```
In [3]:
          import sklearn
          import numpy as np
          import pandas as pd
 In [4]:
         np.random.seed(42)
 In [5]:
          %matplotlib inline
          import matplotlib as mpl
          import matplotlib.pyplot as plt
 In [6]: mpl.rc('axes', labelsize=14)
          mpl.rc('xtick', labelsize=12)
          mpl.rc('ytick', labelsize=12)
 In [8]: import warnings
          warnings.filterwarnings(action="ignore", message="^internal gelsd")
In [15]: HOUSING PATH = "/cxldata/datasets/project/housing/housing.csv"
In [28]: housing = pd.read_csv(HOUSING_PATH)
         housing.head()
In [29]:
Out[29]:
             longitude latitude housing_median_age total_rooms total_bedrooms population households me
               -122.23
                        37.88
                                           41.0
                                                      0.088
                                                                    129.0
                                                                              322.0
                                                                                         126.0
               -122.22
                        37.86
                                           21.0
                                                     7099.0
                                                                   1106.0
                                                                             2401.0
                                                                                        1138.0
               -122.24
                        37.85
                                           52.0
                                                     1467.0
                                                                    190.0
                                                                              496.0
                                                                                         177.0
```

edian_income	median_house_value	ocean_proximity
8.3252	452600.0	NEAR BAY
8.3014	358500.0	NEAR BAY
7.2574	352100.0	NEAR BAY

	4 -1	22.25 37.85		52.0	1627.0	280.0	565.0	259.0	
[33]:	housin	g.info							
t[33]:	<bound< td=""><td>method Data</td><td>Frame.info o</td><td>f</td><td>longitude</td><td>e latitude</td><td>housing_me</td><td>dian_age</td><td>to</td></bound<>	method Data	Frame.info o	f	longitude	e latitude	housing_me	dian_age	to
	0	-122.23	37.88		41.0	880.0		129.0	
	1	-122.22	37.86		21.0	7099.0	1	106.0	
	2	-122.24	37.85		52.0	1467.0		190.0	
	3	-122.25	37.85		52.0	1274.0		235.0	
	4	-122.25	37.85		52.0	1627.0		280.0	
	20525	424 00	20.40		25.0	4665.0			
	20635	-121.09	39.48		25.0	1665.0		374.0	
	20636	-121.21	39.49		18.0	697.0		150.0	
	20637	-121.22	39.43		17.0	2254.0		485.0	
	20638	-121.32	39.43		18.0	1860.0		409.0	
	20639	-121.24	39.37		16.0	2785.0		616.0	
		population	households	median_	income me	edian_house_v	alue \		
	0	322.0	126.0		8.3252	4526	00.0		
	1	2401.0	1138.0		8.3014	3585	00.0		
	2	496.0	177.0		7.2574	3521	00.0		
	3	558.0	219.0		5.6431	3413	00.0		
	4	565.0	259.0		3.8462	3422	00.0		
	20635	845.0	330.0		1.5603	781	00.0		
	20636	356.0	114.0		2.5568	771	00.0		
	20637	1007.0	433.0		1.7000	923	00.0		
	20638	741.0	349.0		1.8672	847	00.0		
	20639	1387.0	530.0		2.3886	894	00.0		
		ocean_proxim	ity						
	0	NEAR	50 C 20						
	1	NEAR							
	2	NEAR							

