## Web Usage Mining

- Recommender Systems
  - Introduction
  - Memory-Based Recommender Systems
  - Model-Based Recommender Systems
- Web Log Mining

### **Recommender Systems**

- Scenario:
  - Users have a potential interest in certain items
- Goal:
  - Provide recommendations for individual users
- Examples:
  - recommendations to customers in an on-line store
  - movie recommendations

	Book 1	Book 2	Book 3	Book 4	Book 5	Book 6
Customer A	Х			Х		
Customer B		Х	Х		Х	
Customer C		Х	Х			
Customer D		Х				Х
Customer E	Х				Х	

### **Recommender Systems**

- User provide recommendations
  - implicit

(buying decisions, click streams, reading time of articles,...)

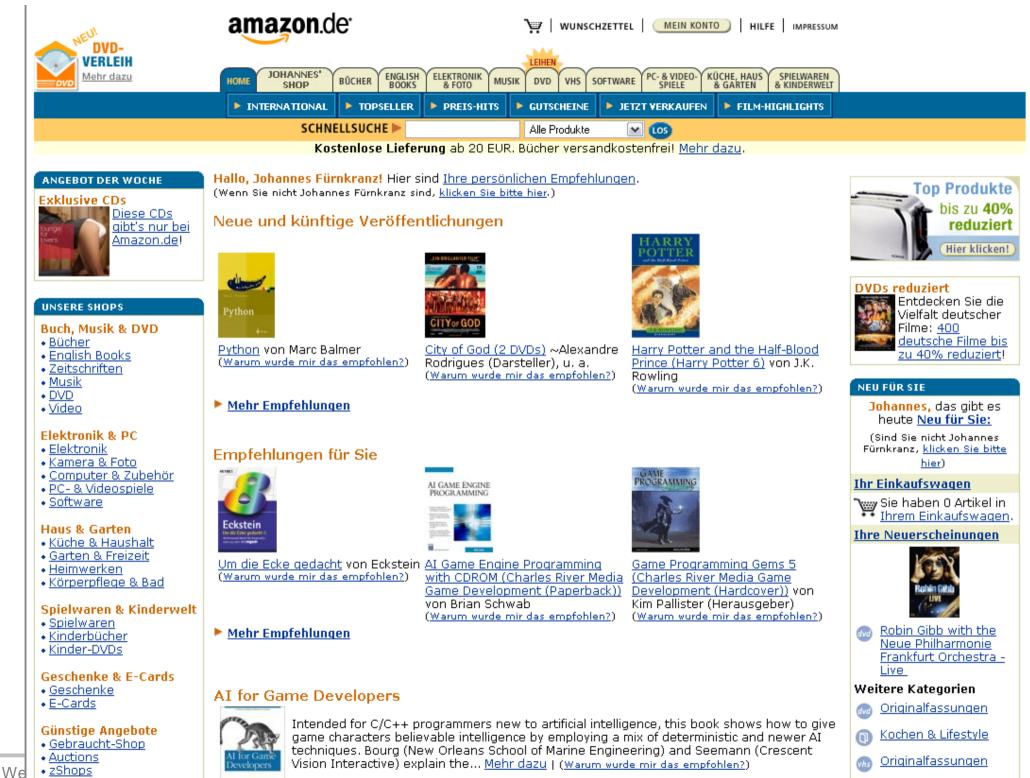
explicit

(feedback forms, texts, mining public sources, ...)

- The recommender system
  - computes recommendations
  - can direct them to the right users
    - filter out items with negative recommendations
    - sort items
    - present evaluations
    - place ads tailored to the user's interests

#### Example: amazon.com

- "If I have 2 million customers on the Web, I should have 2 million stores on the Web" (Jeff Bezos, CEO)
- Types of recommendations:
  - display of customer comments
  - personalized recommendations based on buying decisions
  - customers who bought also bought.... (books/authors/artists)
  - email notifications of new items matching pre-specified criteria
  - explicit feedback (rate this item) to get recommendations
  - customers provide recommendation lists for topics



