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In [20]: # univariate lstm example
from keras.models import Sequential, load_model
from keras.layers import Dense, LSTM, Conv1D, Lambda
from keras.callbacks import LearningRateScheduler
from keras.optimizers import SGD
from keras.losses import Huber
from keras import metrics
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

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In [2]: # split a univariate sequence into samples
def split_sequence(sequence, n_steps):
    X, y = list(), list()
    for i in range(len(sequence)):
        # find the end of this pattern
        end_ix = i + n_steps
        # check if we are beyond the sequence
        if end_ix > len(sequence)-1:
            break
        # gather input and output parts of the pattern
        seq_x, seq_y = sequence[i:end_ix], sequence[end_ix:]
        X.append(seq_x)
        y.append(seq_y)
    return np.array(X), np.array(y)

# define input sequence
raw = pd.read_csv("../Outliers.csv")

# choose a number of time steps
n_steps = 7

# split into samples
X, y = split_sequence(raw.Price, n_steps)
```

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In [3]: # reshape from [samples, timesteps] into [samples, timesteps, features]
n_features = 1
Xreshaped = X.reshape((X.shape[0], X.shape[1], n_features))
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In [37]: # define model
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(n_steps, n_features)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')

# fit model
model.fit(Xreshaped, y, epochs=200, verbose=0)
model.save("rollingLSTM")
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In [38]: model.summary()
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Model: "sequential_5"

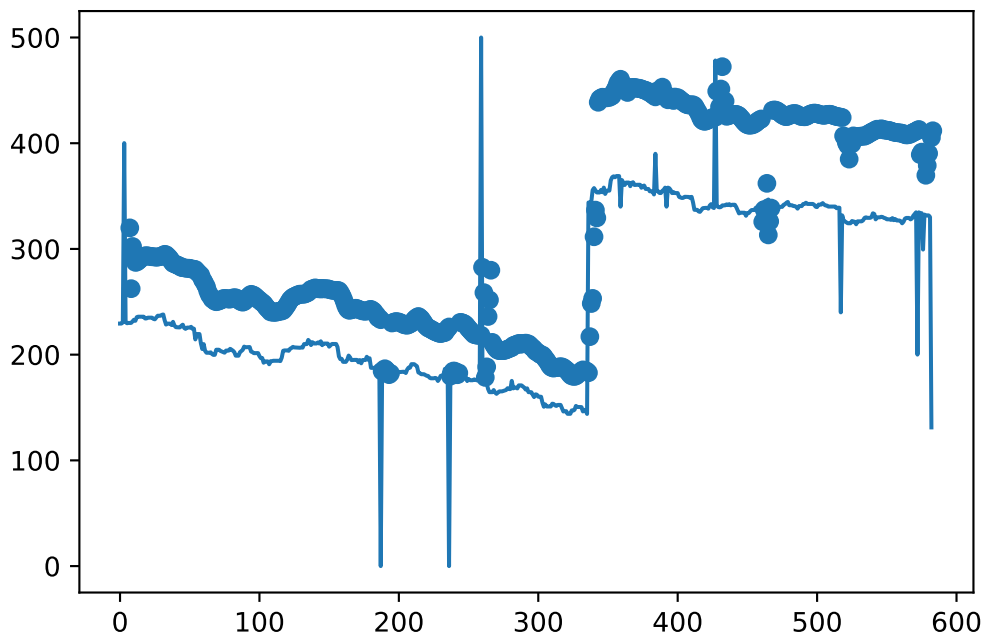
Layer (type)	Output Shape	Param #
=====		
lstm_5 (LSTM)	(None, 50)	10400
dense_5 (Dense)	(None, 1)	51
=====		
Total params: 10,451		
Trainable params: 10,451		
Non-trainable params: 0		

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In [39]: # Predict over the rolling window
y hats = []
for window in range(len(X)):
    y hat = model.predict(X[window].reshape((1, n_steps, n_features)))[0][0]
    y hats.append(y hat)

# pad the missing predictions and add to dataframe
y hats[:0] = [np.nan for _ in range(n_steps)] # [np.nan*n_steps]
raw["Predictions"] = y hats
```

