Advanced Data Analysis

DATA 71200

Class 4

Course Schedule

26-Feb	**Inspecting Data**
4-Mar	Representing Data
11-Mar	Evaluation Methods
18-Mar	Supervised Learning (k-Nearest Neighbors, Linear Models) – *Project 1 Due*
25-Mar	Supervised Learning (Naive Bayes Classifiers and Decision Trees)
1-Apr	Supervised Learning (Support Vector Machines and Uncertainty estimates from Classifiers)

Assignments for this week

- **DataCamp**
  - AI Fundamentals
    - Introduction to AI
  - pandas Foundations
    - Data ingestion & inspection
    - Exploratory data analysis
- **Reading**
  - Ch 2: End-to-End Machine Learning Project. in Géron, Aurélien. (2019). Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow' O'Reilly Media, Inc. 33–66

How to update a forked repository from the web UI on GitHub

https://adrientorris.github.io/github/how-to-update-a-forked-repository-from-the-ui-on-github

Frame the Problem

- **“what exactly is the business (research) objective”**
  - “how does the company (researcher) expect to use and benefit from this model?”
  - will determine
    - “how you frame the problem”
    - “what algorithms you will select”
    - “what performance measure you will use to evaluate your model”
    - "how much effort you should spend tweaking it”

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O’Reilly Media, Inc.

Pipeline

- **“sequence of data processing components is called a data pipeline”**
  - “components typically run asynchronously” and “is fairly self-contained”
  - each component
    - “pulls in a large amount of data”
    - “processes it"
    - “spits out the result in another data store”
    - a later “component in the pipeline pulls this data and spits out its own output”

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O’Reilly Media, Inc.

Pipeline

- **“data flow graph show how the components are connected”**
- **“if a component breaks down, the downstream components can often continue to run normally (at least for a while) by just using the last output from the broken component”**
  - “but a broken component can go unnoticed for some time if proper monitoring is not implemented”

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O’Reilly Media, Inc.

Creating an Isolated Environment

If you would like to work in an isolated environment (which is strongly recommended so you can work on different projects without having conflicting library versions), install virtualenv by running the following pip command:

```
$ pip3 install --user --upgrade virtualenv
Collecting virtualenv
[...]
Successfully installed virtualenv
```

Now you can create an isolated Python environment by typing:

```
$ cd $ML_PATH
$ virtualenv env
Using base prefix '[...]'
New python executable in [...]/ml/env/bin/python3.5
Also creating executable in [...]/ml/env/bin/python
Installing setuptools, pip, wheel...done.
```

Now every time you want to activate this environment, just open a terminal and type:

```
$ cd $ML_PATH
$ source env/bin/activate
```

While the environment is active, any package you install using pip will be installed in this isolated environment, and Python will only have access to these packages (if you also want access to the system's site packages, you should create the environment using virtualenv's `--system-site-packages` option). Check out virtualenv's documentation for more information.

Inspecting Data to Gain Insights

- **Data size and type**
- **Summary statistics**
- **Histograms**
- **Visualizing Geographic Data**

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

```
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
```

