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# Short and Long-term Pattern Discovery over Large-Scale Geo-Spatiotemporal Data

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## Introduction

- ❖ **Geo-spatiotemporal Data:** data that has *location* and *time*
  - ❖ Examples: **Traffic** events, **weather** events, and **crime** events



Traffic events



Weather events

- ❖ **Pattern Discovery:** exploring co-location, co-occurrence patterns that point to cause-and-effect

- ❖ Example 1: *Rain* → *Accident* → *Congestion*
- ❖ Example 2: *Bar-closing* → *Burglary* → *Harassment*

- ❖ **Importance:**

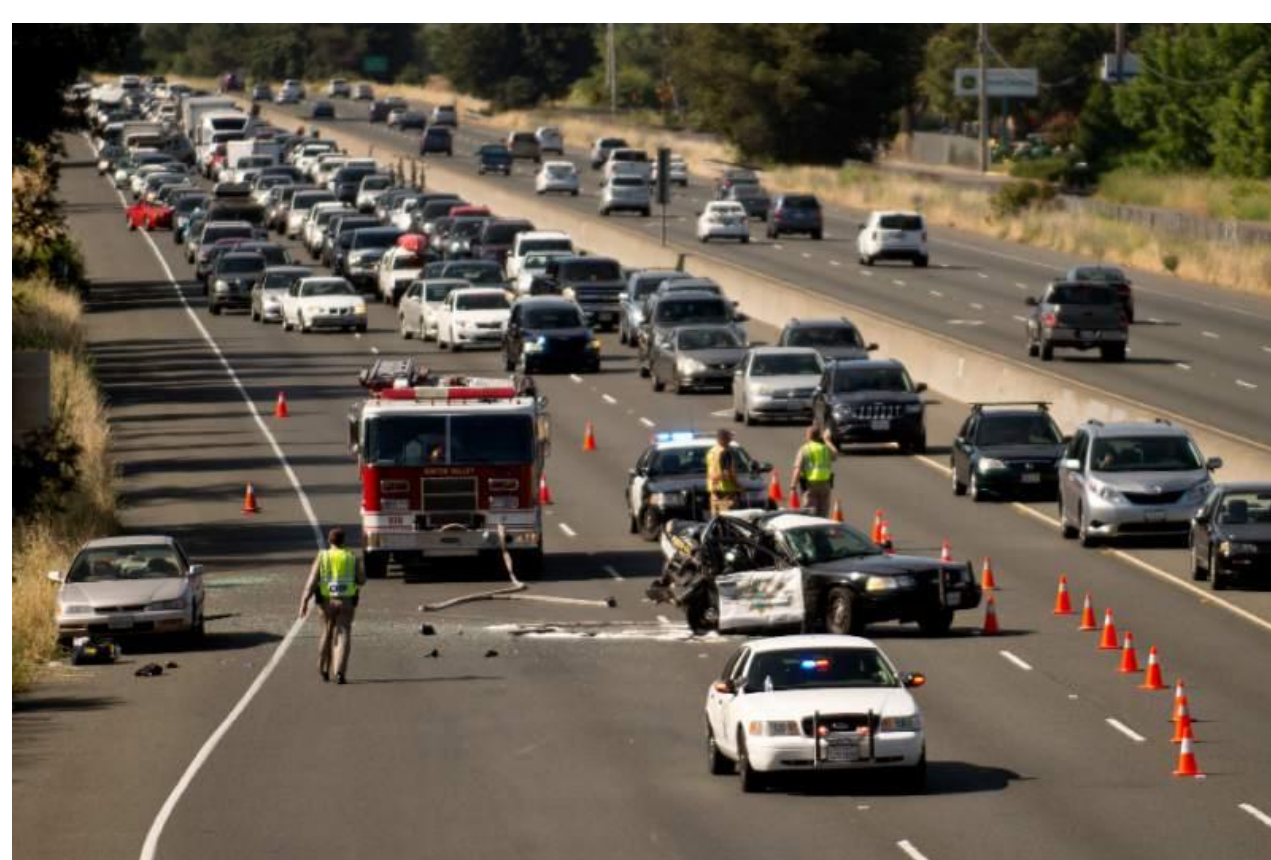
- ❖ **Traffic:** useful for urban planning, traffic management, and prediction
- ❖ **Weather:** useful for disaster prediction and management
- ❖ **Crime:** to raise awareness and safety

