California Housing Price Prediction Project

James Bryant

Objectives

The main objective of this project is to develop a predictive model for housing prices in California based on various features such as total rooms, population, median income, etc. The project aims to explore the relationship between these features and housing prices and build regression models to predict prices accurately.

Housing Price Prediction Project

Objectives

The main objective of this project is to develop a predictive model for housing prices in California based on various features such as total rooms, population, median income, etc. The project aims to explore the relationship between these features and housing prices and build regression models to predict prices accurately.

Methodology

1. **Data Preprocessing**:

   - Loading the dataset
   - Handling missing values
   - Logarithmic transformation of skewed features
   - One-hot encoding of categorical variables
2. **Exploratory Data Analysis (EDA)**:

   - Visualizing distributions of key variables
   - Examining correlations between variables
   - Geographical analysis of housing prices
3. **Modeling**:

   - Implementing linear regression and random forest regression models

- Hyperparameter tuning using grid search

4. **Model Evaluation**:
    - Calculating R^2 score and mean squared error for model performance
5. **Feature Engineering**:
    - Creating new features based on domain knowledge (room ratio, household rooms)
6. **User Interaction**:
    - Accepting user input to predict housing prices based on selected features

Key Findings

- Strong positive correlation between median income and median house value
- Geographical areas with higher population density tend to have higher housing prices
- Random forest regression outperforms linear regression in terms of predictive accuracy

In [1]:
```
# Importing necessary libraries for data analysis and visualization
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Loading the housing dataset from a CSV file into a pandas DataFrame
data = pd.read_csv("housing-2.csv")

# Displaying the loaded dataset to inspect its structure and contents
data
```

Out[2]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popul
0	-122.23	37.88	41.0	880.0	129.0	3
1	-122.22	37.86	21.0	7099.0	1106.0	24
2	-122.24	37.85	52.0	1467.0	190.0	4
3	-122.25	37.85	52.0	1274.0	235.0	5
4	-122.25	37.85	52.0	1627.0	280.0	5
...	...	...	...	...	...	
20635	-121.09	39.48	25.0	1665.0	374.0	8
20636	-121.21	39.49	18.0	697.0	150.0	3
20637	-121.22	39.43	17.0	2254.0	485.0	10
20638	-121.32	39.43	18.0	1860.0	409.0	7
20639	-121.24	39.37	16.0	2785.0	616.0	13

20640 rows × 10 columns

In [3]:
```
# Retrieving concise summary information about the DataFrame, including the
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 [4]:
```
# Dropping rows with missing values (NaN) from the DataFrame in place
data.dropna(inplace=True)
```

In [5]:
```
# Importing train_test_split function from the scikit-learn library to split
from sklearn.model_selection import train_test_split
```

```
X = data.drop(['median_house_value'], axis=1)
y = data['median_house_value']
```

In [6]:
```
y
```

Out[6]:
```
0        452600.0
1        358500.0
2        352100.0
3        341300.0
4        342200.0
           ...
20635     78100.0
20636     77100.0
20637     92300.0
20638     84700.0
20639     89400.0
Name: median_house_value, Length: 20433, dtype: float64
```

In [7]:
```
# Splitting the dataset into training and testing sets using train_test_spli
# test_size=0.2 specifies that 20% of the data will be used for testing, and
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

In [8]:
```
# Combining the features and target variable for the training set into a sin
train_data = X_train.join(y_train)

# Displaying the training data to inspect its structure and contents
train_data
```

Out[8]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popul
20029	-119.03	36.08	19.0	2736.0	549.0	14
2002	-119.78	36.75	31.0	1404.0	379.0	1!
18583	-121.78	36.92	19.0	1515.0	253.0	!
17298	-119.51	34.40	24.0	3422.0	596.0	17
13516	-117.35	34.11	34.0	2104.0	388.0	1!
...	...	...	...	...	...	
473	-122.29	37.86	50.0	2485.0	607.0	13
4338	-118.31	34.08	26.0	1609.0	534.0	18
10776	-117.90	33.65	30.0	2196.0	486.0	1
19888	-119.16	36.28	18.0	2377.0	414.0	13
13301	-117.63	34.07	39.0	2650.0	511.0	1!

