End-to-End Machine Learning Project

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Objectives

- To *write* a machine learning program predicting a numeric value
- To present *a process* for developing a machine learning project
- To explain machine learning *terminologies* via examples

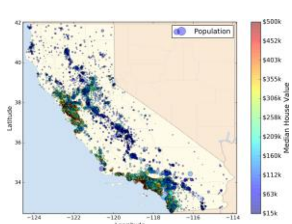
Contents

References

1. Aurelien Geron (2017). Hands on Machine Learning with Scikit Learn and TensorFlow. O'Reilly Media.

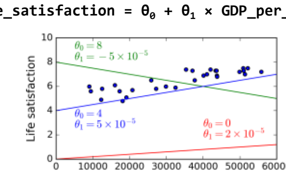
The California Housing Prices Dataset [1]

- This dataset was based on data from the 1990 California census.



Selecting a Model

- life_satisfaction = $\theta_0 + \theta_1 \times$ GDP_per_capita



- housing_price = $\theta_0 + \theta_1 \times$ median_income
- housing_price = $\theta_0 + \theta_1 \times$ median_income + $\theta_2 \times$ total_rooms + $\theta_3 \times$ households

Downloading 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()

fetch_housing_data()
```

Visualizing 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)

housing = load_housing_data()
housing.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	median_income
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	8.3252
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	8.3014
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	7.2574
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	5.6431
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	3.8462

Displaying Information

```
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
```

Counting Values

- Find out *what categories* exist and how many districts belong to each category:

```
housing["ocean_proximity"].value_counts()
```

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

Showing Summary

- Show a *summary* of the numerical attributes:

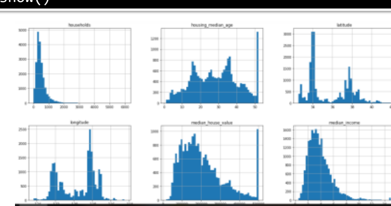
```
housing.describe()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
count	20640.000000	20640.000000	20640.000000	20640.000000	20433.000000	20640.000000	20640.000000
mean	-119.569704	35.631861	28.639486	2635.763081	537.870553	1425.476744	499.539680
std	2.003532	2.135952	12.585558	2181.615252	421.385070	1132.462122	382.329753
min	-124.350000	32.540000	1.000000	2.000000	1.000000	3.000000	1.000000
25%	-121.800000	33.930000	18.000000	1447.750000	296.000000	787.000000	280.000000
50%	-118.490000	34.260000	29.000000	2127.000000	435.000000	1166.000000	409.000000
75%	-118.010000	37.710000	37.000000	3148.000000	647.000000	1725.000000	605.000000
max	-114.310000	41.950000	52.000000	39320.000000	6445.000000	35682.000000	6082.000000

Plotting Histograms

- A histogram for each *numerical attribute*

```
%matplotlib inline
import matplotlib.pyplot as plt
housing.hist(bins=50, figsize=(20,15))
plt.show()
```



Creating 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)
print(len(train_set), "train +", len(test_set), "test")
```

```
16512 train + 4128 test
```

Using **md5** Function

```
import hashlib
count = 0
for i in range (0, 256):
    lastByte = hashlib.md5(np.int64(i)).digest()[-1]
    if lastByte < int(256*0.2):
        count += 1
        #print (lastByte)
print ('Count', count)
```

```
Count 46
```

Using **np.ceil** Function

```
for i in [1.27, 1.45, 1.58, 1.93, 2.11, 2.99]:
    print (i, ' ~= ', np.ceil(i))
```

```
1.27  ~=  2.0
1.45  ~=  2.0
1.58  ~=  2.0
1.93  ~=  2.0
2.11  ~=  3.0
2.99  ~=  3.0
```

Creating A Test Set Using Id

```
import hashlib
def test_set_check(identifier, test_ratio, hash):
    # Put the instance in the test set if this value is lower or equal
to 51 (~20% of 256).
    return hash(np.int64(identifier)).digest()[-1] < 256 * test_ratio

def split_train_test_by_id(data, test_ratio, id_column,
hash=hashlib.md5):
    ids = data[id_column]
    in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio,
hash))
    return data.loc[~in_test_set], data.loc[in_test_set]

housing_with_id = housing.reset_index() # adds an `index` column
train_set, test_set = split_train_test_by_id(housing_with_id, 0.2,
"index")
print(len(train_set), "train +", len(test_set), "test")
```

