Clustering and Labeling of a V2V Communication Dataset

based on CAM and DENM Messages with Malicious Data Injection

Analysis and Implications

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INTRO

VEHICULAR COMMUNICATION SYSTEMS

Computer networks
where vehicles and roadside units (RSU) serve as communicating nodes

VEHICLE-TO-VEHICLE COMMUNICATION (V2V)

Wireless information exchange about the speed and position of nearby vehicles.
Offering great promise in accident prevention.

INTRO

DATASETS

Two different types of messages: Cooperative Awareness Messages (CAM) and Decentralized Environmental Notification Messages (DENM).

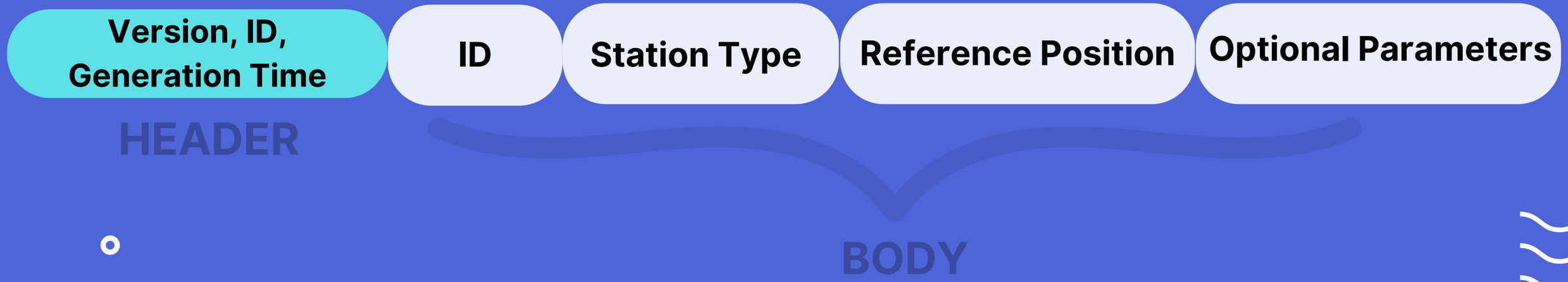
OBJECTIVE OF THE WORK

Data preprocessing, clustering, introduce noise into the provided dataset to simulate potential malicious reports, labeling the data based on clustering and identifying potential outliers.

CAM MESSAGES

defined by the European Telecommunications Standards Institute (ETSI) in 2011

- Basic awareness service by sending status data to **nearby nodes**
- Distributing messages about **presence**, **location**, and **fundamental status**



DENM MESSAGES

defined by the European Telecommunications Standards Institute (ETSI) in 2011

- Notification service regarding **road status**
- Support active road **safety** applications

Version, ID, Generation Time | **Management** | **Situation** | **Location**

HEADER

BODY

CLUSTERING

X-Means Algorithm

A **variant of K-Means algorithm**, determines **automatically** the optimal number of clusters in the data without requiring a predefinited specification, based on **recursion**.

CLUSTERING

X-Means Algorithm

- Initially applies **standard K-Means** with an initial cluster count
- Assesses **clustering quality using a measure** like Sum of Squared Errors (SSE)
- Checks if **splitting clusters** improves overall quality
- Uses criteria like Akaike Information Criterion (AIC) for significant improvements
- **Divides clusters** with K-Means if advantageous

