Lab 2-Demonstrate the steps to build a machine-learning model that predicts the median housing price using the California housing price dataset.

Download the dataset : https://media.geeksforgeeks.org/wp-content/uploads/20240319120216/housing.csv

1. Perform the describe and info steps

```
#1.Import and head
import pandas as pd
url =
"https://media.geeksforgeeks.org/wp-content/uploads/20240319120216/housing
.csv"
housing = pd.read_csv(url)

housing.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocean_proximity
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	NEAR BAY
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	NEAR BAY
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	NEAR BAY
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	NEAR BAY
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	NEAR BAY

```
#Info
housing.info()
```

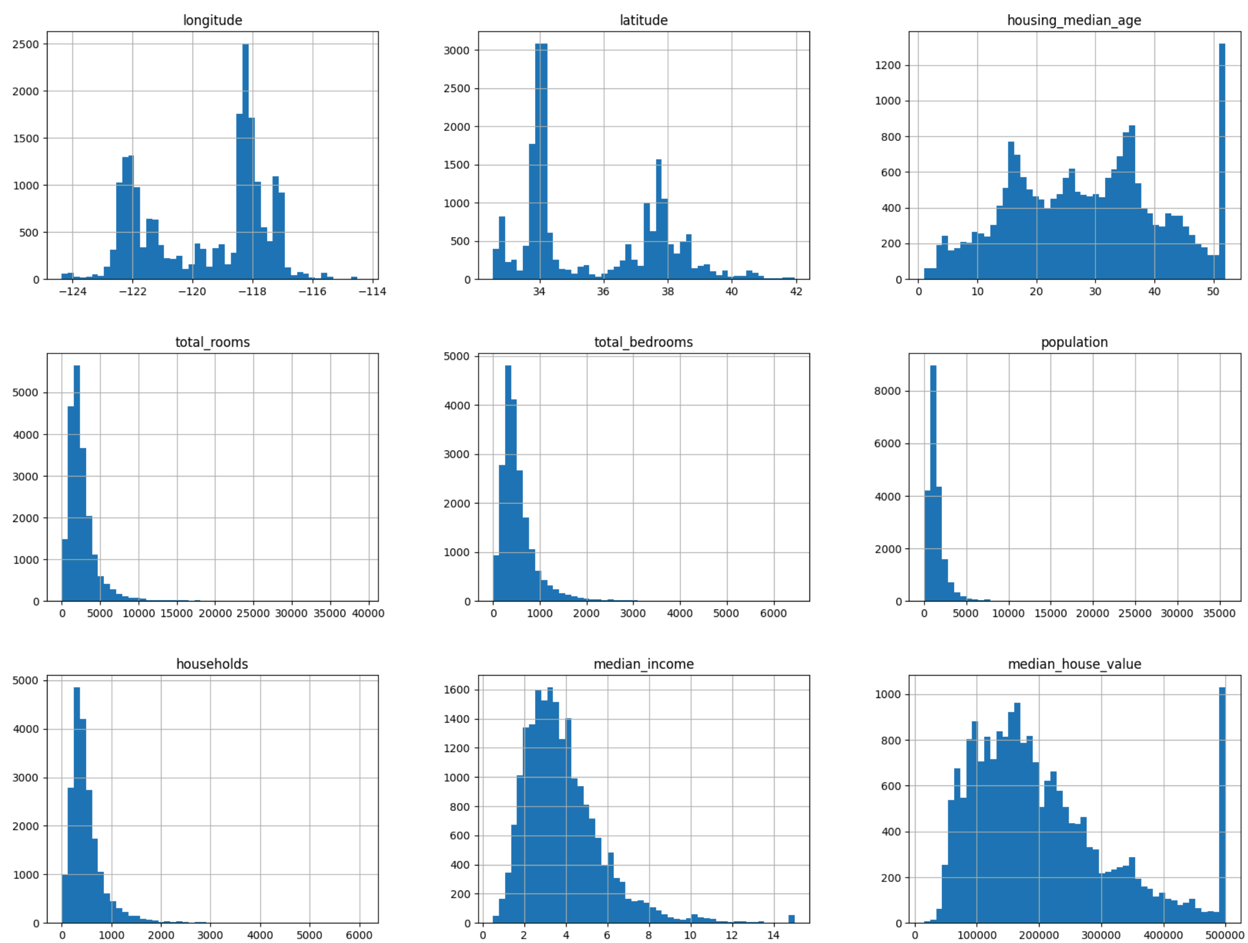
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   longitude           20640 non-null  float64
 1   latitude            20640 non-null  float64
 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
```

```python
#Describe
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	206855.816909
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	115395.615874
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	14999.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	119600.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	179700.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	264725.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	500001.000000

2. Plot the histogram of each feature(Indicate what does histogram indicate on median_income and house_median_age)