```
16362 train + 4278 test
```

Using **train_test_split**

```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(housing,
test_size=0.2, random_state=42)
print(len(train_set), "train +", len(test_set), "test")
```

```
16512 train + 4128 test
```

Important Attribute

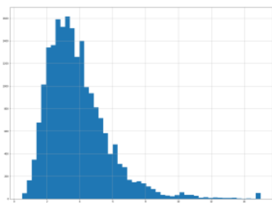
- Suppose you chatted with experts who told you that the median income is a very *important attribute* to predict median housing prices.
- You may want to ensure that the test set is *representative* of the various categories of incomes in the whole dataset.

```
housing["median_income"].value_counts()
```

```
2.5625     21
1.8750     21
5.0000     20
3.0625     19
4.4375     18
           ..
5.7780      1
1.3672      1
```

Plotting **median_income** Histogram

```
%matplotlib inline
import matplotlib.pyplot as plt
housing["median_income"].hist(bins=50, figsize=(20,15))
plt.show()
```



Most median income values are clustered around 2–5 (tens of thousands of dollars), but some median incomes go far beyond 6.

Creating a New Attribute (**income_cat**)

- The following code creates an *income category attribute* by
  - dividing the median income by 1.5 (to limit the number of income categories), and
  - rounding up using ceil (to have discrete categories), and then
  - merging all the categories greater than 5 into category 5:

```
housing["income_cat"] = np.ceil(housing["median_income"] / 1.5)
housing["income_cat"].where(housing["income_cat"] < 5, 5.0,
inplace=True)
housing["income_cat"].value_counts()
```

```
3.0    7236
2.0    6581
4.0    3639
5.0    2362
1.0     822
Name: income_cat, dtype: int64
```

Verifying The Income Category Proportions

```
train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
print ('Training set:')
print (train_set["income_cat"].value_counts() / len(train_set))
print ('Test set:')
print (test_set["income_cat"].value_counts() / len(test_set))
```

```
Training set:
3.0    0.348595
2.0    0.317466
4.0    0.178537
5.0    0.115673
1.0    0.039729
Name: income_cat, dtype: float64
Test set:
3.0    0.358527
2.0    0.324370
4.0    0.167393
5.0    0.109496
1.0    0.040213
Name: income_cat, dtype: float64
```

Using **StratifiedShuffleSplit**

```
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]
```

```
16512 train + 4128 test
```

Verifying The Income Category Proportions

```
print ('Full dataset:')
print (housing["income_cat"].value_counts() / len(housing))
print ('Training set:')
print (strat_train_set["income_cat"].value_counts() / len(strat_train_set))
print ('Test set:')
print (strat_test_set["income_cat"].value_counts() / len(strat_test_set))
```

```
Full dataset:
3.0    0.350581
2.0    0.318847
4.0    0.176308
5.0    0.114438
1.0    0.039826
Name: income_cat, dtype: float64
Training set:
3.0    0.350594
2.0    0.318859
4.0    0.176296
5.0    0.114402
1.0    0.039850
Name: income_cat, dtype: float64
Test set:
3.0    0.350533
2.0    0.318798
4.0    0.176357
5.0    0.114583
1.0    0.039729
Name: income_cat, dtype: float64
```

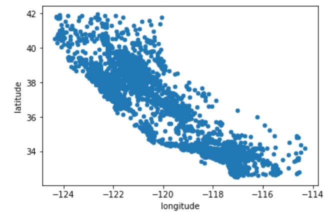
Reverting The Data To Original State

- 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):
    if 'income_cat' in set.columns:
        set.drop(["income_cat"], axis=1,
inplace=True)
# create a copy so you can play with it without
# harming the training set:
housing = strat_train_set.copy()
```

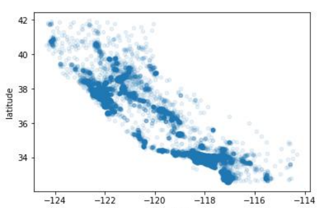
Visualizing Geographical Data

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



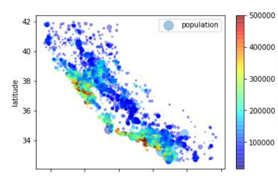
Showing High Density Of Data Points

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



Showing **population** & **median_house_value**

```
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,
)
# The radius of each circle represents the district's population (option s), and
# the color represents the price (option c).
plt.legend()
```



