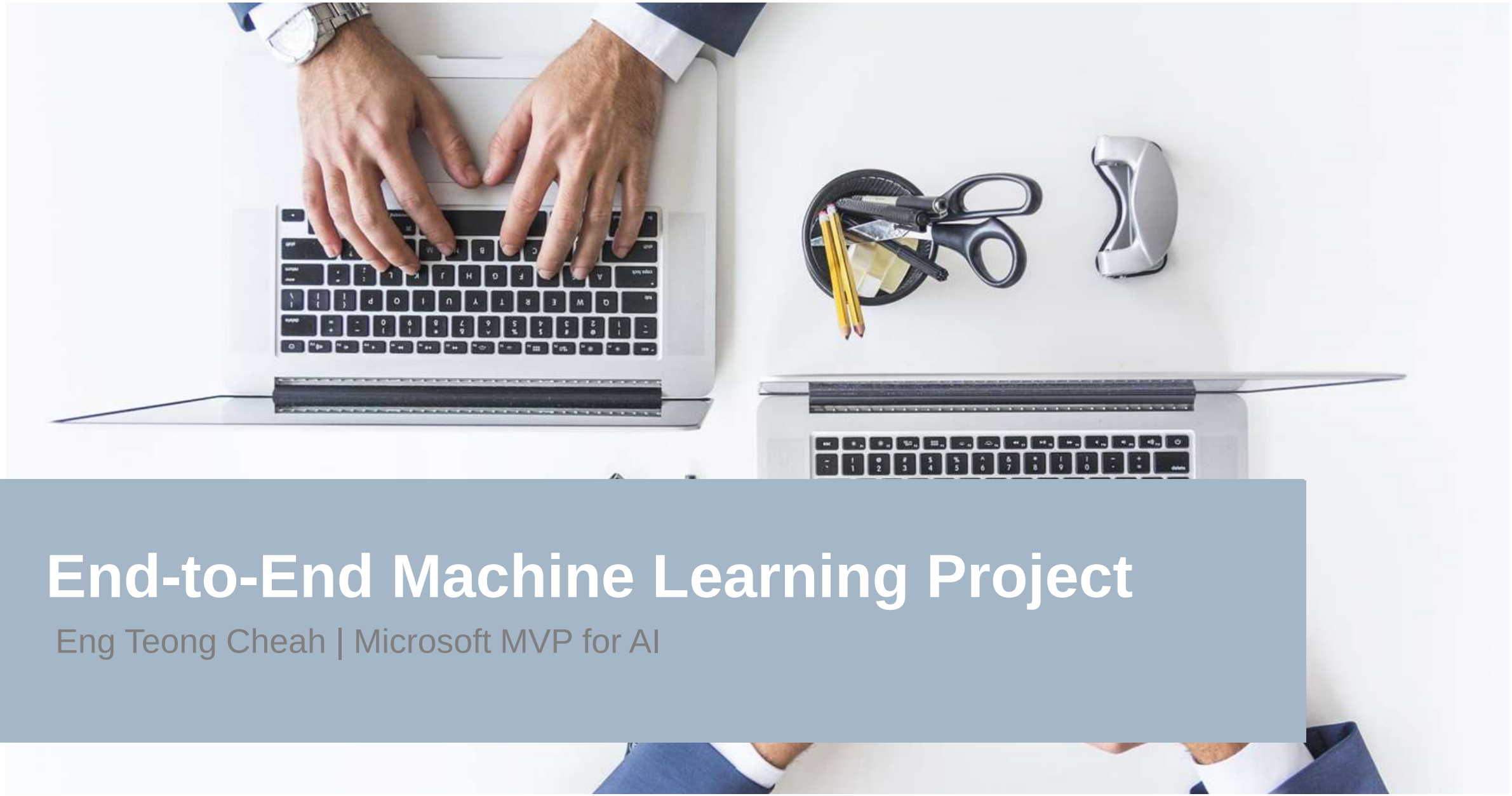

End-to-End Machine Learning Project

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Working with Real Data

Working with Real Data?

