ARIMA FORECASTING & IDENTIFICATION

Dr. Susan Simmons
Institute for Advanced Analytics

Relationship Between AR and MA

- The best part about AR models and MA models is that they are the same thing – approximately.
- In certain situations (stationarity), AR models can be represented as an infinite MA model.
- In certain situations (invertible), MA models can be represented as an infinite AR model.

ARMA Model

- There is nothing to limit both an AR process and an MA process to be in the model simultaneously.
- These "mixed" models are typically used to help reduce the number of parameters needed for good estimation in the model.
- We are going to focus on the most basic model with only one lag of each piece – the ARMA(1,1) model.

$$Y_t = \omega + \phi Y_{t-1} + e_t - \theta e_{t-1}$$

ARMA(1, 1) – ACF, PACF, IACF

- Although these terms can be calculated for the ARMA(1,1) process, they become very complicated.
- There are some important things to note:
 - Characteristics from both are in the correlation functions.
 - All of the functions tail off exponentially as the lags increase.

What does the following models represent?

- ARMA(1,3)
- ARMA(4,2)
- ARMA(1,1)
- ARIMA(1,1,4)
- ARIMA(2,1,1)

MODEL SELECTION

Identification

- There are a couple of different sets of techniques used for model identification for stationary models.
 - Plotting Patterns ACF, PACF, IACF
 - 2. Automatic Selection Techniques (SAS):
 - Minimum Information Criterion MINIC
 - Smallest Canonical Correlation SCAN
 - Extended Sample Autocorrelation Function ESACF
 - 3. Automatic Selection Techniques (R):
 - auto.arima Function Similar to MINIC

Recommendation for automatic scans:

- Make sure the series is stationary (i.e. if it has a trend, or random walk, take care of it)
 - In SAS, if you take differences, it will do the scan on the differenced data
 - In SAS, if you have stationarity about the trend line, you should run the automatic procedures on the residuals (i.e. fit the regression line, get residuals and run residuals through PROC ARIMA)

Automatic Selection Techniques (SAS)

 In addition to the ACF, PACF, and IACF, there are 3 automatic methods for identifying models for the data in SAS – MINIC, SCAN, ESACF. The stationarity was already checked...

```
proc arima data=Time.Hurricanes plot(unpack);
    identify var=MeanVMax nlag=12 minic
    P=(0:12) Q=(0:12);
run;
quit;
```

Minimum Information Criterion												
Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5	MA 6	MA 7				
AR 0	4.58498	4.541439	4.539209	4.515101	4.506568	4.539417	4.508287	4.544625				
AR 1	4.601114	4.537332	4.51762	4.46991	4.479599	4.51957	4.515029	4.558396				
AR 2	4.611816	4.535499	4.511774	4.497311	4.512292	4.555764	4.550454	4.594881				
AR 3	4.53233	4.461663	4.48184	4.523381	4.534056	4.567099	4.580285	4.624875				
AR 4	4.553621	4.497145	4.517672	4.559297	4.570437	4.60408	4.617382	4.66192				

