531 Final Project

-Time series analysis on US Industrial Production

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Summary

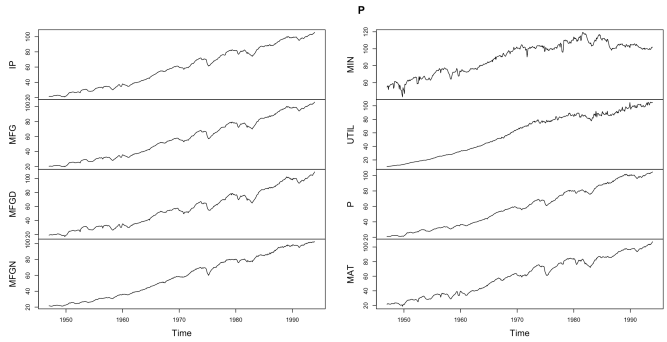
In this project, we focus on multivariate time series and thus we mainly use the tests and models which can deal with multivariate time series. First, we do the stationary and cointegration tests to see if these series have relations. Then we fit VAR and VARX model respectively for all series and the results are pretty good. In addition, we try the AFIMA model on UTIL, one of these series, and find the residual tests perform better but still bad in prediction. Finally, we give the conclusion.

Introduction

This time we would like to take a glance at the US industrial production. It is pretty important for a government to learn about the situation about its industry， which much influences the economy since industry is essential to a whole country. This times is a multivariate time series, which contains 8 components. The data set includes indices of production categorized as Industrial Production (total) (IP), All Manufacturing(MFG),manufacturing/Durable(MFGD),Manufacturing/Nondurable (MFGN), Mining (MIN), Utilities (UTIL), Products (P), Materials (MAT). These eight series are about different kind of industry. Next section we may study their relation and fit models.

Rough description data

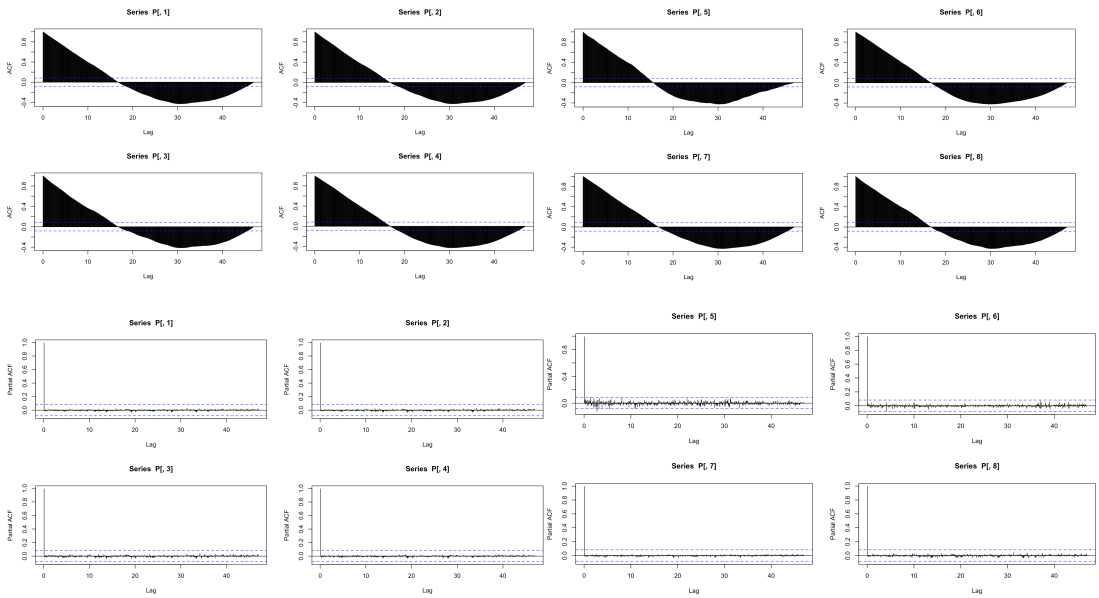
We make the original data as a time series and have the plot. From this plot we can see that our data, all kinds of industry, are generally increasing as time passed. It is interesting to see that the patterns are very similar among IP, MFG, MFGN, MAT. This may indicate that these four series may have strong relation and may be determined by a same factor or reason. Besides, the pattern of Mining is different from others since there are several apparent drops and increase at around 1950, 1974 and 1986. After 1990, all series are increasing except for Mining. Maybe there exists some other factors such as the policy of government that influence the value of Mining.