52.0

1274.0

235.0

558.0

3 -122.25 37.85

219.0

5.6431	341300.0	NEAR BAY
3.8462	342200.0	NEAR BAY

otal_rooms total_bedrooms \

INCHI	DAI
NEAR	BAY
NEAR	BAY
INI	AND
INL	AND
INI	AND
INL	AND
INI	AND
	INI INI INI

[20640 rows x 10 columns]>

In [34]:	housin	g.describe						
Out[34]:	<bound< td=""><td>method NDFr</td><td>ame.describe</td><td>of long</td><td>itude la</td><td>titude</td><td>housing_median_age</td><td>2</td></bound<>	method NDFr	ame.describe	of long	itude la	titude	housing_median_age	2
	0	-122.23	37.88	41.	0 8	880.0	129.0	
	1	-122.22	37.86	21.	0 70	099.0	1106.0	
	2	-122.24	37.85	52.	0 14	467.0	190.0	
	3	-122.25	37.85	52.	0 1	274.0	235.0	
	4	-122.25	37.85	52.	0 10	627.0	280.0	
	20635	-121.09	39.48	25.	0 10	665.0	374.0	
	20636	-121.21	39.49	18.	0 (697.0	150.0	
	20637	-121.22	39.43	17.	0 2	254.0	485.0	
	20638	-121.32	39.43	18.	0 1	860.0	409.0	
	20639	-121.24	39.37	16.	0 2	785.0	616.0	
		population	households	median income	median h	ouse val	ue \	
	0	322.0	126.0	8.3252	317.43	452600	.0	
	1	2401.0	1138.0	8.3014		358500	.0	
	2	496.0	177.0	7.2574		352100	.0	
	3	558.0	219.0	5.6431		341300	.0	
	4	565.0	259.0	3.8462		342200	.0	
	20635	845.0	330.0	1.5603		78100	.0	
	20636	356.0	114.0	2.5568		77100	.0	

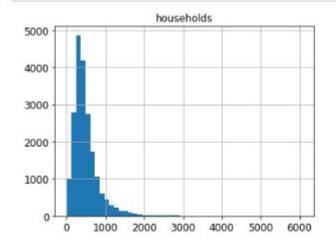
total_rooms total_bedrooms \

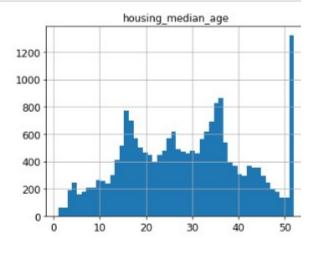
20637	1007.0	433.0	1.7000	92300.0
20638	741.0	349.0	1.8672	84700.0
20639	1387.0	530.0	2.3886	89400.0

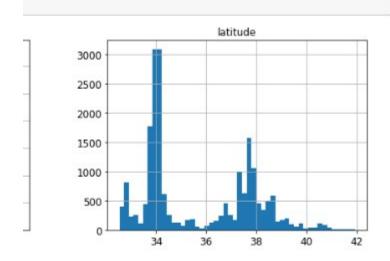
	ocean_proximity
0	NEAR BAY
1	NEAR BAY
2	NEAR BAY
3	NEAR BAY
4	NEAR BAY
20635	INLAND
20636	INLAND
20637	INLAND
20638	INLAND
20639	INLAND

