Point-of-Interest Recommendation Systems in Location-Based Social Networks

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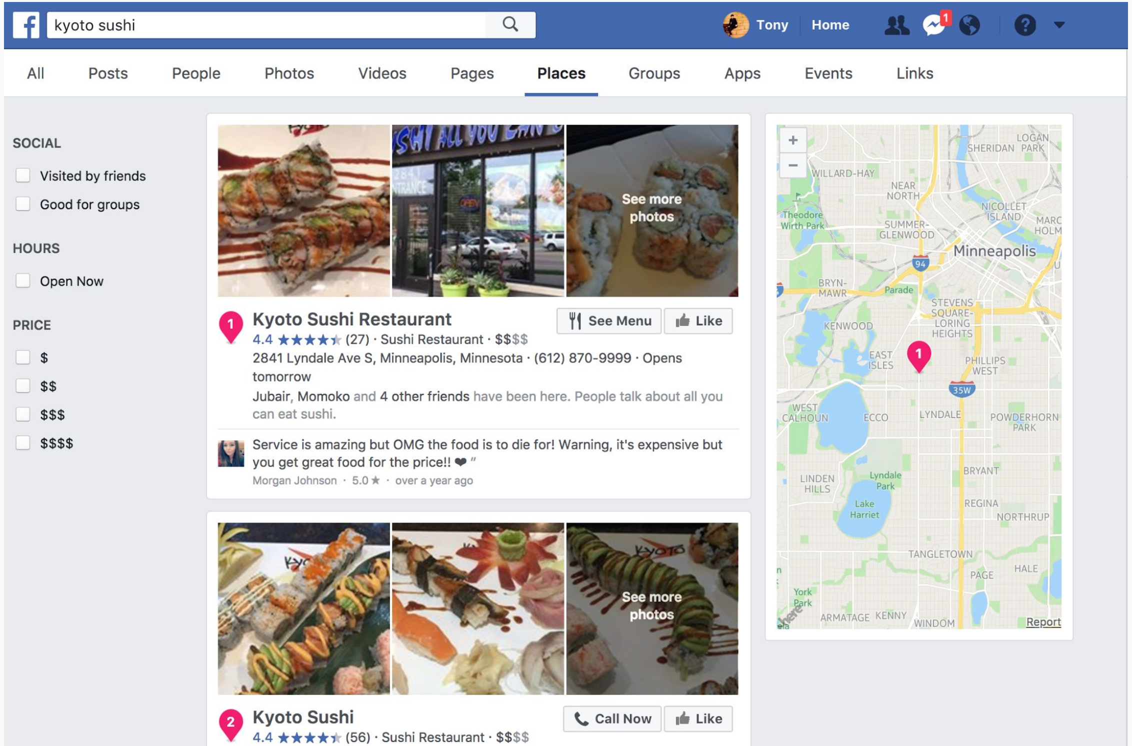
LBSN? POI?

Location-based social networks (**LBSNs**):

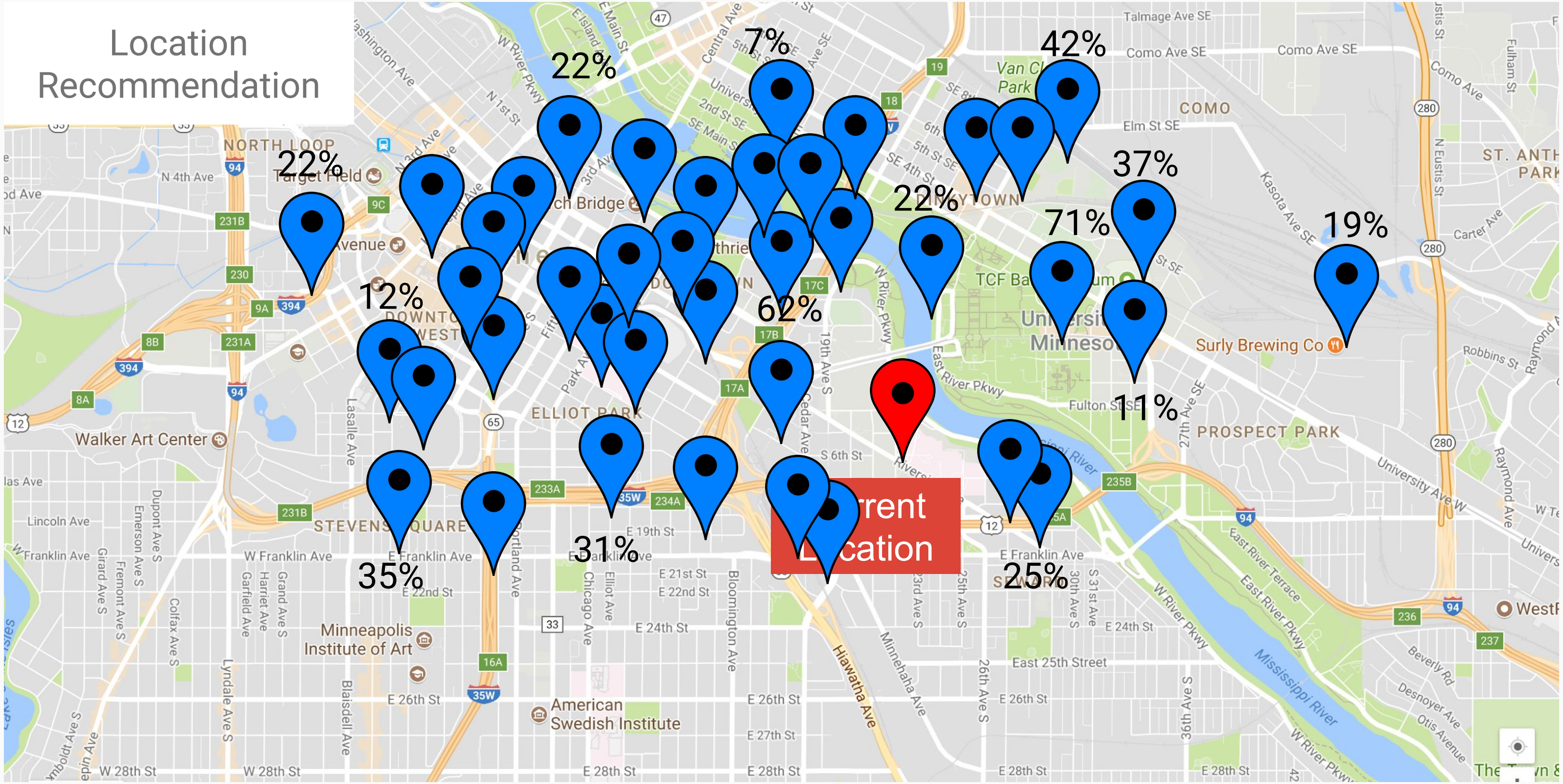
Social networks tied with geographical information

Point-of-interest (**POI**):

A specific location where users show interest (restaurant, bar, cinema, etc.)



Motivation - Big question



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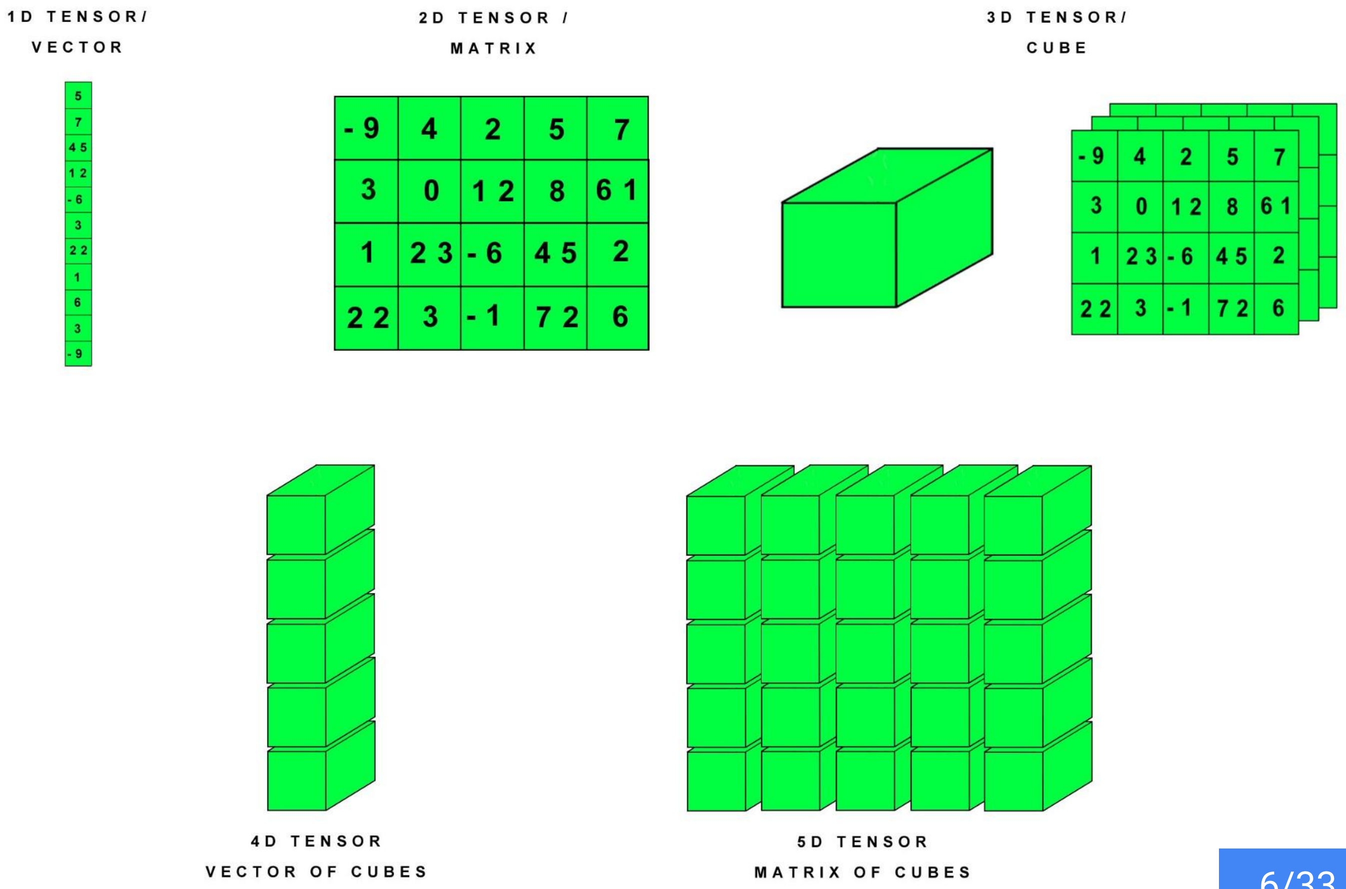
Tensor

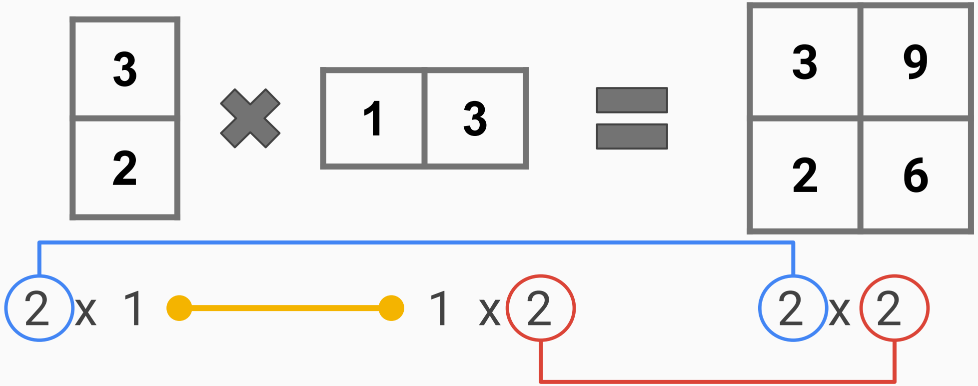
- Generalization of vectors
- Multi-dimensional arrays in Java



Matrix Factorization (MF)

Review:

Matrix multiplication



Matrix Factorization (MF)

A technique to factor a matrix as a product of multiple matrices

$$\begin{bmatrix} 3 & 9 & 3 \\ 2 & 6 & 2 \\ 4 & 12 & 4 \end{bmatrix} = \begin{bmatrix} 3 \\ 2 \\ 4 \end{bmatrix} \times \begin{bmatrix} 1 & 3 & 1 \end{bmatrix}$$

3 x 3   3 x ?   ? x 3

Matrix Factorization (MF)

Question:

Given a matrix of user ratings for different locations, **predict empty ratings** *0 (n/a)*

Location\User	User 1	User 2	User 3
Tony's Sushi	5	4	0 *(n/a)*
Theatre	3	3	1
Dollar Store	0 *(n/a)*	0 *(n/a)*	2

Matrix Factorization (MF)

Matrix *L*

Location\Feature	*shopping*	*food*
Tony's Sushi	?	?
Theatre	?	?
Dollar Store	?	?

×

Matrix *U*

Feature\User	User 1	User 2	User 3
shopping	?	?	?
food	?	?	?

=

Location\User	User 1	User 2	User 3
Tony's Sushi	5	4	0 *(n/a)*
Theatre	3	3	1
Dollar Store	0 *(n/a)*	0 *(n/a)*	2

Matrix Factorization (MF)

Matrix *L*

Location\Feature	*shopping*	*food*
Tony's Sushi	1	5
Theatre	2	1
Dollar Store	5	2

×

Matrix *U*

Feature\User	User 1	User 2	User 3
shopping	1	1	0.1
food	0.8	0.6	0.75

=

Location\User	User 1	User 2	User 3
Tony's Sushi	5	4	0 *(n/a)*
Theatre	3	3	1
Dollar Store	0 *(n/a)*	0 *(n/a)*	2

Matrix Factorization (MF)

Matrix *L*

Location\Feature	*shopping*	*food*
Tony's Sushi	1	5
Theatre	2	1
Dollar Store	5	2

×

Matrix *U*

Feature\User	User 1	User 2	User 3
shopping	1	1	0.1
food	0.8	0.6	0.75

=

Location\User	User 1	User 2	User 3
Tony's Sushi	5	4	1 * 0.1 + 5 * 0.75 = 4
Theatre	3	3	1
Dollar Store	0 *(n/a)*	0 *(n/a)*	2

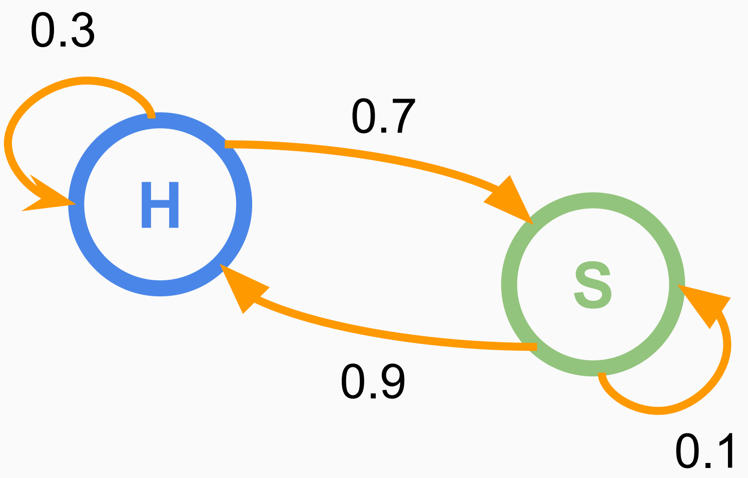
Matrix Factorization (MF)

What's the point?

Based on the calculated predictions, we can make **recommendations**.

Location\User	User 1	User 2	User 3
Tony's Sushi	5	4	4
Theatre	3	3	1
Dollar Store	5	5	2

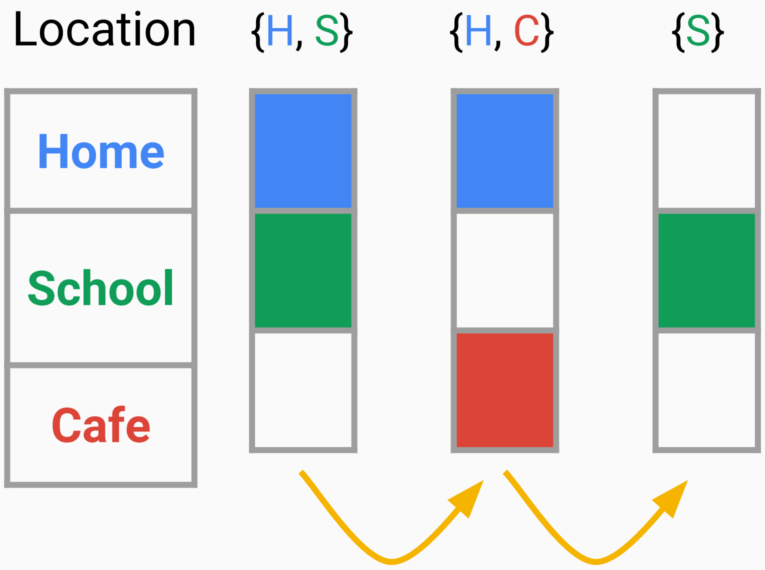
Markov Chain (MC)



Stochastic model to represent different states (locations) and their transitional possibilities.

	Home	School
Home	0.3	0.7
School	0.9	0.1

Markov Chain (MC) for Sets



Each state is now a set of locations instead of a single location.

	Home	School	Cafe	#
Home	1/2	1/2	1/2	2
School	1/1	0/1	1/1	1
Cafe	0/1	1/1	0/1	1

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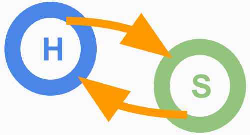
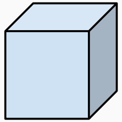
POI Recommendation History over Time

MF / MC



Traditionally used for recommendation systems

FPMC (2010)



Combining MF + MC

FPMC-LR (2013)

FPMC + Only considering nearby locations

TAD-FPMC (2017)

FPMC + Capturing complex behavior of users over time

Factorized Personalized Markov Chain (FPMC)

Problem of Markov chain

One Markov chain is used for all users (Recommendation is not personalized)

How FPMC solves the problem

Having a Markov chain for each user

Factorized Personalized Markov Chain (FPMC)

1. **Make a Markov chain for each user**
2. Stack them one onto another
3. Factor the cubic tensor using tensor factorization
4. Calculate predictions using the factors

From location

To location

User 1

0.2	?	?
0.5	0.1	?
?	?	0.3

User 2

?	?	?
0.3	?	0.1
0.6	?	?

User 3

0.2	0.4	0.7
?	0.1	?
?	0.5	?

Factorized Personalized Markov Chain (FPMC)

1. Make a Markov chain for each user
2. **Stack them one onto another**
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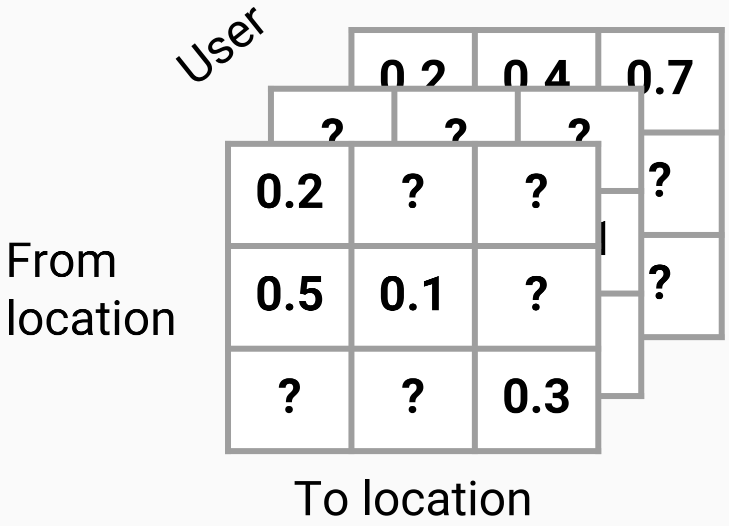

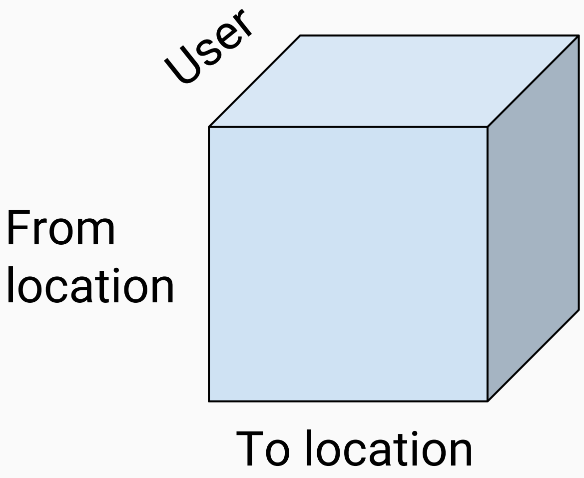

Factorized Personalized Markov Chain (FPMC)

1. Make a Markov chain for each user
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3. **Factor the cubic tensor using tensor factorization**
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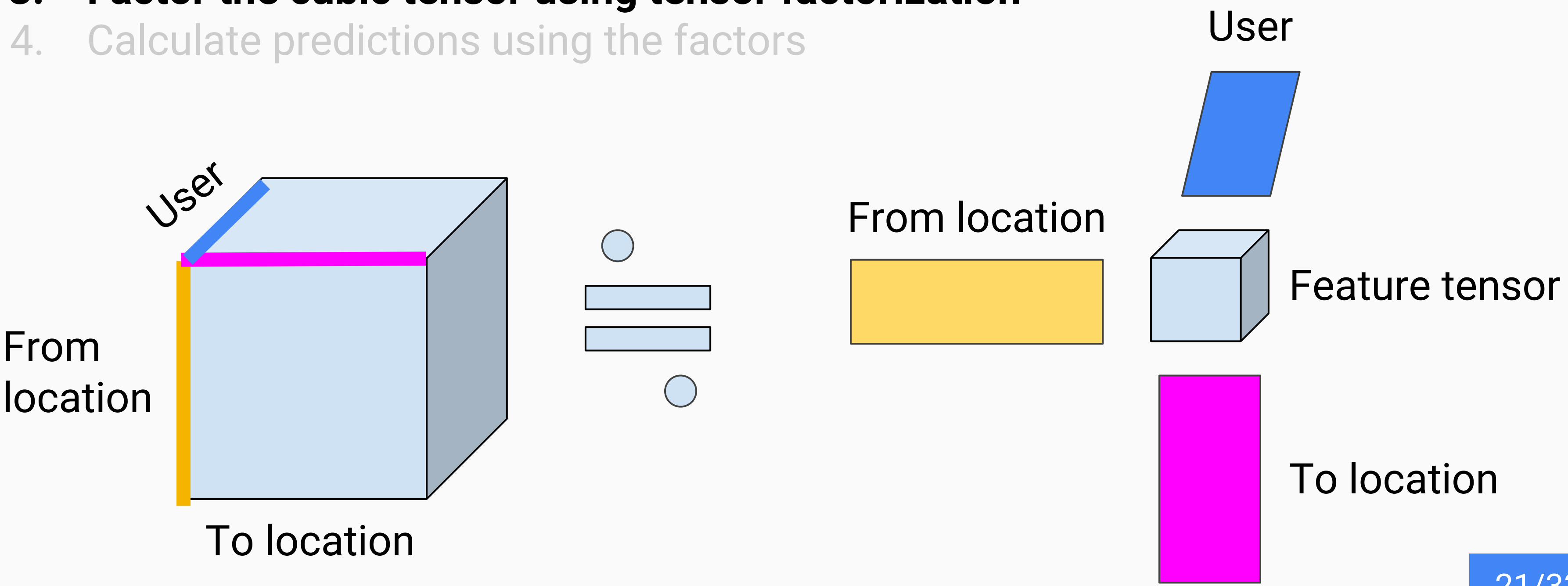
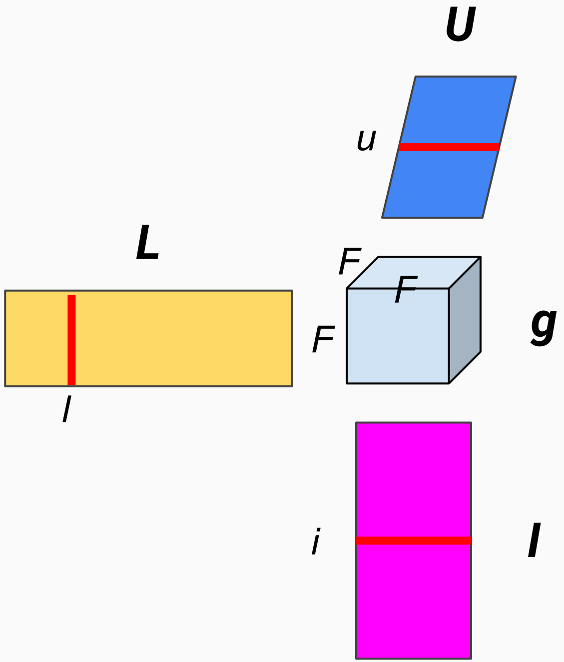


Factorized Personalized Markov Chain (FPMC)

1. Make a Markov chain for each user
2. Stack them one onto another
3. Factor the cubic tensor using tensor factorization
4. **Calculate predictions using the factors**

Probability of user ***u*** going from location ***l*** to location ***i***

$$x_{l,i,u} \approx \sum_{p=1}^{F} \sum_{q=1}^{F} \sum_{r=1}^{F} g_{pqr} L_{lp} I_{iq} U_{ur}$$

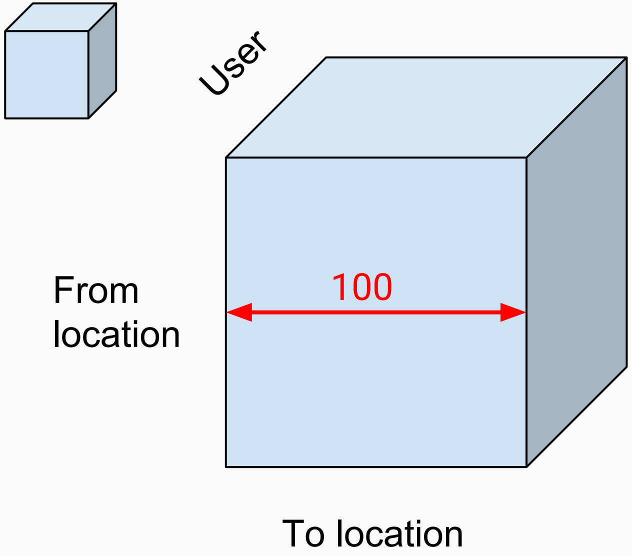


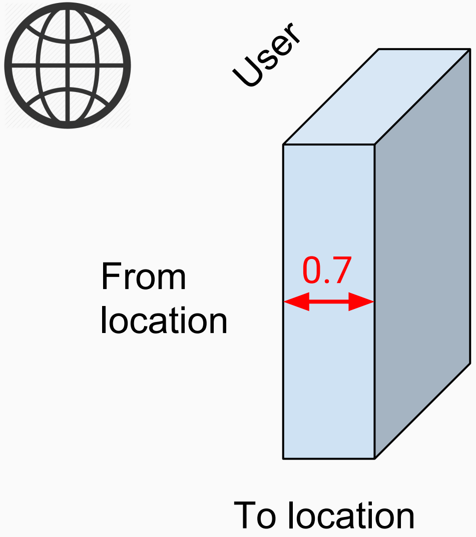
FPMC with Localized Region Constraint (FPMC-LR)

Problems of FPMC		**How FPMC-LR solves the problem**
Generic method for any recommendation systems	→	POI-specific method
Computationally expensive	→	Only consider nearby locations when predictions are made

FPMC with Localized Region Constrain (FPMC-LR)

1. Make a Markov chain for each user
2. Stack them one onto another
3. Factor the **cubic tensor** using tensor factorization
4. Calculate predictions using the factors





Time-Aware Decaying FPMC (TAD-FPMC)

Problem of FPMC-LR

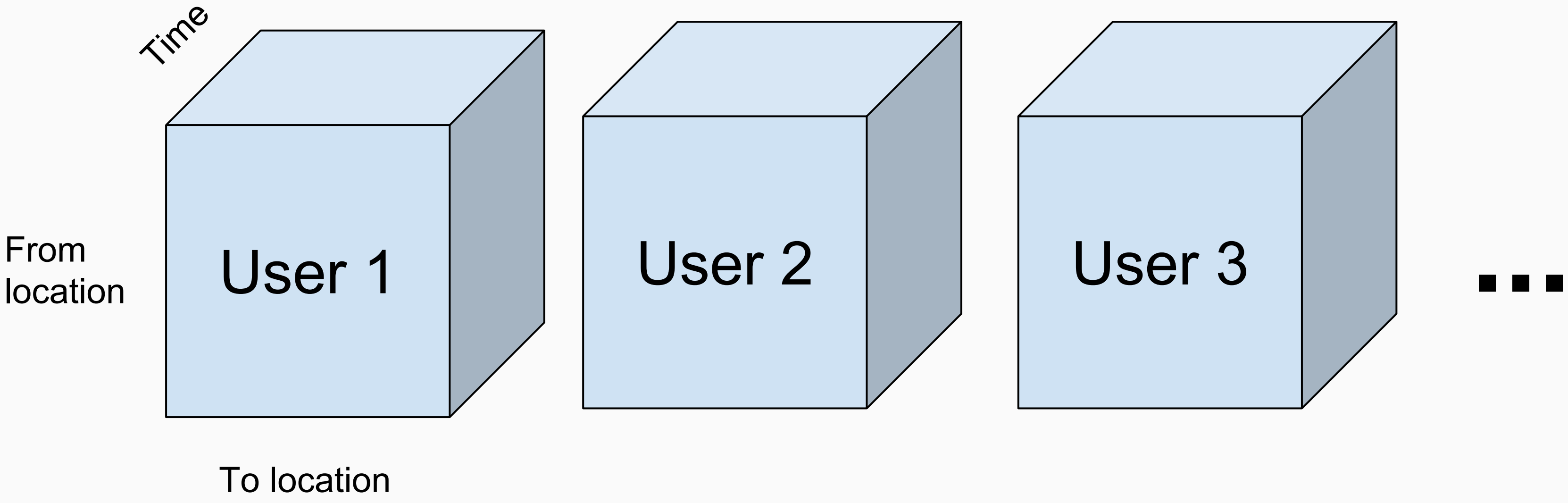
Complex user behavior over time is not incorporated

How TAD-FPMC solves the problem

Adding time variable when calculating the recommendations

Time-Aware Decaying FPMC

1. Make a Markov chain for each user
2. Stack them one onto another
3. Factor the **cubic tensor** using tensor factorization
4. Calculate predictions using the factors



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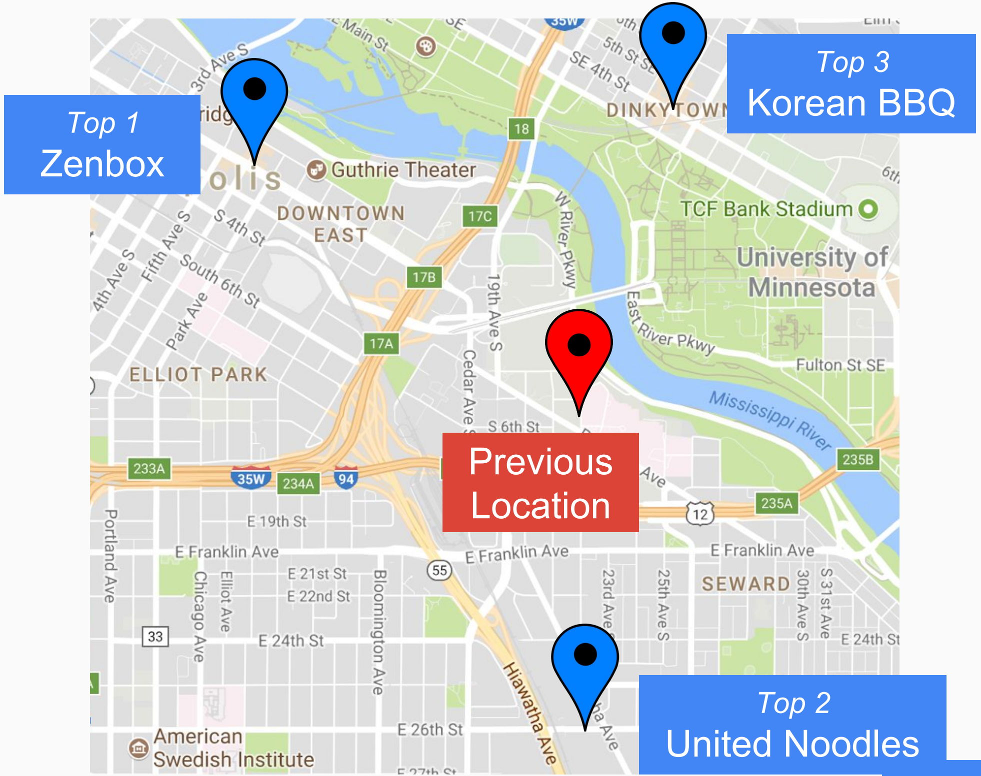
Performance Analysis - Evaluation Metric

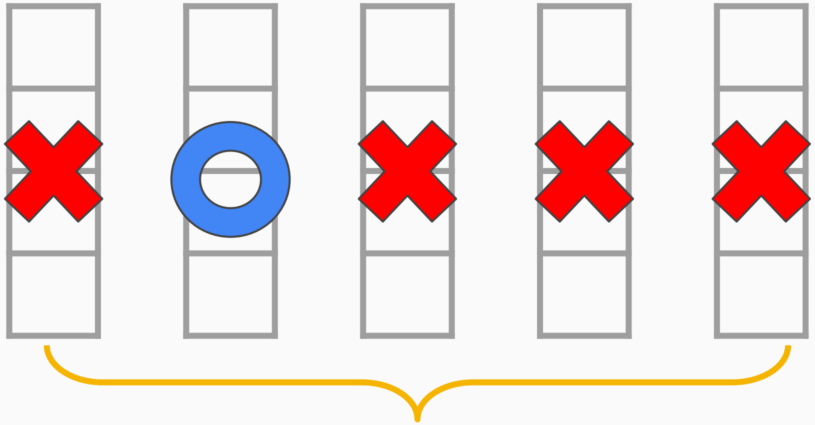
1. Each Algorithm recommends a list of top-N places.
2. Recommendation is correct if the user indeed visited any place in the list at time t.

Top-3 recommendations



$$\text{Precision} = \frac{\text{\# of correct predictions}}{\text{\# of recommendation rounds}} = \frac{1}{5}$$

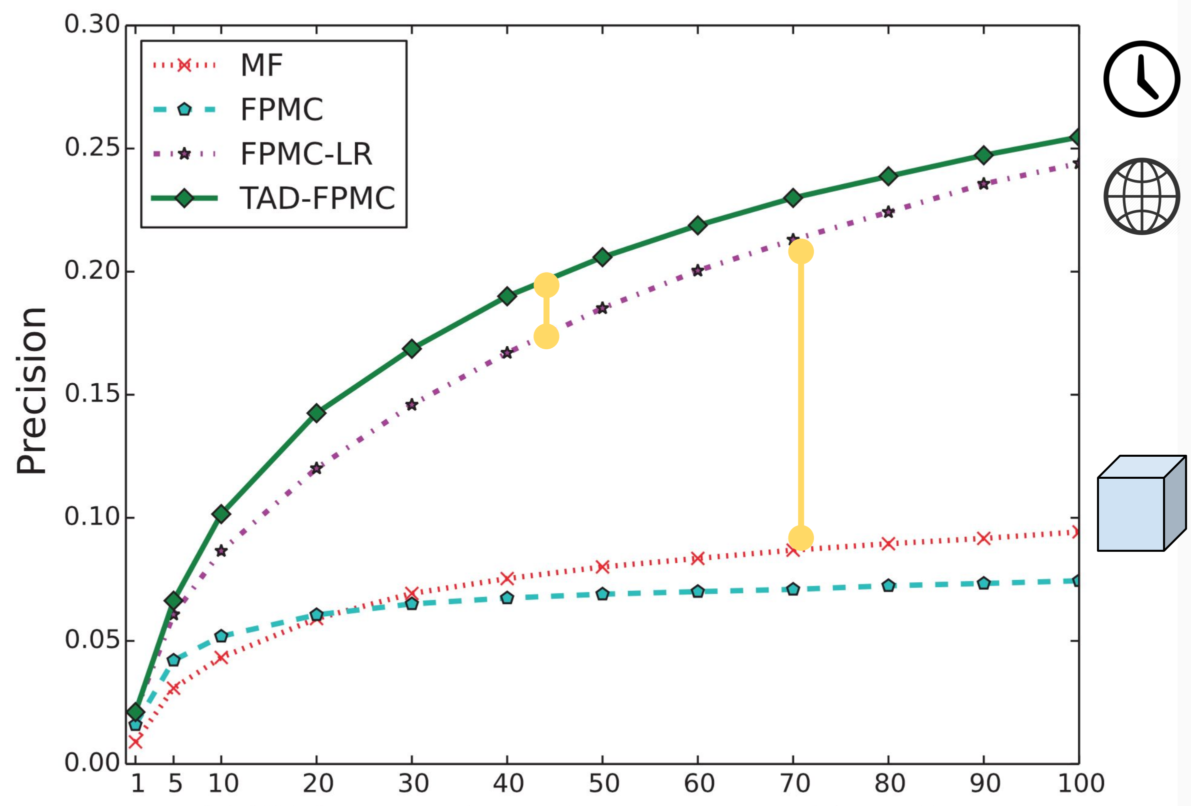
Top-4 Recommendations



5 Rounds

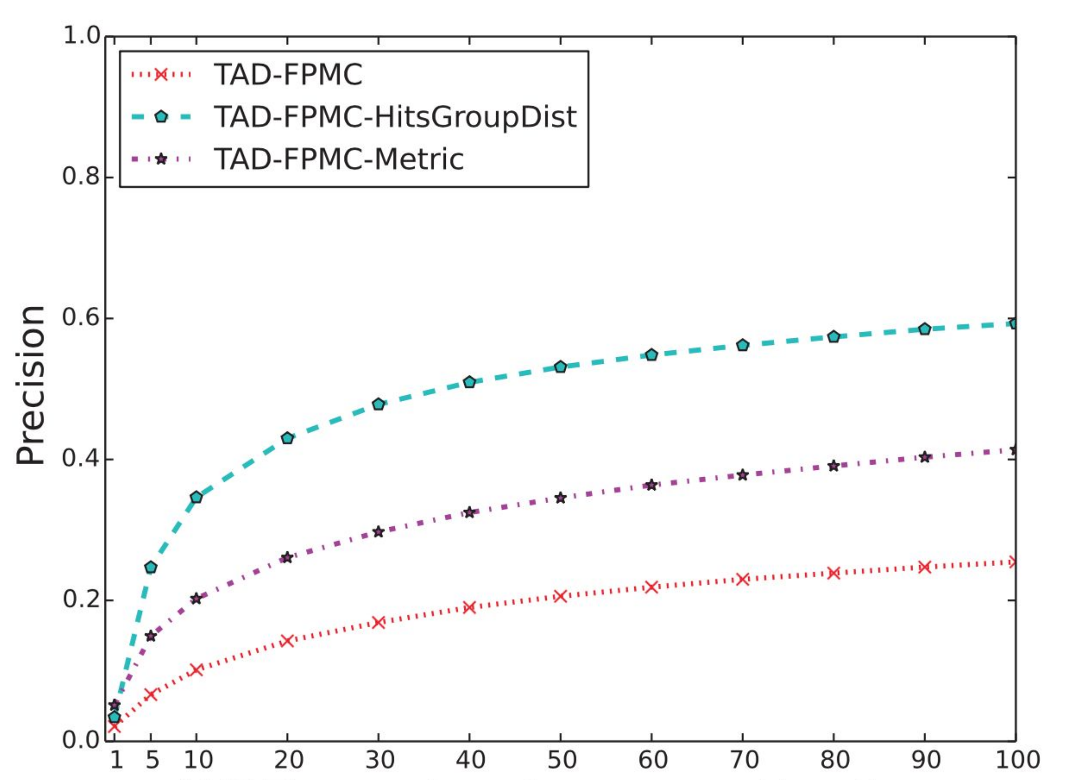
Performance Analysis

POI specific models (FPMC-LR & TAD-FPMC) show much better performance



Size of Top-N list (NYC data)

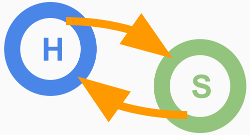
Variations of TAD-FPMC far outperform all existing models



Size of Top-N list (NYC data)

Conclusion

MF / MC



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Questions?

Contact

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https://github.com/frogrammer

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