Looking for Correlations

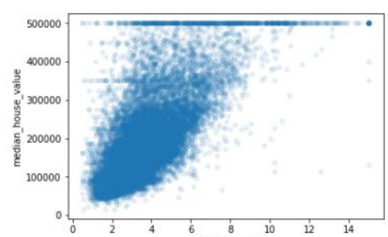
- Compute the *standard correlation coefficient* (also called Pearson's r) between every pair of attributes:

```
# Compute the standard correlation coefficient (also called
Pearson's r)
# between every pair of attributes
corr_matrix = housing.corr()
corr_matrix["median_house_value"].sort_values(ascending=False)
```

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

Plotting A Correlation

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



Experimenting with Attribute Combinations

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

The new **bedrooms_per_room** attribute is much more correlated with the median house value than the total number of rooms or bedrooms.

Preparing Data

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

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000	16512.000000
mean	-119.575834	35.639577	28.653101	2622.728319	534.973890	1419.790819	497.060380
std	2.001860	2.138058	12.574726	2138.458419	412.699041	1115.686241	375.720845
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000	279.000000
50%	-118.510000	34.260000	29.000000	2119.500000	433.000000	1164.000000	408.000000
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.250000	602.000000
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000	5358.000000

Missing Values

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
count	16512.000000	16512.000000	16512.000000	16512.000000	16354.000000	16512.000000	16512.000000
	-119.575834	35.639577	28.653101	2622.728319	534.973890	1419.790819	497.060380
	2.001860	2.138058	12.574726	2138.458419	412.699041	1115.686241	375.720845
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000
25%	-121.800000	33.940000	18.000000	1443.000000	295.000000	784.000000	279.000000
50%	-118.510000	34.260000	29.000000	2119.500000	433.000000	1164.000000	408.000000
75%	-118.010000	37.720000	37.000000	3141.000000	644.000000	1719.250000	602.000000
max	-114.310000	41.950000	52.000000	39320.000000	6210.000000	35682.000000	5358.000000

- Possible solutions:
  - Get rid of the corresponding districts.
  - Get rid of the whole attribute.
  - Set the values to some value (zero, the mean, the median, etc.).

Using **`SimpleImputer`**

```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")
housing_num = housing.drop("ocean_proximity", axis=1)
imputer.fit(housing_num)
#print (imputer.statistics_)
print ('Median values:', housing_num.median().values)
X = imputer.transform(housing_num)
housing_tr = pd.DataFrame(X, columns=housing_num.columns)
housing_tr.describe()
```

```
Median values: [-118.51     34.26     29.      2119.5     433.     1164.      408.
    3.5409]
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
count	16512.000000	16512.000000	16512.000000	16512.000000	16512.000000	16512.000000	16512.000000
mean	-119.575834	35.639577	28.653101	2622.728319	533.998123	1419.790819	497.060380
std	2.001860	2.138058	12.574726	2138.458419	410.839621	1115.686241	375.720845
min	-124.350000	32.540000	1.000000	6.000000	2.000000	3.000000	2.000000

Converting Text Labels To Numbers

- 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, so let's convert these *text labels to numbers*.

```
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
housing_cat = housing["ocean_proximity"]
housing_cat_encoded = encoder.fit_transform(housing_cat)
print ('Original text labels:', encoder.classes_)
print ('New values:', housing_cat_encoded)
```

```
Original text labels: ['<1H OCEAN' 'INLAND' 'ISLAND' 'NEAR BAY' 'NEAR OCEAN']
New values: [0 0 4 ... 1 0 3]
```

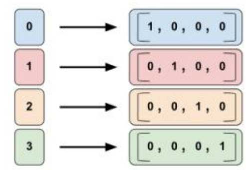
Text Labels To Numbers Issue

- One issue with this representation is that ML algorithms will assume that two nearby values are more similar than two distant values.
- Obviously this is not the case (for example, categories 0 and 4 are more similar than categories 0 and 1).

