Start coding or generate with AI.

```
# Download the data
import os
import tarfile
import urllib.request

DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
HOUSING_PATH = os.path.join("datasets", "housing")
HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"

def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
    if not os.path.isdir(housing_path):
        os.makedirs(housing_path)
    tgz_path = os.path.join(housing_path, "housing.tgz")
    urllib.request.urlretrieve(housing_url, tgz_path)
    housing_tgz = tarfile.open(tgz_path)
    housing_tgz.extractall(path=housing_path)
    housing_tgz.close()
```

```
fetch_housing_data()
```

```
import pandas as pd

def load_housing_data(housing_path=HOUSING_PATH):
    csv_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(csv_path)
```

```
# take a quick look at the data and it's stats.
housing= load_housing_data()
housing.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value	ocear
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252	452600.0	
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014	358500.0	
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574	352100.0	
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431	341300.0	
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462	342200.0	

```
# to get quick description of data.
housing.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
```

```
# number of categories that exists in ocean_proximity
housing['ocean_proximity'].value_counts()
```

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

```
# summary of numerical attributes.
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_hou
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000	20640.000000	2064
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680	3.870671	20685
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753	1.899822	11539
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000	0.499900	1499
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000	2.563400	11960
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000	3.534800	17970
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000	4.743250	26472
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000	15.000100	50000

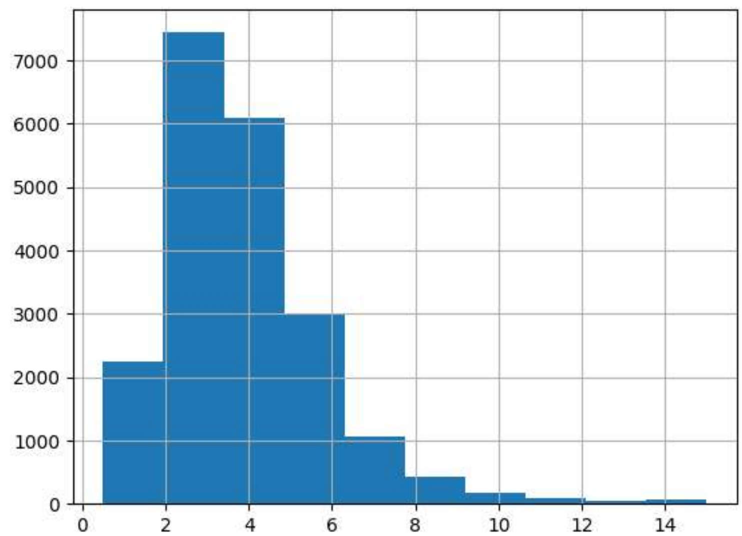
```
%matplotlib inline
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
plt.show()
```

```
# Creation of training and test set.
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
```

```
test_set.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_house_value
20046	-119.01	36.06	25.0	1505.0	NaN	1392.0	359.0	1.6812	47700.0
3024	-119.46	35.14	30.0	2943.0	NaN	1565.0	584.0	2.5313	45800.0
15663	-122.44	37.80	52.0	3830.0	NaN	1310.0	963.0	3.4801	500001.0
20484	-118.72	34.28	17.0	3051.0	NaN	1705.0	495.0	5.7376	218600.0
9814	-121.93	36.62	34.0	2351.0	NaN	1063.0	428.0	3.7250	278000.0

```
housing['median_income'].hist()
plt.show()
```

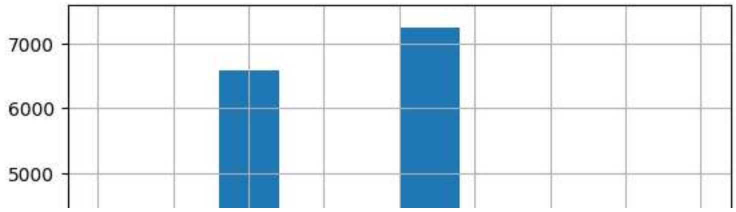


```
import numpy as np
housing["income_cat"] = pd.cut(housing["median_income"],
                               bins=[0., 1.5, 3.0, 4.5, 6., np.inf],
                               labels=[1, 2, 3, 4, 5])
```

```
housing["income_cat"].value_counts()
```

```
3    7236
2    6581
4    3639
5    2362
1     822
Name: income_cat, dtype: int64
```

