

N.E.A.T. - Novel Emergency Analysis Tool

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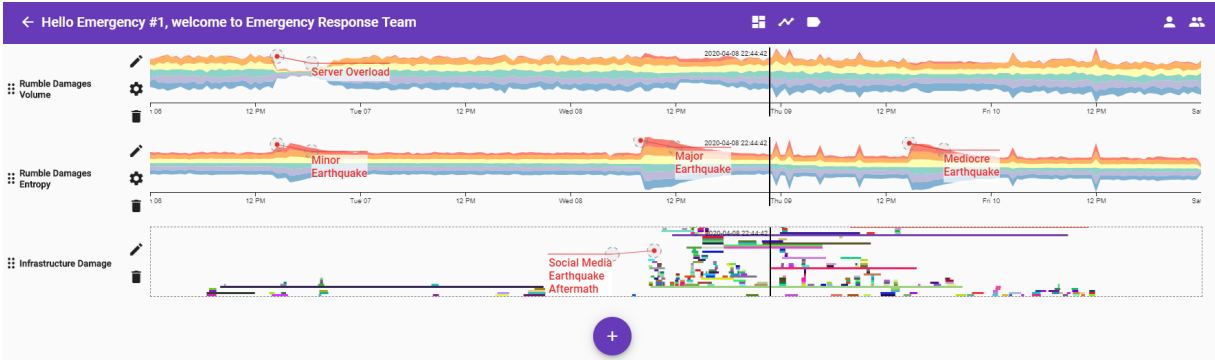


Figure 1: The Timeline View of the Novel Emergency Analysis Tool (N.E.A.T.) showing a live session of emergency responders with their annotations for a disaster case in the fictitious city of St. Himark. Various visualizations, such as stream graphs and lexical episode plots, show three earthquakes and the social media response for infrastructure damage to every single quake.

ABSTRACT

We present N.E.A.T. - a Visual Analytics approach to the collaborative management of large-scale emergencies. N.E.A.T. unifies the analysis and annotation of heterogeneous, uncertainty-afflicted data sources in a single, adjustable screen. Stakeholders can create individual or shared workspaces providing configurable views tailored to the needs of different emergency responders. Within each workspace, annotated findings are automatically shared in real-time for effective collaboration. We illustrate the functionality of the tool and showcase exemplary findings on the St. Himark incident.

1 INTRODUCTION

Major emergencies such as earthquakes or tsunamis often happen unexpectedly, leaving emergency response teams with little or no time to prepare and respond. Consequently, those teams require powerful analysis tools that enable them to quickly and collaboratively assess the situation, distribute available resources, and prevent escalation of the crisis. The VAST Challenge 2019 [1] presents the scenario of a series of earthquakes in the fictitious town of St. Himark. During the catastrophe, a nuclear power plant has been damaged, buildings are collapsing all around the city, flooding occurs, and problems with the sewer systems emerge. All of these disasters must be responded to simultaneously.

We present a novel visual analytics tool N.E.A.T. - the Novel Emergency Analysis Tool. N.E.A.T. combines all available data sources, such as radiation measurements, damage reports, and twitter-like social media data. The system places a strong focus on efficient collaboration between emergency responders using the system concurrently. Users can collaboratively annotate the available charts to share their findings. The targeted users are no visual analytics experts. N.E.A.T. thus focuses on comprehensible visualizations enabling novices to explore disaster data, uncover anomalies, and detect critical conditions effectively.

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2 NOVEL EMERGENCY ANALYSIS TOOL

To streamline collaborative efforts, N.E.A.T. requires users to join a workspace (or create a new one) before beginning the analysis. Any annotations that users create will be automatically synchronized within their current workspace. Consequently, workspaces are a powerful tool to structure information flow and ensure that people receive only information that is relevant for their tasks.

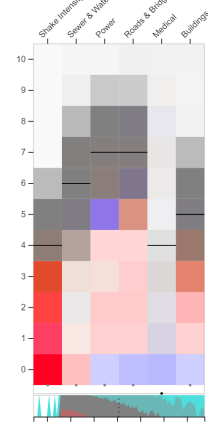
Once users have joined a workspace, they are presented with an initial overview of the data in the timeline view. Multiple stream graphs and different data aggregations support them in selecting a time-slice of interest before switching to the dashboard view. The dashboard view provides a map and text visualizations for in-depth investigations. Afterwards, they return to the timeline view to compare, annotate, and share their insights with their collaborators. The annotation view summarizes all annotations from all users in the workspace and provides collective knowledge in a single interface. The following sections introduce all views in detail.

2.1 Dashboard View

Users can analyze radiation contamination, reported damages, and social media data in the dashboard view presented in Fig. 2.

Damage Report Map – The map shows aggregated damage reports (on a scale from one to ten), e.g., from the *Rumble* app. For each district, the reported damages are categorized and summarized in a glyph. Each category is represented by a cumulative distribution over the damage scores. The color of each rectangle indicates whether the amount of damages has increased (red) or decreased (blue) when comparing the first and second half of the selected period. The overall report volume is mapped to the opacity, and a logarithmic horizon graph at the bottom of the glyph outlines its temporal development.

Radiation Map – The radiation map shows both measurements from static and mobile sensors. A point represents each measurement on the map, where a darker color represents higher radiation contamination. The map can show fre-



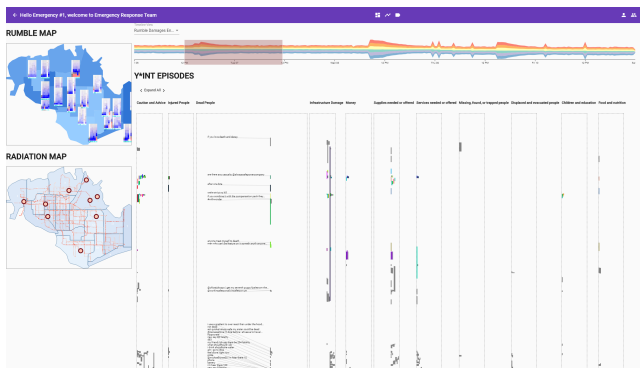







Figure 2: The N.E.A.T. dashboard presents radiation- and damage-report-maps, as well as lexical episodes for social network analysis.

quent radiation measurement routes and indicates that the radiation is highest in the Northwest of the city.

Lexical Episode Plots – We utilize Lexical Episode Plots [2] by Gold et al. to give users a descriptive summary of the social media data, e.g., twitter-like from the *Y-Int* app. Messages are classified into different categories, such as injuries, infrastructure, or supplies. Within each category, n-grams that appear more densely than expected are displayed as an episode. Each episode is represented by a bar that spans the timeline from the first to the last significant mention of an episode keyword¹. The episode keywords (displayed for “Dead People” in Fig. 2) describing each episode bar can be hidden by clicking the particular category title. Furthermore, interactive tooltips enable users to read the full text of underlying messages. Episodes such as closed bridges that are relevant for an extended period receive a longer bar and are easily detected. At the same time, lexical episodes plots also highlight shorter events such as a rapid influx in missing person reports containing repeated keywords.

2.2 Timeline View

Fig. 1 shows the timeline view, which consists of stream graphs and horizontal lexical episode plots to explore the underlying data and display annotations of findings by collaborators. To avoid information overload, users can select which graphs they want to explore, inspect, and compare. The plus icon  at the bottom of the timeline view (Fig. 1) enables the addition of further graphs of the data to the view. Stream graphs and lexical episode plots can be re-ordered via drag and drop ; removed from view ; renamed  or configured . Connecting data across the graphs enables the user to find cross-correlation of events, root-causes, critical incidents, and supports the hypothesis generation and verification.

Stream Graph – Stream graphs [3] are incorporated to visualize data with a temporal aspect and different categories such as, e.g., reports of damages and their strength data from the *Rumble* app. Filtering the stream graphs by category focuses the analysis on critical categories and allows the user to perform cross-correlation analysis. Stream graphs for all temporal data can be added to the timeline view. Various aggregations such as volume, mean, median, sum, standard deviation, and entropy are calculated to enhance the comparison and exploration possibilities. By combining different graphs with annotated findings, users create a master timeline for an event, collecting all available information in a single view. Such a combined view can be used for resource planning or status reporting.

Lexical Episode Plots – The lexical episode plots from the dashboard view can also be added to the master timeline view. To align them with all other timelines, they are rotated by 90 degrees, enabling a comparison to the stream graphs. They facilitate verification

¹Algorithmic details are omitted due to space constraints, but can be found in the original paper by Gold et al. [2].

of assumptions and hypotheses observable in the stream graphs by showing the social media response.

2.3 Annotation View

The annotation view enables the focused exploration of annotations created by collaborators without having to add the respective data graphs to the timeline view. Skimming through the annotations reveals findings that are interesting to all user groups. Once an interesting annotation is found, the respective data graph can be added to the master timeline for closer inspection. Furthermore, the annotation view streamlines collaborative efforts for responding actions by displaying the reasoning of the user next to the annotation.

- 2020-04-06 02:20:06 **Emergency #1: Server Failure**
Server failure or outage either due to too many messages or power failure
Found in chart: Rumble Damages Volume
- 2020-04-06 03:14:11 **Emergency #1: Minor Earthquake**
Minor Earthquake hitting the city. Care for more
Found in chart: Rumble Damages Entropy
- 2020-04-08 07:59:16 **Emergency #1: Major Earthquake**
Major Earthquake hitting city. Prepare for many emergency cases
Found in chart: Rumble Damages Entropy
- 2020-04-08 09:04:11 **Emergency #1: Social Media Earthquake Aftermath**
Earthquake social media aftermath for many infrastructure damages, e.g., schools
Found in chart: Infrastructure Damage
- 2020-04-08 03:12:02 **Emergency #3: Dead people**
Dead and cousin died. Need someone around
Found in chart: Dead People
- 2020-04-09 12:16:47 **Emergency #2: Dead people rumors**
Dead people rumors at about 100
Found in chart: Dead People
- 2020-04-09 06:14:18 **Emergency #2: Dead people rumors**
Dead people rumors at about 600
Found in chart: Dead People
- 2020-04-09 02:33:05 **Emergency #1: Mediocre Earthquake**
Mediocre Earthquake hitting the city. Prepare further help if available
Found in chart: Rumble Damages Entropy
- 2020-04-09 07:05:17 **Emergency #2: Dead people rumors**
Dead people rumors at about 50
Found in chart: Dead People

3 EXEMPLARY FINDINGS

A user can build master timelines for emergency use cases and add annotations that are automatically propagated to the other users. Fig. 1 shows such a master timeline of the St. Himark earthquake incident. It depicts three different sized earthquakes and a nuclear power plant destruction with leaked radiation. A server overload during the first minor earthquake reduces the overall captured Rumble data (top graph). The damage entropy stream graph (middle graph) is unaffected by the overload and makes the three earthquakes immediately apparent supporting the initial hypothesis that the second earthquake caused the worst damages. The lexical episode plot of the infrastructure damage (bottom graph) supports the generated hypothesis by reading over the social media response to the topic. Correlating these two data sources verifies the strength of the earthquake and reduces the overall uncertainty.

The dashboard view reveals that citizens of St. Himark are worried after the first earthquake, asking the power company about any casualties, presumably fearing radioactive contamination. The damage report map shows that the number of reports is quickly declining after the first earthquake. Only *Rumble* users from the northmost Old Town district keep reporting light damages to buildings and road infrastructure, as well as power and water supply.

4 CONCLUSION

The Novel Emergency Analysis Tool (N.E.A.T.) comprises multiple data sources about emergencies enabling the user to draw conclusions about uncertainties through cross-correlation analysis across the different sources. The system places a strong focus on collaborative analysis and synchronizes shared annotations to every participant in real-time distributing the analysis efforts to multiple users and thus increasing the efficiency in a time-critical environment.

A pre-populated live demo of N.E.A.T. with user groups and annotations is available at <https://vcg19.dbvis.de>² and showcases the various collaborative analysis capabilities.

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²Username: dbvis Password: beschte