Time Series Analysis of Global Temperatures

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May 2020

1 Introduction

In this report we will be presenting our analysis of a time series on global temperature anomalies, due to efforts going back to the late 1970's, where a group of NASA scientists at the Goddard Institute for Space Studies (GISS), led by Dr. James Hansen, were laying the foundation for a cohesive analysis of all the available data, by devising a method [3] for summarizing and weaving together all the temperature data gathered from various measurement stations from all over the world.

2 Time series data

The time series represents the changes in global annual mean land surface temperature, relative to the 1951-1980 mean. The data is based on [3] and [2], as made available by NASA's Goddard Institute for Space Studies [5] as shown in Figure 1.

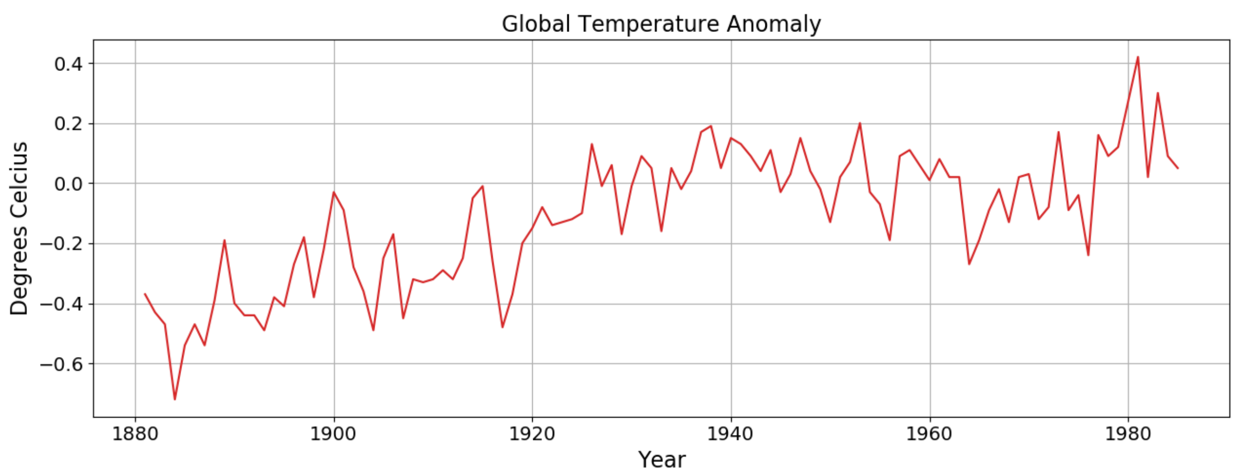

Figure 1: Global annual mean temperature anomalies relative to the 1951-1980 mean.

3 Trending and seasonal components decomposition

The trending component is found by applying a 5th order polynomial fit.

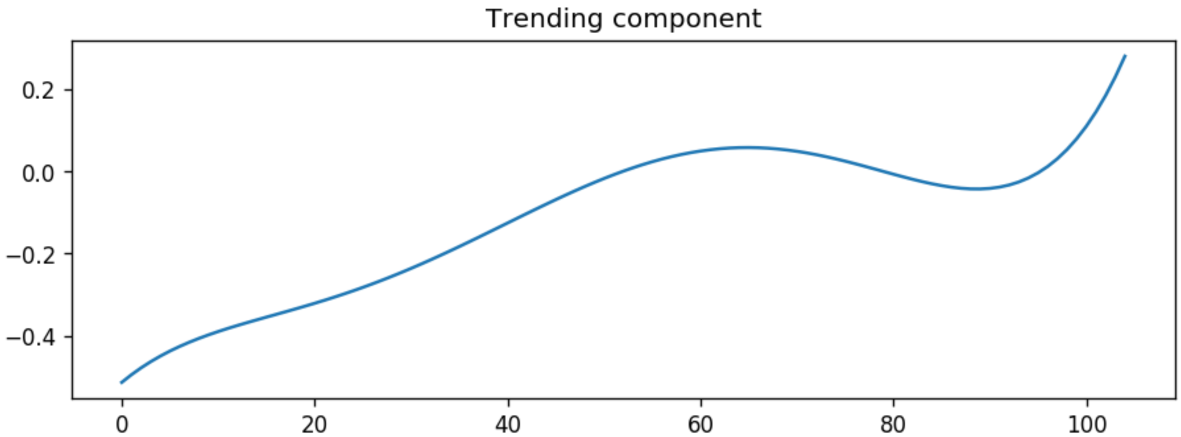

Figure 2: Trending component of the original time series

4 Transforming the data

4.1 Checking for stationarity: ADF

	ADF tests		
	Original data	1^{st} order difference	2^{nd} order difference
Statistic	-1.651	-5.978	-5.541
p-value	0.456	1.864e-7	1.697e-6

Table 1: Results of ADF tests.