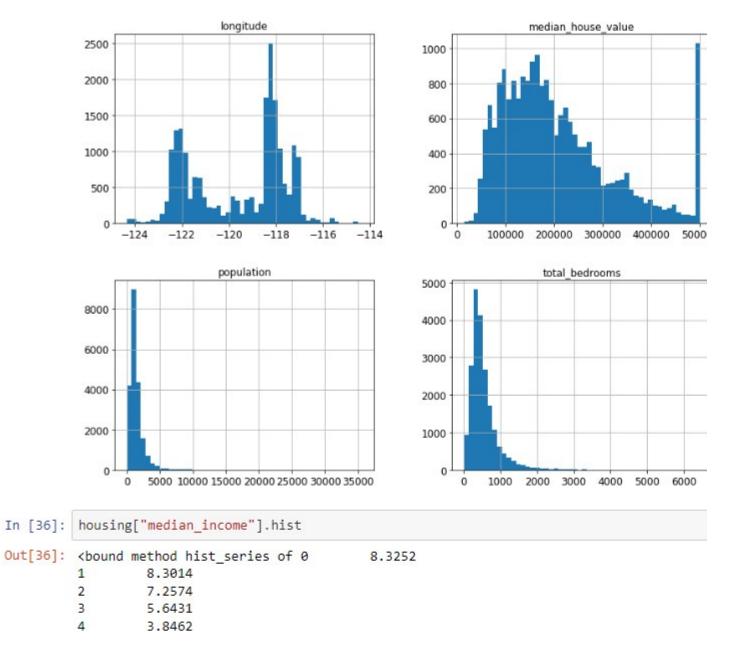
[20640 rows x 10 columns]>

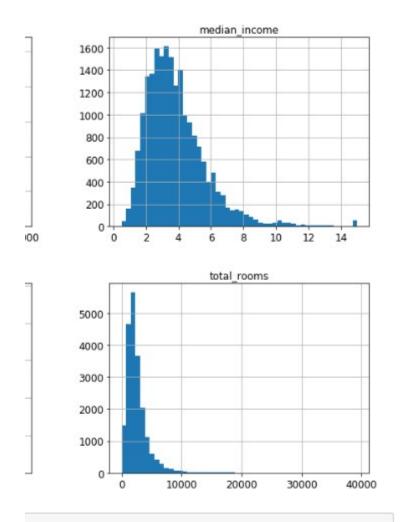
In [35]: housing.hist(bins=50, figsize=(20,15))
plt.show()







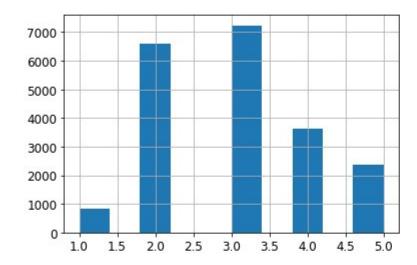




20635 1.5603 20636 2.5568 20637 1.7000 20638 1.8672 20639 2.3886

Name: median_income, Length: 20640, dtype: float64>

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f4577a3a4a8>



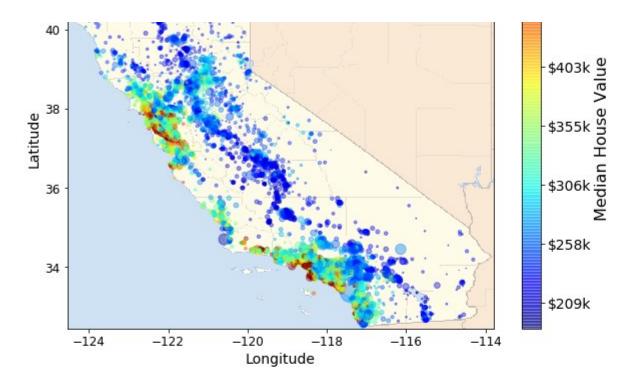
In [40]: from sklearn.model_selection import StratifiedShuffleSplit

In [42]: 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 [44]: for set in (strat train set, strat test set):
             set .drop("income cat", axis=1, inplace=True)
In [48]: housing = strat train set.copy()
In [49]:
         import matplotlib.image as mpimg
         california img=mpimg.imread('/cxldata/datasets/project/housing/california.png')
         ax = housing.plot(kind="scatter", x="longitude", y="latitude", figsize=(10,7),
                                s=housing['population']/100, label="Population",
                                c="median_house_value", cmap=plt.get_cmap("jet"),
                                colorbar=False, alpha=0.4,
         plt.imshow(california_img, extent=[-124.55, -113.80, 32.45, 42.05], alpha=0.5,
                    cmap=plt.get cmap("jet"))
         plt.ylabel("Latitude", fontsize=14)
         plt.xlabel("Longitude", fontsize=14)
         prices = housing["median house value"]
         tick values = np.linspace(prices.min(), prices.max(), 11)
         cbar = plt.colorbar(ticks=tick values/prices.max())
         cbar.ax.set yticklabels(["$%dk"%(round(v/1000)) for v in tick values], fontsize=14
         cbar.set label('Median House Value', fontsize=16)
         plt.legend(fontsize=16)
         plt.show()
                                                                              $500k
                                                          Population
```

\$452k

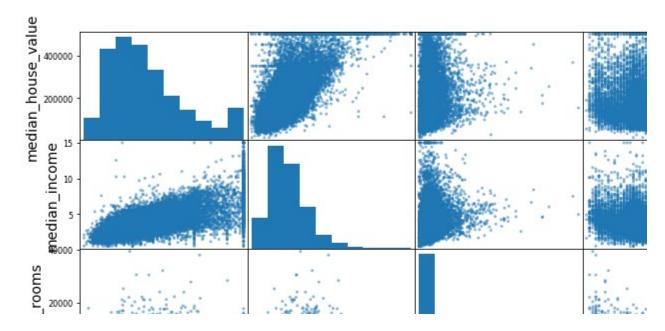
1)		

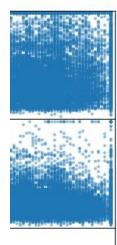


In [53]: housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]

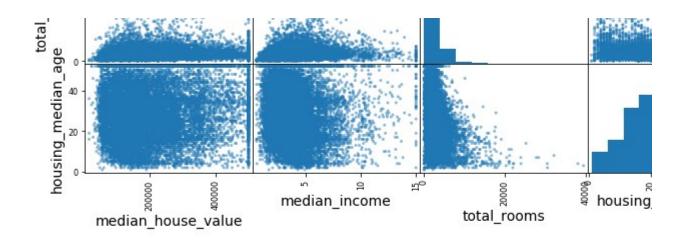
```
In [54]: corr_matrix = housing.corr()
```

