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# 1 Feature Scaling and Normalization

## 1.1 Introduction

Previously, you learned about categorical variables, and about how multicollinearity in continuous variables might cause problems in our linear regression model. Before you start with the actual modeling section of multiple linear regression, it is important to talk about feature scaling and why it is important!

## 1.2 Objectives

You will be able to: * Determine if it is necessary to perform normalization/standardization for a specific model or set of data * Compare the different standardization and normalization techniques * Use standardization/normalization on features of a dataset

## 1.3 Why is feature scaling and normalization important?

### 1.3.1 (Approximately) normal features may yield better results

In the last lesson you saw how applying a log transform resulted in a model with a better $R^2$ value. The key there was that applying log transforms resulted in having more "normal" data distributions for the input features!

### 1.3.2 The variety in feature scales

Often, your dataset will contain features that vary largely in magnitudes. If you leave these magnitudes unchanged, coefficient sizes will fluctuate largely in magnitude as well. This can give the false impression that some variables are less important than others.

Even though this is not always a formal issue when estimating linear regression models, this *can* be an issue in more advanced machine learning models you'll see later. This is because most machine learning algorithms use Euclidean distance between two data points in their computations. Because of that, making sure that features have similar scales is formally required there. Some algorithms even require features to be **zero centric**.

A good rule of thumb is, however, to check your features for normality, and while you're at it, scale your features so they have similar magnitudes, even for a "simple" model like linear regression.

## 1.4 Popular transformations

### 1.4.1 Log transformation

As seen in the previous lesson, a log transformation is a very useful tool when you have data that clearly does not follow a normal distribution. Log transformation can help reduce skewness when you have skewed data, and can help reducing variability of data.

### 1.4.2 Min-max scaling

When performing min-max scaling, you can transform x to get the transformed $x'$ by using the formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

This way of scaling brings all values between 0 and 1.

### 1.4.3 Standardization

When

$$x' = \frac{x - \bar{x}}{\sigma} \tag{2}$$

x' will have mean $\mu = 0$ and $\sigma = 1$

Note that standardization does not make data *more* normal, it will just change the mean and the standard error!

### 1.4.4 Mean normalization

When performing mean normalization, you use the following formula:

$$x' = \frac{x - \text{mean}(x)}{\max(x) - \min(x)} \tag{3}$$

The distribution will have values between -1 and 1, and a mean of 0.

### 1.4.5 Unit vector transformation

When performing unit vector transformations, you can create a new variable x' with a range [0,1]:

$$x' = \frac{x}{||x||} \tag{4}$$

Recall that the norm of x $||x|| = \sqrt{(x_1^2 + x_2^2 + ... + x_n^2)}$

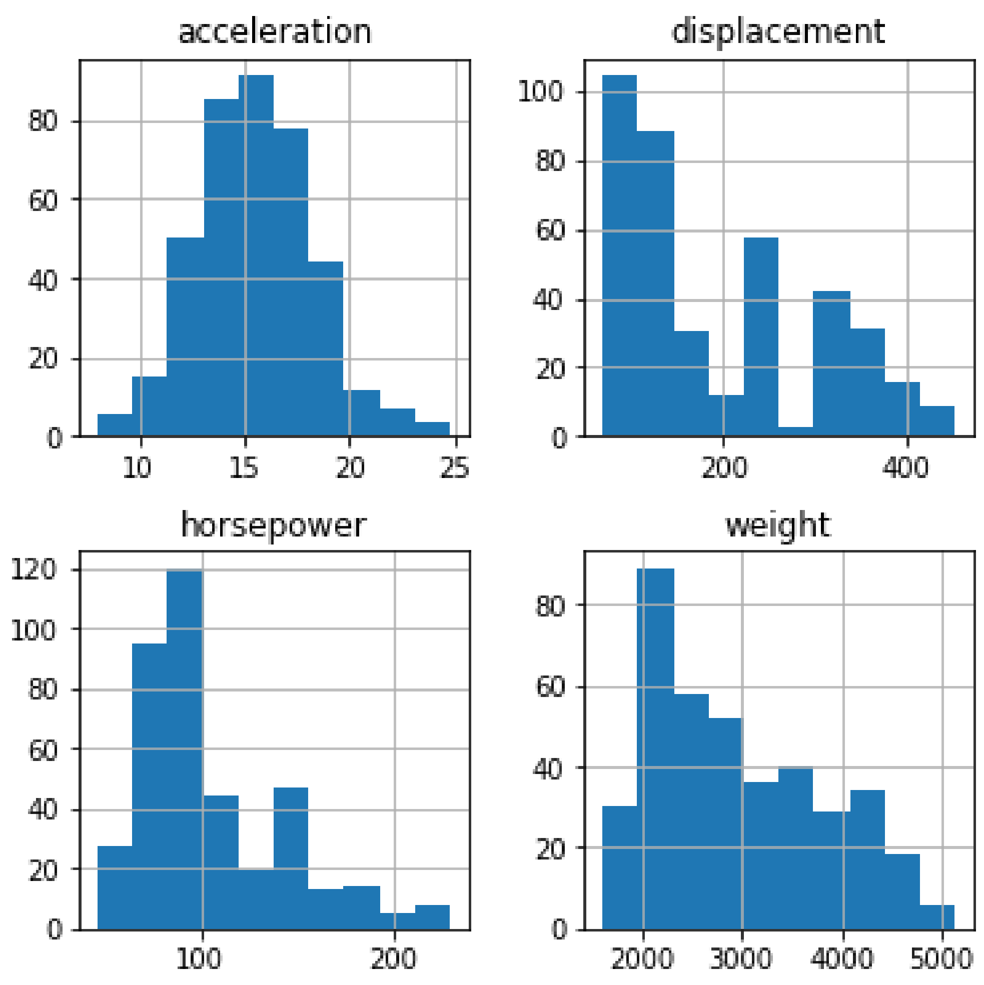
### 1.5 Applying Transformations to the auto-mpg Data

[1]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd

data = pd.read_csv('auto-mpg.csv')
data['horsepower'].astype(str).astype(int) # don't worry about this for now
data_pred = data.iloc[:,1:8]
data_pred.head()
```

[1]:
```
   cylinders  displacement  horsepower  weight  acceleration  model year  \
0          8         307.0         130    3504          12.0          70
1          8         350.0         165    3693          11.5          70
2          8         318.0         150    3436          11.0          70
3          8         304.0         150    3433          12.0          70
4          8         302.0         140    3449          10.5          70

