boston-housing

April 24, 2024

[51]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import ttest_ind, f_oneway, pearsonr
from statsmodels.formula.api import ols
import statsmodels.api as sm
```

[52]:
```
boston_url = 'https://cf-courses-data.s3.us.cloud-object-storage.appdomain.
 ↪cloud/IBMDeveloperSkillsNetwork-ST0151EN-SkillsNetwork/labs/boston_housing.
 ↪csv'
boston_df=pd.read_csv(boston_url)
```

[53]:
```
boston_df.head()
```

[53]:

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	LSTAT	MEDV
0	0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	4.98	24.0
1	1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	9.14	21.6
2	2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	4.03	34.7
3	3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	2.94	33.4
4	4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	5.33	36.2

[54]:
```
boston_df.tail()
```

[54]:

	Unnamed: 0	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	LSTAT	MEDV
501	501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	9.67	22.4
502	502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	9.08	20.6
503	503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	5.64	23.9
504	504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	6.48	22.0
505	505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	7.88	11.9

```
       TAX  PTRATIO  LSTAT  MEDV
501  273.0     21.0   9.67  22.4
502  273.0     21.0   9.08  20.6
503  273.0     21.0   5.64  23.9
504  273.0     21.0   6.48  22.0
505  273.0     21.0   7.88  11.9
```

[55]:
```
boston_df = boston_df.drop(columns=['Unnamed: 0'])
```

[56]:
```
boston_df.head()
```

[56]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575  65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421  78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185  61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998  45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147  54.2  6.0622  3.0  222.0

   PTRATIO  LSTAT  MEDV
0     15.3   4.98  24.0
1     17.8   9.14  21.6
2     17.8   4.03  34.7
3     18.7   2.94  33.4
4     18.7   5.33  36.2
```

[57]:
```
boston_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  LSTAT    506 non-null    float64
 12  MEDV     506 non-null    float64
dtypes: float64(13)
```

```
memory usage: 51.5 KB
```

[58]:
```
boston_df.dtypes
```

[58]:
```
CRIM       float64
ZN         float64
INDUS      float64
CHAS       float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD        float64
TAX        float64
PTRATIO    float64
LSTAT      float64
MEDV       float64
dtype: object
```

[59]:
```
boston_df.shape
```

[59]:
```
(506, 13)
```

[60]:
```
boston_df.describe()
```

[60]:

	CRIM	ZN	INDUS	CHAS	NOX	RM
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000

	AGE	DIS	RAD	TAX	PTRATIO	LSTAT
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	68.574901	3.795043	9.549407	408.237154	18.455534	12.653063
std	28.148861	2.105710	8.707259	168.537116	2.164946	7.141062
min	2.900000	1.129600	1.000000	187.000000	12.600000	1.730000
25%	45.025000	2.100175	4.000000	279.000000	17.400000	6.950000
50%	77.500000	3.207450	5.000000	330.000000	19.050000	11.360000
75%	94.075000	5.188425	24.000000	666.000000	20.200000	16.955000
max	100.000000	12.126500	24.000000	711.000000	22.000000	37.970000

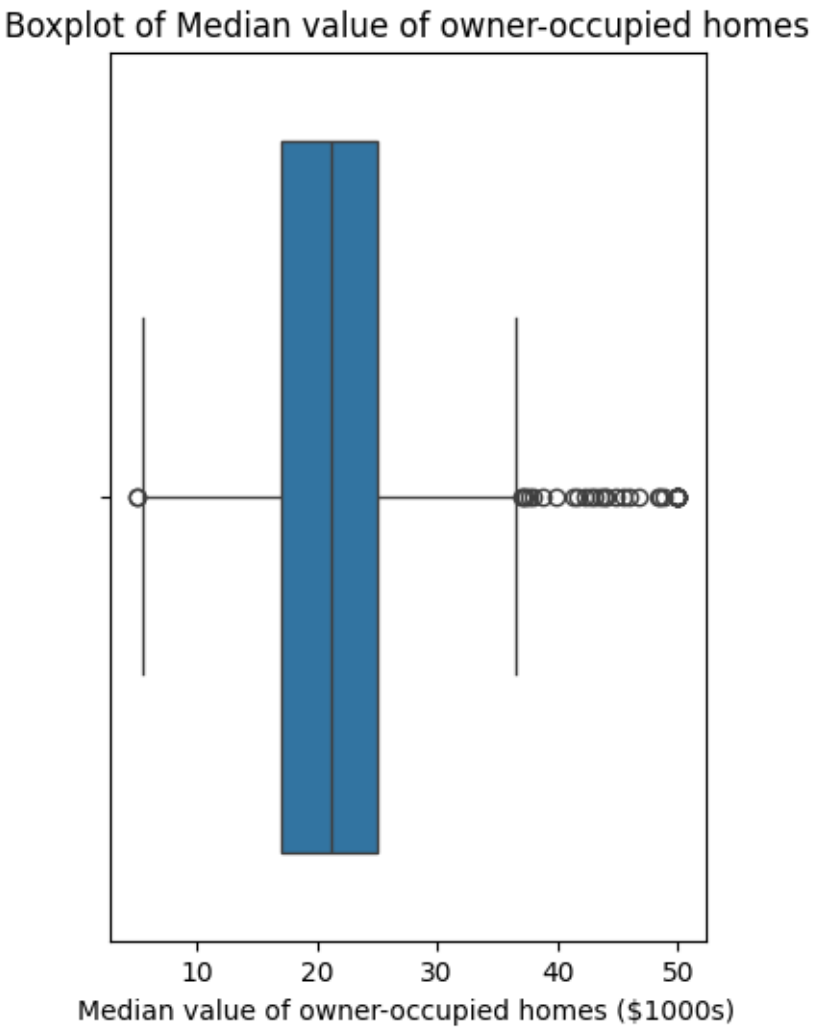
	MEDV
count	506.000000

```
mean    22.532806
std      9.197104
min      5.000000
25%     17.025000
50%     21.200000
75%     25.000000
max     50.000000
```

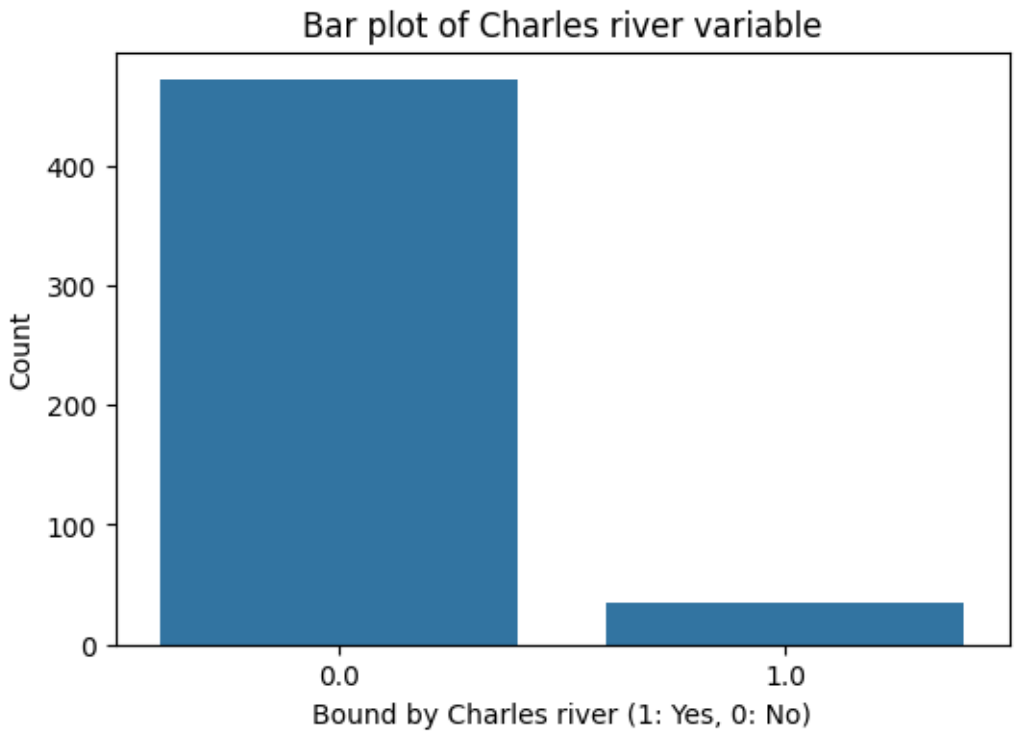
[61]:
```
boston_df.corr()
```

[61]:
```
             CRIM        ZN     INDUS      CHAS       NOX        RM        AGE  \
CRIM     1.000000 -0.200469  0.406583 -0.055892  0.420972 -0.219247  0.352734
ZN      -0.200469  1.000000 -0.533828 -0.042697 -0.516604  0.311991 -0.569537
INDUS    0.406583 -0.533828  1.000000  0.062938  0.763651 -0.391676  0.644779
CHAS    -0.055892 -0.042697  0.062938  1.000000  0.091203  0.091251  0.086518
NOX      0.420972 -0.516604  0.763651  0.091203  1.000000 -0.302188  0.731470
RM      -0.219247  0.311991 -0.391676  0.091251 -0.302188  1.000000 -0.240265
AGE      0.352734 -0.569537  0.644779  0.086518  0.731470 -0.240265  1.000000
DIS     -0.379670  0.664408 -0.708027 -0.099176 -0.769230  0.205246 -0.747881
RAD      0.625505 -0.311948  0.595129 -0.007368  0.611441 -0.209847  0.456022
TAX      0.582764 -0.314563  0.720760 -0.035587  0.668023 -0.292048  0.506456
PTRATIO  0.289946 -0.391679  0.383248 -0.121515  0.188933 -0.355501  0.261515
LSTAT    0.455621 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339
MEDV    -0.388305  0.360445 -0.483725  0.175260 -0.427321  0.695360 -0.376955

              DIS       RAD       TAX   PTRATIO     LSTAT      MEDV
CRIM    -0.379670  0.625505  0.582764  0.289946  0.455621 -0.388305
ZN       0.664408 -0.311948 -0.314563 -0.391679 -0.412995  0.360445
INDUS   -0.708027  0.595129  0.720760  0.383248  0.603800 -0.483725
CHAS    -0.099176 -0.007368 -0.035587 -0.121515 -0.053929  0.175260
NOX     -0.769230  0.611441  0.668023  0.188933  0.590879 -0.427321
RM       0.205246 -0.209847 -0.292048 -0.355501 -0.613808  0.695360
AGE     -0.747881  0.456022  0.506456  0.261515  0.602339 -0.376955
DIS      1.000000 -0.494588 -0.534432 -0.232471 -0.496996  0.249929
RAD     -0.494588  1.000000  0.910228  0.464741  0.488676 -0.381626
TAX     -0.534432  0.910228  1.000000  0.460853  0.543993 -0.468536
PTRATIO -0.232471  0.464741  0.460853  1.000000  0.374044 -0.507787
LSTAT   -0.496996  0.488676  0.543993  0.374044  1.000000 -0.737663
MEDV     0.249929 -0.381626 -0.468536 -0.507787 -0.737663  1.000000
```

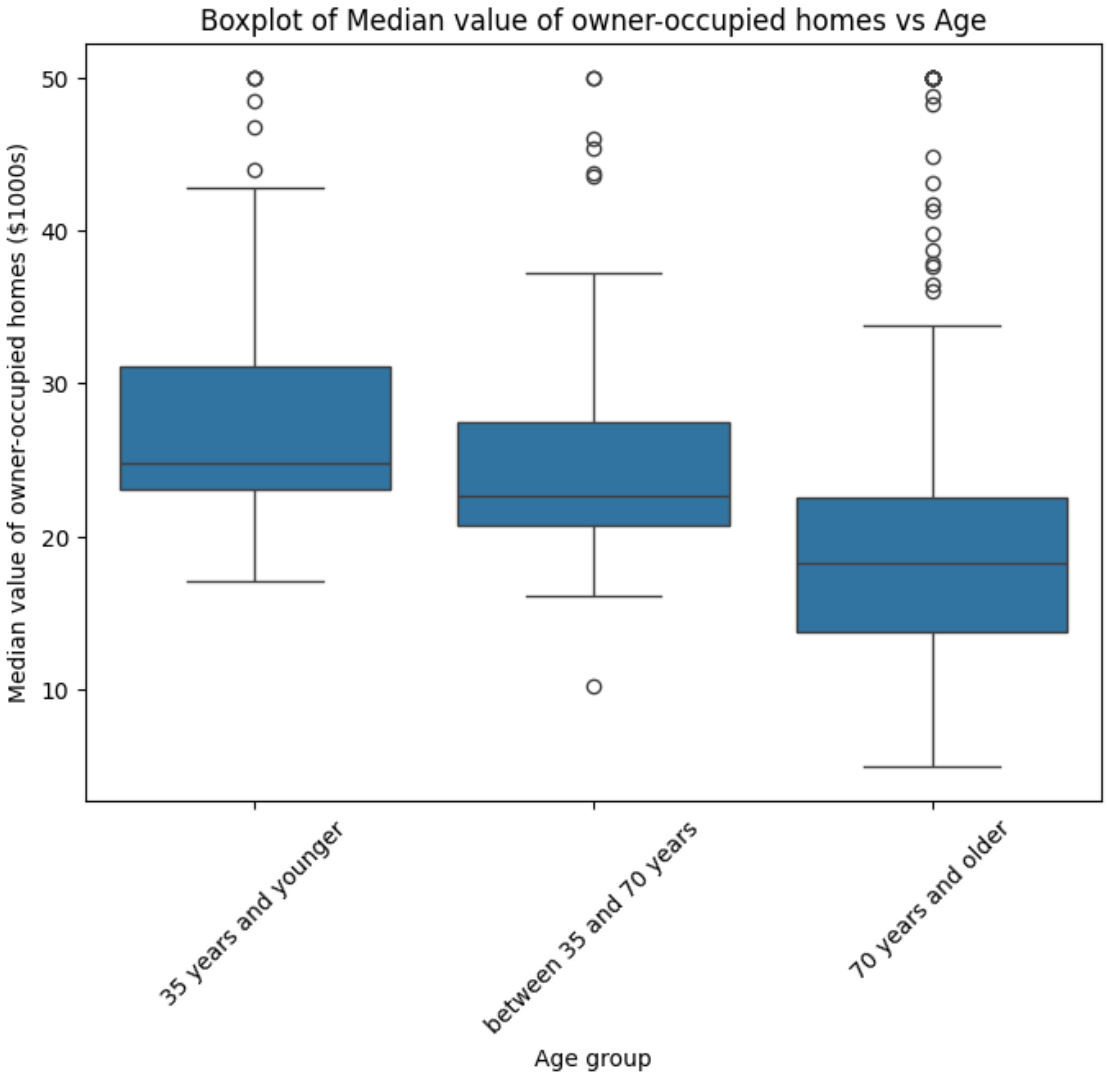
[62]:
```
plt.figure(figsize=(4, 6))
sns.boxplot(x=boston_df['MEDV'])
plt.title('Boxplot of Median value of owner-occupied homes')
plt.xlabel('Median value of owner-occupied homes ($1000s)')
plt.show()
```



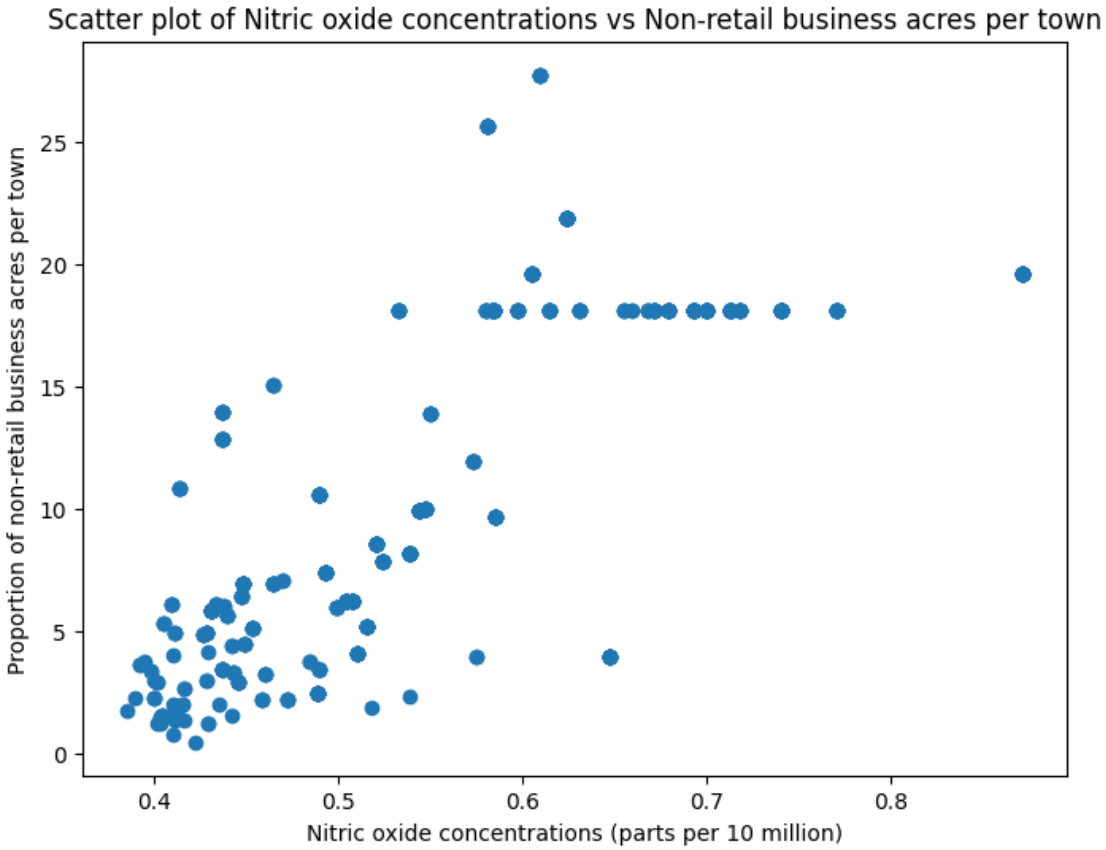
[63]:
```
plt.figure(figsize=(6, 4))
sns.countplot(x='CHAS', data=boston_df)
plt.title('Bar plot of Charles river variable')
plt.xlabel('Bound by Charles river (1: Yes, 0: No)')
plt.ylabel('Count')
plt.show()
```



