DESCRIPTION

Background of Problem Statement:
The US Census Bureau has published California Census Data which has 10 types of metrics such as the population, median income, median housing price, and so on for each block group in California. The dataset also serves as an input for project scoping and tries to specify the functional and non-functional requirements for it.

Problem Objective:
The project aims at building a model of housing prices to predict median house values in California using the provided dataset. This model should learn from the data and be able to predict the median housing price in any district, given all the other metrics. Districts or block groups are the smallest geographical units for which the US Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people). There are 20,640 districts in the project dataset.

Domain: Finance and Housing

Analysis Tasks to be performed:

1. Build a model of housing prices to predict median house values in California using the provided dataset.
2. Train the model to learn from the data to predict the median housing price in any district, given all the other metrics.
3. Predict housing prices based on median_income and plot the regression chart for it.

1. **Load the data:**
   - Read the “housing.csv” file from the folder into the program.
   - Print first few rows of this data.
   - Extract input (X) and output (Y) data from the dataset.
2. **Handle missing values:**
   - Fill the missing values with the mean of the respective column.
3. **Encode categorical data:**
   - Convert categorical column in the dataset to numerical data.
4. **Split the dataset:**
   - Split the data into 80% training dataset and 20% test dataset.
5. **Standardize data:**
   - Standardize training and test datasets.
6. **Perform Linear Regression :**
   - Perform Linear Regression on training data.
   - Predict output for test dataset using the fitted model.
   - Print root mean squared error (RMSE) from Linear Regression
   - [HINT: Import mean_squared_error from sklearn.metrics]
7. **Bonus exercise: Perform Linear Regression with one independent variable :**
   - Extract just the median_income column from the independent variables (from X_train and X_test).
   - Perform Linear Regression to predict housing values based on median_income.
   - Predict output for test dataset using the fitted model.
   - Plot the fitted model for training data as well as for test data to check if the fitted model satisfies the test data.

Dataset Description :
Field Description

longitude (signed numeric - float) : Longitude value for the block in California, USA
latitude (numeric - float) : Latitude value for the block in California, USA
housing_median_age (numeric - int) : Median age of the house in the block
total_rooms (numeric - int) : Count of the total number of rooms (excluding bedrooms) in all houses in the block
total_bedrooms (numeric - float) : Count of the total number of bedrooms in all houses in the block
population (numeric - int) : Count of the total number of population in the block
households (numeric - int) : Count of the total number of households in the block
median_income (numeric - float) : Median of the total household income of all the houses in the block
ocean_proximity (numeric - categorical) : Type of the landscape of the block [Unique Values : 'NEAR BAY', 'OCEAN', 'INLAND', 'NEAR OCEAN', 'ISLAND']
median_house_value (numeric - int) : Median of the household prices of all the houses in the block

The analysis results to be provided with insights wherever applicable.

Load the Data - Read file, View first few rows, Extract Input & Output

In [1]:
```python
import numpy as np
import pandas as pd
data_set = pd.read_excel("C:/Users/VAIO/Downloads/SimpliLearn/Python/Assessment/California_House_Pricing.xlsx")
data_set.head(10)
```

Out[1]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_proximity	median_house_value
0	-122.23	37.88	41	880	129.0	322	126	8.3252	NEAR BAY	452600
1	-122.22	37.86	21	7099	1106.0	2401	1138	8.3014	NEAR BAY	358500
2	-122.24	37.85	52	1467	190.0	496	177	7.2574	NEAR BAY	352100
3	-122.25	37.85	52	1274	235.0	558	219	5.6431	NEAR BAY	341300
4	-122.25	37.85	52	1627	280.0	565	259	3.8462	NEAR BAY	342200
5	-122.25	37.85	52	919	213.0	413	193	4.0368	NEAR BAY	269700
6	-122.25	37.84	52	2535	489.0	1094	514	3.6591	NEAR BAY	299200
7	-122.25	37.84	52	3104	687.0	1157	647	3.1200	NEAR BAY	241400
8	-122.26	37.84	42	2555	665.0	1206	595	2.0804	NEAR BAY	226700
9	-122.25	37.84	52	3549	707.0	1551	714	3.6912	NEAR BAY	261100

Inference: We can see that the data set has only one categorial variable 'ocean_proximity' present. Which we would require to encoded for further analysis

In [2]:
```python
# View the information, Description and Shape of the dataset
```

In [3]:
```python
data_set.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null int64
total_rooms           20640 non-null int64
total_bedrooms        20433 non-null float64
population            20640 non-null int64
households            20640 non-null int64
median_income         20640 non-null float64
ocean_proximity       20640 non-null object
median_house_value    20640 non-null int64
dtypes: float64(4), int64(5), object(1)
memory usage: 1.6+ MB
```

