How to Use Power Transforms for Time Series Forecast Data with Python

by **Jason Brownlee** on January 25, 2017 in **Time Series**

Last Updated on August 28, 2019

Data transforms are intended to remove noise and improve the signal in time series forecasting.

It can be very difficult to select a good, or even best, transform for a given prediction problem. There are many transforms to choose from and each has a different mathematical intuition.

In this tutorial, you will discover how to explore different power-based transforms for time series forecasting with Python.

After completing this tutorial, you will know:

- How to identify when to use and how to explore a square root transform.
- How to identify when to use and explore a log transform and the expectations on raw data.
- How to use the Box-Cox transform to perform square root, log, and automatically discover the best power transform for your dataset.

Discover how to prepare and visualize time series data and develop autoregressive forecasting models in my new book, with 28 step-by-step tutorials, and full python code.

Let's get started.

- **Updated Apr/2019**: Updated the link to dataset.
- **Updated Aug/2019**: Updated data loading to use new API.

Airline Passengers Dataset

The Airline Passengers dataset describes a total number of airline passengers over time.

The units are a count of the number of airline passengers in thousands. There are 144 monthly observations from 1949 to 1960.

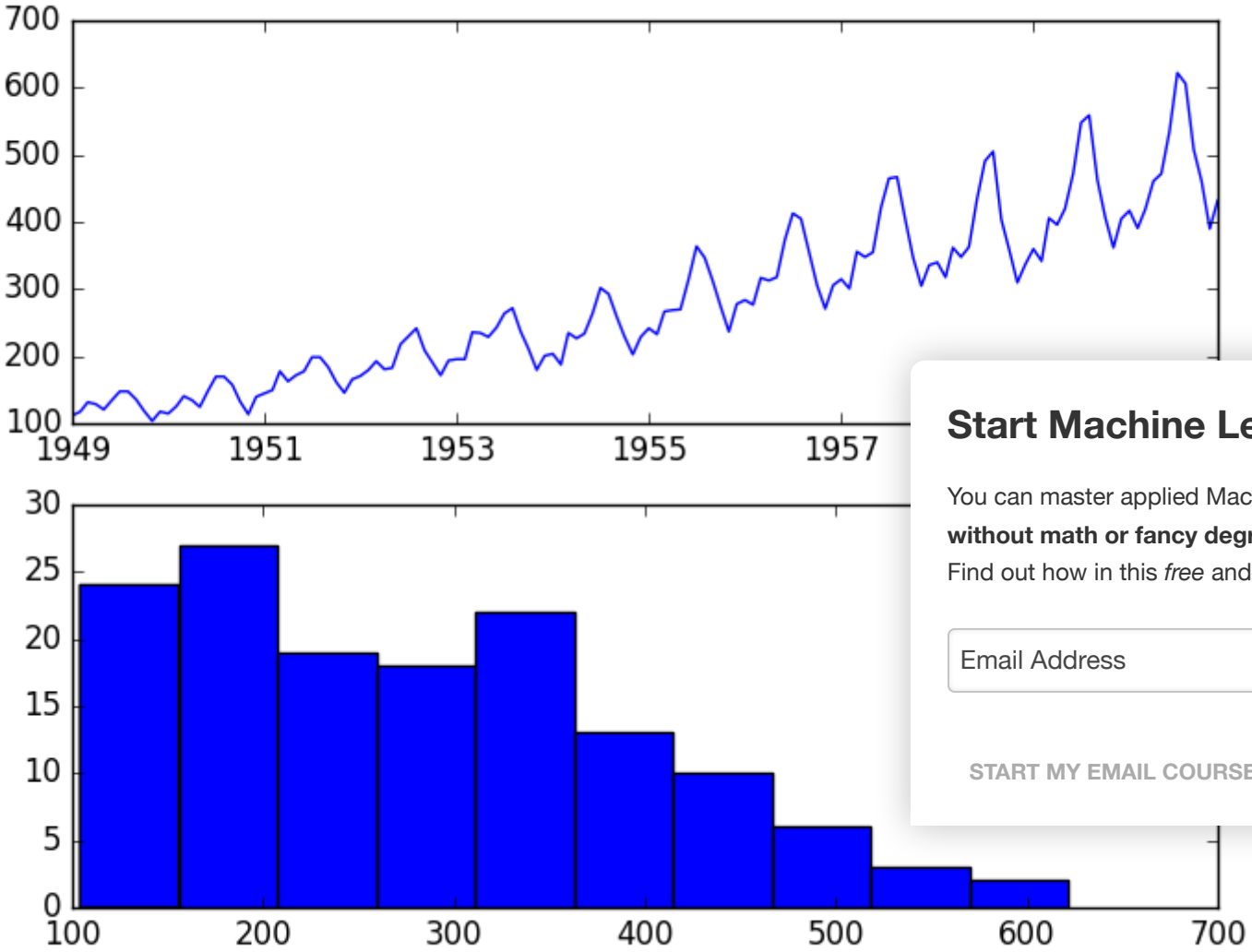
- Download the dataset.

Download the dataset to your current working directory with the filename "*airline-passengers.csv*".

The example below loads the dataset and plots the data.

```
from pandas import read_csv
from matplotlib import pyplot
series = read_csv('airline-passengers.csv', header=0, index_col=0)
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(series)
# histogram
pyplot.subplot(212)
pyplot.hist(series)
pyplot.show()
```


Running the example creates two plots, the first showing the time series as a line plot and the second showing the observations as a histogram.



Airline Passengers Dataset Plot

The dataset is non-stationary, meaning that the mean and the variance of the observations change over time. This makes it difficult to model by both classical statistical methods, like ARIMA, and more sophisticated machine learning methods, like ne

Start Machine Learning

This is caused by what appears to be both an increasing trend and a seasonality component.

In addition, the amount of change, or the variance, is increasing with time. This is clear when you look at the size of the seasonal component and notice that from one cycle to the next, the amplitude (from bottom to top of the cycle) is increasing.

In this tutorial, we will investigate transforms that we can use on time series datasets that exhibit this property.

Square Root Transform

A time series that has a quadratic growth trend can be made linear by taking the square root.

Let's demonstrate this with a quick contrived example.

