GeoLifecycle: User Engagement in Geographical Change and Churn Prediction in LBSNs

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Why User Engagement and Churn Prediction?

❖ Proliferation of Location-Based Social Networks (LBSNs)

- Heavily rely on User Generated Content (e.g., reviews)
- Users can stop contributing at any time

Main Goal: Maintainability → Analysis: User Engagement → Application: Churn Prediction

Leave or Stay?

✓ 20 important stats and facts, March 2018. URL: https://expandedramblings.com/index.php/by-the-numbers-interesting-foursquare-user-stats/
✓ Yelp Factsheet, August 2018. URL: https://www.yelp.com/factsheet
✓ 2002. Expert Systems with Applications. Turning telecommunications call details to churn prediction: a data mining approach. Wei and Chiu.
✓ 2012. WWW. Churn Prediction in New Users of Yahoo! Answers. Dror et al.

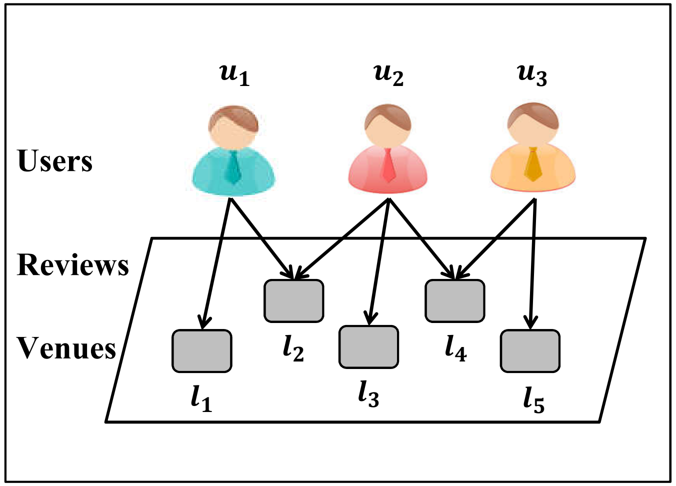
Challenges

❖ Limitations

- **Unclear how users engage with LBSNs**

  - LBSNs can capture online and offline experiences of users

Overview of LBSNs



- **Effects of various aspects (e.g., temporal, social, linguistics) are not fully studied**

  - Novel Offline Feature : Geographic, Venue-specific features
  - New Platform (Not studied yet)

✓ 2018. IMWUT. Revisitation in Urban Space vs. Online: A Comparison across POIs, Websites, and Smartphone Apps. H Cao et al.
✓ 2013. WWW. No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities. Danescu-Niculescu-Mizil et al.
✓ 2015. WWW. All Who Wander: On the Prevalence and Characteristics of Multi-community Engagement. Tan and Lee.

Challenges

❖ Limitations

- Less Attention on churning of highly active producer-type users who contribute a majority of reviews

❖ Focus & Scope

- Focus on highly active producer-type users
- Limit the scope of user engagement to reviewing behaviors

✓ 2018. IMWUT. Revisitation in Urban Space vs. Online: A Comparison across POIs, Websites, and Smartphone Apps. H Cao et al.
✓ 2013. WWW. No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities. Danescu-Niculescu-Mizil et al.
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Examined Research Questions

RQ1: How do highly active producer-type users engage in the services of LBSNs in terms of **geographical** exploration?

RQ2: How do **engagement patterns** of highly active producer-type users manifest themselves in various aspects?

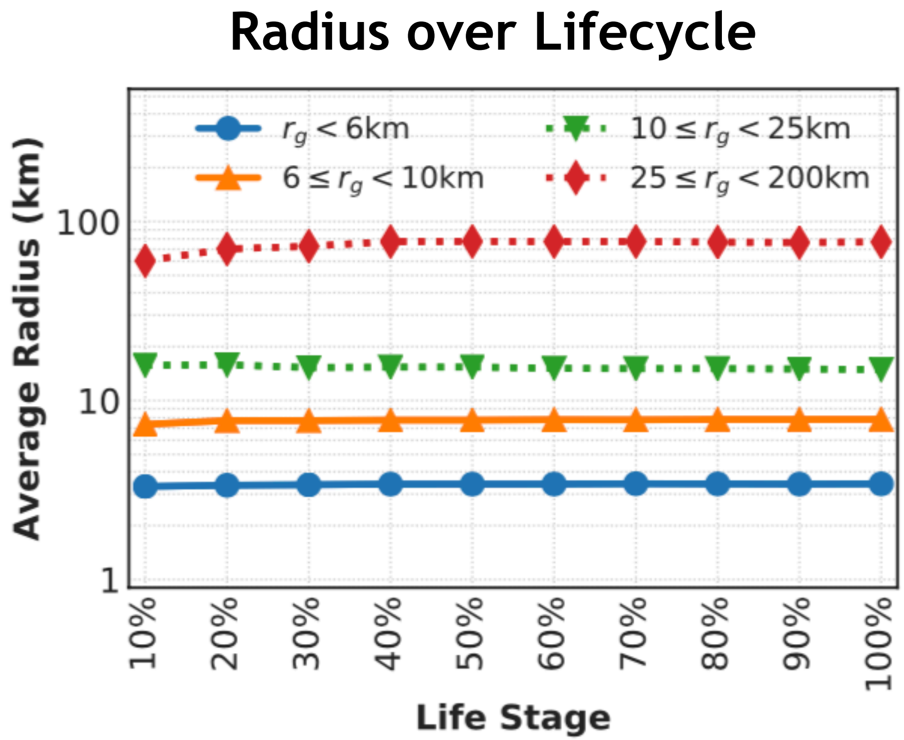
RQ3: To what extent **can we predict** the churning of users with significant contributions within a given period of time?

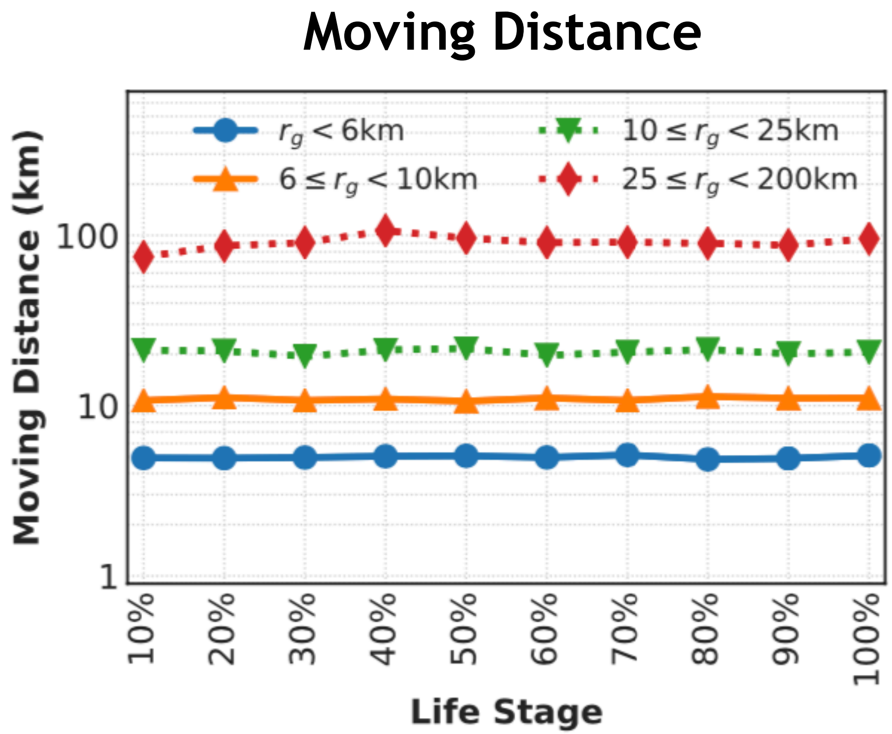
✓ Yelp dataset: https://www.yelp.com/dataset

✓ Foursquare dataset: Y. Chen, et al. 2018. Measurement and Analysis of the Swarm Social Network With Tens of Millions of Nodes. IEEE Access

RQ1

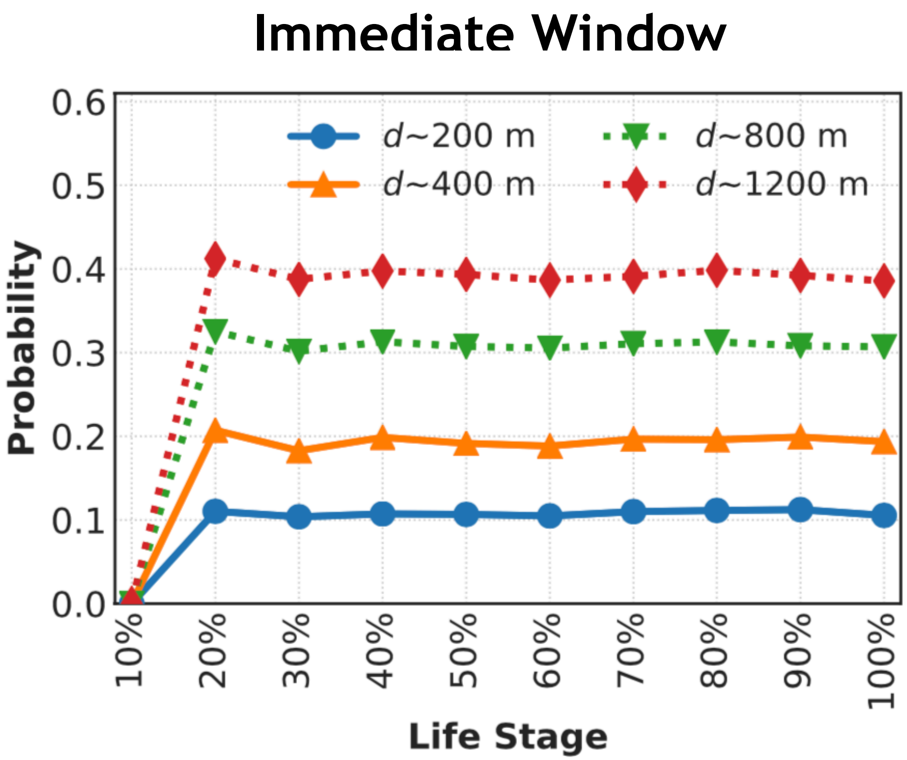
- **Geographical engagement patterns:** How do highly active producer-type users engage in the services of LBSNs in terms of geographical exploration?
  - $r_g(t)$: The **average radius** using a user's trajectory up to t^{th} reviews

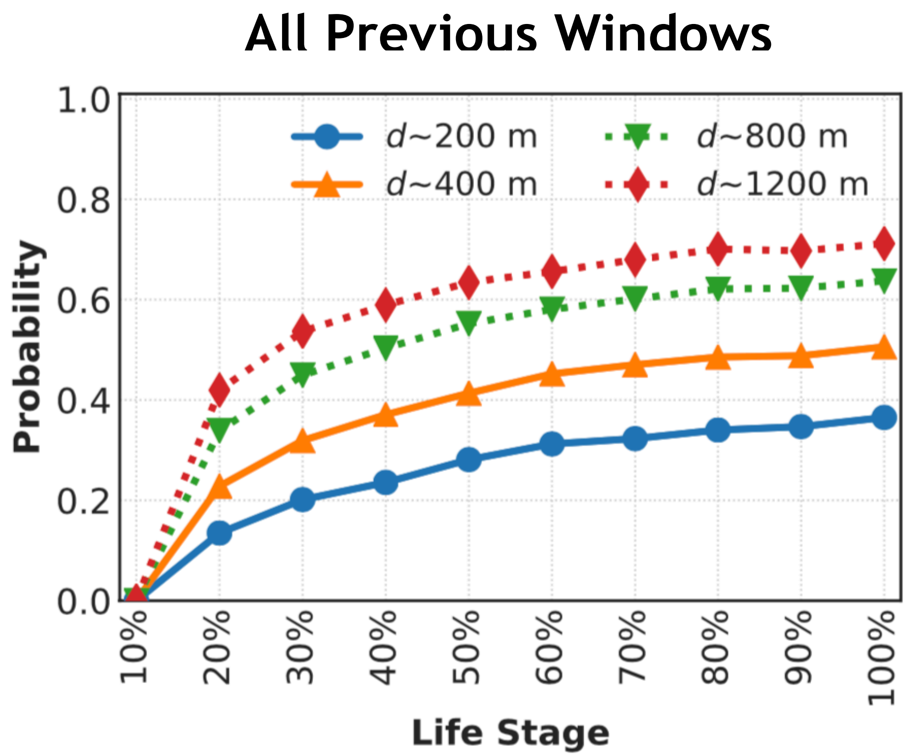




RQ1

- **Human life course**: will users settle down or keep exploring geographically?
  - d : Distance to define neighborhoods

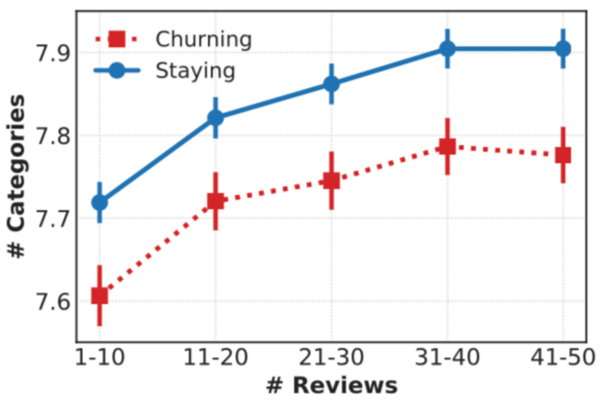




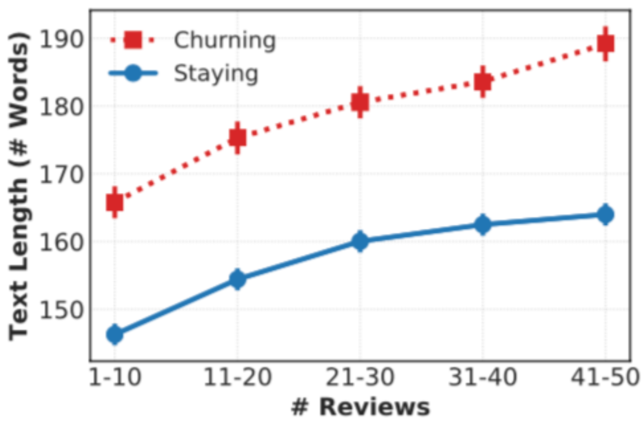
RQ2

- How do **engagement patterns** of highly active producer-type users manifest themselves in various aspects?

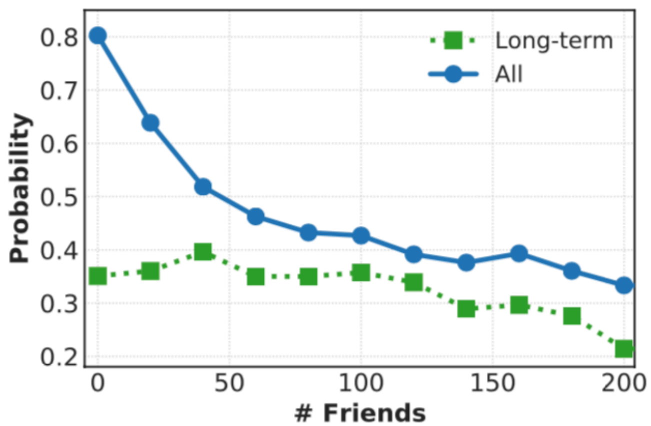
Venue-specific Aspect



Linguistic Aspect



Social Aspect



RQ3

- **Churn Prediction Task:** To what extent **can we predict churning** of users with significant contributions within a given period of time?

Classifiers

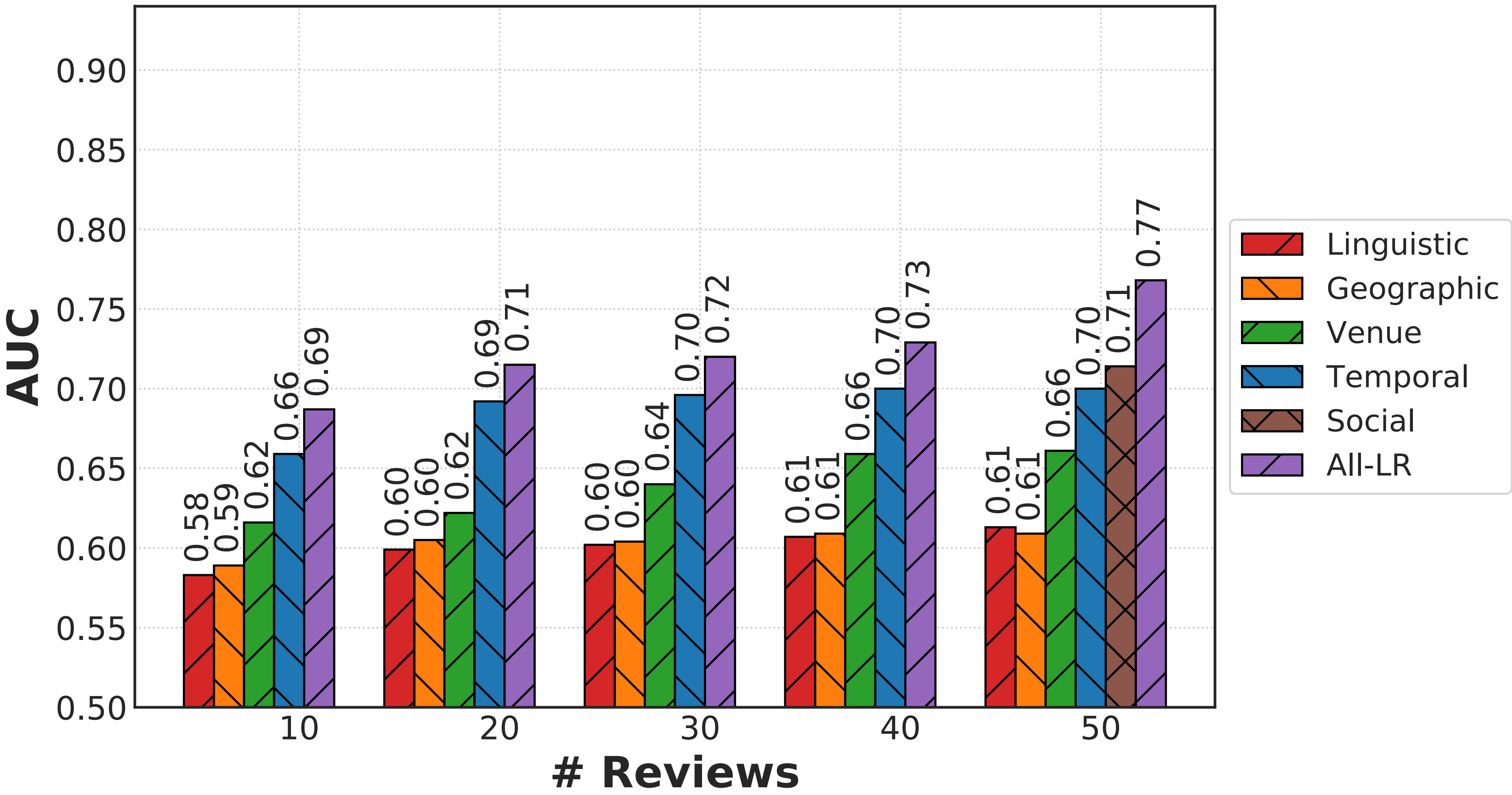
1. Logistic Regression (LR) with L2-Regularization

2. Stacked LSTMs

Models

(F1) Temporal feature (Baseline)
(F2) Geographic feature
(F3) Venue property
(F4) Social feature
(F5) Linguistic feature
(F6) Top2 (based on feature importance)
(F7) Top2+Geo2
(F8) All
(F9:F15) Leave-one-out

RQ3



AUC
0.90
0.85
0.80
0.75
0.70
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0.60
0.55
0.50
0.58
0.59
0.62
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0.60
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0.69
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0.61
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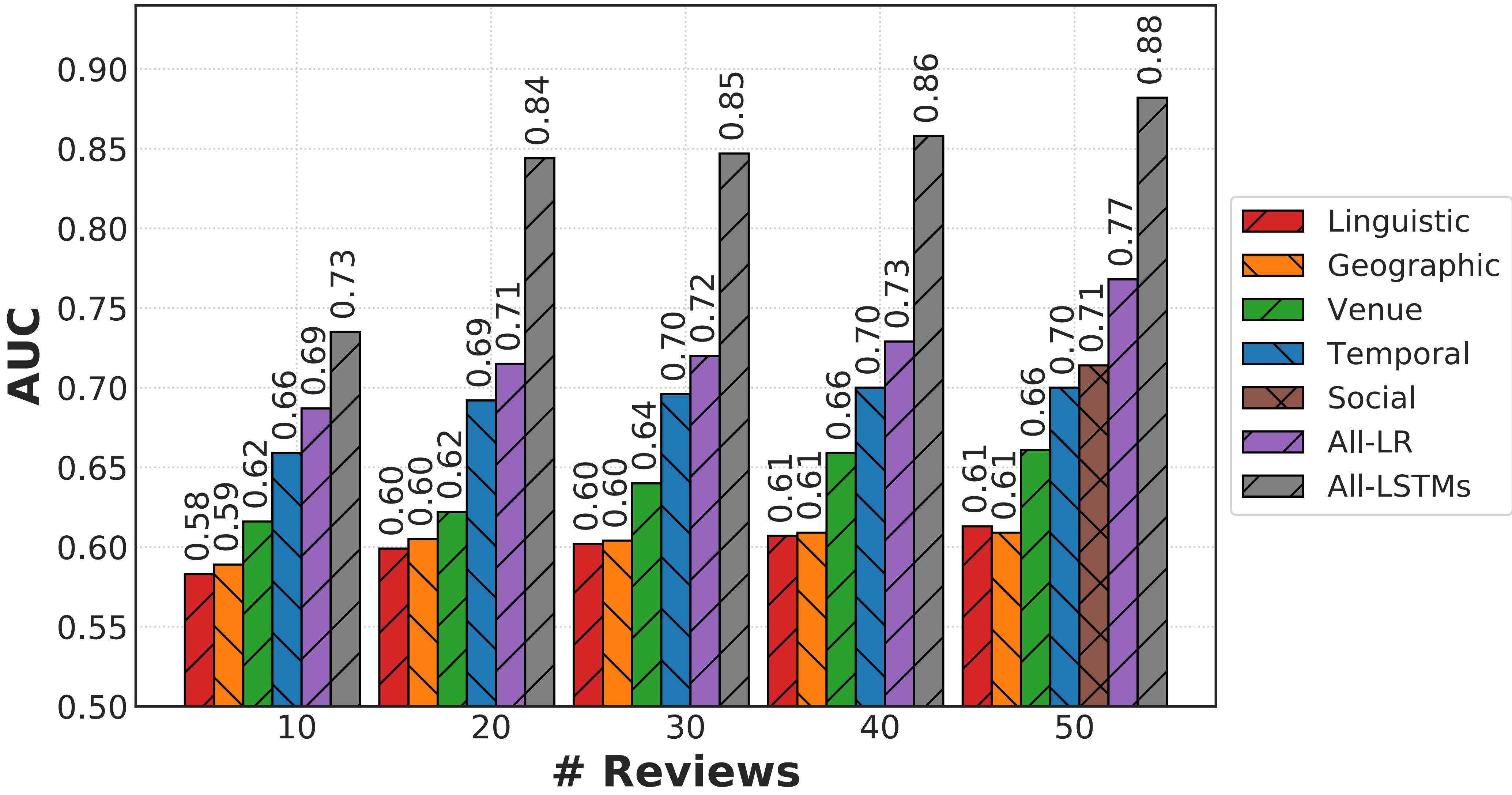
0.71
0.77
10
20
30
40
50
Reviews
Linguistic
Geographic
Venue
Temporal
Social
All-LR

RQ3



AUC
Reviews
0.50
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0.77
0.88
Linguistic
Geographic
Venue
Temporal
Social
All-LR
All-LSTMs

Contributions

- Users **constantly wander** around diverse offline places
- The behavioral differences between churners and stayers are significant and are exhibited with their **first 10 reviews**
- LR models based on our findings **significantly improve the performance** over the baseline on the churn prediction task
- We achieve even higher performance in the task by employing a deep learning model

Take-Home Messages

- The average radii and moving distance of users are determined within 5-10 reviews and stable over their lifecycle
  - ➢ **More personalized services based on a user's average radius and moving distance**

- Users constantly write reviews to diverse locations
  - ➢ **Recommend to a user different venues located in geographically different neighborhoods that the user have not reviewed yet**

- We can accurately predict churning users
  - ➢ **Gamification techniques such as badges and rewards could be used to increase engagement levels of users**

Thank you!

Any questions?

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