PREDICTIONS IN TIME SERIES USING REGRESSION MODELS pdf

1: Time series - Wikipedia

Predictions in Time Series Using Regression Models is an excellent reference book for researchers . This book is a valuable addition to the extensive literature on the analysis of time series. I strongly recommend it .

February 6, Introduction Time Series referred as TS from now is considered to be one of the less known skills in the analytics space Even I had little clue about it a couple of days back. But as you know our inaugural Mini Hackathon is based on it, I set myself on a journey to learn the basic steps for solving a Time Series problem and here I am sharing the same with you. These will definitely help you get a decent model in our hackathon today. Before going through this article, I highly recommend reading A Complete Tutorial on Time Series Modeling in R , which is like a prequel to this article. It focuses on fundamental concepts and is based on R and I will focus on using these concepts in solving a problem end-to-end along with codes in Python. Our journey would go through the following steps: What makes Time Series Special? How to make a Time Series Stationary? Forecasting a Time Series 1. As the name suggests, TS is a collection of data points collected at constant time intervals. These are analyzed to determine the long term trend so as to forecast the future or perform some other form of analysis. But what makes a TS different from say a regular regression problem? There are 2 things: It is time dependent. Along with an increasing or decreasing trend, most TS have some form of seasonality trends, i. For example, if you see the sales of a woolen jacket over time, you will invariably find higher sales in winter seasons. Because of the inherent properties of a TS, there are various steps involved in analyzing it. These are discussed in detail below. Lets start by loading a TS object in Python. Please note that the aim of this article is to familiarize you with the various techniques used for TS in general. The example considered here is just for illustration and I will focus on coverage a breadth of topics and not making a very accurate forecast. Lets start by firing up the required libraries: This specifies the column which contains the date-time information. A key idea behind using Pandas for TS data is that the index has to be the variable depicting date-time information. This specifies a function which converts an input string into datetime variable. If the data is not in this format, the format has to be manually defined. Something similar to the dataparse function defined here can be used for this purpose. Now we can see that the data has time object as index and Passengers as the column. We can cross-check the datatype of the index with the following command: As a personal preference, I would convert the column into a Series object to prevent referring to columns names every time I use the TS. Please feel free to use as a dataframe is that works better for you. Lets start by selecting a particular value in the Series object. This can be done in following 2 ways: Specific the index as a string constant: Suppose we want all the data upto May This can be done in 2 ways: Specify the entire range: There are 2 things to note here: Unlike numeric indexing, the end index is included here. For instance, if we index a list as a[: The indices have to be sorted for ranges to work. Consider another instance where you need all the values of the year This can be done as: Similarly if you all days of a particular month, the day part can be omitted. Now, lets move onto the analyzing the TS. How to Check Stationarity of a Time Series? A TS is said to be stationary if its statistical properties such as mean, variance remain constant over time. But why is it important? Most of the TS models work on the assumption that the TS is stationary. Intuitively, we can sat that if a TS has a particular behaviour over time, there is a very high probability that it will follow the same in the future. Also, the theories related to stationary series are more mature and easier to implement as compared to non-stationary series. Stationarity is defined using very strict criterion. However, for practical purposes we can assume the series to be stationary if it has constant statistical properties over time, ie. Lets move onto the ways of testing stationarity. First and foremost is to simple plot the data and analyze visually. The data can be plotted using following command: So, more formally, we can check stationarity using the following: We can plot the moving average or moving variance and see if it varies with time. But again this is more of a visual technique. This is one of the statistical tests for checking stationarity. Here the null hypothesis is that the TS is non-stationary. Refer this article for details. These concepts might not sound very intuitive at this point. I recommend going through the prequel article. The book is a bit stats-heavy, but if you have the skill to read-between-lines, you can understand the concepts and tangentially touch the statistics. Please feel free to discuss the code in comments if you face challenges in grasping it. Also, the test statistic is way more than the critical values. Note that the signed values should be compared and not the absolute values. Though stationarity assumption is taken in many TS models, almost none of practical time series are stationary. Actually, its almost impossible to make a series perfectly stationary, but we try to take it as close as possible. Lets understand what is making a TS non-stationary. There are 2 major reasons behind non-stationaruty of a TS: Trend â€" varying mean over time. For eg, in this case we saw that on average, the number of passengers was growing over time. Seasonality â€" variations at specific time-frames. The underlying principle is to model or estimate the trend and seasonality in the series and remove those from the series to get a stationary series. Then statistical forecasting techniques can be implemented on this series. The final step would be to convert the forecasted values into the original scale by applying trend and seasonality constraints back. Some might work well in this case and others might not. But the idea is to get a hang of all the methods and not focus on just the problem at hand. For example, in this case we can clearly see that the there is a significant positive trend. So we can apply transformation which penalize higher values more than smaller values. These can be taking a log, square root, cube root, etc. Lets take a log transform here for simplicity: But its not very intuitive in presence of noise. So we can use some techniques to estimate or model this trend and then remove it from the series. There can be many ways of doing it and some of most commonly used are: Smoothing refers to taking rolling estimates, i. There are can be various ways but I will discuss two of those here. Here we can take the average over the past 1 year, i. Pandas has specific functions defined for determining rolling statistics. Lets subtract this from the original series. Note that since we are taking average of last 12 values, rolling mean is not defined for first 11 values. This can be observed as: Lets drop these NaN values and check the plots to test stationarity. The rolling values appear to be varying slightly but there is no specific trend. There can be many technique for assigning weights. A popular one is exponentially weighted moving average where weights are assigned to all the previous values with a decay factor. This can be implemented in Pandas as:

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2: forecasting - Predicting future values with a regression model - Cross Validated

statistical problems for such time series models, and mainly to problems of the estimation of unknown parameters of models and to problems of the prediction of time series modeled by regression models.

Exploratory analysis The clearest way to examine a regular time series manually is with a line chart such as the one shown for tuberculosis in the United States, made with a spreadsheet program. The number of cases was standardized to a rate per , and the percent change per year in this rate was calculated. The use of both vertical axes allows the comparison of two time series in one graphic. Autocorrelation analysis to examine serial dependence Spectral analysis to examine cyclic behavior which need not be related to seasonality. For example, sun spot activity varies over 11 year cycles. Separation into components representing trend, seasonality, slow and fast variation, and cyclical irregularity: Curve fitting Curve fitting [5] [6] is the process of constructing a curve , or mathematical function , that has the best fit to a series of data points, [7] possibly subject to constraints. A related topic is regression analysis , [14] [15] which focuses more on questions of statistical inference such as how much uncertainty is present in a curve that is fit to data observed with random errors. Fitted curves can be used as an aid for data visualization, [16] [17] to infer values of a function where no data are available, [18] and to summarize the relationships among two or more variables. The construction of economic time series involves the estimation of some components for some dates by interpolation between values "benchmarks" for earlier and later dates. Interpolation is estimation of an unknown quantity between two known quantities historical data , or drawing conclusions about missing information from the available information "reading between the lines". This is often done by using a related series known for all relevant dates. A different problem which is closely related to interpolation is the approximation of a complicated function by a simple function also called regression. The main difference between regression and interpolation is that polynomial regression gives a single polynomial that models the entire data set. Spline interpolation, however, yield a piecewise continuous function composed of many polynomials to model the data set. Extrapolation is the process of estimating, beyond the original observation range, the value of a variable on the basis of its relationship with another variable. It is similar to interpolation , which produces estimates between known observations, but extrapolation is subject to greater uncertainty and a higher risk of producing meaningless results. Function approximation In general, a function approximation problem asks us to select a function among a well-defined class that closely matches "approximates" a target function in a task-specific way. One can distinguish two major classes of function approximation problems: First, for known target functions approximation theory is the branch of numerical analysis that investigates how certain known functions for example, special functions can be approximated by a specific class of functions for example, polynomials or rational functions that often have desirable properties inexpensive computation, continuity, integral and limit values, etc. Second, the target function, call it g, may be unknown; instead of an explicit formula, only a set of points a time series of the form x, g x is provided. Depending on the structure of the domain and codomain of g, several techniques for approximating g may be applicable. For example, if g is an operation on the real numbers , techniques of interpolation , extrapolation , regression analysis , and curve fitting can be used. If the codomain range or target set of g is a finite set, one is dealing with a classification problem instead. A related problem of online time series approximation [24] is to summarize the data in one-pass and construct an approximate representation that can support a variety of time series queries with bounds on worst-case error. To some extent the different problems regression , classification , fitness approximation have received a unified treatment in statistical learning theory , where they are viewed as supervised learning problems. Prediction and forecasting[edit] In statistics , prediction is a part of statistical inference. One particular approach to such inference is known as predictive inference , but the prediction can be undertaken within any of the several approaches to statistical inference. Indeed, one description of statistics is that it provides a means of transferring knowledge about a sample of a population to the whole population, and to other related populations, which is not necessarily the same as prediction over time. When information is transferred across time, often to specific points in time, the process is known as forecasting. Fully formed statistical models for stochastic simulation purposes, so as to generate alternative versions of the time series, representing what might happen over non-specific time-periods in the future Simple or fully formed statistical models to describe the likely outcome of the time series in the immediate future, given knowledge of the most recent outcomes forecasting. Forecasting on large scale data is done using Spark which has spark-ts as a third party package. Statistical classification Assigning time series pattern to a specific category, for example identify a word based on series of hand movements in sign language.

