FluidRating: A Time-Evolving Rating Scheme in Trust-based Recommendation Systems Using Fluid Dynamics

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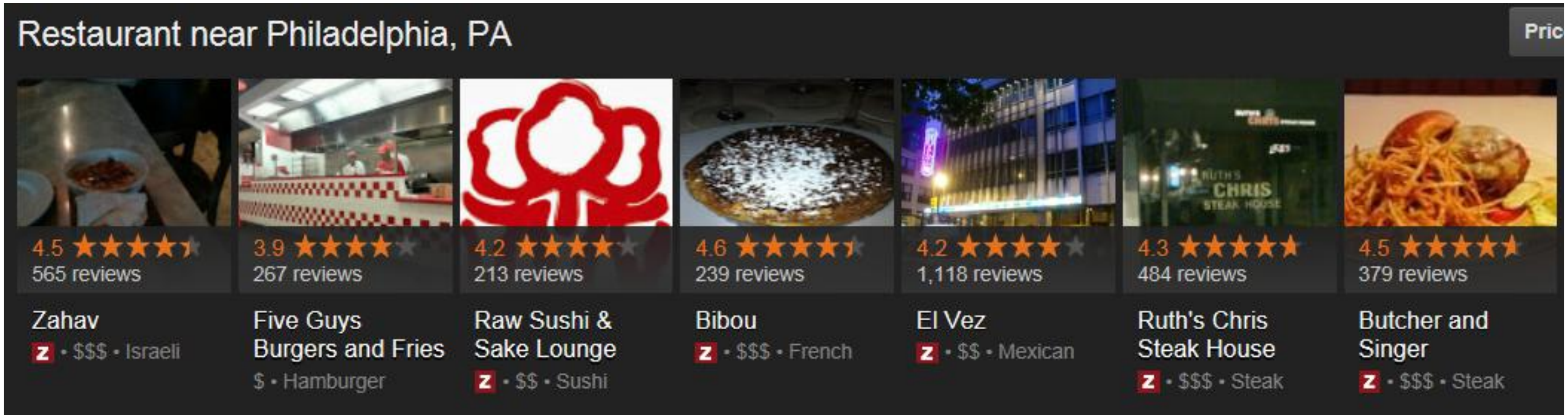
Outline

1. Trust-based Recommendation
2. Motivation
3. Problem
4. Solution: FluidRating
5. Experimental Evaluation
6. Conclusion & Future Work

Personalized Recommendation

Too many choices in daily life:
which restaurant for dinner,
which movie to watch,
which product to purchase....



Personalized recommendation

1. Trust-based Recommendation

- Two types of information
  - user to user: web of trust
  - user to item: review, rating
- Basic idea
  - use the knowledge of a trust network among users, to provide personalized recommendations by aggregating the opinions of their trusted friends

2. Motivation

- Consider time-evolving effects
  - users receive different influences at different times
  - upon receiving an influence, users' reactions can vary
- Differentiate direct and indirect influences
- Capture user features
  - key feature we are considering: persistency
  - how much one insists on his or her opinion

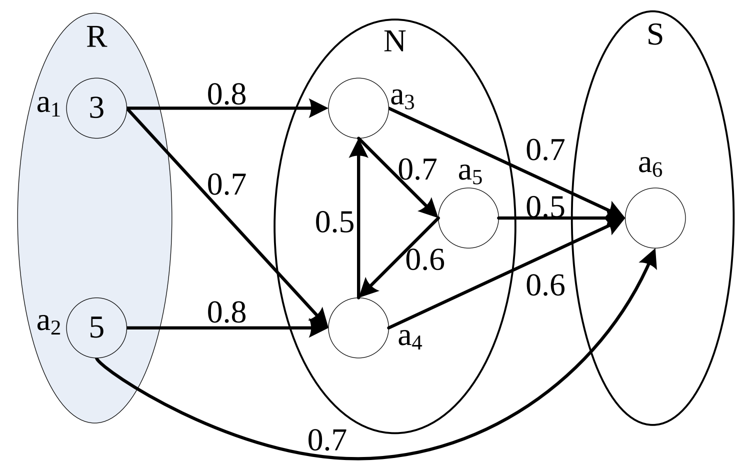
High quality personalized recommendation

