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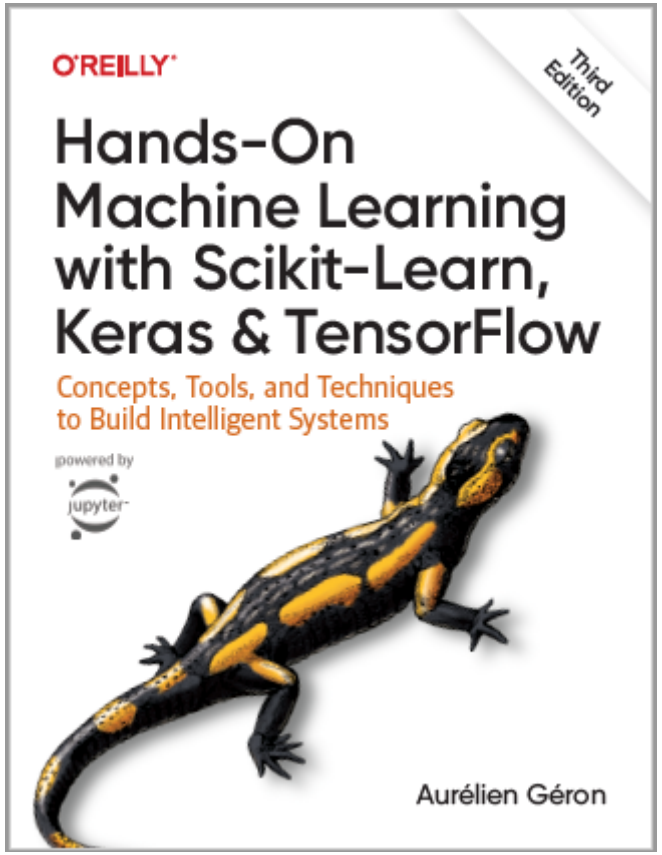
DeCAIR

End-to-End Machine Learning Project

Prof. Gheith Abandah

Reference

- Chapter 2: **End-to-End Machine Learning Project**



- Aurélien Géron, **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**, O'Reilly, 3rd Edition, 2022
  - Material: https://github.com/ageron/handson-ml3

The 7 Steps of Machine Learning

- YouTube Video: **The 7 Steps of Machine Learning** from Google Cloud Platform

https://youtu.be/nKW8Ndu7Mjw

Caution: *Alcohol is forbidden in the Islamic religion and causes addiction and has negative effects on health.*

Outline

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
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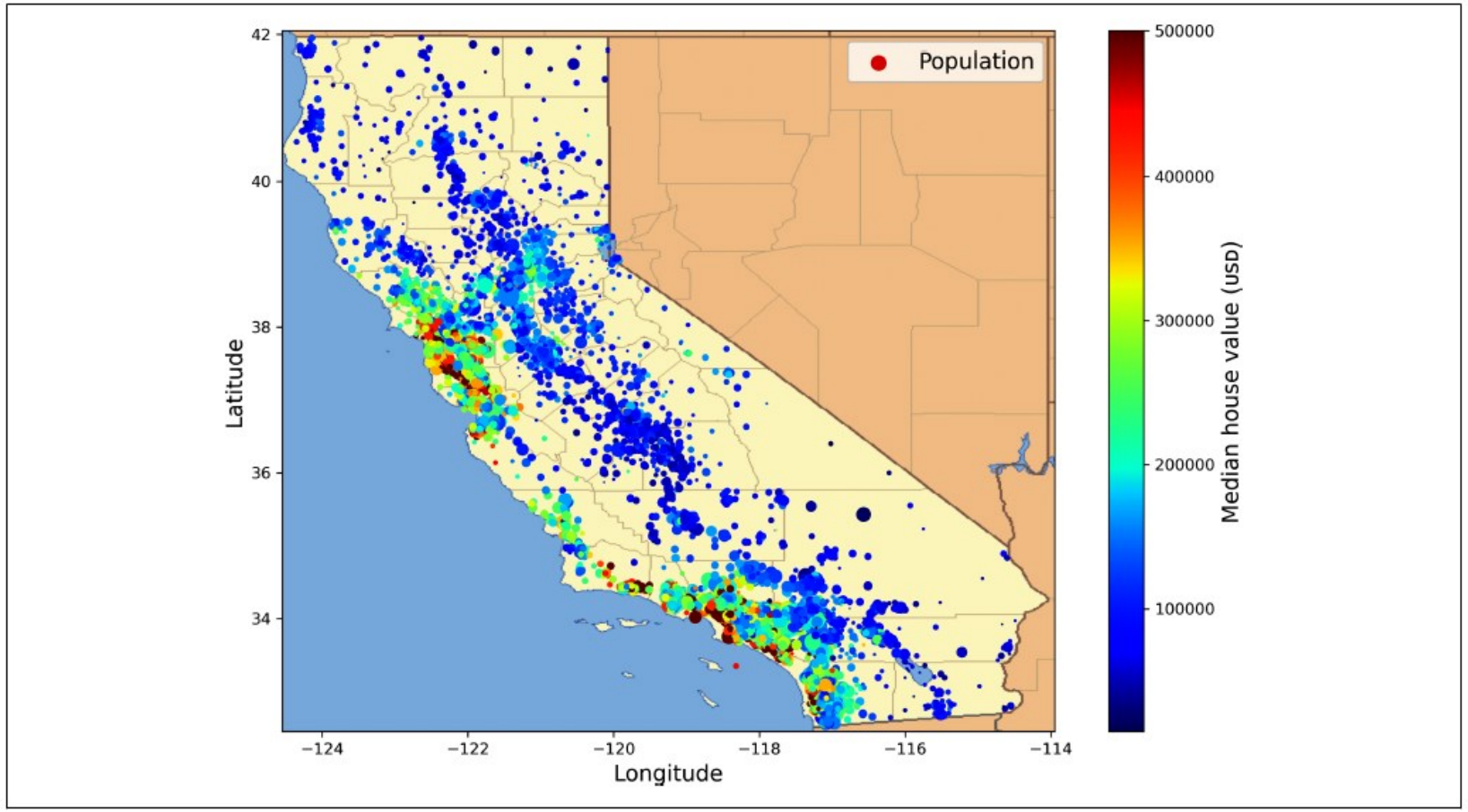
9. Exercises