   origin
0       1
1       1
2       1
3       1
4       1
```

Let's have a look at our continuous features: `'acceleration'`, `'displacement'`, `'horsepower'`, and `'weight'`. While you have seen that removing correlated features is often the best course of action, let's first get a sense of how you can transform each one of them!

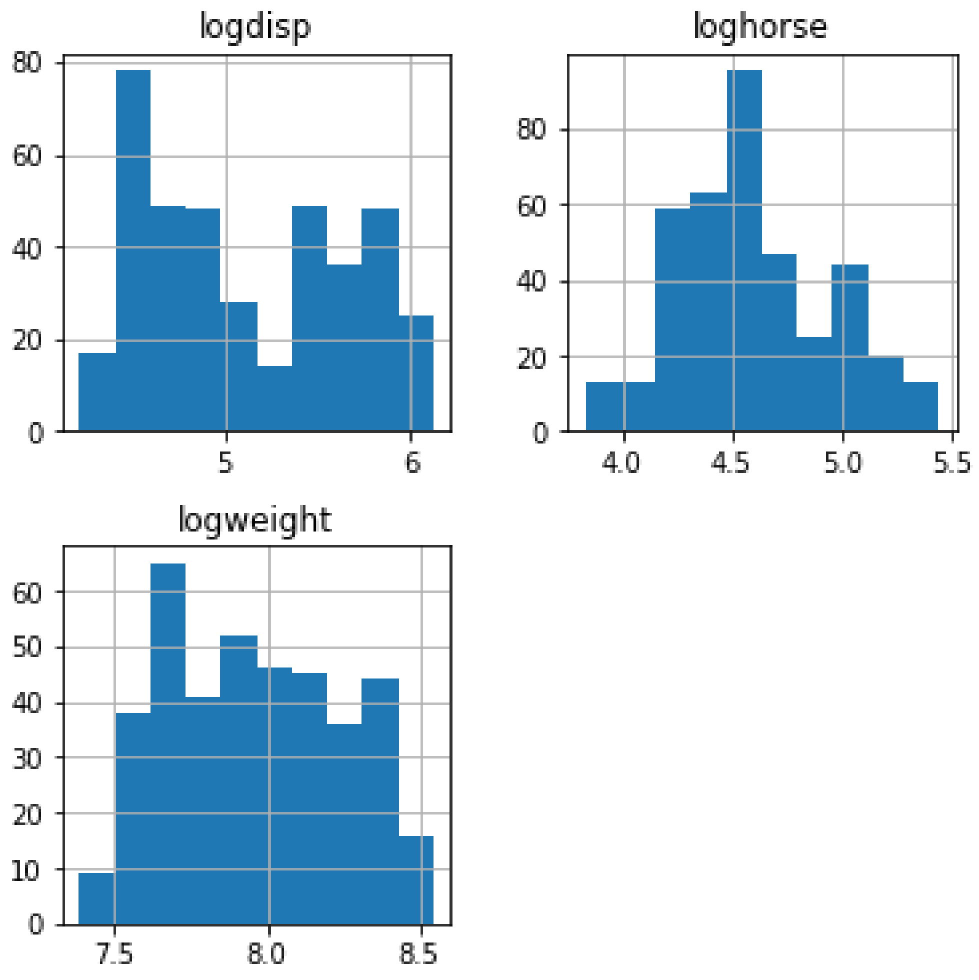
[5]:
```
to_pick = ['acceleration', 'displacement', 'horsepower', 'weight']
data_pred[to_pick].hist(figsize  = [6, 6]);
```



You can tell that skewness is an issue for most of our variables (except `'acceleration'`), and that some features e.g. `'weight'` are much bigger in magnitude than others!

Let's transform our data in two phases: first, let's try to make our data look more normal, and second, let's perform feature scaling to manage the difference in magnitude!

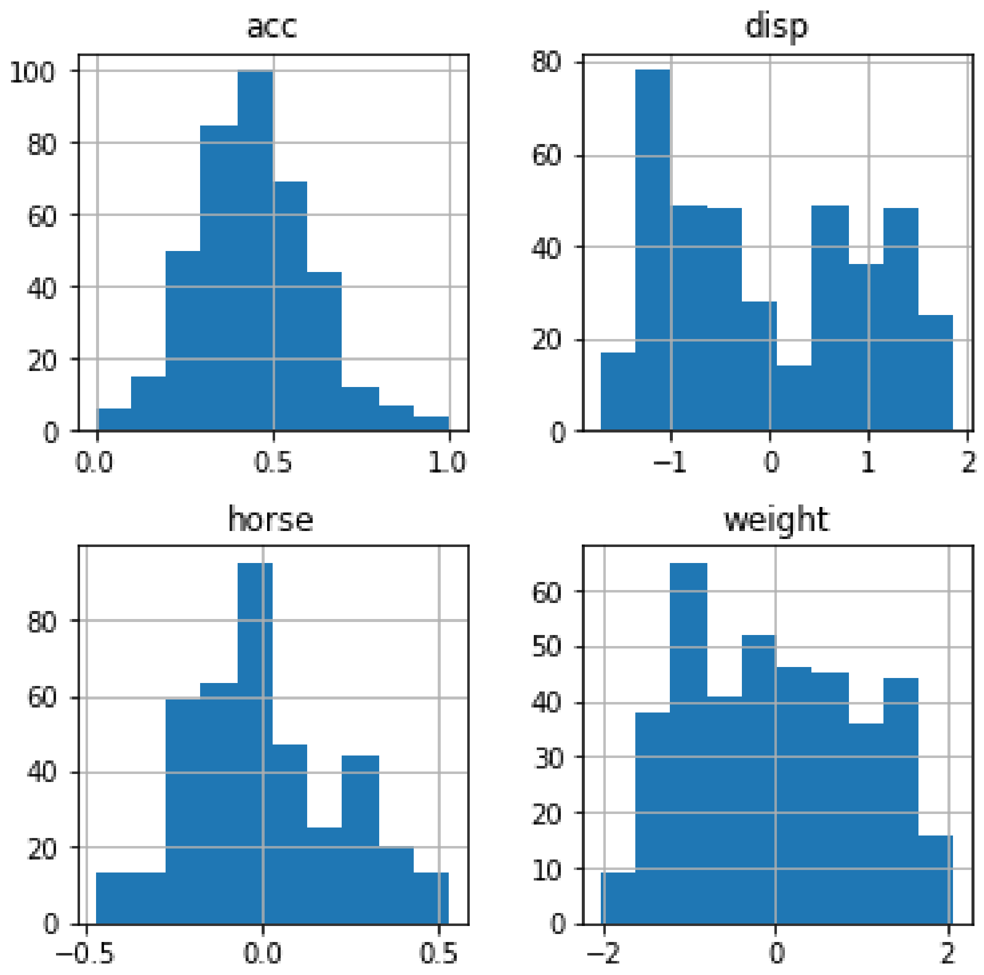
[6]:
```
import numpy as np
data_log = pd.DataFrame([])
data_log['logdisp'] = np.log(data_pred['displacement'])
data_log['loghorse'] = np.log(data_pred['horsepower'])
data_log['logweight'] = np.log(data_pred['weight'])
data_log.hist(figsize  = [6, 6]);
```



Although our new variables don't look perfectly normal, there is clearly an improvement in terms of skewness. Now, let's perform min-max scaling (on `'acceleration'`), standardization (on `'logdisp'` and `'logweight'`), and mean normalization (on `'loghorse'`).

[4]:
```
acc = data_pred['acceleration']
logdisp = data_log['logdisp']
loghorse = data_log['loghorse']
logweight = data_log['logweight']