2. Motivation

- Existing trust-based recommendation methods
  - calculate at the current time
  - take direct friends, and friends of friends, equally
  - assume adoption of all influences
- In real life
  - time-evolving system
  - closer friends have more opportunities for influence
  - upon receiving influence, different users may take different actions (depending on user features)

Problem
System setting: Rating network

- Nodes
  - raters $R = \{a_1, a_2\}$
  - non-raters $N = \{a_3, a_4, a_5\}$
  - sink $S = \{a_6\}$
- Influence relations
  - converted from trust relations
  - from raters to sink
  - from raters to non-raters, then to sink



Problem
Time-evolving rating prediction

- Tasks
  - predict rating efficiently
  - reflect time-evolving effect
  - capture user features

Solution

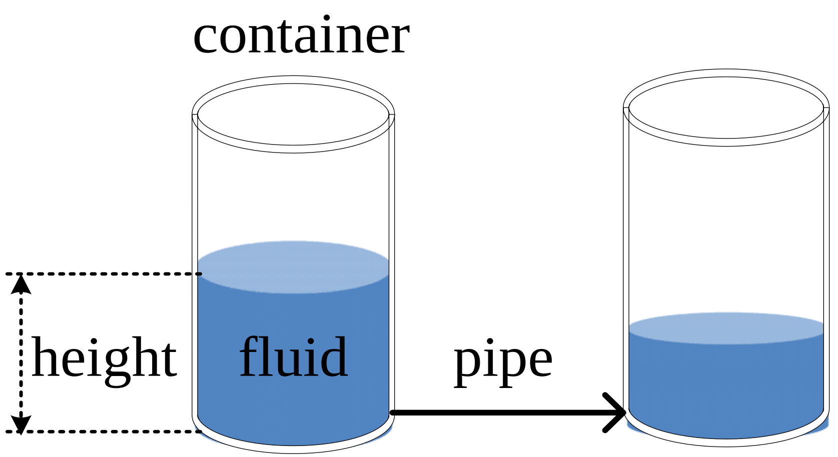
- Time-evolving opinion formulation process
  - each user receives the influence
  - updates his own opinion
  - propagates his opinion to other friends
- Discretized view
  - each user exchanges his opinions with those of his neighbors
- Model the process using fluid dynamics theory

Solution

- Social principles
  - Principle 1: First Influence Dominates.
  - Principle 2: Stronger Influence Dominates.
- Physical principles
  - Principle 3: Mass Conservation.
  - Principle 4: Energy Conservation.

Solution

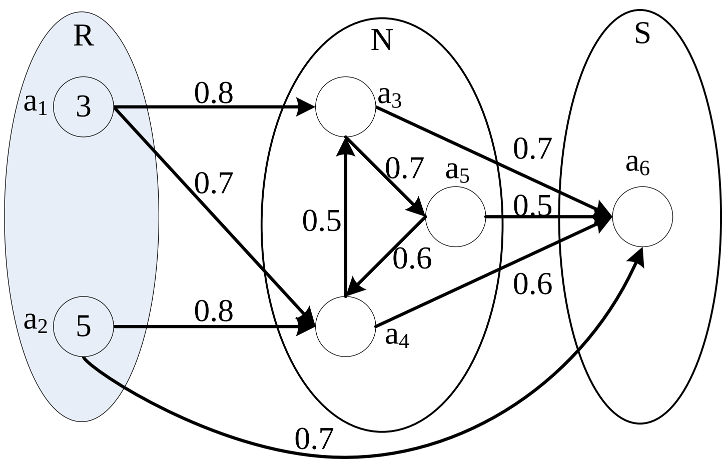
- FluidRating: three components
  - container: user
  - pipe: influence relation
  - fluid: recommendation
    - temperature as rating
    - height as persistency



