MINING FREQUENT GENERALIZED PATTERNS FOR WEB PERSONALIZATION

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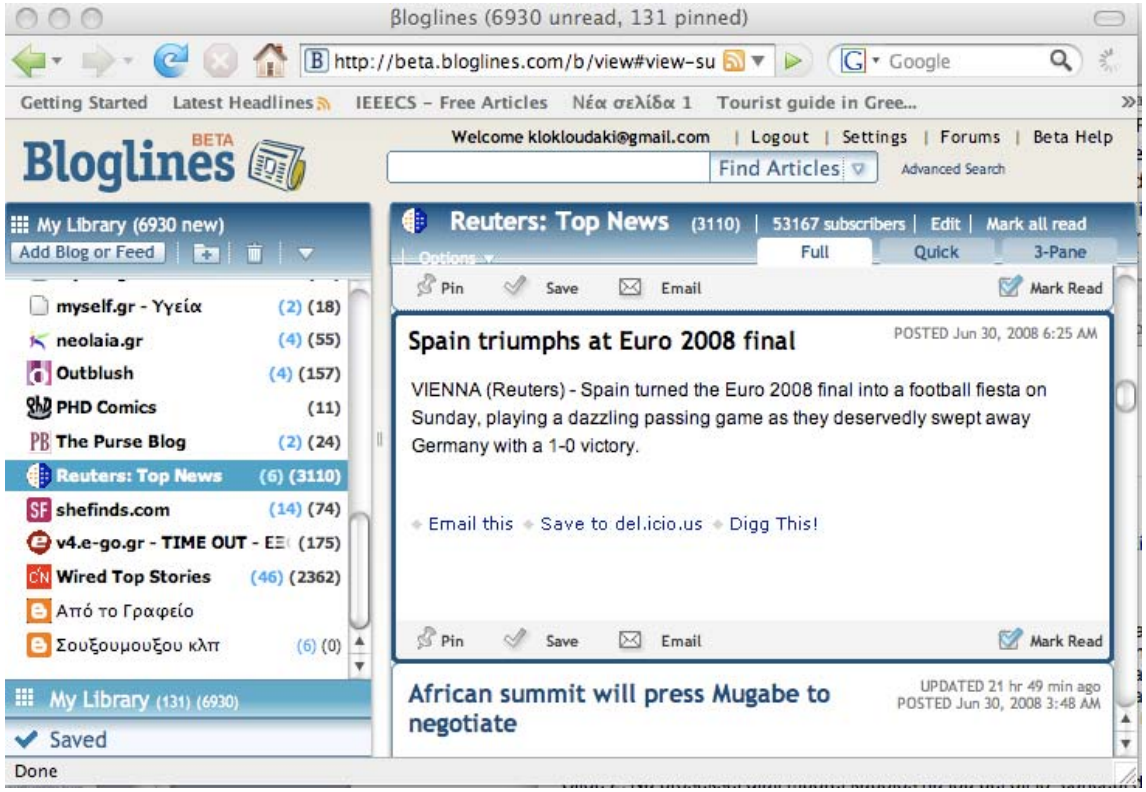
Mining Social Data - ECAI 2008

Motivation



- Huge amounts of social data generated in a regular basis
- Information overload remains a problem, even if the user chooses to monitor a subset of those (e.g. using blog aggregators)
- Need to personalize the content by providing recommendations to the user

Motivation

- Association Rule Mining (ARM): data mining technique used to identify item co-occurrence in “market baskets”
  - E.g. items bought, web pages visited, etc.
  - A, B → C [confidence, support]
- Useful for making **recommendations**
- PROBLEM: In environments with continually updated content (blogs, newspaper sites), we have limited or no transaction information for new items
  - The **cold-start problem** : how to make suggestions in the absence of transaction history (i.e. for the new items)

Motivation

- SOLUTION: Generalize frequent patterns using hierarchical organization of the content (i.e. taxonomies)
  - Generalized Pattern Mining algorithms [AprioriAll, AprioriSome, DynamicSome, CDIST, CDIST_O, CWIN, CMINWIN, Collaborative Filtering, Content-Based Filtering, Markov Models, Sequential Pattern Mining algorithm, GSP, FP-Growth, GP-Close]

Our Solution

- Combine the forces of:
  - *FP-Growth:* An association rule mining algorithm
  - *GP-Close:* A generalized pattern mining algorithm
- Why both?
  - When the performance of the FP-Growth algorithm is combined with the taxonomic features of GP-Close we are able to provide a solution to the cold-start problem

Outline

- Motivation
- **Preliminaries**
  - **FP-Growth**
  - **GP-Close**
- The FGP Algorithm
- Experimental Evaluation
- Future Work
- References

FP-Growth (1/2)

- A well-known association rule mining (ARM) algorithm, proposed by Han et al. [Han04]
- Two phases:
  - Scan the transaction database, in order to find the frequent items of each session and store them in descending frequency order
  - Construct the FP-tree