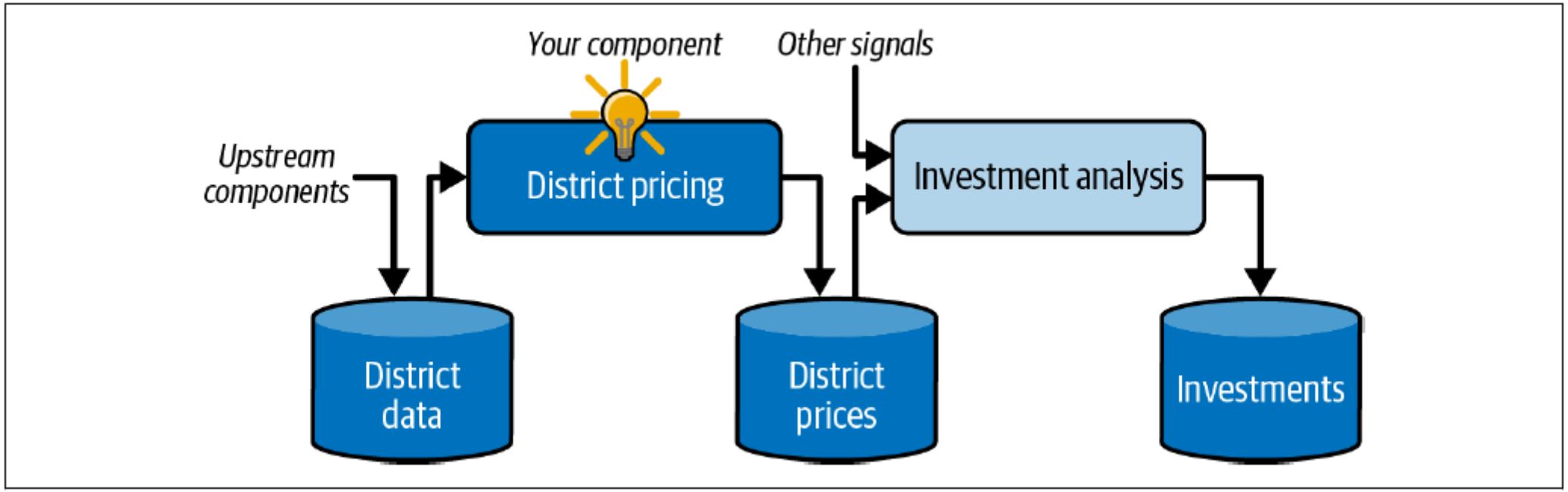
Working with Real Data

- Popular open data repositories:
  - OpenML.org
  - Kaggle.com
  - PapersWithCode.com
  - UC Irvine Machine Learning Repository
  - Amazon's AWS datasets
  - TensorFlow Datasets
  - IEEE DataPort
- Meta portals (they list open data repositories):
  - Google Dataset Search
  - http://dataportals.org/
  - http://opendatamonitor.eu/
- Other pages listing many popular open data repositories:
  - Wikipedia's list of Machine Learning datasets
  - Quora.com
  - Datasets subreddit

1. Look at the Big Picture: CA Housing Data

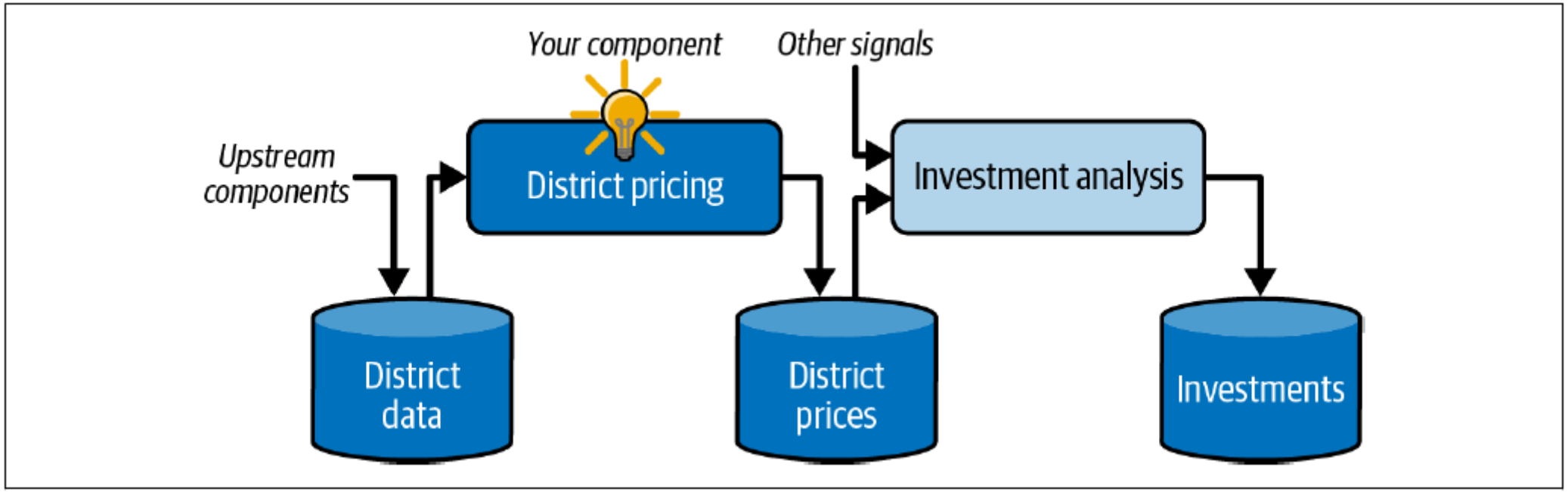


1.1. Frame the Problem



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?
Instance-based or Model-based learning?

1.1. 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?
Instance-based or **Model-based** learning?

1.2. Select a Performance Measure

- **Root Mean Square Error (RMSE)**

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

- m is the number of samples
- $\mathbf{x}^{(i)}$ is the feature vector of Sample i
- $y^{(i)}$ is the label or desired output
- $\mathbf{X}$ is a matrix containing all the feature values

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

1.2. Select a Performance Measure

- **Mean Absolute Error**

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

- MAE is better than RMSE when there are outlier samples.

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2. Get the Data

- If you didn’t do it before, it is time now to **download** the **Jupyter notebooks** of the textbook from

  https://github.com/ageron/handson-ml3

- It is recommended to run these notebooks on Google Colab at https://homl.info/colab3

- The following slides summarize the code used in Notebook 2.

2. Get the Data

1. Download the **`housing.tgz`** file from **Github** using **`urllib.request.urlretrieve()`** from the **`urllib`** package
2. Extract the data from this compressed tar file using **`tarfile.open()`** and **`extractall()`**. The data will be in the CSV file **`housing.csv`**
3. Read the CSV file into a Pandas DataFrame called **`housing`** using **`pandas.read_csv()`**

2.1. Take a Quick Look at the Data Structure

- Display the top five rows using the DataFrame's `head()` method
- The `info()` method is useful to get a quick description of the data
- To find categories and repetitions of some column use `housing.['key'].value_counts()`
- The `describe()` method shows a summary of the numerical attributes.
- Show histogram using the `hist()` method and `matplotlib.pyplot.show()`

