In [1]:

import pandas as pd

housing = pd.read_csv("/content/drive/MyDrive/housing.csv")
housing.head()

Out[1]:

	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	
4									<u> </u>

In [2]:

housing.describe()

Out[2]:

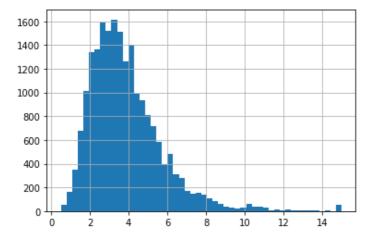
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_i
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.
std	2.003532	2.135952	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.
4								

In [3]:

housing['median_income'].hist(bins=50)

Out[3]:

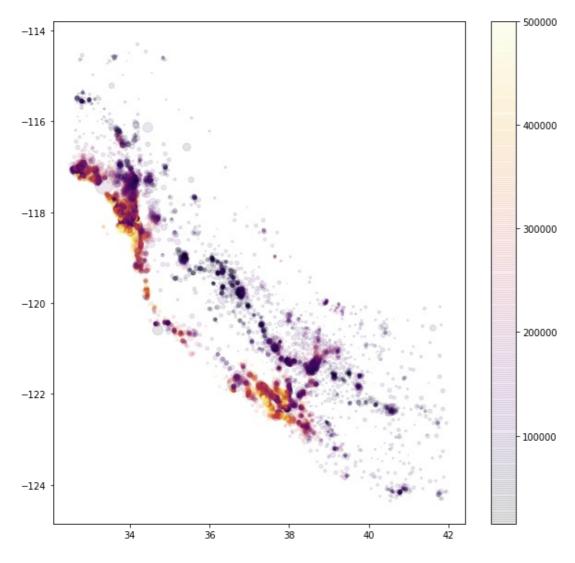
 ${\tt <matplotlib.axes._subplots.AxesSubplot}$ at ${\tt 0x7f59259a2390>}$



```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,10))
plt.scatter(x=housing['latitude'], y=housing['longitude'], alpha=0.1, s=housing['population
']/100, c=housing['median_house_value'], cmap='inferno')
plt.colorbar()
```

Out[4]:

<matplotlib.colorbar.Colorbar at 0x7f5924120fd0>



In [5]:

```
corr_matrix = housing.corr()
corr_matrix['median_house_value'].sort_values(ascending=False)
```

Out[5]:

```
median house value
                    1.000000
median_income
                     0.688075
total rooms
                     0.134153
                    0.105623
housing_median_age
                    0.065843
households
total bedrooms
                    0.049686
population
                    -0.024650
longitude
                    -0.045967
latitude
                    -0.144160
Name: median_house_value, dtype: float64
```

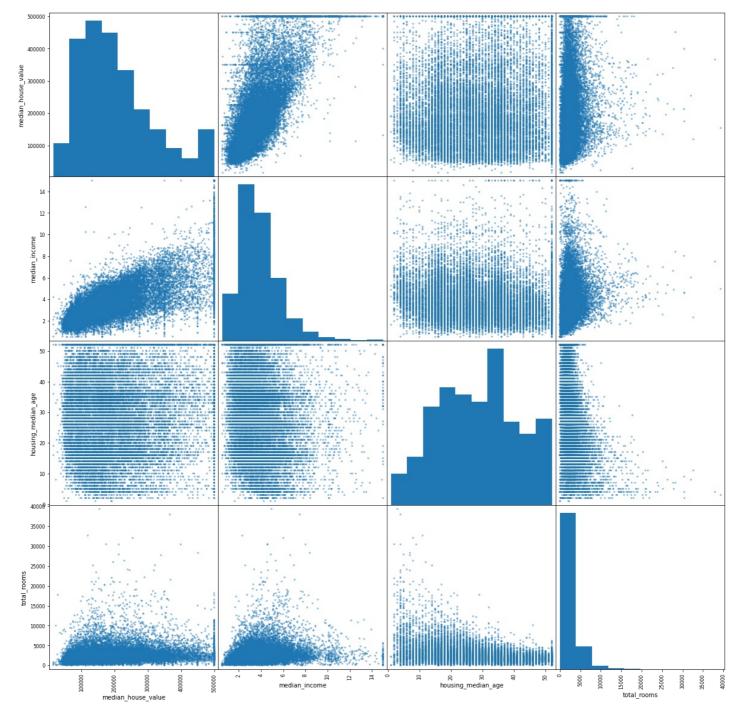
In [6]:

```
from pandas.plotting import scatter_matrix

attributes = ['median_house_value', 'median_income', 'housing_median_age', 'total_rooms']
scatter_matrix(housing[attributes], figsize=(20,20))
```

