Recommender Systems

Francesco Ricci

Database and Information Systems

Free University of Bozen, Italy

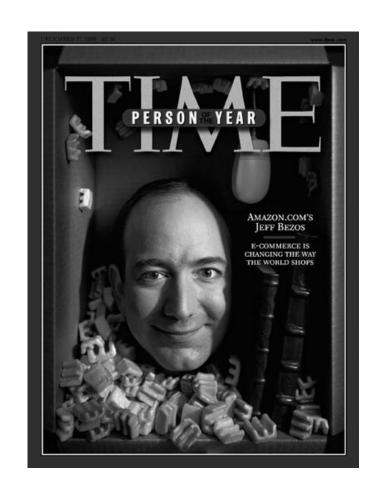
fricci@unibz.it

Content

- ☐ Example of Recommender System
- ☐ The basic idea of collaborative-based filtering
- ☐ Collaborative-based filtering: technical details
- ☐ Content-based filtering
- ☐ Knowledge-based recommender systems
- ☐ Evaluating recommender systems
- ☐ Challenges

Jeff Bezos

- □ "If I have 3 million customers on the Web, I should have 3 million stores on the Web"
 - ☐ Jeff Bezos, CEO of Amazon.com
 - □ Degree in Computer Science
 - □\$4.3 billion, ranked no. 147 in the Forbes list of the World's Wealthiest People

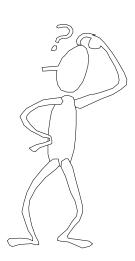


[Person of the Year-1999]

What movie should I see?



VERYBODY RUNS JUNE 2



The Internet Movie Database (IMDb) provides information about actors, films, television shows, television stars, video games and production crew personnel.

Owned by Amazon.com since 1998, as of June 21, 2006 IMDb featured 796,328 titles and 2,127,371 people.

Movie Lens



helping you find the right movies

Welcome to MovieLens!

Free, personalized, non-commercial, ad-free, great movie recommendations.

Have questions? Take the MovieLens Tour for answers.

Not a member? Join MovieLens now.

Need a gift idea? Try MovieLens QuickPick!

New to MovieLens?

Join today!

You get **great recommendations** for movies while **helping us do research**. Learn more:

- Try out QuickPick: Our Movie Gift Recommender
- Take the MovieLens Tour
- Read our Privacy Policy
- See our Browser Requirements
- Learn about Our Research

Hello MovieLens Users!

Please log in:

Password:

Save login: □

Log into MovieLens

Forgot your password?

New member? Join now

MovieLens is a free service provided by GroupLens Research at the University of Minnesota. We sometimes study how our members use MovieLens in order to learn how to build better recommendation systems. We promise to never give your personal information to anyone; see our privacy policy for more information.

Movielens Approach

- ☐ You rate/ evaluate some movies on a 1 ("Awful") to 5 ("Must to see") scale
 - ☐ The system stores your ratings and build your user model
- ☐ You ask for recommendations, i.e., movies that you would like and you have not seen yet
 - ☐ The system exploits your user model and the user model of other "similar" users to compute some predictions, i.e., it guess what will be your rating for some movies and displays those movies having higher predicted ratings
- ☐ You browse the list of recommendations and eventually decide to watch one of these recommended movies.

So far you have rated **0** movies.

MovieLens needs at least 15 ratings from you to generate predictions for you.

Please rate as many movies as you can from the list below.

next >

		Пенсу
	Your Rating	Movie Information
***	3.0 stars 🕶	Austin Powers: International Man of Mystery (1997) Action, Adventure, Comedy
****	4.0 stars	Contact (1997) Drama, Sci-Fi
???	Not seen 🕶	Crouching Tiger, Hidden Dragon (Wu Hu Zang Long) (2000) Action, Adventure, Drama, Fantasy, Romance
???	Not seen 💌	Demolition Man (1993) Action, Comedy, Sci-Fi
???	Not seen 💌	Eraser (1996) Action, Drama, Thriller
???	Not seen 💌	Maverick (1994) Action, Comedy, Western
****	4.5 stars 💌	Philadelphia (1993) Drama
****	3.5 stars 💌	Piano, The (1993) Drama, Romance
???	Not seen 🕶	Toy Story 2 (1999) Adventure, Animation, Children, Comedy, Fantasy
****	3.5 stars 🕶	X-Men (2000) Action, Adventure, Sci-Fi
		next >

To get a new set of movies click the next> link.

movielens

helping you find the right movies

Welcome

You've rated 16 movies.

You're the 26th visitor in the past hour.

★★★★ = Must See
 ★★★☆ = Will Enjoy
 ★★☆☆☆ = It's OK
 ★☆☆☆☆ = Fairly Bad
 ★☆☆☆☆ = Awful

Home | Forums | Manage Buddies | Your Account | Help

Shortcuts	Search									
Search Titles Go! Use selected buddies!										
Combine All Genres Domain: All m	All Dates 🕶									
Tag: Use selected buddies! Go!										
Advance	d Search									
Select E □Test Buddy What are	,									

	_	·	
	Dates: All	You've searched for all titles . ound 8220 movies, sorted by Prediction Genres: All Exclude Genres: None Domain: All Format: All Languages: All Friendly Page Download Results Suggest a Title	
		Netflix queue (178), Futuristmovies.com (134), My DVD tography) (90), Oscar (Best Picture) (85), (about tags)	s (123),
	1	Page 1 of 548 Go to page: .109218327436545last page	age 2>
(hide) Predictions for you ₹	Your Ratings	Movie Information	Wish List
****	Not seen 💌	Cat Returns, The (Neko no ongaeshi) (2002) DVD info imdb Adventure, Animation, Children, Fantasy - Japanese	
[add ta	g] Popular tags:	anime 🖪, cats 🖪, In Netflix queue 🖪	
****	Not seen 💌	Immigrant, The (1917) DVD VHS info imdb add tag Comedy - Silent	
****	Not seen 💌	Experiment, The (Das Experiment) (2001) DVD VHS info imdb add tag Drama, Thriller - German	
****	Not seen 💌	Thesis (Tesis) (1996) DVD info imdb add tag Drama, Horror, Thriller - Spanish	
****	Not seen 💌	Howl's Moving Castle (Hauru no ugoku shiro) (2004) DVD infolimdb Adventure, Animation, Children, Fantasy, Romance - Japanese	
[add ta	g] Popular tags:	06 Oscar Nominated Best Movie - Animation 🖪, In Netflix queu	e H
****	Not seen 💌	Why We Fight (2005) info imdb Documentary	
[add ta	g] Popular tags:	Military 🖪, In Netflix queue 🖪, controversial 🖪	

movielens

helping you find the right movies

Welcome

You've rated 32 movies. You're the 26th visitor in the past hour. **** = Must See **** = Will Enjoy ★☆☆☆☆ = Awful

Home | Forums | Manage Buddies | Your Account | Help

Shortcuts

Search

- Top Picks For You
- Your Ratings
- Your Wishlist
- Newest Additions
- Rate Random Movies
- Most Often Rated



- Suggest Title
- About Your Ratings
- New Drama

V for Vendetta (2006) Inside Man (2006) Match Point (2005)

New DVDs.

Capote (2005) Walk the Line (2005) Good Night, and Good...

- New Movies

V for Vendetta (2006) Why We Fight (2005) Inside Man (2006)

How to create shortcuts Publish your shortcuts

V for Vendetta (2006)

Your Prediction: ★★★★★ Rate This Movie: Not seen ▼

Wish List:

Movie Information

Starring: Natalie Portman, Hugo Weaving, Stephen Rea, John Hurt

Directed by: James McTeique

Genres: Action, Drama, Sci-Fi, Thriller

Language: English

Average rating: **** (4 stars)

Rated by: 128 users

Links: IMDb, Rotten Tomatoes

Movie Tags (more about tags) Add and edit tags here

My Tags [edit]

- none

[add new tags]

Popular tags:

Click on this icon (11) to add a tag to your list!

- comic book (2)
- revenge (1)
- Alan Moore (1)
- john hurt (1)
- \blacksquare 1984 (1)
- guy fawkes (1)
- Futuristmovies.com (1)
- revolutionary (1)
- disacknowledged (1)

Forum Posts

These posts mention V for Vendetta (2006)

Write about V for Vendetta (2006) in the MovieLens Forums!

Related Forum Posts

These posts mention movies similar to V for Vendetta (2006)

Topic	Author
Re: Fitting into movie groups	(shitdisturber)
Re: What's the last thing you watched an	(PolarisDiB)
Re: Fitting into movie groups	(FarmerF)
Re: Fitting into movie groups	(Bec1029)
Re: Ask Dr. Vigilans	(Vigilans)
Ask Dr. Vigilans	(PolarisDiB)
Re: Fitting into movie groups	(Ryuukuro)
Re: What's the last thing you watched an	(vargus)
Dor What's the last thing	

What travel should I do?



I would like to escape from this ugly an tedious work life and relax for two weeks in a sunny place. I am fed up with these crowded and noisy places ... just the sand and the sea ... and some "adventure".