When you are learning about Machine Learning it is best to actually experiment with real-world data, not just artificial datasets. Fortunately, there are thousands of open datasets to choose from, ranging across all sorts of domains. Here are a few places you can look to get data:

- Popular open data repositories:
    - UC Irvine Machine Learning Repository
    - Kaggle datasets
    - Amazon’s AWS datasets
- Meta portals (they list open data repositories):
    - http://dataportals.org/
    - http://opendatamonitor.eu/
    - http://quandl.com/

Working with Real Data?

- Other pages listing many popular open data repositories:
    - Wikipedia’s list of Machine Learning datasets
    - Quora.com question
    - Datasets subreddit

Look at the Big Picture

The first task you are asked to perform is to **build a model** of housing prices in California using the California census data. This data has metrics such as the population, median income, median housing price, and so on for each block group 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 just call them “districts” for shot.

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

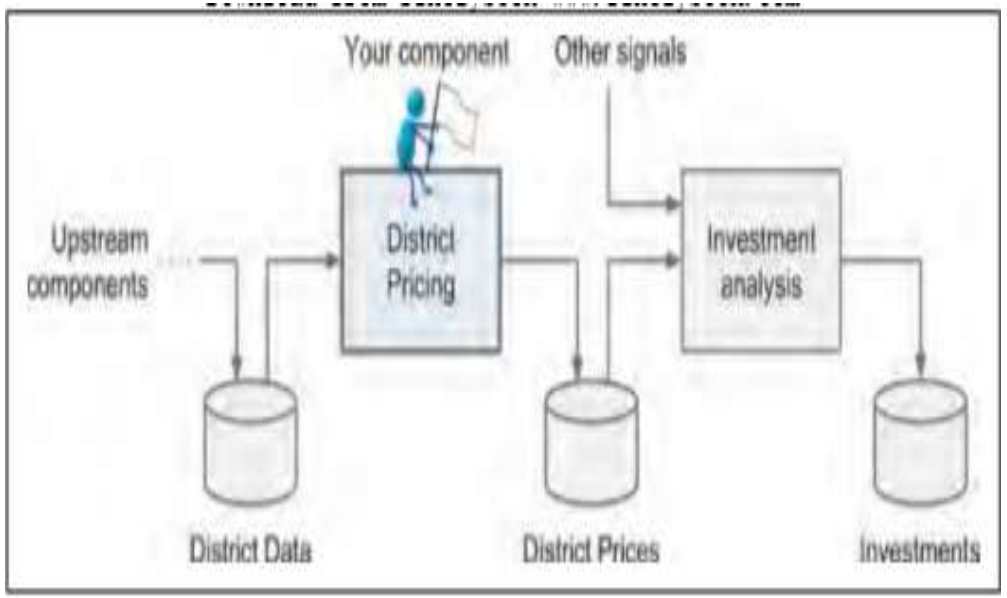
Question:
What exactly is the business objective; building a model is probably not the end goal. How does the company expect to use and benefit form this model?

This is important because it will determine how you frame the problem, what algorithms you will select, what performance measure you will use to evaluate your model, and how much effort you should spend tweaking it.

Frame the Problem

Answer:

Your model's output (a prediction of a district's, median housing price) will be fed to another Machine Learning system, 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

Question:

What the current solution looks like (if any). It will often give you a reference performance, as well as insights on how to solve the problem.

Frame the Problem

Answer:
The district housing prices are currently estimated manually by experts: a team gathers up-to-data information about a district (excluding median housing prices), and they use complex rules to come up with an estimate. This is costly and time-consuming, and their estimates are not great; their typical error rate is about 15%.

Frame the Problem

With all this information you are now ready to start designing your system.
First, 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?

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). Moreover, it is also a typical regression task, since you are asked to predict the value. More specifically, this is a *multivariate regression* problem since the system will use multiple features to make a prediction (it will use the district's population, the median income, etc.)

You predicted life satisfaction based on just one feature, the GDP per capita, so it was a *univariate regression* problem.

Finally, there is no continuous flow of data coming in 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

A typical performance measure for regression problems is the Root Mean Square Error (RMSE). It measures the standard deviation of the errors the system makes in its prediction.

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

Check the Assumptions

It is good practice to list and verify the assumptions that were made so far (by you or others); this can catch serious issues early on.

