Poster Abstract: Geo-Distributed Driving Maneuver Anomaly Detection

Miaomiao Liu
University of California, Merced, USA
mliu71@ucmerced.edu

Wan Du
University of California, Merced, USA
wdu3@ucmerced.edu

ABSTRACT

Auto-Encoder has been widely applied to anomaly detection areas. In this paper, we present a geo-distributed driving maneuver anomaly detection system based on auto-encoder. The auto-encoder is trained by using the normal driving data, so it memorizes the feature of normal driving pattern. The well trained auto-encoder is able to work as a classifier during the detection phase, it will tell whether the input data is normal or abnormal. To further improve the detection accuracy, we divide a city into a set of sub-regions by maximizing the spatial contrast within the same sub-region and minimizing the spatial contrast among different sub-regions. To examine performance of the proposed system, we evaluate it using a large dataset of GPS trajectories. The experiment results show our system achieves high detection accuracy.

CCS CONCEPTS

• **Applied computing** → **Transportation**; • **Information systems** → **Geographic information systems**.

KEYWORDS

geo-distributed, region partitioning, anomaly detection

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1 INTRODUCTION

Improving road safety and reducing road traffic deaths is a global burden. The number of road traffic deaths per year has increased from 1.15 million a year in 2000 to 1.35 million in 2016 worldwide. Most of the fatal crashes are the result of people driving anomaly, such as speeding, distracted driving, or driving under the influence of drugs, alcohol [3].

This paper presents a geo-distributed driving maneuver anomaly detection system, which leverages unsupervised deep auto-encoder and graph-based geographical partitioning to detect driving maneuver anomaly of vehicles. The auto-encoder learns driving features from historical data of normal driving maneuvers by considering temporal driving correlation of individual drivers and spatial peer dependency of all drivers. Once the auto-encoder memorized the data feature of normal driving maneuver well, the data which has different feature from normal data will be considered as anomalies during inference. Moreover, according to the First Law of Geography, *"everything is related to everything else, but near things are more related than distant things"*, we develop a geographical partitioning algorithm that divides a city into several sub-regions to improve the detection accuracy in each sub-region. We formulate the geographical partitioning problem into an optimization problem that maximizes the spatial peer correlation within each sub-region and minimizes the spatial peer correlation among different sub-regions. Finally, we train a specific driving maneuver anomaly detection model for each sub-region and perform in-situ updating of these models by incremental training.

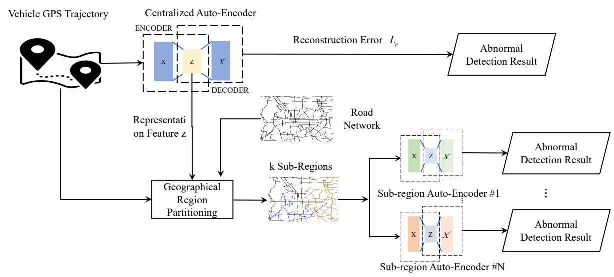

Figure 1: System architecture.

2 DESIGN

Figure 1 depicts the system architecture of our driving anomaly detection system, which mainly contains a centralized deep auto-encoder model for anomaly detection of driving maneuvers, a geographical region partitioning algorithm and a set of auto-encoders for anomaly detection in sub-regions.

An auto-encoder is composed of an encoder and a decoder. We first convert the vehicle GPS trajectory sensed from each driver into a sequence of driving state vectors x. The encoder projects the driving state vector x into a lower-dimensional feature, *i.e.*, representation feature z. The decoder reconstructs the representation feature z to $\hat{x}$. The more similar the original feature x and the reconstructed feature $\hat{x}$, the more accurate the auto-encoder model is. The encoder in this work incorporates Gated Recurrent Unit (GRU) [1], one of the gating mechanisms in Recurrent Neural Networks. GRU is able to capture the temporal dependency of the input features [2]. So the representation feature is updated as z_t = GRU(z_{t-1}, x_t), which means the representation of driving feature not just depends on the driving maneuvers happened during current time window, but also related to the previous one.

In this work, the auto-encoder is trained using normal driving maneuvers. The training objective is to minimize the difference

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between the original driving state vectors and the reconstructed driving state vectors. When training the auto-encoder, we consider both the temporal data of individual vehicle and the vehicle-vehicle spatial correlation. Since the auto-encoder is trained by normal historical driving data, it cannot reconstruct the driving anomaly data accurately. The reconstruction error L_e of deep auto-encoder is used to detect the driving anomalies.

According to the First Law of Geography, a sub-region has more strong spatial correlation than a big city. To leverage the local spatial contrast and further improve the anomaly detection accuracy, we partition a city into several sub-regions by a geographical region partitioning algorithm. We formulate the geographical region partitioning problem as a graph partitioning problem. To solve this problem, we construct the road network of a city as an undirected weighted graph $G =< V, E, W >$. We treat the road segments as vertices of the graph, and there is an edge between two vertices if these two road segments they represent are geographically connected. The weight of each edge is calculated by considering the spatial correlation between the drivers of these two road segments.

The objective of the graph partitioning is to divide vertices $v_x \in V$ into n subsets $V_1, V_2, \dots, V_n$. The spatial contrast within one subset V_i should be strong and the spatial contrast among different sub-regions (V_i and V_j) should be weak. We formulate this problem as an optimization problem. Its objective is shown as follows:

$$max \ \frac{1}{M_1} \sum_{v_m, v_k \in V_i} w(v_m, v_k) - \frac{1}{M_2} \sum_{v_m \in V_i, v_l \in V_j} w(v_m, v_l), \quad v_m \neq v_k \neq v_l, V_i \neq V_j \tag{1}$$

where V_i and V_j are two sub-graphs of the graph $G = (V, E)$, vertex v_m and v_k are the vertices belong to the same sub-graph V_i, v_l is the vertices belong to a different sub-graph V_j. $w(v_m, v_k)$ and $w(v_m, v_l)$ are the weight of edge $e(v_m, v_k)$ and edge $e(v_m, v_l)$. The edges $e(v_m, v_l)$ connects sub-graph V_i and V_j. M_1 is the total number of edge of the sub-graph V_i and M_2 is the total number of edge that connects sub-graphs V_i and V_j. The first part of the objective is the average weight within a sub-graph V_i, the second part is the average weight that connects two sub-graphs V_i and V_j.

We leverage the Normalized Cut algorithm to solve the optimization problem. After region partitioning, we train a specific anomaly detection model based on deep auto-encoder for each sub-region and update these models by incremental training.

3 EVALUATION

We compare the performance of our system with two baselines.

- **Centralized Model.** The centralized model is a simple version of the proposed system. It is a general auto-encoder model and was trained by using all the vehicle data collected from the entire city.
- **Single-User Model.** We implement a similar version of pBEAM [4], which is the latest driving anomaly detection system. The single-user model is trained by using the driving data collects from each individual driver.

We found for our dataset, when we divide the city into 4 sub-regions, the proposed system shows best performance. We calculate the average accuracy of 4 sub-region models. Similarly, we use the average accuracy of all single-user models show the single-user model performance. The dimension size of the representation feature is defined as 20 for the above three scenarios.

3.1 Performance over all models

Figure 2 shows the performance of our proposed system *GeoDMA* and two baselines. The proposed system outperforms the centralized model and the single-user model in all four performance metrics. It achieves 93.1%, 78.4%, 0.85 and 0.86 in Precision, Recall, F1 score and AUC respectively. The performance under these 4 metrics improves around 8.3%, 1.3%, 4.2% and 4.7% than the centralized model and 13.5%, 1.8%, 3.8% and 5.2% higher than the single-user model. This is because our system considers the local spatial contrast as well as vehicle-vehicle dependency when train the model.

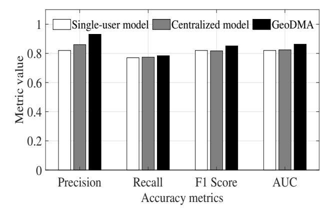

Figure 2: Overall performance comparison.

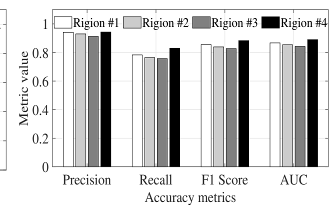

Figure 3: Performance comparison of each region.

3.2 Performance over different regions

Figure 3 demonstrates the performance of the model trained for each sub-region. All of these 4 sub-region models achieve better performance than the centralized model, making it around 9.7%, 6.0%, 8.1% and 9.4% higher than centralized model in Precision, Recall, F1 score and AUC respectively. Besides, the performance of these 4 sub-region models under the same performance metric does not show much difference.

4 CONCLUSION

This paper presents a geo-distributed driving anomaly detection system. It leverages unsupervised deep auto-encoder and geo-distributed partitioning for driving maneuver anomaly detection. Experiment results on a large-scale vehicle trajectory dataset show that our proposed system outperforms the baseline systems.

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REFERENCES

[1] Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. *arXiv preprint arXiv:1412.3555* (2014).
[2] Pengyang Wang, Yanjie Fu, Jiawei Zhang, Pengfei Wang, Yu Zheng, and Charu Aggarwal. 2018. You are how you drive: Peer and temporal-aware representation learning for driving behavior analysis. In *ACM SIGKDD*.
[3] WHO. [n.d.]. Global Status Report on Road Safety 2018. https://www.who.int/violence_injury_prevention/road_safety_status/2018/en/.
[4] Xingzhou Zhang, Mu Qiao, Liangkai Liu, Yunfei Xu, and Weisong Shi. 2019. Collaborative cloud-edge computation for personalized driving behavior modeling. In *ACM/IEEE SEC*.