ATOC7500 – Application Lab #2
Regression, Autocorrelation, Red Noise Timeseries
in class Feb. 10/15, 2022

Notebook #1 – Autocorrelation and Effective Sample Size using Fort Collins, Colorado weather observations
ATOC5860_applicationlab2_AR1_Nstar.ipynb

LEARNING GOALS:
1) Calculate the autocorrelation at a range of lags using two methods available in python (np.correlate, dot products)
2) Estimate the effective sample size (N*) using the lag-1 autocorrelation
3) Evaluate the influence of changing the sampling frequency and the specified weather variable on the memory/redness of the data as quantified by the autocorrelation and N*.

DATA and UNDERLYING SCIENCE:
In this notebook, you will analyze the memory (red noise) in weather observations from Fort Colins, Colorado at Christman Field. The observations are from one year, but are sampled hourly. The default settings for the notebook analyze the air temperature in degrees F sampled once daily (every midnight). But other standard weather variables and sampling frequencies can also be easily analyzed. The file containing the data is called christman_2016.csv and it is a comma-delimited text file.

Non-exhaustive Questions to guide your analysis of Notebook #1:

1) Start with the default settings in the code. In other words – Read in the data and find the air temperature every 24 hours (every midnight) over the entire year. Calculate the lag-1 autocorrelation using np.correlate and the direct method using dot products. Compare the python syntax for calculating the autocorrelation with the formulas in Barnes. Equation numbers are provided to refer you back to the Barnes Notes. What is the lag-1 autocorrelation?

The lab-1 autocorrelation is 0.846 for both methods (np.correlate and the dot product equation).

2) Calculate the autocorrelation at a range of lags using np.correlate and the direct method using dot products. Compare the python syntax for calculating the autocorrelation with the formulas in Barnes. Equation numbers are provided to refer you back to the Barnes Notes. How does the autocorrelation change as you vary the lag from -40 days to +40 days?

The autocorrelation seems to be symmetric about 0 with the lowest autocorrelation at ±40. It increases gradually as we approach 0 from ±40, but then spikes at 0.

3) Calculate the effective sample size (N*) and compare it to your original sample size (N). Equation numbers are provided to refer you back to the Barnes Notes. How much memory is there in temperature sampled every midnight?

Of the 366 observations, only 31 provide independent information—that's less than 10%! The autocorrelation is 0.846, so temperature has a lot of memory.

4) Now you are ready to tinker … i.e., make minor adjustments to the code with the parameters set in the code to see how your results change. *Suggestion: Make a copy of the notebook for your tinkering so that you can refer back to your original answers and the unmodified original code.* For example: Repeat steps 1-3) above with a different variable (e.g., relative humidity (RH), wind speed (wind_mph)). Repeat steps 1-3) above with a different temporal sampling frequency (e.g., every 12 hours, every 6 hours, every 4 days). How do your answers change?

Variables like relative humidity and pressure had very high autocorrelation on daily timescales, which only increases on higher temporal scales. Other variables like wind were not autocorrelated on daily timescales, but were fairly well correlated on hourly timescales.

Notebook #2 – Red noise time series generation, Regression, and Statistical Significance Testing While Regressing

ATOC5860_applicationlab2_AR1_regression_AO.ipynb

LEARNING GOALS:

1) Calculate and analyze the autocorrelation at a range of lags using output from an EOF analysis (the Arctic Oscillation Index).
2) Generate a red noise time series with equivalent memory as an observed time series (i.e., given lag-1 autocorrelation).
3) Correlate two time series and calculate the statistical significance.
4) Evaluate the statistical significance obtained in the context of the number of chances provided for success. What happens when you go "fishing" for correlations and give yourself lots of opportunity for success? Can you critically evaluate the chances that your regression is statistically different than 0 just by chance?

DATA and UNDERLYING SCIENCE:

In this notebook, you will analyze the monthly Arctic Oscillation (AO) timeseries from January 1950 to present. The AO timeseries comes from an Empirical Orthogonal Function (EOF) analysis. We will implement EOFs in the next application lab so in this lab we are actually using multiple analysis methods introduced in this class, some that you have learned and some that you are still yet to learn ☺.

