Financial Time Series Data Processing for Machine Learning

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ABSTRACT

This article studies the financial time series data processing for machine learning. It introduces the most frequent scaling methods, then compares the resulting stationarity and preservation of useful information for trend forecasting. It proposes an empirical test based on the capability to learn simple data relationship with simple models. It also speaks about the data split method specific to time series, avoiding unwanted overfitting and proposes various labelling for classification and regression.

Keywords: Machine Learning, Financial Time Series, Data Processing

1 INTRODUCTION

In the field of machine learning Time Series are very special data needed their specific processing and methods[1][2].

On top of that, Financial data adds a big challenge due to their proportion of randomness and their non-stationary nature[4][3].

There is a lot of research relative to the Financial Market forecast with Machine Learning[5].

However, many studies only cover one type of data scaling or labelling while the decisions made on this step can have a huge impact on the results. Not only in term of pure model performances metrics but in term of capabilities to really implement a profitable trading strategy based on the model.

This study covers the following points:

- Pre-processing and Stationarity
- Pre-processing and preservation of useful prices relationships
- Labelling for classifiers and regressors

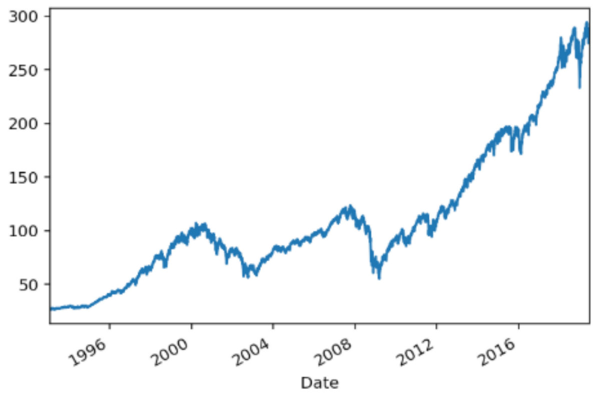
2 STATIONARITY

Before to work on any price forecast model we need to pre-process our historical prices then we have to make sure the resulting data are stationary.

We evaluate three of the most frequent pre-processing, starting by the price returns, then two scaling methods: *MinMax* and *Standardization*.

For this purpose, we use the SPY daily closing prices between 1993 and 2019.

Figure 1: SPY daily closing prices



Let's first apply an Augmented Dickey-Fuller test[6][7] to the raw data as reference.

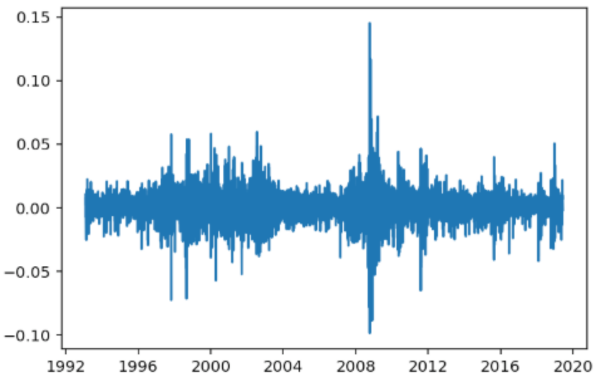
For such a sample size, the ADF of a dataset with trend must be below -3.96 to reject the null hypothesis with a 1% confidence [8].

- ADF Statistic: -0.226901
- p-value: 0.991042

As expected with an ADF of -0.22 p-value of 0.99 the process is not stationary.

The most common way to make a time series stationary is differencing. In the case of financial data we can simply compute the returns.

Figure 2: SPY daily returns



So, when applied on returns the ADF test gives:

- ADF Statistic: -14.954070
- p-value: 0.000000

This confirms the time series of returns is stationary.

3 SCALING

The returns data could be a good baseline, especially because the resulting very small values, near from 0 makes them directly compatible with a deep learning approach.

While this is very suitable for a single feature time series, if we use multiple features like the High/Low prices, the Volume or any technical indicator we can face an issue by simply using such a return-based method as it does not preserve the information of the position of a feature relative to each other.

In this situations some other scaling methods must be used like *MinMax* or *Standardization*. They are widely used in Machine Learning and enable to keep the relative position of each feature.

Before to evaluate these scaling methods, let's first introduce another aspect of data processing for time series in Machine Learning context, the slicing.

When doing Machine Learning on Financial Time Series, the model generally takes a time window as input, for instance 20 consecutive closing prices. The number of prices used for this time window is defined as the *lookback period*.

A frequent label found in many papers is the next price change, but we will see later this can be more sophisticated.