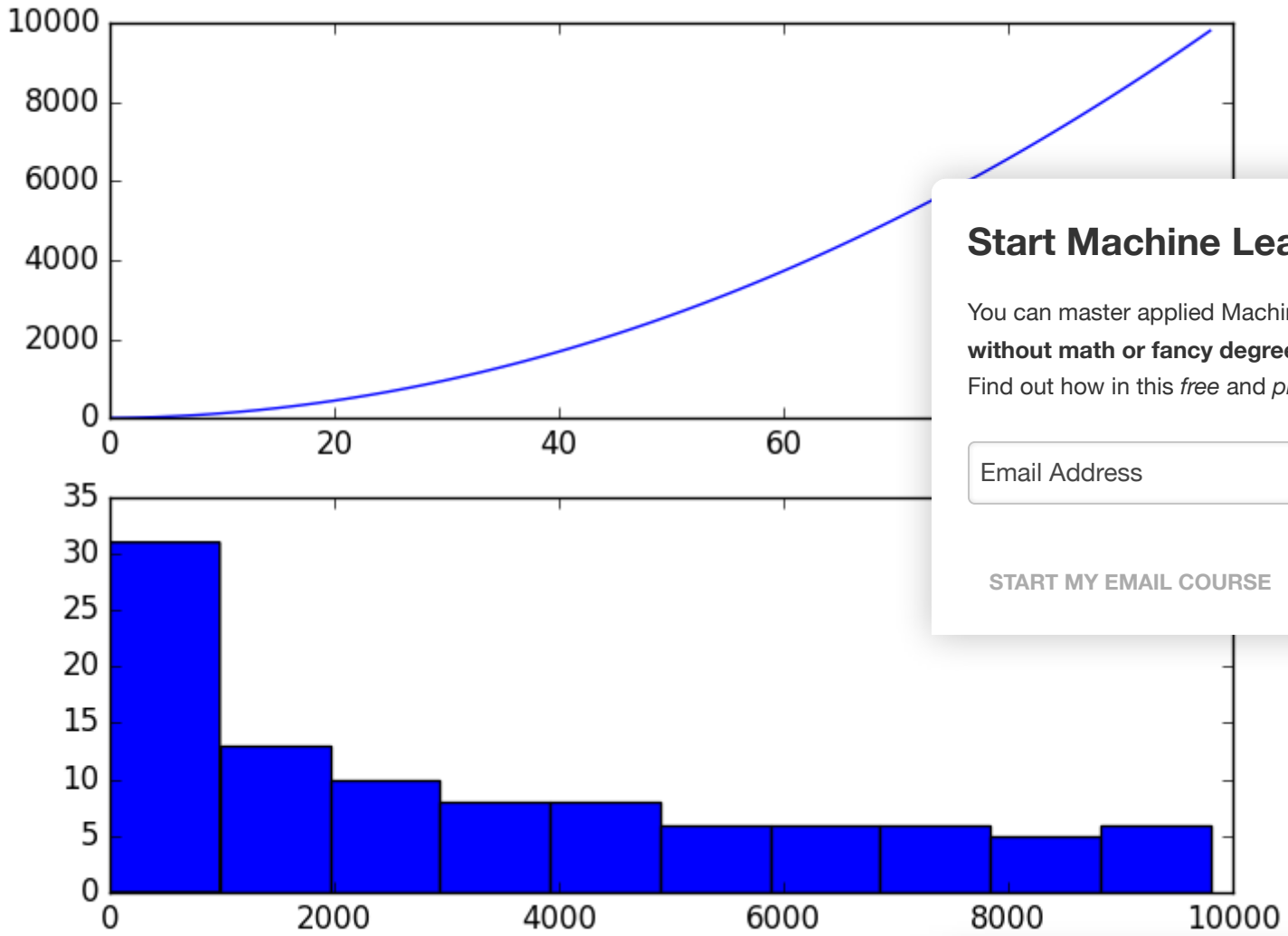
Consider a series of the numbers 1 to 99 squared. The line plot of this series will show a quadratic growth trend and a histogram of the values will show an exponential distribution with a long trail.

The snippet of code below creates and graphs this series.

```
from matplotlib import pyplot
series = [i**2 for i in range(1,100)]
# line plot
pyplot.plot(series)
pyplot.show()
```

```
# histogram
pyplot.hist(series)
pyplot.show()
```

Running the example plots the series both as a line plot over time and a histogram of observations.



Quadratic Time Series

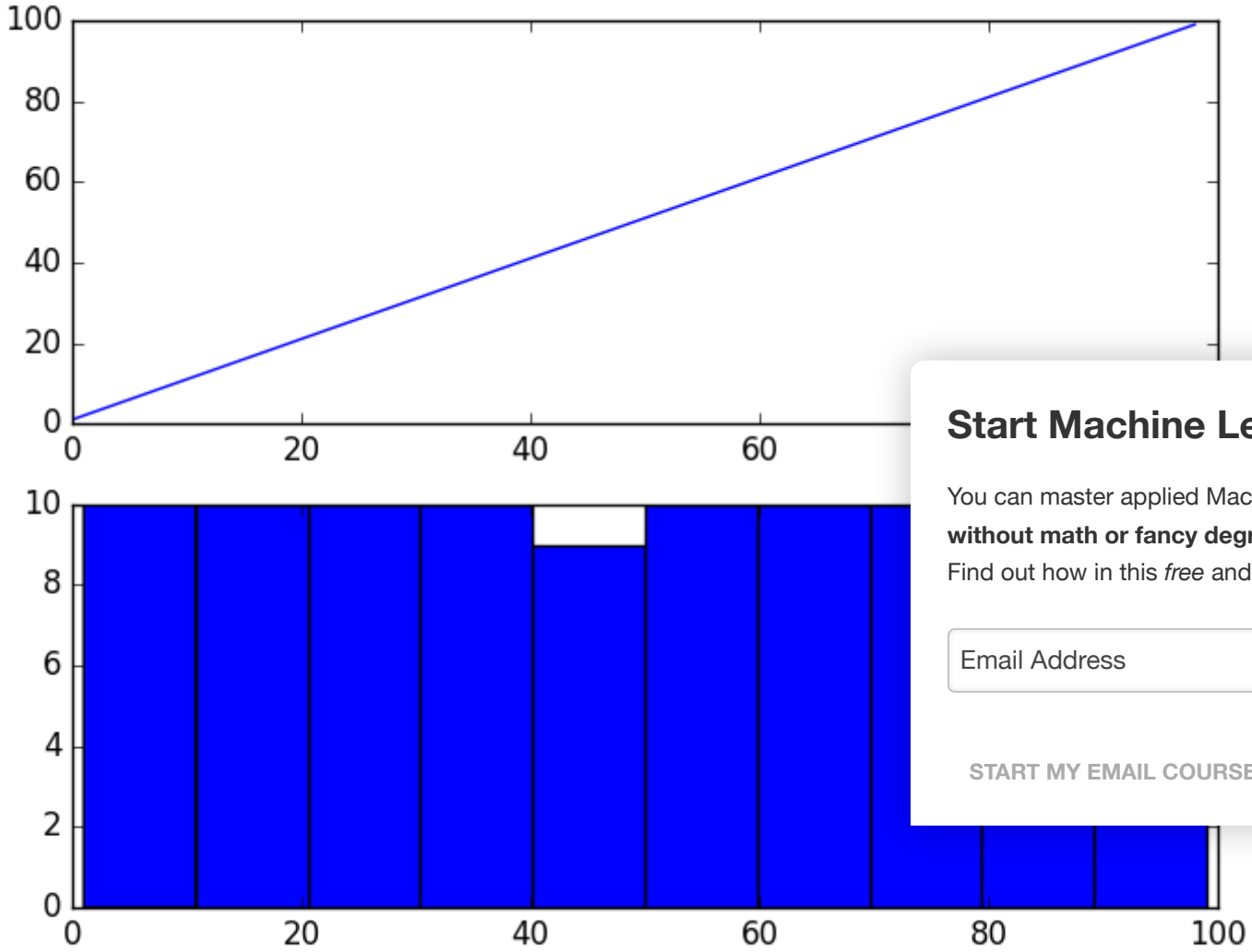
If you see a structure like this in your own time series, you may have a quadratic growth trend. This can be removed or made linear by taking the inverse operation of the squaring procedure, which is the square root.