Minimum Table Value: BIC(3,1) = 4.461663

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```
proc arima data=Time.Hurricanes plot(unpack);
    identify var=MeanVMax nlag=12 scan
    P=(0:12) Q=(0:12);
run;
quit;
```

ARMA(p+d,q)
Tentative
Order Selection
Tests

SCAN

p+d q

1 1

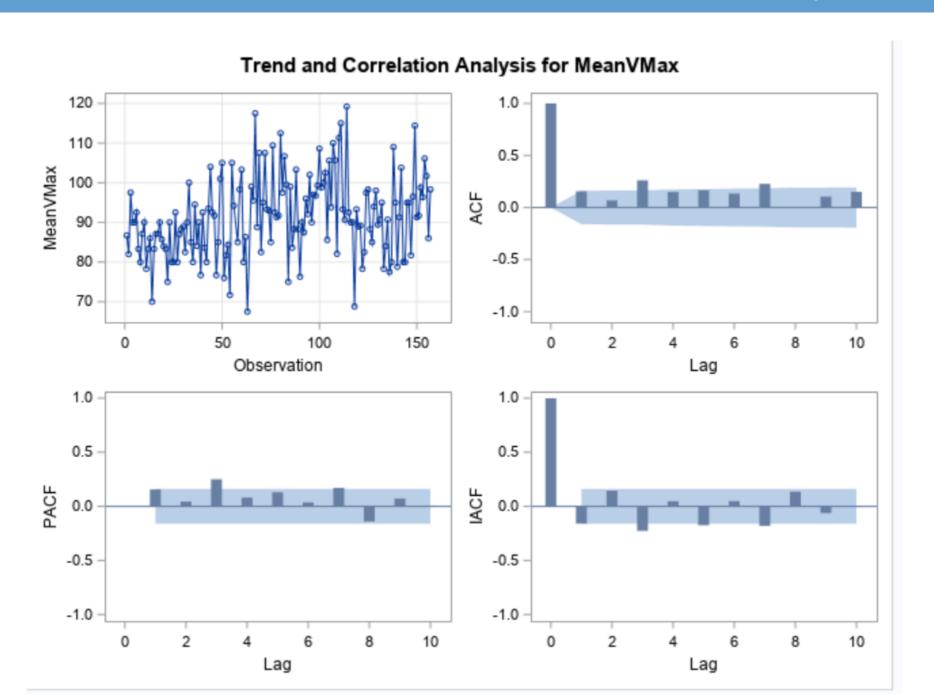
7 0

0 7

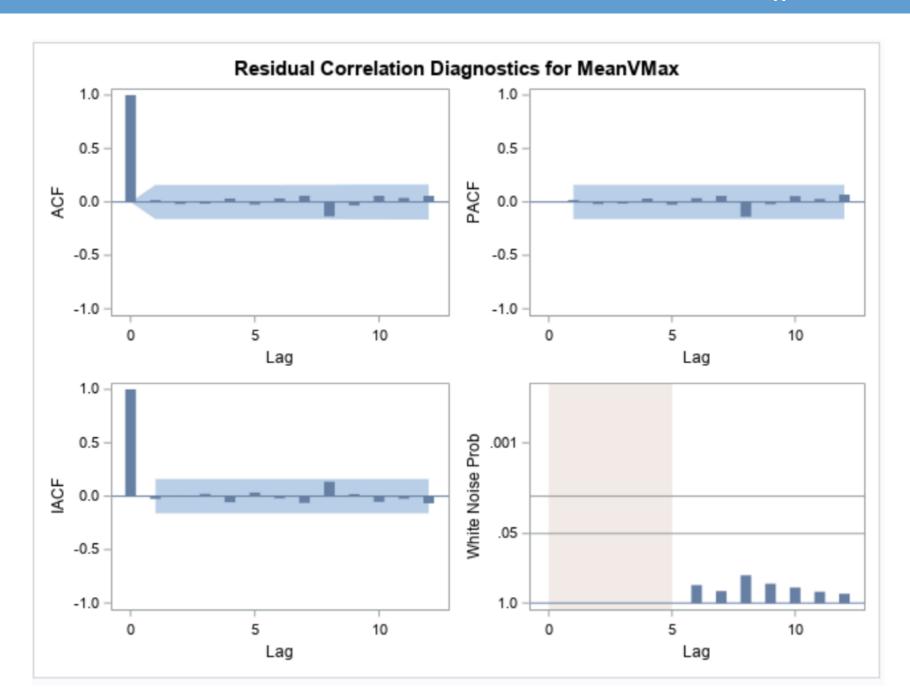
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```
proc arima data=Time.Hurricanes plot(unpack);
    identify var=MeanVMax nlag=12 esacf
    P=(0:12) Q=(0:12);
run;
quit;
```



Correlations of Parameter Estimates											
Parameter	MU	MA1,1	MA1,2	MA1,3	AR1,1	AR1,2					
MU	1.000	0.025	0.073	0.030	0.029	0.055					
MA1,1	0.025	1.000	-0.448	-0.649	0.886	-0.703					
MA1,2	0.073	-0.448	1.000	0.510	-0.486	0.845					
MA1,3	0.030	-0.649	0.510	1.000	-0.442	0.598					
AR1,1	0.029	0.886	-0.486	-0.442	1.000	-0.790					
AR1,2	0.055	-0.703	0.845	0.598	-0.790	1.000					



Automatic Selection Techniques (R)

 In addition to the ACF, PACF, and IACF, there are 2 automatic methods for identifying models for the data in R – auto.arima, EACF.