We can also get the summary of this series:

```
> summary(P)
      IP              MFG              MFGD             MFGN             MIN
 Min.   : 20.70   Min.   : 19.70   Min.   : 17.20   Min.   : 21.00   Min.   : 43.10
 1st Qu.: 34.40   1st Qu.: 32.30   1st Qu.: 31.98   1st Qu.: 32.92   1st Qu.: 73.53
 Median : 59.50   Median : 55.90   Median : 54.60   Median : 58.25   Median : 98.90
 Mean   : 59.80   Mean   : 57.45   Mean   : 56.48   Mean   : 58.85   Mean   : 89.57
 3rd Qu.: 81.62   3rd Qu.: 77.83   3rd Qu.: 76.03   3rd Qu.: 80.00   3rd Qu.:103.60
 Max.   :105.70   Max.   :106.00   Max.   :109.40   Max.   :102.40   Max.   :119.40
     UTIL              P                MAT
 Min.   : 10.00   Min.   : 21.00   Min.   : 18.80
 1st Qu.: 29.15   1st Qu.: 33.58   1st Qu.: 35.30
 Median : 66.85   Median : 58.10   Median : 61.25
 Mean   : 59.16   Mean   : 59.28   Mean   : 60.29
 3rd Qu.: 85.62   3rd Qu.: 80.20   3rd Qu.: 82.55
 Max.   :105.40   Max.   :104.70   Max.   :107.30
```

Besides, we can also have a look at acf and pacf. We can see that all series have similar acf and pacf results in the plot. The acf is first decreasing and then negatively increasing and decreasing. For pacf, it seems that all pacfs cut off after lag0. Thus we may think that all series have AR model, and thus we can fit a VAR model among this multivariate series.



Data Analysis

1. Stationary test

For better analysis, we first need to check the stationary of each series. Here, we use adf and kpss tests to check if each series is stationary. In the table, we could find that the p-values of adf tests for all series are smaller than 0.05 except for MIN and UTIL while those of kpss tests (both level and trend) for all series are smaller than 0.01. The results imply that most series have a heteroskedasticity or structural break.

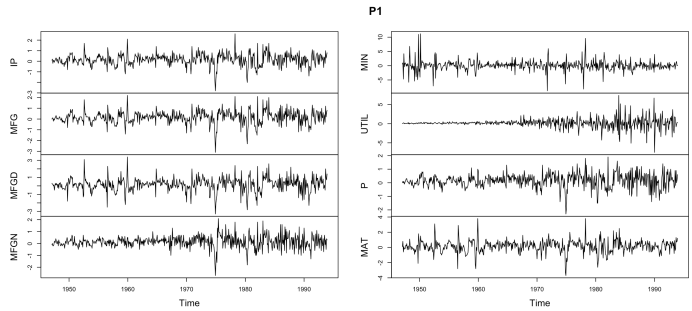
	IP	MFG	MFGD	MFGN	MIN	UTIL	P	MAT
adf	<0.01	0.02418	0.0491	0.04228	0.7955	0.9722	0.03206	<0.01
Kpss(level)	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Kpss(trend)	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

After taking the difference of them, we try those tests again:

	diff(IP)	diff(MFG)	diff(MFGD)	diff(MFGN)	diff(MIN)	diff(UTIL)	diff(P)	diff(MAT)
adf	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01
Kpss(level)	>0.1	>0.1	>0.1	>0.1	>0.1	>0.1	>0.1	>0.1
Kpss(trend)	>0.1	>0.1	>0.1	>0.1	>0.1	>0.1	>0.1	>0.1

Now we can see that all series are stationary. The test results also suggest that each series is $\mathbf{I}(1)$.

Therefore, we would study the difference of the series instead of the original data. We can see the plot of the data taken difference:



2. cointegration test

Since this is a multivariate time series we are studying, we would like to see if there exists cointegration.

