Problem Statement

In this case study, we examine the Housing Prices in California to figure out what factors influence prices the most. The inteligence will be relevant for the companies to determine the income of the household, which can then be utilized to incorporate targeted ads.

Link to Dataset - https://www.kaggle.com/camnugent/california-housing-prices

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
from plotly import express as px
```

In [2]:

```
pd.set_option('max.column', None)
```

In [3]:

```
data = pd.read_csv("CaliDataset.csv")
```

Data Exploration

In [4]:

```
data.keys()
```

Out[4]:

```
Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
       'total_bedrooms', 'population', 'households', 'median_income',
       'median_house_value', 'ocean_proximity'],
      dtype='object')
```

- **Let's check the random ten number of data samples, so we can easly understand the behaviour and what types of data type stored in particular features.**

In [5]:

```
data.sample(10)
```

Out[5]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	media
13014	-121.17	38.69	5.0	7138.0	1227.0	2623.0	1139.0	5.6902	
5906	-118.43	34.30	28.0	271.0	61.0	246.0	62.0	1.7062	
4327	-118.33	34.08	52.0	1777.0	454.0	671.0	439.0	3.5083	
17259	-119.72	34.42	31.0	1524.0	383.0	1257.0	398.0	2.6019	
8208	-118.17	33.79	32.0	2171.0	672.0	3002.0	648.0	2.3750	
16599	-120.70	35.76	15.0	1914.0	425.0	1130.0	421.0	2.2165	
19045	-121.82	38.46	10.0	6331.0	1181.0	3419.0	1110.0	3.7083	
2442	-119.61	36.57	42.0	2242.0	521.0	1359.0	483.0	1.5833	
11741	-121.13	38.87	48.0	1127.0	NaN	530.0	186.0	3.0917	

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	media
6258	-117.96	34.05	36.0	1475.0	270.0	1149.0	284.0	3.0904	

- **Target Feature**

In [6]:

```
TARGET_FEATURE = 'median_house_value'

Y = data[TARGET_FEATURE]

Y.head(10)
```

Out[6]:

```
0    452600.0
1    358500.0
2    352100.0
3    341300.0
4    342200.0
5    269700.0
6    299200.0
7    241400.0
8    226700.0
9    261100.0
Name: median_house_value, dtype: float64
```

In [7]:

```
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
```

As we can see in the output.

1. **There are 20640 entries**
2. **There are total 10 features (0 to 9)**
3. **There are two types of datatype dtypes: float64(8) and object(1)**
4. **Also, we can check how many missing values are there in the Non-Null Count column. We can observe that one column has missing values. (total_bedrooms)**

In [8]:

```
data.describe()
```

Out[8]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_i
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_i
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.

- **Here, describe() method provides us the complete calculations details about the dataset. i.e. let's take the price feature for example. It shows the what's the min, max, mean(average) and std(standard deviation) of price feature.**

- **Numerical Features**

In [9]:

```
numeric_features = data.select_dtypes(['int', 'float']).columns
numeric_features , len(numeric_features)
```

Out[9]:

```
(Index(['longitude', 'latitude', 'housing_median_age', 'total_rooms',
        'total_bedrooms', 'population', 'households', 'median_income',
        'median_house_value'],
       dtype='object'), 9)
```

- **Categorical Features**

In [10]:

```
categorical_features = data.select_dtypes('object').columns
categorical_features, len(categorical_features)
```

Out[10]:

```
(Index(['ocean_proximity'], dtype='object'), 1)
```

In [11]:

```
print("Number of 'Numerical' Features are:", len(numeric_features) )
print("Number of 'Categorical' Features are:", len(categorical_features) )
```