🙈 Kindor 9. Esmilio



#### IHRE EMPFEHLUNGEN

<u>Alle Produkte</u> Alles gebraucht

#### Ihre Favoriten

Ändern

<u>English Books</u> <u>Software</u> <u>DVD</u> <u>Bücher</u>

#### Mehr Shops

Zeitschriften <u>Musik</u> <u>Klassik</u> <u>VHS</u> <u>PC- & Videospiele</u> <u>Spielwaren & Kinderwelt</u> <u>Elektronik</u> <u>Computer & Zubehör</u> <u>Kamera & Foto</u> <u>Küche & Haushalt</u> <u>Heimwerken</u> <u>Garten</u> Körperpflege & Bad

#### Persönliche Empfehlungen

Hallo, Johannes Fürnkranz. Entdecken Sie die heute vorgestellten Empfehlungen. (Wenn Sie nicht Johannes Fürnkranz sind, <u>klicken Sie hier</u>.)

#### <u>Software Empfehlungen</u>

Lernspaß - 1. Klasse

#### LERNSPASS T Aus der Amazon.de-Redaktion

Verheißungsvoll klingt der Titel, bei dem sich wohl alle Eltern erträumen, es möge den eigenen Kindern zeitlebens so ergehen: *Lernen macht Spaβ*. Diese Software unterstützt Erstklässler in den Fächern Mathematik und Deutsch, steigert ihr Konzentrationsvermögen… <u>Mehr dazu</u>

Mehr gibt es in <u>Kinder & Familie, Schule & Studium</u>, und anderen <u>Software Empfehlungen</u>

#### DVD-Empfehlungen The King And I [UK IMPORT]

#### Kingel Aus der Amazon de-Redaktion

Der König und ich ist der dritte Broadway-Hit des berühmten Komponistenduos Rogers & Hammerstein. Der Film zeigt eine schauspielerische Leistung Yul Brynners, die seiner Karriere einen Schwung nach oben verlieh. Brynner wiederholte seinen Bühnenerfolg in der Hauptrolle und bewies den... <u>Mehr dazu</u>

Mehr gibt es in Originalfassungen, und anderen DVD-Empfehlungen

#### <u>Buch-Empfehlungen</u>

#### Guck mal, was hier passiert!

#### 👞 🐺 Kurzbeschreibung

Ein Wimmelbilderbuch zum Schauen, Entdecken, Wiedererkennen und natürlich zum Geschichtenerfinden und -erzählen. (Ab 2 Jahren.)

Mehr gibt es in Kochen & Lifestyle, und anderen Buch-Empfehlungen

#### <u>Verbessern Sie Ihre</u> Empfehlungen

Haben wir mit den empfohlenen Artikeln Ihren Geschmack noch nicht ganz getroffen? Lassen Sie uns genauer wissen, was Sie interessiert:

<u>Ändern Sie Ihre</u> <u>bisherigen Angaben</u>

<u>Wählen Sie Ihre</u> <u>bevorzugten</u> Interessensgebiete

<u>Bewerten Sie Artikel, die</u> <u>Sie schon haben</u>

Empfohlene Autoren, Künstler & Regisseure



- Samba kurz & gut
- Um die Ecke gedacht
- <u>Agile</u>
  <u>Softwareentwicklung</u>
  <u>im Großen</u>

Mehr Autoren



• Anthology [DOPPEL-CD] © J. Fürnkranz



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#### Kunden, die diesen Artikel gekauft haben, kauften auch:



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Quelle: http://fun.sdinet.de/pics/german/waschmaschine.jpg, gefunden von Erik Tews

### **Recommendation Techniques**

- non-personalized recommendations
  - most frequently bought items (Harry Potter)
- attribute-based recommendations
  - books of the same authors
  - books with similar titles
  - books in same category
- item-to-item correlations
  - users who bought this book, also bought...
  - items are similar if they are bought by the same users
- user-to-user correlations
  - people like you also bought...
  - users are similar if they buy the same items