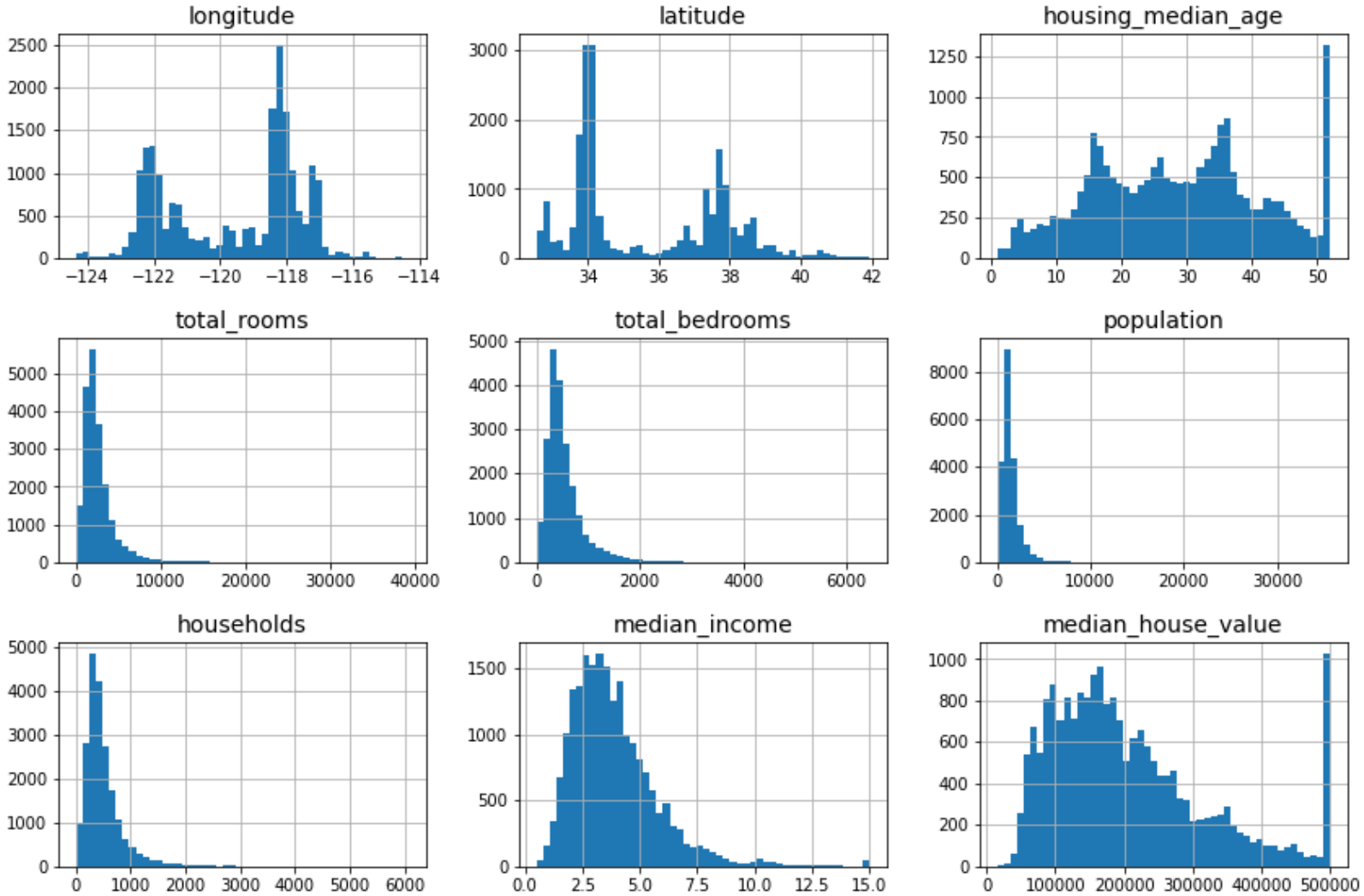
```
housing.info()
```

```
<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
```

207 missing features

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

A histogram for each numerical attribute



2.2. Create a Test Set

- **Split** the available data randomly to:
  - Training set (80%)
  - Test set (20%)
- The example defines a function called `split_train_test()` for illustration.
- Scikit-Learn has `train_test_split()`.
- Scikit-Learn also has `StratifiedShuffleSplit()` that does stratified sampling.
- **Stratification** ensures that the test samples are representative of the target categories.

2.2.1. Create a Test Set: User-defined function

```
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]
```

You can then use this function like this:

```
>>> train_set, test_set = split_train_test(housing, 0.2)
>>> print(len(train_set), "train +", len(test_set), "test")
16512 train + 4128 test
```

2.2.2. Create a Test Set: Using Scikit-Learn functions

```
from sklearn.model_selection import train_test_split

