



TasteWeights

A Visual Interactive Hybrid Recommender System

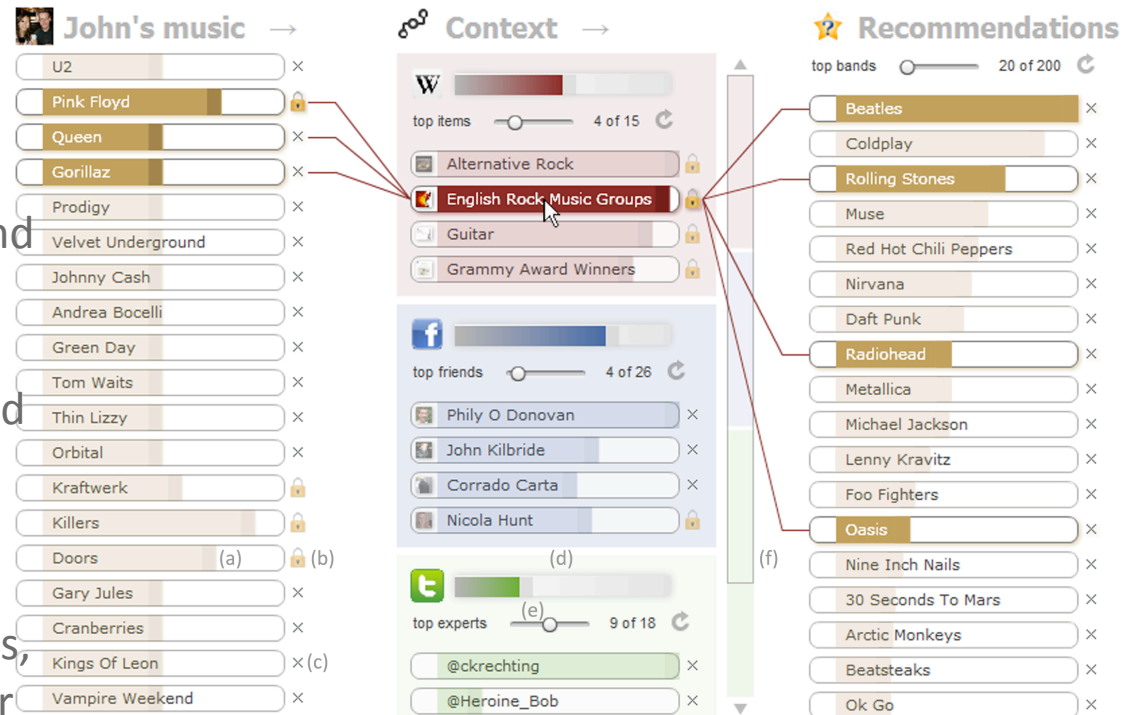
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Motivation

Problems

- Many traditional recommenders are “black boxes” and lack explanation and control [Herlocker]
- “Why am I being recommended this movie? I don’t like horror films.”
- Even in modern recommenders, data can be static, outdated or simply irrelevant from the beginning.
- Data about users and items is spread far and wide.



Motivation

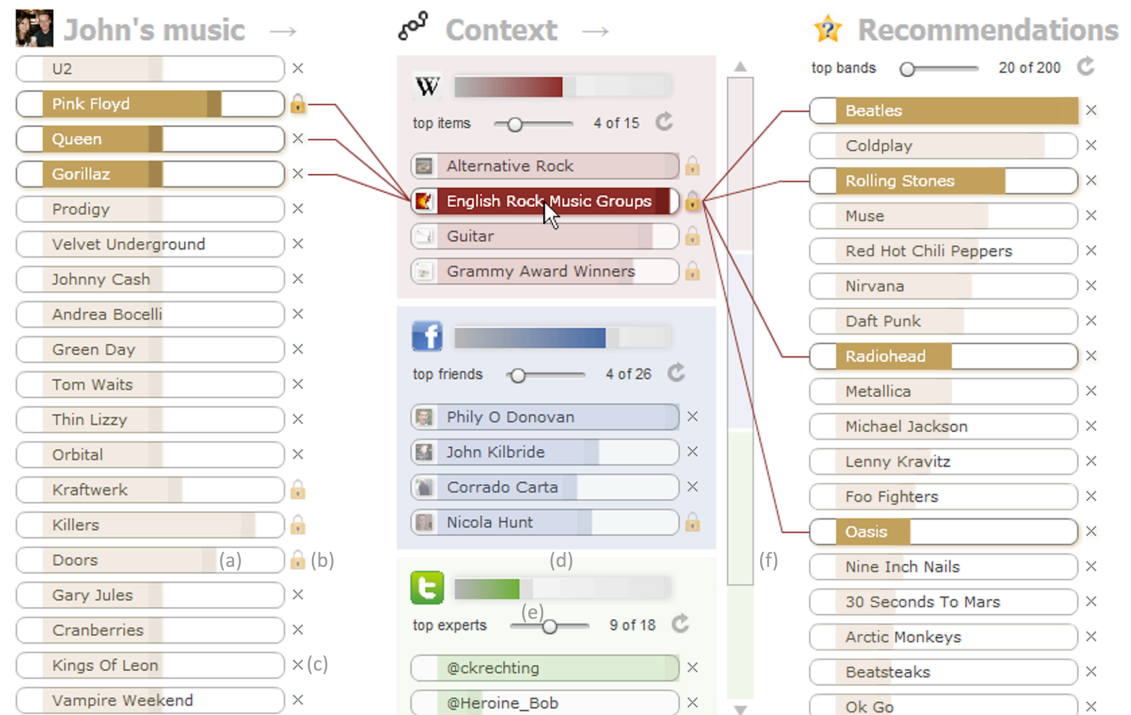
Challenges:

- Need for more dynamic, more adaptable algorithms that can cope with diverse data from APIs.
- And, we need an interface that can keep up...