Table 1 shows the results of the Augmented Dickey Fuller test (ADF test) with the null hypothesis that the given time series is not stationary. The p-value of 0.456 for the original data is significantly higher than 0.05 which is commonly used as cutoff value. This gives a good indication that the time series is not stationary.

4.2 Differencing

In order to transform the time series into a stationary series, the method of differencing was used. This means that the difference between each concecutive value is computed and used as a time serie instead. Results from the ADF test in Table 1 indicate that already after one differencing step the series has become stationary.

5 Finding a model

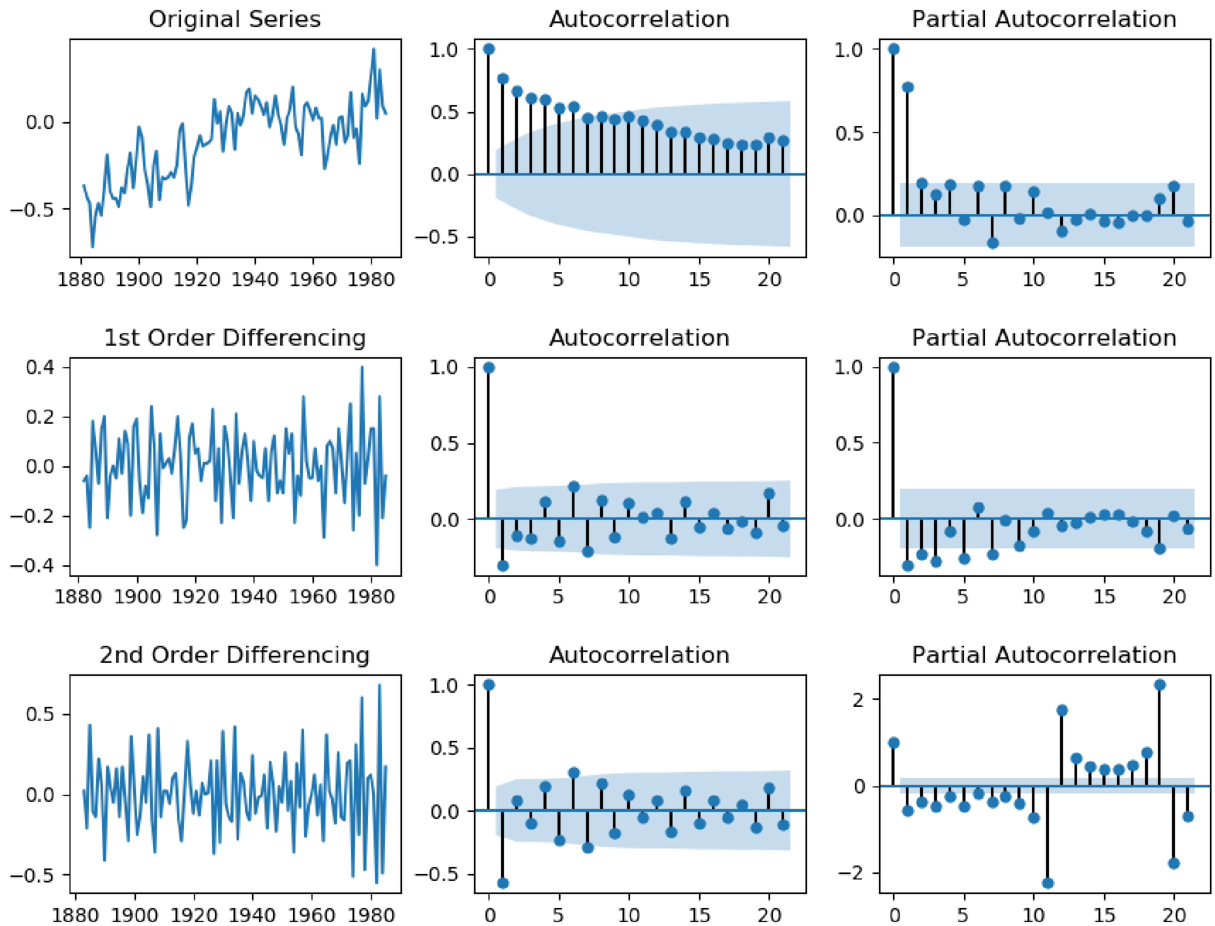

Figure 3: Plots for the original time series and the 1st and 2nd order differencing results, and their corresponding ACF and PACF plots.