## Contributions

- ❖ A **new Framework** to explore two types of patterns
  - ❖ **Short-term (propagation):** short-term cause-and-effect
  - ❖ **Long-term (influential):** impact of a temporally long event on its neighborhood
- ❖ A **new Dataset** of geo-spatiotemporal events (i.e. traffic and weather events)

## Challenges

- ❖ **Problem:** No *special purpose* framework exists for geo-spatiotemporal data
- ❖ How about existing *general-purpose* frameworks?
  - ❖ Such as: *Huan et al. 2004*, *Mohan et al. 2010*, and *Shekar et al. 2015*
  - ❖ Challenge: simplistic assumptions to achieve reasonable runtime

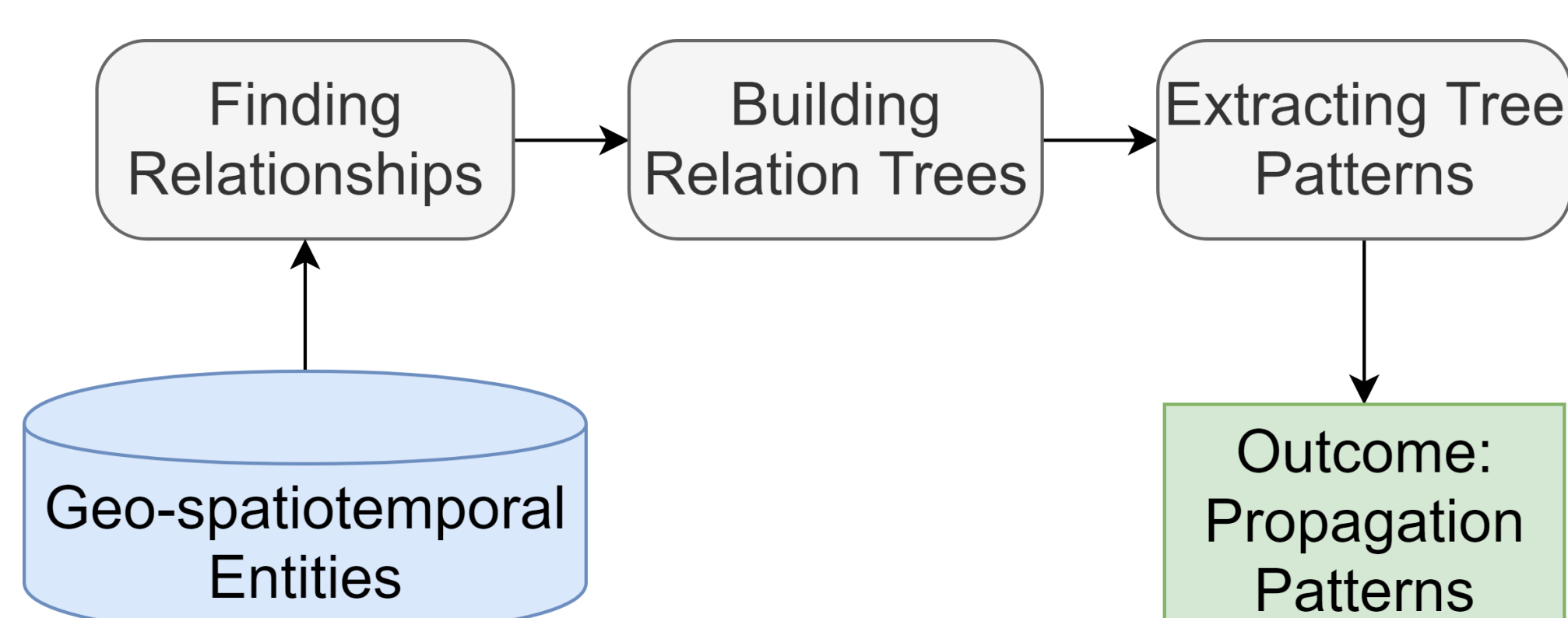


- ❖ Outcome: not useful for geo-spatiotemporal data

## Propagation Patterns

- ❖ **Propagation or Short-term Patterns:** A group of **temporally** co-occurring, **spatially** co-located, and **semantically** relevant events

- ❖ **How to be discovered?** We propose a multi-step process



- ❖ **The Multi-Step Process**

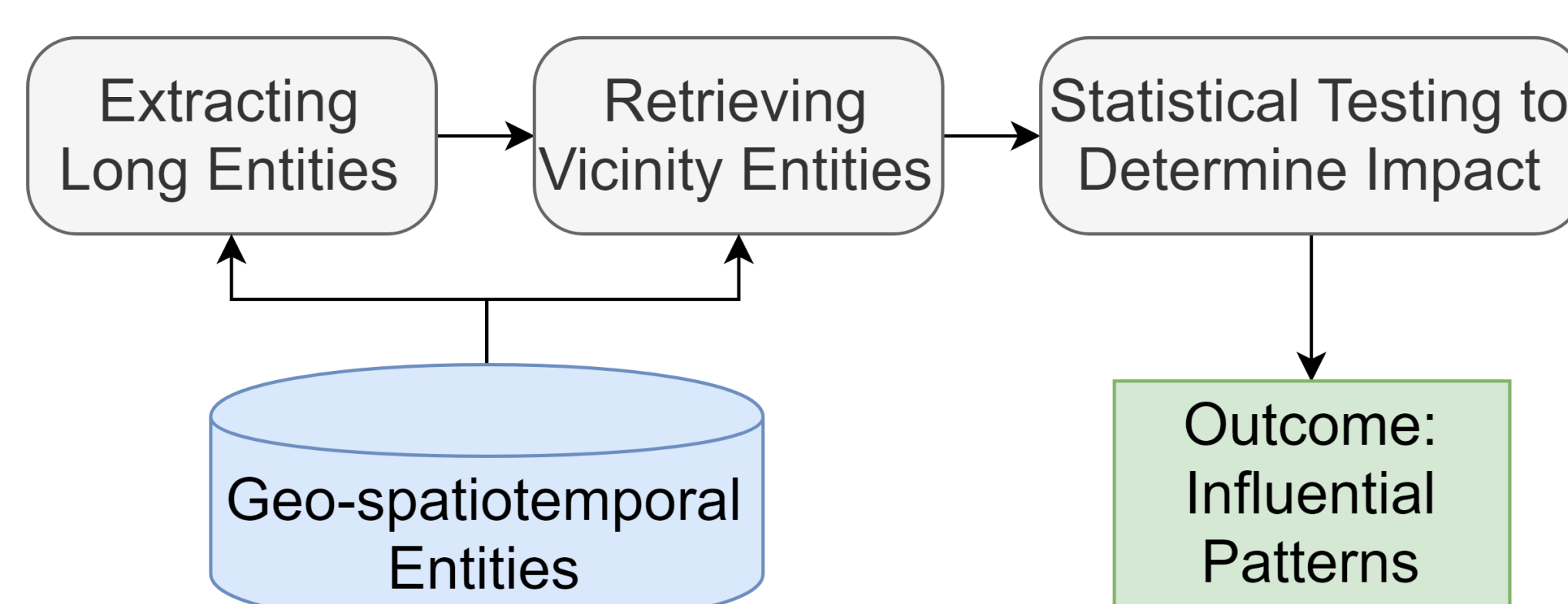
1. Identify **child-parent** relations
2. Build a **forest** of relation trees
3. Extract embedded, un-ordered frequent **tree patterns** (Zaki 2005)

## Influential Patterns

- ❖ The impact of a temporally long-term event on its spatiotemporal neighborhood

Example: *major construction* → *more traffic jams*

- ❖ **How to be discovered?**



- ❖ Examining spatiotemporal neighborhood of long events
  - ❖ Spatial neighborhood **radius:** 14 miles
  - ❖ Comparing *current* with *before* and *after time intervals*
  - ❖ Using **two-sample t-test**
  - ❖ T-tests: **positive** and **negative** impact test
- ❖ **Outcome:**
  - ❖ **Positive** impact: existence of a long-term event → *more traffic issues*
  - ❖ **Negative** impact: existence of a long-term event → *less traffic issues*

## Dataset

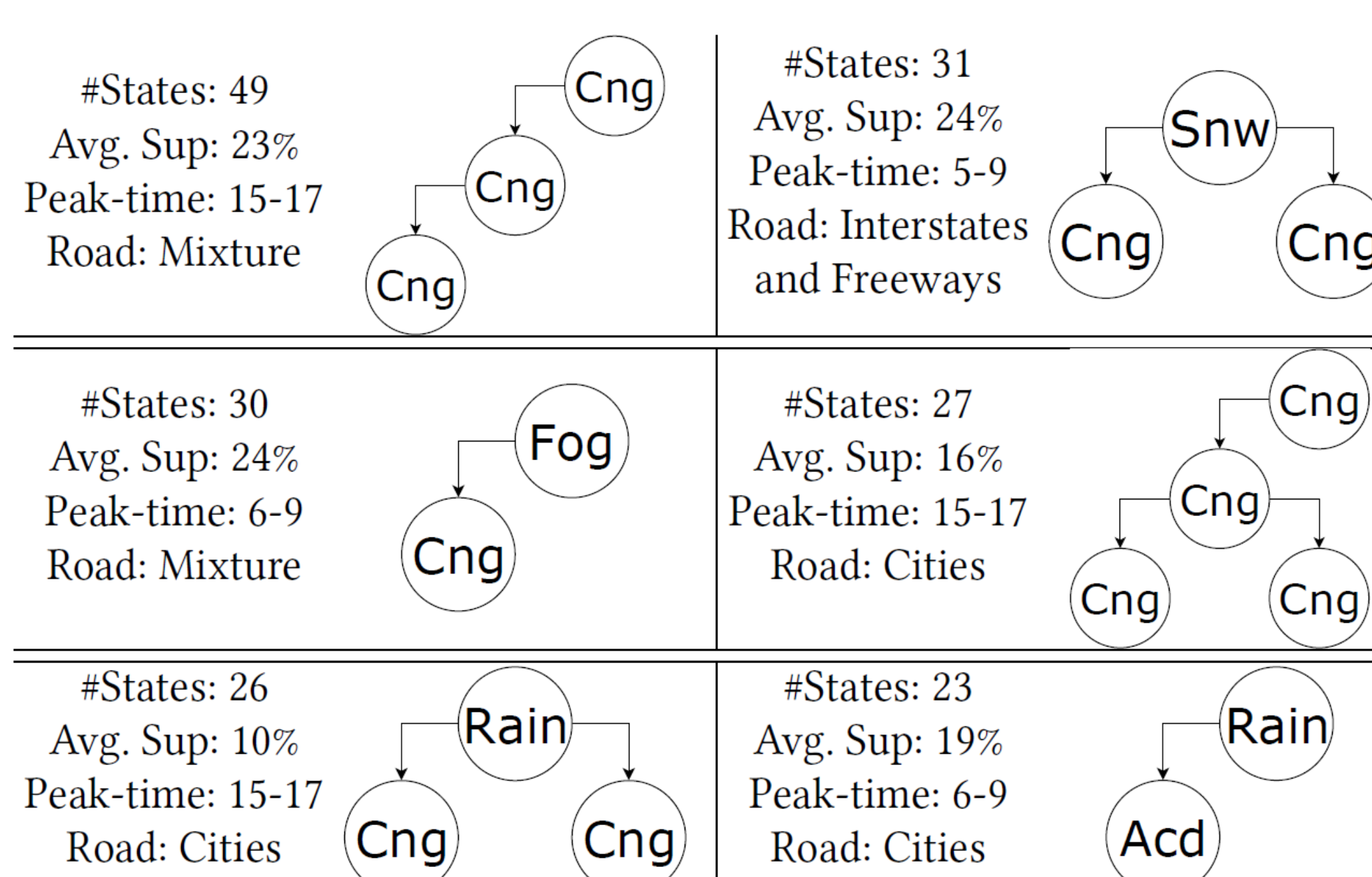
- ❖ Large-scale Traffic and Weather Events Dataset
- ❖ Covers the contiguous United States (50 states) from August 2016 to August 2018
- ❖ Contains 15 million events, 13 million traffic and 2 million weather events

[Scan to access the dataset](#)

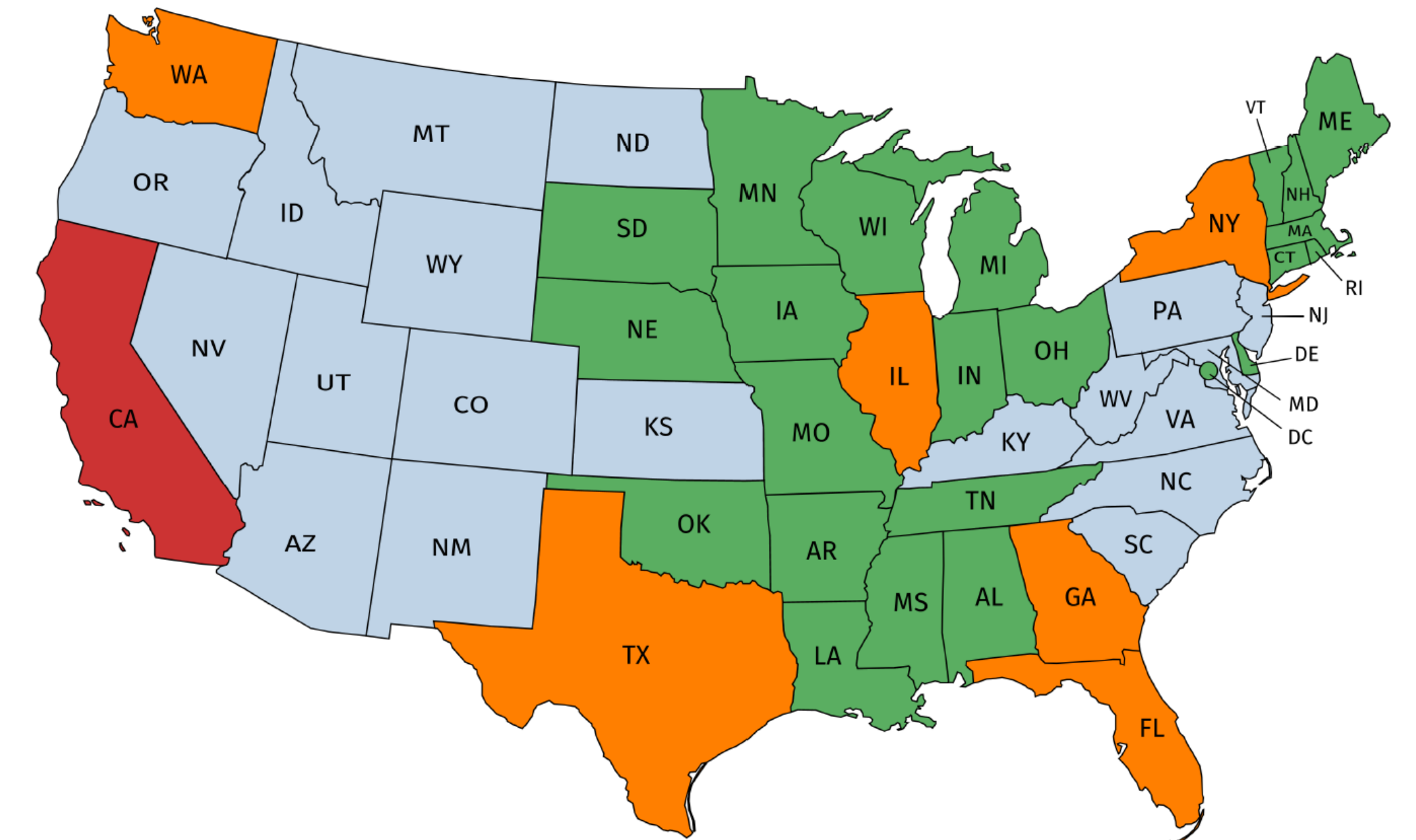


## Results (Short-term)

- ❖ **Pattern discovery level:** Cities
  - ❖ To account for diversity
  - ❖ Assigned **core** patterns to corresponding state
- ❖ Extracted Relations: ~ 6 million
- ❖ Extracted Trees: ~ 1.7 million
- ❖ Extracted 708 patterns for 50 states, **90 unique** patterns



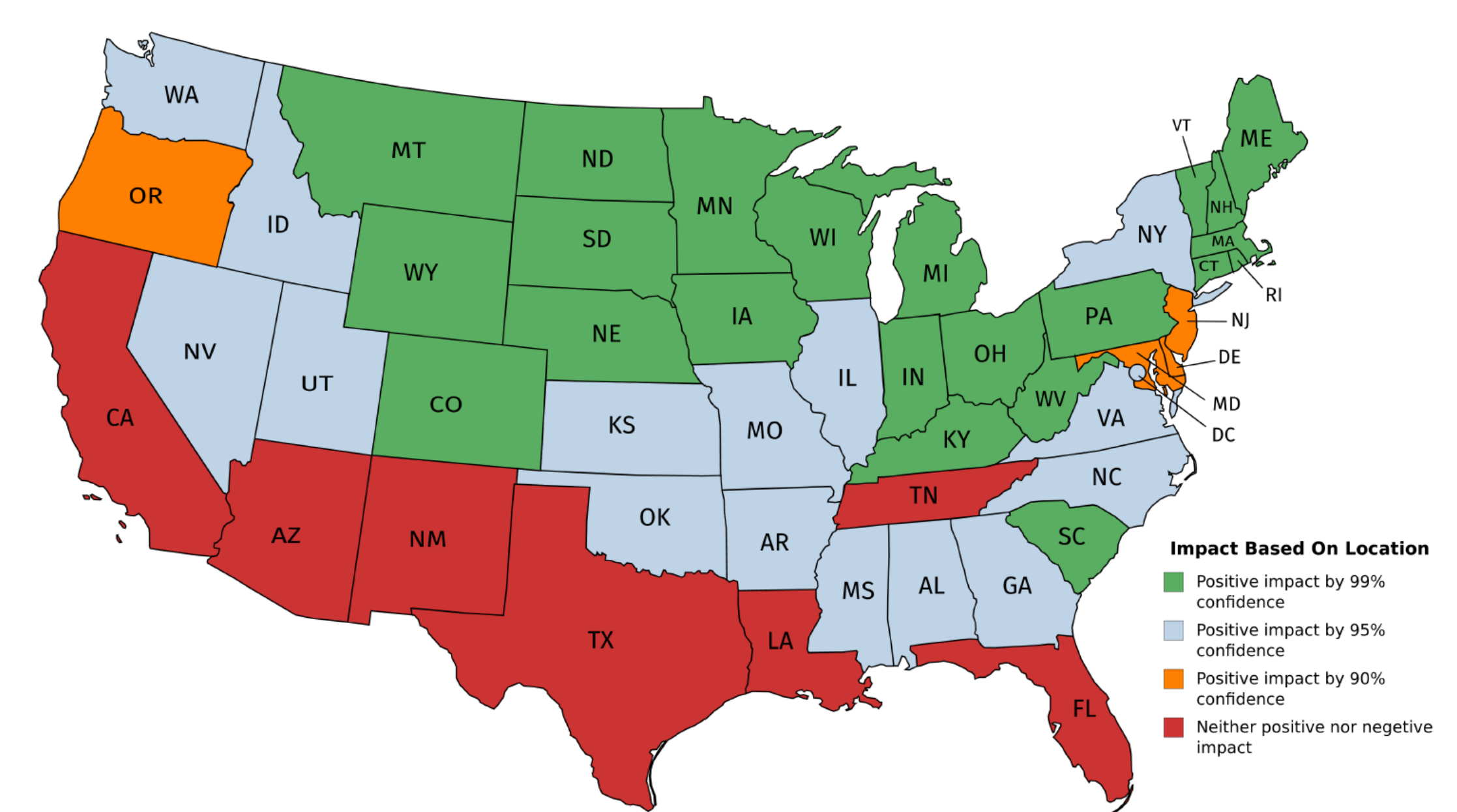
- ❖ **Clustering:** categorized states into four clusters by K-Means based on their short-term patterns



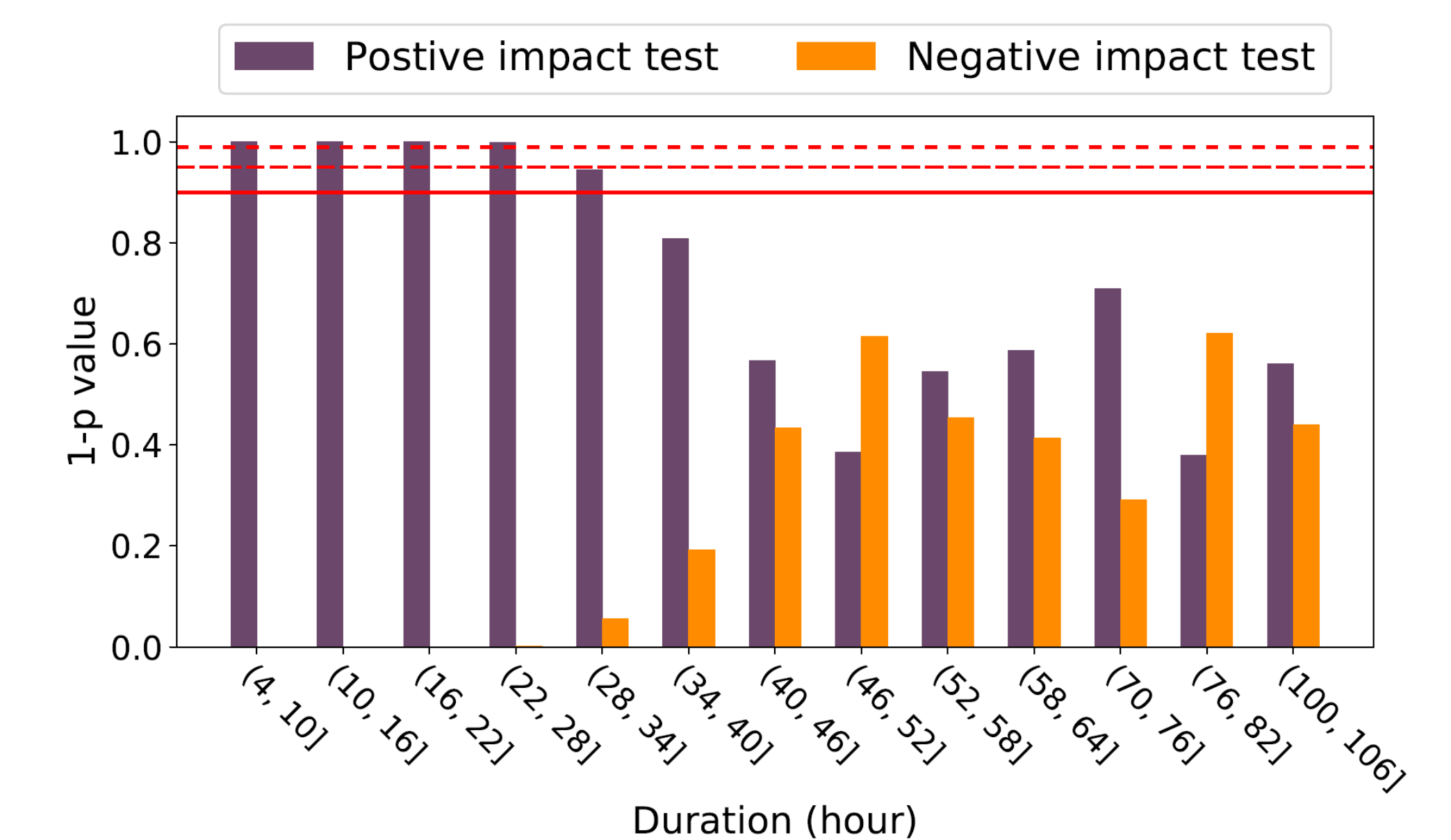
## Results (long-term)

- ❖ **Long events:** 145,000 (duration > 5 hours)
- ❖ Majority: *Rain*, *Snow*, and *Construction*

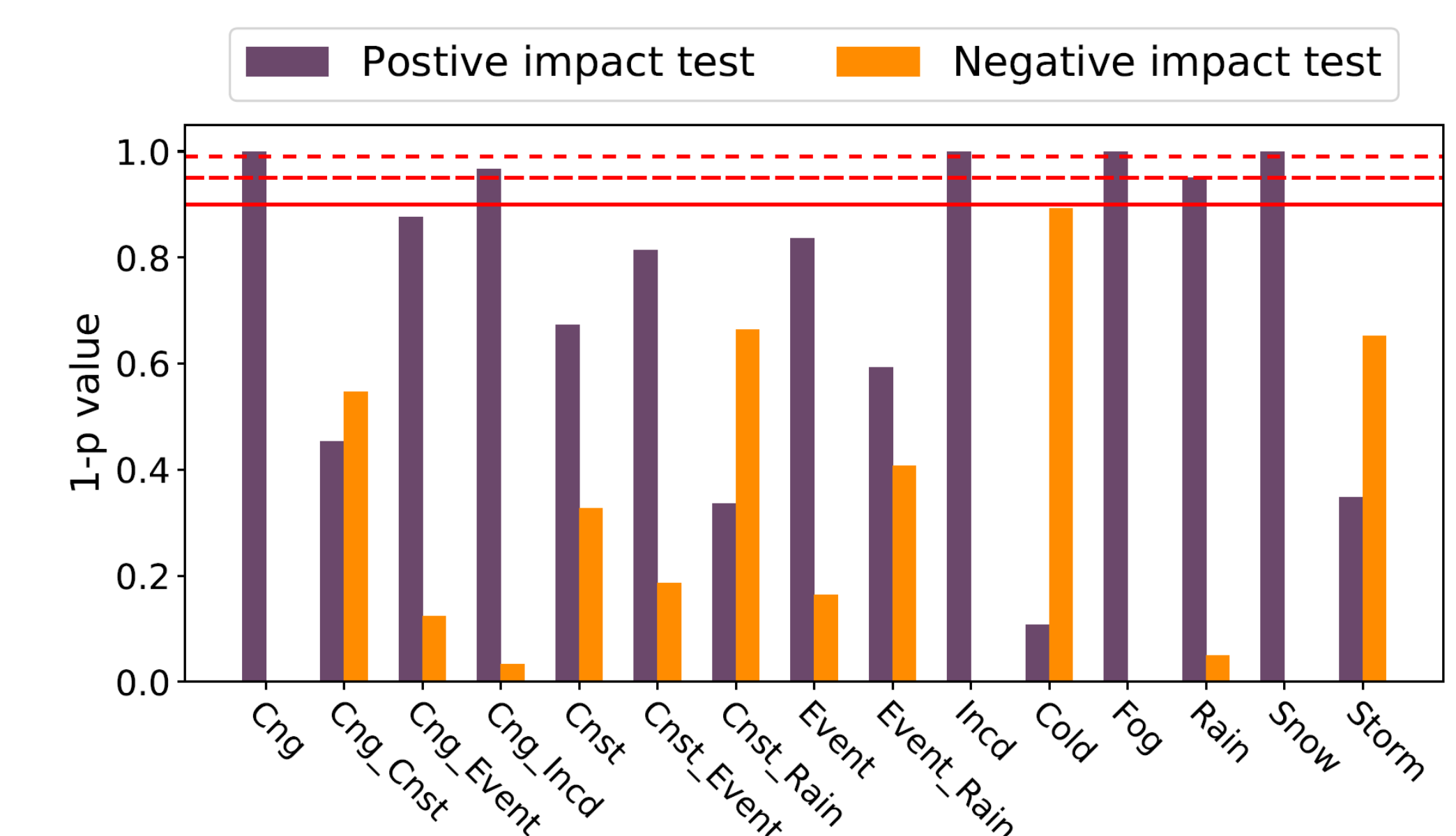
- ❖ **Impact based on Location of Event**



- ❖ **Impact based on Duration of Event**



- ❖ **Impact based on Type of Event**



## Conclusion and More

- ❖ Introduced a new framework to discover *geo-spatiotemporal* patterns
- ❖ Constructed and shared a new *dataset*
- ❖ Gleaned various *insights* from these patterns

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