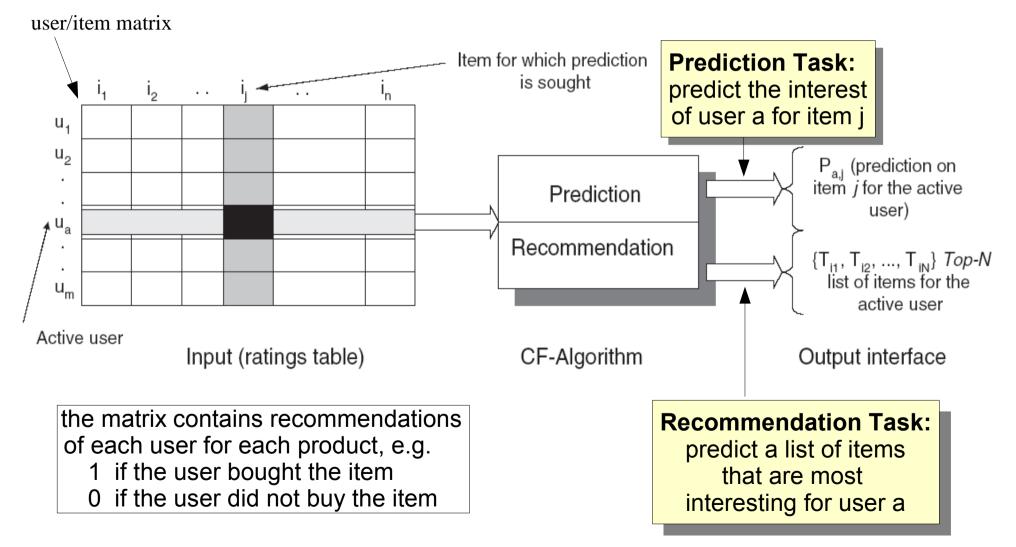
#### **Attribute-Based Recommendations**

- Recommendations depend on properties of the items
- Each item is described by a set of attributes
  - Movies: e.g director, genre, year, actors
  - Documents: bag-of-word
- Similarity metric defines relationship between items
  - e.g. cosine similarity

## **Collaborative Filtering**

- Recommends products to a target customer based on opinions of other customers
- Representation:
  - user/item matrix (customer/product matrix)
  - similar to document/term matrix
- Neighborhood formation:
  - identify similar customers based on similar buying decisions / recommendations (e.g., cosine similarity), may be optional (i.e., all users are neighborhood)
- Recommendation System:
  - derive a recommendation based on the information obtained from similar customers (e.g., most frequent items in neighborhood, weighted sum,...)

# **Collaborative Filtering (CF)**



Source: Sarwar, Karypis, Konstan, Riedl, WWW-10, 2001

### **Memory-Based Collaborative Filtering**

- Simple approach:
  - The weight that user u<sub>a</sub> attributes to an item i is the sum of the votes that the item receives from other users
  - weighted by the similarity of the user to the other users

$$v_p(u_a, i) = \kappa \sum_{u \in U} w(u_a, u) \cdot v(u, i)$$

 $v(u,i) \dots \text{ vote of user } u \text{ for item } i$   $v_p \dots \text{ predicted vote}$   $w(u_1,u_2) \dots \text{ weight between user } u_1 \text{ and user } u_2$   $u_a \dots \text{ active user}$   $\kappa \dots \text{ normalization factor for weights in the sum } \kappa = \frac{1}{\sum_{u \in U} w(u_a, u)}$ 

### **Memory-Based Collaborative Filtering**

- Problem with the simple approach:
  - different users may have different scales
  - a recommendation of 6 out of 10 may be pretty good for critical users, or quite bad for others
- Solution:
  - Only consider deviations from the mean
    - normalize each vote with the average vote m(u) of that user so that a vote of 0 is an average vote
    - add the predicted average deviation to the average vote of the active user

$$v_p(u_a, i) = m(u_a) + \kappa \sum_{u \in U} w(u_a, u)(v(u, i) - m(u))$$

m(u) ... expected value (mean) over all votes of user

$$\kappa = \frac{1}{\sum_{u \in U} w(u_a, u)}$$

#### **Memory-Based Collaborative Filtering**

- The weight matrix  $w(u_1, u_2)$  user-to-user correlations
- can be measured in different ways, e.g.:
  - cosine similarity:

$$w(u_1, u_2) = \frac{\sum_{i \in I} v(u_1, i) \cdot v(u_2, i)}{\sqrt{\sum_{i \in I_{u_1}} v(u_1, i)^2 \cdot \sum_{i \in I_{u_2}} v(u_2, i)^2}}$$