Solutions?

User interfaces help to explain provenance of a recommendation. This can improve users' understanding of the underlying system and contribute to better user experience and greater satisfaction

Interaction allows users to: tweak otherwise hidden systems settings; provide updated preference data, recommendation feedback etc. etc.



TasteWeights: Background

Initial Work on Graph-based Representations of Collaborative Filtering Algorithms:

PeerChooser : Based on static MovieLens data

SmallWorlds: Web-based, dynamic data from Facebook API.

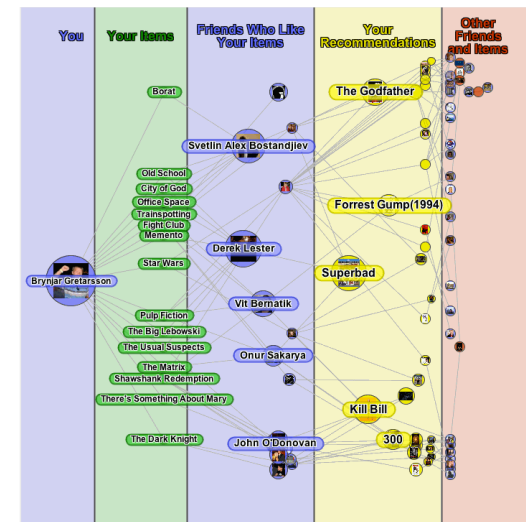
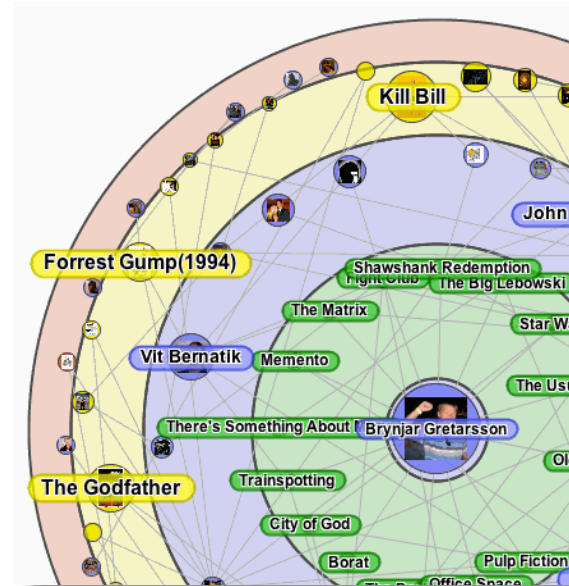
Issues discovered during evaluations:

PeerChooser: Interaction with nodes that represent movie genres ...too coarse.

SmallWorlds: A “complete” representation, but far too complicated view.

Learning from evaluations:

Abstraction, Detail-on-demand, Interactive Visual Cues, Cleaner game-like graphics, and more flexible API connectivity. Focus on “social” recommendation.





Interactive, Trust-based Recommendation for the Social Web

Live at <http://apps.facebook.com/smallworlds>

Interactive, Trust-based Recommender for Facebook Data

Supports user interaction to update information at recommendation time

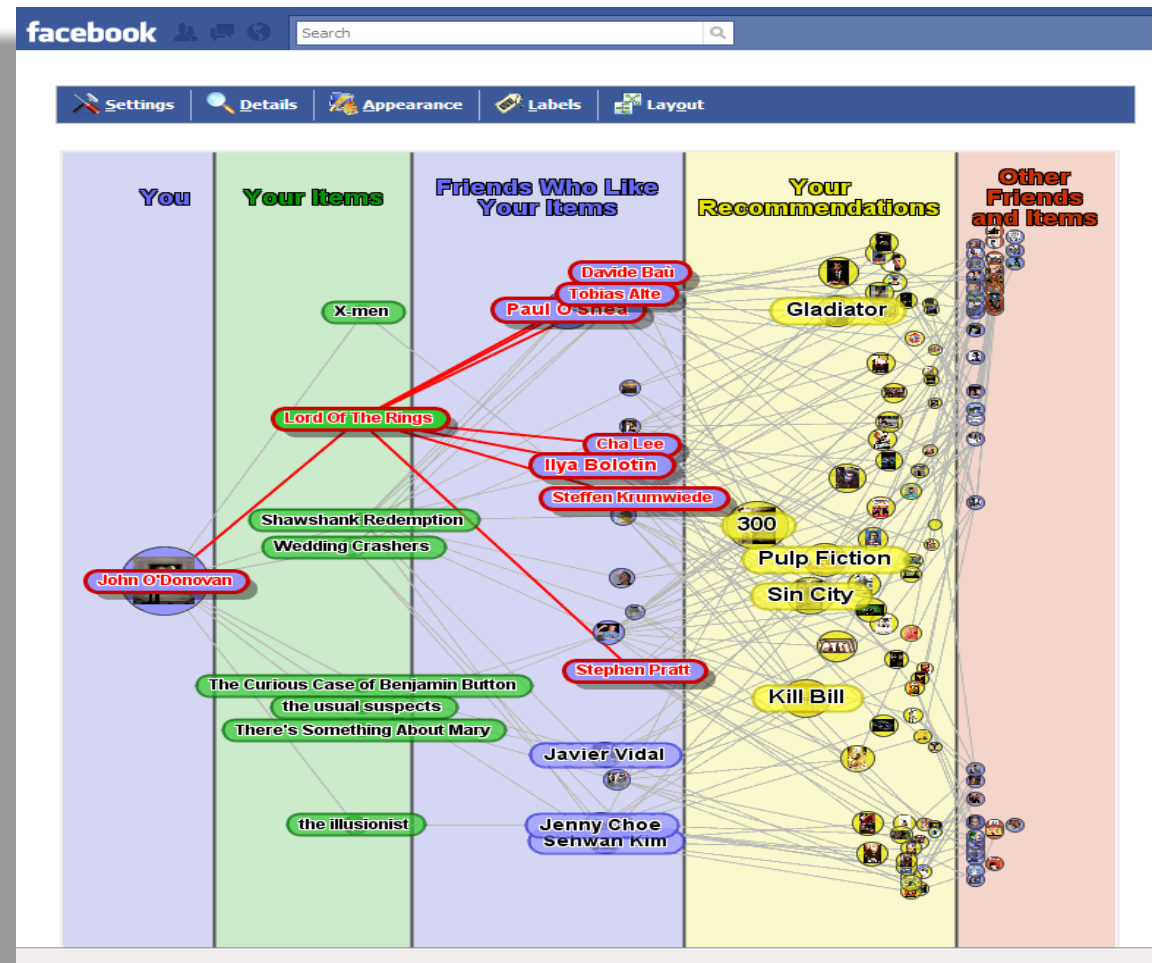
>Solves stale data problem.

