   3.0
302   1   3   0       0      0      1   3.0

[303 rows x 7 columns]
```

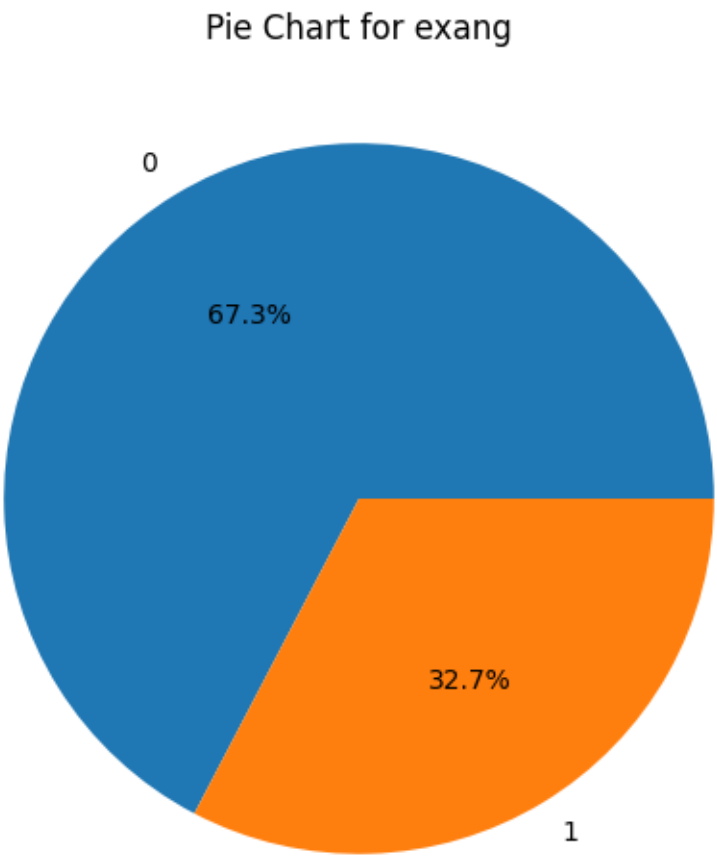
[436]:
```
for column in categorical_df.columns:
    plt.figure(figsize=(6, 6))
    categorical_df[column].value_counts().plot(kind='pie', autopct='%1.1f%%')
    plt.title(f'Pie Chart for {column}')
    plt.ylabel('')
    plt.show()
```

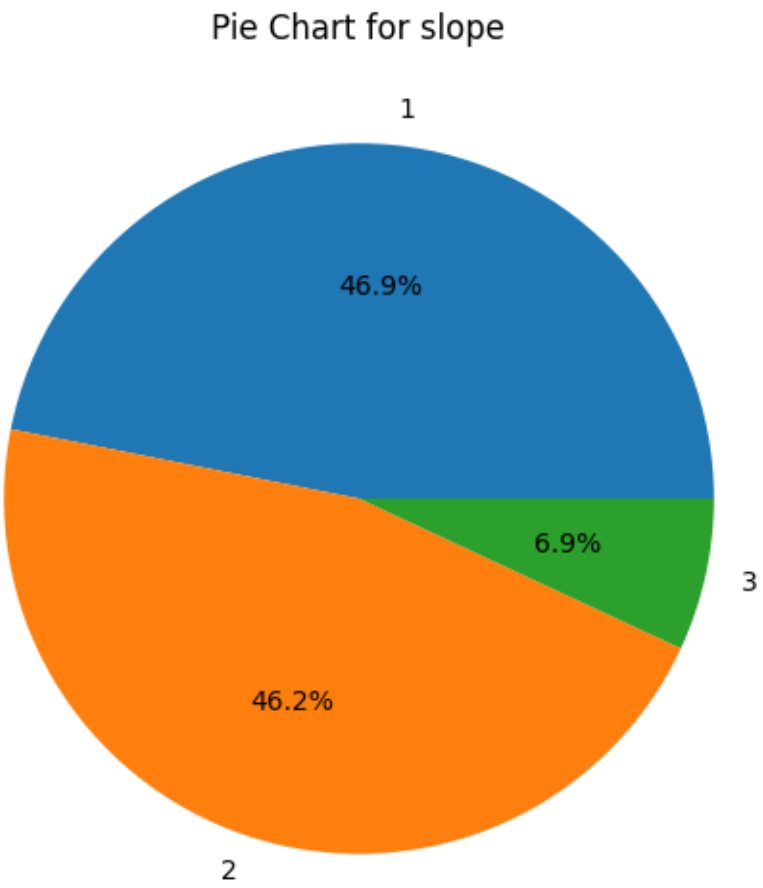


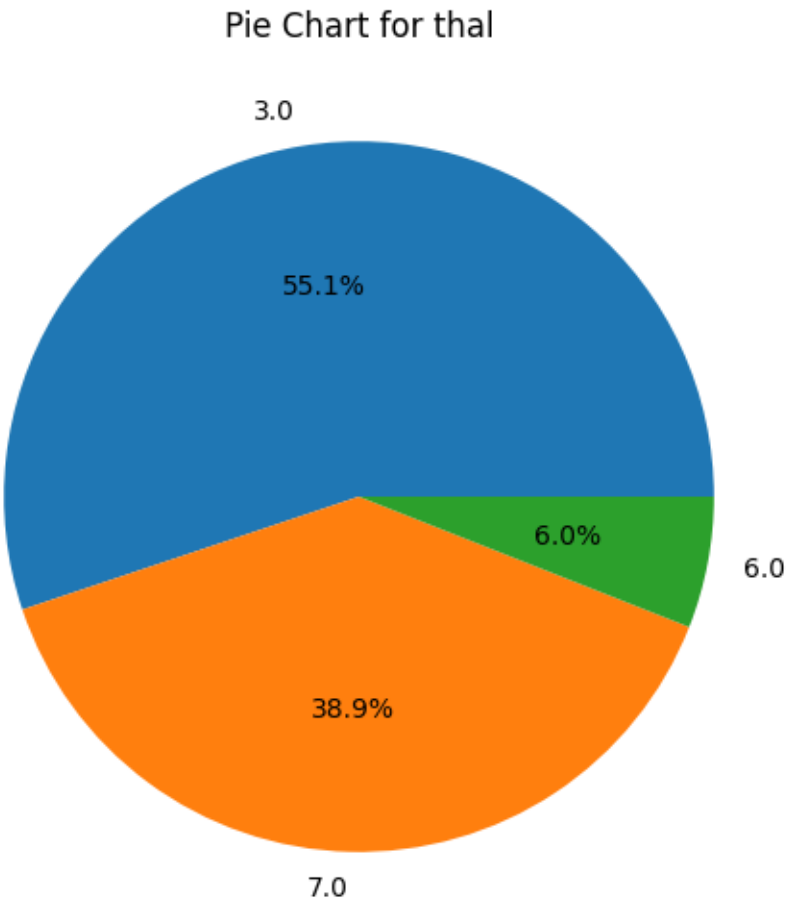

Pie Chart for cp
4
47.5%
7.6%
1
28.4%
16.5%
3
2


Pie Chart for fbs
0
85.1%
14.9%
1


Pie Chart for restecg
0
49.8%
1.3%
1
48.8%
2


Pie Chart for exang
0
67.3%
32.7%
1


Pie Chart for slope
1
46.9%
6.9%
3
46.2%
2



Rozkład wartości atrybutów kategorycznych jest różny, w większości przypadków nierównomierny, zależnie od atrybutu. w niektórych przypadkach jest spora dysproporcja w danych, ale przeważnie dla jednego z 3 przypadków. np. **thal,slope,restec** W przypadku **sex, fbs** znacznie przeważa jedna kategoria. Najbardziej równomierny jest zbiór **cp**

0.6 5. Czy występują cechy brakujące i jaką strategię możemy zastosować żeby je zastąpić?

[437]:
```
X.isnull().sum().sort_values(ascending=False)
```

[437]:
```
ca          4
thal        2
age         0
sex         0
cp          0
trestbps    0
chol        0
```

