Intro to Machine Learning

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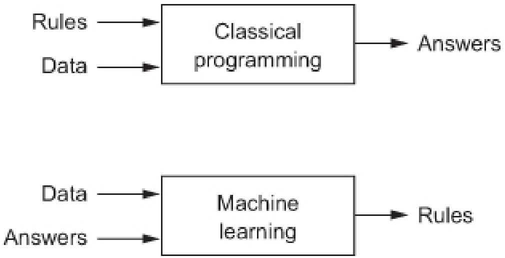
Text Data Course, Bocconi 2018

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.

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'])
X

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 for x 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):

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

  - 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.
  - 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:

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

  which corresponds to the L1 norm or quantile regression.
- 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

```
from sklearn.model_selection import train_test_split
train_set, test_set = train_test_split(df1, test_size=0.2)
```

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)

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(df1)
df1 = pd.DataFrame(X,columns=df1.columns)
```

Data Prep for Machine Learning (2)

- Categorical variables:

```
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
judge_fes = enc.fit_transform(judge.values.reshape(-1,1))
```

- 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

```
from sklearn.ensemble import RandomForestRegressor
forest_reg = RandomForestRegressor()

from sklearn.model_selection import cross_val_score
scores = cross_val_score(forest_reg,
                         df1[features],
                         df1['anycites'],

print(scores.mean(),scores.std())
```

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')
```