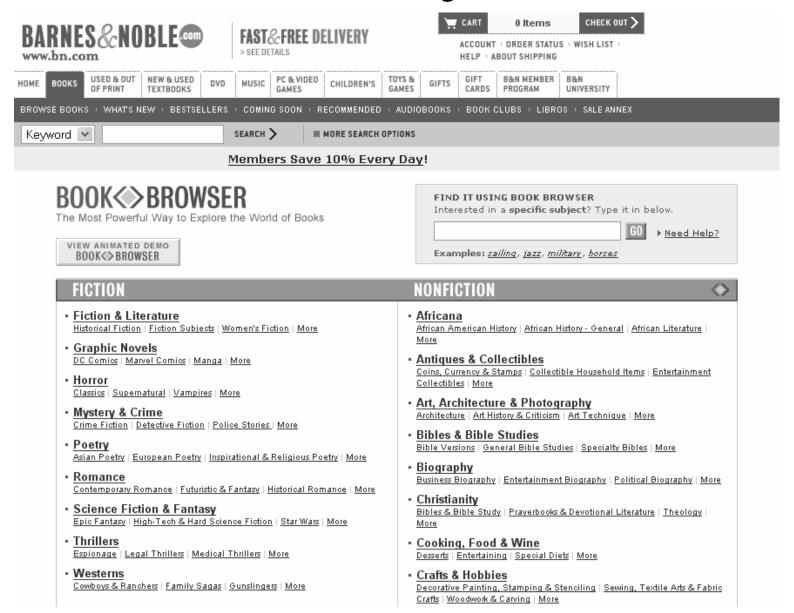


 I would like to bring my wife and my children on a holiday ... it should not be to expensive. I prefer mountainous places... not to far from home. Children parks, easy paths and good cuisine are a must.



 I want to experience the contact with a completely different culture. I would like to be fascinated by the people and learn to look at my life in a totally different way.

What book should I buy?



Example: Book recommendation

Ephemeral

- I'm taking two weeks off
- Novel
- •I'm interested in a Polish writer
- Should be a travel book
- •I'd like to reflect on the meaning of life



- Dostoievsky
- Stendhal
- Checov
- Musil
- Pessoa
- Sedaris
- Auster
- Mann

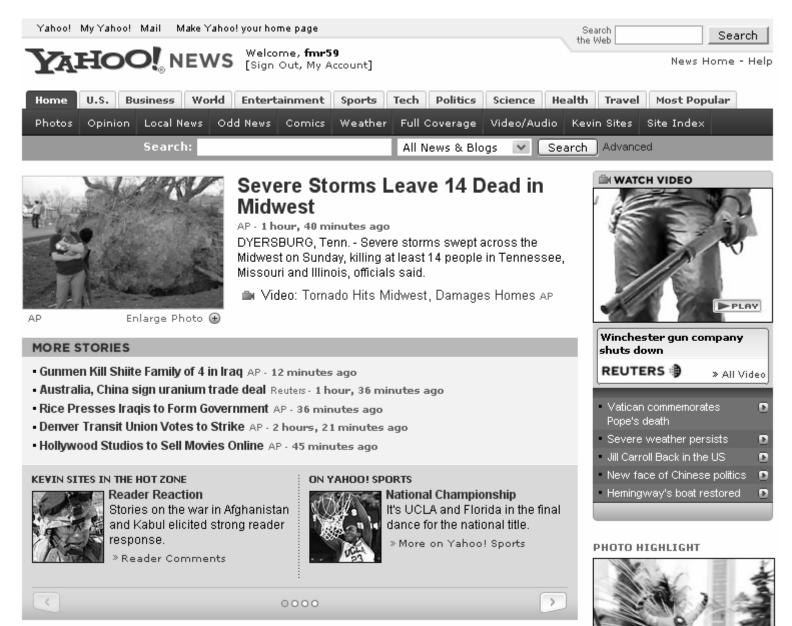


User

Recommendation

Joseph Conrad, Hearth of darkness

What news should I read?



Examples

- Some examples found in the Web:
 - **1. Amazon.com** looks in the user past buying history, and recommends product bought by a user with similar buying behavior
 - 2. **Tripadvisor.com** Quoting product reviews of a community of users
 - 3. Activebuyersguide.com make questions about searched benefits to reduce the number of candidate products
 - 4. **Trip.com** make questions and exploits to constraint the search (exploit standardized profiles)
 - **5. Smarter Kids** self selection of a user profile classification of products in user profiles.

The Problem

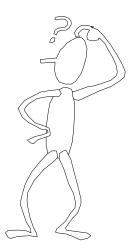






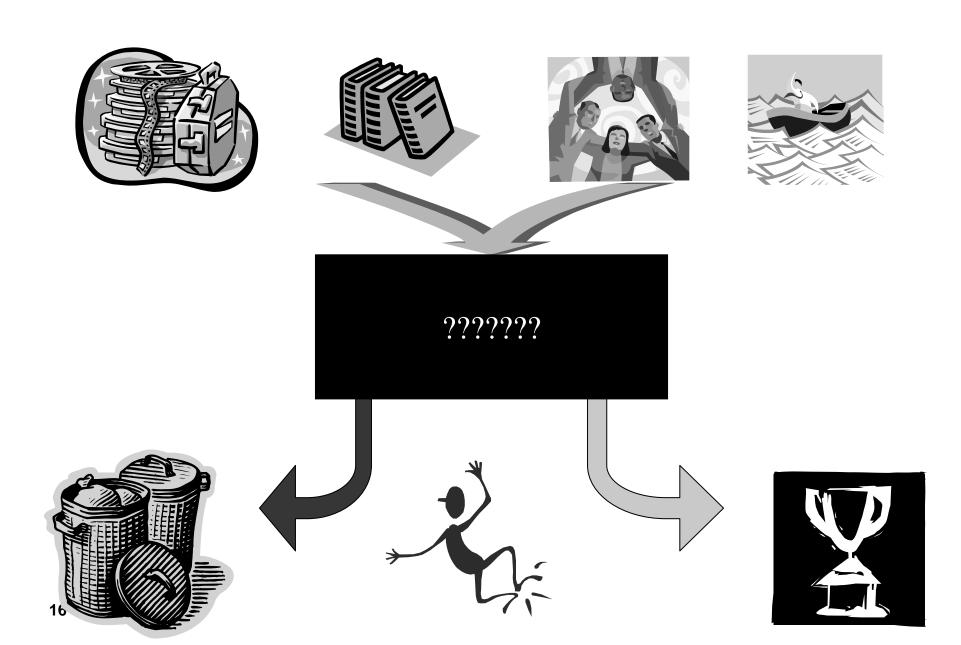








A Solution

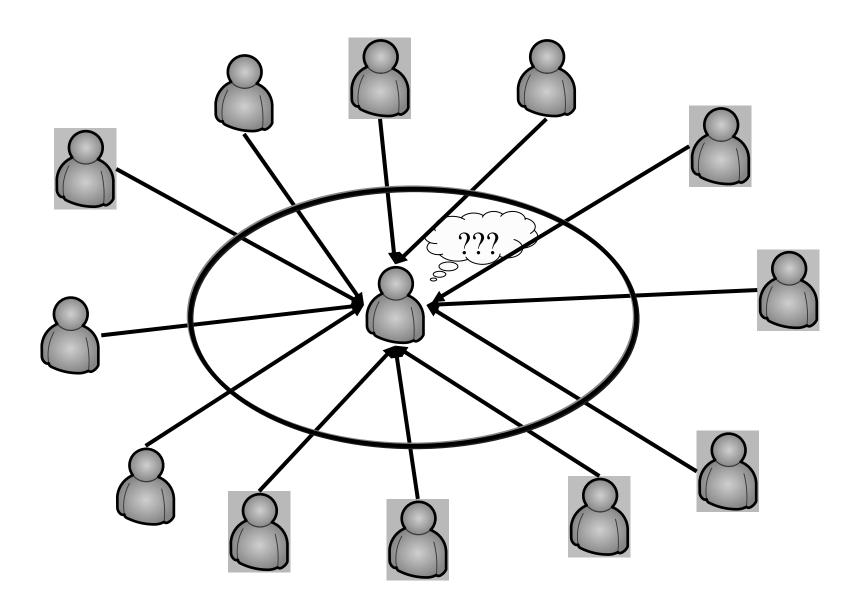


Original Definition of RS

- ☐ In everyday life we rely on recommendations from other people either by word of mouth, recommendation letters, movie and book reviews printed in newspapers ...
- □ In a typical recommender system people provide recommendations as inputs, which the system then aggregates and directs to appropriate recipients
 - ■Aggregation of recommendations
 - Match the recommendations with those searching for recommendations

[Resnick and Varian, 1997]

Social Filtering



Recommender Systems

- ☐ A **recommender system** helps to make choices without sufficient personal experience of the alternatives
 - ☐ To **suggest products** to their customers
 - ☐ To provide consumers with **information to help them decide** which products to purchase
- ☐ They are based on a number of **technologies**:
 - ☐ information filtering: search engines
 - machine learning: classification learning
 - adaptive and personalized system: adaptive hypermedia
 - □ user modeling

Information Overload

☐ Internet = information overload, i.e., the state of having too much information to make a decision or remain informed about a topic: ☐ Too much mails, too much news, to much papers, ... ☐ Information retrieval technologies (a search engine like Google) can assist a user to **locate** content if the user knows exactly what he is looking for (with some difficulties!) ☐ The user must be able to say "yes this is what I need" when presented with the right result ☐ But in many information search task, e.g., product selection, the user is ☐ not aware of the range of available options may not know what to search ☐ if presented with some results may not be able to choose.

Ratings

◯◯ Traveler Reviews (1-1	of 1)	
Language: English first	Sort by: Date: Newest first]
Traveler reviews (1-1 of 1)		

Traveler rating: 00000

Bolzano: Hotel Gasthof Gruner Baum

Glurns/Glorenza: "A complete find....one of the

loveliest places to stay"

Oct 15, 2006 gascony, london

Gasthof Gruner Baum in the Southern Tyrol is a truly wonderful little hotel. The hotel is in the town square of Glurns (Glorenza depending on your choice of the german or italian version!). The old hotel has been completely refurbished by the local owner/manager and is a fantastic marriage of traditional and modern funky.....it's a really beautiful place. The value of your overnight accomodation is really quite tremendous --- a lovely room, dinner (3-5 courses!) and breakfast for under £50 per person...

i would prefer not to recommend this hotel for fear of not being able to get a reservation myself next time but the owners deserve to have the recommendation.

This TripAdvisor Member:

Liked: the location and the food!

Disliked: the bar lacked a bit of atmosphere but that

might have been due to time of the year

My experience with this property took place in:

September, 2006

Would I recommend this hotel to my best friend? absolutely!

My ratings for this hotel are:

ooooo Value

00000Rooms

0000 Location

0000 Cleanliness

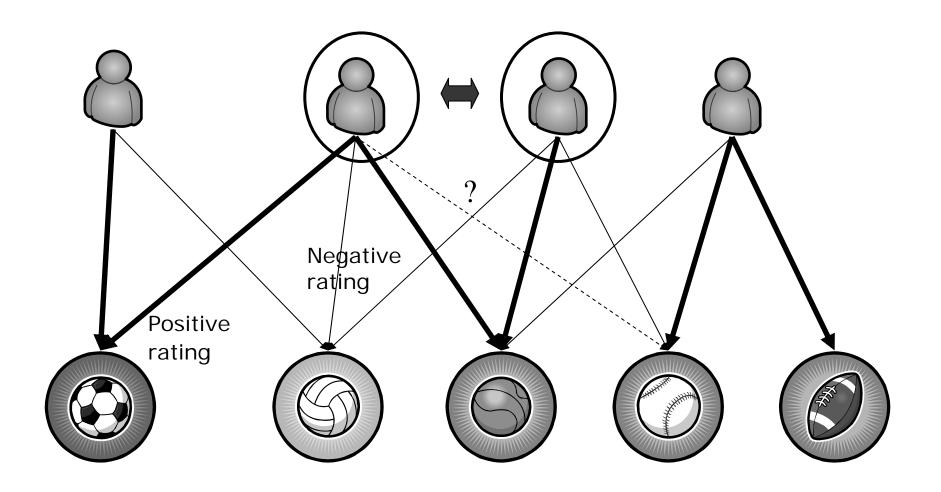
OOOO Check in / front desk

ooooo Service

I recommend this hotel

for: Young singles, An amazing honeymoon, A romantic getaway, Older travelers, Families with young children, Tourists

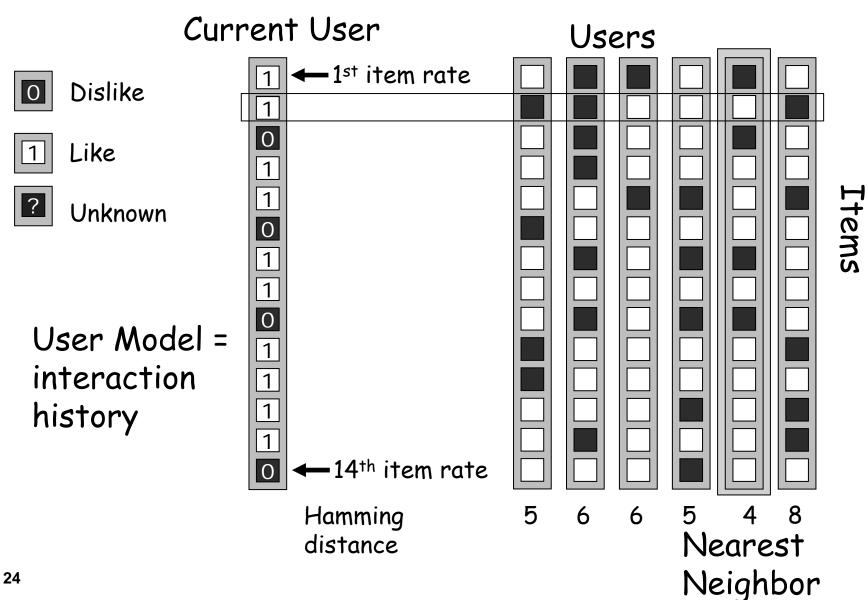
Collaborative Filtering



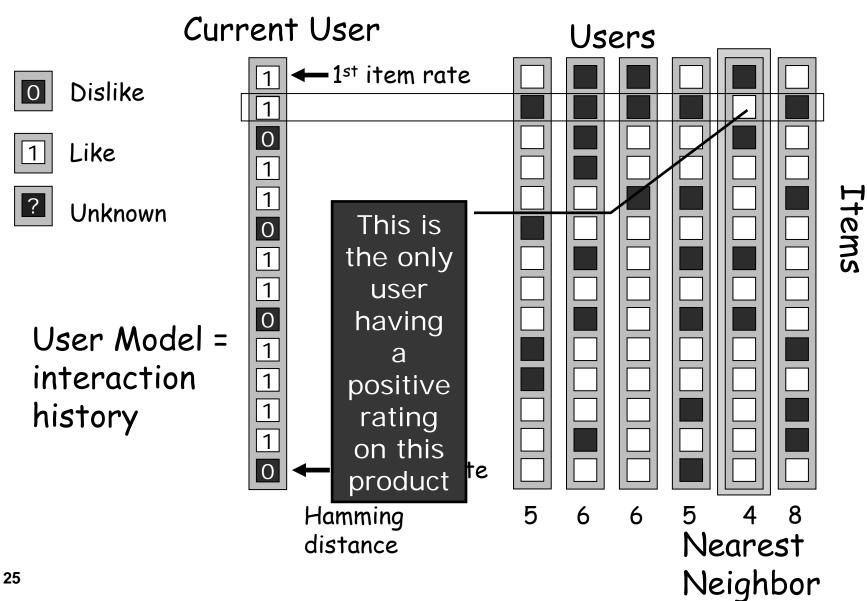
Collaborative-Based Filtering

- ☐ The collaborative based filtering recommendation techniques proceeds in these steps:
 - For a target/active user (the user to whom a recommendation has to be produced) the set of his ratings is identified
 - 2. The users more similar to the target/active user (according to a similarity function) are identified (neighbor formation)
 - 3. The products bought by these similar users are identified
 - 4. For each one of these products a prediction of the rating that would be given by the target user to the product is generated
 - 5. Based on this predicted rating a set of top N products are recommended.

Nearest Neighbor Collaborative-Based Filtering



1-Nearest Neighbor can be easily wrong



Matrix of ratings

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24 25
	а			1		4	5			4		3					2			4		2			
	b			4							3							5	1		3				
	С		5		4			4						3		5					4		5		
	d								3				5				3			4		2			3
	e		3					5			4	5				5					1			5	4
	T			4				1	_	3	5	_	4	1		5	4	4	_	4		_		3	
	g	2	4				4		2		_	5		1	4	5		4	2	4		5		_	4
	h			2		1		4		3	5		4	2	_	5	4	5		_				5	•
Llcore			1					3			5				5		4	4		5			4		3
Users	J		_	4			4			2	5	_		1		5		4	2	4				4	2
	k		5			3	4		3	2		5		1	5		4	4	2	4	4				2
	m	5		3		3			5	3		5	4		5	4 5	3	4	2	4	4	5	4		3 4
	n	,		1		4	5		,	,	4	5	4	1	5	,	4		3	4	4	,	4	3	4
	0			4		•	4				5	,	4		5		*	4	2		5		5	,	3
	р				4			5			•				•	5	4		2	4	4	5	4		2
	q					3			3					1	5		4	4		4			4		3
	r		4			1	4		2					2		5		4				5	4		4
	s			2		4		4			5			1			4		2	4		4		5	
	t		1		4			3					4		5	5		4			4				3
	u			2		1		4		3				1		5	4		2	4		5	4		
	٧					4	5				4	3		5			2					2			5
	w				2			2		3			5			4	5		4	2		3	4		
	Х	4			5				3		3				4	5					1				
200	У			1			3				2	3						3	3		5		4		

Items

Collaborative-Based Filtering

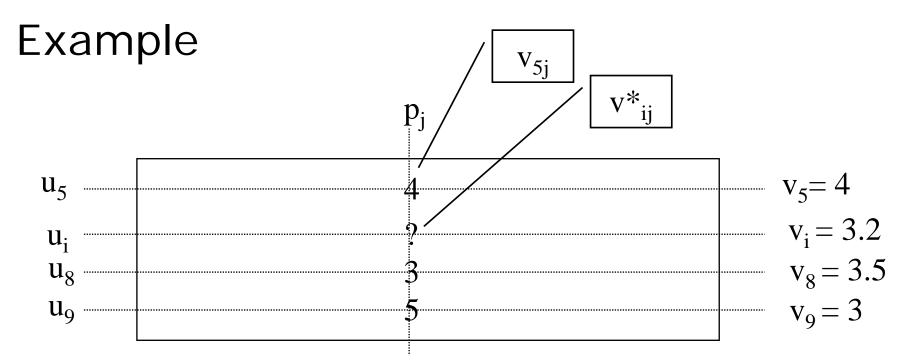
- lacktriangle A collection of user u_i , i=1, ..., m and a collection of products p_j , j=1, ..., m
- $\hfill \hfill \hfill$
- ☐ Prediction for user i and product j is computed as:

$$v^*_{ij} = v_i + K \sum_{v_{ki} \neq ?} u_{ik} (v_{kj} - v_k)$$

lacktriangle Where, v_i is the average rating of user i, K is a normalization factor such that the sum of u_{ik} is 1, and

$$u_{ik} = \frac{\sum_{j} (v_{ij} - v_i)(v_{kj} - v_k)}{\sqrt{\sum_{j} (v_{ij} - v_i)^2 \sum_{j} (v_{kj} - v_k)^2}}$$
 Similarity of users i and k

■ Where the sum (and averages) is over j s.t. v_{ij} and v_{kj} are not "?".