Because the example is perfectly quadratic, we would expect the line plot of the transformed data to show a straight line. Because the source of the squared series is linear, we would expect the histogram to show a uniform distribution.

The example below performs a *sqrt()* transform on the time series and plots the result.

```
from matplotlib import pyplot
from numpy import sqrt
series = [i**2 for i in range(1,100)]
# sqrt transform
transform = series = sqrt(series)
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(transform)
# histogram
pyplot.subplot(212)
pyplot.hist(transform)
pyplot.show()
```

We can see that, as expected, the quadratic trend was made linear.



Square Root Transform of Quadratic Time Series

It is possible that the Airline Passengers dataset shows a quadratic growth. If this is the case, then we could expect a square root transform to reduce the growth trend to be linear and change the distribution of observations to be perhaps nearly Gaus

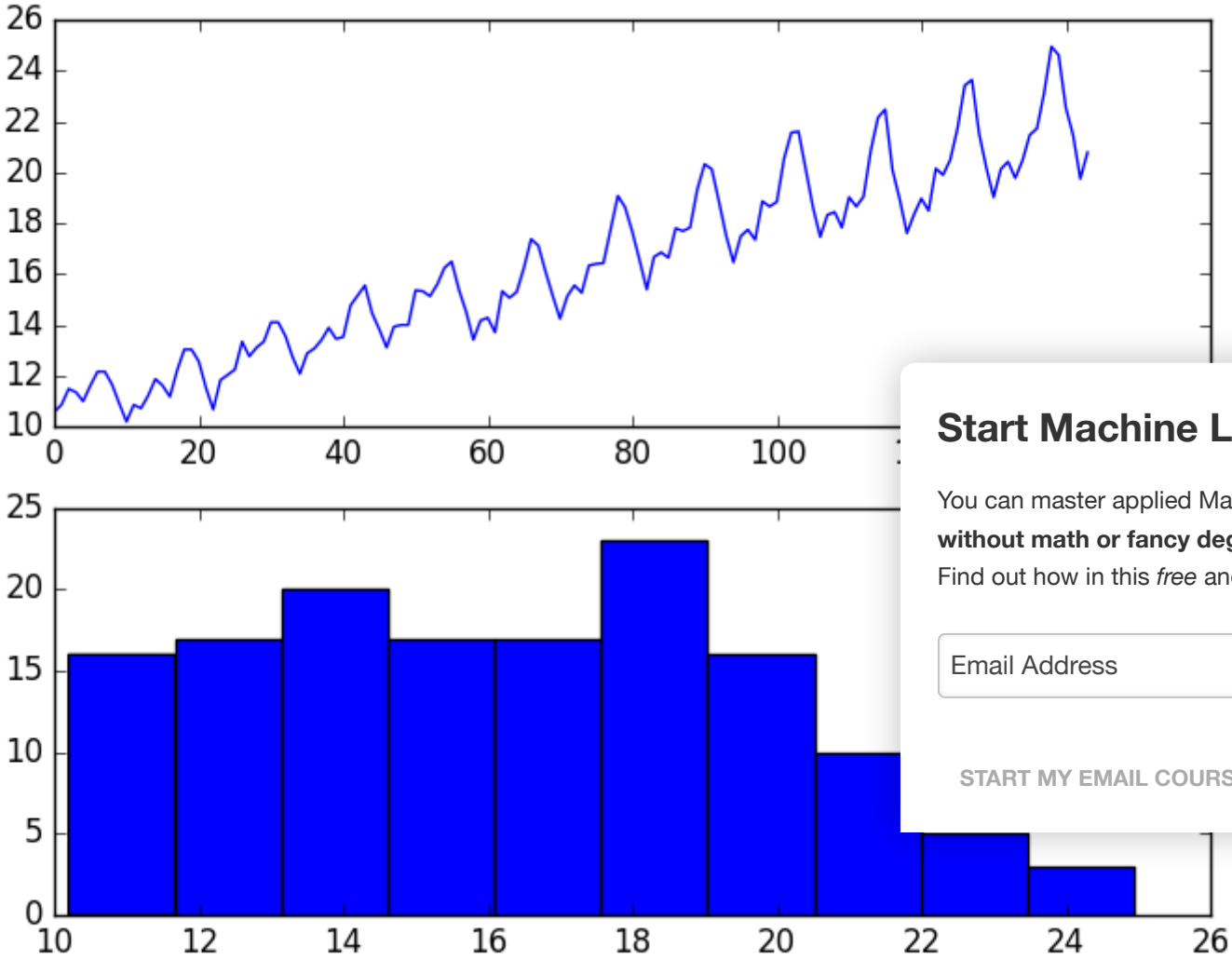
Start Machine Learning

The example below performs a square root of the dataset and plots the results.

```
from pandas import read_csv
from pandas import DataFrame
from numpy import sqrt
from matplotlib import pyplot
series = read_csv('airline-passengers.csv', header=0, index_col=0)
dataframe = DataFrame(series.values)
dataframe.columns = ['passengers']
dataframe['passengers'] = sqrt(dataframe['passengers'])
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(dataframe['passengers'])
# histogram
pyplot.subplot(212)
pyplot.hist(dataframe['passengers'])
pyplot.show()
```

We can see that the trend was reduced, but was not removed.

The line plot still shows an increasing variance from cycle to cycle. The histogram still shows a long exponential or long-tail distribution.



Square Root Transform of Airline Passengers Dataset Plot

Log Transform

A class of more extreme trends are exponential, often graphed as a hockey stick.

Start Machine Learning

Time series with an exponential distribution can be made linear by taking the logarithm of the values. This is called a log transform.

