

Effective Missing Data Prediction for Collaborative Filtering

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- 1 Introduction
 - Simple Examples of Recommender System
 - Definitions of Some Concepts
 - A Simple CF Example
 - Pearson Correlation Coefficient
 - Significance Weighting
- 2 Missing Data Prediction
 - Collaborative Filtering Challenges
 - User-Item Matrix
 - Similar Neighbors Selection
 - Missing Data Prediction
 - Parameter Discussion
- 3 Empirical Analysis
 - Datasets
 - Metrics
 - Summary of Experiments
 - Comparisons
 - Impact of Parameters
- 4 Conclusions and Future Work
 - Conclusions and Future Work

Search Using Google

Google

[Web](#)
[Images](#)
[Groups](#)
[News](#)
[Scholar](#)
[Desktop](#)
[more »](#)

[Advanced Search](#)
[Preferences](#)

Search: the web pages from Hong Kong

Web

55 results stored on your computer - [Hide](#) - [About](#)
<http://www.google.com/sup..> - [google.com](#) - [google.ae](#) - [google.com.af](#) - [google](#)

[Google](#)
 Enables users to search the Web, Usenet, and images. Features include PageRank, caching and translation of results, and an option to find similar pages.
www.google.com/ - 5k - [Cached](#) - [Similar pages](#)

[Google](#)
 The local version of this pre-eminent search engine, offering UK-specific pages as well as world results.
www.google.co.uk/ - 4k - [Cached](#) - [Similar pages](#)

[Google](#)
 Google.ca offered in: Français - Advertising Programs - Business Solutions - About Google - Go to Google.com. ©2007 Google.
www.google.ca/ - 4k - [Cached](#) - [Similar pages](#)

Search Using Google

The screenshot shows a Google search interface with the query 'google' entered in the search box. The search results are categorized under 'Web' and show 55 results stored on the user's computer. The first result is for 'http://www.google.com/sup...' with links to 'google.com', 'google.ae', and 'google.com.af'. The second result is for 'Google' with a description: 'Enables users to search the Web, Usenet, and images. Features include PageRank, caching and translation of results, and an option to find similar pages.' The link 'Similar pages' is circled in red. The third result is for 'Google' with a description: 'The local version of this pre-eminent search engine, offering UK-specific pages as well as world results.' The fourth result is for 'Google.ca' with a description: 'Google.ca offered in: Français - Advertising Programs - Business Solutions - About Google - Go to Google.com. ©2007 Google.'

Web

55 results stored on your computer - [Hide](#) - [About](#)

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[Google](#)
Google.ca offered in: Français - Advertising Programs - Business Solutions - About Google - Go to Google.com. ©2007 Google.
[www.google.ca/](#) - 4k - [Cached](#) - [Similar pages](#)

Search Using Google

The screenshot shows a Google search results page. At the top, the Google logo is on the left, and navigation links for 'Web', 'Images', 'Groups', 'News', 'Scholar', 'Desktop', and 'more »' are on the right. Below the logo is a search bar containing the text 'related:www.google.com/'. To the right of the search bar is a 'Search' button and a link to 'Advanced Search Preferences'. Below the search bar, there are radio buttons for 'the web' (selected) and 'pages from Hong Kong'. The main content area is titled 'Web' and lists several search results:

- Live Search**: Microsoft provides search of the web, news, images and its own encyclopedia, Encarta. Also offers desktop search via a toolbar. [search.msn.com/ - 6k - 11 Mar 2007 - Cached - Similar pages](#)
- Yahoo!**: Welcome to Yahoo!, the world's most visited home page. Quickly find what you're searching for, get in touch with friends and stay in-the-know with the ... [www.yahoo.com/ - 73k - 11 Mar 2007 - Cached - Similar pages](#)
- AltaVista**: AltaVista provides the most comprehensive search experience on the Web! [www.altavista.com/ - 18k - Cached - Similar pages](#)
- MetaCrawler Web Search Home Page**: Popular Searches: Online Churches - Blue Book Value - Obituaries - Auto Loan - Airline Tickets - Gift Baskets - See what the world is searching for? ... [www.metacrawler.com/ - 24k - 11 Mar 2007 - Cached - Similar pages](#)
- MSN.com**: MSN's all-in-one Internet portal, the home of Hotmail, MSN Messenger, MSNBC News, Fox Sports, Slate Magazine and more information you care about. [www.msn.com/ - 38k - 11 Mar 2007 - Cached - Similar pages](#)
- Dogpile Web Search Home Page**: Dogpile.com makes searching the Web easy, because it has all the best search engines piled into one. So you get better results from more of the web. [www.dogpile.com/ - 25k - 11 Mar 2007 - Cached - Similar pages](#)
- Homepage HotBot Web Search**: Offers a search powered by a choice of Google or AskJeeves. There are options to block offensive language, customize search results, and skins. [www.hotbot.com/ - 9k - Cached - Similar pages](#)