Users' similarities: $u_{i5} = 0.5$, $u_{i8} = 0.5$, $u_{i9} = 0.8$

$$v_{ij}^* = v_i + K \sum_{v_{ki} \neq ?} u_{ik} (v_{kj} - v_k)$$

$$v^*_{ij} = 3.2 + 1/(0.5 + 0.5 + 0.8) * [0.5 (4 - 4) + 0.5 (3 - 3.5) + 0.8 (5 - 3)]$$

= 3.2 + 1/1.8 * [0 - 0.25 + 1.6] = 3.2 + 0.75 = 3.95

Proximity Measure: Cosine

□ Correlation can be replaced with a typical Information Retrieval similarity measure (u_i and u_j are two users, with ratings v_{ik} and v_{jk} , k=1, ..., m)

$$\cos(u_{i}, u_{j}) = \frac{\sum_{k=1}^{m} v_{ik} v_{jk}}{\sqrt{\sum_{k=1}^{m} v_{ik}^{2} \sum_{k=1}^{m} v_{jk}^{2}}}$$

- ☐ This has been shown to provide worse results by someone [Breese et al., 1998]
- ☐ But many uses cosine [Sarwar et al., 2000] and somebody reports that it performs better [Anand and Mobasher, 2005]

Evaluating Recommender Systems

- ☐ The majority focused on system's accuracy in supporting the "find good items" user's task
- Assumption: "if a user could examine all items available, he could place them in a ordering of preference"
 - 1. Measure how good is the system in predicting the exact rating value (value comparison)
 - 2. Measure how well the system can predict whether the item is relevant or not (relevant vs. not relevant)
 - 3. Measure how close the predicted ranking of items is to the user's true ranking (ordering comparison).

How Accuracy Has Been Measured

- ☐ Split the available data (so you need to collect data first!), i.e., the user-item ratings into two sets: training and test
- Build a model on the training data
 - ☐ For instance, in a nearest neighbor (memory-based) CF simply put the ratings in the training in a separate set
- ☐ Compare the predicted rating on each test item (user-item combination) with the actual rating stored in the test set
- ☐ You need a metric to compare the predicted and true rating

Accuracy: Comparing Values

- Measure how close the recommender system's predicted ratings are to the true user ratings (for all the ratings in the test set).
- □ Predictive accuracy (rating): Mean Absolute Error (MAE), p_i is the predicted rating and r_i is the true one:

$$MAE = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N}$$

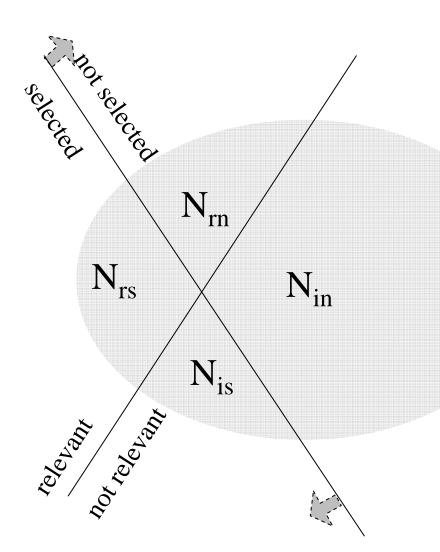
- □ Variation 1: mean squared error (take the square of the differences), or root mean squared error (and then take the square root). These emphasize large errors.
- □ Variation 2: Normalized MAE MAE divided by the range of possible ratings allowing comparing results on different data sets, having different rating scales.

Precision and Recall

	Selected	Not Selected	Total
Relevant	N_{rs}	N_{rn}	N_r
Irrelevant	N_{is}	N_{in}	N_i
Total	N_s	N_n	N

- ☐ The rating scale must be binary or one must transform it into a binary scale (e.g. items rated above 4 vs. those rated below)
- \Box **Precision** is the ratio of relevant items selected by the recommender to the number of items selected (N_{rs}/N_s)
- □ **Recall** is the ratio of relevant items selected to the number of relevant (N_{rs}/N_r)
- □ Precision and recall are the most popular metrics for evaluating information retrieval systems.

Precision and Recall



Precision =
$$N_{rs} / (N_{rs} + N_{is})$$

Recall = $N_{rs} / (N_{rs} + N_{rn})$

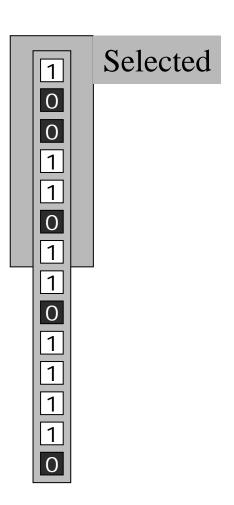
To improve both P and R you need to bring the lines closer together - i.e. better determination of relevance.

Example – Complete Knowledge

- We assume to know the relevance of all the items in the catalogue for a given user
- ☐ The orange portion is that recommended by the system

Precision=4/7=0.57

Recall=4/9=0.44



Example – Incomplete Knowledge

- We do not know the relevance of all the items in the catalogue for a given user
- ☐ The orange portion is that recommended by the system

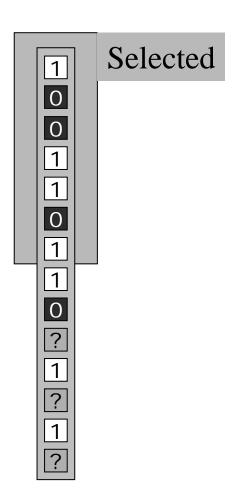
Precision=4/7=0.57 – As before

Recall=4/?

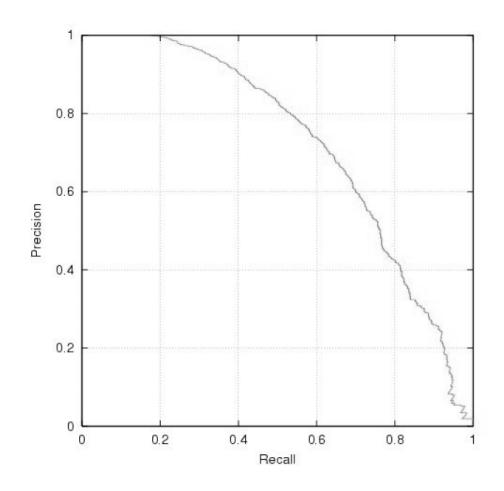
4/10 <= R <= 4/7

4/10 if all unknown are relevant

4/7 if all unknown are irrelevant



Precision vs. Recall

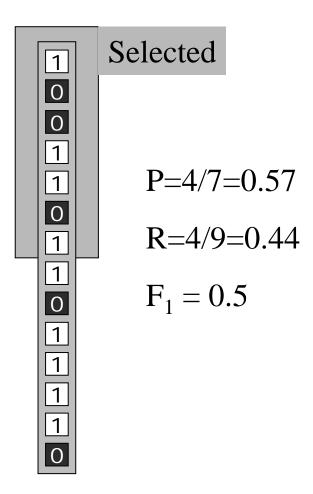


A typical precision and recall curve

F1

- □ Combinations of Recall and Precision such as F₁
- ☐ Typically systems with high recall have low precision and vice versa

$$F_1 = \frac{2PR}{P+R}$$



Problems with Precision and Recall

☐ To compute them we must know what items are relevant and what are not relevant □ Difficult to know what is relevant for a user in a recommender system that manages thousands/millions of products ☐ May be easier for some tasks where, given the user or the context, the number of recommendable products is small only a small portion could fit ☐ Recall is more difficult to estimate (knowledge of all the relevant products) ☐ Precision is a bit easier – you must know what part of the selected products are relevant (you can ask to the user after the recommendation – but has not been done in this way - not many evaluations did involve real users).

Example of Evaluation of a Collaborative Filtering Recommender System

- Movie data: 3500 users, 3000 movies, random selection of 100,000 ratings – obtained a matrix of 943 users and 1682 movies
 - \square Sparsity = 1 100,000 / 943*1682 = 0.9369)
 - \Box On average there are $100.000 \ \sqrt{943} = 106$ ratings per user
- E-Commerce data: 6,502 customers, 23,554 products and 97,045 purchase records
 - **□** Sparsity = 0.9994
 - ☐ On average 14.9 ratings per user
- □ **Sparsity** is the proportion of missing ratings over all the possible ratings (#missing-ratings/#all-possible-ratings).

All the possible ratings

Evaluation Procedure

☐ They evaluate top-N recommendation (10) recommendations for each user) ☐ Separate ratings in training and test sets (80% - 20%) ☐ Use the training to make the prediction ☐ Compare (precision and recall) the items in the test set of a user with the top N recommendations for that user ☐ Hit set is the intersection of the top N with the test (selected-relevant) ☐ Precision = size of the hit set / size of the top-N set ☐ Recall = size of the hit set / size of the test set (they assume that all the items not rated are not relevant optimistic assumption) ☐ They used the cosine metric in the CF prediction method.