Out[6]:

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f59240c77f0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f59228374a8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5922869710>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f592281c978>],
       [<matplotlib.axes. subplots.AxesSubplot object at 0x7f59227cdbe0>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f5922783e48>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f59227430f0>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f59226f8320>],
       [<matplotlib.axes. subplots.AxesSubplot object at 0x7f59226f8390>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f59226dd828>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f5922693a90>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f5922646cf8>],
       [<matplotlib.axes. subplots.AxesSubplot object at 0x7f59225fdf60>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f59225ba208>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f5922570470>,
        <matplotlib.axes. subplots.AxesSubplot object at 0x7f59225a26d8>]],
      dtype=object)
```



In [7]:
housing.plot(kind='scatter',x='median income',y='median house value',alpha=0.1)

Out[7]:

In [8]:

housing.columns

Out[8]:

In [9]:

```
housing['population_per_household'] = housing['population'] / housing['households']
housing['bedrooms_per_room'] = housing['total_bedrooms'] / housing['total_rooms']
housing['rooms_per_household'] = housing['total_rooms'] / housing['households']
```

In [10]:

```
corr_matrix = housing.corr()
corr_matrix['median_house_value'].sort_values(ascending=False)
```

Out[10]:

median_house_value	1.000000
median_income	0.688075
rooms_per_household	0.151948
total_rooms	0.134153
housing_median_age	0.105623
households	0.065843
total_bedrooms	0.049686
population_per_household	-0.023737
population	-0.024650
longitude	-0.045967
latitude	-0.144160
bedrooms_per_room	-0.255880
Name: median_house_value,	dtype: float64

In [11]:

housing.head()

Out[11]:

	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	
					1000000000				

```
In [12]:
```

```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
```

In [13]:

```
print(len(train_set))
print(len(test_set))
```

16512 4128

In [14]:

```
import numpy as np
housing['income_cat'] = np.ceil(housing['median_income']/1.5)
housing['income_cat'].where(housing['income_cat']<5,5.0,inplace=True)</pre>
```

In [15]:

housing.head()

Out[15]:

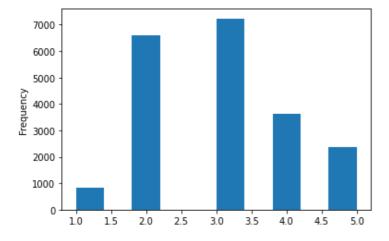
	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_ho
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	
3	-122.25	37.85	52.0	1274.0	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	
4)

In [16]:

```
housing['income_cat'].plot(kind='hist',)
```

Out[16]:

<matplotlib.axes. subplots.AxesSubplot at 0x7f59127a6358>



In [17]:

```
from sklearn.model_selection import StratifiedShuffleSplit
split = StratifiedShuffleSplit(n_splits=1,test_size=0.2, random_state=42)
for train_index, test_index in split.split(housing,housing['income_cat']):
    strat_train_set = housing.loc[train_index]
    strat_test_set = housing.loc[test_index]
```

In [18]:

housing (lincome cat') value counts() / len(housing (lincome cat'))