Makes the ACF algorithm transparent and understandable.

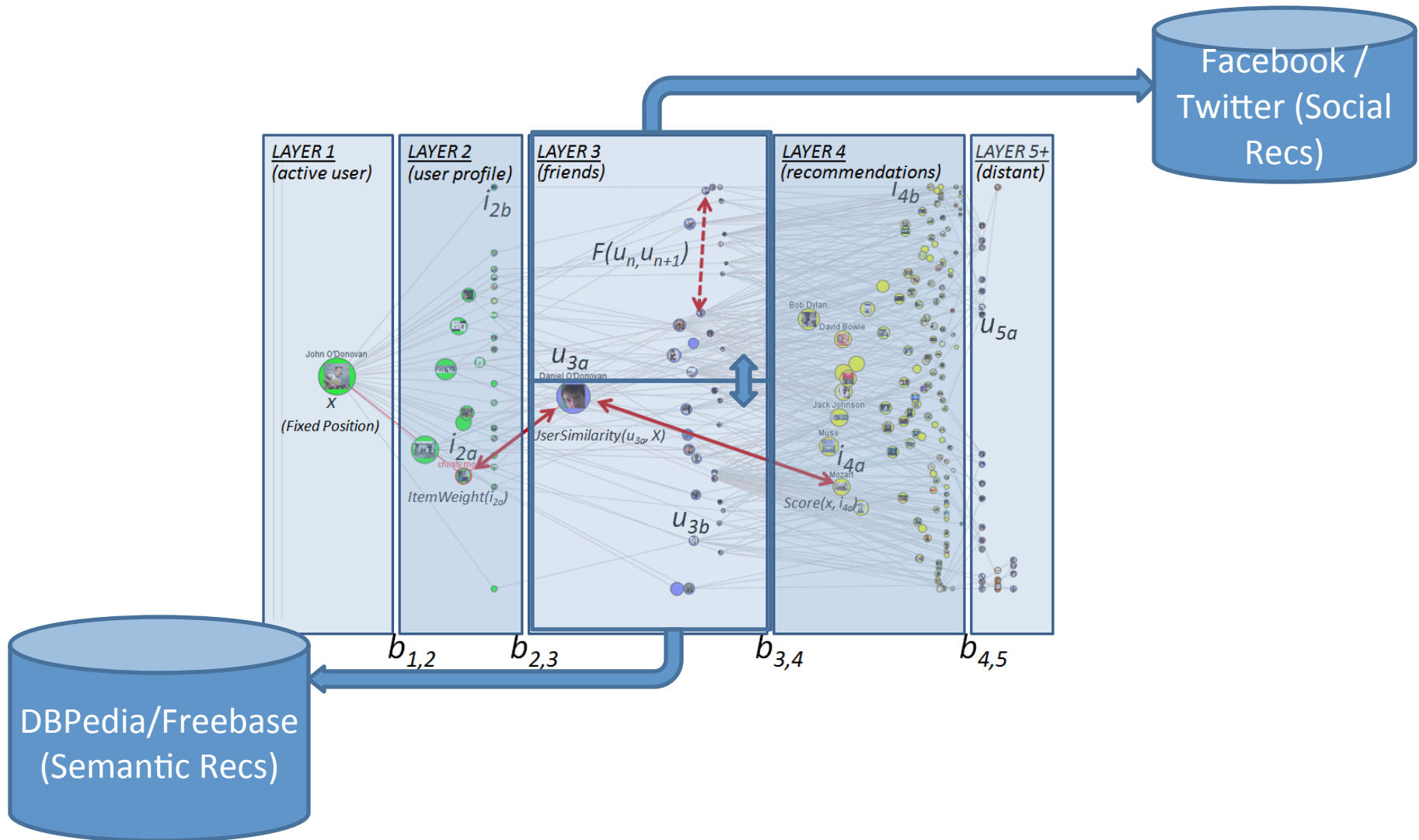
>increases satisfaction, acceptance etc.

Enables fast visual exploration of the data

>what-if scenarios
>increases learning



Combining Social and Semantic Recommendations



TasteWeights Design

The image shows a screenshot of the TasteWeights web application interface, which is designed to help users discover new music based on their existing tastes and social context. The interface is divided into three main sections: "John's music", "Context", and "Recommendations".

