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Define the probleme

In [24]:
```
import matplotlib.image as mpimg
img = mpimg.imread('1.jpg')
plt.imshow(img)
plt.axis('off')
plt.show()
```

Qu'est-ce que le dataset California Housing ?

Le dataset California Housing est un ensemble de données largement utilisé dans l'apprentissage automatique pour s'entraîner à résoudre des problèmes de régression. Il contient des informations sur les propriétés immobilières en Californie, telles que :#• Données démographiques: population, revenu médian, etc# • Caractéristiques des propriétés: nombre de pièces, âge moyen des maisons, et# • Localisation géographique: latitude, longitu#. • Variable cible: prix médian d maisonsn.

Quel problème d'apprentissage automatique résout-on avec ce dataset ?

L'objectif principal est de prédire le prix médian d'une maison en Californie en fonction des autres caractéristiques disponibles dans le dataset. C'est un problème typique de régression.

In [100…
```
# import librairies and modules
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,mean_absolute_error,r2_score
%matplotlib inline
```

In [101…
```
# Load the dataset and create a dataframe from this
# import the dataset
house_data = pd.read_csv('housing.csv')
house_data
```

Out[101]:

	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
...	...	...	...	...	...	...	...	...	...	...
20635	-121.09	39.48	25.0	1665.0	374.0	845.0	330.0	1.5603	78100.0	INLAND
20636	-121.21	39.49	18.0	697.0	150.0	356.0	114.0	2.5568	77100.0	INLAND
20637	-121.22	39.43	17.0	2254.0	485.0	1007.0	433.0	1.7000	92300.0	INLAND
20638	-121.32	39.43	18.0	1860.0	409.0	741.0	349.0	1.8672	84700.0	INLAND
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0	530.0	2.3886	89400.0	INLAND

20640 rows × 10 columns

Exploring the dataset

Provides a summury of dataframe

In [102…
```
print(house_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
None
```

Generates descriptive statistiques for numerical column

In [103…
```
house_data.describe()
```

Out[103]:

	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

Displays the first few rows of dataframe

In [104…
```
house_data.head()
```

Out[104]:

	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

Checking missing value in a dataset¶

In [105…
```
house_data.isnull().sum()
```

Out[105]:
```
longitude               0
latitude                0
housing_median_age      0
total_rooms             0
total_bedrooms        207
population              0
households              0
median_income           0
median_house_value      0
ocean_proximity         0
dtype: int64
```

Data cleaning (handling missing values and irrevelant columns)

In [107…
```
###  Filling missing values in the total_bedrooms column(Median is the mid point value)
house_data['total_bedrooms']= house_data['total_bedrooms'].fillna(house_data['total_bedrooms'].mean())
```

Mesuring the statistics relationship betwen a housing_data variables

In [108…
```
print(house_data.isnull().sum())
```

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

Find outliers

In [110…
```
# To calculate the quartiles and IQR
Q1 = house_data['median_house_value'].quantile(0.25)
Q3 =  house_data['median_house_value'].quantile(0.75)
IQR = Q3 - Q1
# Define the outliers limits
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3  + 1.5 * IQR
# identify the ouliers values
outliers = house_data[(house_data['median_house_value']< lower_bound) | (house_data['median_house_value']> upper_bound)]
print("valeurs aberrantes détéctées: ")
print(outliers)
```

```
valeurs aberrantes détéctées:
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
89       -122.27     37.80                52.0        249.0            78.0
140      -122.18     37.81                30.0        292.0            38.0
459      -122.25     37.87                52.0        609.0           236.0
489      -122.25     37.86                48.0       2153.0           517.0
493      -122.24     37.86                52.0       1668.0           225.0
...          ...       ...                 ...          ...             ...
20422    -118.90     34.14                35.0       1503.0           263.0
20426    -118.69     34.18                11.0       1177.0           138.0
20427    -118.80     34.19                 4.0      15572.0          2222.0
20436    -118.69     34.21                10.0       3663.0           409.0
20443    -118.85     34.27                50.0        187.0            33.0

       population  households  median_income  median_house_value  \
89          396.0        85.0         1.2434            500001.0
140         126.0        52.0         6.3624            483300.0
459        1349.0       250.0         1.1696            500001.0
489        1656.0       459.0         3.0417            489600.0
493         517.0       214.0         7.8521            500001.0
...           ...         ...            ...                 ...
20422       576.0       216.0         5.1457            500001.0
20426       415.0       119.0        10.0472            500001.0
20427      5495.0      2152.0         8.6499            500001.0
20436      1179.0       371.0        12.5420            500001.0
20443       130.0        35.0         3.3438            500001.0

      ocean_proximity
89           NEAR BAY
140          NEAR BAY
459          NEAR BAY
489          NEAR BAY
493          NEAR BAY
...               ...
20422       <1H OCEAN
20426       <1H OCEAN
20427       <1H OCEAN
20436       <1H OCEAN
20443       <1H OCEAN

[1071 rows x 10 columns]
```