```
Original text labels: ['<1H OCEAN' 'INLAND' 'ISLAND'
'NEAR BAY' 'NEAR OCEAN']
New values: [0 0 4 ... 1 0 3]
```

One-Hot Encoding (I)

- 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).



One-Hot Encoding (II)

ocean_proximity (label)	ocean_proximity (number)	median_income
<1H OCEAN	0	
INLAND	1	
ISLAND	2	
NEAR BAY	3	
NEAR OCEAN	4	

We now have 5 new columns in our dataset.

<1H OCEAN	INLAND	ISLAND	NEAR BAY	NEAR OCEAN	median_income
1	0	0	0	0	
0	1	0	0	0	
0	0	1	0	0	
0	0	0	1	0	
0	0	0	0	1	

Using **`OneHotEncoder`**

```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
encoder = LabelEncoder()
housing_cat = housing["ocean_proximity"]
housing_cat_encoded = encoder.fit_transform(housing_cat)
encoder = OneHotEncoder(categories='auto')
housing_cat_1hot =
encoder.fit_transform(housing_cat_encoded.reshape(-1,1))
print (housing_cat_1hot.shape)
print ('One-hot values:')
print (housing_cat_1hot.toarray())
```

```
(16512, 5)
One-hot values:
[[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.]]
```

Using **`LabelBinarizer`**

```
from sklearn.preprocessing import LabelBinarizer
encoder = LabelBinarizer()
housing_cat_1hot = encoder.fit_transform(housing_cat)
print (housing_cat_1hot.shape)
print ('One-hot values:')
print (housing_cat_1hot)
```

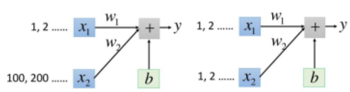
```
(16512, 5)
One-hot values:
[[1 0 0 0 0]
 [1 0 0 0 0]
 [0 0 0 0 1]
 ...
 [0 1 0 0 0]
 [1 0 0 0 0]
 [0 0 0 1 0]]
```

Custom Transformers

```
from sklearn.base import BaseEstimator, TransformerMixin
rooms_ix, bedrooms_ix, population_ix, household_ix = 3, 4, 5, 6
class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room = True): # no *args or **kargs
        self.add_bedrooms_per_room = add_bedrooms_per_room

    def fit(self, X, y=None):
        return self # nothing else to do

    def transform(self, X, y=None):
        rooms_per_household = X[:, rooms_ix] / X[:, household_ix]
        population_per_household = X[:, population_ix] / X[:, household_ix]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
            return np.c_[X, rooms_per_household, population_per_household,
bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]

attr_adder = CombinedAttributesAdder(add_bedrooms_per_room=False)
housing_extra_attribs = attr_adder.transform(housing.values)
housing_extra_attribs
```

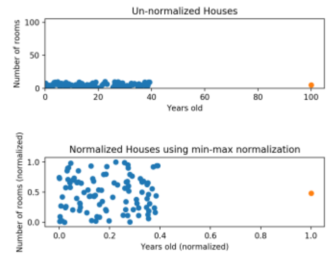
Feature Scaling

- 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.



Min-Max Scaling

- *Min-max scaling* (many people call this *normalization*) is quite simple: values are shifted and rescaled so that they end up ranging from 0 to 1.



Implementing Min-Max Scaling

- We do this by **`subtracting the min value and dividing by the max minus the min`**.

```
import numpy as np
x1 = [89, 72, 94, 69]
x1_min = np.min(x1)
print ('x1 min:', x1_min)
x1_max = np.max(x1)
print ('x1 max:', x1_max)
x1_scaled = (x1 - x1_min)/(x1_max - x1_min)
print ('x1_scaled:', x1_scaled)
```

```
x1 min: 69
x1 max: 94
x1_scaled: [0.8  0.12 1.   0.  ]
```

Using `MinMaxScaler`

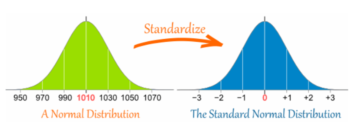
```
from sklearn.preprocessing import MinMaxScaler
x1 = [[89], [72], [94], [69]]
minMaxScaler = MinMaxScaler()
x1_scaled = minMaxScaler.fit_transform(x1)
#value(i) = (value(i) - min)/(max  - min)
print ('x1_scaled:')
print (x1_scaled)

x2 = [[89, 0.8], [72, 0.12], [94, 1], [69, 0]]
x2_scaled = minMaxScaler.fit_transform(x2)
print ('x2_scaled:')
print (x2_scaled)
```