Figure 2-6. Housing info

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

```
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	537.870553
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(

Figure 2-7. Summary of each numerical attribute

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

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

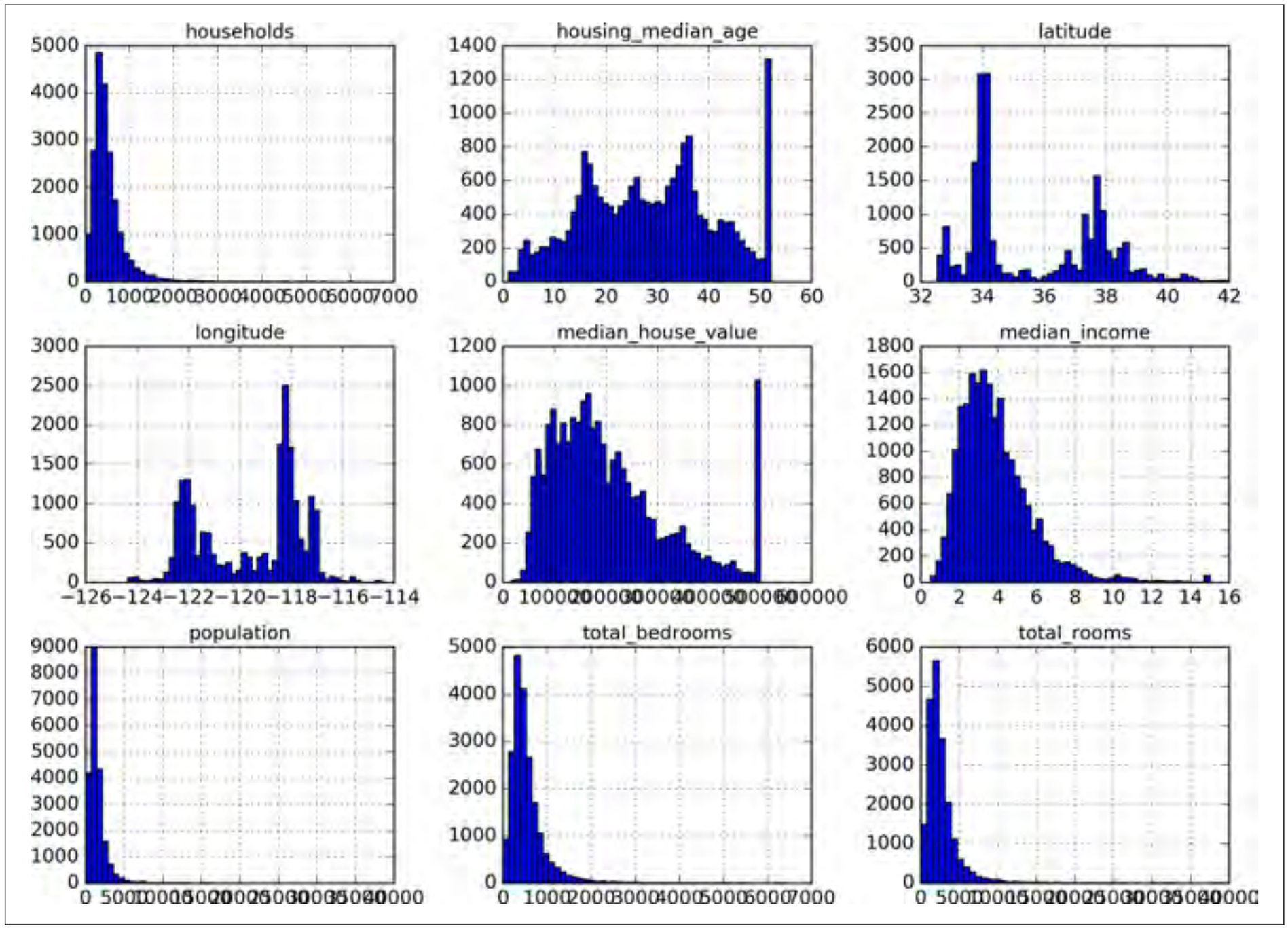
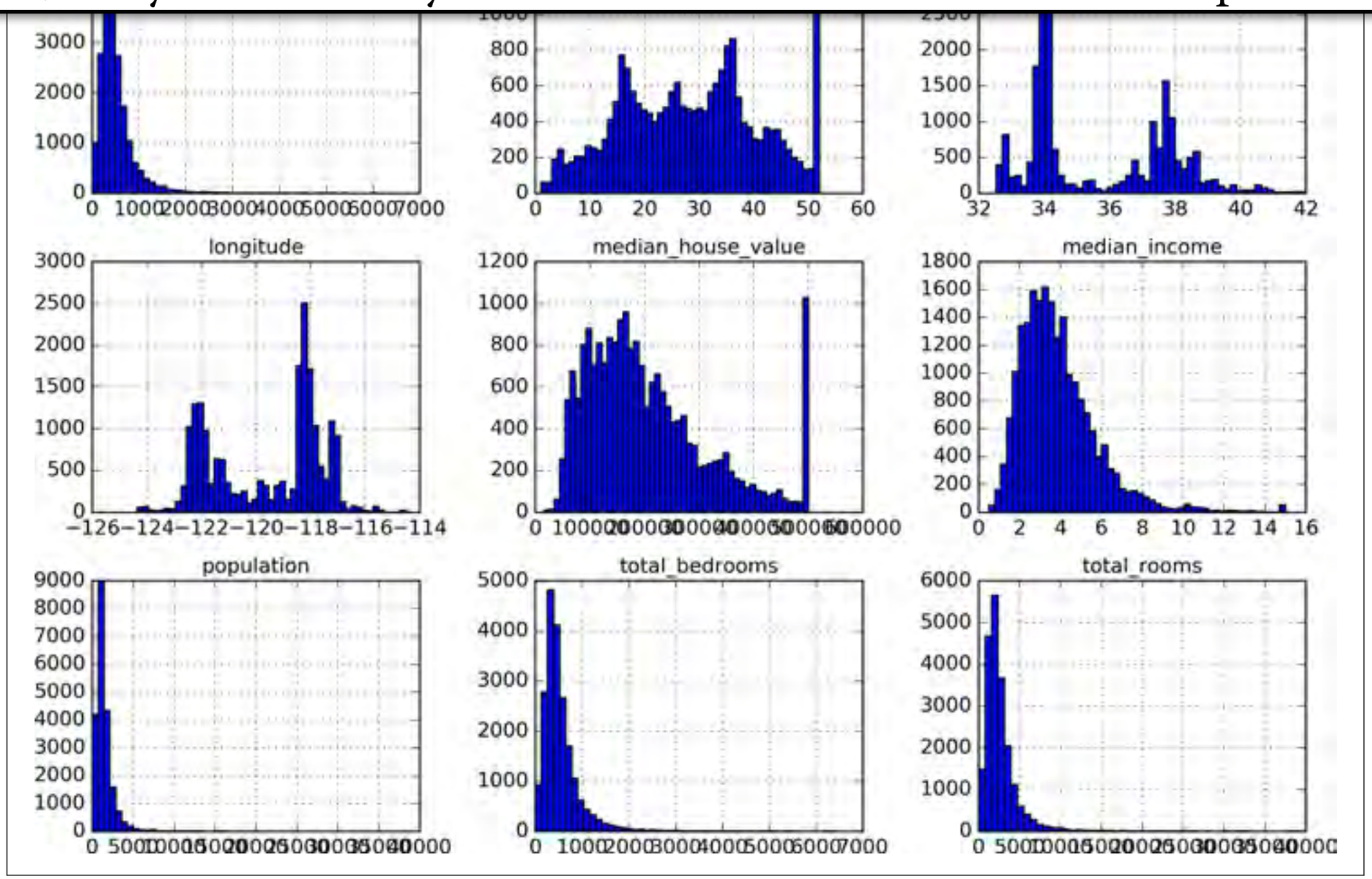


Figure 2-8. A histogram for each numerical attribute

First, the median income attribute does not look like it is expressed in US dollars (USD). After checking with the team that collected the data, you are told