3: Time Series Analysis in Python: An Introduction â€“ Towards Data Science

The aim of this book is to give an unified approach to the solution of statistical problems for such time series models, and mainly to problems of the estimation of unknown parameters of models and to problems of the prediction of time series modeled by regression models.

I love Data Science. We asked a data scientist, Neelabh Pant, to tell you about his experience of forecasting exchange rates using recurrent neural networks. As an Indian guy living in the US, I have a constant flow of money from home to me and vice versa. If the dollar is weaker, you spend less rupees to buy the same dollar. Looking at the strengths of a neural network, especially a recurrent neural network, I came up with the idea of predicting the exchange rate between the USD and the INR. There are a lot of methods of forecasting exchange rates such as: Purchasing Power Parity PPP , which takes the inflation into account and calculates inflation differential. Relative Economic Strength Approach, which considers the economic growth of countries to predict the direction of exchange rates. Econometric model is another common technique used to forecast the exchange rates which is customizable according to the factors or attributes the forecaster thinks are important. There could be features like interest rate differential between two different countries, GDP growth rates, income growth rates, etc. Time series model is purely dependent on the idea that past behavior and price patterns can be used to predict future price behavior. Sequence problems Let us begin by talking about sequence problems. The simplest machine learning problem involving a sequence is a one to one problem. Linear regression, classification, and even image classification with convolutional network fall into this category. We can extend this formulation to allow for the model to make use of the pass values of the input and the output. It is known as the one to many problem. The one to many problem starts like the one to one problem where we have an input to the model and the model generates one output. However, the output of the model is now fed back to the model as a new input. The model now can generate a new output and we can continue like this indefinitely. You can now see why these are known as recurrent neural networks. In other words, they can retain state from one iteration to the next by using their own output as input for the next step. In programming terms this is like running a fixed program with certain inputs and some internal variables. The simplest recurrent neural network can be viewed as a fully connected neural network if we unroll the time axes. The weight multiplying the current input xt, which is u, and the weight multiplying the previous output yt-1, which is w. This formula is like the exponential weighted moving average EWMA by making its pass values of the output with the current values of the input. One can build a deep recurrent neural network by simply stacking units to one another. A simple recurrent neural network works well only for a short-term memory. We will see that it suffers from a fundamental problem if we have a longer time dependency. This is a problem because we want our RNNs to analyze text and answer questions, which involves keeping track of long sequences of words. LSTM has an internal state variable, which is passed from one cell to another and modified by Operation Gates. Forget Gate It is a sigmoid layer that takes the output at t-1 and the current input at time t and concatenates them into a single tensor and applies a linear transformation followed by a sigmoid. Because of the sigmoid, the output of this gate is between 0 and 1. This number is multiplied with the internal state and that is why the gate is called a forget gate. Input Gate The input gate takes the previous output and the new input and passes them through another sigmoid layer. This gate returns a value between 0 and 1. The value of the input gate is multiplied with the output of the candidate layer. This layer applies a hyperbolic tangent to the mix of input and previous output, returning a candidate vector to be added to the internal state. The internal state is updated with this rule: The previous state is multiplied by the forget gate and then added to the fraction of the new candidate allowed by the output gate. Output Gate This gate controls how much of the internal state is passed to the output and it works in a similar way to the other gates. These three gates described above have independent weights and biases, hence the network will learn how much of the past output to keep, how much of the current input to keep, and how much of the internal state to send out to the output. In a recurrent neural network, you not only give the network the data, but also the state of the network one moment before. It is a story where the main character is Neelabh and something happened on the road. As you listen to all my other sentences you have to keep a bit of information from all past sentences around in order to understand the entire story. Another example is video processing, where you would again need a recurrent neural network. What happens in the current frame is heavily dependent upon what was in the last frame of the movie most of the time. Over a period of time, a recurrent neural network tries to learn what to keep and how much to keep from the past, and how much information to keep from the present state, which makes it so powerful as compared to a simple feed forward neural network. Time Series Prediction I was impressed with the strengths of a recurrent neural network and decided to use them to predict the exchange rate between the USD and the INR. The dataset used in this project is the exchange rate data between January 2, and August 10, We have a total of 13, records starting from January 2, to August 10, One can see that there was a huge dip in the American economy during â€", which was hugely caused by the great recession during that period. It was a period of general economic decline observed in world markets during the late s and early s. Many of the newer developed economies suffered far less impact, particularly China and India, whose economies grew substantially during this period. Test-Train Split Now, to train the machine we need to divide the dataset into test and training sets. It is very important when you do time series to split train and test with respect to a certain date. In our experiment, we will define a date, say January 1, , as our split date. The training data is the data between January 2, and December 31, , which are about 11, training data points. The test dataset is between January 1, and August 10, , which are about 2, points. Train-Test Split The next thing to do is normalize the dataset. You only need to fit and transform your training data and just transform your test data. Normalizing or transforming the data means that the new scale variables will be between zero and one. This basically takes the price from the previous day and forecasts the price of the next day. As a loss function, we use mean squared error and stochastic gradient descent as an optimizer, which after enough numbers of epochs will try to look for a good local optimum. Below is the summary of the fully connected layer. Since we split the data into training and testing sets we can now predict the value of testing data and compare them with the ground truth. Ground Truth blue vs Prediction orange As you can see, the model is not good. It essentially is repeating the previous values and there is a slight shift. The fully connected model is not able to predict the future from the single previous value. Let us now try using a recurrent neural network and see how well it does. Long Short-Term Memory The recurrent model we have used is a one layer sequential model. We used 6 LSTM nodes in the layer to which we gave input of shape 1,1 , which is one input given to the network with one value. The summary of the model is shown above. It is still underestimating some observations by certain amounts and there is definitely room for improvement in this model. One can always try to change the configuration by changing the optimizer. Another important change I see is by using the Sliding Time Window method, which comes from the field of stream data management system. This approach comes from the idea that only the most recent data are important. One can show the model data from a year and try to make a prediction for the first day of the next year. Sliding time window methods are very useful in terms of fetching important patterns in the dataset that are highly dependent on the past bulk of observations. Try to make changes to this model as you like and see how the model reacts to those changes. Dataset I made the dataset available on my github account under deep learning in python repository. Feel free to download the dataset and play with it. Try to keep up with the news of different artificial intelligence conferences. Conclusion LSTM models are powerful enough to learn the most important past behaviors and understand whether or not those past behaviors are important features in making future predictions. There are several applications where LSTMs are highly used. Applications like speech recognition, music composition, handwriting recognition, and even in my current research of human mobility and travel predictions. According to me, LSTM is like a model which has its own memory and which can behave like an intelligent human in making decisions. Thank you again and happy machine learning!

