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MATH 62.2

Time Series Modeling of Philippine Political Violence Fatalities

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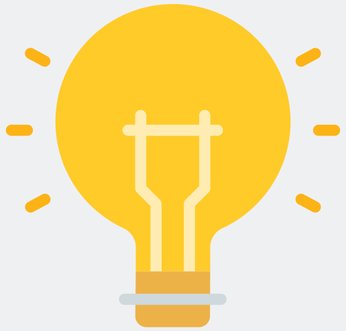
Title Page Introduction

Introduction



Introduction

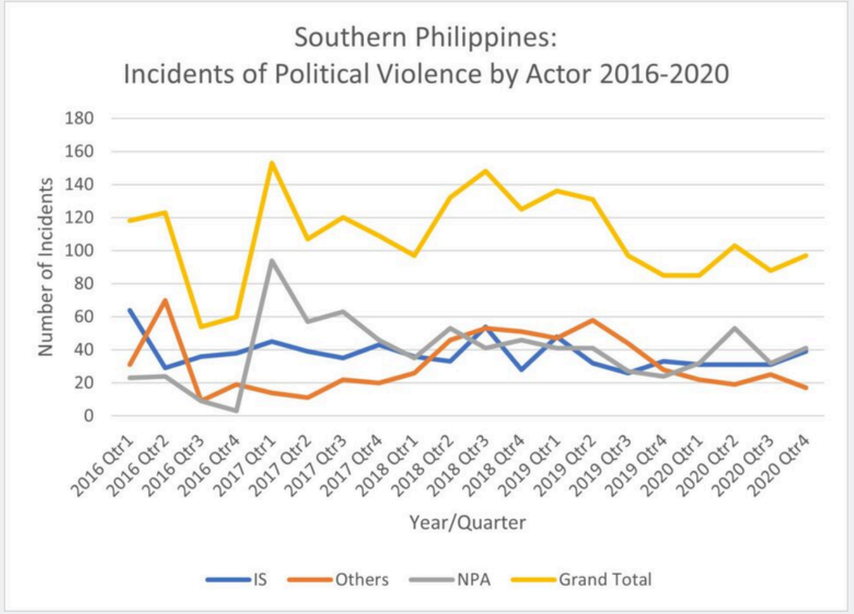
Philippine Politics

- influenced by cultural, historical, and social factors
- acquisition and use of power
- still overpowered by issues of poverty, corruption, and crime

arts.ubc.ca/news/why-we-should-care-about-philippine-politics-qa-with-dr-nora-angeles-about-the-return-of-a-marcos-presidency/

Political Violence

- hostile and aggressive acts motivated by political goals
- includes the following:
  - extrajudicial killings
  - election-related violence
  - rebellion of insurgent groups



https://www.newmandala.org/down-but-not-out-political-violence-in-the-southern-philippines-from-2016-2020/

Extrajudicial Killings

29,000 were killed

https://time.com/philippines-rodrigo-duterte-drug-war-local-photographers/

Maguindanao Massacre

58 media workers were killed

https://ipi.media/verdict-looms-10-years-after-philippine-press-massacre/

https://pinglacson.net/2019/12/19/on-the-verdict-on-the-maguindanao-massacre/

Moro Rebellion

fatalities and displacement of communities

https://www.ucanews.com/news/five-dead-in-new-mindanao-conflict/69317

https://www.dw.com/en/philippines-ending-clan-wars-crucial-to-sustaining-peace-in-muslim-south/a-64624559

Significance

1. **Predicting Future Trends**
   - beneficial for the government so they can make efficient decisions based on previous data for allocating resources, preventing conflicts, and promoting peace across the nation
2. **Assessing Policy Interventions.**
   - Using the model, authorities can conduct a comprehensive evaluation of the implementation of policy interventions in combating political violence

Scope and Limitations

- will not do forecasting, estimation, or in-depth analysis
- does not guarantee the production of the best possible model

Statement of the Problem

What are the trends in the occurrence of political violence in the Philippines?