```
Number of 'Numerical' Features are: 9
Number of 'Categorical' Features are: 1
```

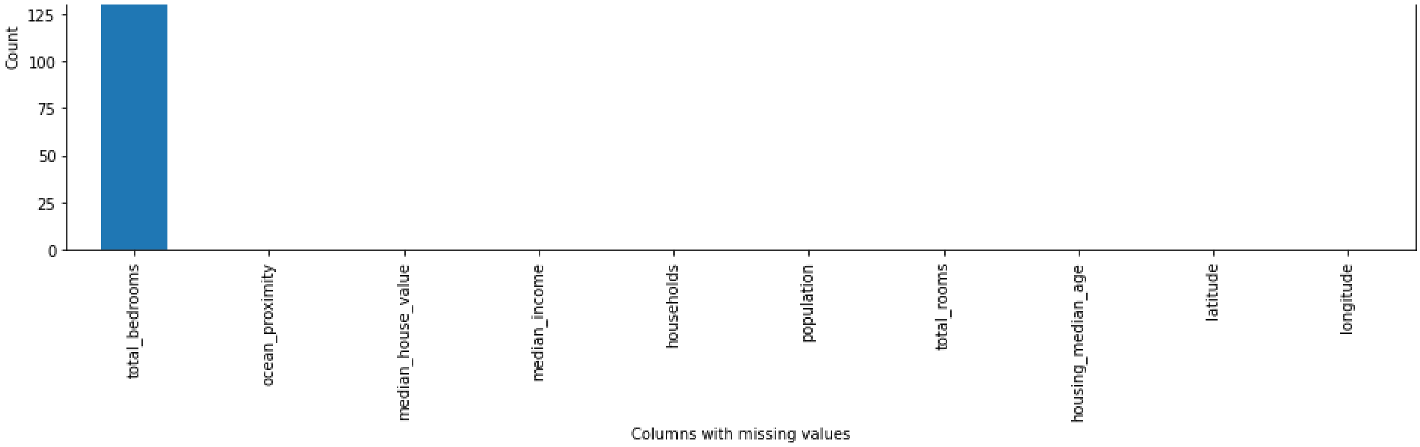
Data Pre-Processing

In [12]:

```
missing = data.isna().sum().sort_values(ascending=False)
missing.plot.bar(figsize=(16,5))
plt.xlabel('Columns with missing values')
plt.ylabel('Count')
```

Out[12]:

```
Text(0, 0.5, 'Count')
```



In [13]:

```
missing
```

Out[13]:

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

- **In above output, We can clearly see that, There is only one value (total_bedrooms) that has null values. So we have to fill some statastical values.**

- **Filling Missing Values**

In [14]:

```
data[['total_bedrooms']].describe(include='all')
```

Out[14]:

	total_bedrooms
count	20433.000000
mean	537.870553
std	421.385070
min	1.000000
25%	296.000000
50%	435.000000
75%	647.000000
max	6445.000000

- **As we can see there is only one feature that has categorical values and rest all have numerical features.**

In [15]:

```
data['total_bedrooms'] = data['total_bedrooms'].fillna(data['total_bedrooms'].mode()[0])
data.isna().any()
```

Out[15]:

```
longitude             False
latitude              False
housing_median_age    False
total_rooms           False
total_bedrooms        False
population            False
households            False
median_income         False
median_house_value    False
ocean_proximity       False
dtype: bool
```

- **All missing values are filled.**

- **Getting total number of unique values and removing columns which have huge number of unique values.**

In [16]:

```
print("Total Records :", len(data) )

for col in categorical_features:
    print("Total Unique Records of "+ col + " =",  len(data[col].unique()))
```

```
Total Records : 20640
Total Unique Records of ocean_proximity = 5
```

- **Now, we convert categorical values into numerical values.**

In [17]:

```
data[categorical_features].value_counts()
```

Out[17]:

```
ocean_proximity
<1H OCEAN        9136
INLAND           6551
NEAR OCEAN       2658
NEAR BAY         2290
ISLAND              5
dtype: int64
```

In [18]:

```
from sklearn.preprocessing import LabelEncoder
for column in categorical_features:
    l_encoder = LabelEncoder()
    data[column] = l_encoder.fit_transform(data[column])
```

In [19]:

```
data.head(10)
```

Out[19]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	
5	-122.25	37.85	52.0	919.0	213.0	413.0	193.0	4.0368	
6	-122.25	37.84	52.0	2535.0	489.0	1094.0	514.0	3.6591	

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
7	-122.25	37.84	52.0	3104.0	687.0	1157.0	647.0	3.1200	
8	-122.26	37.84	42.0	2555.0	665.0	1206.0	595.0	2.0804	
9	-122.25	37.84	52.0	3549.0	707.0	1551.0	714.0	3.6912	

In [20]:

```
training_features = list(numeric_features) + list(categorical_features)

# Remove 'Price' Feature from list
training_features.remove('median_house_value')

# Final list of Training Features
training_features
```

Out[20]:

```
['longitude',
 'latitude',
 'housing_median_age',
 'total_rooms',
 'total_bedrooms',
 'population',
 'households',
 'median_income',
 'ocean_proximity']
```

- **Now, we use MinMaxScaler to normalize our dataset.**

In [21]:

```
from sklearn.preprocessing import MinMaxScaler
minMaxNorm = MinMaxScaler()
minMaxNorm.fit(data[training_features])
X = minMaxNorm.transform(data[training_features])
X
```

Out[21]:

```
array([[0.21115538, 0.5674814 , 0.78431373, ..., 0.02055583, 0.53966842,
        0.75      ],
       [0.21215139, 0.565356  , 0.39215686, ..., 0.18697583, 0.53802706,
        0.75      ],
       [0.21015936, 0.5642933 , 1.        , ..., 0.02894261, 0.46602805,
        0.75      ],
       ...,
       [0.31175299, 0.73219979, 0.31372549, ..., 0.07104095, 0.08276438,
        0.25      ],
       [0.30179283, 0.73219979, 0.33333333, ..., 0.05722743, 0.09429525,
        0.25      ],
       [0.30976096, 0.72582359, 0.29411765, ..., 0.08699227, 0.13025338,
        0.25      ]])
```

In [22]:

```
Y = data['median_house_value']
Y
```

Out[22]:

```
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: 20640, dtype: float64
```

Prediction is the data mining task which is needed to solve the problem statement, as we need to predict the house of a price based on several factors like its location, number of bedroom, etc,. As we need to predict a specific price and not a price range, classification is not the major task.

- **Splitting Train and Test Dataset**

In [23]:

```
from sklearn.model_selection import train_test_split
train_X, test_X, train_Y, test_Y = train_test_split(X, Y, test_size=0.2)
print("Total size: ", data.shape[0])
print("Train size: ", train_X.shape, train_Y.shape)
print("Test size: ", test_X.shape, test_Y.shape)
```

```
Total size:  20640
Train size:  (16512, 9) (16512,)
Test size:  (4128, 9) (4128,)
```

In [24]:

```
models_summary = pd.DataFrame([],
                              columns=['Model_name',
                                       'Prediction_Score',
                                       'Mean_Absolute_error'
                                      ])
models_summary
```

Out[24]:

Model_name	Prediction_Score	Mean_Absolute_error

In [25]:

```
from sklearn.ensemble import  AdaBoostRegressor
from sklearn.ensemble import  GradientBoostingRegressor
from sklearn.ensemble import  RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
```

In [26]:

```
ADB_model = AdaBoostRegressor(n_estimators=400, learning_rate=0.25)
ADB_model.fit(train_X,train_Y)
y_train = ADB_model.predict(train_X)
print("The train accuracy score : {} ".format(r2_score(train_Y, y_train)))
y_adb_predict = ADB_model.predict(test_X)
print("The test accuracy score : {} ".format(r2_score(test_Y, y_adb_predict)))
score = ADB_model.score(test_X, test_Y)
score
```

```
The train accuracy score : 0.38510724399721463
The test accuracy score : 0.37805881781154904
```

Out[26]:

```
0.37805881781154904
```

In [27]:

```
mae = mean_absolute_error(test_Y, y_adb_predict)
models_summary = models_summary.append({
    'Model_name': ADB_model.__class__.__name__,
```

```
    'Prediction_Score': r2_score(test_Y, y_adb_predict),
    'Mean_Absolute_error' : mae
}, ignore_index=True)

models_summary.sort_values('Prediction_Score', ascending=False)
```

Out[27]:

	Model_name	Prediction_Score	Mean_Absolute_error
0	AdaBoostRegressor	0.378059	78527.783462

In [28]:

```
Dtree_model = DecisionTreeRegressor(random_state=1, max_depth=6, min_samples_split=6)
Dtree_model.fit(train_X, train_Y)
y_train = Dtree_model.predict(train_X)
print("The train accuracy score : {} ".format(r2_score(train_Y, y_train)))
y_dtree_predict = Dtree_model.predict(test_X)
print("The test accuracy score : {} ".format(r2_score(test_Y, y_dtree_predict)))
```

```
The train accuracy score : 0.6946824987893929
The test accuracy score : 0.6596631950247303
```

In [29]:

```
models_summary = models_summary.append({
    'Model_name': Dtree_model.__class__.__name__,
    'Prediction_Score': r2_score(test_Y, y_dtree_predict),
    'Mean_Absolute_error' : mean_absolute_error(test_Y, y_dtree_predict)
}, ignore_index=True)

models_summary.sort_values('Prediction_Score', ascending=False)
```

Out[29]:

	Model_name	Prediction_Score	Mean_Absolute_error
1	DecisionTreeRegressor	0.659663	46746.006450
0	AdaBoostRegressor	0.378059	78527.783462

In [30]:

```
GBR_model = GradientBoostingRegressor(n_estimators=250, random_state=1, learning_rate=0.2
7, max_depth=6, min_samples_split=6)
GBR_model.fit(train_X, train_Y)
y_train = GBR_model.predict(train_X)
print("The train accuracy score : {} ".format(r2_score(train_Y, y_train)))
y_gbr_predict = GBR_model.predict(test_X)
print("The test accuracy score : {} ".format(r2_score(test_Y, y_gbr_predict)))
```

