Jupyter: Training Linear Models
Linear Regression using Normal Equation

CS550 Homework
Shoumya Singh
ID-19566

Process

1. Follow the procedure mentioned in Chapter 4 – Training Linear Models to make it work on Colab.
2. Save the abalone_train.cvs to a local drive
   - Note: the abalone_train.cvs has this format

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

3. Change the process mentioned in Step 1 by reading CVS test data from a local drive : abalone_train.cvs
   - Process
     1. You can modify the code in Linear regression using the Normal Equation. Instead of reading random data

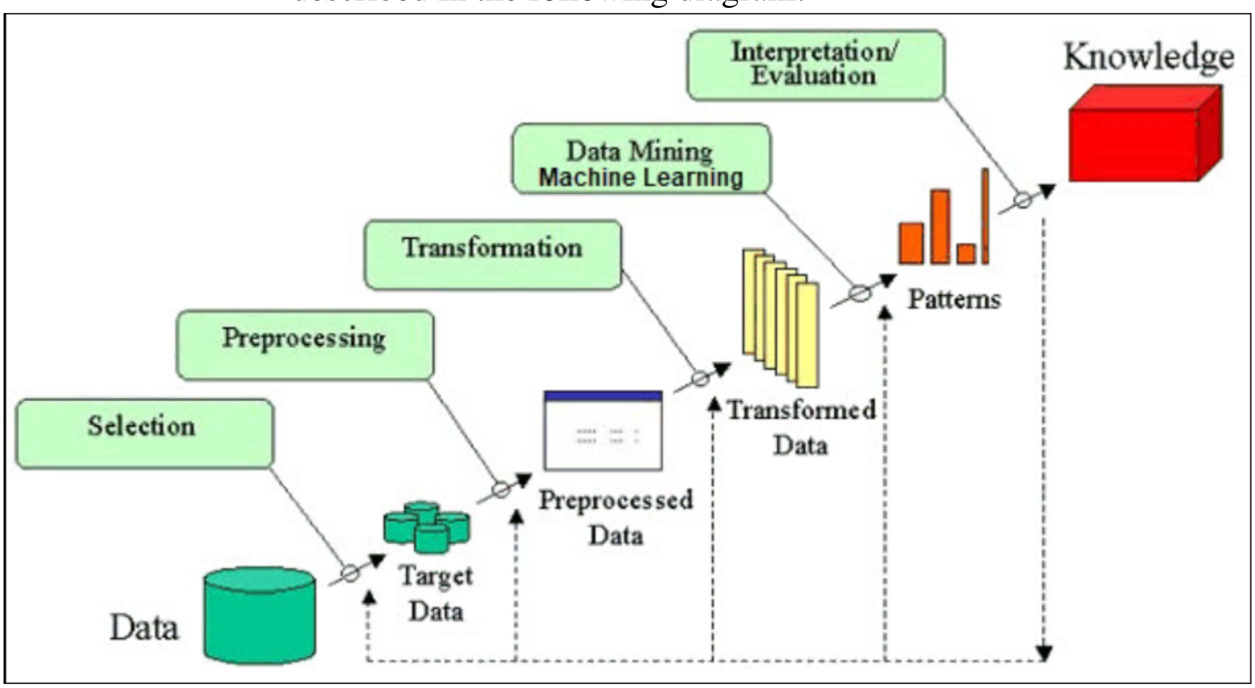
```
2.
3. import numpy as np
4. X = 2 * np.random.rand(100, 1)
5. y = 4 + 3 * X + np.random.randn(100, 1)
```

You need to read data from a local drive and transfornm the data to fit the Python code.

```
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)
```

4. There is one more line you need to modify to make the complete process work.
    - References
        - Except for "Preprocessing", this exercise involves all the steps described in the following diagram.



- Array Reshape

    - Get Started: 3 Ways to Load CSV files into Colab
    - R for Linear Regression
    - Load CSV data
        - abalone_train.csv (local copy)

2. Adding the project to your portofolio
    a. Please use Google Slides to document the project
    b. Please link your presentation on GitHub using this structure

```
Machine Learning
  - Supervised Learning
    + Linear Regression using Normal Equation
```

3. Submit
    . The URLs of the Google Slides and GitHub web pages related to this project.
    a. A PDF file of your Google Slides

