KDD2018

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

Pengyang Wang, Yanjie Fu, Jiawei Zhang,

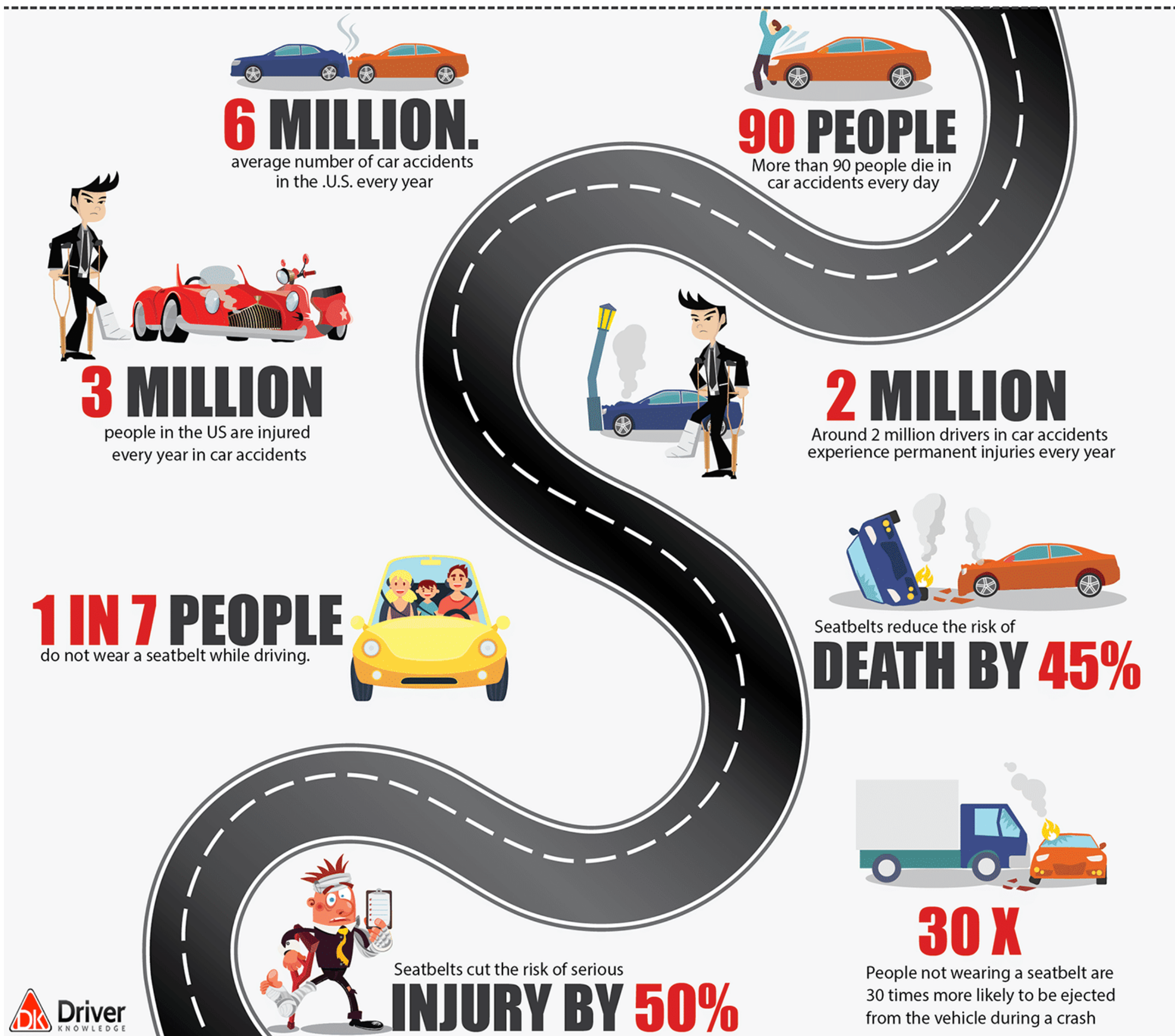
Pengfei Wang, Yu Zheng, Charu Aggarwal

Outline

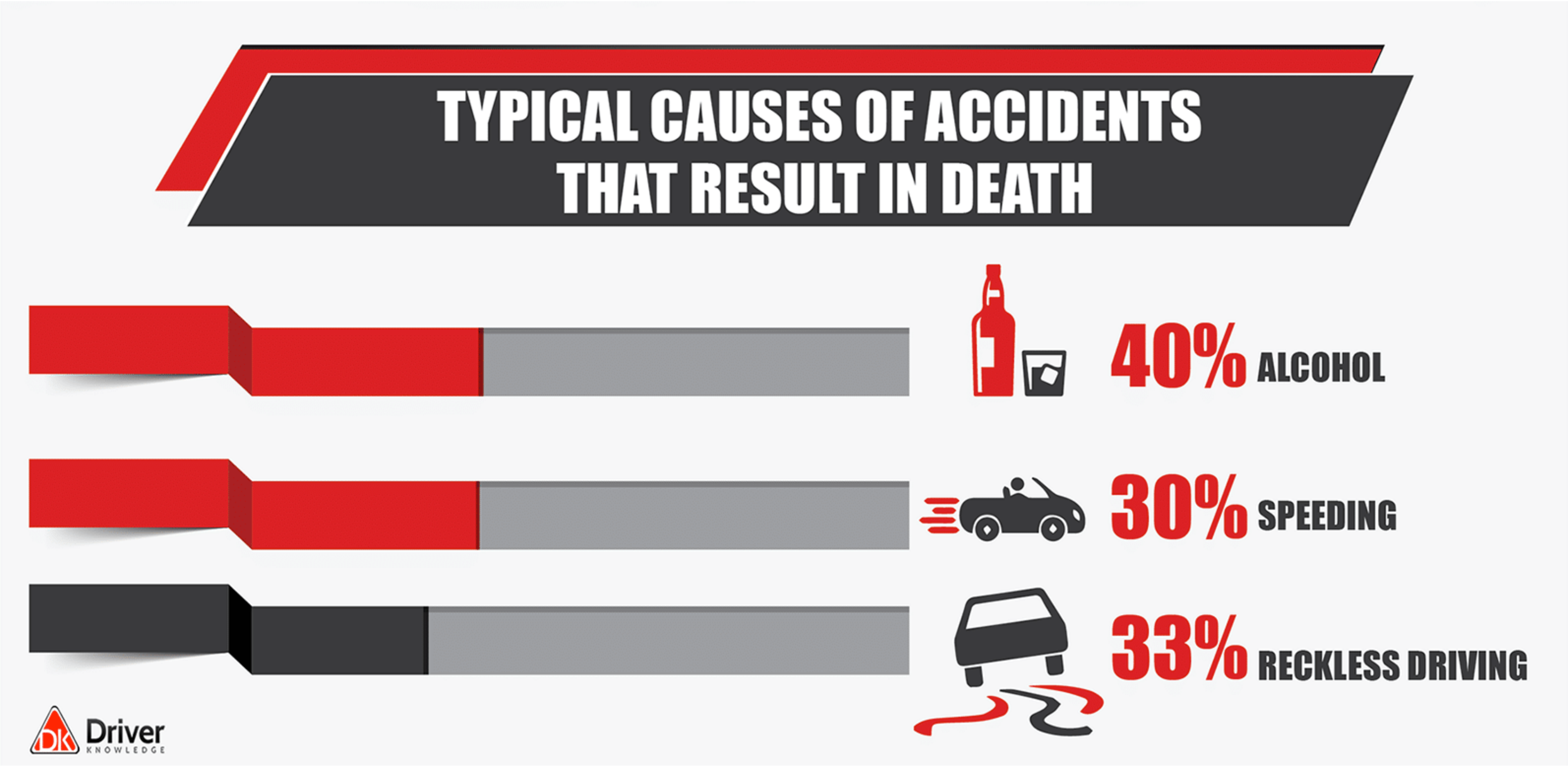
- **Background and Motivation**
- Definition and Problem Statement
- Methodology
- Application
- Evaluation
- Conclusion

Background and Motivation

□ Car accident facts

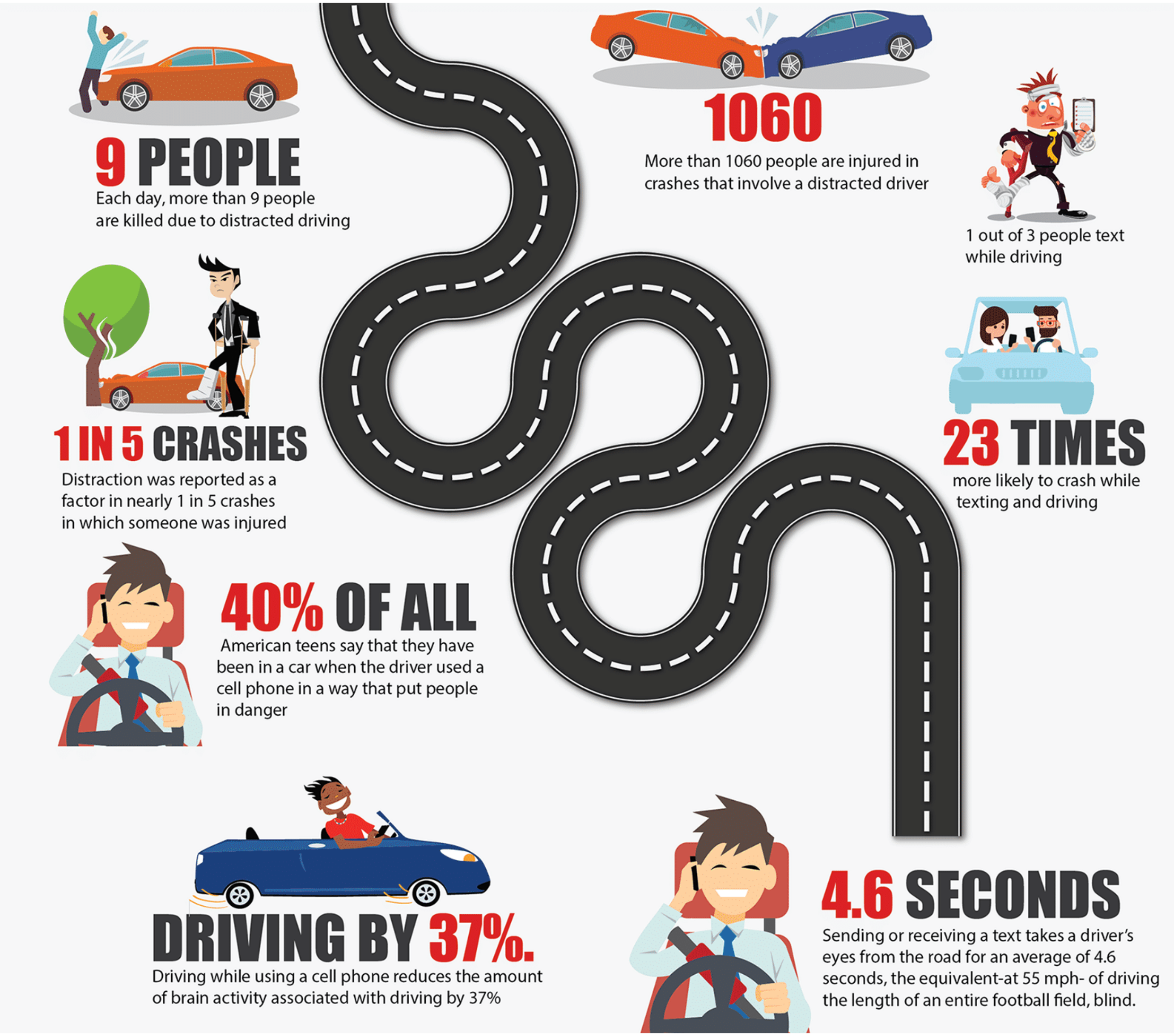


Driving Behaviors



Driving Behaviors

It is essential to learn the pattern of driving behaviors



Challenges & Insights

- **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

Challenges & Insights

- **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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Definition I

- **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

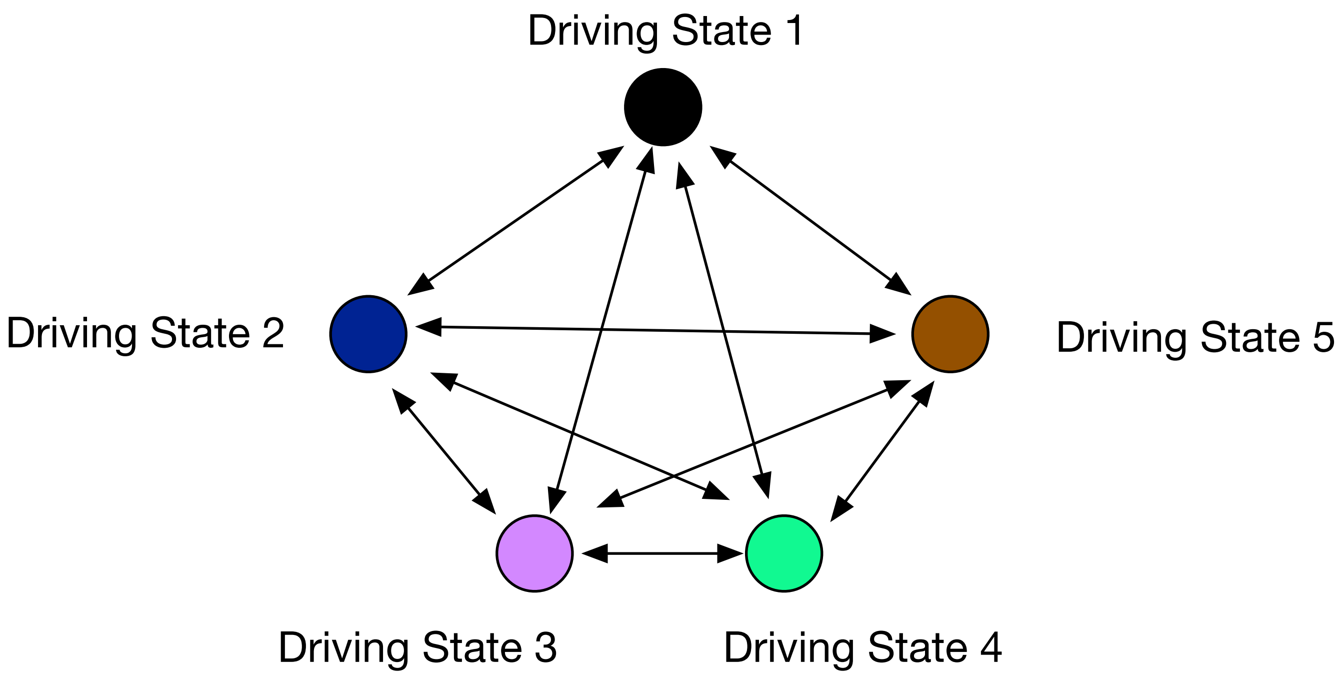
Definition II

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

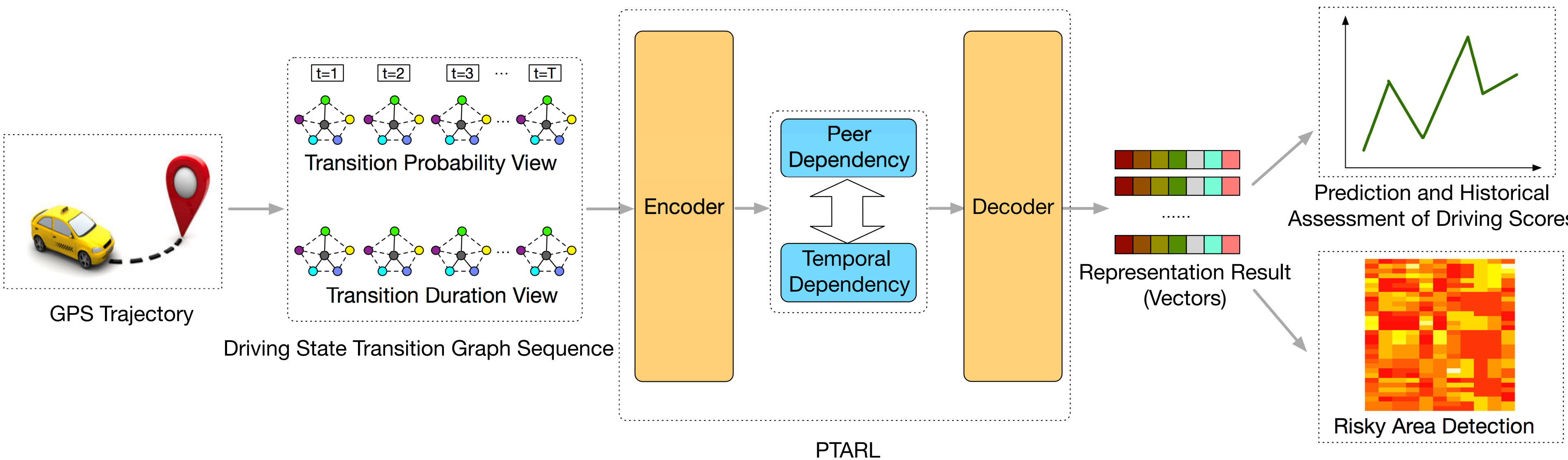
- **Given**
  - a driver (a vehicle)
  - corresponding GPS trajectories $D = [< t, \varphi_t, \lambda_t >]_{t=1}^{T}$
- **Objective**
  - learning a mapping function $f : D \rightarrow V$

$$\mathbf{V} = [\mathbf{v}_n]_{n=1}^{N}$$

a sequence of time-varying yet relational vectorized representations

- **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

Framework Overview



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Methodology

- Construction of multi-view driving state transition graphs

- Peer and temporal-aware representation learning

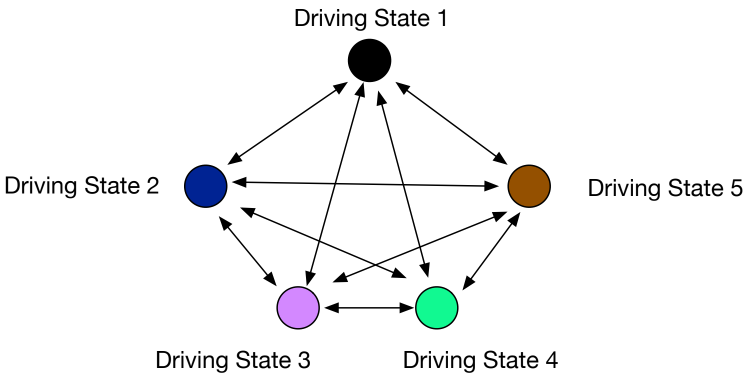
Construction of multi-view driving state transition graphs

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

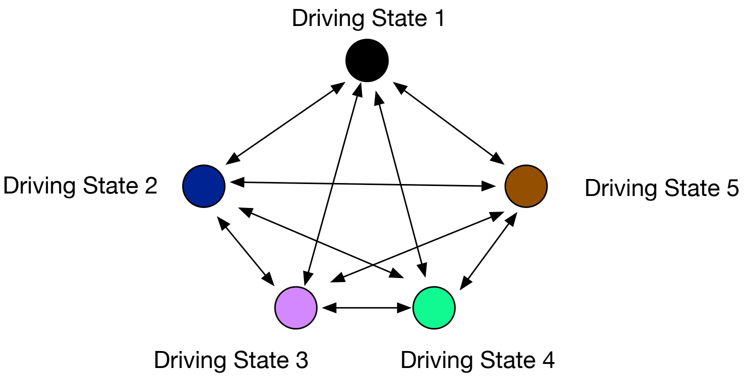
(1)acceleration while turning right,
(2)acceleration while turning left,
(3)acceleration while straightforward,
(4)deceleration while turning right,
(5)deceleration while turning left,
(6)deceleration while straightforward,
(7)constant speed while turning right,
(8)constant speed while turning left,
(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

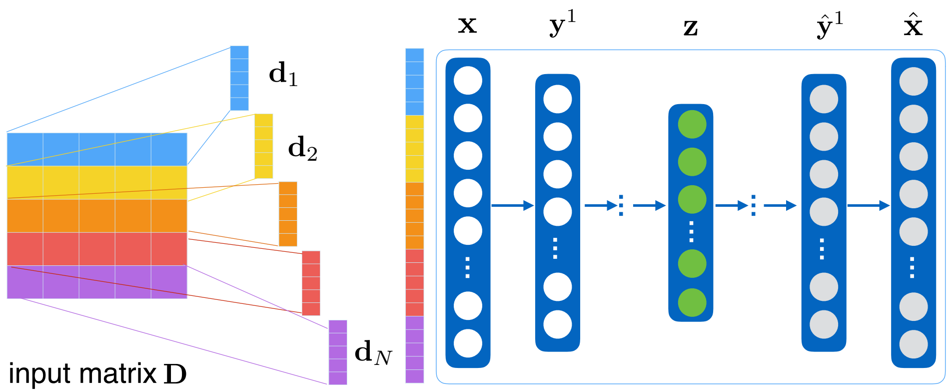
- Intuition 1: Structural Reservation
- Intuition 2: Temporal Dependency
- Intuition 3: Peer Dependency

For Intuition 1: Structural Reservation

Base Model - Autoencoder

$$\begin{cases} \mathbf{y}_i^1 & = \sigma(\mathbf{W}^1\mathbf{x}_i + \mathbf{b}^1), \\ \mathbf{y}_i^k & = \sigma(\mathbf{W}^k\mathbf{y}_i^{k-1} + \mathbf{b}^k), \forall k \in \{2, 3, \cdots, o\}, \\ \mathbf{z_i} & = \sigma(\mathbf{W}^{o+1}\mathbf{y}_i^o + \mathbf{b}^{o+1}). \end{cases}$$

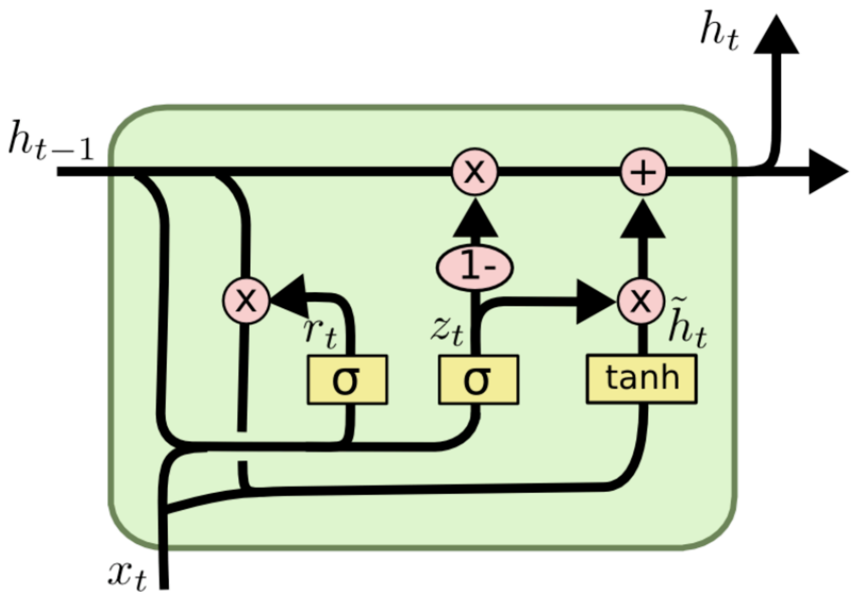
$$\begin{cases} \hat{\mathbf{y}}_i^o & = \sigma(\hat{\mathbf{W}}^{o+1}\mathbf{z}_i + \hat{\mathbf{b}}^{o+1}), \\ \hat{\mathbf{y}}_i^{k-1} & = \sigma(\hat{\mathbf{W}}^k\hat{\mathbf{y}}_i^k + \hat{\mathbf{b}}^k), \forall k \in \{2, 3, \cdots, o\}, \\ \hat{\mathbf{x}}_i & = \sigma(\hat{\mathbf{W}}^1\hat{\mathbf{y}}_i^1 + \hat{\mathbf{b}}^1). \end{cases}$$



For Intuition 2: TemporalDependency

$$\begin{cases} & \#Sequential \quad Encode \quad Step \\ (\mathbf{y}_i^1)^\tau & = \sigma(\mathbf{W}^1 \mathbf{x}_i^\tau + \mathbf{b}^1), \\ (\mathbf{y}_i^k)^\tau & = \sigma(\mathbf{W}^k (\mathbf{y}_i^{k-1})^\tau + \mathbf{b}^k), \forall k \in \{2, 3, \cdots, o\}, \\ \mathbf{z}_i^\tau & = (1 - c^\tau)\mathbf{z}_i^{\tau-1} + c^\tau \tilde{\mathbf{z}}_i^\tau. \end{cases}$$

$$\begin{cases} & \#Sequential \quad Decode \quad Step \\ (\hat{\mathbf{y}}_i^o)^\tau & = \sigma(\hat{\mathbf{W}}^{o+1} \mathbf{z}_i^\tau + \hat{\mathbf{b}}^{o+1}), \\ (\hat{\mathbf{y}}_i^{k-1})^\tau & = \sigma(\hat{\mathbf{W}}^k (\hat{\mathbf{y}}_i^k)^\tau + \hat{\mathbf{b}}^k), \forall k \in \{2, 3, \cdots, o\}, \\ \hat{\mathbf{x}}_i^\tau & = \sigma(\hat{\mathbf{W}}^1 (\hat{\mathbf{y}}_i^1)^\tau + \hat{\mathbf{b}}^1). \end{cases}$$



For Intuition 3: Peer Dependency

$$\mathcal{H}_c(G^\tau) = \sum_{u_i \in \mathcal{U}} \sum_{u_j \in \mathcal{U}, u_i \neq u_j} s_{i,j}^\tau \cdot \left\| \mathbf{z}_i^\tau - \mathbf{z}_j^\tau \right\|_2^2$$

the similarity of driving behavior between the driver u_i and u_j at the time slot τ.

Objective Function

$$\min \frac{1}{2} \sum_{\tau \in \mathcal{T}} \{ \underbrace{\sum_{u_i \in \mathcal{U}(n)} \|(\mathbf{x}_i^{\tau} - \hat{\mathbf{x}}_i^{\tau})\|_2^2}_{\text{Temporal Dependencies}} + \underbrace{\alpha \cdot \mathcal{H}_c(G^{\tau})}_{\text{Peer Dependencies}} \}$$

Temporal Dependencies

Peer Dependencies

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Application

- Prediction and Historical Assessment of Driving Scores

- Risky Area Detection

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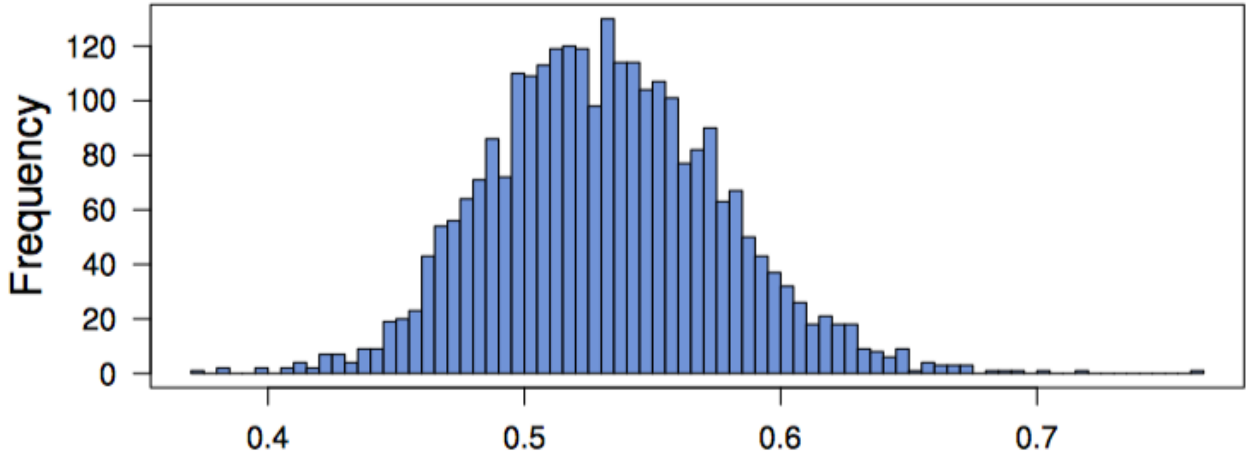
Evaluation