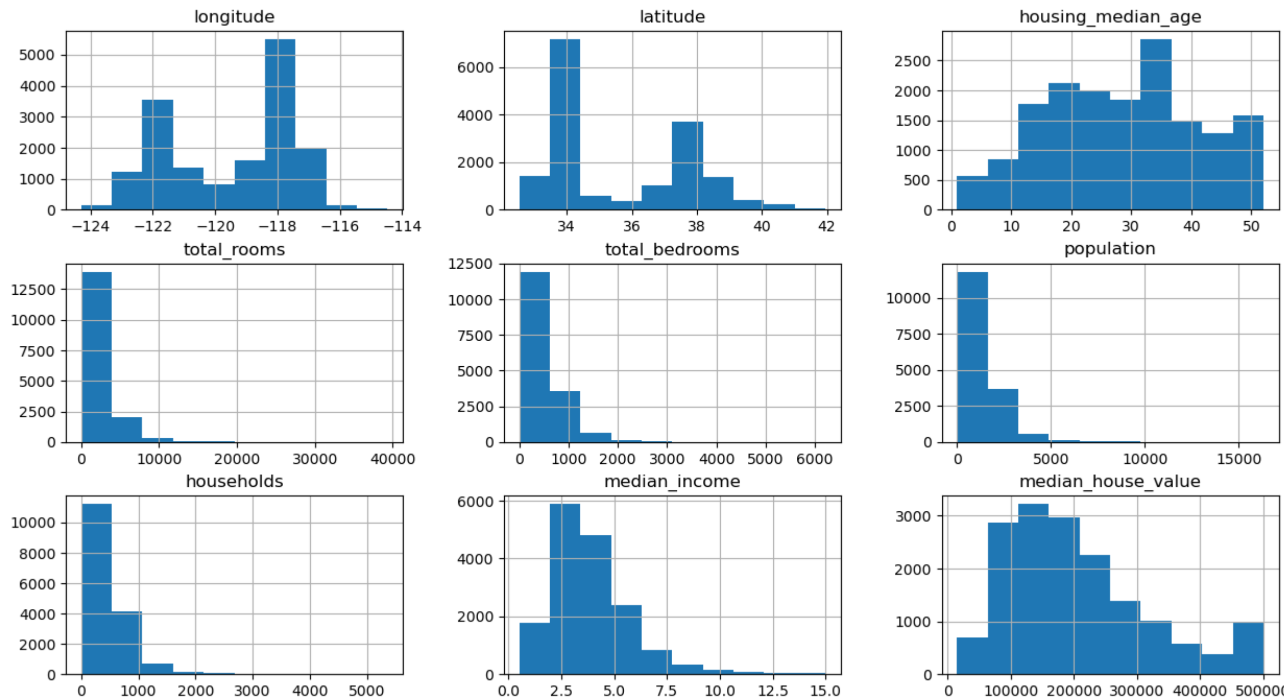
16346 rows × 10 columns

In [9]:

```
# Creating histograms for all columns in the training dataset with a specifi
train_data.hist(figsize=(15,8))
```

Out[9]:

```
array([[<Axes: title={'center': 'longitude'}>,
        <Axes: title={'center': 'latitude'}>,
        <Axes: title={'center': 'housing_median_age'}>],
       [<Axes: title={'center': 'total_rooms'}>,
        <Axes: title={'center': 'total_bedrooms'}>,
        <Axes: title={'center': 'population'}>],
       [<Axes: title={'center': 'households'}>,
        <Axes: title={'center': 'median_income'}>,
        <Axes: title={'center': 'median_house_value'}>]], dtype=object)
```



In [10]:
```
# Calculating the correlation matrix for the training dataset to examine pai
train_data.corr()
```

Out[10]:

	longitude	latitude	housing_median_age	total_rooms	total_l
longitude	1.000000	-0.924516	-0.113431	0.046219	
latitude	-0.924516	1.000000	0.016614	-0.035582	-
housing_median_age	-0.113431	0.016614	1.000000	-0.363253	-
total_rooms	0.046219	-0.035582	-0.363253	1.000000	
total_bedrooms	0.071467	-0.067584	-0.323945	0.928917	
population	0.102438	-0.110119	-0.304944	0.860767	
households	0.057355	-0.072135	-0.306201	0.915497	
median_income	-0.016864	-0.077470	-0.117248	0.197800	-
median_house_value	-0.043570	-0.146303	0.102405	0.132072	