Searching Products on Amazon.com



- If a user is viewing the palm Treo 750 Smartphone on Amazon.com, other related information will be recommended to user besides the specification of Treo 750

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Searching Products on Amazon.com

Customers who viewed this item also viewed

[Samsung i607 BlackJack Smartphone \(Cingular\)](#) by Samsung

[BlackBerry 8100c Pearl \(Cingular\)](#) by BlackBerry

[Cingular 8525 PDA Phone \(Cingular\)](#) by HTC

[Sony Ericsson W810i Phone \(Cingular\)](#) by Sony Ericsson



Customers who bought this item also bought

[PREMIUM RAPID CAR CHARGER for PALM TREO 650 / 680 / 700 / 700w / 700p / 700wx / 750](#) by Mybat

[Platinum Skin Case w/Swivel Clip --Treo 650 700w 700p](#)

[OEM 2GB MINISD Mini Secure Digital \(SD\) Card 2 GB \(Bulk Package\)](#) by OEM

[palm Treo 680 Smartphone \(Cingular\)](#) by Palm

- These methods are very popular in many online recommendation systems

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[Cingular 8525 PDA Phone \(Cingular\)](#) by HTC

[Sony Ericsson W810i Phone \(Cingular\)](#) by Sony Ericsson



Customers who bought this item also bought

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More Complicated Recommendations

Sign In

What is your e-mail address?

My e-mail address is

Do you have an Amazon.com password?

No, I am a new customer.

Yes, I have a password:

[Sign in using our secure server](#)



Search for items to rate

1 Use the search box above to find your favorite books, movies, albums, artists, authors and brands.

2 Tell us what you think of the items we return for your search by rating the item or telling us you already own them.



3 Repeat until the Recommendations you find in Your Amazon.com reflect your tastes and interests.

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More Complicated Recommendations

Search for items to rate

Music

Enrique

GO

Search results for **Enrique** in Music:

1.



Escape

~ Enrique Iglesias

Your tags:

Add (What's this?)

Rate it

X|☆☆☆☆☆

I Own It

2.



Enrique

~ Enrique Iglesias

Your tags:

Add (What's this?)

Rate it

X|☆☆☆☆☆

I Own It

3.



Seven

~ Enrique Iglesias

Your tags:

Add (What's this?)

Rate it

X|☆☆☆☆☆

I Own It

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Add (What's this?)

Saved

X | ★★★★★

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Saved



I Own It

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Your tags:

Add (What's this?)

Saved



I Own It

3.



Seven

~ Enrique Iglesias

Your tags:

Add (What's this?)

Saved







I Own It

More Complicated Recommendations

Search for items to rate

Search results for **Enrique** in Music:

1.		<u>Escape</u> ~ Enrique Iglesias Your tags: <input type="text"/> <input type="button" value="Add"/> (What's this?)	<div style="border: 1px solid green; border-radius: 15px; padding: 10px; background-color: #e0f0e0;"> <p style="text-align: center;">Five Scales</p> <p>★ I hate it</p> <p>★★ I don't like it</p> <p>★★★ It's ok</p> <p>★★★★ I like it</p> <p>★★★★★ I love it</p> </div>	<input checked="" type="checkbox"/> Saved <input checked="" type="checkbox"/>  <input type="checkbox"/> I Own It
2.		<u>Enrique</u> ~ Enrique Iglesias Your tags: <input type="text"/> <input type="button" value="Add"/> (What's this?)		<input checked="" type="checkbox"/> Saved <input checked="" type="checkbox"/>  <input type="checkbox"/> I Own It
3.		<u>Seven</u> ~ Enrique Iglesias Your tags: <input type="text"/> <input type="button" value="Add"/> (What's this?)		<input checked="" type="checkbox"/> Saved <input checked="" type="checkbox"/>  <input type="checkbox"/> I Own It

More Complicated Recommendations

The screenshot displays two rows of product recommendations from Amazon.com. Each row is titled "Today's Recommendations For You" and includes a navigation bar with "amazon.com", "Help", "See All 41 Product Categories", "Your Account", "Cart", "Your Lists", "Help", and "RSS". Below the title, there is a link to "see all recommendations".

Row 1 Recommendations:

- Ricky Martin**: Ricky Martin (Audio CD)
- Think Place Music**: Think Place Music: Simple Back For Easy Streaming...
- Black Antennas**: Black Antennas (Audio CD)
- Opera De L'Acier**: Opera De L'Acier (Audio CD)
- Latest Mobile**: Latest Mobile: Express Yourself: Headset

Row 2 Recommendations:

- Motorola STABLISK**: Motorola STABLISK: Phone (Covariate)
- Yveses**: Yveses (Audio CD)
- Shane's (Shane, 2006)**: Shane's (Shane, 2006) (Audio CD)
- Erasmus**: Erasmus: Vehicle: Headset: A Headset For Easy Streaming...
- The Real One**: The Real One (Audio CD)

- The technique Amazon.com adopts is called Collaborative Filtering!

More Complicated Recommendations

The screenshot displays the Amazon.com interface for personalized recommendations. At the top, there are navigation links for 'amazon.com', 'Help', 'See All 41 Product Categories', 'Your Account', 'Cart', 'Your Lists', 'Help', and 'RSS'. Below this is a secondary navigation bar with links for 'Your browsing history', 'Recommended For You', 'Rate These Items', 'Browse Your Recommendations', 'Your Profile', and 'Learn More'.

The main content area is titled 'Today's Recommendations For You' and includes a sub-header 'Here's a daily sample of items recommended for you. Click here to [see all recommendations](#).' The first row of recommendations features five items: 'Ricky Martin' (Audio CD), 'Three Piece Music Combo Bag for Easy Straps...', 'Black Antennas' (Audio CD), 'Goran Ilievski' (Audio CD), and 'Lightest Mobile, Earpiece Bluetooth Headset'. The second row features: 'Motorola STABLISK Phone (Covariate)', 'Judas' (Audio CD), 'Shane (Soundtrack) (Audio CD)', 'Emerson Vehicle Speaker Adapter for Easy Straps...', and 'The Real Life' (Audio CD). Each item is accompanied by a small image and a left or right navigation arrow.

- The technique Amazon.com adopts is called Collaborative Filtering!

Google

- Similarity calculation
- Link analysis

Amazon – Simple Example

- User-item matrix is consisted of lots of 0s and 1s
- Frequent pattern mining

Amazon – Complicated Example

- User-item matrix is consisted of lots of ratings which are rated by different users
- Predict other missing data as accurate as possible

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Definition of Recommendation Systems

- Computer programs
- Predict items that a user may be interested in
- Items could be movies, music, books, news, web pages, etc.
- Given some information about the user's profile



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Definition of Collaborative Filtering

- Making automatic predictions (filtering) about the interests of a user
- By collecting taste information from many other users (collaborating)



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User-based Collaborative Filtering

	Items													
Users	u ₁													
	u ₂	1	3		4		2		5			3	4	
	u ₃													
	u ₄		3		4			3	4		3	4		4
	u ₅													
	u ₆	1			3	5	2		4	1			3	

User-based Collaborative Filtering

	Items													
Users	u_1													
	u_2	1	3		4		2		5		3	4		
	u_3													
	u_4		3		4			3	4		3	4		4
	u_5													
	u_6	1			3	5	2		4	1			3	

User-based Collaborative Filtering

	Items												
Users	u ₁												
	u ₂	1	3		4		2		5		3	4	
	u ₃												
	u ₄		3		4			3	4		3	4	4
	u ₅												
	u ₆	1			3	5	2		4	1		3	

User-based Collaborative Filtering

Items

Users	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8	Item 9	Item 10
u_1										
u_2	1	3	4	2	5			3	4	
u_3										
u_4		3	4		3	4		3	4	4
u_5										
u_6	1		3	5	2	4	1		3	

User-based Collaborative Filtering

	Items											
Users	u ₁											
	u ₂	1	3	4	2		5			3	4	
	u ₃											
	u ₄		3	4			3	4		3	4	4
	u ₅											
	u ₆	1		3	5	2		4	1		3	