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Methods

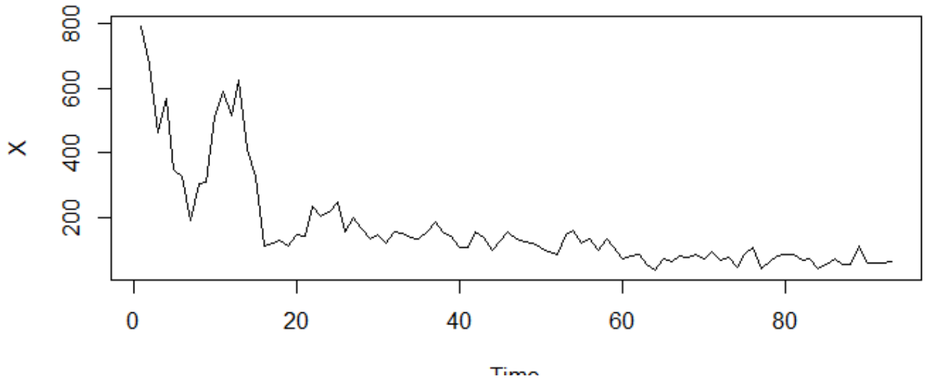
Methods

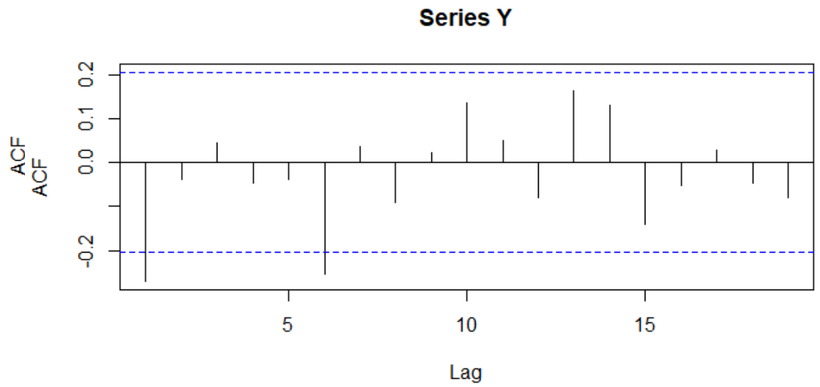
Theoretical Framework

- Time Series data

$$X_t = \sum_{j=-\infty}^{\infty} \psi_j Z_{t-j}$$

- Linear Processes
  - AR: $X_t = \phi_0 + \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + Z_t$
  - MA: $X_t = \mu + Z_t + \theta_1 Z_{t-1} + \cdots + \theta_q Z_{t-q}$
  - ARMA: $X_t = \phi_1 X_{t-1} + \cdots + \phi_p X_{t-p} + \alpha + Z_t + \theta_1 Z_{t-1+\cdots+\theta_q Z_{t-q}}$
- Stationarity
- Autocorrelation





