In [77]:
```
#House Value Prediction Using Linear Regression and Random Forest

#Introduction

'''
Problem Statement:

Consider a real estate company that has a dataset containing the prices of properti
Essentially, the company wants to identify the variables affecting house prices, to

'''
```

Out[77]:
```
'\nProblem Statement:\n\nConsider a real estate company that has a dataset contain
ing the prices of properties in California. It wishes to use the data to predict t
he sale prices of the properties based on important factors such as number of bedr
ooms, ocean proximity, household income, etc.\nEssentially, the company wants to i
dentify the variables affecting house prices, to create a model that quantitativel
y relates house prices with structural and spatial determinants and engineered fea
tures, and to know the accuracy of the model, i.e. how well these variables can pr
edict house prices.\n\n'
```

In [78]:
```
#Dataset Overview

'''
The data includes information about houses found in a given California district and
The columns are as follows:
1. longitude: A measure of how far west a house is; a higher value is farther west
2. latitude: A measure of how far north a house is; a higher value is farther north
3. housingMedianAge: Median age of a house within a block; a lower number is a newe
4. totalRooms: Total number of rooms within a block
5. totalBedrooms: Total number of bedrooms within a block
6. population: number of people residing within a block
7. households: number of households, a group of people residing within a home unit,
8. medianIncome: Median income for households within a block of houses (measured in
9. medianHouseValue: Median house value for households within a block (measured in
10. oceanProximity: Location of the house w.r.t ocean/sea


Below is a PowerBI report of the data for initial data inspection. It shows how the
'''
```

Out[78]:
```
'\nThe data includes information about houses found in a given California district
and some summary statistics about them based on the 1990 census data.It is the dat
aset used in the second chapter of Aurélien Géron\'s recent book \'Hands-On Machin
e learning with Scikit-Learn and TensorFlow\'.\nThe columns are as follows:\n1. lo
ngitude: A measure of how far west a house is; a higher value is farther west\n2.
latitude: A measure of how far north a house is; a higher value is farther north\n
3. housingMedianAge: Median age of a house within a block; a lower number is a new
er building\n4. totalRooms: Total number of rooms within a block\n5. totalBedroom
s: Total number of bedrooms within a block\n6. population: number of people residi
ng within a block\n7. households: number of households, a group of people residing
within a home unit, for a block\n8. medianIncome: Median income for households wit
hin a block of houses (measured in tens of thousands of US Dollars)\n9. medianHous
eValue: Median house value for households within a block (measured in US Dollars)
\n10. oceanProximity: Location of the house w.r.t ocean/sea\n\n\nBelow is a PowerB
I report of the data for initial data inspection. It shows how the target variabl
e, "Median House Value" is affected by variables such as Latitude, longitude, Medi
an Income, and Sum of rooms.\n'
```

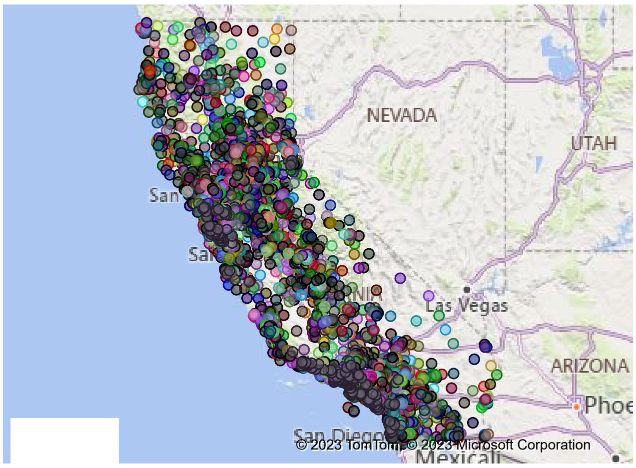
In [79]:
```
from IPython.display import IFrame
IFrame(src="https://app.powerbi.com/view?r=eyJrIjoiMGIzOGY2MjQtMGVlMC00MmU1LWEzNDQ
```

Out[79]:

House Value Prediction using Linear Reg
Data Overvie

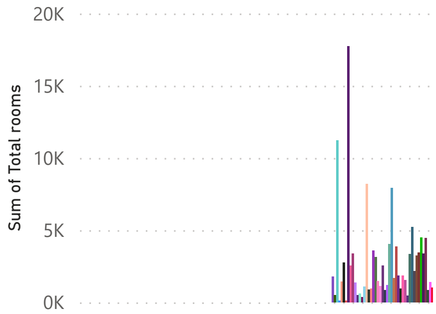
Median House Value, Latitude and Longitude

Median Hous... 14999 22500 25000 26600 27500



Sum of Total rooms by Median House

Median House Value 14999 17500 22500



[Microsoft Power BI]

In [80]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [81]:
```
df=pd.read_csv("C:/Users/Iqra Javaid/OneDrive/Desktop/Spring Term/AI and Machine Le
```