In [4]:
```python
data_set.describe()
```

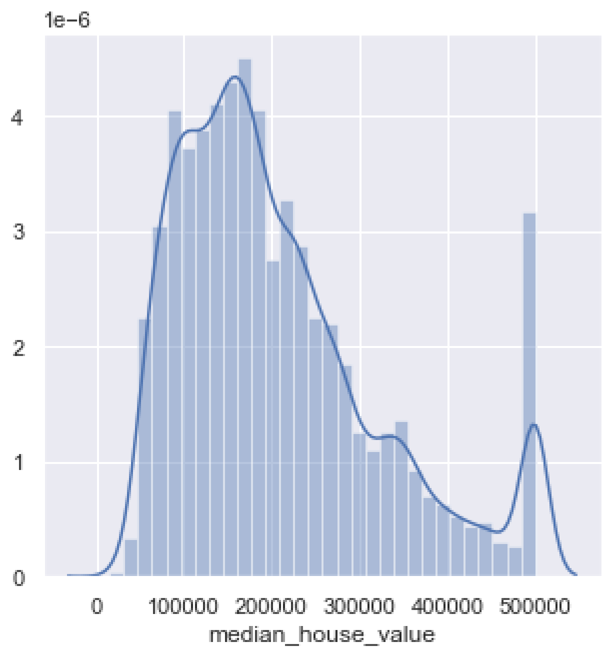
Out[4]:

	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

In [5]:
```python
data_set.shape
```

Out[5]: (20640, 10)

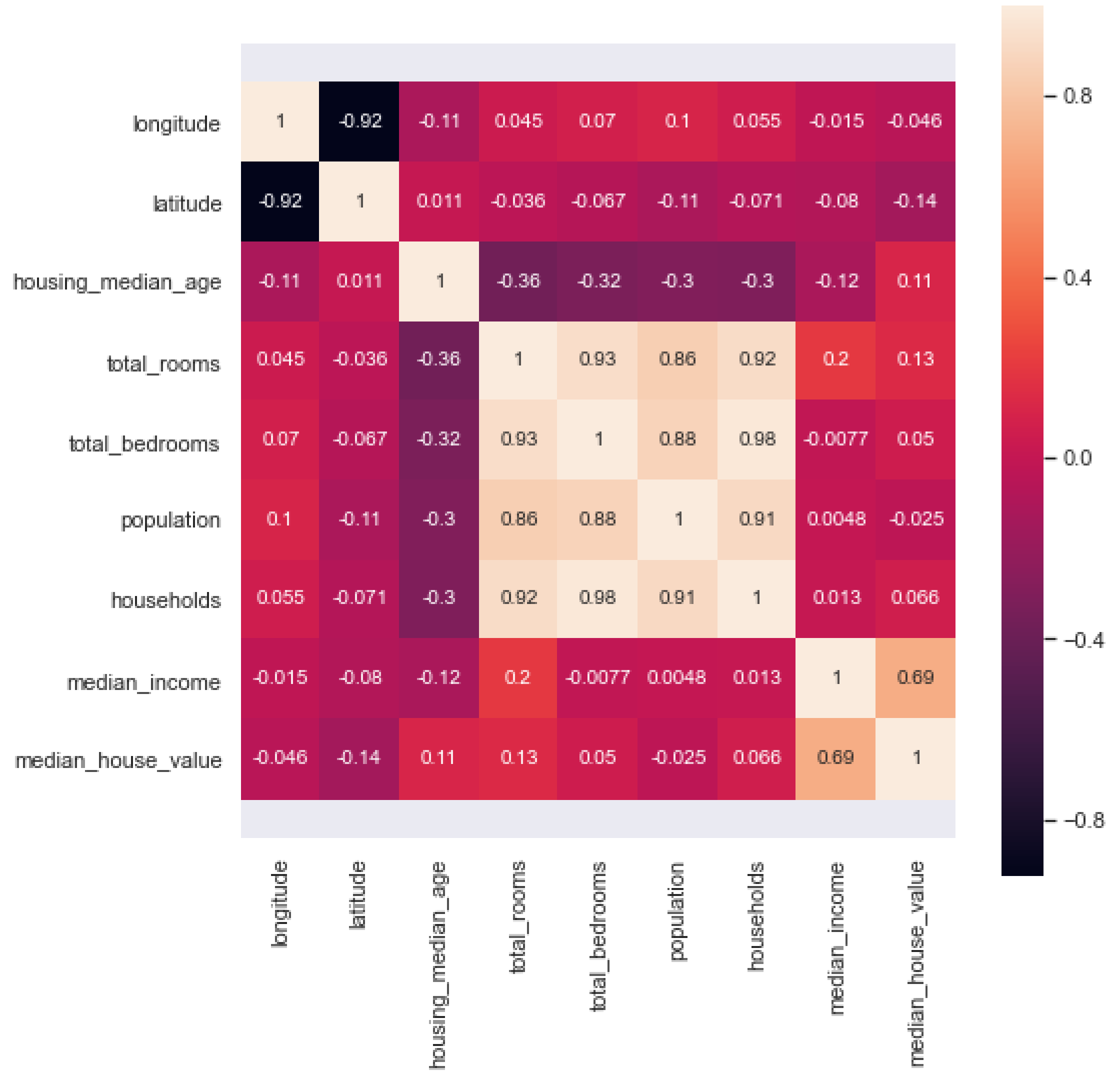
In [38]:
```python
# Visualize the distribution of the median price of house in the districts
import seaborn as sns
import matplotlib.pyplot as plt
sns.set(rc={'figure.figsize':(5,5)})
sns.distplot(data_set['median_house_value'], bins=30)
plt.show()
```



