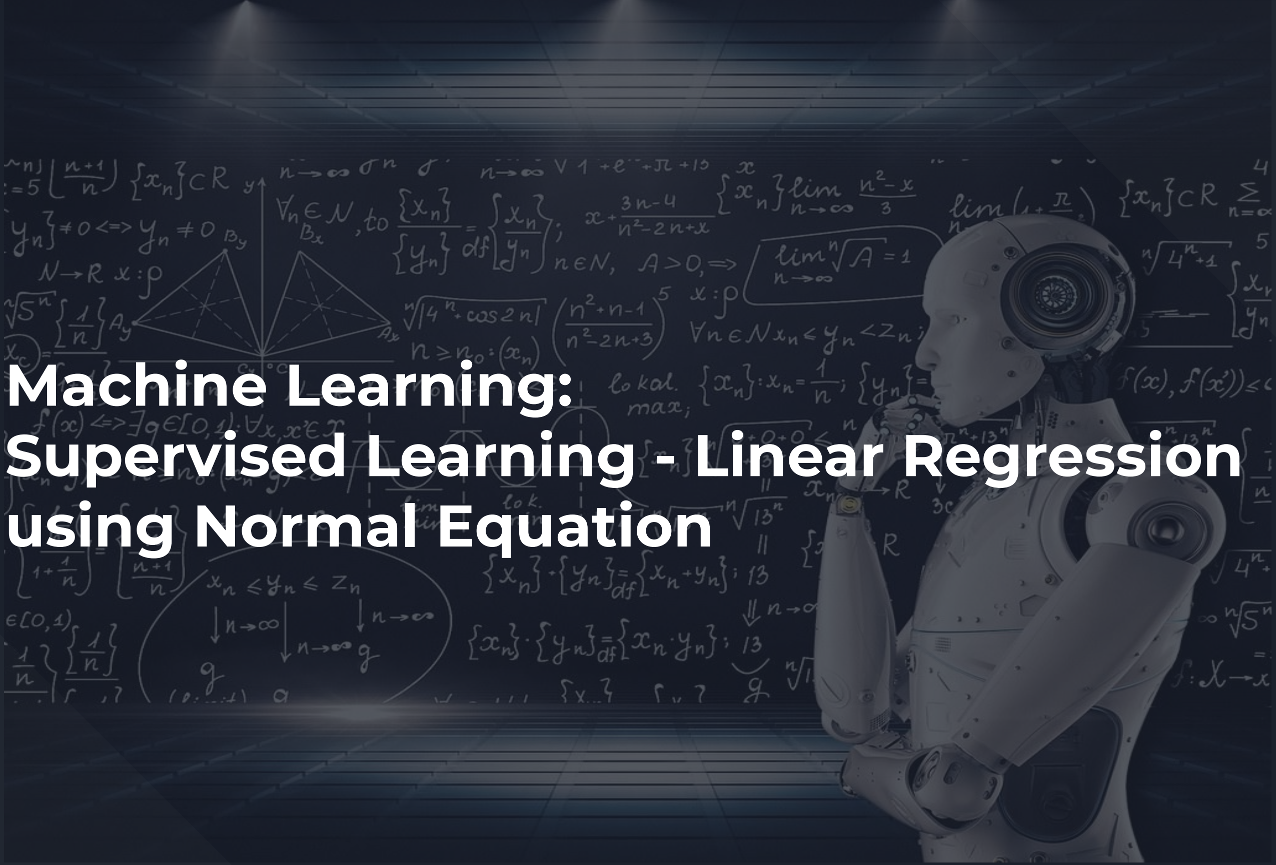
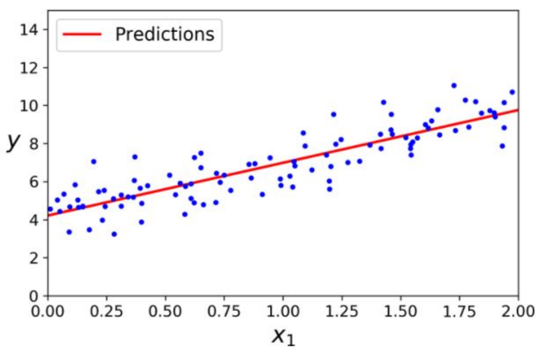


Machine Learning: Supervised Learning - Linear Regression using Normal Equation

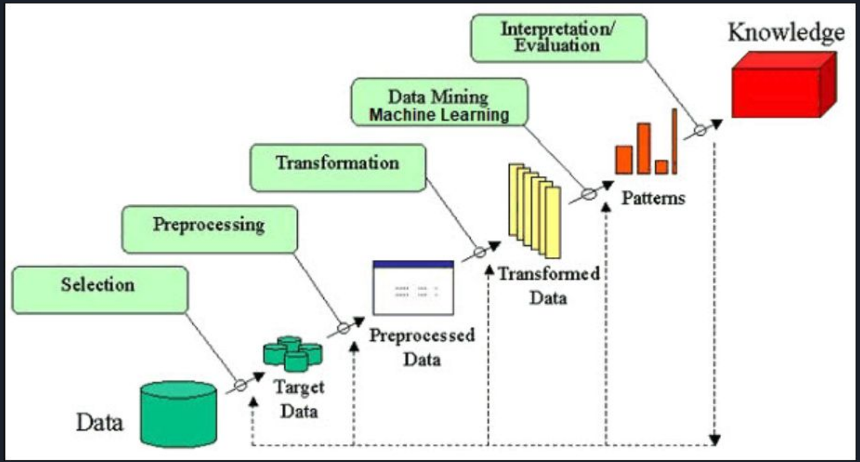


Shoumya Singh

Table of Content

Linear Regression using Normal Equation

- Linear regression is one of the most important and popular predictive techniques in data analysis. Normal Equation is an analytical approach to Linear Regression with a Least Square Cost Function.
- A regression is a statistical analysis assessing the association between two variables. It is used to find the relationship between two variables.
- In this project we are performing everything except preprocessing data.



Project Description

- Follow the procedure mentioned in Training Linear Models and make work in Colab.
- Save the abalone_train.cvs to a local drive and upload in step 3.

names=["Length", "Diameter", "Height", "Whole weight", "Shucked weight","Viscera weight", "Shell weight", "Age"])

Step 1

Setup Colab and import a few common modules, ensure MatplotLib plots figures .

Step 2

Modify the reading random data

Step 3

Replace the code and upload the data file.

Step 4

Plot the data and get the data distribution.

Step 5

Linear Regression equation values

Step 6

Plot linear regression

Step 7

Linear model prediction plot

Step 8

Linear regression using the Normal Equation.

Table of Content

Implementation

Step 1:

Setup Colab and import a few common modules, ensure MatplotLib plots figures inline and prepare a function to save the figures.

```python
# Python ≥3.5 is required
import sys
assert sys.version_info >= (3, 5)

# Scikit-Learn ≥0.20 is required
import sklearn
assert sklearn.__version__ >= "0.20"

# Common imports
import numpy as np
import os

# to make this notebook's output stable across runs
np.random.seed(42)

# To plot pretty figures
%matplotlib inline
import matplotlib as mpl
import matplotlib.pyplot as plt
mpl.rc('axes', labelsize=14)
mpl.rc('xtick', labelsize=12)
mpl.rc('ytick', labelsize=12)

# Where to save the figures
PROJECT_ROOT_DIR = "."
CHAPTER_ID = "training_linear_models"
IMAGES_PATH = os.path.join(PROJECT_ROOT_DIR, "images", CHAPTER_ID)
os.makedirs(IMAGES_PATH, exist_ok=True)

def save_fig(fig_id, tight_layout=True, fig_extension="png", resolution=300):
    path = os.path.join(IMAGES_PATH, fig_id + "." + fig_extension)
    print("Saving figure", fig_id)
    if tight_layout:
        plt.tight_layout()
    plt.savefig(path, format=fig_extension, dpi=resolution)
```

Implementation

Step 2:

Modify the reading random data

```python
import numpy as np

X = 2 * np.random.rand(100, 1)
y = 4 + 3 * X + np.random.randn(100, 1)
```

Step 3:

Replace the code and upload the data file.

```python
import numpy as np
import pandas as pd

# X = 2 * np.random.rand(100, 1)
# y = 4 + 3 * X + np.random.randn(100, 1)
from google.colab import files
uploaded  = files.upload()

import io
abalone = pd.read_csv(
    io.BytesIO(uploaded['abalone_train.csv']),
    names=["Length", "Diameter", "Height", "Whole weight", "Shucked weight",
           "Viscera weight", "Shell weight", "Age"])
# X1 is
#     0        0.435
#     1        0.585
#     2        0.655
#     .....
X1 = abalone["Length"]

# X2 is
#     array([0.435, 0.585, ...., 0.45])
X2 = np.array(X1)

# X is
#     array([[0.435],
#            [0.585],
#            [0.655],
#            ...,
#            [0.53 ],
#            [0.395],
#            [0.45 ]])
X = X2.reshape(-1, 1)

y1 = abalone["Height"]
y2 = np.array(y1)
y = y2.reshape(-1, 1)
```

Choose Files abalone_train.csv

- **abalone_train.csv**(text/csv) - 145915 bytes, last modified: 5/26/2021 - 100% done

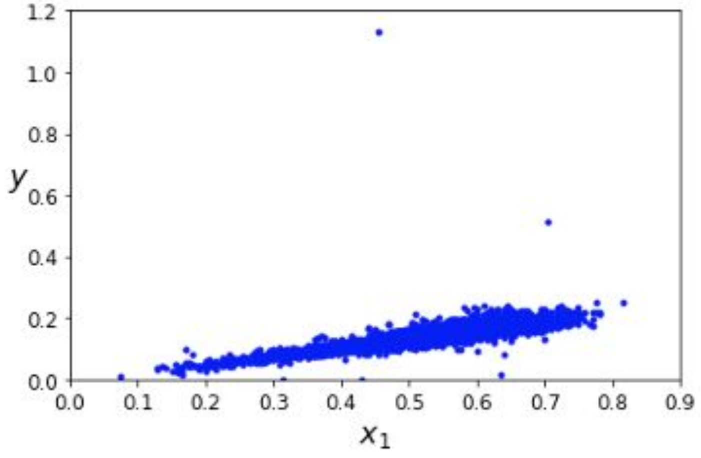
```
Saving abalone_train.csv to abalone_train.csv
```

Implementation

Step 4:
Plot the data and get the data distribution.

```
plt.plot(X, y, "b.")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.axis([0, 0.9, 0, 1.2])
save_fig("generated_data_plot")
plt.show()
```

```
Saving figure generated_data_plot
```



Step 5:
Linear Regression equation values.

