Multi-Dimensional Ensemble Framework for Mobility Anomaly Detection and Classification with Focus on Group Behaviors and Knowledge Graph representation.

Abstract:

The evolution of anomaly analysis has advanced from simply identifying outliers to the more complex task of both detecting and classifying anomalies into meaningful types. While significant research exists on individual anomalies in mobility data, there remains a critical gap in frameworks that systematically detect and classify group anomalies—collective behavioral deviations that cannot be identified by examining individual trajectories alone. This paper introduces a novel multi-dimensional ensemble framework that addresses both individual and group-level anomalies across distinct taxonomic categories: point anomalies (location, time, and POI-based), contextual anomalies (temporal, spatial, and POI contexts), collective anomalies (sequential, trajectory, and group patterns), and distributional anomalies (mobility rate, stay duration, and entropy variations).

The proposed framework follows a structured pipeline comprising data preparation, feature engineering, multi-level anomaly detection, case study analysis, and classification. Our architecture implements the five fundamental dimensions for anomaly classification while emphasizing group-level features: density changes, flow patterns, and transition probabilities that reveal emergent collective behaviors. For detection, we employ specialized algorithms targeting both individual and group anomalies, including statistical methods and machine learning techniques. What distinguishes our approach is the integration of group-aware detection mechanisms that can identify anomalies emerging only at collective levels—patterns invisible when examining trajectories in isolation but significant when analyzed as interconnected movements across multiple entities.

A key innovation of our approach is the dual focus on both detection and classification through a knowledge graph representation that captures the semantic relationships between individual and group anomaly types. This graph-based demonstration enables nuanced classification by modeling how individual anomalies (evacuation, shelter-seeking, avoidance, panic) evolve into or contribute to group anomalies (congregation, mass evacuation, flow disruption) through their underlying spatiotemporal characteristics. Our methodology addresses the inherent challenges in group mobility anomaly analysis: sparse labeled examples, complex interdependencies between individual actions, emergent behaviors that appear normal in isolation, and the contextual nature of what constitutes anomalous group movement.

Experiments on the YJMob100K dataset demonstrate that our ensemble approach achieves superior classification performance compared to single-algorithm methods, with improved precision, recall, F1 scores, and silhouette scores across anomaly types. The framework also provides enhanced explainability, offering insights into why certain behaviors are flagged as anomalous. This work contributes a generalizable methodology for mobility anomaly classification that can be extended to various spatiotemporal datasets, supporting applications in urban planning, transportation optimization, and public safety

Keywords: anomaly detection, mobility data, ensemble learning, knowledge graph, collective behavior analysis, spatiotemporal patterns, explainable anomaly detection, emergent phenomena.