Inference: Above graph respresents that the 'median_house_value' is skewed towards right. This tells us, there are some outliners present in the right side. Also the mean of the feature is grater than the media.

In [7]:
```python
# Visualize the co-relation between the coefiicients
california_corr = data_set.corr()
plt.subplots(figsize=(8,8))
ax = sns.heatmap(california_corr,square=True,annot=True)
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[7]: (9.5, -0.5)



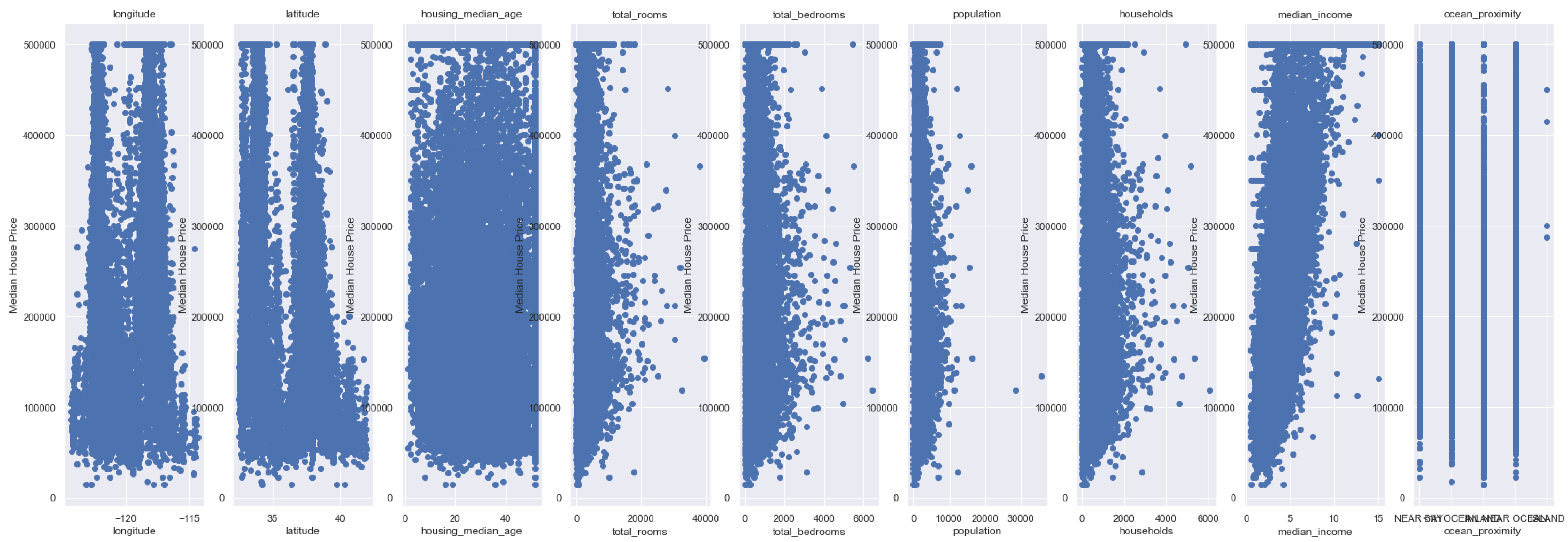
In [8]:
```python
# Extracting the Input data (X) and Output data (Y)
X = data_set.iloc[:,0:9]
Y = data_set['median_house_value']
```

In [9]:
```python
# View the rows and columns in X and Y
X.shape, Y.shape
```

Out[9]: ((20640, 9), (20640,))

In [10]:
```python
# Visualize the relation of each input feature with output feature using scatter plot
plt.figure(figsize=(30, 10))
Features = X.columns

for i, col in enumerate(Features):
    plt.subplot(1, len(Features) , i+1)
    x = data_set[col]
    y = Y
    plt.scatter(x, y)
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('Median House Price')
```



Handle missing values

In [11]:
```python
# Finding out if any column has Nan or null values in the data set
X.isnull().any()
```

Out[11]:
```
longitude             False
latitude              False
housing_median_age    False
total_rooms           False
total_bedrooms         True
population            False
households            False
median_income         False
ocean_proximity       False
dtype: bool
```

Inference: There is only one feature in the whole data set which has missing values present in it. Feature name - 'total_bedrooms'

We will be using SimpleImputer function from Impute package, to check the missing values for all feature except the categorial data. The mean is taken for each column, and the missing values for the columns are filled with the respective mean value.

In [12]:
```python
# Fill the NaN values with the average of the coulum (NOTE: We are doing it only for column have interger values)
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer.fit(X.iloc[:,:-1])
X.iloc[:,:-1] = imputer.transform(X.iloc[:,:-1])
```

We will be using Imputer function to check the messing values for all feature except the categorial data. The mean is taken for each column, and the missing values for the columns are filled with the respective mean value.

In [13]:
```
# Verify if the NaN value has been replaced by the average of the column value
X.isna().any()
```

Out[13]:
```
longitude             False
latitude              False
housing_median_age    False
total_rooms           False
total_bedrooms        False
population            False
households            False
median_income         False
ocean_proximity       False
dtype: bool
```

Observation: As we can see from above results that the missing values have been filled with the mean value of the column.

Encode categorical data

Encoding the categorical data using OneHotEncoder

In [14]:
```
# Converting the Categorical value into Numbers using OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[8])],remainder='passthrough')
X = ct.fit_transform(X)
```

In [15]:
```
X.shape
```

Out[15]:
```
(20640, 13)
```

In [16]:
```
# View the encoded (numpy array) categorical data by converting it to Data Frame
X_Frame = pd.DataFrame(X, columns =["0","1","2","3","4","longitude","latitude","housing_median_age","total_rooms","total_bedrooms","population","households","median_income"])
X_Frame.head()
```

Out[16]:

	0	1	2	3	4	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	0.0	0.0	0.0	1.0	0.0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252
1	0.0	0.0	0.0	1.0	0.0	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014
2	0.0	0.0	0.0	1.0	0.0	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574
3	0.0	0.0	0.0	1.0	0.0	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431
4	0.0	0.0	0.0	1.0	0.0	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462

Observation: The categorical data was successfully handled using the OneHotEncoder

Split the dataset

In [17]:
```
# Splitting the data in 80-20 ratio with random_state value as 20
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=.20, random_state=20)
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[17]:
```
((16512, 13), (4128, 13), (16512,), (4128,))
```