```
The train accuracy score : 0.9702968116101536
The test accuracy score : 0.8282769386842936
```

In [31]:

```
models_summary = models_summary.append({
    'Model_name': GBR_model.__class__.__name__,
    'Prediction_Score': r2_score(test_Y, y_gbr_predict),
    'Mean_Absolute_error' : mean_absolute_error(test_Y, y_gbr_predict)
}, ignore_index=True)

models_summary.sort_values('Prediction_Score', ascending=False)
```

Out[31]:

	Model_name	Prediction_Score	Mean_Absolute_error
2	GradientBoostingRegressor	0.828277	31304.486244
1	DecisionTreeRegressor	0.659663	46746.006450

	Model_name	Prediction_Score	Mean_Absolute_error
0	AdaBoostRegressor	0.378059	78527.783462

In [32]:

```
RFR_model = RandomForestRegressor(random_state=1,n_estimators=250, max_depth=18, min_sam
ples_split=4)
RFR_model.fit(train_X, train_Y)
y_train = RFR_model.predict(train_X)
print("The train accuracy score : {} ".format(r2_score(train_Y, y_train)))
y_rfr_predict = RFR_model.predict(test_X)
print("The test accuracy score : {} ".format(r2_score(test_Y, y_rfr_predict)))
```

```
The train accuracy score : 0.9621466176246058
The test accuracy score : 0.8166412832738121
```

In [33]:

```
models_summary = models_summary.append({
    'Model_name': RFR_model.__class__.__name__,
    'Prediction_Score': r2_score(test_Y, y_rfr_predict),
    'Mean_Absolute_error' : mean_absolute_error(test_Y, y_rfr_predict)
}, ignore_index=True)

models_summary.sort_values('Prediction_Score', ascending=False)
```

Out[33]:

	Model_name	Prediction_Score	Mean_Absolute_error
2	GradientBoostingRegressor	0.828277	31304.486244
3	RandomForestRegressor	0.816641	32014.729639
1	DecisionTreeRegressor	0.659663	46746.006450
0	AdaBoostRegressor	0.378059	78527.783462

In [34]:

```
XGBR_model = XGBRegressor(n_estimators=300, learning_rate=0.15, max_depth=6)
XGBR_model.fit(train_X, train_Y)
y_train = XGBR_model.predict(train_X)
print("The train accuracy score : {} ".format(r2_score(train_Y, y_train)))
y_xgbr_predict = XGBR_model.predict(test_X)
print("The test accuracy score : {} ".format(r2_score(test_Y, y_xgbr_predict)))
```

```
[19:20:37] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
The train accuracy score : 0.9558085903401108
The test accuracy score : 0.8348795673033752
```

In [35]:

```
models_summary = models_summary.append({
    'Model_name': XGBR_model.__class__.__name__,
    'Prediction_Score': r2_score(test_Y, y_xgbr_predict),
    'Mean_Absolute_error' : mean_absolute_error(test_Y, y_xgbr_predict)
}, ignore_index=True)

models_summary.sort_values('Prediction_Score', ascending=False)
```

Out[35]:

	Model_name	Prediction_Score	Mean_Absolute_error
4	XGBRegressor	0.834880	30715.403834
2	GradientBoostingRegressor	0.828277	31304.486244
3	RandomForestRegressor	0.816641	32014.729639
1	DecisionTreeRegressor	0.659663	46746.006450

	Model_name	Prediction_Score	Mean_Absolute_error
0	AdaBoostRegressor	0.378059	78527.783462

In [36]:

```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
xgbr_model = XGBRegressor() # {'objective': 'reg:squarederror' }

params = {
    'n_estimators': [110, 120, 130, 140],
    'learning_rate': [ 0.05, 0.075, 0.1],
    'max_depth': [ 7, 9],
    'reg_lambda': [0.3, 0.5]
}

xgb_reg = GridSearchCV(estimator=xgbr_model, param_grid=params, cv=5, n_jobs=-1)

xgb_reg.fit(train_X, train_Y)

xgbr_model_score = xgb_reg.best_score_

xgbr_model_pred = xgb_reg.predict(test_X)

mae = mean_absolute_error(test_Y, xgbr_model_pred)

print("Best score: %0.3f" % xgb_reg.best_score_)
print("Best parameters set:", xgb_reg.best_params_)

print("mean_absolute_error :", mae)
```

```
[19:30:37] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now dep
recated in favor of reg:squarederror.
Best score: 0.828
Best parameters set: {'learning_rate': 0.1, 'max_depth': 7, 'n_estimators': 140, 'reg_lam
bda': 0.5}
mean_absolute_error : 30647.608274474624
```

In [37]:

```
models_summary = models_summary.append({
    'Model_name': 'XGBRegressor_HyperParamsTunning',
    'Prediction_Score': xgbr_model_score,
    'Mean_Absolute_error' : mae
}, ignore_index=True)

models_summary.sort_values('Prediction_Score', ascending=False)
```

Out[37]:

	Model_name	Prediction_Score	Mean_Absolute_error
4	XGBRegressor	0.834880	30715.403834
2	GradientBoostingRegressor	0.828277	31304.486244
5	XGBRegressor_HyperParamsTunning	0.827650	30647.608274
3	RandomForestRegressor	0.816641	32014.729639
1	DecisionTreeRegressor	0.659663	46746.006450
0	AdaBoostRegressor	0.378059	78527.783462

After trying the most used regressor models, we found the R2 score of XGB Regressor to be highest, which was further tuned more to improve the score to 0.834880, which is better as the closer the value of R2 score to 1 the better the prediction is.

Data Visualisation

In [48]:

```
import plotly.express as ex
ex.pie(data,names='ocean_proximity',title='Proportion of Locations of the house w.r.t oce
an/sea')
```

We can see here that majority of the houses are close to the sea.

In [39]:

```
data['median_house_value'].skew()
```

Out[39]:

```
0.9777632739098341
```

- **The income data from the data we got is skewd but normaly we expect the the number of houses with comparatively lower prices to be of large number. Majority of the population wont be able afford the higher houseprices thus as the demand is more for comparatively lower priced houses the houses are constructed and priced that way,**

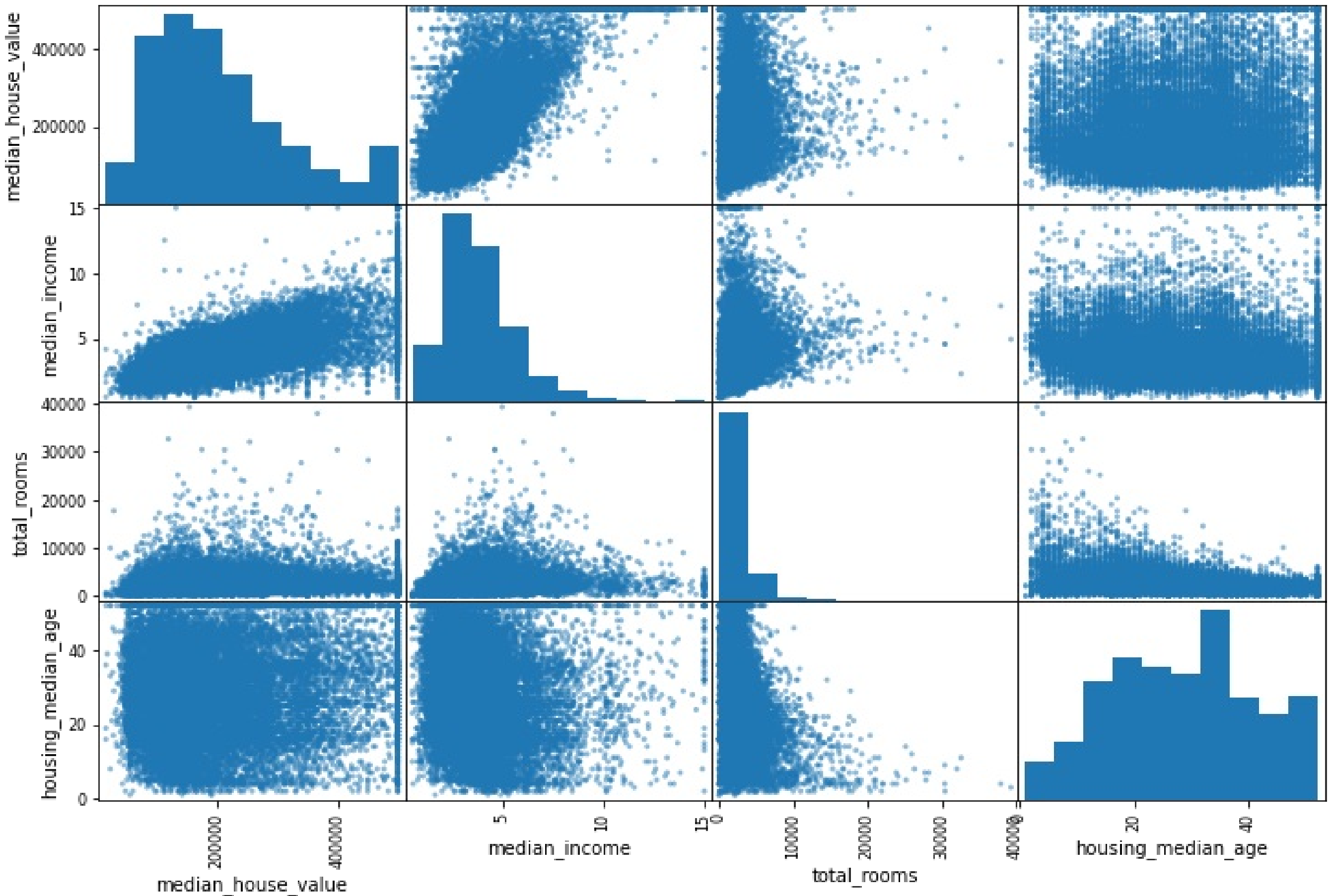
In [43]:

```
from pandas.plotting import scatter_matrix
sct_features = ["median_house_value", "median_income","total_rooms","housing_median_age"]
scatter_matrix(data[sct_features],figsize=(12,8))
```

Out[43]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7fa4179d4990>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa41795f9d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa41790a690>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4178d4710>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fa41784ad90>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa41780c450>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4177c3ad0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4177f0790>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7fa4177bb850>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa41776fed0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7fa417731550>,
```

```
 <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4176e9bd0>],
[<matplotlib.axes._subplots.AxesSubplot object at 0x7fa4176a9290>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7fa417661910>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7fa417617f90>,
 <matplotlib.axes._subplots.AxesSubplot object at 0x7fa4175d9650>]],
dtype=object)
```



This visualization gives us an idea about the relation of median_house_value with other attributes.

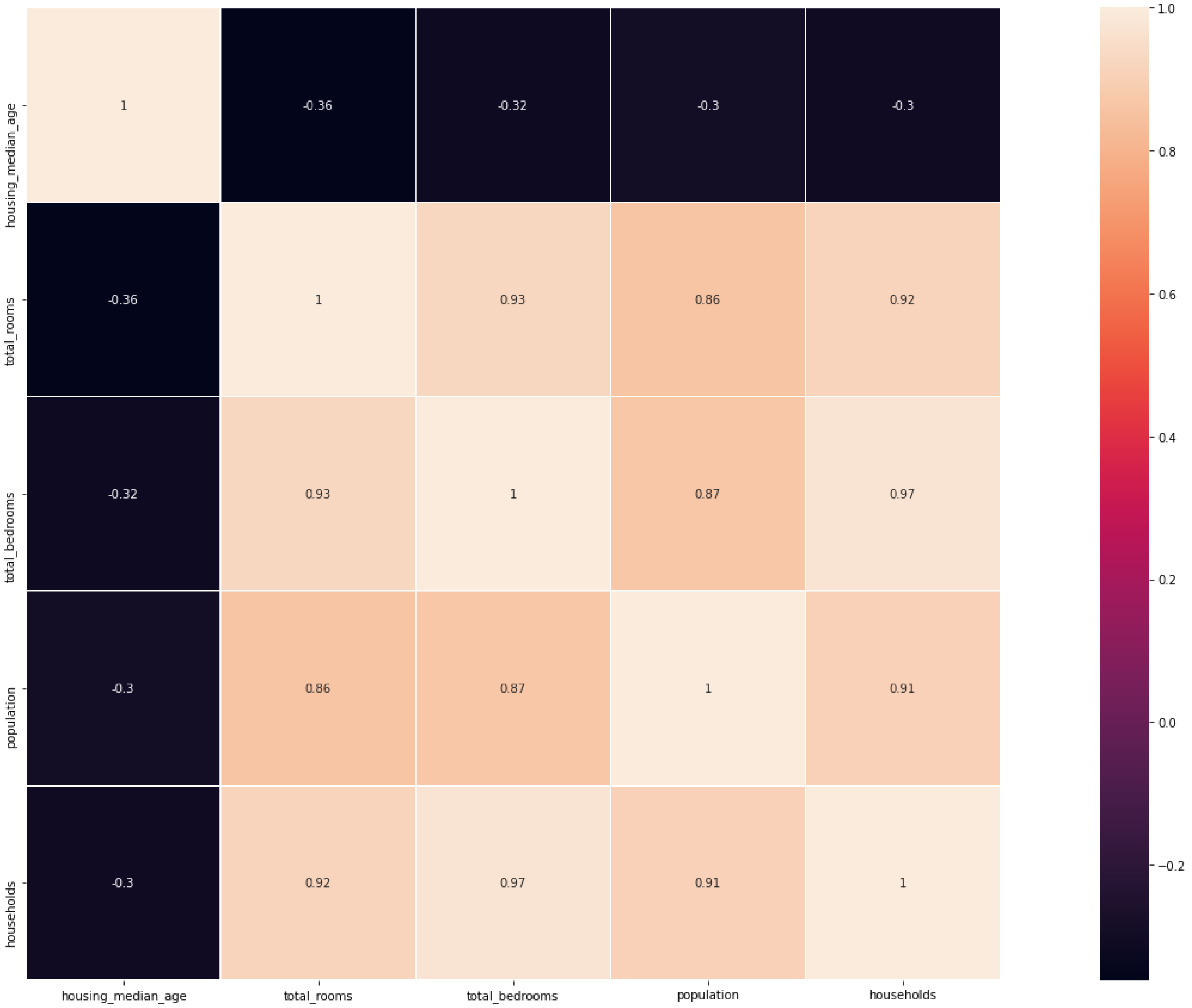
In [46]:

```
from plotly.subplots import make_subplots
import plotly.graph_objs as go
fig = make_subplots(1,2)
fig.add_trace(go.Histogram(x=data['median_house_value']),1,1)
fig.add_trace(go.Box(y=data['median_house_value'],boxpoints='all',line_color='orange'),1,
2)
fig.update_layout(height=500, showlegend=False,title_text="Median income distribution and
Box Plot")
```

