Mobility Irregularity Detection with Smart Transit Card Data

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What is mobility irregularity?

Smart Transit records inconsistent with the normal passenger profiles:
repetitive stops and preferred time slots

Why detecting irregularity is important?
Refine future transit routes and stops
Avoid financial loss of passengers

| Chatswood Station | North Sydney Station | Vehicle |
|-------------------|----------------------|---------|
| 4/22 17:27        | 4/22 18:01           | Train 1 |

| Milsons Point Station | Town Hall Station | Vehicle |
|-----------------------|-------------------|---------|
| 4/04 8:14             | 4/04 8:25         | Train 9 |
| 4/05 8:15             | 4/05 8:26         | Train 1 |
| ...                   | ...               | ...     |
| 4/19 8:23             | 4/19 8:32         | Train 9 |
| 4/20 8:21             | 4/20 8:31         | Train 9 |
Related Works and Major Challenges

- Passenger profiling:

  How to represent a passenger profile with route-stop features?

  convolutional-based [1] or graph-based methods [2, 3] to extract spatial layout of routes

  sequential models [4] to represent temporal relations between historical records

  **Challenge:**

  passenger information are fused within a certain region to compute node features

  can not provide personalized extraction, typical graph convolutional networks don’t work
Related Works and Major Challenges

- Irregularity detection

How to distinguish irregular patterns from normal patterns of a passenger?

Similarity-based [5] and reconstruction-based [6, 7] methods are proposed to filter out anomalies

**Challenge:**

High intra-class variance

A normal record of a passenger can be irregular to other passengers

Hard to detect irregularity within few shots
Methodology: Personalised spatial-temporal similarity learning

- Personalized spatial-temporal passenger profiling

Route-to-Stop Embedding (R2S)

\[ e_i = E(s_{i1}, s_{i2}, r_i) = (F[h(r_i) \circ s_{i1}], F[h(r_i) \circ s_{i2}]) \]

Repetitive and Time Invariant Pattern

\[
    u_i = LSTM(e_i, u_{i-1}), \quad \text{s.t.} \quad 2 \leq i \leq N, u_1 = 0
\]

\[
    a = \text{softmax}(u \ast W^u) \in \mathbb{R}^{N \times 1}, \quad u_N = \sum_{i=0}^{N} a_i u_i
\]

Recency Mobility Pattern

\[ u_{N+1} = FCN(e_{N+1}) \]
Methodology: Personalised spatial-temporal similarity learning

- Few shot similarity learning

\[
P_{\text{fraud}} = (u_{N+1})^T M_1 u_N + b_1
\]
\[
P_{\text{normal}} = (u_{N+1})^T M_2 u_N + b_2
\]
\[
P(u_{N+1}, u_N) = \text{softmax}(P_{\text{fraud}}, P_{\text{normal}})
\]

Loss function:

\[
\mathcal{L}(u_{N+1}, u_N) = -\mathbb{E}_{u_{N+1} \sim u_N} \log[P(u_{N+1}, u_N)]
- \mathbb{E}_{u_{N+1} \neq u_N} \log[1 - P(u_{N+1}, u_N)]
\]
Experiments and Results

- A case study on Sydney Opal Transit Card Data is tested for three months.
- Our model (R2S-Sim) model gains significant improvements on F1 and accuracy.
- Using only 5 historical records could achieve SOTA results.
Experiments and Results

- KL divergence between normal and irregular records are displayed
- A clearer decision boundary is learnt
Conclusions

- Route-to-stop embedding explores spatial correlations between routes and transit stops.

- A learnable similarity function measures the distance between repetitive invariant mobility pattern and recency pattern.

- We conduct experiments on a large-scale real-world dataset. Using 20% of the total fraudulent data can achieve SOTA performance.
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THANK YOU

Stay Healthy and Safe 😊

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