In [84]:
```
#Preliminary Analysis
#Data cleansing and Exploratory Analysis

'''
First the data is checked for any null values. 207 null values were found in the co
After that, a linear regression model is built. The data is then prepared to define

A heatmap of the correlation matrix between the different variables in the training
There is a high negative correlation between longitude and median_house_value. A hi
To investigate this relationship further, a scatter plot of the longitude values ag

The categorical values in the column ocean_proximity are separated into columns to
From the heatmap of the correlation matrix, it can be observed that houses located
A scatter plot of house value by location is created which shows how the value of h
```

```
Two features namely bedroom_ratio and household_rooms are engineered to improve the
The bedroom ratio can also provide insights into the current market demand for cert
```

Out[84]:

```
'\nFirst the data is checked for any null values. 207 null values were found in th
e column total_bedrooms and were removed consequently.\nAfter that, a linear regre
ssion model is built. The data is then prepared to define the predictor and respon
se variables. The target variable is "median_house_value".\n\nA heatmap of the cor
relation matrix between the different variables in the training data is produced.
There is a high positive correlation between households and median income with the
target variable median_house_value.\nThere is a high negative correlation between
longitude and median_house_value. A high negative correlation between house value
and longitude means that as the longitude values increase (moving to the west), th
e house values decrease. This indicates that houses located in the western part of
the area tend to have lower values than those located in the eastern part. This re
lationship could be due to a number of factors such as location, neighborhood, ame
nities, or accessibility.\nTo investigate this relationship further, a scatter plo
t of the longitude values against the house values is created;  a regression line
to visualize the trend is included. \n\nThe categorical values in the column ocean
_proximity are separated into columns to understand the relationship between them
and the target variable, as part of data pre-processing.\nFrom the heatmap of the
correlation matrix, it can be observed that houses located closer to the ocean ten
d to have a higher value due to their proximity to the water and the views they of
fer. The high positive correlation between the variable <1H OCEAN and median_house
_value confirms this. Similarly, houses located inland tend to have a lower value
compared to houses located closer to the ocean. This is because proximity to the o
cean is often considered a desirable feature in real estate, and houses located cl
oser to the water typically command a higher price. The negative correlation betwe
en median_house_value and feature engineered column INLAND confirms this.\nA scatt
er plot of house value by location is created which shows how the value of houses
is distributed across different geographical locations within the region. It can b
e used to spot clusters of high and low value neighbourhoods and help gain insight
s into the local housing market. To further improve the analysis, geographical fea
tures such as local amenities, landmarks, etc can be added to the dataset to study
their effect on the house value. \n\nTwo features namely bedroom_ratio and househo
ld_rooms are engineered to improve the performance of the models. The bedroom rati
o can be a strong predictor of the value of a property. Properties with a higher b
edroom ratio may command a higher price, as they are often considered more functio
nal and desirable.\nThe bedroom ratio can also provide insights into the current m
arket demand for certain types of properties. For example, if there is a high dema
nd for family homes with multiple bedrooms, properties with a high bedroom ratio m
ay be more attractive to buyers and renters. Similarly, household rooms can provid
e insight into the room functionality of a property and is used to improve the acc
uracy of the model. '
```

In [85]:

```
df.describe() #summary statistics
```

Out[85]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	populati
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.4767
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000

In [86]:
```
df.isnull().sum() #check for nulls in the data
```

Out[86]:
```
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
```

In [87]:
```
df.dropna(inplace=True) #pre-processing to remove null values
```

In [88]:
```
from sklearn.model_selection import train_test_split #import train test split from
```

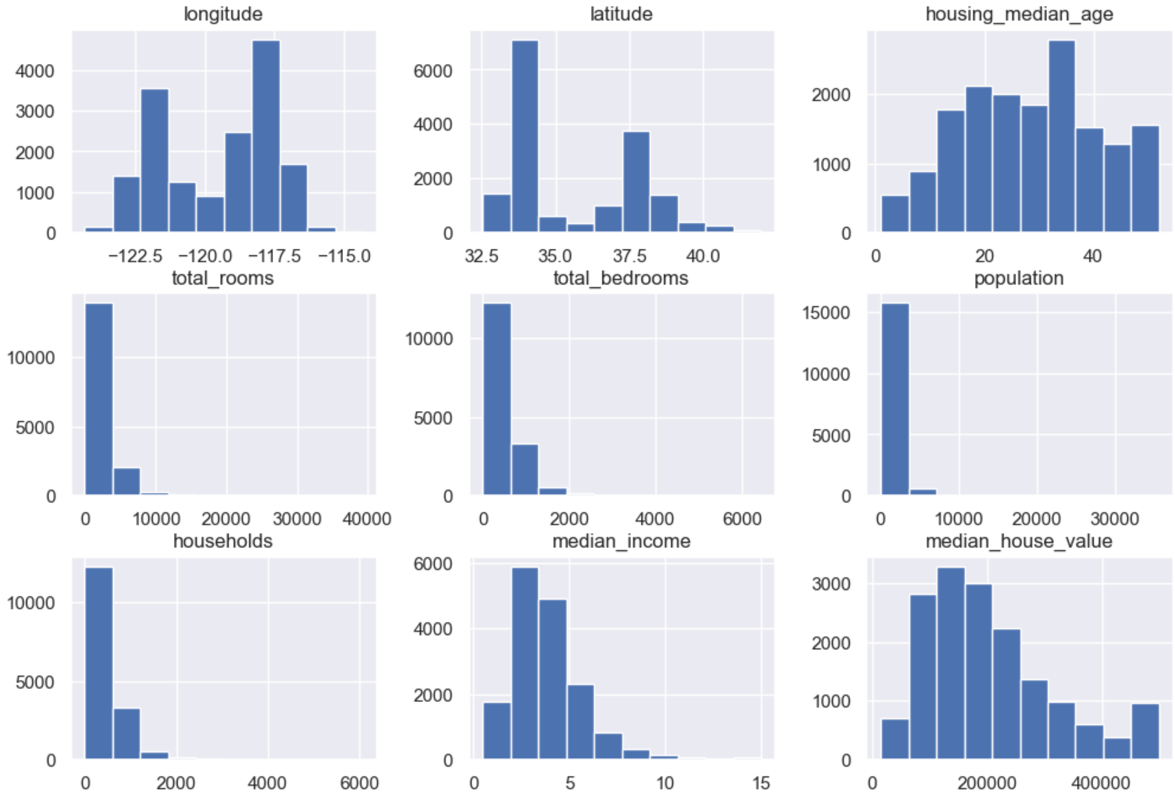
In [89]:
```
X=df.drop(['median_house_value'], axis=1) #x is the dataframe without the target va
#median house value is our target variable, it is what we'll be predicting
Y=df['median_house_value']
```