Generation of recommendations

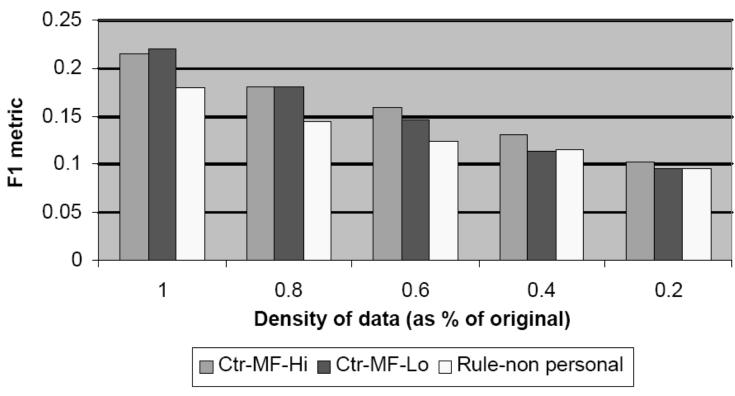
☐ Instead of using the average

$$v^*_{ij} = v_i + K \sum_{v_{kj} \neq ?} u_{ik} (v_{kj} - v_k)$$

- ☐ They used the **most-frequent item**recommendation method
 - ☐ Looks in the neighbors (users similar to the target user) scanning the purchase data
 - ☐ Compute a frequency count of the products (the frequency of a product in the neighbors purchases)
 - ☐ Sort the products according to the frequency
 - ☐ Returns the N most frequent products

Comparison with Association Rules

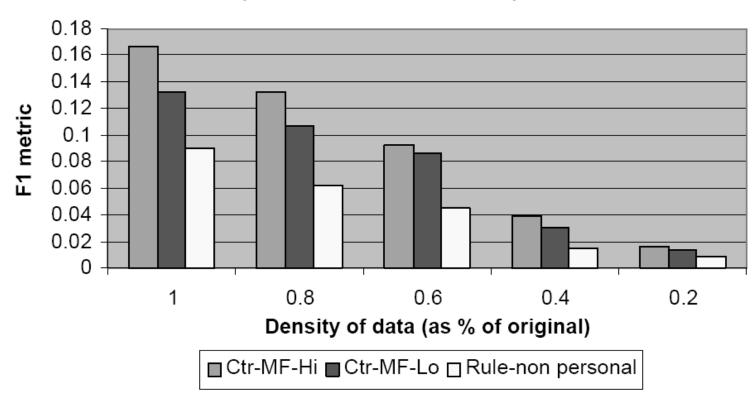
Different Recommendation Algorithms (MovieLens data set)



"Lo" and "Hi" means low (=20) and original dimensionality for the products dimension achieved with LSI (Latent Semantic Indexing)

Comparison with Association Rules

Different Recommendation Algorithms (E-Commerce data set)



"Lo" and "Hi" means low (=20) and original dimensionality for the products dimension achieved with LSI (Latent Semantic Indexing)

"Core" Recommendation Techniques

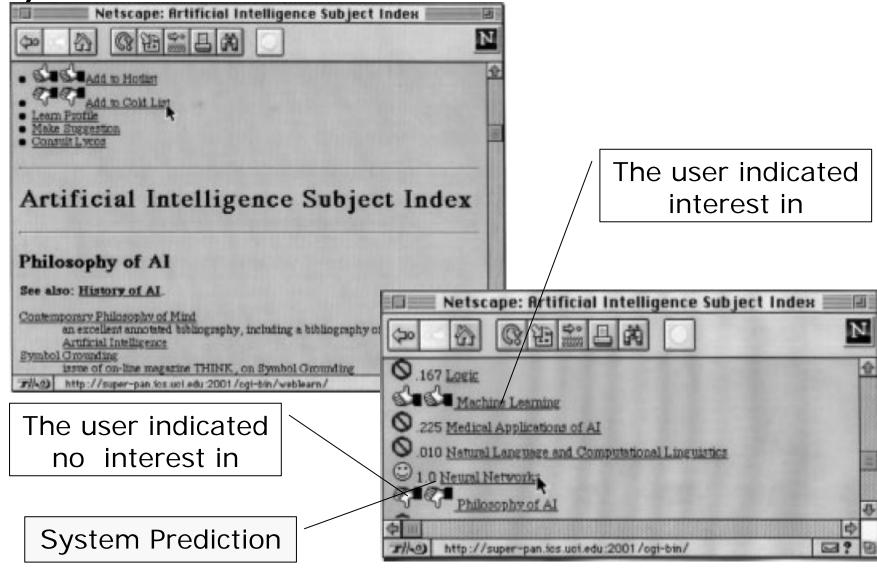
U is a set of usersI is a set of items/products

Technique	Background	Input	Process
Collaborative	Ratings from U of items in I.	Ratings from u of items	Identify users in U similar
		in I.	to u , and extrapolate from
			their ratings of i.
Content-based	Features of items in I	u's ratings of items in I	Generate a classifier that
			fits u's rating behavior and
			use it on i.
Demographic	Demographic information	Demographic	Identify users that are
	about U and their ratings of	information about u .	demographically similar to
	items in I.		 u, and extrapolate from
			their ratings of i.
Utility-based	Features of items in I.	A utility function over	Apply the function to the
		items in I that describes	items and determine i's
		u's preferences.	rank.
Knowledge-	Features of items in I.	A description of u's	Infer a match between i
based	Knowledge of how these	needs or interests.	and u's need.
	items meet a user's needs.		

Content-Based Recommender

☐ Has its root in Information Retrieval (IR) ☐ It is mainly used for recommending **text-based products** (web pages, usenet news messages) – products for which you can find a textual description ☐ The items to recommend are "described" by their associated features (e.g. keywords) ☐ The User Model can be structured in a "similar" way as the content: for instance the features/keywords more likely to occur in the preferred documents ☐ Then, for instance, text documents can be recommended based on a comparison between their content (words appearing in the text) and a user model (a set of preferred words) ☐ The user model can also be a **classifier** based on whatever technique (e.g., Neural Networks, Naive Bayes, C4.5).

Syskill & Webert User Interface



Content Model: Syskill & Webert

- A document (HTML page) is described as a set of Boolean features (a word is present or not)
- □ A feature is considered important for the prediction task if the Information Gain is high
- □ Information Gain: $G(S,W) = E(S) [P((W \text{ is present}) *E(S_{W \text{ is absent}})]$ present) + $P(W \text{ is absent}) *E(S_{W \text{ is absent}})]$

$$E(S) = \sum_{c \in \{hot, cold\}} -p(S_c) \log_2(p(S_c))$$

- E(S) is the Entropy of a labeled collection (how randomly the two labels are distributed)
- W is a word a Boolean feature (present/not-present)
- ☐ S is a set of documents, S_{hot} is the subset of interesting documents
- ☐ They have used the 128 most informative words (highest information gain).

Learning

☐ They used a Bayesian classifier (one for each user), where the probability that a document $w_1=v_1$, ..., $w_n=v_n$ (e.g. car=1, story=0, ..., price=1) belongs to a class (cold or hot) is

$$P(C=hot|w_1=v_1,...,w_n=v_n) \cong P(C=hot) \prod_j P(w_j=v_j|C=hot)$$

- Both $P(w_j = v_j | C = hot)$ (i.e., the probability that in the set of the documents liked by a user the word w_j is present or not) and P(C = hot) is estimated from the training data
- ☐ After training on 30/40 examples it can predict hot/cold with an accuracy between 70% and 80%.

A Better Model for the Document

☐ TF-IDF means Term Frequency — Inverse Document Frequency

$$d_{t_i} = \left(0.5 + 0.5 \frac{tf_i}{tf_{max}}\right) \left(\log \frac{n}{df_i}\right)$$

The less frequent the word is in the corpus the greater is this

The greater the frequency of the word the greater is this term

- ☐ tf_i is the number of times word t_i appears in document d (the term frequency),
- \Box df_i is the number of documents in the corpus which contain t_i (the document frequency),
- □ n is the number of documents in the corpus and tf_{max} is the maximum term frequency over all words in d.

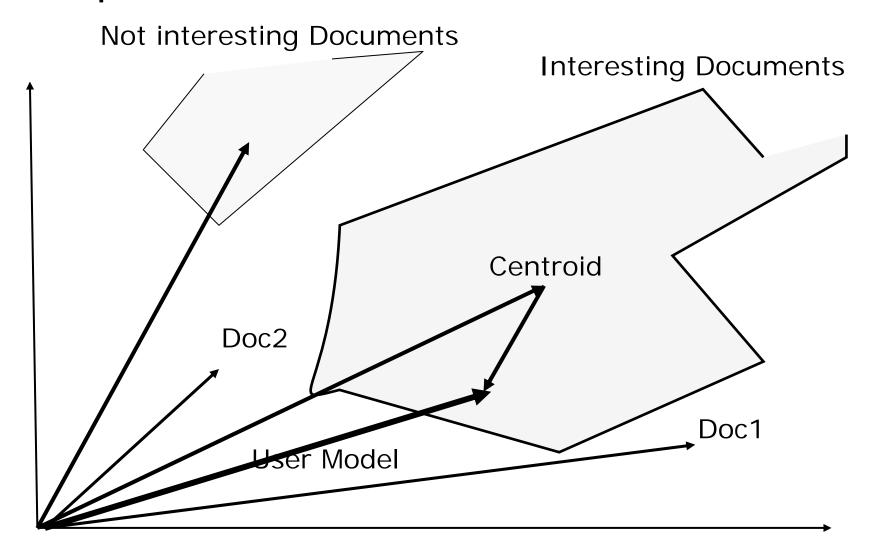
Computing TF-IDF -- An Example

- ☐ Given a document D containing terms (a, b, and c) with given frequencies:
 - \square freq(a,D)=3, freq(b,D)=2, freq(c,D)=1
- ☐ Assume collection contains 10,000 documents and the term total frequencies of these terms are:
 - \square $N_a = 50$, $N_b = 1300$, $N_c = 250$
- ☐ Then:
 - \Box a: tf = 3/3; idf = log(10.000/50) = 5.3; tf-idf = 5.3
 - \Box b: tf = 2/3; idf = log(10.000/1300) = 2.0; tf-idf = 1.3
 - \Box c: tf = 1/3; idf = log(10.000/250) = 3.7; tf-idf = 1.2

Using TF-IDF

- ☐ One can build a classifier (e.g. Bayesian) as before, where instead of using a Boolean array for representing a document, the array now contains the tf-idf values of the selected words (a bit more complex because features are not Boolean anymore)
- ☐ But can also build a **User Model** by (Rocchio, 1971)
 - ☐ Average of the tf-idf representations of interesting documents of a user (Centroid)
 - ☐ Subtracting a fraction of the average of the not interesting documents (0.25 in [Pazzani & Billsus, 1997]
- ☐ Then new documents close (cosine distance) to this user model are recommended.

Example



Doc1 is estimated more interesting than Doc2

Problems of Content-Based Recommenders

- □ A very shallow analysis of certain kinds of content can be supplied
- ☐ Some kind of items are not amenable to any feature extraction methods with current technologies (e.g. movies, music)
- ☐ Even for texts (as web pages) the IR techniques cannot consider multimedia information, aesthetic qualities, download time (any ideas about to use them?)
 - □Hence if you rate positively a page it could be not related to the presence of certain keywords!

