

# Making Data Personal: Kidnapping by Terrorists

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## INTRODUCTION

### Problem

With recent terrorism events drawing the worlds attention, the media produced many visualizations focusing on the recent incidents in particular regions of the world. However, most of previous works do not focus on a specific type of act of terrorism, and they used traditional way to visualize the information such as bar charts, line graphs and map plots. Although the topic of terrorism often involves lives, these traditional visualizations do not carry much emotional weight. From the story telling point of view, the purpose of the visualization is not only to show data but also to increase empathy of the reader, and it is critical to know the emotional impact of the visualization elements on the audience. Through this paper, we explore a way to increase emotional relevancy of a visualization without loss of data.

### Motivation

Kidnapping as an act of terrorism is one of the more probable scenarios for individuals regardless of their nationality. However, there has not been enough visualization done on this particular domain. Given the problems we identified in the previous section, the visualization of kidnapping data is suitable for testing emotional response on, due to its more immediate relevancy to individuals.

Additionally, we aim to provide an overview about the evolution of kidnapping by terrorists. The overall pattern in key aspects of kidnapping incidents such as location, target type, and death rate among victims have been changing over time, so the audience should be able to explore those through the visualization. Our goal is to provide a high level year-over-year overview, and at the same time, allow the readers to see details of each year seamlessly.

## RELATED WORK

We have reviewed previous data visualization work on Global Terrorism Dataset, and discovered the following:

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*CHI 2009*, April 4 - 9, 2009, Boston, Massachusetts, USA.  
Copyright 2009 ACM 978-1-60558-246-7/09/04...\$5.00.

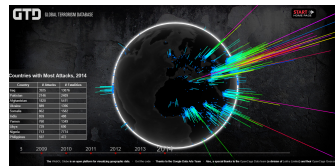


Figure 1: WebGL Globe

is no color legend, 2) the length of the spikes is warped by perspective and hard to compare with others, and 3) it is difficult to compare the data across different years as they are on separate views.

GTD 2014 World Map [2] is a static heatmap that displays the concentration of terrorism activities in each region for 2014. The color scheme was intuitive, but it was impossible to get more information about the attacks.

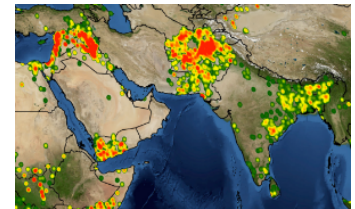


Figure 2: 2014 World Map



Figure 3: Global Terrorism in 2014

Global Terrorism in 2014 [3] is an interactive visualization plotting the progression of terrorist attacks around the world. The visualization provided additional context around some particular attacks (if available) which was helpful. However, the color scheme was not explained, and the data points overlapped each other over time, giving the illusion that terrorism happens in increasing scales all the time.

World of Terror [4] is one of the better interactive visualization done in this domain. It starts from small snippets of attack patterns by major terrorist organiza-

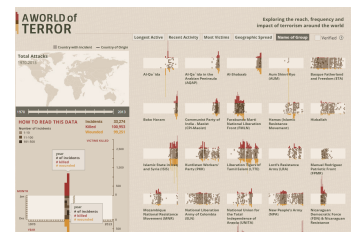


Figure 4: World of Terror

tions, and allows re-ordering of those snippets based on several criteria such as most victims, geographic spread, and longest active, etc. However, it only provides very high level data without any context of the attack.

By reviewing the previous works, we realized that although there have been efforts to communicate the patterns in terrorism, none does a great job offering an interactive exploration of more detailed data. Most of them gloss over the increasing numbers of occurrences and perpetrators, but we could not find more information on what weapons they used or even who the victims were.

Furthermore, we noticed that despite learning the horrifying growth of terrorism, we felt generally neutral about the information, even slightly glad that we did not live in the Middle Eastern regions. There was a lack of emotional connection compounded by the fact that most visualizations were clinically similar to each other: charts with numbers or simple geometric shapes to indicate the severity of terrorism.

To tackle the issue of lack of personal relevancy to terrorism-related visualizations, we researched anthropomorphism and its effect on perception. One interesting study by Pankaj Aggarwal and Ann L. McGill suggests that "literal anthropomorphizing, which involves mistaking an object for a real person, may produce relatively lower evaluations if subsequent realization of the mistaken perception leads to negative affect and self-admonishment" while "if people's attention is drawn to these surprising, human-like features", they tend to respond positively [5]. Based on that study, we realized that it is important to anthropomorphise our data to the right schema in order to increase emotional relevancy from the audience.

**METHODS**

**Dataset**

We used the Global Terrorism Database (GTD) [6], which is an open-source database including information on terrorist events around the world from 1970 through 2014 compiled by University of Maryland. There were a total of 8677 data entries for kidnapping by terrorists. Approximately 7700 incidents had no ransom demanded, and within incidents known to have ransom demanded, only about 530 cases had the known amount of the ransom. We used the data with known ransom amount for testing the emotional impact of two different visualizations (see the next section on A/B testing). We used the data for no-ransom cases for our final visualization as they are the majority. In order to optimize the performance, we preprocessed the raw data provided in Excel file into a JSON file containing the fields required for the final visualization.

**Approach: A/B testing**

In order to estimate the difference in emotional resonance when shown different visualizations, we ran the following test; firstly, we created a rough model of the kidnapped vic-

tim's survival rate ( $= \frac{\text{total number killed}}{\text{total number kidnapped}}$ ) as a function of the amount of ransom paid as a percentage of demanded amount. The survival rate was computed for bins each of 10% (i.e. for each 10% paid out of the demanded amount), and using R, we fit a sigmoid function which best approximated the data pattern. The resulting model is the following ( $x$  is % of demanded ransom paid, and  $y$  is survival rate):

$$y = \frac{1}{1 + e^{-2.9854(x+0.2892)}}$$

Due to lack of data points, this model was not statistically significant, but an approximate model to base the visualizations on was sufficient for the purpose of our test.

Next, we created two visualizations to allow users explore the relationship between the victim survival rate and the ransom paid.

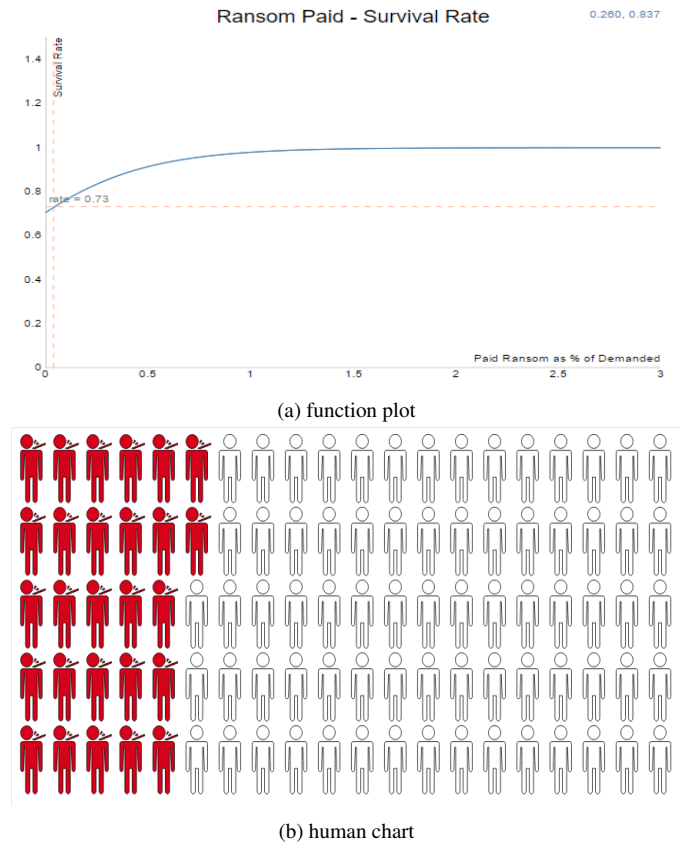


Figure 5: Two visualizations of survival rate

We created a simple line plot of the function (figure 5a) mostly utilizing Function Plot [7], a D3 based library. Then as an alternative, we visualized the percentage of people survived using 100 human figures that changes color and shape depending on their survival status (figure 5b). As the users adjust the amount of ransom demanded and paid, figure 5a updates the annotation line and labels to show chance of survival at the provided user inputs, and figure 5b shows more

or less of the dead human figures.

In order to estimate difference in emotional resonance of the audience to these two visualizations, we randomly divided 60 people into two groups of 30. Then, one group was shown figure 5a (Group A), the other was shown figure 5b (Group B), and everyone was asked (1) to come up with an amount they are willing to pay for 100 kidnapped victims when demanded one million dollars, and (2) share any reaction and feedback on the visualization.

Our hypothesis was that people who saw the human chart would react more emotionally and thus would be more willing to pay a higher ransom when prompted.

## RESULT

### Results from user testing

We collected about 60 responses: 30 for each visualization. Figure 6 shows the distribution of how much people are willing to pay for a million dollar ransom after viewing the provided visualization. Those who saw the chart with human figures (Group B) were willing to pay 200,000 more on average than those who saw the function plot visualization (Group A). Another interesting observation was that the lowest quartile value for Group B was lower than that of Group A. The qualitative feedback from the lowest quartile of Group B consistently stated that would prefer to see numbers rather than the human figures, because they want to make a rational decision. Based on such feedback, we infer that there exists a fraction of audience that would resist against emotional factors in the visualization.

The qualitative feedback from the audience further explained the difference between the two groups. Those in Group B mostly had very emotional response such as "it is very depressing," "Sad and violent," "it made me feel very bad about myself, and "it was very difficult to not pay the amount needed to save everyone." On the other hand, those in Group A commented on the numerical aspect or graphical details of the visualization, such as "make survival rate more apparent by using bigger fonts", "it was like answering a math question", and "I would like to see the slope of the graph to see marginal increase (in survival rate) per dollar paid."

### Visualization for Kidnapping-By-Terrorists Data

Based on the user testing, we decided to use the human figures as our final visualization of the history of kidnapping by terrorists in order to increase the emotional engagement

of the audience. We implemented the site with D3 and used Adobe Illustrator to create our own human figures.

As shown in figure 7, we convey seven dimensions of information on one visualization: a heatmap slider for timeline and trend of death rate of kidnapping victims, color for region or target type, width of the figure container for the total number of kidnapping victims per year, and different human figures for the victims' status (alive or dead).

One of the key designs of our visualization is the 100 human figures. Since the raw count of kidnapped people ranges from 13 to 13370, we found it difficult to draw as many human figures and simultaneously allocate them such that all figures would fit within one screen. So we instead set the width of the 100 figure container to correspond to the total number of kidnappings per year and indicate on the right corner how many actual people one human figure counts for.

Also by having exactly 100 human figures, the color and type of human figures is determined by the percentage of attributes rather than actual raw count, making comparisons across the years easier. For those who want exact numbers, they can hover over the color legend to get the raw count rather than laboriously calculating it.

Another key design is the fill color of the human figures. We decided to keep the dead people only outlined because a lot of the feedback we got from the A/B testing stated that the dead figures were too macabre. Since we didn't want to distract the audience from the data, we tried to strike a balance between shock value and actual learning value by putting minimal color on the dead figures.

Check out the full visualization at: <http://kidnapping-a.herokuapp.com>

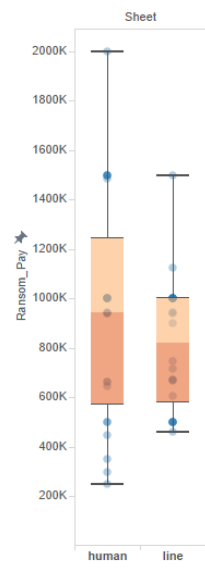


Figure 6: Survey result box plot

## DISCUSSION

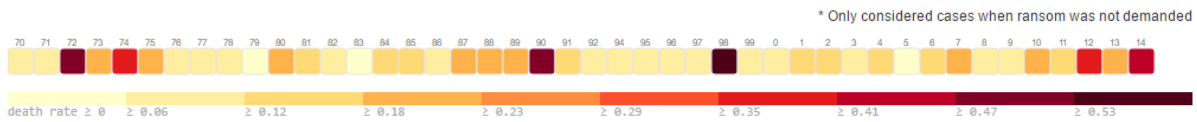
The general response to the visualization has been positive, especially with many commenting on how it breaks the general stereotypes of terrorism. For instance, many of the users were surprised to learn that there was a significant number of kidnapping done in South Asia and Europe during 1994 and 1995.

Users were also able to explore multiple aspects of the data and ask various questions such as "Which year has the highest death rate? 1998", "Which target group got kidnapped the most during the 1970s? government officials and business people", and "Has the number of kidnapping by terrorists been growing at a constant rate? No".

Some users asked why we didn't use a map to portray exactly where the kidnappings happened. We did briefly consider that option, but we then realized that because the data for each year is intensely populated on one or two regions, most of the map would be just empty space serving no purpose. In addition, some data points can be occluded because of the proximity of countries and difference of data point sizes.

# Kidnapping by Terrorists: 1970~2014

## Annual Kidnap Death Rate Heatmap & Breakdown by Categories



In 2014, there were 1197 incidents. 13370 were kidnapped, 6144 were killed.

Click to toggle:

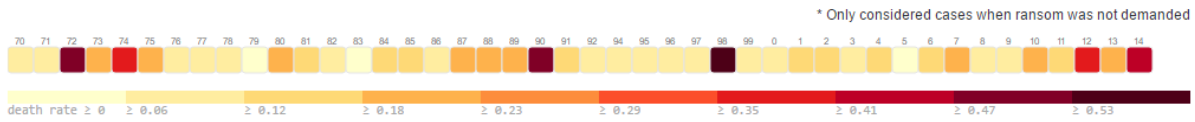
- North America
- Western Europe
- Middle East & North Africa
- South Asia
- East Asia
- Central & South America
- Eastern Eur. & Centr. Asia
- Sub-Saharan Africa
- Southeast Asia
- Oceania



Figure 7: 2014 kidnapping incidents by region

# Kidnapping by Terrorists: 1970~2014

## Annual Kidnap Death Rate Heatmap & Breakdown by Categories



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Click to toggle:

- Government
- Business
- Journalists & Media
- NGO
- Transit & Infra
- Civilians & Properties
- Military / Police
- Educational Institution
- Religious Figures
- Other

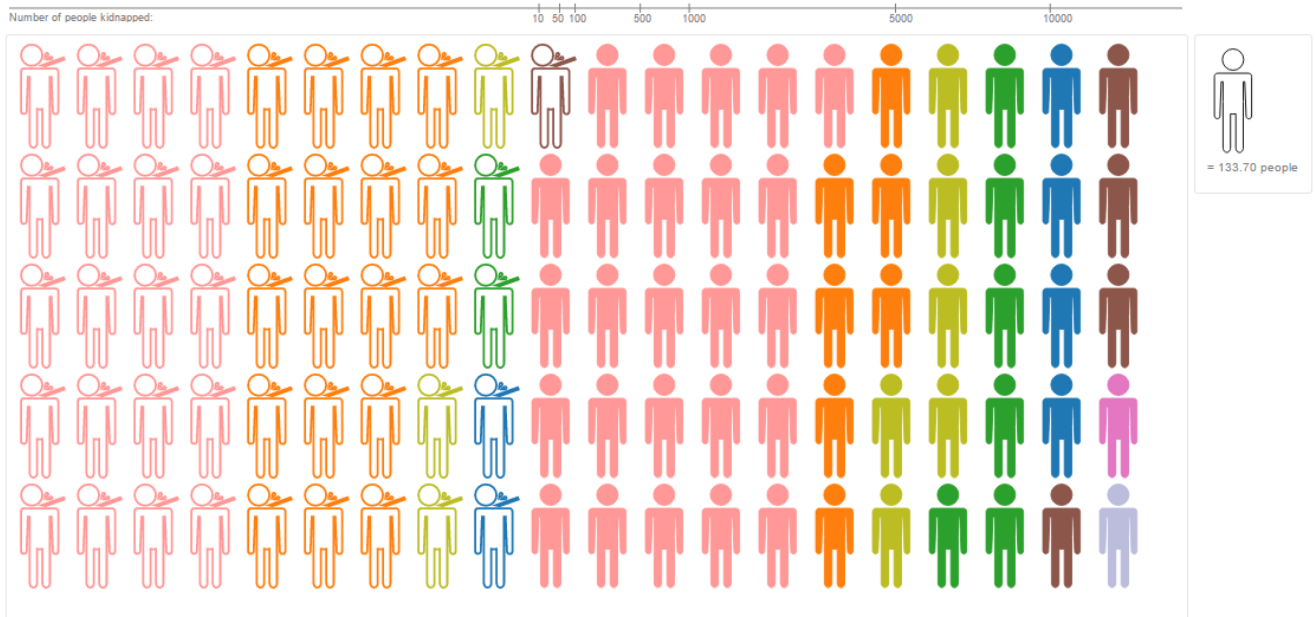


Figure 8: 2014 kidnapping incidents by target type

Overall, users seemed to show empathy to the numbers, especially when exploring target type, as there was a surge in civilian kidnappings over the years. Some even actively asked the specifics of the kidnapping results, whether the victims were unharmed and released or rescued.

## **FUTURE WORKS**

We note a couple interesting avenues of exploration to further this study. First of all, we would like to gauge how much emotional response is optimal - that is, to increase empathy of the audience without distracting them from learning the facts. In order to explore this topic, we suggest a user study with 3-4 visualizations with varied extent of emotional elements and compare the audience's willingness to pay the ransom as well as their accuracy in answering factual questions.

Secondly, we would like to explore ways to provide context around the annual overview visualization. Our current visualization does not provide additional information such as important world events or active terrorist groups that would help the audience make deeper understanding of the reasons behind the statistics they see for a particular year. The data provided by GTD does not contain such contextual information, so we plan to scrap news articles on terrorism kidnapping incidents from the web and display them for each year on the side.

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