In [90]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.2) #20 percen
```

In [91]:
```
train_data= X_train.join(Y_train)
```

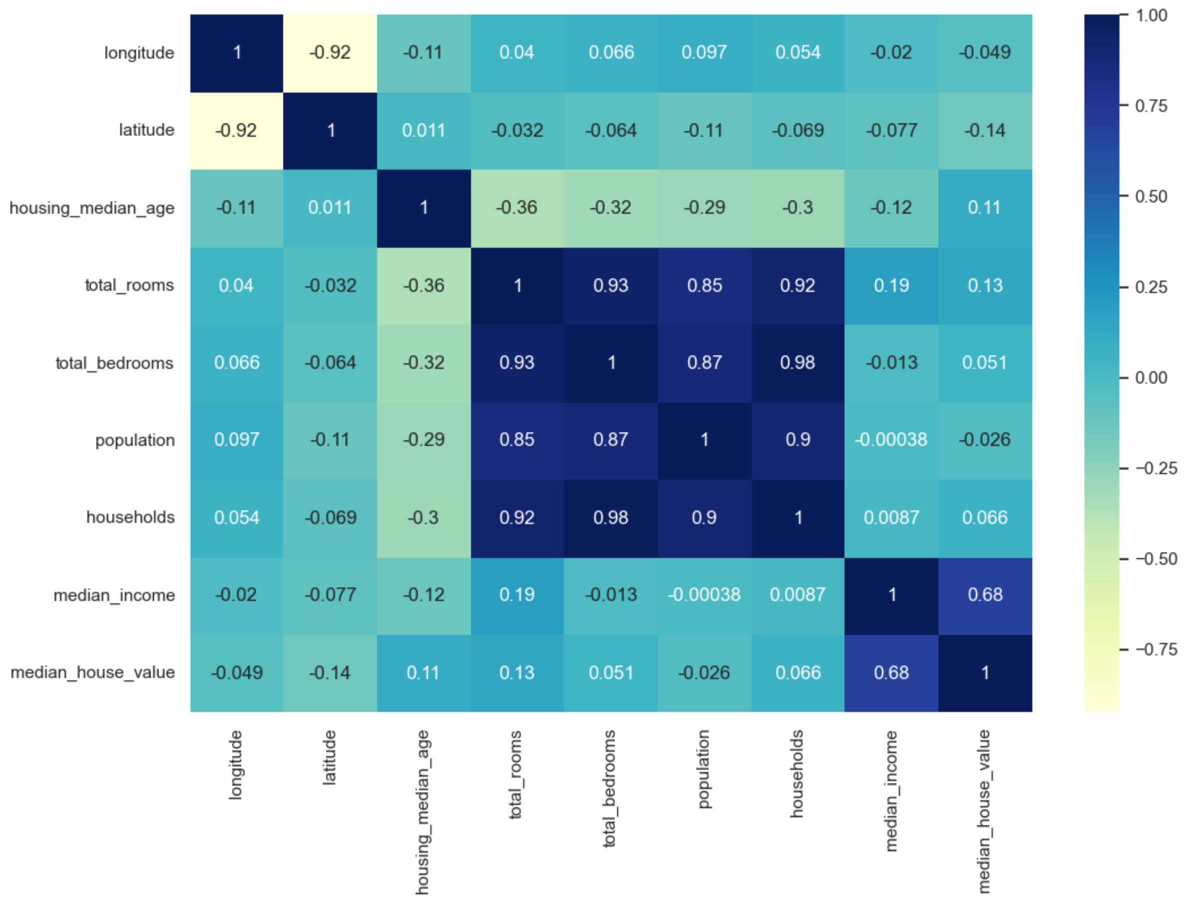
In [92]:
```
train_data.hist(figsize=(12,8))  #variation in the different features and their co
```

Out[92]:
```
array([[<AxesSubplot:title={'center':'longitude'}>,
        <AxesSubplot:title={'center':'latitude'}>,
        <AxesSubplot:title={'center':'housing_median_age'}>],
       [<AxesSubplot:title={'center':'total_rooms'}>,
        <AxesSubplot:title={'center':'total_bedrooms'}>,
        <AxesSubplot:title={'center':'population'}>],
       [<AxesSubplot:title={'center':'households'}>,
        <AxesSubplot:title={'center':'median_income'}>,
        <AxesSubplot:title={'center':'median_house_value'}>]],
      dtype=object)
```



In [93]:
```
plt.figure(figsize=(12,8))
sns.heatmap(train_data.corr(), annot=True, cmap="YlGnBu")
