CoolStatsBlog

Abbas Keshvani's plain English blog

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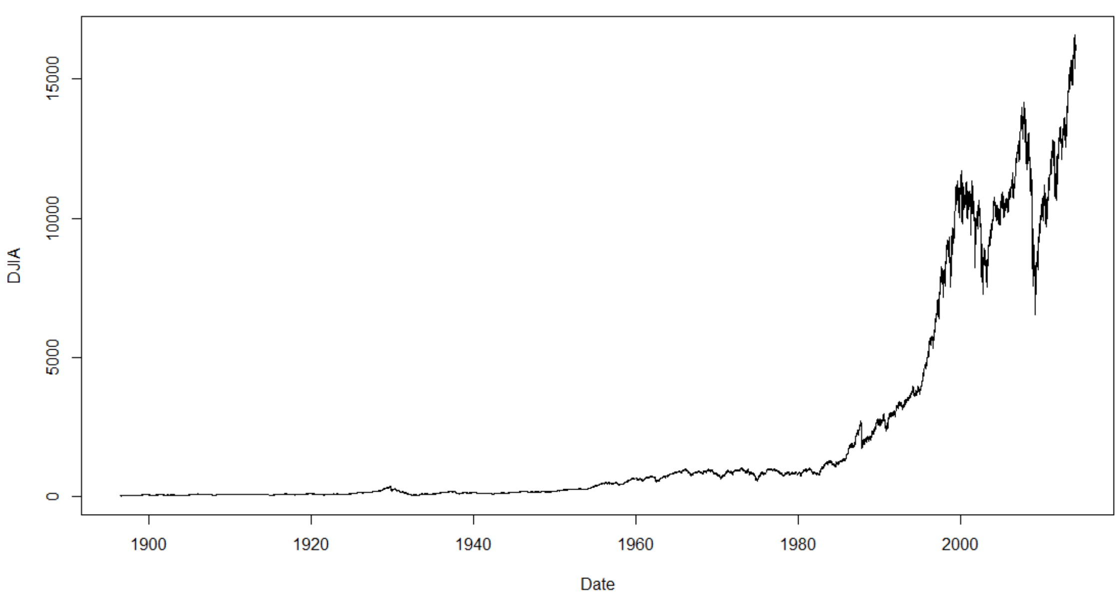
Using AIC to Test ARIMA Models

Time Series August 14, 2013August 15, 2017 2 Minutes

The Akaike Information Critera (AIC) is a widely used measure of a statistical model. It basically quantifies 1) the goodness of fit, and 2) the simplicity/parsimony, of the model into a single statistic.

When comparing two models, the one with the lower AIC is generally "better". Now, let us apply this powerful tool in comparing various ARIMA models, often used to model time series.

