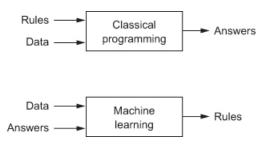
Intro to Machine Learning

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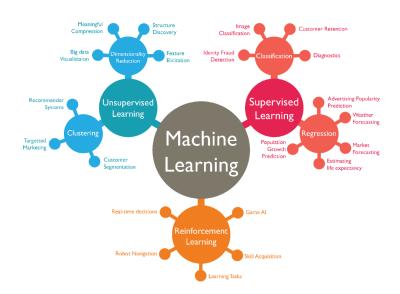
Text Data Course, Bocconi 2018

What is machine learning?



- ▶ In classical computer programming, humans input the rules and the data, and the computer provides answers.
- ► In machine learning, humans input the data and the answers, and the computer learns the rules.

The Machine Learning Landscape



A Machine Learning Project, End-to-End

Aurelien Geron, *Hands-on machine learning with Scikit-Learn & TensorFlow*, Chapter 2:

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

Our First Data Set

```
import pandas as pd
df1 = pd.read_csv('death-penalty-cases.csv')
from sklearn.feature extraction.text import CountVectorizer
vectorizer = CountVectorizer(stop_words='english',
                              max features=4)
X = vectorizer.fit transform(df1['snippet'])
Х
X = X.todense()
X = X / X.sum(axis=1) \# counts to frequencies
words = vectorizer.get feature names()
for i, word in enumerate(words):
    column = X[:,i]
    df1['x_''+word] = column
df1.head()
```

Inspecting Data

```
import numpy as np
df1['logcites'] = np.log(1+df1['citeCount'])
features = ['x_'+x \text{ for } x \text{ in words}]
keepcols = ['logcites'] + features
df1 = df1[keepcols]
corr matrix = df1.corr()
corr_matrix['logcites'].sort_values(ascending=False
from pandas. plotting import scatter matrix
scatter_matrix(df1)
df1.plot(kind='scatter', x='x_death', y='logcites',
```

Select a performance measure

▶ A typical performance measure for regression problems is Root Mean Squared Error (RMSE):

RMSE(X, h) =
$$\sqrt{\frac{1}{m} \sum_{i=1}^{m} (h(x_i) - y_i)^2}$$

- m, the number of rows/observations
- ➤ X, the feature set, with row x_i
- Y, the outcome, with item y_i
- $h(x_i)$ the model prediction (hypothesis)
- In econometrics, we are familiary with RMSE because that is the cost function that motivates the OLS estimator.
 - \blacktriangleright it corresponds to the Euclidian norm or L2 norm, notated as $||\cdot||_2$

Other cost functions

- ▶ We will see that in machine learning, while RMSE is a good baseline, other cost functions are sometimes used.
 - for regression tasks, I personally like R^2 .
- For example, Mean Absolute Error:

MAE
$$(X, h) = \frac{1}{m} \sum_{i=1}^{m} |h(x_i) - y_i|$$

which corresponds to the L1 norm or quantile regression.

 \blacktriangleright More generally, the k-norm for a vector v is

$$||v|| = (\sum_{i=1}^{m} |v_i|^k)^{\frac{1}{k}}$$

where a higher norm index focuses on large values and neglects small ones.

- e.g., the L2 norm is more sensitive to outliers than the L1 norm.
- ▶ The L0 norm gives the number of non-zero elements in the vector, while the L- ∞ norm gives the maximum absolute value in the vector.

Create a Test Set

```
\begin{array}{lll} \textbf{from} & \text{sklearn.model\_selection} & \textbf{import} & \text{train\_test\_split} \\ & \text{train\_set} \;, \; \; \text{test\_set} = \; \text{train\_test\_split} \left( \, \text{df1} \;, \; \; \text{test\_size} \, = \! 0.2 \right) \end{array}
```

Our first machine learning model

```
from sklearn.linear_model import LinearRegression
lin_reg = LinearRegression()
Xtrain = train[features]
Ytrain = train['logcites']
lin_reg.fit(Xtrain, Ytrain)
lin_reg.coef_
```

In-Sample Performance

```
from sklearn.metrics import mean_squared_error
Ytrain_pred = lin_reg.predict(Xtrain)
train_mse = mean_squared_error(Ytrain, Ytrain_pred)
train_mse
```

Out-of-Sample Performance

```
Xtest = test [features]
Ytest = test ['logcites']
Ytest_pred = lin_reg.predict(Xtest)
test_mse = mean_squared_error(Ytest, Ytest_pred)
test_mse
```

Data Prep for Machine Learning (1)

- ▶ Not too different from data prep for econometrics
 - ▶ See Geron Chapter 2, pp. 61-68 for pandas and sklearn syntax.
- Missing values:

```
judge.fillna(0,inplace=True)
from sklearn.preprocessing import Imputer
```

- Feature scaling
 - ► This is often necessary for ML models to work (e.g. lasso/ridge require standardizing)

```
\label{eq:from_sklearn.preprocessing_import} \begin{array}{ll} \textit{from} & \textit{sklearn.preprocessing} & \textit{import} \\ \textit{scaler} & = & \textit{StandardScaler()} \\ \textit{X} & = & \textit{scaler.fit\_transform(df1)} \\ \textit{df1} & = & \textit{pd.DataFrame(X,columns=df1.columns)} \end{array}
```

Data Prep for Machine Learning (2)

Categorical variables:

```
\label{eq:continuous_continuous_continuous} \begin{array}{ll} \textbf{from} & \textbf{sklearn.preprocessing import OneHotEncoder} \\ \textbf{enc} & = & \textbf{OneHotEncoder()} \\ \textbf{judge\_fes} & = & \textbf{enc.fit\_transform(judge.values.reshape(-1,1))} \end{array}
```

- Custom data prep pipelines
 - use for multiple steps, e.g. fill missing, then make dummies, then scale, etc.

from sklearn.pipeline import Pipeline

Scikit-Learn Design Principles

Consistency:

- Estimator: An object that can estimate parameters. Estimation is performed by fit() method. Exogenous parameters (provided by the researcher) are called hyperparameters.
- Transformer: An object that transforms a data set.
 Transformation is performed by the transform() method.
 The convenience method fit_transform() both fits an estimator and returns the transformed input data set.
- Predictor: An object that forms a prediction from an input data set. The predict() method forms the predictions. It also has a score() method that measures the quality of the predictions given a test set.
- Inspection: Hyperparameters and parameters are accessible.
 Learned parameters have an underscore suffix (e.g. lin_reg.coef_)
- ▶ **Non-proliferation of classes:** Use native Python data types; existing building blocks are used as much as possible.
- Sensible defaults: Provides reasonable default values for hyperparameters – easy to get a good baseline up and running.

Cross-Validation

Grid Search

```
from sklearn.model selection import GridSearchCV
param\_grid = \{ 'n\_estimators' : [3, 10, 30], \}
               'max features': [2, 4],
               'bootstrap': [True, False]}
grid_search = GridSearchCV(forest_reg ,
                            param grid.
                            cv=3)
grid_search.fit(df1[features],df1['logcites'])
grid_search.best_params_
grid_search.best_score_
```

Saving and Loading Models

```
from sklearn.externals import joblib
joblib.dump(forest_reg,'forest_reg.pkl')
forest_reg = joblib.load('forest_reg.pkl')
```