Time Series with ARIMAS

MSDS 7333

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World Changers Shaped Here

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ARIMAS

- AutoRegressive
- Integrated
- Moving Average

My my my, that’s a lot of fancy words

- Yes
- Autoregressive
  - Current prediction depends on the past results
  - Similar to a Markov chain, but can be longer than 1 step
- Integrated
  - Not only is the past result import, but the DIFFERENCES between the past results are important
- Moving Average
  - The average of previous results is also important

Where to start

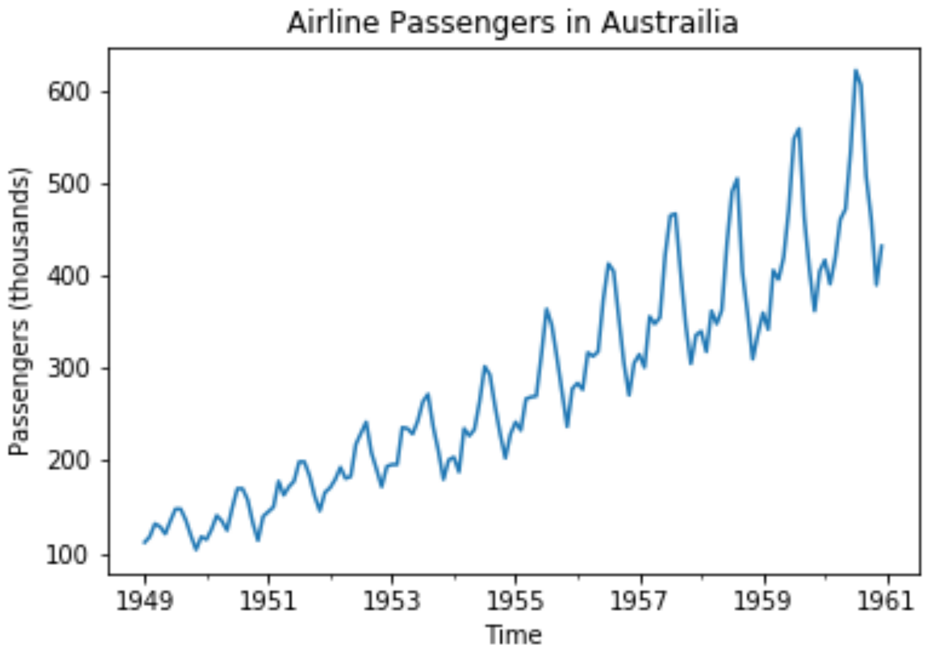
- ARIMAS is really a group of models with three parameters:
  - p: autoregressive part
  - d: Integrated part
  - q: Moving average part
- The trick is to find the right (p,d,q) combination to properly fit your model

- Thanks, Captain Obvious!

Requirements

- Time Series
  - Linear time only (sorry, Special Relativity)
- The series must be stationary
  - No trends
  - No seasonal patterns
    - Really? Yeah, really
  - This seems like a very strict requirement
    - Yup

So how do we model something like this?

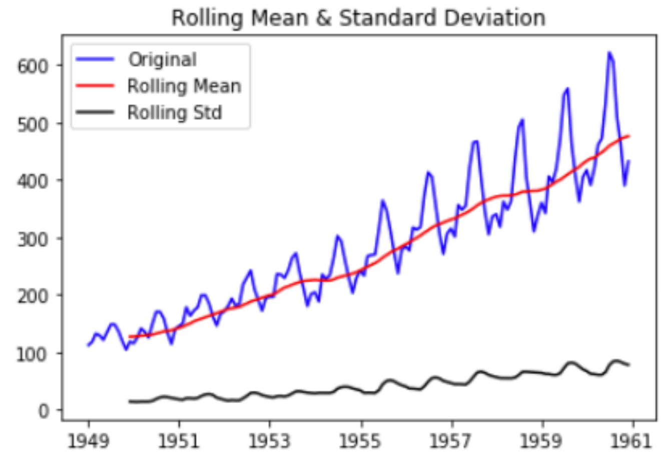


- It has a trend
- It has a seasonal Pattern
- Pretty sure it is not stationary

Make it stationary!