```
housing['income_cat'].hist()
plt.show()
```




```
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]
```

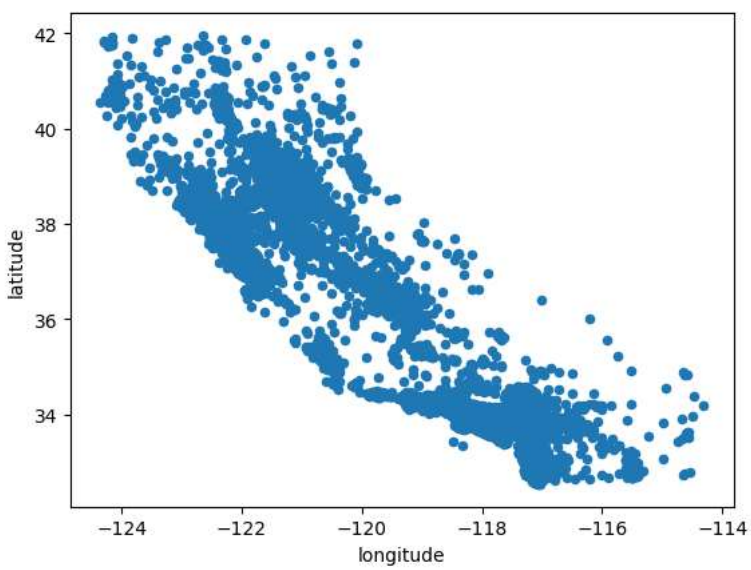
```
# lets see if it worked or not
strat_test_set['income_cat'].value_counts()/ len(strat_test_set)
```

```
3    0.350533
2    0.318798
4    0.176357
5    0.114341
1    0.039971
Name: income_cat, dtype: float64
```

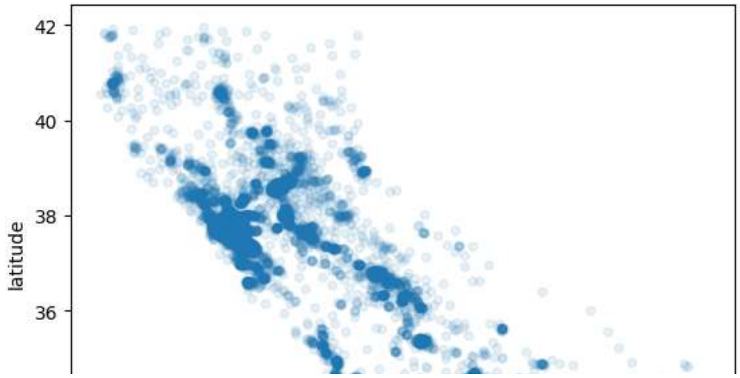
```
# Now you should remove the income_cat attribute so the data is back to its original state.
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

```
# let's create copy of the dataset to play with it
housing= strat_train_set.copy()
```