```
Out[55]: array([[<matplotlib.axes. subplots.AxesSubplot object at 0x7f45776bc780>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f457081cd68>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f4577681358>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f4574ef5908>],
                (<matplotlib.axes. subplots.AxesSubplot object at 0x7f4574f22eb8>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f4574edc4a8>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f4574e8da58>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f45780314a8>],
                (<matplotlib.axes. subplots.AxesSubplot object at 0x7f45780315f8>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f45779d83c8>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f457809f588>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f4577a0f6d8>],
                (<matplotlib.axes. subplots.AxesSubplot object at 0x7f4577a28128>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f45778f1320>,
                 <matplotlib.axes. subplots.AxesSubplot object at 0x7f4578209cf8>,
                 <matplotlib.axes._subplots.AxesSubplot object at 0x7f457841c0f0>]],
               dtype=object)
```





. .



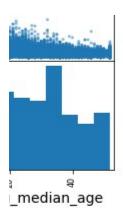
In [56]: housing.describe()

Out[56]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000
mean	-119.575834	35.639577	28.653101	2622.728319	534.973890	1419.790819
std	2.001860	2.138058	12.574726	2138.458419	412.699041	1115.686241
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000
50%	-118.5 <mark>10</mark> 000	34.260000	29.000000	2119.500000	433.000000	1164.000000
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.250000
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000

In [61]: housing = strat_train_set.drop("median_house_value", axis=1)

In [62]: housing_labels = strat_train_set["median_house_value"].copy()



1	households	median_income	median_house_value	roor
)	16512.000000	16512.000000	16512.000000	
)	497.060380	3.875589	206990.920724	
ı	375.720845	1.904950	115703.014830	
)	2.000000	0.499900	14999.000000	
)	279.000000	2.566775	119800.000000	
)	408.000000	3.540900	179500.000000	
)	602.000000	4.744475	263900.000000	
)	5358.000000	15.000100	500001.000000	
				E

```
In [63]: from sklearn.impute import SimpleImputer
In [64]: imputer = SimpleImputer(strategy="median")
In [65]: housing num = housing.drop("ocean proximity", axis=1)
In [66]: imputer.fit(housing_num)
Out[66]: SimpleImputer(add_indicator=False, copy=True, fill_value=None,
                        missing_values=nan, strategy='median', verbose=0)
In [67]: X = imputer.transform(housing num)
          housing_tr = pd.DataFrame(X, columns=housing_num.columns,
                                index=housing.index)
In [70]:
         housing_cat = housing[["ocean_proximity"]]
         housing_cat.head(10)
In [71]:
Out[71]:
                ocean_proximity
          17606
                    <1H OCEAN
          18632
                    <1H OCEAN
                  NEAR OCEAN
          14650
           3230
                       INLAND
           3555
                    <1H OCEAN
                       INLAND
          19480
                    <1H OCEAN
           8879
                       INI AND
          13685
```

