ZNEUS - Project 1

In [8]:
```
!pip install shapely
```

```
Requirement already satisfied: shapely in c:\users\matze\appdata\local\programs\pyth
on\python312\lib\site-packages (2.1.2)
Requirement already satisfied: numpy>=1.21 in c:\users\matze\appdata\local\programs
\python\python312\lib\site-packages (from shapely) (2.2.6)
```

```
[notice] A new release of pip is available: 24.2 -> 25.3
[notice] To update, run: python.exe -m pip install --upgrade pip
```

In [9]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
import pylab as py
from scipy import stats
from scipy.stats import pearsonr
import sklearn
import sklearn.preprocessing as preprocessing
from sklearn.feature_selection import SelectKBest, f_regression
from sklearn.pipeline import Pipeline
from shapely import Polygon, Point
from typing import List
import os
import joblib
import plotly.io as pio
TRANSFORMED_PATH = "data/transformed"
r_seed = 42
```

1. EDA

1.1 Loading Dataset

In [10]:
```
df = pd.read_csv('data/houses.csv')
df.head()
```

Out[10]:

	median_house_value	median_income	housing_median_age	total_rooms	total_bedrooms
0	452600.0	8.3252	41.0	880.0	129.0
1	358500.0	8.3014	21.0	7099.0	1106.0
2	352100.0	7.2574	52.0	1467.0	190.0
3	341300.0	5.6431	52.0	1274.0	235.0
4	342200.0	3.8462	52.0	1627.0	280.0

1.2 Info about dataset

In [11]:
```
print(df.info(),"\n")

print("Unique values:")
for col in df.columns:
    print("\t",col + " počet unikátnych záznamov: ", len(df[col].unique()))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   median_house_value  20640 non-null  float64
 1   median_income       20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20640 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   latitude            20640 non-null  float64
 8   longitude           20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
None

Unique values:
         median_house_value počet unikátnych záznamov:  3842
         median_income počet unikátnych záznamov:  12928
         housing_median_age počet unikátnych záznamov:  52
         total_rooms počet unikátnych záznamov:  5926
         total_bedrooms počet unikátnych záznamov:  1928
         population počet unikátnych záznamov:  3888
         households počet unikátnych záznamov:  1815
         latitude počet unikátnych záznamov:  862
         longitude počet unikátnych záznamov:  844
```

This dataset contains 9 columns and 20640 entries, all columns are of type float64, therefore are numerical.

Some columns have a lot of unique values.

Target column is **median_house_value**.

1.3 Duplicates

In [12]:
```
duplicates = df.duplicated()
print(df[duplicates])
```

```
Empty DataFrame
Columns: [median_house_value, median_income, housing_median_age, total_rooms, total_
bedrooms, population, households, latitude, longitude]
Index: []
```

This implicates, that there are no duplicates.

1.4 Missing data

In [13]:
```
print(df.isna().sum())
```

```
median_house_value    0
median_income         0
housing_median_age    0
total_rooms           0
total_bedrooms        0
population            0
households            0
latitude              0
longitude             0
dtype: int64
```

There are also no missing data, what a nice dataset.

1.5 Outliers

In [14]:
```
def count_outliers(column):
    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR
    return column[(column < lower) | (column > upper)].shape[0]

#apply to all columns
outliers_count = df.apply(count_outliers)

print(outliers_count)
```

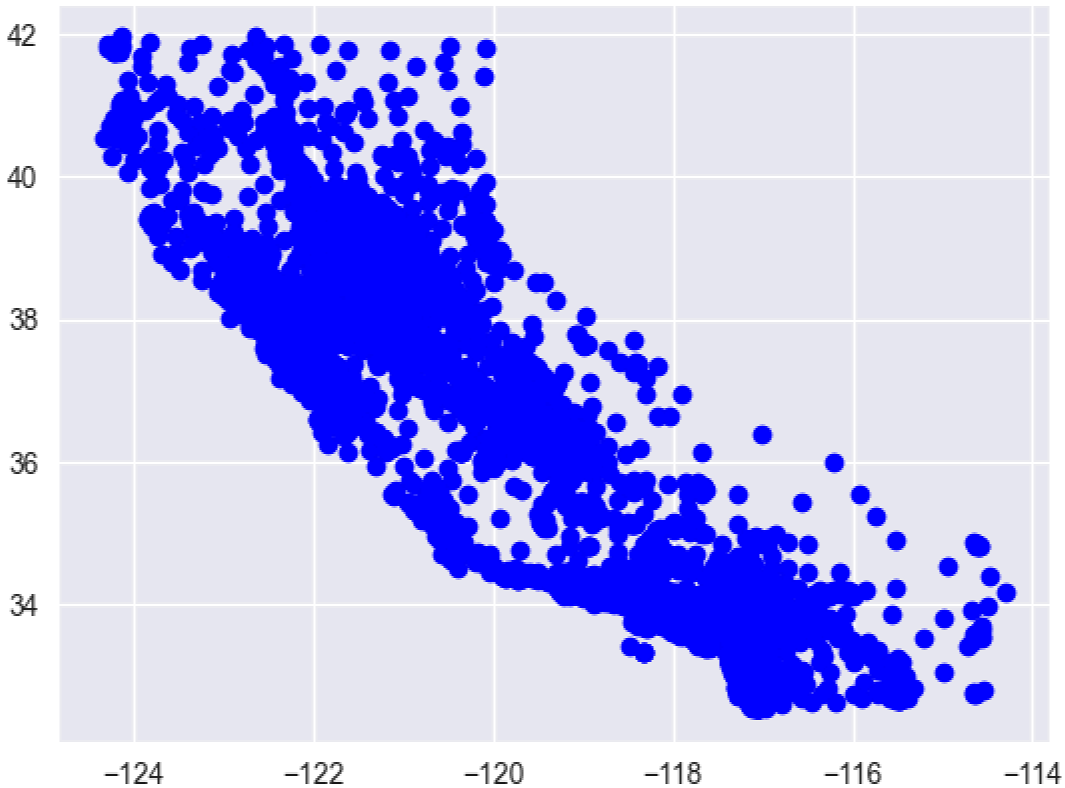
```
median_house_value    1071
median_income          681
housing_median_age       0
total_rooms           1287
total_bedrooms        1282
population            1196
households            1220
latitude                 0
longitude                0
dtype: int64
```

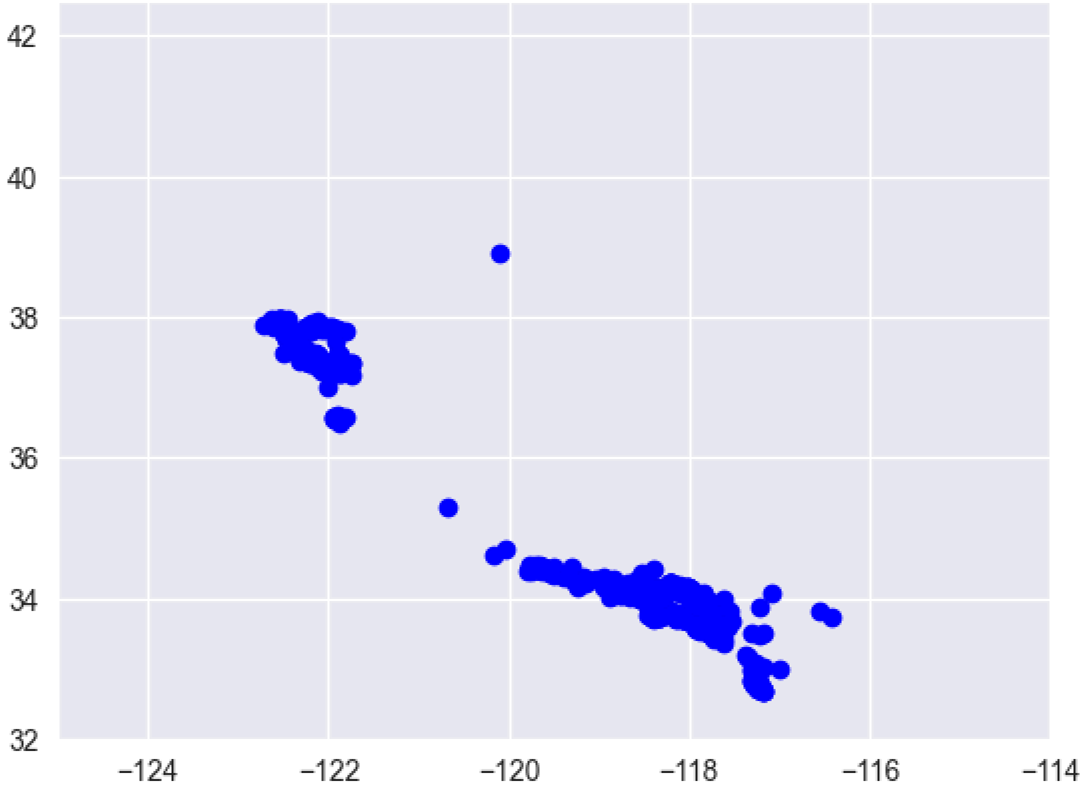
We can see, that we have numerous outliers in some columns.

In [15]:
```
def get_outliers(column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR
```

```python
    return df[(df[column] < lower) | (df[column] > upper)]

outs = get_outliers("median_house_value")
house_outs = get_outliers("median_income")
plt.figure()
plt.scatter(df["longitude"], df["latitude"], color='blue', marker='o')
plt.figure()
plt.scatter(outs["longitude"], outs["latitude"], color='blue', marker='o')
plt.xlim(-125, -114)
plt.ylim(32, 42.5)
```

Out[15]: (32.0, 42.5)



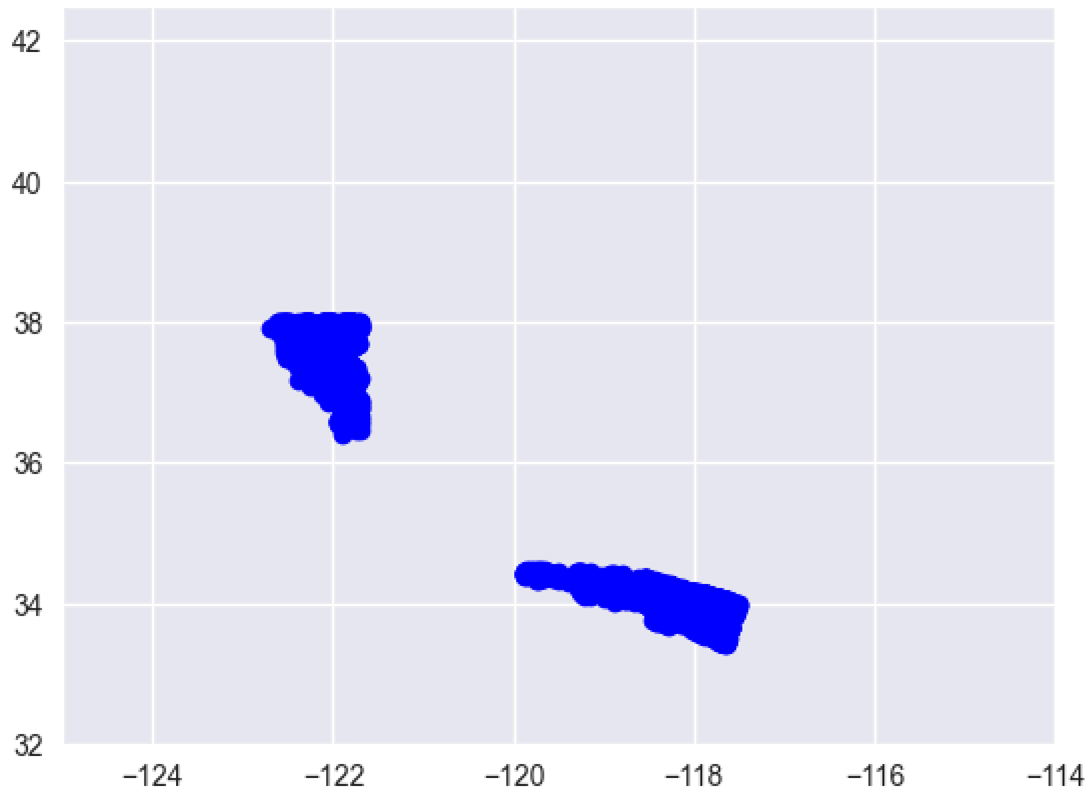


In [16]:

```
def set_is_san_francisco(df: pd.DataFrame):
    df["is_san_francisco"] = ((df["longitude"] <= -121.7) & (df["longitude"] > -122
        & (df["latitude"] > 36.3) & (df["latitude"] <= 38)).astype(int)

la_polygon = Polygon([
    (-119.9, 34.5),
    (-118.6, 34.4),
    (-117.5, 34),
    (-117.65, 33.4),
    (-119.9, 34.4),
])
def set_is_los_angeles(df: pd.DataFrame):
    df["is_los_angeles"] = df.apply(
        lambda row: int(la_polygon.contains(Point(row["longitude"], row["latitude"]
        axis=1
    )

set_is_san_francisco(df)
set_is_los_angeles(df)
plt.figure()
_df = df[(df["is_san_francisco"] == 1) | (df["is_los_angeles"] == 1)]
plt.scatter(_df["longitude"], _df["latitude"], color='blue', marker='o')
plt.xlim(-125, -114)
plt.ylim(32, 42.5)
```

Out[16]:

```
(32.0, 42.5)
```



As we can see most of the outliers are focused in specific areas indicating that they are probably result of being located in big cities such as LA

1.5.1 Outlier imputation

In [17]:
```
def clip_outliers(column):
    Q1 = column.quantile(0.25)
    Q3 = column.quantile(0.75)
    IQR = Q3 - Q1
    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR

    return column.clip(lower, upper) #if value is lower then min, replace it with m

#apply to all
df.apply(clip_outliers)
```

Out[17]:

	median_house_value	median_income	housing_median_age	total_rooms	total_bedro
0	452600.0	8.013025	41.0	880.000	1
1	358500.0	8.013025	21.0	5698.375	11
2	352100.0	7.257400	52.0	1467.000	1
3	341300.0	5.643100	52.0	1274.000	2
4	342200.0	3.846200	52.0	1627.000	2
...	...	...	...	...	
20635	78100.0	1.560300	25.0	1665.000	3
20636	77100.0	2.556800	18.0	697.000	1
20637	92300.0	1.700000	17.0	2254.000	4
20638	84700.0	1.867200	18.0	1860.000	4
20639	89400.0	2.388600	16.0	2785.000	6

20640 rows × 11 columns

1.6 Valid data ranges

In [18]:

```
#latitude
invalid_lat = df[(df['latitude'] < -90) | (df['latitude'] > 90)]
print("Počet invalid latitude:", invalid_lat.shape[0])

#longitude
invalid_long = df[(df['longitude'] < -180) | (df['longitude'] > 180)]
print("Počet invalid longitude:", invalid_long.shape[0])

#negative values in other columns
df.min()
```

```
Počet invalid latitude: 0
Počet invalid longitude: 0
```

Out[18]:

```
median_house_value    14999.0000
median_income             0.4999
housing_median_age        1.0000
total_rooms               2.0000
total_bedrooms            1.0000
population                3.0000
households                1.0000
latitude                 32.5400
longitude              -124.3500
is_san_francisco          0.0000
is_los_angeles            0.0000
dtype: float64
```

There are no negative values or zero values in other columns, this is okay. Lat and Long are both in valid ranges.

1.7 Summary statistics

In [19]:

```
df.describe()
```

Out[19]:

	median_house_value	median_income	housing_median_age	total_rooms	total_bedr
count	20640.000000	20640.000000	20640.000000	20640.000000	20640.0(
mean	206855.816909	3.870671	28.639486	2635.763081	537.8!
std	115395.615874	1.899822	12.585558	2181.615252	421.2/
min	14999.000000	0.499900	1.000000	2.000000	1.0(
25%	119600.000000	2.563400	18.000000	1447.750000	295.0(
50%	179700.000000	3.534800	29.000000	2127.000000	435.0(
75%	264725.000000	4.743250	37.000000	3148.000000	647.0(
max	500001.000000	15.000100	52.000000	39320.000000	6445.0(

In [20]:

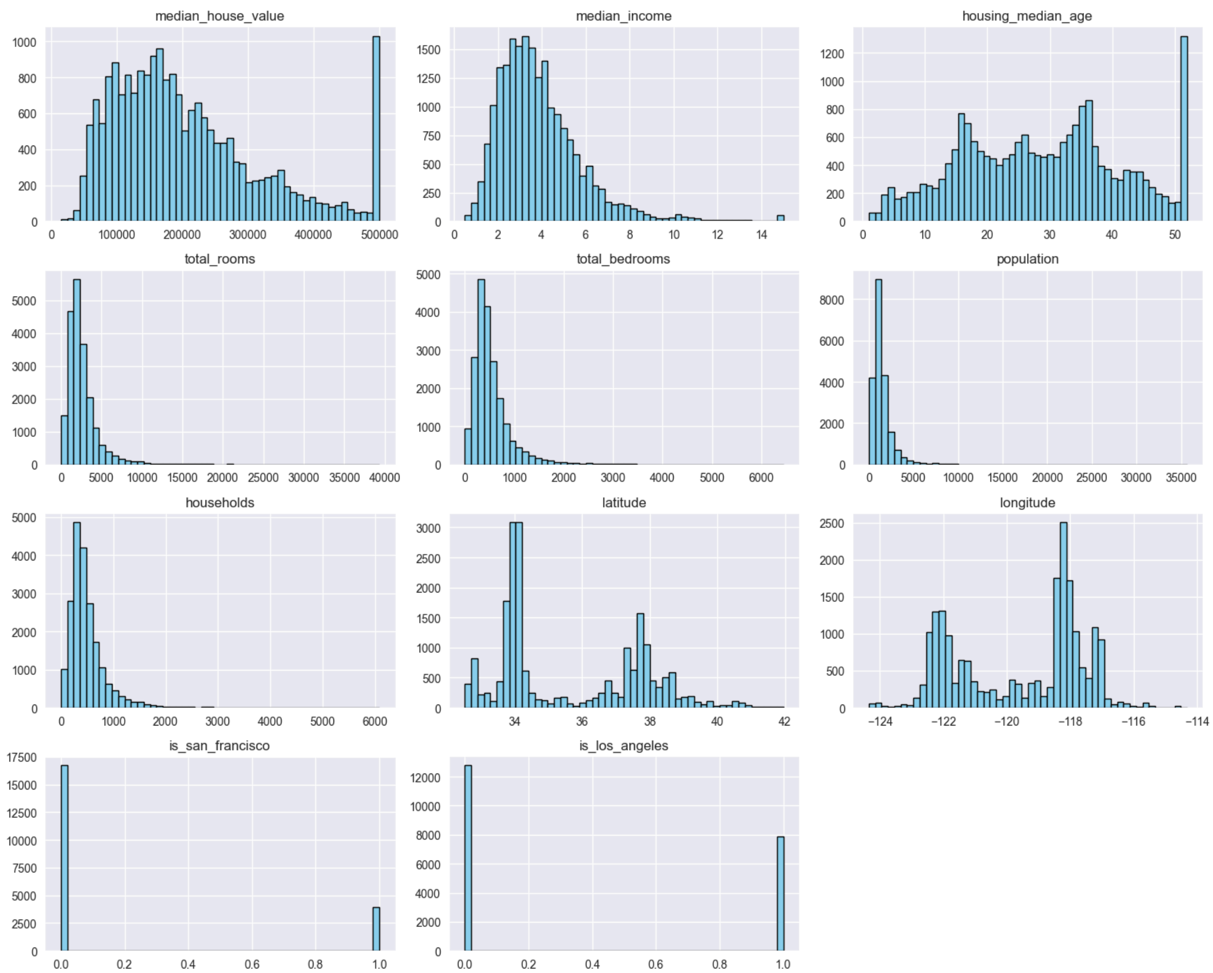
```
print("Other stats:")
for col in df.columns:
    print("\t",col,":")
    print("\t\t","mean", np.mean(df[col]))
    print("\t\t","median", np.median(df[col]))
    print("\t\t","mode", stats.mode(df[col])[0])
    print("\t\t","variance", np.var(df[col]),"\n")
```

```
Other stats:
	median_house_value :
		mean 206855.81690891474
		median 179700.0
		mode 500001.0
		variance 13315503000.818077

	median_income :
		mean 3.8706710029069766
		median 3.5347999999999997
		mode 3.125
		variance 3.609147689697444

	housing_median_age :
		mean 28.639486434108527
		median 29.0
		mode 52.0
		variance 158.38858617035862

	total_rooms :
		mean 2635.7630813953488
		median 2127.0
		mode 1527.0
		variance 4759214.512668024

	total_bedrooms :
		mean 537.8980135658915
		median 435.0
		mode 280.0
		variance 177441.20088752697

	population :
		mean 1425.4767441860465
		median 1166.0
		mode 891.0
		variance 1282408.3220366866

	households :
		mean 499.5396802325581
		median 409.0
		mode 306.0
		variance 146168.95772780472

	latitude :
		mean 35.63186143410853
		median 34.26
		mode 34.06
		variance 4.562071602892517

	longitude :
		mean -119.56970445736432
		median -118.49
		mode -118.31
		variance 4.0139448835847835

	is_san_francisco :
```

```
            mean 0.19050387596899224
            median 0.0
            mode 0
            variance 0.15421214920978307

    is_los_angeles :
            mean 0.3814437984496124
            median 0.0
            mode 0
            variance 0.2359444270739439
```

1.8 Visualize data

In [21]:
```python
df.hist(bins=50, figsize=(15, 12), color='skyblue', edgecolor='black')
plt.tight_layout()
plt.show()
```



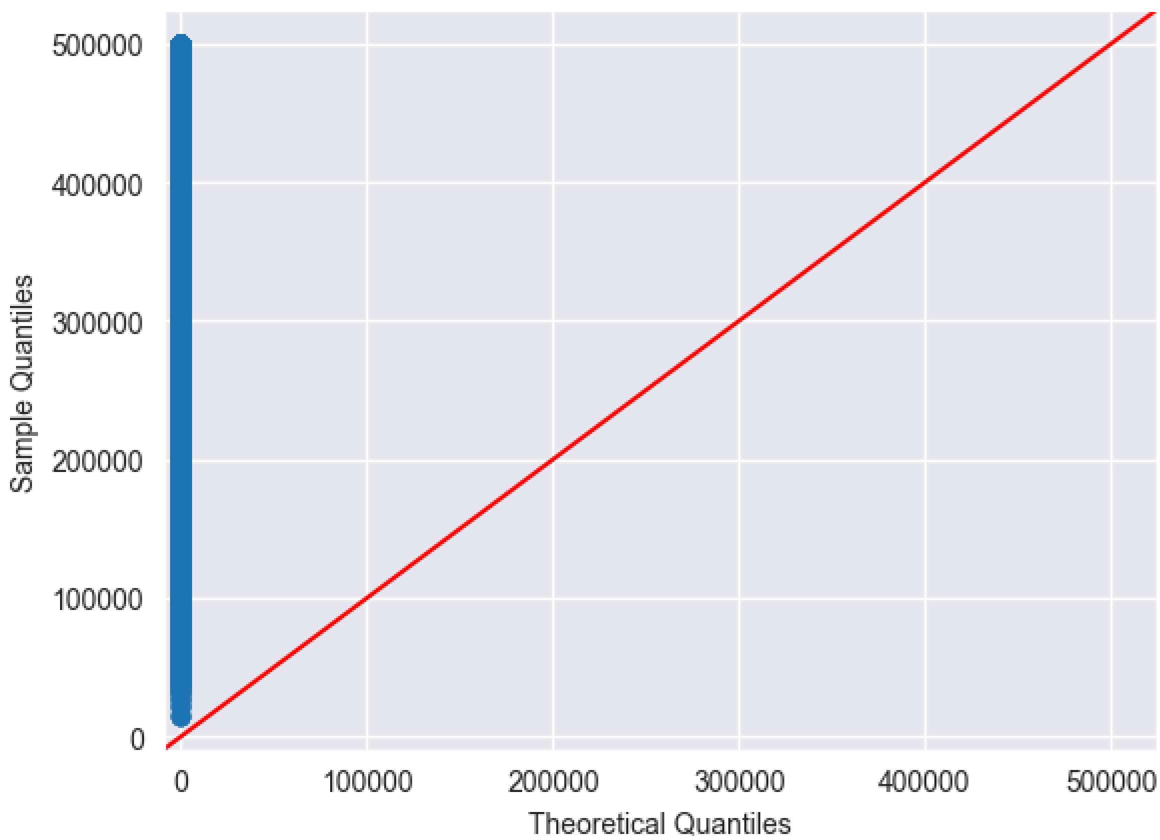
None of these distributions appear normal, lets run some tests.

1.8.1 Test for normality

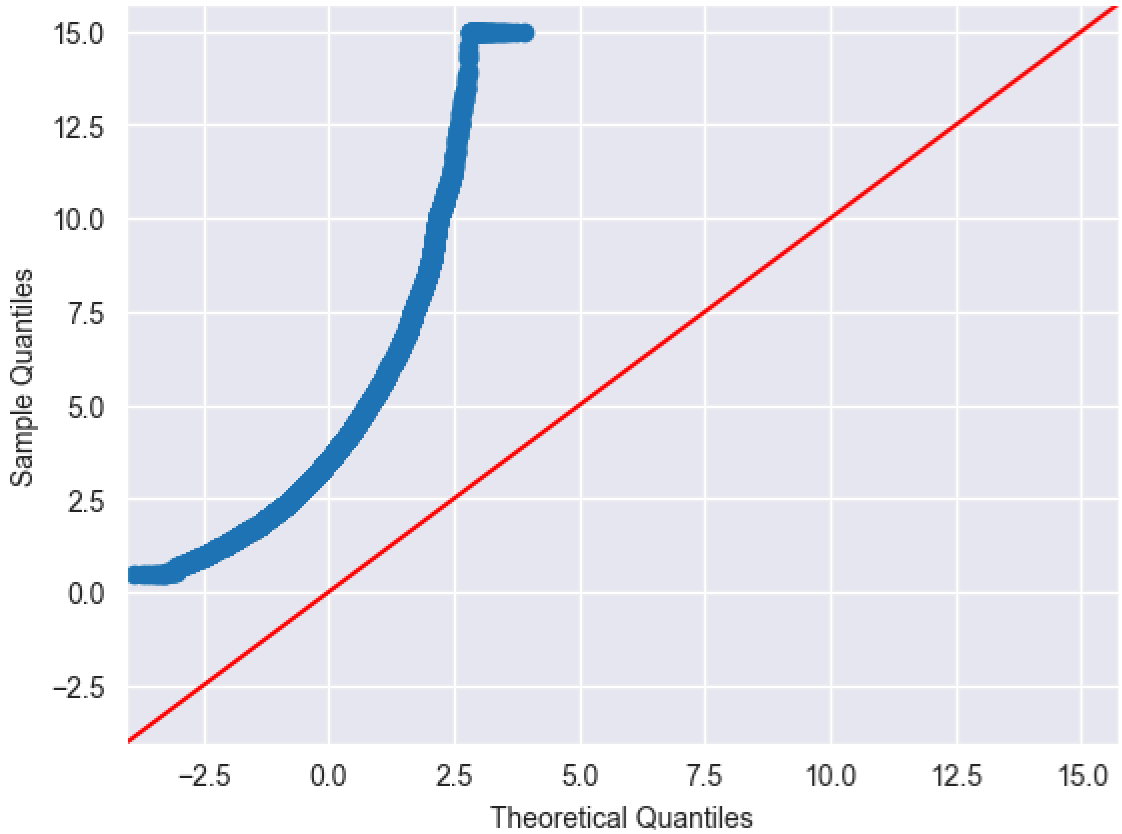
In [22]:
```python
def check_normal(col):
    print(col.name,":")
    #draw qqplot
```

