Ahmedabad University

CSE523: Machine Learning

Weekly Report 1

Group Name - Logistic Legends

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Group Details:

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Identify Abnormal driving behavior using Spatio-Temporal analysis

Problem Statement:

Developing a binary classifier to identify abnormal driving behavior from trajectory data using spatio-temporal analysis.

→ Assumption: Drivers behave similarly in the same patch of road.
→ Even if within certain parts of the road, drivers tend to follow similar patterns, deviations from these norms may signal unusual behavior.
→ Using trajectory data, a binary classifier can distinguish between "normal" and "abnormal" driving patterns by extracting spatial and temporal variables.

Literature survey:

1. **Real-time detection of abnormal driving behavior based on long short-term memory network and regression residuals**

- The LSTM algorithm is used to detect the different types of abnormalities and real time abnormal driving behavior.
- Analyses by threshold of vehicle kinematics parameters
- Abnormal behavior due to magnitude.

2. Unusual Driving behavior Detection in videos using Deep learning models

- CNN algorithm is utilized for feature extraction and classification of abnormal driving behaviors. CNNs are deep learning models commonly used for image processing.
- This approach allows the model to learn from the videos and figures out important details, like whether the driver is driving normally or abnormally.

3. Recognition method of abnormal driving behavior using the bidirectional gated recurrent unit and convolutional neural network

- CNN-BiGRU algorithm: "CNN" - Capturing non-linear relations from long-term trends of sequences. "BiGRU" - Extracting features of time series from driving parameters.
- To create a dataset: Analyzes actual car driving data, involving "high acceleration" and "steering position".

4. Abnormal driving behavior detection based on an improved Ant colony algorithm

- Novel approach for detecting abnormal driving behavior by measuring the preference path length of drivers and Ant Colony Algorithm.
- Cumulative conversion probability of operation switching.
- Measure the conversion probability between driving patterns based on an improved ant colony algorithm.

Approach:

Support Vector Machine (SVM) to classify trajectories as either "normal" or "abnormal" based on spatio-temporal features extracted from the dataset.

- We will process the dataset and then clean the data so that we can process it.
- Then we will extract features like Speed, acceleration, direction changes.
- Split the dataset into training and testing.
- SVM algorithm
- Train model on training data
- Testing

Datasets Discussions:

- The dataset consists of GPS trajectory data collected from vehicle tracking systems installed in a fleet of commercial vehicles.
- It comprises a total of 10,000 trajectories, each representing the movement of a single vehicle over a specific time period and distance.

1	trip_id	driver_id	date	duration_s	distance_r	city
2	T-1	D-1	30-01-2018	2030	28094.74	Atlanta (GA)
3	T-2	D-1	04-01-2018	1237	30989.1	Atlanta (GA)
4	T-3	D-1	21-01-2018	428	5943.922	Atlanta (GA)
5	T-4	D-1	08-11-2017	1725	31447.24	Atlanta (GA)
6	T-5	D-1	02-01-2018	1253	30887.19	Atlanta (GA)
7	T-6	D-1	05-12-2017	2085	31885.23	Atlanta (GA)
8	T-7	D-1	22-01-2018	1359	30701.7	Atlanta (GA)
9	T-8	D-1	29-01-2018	1266	31200.08	Atlanta (GA)
10	T-9	D-1	03-02-2018	1250	11478.52	Atlanta (GA)
11	T-10	D-1	18-12-2017	1452	31063.4	Atlanta (GA)
12	T-11	D-1	12-12-2017	426	5267.901	Atlanta (GA)
13	T-12	D-1	19-01-2018	1339	31221.22	Atlanta (GA)
14	T-13	D-1	15-12-2017	1274	31865.56	Atlanta (GA)
15	T-14	D-1	11-12-2017	1370	30540.92	Atlanta (GA)
16	T-15	D-1	03-11-2017	431	4830.629	Atlanta (GA)
17	T-16	D-1	21-01-2018	1162	7961.888	Atlanta (GA)
18	T-17	D-1	04-11-2017	1154	20015.37	Atlanta (GA)
19	T-18	D-1	18-10-2017	973	8537.891	Atlanta (GA)
20	T-19	D-1	02-10-2017	1926	32225.32	Atlanta (GA)
21	T-20	D-1	01-02-2018	398	4288.534	Atlanta (GA)
22	T-21	D-1	07-10-2017	663	2334.915	Atlanta (GA)
23	T-22	D-1	01-11-2017	1865	28584.36	Atlanta (GA)
24	T-23	D-1	08-02-2018	536	6145.702	Atlanta (GA)
25	T-24	D-1	21-11-2017	1150	29948.67	Atlanta (GA)
26	T-25	D-1	27-10-2017	1332	28910.39	Atlanta (GA)
27	T-26	D-1	24-10-2017	1147	9991.667	Atlanta (GA)
28	T-27	D-1	27-12-2017	1322	31616.98	Atlanta (GA)

References:

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