Standardizing the data: Feature Scaling

In [18]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train[:,5:] = sc.fit_transform(x_train[:,5:])
x_test[:,5:] = sc.transform(x_test[:,5:])
```

In [19]:
```
# Convert the numpy array to Data Frame to view the features description of x_train
X_Train_Frame = pd.DataFrame(x_train, columns =["0","1","2","3","4","longitude","latitude","housing_median_age","total_rooms","total_bedrooms","population","households","median_i
ncome"])
X_Train_Frame.head()
```

Out[19]:

	0	1	2	3	4	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	1.0	0.0	0.0	0.0	0.0	0.718815	-0.800679	-0.049918	0.205997	0.786418	0.462297	0.883218	-0.726070
1	0.0	0.0	0.0	0.0	1.0	1.184006	-1.306996	0.267283	-0.275105	-0.343962	-0.391134	-0.289829	-0.322943
2	0.0	0.0	0.0	0.0	1.0	0.673796	-0.852249	0.980984	-0.882056	-0.892316	-0.741376	-0.831640	-0.043838
3	1.0	0.0	0.0	0.0	0.0	0.613772	-0.744422	1.060284	-0.438569	-0.425734	-0.392944	-0.426597	-0.669481
4	1.0	0.0	0.0	0.0	0.0	0.773838	-0.833496	0.187982	-0.326652	-0.500291	-0.354029	-0.384515	0.773735

Observation: Since the data was not scaled, hence by feature scaling we have standarized the data accross all the columns. This would help improving the prediction.

In [20]:
```
X_Train_Frame.describe()
```

Out[20]:

	0	1	2	3	4	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
count	16512.000000	16512.000000	16512.000000	16512.000000	16512.000000	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04	1.651200e+04
mean	0.443677	0.315952	0.000242	0.111192	0.128937	-1.804606e-13	-4.450769e-14	6.488404e-17	-2.960460e-17	-4.998806e-15	5.364868e-17	2.334565e-17	-9.227121e-15
std	0.496833	0.464908	0.015563	0.314379	0.335140	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00	1.000030e+00
min	0.000000	0.000000	0.000000	0.000000	0.000000	-2.392466e+00	-1.442951e+00	-2.191021e+00	-1.216412e+00	-1.286747e+00	-1.283481e+00	-1.307697e+00	-1.775002e+00
25%	0.000000	0.000000	0.000000	0.000000	0.000000	-1.111939e+00	-7.913031e-01	-8.429192e-01	-5.458414e-01	-5.772531e-01	-5.757579e-01	-5.791457e-01	-6.882738e-01
50%	0.000000	0.000000	0.000000	0.000000	0.000000	5.387408e-01	-6.412834e-01	2.938216e-02	-2.314532e-01	-2.357340e-01	-2.309464e-01	-2.345961e-01	-1.785737e-01
75%	1.000000	1.000000	0.000000	0.000000	0.000000	7.788396e-01	9.761169e-01	6.637832e-01	2.426831e-01	2.548990e-01	2.722431e-01	2.782831e-01	4.623087e-01
max	1.000000	1.000000	1.000000	1.000000	1.000000	2.539565e+00	2.963879e+00	1.853285e+00	1.704039e+01	1.420908e+01	2.456652e+01	1.468361e+01	5.858102e+00

In [21]:
```
# Convert the numpy array to Data Frame to view the features description of x_train
X_Test_Frame = pd.DataFrame(x_test, columns =["0","1","2","3","4","longitude","latitude","housing_median_age","total_rooms","total_bedrooms","population","households","median_inc
ome"])
X_Test_Frame.head()
```

Out[21]:

	0	1	2	3	4	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	1.0	0.0	0.0	0.0	0.0	0.833862	-0.702229	-0.287818	0.209247	0.767178	1.309393	0.664915	-0.636896
1	1.0	0.0	0.0	0.0	0.0	-1.106937	0.788592	-1.715221	-0.302968	-0.502696	-0.338643	-0.516022	1.243507
2	0.0	0.0	0.0	1.0	0.0	-1.357040	1.018310	0.743083	-0.901560	-0.868266	-0.974870	-0.905284	-0.979328
3	0.0	1.0	0.0	0.0	0.0	-0.951873	0.605756	-0.129218	-0.267675	-0.288645	-0.173025	-0.429227	0.408457
4	0.0	0.0	0.0	1.0	0.0	-1.342034	1.004246	1.853285	-0.737168	-0.762443	-0.849978	-0.747475	-0.365687

Perform Linear Regression

In [22]:
```
# Create object for Linear Regression and fit the data into it
from sklearn.linear_model import LinearRegression
classifier = LinearRegression()
classifier.fit(x_train , y_train)
```

Out[22]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [23]:
```
# Find the Coefficient and Intercept of the Line
coefficient = classifier.coef_
intercept = classifier.intercept_
print("The intercept value is: ", intercept, "\n")
print("The coefficient values are: ", coefficient)
```