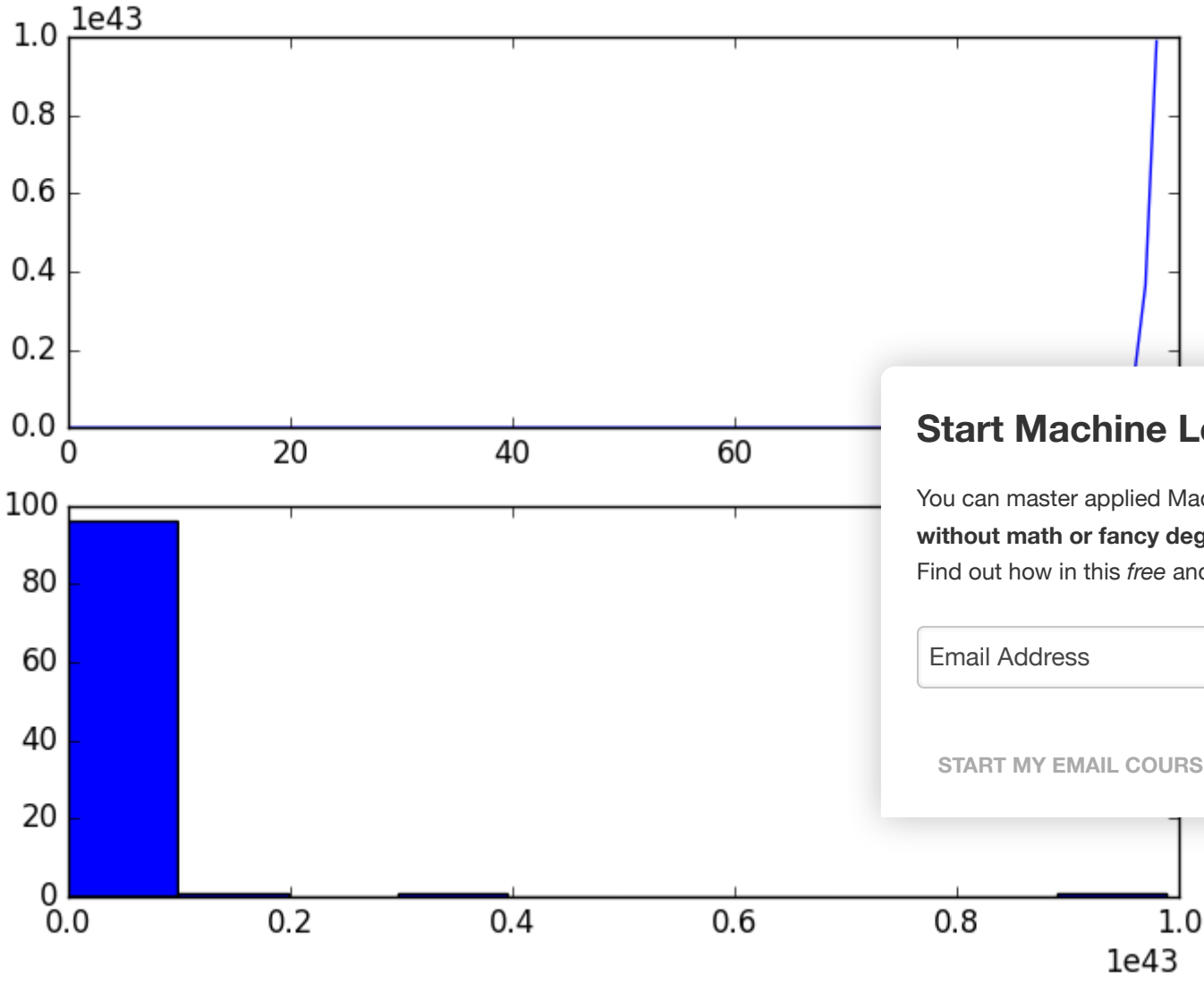
As with the square and square root case above, we can demonstrate this with a quick example.

The code below creates an exponential distribution by raising the numbers from 1 to 99 to the value *e*, which is the base of the natural logarithms or Euler's number (2.718…).

```
from matplotlib import pyplot
from math import exp
series = [exp(i) for i in range(1,100)]
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(series)
# histogram
pyplot.subplot(212)
pyplot.hist(series)
pyplot.show()
```

Running the example creates a line plot of the series and a histogram of the distribution of observat

We see an extreme increase on the line graph and an equally extreme long tail distribution on the hi



Exponential Time Series

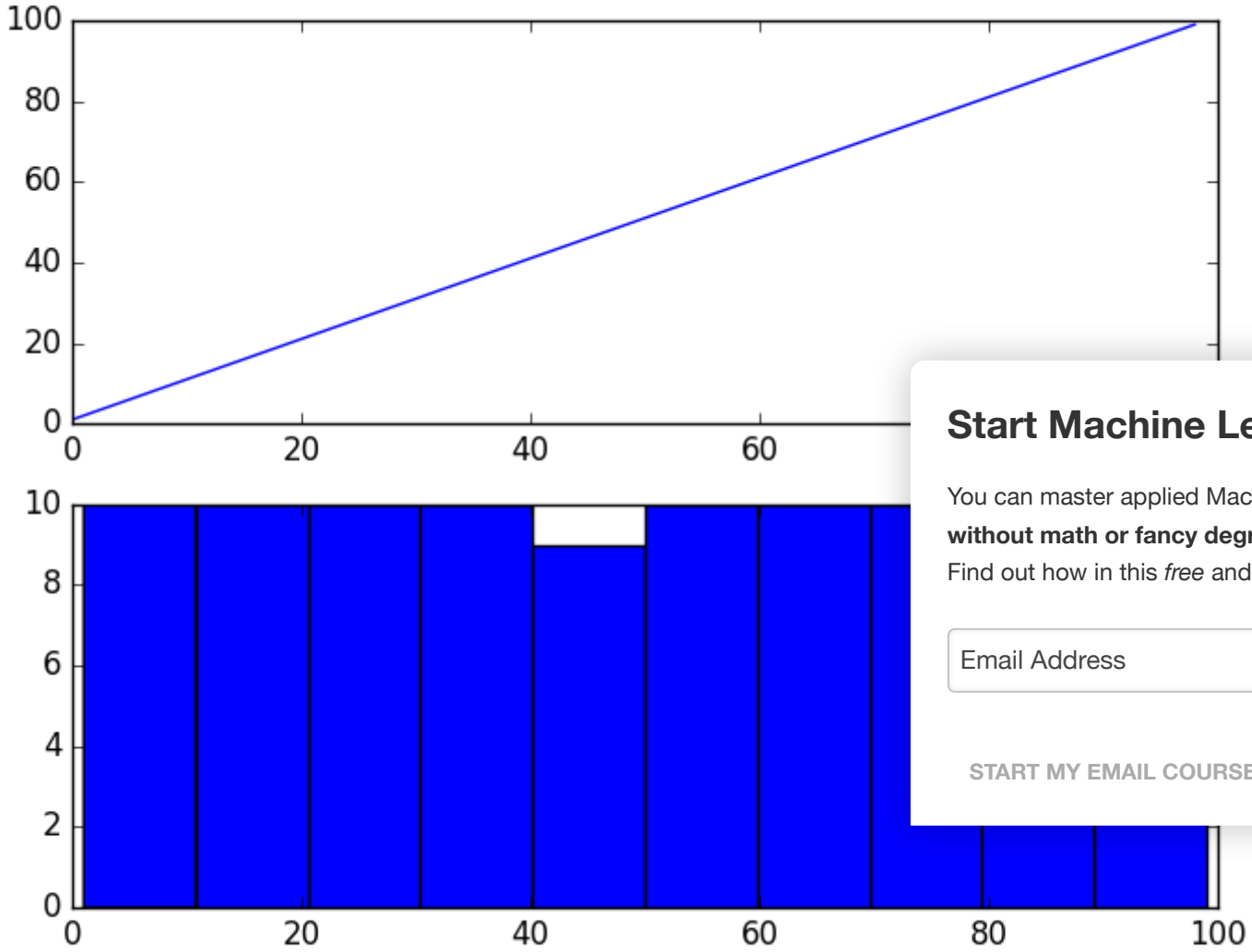
Again, we can transform this series back to linear by taking the natural logarithm of the values.

This would make the series linear and the distribution uniform. The example below demonstrates th

Start Machine Learning

```
from matplotlib import pyplot
from math import exp
from numpy import log
series = [exp(i) for i in range(1,100)]
transform = log(series)
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(transform)
# histogram
pyplot.subplot(212)
pyplot.hist(transform)
pyplot.show()
```

Running the example creates plots, showing the expected linear result.