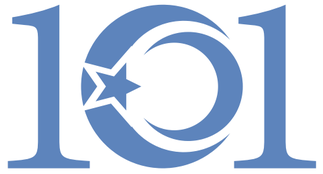
Data Collection

CSV Dataset

Humanitarian Data Exchange

Political Violence Fatalities

Jan 2016 to May 2024

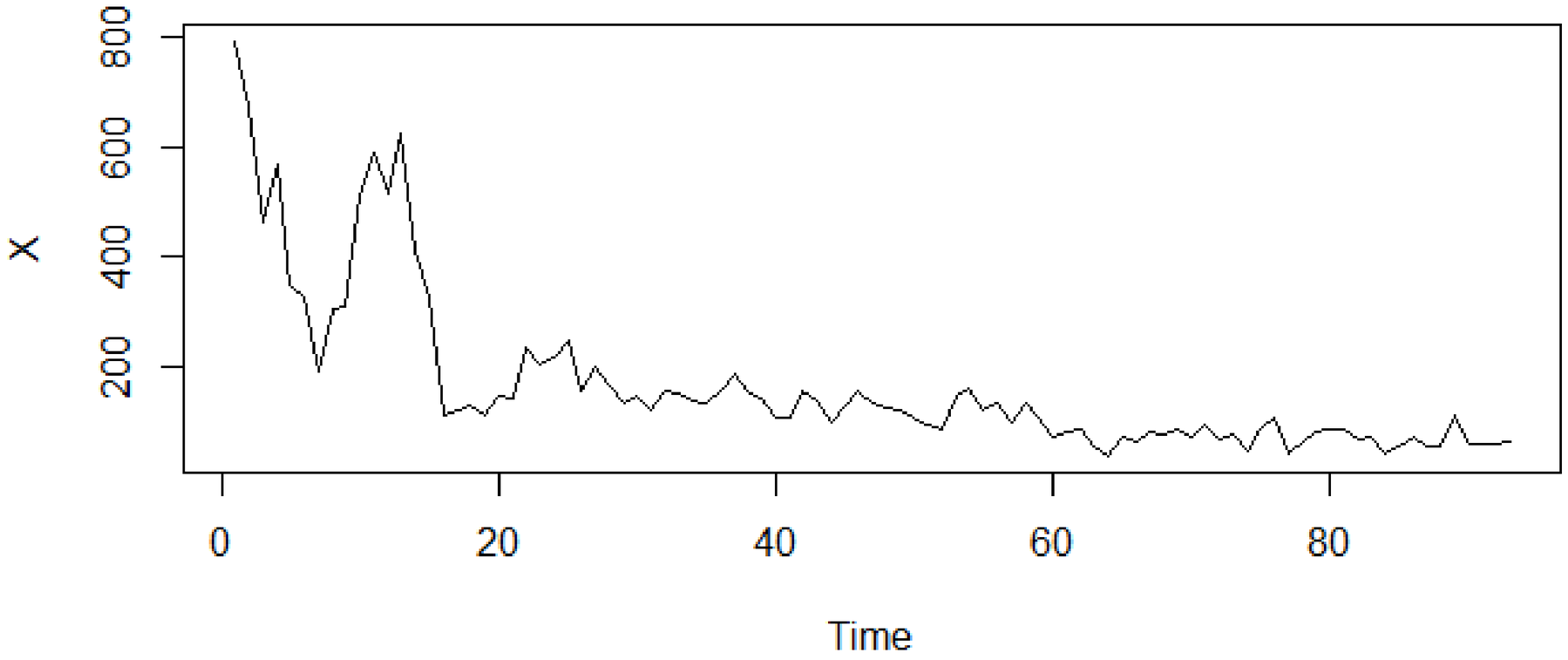


Monthly

Assumptions

- Only trend or seasonality
- Seasonality can be dealt with backward first-order differencing
- Trend is linear
- Level of significance is $\alpha = 0.05$.

Data Exploration



Data has large values, so we use **log transformation**.

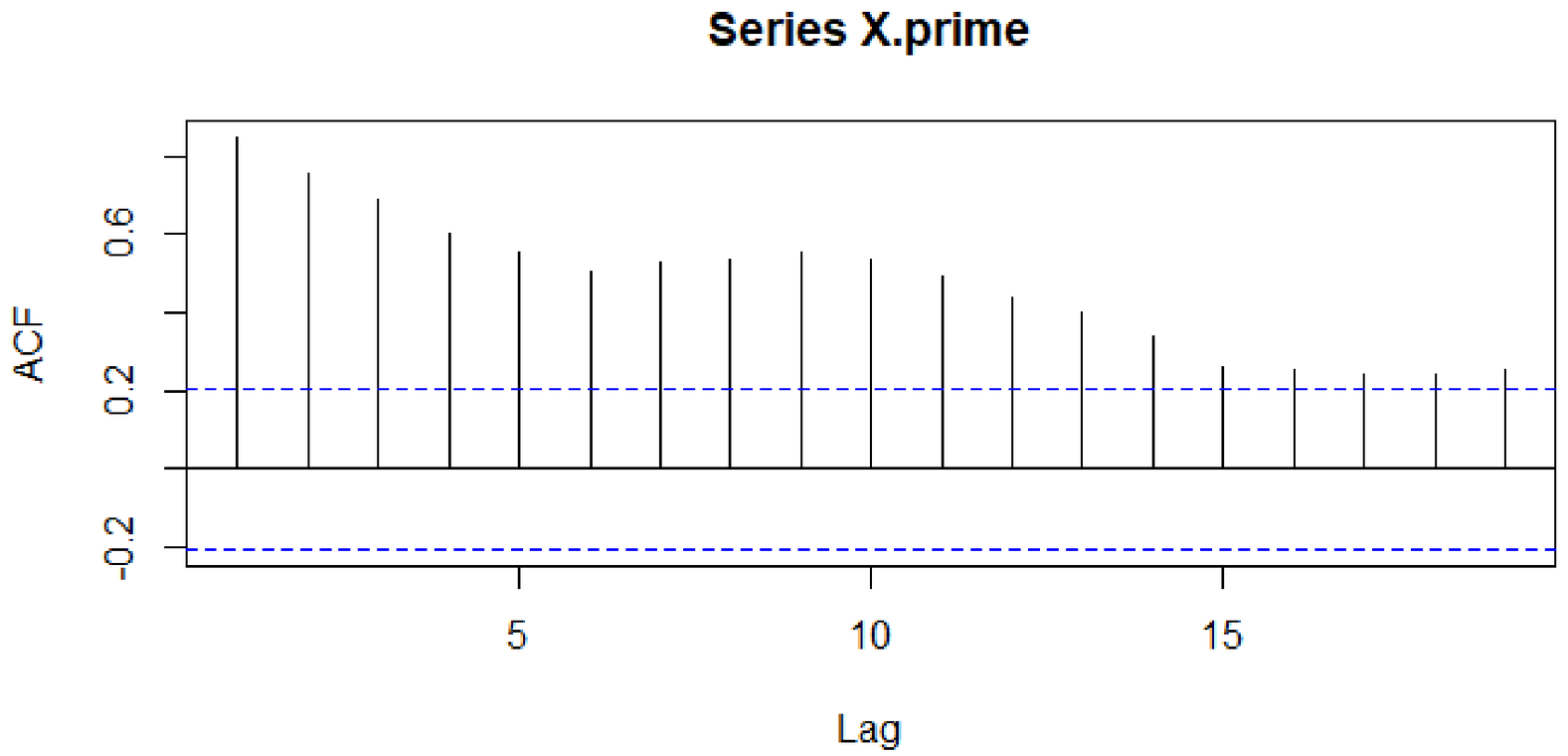
Data Exploration

```
        Augmented Dickey-Fuller Test

data:  X.prime
Dickey-Fuller = -4.4955, Lag order = 4, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(X.prime) : p-value smaller than printed p-value
```

By the ADF test, the data is **stationary**.

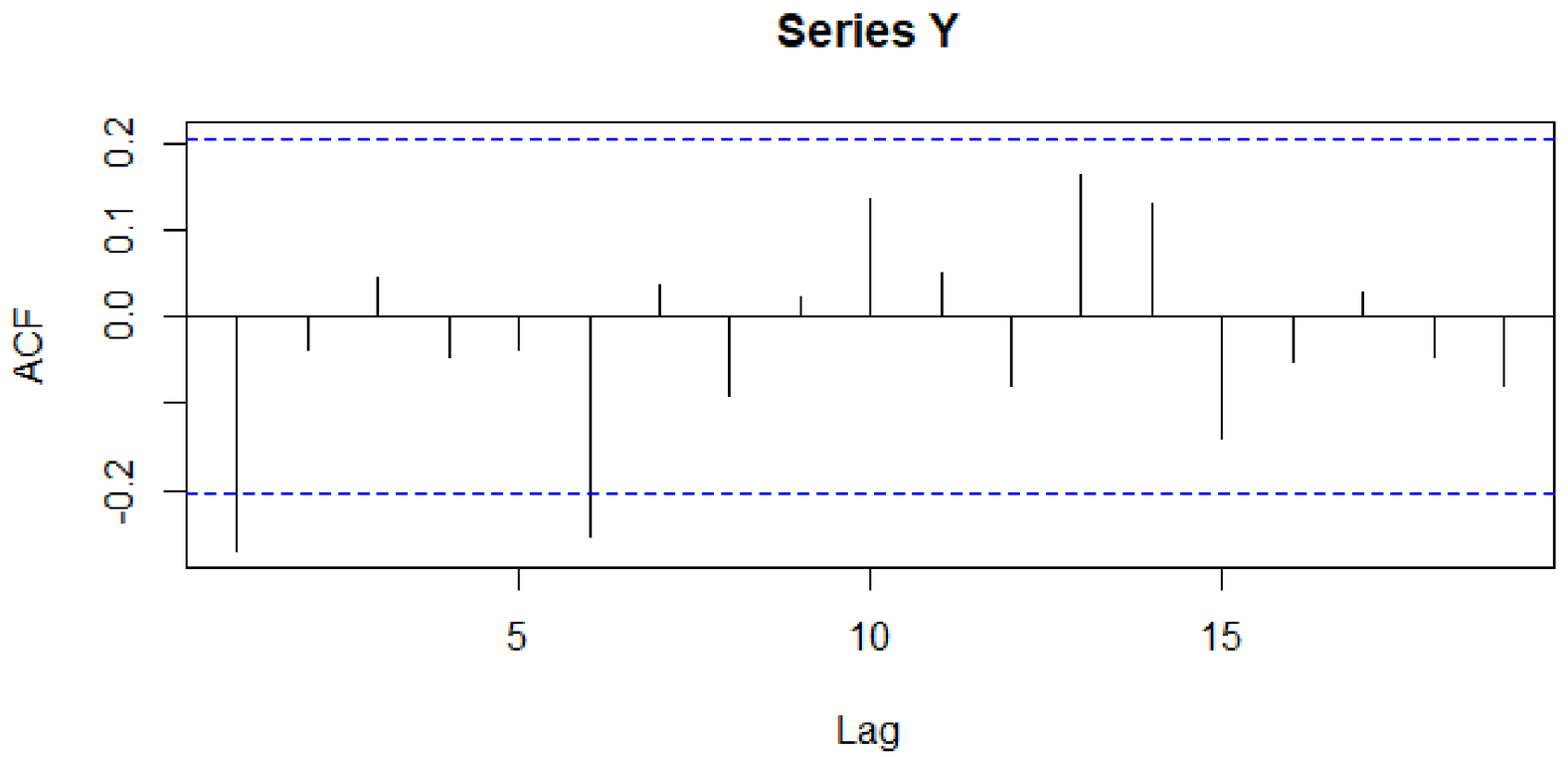
```
        Box-Ljung test

data:  X.prime
X-squared = 68.883, df = 1, p-value < 2.2e-16
```

Using the Ljung-Box test, we also find that the data has **serial correlation**.

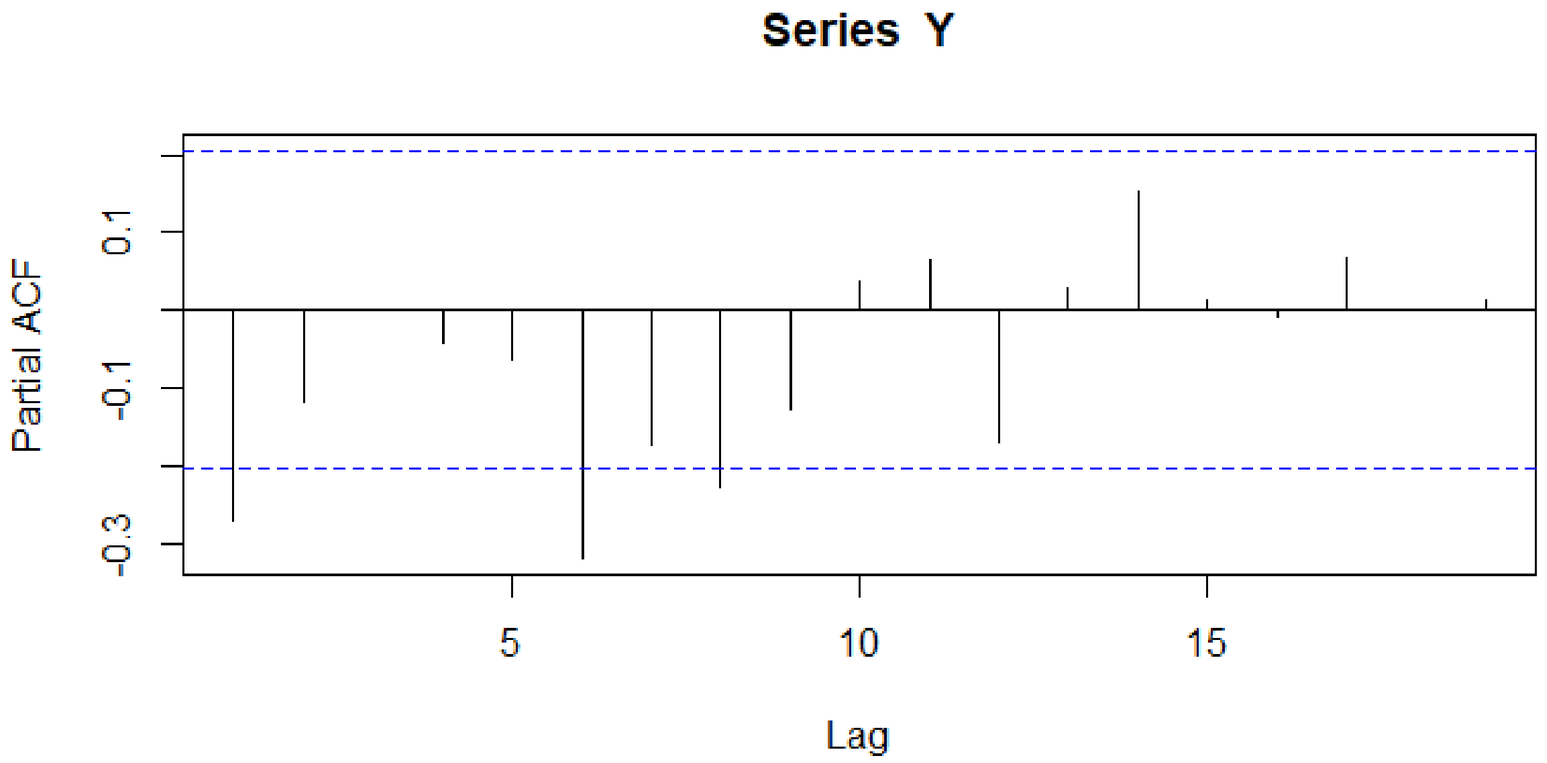


However, looking at the ACF correlogram, there is **potential seasonality**.
Thus, we use backward first-order differencing

Data Exploration



The new ACF cuts-off at lag 1, but spikes at lag 6. We consider **MA(1)** and **MA(6)**.



The PACF correlogram cuts-off at lag 1, but spikes at lags 6 and 8.
Hence, we consider **AR(1), AR(6), and AR(8)**.

We also consider ARMA(1, 1), ARMA(1, 6), ARMA(6, 1), ARMA(6, 6), ARMA(8, 1), and ARMA(8, 6).

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Results and Discussion

Model Selection

Out of the 11 candidate models, **ARMA(6,1)** was chosen as the best model since it had the **lowest AIC**.

Model	AIC Score
AR(1)	46.27
AR(6)	42.24
AR(8)	36.39

Model	AIC Score
MA(1)	44.95
MA(6)	38.02

Model	AIC Score
ARMA(1, 1)	39.36
ARMA(6,1)	**35.16**
ARMA(8,1)	36.79

Model	AIC Score
ARMA(1,6)	38.47
ARMA(6,6)	36.92
ARMA(8,6)	39.67

The Model

From R, μ is **-0.0235**.
Solving for α, we get:

$$\alpha = \mu(1 - \phi_1 - \phi_2 - \phi_3 - \phi_4 - \phi_5 - \phi_6)$$

$$\alpha = -0.0235(1 - 0.1985 + 0.0027 - 0.0338 + 0.1066 + 0.1463 + 0.3384)$$

$$\implies \alpha = -0.0320$$

Hence, the model can be written in functional form as

$$Y_t = -0.0320 + 0.1985Y_{t-1} - 0.0027Y_{t-2} + 0.0338Y_{t-3} - 0.1066Y_{t-4} - 0.1463Y_{t-5} - 0.3384Y_{t-6} + Z_t - 0.6863Z_{t-1}$$

Model Interpretation

$$Y_t = -0.0320 + 0.1985Y_{t-1} - 0.0027Y_{t-2} + 0.0338Y_{t-3} - 0.1066Y_{t-4} - 0.1463Y_{t-5} - 0.3384Y_{t-6} + Z_t - 0.6863Z_{t-1}$$

Note: Since we're dealing with differenced data, it's better to interpret the model in terms of spikes and dips.