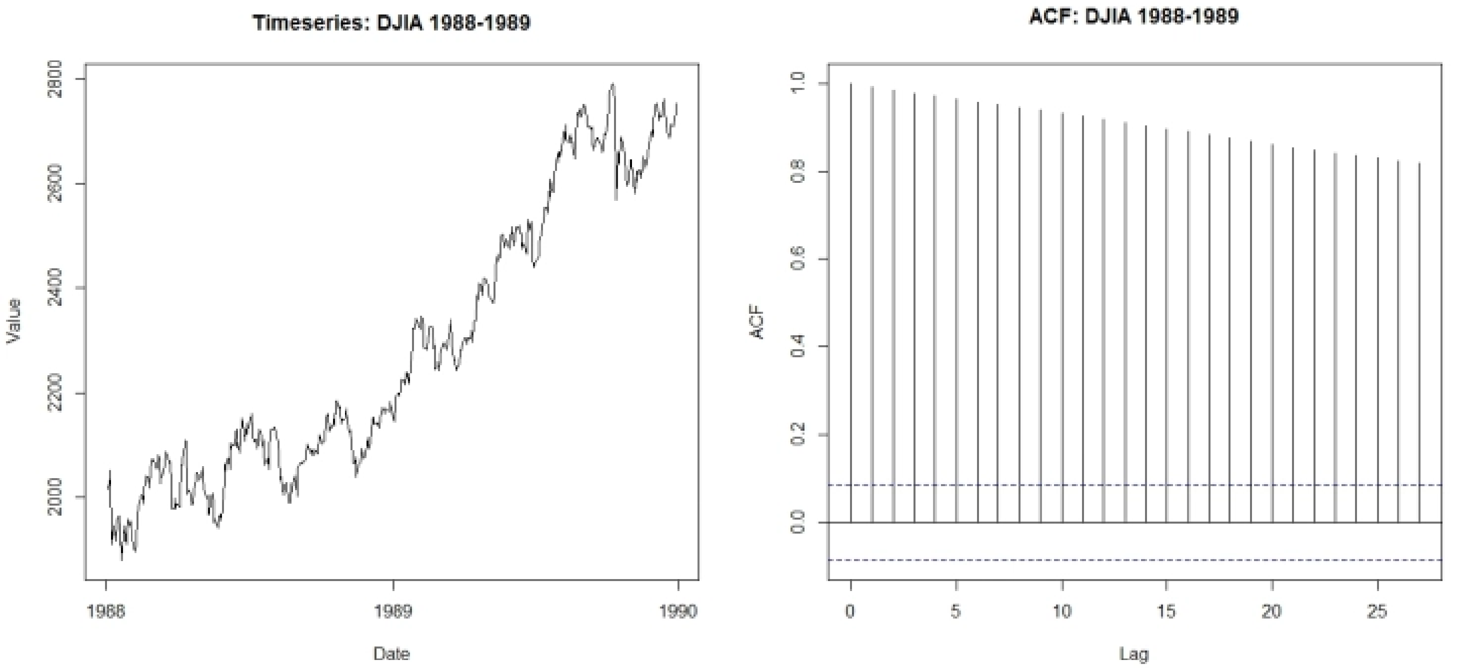
The dataset we will use is the Dow Jones Industrial Average (DJIA), a stock market index that constitutes 30 of America's biggest companies, such as Hewlett Packard and Boeing. First, let us perform a time plot of the DJIA data. This massive dataframe comprises almost 32000 records, going back to the index's founding in 1896. There was an actual lag of 3 seconds between me calling the function and R spitting out the below graph!



(https://coolstatsblog.files.wordpress.com/2013/08/djia-since-time.png)

Dow Jones Industrial Average since March 1896

But it immediately becomes apparent that there is a lot more at play here than an ARIMA model. Since 1896, the DJIA has seen several periods of rapid economic growth, the Great Depression, two World Wars, the Oil shock, the early 2000s recession, the current recession, *etcetera*. Therefore, I opted to narrow the dataset to the period 1988-1989, which saw relative stability. As is clear from the timeplot, and slow decay of the ACF, the DJIA 1988-1989 timeseries is not stationary:



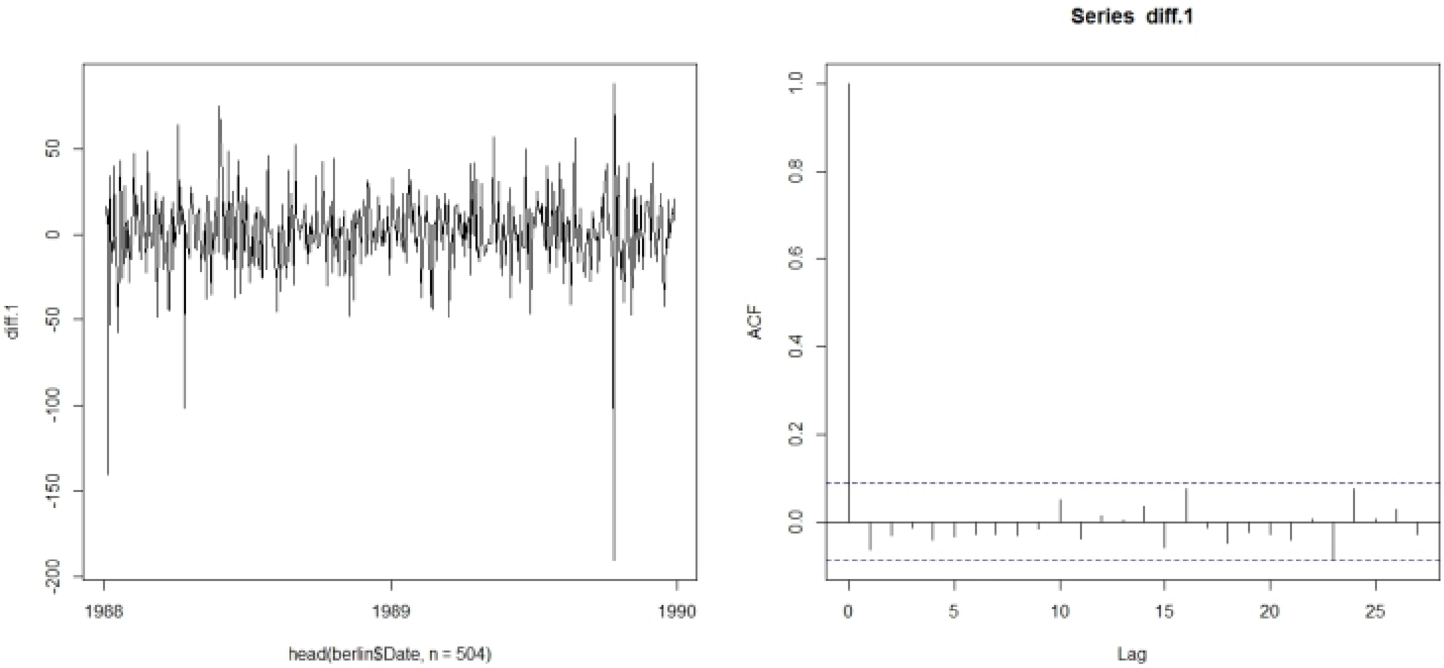
(https://coolstatsblog.files.wordpress.com/2013/08/berlin2.jpeg)

Time plot (left) and AIC (right): DJIA 1988-1989

So, we may want to take the first difference of the DJIA 1988-1989 index. This is expressed in the equation below:

$\Delta Y = Y_t - Y_{t-1}$

The first difference is thus, the difference between an entry and entry preceding it. The timeseries and AIC of the First Difference are shown below. They indicate a stationary time series.



(https://coolstatsblog.files.wordpress.com/2013/08/fd.jpeg)

First Difference of DJIA 1988-1989: Time plot (left) and ACF (right)

Now, we can test various ARMA models against the DJIA 1988-1989 First Difference. I will test 25 ARMA models: ARMA(1,1); ARMA(1,2), … , ARMA(3,3), … , ARMA(5,5). To compare these 25 models, I will use the AIC.

		p in AR(p)					
		0	1	2	3	4	5
q in MA(q)	0	4588.666	4588.472	4589.884	4591.619	4592.181	4593.312
	1	4588.618	4584.675	4586.262	4588.261	4590.172	4592.002
	2	4590.031	4586.263	4588.317	4590.25	4590.726	4594.104
	3	4591.883	4589.089	4583.762	4593.013	4589.644	4590.99
	4	4592.883	4590.161	4592.254	4594.099	4583.88	4586.875
	5	4594.055	4590.793	4594.07	4596.018	4586.779	4587.788

(https://coolstatsblog.files.wordpress.com/2013/08/aic5.jpg)

Table of AICs: ARMA(1,1) through ARMA(5,5) I have

highlighted in green the two models with the lowest AICs. Their low AIC values suggest that these models nicely straddle the requirements of goodness-of-fit and parsimony. I have also highlighted in red the worst two models: i.e. the models with the highest AICs. Since ARMA(2,3) is the best model for the *First Difference of* DJIA 1988-

1989, we use **ARIMA(2,1,3)** for DJIA 1988-1989.

The AIC works as such: Some models, such as ARIMA(3,1,3), may offer better fit than ARIMA(2,1,3), but that fit is not worth the loss in parsimony imposed by the addition of additional AR and MA lags. Similarly, models such as ARIMA(1,1,1) may be more parsimonious, but they do not explain DJIA 1988-1989 well enough to justify such an austere model.

Note that the AIC has limitations and should be used heuristically. The above is merely an illustration of how the AIC is used. Nonetheless, it suggests that between 1988 and 1989, the DJIA followed the below ARIMA(2,1,3) model:

$$\Delta Y_t = \phi_2 Y_{t-2} + \phi_1 Y_{t-1} + \theta_3 \epsilon_{t-3} + \theta_2 \epsilon_{t-2} + \theta_1 \epsilon_{t-1} + \epsilon_t$$

Next: Determining the above coefficients, and forecasting the DJIA.