```
4937
                   <1H OCEAN
           4861
                   <1H OCEAN
In [72]: from sklearn.preprocessing import OneHotEncoder
In [73]: cat encoder = OneHotEncoder()
         housing_cat_1hot = cat_encoder.fit_transform(housing cat)
         housing cat 1hot
Out[73]: <16512x5 sparse matrix of type '<class 'numpy.float64'>'
                 with 16512 stored elements in Compressed Sparse Row format>
In [74]: housing cat 1hot.toarray()
Out[74]: array([[1., 0., 0., 0., 0.],
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 0., 1.],
                [0., 1., 0., 0., 0.],
                [1., 0., 0., 0., 0.],
                [0., 0., 0., 1., 0.]])
In [78]: from sklearn.base import BaseEstimator, TransformerMixin
In [79]: rooms ix, bedrooms ix, population ix, households ix = 3, 4, 5, 6
         class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
             def init (self, add bedrooms per room=True):
                 self.add_bedrooms_per_room = add_bedrooms_per room
             def fit(self, X, y=None):
                 return self
             def transform(self, X):
                         on bousehold - VI: nooms ivl / VI: bouseholds ivl
```

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```
population_per_household = X[:, population_ix] / X[:, households_ix]
                 if self.add_bedrooms_per_room:
                     bedrooms per room = X[:, bedrooms ix] / X[:, rooms ix]
                     return np.c [X, rooms per household, population per household,
                                   bedrooms per room]
                 else:
                     return np.c [X, rooms per household, population per household]
         attr adder = CombinedAttributesAdder(add bedrooms per room=False)
         housing_extra_attribs = attr_adder.transform(housing.values)
In [83]: col_names = "total_rooms", "total_bedrooms", "population", "households"
         rooms ix, bedrooms ix, population ix, households ix = [
             housing.columns.get loc(c) for c in col names]
         housing extra attribs = pd.DataFrame(
             housing extra attribs,
             columns=list(housing.columns)+["rooms per household", "population per househol
             index=housing.index)
         housing_extra_attribs.head()
         from sklearn.pipeline import Pipeline
         from sklearn.preprocessing import StandardScaler
         num pipeline = Pipeline([
                 ('imputer', SimpleImputer(strategy="median")),
                 ('attribs adder', CombinedAttributesAdder()),
                 ('std_scaler', StandardScaler()),
             1)
         housing_num_tr = num_pipeline.fit_transform(housing_num)
         from sklearn.compose import ColumnTransformer
         num attribs = list(housing num)
```

rooms_per_nousenoid = x[:, rooms_ix] / x[:, nousenoids_ix]

```
ld"],
```

```
cat attribs = ["ocean proximity"]
         full_pipeline = ColumnTransformer([
                 ("num", num_pipeline, num_attribs),
                 ("cat", OneHotEncoder(), cat_attribs),
             1)
In [84]: housing prepared = full pipeline.fit transform(housing)
In [87]: from sklearn.tree import DecisionTreeRegressor
In [88]: tree_reg = DecisionTreeRegressor(random_state=42)
         tree_reg.fit(housing_prepared, housing_labels)
Out[88]: DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                               max_features=None, max_leaf_nodes=None,
                               min_impurity_decrease=0.0, min_impurity_split=None,
                               min_samples_leaf=1, min_samples_split=2,
                               min weight fraction leaf=0.0, presort='deprecated',
                               random state=42, splitter='best')
In [89]: from sklearn.metrics import mean squared error
In [90]: housing_predictions = tree_reg.predict(housing_prepared)
In [91]: tree_mse = mean_squared_error(housing_labels, housing_predictions)
         tree_rmse = np.sqrt(tree_mse)
         tree rmse
Out[91]: 0.0
In [95]: from sklearn.ensemble import RandomForestRegressor
```