For example, the district prices that your system, and we assume that these prices are going to be used as such. But what if the downstream system actually converts the prices into categories (e.g., “cheap”, “medium”, or “expensive”) and then uses those categories instead of the prices themselves?

Check the Assumptions

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, not a regression task. You don't want to find this out after working on a regression system for a months.

Fortunately, after talking with the team in charge of the downstream system, you are confident that they do indeed need the actual prices, not categories.

Get the Data

It’s time to get your hands dirty.
Don’t hesitate to pick up your laptop and walk through the following code examples in a Jupyter notebook.

Create the Workspace

1. You need to have Python installed.
2. Create a workspace directory for your Machine Learning code and datasets.

You need a number of Python modules: Jupyter, NumPy, Pandas, Matplotlib and Scikit-Learn.

Download the Data

In typical environments your data would be available in a relational database (or some other common datastore) and spread across multiple tables/documents/files.
To access it, you would first need to get your credentials and access authorizations, and familiarize yourself with the data schema.

In this project, however, things are much simpler: you will download a single compressed file, ***housing.tgz***, which contains a comma-separated value (CSV) file called ***housing.csv*** with all the data.

Download the Data

Here is the function to fetch data:

```
import os
import tarfile from six.moves
import urllib
    DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml/master/"
    HOUSING_PATH = "datasets/housing"
    HOUSING_URL = DOWNLOAD_ROOT + HOUSING_PATH + "/housing.tgz"

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

Take a Quick Look at the Data Structure

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

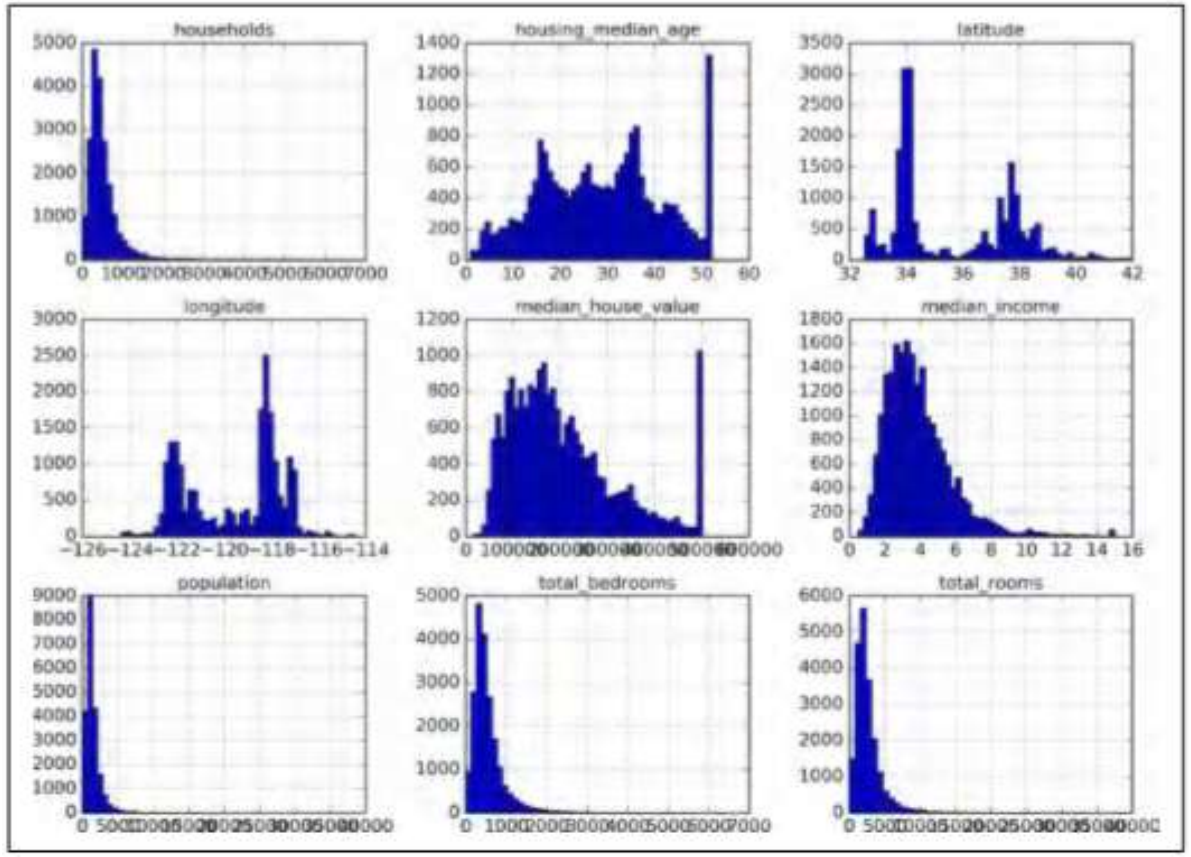
Take a Quick Look at the Data Structure

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

