Analysis of Executions in the United States since the 1976 Supreme Court Decision

Introduction

For many years, the capital punishment also known as the death penalty has been a divisive topic in the US with ramifications for society, ethics, and the law. A major turning point was reached in 1976 when the Supreme Court decided in Gregg v. Georgia, which reinstated the capital sentence and allowed executions to continue in the United States. Ever since, there has been constant examination and research on the frequency of executions as well as the legal discussions that surround them. Using statistical techniques in R, this paper seeks to present a thorough examination of executions in the US since the historic 1976 Supreme Court ruling. And more this analysis aims to answer the following questions,

- What are the trend and seasonality patterns in executions in the United States since 1976?
- Can we identify an appropriate ARIMA model to describe the data?
- How accurate are our forecasts for future executions?

Data Acquisition

The dataset used for this analysis was obtained from the Wolfram Data Repository, comprises information on executions in the United States since 1976 to 2018. It contains information such as the date of execution, the method of execution, and demographic information about the people who were executed. The dataset consists of 40 observations, with each observation representing the number of executions in a specific year. Despite its modest size, this dataset offers a useful way to look at trends and patterns in the use of the death penalty in the United States.

Exploratory Data Analysis

We started our investigation by performing exploratory data analysis (EDA) in order to learn more about the composition and properties of the dataset. This included creating a time series plot to show the pattern of executions over the years (Figure 1 & 2). The number of executions appears to have increased over the first two decades from 1976 and decreased over the past two decades. However, there might also be some fluctuations within years, suggesting the possibility of trend or seasonality in the data. To further comprehend the central trend and fluctuation of the execution counts, we also looked at summary statistics.

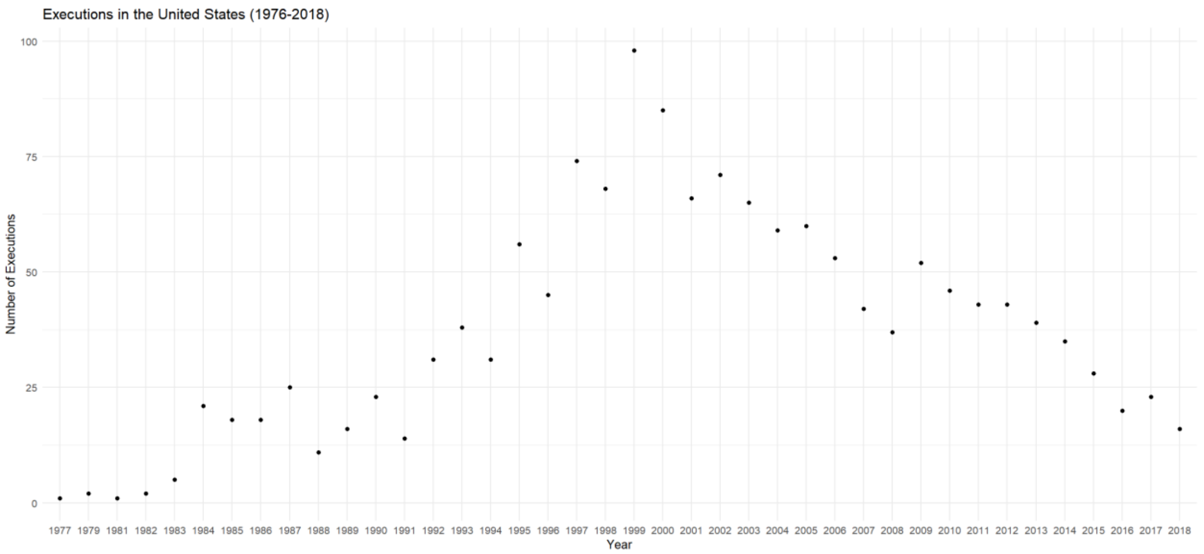

Figure 1 Yearly Executions in the US (1976-2018)

