Which App Will You Use Next? Collaborative Filtering with Interactional Context

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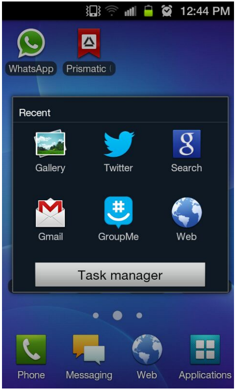

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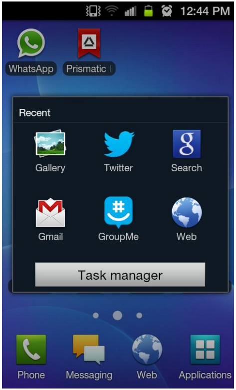

Recommend an app to use *next*

Which App Will You Use Next?

- Users click on items (apps) that are of interest in the *current* context
- Sequence of recently used items should help better zero in on the items the user would click next
- Applicable in settings where items are generally used repeatedly
  - listening to music from online radio
  - browsing products on shopping websites
  - ...

Problem Setting

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- Setting
  - Users $\mathcal{U} = \{u_1, u_2, \ldots, u_{|\mathcal{U}|}\}$ and items $\mathcal{I} = \{a_1, a_2, \ldots, a_{|\mathcal{I}|}\}$
  - Their history of sessions $\mathcal{S}$

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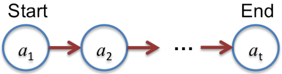
  - Sequence of items accessed by a user over a certain contiguous period



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    e.g. articles read by an online user when she is signed in

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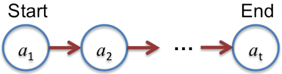

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    e.g. articles read by an online user when she is signed in
- Problem

  Given a specific user $u \in \mathcal{U}$

  with session *in progress* $s = \langle a_{i_1}, a_{i_2}, \ldots, a_{i_t} \rangle$, for some $t \geq 1$

  Recommend the best candidate item $a_{i_{t+1}} \in \mathcal{I}$

Main Differences

- Past sessions — implicit feedback in the form of click sequences
- Session in progress — interactional context (Dourish, 2004)

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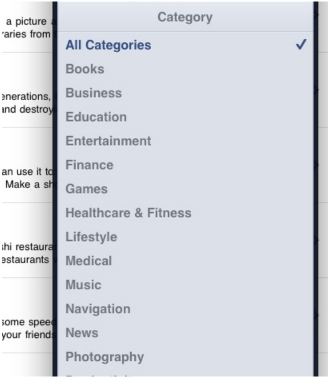
	Our problem	Traditional CF
Item interaction	Brief and repetitive	Usually once (watched/rated)
Feedback	Implicit (ordered clicks)	Explicit (ratings/comments)
Recommendations while user interacts	Dynamic	Static
Context	Interactional	Representational

Representational vs. Interactional Context

Representational Context:

user specifies preferences globally



Representational vs. Interactional Context

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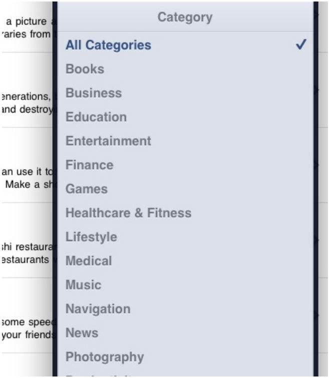

Interactional Context:

user preferences change between sessions

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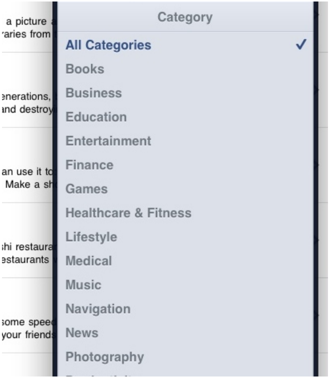