```
The intercept value is:  -1.1577925698238064e+16

The coefficient values are:  [ 1.15779257e+16  1.15779257e+16  1.15779257e+16  1.15779257e+16
  1.15779257e+16 -5.44770000e+04 -5.57420000e+04  1.33080000e+04
 -8.56122461e+03  2.88875000e+04 -4.95047500e+04  3.39892500e+04
  7.26705000e+04]
```

In [24]:
```
# Print the coefficient for each feature
feature_wise_coeff = list(zip(X_Train_Frame.columns,coefficient))
feature_wise_coeff
```

Out[24]:
```
[('0', 1.1577925698457518e+16),
 ('1', 1.1577925698418368e+16),
 ('2', 1.1577925698606e+16),
 ('3', 1.157792569845186e+16),
 ('4', 1.1577925698459772e+16),
 ('longitude', -54477.0),
 ('latitude', -55742.0),
 ('housing_median_age', 13308.0),
 ('total_rooms', -8561.224609375),
 ('total_bedrooms', 28887.5),
 ('population', -49504.75),
 ('households', 33989.25),
 ('median_income', 72670.5)]
```

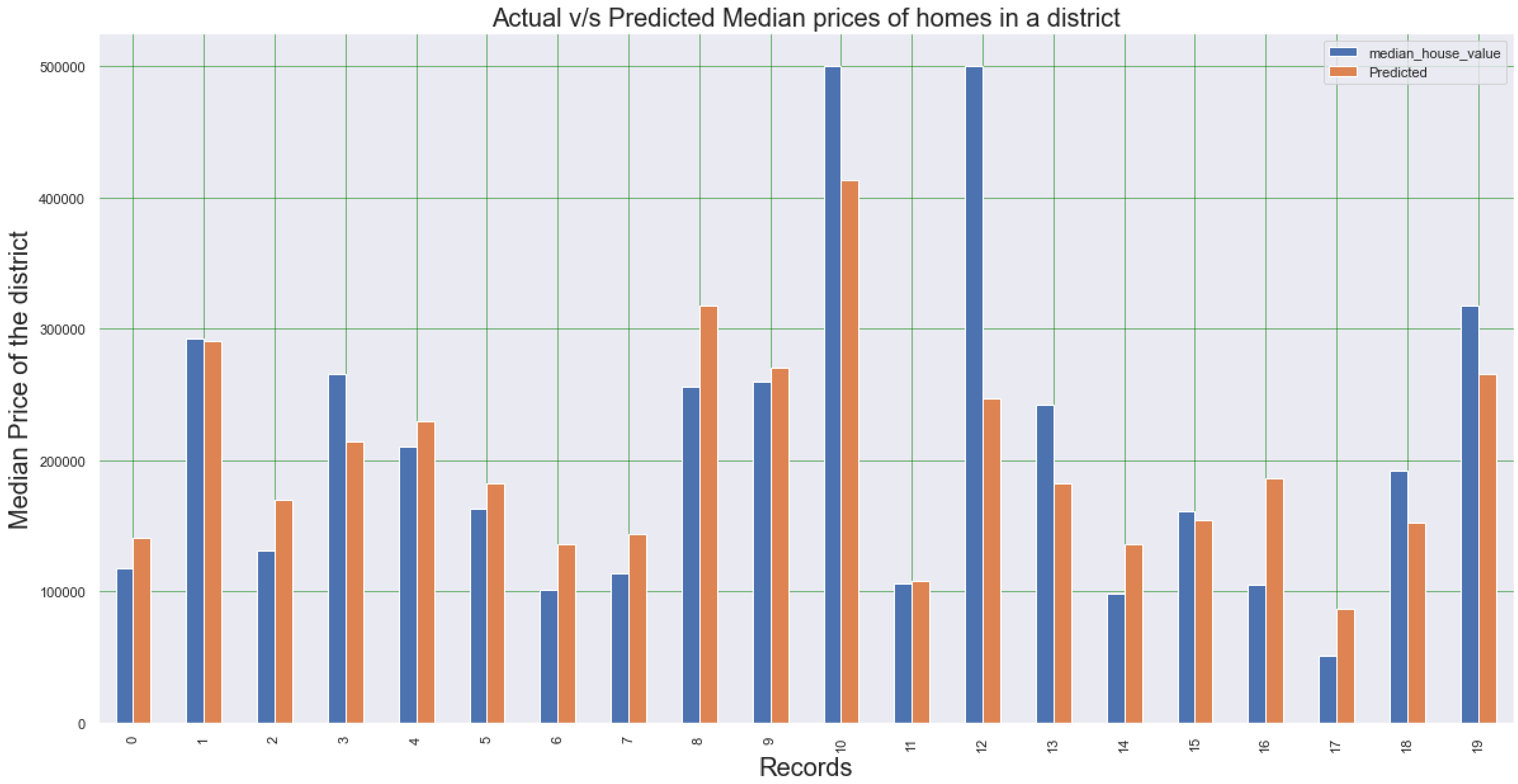
In [25]:
```
y_pred = classifier.predict(x_test)
y_predicted = pd.DataFrame(y_pred, columns=['Predicted'])
y_predicted = y_predicted.astype(int)
```

In [26]:
```
Observed_Predicted_Table =pd.concat([y_test.reset_index(drop=True),y_predicted],axis=1)
Observed_Predicted_Table.head()
```

Out[26]:

	median_house_value	Predicted
0	117600	141206
1	292200	290636
2	131300	169808
3	265900	214286
4	210200	229974

In [27]:
```
# Visualize the Observed and Predicted values
import matplotlib.pyplot as plt
%matplotlib inline
Observed_Predicted_Table_Split = Observed_Predicted_Table.head(20)
Observed_Predicted_Table_Split.plot(kind='bar',figsize=(20,10))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.xlabel("Records",  fontdict = {'fontsize' : 20})
