Web Data Mining

Lecture 9: Web Usage Mining/Web Analytics

Jaroslav Kuchař & Milan Dojčinovski

jaroslav.kuchar@fit.cvut.cz, milan.dojchinovski@fit.cvut.cz



Czech Technical University in Prague - Faculty of Information Technologies - Software and Web Engineering





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Overview

- Web Usage Mining
- Collecting and Preprocessing
- Pattern Discovery
- Web Analytics

Web Usage Mining (Recall)

Motivation

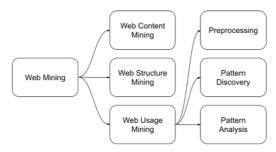
- Huge amount of clickstream, transaction data, and user profile data

Main ideas

- Discover usage patterns from Web data to understand and better serve the needs of web-based applications.
- Extracting useful information from server logs.
- Process of finding out what users are looking on Internet.

Views

- Web Usage Mining
 - → research field
- Web Analytics
 - → practical application of the analysis of clickstream data



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Web Usage Mining (cont.)

Categories

- General Access Pattern Tracking
 - → Analysis of user patterns and general trends to get overview about the overall behavior
- Customized Usage Tracking
 - → Analyses individual trends where the goal is to customize pages to individual users.

Applications

- Usage characterization
 - \rightarrow web analytics, ...
- System improvement and site modifications
 - \rightarrow web sites optimization, ...
- Personalization
 - → user and customer behavior modeling
- Business intelligence
 - → web marketing/advertising
 - → recommender systems

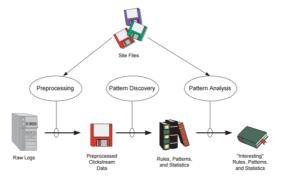
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WUM Process

• Three inter-dependent stages

- data collection and pre-processing
 - → cleaning, transactions identifications
 - → enhancements site structure, semantics, ...
- pattern discovery
 - → detection of hidden patterns using statistical, database, machine learning operations
 - → summary statistics resources, sessions, users
- pattern analysis
 - \rightarrow filtering, aggregations
 - → validations, interpretations



Srivastava et al. (2000). Web usage mining: Discovery and applications of usage patterns from web data.

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WUM Input Data

Usage Data

- Primary source
- Web and application server logs
- Main information
 - → time, (IP address), resource + parameters, status, HTTP method, User-Agent, cookies (optionally)
- Aggregations
 - \rightarrow pageview
 - → collection of resources representing one user-action e.g. reading article, viewing a product page etc.
 - \rightarrow session
 - → sequence of pageviews during one user visit
- Apache Access Log Example:

```
1 | 127.0.0.1 - frank [10/Oct/2000:13:55:36 -0700] \
2 | "GET /apache_pb.gif HTTP/1.0" 200 2326 "http://www.example.com/start.
3 | "Mozilla/4.08 [en] (Win98; I ;Nav)"
```

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WUM Input Data (cont.)

Content Data

- Collection of objects and relationships
- Usually textual data and multimedia (e.g. HTML, images)
- Semantic and structural medatada (e.g. keywords, HTTP variables/headers)
- Domain ontology (e.g. page categories)

• Structure Data

- Content organization within the site
- Hyperlink structure
 - → links connecting various resources as a graph
 - → intra-page links forming a structure of information within one resource

User Data

- User profile information
 - \rightarrow usually from registration forms etc.
 - → demographics, user ratings, historic data (e.g. purchases), explicit/implicit user interests.

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Data Collecting

Data Collecting

- Explicitly
 - \rightarrow The simplest method
 - → Usually based on filling forms, questionnaires, providing ratings.
 - \rightarrow *Potentially high quality*
 - \rightarrow Issues
 - → Users dislike spending time submitting any data.
 - → Privacy concerns with providing any personal data.
- Implicitly
 - \rightarrow *Non-invasive way*
 - → Does not require an intervention of any user.
 - \rightarrow Inferring information from user interactions.
 - → Many channels: clicks, gestures, posture, eye tracking, language and choice of words, ...
 - \rightarrow Issues
 - \rightarrow Difficulties with interpretations of available interactions.
 - \rightarrow Privacy issues with monitoring of users.

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Implicit Data Collecting

- Web/Search logs
 - Original source of usage data
 - Limited information
- Proxy servers
 - Complex data from multiple sources, web sites
 - Requires using the proxy server
- TCP/IP packet sniffers
 - Too limited application
- Browser/Desktop agents
 - For advanced analysis of multiple implicit data channels
 - → includes specific hardware e.g. eye-trackers
 - Requires installation and usage of the agent
- Client-side JavaScript trackers
 - Most popular technique
 - Complex approaches allowing collecting many relevant data without any requirements on installation of additional SW.

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Client-side JavaScript trackers

Collected data

- Domain name
- Random user identifier
 - → Usually created at the time of the first visit
 - → Often includes timestamp
- Refferal
 - \rightarrow Information about the first time visit relation
 - → domain name, search vs campaign etc.
- \rightarrow search term
- Referrer
 - → Information about the current relation
- User + User-Agent data
- Custom variables

Cookies

- Using cookies (first/third-party) to store data across many pageviews
- Usually combinations of many cookies
 - → session cookie
 - \rightarrow request rate cookies
 - → "permanent" user id cookie

Data transfer

- usually as a part of the query string
- returning "invisible" image deals with JS blocking etc. (1x1 transparent gif), no cache, random identifier

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Client-side JavaScript trackers (cont.)

• Piwik.org

- Leading open source web analytics platform

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Client-side CSS tracking

Two features of CSS

- the ability to inject content into HTML elements
- the ability to change the style after a user performs an action.

```
// general idea
#link:active::after {
    content: url("https://example.com/track?action=link_clicked");
}

// Browser detection
gesupports (-webkit-appearance:none) and (not (-ms-ime-align:auto)) {
    #chrome_detect::after {
        content: url("https://example.com/track?action=browser_chrome");
}

// OS detection
font-face {
    font-family: Font1;
    src: url("https://evil.com/track?action=font1");
}

#font_detection {
    font-family: Calibri, Font1;
}
```

https://github.com/jbtronics/CrookedStyleSheets

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Preprocessing

• Data cleaning

- removing of irrelevant items, log entries produced by spiders and crawlers or error log entries.
 - → references to image, css, multimedia or script files
 - → specific user-agents/IP addresses including lists of well-known bots
 - → heuristic methods to identify bots not well identified
 - \rightarrow entries with status codes not conforming to 2XX

• Pageview identification

- heavily dependent on the way of collecting data and domain specific definition
 - → access log entries vs JS trackers
 - → viewing a specific page vs product view or purchase

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Preprocessing (cont.)

• User identification

- assigning unique user identifier to all entries coming from one user
- Approaches
 - → using unique client-side cookies
 - \rightarrow IP address generally not sufficient (e.g. proxy, NAT, ...)
 - \rightarrow IP address + User-Agent
 - \rightarrow fingerprints
 - → HTTP Headers, Plugins, Fonts, Canvas, ...
 - → application level identifiers
 - \rightarrow combinations

```
for (plugin of navigator.plugins) { console.log(plugin.name); }
console.log(navigator.userAgent);
console.log(screen.width + "x" +screen.height)

Widevine Content Decryption Module
Chrome PDF Viewer
Native Client

Mozilla/5.0 (Macintosh; Intel Mac OS X 10_12_4) ...

1680x1050
```

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Preprocessing (cont.)

• Session identification

- grouping of log entries to sequences related to one user visit
- using time-based or navigation based heuristics
 - \rightarrow Total duration of one session is no longer than a threshold e.g. 30 minutes
 - \rightarrow Total time spent on the page cannot be longer then a threshold e.g. 10 minutes
 - → The referrer of the currently visited page should be already part of the session, otherwise start a new session.

• Path completion

- automatic detection of missing entry
- can be caused by caching, proxy servers or any corrupted communication
 - → Site structure can help to fill missing entries
 - → Many candidate solutions can be available
 - → *Using the fewest number of "back" references heuristic*
 - → Identify patterns from existing user patterns

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Overview

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Data Modeling

- The results of preprocessing *Pageviews* $\rightarrow P = \{p_1, p_2, \dots, p_n\}$

$$\rightarrow P = \{p_1, p_2, \dots, p_n\}$$

- Weights:
 - $\rightarrow binary$
 - \rightarrow represents existence (1) or non-existence (0)
 - \rightarrow function of the duration
 - \rightarrow reflects the time spent on the page (not available for the last pageview mean
 - \rightarrow order of the pageview
 - \rightarrow higher is better
 - \rightarrow combinations or heuristics \rightarrow e.g. $(ln(o) + 1) \times t$
- Transactions
 - $\rightarrow T = \{t_1, t_2, \dots, t_m\}$
 - → where each transaction is a set of pageviews
 - $\rightarrow t = \langle (p_1, w(p_1)), (p_2, w(p_2)), \dots \rangle$

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Data Modeling (cont.)

• User-pageview matrix or transaction matrix (UPM)

$$-t = (w_{p_1}, w_{p_2}, \dots, w_{p_n})$$

- Simple representation
- For situations when the order of pageviews is not relevant
- Columns usually represent pageviews all unique page identifiers
 - → Can be extended about events within one page
 - \rightarrow *Issues with dimensionality*

	A.html	B.html	C.html	D.html	E.html	F.html
t_1	20	9	0	0	0	168
t_2	0	0	32	4	0	0
t_3	21	0	0	46	114	0
t_4	0	0	21	11	0	0

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Semantic Information Integration

- Description of each pageview
 - Issues with granularity
 - → URI identifier does not provide any information and is too "fine grained"
 - Features
 - → Semantic descriptions
 - → extracted keywords/data from the page
 - \rightarrow taxonomies
 - \rightarrow e.g. product price, category, ...
 - \rightarrow Classifications
 - \rightarrow e.g. product detail, navigation, general, ...
- Each feature is assigned during the data collecting phase or linked from an internal knowledge-base

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Semantic Information Integration (cont.)

• Pageview-feature matrix (PFM)

$$-p = (fw(f_1), fw(f_2), \dots)$$

 $-fw(f_i)$ is the weight of the feature in the pageview

					f_5	f_6	
A.html	1	1	0	0	0	1	
B.html	0	0	1	1	0	0	
C.html	1	0	0	1	1	0	
D.html	0	0	1	1	0	0	

• Content-enhanced transaction matrix or Transactionfeature matrix (TFM) $- TFM = UPM \times PFM$

						f_6	
t_1	20	12	12	5	0	0	
t_2	0	0	32	4	0	0	

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Data Modeling - Example

• User transactions/visits/sessions

transaction	order	URL	Duration
1	1	Norway.html	60
1	2	AlpTrip.html	120
1	3	Ski.html	240
2	1	Belgium.html	30
2	2	Norway.html	2
2	3	Belgium.html	240

• User-pageview matrix (UPM)

1		AlpTrip.html	Belgium.html	Ski.html	Norway.html
	t_1	120	0	240	60
	t_2	0	270	0	2

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Data Modeling - Example (cont.)

• Pageview-feature matrix (PFM)

	Adventure	Leisure	Europe	USA	Norway	Alps	Belgium
AlpTrip.html	1	0	1	0	0	1	0
Belgium.html	0	1	1	0	0	0	1
Ski.html	1	0	1	0	0	1	0
Norway.html	0	1	1	0	1	0	0

• Content-Enhanced transaction matrix or Transaction-feature matrix (TFM)

	Adventure	Leisure	Europe	USA	Norway	Alps	Belgium
t_1	360	60	420	0	60	360	0
t_2	0	281	281	0	2	0	279

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Pattern Discovery - Clustering

- Views
 - User clusters
 - Page clusters
- Algorithms
 - standard clustering algorithm such as k-means
 - → similarities in clusters are maximized and similarities between clusters are minimized
 - \rightarrow using cosine similarity etc.
- Clustering of users
 - the most commonly used task
 - the goal is to find clusters of users that exhibiting similar browsing patterns
 - application in market segmentations, personalizations, user communities

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Clustering Example

• Clustering using using pageviews

	A.html	B.html	C.html	D.html	E.html	F.html
user ₁	0	0	1	1	0	0
user ₄	0	0	1	1	0	0
user ₇	0	0	1	1	0	0
_						
$user_0$	1	1	0	0	0	1
user ₃	1	1	0	0	0	1
user ₆	1	1	0	0	0	1
user ₉	0	1	1	0	0	1
_						
user ₂	1	0	0	1	1	0
user ₅	1	0	0	1	1	0
user ₈	1	0	0	1	1	0

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Clustering Example (cont.)

- Clustering using semantic features semantic description of each page

 - page classifications

Cluster	#Transactions	Descriptions
1	788	Hiking
2	1398	Bulgaria, Montenegro, Corsica, Last Minute, Search
3	779	Mountaineering, Climbing school, Alpine hiking, Rafts
4	2084	Package holiday, Tour details
5	596	Expeditions, Exotic holidays

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Pattern Discovery - Association Analysis

- Association Analysis
 - Can find groups of items or pages that are commonly accessed (purchased) together.
 - Typically uses well known Apriori
 - Application in web structure optimizations or recommendations
- Example
 - Association rule
 - \rightarrow /special-offers/ & /products/software/ \rightarrow /shopping-cart/
 - "promotional campaign on software products is positively affecting online sales"

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Association Rule Mining

- Mining of association rules is a fundamental data mining task
 - Its objective is to find all co-occurrence relationships, called associations
 - First introduced in 1993 by Agrawal
 - → Apriori algorithm
- Well-known application
 - Market basket data analysis
 - \rightarrow {Cheese} \rightarrow {Beer}
 - \rightarrow support = 10%, confidence = 80%
 - → 10% customers buy Cheese and Beer together
 - → those who buy Cheese also buy Beer 80% of the time

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Association Rules

Association Rule

- An implication expression $X \rightarrow Y$
 - $\rightarrow X$ is an antecedent
 - $\rightarrow Y$ is a consequent

Metrics

 \rightarrow Fraction of transactions that contain both X and Y

 \rightarrow Measures how often items in Y appears in transactions that contain X

Example

$$-\{Milk, Diaper\} \rightarrow \{Beer\}$$

$$\rightarrow support = \frac{|Milk, Diaper, Beer|}{|T|} = 2/5 = 0.4$$

$$\rightarrow confidence = \frac{|Milk, Diaper, Beer|}{|Milk, Diaper|} = 2/3 = 0.67$$

Transaction	
1	{Bread, Milk}
2	{Bread, Diaper, Beer, Eggs}
3	{Milk, Diaper, Beer, Coke}
4	{Bread, Milk, Diaper, Beer}
5	{Bread, Milk, Diaper, Coke}

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Apriori Algorithm

- Apriori Algorithm
 Introduced in 1993 by Agrawal
 - Parameters
 - → Minsup minimum support of rules
 - → Minconf minimum confidence of rules
 - Two steps
 - → Generate all frequent itemsets
 - \rightarrow A frequent itemset is an itemset that has transaction support above minsup
 - → Generate all confident association rules from the frequent itemsets
 - \rightarrow A confident association rule is a rule with confidence above minconf

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Apriori Algorithm (cont.)

• Step 1

```
Ck = Candidate itemset of size k

Lk = frequent itemset of size k

L1 = {frequent items}

for (k=1; Lk.size() != 0; k++):

Ck+1 = candidates generated from Lk

for each transaction t in database do:
    increment the count of all candidates in Ck+1

that are contained in t

Lk+1 = candidates in Ck+1 with min_support

return all Lk
```

• Step 2

```
For each frequent itemset 1, generate all nonempty subsets of 1.
For every nonempty subset s of 1, output the rule s -> (1-s) if support(1) / support(s) >= minconf
```

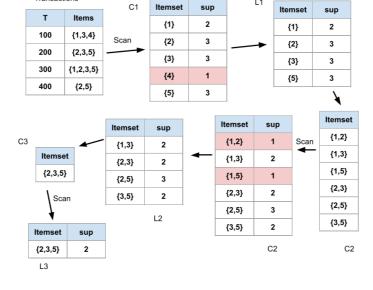
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Apriori Algorithm Example

Transactions

• Min support = 50%



 $https://webdocs.cs.ualberta.ca/\sim zaiane/courses/cmput499/slides/Lect10/sld054.htm$

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Apriori Algorithm Example 2

- Apriori is not able to work with numeric values
 - There is a requirement to properly preprocess the data
- Preprocessing
 - Discretization to binary values
 - \rightarrow loss of information
 - Binarization
 - → increased number of dimensions
- Example
 - Content-Enhanced transaction matrix or Transaction-feature matrix (TFM)

	Adventure	Leisure	Europe	USA	Norway	Alps	Belgium
t_1	360	60	420	0	60	360	0
t_2	0	281	281	0	2	0	279
	Adventure	Leisure	Europe	USA	Norway	Alps	Belgium
<i>t</i> ₁		Leisure 1	Europe 1	USA 0	Norway 1	Alps 1	Belgium 0

	AdventureH	AdventureM	AdventureL(<50)	LeisureH(>200)	LeisureM	LeisureL(<50)	
t	1	0	0	0	1	0	
t_2	2 0	0	1	1	0	0	

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Apriori Algorithm Example 2 (cont.)

- Example of task
 - Format of rules
 - \rightarrow Antecedent
 - \rightarrow temporal information, referral information
 - \rightarrow Consequent
 - \rightarrow Purchase flag
 - Settings
 - \rightarrow min support = 2% (e.g. 50 transactions)
 - \rightarrow min confidence = 70%
 - Results
 - → {Referral=GoogleSearch, Hour=Morning} → {Purchase=True}
 - \rightarrow support= 3%, confidence = 75%

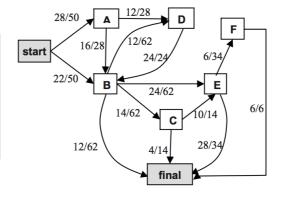
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Sequential and Navigational Patterns

- Sequential and Navigational Patterns Similar to association rules
 - - \rightarrow take into account temporal information = order of pageviews
- Markov models can be used as the underlying concept for the sequential modeling.

Frequen
cy
10
4
10
6
12
8



Liu, B. "Web Data Mining", Springer-Verlag Berlin Heidelberg, 2011. ISBN 978-3-642-19459-7.

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Overview

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Web Analytics

Web Analytics

- General Access Pattern Tracking
 - → Analysis of user patterns and general trends to get overview about the overall behavior.
- Collecting data, analysis and reporting

Two main categories

- Traffic analysis
 - \rightarrow pageviews
 - \rightarrow sessions
 - $\rightarrow visitors$
 - → time on page
 - \rightarrow bounce rate
- E-commerce analysis
 - → Conversion, Conversion rate
 - \rightarrow Revenue
 - → Campaigns
 - → Impressions
 - → CTR click through rate, CPC cost per click

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Web Analytics

• Main overview

- Number of pageviews
- Number of sessions
- $-{\it Number\ of\ visitors/unique}$
 - → returning visitors

Time on Page and Time on Site

- Time on the last page issue
 - \rightarrow the average value from all previous pages
 - → specific hacks JavaScript onbeforeunload event
- Tabbed browsing
 - → identification and represent as separate sessions
 - \rightarrow normalize as one session
 - → specific hacks JavaScript visibilitychange event

Bounce rate

- "I came, I puked, I left."
- the percentage of sessions on your website with only one page view
- Specific use cases
 - $\rightarrow Rlogs$

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Web Analytics (cont.)

- Conversion rates
 - Outcomes divided by Unique Visitors (or Visits)
- Conversions desired outcome
 - Macro conversion
 - → *Limited amount*
 - → Submitted order
 - → Registration to a newsletter
 - Micro conversions
 - → Higher amount
 - → More complex solutions and issues with the interpretation
 - → product ratings
 - → video consumption
 - → shopping basket operations
 - → dynamic content interactions
 - **→** ...

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Web Analytics (cont.)

- Conversion funnel
 - describe the journey a consumer takes through an ecommerce website and finally converting to a sale





King, B.A. "Website Optimization: Speed, Search Engine Conversion Rate Secrets", O'Reilly Media, 2008. ISBN 978-0596515089.

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Web Analytics (cont.)

- Campaigns *Sources*
 - - \rightarrow Medium
 - → organic, cpc, banner, email, referral, none
 - \rightarrow Source
 - → google, seznam, facebook, direct
 - → Search terms
 - \rightarrow Example
 - $\rightarrow http://www.example.com/?$ utm_medium=cpc&utm_source=google
- Landing and exit pages
 First and last pages of user sessions.

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