```
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
```

Take a Quick Look at the Data Structure

Call the ***hist()*** method on the whole dataset, and it will plot a histogram for each numerical attribute. For example, you can see that slightly over 800 districts have a ***median house value*** equal to about $500,000.



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, you 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***.

Create a Test Set

Creating a test set is theoretically quite simple: just pick some instances randomly, typically 20% of the dataset, and set them aside:

```
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]
```

Create a Test Set

You can then use this function like this:

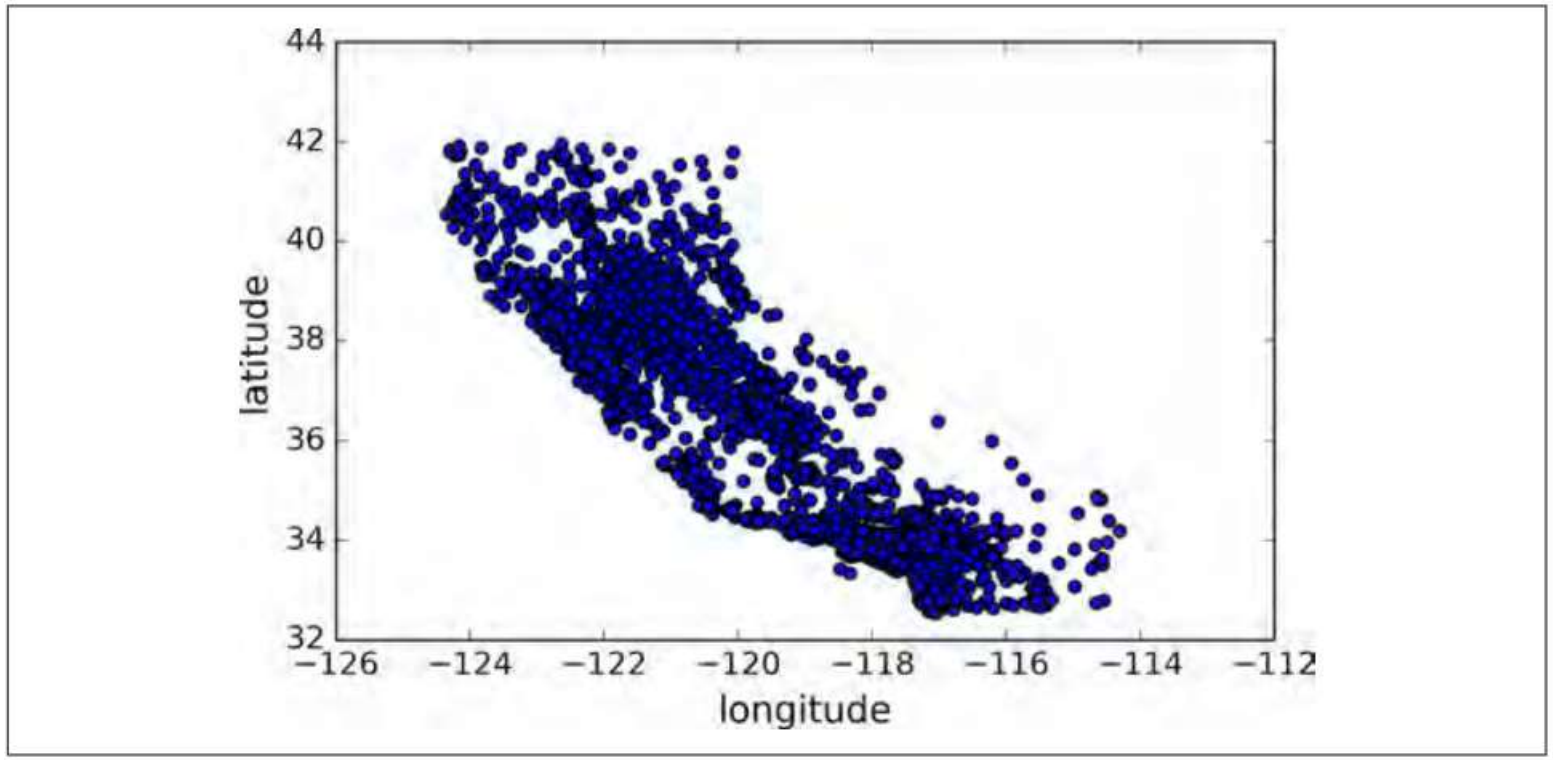
```
>>> train_set, test_set = split_train_test(housing, 0.2)
>>> print(len(train_set), "train +", len(test_set), "test")
16512 train + 4128 test
```

Discover and Visualize the Data to Gain Insights

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.

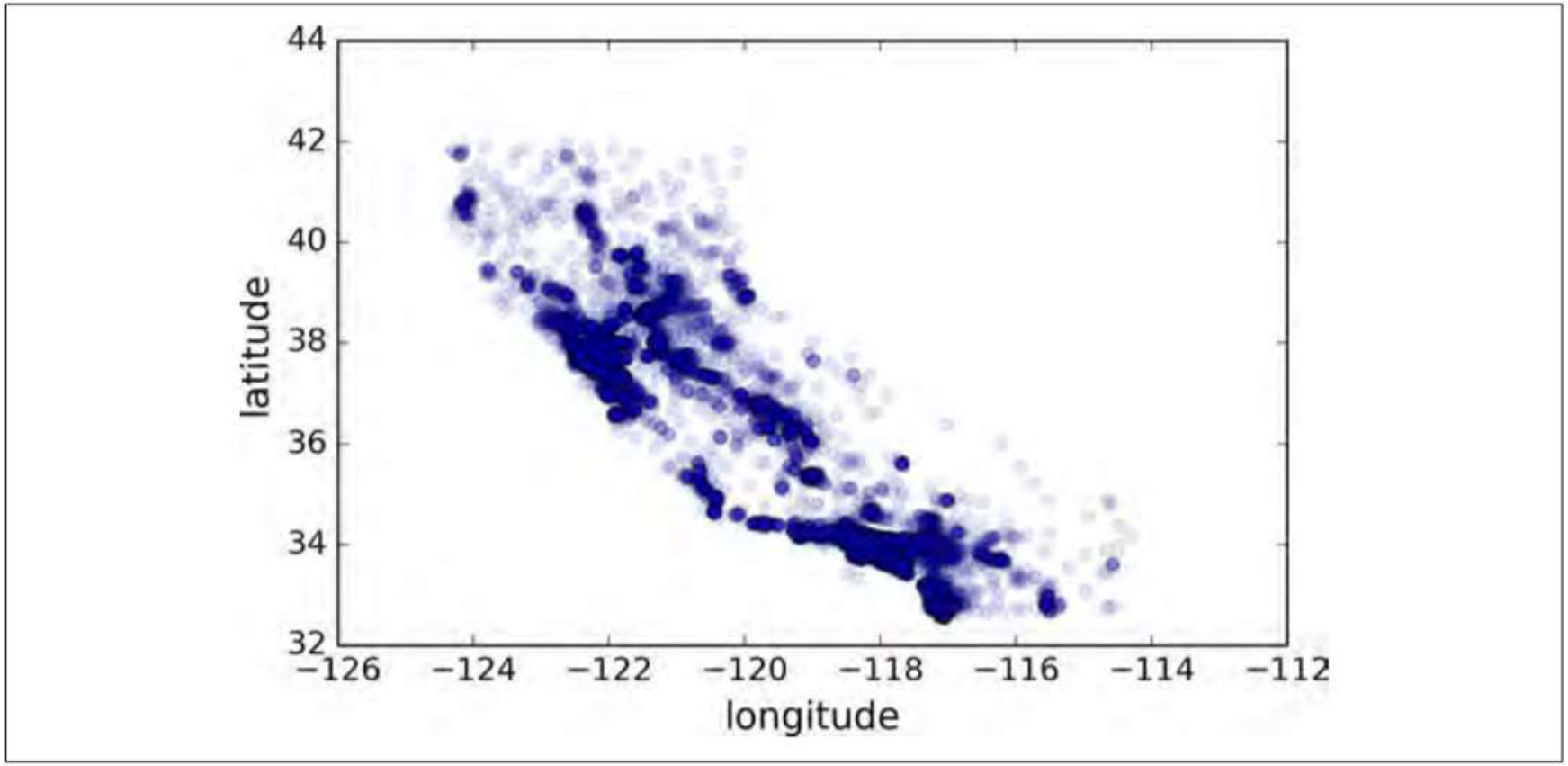
Visualizing Geographical Data

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



Visualizing Geographical Data

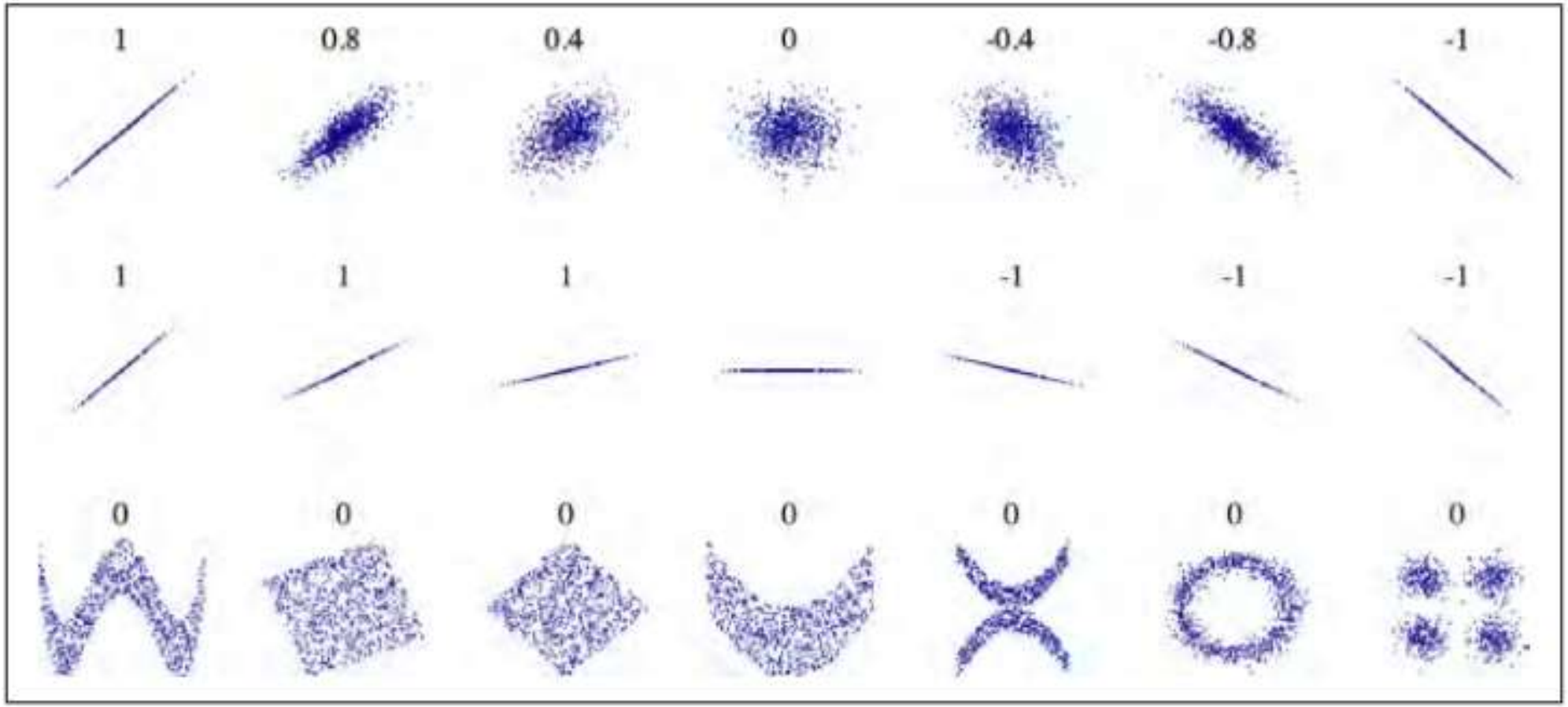
This looks like California all right, but other than that it is hard to see any particular pattern. Setting the alpha option to 0.1 makes it much easier to visualize the places where there is a high density of data points