So let's assume a time series of T consecutive stock returns $\{r_0, \ldots, r_{T-1}\}$

Building a training set S consists on creating as series of K slices $S = \{S_0, \ldots, S_{K-1}\}$, each of size $n > 1$, where $S_t = \{r_{t-n}, \ldots, r_{t-1}\}$.

For a model predicting the next return the label is defined by $y_{t-n} = r_t$.

Each S_t slice is created by incrementing t by steps of 1 or more. As an example, for an increment of 1, and a slice size of 20 returns, the first two sets are:

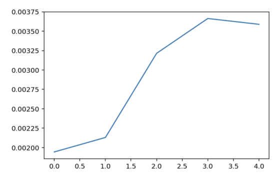
$$(S_0 = \{r_0, \ldots, r_{19}\}, y_0 = r_{20})$$
$$(S_1 = \{r_1, \ldots, r_{20}\}, y_1 = r_{21})$$

After the slicing was done, we have K slices than can be scaled independently from each other.

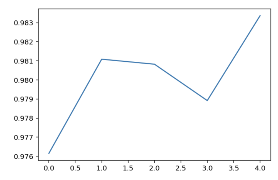
We expect our Machine Learning model to identify price patterns leading to up or down move. Scaling each slice independently can make the training easier by removing the global range effect due to the long-term market trend.

For instance, here are the first and last slices when we scale first with a *minmax* then slice (Figures 3a, 3b) and when we slice first then scale (Figures 3c, 3d).

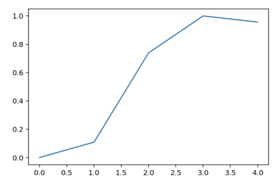
Figure 3: Compare scale then slice, with slice then scale



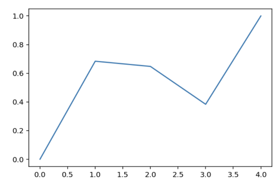
(a) First slice



(b) Last slice



(c) First slice



(d) Last slice

It clearly appears Figure 5 that slicing first then scaling enables getting each training example being within the same range, so making easier the model training.

Now let's find the best scaling method in a more formal way.

For this purpose, we scale the training set then do the following:

- Check stationarity with ADF
- Check if the information is preserved for machine learning context by training a simple model identifying simple prices relationship into slices

We assume that if the model cannot learn a very simple price relationship inside each slice, like for instance identifying if the last close of the slice is above the close 5 bars ago, then there is nearly no chance for the model to be able to learn any price pattern leading to the future price changes.

If a simple price relationship is preserved, we expect the model to learn it nearly perfectly.

So, the scaling method we select is the one enabling a model to learn simple prices relationship inside a slice with the best efficiency.

We test two common scaling methods, the *MinMax* and the *Standardization*.

MinMax

Scale each slice into a $[0, 1]$ or $[-1, 1]$ range

Assume x_{min} and x_{max} the smallest and highest x values. And assume min and max the feature range, so $[0, 1]$ for instance.

$$z = \frac{x - x_{min}}{x_{max} - x_{min}}(max - min) + min$$

Standardization

Scale each slice by removing the mean and scaling to unit variance.

$$z = \frac{x - \mu}{\sigma}$$

- μ : mean
- σ : standard deviation

After scaling and reshaping the SPY prices we apply an ADF test.

Scaling	ADF	p-value
MinMax	-41.72	0.000
Standardization	-56.90	0.000

Table 1: ADF Test per scaling

Each Scaling method results in a non-stationary dataset.

If prices relationship is preserved, we assume a simple model can be trained to identify conditions like:

- $C_t > C_{t-5}$[1]
- $C_t > EMA5_t$[2]
- $C_t > HC10_t$[3]

The third one is the most complex as the highest close over the past 10 bars is not always at the same position.

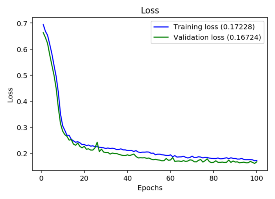
We create a binary label for each of these conditions then train the following LSTM model.

Lookback (Slices)	20 bars
Features	Close
1 LSTM	64 units (tanh)
1 Dense output	2 units (softmax)
Bias	No
Dropout	No
Recurrent Dropout	No
Optimizer	Adam
Epochs	100
Batch Size	64
Training/Validation	80/20

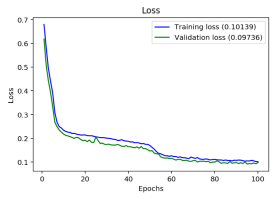
Table 2: Model Detail and Hyperparameters

Using 2 units output with softmax instead of a single unit binary output with sigmoid enables making the models more generic when increasing the number of classes.