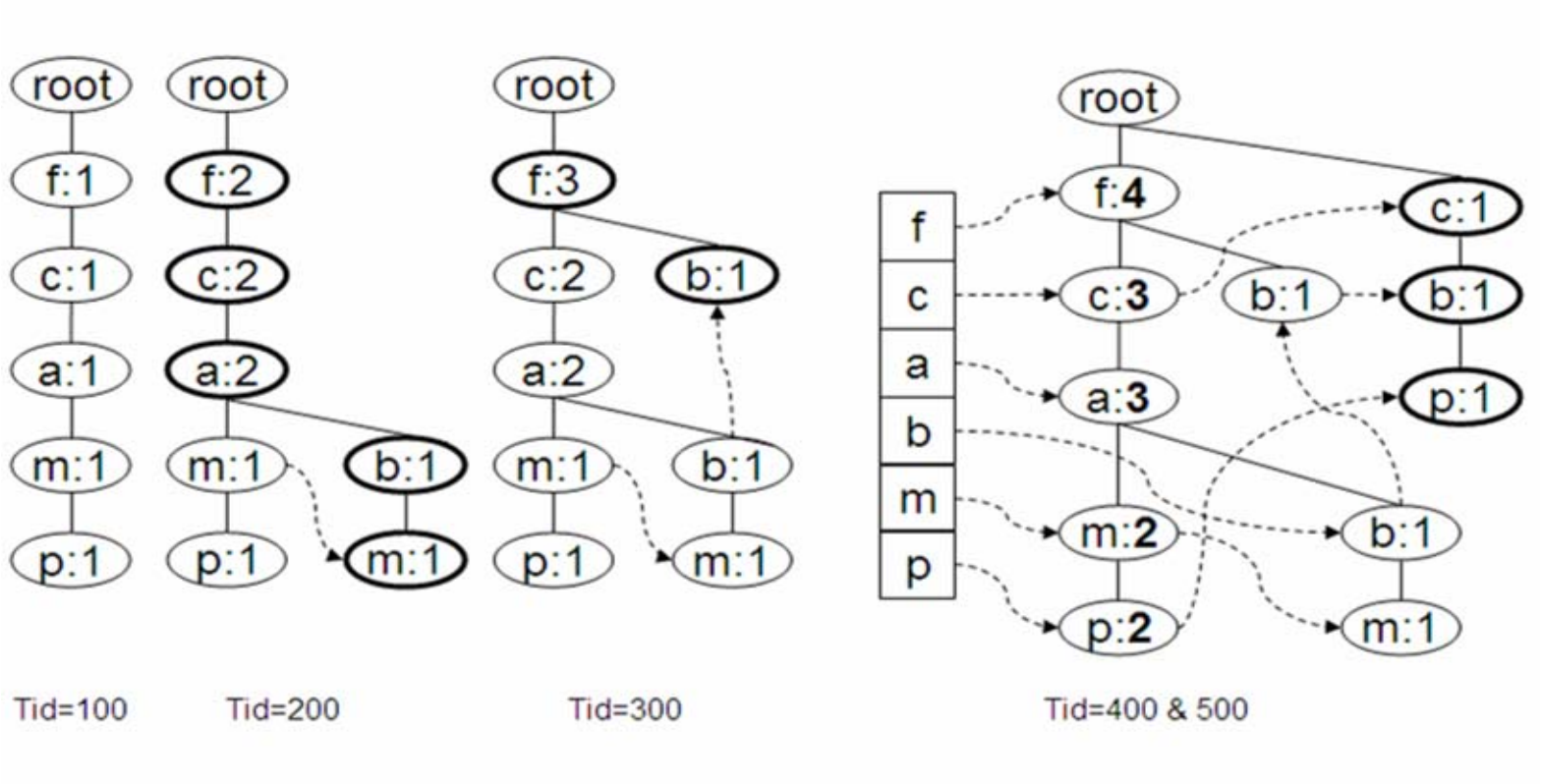
FP-Growth example (1/2)

- Transaction table

TID	Itemset	**Ordered frequent items (min freq=3)**
100	f, a, c, a, d, g, i, a, m, c, p	f, c, a, m, p
200	a, b, c, f, c, l, a, m, o	f, c, a, b, m
300	b, f, h, j, o, f	f, b
400	b, c, k, s, p, c, b	c, b, p
500	a, c, f, c, e, l, f, p, m, n, a	f, c, a, m, p

FP-Growth example (2/2)

- The FP-tree construction process



GP-Close (1/2)

- A frequent pattern mining algorithm, designed by Jiang et. al. [Jia06, Jia07] to work on transaction data
  - Makes use of a taxonomy
- Deals with the **over-generalization problem**:
  - If any items are subsumed by other, more specialized ones, remove the former from the closure enumeration tree
- The aforementioned problem is proven to be equivalent to closed pattern discovery