User-based Collaborative Filtering

		Items									
Users	u_1										
	u_2	1	3	4	2	5			3	4	
	u_3										
	u_4		3	4		3	4		3	4	4
	u_5										
	u_6	1		3	5	2		4	1		3

User-based Collaborative Filtering

- User-based collaborative filtering predicts the ratings of active users based on the ratings of similar users found in the user-item matrix
- The similarity between users could be defined as:

$$Sim(a, u) = \frac{\sum_{i \in I(a) \cap I(u)} (r_{a,i} - \bar{r}_a) \cdot (r_{u,i} - \bar{r}_u)}{\sqrt{\sum_{i \in I(a) \cap I(u)} (r_{a,i} - \bar{r}_a)^2} \cdot \sqrt{\sum_{i \in I(a) \cap I(u)} (r_{u,i} - \bar{r}_u)^2}}$$

- $Sim(a, u)$ is ranging from $[-1, 1]$, and a larger value means users a and u are more similar

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User-based Collaborative Filtering

	Items											
Users	u ₁											
	u ₂			4	4	4				4		
	u ₃											
	u ₄			2	2	2				2		
	u ₅											
	u ₆											

User-based Collaborative Filtering

	Items									
Users	u_1									
u_2			4	4	4			4		
u_3										
u_4			2	2	2			2		
u_5										
u_6										

The similarity between u_2 and u_4 equals to 1.

Item-based Collaborative Filtering

- Item-based collaborative filtering predicts the ratings of active users based on the information of similar items computed
- The similarity between items could be defined as:

$$Sim(i, j) = \frac{\sum_{u \in U(i) \cap U(j)} (r_{u,i} - \bar{r}_i) \cdot (r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u \in U(i) \cap U(j)} (r_{u,i} - \bar{r}_i)^2} \cdot \sqrt{\sum_{u \in U(i) \cap U(j)} (r_{u,j} - \bar{r}_j)^2}}$$

- Like user similarity, item similarity $Sim(i, j)$ is also ranging from $[-1, 1]$

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An Example

		Items												
Users														
		1	3	2	5	3	2	3						
								3	2	1	5	4	1	4

An Example

		Items											
Users	1	3	2	5	3	2	3						
							3	2	1	5	4	1	4

An Example

	Items												
Users	1	3	2	5	3	2	3						
							3	2	1	5	4	1	4

Do these two
users really
have the same
taste???

Significance Weighting

- We use the following equation to solve this problem:

$$Sim'(a, u) = \frac{Min(|I_a \cap I_u|, \gamma)}{\gamma} \cdot Sim(a, u),$$

where $|I_a \cap I_u|$ is the number of items which user a and user u rated in common

- Then the similarity between items could be defined as:

$$Sim'(i, j) = \frac{Min(|U_i \cap U_j|, \delta)}{\delta} \cdot Sim(i, j),$$

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User-Item Matrix

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_n
u_1	$r_{1,1}$			$r_{1,4}$						
u_2		$r_{2,2}$						$r_{2,8}$		
u_3						$r_{3,6}$				
u_4				$r_{4,4}$						$r_{4,n}$
u_5			$r_{5,3}$				$r_{5,7}$			
u_6									$r_{6,9}$	
u_m			$r_{m,2}$							$r_{m,n}$

(a)

Challenges of Collaborative Filtering

- Data Sparsity
- Prediction Accuracy
- Scalability

User-Item Matrix

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_n
u_1	$r_{1,1}$			$r_{1,4}$						
u_2		$r_{2,2}$						$r_{2,8}$		
u_3						$r_{3,6}$				
u_4				$r_{4,4}$						$r_{4,n}$
u_5			$r_{5,3}$				$r_{5,7}$			
u_6									$r_{6,9}$	
u_m			$r_{m,2}$							$r_{m,n}$

(a)

Challenges of Collaborative Filtering

- Data Sparsity
- Prediction Accuracy
- Scalability

User-Item Matrix

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_n
u_1	$r_{1,1}$			$r_{1,4}$						
u_2		$r_{2,2}$						$r_{2,8}$		
u_3						$r_{3,6}$				
u_4				$r_{4,4}$						$r_{4,n}$
u_5			$r_{5,3}$				$r_{5,7}$			
u_6									$r_{6,9}$	
u_m			$r_{m,2}$							$r_{m,n}$