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

Also supports stratification on the target class.

```
strat_train_set, strat_test_set = train_test_split(
    housing, test_size=0.2, stratify=housing["income_cat"], random_state=42)
```

2.2.2. Create a Test Set: Using Scikit-Learn functions

This class supports stratification and multiple splits.

```
from sklearn.model_selection import StratifiedShuffleSplit

splitter = StratifiedShuffleSplit(n_splits=10, test_size=0.2, random_state=42)
strat_splits = []
for train_index, test_index in splitter.split(housing, housing["income_cat"]):
    strat_train_set_n = housing.iloc[train_index]
    strat_test_set_n = housing.iloc[test_index]
    strat_splits.append([strat_train_set_n, strat_test_set_n])
```

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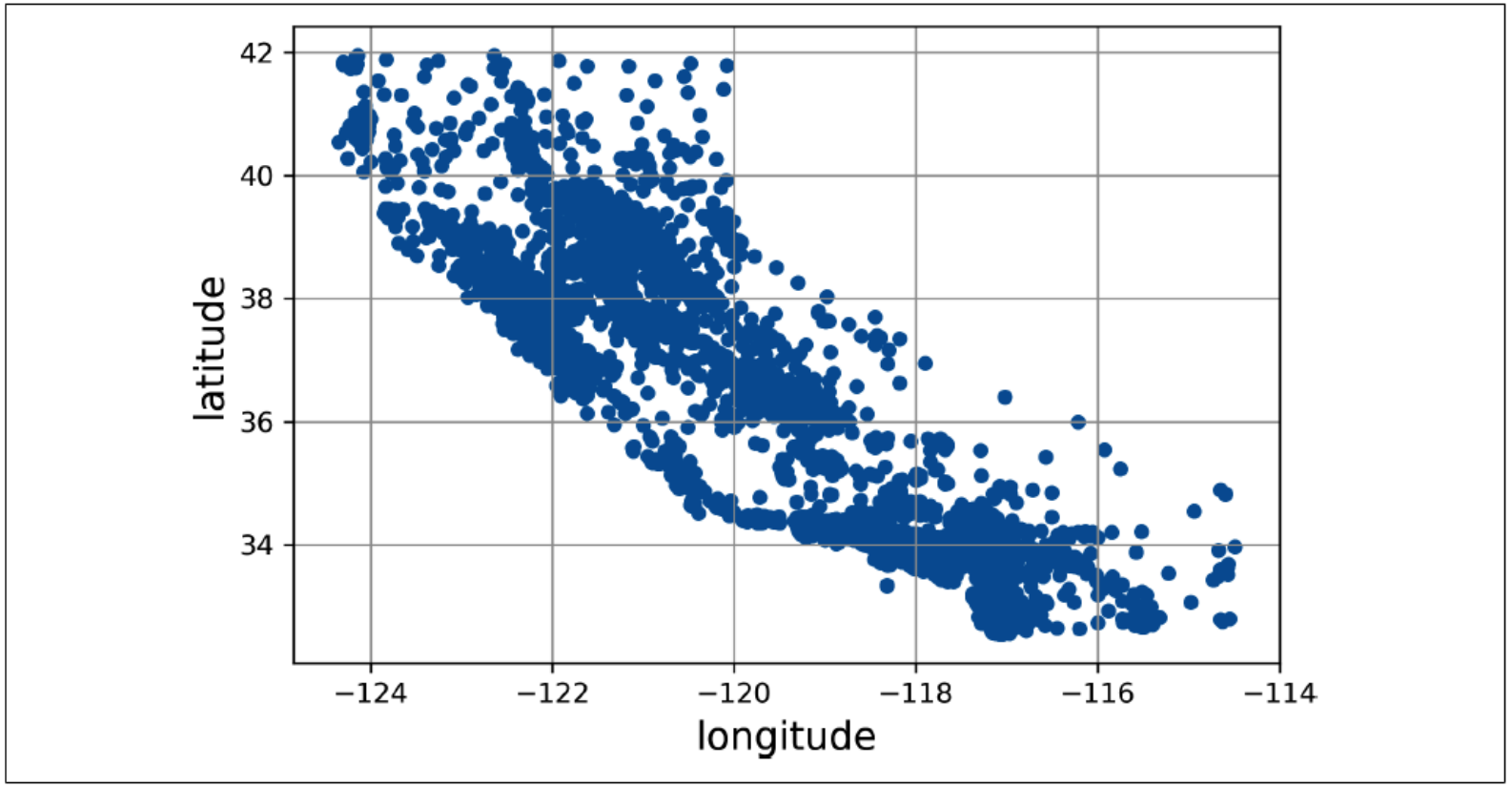
3. Discover and Visualize the Data to Gain Insights

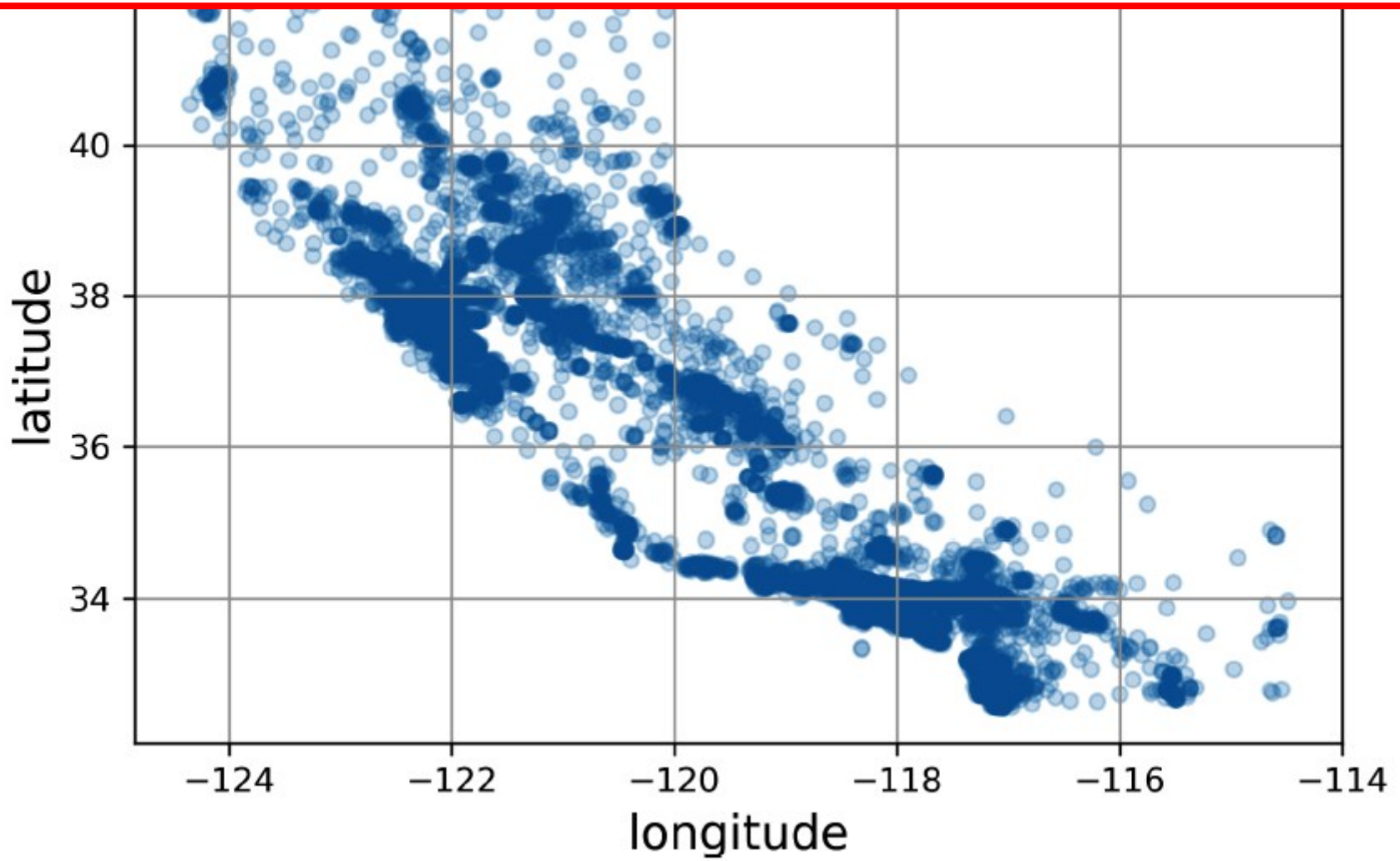
- **Visualize** geographical data using scatter plot:

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



- **Add** transparency.