4: forecasting - Weather data in time series predictions - Cross Validated

Ex-ante versus ex-post forecasts. When using regression models for time series data, we need to distinguish between the different types of forecasts that can be produced, depending on what is assumed to be known when the forecasts are computed.

Quandl does not have number of shares data, but I was able to find average yearly stock shares for both companies with a quick Google search. Is is not exact, but will be accurate enough for our analysis. Sometimes we have to make do with imperfect data! We do the same process with the GM data and then merge the two. Merging is an essential part of a data science workflow because it allows us to join datasets on a shared column. In this case, we have stock prices for two different companies on the same dates and we therefore want to join the data on the date column. After merging, we rename the columns so we know which one goes with which car company. We can see General Motors started off our period of analysis with a market cap about 30 times that of Tesla! Do things stay that way over the entire timeline? Tesla even surpasses GM in value during ! During that period, Tesla sold about 48, cars while GM sold 1,, GM was valued less than Tesla during a period in which it sold 30 times more cars! This definitely displays the power of a persuasive executive and a high-quality â€" if extremely low-quantity â€" product. When will this happen? For that we turn to additive models for forecasting, or in other words, predicting the future. Prophet is designed for analyzing time series with daily observations that display patterns on different time scales. It also has advanced capabilities for modeling the effects of holidays on a time-series and implementing custom changepoints, but we will stick to the basic functions to get a model up and running. Prophet, like quandl, can be installed with pip from the command line. We first import prophet and rename the columns in our data to the correct format. We then create prophet models and fit them to the data, much like a Scikit-Learn machine learning model: This hyperparameter is used to control how sensitive the trend is to changes , with a higher value being more sensitive and a lower value less sensitive. This value is used to combat one of the most fundamental trade-offs in machine learning: If we fit too closely to our training data, called overfitting , we have too much variance and our model will not be able to generalize well to new data. On the other hand, if our model does not capture the trends in our training data it is underfitting and has too much bias. When a model is underfitting, increasing the changepoint prior allows more flexibility for the model to fit the data, and if the model is overfitting, decreasing the prior limits the amount of flexibility. The effect of the changepoint prior scale can be illustrated by graphing predictions made with a range of values: The higher the changepoint prior scale, the more flexible the model and the closer it fits to the training data. This may seem like exactly what we want, but learning the training data too well can lead to overfitting and an inability to accurately make predictions on new data. We therefore need to find the right balance of fitting the training data and being able to generalize to new data. As stocks vary from day-to-day, and we want our model to capture this, I increased the flexibility after experimenting with a range of values. In the call to create a prophet model, we can also specify changepoints, which occur when a time-series goes from increasing to decreasing, or from increasing slowly to increasing rapidly they are located where the rate change in the time series is greatest. Changepoints can correspond to significant events such as product launches or macroeconomic swings in the market. If we do not specify changepoints, prophet will calculate them for us. To make forecasts, we need to create what is called a future dataframe. We specify the number of future periods to predict two years and the frequency of predictions daily. We then make predictions with the prophet model we created and the future dataframe: We can visualize predictions with the prophet plot function. The region of uncertainty increases the further out in the future the prediction is made because initial uncertainty propagates and grows over time. This is observed in weather forecasts which get less accurate the further out in time they are made. We can also inspect changepoints identified by the model. Again, changepoints represent when the time series growth rate significantly changes goes from increasing to decreasing for example.

5: Using LSTMs to forecast time-series â€“ Towards Data Science

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Stationary Series There are three basic criterion for a series to be classified as stationary series: The mean of the series should not be a function of time rather should be a constant. The variance of the series should not a be a function of time. This property is known as homoscedasticity. Following graph depicts what is and what is not a stationary series. Notice the varying spread of distribution in the right hand graph 3. In the following graph, you will notice the spread becomes closer as the time increases. The reason I took up this section first was that until unless your time series is stationary, you cannot build a time series model. There are multiple ways of bringing this stationarity. Some of them are Detrending, Differencing etc. You might know the concept well. But, I found many people in the industry who interprets random walk as a stationary process. In this section with the help of some mathematics, I will make this concept crystal clear for ever. Imagine a girl moving randomly on a giant chess board. In this case, next position of the girl is only dependent on the last position. You want to predict the