Problems of Content-Based Recommenders (2)

- □ Over-specialization: the system can only recommend items scoring high against a user's profile the user is recommended with items similar to those already rated
- ☐ Requires user feed-backs: the pure content-based approach (similarly to CF) requires user feedback on items in order to provide meaningful recommendations
- ☐ It tends to recommend expected items this tends to increase trust but could make the recommendation not much useful (no serendipity)
- ☐ Works better in those situations where the "products" are generated dynamically (news, email, events, etc.) and there is the need to check if these items are relevant or not.

Knowledge Based Recommender

☐ Suggests products based on inferences about a user's needs and preferences ☐ Functional knowledge: about how a particular item meets a particular user need ☐ The **user model** can be any knowledge structure that supports this inference ☐ A query ☐ A case (in a case-based reasoning system) ☐ An adapted similarity metric (for matching) ☐ A part of an ontology ☐ There is a large use of domain knowledge encoded in a knowledge representation language/approach.

ActiveBuyersGuide

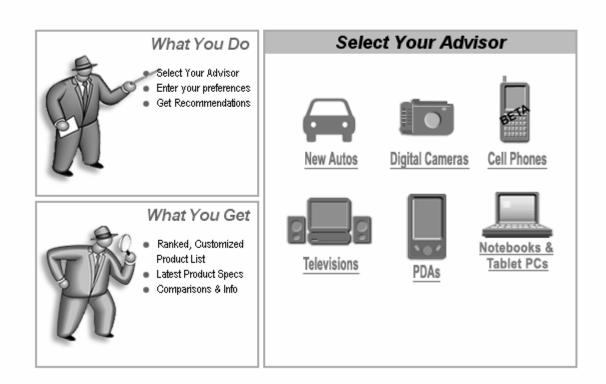
digital camera product advisor Find by: Product Use Product Features	camcorder product advisor Find by: Product Use Product Features	mp3 player product advisor Find by: Product Use Product Features
I need photo quality high enough for More Info 5" x 7" prints (2 megapixels) 8" x 10" prints (4 megapixels) 11" x 14" prints (6 megapixels) No preference	I need a camcorder for More Info Occasional & casual recordings Home and vacation movies Business productions No preference	My MP3 player (Digital Music Player) needs to be compatible with a More Info select all that apply Windows operating Mac operating system system
My camera should fit inside a More Info Shirt Backpack pocket No Waist preference pack	I want to zoom in on subjects across a More Info Playground (40 ft. away) Tennis court (60 ft. away) Park (80 ft. away) No preference	I want my MP3 player to hold More Info A handful of songs (less than 128 MB) A few dozen songs (128 MB - 512 MB) Hundreds of songs (512 MB - 5 GB)
I prefer cameras that have an Epinions.com rating of at leastselect	I prefer camcorders that have an Epinions.com rating of	Thousands of songs (5 GB or more)No preference
I want to spend More Info From \$ up to \$	at leastselect GET RESULTS I want to spend More Info	I prefer MP3 players that have an Epinions.com rating of at leastselect
I want to zoom in on subjects across a More Info Small room (8 ft.	From \$ up to \$	GET RESULTS
away) Living room (15 ft. away) Backyard (35 ft. away) No preference	My camcorder should fit inside a More Info Shirt Backpack pocket No Waist preference pack	I want to spend More Info From \$ up to \$
My preferred brands More Info select all that apply Canon Fujifilm Kodak Nikon Olympus Sony more brands MORE GUIDANCE GET RESULTS	My preferred brands More Info check all clear all Canon JVC Panasonic Samsung Sony more brands	My preferred brands More Info check all clear all Apple/iPod Creative Labs iRiver Lexar RCA Rio more brands
	MODE CUITDANCE CET DECIVITO	MORE GUIDANCE GET RESULTS

www.myproductadvisor.com

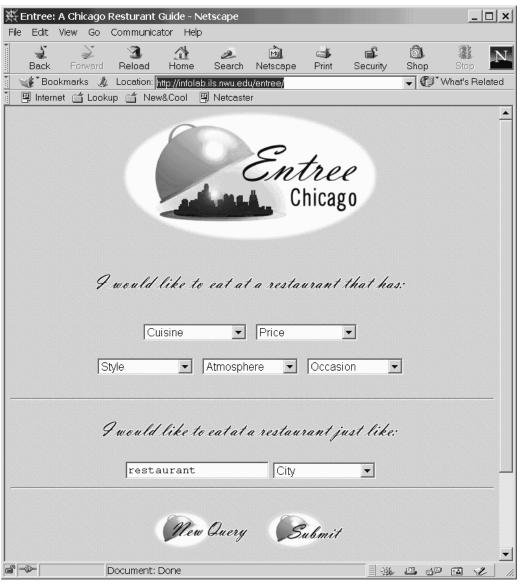


Welcome to My Product Advisor

Receive an unbiased list of product recommendations based on your individual preferences. No ads, no selling, no registration. Jumpstart your shopping process!



Entrée: Case-Based Recommender



- ☐ Entree is a restaurant recommender system it finds restaurants:
 - in a new city
 similar to
 restaurants the
 user knows and
 likes
 - or those
 matching some
 user goals (case
 features).

Partial Match



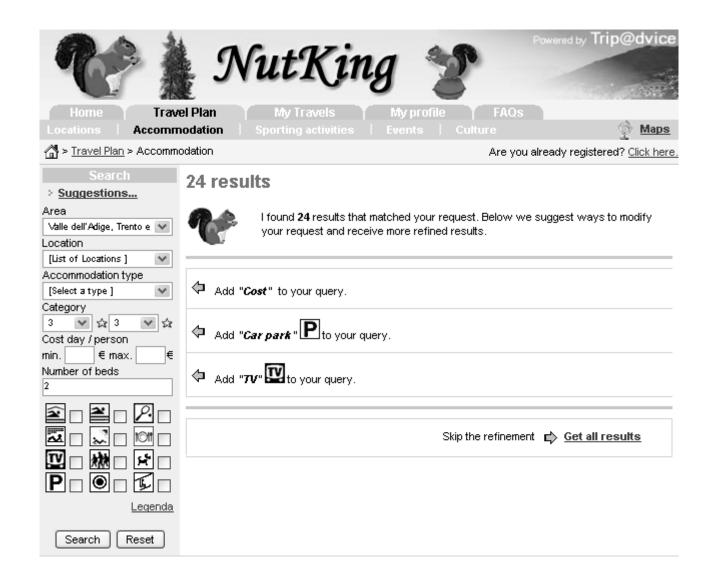
☐ In general, only a subset of the preferences will be matched in the recommended restaurant.



http://itr.itc.it:8080/dev/jsp/index.jsp



Query Tightening





Webmaster



Travel Plan

New Travel Plan

Suggested Travels

> Travel Plan > Suggested Travels

New Travel Plan

We recommend



These are the travel plans we re We have examined travel plans Click on the name for details.

Garda Lake in July

Description:

From 2002-07-01 To 2002-07-13 Locations: RIVA DEL GARDA

Accommodation: RESIDENCE SPIAGGIA Sporting activities: Malga Grassi; Fraglia

Vacanza in montagna 2002

Description: Con la famiglia nel Primiero From 2002-09-06 To 2002-09-15 Locations: IMER

Accommodation: AL BIVIO

Sporting activities: Passeggiata Passo Ro

e rit.

Culture: Palazzo del Dazio o delle Miniere ; Castel Pietra ; Museo della Grande Guerra s

TRAVEL 09-12-2002

Description: val di fassa



From 2002-07-01 To 2002-07-01 Accommodation: RESIDENCE DOLOMIA

Sporting activities: Pozza-Buffaure-Sela I Culture: Torre di Pozza ; Molin de Pezol - m

[Ricci et al., 2002]

Suggested Travel Plan

Here's a trip we recommend. If you like you can save this as your trip.

Garda Lake in July

General information

Name: Garda Lake in July

Description:

Start date: 2002-07-01 End date: 2002-07-13

Travel plan preferences

Travel companions: with family Activities:Sports Relaxing Accommodation: apartment / between 20 and Whine and Food 40 € Transport: Enviroment and Period: car Landscape

Length of stay: July two weeks

The travel plan includes:

Locations: RIVA DEL GARDA

Description



In Riva, Lake Garda is particularly charming. The colour blue of the water is more intense, the sunlight more vivid and the air is oxygenated by the mountains and purified by the Lake Garda breeze which blows and fills the coloured sails of the windsurfs. The beaches, surrounded by vegetation or...more

Mountaineering

Swimming

Services

Museums

林

Windsurfing

Classical music

Pop music

Mountain bike

Places of historic interest

Eno-gastronomic events

A Sailing Jazz

Give us your feedback

Accommodation: RESIDENCE SPIAGGIA

Details



Address: Telephone:

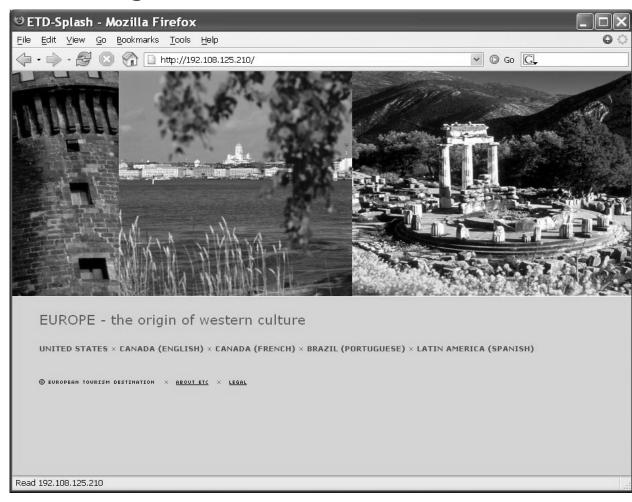
Fax:

Web: www.rivadelgarda.com/spiaggia

E-mail: Max Cost: 25 €

www.visiteurope.com

- ☐ Major European Tourism Destination Portal of the European Travel Commission (ETC)
- ☐ 34 National Tourism Organizations
- ☐ Project started 2004
- ☐ Consortium: EC3, TIScover, ITC-irst, Siemens, Lixto
- ☐ On line since April 06
- □ 500.000 page views/month
- ☐ 100.000 visitors/month



Evaluation of RS

	nere are many criteria for evaluating RS
Ţ	☐ User satisfaction/usability
Ţ	☐ User effort (e.g. time or rec. cycles required)
Ţ	■ Accuracy of the prediction
[Success of the prediction (the product is bought after the recommendation)
Ţ	☐ Coverage (recall)
Ţ	☐ Confidence in the recommendation (trust)
Ţ	Understandability of the recommendation
Ţ	☐ Degree of novelty brought by the recommendation (serendipity)
Ţ	☐ Transparency
Ţ	☐ Quantity
Ţ	☐ Diversity
Ţ	☐ Risk minimization
Ţ	Cost effective (the cheapest product having the required features)
Ţ	☐ Robustness of the method (e.g. against an attack)
Г	7 Scalability

Challenges

- □ Generic user models (multiple products and tasks)
- ☐ Generic recommender systems (multiple products and tasks)
- Distributed recommender system (users and products data are distributed)
- Portable recommender systems (user data stored at user side)
- ☐ (user) Configurable recommender systems
- Multi strategy adapted to the user
- Privacy protecting RS
- ☐ Context dependent RS
- Emotional and values aware RS
- Trust and recommendations
- Persuasion technologies
- Easily deployable RS
- Group recommendations

Challenges (2)

☐ Listening customers

☐ Recommender systems and ontologies

- ☐ Interactive Recommendations sequential decision making ■ Hybrid recommendation technologies ☐ Consumer Behavior and Recommender Systems ☐ Complex Products recommendations ■ Mobile Recommendations ☐ Business Models for Recommender Systems ☐ High risk and value recommender systems ■ Recommendation and negotiation □ Recommendation and information search ■ Recommendation and configuration
- 69

Summing up

- □ At the beginning user recommendations (ratings/evaluations) are used to build new recommendations – collaborative or social filtering
 - ☐ The recommender system is a machine that burns recommendations to build new recommendations
- ☐ The expansion many new methods are introduced (content-based, hybrid, clustering, ...)
 the aim is to tackle information overload and improve the behavior of CF methods (considering context and product descriptions)

Summing up (2)

- □ Decision support recommender systems are tools for helping users to take decision (what product to buy or what news to read)
 - ☐ The gain in "utility" (personalized) without and with recommendation is the metric;
 - ☐ Information search and processing cannot be separated from the RS research;
 - ☐ The recommendation process becomes an important factor
 - ☐ Conversational systems are introduced
 - More adaptive and flexible conversations should be supported

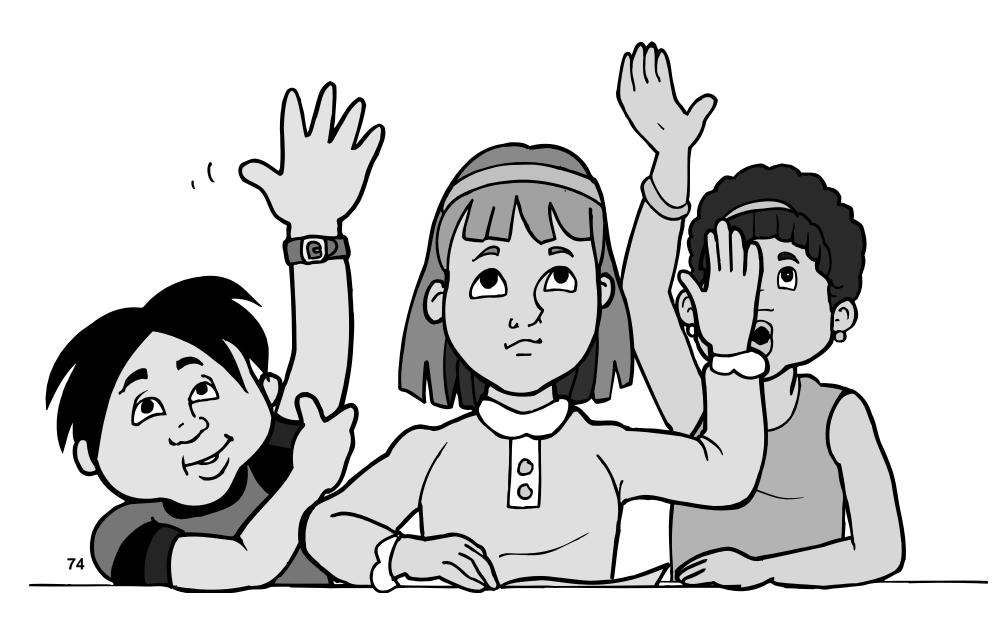
Conclusions

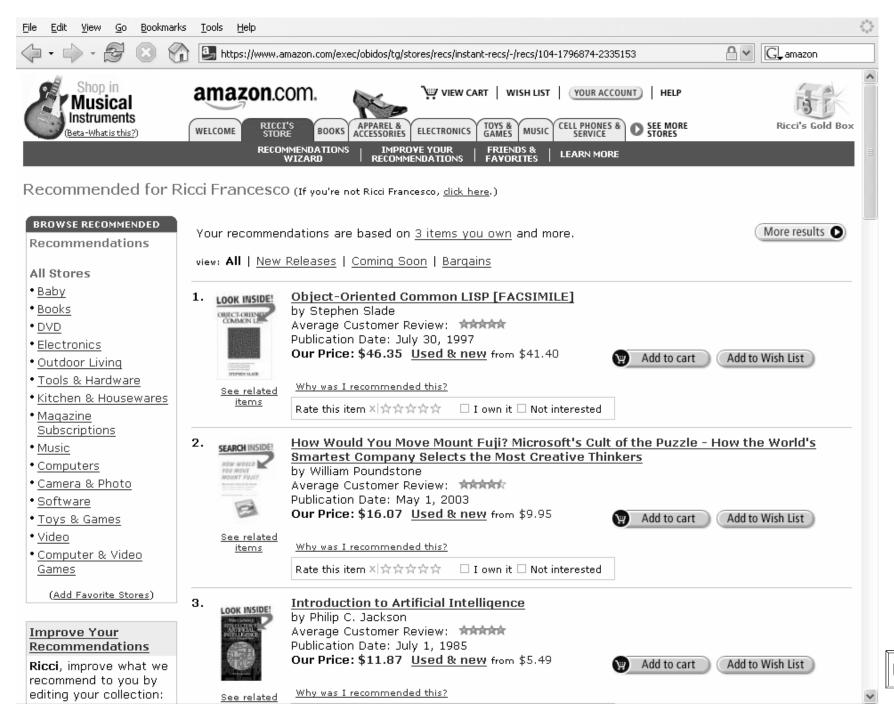
- □ A recommender system main task is helping to choose products that are potentially more interesting to the user from a large set of options
- □ Recommender systems "personalize" the humancomputer interaction – make the interaction adapted to the specific needs and characteristics of the user
- ☐ Personalization is a complex topic: many factors and there is no single theory that explain all.

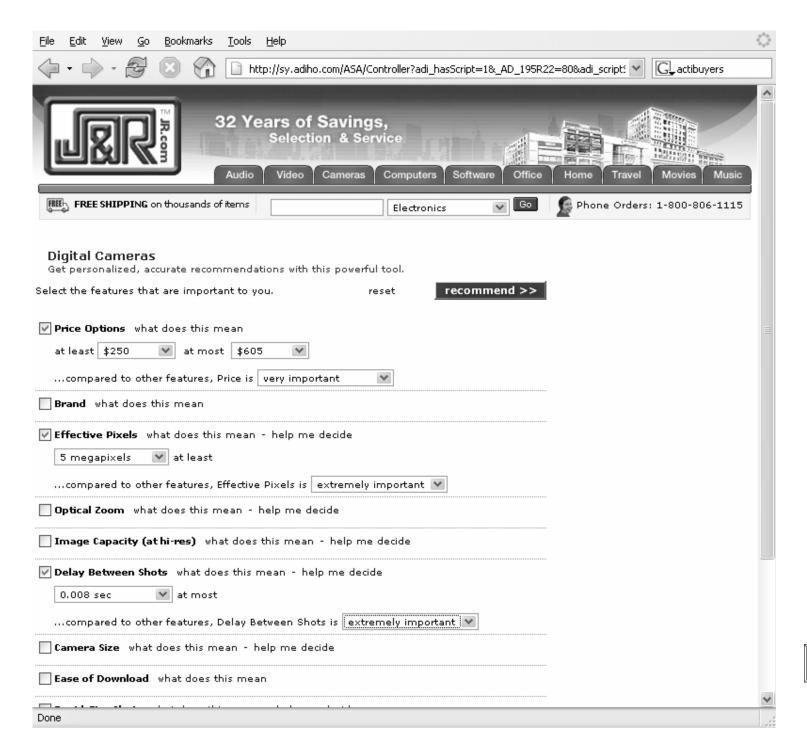
It's all about You



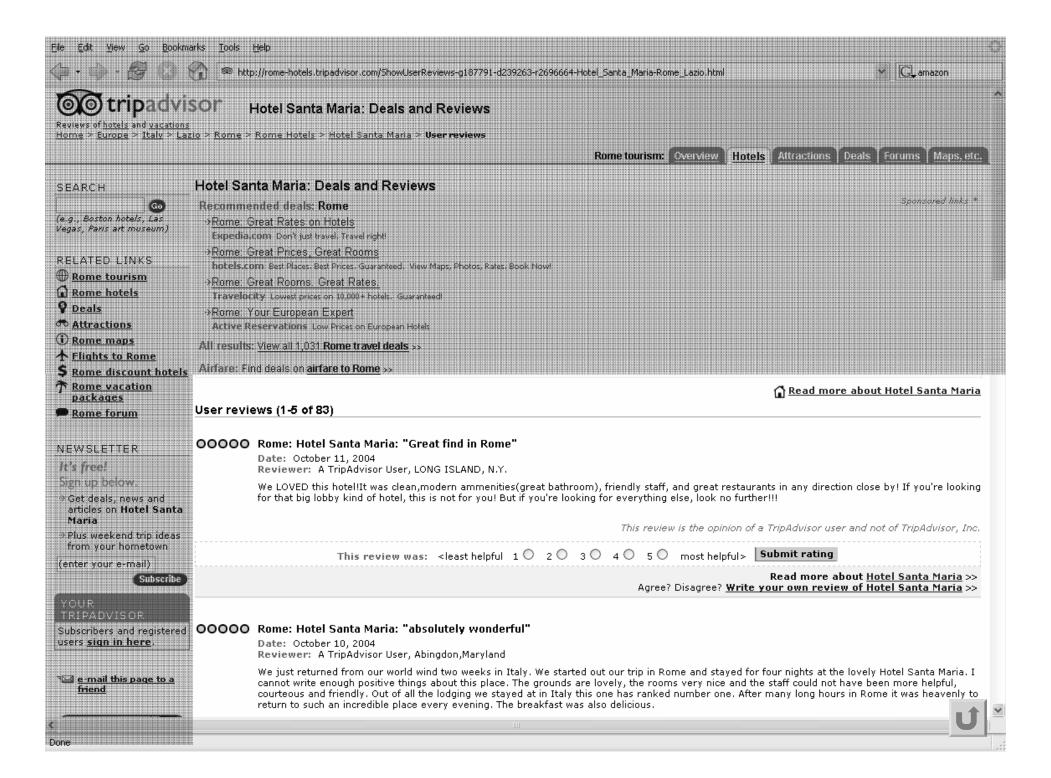
Questions?



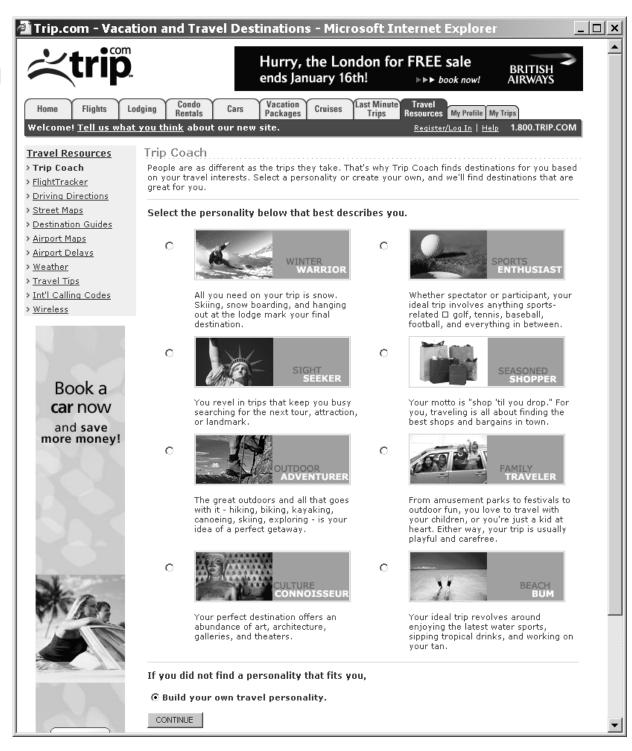




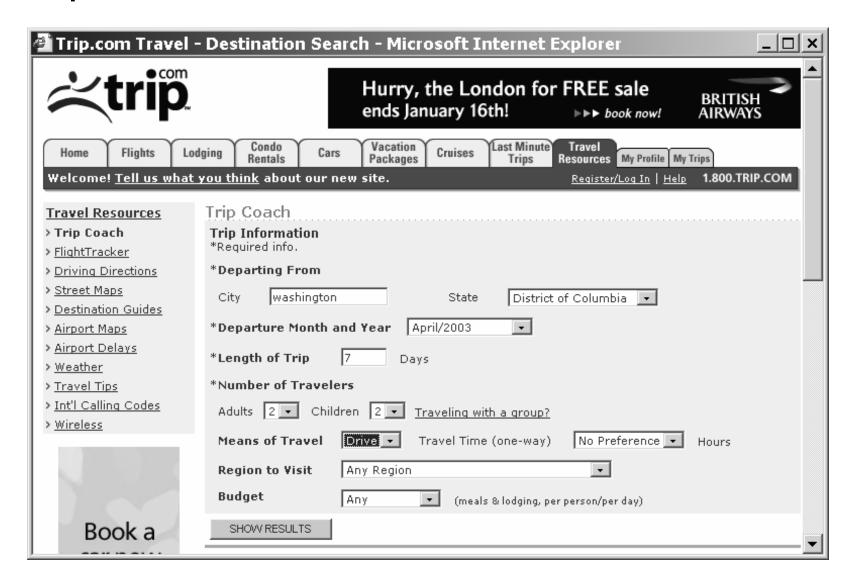




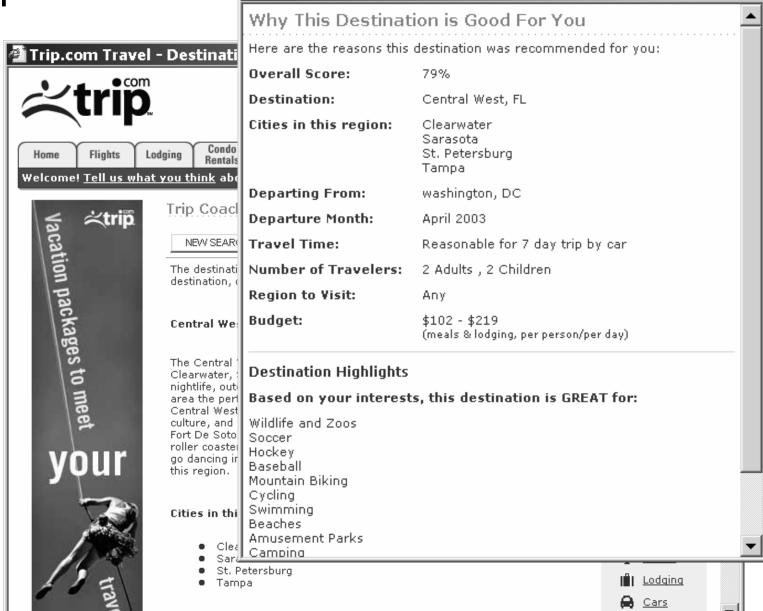
Trip.com



Trip.com



Trip.com



🗿 Why This Destination is Good For You - Mi... 🖃 🗖







NOW PLAYING MOVIE / TV NEWS MY MOVIES

DVD / VIDEO MESSAGE BOARDS SHOWTIMES & TICKETS IMDbpro

Earth's Biggest Movie Database™

Home | Top Movies | Photos | Independent Film | Browse | Help

Login | Register to personalize

All go

More searches | Tips IMDbPro.com free trial

Tops at the Box Office

- 1 The Prestige
- ≥ The Departed
- ⇒ Flags of Our Fathers
- 4 Open Season
- ≤ Flicka

▶ more

Opening this Week

- · Running with Scissors
- Babel
- · Saw III
- · <u>Tideland</u>
- · Catch a Fire
- · Death of a President

▶ more

Coming Soon

- Borat: Cultural Learnings of America for Make Benefit Glorious Nation of Kazakhstan
- * The Santa Clause 3: The Escape Clause
- Volver
- Flushed Away
- · Stranger Than Fiction
- Fur: An Imaginary Portrait of Diane Arbus
- · The Return
- A Good Year
- · Harsh Times
- Casino Royale

The Internet Movie Database

Visited by over 42 million movie lovers each month!

Welcome to the Internet Movie Database, the biggest, best, most award-winning movie site on the planet. Want to make IMDb your home page? Drag this link onto your # Home button.

Watch This: Trailers and More



Trailer for Arthur and the Invisibles

Trailer for 300

Trailer for Charlotte's Web

Trailer for Eragon

Trailer for Stranger Than Fiction

Trailer for For Your Consideration

Trailer for Deck the Halls

Trailer for Sur's Up

More Trailers

Today's IMDb Poll Question Is:



Do you think box office lists should be adjusted for inflation? (Suggested by "rwdaniel") (vote)

Amazon Unbox Video Downloads



Introducing Amazon.com Unbox, a new digital video download service. Unbox offers thousands of TV shows (including those that aired last night!), movies, and more with DVD picture quality, triple the video quality of the leading commercial internet video services delivering content. Unbox also boasts RemoteLoad technology, which allows customers to buy from one PC and download to another, and progressive download, which means that the typical broadband customer can start watching any Unbox TV show or movie within 3 to 7 minutes after ordering. Visit www.amazon.com/unbox to try the Unbox

service and get your first TV show free.

Ú

Movie and TV News

Wed 25 October 2006:

Celebrity News

- Holmes & Cruise Confirm
 Italian Wedding Plans
- <u>Limbaugh Blasts</u>
 <u>Parkinson's Sufferer Fox</u>
 for "Acting"
- Madonna and Malawian Authorities Dismiss Father's Claims

Studio Briefing

- 'The Prestige' Works Box Office Magic
- · <u>Redstone Defends Cruise</u> <u>Ouster</u>
- Paramount To Provide
 Films Online Through
 AOL

Born Today

Wednesday, 25 October 2006:



Billy Barty (1924-2000)

next>

all birthdays