```
housing.plot(kind="scatter", x="longitude", y="latitude", grid=True, alpha=0.2)
plt.show()
```



3. Discover and Visualize the Data to Gain Insights

- **Add** size, color, and legend.

```
housing.plot(kind="scatter", x="longitude", y="latitude", grid=True,
             s=housing["population"] / 100, label="population",
             c="median_house_value", cmap="jet", colorbar=True,
             legend=True, sharex=False, figsize=(10, 7))
plt.show()
```

s: size, **c**: color, **cmap**: color map blue to red

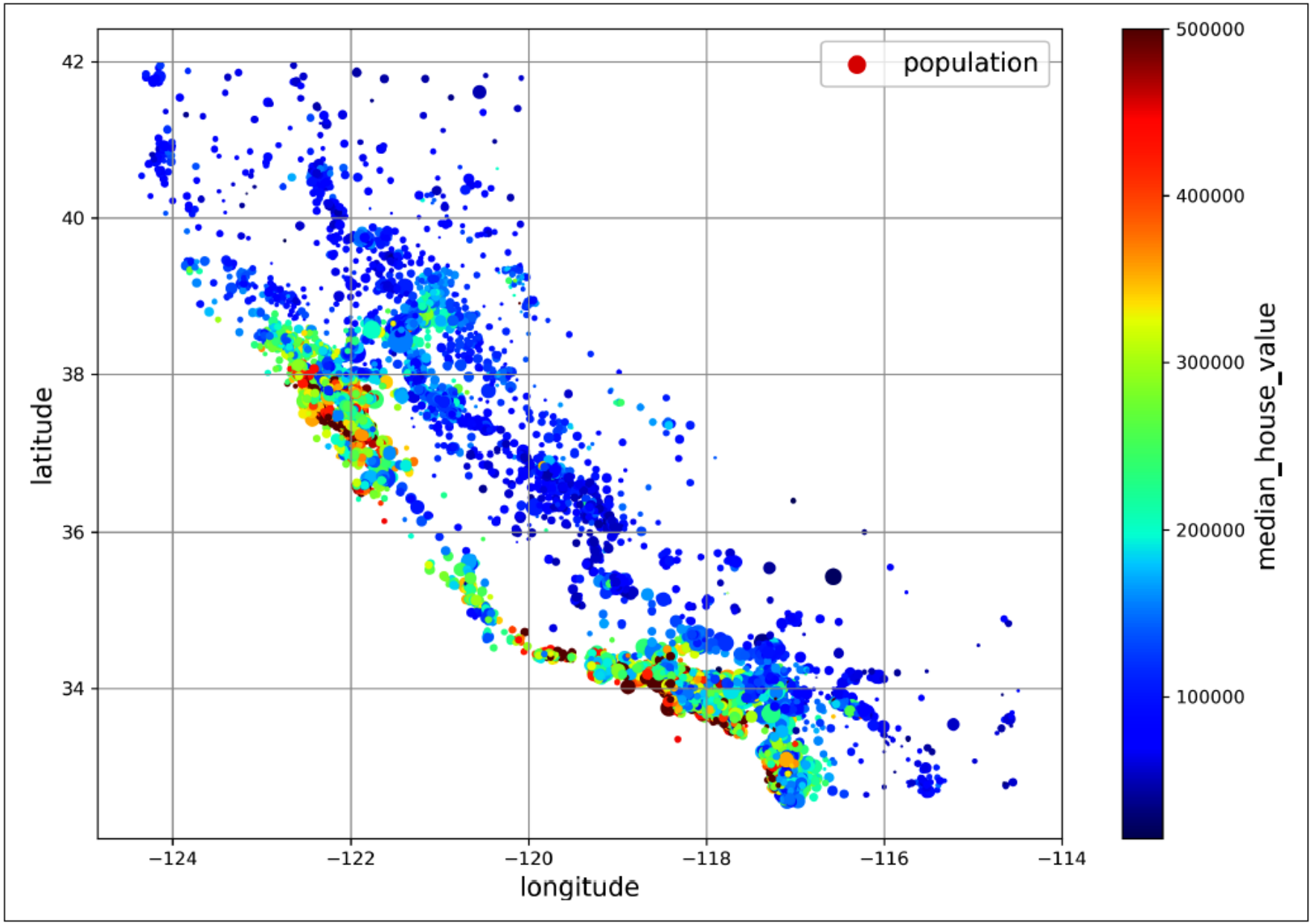


Figure 2-13. California housing prices: red is expensive, blue is cheap, larger circles indicate areas with a larger population

3.1. Looking for Correlations

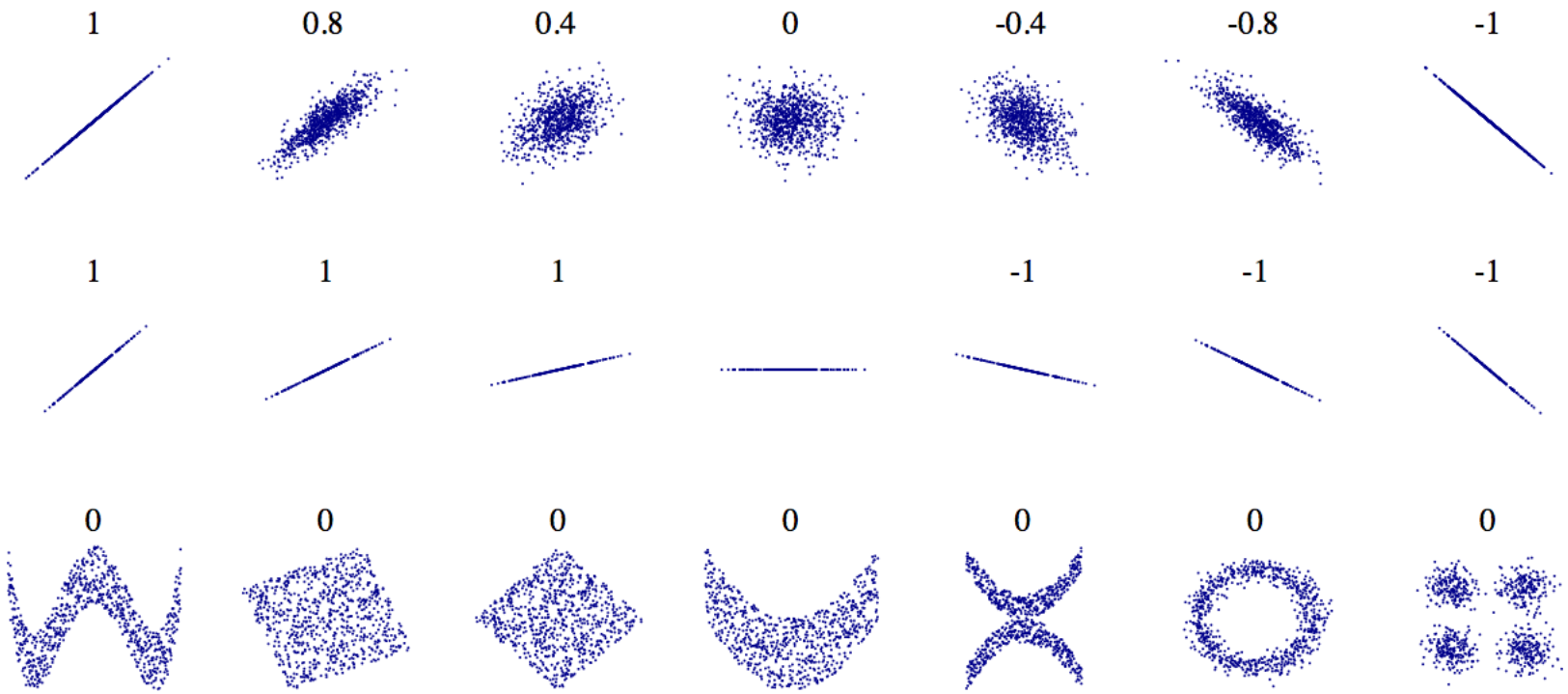
- Compute the **standard correlation coefficient** (also **called Pearson's *r***) between every pair of attributes using `corr_matrix = housing.corr()`

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

```
>>> 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
```

3.1. Looking for Correlations

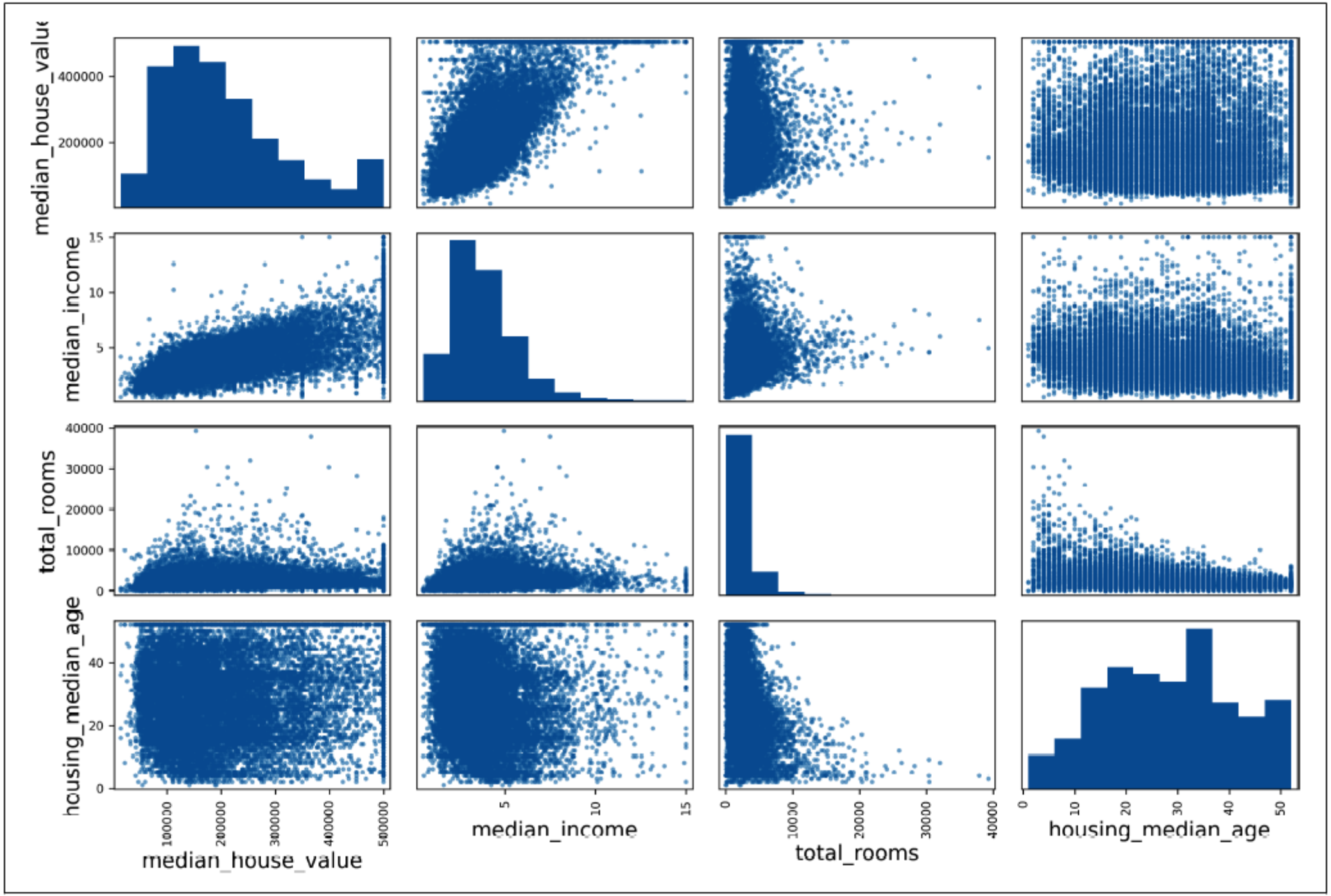
- Zero linear correlation (***r* = 0**) does not guarantee **independence**.



3.2. Pandas Scatter Matrix