```
x1_scaled:
[[0.8 ]
 [0.12]
 [1.  ]
 [0.  ]]
x2_scaled:
[[0.8  0.8 ]
 [0.12 0.12]
 [1.   1.  ]
 [0.   0.  ]]
```

Standardization

- First it subtracts the mean value (so standardized values always have a zero mean), and then it divides by the variance so that the resulting distribution has unit variance.

$$Mean(\mu) = \frac{\sum_{i=1}^{n} x_i}{n} \qquad StandardDeviation(\sigma) = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}}$$



Example

```
import numpy as np
x1 = [89, 72, 94, 69]
x1_mu = np.sum(x1)/len(x1)
print ('x1_mu:', x1_mu)
x1_std = np.sqrt(np.sum((x1 - x1_mu)**2)/4)
print ('x1_std:', x1_std)
x1_normalized = (x1 - x1_mu)/x1_std
print ('x1_normalized:', x1_normalized)
```

```
x1_mu: 81.0
x1_std: 10.700467279516348
x1_normalized: [ 0.7476309  -0.84108476  1.21490022 -1.12144635]
```

Using `StandardScaler`

```
from sklearn.preprocessing import StandardScaler
x1 = [[89], [72], [94], [69]]
standardScaler = StandardScaler()
x1_normalized = standardScaler.fit_transform(x1)
#value(i) = (value(i) - mean)/(variance) ### unit variance
print ('x1_normalized:')
print (x1_normalized)
x2 = [[89, 0.8], [72, 0.12], [94, 1], [69, 0]]
x2_normalized = standardScaler.fit_transform(x2)
print ('x2_normalized:')
print (x2_normalized)
```

```
x1_normalized:
[[ 0.7476309 ]
 [-0.84108476]
 [ 1.21490022]
 [-1.12144635]]
x2_normalized:
[[ 0.7476309   0.7476309 ]
 [-0.84108476 -0.84108476]
 [ 1.21490022  1.21490022]
 [-1.12144635 -1.12144635]]
```

Transformation Pipelines (I)

```
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
print(housing_num.iloc[[0]])
num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
    ])
housing_num_tr = num_pipeline.fit_transform(housing_num)
housing_num_tr [0]
```

```
longitude  latitude  housing_median_age  total_rooms  total_bedrooms  \
17606    -121.89     37.29                38.0       1568.0
351.0

       population  households  median_income
17606       710.0       339.0         2.7042

array([-1.15604281,  0.77194962,  0.74333089, -0.49323393, -0.44543821,
       -0.63621141, -0.42069842, -0.61493744, -0.31205452, -0.08649871,
        0.15531753])
```

Transformation Pipelines (II)

```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import LabelBinarizer
class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X[self.attribute_names].values

class LabelBinarizerPipelineFriendly(LabelBinarizer):
    def fit(self, X, y=None):
        """This change would allow us to fit the model based on the X input."""
        super(LabelBinarizerPipelineFriendly, self).fit(X)

    def transform(self, X, y=None):
        return super(LabelBinarizerPipelineFriendly, self).transform(X)

    def fit_transform(self, X, y=None):
        return super(LabelBinarizerPipelineFriendly, self).fit(X).transform(X)
```

Transformation Pipelines (III)

```
from sklearn.impute import SimpleImputer
from sklearn.pipeline import FeatureUnion
# housing_num = housing.drop("ocean_proximity", axis=1)
# print (list(housing_num))
num_attribs = list(housing_num)
cat_attribs = ["ocean_proximity"]

num_pipeline = Pipeline([
    ('selector', DataFrameSelector(num_attribs)),
    ('imputer', SimpleImputer(strategy="median")),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler()),
    ])

cat_pipeline = Pipeline([
    ('selector', DataFrameSelector(cat_attribs)),
    ('label_binarizer', LabelBinarizerPipelineFriendly()),
    ])

full_pipeline = FeatureUnion(transformer_list=[
    ("num_pipeline", num_pipeline),
    ("cat_pipeline", cat_pipeline),
    ])
```

Transformation Pipelines (IV)

```
housing_prepared = full_pipeline.fit_transform(housing)
print ('Shape:', housing_prepared.shape)
print ('First row:')
print (housing_prepared[0])
```

```
Shape: (16512, 16)
First row:
[-1.15604281  0.77194962  0.74333089 -0.49323393 -0.44543821 -
0.63621141
 -0.42069842 -0.61493744 -0.31205452 -0.08649871  0.15531753  1.
  0.          0.          0.          0.        ]
```

Training A **LinearRegression** Model