```
    sm.qqplot(col, line='45')
    py.show()

    #perform KS test, we dont do shapiro because we hove more than 5000 samples
    kolmogorov_smirnov = stats.kstest(col, "norm")

    #interpret results
    alpha = 0.05

    print("Kolmogorov-Smirnov test:", kolmogorov_smirnov)
    if kolmogorov_smirnov.pvalue > alpha:
        print('Normal distribution (fail to reject H0)\n')
    else:
        print('Another distribution (reject H0)\n')

for col in df:
    check_normal(df[col])
```

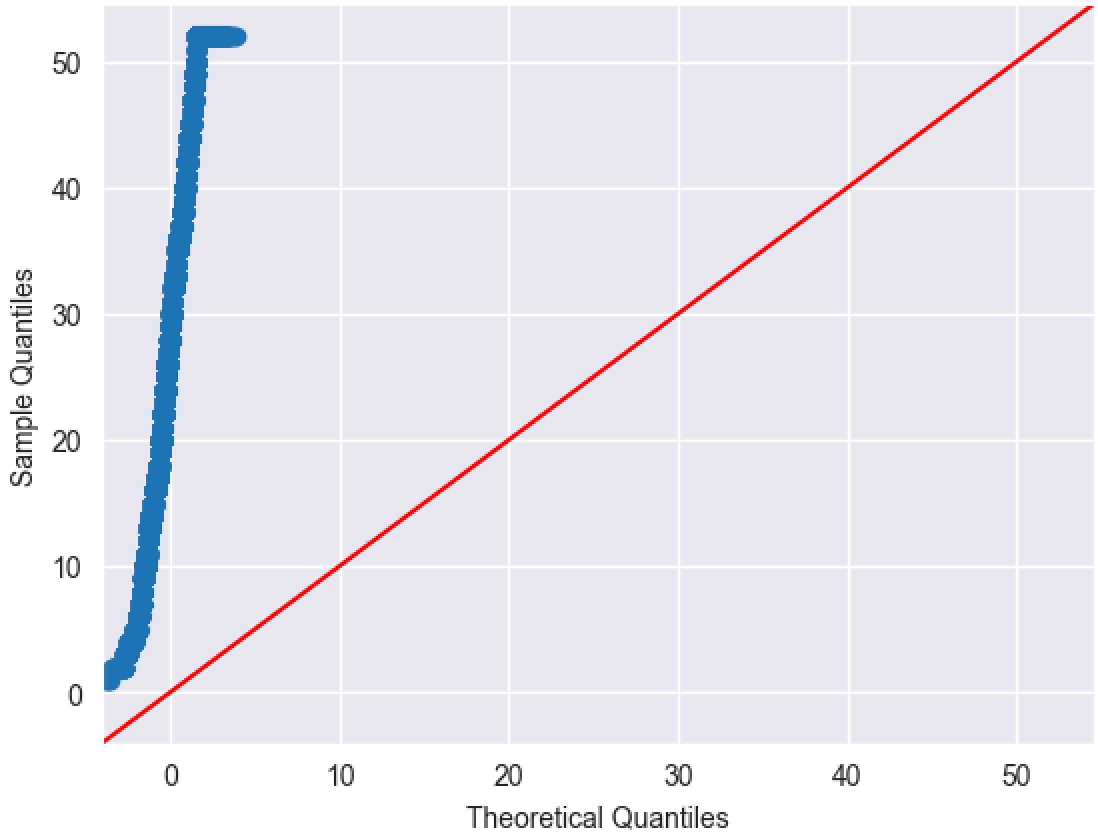
```
median_house_value :
```



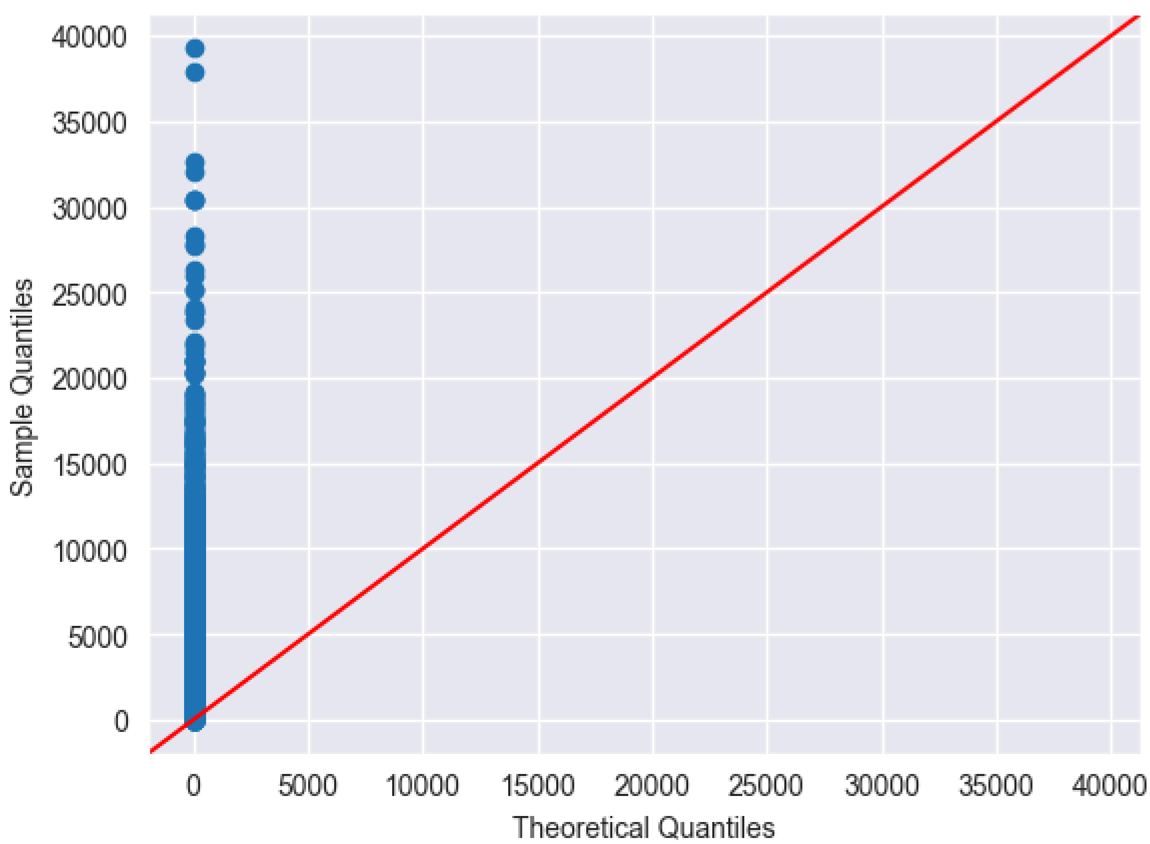

```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(1.0), pvalue=np.float64
(0.0), statistic_location=np.float64(14999.0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

median_income :
```



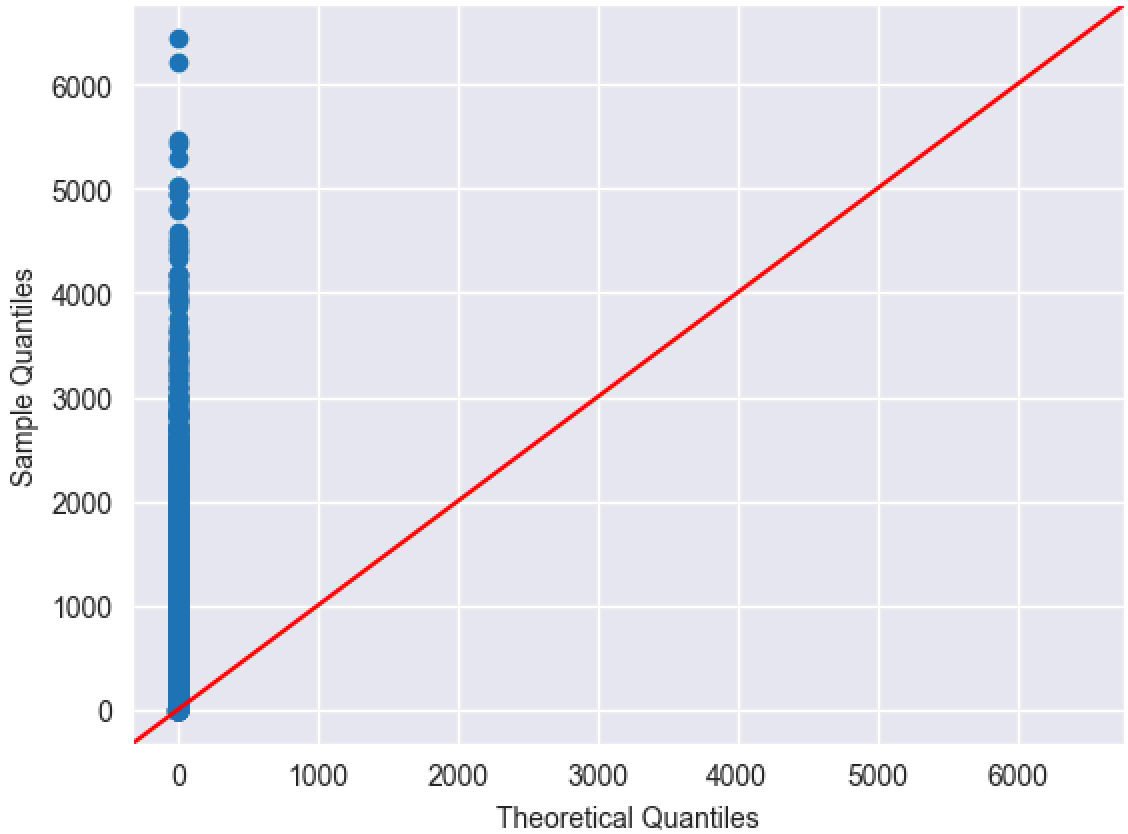

```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.8953266796146241), pval
ue=np.float64(0.0), statistic_location=np.float64(1.5809), statistic_sign=np.int8(-
1))
Another distribution (reject H0)