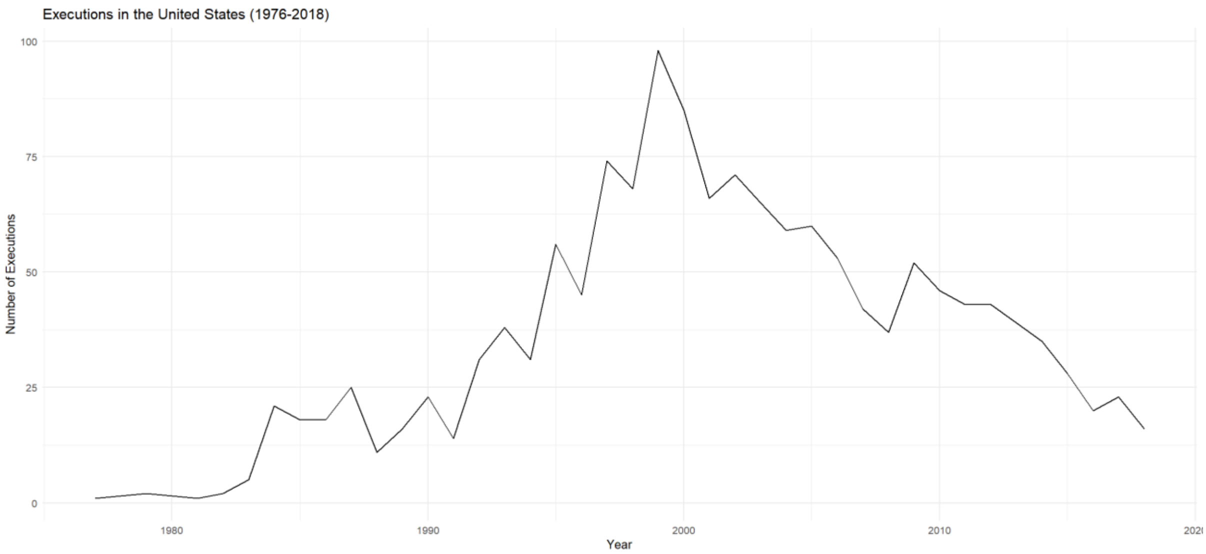

Figure 2: Yearly Executions in the US (1976-2018)

Decomposition of Time Series

To further understand the underlying components of the time series, we used decomposition techniques. The time series was divided into Seasonal, Trend, and Remainder components using the Seasonal and Trend decomposition Loess (STL) method (Figure 2). The breakdown verified that there was an initial increasing tendency, followed by a declining trend, as well as some seasonal variance within the years.

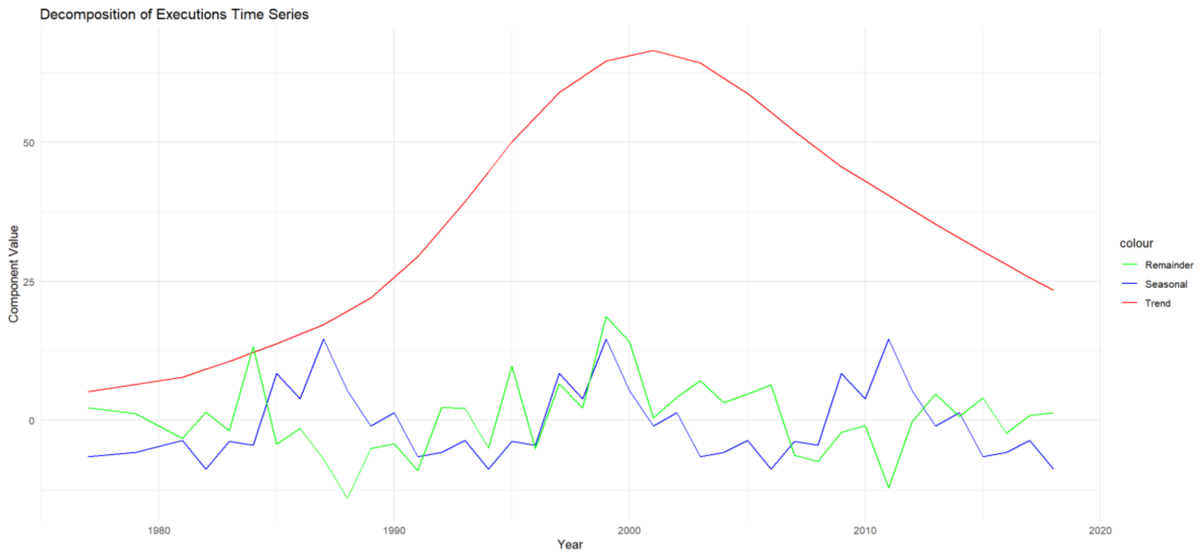

Figure 3: Decomposition of Executions Time Series

Model Fitting

Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots

Then we proceeded with modeling the time series using the Autoregressive Integrated Moving Average (ARIMA) model. The selection of appropriate parameters (p, d, q) for the ARIMA model involved analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The PACF plot displayed a significant spike (above the confidence interval) at lag 1, indicating an AR(1) component might be present. The ACF plot displayed significant spikes (above the confidence interval) in the first six lags suggesting an MA(6) model might be present. Based on these diagnostics, we tentatively set p = 1 and q = 6. We have used first-order differencing (d = 1) for the ARIMA model, because we observed that ACF plot has a slow decay and the PACF plot has a sharp cutoff after the first lag.