How do you find the AO value each month? To identify the atmospheric circulation patterns that explain the most variance, NOAA regularly applies EOF analysis to the monthly mean 1000-hPa height anomalies poleward of 20° latitude for the Northern Hemisphere. The AO spatial pattern (Figure 1 below) emerges as the first EOF (explaining the most variance, 19%). The AO timeseries we will analyze is a measure of the amplitude of the pattern in Figure 1 in a given month. In other words – the AO timeseries is the first principal component (a timeseries) associated with the first EOF (a spatial structure). More information on the EOF analysis here:
http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/history/method.shtml

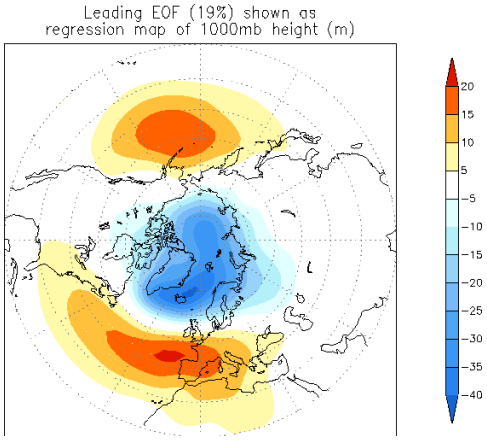


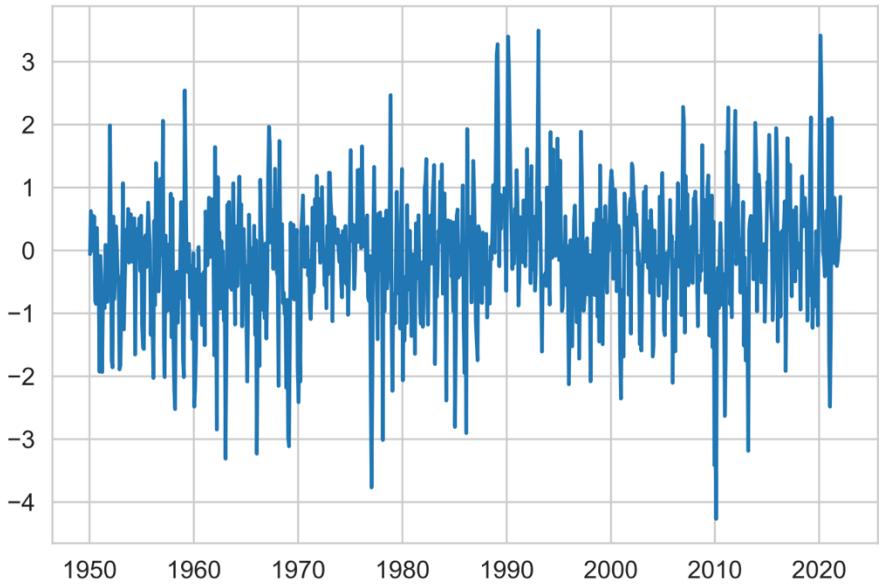
Figure 1. The loading pattern of the Arctic Oscillation (AO), i.e., the structure explaining the most variance of monthly mean 1000mb height during 1979-2000 period. In other words – this is the first EOF.

The data are available and regularly updated here:
http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/norm.nao.monthly.b5001.current.ascii

You can work with the data directly on the web (assuming you have an internet connection). I have also downloaded the data and made them available – The name of the data file is "monthly.ao.index.b50.current.ascii".

Questions to guide your analysis of Notebook #2:

1) Start with the default settings in the code. First read in the Arctic Oscillation (AO) data. Look at your data!! Plot it as a timeseries. Save the timeseries plot as a postscript file and put it in this document.



y-axis: AO index, x-axis: time

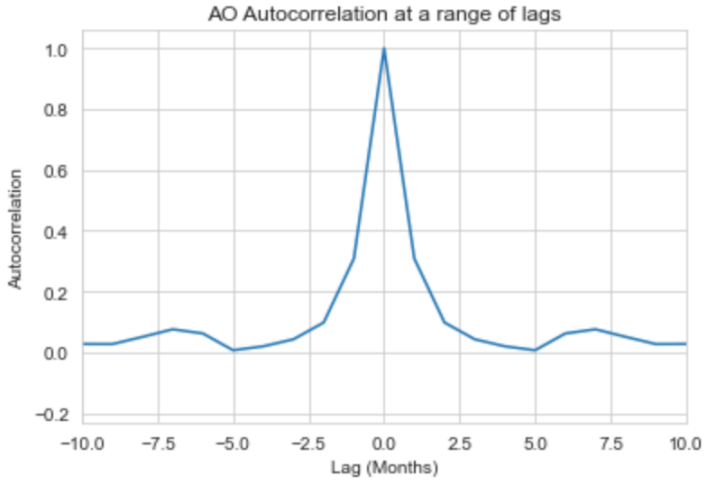
2) Calculate the lag-one autocorrelation (AR1) of the AO data and record it here. Use two methods (np.correlate, dot products). Check that they give you the same result. Interpret the value. How much memory (red noise) is there in the AO from month to month?

