You Are How You Drive: Peer and Temporal-Aware Representation Learning for Driving Behavior Analysis

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Outline

- **Background and Motivation**
  - Definition and Problem Statement
  - Methodology
  - Application
  - Evaluation
  - Conclusion
# Background and Motivation

## Car accident facts

- **6 MILLION.** Average number of car accidents in the U.S. every year.
- **3 MILLION.** People in the US are injured every year in car accidents.
- **90 PEOPLE.** More than 90 people die in car accidents every day.
- **2 MILLION.** Around 2 million drivers in car accidents experience permanent injuries every year.
- **1 IN 7 PEOPLE.** Do not wear a seatbelt while driving.
- **Seatbelts cut the risk of serious INJURY BY 50%.**
- **30 X.** People not wearing a seatbelt are 30 times more likely to be ejected from the vehicle during a crash.
- **Seatbelts reduce the risk of DEATH BY 45%.**
Driving Behaviors

TYPICAL CAUSES OF ACCIDENTS THAT RESULT IN DEATH

- 40% Alcohol
- 30% Speeding
- 33% Reckless Driving
Driving Behaviors

It is essential to learn the pattern of driving behaviors

9 PEOPLE
Each day, more than 9 people are killed due to distracted driving

1 IN 5 CRASHES
Distraction was reported as a factor in nearly 1 in 5 crashes in which someone was injured

40% OF ALL
American teens say that they have been in a car when the driver used a cell phone in a way that put people in danger

DRIVING BY 37%
Driving while using a cell phone reduces the amount of brain activity associated with driving by 37%

1060
More than 1060 people are injured in crashes that involve a distracted driver

23 TIMES
More likely to crash while texting and driving

4.6 SECONDS
Sending or receiving a text takes a driver’s eyes from the road for an average of 4.6 seconds, the equivalent at 55 mph- of driving the length of an entire football field, blind.
Challenge I: GPS traces – Non-applicable

GPS traces (e.g., time, latitude, longitude) encode the driving operations, states, and styles in a semantically implicit way

Insight I:

Transforming GPS traces into graphs

Convenient for representation learning
Challenge II: How to model dependencies?

peer dependencies
temporal dependencies

Insight II

jointly model the graph-graph peer dependency across drivers, as well as the current-past temporal dependency within a driver, in representation learning.
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Driving Operation

Driving operations are defined as a set of activities and steps that a driver operates when driving a vehicle, according to the driver’s personal judgment, experience and skills.

- **Speed-related:** acceleration, deceleration, constant speed
- **Direction-related:** turning left, turning right, moving straight
Definition II

- Driving State

A driving state concerns the way that a vehicle moves at a specific time point or in a small time window. In other words, a driving state of a vehicle contains both the speed status (i.e., acceleration, deceleration, constant speed) and the direction status (i.e., turning left, turning right, moving straight) of a vehicle. For instance, a driving state example of a car can be <constant speed, moving straight>. 
Definition III

Driving State Transition Graph
Problem Statement

- **Given**
  - a driver (a vehicle)
  - corresponding GPS trajectories \( D = [\langle t, \varphi_t, \lambda_t \rangle]_{t=1}^T \)

- **Objective**
  - learning a mapping function \( f : D \rightarrow V \)
    \[ V = [v_n]_{n=1}^N \]

- **Core tasks**
  - Constructing multi-view driving state transition graphs
  - Automated profiling of driving behavior via peer and temporal-aware representation learning
  - Applications to transportation safety

A sequence of time-varying yet relational vectorized representations
Framework Overview

Driving State Transition Graph Sequence

GPS Trajectory

Transition Probability View

Transition Duration View

Encoder

Peer Dependency

Temporal Dependency

Decoder

Representation Result (Vectors)

Prediction and Historical Assessment of Driving Scores

Risky Area Detection

PTARL
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Methodology

- Construction of multi-view driving state transition graphs
- Peer and temporal-aware representation learning
Construction of multi-view driving state transition graphs

- **Detecting Driving Operations**
  - Detection of driving-related operations.
  - Detection of direction-related operations.

- **Extracting Driving State Sequences**
  1. Acceleration while turning right,
  2. Acceleration while turning left,
  3. Acceleration while straightforward,
  4. Deceleration while turning right,
  5. Deceleration while turning left,
  6. Deceleration while straightforward,
  7. Constant speed while turning right,
  8. Constant speed while turning left,
  9. Constant speed while straightforward
Construction of multi-view driving state transition graphs

- Constructing Multi-view Driving State Transition Graphs

Transition probability view

Transition duration view
Peer and temporal-aware representation learning

- Intuition 1: Structural Reservation
- Intuition 2: Temporal Dependency
- Intuition 3: Peer Dependency
For Intuition 1: Structural Reservation

□ Base Model - Autoencoder

\[
\begin{align*}
\hat{y}_i^1 &= \sigma(W^1 x_i + b^1), \\
\hat{y}_i^k &= \sigma(W^k \hat{y}_i^{k-1} + b^k), \forall k \in \{2, 3, \cdots, o\}, \\
\hat{z}_i &= \sigma(W^{o+1} \hat{y}_i^o + b^{o+1}).
\end{align*}
\]

\[
\begin{align*}
\hat{y}_i^o &= \sigma(\hat{W}^{o+1} \hat{z}_i + \hat{b}^{o+1}), \\
\hat{y}_i^{k-1} &= \sigma(\hat{W}^k \hat{y}_i^k + \hat{b}^k), \forall k \in \{2, 3, \cdots, o\}, \\
\hat{x}_i &= \sigma(\hat{W}^1 \hat{y}_i^1 + \hat{b}^1).
\end{align*}
\]
For Intuition 2: Temporal Dependency

\[\begin{align*}
\text{#Sequential Encode Step} \\
(y_1^1)^\tau &= \sigma(W^1x_i^\tau + b^1), \\
(y_k^k)^\tau &= \sigma(W^k(y_{k-1}^{k-1})^\tau + b^k), \forall k \in \{2, 3, \ldots, o\}, \\
z_i^\tau &= (1 - c^\tau)z_i^{\tau-1} + c^\tau \tilde{z}_i^\tau.
\end{align*}\]

\[\begin{align*}
\text{#Sequential Decode Step} \\
(\hat{y}_i^o)^\tau &= \sigma(\hat{W}^{o+1}z_i^\tau + \hat{b}^{o+1}), \\
(\hat{y}_i^{k-1})^\tau &= \sigma(\hat{W}^k(\hat{y}_i^k)^\tau + \hat{b}^k), \forall k \in \{2, 3, \ldots, o\}, \\
\hat{x}_i^\tau &= \sigma(\hat{W}^1(\hat{y}_1^1)^\tau + \hat{b}^1).
\end{align*}\]
For Intuition 3: Peer Dependency

\[ H_c(G^\tau) = \sum_{u_i \in U} \sum_{u_j \in U, u_i \neq u_j} s_{i,j}^\tau \cdot \| z_i^\tau - z_j^\tau \|_2^2 \]

the similarity of driving behavior between the driver \( u_i \) and \( u_j \) at the time slot \( \tau \).
Objective Function

\[
\min \frac{1}{2} \sum_{\tau \in \mathcal{T}} \sum_{u_i \in \mathcal{U}(n)} \| (x_i^\tau - \hat{x}_i^\tau) \|_2^2 + \alpha \cdot \mathcal{H}_c(G^\tau)
\]
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Application

- Prediction and Historical Assessment of Driving Scores
- Risky Area Detection
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- **Evaluation**
- Conclusion and Future Work
□ Data Description

From Beijing City

<table>
<thead>
<tr>
<th>Properties</th>
<th>Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of drivers</td>
<td>10,357</td>
</tr>
<tr>
<td>Time range</td>
<td>Feb.2 - Feb.8</td>
</tr>
<tr>
<td>City</td>
<td>Beijing</td>
</tr>
</tbody>
</table>

Driving Score Distribution
Baselines

(1) Auto-Encoder: minimizes the loss between the original feature representations and reconstructed ones.

(2) DeepWalk: uses local information obtained from truncated random walks to learn latent representations.

(3) LINE: optimizes the objective function that preserves both the local and global network structures with an edge-sampling algorithm.

(4) Driving State Vector (DSV): the traditional transportation approach.
Evaluation

- **Evaluation Metrics**
  - **Square Error**
    - Measure regression errors
  - **Coefficient of Determination**
    - Measure the regression accuracy
  - **Normalized Discounted Cumulative Gain (NDCG@N)**
    - Evaluate the ranking performance at TopN
  - **Kendall’s Tau Coefficient (Tau)**
    - Measure the overall ranking accuracy.
Overall performance

Square Error
- Auto-Encoder
- DeepWAalk
- CNN
- PTARL

R^2
- Auto-Encoder
- DeepWAalk
- CNN
- PTARL

NDCG@N
- Auto-Encoder
- DeepWAalk
- CNN
- PTARL

Tau
- Auto-Encoder
- DeepWAalk
- CNN
- PTARL
Robustness Check

Robustness check in the score-based group
Robustness Check

Robustness check in the driving-state-based group
Study of Peer and Temporal Dependencies

Square Error

- Auto-Encoder
- PTARL-peer
- PTARL-temporal
- PTARL

$\tau$

- Auto-Encoder
- PTARL-peer
- PTARL-temporal
- PTARL

$R^2$

- Auto-Encoder
- PTARL-peer
- PTARL-temporal
- PTARL

NDCG@N

- Auto-Encoder
- PTARL-peer
- PTARL-temporal
- PTARL

@5 @10 @15 @20
Study of Performance in Different Views

Square Error

Transition Probability View
Transition Duration View
PTARL

0.2
0.3
0.4
0.5
0.6
Square Error

0.7

Transition Probability View
Transition Duration View
PTARL

0.0
0.5

R²

-1.0

Transition Probability View
Transition Duration View
PTARL

0.0
0.2
0.4
0.6
0.8
1.0

NDCG@N

@5
@10
@15
@20

0.0
0.2
0.4
0.6
0.8
1.0

Translation Probability View
Transition Duration View
PTARL

0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

Transition Probability View
Transition Duration View
PTARL

0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1.0

Transition Probability View
Transition Duration View
PTARL
Historical Assessment of Driving Scores

![Graph showing driving scores over time for riskier and safer drivers. The x-axis represents time in units, and the y-axis represents score values. The graph includes two lines: one for riskier drivers and another for safer drivers.](image)
Risky Area Detection
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Conclusion

- We investigated driving behavior analysis from the perspective of representation learning.
- We developed an analytic framework that jointly modeled the peer and temporal dependencies by:
  - constructing multi-view driving state transition graphs from GPS traces to characterize driving behavior,
  - incorporating the idea of gated recurrent unit to model both the graph-graph peer dependency and integrating graph-graph peer penalties to capture the current-past temporal dependency in a unified optimization framework,
  - applying our proposed method to enable the applications of driving score prediction and risky area detection.
- The method is effective.
Thanks!

Questions?