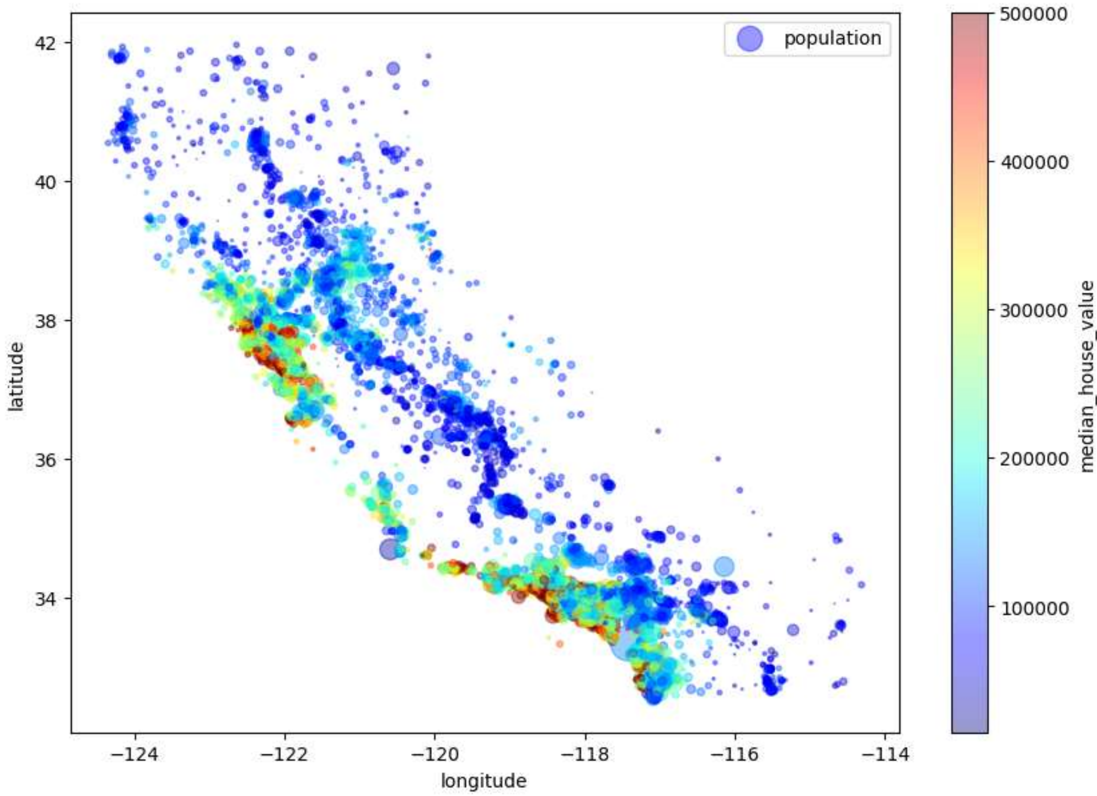
```
housing.plot(kind="scatter", x="longitude", y="latitude")
plt.show()
```




```
# it's hard to see any pattern here let's reduce alpha
housing.plot(kind='scatter', x='longitude', y='latitude', alpha=0.1)
plt.show()
```




```
# let's make it clearer
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
             s=housing["population"]/100, label="population", figsize=(10,7),
             c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
             sharex=False)
plt.legend()
plt.show()
# The radius of each circle represents the district’s population (option s), and the color represents the price (option c).
# We will use a predefined color map (option cmap) called jet, which ranges from blue(low values) to red (high prices).
```




```
# let's look for correlations
corr_matrix= housing.corr()
```

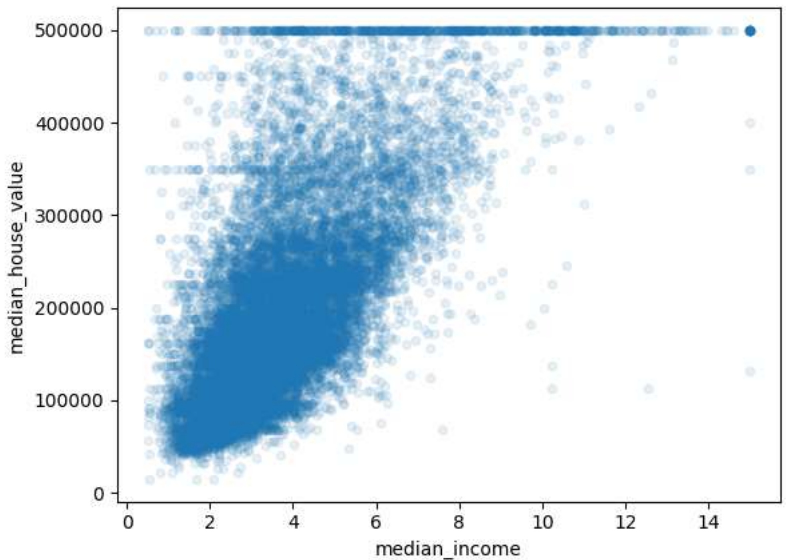
```
<ipython-input-26-d5fd65328a40>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  corr_matrix= housing.corr()
```

```
#lets see the correlation with median_house_value
corr_matrix['median_house_value'].sort_values(ascending=False)
```

```
median_house_value    1.000000
median_income         0.687151
total_rooms           0.135140
housing_median_age    0.114146
households            0.064590
total_bedrooms        0.047781
population           -0.026882
```

```
longitude            -0.047466
latitude             -0.142673
Name: median_house_value, dtype: float64
```

```
housing.plot(kind="scatter", x="median_income", y="median_house_value",
             alpha=0.1)
plt.show()
```