```python
housing.hist(bins=50, figsize=(20,15))
plt.show()
```



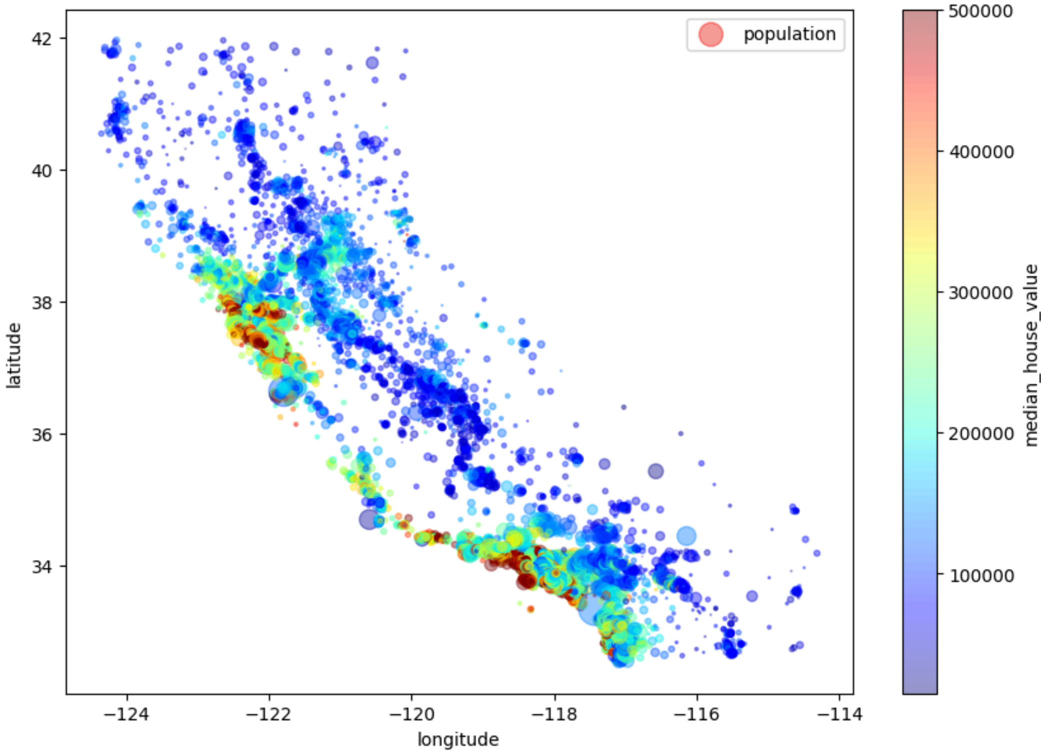
3. Demonstrate the process of creating a test set(write the difference between random and stratified test set)

```
#Random test set
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(housing, test_size=0.2,
random_state=42)

#Stratified test set based on income category
import numpy as np
housing["income_cat"] = pd.cut(
    housing["median_income"],
    bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
    labels=[1, 2, 3, 4, 5]
)
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing,
housing["income_cat"]):
    strat_train_set = housing.loc[train_index]
    strat_test_set = housing.loc[test_index]
```

4. List the geographical features from the dataset and plot a graph to Visualize Geographical Data(what does the graph indicate w.r.t housing prices and location)

```
housing.plot(kind="scatter", x="longitude", y="latitude",
             alpha=0.4,
             s=housing["population"]/100,
             label="population",
             figsize=(10,7),
             c="median_house_value",
             cmap=plt.get_cmap("jet"),
             colorbar=True)

plt.legend()
plt.show()
```

...



5. Plot a graph to show features correlation with housing price. Which feature corelates to the maximum. Plot the graph for that with housing price and analyze what the graph indicate.

```
#Correlation with Housing Price
corr_matrix = housing.corr(numeric_only=True)