(a)

Challenges of Collaborative Filtering

- Data Sparsity
- Prediction Accuracy
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- Propose an algorithm to increase the density of User-Item Matrix
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- Adopt significance weighting
- Linearly combine user information with item information
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- Our algorithm increases 6.24% of prediction accuracy over other state-of-the-art methods in average

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(a)

Predicted User-Item Matrix

	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_n
u_1	$\hat{r}_{1,1}$	0	$\hat{r}_{1,3}$	$\hat{r}_{1,4}$	0	$\hat{r}_{1,6}$	0	$\hat{r}_{1,8}$	$\hat{r}_{1,9}$	0
u_2	0	$\hat{r}_{2,2}$	0	$\hat{r}_{2,4}$	$\hat{r}_{2,5}$	0	$\hat{r}_{2,7}$	$\hat{r}_{2,8}$	0	$\hat{r}_{2,n}$
u_3	$\hat{r}_{3,1}$	0	$\hat{r}_{3,3}$	$\hat{r}_{3,4}$	$\hat{r}_{3,5}$	$\hat{r}_{3,6}$	0	$\hat{r}_{3,8}$	$\hat{r}_{3,9}$	0
u_4	$\hat{r}_{4,1}$	$\hat{r}_{4,2}$	0	$\hat{r}_{4,4}$	$\hat{r}_{4,5}$	$\hat{r}_{4,6}$	$\hat{r}_{4,7}$	0	$\hat{r}_{4,9}$	$\hat{r}_{4,n}$
u_5	$\hat{r}_{5,1}$	$\hat{r}_{5,2}$	$\hat{r}_{5,3}$	0	$\hat{r}_{5,5}$	0	$\hat{r}_{5,7}$	$\hat{r}_{5,8}$	$\hat{r}_{5,9}$	$\hat{r}_{5,n}$
u_6	$\hat{r}_{6,1}$	$\hat{r}_{6,2}$	0	$\hat{r}_{6,4}$	$\hat{r}_{6,5}$	$\hat{r}_{6,6}$	$\hat{r}_{6,7}$	0	$\hat{r}_{6,9}$	$\hat{r}_{6,n}$
u_m	$\hat{r}_{m,1}$	0	$\hat{r}_{m,2}$	$\hat{r}_{m,4}$	0	$\hat{r}_{m,6}$	0	$\hat{r}_{m,8}$	$\hat{r}_{m,9}$	$\hat{r}_{m,n}$

(b)

Similar Neighbors Selection

- For every missing data $r_{u,i}$, a set of similar users $S(u)$ towards user u can be generated according to:

$$S(u) = \{u_a | Sim'(u_a, u) > \eta, u_a \neq u\}$$

where $Sim'(u_a, u)$ is computed using Significance Weighting, and η is the **user similarity threshold**

- At the same time, for every missing data $r_{u,i}$, a set of similar items $S(i)$ towards item i can be generated according to:

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Missing Data Prediction Algorithm

- Given the missing data $r_{u,i}$, if $S(u) \neq \emptyset \wedge S(i) \neq \emptyset$, the prediction of missing data $P(r_{u,i})$ is defined as:

$$P(r_{u,i}) = \lambda \times \left(\bar{u} + \frac{\sum_{u_a \in S(u)} Sim'(u_a, u) \cdot (r_{u_a, i} - \bar{u}_a)}{\sum_{u_a \in S(u)} Sim'(u_a, u)} \right) + (1 - \lambda) \times \left(\bar{i} + \frac{\sum_{i_k \in S(i)} Sim'(i_k, i) \cdot (r_{u, i_k} - \bar{i}_k)}{\sum_{i_k \in S(i)} Sim'(i_k, i)} \right)$$

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- This consideration is different from all other existing prediction or smoothing methods – they always try to predict all the missing data in the user-item matrix, which will predict some missing data with bad quality

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Parameter

- γ
- δ
- η
- θ
- λ

Discussion on γ and δ

- Employed to avoid overestimating the user similarities and item similarities
- Too high \implies users or items do not have enough neighbors \implies decrease of prediction accuracy
- Too low \implies overestimate problem still exists \implies decrease of prediction accuracy