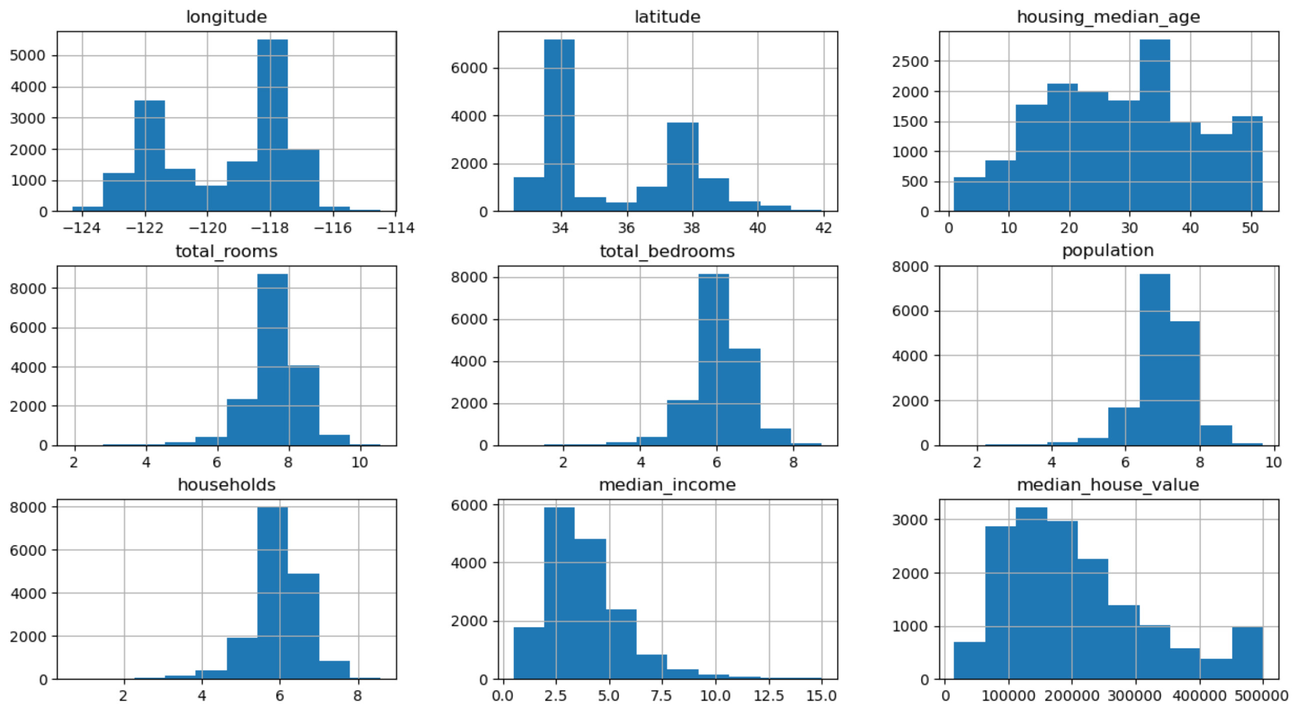
In [11]:
```
# Creating a heatmap of the correlation matrix for the training dataset usir
plt.figure(figsize = (15,8))
sns.heatmap(train_data.corr(),annot=True,cmap="viridis")
```

Out[11]: <Axes: >

In [12]:
```python
# Applying logarithmic transformation to selected features to handle skewed
train_data['total_rooms'] = np.log(train_data['total_rooms']+1)
train_data['total_bedrooms'] = np.log(train_data['total_bedrooms']+1)
train_data['population'] = np.log(train_data['population']+1)
train_data['households'] = np.log(train_data['households']+1)
```

In [13]:
```python
# Creating histograms for all columns in the transformed training dataset wi
train_data.hist(figsize=(15,8))
```