Autocorrelation for both methods: 0.30855

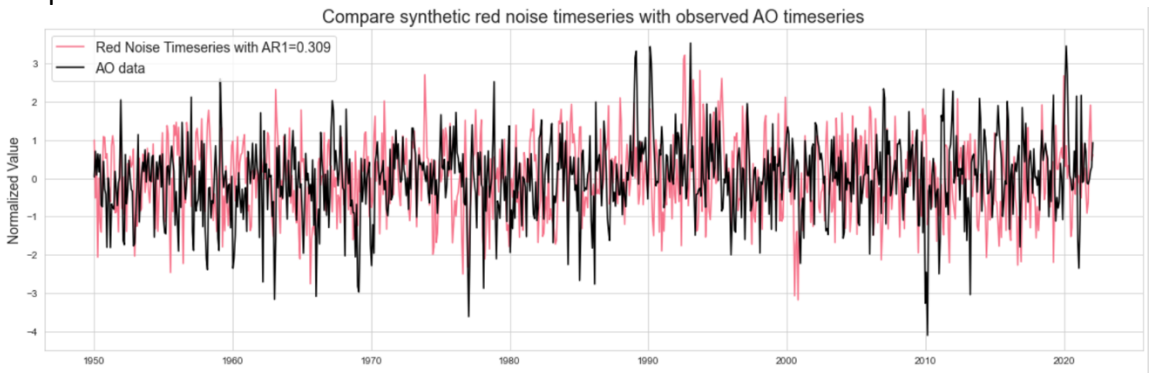
This is a relatively low value (compared to something like daily temperature) so there is so but not much memory in this variable.

3) Calculate and plot the autocorrelation of the AO data at all lags. Describe your results. How red are the data at lags other than lag=1? Is there any interesting behavior of the autocorrelation as a function of lag? What would you expect for red noise timeseries with an AR1=value reported in 2)?

It seems there's a lag at 1 month and a small signal also at 6 months. The graph shows the large spike that we would expect based on the calculated autocorrelation, but then two bumps at ±6 months.



4) Generate a synthetic red noise time series with the same lag-1 autocorrelation as the AO data. Your synthetic dataset should have different time evolution but the same memory as the AO. Plot the AO timeseries and the synthetic red noise time series. Put the plot below.



5) Do you expect to find any correlation between the two datasets, i.e., the synthetic red noise and the actual AO data? What is the correlation between the synthetic red noise and the actual AO data? Calculate a regression coefficient and other associated regression statistics.

Since red noise is random, I do not expect to see any correlation between the actual data and the synthetic red noise.

Slope = -0.042; r = -0.041, intercept = -0.003, p = 0.23, std. error = 0.035

6) Next -- Have some fun and go “fishing for correlations”. What happens if you try correlating subsets of the two datasets many times? When you try 200 times -- what is the maximum correlation/variance explained you can obtain between the synthetic red noise and the actual data? *Note: you are effectively searching for a high correlation with no a priori reason to do so.... THIS IS NOT good practice for science but we are doing it here because it is instructive to see what happens :)*

When correlating subsets of the datasets many times, we can generate some very high correlations. I created random red noise and ran the cells several times and found r values upwards of 0.65. Fairly large amounts of variance (>40%) are explained in these cases. Thus, we’re showing that we should be very careful when searching for high correlation, and we should make sure we have enough info and good reason to do so.

7) Calculate the correlation statistics for the highest correlation obtained in question 6). Two methods are provided - they should give you the same answers. Place a confidence interval on your correlation. Because you have found a correlation that is not equal to 0, use the Fisher-Z Transformation. Did your "fishing" for a statistically significant correlation work? Is your highest correlation statistically significant (i.e., can you reject the null hypothesis that the correlation is zero)? Write out the steps for hypothesis testing and use the values you calculate to formally assess.

In this test, we reject the null hypothesis that the correlation is zero. The 95% confidence interval (0.26 to 0.86) does not contain zero, which means that we reject the null. Here we’ve shown that we can find a statistically significant correlation, even when it doesn’t necessarily make sense to do so.

8) You went searching for correlations, you searched long and hard (200 times!) You should have been concerned that the largest correlation you found would be a false positive. Do you think you found a false positive? Explain what you found and potentially why you think it is important statistically but not physically. What lessons did you learn by “fishing for correlations”?

In this case, it seems we’ve found a false positive. This shows that it’s important to have a priori information when choosing to subset data and look for correlations. There should be some kind of physical meaning and logic to investigating correlation.

FOR FUN: Check out - https://www.tylervigen.com/spurious-correlations