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19

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In [97]: forest reg = RandomForestRegressor(n estimators=30, random state=42)
          forest reg.fit(housing prepared, housing labels)
 Out[97]: 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=30, n_jobs=None, oob_score=False,
                                random state=42, verbose=0, warm start=False)
 In [98]: housing predictions = forest reg.predict(housing prepared)
 In [99]: forest mse = mean squared error(housing labels, housing predictions)
          forest rmse = np.sqrt(forest mse)
          forest rmse
 Out[99]: 19561.601906818396
In [102]: def display scores(scores):
              print("Scores:", scores)
              print("Mean:", scores.mean())
              print("Standard deviation:", scores.std())
In [104]: from sklearn.model selection import cross val score
In [105]: scores = cross val score(tree reg, housing prepared, housing labels,
                                   scoring="neg mean squared error", cv=10)
          tree rmse scores = np.sqrt(-scores)
          display scores(tree_rmse scores)
          Scores: [70194.33680785 66855.16363941 72432.58244769 70758.73896782
           71115.88230639 75585.14172901 70262.86139133 70273.6325285
           75366 97053553 74334 657369371
```

	100
	(8)
	7.5

```
Standard deviation: 2439.4345041191004
In [107]: forest scores = cross_val score(forest_reg, housing_prepared, housing_labels,
                                          scoring="neg mean squared error", cv=10)
          forest rmse scores = np.sqrt(-forest scores)
          display scores(forest rmse scores)
          Scores: [50141.36385885 47640.30832627 50921.08943207 52659.54280148
           49506.38494424 54204.85834912 49214.04467119 47790.14481191
           53869.80154598 51020.523774261
          Mean: 50696.80625153554
          Standard deviation: 2193.098737823643
In [111]: from sklearn.model selection import GridSearchCV
In [112]: param grid = [
              {'n estimators': [3, 10, 30], 'max features': [2, 4, 6, 8]},
              {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
In [113]: forest_reg = RandomForestRegressor(random_state=42)
          grid_search = GridSearchCV(forest_reg, param_grid, cv=5,
                                     scoring='neg mean squared error',
                                     return train score=True)
          grid_search.fit(housing_prepared, housing_labels)
Out[113]: 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.
```

/5300.8/952553 /1231.05/2002/|

Mean: 71407.68766037929

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```
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=42,
                                                       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=True,
                       scoring='neg mean squared error', verbose=0)
In [114]: grid search.best params
Out[114]: {'max_features': 8, 'n_estimators': 30}
In [115]: grid search.best estimator
Out[115]: RandomForestRegressor(bootstrap=True, ccp alpha=0.0, criterion='mse',
                                max depth=None, max features=8, 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=42, verbose=0, warm_start=False)
In [116]: cvres = grid_search.cv_results_
          for mean score, params in zip(cvres["mean test score"], cvres["params"]):
              print(np.sqrt(-mean score), params)
          63669.11631261028 {'max_features': 2, 'n_estimators': 3}
          55627.099719926795 {'max_features': 2, 'n_estimators': 10}
```

```
53384.57275149205 {'max_features': 2, 'n_estimators': 30}
          60965.950449450494 {'max_features': 4, 'n_estimators': 3}
          52741.04704299915 {'max features': 4, 'n estimators': 10}
          50377.40461678399 {'max features': 4, 'n estimators': 30}
          58663.93866579625 {'max features': 6, 'n estimators': 3}
          52006.19873526564 {'max_features': 6, 'n_estimators': 10}
          50146.51167415009 {'max features': 6, 'n estimators': 30}
          57869.25276169646 {'max features': 8, 'n estimators': 3}
          51711.127883959234 {'max features': 8, 'n estimators': 10}
          49682.273345071546 {'max_features': 8, 'n_estimators': 30}
          62895.06951262424 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
          54658.176157539405 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
          59470.40652318466 {'bootstrap': False, 'max features': 3, 'n estimators': 3}
          52724.9822587892 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
          57490.5691951261 {'bootstrap': False, 'max features': 4, 'n_estimators': 3}
          51009.495668875716 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
In [124]: final model = grid search.best estimator
In [125]: X test = strat test set.drop("median house value", axis=1)
          y test = strat test set["median house value"].copy()
In [126]: X test prepared = full pipeline.transform(X test)
In [127]: final predictions = final model.predict(X test prepared)
In [128]: final mse = mean squared error(y test, final predictions)
          final rmse = np.sqrt(final mse)
In [129]: final rmse
Out[129]: 47730.22690385927
```

In []: