# NAVAL POSTGRADUATE SCHOOL

**MONTEREY, CALIFORNIA**

# THESIS

**UNDERSTANDING TERRORIST ORGANIZATIONS BY ANALYZING THEIR HISTORICAL DATA**

by

Murat Yalçın

June 2017


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In this research we analyzed PKK data and try to find a model which gives good predictions about the PKK's future events. By analyzing PKK data, we tried to find answer to following questions: How can we predict future events from the terrorist group PKK by looking at its past behavior? How can we decrease the success rate of attacks by analyzing successful past terrorist events? Can we think like the PKK leaders are thinking, to understand the PKK on a tactical level?

To answer these questions, we first made exploratory time series analysis on PKK data. Then we explored that how the self-exciting hurdle model, may predict the future events of the PKK by looking at the historical events. Finally, we tried to find better predictive model for the PKK events.

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**UNDERSTANDING TERRORIST ORGANIZATIONS BY ANALYZING THEIR HISTORICAL DATA**

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Submitted in partial fulfillment of the
requirements for the degree of

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In this research we analyzed PKK data and try to find a model which gives good predictions about the PKK's future events. By analyzing PKK data, we tried to find answer to following questions: How can we predict future events from the terrorist group PKK by looking at its past behavior? How can we decrease the success rate of attacks by analyzing successful past terrorist events? Can we think like the PKK leaders are thinking, to understand the PKK on a tactical level?

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# EXECUTIVE SUMMARY

The world is suffering from terrorism for a long time and generally first solution to the terrorism thought to be the using military power. The PKK is rooted terrorist organization and acting in Turkey more than 30 years. As general trend, Turkish authorities put, using the military power to first place and not much attention to the scientific part. Although, PKK is acting more than 30 years, its historical data not yet analyzed to shed a light to the future. We wanted to fill this gap by analyzing PKK data and coming up with information that may be helpful to decision makers, for their future decisions about the PKK.

First of all, we used two data sources for our analysis. Global Terrorism Database (GTD), a collection of data related to terrorist organizations around the world, and augmented GTD data created by Edem. Since GTD has missing PKK events, Erdem searched through Turkish newspapers and found missing events and build the extended form of GTD. From these two data sets we created two more data sets for analysis purposes. First, cities data with information related with each city. Second, time series data, which has ones for event days and zeros for non-event days.

Then, we explored, how PKK events are in correlation with important days in Turkey. We observed that GDP, months, Sacrifice and Nowruz Festivals are important predictors for PKK events. Monthly effect on the PKK events is very strong, because the PKK prefer spring and summer times to attack. During winter time, they stay in their hide-outs.

We also analyzed cities data to see, how economy, education and unemployment affects to the PKK events. Not surprisingly the PKK events have positive correlation with economy and education level, negative correlation with unemployment rate. Also, by analyzing cities data, we explored cities, with high number of events, are in the eastern or southeastern part of the Turkey.

In addition, we analyzed PKK data as a time series and explored seasonality in data. Why, seasonality is strong in PKK data, is explained above. Also by using Holt-

winters additive and multiplicative models, we revealed, possible future events. These two models are not perfect fit with data and their predictions are not accurate enough to take precautions for possible events by only looking at them. However, they have prediction power and very well follow trend on historical data. Holt-winters multiplicative model predicts more PKK events in the future than additive model.

Moreover, we used self-exciting hurdle model to predict PKK events. Self-exciting hurdle model has two models in it. Self-exciting and baseline model. Self-exciting part looks at the historical events by using decay function to capture sudden changes. Self-exciting part is not affected from the variables that have effect on the PKK events. Baseline part looks for only predictors that have effect on events. Contrary to Self-exciting part, baseline part is not get affected from the historical events. When we add baseline part to model it didn't changed the probabilities of future events much. So we tried to replace this part of self-exciting hurdle model with better model. We used previous event days as a predictor and tried to replace it with baseline part. For $Y_{t-1}$ is the predictor looking only yesterday. $Y_{t-2}$ is the predictor looking two days ago and so forth.

The model that we tried, gave almost same results with self-exciting part. However, self-exciting part is really good at following events with decay function. New model couldn't follow events as good as self-exciting model. For optimization, as Porter and White used, we also used nlminb() function in stats package.

Finally, according to all analysis and exploration, we wrote the conclusion that may help to decision makers and the people who are working on terrorist organizations.

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# I. INTRODUCTION

Turkey has been suffering from terrorism since the foundation of Armenian Secret Army for the Liberation of Armenia (ASALA) in 1975. Based on the Global Terrorism Database (GTD), a collection of data related to terrorist organizations around the world, shows that Turkey was the 8th most frequently attacked country between 1970 and 2007 (see Table 1). Since its geostrategic position, Turkey either experienced terrorism on its own on land, or felt the effect of terrorism on its adjacent neighbors' soil. The Armenian based terrorist organization known as ASALA, targeted Turkey until the 1980s. At that point, the Kurdistan Workers' Party (PKK) started its terrorist activities.

The focus of this thesis is to better understand PKK activities based on PKK terrorist events that occurred in Turkey between 1984 and 2015. These events are extracted from the GTD and from Turkish newspapers.

## A. AN OVERVIEW OF THE RESEARCH

### 1. A Brief History of the PKK and Its Effect on Turkey

"The PKK's predecessor organization, known as Kongra-Gel, was founded by Abdullah Ocalan in 1974 as a Marxist-Leninist separatist terrorist organization and formally named the Kurdistan Workers' Party in 1978. The group is composed primarily of Turkish Kurds. In 1984, the PKK began its campaign of armed violence, which has resulted in some 30,000 casualties as of 2016. The PKK has aimed to establish an independent Kurdish state in southeast Turkey, northern Iraq, and parts of Iran and Syria"( Bureau of Counterterrorism, Country Reports on Terrorism, 2013)

. In support of this mission, the PKK has targeted various groups. The majority of PKK's targets are military forces. However, the PKK does not hesitate to attack vulnerable and innocent government official workers. The PKK has tried to suppress villagers and local people, who oppose the PKK, by attacking villages and kidnapping their children. In addition, the PKK has conducted various types of attacks on commercial facilities to disrupt economic welfare of the region. Also, between 1993 and

1995 the PKK attacked Turkish diplomats in European cities. The PKK attacks are not limited to Turkish citizens, south-eastern region of Turkey, where PKK operates, has many natural wonders that attract tourists. The PKK has kidnapped foreign tourists and bombed tourist hotels to prevent tourist from visiting Turkey.(AAB et al., n.d.) To harm Turkey and its people, the PKK has used different attack types for different targets. Geographically, the PKK has carried out terrorist activities not only in Turkey but also in Europe and different parts of the world. Based on the GTD, the PKK has the 10th highest attack rate and the 12th highest fatality rate among terrorist organizations worldwide. (see Table 2)

Table 1. Percentage of Total Attacks for the Twenty Most Frequently Attacked Countries, 1970-2007. Adapted from LaFree (2010).

| Country | Cumulative % of All Attacks | Cumulative % of All Countries |
|---|---|---|
| Colombia | 8.16 | 0.48 |
| Peru | 15.44 | 0.96 |
| El Salvador | 21.87 | 1.44 |
| India | 27.08 | 1.92 |
| Northern Ireland | 31.62 | 2.40 |
| Spain | 35.44 | 2.88 |
| Iraq | 39.25 | 3.37 |
| Turkey | 42.49 | 3.85 |
| Sri Lanka | 45.64 | 4.33 |
| Pakistan | 48.70 | 4.81 |
| Philippines | 51.71 | 5.29 |
| Chile | 54.46 | 5.77 |
| Israel | 57.05 | 6.25 |
| Guatemala | 59.49 | 6.73 |
| Nicaragua | 61.88 | 7.21 |
| South Africa | 64.20 | 7.69 |
| Lebanon | 66.51 | 8.17 |
| Algeria | 68.50 | 8.65 |
| Italy | 70.29 | 9.13 |
| United States | 71.93 | 9.62 |
| Source: Global Terrorism Database | | |

"Turkey has been suffering from separatist terrorism, in the form of the PKK, since the mid-1980s. Between 1988 and 2015, it is estimated that 4,300 civilians and 6,850 security force members and military personnel were killed by PKK terrorist activities"(29th et al., 2016). Since 1984, the total life cost of the PKK is estimated to be 40,000.

Table 2. Twenty Most Active Terrorist Organizations in terms of Attack Frequency and Fatalities, 1970 to 2006 Adapted from LaFree (2010).

| | Most Frequent Perpetrators | | Most Fatalities | |
|---|---|---|---|---|
| Rank | Organization | Frequency | Organization | Fatality Count |
| 1 | Shining Path (SL) | 2817 | Shining Path (SL) | 6057 |
| 2 | Basque Fatherland and Freedom (ETA) | 1378 | Liberation Tigers of Tamil Eelam (LTTE) | 4038 |
| 3 | Farabundo Marti National Liberation Front (FMLN) | 1249 | Al Qaeda | 3460 |
| 4 | Irish Republican Army (IRA) | 1165 | Hutus | 3222 |
| 5 | Revolutionary Armed Forces of Colombia (FARC) | 1066 | Mozambique National Resistance Movement (MNR) | 2247 |
| 6 | National Liberation Army of Colombia (ELN) | 784 | Farabundo Marti National Liberation Front (FMLN) | 1856 |
| 7 | Hamas (Islamic Resistance Movement) | 608 | Revolutionary Armed Forces of Colombia (FARC) | 1791 |
| 8 | Liberation Tigers of Tamil Eelam (LTTE) | 569 | Tanzim Qa'idat al-Jihad fi Bilad al-Rafidayn | 1646 |
| 9 | Manuel Rodriguez Patriotic Front (FPMR) | 568 | Nicaraguan Democratic Force (FDN) | 1342 |
| 10 | Kurdish Workers Party (PKK) | 535 | National Union for the Total Independence of Angola (UNITA) | 1151 |
| 11 | New People's Army (NPA) | 472 | New People's Army (NPA) | 1084 |
| 12 | Corsican National Liberation Front (FLNC) | 455 | Kurdistan Workers' Party (PKK) | 1071 |
| 13 | Taliban | 438 | Lord's Resistance Army (LRA) | 1060 |
| 14 | Tupac Amaru Revolutionary Movement (MRTA) | 412 | Hizballah | 899 |
| 15 | Communist Party of Nepal-Maoists (CPN-M) | 403 | Taliban | 876 |
| 16 | M-19 (Movement of April 19) | 321 | Tutsi | 858 |
| 17 | Nicaraguan Democratic Force (FDN) | 287 | Armed Islamic Group (GIA) | 807 |
| 18 | People's Liberation Front (JVP) | 274 | Irish Republican Army (IRA) | 728 |
| 19 | Movement of the Revolutionary Left (MIR) (Chile) | 257 | National Liberation Army of Colombia (ELN) | 646 |
| 20 | al-Fatah | 243 | Hamas (Islamic Resistance Movement) | 630 |

"In addition to lives lost, conservative estimates calculate that the PKK terror has maimed, injured, or resulted in the conviction of 200,000 people over the course of more than 30 years of terrorist activity." (Karaca, 2010)

"There are various factors that explain the long-lasting existence of the PKK, from external support to funds generated through illegal activities like drug and arm smuggling." (Karaca, 2010) One of the most important factor contributing to the PKK's existence is the failure of decision makers to understand PKK at the strategic and tactical level and to provide reasonable response to the PKK in the light of its strategy.

Several states and organizations, including the European Union, United States and the North Atlantic Treaty Organization (NATO), have listed the PKK as a terrorist organization.(Phillips, n.d.) However, although PKK has been conducting terrorist activities all around the world since 1984 and is recognized as a terrorist organization by many international organizations and countries, we have yet to analyze its tactical and strategic evolution.

While PKK is one of the deeply rooted, largest active terrorist organization, which has capacity to operate in the various regions of the world, it has not often been the subject of analytical and detailed studies. This research aims to understand how PKK operates at the tactical and strategic level by analyzing historical PKK events gathered from several sources.

## 2. About Data

There are several organizations collecting terrorist data. "The Global Terrorism Database is an open-source publicly available database of over 87,000 terrorist events around the world from 1970 through 2008. The database is continually updated with new information and is believed to be the most comprehensive database of its kind." (Porter & White, 2012) Although the GTD is very comprehensive, it has only 1,449 PKK events between 1984 and 2016 in its database. Clearly GTD is missing many PKK events. Osman Erdem (personal communication), M.S. Candidate Mercyhurst University, has increased this number to 3,487 by searching through Turkish newspapers. The data used in this thesis is the extended version of GTDs, created by Erdem. Each event is labeled with information consistent with information found in the GTD such as date, geolocation, target type, attack type, weapon type, number of kills etc. These extra 2000 events however, have not been subjected to any sort of analysis or visualization.

While both of the GTD data and the data provided by Erdem are useful, they contain some major flaws. First, the data lacks of information about the number of terrorists involved in each event and the number of government forces used against terrorist attacks. Although conventional and unconventional war differ in many respects, there are inherent factors in war that affect both regular and irregular battle. One of these is force level. Hughes and Yigit both agree that force ratio is the dominant factor in war. Hughes' salvo models (Hughes, 1995) explicitly states that force level is the most important factor in naval war. Yigit comes up with the same outcome as Hughes, for land war. "After making campaign-wise grouping and analysis, it is found that the force ratio is a valid estimator of the battle outcome." (Yigit, 2000) By knowing the size of each side, we would able to see how the number of PKK members affects the result of attack and how the government's forces could change the course of an attack or event. Second, the data doesn't have information about the weather on the day of each event. Weather is another important factor that determines the result of battle. Knowing the weather information would help us understand how the PKK is affected by weather conditions and what kind of weather it prefer for certain types of events. From my personal experience, I know that, PKK generally prefer foggy and rainy days to attack, because bad weather conditions effect soldiers' thermal and night vision negatively. Besides understanding how PKK is affected by weather and how it used weather to its advantage, we may also be able understand how government forces are affected from weather conditions. Which weather conditions increase the loss of government forces and success of PKK attack? Without weather data we won't be able answer all those questions. Third, data also lacks variables like the intentions and strategies of the PKK. In order to understand the aim of each attack, knowing the intentions of PKK would be very beneficial. Even if terrorist organization's Improvised Explosive Device (IED) explode unintentionally, it may still harm government forces. Without understanding the purpose behind each attack, we may not be able to learn when and where we should expect terrorist events and take precautions against PKK's attacks. Finally, the data lacks information about related events. Like other terrorist organizations, the PKK wants to keep its public image as strong and powerful as possible. To do that, terrorist organizations tend to retaliate against government forces after successful counter terrorist operations or unsuccessful terrorist attacks. Having the information about, which events are related to each other and how they differ from other events, may give us opportunity to understand the trend of terrorist attacks. Even with this missing information he augmented GTD data is valuable and may give us chance to understand certain things about the PKK and use it for future counter terrorist operations.

## B. THE PURPOSE OF THE RESEARCH

Counterterrorism requires elaborate thinking and planning. To be successful on different fronts, the government needs to choose a counterterrorism strategy according to specific features of the terrorist organization (Karaca, 2010). This study intends to find reasonable and rational facts about PKK that can be used for planning the counterterrorism operations.

This research aims to identify trends and extract basic features of PKK attacks. After determining trends, the study carries out deep analysis to reveal PKK' tactical and strategic level of thinking.

Terrorism is not only a threat for personal safety and public perception, but also for international relations (Kyung, Gill, & Casella, 2011). Because of these reasons, terrorism is very important problem. Our aim is to make contribution to prevent terrorism specifically in Turkey and to also serve as an example that might be applied to the study of terrorism in other parts of the world.

### 1. Difficulties with analyzing terrorist data

There are two main issues with terrorist data which make analysis very difficult. First, terrorist attacks are very rare. When we look at the period, between two specific times, it is not surprising to see, 80-90% of daily number of terrorist attacks are zero. On the other hand, special days for terrorists or political reasons may lead terrorists to carry out coordinated attacks in multiple places at the same day. So, besides having huge number of zeros, having extreme numbers of attacks in a single day, in terrorist data, is also normal. Having large number of zeros and extreme numbers in the same data, make analysis and fitting model challenging. Second, we expect like the Provisional Irish Republican Army terrorist events (Tench, Fry, & Gill, 2016), that PKK events are spatially dependent, and like Indonesian terrorist events (Porter & White, 2012) that PKK events are also temporally dependent in that they tend to clump together in time. Third, terrorist events are hugely dependent on politics and many other factors. These features make terrorist data unsuitable for analysis with standard models.

Besides natural features of terrorist events, terrorists deliberately try to make some of their attacks publically known while hiding their unsuccessful or prestige harming attacks (Kyung et al., 2011).

"A terrorist attack might seem like one of the least predictable of events. Terrorists work in small, isolated cells, often using simple weapons and striking at random. Indeed, the element of unpredictability is part of what makes terrorists so scary – you never know when or where they will strike." (Ana Swanson, 2016).

Further, although, the PKK has a hierarchical structure, it's seen that, some local leaders carry out attacks without receiving order from higher authorities. Having these arbitrary attacks makes analysis very difficult. Also unveiling strategical and tactical thinking of PKK, becomes more convoluted than thought.

## C. THESIS OUTLINE

In first chapter, we described four data sets. GTD and Erdem's data are the main resources that we created time series and cities data sets from them. Than we analyzed augmented GTD, cities and time series data sets.

In second chapter, we explored how PKK data fits with self-exciting hurdling model. Than we extracted pros and cons of self-exciting hurdle model and tried to fit better model that we observed problematic.

In third chapter, we wrote conclusion that we come up with after all analysis of PKK data.

# II. EXPLORATORY RESULTS OF PKK DATA

## A. DATA DESCRIPTION

### 1. Augmented GTD Data

The data, which has PKK events between August 8, 1984 and December 31, 2015, has 23 columns and 3,487 rows. Of the 3,487 rows, 1449 are extracted from the GTD and 2038 are extracted from Turkish newspapers. Rows represent single PKK events, so there are 3,487 events recorded in that time period. Columns or variables in the PKK data contain information about each single event. Table 2.1 contains the names of the columns, which we are interested in for our analysis, along with a brief description of each one. The first column is the Date column with the day, month, and year of the event. Six columns, Latitude, Longitude, City, Province, Region, and Country contain information about the location of each event. Since all events occur in in Turkey, this column has a single value "Turkey". The City column shows in which city event occurred. The coordinates of an event specifically indicates the point where an attack occurred. However, when data collectors cannot determine the exact coordinates of the events, the coordinates are set to the city center where the incident occurred. The Attack Type column, categorizes events to eight different attack types which are Armed Assault, Bombing/Explosion, Assassination, Facility/Infrastructure Attack, Hijacking, Hostage Taking, Unarmed Assault and Unknown. The Target Type column, separates events according to nineteen different target types ranging from Educational Institution to Military. The Weapon Type column, gives information about which weapon type used by PKK in an each event. The Weapon Type column is categorized as Chemical, Explosives/Bomb/Dynamite, Firearms, Incendiary and Melee. Other columns also gives information about how many security forces and terrorists died in each event. (See Table 3)

Table 3. Variables in PKK data Adapted from GTD

| Variable Name | Description |
|---|---|
| Date | The date of the event in DD/MM/YYYY format. |
| County | The country of the event, for example Turkey. |
| Region | The region of the event, South-East Anatolia. Turkey has geographically seven regions (See Figure 1) |
| City | The city of the event, for example Siirt. |
| District | The district of the event, for example Eruh. |
| Latitude-Longitude | The geographical coordinate of the event or if unavailable, the geographical coordinates of the city center. |
| Attack Type | The attack type with 8 levels: Armed Assault, Bombing/Explosion, Assassination, Facility/Infrastructure Attack, Hijacking, Hostage Taking, Unarmed Assault and Unknown. |
| Target Type | The target type with 19 levels: Airports & Aircraft, Business, Educational Institution, Food or Water Supply, Government (Diplomatic, Government (General), Journalists & Media, Maritime, Military, NGO, Police, Political Party, Private Citizens & Property, Religious Figures/Institutions, Telecommunication, Tourists, Transportation, Unknown, Utilities. |
| Weapon Type | The weapon type with 5 levels: Chemical, Explosives/Bomb/Dynamite, Firearms, Incendiary and Melee |
| Nkill | Number of security forces died of the event. |
| Nkillter | Number of terrorists died of the event. |
| Source | Event data source GDT or not GTD |

### 2. Cities Data

From the augmented GTD data, we construct two more data sets to facilitate explanation and analysis. The first of these two data sets focuses on the spatial distribution of the attacks, specifically the focus on the 81 that events occur in or near. The second data set focuses on the temporal aspect of the events. The cities' data set has 81 rows, one for each city and a column of city names. It also contains a Number of Events column, with the total number of events for each city that occurred between 1984 and 2015; Illiteracy Rate, Unemployment Rate, GDP and College Graduate Percent columns have information for each city. These data are collected from www.data.worldbank.org/data, and www.tuik.gov.tr

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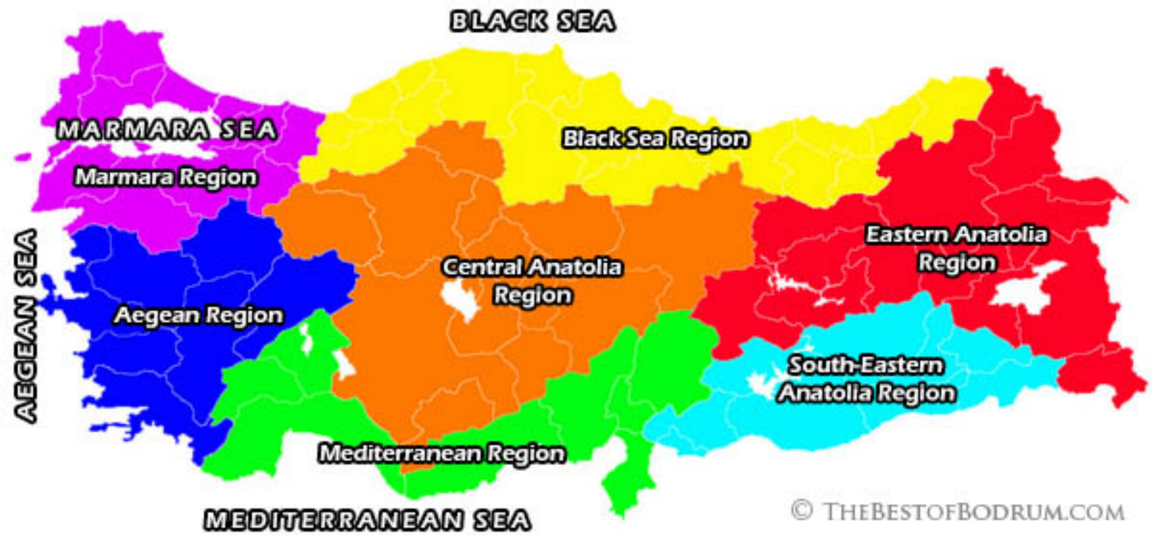



Figure 1. Turkey's Regions. Source:Thebestofbodrum.com

### 3. Time Series Data

A second data set, created for the purposes of studying the time component of the events, has 11461 rows and 15 columns. This data has one row for each day from August 8, 1984 through December 31, 2015. It contains a column with the number of events that occur on each day and the column "response" which is a binary variable of zeros and ones. The days, which have at least one event, are labeled with ones and rest with zeros. The rest of the columns serve as predictor or explanatory variables. These variables indicate holidays and other times of the year which might affect PKK's terrorist actions. These are the Ramadan month and festival, the Sacrifice festival, Nowruz festival. Also included in this data set are the month and year of the attack. The month is used to account for the seasonal component to terrorist attacks. The gross domestic product (GDP) for each year are also included. Finally, a variable t = 1, 2, … 11461 which starts with 1 on August 8, 2015 and ends with 11461 on December 31, 2015 is used in place of the date to help explore general trends in events.

## B. EXPLONATORY ANALYSIS OF EVENT LOCATIONS

### 1. Frequency in Regions and Cities

Between 1984 and 2015, there were 136,300 terrorist incidents all around the world.(GTD) Of these attacks 2.55 percent (3487) were committed by the PKK. The south-eastern part of Turkey, in which Kurdish population is high, is used by the PKK as an area of operation. The PKK has more terrorist events and activities in the Southeastern and Eastern regions, then any other regions of Turkey. Figure 2 shows the distribution of the number of attacks by region and Figure 3 maps the coordinates of the attack locations. The main reason the PKK carries out its attacks in this region is support of local people to PKK.

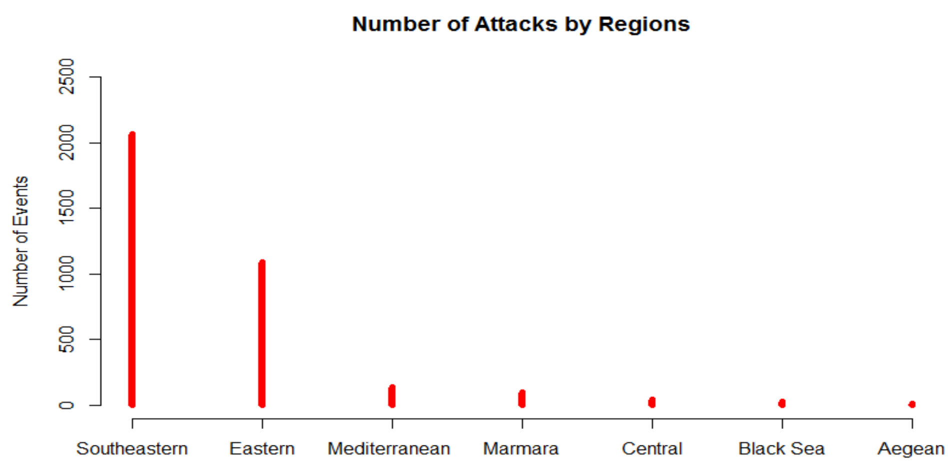



Figure 2. Number of Attacks by Regions Between 1984 and 2015 Adapted from GTD

When we look at the PKK events from geographical perspective, the PKK carried out its actions in eastern part of the Turkey. (See Figure 3). Some cities like, Tunceli, Bingöl, Siirt, Şırnak, Hakkari, Mardin, Diyarbakır, Batman have very high terrorist event rate. Number of events for these cities are 246, 209, 231, 574, 416, 282, 355 122 respectively.

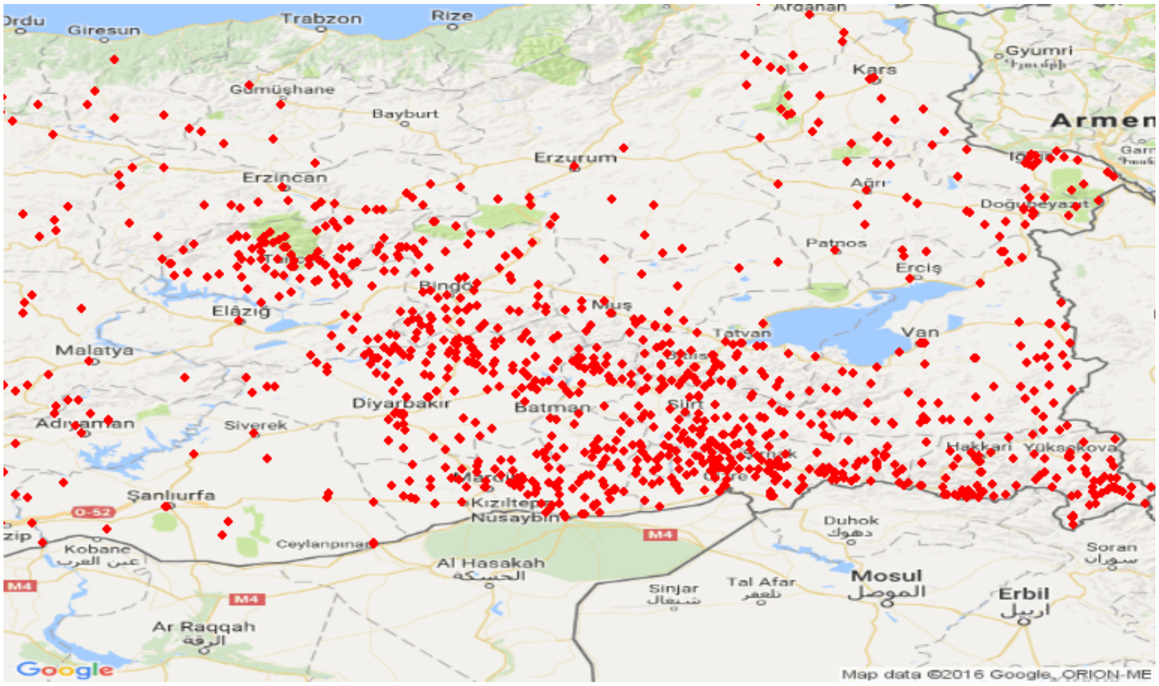



Figure 3. PKK Events In Turkey Between 1984 and 2015 Adapted from GTD

### 2. Relationship Between Number of Attacks and Other Variables

To see the effects of illiteracy, unemployment, GDP and high education level to PKK events, we use the cities data set. Not surprisingly, the number of PKK events in each city, has high correlation with illiteracy, unemployment and education level. (See Figure 4) PKK events increase exponentially, when illiteracy and unemployment rate increase. We also observe increase in PKK events, when GDP and education level decrease. (See Figure 5)

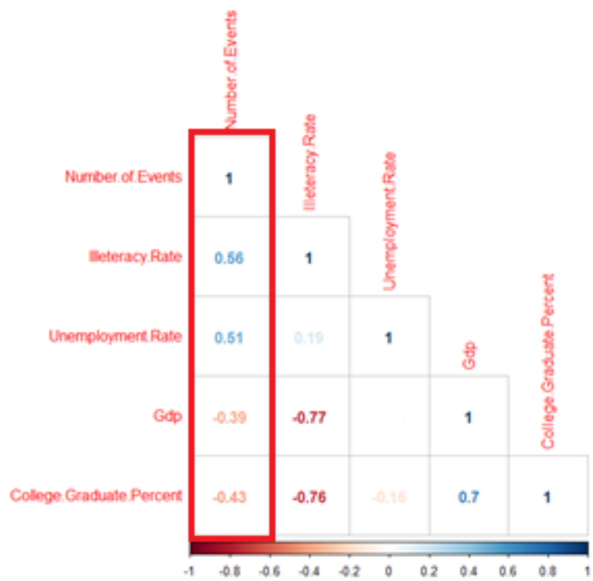



Figure 4. Correlation Matrix. Adapted from GTD

Of the 81 cities, only 50 have at least one event between 1984 and2015. These are the cities in southern and eastern Turkey. 31 cities with no events are in western and northern Turkey.

There are 28 cities with at least 10 events between 1984 and 2015. From those cities only 2 (Adana and Istanbul) in the western part of Turkey. 26 cities, with 10 or higher events, are all in the eastern and southeastern part of Turkey. This is not surprising, because these cities have high Kurdish population. The PKK needs local peoples support to survive and mostly the PKK gains this support willingly or unwillingly from Kurdish people. There are Kurdish tribes doesn't support PKK and they fight against PKK with Turkish security forces. However, there are Kurdish tribes doesn't want to support PKK, since the PKK threaten their lives and Turkish security forces are not able to save them from PKK danger, they unwillingly do what the PKK say them to do.

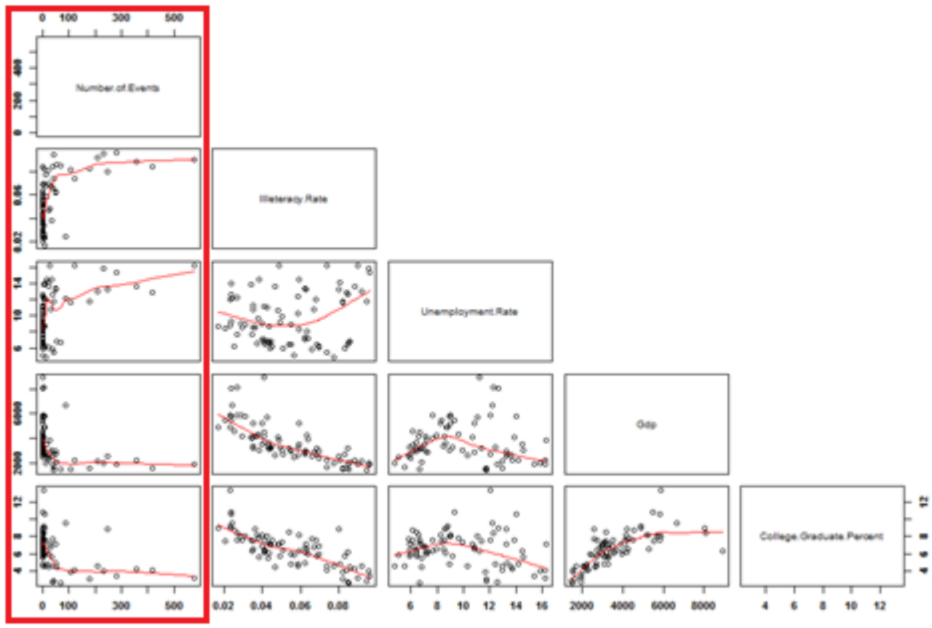



Figure 5. Scatter Plots of Important Predictors Adapted from GTD

## C. OTHER VARIABLES

The PKK mostly used armed assault and bombing / IED as an primary attack type. (See Figure 7) Attacking facilities and taking hostages of facility workers, are also in the PKK's attack type list. The PKK doesn't have specific region for specific attack types. Although, Eastern and Southeastern part of Turkey are main operation area for PKK, they have almost evenly distributed attacks in the region.

Are PKK events are Non-Homogenous Poisson Process (NHPP) spatially? Kinhom Plot in {spatstat} package, shows that events doesn't distributed according to NHPP.

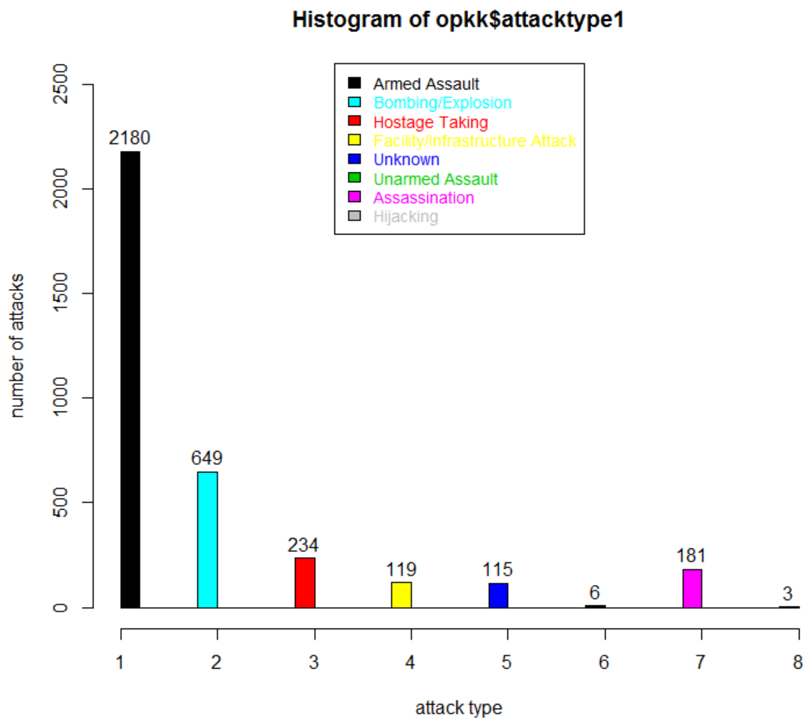



Figure 6. PKK Attack Types Adapted from GTD

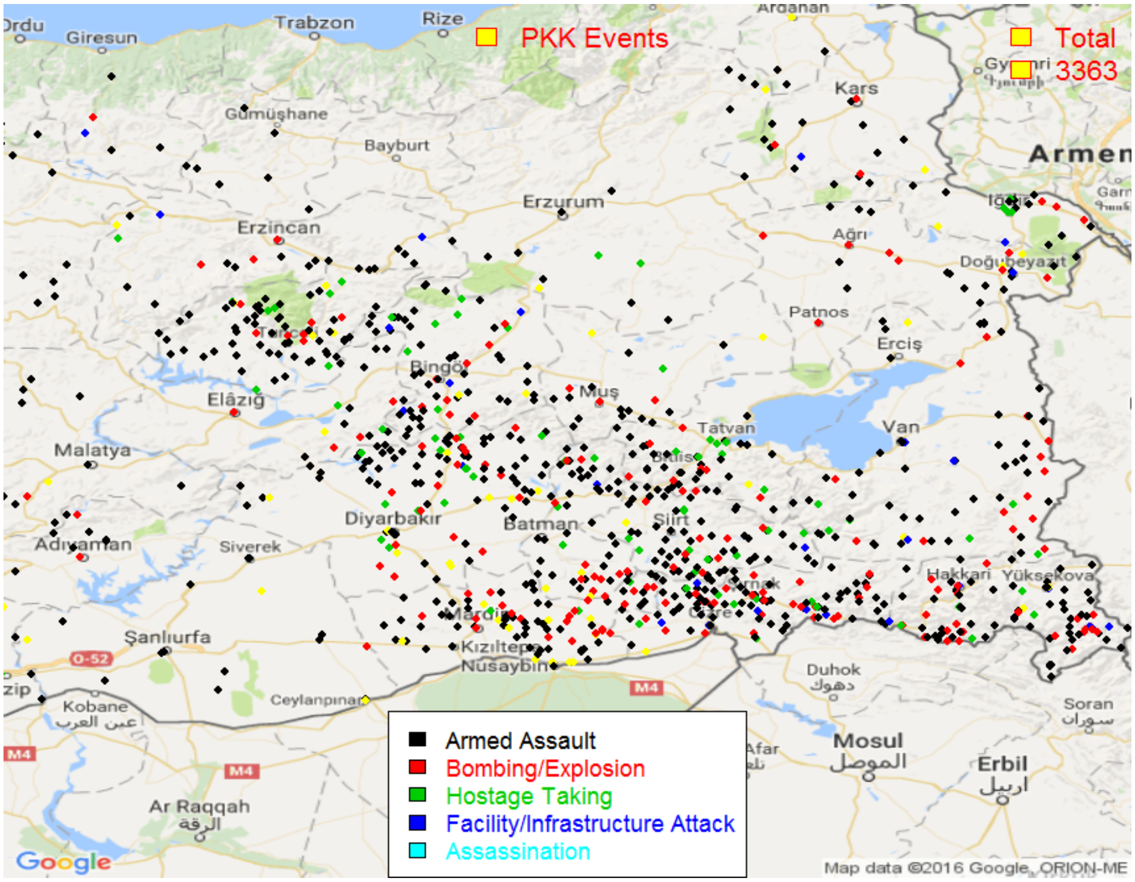



Figure 7. PKK Events by Attack Types Adapted from GTD

## D. EXPLORATORY TIME SERIES ANALYSIS

Time series is a sequence of events in successive order. Seasonality of data makes time series powerful to predict future observations. "Time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation) that should be accounted for." (Engineering Statistics Handbook)

When we look at the PKK attacks in yearly basis, between 1984 and 1991, the PKK has average 104 attacks. However, between 1992 and 1994, average number of attacks skyrockets to 364. Between 1995 and 1998, average events drops to 124. Between 1999 and 2004, we observe 8 events on average. Since leader of PKK captured by Turkish Special Forces in Kenya in 1999, there were unilateral cease-fire on PKK side between 1999 and 2004. That’s why we observe very few events in this period. After 2004 annual number of attacks differs from 21 to 151 (see Figure 8). Turkish government wanted to solve PKK problem with peace talks with PKK leader. It is not known when exactly Turkish government started solution process with PKK. However, it is known that Turkish intelligence started talks with PKK in 2009 and peace process ended in 2015. (Akin Unver, 2016) Average PKK attacks between 2004 and 2009 are 76 and between 2009 and 2015 are 77, which doesn’t show any sign of solution process according to number of events.

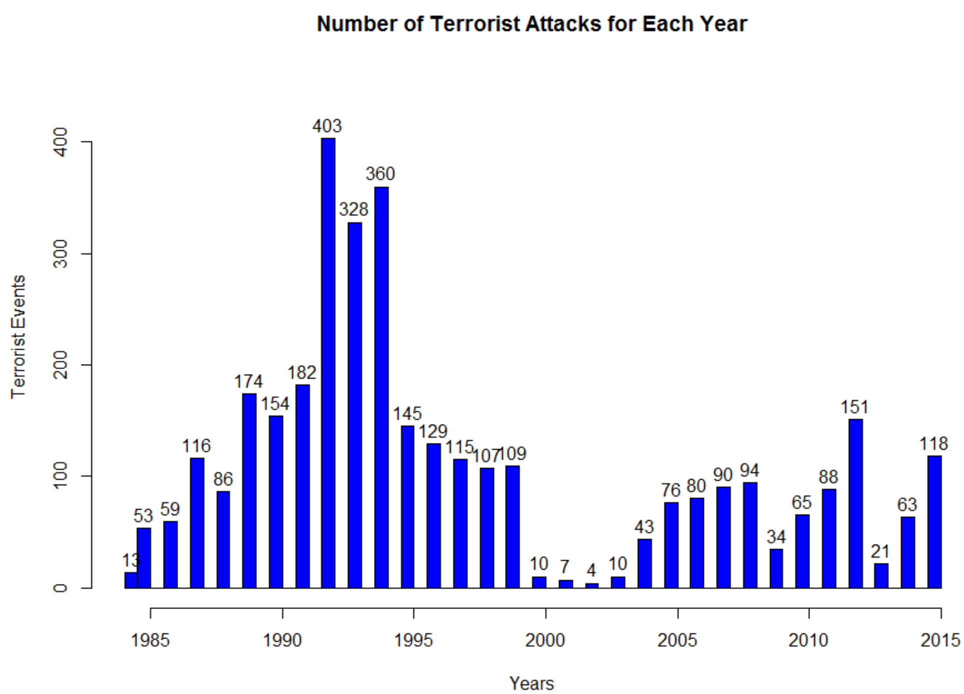



Figure 8. Number of PKK Attacks by Year Adapted from GTD

In addition to general trends, closer inspection reveals seasonal trends in the numbers of attacks. Some of this seasonality is evident in the yearly peaks or valleys of Figure 9, where the daily number of events and plotted for the entire 1984 – 2015 time period. The seasonal trend is even more evident in Table 4, which gives the number and proportion of attacks by month for the 1984 – 2015 time period.

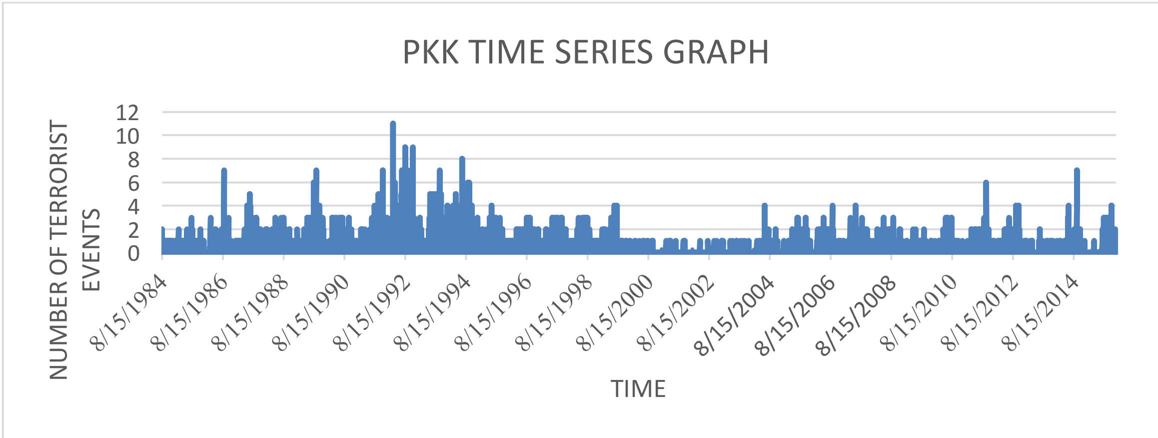



Figure 9. PKK Events 1984-2015 Adapted from GTD

Table 4. Number of Events by Months Adapted from GTD

| Months | Number of Events | Percentage |
|---|---|---|
| January | 112 | 3.21 |
| February | 74 | 2.12 |
| March | 204 | 5.85 |
| April | 230 | 6.6 |
| May | 321 | 9.21 |
| June | 406 | 11.64 |
| July | 421 | 12.07 |
| August | 515 | 14.77 |
| September | 481 | 13.79 |
| October | 391 | 11.21 |
| November | 208 | 5.97 |
| December | 124 | 3.56 |
| Total | 3487 | 100 |

The most important factor in the timing of terrorist events is the weather. The PKK generally prefer spring and summer times for terrorist actions. Winter time is very disadvantages for terrorists, because snow makes their foot prints easily visible to aerial observation. So, terrorists want to minimize their movements during winter times and maximize their activities in spring and summer times. This feature of terrorist activities, enable us to implement time series techniques to terrorist data.

To explore the general and seasonal trends more thoroughly, we extract two time periods from the 1984 – 2015 daily time-series: The period from 1984-1999, prior to the unilateral PKK truce and the period form 1999-2004 after truce. Although, some attacks, 31 attacks in four years, do occur during the truce, our primary focus is an what happened during periods of PKK operation.

We fit non-parametric smoothers to each of these time series, using the Seasonal-Trend Loess (STL) smoother of Hyndman RJ (2016) and implemented using the stl() function of the R package forecast. Hyndman RJ (2016) This smoother is additive with a seasonal component and a trend component. The advantage of using STL for exploration is that parametric functions of the two components do not need to be specified. Further, although the model is additive, the seasonal component is allowed to vary from year to year. Details of the fitting algorithm and recommendations for its use are given in Hyndman RJ (2016).

Using the default stl() settings, Figure 10 shows the pre-truce time series (first plot) and the seasonal and trend components (second and third plots respectfully) and finally the remainder which indicates the difference between actual time-series values and the sum of the seasonal and trend terms. Scale indicators (vertical bars on the right side), show us relative magnitude of the decomposed components.

On the data component; we might consider the bar as 1 unit of variation. The seasonal panel scale bar is much longer than the data component scale bar, shows that the seasonality in the PKK data is very large in relation to the variation in the PKK data. In other words, if we shrunk the seasonal component such that the box became the same size as that in the data component, the range of variation on the shrunk seasonal panel would be similar to but more smaller than that on the data component.

If we look at the trend component; the scale bar is larger than data component and slightly smaller than seasonal panel, showing that seasonal component has slightly larger variation as compared to trend component. Also, residuals component (remainder) has larger variation then the trend component. As such, we understand that PKK data exhibits a trend.

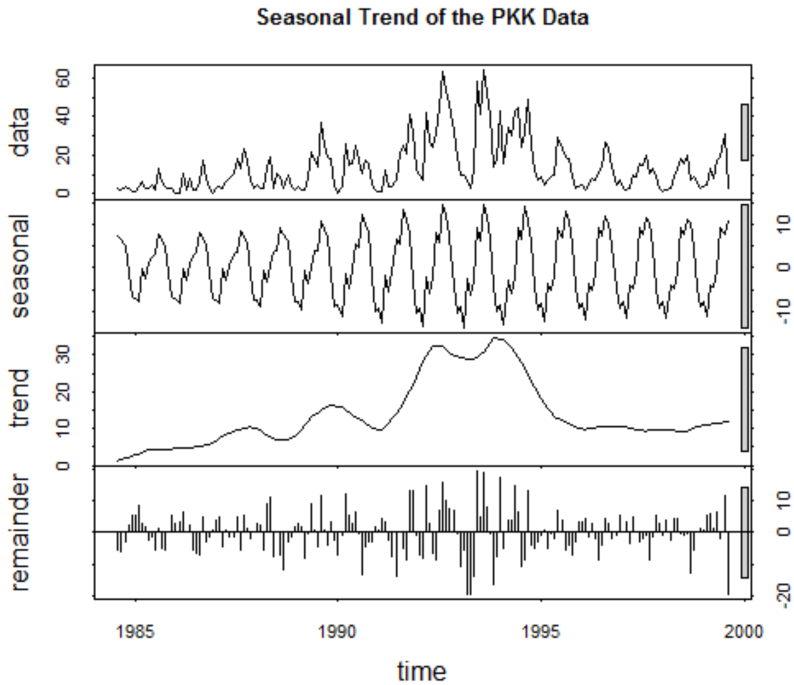



Figure 10. How Good Data Fits Time Series Adapted from GTD

General trend of increasing in the numbers of attack with the greatest number of attacks occur between 1992-1995. Followed by a sharp decrease and a leveling off in the number of attacks between 1996 and 1999. In addition to the general trend, we see evidence of shorter cycles of increased and decreased activity.

The seasonal tend shows, a strong seasonal trend that has a very similar shape from year to year. The greatest difference in the shape is that, it seems more pronounced between 1993 and 1995, during the period of the greatest number of attacks.

The remainder shows a pattern similar to the seasonal component in that, it varies more between 1993 and 1995 than it doesn't other years.

Figure 11, a plot of the remainder against the combined seasonal and trend components shows that, the day to day variability in the numbers of events increases as the daily numbers of events tend to increase. This pattern of increasing variability is expected for time series of counts such as the daily numbers of events.

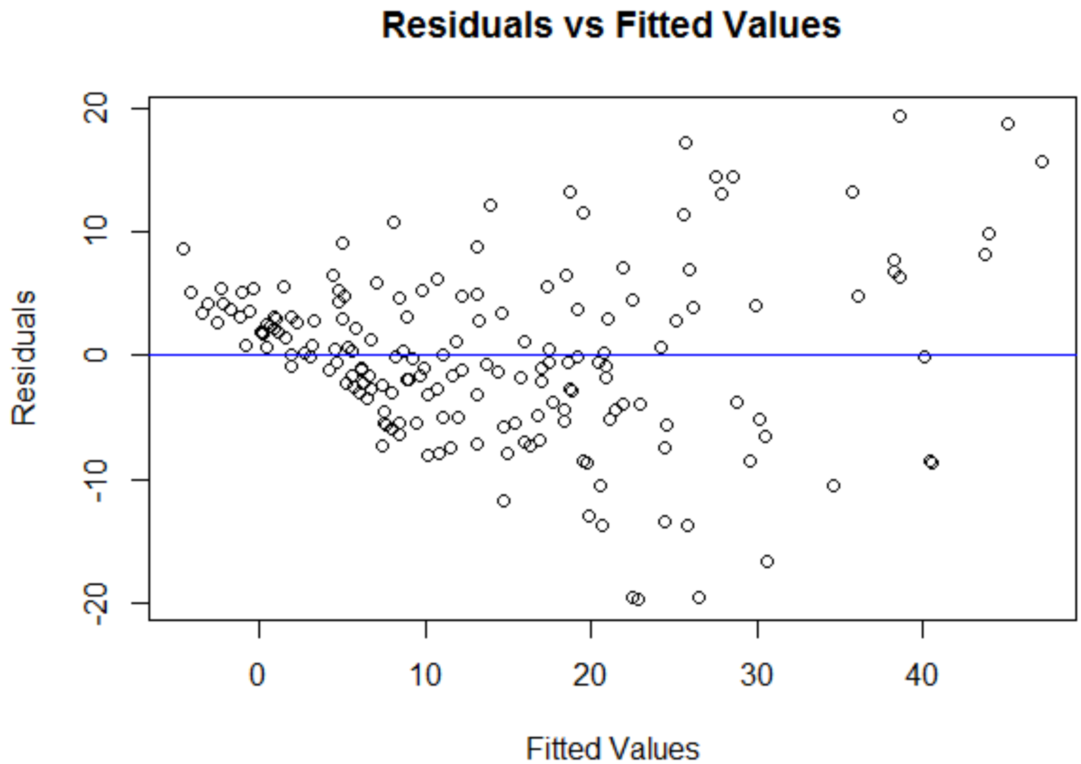



Figure 11. Remainder vs Combined Seasonal and Trend Components

The algorithm used to fit the STL smoother minimizes the remainder sums of squares, where each observation is weighted equally. This presumes that the response variable ( in this case daily number of events) has constant variance. When it does not in same cases, the response is transformed to stabilize the variance. Applying the log transformation to the number of events (where days with no events are given a value of 0.05) and then fitting on STL smoother, gives remainders with more constant variability, indicating that the log transformation is stabilizing the variance of the number of events. This can be seen in Figure 11 where the remainder terms of the STL smoother fit to the log of the number of events is plotted against the combined trend and seasonal components.

We also fit the STL smoother to the square root of the number of daily events with similar results. In addition to stabilizing the variance, the log transformation gives seasonal trends that are more consistent from year to year. Figure 11, which is on the log-scale shows this and shows a similar general trend to that of Figure 10.

Finally, fitting an additive STL smoother to the log of the number of daily events is equivalent to fitting a model that is multiplicative in its seasonal trend and remainder components.

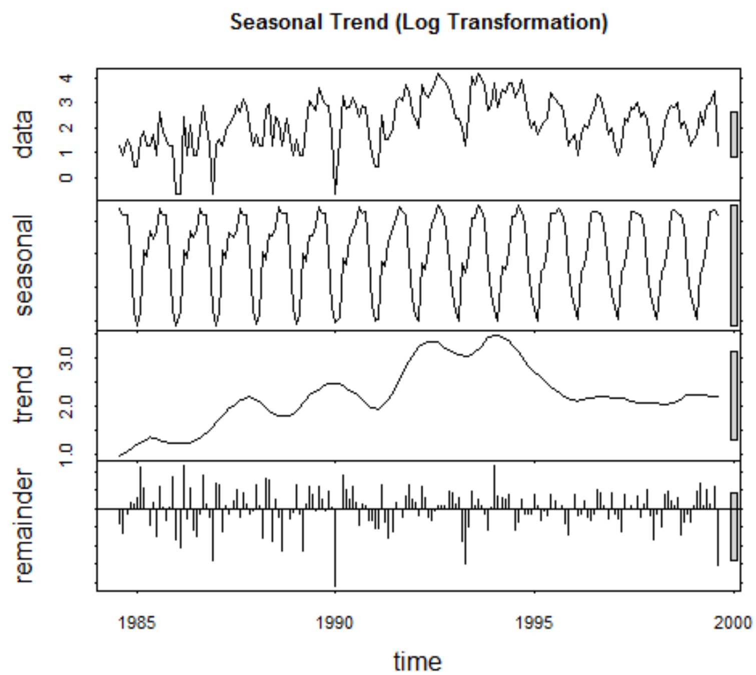



Figure 12. Log Transformation Adapted from GTD

We used Holt-Winters' additive and multiplicative models to predict future events of the PKK. Holt-Winters' additive model predicts 0 to 20 events for next couple of years. (See Figure 14) However, Holt-Winters' multiplicative model, prediction line is smoother than additive model. Also, when we look at the residuals of both models, multiplicative model has better residuals plot then additive model. Comparison plot of additive and multiplicative models in Figure 16 shows that, multiplicative model predicts more events than additive model in the future.

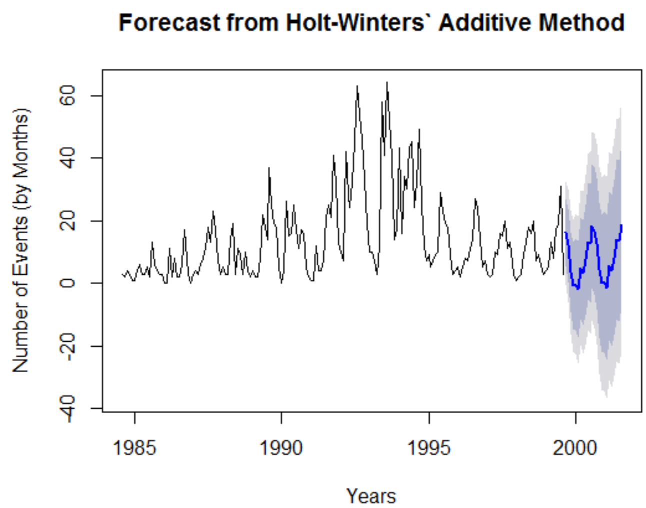



Figure 13. PKK Data Holt-Winters Predict Adapted from GTD

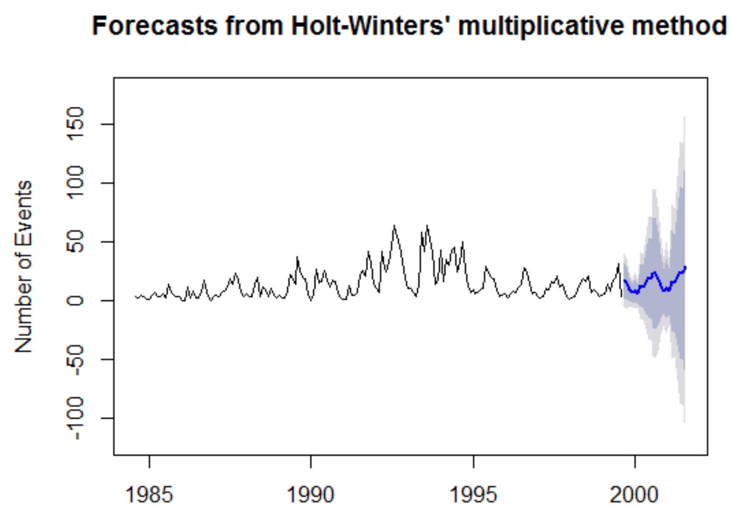



Figure 14. PKK Data Holt-Winters Predict Adapted from GTD

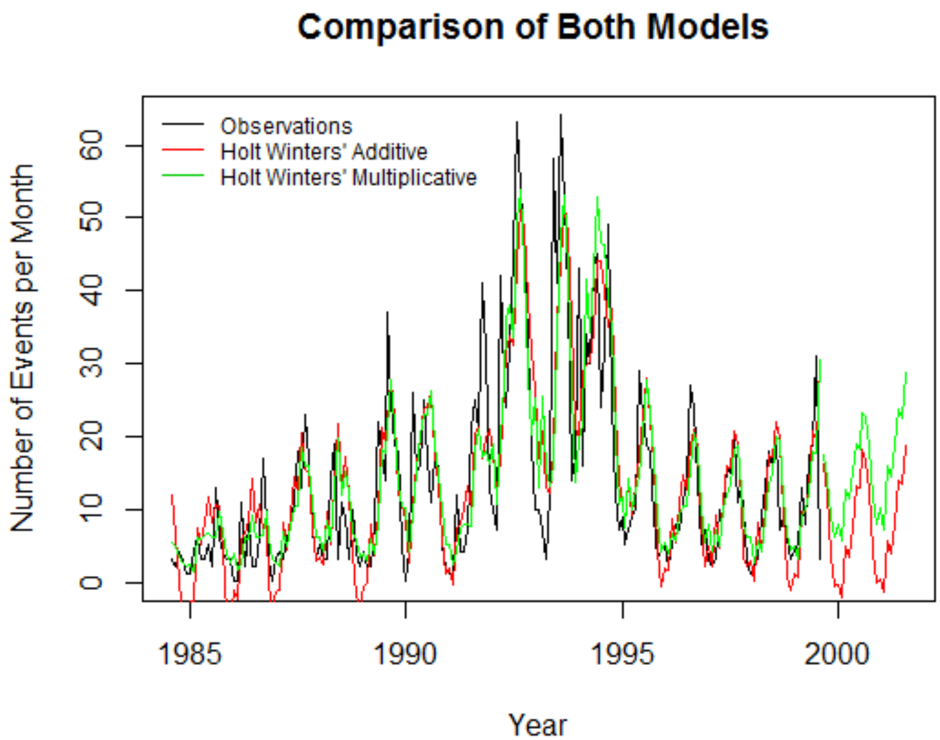



Figure 15. Comparison of Additive and Multiplicative Models Adapted from GTD

# III. FITTING DATA TO SELF-EXCITING MODEL

## A. ABOUT SELF-EXCITING HURDLE MODEL(PORTER & WHITE, 2012)

Porter and White, examined the terrorist data to come up with dynamic predictive model of future terrorist events. They used terrorist data, which has terrorist events in Indonesia between 1994 and 2007. Their aim is to create a dynamic model, by considering self-exciting feature of terrorist events. Their model estimates the probability of future events, by looking terrorist past events. Self-exciting hurdle model consist of two components. Baseline and Self-Exciting part. Baseline part is a function of predictors or variables that has an effect on terrorist events. Self-Exciting part, tries to capture future events by looking at the previous event day. Self-Exciting part uses decay function to capture sudden increase and decrease in the probabilities of events.

Self-Exciting Hurdle Model, produces a probability of having terrorist event tomorrow, by looking at the previous event days.

## B. PREDICTORS OF PKK DATA

The month is the most effective predictor for PKK events. PKK members prefer to stay in their cells during winter and carry out terrorist events during spring and summer. (See Figure 16) Monthly trend can be seen more explicitly in figure 17.

```
Call:
glm(formula = response ~ lo(X, span = 0.3) + as.factor(month) +
    as.factor(ramadan) + as.factor(gdp), family = "binomial",
    data = date)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5896  -0.8246  -0.5511   0.9491   2.6474

Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
(Intercept)               -3.794556   0.854009  -4.443 8.86e-06 ***
lo(X, span = 0.3)         -0.001409   0.003749  -0.376  0.70716
as.factor(month)2         -0.153105   0.237339  -0.645  0.51887
as.factor(month)3          0.707187   0.289152   2.446  0.01446 *
as.factor(month)4          0.778756   0.383718   2.030  0.04241 *
as.factor(month)5          1.155867   0.484600   2.385  0.01707 *
as.factor(month)6          1.570959   0.591657   2.655  0.00793 **
as.factor(month)7          1.553756   0.701690   2.214  0.02681 *
```

```
as.factor(month)8            1.945287    0.814783    2.387   0.01696 *
as.factor(month)9            1.908790    0.926432    2.060   0.03936 *
as.factor(month)10           1.745936    1.038960    1.680   0.09287 .
as.factor(month)11           1.120369    1.153108    0.972   0.33125
as.factor(month)12           0.498274    1.268208    0.393   0.69440
```

Figure 16. Month Effect on PKK Events Adapted from GTD

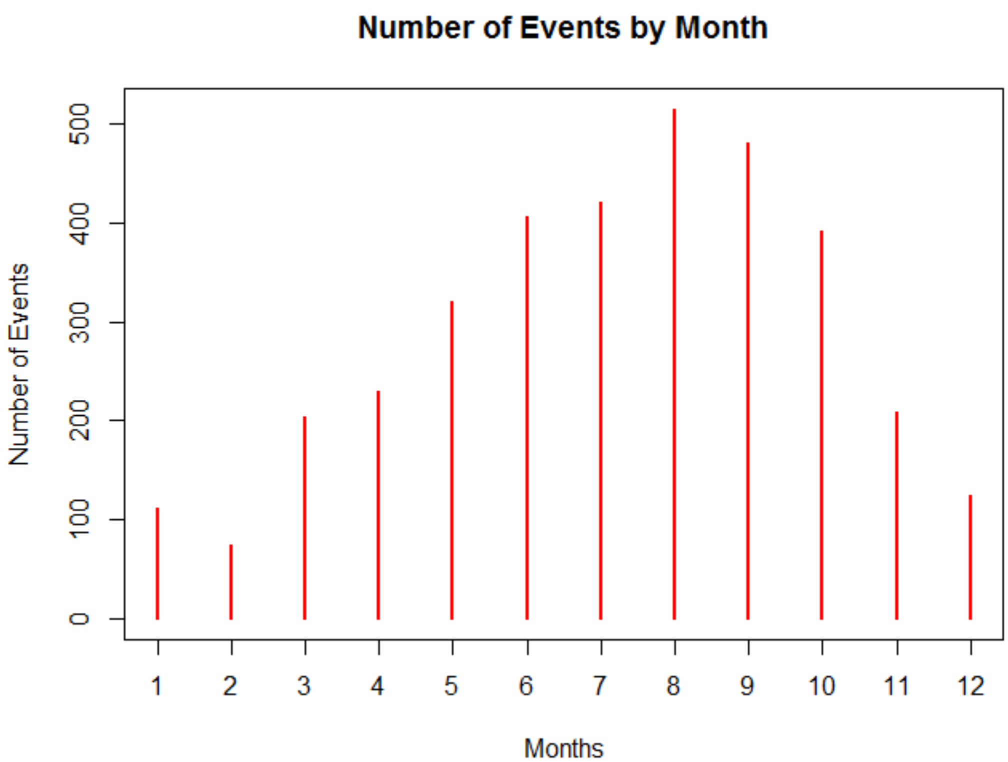



Figure 17. Number of Events by Month Adapted from GTD

When we look at the partial residuals for each month, spring and summer months (May, June, July, August, September and October) has less residuals than the other months (see Figure 18). This is another way to see seasonal trend in PKK data.

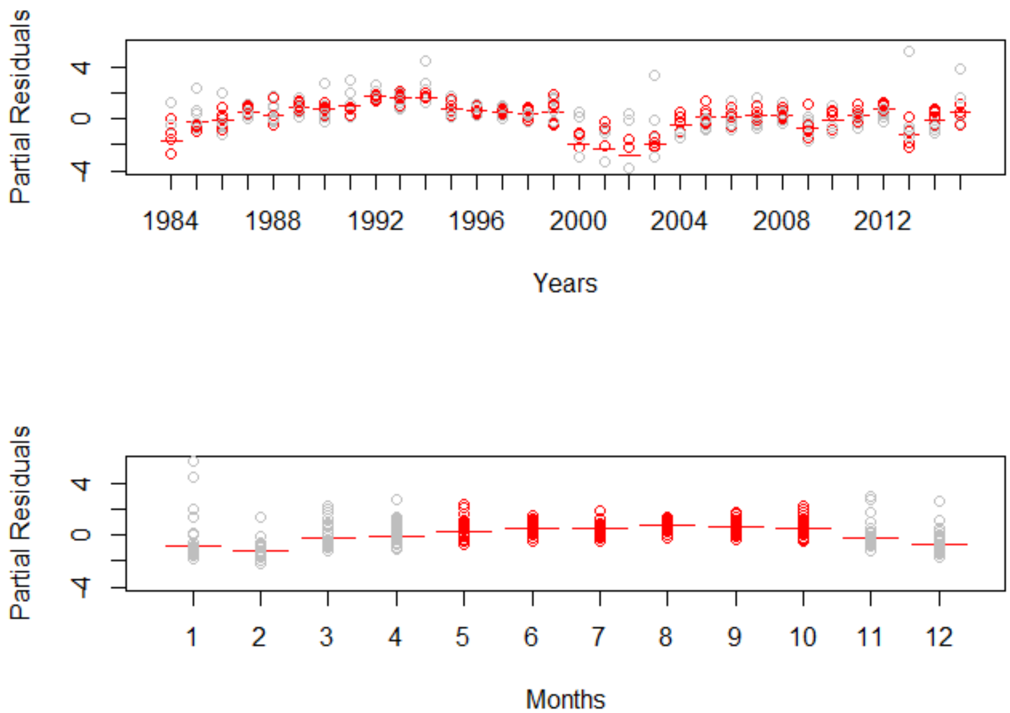



Figure 18. Partial Residuals Adapted from GTD

The economy is the second important predictor for PKK events. Its common knowledge that, bad economic situation results more terrorist activities and anarchy. Sacrifice festival is another special day PKK prefer to carry out terrorist events to disturb people on their happy days. Nowruz is the new year celebration in Turkey. According to PKK data, Nowruz is the least effective day according to PKK data (see Figure 16).

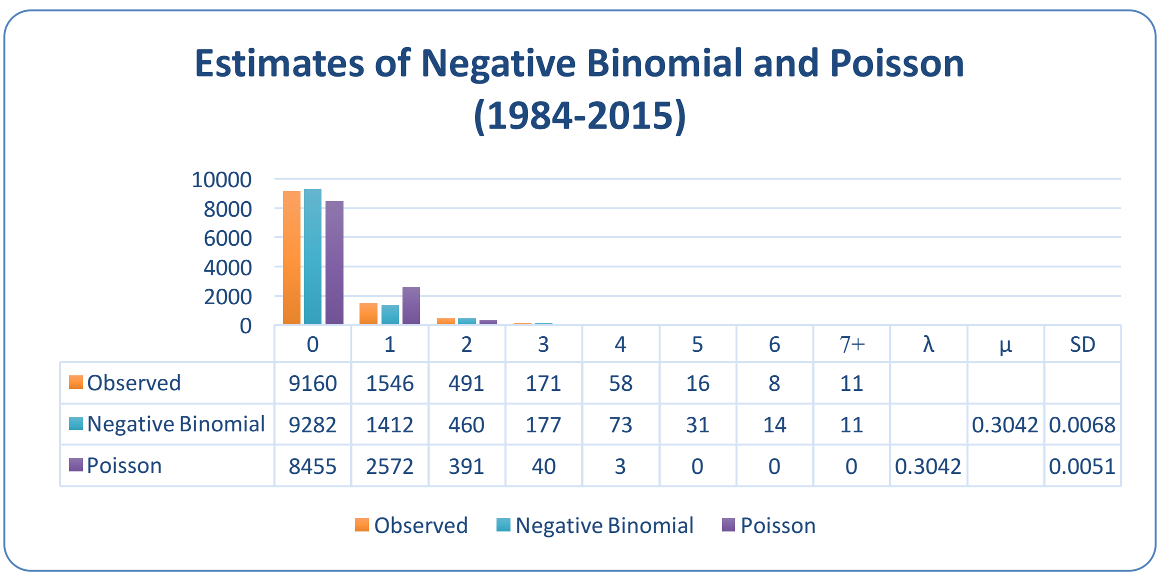
```
Anova for Parametric Effects
Df  Sum Sq Mean Sq F value  Pr(>F)
lo(X, span = 0.3)        1    74.4  74.427 72.5986 < 2e-16 ***
as.factor(month)        11   356.0  32.368 31.5726 < 2e-16 ***
as.factor(sacrifice)     1     4.0   4.040  3.9411 0.04715 *
as.factor(gdp)          31  1169.7  37.732 36.8054 < 2e-16 ***
as.factor(nowruz)        1     3.5   3.475  3.3898 0.06563 .
Residuals            11410 11697.5   1.025
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 19. Important Predictors of PKK Events Adapted from GTD

## C. FITTING DATA KNOWN DISRIBUTIONS

Knowing and understanding which distribution best fits the data makes analysis more robust and accurate. However fitting terrorist data to any distribution is more involved than it seems. There are innumerable factors triggers terrorist events and makes them very convoluted for analysis. The day by day data, from 1984 through 2016 was examined to inform model construction. Negative Binomial captures the tail distribution better than Poisson, however, Negative Binomial underestimates the days with one event and overestimates the days with 2-3 events.

80% of the days are zero's representing no terrorist events. 13.5% of days has all 1's representing only one event for that day. 4% two events, 1.4% three events and 0.5% four events. When we look at the Figure 1, we see that Negative Binomial Distribution(r,p) fits the PKK data better than Poisson Distribution(λ) (See Figure 19).




| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7+ | λ | µ | SD |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Observed | 9160 | 1546 | 491 | 171 | 58 | 16 | 8 | 11 | | | |
| Negative Binomial | 9282 | 1412 | 460 | 177 | 73 | 31 | 14 | 11 | | 0.3042 | 0.0068 |
| Poisson | 8455 | 2572 | 391 | 40 | 3 | 0 | 0 | 0 | 0.3042 | | 0.0051 |

Figure 20. Negative Binomial – Poisson Fit to PKK Data Adapted from GTD

Pearson's Chi-squared test value for Poisson is 965.6 and Negative Binomial 12.64. Pearson’s Chi-squared test shows us Negative Binomial fits better than Poisson distribution.

## D. FITTING DATA TO SELF-EXCITING HURDLE MODEL

K – Function is used to reveal clustering. If there is no clustering and probabilities are estimated correctly, K (t) – t is expected to be 0. (See Figure 20) For the most part K (t) – t plot stays between -5 and +5, which is an indicator that the PKK data doesn’t show much clustering.

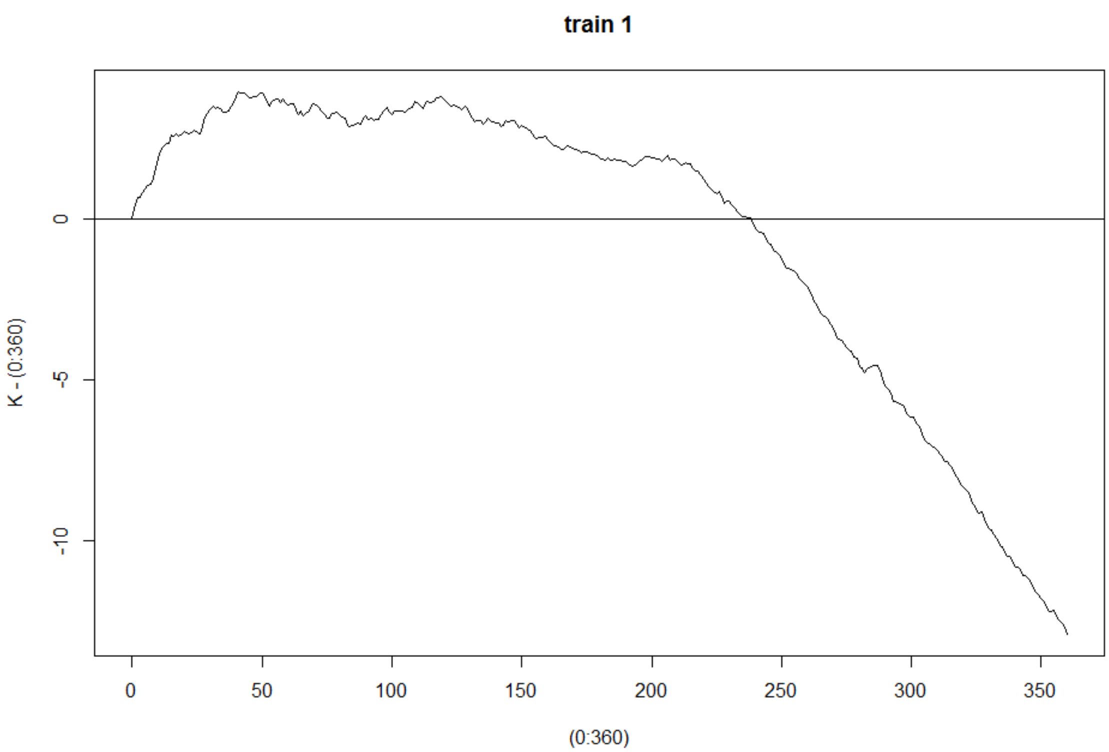



Figure 21. K(t) – t (1984-1999) Adapted from GTD

Pearson's Chi-squared test value for Poisson is 1038 and Negative Binomial 29.52. (Looking at the square root of the contributions of each observation to the Chi-squared test stat:

The Negative Binomial distribution underestimates the number of days with 1 or 2 events, but overestimates the tail probabilities including the number of zeros.

r

-1.2663071 3.5660502 1.4453825 -0.4509876 -1.7556172 -2.6940795 -1.6035675 0.0000000 )

The reason why Negative Binomial distribution(r,p) fits the data better then Poisson Distribution(λ) is (X~Poisson(λ)), Var(λ)=E[λ]= λ, where the number of events are much variable than expected with a Poisson Distribution. This is not surprising, since events exponentially positively dependent.

Baseline should capture the probabilities of future events by looking at the predictors of events. However, for our dataset, baseline does not make much difference. Running the model with and without Baseline part doesn't change much. So, self-exciting part looks at the history and model mostly shaped by self-exciting part. Baseline is not as much as effective as we expected. The PKK data has strong seasonal trend, so according to our findings Baseline part should affect model for the PKK data because of seasonality in it. For self-exciting hurdle model X.t=B.t + S.t , however even if we keep B.t constant like in figure 21, model doesn't change much.

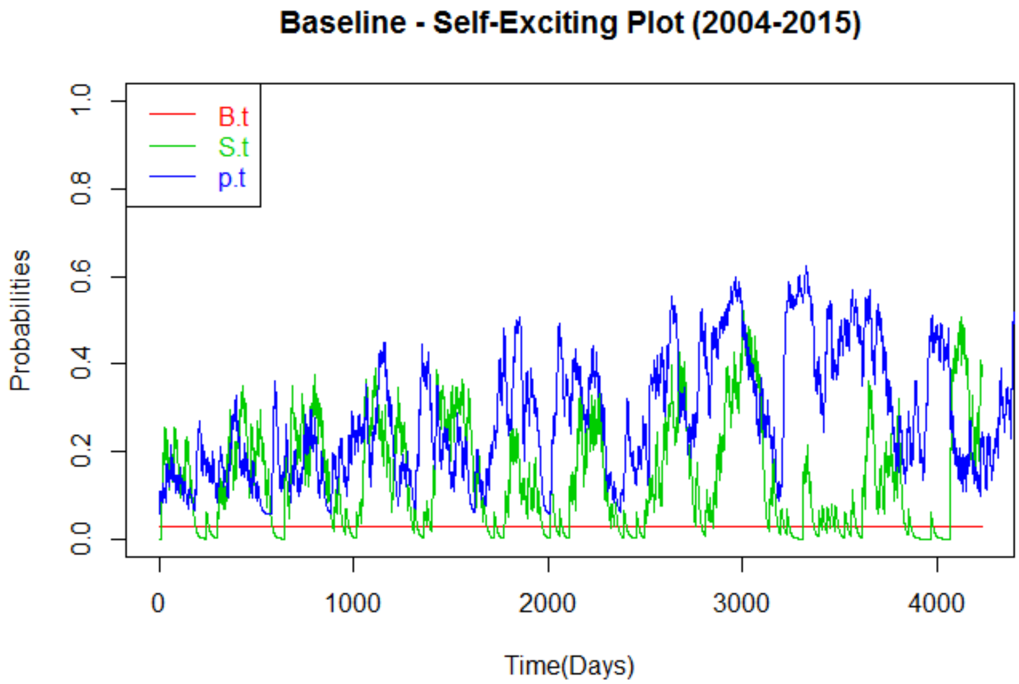



Figure 22. Beta[0] Baseline(log.L=2644.6) Adapted from GTD

In Figure 22 and 23, we see predicted probabilities by self-exciting hurdle model, and smoothed actual events together. We plotted 1984-1999 and 2004-2015 in separately. In both plots, predicted probability plot fits well with smoothed actual events plot. This is good indicator that self-exciting hurdle model has prediction capability.

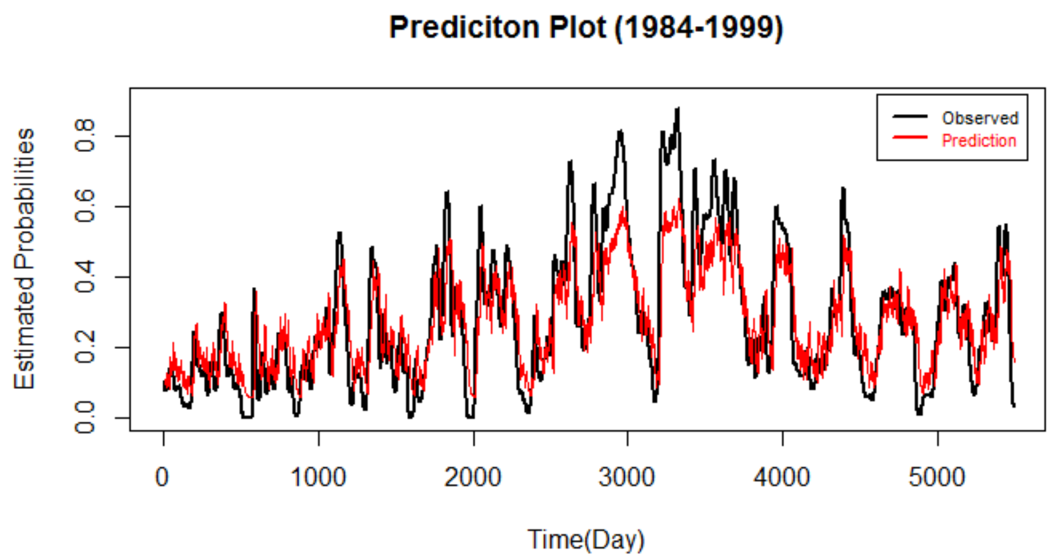



Figure 23. Prediction-Observed Plot Adapted from GTD

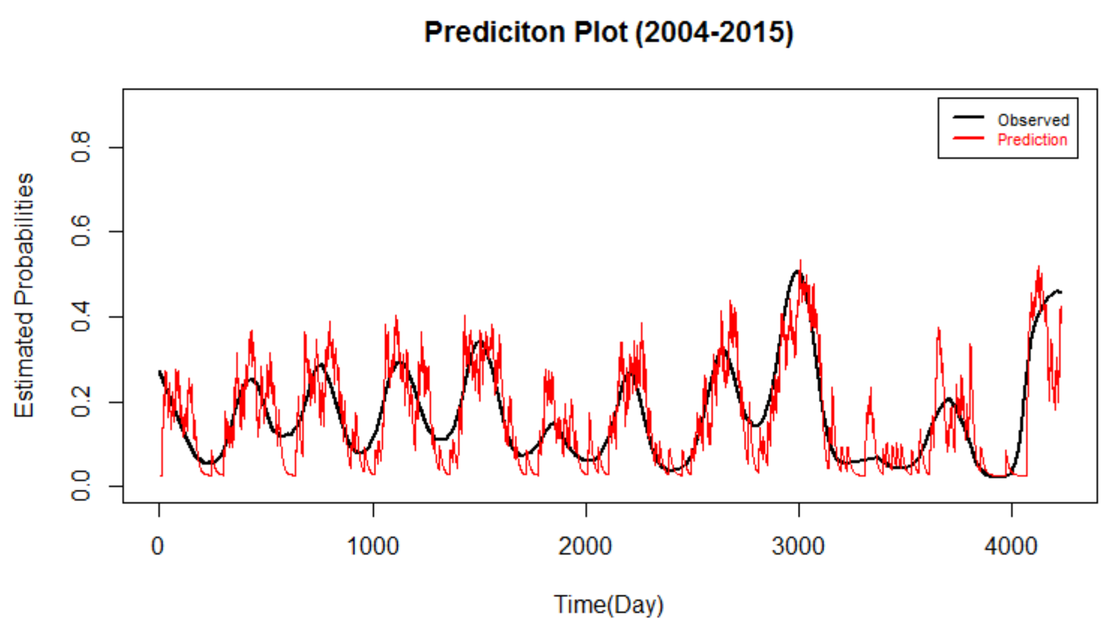



Figure 24. Prediction-Observed Plot Adapted from GTD

When we fit the PKK data to the Self-Exciting Hurdle Model, probabilities for each day stay below the 0.5. (See Figure 24) However, probabilities very well capture the event days. Higher probabilities on the event days and the lower probabilities on non-event days. (See Figure 25-26) – In some figures we used the time (x-axis) between 0 and 1000, for better visualization purposes. When we tried to put 5000 events in a single plot, it didn't serve our aim of showing how good, local maxima's and actual event days fit. – If we try to use sigmoid function and let probabilities greater than 0.5 indicate event days and less than 0.5 non-event days, we end up with 99% of non-event predictions. Since the predicted probabilities very well capture the event day trends, instead of sigmoid function, we tried to use local maximums of probabilities. (See Figure 27) When we capture the local maximums of predicted probabilities and threat them as an event days, we see very good match of actual events and predicted events.

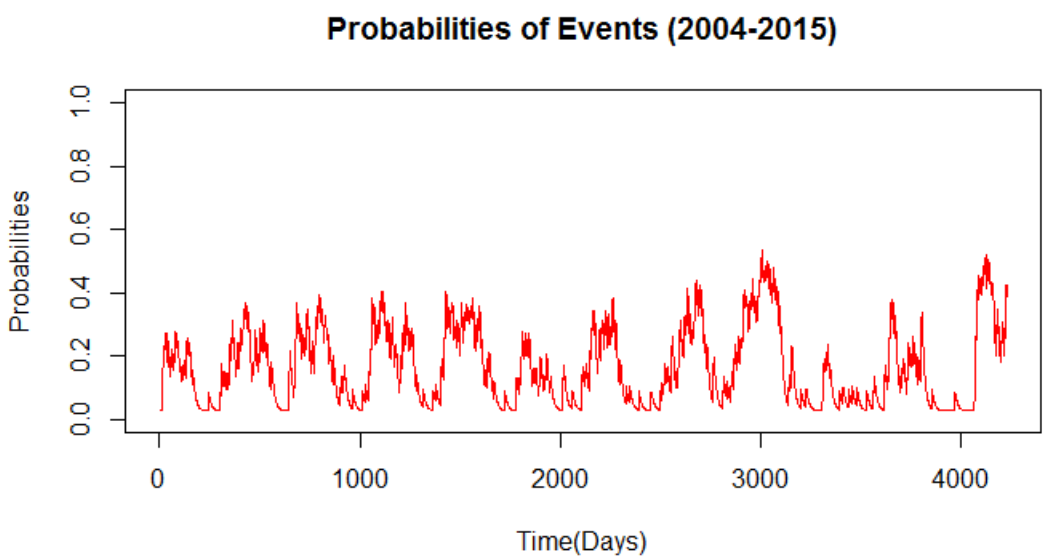



Figure 25. Probabilities of Events Between 2004 and 2015 Adapted from GTD

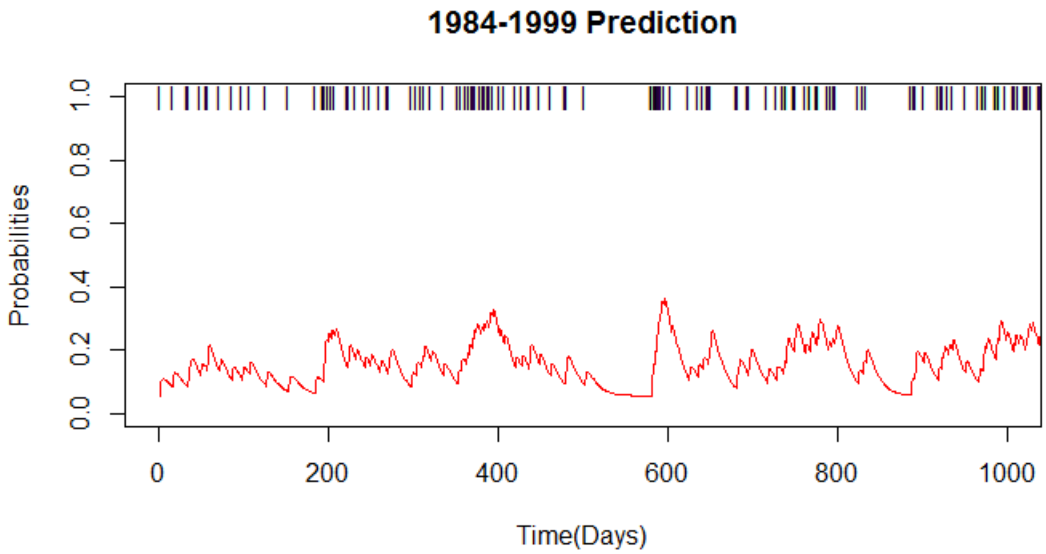



Figure 26. Event Days – Predicted Probabilities Adapted from GTD

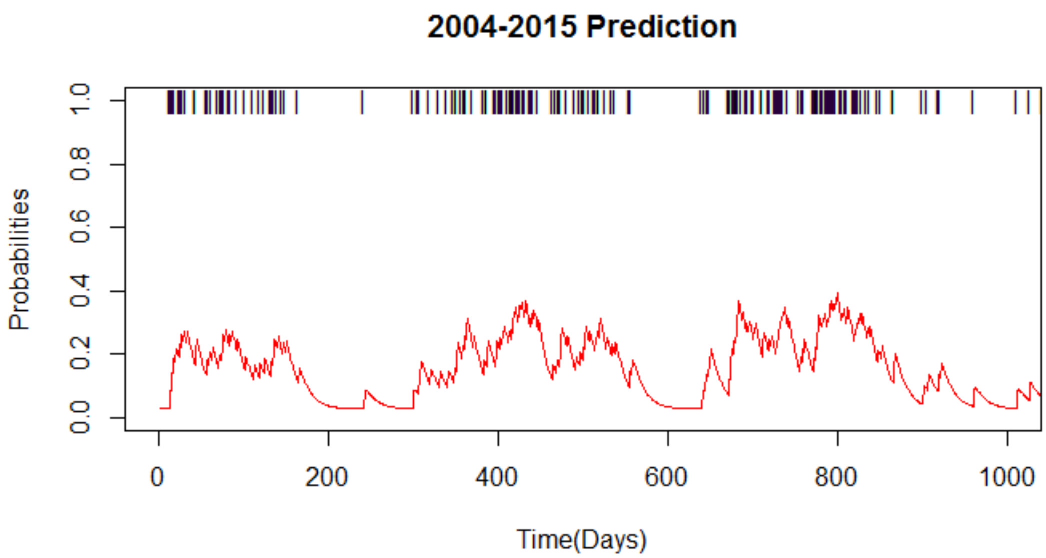



Figure 27. Event Days – Predicted Probabilities Adapted from GTD

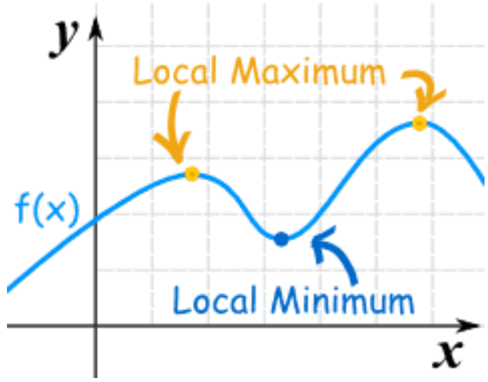



Figure 28. Local Maximum ( http://www.mathsisfun.com)

In figures 28 and 29, we plotted actual events (black strips) with predicted events, local maximums, (green strips). We observed very good match of local maximum's and real events. Even though, Self-Exciting Hurdle Model doesn't give probabilities close to one, for event days and probabilities close to zero for non-event days, it is very well following the trend in the PKK data. To be able to use this feature of model, using local maximums could be an advantageous for prediction purposes.

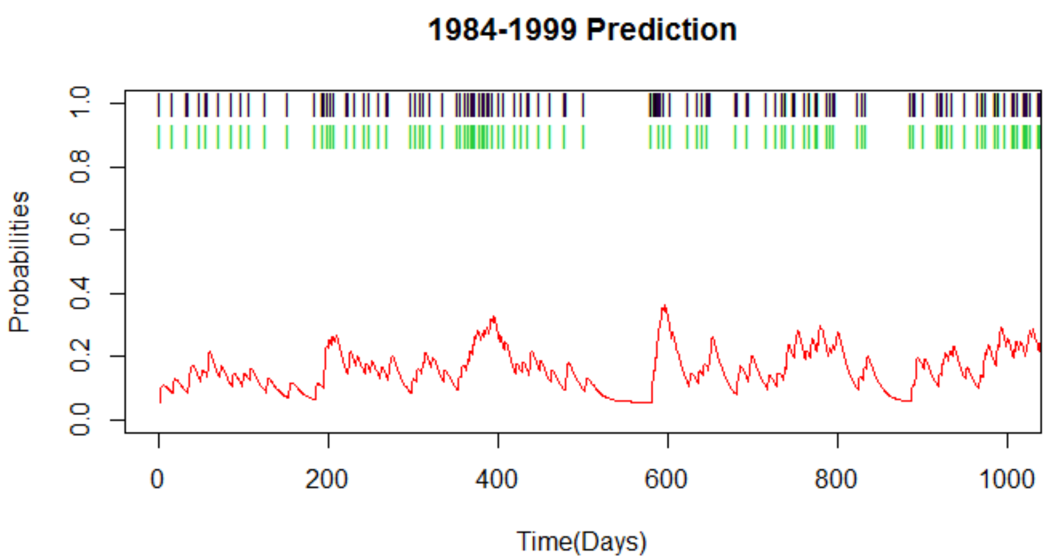



Figure 29. Actual Events – Local Maximums Adapted from GTD

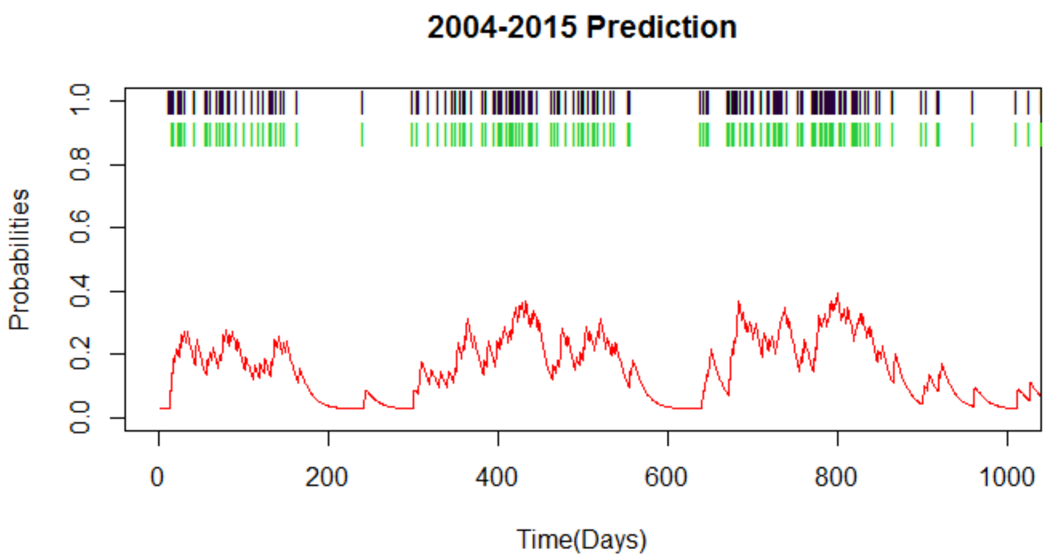



Figure 30. Actual Events – Local Maximums Adapted from GTD

By using the local maximums of predicted probabilities, we observed that, 500 event days out of 705 actual event day between 2004 and 2015. So 71% of PKK events captured with this method.

With same technique, for events between 1984 and 1999, 866 (57.16%) of events predicted from 1550 actual events.

When we look at the whole data from 1984 to 2015, 61.4% of total events captured by using local maximum's of predicted probabilities.

## E. USING LOCAL MAXIMUMS FOR PREDICTION

As we see above, self-exciting hurdle model is good with his self-exciting part, however baseline part doesn't have much effect on the model. So we tried new way that may be used for Baseline Part. We take number of days prior to the event day as an predictor. Yt-1 is the predictor that only take into consideration of yesterday. If there is an event yesterday today's prediction is 1. If there is not event yesterday today's prediction is 0. We used Yt-1 to Yt-10 to see how data will response this technique. Aside from having 10 predictors of Yt-1 to Yt-10, we fit gam model with "Months", “GDP”, “Sacrifice” and “Nowruz” as predictors. Gam model shows us, all predictors from Yt-1 to Yt-10 are important. Probabilities, that model gives us in Figure 31, look good at following the event days and capturing the general trend in data, like giving very high probabilities between 1992 and 1995, very low probabilities during unilateral truce.

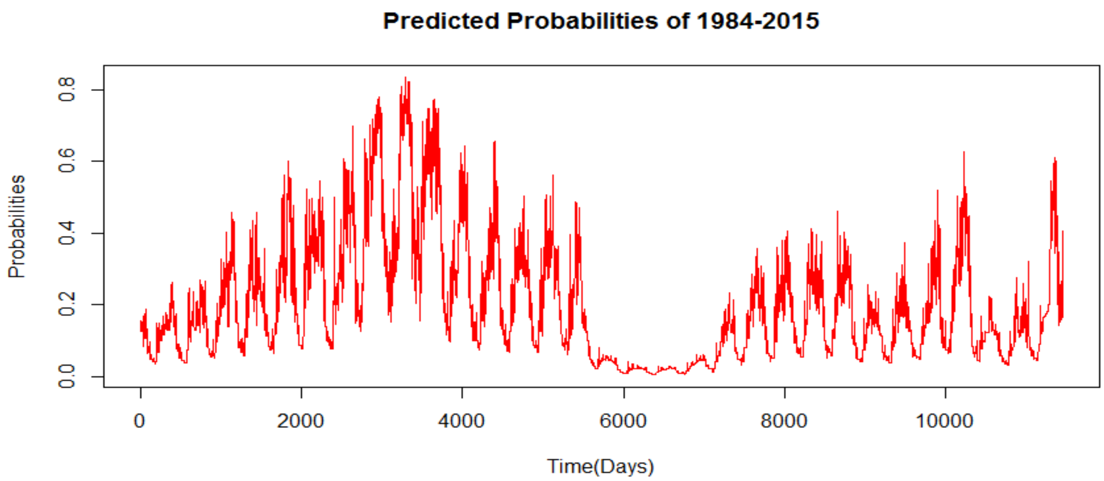



Figure 31. Predicted Probabilities (1984-2015) Adapted from GTD

When we compare the predicted probabilities of both self-exciting and gam model, both model is doing good in following event days. However, although self-exciting predicted probabilities are all below 0.5, gam model probabilities are reaching 0.8s (See Figure 32 and 33).

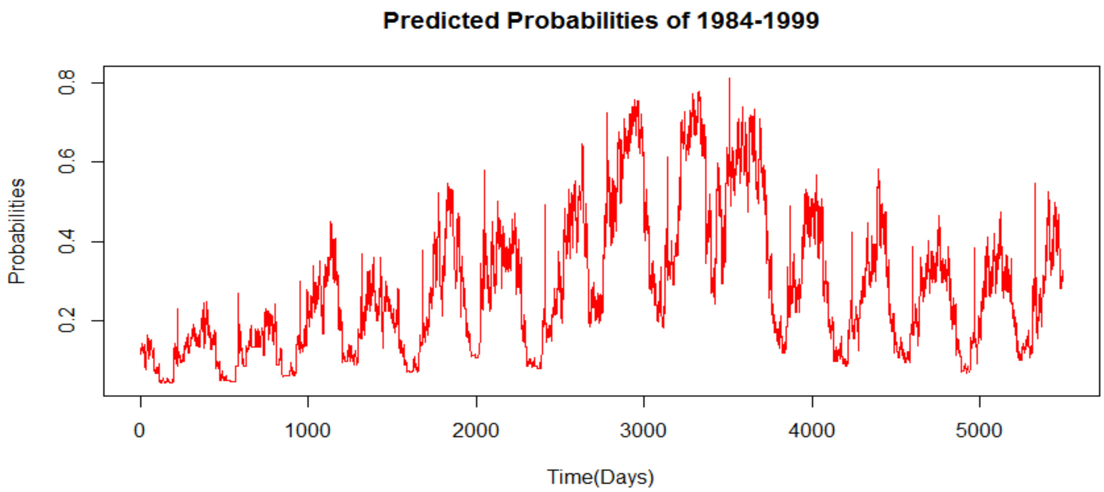



Figure 32. Predicted Probabilities (1984-1999) Adapted from GTD

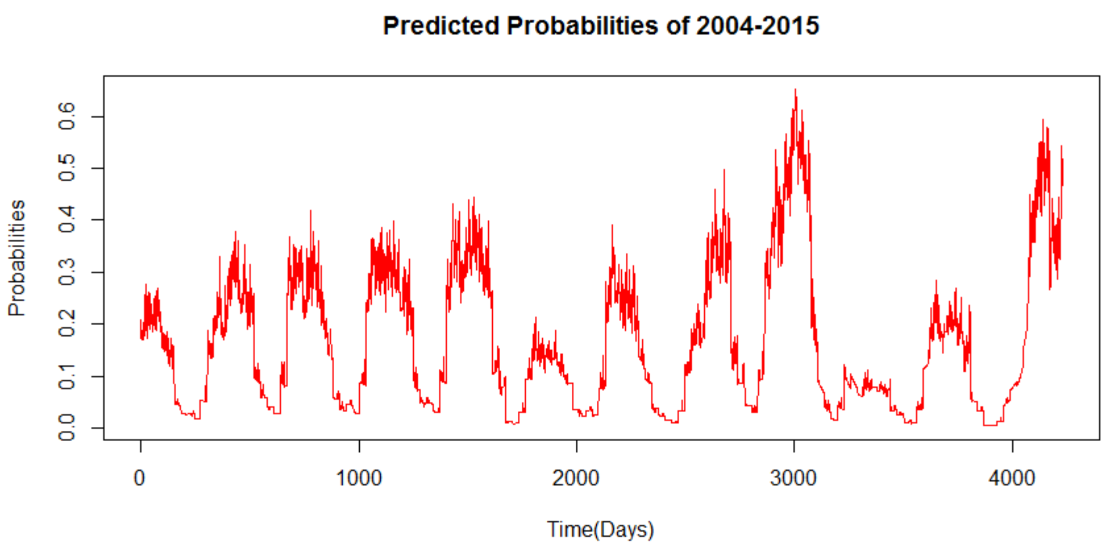



Figure 33. Predicted Probabilities (2004-2015) Adapted from GTD

A predicted probability with smoothed actual event plots does not differ much from each other. Both self-exciting and gam model give the almost same fit. We see that both models are following the same trend. (See Figure 34 and 35)

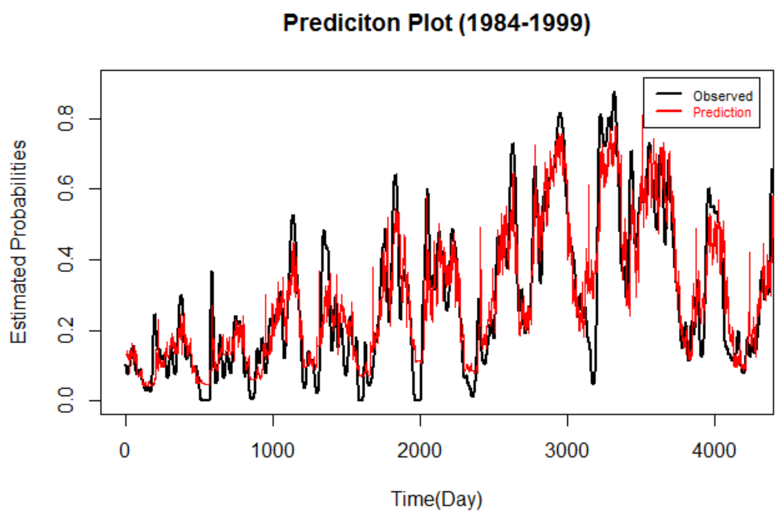



Figure 34. Prediction-Actual Plot (1984-1999) Adapted from GTD

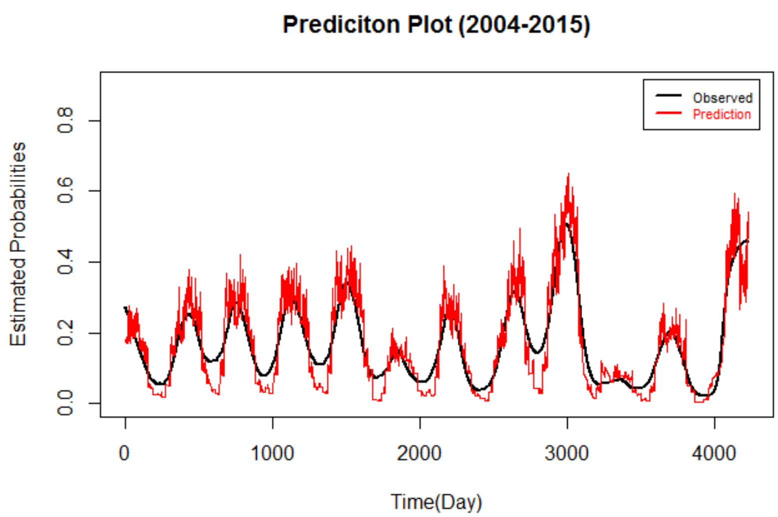



Figure 35. Prediction-Actual Plot (2004-2015) Adapted from GTD

To see which model is better in following event days and adapts quickly to changes, we used local maximums method. For the years between 1984 and 1999, 313 of gam model's prediction local maximum fit within 1550 actual events. It only matches with 20% percent of actual events. This number was 71% for self-exciting model. For the years between 2004 and 2015, 209 of gam model's prediction local maximum fit within

705 actual events. It matches with 30% of actual events. This number was 61.4% for self-exciting model.

Plots of actual events (black strips) with predicted (green strip) in Figures 36 and 37, clearly shows that gam model overestimates the event days. Self-exciting model is giving better predictions than gam model, according to local maximums. Main reason for this, self-exciting model is using g function, which is has very steep shape and capturing changes very quickly.

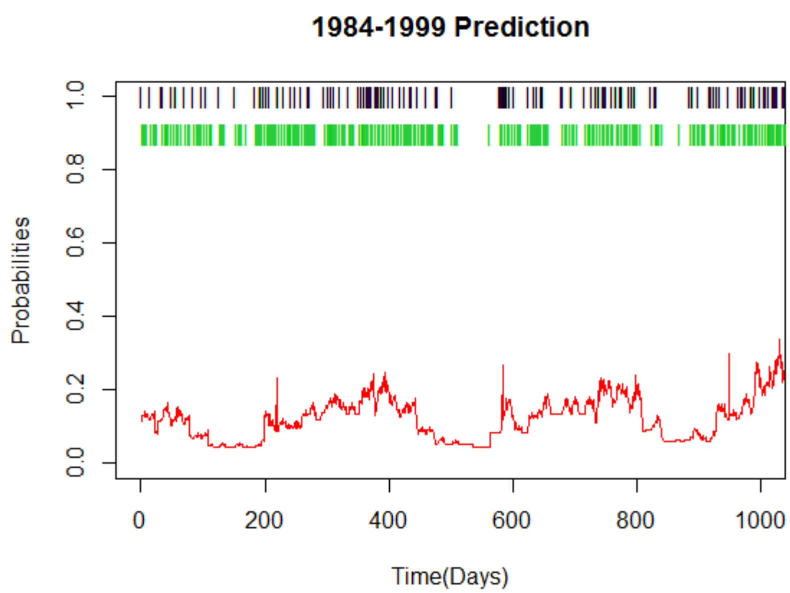



Figure 36. Gams Model Fit With Local Maximums (1984-1999) Adapted from GTD

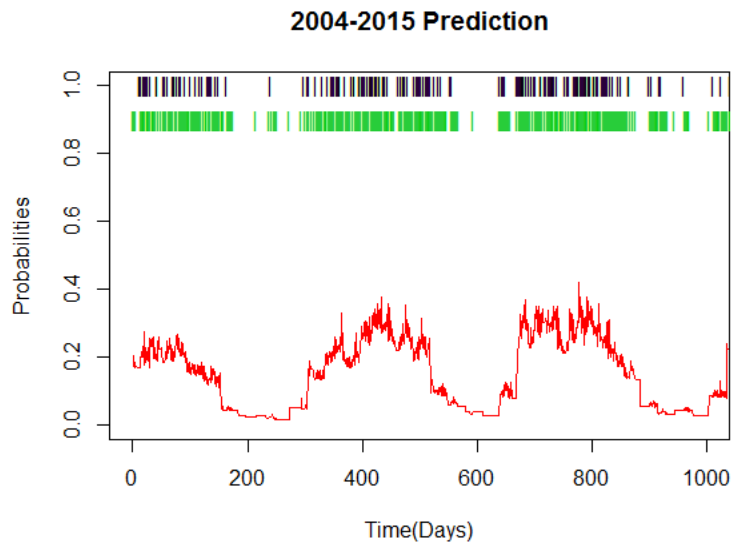



Figure 37. Gams Model Fit With Local Maximums (2004-2015) Adapted from GTD

# IV. CONCLUSION

In this paper, we tried to shed a light to the PKK problem by analyzing its historical data. Every data has important information and waits for analyst to unveil these information. PKK is carrying out terrorist activities since 1984 in Turkey and not a single statistical analysis done to the PKK past events. There are important facts should be mentioned here, and decision makers may use them for future decision about PKK.

First, we made our analysis with the data GTD and ERDEM provided us. We were hoping to reach much more rich data then GTD, in Turkish sources, because the PKK is the Turkey's problem, Turkish security forces are either take action in the PKK's events or they are the first people reach to the event area and collect information about event from local people. For better analysis in the future, Turkey should collect and store data more professionally. Data should include every detail about each event. How is the weather in event day and any changes observed in the weather? How region is effected events? How transportation is being affected from the terrain (generally for security forces to reach event area)? Is there a concrete or soil road to event area? At what time event happened? In the early morning or later in the night? What is the number of terrorist members, carried out attack? Number of security forces involved in each event? What kind of tactic they used? What kind of arms they used? How long event lasted? How many hours later, security forces could reach the event area? Number of deaths and injured for each side? Which events are related with each other? Before and after action analysis? Any important person gave speech and talked about the PKK problem, before and after each PKK events? Etc. these kind of questions should be answered and stored neatly after each event. By this way, we may be able to see more facts about the PKK or any other terrorist organization.

Second, basic analysis of the PKK data, shows us, education level, economic situation and employment rate are very important factors that has effect on PKK events. Turkey's leaders should consider this fact and take necessary precautions for the welfare of eastern and south-eastern part of Turkey.

Third, seasonal trend is very obvious in data. Turkey should expect more terrorist events in spring and summer times.

Fourth, prediction models could be used to predict future events of the PKK. In this research, we tried two models to predict future events of the PKK. Self-exciting model, gam model and local maximum technique to fit actual event days with predicted event days. Every terrorist organization has its own characteristics so; fitting one single model to all terrorist organizations may not be very effective and efficient way. A model could be created specific for the PKK to estimate probabilities of future events.

Finally, aim of this research is not to solve 30-years lasting problem in a few months. However, if this paper has a small contribution to the PKK problem in Turkey, purpose of the research and time spend on it worth to do.

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