5.1 ARIMA

To achieve stationarity, differencing was used. To account for this, an ARIMA model is appropriate.

5.2 Model parameters

The order of the AR term, p, is the number of lag observations included in the ARIMA. To find an appropriate order, the PACF is studied to pick the recent and highly correlated observations. The recent three observations are above the significance level for PACF of the first order differencing series in figure 3, so we set $p = 3$.

The order of the integration required, d, is the number of repeated differencing operations that were carried out in order to obtain a stationary time series from the original data. As motivated by Table 1, we set $d = 1$.

The order of the MA term, q, is the order of moving average. To find a suitable order, the ACF is analysed. The ACF of the first order differencing series in figure 3 shows that the first lag is above the significance level, so we set the MA parameter $q = 1$.

The resulting coefficients in the Φ and Θ polynomials, their roots and the p-values for each coefficient is shown in table 2.

Term	Coeff	Root	P-value
const	0.006		0.039
ϕ_1	0.233	$0.997 - 1.536j$	0.115
ϕ_2	-0.083	$0.997 + 1.536j$	0.468
ϕ_3	-0.108	$-2.765 + 0.000j$	0.365
θ_1	-0.781	$1.281 + 0.000j$	0.000

Table 2: Information about the the fitted ARIMA models parameter.

It is worth mentioning that AR components tend to be correlated which increase their P-values when several AR-components are used simultaneously. Therefore these P-values should be taken with a grain of salt and the model might still be a reasonable one even with large P-values for some components [4].

6 Performance analysis

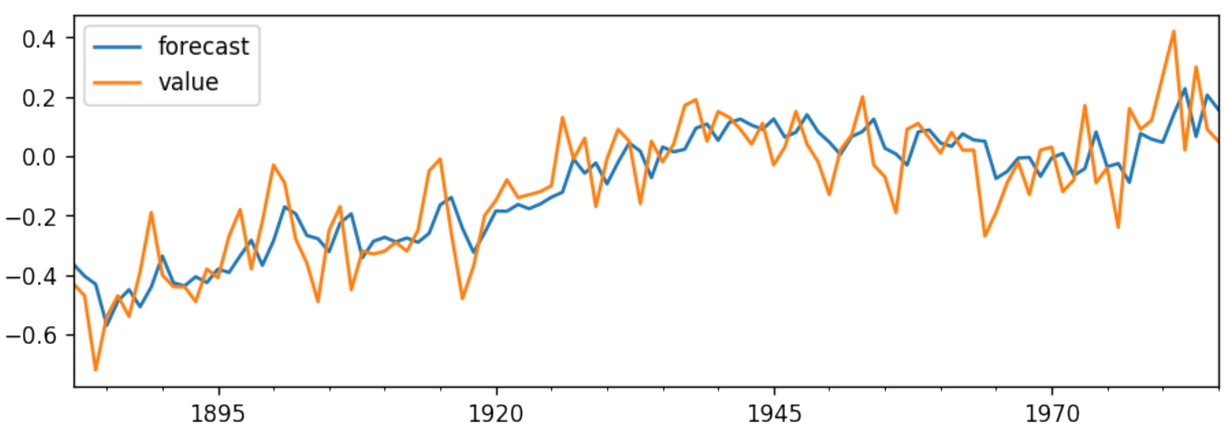

Figure 4: Comparison of ARIMA(3,1,1) (blue) and real time series (orange).