In [111…
```
# to delete the ouliers value
house_data_cleaned = house_data[(house_data['median_house_value'] >= lower_bound) & (house_data['median_house_value']<= upper_bound)]
```

In [112…
```
print(" données sans valeurs  aberrantes : ")
print(house_data_cleaned)
```

```
 données sans valeurs  aberrantes :
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
0        -122.23     37.88                41.0        880.0           129.0
1        -122.22     37.86                21.0       7099.0          1106.0
2        -122.24     37.85                52.0       1467.0           190.0
3        -122.25     37.85                52.0       1274.0           235.0
4        -122.25     37.85                52.0       1627.0           280.0
...          ...       ...                 ...          ...             ...
20635    -121.09     39.48                25.0       1665.0           374.0
20636    -121.21     39.49                18.0        697.0           150.0
20637    -121.22     39.43                17.0       2254.0           485.0
20638    -121.32     39.43                18.0       1860.0           409.0
20639    -121.24     39.37                16.0       2785.0           616.0

       population  households  median_income  median_house_value  \
0           322.0       126.0         8.3252            452600.0
1          2401.0      1138.0         8.3014            358500.0
2           496.0       177.0         7.2574            352100.0
3           558.0       219.0         5.6431            341300.0
4           565.0       259.0         3.8462            342200.0
...           ...         ...            ...                 ...
20635       845.0       330.0         1.5603             78100.0
20636       356.0       114.0         2.5568             77100.0
20637      1007.0       433.0         1.7000             92300.0
20638       741.0       349.0         1.8672             84700.0
20639      1387.0       530.0         2.3886             89400.0

      ocean_proximity
0            NEAR BAY
1            NEAR BAY
2            NEAR BAY
3            NEAR BAY
4            NEAR BAY
...               ...
20635          INLAND
20636          INLAND
20637          INLAND
20638          INLAND
20639          INLAND

[19569 rows x 10 columns]
```

Dropping a ocean_proximity column

In [123…
```
house_data_cleaned =house_data_cleaned.drop(columns=['ocean_proximity'])
```

In [124…
```
house_data_cleaned.corr()
```

Out[124]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
longitude	1.000000	-0.924031	-0.101691	0.044735	0.070191	0.101638	0.056346	-0.010808	-0.047342
latitude	-0.924031	1.000000	0.006104	-0.033798	-0.068286	-0.114359	-0.073547	-0.076249	-0.149100
housing_median_age	-0.101691	0.006104	1.000000	-0.372715	-0.326596	-0.294893	-0.310343	-0.197628	0.061480
total_rooms	0.044735	-0.033798	-0.372715	1.000000	0.931110	0.859642	0.921278	0.226557	0.147526
total_bedrooms	0.070191	-0.068286	-0.326596	0.931110	1.000000	0.875347	0.973927	0.024602	0.078245
population	0.101638	-0.114359	-0.294893	0.859642	0.875347	1.000000	0.909218	0.045413	0.017764
households	0.056346	-0.073547	-0.310343	0.921278	0.973927	0.909218	1.000000	0.049055	0.099352
median_income	-0.010808	-0.076249	-0.197628	0.226557	0.024602	0.045413	0.049055	1.000000	0.644267
median_house_value	-0.047342	-0.149100	0.061480	0.147526	0.078245	0.017764	0.099352	0.644267	1.000000

dropping column and splitting data

In [125…
```
X = house_data_cleaned.drop(columns=['median_house_value'])
y = house_data_cleaned['median_house_value']
```