Log Transformed Exponential Time Series

Our Airline Passengers dataset has a distribution of this form, but perhaps not this extreme.

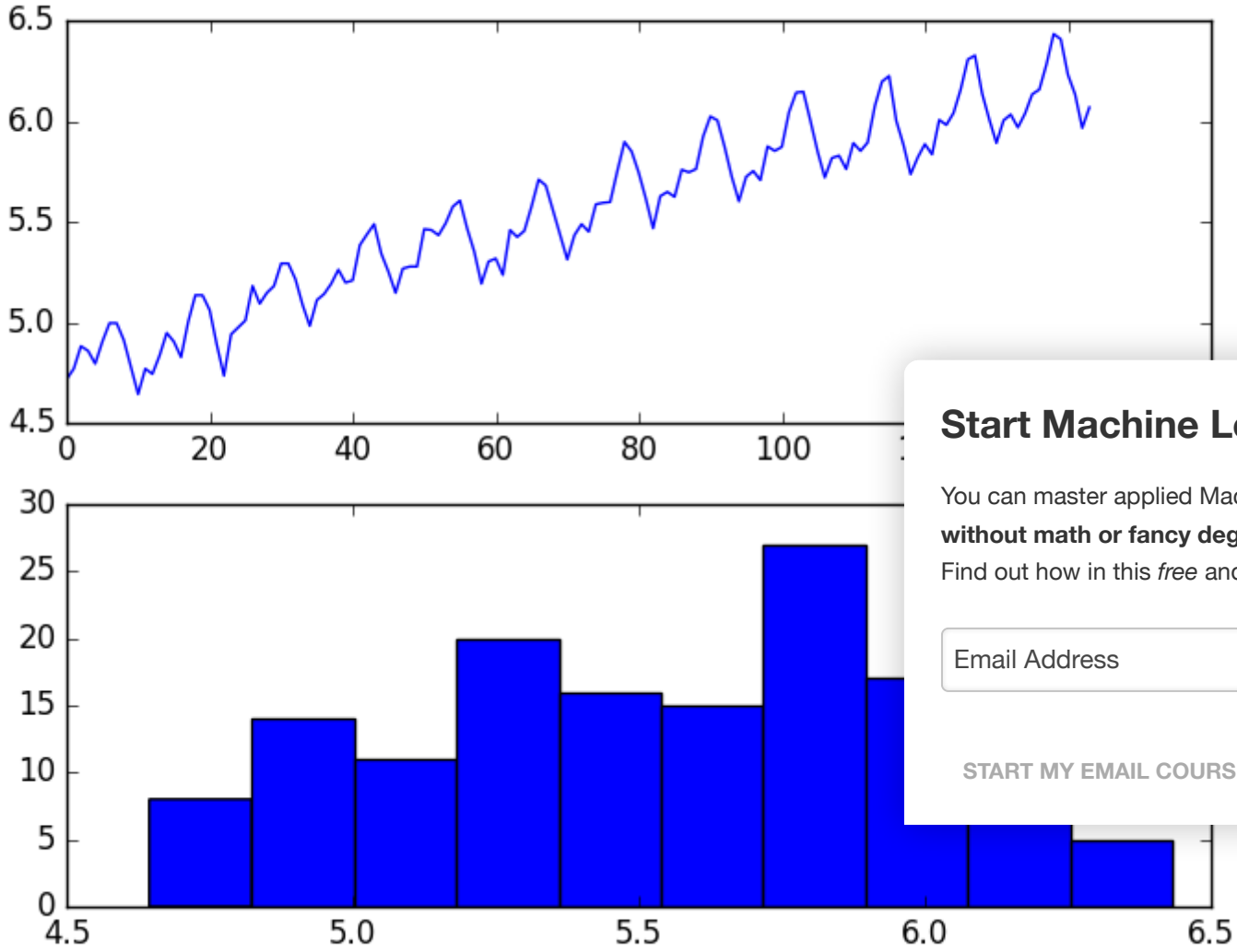
The example below demonstrates a log transform of the Airline Passengers dataset.

Start Machine Learning

```
from pandas import read_csv
from pandas import DataFrame
from numpy import log
from matplotlib import pyplot
series = read_csv('airline-passengers.csv', header=0, index_col=0)
dataframe = DataFrame(series.values)
dataframe.columns = ['passengers']
dataframe['passengers'] = log(dataframe['passengers'])
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(dataframe['passengers'])
# histogram
pyplot.subplot(212)
pyplot.hist(dataframe['passengers'])
pyplot.show()
```

Running the example results in a trend that does look a lot more linear than the square root transfor
growth and variance.

The histogram also shows a more uniform or squashed Gaussian-like distribution of observations.



Log Transform of Airline Passengers Dataset Plot

Log transforms are popular with time series data as they are effective at removing exponential variance.

It is important to note that this operation assumes values are positive and non-zero. It is common to transform observations by adding a fixed constant to ensure all input values meet this requirement. For example:

```
transform = log(constant + x)
```

Where *transform* is the transformed series, *constant* is a fixed value that lifts all observations above zero, and *x* is the time series.

Box-Cox Transform

The square root transform and log transform belong to a class of transforms called power transforms.

The Box-Cox transform is a configurable data transform method that supports both square root and log transform, as well as a suite of related transforms.

More than that, it can be configured to evaluate a suite of transforms automatically and select a bes ut power-based change in your time series. The resulting series may be more linear and the resulting c on the underlying process that generated it.

The *scipy.stats* library provides an implementation of the Box-Cox transform. The boxcox() function he type of transform to perform.

Below are some common values for lambda

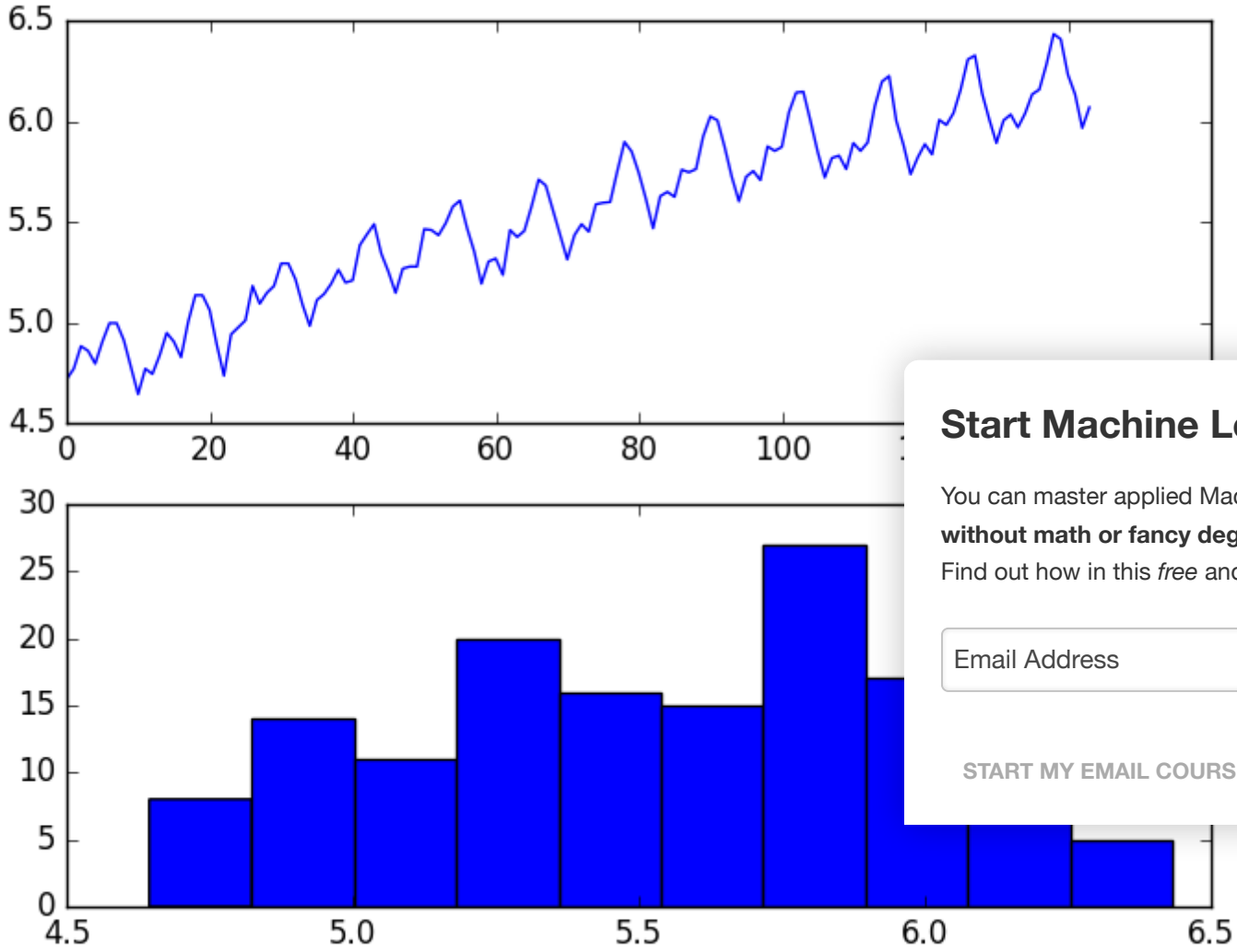
- *lambda* = -1. is a reciprocal transform.
- *lambda* = -0.5 is a reciprocal square root transform.
- *lambda* = 0.0 is a log transform.
- *lambda* = 0.5 is a square root transform.
- *lambda* = 1.0 is no transform.

For example, we can perform a log transform using the *boxcox()* function as follows:

```
from pandas import read_csv
from pandas import DataFrame
from scipy.stats import boxcox
from matplotlib import pyplot
series = read_csv('airline-passengers.csv', header=0, index_col=0)
```

```
dataframe = DataFrame(series.values)
dataframe.columns = ['passengers']
dataframe['passengers'] = boxcox(dataframe['passengers'], lmbda=0.0)
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(dataframe['passengers'])
# histogram
pyplot.subplot(212)
pyplot.hist(dataframe['passengers'])
pyplot.show()
```

Running the example reproduces the log transform from the previous section.



BoxCox Log Transform of Airline Passengers Dataset Plot

We can set the lambda parameter to None (the default) and let the function find a statistically tuned value.

The following example demonstrates this usage, returning both the transformed dataset and the ch

Start Machine Learning

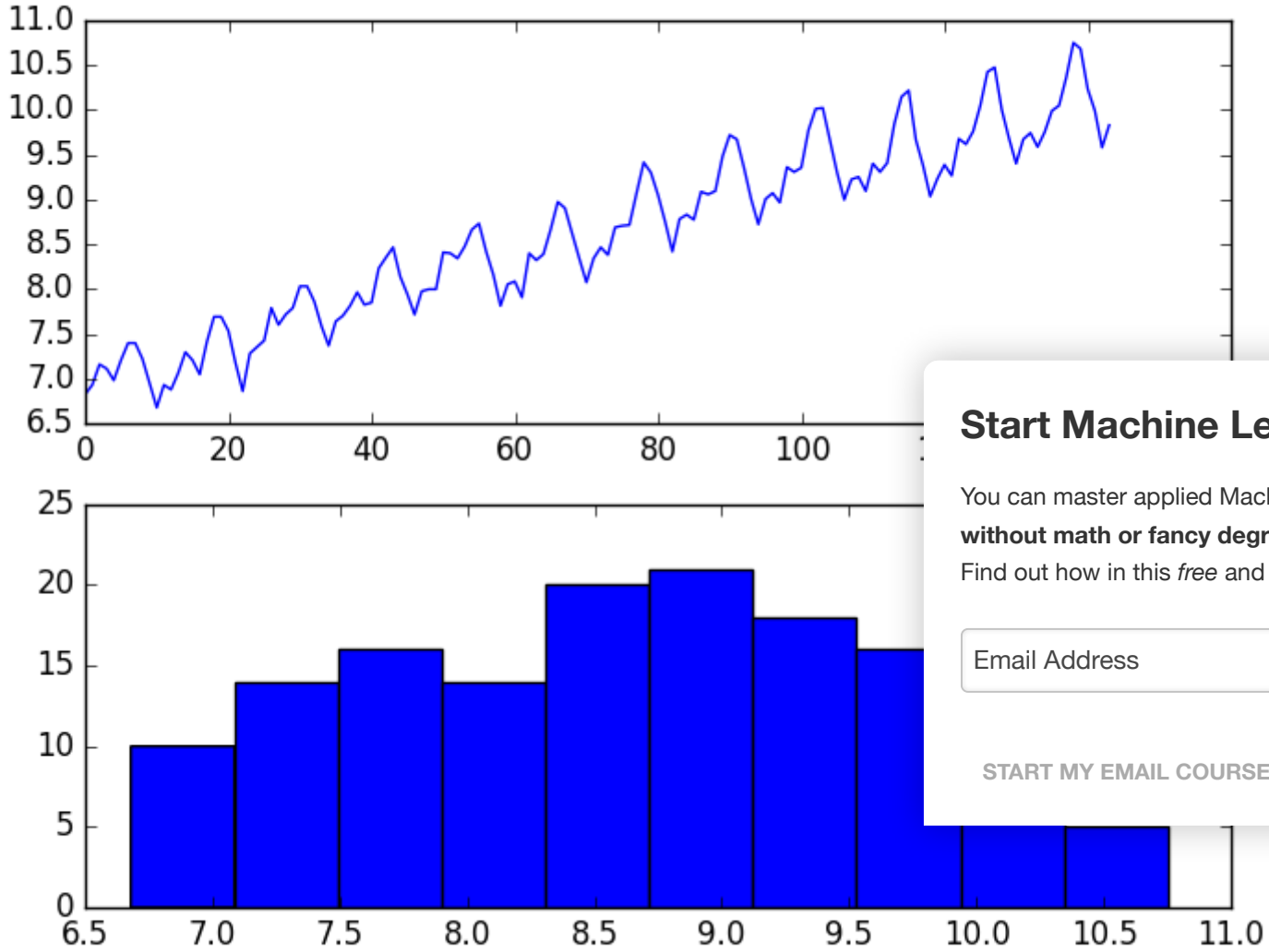
```
from pandas import read_csv
from pandas import DataFrame
from scipy.stats import boxcox
from matplotlib import pyplot
series = read_csv('airline-passengers.csv', header=0, index_col=0)
dataframe = DataFrame(series.values)
dataframe.columns = ['passengers']
dataframe['passengers'], lam = boxcox(dataframe['passengers'])
print('Lambda: %f' % lam)
pyplot.figure(1)
# line plot
pyplot.subplot(211)
pyplot.plot(dataframe['passengers'])
# histogram
pyplot.subplot(212)
pyplot.hist(dataframe['passengers'])
pyplot.show()
```

Running the example discovers the *lambda* value of 0.148023.