GP-Close (2/2)

- Find all frequent 1-item sets
  - Can be either taxonomy categories or items
- Sort them in a length decreasing – support increasing manner
- Generate the closed closures of length k, based on the closures of length k-1 and the children of the root

- Two pruning techniques (Subtree pruning and Child-Closure pruning) manage to reduce the pattern search space

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- Motivation
- Preliminaries
- **The FGP Algorithm**
  - **Algorithm Outline**
  - **Algorithm Example**
- Experimental Evaluation
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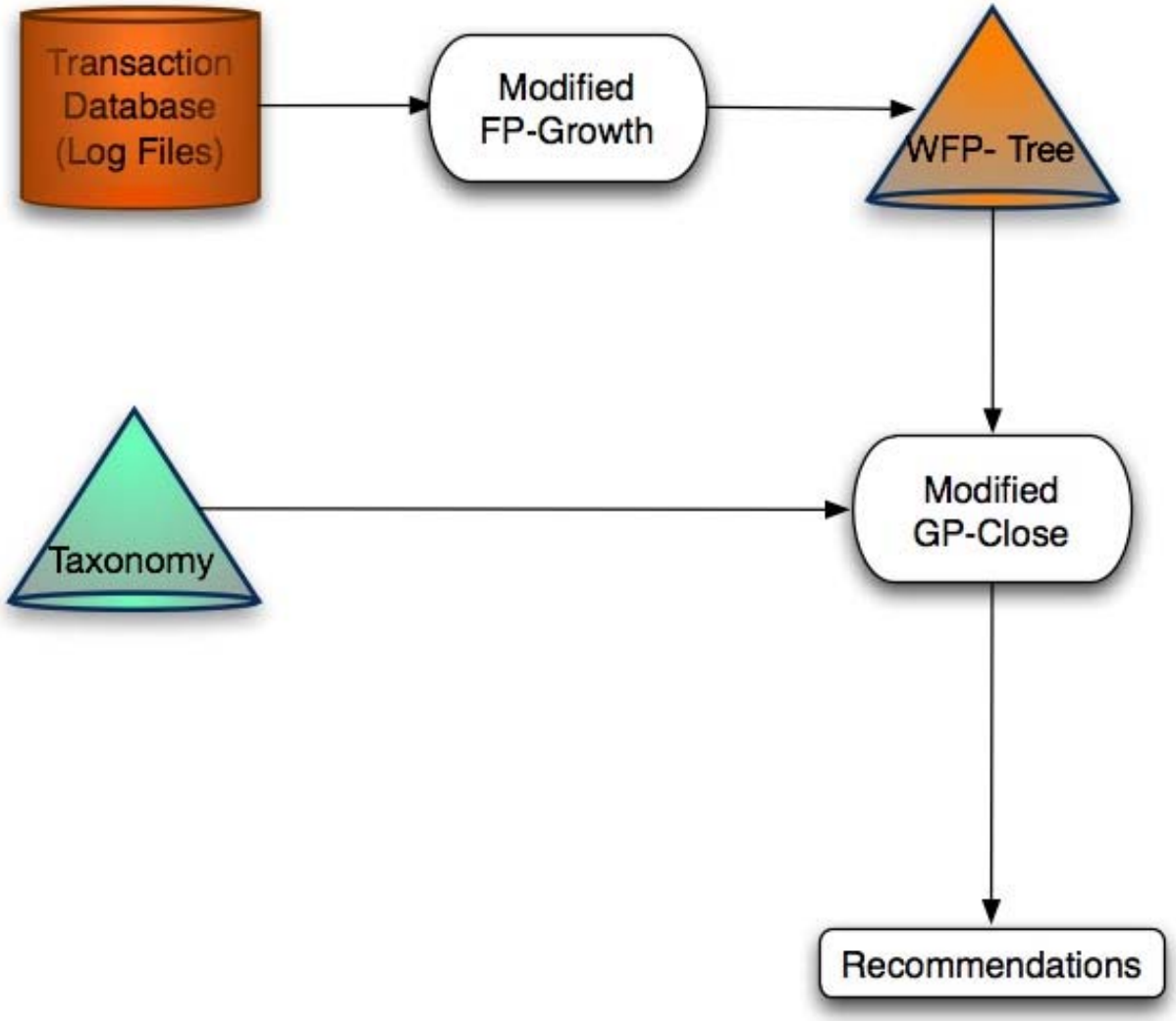
The FGP algorithm (1/2)

- Combines the forces of FP-Growth and GP-Close
  - GP-Close input is the FP-tree and the taxonomy (and NOT the transaction database)
- Requires modifications of the aforementioned algorithms