plt.ylabel("Median Price of the district",  fontdict = {'fontsize' : 20})
plt.title("Actual v/s Predicted Median prices of homes in a district",  fontdict = {'fontsize' : 20})
plt.show()
```



In [28]:
```
# Find the Root Mean Squared Error
from sklearn.metrics import mean_squared_error
rmse = np.sqrt(mean_squared_error(y_test, y_predicted))
rmse
```

Out[28]: 71198.66070920265

Bonus exercise: Perform Linear Regression with one independent variable

In [29]:
```
# Extract the median_income column from the independent variables (from X_train and X_test):
x_train_median_income = X_Train_Frame["median_income"]
x_train_median_income = pd.DataFrame(x_train_median_income)
x_train_median_income.head()
```

Out[29]:

	median_income
0	-0.726070
1	-0.322943
2	-0.043838
3	-0.669481
4	0.773735

In [30]:
```
x_test_median_income = X_Test_Frame["median_income"]
x_test_median_income = pd.DataFrame(x_test_median_income)
x_test_median_income.head()
```

Out[30]:

	median_income
0	-0.636896
1	1.243507
2	-0.979328
3	0.408457
4	-0.365687

In [31]:
```
classifier.fit(x_train_median_income,y_train)
```

Out[31]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

In [32]:
```
# Predict the value
y_pred_median_income = classifier.predict(x_test_median_income)
y_predicted_median_income = pd.DataFrame(y_pred_median_income, columns=['Predicted'])
y_predicted_median_income = y_predicted_median_income.astype(int)
y_predicted_median_income.head()
```

Out[32]:

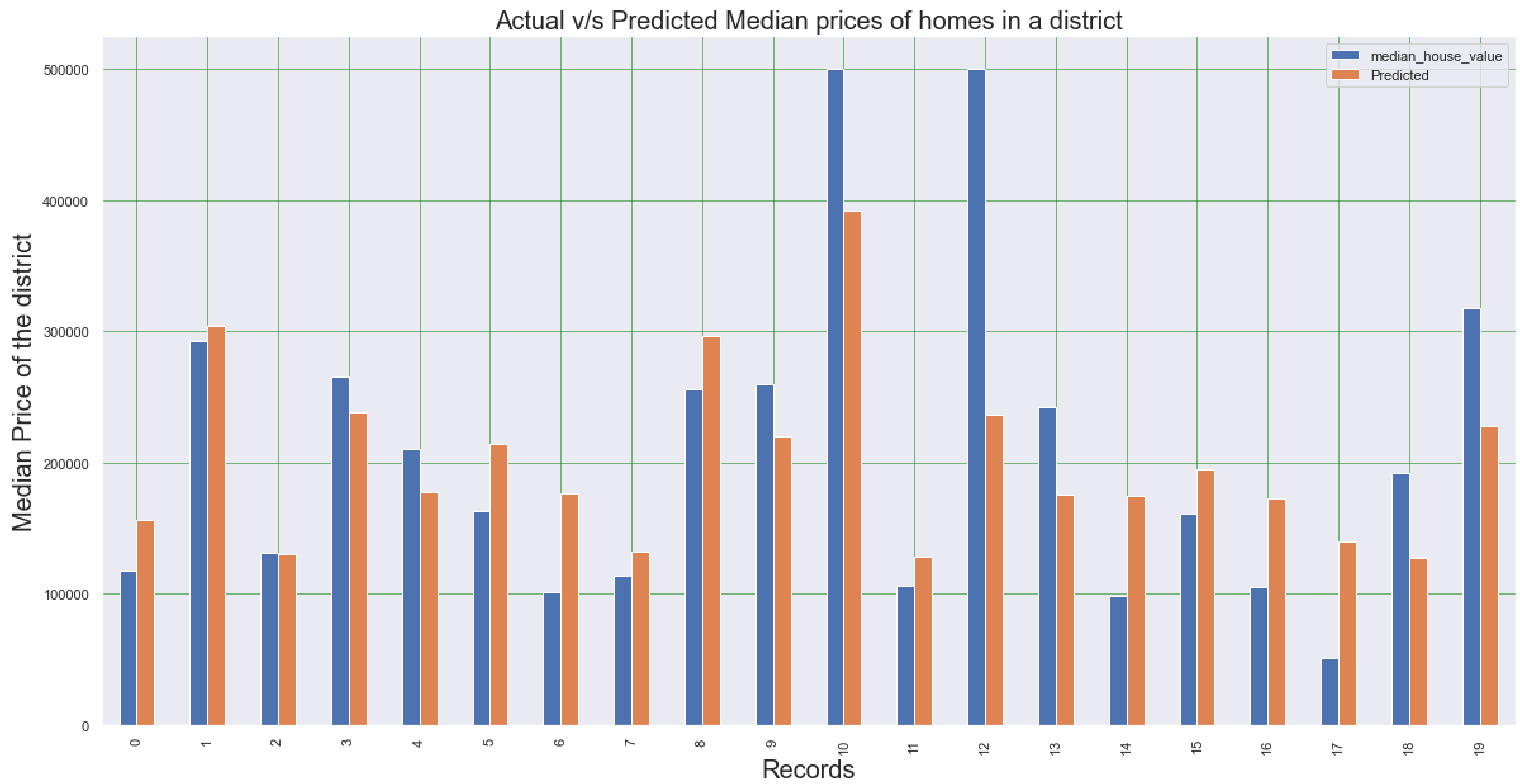
	Predicted
0	156751
1	304465
2	129852
3	238868
4	178056

In [33]:
```