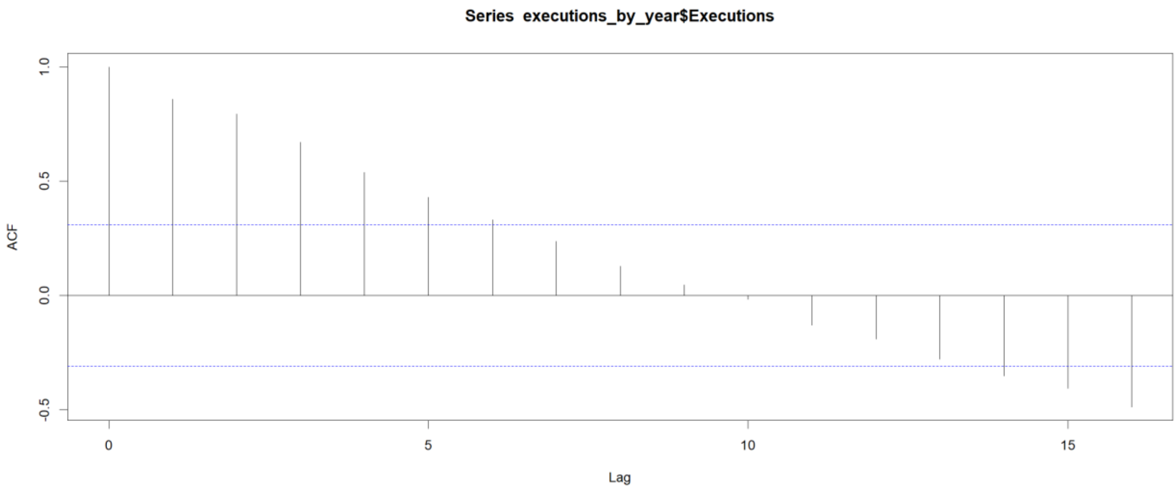

Figure 4: Autocorrelation Function Plot

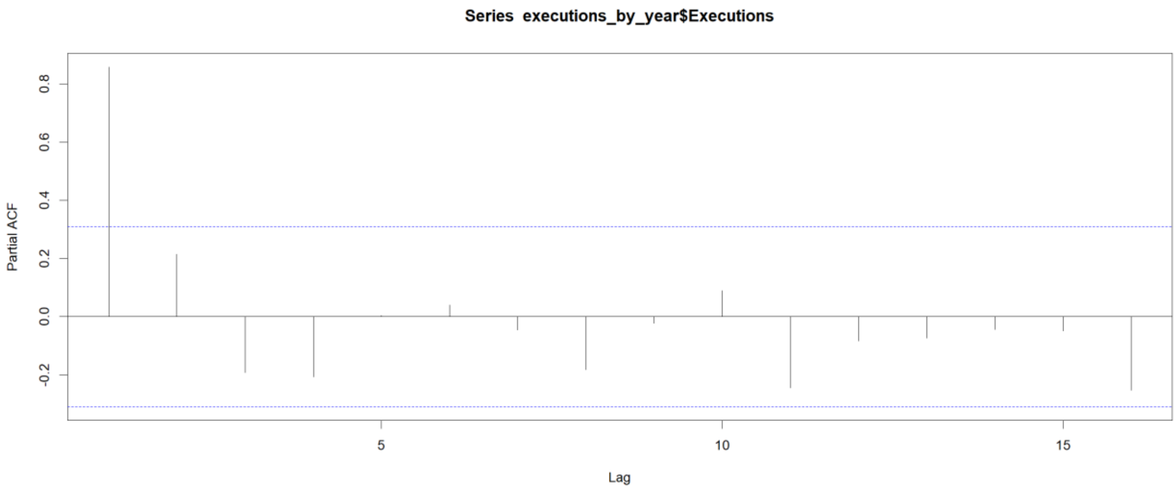

Figure 5: Partial Autocorrelation Function Plot

ARIMA Model Selection

Based on the ACF and PACF plots, an ARIMA(1,1,6) model was initially chosen. The ARIMA function in R was used to fit the model to the data and the model assumptions were assessed through the model summary. It's important to note that alternative models were also considered by comparing their AIC values. But the model with the lowest AIC value is considered the best fit for the data.

```
arima(x = executions_by_year$Executions, order = c(1, 1, 6))

Coefficients:
         ar1      ma1     ma2     ma3      ma4     ma5     ma6
      0.0255  -0.4624  0.6640  0.1724  -0.0020  0.4990  0.4042
s.e.  0.3382   0.3220  0.2782  0.3031   0.2021  0.2066  0.2284

sigma^2 estimated as 69.88:  log likelihood = -142.53,  aic = 301.07
```

Forecasting

For the next twelve years (2019–2030), the number of executions was predicted using the selected ARIMA model. The expected number of executions is shown together with confidence ranges in the prediction plot (Figure 2). It's crucial to interpret this forecast with caution, as inherent uncertainties exist in any prediction.