- What does stationary mean, anyway?
  - Separate lecture
  - Short answer: Apply the Dickey-Fuller Test
  - Shorter answer: No Trends!

Look at our Example



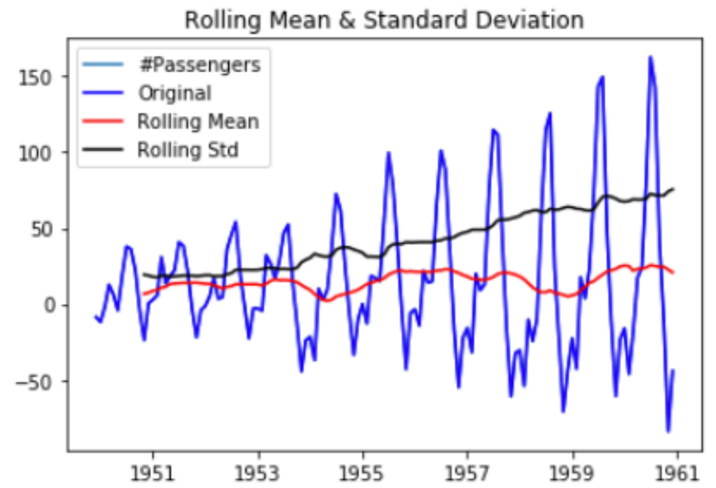

```
Results of Dickey-Fuller Test:
Test Statistic                   0.815369
p-value                          0.991880
#Lags Used                      13.000000
Number of Observations Used    130.000000
Critical Value (1%)             -3.481682
Critical Value (5%)             -2.884042
Critical Value (10%)            -2.578770
dtype: float64
```

Obvious Trend (NON STATIONARY!)

Test Statistic is greater than critical value(s)

'Lags' is just the number of values to compute rolling statistics.
In this case 12(+1)

Let's get rid of the mean

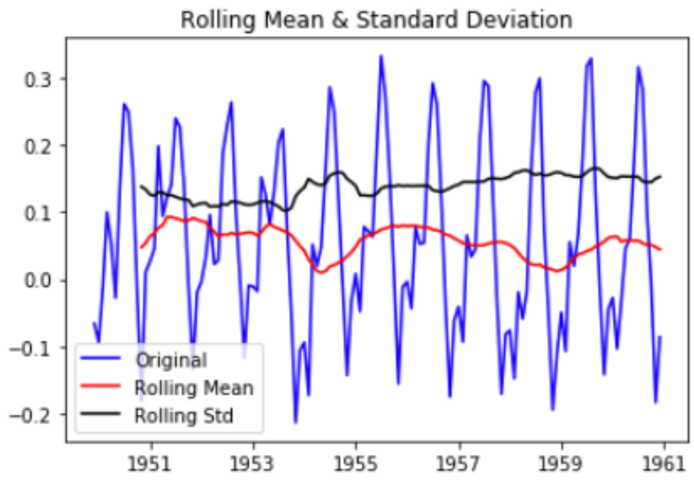


Results of Dickey-Fuller Test:

Test Statistic	-3.164968
p-value	0.022104
#Lags Used	13.000000
Number of Observations Used	119.000000
Critical Value (1%)	-3.486535
Critical Value (5%)	-2.886151
Critical Value (10%)	-2.579896

- Hmm…there still seems to be an increasing pattern over time, but it passes the stationary test!!
- DANGER, WILL ROBINSON!!!

Much better after log transform




```
Results of Dickey-Fuller Test:
Test Statistic                  -3.162908
p-value                          0.022235
#Lags Used                      13.000000
Number of Observations Used    119.000000
Critical Value (1%)             -3.486535
Critical Value (5%)             -2.886151
Critical Value (10%)            -2.579896
```

- Still need to deal with our seasonality!
- Notice the stats didn't actually change!

But why 12 for moving average?

- Seasonality to Data
- Using 5 doesn’t work as well…
- Using the rolling average is important

So we got the series stationary - now what?