Hurricane.ts2<-Hurricane.ts%>% na_interpolation(option = "spline")

auto.arima(Hurricane.ts2)

Series: Hurricane.ts2

ARIMA(0,1,1)

Coefficients:

ma1

-0.9050

s.e. 0.0429

sigma^2 estimated as 95.59: log likelihood=-577.39 AIC=1158.79 AICc=1158.87 BIC=1164.89

Hurricane.model<-Arima(Hurricane.ts2,order=c(2,0,3)) summary(Hurricane.model)

Series: Hurricane.ts2 ARIMA(2,0,3) with non-zero mean

Coefficients:

ar1 ar2 ma1 ma2 ma3 mean 0.2387 0.6373 -0.1160 -0.7093 0.1592 91.2544 s.e. 0.1904 0.1921 0.2031 0.1439 0.1088 1.9170

FORECASTING

Estimation Methods – CLS

- Conditional Least Squares estimators are the following:
 - Generally inferior to MLE for small samples
 - More computationally efficient than MLE
 - Are the DEFAULT in PROC ARIMA
- "Conditional" least squares comes from the fact that estimation of the parameter estimates is conditioned on unobserved past values being equal to the sample mean.

Estimation Methods – MLE

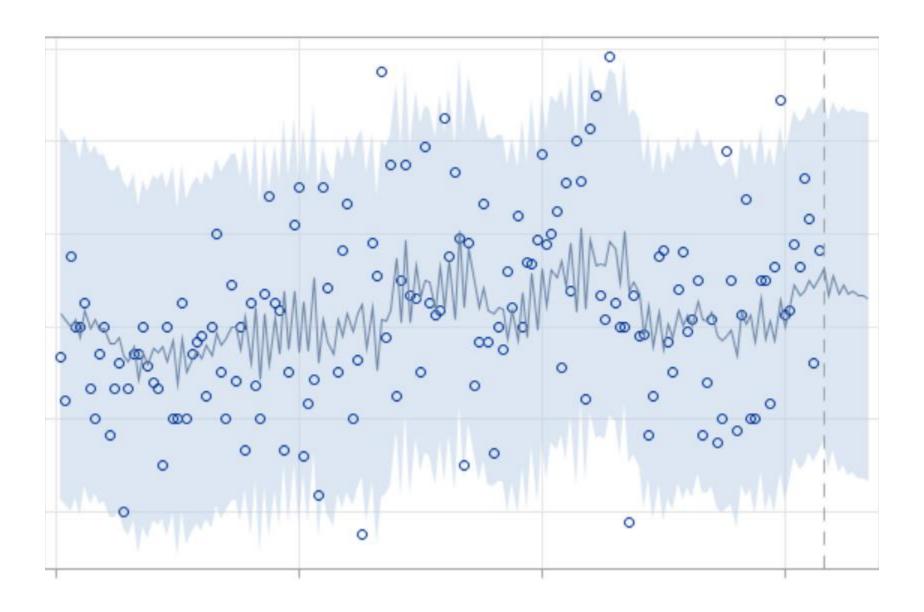
- Maximum Likelihood estimators are the following:
 - Superior to other estimates, especially in small samples.
 - Least efficient computationally, therefore not made the default when PROC ARIMA was created in 1980.
 - To help keep upward compatibility in SAS, the defaults have stayed the same in PROC ARIMA.
 - Method of choice by most forecasting professionals as well as SAS.

Optimization Algorithms

- CLS and ML algorithms are not guaranteed to find an optimal solution.
- Problems:
 - Local Maxima/Minima
 - Ridges (no improvement in any direction, but stopping rule not satisfied)
 - Stability Problems
 - Others

Forecasting – SAS

```
proc arima data=Time.Hurricanes plot=all;
    identify var=MeanVMax nlag=10;
    estimate p=___ q=___ method=ML;
    forecast lead=10;
run;
quit;
```



Forecasting – R

forecast(Hurricane.model, h = 10) plot(forecast(Hurricane.model, h = 10))

asts from ARIMA(2,0,3) with non-

