Instability of Online Learning for Stateful LSTM for Time Series Forecasting

by **Jason Brownlee** on April 24, 2017 in **Long Short-Term Memory Networks**

Some neural network configurations can result in an unstable model.

This can make them hard to characterize and compare to other model configurations on the same problem using descriptive statistics.

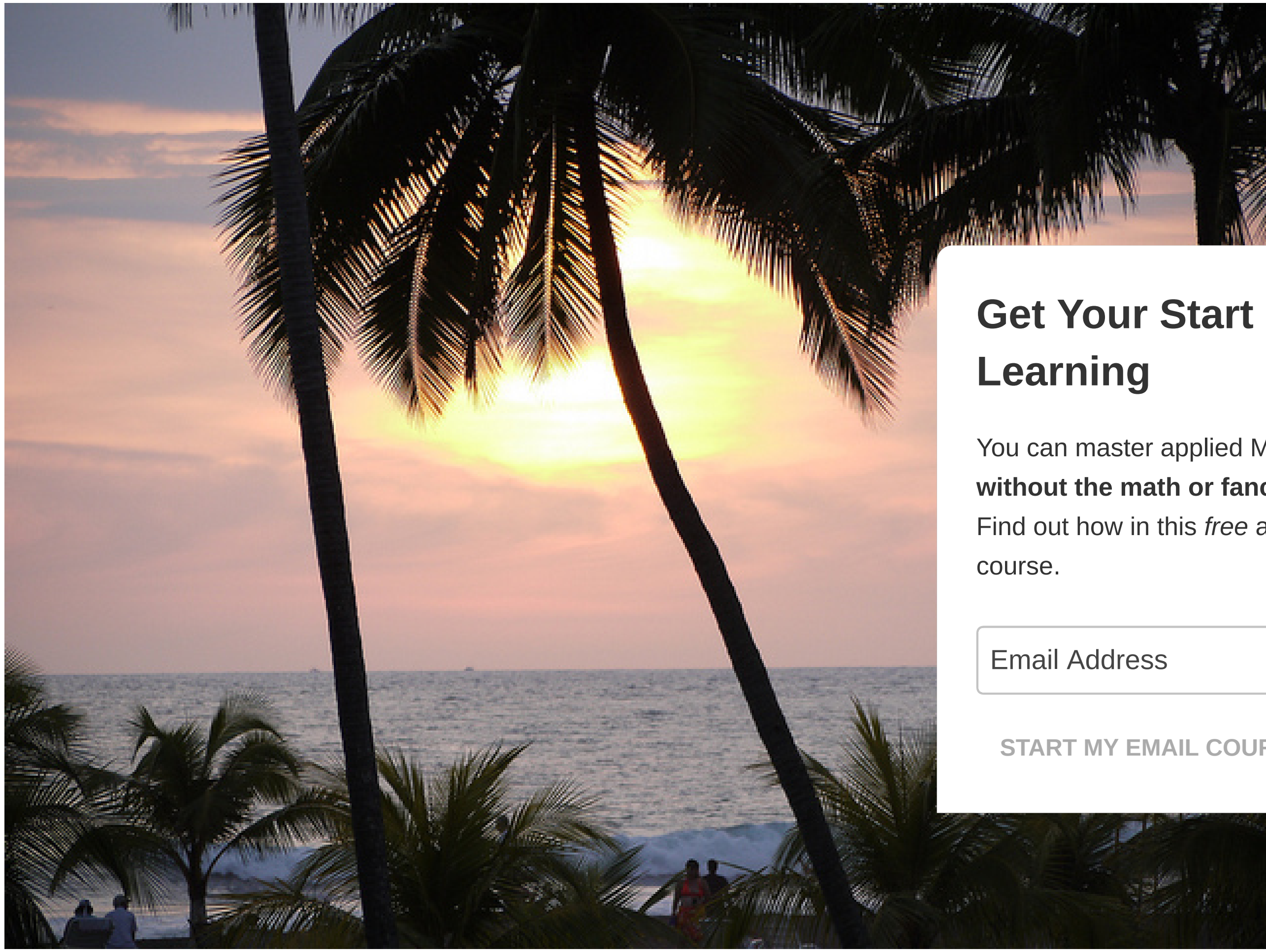
One good example of a seemingly unstable model is the use of online learning (a batch size of 1) for a stateful Long Short-Term Memory (LSTM) model.

In this tutorial, you will discover how to explore the results of a stateful LSTM fit using online learning on a standard time series forecasting problem.

After completing this tutorial, you will know:

- How to design a robust test harness for evaluating LSTM models on time series forecasting pro[redacted]
- How to analyze a population of results, including summary statistics, spread, and distribution of results.
- How to analyze the impact of increasing the number of repeats for an experiment.

Let's get started.



Instability of Online Learning for Stateful LSTM for Time Series Forecasting
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Model Instability

When you train the same network on the same data more than once, you may get very different results.

This is because neural networks are initialized randomly and the optimization nature of how they are fit to the training data can result in different final weights within the network. These different networks can in turn result in varied predictions given the same input data.

As a result, it is important to repeat any experiment on neural networks multiple times to find an averaged expected performance.

For more on the stochastic nature of machine learning algorithms like neural networks, see the post:

- Embrace Randomness in Machine Learning

The batch size in a neural network defines how often the weights within the network are updated given exposure to a training dataset.

A batch size of 1 means that the network weights are updated after each single row of training data. ork that can learn quickly, but a configuration that can be quite unstable.

In this tutorial, we will explore the instability of online learning for a stateful LSTM configuration for tir

We will explore this by looking at the average performance of an LSTM configuration on a standard t number of repeats of the experiment.

That is, we will re-train the same model configuration on the same data many times and look at the p nd review how unstable the model can be.

Tutorial Overview

This tutorial is broken down into 6 parts. They are:

1. Shampoo Sales Dataset
2. Experimental Test Harness
3. Code and Collect Results
4. Basic Statistics on Results
5. Repeats vs Test RMSE
6. Review of Results

Environment

This tutorial assumes you have a Python SciPy environment installed. You can use either Python 2 or 3 with this example.

This tutorial assumes you have Keras v2.0 or higher installed with either the TensorFlow or Theano backend.

This tutorial also assumes you have scikit-learn, Pandas, NumPy, and Matplotlib installed.

Next, let's take a look at a standard time series forecasting problem that we can use as context for this experiment.

If you need help setting up your Python environment, see this post:

- How to Setup a Python Environment for Machine Learning and Deep Learning with Anaconda

Shampoo Sales Dataset

This dataset describes the monthly number of sales of shampoo over a 3-year period.

The units are a sales count and there are 36 observations. The original dataset is credited to Makridakis, Wheelwright, and Hyndman (1998).

You can download and learn more about the dataset here.

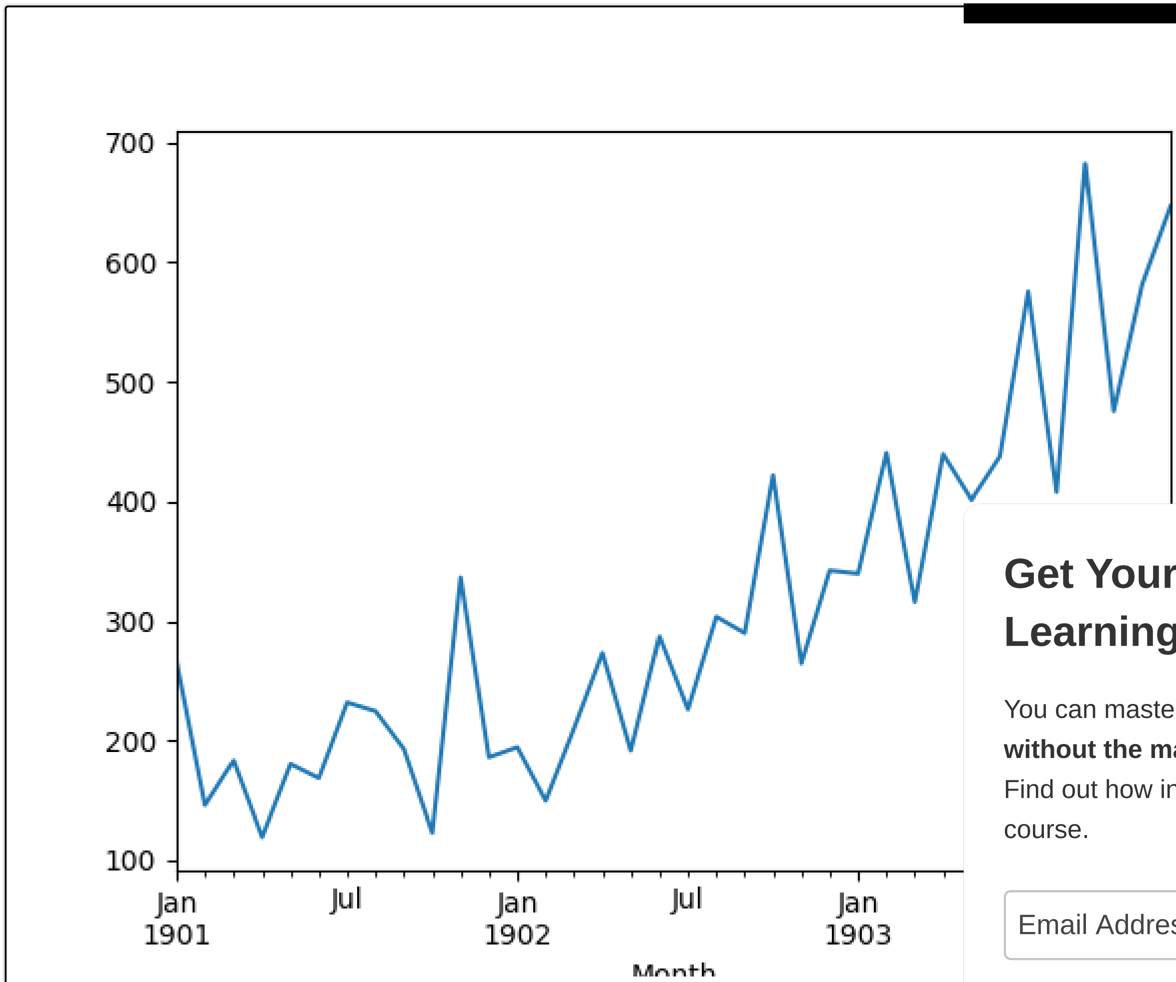
The example below loads and creates a plot of the loaded dataset. [redacted]

```
# load and plot dataset
from pandas import read_csv
from pandas import datetime
from matplotlib import pyplot
# load dataset
def parser(x):
    return datetime.strptime('190'+x, '%Y-%m')
series = read_csv('shampoo-sales.csv', header=0, parse_dates=[0], index_col=0, squeeze=True, date_parser=parser)
# summarize first few rows
print(series.head())
# line plot
series.plot()
pyplot.show()
```

Running the example loads the dataset as a Pandas Series and prints the first 5 rows.

```
Month
1901-01-01 266.0
1901-02-01 145.9
1901-03-01 183.1
1901-04-01 119.3
1901-05-01 180.3
Name: Sales, dtype: float64
```

A line plot of the series is then created showing a clear increasing trend.



Line Plot of Shampoo Sales Dataset

Next, we will take a look at the LSTM configuration and test harness used in the experiment.

Experimental Test Harness

This section describes the test harness used in this tutorial.

Data Split

We will split the Shampoo Sales dataset into two parts: a training and a test set.

The first two years of data will be taken for the training dataset and the remaining one year of data will be used for the test set.

Models will be developed using the training dataset and will make predictions on the test dataset.

The persistence forecast (naive forecast) on the test dataset achieves an error of 136.761 monthly shampoo sales. This provides a lower acceptable bound of performance on the test set.

Model Evaluation

A rolling-forecast scenario will be used, also called walk-forward model validation.

Each time step of the test dataset will be walked one at a time. A model will be used to make a forec ue from the test set will be taken and made available to the model for the forecast on the next time step

This mimics a real-world scenario where new Shampoo Sales observations would be available each g month.

This will be simulated by the structure of the train and test datasets.

All forecasts on the test dataset will be collected and an error score calculated to summarize the skil E) will be used as it punishes large errors and results in a score that is in the same units as the forecas

Data Preparation

Before we can fit an LSTM model to the dataset, we must transform the data.

The following three data transforms are performed on the dataset prior to fitting a model and making a forecast.

1. **Transform the time series data so that it is stationary**. Specifically a lag=1 differencing to remove the increasing trend in the data.
2. **Transform the time series into a supervised learning problem**. Specifically the organization of data into input and output patterns where the observation at the previous time step is used as an input to forecast the observation at the current time step

3. **Transform the observations to have a specific scale**. Specifically, to rescale the data to valu[redacted]c tangent activation function of the LSTM model.

These transforms are inverted on forecasts to return them into their original scale before calculating and error score.

LSTM Model

We will use a base stateful LSTM model with 1 neuron fit for 1000 epochs.

A batch size of 1 is required as we will be using walk-forward validation and making one-step forecasts for each of the final 12 months of test data.

A batch size of 1 means that the model will be fit using online training (as opposed to batch training or mini-batch training). As a result, it is expected that the model fit will have some variance.

Ideally, more training epochs would be used (such as 1500), but this was truncated to 1000 to keep r

The model will be fit using the efficient ADAM optimization algorithm and the mean squared error los

Experimental Runs

Each experimental scenario will be run 100 times and the RMSE score on the test set will be recorde

All test RMSE scores are written to file for later analysis.

Let's dive into the experiments.

Code and Collect Results

The complete code listing is provided below.

It may take a few hours to run on modern hardware.

```
from pandas import DataFrame
from pandas import Series
from pandas import concat
from pandas import read_csv
```

```
from pandas import datetime
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from math import sqrt
import matplotlib
import numpy
from numpy import concatenate

# date-time parsing function for loading the dataset
def parser(x):
    return datetime.strptime('190'+x, '%Y-%m')

# frame a sequence as a supervised learning problem
def timeseries_to_supervised(data, lag=1):
    df = DataFrame(data)
    columns = [df.shift(i) for i in range(1, lag+1)]
    columns.append(df)
    df = concat(columns, axis=1)
    return df

# create a differenced series
def difference(dataset, interval=1):
    diff = list()
    for i in range(interval, len(dataset)):
        value = dataset[i] - dataset[i - interval]
        diff.append(value)
    return Series(diff)

# invert differenced value
def inverse_difference(history, yhat, interval=1):
    return yhat + history[-interval]

# scale train and test data to [-1, 1]
def scale(train, test):
    # fit scaler
    scaler = MinMaxScaler(feature_range=(-1, 1))
    scaler = scaler.fit(train)
    # transform train
    train = train.reshape(train.shape[0], train.shape[1])
    train_scaled = scaler.transform(train)
    # transform test
    test = test.reshape(test.shape[0], test.shape[1])
    test_scaled = scaler.transform(test)
    return scaler, train_scaled, test_scaled
```

```python

# inverse scaling for a forecasted value
def invert_scale(scaler, X, yhat):
    new_row = [x for x in X] + [yhat]
    array = numpy.array(new_row)
    array = array.reshape(1, len(array))
    inverted = scaler.inverse_transform(array)
    return inverted[0, -1]

# fit an LSTM network to training data
def fit_lstm(train, batch_size, nb_epoch, neurons):
    X, y = train[:, 0:-1], train[:, -1]
    X = X.reshape(X.shape[0], 1, X.shape[1])
    model = Sequential()
    model.add(LSTM(neurons, batch_input_shape=(batch_size, X.shape[1], X.shape[2]), stateful=True))
    model.add(Dense(1))
    model.compile(loss='mean_squared_error', optimizer='adam')
    for i in range(nb_epoch):
        model.fit(X, y, epochs=1, batch_size=batch_size, verbose=0, shuffle=False)
        model.reset_states()
    return model

# make a one-step forecast
def forecast_lstm(model, batch_size, X):
    X = X.reshape(1, 1, len(X))
    yhat = model.predict(X, batch_size=batch_size)
    return yhat[0,0]

# run a repeated experiment
def experiment(repeats, series):
    # transform data to be stationary
    raw_values = series.values
    diff_values = difference(raw_values, 1)
    # transform data to be supervised learning
    supervised = timeseries_to_supervised(diff_values, 1)
    supervised_values = supervised.values[1:,:]
    # split data into train and test-sets
    train, test = supervised_values[0:-12, :], supervised_values[-12:, :]
    # transform the scale of the data
    scaler, train_scaled, test_scaled = scale(train, test)
    # run experiment
    error_scores = list()
    for r in range(repeats):
        # fit the base model
        lstm_model = fit_lstm(train_scaled, 1, 1000, 1)
        # forecast test dataset
        predictions = list()
```

```
        for i in range(len(test_scaled)):
            # predict
            X, y = test_scaled[i, 0:-1], test_scaled[i, -1]
            yhat = forecast_lstm(lstm_model, 1, X)
            # invert scaling
            yhat = invert_scale(scaler, X, yhat)
            # invert differencing
            yhat = inverse_difference(raw_values, yhat, len(test_scaled)+1-i)
            # store forecast
            predictions.append(yhat)
        # report performance
        rmse = sqrt(mean_squared_error(raw_values[-12:], predictions))
        print('%d) Test RMSE: %.3f' % (r+1, rmse))
        error_scores.append(rmse)
    return error_scores

# execute the experiment
def run():
    # load dataset
    series = read_csv('shampoo-sales.csv', header=0, parse_dates=[0], index_col=0, sque
    # experiment
    repeats = 100
    results = DataFrame()
    # run experiment
    results['results'] = experiment(repeats, series)
    # summarize results
    print(results.describe())
    # save results
    results.to_csv('experiment_stateful.csv', index=False)

 # entry point
run()
```


Running the experiment saves the RMSE scores of the fit model on the test dataset.

Results are saved to the file “*experiment_stateful.csv*“.

A truncated listing of the results is provided below.

Re-running the experiment yourself may give a different population of results because we did not seed the random number generator.

```
...
116.39769471284067
105.0459745537738
93.57827109861229
```

```
128.973001927212
97.02915084460737
198.56877142225886
113.09568645243242
97.84127724751188
124.60413895331735
111.62139008607713
```

Basic Statistics on Results

We can start off by calculating some basic statistics on the entire population of 100 test RMSE scores.

Generally, we expect machine learning results to have a Gaussian distribution. This allows us to report the mean and standard deviation of a model and indicate a confidence interval for the model when making predictions on unseen data.

The snippet below loads the result file and calculates some descriptive statistics.

```
from pandas import DataFrame
from pandas import read_csv
from numpy import mean
from numpy import std
from matplotlib import pyplot
# load results file
results = read_csv('experiment_stateful.csv', header=0)
# descriptive stats
print(results.describe())
# box and whisker plot
results.boxplot()
pyplot.show()
```


Running the example prints descriptive statistics from the results.

We can see that on average, the configuration achieved an RMSE of about 107 monthly shampoo sales with a standard deviation of about 17.

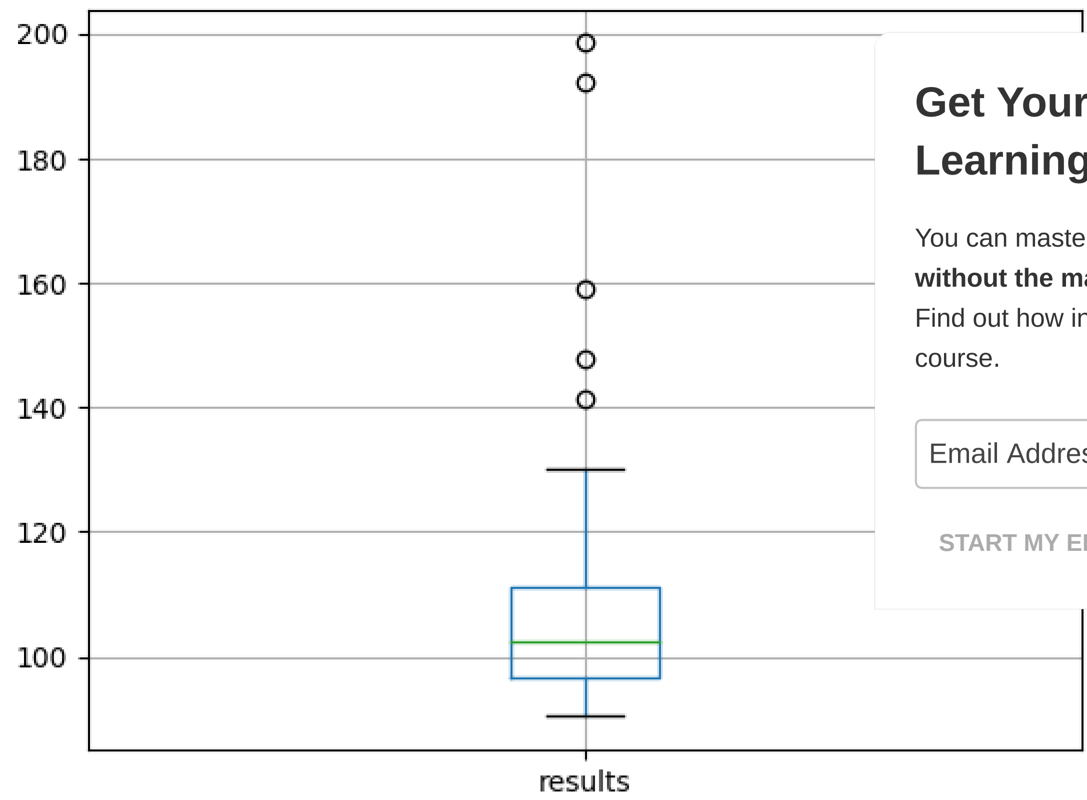
We can also see that the best test RMSE observed was about 90 sales, whereas the worse was just under 200, which is quite a spread of scores.

```
            results
count    100.000000
mean     107.051146
std       17.694512
min       90.407323
```

```
25%      96.630800
50%     102.603908
75%     111.199574
max     198.568771
```

To get a better idea of the spread of the data, a box and whisker plot is also created.

The plot shows the median (green line), middle 50% of the data (box), and outliers (dots). We can see quite a spread to the data towards poor RMSE scores.



Box and Whisker Plot of 100 Test RMSE Scores on the Shampoo Sales Dataset

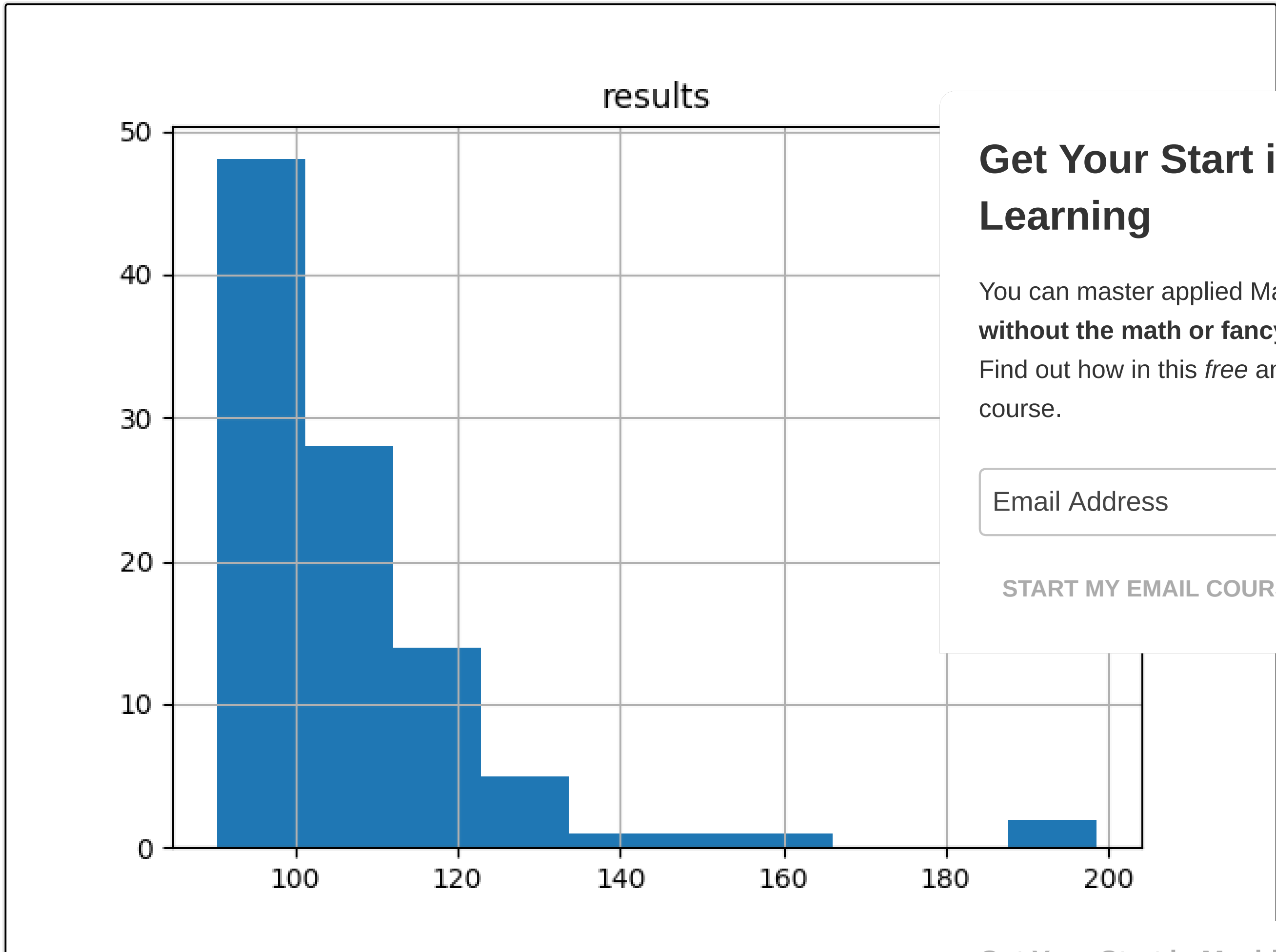
[redacted]

A histogram of the raw result values is also created.

The plot suggests a skewed or even an exponential distribution with a mass around an RMSE of 100 and a long tail leading out towards an RMSE of 200.

The distribution of the results are clearly not Gaussian. This is unfortunate, as the mean and standard deviation cannot be used directly to estimate a confidence interval for the model (e.g. 95% confidence as 2x the standard deviation around the mean).

The skewed distribution also highlights that the median (50th percentile) would be a better central tendency to use instead of the mean for these results. The median should be more robust to outlier results than the mean.



Histogram of Test RMSE Scores on Shampoo Sales Datase

Repeats vs Test RMSE

We can start to look at how the summary statistics for the experiment change as the number of repeats is increased from 1 to 100.

We can accumulate the test RMSE scores and calculate descriptive statistics. For example, the score from one repeat, the scores from the first and second repeats, the scores from the first 3 repeats, and so on to 100 repeats.

We can review how the central tendency changes as the number of repeats is increased as a line plot. We'll look at both the mean and median.

Generally, we would expect that as the number of repeats of the experiment is increased, the distribution would increasingly better match the underlying distribution, including the central tendency, such as the mean.

The complete code listing is provided below.


```
from pandas import DataFrame
from pandas import read_csv
from numpy import median
from numpy import mean
from matplotlib import pyplot
import numpy
# load results file
results = read_csv('experiment_stateful.csv', header=0)
values = results.values
# collect cumulative stats
medians, means = list(), list()
for i in range(1,len(values)+1):
    data = values[0:i, 0]
    mean_rmse, median_rmse = mean(data), median(data)
    means.append(mean_rmse)
    medians.append(median_rmse)
    print(i, mean_rmse, median_rmse)
# line plot of cumulative values
line1, = pyplot.plot(medians, label='Median RMSE')
line2, = pyplot.plot(means, label='Mean RMSE')
pyplot.legend(handles=[line1, line2])
pyplot.show()
```

The cumulative size of the distribution, mean, and median is printed as the number of repeats is increased. A truncated output is listed below.

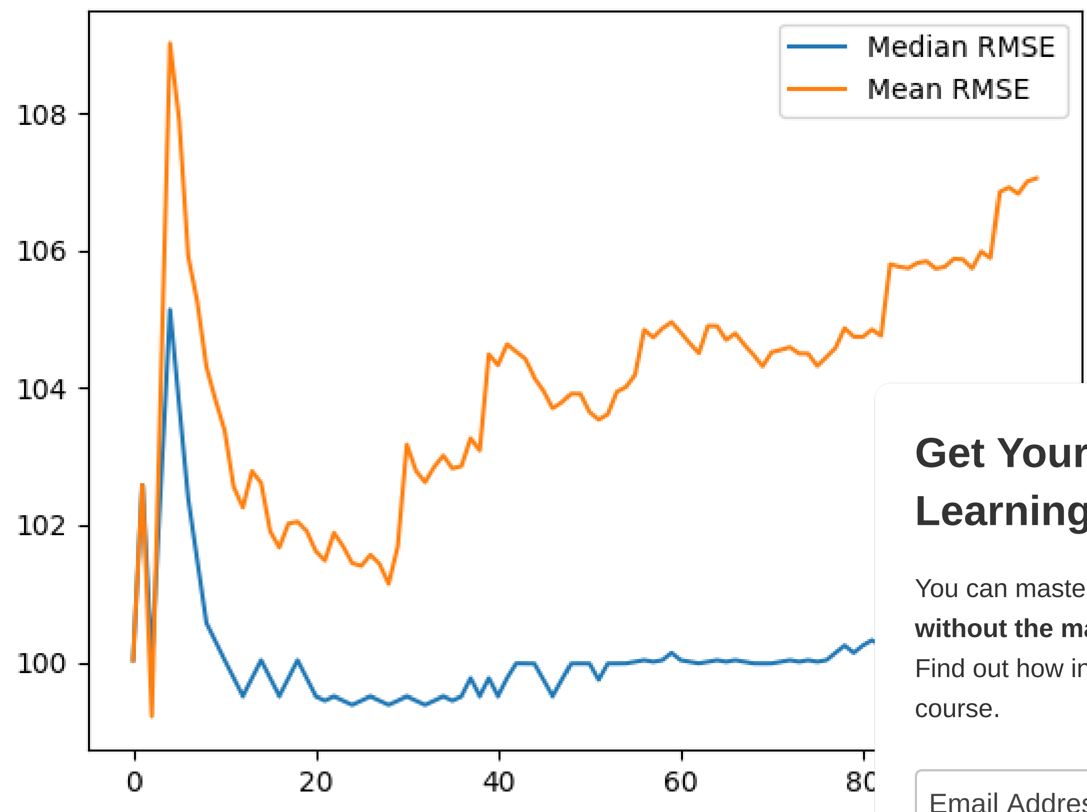
```
...
```

```
90 105.759546832 101.477640071
91 105.876449555 102.384620485
92 105.867422653 102.458057114
93 105.735281239 102.384620485
94 105.982491033 102.458057114
95 105.888245347 102.384620485
96 106.853667494 102.458057114
97 106.918018205 102.531493742
98 106.825398399 102.458057114
99 107.004981637 102.531493742
100 107.051145721 102.603907965
```

A line plot is also created showing how the mean and median change as the number of repeats is increased.

The results show that the mean is more influenced by outlier results than the median, as expected.

We can see that the median appears quite stable down around 99-100. This jumps to 102 towards th SE scores at later repeats.



Line Plots of Mean and Median Test RMSE vs Number of Rep

Review of Results

We made some useful observations from 100 repeats of a stateful LSTM on a standard time series forecasting problem.

Specifically:

- We observed that the distribution of results is not Gaussian. It may be a skewed Gaussian or an exponential distribution with a long tail and outliers.
- We observed that the distribution of results did not stabilize with the increase of repeats from 1 t

The observations suggest a few important properties:

- The choice of online learning for the LSTM and problem results in a relatively unstable model.
- The chosen number of repeats (100) may not be sufficient to characterize the behavior of the model.

This is a useful finding as it would be a mistake to make strong conclusions about the model from 100 or fewer repeats of the experiment.

This is an important caution to consider when describing your own machine learning results.

This suggests some extensions to this experiment, such as:

- Explore the impact of the number of repeats on a more stable model, such as one using batch or mini-batch learning.
- Increase the number of repeats to thousands or more in an attempt to account for the general in

Summary

In this tutorial, you discovered how to analyze experimental results from LSTM models fit using onlin

You learned:

- How to design a robust test harness for evaluating LSTM models on time series forecast proble
- How to analyze experimental results, including summary statistics.
- How to analyze the impact of increasing the number of experiment repeats and how to identify a

Do you have any questions?
Ask your questions in the comments below and I will do my best to answer.

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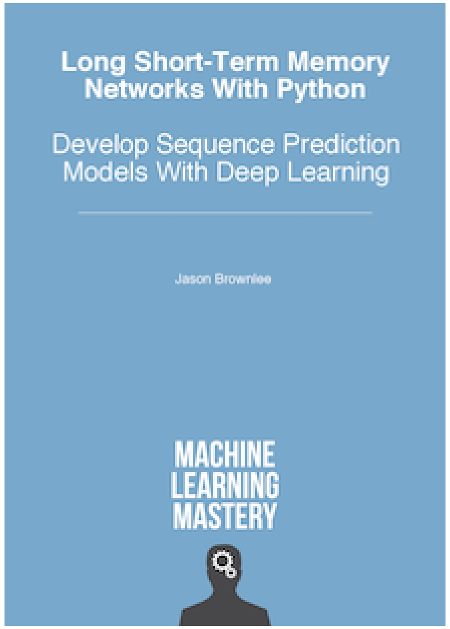

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About Jason Brownlee

Dr. Jason Brownlee is a husband, proud father, academic researcher, author, professional devel to helping developers get started and get good at applied machine learning. Learn more.
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2 Responses to *Instability of Online Learning for Stateful LSTM for Time Series Forecasting*

Cao May 31, 2017 at 8:48 pm # REPLY

Dear Jason,

always thank you for your posts, which are really helpful.

i am a beginner of machine learning, and i stuck in some questions for a longtime.

1.what is the online learning? batch size=1 is online and dynamic?

2.how to set a lstm structure, which can dynamic add new data every minutes, and update the weight ar
next minute data.

thank you again, jason.

Jason Brownlee June 2, 2017 at 12:47 pm #

Online learning means the model is updated after each training pattern.

The structure does not change. You need to find a structure that achieves good results on your prob

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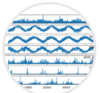

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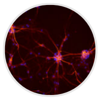

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