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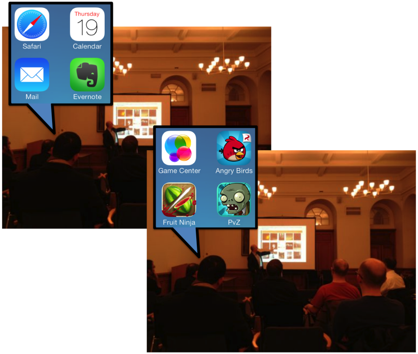

Representational vs. Interactional Context

Representational Context:

- What most context-aware CF methods have used
- Form of information provided as attributes — delineable and stable e.g. location, time and interests
- Defined *before* user interaction and influences user action
- Context and activity are separable

Interactional Context:

- Relatively unexplored
- Scope of context is defined dynamically — should be inferred from user interaction
- Context *arises* from user interaction
- Context is a relational property — relevant to some particular activity

Proposed Method: iConRank

Implicit Feedback via Click Sequences

- Session data examples:

$\langle$browser, maps, messages$\rangle$
$\langle$mail, phone, settings, phone, browser, phone, browser, search$\rangle$
$\langle$phone, calendar, messages, camera$\rangle$
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- User-item count matrix is *not* a good choice (Hu et al, 2008)
  - Need only ranking of items
  - Hard to gauge user preferences with clicks — no explicit scale
  - Want to model session history as sequences instead of counts

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  - Need only ranking of items
  - Hard to gauge user preferences with clicks — no explicit scale
  - Want to model session history as sequences instead of counts
- Simple and effective way to model sequences → Markov models
  - State space: set of items $\mathcal{I}$
  - State transition probability matrix $M \in \mathbb{R}^{|\mathcal{I}| \times |\mathcal{I}|}$
    - $M(i, j)$: probability that item j is clicked immediately after item i (first-order Markov model)
    - Estimated from training session data

Markov Modeling

Two extreme case Markov models:

- Individual-level
  - Estimated from session data of each user
  - Training data for a given user is too sparse to estimate $|\mathcal{I}| \times |\mathcal{I}|$ parameters
- Global-level
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Our approach:

- Cluster-level Markov model
  - Group users with common navigational patterns
  - Conforms with the basic idea of collaborative filtering

    "Combine preferences from *similar* users to make recommendations"

Behavioral Clustering

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$$d_{KL}(x, y) = \sum_{i=1}^{p} x_i \log_2 \left(\frac{x_i}{y_i} \right)$$

- Optimize k-means objective and compute centroid M_k of cluster π_k (Banerjee et al, 2005)

$$M_k = \frac{1}{|\pi_k|} \sum_{u \in \pi_k} M^{(u)}$$

Distance between user u and cluster π_k (centroid M_k)

$$d(u, \pi_k) = \frac{1}{|\mathcal{I}|} \sum_{i=1}^{|\mathcal{I}|} d_{KL}(M^{(u)}(i, \cdot), M_k(i, \cdot))$$

Neighborhood-based Model

Predicted rating $\hat{r}_{u,i}$ of user u and item i:

$$\hat{r}_{u,i} = b_{u,i} + \sum_{j \in \mathcal{N}(i)} w(i,j)(r_{u,j} - b_{u,j})$$

$\Rightarrow$ Weighted combination of "k-nearest neighbor" items (or users).

- $r_{u,i}$: rating of item i by user u
- $b_{u,i}$: rating bias — user and item bias
- $w(i,j)$: weights proportional to similarity between items i and j
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Two main changes

- Bias: introduce interactional context bias
- Weights (neighborhood): cluster-level Markov models

Incorporating Interactional Context

Introduce context bias $c_{u,i}$

$$f_{u,i} = b_{u,i} + \alpha \sum_{j \in \mathcal{N}(i)} w(i,j)(f_{u,j} - b_{u,j}) + (1-\alpha) c_{u,i}$$

- Context bias:

$$c_{u,i} = \begin{cases} 1, & \text{if item } a_i \text{ appears in current session } s \\ 0, & \text{otherwise} \end{cases}$$

- $\alpha \in [0,1]$: tradeoff between current context and information from past sessions
- Recurrence: want to estimate all item scores as session progresses

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- Recurrence: want to estimate all item scores as session progresses

Let $z_{u,i} = f_{u,i} - b_{u,i}$ to remove the click (rating) bias:

$$z_{u,i} = \alpha \sum_{j \in \mathcal{N}(i)} w(i,j) z_{u,j} + (1-\alpha) c_{u,i}.$$

Similarity and Neighborhood

Let $w(i,j) = M(j,i)$

$$z_{u,i} = \alpha \sum_{j \in \mathcal{N}(i)} w(i,j) z_{u,j} + (1-\alpha) c_{u,i}$$

$$\Downarrow$$

$$\mathbf{z}_u = \alpha M^T \mathbf{z}_u + (1-\alpha)\mathbf{c}_u$$

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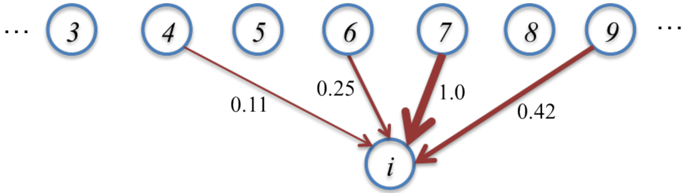
- Items that tend to transition to i more often receive higher similarity
- $\mathcal{N}(i)$ corresponds to items that transition to i in the Markov graph



Personalized PageRank

Normalize $\mathbf{z}_u$ to sum to 1

$$\mathbf{z}_u = (\alpha M + (1-\alpha)\mathbf{1}\mathbf{c}_u^T)^T \mathbf{z}_u$$

Personalized PageRank!

using Markov graph M and personalization vector $\mathbf{c}_u$

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Recall $z_{u,i} = f_{u,i} - b_{u,i}$

- Since focus is on item transitions, we set $b_{u,i}$ to be user u's transition probabilities of item a_{i_t} to other items
- Final score

$$f_{u,i} = z_{u,i} + M^{(u)}(i_t, i)$$

where $M^{(u)}$ is the transition probability matrix of user u

iConRank Algorithm

1. (**Offline step**) Cluster users $\mathcal{U}$ with past sessions $\mathcal{S}$ into k clusters using k-means algorithm. Compute transition matrix M_k for each cluster k:

$$M_k = \frac{1}{|\pi_k|} \sum_{u \in \pi_k} M^{(u)}$$

2. Compute personalized PageRank

$$\mathbf{z}_u = (\alpha M_k + (1-\alpha)\mathbf{1}\mathbf{c}_u^T)^T \mathbf{z}_u$$

   with current $\mathbf{c}_u$ and $k = \pi(u)$ is the cluster user u is assigned to
3. Compute scores $f_{u,i} = z_{u,i} + M^{(u)}(i_t, i)$
4. Rank items using $f_{u,i}$ and return the top-N items as recommendations for $a_{i_{t+1}}$

iConRank Algorithm

- Efficiency
  - Clustering step is done *offline* — independent of current session
  - Use the *linearity property* of personalized PageRank:

$$\mathbf{z}_u(\beta \mathbf{v}_1 + (1-\beta)\mathbf{v}_2) = \beta \mathbf{z}_u(\mathbf{v}_1) + (1-\beta)\mathbf{z}_u(\mathbf{v}_2)$$

  where $\mathbf{z}_u(\mathbf{v})$ is the PageRank using personalization vector $\mathbf{v}$

    - Pre-compute $\mathbf{z}_u(\mathbf{e}_{i_j})$, then $\mathbf{z}_u(\mathbf{c}_u) = \sum_{j=1}^{t} c_{u,i_j} \cdot \mathbf{z}_u(\mathbf{e}_{i_j})$
    - Only need to pre-compute for apps installed on a device

- Cold start
  - No current session: use uniform distribution as $\mathbf{c}_u$
  - New user: use global-level Markov model instead of M_k

Experimental Results

Datasets

Two real-life datasets:

- `Apps`:
  - Proprietary dataset obtained from a manufacturer of mobile devices[1]
  - Session is started when screen=on and ended when the screen=off and at least one minute has elapsed ('home' app removed from dataset)
- `LastFM`:
  - Publicly available dataset from `last.fm`
  - Session ended if there is no other artist streamed within an hour from the last artist

Statistic	Apps	LastFM
# of users	17,062	941
# of items (apps/artists)	9,583	98,412
# of training sessions	1,167,171	644,001
# of testing sessions	459,899	95,038
Average session length	6.53	18.33
Median session length	3	7

[1] *The data provided to us was highly anonymized and contained only generic identifiers that cannot be correlated or traced back to actual users*

Behavioral Clusters

- Cluster Stats

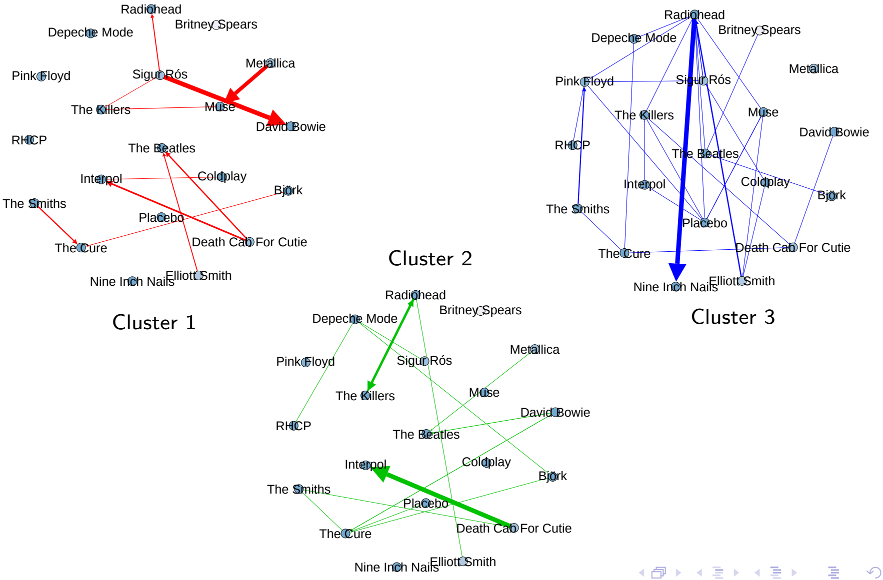
Dataset	Cluster	Users	nnz(M_k)	Session Length Avg.	Session Length Median
Apps	1	4,695	68,967	6.37	3
	2	5,711	73,121	6.32	3
	3	6,656	78,963	6.83	3
LastFM	1	327	1,733,056	19.15	7
	2	320	1,500,913	18.55	7
	3	294	1,227,933	17.01	7

- Top transitions in Apps dataset

Cluster1	Cluster2	Cluster3
(contacts,phone)	(phone,dialer)	(phone,dialer)
(message,contacts)	(*search,browser*)	(1,phone)
(contacts,dialer)	(*mail,browser*)	(phone,2)
(*settings,phone*)	(message,mail)	(phone,3)
(*data,settings*)	(*calendar,mail*)	(4,phone)
(*camera,photo*)	(*browser,video*)	(5,phone)
(*contacts,settings*)	(*phone,browser*)	(message,mail)

Behavioral Clusters

Transitions between top-20 artists



Evaluation

Compared methods:

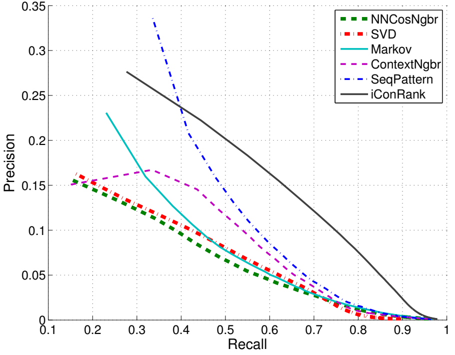
- Methods using user-item count matrix:
  - NNCosNgbr: neighborhood-based model using cosine similarity
  - SVD: singular value decomposition
- Methods using user's current session:
  - **iConRank**: our proposed method
  - Markov: global-level Markov model
  - ContextNgbr: same as NNCosNgbr except that the k-nearest neighbors are computed from items in the current session
  - SeqPattern: sequence mining algorithm (Hariri et al, 2012)

Performance measure: recall at top-N (Cremonesi et al, 2010)

Results

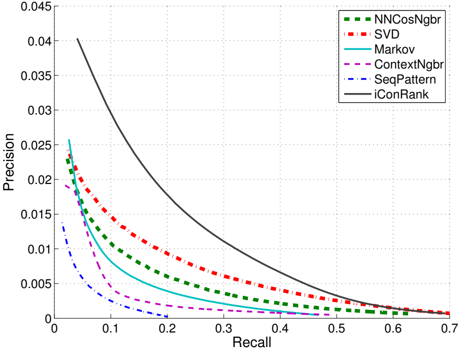
- Apps

Method	Recall@N			
	$N=5$	$N=10$	$N=15$	$N=20$
NNCosNgbr	0.4301	0.5478	0.6167	0.6636
SVD	0.4574	0.5853	0.6480	0.6851
Markov	0.4592	0.5744	0.6370	0.6754
ContextNgbr	0.5266	0.6248	0.6739	0.7045
SeqPattern	0.5517	0.6451	0.6899	0.7223
iConRank	**0.6701**	**0.7927**	**0.8386**	**0.8632**



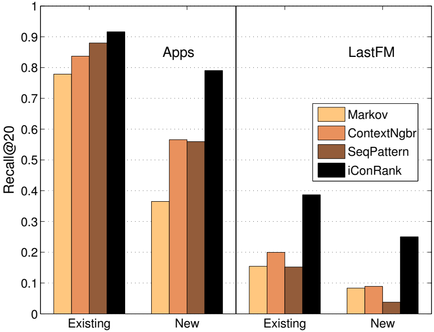
- LastFM

Method	Recall@N			
	$N=5$	$N=10$	$N=15$	$N=20$
NNCosNgbr	0.0691	0.1044	0.1328	0.1560
SVD	0.0810	0.1286	0.1633	0.1922
Markov	0.0631	0.0905	0.1113	0.1285
ContextNgbr	0.0597	0.0775	0.0884	0.0971
SeqPattern	0.0371	0.0536	0.0656	0.0748
iConRank	**0.1277**	**0.1882**	**0.2304**	**0.2633**

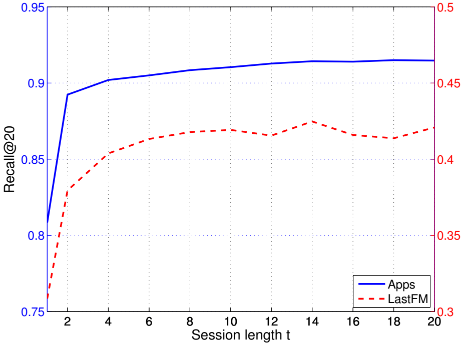


Results

- Performance on existing and new items



- Performance as more of the current session revealed



Conclusions

- Collaborative filtering with interactional context
- Applicable in many click-based interactive systems
- Proposed novel method: iConRank
  - Personalized and dynamic recommendations given the current session (interactional context) — recommendations are updated as the user interacts with the system
  - Behavioral clustering — recommendations using past item transitions and transitions from users with similar navigational patterns
  - Superior recommendations than other competitive methods on two real-life datasets
  - Scalable and can be efficiently implemented on devices with limited processing power

Thank You!

References

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