```
Out[18]:
3.0
        0.350581
        0.318847
2.0
4.0
        0.176308
5.0
        0.114438
        0.039826
1.0
Name: income_cat, dtype: float64
In [19]:
for set in (strat train set, strat test set):
  set .drop("income cat", axis=1, inplace=True)
In [20]:
housing = strat train set.copy()
In [21]:
housing.describe()
Out[21]:
          longitude
                       latitude housing_median_age
                                                  total_rooms total_bedrooms
                                                                              population
                                                                                         households median i
count 16512.000000 16512.000000
                                     16512.000000
                                                 16512.000000
                                                               16354.000000
                                                                           16512.000000 16512.000000
                                                                                                      16512.
 mean
        -119.575834
                     35.639577
                                        28.653101
                                                  2622.728319
                                                                 534.973890
                                                                            1419.790819
                                                                                         497.060380
  std
          2.001860
                      2.138058
                                        12.574726
                                                  2138.458419
                                                                 412.699041
                                                                            1115.686241
                                                                                         375.720845
                                                                                                         1.
        -124.350000
                     32.540000
                                                                               3.000000
                                                                                           2.000000
  min
                                         1.000000
                                                     6.000000
                                                                   2.000000
                                                                                                         0.
                                                                                         279.000000
        -121.800000
                     33.940000
                                                  1443.000000
                                                                 295.000000
                                                                             784.000000
                                                                                                         2.
 25%
                                        18.000000
 50%
        -118.510000
                     34.260000
                                        29.000000
                                                  2119.500000
                                                                 433.000000
                                                                            1164.000000
                                                                                         408.000000
 75%
        -118.010000
                     37.720000
                                        37.000000
                                                  3141.000000
                                                                 644.000000
                                                                            1719.250000
                                                                                         602.000000
                                                                                                         4.
        -114.310000
                     41.950000
                                        52.000000 39320.000000
                                                                6210.000000 35682.000000
                                                                                         5358.000000
                                                                                                         15.
 max
                                                                                                         |\bullet|
In [22]:
housing = strat train set.drop(["median house value", 'population per household', 'bedrooms
 per room','rooms per household'], axis=1)
housing labels = strat train set["median house value"].copy()
In [23]:
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='median')
housing num = housing.drop('ocean proximity',axis=1)
imputer.fit(housing num)
Out[23]:
SimpleImputer(add indicator=False, copy=True, fill_value=None,
                missing values=nan, strategy='median', verbose=0)
In [24]:
imputer.statistics
Out[24]:
array([-118.51],
                                    29.
                                             , 2119.5
                                                             433.
                       34.26
                                                                       , 1164.
         408.
                         3.5409])
```

In [25]:

```
X = imputer.transform(housing_num)
```

In [26]:

```
housing_tr = pd.DataFrame(data=X,columns=housing_num.columns)
housing_tr.head()
```

Out[26]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0	2.7042
1	-121.93	37.05	14.0	679.0	108.0	306.0	113.0	6.4214
2	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0	2.8621
3	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0	1.8839
4	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0	3.0347

Label Encoding

```
In [27]:
```

```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
housing_cat = housing['ocean_proximity']
housing_cat_encoded = encoder.fit_transform(housing_cat)
print(housing_cat_encoded.shape)
print(encoder.classes_)

(16512,)
['<1H OCEAN' 'INLAND' 'ISLAND' 'NEAR BAY' 'NEAR OCEAN']</pre>
```

Now applying One Hot Encoding

```
In [28]:
```

```
from sklearn.preprocessing import OneHotEncoder
onehotenco = OneHotEncoder()
housing_cat_1hot = onehotenco.fit_transform(housing_cat_encoded.reshape(-1,1))
housing_cat_1hot
```

Out[28]:

```
<16512x5 sparse matrix of type '<class 'numpy.float64'>' with 16512 stored elements in Compressed Sparse Row format>
```

In [29]:

```
housing_tr['ocean_proximity'] = housing_cat_encoded
```

In [30]:

```
housing_tr.head()
```

Out[30]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	ocean_prox
0	-121.89	37.29	38.0	1568.0	351.0	710.0	339.0	2.7042	
1	-121.93	37.05	14.0	679.0	108.0	306.0	113.0	6.4214	
2	-117.20	32.77	31.0	1952.0	471.0	936.0	462.0	2.8621	
3	-119.61	36.31	25.0	1847.0	371.0	1460.0	353.0	1.8839	
4	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1463.0	3.0347	
4									

SELECT AND TRAIN A MODEL