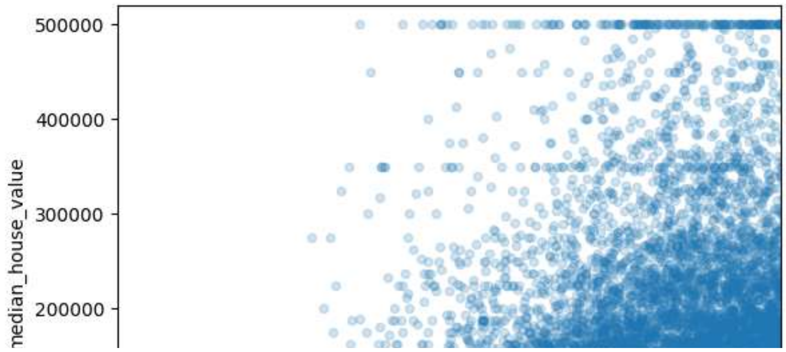



```
# EXPERIMENTING WITH ATTRIBUTE COMBINATIONS
# the total number of rooms in a district is not very useful if you don’t know how many households there are.
# What you really want is the number of rooms per household.
housing["rooms_per_household"] = housing["total_rooms"]/housing["households"]
housing["bedrooms_per_room"] = housing["total_bedrooms"]/housing["total_rooms"]
housing["population_per_household"]=housing["population"]/housing["households"]
```

```
#now lets look at the correlation matrix
corr_matrix= housing.corr()
corr_matrix['median_house_value'].sort_values(ascending=False)
```

```
<ipython-input-30-c517d49ae403>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version
  corr_matrix= housing.corr()
median_house_value          1.000000
median_income               0.687151
rooms_per_household         0.146255
total_rooms                 0.135140
housing_median_age          0.114146
households                  0.064590
total_bedrooms              0.047781
population_per_household   -0.021991
population                 -0.026882
longitude                  -0.047466
latitude                   -0.142673
bedrooms_per_room          -0.259952
Name: median_house_value, dtype: float64
```

```
housing.plot(kind="scatter", x="rooms_per_household", y="median_house_value",
             alpha=0.2)
plt.axis([0, 5, 0, 520000])
plt.show()
```




```
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income	median_hou
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000	16512.000000	16512.000000	1651
mean	-119.575635	35.639314	28.653404	2622.539789	534.914639	1419.687379	497.011810	3.875884	20700
std	2.001828	2.137963	12.574819	2138.417080	412.665649	1115.663036	375.696156	1.904931	11570
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000	0.499900	1499
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000	279.000000	2.566950	11980
50%	-118.510000	34.260000	29.000000	2119.000000	433.000000	1164.000000	408.000000	3.541550	17950
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.000000	602.000000	4.745325	26390
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000	5358.000000	15.000100	50000

```
housing = strat_train_set.drop("median_house_value", axis=1) # drop labels for training set
housing_labels = strat_train_set["median_house_value"].copy()
```

```
# DATA Cleaning
# we will fill the the numerical missing values with their medians.
# Scikit-Learn provides a handy class to take care of missing values: SimpleImputer
from sklearn.impute import SimpleImputer
imputer= SimpleImputer(strategy='median')
```


```
# DATA Cleaning
# we will fill the the numerical missing values with their medians.
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from sklearn.impute import SimpleImputer
imputer= SimpleImputer(strategy='median')
```


```
#since median can only be computed on numerical attributes.
housing_num= housing.drop('ocean_proximity', axis=1)
```

```
imputer.fit(housing_num)
```

```
▾ SimpleImputer
SimpleImputer(strategy='median')
```

```
imputer.statistics_
```

```
array([-118.51   ,   34.26   ,   29.     , 2119.     ,  433.     ,
       1164.     ,  408.     ,    3.54155])
```

```
#checking if it is same as the median
housing_num.median().values
```

```
array([-118.51   ,   34.26   ,   29.     , 2119.     ,  433.     ,
       1164.     ,  408.     ,    3.54155])
```

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

```
# HANDLING CATEGORICAL ATTRIBUTES
housing_cat = housing[["ocean_proximity"]]
housing_cat.head(10)
```

	ocean_proximity
12655	INLAND
15502	NEAR OCEAN
2908	INLAND
14053	NEAR OCEAN
20496	<1H OCEAN
1481	NEAR BAY
18125	<1H OCEAN
5830	<1H OCEAN
17989	<1H OCEAN
4861	<1H OCEAN

