

# Hands on ML Chapter 2 End to End Project

## California Real Estate Prices

Our task is to use California census data to build a model of housing prices in the state.

```
In [1]: ### Fetch the data
import os
import tarfile
import urllib

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):
    os.makedirs(housing_path, exist_ok=True)
    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()
```

```
In [2]: fetch_housing_data()
```

```
In [3]: ### Load the data
import pandas as pd

# This function returns a pandas DataFrame object containing all the data.
def load_housing_data(housing_path=HOUSING_PATH):
    csv_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(csv_path)
```

```
In [4]: # Lets take a look at the top five rows
housing = load_housing_data()
housing.head()
# Each row represents one district
```

Out[4]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0

```
In [5]: # Quick description of the data
housing.info()
# Notice total_bedrooms has 20433 features -> missing 207 districts. We will need to fix this later.
```

```
<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
```

```
In [6]: # Notice ocean_proximity is an 'object' which in this case is most likely text.
housing["ocean_proximity"].value_counts()
```

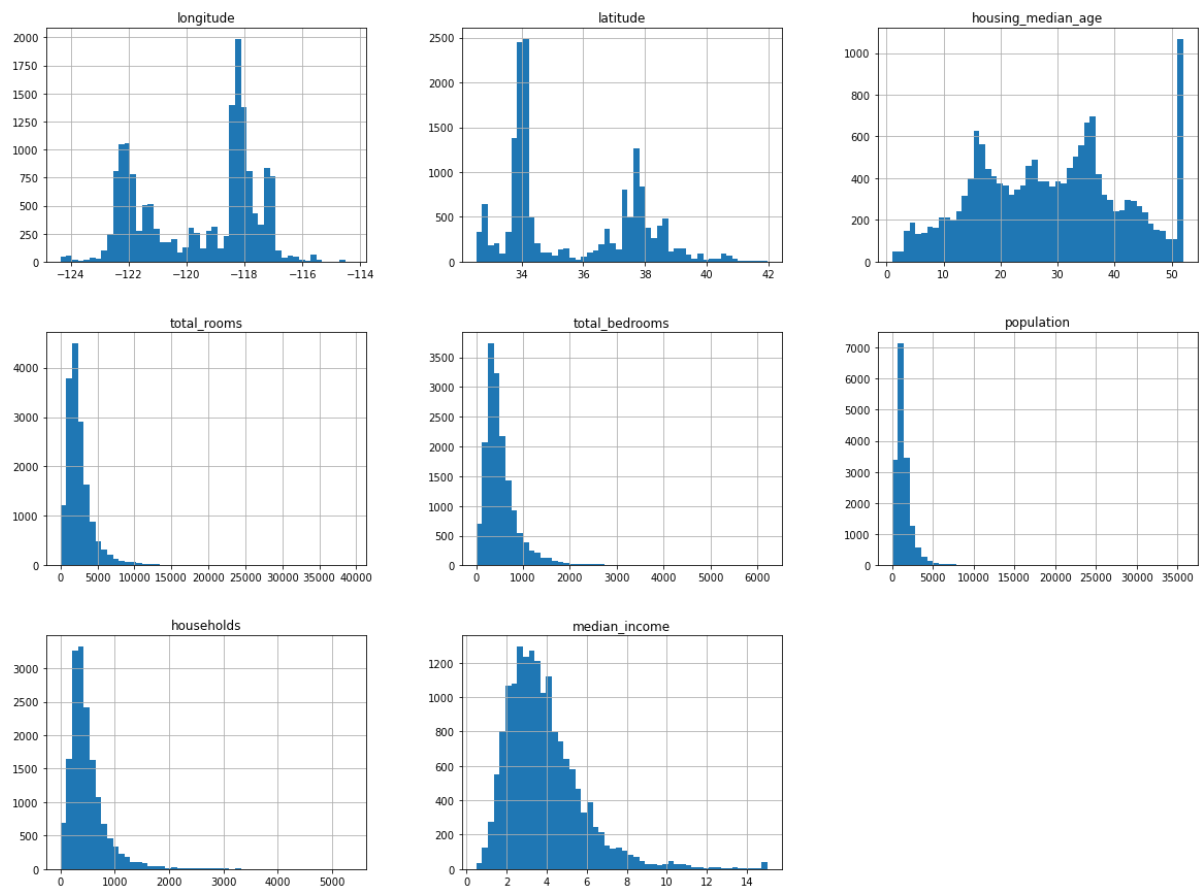
```
Out[6]: <1H OCEAN      9136
INLAND          6551
NEAR OCEAN      2658
NEAR BAY        2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

```
In [7]: # Describe shows a summary of the numerical attributes.
housing.describe()
```

```
Out[7]:
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	popul
<b>count</b>	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.00
<b>mean</b>	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.47
<b>std</b>	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.46
<b>min</b>	-124.350000	32.540000	1.000000	2.000000	1.000000	3.00
<b>25%</b>	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.00
<b>50%</b>	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.00
<b>75%</b>	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.00
<b>max</b>	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.00

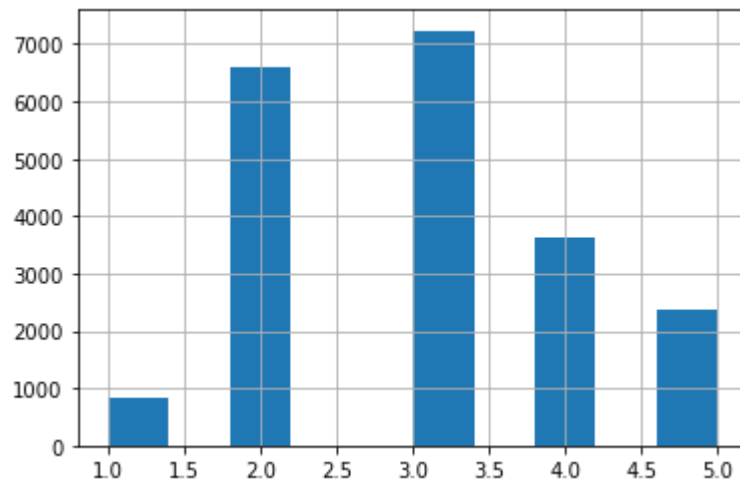
```
In [49]: # We can also plot a histogram of each numerical attribute to get a feel for our data
%matplotlib inline
# ^ Jupyter notebook command for inline matplotlib
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
plt.show()
# Notice:
# 1. The median income does not look like it is in USD. The number represents roughly 3~$30,000 etc.
#    It is also capped between 0.5-15.0 (4.999-15.0001)
# 2. The housing median age and median house value are also capped.
#    The median house value being capped may be a serious problem as that is what we are trying to predict.
# 3. The attributes all have very different scales.
# 4. Many of the histograms are tail-heavy, ideally we want a more bell-shaped distribution.
```



## Create a Test Set

```
In [9]: ### Create a Test Set  
# We are going to use stratified sampling based on median income by creating a  
n income_category attribute.  
# First we need to create the income categories as follows:  
import pandas as pd  
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"].hist()
```

Out[9]: <AxesSubplot:>



```

In [10]: # This is a possible implementation of splitting the data into a training set
         # and test set using the row
         # numbers as unique id's so the test set doesn't change on each iteration of t
         # he model.

         #from zlib import crc32

         #def test_set_check(identifier, test_ratio):
         #    return crc32(np.int64(identifier)) & 0xffffffff < test_ratio * 2**32

         #def split_train_test_by_id(data, test_ratio, id_column):
         #    ids = data[id_column]
         #    in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio))
         #    return data.loc[~in_test_set], data.loc[in_test_set]

         # adds an Index column
         #housing_with_id = housing.reset_index()
         #train_set, test_set = split_train_test_by_id(housing_with_id, 0.2, "index")

         #housing_with_id["id"] = housing["Longitude"] * 1000 + housing["Latitude"]
         #train_set, test_set = split_train_test_by_id(housing_with_id, 0.2, "id")

         ## We are going to use the following implementation using Scikit-Learn's funct
         ## ions to split the dataset into
         ## multiple subsets.
         from sklearn.model_selection import train_test_split

         train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42
         )

         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]

         # Check if this worked correctly by looking at the income category proportions
         # in the test set
         strat_test_set["income_cat"].value_counts() / len(strat_test_set)

```

```

Out[10]: 3    0.350533
         2    0.318798
         4    0.176357
         5    0.114583
         1    0.039729
         Name: income_cat, dtype: float64

```

```

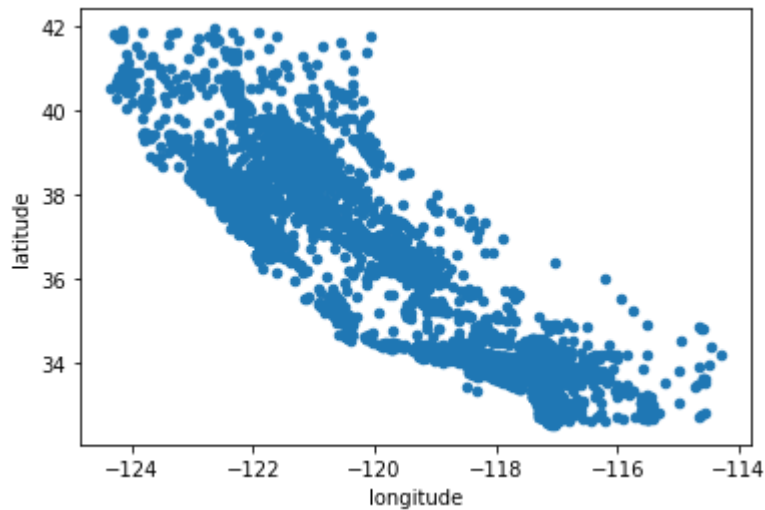
In [11]: # Remove income_cat attribute so the data is back to its original state
         # for set_ in (strat_train_set, strat_test_set):
         #     set_.drop("income_cat", axis=1, inplace=True)

```

## Discover and Visualize the Data to Gain Insights

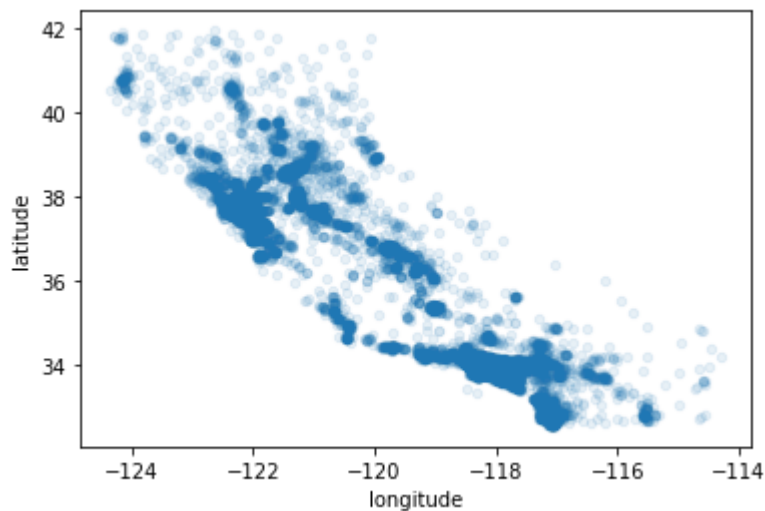
```
In [12]: housing = strat_train_set.copy() # We are only working with the training set from here on out.  
housing.plot(kind="scatter", x="longitude", y="latitude")
```

Out[12]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



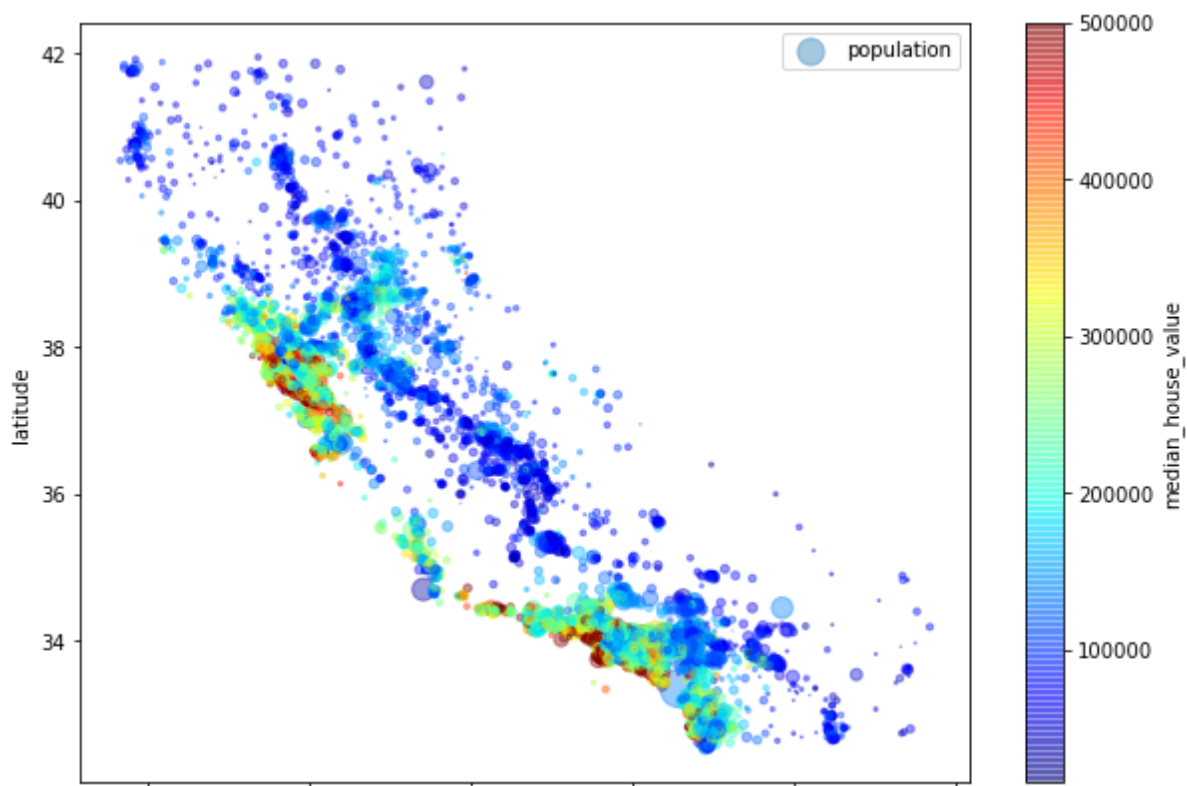
```
In [13]: housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```

Out[13]: <AxesSubplot:xlabel='longitude', ylabel='latitude'>



```
In [14]: 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,  
                    )  
plt.legend()
```

Out[14]: <matplotlib.legend.Legend at 0x1b14d025760>



```
In [15]: ## Looking for Correlations  
# Compute the standard correlation coefficient (Pearson's r) between every pair of attributes  
corr_matrix = housing.corr()  
  
# Look at how much each attribute correlates with the median house value  
corr_matrix["median_house_value"].sort_values(ascending=False)
```

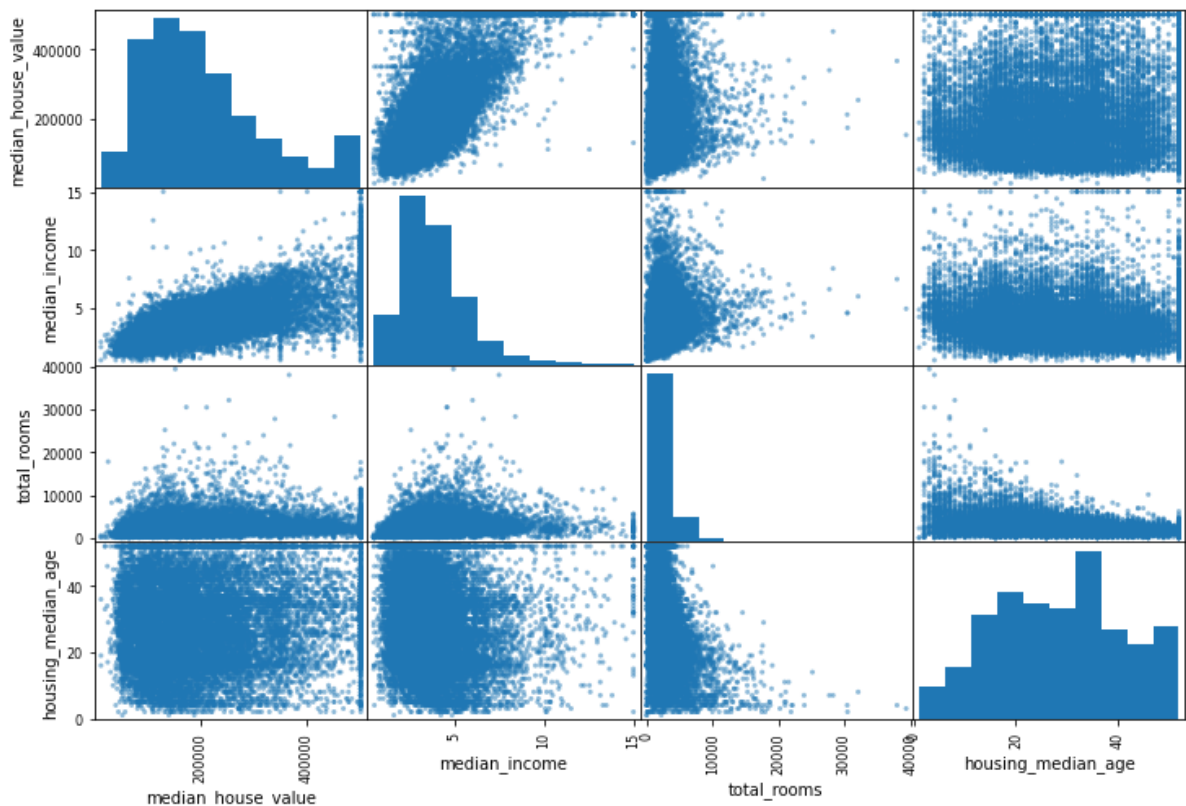
```
Out[15]: median_house_value    1.000000  
median_income    0.687160  
total_rooms    0.135097  
housing_median_age    0.114110  
households    0.064506  
total_bedrooms    0.047689  
population    -0.026920  
longitude    -0.047432  
latitude    -0.142724  
Name: median_house_value, dtype: float64
```



```
In [16]: # Scatter matrix plots used to plot every numerical attribute against every other numerical attribute,
# plus a histogram of each numerical attribute
from pandas.plotting import scatter_matrix

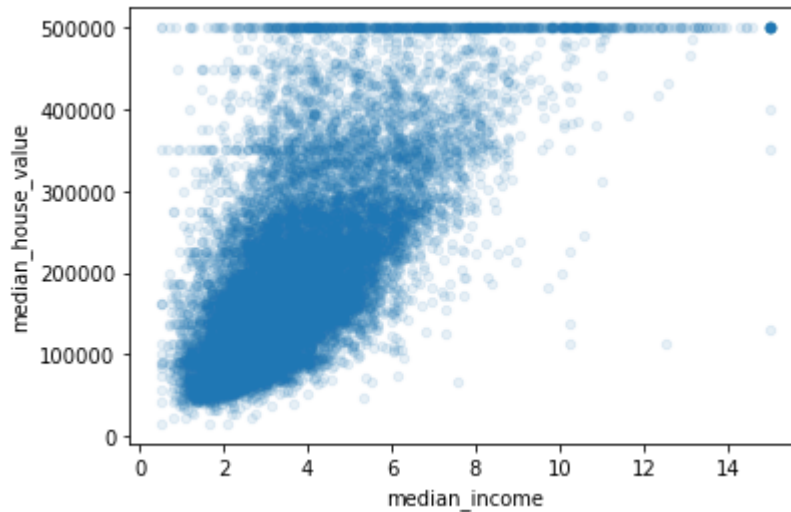
# Here are just a few since 11*11=121 plots
attributes=["median_house_value", "median_income", "total_rooms", "housing_median_age"]
scatter_matrix(housing[attributes], figsize=(12,8))
```

```
Out[16]: array([[<AxesSubplot:xlabel='median_house_value', ylabel='median_house_value'>,
<AxesSubplot:xlabel='median_income', ylabel='median_house_value'>,
<AxesSubplot:xlabel='total_rooms', ylabel='median_house_value'>,
<AxesSubplot:xlabel='housing_median_age', ylabel='median_house_value'>],
[<AxesSubplot:xlabel='median_house_value', ylabel='median_income'>,
<AxesSubplot:xlabel='median_income', ylabel='median_income'>,
<AxesSubplot:xlabel='total_rooms', ylabel='median_income'>,
<AxesSubplot:xlabel='housing_median_age', ylabel='median_income'>],
[<AxesSubplot:xlabel='median_house_value', ylabel='total_rooms'>,
<AxesSubplot:xlabel='median_income', ylabel='total_rooms'>,
<AxesSubplot:xlabel='total_rooms', ylabel='total_rooms'>,
<AxesSubplot:xlabel='housing_median_age', ylabel='total_rooms'>],
[<AxesSubplot:xlabel='median_house_value', ylabel='housing_median_age'>,
<AxesSubplot:xlabel='median_income', ylabel='housing_median_age'>,
<AxesSubplot:xlabel='total_rooms', ylabel='housing_median_age'>,
<AxesSubplot:xlabel='housing_median_age', ylabel='housing_median_age'>]],
dtype=object)
```



```
In [17]: # median_income to "median_house_value" seems to be the most promising correlation
housing.plot(kind="scatter", x="median_income", y="median_house_value", alpha=0.1)
# Notice also that the price cap at 500,000 is clearly visible
# Notice also that there is another line around 350,000
# We may want to remove these data quirks to prevent our model from reproducing them
```

```
Out[17]: <AxesSubplot:xlabel='median_income', ylabel='median_house_value'>
```



```
In [18]: ## Create new attribute combinations
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"]

# check out the new combinations
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

```
Out[18]: median_house_value      1.000000
median_income      0.687160
rooms_per_household 0.146285
total_rooms        0.135097
housing_median_age  0.114110
households         0.064506
total_bedrooms     0.047689
population_per_household -0.021985
population         -0.026920
longitude          -0.047432
latitude           -0.142724
bedrooms_per_room  -0.259984
Name: median_house_value, dtype: float64
```

# Prepare the Data for ML Learning Algorithms

```
In [21]: housing = strat_train_set.drop("median_house_value", axis=1) # Note that drop
() makes a copy
housing_labels = strat_train_set["median_house_value"].copy()

## Data cleaning
# take care of missing attributes
#housing.dropna(subset=["total_bedrooms"]) # option 1 drop corresponding distr
icts
#housing.drop("total_bedrooms", axis=1) # option 2 drop the whole attribute
#median = housing["total_bedrooms"].median() # option 3 set missing attributes
to the mean
#housing["total_bedrooms"].fillna(median, inplace=True)

# option 3 using scikit learn
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
housing_numerical_attributes = housing.drop("ocean_proximity", axis=1)
imputer.fit(housing_numerical_attributes)

# compute median of each attribute
imputer.statistics_
housing_numerical_attributes.median().values

# transform the training set by replacing missing values with the learned valu
es
X = imputer.transform(housing_numerical_attributes)

# If you want to turn it back into a pandas dataframe object...
housing_transformed = pd.DataFrame(X, columns=housing_numerical_attributes.col
umns, index=housing_numerical_attributes.index)
# ^ Note this is just to demonstrate, we don't use 'housing_transformed' agai
n.
housing_transformed.head()
```

Out[21]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	household
17606	-121.89	37.29	38.0	1568.0	351.0	710.0	
18632	-121.93	37.05	14.0	679.0	108.0	306.0	
14650	-117.20	32.77	31.0	1952.0	471.0	936.0	
3230	-119.61	36.31	25.0	1847.0	371.0	1460.0	
3555	-118.59	34.23	17.0	6592.0	1525.0	4459.0	1.

```
In [22]: ## Handling text and categorical attributes
housing_categorical_attributes = housing[["ocean_proximity"]]
housing_categorical_attributes.head(10)
```

```
Out[22]:
```

	ocean_proximity
17606	<1H OCEAN
18632	<1H OCEAN
14650	NEAR OCEAN
3230	INLAND
3555	<1H OCEAN
19480	INLAND
8879	<1H OCEAN
13685	INLAND
4937	<1H OCEAN
4861	<1H OCEAN

```
In [23]: from sklearn.preprocessing import OrdinalEncoder
ordinal_encoder = OrdinalEncoder()
housing_categorical_attributes_encoded = ordinal_encoder.fit_transform(housing_categorical_attributes)
```

```
In [24]: housing_categorical_attributes_encoded[:10]
```

```
Out[24]: array([[0.],
                [0.],
                [4.],
                [1.],
                [0.],
                [1.],
                [0.],
                [1.],
                [0.],
                [0.]])
```

```
In [25]: ordinal_encoder.categories_
```

```
Out[25]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
                dtype=object)]
```

```
In [26]: from sklearn.preprocessing import OneHotEncoder
cat_encoder = OneHotEncoder()
housing_categorical_attributes_1hot = cat_encoder.fit_transform(housing_categorical_attributes)
housing_categorical_attributes_1hot
```

```
Out[26]: <16512x5 sparse matrix of type '<class 'numpy.float64'>'
         with 16512 stored elements in Compressed Sparse Row format>
```

```
In [27]: housing_categorical_attributes_1hot.toarray()
```

```
Out[27]: 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 [28]: cat_encoder.categories_
```

```
Out[28]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
                dtype=object)]
```

```
In [29]: ## Custom Transformers

# Here is an example of a small transformer class that adds the combined attri
butes we created above

# The 'add_bedrooms_per_room' hyperparameter will allow us to easily find out
if
# adding this attribute helps the ML algorithm or not.

from sklearn.base import BaseEstimator, TransformerMixin

rooms_index, bedrooms_index, population_index, households_index = 3, 4, 5, 6 #
The column in X

class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room = True): # no *args or **kwargs
        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, y=None):
        rooms_per_household = X[:, rooms_index] / X[:, households_index]
        population_per_household = X[:, population_index] / X[:, households_in
dex]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_index] / X[:, rooms_index]
            return np.c_[X, rooms_per_household, population_per_household, bed
rooms_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 [30]: ## Feature Scaling

# We perform this below as part of the pipeline
```

```
In [31]: ## Transformation Pipelines

# Here is a small pipeline for the numerical attributes

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

numerical_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('attrs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()), # Notice here we are doing the feature s
    caling using sklearn StandardScaler
])

housing_numerical_attributes_transformed = numerical_pipeline.fit_transform(ho
using_numerical_attributes)
# ^ Note that we don't use this result, we use the numerical pipeline below in
the full pipeline
```

```
In [32]: # Full pipeline to apply all the transformations to the housing data

from sklearn.compose import ColumnTransformer

numerical_attris = list(housing_numerical_attributes)
categorical_attris = ["ocean_proximity"]

full_pipeline = ColumnTransformer([
    ('num', numerical_pipeline, numerical_attris),
    ('cat', OneHotEncoder(), categorical_attris),
])

# ^ This is really the 'data transformation pipeline'

housing_prepared = full_pipeline.fit_transform(housing)
```

## Select and Train a Model

```
In [34]: # Linear Regression Model
from sklearn.linear_model import LinearRegression

# Train the model
linear_reg = LinearRegression()
linear_reg.fit(housing_prepared, housing_labels)

# Test the Linear Regression Model
some_data = housing.iloc[:5]
some_labels = housing_labels.iloc[:5]
some_data_prepared = full_pipeline.transform(some_data)
print('Predictions:', linear_reg.predict(some_data_prepared))
print('Labels:', list(some_labels))
# These are not very accurate
```

```
Predictions: [210644.60459286 317768.80697211 210956.43331178 59218.98886849
189747.55849879]
Labels: [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
```

```
In [35]: # Lets measure the RMSE on the whole training set.
from sklearn.metrics import mean_squared_error
housing_predictions = linear_reg.predict(housing_prepared)
linear_mse = mean_squared_error(housing_labels, housing_predictions)
linear_rmse = np.sqrt(linear_mse)
print(linear_rmse)
# These results are not very good, high error on the training set means the model is underfitting the training data.
# Either:
# the features do not provide enough info to make a good prediction,
# or we need to constrain or the model (regularize it),
# or the model isn't powerful enough.
```

```
68628.19819848923
```

```
In [36]: # Let's try a more powerful model.
# Decision Tree Regressor
from sklearn.tree import DecisionTreeRegressor

# Train the model
decision_tree_reg = DecisionTreeRegressor()
decision_tree_reg.fit(housing_prepared, housing_labels)

# Test the model
housing_predictions = decision_tree_reg.predict(housing_prepared)
decision_tree_mse = mean_squared_error(housing_labels, housing_predictions)
decision_tree_rmse = np.sqrt(decision_tree_mse)
print(decision_tree_rmse)
# The error is showing up as zero, this can't be right.
# Low error (in this case zero error) on the training set means the model is overfitting the training data.
```

```
0.0
```

```
In [37]: # k-fold cross-validation
from sklearn.model_selection import cross_val_score
scores = cross_val_score(decision_tree_reg, housing_prepared, housing_labels,
scoring="neg_mean_squared_error", cv=10)
decision_tree_rmse_scores = np.sqrt(-scores)

def display_scores(scores):
    print("Scores:", scores)
    print("Mean:", scores.mean())
    print("Standard deviation:", scores.std())

display_scores(decision_tree_rmse_scores)
# We can see the decision tree regressor actually performed worse than Linear
regression from how badly it is overfitting.
```

Scores: [67960.42510836 67376.42270742 70741.27154365 69176.31261707  
70590.30119684 74088.07056824 70523.86371319 71638.65086703  
78298.33579674 70620.43607771]  
Mean: 71101.4090196249  
Standard deviation: 2990.111267490658

```
In [38]: # Lets compute the cross validation scores for linear regression model just to
be safe.
linear_reg_scores = cross_val_score(linear_reg, housing_prepared, housing_labels,
scoring="neg_mean_squared_error", cv=10)
linear_reg_rmse_scores = np.sqrt(-linear_reg_scores)
display_scores(linear_reg_rmse_scores)
# We have confirmed that the decision tree regressor model is overfitting so much
its performance is worse.
```

Scores: [66782.73843989 66960.118071 70347.95244419 74739.57052552  
68031.13388938 71193.84183426 64969.63056405 68281.61137997  
71552.91566558 67665.10082067]  
Mean: 69052.46136345083  
Standard deviation: 2731.6740017983434

```
In [39]: # Let's try one more model
# Random Forest Regressor
# - This works by training many Decision Trees on random subsets of the features,
then averaging out their predictions.

# Train the model
from sklearn.ensemble import RandomForestRegressor
random_forest_reg = RandomForestRegressor()
random_forest_reg.fit(housing_prepared, housing_labels)

# Test the model on the training set
housing_predictions = random_forest_reg.predict(housing_prepared)
random_forest_mse = mean_squared_error(housing_labels, housing_predictions)
random_forest_rmse = np.sqrt(random_forest_mse)
print(random_forest_rmse)
```

18663.248064432224

```
In [55]: # This looks a lot better, Let's look at the cross validation scores
```



```
In [40]: # Test the random forest model on the validation set
scores = cross_val_score(random_forest_reg, housing_prepared, housing_labels,
scoring="neg_mean_squared_error", cv=10)
random_forest_rmse_scores = np.sqrt(-scores)

display_scores(random_forest_rmse_scores)
```

```
Scores: [49568.3417132  47315.08712098 49854.13492773 52209.914778
 49528.74754482 53516.14223867 48688.10995098 47887.98583279
 52876.88005253 50272.84261808]
Mean: 50171.81867777926
Standard deviation: 1977.9470620493362
```

```
In [57]: # Notice that the forest_rmse (training set error) is much lower than the scores
from the cross-validation.
# This means the model is still overfitting the training set.

# Possible solutions for overfitting include:
# simplify the model,, constraint it (regularization), or get a lot more training data
```

```
In [54]: # Let's try the Support Vector Machine Regressor model
from sklearn.svm import SVR

# Train the model
svm_reg = SVR(kernel="linear")
svm_reg.fit(housing_prepared, housing_labels)

# Test the model on the training set
housing_predictions = svm_reg.predict(housing_prepared)
svm_mse = mean_squared_error(housing_labels, housing_predictions)
svm_rmse = np.sqrt(svm_mse)
print(svm_rmse)
```

```
111094.6308539982
```

```
In [58]: # This looks pretty bad, Let's look at the cross validation scores
```

```
In [59]: # Test the SVM model on the validation set
scores = cross_val_score(svm_reg, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)
svm_reg_rmse_scores = np.sqrt(-scores)

display_scores(svm_reg_rmse_scores)
```

```
Scores: [105342.09141998 112489.24624123 110092.35042753 113403.22892482
 110638.90119657 115675.8320024 110703.56887243 114476.89008206
 113756.17971227 111520.1120808 ]
Mean: 111809.84009600841
Standard deviation: 2762.393664321567
```

```
In [60]: # This still looks pretty awful. Let's try a different SVM Kernel and mess around with the gamma, C, and epsilon values

# gamma {'scale', 'auto'} is the Kernel coefficient for 'rbf', 'poly', and 'sigmoid'
# C {float, default = 1.0} is the regularization parameter
# epsilon {float, default = 0.1} is the epsilon in the SVR model

# See https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVR.html for details

# default: svm_reg = SVR(kernel="rbf", gamma='scale', C=1.0, epsilon=0.1)
```

```
In [61]: # Support Vector Machine Regressor - Continued

# Train the model
svm_reg = SVR(kernel="rbf", gamma='scale', C=3.0, epsilon=0.1)
svm_reg.fit(housing_prepared, housing_labels)

# Test the model on the training set
housing_predictions = svm_reg.predict(housing_prepared)
svm_mse = mean_squared_error(housing_labels, housing_predictions)
svm_rmse = np.sqrt(svm_mse)
print(svm_rmse)

# Test the SVM model on the validation set
scores = cross_val_score(svm_reg, housing_prepared, housing_labels, scoring="neg_mean_squared_error", cv=10)
svm_reg_rmse_scores = np.sqrt(-scores)

display_scores(svm_reg_rmse_scores)

117846.60742277169
Scores: [110779.4889748  118876.25647598 116314.6702655  119791.93555743
 116947.42903547 121672.7246191  116952.82703015 120842.75274804
 119700.49689316 117370.94945319]
Mean: 117924.95310528048
Standard deviation: 2931.9050857954962
```

```
In [62]: # The SVM results do not look good, maybe this isn't the best model for this task.
# We could still use GridSearch to mess around with the gamma, C, and epsilon values for further exploration,
# see exercise solutions below
```

```
In [63]: ## Save Models:
import joblib

joblib.dump(linear_reg, "linear_regression_model.pkl") # Save the Linear Regression Model
joblib.dump(decision_tree_reg, "decision_tree_regressor_model.pkl") # Save the Decision Tree Model
joblib.dump(random_forest_reg, "random_forest_regressor_model.pkl") # Save the Random Forest Model
joblib.dump(svm_reg, "support_vector_machine_regressor_model.pkl") # Save the Support Vector Machine Model

## Load Models:
# lin_reg_model_loaded = joblib.load("lin_reg_model.pkl") # Load the Linear Regression Model
```

```
Out[63]: ['support_vector_machine_regressor_model.pkl']
```

## Fine-Tune Your Model

**Grid Search CV to experiment with hyperparameter combinations on RandomForestRegressor**

```
In [81]: from sklearn.model_selection import GridSearchCV

param_grid = [
    {
        'n_estimators': [3, 10, 30, 100],
        'max_features': [2, 4, 6, 8, 10]
    },
    {
        'bootstrap': [False],
        'n_estimators': [3, 10, 30, 100],
        'max_features': [2, 3, 4, 6, 8, 10]
    },
]

random_forest_reg = RandomForestRegressor()

grid_search = GridSearchCV(random_forest_reg, param_grid, cv=5, scoring='neg_mean_squared_error', return_train_score=True)

grid_search.fit(housing_prepared, housing_labels)
```

```
Out[81]: GridSearchCV(cv=5, estimator=RandomForestRegressor(),
                      param_grid=[{'max_features': [2, 4, 6, 8, 10],
                                   'n_estimators': [3, 10, 30, 100]},
                                   {'bootstrap': [False],
                                    'max_features': [2, 3, 4, 6, 8, 10],
                                    'n_estimators': [3, 10, 30, 100]}],
                      return_train_score=True, scoring='neg_mean_squared_error')
```

```
In [82]: # Explore best parameter combinations:  
print(grid_search.best_params_)
```

```
{'bootstrap': False, 'max_features': 6, 'n_estimators': 100}
```

```
In [83]: print(grid_search.best_estimator_)
```

```
RandomForestRegressor(bootstrap=False, max_features=6)
```

```
In [84]: # Grid Search Evaluation Scores:
cvres = grid_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
63211.03853672407 {'max_features': 2, 'n_estimators': 3}
56034.5147579656 {'max_features': 2, 'n_estimators': 10}
52928.42291110197 {'max_features': 2, 'n_estimators': 30}
51964.88145085111 {'max_features': 2, 'n_estimators': 100}
60530.25010864527 {'max_features': 4, 'n_estimators': 3}
52844.69735283786 {'max_features': 4, 'n_estimators': 10}
50865.44552614693 {'max_features': 4, 'n_estimators': 30}
49731.23013985973 {'max_features': 4, 'n_estimators': 100}
59475.05098749464 {'max_features': 6, 'n_estimators': 3}
52608.673755902215 {'max_features': 6, 'n_estimators': 10}
49955.112006627714 {'max_features': 6, 'n_estimators': 30}
49265.20432866328 {'max_features': 6, 'n_estimators': 100}
59066.05982549296 {'max_features': 8, 'n_estimators': 3}
52433.81728973791 {'max_features': 8, 'n_estimators': 10}
50045.26008148687 {'max_features': 8, 'n_estimators': 30}
49409.23410830111 {'max_features': 8, 'n_estimators': 100}
58915.383393140415 {'max_features': 10, 'n_estimators': 3}
52168.0389061894 {'max_features': 10, 'n_estimators': 10}
50162.13332003433 {'max_features': 10, 'n_estimators': 30}
49557.03223877481 {'max_features': 10, 'n_estimators': 100}
62719.56086662608 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
53807.18477738074 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
51953.27604104431 {'bootstrap': False, 'max_features': 2, 'n_estimators': 30}
50833.915404223924 {'bootstrap': False, 'max_features': 2, 'n_estimators': 100}
61183.1618441438 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52676.95256494929 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
50150.466695685405 {'bootstrap': False, 'max_features': 3, 'n_estimators': 30}
49651.39479392064 {'bootstrap': False, 'max_features': 3, 'n_estimators': 100}
58213.654152968265 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
52057.20332564132 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
49640.096935294656 {'bootstrap': False, 'max_features': 4, 'n_estimators': 30}
48834.2497568854 {'bootstrap': False, 'max_features': 4, 'n_estimators': 100}
56989.99649358026 {'bootstrap': False, 'max_features': 6, 'n_estimators': 3}
51216.24188644808 {'bootstrap': False, 'max_features': 6, 'n_estimators': 10}
49050.437979995026 {'bootstrap': False, 'max_features': 6, 'n_estimators': 30}
48537.192628134784 {'bootstrap': False, 'max_features': 6, 'n_estimators': 100}
57679.48106694756 {'bootstrap': False, 'max_features': 8, 'n_estimators': 3}
51160.97696595444 {'bootstrap': False, 'max_features': 8, 'n_estimators': 10}
49219.96743746264 {'bootstrap': False, 'max_features': 8, 'n_estimators': 30}
48668.13727939909 {'bootstrap': False, 'max_features': 8, 'n_estimators': 100}
57739.9865698914 {'bootstrap': False, 'max_features': 10, 'n_estimators': 3}
51456.748143697485 {'bootstrap': False, 'max_features': 10, 'n_estimators': 10}
50003.27761288673 {'bootstrap': False, 'max_features': 10, 'n_estimators': 30}
49362.923772717426 {'bootstrap': False, 'max_features': 10, 'n_estimators': 100}
```

## Randomized Search CV to experiment with hyperparameter combinations on RandomForestRegressor

In [85]: *# This is used when you need to randomly sample large hyperparameter spaces*

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint

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

random_forest_reg = RandomForestRegressor(random_state=42)

random_search = RandomizedSearchCV(random_forest_reg,
                                   param_distributions=param_distributions,
                                   n_iter=10,
                                   cv=5,
                                   scoring='neg_mean_squared_error',
                                   random_state=42)

random_search.fit(housing_prepared, housing_labels)
```

Out[85]: RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(random\_state=42),  
param\_distributions={'max\_features': <scipy.stats.\_distn\_i  
nfrastucture.rv\_frozen object at 0x000001B112224C40>,  
'n\_estimators': <scipy.stats.\_distn\_i  
nfrastucture.rv\_frozen object at 0x000001B11247EF40>},  
random\_state=42, scoring='neg\_mean\_squared\_error')

In [100]: *# Explore best random search parameter combinations:*

```
print(random_search.best_params_)

{'max_features': 7, 'n_estimators': 180}
```

In [87]: print(random\_search.best\_estimator\_)

```
RandomForestRegressor(max_features=7, n_estimators=180, random_state=42)
```

```
In [88]: # Random Search Evaluation Scores:
cvres = random_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

```
49150.70756927707 {'max_features': 7, 'n_estimators': 180}
51389.889203389284 {'max_features': 5, 'n_estimators': 15}
50796.155224308866 {'max_features': 3, 'n_estimators': 72}
50835.13360315349 {'max_features': 5, 'n_estimators': 21}
49280.9449827171 {'max_features': 7, 'n_estimators': 122}
50774.90662363929 {'max_features': 3, 'n_estimators': 75}
50682.78888164288 {'max_features': 3, 'n_estimators': 88}
49608.99608105296 {'max_features': 5, 'n_estimators': 100}
50473.61930350219 {'max_features': 3, 'n_estimators': 150}
64429.84143294435 {'max_features': 5, 'n_estimators': 2}
```

```
In [89]: # In this case, the Random Search didn't find better parameters than the Grid
Search
```

## Analyze the Best Models and Their Error

```
In [90]: # Let's look at the relative importance of each attribute for making accurate
predictions
feature_importances = grid_search.best_estimator_.feature_importances_
random_tree_reg_feature_importances = feature_importances # Note we need this
later in Exercise 3
extra_attribs = ["rooms_per_household", "pop_per_hhold", "bedrooms_per_room"]
cat_encoder = full_pipeline.named_transformers_["cat"]
cat_one_hot_attribs = list(cat_encoder.categories_[0])
attributes = numerical_attribs + extra_attribs + cat_one_hot_attribs
print(sorted(zip(feature_importances, attributes), reverse=True))

# With this info we can see the relative importance of each attribute for making
an accurate prediction
# and which are less useful that we should maybe drop in the future.
# Ex. it appears that the <1H OCEAN category is the only useful ocean_proximity
category
```

```
[(0.32820383909931383, 'median_income'), (0.143077997543386, 'INLAND'), (0.10
804589057862227, 'pop_per_hhold'), (0.08119879731256048, 'longitude'), (0.080
087908597283, 'bedrooms_per_room'), (0.07499945447052753, 'latitude'), (0.054
69985129854927, 'rooms_per_household'), (0.04263139319651873, 'housing_median
_age'), (0.016806938836952563, 'total_rooms'), (0.016565035217440644, 'popula
tion'), (0.01564709777088628, 'households'), (0.015601740074349257, 'total_be
drooms'), (0.01310521958261995, '<1H OCEAN'), (0.005020450659939618, 'NEAR OC
EAN'), (0.004234867399445356, 'NEAR BAY'), (7.351836160527607e-05, 'ISLAND')]
```

## Evaluate Your System on the Test Set



```
In [47]: 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()  
  
X_test_prepared = full_pipeline.transform(X_test)  
  
final_predictions = final_model.predict(X_test_prepared)  
  
final_mse = mean_squared_error(y_test, final_predictions)  
final_rmse = np.sqrt(final_mse)  
print(final_rmse)  
# The final_rmse (generalization error) may not be enough to convince you to launch your model.
```

46372.31934924472

```
In [48]: # In order to have an idea of how precise this estimate is, let us do the following:  
  
# Compute a 95% confidence interval for the generalization of the error to get an idea of how precise our estimate is  
from scipy import stats  
confidence = 0.95  
squared_errors = (final_predictions - y_test) ** 2  
generalizedError = np.sqrt(stats.t.interval(confidence, len(squared_errors) - 1, loc=squared_errors.mean(), scale=stats.sem(squared_errors)))  
print(generalizedError)  
# We see that our system is not better than the experts' price estimates, but it may still be good enough to launch  
# to free up more of their time for other productive tasks.
```

[44377.82362471 48284.49827834]

## Exerice Solutions

### 1. Try SVM Regressor with various hyper parameters

```
In [69]: param_grid = [  
    {  
        'kernel': ['linear'],  
        'C': [10., 30., 100., 300., 1000., 3000., 10000., 30000.0]  
    },  
    {  
        'kernel': ['rbf'],  
        'C': [1.0, 3.0, 10., 30., 100., 300., 1000.0],  
        'gamma': [0.01, 0.03, 0.1, 0.3, 1.0, 3.0]  
    },  
]  
  
svm_reg = SVR()  
grid_search = GridSearchCV(svm_reg, param_grid, cv=5, scoring='neg_mean_square  
d_error', verbose=2)  
grid_search.fit(housing_prepared, housing_labels)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits
[CV] C=10.0, kernel=linear .....

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worke
rs.

[CV] ..... C=10.0, kernel=linear, total= 3.6s
[CV] C=10.0, kernel=linear .....

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 3.5s remaining: 0.
0s
```

```
[CV] ..... C=10.0, kernel=linear, total= 3.6s
[CV] C=10.0, kernel=linear .....
[CV] ..... C=10.0, kernel=linear, total= 3.5s
[CV] C=10.0, kernel=linear .....
[CV] ..... C=10.0, kernel=linear, total= 3.5s
[CV] C=10.0, kernel=linear .....
[CV] ..... C=10.0, kernel=linear, total= 3.5s
[CV] C=30.0, kernel=linear .....
[CV] ..... C=30.0, kernel=linear, total= 3.5s
[CV] C=30.0, kernel=linear .....
[CV] ..... C=30.0, kernel=linear, total= 3.5s
[CV] C=30.0, kernel=linear .....
[CV] ..... C=30.0, kernel=linear, total= 3.7s
[CV] C=30.0, kernel=linear .....
[CV] ..... C=30.0, kernel=linear, total= 3.6s
[CV] C=30.0, kernel=linear .....
[CV] ..... C=30.0, kernel=linear, total= 3.6s
[CV] C=100.0, kernel=linear .....
[CV] ..... C=100.0, kernel=linear, total= 3.5s
[CV] C=100.0, kernel=linear .....
[CV] ..... C=100.0, kernel=linear, total= 3.5s
[CV] C=100.0, kernel=linear .....
[CV] ..... C=100.0, kernel=linear, total= 3.6s
[CV] C=100.0, kernel=linear .....
[CV] ..... C=100.0, kernel=linear, total= 3.5s
[CV] C=100.0, kernel=linear .....
[CV] ..... C=100.0, kernel=linear, total= 3.5s
[CV] C=300.0, kernel=linear .....
[CV] ..... C=300.0, kernel=linear, total= 3.6s
[CV] C=300.0, kernel=linear .....
[CV] ..... C=300.0, kernel=linear, total= 3.6s
[CV] C=300.0, kernel=linear .....
[CV] ..... C=300.0, kernel=linear, total= 3.7s
[CV] C=300.0, kernel=linear .....
[CV] ..... C=300.0, kernel=linear, total= 3.6s
[CV] C=300.0, kernel=linear .....
[CV] ..... C=300.0, kernel=linear, total= 3.5s
[CV] C=1000.0, kernel=linear .....
[CV] ..... C=1000.0, kernel=linear, total= 3.7s
[CV] C=1000.0, kernel=linear .....
[CV] ..... C=1000.0, kernel=linear, total= 3.7s
[CV] C=1000.0, kernel=linear .....
[CV] ..... C=1000.0, kernel=linear, total= 3.7s
[CV] C=1000.0, kernel=linear .....
[CV] ..... C=1000.0, kernel=linear, total= 3.8s
[CV] C=1000.0, kernel=linear .....
[CV] ..... C=1000.0, kernel=linear, total= 3.7s
[CV] C=3000.0, kernel=linear .....
[CV] ..... C=3000.0, kernel=linear, total= 4.0s
[CV] C=3000.0, kernel=linear .....
[CV] ..... C=3000.0, kernel=linear, total= 3.9s
[CV] C=3000.0, kernel=linear .....
[CV] ..... C=3000.0, kernel=linear, total= 4.1s
[CV] C=3000.0, kernel=linear .....
[CV] ..... C=3000.0, kernel=linear, total= 4.1s
[CV] C=3000.0, kernel=linear .....
[CV] ..... C=3000.0, kernel=linear, total= 3.9s
```

```

[CV] C=10000.0, kernel=linear .....
[CV] ..... C=10000.0, kernel=linear, total= 5.3s
[CV] C=10000.0, kernel=linear .....
[CV] ..... C=10000.0, kernel=linear, total= 5.4s
[CV] C=10000.0, kernel=linear .....
[CV] ..... C=10000.0, kernel=linear, total= 5.4s
[CV] C=10000.0, kernel=linear .....
[CV] ..... C=10000.0, kernel=linear, total= 5.0s
[CV] C=10000.0, kernel=linear .....
[CV] ..... C=10000.0, kernel=linear, total= 4.7s
[CV] C=30000.0, kernel=linear .....
[CV] ..... C=30000.0, kernel=linear, total= 8.5s
[CV] C=30000.0, kernel=linear .....
[CV] ..... C=30000.0, kernel=linear, total= 8.6s
[CV] C=30000.0, kernel=linear .....
[CV] ..... C=30000.0, kernel=linear, total= 9.1s
[CV] C=30000.0, kernel=linear .....
[CV] ..... C=30000.0, kernel=linear, total= 8.7s
[CV] C=30000.0, kernel=linear .....
[CV] ..... C=30000.0, kernel=linear, total= 7.6s
[CV] C=1.0, gamma=0.01, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.01, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.01, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.01, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.01, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.01, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.01, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.01, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.01, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.01, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.03, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.03, kernel=rbf, total= 5.9s
[CV] C=1.0, gamma=0.03, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.03, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.03, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.03, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.03, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.03, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.03, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.03, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.1, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.1, kernel=rbf, total= 5.9s
[CV] C=1.0, gamma=0.1, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.1, kernel=rbf, total= 6.0s
[CV] C=1.0, gamma=0.1, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.1, kernel=rbf, total= 5.9s
[CV] C=1.0, gamma=0.1, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.1, kernel=rbf, total= 5.9s
[CV] C=1.0, gamma=0.1, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.1, kernel=rbf, total= 5.9s
[CV] C=1.0, gamma=0.3, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.3, kernel=rbf, total= 5.7s
[CV] C=1.0, gamma=0.3, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.3, kernel=rbf, total= 5.8s
[CV] C=1.0, gamma=0.3, kernel=rbf .....
[CV] ..... C=1.0, gamma=0.3, kernel=rbf, total= 5.7s
[CV] C=1.0, gamma=0.3, kernel=rbf .....

```

[illegible]



[illegible]



[illegible]

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file:///C:/Users/frede/Downloads/Housing.html



```
In [71]: # Let's do this for the SVM Regressor

from scipy.stats import expon, reciprocal

# see https://docs.scipy.org/doc/scipy/reference/stats.html
# for `expon()` and `reciprocal()` documentation and more probability distribution functions.

param_distributions = {
    'kernel': ['linear', 'rbf'],
    'C': reciprocal(20, 200000),
    'gamma': expon(scale=1.0),
}

svm_reg = SVR()
random_search = RandomizedSearchCV(svm_reg,
                                   param_distributions=param_distributions,
                                   n_iter=50,
                                   cv=5,
                                   scoring='neg_mean_squared_error',
                                   verbose=2,
                                   random_state=42)

random_search.fit(housing_prepared, housing_labels)
```

Fitting 5 folds for each of 50 candidates, totalling 250 fits

[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear .....

[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.

[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear, total= 3.6s

[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear .....

[Parallel(n\_jobs=1)]: Done 1 out of 1 | elapsed: 3.5s remaining: 0.0s

[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear, total= 3.6s  
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear .....  
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear, total= 3.6s  
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear .....  
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear, total= 3.7s  
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear .....  
[CV] C=629.782329591372, gamma=3.010121430917521, kernel=linear, total= 3.7s  
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf .....  
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total= 7.3s  
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf .....  
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total= 7.5s  
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf .....  
[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total= 7.4s  
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[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total= 7.5s  
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[CV] C=26290.206464300216, gamma=0.9084469696321253, kernel=rbf, total= 7.6s  
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....  
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf, total= 6.0s  
[CV] C=84.14107900575871, gamma=0.059838768608680676, kernel=rbf .....  
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[CV] C=171377.39570378003, gamma=0.628789100540856, kernel=linear, total= 22.8s

```

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[CV] C=5385.293820172355, gamma=0.18696125197741642, kernel=linear, total=
4.3s
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4.4s
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4.5s
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4.3s
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4.4s
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9.2s
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9.1s
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9.8s
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9.3s
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8.5s
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s
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s
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s
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s
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s
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[CV] C=61.54360542501371, gamma=0.6835472281341501, kernel=linear, total=

```

3.5s  
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[CV] C=135.76775824842434, gamma=0.838636245624803, kernel=linear, total= 3.6s  
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[CV] C=135.76775824842434, gamma=0.838636245624803, kernel=linear, total= 3.6s  
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[CV] C=135.76775824842434, gamma=0.838636245624803, kernel=linear, total= 3.6s  
[CV] C=135.76775824842434, gamma=0.838636245624803, kernel=linear ....  
[CV] C=135.76775824842434, gamma=0.838636245624803, kernel=linear, total= 3.6s

3.5s  
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in  
[CV] C=151136.20282548846, gamma=1.4922453771381408, kernel=rbf .....  
[CV] C=151136.20282548846, gamma=1.4922453771381408, kernel=rbf, total= 1.1m  
in  
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[CV] C=151136.20282548846, gamma=1.4922453771381408, kernel=rbf, total= 1.0m  
in  
[CV] C=151136.20282548846, gamma=1.4922453771381408, kernel=rbf .....  
[CV] C=151136.20282548846, gamma=1.4922453771381408, kernel=rbf, total= 1.3m  
in  
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[CV] C=151136.20282548846, gamma=1.4922453771381408, kernel=rbf, total= 1.3m  
in  
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3.7s  
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[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear, total=  
3.6s  
[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear ....  
[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear, total=  
3.7s  
[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear ....  
[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear, total=  
3.6s  
[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear ....  
[CV] C=761.4316758498783, gamma=2.6126336514161914, kernel=linear, total=  
3.6s  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear ...  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear, total=  
18.4s  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear ...  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear, total=  
17.8s  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear ...  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear, total=  
29.9s  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear ...  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear, total=  
18.9s  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear ...  
[CV] C=97392.81883041795, gamma=0.09265545895311562, kernel=linear, total=  
15.5s  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear ....  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear, total=  
4.0s  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear ....  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear, total=  
4.1s  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear ....  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear, total=  
3.9s  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear ....  
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear, total=

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4.1s
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear ....
[CV] C=2423.0759984939164, gamma=3.248614270240346, kernel=linear, total=
3.8s
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear ....
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear, total=
3.7s
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear ....
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear, total=
3.6s
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear ....
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear, total=
3.6s
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear ....
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear, total=
3.6s
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear ....
[CV] C=717.3632997255095, gamma=0.3165604432088257, kernel=linear, total=
3.6s
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf .....
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf, total= 6.6
s
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf .....
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf, total= 6.6
s
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf .....
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf, total= 6.6
s
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf .....
[CV] C=4446.667521184072, gamma=3.3597284456608496, kernel=rbf, total= 6.5
s
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear ...
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3.9s
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear ...
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear, total=
4.2s
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear ...
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear, total=
4.2s
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear ...
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear, total=
4.0s
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear ...
[CV] C=2963.564121207815, gamma=0.15189814782062885, kernel=linear, total=
3.9s
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear ...
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear, total=
3.4s
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear ...
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear, total=
3.5s
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear ...
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear, total=

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3.5s
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear ...
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear, total=
3.6s
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear ...
[CV] C=91.64267381686706, gamma=0.01575994483585621, kernel=linear, total=
3.4s
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf .....
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf, total=
5.9s
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf .....
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf, total=
6.0s
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf .....
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf, total=
6.0s
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf .....
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf, total=
6.0s
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf .....
[CV] C=24547.601975705915, gamma=0.22153944050588595, kernel=rbf, total=
5.9s
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf .....
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf, total= 5.
9s
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf .....
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf, total= 5.
9s
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf .....
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf, total= 5.
9s
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf .....
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf, total= 5.
8s
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf .....
[CV] C=22.76927941060928, gamma=0.22169760231351215, kernel=rbf, total= 5.
8s
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear ...
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear, total=
5.8s
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear ...
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear, total=
6.2s
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear ...
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear, total=
6.3s
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[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear, total=
6.4s
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear ...
[CV] C=16483.850529752886, gamma=1.4752145260435134, kernel=linear, total=
5.5s
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[CV] C=101445.66881340064, gamma=1.052904084582266, kernel=rbf, total= 29.2
s
[CV] C=101445.66881340064, gamma=1.052904084582266, kernel=rbf .....
[CV] C=101445.66881340064, gamma=1.052904084582266, kernel=rbf, total= 27.8

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S  
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S  
[CV] C=101445.66881340064, gamma=1.052904084582266, kernel=rbf .....  
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S  
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S  
[CV] C=56681.80859029545, gamma=0.9763011917123741, kernel=rbf .....  
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S  
[CV] C=56681.80859029545, gamma=0.9763011917123741, kernel=rbf .....  
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S  
[CV] C=56681.80859029545, gamma=0.9763011917123741, kernel=rbf .....  
[CV] C=56681.80859029545, gamma=0.9763011917123741, kernel=rbf, total= 12.0  
S  
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S  
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[CV] C=56681.80859029545, gamma=0.9763011917123741, kernel=rbf, total= 12.9  
S  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf .....  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf, total= 5.7  
S  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf .....  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf, total= 5.7  
S  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf .....  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf, total= 5.7  
S  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf .....  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf, total= 5.7  
S  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf .....  
[CV] C=48.15822390928914, gamma=0.4633351167983427, kernel=rbf, total= 5.7  
S  
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[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf, total= 5.7  
S  
[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf .....  
[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf, total= 5.7  
S  
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[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf, total= 5.6  
S  
[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf .....  
[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf, total= 5.6  
S  
[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf .....  
[CV] C=399.7268155705774, gamma=1.3078757839577408, kernel=rbf, total= 5.6  
S  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear ...  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear, total=

3.5s  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear ...  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear, total=  
3.6s  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear ...  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear, total=  
3.5s  
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[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear, total=  
3.5s  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear ...  
[CV] C=251.14073886281363, gamma=0.8238105204914145, kernel=linear, total=  
3.5s  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear ....  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear, total=  
3.5s  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear ....  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear, total=  
3.5s  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear ....  
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3.5s  
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[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear, total=  
3.5s  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear ....  
[CV] C=60.17373642891687, gamma=1.2491263443165994, kernel=linear, total=  
3.4s  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf .....  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf, total= 5.  
8s  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf .....  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf, total= 5.  
8s  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf .....  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf, total= 5.  
8s  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf .....  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf, total= 5.  
8s  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf .....  
[CV] C=15415.161544891856, gamma=0.2691677514619319, kernel=rbf, total= 5.  
8s  
[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear ....  
[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear, total=  
3.8s  
[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear ....  
[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear, total=  
3.9s  
[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear ....  
[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear, total=  
3.8s  
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[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear, total=  
3.8s  
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[CV] C=1888.9148509967113, gamma=0.739678838777267, kernel=linear, total=



3.7s  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear .....  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear, total= 3.5s  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear .....  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear, total= 3.5s  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear .....  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear, total= 3.5s  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear .....  
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[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear .....  
[CV] C=55.53838911232773, gamma=0.578634378499143, kernel=linear, total= 3.5s  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf .....  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf, total= 5.6s  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf .....  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf, total= 5.6s  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf .....  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf, total= 5.6s  
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[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf, total= 5.6s  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf .....  
[CV] C=26.714480823948186, gamma=1.0117295509275495, kernel=rbf, total= 5.6s  
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[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear, total= 4.3s  
[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear ...  
[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear, total= 4.1s  
[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear ...  
[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear, total= 4.2s  
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[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear, total= 4.1s  
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[CV] C=3582.0552780489566, gamma=1.1891370222133257, kernel=linear, total= 4.0s  
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[CV] C=198.7004781812736, gamma=0.5282819748826726, kernel=linear, total= 3.5s  
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[CV] C=198.7004781812736, gamma=0.5282819748826726, kernel=linear, total=

3.5s  
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[CV] C=198.7004781812736, gamma=0.5282819748826726, kernel=linear, total= 3.5s  
3.5s  
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[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear, total= 3.6s  
3.6s  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear ....  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear, total= 3.5s  
3.5s  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear ....  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear, total= 3.6s  
3.6s  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear ....  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear, total= 3.5s  
3.5s  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear ....  
[CV] C=129.8000604143307, gamma=2.8621383676481322, kernel=linear, total= 3.5s  
3.5s  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf .....  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf, total= 5.7s  
5.7s  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf .....  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf, total= 5.7s  
5.7s  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf .....  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf, total= 5.7s  
5.7s  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf .....  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf, total= 5.7s  
5.7s  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf .....  
[CV] C=288.4269299593897, gamma=0.17580835850006285, kernel=rbf, total= 5.7s  
5.7s  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear ....  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear, total= 4.5s  
4.5s  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear ....  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear, total= 4.5s  
4.5s  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear ....  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear, total= 4.7s  
4.7s  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear ....  
[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear, total= 4.6s  
4.6s  
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[CV] C=6287.039489427172, gamma=0.3504567255332862, kernel=linear, total= 4.4s  
4.4s  
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .....  
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf, total= 21.8s  
21.8s  
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .....  
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25.0s  
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .....  
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf, total= 23.5s  
23.5s

```

S
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .....
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf, total= 24.3
S
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf .....
[CV] C=61217.04421344494, gamma=1.6279689407405564, kernel=rbf, total= 22.4
S
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf .....
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total= 5.9s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf .....
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total= 5.9s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf .....
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total= 5.8s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf .....
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total= 5.9s
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf .....
[CV] C=926.9787684096649, gamma=2.147979593060577, kernel=rbf, total= 5.9s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear .....
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total= 9.
2s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear .....
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total= 9.
0s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear .....
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total= 8.
3s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear .....
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total= 9.
4s
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear .....
[CV] C=33946.157064934, gamma=2.2642426492862313, kernel=linear, total= 8.
5s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total= 2
4.1s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total= 1
6.8s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total= 2
6.2s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total= 1
8.8s
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear ....
[CV] C=84789.82947739525, gamma=0.3176359085304841, kernel=linear, total= 1
4.3s

```

[Parallel(n\_jobs=1)]: Done 250 out of 250 | elapsed: 37.1min finished

```
Out[71]: RandomizedSearchCV(cv=5, estimator=SVR(), n_iter=50,  
                             param_distributions={'C': <scipy.stats._distn_infrastructu  
re.rv_frozen object at 0x000001B1001B40D0>,  
                             'gamma': <scipy.stats._distn_infrastr  
ucture.rv_frozen object at 0x000001B111B38DC0>,  
                             'kernel': ['linear', 'rbf']},  
                             random_state=42, scoring='neg_mean_squared_error',  
                             verbose=2)
```

```
In [73]: print(random_search.best_params_)  
print(random_search.best_estimator_)  
  
{'C': 157055.10989448498, 'gamma': 0.26497040005002437, 'kernel': 'rbf'}  
SVR(C=157055.10989448498, gamma=0.26497040005002437)
```

```
In [ ]: # This time the search found a good set of hyperparameters for the RBF kernel.  
# Randomized search tends to find better hyperparameters than grid search in t  
he same amount of time.
```

```
In [74]: # Random Search Evaluation Scores:  
negative_mse = random_search.best_score_  
rmse = np.sqrt(-negative_mse)  
print(rmse)
```

54767.960710084146

```
In [ ]: # This is getting a lot closer to the performance of the random tree regresso  
r, but it's still not as good.
```

```
In [75]: # Random Search Evaluation Cross Validation Scores:
cvres = random_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print(np.sqrt(-mean_score), params)
```

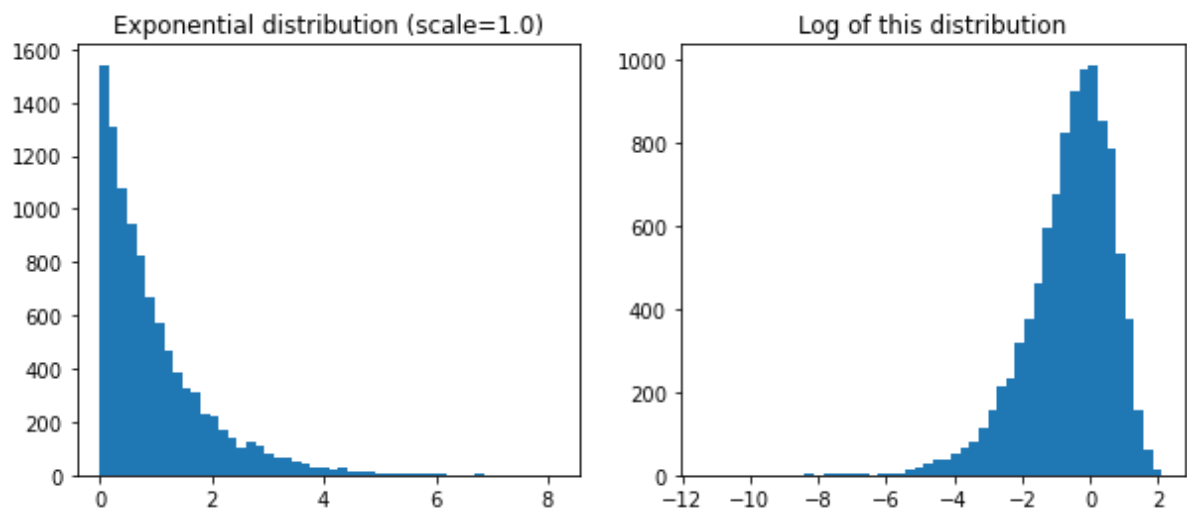
```
70487.7237017999 {'C': 629.782329591372, 'gamma': 3.010121430917521, 'kernel': 'linear'}
65152.0053324654 {'C': 26290.206464300216, 'gamma': 0.9084469696321253, 'kernel': 'rbf'}
100293.25860091094 {'C': 84.14107900575871, 'gamma': 0.059838768608680676, 'kernel': 'rbf'}
70574.10617249804 {'C': 432.37884813148855, 'gamma': 0.15416196746656105, 'kernel': 'linear'}
118838.9539854597 {'C': 24.17508294611391, 'gamma': 3.503557475158312, 'kernel': 'rbf'}
70029.31697470722 {'C': 113564.03940586245, 'gamma': 0.0007790692366582295, 'kernel': 'rbf'}
107662.7096409836 {'C': 108.30488238805073, 'gamma': 0.3627537294604771, 'kernel': 'rbf'}
77563.09297583395 {'C': 21.344953672647435, 'gamma': 0.023332523598323388, 'kernel': 'linear'}
62578.81054092114 {'C': 5603.270317432516, 'gamma': 0.15023452872733867, 'kernel': 'rbf'}
54767.960710084146 {'C': 157055.10989448498, 'gamma': 0.26497040005002437, 'kernel': 'rbf'}
70364.56459025714 {'C': 27652.464358739708, 'gamma': 0.2227358621286903, 'kernel': 'linear'}
70356.32992013592 {'C': 171377.39570378003, 'gamma': 0.628789100540856, 'kernel': 'linear'}
70374.9596621843 {'C': 5385.293820172355, 'gamma': 0.18696125197741642, 'kernel': 'linear'}
118802.64114676064 {'C': 22.59903216621323, 'gamma': 2.850796878935603, 'kernel': 'rbf'}
70362.58602083729 {'C': 34246.75194632794, 'gamma': 0.3632878599687583, 'kernel': 'linear'}
100450.29228566251 {'C': 167.7278956080511, 'gamma': 0.2757870542258224, 'kernel': 'rbf'}
72624.98934432027 {'C': 61.54360542501371, 'gamma': 0.6835472281341501, 'kernel': 'linear'}
111159.67724229675 {'C': 98.73897389920914, 'gamma': 0.4960365360493639, 'kernel': 'rbf'}
63169.93892419065 {'C': 8935.505635947808, 'gamma': 0.37354658165762367, 'kernel': 'rbf'}
71258.47476709314 {'C': 135.76775824842434, 'gamma': 0.838636245624803, 'kernel': 'linear'}
62838.44584088588 {'C': 151136.20282548846, 'gamma': 1.4922453771381408, 'kernel': 'rbf'}
70478.72525452363 {'C': 761.4316758498783, 'gamma': 2.6126336514161914, 'kernel': 'linear'}
70352.5125626773 {'C': 97392.81883041795, 'gamma': 0.09265545895311562, 'kernel': 'linear'}
70403.13959481634 {'C': 2423.0759984939164, 'gamma': 3.248614270240346, 'kernel': 'linear'}
70476.30827614202 {'C': 717.3632997255095, 'gamma': 0.3165604432088257, 'kernel': 'linear'}
106956.84165347065 {'C': 4446.667521184072, 'gamma': 3.3597284456608496, 'kernel': 'rbf'}
70395.28759239399 {'C': 2963.564121207815, 'gamma': 0.15189814782062885, 'kernel': 'linear'}
71759.26815837105 {'C': 91.64267381686706, 'gamma': 0.01575994483585621, 'kernel': 'linear'}
57812.89042268699 {'C': 24547.601975705915, 'gamma': 0.22153944050588595, 'kernel': 'linear'}
```

```

rnel': 'rbf'}
114677.53379803285 {'C': 22.76927941060928, 'gamma': 0.22169760231351215, 'ke
rnel': 'rbf'}
70370.76656627818 {'C': 16483.850529752886, 'gamma': 1.4752145260435134, 'ker
nel': 'linear'}
60052.28891896938 {'C': 101445.66881340064, 'gamma': 1.052904084582266, 'kern
el': 'rbf'}
61481.27261343283 {'C': 56681.80859029545, 'gamma': 0.9763011917123741, 'kern
el': 'rbf'}
114571.2386400452 {'C': 48.15822390928914, 'gamma': 0.4633351167983427, 'kern
el': 'rbf'}
111660.72456364948 {'C': 399.7268155705774, 'gamma': 1.3078757839577408, 'ker
nel': 'rbf'}
70769.46638036826 {'C': 251.14073886281363, 'gamma': 0.8238105204914145, 'ker
nel': 'linear'}
72677.26222787892 {'C': 60.17373642891687, 'gamma': 1.2491263443165994, 'kern
el': 'linear'}
59278.486452716556 {'C': 15415.161544891856, 'gamma': 0.2691677514619319, 'ke
rnel': 'rbf'}
70408.73062596374 {'C': 1888.9148509967113, 'gamma': 0.739678838777267, 'kern
el': 'linear'}
72902.98919438479 {'C': 55.53838911232773, 'gamma': 0.578634378499143, 'kerne
l': 'linear'}
118062.4067893129 {'C': 26.714480823948186, 'gamma': 1.0117295509275495, 'ker
nel': 'rbf'}
70386.9630554019 {'C': 3582.0552780489566, 'gamma': 1.1891370222133257, 'kern
el': 'linear'}
70919.0290566038 {'C': 198.7004781812736, 'gamma': 0.5282819748826726, 'kerne
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71312.85405560398 {'C': 129.8000604143307, 'gamma': 2.8621383676481322, 'kern
el': 'linear'}
89483.75607147012 {'C': 288.4269299593897, 'gamma': 0.17580835850006285, 'ker
nel': 'rbf'}
70378.47205891725 {'C': 6287.039489427172, 'gamma': 0.3504567255332862, 'kern
el': 'linear'}
68027.93134796123 {'C': 61217.04421344494, 'gamma': 1.6279689407405564, 'kern
el': 'rbf'}
111760.98691537287 {'C': 926.9787684096649, 'gamma': 2.147979593060577, 'kern
el': 'rbf'}
70362.66297948634 {'C': 33946.157064934, 'gamma': 2.2642426492862313, 'kerne
l': 'linear'}
70352.83535012191 {'C': 84789.82947739525, 'gamma': 0.3176359085304841, 'kern
el': 'linear'}
```

```
In [76]: # Let's look at the exponential distribution we used, with scale=1.0. Note that some samples are much larger or  
# smaller than 1.0, but when you look at the log of the distribution, you can see that most values are actually  
# concentrated roughly in the range of  $\exp(-2)$  to  $\exp(+2)$ , which is about 0.1 to 7.4.
```

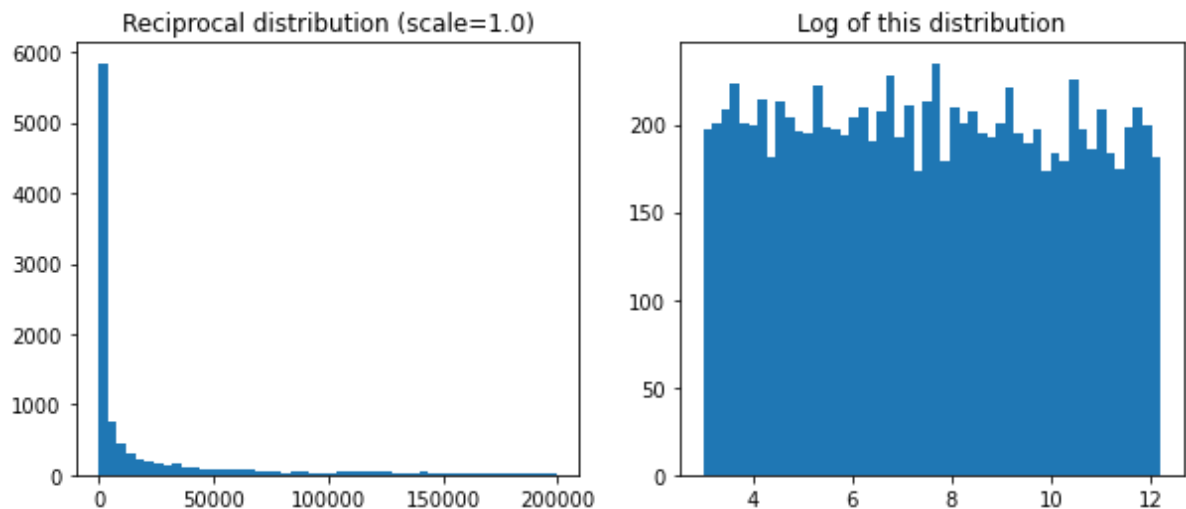
```
expon_distrib = expon(scale=1.)  
samples = expon_distrib.rvs(10000, random_state=42)  
plt.figure(figsize=(10, 4))  
plt.subplot(121)  
plt.title("Exponential distribution (scale=1.0)")  
plt.hist(samples, bins=50)  
plt.subplot(122)  
plt.title("Log of this distribution")  
plt.hist(np.log(samples), bins=50)  
plt.show()
```





```
In [77]: # The distribution we used for C looks quite different: the scale of the samples
# is picked from a uniform distribution
# within a given range, which is why the right graph, which represents the log
# of the samples, looks roughly constant.
# This distribution is useful when you don't have a clue of what the target scale is:

reciprocal_distrib = reciprocal(20, 200000)
samples = reciprocal_distrib.rvs(10000, random_state=42)
plt.figure(figsize=(10, 4))
plt.subplot(121)
plt.title("Reciprocal distribution (scale=1.0)")
plt.hist(samples, bins=50)
plt.subplot(122)
plt.title("Log of this distribution")
plt.hist(np.log(samples), bins=50)
plt.show()
```



```
In [78]: # The reciprocal distribution is useful when you have no idea what the scale of
# the hyperparameter should be
# (indeed, as you can see on the figure on the right, all scales are equally likely,
# within the given range),
# whereas the exponential distribution is best when you know (more or less) what
# the scale of the hyperparameter should be.
```

### 3. Try adding a transformer in the preparation pipeline to select only the most important attributes

```
In [91]: def indices_of_top_k(array, k):
        return np.sort(np.argpartition(np.array(array), -k)[-k:])

class TopFeatureSelector(BaseEstimator, TransformerMixin):
    def __init__(self, feature_importances, k):
        self.feature_importances = feature_importances
        self.k = k
    def fit(self, X, y=None):
        self.feature_indices_ = indices_of_top_k(self.feature_importances, self.k)
        return self
    def transform(self, X):
        return X[:, self.feature_indices_]

# Note that this feature selector assumes you have already computed the feature importances
```

```
In [92]: k = 5
        top_k_feature_indices = indices_of_top_k(random_tree_reg_feature_importances, k)
        top_k_feature_indices
```

```
Out[92]: array([ 0,  7,  9, 10, 12], dtype=int64)
```

```
In [93]: np.array(attributes)[top_k_feature_indices]
```

```
Out[93]: array(['longitude', 'median_income', 'pop_per_hhold', 'bedrooms_per_room',
                'INLAND'], dtype='<U19')
```

```
In [94]: # Let's double check that these are indeed the top k features:
        sorted(zip(random_tree_reg_feature_importances, attributes), reverse=True)[:k]
```

```
Out[94]: [(0.32820383909931383, 'median_income'),
          (0.143077997543386, 'INLAND'),
          (0.10804589057862227, 'pop_per_hhold'),
          (0.08119879731256048, 'longitude'),
          (0.080087908597283, 'bedrooms_per_room')]
```

```
In [95]: # Now let's create a new pipeline that runs the previously defined preparation pipeline, and adds top k feature selection:
        preparation_and_feature_selection_pipeline = Pipeline([
            ('preparation', full_pipeline),
            ('feature_selection', TopFeatureSelector(random_tree_reg_feature_importances, k))
        ])
```

```
In [96]: housing_prepared_top_k_features = preparation_and_feature_selection_pipeline.fit_transform(housing)
```

```
In [97]: # To check, Let's look at the features of the first 3 instances and compare them to the top k features
housing_prepared_top_k_features[0:3]

Out[97]: array([[ -1.15604281,  -0.61493744,  -0.08649871,   0.15531753,   0.          ],
                [ -1.17602483,   1.33645936,  -0.03353391,  -0.83628902,   0.          ],
                [  1.18684903,  -0.5320456 ,  -0.09240499,   0.4222004 ,   0.          ]])

In [98]: housing_prepared[0:3, top_k_feature_indices]

Out[98]: array([[ -1.15604281,  -0.61493744,  -0.08649871,   0.15531753,   0.          ],
                [ -1.17602483,   1.33645936,  -0.03353391,  -0.83628902,   0.          ],
                [  1.18684903,  -0.5320456 ,  -0.09240499,   0.4222004 ,   0.          ]])

In [99]: # They match, Looks good!
```

