

# ISA 444: Business Forecasting

## 19 - ARIMA Models (Cont.)

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Spring 2021

# Outline

- 1 **Preface**
- 2 Some Measures of Goodness of Fit
- 3 The `auto.arima()` Function
- 4 Recap

# Recap of What we Have Covered Last Two Weeks

**ARIMA Models:** Models we considered may have three components, an autoregressive component (AR), integrated (I for differencing) and a moving average component (MA).

## Main Learning Outcomes from Last 3 Classes

- Describe the behavior of the ACF and PACF of an ARMA (p,q) process.
- Fit an ARMA model to a time series, evaluate the residuals of a fitted ARMA model to assess goodness of fit, use the Ljung-Box test for correlation among the residuals of an ARIMA model.
- Use nonseasonal differencing to attain stationarity for a time series.
- Fit an ARIMA model to a time series, evaluate the residuals of a fitted ARMA model to assess goodness of fit, use the Ljung-Box test for correlation among the residuals of an ARIMA model.
- Show that you can fit reasonable ARIMA models based on both simulated and actual data cases.

# Learning Outcomes for Today's Class

## Main Learning Outcomes

- Describe AIC, AICc, and BIC and how they are used to measure model fit.
- Describe the algorithm used within the `auto.arima()` function to fit an ARIMA model.
- Describe the results of the `auto.arima()` function.

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## Additional Measures of Goodness of Fit [1]

**Akaike's Information Criterion:** Akaike suggests measuring the goodness of fit of a model by balancing the error of the fit against the number of parameters in the model.<sup>1</sup>

$$AIC = 2k - 2 \ln(\hat{L}),$$

where  $k$  is the number of parameters in the model and  $\hat{L}$  is the sample likelihood function. The value of  $k$  that gives a minimum AIC gives the best model. This is simply a penalty imposed on the error variance for the number of parameters in the model.

**Bias Corrected AIC:**  $AICc = AIC + \frac{2k^2+2k}{n-k-1}$ .

The AICc is usually preferred over the AIC.

**Bayesian Information Criterion:**  $BIC = \ln(n)k - 2 \ln(\hat{L})$ .

BIC is also known as the Schwarz Information Criterion (SIC). The BIC has a larger penalty for model size and tends to choose smaller models.

# Additional Measures of Goodness of Fit [2]

## Studies have shown:

- BIC does well at getting correct model in large samples.
- AICc tends to get correct models in smaller samples with a large number of parameters.

## Why did we discuss these metrics today?

- They were printed with some of the models that we have examined in class.
- They are used with the `auto.arima()`, which comes from the `forecast package` (loaded with `fpp2`).

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<sup>1</sup>Slides are based on [Dr. Allison Jones-Farmer's](#) lecture notes, Miami University, Spring 2020.

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## The `auto.arima()` Function [1]

The `auto.arima()` function can be used to automatically fit ARIMA models to a time series. It is a useful function, but it should be used with caution.<sup>2</sup>

### The function

- Uses “brute force” to fit many models and then selects the “best” based on a certain model criterion
- Works best when the data are stationary, but can be used with nonstationary data
- Tends to overfit the data
- Should always be used as a starting point for selecting a model and all models derived from the `auto.arima()` function should be properly vetted and evaluated.

The `auto.arima()` function combines

- Unit root tests (KPSS by default)
- Minimization of AICc to obtain an  $ARIMA(p, d, q)$  model using the following algorithm:

## The `auto.arima()` Function [2]

- ❶ Determine the number of differences,  $d$ , using a sequence of KPSS tests.
- ❷ Determine  $p$  and  $q$  by minimizing AICc after differencing the data  $d$  times. Rather than considering all possible  $p$  and  $q$  combinations, a stepwise approach is taken.
  - The best initial model with lowest AICc is selected from the following four:
    - ARIMA  $(2,d,2)$ ,
    - ARIMA  $(0,d,0)$ ,
    - ARIMA  $(1,d,0)$ , and
    - ARIMA  $(0,d,1)$ .*If  $d=0$ , then a constant,  $c$ , is included. If  $d \geq 1$ , then the constant is set to 0. The results of this step is called the current model.*
  - Variations on the current model are considered by
    - Vary  $p$  and/or  $q$  from current model by  $\pm 1$
    - Include/exclude  $c$  from current model.

## The `auto.arima()` Function [3]

- The best model considered so far (either current or one of variations) becomes the *new current model*.
- Repeat previous step until no lower AICc can be found.

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<sup>2</sup>Slides are based on [Dr. Allison Jones-Farmer's](#) lecture notes, Miami University, Spring 2020.

# Live Coding: Example 1

In class, we will use a different snapshot of the GNP data that we have explored in class so far. The purpose of this different snapshot is two-fold:

- We are not sure whether the model we fit last class would be appropriate (so this is somewhat of a revision of what to do in order to fit the “best” ARIMA model by hand).
- Walk you through the process of finding the model selected from the `auto.arima()`

```
pacman::p_load(astsa)
gnpData = gnp # will be loaded from the astsa package until 2002

# We will build on this example in class
```

## Live Coding: Example 2 (Many Datasets/Models)

Similar to what we did in class 11 (Slide 5), but using the `auto.arima()` instead of `holt()`.

```
crypto = tq_get(c('BTC-USD', 'ETH-USD', 'LTC-USD', 'ADA-USD', 'LINK-USD',  
                 'ZIL-USD'),  
               from = '2020-10-15', to = '2021-03-03')
```

```
crypto %<>% select(c(symbol, date, adjusted))  
is_grouped_df(crypto) # answer was FALSE (so we will group it)
```

```
## [1] FALSE
```

```
crypto %<>% group_by(symbol) %>% mutate(adjustedLog = log(adjusted))
```

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# Summary of Main Points

## Main Learning Outcomes

- Describe AIC, AICc, and BIC and how they are used to measure model fit.
- Describe the algorithm used within the `auto.arima()` function to fit an ARIMA model.
- Describe the results of the `auto.arima()` function.

# Things to Do to Prepare for Next Class

- Thoroughly read Chapters 6.2 – 6.8 of our textbook.
- Go through the slides, examples and make sure you have a good understanding of what we have covered.
- Go through the posted assignment (see next slide)



## Graded Assignment 17: Evaluating your Understanding

Please go to [Canvas \(click here\)](#) and answer the questions. **The assignment is due April 5, 2021 [11:40 AM, Ohio local time].**

**What/Why/Prep?** The purpose of this assignment is to evaluate your understanding and retention of ARIMA modeling. To reinforce your understanding of the covered material, I also suggest reading Chapter 6.1 – 6.8 of the book.

### General Guidelines:

- Individual assignment.
- This is **NOT** a timed assignment.
- Proctorio is NOT required for this assignment.
- You will need to have R installed (or accessible through the [Remote Desktop](#))

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