John's music (left panel): This section displays a list of 20 music bands that John has listened to. Each band name is followed by a progress bar indicating how much of the band's music John has listened to, and a small 'x' icon to remove the band from the list. The bands listed are: U2, Pink Floyd, Queen, Gorillaz, Prodigy, Velvet Underground, Johnny Cash, Andrea Bocelli, Green Day, Tom Waits, Thin Lizzy, Orbital, Kraftwerk, Killers, Doors, Gary Jules, Cranberries, Kings Of Leon, and Vampire Weekend. Red lines connect the "English Rock Music Groups" context item to the bands in this list that are highlighted in gold: Pink Floyd, Queen, Gorillaz, and Radiohead.

Context (middle panel): This section shows the user's current context, which is "English Rock Music Groups". It includes a slider for "top items" (4 of 15) and a list of related items: Alternative Rock, Guitar, and Grammy Award Winners. Below this, there is a section for "top friends" (4 of 26) with a list of friends: Phily O Donovan, John Kilbride, Corrado Carta, and Nicola Hunt. At the bottom, there is a section for "top experts" (9 of 18) with a list of experts: @ckrechting and @Heroine_Bob. Red lines connect the "English Rock Music Groups" context item to the bands in the "John's music" list that are highlighted in gold: Pink Floyd, Queen, Gorillaz, and Radiohead.

Recommendations (right panel): This section displays a list of 20 recommended music bands. Each band name is followed by a progress bar indicating how much of the band's music the user has listened to, and a small 'x' icon to remove the band from the list. The bands listed are: Beatles, Coldplay, Rolling Stones, Muse, Red Hot Chili Peppers, Nirvana, Daft Punk, Radiohead, Metallica, Michael Jackson, Lenny Kravitz, Foo Fighters, Oasis, Nine Inch Nails, 30 Seconds To Mars, Arctic Monkeys, Beatsteaks, and Ok Go. Red lines connect the "English Rock Music Groups" context item to the bands in this list that are highlighted in gold: Beatles, Rolling Stones, Radiohead, and Oasis.

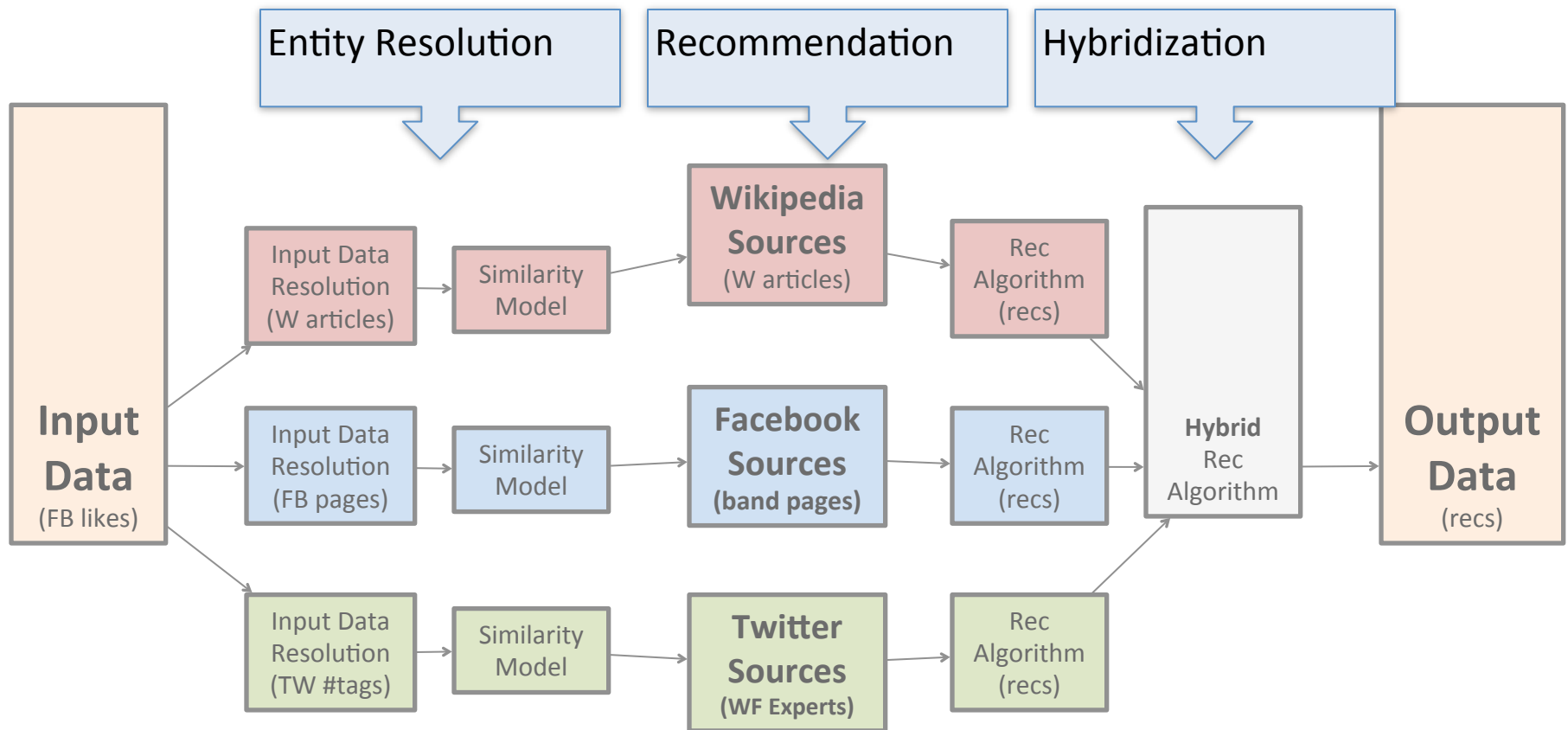
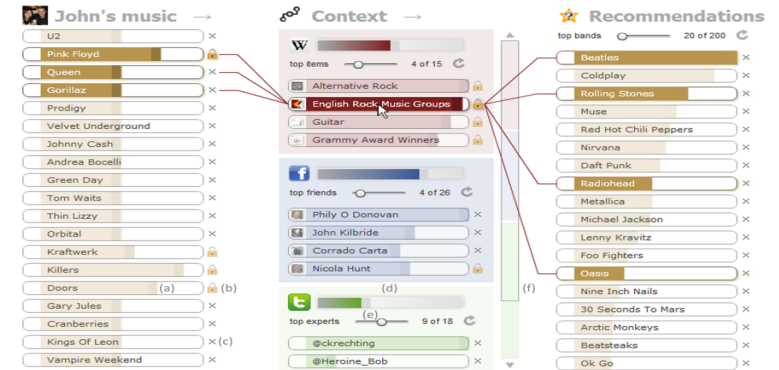
Labels (a) through (f) are placed near specific elements in the interface: (a) is near "Doors", (b) is near a lock icon, (c) is near "Kings Of Leon", (d) is near the "English Rock Music Groups" context item, (e) is near the "top experts" slider, and (f) is near the "Recommendations" section.