Out[13]:
```
array([[<Axes: title={'center': 'longitude'}>,
        <Axes: title={'center': 'latitude'}>,
        <Axes: title={'center': 'housing_median_age'}>],
       [<Axes: title={'center': 'total_rooms'}>,
        <Axes: title={'center': 'total_bedrooms'}>,
        <Axes: title={'center': 'population'}>],
       [<Axes: title={'center': 'households'}>,
        <Axes: title={'center': 'median_income'}>,
        <Axes: title={'center': 'median_house_value'}>]], dtype=object)
```



In [14]:

```
# Encoding categorical variable 'ocean_proximity' using one-hot encoding anc
train_data = train_data.join(pd.get_dummies(train_data.ocean_proximity)).drc

# Displaying the modified training dataset after one-hot encoding
train_data
```

Out[14]:

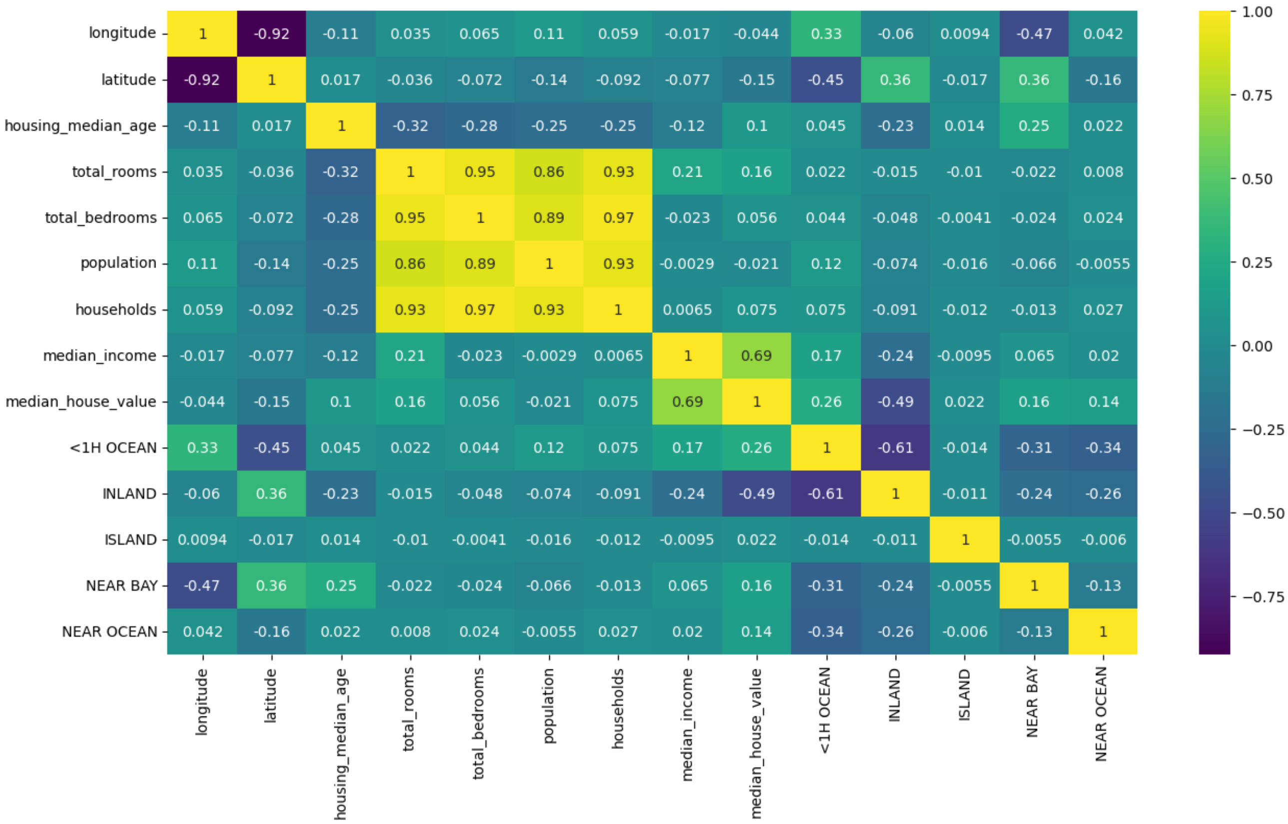
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popul
20029	-119.03	36.08	19.0	7.914618	6.309918	7.26
2002	-119.78	36.75	31.0	7.247793	5.940171	7.32
18583	-121.78	36.92	19.0	7.323831	5.537334	6.88
17298	-119.51	34.40	24.0	8.138273	6.391917	7.47
13516	-117.35	34.11	34.0	7.652071	5.963579	7.36
...	...	...	...	...	...	
473	-122.29	37.86	50.0	7.818430	6.410175	7.21
4338	-118.31	34.08	26.0	7.383989	6.282267	7.53
10776	-117.90	33.65	30.0	7.694848	6.188264	7.03
19888	-119.16	36.28	18.0	7.774015	6.028279	7.21
13301	-117.63	34.07	39.0	7.882692	6.238325	7.33