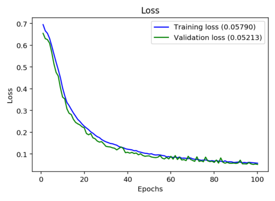
Figure 4: Loss of each model per scaling



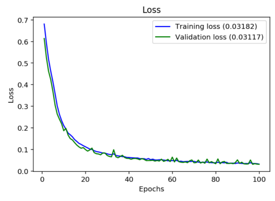
(a) $C_t > C_{t-5}$ minmax



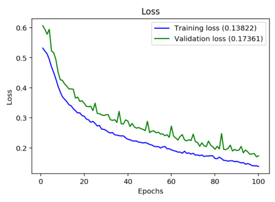
(b) $C_t > C_{t-5}$ std



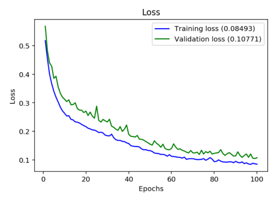
(c) $C_t > EMA5_t$ minmax



(d) $C_t > EMA5_t$ std



(e) $C_t > HC10_t$ minmax



(f) $C_t > HC10_t$ std

[1]C_t: closing price at time t, C_{t-5} closing price 5 periods (days) ago
[2]EMA5 : 5 periods Exponential Moving Average
[3]HC10: Highest close of the 10 last bars

The precisions on validation set are the following:

Scaling	MinMax	Standardization
$C_t > C_{t-5}$	0.920	0.978
$C_t > EMA5_t$	0.993	0.998
$C_t > HC10_t$	0.910	0.904

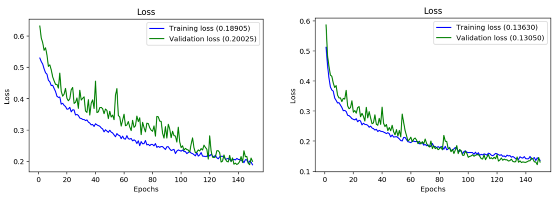
Table 3: Precision of each model per scaling

The two first cases are learned with a nearly perfect generalization.

The last case shows that validation loss is slightly not as good as the training but seems to be able to continue to improve if we increase the number of epochs.

By training the same LSTM on 150 epochs with 0.2 dropout and 0.2 recurrent dropout to improve the generalization, we get the following loss.

Figure 5: HC10 model on 150 Epochs with dropouts



(a) $C_t > HC10_t$ minmax (b) $C_t > HC10_t$ std

The precisions on validation set are the following:

Scaling	MinMax	Standardization
$C_t > HC10_t$	0.970	0.968

Table 4: HC10 Precision per scaling

These scaling methods preserve the prices relationship. It's also the case if we add new features like High, Low, or any overlaid indicator[4]. So, for instance the relative position of a closing price and a moving average is preserved.

The two scaling methods gives similar results but *Standardization* looks a little bit better , especially when looking at the validation loss shape in the last case.

4 DATA SPLIT

In machine learning, splitting data into a training, validation and test set is often performed by using the following process:

1. Shuffle the full data set
2. Split into training/validation/test sets

[4]An indicator plotted to the same chart than the prices (e.g. moving averages, Bollinger Bands)

On time series this process leads to a risk of partially fitting to validation and test set during training so getting very good metrics while getting poor results when applying the resulting trading strategy to real-time data.

Remind the training set $S = \{S_0, \ldots, S_{K-1}\}$ has K overlapped slices $S_t = \{r_{t-n}, \ldots, r_{t-1}\}$.

Assume we have these two first slices:

$$(S_0 = \{r_0, \ldots, r_{19}\}, y_0 = r_{20})$$
$$(S_1 = \{r_1, \ldots, r_{20}\}, y_1 = r_{21})$$

If we shuffle before to split, we can have S_0 in the training set while S_1 can be part of the validation set.

In this case S_0 and S_1 have $\{r_1, \ldots, r_{19}\}$, so 95% of their data, in common.

If the shuffle is uniform, the biggest proportion of data in the validation set slices will also be part of the training set. In the example above for instance, up to 95% of the validation set data can be part of the training set slices.

So, depending on the model type, while fitting the training set, we also have a chance to partially fit the validation set. This can result in unreliable validation loss showing good results without overfitting while its real metrics on very new data taken independently can be poor with a strong overfitting.