- **Relationship Between median_housing_value And Other Variables.**

In [40]:

```
corr_mat = data[['housing_median_age','total_rooms','total_bedrooms','population','househ
olds']].corr()
f, ax = plt.subplots(figsize=(30, 15))
sns.heatmap(corr_mat, vmax=1 , square=True,annot=True,linewidths=.5);
```



Now, we plot the housing data with respect to the latitude and longitude given. With this, we come to know the population density and the median house vale, which we observe that they go hand-in-hand.

In [41]:

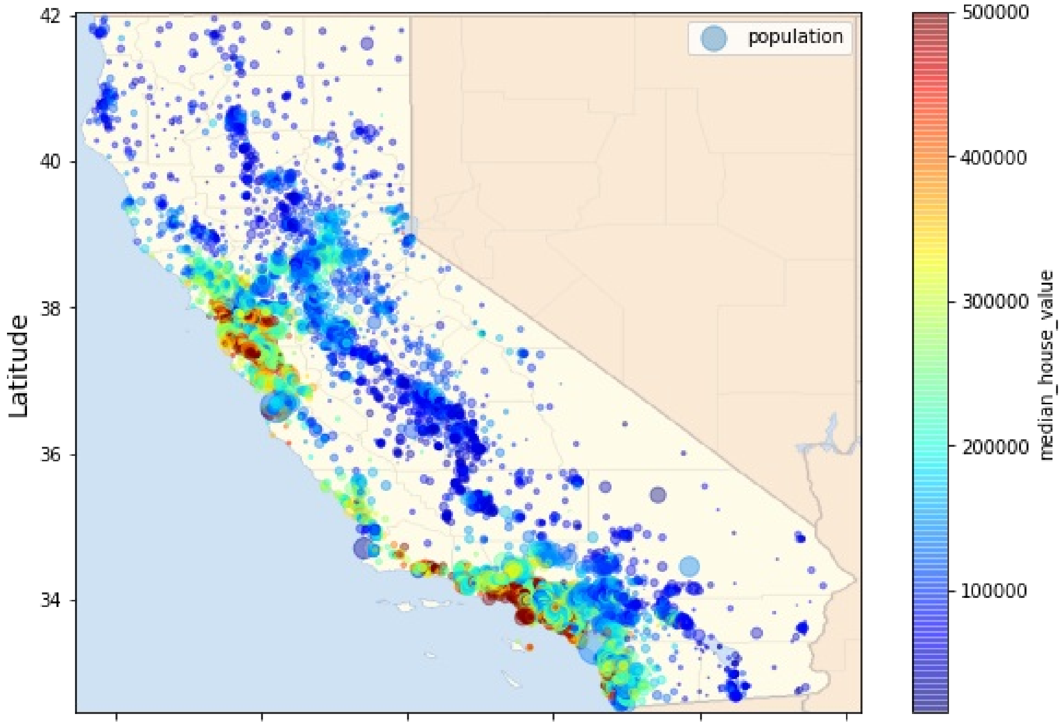
```
import matplotlib.image as mpimg

california_img=mpimg.imread('./california.png')

housing_plot = data[['longitude','population','latitude','median_house_value']]
```