16346 rows × 14 columns

In [15]:

```
# Creating a heatmap of the correlation matrix for the modified training dat
plt.figure(figsize = (15,8))
sns.heatmap(train_data.corr(),annot=True,cmap="viridis")
```

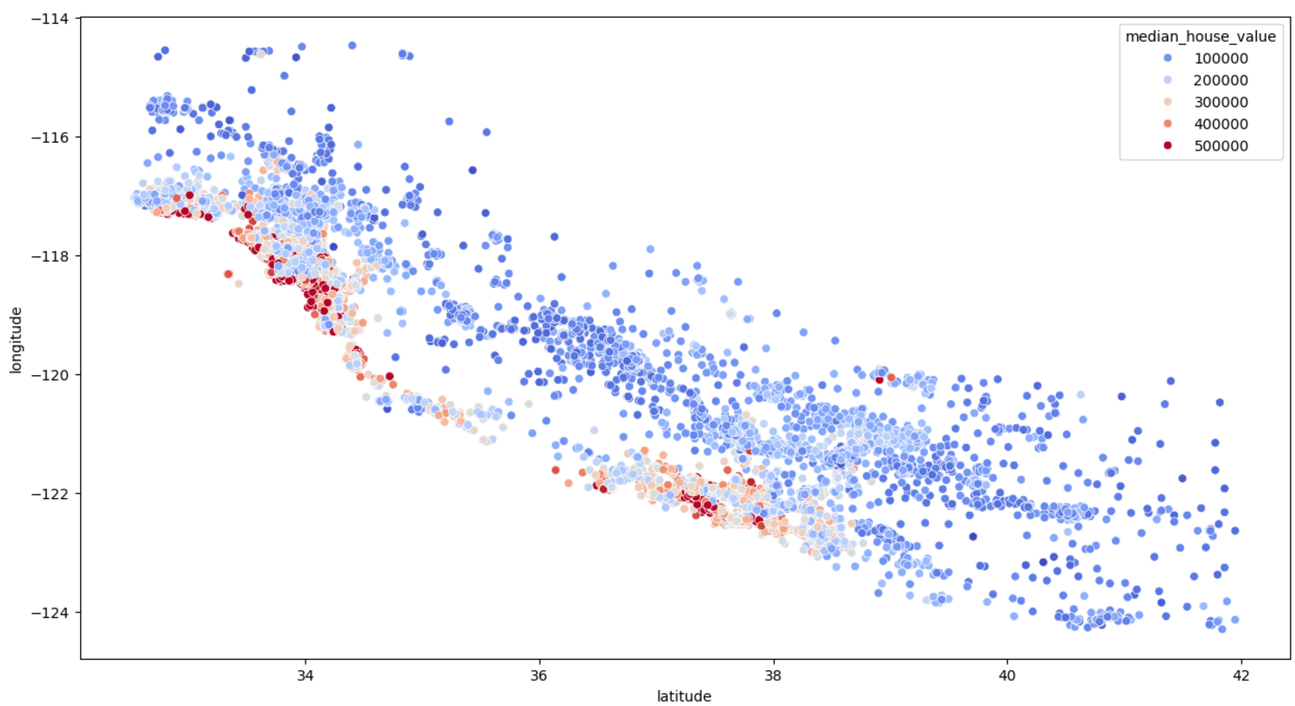
Out[15]: <Axes: >



In [16]:

```
# Creating a scatter plot to visualize the geographical distribution of hous
plt.figure(figsize=(15,8))
sns.scatterplot(x='latitude', y='longitude', data=train_data, hue='median_ho
```