- correlation:  $w(u_{1}, u_{2}) = \frac{\sum_{i \in I_{u_{1}} \cap I_{u_{2}}} v_{m}(u_{1}, i) \cdot v_{m}(u_{2}, i)}{\sqrt{\sum_{i \in I_{u_{1}} \cap I_{u_{2}}} v_{m}(u_{1}, i)^{2} \cdot \sum_{i \in I_{u_{1}} \cap I_{u_{2}}} v_{m}(u_{2}, i)^{2}}}$ 
  - = cosine similarity of adjusted votes  $v_m(u,i)=v(u,i)-m(u)$ restricted to all items where both users vote

#### **Extensions**

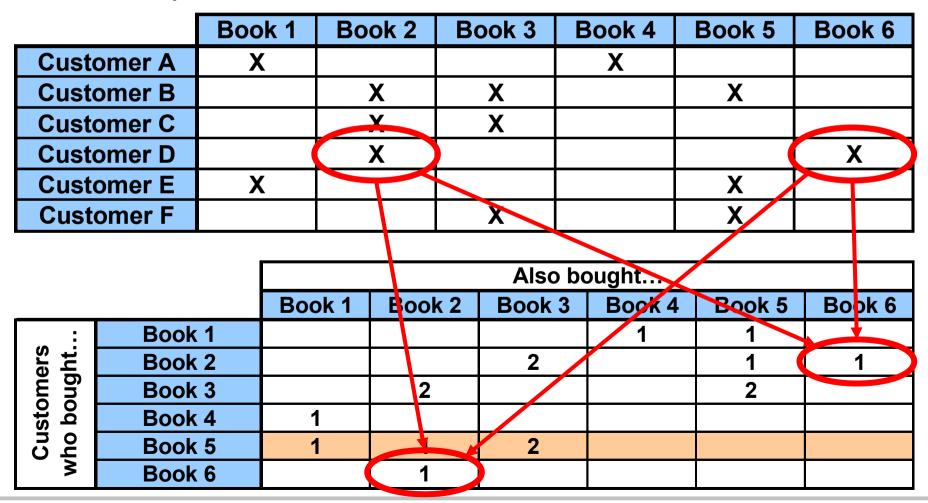
- Default Voting
  - default votes for items without explicit votes
  - allows to compute correlation from union instead of intersection (more items → more reliable)
- Inverse user frequency
  - reduce weights for objects popular with many users
  - assumption: universally liked items are less useful
    - cf. IDF
- Combine collaborative filtering with content-based similarities
  - user similarities: based on user profiles
  - item similarities:
    - e.g., product categories, textual similarities, etc.

## Extensions (Ctd.)

- Addition of pseudo users
  - use background knowledge (e.g., musical genres)
  - generate pseudo users that comment positively on all items of the genre
  - might be extracted automatically by wrappers (Cohen & Fan 2000)

#### **Item Correlations**

 Past purchases are transformed into relationships of common purchases



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#### **Item Correlations**

- Such correlation tables can then used to made recommendations
- If a visitor has some interest in Book 5, he will be recommended to buy Book 3 as well

		Also bought						
		Book 1	Book 2	Book 3	Book 4	Book 5	Book 6	
	Book 1				1	1		
ustomers to bought	Book 2			2		1	1	
bno	Book 3		2			2		
bc	Book 4	1						
cu: who	Book 5	1	1	2				
3	Book 6		1					

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### Problems with Memory-Based Collaborative Filtering

- Cold Start:
  - There needs to be enough other users already in the system to find a match.
- Sparsity:
  - If the user/ratings matrix is sparse, it is hard to find users that have rated the same items (likely to happen with many items)
- First Rater:
  - Cannot recommend an item that has not been previously rated (e.g., New items, Esoteric items, ...)
- Popularity Bias:
  - Cannot recommend items to someone with unique tastes.
  - Tends to recommend popular items.