The proper way to split and shuffle the training set for Financial Time Series is the following:

1. Split into training/validation/test sets

   The split is performed over S such as:

$$train = \{S_0, \ldots, S_{ts-1}\} \quad (1)$$
$$val = \{S_{ts}, \ldots, S_{ts+vs-1}\} \quad (2)$$
$$test = \{S_{ts+vs}, \ldots, S_{K-1}\} \quad (3)$$

   Where:

   - ts : training set size
   - vs : validation set size
   - K : total number of slices

2. Shuffle the training set

   So only $train = \{S_0, \ldots, S_{ts-1}\}$ is shuffled.

5 FEATURES

In Financial time series the raw features are the Open, High, Low, Close and the Volume[5].

To take a decision, traders often use technical indicators calculated from these features. These indicators can be used as additional features to help the model.

When used as input in a Neural Network model, these indicators must be scaled but the method to use differs depending on their nature. The overlaid indicators must be scaled but the separated indicators are generally moving in a narrow range of values, no matter if the price of the instrument is around 10 or 1000, so they need to be scaled separately with specific methods.

The overlaid indicators must be scaled all together with the prices to preserve their relationship. For instance this enable the model to use the relation between the closing price and one or several indicators like moving averages.

The Volume and the separated indicators must have their own independent scaling.

The not bounded indicators must be scaled with *MinMax* or *Standardization*.

The bounded indicators can benefit from being divided by their maximum value (100 for the RSI). This preserve fixed values that can make sense for traders, like the overbought/oversold levels. For instance, 70/30 for the RSI becomes 0.7/0.3 in the scaled version.

Note that when using another type of model like Random Forest or XGBoost, the scaling is not always required. Everything depends on the nature of the data. For instance the RSI is bounded between 0 and 100, so it can directly be used in a Random Forest without any scaling.

When using a single feature, like the closing prices, the input shape is simply defined by (m, s)

When using multiple features, like the high, low, close and volume, the input shape becomes (m, s, i)

- m : samples
- s : timesteps
- i : features

If we build a training data set with 1000 slices of 20 bars, each with open, high, low, close and volume, the training set shape is : $(1000, 20, 5)$

When a model does not accept three dimensional inputs, a reshape could be necessary. Making the previous example flattened with a shape of $(1000, 100)$

[5]As an OTC Market, the Forex does not includes the Volume. When present, it's only a synthetic indicator built from the number of ticks during the period. Many people use it as a proxy for the market activity.

6 LABELING

Labelling can have a major influence on a model training to Financial Time Series. Some labels can also results in non-tradable strategies. For instance, predicting a technical indicator created from lagged prices can be not usable for real trading, even when getting very accurate predictions.

Models can be of two type, classifier or regressor. A classifier generally attempts to predict the probability for the market to go Up or Down for a given time horizon while a regressor tries to predict the future price.

By far, the most frequent label found in the literature is the next return. However, many other labels can be used.

Table 5 shows some examples of the labels we often use in our research at Lusis.

Label	Description
N bars Up/Down	Classifier on $C_{t+n} > C_t$
N bars price change	Regressor on $C_{t+n} - C_t$
N bars log returns	Regressor on $log(\frac{C_{t+n}}{C_t})$
N bars Moving Average	Classifier on $MA_{t+n} > MA_t$
N bars trend Strength	Regressor on Trend
N bars trend Direction	Classifier on Trend
%Q after N bars	Regressor on %Q
QClass after N bars	Classifier on QClass

Table 5: Labels often used in our research

%Q[6] is a specific metric we especially created for focusing on the most tradable models.

If C_t is the closing price at time t, assume the corresponding time series slice of size m ending by C_t is defined by $S_t = C_{t-m+1}, \ldots, C_t$

Then

$$\%Q_{t+1}^{t+n} = \frac{HH_{t+1}^{t+n} - C_t}{HH_{t+1}^{t+n} - LL_{t+1}^{t+n}}$$

Where

- n : time horizon in number of bars
- $\%Q_{t+1}^{t+n}$: %Q between $t+1$ and $t+n$
- HH_{t+1}^{t+n} : Highest High price between $t+1$ and $t+n$
- LL_{t+1}^{t+n} : Lowest Low price between $t+1$ and $t+n$

So %Q is interpreted as following:

- $\%Q = 1$ when we have a perfect up move without any drawdown during the next n bars

[6]*Q* stands for *Quality*

- $\%Q = 0$ when we have a perfect down move without any drawup during the next n bars
- $\%Q = 0.5$ when we have an equally Up and Down move during the next n bars

So the nearest from 1 or 0 %Q is, the more tradable the prediction is. It corresponds to conditions where the MAE[7] is lower than the MFE[8] between t and $t + n$.