Looking for Correlations

The correlation coefficient ranges from -1 to 1.
When it is close to 1, it means that there is a strong positive correlations.
For example, the median house value tends to go up when then median income goes up.
When 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 zero mean that there is no linear correlation.

Looking for Correlations



Experimenting with Attribute Combinations

One last thing you may want to do before actually preparing the data for Machine Learning algorithms is to try out various attribute combinations.

For example, the total number of rooms in a district is not very useful if you don’t know how many households there are.
What you really want is the number of rooms per household.
Similarly, the total number of bedrooms by itself is not very useful: you probably want to compare it to the number of rooms. And the population per household also seems like an interesting attribute combination to look at.

Prepare the Data for Machine Learning Algorithms

Instead of just doing this manually, you should write functions to do that, for several good reasons:

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

Data Cleaning

Most of Machine Learning algorithms cannot work with missing features, so let's create a few functions to take care of them. You noticed 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.)

Handling Text and Categorical Attributes

Earlier we left out the categorical attribute ***ocean_proximity*** because it is a text attribute so we cannot compute its median. Most Machine Learning algorithms prefer to work with numbers anyway.

Custom Transformers

Although Scikit-Learn provides many useful transformers, you will need to write your own for task such as custom cleanup operations or combining specific attributes. You will want your transformer to work seamlessly with Scikit-Learn functionalities(such as pipelines), and since Scikit-Learn relies on duck typing(not inheritance), all you need is to create a class and implement 3 methods: **fit()** (returning **self**), ***transform()***, and ***fit_transform()***.

Feature Scaling

One of the most important transformation 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: ***min-max scaling*** and ***standardization***.

Transformation Pipelines

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

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

num_pipeline = Pipeline([
  ('imputer', Imputer(strategy="median")),
  ('attribs_adder', CombinedAttributesAdder()),
  ('std_scaler', StandardScaler()),
])
housing_num_tr = num_pipeline.fit_transform(housing_num)
```

