Time Series Forecasting

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1 Introduction

1.1 Time Series Forecasting

Making predictions about the future is called extrapolation in the classical statistical handling of time series data.

More modern fields focus on the topic and refer to it as time series forecasting.

Forecasting involves taking models fit on historical data and using them to predict future observations.

Descriptive models can borrow for the future (i.e. to smooth or remove noise), they only seek to best describe the data.

An important distinction in forecasting is that the future is completely unavailable and must only be estimated from what has already happened.

The skill of a time series forecasting model is determined by its performance at predicting the future. This is often at the expense of being able to explain why a specific prediction was made, confidence intervals and even better understanding the underlying causes behind the problem.

1.2 Time Series Analysis

When using classical statistics, the primary concern is the analysis of time series.

Time series analysis involves developing models that best capture or describe an observed time series in order to understand the underlying causes. This field of study seeks the "why" behind a time series dataset.

This often involves making assumptions about the form of the data and decomposing the time series into constitution components.

2 Usual issues

2.1 Data availability

More data is often more helpful, offering greater opportunity for exploratory data analysis, model testing and tuning, and model fidelity.

2.2 Time span

Shorter time horizons are often easier to predict with higher confidence.

2.3 Data refreshing

Updating forecasts as new information becomes available often results in more accurate predictions.

2.4 Sampling rates

Often forecasts can be made at a lower or higher frequencies, allowing you to harness down-sampling, and up-sampling of data, which in turn can offer benefits while modeling.

3 Algorithms

A lot of research has been invested into using MLPs for time series forecasting with modest results. Perhaps the most promising area in the application of deep learning methods to time series forecasting are in the use of CNNs, LSTMs and hybrid models.

3.1 MLPs

Multilayer Perceptrons, or MLPs for short, can be used to model univariate time series forecasting problems. Univariate time series are a dataset comprised of a single series of observations with a temporal ordering and a model is required to learn from the series of past observations to predict the next value in the sequence. MLP models usually consist of multiple hidden layers of nodes, and an output layer used to make predictions.

3.1.1 Univariate

Univariate time series are a dataset comprised of a single series of observations with a temporal ordering and a model is required to learn from the series of past observations to predict the next value in the sequence.

3.1.2 Multivariate

Multivariate time series data means data where there is more than one observation for each time step. There are two main models that we may require with multivariate time series data.Those are Multiple Input Series and Multiple Parallel Series.

3.2 Cnns

3.2.1 Univariate CNN

Although traditionally developed for two-dimensional image data, CNNs can be used to model univariate time series forecasting problems. Univariate time series are datasets comprised of a single series of observations with a temporal ordering and a model is required to learn from the series of past observations to predict the next value in the sequence.

3.2.2 Multivariate CNN

Multivariate time series data means data where there is more than one observation for each time step. There are two main models that we may require with multivariate time series data. Those are Multiple Input Series and Multiple Parallel Series.

3.2.3 Multi-headed CNN

There is another, more elaborate way to model the problem. Each input series can be handled by a separate CNN and the output of each of these submodels can be combined before a prediction is made for the output sequence.

3.2.4 Multi-step CNN

In practice, there is little diFFerence to the 1D CNN model in predicting a vector output that represents diFFerent output variables (as in the previous example), or a vector output that represents multiple time steps of one variable.

3.2.5 Multivariate Multi-step CNN

In the previous sections, we have looked at univariate, multivariate, and multi-step time series forecasting. It is possible to mix and match the different types of 1D CNN models presented so far for the different problems. This too applies to time series forecasting problems that involve multivariate and multi-step forecasting, but it may be a little more challenging.

3.3 Lstms

3.3.1 Univariate LSTM

LSTMs can be used to model univariate time series forecasting problems. These are problems comprised of a single series of observations and a model is required to learn from the series of past observations to predict the next value in the sequence.

3.3.2 Multivariate LSTM

Multivariate time series data means data where there is more than one observation for each time step. There are two main models that we may require with multivariate time series data Thos are Multiple Input Series and Multiple Parallel Series.

3.3.3 Multi-step LSTM

A time series forecasting problem that requires a prediction of multiple time steps into the future can be referred to as multi-step time series forecasting. Specifically, these are problems where the forecast horizon or interval is more than one time step.

3.3.4 Multivariate Multi-step LSTM

In the previous sections, we have looked at univariate, multivariate, and multi-step time series forecasting. It is possible to mix and match the different types of LSTM models presented so far for the different problems. This too applies to time series forecasting problems that involve multivariate and multi-step forecasting, but it may be a little more challenging.

4 Summary

These types of networks are used as layers in a broader model that also has one or more MLP layers. Technically, these are a hybrid type of neural network architecture.

Perhaps the most interesting work comes from the mixing of the different types of networks together into hybrid models.

For example a stack of layers with a CNN on the input, LSTM in the middle, and MLP at the output. This is called a CNN LSTM architecture.

The network types can also be stacked in specific architectures to unlock new capabilities that use CNN and MLP networks that can be added to a new LSTM model. Also, the encoder-decoder LSTM networks that can be used to have input and output sequences of differing lengths.

Time series forecasting is a very important problem in machine learning so depending on the dataset our model can very well vary.Exploring different networks is usually the key for finding the best predictions.