In [1]:
```
import numpy
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from scipy.stats.mstats import normaltest
```

In [3]:
```
data = pd.read_csv('../data/california_housing_pricing.csv')
data.head()
```

Out[3]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households |
|---|---|---|---|---|---|---|---|
| **0** | -122.23 | 37.88 | 41.0 | 880.0 | 129.0 | 322.0 | 126.0 |
| **1** | -122.22 | 37.86 | 21.0 | 7099.0 | 1106.0 | 2401.0 | 1138.0 |
| **2** | -122.24 | 37.85 | 52.0 | 1467.0 | 190.0 | 496.0 | 177.0 |
| **3** | -122.25 | 37.85 | 52.0 | 1274.0 | 235.0 | 558.0 | 219.0 |
| **4** | -122.25 | 37.85 | 52.0 | 1627.0 | 280.0 | 565.0 | 259.0 |

In [4]:
```
data_dictionary = pd.read_csv('../data/data_dictionary.csv')
data_dictionary
```

Out[4]:

| | Field | Meaning |
|---|---|---|
| **0** | longitude | A measure of how far west a house is; a highe... |
| **1** | latitude | A measure of how far north a house is; a high... |
| **2** | housing_median_age | Median age of a house within a block; a lower... |
| **3** | total_rooms | Total number of rooms within a block |
| **4** | total_bedrooms | Total number of bedrooms within a block |
| **5** | population | Total number of people residing within a block |
| **6** | households | Total number of households, a group of people... |
| **7** | median_income) | Median income for households within a block o... |
| **8** | median_house_value) | Median house value for households within a bl... |
| **9** | ocean_proximityea | Location of the house w.r.t ocean/s |

In [5]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20433 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   median_income       20640 non-null  float64
 8   median_house_value  20640 non-null  float64
 9   ocean_proximity     20640 non-null  object 
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

In [6]:
```
data.total_bedrooms = data.total_bedrooms.fillna(data.total_bedrooms.median())
```

In [7]:
```
numeric_cols = list(data.select_dtypes([int, float]).columns)
numeric_cols
```

Out[7]:
```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income',
 'median_house_value']
```

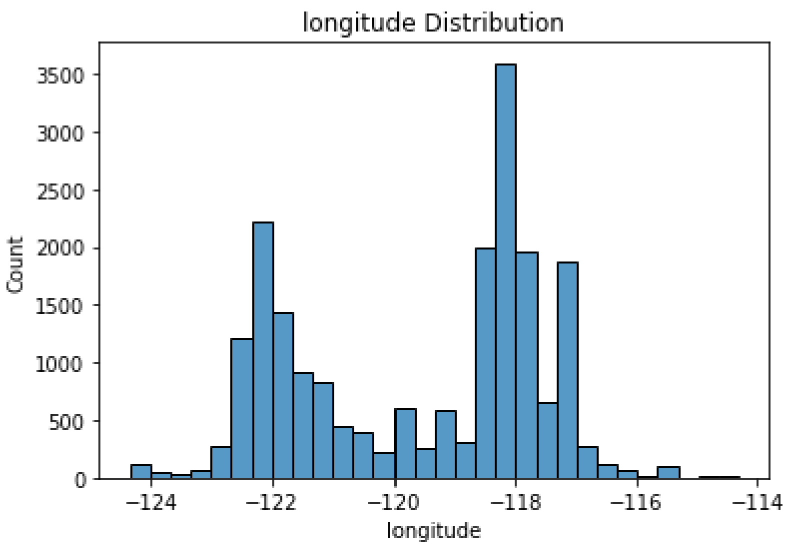
# EDA

In [8]:
```
normaltest(data.median_house_value.values)
```

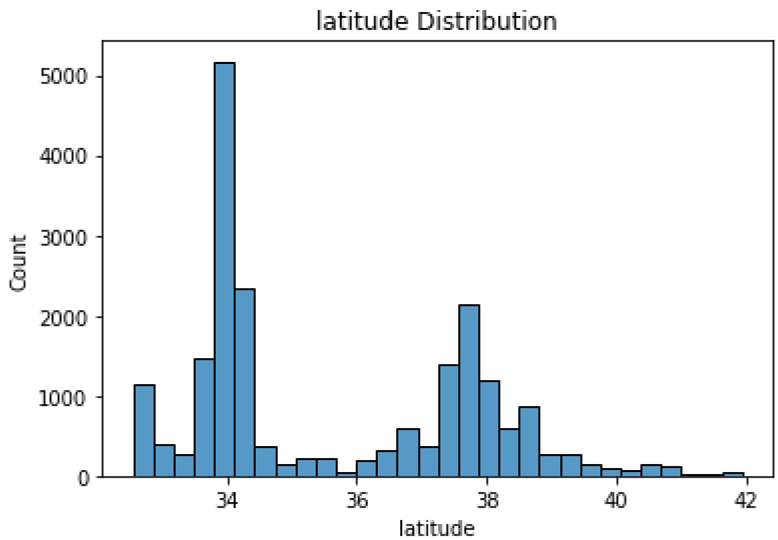
Out[8]:
```
NormaltestResult(statistic=2430.931051066072, pvalue=0.0)
```

In [9]:
```
for col in numeric_cols:
    _, pvalue = normaltest(data[col].values)
    if pvalue < 0.05:
        result = 'not normally distributed'
    else:
        result = 'normally distributed'
    print('Normality Test P-value:',str(pvalue),',    Decision: ',result)

    plt.figure(figsize=(6,4))
    sns.histplot(data=data, x = col, bins=30)
    plt.title(f'{col} Distribution')
    plt.show()
```

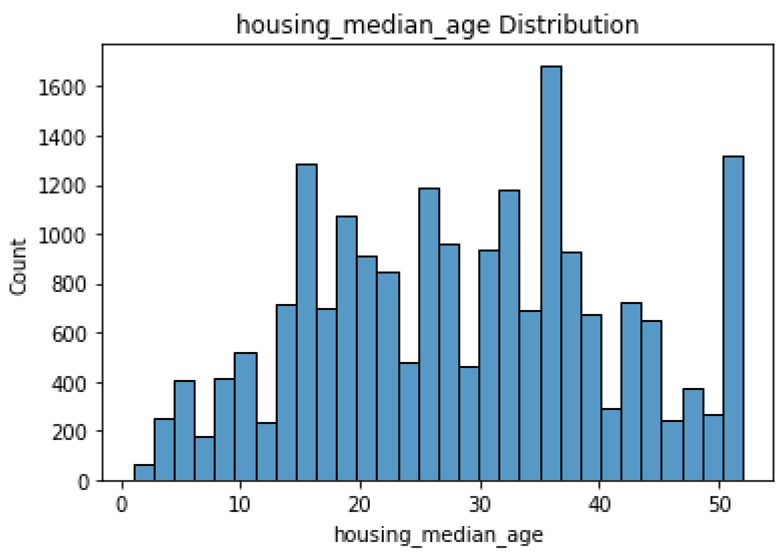
```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



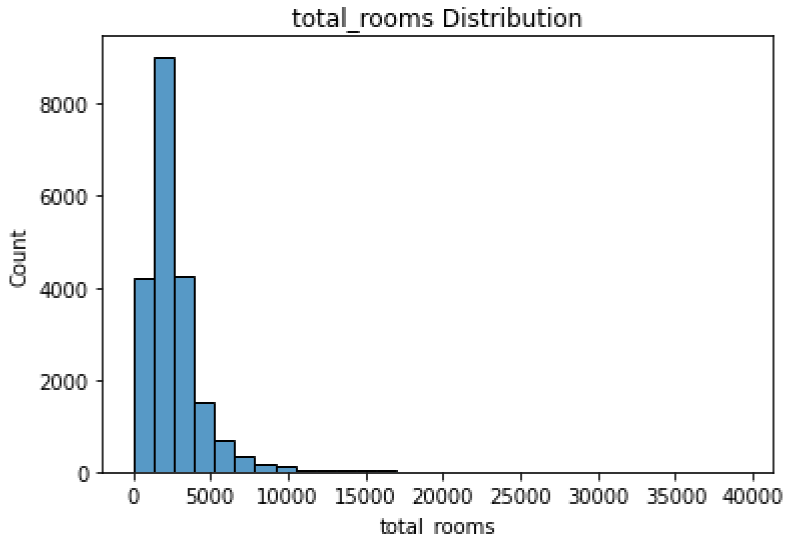

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



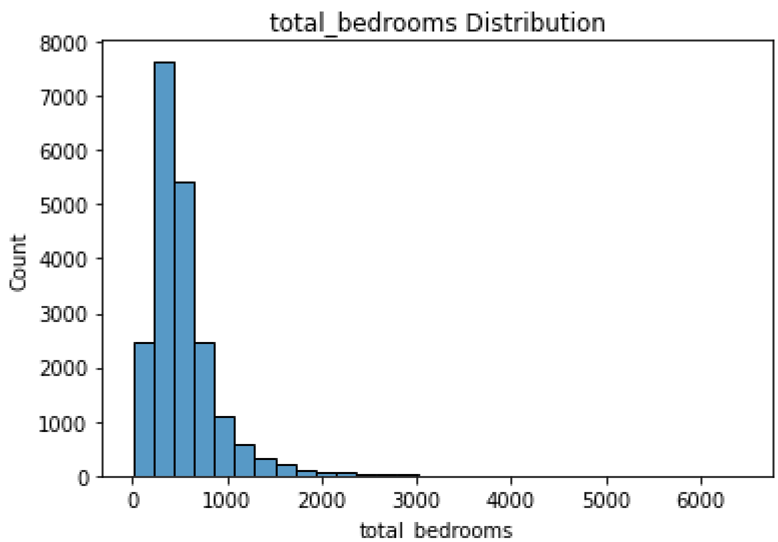

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



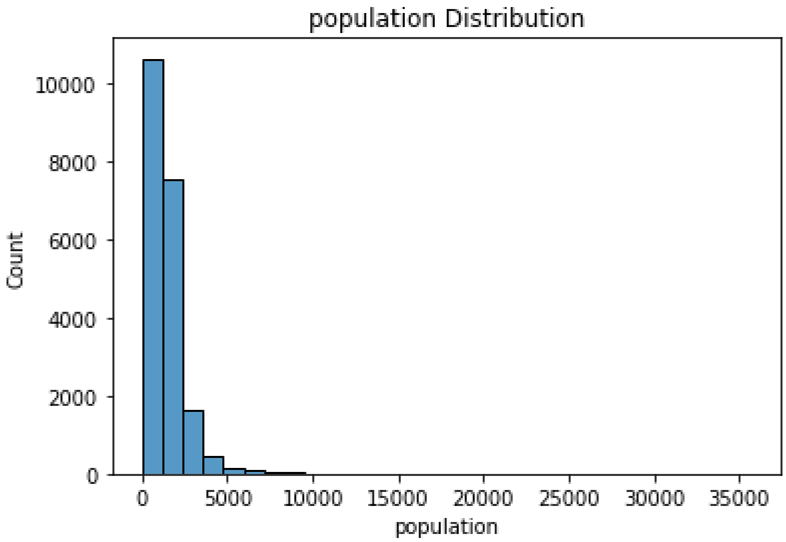

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



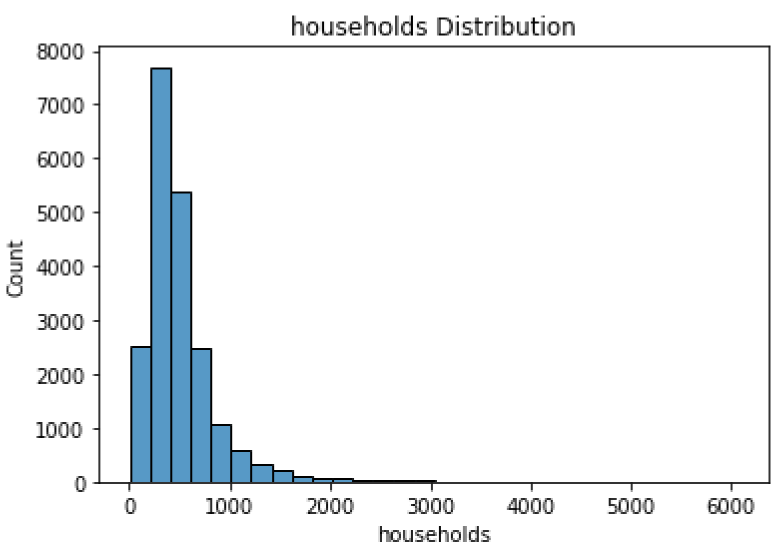

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



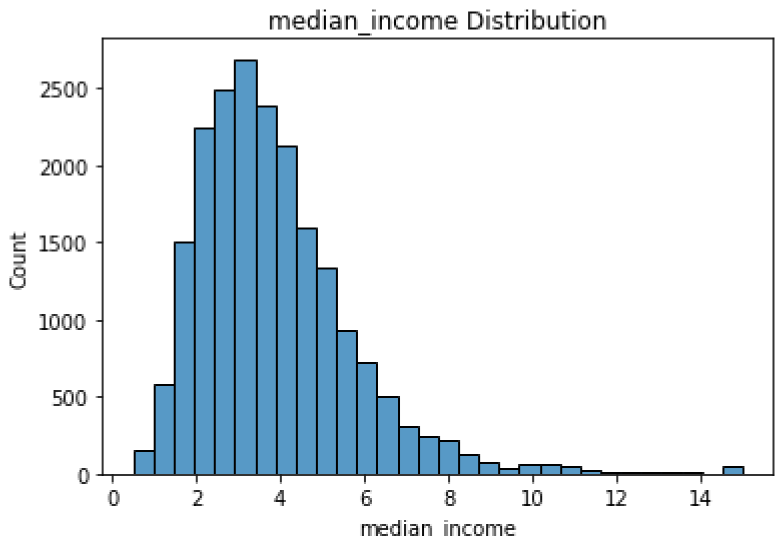

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



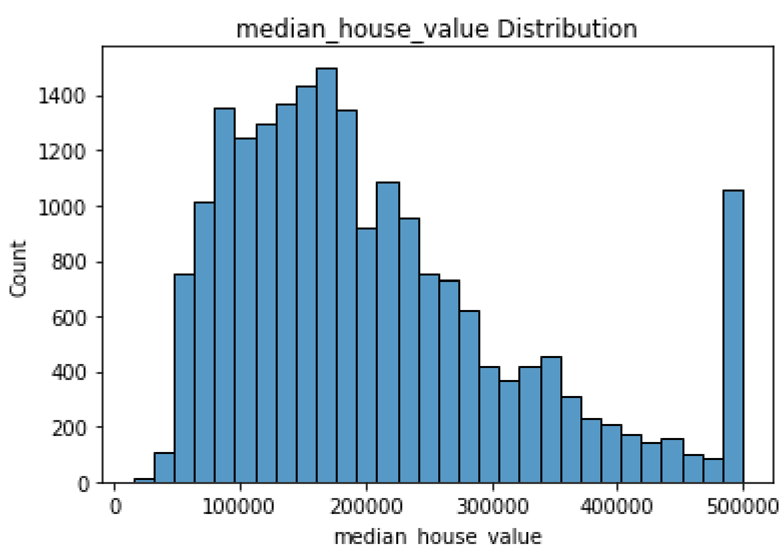

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



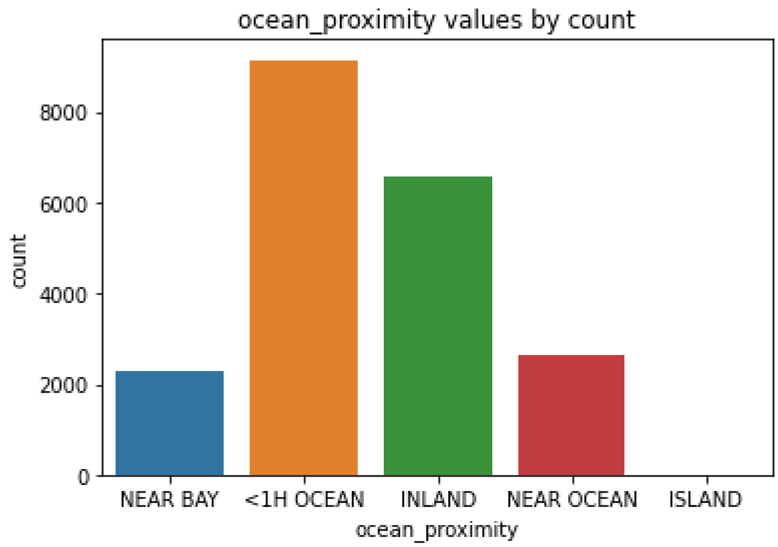

```
Normality Test P-value: 0.0 ,    Decision:  not normally distributed
```



The numeric columns including the targte are not normally distributed

In [10]:
```
sns.countplot(x = data.ocean_proximity)
plt.title('ocean_proximity values by count');
```

Out[10]:
```
Text(0.5, 1.0, 'ocean_proximity values by count')
```




## Features Selection

In this section, I'll conduct statistical stest to determine which features have siginificant relationships with the target in order to select them for the model.

FOr the numeric features, I'll use correlation test, and for the categorical features, I'll use ANOVA test.

In [11]:
```
import scipy.stats
```

Testing the significance of the numeric features

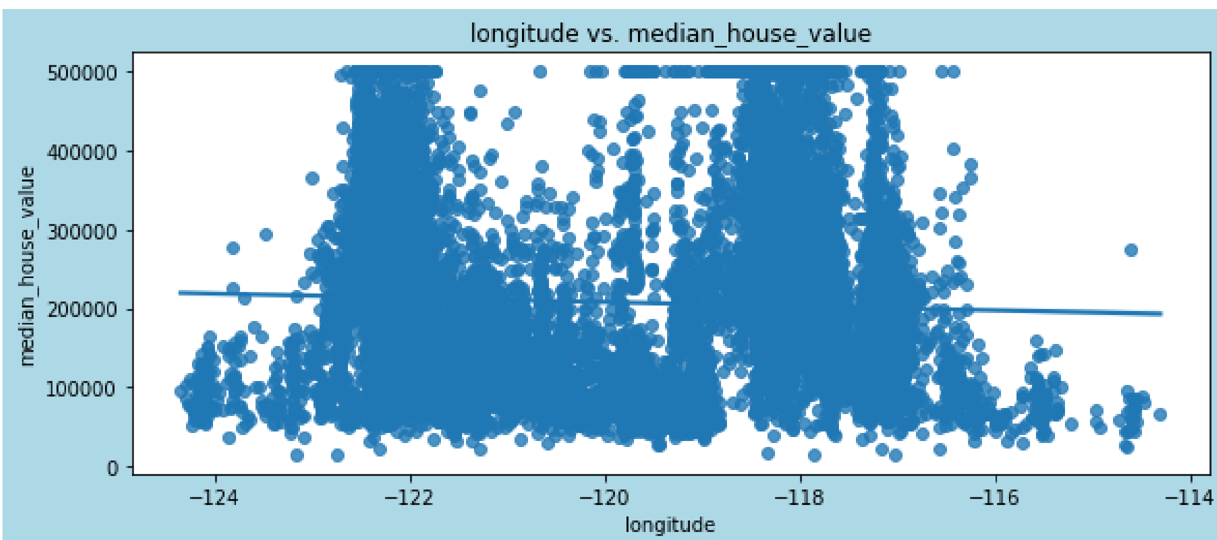
In [12]:
```
numeric_cols_stats = [col for col in numeric_cols if col != 'median_house_value']
```

In [13]:
```
numeric_cols_stats
```

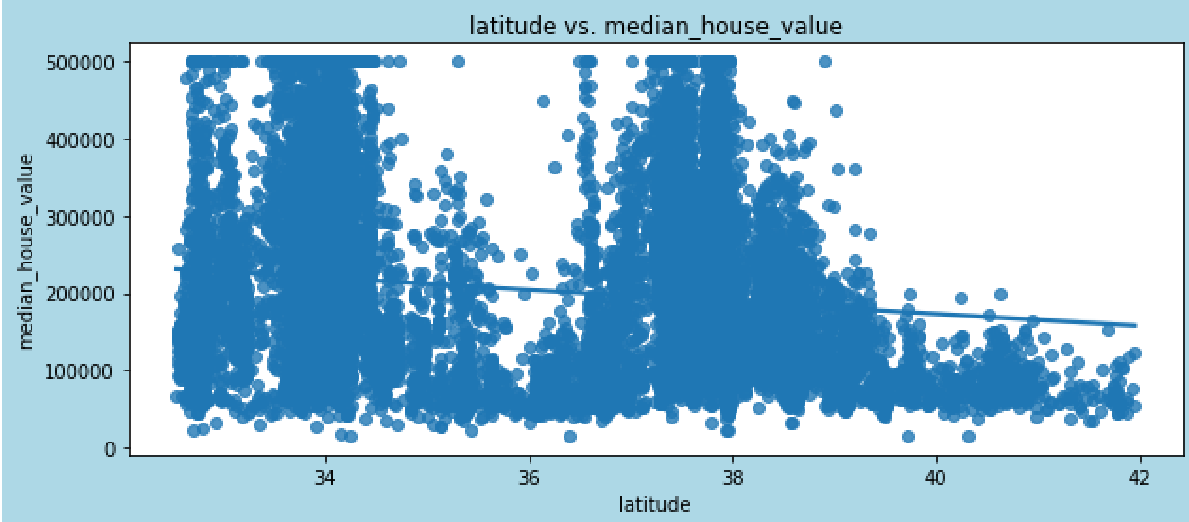
Out[13]:
```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income']
```

In [14]:
```
significant_features = []
for col in numeric_cols_stats:
    corr, pvalue = scipy.stats.pearsonr(data[col],data['median_house_value'])
    print(f'{col} vs. median_house_value Results:\n')
    print('Correlation Coefficient:',corr)
    print('p_value:',pvalue)