scaled_acc = (acc - min(acc)) / (max(acc) - min(acc))
scaled_disp = (logdisp - np.mean(logdisp)) / np.sqrt(np.var(logdisp))
scaled_weight = (logweight - np.mean(logweight)) / np.sqrt(np.var(logweight))
scaled_horse = (loghorse - np.mean(loghorse)) / (max(loghorse) - min(loghorse))

data_cont_scaled = pd.DataFrame([])
data_cont_scaled['acc'] = scaled_acc
data_cont_scaled['disp'] = scaled_disp
```

```
data_cont_scaled['horse'] = scaled_horse
data_cont_scaled['weight'] = scaled_weight

data_cont_scaled.hist(figsize = [6, 6]);
```



Great! You rescaled your features.

## 1.6 Additional research

Scikit-learn provides automatic tools to scale features, see, among others, `MinMaxScaler`, `StandardScaler`, and `Normalizer`. Have a look at these built-in functions and some code examples here: http://scikit-learn.org/stable/modules/classes.html#module-sklearn.preprocessing!

To learn more about feature scaling in general, you can have a look at this blogpost: https://sebastianraschka.com/Articles/2014_about_feature_scaling.html (up until "bottom-up approaches").

## 1.7 Summary

In this lesson, you learned about why feature scaling is important, and *how* to use it to transform your features.