```
from pandas.plotting import scatter_matrix

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


median_house_value
median_income
total_rooms
housing_median_age
400000
200000
15
10
5
40000
30000
20000
10000
0
40
20
0
100000
200000
300000
400000
500000
5
10
15
0
10000
20000
30000
40000
0
10
20
30
40
50

3.3. Experimenting with Attribute Combinations

```
housing["rooms_per_house"] = housing["total_rooms"] / housing["households"]
housing["bedrooms_ratio"] = housing["total_bedrooms"] / housing["total_rooms"]
housing["people_per_house"] = housing["population"] / housing["households"]
```

```
>>> corr_matrix = housing.corr()
>>> corr_matrix["median_house_value"].sort_values(ascending=False)
median_house_value    1.000000
median_income         0.688380
rooms_per_house       0.143663
total_rooms           0.137455
housing_median_age    0.102175
households            0.071426
total_bedrooms        0.054635
population           -0.020153
people_per_house     -0.038224
longitude            -0.050859
latitude             -0.139584
bedrooms_ratio       -0.256397
Name: median_house_value, dtype: float64
```

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4. Prepare the Data for Machine Learning Algorithms

- **Split** to train and test (Done)
- **Separate** features from response
- Handle **missing** data
- Handle text and **categorical** features
- **Scale** (normalize) features
- Build preparation **pipeline**

4. Prepare the Data for Machine Learning Algorithms

- **Separate** the **features** from the **response**.

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

- **Options** of handling **missing features**:
  1. **Get rid** of the corresponding **districts**
  2. **Get rid** of the whole **attribute**
  3. **Set the values** to some value (0, mean, median, etc.)

```
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)
```

4.1. Handling Missing Features Using Scikit-Learn

- **Scikit-Learn** class design is consistent and simple
  - Estimators `.fit()`
  - Transformers `.transform()`
  - Predictors `.predict()`
  - Inspection `.statistics_`

4.1. Handling Missing Features Using Scikit-Learn

- Use **`SimpleImputer`** on the numerical features. Need to remove categorical variables before doing the fit. The attribute **`statistics_`** has the means.

```
from sklearn.preprocessing import SimpleImputer
imputer = SimpleImputer(strategy="median")
housing_num = housing.drop("ocean_proximity", axis=1)
imputer.fit(housing_num)
>>> imputer.statistics_
array([ -118.51 , 34.26 , 29. , 2119. , 433. , 1164. , 408. , 3.5414])
>>> housing_num.median().values
array([ -118.51 , 34.26 , 29. , 2119. , 433. , 1164. , 408. , 3.5414])
X = imputer.transform(housing_num)
```

NumPy array

Can be used multiple times.

4.2. Handling Text and Categorical Attributes

- **`ocean_proximity`** is categorical feature.

```
>>> 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
```

4.2. Handling Text and Categorical Attributes

- Most machine learning algorithms prefer to work with numbers.
  Converting to numbers:

```
>>> 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.]])
```

Numerical values imply distances

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

4.2. Handling Text and Categorical Attributes

- To ensure encoding neutrality, we can use the one-hot encoding.

```
>>> 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>
>>> housing_cat_1hot.toarray()
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.]])
```

Converts sparse matrix to dense matrix.

4.3. Feature Scaling

- ML algorithms generally **don't perform well** when the input numerical attributes have **very different scales**.

- Scaling techniques:
  - **Min-max scaling**

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

  - **Standardization**

$$x' = \frac{x - \bar{x}}{\sigma}$$

  - **Shrink heavy tails**

4.3. Feature Scaling

- **Min-max scaling**

```
from sklearn.preprocessing import MinMaxScaler

min_max_scaler = MinMaxScaler(feature_range=(-1, 1))
housing_num_min_max_scaled = min_max_scaler.fit_transform(housing_num)
```

-1 to 1 scaling instead of 0 to 1 scaling

- **Standardization**

```
from sklearn.preprocessing import StandardScaler

std_scaler = StandardScaler()
housing_num_std_scaled = std_scaler.fit_transform(housing_num)
```

4.3. Feature Scaling

- **Shrink heavy tails**

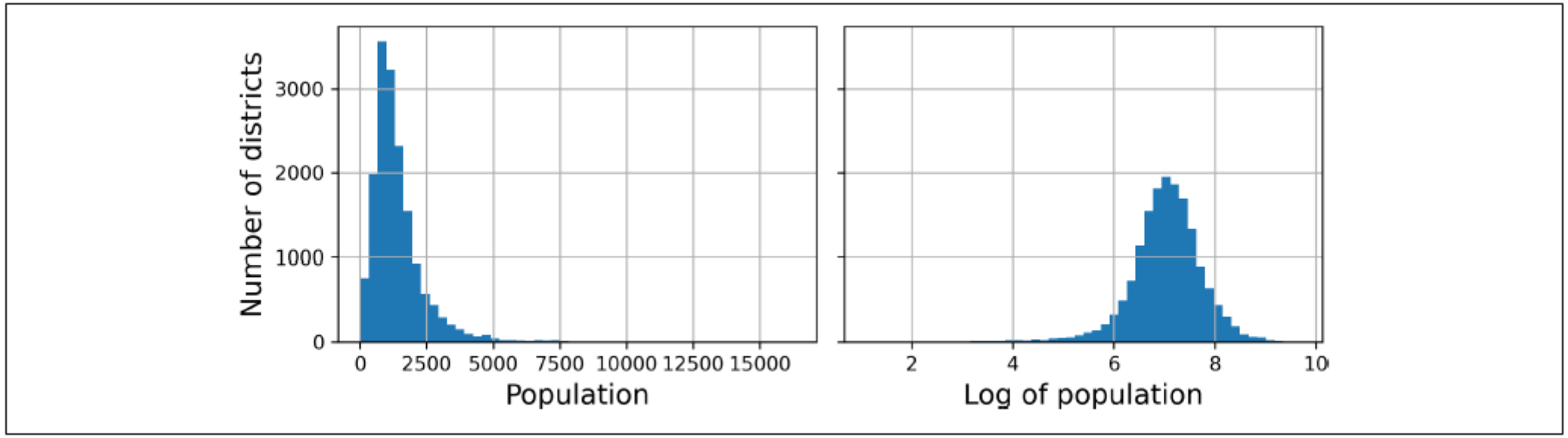


Figure 2-17. Transforming a feature to make it closer to a Gaussian distribution

4.4. Custom Transformers

- Scikit-Learn allows you to create your **own transformers**.
- For transformers that don't require any training, use **`FunctionTransformer`**.

```
from sklearn.preprocessing import FunctionTransformer

log_transformer = FunctionTransformer(np.log, inverse_func=np.exp)
log_pop = log_transformer.transform(housing[["population"]])
```

- Can also use it to **combine features**.

```
>>> ratio_transformer = FunctionTransformer(lambda X: X[:, [0]] / X[:, [1]])
>>> ratio_transformer.transform(np.array([[1., 2.], [3., 4.]]))
array([[0.5 ],
       [0.75]])
```

4.4. Custom Transformers

- For creating a custom transformer that requires an estimator function, create a class and implement three methods: `fit()` (returning self), `transform()`, and `fit_transform()`. Include base classes:
  - `TransformerMixin` to get `fit_transform()`
  - `BaseEstimator` to get `get_params()` and `set_params()`