that the data has been scaled and capped at 15 (actually 15.0001) for higher median incomes, and at 0.5 (actually 0.4999) for lower median incomes. Working with preprocessed attributes is common in Machine Learning, and it is not necessarily a problem, but you should try to understand how the data was computed.



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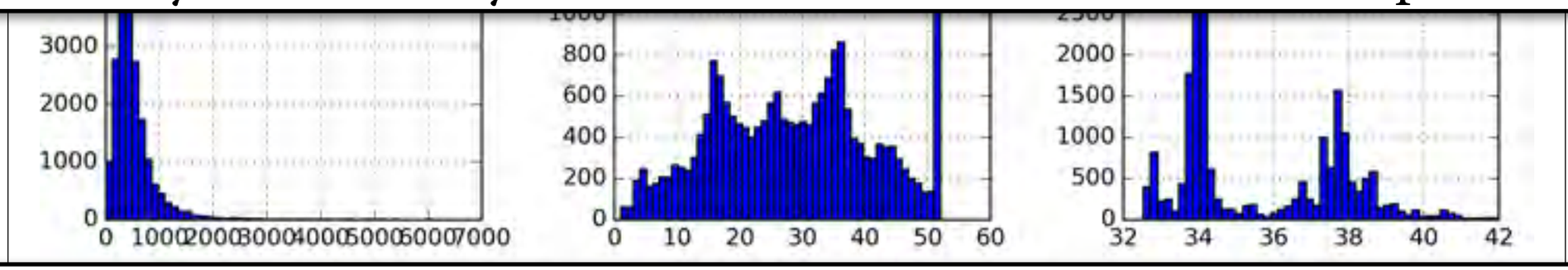

The housing median age and the median house value were also capped. The latter may be a serious problem since it is your target attribute (your labels). Your Machine Learning algorithms may learn that prices never go beyond that limit. You need to