```
# By default, the OneHotEncoder class returns a sparse array, but we can convert it to a dense array if needed by calling the toarray() meth
# or by setting 'sparse' attribute to False
from sklearn.preprocessing import OneHotEncoder

cat_encoder = OneHotEncoder(sparse=False)
housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
housing_cat_1hot
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_output` i
  warnings.warn(
array([[0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 1.],
       [0., 1., 0., 0., 0.],
       ...,
       [1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.]])
```

```
#CUSTOM TRANSFORMATIONS
from sklearn.base import BaseEstimator, TransformerMixin

# column index
rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True): # no *args or **kargs
        self.add_bedrooms_per_room = add_bedrooms_per_room
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        rooms_per_household = X[:, rooms_ix] / X[:, households_ix]
        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)
```

```
# TRANSFORMATION PIPELINES
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', CombinedAttributesAdder()),
        ('std_scaler', StandardScaler()),
    ])

housing_num_tr = num_pipeline.fit_transform(housing_num)
# The pipeline exposes the same methods as the final estimator. In this example, the last estimator is a StandardScaler,
# which is a transformer, so the pipeline has a transform() method that applies all the transforms to the data in sequence
#(and of course also a fit_transform() method, which is the one we used).
```

```
from sklearn.compose import ColumnTransformer
num_attribs = list(housing_num)
cat_attribs = ["ocean_proximity"]

full_pipeline = ColumnTransformer([
        ("num", num_pipeline, num_attribs),
        ("cat", OneHotEncoder(), cat_attribs),
    ])

housing_prepared = full_pipeline.fit_transform(housing)
```

```
housing_prepared
```

```
array([[-0.94135046,  1.34743822,  0.02756357, ...,  0.        ,
         0.        ,  0.        ],
       [ 1.17178212, -1.19243966, -1.72201763, ...,  0.        ,
         0.        ,  1.        ],
       [ 0.26758118, -0.1259716 ,  1.22045984, ...,  0.        ,
         0.        ,  0.        ],
       ...,
       [-1.5707942 ,  1.31001828,  1.53856552, ...,  0.        ,
         0.        ,  0.        ],
       [-1.56080303,  1.2492109 , -1.1653327 , ...,  0.        ,
         0.        ,  0.        ],
       [-1.28105026,  2.02567448, -0.13148926, ...,  0.        ,
         0.        ,  0.        ]])
```

```
# Let's train a linear regression model
from sklearn.linear_model import LinearRegression
lin_reg= LinearRegression()
lin_reg.fit(housing_prepared, housing_labels)
```

```
▾ LinearRegression
LinearRegression()
```

```
from sklearn.metrics import mean_squared_error

housing_predictions = lin_reg.predict(housing_prepared)
lin_mse = mean_squared_error(housing_labels, housing_predictions)
lin_rmse = np.sqrt(lin_mse)
lin_rmse
```

```
68627.87390018745
```

```
from sklearn.tree import DecisionTreeRegressor
tree_reg= DecisionTreeRegressor()
tree_reg.fit(housing_prepared, housing_labels)
```

```
▾ DecisionTreeRegressor
DecisionTreeRegressor()
```

```
#Let's evatuale on training set
housing_predictions = tree_reg.predict(housing_prepared)
tree_mse = mean_squared_error(housing_labels, housing_predictions)
tree_rmse = np.sqrt(tree_mse)
tree_rmse
```

```
0.0
```

```
# cross validation use the train_test_split function to split the training set into a
# smaller training set and a validation set, then train your models against the smaller training
#set and evaluate them against the validation set.
from sklearn.model_selection import cross_val_score

scores = cross_val_score(tree_reg, housing_prepared, housing_labels,
                         scoring="neg_mean_squared_error", cv=10)
tree_rmse_scores = np.sqrt(-scores)

# (Scikit-Learn’s cross-validation features expect a utility function (greater is better) rather than a
# cost function (lower is better), so the scoring function is actually the opposite of the MSE (i.e., a negative value),
# which is why the preceding code computes -scores before calculating the square root)
```

```
# let's see the scores
def display_scores(scores):
    print("Scores:", scores)
    print("Mean:", scores.mean())
    print("Standard deviation:", scores.std())

display_scores(tree_rmse_scores)
```

```
Scores: [72623.63356609 71441.21512518 67604.12155368 70557.75011261
 68898.94672724 77673.36817636 71173.36569543 74026.97930139
 68031.11090107 72315.98774143]
Mean: 71434.64789004752
Standard deviation: 2852.302534627774
```