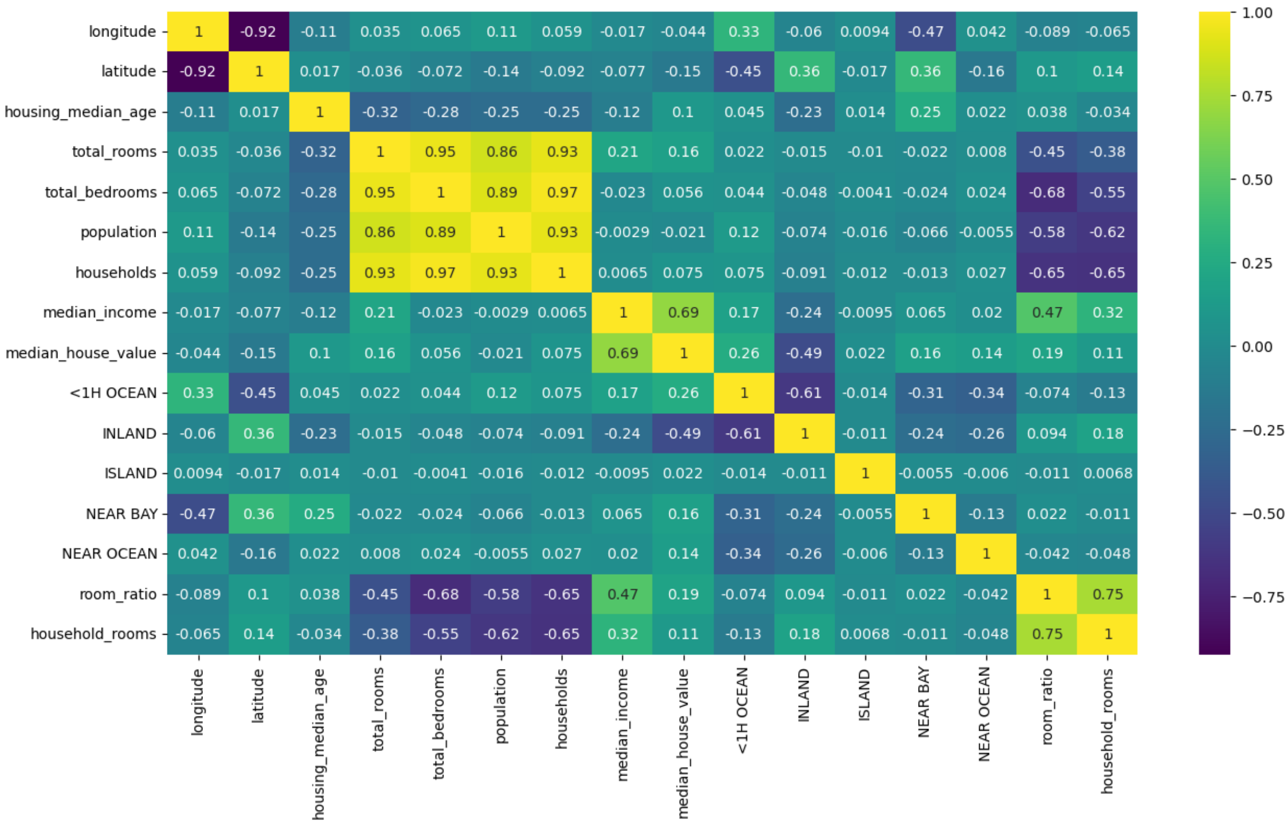
Out[16]: `<Axes: xlabel='latitude', ylabel='longitude'>`



In [17]:
```
# Calculating additional features by performing mathematical operations on e
train_data['room_ratio'] = train_data['total_rooms']/train_data['total_bedro
train_data['household_rooms'] = train_data['total_rooms']/train_data['househ
```