position of the girl with time. How accurate will you be? Of course you will become more and more inaccurate as the position of the girl changes. This is the randomness the girl brings at every point in time. Now, if we recursively fit in all the Xs, we will finally end up to the following equation: Er t Now, lets try validating our assumptions of stationary series on this random walk formulation: Is the Mean constant? E[Er t] We know that Expectation of any Error will be zero as it is random. Is the Variance constant? Hence, we infer that the random walk is not a stationary process as it has a time variant variance. Also, if we check the covariance, we see that too is dependent on time. Let us introduce a new coefficient in the equation to see if we can make the formulation stationary. Here we will interpret the scatter visually and not do any test to check stationarity. Here is the plot for the time series: Increase the value of Rho to 0. You might notice that our cycles have become broader but essentially there does not seem to be a serious violation of stationary assumptions. This series also is not violating non-stationarity significantly. This obviously is an violation to stationary conditions. We will find the mathematical reason to this. Now, if X moves to any direction from zero, it is pulled back to zero in next step. The only component which can drive it even further is the error term. Error term is equally probable to go in either direction. What happens when the Rho becomes 1? No force can pull the X down in the next step. Here is a small tweak which is made for our equation to convert it to a Dickey Fuller test: Stationary testing and converting a series into a stationary series are the most critical processes in a time series modelling. You need to memorize each and every detail of this concept to move on to the next step of time series modelling. I have used an inbuilt data set of R called AirPassengers. Loading the Data Set Following is the code which will help you load the data set and spill out a few top level metrics. Median Mean 3rd Qu. The variance and the mean value in July and August is much higher than rest of the months. Even though the mean value of each month is quite different their variance is small. Hence, we have strong seasonal effect with a cycle of 12 months or less. Exploring data becomes most important in a time series model â€” without this exploration, you will not know whether a series is stationary or not. As in this case we already know many details about the kind of model we are looking out for. We will also take this problem forward and make a few predictions. We will now develop a knack for these terms and understand the characteristics associated with these models. But before we start, you should remember, AR or MA are not applicable on non-stationary series. Next, we will look at the characteristics of these models. But the primary component of the GDP is the former one. Hence, we can formally write the equation of GDP as: The numeral one 1 denotes that the next instance is solely dependent on the previous instance. The alpha is a coefficient which we seek so as to minimize the error function. Notice that x t- 1 is indeed linked to x t-2 in the same fashion. Hence, any shock to x t will gradually fade off in future. During winters, very few vendors purchased juice bottles. However, after a few days, the climate became cold again. A manufacturer produces a certain type of bag, which was readily available in the market. So, one day he did some experiment with the design and produced a different type of bag. This type of bag was not available anywhere in the market. Thus, he was able to sell the entire stock of bags lets call this as x t. Lets call this gap as the error at that time point. Following is a simple formulation to depict the scenario: Did you notice the difference between MA and AR model? The AR model has a much lasting effect of the shock. This directly flows from the fact that covariance between x t and x t-n is zero for MA models something which we refer from the example taken in the previous section. However, the correlation of x t and x t-n gradually declines with n becoming larger in the AR model. The correlation plot can give us the order of MA model. Is it an AR or MA process? What order of AR or MA process do we need to use? ACF is a plot of total correlation between different lag functions. We are interested in the correlation of x t with x t-1 , x t-2 and so on. In a moving average series of lag n, we will not get any correlation between x t and x t â€” n Hence, the total correlation chart cuts off at nth lag. So it becomes simple to find the lag for a MA series. For an AR series this correlation will gradually go down without any cut off value. So what do we do if it is an AR series? Here is the second trick. If we find out the partial correlation of each lag, it will cut off after the degree of AR series. Hence, the partial correlation function PACF will drop sharply after the 1st lag. Following are the examples which will clarify any doubts you have on this concept: Now is the time to join these pieces and make an interesting story. Nevertheless, the same has been delineated briefly below: The details we are interested in pertains to any kind of trend, seasonality or random behaviour in the series. We have covered this part in the second part of this series. Dickey â€” Fuller is one of the popular test to check the same. We have covered this test in the first part of this article series. What if the series is found to be non-stationary? There are three commonly used technique to make a time series stationary: Here, we simply remove the trend component from the time series. This is the commonly used technique to remove non-stationarity. Here we try to model the differences of the terms and not the actual term. Now, we have three parameters p: More on this has been discussed in the applications part below.

6: Complete guide to create a Time Series Forecast (with Codes in Python)

After finalizing, you may want to save the model to file, e.g. via the Keras API. Once saved, you can load the model any time and use it to make predictions.

Fitting time series regression models Why do simple time series models sometimes outperform regression models fitted to nonstationary data? There may be some "omitted variable", say Z, which could in principle explain some of the discrepancy in the relationship between X and Y--but this is not the only possibility. For example, the nature of the relationship between X and Y may simply change over time. Remember that if X and Y are nonstationary, this means that we cannot necessarily assume their statistical properties such as their correlations with each other are constant over time. If the variables X and Z change relatively slowly from period to period, it is possible that the information X t and Z t contain with respect to Y t is already contained in Y t-1 , Y t-2 , etc. In other words, recent values of Y might be good "proxies" not only for the effect of X but also for the effects of any omitted variables. Business and macroeconomic times series often have strong contemporaneous correlations, but significant leading correlations--i. Thus, regression models may be better at predicting the present than the future. How to get the best of both worlds--regression and time series models: Stationarize the variables by differencing, logging, deflating, or whatever before fitting a regression model. If you can find transformations that render the variables stationary, then you have greater assurance that the correlations between them will be stable over time. Stationarizing also implicitly brings the recent history of the variables into the forecast. Use lagged versions of the variables in the regression model. This allows varying amounts of recent history to be brought into the forecast Lagging of independent variables is often necessary in order for the regression model to be able to predict the future--i. It often helps to do both--i. Determine which transformations if any are needed to stationarize each variable by looking at time series plots and autocorrelation plots Time series plots of stationary variables should have a well-defined mean and a relatively constant variance i. The autocorrelations of a nonstationary variable will be strongly positive and non-noisy-looking out to a high number of lags often 10 or more --i. If the lag-1 autocorrelation is already negative, no more differencing is needed. If the lag-1 autocorrelation is Look at autocorrelations of the stationarized dependent variable e. Look at cross-correlations between the stationarized dependent variable the "first" series and stationarized independent variables the "second" series. A significant cross-correlation at a positive lag indicates that the independent variable may be significant when lagged by that number of periods. The cross-correlation function, like the autocorrelation function, is typically noisy. Cross-correlations at lags of 3 or more are often merely accidental except where seasonal effects are important. Generally you should take seriously only the cross-correlations at lags 0, 1, and 2. You could also include DIFF X as indicated by the cross-correlation at lag 0, but this would preclude being able to predict one period ahead. If your dependent variable is DIFF Y , then the forecast reports and graphs produced by your model will all be for differences of Y, not for Y in its original units. The regression procedure does not automatically "undifference" the output for you. If you wish to print or plot undifferenced forecasts, you will need to use spreadsheet commands either in Statgraphics or Excel to add the predicted differences to the previous actual values in order to get predictions for Y itself in each period. For stock price data, on which you would probably use a DIFF LOG transformation, obtaining results in differenced terms is not necessarily bad: You can use a "stepwise" approach to model-fitting but beware of over-fitting the data. Be cautious in choosing how many lags and how many different independent variables to include at the beginning of the process. The Multiple Regression procedure includes automatic stepwise regression as a right-mouse-button option. The "forward" method is usually safer. The Advanced Regression module contains an all-possible-regressions option "Regression Model Selection" procedure -- but beware! Ideally you should withhold data during the model-selection process as well as during the final testing of the model. The Multiple Regression procedure does not offer any options for validation, alas. The Advanced Regression module includes a validation option in all its procedures: The Forecasting procedure can be used to fit regression models to lagged and differenced data and to validate them. Forecasts will be automatically "undifferenced" in the output reports and graphs.