check with your client team (the team that will use your system's output) to see if this is a problem or not. If they tell you that they need precise predictions even beyond $500,000, then you have mainly two options:

a. Collect proper labels for the districts whose labels were capped.

b. Remove those districts from the training set (and also from the test set, since your system should not be evaluated poorly if it predicts values beyond $500,000).

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

Finally, many histograms are *tail heavy*: they extend much farther to the right of the median than to the left. This may make it a bit harder for some Machine Learning algorithms to detect patterns. We will try transforming these attributes later on to have more bell-shaped distributions.

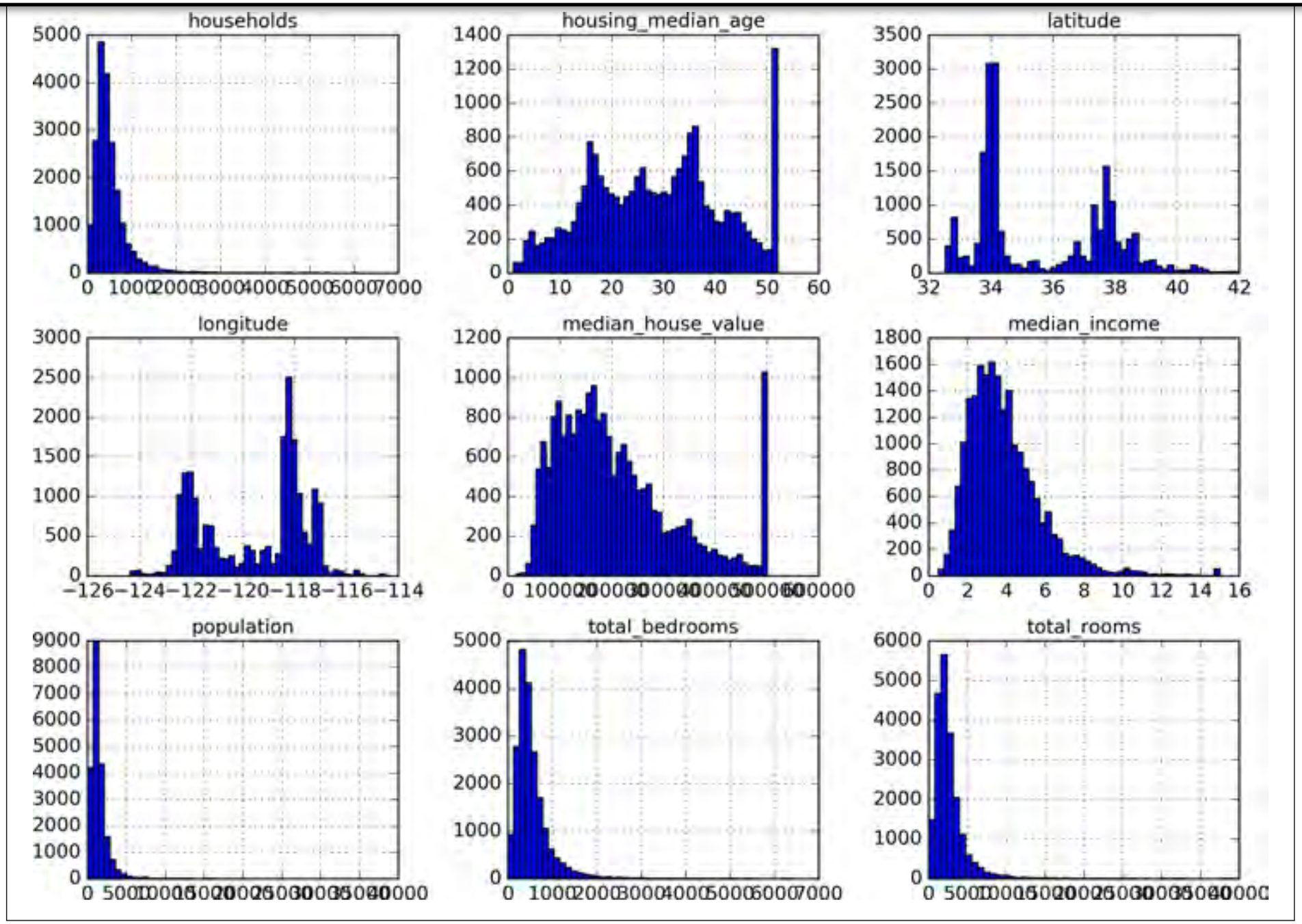

Figure 2-8. A histogram for each numerical attribute

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

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

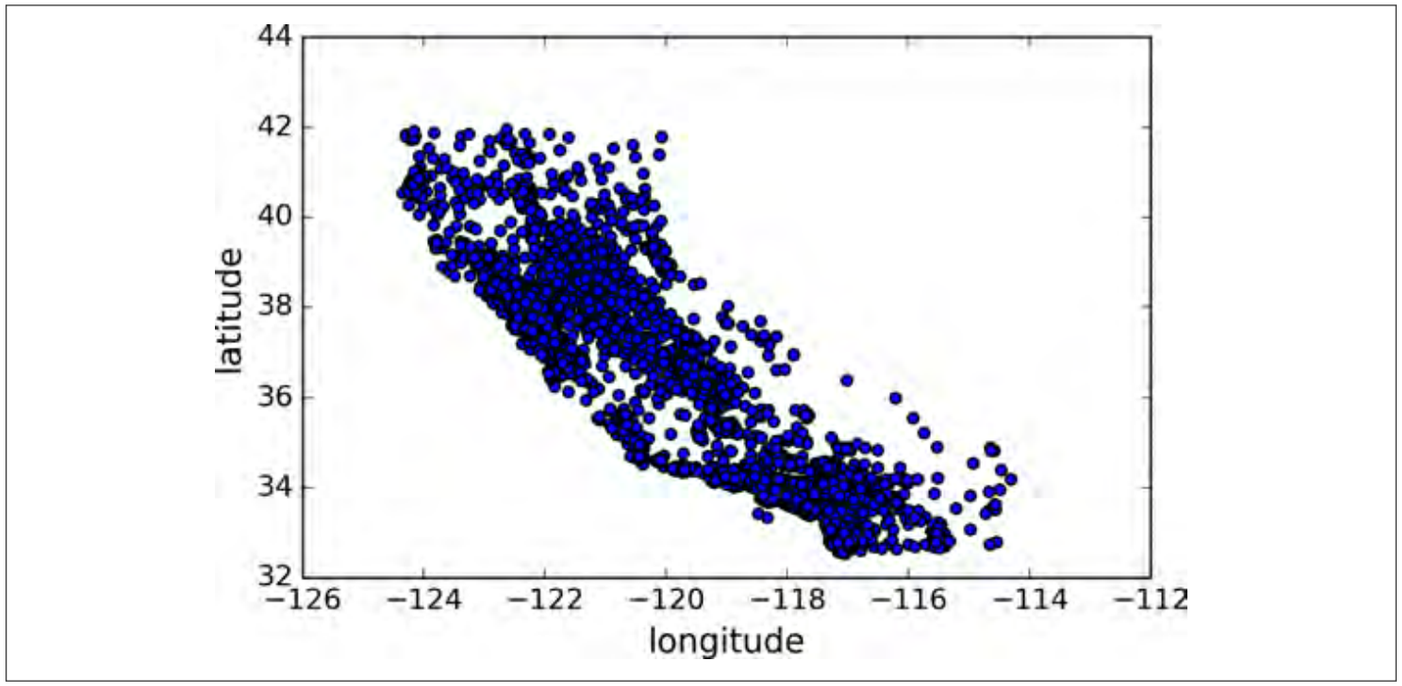

Figure 2-11. A geographical scatterplot of the data

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

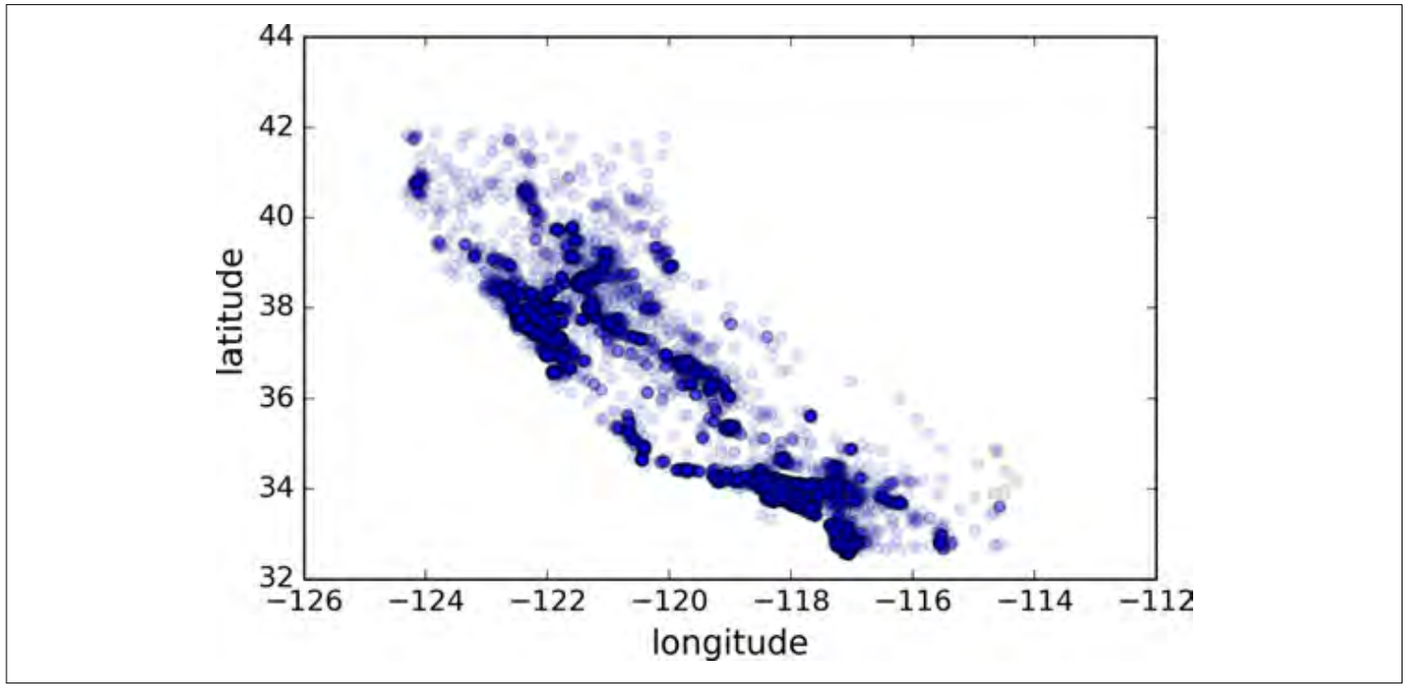

Figure 2-12. A better visualization highlighting high-density areas

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