- Time to find p, d, q
  - Use intuition
  - Use ~~high explosive~~ brute force

Intuition Method

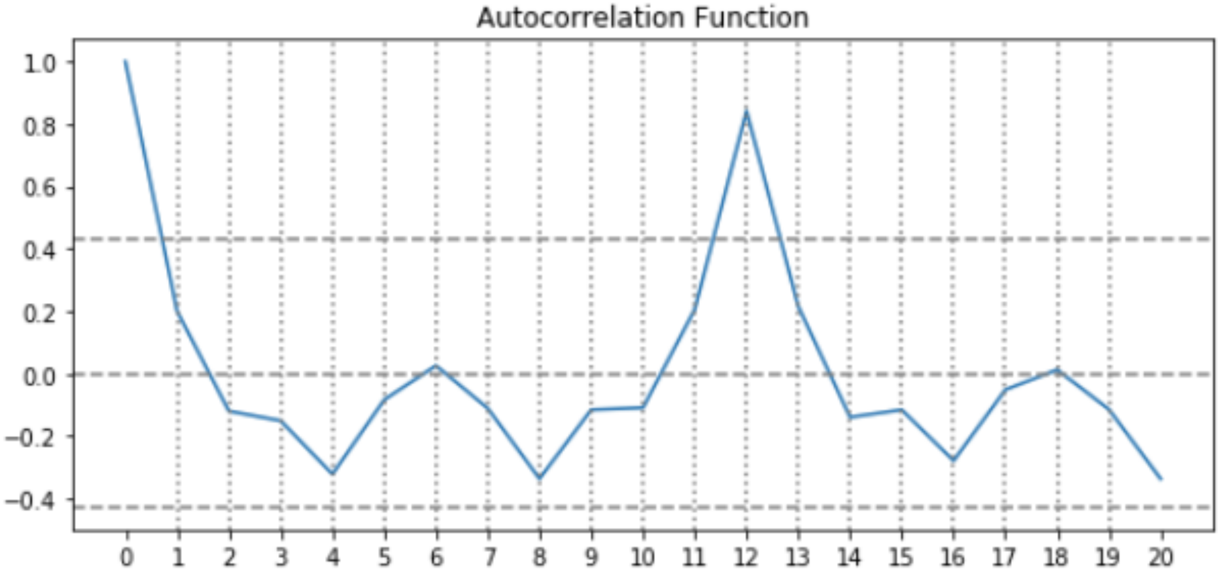
- Use Autocorrelation, Partial Autocorrelation

Rules for ‘d’

Identifying the order of differencing and the constant:

- Rule 1: If the series has positive autocorrelations out to a high number of lags (say, 10 or more), then it probably needs a higher order of differencing.
- Rule 2: If the lag-1 autocorrelation is zero or negative, or the autocorrelations are all small and patternless, then the series does *not* need a higher order of differencing. If the lag-1 autocorrelation is -0.5 or more negative, the series may be overdifferenced. **BEWARE OF OVERDIFFERENCING.**
- Rule 3: The optimal order of differencing is often the order of differencing at which the standard deviation is lowest. (Not always, though. Slightly too much or slightly too little differencing can also be corrected with AR or MA terms. See rules 6 and 7.)
- Rule 4: A model with <u>no</u> orders of differencing assumes that the original series is stationary (among other things, mean-reverting). A model with <u>one</u> order of differencing assumes that the original series has a constant average trend (e.g. a random walk or SES-type model, with or without growth). A model with <u>two</u> orders of total differencing assumes that the original series has a time-varying trend (e.g. a random trend or LES-type model).
- Rule 5: A model with <u>no</u> orders of differencing normally includes a constant term (which allows for a non-zero mean value). A model with <u>two</u> orders of total differencing normally does <u>not</u> include a constant term. In a model with <u>one</u> order of total differencing, a constant term should be included if the series has a non-zero average trend.

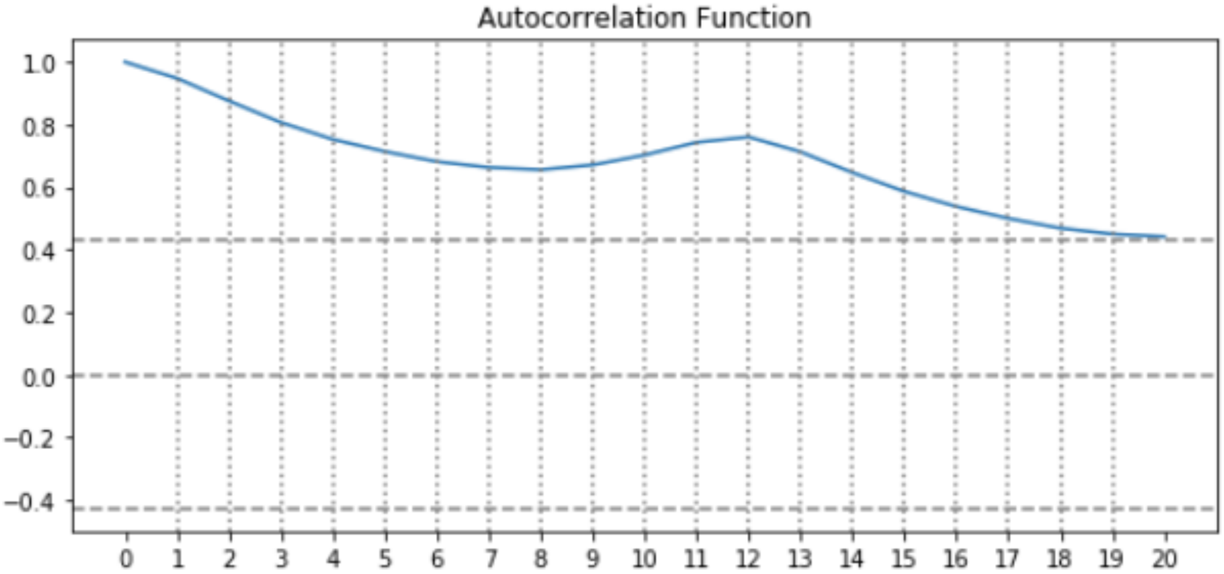
‘d’ examples (our differenced/stationary plot)



Rule 1: NO
(almost immediately drops below UCL)

Rule 2: Yes
At label 1 the value is ~ 0

‘d’ example (raw airline population)



Rule 1: Yes—above UCL to 20

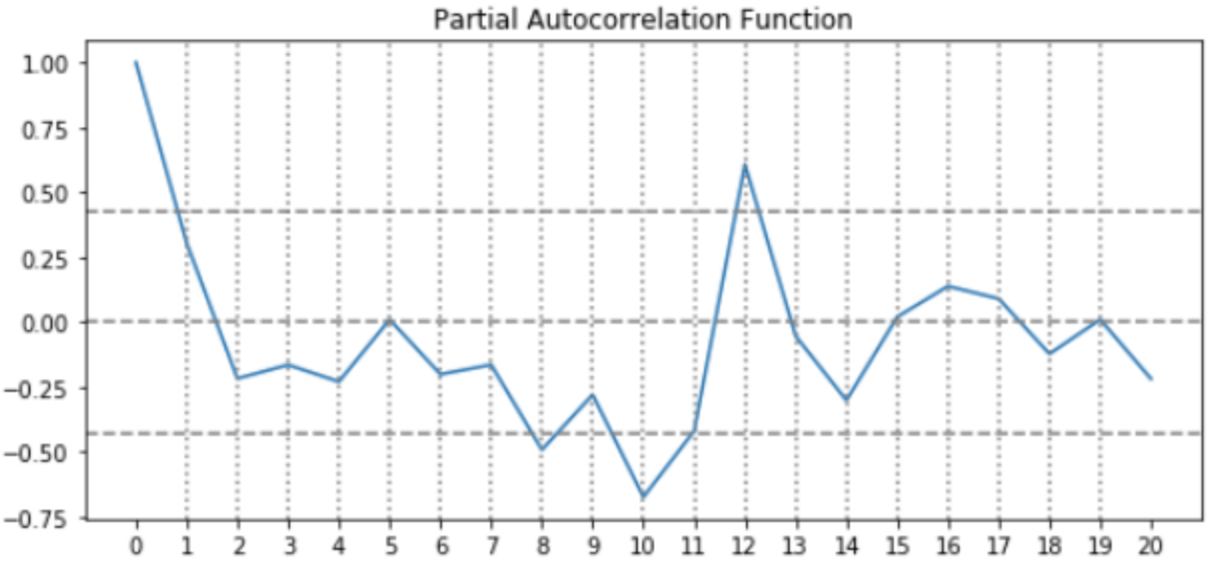
Rule 2: No. At label 1 the value is ~ 2X UCL