```
# let's look for scores for linear regression:
lin_scores = cross_val_score(lin_reg, housing_prepared, housing_labels,
                             scoring="neg_mean_squared_error", cv=10)
lin_rmse_scores = np.sqrt(-lin_scores)
display_scores(lin_rmse_scores)
# the Decision Tree model is overfitting so badly that it performs worse than the Linear Regression model.
```

```
Scores: [71762.76364394 64114.99166359 67771.17124356 68635.19072082
 66846.14089488 72528.03725385 73997.08050233 68802.33629334
 66443.28836884 70139.79923956]
Mean: 69104.07998247063
Standard deviation: 2880.3282098180634
```

```
# let's try Random Forest Regressor
# (Random Forests work by training many Decision Trees on random subsets of the features,
# then averaging out their predictions)
from sklearn.ensemble import RandomForestRegressor

forest_reg = RandomForestRegressor(n_estimators=100, random_state=42)
forest_reg.fit(housing_prepared, housing_labels)
```

```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

```
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
forest_rmse
```

```
18650.698705770003
```

```
from sklearn.model_selection import cross_val_score

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: [51559.63379638 48737.57100062 47210.51269766 51875.21247297
 47577.50470123 51863.27467888 52746.34645573 50065.1762751
 48664.66818196 54055.90894609]
Mean: 50435.58092066179
Standard deviation: 2203.3381412764606
```

```
from sklearn.model_selection import GridSearchCV

param_grid = [
    # try 12 (3×4) combinations of hyperparameters
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
    # then try 6 (2×3) combinations with bootstrap set as False
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
  ]

forest_reg = RandomForestRegressor(random_state=42)
# train across 5 folds, that's a total of (12+6)*5=90 rounds of training
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)
```

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

```
# best parameters
grid_search.best_params_
```

```
{'max_features': 8, 'n_estimators': 30}
```

```
# Let's look at the score of each hyperparameter combination tested during the grid search:
cvres = grid_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
63895.161577951665 {'max_features': 2, 'n_estimators': 3}
54916.32386349543 {'max_features': 2, 'n_estimators': 10}
52885.86715332332 {'max_features': 2, 'n_estimators': 30}
60075.3680329983 {'max_features': 4, 'n_estimators': 3}
52495.01284985185 {'max_features': 4, 'n_estimators': 10}
50187.24324926565 {'max_features': 4, 'n_estimators': 30}
58064.73529982314 {'max_features': 6, 'n_estimators': 3}
51519.32062366315 {'max_features': 6, 'n_estimators': 10}
49969.80441627874 {'max_features': 6, 'n_estimators': 30}
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52459.79624724529 {'max_features': 8, 'n_estimators': 10}
49898.98913455217 {'max_features': 8, 'n_estimators': 30}
62381.765106921855 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54476.57050944266 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59974.60028085155 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52754.5632813202 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
57831.136061214274 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51278.37877140253 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

```
# RANDOMIZED SEARCH
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

param_distribs = {
        'n_estimators': randint(low=1, high=200),
        'max_features': randint(low=1, high=8),
    }

forest_reg = RandomForestRegressor(random_state=42)
rnd_search = RandomizedSearchCV(forest_reg, param_distributions=param_distribs,
                                n_iter=10, cv=5, scoring='neg_mean_squared_error', random_state=42)
rnd_search.fit(housing_prepared, housing_labels)
```

```
▸ RandomizedSearchCV
▸ estimator: RandomForestRegressor
  ▸ RandomForestRegressor
```

```
# Let's look at the score of each hyperparameter combination tested
cvres = rnd_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
49117.55344336652 {'max_features': 7, 'n_estimators': 180}
51450.63202856348 {'max_features': 5, 'n_estimators': 15}
50692.53588182537 {'max_features': 3, 'n_estimators': 72}
50783.614493515 {'max_features': 5, 'n_estimators': 21}
49162.89877456354 {'max_features': 7, 'n_estimators': 122}
50655.798471042704 {'max_features': 3, 'n_estimators': 75}
50513.856319990606 {'max_features': 3, 'n_estimators': 88}
49521.17201976928 {'max_features': 5, 'n_estimators': 100}
50302.90440763418 {'max_features': 3, 'n_estimators': 150}
65167.02018649492 {'max_features': 5, 'n_estimators': 2}
```