    if pvalue < 0.05:
        significant_features.append(col)
        if corr > 0:
            print(f'There is a significant evidence of a positive relationship be
        else:
            print(f'There is a significant evidence of a negative relationship be
    else:
        print(f'There is no significant relationship between {col} and Median Hou

    plt.figure(figsize = (10,4), facecolor='lightblue')
    plt.title(f'{col} vs. median_house_value')
    sns.regplot(x=data[col], y=data['median_house_value'],data=data)
    plt.show()
```

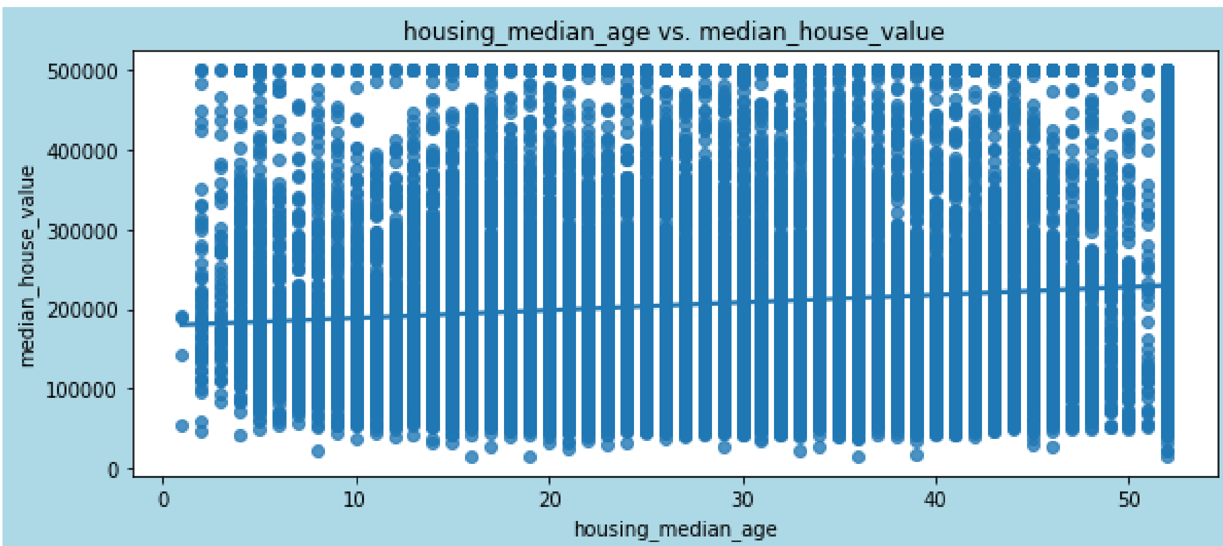
```
longitude vs. median_house_value Results:

Correlation Coefficient: -0.04596661511797848
p_value: 3.923322071106899e-11
There is a significant evidence of a negative relationship between longitude an
d Median House Value
```



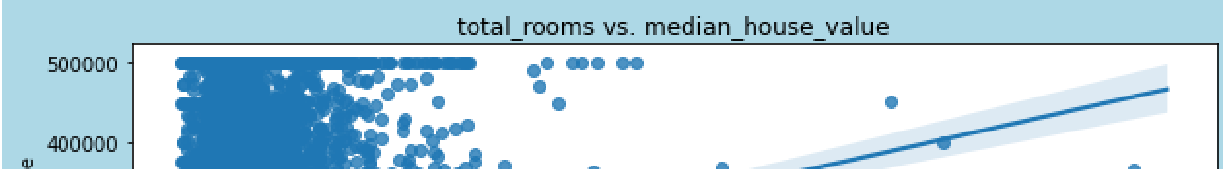

```
latitude vs. median_house_value Results:

Correlation Coefficient: -0.1441602768746593
p_value: 2.9398592907424878e-96
There is a significant evidence of a negative relationship between latitude and
Median House Value
```



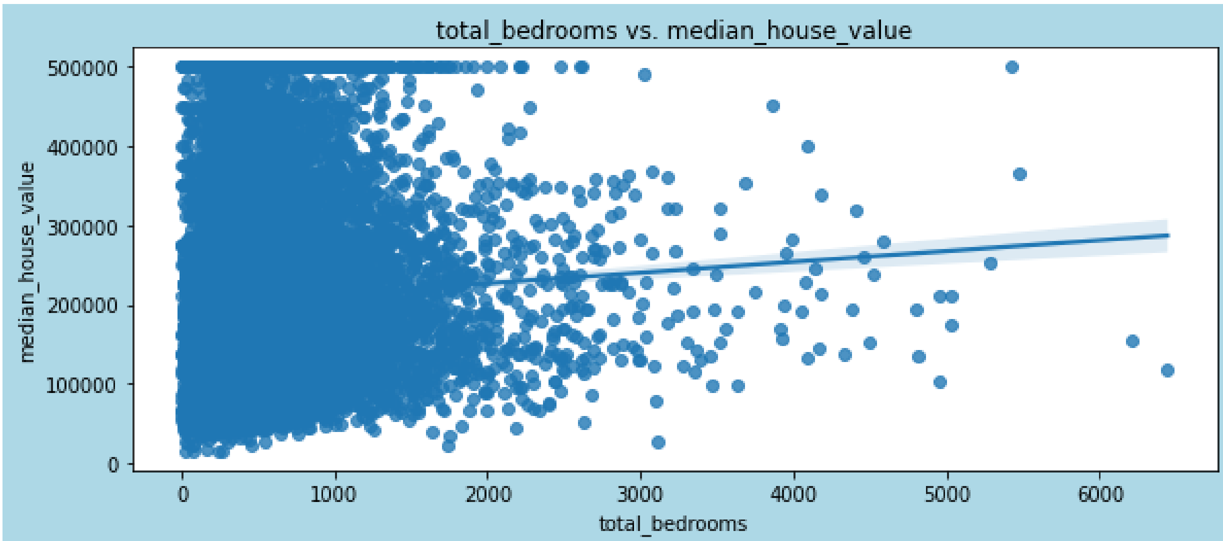

```
housing_median_age vs. median_house_value Results:

Correlation Coefficient: 0.10562341249320993
p_value: 2.7618606761502365e-52
There is a significant evidence of a positive relationship between housing_medi
an_age and Median House Value
```



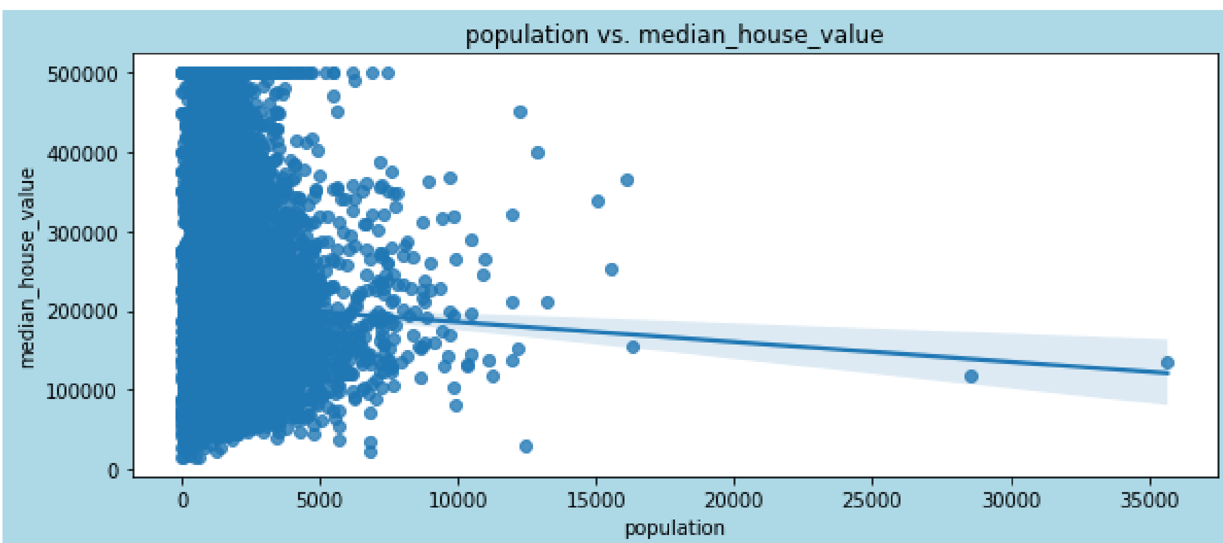