#the heatmap of correlation below is a visual representation of the correlation mat
```

Out[93]: <AxesSubplot:>



In [94]:
```
train_data
```

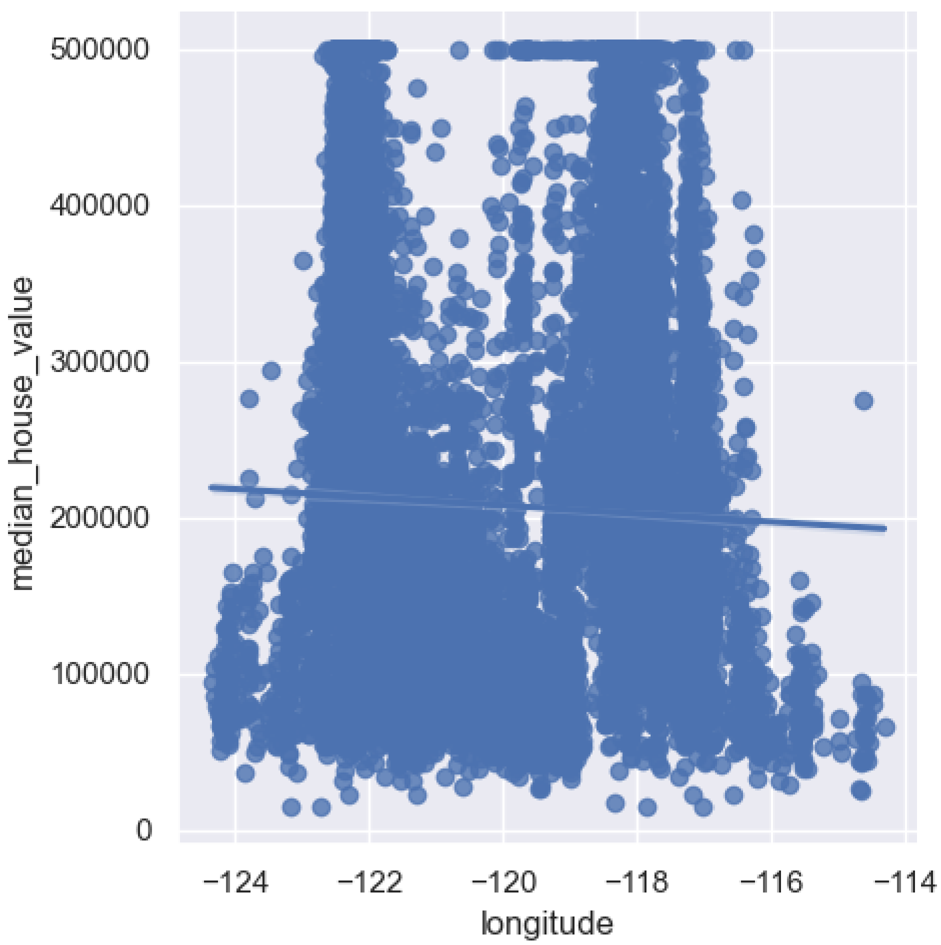
Out[94]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	housel
10041	-121.06	39.21	52.0	1452.0	309.0	637.0	
6651	-118.14	34.15	41.0	1256.0	407.0	855.0	
5126	-118.28	33.99	38.0	1454.0	323.0	1098.0	
16320	-121.34	37.99	11.0	4487.0	868.0	2195.0	
7363	-118.20	33.97	28.0	2474.0	702.0	2830.0	
...	...	...	...	...	...	...	
11108	-117.89	33.85	18.0	2036.0	414.0	1292.0	
8479	-118.32	33.93	34.0	1536.0	273.0	804.0	
18368	-121.98	37.16	42.0	2533.0	433.0	957.0	
604	-122.08	37.69	36.0	2350.0	499.0	1105.0	
4326	-118.32	34.08	52.0	1164.0	257.0	575.0	

16346 rows × 10 columns

In [95]:

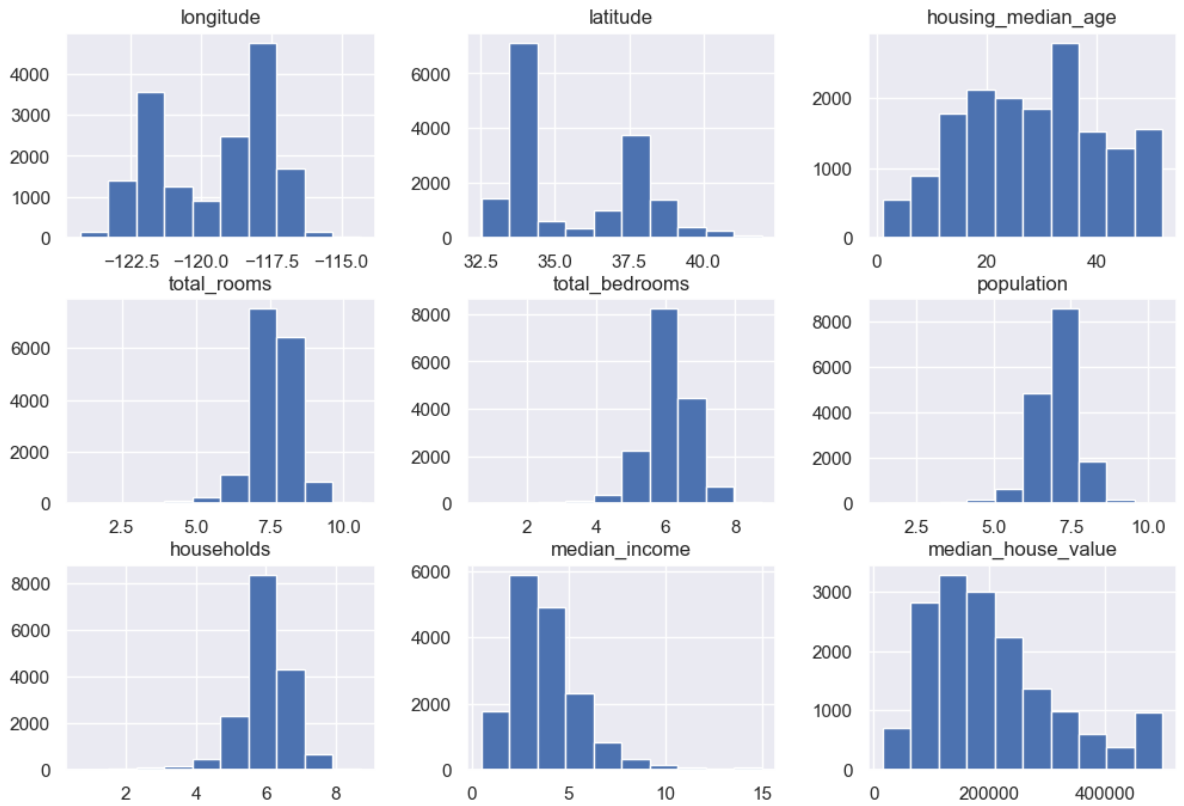
```
# scatter plot with regression line to study negative correlation of longitude with
sns.lmplot(x='longitude', y='median_house_value', data=df)