## 4. Try creating a single pipeline that does the full data preparation plus the final prediction

```
In [117]: prepare_and_select_and_predict_pipeline = Pipeline([
            ('preparation', full_pipeline),
            ('feature_selection', TopFeatureSelector(feature_importances, k)),
            ('random_forest', RandomForestRegressor(n_estimators = 100)) # These parameters are from above
        ])
```

```
In [118]: prepare_and_select_and_predict_pipeline.fit(housing, housing_labels)
```

```
Out[118]: Pipeline(steps=[('preparation',
                             ColumnTransformer(transformers=[('num',
                                                                 Pipeline(steps=[('imputer',
                                                                 SimpleImputer(
strategy='median')),
                                                                 ('attribs_adder',
                                                                 CombinedAttributesAdder()),
                                                                 ('std_scaler',
                                                                 StandardScaler())]),
                                                                 ['longitude', 'latitude',
                                                                 'housing_median_age',
                                                                 'total_rooms',
                                                                 'total_bedrooms',
                                                                 'population', 'household
s',
                                                                 'median_income']),
                                                                 ('cat', OneHotEncoder(...
('feature_selection',
TopFeatureSelector(feature_importances=array([8.11987973e-0
2, 7.49994545e-02, 4.26313932e-02, 1.68069388e-02,
1.56017401e-02, 1.65650352e-02, 1.56470978e-02, 3.28203839e-01,
5.46998513e-02, 1.08045891e-01, 8.00879086e-02, 1.31052196e-02,
1.43077998e-01, 7.35183616e-05, 4.23486740e-03, 5.02045066e-03])),
k=5)),
('random_forest', RandomForestRegressor())])])
```

```
In [119]: # Let's try the full pipeline on a few instances:

some_data = housing.iloc[:4]
some_labels = housing_labels.iloc[:4]

print("Predictions:\t", prepare_and_select_and_predict_pipeline.predict(some_data))
print("Labels:\t\t", list(some_labels))

Predictions:      [264037.   342019.01 209587.    52427. ]
Labels:          [286600.0, 340600.0, 196900.0, 46300.0]
```

```
In [120]: # We can see that the full pipeline is working
```

## 5. Automatically explore some preparation options using GridSearchCV

```
In [121]: param_grid = [{
            'preparation__num__imputer__strategy': ['mean', 'median', 'most_frequent'
            ],
            'feature_selection__k': list(range(1, len(feature_importances) + 1))
        }]

grid_search_prep = GridSearchCV(prepare_and_select_and_predict_pipeline, param
_grid, cv=5,
                                scoring='neg_mean_squared_error', verbose=2)
grid_search_prep.fit(housing, housing_labels)
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worke
rs.

[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean, total
= 1.2s
[CV] feature_selection__k=1, preparation__num__imputer__strategy=mean

[Parallel(n_jobs=1)]: Done 1 out of 1 | elapsed: 1.1s remaining: 0.
0s
```

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[illegible]

```
[feature_selection_k=4, preparation_num_imputer_strategy=median, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=median]
[CV feature_selection_k=4, preparation_num_imputer_strategy=median, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=most_frequent, total= 2.4s]
[CV feature_selection_k=4, preparation_num_imputer_strategy=mean, total= 3.1s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=mean, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=mean, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=mean, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=mean, total= 3.1s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=mean, total= 3.1s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=mean, total= 3.1s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=median, total= 3.1s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=median, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=median, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=median, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=median, total= 3.0s]
[CV feature_selection_k=5, preparation_num_imputer_strategy=median, total= 3.0s]
```

[illegible]

```

t
[CV] feature_selection__k=6, preparation_num_imputer_strategy=most_frequent, total= 3.5s
[CV] feature_selection__k=6, preparation_num_imputer_strategy=most_frequent
t
[CV] feature_selection__k=6, preparation_num_imputer_strategy=most_frequent, total= 3.5s
[CV] feature_selection__k=6, preparation_num_imputer_strategy=most_frequent
t
[CV] feature_selection__k=6, preparation_num_imputer_strategy=most_frequent, total= 3.5s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean, total = 4.2s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean, total = 4.2s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean, total = 4.2s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean, total = 4.2s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=7, preparation_num_imputer_strategy=mean, total = 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median, total= 4.2s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median
[CV] feature_selection__k=7, preparation_num_imputer_strategy=median, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent
t
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent
t
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent
t
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent, total= 4.1s
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent
t
[CV] feature_selection__k=7, preparation_num_imputer_strategy=most_frequent, total= 4.1s

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```
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean, total
= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean, total
= 5.2s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean, total
= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=9, preparation_num_imputer_strategy=mean, total
= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median, tot
al= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median, tot
al= 5.2s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median, tot
al= 5.2s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median, tot
al= 5.2s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median
[CV] feature_selection_k=9, preparation_num_imputer_strategy=median, tot
al= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t, total= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t, total= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t, total= 5.1s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t, total= 5.2s
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t
[CV] feature_selection_k=9, preparation_num_imputer_strategy=most_frequen
t, total= 5.2s
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean, tota
l= 5.8s
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean, tota
l= 5.7s
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean, tota
l= 5.8s
[CV] feature_selection_k=10, preparation_num_imputer_strategy=mean
```

[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=mean, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=mean, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median, total= 5.8s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=median, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent, total= 5.7s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent, total= 5.8s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent, total= 5.8s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent, total= 5.8s  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=10, preparation\_num\_imputer\_strategy=most\_frequent, total= 5.7s  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean, total= 6.3s  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean, total= 6.3s  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean, total= 6.3s  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean, total= 6.4s  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=mean, total= 6.3s  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=11, preparation\_num\_imputer\_strategy=median, to

```

tal= 6.3s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median, to
tal= 6.4s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median, to
tal= 6.3s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median, to
tal= 6.3s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median
[CV] feature_selection__k=11, preparation_num_imputer_strategy=median, to
tal= 6.3s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent, total= 6.4s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent, total= 6.3s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent, total= 6.2s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent, total= 6.3s
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=11, preparation_num_imputer_strategy=most_frequ
ent, total= 6.2s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean, tota
l= 6.8s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean, tota
l= 7.0s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean, tota
l= 6.9s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean, tota
l= 7.0s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=12, preparation_num_imputer_strategy=mean, tota
l= 6.8s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=median
[CV] feature_selection__k=12, preparation_num_imputer_strategy=median, to
tal= 6.9s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=median
[CV] feature_selection__k=12, preparation_num_imputer_strategy=median, to
tal= 6.8s
[CV] feature_selection__k=12, preparation_num_imputer_strategy=median
[CV] feature_selection__k=12, preparation_num_imputer_strategy=median, to
tal= 6.9s

```



[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=median, total= 6.9s  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=median, total= 6.8s  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent, total= 6.8s  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent, total= 6.8s  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent, total= 6.8s  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent, total= 6.8s  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent  
[CV] feature\_selection\_k=12, preparation\_num\_imputer\_strategy=most\_frequent, total= 6.8s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean, total= 7.0s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean, total= 7.0s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean, total= 7.0s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean, total= 7.0s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=mean, total= 6.9s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median, total= 6.9s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median, total= 6.9s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median, total= 7.0s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=median, total= 7.1s  
[CV] feature\_selection\_k=13, preparation\_num\_imputer\_strategy=most\_frequent

```

nt
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent, total= 7.1s
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent, total= 7.3s
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent, total= 7.2s
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent, total= 7.3s
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=13, preparation_num_imputer_strategy=most_frequ
ent, total= 7.2s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean, tota
l= 7.3s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean, tota
l= 7.1s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean, tota
l= 7.1s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean, tota
l= 7.1s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean
[CV] feature_selection__k=14, preparation_num_imputer_strategy=mean, tota
l= 7.0s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median, to
tal= 7.0s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median, to
tal= 7.0s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median, to
tal= 7.0s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median, to
tal= 7.1s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median
[CV] feature_selection__k=14, preparation_num_imputer_strategy=median, to
tal= 7.0s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=14, preparation_num_imputer_strategy=most_frequ
ent, total= 7.0s
[CV] feature_selection__k=14, preparation_num_imputer_strategy=most_frequ
ent
[CV] feature_selection__k=14, preparation_num_imputer_strategy=most_frequ
ent, total= 7.0s

```

```
[CV] feature_selection_k=14, preparation_num_imputer_strategy=most_frequent, total= 7.0s
[CV] feature_selection_k=14, preparation_num_imputer_strategy=most_frequent, total= 7.0s
[CV] feature_selection_k=14, preparation_num_imputer_strategy=most_frequent, total= 7.0s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=mean, total= 7.0s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=mean, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=mean, total= 7.0s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=mean, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=mean, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=median, total= 7.0s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=median, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=median, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=median, total= 7.2s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=median, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=most_frequent, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=most_frequent, total= 7.1s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=most_frequent, total= 7.0s
[CV] feature_selection_k=15, preparation_num_imputer_strategy=most_frequent, total= 7.0s
```

[illegible]

```
[Parallel(n_jobs=1)]: Done 240 out of 240 | elapsed: 18.6min finished
```

```

Out[121]: GridSearchCV(cv=5,
                        estimator=Pipeline(steps=[('preparation',
                                                    ColumnTransformer(transformers=[('nu
m',
                                                                                               Pipe
line(steps=[('imputer',
SimpleImputer(strategy='median')),
('attrs_adder',
CombinedAttributesAdder()),
('std_scaler',
StandardScaler())])),
('longitude',
('latitude',
('housing_median_age',
('total_rooms',
('total_bedrooms',
('population',
('households',
('median_income...',
5.46998513e-02, 1.08045891e-01, 8.00879086e-02, 1.31052196e-02,
1.43077998e-01, 7.35183616e-05, 4.23486740e-03, 5.02045066e-03])),
('random_forest',
RandomForestRegressor()))]),
param_grid=[{'feature_selection_k': [1, 2, 3, 4, 5, 6, 7, 8, 9,
10, 11, 12, 13, 14, 15, 16],
'preparation_num_imputer_strategy': ['mean',
'median',
'most_frequent']}]},
scoring='neg_mean_squared_error', verbose=2)

```

```
In [122]: grid_search_prep.best_params_
```

```
Out[122]: {'feature_selection_k': 8, 'preparation_num_imputer_strategy': 'median'}
```

```
In [124]: # Above it looks like 'median' is the best imputer strategy and 8 features are useful.  
  
# In the solutions:  
# The best imputer strategy is 'most_frequent' and almost all the features are useful (15 out of 16)  
# The last one (ISLAND) just seems to add noise
```