```
total_rooms vs. median_house_value Results:

Correlation Coefficient: 0.1341531138065631
p_value: 1.6893845634754333e-83
There is a significant evidence of a positive relationship between total_rooms
and Median House Value
```




```
total_bedrooms vs. median_house_value Results:

Correlation Coefficient: 0.049456861920854564
p_value: 1.1671461983715622e-12
There is a significant evidence of a positive relationship between total_bedroo
ms and Median House Value
```

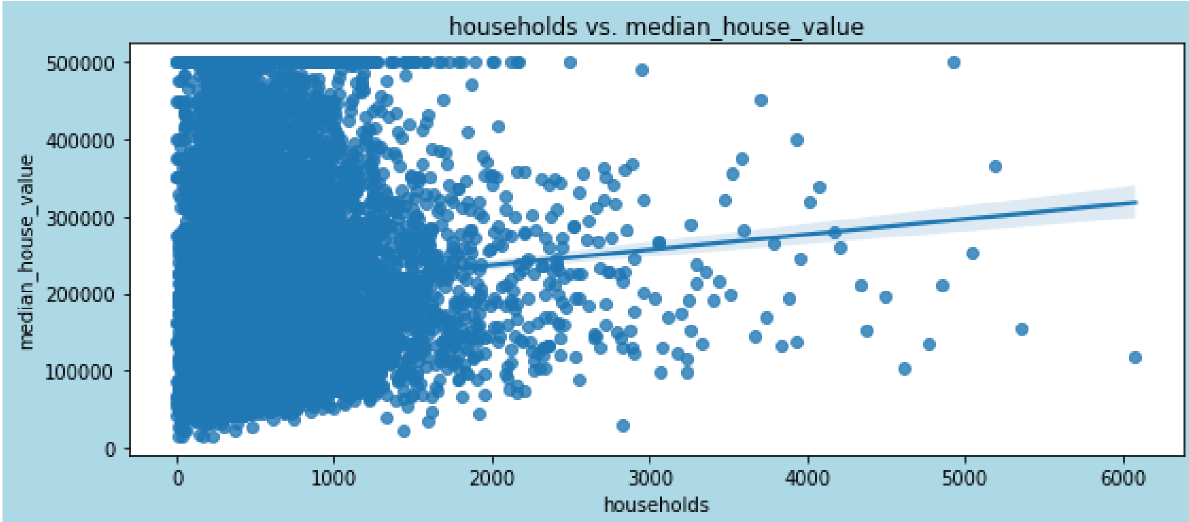



```
population vs. median_house_value Results:

Correlation Coefficient: -0.02464967888889489
p_value: 0.0003976307847911049
There is a significant evidence of a negative relationship between population a
nd Median House Value
```

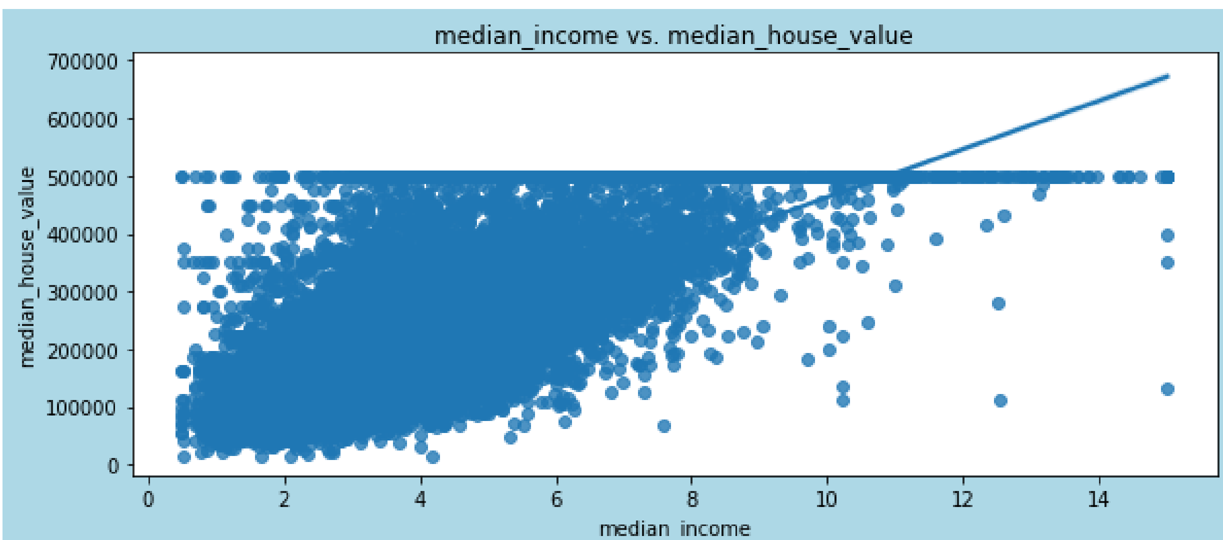



```
households vs. median_house_value Results:

Correlation Coefficient: 0.06584265057005645
p_value: 2.8234206519537093e-21
```

```
There is a significant evidence of a positive relationship between households a
```




