Mobility Irregularity Detection with Smart Transit Card Data

Never Stand Still | Faculty of Enginering | School of Computer Science and Enginering

Xuesong Wang, Lina Yao, Wei Liu, Can Li, Lei Bai, and S. Travis Waller

University of New South Wales

Outline

1 Background

2 Related Works and Major Challenges

3 Methodology

4 Experiments and Results

5 Conclusion

Background

- 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

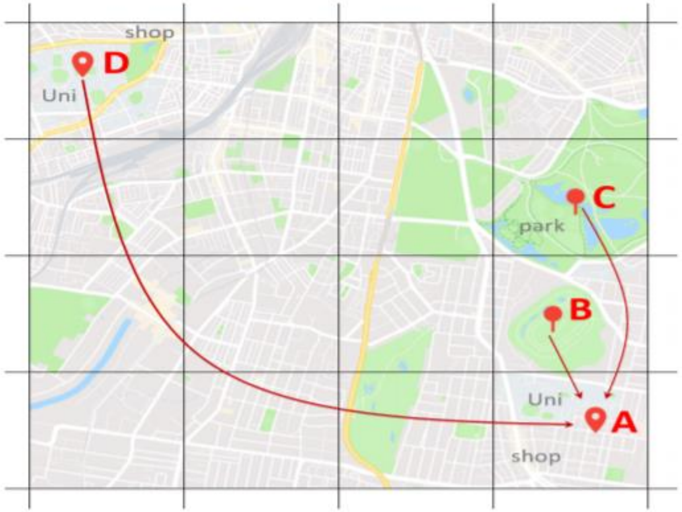
Related Works and Major Challenges

- 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

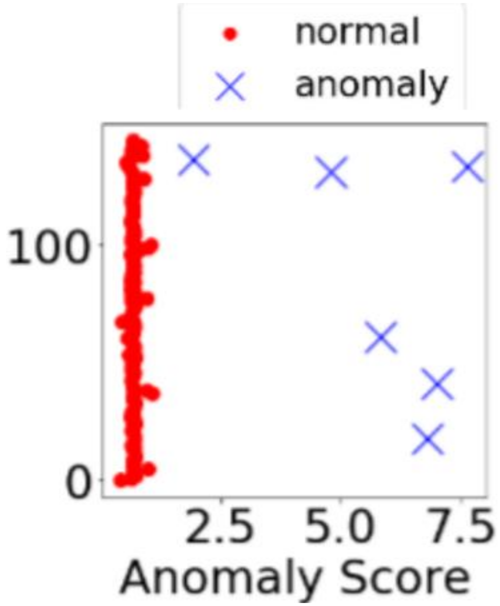
can not provide personalized extraction, typical graph convolutional networks don’t work

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



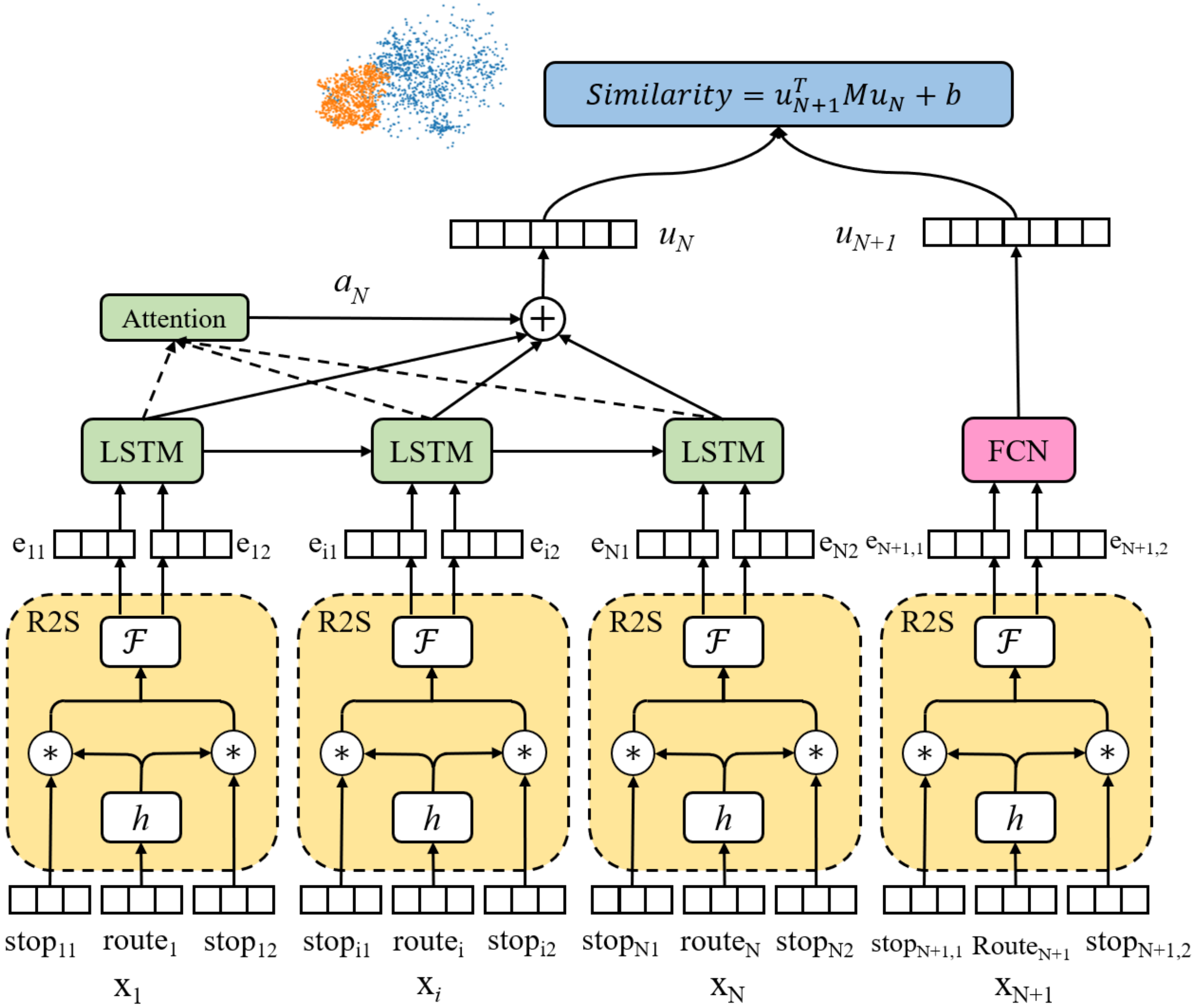
Challenge:

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)

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

Repetitive and Time Invariant Pattern

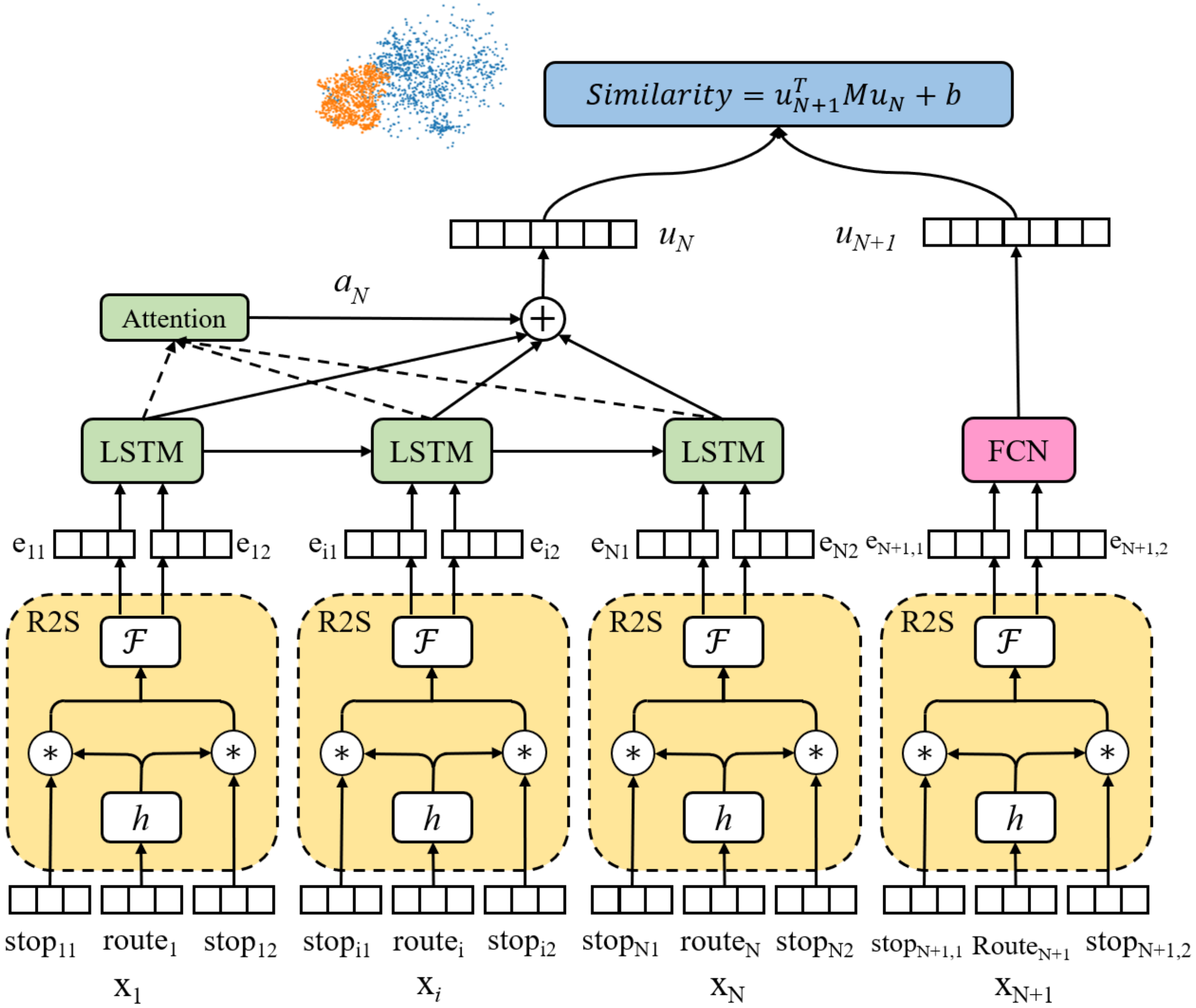
$$u_i = LSTM(e_i, u_{i-1}), \quad \text{s.t.} \quad 2 \le i \le N, u_1 = \mathbf{0}$$

$$a = softmax(\mathbf{u} * W^u) \in \mathbb{R}^{N \times 1}, \qquad u_N = \sum_{i=0}^{N} a_i u_i$$

Recency Mobility Pattern

$$u_{N+1} = FCN(e_{N+1})$$

Methodology: Personalised spatial-temporal similarity learning



- Few shot similarity learning

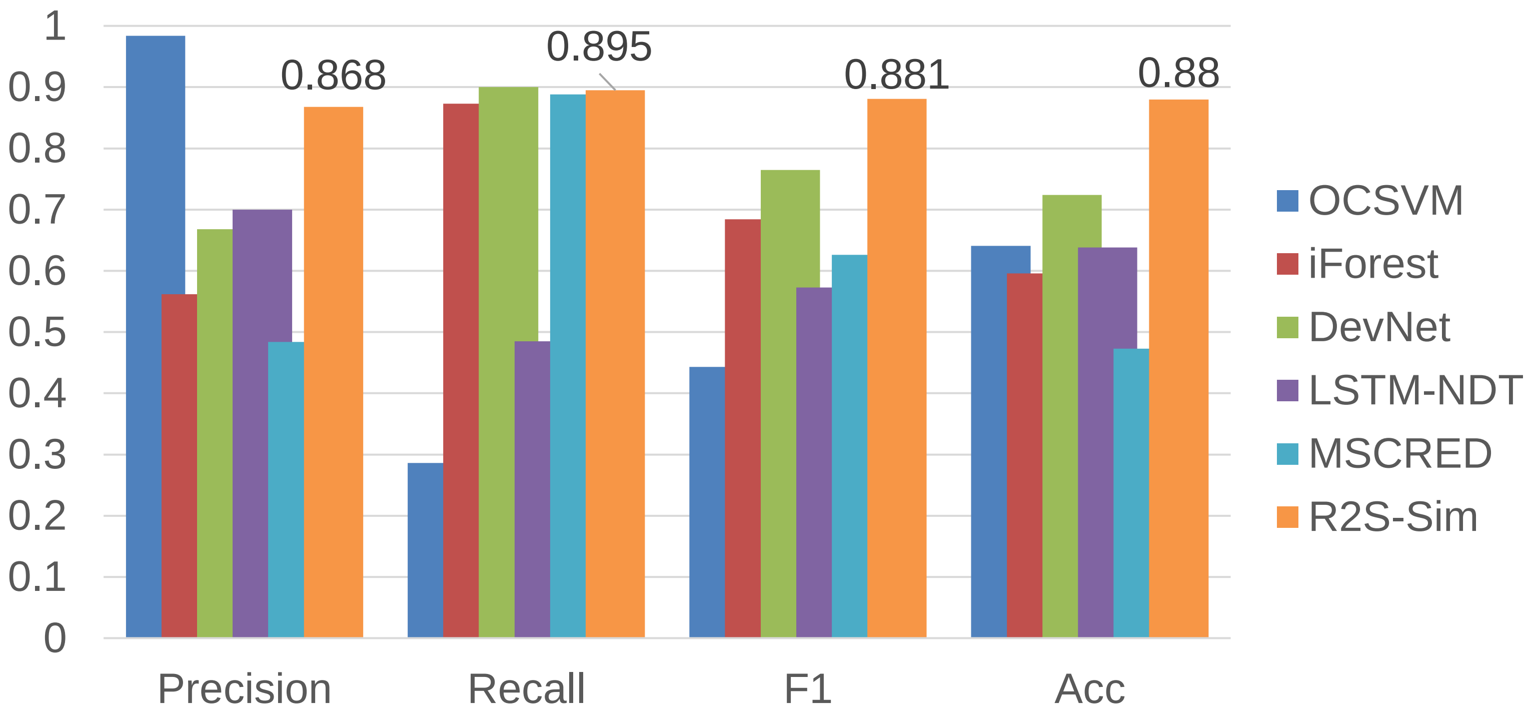
$$P_{fraud} = (u_{N+1})^T M_1 u_N + b_1$$
$$P_{normal} = (u_{N+1})^T M_2 u_N + b_2$$
$$P(u_{N+1}, u_N) = softmax([p_{fraud}, p_{normal}])$$

Loss function:

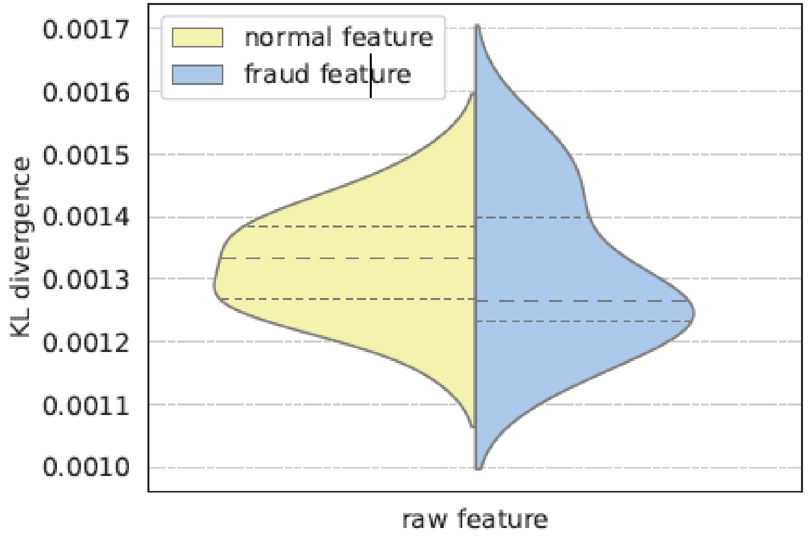
$$\mathcal{L}(u_{N+1}, u_N) = -\mathbb{E}_{u_{N+1} \sim u_N} \log[P(u_{N+1}, u_N)] - \mathbb{E}_{u_{N+1} \not\sim u_N} \log[1 - P(u_{N+1}, u_N)]$$

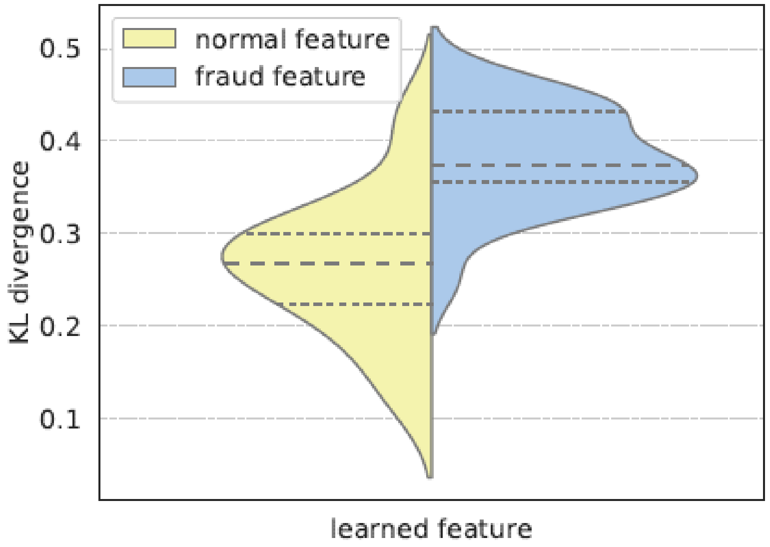
Experiments and Results

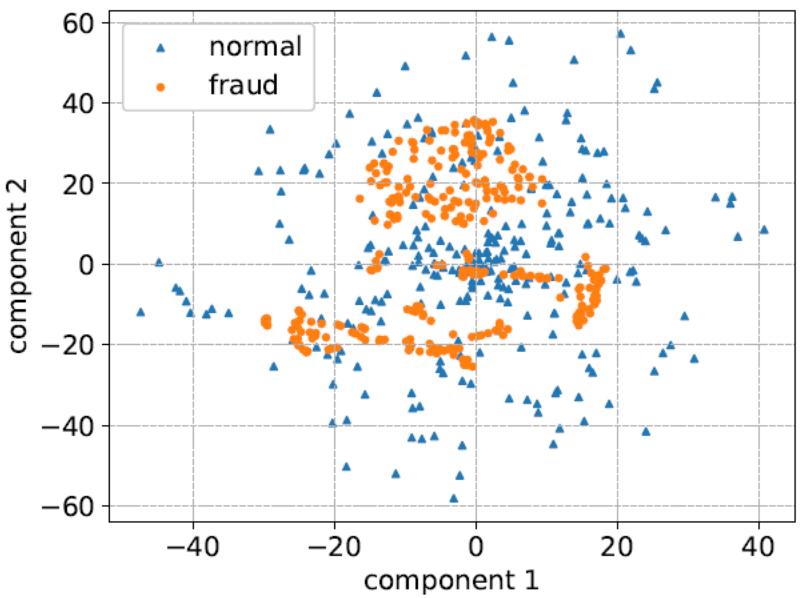
- A case study on Sydney Opal Transit Card Data is tested for three months
- Our model (R2S-Sim) model gains signicant improvements on F1 and accuracy
- Using only 5 historical records could achieve SOTA results

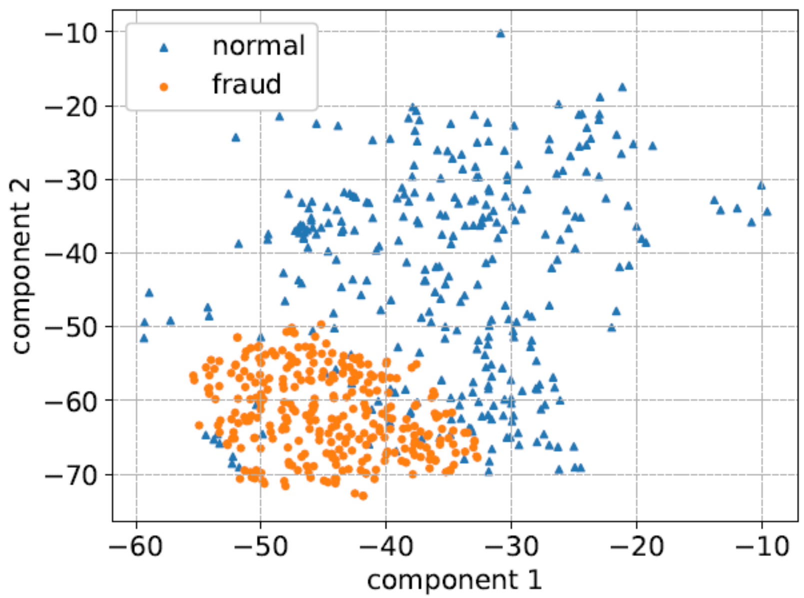


Experiments and Results









- 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.

References

[1] Yao, H., Tang, X.,Wei, H., Zheng, G., Li, Z.: Revisiting spatial-temporal similarity: A deep learning framework for traffic prediction. AAAI, 2019

[2] Bai, L., Yao, L., Kanhere, S.,Wang, X., Sheng, Q., et al.: Stg2seq: Spatial-temporal graph to sequence model for multi-step passenger demand forecasting. IJCAI, 2019

[3] Guo, S., Lin, Y., Feng, N., Song, C., Wan, H.: Attention based spatial-temporal graph convolutional networks for traffic flow forecasting. AAAI, 2019

[4] Lan, W., Xu, Y., Zhao, B.: Travel time estimation without road networks: An urban morphological layout representation approach. IJCAI, 2019

[5] Pang, G., Shen, C., van den Hengel, A.: Deep anomaly detection with deviation networks. KDD, 2019

[6] Zhang, C., Song, D., Chen, Y., Feng, X., Lumezanu, C., Cheng, W., Ni, J., Zong, B., Chen, H., Chawla, N.V.: A deep neural network for unsupervised anomaly detection and diagnosis in multivariate time series data. AAAI, 2019

[7] Hundman, K., Constantinou, V., Laporte, C., Colwell, I., Soderstrom, T.: Detecting spacecraft anomalies using lstms and nonparametric dynamic thresholding. KDD, 2018

THANK YOU

Stay Healthy and Safe 😇

xuesong.wang1@unsw.edu.au

05/2020