Rules for ‘p’, ‘q’

Identifying the numbers of AR and MA terms:

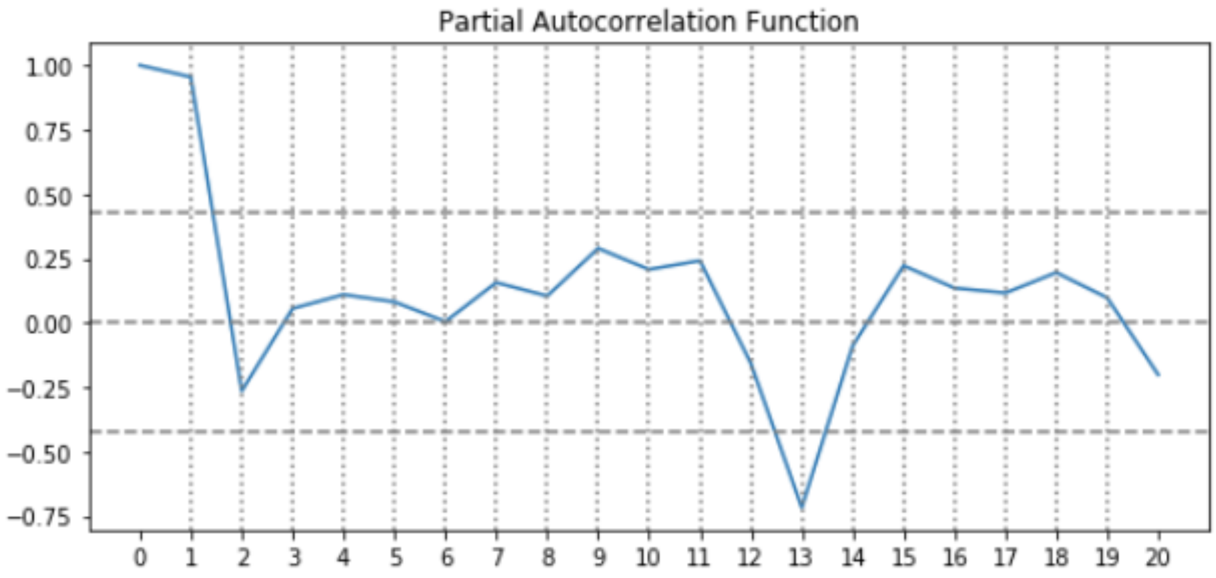
- Rule 6: If the partial autocorrelation function (PACF) of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is positive--i.e., if the series appears slightly "underdifferenced"--then consider adding one or more AR terms to the model. The lag beyond which the PACF cuts off is the indicated number of AR terms.
- Rule 7: If the autocorrelation function (ACF) of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is negative--i.e., if the series appears slightly "overdifferenced"--then consider adding an MA term to the model. The lag beyond which the ACF cuts off is the indicated number of MA terms.
- Rule 8: It is possible for an AR term and an MA term to cancel each other's effects, so if a mixed AR-MA model seems to fit the data, also try a model with one fewer AR term and one fewer MA term--particularly if the parameter estimates in the original model require more than 10 iterations to converge. **BEWARE OF USING MULTIPLE AR TERMS AND MULTIPLE MA TERMS IN THE SAME MODEL.**
- Rule 9: If there is a unit root in the AR part of the model--i.e., if the sum of the AR coefficients is almost exactly 1--you should reduce the number of AR terms by one and increase the order of differencing by one.
- Rule 10: If there is a unit root in the MA part of the model--i.e., if the sum of the MA coefficients is almost exactly 1--you should reduce the number of MA terms by one and reduce the order of differencing by one.
- Rule 11: If the long-term forecasts* appear erratic or unstable, there may be a unit root in the AR or MA coefficients.