housing_median_age :
```



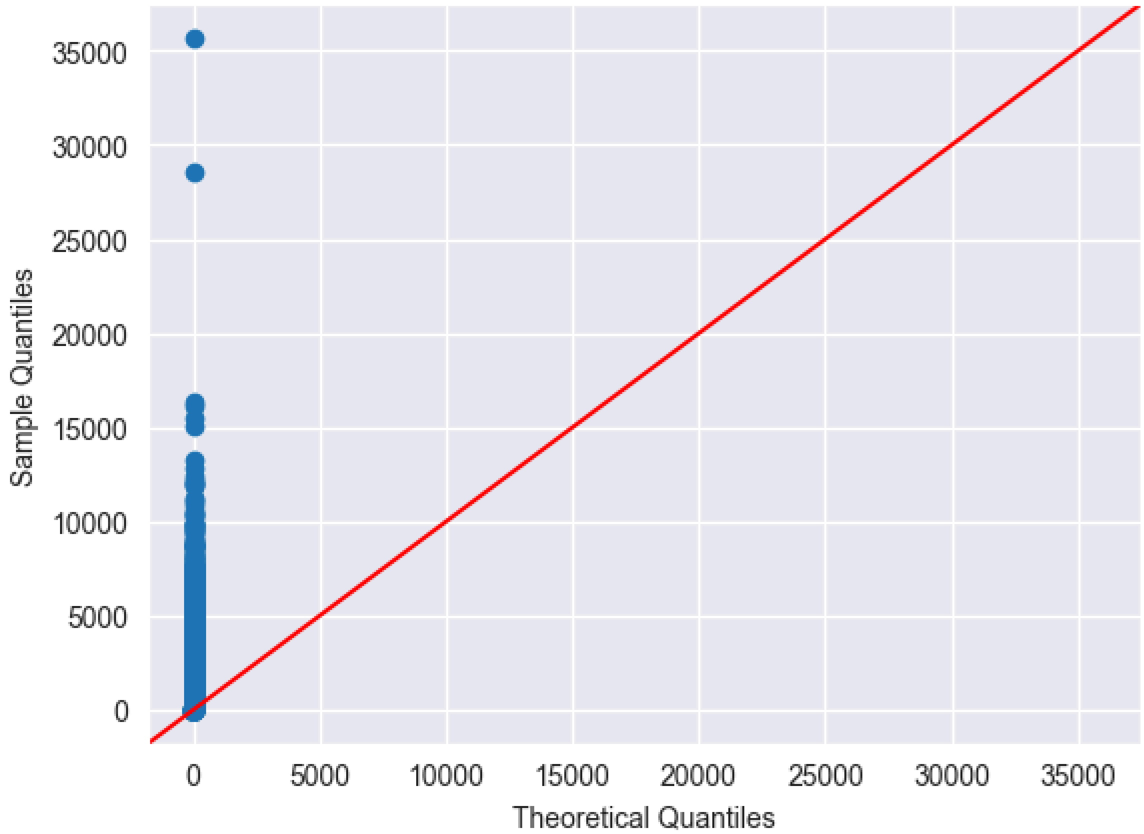

```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.9956462259993777), pval
ue=np.float64(0.0), statistic_location=np.float64(3.0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

total_rooms :
```



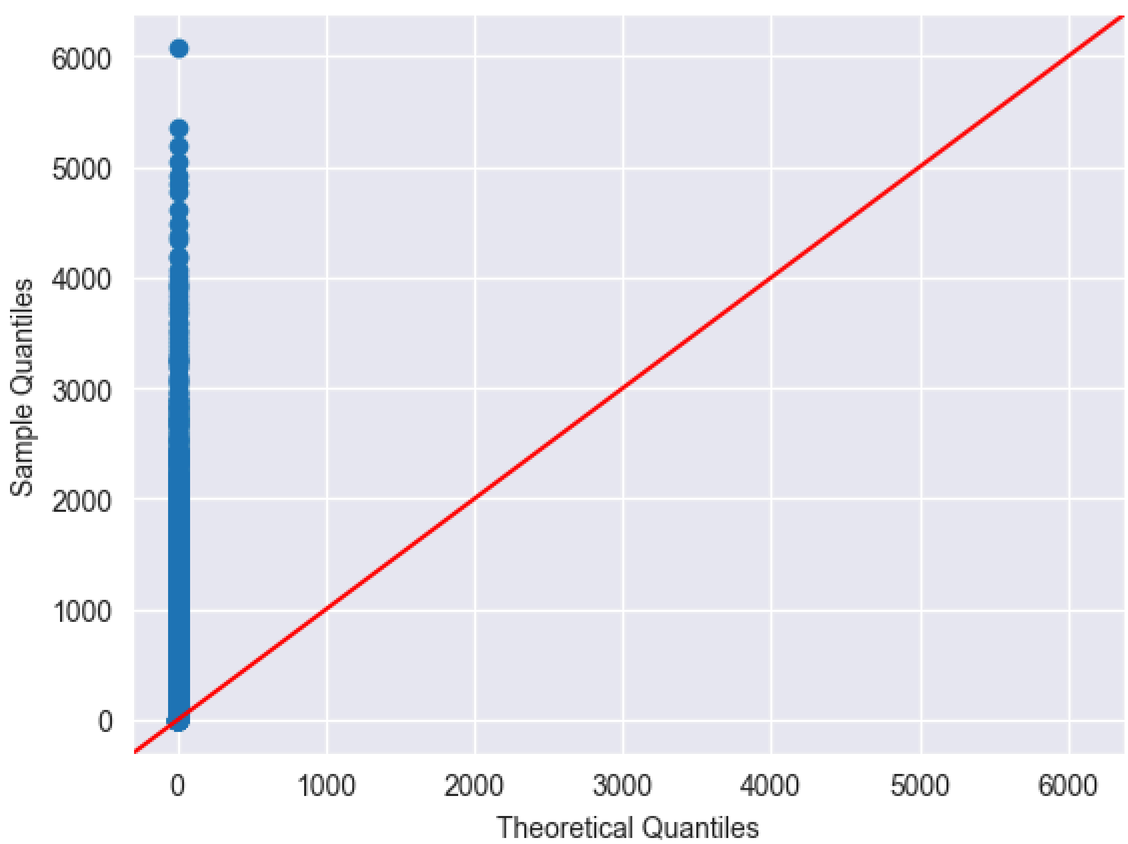
```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.9999515494010092), pval
ue=np.float64(0.0), statistic_location=np.float64(6.0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

total_bedrooms :
```



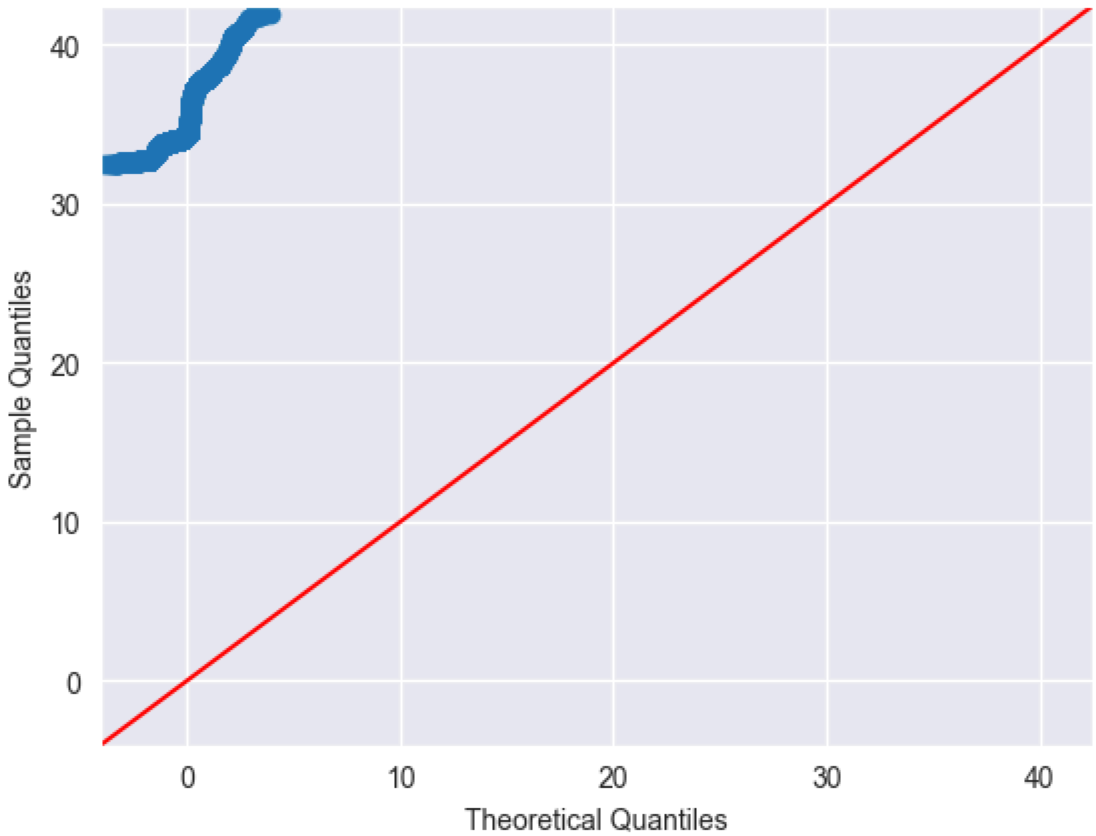

```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.999580731858942), pvalu
e=np.float64(0.0), statistic_location=np.float64(4.0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

population :
```



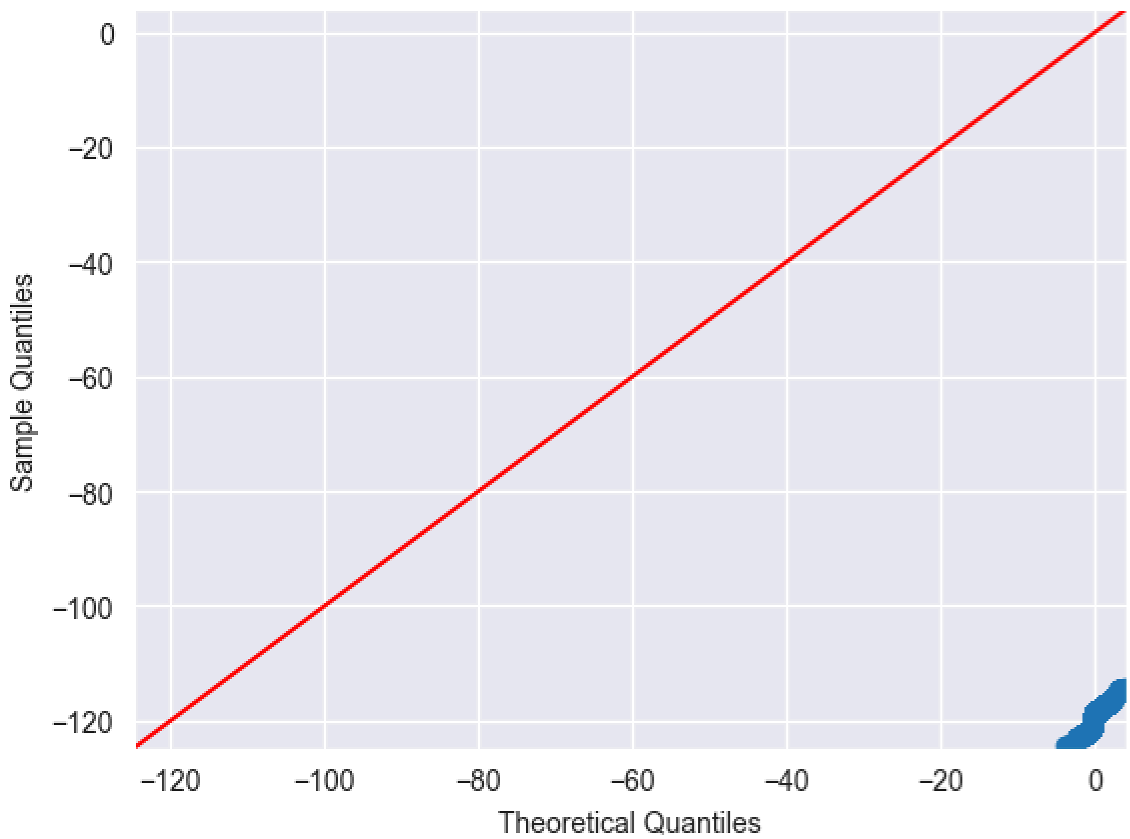

```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.9999512637360249), pval
ue=np.float64(0.0), statistic_location=np.float64(5.0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