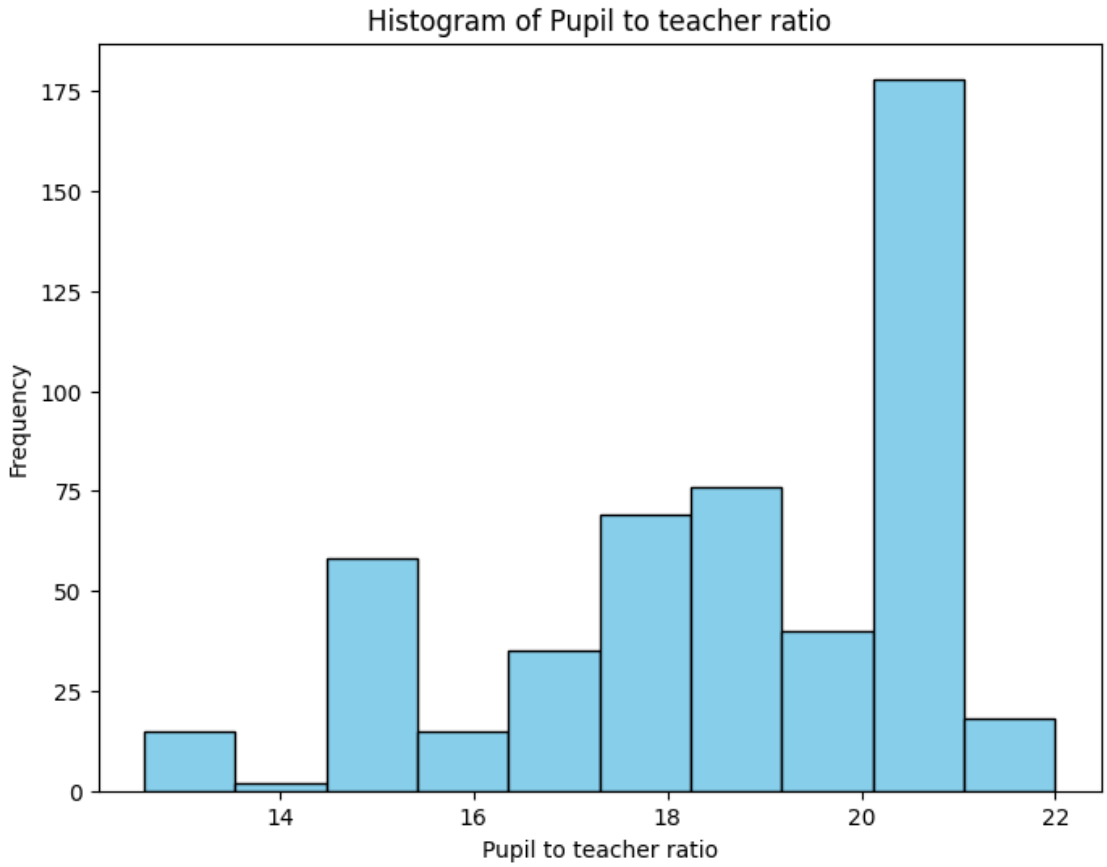
[64]:
```
# Discretize the age variable into three groups
boston_df['AGE_group'] = pd.cut(boston_df['AGE'], bins=[0, 35, 70, np.inf],␣
 ↪labels=['35 years and younger', 'between 35 and 70 years', '70 years and␣
 ↪older'])

plt.figure(figsize=(8, 6))
sns.boxplot(x='AGE_group', y='MEDV', data=boston_df)
plt.title('Boxplot of Median value of owner-occupied homes vs Age')
plt.xlabel('Age group')
plt.ylabel('Median value of owner-occupied homes ($1000s)')
plt.xticks(rotation=45)
plt.show()
```



[65]:
```
plt.figure(figsize=(8, 6))
plt.scatter(boston_df['NOX'], boston_df['INDUS'])
plt.title('Scatter plot of Nitric oxide concentrations vs Non-retail business␣
 ↪acres per town')
plt.xlabel('Nitric oxide concentrations (parts per 10 million)')
plt.ylabel('Proportion of non-retail business acres per town')
plt.show()
```



[66]:
```
plt.figure(figsize=(8, 6))
plt.hist(boston_df['PTRATIO'], bins=10, color='skyblue', edgecolor='black')
plt.title('Histogram of Pupil to teacher ratio')
plt.xlabel('Pupil to teacher ratio')
plt.ylabel('Frequency')
plt.show()
```



[67]:
```
# Separate data into two groups based on Charles river (0: Not bounded, 1:␣
 ↪Bounded)
bounded = boston_df[boston_df['CHAS'] == 1]['MEDV']
not_bounded = boston_df[boston_df['CHAS'] == 0]['MEDV']

# Perform t-test
t_statistic, p_value = ttest_ind(bounded, not_bounded)

print("T-statistic:", t_statistic)
print("P-value:", p_value)

alpha = 0.05
if p_value < alpha:
    print("Reject Null Hypothesis: There is a significant difference in median␣
 ↪value of houses bounded by the Charles river and those not bounded by the␣
 ↪river.")
else:
```

```
    print("Fail to Reject Null Hypothesis: There is no significant difference␣
 ↪in median value of houses bounded by the Charles river and those not bounded␣
 ↪by the river.")
```

```
T-statistic: 3.996437466090509
P-value: 7.390623170519905e-05
Reject Null Hypothesis: There is a significant difference in median value of
houses bounded by the Charles river and those not bounded by the river.
```