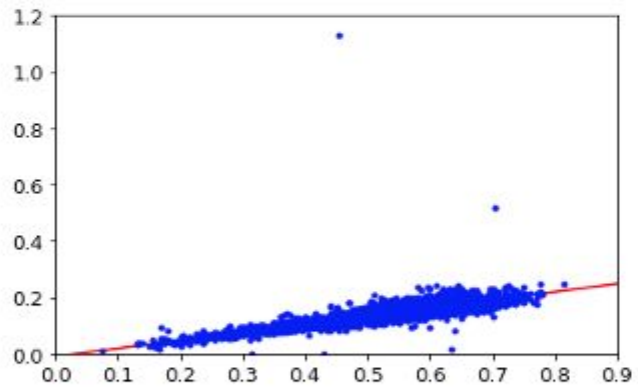
```
[26] X_b = np.c_[np.ones((3320, 1)), X]  # add x0 = 1 to each instance
     theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)

[27] theta_best

     array([[-0.0108267 ],
            [ 0.28716253]])

[28] X_new = np.array([[0], [2]])
     X_new_b = np.c_[np.ones((2, 1)), X_new]  # add x0 = 1 to each instance
     y_predict = X_new_b.dot(theta_best)
     y_predict

     array([[-0.0108267 ],
            [ 0.56349837]])
```

Implementation

Step 6:

Plot linear regression.

```python
plt.plot(X_new, y_predict, "r-")
plt.plot(X, y, "b.")
plt.axis([0, 0.9, 0, 1.2])
plt.show()
```

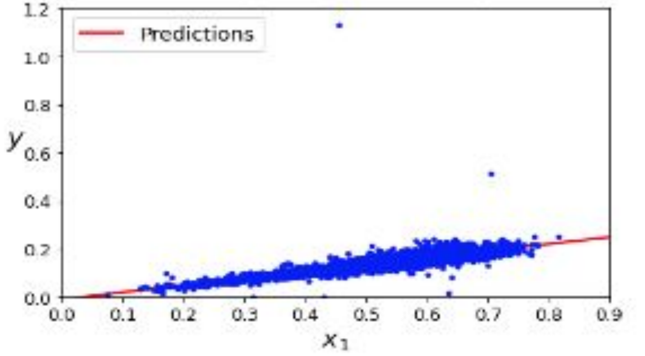


Step 7:

Linear model prediction plot.

```python
plt.plot(X_new, y_predict, "r-", linewidth=2, label="Predictions")
plt.plot(X, y, "b.")
plt.xlabel("$x_1$", fontsize=18)
plt.ylabel("$y$", rotation=0, fontsize=18)
plt.legend(loc="upper left", fontsize=14)
plt.axis([0, 0.9, 0, 1.2])
save_fig("linear_model_predictions_plot")
plt.show()
```

```
Saving figure linear_model_predictions_plot
```



Implementation

Step 8:

Linear regression using the Normal Equation.

```python
from sklearn.linear_model import LinearRegression

lin_reg = LinearRegression()
lin_reg.fit(X, y)
lin_reg.intercept_, lin_reg.coef_
```

```
(array([-0.0108267]), array([[0.28716253]]))
```

```
[33] lin_reg.predict(X_new)
```

```
array([[-0.0108267 ],
       [ 0.56349837]])
```

The `LinearRegression` class is based on the `scipy.linalg.lstsq()` function (the name stands for "least squares"), which you could call directly:

```
[34] theta_best_svd, residuals, rank, s = np.linalg.lstsq(X_b, y, rcond=1e-6)
     theta_best_svd
```

```
array([[-0.0108267 ],
       [ 0.28716253]])
```

This function computes $\mathbf{X}^{+}\mathbf{y}$, where $\mathbf{X}^{+}$ is the *pseudoinverse* of $\mathbf{X}$ (specifically the Moore-Penrose inverse). You can use `np.linalg.pinv()` to compute the pseudoinverse directly:

```python
np.linalg.pinv(X_b).dot(y)
```

```
array([[-0.0108267 ],
       [ 0.28716253]])
```

Bibliography/References

- https://www.geeksforgeeks.org/ml-normal-equation-in-linear-regression/
- https://towardsdatascience.com/performing-linear-regression-using-the-normal-equation-6372ed3c57
- https://colab.research.google.com/github/ageron/handson-ml2/blob/master/04_training_linear_models.ipynb#scrollTo=QnCG6urlNAUM

ThankYou