

Chapple, Andrew G.

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EERI
Economics and Econometrics Research Institute
Avenue Louise
1050 Brussels
Belgium

Tel: +32 2271 9482
Fax: +32 2271 9480
www.eeri.eu

Modeling ISIL terror attacks and their fatality rates with a Bayesian reversible jump marked point process

Andrew G. Chapple

Department of Statistics, Rice University, Houston, Texas. agc6@rice.edu

Abstract

This paper attempts to find different time periods since ISIL's formation in 2013 in which the rate of ISIL attacks or their effectiveness in terms of fatalities differ. A Bayesian model is presented for marked point process data that separates the time scale into disjoint intervals as a function of the rate of the attacks and the average number of fatalities for each attack which are the marks for the model. The model is endowed with priors to discourage intervals with few events and borrow strength among rates and intensities of adjacent intervals and uses the reversible jump approach introduced by Green (1996) to allow the number of intervals to vary as a function of the rates and intensities of attacks. Application results show that the hazard of an ISIL attack has increased drastically since 6/8/2014 since they took Mosul and again increased after 2/23/16, which corresponds with major military intervention.

Keywords: Marked Point Process, Bayesian Analysis, Reversible Jump, ISIL.

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Abstract

This paper attempts to find different time periods since ISIL's formation in 2013 in which the rate of ISIL attacks or their effectiveness in terms of fatalities differ. A Bayesian model is presented for marked point process data that separates the time scale into disjoint intervals as a function of the rate of the attacks and the average number of fatalities for each attack which are the marks for the model. The model is endowed with priors to discourage intervals with few events and borrow strength among rates and intensities of adjacent intervals and uses the reversible jump approach introduced by Green (1996) to allow the number of intervals to vary as a function of the rates and intensities of attacks. Application results show that the hazard of an ISIL attack has increased drastically since 6/8/2014 since they took Mosul and again increased after 2/23/16, which corresponds with major military intervention.

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1 Introduction

Since formally declaring itself a caliphate on June 29, 2014, the Islamic State of Iraq and the Levant (ISIL) has become the most deadly terror organization in the world (BBC, 2015). Over 5000 ISIL attacks have been carried out world wide with most occurring in the Middle East. They have recently lost a lot of territory due to military intervention, but it is not clear if this has decreased their ability to carry out many devastating attacks or if ISIL has become more dangerous as they gained more experience.

To analyze these trends, we view attacks as a marked point process as described by Jacobsen (2006) and Daley and Vere-Jones (2003). We model the rate of the attacks over time with marks corresponding to the number of fatalities. To find the times, or changepoints, where ISIL attacks varied significantly, we assume a Bayesian model that allows the locations of these changepoints to vary. We also allow the number of changepoints to vary using reversible jump Markov chain Monte Carlo as introduced by Green (1996). Examples of Bayesian reversible jump methods for other point process applications can be seen in Gasbarra and Karia (2000), Centanni and Minozzo (2006), Gunawardana et al. (2011) and Ge and Colins (2011). Our approach differs in that we model the location of the changepoints as a function of both the rates of the attacks and the mean fatality counts during each interval. We use the piecewise exponential model that incorporates both the rates of ISIL terror attacks and the number of fatalities. This approach has been used to model the rate, or hazard, of events including coal mining data and mass shooting data and allows the number of intervals and the risk of an event within those intervals to vary as in Green (1996) and Chapple (2016).

Posterior inference from this model can be used to determine the effectiveness of military campaigns or other extraneous circumstances on the ability for ISIL to carry out attacks. Data from the National Consortium for the Study of Terrorism and Responses to Terrorism (START, 2018) was examined to see if the rates or intensities of ISIL attacks changed over time. Since this data only consists of terror

attacks up until 2016, data coming from January 1, 2017 to March 31, 2018 was obtained from another source obtained through crowdsourcing and Story Maps (2018). The model is applied and picks out several interesting intervals of significant changes in ISIL’s effectiveness that match up to major news stories or events.

The rest of the paper is outlined as follows. In section 2, the model and prior distributions for the marked point process are described and the piecewise exponential model featuring intensities is established. In section 3, the details for the Markov Chain Monte Carlo sampling scheme are discussed, particularly the reversible jump moves, with acceptance ratios that are a function of both the current rate and intensity. Section 4 discusses the application to the ISIL database while section 5 ends the paper with a discussion. Code to execute this sampler is available in the package PieceExpIntensity on CRAN at <http://cran.r-project.org>.

2 Model and Prior Distributions

We require a model that can identify intervals of time where the rate or fatality capabilities of ISIL changed over time. Let $X_i > 0$ denote the i th ISIL attack time since April 18, 2013 and $Y_i \in \{0, 1, \dots\}$ denote the number of fatalities due to attack i . (X_i, Y_i) forms a marked point process as described by Jacobsen (2006) and Daley and Vere-Jones (2003). Define $\mathbf{s} = (s_0 = 0, s_1, \dots, s_J, s_{J+1} = X_{\max})$ as a random partition of the time scale from 0 to the most recent attack time since April 18, 2013. These attacks X_1, \dots, X_n occur from 4/18/13 to 3/31/18. For all $t \in (s_{j-1}, s_j]$, we assume that the risk of an ISIL attack is $h(t) = \exp(\lambda_j)$ and that the conditional distribution of the intensity is $Y|X \in (s_{j-1}, s_j] = \text{Poisson}(\exp(\theta_j))$. Given a time scale partition \mathbf{s} , the pairs of (X_i, Y_i) are independent for $i = 1, \dots, n$. The data will help determine a partition \mathbf{s} where the frequency or deadliness of ISIL attacks vary. These assumptions lead to the likelihood

$$L(\mathbf{X}, \mathbf{Y}|\mathbf{s}, \lambda, \mu) = \prod_{j=1}^{J+1} \exp \left[d_j \{ \lambda_j - \exp(\theta_j) \} - \exp(\lambda_j) \sum_{i \in R_j} \Delta_{ij} \right] \frac{\exp(\theta_j)^{\sum_{k \in D_j} Y_k}}{\prod_{k \in D_j} Y_k!},$$

where d_j is the number of events in the interval $(s_{j-1}, s_j]$, R_j is the set of ISIL attacks in the data set that have not yet occurred by time s_{j-1} , D_j is the set of attacks that happened between s_{j-1} and s_j , and $\Delta_{ij} = \min(X_i, s_j) - s_{j-1}$. Endowing the parameters $J, \mathbf{s}, \boldsymbol{\lambda}, \boldsymbol{\theta}$ with priors with Bayesian methods allows the data to infer about ISIL attack trends. We assume that the positions \mathbf{s} are a priori uniform but that they are spaced out in a way to discourage intervals with few events. This is done by drawing $2J + 1$ uniform random variables from 0 to X_{\max} and taking the even order statistics as \mathbf{s} . Formally, this prior is:

$$\mathbf{s}|J \propto \frac{(2J + 1)! \prod_{j=1}^{J+1} (s_j - s_{j-1})}{s_{J+1}^{2J+1}}$$

Since we do not know how many times the rate and severity of these attacks changed, we do not fix J and assume that J takes values in the set $\{0, 1, \dots, J_{\max}\}$ with equal probability. This discrete uniform prior distribution allows the data to fully infer the value of J . We impose spatial dependency in the vectors $\boldsymbol{\theta}$ and $\boldsymbol{\lambda}$ with the following priors:

$$\lambda_1 \sim N(0, 25), \quad \lambda_j | \lambda_{j-1}, \sigma_\lambda^2 \sim N(\lambda_{j-1}, \sigma_\lambda^2) \quad \text{and} \quad \theta_1 \sim N(0, 25), \quad \theta_j | \theta_{j-1}, \sigma_\theta^2 \sim N(\theta_{j-1}, \sigma_\theta^2).$$

Here $N(\cdot, \cdot)$ denotes a normal distribution with some mean and variance. Finally, we assume that $\sigma_\theta^2 \propto 1/\sigma_\theta^2$ and $\sigma_\lambda^2 \propto 1/\sigma_\lambda^2$ to encourage some dependency between adjacent intervals.

3 Markov Chain Monte Carlo

We perform a reversible jump Markov chain Monte Carlo sampling scheme on the parameters $J, \mathbf{s}, \boldsymbol{\lambda}, \boldsymbol{\theta}$. We recommend at least 10,000 iterations to explore the sample space and obtain convergence for J . For the sampling scheme, we perform 2 Gibbs steps, 2 Metropolis-Hastings moves, and one reversible jump move. A generic iteration does the following:

1. Metropolis Hastings move on $\mathbf{s}|J$. We shuffle the entries of \mathbf{s} for $j = 1, \dots, J$ if $J > 0$ by proposing $s_j^* \sim \text{Unif}[s_{j-1}, s_{j+1}]$ and do not change $\boldsymbol{\lambda}$ or $\boldsymbol{\theta}$. This move is accepted based on the likelihood ratio and the prior ratio for $\mathbf{s}|J$.
2. Metropolis Hastings moves on $\boldsymbol{\lambda}$ and $\boldsymbol{\theta}$. Let $\boldsymbol{\gamma}$ denote either of these vectors. For $j = 1, \dots, J+1$, we propose $\gamma_j^* \sim \text{Unif}[\gamma_j - .25, \gamma_j + .25]$ as seen in Haneuse et al. (2008) and accept based on the likelihood ratio and the prior ratio for $\gamma_j|\gamma_{(-j)}, \mathbf{s}, \sigma_\gamma^2$.
3. Gibbs step on σ_λ^2 and σ_θ^2 by drawing σ_γ^2 from an inverse gamma distribution with parameters $J/2 + 1$ and $\sum_{j=1}^{J+1} (\gamma_{j+1} - \gamma_j)^2$ for $\gamma \in \{\lambda, \theta\}$.
4. Metropolis Hastings Green move on $J, \mathbf{s}, \boldsymbol{\lambda}, \boldsymbol{\theta}$ which is done every iteration via add and delete moves (if applicable).

- **Add:** For an add move, we propose $J^* = J + 1$ and add an extra split point by drawing it from $\text{Unif}[0, X_{\max}]$ to obtain \mathbf{s}^* . Let s_* denote the location of this additional split point and given that $s_* \in (s_{j-1}, s_j)$, we define the new values γ_j^* and γ_{j+1}^* for $\boldsymbol{\gamma} = \{\boldsymbol{\lambda}, \boldsymbol{\theta}\}$ via the multiplicative perturbation of $\exp[\gamma_{j+1}^*]/\exp[\gamma_j^*] = (1 - U_\gamma)/U_\gamma$ suggested by Green (1995) and a weighted average $(s_* - s_{j-1})\gamma_j^* + (s_j - s_*)\gamma_{j+1}^* = (s_j - s_{j-1})\gamma_j$ which yields the new values.

$$\gamma_j^* = \gamma_j - \frac{s_j - s_*}{s_j - s_{j-1}} \log\left(\frac{1 - U_\gamma}{U_\gamma}\right) \quad \text{and} \quad \gamma_{j+1}^* = \gamma_j + \frac{s_* - s_{j-1}}{s_j - s_{j-1}} \log\left(\frac{1 - U_\gamma}{U_\gamma}\right).$$

Here $U_\gamma \sim \text{Unif}[0, 1]$ is drawn for both $\boldsymbol{\lambda}, \boldsymbol{\theta}$ separately. $J^*, \mathbf{s}^*, \boldsymbol{\lambda}^*, \boldsymbol{\theta}^*$ is accepted over the previous values with probability equal to the product of the likelihood ratio, the prior ratio and the following Jacobians to maintain detailed parameter balance between the parameter spaces.

$$\left| \begin{array}{cc|cc} d\lambda_j^*/d\lambda_j & d\lambda_j^*/dU_\lambda & d\theta_j^*/d\theta_j & d\theta_j^*/dU_\theta \\ d\lambda_{j+1}^*/d\lambda_{j+1} & d\lambda_j^*/dU_\lambda & d\theta_{j+1}^*/d\theta_{j+1} & d\theta_j^*/dU_\theta \end{array} \right| = [U_\lambda(1 - U_\lambda)U_\theta(1 - U_\theta)]^{-1}$$

- **Delete:** For a delete move, we randomly choose some $j = 1, \dots, J$ and propose removing s_j from \mathbf{s}^* . For $\gamma_j \in \{\lambda_j, \theta_j\}$ we set $\gamma_j^* = [\gamma_j(s_j - s_{j-1}) + \gamma_{j+1}(s_{j+1} - s_j)]/(s_{j+1} - s_{j-1})$. We accept $J^*, \mathbf{s}^*, \boldsymbol{\lambda}^*, \boldsymbol{\theta}^*$ with probability equal to the likelihood ratio, prior ratio and the Jacobians.

$$\left| \begin{array}{cc|cc} d\lambda_j^*/d\lambda_j & d\lambda_j/d\lambda_{j+1} & d\theta_j^*/d\theta_j & d\theta_j^*/d\theta_{j+1} \\ dU_\lambda/d\lambda_j & dU_\lambda/d\lambda_{j+1} & dU_\theta/d\theta_j & dU_\theta/d\theta_{j+1} \end{array} \right| = U_\lambda(1 - U_\lambda)U_\theta(1 - U_\theta)$$

Again here $U_\gamma \sim \text{Unif}[0, 1]$ is drawn for both $\boldsymbol{\lambda}, \boldsymbol{\theta}$ separately.

We try both delete moves if $J > 0$ and add moves if $J < J_{\max}$ at every iteration. This could result in shuffling \mathbf{s} with adjusted values for $\boldsymbol{\lambda}, \boldsymbol{\theta}$ if both an add and delete move are executed within an iteration.

After the sampling scheme has been carried out, we burn in the first half of the samples and draw inference on how the rate and intensity of events have changed over time by looking at posterior samples that have J values equal to the mode of J^{mode} over all posterior samples. Generally, one mode is selected at a significantly higher proportion than the second most visited value of J but if two values of J are visited often, then posterior inference should be conducted for both values of J . In general, the two values will be J^{mode} and $J^{\text{mode}} + 1$ or $J^{\text{mode}} - 1$. The extra split point seen in one set of samples may not lead to very different inferential conclusions.

4 Application

We used data from the National Consortium for the Study of Terrorism and Responses to Terrorism (START, 2018). We looked at only data from after April 18, 2013, since the first ISIL attack in this database occurred on this date. Since this data only consists of terror attacks up until 2016, data coming from January 1, 2017 to March 31, 2018 were obtained from Story Maps (2018). Only confirmed ISIL attacks were analyzed. Here the Las Vegas shooting was not included although ISIL claimed responsibility. We removed any data points where the number of fatalities were not available, leaving 5054 attacks since April 18, 2013. The average number of fatalities over the entire dataset was 7.48.

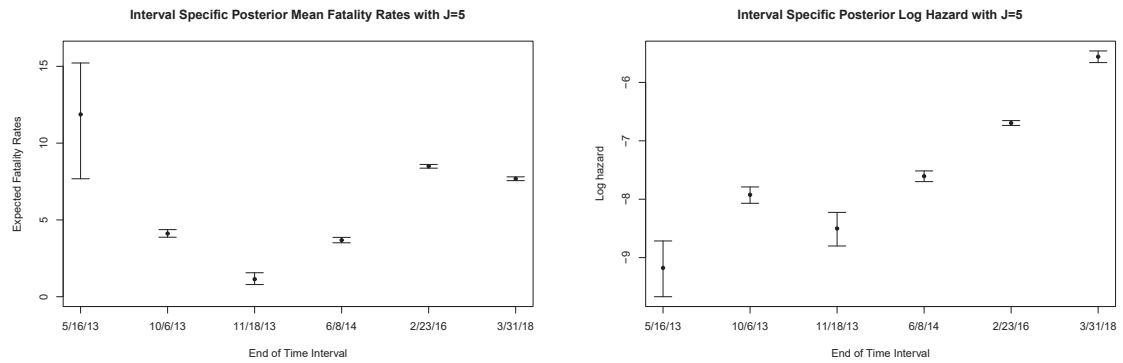


Figure 1: Posterior means and credible intervals for each interval of $\mathbf{s} | J^{\text{mode}} = 5$.

We applied the PieceExpIntensity package to the data with a maximum allowed $J_{\text{max}} = 20$ split points and 100,000 iterations, burning in the first half of the posterior samples. In the posterior distribution, values of $J = 5, 6, 7, 8, 9$ were seen with $J = 5$ occurring in about 45 % of the posterior samples and $J = 6$ occurring in about 44 % of samples. For samples containing $J = J^{\text{mode}} = 5$ split points, the mean location these changepoints was 5/16/13, 10/6/13, 11/18/13, 6/8/14, and 2/23/16. When $J = 6$, the last 4 posterior mean changepoints are identical to those for the model with $J = 5$, and the extra changepoint occurs in the time interval 4/18/13 to 10/6/13 which does not affect inferential conclusions as the posterior credible intervals for both $\exp(\theta_j)$ and λ_j overlap for $j = 1, 2$.

We examine the posterior samples of $\mathbf{s}, \boldsymbol{\lambda}, \boldsymbol{\theta} | J = 5$ to draw inference on ISIL's effectiveness. Plots of the posterior means and credible intervals for $\exp[\boldsymbol{\theta}]$ and $\boldsymbol{\lambda}$ is shown in figure 1 for $J = 5$. Credible intervals that do not overlap are considered significantly different. We see that in general, the risk of an ISIL terror attack has increased over time, with the most recent interval from 2/23/16 to 3/31/2018 having the highest log risk. The three time intervals from 5/16/13 to 6/8/14 had the lowest mean fatality counts per attack, which nearly doubled on the interval 6/8/14-2/23/16. ISIL took the major Iraqi city Mosul between June 4th and June 10th, 2014 (BBC, 2017), suggesting that their attack effectiveness improved after gaining more territory and members.

The start of the interval with the highest risk of attacks occurred a few days after a successful U.S. airstrike on Libyan ISIL members including a senior leader, Nouredine Chouchane, on February 19 (Greg and Starr, 2016). Chouchane was involved in the planning of several attacks and the influx of ISIL combatants in Libya. After his death the average number of fatalities decreased significantly by about 1 but the log hazard of a ISIL attack also increased significantly. This time period also corresponds with increased military intervention by the United States. It appears that the increase in the military push back, which resulted in a significant loss of ISIL territory, has emboldened ISIL members to carry out more terror attacks. This increase could also be due to ISIL recruiting more members from their founding until overtaking Mosul or that ISIL is feeling the pressure of losing their lands and attempting to dissuade further invasion with more terror attacks when they have the ability to do so.

5 Discussion

A Bayesian reversible jump marked changepoint model was developed to assess whether the effectiveness and ability of ISIL attacks have changed over time. This models changepoints as a functions of the rates of attacks and the number of fatalities of each attack to determine what time periods that rates and effectiveness differ. The results suggest that hazard of ISIL attacks have actually increased as they've lost their territory in the Middle East as has their ability to cause fatalities. While ISIL may have lost military capabilities, their ability to carry out terror attacks has improved over time. R Code is available in the package PieceExpIntensity on CRAN.

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