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The regression option gives a "data error" message if there is more than 1 missing value at the beginning of a regressor, which will be the case if the total number of lags or differences is more than 1. The regressor could either be lagged by one period, or else differenced, but not both. Then delete any rows at the beginning of the file that contain missing values of these variables. Another bug in the Forecasting procedure: However, the plot that is actually drawn is a cross-correlation plot of the input variable e. Once you have the Descriptive Methods analysis window set up to do cross-correlations of the residuals of one model, it is easy to get plots for the residuals of other models: The Descriptive Methods window will now immediately show the cross-correlations of the new residuals versus the second time series that was previously specified.

7: A Complete Tutorial on Time Series Modeling in R

The Statsbot team has already published the article about using time series analysis for anomaly www.enganchecubano.com, we'd like to discuss time series prediction with a long short-term memory model (LSTMs).

LSTMs can almost seamlessly model problems with multiple input variables. So long as we figure out a way to convert all our input variables to be represented in a 3D vector form, we are good use LSTM. In particular we can â€” Flexibility to use several combinations of seq2seq LSTM models to forecast time-series â€” many to one model useful when we want to predict at the current timestep given all the previous inputs , many to many model useful when we want to predict multiple future time steps at once given all the previous inputs and several other variations on these. We can customize several things for example â€" the size of look-back window to predict at the current step, the number of time steps we want to predict into the future, feeding the current prediction back into the window to make prediction at the next time step this technique also known as moving-forward window and so on. So take this with a pinch of salt. A simple sine-wave as a model data set to model time series forecasting is used. You can find my own implementation of this example here at my github profile. The core idea and the data for this example has been taken from this blog but have made my own changes to it for easy understanding. So how does our given data look like? Below is the plot of the entire sine wave dataset. Next, we will use the window between 1 to 51 data points as input X to predict y2 i. We will look at couple of approaches to predict the output â€" a. Forecasting step by step on the test data set, b. Feed the previous prediction back into the input window by moving it one step forward and then predict at the current time step. Now lets dive into the details â€" Data preparation â€" Normalizing the data using minmax scaler refer below code snippet 2. Fix the moving window size to be For this purpose we use pandas shift function that shifts the entire column by the number we specify. In the below code snippet, we shifted the column up by 1 hence used Note â€" we dropped all the rows that contain the Nan values in the above code snippet. If you look at the toy data set closely, you can observe that this models the input data in the fashion we want to input into the LSTM. The last column in the above table becomes the target y and the first three columns become our input x1,x2 and x3 features. If you are familiar with using LSTM for NLP, then you can look at this as a fixed sequence of length 3 of sentence containing 3 words each and we are tasked with predicting the 4th word. So we need 50 time steps to go through each word vector in the sentence as an input to the LSTM at each time step. Like this, we need to iterate over all the sentences in the train data to extract the pattern between the words in all sentences. This is exactly what we want here in the time series forecast as well â€" we want to identify all the patterns that exist between each of the previous values in the window to predict the current time step! Model Architecture â€" Below is the model architecture used that is quite self-explanatoryâ€" Its a double stacked LSTM layers with the output from the first LSTM at each time step is being fed to the second LSTM Model architecture Making predictions â€" Predicting step by step on the test data refer to the below code snippet. This is quite straight forward. Given all the learned parameters from train data, we are using them to predict on all the test sequences one at a time. The plot of predictions vs actuals almost overlap with each other to the extent that we cannot distinguish the blue curve and red curve in the below plot. However, the above is usually not a realistic way in which predictions are done, as we will not have all the future window sequences available with us. So, if we want to predict multiple time steps into the future, then a more realistic way is to predict one time step at a time into the future and feed that prediction back into the input window at the rear while popping out the first observation at the beginning of the window so that the window size remains same. Refer to the below code snippet that does this part â€" the comments in the code are self explanatory if you go through the code in my github link that I mentioned above â€" Using this prediction model, the results are plotted below â€" As can be seen, quite understandably, the farther we try to predict in time, more the error at each time-step that builds up on the previous predicted error. However, the function still behaves like a dampening sine-wave! As I said earlier, this is more realistic modelling of any time series problem since we would not have all the future sequences in hand with us. This code can very well be extended to predicting any time series in general. Note that you may need to take care of other aspects of data preparation like de-trending the series, differencing to stationarize the data and so on before it is fed to LSTM to forecast. In case there are some takeaways from this article, please show your appreciation by clapping:

8: A Guide For Time Series Prediction Using Recurrent Neural Networks (LSTMs)

We could use a classification model instead of a regression model, sorting into quintile buckets by predicting bucket probability and minimizing cross-entropy, which might be a more appropriate objective function.

I am really confused with regards to what method to use for forecasting the target variable. Start with the same things as you would started with analyzing this data as usual: Think about your problem: What is your data? What do you want to know? Does your data enable you to answer the question that you are asking? If not, maybe you can rephrase your question to answerable one? Is there any pattern in your data that makes forecast possible if it is purely random than your options are limited; search for "forecastability". Consider if your data is sufficient for forecasting e. If you are modeling time-series than you have to thing about nature of the series: Are there any things that happen with some regularity that influence your data? Is your data autocorrelated? Finally, do you have any a priori knowledge about your data e. Take all those cases into consideration. You can find a friendly popular introduction to thinking about forecasting in Nate Silvers book The Signal and the Noise. See also The Black Swan by Taleb for critique and examples of forecasts going wrong. Now, after spending some time with looking and thinking about your data you have to choose appropriate method or model for it. If it is time-series data than consider one of the multiple methods for modeling and forecasting time-series e. You can include time component in regression or generalized linear model and in some cases this is preferable method. Sometimes you need non-linear models , machine learning methods or other. If you want to include out-of-data information in your model you may need a Bayesian model. You may be also interested in conducting simulation and then base your judgment based on possible scenarios that emerged from simulation. There is too many possible choices to summarize them in a single answer, so if you are not familiar with those methods than start with some statistics handbook, check also handbooks on time-series e. Chatfield, and forecasting e. Notice also that sometimes simpler methods perform better than the complicated ones. If you made your forecast, then you have to asses its performance. Remember that in most cases perfect forecast is not possible, you are looking for the best one you can get from this data and with the tools that you have. Remember also that it is often the case that if you take few forecasts made using different methods and take weighted average of them, then the averaged forecast ofter outperforms individual forecasts. For example, my data set has monthly customer profit which is my target variable and a set of predictor variables balances of different accounts for one year for each customer. It is hard to comment on this one, because it really depends on what is your data and what you want to forecast, but reviewing the literature should help you to get some insight about methods that fit your problem check the links I provided and the books I refer to for some introduction. I need to predict the profit for the next 5 years. I am confused in that I do not have the data predictor variables for the future. You build a model using the data that you have and then use this data to make educated guesses about the future. This part is tricky because you have to consider if it is really the case that model estimated on the data you have is adequate for applying it to the future e. Remember that your forecast would probably be wrong, provide a prediction interval so to asses possible variability of the future values rather than single point estimate. Finally, remember that all models are wrong and you are looking for a useful one. The Signal and the Noise: The Analysis of Time Series: The Impact of the Highly Improbable.

9: Time Series Regression - MATLAB & Simulink

Using LSTMs to forecast time-series There are several time-series forecasting techniques like auto regression (AR) models, moving average (MA) models, Holt-winters, ARIMA etc., to name a few. So, what is the need for yet another model like LSTM-RNN to forecast time-series?

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