```
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(housing_prepared, housing_labels)
print (lin_reg.coef_)
print (lin_reg.intercept_)
```

```
[-55650.4116403  -56716.45236929  13732.83841856  -1933.1277138
   7330.04062103 -45708.26306673  45455.47519691  74714.39134154
   6605.12802802   1042.95709453   9249.75886697 -18016.52432168
 -55219.15208555 110357.78363967 -22479.84008184 -14642.2671506
]
236914.99732815966
```

Evaluating On The Training Set

```
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)
print ('mean_squared_error:',lin_rmse)
```

```
mean_squared_error: 68628.19819848923
```

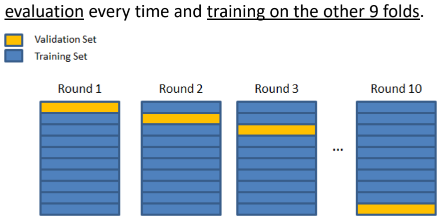
Training A **DecisionTreeRegressor** Model

```
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)
print ('mean_squared_error:',tree_rmse)
#Wait, what!? No error at all?
```

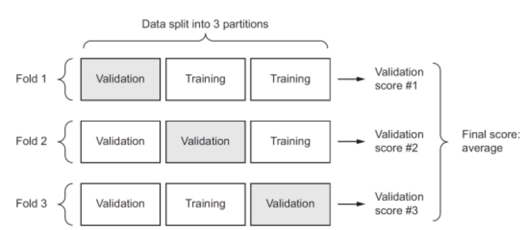
```
mean_squared_error: 0.0
```

Cross-Validation

- *K-fold cross-validation*: it 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.



3-Fold Cross-Validation



Implementing Cross-Validation for **`DecisionTreeRegressor`** Model

```
from sklearn.model_selection import cross_val_score

#K-fold cross-validation: it 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.

scores = cross_val_score(tree_reg, housing_prepared, housing_labels,
scoring="neg_mean_squared_error", cv=10)
#Scoring function is actually the opposite of the MSE
rmse_scores = np.sqrt(-scores)
print ('Scores:', rmse_scores,
       '\nMean:', rmse_scores.mean(),
       '\nStandard deviation:', rmse_scores.std())
```

```
Scores: [69620.04634401 67314.0053051  71245.98857128 68512.45491186
 70669.67355628 75914.70874155 70481.54567057 72889.21326715
 76972.58738202 70385.33144871]
Mean: 71400.55551985327
Standard deviation: 2903.201497989529
```

Implementing Cross-Validation for **`LinearRegression`** Model

```
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)
print ('Scores:', lin_rmse_scores,
       '\nMean:', lin_rmse_scores.mean(),
       '\nStandard deviation:', lin_rmse_scores.std())
```

```
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: 2731.6740017983425
```

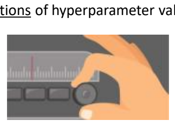
Training A **`RandomForestRegressor`** Model

```
from sklearn.ensemble import RandomForestRegressor
forest_reg = RandomForestRegressor(n_estimators = 10)
forest_reg.fit(housing_prepared, housing_labels)
housing_predictions = forest_reg.predict(housing_prepared)
forest_mse = mean_squared_error(housing_labels, housing_predictions)
forest_rmse = np.sqrt(forest_mse)
print(forest_rmse)
forest_scores = cross_val_score(forest_reg, housing_prepared,
housing_labels,
                                scoring="neg_mean_squared_error", cv=10)
forest_rmse_scores = np.sqrt(-forest_scores)
print ('Scores:', forest_rmse_scores,
       '\nMean:', forest_rmse_scores.mean(),
       '\nStandard deviation:', forest_rmse_scores.std())
```

```
19159.69781070503
Scores: [49693.59343585 47610.26422407 49860.45540937 52559.4762028
 49744.46141088 53065.4795352  49332.24483043 48626.79343336
 52956.45645194 50728.1591404 ]
Mean: 50417.7384074277
Standard deviation: 1780.3080602735956
```

Fine-Tune Your Model

- Let's assume that you now have a shortlist of promising models.
- You now need to *fine-tune* them.
  - One way to do that would be to fiddle with the *hyperparameters* manually, until you find a great combination of hyperparameter values.
  - 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 hyperparameter values, using cross-validation.



Grid Search (I)

```
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')
grid_search.fit(housing_prepared, housing_labels)
```

Grid Search (II)