```
median_income vs. median_house_value Results:

Correlation Coefficient: 0.6880752079585479
p_value: 0.0
There is a significant evidence of a positive relationship between median_incom
e and Median House Value
```




In [15]:
```
significant_features
```

Out[15]:
```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income']
```

In [16]:
```
data.columns
```

Out[16]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

In [17]:
```
list(data.ocean_proximity.value_counts().index)
```

Out[17]:
```
['<1H OCEAN', 'INLAND', 'NEAR OCEAN', 'NEAR BAY', 'ISLAND']
```

Testing the significance of the categorical feature

State the hypothesis

- $H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (the population means are equal)
- $H_1$ : At least one of the means differ

In [18]:
```
_, p_value = scipy.stats.f_oneway(data[data['ocean_proximity'] == '<1H OCEAN']['r
                                  data[data['ocean_proximity'] == 'INLAND']['medi
                                  data[data['ocean_proximity'] == 'NEAR OCEAN']['
                                  data[data['ocean_proximity'] == 'NEAR BAY']['me
                                  data[data['ocean_proximity'] == 'ISLAND']['medi
                                 )
print('P-values: ', str(p_value))
if p_value < 0.05:
    print('There is a statistical evidence that ocean_proximity has a significant
    significant_features.append('ocean_proximity')
else:
        print('There is no statistical evidence that ocean_proximity has a signif
```

```
P-values:  0.0
There is a statistical evidence that ocean_proximity has a significant relation
ship with median_house_value
```

In [19]:
```
significant_features
```

Out[19]:
```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income',
 'ocean_proximity']
```

As shown from the statistical analysis, ALL the features have significant relationship with the target.

# Features Engineering

In this section, I'll use pandas to transfrom the categroical features "ocean_proximity" to multiple features each for each distinct value in the original "ocean_proximity" feature.

In [20]:
```
# from sklearn.preprocessing import OneHotEncoder, LabelEncoder
```

In [21]:
```
df = data.copy()
```

In [22]:
```
ocean_proximity_ohc = pd.get_dummies(df['ocean_proximity'], drop_first=True)
```

In [23]:
```
df.drop('ocean_proximity', axis=1, inplace=True)
```

In [24]:
```
df = pd.concat([df, ocean_proximity_ohc], axis =1)
df.head()
```

Out[24]:

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households |
|---|---|---|---|---|---|---|---|
| **0** | -122.23 | 37.88 | 41.0 | 880.0 | 129.0 | 322.0 | 126.0 |
| **1** | -122.22 | 37.86 | 21.0 | 7099.0 | 1106.0 | 2401.0 | 1138.0 |
| **2** | -122.24 | 37.85 | 52.0 | 1467.0 | 190.0 | 496.0 | 177.0 |
| **3** | -122.25 | 37.85 | 52.0 | 1274.0 | 235.0 | 558.0 | 219.0 |
| **4** | -122.25 | 37.85 | 52.0 | 1627.0 | 280.0 | 565.0 | 259.0 |

Selecting the features and target

In [25]:
```
# select the features
X = df.drop('median_house_value',axis=1)

# select the target
y = df.median_house_value
```

Although it is not necessary to normalize the targte varibale, sometimes it may lead to better model.

In [26]:
```
# normalize the target (as much as possible)
y = numpy.log1p(y)
```

# Spliting the Data and Buidling the Model

In [61]:
```
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import KFold , cross_val_predict
from sklearn.linear_model import LinearRegression, Lasso, Ridge
from sklearn.linear_model import ElasticNet
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import r2_score
```

In [28]:
```
kf = KFold(shuffle=True, random_state = 2, n_splits = 5)
```

### Linear Model without Regularization

In [29]:
```
estimator = Pipeline([("polynomial_features", PolynomialFeatures()),
                      ("scaler", StandardScaler()),
                      ("ridge_regression", LinearRegression())])

params = {'polynomial_features__degree': [1, 2, 3]}

grid = GridSearchCV(estimator, params, cv=kf)
```

In [30]:
```
grid.fit(X, y)
```

Out[30]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2, shuffle=True),
             estimator=Pipeline(steps=[('polynomial_features',
                                        PolynomialFeatures()),
                                       ('scaler', StandardScaler()),
                                       ('ridge_regression',
                                        LinearRegression())]),
             param_grid={'polynomial_features__degree': [1, 2, 3]})
```

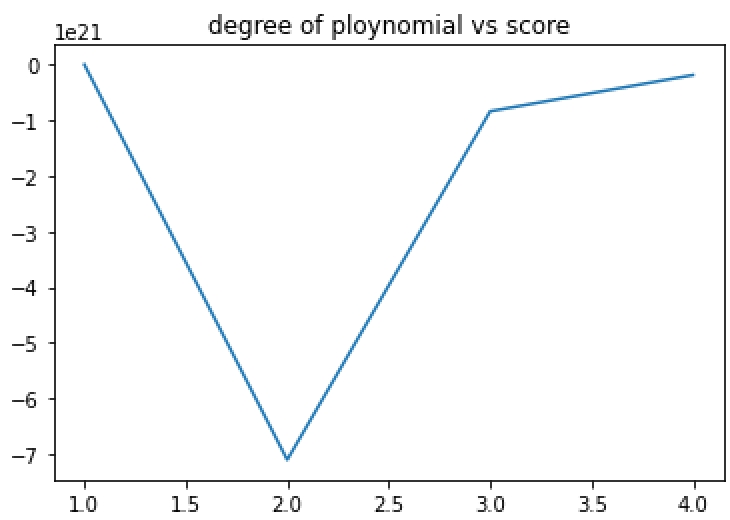
In [31]:
```
grid.best_score_.round(2), grid.best_params_
```