We can see that this is very close to a lambda value of 0.0, resulting in a log transform and stronger

```
Lambda: 0.148023
```

The line and histogram plots are also very similar to those from the log transform.



BoxCox Auto Transform of Airline Passengers Dataset Plot

Summary

In this tutorial, you discovered how to identify when to use and how to use different power transform

Start Machine Learning

Specifically, you learned:

- How to identify a quadratic change and use the square root transform.
- How to identify an exponential change and how to use the log transform.
- How to use the Box-Cox transform to perform square root and log transforms and automatically optimize the transform for a dataset.

Do you have any questions about power transforms, or about this tutorial?
Ask your questions in the comments below and I will do my best to answer.

Jason Brownlee, PhD is a machine learning specialist who teaches developers how to get results with modern machine learning methods via hands-on tutorials.

View all posts by Jason Brownlee →

‹ How to Reframe Your Time Series Forecasting Problem

How to Make Predictions for Time Series Forecasting with Python ›

51 Responses to *How to Use Power Transforms for Time Series Forecast D*

Shane Keller November 28, 2017 at 2:36 pm #

Thanks for this article. A lot of people write about log transformations and provide no explanati
fills in a lot of the gaps. Thanks!

Shane Keller November 28, 2017 at 3:03 pm #

A few follow up questions:
– Assuming the minimum value of a variable is > 0, are there situations in which you would not try and use Box-Cox? The scipy.stats.boxplot module will also decide when a transformation is unnecessary, so seems like there's no harm in trying it for every variable. I'd imagine the main cost is loss of interpretability if you're visualizing model results.
– In situations where you shouldn't use a Box-Cox, what alternative transformations do you recommend?

Jason Brownlee November 29, 2017 at 8:18 am #

REPLY

I agree, try, evaluate and adopt if a transform lifts skill. Often model skill is the goal for

A “Yeo-Johnson transformation” can be used as an alternative to box-cox:
https://en.wikipedia.org/wiki/Power_transform#Yeo-Johnson_transformation

Abhi July 25, 2019 at 11:40 am #

REPLY

Thanks for the blog. It’s very helpful for me since I’m currently working on a project where I need to log transform the data.

I have the following question, if I fit the transformed data to extract information such as the mean and variance or the forecasted value. Does scipy have a way to transform the data back?

Jason Brownlee July 25, 2019 at 2:12 pm #

Off hand, I don’t think so.

You can invert the power transform if you know the lambda.

I show how here:
https://machinelearningmastery.com/machine-learning-data-transforms-for-time-series-forecas

Joachim Hagege December 21, 2017 at 4:48 am #

Hi, thanks much for the tutorial.
When taking the square root of the airline, you say we expect the distribution to be Gaussian, while in the previous example with generated quadratic data, you expected a uniform distribution.
When will we expect one over the other ?
Thanks !

Jason Brownlee December 21, 2017 at 5:30 am #

It really depends on the data.

Yasen March 4, 2018 at 4:43 am #

REPLY

Please, help!
after writing the first code line from the first example I have got the following error message:

>>> from pandas import Series

Traceback (most recent call last):
File “”, line 1, in
from pandas import Series
ImportError: No module named pandas
>>>

Jason Brownlee March 4, 2018 at 6:06 am #

You need to install Pandas. This tutorial will help you:
https://machinelearningmastery.com/setup-python-environment-machine-learning-deep-learning-a

Kim April 18, 2018 at 6:01 am #

REPLY

Dear Jason, I love this tutorial!

Much of the data I work with contains many zeros and is heavily skewed to the right. I have sometimes added a small value (like 0.1) to each record in order to perform a log transformation.

Can the Box-Cox package handle data that contains zeros?

Thanks again for your great information 🙂

Start Machine Learning

Jason Brownlee April 18, 2018 at 8:17 am #

REPLY

Generally, no.

Nevertheless, try it (with an offset to get all values >0) to see if it has an impact.

Charles July 3, 2018 at 5:49 am #

REPLY

FYI – scipy.stats.boxcox is buggy. 🙁

Jason Brownlee July 3, 2018 at 6:29 am #

Why do you say that?

Charles July 17, 2018 at 9:24 pm #

This thread shows the problem. I ran into the problem running your code but on my da

https://github.com/scipy/scipy/issues/6873

The problem occurs when stats.boxcox calls stats.boxcox_normmax Very annoying.

Jason Brownlee July 18, 2018 at 6:33 am #

REPLY

Sorry to hear that.

Sundeep Nayakanti July 16, 2018 at 2:02 am #

REPLY

Hi Jason, thanks for your blog.. It is good as like your other blog posts. However got a questions, if I use to box_cox to automatically use for transformation for my series, how can I convert it back..i meant transform back to original values..is there a function that does automatically as well?

Jason Brownlee July 16, 2018 at 6:12 am #

REPLY

You can invert the process with a function like the following:

```
# invert a boxcox transform for one value
def power_transform_invert_value(value, lam):
    from math import log
    from math import exp
    # log case
    if lam == 0:
        return exp(value)
    # all other cases
    return exp(log(lam * value + 1) / lam)
```


doug August 25, 2018 at 5:08 pm #

nice one; i was interested in a first-principles explanation of Box-Cox; at university many years ago, I did a lot of work in python so i didn't use your code; however, your use of clear shot snippets to explain step-by-step what is B-C, is excellent

Jason Brownlee August 26, 2018 at 6:23 am #

REPLY

Thanks Doug, I'm happy it was useful.

Kingsley Udeh September 16, 2018 at 7:31 pm #

Start Machine Learning

Hi Jason,

How do we inverse the log transformed data or time series back to the original time series scale?

Secondly, I used log transform on my time series data that shows exponential growth trends, to make it linear, and I had a histogram plot that is more uniform and Gaussian-like distribution. The log transform lifted model skills tremendously, but in log scale, rather than the original time series scale. In addition, I did not do any further transform on my time series data, even though, they contain zeroes and negative values. Does it really matter?

Regards,
Kingsley

Thanks

Jason Brownlee September 17, 2018 at 6:29 am #

The inverse of log is exp()

The transforms required really depend on your data.

Kingsley Udeh September 17, 2018 at 7:59 am #

Thanks

Jason Brownlee September 17, 2018 at 2:07 pm #

REPLY

I'm happy that it helped.