In [18]:
```
# Creating a heatmap of the correlation matrix for the training dataset afte
plt.figure(figsize = (15,8))
sns.heatmap(train_data.corr(),annot=True,cmap="viridis")
```

Out[18]: <Axes: >



In [19]:
```
# Importing necessary modules from scikit-learn for linear regression and da
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler

# Instantiating StandardScaler to standardize features
scaler = StandardScaler()

# Separating features (X_train) and target variable (y_train) from the train
X_train,y_train = train_data.drop(['median_house_value','ISLAND'], axis=1),t

# Standardizing the features using StandardScaler
X_train_s = scaler.fit_transform(X_train)

# Instantiating LinearRegression model and fitting it to the standardized tr
reg = LinearRegression()
reg.fit(X_train_s, y_train)
```

Out[19]:

```
▾ LinearRegression
LinearRegression()
```

In [20]:

```
# Combining features and target variable for the testing set into a single D
test_data = X_test.join(y_test)

# Applying logarithmic transformation to selected features in the testing se
test_data['total_rooms'] = np.log(test_data['total_rooms']+1)
test_data['total_bedrooms'] = np.log(test_data['total_bedrooms']+1)
test_data['population'] = np.log(test_data['population']+1)
test_data['households'] = np.log(test_data['households']+1)

# Encoding categorical variable 'ocean_proximity' in the testing set using o
test_data = test_data.join(pd.get_dummies(test_data.ocean_proximity)).drop([

# Calculating additional features in the testing set by performing mathemati
test_data['room_ratio'] = test_data['total_rooms']/test_data['total_bedrooms
test_data['household_rooms'] = test_data['total_rooms']/test_data['househol
```

In [21]:

```
# Displaying the modified testing dataset after preprocessing
test_data
```

Out[21]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popula
2362	-119.58	36.83	13.0	8.721928	6.761573	7.81
12583	-121.43	38.52	30.0	8.204672	6.852243	7.98
4494	-118.21	34.06	52.0	6.154858	4.753590	6.07
12792	-121.46	38.65	14.0	8.060856	6.313548	7.48
10443	-117.60	33.42	23.0	7.817223	6.135565	6.95
...	...	...	...	...	...	
4069	-118.48	34.16	30.0	8.162801	6.285998	7.26
18878	-122.24	38.07	13.0	8.603738	7.085901	7.99
5333	-118.45	34.04	19.0	8.111028	6.918695	7.51
6948	-118.08	33.99	36.0	7.613325	6.381816	7.61
17340	-120.45	34.86	23.0	8.136226	6.658011	7.30

4087 rows × 16 columns

In [22]:
```
# Separating features (X_test) and target variable (y_test) from the modifie
X_test,y_test = test_data.drop(['median_house_value'], axis=1),test_data['me
```

In [23]:
```
# Checking if 'ISLAND' column exists in the testing dataset, if not, adding
if 'ISLAND' not in test_data.columns:
    test_data['ISLAND'] = 0

# Printing the columns of the testing dataset after checking and adding 'ISL
print(test_data.columns)
```

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', '<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY',
       'NEAR OCEAN', 'room_ratio', 'household_rooms'],
      dtype='object')
```

In [24]:
```
# Print unique feature names in the training and testing datasets
print("Unique feature names in the training dataset:", X_train.columns)
print("Unique feature names in the testing dataset:", X_test.columns)
```

```
Unique feature names in the training dataset: Index(['longitude', 'latitude'
, 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       '<1H OCEAN', 'INLAND', 'NEAR BAY', 'NEAR OCEAN', 'room_ratio',
       'household_rooms'],
      dtype='object')
Unique feature names in the testing dataset: Index(['longitude', 'latitude',
'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       '<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN', 'room_rati
o',
       'household_rooms'],
      dtype='object')
```

In [25]:
```
# Reindexing the columns of the testing dataset to match the order of column
X_test = X_test.reindex(columns=X_train.columns, fill_value=0)