# display the plot
plt.show()

#the negative slope of the regression line confirms the negative correlation betwe
```



In [96]:
```
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)
#from the histogram, we can tell that most of the data is skewed (right skewed for
```

In [97]:
```
train_data.hist(figsize=(12,8)) #now looks more like gaussian normal distribution
```

Out[97]:
```
array([[<AxesSubplot:title={'center':'longitude'}>,
        <AxesSubplot:title={'center':'latitude'}>,
        <AxesSubplot:title={'center':'housing_median_age'}>],
       [<AxesSubplot:title={'center':'total_rooms'}>,
        <AxesSubplot:title={'center':'total_bedrooms'}>,
        <AxesSubplot:title={'center':'population'}>],
       [<AxesSubplot:title={'center':'households'}>,
        <AxesSubplot:title={'center':'median_income'}>,
        <AxesSubplot:title={'center':'median_house_value'}>]],
      dtype=object)
```



In [98]:
```
df.dropna(inplace=True)
```

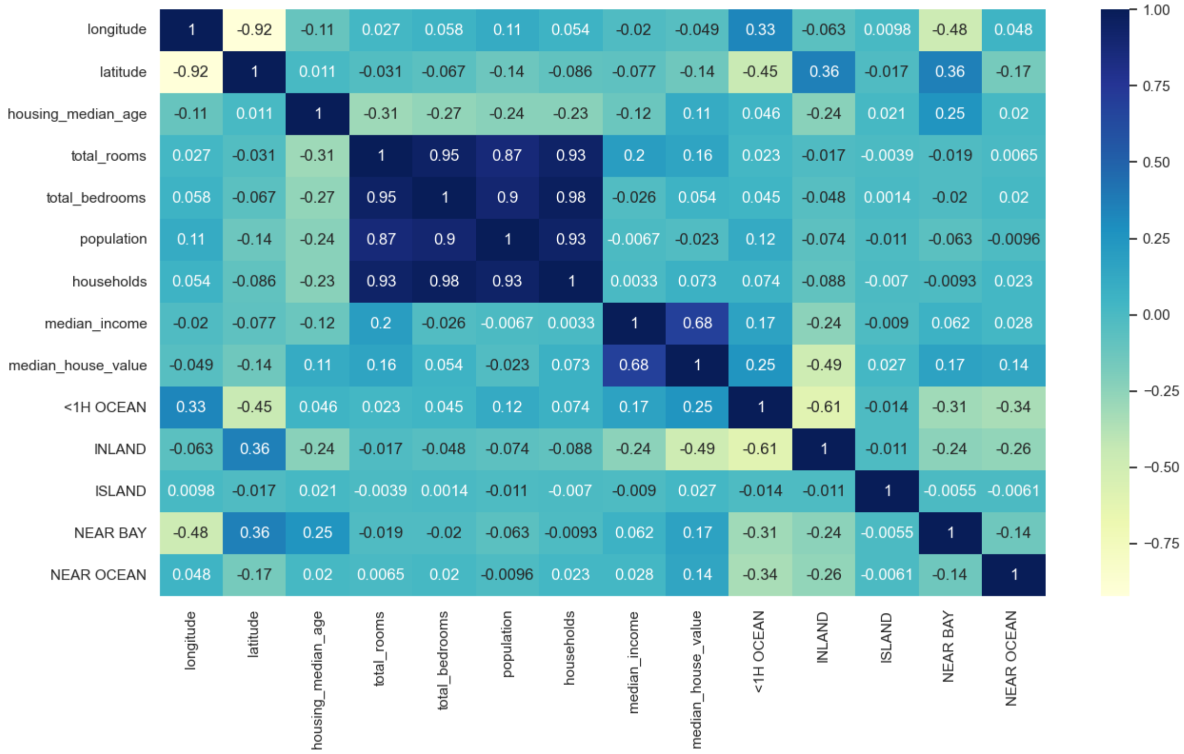
In [99]:
```
train_data.ocean_proximity.value_counts() #we want to make separate columns for the
```

Out[99]:
```
<1H OCEAN     7182
INLAND        5212
NEAR OCEAN    2130