We try several tests here, and give the test results:

2.1 Engle-Granger conintergration test

```
      1pct  5pct 10pct
tau1 -2.58 -1.95 -1.62
                tau1
statistic -24.44481
                tau1
statistic -25.20897
                tau1
statistic -23.21884
                tau1
statistic -22.46685
                tau1
statistic -20.35981
                tau1
statistic -20.21795
                tau1
statistic -20.70671
                tau1
statistic -20.14294
```

We do the Engle-Granger cointergration test. From the results, we can get th critical values at certain levels of confidence: 10%, 5% and 1% respectively an the statistics for each time series. From the output we can see that overall a eight statistics are smaller than the 1% level. Therefore, the residuals ar stationary. Thus, they all reject the null hypothesis and they are cointergratec [,2], X[,4] and X[,5] are strongly smaller than 1% level. Therefore the residual are stationary. Thus, they all reject the null hypothesis and they ar cointergrated.

2.2 Pillips-Ouliaris conintergration test

Now we try on Pillips-Ouliaris cointegaration test and give the results:

```
                 10pct    5pct    1pct
critical values 50.3537 57.7855 76.7705          [1] 364.612
```

The value of the statistics we compute is much larger than 1% level. Therefore, we can reject the null hypothesis that there is no cointegration.

2.3 Johansen procedure

```
            10pct   5pct   1pct
r <= 7 |     7.52   9.24  12.97
r <= 6 |    17.85  19.96  24.60
r <= 5 |    32.00  34.91  41.07
r <= 4 |    49.65  53.12  60.16
r <= 3 |    71.86  76.07  84.45
r <= 2 |    97.18 102.14 111.01
r <= 1 |   126.58 131.70 143.09
r = 0  |   159.48 165.58 177.20
```

```
[1]   3.989631  15.940530  35.322968  59.372269 103.666505 166.754880 250.232877
[8] 361.077133
```

Obviously, we do reject r<=5 and accept r<=6. That is, we assume r=6 which also means there is cointegration.

3. Granger test

3.1 Granger causality test

	F-statistic	p-value
MFG -> IP	1.8920	0.0589
MFGD -> IP	1.5391	0.1408
MFGN -> IP	3.6108	0.0004
MIN -> IP	2.0040	0.0440
UTIL -> IP	1.0735	0.3801
P -> IP	1.4667	0.1664
MAT -> IP	1.6641	0.1044
IP -> MFG	2.9911	0.0027
MFGD -> MFG	2.5939	0.0087
MFGN -> MFG	3.1350	0.0018
MIN -> MFG	2.4370	0.0135
UTIL -> MFG	1.6089	0.1193
P -> MFG	1.3366	0.2225
MAT -> MFG	3.7884	0.0002
IP -> MFGD	5.5232	0.0000
MFG -> MFGD	5.2798	0.0000
MFGN -> MFGD	5.0828	0.0000
MIN -> MFGD	2.8288	0.0044
UTIL -> MFGD	1.1434	0.3322
P -> MFGD	3.3137	0.0010
MAT -> MFGD	4.9851	0.0000
IP -> MFGN	3.6962	0.0003
MFG -> MFGN	2.3291	0.0183
MFGD -> MFGN	2.2608	0.0221
MIN -> MFGN	1.3050	0.2382
UTIL -> MFGN	3.1340	0.0018
P -> MFGN	3.1603	0.0017
MAT -> MFGN	2.3507	0.0172
IP -> MIN	2.6863	0.0067
MFG -> MIN	2.2473	0.0229
MFGD -> MIN	2.3275	0.0184
UTIL -> MIN	2.4694	0.0124
P -> MIN	2.2073	0.0256
MAT -> MIN	3.7612	0.0003
IP -> UTIL	1.9875	0.0460
MFG -> UTIL	2.6538	0.0073
MFGD -> UTIL	2.3393	0.0178
MFGN -> UTIL	3.1133	0.0019
MIN -> UTIL	0.8052	0.5982
P -> UTIL	3.2351	0.0013
MAT -> UTIL	1.4625	0.1681
IP -> P	2.6716	0.0069
MFG -> P	1.8145	0.0718
MFGD -> P	0.5007	0.8560
MFGN -> P	2.9746	0.0029
MIN -> P	1.3735	0.2053
UTIL -> P	2.2200	0.0247
MAT -> P	2.8972	0.0036
IP -> MAT	4.6005	0.0000
MFG -> MAT	5.4966	0.0000
MFGD -> MAT	2.9697	0.0029
MFGN -> MAT	6.7027	0.0000
MIN -> MAT	2.8077	0.0047
UTIL -> MAT	0.7523	0.6451
P -> MAT	5.2150	0.0000

By using 8 past observations, we can see generally the p-values are smaller than 0.05. 8 observations do help IP to forecast other series since the p-values are smaller than 0.05, which is pretty reasonable. And it is a little hard to use Mining to predict other series. But in general, those series can predict other some series, which shows their relation in real world.