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


plt.imshow(california_img, extent=[-124.55, -113.80, 32.45, 42.05], alpha=0.5)
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)
plt.legend()
plt.show()
```



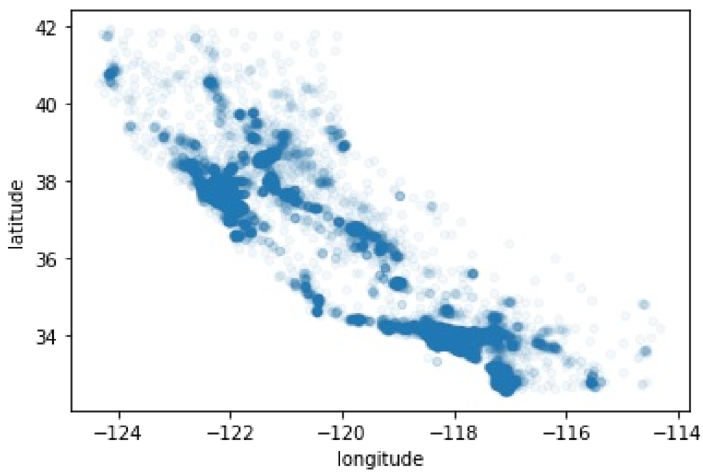
- **It helps you to know the density by overlapping the circle if this area have a lot of house there, also other area that have small number of house will be appear because of its opacity will be low.**
- **Not just alpha, other parameters of the graph can help you discover more pattern**

In [44]:

```
data.plot(kind="scatter", x="longitude", y = "latitude", alpha=.05)
```

Out[44]:

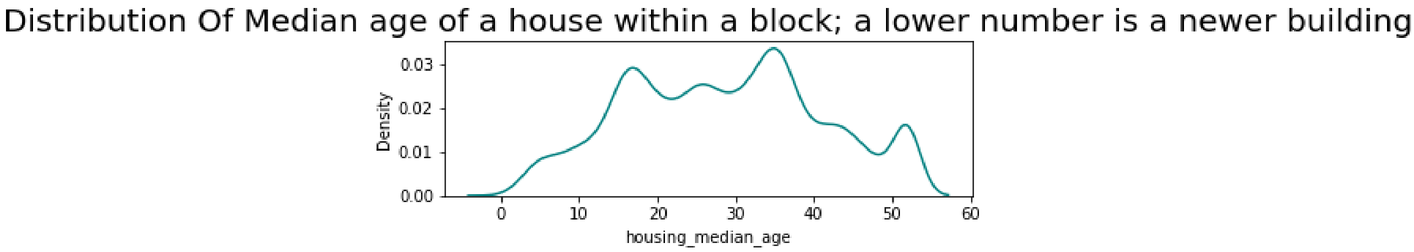
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa417531b50>
```

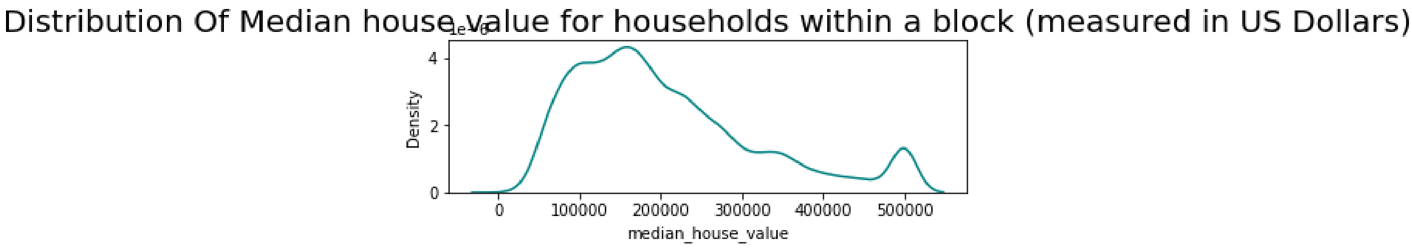


In [45]:

```
plt.subplot(2,1,1)
plt.title('Distribution Of Median age of a house within a block; a lower number is a newe
r building',fontsize=20)
sns.kdeplot(data['housing_median_age'],color='teal')
```

```
plt.show()
plt.subplot(2,1,2)
plt.title('Distribution Of Median house value for households within a block (measured in US Dollars)',fontsize=20)
sns.kdeplot(data['median_house_value'],color='teal')
plt.show()
```





From the above plot we can see that both features follow a multimodal distribution, meaning we have underlaying groups in our data.