NEAR BAY      1818
ISLAND           4
Name: ocean_proximity, dtype: int64
```

In [100…
```
train_data=train_data.join(pd.get_dummies(train_data.ocean_proximity)).drop(['ocean
```

In [101…
```
plt.figure(figsize=(15,8))
sns.heatmap(train_data.corr(),annot=True, cmap='YlGnBu') # high positive correlati
#negative correlation of median_house_value with INLAND
```

Out[101]:
```
<AxesSubplot:>
```



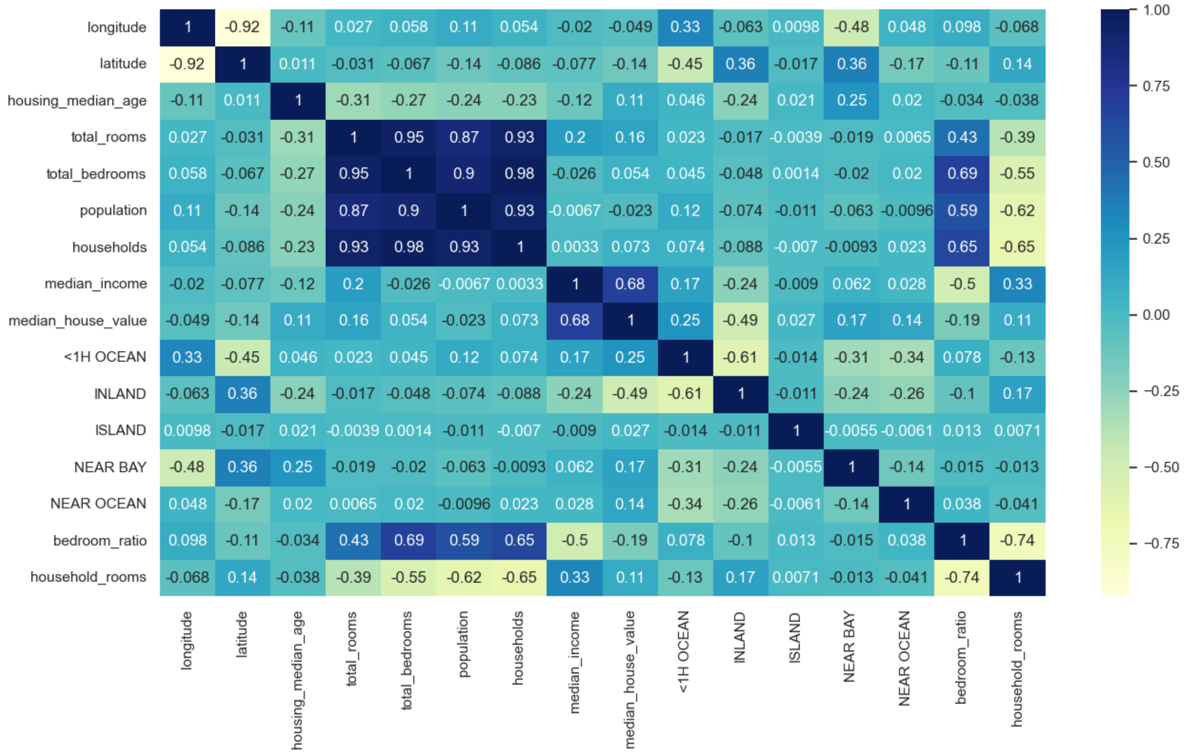
In [102…
```
#House value by location
sns.set() #to use default seaborn parameters
sns.set_style('darkgrid')
plt.figure(figsize=(15,8))
sns.scatterplot(x="latitude", y="longitude", data=train_data, hue="median_house_va
```

Out[102]: <AxesSubplot:xlabel='latitude', ylabel='longitude'>

In [103…
```
#Feature engineering
train_data['bedroom_ratio']=train_data['total_bedrooms']/train_data['total_rooms']
train_data['household_rooms']= train_data['total_rooms']/train_data['households'] 
#here we engineered two feature that are important in terms of correlation to our 
```

In [114…
```
plt.figure(figsize=(15,8))
sns.heatmap(train_data.corr(),annot=True, cmap='YlGnBu')
```

Out[114]: <AxesSubplot:>



In [104…