Example: Standard Scaler

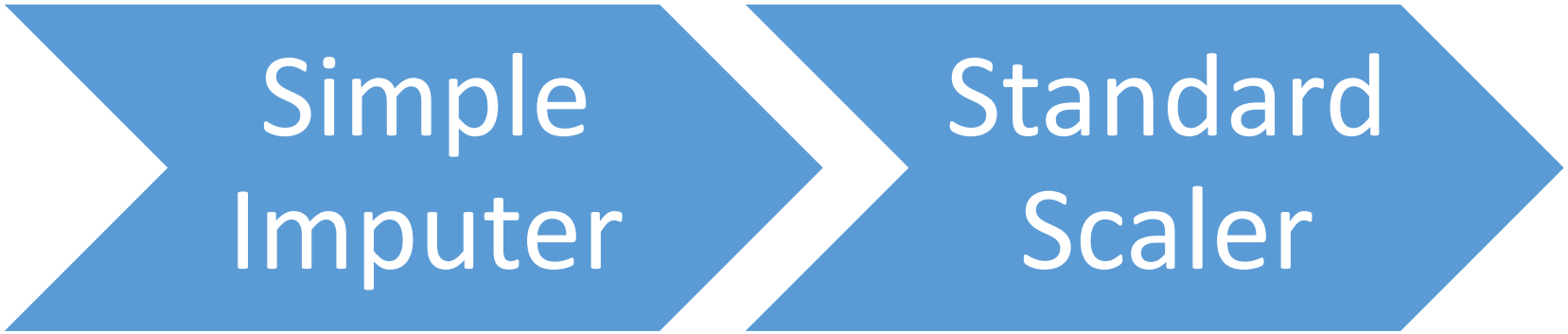
```python
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.utils.validation import check_array, check_is_fitted

class StandardScalerClone(BaseEstimator, TransformerMixin):
    def __init__(self, with_mean=True):  # no *args or **kwargs!
        self.with_mean = with_mean

    def fit(self, X, y=None):  # y is required even though we don't use it
        X = check_array(X)  # checks that X is an array with finite float values
        self.mean_ = X.mean(axis=0)
        self.scale_ = X.std(axis=0)
        self.n_features_in_ = X.shape[1]  # every estimator stores this in fit()
        return self  # always return self!

    def transform(self, X):
        check_is_fitted(self)  # looks for learned attributes (with trailing _)
        X = check_array(X)
        assert self.n_features_in_ == X.shape[1]
        if self.with_mean:
            X = X - self.mean_
        return X / self.scale_
```

4.5. Transformation Pipelines




```
from sklearn.pipeline import Pipeline

num_pipeline = Pipeline([
    ("impute", SimpleImputer(strategy="median")),
    ("standardize", StandardScaler()),
])


housing_num_tr = num_pipeline.fit_transform(housing_num)
```

4.5. Transformation Pipelines

- If you don’t want to name the transformers, you can use the **`make_pipeline()`** function,.

```
from sklearn.pipeline import make_pipeline

num_pipeline = make_pipeline(SimpleImputer(strategy="median"), StandardScaler())
```

4.6. Full Pipeline

- Can combine multiple pipeline paths using **`ColumnTransformer`**.

```
from sklearn.compose import ColumnTransformer

num_attribs = ["longitude", "latitude", "housing_median_age", "total_rooms",
               "total_bedrooms", "population", "households", "median_income"]
cat_attribs = ["ocean_proximity"]

cat_pipeline = make_pipeline(
    SimpleImputer(strategy="most_frequent"),
    OneHotEncoder(handle_unknown="ignore"))

preprocessing = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", cat_pipeline, cat_attribs),
])
```

4.6. Full Pipeline

- Can automate attribute selection using **`make_column_selector()`** and **`make_column_transformer()`** to avoid naming the pipelines.

```
from sklearn.compose import make_column_selector, make_column_transformer

preprocessing = make_column_transformer(
    (num_pipeline, make_column_selector(dtype_include=np.number)),
    (cat_pipeline, make_column_selector(dtype_include=object)),
)
```

- Using the full pipeline is straight forward.

```
housing_prepared = preprocessing.fit_transform(housing)
```

Dense array

Full Pipeline Used in the Reference Book (1/3)

```
def column_ratio(X):
    return X[:, [0]] / X[:, [1]]

def ratio_name(function_transformer, feature_names_in):
    return ["ratio"]  # feature names out

def ratio_pipeline():
    return make_pipeline(
        SimpleImputer(strategy="median"),
        FunctionTransformer(column_ratio, feature_names_out=ratio_name),
        StandardScaler())

log_pipeline = make_pipeline(
    SimpleImputer(strategy="median"),
    FunctionTransformer(np.log, feature_names_out="one-to-one"),
    StandardScaler())
cluster_simil = ClusterSimilarity(n_clusters=10, gamma=1., random_state=42)
default_num_pipeline = make_pipeline(SimpleImputer(strategy="median"),
                                     StandardScaler())
```

Full Pipeline Used in the Reference Book (2/3)

```
preprocessing = ColumnTransformer([
        ("bedrooms", ratio_pipeline(), ["total_bedrooms", "total_rooms"]),
        ("rooms_per_house", ratio_pipeline(), ["total_rooms", "households"]),
        ("people_per_house", ratio_pipeline(), ["population", "households"]),
        ("log", log_pipeline, ["total_bedrooms", "total_rooms", "population",
                               "households", "median_income"]),
        ("geo", cluster_simil, ["latitude", "longitude"]),
        ("cat", cat_pipeline, make_column_selector(dtype_include=object)),
    ],
    remainder=default_num_pipeline)  # one column remaining: housing_median_age
```

Full Pipeline Used in the Reference Book (3/3)

```
>>> housing_prepared = preprocessing.fit_transform(housing)
>>> housing_prepared.shape
(16512, 24)
>>> preprocessing.get_feature_names_out()
array(['bedrooms__ratio', 'rooms_per_house__ratio',
       'people_per_house__ratio', 'log__total_bedrooms',
       'log__total_rooms', 'log__population', 'log__households',
       'log__median_income', 'geo__Cluster 0 similarity', [...],
       'geo__Cluster 9 similarity', 'cat__ocean_proximity_<1H OCEAN',
       'cat__ocean_proximity_INLAND', 'cat__ocean_proximity_ISLAND',
       'cat__ocean_proximity_NEAR BAY', 'cat__ocean_proximity_NEAR OCEAN',
       'remainder__housing_median_age'], dtype=object)
```

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7. Present your solution
8. Launch, monitor, and maintain your system
9. Exercises

5. Select and Train a Model

1) **Linear regressor**
2) Using **RMSE** for evaluation
3) **Decision tree regressor**
4) **k-fold** cross validation
5) **Random forests regressor**

5. Select and Train a Model

- Let us start by training a simple **linear regressor**.

```
from sklearn.linear_model import LinearRegression

lin_reg = make_pipeline(preprocessing, LinearRegression())
lin_reg.fit(housing, housing_labels)
```

- Try it out on five instances from the training set.

```
>>> housing_predictions = lin_reg.predict(housing)
>>> housing_predictions[:5].round(-2)  # -2 = rounded to the nearest hundred
array([243700., 372400., 128800.,  94400., 328300.])
>>> housing_labels.iloc[:5].values
array([458300., 483800., 101700.,  96100., 361800.])
```

47% off

9% off

5.1. Evaluate the Model on the Entire Training Set

- Use RMSE

```
>>> from sklearn.metrics import mean_squared_error
>>> lin_rmse = mean_squared_error(housing_labels, housing_predictions,
...                               squared=False)
...
>>> lin_rmse
68687.89176589991
```

This is not a satisfactory result as the **median_housing_values** range between $120,000 and $265,000.