# Create a new Data Frame with Observed and Predicted Value
Observed_Predicted_Table_MI =pd.concat([y_test.reset_index(drop=True),y_predicted_median_income],axis=1)
Observed_Predicted_Table_MI.head()
```

Out[33]:

	median_house_value	Predicted
0	117600	156751
1	292200	304465
2	131300	129852
3	265900	238868
4	210200	178056

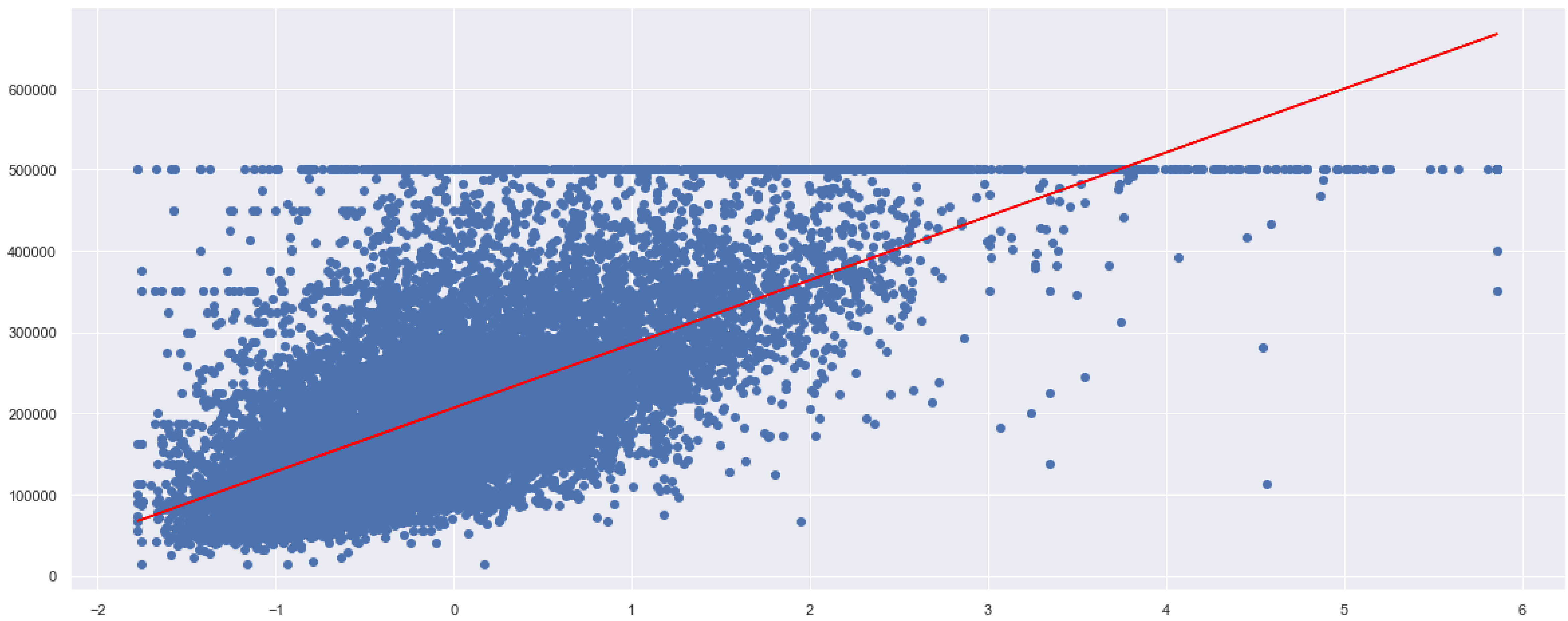
In [34]:
```
# Visualize the Observed and Predicted values
import matplotlib.pyplot as plt
%matplotlib inline
Observed_Predicted_Table_Split_MI = Observed_Predicted_Table_MI.head(20)
Observed_Predicted_Table_Split_MI.plot(kind='bar',figsize=(20,10))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.xlabel("Records",  fontdict = {'fontsize' : 20})
plt.ylabel("Median Price of the district",  fontdict = {'fontsize' : 20})
plt.title("Actual v/s Predicted Median prices of homes in a district",  fontdict = {'fontsize' : 20})
plt.show()
```



In [35]:
```
# Find the Root Mean Squared Error
from sklearn.metrics import mean_squared_error
rmse_mi = np.sqrt(mean_squared_error(y_test, y_predicted_median_income))
rmse_mi
```

Out[35]: 84351.50568485045

In [36]:
```
#Plot the fitted model for training data as well as for test data to check if the fitted model satisfies the test data.
plt.figure(figsize=(20,8))
plt.scatter(x_train_median_income,y_train)
plt.plot(x_train_median_income,classifier.predict(x_train_median_income),color='red')
plt.show()
```



In [37]:
```
plt.figure(figsize=(20,8))
plt.scatter(x_test_median_income,y_test)
plt.plot(x_test_median_income,classifier.predict(x_test_median_income),color='green')
plt.show()
```