```
#Methods
#1. Linear Regression
'''

The first Machine Learning algorithm used for predicting the value of a residentia
To evaluate the performance of the model, first the data is split into training and
Test data is pre-processed in the same way as the training data. Feature engineeri
Finally, the test data is used to evaluate the performance of the trained model. Pr
The model is then evaluated using mean_squared_error, mean_absolute_error, and r2_s
'''
```

Out[104]:

```
'\nThe first Machine Learning algorithm used for predicting the value of a residen
tial property in California Region is Linear Regression because of its linearity a
nd interpretability. Moreover, because the dataset in use has a moderate number of
features and a small number of observations, Linear Regression performs well. It i
s also relatively computationally efficient. However, the performance of the Linea
r Regression model may be limited in this case by the quality and quantity of the
data as it sits at a size between being too toyish and too cumbersome.\nTo evaluat
e the performance of the model, first the data is split into training and test set
s. X_train includes all variables except the target variable, wehereas, Y_train co
ntains only the target variable. The method reg.fit is used to train the regressio
n model on the dataset. \n\n'
```

In [105…

```
#Linear Regression
from sklearn.linear_model import LinearRegression
X_train, Y_train= train_data.drop(['median_house_value'],axis=1),train_data['media
reg=LinearRegression()
reg.fit(X_train, Y_train)
```

Out[105]:

```
LinearRegression()
```

In [106…

```
test_data=X_test.join(Y_test)

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)

test_data=test_data.join(pd.get_dummies(test_data.ocean_proximity)).drop(['ocean_pr
```

```
test_data['bedroom_ratio']=test_data['total_bedrooms']/test_data['total_rooms']
test_data['household_rooms']= test_data['total_rooms']/test_data['households']

X_test, Y_test= test_data.drop(['median_house_value'],axis=1),test_data['median_hou
y_pred=reg.predict(X_test)
```

In [107…

```
y_pred
```

Out[107]:

```
array([167364.29034146, 351818.6695751 , 151460.11540519, ...,
       422024.62123489, 307825.70371903, 168783.69772651])
```

In [108…

```
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
mse = mean_squared_error(Y_test, y_pred)
rmse = mean_squared_error(Y_test, y_pred, squared=False)
mae = mean_absolute_error(Y_test, y_pred)
r2 = r2_score(Y_test, y_pred)

print("Mean Squared Error: ", mse)
print("Root Mean Squared Error: ", rmse)
print("Mean Absolute Error: ", mae)
print("R-squared: ", r2)
```

```
Mean Squared Error:  4349730954.61099
Root Mean Squared Error:  65952.4901319957
Mean Absolute Error:  47650.14642921123
R-squared:  0.681082570469806
```

In [21]:

```
test_data
```

Out[21]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househ
17456	-120.43	34.69	33.0	7.628031	5.924256	6.973543	5.88
11910	-117.41	33.96	24.0	8.407825	6.804615	7.782807	6.71
17609	-121.92	37.29	34.0	6.850126	4.912655	5.937536	4.94
18097	-122.05	37.33	17.0	8.209308	6.715383	7.218910	6.54
18880	-122.26	38.10	30.0	8.107117	6.965080	7.492760	6.89
...	...	...	...	...	...	...	
8559	-118.41	33.92	32.0	7.859799	6.410175	7.032624	6.32
7271	-118.23	33.99	5.0	6.561031	5.318120	6.733402	5.29
18217	-122.08	37.40	23.0	6.693324	5.068904	5.924256	5.05
6604	-118.17	34.18	38.0	7.155396	5.446737	6.720220	5.47
14716	-117.05	32.80	23.0	8.104703	5.996452	7.018402	5.95

4087 rows × 16 columns

In [ ]:

In [109…

```
reg.score(X_test,Y_test)
```

Out[109]:

```
0.681082570469806
```

In [ ]:
```
#Methods
#2. Random Forest Regressor
'''
The second algorithm used for house value prediction is Random Forest Regressor. It
An instance of the RandomForestRegressor class is created with n_estimators=[3,10,3
Random Forest is particularly suitable for this type of prediction as it reeduces o
The trees are trained on different subsets of the data and different subsets of fea

Forest.score() method is used to evaluate the performance of the trained model on t