```
fbs         0
restecg     0
thalach     0
exang       0
oldpeak     0
slope       0
dtype: int64
```

[438]:
```
y.isnull().sum()
```

[438]:
```
num    0
dtype: int64
```

W przypadku **ca** uzupełnię brakujące wartości średnią. Ponieważ jest to wartość numeryczna. W przypadku **thal** uzupełnię je modą, ponieważ jest to atrybut kategoryczny.

[439]:
```
X
```

[439]:
```
      age  sex  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0      63    1   1       145   233    1        2      150      0      2.3
1      67    1   4       160   286    0        2      108      1      1.5
2      67    1   4       120   229    0        2      129      1      2.6
3      37    1   3       130   250    0        0      187      0      3.5
4      41    0   2       130   204    0        2      172      0      1.4
..    ...  ...  ..       ...   ...  ...      ...      ...    ...      ...
298    45    1   1       110   264    0        0      132      0      1.2
299    68    1   4       144   193    1        0      141      0      3.4
300    57    1   4       130   131    0        0      115      1      1.2
301    57    0   2       130   236    0        2      174      0      0.0
302    38    1   3       138   175    0        0      173      0      0.0

     slope   ca  thal
0        3  0.0   6.0
1        2  3.0   3.0
2        2  2.0   7.0
3        3  0.0   3.0
4        1  0.0   3.0
..     ...  ...   ...
298      2  0.0   7.0
299      2  2.0   7.0
300      2  1.0   7.0
301      2  1.0   3.0
302      1  NaN   3.0

[303 rows x 13 columns]
```

[440]:
```
X.loc[:, 'ca'] = X['ca'].fillna(X['ca'].mean())
most_frequent_category = X['thal'].mode().iloc[0]
```

```
X.loc[:, 'thal'] = X['thal'].fillna(most_frequent_category)
X.isnull().sum().sort_values(ascending=False)
```

[440]:
```
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
dtype: int64
```

0.7 6. kod przekształcający dane do macierzy cech liczbowych (przykłady × cechy).

[441]:
```
df = pd.get_dummies(X, columns=['cp', 'restecg', 'slope', 'thal'],
                                prefix=['cp', 'restecg', 'slope', 'thal']).
 ↪astype('int64')
df
```

[441]:

	age	sex	trestbps	chol	fbs	thalach	exang	oldpeak	ca	cp_1	…	\
0	63	1	145	233	1	150	0	2	0	1	…	
1	67	1	160	286	0	108	1	1	3	0	…	
2	67	1	120	229	0	129	1	2	2	0	…	
3	37	1	130	250	0	187	0	3	0	0	…	
4	41	0	130	204	0	172	0	1	0	0	…	
..	…	…	…	…	…	…	…	…	..	…	…	
298	45	1	110	264	0	132	0	1	0	1	…	
299	68	1	144	193	1	141	0	3	2	0	…	
300	57	1	130	131	0	115	1	1	1	0	…	
301	57	0	130	236	0	174	0	0	1	0	…	
302	38	1	138	175	0	173	0	0	0	0	…	

	cp_4	restecg_0	restecg_1	restecg_2	slope_1	slope_2	slope_3	\
0	0	0	0	1	0	0	1	
1	1	0	0	1	0	1	0	
2	1	0	0	1	0	1	0	
3	0	1	0	0	0	0	1	
4	0	0	0	1	1	0	0	
..	…	…	…	…	…	…	…	
298	0	1	0	0	0	1	0	

```
299     1          1          0          0        0        1        0
300     1          1          0          0        0        1        0
301     0          0          0          1        0        1        0
302     0          1          0          0        1        0        0

     thal_3.0  thal_6.0  thal_7.0
0           0         1         0
1           1         0         0
2           0         0         1
3           1         0         0
4           1         0         0
..        …       …       …
298         0         0         1
299         0         0         1
300         0         0         1
301         1         0         0
302         1         0         0

[303 rows x 22 columns]
```