

Personal vs. Social

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Motivation: Find a Restaurant for Dinner



K closest restaurants...!!

Consider five closest restaurants for dinner

1 Restaurant 1:

• Hour and a half wait

2 Restaurant 2:

• Does not meet my dietary

3 Restaurant 3:

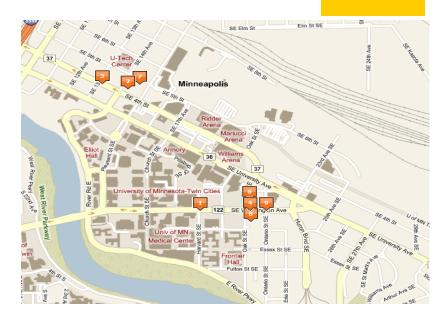
• Way too expensive

4 *Restaurant 4:*

• Closed for remodeling

5 *Restaurant* 5:

• 30 minute drive-time, bad traffic accident along the route



Closest is NOT always Better



A personalized answer that is aware of user preferences and surrounding contextual information,

Personalization



Preference Queries



Recommender Systems



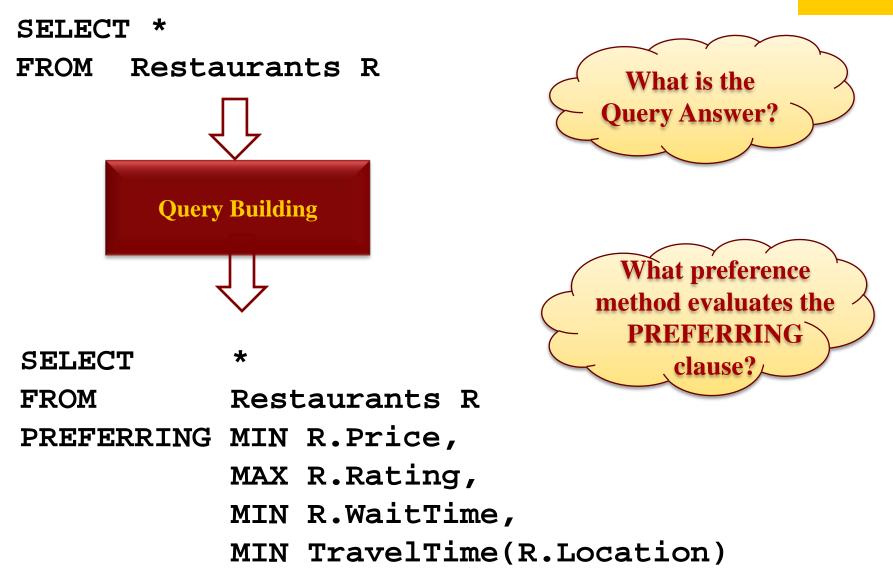
Context-Awareness Privacy Efficiency

VS.

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Preference Queries



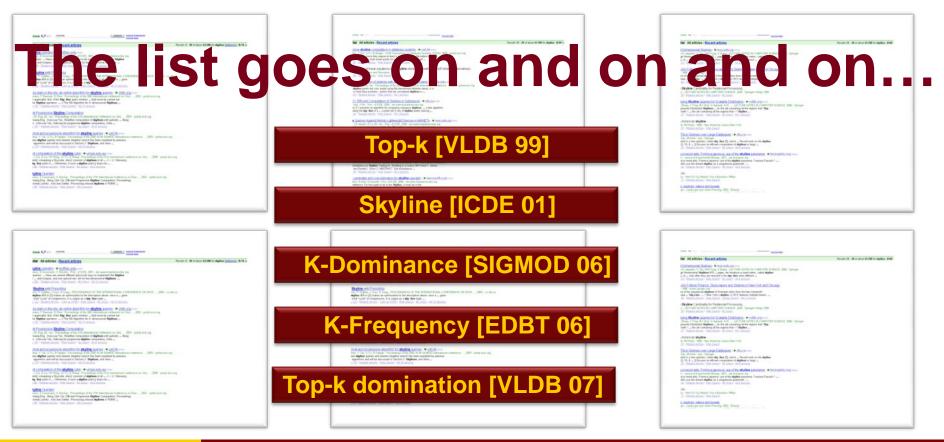


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Preference Evaluation Methods

Quick Exercise

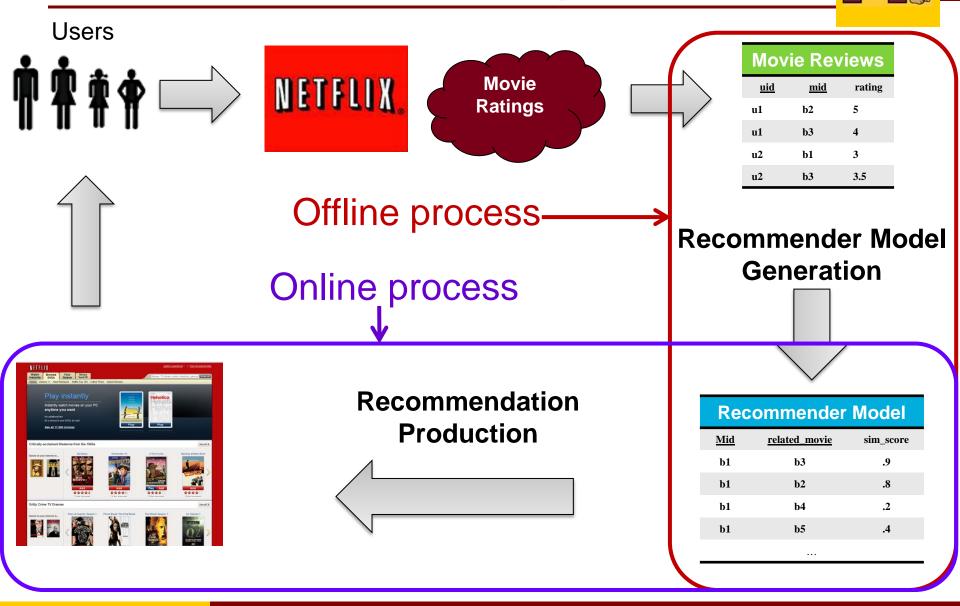
- 1 Go to scholar.google.com
- 2 Search for papers on preference evaluation methods
- 3 How many results do you get back?



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Recommender Systems



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Context-Awareness



- User Context / Preference
 - □ Stored in the Client side: User location, health status, budget, etc...
- Database Context
 - □ Stored in the database side: restaurant waiting time, price, today's specialty
- **Environmental Context**
 - □ Stored in a third-party: Traffic, weather, road network, transportation

Preference Queries

Context requirements are added in the PREFERRING clause of the SQL Query

Recommenderr Systems

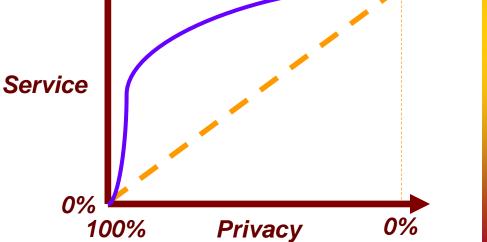
- Context requirements are considered as an after thought problem
- The model is built first, then the contextual conditions are tested

Privacy



Preference Queries

You always need to give up something (e.g., location, preference, context) to get the service. 100%



Recommender Systems

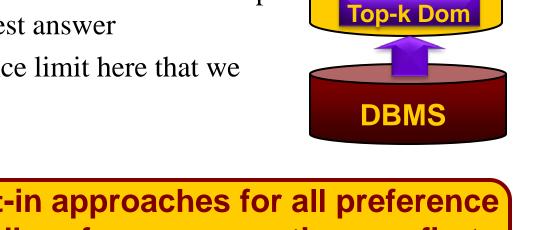
- Recommendation information can be obtained without revealing much information where a fake identity can be used
- If actual identity is used, e.g., social networking, privacy would be a major threat
- Adding context information would reveal privacy

The challenge here is not only how to protect user privacy, but also, how to obtain the services after protecting the privacy

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Efficiency (Preference Queries)

- With the exception of ranking queries, most of the existing work in preference queries focus on either:
- 1. Finding new meanings of the best answer
 - We really have enough of these...!!!
- 2. Finding smart algorithms to be evaluated on top of a DBMS to find the best answer
 - There is a performance limit here that we cannot go beyondI







Preference

Evaluation

Top-k

Skyline

K-Dom

K-Freq

Efficiency (Recommender Systems)



- The main focus is mainly on the quality of the answer as the expensive process of model generation is done offline
- New environments (e.g., social networks and online news) require fast recommendation process as user opinions expressed instantly

Fraternity of the Wired Works in the Wee Hours

By JENNA WORTHAM Published: July 25, 2010

"Recommend" button

NEW YORK - After college, most people do their best to avoid having to pull any more all-nighters. But for some, even after graduation, the wee hours of the morning are the most productive.



Enlarge This Image That is what led Amber Lambke and Allan Grinshtein to start a group called the New York Nightowls, a sort of study hall for entrepreneurs, freelancers and software developers who gather at 10 every Tuesday night

1	ACEBOOK
6 1	WITTER
V P	RECOMMEND
	BIGN IN TO E- MAIL
₿ F	PRINT
F	REPRINTS

SHARE 9



It is time to for finding efficient methods for online model generation

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Our Work in Minnesota

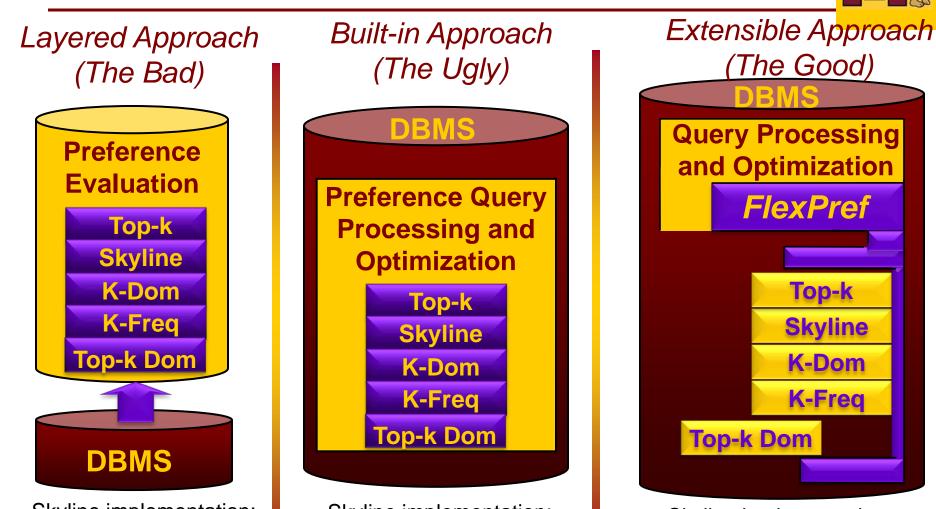




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FlexPref





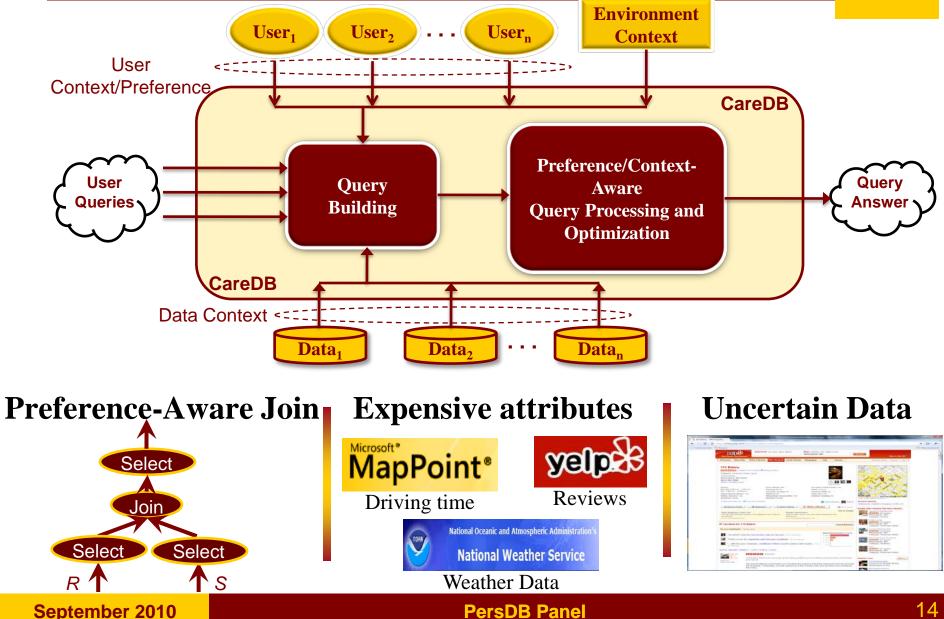
Skyline implementation: ~200 lines of code (selection by nature) Bad Performance

Skyline implementation: ~2000 lines of code for selection only Good Performance Skyline implementation: ~300 lines of code for selection and join Good Performance

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CareDB

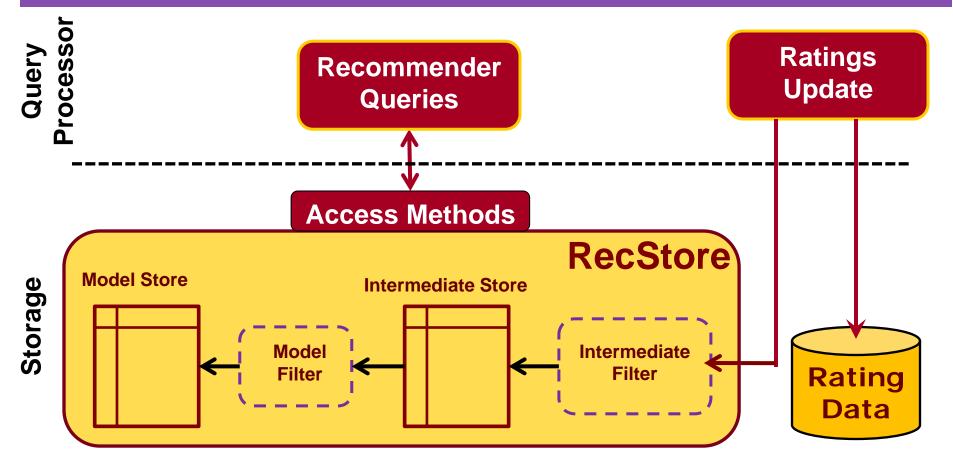




RecStore



SELECT M.itm as RecItem, SUM(M.sim*U.rating)/SUM(M.sim) as Prediction
FROM Model M, usrXMovies U
WHERE M.rel_itm = U.itmId AND M.itm NOT IN (select itmId FROM U)
GROUP BY M.itm ORDER BY Prediction DESC;





Thanks



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Acknowledgments





NSF- CAREER: Extensible Personalization of Spatial and Spatio-temporal Database Management Systems. 2010 - 2015



NSF- IIS: Towards Ubiquitous Location Services: Scalability and Privacy of Location-based Continuous Queries. 2008 - 2011



NSF- IIS: Preference- And Context-Aware Query Processing for Location-based Data-based servers. 2008 -2011



Microsoft^{*}

Microsoft[®]

- **NSF- CNS:** Infrastructure for Research in Spatio-Temporal and Context-Aware Systems and Applications. 2007 - 2011 Microsoft Research. Microsoft Unrestricted Gift, 2009 Research
- Microsoft Research. Microsoft Unrestricted Gift, 2010 Research