[68]:
```
# Perform ANOVA
result = ols('MEDV ~ C(AGE_group)', data=boston_df).fit()
anova_table = sm.stats.anova_lm(result, typ=2)

print(anova_table)

p_value_anova = anova_table['PR(>F)'][0]

alpha = 0.05
if p_value_anova < alpha:
    print("Reject Null Hypothesis: There is a significant difference in median␣
 ↪values of houses for at least one proportion of owner occupied units built␣
 ↪prior to 1940.")
else:
    print("Fail to Reject Null Hypothesis: There is no significant difference␣
 ↪in median values of houses for each proportion of owner occupied units built␣
 ↪prior to 1940.")
```

```
                   sum_sq     df          F        PR(>F)
C(AGE_group)   5401.731883    2.0  36.40765  1.710501e-15
Residual      37314.563532  503.0       NaN           NaN
Reject Null Hypothesis: There is a significant difference in median values of
houses for at least one proportion of owner occupied units built prior to 1940.

C:\Users\USER\AppData\Local\Temp\ipykernel_13828\325443091.py:7: FutureWarning:
Series.__getitem__ treating keys as positions is deprecated. In a future
version, integer keys will always be treated as labels (consistent with
DataFrame behavior). To access a value by position, use `ser.iloc[pos]`
  p_value_anova = anova_table['PR(>F)'][0]
```

[69]:
```
# Perform Pearson correlation
correlation, p_value_corr = pearsonr(boston_df['NOX'], boston_df['INDUS'])

print("Correlation coefficient:", correlation)
print("P-value:", p_value_corr)

alpha = 0.05
if p_value_corr < alpha:
```

```
    print("Reject Null Hypothesis: There is a relationship between Nitric oxide␣
 ↪concentrations and proportion of non-retail business acres per town.")
else:
    print("Fail to Reject Null Hypothesis: There is no relationship between␣
 ↪Nitric oxide concentrations and proportion of non-retail business acres per␣
 ↪town.")
```

```
Correlation coefficient: 0.7636514469209156
P-value: 7.91336106123623e-98
Reject Null Hypothesis: There is a relationship between Nitric oxide
concentrations and proportion of non-retail business acres per town.
```

[70]:
```
# Perform regression analysis
result_regression = ols('MEDV ~ DIS', data=boston_df).fit()

print(result_regression.summary())

p_value_regression = result_regression.pvalues['DIS']

alpha = 0.05
if p_value_regression < alpha:
    print("Reject Null Hypothesis: The weighted distance to the five Boston␣
 ↪employment centres has an impact on the median value of owner occupied homes.
 ↪")
else:
    print("Fail to Reject Null Hypothesis: The weighted distance to the five␣
 ↪Boston employment centres has no impact on the median value of owner␣
 ↪occupied homes.")
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   MEDV   R-squared:                       0.062
Model:                            OLS   Adj. R-squared:                  0.061
Method:                 Least Squares   F-statistic:                     33.58
Date:                Wed, 24 Apr 2024   Prob (F-statistic):           1.21e-08
Time:                        17:15:57   Log-Likelihood:                -1823.9
No. Observations:                 506   AIC:                             3652.
Df Residuals:                     504   BIC:                             3660.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     18.3901      0.817     22.499      0.000      16.784      19.996
DIS            1.0916      0.188      5.795      0.000       0.722       1.462
==============================================================================
Omnibus:                      139.779   Durbin-Watson:                   0.570
```

Prob(Omnibus):	0.000	Jarque-Bera (JB):	305.104
Skew:	1.466	Prob(JB):	5.59e-67
Kurtosis:	5.424	Cond. No.	9.32

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
Reject Null Hypothesis: The weighted distance to the five Boston employment centres has an impact on the median value of owner occupied homes.