Select and Train a Model

At last! 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.

Fine-Tune Your Model

Let’s assume that you now have a shortlist of promising models. You now need to fine-tune them.

Grid Search

One way to do that would be to fiddle with the hyperparameters manually, until you find a great combination of hyperparameter values. This would be very tedious work, and you may not have time to explore many combinations.

Instead you should get Scikit-Learn's GridSearchCV to search for you. All you need to do is tell it which hyperparameters you want it to experiment with, and what values to try out, and it will evaluate all the possible combinations of hyperparameters values, using cross-validation.

Randomized Search

This approach has 2 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).
- You have more control over the computing budget you want to allocate to hyper-parameter search, simply by setting the number of iterations.

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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 Tree they rely on), especially if the individual models very different types of errors.

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_pipelines*** to transform the data (call ***transform(),*** not ***fit_transform()***!), and evaluate the final model on the test set.

Launch, Monitor and Maintain Your System

Finally, you will generally want to train your models on a regular basis using fresh data. You should automate this process as much as possible.
If you don’t, you are very likely to refresh your model only every six months (at best), and your system’s performance may fluctuate severely over time.
If your system is an online learning system, you should make sure you save snapshots of its state at regular intervals so you can easily roll back to a previously working state.

Thanks!

Does anyone have any questions?

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Blog: https://ceteongvanness.wordpress.com

Resources

Hands-On Machine Learning with Scikit-Learn and TensorFlow