

State College December example continued.

Statistical Significance Testing

What we really want to know with the linear trend or correlation, is whether the trend is valid. In statistics, we call this “statistically significant.” To assess this, we have several tools. This class is just scratching the surface.

First, we look at the correlation coefficient, r . If you remember from the tool, under “Trend Lines,” we got results that gave us the correlation coefficient. For this dataset, $r=0.1931$

Plot #1

Linear Regression

All Data Viewport

Equation:

$Y=0.0246*X+-16.7749$

Correlation Coefficient (r):

$r=0.1931$

Standard Error of the Slope (S_b):

$S_b=0.0122$

Two-Tailed P Value (P):

$P=0.0463$

Now, we go to the statistics calculator at: <http://vassarstats.net/tabs.html#r> . In this calculator, we put in N , the number of points in our dataset (107 years), and the r value from above, and click “Calculate”:

$N =$	107	$r =$	0.1931
Reset		Calculate	
t		df	
2.02		105	
P	one-tailed	0.0231	
	two-tailed	0.0463	

[Return to Top](#)

It returns several values. We will concentrate mainly on the p-values on the bottom. First we need to decide whether the one-tailed test or the two-tailed test is more appropriate. If we have the hypothesis that the correlation should be positive (or negative), then the one-tailed test is more appropriate. If our hypothesis is that we do not suspect a relationship between the two variables (also called the “null hypothesis”), then we use a two-tailed test.

Here, it is probably appropriate to use the one-tailed test, as we suspected prior to doing this exercise that the December temperatures in State College have been warming over time. It is not terribly important to get this correct here, as we are looking for the value of p to be lower than 0.05 for 95% statistical significance. Since both one-tailed and two-tailed values of p are lower than 0.05, this trend is significant no matter which hypothesis we had initially.

Autocorrelation Testing

The next thing we need to worry about is autocorrelation of the residuals. Residuals is just a fancy way of saying the data that is left over after we remove the part of our time series that has been described by our model. If you look at the plot of the trend line over the original data, the residuals would be how far each data point is from the line. In other words, we have broken up the data into two components: temperature = model temperature + residual temperature.

The tool calculates the autocorrelation of the residuals when we run the Regression Model:

Results: Coefficient Values

```
c0 (mean offset): -16.7749
c1 (year): 0.0246
--Model Residuals--
R2 Value: 0.037275
mo(lag=1): -0.113537
```

Run *Model fitted values will be added to plot list as 'ModelOutput'

The lag-one autocorrelation is sometimes called ρ , or ρ , but here it is called “mo (lag=1)”. The autocorrelation is a measure of how one timestep is related to the previous timestep. If the data at subsequent timesteps are unrelated after we remove the modeled trend, then the value for autocorrelation will be low. Here, it is -0.113537. To assess whether is significantly different from 0, we are again going to use the statistical tool:

N = 106		r = -0.1135	
Reset		Calculate	
t		df	
-1.17		104	
p	one-tailed	0.1233	
	two-tailed	0.2467	

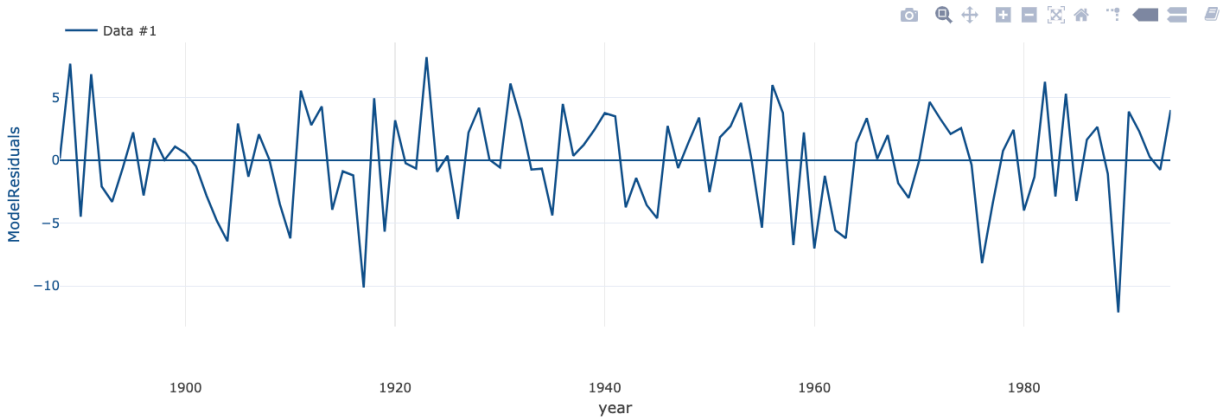
[Return to Top](#)

Now, the N is 106 years, as when looking at the relationship between one timestep and its predecessor, you end up having one fewer comparisons. We see here that both the one-tailed and two-tailed p values are greater than 0.05, which means that the autocorrelation is not

significantly different from 0. This is good, as it means that there is not an issue with autocorrelation with residuals in our model. That is, according to this test, the linear model has removed most of the signal.

Plotting the Model Residuals

One last thing we want to look at when assessing our model is the plot of the model residuals.



If we plot year (x-axis) vs. model residuals (y-axis), we can see that there does not seem to be a general long-term pattern anymore, but there is still a good deal of year to year variability left in our data. All of this means that while the linear trend is significant, we may want to use a more complicated model to fully describe our temperature data. Using the model that we developed to predict future December temperatures in State College is not likely to very good overall. In problem set 2 and lesson 3, we go through this whole process again, but using multiple predictors for temperature rather than just time.