%Q corresponds to a risk/reward ratio. For instance, $\%Q = .75$ is a 1:3 risk/reward.

The QClass label derivates from %Q by using thresholds as class separators.

Class	Condition	Meaning
0	$\%Q >= 0.6$	Up
1	$0.4 < \%Q < 0.6$	Neutral
2	$\%Q <= 0.4$	Down

Table 6: QClass example

The *Trend Strength* and *Trend Direction* labeling can be built by different ways. It can, for instance, be based on the shape of a linear regression, or on the percentage of closing prices above a simple moving average[9].

7 LONG TERM TREND BIAS

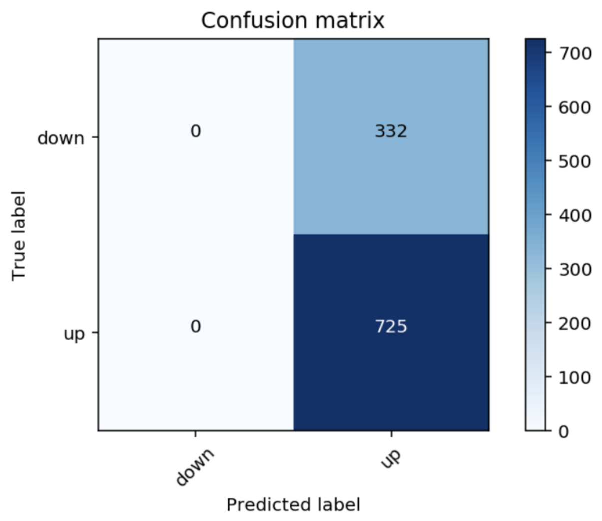
Presence of a Long Term Up Trend on stock market can make the model training to fit the Upside moves only.

Figure 6 illustrates this effect for the following model applied to SPY daily data.

Lookback (Slices)	20 bars
Features	Close
Label	20 bars up/down
1 LSTM	20 units (tanh)
1 Dense output	2 units (softmax)
Bias	No
Dropout	No
Recurrent Dropout	No
Optimizer	Adam
Epochs	100
Batch Size	64

Table 7: Model Detail and Hyperparameters

Figure 6: Confusion Matrix on Validation Set

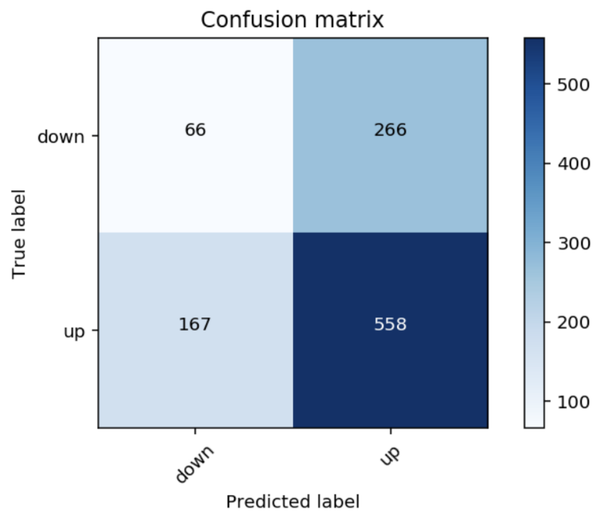


The model only predicts the *Up* label, resulting in a validation precision of 0.6859 that correspond to the class imbalance as seen in the confusion matrix.

The simplest way to fight this consists on downsampling the *Up* labels on the training set in order to get a perfectly even class balance.

Retraining the same model results in a different confusion Matrix not only predicting the Upside anymore.

Figure 7: Confusion Matrix on Validation Set



Note that intraday data are less subject to such bias.

[7]Maximum Adverse Excursion

[8]Maximum Favorable Excursion

[9]When prices are rising up, a majority of them are above their moving average

8 CONCLUSION

This article covered the specificity of Financial Time Series data and the processing practice that can be applied to start a research project in good conditions.

It explains how to properly scale, slice and test the stationarity of the dataset.

It also speaks about features and proposed different labeling methods.

Time Series are not like any other data. The classical pre-processing methods generally used cannot directly be applied.

On top of that, their Financial nature means they follow a stochastic process, which is even adding another level of complexity.

The methods shown in this document can be applied to any financial instrument (Equities, Commodities, Forex, ...) and to any timescales (daily, hourly, 5 minutes, ...).

Selecting features, scaling and labelling is part the whole Machine Learning Research process. Comparing different combinations of features and labels can sometimes have more impacts on the results than hyperparameters tuning.

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