households :
```



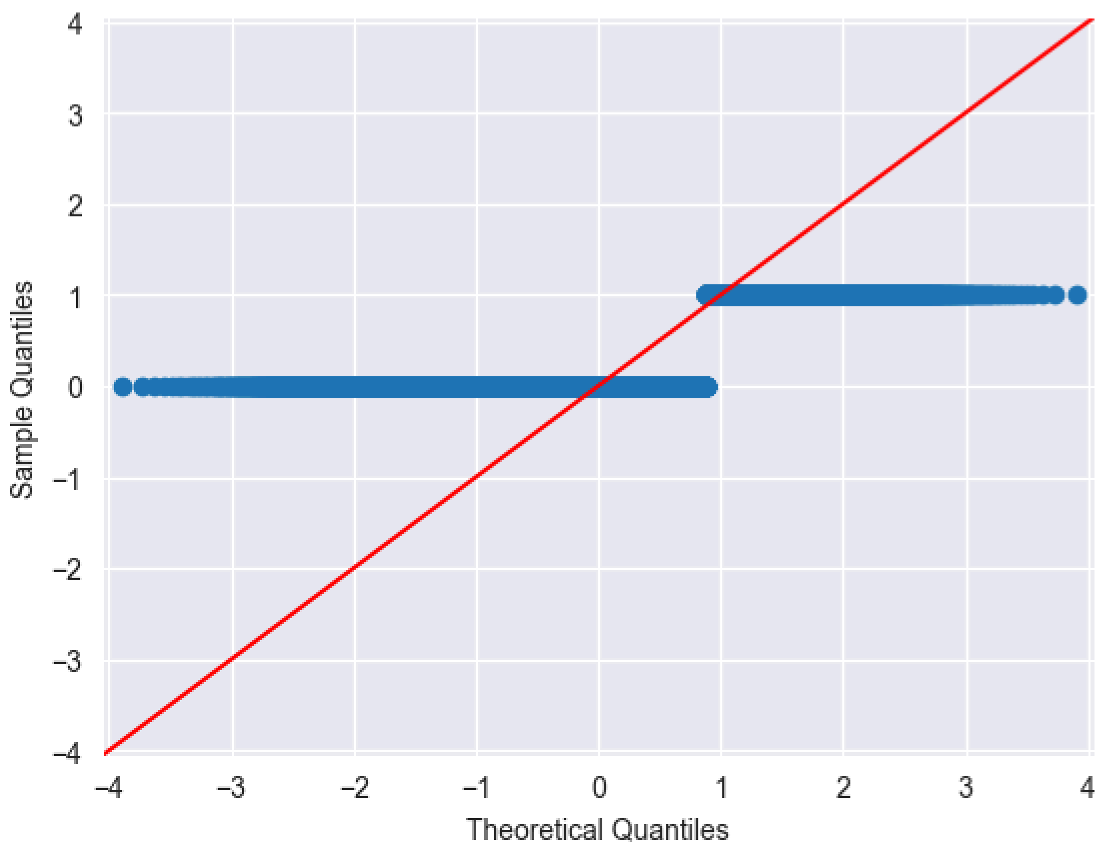
```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.999580731858942), pvalu
e=np.float64(0.0), statistic_location=np.float64(4.0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

latitude :
```



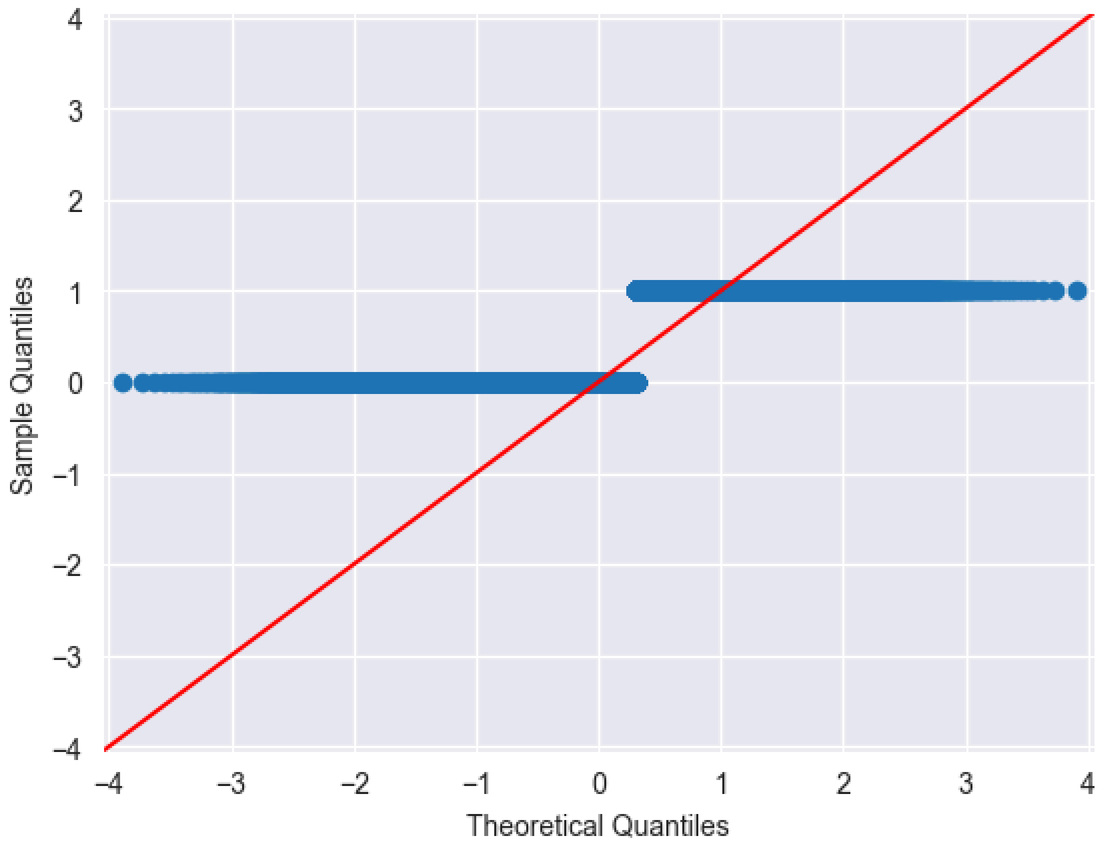

```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(1.0), pvalue=np.float64
(0.0), statistic_location=np.float64(32.54), statistic_sign=np.int8(-1))
Another distribution (reject H0)

longitude :
```




```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(1.0), pvalue=np.float64
(0.0), statistic_location=np.float64(-114.31), statistic_sign=np.int8(1))
Another distribution (reject H0)

is_san_francisco :
```



```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.5), pvalue=np.float64
(0.0), statistic_location=np.int64(0), statistic_sign=np.int8(-1))
Another distribution (reject H0)

is_los_angeles :
```

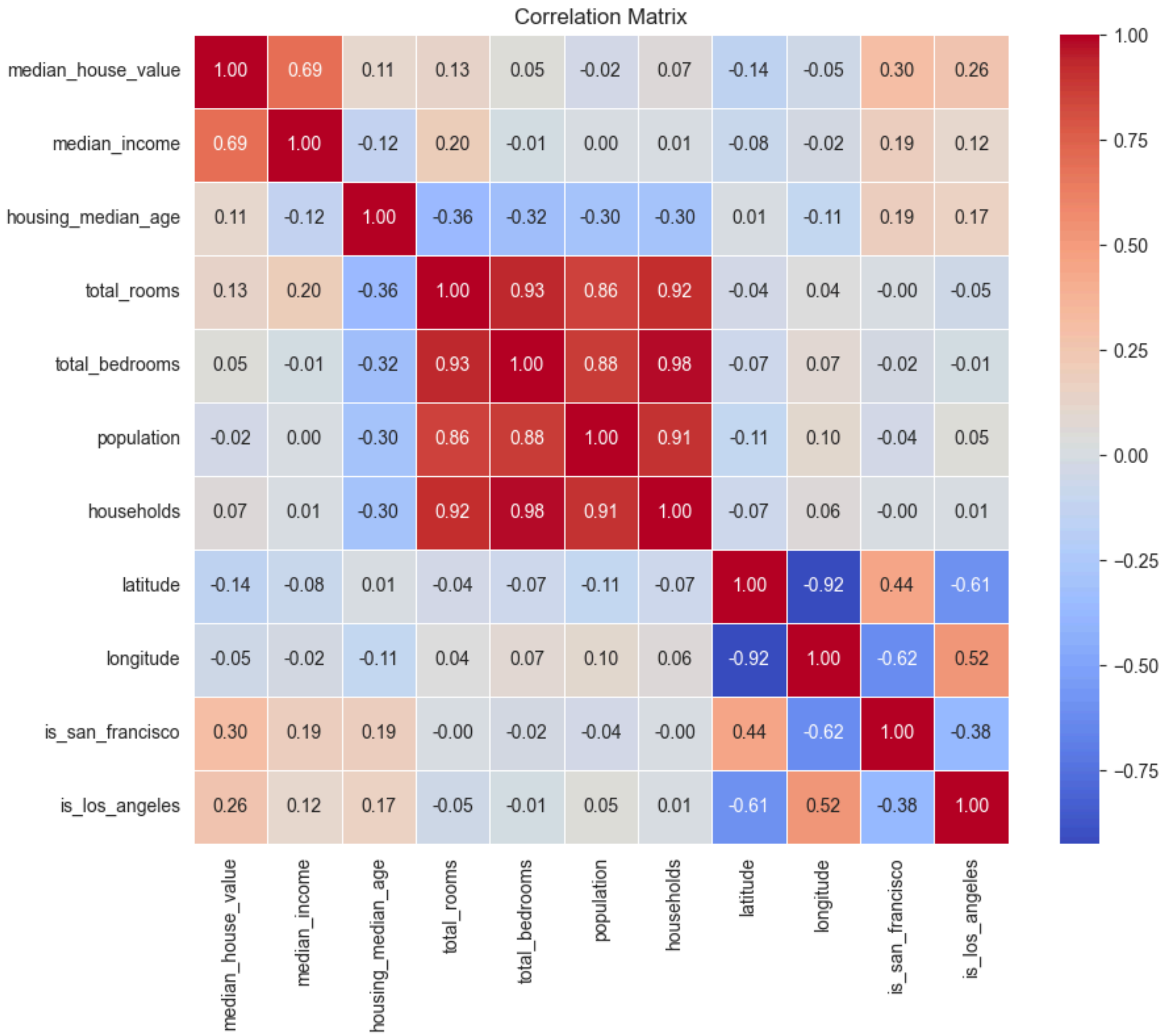



```
Kolmogorov-Smirnov test: KstestResult(statistic=np.float64(0.5), pvalue=np.float64
(0.0), statistic_location=np.int64(0), statistic_sign=np.int8(-1))
Another distribution (reject H0)
```

1.9 Correlations

In [23]:

```
correlation_matrix = df.corr()