### **Model-Based Collaborative Filtering**

- learn an explicit model that predicts ratings and/or items
- examples
  - clustering of users
    - each user is characterized by her recommendations
    - apply any clustering algorithm that works for clustering documents
  - clustering of items
    - each item is characterized by the users that recommend it
    - apply any clustering algorithm that works for clustering documents
  - clustering of both users and items (*co-clustering*)
    - advantage: items and users are mutually dependent, a good clustering needs to consider both dimensions.
  - association rules
    - model associations between items
    - advantage: explicit, understandable representation

### Clustering

	Book 1	Book 2	Book 3	Book 4	Book 5	Book 6
Customer A	Х			Х		
Customer B		Х	Х		Х	
Customer C		Х	Х			
Customer D		Х				Х
Customer E	Х				Х	

- Two Clusters based on similarity on bought items
  - Customers B, C and D are clustered together
  - Customers A and E are clustered into another group
- « Typical » preferences for **CLUSTER BCD** are:
  - Book 2, very high
  - Book 3, high
  - Books 5 and 6, may be recommended
  - Books 1 and 4, not recommended at all

### Clustering

	Book 1	Book 2	Book 3	Book 4	Book 5	Book 6
Customer A	Х			Х		
Customer B		Х	Х		Х	
Customer C		Х	Х			
Customer D		Х				Х
Customer E	Х				Х	
Customer F			Х		Х	

- How do we recommend within a cluster?
- Any customer that will be classified as a member of CLUSTER BCD will receive recommendations based on preferences of the group:
  - Book 2 will be highly recommended to Customer F
  - Book 6 will also be recommended to some extent

#### **Problems**

- Customers may belong to more than one cluster
  - in our example: Customer F could fit to both clusters
- there may be overlap in items between clusters
  - clusters may be overlapping (one example may belong to different clusters)
- Possible solution:
  - average predictions of all fitting clusters
  - weighted by their importance

### **Co-Clustering**

- Cluster users and items simultaneously
  - Mutual reinforcement of similarity
  - separate clusterings might be suboptimal
- Need advanced clustering techniques
  - e.g., (Ungar & Foster, 1998)

	Batman	Rambo	Andre	Hiver	Whispers	StarWars
Lyle			1			1
Ellen			1	1		1
Jason				1	1	
Fred	1					1
Dean	1	1				1
Karen	?	?	1	?	?	?

From Clustering methods in collaborative filtering, by Ungar and Foster

### **Association Rule Discovery**

- Association Rules describe frequent co-occurences in sets
  - generalize correlation tables to correlations between more than two values
- Example Problems:
  - Which products are frequently bought together by customers? (Basket Analysis)
    - DataTable = Receipts x Products
    - Results could be used to change the placements of products in the market
  - Which courses tend to be attended together?
    - DataTable = Students x Courses
    - Results could be used to avoid scheduling conflicts....
  - Which words co-occur in a text?
    - cf. efficient generation of n-grams

#### **Association Rules**

• General Form:

$$A_1, A_2, ..., A_n \Longrightarrow B_1, B_2, ..., B_m$$

- Interpretation:
  - When items A<sub>i</sub> appear, items B<sub>i</sub> also appear with a certain probability
- Examples:
  - Bread, Cheese => RedWine.

Customers that buy bread and cheese, also tend to buy red wine.

MachineLearning => WebMining, MLPraktikum. Students that take 'Machine Learning' also take 'Web Mining' and the 'Machine Learning Praktikum'

### **Basic Quality Measures**

#### Support

$$s(A \to B) = \frac{n(A \cup B)}{n}$$

relative frequency of examples for which both the head and the body of the rule are true

- Confidence c(A→B)= n(A∪B)/n(A)
  relative frequency of examples for which the head is true among those for which the body is true
- Example:
  - Bread, Cheese => RedWine (S = 0.01, C = 0.8)

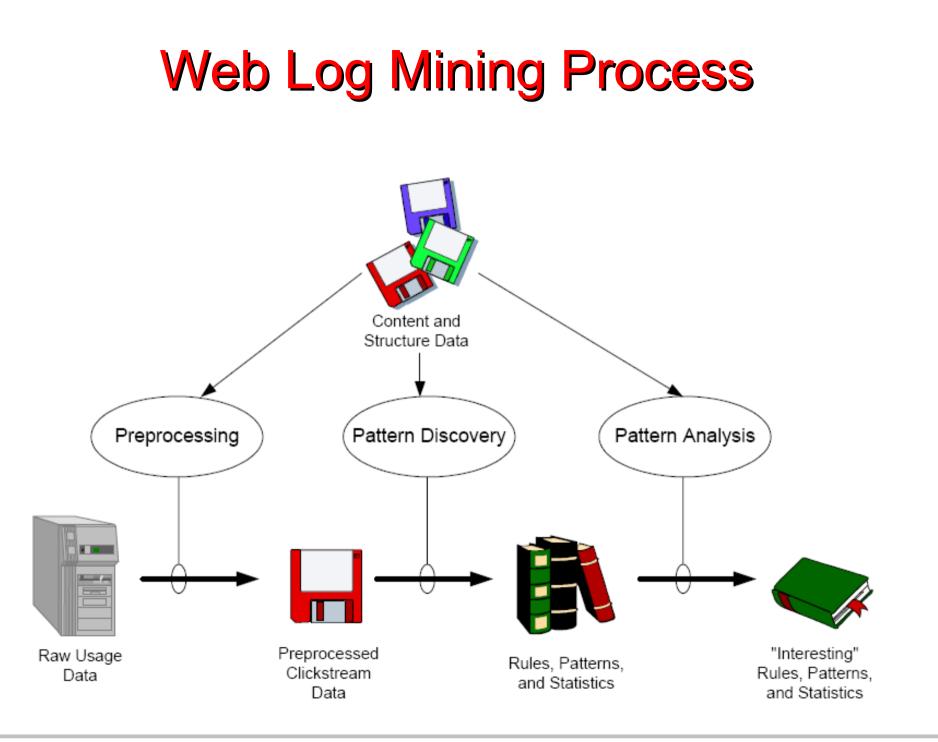
80% of all customers that bought bread and cheese also bought red wine. 1% of all customers bought all three items.

#### Using Association Rules for Recommendations

- APRIORI:
  - efficient algorithm for finding all rules that have a given mimimum support and a given minimum confidence
  - phase 1: find frequent item sets ( $\rightarrow$  n-grams)
  - phase 2: construct all rules with min confidence from item set
- Simple Use of APRIORI for recommendations:
  - **1.** Input: database of all customers x all items they have bought
  - 2. Find association rules
  - 3. Find all rules whose conditions match the items previously bought by the active user
  - 4. Sort these rules by their confidence
  - 5. Predict the first N items on the top of the list

# Web Log Mining

- Applying Data Mining techniques to the discovery of usage patterns in Web sites
  - e.g.: Find association rules that capture which pages are frequently visited in succession to each other
- Goals
  - improvement of site design and site structure
  - generation of dynamic recommendations
  - improving marketing
- Phases
  - data collection
  - pre-processing
  - pattern discovery
  - pattern analysis