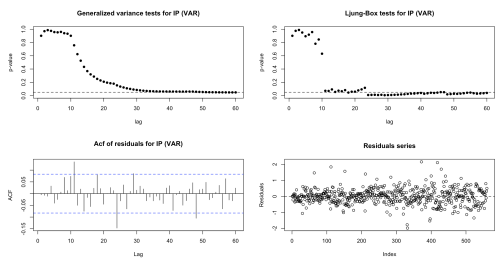
4. Fit VAR model

We try to fit the data with VAR model, and do the residual analysis and prediction:

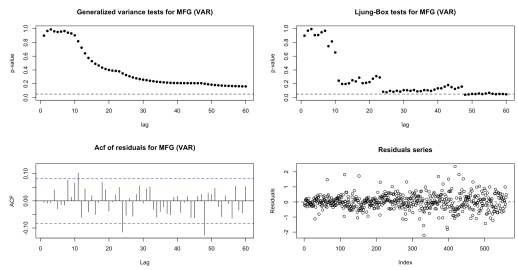
4.1 Residual analysis

After fitting the model, we compute the residual for each series. And we apply the Generalized variance test and Ljung-Box test to check if the model fits each series well.

For IP:

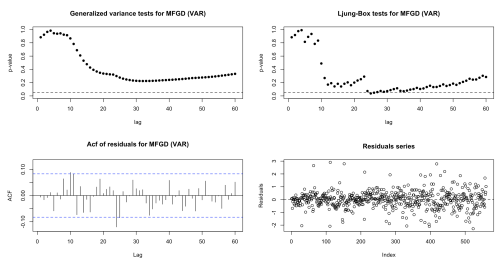


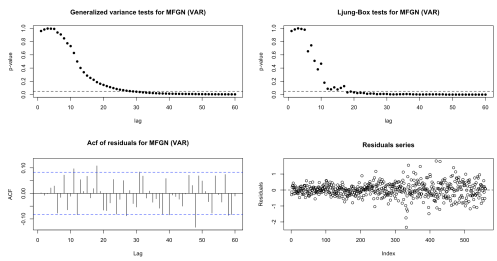
For MFG:



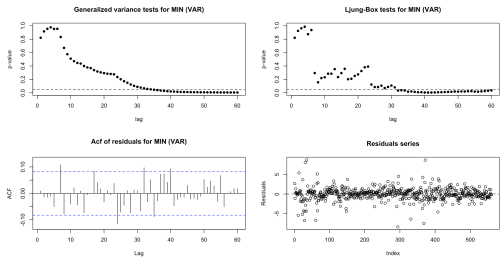
For MFGD:

For MFGN:

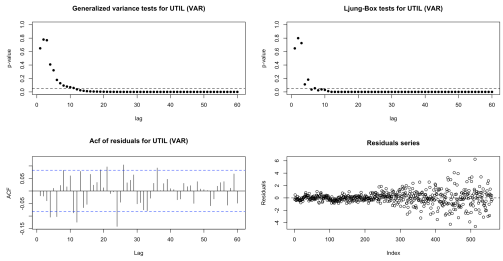




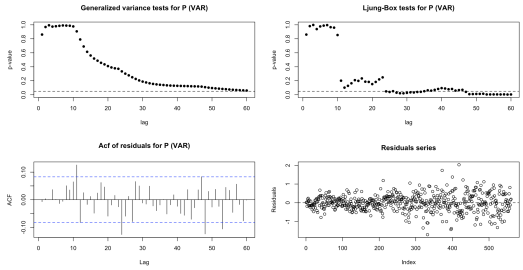
For MIN:



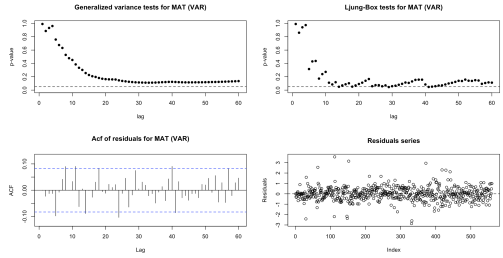
For UTIL:



For P:



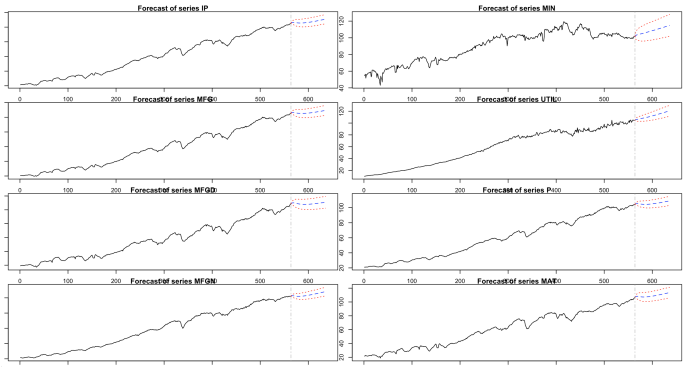
For MAT:

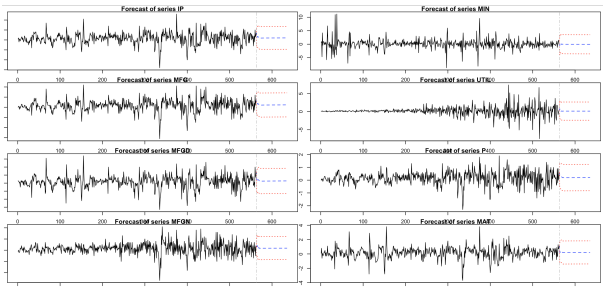


We can see that the test results of residuals perform pretty well, showing that many p-values are far from 0. This indicates that the residuals are very close to white noise, which is what we want. In a word, VAR model works well for our data.

4.2 Prediction of VAR

Based on VAR model, we do the prediction in 6 years:





The forecast shows that in future the indices of all kinds of industry are still increasing for 6 years.

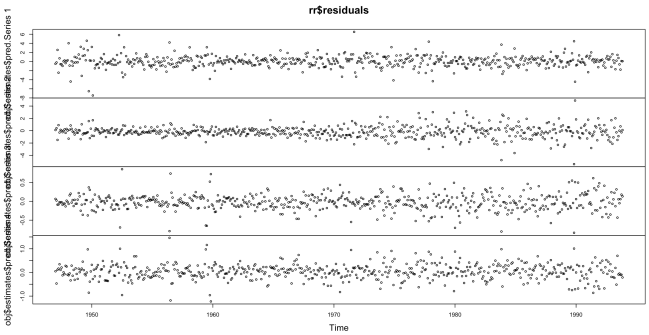
5. Fit VARX model

5.1 Four inputs and Four outputs

We regard the LRM, LRY and LPY as input and the IBO and IDE as output. Then we fit the VARX model. We check the stability and the residuals of this model. The output shows that this model is stable. The residuals are nearly all 0. Finally, we do the forecast and give the plots, too.

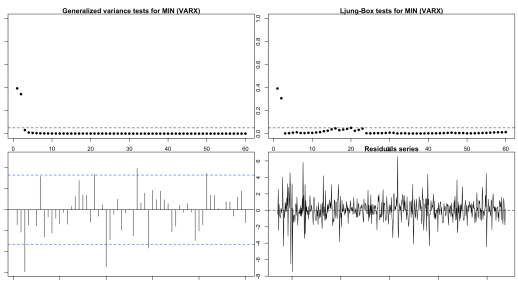
```
The system is stable.
[1] TRUE
```

5.1.1 Residual analysis

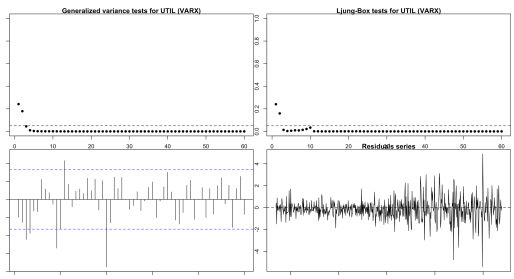


The residuals of this model are around 0. We can also use Generalized variance test and Ljung-Box test to check the residuals:

For MIN:

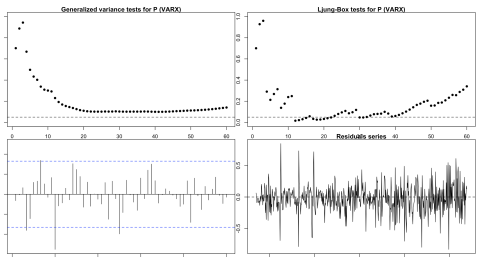


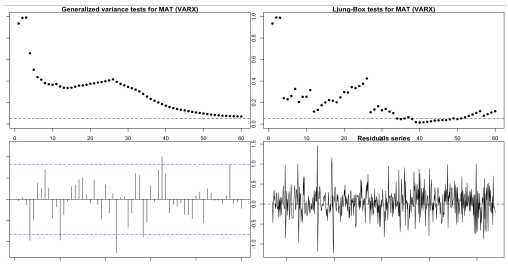
For UTIL



For P:

For MAT:

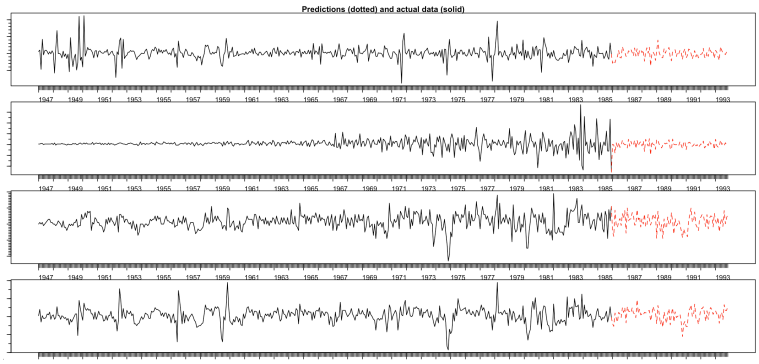




For MIN and UTIL, we can see the residual tests show many p-values are 0, which means the linear models are not suitable for MIN and UTIL. Using first four factors to predict MIN and UTIL performs bad. However, they can successfully do the regression on both P and MAT since the residual tests show the residuals are close to white noise.

5.1.2 Prediction of VARX

In addition, we use the data to do the forecast from 1986 to 1993 on MIN, UTIL, P and MAT:



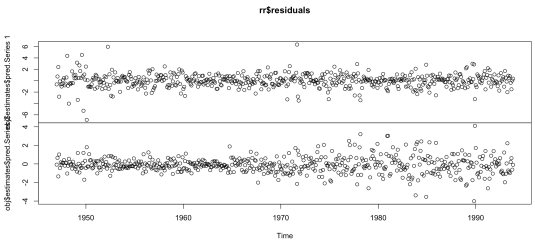
We can see the forecast on these four components is quite similar to the original log(P1).

5.2 Six inputs and two outputs

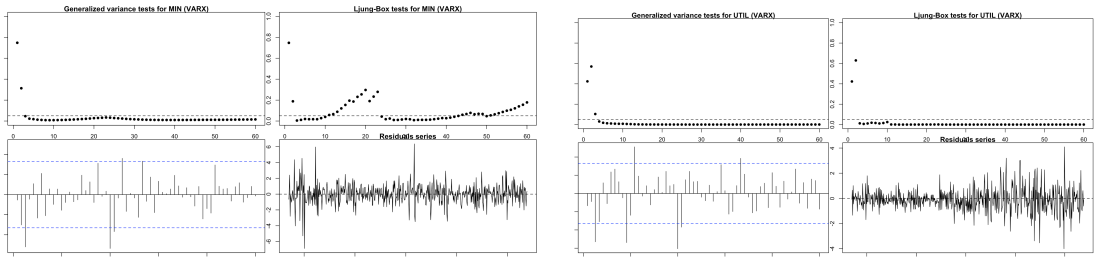
According to what we have tried, the model on MIN and UTIL is not so good. We would like to regard these two factors as output while others as input.

5.2.1 Residual analysis

After fitting this new model, we can compute and plot the residuals: It seems that the residuals are around 0.