corr_matrix["median_house_value"].sort_values(ascending=False)
```

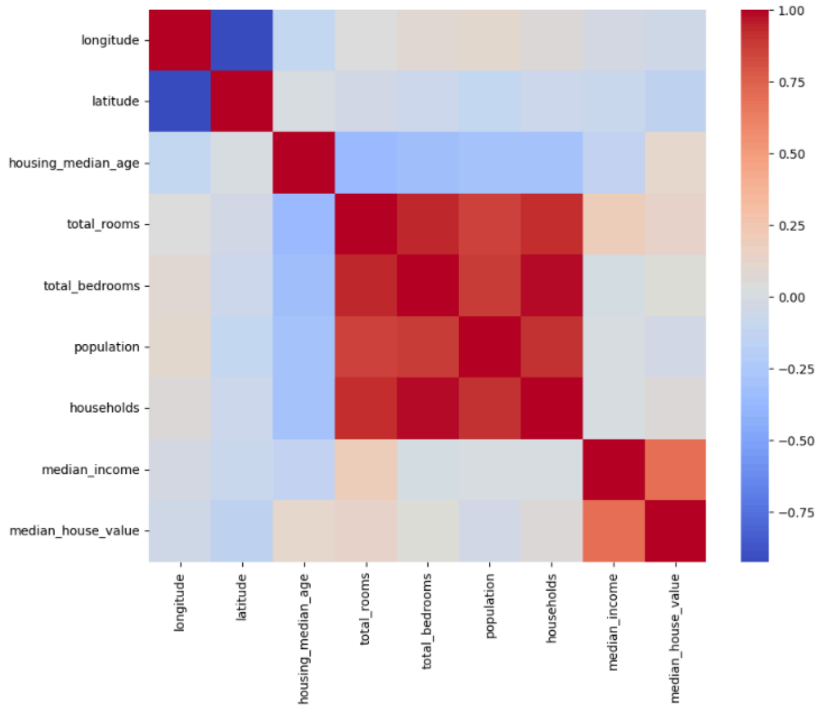
...

	median_house_value
median_house_value	1.000000
median_income	0.688075
total_rooms	0.134153
housing_median_age	0.105623
households	0.065843
total_bedrooms	0.049686
population	-0.024650
longitude	-0.045967
latitude	-0.144160

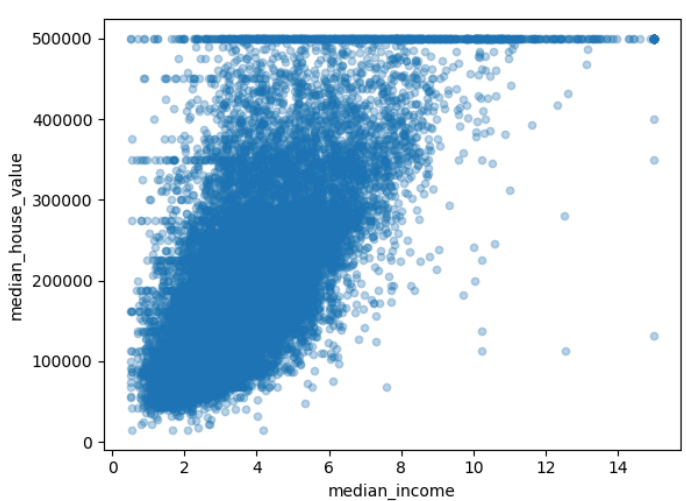
dtype: float64

```
#Correlation graph
import seaborn as sns

plt.figure(figsize=(10,8))
sns.heatmap(corr_matrix, annot=False, cmap="coolwarm")
plt.show()
```

...




```
#Plot median_income vs price
housing.plot(kind="scatter", x="median_income", y="median_house_value",
alpha=0.3)
plt.show()
```



6. List the features that could be combined to improve correlation and plot again to see if correlation has improved.

```
#6. List the features that could be combined to improve correlation and
plot again to see if correlation has improved
housing["rooms_per_household"] = housing["total_rooms"] /
housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"] /
housing["total_rooms"]
housing["population_per_household"] = housing["population"] /
housing["households"]
corr_matrix = housing.corr(numeric_only=True)
corr_matrix["median_house_value"].sort_values(ascending=False)
```

...

	median_house_value
median_house_value	1.000000
median_income	0.688075
rooms_per_household	0.151948
total_rooms	0.134153
housing_median_age	0.105623
households	0.065843
total_bedrooms	0.049686
population_per_household	-0.023737
population	-0.024650
longitude	-0.045967
latitude	-0.144160
bedrooms_per_room	-0.255880

dtype: float64

7. List the features that needs to be cleaned and demonstrate the process of cleaning.

```
housing.dropna(subset=["total_bedrooms"])
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
housing_num = housing.drop("ocean_proximity", axis=1)
imputer.fit(housing_num)
housing_num_imputed = imputer.transform(housing_num)
```

8. Is there any categorical data that needs to be converted to numerical? If so explain the method used to convert and code the same and show the output.

```
from sklearn.preprocessing import OneHotEncoder
housing_cat = housing[["ocean_proximity"]]
encoder = OneHotEncoder()
housing_cat_1hot = encoder.fit_transform(housing_cat)
housing_cat_1hot.toarray()
```

```
array([[0., 0., 0., 1., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 1., 0.],
       ...,
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

9. Discuss the importance of feature scaling.

```
#Scaling
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
housing_scaled = scaler.fit_transform(housing_num)
```

10. Design a pipeline inculcating (Custom transform, feature scaling and encoding). Explain how it works

```
#Custom Transformer
from sklearn.base import BaseEstimator, TransformerMixin

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True):
        self.add_bedrooms_per_room = add_bedrooms_per_room

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        rooms_per_household = X[:, 3] / X[:, 6]
        population_per_household = X[:, 5] / X[:, 6]
```

```python
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, 4] / X[:, 3]
            return np.c_[X, rooms_per_household,
                         population_per_household,
                         bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household,
                         population_per_household]
#Full Pipeline
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

num_attribs = list(housing.drop("ocean_proximity", axis=1))
cat_attribs = ["ocean_proximity"]

num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('scaler', StandardScaler()),
])

full_pipeline = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", OneHotEncoder(), cat_attribs),
])

housing_prepared = full_pipeline.fit_transform(housing)
```