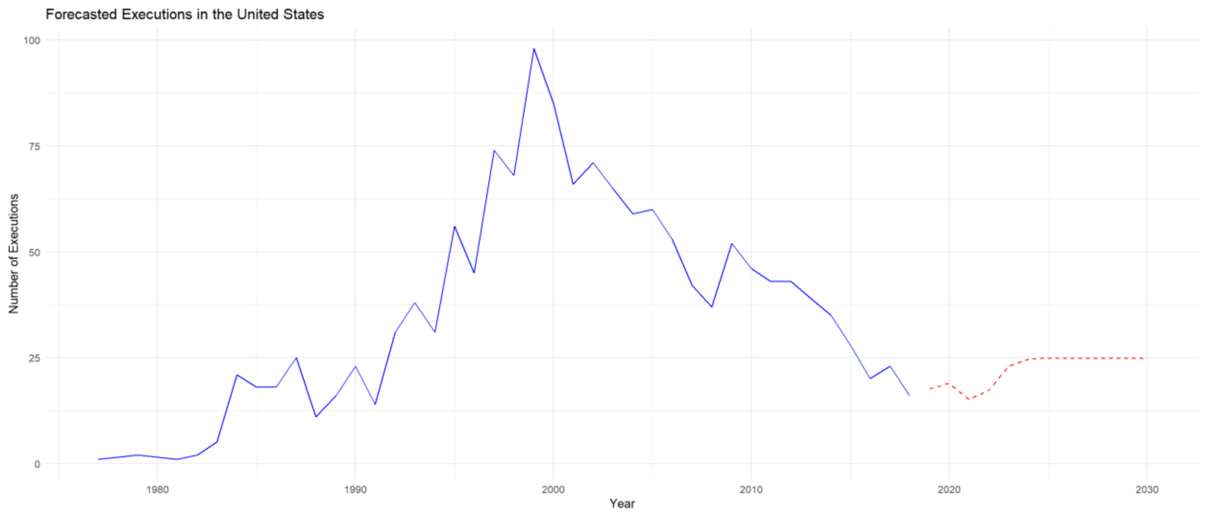

Figure 6: Forecasted Executions in United States till 2030

To assess the forecast accuracy, metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) have been used. When choosing and analyzing these indicators, it is advised to refer to appropriate sources.

```
Mean Absolute Error (MAE): 15.78551
Mean Absolute Percentage Error (MAPE): 41.07498 %
Mean Squared Error (MSE): 355.479
Root Mean Squared Error (RMSE): 18.85415
```

The Mean Absolute Percentage Error (MAPE) indicates that, on average, our forecasts deviate from the actual values by approximately 41.07%. This suggests a moderate level of accuracy, but it's important to consider the limitations of MAPE. MAPE can be sensitive to very low actual values, potentially exaggerating the errors for years with few executions.

The Root Mean Squared Error (RMSE) of 18.85415 suggests that the typical forecast error, on average, is approximately 18.85 executions. A lower RMSE is desirable, but the interpretation depends on the scale of our data. For instance, an RMSE of 2 executions might be significant if the typical number of executions per year is low.

Conclusions

From 1976 to 2018, there may have been an increase and decrease trend in US executions, according to the data. Additionally, seasonality patterns were found, indicating variations among years. For capturing these patterns, an ARIMA(1,1,6) model (or maybe another model with the lowest AIC) could be appropriate. Because forecasting models are inherently unpredictable, it is important to proceed with caution when evaluating the forecast's accuracy, which offers a forecast of future executions.

Limitations and Recommendations

This study focused on data at the national level. Analyzing executions by state or area could provide additional insight into regional differences. Furthermore, more complete models could result from adding data on variables like crime rates and changes in laws that may have an impact on executions.

However, we have come up with several key features regarding limitations and recommendations for them,

- **Data collection:** To increase the precision of the analysis and modeling, gather a bigger dataset over an extended period of time. Furthermore, confirm the accuracy and consistency of the data by cross-referencing it with other sources.

- **Data quality:** The forecasts' accuracy depends on how good and trustworthy the source data is. Predictions that are not trustworthy might result from skewed forecasts and discrepancies in the dataset.

- **Model Selection:** To better capture the underlying trends in the data, investigate different time series modeling techniques such as seasonal ARIMA, exponential smoothing, or machine learning approaches. To determine which model best fits the data, think about utilizing automated model selection techniques. Estimate accuracy could be increased by investigating complex models or adding more variables that affect executions.

- **Validation:** To make sure the chosen model is suitable for forecasting, validate it using the proper diagnostic tests, such as residual analysis, the Ljung-Box test, and cross-validation methods. Perform sensitivity tests as well to evaluate how resilient the forecasts are to modifications in the model's parameters.

References

The dataset used in this analysis was sourced from **Wolfram Data Repository** and it is about executions (the death penalty) in the United States since the 1976 Supreme Court decision in Gregg v. Georgia (428 U.S. 153)