Demo

http://www.youtube.com/watch?v=9_JgynePm9w&hd=1

Approach

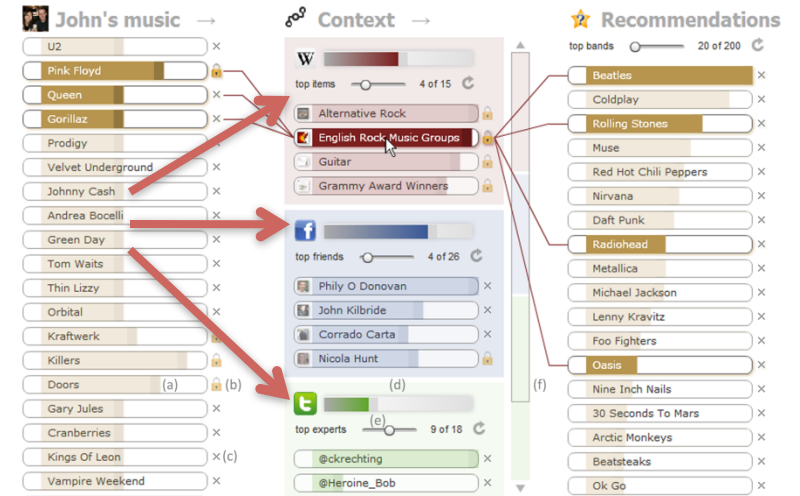
Parallel hybrid recommender system



Recommendation Sources

Input Data Resolution

Mapping between Wikipedia articles
Facebook pages, and Twitter #tags



Similarity Models

Wikipedia

(Data source: DBpedia)

$$W_{wiki_i} = \sum_{Linked(profile_j, wiki_i)} W_{profile_j}$$

Facebook

(Data source: Facebook Graph API)

$$W_{friend_i} = \frac{TWCI_{user, friend_i}}{\sqrt{TWI_{user}^2 \cdot TWI_{friend_i}^2}}$$

Twitter

(Data source: wefollow.com)

$$S_{expert_i, item_j} = \frac{|Experts_{item_j}| - Rank_{expert_i, item_j}}{|Experts_{item_j}|}$$

$$W_{expert_i} = \sum_{Linked(profile_i, expert_i)} (W_{profile_j} \cdot S_{expert_i, profile_j})$$

Generating Recs.

Individual Source

$$W_{rec_i, source_j} = \sum_{Linked(rec_i, item_k)} W_{item_k}$$

Hybrid Strategies

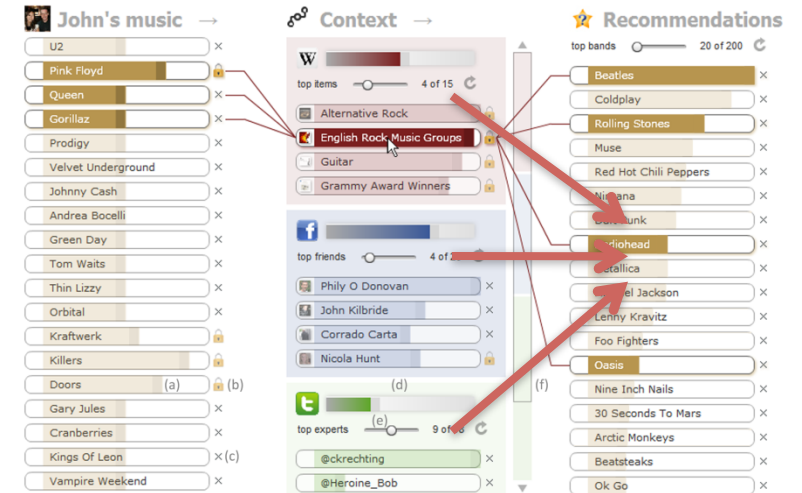
Weighted

$$W_{rec_i} = \sum_{source_j \in sources} (W_{rec_i, source_j} \cdot W_{source_j})$$

Mixed

Cross-source

$$W_{rec_i} = \sum_{source_j \in sources} (W_{rec_i, source_j} \cdot W_{source_j}) \cdot |Sources_{rec_i}|$$



Evaluation

Goals

- Evaluate combining social and semantic recommendations
- Evaluate explanation and transparency in a hybrid recommender
- Evaluate interaction in a hybrid recommender

Setup

Supervised user study. 32 participants from the human subject pool at UCSB

Procedure

Pre-questionnaire

Tasks

- Interact with Profile*
- Interact with Sources*
- Interact with Full interface*
- Rate recommendations*

Post-questionnaire (Explanation & Interaction)

Evaluation: Accuracy

Experiment

One-way repeated measures ANOVA

Compared 9 recommendation methods (below) in terms of rec. accuracy

Method (independent variable)

Single-source: Wikipedia, Facebook, Twitter

Hybrid: Weighted, Mixed, Cross-source

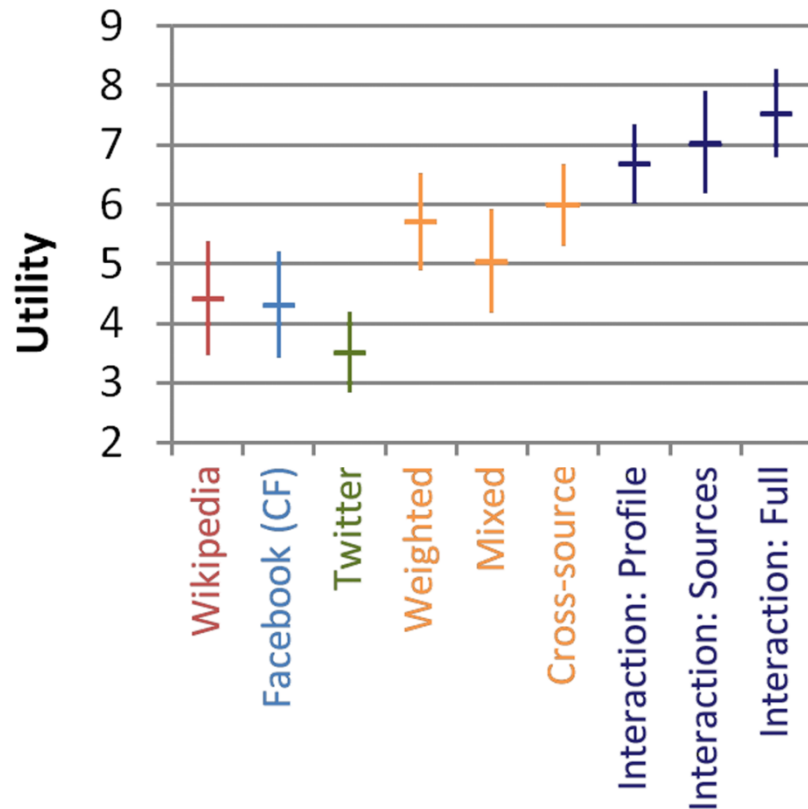
Interaction: Profile, Sources, Full

Accuracy (dependent variable)

Measured in terms of “**Utility**”

$$R_u = \sum_j \frac{\max(r_{uij} - d, 0)}{2^{\frac{j-1}{\alpha-1}}}$$

Results: Accuracy

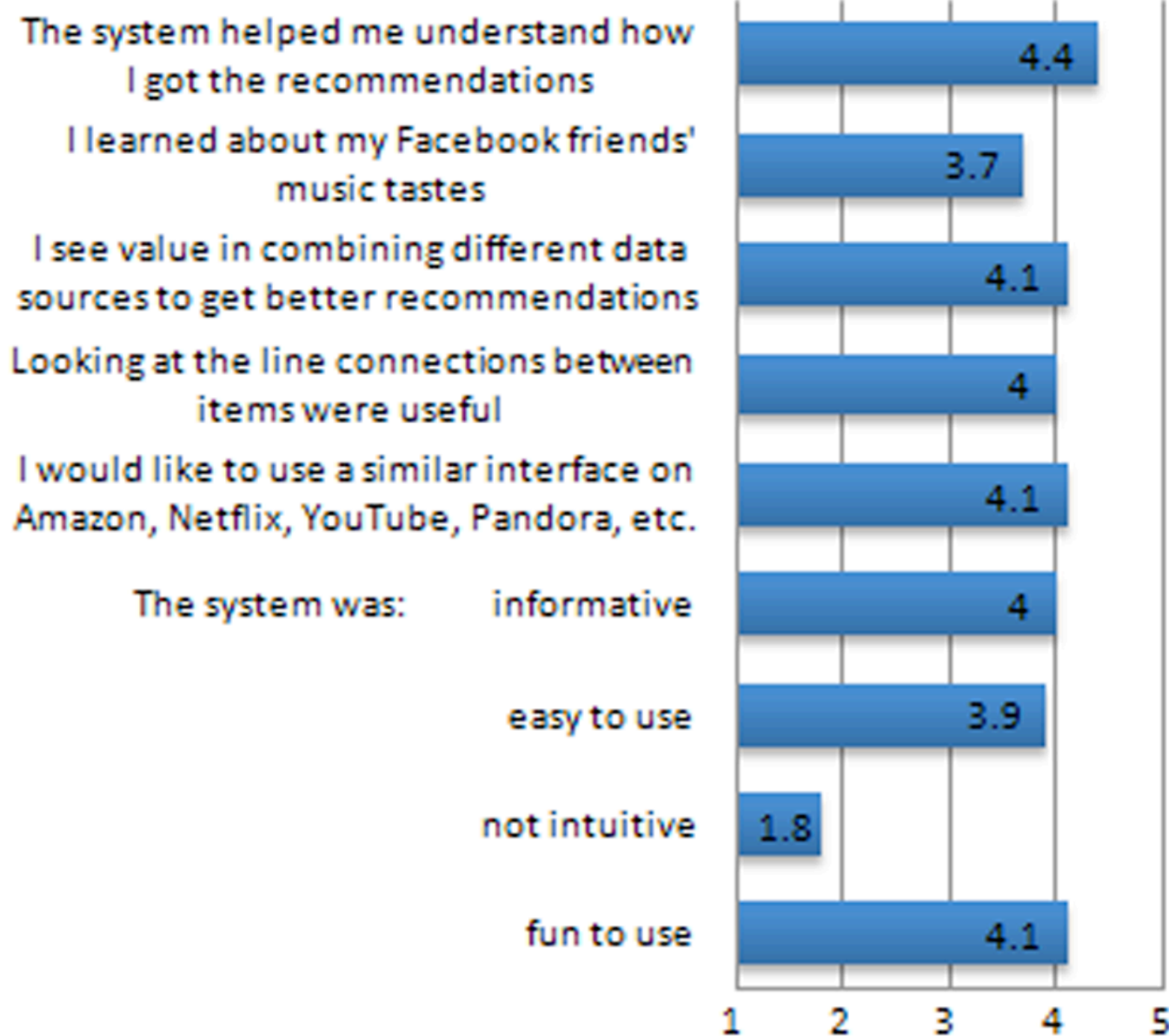


Plot of means of recommendation methods over utility with 95% confidence intervals

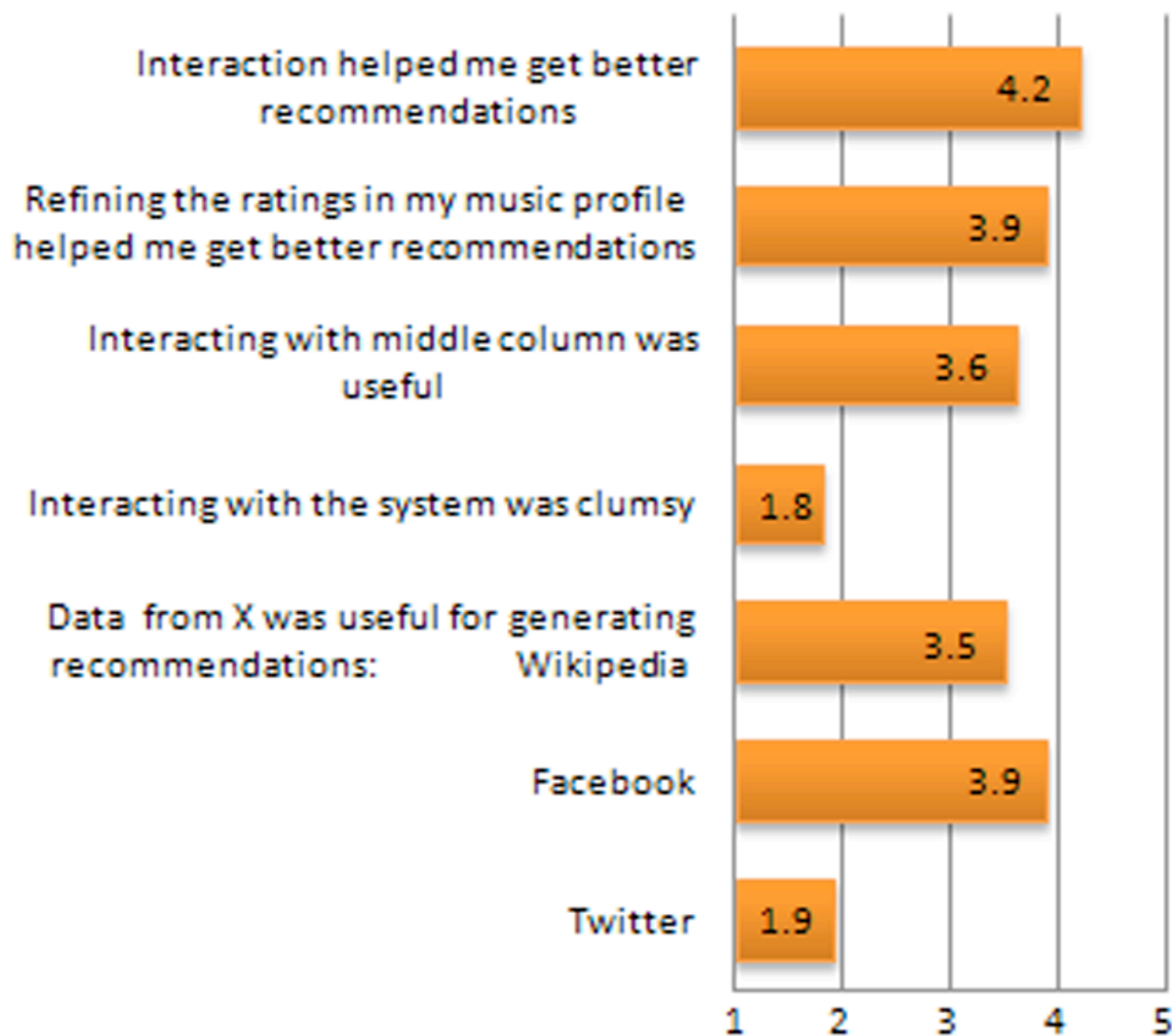
Method 1	Method 2	Diff	Lower	Upper	P Val
Cross Hybrid	Wikipedia	1.568	0.119	3.017	0.023
Cross Hybrid	Facebook (CF)	1.678	0.229	3.127	0.011
Cross Hybrid	Twitter	2.477	1.028	3.926	0.000
Full Interaction	Cross Hybrid	1.542	0.935	2.991	0.027

Results from a Tukey post-hoc analysis of the recommendation methods: multiple comparisons of means with 95% family-wise confidence level

Explanation & Learning



Interaction



Results: Diversity

TasteWeights on LinkedIn Data

Case Study: Portability of TW interface

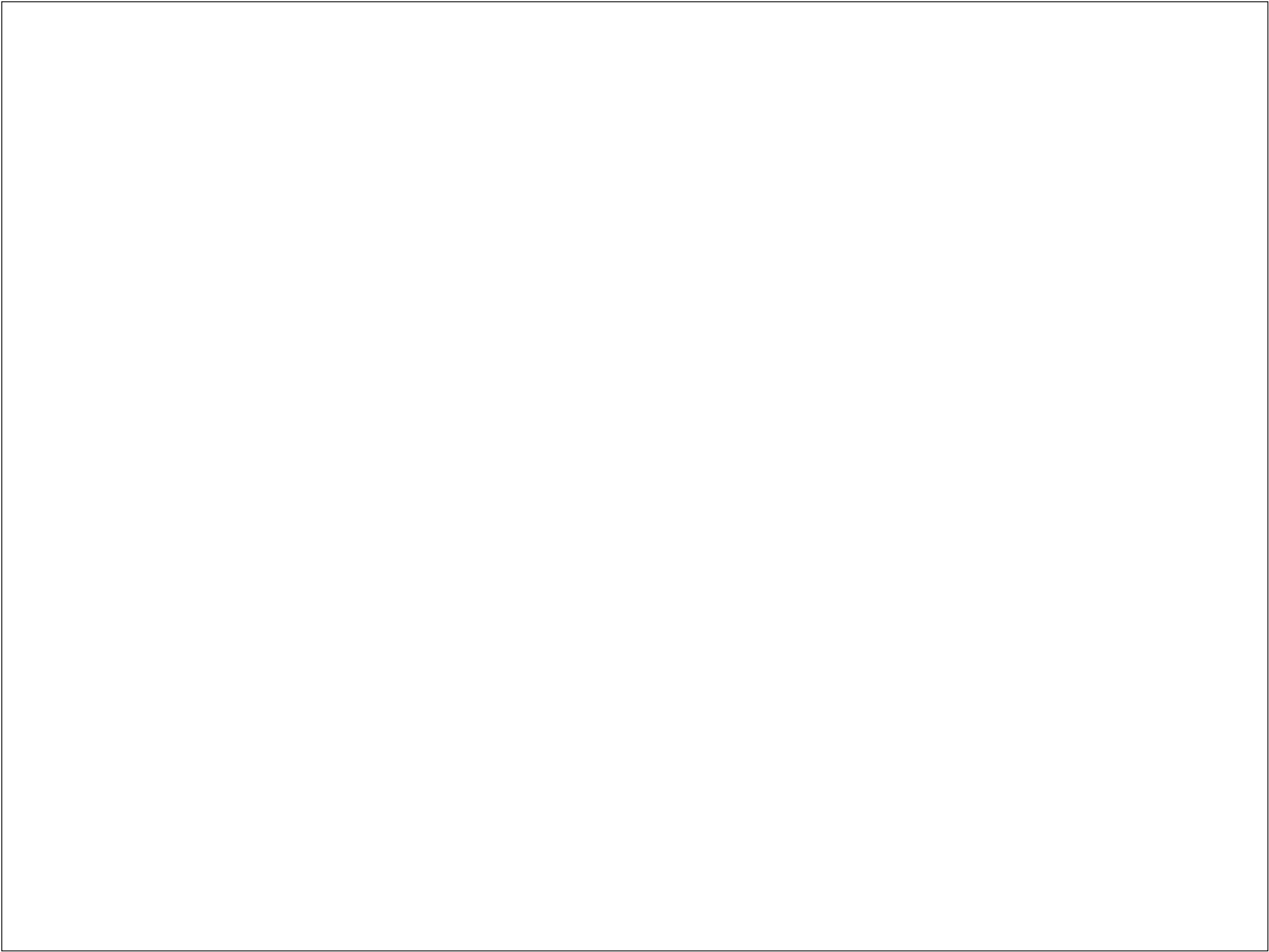
- Developed a Social-Semantic Recommendation algorithm for data from LinkedIn API
- Personalized for one “active” logged-in user.
- Visualized the algorithm in TasteWeights interface

Algorithm:

- Map profile items to noun-phrases
- Resolve to Wikipedia articles
- e.g.: ph.D => PHD, UCSB => UC Santa Barbara
- Compute similarity based on overlap in resolved entities.

Features

- Segmented / Organized user profile
- Interactive profile weighting
- Interactive weighting of social connections
- Dynamic re-ranking of recommendations (visual feedback)
- Provenance views to show effects of each interaction.



Conclusions

UI and interaction design are important considerations for RSs

- Increased explanation, provenance
- Expose otherwise hidden controls (e.g: control of hybrid recommender)
- Helps ease the stale data problem
- Support user input at various granularity (recommended item, recommendation partner, profile items etc)
- Increase ambient learning.
- Promote interest in the recommender system (game-like feel)

Contributions:

- Demonstrated a novel interactive RS
- Hybrid of recommendations from Wikipedia, Facebook and Twitter
- Evaluated via a 32 person supervised user study at UCSB.
- Demonstrated portability of the system on LinkedIn's API.

Results

- Interaction increases user satisfaction in all conditions. (more interaction = higher accuracy)
- Cross-source hybrid strategy outperformed individual source strategies.

After the break... Inspectability and

In this work we touched on the ideas of inspectability and control in the context of our hybrid recommender system.

In the next talk, Bart Knijnenburg (UC Irvine) will present results from a larger study that focuses on a general analysis of inspectability and control in social recommenders. This study used some components from our TasteWeights system.

Thanks for listening!