```
In [31]:
from sklearn.linear model import LinearRegression
lin reg = LinearRegression()
lin reg.fit(housing tr,housing labels)
Out[31]:
LinearRegression(copy X=True, fit intercept=True, n jobs=None, normalize=False)
In [32]:
some data = housing tr.iloc[:5]
some label = housing labels[:5]
print("prediction", lin reg.predict(some data))
print("label's", list(some label))
prediction [207901.47824371 323216.63913327 205102.81901373 75423.92526847
188676.687806421
label's [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
In [33]:
from sklearn.metrics import mean squared error
# housing labels = housing labels.reshape(-1,1)
housing predictions = lin reg.predict(housing tr)
lin mse = mean squared error(housing predictions, housing labels)
lin mse = np.sqrt(lin mse)
print(lin mse)
69957.9936286799
In [34]:
from sklearn.tree import DecisionTreeRegressor
tree reg = DecisionTreeRegressor()
tree_reg.fit(housing_tr, housing_labels)
housing_predictions = tree_reg.predict(housing_tr)
tree mse = mean squared error(housing labels, housing predictions)
tree_rmse = np.sqrt(tree_mse)
tree rmse
Out[34]:
0.0
In [35]:
from sklearn.model selection import cross val score
scores = cross val score(tree reg, housing tr, housing labels, scoring='neg mean squared err
or', cv=10)
tree rmse score = np.sqrt(-scores)
def display score(scores):
 print('Scores:', scores)
  print('Mean:', scores.mean())
  print('Standard Deviation', scores.std())
display_score(tree_rmse_score)
Scores: [65589.79204859 71283.27542878 70717.66887942 72235.16386952
```

66418.63883654 74438.29528469 68702.62576639 70137.14813444

72324.04794659 69890.161794961

.....

```
Mean: 70173.68179899339
Standard Deviation 2567.994316412716
In [36]:
lin score = cross val score(lin reg, housing tr, housing labels, scoring='neg mean squared
error', cv=10)
lin rmse score = np.sqrt(-lin score)
display score(lin rmse score)
Scores: [68230.55806124 68520.93622918 69600.91124405 74990.90394949
 68974.73419338 72198.27981692 66607.90832448 69745.60718443
 73514.29993282 68943.8776868 1
Mean: 70132.8016622785
Standard Deviation 2472.4661735125324
In [37]:
from sklearn.ensemble import RandomForestRegressor
forest reg = RandomForestRegressor()
forest reg.fit(housing tr, housing labels)
Out[37]:
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max depth=None, max features='auto', max leaf nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min impurity split=None, min samples leaf=1,
                      min samples split=2, min weight fraction leaf=0.0,
                      n estimators=100, n jobs=None, oob score=False,
                      random state=None, verbose=0, warm start=False)
In [38]:
forest_score = cross_val_score(forest_reg,housing_tr,housing_labels, scoring='neg_mean_s
quared error', cv=10)
forest rmse score = np.sqrt(-forest score)
display score(forest rmse score)
Scores: [47822.23905053 46766.25819041 50142.31518706 51395.03252716
 49990.2402097 53559.27403843 48386.59358769 50832.50422872
 52584.05782371 50592.12823831]
Mean: 50207.06430817236
Standard Deviation 1993.23814669634
In [39]:
housing predictions = forest reg.predict(housing tr)
forest mse = mean squared error(housing labels, housing predictions)
forest_rmse = np.sqrt(forest mse)
forest rmse
Out[39]:
18628.591256239313
In [40]:
from sklearn.model selection import GridSearchCV
param grid = [
{'n estimators': [3, 10, 30], 'max features': [2, 4, 6, 8]},
{'bootstrap': [False], 'n estimators': [3, 10], 'max features': [2, 3, 4]},
forest reg = RandomForestRegressor()
grid search = GridSearchCV(forest reg,param grid,cv=5,scoring='neg mean squared error')
grid search.fit(housing tr,housing labels)
Out[40]:
GridSearchCV(cv=5, error score=nan,
```