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)
```

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

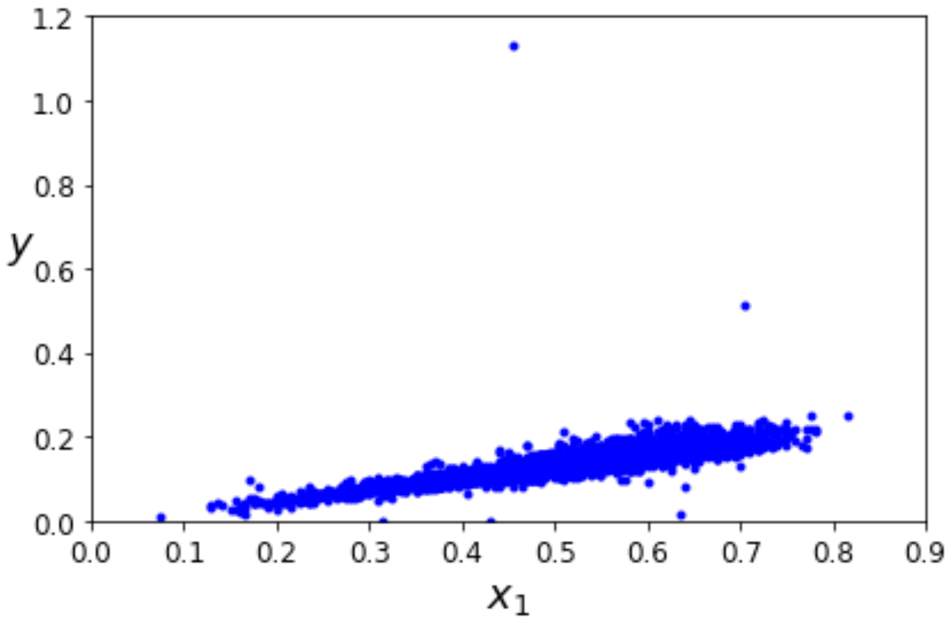
- **abalone_train.csv**(text/csv) - 145915 bytes, last modified: 5/26/2021 - 100% done

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

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

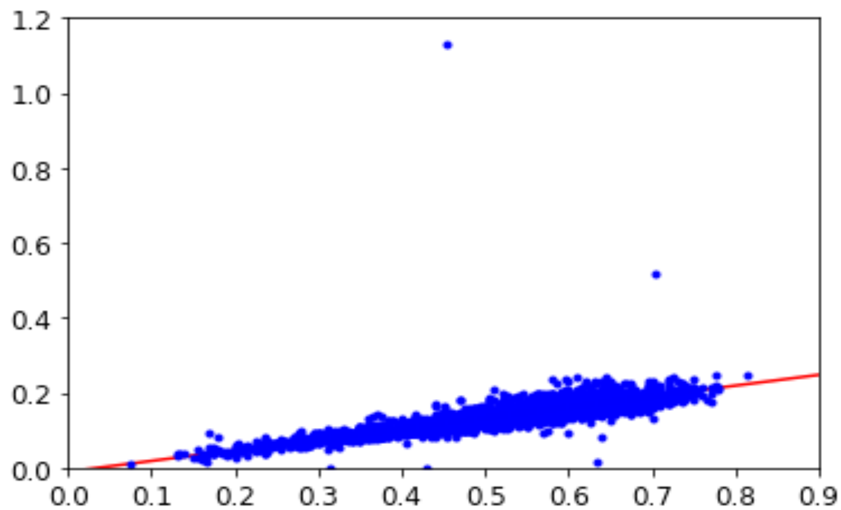
```
[26] X_b = np.c_[np.ones((3320, 1)), X]  # add x0 = 1 to each instance
     theta_best = np.linalg.inv(X_b.T.dot(X_b)).dot(X_b.T).dot(y)
```

```
[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]])
```

Step 6: Plot linear regression.

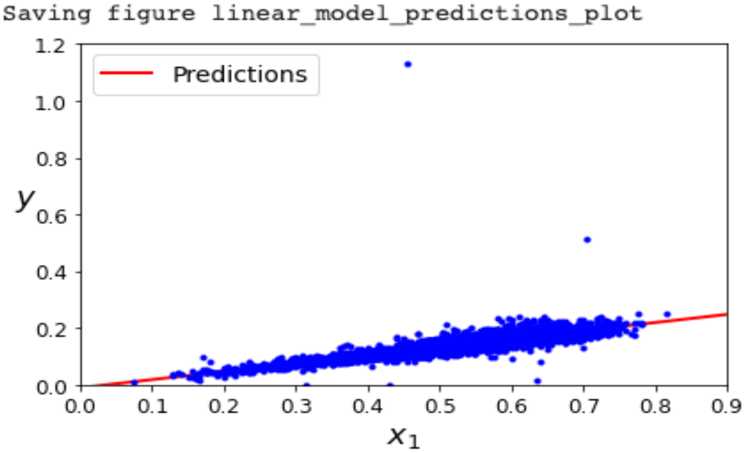
```
plt.plot(X_new, y_predict, "r-")
plt.plot(X, y, "b.")
plt.axis([0, 0.9, 0, 1.2])
plt.show()
```



Step 7: Linear model prediction plot

```
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
```



Step 8: Linear regression using the Normal Equation.

```
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:

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

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