A param_grid that specifies the values to try for each hyperparameter is defined. A
Then the training data is fitted to the model using grid_search.fit(X_train, Y_trai
The grid_search.best_estimator_ gives the best set of hyperparameters found during

'''
```

In [110…
```
from sklearn.ensemble import RandomForestRegressor
forest=RandomForestRegressor()
forest.fit(X_train,Y_train)
y_pred_RFR=forest.predict(X_test) #predict values using trained model
```

In [111…
```
# y_pred_RFR=forest.predict([256265.24,2313])
print(X_test)
print(y_pred_RFR)
```

```
       longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
9737     -121.76     36.77                27.0     7.383368        6.222576
17481    -119.81     34.45                24.0     8.210396        6.342121
12373    -116.45     33.80                 9.0     8.618847        7.095893
3664     -118.37     34.23                32.0     7.275865        5.762051
7106     -118.01     33.90                26.0     7.995980        6.514713
...          ...       ...                 ...          ...             ...
16556    -121.29     37.80                 6.0     4.709530        3.295837
16683    -120.57     35.11                18.0     7.979681        6.322565
17854    -121.89     37.46                 5.0     7.326466        5.231109
18147    -122.04     37.35                28.0     7.367077        5.579730
13182    -117.71     33.97                10.0     9.292565        7.731492

       population  households  median_income  <1H OCEAN  INLAND  ISLAND  \
9737     7.616776    6.212606         2.3384          1       0       0
17481    7.349231    6.347389         6.5173          0       0       0
12373    7.733684    6.916715         3.6161          0       1       0
3664     7.071573    5.743003         3.6000          1       0       0
7106     7.412160    6.444131         4.6094          1       0       0
...           ...         ...            ...        ...     ...     ...
16556    4.248495    3.218876         3.7292          0       1       0
16683    6.974479    6.315358         3.5242          1       0       0
17854    6.559615    5.231109        10.3798          1       0       0
18147    6.546785    5.602119         5.6780          1       0       0
13182    8.775704    7.696213         3.8510          0       1       0

       NEAR BAY  NEAR OCEAN  bedroom_ratio  household_rooms
9737          0           0       0.842783         1.188449
17481         0           1       0.772450         1.293508
12373         0           0       0.823300         1.246090
3664          0           0       0.791940         1.266909
7106          0           0       0.814748         1.240816
...         ...         ...            ...              ...
16556         0           0       0.699823         1.463098
16683         0           0       0.792333         1.263536
17854         0           0       0.714002         1.400557
18147         0           0       0.757387         1.315052
13182         0           0       0.832008         1.207421

[4087 rows x 15 columns]
[176745.   401742.43 127415.   ... 472654.52 322711.07 150940.  ]
```

In [112…

```python
mse = mean_squared_error(Y_test, y_pred_RFR)
rmse = mean_squared_error(Y_test, y_pred_RFR, squared=False)
mae = mean_absolute_error(Y_test, y_pred_RFR)
r2 = r2_score(Y_test, y_pred_RFR)

print("Mean Squared Error: ", mse)
print("Root Mean Squared Error: ", rmse)
print("Mean Absolute Error: ", mae)
print("R-squared: ", r2)
```

```
Mean Squared Error:  2427854962.642315
Root Mean Squared Error:  49273.26823585295
Mean Absolute Error:  32224.916405676533
R-squared:  0.8219923779108175
```

In [113…

```python
forest.score(X_test,Y_test) #method used to evaluate the performance of the trained
```

Out[113]:

```
0.8219923779108175
```

In [30]:

```python
from sklearn.model_selection import GridSearchCV
forest=RandomForestRegressor()
```

```
param_grid={

    "n_estimators":[3,10,30],
    "max_features":[2,4,6,8]

} #provide parameter grid for grid search, specify the different hyperparameters th

grid_search= GridSearchCV( forest,param_grid, cv=5, scoring="neg_mean_squared_error

grid_search.fit(X_train,Y_train) #fit this grid search onto X_train
```

Out[30]:
```
GridSearchCV(cv=5, estimator=RandomForestRegressor(),
             param_grid={'max_features': [2, 4, 6, 8],
                         'n_estimators': [3, 10, 30]},
             return_train_score=True, scoring='neg_mean_squared_error')
```

In [35]:
```
best_forest= grid_search.best_estimator_ #gives the best set of hyperparameters fo
```

In [33]:
```
best_forest.score(X_test,Y_test) #evaluate the model using evaluation metric
```

Out[33]:
```
0.8223371804634941
```

In [ ]:
```
#Results
'''
As per the evaluation of both models used, Random Forest has a higher accuracy of p

The regression score of 0.68 suggests that the model explains 68% of the variance i
There is likely still room for improvement. It is noteworthy to mention that the pe
Lower MSE and RMSE indicate better performance.

The best_forest.score of 0.8223 suggests that the model is able to explain a signi
A higher score indicates better performance, so a score of 0.8223 suggests that the
It's also possible that different evaluation metrics could provide different perspe
Therefore, the Random Forest Regressor is a more powerful algorithm for predicting
The data was scaled but as it did not significantly improve the accuracy, it isn't



'''
```