#visualize the correlation matrix in a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=
plt.title('Correlation Matrix')
plt.show()
```



We can see, that columns: median_income (0.69) is strongly positively correlated with the target column.

Other columns are correlated between each other such as: total_rooms - households,population, total_bedrooms, hoouse_median_age and more.

1.10 Hypothesis testing

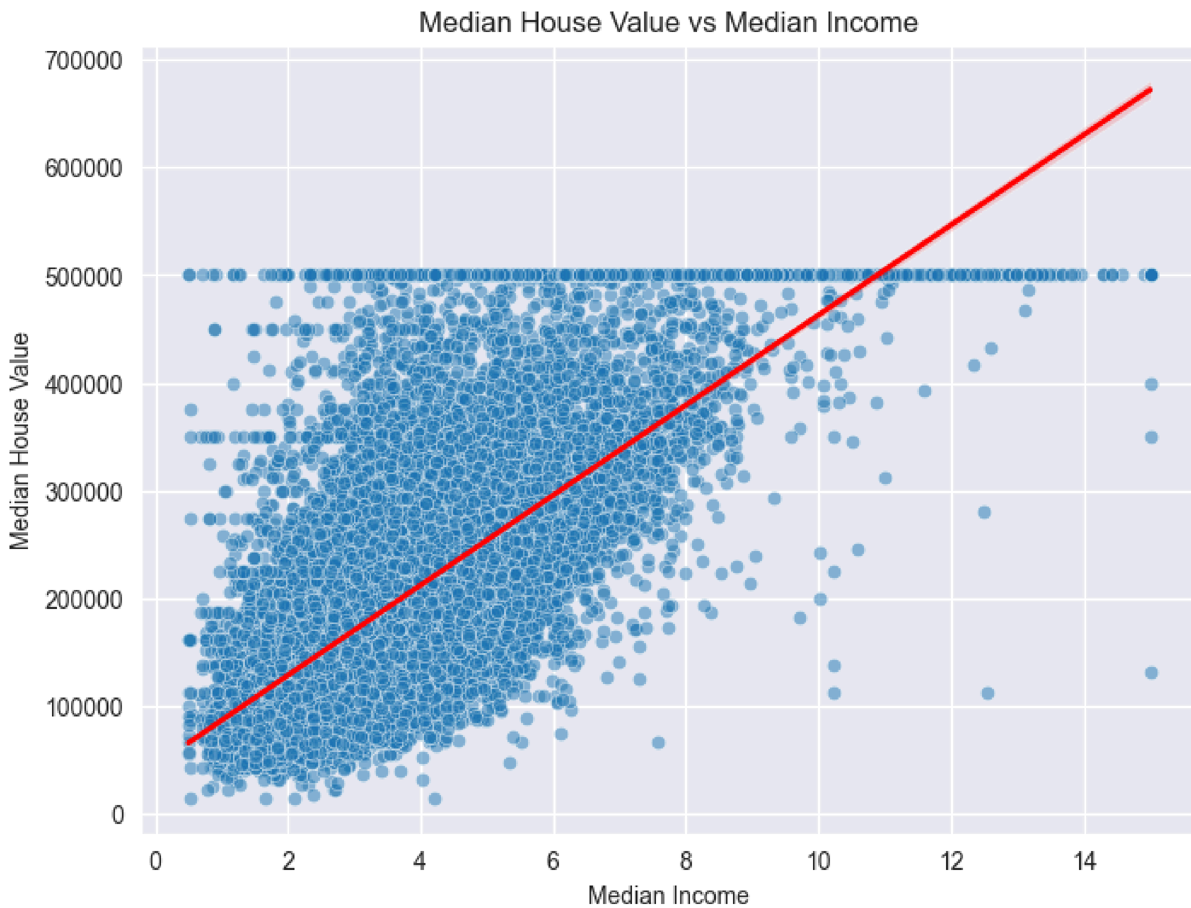
H0 - median_house_value is not dependent on median_income

H1 - median_house_value increases as median_income increases

1.10.1 Scatterplot and regression plot

In [24]:
```
plt.figure(figsize=(8,6))
sns.scatterplot(x='median_income', y='median_house_value', data=df, alpha=0.5)
sns.regplot(x='median_income', y='median_house_value', data=df, scatter=False, colo
plt.title('Median House Value vs Median Income')
plt.xlabel('Median Income')
```

```
plt.ylabel('Median House Value')
plt.show()
```



We can see the positive correlation, if we increase median income, we increase median house value as well.

House values are capped at 500000, probably dataset cap. There are notable outliers.

1.10.2 Statistical test

In [25]:
```
corr, p_value = pearsonr(df['median_income'], df['median_house_value'])
print(f"Pearson correlation: {corr:.2f}")
print(f"P-value: {p_value:.5f}")
```

```
Pearson correlation: 0.69
P-value: 0.00000
```

We can confirm from **p-value < 0.05** that the relation is statistically significant, therefore the reject **H0**.

In [26]:
```
stat, p = stats.ks_2samp(df["total_bedrooms"], df["population"])
print(f"KS statistic: {stat}, p-value: {p}")
```

```
KS statistic: 0.59515503875969, p-value: 0.0
```

1.11 Evaluation metrics:

- **MSE - Mean Squared Error**, because we are doing Regression task.

Data preprocessing

Dataset division

In [27]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   median_house_value  20640 non-null  float64
 1   median_income       20640 non-null  float64
 2   housing_median_age  20640 non-null  float64
 3   total_rooms         20640 non-null  float64
 4   total_bedrooms      20640 non-null  float64
 5   population          20640 non-null  float64
 6   households          20640 non-null  float64
 7   latitude            20640 non-null  float64
 8   longitude           20640 non-null  float64
 9   is_san_francisco    20640 non-null  int64  
 10  is_los_angeles      20640 non-null  int64  
dtypes: float64(9), int64(2)
memory usage: 1.7 MB
```

In [28]:
```
# 70 - 15 - 15 split
x = df.drop("median_house_value", axis=1)
y = df[["median_house_value"]]
x_train, x_test, y_train, y_test = sklearn.model_selection.train_test_split(
    x, y, test_size=0.3, random_state=r_seed
)
x_test, x_val, y_test, y_val = sklearn.model_selection.train_test_split(
    x_test, y_test, test_size=0.5, random_state=r_seed
)
x_train.shape, x_test.shape, x_test.shape, y_train.shape, y_test.shape, y_val.shape
```

Out[28]:
```
((14448, 10), (3096, 10), (3096, 10), (14448, 1), (3096, 1), (3096, 1))
```

Normalization

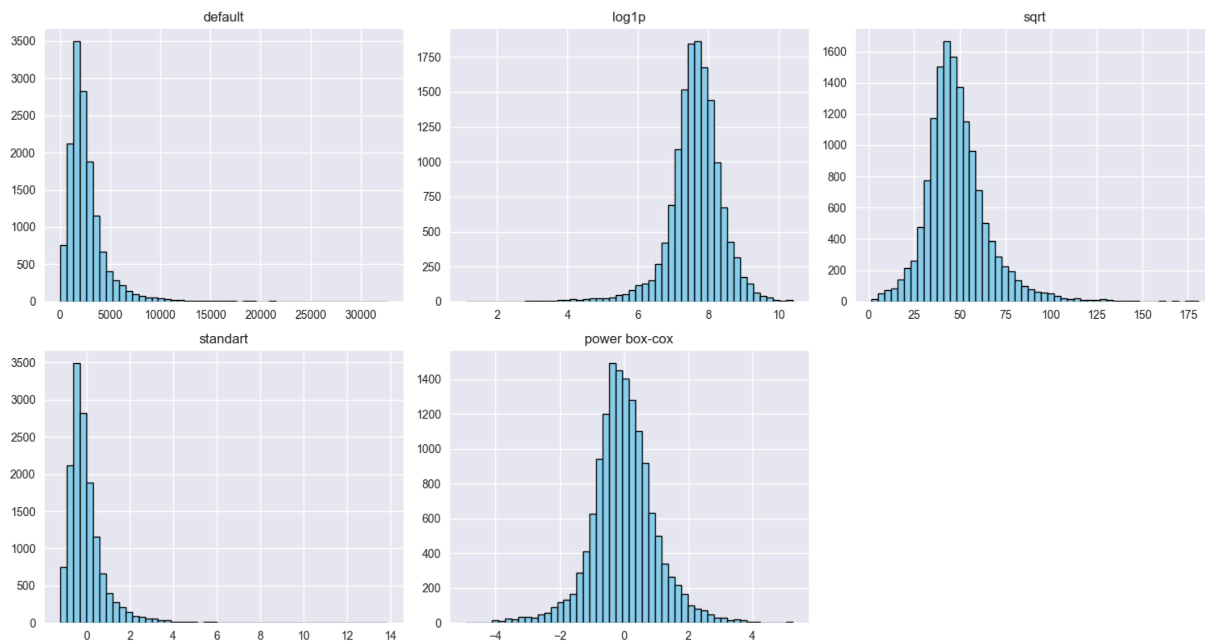
In [29]:
```
def show_transformations(dfs: List[any], columns: int = 3, bins: int = 50):
    n = len(dfs)
    rows = (n + columns - 1) // columns

    fig, axes = plt.subplots(rows, columns, figsize=(5 * columns, 4 * rows))
    axes = axes.flatten()
    for i, df in enumerate(dfs):
        axes[i].hist(df[0], bins=bins, color='skyblue', edgecolor='black')
        axes[i].set_title(df[1])
    for j in range(i + 1, len(axes)):
```

```
        fig.delaxes(axes[j])
    plt.tight_layout()
    plt.show()
```

In [30]:
```
def test_transformations(data, dfs: List[any] = [], columns: int = 3, bins: int = 5
    standart = preprocessing.StandardScaler().fit_transform(data)
    power_box = preprocessing.PowerTransformer(method='box-cox').fit_transform(data
    show_transformations([(data, "default"), (np.log1p(data), "log1p"), (np.sqrt(da
                         (standart, "standart"), (power_box, "power box-cox"), *dfs],
```

total_rooms

In [31]:
```
test_transformations(x_train[["total_rooms"]])
```



log transformation skewed data to the left, so it is to much

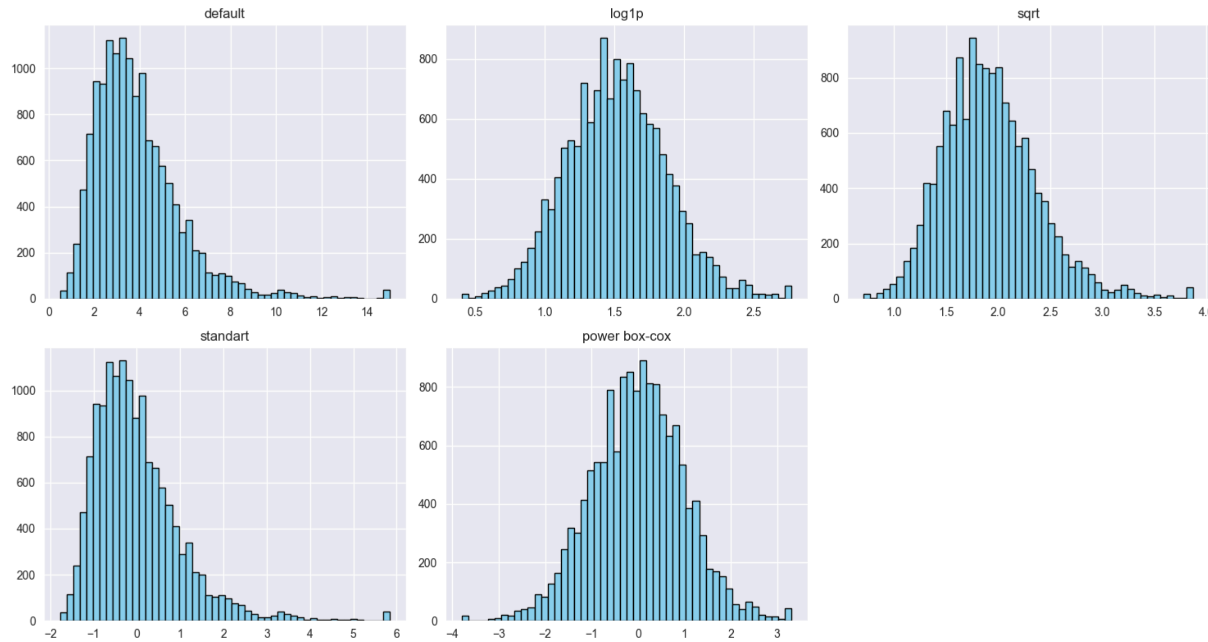
sqrt transformation made the data less right skewed but it is not symetrical

standard scaler haven't dont much that is expected considering that this transformer expects roughly normal distribution