Example



All rules: No

Example



1 AR term (rule 6)

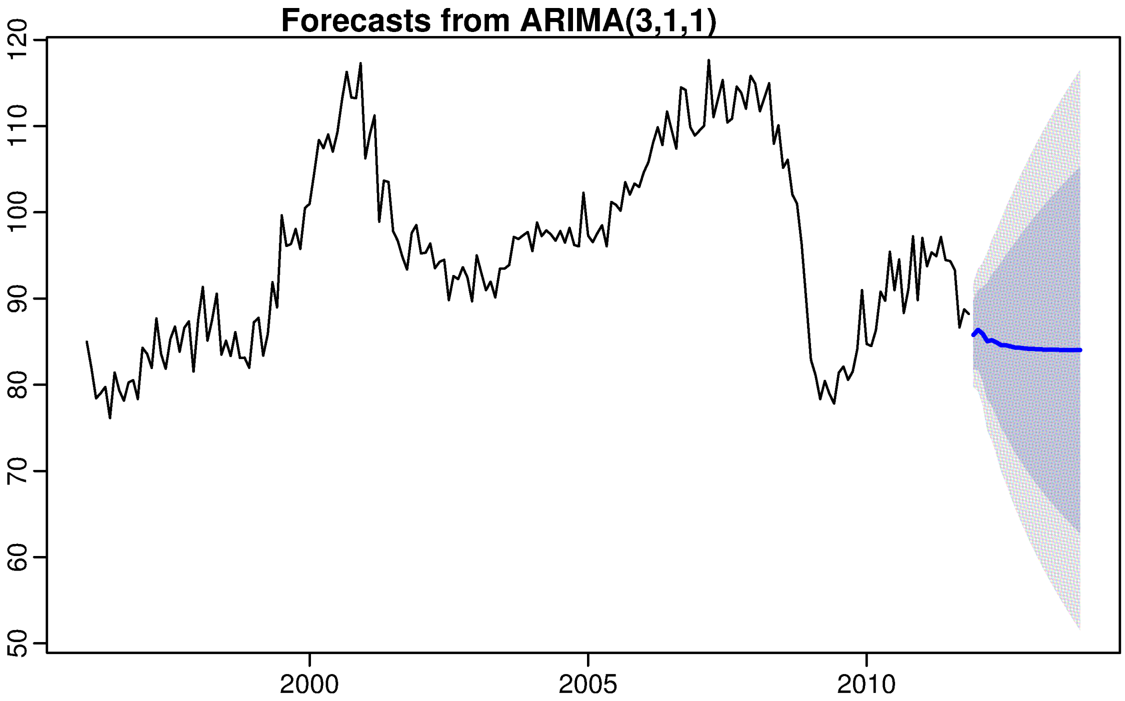
Brute Force (Grid Search)

- Generally the parameters p, d, q are between 0 and 3
- So we only need 27 runs to get the best fit
- Use them all in a for loop

But wait

- ARIMAS is nice as there are only 3 parameters that take on discrete values
- Linear regression has 2 parameters we can vary over a huge range (continuous)
  - N * M values (N, M are the paranters)
  - ~ n^2 pick 5 each, 25 runs
- XGBOOST has 5-6 tuning parameters
  - N^5 pick 5 each 3125 runs….
- It pays to know what your parameters do!!!!

We didn’t talk about prediction!!!



- Predict 1 point at a time
- Horrible confidence intervals

References

- https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/
- https://people.duke.edu/~rnau/411arim.htm
- https://machinelearningmastery.com/arima-for-time-series-forecasting-with-python/

Assignment

- Pick a stock
  - Any stock
- Get 4 years worth of data
- Try and estimate the parameters p, d, q using techniques discussed for the stock data
- Do a grid search for parameters
- What is your final decision on parameters and WHY

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