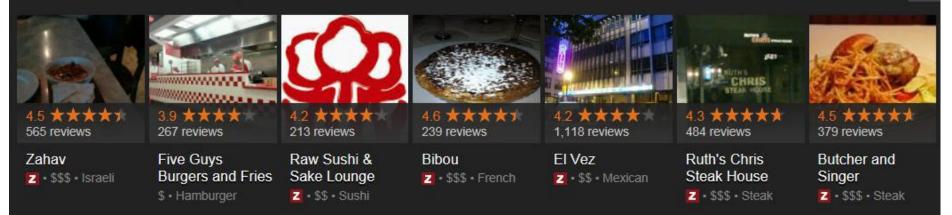
DynFluid: Predicting Time-Evolving Rating in Recommendation Systems via Fluid Dynamics

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1. Personalized Recommendation

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

Restaurant near Philadelphia, PA



Pric

1. Personalized Recommendation

Two types of trust-based recommendations friend advices and public channel

Apple iPhone 5S 16GB from £428.89 to £1.373.00 (25 offers) · Product Information Image: Strategy of the strat	Product Description
**** (25) Look & Feel Revi	w only ews with images (8) hond reviews (1) Public Broadcast Channel
1-15 of 49 reviews • ChemicalRo • ChemicalRo • Shiny, New, Looks Fab, Does Exactly What You Want • It's Expensive! •that I changed my mind! == Apple are a technology giant all across the world, most people have heard copying each others products. Or because they bring out new phones every few months, or at least it feels that way ship them out personalised if you pay for it" Read review 23.10.2013 Ciao members have rated this review on average: ===== exceptional	

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 impact
- O Users have different features

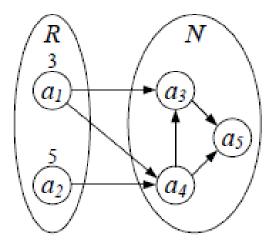
3. System Setting

Nodes

- 🔾 Raters, R
- O Non-raters, N

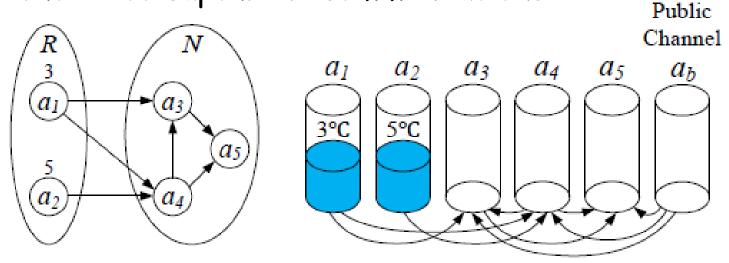
Influence Relationships

- Converted from trust relations
- Among raters and non-raters
- Each relationship is weighted



4. Model

Fluid Model to capture recommendations

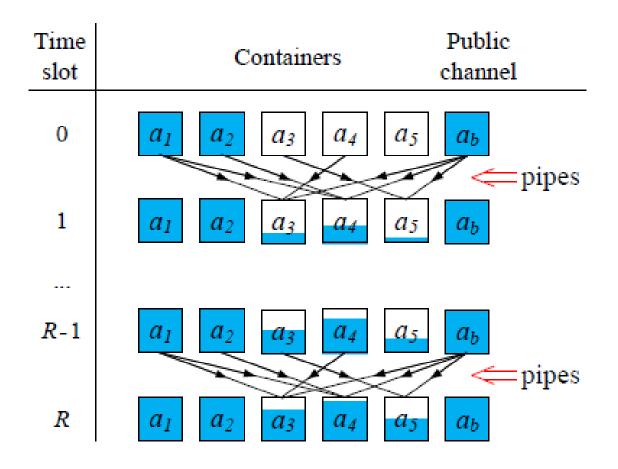


Containers -> Users

Container fluid height -> User persistency Fluid temperature -> User Rating Score Public channel -> A special public container

4. Model

Discrete approach to compute fluid update



4. Model

Container fluid volume update rule:

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

Container fluid temperature update rule:

$$t_a(i+1) = \frac{\begin{bmatrix} s_a(i) - \sum s_{aa'}(i) \end{bmatrix} \cdot t_a(i) + \sum \begin{bmatrix} s_{a'a}(i) \cdot t_{a'a}(i) \end{bmatrix}}{a' \in N_a^-}}{s_a(i+1)}$$

5. Theorem and Property

Theorem 1: If we use a constant value (denoted by h) to initialize the fluid heights of all the raters and the public channel, then the fluid heights of all the nonraters will always be no larger than h, during the fluid updating process.

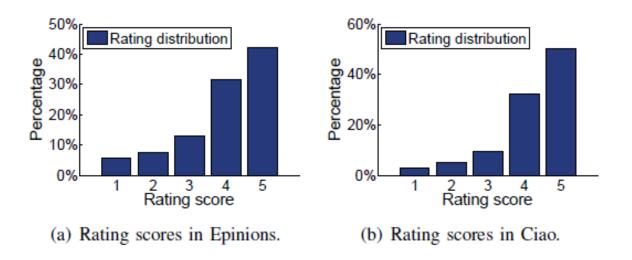
Theorem 2: If we use a constant value (denoted by h) to initialize the fluid heights of all the raters and the public channel, then, after a time period that is sufficiently long, the fluid heights of all the nonraters will be h.

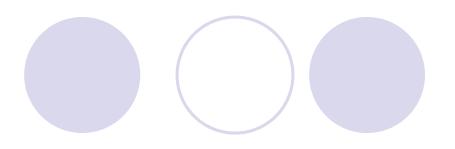
5. Theorem and Property

Property 1: In DynFluid, the opinion influence from a user, a, to another user, a', decays monotonously with respect to the hop-count distance from a to a'.

Property 2: In DynFluid, the certainty of the rating prediction for a non-rater can be measured by the fluid height (or persistency) of that non-rater.

- Epinions dataset consists of 49,290 users who rated a total of 139,738 different products. The total number of issued trust relationships is 487,181.
- The Ciao dataset consists of 2,248 users who rated a total of 16,861 different products. The total number of issued trust relationships is 57,544





Performance metric

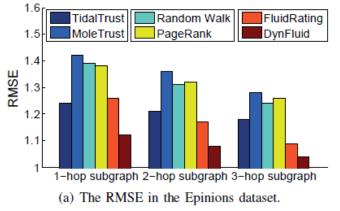
- Root mean squared error (RMSE)
- F-score (harmonic mean of precision and recall)

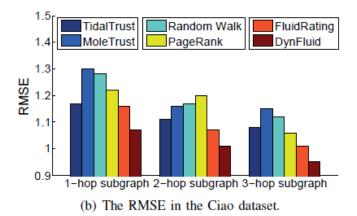
Default parameters

- Time slot length is 0.1
- Rounds of update is 10
- Cross-sectional areas of all the containers are 1
- Initial temperature of the public channel is the average score of all the raters.

Comparison algorithms: TidalTrust, MoleTrust, Random Walk, PageRank, and FluidRating

Epinions and Ciao result (RMSE and F-score):







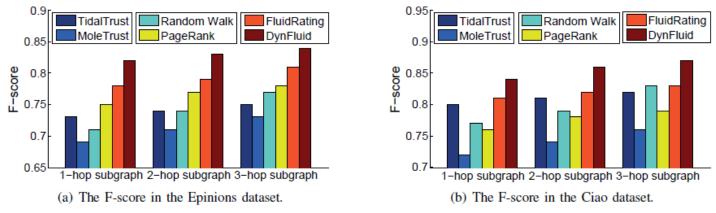
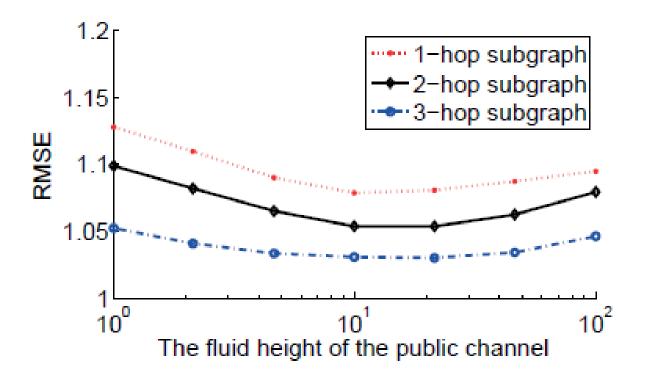
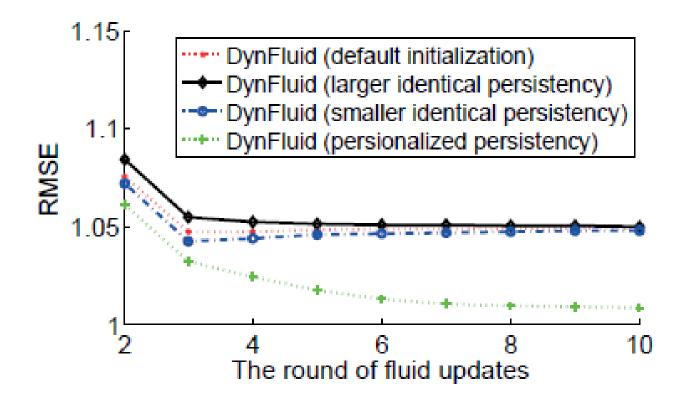


Fig. 7. Compare DynFluid with the other methods, in terms of the F-score metric.

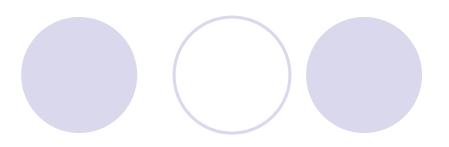
Impact of the public channel (Epinions):



Impact of the user persistency (Epinions):



7. Conclusion



Conclusion:

- Our model can reflect the time-evolving feature
- Differentiate direct and indirect influence
- Public Channel is very effective
- Reflect the user personality feature (persistency)

Future Work

- Update the discrete computation model
- Capture more user features