power transformer made the data look roughly symetrical

median_income

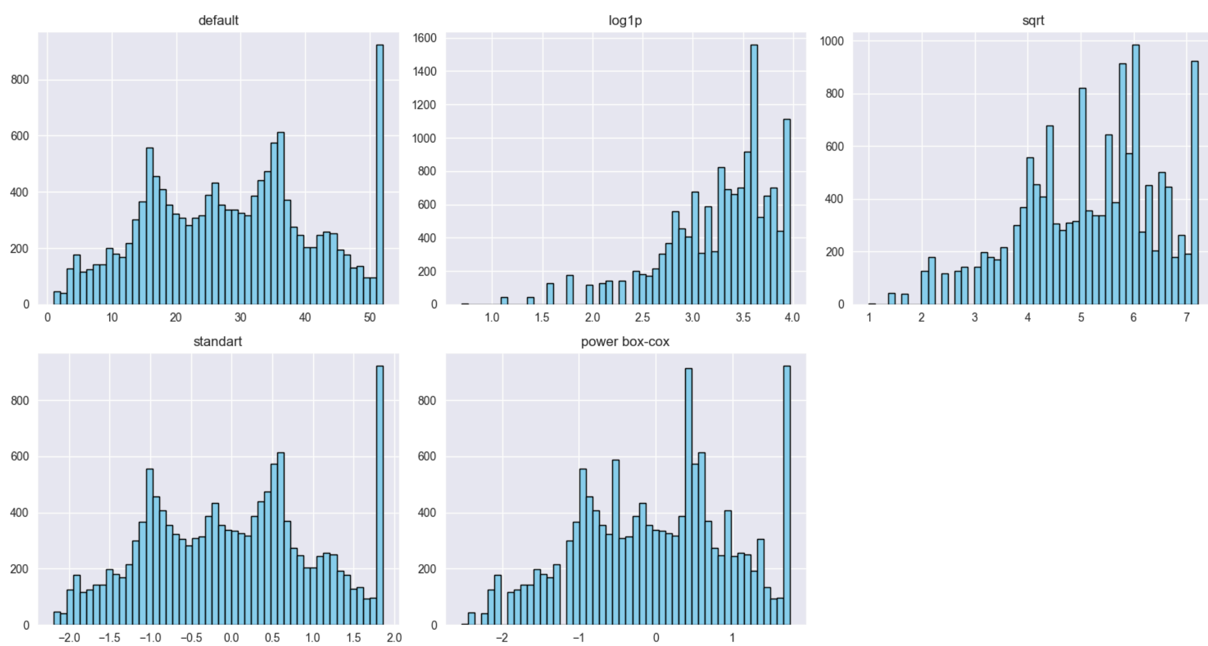
In [32]:
```
param = "median_income"
test_transformations(x_train[[param]])
```



Both log and power transformation appear symmetric

housing_median_age

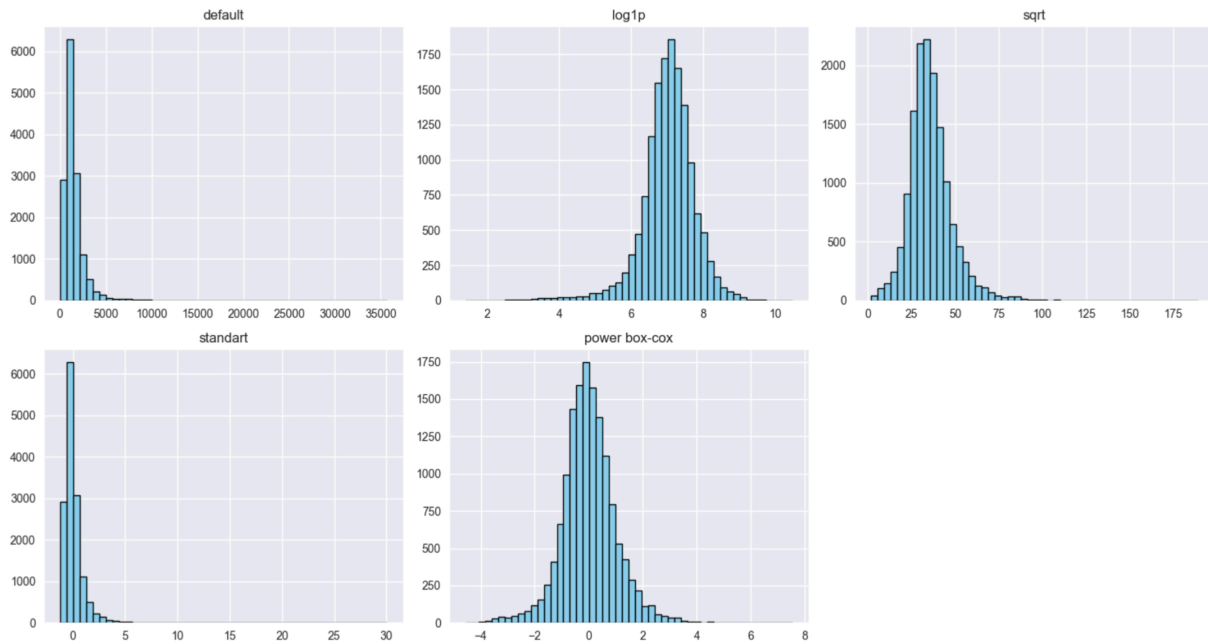
In [33]:
```
param = "housing_median_age"
test_transformations(x_train[[param]])
```



None of the transformations above were able to make the data more normal or symmetric, so the Min-Max scaler can be used to preserve the original metric units

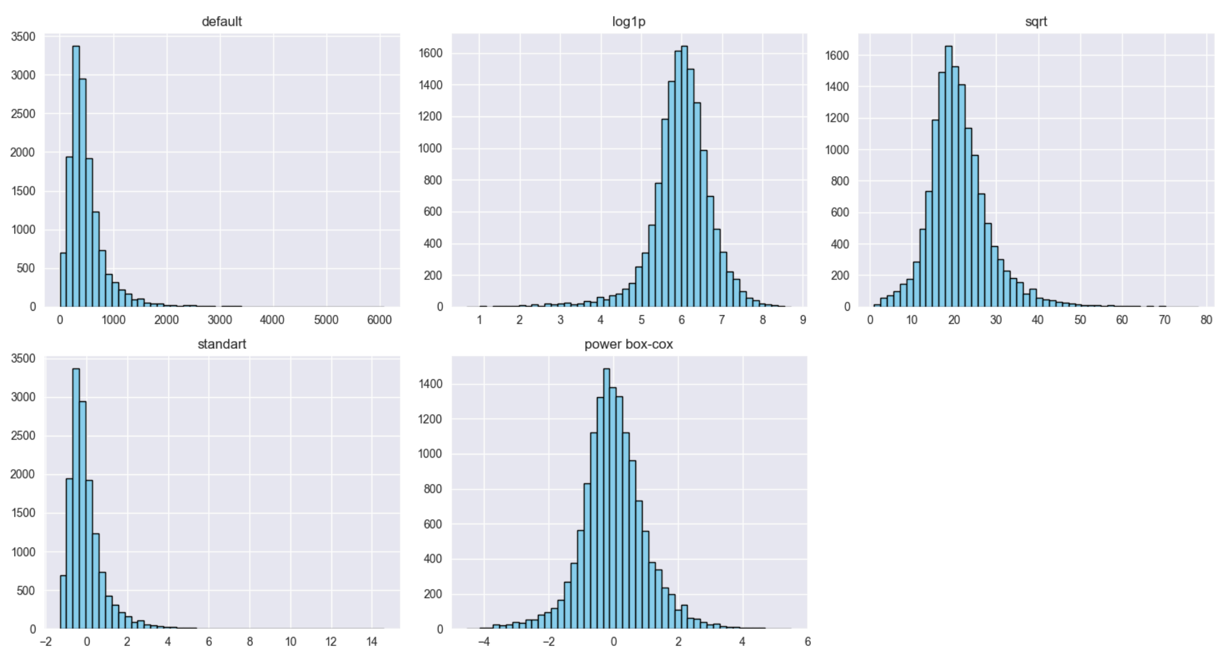
population

In [34]:
```
param = "population"
test_transformations(x_train[[param]])
```



households

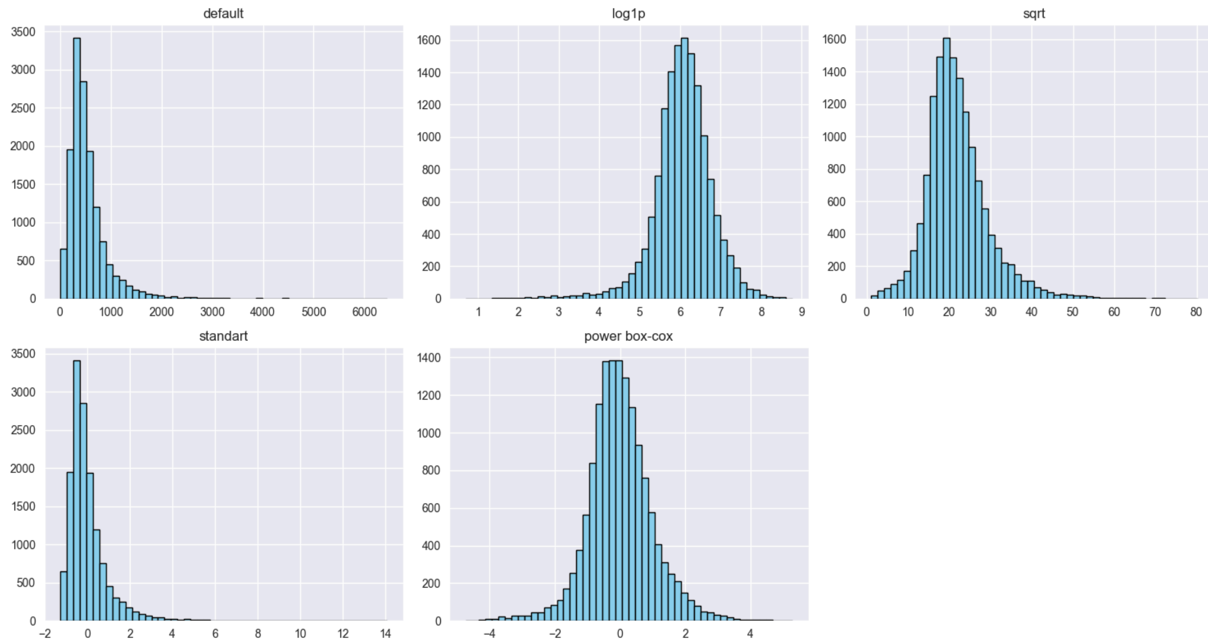
In [35]:
```
param = "households"
test_transformations(x_train[[param]])
```



Households appear the least skewed after the power transformation

total_bedrooms

In [36]:
```
param = "total_bedrooms"
test_transformations(x_train[[param]])
```



latitude & longtitude

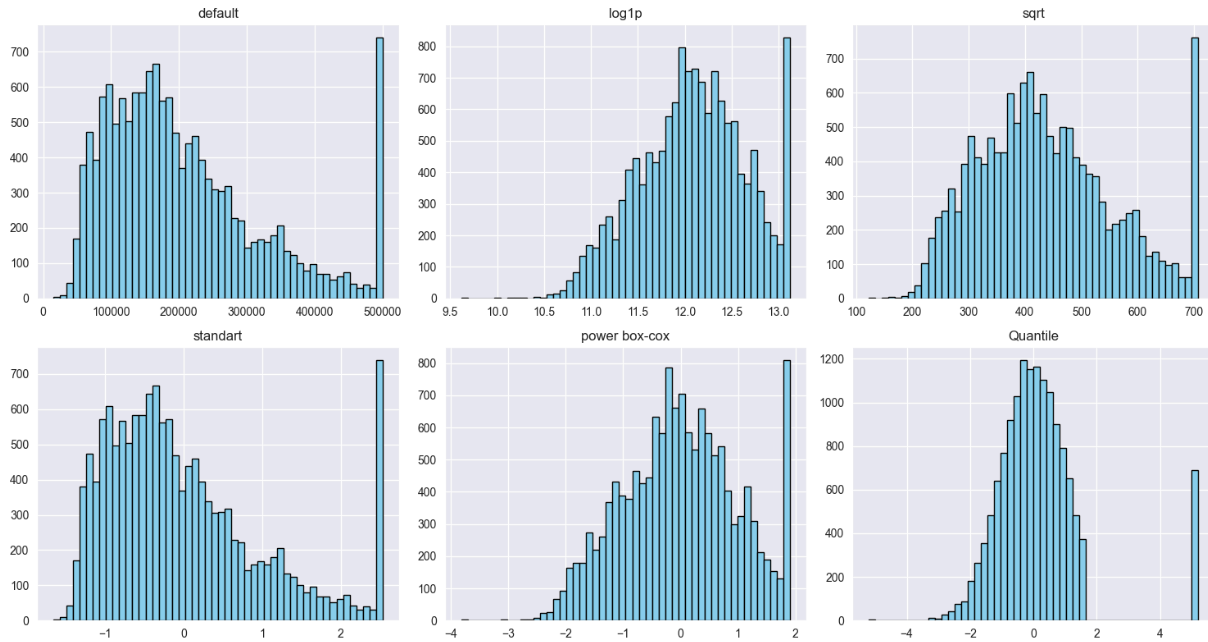
Since it is a location metric and its original units are importent MinMax transformer will be used