5.2. Try the Decision Tree Regressor

```
from sklearn.tree import DecisionTreeRegressor

tree_reg = make_pipeline(preprocessing, DecisionTreeRegressor(random_state=42))
tree_reg.fit(housing, housing_labels)
```

```
>>> housing_predictions = tree_reg.predict(housing)
>>> tree_rmse = mean_squared_error(housing_labels, housing_predictions,
...                                squared=False)
...
>>> tree_rmse
0.0
```

Overfitting: It has memorized the entire training set!

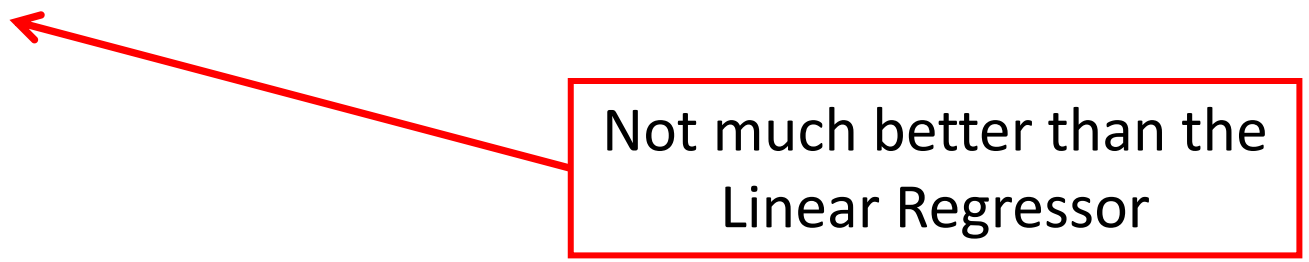
5.3. Better Evaluation Using Cross-Validation

- Segment the training data into **10 sets** and repeat training and evaluation 10 times.

```
from sklearn.model_selection import cross_val_score

tree_rmses = -cross_val_score(tree_reg, housing, housing_labels,
                              scoring="neg_root_mean_squared_error", cv=10)
```

```
>>> pd.Series(tree_rmses).describe()
count       10.000000
mean     66868.027288
std       2060.966425
min      63649.536493
25%      65338.078316
50%      66801.953094
75%      68229.934454
max      70094.778246
dtype: float64
```



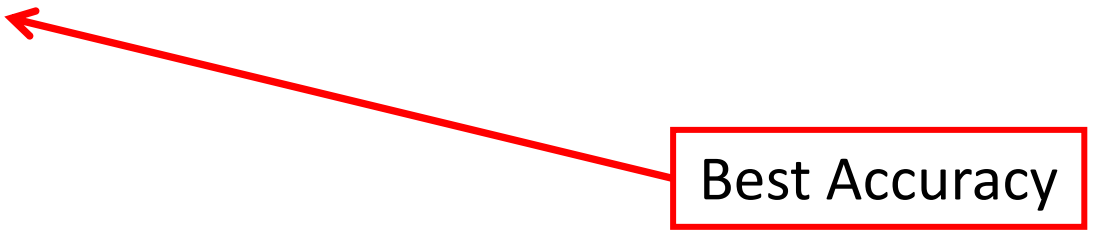
5.4. Try the Random Forests Regressor

- Repeating training and evaluation:

```
from sklearn.ensemble import RandomForestRegressor

forest_reg = make_pipeline(preprocessing,
                           RandomForestRegressor(random_state=42))
forest_rmses = -cross_val_score(forest_reg, housing, housing_labels,
                                scoring="neg_root_mean_squared_error", cv=10)
```

```
>>> pd.Series(forest_rmses).describe()
count       10.000000
mean     47019.561281
std       1033.957120
min      45458.112527
25%      46464.031184
50%      46967.596354
75%      47325.694987
max      49243.765795
dtype: float64
```



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6. Fine-Tune Your Model

- Fine-tune your system by fiddling with:
  - The hyperparameters
  - Removing and adding features
  - Changing feature preprocessing techniques
- Can experiment manually. But it is best to automate this process using Scikit-Learn:
  - **`GridSearchCV`**
  - or **`RandomizedSearchCV`**

6.1. Grid Search

- Can automate exploring a search space of $3 \times 3 + 2 \times 3 = 9 + 6 = 15$

```
from sklearn.model_selection import GridSearchCV

full_pipeline = Pipeline([
    ("preprocessing", preprocessing),
    ("random_forest", RandomForestRegressor(random_state=42)),
])
param_grid = [
    {'preprocessing__geo__n_clusters': [5, 8, 10],
     'random_forest__max_features': [4, 6, 8]},
    {'preprocessing__geo__n_clusters': [10, 15],
     'random_forest__max_features': [6, 8, 10]},
]
grid_search = GridSearchCV(full_pipeline, param_grid, cv=3,
                           scoring='neg_root_mean_squared_error')
grid_search.fit(housing, housing_labels)
```

6.2 Examine the Results of Your Grid Search

- Can examine the best hyperparameters using:

```
>>> grid_search.best_params_
{'preprocessing__geo__n_clusters': 15, 'random_forest__max_features': 6}
```

- Can examine all search results using:

```
>>> cv_res = pd.DataFrame(grid_search.cv_results_)
>>> cv_res.sort_values(by="mean_test_score", ascending=False, inplace=True)
>>> [...]  # change column names to fit on this page, and show rmse = -score
>>> cv_res.head()  # note: the 1st column is the row ID
   n_clusters max_features  split0  split1  split2  mean_test_rmse
12         15            6   43460   43919   44748           44042
13         15            8   44132   44075   45010           44406
14         15           10   44374   44286   45316           44659
7          10            6   44683   44655   45657           44999
9          10            6   44683   44655   45657           44999
```

Dictionary

Best Tuned Accuracy

6.2 Evaluate Your System on the Test Set

- The final model is the best estimator found by the grid search.

```
>>> final_model = rnd_search.best_estimator_  # includes preprocessing
```

- To evaluate it on the test set, transform the test features, predict using transformed features, and evaluate accuracy.

```
X_test = strat_test_set.drop("median_house_value", axis=1)
y_test = strat_test_set["median_house_value"].copy()

final_predictions = final_model.predict(X_test)

final_rmse = mean_squared_error(y_test, final_predictions, squared=False)
print(final_rmse)  # prints 41424.40026462184
```

6.3 Save Your Best Model for the Production System

- Save your best mode:

```
import joblib

joblib.dump(final_model, "my_california_housing_model.pkl")
```

- Load and use your model in the production system:

```
final_model_reloaded = joblib.load("my_california_housing_model.pkl")

new_data = [...]  # some new districts to make predictions for
predictions = final_model_reloaded.predict(new_data)
```

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7. Present Your Solution

- Present your solution highlighting:
  - What you have learned
  - What worked and what did not
  - What assumptions were made
  - What your system's limitations are
- Document everything, and create nice presentations with:
  - Clear visualizations
  - Easy-to-remember statements, e.g., "the median income is the number one predictor of housing prices".

8. Launch, Monitor, and Maintain Your System

- Prepare your production program that uses your best trained model and launch it.
- Monitor the accuracy of your system. Also monitor the input data.
- Retrain your system periodically using fresh data.

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Exercise

- Try a Support Vector Machine regressor (`sklearn.svm.SVR`), with various hyperparameters such as `kernel="linear"` (with various values for the `C` hyperparameter) or `kernel="rbf"` (with various values for the `C` and `gamma` hyperparameters). Note that support vector machines don't scale well to large datasets, so you should probably train your model on just the first 5,000 instances of the training set and use only 3-fold cross-validation, or else it will take hours. Don't worry about what the hyperparameters mean for now; we'll discuss them in Chapter 5. How does the best SVR predictor perform?