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- Too high \implies few missing data need to be predicted \implies user-item matrix is very sparse
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- Determines how closely the rating prediction relies on user information or item information
- $\lambda = 1 \implies$ prediction depends completely upon user-based information
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Table: The relationship between parameters with other CF approaches (MDP: Mission Data Predicted)

λ	η	θ	Related CF Approaches
1	1	1	User-based CF without MDP
0	1	1	Item-based CF without MDP
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Movielens

- It contains 100,000 ratings (1-5 scales) rated by 943 users on 1,682 movies, and each user at least rated 20 movies. The density of the user-item matrix is:

$$\frac{100000}{943 \times 1682} = 6.30\%$$

- The statistics of dataset MovieLens is summarized in the following table:

Table: Statistics of Dataset MovieLens

Statistics	User	Item
Min. Num. of Ratings	20	1
Max. Num. of Ratings	737	583
Avg. Num. of Ratings	106.04	59.45

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Mean Absolute Errors

- We use the Mean Absolute Error (MAE) metrics to measure the prediction quality of our proposed approach with other collaborative filtering methods
- MAE is defined as:

$$MAE = \frac{\sum_{u,i} |r_{u,i} - \hat{r}_{u,i}|}{N},$$

where $r_{u,i}$ denotes the rating that user u gave to item i , and $\hat{r}_{u,i}$ denotes the rating that user u gave to item i which is predicted by our approach, and N denotes the number of tested ratings

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- Comparisons with Traditional PCC Methods
- Comparisons with State-of-the-Art Algorithms
- Impact of Missing Data Prediction
- Impact of γ and δ
- Impact of λ
- Impact of η and θ

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- **Comparisons with Traditional PCC Methods**
- Comparisons with State-of-the-Art Algorithms
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Comparisons with Traditional PCC Methods

- User-based collaborative filtering using Pearson Correlation Coefficient
- Item-based collaborative filtering using Pearson Correlation Coefficient

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Comparisons with State-of-the-Art Algorithms

- Similarity Fusion (SF) [J. Wang, et al., SIGIR 2006]
- Smoothing and Cluster-Based PCC (SCBPCC) [G. Xue, et al., SIGIR 2005]
- Aspect Model (AM) [T. Hofmann, TOIS 2004]
- Personality Diagnosis (PD) [D. M. Pennock, et al., UAI 2000]

Summary of Experiments

- Comparisons with Traditional PCC Methods
- Comparisons with State-of-the-Art Algorithms
- **Impact of Missing Data Prediction**
- Impact of γ and δ
- Impact of λ
- Impact of η and θ

Impact of Missing Data Prediction

- Effective Missing Data Prediction (EMDP)
- Predict Every Missing Data (PEMD)

Summary of Experiments

- Comparisons with Traditional PCC Methods
- Comparisons with State-of-the-Art Algorithms
- Impact of Missing Data Prediction
- **Impact of γ and δ**
- **Impact of λ**
- **Impact of η and θ**

Impact of Parameters

- Impact of each parameter

MAE Comparisons with PCC Methods

Table: MAE comparison with other approaches (A smaller MAE value means a better performance)

Training Users	Methods	Given5	Given10	Given20
MovieLens 300	EMDP	0.784	0.765	0.755
	UPCC	0.838	0.814	0.802
	IPCC	0.870	0.838	0.813
MovieLens 200	EMDP	0.796	0.770	0.761
	UPCC	0.843	0.822	0.807
	IPCC	0.855	0.834	0.812
MovieLens 100	EMDP	0.811	0.778	0.769
	UPCC	0.876	0.847	0.811
	IPCC	0.890	0.850	0.824

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MAE Comparisons with State-of-the-Art Algorithms

Table: MAE comparison with state-of-the-art algorithms (A smaller MAE value means a better performance)

Num. of Training Users Ratings Given	100			200			300		
	5	10	20	5	10	20	5	10	20
EMDP	0.807	0.769	0.765	0.793	0.760	0.751	0.788	0.754	0.746
SF	0.847	0.774	0.792	0.827	0.773	0.783	0.804	0.761	0.769
SCBPCC	0.848	0.819	0.789	0.831	0.813	0.784	0.822	0.810	0.778
AM	0.963	0.922	0.887	0.849	0.837	0.815	0.820	0.822	0.796
PD	0.849	0.817	0.808	0.836	0.815	0.792	0.827	0.815	0.789
PCC	0.874	0.836	0.818	0.859	0.829	0.813	0.849	0.841	0.820