Out[31]:
```
(0.66, {'polynomial_features__degree': 1})
```

In [32]:
```
degrees = [1,2,3,4]
lin_dict = {'degree':degrees, 'score':[]}

lr = LinearRegression()
s = StandardScaler()
for d in degrees:
    pf = PolynomialFeatures(degree=d)

    estimator = Pipeline([("polynomial_features", pf),
                          ("scaler", s),
                          ("linear_regression", lr)])

    y_red = cross_val_predict(estimator, X, y, cv = kf)

    score = numpy.round(r2_score(y,y_red),2)

    lin_dict['score'].append(score)
```

In [33]:
```
lin_df = pd.DataFrame(lin_dict)
print(lin_df.sort_values('score', ascending=False))

plt.plot(lin_df['degree'], lin_df['score'])
plt.title('degree of ploynomial vs score');
```

```
   degree         score
0       1  6.600000e-01
3       4 -1.896192e+20
2       3 -8.410814e+20
1       2 -7.105933e+21
```




This verifies that the gridserach method output the best model prediction

# Linear Regression with L2 Regularization (Ridge)

In [34]:
```
rr_estimator = Pipeline([("polynomial_features", PolynomialFeatures()),
                      ("scaler", StandardScaler()),
                      ("ridge_regression", Ridge())])

rr_params = {'polynomial_features__degree': [1, 2, 3],
          'ridge_regression__alpha': numpy.geomspace(0.00001, 100000, 11)
         }

rr_grid = GridSearchCV(rr_estimator, rr_params, cv=kf)
```

In [35]:
```
rr_grid.fit(X,y)
```

Out[35]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2, shuffle=True),
             estimator=Pipeline(steps=[('polynomial_features',
                                        PolynomialFeatures()),
                                       ('scaler', StandardScaler()),
                                       ('ridge_regression', Ridge())]),
             param_grid={'polynomial_features__degree': [1, 2, 3],
                         'ridge_regression__alpha': array([1.e-05, 1.e-04, 1.e-
03, 1.e-02, 1.e-01, 1.e+00, 1.e+01, 1.e+02,
       1.e+03, 1.e+04, 1.e+05])})
```

In [36]:
```
numpy.round(rr_grid.best_score_,3), rr_grid.best_params_
```

Out[36]:
```
(0.713, {'polynomial_features__degree': 3, 'ridge_regression__alpha': 1000.0})
```

# Linear Regression with L1 Regularization (LASSO)

In [41]:
```
lr_estimator = Pipeline([("polynomial_features", PolynomialFeatures()),
                         ("scaler", StandardScaler()),
                         ("lasso_regression", Lasso(max_iter = 100000))])

lr_params = {'polynomial_features__degree': [1,2,3],
             'lasso_regression__alpha': [0.001, 0.01, 0.1,1,10]
             }

lr_grid = GridSearchCV(lr_estimator, lr_params, cv=kf)
```

In [42]:
```
lr_grid.fit(X,y)
```

Out[42]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2, shuffle=True),
             estimator=Pipeline(steps=[('polynomial_features',
                                        PolynomialFeatures()),
                                       ('scaler', StandardScaler()),
                                       ('lasso_regression',
                                        Lasso(max_iter=100000))]),
             param_grid={'lasso_regression__alpha': [0.001, 0.01, 0.1, 1, 10],
                         'polynomial_features__degree': [1, 2, 3]})
```

In [40]:
```
numpy.round(lr_grid.best_score_,3), lr_grid.best_params_
```

Out[40]:
```
(0.716, {'lasso_regression__alpha': 0.001, 'polynomial_features__degree': 3})
```

## ElasticNet

In [65]:
```
alphas = numpy.array([0.005, 0.05, 0.1, 1, 5, 20, 50, 80, 100, 120,140])
l1_ratios = numpy.linspace(0.1, 0.9, 9)
```

In [68]:
```
en_estimator = Pipeline([("polynomial_features", PolynomialFeatures()),
                         ("scaler", StandardScaler()),
                         ("elasticNet_regression", ElasticNet(max_iter = 100000))

en_params = {'polynomial_features__degree': [1,2,3],
             'elasticNet_regression__alpha': alphas,
             'elasticNet_regression__l1_ratio': l1_ratios
             }

en_grid = GridSearchCV(en_estimator, en_params, cv=kf)
```

In [69]:
```
en_grid.fit(X,y)
```

Out[69]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=2, shuffle=True),
             estimator=Pipeline(steps=[('polynomial_features',
                                        PolynomialFeatures()),
                                       ('scaler', StandardScaler()),
                                       ('elasticNet_regression',
                                        ElasticNet(max_iter=100000))]),
             param_grid={'elasticNet_regression__alpha': array([5.0e-03, 5.0e-0
2, 1.0e-01, 1.0e+00, 5.0e+00, 2.0e+01, 5.0e+01,
       8.0e+01, 1.0e+02, 1.2e+02, 1.4e+02]),
                         'elasticNet_regression__l1_ratio': array([0.1, 0.2, 0.
3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]),
                         'polynomial_features__degree': [1, 2, 3]})
```

In [70]:
```
numpy.round(en_grid.best_score_,3), en_grid.best_params_
```

Out[70]:
```
(0.715,
 {'elasticNet_regression__alpha': 0.005,
  'elasticNet_regression__l1_ratio': 0.2,
  'polynomial_features__degree': 3})
```

From the scores registered, the lasso regression model has the best score. However, lasso model has tendency to bias, therefore, I will use ElsticNet.

In [71]:
```
from sklearn.model_selection import train_test_split
```

In [72]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.1, random_s
```

In [74]:
```
best_estimator = Pipeline([("polynomial_features", PolynomialFeatures(degree=3)),
                           ("scaler", StandardScaler()),
                           ("elasticNet_regression", ElasticNet(alpha = 0.005, l1

best_estimator.fit(X_train, y_train)
best_estimator.score(X_train, y_train).round(2)
```

Out[74]:
```
0.73
```

In [75]:
```
y_predict = best_estimator.predict(X_test)
```

In [76]:
```
r2_score(y_predict, y_test)
```

Out[76]:
```
0.6013673693934608
```

In [77]:
```
import joblib
```

In [ ]:
```
joblib.dump(en_grid, 'en_grid.pkl')
```

In [ ]: