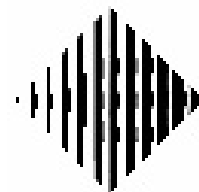
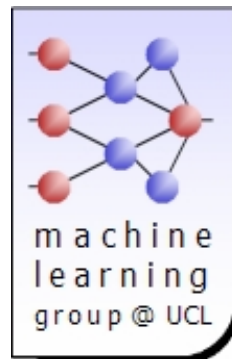


# Recommender systems: an overview

François Fouss and Marco Saerens  
{francois.fouss,marco.saerens}@ucLouvain.be  
Université catholique de Louvain (UCL)  
Institut d'Administration et de Gestion (IAG)  
Unité de Systèmes d'Information (ISYS)



Université catholique de Louvain

Université partenaire de l'Académie universitaire 'Louvain'



# Outline

- Introduction
- Typology of recommender systems
  - Preference indicators
  - Recommendation approach
  - Recommendation technique
  - Direct or indirect method
  - Provided results
- Algorithms
  - Feature-analysis based
  - Link-analysis based
- Validation
  - Cross-validation
  - Performance measures
- Experimental results



# Outline

- **Introduction**
- Typology of recommender systems
- Algorithms
- Validation
- Experimental results



# Definition

« Recommender systems try to provide people with **recommendations** of items they will appreciate, based on their past **preferences**, **history** of purchase, and **demographic** information »

for a review of the state-of-the-art on recommender systems: *Adomavicius and Tuzhilin, 2005*



# Everyday examples of recommender systems

Amazon.com: The Good Shepherd (Widescreen Edition): DVD: Alec Baldwin, Matt Damon, Robert De Niro, Keir Dullea, Michael Gambon, William Hurt, Timothy Hutton, Angelina Jolie, Daniel Kash, ...

File Edit View History Bookmarks Tools Help

http://www.amazon.com/gp/product/B000MXPE7O/ref=amb\_link\_4227172\_5/104-1366178-4690319?pf\_rd\_m=ATVPDKIKX0DER&pf\_rd\_s=center-6&p

Google Search Check AutoLink AutoFill Subscribe Options



Buy a DVD get a **FREE TV Show\***

[The Good Shepherd](#) is now available to download for **\$14.99** from Amazon Unbox. Never tried video downloads? Get a FREE TV show download from Amazon Unbox when you buy a DVD. [See Details](#)

---

### Better Together

Buy this DVD with [The Departed \(Two-Disc Special Edition\) DVD](#) ~ Leonardo DiCaprio today!

 + 

**Total List Price:** \$64.97  
**Buy Together Today:** **\$37.48**

[Buy both now!](#)

---

### What do customers ultimately buy after viewing this item?

68% buy the item featured on this page: [The Good Shepherd \(Widescreen Edition\) DVD](#) ~ Alec Baldwin ★★★★★ \$16.99

10% buy [Blood Diamond \(Two-Disc Special Edition\) DVD](#) ~ Leonardo DiCaprio ★★★★★ \$21.99

8% buy [The Departed \(Two-Disc Special Edition\) DVD](#) ~ Leonardo DiCaprio ★★★★★ \$20.49

8% buy [Casino Royale \(Two-Disc Widescreen Edition\) DVD](#) ~ Daniel Craig ★★★★★ \$15.99

6% buy [Babel](#) DVD ~ Brad Pitt ★★★★★ \$19.99

[Compare these items](#) [Explore Similar Items](#)

---

### Plot Summary

**Genres:** [Drama](#), [Thriller](#)

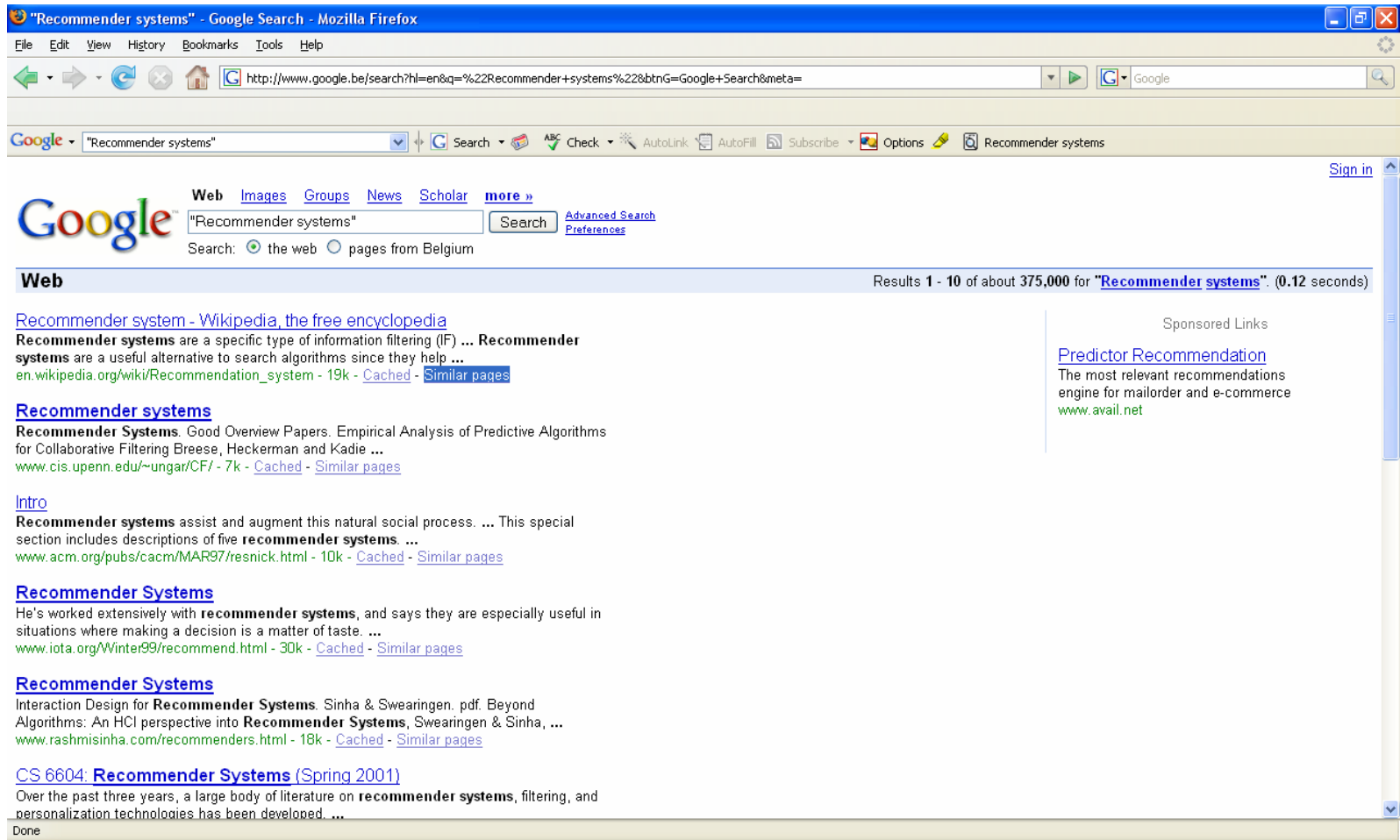
**Tagline:** Edward Wilson believed in America, and he would sacrifice everything he loved to protect it.

**Plot Outline** The tumultuous early history of the Central Intelligence Agency is viewed through the prism of one man's life.

**Plot Synopsis:** Edward Wilson, the only witness to his father's suicide and member of the Skull and Bones Society while a student at Yale, is a morally upright young man who values honor and discretion, qualities that help him to be recruited for a career in the newly founded Office of Strategic Services (OSS, the predecessor of the Central Intelligence Agency). While working there, his ideals gradually turn to suspicion influenced by the Cold War paranoia present within the office. Eventually, he becomes an influential veteran operative, while

Done

# Everyday examples of recommender systems



The screenshot shows a Mozilla Firefox browser window with the title '"Recommender systems" - Google Search - Mozilla Firefox'. The address bar contains the URL <http://www.google.be/search?hl=en&q=%22Recommender+systems%22&btnG=Google+Search&meta=>. The search bar contains the text "Recommender systems". Below the search bar, the Google logo is visible, along with navigation links for Web, Images, Groups, News, Scholar, and more. The search results are displayed under the heading "Web". The first result is "Recommender system - Wikipedia, the free encyclopedia", which describes recommender systems as a type of information filtering (IF) and a useful alternative to search algorithms. The second result is "Recommender Systems. Good Overview Papers. Empirical Analysis of Predictive Algorithms for Collaborative Filtering Breese, Heckerman and Kadie ...", which provides a good overview of the field. The third result is "Intro", which discusses how recommender systems assist and augment the natural social process. The fourth result is "Recommender Systems", which mentions that the author has worked extensively with recommender systems and says they are especially useful in situations where making a decision is a matter of taste. The fifth result is "Recommender Systems", which discusses the interaction design for recommender systems. The sixth result is "CS 6604: Recommender Systems (Spring 2001)", which mentions that over the past three years, a large body of literature on recommender systems, filtering, and personalization technologies has been developed. On the right side of the search results, there are sponsored links for "Predictor Recommendation", described as the most relevant recommendations engine for mailorder and e-commerce, with the website [www.avail.net](http://www.avail.net).

"Recommender systems" - Google Search - Mozilla Firefox

File Edit View History Bookmarks Tools Help

<http://www.google.be/search?hl=en&q=%22Recommender+systems%22&btnG=Google+Search&meta=>

Google "Recommender systems" Search [Advanced Search](#) [Preferences](#)

Search: ☒ the web ☐ pages from Belgium

**Web** Results 1 - 10 of about 375,000 for **"Recommender systems"**. (0.12 seconds)

[Recommender system - Wikipedia, the free encyclopedia](#)  
**Recommender systems** are a specific type of information filtering (IF) ... **Recommender systems** are a useful alternative to search algorithms since they help ...  
[en.wikipedia.org/wiki/Recommendation\\_system](http://en.wikipedia.org/wiki/Recommendation_system) - 19k - [Cached](#) - [Similar pages](#)

[Recommender systems](#)  
**Recommender Systems.** Good Overview Papers. Empirical Analysis of Predictive Algorithms for Collaborative Filtering Breese, Heckerman and Kadie ...  
[www.cis.upenn.edu/~ungar/CF/](http://www.cis.upenn.edu/~ungar/CF/) - 7k - [Cached](#) - [Similar pages](#)

[Intro](#)  
**Recommender systems** assist and augment this natural social process. ... This special section includes descriptions of five **recommender systems**. ...  
[www.acm.org/pubs/cacm/MAR97/resnick.html](http://www.acm.org/pubs/cacm/MAR97/resnick.html) - 10k - [Cached](#) - [Similar pages](#)

[Recommender Systems](#)  
He's worked extensively with **recommender systems**, and says they are especially useful in situations where making a decision is a matter of taste. ...  
[www.iota.org/Winter99/recommend.html](http://www.iota.org/Winter99/recommend.html) - 30k - [Cached](#) - [Similar pages](#)

[Recommender Systems](#)  
Interaction Design for **Recommender Systems**. Sinha & Swearingen. pdf. Beyond Algorithms: An HCI perspective into **Recommender Systems**, Swearingen & Sinha, ...  
[www.rashmisinha.com/recommenders.html](http://www.rashmisinha.com/recommenders.html) - 18k - [Cached](#) - [Similar pages](#)

[CS 6604: Recommender Systems \(Spring 2001\)](#)  
Over the past three years, a large body of literature on **recommender systems**, filtering, and personalization technologies has been developed. ...

Done

Sponsored Links

[Predictor Recommendation](#)  
The most relevant recommendations engine for mailorder and e-commerce  
[www.avail.net](http://www.avail.net)

# MovieLens

**movieLens**  
helping you find the *right* movies

Welcome francois@fouss.be ([Log Out](#))

You're in the  **Bear Group** ([what's this?](#))

You've rated **7** movies.

You're the *19th* visitor in the past hour.

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

So far you have rated **7** 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 >](#)

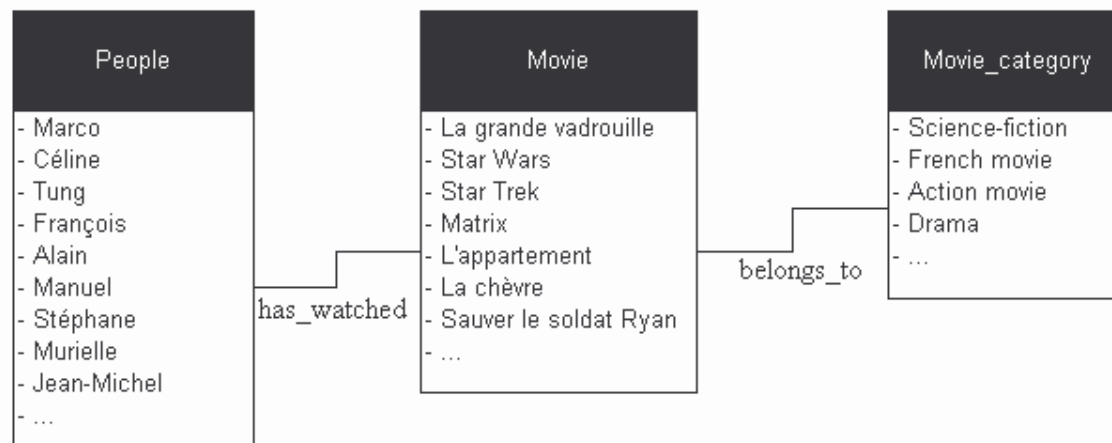
Your Rating		Movie Information
???	<input type="text" value="Not seen"/>	<b>Absent Minded Professor, The (1961)</b> Children, Comedy, Fantasy
???	<input type="text" value="Not seen"/>	<b>Death and the Maiden (1994)</b> Drama, Thriller
???	<input type="text" value="Not seen"/>	<b>Eye for an Eye (1996)</b> Drama, Thriller
★★★★	<input type="text" value="3.5 stars"/>	<b>King Kong (1976)</b> Action, Adventure, Horror
???	<input type="text" value="Not seen"/>	<b>Last Picture Show, The (1971)</b> Drama
★★★★	<input type="text" value="3.5 stars"/>	<b>Longest Day, The (1962)</b> Action, Drama, War
???	<input type="text" value="Not seen"/>	<b>Red Dawn (1984)</b> Action, Drama, War
???	<input type="text" value="Not seen"/>	<b>Speechless (1994)</b> Comedy, Romance
???	<input type="text" value="Not seen"/>	<b>Tales From the Crypt Presents: Demon Knight (1995)</b> Horror
???	<input type="text" value="Not seen"/>	<b>World According to Garp, The (1982)</b> Comedy, Drama, Romance

[next >](#)

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

# Other examples

- MovieLens ([movielens.umn.edu](http://movielens.umn.edu))



- Hollywood Video ([www.hollywoodvideo.com](http://www.hollywoodvideo.com))
- Netflix ([www.netflix.com](http://www.netflix.com))
- Jester ([shadow.ieor.berkeley.edu/humor](http://shadow.ieor.berkeley.edu/humor))
- WikiLens ([www.wikilens.org](http://www.wikilens.org))
- etc.



# Outline

- Introduction
- **Typology of recommender systems**
  - Preference indicators
  - Recommendation approach
  - Recommendation technique
  - Direct or indirect method
  - Provided results
- Algorithms
- Validation
- Experimental results



# Preference indicators

- Rating triplet or co-occurrence pair
- Explicit or implicit



# Rating triplet

- A rating triplet has the form  $(u, i, r)$

where

- $u$  corresponds to the index of a **user**
- $i$  corresponds to the index of an **item**
- $r$  corresponds to the **rating** provided by user  $u$  to item  $i$

8	689	4
9	7	4
9	50	5
9	201	5
9	242	4
9	276	4
9	294	4
9	371	5
9	385	5
9	402	4
9	483	5
9	615	4
9	690	1
10	1	4
10	4	4
10	9	4



# Co-occurrence pair

- A co-occurrence pair has the form  $(u,i)$

where

- $u$  corresponds to the index of a **user**
- $i$  corresponds to the index of an **item**
- the occurrence of the pair  $(u,i)$  means that user  $u$  has **bought / watched / consumed** item  $i$

22	2
22	4
22	17
22	21
22	24
22	29
22	50
22	53
22	62
22	68
22	85
22	89
22	94





# Explicit preference indicators

## ■ Explicitly provided by the user

Examples:

- asking a person to rate an item
- asking a person to rank a set of items
- asking a person to choose between items
- etc.



# Implicit preference indicators

## ■ Implicitly gathered

*Claypool 2001*

### Examples:

- observing the items that a person views in his/her online shopping
- saving information about the time spent on a page
- observing the mouse clicks
- etc.



# Recommendation approaches

- Content-based approaches
- Collaborative approaches
- Hybrid approaches



# Content-based approaches

*Belkin 1992, Baeza-Yates 1999*

1. Discover patterns among items
2. Find similar items

have their roots in the information retrieval and information filtering communities

Shortcomings:

- hardly deal with new users
- difficulties to distinguish items
- overspecialization



# Collaborative approaches

*Goldberg 1992, Maes 1995*

1. Analyze the ratings previously given by the person of interest
2. Find neighbours of users or items

## Shortcomings:

- hardly deal with new users
- hardly recommend new items
- sparsity



# Hybrid approaches

*Balabanovic 1997, Basilico 2004, Basu 1998*

- combine content-based and collaborative approaches
- take advantage of both approaches
- various kinds of combination



# Recommendation techniques

- Model-based techniques
- Memory-based techniques



# Model-based techniques

- develop a model of users ratings
- apply the model to new information
- *Examples*
  - *decision trees models*
  - *latent class models*
  - *artificial neural networks models*
  - *etc.*





# Memory-based techniques

- use various statistical techniques to recommend items to users
- by determining a neighbourhood for users or items, or not
- *Examples:*
  - *Pearson correlation coefficient*
  - *cosine correlation coefficient*
  - *link-based techniques*
  - *etc.*



# Direct or indirect methods

## ■ Direct method

compute **directly** the similarities between a given person and the items

## ■ User-based indirect method

find the **nearest neighbours** of the **user** of interest and proceed from there

## ■ Item-based indirect method

*Karypis 2001*

find the **nearest neighbours** of **each item** rated by the user of interest and proceed from there



# Provided results

## ■ Prediction

Numerical value expressing the predicted likelihood that a user will like an item

## ■ Recommendation

List of items that a user will like the most



# Outline

- Introduction
- Typology of recommender systems
- **Algorithms**
  - Feature-analysis based
  - Link-analysis based (random-walk, kernel-based, and web-mining algorithms)
- Validation
- Experimental results

# Traditional approach

- Data are in the form

	Variables					
	$X_1$	$X_2$		$X_j$		$X_p$
Individuals	1					
	2					
	$i$			$x_{ij}$		
	$n$					

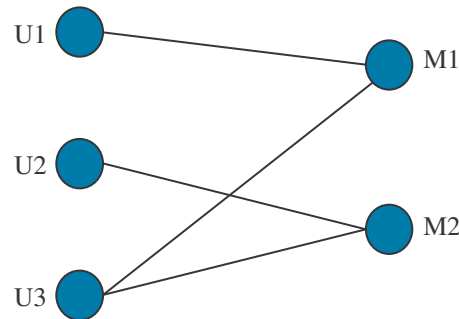
Individual 1: age=22, gender='F', occupation='student',...  
Individual 2: age=53, gender='M', occupation='artist',...  
...  
Individual  $n$ : age=35, gender='F', occupation='lawyer',...

- Traditional algorithms of data mining, machine learning, and statistics exploit these features for clustering / classification / recommendation / etc.

→ **feature-analysis based**

# Another approach

- Data are viewed as **links**, leading to a graph (very popular for web pages ranking – **PageRank**, **HITS**)



→ **link-analysis based**



# Feature-analysis based algorithms

- Cosine correlation coefficient
  - Binary similarities
  - Latent class model
  - etc.
- 
- For comparison:
    - ‘Basic’ algorithm which recommends first, for each user, the most rated item (best-seller recommendation)



# Cosine correlation coefficient

$$\cos(i, j) = (\mathbf{v}_i^T \mathbf{v}_j) / (\|\mathbf{v}_i\| \|\mathbf{v}_j\|)$$

where  $\mathbf{v}_i$  ( $\mathbf{v}_j$ ) is a binary vector containing the items user  $i$  ( $j$ ) has rated (or not)

$$\mathbf{v}_i = [0 \ 1 \ 1 \ 0 \dots 0]^T \quad \mathbf{v}_j = [1 \ 1 \ 0 \ 0 \dots 0]^T$$



# Binary similarities

*Johnson and Wichern, 2002*

## ■ Define a frequency table

		Individual $j$		Totals
		1	0	
Individual $i$	1	$a$	$b$	$a + b$
	0	$c$	$d$	$c + d$
Totals		$a + c$	$b + d$	$p = a + b + c + d$

and use, for example, the « ratio of matches to mismatches with 0-0 matches excluded »

$$sim(i, j) = s(\mathbf{v}_i, \mathbf{v}_j) = \frac{a}{b+c}$$



# Binary similarities: examples

Coefficient	Rationale
1. $\frac{a + d}{p}$	Equal weights for 1-1 matches and 0-0 matches.
2. $\frac{2(a + d)}{2(a + d) + b + c}$	Double weight for 1-1 matches and 0-0 matches.
3. $\frac{a + d}{a + d + 2(b + c)}$	Double weight for unmatched pairs.
4. $\frac{a}{p}$	No 0-0 matches in numerator.
5. $\frac{a}{a + b + c}$	No 0-0 matches in numerator or denominator. (The 0-0 matches are treated as irrelevant).
6. $\frac{2a}{2a + b + c}$	No 0-0 matches in numerator or denominator. Double weight for 1-1 matches.
7. $\frac{a}{a + 2(b + c)}$	No 0-0 matches in numerator or denominator. Double weight for unmatched pairs.
8. $\frac{a}{b + c}$	Ratio of matches to mismatches with 0-0 matches excluded.



# Latent Class

*Hofman et al. 1999, Delannay 2006*

- clustering model
- assumes that the preferences of a user are established through a **latent** variable (i.e., a **non-observable** variable)
- standard procedure: **Expectation-Maximization (EM)** algorithm

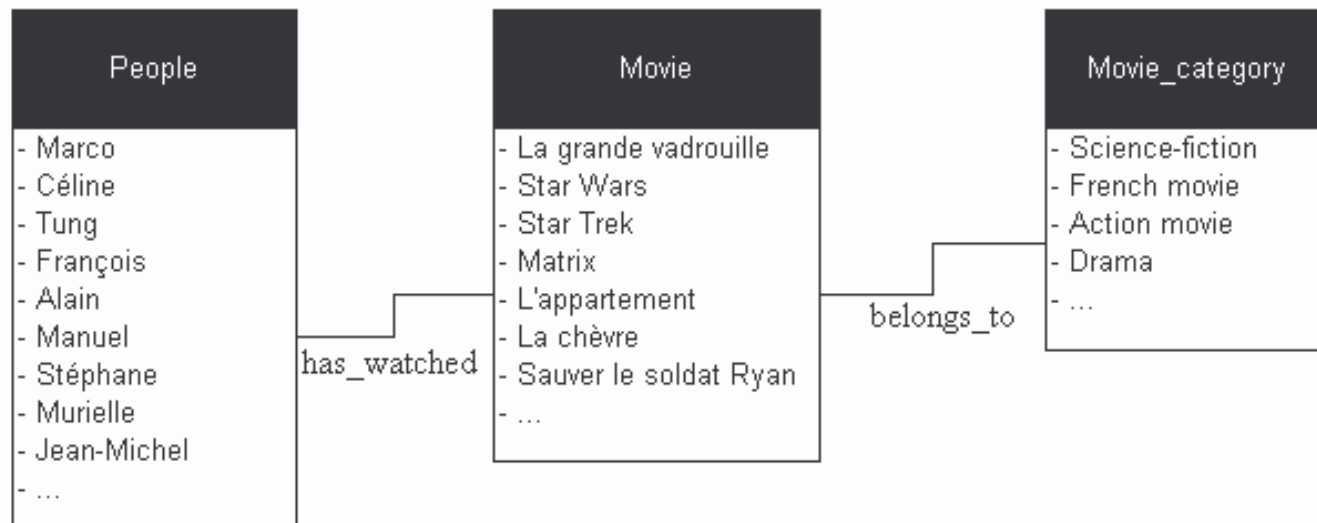


# Link-analysis based algorithms

- Random-walk based algorithms
- Kernel-based algorithms
- Web-mining based algorithms

# Some definitions:

## Remember our movie example



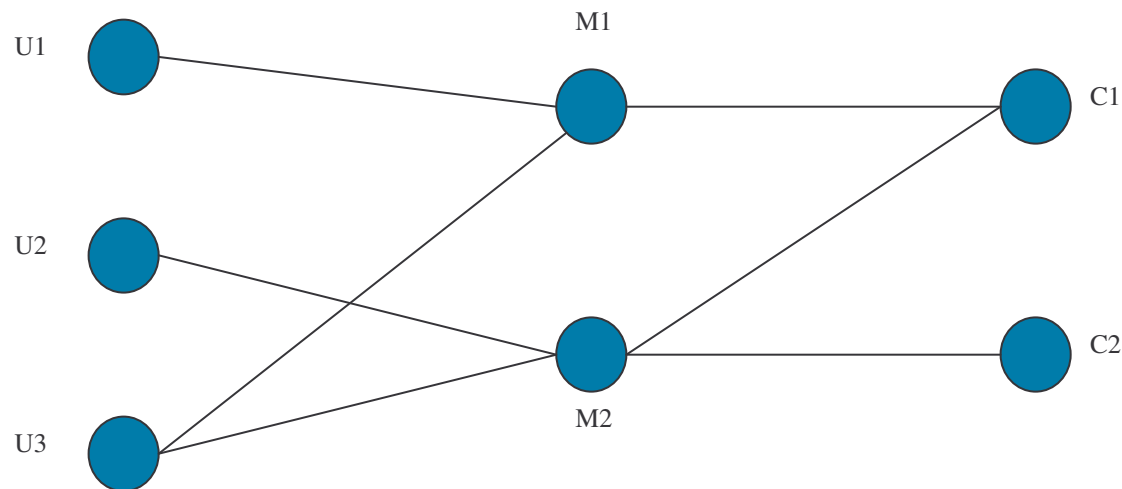
from which, we define

- a weighted graph
- an adjacency matrix
- the transition matrix
- a random-walk model on the graph

# The weighted graph associated with a database

- Database elements correspond to **nodes** of the graph
- Database links correspond to **edges**

Example: a database containing 3 users, 2 movies and 2 movie categories:



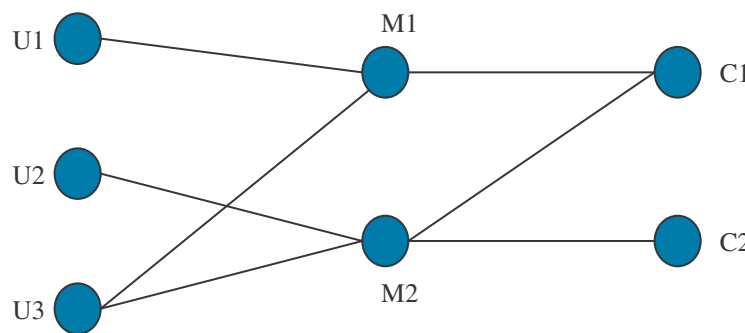
# The adjacency matrix

- The elements  $a_{ij}$  of the adjacency matrix  $\mathbf{A}$  of a weighted, undirected, graph are defined as

$$a_{ij} = \begin{cases} w_{ij} & \text{if node } i \text{ is connected to node } j \\ 0 & \text{otherwise} \end{cases}$$

where  $\mathbf{A}$  is symmetric

- The  $w_{ij} \geq 0$  represent the strength of relationship between node  $i$  and node  $j$



$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

# The transition matrix

- We define  $\mathbf{P}$  as the transition matrix whose entries are

$$p_{ij} = \frac{a_{ij}}{a_{i.}} \text{ where } a_{i.} = \sum_{j=1}^n a_{ij}$$

- Remember our example:

$$\mathbf{A} = \begin{pmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$

$$\mathbf{P} = \begin{pmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ \frac{1}{3} & 0 & \frac{1}{3} & 0 & 0 & \frac{1}{3} & 0 \\ 0 & \frac{1}{4} & \frac{1}{4} & 0 & 0 & \frac{1}{4} & \frac{1}{4} \\ 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \end{pmatrix}$$





# Link-analysis based algorithms

## ■ Random-walk based algorithms

- The average first-passage time
- The average commute time
- The pseudoinverse of the Laplacian matrix of the graph

## ■ Kernel-based algorithms

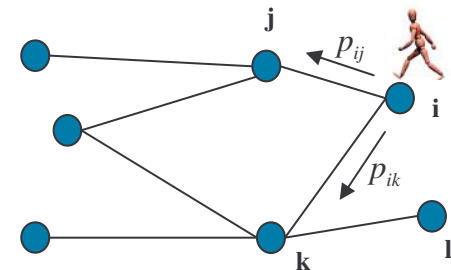
## ■ Web-mining based algorithms

# A random-walk model on the graph

- Every node is associated to a **state** of a Markov chain
- We define a random variable,  $s(t)$ , representing the state of the Markov model at time step  $t$
- The random walk is defined by the single-step **transition probabilities**

$$P(s(t+1) = j | s(t) = i) = p_{ij} = \frac{a_{ij}}{a_{i.}}$$

$$\text{where } a_{i.} = \sum_{j=1}^n a_{ij}$$



- In other words, to any state or node  $i$ , we associate a probability of jumping to an adjacent node,  $s(t+1) = j$ , which is proportional to the weight  $w_{ij}$  of the edge connecting  $i$  and  $j$



# Average first-passage time

- $m(k|i)$  = average number of steps a random walker, starting in state  $i$ , will take to enter state  $k$  for the first time

$$\begin{cases} m(k|i) = 1 + \sum_{\substack{j=1 \\ j \neq k}}^n p_{ij} m(k|j), \text{ for } i \neq k \\ m(k|k) = 0 \end{cases}$$

- These equations can be used in order to iteratively compute the first-passage times.



# Average commute time

- $n(i,j) = m(j|i) + m(i|j)$  = average number of **steps** a random walker, starting in state  $i \neq j$ , will take before entering a given state  $j$  for the first time, and go back to  $i$
- Note: while  $n(i,j)$  is **symmetric** by definition,  $m(i|j)$  is not.



# The Laplacian matrix

- The Laplacian matrix  $\mathbf{L}$  of the graph is defined by

$$\mathbf{L} = \mathbf{D} - \mathbf{A}$$

where  $\mathbf{D} = \text{diag}(a_{i.})$  with  $d_{ii} = [\mathbf{D}]_{ii} = a_{i.} = \sum_{j=1}^n a_{ij}$

Properties:

- $\mathbf{L}$  is doubly centered
- $\mathbf{L}$  is symmetric
- $\mathbf{L}$  is positive semidefinite
- We suppose that the graph is connected, so that the rank of  $\mathbf{L}$  is  $n - 1$ , where  $n$  is the number of nodes



## Pseudoinverse of the Laplacian matrix ( $\mathbf{L}^+$ )

- The rank of  $\mathbf{L}$  is  $n-1$
- $\mathbf{L}$  is **not** invertible
  - ⇒ use of the pseudoinverse ( $\mathbf{L}^+$ )
- It can be shown that  $\mathbf{L}^+$  matrix contains the **inner products** of node vectors in a transformed space and can then be considered as a **similarity measure** between the nodes.



# Link-analysis based algorithms

- Random-walk based algorithms
- **Kernel-based algorithms**
- Web-mining based algorithms



# Kernel-based algorithms

- In a few words, a kernel is simply
  - An inner product matrix
- That is, a matrix containing inner products as entries,

$$[\mathbf{K}]_{ij} = k_{ij} = \mathbf{x}_i^T \mathbf{x}_j$$

defined in some abstract inner product space, called the **feature space**





# Kernel-based algorithms examples

- The exponential diffusion kernel

$$\mathbf{K}_{\text{ED}} = \sum_{k=0}^{\infty} \frac{\alpha^k \mathbf{A}^k}{k!} = \exp(\alpha \mathbf{A})$$

- The Laplacian exponential diffusion kernel

$$\mathbf{K}_{\text{LED}} = \exp(-\alpha \mathbf{L})$$

- The von Neumann diffusion kernel

$$\mathbf{K}_{\text{VND}} = \sum_{k=0}^{\infty} \alpha^k \mathbf{A}^k = (\mathbf{I} - \alpha \mathbf{A})^{-1}$$

- The regularized Laplacian kernel

$$\mathbf{K}_{\text{RL}} = (\mathbf{I} + \alpha \mathbf{L})^{-1}$$

- The commute time kernel

$$\mathbf{K}_{\text{CT}} = \mathbf{L}^+$$



# Kernel-based algorithms: examples

- The Markov diffusion kernel

$$\mathbf{K}_{\text{MD}}(t) = \mathbf{Z}(t)\mathbf{Z}^{\text{T}}(t) \text{ with } \mathbf{Z}(t) = \frac{1}{t} \sum_{\tau=1}^t \mathbf{P}^{\tau}$$

- The cross-entropy diffusion matrix

$$\mathbf{K}_{\text{CED}}(t) = \mathbf{Z}(t) \log(\mathbf{Z}^{\text{T}}(t)) + \log(\mathbf{Z}(t))\mathbf{Z}^{\text{T}}(t)$$

Each of these 7 quantities provides similarity measures between the nodes of the graph



# Link-analysis based algorithms

- Random-walk based algorithms
- Kernel-based algorithms
- **Web-mining based algorithms**
  - A variant of HITS algorithm
  - A variant of PageRank algorithm (called ItemRank)



# HITS algorithm

- The model proposed by Kleinberg is based on two concepts
  - **Hub** pages
  - **Authority** pages
- These are two categories of web pages
- These two concepts are strongly connected



# HITS algorithm

## Original algorithm

- A page's **authority score** is proportional to the sum of the hub scores that link to it
- A page's **hub score** is itself proportional to the sum of the authority scores that it links to

## Application to collaborative recommendation

- A **user's score** is proportional to the sum of the scores of the items rated by the user.
- An **item's score** is itself proportional to the sum of the scores of the users that have rated this item



# HITS algorithm

- Leading to the following iterative procedure

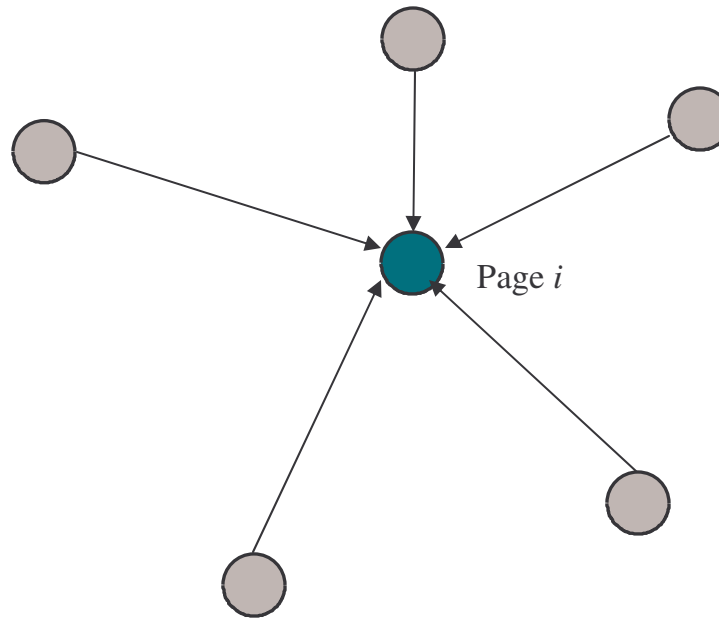
$$\begin{aligned}\mathbf{U}_{ij}^{(k)} &= \sum_{l=1}^I \sum_{m=1}^I a_{il} a_{jm} \mathbf{I}_{lm}^{(k-1)} \\ \mathbf{I}_{ij}^{(k)} &= \sum_{l=1}^U \sum_{m=1}^U a_{li} a_{mj} \mathbf{U}_{lm}^{(k-1)}\end{aligned}$$

where  $k$  denotes the  $k$ th iteration,  $U$  is the number of users,  $I$  the number of items,  $\mathbf{U}$  is a  $U \times U$  matrix containing users' scores,  $\mathbf{I}$  is a  $I \times I$  matrix containing items' scores, and  $a_{ij}$  is extracted from the adjacency matrix.

- Notice that to ensure the convergence of the iterative procedure, we have to normalize the scores at each step

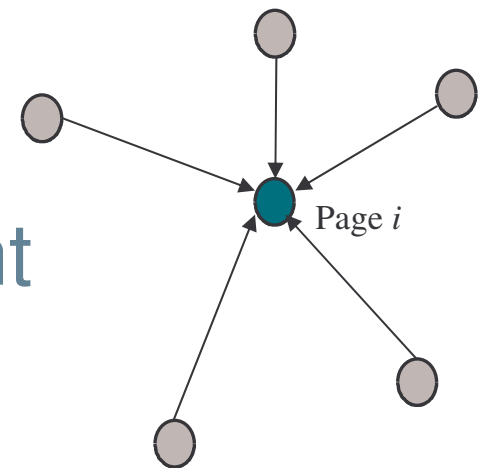
# PageRank algorithm

- To each web page we associate a score,  $x_i$ 
  - The score of page  $i$ ,  $x_i$ , is proportional to the weighted averaged score of the pages pointing to page  $i$



# PageRank algorithm

- A page with a **high score** is a page that is pointed by
  - many pages
  - having each a high score
- Thus a page is an **important page** if
  - it is pointed by **many, important, pages**







# PageRank

- Remember PageRank iterative procedure:

$$\mathbf{PR}_{i+1} = \alpha \mathbf{B}^T \mathbf{PR}_i + (1 - \alpha) \frac{1}{N} \mathbf{1}_N$$

where  $\mathbf{PR}_i$  is the vector containing the pages' scores at step  $i$ ,  $\mathbf{B}$  is a stochastic matrix,  $0 < \alpha < 1$ , and  $\mathbf{1}_N$  is a column vector made of  $N$  ones.



# ItemRank

*Gori and Pucci 2006*

$$\mathbf{IR}_{U_i} = \alpha \mathbf{C} \mathbf{IR}_{U_i} + (1 - \alpha) \mathbf{d}_{U_i}$$

where the stochastic matrix  $\mathbf{B}$  will be the correlation matrix  $\mathbf{C}$  (whose element  $i, j$  contain the number of items co-rated by users  $i$  and  $j$ ), vector  $\mathbf{d}_{U_i}$  has been build according to user  $U_i$  preferences

$$\mathbf{d}_{U_i}(k) = \begin{cases} 0 & \text{if user } U_i \text{ has not rated item } I_k \\ R_{U_i I_k} / N_{U_i} & \text{otherwise} \end{cases}$$

where  $R_{U_i I_k}$  is the rating provided by user  $U_i$  for item  $I_k$  and  $N_{U_i}$  is the number of items rated by user  $U_i$ .



# Outline

- Introduction
- Typology of recommender systems
- Algorithms
- **Validation**
  - Cross-validation
  - Performance measures
- Experimental results



# Cross-validation

- 10-fold cross-validation (using a training set and a test set)
  - Each test set contains 10% of the ratings (10,000 ratings)
  - The average result across all 10 trials is computed
- In other words, we ‘hide’ some existing links for the computation of the recommendations (these hidden links form the test set)



# Performance measures

- Mean Absolute Error (MAE)
- Precision
- Recall
- Degree of agreement
- etc.



# Performance evaluation

For each user

1. take only the **non-watched** movies
2. **rank them** according to the corresponding algorithm
3. compute the **performance measure** between this ranking and watched movies from the test set

Compute the average result

	Degree of agreement	Recall
Random ranking	<b>0.5</b>	<b>close to 0.0</b>
Ideal ranking	<b>1.0</b>	<b>close to 1.0</b>



# Outline

- Introduction
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# Experimental results

- Results on the real MovieLens database
  - 943 users, 1682 movies, 19 movie categories
  - 100,000 ratings
- Experiment: suggest movies to people  
(for each algorithm the closest non-watched movie is proposed first to the user)



# Some results

MovieLens dataset									
Direct method (in %)									
	Basic	Binary	Cosine	Latent Class	L <sup>+</sup>	K <sub>RL</sub>	K <sub>MD</sub>	ItemRank	HITS
<b>Agreement</b>	85.98	/	/	<b>93.16</b>	91.11	91.17	92.74	89.29	/
<b>Recall 10</b>	11.02	/	/	<b>20.84</b>	16.31	18.85	<b>20.66</b>	15.71	/
<b>Recall 20</b>	17.43	/	/	<b>31.94</b>	26.39	28.43	31.07	24.17	/
User-based indirect method (in %)									
<b>Agreement</b>	90.13	92.64	92.66	/	<b>92.90</b>	<b>92.93</b>	92.58	/	90.07
<b>Neighbours</b>	20	100	70	/	100	100	90	/	30
<b>Recall 10</b>	17.23	20.76	20.68	/	<b>21.43</b>	21.00	20.66	/	17.05
<b>Neighbours</b>	50	50	60	/	40	30	50	/	50
<b>Recall 20</b>	25.60	31.13	31.29	/	<b>32.20</b>	31.80	31.27	/	25.37
<b>Neighbours</b>	30	50	40	/	50	40	30	/	30
Item-based indirect method (in %)									
<b>Agreement</b>	88.03	<b>93.27</b>	92.78	/	92.13	92.29	92.43	/	86.81
<b>Neighbours</b>	100	100	100	/	70	100	70	/	100
<b>Recall 10</b>	6.28	<b>18.92</b>	17.29	/	16.41	16.93	16.57	/	5.81
<b>Neighbours</b>	100	20	20	/	40	30	30	/	100
<b>Recall 20</b>	11.59	<b>30.81</b>	28.72	/	27.98	27.11	26.67	/	11.07
<b>Neighbours</b>	80	20	30	/	40	30	20	/	100



# Analyzing the results

- The best results overall are provided by 'Binary', 'Latent Class',  $L^+(K_{CT})$ ,  $K_{RL}$ , and  $K_{MD}$ .
- Laplacian-based kernels perform better than adjacency-matrix based kernels
- Web-mining based algorithms (i.e., HITS and ItemRank) provide poor results (as well as most random-walk algorithms).
- Link-analysis algorithms provide results comparable to feature-based algorithms.



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