De-anonymization of Mobility Trajectories: Dissecting the Gaps between Theory and Practice

Huandong Wang[1], Chen Gao[1], Yong Li[1], Gang Wang[2], Depeng Jin[1], Jingbo Sun[3]

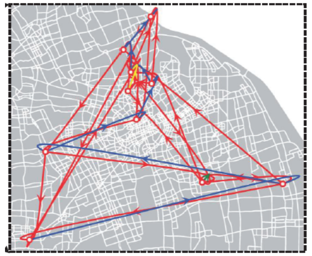
[1]Tsinghua University, China

[2]Virginia Tech

[3]China Telecom Beijing Research Institute

Increasing Concern on Privacy/Security

- **Anonymized user trajectories are increasingly collected by ISPs**
  - High research and business value
- **Growing privacy concern**
  - ISPs are motivated to monetize or share user trajectory data
- **De-anonymization attack**
  - How likely users can be de-anonymized in the shared ISP trajectory dataset?



Now Those Privacy Rules Are Gone, This Is How ISPs Will Actually Sell Your Personal Data

Thomas Fox-Brewster, FORBES STAFF
I cover crime, privacy and security in digital and physical forms. FULL BIO

De-anonymization Attack: Theory and Practice

- **Appalling Theoretical Privacy Bound**
  - 4 location points uniquely re-identify 95% users [Scientific Report 2013]

Is this true in practice?

- **Practical Challenge: Lack of large real-world *ground-truth* datasets**
  - Small datasets
    - 1717 users in [WWW 2016]
  - Synthetized datasets
    - Parts of the same dataset [TON 2011]

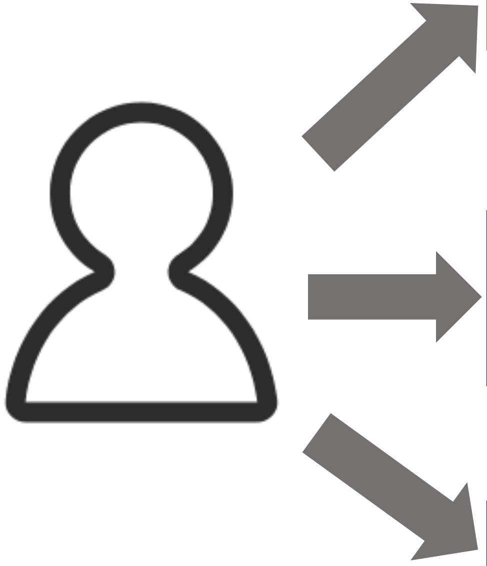
Our Approach: Collect Three Real-world Ground-truth Datasets

Ground-Truth: Traces from the same set of users

Dataset	Total# Users	Total# Records
ISP	2,161,500	134,033,750
Weibo App-level	56,683	239,289
Weibo Check-in (Historical)	10,750	141,131
Weibo Check-in (One-week)	506	873
Dianping App-level	45,790	107,543

- **ISP Dataset**
  - Shanghai, 4/19-4/26, 2016 (victim dataset)
  - 2 million users
  - Access logs to cellular tower → Location traces
- **Weibo Dataset:** One of the largest social networks in China (external information)
- **Dianping Dataset:** “Chinese Yelp” (external information)

How to Obtain the Ground-Truth?



