Web Mining

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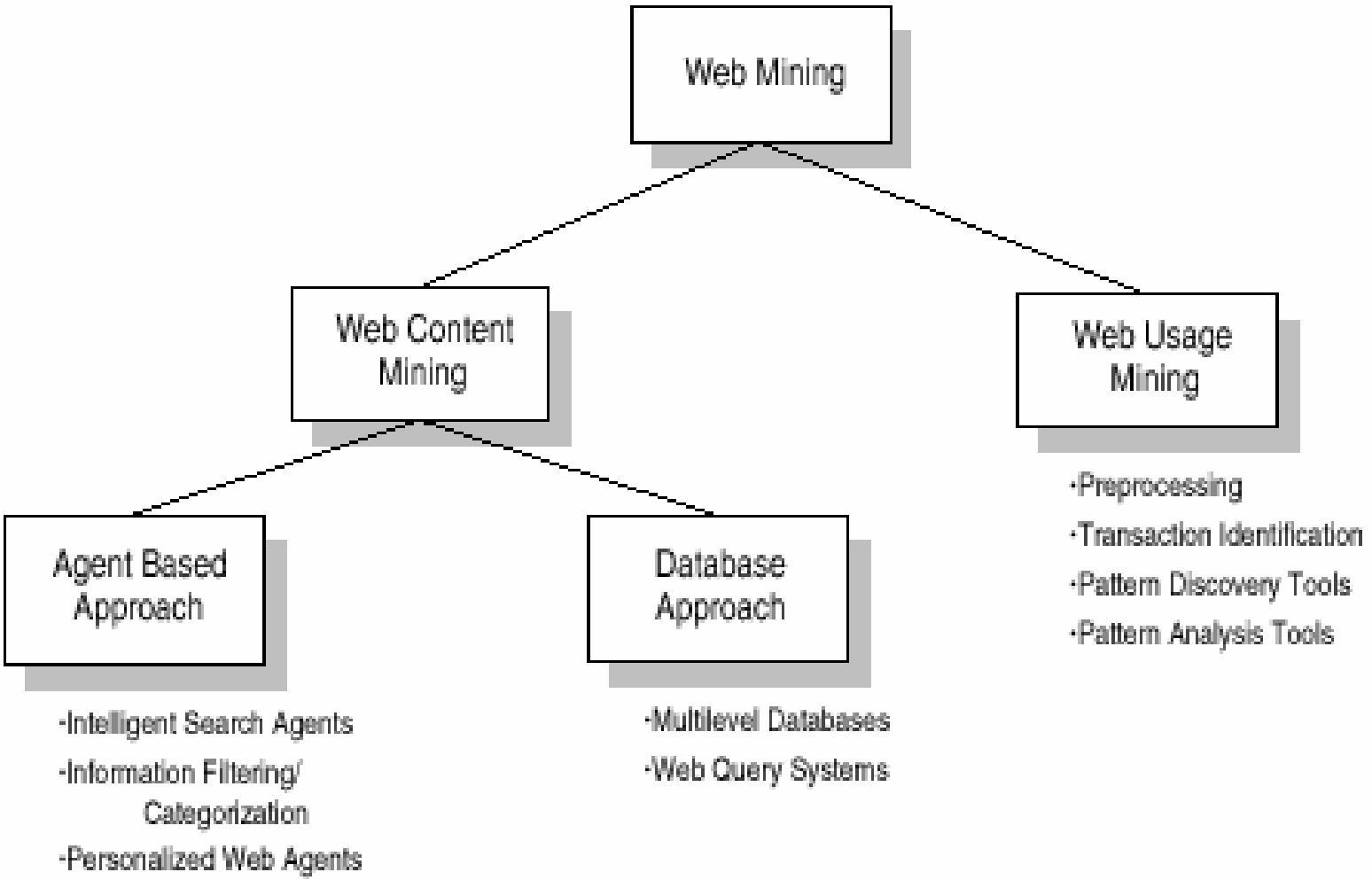
Data mining and the web

Web Mining: *the discovery and analysis of useful information from the World Wide Web.*

- **web content mining**
  - aims at constructing higher-level models of organization of semi-structured data contained in web sites;
- **web structure mining** (also part of content mining)
  - aims at constructing models of web site structure in terms of page interconnections.
- **web usage mining** (or web log mining)
  - aims at discovering usage patterns from web logs of browsers, web servers and proxy servers;

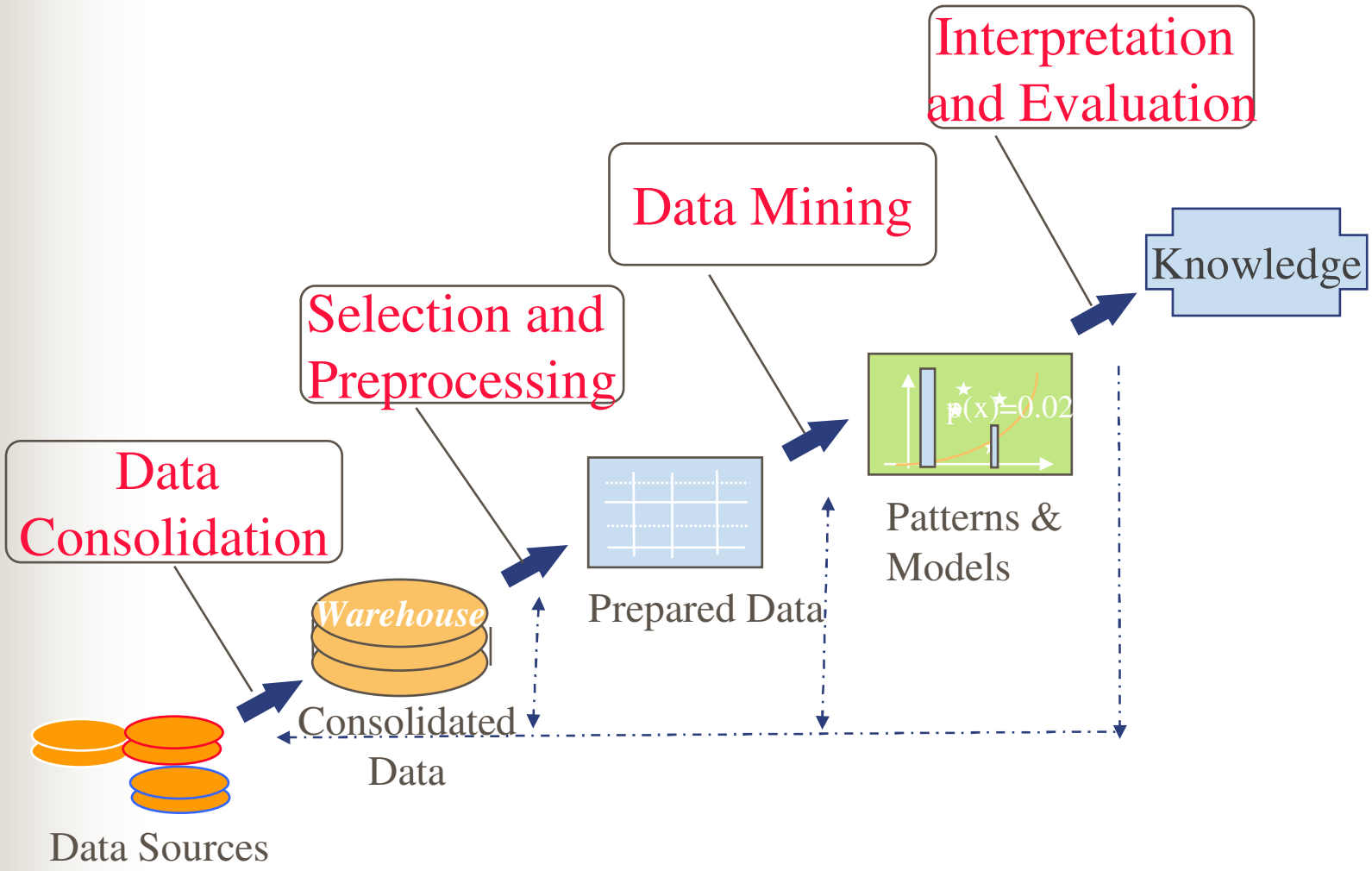
Web mining taxonomy



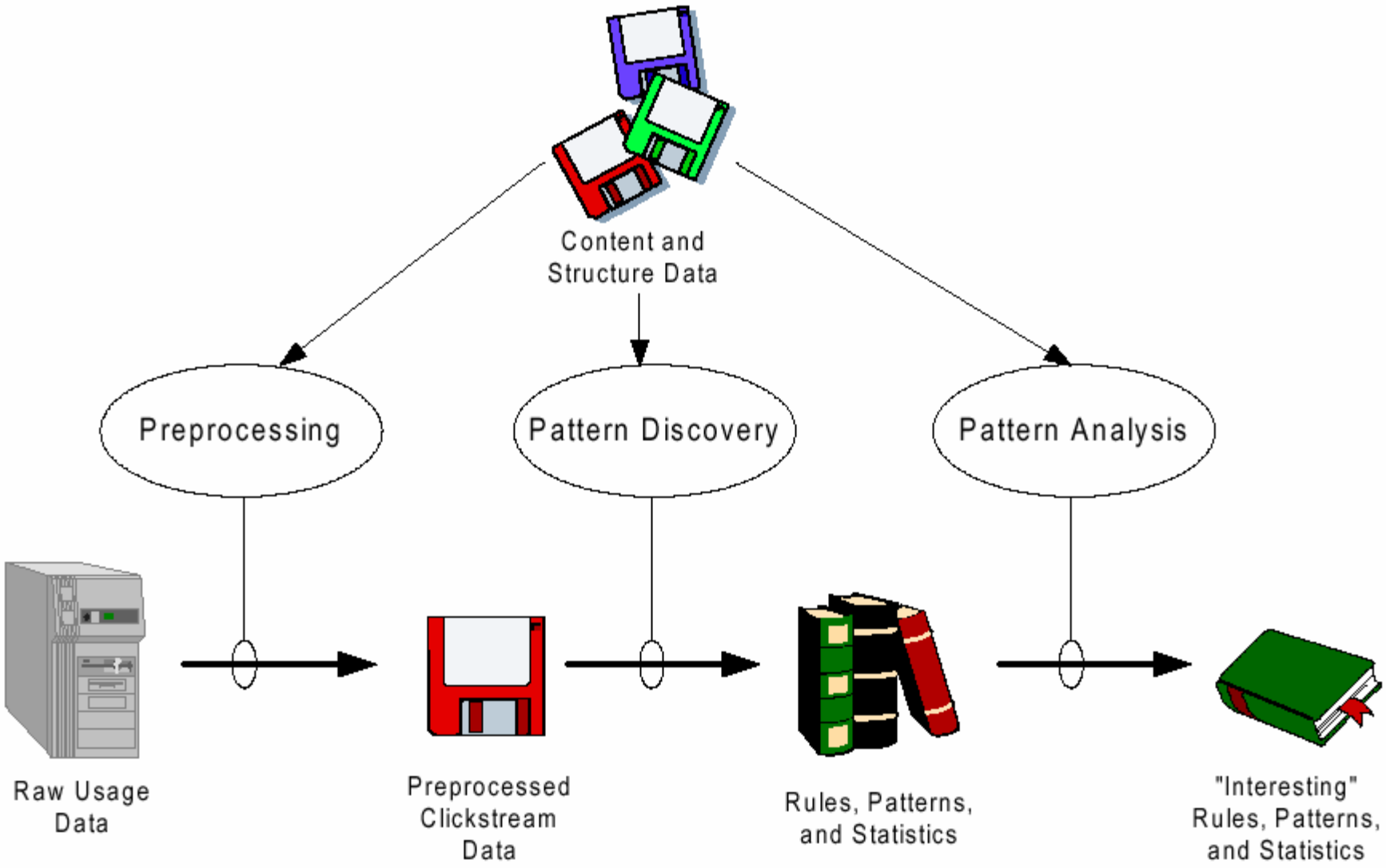
Web usage mining

- Focus on the analysis and discovery of usage patterns and models on the basis of historical data: the web log files which record previous access to web objects.
- Web log files provide a large source of data for DM, as web servers and proxy servers store order of millions logs every day.
- Various application domains:
  - web site redesign and restructuring,
  - self-adapting web sites,
  - recommendation systems in e-commerce

The KDD process



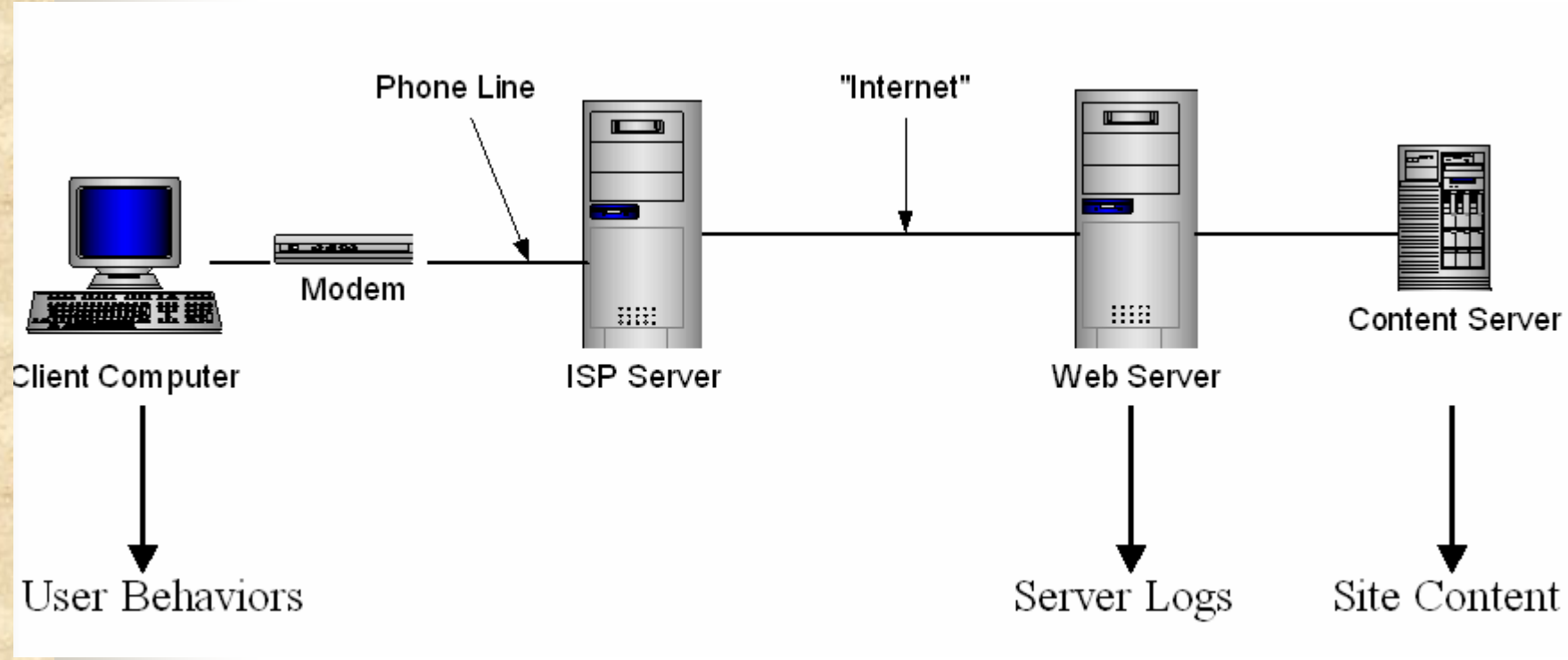
The Web Usage Mining Process



Web Mining:

Preprocessing

Client/Server Interaction



Web data sources

- Client
  - Registration data
  - Browser
  - Agents (e.g., applets, jscript, ecc.)
- Web Server
  - HTTP Clickstream
  - Content/Application Server (e.g., Vignette, Broadvision)
  - Packet Sniffer (e.g., Accrue)
  - Other (database log, file system log, ecc.)
- ISP o Proxy
  - HTTP Clickstream
  - Packet Sniffer

HTTP Clickstream: ECLF

- Extended Common Log Format (a row per HTTP request)

213.213.31.41 - - [15/Apr/2000:04:00:04 +0200] "GET images/h/h_home.gif HTTP/1.1" 200 1267 "http://www.di.unipi.it/" "MSIE 4.01; Windows 98“

- Host: **213.213.31.41** *(or reverse address lookup)*
- Ident e Authuser: **- -** *(IDs for IDENTD and HTTP/SSL)*
- Time: **[15/Apr/2000:04:00:04 +0200]** *(end-of-answer time)*
- HTTP Request: **"GET images/h/h_home.gif HTTP/1.1"**
- Status: **200** *(=OK, 3xx=redirection, 4xx=client error, etc.)*
- Bytes: **1267** *(number of transmitted to the Client)*
- Referrer: **"http://www.di.unipi.it/"**
- User agent: **"MSIE 4.01; Windows 98"**

HTTP Clickstream

Sometimes other data are available:

- Server Computer ID, Time-to-Serve, Content-Type, Expires, Last-Modified, No-cache, ...
- Cookies
  - Mechanism to handle the status of a session/to identify users
  - Cookie = string exchanged between client and server
    - Persistent / active only for actual session
    - Stored on the client side
    - Can be refused/cancelled by user

Terminology

- **Page file**: file accessed by a single HTTP request
- **Page view**: set of *page files* which compose a single page displayed in a browser.
  - Its page files can be retrieved from different servers
- **(local) User session:** set of page views retrieved by a user from the Web Server to achieve some goal.
  - Available at the Web Server level
  - Partially hidden by Browser and Proxy caching
- **Global user session**: set of page views retrieved by a user from the whole Web to achieve some goal.
  - Available only at the Client level
  - Partially available at the Proxy/ISP level because of Browser caching

Drinking from the Fire hose

- HTTP Clickstream is a “poor” data source
- Log preprocessing needed before data mining
- Preprocessing issues:
  1. Request Preprocessing
  2. User Identification
  3. Page Identification
  4. Page Content Identification
  5. Computing the Dwell time
  6. Session Identification
  7. Path Completion

1. Request Preprocessing

- URL are not unique IDs for web resources
  - E.g.: http://www.DI.unipi.IT = http://www.di.unipi.it, etc.
- Field extraction
  - Host, Path, Filename, File Extension, Query String
- Request selection
  - Filter out visits of robots
    - Several Heuristics: Known names/substrings, repeated accesses to the same page, too quick clickstream, data mining approaches, etc.
  - Analisys-dependent selection
    - E.g.: Only GET requests, or successful (code 200) requests, etc.

2. User Identification

- **IP** (+ User Agent)
  - Always possible, but not reliable (IP recycling by ISP + Proxy masking)
- **Cookies**
  - Can be refused by users, but are (quite) reliable and can be shared among different sites.
- **Embedded SessionID** (volatile cookies)
  - For a single visit: http://www.di.unipi.it/?session=123456
- **Client-side tracking** (modified browser)
  - Reliable, but invasive (privacy)
- **Authentication**
  - Maximal reliability, but invasive (privacy)
- **Others**:
  - Path analysis, ID Ethernet, ID CPU

3. Pageview Identification

Associates each request with its corresponding page view.

Referrer-based

- Page view = A + all requests having referrer A, till next request for A
  - Problems: multiframe pages (have several referrers); client and proxy caching can mask “next request for A”; external referrers
- **Analysis of HTML content**
  - Page View = A + all page files embedded in A (e.g.: <img>)
    - Problems: dynamic pages
- **Application/content server**
  - Access log at the application/content server
    - Very general but expensive

4. Page Content Identification

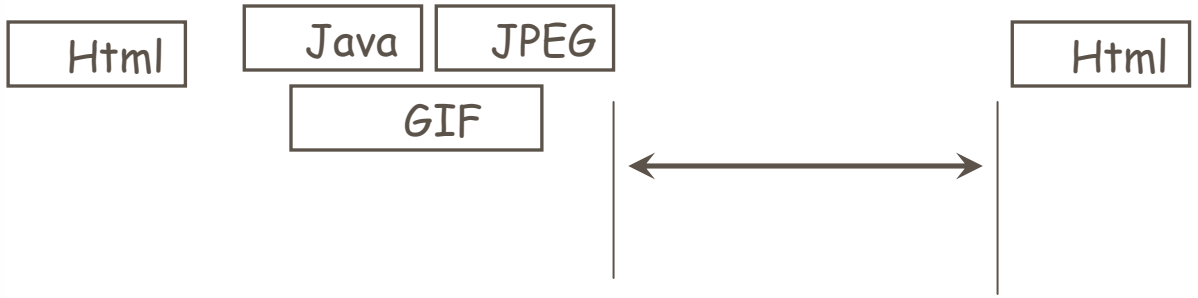
Associates each page view with a classification of its content

- E.g.: events in e-commerce = view, click-through, buy, bid, shoopping cart change

- **Explicit identification**
  - Made by web administrators
    - Expensive, not general
- **Analysis of HTML content**
  - Automatic natural language analysis techniques
    - Limits with dynamic pages, input pages
- **Application/content server log**
  - Content log at the application/content server level
    - Very general but expensive

5. Computing Dwell time

- **Dwel time:** time between the end of a page view loading and the beginning of next request from the same user



- Computing the PageView loading time:
  - Approximation based on PageView size
  - Experimental values
  - Special cases: streamining video
- Dwell time=0 ➔ loading aborted ➔ unsatified user

6. Session Identification

- A set of accesses from a user can be associated with different goals
- **User session** = *set of page views/files requested by a single user to the Web Server for a specific "goal".*
- **Objective**: given a sequence of page files/views

$$\langle p_1, \ldots, p_n \rangle$$

requested by a user, discover subsequences

$\langle p_1, \ldots, p_{n1} \rangle \quad \langle p_{n1+1}, \ldots, p_{n2} \rangle \quad \ldots \quad \langle p_{n(k-1)+1}, \ldots, p_{nk} \rangle$

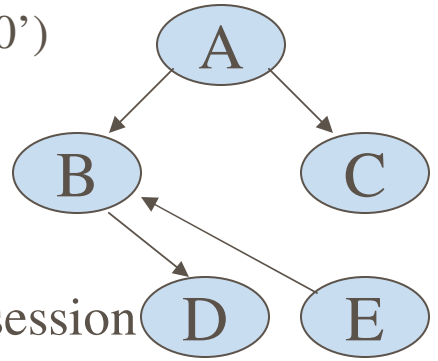
corresponding to different "goals".

6. Session Identification

Heuristics

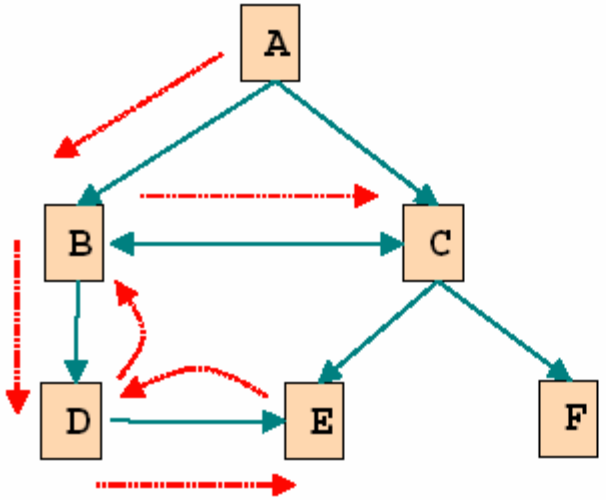
- **Time-oriented**
  - Subsequences must have limited time extensions:
    - Time between p_1 and p_{n1} must be ≤ t' (typical value: 30')
    - Time between p_i and p_{i+1} must be ≤t"
  - Navigational vs. Content pages
- **Navigation-oriented**
  - Linkage: "jump" to a non-reachable page → end of session
    - E.g.: Links=A→B, A→C, B→D, C→E

      The <A B D C E B> sequence is divided in <A B D C> and <E B>
    - Topology of the site is requested
  - Maximal Forward Reference: backtrack → end of session
    - E.g.: <A B D C B> yields: <A B D>, <A C> and <A B>



7. Path Completion

- **Objective**: deducing requests not logged because were satisfied by caches between user and web server.



User's navigation path:
A => B => D => E
=> D => B => C

URL	Referrer
A	--
B	A
D	B
E	D
C	B

- Missing path: from E to C
  - Shorthest solution: E → D → B → C
  - It is not unique!

Web Mining

Data mining tasks

Data Mining

- General objective: Search for common patterns in a data set.
- NOT a replacement for:
  - Session Analysis
  - Static Aggregation and Statistics (Reports)
  - OLAP

Common Data Mining Tasks

- Frequent Itemsets
- Association Rules
- Clustering
- Classification
- Sequential Patterns

Frequent Itemsets

- Find groups of items that appear together in a "transaction" with some frequency.
- Similar to statistical correlation.
- Standard measure used is "support", which gives the percentage of transactions that an itemset appears in.
- For example, "Items `A` and `B` appear together in *s%* of the transactions."

Frequent Itemset

Example

- *The "Home Page" and "Shopping Cart Page" are accessed together in 20% of the sessions.*
- *The "Donkey Kong Video Game" and "Stainless Steel Flatware Set" product pages are accessed together in 1.2% of the sessions.*

NB: transactions are defined as sets of visited web pages (e.g.: user sessions).

Association Rules

- Similar to Frequent itemsets, except a directionality is introduced to each rule.
- Instead of just *"A and B appear together frequently (with support s%)"*, we get:

  "When A appears, B also appears x% of the time"

  "When B appears, A also appears y% of the time"
- The *x* and *y* values are referred to as Confidence.

Association Rules

Example

- *When the "Shopping Cart Page" is accessed in a session, the "Home Page" is also accessed 100% of the time.*
- *When the "Shipping conditions" page is accessed in a session, a purchase is performed 75% of the time.*

Clustering

- Form groups of similar items.
- Often difficult to define similarity.
- Two types of clustering
  - Number of groups are predetermined.
  - Number of groups are automatically determined by the algorithm.

Clustering

Page Clustering: Example

Usage-based frequent itemsets are clustered:

- *"Donkey Kong Video Game", "Pokemon Video Game", and "Video Game Caddy" product pages are related.*

Graph partitioning of web site structure:

- *"DM homepage", "DM bibliography", "DM teaching" link only (and are linked only by) each other.*

Based on content dissimilarity between pages:

- *"Donkey Kong Video Game", "Pocket Donkey Kong", and "Donkey Kong 2" (on different sites) have similar contents.*

Clustering

User session Clustering: Example

User Transaction Clustering:

- *Transactions=sets of URLs (pages in a session) as binary vectors*
- *K-means on transactions*

Association rule hyper-graph partitioning:

- *Arcs A→B represent associations between URLs A and B*
- *Clustering by partitioning the graph*

Classification

- Discover rules that will predict what group an item belongs to.
- Similar to clustering, with the concept that every item belongs to a group or class.
- Usually requires “training”, where a classifier is “shown” examples of different groups in order to learn how to classify new items as they arrive.

Classification

Example

Classify pages on content

- *“Donkey Kong Video Game”, “Pokemon Video Game”, and “Video Game Caddy” product pages contain words “game”, “console”, … => they are all part of the Video Games product group.*

Classify sessions/users

- *The user who visits both the "Delivery options" and "How to pay" pages, falls in the "Probable customers" category.*

Sequential Patterns

- Sequential patterns add an extra dimension to frequent itemsets and association rules - time.
- Items can appear before, after, or at the same time as each other.

Sequential Patterns

Example

Time-forward associations:

- *50% of users who visited the "Video Game Caddy" page, later visited also the "Donkey Kong Video Game" page. This occurs in 1% of the sessions.*

Time-backward associations:

- *30% of clients who visited* **/products/software/** *had done a search in* **Yahoo** *using the keyword "software" before their visit.*

Sequences:

- *In 2% of sessions the user visited "Institute homepage" then "Contact info" then "Tom's personal page".*

Data Mining: Pro and cons

- Advantages:
  - Discovery complex patterns that were not obvious through other tools.
  - Reduce vast amounts of data to a small number of rules or patterns.
- Disadvantages:
  - Requires the most resources.
  - No “out of box” solutions.
  - Discovered patterns are often obvious and already known.

Filtering interesting patterns

Means:

- web structure information

Hypothesis:

- Domain knowledge can be derived from content and structure of a site, to define "expected patterns"

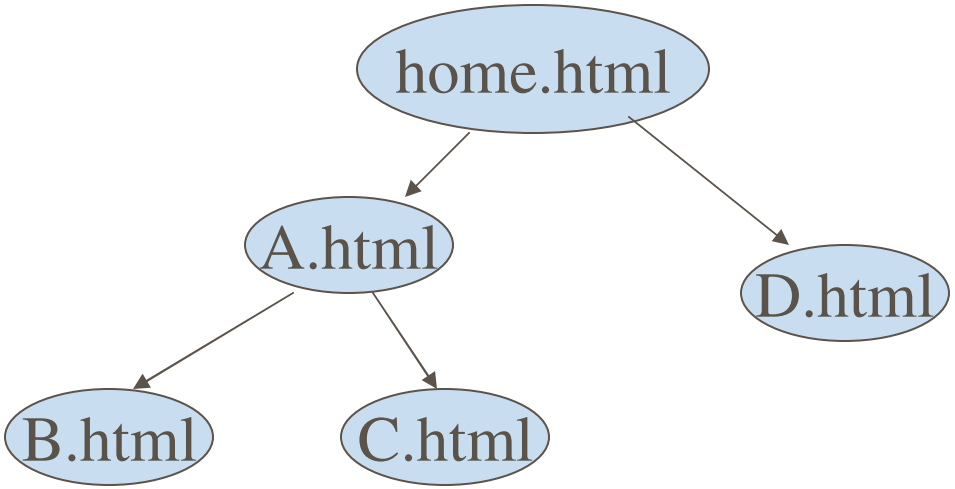
"Subjective interestingness":

- Measures deviation from expected patterns

Filtering interesting patterns

Expected patterns: Example

Site structure:



Rule **B.html → A.html** is expected (thus not interesting).

Rule **D.html → C.html** is unexpected (thus interesting).

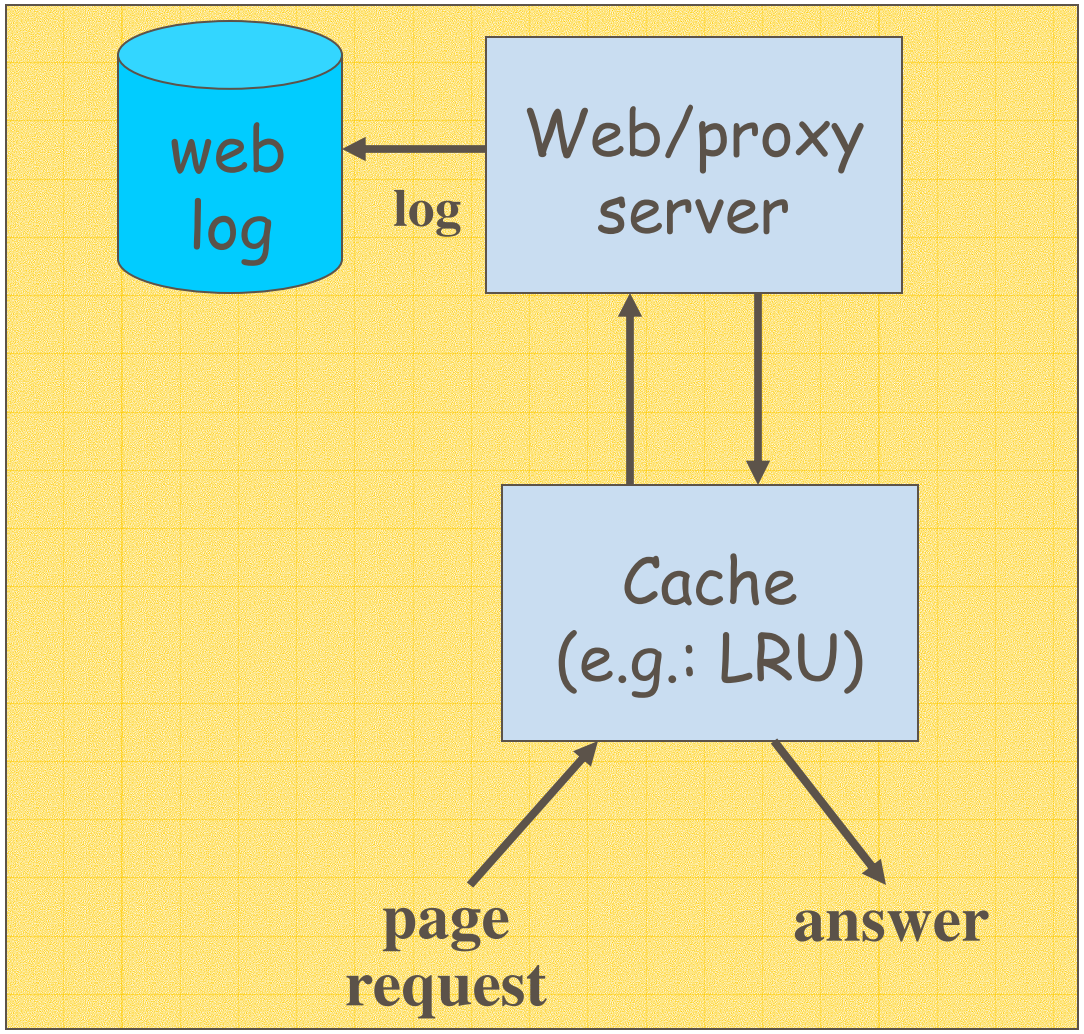
Applications

1. Web mining for Web caching

Web caching

- **Web caching is the temporary storage of web objects for later retrieval**
- **It can be performed at:**
  - client level
  - proxy level
  - server level
- **Caching may**
  - **reduce bandwidth**
  - **reduce server load**
  - **reduce latency**
  - **improve reliability**

Web caching: basic schema



Objectives

- Intelligent web caching:

  → *extend the (LRU) policy of web/proxy servers by making it sensible to web access models extracted from history log data using data mining techniques*

- Design of an intelligent web caching system
  - *model extraction*
  - *definition of a cache replacement policy that exploit extracted data mining models*

Data mining techniques adopted

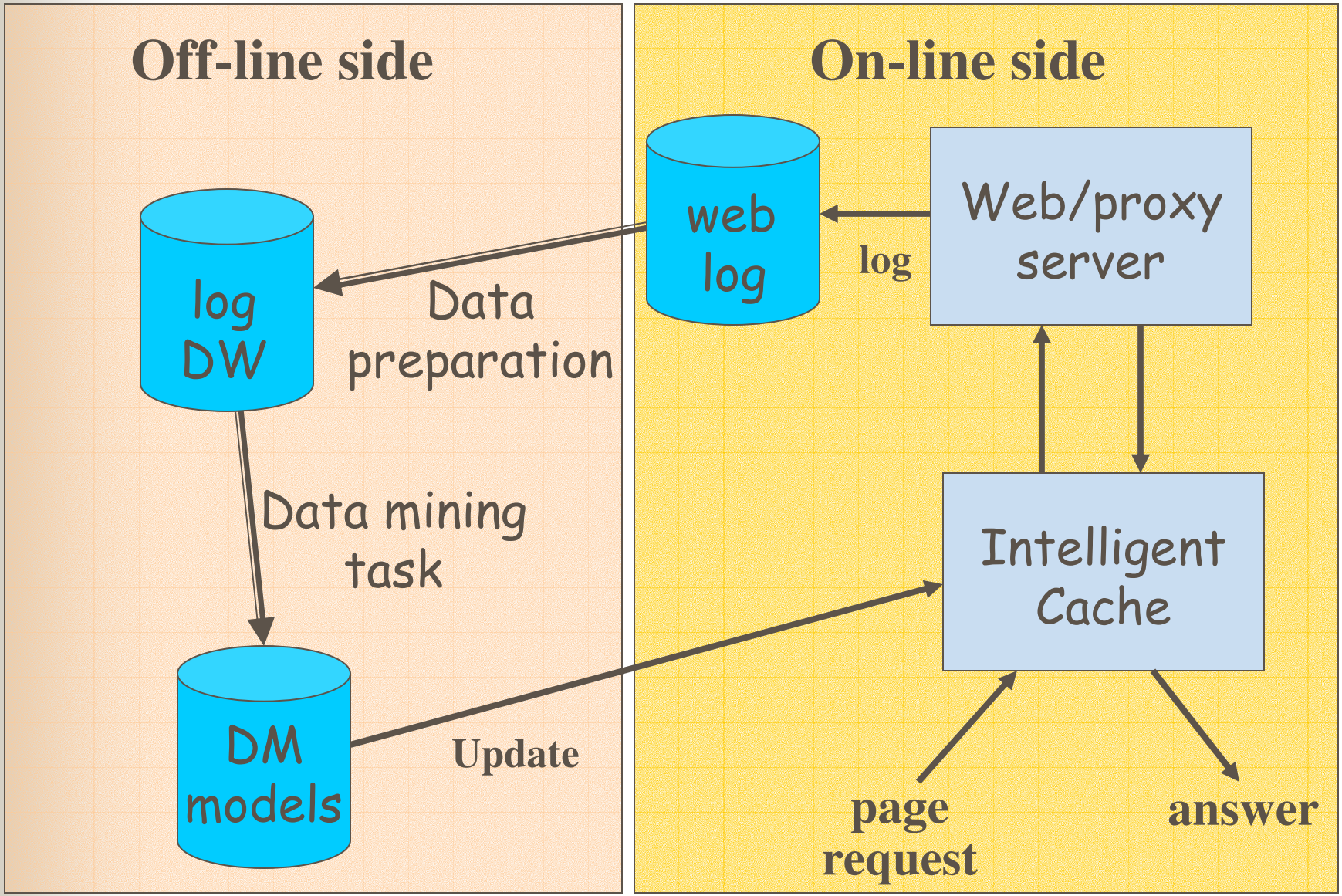
- Association rules
  - we extract from the web logs rules of the form A => B, where A and B are web documents
  - rule means that when the web document A is requested, then B is also likely to be requested within the same user session.
  - in the cache replacement algorithm: if A is requested, and therefore kept in the cache if present according to the LRU policy, then also B is treated analogously.

Data mining techniques adopted

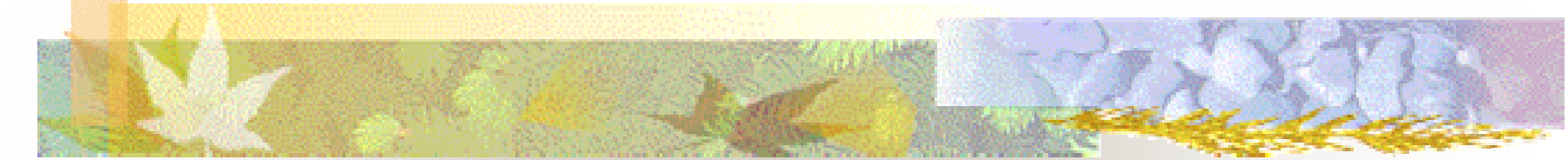
- Classification
  - we develop a decision tree:

    A model capable to predict, given a request of a web document A, the time of the next future request of A given other properties of A itself.
  - the prediction is based on the historical data contained in the web logs.
  - the prediction is used to assign a weight to A in the cache.

Intelligent web caching: Architecture



Applications



2. Web Mining for e-commerce: Personalization

Web Personalization

Three aspects of a Web site affect its utility in providing the intended service to its users:

- Content
- Layout of individual pages
- Structure of the entire Web site itself

Personalization/Recommendation

- The Problem
  - dynamically serve customized content (pages, products, recommendations, etc.) to users based on their profiles, preferences, or expected interests
- Personalization v. Customization
  - Customization: user controls and customizes the site or the product based on his/her preferences
    - usually manual, but sometimes semi-automatic based on a given user profile
  - Personalization: done automatically based on the user's actions, the user's profile, and (possibly) the profiles of others with "similar" profiles

Customization Example

my.yahoo.com

Personalization Example

amazon.com

(Traditional) Personalization Methods

- Currently, the most used technique for web personalization is *collaborative filtering*.

  E.g.: k-Nearest-Neighbor approach:
  - Each visitor is mapped to the *k* most similar past users (similar=same ratings to items, same page accesses, etc.)
  - A set of items is proposed to the visitor, obtained from the analysis of her/his *neighborhood*'s past activity
- Limitations of this method:
  - not scalable to large number of items (slow on-line kNN)
  - does not integrate additional site information such as content/navigational pages

Web Mining for Personalization

- Web mining approach: dividing the process
  1. (slow) offline pattern discovery
  2. (fast) online application of discovered patterns
- It provides the tools to analyze Web log data in a user-centric manner such as segmentation, profiling, and clickstream discovery.
- Data mining results to create decision rules for customizing Web site content based on an individual user's behavior.

Association-based Personalization

Basic Idea

- Match left-hand side of rules with the active user session and recommend items in the rule's consequent
- Ordering of accessed pages is not taken into account
- Good recommendation *accuracy*, but the main problem is *coverage*
- Tradeoff: Coverage vs. Computational cost:
  - high support thresholds lead to low coverage and may eliminate important, but infrequent items from consideration
  - low support thresholds result in very large model sizes and computationally expensive pattern discovery phase

Association-based Personalization

The approach of Mobasher et al.

- Avoid offline generation of all association rules; generate recommendations directly from itemsets
  - discovered frequent itemsets of are stored into an “itemset graph” (an extension of lexicographic tree structure of Agrawal, et al 1999)
  - recommendation generation can be done in constant time by doing a directed search to a limited depth
- Frequent itemsets are matched against a user's active session *S* by performing a search of graph to depth |S|
- A recommendation *r* is an item at level |S+1| whose recommendation score is the confidence of rule *S* ==> *r*

Sequence-based Personalization

Basic Idea

- Take the ordering of accessed items into account
- Two basic approaches:
  - use contiguous sequences (e.g., Web navigational patterns)
  - use general sequential patterns
- Contiguous sequential patterns are often modelled as Markov chains:
  - Usually applied to prefetching
  - In context of recommendations, they can achieve higher accuracy than other methods, but may be difficult to obtain reasonable coverage

Sequence-based Personalization

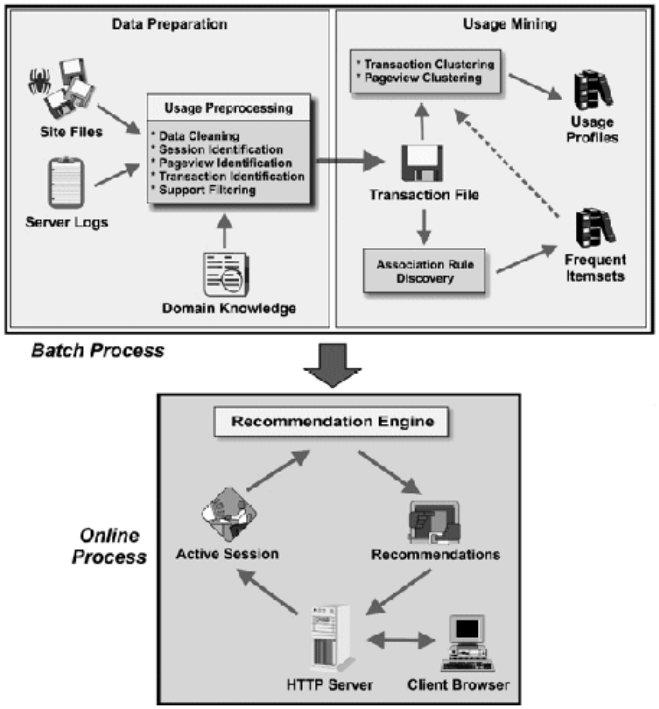
The approach of Gaul and Schmidt-Thieme

- Recommendations are based on frequent patterns of past behaviour
- A recommender is a predictor for a class of events (access to pages, form submissions, etc.)
- A *navigation history* is a set, a sequence or a more complex structure of events
- A collection of recommenders provide suggestions and a combination/selection is proposed to the user

Usage profiles for Personalization

Mobasher, Dai, Luo, Nakagawa

- Clustering to identify transaction clusters.
- New technique to identify user profiles from transaction clusters
- The general architecture presented has two components:



← (offline) Web usage analysis

← (online) Recommendation

Other Personalization Tasks

Spiliopoulou et al.: Improving Sites

- Effectiveness of a Web site in providing users with the content they need in the most optimized manner is the key to retaining them.
- Web Usage Miner: a navigation pattern Q.L.

```
SELECT  t       FROM NODE AS x y z
TEMPLATE    x*y*z   AS   t
WHERE x.support>=20  AND  (y.support/x.support) >= 0.5
        AND (z.support/y.support) >= 0.15
```

  - *Conversion* rates over different kinds of patterns are used to understand the site usage.

→ Suggestions to improve site content/structure

Other Personalization Tasks

Perkowitz & Etzioni: Adaptive Web Sites/1

The **IndexFinder** consists of three phases:

- *Log processing*: Establishment of sessions as sets of page requests
- *Cluster mining*: Grouping of co-occuring non-linked pages with help of the site graph
- *Conceptual clustering*:
  - The representative concept of each cluster is identified.
  - Cluster members not adhering to this concept are removed from the cluster.
  - Pages adhering to this concept and not appearing in the cluster are attached to the cluster.

Other Personalization Tasks

Perkowitz & Etzioni: Adaptive Web Sites/2

- For each cluster, the **IndexFinder** presents to the Web designer:
  - An index page with links to all pages of a cluster
- The Web designer decides:
  - whether the new page should indeed be established
  - what its label should be
  - where it should be located in the site

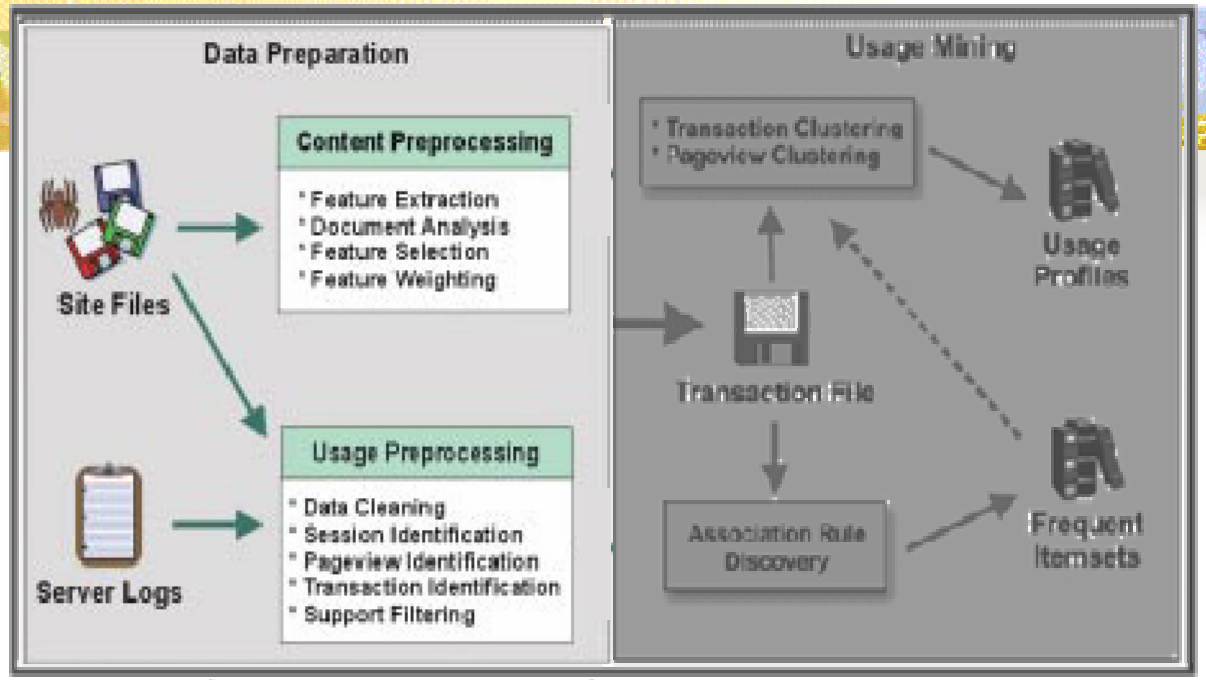
Usage profiles for Personalization

step by step

(Mobasher, Dai, Luo, Nakagawa)

①

Preprocessing



Batch Process

Online Process

Preprocessing/1

- Data cleaning
  - Requests for .gif, .GIF, .jpg, .JPG, ... (editable list) are filtered out
- User identification
  - IP+Agent name to distinguish users
  - Referrers and site topology: access to a page not reachable from visited pages ➔ new user
- Session identification
  - Time-oriented: maximum threshold between contiguous requests. Default:30 minutes.

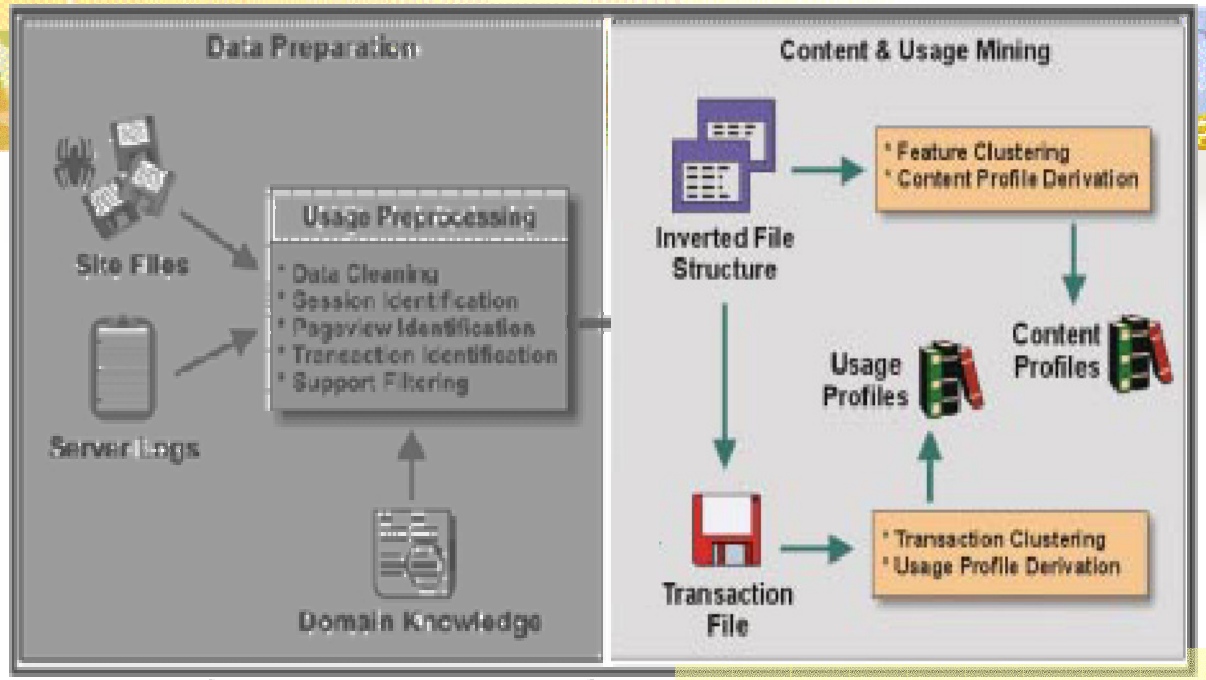
Preprocessing/2

- Path completion
  - Standard approach, selecting minimal-length paths
- Transaction identification (= sub-parts of sessions)
  - 3 Techniques, analogous to session identification:
    - **Reference lenght**: time-out between contiguous requests
    - **Maximal forward reference**: backtrack ➔ new transaction
    - **Time window**: time-out between first and last requests

Preprocessing/3

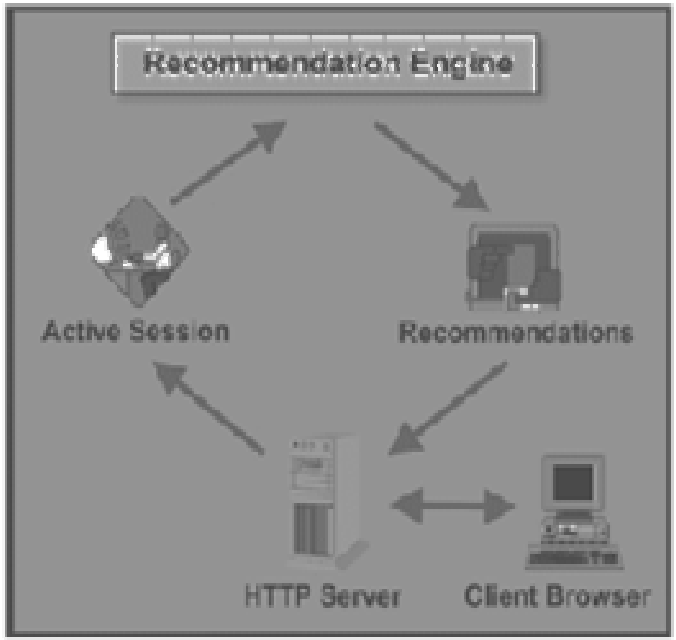
Format:

- Transactions are represented as vectors
  - Dimensions: one for each possible page view
  - Values: for each page view *p*, its *weight*:
    - w(*p*)∈ [0,1] If *p* is in the transaction
    - 0 Otherwise
  - Computing *w(p)*:
    - From site structure analysis
    - By domain experts



Batch Process

Profile extraction



Online Process

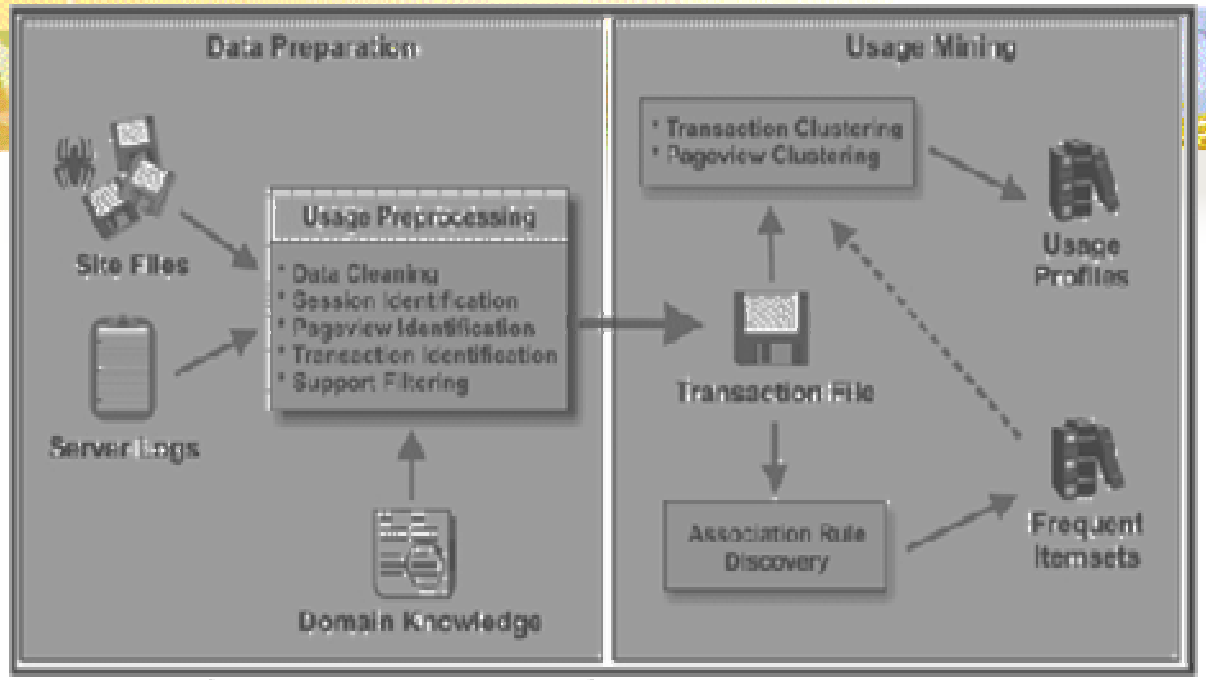
Computing aggregate profiles

- Transaction clustering
  - Standard k-means clustering over the vector representation of transactions
  - Result: set of clusters TC= $\{c_1, \ldots, c_n\}$
- For each cluster *c*, extract its corresponding profile:
  - compute the *mean vector mc* of *c*
  - normalise values so that min=0 and max=1
  - components $< \mu$ are set to 0 ➔ the page view is discarded

Computing aggregate profiles

Example

Table 1. User behavior profiles.		
	Weight	**Pageview URI**
Profile 1	0.78	Call for Papers
	0.67	CFP: ACR 1999 Asia-Pacific Conference
	0.64	CFP: Society For Consumer Psychology Conference
	0.61	ACR 1999 Annual Conference
	0.55	CFP: ACR 1999 European Conference
	0.52	CFP: Int'l Conference on Marketing and Development
	0.50	Conference Update
Profile 2	0.82	CFP: Journal of Psychology and Marketing II
	0.71	CFP: Society For Consumer Psychology Conference
	0.68	Conference Update
	0.68	CFP: Journal of Consumer Psychology II
	0.56	CFP: Conference on Gender, Marketing and Consumer Behavior
	0.52	Online Archives



Batch Process

Recommendation

③

Online Process

Computing Recommendations

- The active session ***s*** of a user is considered
  - Sliding window: take only last *n* page views
  - Compute its vector representation, with weights
- Match *s* with all profiles *mc* (clusters C) *:*
  - Normalised cosine similarity: $$match(S,C) = \frac{\sum_k w_k^C \cdot S_k}{\sqrt{\sum_k (S_k)^2 \times \sum_k (w_k^C)^2}}$$
- Compute the *recommendation scores*, for all $p \in C$:

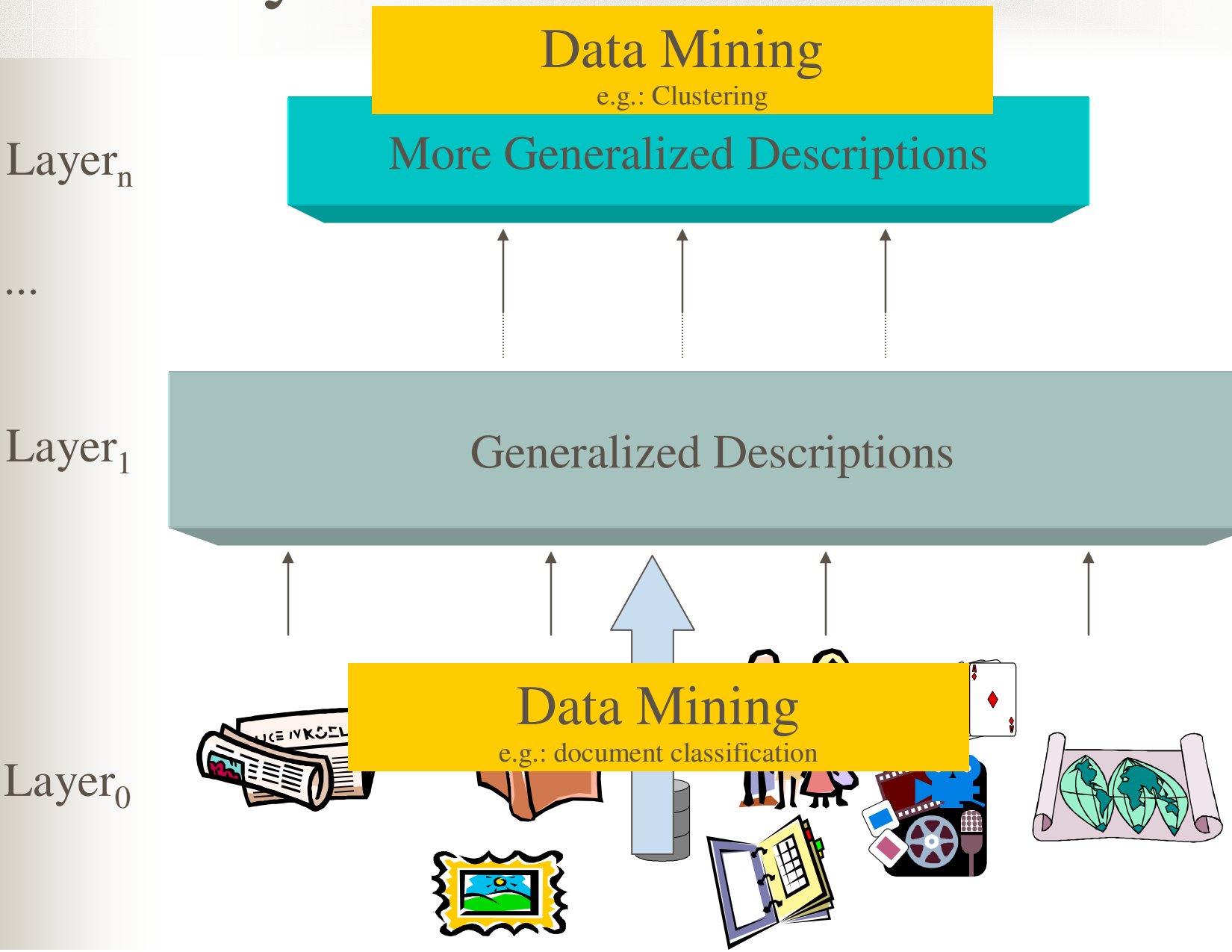
$$Rec(S, p) = \sqrt{weight(p, C) \cdot match(S, C)}$$

- Add *k* best recommendations to the last page requested

Research topics

- All steps of the process can be improved
  - Preprocessing: user identification means, better session heuristics, etc.
  - Mining: new algorithms for web data, ...
  - Pattern analysis: more effective filtering strategies, qality evalution methodologies, ...
- XML: exploiting DTD semantic information
- Web wharehousing: multi-abstraction level organisation of the data on the web (→next slide)
- ...

Multilayered Web Information Base



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