An outline of FGP

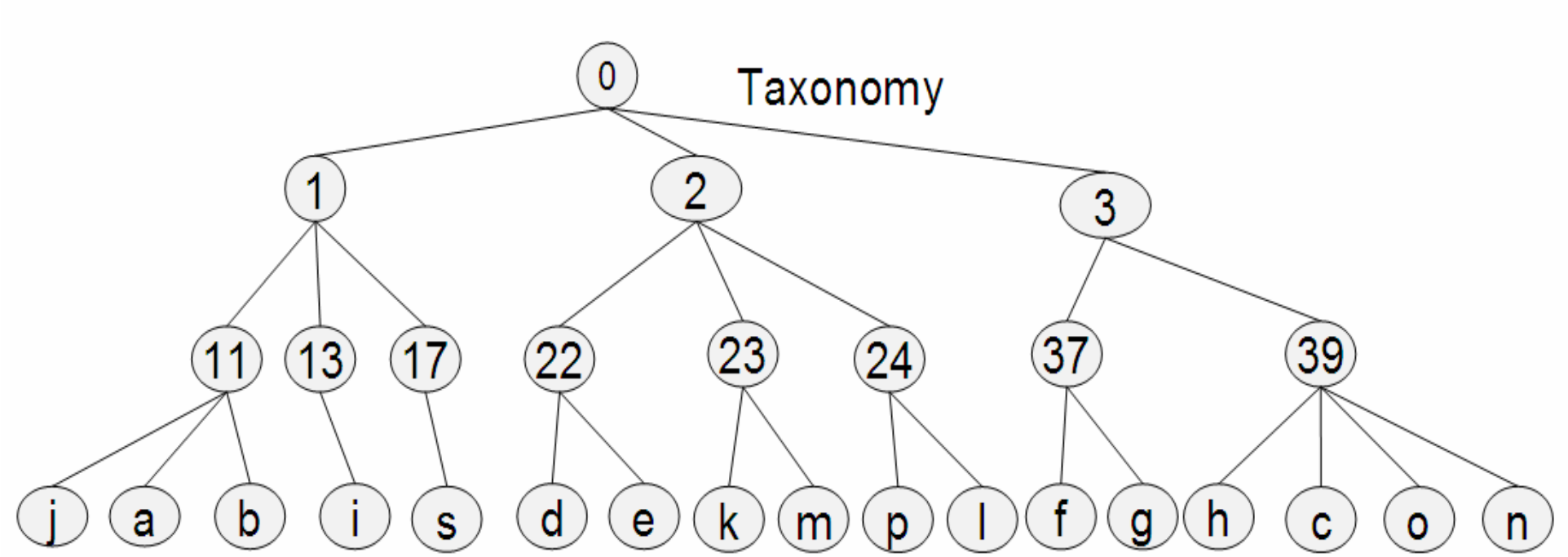


The FGP algorithm (2/2)

- Scan the transaction database and construct the so-called WFP-tree (including weight information in the nodes)
- Create generalized 1-item sets using the taxonomy
  - Sort 1-item sets in increasing support order
  - Implement a modified Child-Closure pruning
- Combine 1-item sets to create the complete closure enumeration tree
  - Implement a modified Subtree pruning
- Produce the closure enumeration tree levels, until it is not possible to expand the tree any more

FGP Example (1/6)