```
housing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4,
    s=housing["population"]/100, label="population",
    c="median_house_value", cmap=plt.get_cmap("jet"), colorbar=True,
)
plt.legend()
```

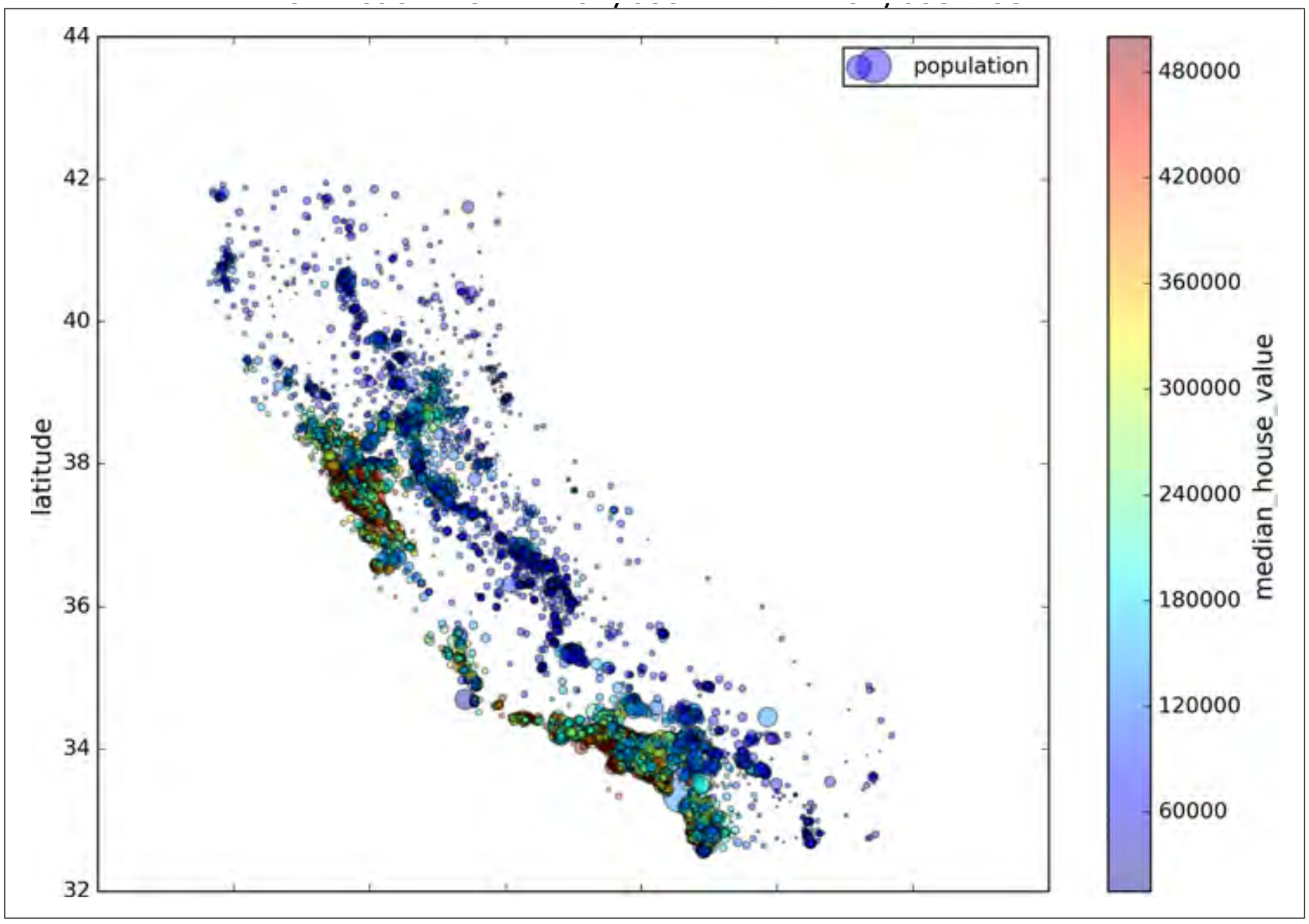

Figure 2-13. California housing prices

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

Look for Correlations