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Num. of Training Users Ratings Given	100			200			300		
	5	10	20	5	10	20	5	10	20
EMDP	0.807	0.769	0.765	0.793	0.760	0.751	0.788	0.754	0.746
SF	0.847	0.774	0.792	0.827	0.773	0.783	0.804	0.761	0.769
SCBPCC	0.848	0.819	0.789	0.831	0.813	0.784	0.822	0.810	0.778
AM	0.963	0.922	0.887	0.849	0.837	0.815	0.820	0.822	0.796
PD	0.849	0.817	0.808	0.836	0.815	0.792	0.827	0.815	0.789
PCC	0.874	0.836	0.818	0.859	0.829	0.813	0.849	0.841	0.820

Impact of Missing Data Prediction

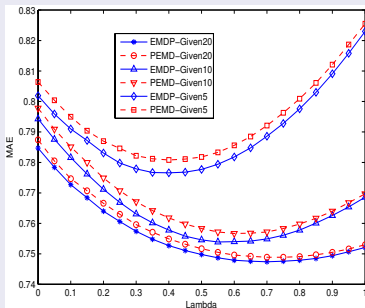


Figure: MAE Comparison of EMDP and PEMD (A smaller MAE value means a better performance)

Impact of γ and δ

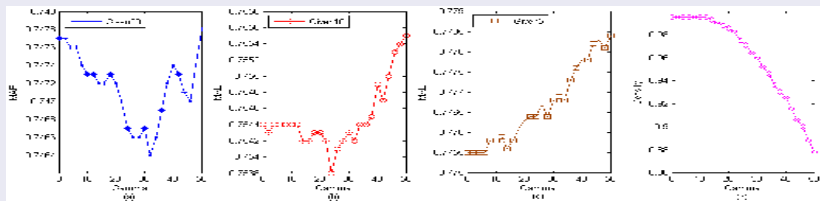


Figure: Impact of γ and δ on MAE and Matrix Density

Impact of λ

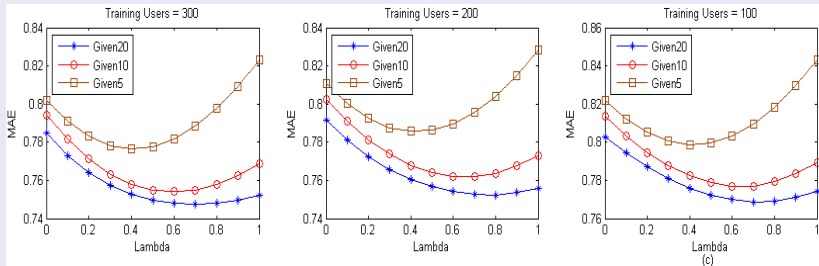


Figure: Impact of λ on MAE

Impact of η and θ

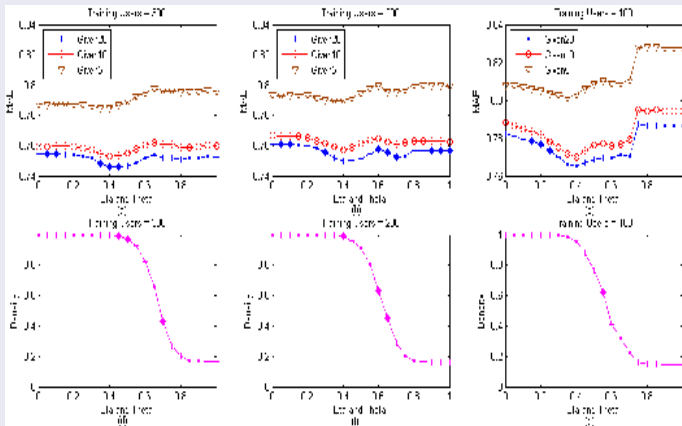


Figure: Impact of η and θ on MAE and Density

Conclusions

- Proposes an **effective missing data prediction algorithm** for Collaborative Filtering
- **Combines** users information and items information together
- **Outperforms** other state-of-the-art collaborative filtering approaches

Future Work

- Explore the relationship between user information and item information
- Scalability analysis and improvement of our algorithm
- Employ more metrics to measure our algorithm

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Q & A

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- Thanks!