- Input taxonomy



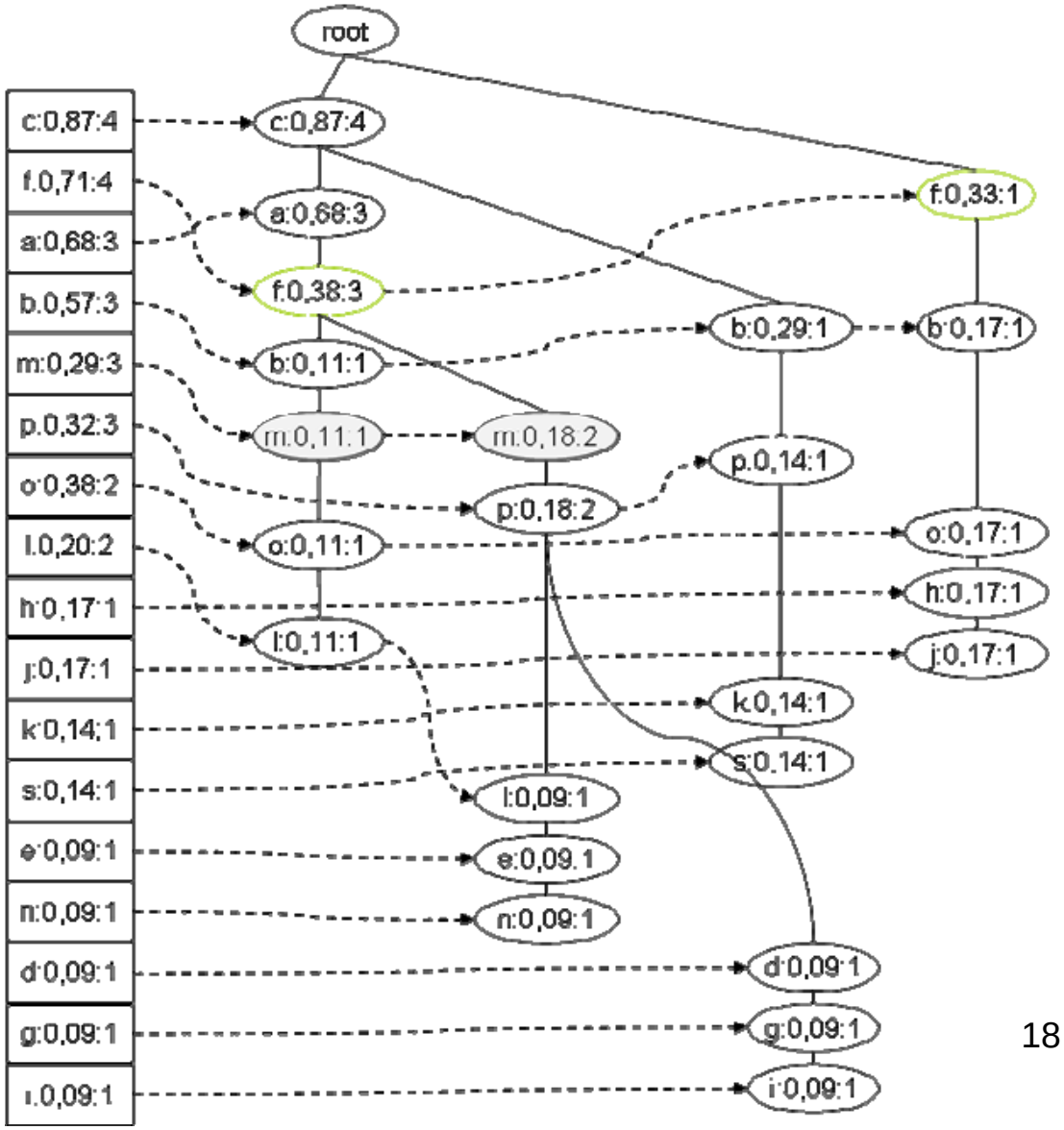
FGP Example (2/6)

- Transaction Database (including sessionized Web log data)

TID	Session items (PID, hits)	Total hits/session
100	(a,3), (c,2), (f,1), (d,1), (g,1), (i,1), (m,1), (p,1)	11
200	(a,2), (c,2), (b,1), (f,1), (l,1), (m,1), (o,1)	9
300	(f,2), (b,1), (h,1), (j,1), (o,1)	6
400	(b,2), (c,2), (k,1), (s,1), (p,1)	7
500	(a,2), (f,2), (c,2), (e,1), (l,1), (p,1), (m,1), (n,1)	11

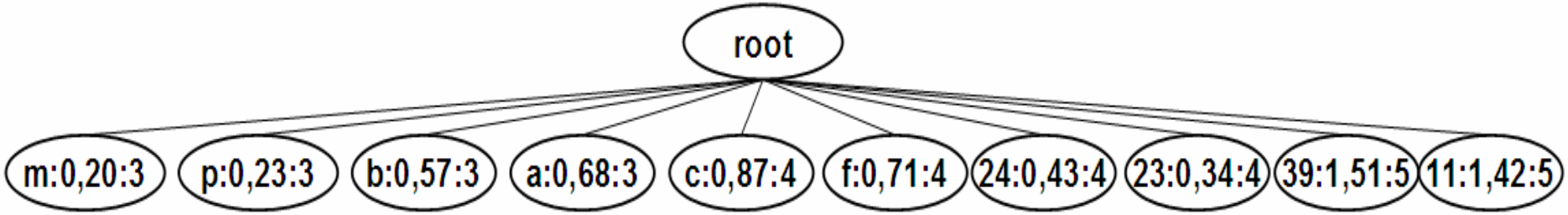
FGP Example (3/6)

- The WFP-tree



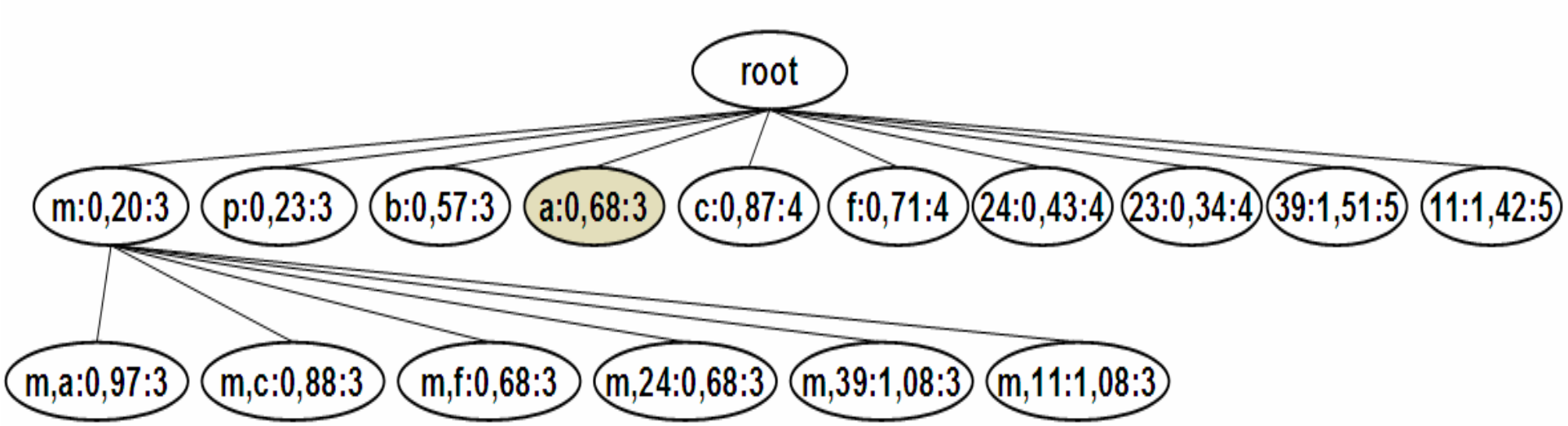
FGP Example (4/6)

- Create generalized 1-item sets using the taxonomy
  - Find all leaf nodes, which are descendants of this node
  - Scan the WFP-tree
    - If there is a path containing all previously computed items, add the support of the corresponding items to the total value
  - Subtract multiple occurrences of the same node in a path in the support counting



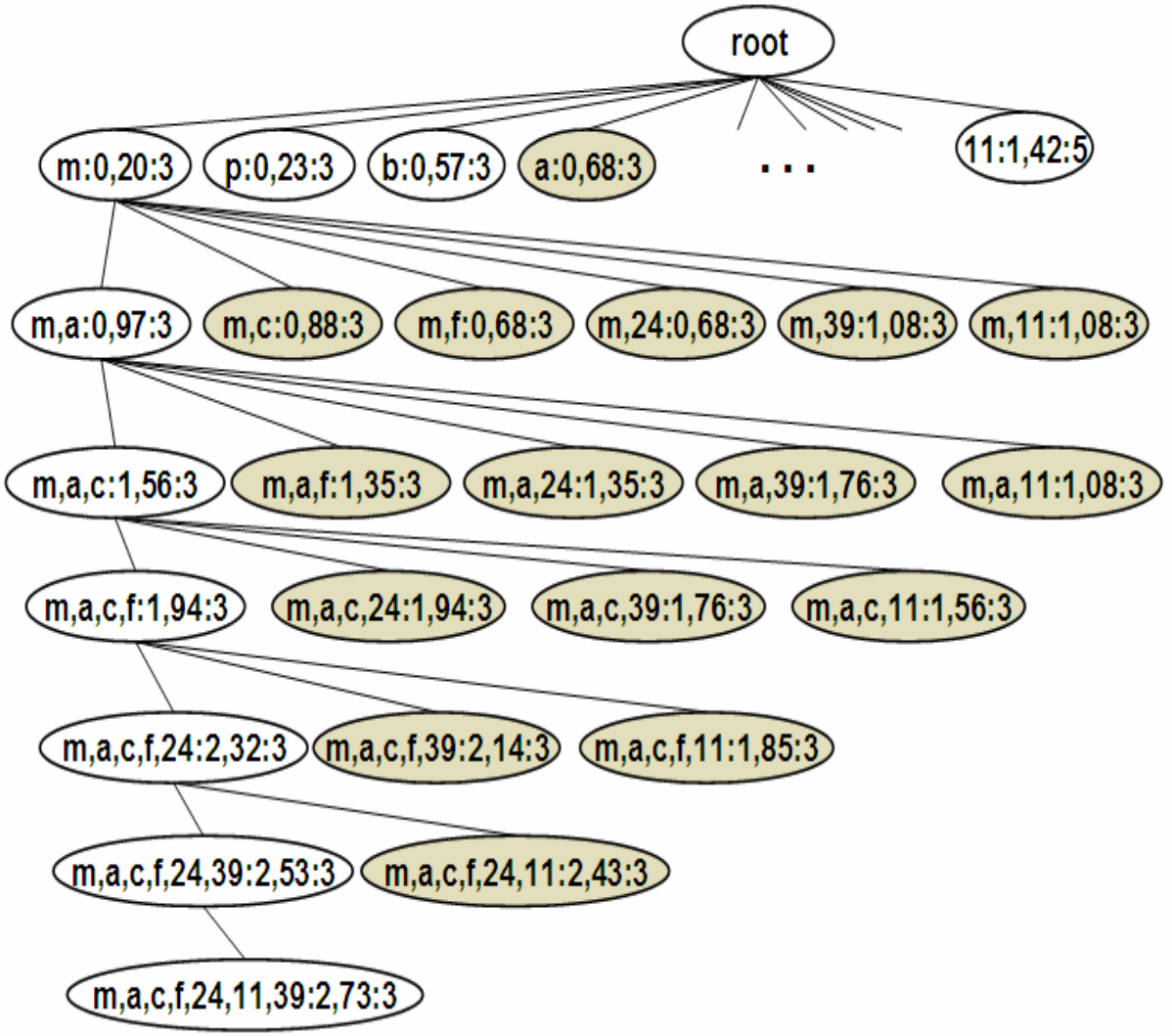
FGP Example (5/6)

- Find frequent k-item sets (k>1)
  - Find all descendants of the items included in this closure enumeration tree node, that are taxonomy leaves
  - Find the latter in the WFP-tree
  - Check existence of a path containing a representative from each category
    - If there is such a path, increment support of each element
  - Total weight = sum of weights of all nodes in this path



FGP Example (6/6)

- Expand 1-item sets
- Prune nodes that have the same support as one of their direct ancestors



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Evaluation of FGP (1/5)

- Data set statistics

Total number of files	31
Average number of page hits per day	8708
Average number of sessions per day	882
Average session length (in page hits)	8.5
Average time for CE tree creation	17.2 sec
Average number of k-item sets per day (FP-Growth)	7
Average number of generalized k-item sets per day	56
Overall maximum rule length	8

Evaluation of FGP (2/5)

- Observation: The utilization of the taxonomic information results in the increase in the number of generated rules (56 vs. 7)
- Typically, we should measure the number of recommendations selected by the users
- We do not have real-time feedback on the recommendations

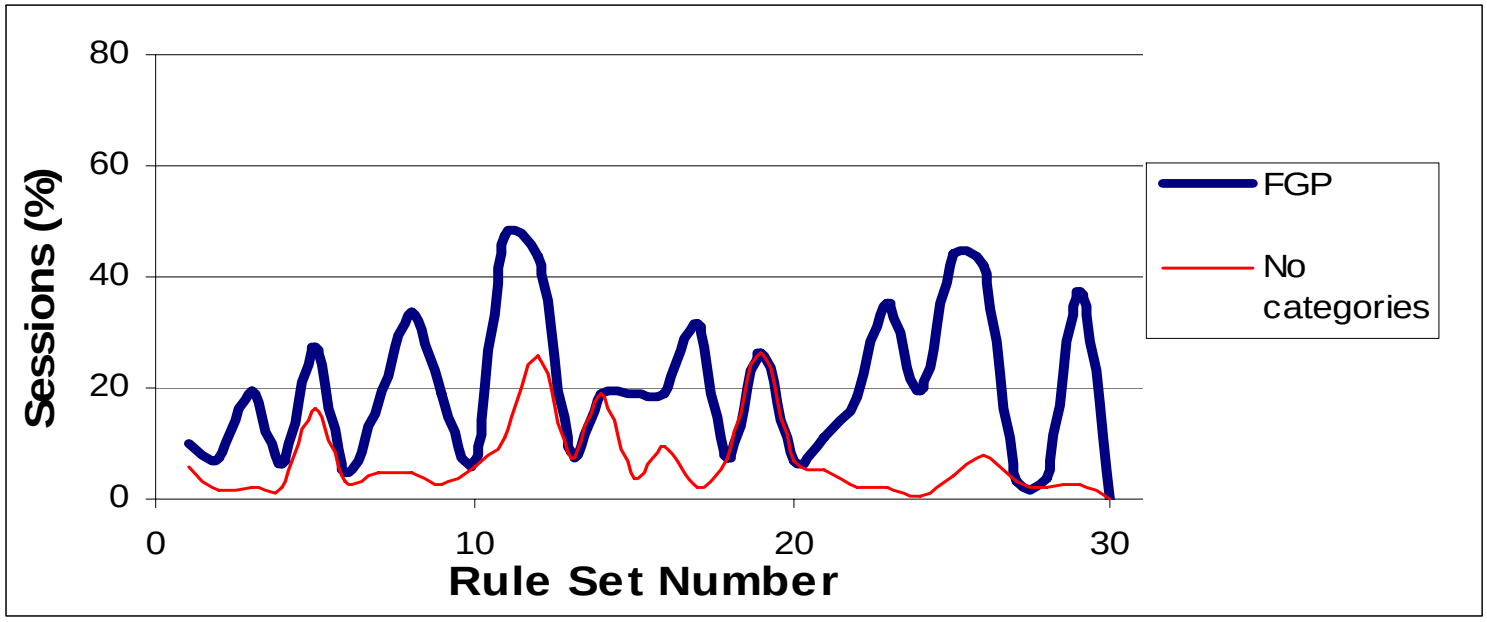
Evaluation of FGP (3/5)