In [117…
```
house_data_cleaned.head(3)
```

Out[117]:

	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

In [126…
```
X_train, X_test, y_train, y_test= train_test_split(X,y, test_size=0.2, random_state = 42)
```

In [127…
```
print(X_train.shape,X_test.shape)
```

```
(15655, 8) (3914, 8)
```

Standardize the features

In [128…
```
Scaler = StandardScaler()
X_train_scaled = Scaler.fit_transform(X_train)
X_test_scaled = Scaler.transform(X_test)
```

initialise and train the regression model

In [129…
```
model = LinearRegression()
model.fit(X_train_scaled, y_train)
```

Out[129]:
```
▾ LinearRegression
LinearRegression()
```

Making predictions

In [130…
```
y_pred= model.predict(X_test_scaled)
y_pred
```

Out[130]:
```
array([ 74747.38050415, 128726.2701118 , 261189.13900352, ...,
       169719.22186104, 228841.10418274, 133428.93214741])
```

Evaluate the model : using Mean Squared Error (MSE), Mean Absolute Error (MAE) and R2 (determination coefficient)

In [131…
```
MAE = mean_absolute_error(y_test,y_pred)
MSE = mean_squared_error(y_test,y_pred)
r2 = r2_score(y_test,y_pred)
```

In [132…
```
print("Mean Absolute Error:" , MAE)
print("Mean Squared Error:" , MSE)
print("R- Squared:", r2)
```

```
Mean Absolute Error: 44585.379349951014
Mean Squared Error: 3585071186.9282236
R- Squared: 0.6123494081149208
```