is_san_francisco & is_los_angeles

These are boolean features so there is no need to normalize or rescale them

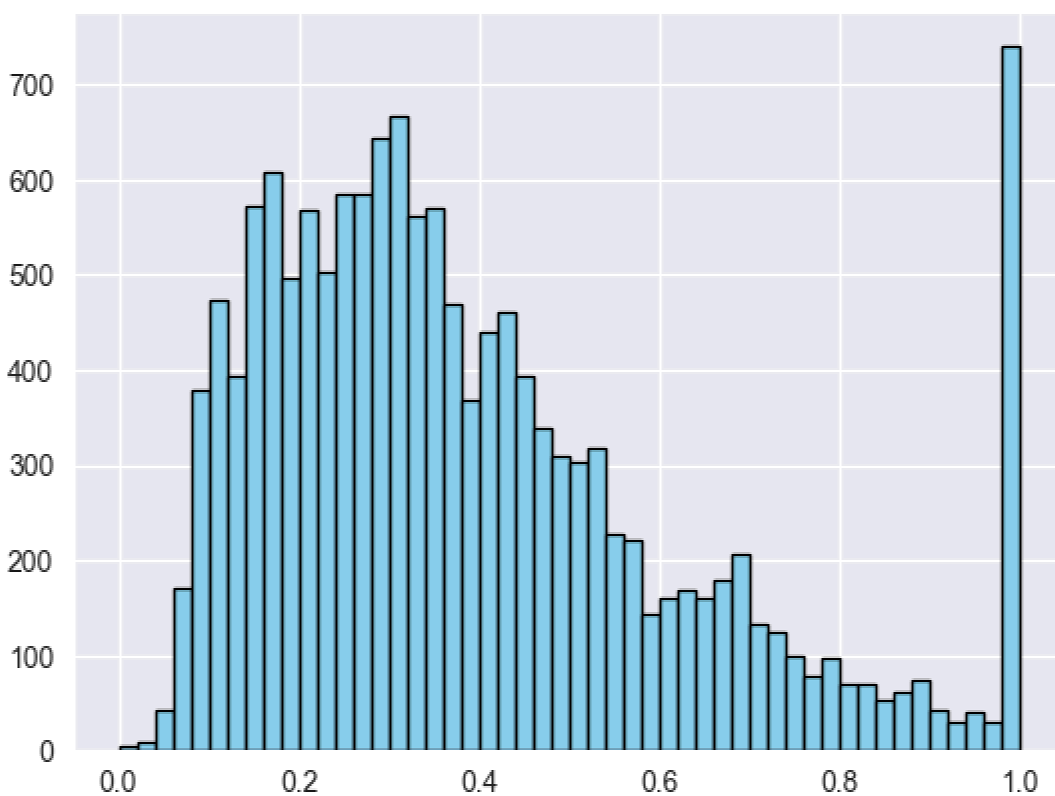
median_house_value

In [37]:
```
quantile = preprocessing.QuantileTransformer(output_distribution='normal', random_s
    .fit_transform(y_train)
test_transformations(y_train, [(quantile, "Quantile")])
```



Sqrt transformation was applied to the predicted variable. Because it spans a large range of values a MinMax scaler should then be used to further normalize it

In [38]:
```
house_value_transformer = Pipeline([
    # ('sqrt', preprocessing.FunctionTransformer(np.sqrt, validate=True)),
    ('scaler', preprocessing.MinMaxScaler())
])

y_train_s = house_value_transformer.fit_transform(y_train)
_ = plt.hist(y_train_s, bins=50, color='skyblue', edgecolor='black')
```



Feature selection

In [39]:
```
x_train.var()
```

Out[39]:
```
median_income         3.628676e+00
housing_median_age    1.591038e+02
total_rooms           4.678804e+06
total_bedrooms        1.762209e+05
population            1.300113e+06
households            1.460931e+05
latitude              4.561395e+00
longitude             4.011729e+00
is_san_francisco      1.548901e-01
is_los_angeles        2.354123e-01
dtype: float64
```

All features have sufficiently high variance

In [40]:
```
selector = SelectKBest(f_regression, k='all')
selector.fit_transform(x_train, y_train)
scores = selector.scores_

ranking = (
    pd.DataFrame({
        "Feature": x_train.columns,
        "F_score": scores,
    })
    .sort_values(by="F_score", ascending=False)
    .reset_index(drop=True)
)

print(ranking)
```

```
              Feature       F_score
0       median_income  13000.094763
1    is_san_francisco   1469.736783
2      is_los_angeles   1049.902026
3            latitude    295.272032
4         total_rooms    273.956091
5  housing_median_age    165.884984
6          households     63.002647
7      total_bedrooms     37.099764
8           longitude     35.263954
9          population      8.546627
```

```
C:\Users\matze\AppData\Local\Programs\Python\Python312\Lib\site-packages\sklearn\uti
ls\validation.py:1339: DataConversionWarning: A column-vector y was passed when a 1d
array was expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

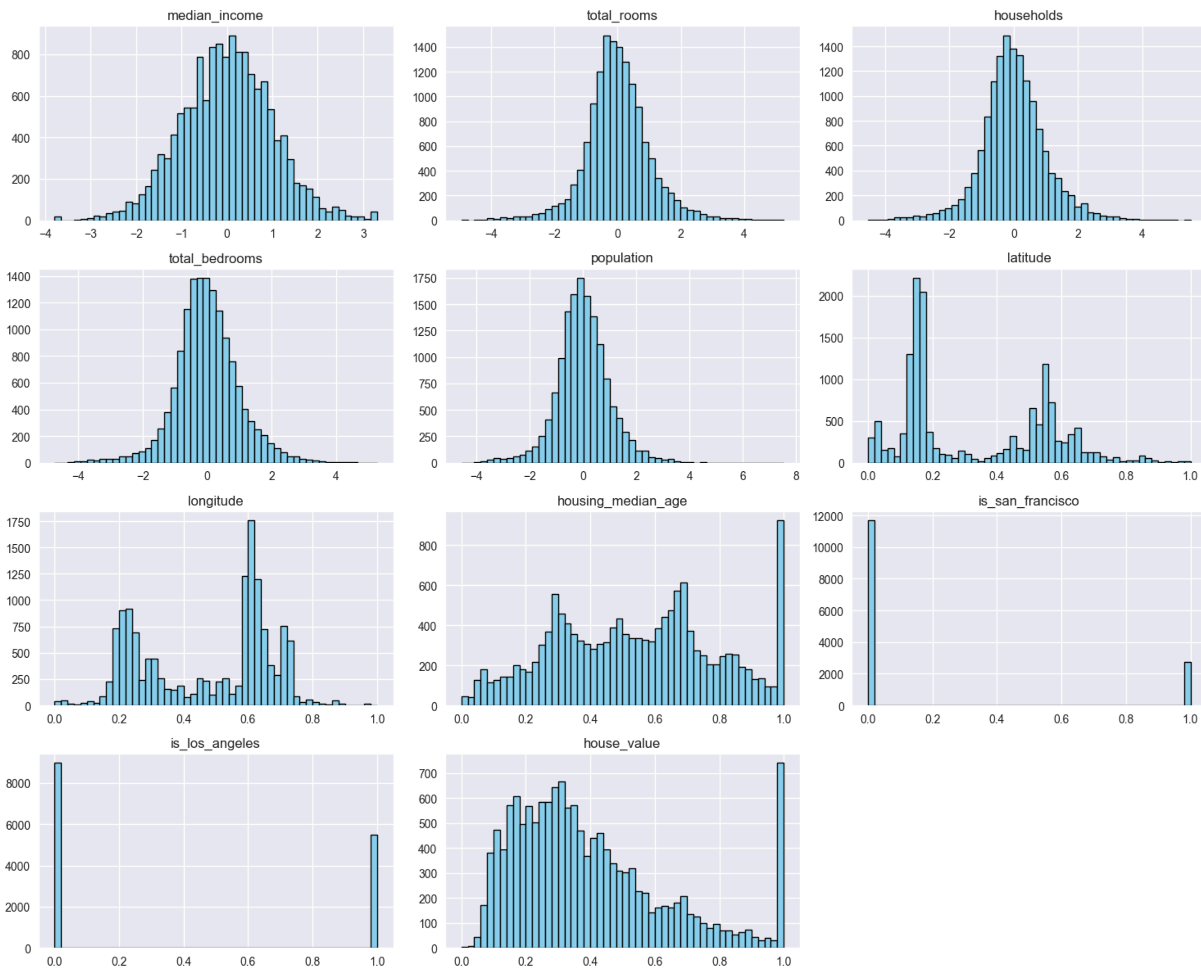
As was noted before features "total_rooms", "total_bedrooms", "population" and "households" have significant correlation, since population has the weakest correlation with predicted variable we can discard it. Also "total_bedrooms" is going to be removed, since it is less correlated with predicted variable then "total_rooms"

In [41]:
```
def save_transformed(transformer, col_order: List[str], x_train, x_test, x_eval, y_
    assert col_order[-1] == "house_value"
    data = x_train.copy()
    data["house_value"] = y_train
    preprocessor.fit(data)
    X_train = preprocessor.transform(data)
    X_train = pd.DataFrame(
        X_train,
        columns=col_order
    )

    data = x_test.copy()
    data["house_value"] = y_test
    X_test = preprocessor.transform(data)
    X_test = pd.DataFrame(
        X_test,
        columns=col_order
    )

    data = x_val.copy()
    data["house_value"] = y_val
    X_val = preprocessor.transform(data)
    X_val = pd.DataFrame(
        X_val,
        columns=col_order
    )

    os.makedirs(path, exist_ok=True)
    X_train.to_csv(f"{path}/train.csv", index=False)
    X_test.to_csv(f"{path}/test.csv", index=False)
    X_val.to_csv(f"{path}/eval.csv", index=False)

    fitted_house_value_transformer = transformer.named_transformers_["predicted"]
    joblib.dump(fitted_house_value_transformer, f"{path}/house_value_scaler.pkl")
    return X_train, X_test, X_val
```

In [42]:
```
from sklearn.compose import ColumnTransformer

preprocessor = ColumnTransformer(
    transformers=[
        ("num", preprocessing.PowerTransformer(method='box-cox'), ["median_income",
            "households", "total_bedrooms", "population"]),
        ("loc", preprocessing.MinMaxScaler(), ["latitude", "longitude", "housing_me
        ("bool", preprocessing.FunctionTransformer(), ["is_san_francisco", "is_los_
        ("predicted", house_value_transformer, ["house_value"])
    ]
)
col_order = (
    ["median_income", "total_rooms", "households", "total_bedrooms", "population"]
    ["latitude", "longitude", "housing_median_age"] +
    ["is_san_francisco", "is_los_angeles"] +
    ["house_value"]
```

```
)
path = f"{TRANSFORMED_PATH}/full_features"
X_train, _, _ = save_transformed(preprocessor, col_order, x_train, x_test, x_val, y
```

In [43]:
```
X_train.hist(bins=50, figsize=(15, 12), color='skyblue', edgecolor='black')
plt.tight_layout()
plt.show()
```



In [44]:
```
preprocessor = sklearn.compose.ColumnTransformer(
    transformers=[
        ("num", preprocessing.PowerTransformer(method='box-cox'), ["median_income",
        ("loc", preprocessing.MinMaxScaler(), ["housing_median_age"]),
        ("bool", preprocessing.FunctionTransformer(), ["is_san_francisco", "is_los_
        ("predicted", house_value_transformer, ["house_value"])
    ]
)
col_order = (
    ["median_income", "total_rooms"] +
    ["housing_median_age"] +
    ["is_san_francisco", "is_los_angeles"] +
    ["house_value"]
)
path = f"{TRANSFORMED_PATH}/small"
X_train, _, _ = save_transformed(preprocessor, col_order, x_train, x_test, x_val, y
```

In [45]:

```
X_train.hist(bins=50, figsize=(15, 12), color='skyblue', edgecolor='black')
plt.tight_layout()
plt.show()
```