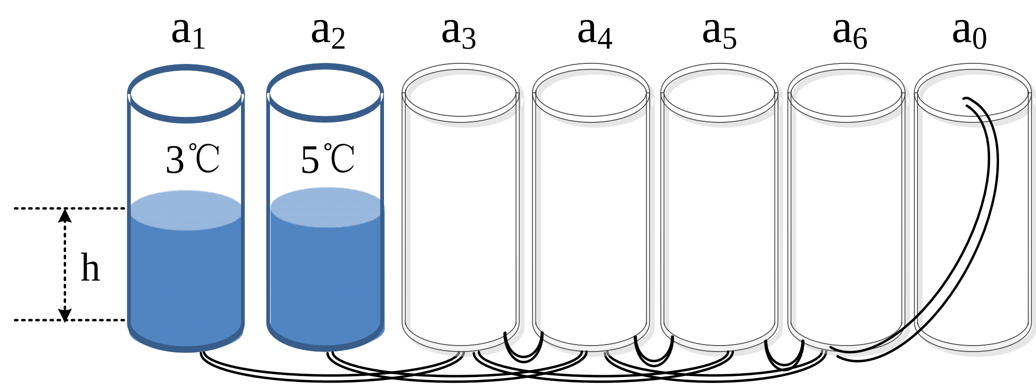
- Influence: two micro steps
  - compare persistency (fluid height)
  - fluid flowing from one container to another

Solution

- FluidRating
  - from rating network to fluid dynamics system



rating network



fluid dynamics system

Solution

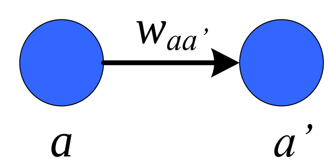
- FluidRating: 3 steps
  - Fluid Updating Preparation
    - Calculate the fluid volume that will flow (each pair of users)
  - Fluid Updating Execution
    - Let fluid flow and mix (all users)
  - Sample Aggregation
    - collect and aggregate samples (from multiple rounds)

Solution

- Step 1: Fluid Updating Preparation
  - the speed of efflux: Torricelli's law

$$v_{aa'} = \sqrt{2g(h_a - h_{a'})}$$

  - the volume of fluid that will flow



$$s_{aa'} = \sqrt{2g[h_a(i) - h_{a'}(i)]} \cdot w_{aa'} \cdot \Delta$$

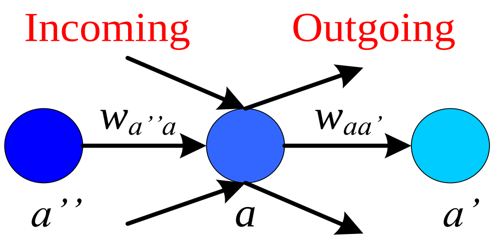
  - the temperature of fluid that will flow

$$t_{aa'} = t_a$$

Solution

- Step 2: Fluid Updating Execution
  - the updated volume

$$s_a(i+1) = s_a(i) - \sum_{a'\in N_a^{out}} s_{aa'} + \sum_{a''\in N_a^{in}} s_{a''a}$$

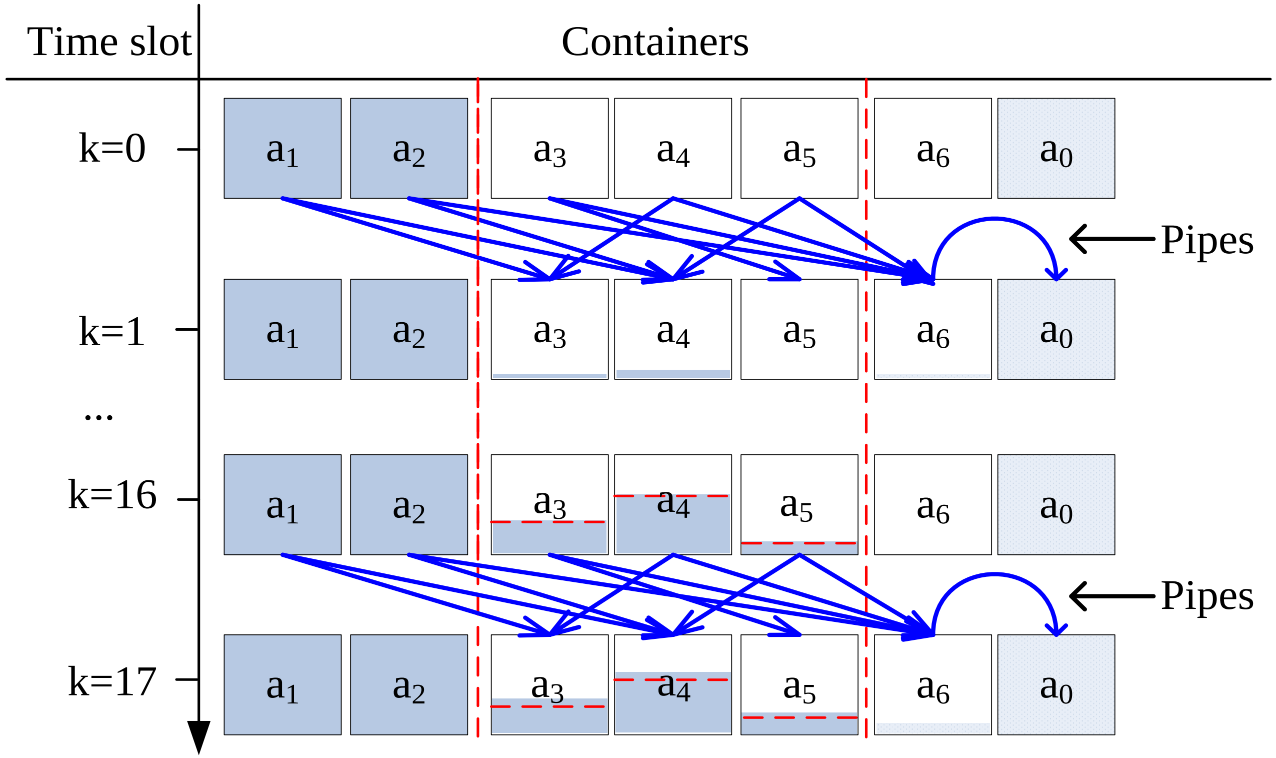


  - the updated temperature

$$t_a(i+1) = \frac{t_a(i)\cdot[s_a(i) - \sum_{a'\in N_a^{out}} s_{aa'}] + \sum_{a''\in N_a^{in}} t_{a''a}\cdot s_{a''a}}{s_a(i+1)}$$

Solution

- Step 2: Fluid Updating Execution
  - example

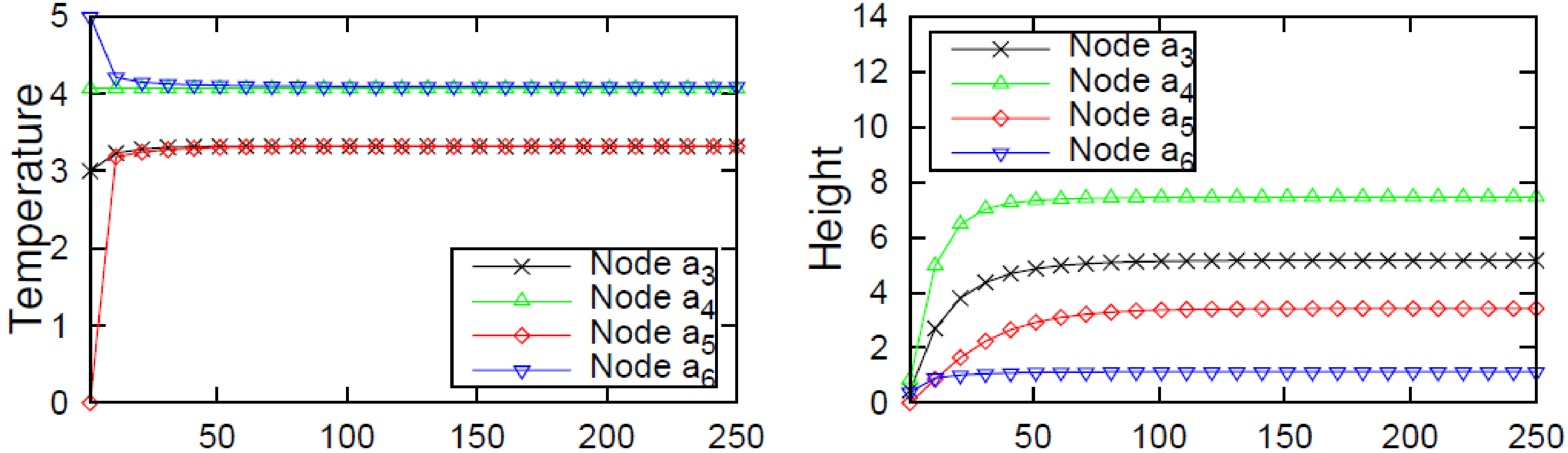


Solution

- Step 3: sample aggregation
  - aggregation sequence can be uniform or non-uniform
  - give earlier samples more weight

$$t_{a_n} = \sum_{i=1}^{k} q^{1+c(i-1)} \cdot t_{a_n}(i)$$

Convergence of Example Scenario



The height and temperature become stable after some time

The varition decreases with iterations

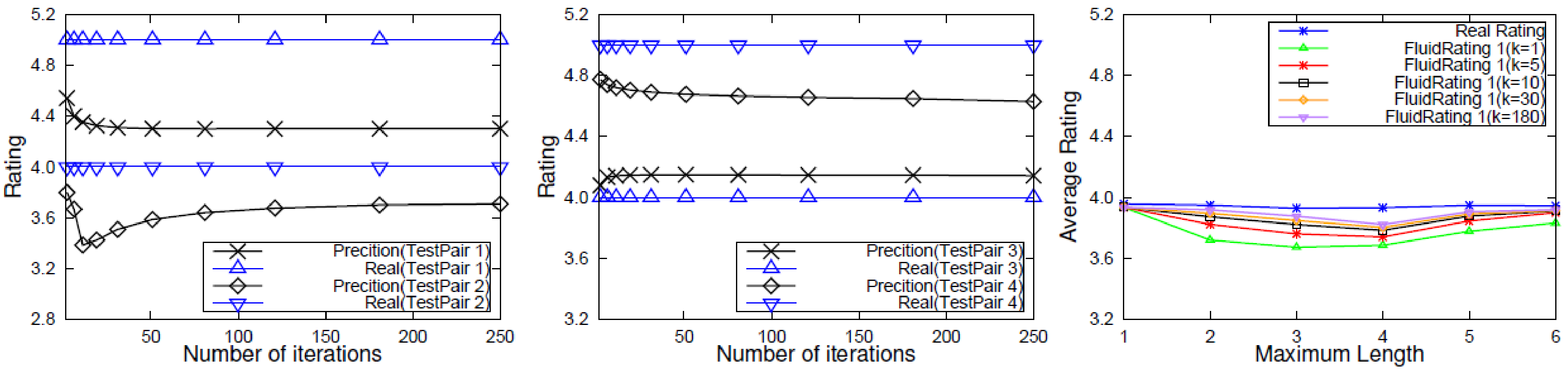
Experimental Evaluation

- Data set: Epinions
- Test method: Leave-one-out
- Metric: RMSE $RMSE = \sqrt{\sum (r_{u,i} - \hat{r}_{u,i})^2} / D$

Parameter	Description	Default value
h	fluid height in rater's container	10
b	cross-sectional area of containers	1
k	number of interations	250
Δ	time slot	0.04
c	(non-)uniform aggregation	(1)0
q	uniform aggregation	$1/k$
	nonuniform aggregation	[0.1,0.9]

Experimental Evaluation

- The effects of first influence

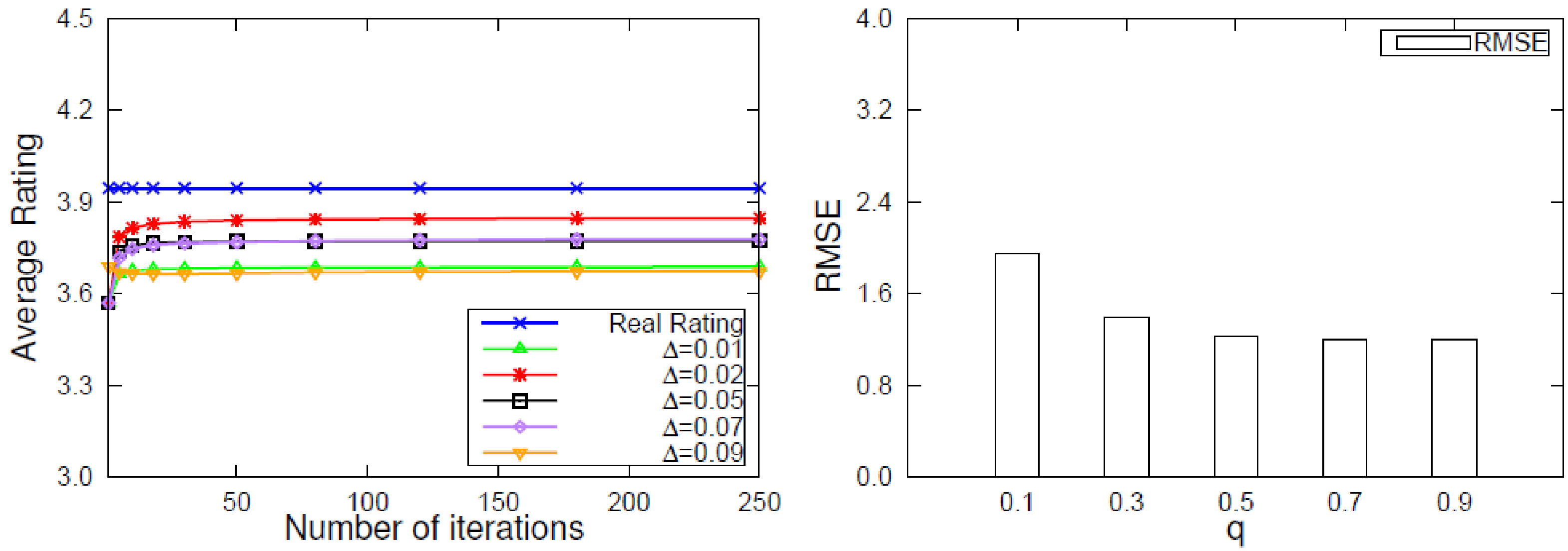


(a) Test pairs 1 and 2 (b) Test pairs 3 and 4 (c) All test pairs

- (a) and (b) show four different patterns of 4 user/item test pairs. In all the four patterns, the first samples give predictions close to the real truth.
- (c) provides a comparison of the average ratings with respect to the number of iterations (i.e., *k*) and the maximum length

Experimental Evaluation

- The effects of impact factors

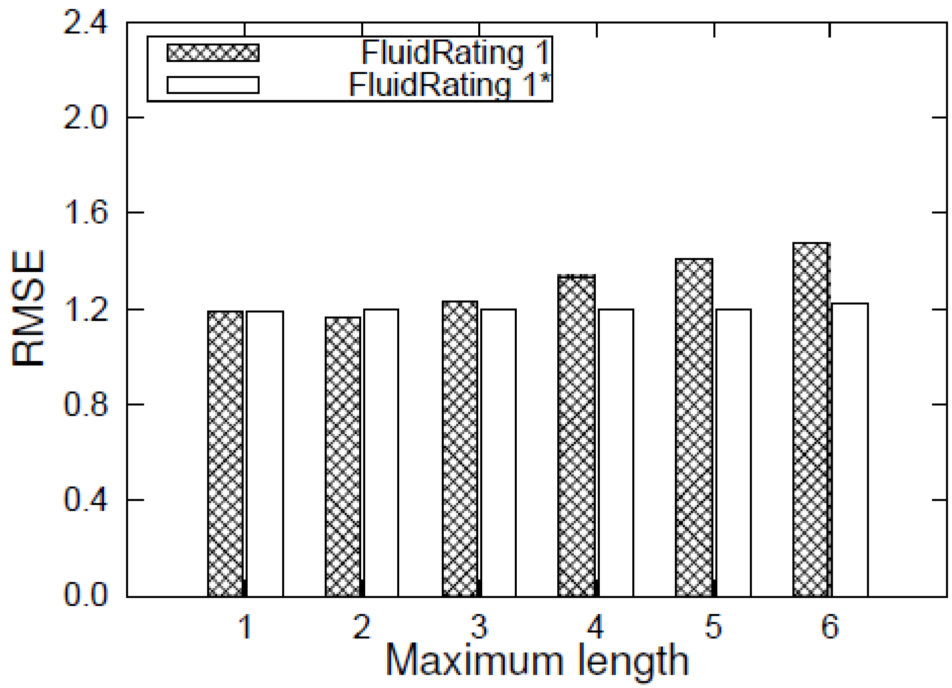


The left figure depicts the average predicted rating with FluidRating 1, and different settings of the time slot duration.

The right figure shows the RMSE of FluidRating 1 with *c=1*, and *q* changing from 0.1 to 0.9.

Experimental Evaluation

- The effects of aggregation methods

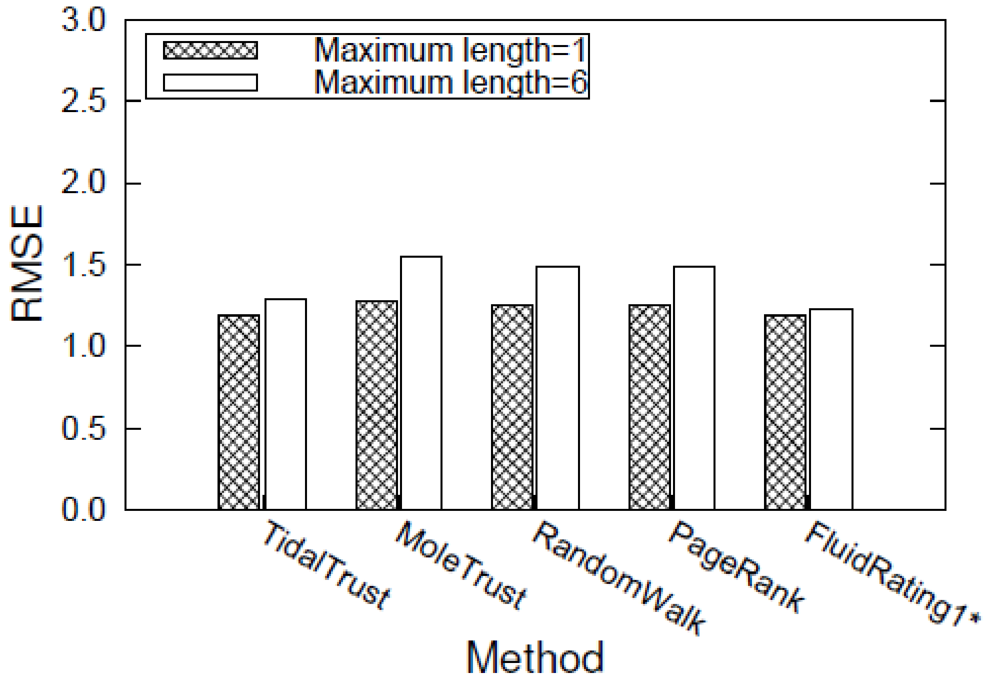


This figure compares FluidRating 1 with c = 0, c = 1, and q = 0.5; the latter is denoted as FluidRating 1*.

Finding: When we put more weight on the earlier influence, the accuracy is improved.

Experimental Evaluation

- Comparison of Multiple Methods



The comparison of several trust-based recommendation methods

Finding: FluidRating beats others; the RMSE of using FluidRating 1* is 4.812% less than that of using TidalTrust when the maximum length=6

Summary of Experiments

- Validate the time-evolving effects
- Validate the existence of first influence
- Test the effects of several factors
  - iteration number
  - time duration
  - aggregation sequence
  - sample approach (see details in paper)

Conclusion & Future Work

- Conclusion
  - FluidRating can reflect the time-evolving feature
  - differentiate direct and indirect influence
  - reflect the user personality feature (persistency)
- Future work
  - More personality features (e.g., persuasiveness)
  - Real experience evolution

Thank you for your attention

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