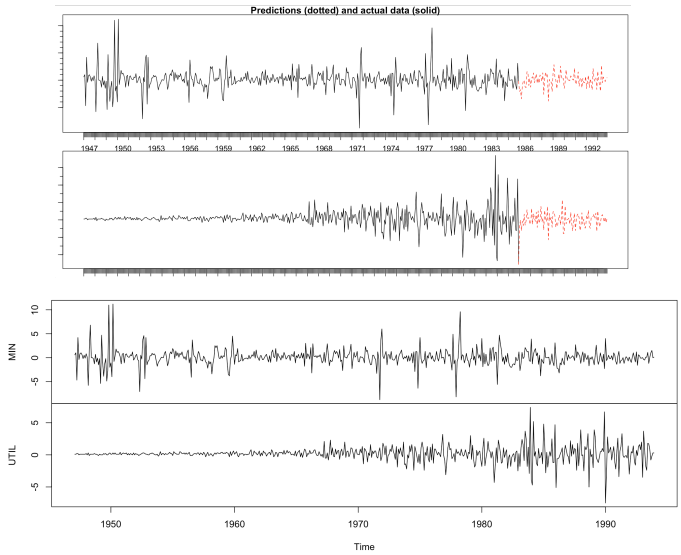
We can check it by a further step: using Generalized variance test and Ljung-Box test.



Though the p-value performs better in Ljung-Box test for MIN than it does before, unfortunately, the results still suggest this model is not good for regression on MIN and UTIL because the majority of p-values are 0.

5.2.2 Prediction of VARX

We can still take a glance at the prediction on MIN and UTIL, compared with the original data.



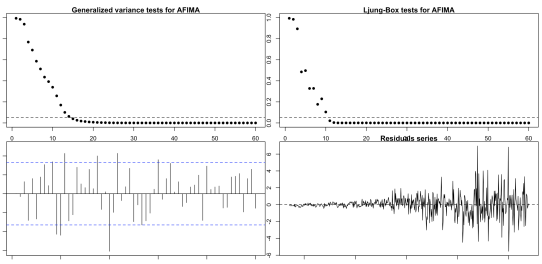
By comparing with the original data, we can see the prediction is still biased, especially for UTIL. This indicates that UTIL may be influenced by some other factors and we may try other models on UTIL respectively.

6. AFIMA for UTIL

Since UTIL is a little different from other series, we would like to try to fit the AFIMA model on UTIL.

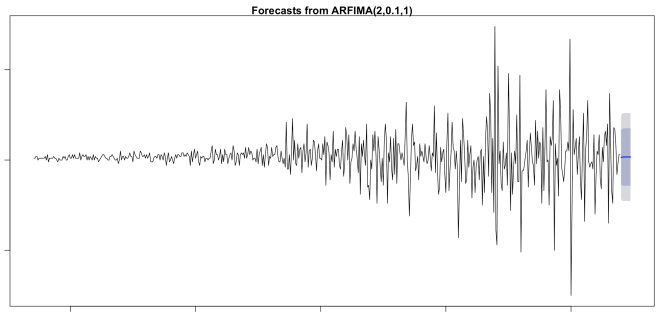
By fitting the AFIMA, we find the estimate d=0.1. Thus, our AFIMA model is AFIMA(2,0.1,1).

6.1 Residual analysis



As is shown, those two tests of residual perform better than those in VAR and VARX. More p-values are larger than 0. This indicates that this model is better for UTIL.

6.2 Prediction of AFIMA



However, when we do the forecast, the prediction performs not so well as residual analysis. In a word, this model is still not good enough to give a good prediction for UTIL. Maybe AFIMA is not the best model for it or there is no one that could fit the UTIL very well since the theory is always different from the real world.

Conclusion

In conclusion, to analyze this multivariate time series, we check their stationary and cointegration. Since there does exist cointegration among them, it shows that those series own relation with others, like linear combination. Therefore, we then try VAR model and VARX model. After doing residual analysis, we find the model in general, fit the data well since the residuals are close to white noise. But for UTIL, the results preform bad. It indicates that we may use other models to fit this data. After using the AFIMA, though the residual diagnosis works better, the prediction is still bad. As we once mentioned before, government policy, weather condition and economical condition may all be the factors that can influence the utility. As what we have been told in class that in the real world, many theories may not work so well since maybe there are too many potential factors in the real world which we cannot describe by formulas. Unfortunately, for UTIL, we might not find one that is the really perfect and useful enough to fit it.

Reference

1.Data source

http://www2.stat.duke.edu/~mw/ts_data_sets.html

http://www2.stat.duke.edu/~mw/data-sets/ts_data/industrial_production