```
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
```

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

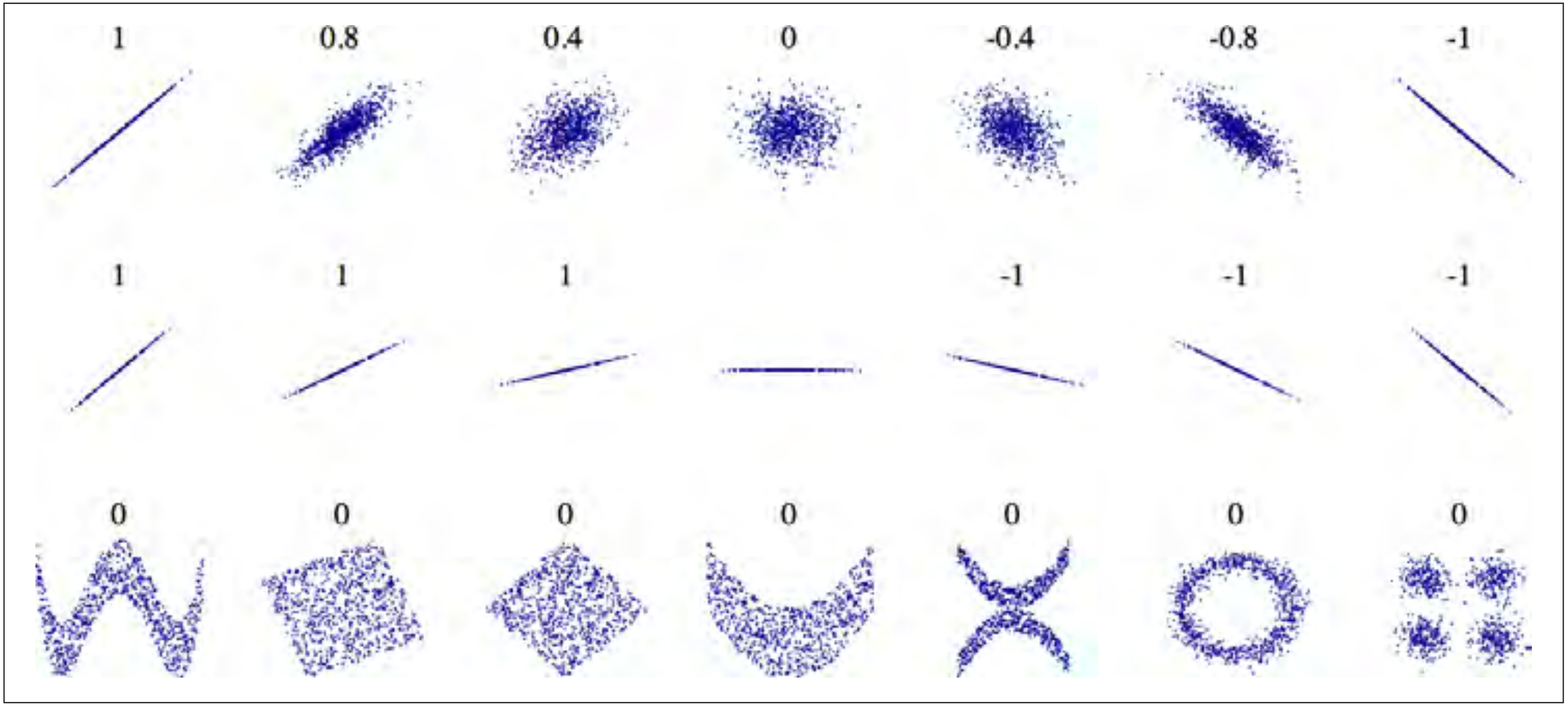

Figure 2-14. Standard correlation coefficient of various datasets (source: Wikipedia; public domain image)

Géron, Aurélien. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* O'Reilly Media, Inc.