```
GridSearchCV(cv=5, error_score='raise-deprecating',
       estimator=RandomForestRegressor(bootstrap=True,
criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators='warn',
n_jobs=None,
           oob_score=False, random_state=None, verbose=0,
warm_start=False),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid=[{'n_estimators': [3, 10, 30], 'max_features':
[2, 4, 6, 8]}, {'bootstrap': [False], 'n_estimators': [3, 10],
'max_features': [2, 3, 4]}],
       pre_dispatch='2*n_jobs', refit=True,
return_train_score='warn',
       scoring='neg_mean_squared_error', verbose=0)
```

Randomized Search

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

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.

Best Params and Estimators

```
print ('Best params:', grid_search.best_params_)
print ('Best estimator:', grid_search.best_estimator_)
cvres = grid_search.cv_results_
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    print('Score:' + str(np.sqrt(-mean_score)) + '. Params:' + str(params))
```

```
Best params: {'max_features': 8, 'n_estimators': 30}
Best estimator: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features=8, max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           n_estimators=30, n_jobs=None, oob_score=False,
           random_state=None, verbose=0, warm_start=False)
Score:64024.116293446605. Params:{'max_features': 2, 'n_estimators': 3}
Score:55679.78536794131. Params:{'max_features': 2, 'n_estimators': 10}
Score:52900.382409469916. Params:{'max_features': 2, 'n_estimators': 30}
Score:59204.39184490757. Params:{'max_features': 4, 'n_estimators': 3}
Score:53256.201306677816. Params:{'max_features': 4, 'n_estimators': 10}
Score:50400.79273643548. Params:{'max_features': 4, 'n_estimators': 30}
Score:58604.89490344707. Params:{'max_features': 6, 'n_estimators': 3}
Score:52539.25788763814. Params:{'max_features': 6, 'n_estimators': 10}
Score:50103.95445543871. Params:{'max_features': 6, 'n_estimators': 30}
Score:58879.52246940387. Params:{'max_features': 8, 'n_estimators': 3}
Score:52468.90176629722. Params:{'max_features': 8, 'n_estimators': 10}
Score:50070.43194917535. Params:{'max_features': 8, 'n_estimators': 30}
Score:62625.655034087446. Params:{'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
Score:54434.70562810467. Params:{'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
```

Analyzing The Best Model

- With this information, you may want to try dropping some of the *less useful features*.

```
feature_importances = grid_search.best_estimator_.feature_importances_
print(feature_importances)
extra_attribs = ["rooms_per_hhold", "pop_per_hhold",
"bedrooms_per_room"]
cat_one_hot_attribs = list(encoder.categories_)
attributes = num_attribs + extra_attribs + cat_one_hot_attribs
sorted(zip(feature_importances, attributes), reverse=True)
```

```
[(0.3813686052041648, 'median_income'),
 (0.10906780251822537, 'pop_per_hhold'),
 (0.07083179669883576, 'longitude'),
 (0.06281901814027986, 'latitude'),
 (0.05965235896647321, 'bedrooms_per_room'),
 (0.04304971988356684, 'housing_median_age'),
 (0.04039453394736901, 'rooms_per_hhold'),
 (0.01610986532246578, 'total_rooms'),
 (0.01492544264738153, 'population'),
 (0.01458129493451622, 'total_bedrooms'),
 (0.01408544363152419, 'households'),
 (0.006308424576666818, array([0, 1, 2, 3, 4]))]
```

Evaluating The Best 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)
print ('RMSE:', final_rmse)
```

```
RMSE: 47610.101414786746
```

Launch, Monitor, and Maintain Your System

- You need to get your solution ready for production, in particular by plugging the *production input data sources* into your system and writing tests.
- You also need to write monitoring code to check your system's live performance at regular intervals and trigger *alerts* when it drops.
- Evaluating your system's performance will require sampling the system's predictions and evaluating them. This will generally require a *human analysis*.
- Finally, you will generally want to train your models on a regular basis using *fresh data*.

ML Project Checklist

- Frame the *problem* and look at the big picture.
- Get the *data*.
- Explore the data to *gain insights*.
- Prepare the data to better expose the *underlying data patterns* to Machine Learning algorithms.
- Explore many *different models* and short-list the best ones.
- *Fine-tune* your models and combine them into a great solution.
- Present your *solution*.
- *Launch*, monitor, and maintain your system.

Thank You for Your Time