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In [6]: plt.scatter(range(len(y hats)), y hats)
plt.plot(range(len(raw.Price)-1), raw.Price.drop(raw.Price[raw.Price > 1000].index))
#plt.xlim(-1,10)
```

Out[6]: [<matplotlib.lines.Line2D at 0x28d53a309c8>]

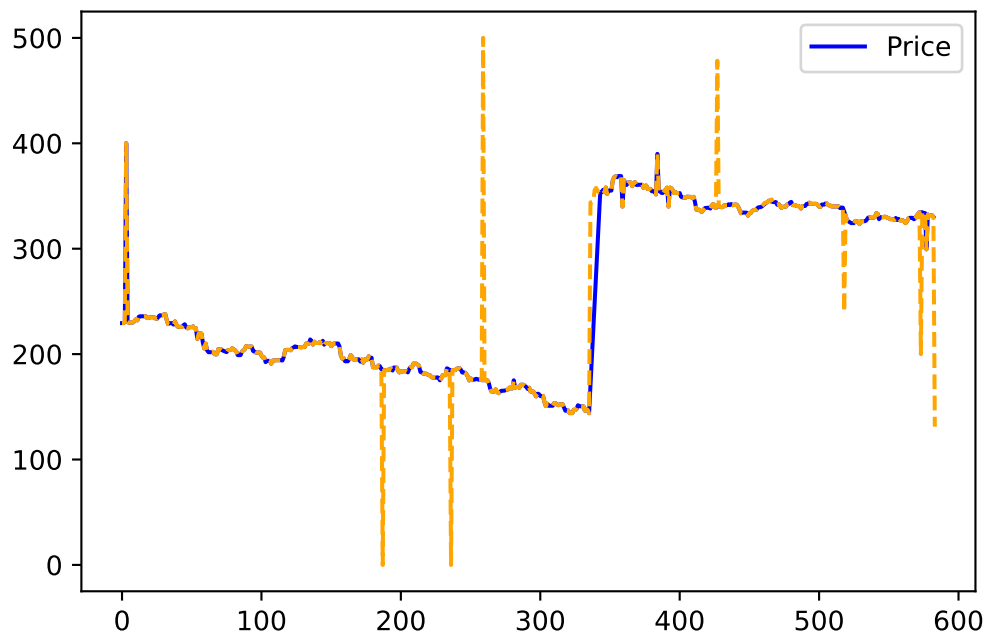


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In [7]: # calculate residuals and add to original dataframe
raw["Residuals"] = raw.Price - raw.Predictions
# analyse residuals to find outliers
resiStats = raw.Residuals.describe()
IQR = resiStats[6] - resiStats[4]
lowerBound, upperBound = resiStats[4] - 1.5* IQR, resiStats[6] + 1.5* IQR
# flag anomalies in original dataframe
raw["Anomaly"] = (raw.Residuals > upperBound) | (raw.Residuals < lowerBound)
```

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In [8]: # visualise data
fig, ax = plt.subplots()
raw[["Price"]][raw.Anomaly == False].plot(ax=ax, color="b")
raw.Price.drop(raw[raw.Residuals == raw.Residuals.max()].index).plot(ax=ax, style="-")

# visually looks good, how can we prove statistically that we have found all/most an
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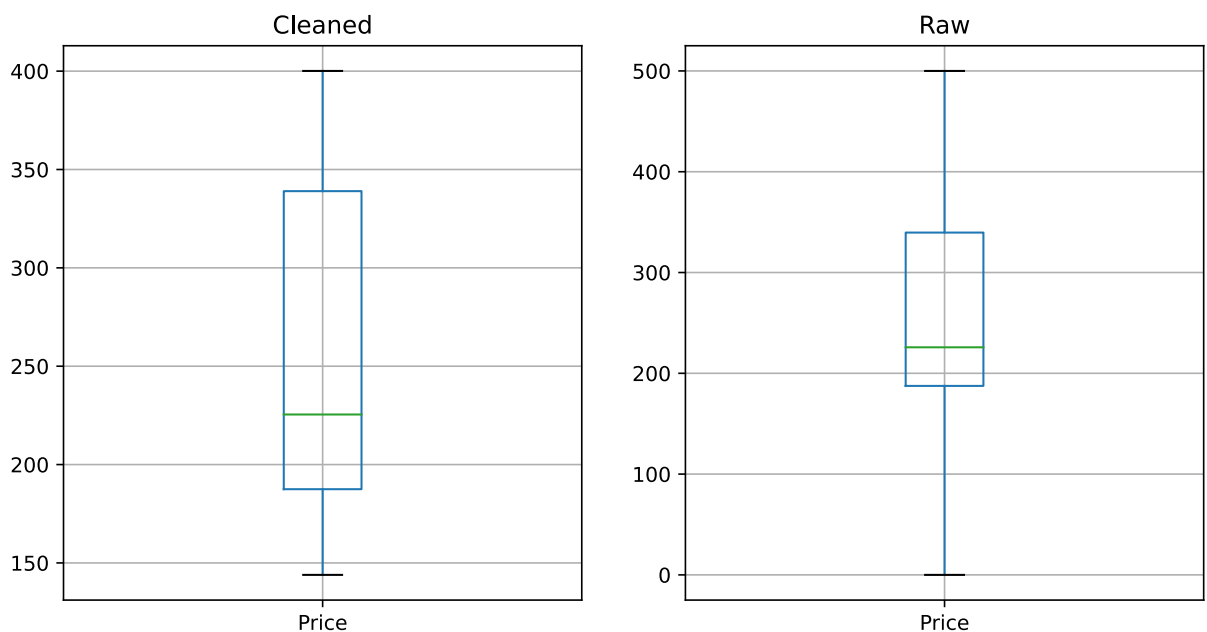
Out[8]: <AxesSubplot:>



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In [9]: fig, ax = plt.subplots(1,2, figsize=[10,5])
raw[["Price"]][raw.Anomaly == False].boxplot(ax=ax[0])
ax[0].set_title("Cleaned")
raw[["Price"]].drop(raw.Residuals == raw.Residuals.max()).index).boxplot(ax=ax[1]
ax[1].set_title("Raw")

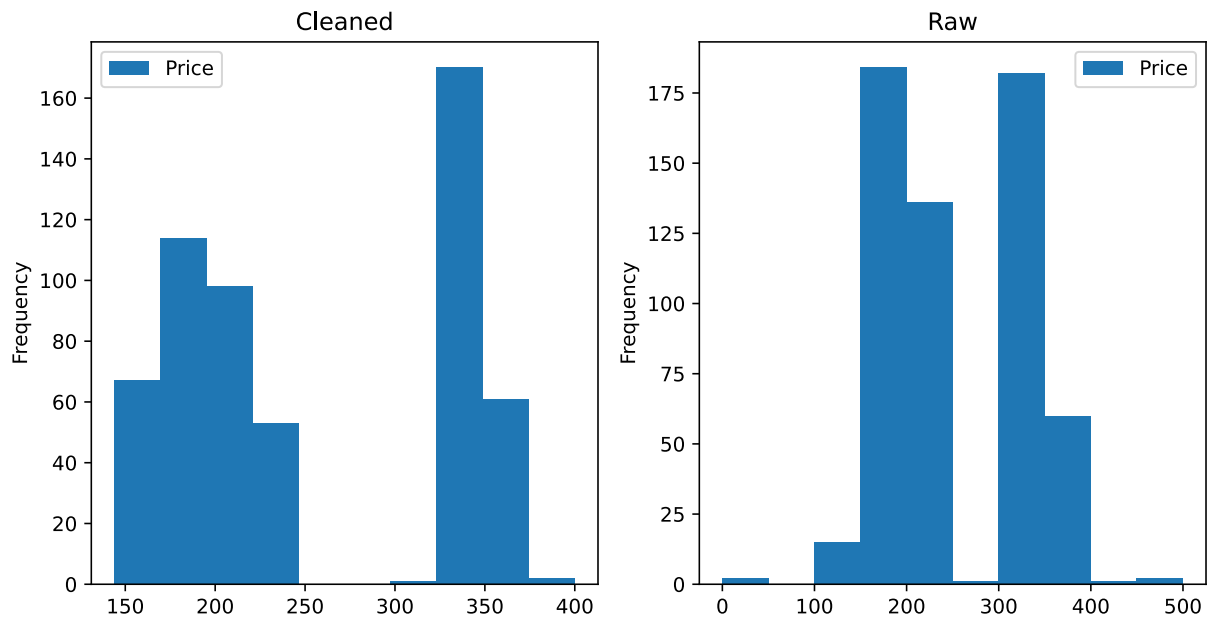
# have we found all anomalies? what is the success criteria?
```

Out[9]: Text(0.5, 1.0, 'Raw')



```
In [10]: fig, ax = plt.subplots(1,2, figsize=[10,5])
raw[["Price"]][raw.Anomaly == False].plot.hist(ax=ax[0])
ax[0].set_title("Cleaned")
raw[["Price"]].drop(raw.Residuals == raw.Residuals.max()).index).plot.hist(ax=ax
ax[1].set_title("Raw")
```

Out[10]: Text(0.5, 1.0, 'Raw')



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In [11]: fig, ax = plt.subplots(1,2, figsize=[10,5])
raw[["Price"]][raw.Anomaly == False].diff(1).plot(ax=ax[0])
ax[0].set_title("Cleaned")
raw[["Price"]].drop(raw[raw.Residuals == raw.Residuals.max()].index).diff(1).plot(ax=ax[1])
ax[1].set_title("Raw")

# we can see some false negatives in there
```

Out[11]: Text(0.5, 1.0, 'Raw')