```
from pandas.tools.plotting import scatter_matrix

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

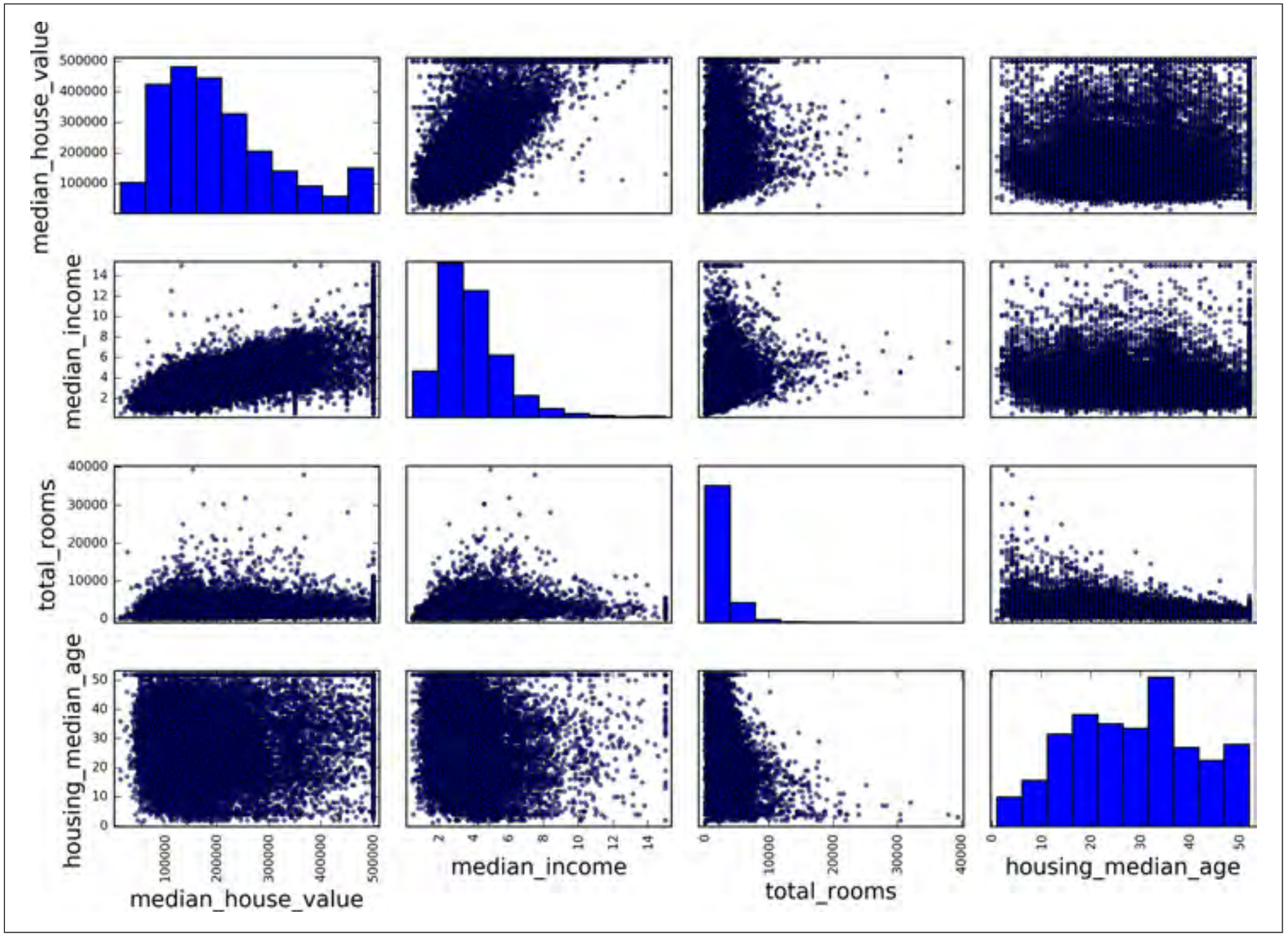

Figure 2-15. Scatter matrix

```
from pandas.tools.plotting import scatter_matrix

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

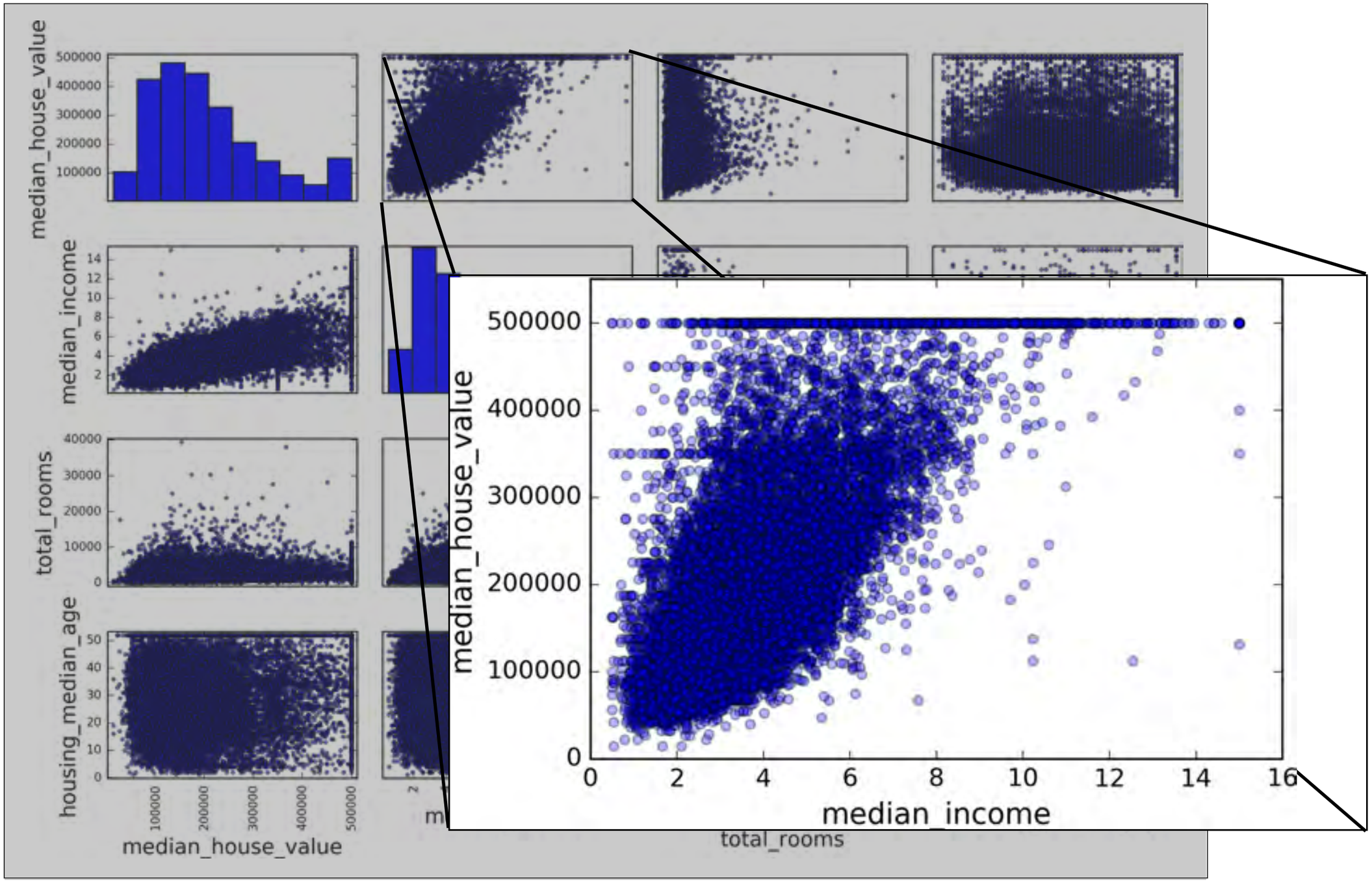

Figure 2-15. Scatter matrix

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In-Class Activity

- **Replicate some of the plots from the California Housing Dataset with the Boston Housing Dataset included with scikit learn**

  - ```
    import pandas as pd
    from sklearn.datasets import load_boston
    boston = load_boston()
    boston_pd = pd.DataFrame(boston.data)
    ```

- **Be sure to add median value to the main dataframe**

  - ```
    boston_pd.columns = boston.feature_names
    ```
  - ```
    boston_pd['MEDV'] = boston.target
    ```

- **Generate a histogram for all of the data columns**

- **Generate a scatter matrix for the attributes "MEDV", "LSTAT", “RM”, "AGE"**

Also check out: https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html
    ```

Project 1

- **Due March 18**
- **Start exploring potential datasets**
  - kaggle.com
  - archive.ics.uci.edu/ml/datasets.php
  - libguides.nypl.org/eresources
  - opendata.cityofnewyork.us/data/
- **The data set will need to be labeled as you are going to use it for both supervised and unsupervised learning tasks**

Paired Question

- **What do you most want to learn to do with machine learning?**
  - What kind of data are you interested in working with?
  - What kind of questions do you want to be able to ask of your data?

Assignments for next week

- **DataCamp**
  - Preprocessing for Machine Learning in Python
    - Introduction to Data Preprocessing
    - Standardizing Data
    - *Feature Engineering* (March 11)
    - *Selecting features for modeling* (March 11)

- **Reading**
  - Ch 4: "Representing Data/Engineering Features"in Guido, Sarah and Andreas C. Muller. (2016). Introduction to Machine Learning with Python, O'Reilly Media, Inc. 213–55.