# Transform both training and testing datasets using the fitted scaler
X_train_s = scaler.transform(X_train)
X_test_s = scaler.transform(X_test)
```

In [26]:
```
# Calculating the R^2 score of the linear regression model on the standardiz
reg.score(X_test_s, y_test)
```

Out[26]: 0.6851408382908369

In [27]:
```
# Importing RandomForestRegressor from scikit-learn for random forest regres
from sklearn.ensemble import RandomForestRegressor

# Instantiating RandomForestRegressor model
```

```
forest = RandomForestRegressor()

# Fitting the RandomForestRegressor model to the training data
forest.fit(X_train, y_train)
```

Out[27]:

```
▾ RandomForestRegressor
RandomForestRegressor()
```

In [28]:

```
# Calculating the R^2 score of the random forest regression model on the tes
forest.score(X_test, y_test)
```

Out[28]: 0.8225764724963627

In [29]:

```
# Importing RandomForestRegressor and GridSearchCV from scikit-learn for hyp
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV

# Defining the grid of hyperparameters for tuning
param_grid = {'n_estimators': [3, 10, 30],
              'max_features': [2, 4, 6, 8]}
# Instantiating RandomForestRegressor model
forest = RandomForestRegressor()

# Instantiating GridSearchCV to perform hyperparameter tuning using cross-va
grid_search = GridSearchCV(estimator=forest, param_grid=param_grid, cv=5,
                           scoring='neg_mean_squared_error', return_train_sc

# Fitting the GridSearchCV object to the standardized training data
grid_search.fit(X_train_s, y_train)
```

Out[29]:

```
▸ GridSearchCV
▸ estimator: RandomForestRegressor
    ▸ RandomForestRegressor
```

In [30]:

```
# Extracting the best performing RandomForestRegressor model from the grid s
best_forest = grid_search.best_estimator_
```

In [31]:

```
# Calculating the R^2 score of the best performing RandomForestRegressor moc
best_forest.score(X_test_s, y_test)
```

Out[31]: 0.8197602109142295

In [32]:

```
# Printing the columns of the testing dataset
test_data.columns
```

Out[32]:
```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', '<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY',
       'NEAR OCEAN', 'room_ratio', 'household_rooms'],
      dtype='object')
```

In [33]:
```python
# Defining a list of selected features
selected_features = ['total_rooms', 'total_bedrooms', 'population', 'househo

# Function to get customer input for selected features
def get_customer_input():
    features = {}
    for feature in selected_features:
        features[feature] = float(input(f"Enter value for {feature}: "))
    return features

# Getting customer input for selected features
customer_input = get_customer_input()

# Creating a DataFrame with customer input data for selected features
input_data_selected = pd.DataFrame(customer_input, index=[0])[selected_featu

# Instantiating LinearRegression model and fitting it to the training data w
reg_selected = LinearRegression()
reg_selected.fit(X_train[selected_features], y_train)

# Predicting house prices using the trained regression model with selected f
predicted_price_regression_selected = reg_selected.predict(input_data_select

# Displaying the predicted price using regression model with selected featur
print("Predicted price using regression model with selected features:", prec
```

```
Predicted price using regression model with selected features: [182737.18149
011]
```

In [ ]:
```python
# Importing RandomForestRegressor from scikit-learn for random forest regres
from sklearn.ensemble import RandomForestRegressor

# Defining a list of selected features
selected_features = ['total_rooms', 'total_bedrooms', 'population', 'househo

# Function to get customer input for selected features
def get_customer_input():
    features = {}
    for feature in selected_features:
        features[feature] = float(input(f"Enter value for {feature}: "))
    return features

# Getting customer input for selected features
customer_input = get_customer_input()
```

```
# Creating a DataFrame with customer input data for selected features
input_data_selected = pd.DataFrame(customer_input, index=[0])[selected_featu

# Instantiating RandomForestRegressor model and fitting it to the training d
forest_selected = RandomForestRegressor()
forest_selected.fit(X_train[selected_features], y_train)

# Predicting house prices using the trained random forest model with selecte
predicted_price_forest_selected = forest_selected.predict(input_data_selecte

# Displaying the predicted price using random forest model with selected fea
print("Predicted price using random forest model with selected features:", p
print("Input data for prediction:")
```