Data Description

From Beijing City

Properties	Statistics
Number of drivers	10,357
Time range	Feb.2 - Feb.8
City	Beijing



Driving Score Distribution

Evaluation

- **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

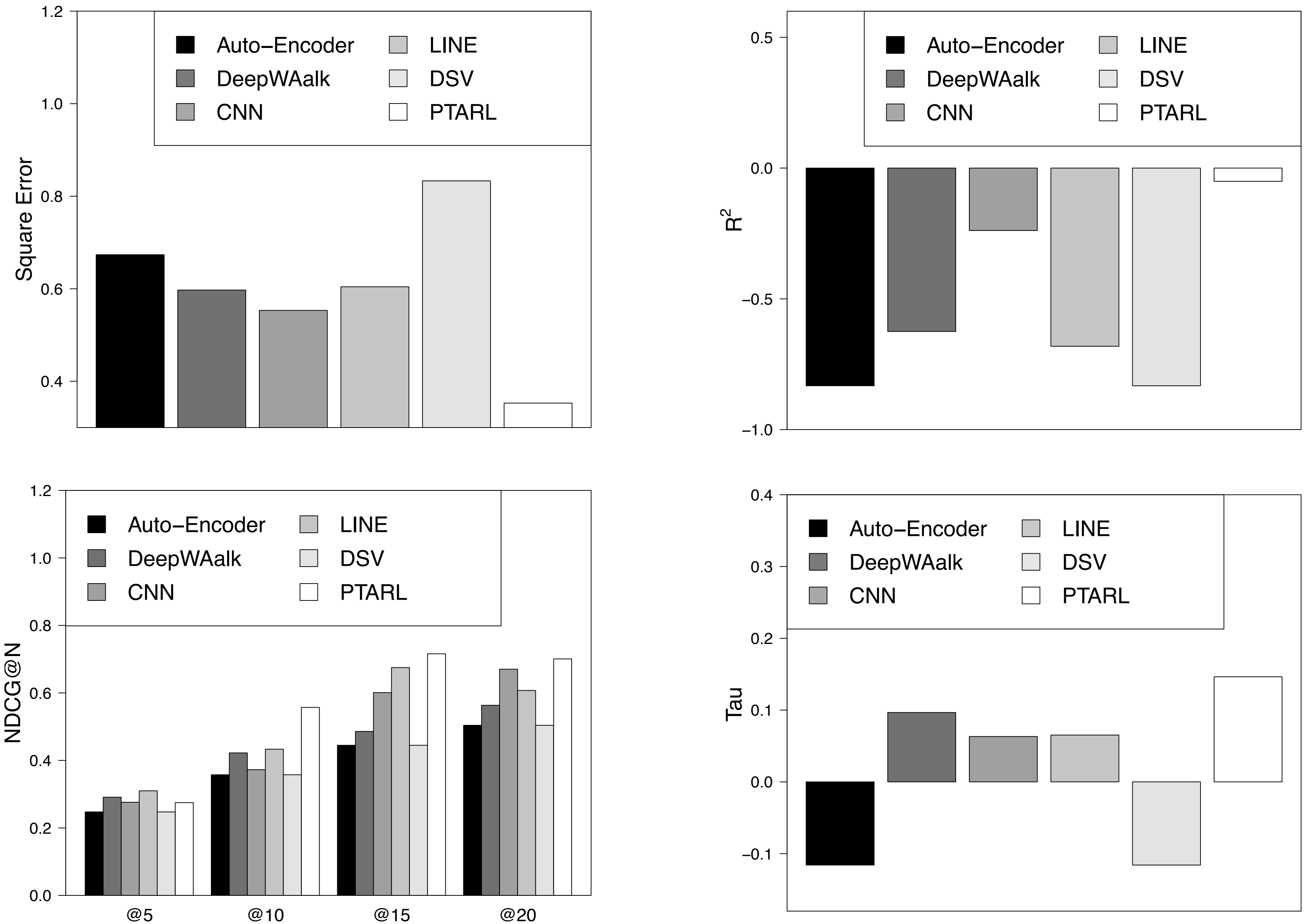
- **Normalized Discounted Cumulative Gain(NDCG@N)**

  - Evaluate the ranking performance at TopN

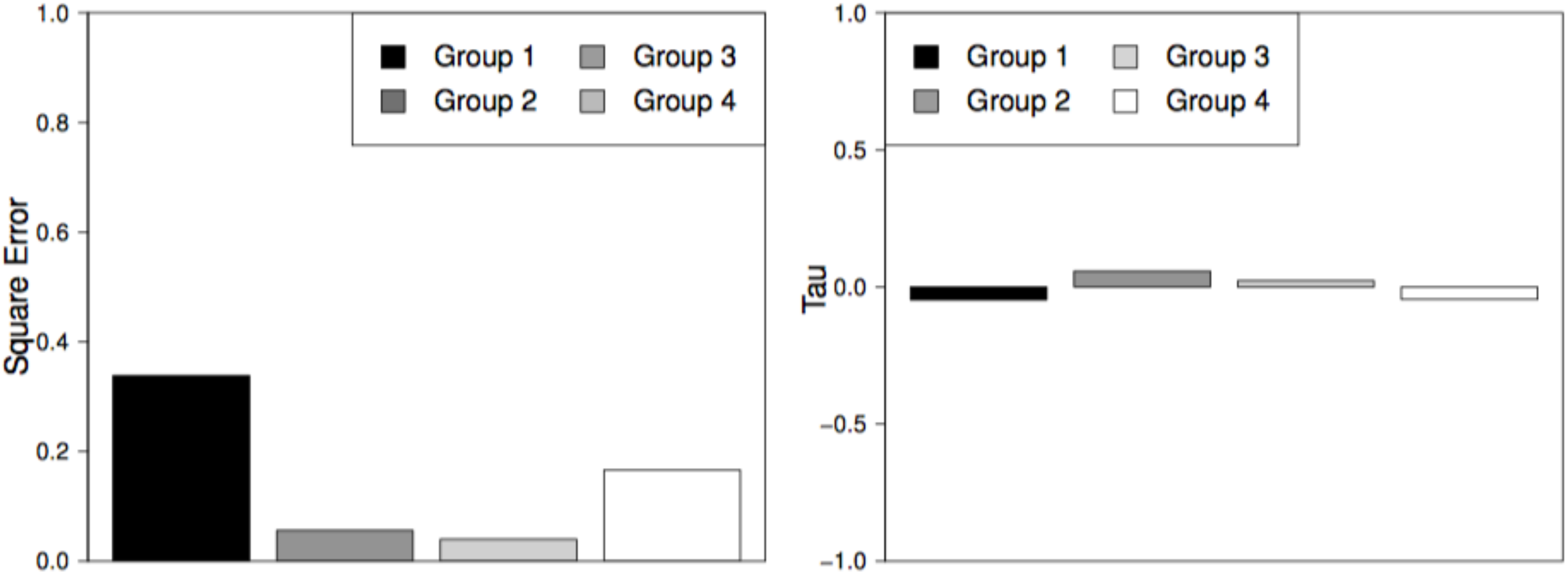
- **Kendall's Tau Coefficient(Tau)**

  - Measure the overall ranking accuracy.

Overall performance

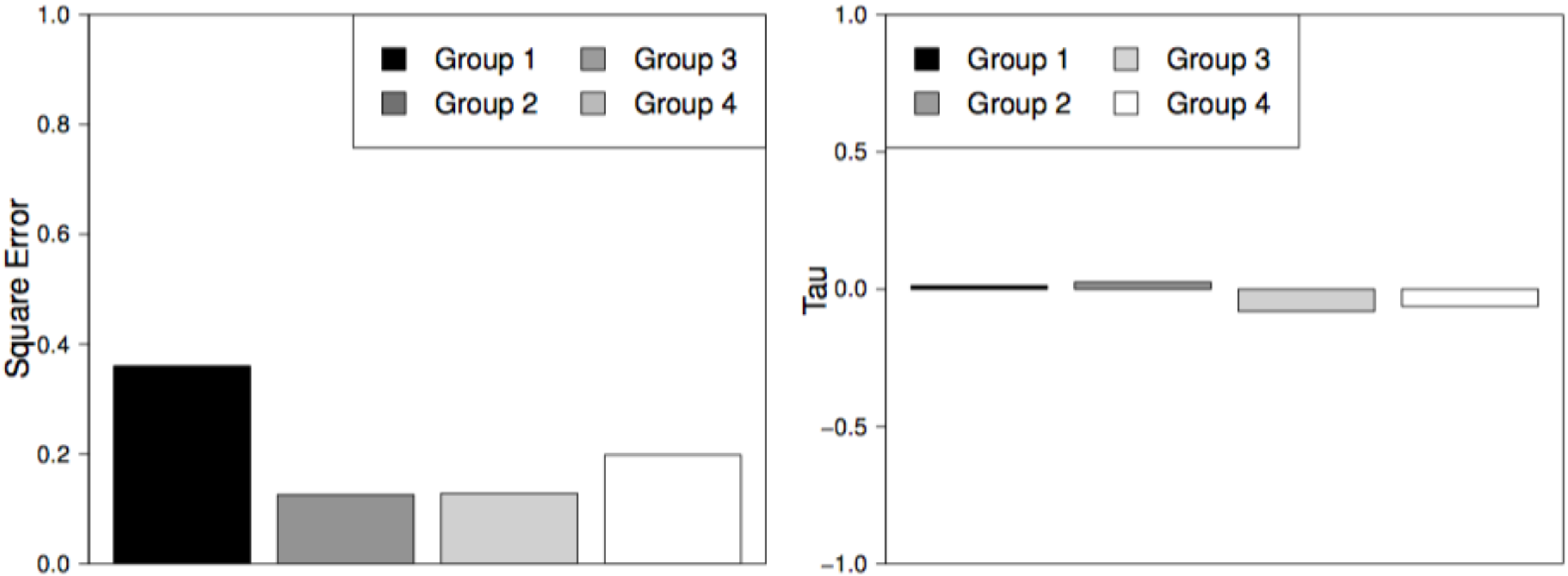


Robustness Check



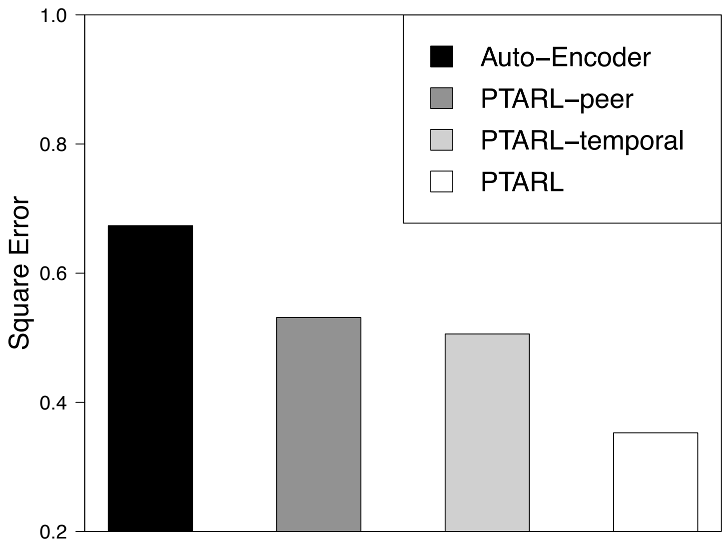
Robustness check in the score-based group

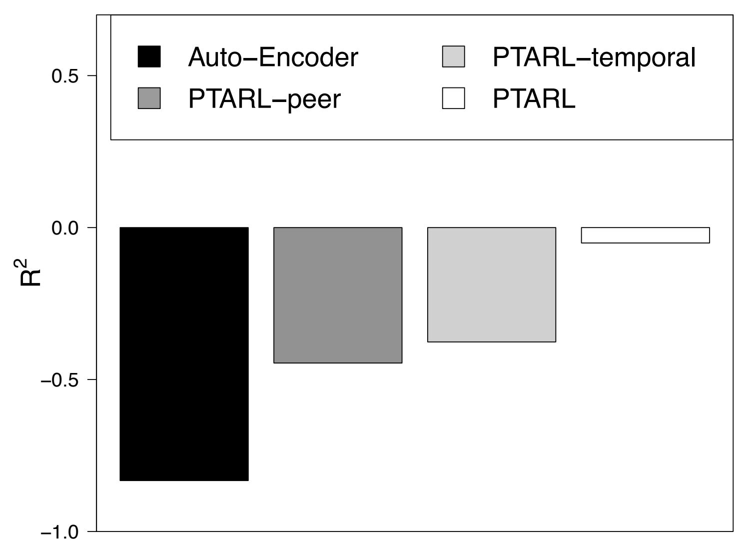
Robustness Check

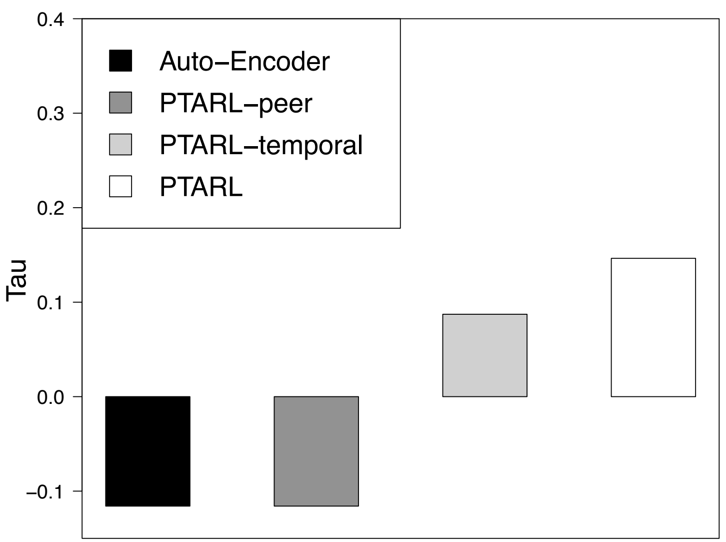


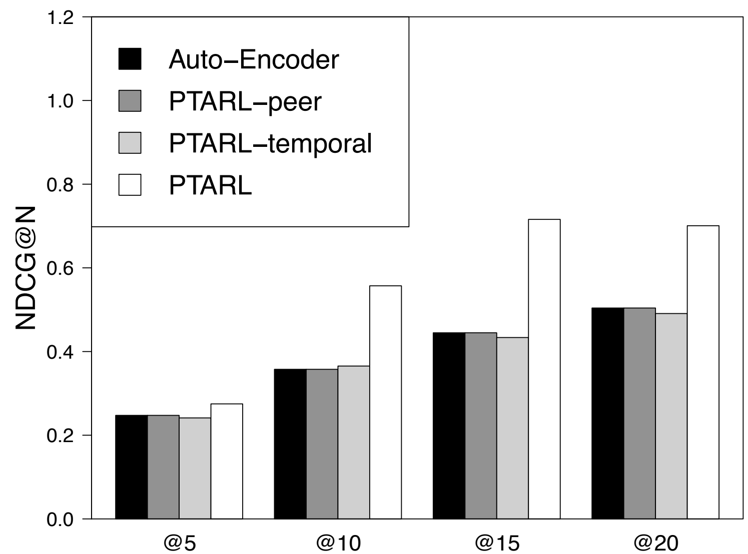
Robustness check in the driving-state-based group

Study of Peer and Temporal Dependencies

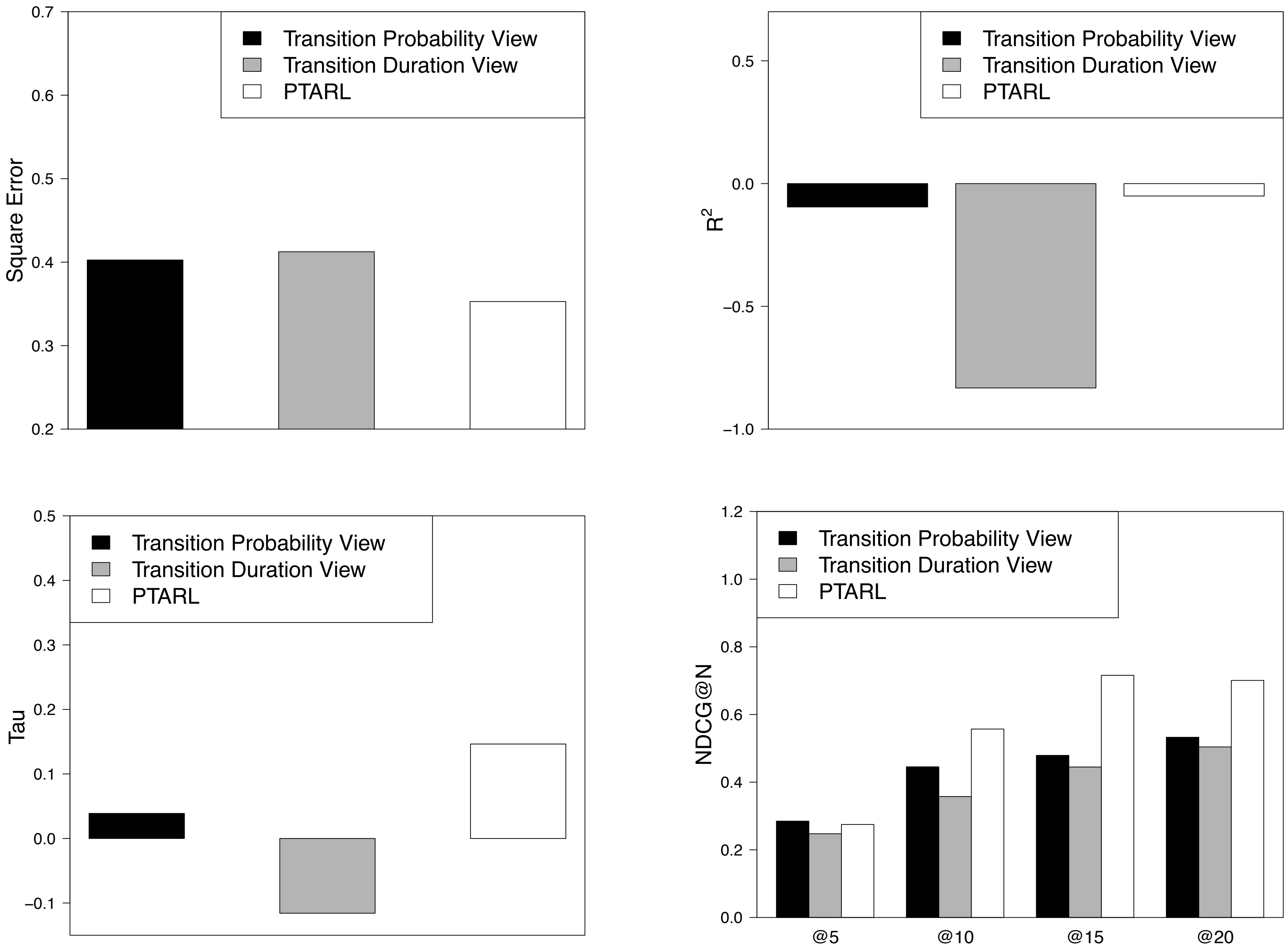




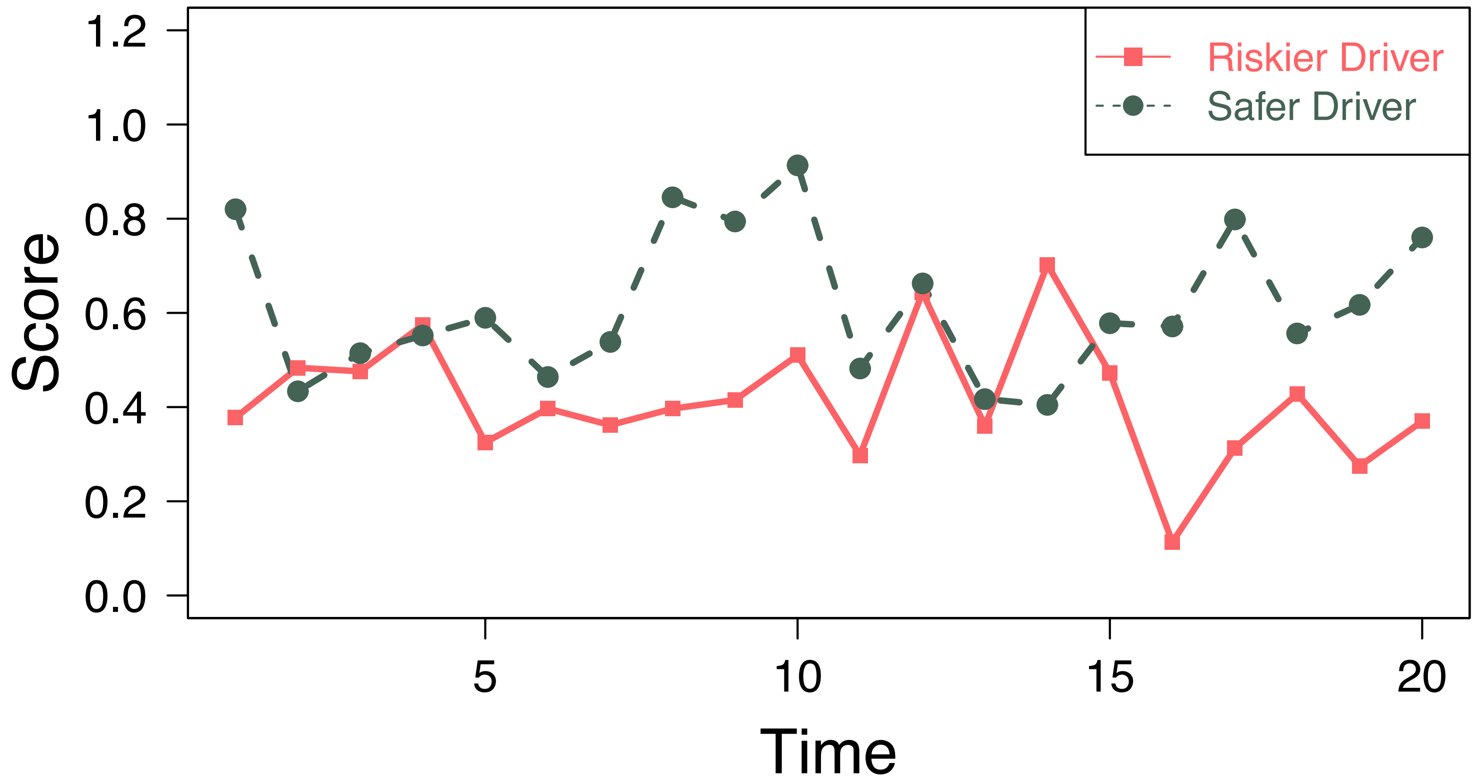




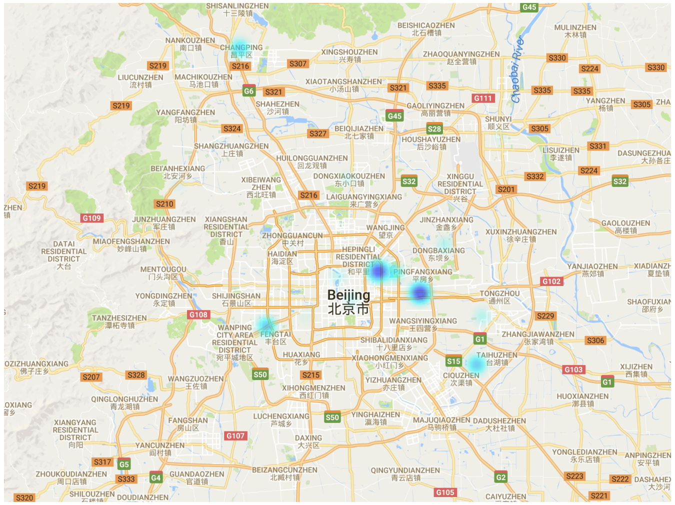
Study of Performance in Different Views



Historical Assessment of Driving Scores



Risky Area Detection



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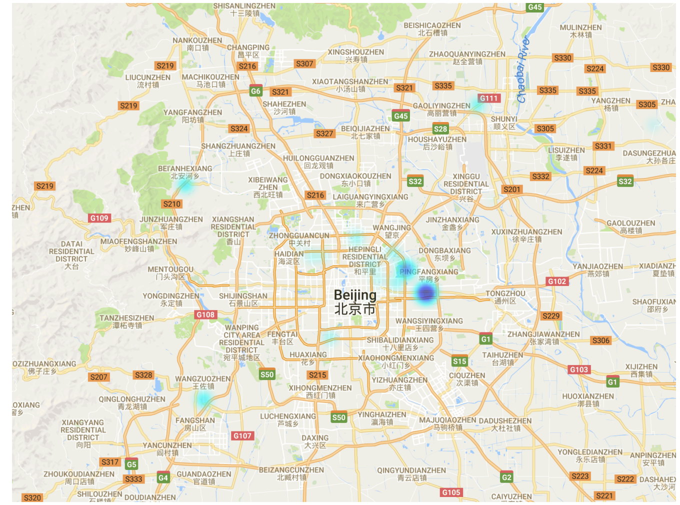

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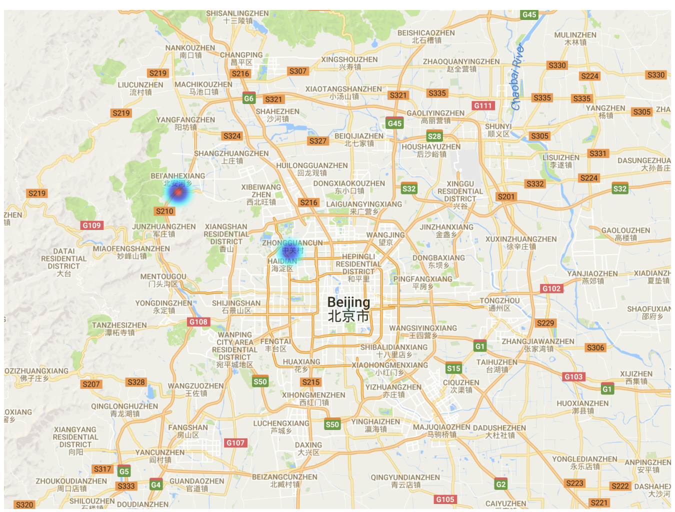

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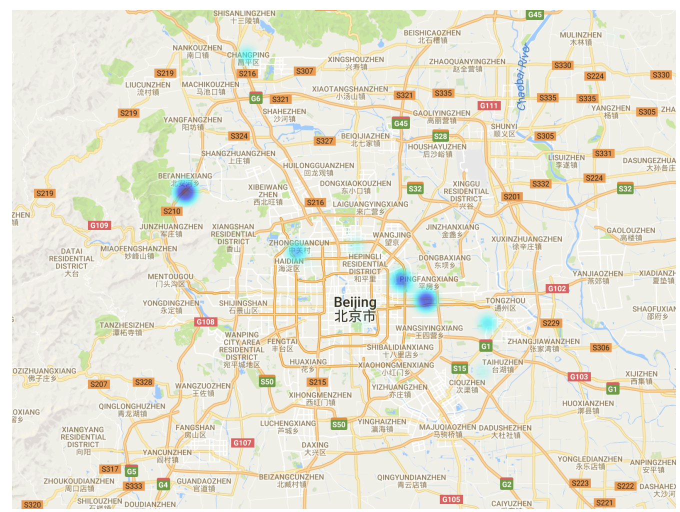

t=4

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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
  - 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?