Santosh November 10, 2018 at 8:20 pm #

REPLY

Hi Jason,

Thanks a lot for the great post. So my question is that, the box-cox algorithm helps to determine if there is any trend or seasonality. How do we remove that trend and make the time series stationary ? Do we need to substract the trend or seasonality factor from the original data set and feed to the ARIMA model to decide the value of p,q and d? If you have any article related to this, please share.

Also, for an ARIMA model, a stationary time series is mandatory ? I have a data set similar to the air passeneger data set. I have the data set from 2014 to 2017. I want to predict it for 2018.

Your help will be highly appreciated 🙂

Jason Brownlee November 11, 2018 at 6:01 am #

REPLY

No, box-cox shifts a data distribution to be more Gaussian.

You can remove a trend using a difference transform.

When using ARIMA, it can perform this differencing for you.

Mada December 27, 2018 at 11:01 am #

Thank you for your post. It is very useful.
My time series data is multiplicative.
2 Questios::

1. What do I need to calculate log of? Dependent variable Y or Resduals r? To elaborate,
Once I calculate log(Y), should I then calculate residual as r = log(Y) /(trend x seasonality). Or should I calculate r = Y/(tend x seasonality) and then calculate log (r)?

2. If my trend and seasonality are independent variables (features) then should I also calculate log of them before doing
r = log(Y) /(trend x seasonality)

Jason Brownlee December 28, 2018 at 5:43 am #

You transform the raw data that you're modeling.

I recommend subtracting the trend and seasonality from the data first, e.g. make the series stationary.

Mada December 31, 2018 at 5:01 am #

REPLY

But if I substract seasonality and trend then it will make the data negative? And you mentioned calculating log of negative data isn't allowed

Jason Brownlee December 31, 2018 at 6:15 am #

REPLY

You can force the data to be positive by adding an offset.

Thomas van Rijsselt March 8, 2019 at 7:52 am #

Hi Jason,

Currently working through your eBook on TimeSeries. Learned loads already, very exciting.

If I run the code of the Box-Cox with optimized Lambda, my Lambda is optimized for 8.4.
Have you seen this issue before?

Thanks,
Thomas

Jason Brownlee March 8, 2019 at 8:02 am #

REPLY

Wow, that is a massive value.

No, I have not seen that before.

dhandapani January 8, 2020 at 5:02 am #

REPLY

Hi Dr Jason,
Good article!!

I want to transform Generalized Normal Distribution to Normal Distribution (through uniform distribution??, read from some literature, there not much ICDF is available for Gennorm). I follow similar technique of that you have indicated. Not able to get the required outcome!
Can you help me out please?

Jason Brownlee January 8, 2020 at 8:33 am #

Sorry, I don't have a tutorial on this topic – I don't have good off the cuff advice.

raymond paller January 18, 2020 at 3:35 am #

Hi. Useful post. Thank-you.

Let me see if I understand you correctly from a Mada's question from above so I can avoid any foobar-ing on my part. If I am doing ARIMA I should be doing the differencing BEFORE applying Box_cox or Yeo? Then do Box_cox?

Jason Brownlee January 18, 2020 at 8:51 am #

REPLY

Thanks.

Yes, differencing first. I outline a suggested ordering here:
https://machinelearningmastery.com/machine-learning-data-transforms-for-time-series-forecasting/

Saurabh February 26, 2020 at 12:51 am #

REPLY

Hi Jason,

As always, it's a treat reading your articles. Just a quick question.

I have seen people applying Box-Cox transform AFTER performing train-test split. Which is okay until there is not data leakage in pipeline. But is it really required to perform ANY transformation (including differences etc.) on test data? We anyways inverse transform the predictions generated using train data before actual model evaluation.

In short, you do we apply any transformation on test data when it's supposed to be hidden during training?

Jason Brownlee February 26, 2020 at 8:23 am #

Thanks.

Correct. Calculate on training, apply to train, test, and any other data.

Kabilan April 20, 2020 at 3:11 am #

Hello Jason,
Great tutorial! Will the transforms hold good if I'm performing time series classification?

Jason Brownlee April 20, 2020 at 5:30 am #

REPLY

Perhaps develop a prototype for your dataset and discover the answer.

Kabilan April 20, 2020 at 10:01 pm #

Thank you very much! I will try it out!!

Jason Brownlee April 21, 2020 at 5:56 am #

REPLY

You're welcome.

Chris June 3, 2020 at 7:29 am #

REPLY

Hello Jason, thanks for this awesome post! I've searched through the internet but am still confused about how we apply power transformation to multiple examples. Say if we have about 20 univariate datapoints of length 20, do we treat each datapo concatenate all of the datapoints since they are describing the same variable? Thanks!

Jason Brownlee June 3, 2020 at 8:06 am #

Each "series" would be a separate input feature:
https://machinelearningmastery.com/faq/single-faq/what-is-the-difference-between-samples-times

Shiv June 3, 2020 at 11:17 pm #

REPLY

Hi Jason,

If I have a time series with no general trend but a strong seasonality, and its distribution is bi-modal. What transform should I use ? Without any transforms, I have used a DNN and it pretty much works good but I am curious to know if there's any room for improvement using transforms, if yes which one? Thanks!

Jason Brownlee June 4, 2020 at 6:22 am #

Seasonal transform to remove the seasonality.

Chris June 4, 2020 at 4:46 am #

REPLY

Thank you for the prompt reply. Another doubt I had is about minmax scaler. In the case of scaling univariate time series to 0-1, we should treat each datapoint in training set as the same feature instead of each single datapoint as a feature, right? Otherwise we won't have shared min/max parameter?

Jason Brownlee June 4, 2020 at 6:32 am #

REPLY

Correct.

SHRUTI PANDEY July 3, 2020 at 7:46 pm #

Hi Jason, I am reading your book on time-series. I wanted to ask you two questions:
1. Do we remove seasonality and trend before applying power transform?
2. Which power transform is better for data like the mean temperature of a city?

Thanks in advance!

Jason Brownlee July 4, 2020 at 5:56 am #

REPLY

Great questions.

Yes. This can help with the order of transforms:
https://machinelearningmastery.com/machine-learning-data-transforms-for-time-series-forecasting/

Perhaps test a few transforms and discover which results in a better performing model on your dataset.

Start Machine Learning

Veron July 24, 2020 at 12:27 pm #

REPLY

My time series experienced a huge fall in values that makes it non-stationary.

I got a lambda value =1 which means no transformation is needed. However, the time series is still non-stationary.

What should I do for time series with abrupt change?

Jason Brownlee July 24, 2020 at 1:37 pm #

REPLY

I believe they call this a regime change. Perhaps there are techniques designed specifically for that, you can try checking the literature.

Perhaps manually separate the data before and after the change in level and model them as separa

Leave a Reply

Name (required)

Email (will not be published) (required)

Start Machine Learning

Website

SUBMIT COMMENT

Welcome!
My name is *Jason Brownlee* PhD, and I **help developers** get results with **machine learning**.
Read more

Never miss a tutorial:

Picked for you:


How to Create an ARIMA Model for Time Series Forecasting in Python


How to Convert a Time Series to a Supervised Learning Problem in Python


11 Classical Time Series Forecasting Methods in Python (Cheat Sheet)


Time Series Forecasting as Supervised Learning

How To Backtest Machine Learning Models for Time Series Forecasting

Start Machine Learning