predicting a small sample of data

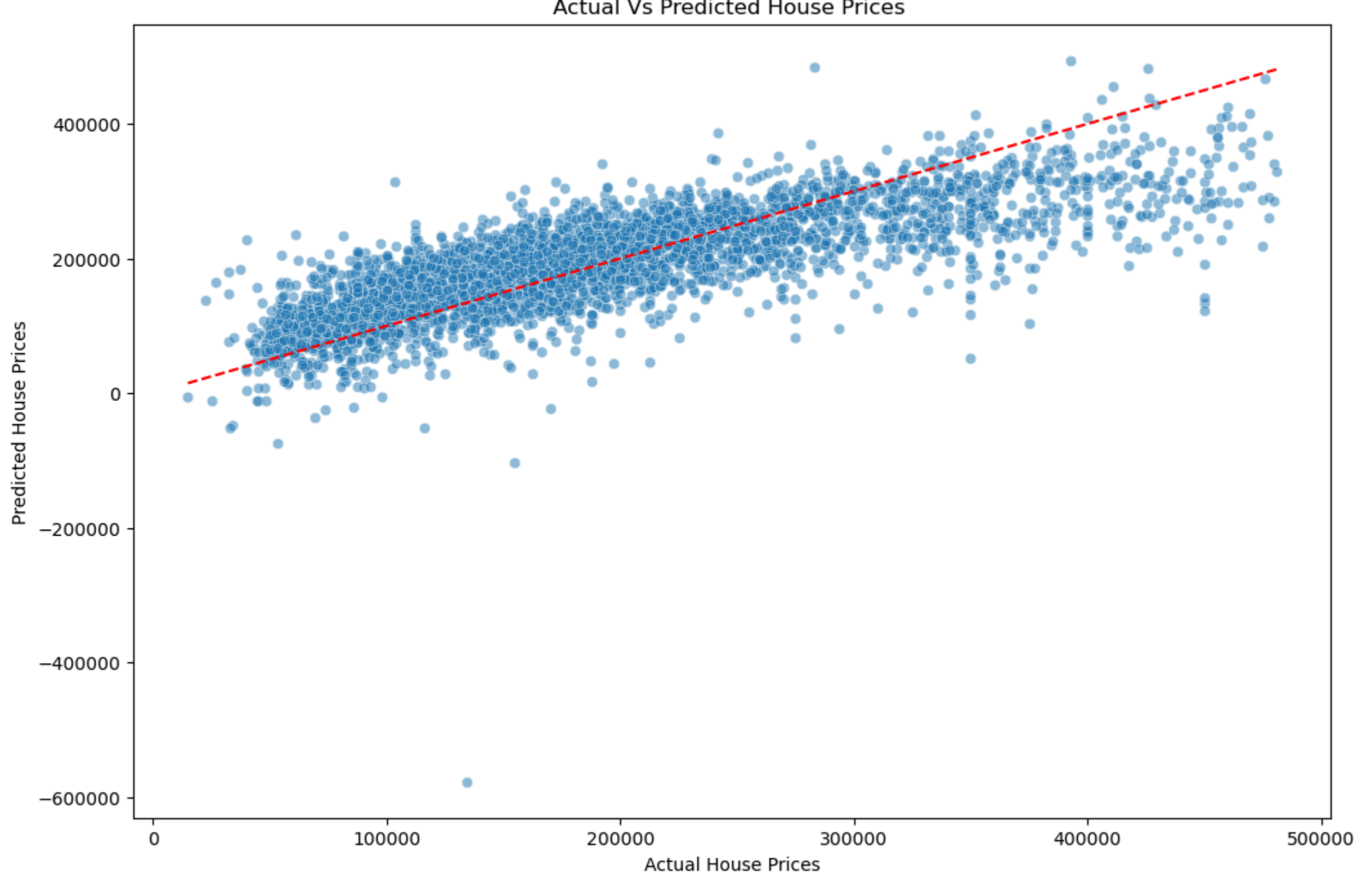
In [136…
```
Sample_data = X_test.head()
Sample_data_scaled =  Scaler.transform(Sample_data)
predictions = model.predict(Sample_data_scaled)
```

In [137…
```
print(" Prédictions:", predictions)
print("Actual values:", y_test.head().values)
```

```
 Prédictions: [ 74747.38050415 128726.2701118  261189.13900352 171205.84624638
 199909.7129558 ]
Actual values: [ 55200.  97800. 245300. 162100. 163100.]
```

