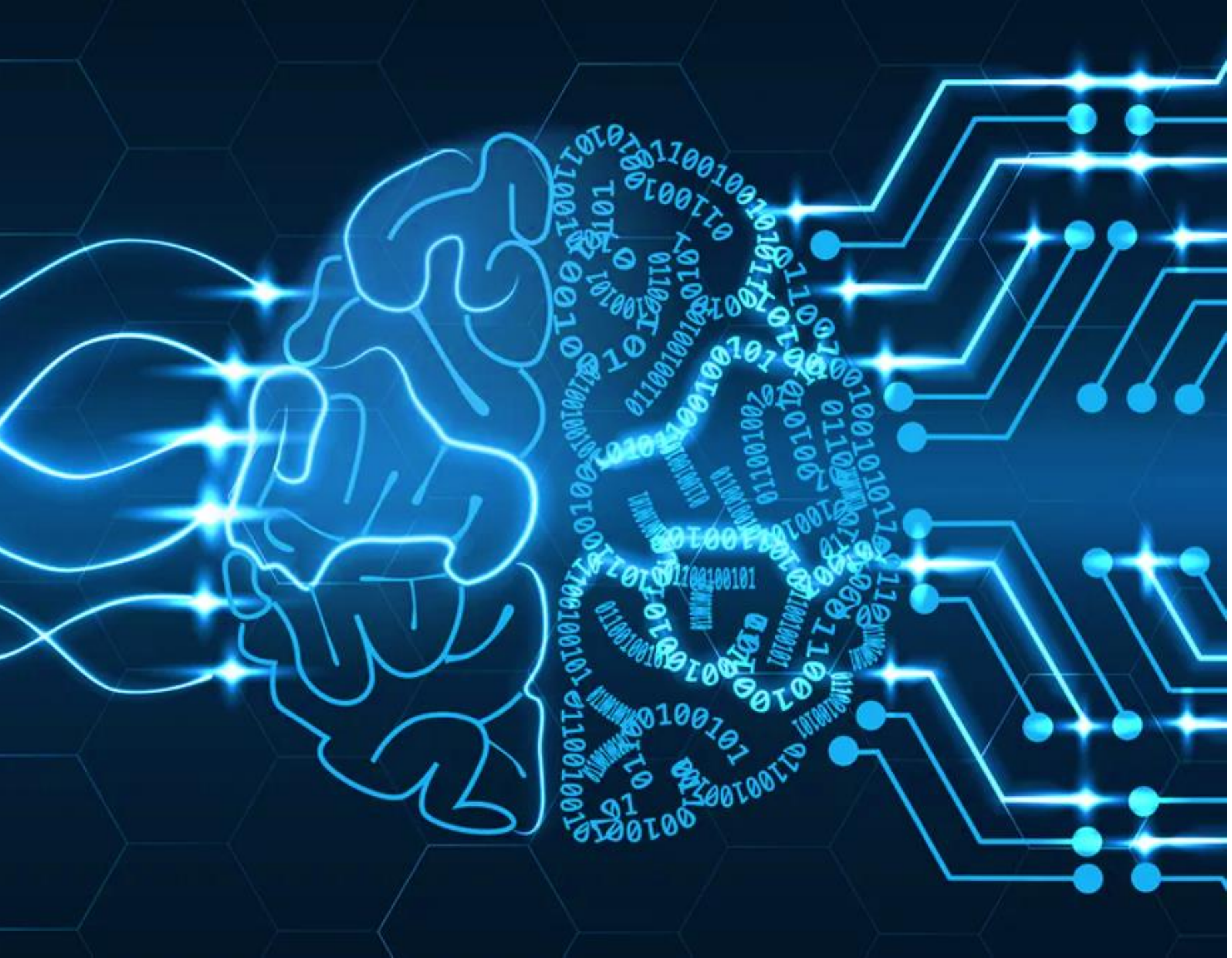


آماده سازی داده در یادگیری ماشین

دکتر مهدی شریف‌زاده
سعیدرضا زواشکیانی
بهمن ۱۴۰۱


بسم الله الرحمن الرحیم

End-to-End Machine Learning Projects

- ✓ In this chapter, we cover the entire process of building a machine learning model with a focus on end-to-end projects. We cover subtopics including:
  - ✓ Framing the Problem
  - ✓ Selection of Performance Metric
  - ✓ Splitting Data
  - ✓ Exploratory Data Analysis
  - ✓ Train & Fine-Tune Model
  - ✓ Launch, Monitor, and Maintain System
- ✓ The goal is to develop a deep understanding of each step and its importance in creating an effective machine learning solution.

End-to-End Machine Learning Projects

In this chapter you will work through an example project end to end, pretending to be a recently hired data scientist at a real estate company. Here are the main steps you will go through:

1. Look at the big picture.
2. Get the data.
3. Discover and visualize the data to gain insights.
4. Prepare the data for Machine Learning algorithms.
5. Select a model and train it.
6. Fine-tune your model.
7. Present your solution.
8. Launch, monitor, and maintain your system .

Working with Real Data

When you are learning about Machine Learning, it is best to experiment with real-world data, not artificial datasets.
In this chapter we'll use the California Housing Prices dataset from the StatLib repository.
This dataset is based on data from the 1990 California census. For teaching purposes I've added a categorical attribute and removed a few features.

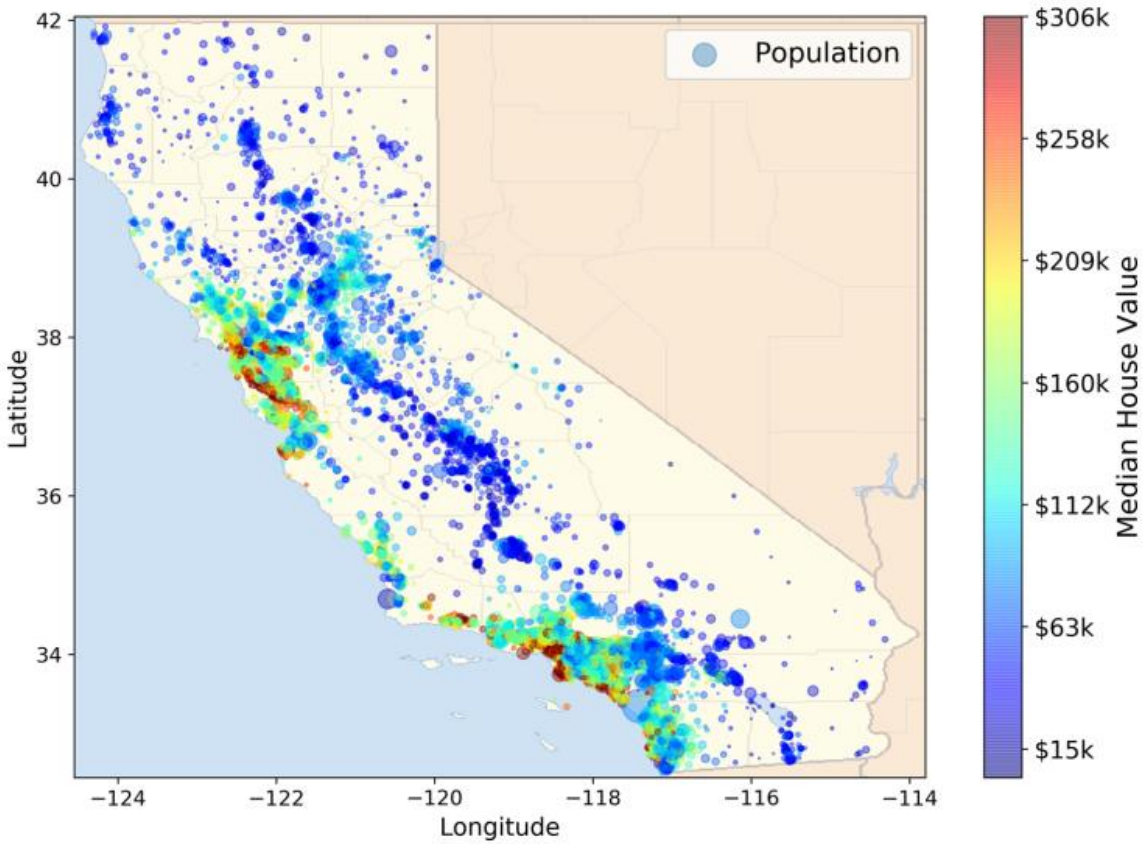


Figure 2-1. California housing prices

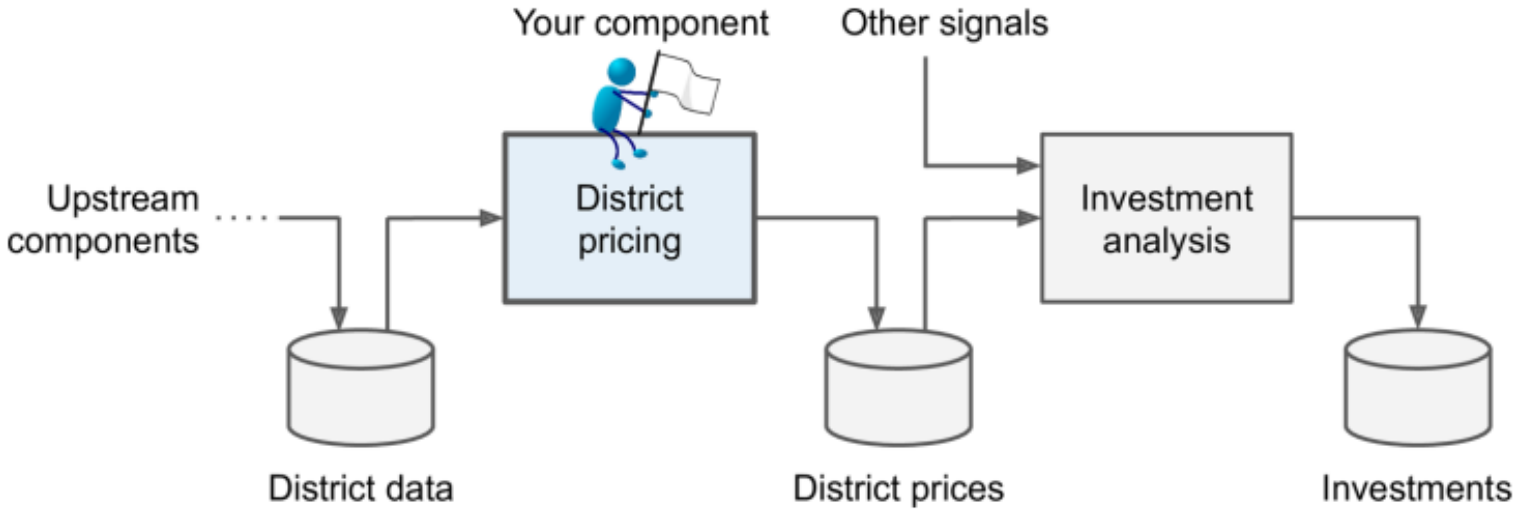
Look at the Big Picture

We use California census data to build a model of housing prices in the state. This data includes metrics such as the population, median income, and median housing price for each block group in California. Block groups are the smallest geographical unit for which the US Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people). We will call them “districts” for short.
Your model should learn from this data and be able to predict the median housing price in any district, given all the other metrics

Frame the Problem

The first question to is what exactly the objective is. Building a model is probably not the end goal. How do you expect to use and benefit from this model? Knowing the objective is important because it will determine how you frame the problem, which algorithms you will select, which performance measure you will use to evaluate your model, and how much effort you will spend tweaking it.

Suppose that your model's output (a prediction of a district's median housing price) will be fed to another Machine Learning system (see the figure), along with many other signals. This downstream system will determine whether it is worth investing in a given area or not. Getting this right is critical, as it directly affects revenue



Frame the Problem

The next question to is what the current solution looks like (if any). The current situation will often give you a reference for performance, as well as insights on how to solve the problem. By questioning people you realize that the district housing prices are currently estimated manually by experts: a team gathers up-to-date information about a district, and when they cannot get the median housing price, they estimate it using complex rules.

This is costly and time-consuming, and their estimates are not great; in cases where they manage to find out the actual median housing price, they often realize that their estimates were off by more than 20%. This is why it would be useful to train a model to predict a district's median housing price, given other data about that district. The census data looks like a great dataset to exploit for this purpose, since it includes the median housing prices of thousands of districts, as well as other data

Frame the Problem

With all this information, you need to frame the problem: is it supervised, unsupervised, or Reinforcement Learning? Is it a classification task, a regression task, or something else? Should you use batch learning or online learning techniques?

Frame the Problem

It is clearly a typical supervised learning task, since you are given *labeled* training examples (each instance comes with the expected output, i.e., the district's median housing price). It is also a typical regression task, since you are asked to predict a value. More specifically, this is a *multiple regression* problem, since the system will use multiple features to make a prediction (it will use the district's population, the median income, etc.). It is also a *univariate regression* problem, since we are only trying to predict a single value for each district. If we were trying to predict multiple values per district, it would be a *multivariate regression* problem. Finally, there is no continuous flow of data coming into the system, there is no particular need to adjust to changing data rapidly, and the data is small enough to fit in memory, so plain batch learning should do just fine.

Select a Performance Measure

The next step is to select a performance measure. A typical performance measure for regression problems is the Root Mean Square Error (RMSE). It gives an idea of how much error the system typically makes in its predictions, with a higher weight for large errors. This equation shows the mathematical formula to compute the RMSE

$$\mathrm{RMSE}\left(\mathbf{X}, h\right) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(h\left(\mathbf{x}^{(i)}\right) - y^{(i)}\right)^2}$$

Select a Performance Measure

$$\text{RMSE}(\mathbf{X}, h) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(h\left(\mathbf{x}^{(i)}\right) - y^{(i)}\right)^2}$$

- m is the number of instances in the dataset you are measuring the RMSE on.
  For example, if you are evaluating the RMSE on a validation set of 2,000 districts, then $m = 2{,}000$.
- $\boldsymbol{x}^{(i)}$ is a vector of all the feature values (excluding the label) of the i^{th} instance in the dataset, and $y^{(i)}$ is its label (the desired output value for that instance)
  For example, if the first district in the dataset is located at longitude –118.29°, latitude 33.91°, and it has 1,416 inhabitants with a median income of $38,372, and the median house value is $156,400 (ignoring the other features for now), then:

$$\boldsymbol{x}^{(1)} = \begin{pmatrix} -118.29 \\ 33.91 \\ 1{,}416 \\ 38{,}372 \end{pmatrix} \text{ and } y^{(1)} = 156{,}400$$

Select a Performance Measure

$$\text{RMSE}(\mathbf{X}, h) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(h\left(\mathbf{x}^{(i)}\right) - y^{(i)}\right)^2}$$

- $\boldsymbol{X}$ is a matrix containing all the feature values (excluding labels) of all instances in the dataset. There is one row per instance, and the i^{th} row is equal to the transpose of $\boldsymbol{x}^{(i)}$, noted $\left(\boldsymbol{x}^{(i)}\right)^T$.

  For example, if the first district is as just described, then the matrix **X** looks like this:

$$\boldsymbol{X} = \begin{pmatrix} \left(\boldsymbol{x}^{(1)}\right)^T \\ \left(\boldsymbol{x}^{(2)}\right)^T \\ \vdots \\ \left(\boldsymbol{x}^{(1999)}\right)^T \\ \left(\boldsymbol{x}^{(2000)}\right)^T \end{pmatrix} = \begin{pmatrix} -118.29 & 33.91 & 1{,}416 & 38{,}372 \\ \vdots & \vdots & \vdots & \vdots \end{pmatrix}$$

Select a Performance Measure

$$\text{RMSE}(\mathbf{X}, h) = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(h\left(\mathbf{x}^{(i)}\right) - y^{(i)}\right)^2}$$

- h is your system's prediction function, also called a *hypothesis*. When your system is given an instance's feature vector $\boldsymbol{x}^{(i)}$, it outputs a predicted value $\hat{y}^{(i)} = h(\boldsymbol{x}^{(i)})$ for that instance ($\hat{y}$ is pronounced "y-hat").

  For example, if your system predicts that the median housing price in the first district is \$158,400, then $\hat{y}^{(1)} = h(\boldsymbol{x}^{(1)}) = 158{,}400$. The prediction error for this district is $\hat{y}^{(1)} - y^{(1)} = 2{,}000$.
- $RMSE(\boldsymbol{X}, h)$ is the cost function measured on the set of examples using your hypothesis *h*.
- We use lowercase italic font for scalar values (such as m or y) and function names (such as h), lowercase bold font for vectors (such as $\boldsymbol{x}^{(i)}$), and uppercase bold font for matrices (such as $\boldsymbol{X}$)

Select a Performance Measure

Even though the RMSE is generally the preferred performance measure for regression tasks, in some contexts you may prefer to use another function. For example, suppose that there are many outlier districts. In that case, you may consider using the *mean absolute error* (MAE, also called the average absolute deviation)

$$\mathrm{MAE}\left(\mathbf{X}, h\right) = \frac{1}{m}\sum_{i=1}^{m}\left|h\left(\mathbf{x}^{(i)}\right) - y^{(i)}\right|$$

Check the Assumptions

Lastly, it is good practice to list and verify the assumptions that have been made so far (by you or others); this can help you catch serious issues early on. For example, the district prices that your system outputs are going to be fed into a downstream Machine Learning system, and you assume that these prices are going to be used as such. But what if the downstream system converts the prices into categories (e.g., “cheap,” “medium,” or “expensive”) and then uses those categories instead of the prices themselves? In this case, getting the price perfectly right is not important at all; your system just needs to get the category right. If that’s so, then the problem should have been framed as a classification task, not a regression task. You don’t want to find this out after working on a regression system for months

Get Into Coding!

First download the data (All you need to know about this code is that it downloads the dataset as a csv file)
Now when you call fetch_housing_data(), it creates a *datasets/housing* directory in your workspace, downloads the *housing.tgz* file, and extracts the *housing.csv* file from it in this directory.

```
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()
```

Get Into Coding!

Now let’s load the data using pandas. Once again, you should write a small function to load the data:

```
import pandas as pd

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

Let’s take a look at the top five rows using the DataFrame’s head() method

```
In [5]: housing = load_housing_data()
        housing.head()
```

Out[5]:

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

Get Into Coding!

Each row represents one district. There are 10 attributes (you can see the first 6 in the screenshot): longitude, latitude, housing_median_age, total_rooms, total_bedrooms, population, households, median_income, median_house_value, and ocean_proximity

```
In [5]: housing = load_housing_data()
        housing.head()
```

Out[5]:

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

Get Into Coding!

The info() method is useful to get a quick description of the data, in particular the total number of rows, each attribute's type, and the number of nonnull values

There are 20,640 instances in the dataset, which means that it is fairly small by Machine Learning standards, but it's perfect to get started. Notice that the total_bedrooms attribute has only 20,433 nonnull values, meaning that 207 districts are missing this feature. We will need to take care of this later.

```
In [6]: housing.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

Get Into Coding!

All attributes are numerical, except the ocean_proximity field. Its type is object, so it could hold any kind of Python object. But since you loaded this data from a CSV file, you know that it must be a text attribute. When you looked at the top five rows, you probably noticed that the values in the ocean_proximity column were repetitive, which means that it is probably a categorical attribute. You can find out what categories exist and how many districts belong to each category by using the value_counts() method:

```
>>> housing["ocean_proximity"].value_counts()
<1H OCEAN     9136
INLAND        6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND           5
Name: ocean_proximity, dtype: int64
```

Get Into Coding!

Let’s look at the other fields. The describe() method shows a summary of the numerical attributes .

Note that the null values are ignored (so, for example, the count of total_bedrooms is 20,433, not 20,640)

```
In [8]: housing.describe()
```

Out[8]:

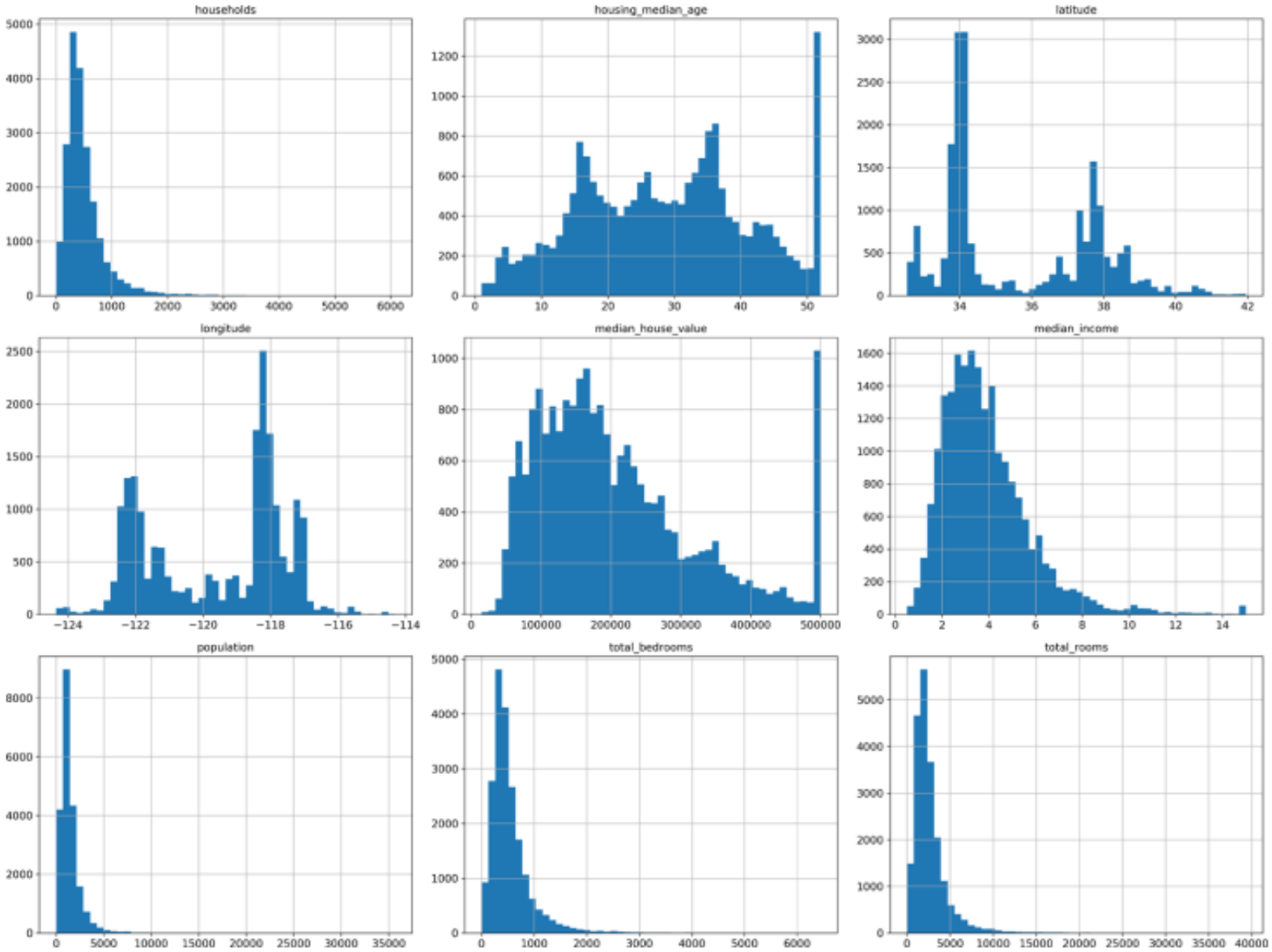
	longitude	latitude	housing_median_age	total_rooms	total_bedr
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000(
mean	-119.569704	35.631861	28.639486	2635.763081	537.87055(
std	2.003532	2.135952	12.585558	2181.615252	421.38507(
min	-124.350000	32.540000	1.000000	2.000000	1.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.00000(
50%	-118.490000	34.260000	29.000000	2127.000000	435.00000(
75%	-118.010000	37.710000	37.000000	3148.000000	647.00000(
max	-114.310000	41.950000	52.000000	39320.000000	6445.0000(

Get Into Coding!

Another quick way to get a feel of the type of data you are dealing with is to plot a histogram for each numerical attribute. A histogram shows the number of instances (on the vertical axis) that have a given value range (on the horizontal axis). You can either plot this one attribute at a time, or you can call the hist() method on the whole dataset (as shown in the following code example), and it will plot a histogram for each numerical attribute

```
%matplotlib inline   # only in a Jupyter notebook
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
plt.show()
```

Get Into Coding!



Create a Test Set

It may sound strange to voluntarily set aside part of the data at this stage. After all, you have only taken a quick glance at the data, and surely you should learn a whole lot more about it before you decide what algorithms to use, right? This is true, but your brain is an amazing pattern detection system, which means that it is highly prone to overfitting: if you look at the test set, you may stumble upon some seemingly interesting pattern in the test data that leads you to select a particular kind of Machine Learning model. When you estimate the generalization error using the test set, your estimate will be too optimistic, and you will launch a system that will not perform as well as expected. This is called *data snooping* bias.

Creating a test set is theoretically simple: pick some instances randomly, typically 20% of the dataset (or less if your dataset is very large), and set them aside:

Create a Test Set

```
import numpy as np

def split_train_test(data, test_ratio):
    shuffled_indices = np.random.permutation(len(data))
    test_set_size = int(len(data) * test_ratio)
    test_indices = shuffled_indices[:test_set_size]
    train_indices = shuffled_indices[test_set_size:]
    return data.iloc[train_indices], data.iloc[test_indices]

>>> train_set, test_set = split_train_test(housing, 0.2)
>>> len(train_set)
16512
>>> len(test_set)
4128
```

Create a Test Set

Scikit-Learn provides a few functions to split datasets into multiple subsets in various ways. The simplest function is train_test_split(), which does pretty much the same thing as the function split_train_test(), with a couple of additional features. First, there is a random_state parameter that allows you to set the random generator seed. Second, you can pass it multiple datasets with an identical number of rows, and it will split them on the same indices (this is very useful, for example, if you have a separate DataFrame for labels):

```
from sklearn.model_selection import train_test_split

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

Create a Test Set

So far we have considered purely random sampling methods. This is generally fine if your dataset is large enough (especially relative to the number of attributes), but if it is not, you run the risk of introducing a significant sampling bias. When a survey company decides to call 1,000 people to ask them a few questions, they don't just pick 1,000 people randomly in a phone book. They try to ensure that these 1,000 people are representative of the whole population. For example, the US population is 51.3% females and 48.7% males, so a well-conducted survey in the US would try to maintain this ratio in the sample: 513 female and 487 male. This is called *stratified sampling*: the population is divided into homogeneous subgroups called *strata*, and the right number of instances are sampled from each stratum to guarantee that the test set is representative of the overall population. If the people running the survey used purely random sampling, there would be about a 12% chance of sampling a skewed test set that was either less than 49% female or more than 54% female. Either way, the survey results would be significantly biased

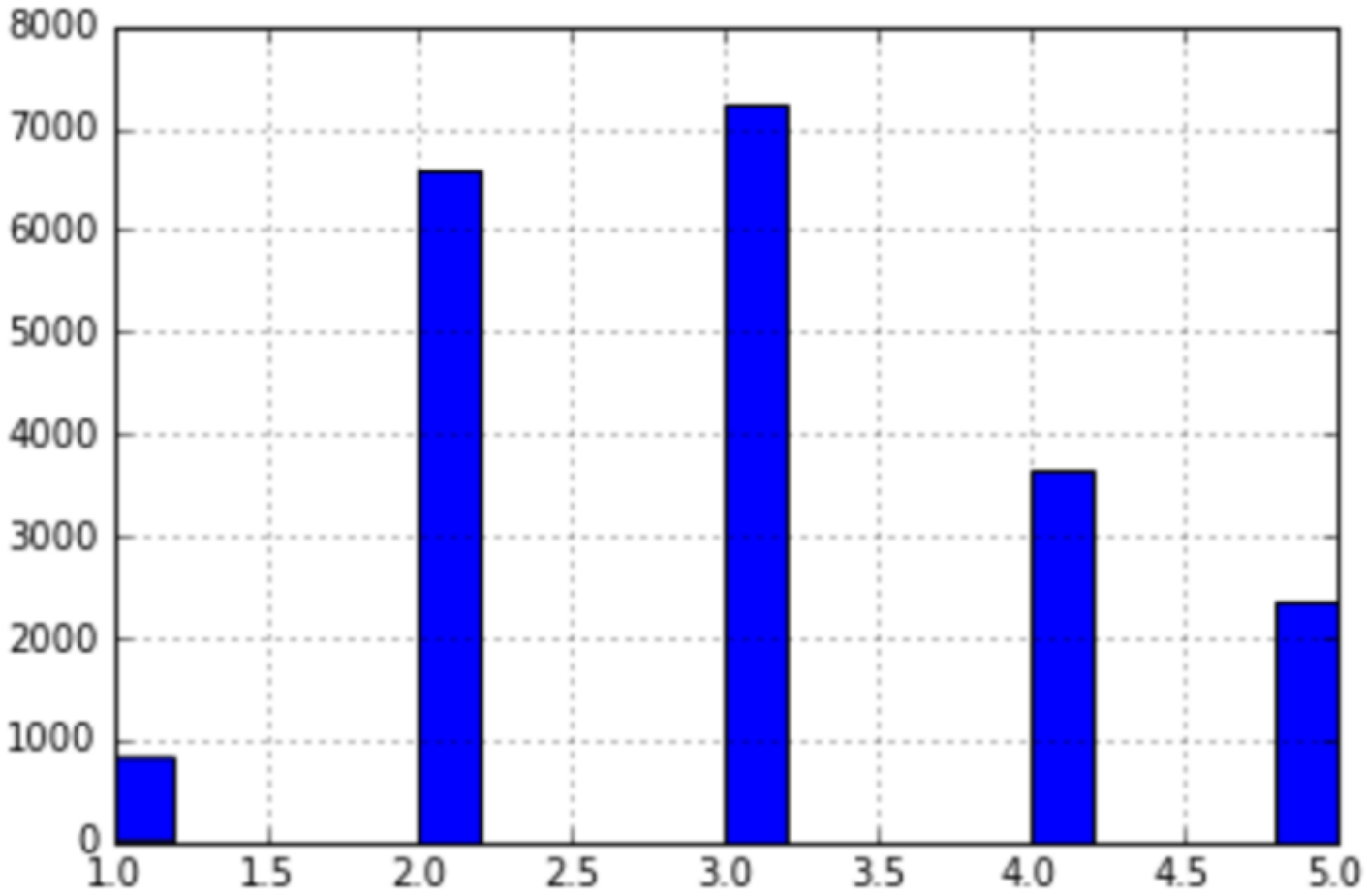
Create a Test Set

Suppose you chatted with experts who told you that the median income is a very important attribute to predict median housing prices. You may want to ensure that the test set is representative of the various categories of incomes in the whole dataset. Since the median income is a continuous numerical attribute, you first need to create an income category attribute. Let's look at the median income histogram more closely, most median income values are clustered around 1.5 to 6 (i.e., $15,000–$60,000), but some median incomes go far beyond 6. It is important to have a sufficient number of instances in your dataset for each stratum, or else the estimate of a stratum's importance may be biased. This means that you should not have too many strata, and each stratum should be large enough. The following code uses the pd.cut() function to create an income category attribute with five categories (labeled from 1 to 5): category 1 ranges from 0 to 1.5 (i.e., less than $15,000), category 2 from 1.5 to 3, and so on:

Create a Test Set

```
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()
```



Create a Test Set

Now you are ready to do stratified sampling based on the income category. For this you can use Scikit-Learn's StratifiedShuffleSplit class:

```
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]
```

```
>>> strat_test_set["income_cat"].value_counts() / len(strat_test_set)
3    0.350533
2    0.318798
4    0.176357
5    0.114583
1    0.039729
Name: income_cat, dtype: float64
```

Create a Test Set

With similar code you can measure the income category proportions in the full dataset. This figure compares the income category proportions in the overall dataset, in the test set generated with stratified sampling, and in a test set generated using purely random sampling. As you can see, the test set generated using stratified sampling has income category proportions almost identical to those in the full dataset, whereas the test set generated using purely random sampling is skewed.

	Overall	Stratified	Random	Rand. %error	Strat. %error
1	0.039826	0.039729	0.040213	0.973236	-0.243309
2	0.318847	0.318798	0.324370	1.732260	-0.015195
3	0.350581	0.350533	0.358527	2.266446	-0.013820
4	0.176308	0.176357	0.167393	-5.056334	0.027480
5	0.114438	0.114583	0.109496	-4.318374	0.127011

Create a Test Set

Now you should remove the income_cat attribute so the data is back to its original state:

```
for set_ in (strat_train_set, strat_test_set):
    set_.drop("income_cat", axis=1, inplace=True)
```

We spent quite a bit of time on test set generation for a good reason: this is an often neglected but critical part of a Machine Learning project. Moreover, many of these ideas will be useful later when we discuss cross-validation. Now it’s time to move on to the next stage: exploring the data

Discover and Visualize Data to Gain Insight

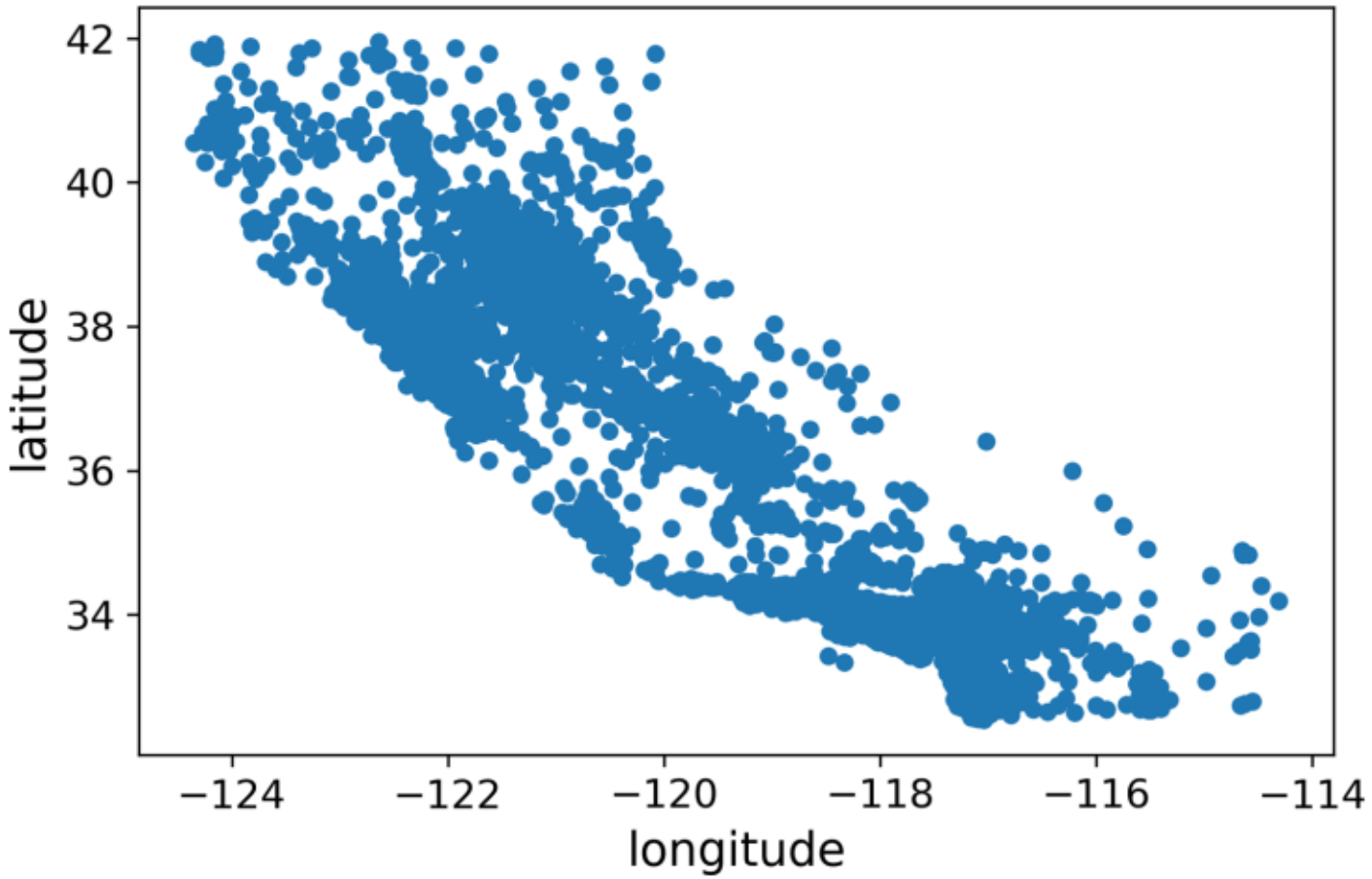
First, make sure you have put the test set aside and you are only exploring the training set. Also, if the training set is very large, you may want to sample an exploration set, to make manipulations easy and fast. In our case, the set is quite small, so you can just work directly on the full set. Let's create a copy so that you can play with it without harming the training set:

```
housing = strat_train_set.copy()
```

Discover and Visualize Data to Gain Insight

Since there is geographical information (latitude and longitude), it is a good idea to create a scatterplot of all districts to visualize the data

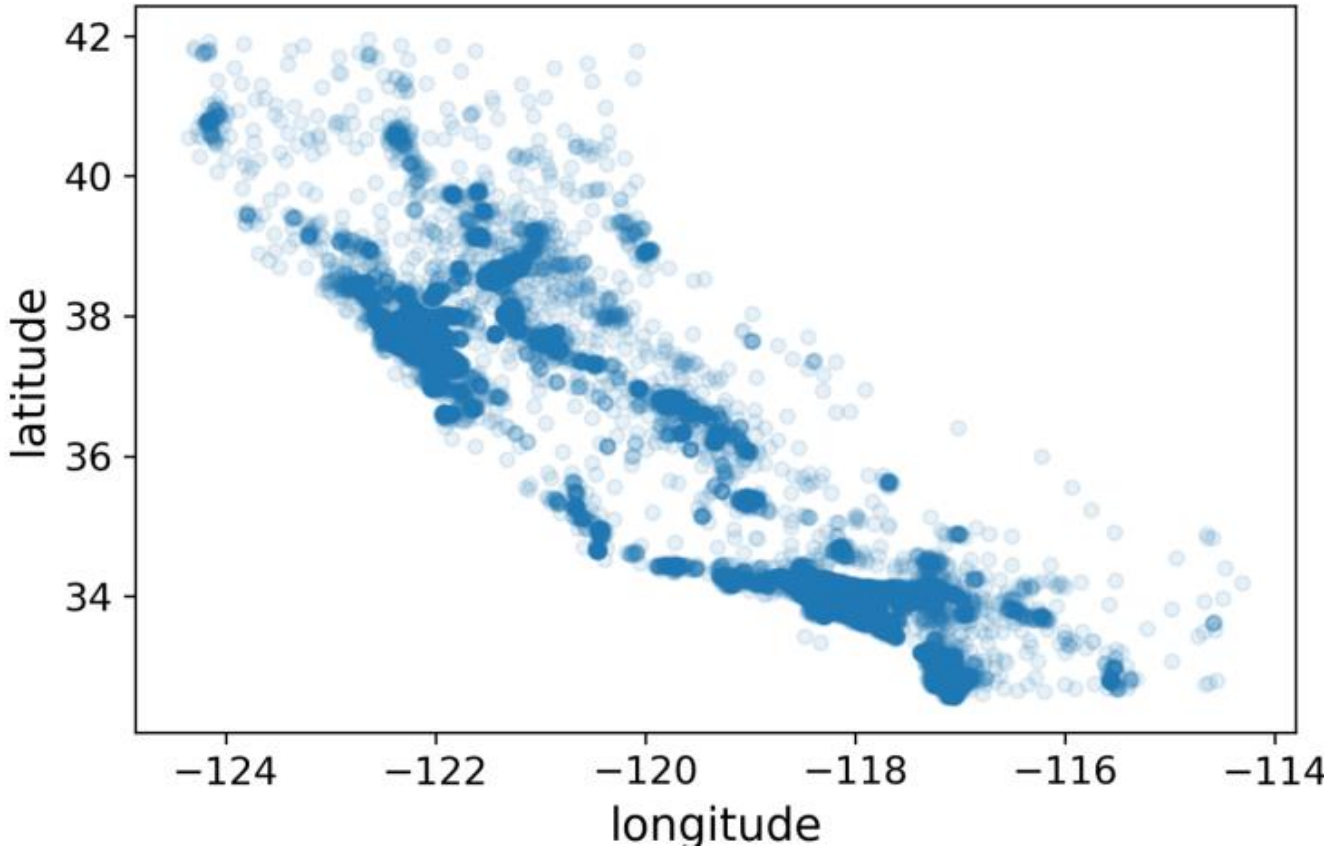
```
housing.plot(kind="scatter", x="longitude", y="latitude")
```



Discover and Visualize Data to Gain Insight

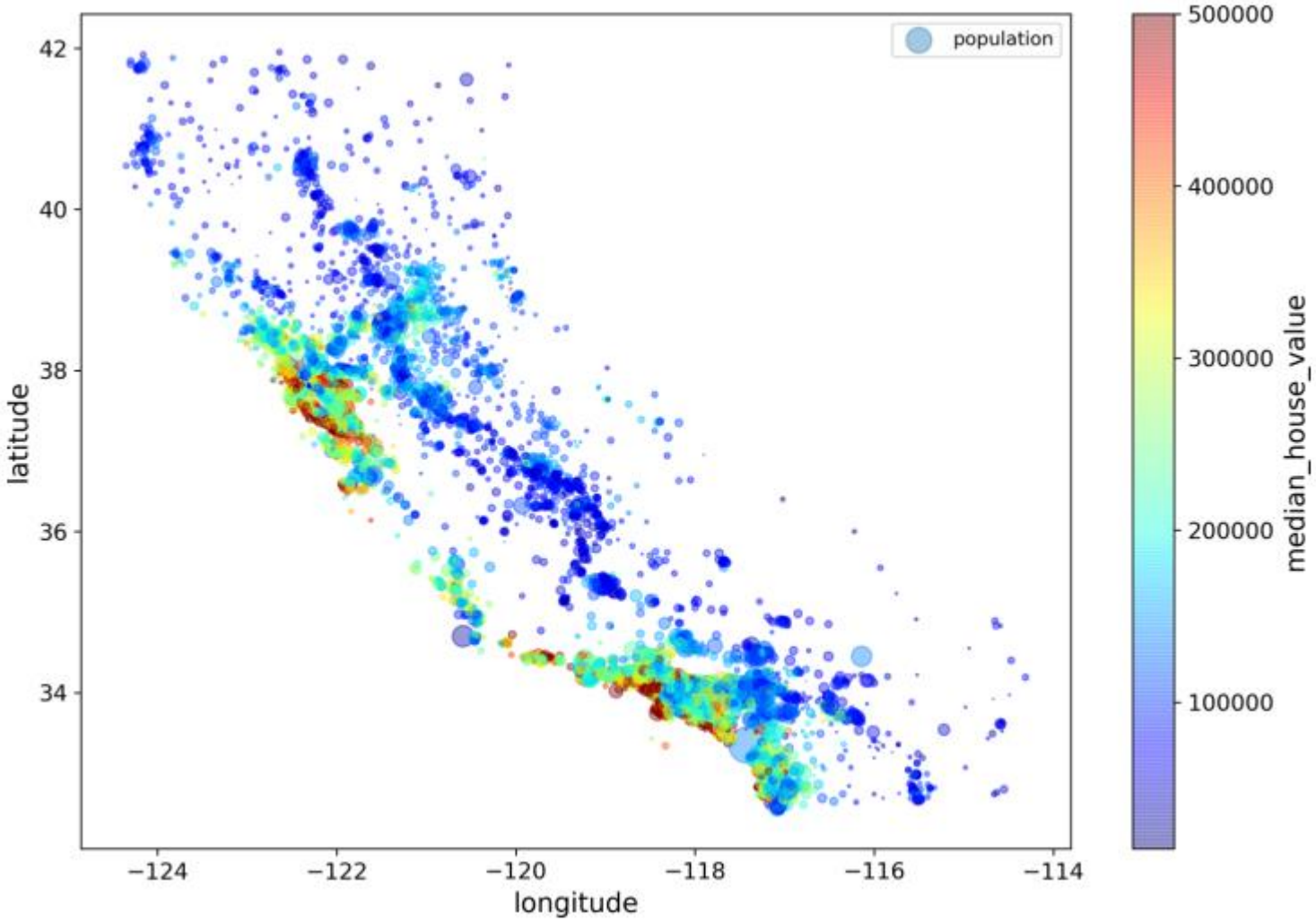
This looks like California all right, but other than that it is hard to see any particular pattern. Setting the alpha option to 0.1 makes it much easier to visualize the places where there is a high density of data points

```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.1)
```



Discover and Visualize Data to Gain Insight

Now let's look at the housing prices. The radius of each circle represents the district's population (option s), and the color represents the price (option c). We will use a predefined color map (option cmap) called jet, which ranges from blue (low values) to red (high prices)



Discover and Visualize Data to Gain Insight

Since the dataset is not too large, you can easily compute the *standard correlation coefficient* (also called *Pearson's r*) between every pair of attributes using the corr() method:

```
corr_matrix = housing.corr()

>>> corr_matrix["median_house_value"].sort_values(ascending=False)
median_house_value    1.000000
median_income         0.687170
total_rooms           0.135231
housing_median_age    0.114220
households            0.064702
total_bedrooms        0.047865
population           -0.026699
longitude            -0.047279
latitude             -0.142826
Name: median_house_value, dtype: float64
```

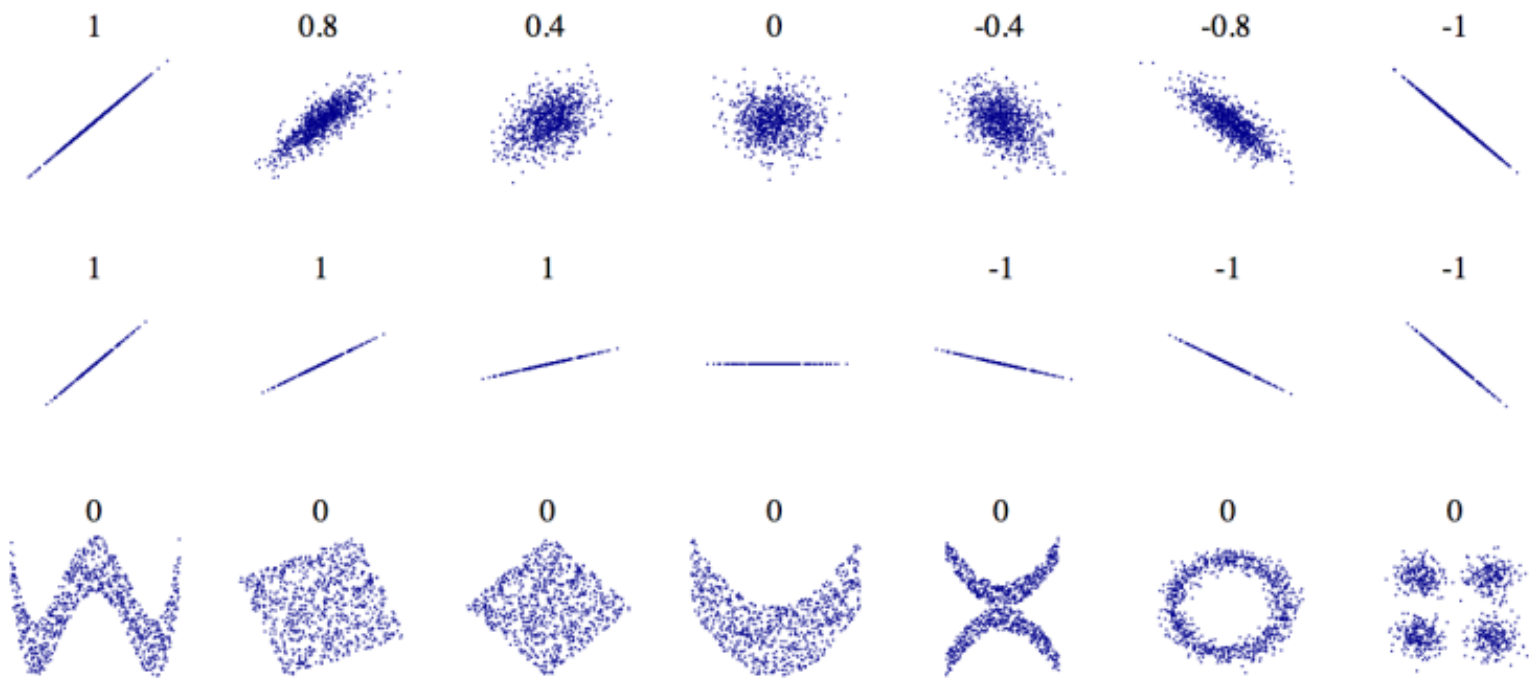
Discover and Visualize Data to Gain Insight

The correlation coefficient ranges from –1 to 1. When it is close to 1, it means that there is a strong positive correlation; for example, the median house value tends to go up when the median income goes up. When the coefficient is close to –1, it means that there is a strong negative correlation; you can see a small negative correlation between the latitude and the median house value (i.e., prices have a slight tendency to go down when you go north). Finally, coefficients close to 0 mean that there is no linear correlation. Next slide shows various plots along with the correlation coefficient between their horizontal and vertical axes.

```
>>> corr_matrix["median_house_value"].sort_values(ascending=False)
median_house_value    1.000000
median_income         0.687170
total_rooms           0.135231
housing_median_age    0.114220
households            0.064702
total_bedrooms        0.047865
population           -0.026699
longitude            -0.047279
latitude             -0.142826
Name: median_house_value, dtype: float64
```

Discover and Visualize Data to Gain Insight

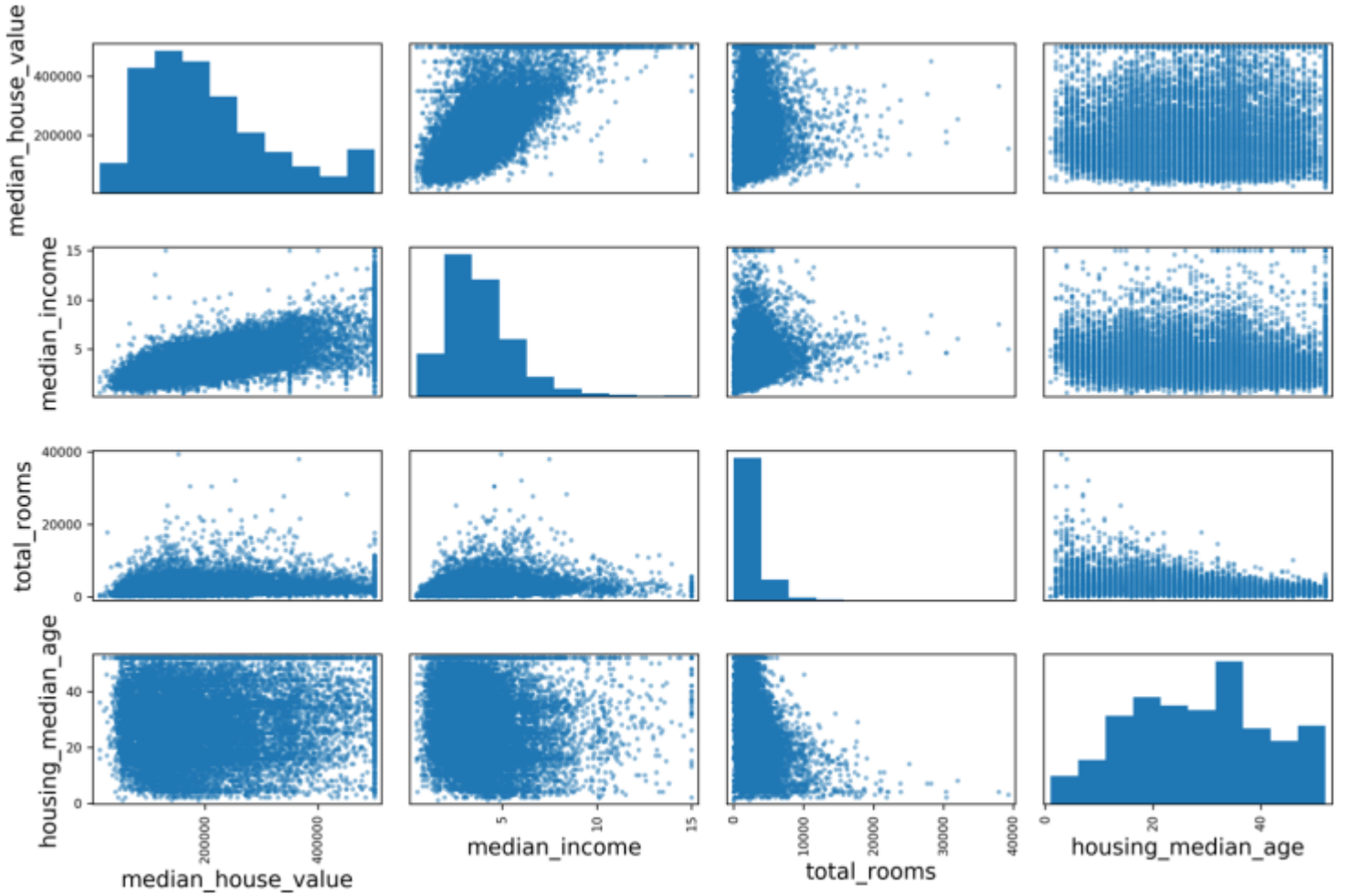
The correlation coefficient measures the strength of a relationship between two variables and ranges from -1 to 1. A coefficient close to 1 indicates strong positive correlation, -1 indicates strong negative correlation, and close to 0 indicates no linear correlation. This figure displays various plots with their respective correlation coefficients.



Discover and Visualize Data to Gain Insight

Another way to check for correlation between attributes is to use the pandas scatter_matrix() function, which plots every numerical attribute against every other numerical attribute. Since there are now 11 numerical attributes, you would get $11^2 = 121$ plots, which would not fit on a page—so let's just focus on a few promising attributes that seem most correlated with the median housing value

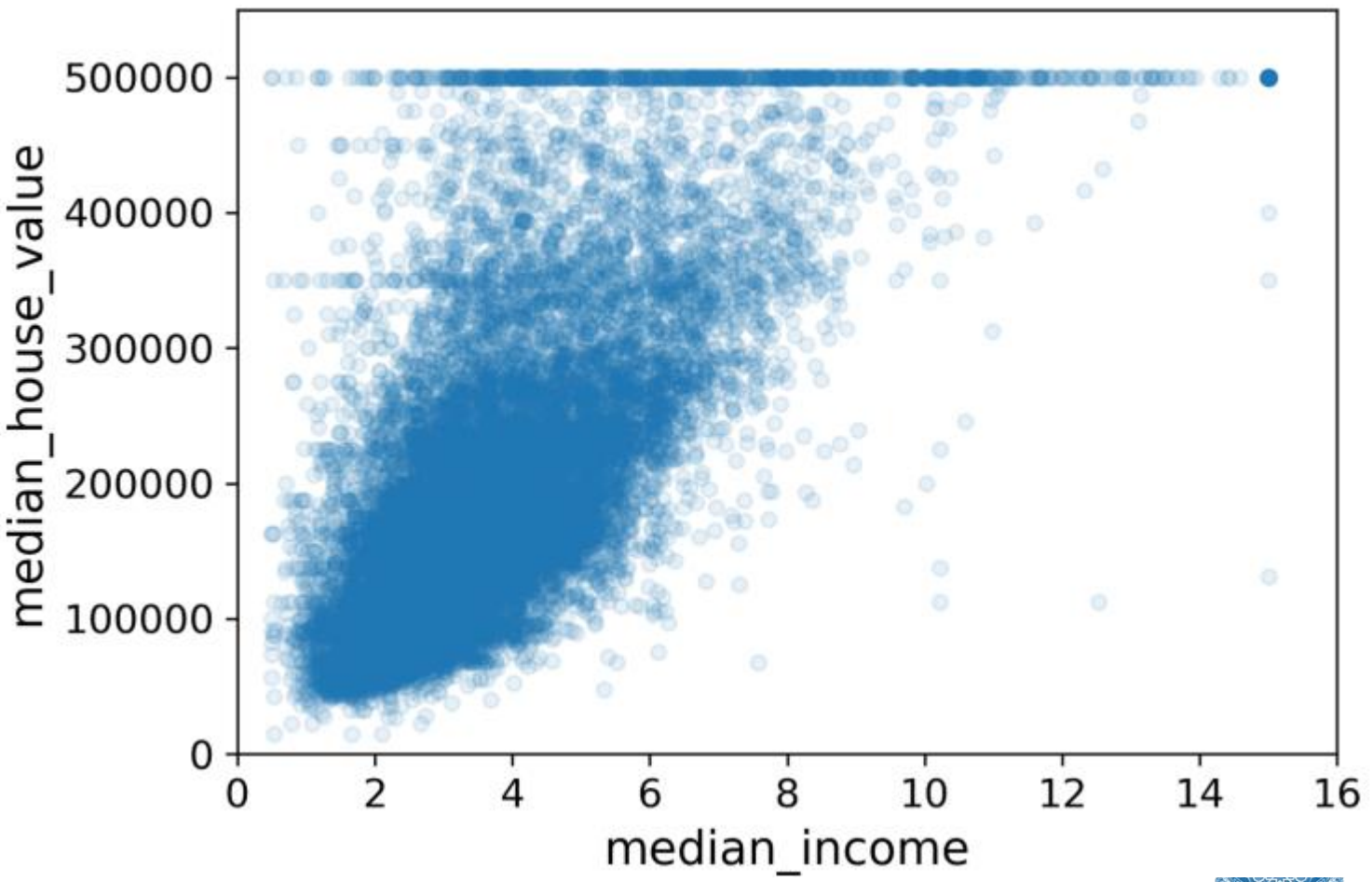
```
from pandas.plotting import scatter_matrix

attributes = ["median_house_value", "median_income", "total_rooms",
              "housing_median_age"]
scatter_matrix(housing[attributes], figsize=(12, 8))
```



Discover and Visualize Data to Gain Insight

The main diagonal (top left to bottom right) would be full of straight lines if pandas plotted each variable against itself, which would not be very useful. So instead pandas displays a histogram of each attribute (other options are available; see the pandas documentation for more details). The most promising attribute to predict the median house value is the median income, so let's zoom in on their correlation scatterplot

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



Discover and Visualize Data to Gain Insight

Identified data quirks and correlations, need to clean and transform data before using in ML algorithm. Try different attribute combinations, such as rooms per household, bedrooms vs. rooms, and population per household.

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

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

Discover and Visualize Data to Gain Insight

New attribute, bedrooms per room, more correlated with median house value. Lower ratio leads to higher prices. Rooms per household more informative than total rooms. Quick exploration leads to first good prototype, but iterative process for more insights.

Prepare the Data for ML Algorithms

It’s time to prepare the data for your Machine Learning algorithms. Instead of doing this manually, you should write functions for this purpose, for several good reasons:

- This will allow you to reproduce these transformations easily on any dataset (e.g., the next time you get a fresh dataset).
- You will gradually build a library of transformation functions that you can reuse in future projects.
- You can use these functions in your live system to transform the new data before feeding it to your algorithms.
- This will make it possible for you to easily try various transformations and see which combination of transformations works best.

Prepare the Data for ML Algorithms

But first let’s revert to a clean training set (by copying strat_train_set once again). Let’s also separate the predictors and the labels, since we don’t necessarily want to apply the same transformations to the predictors and the target values (note that drop() creates a copy of the data and does not affect strat_train_set):

```
housing = strat_train_set.drop("median_house_value", axis=1)
housing_labels = strat_train_set["median_house_value"].copy()
```

Prepare the Data for ML Algorithms

Most Machine Learning algorithms cannot work with missing features, so let's create a few functions to take care of them. We saw earlier that the total_bedrooms attribute has some missing values, so let's fix this. You have three options:

1. Get rid of the corresponding districts.
2. Get rid of the whole attribute.
3. Set the values to some value (zero, the mean, the median, etc.).

You can accomplish these easily using DataFrame's dropna(), drop(), and fillna() methods:

```
housing.dropna(subset=["total_bedrooms"])    # option 1
housing.drop("total_bedrooms", axis=1)       # option 2
median = housing["total_bedrooms"].median()  # option 3
housing["total_bedrooms"].fillna(median, inplace=True)
```

Prepare the Data for ML Algorithms

If you choose option 3, you should compute the median value on the training set and use it to fill the missing values in the training set. Don't forget to save the median value that you have computed. You will need it later to replace missing values in the test set when you want to evaluate your system, and also once the system goes live to replace missing values in new data.

Scikit-Learn provides a handy class to take care of missing values: SimpleImputer. Here is how to use it. First, you need to create a SimpleImputer instance, specifying that you want to replace each attribute's missing values with the median of that attribute: (the median can only be computed on numerical attributes, you need to create a copy of the data without the text attribute ocean_proximity)

```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy="median")

housing_num = housing.drop("ocean_proximity", axis=1)

imputer.fit(housing_num)
```

Prepare the Data for ML Algorithms

The imputer has simply computed the median of each attribute and stored the result in its statistics_ instance variable. Only the total_bedrooms attribute had missing values, but we cannot be sure that there won't be any missing values in new data after the system goes live, so it is safer to apply the imputer to all the numerical attributes:

```
>>> imputer.statistics_
array([ -118.51 , 34.26 , 29. , 2119.5 , 433. , 1164. , 408. , 3.5409])
>>> housing_num.median().values
array([ -118.51 , 34.26 , 29. , 2119.5 , 433. , 1164. , 408. , 3.5409])

X = imputer.transform(housing_num)

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

Prepare the Data for ML Algorithms

So far we have only dealt with numerical attributes, but now let's look at text attributes. In this dataset, there is just one: the ocean_proximity attribute. Let's look at its value for the first 10 instances

```
>>> housing_cat = housing[["ocean_proximity"]]
>>> housing_cat.head(10)
       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
```

Prepare the Data for ML Algorithms

It’s not arbitrary text: there are a limited number of possible values, each of which represents a category. So this attribute is a categorical attribute. Most Machine Learning algorithms prefer to work with numbers, so let’s convert these categories from text to numbers. For this, we can use Scikit-Learn’s OrdinalEncoder class:

```
>>> from sklearn.preprocessing import OrdinalEncoder
>>> ordinal_encoder = OrdinalEncoder()
>>> housing_cat_encoded = ordinal_encoder.fit_transform(housing_cat)
>>> housing_cat_encoded[:10]
array([[0.],
       [0.],
       [4.],
       [1.],
       [0.],
       [1.],
       [0.],
       [1.],
       [0.],
       [0.]])
```

```
>>> ordinal_encoder.categories_
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

Prepare the Data for ML Algorithms

One issue with this representation is that ML algorithms will assume that two nearby values are more similar than two distant values. This may be fine in some cases (e.g., for ordered categories such as “bad,” “average,” “good,” and “excellent”), but it is obviously not the case for the ocean_proximity column (for example, categories 0 and 4 are clearly more similar than categories 0 and 1).

Prepare the Data for ML Algorithms

To fix this issue, a common solution is to create one binary attribute per category: one attribute equal to 1 when the category is “<1H OCEAN” (and 0 otherwise), another attribute equal to 1 when the category is “INLAND” (and 0 otherwise), and so on. This is called *one-hot encoding*, because only one attribute will be equal to 1 (hot), while the others will be 0 (cold). The new attributes are sometimes called *dummy* attributes. ScikitLearn provides a OneHotEncoder class to convert categorical values into onehot vectors

```
>>> from sklearn.preprocessing import OneHotEncoder
>>> cat_encoder = OneHotEncoder()
>>> housing_cat_1hot = cat_encoder.fit_transform(housing_cat)
>>> housing_cat_1hot
<16512x5 sparse matrix of type '<class 'numpy.float64'>'
  with 16512 stored elements in Compressed Sparse Row format>

>>> cat_encoder.categories_
[array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
       dtype=object)]
```

Prepare the Data for ML Algorithms

One of the most important transformations you need to apply to your data is *feature scaling*. With few exceptions, Machine Learning algorithms don't perform well when the input numerical attributes have very different scales. This is the case for the housing data: the total number of rooms ranges from about 6 to 39,320, while the median incomes only range from 0 to 15. Note that scaling the target values is generally not required.

There are two common ways to get all attributes to have the same scale: *minmax scaling* and *standardization*.

Min-max scaling (many people call this *normalization*) is the simplest: values are shifted and rescaled so that they end up ranging from 0 to 1. We do this by subtracting the min value and dividing by the max minus the min. ScikitLearn provides a transformer called MinMaxScaler for this. It has a feature_range hyperparameter that lets you change the range if, for some reason, you don't want 0–1

Prepare the Data for ML Algorithms

Standardization is different: first it subtracts the mean value (so standardized values always have a zero mean), and then it divides by the standard deviation so that the resulting distribution has unit variance. Unlike min-max scaling, standardization does not bound values to a specific range, which may be a problem for some algorithms (e.g., neural networks often expect an input value ranging from 0 to 1). However, standardization is much less affected by outliers. For example, suppose a district had a median income equal to 100 (by mistake). Min-max scaling would then crush all the other values from 0– 15 down to 0–0.15, whereas standardization would not be much affected. Scikit-Learn provides a transformer called StandardScaler for standardization

Prepare the Data for ML Algorithms

As you can see, there are many data transformation steps that need to be executed in the right order. Fortunately, Scikit-Learn provides the Pipeline class to help with such sequences of transformations. Here is a small pipeline for the numerical attributes:

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

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


        ('std_scaler', StandardScaler()),
    ])

housing_num_tr = num_pipeline.fit_transform(housing_num)
```

Prepare the Data for ML Algorithms

Pipeline constructor takes list of name/estimator pairs. All but last must be transformers. Names can be anything, used for hyperparameter tuning. Pipeline's fit() method calls fit_transform() on all transformers, final estimator's fit() method is called. Pipeline has same methods as final estimator, including fit_transform() and transform().

Prepare the Data for ML Algorithms

Handled categorical and numerical columns separately. ColumnTransformer introduced in Scikit-Learn v0.20 to handle all columns, appropriate transformations applied to each. Works with pandas DataFrames.

```
from sklearn.compose import ColumnTransformer

num_attribs = list(housing_num)
cat_attribs = ["ocean_proximity"]

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

housing_prepared = full_pipeline.fit_transform(housing)
```

Prepare the Data for ML Algorithms

Import ColumnTransformer class, get list of numerical and categorical column names. Construct ColumnTransformer using list of tuples containing name, transformer, list of columns to apply to. In example, numerical columns use num_pipeline and categorical use OneHotEncoder. Apply ColumnTransformer to housing data, it applies each transformer to appropriate columns and concatenates outputs. OneHotEncoder returns sparse matrix, num_pipeline returns dense matrix, ColumnTransformer estimates final matrix density (default sparse_threshold=0.3) and returns sparse/dense accordingly. Preprocessing pipeline takes full housing data and applies appropriate transformations to each column.

Select and Train a Model

You framed the problem, you got the data and explored it, you sampled a training set and a test set, and you wrote transformation pipelines to clean up and prepare your data for Machine Learning algorithms automatically. You are now ready to select and train a Machine Learning model.

Select and Train a Model

The good news is that thanks to all these previous steps, things are now going to be much simpler than you might think. Let's first train a Linear Regression model

```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(housing_prepared, housing_labels)
```

```
>>> some_data = housing.iloc[:5]
>>> some_labels = housing_labels.iloc[:5]
>>> some_data_prepared = full_pipeline.transform(some_data)
>>> print("Predictions:", lin_reg.predict(some_data_prepared))
Predictions: [ 210644.6045  317768.8069  210956.4333  59218.9888
189747.5584]
>>> print("Labels:", list(some_labels))
Labels: [286600.0, 340600.0, 196900.0, 46300.0, 254500.0]
```

```
>>> from sklearn.metrics import mean_squared_error
>>> housing_predictions = lin_reg.predict(housing_prepared)
>>> lin_mse = mean_squared_error(housing_labels, housing_predictions)
>>> lin_rmse = np.sqrt(lin_mse)
>>> lin_rmse
68628.19819848922
```

Select and Train a Model

Let’s train a DecisionTreeRegressor. This is a powerful model, capable of finding complex nonlinear relationships in the data (Decision Trees are presented in more detail later in the course). The code should look familiar by now

```
from sklearn.tree import DecisionTreeRegressor

tree_reg = DecisionTreeRegressor()
tree_reg.fit(housing_prepared, housing_labels)
```

```
>>> housing_predictions = tree_reg.predict(housing_prepared)
>>> tree_mse = mean_squared_error(housing_labels, housing_predictions)
>>> tree_rmse = np.sqrt(tree_mse)
>>> tree_rmse
0.0
```

No error at all? Could this model really be absolutely perfect? Of course, it is much more likely that the model has badly overfit the data. How can you be sure? As we saw earlier, you don’t want to touch the test set
until you are ready to launch a model you are confident about, so you need to use part of the training set for training and part of it for model validation

Select and Train a Model

One way to evaluate the Decision Tree model would be to use the train_test_split() function to split the training set into a smaller training set and a validation set, then train your models against the smaller training set and evaluate them against the validation set. It's a bit of work, but nothing too difficult, and it would work fairly well.
A great alternative is to use Scikit-Learn's *K-fold cross-validation* feature. The following code randomly splits the training set into 10 distinct subsets called *folds*, then it trains and evaluates the Decision Tree model 10 times, picking a different fold for evaluation every time and training on the other 9 folds. The result is an array containing the 10 evaluation scores:

```
from sklearn.model_selection import cross_val_score
scores = cross_val_score(tree_reg, housing_prepared, housing_labels,
                         scoring="neg_mean_squared_error", cv=10)
tree_rmse_scores = np.sqrt(-scores)
```

Select and Train a Model

```
>>> def display_scores(scores):
...     print("Scores:", scores)
...     print("Mean:", scores.mean())
...     print("Standard deviation:", scores.std())
...
>>> display_scores(tree_rmse_scores)
Scores: [70194.33680785 66855.16363941 72432.58244769 70758.73896782
 71115.88230639 75585.14172901 70262.86139133 70273.6325285
 75366.87952553 71231.65726027]

Mean: 71407.68766037929
Standard deviation: 2439.4345041191004

>>> lin_scores = cross_val_score(lin_reg, housing_prepared, housing_labels,
...                              scoring="neg_mean_squared_error", cv=10)
...
>>> lin_rmse_scores = np.sqrt(-lin_scores)
>>> display_scores(lin_rmse_scores)
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: 2731.674001798348
```

Select and Train a Model

Let’s try one last model now: the RandomForestRegressor. As we will see in Chapter 7, Random Forests work by training many Decision Trees on random subsets of the features, then averaging out their predictions. Building a model on top of many other models is called *Ensemble Learning*, and it is often a great way to push ML algorithms even further. We will skip most of the code since it is essentially the same as for the other models:

```
>>> from sklearn.ensemble import RandomForestRegressor
>>> forest_reg = RandomForestRegressor()
>>> forest_reg.fit(housing_prepared, housing_labels)
>>> [...]
>>> forest_rmse
18603.515021376355

>>> display_scores(forest_rmse_scores)
Scores: [49519.80364233 47461.9115823  50029.02762854 52325.28068953
 49308.39426421 53446.37892622 48634.8036574  47585.73832311
 53490.10699751 50021.5852922 ]
Mean: 50182.303100336096
Standard deviation: 2097.0810550985693
```

Select and Train a Model

This is much better: Random Forests look very promising. However, note that the score on the training set is still much lower than on the validation sets, meaning that the model is still overfitting the training set. Possible solutions for overfitting are to simplify the model, constrain it (i.e., regularize it), or get a lot more training data. Before you dive much deeper into Random Forests, however, you should try out many other models from various categories of Machine Learning algorithms (e.g., several Support Vector Machines with different kernels, and possibly a neural network), without spending too much time tweaking the hyperparameters. The goal is to shortlist a few (two to five) promising models.

Fine-tune the Model

Grid Search

GridSearchCV can search for the best combination of hyperparameter values for a RandomForestRegressor. Just specify the hyperparameters and their values to try, and it will use cross-validation to evaluate all combinations.

```
from sklearn.model_selection import GridSearchCV

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

forest_reg = RandomForestRegressor()

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

grid_search.fit(housing_prepared, housing_labels)
```

Fine-tune the Model

Scikit-Learn's GridSearchCV can search for the best hyperparameter values for the RandomForestRegressor. Just specify the hyperparameters to experiment with and the values to try. The example explores 12 + 6 = 18 combinations of hyperparameter values through 5-fold cross validation, resulting in a total of 90 rounds of training.

```
from sklearn.model_selection import GridSearchCV

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

forest_reg = RandomForestRegressor()

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

grid_search.fit(housing_prepared, housing_labels)
```

```
>>> grid_search.best_params_
{'max_features': 8, 'n_estimators': 30}
```

Fine-tune the Model

```
>>> cvres = grid_search.cv_results_
>>> for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
...     print(np.sqrt(-mean_score), params)
...
```

```
63669.05791727153 {'max_features': 2, 'n_estimators': 3}
55627.16171305252 {'max_features': 2, 'n_estimators': 10}
53384.57867637289 {'max_features': 2, 'n_estimators': 30}
60965.99185930139 {'max_features': 4, 'n_estimators': 3}
52740.98248528835 {'max_features': 4, 'n_estimators': 10}
50377.344409590376 {'max_features': 4, 'n_estimators': 30}
58663.84733372485 {'max_features': 6, 'n_estimators': 3}
52006.15355973719 {'max_features': 6, 'n_estimators': 10}
50146.465964159885 {'max_features': 6, 'n_estimators': 30}
57869.25504027614 {'max_features': 8, 'n_estimators': 3}
51711.09443660957 {'max_features': 8, 'n_estimators': 10}
49682.25345942335 {'max_features': 8, 'n_estimators': 30}
62895.088889905004 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
54658.14484390074 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
59470.399594730654 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
52725.01091081235 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
57490.612956065226 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
51009.51445842374 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

Fine-tune the Model

Randomized Search

The grid search approach is fine when you are exploring relatively few combinations, like in the previous example, but when the hyperparameter search space is large, it is often preferable to use RandomizedSearchCV instead. This class can be used in much the same way as the GridSearchCV class, but instead of trying out all possible combinations, it evaluates a given
number of random combinations by selecting a random value for each hyperparameter at every iteration. This approach has two main benefits:

If you let the randomized search run for, say, 1,000 iterations, this approach will explore 1,000 different values for each hyperparameter (instead of just a few values per hyperparameter with the grid search approach).

Simply by setting the number of iterations, you have more control over the computing budget you want to allocate to hyperparameter search.

Fine-tune the Model

Ensemble Methods

Another way to fine-tune your system is to try to combine the models that perform best. The group (or “ensemble”) will often perform better than the best individual model (just like Random Forests perform better than the individual Decision Trees they rely on), especially if the individual models make very different types of errors. We will cover this topic in more detail in Chapter 7

Fine-tune the Model

Analyze the Best Models and Their Errors

You will often gain good insights on the problem by inspecting the best models. For example, the RandomForestRegressor can indicate the relative importance of each attribute for making accurate predictions:

```
>>> feature_importances = grid_search.best_estimator_.feature_importances_
>>> feature_importances
array([7.33442355e-02, 6.29090705e-02, 4.11437985e-02, 1.46726854e-02,
       1.41064835e-02, 1.48742809e-02, 1.42575993e-02, 3.66158981e-01,
       5.64191792e-02, 1.08792957e-01, 5.33510773e-02, 1.03114883e-02,
       1.64780994e-01, 6.02803867e-05, 1.96041560e-03, 2.85647464e-03])

>>> extra_attribs = ["rooms_per_hhold", "pop_per_hhold", "bedrooms_per_room"]
>>> cat_encoder = full_pipeline.named_transformers_["cat"]
>>> cat_one_hot_attribs = list(cat_encoder.categories_[0])
```

Fine-tune the Model

With this information, you may want to try dropping some of the less useful features (e.g., apparently only one ocean_proximity category is really useful, so you could try dropping the others).
You should also look at the specific errors that your system makes, then try to understand why it makes them and what could fix the problem (adding extra features or getting rid of uninformative ones, cleaning up outliers, etc.)

```
>>> attributes = num_attribs + extra_attribs + cat_one_hot_attribs
>>> sorted(zip(feature_importances, attributes), reverse=True)
[(0.3661589806181342, 'median_income'),
 (0.1647809935615905, 'INLAND'),
 (0.10879295677551573, 'pop_per_hhold'),
 (0.07334423551601242, 'longitude'),
 (0.0629090704826203, 'latitude'),
 (0.05641917918195401, 'rooms_per_hhold'),
 (0.05335107734767581, 'bedrooms_per_room'),
 (0.041143798478729635, 'housing_median_age'),
 (0.014874280890402767, 'population'),
 (0.014672685420543237, 'total_rooms'),
 (0.014257599323407807, 'households'),
 (0.014106483453584102, 'total_bedrooms'),
 (0.010311488326303787, '<1H OCEAN'),
 (0.002856474637320158, 'NEAR OCEAN'),
 (0.00196041559947807, 'NEAR BAY'),
 (6.028038672736599e-05, 'ISLAND')]
```

Fine-tune the Model

Evaluate Your System on the Test Set

After tweaking your models for a while, you eventually have a system that performs sufficiently well. Now is the time to evaluate the final model on the test set. There is nothing special about this process; just get the predictors and the labels from your test set, run your full_pipeline to transform the data (call transform(), *not* fit_transform()—you do not want to fit the test set!), and evaluate the final model on the test set:

```
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)   # => evaluates to 47,730.2
```

Launch, Monitor, and Maintain the System

To ensure that the model's performance remains stable over time, it is necessary to monitor it regularly. One approach is to track downstream metrics, such as the number of recommended products sold in a recommender system, and compare it to non-recommended products. If there is a decrease in performance, it could indicate that the model needs to be retrained on fresh data or that the data pipeline is broken. Monitoring the model's performance is important to detect and address any issues early, as the world changes and the model may not be adapted to current data if it was only trained on outdated data.

Launch, Monitor, and Maintain the System

To ensure the long-term success of your deployed model, you need to set up a monitoring system. This system will check the model's performance at regular intervals and trigger alerts if it drops. In some cases, the model's performance can be inferred from downstream metrics, such as the number of recommended products sold in a recommender system. In other cases, human analysis is necessary to determine the model's performance. This could involve sending a sample of the model's classified images to human raters for evaluation. To set up a monitoring system, you need to define processes for how to handle failures and prepare for them, which can be a lot of work but is essential for the longevity of your model.

Launch, Monitor, and Maintain the System

If the data keeps evolving, you will need to update your datasets and retrain your model regularly. You should probably automate the whole process as much as possible. Here are a few things you can automate:

- Collect fresh data regularly and label it (e.g., using human raters).
- Write a script to train the model and fine-tune the hyperparameters automatically. This script could run automatically, for example every day or every week, depending on your needs.
- Write another script that will evaluate both the new model and the previous model on the updated test set, and deploy the model to production if the performance has not decreased (if it did, make sure you investigate why).