- Use FGP to generate recommendations for a day and then validate them using transaction information of the next day:
  - FGP produces generalized *k*-item sets.
  - If a user has viewed articles belonging to the *k-1* categories of the set, recommend the k^{th} item (or items from the k^{th} category)

- In our experiments, we find generalized frequent item sets of day k (0<=k<=30) and attempt to locate them in the logs of day k+1

Evaluation of FGP (4/5)

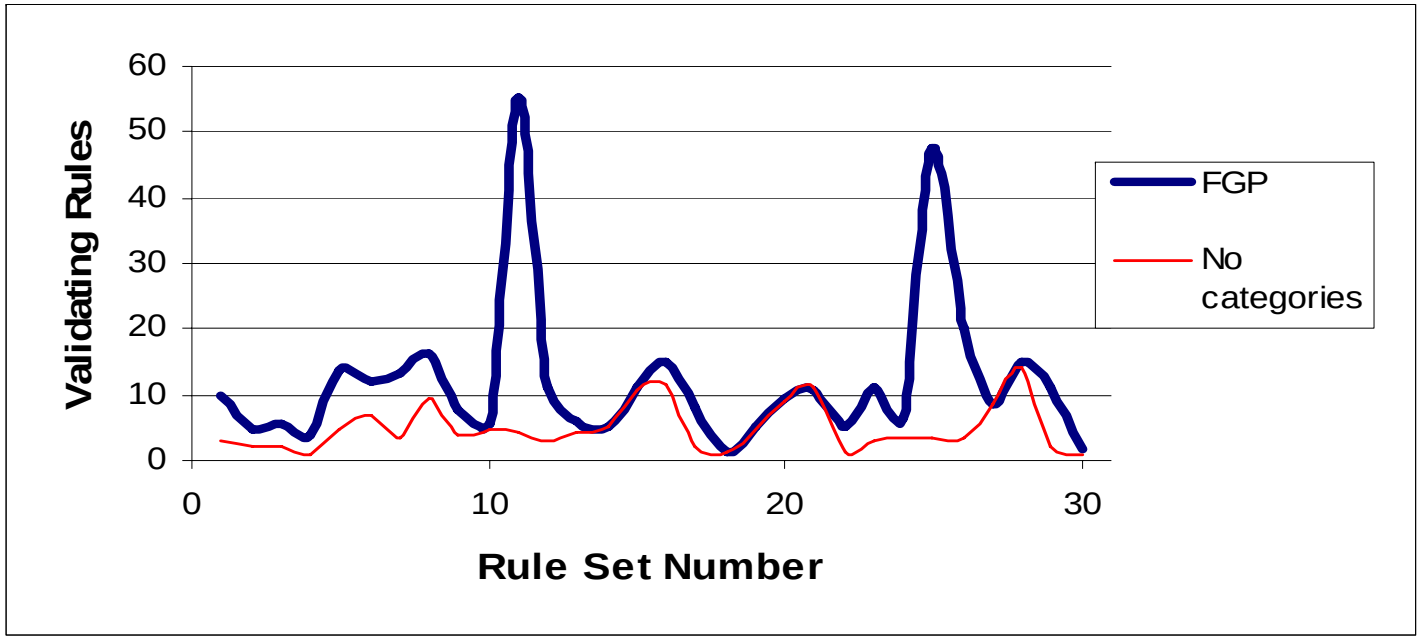
- Two metrics of validity
  - **session coverage (SC) = validSessions/allSessions**



- Valid sessions are those that match at least one rule

Evaluation of FGP (5/5)

– Count the number of rules that a session validates



– In both metrics FGP is better than FP-Growth

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Future Work

- We focused on combining an ARM and a generalized pattern mining algorithm
- The order, in which pages are visited in a session are of no importance
  - Modify FGP to perform frequent generalized sequence mining
- Extend the algorithm to support multiple category assignments for a page (useful in blog aggregators)
  - This implies the creation of a taxonomy graph instead of a tree
- In the case of social data, user tags should be mapped to predefined taxonomies in order to apply FGP
- Implement a real-time application and apply our recommendation engine. This will allow us to perform a user-based evaluation

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References

- **FP-Growth**
  - [Han04] J. Han, J. Pei, Y. Yin, R. Mao, Mining Frequent Patterns without Candidate Generation: A Frequent-Pattern Tree Approach, Data Mining and Knowledge Discovery, 8, p. 53-87, Kluwer Academic Publishers, 2004
- **GP-Close**
  - [Jia06] T. Jiang, A. Tan, Mining RDF Metadata for Generalized Association Rules, Lecture Notes in Computer Science 4080, Database and Expert Systems Applications, Springer-Verlag, 2006
  - [Jia07] T. Jiang, A. Tan, K. Wang, Mining Generalized Associations of Semantic Relations from Textual Web Content, Transactions on Knowledge and Data Engineering, Vol.19, No.2, February 2007

Any questions?

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Thank you!