#### Raw Data: Web Logs

#	IP	ld	Acces	Time	Method/URL/Protocol	Status	Bytes	Referer	Agent
1	165.182.168.101	-	-	16/06/2002:16:24:06	GET p1.htm HTTP/1.1	200	3821	out.htm	Mozilla/4.0 (MSIE 5.5; WinNT 5.1)
2	165.182.168.101	-	-	16/06/2002:16:24:10	GET A.gif HTTP/1.1	200	3766	p1.htm	Mozilla/4.0 (MSIE 5.5; WinNT 5.1)
3	165.182.168.101	-	-	16/06/2002:16:24:57	GET B.gif HTTP/1.1	200	2878	p1.htm	Mozilla/4.0 (MSIE 5.5; WinNT 5.1)
4	204.231.180.195	-	-	16/06/2002:16:32:06	GET p3.htm HTTP/1.1	304	0	-	Mozilla/4.0 (MSIE 6.0; Win98)
5	204.231.180.195	-	-	16/06/2002:16:32:20	GET C.gif HTTP/1.1	304	0	-	Mozilla/4.0 (MSIE 6.0; Win98)
6	204.231.180.195	-	-	16/06/2002:16:34:10	GET p1.htm HTTP/1.1	200	3821	p3.htm	Mozilla/4.0 (MSIE 6.0; Win98)
7	204.231.180.195	-	-	16/06/2002:16:34:31	GET A.gif HTTP/1.1	200	3766	p1.htm	Mozilla/4.0 (MSIE 6.0; Win98)
8	204.231.180.195	-	-	16/06/2002:16:34:53	GET B.gif HTTP/1.1	200	2878	p1.htm	Mozilla/4.0 (MSIE 6.0; Win98)
9	204.231.180.195	-	-	16/06/2002:16:38:40	GET p2.htm HTTP/1.1	200	2960	p1.htm	Mozilla/4.0 (MSIE 6.0; Win98)
10	165.182.168.101	-	-	16/06/2002:16:39:02	GET p1.htm HTTP/1.1	200	3821	out.htm	Mozilla/4.0 (MSIE 5.01; WinNT 5.1)
11	165.182.168.101	-	-	16/06/2002:16:39:15	GET A.gif HTTP/1.1	200	3766	p1.htm	Mozilla/4.0 (MSIE 5.01; WinNT 5.1)
12	165.182.168.101	-	-	16/06/2002:16:39:45	GET B.gif HTTP/1.1	200	2878	p1.htm	Mozilla/4.0 (MSIE 5.01; WinNT 5.1)
13	165.182.168.101	-	-	16/06/2002:16:39:58	GET p2.htm HTTP/1.1	200	2960	p1.htm	Mozilla/4.0 (MSIE 5.01; WinNT 5.1)
14	165.182.168.101	-	-	16/06/2002:16:42:03	GET p3.htm HTTP/1.1	200	4036	p2.htm	Mozilla/4.0 (MSIE 5.01; WinNT 5.1)
15	165.182.168.101	-	-	16/06/2002:16:42:07	GET p2.htm HTTP/1.1	200	2960	p1.htm	Mozilla/4.0 (MSIE 5.5; WinNT 5.1)
16	165.182.168.101	-	-	16/06/2002:16:42:08	GET C.gif HTTP/1.1	200	3423	p2.htm	Mozilla/4.0 (MSIE 5.01; WinNT 5.1)
17	204.231.180.195	-	-	16/06/2002:17:34:20	GET p3.htm HTTP/1.1	200	2342	out.htm	Mozilla/4.0 (MSIE 6.0; Win98)
18	204.231.180.195	-	-	16/06/2002:17:34:48	GET C.gif HTTP/1.1	200	3423	p2.htm	Mozilla/4.0 (MSIE 6.0; Win98)
19	204.231.180.195	-	-	16/06/2002:17:35:45	GET p4.htm HTTP/1.1	200	3523	p3.htm	Mozilla/4.0 (MSIE 6.0; Win98)
20	204.231.180.195	-	-	16/06/2002:17:35:56	GET D.gif HTTP/1.1	200	3231	p4.htm	Mozilla/4.0 (MSIE 6.0; Win98)
21	204.231.180.195	-	-	16/06/2002:17:36:06	GET E.gif HTTP/1.1	404	0	p4.htm	Mozilla/4.0 (MSIE 6.0; Win98)

### Preprocessing

- Identify user sessions in the log
  - so that we can see what individual users are doing
- Problems:
  - User Identification
    - Same IP does not need to be the same user
  - Session Time
    - Does a long break mean the user's session has ended?
  - Missing pages
    - not all retrieved pages appear in user log (e.g., might have been retrieved from user cache)

### Some Heuristics for Session Identification

- Timeout:
  - if the time between pages requests exceeds a certain limit, it is assumed that the user is starting a new session
- IP/Agent
  - Different agent types for an IP address represent different sessions
- Referring page:
  - If the referring page for a request is not part of an open session, it is assumed that the request is coming from a different session.
- Same IP-Agent/different sessions (Closest):
  - Assigns the request to the session that is closest to the referring page at the time of the request.
- Same IP-Agent/different sessions (Recent):
  - In case of a tie, assign the request to the session with the most recent referrer access in terms of time

### **Data Analysis**

Session traces can be mined for various useful patterns

- Basic statistics
  - Which pages are most frequently accessed?
  - Feedback about interestingness of content/products on these pages
- Association Rules
  - Which pages are accessed together?
    - products/contents of related interest
  - Which paths are frequently taken?
    - maybe provide a shortcut link to improve user satisfaction
- Clustering
  - find clusters of similar pages or clusters of similar users