```
estimator=RandomForestRegressor(bootstrap=True, ccp alpha=0.0,
                                             criterion='mse', max_depth=None,
                                             max features='auto',
                                             max_leaf_nodes=None,
                                             max samples=None,
                                             min impurity decrease=0.0,
                                             min impurity split=None,
                                             min samples leaf=1,
                                             min samples split=2,
                                             min weight fraction leaf=0.0,
                                             n estimators=100, n jobs=None,
                                             oob_score=False, random_state=None,
                                             verbose=0, warm start=False),
             iid='deprecated', n_jobs=None,
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n estimators': [3, 10, 30]},
                         {'bootstrap': [False], 'max features': [2, 3, 4],
                          'n estimators': [3, 10]}],
             pre dispatch='2*n jobs', refit=True, return train score=False,
             scoring='neg mean squared error', verbose=0)
grid search.best params
{'max_features': 4, 'n_estimators': 30}
grid search.best estimator
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max depth=None, max features=4, max leaf nodes=None,
                      max samples=None, min impurity decrease=0.0,
                      min impurity split=None, min samples leaf=1,
                      min samples split=2, min weight fraction leaf=0.0,
                      n estimators=30, n jobs=None, oob score=False,
                      random state=None, verbose=0, warm start=False)
cvres = grid search.cv results
cvres df = pd.DataFrame(cvres)
cvres_df = cvres_df[["mean_test_score","params"]]
cvres df['mean test score'] = -cvres_df["mean_test_score"]
```

In [44]:

In [43]:

In [41]:

Out[41]:

In [42]:

Out[42]:

cvres df

Out[44]:

m	nean_test_score	params
0	3.855828e+09	{'max_features': 2, 'n_estimators': 3}
1	2.957060e+09	{'max_features': 2, 'n_estimators': 10}
2	2.708003e+09	{'max_features': 2, 'n_estimators': 30}
3	3.446072e+09	{'max_features': 4, 'n_estimators': 3}
4	2.752787e+09	{'max_features': 4, 'n_estimators': 10}
5	2.537503e+09	{'max_features': 4, 'n_estimators': 30}
6	3.436985e+09	{'max_features': 6, 'n_estimators': 3}
7	2.738078e+09	{'max_features': 6, 'n_estimators': 10}
8	2.539674e+09	{'max_features': 6, 'n_estimators': 30}

9	mean3t451736009	{'max_features': 8, 'n_estima pasins }
10	2.783666e+09	{'max_features': 8, 'n_estimators': 10}
11	2.601937e+09	{'max_features': 8, 'n_estimators': 30}
12	3.715371e+09	{'bootstrap': False, 'max_features': 2, 'n_est
13	2.811944e+09	{'bootstrap': False, 'max_features': 2, 'n_est
14	3.406680e+09	{'bootstrap': False, 'max_features': 3, 'n_est
15	2.700748e+09	{'bootstrap': False, 'max_features': 3, 'n_est
16	3.229060e+09	{'bootstrap': False, 'max_features': 4, 'n_est
17	2.658038e+09	{'bootstrap': False, 'max_features': 4, 'n_est

In [45]:

```
final model = grid_search.best_estimator_
X test = strat test set.drop('median house value',axis=1)
y test = strat test set['median house value'].copy()
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
X_test_cat = X_test['ocean_proximity']
X test cat encoded = encoder.fit transform(X test cat)
X_test['ocean_proximity'] = X_test_cat_encoded
for i in X test.columns:
  X test[i].fillna(X test[i].median(),inplace=True)
X test.drop(columns=['population per household','bedrooms per room','rooms per household'
],inplace=True)
final_predictions = final_model.predict(X_test)
final mse = mean squared error(y test, final predictions)
final rmse = np.sqrt(final mse)
print(final rmse)
```

47862.778264449844

In [46]:

```
## 47269 is the final rmse value
```

In [46]: