# GMove: Group-Level Mobility Modeling Using Geo-Tagged Social Media

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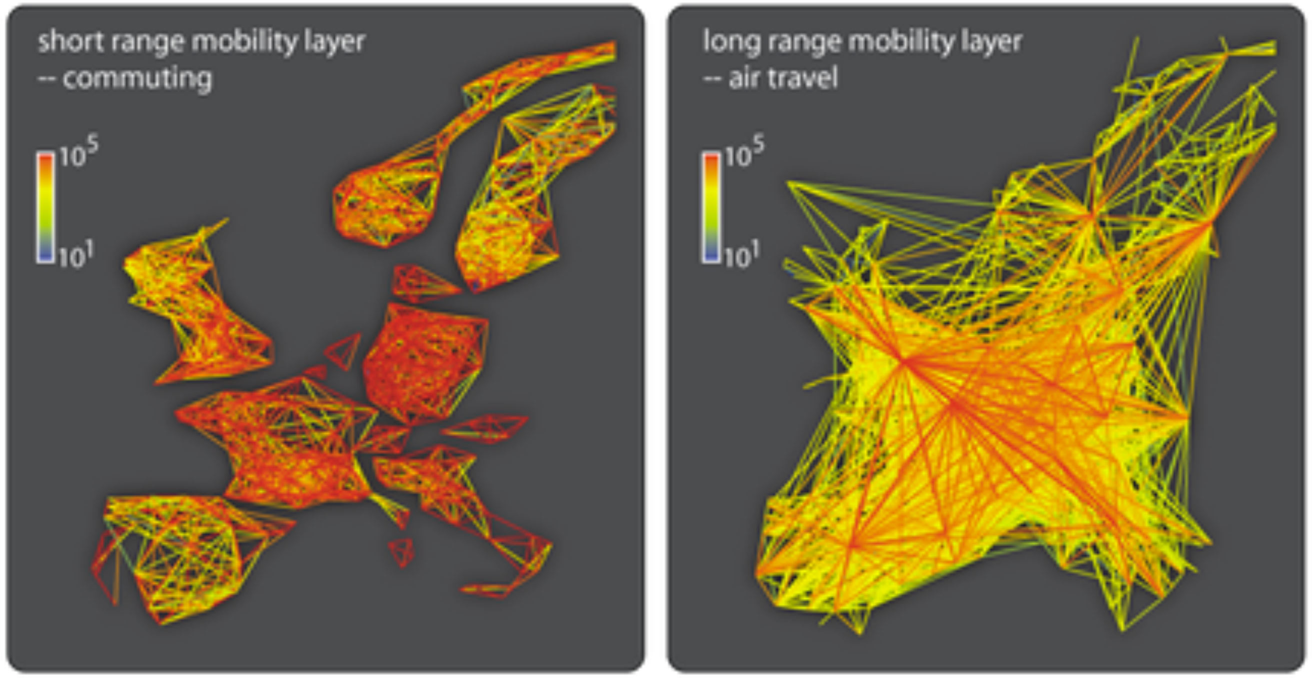
# Background

- Mobility modeling aims at understanding human movement regularity.

- It is important to many applications:
  - Urban planning
  - Traffic scheduling
  - Location prediction
  - Activity recommendation
  - ……



# Background

- Previous studies mostly use **GPS trace data** to model human mobility.

- The recent prevalence of *geo-tagged social media* (**GeoSM**) brings new opportunities to this task:

  - In addition to spatial and temporal information, each GeoSM record (e.g., tweet, Facebook post) also has text.

  - The GeoSM data has a much larger size and a much better coverage of the population than GPS trace data.

# Our Goal

- We aim to unveil human movement regularity using large-scale GeoSM data.

- Specifically, we answer the following two questions:

1. What are the intrinsic states underlying people's movements?
    - Here, a state should provide a 3W (where-what-when) view regarding the user's activity.
2. How do people move sequentially between those latent states?

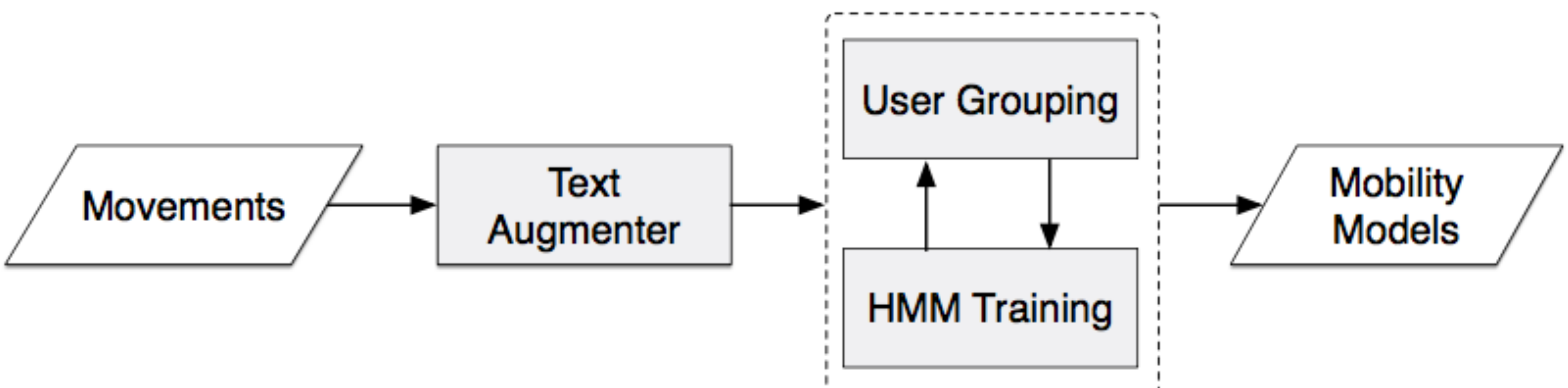
# Challenges

- Dilemma for mobility modeling using GeoSM data:
  - Each user typically has limited GeoSM records, learning a model for every user suffers from severe ***data sparsity***.
  - Different users have totally different moving behaviors, learning one model for all the users suffers from ***data inconsistency***.
- GeoSM (e.g., tweets) have very short text, making it hard to model the semantics of human activities.

# Method Overview

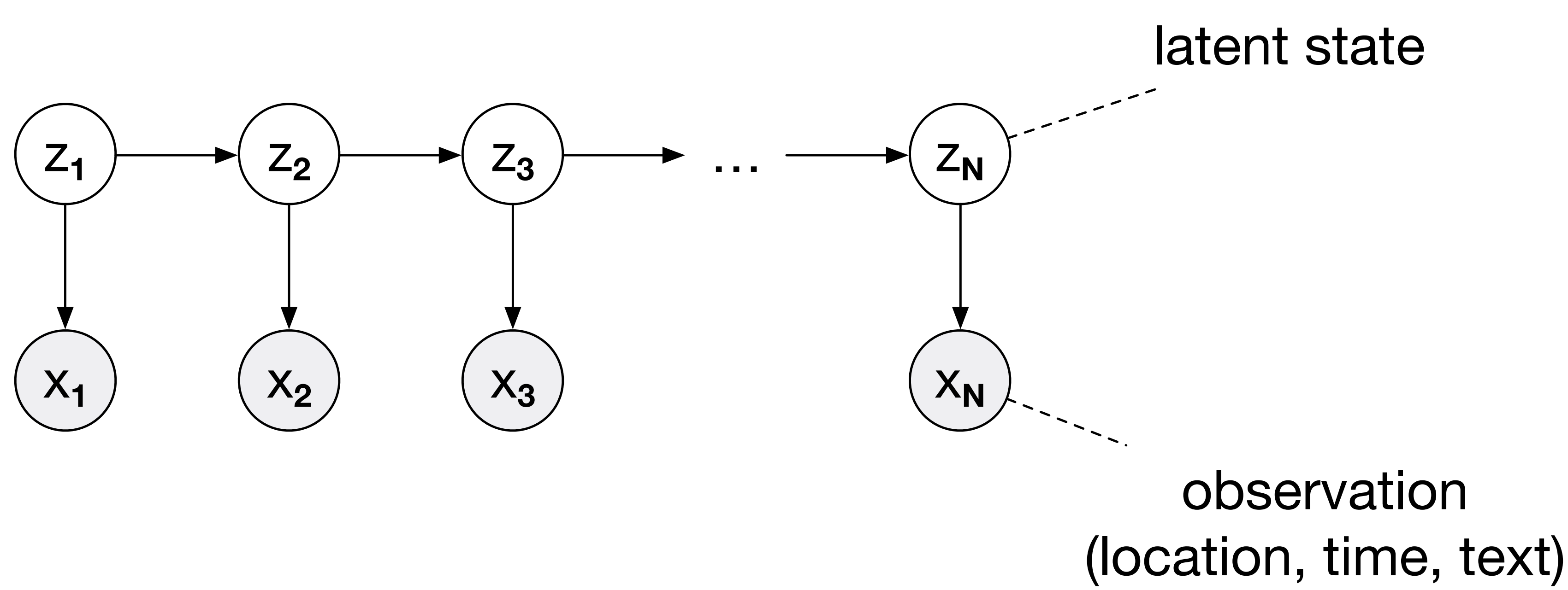
- Relying on Hidden Markov Model, we propose an effective method named GMove.

- Two key modules of GMove:
  - **HMM ensemble learner**: performs group-level HMM learning
  - **Text augmenter**: reduces text sparsity using spatiotemporal signals



# Module 1: HMM Ensemble Learner

- Hidden Markov Model (HMM) for mobility modeling:
  - It assumes multiple latent states (e.g., working at office) that govern a user's movements.
  - The sequence of the latent states follows Markov process.




Note that, as the raw trajectory of each user is sparse, we impose a time constraint (e.g., three hours) to extract dense subsequences for model training.

# Module 1: HMM Ensemble Learner

- We group like-behaved users (e.g., Stanford students) and train an HMM for each group:
  - Reduce data sparsity by aggregating the movements of multiple users.
  - Not compromising data consistency because the users in the same group share significant movement regularity.

| | Data Sparsity | Data Consistency |
|---|---|---|
| Individual Level | X | O |
| Group Level | O | O |
| Global Level | O | X |

Each user has limited records.

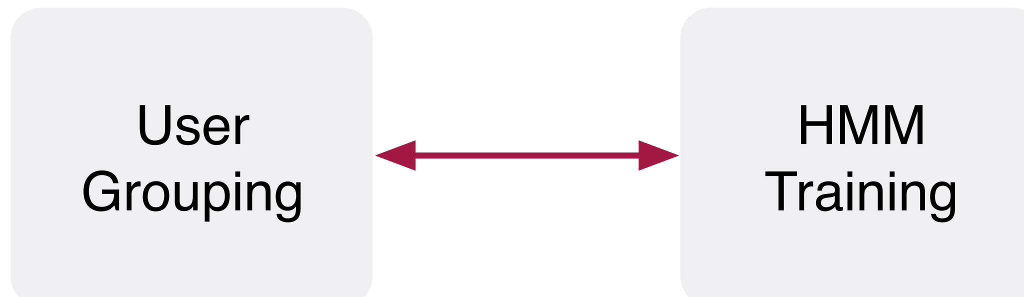
Different moving patterns are mixed.

# How to Obtain Quality User Groups?

- User grouping and mobility modeling mutually enhance each other:
  - Better user grouping leads to more consistent movement data within each group, which can improve the quality of the HMMs.
  - Better HMMs can better reveal movement regularities, which helps infer the group a user belongs to.

# An Iterative Process

- GMove alternates between user grouping and HMM training.




- HMM Training
  - Assume the group memberships of different users are fixed
  - Learn one HMM for each group g
- User Grouping
  - Assume the HMMs of different groups are already learnt
  - For user *u*, update the membership vector by computing the posterior probability that *u* belongs to group g

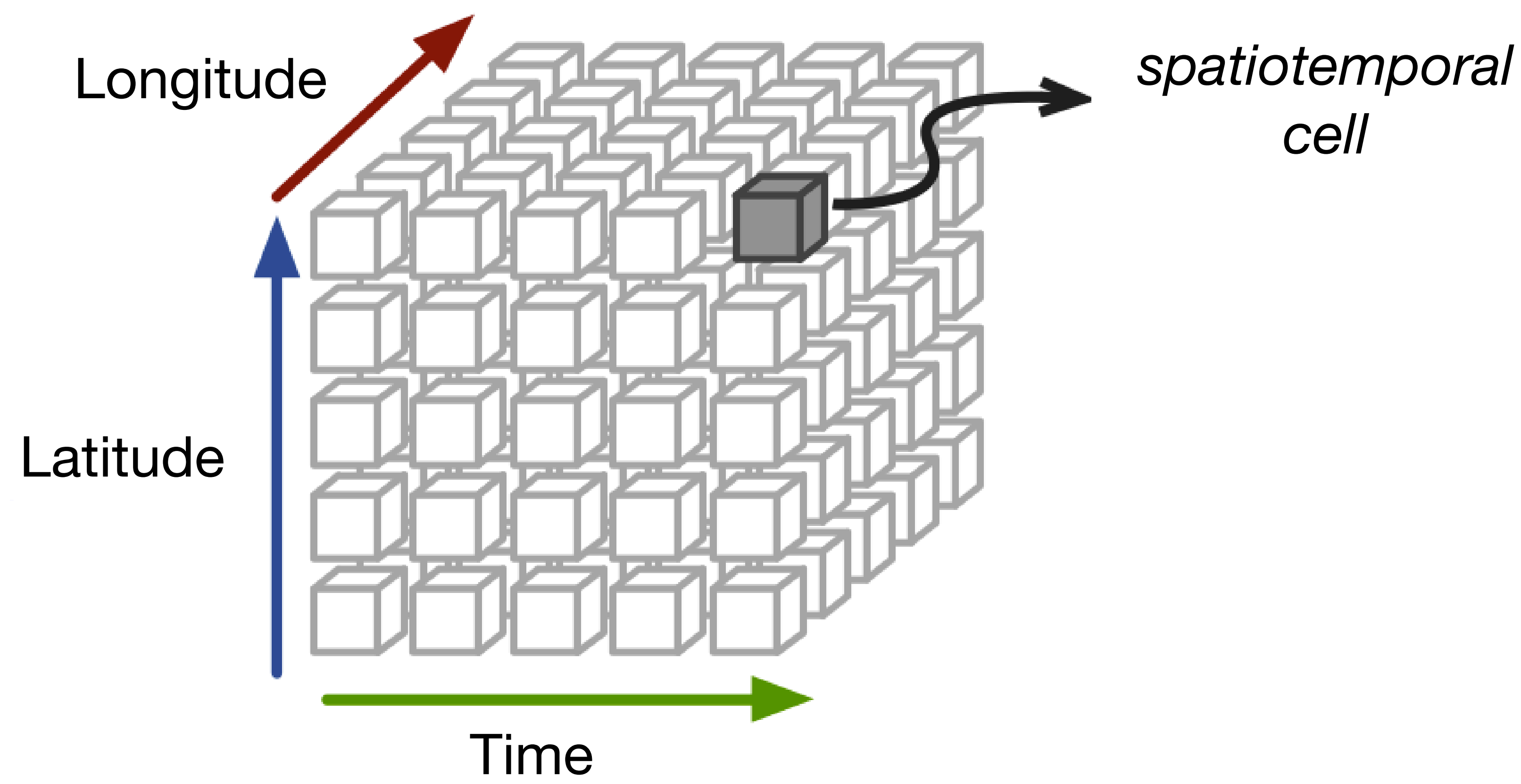
# Module 2: Text Augmenter

- Why do we need the text augmenter?
  - The raw text messages are too short.
  - The spatiotemporal distributions of different words can unveil their semantical correlation.

- E.g., consider two users watching the Lakers' game at the Staples Center.
  - They may post two tweets using two different keywords: "lakers" and "staplescenter".
  - Although those two keywords do not co-occur in the same tweet, they are spatially and temporally close, and thus correlated.

# Text Augmentation

- We discretize the space *D* into equal-size cells.
    - For each keyword ***k***, we use its spatiotemporal distribution over the 3-D cube to obtain a vector $\boldsymbol{V_k}$.
    - Given two keywords, we compute their correlation as the cosine distance between their vectors.



# Text Augmentation

- Once keyword correlations are computed, we perform weighted sampling to augment raw messages.

**Algorithm 1:** Text augmentation.

**Input**: A GSM record $x$, the target length $L$.
**Output**: The augmented text message of $x$.

$A_x \leftarrow$ The original text message $e_x$;
**while** $len(A_x) < L$ **do**
    Sample a word $w \in e_x$ with probability $\frac{TF\text{-}IDF(w)}{\sum_{v \in e_x} TF\text{-}IDF(v)}$;
    Sample a word $v \in \mathcal{N}_w$ with probability $\frac{corr(w,v)}{\sum_{u \in \mathcal{N}_w} corr(w,u)}$;
    Add $v$ into $A_x$;
**return** $A_x$;

# Experiments

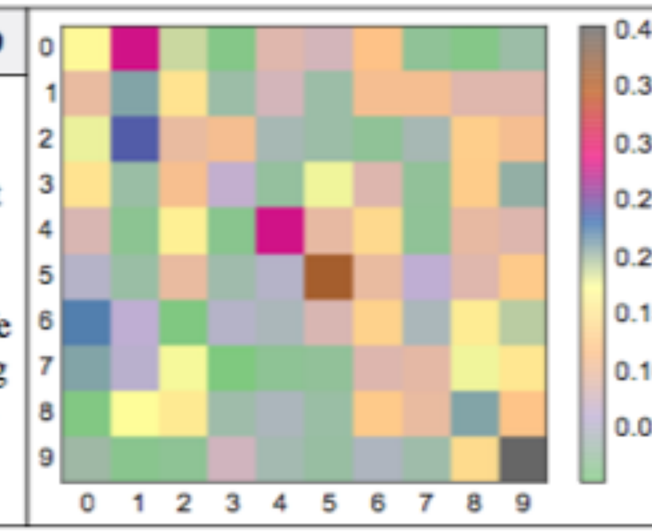
- Data Sets:
  - LA: ~0.6 million geo-tagged tweets published in Los Angeles.
  - NY: ~0.7 million geo-tagged tweets published in New York.

# Case Study: Text Augmentation

| Data | Raw tweet message | Augmented message |
|---|---|---|
| LA | Y'all just kobe fans not lakers. Let's go lakers!! | fans(11), game(7), kobe(19), jeremy(6), lakers(26), injury(8), staples(8), center(4), nba(9), bryant(12) |
| | Fun night! @ Universal Studios Hollywood http://t.co/wMibfyleTW | fun(4), universal(20), studio(16), hollywood(18), night(5), party(7), fame(6), people(13), play(11) |
| NY | Nothing better...fresh off the oven! #Italian #bakery #pizza | fresh(7), oven(21), italian(19), bakery(12), pizza(14), bread(6), cook(5), food(12), kitchen(4) |
| | My trip starts now! @ JFK Airport | jfk(24), international(5), trip(9), travel(6), john(13), kennedy(14), terminal(8), start(6), now(3), airport(12) |

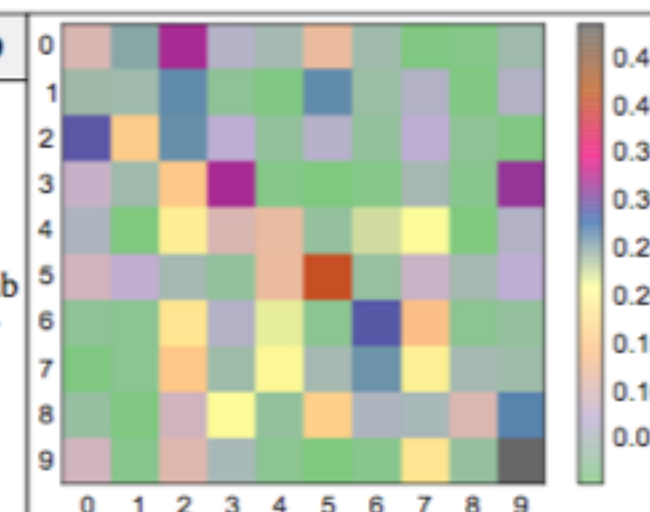
# Example Group-Level Mobility Models


| State 0 | State 1 | State 2 | State 3 | State 4 | State 5 | State 6 | State 7 | State 8 | State 9 |
|---|---|---|---|---|---|---|---|---|---|
| home | school | food | friend | buy | santa | wait | suck | home | night |
| morning | ucla | restaurant | hahaha | shop | monica | dinner | gym | rest | music |
| coffee | course | dinner | dream | mall | beach | food | football | sleep | tonight |
| dude | midterm | grill | song | beautiful | sunset | worst | team | live | bar |
| apartment | class | love | child | happy | dinner | grill | game | game | tbh |
| day | food | deli | birthday | mine | baby | restaurant | play | drink | nightlife |
| hall | drink | worst | drink | apparel | venice | delicious | buster | bed | evening |
| run | damn | come | kiss | bag | shore | amazing | let | show | movie |
| house | friend | waiter | bday | clothes | life | gather | beat | time | beer |
| sleep | stay | chipotle | snapchat | day | please | love | boy | miss | like |



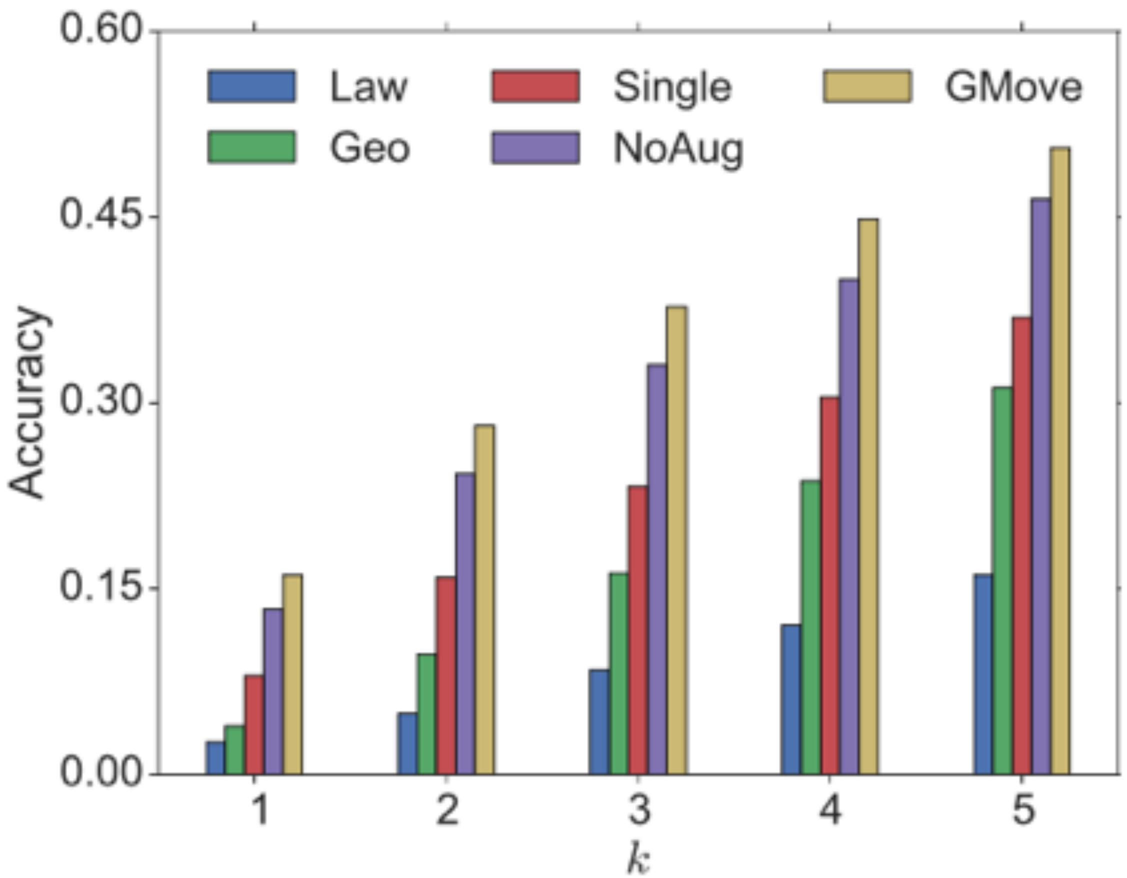

(a) The mobility model for the first user group (students).


| State 0 | State 1 | State 2 | State 3 | State 4 | State 5 | State 6 | State 7 | State 8 | State 9 |
|---|---|---|---|---|---|---|---|---|---|
| hotel | restaurant | lax | universal | food | venice | shopping | night | food | club |
| sleep | food | travel | studio | restaurant | beach | buy | hotel | table | night |
| miss | amazing | airport | night | chinese | people | shop | live | taste | music |
| building | eat | international | party | mexican | life | clothes | lounge | salad | girl |
| center | lunch | come | hollywood | spicy | spa | cheap | place | quiet | nightclub |
| plaza | grill | flylax | buster | hometown | sunshine | sales | taxi | deli | money |
| flight | american | arrival | friend | taste | beautiful | nice | shower | hot | drink |
| home | deli | terminal | happy | china | santa | women | sleep | steak | sleep |
| city | together | train | haloween | town | monica | mall | queen | dining | dance |
| inn | pancake | depart | club | delicious | food | men | terminal | fame | rock |

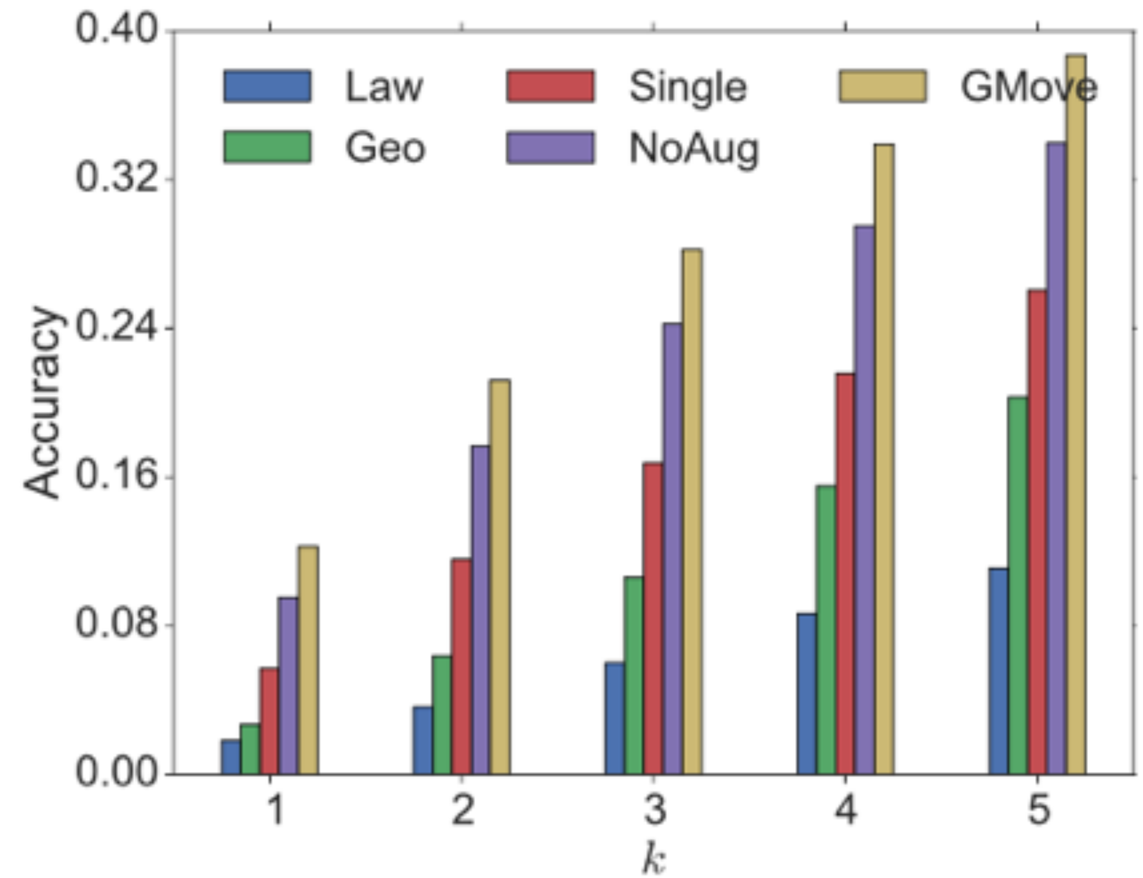



(b) The mobility model for the second user group (tourists).

# Quantitative Evaluation: Location Prediction




(a) LA




(b) NY

# Summary

- We study the problem of group-level mobility modeling using geo-tagged social media.
- We propose the GMove method:
  - It alternates between user grouping and HMM training to learn group-level models.
  - It leverages keyword spatiotemporal correlations to reduce text sparsity.
- Our experiments show that GMove can effectively retrieve group-level mobility models.

# Thanks!