ISP Traces

Weibo ID in HTTP Request

Weibo → Check-ins
→ GPS in ULR parameter

Dianping ID in HTTP Request

Dianping → GPS in ULR paramet

Ethical approval obtained from Wei

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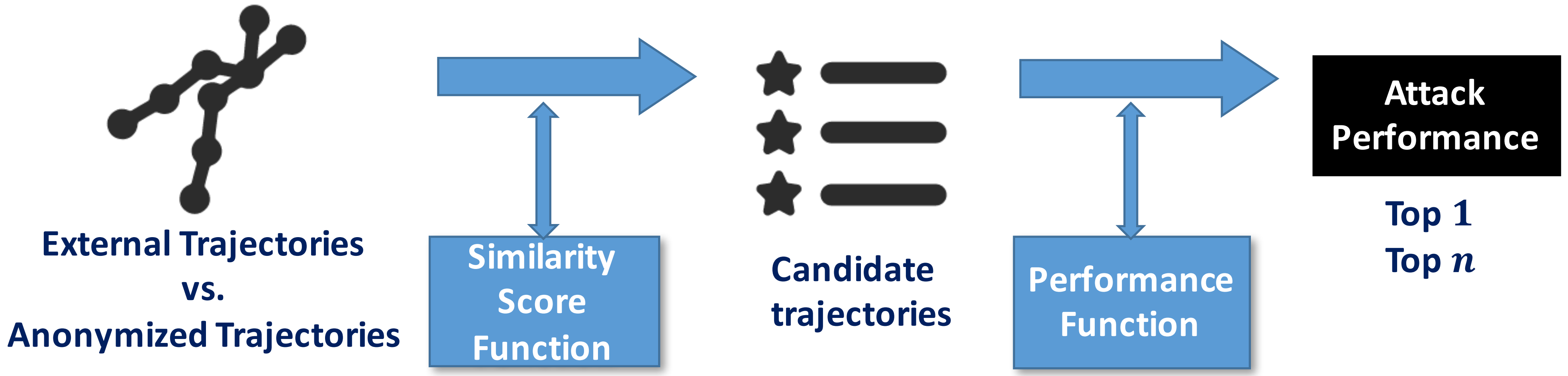
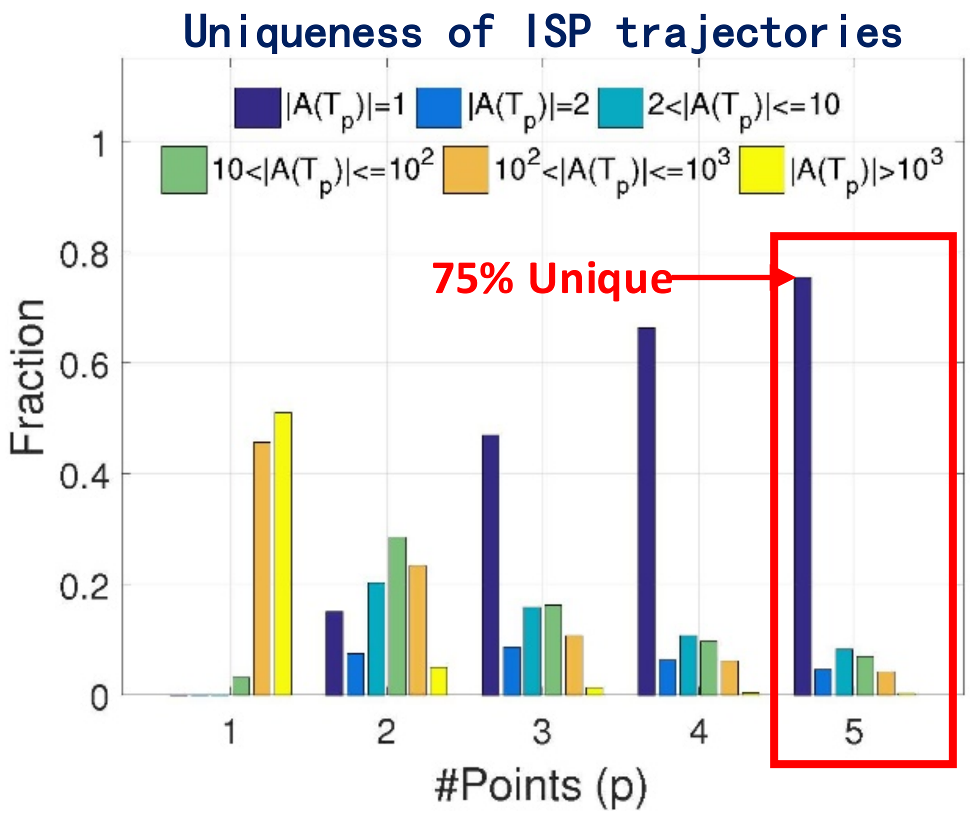
De-anonymization Attack: Threat Model

- **Anonymized Trajectory Data Published by ISP**
  - Anonymization: Replace user identity with the pseudonym
- **Adversary**
  - Match the anonymized traces (e.g., ISP traces) and external traces (e.g., Weibo/Dianping traces)
  - Social network has PII → real-world identifier



De-anonymization: Theoretical Bound based on Uniqueness

- Number of points sufficient to uniquely identify a trajectory
- T_p: Randomly sampled *p* points
- $A(T_p)$: find all trajectories containing the *p* points of T_p
- **Uniqueness**: $|A(T_p)| = 1$?



5 points are sufficient to uniquely identify 75% trajectories!

High potential risk of trajectories to be de-anonymized!

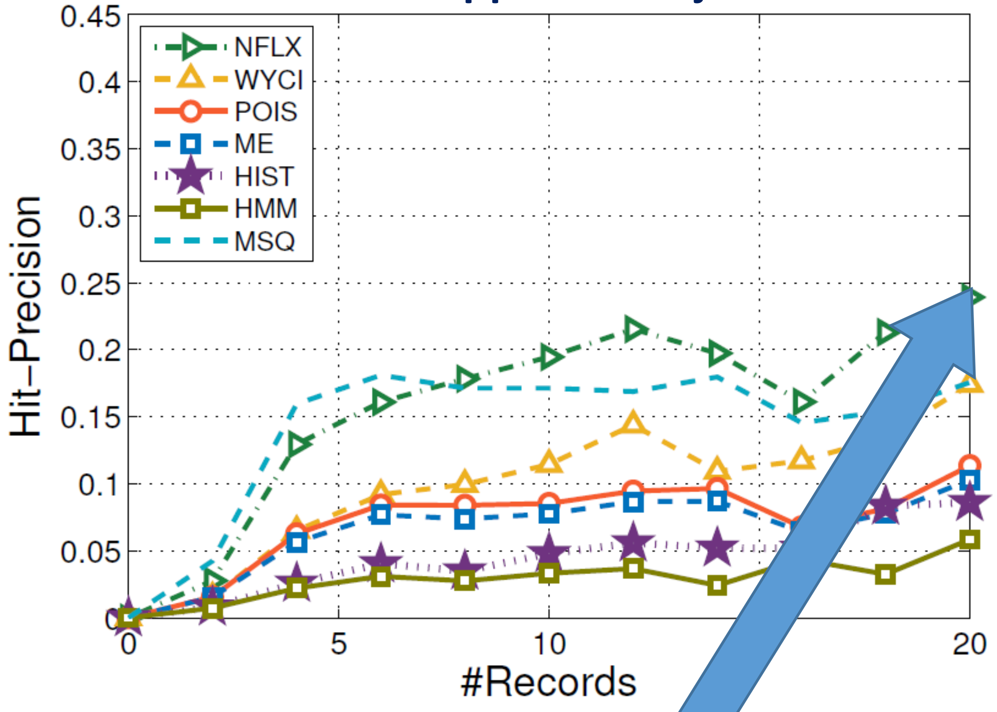
De-anonymization Attack: Actual Performance

Implement 7 state-of-the-art algorithms

- "Encountering" event
  - **POIS** [WWW 2016]
  - **ME** [AIHC 2016]
- Individual user's mobility patterns
  - **HMM** [IEEE SP 2011]
  - **WYCI** [WOSN 2014]
  - **HIST** [TIFS 2016]
- Tolerating temporal/spatial mismatches
  - **NFLX** [IEEE SP 2008]
  - **MSQ** [TON 2013]

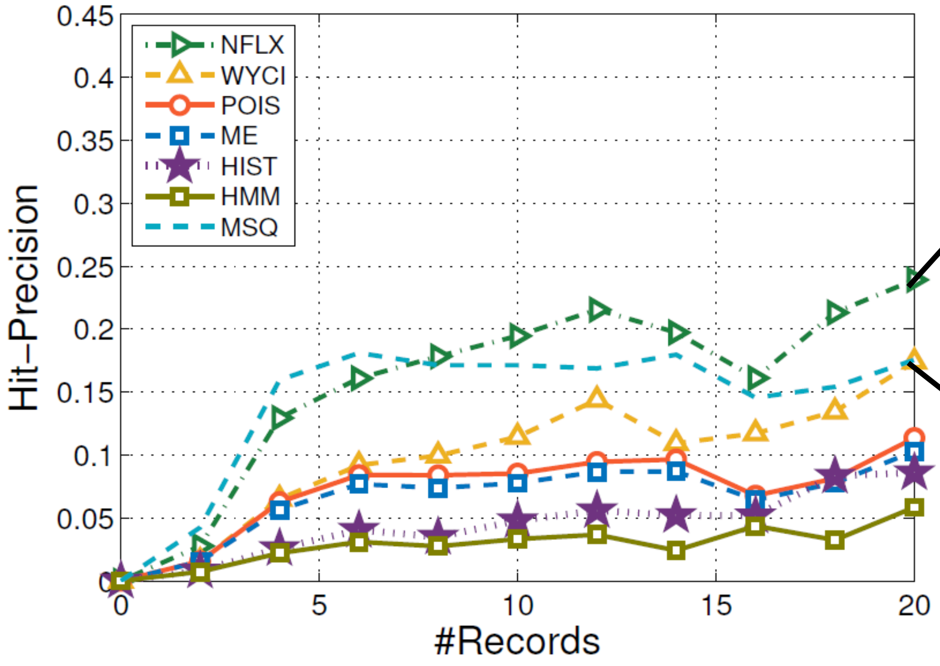
Hit-precision $$h(x) = \begin{cases} \frac{k-(x-1)}{k}, & \text{if } k \geq x \geq 1, \\ 0, & \text{if } x > k. \end{cases}$$

Actual Performance Based on Weibo's App-level Trajectories



Maximum hit-precision is only 25% !
Far from the privacy bound !

Reasons Behind Underperformance



Algorithms with best performance

NFLX [IEEE SP 2008]

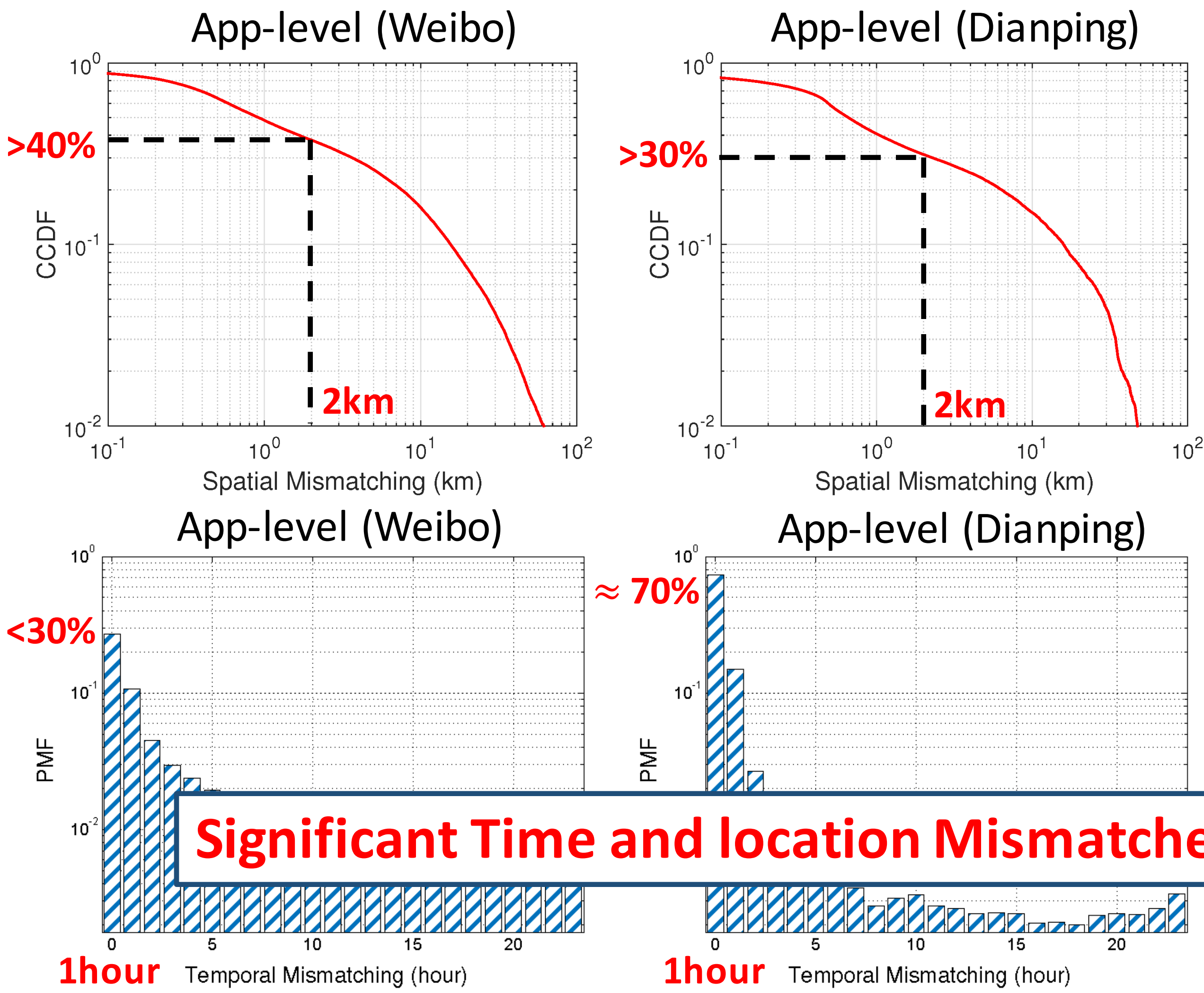
- Similarity function
  - Minimum time gap between users' visits to the same location
- **Tolerate temporal mismatches**

MSQ [TON 2013]

- Similarity function
  - Square root of distance between trajectories
- **Tolerate spatial mismatches**

Existing algorithms tolerating spatio-temporal mismatches have the best performance

Reasons Behind Underperformance: Large Spatio-Temporal Mismatches



Spatial mismatches of over 40% records ≥ 2km

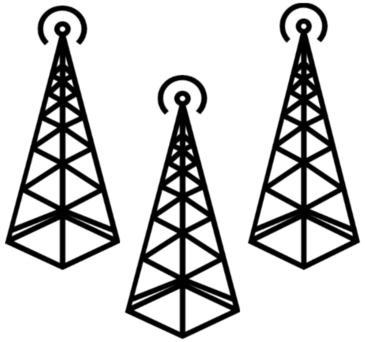
Temporal mismatches of over 30% records

Significant Time and location Mismatches between Different Datasets!

Potential Reasons behind the Mismatches

- **GPS errors**
  - GPS unreachable locations (Indoor, underground)
  - Lazy GPS updating mechanisms [UbiComp 2007]

- **Deployment of base stations**
  - Lower density → larger mismatches

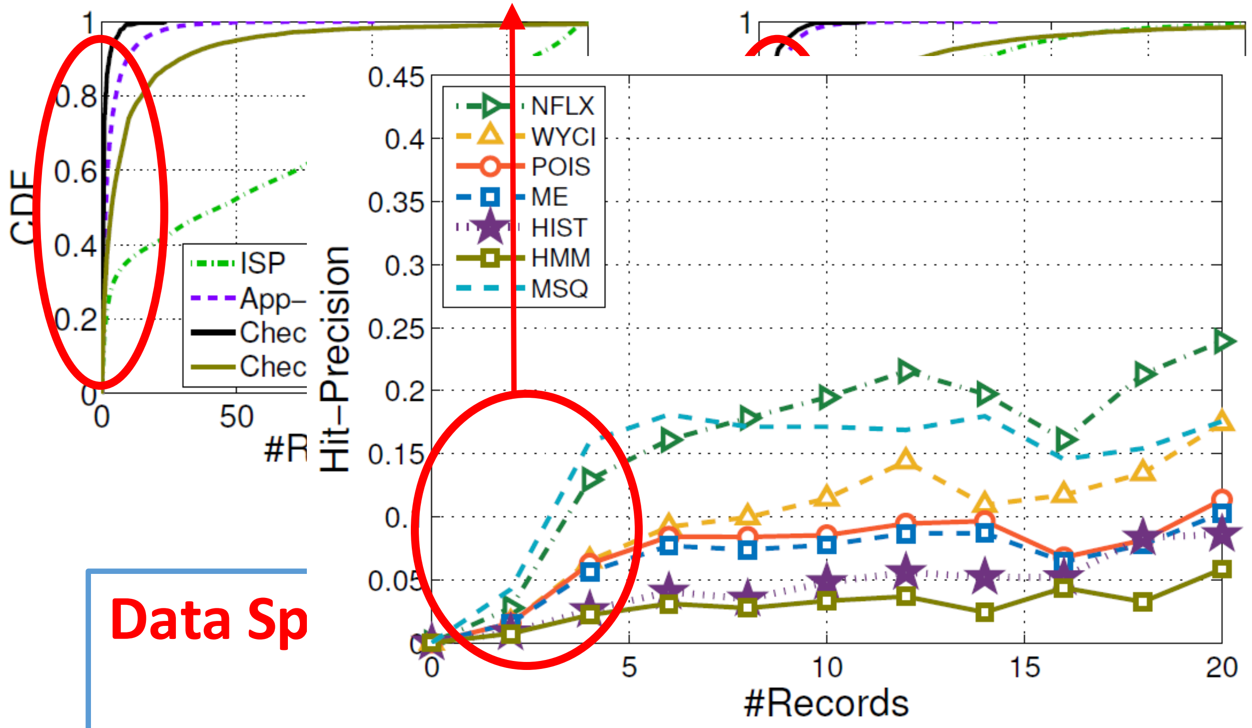


- **User behavior**
  - 39.9% remote (fake) check-ins [ICWSM 2016]
  - Earn virtual rewords, compete with their friends

Reasons Behind Underperformance: Data Sparsity

Sparser location records → Worse performance

Cumulative distribution function (CDF)



The vast majority of users have sparse location records!

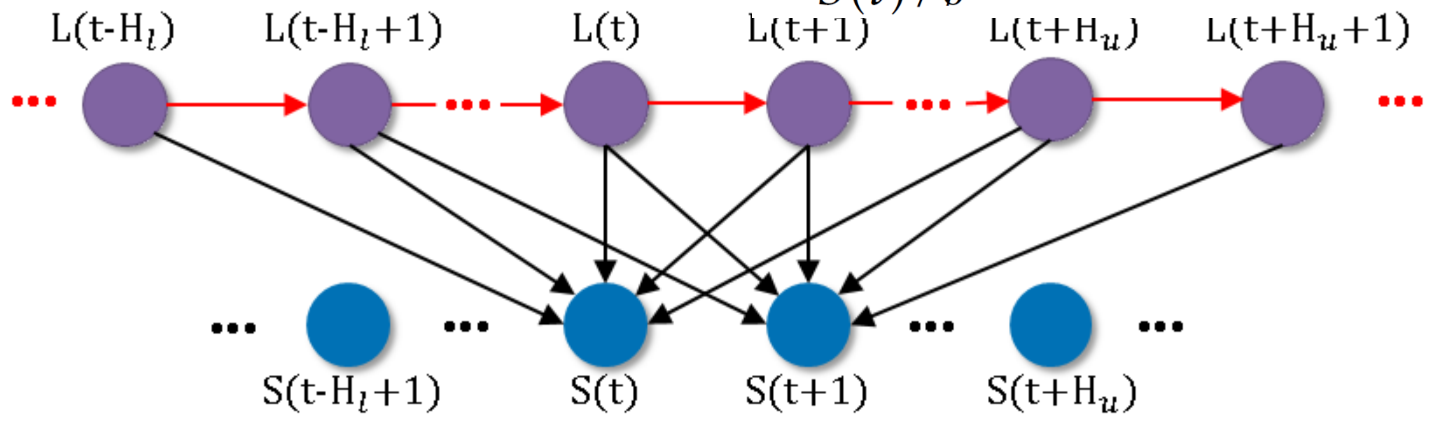
Data Sp **!**

ling!

Can we bridge this gap?

Our De-anonymization Method

$$D_{\mathrm{GM}}(\boldsymbol{S}, \boldsymbol{L}) = \log p(\boldsymbol{S}|\boldsymbol{L}) = \prod_{S(t)\neq\emptyset} p(S(t)|\boldsymbol{L}).$$



■ **1) Modelling Spatio-Temporal Mismatches**: Gaussian Mixture Model (GMM)

$$P(S(t)|L) = \sum_{p=-H_l}^{H_u} \pi(p) \cdot \mathcal{N}(S(t)|L(t-p), \sigma^2(p))$$

- ➢ Parameters chosen by empirical values or estimated by EM algorithm

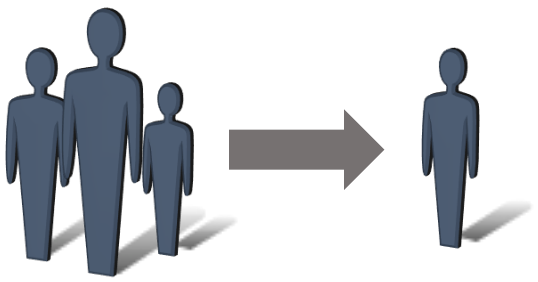
■ **2) Modelling Users' Mobility Pattern**: Markov Model

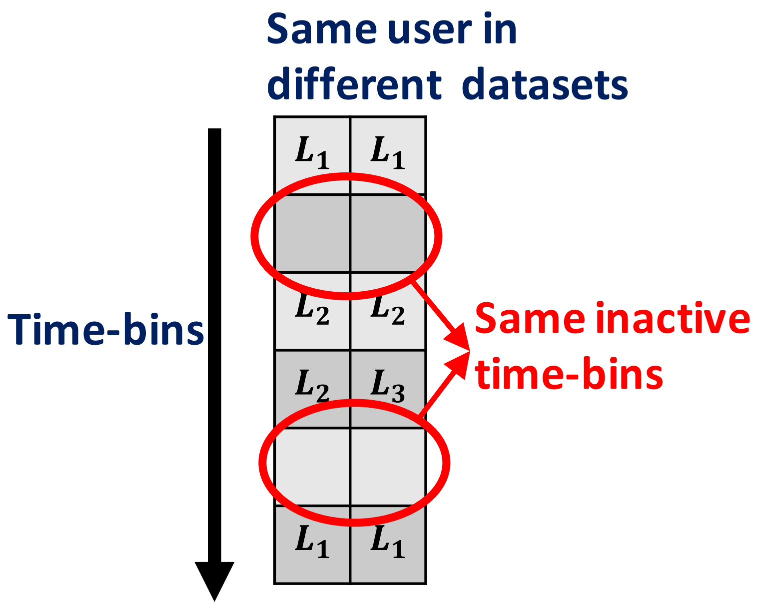
- ➢ Solving the **data sparsity** issue: rare "encountering" event
- ➢ Missing locations are estimated by Markov Model

Our De-anonymization Method

■3) Use Location Context

- Solve the **data sparsity** issue
- Use aggregated user behavior at locations
- To infer individual user behavior (location transition probability)



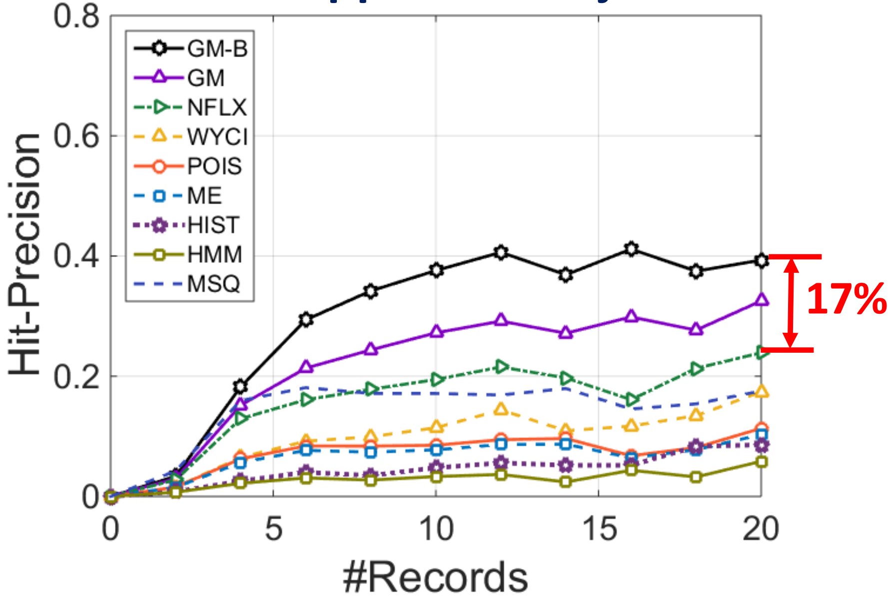


■4) Use Time Context

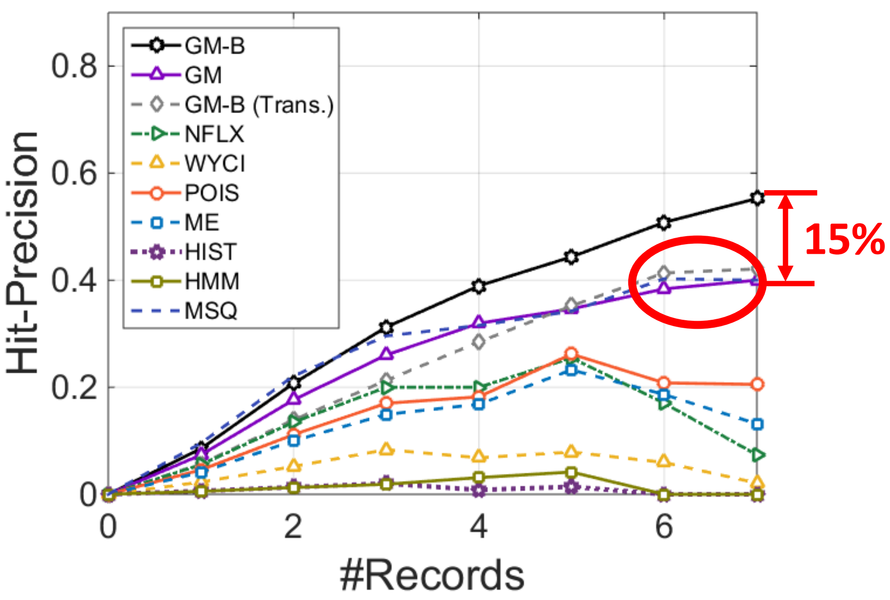
- "Whether the user is active" is helpful
- Modelling user inactive period (previously ignored feature)

Performance Evaluation

Weibo's App-Level Trajectories



Dianping's App-Level Trajectories



- 7 state-of-the-art algorithms
- Our proposed algorithm: **GM-B**, **GM**
- Transferred parameters: GM-B (Trans.)

Our proposed algorithms outperform baselines by over 17%

Summary

- **Large-scale Ground-truth Datasets**
  - ISP trajectories with over 2 million users
  - 2 different social networks, 2 different types of external information
- **Demonstrate the Gaps between Theory and Practice**
  - High theoretical bound
  - Low actual performance
- **Bridge the Gaps between Theory and Practice**
  - Considering spatio-temporal mismatches, data sparsity, location/time context
  - Improve the performance → confirm our observations

Thanks you!

For Data Sample and Code, Please Contact

whd14@mails.tsinghua.edu.cn
liyong07@tsinghua.edu.cn

Reference

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Metric of the ranking

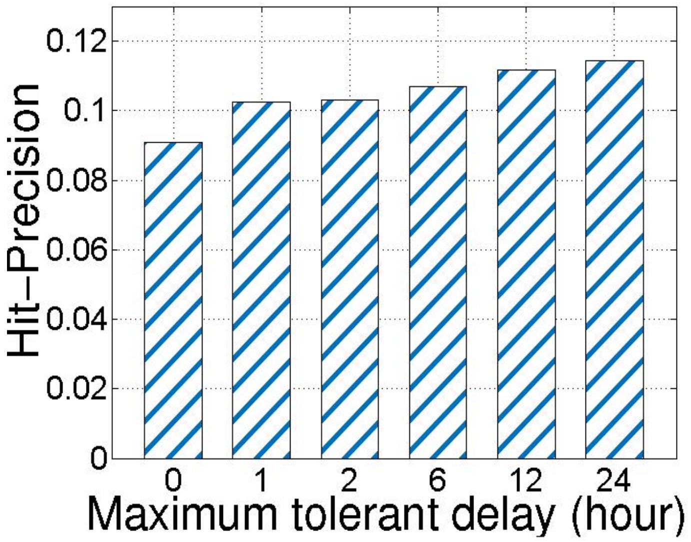
- Hit-precision：

$$h(x) = \begin{cases} \frac{k-(x-1)}{k}, & \text{if } k \geq x \geq 1, \\ 0, & \text{if } x > k. \end{cases}$$

- If the right one rank 1 in candidate trajectories, $h(x) = 1$.
- If the right one rank 3 in candidate trajectories, $h(x) = (k - 2)/k$.

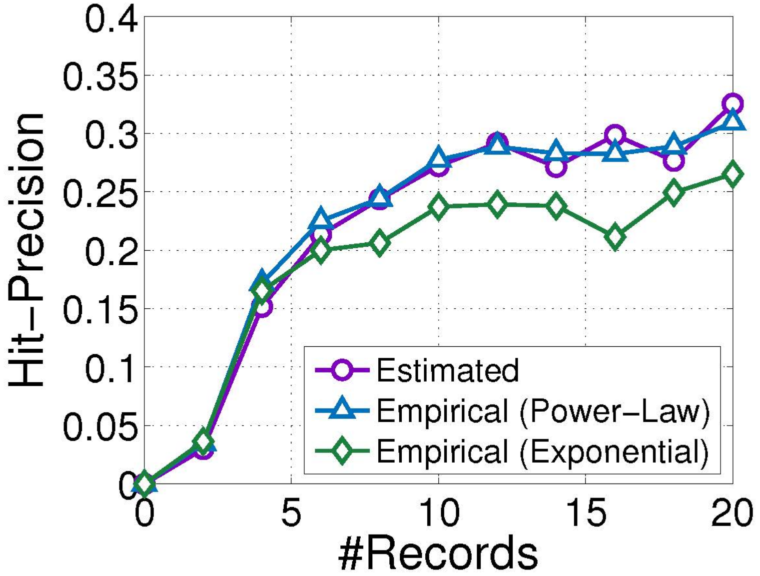
Performance Evaluation: Parameter Study

Impact of Maximum Tolerant Delay



- **Larger Tolerant Delay=>Better Performance**
  - 0->1: Significant improvement
  - 12->24: Little improvement

Impact of Parameters in GMM



- **Comparable Performance**
  - Empirical vs. Estimated
  - Robust to parameter settings.