Model Interpretation

$$Y_t = -0.0320 + 0.1985Y_{t-1} - 0.0027Y_{t-2} + 0.0338Y_{t-3} - 0.1066Y_{t-4} - 0.1463Y_{t-5} - 0.3384Y_{t-6} + Z_t - 0.6863Z_{t-1}$$

AR Component

- **Positive coefficient:** an increase in past differences leads to a higher predicted change in fatalities at time t
- **Negative coefficient** suggests an inverse relationship.

MA Component

- **Negative coefficient:** an increase in past white noise differences reduces the predicted change in fatalities at time t

Model Interpretation

$$Y_t = -0.0320 + 0.1985Y_{t-1} - 0.0027Y_{t-2} + 0.0338Y_{t-3} - 0.1066Y_{t-4} - 0.1463Y_{t-5} - 0.3384Y_{t-6} + Z_t - 0.6863Z_{t-1}$$

AR Component

- Smallest coefficient is 0.0027.
- Largest coefficient is 0.3384, which is for lag-6.
  - ~~may indicate low persistence in political violence events~~
- The trajectory that would lead to high Y_t
  - gradual increase in fatalities from very small values or negative values

Model Interpretation

$$Y_t = -0.0320 + 0.1985Y_{t-1} - 0.0027Y_{t-2} + 0.0338Y_{t-3} - 0.1066Y_{t-4} - 0.1463Y_{t-5} - 0.3384Y_{t-6} + Z_t - 0.6863Z_{t-1}$$

MA Component

- recent noise tends to dampen extreme changes in fatalities

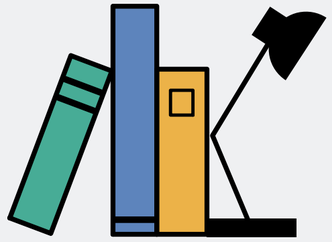
Intercept

- baseline change in fatalities when no other factors are considered

Key Insights

Policy Implications

- If consecutive increases persist, targeted interventions are needed.
- The system tends to self-correct, but policymakers should still monitor and act when necessary.
- Set risk thresholds based on predicted changes.
    - ensure efficient resource allocation



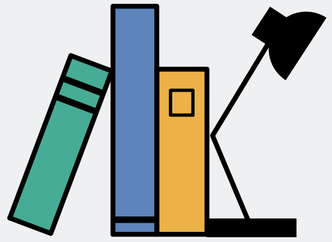
Sources

01 **Timeline: The Maguindanao killings and the struggle for justice, Dec. 2019.**

02 **P. J. Brockwell and R. A. Davis. Introduction to Time Series and Forecasting. Springer Texts in Statistics. Springer Cham, 3 edition, Aug. 2016.**

03 **E. Gutierrez and S. J. Borras. The Moro Conflict: Landlessness and Misdirected State Policies, Jan. 2004. ISBN: 9781932728149.**

04 **H. Johnson and C. Giles. Philippines drug war: Do we know how many have died? BBC, Nov. 2019.**

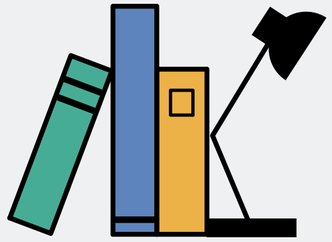


Sources

05 **C. J. Montiel. Philippine Political Culture and Governance. In Philippine Political Culture: View from Inside the Halls of Power, page 95. Philippine Governance Forum, 2002.**

06 **S. Rogers. Philippine Politics and the Rule of Law. Journal of Democracy, 15(4):111–125, Oct. 2004.**

07 **R. H. Shumway and D. S. Stoffer. Time Series Analysis and Its Applications. With R Examples. Springer Texts in Statistics. Springer Cham, 4 edition, Apr. 2017.**



Sources

08 **R. S. Tsay. An introduction to analysis of financial data with R. John Wiley & Sons, 2014.**