Create a scatter plot

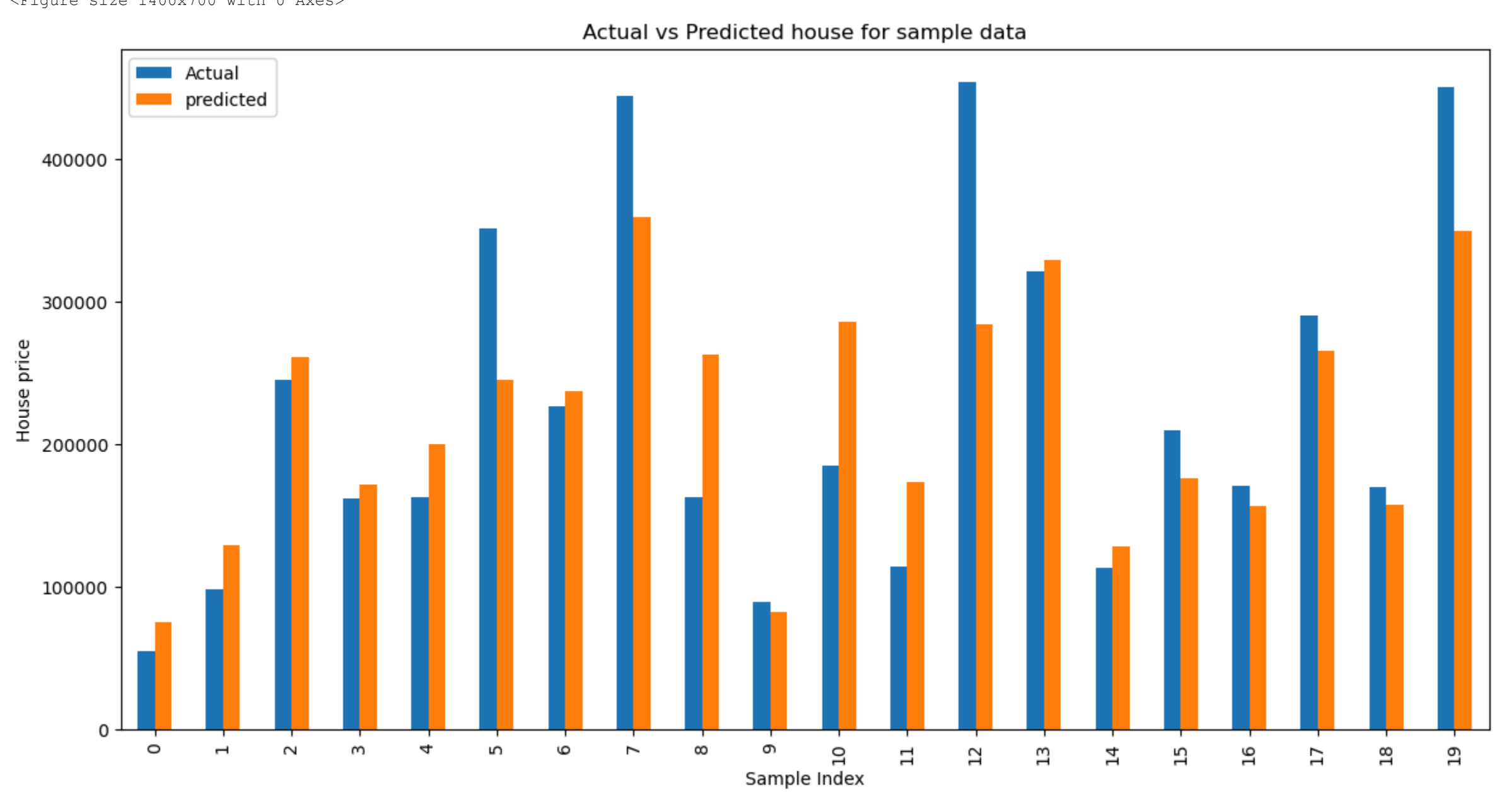
In [139…
```
plt.figure(figsize= (12,8))
sns.scatterplot( x=y_test,y=y_pred, alpha = 0.5)
plt.plot([min(y_test),max(y_test)], [min(y_test),max(y_test)], color ='red', linestyle='--')
plt.xlabel('Actual House Prices')
plt.ylabel('Predicted House Prices')
plt.title("Actual Vs Predicted House Prices ")
plt.show()
```



Creating a bar plot

In [148…
```
sample_size = 20
indices = np.arange(sample_size)
actual_prices = y_test[:sample_size].values
predicted_prices = y_pred[:sample_size]
Sample_df = pd.DataFrame({
    'Actual' :actual_prices,
    'predicted' : predicted_prices
})
plt.figure(figsize=(14,7))
Sample_df.plot(kind='bar',figsize=(14,7))
plt.xlabel('Sample Index')
plt.ylabel('House price')
plt.title( 'Actual vs Predicted house for sample data')
plt.show()
```

```
<Figure size 1400x700 with 0 Axes>
```



Save the housing model

import joblib

joblib.dump(model,'california_house_prices_scaler.pkl')

In [152…
```
model_scaler  = {
    'model' : model,
    'scaler' : Scaler}
joblib.dump(model_scaler, 'model_scaler.pkl')
```

Out[152]:
```
['model_scaler.pkl']
```