Analysis conducted on R. Credits to the St Louis Fed for the DJIA data.

Abbas Keshvani

Tagged:
AIC,
Akaike information criterion,
ARIMA,
ARMA,
autoregressive,
Autoregressive integrated moving average,
Dow Jones Industrial Average,
Models,
Moving average

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22 thoughts on “Using AIC to Test ARIMA Models”

Pingback: Forecasting a Timeseries | CoolStatsBlog
SARR says:
April 16, 2014 at 8:47 pm
Hello there!
It’s again me.
As you redirected me last time on this post. I wanted to ask why did you exclude p=0 and q=0 parameters while

you were searching for best ARMA oder (=lowest AIC).
I am asking all those questions because I am working on python and there is no equivalent of auto arima or things like that.
Thanks anyway for this blog

↻ Reply

Abbas Keshvani says:
April 17, 2014 at 12:01 pm
Hi! It's because p=0, q=0 had an AIC of 4588.66, which is not the lowest, or even near.

If you find this blog useful, do tell your friends!

↻ Reply

Daniel Medina says:
April 26, 2014 at 6:25 pm
Hello Abbas!

i have two questions.
1. What is the command in R to get the table of AIC for model ARMA?
2. If the values AIC is negative, still choose the lowest value of AIC, ie, that -140 -210 is better?

Thank for your help.

↻ Reply

Abbas Keshvani says:
April 26, 2014 at 6:55 pm
Hi Daniel,

1. There is no fixed code, but I composed the following lines:

```
aic<-matrix(NA,6,6)
for(p in 0:5)
{
for(q in 0:5)
{
a.p.q<-arima(timeseries,order=c(p,0,q))
aic.p.q<-a.p.q$aic
aic[p+1,q+1]<-aic.p.q
}
}
aic
```

2. You can have a negative AIC. Pick the lower one.

If you like this blog, please tell your friends.

↻ Reply

SARR says:
May 2, 2014 at 2:01 pm

Hi Abbas!
I have 3 questions:
I come to you because usually you explain things simplier with simple words.
1)Can you explain me how to detect seasonality on a time series and how to implement it in the ARIMA method?
2)Also I would like to know if you have any knowlege on how to choose the right period (past datas used) to make the forecast?
3) Finally, I have been reading papers on Kalman filter for forecasting but I don't really know why we use it and what it does?
Can you help me ? Thanks
🙂

Reply

SARR says:
May 2, 2014 at 2:05 pm
In addition to my previous post I was asking a method of detection of seasonality which was not by analyzing visually the ACF plot (because I read your post : How to Use Autocorreation Function (ACF) to Determine Seasonality?)
My goal is to implement an automatic script on python.That's why I am asking!
Thanks for answering my questions (lol,don't forget the previous post)
🙂

Reply

Abbas Keshvani says:
May 3, 2014 at 5:34 am
Hi SARR,
1) I'm glad you read my seasonality post. I posted it because it is the simplest, most intuitive way to detect seasonality. For python, it depends on what method you are using. I personally favor using ACF, and I do so using R. You can make the process automatic by using a do-loop. See my response to Daniel Medina for an example of a do-loop.
2) Choose a period without too much "noise". You want a period that is stable and predictable, since models cannot predict random error terms or "noise'. So choose a straight (increasing, decreasing, whatever) line, a regular pattern, etc…
3) Kalman filter is an algorithm that determines the best averaging factor (coefficients for each consequent state) in forecasting. If you're interested, watch this blog, as I will post about it soon.

Tell your friends!

Abbas

Vivek Arulnathan says:
February 19, 2015 at 2:57 pm
Hi,

Nice write up. I am working on some statistical work at university and I have no idea about proper statistical analysis. But I found what I read on your blog very useful. Thanks for that.

I have a doubt about AIC though. I am working on ARIMA models for temperature and electricity consumption analysis and trying to determine the best fit model using AIC. All my models give negative AIC value. For example, I have -289, -273, -753, -801, -67, 1233, 276,-796. I know the lower the AIC, it is better. But in the case of negative values, do I take lowest value (in this case -801) or the lowest number among negative & positive values (67)??

Hoping for your reply.

Cheers

↻ Reply

Abbas Keshvani says:
March 20, 2015 at 12:40 pm
Hi Vivek, thanks for the kind words. Use the lowest: -801.

↻ Reply

Namrata says:
November 6, 2015 at 3:21 pm
Hi,
Thank you for enlightening me about aic. I have a question and would be glad if you could help me. Do you have the code to produce such an aic model in MATLAB?

↻ Reply

Abbas Keshvani says:
June 4, 2016 at 4:53 am
Sorry Namrata. I do not use Matlab. Once you get past the difficulty of using R, you'll find it faster and more powerful than Matlab.

↻ Reply

thsj says:
January 2, 2016 at 8:56 pm
thank you

↻ Reply

Deepesh Singh says:
August 15, 2016 at 5:19 pm
Hi Abbas,
Thanks for this wonderful piece of information. I have few queries regarding ARIMA:
1. Why do we need to remove the trend and make it stationary before applying ARMA? Won't it remove the necessary trend and affect my forecast?
2. Apart from AIC and BIC values what other techniques we use to check fitness of the model like residuals check?
3. What are the limitation (disadvantages) of ARIMA?

Sorry for trouble but I couldn't get these answers on Google.

Thanks a lot,
Deepesh Singh

↻ Reply

Abbas Keshvani says:
September 2, 2016 at 4:14 pm
Thanks for the kind feedback Deepesh.

A simple ARMA(1,1) is Y_t = a*Y_(t-1) + b*E_(t-1).

Now Y_t is simply a constant [times] Y_(t-1) [plus] a random error. The error is not biased to always be positive or negative, so every Y_t can be bigger or smaller than Y_(t-1). The series is not "going anywhere", and is thus stationary.

So any ARMA must be stationary. If a series is not stationary, it cannot be ARMA.

↻ Reply

Pingback: Time Series Analysis Baby Steps Using R | Code With Competency

Sandra says:
October 17, 2016 at 7:00 am
Hi Abbas,

How can I modify the below code to populate the BIC matrix instead of the AIC matrix?

```
aic<-matrix(NA,6,6)
for(p in 0:5)
{
for(q in 0:5)
{
a.p.q<-arima(timeseries,order=c(p,0,q))
aic.p.q<-a.p.q$aic
aic[p+1,q+1]<-aic.p.q
}
}
aic
```

↻ Reply

Anonymous says:
January 24, 2018 at 10:55 am
thank you so much for useful code.now i don't have to go through rigourous data exploration everytime while doing time series

↻ Reply

Zed says:
August 22, 2018 at 4:49 pm
If the lowest AIC model does not meet the requirements of model diagnostics then is it wise to select model only based on AIC?

↻ Reply

Gulam Rather says:
November 3, 2018 at 5:04 pm

Hi Abbas,
Could you please let me know the command in R where we can use d value obtained from GPH method to be fitted in ARFIMA model to obtain minimum AIC values for forecast?
fracdiff function in R gives d value using AML method which is different from d obtained from GPH method.

Ꮼ Reply

Girijesh Singh says:
January 24, 2019 at 11:06 am
Hi Sir,
I am working to automate Time – Series prediction using ARIMA by following this link
https://github.com/susanli2016/Machine-Learning-with-Python/blob/master/Time%20Series%20Forecastings.ipynb
I have a concern regarding AIC value. In the link, they are considering a range of (0, 2) for calculating all possible of (p, d, q) and hence corresponding AIC value. And for AIC value = 297 they are choosing (p, d, q) = SARIMAX(1, 1, 1)x(1, 1, 0, 12) with a MSE of 151.

Now when I increase this range to (0, 3) from (0, 2) then lowest AIC value become 116 and hence I am taking the value of the corresponding (p, d, q) but my MSE is 34511.37 which is way more than the previous MSE.
I am unable to understand why this MSE value is so high if I am taking lower AIC value.

Any help would be highly appreciated.

Thanks,
Girijesh Singh

Ꮼ Reply

Pingback: Forecasting Time Series Data Using Splunk Machine Learning Toolkit - Part II - Discovered Intelligence