6.1 Error analysis

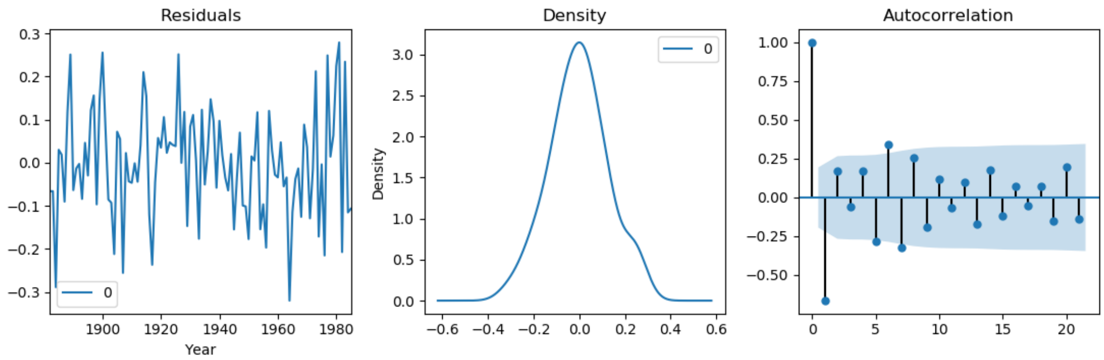

Figure 5: Residuals from ARIMA(3,1,1)-model.

Figure 5 shows a plot of the residuals along with a histogram and the ACVF. The histogram of residuals seem roughly normally distributed with a mean at -0.0021 which is very close to 0. In the ACVF plot most lags have correlations with insignificant values. There is one exception at lag $h = 1$ with correlation far beyond the significance threshold which could indicate time dependent residuals. A Breusch–Godfrey test [1] was performed which is used to assess whether or not a time series is serially correlated with the null hypothesis that it is not. When applying the test to our residuals the obtained p-value is 0.713 which give us no reason to reject the null hypothesis and we conclude that the residuals are serially uncorrelated.

6.2 Forecasting

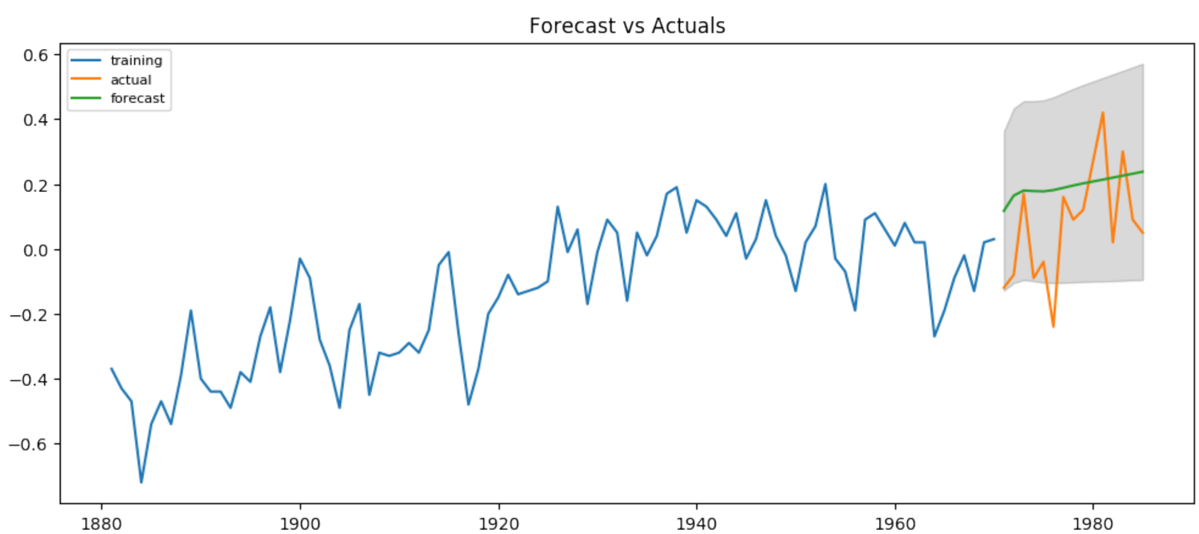

Figure 6: Comparison of ARIMA(3,1,1) forecast and confidence interval to actual data.

Figure 6 shows a plot of the forecast of the time series from 1971 to 1985 with 95% confidence intervals. The mean-squared error of the prediction is 0.023 and the mean absolute error is 0.151.

7 Conclusion

Time series data for global annual temperature anomalies from year 1880 through 1985 were analysed and modeled. An ARIMA(3,1,1) model was found to be the best fit for our time series, through ADF testing and (P)ACF analysis of the original and transformed versions of the data. The residuals was analysed to see how well the model captured the time series structure. The data was also used to train our model in order to test its predictive power.

Bibliography

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