CLUSTERING

X-Means Algorithm

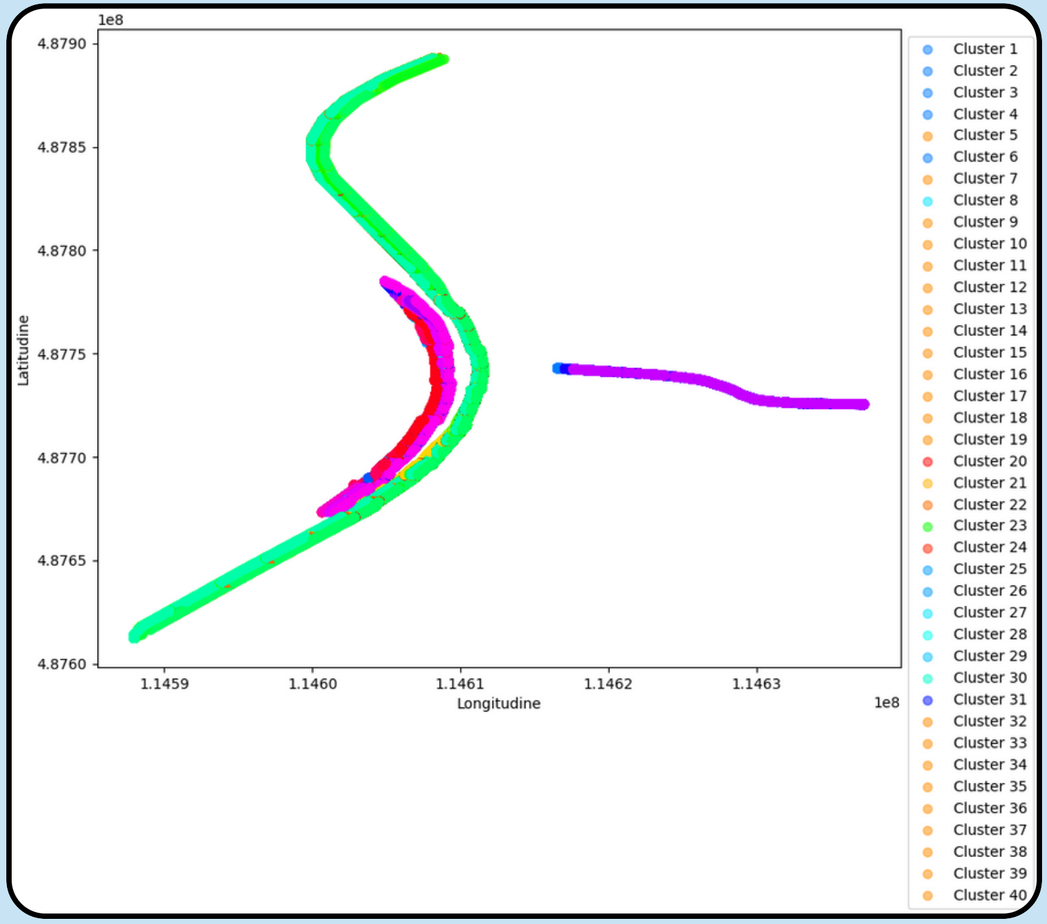
- Repeats **division and evaluation for existing clusters** and allows potential creation of new sub-clusters for improved clustering
- **Stops** when **no further cluster division** is possible; halts if the division **doesn't significantly enhance results** compared to complexity
- Returns **optimal clusters determined automatically**

CLUSTERING

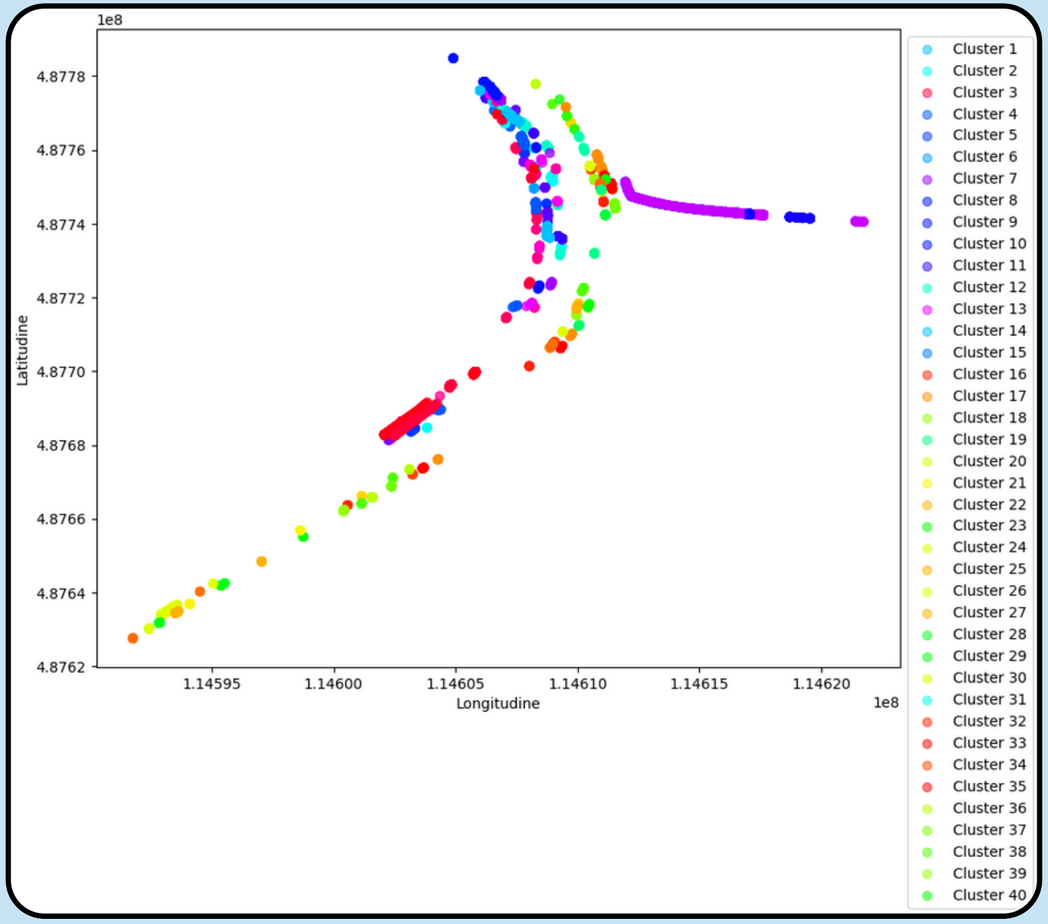
X-Means Algorithm

- **Longer computational time** compared to traditional K-Means due to iterative nature
- Suitable for **specific objectives** without requiring a predefined cluster count
- Part of ***pyclustering*** open-source library

CLUSTERING



Clustering of the provided CAM dataset

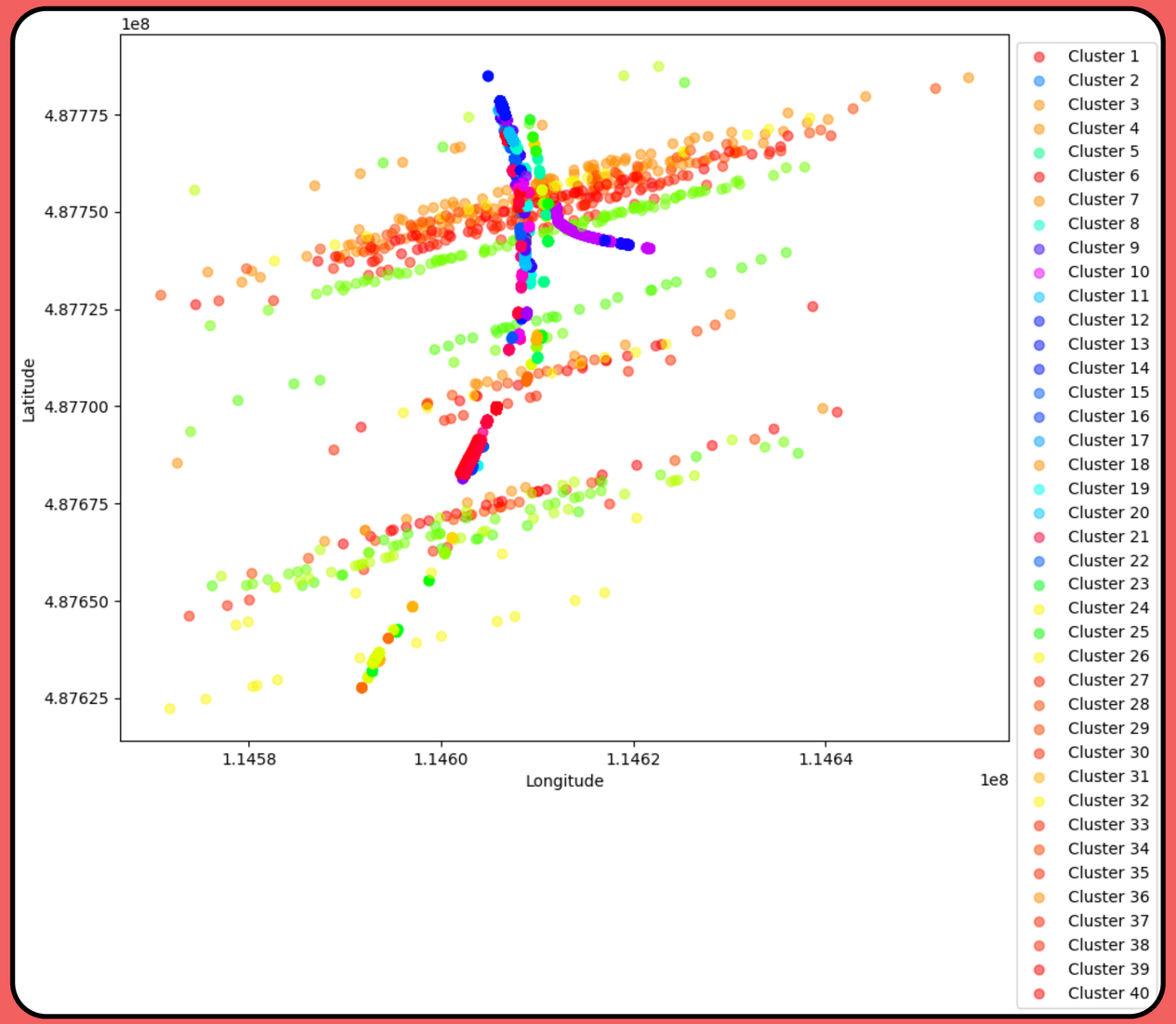


Clustering of the provided DENM dataset

DATA CONTAMINATION

- Varied coordinates using a **Gaussian distribution** (mean: 0, standard deviation: 1) multiplied by a factor of 100
- Kept variations within **a range of approximately 100 to 900 meters on the map**, considering degree-based coordinates
- Contaminated data based on the number of sources to simulate malicious vehicles
- Focused contamination on **sources with eventType value 97**, representing the most significant cluster
- Contaminated **20% (8 sources) of this specific eventType**

DATA
C



Clustering Following Data Contamination

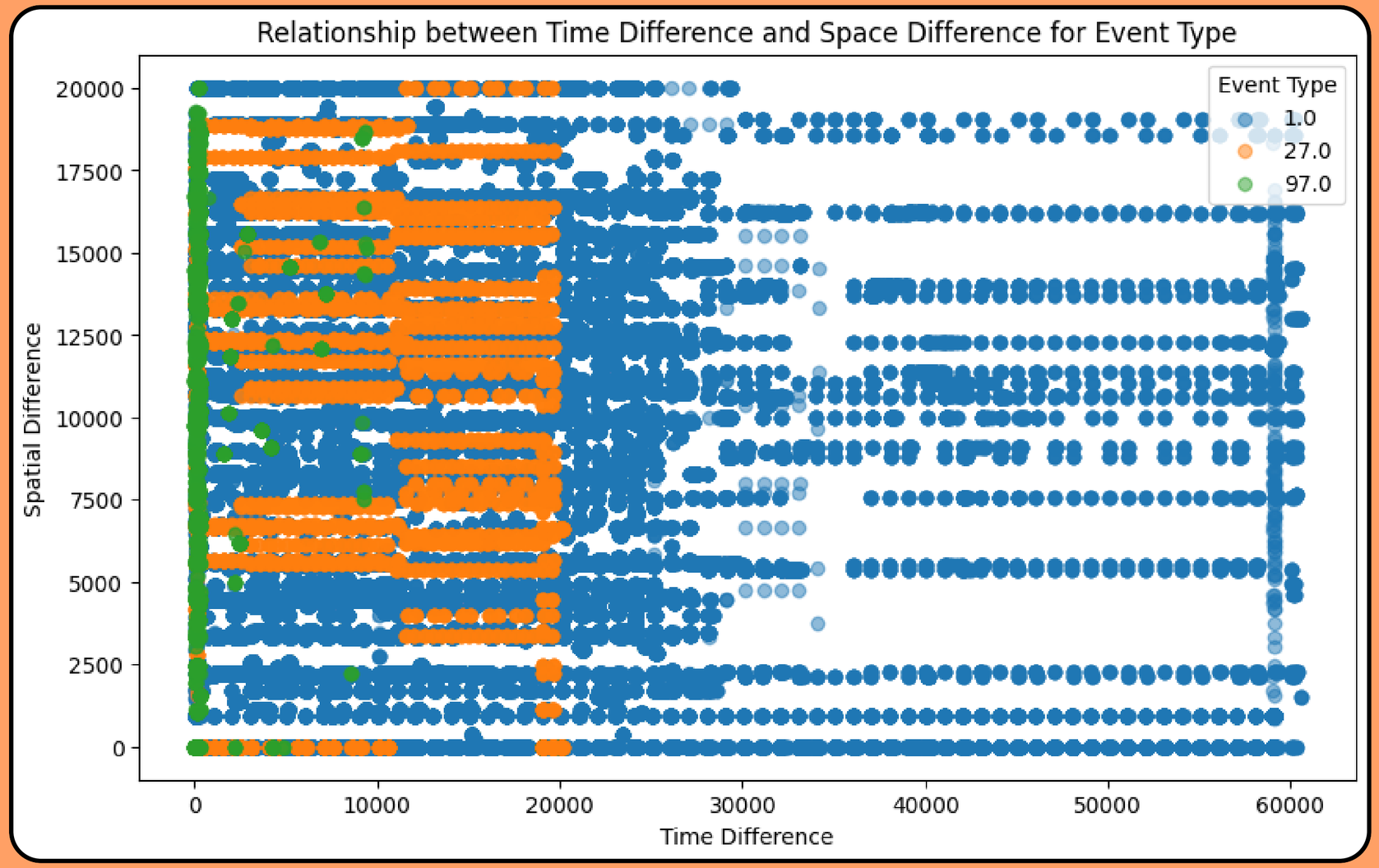
EVENT TYPE ANALYSIS

Conversion of simulation time to UTC for consistency

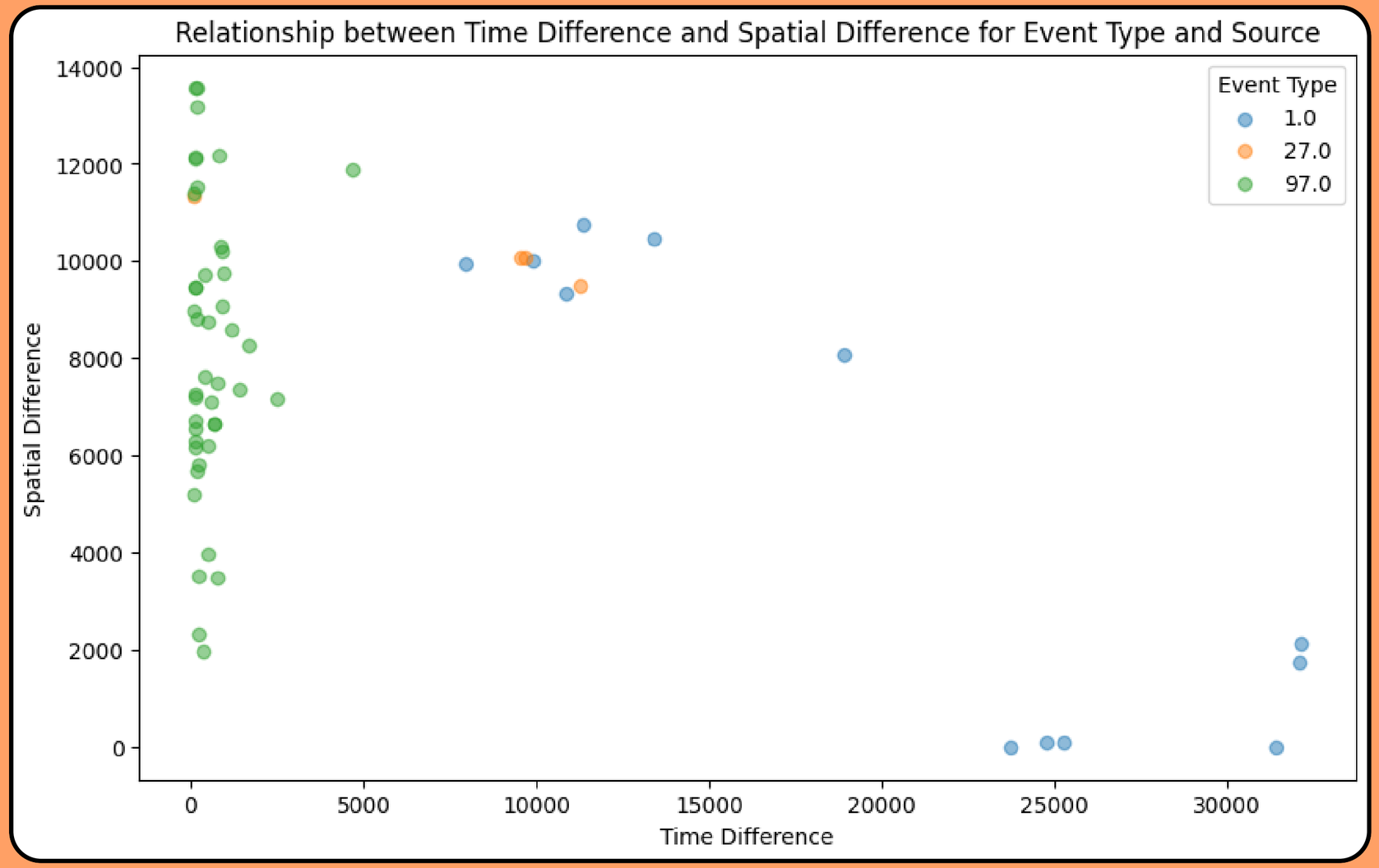
CauseCodeType_dangerousEndOfQueue = 27
CauseCodeType_collisionRisk = 97
CauseCodeType_trafficCondition = 1

Conversion of coordinates to radians, used the Haversine formula to calculate angular distance on Earth's surface, multiplied the result by Earth's radius for spatial difference

EVENT TYPE A


Relationship between Time Difference and Space Difference for Event Type
Event Type
1.0
27.0
97.0
Spatial Difference
20000
17500
15000
12500
10000
7500
5000
2500
0
0
10000
20000
30000
40000
50000
60000
Time Difference

EVENT TYPE A


Relationship between Time Difference and Spatial Difference for Event Type and Source
Spatial Difference
Time Difference
Event Type
1.0
27.0
97.0
14000
12000
10000
8000
6000
4000
2000
0
0
5000
10000
15000
20000
25000
30000

OUTLIER DETECTION

- **DBSCAN** (Density-Based Spatial Clustering of Applications with Noise) **algorithm**

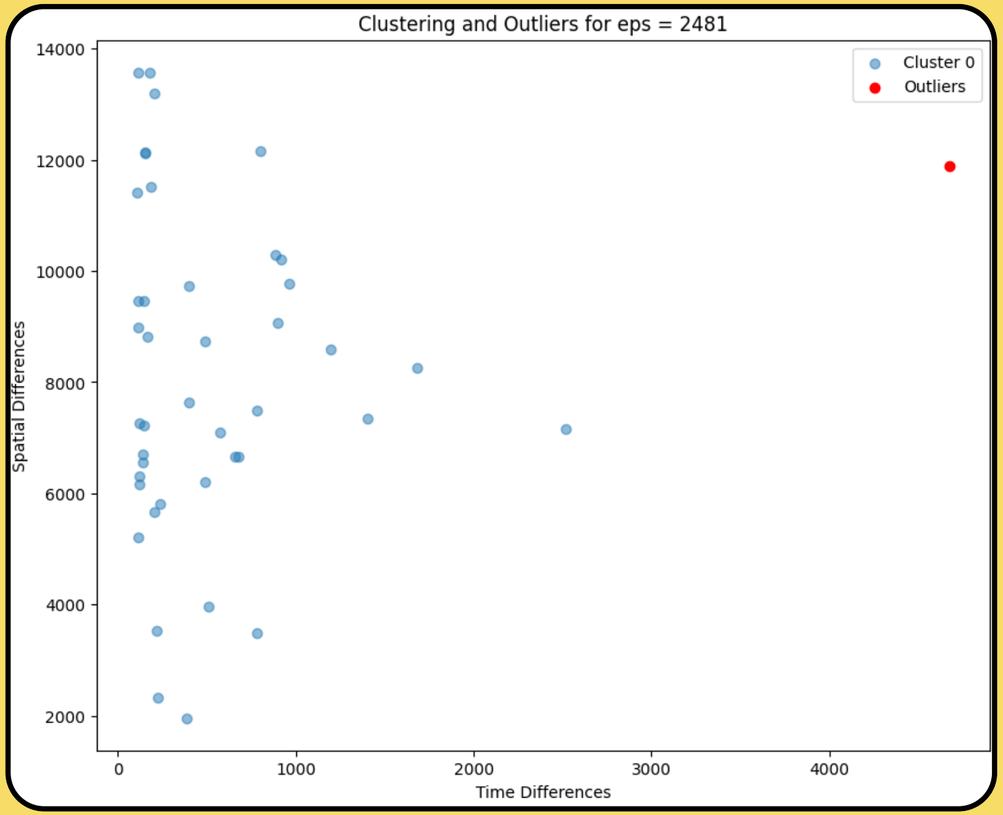
⟶ Groups points based on the data density in space

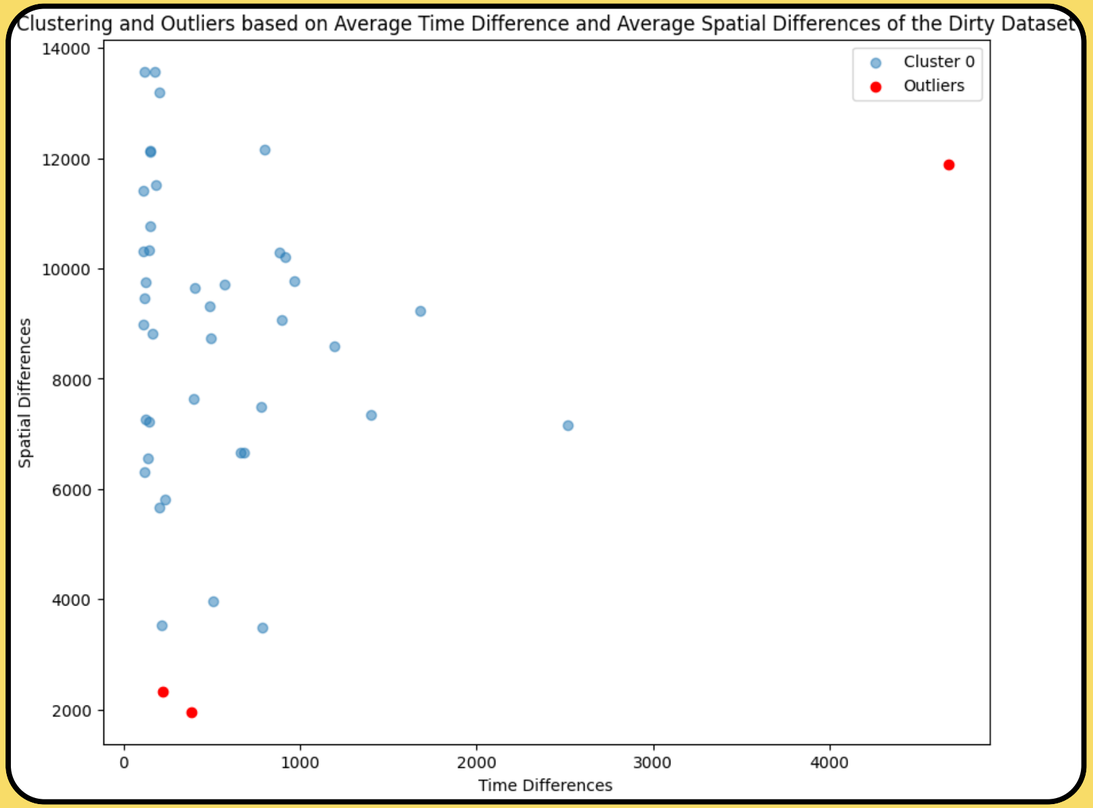
⟶ Two parameters:
  - **epsilon (ε)**, the maximum distance between two points to consider them part of the same cluster;
  - **minPoints**, the minimum number of points required to form a cluster.

- Experiment varying **epsilon values** to find the optimal configuration

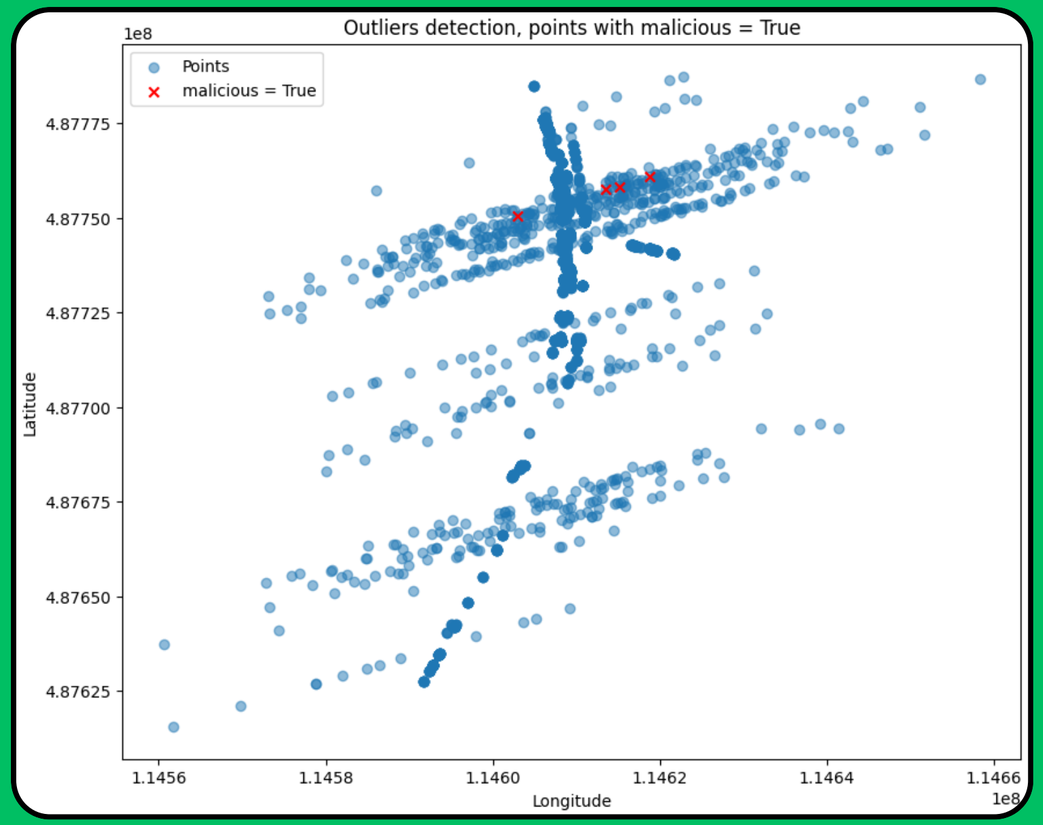
⟶ The best epsilon is the fewest possible outliers, the data we are working with is clean!

OUTLIER
D

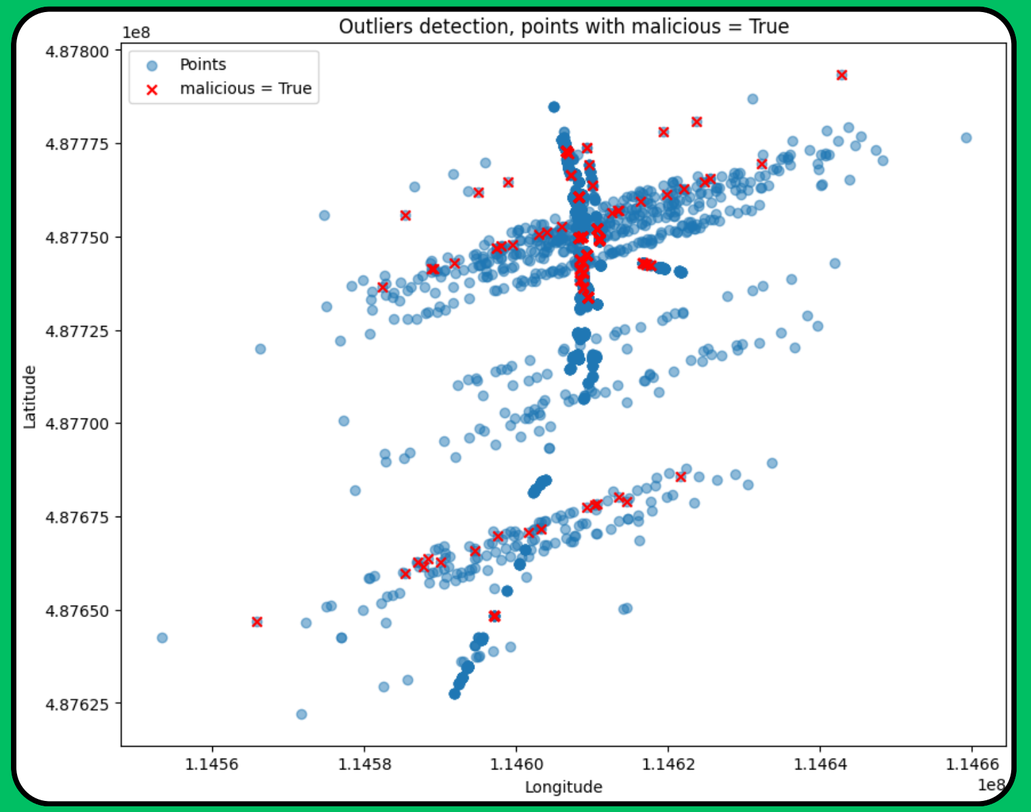

Clustering and Outliers for eps = 2481
Cluster 0
Outliers
Spatial Differences
Time Differences
14000
12000
10000
8000
6000
4000
2000
0
1000
2000
3000
4000


Clustering and Outliers based on Average Time Difference and Average Spatial Differences of the Dirty Dataset
Cluster 0
Outliers
Spatial Differences
Time Differences
14000
12000
10000
8000
6000
4000
2000
0
1000
2000
3000
4000

LABELING - EXPERIMENTS

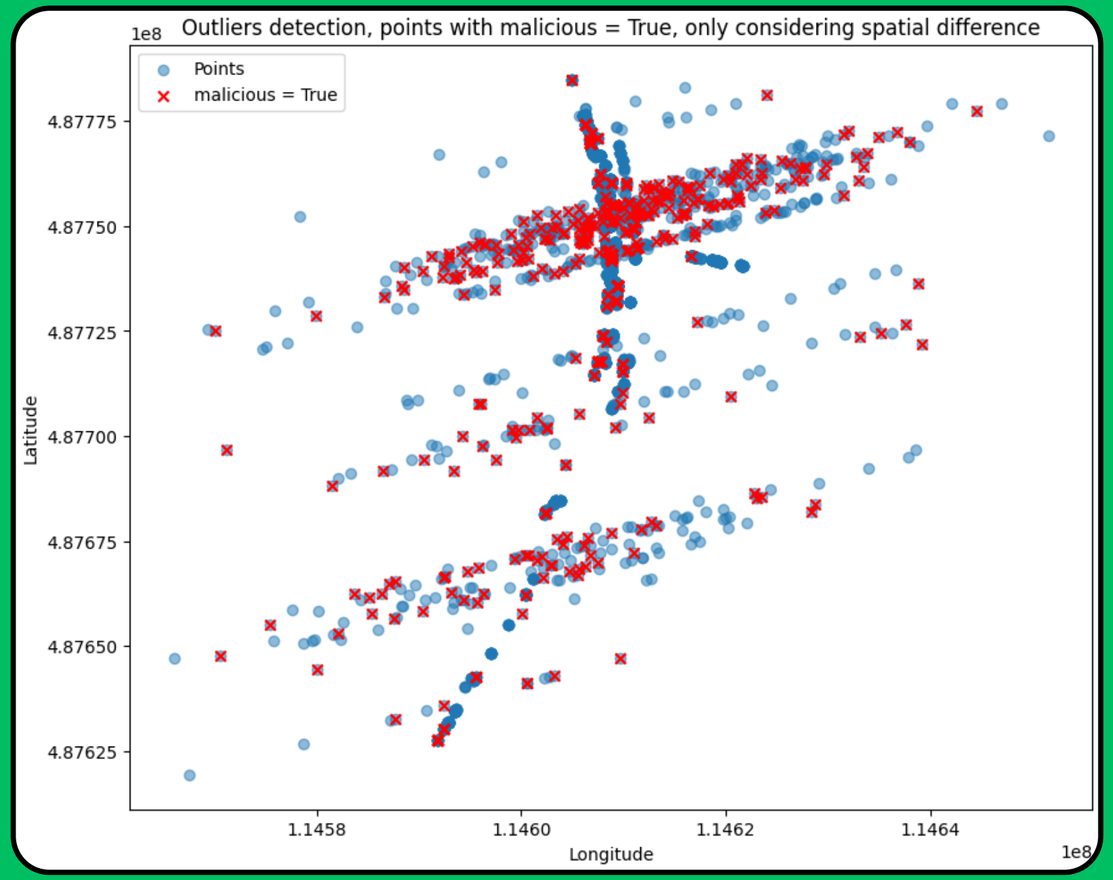


Outliers detection for epsilon = 2481 with the dirty dataset



Outliers detection for epsilon = 1281 with the dirty dataset

LABELING - EXPERIMENTS



Outliers detection, points with malicious = True, only considering spatial difference

DISCUSSION

The algorithm works and provides a solid foundation for creating a useful tool for detecting malicious actors in the context of road safety.

Through experiments in labeling, we observe that, by studying and making various attempts, it becomes evident that **better results can be achieved from the model.**

Future developments may involve refining the outlier recognition technique, exploring additional machine learning techniques, and expanding the dataset.

CONCLUSIONS

Algorithm’s actual efficacy: ability to discern the spatiotemporal differences between CAM and DENM messages. It **can, based on messages sent within a similar time and space, distinguish potential malicious ones**. In a real-world application, this tool would prove efficient.

An attacker might lack precision, **unaware of such analytical tools**, thereby **transmitting messages from a distant space or time** for a specific event, **promptly flagged by the algorithm**.

Thanks for the attention!