

Papers on

### Association mining

#### **1. Mining association rules between sets of items in large databases - Rakesh Agarwal, Tomasz Imielinski, Arun Swami [1993]**

- Consequent (item appearing as a result of a rule), Antecedent (items contributing to the rule)
- Given a set of transactions and items, we need to find all rules that satisfy certain constraints. They can be 1. Syntactic constraints: Involves restrictions on items that appear in rule (eg. constraint on what should appear in antecedent and consequent for example) and 2. Support constraints: Restrictions on number of transactions in T that 'support' the rule (support - number of patterns that contain both rule A and B divided by the total number of patterns (percentage of patterns for which the rule is correct - measure of rule's ) and confidence - number of patterns that contain both A and B divided by the number of patterns that contain A - measure of rule's strength)
- Support is important for two reasons - 1. Statistical significance 2. We can filter by setting threshold
- Number of passes need to be carefully chosen beforehand in order to avoid measurement wastage
- Two steps : Join and Prune (<https://www.youtube.com/watch?v=ITmup2GaWdI>)
- Disadvantage - we make a lot of useless combinations (to avoid it we use FP growth algo - not required)

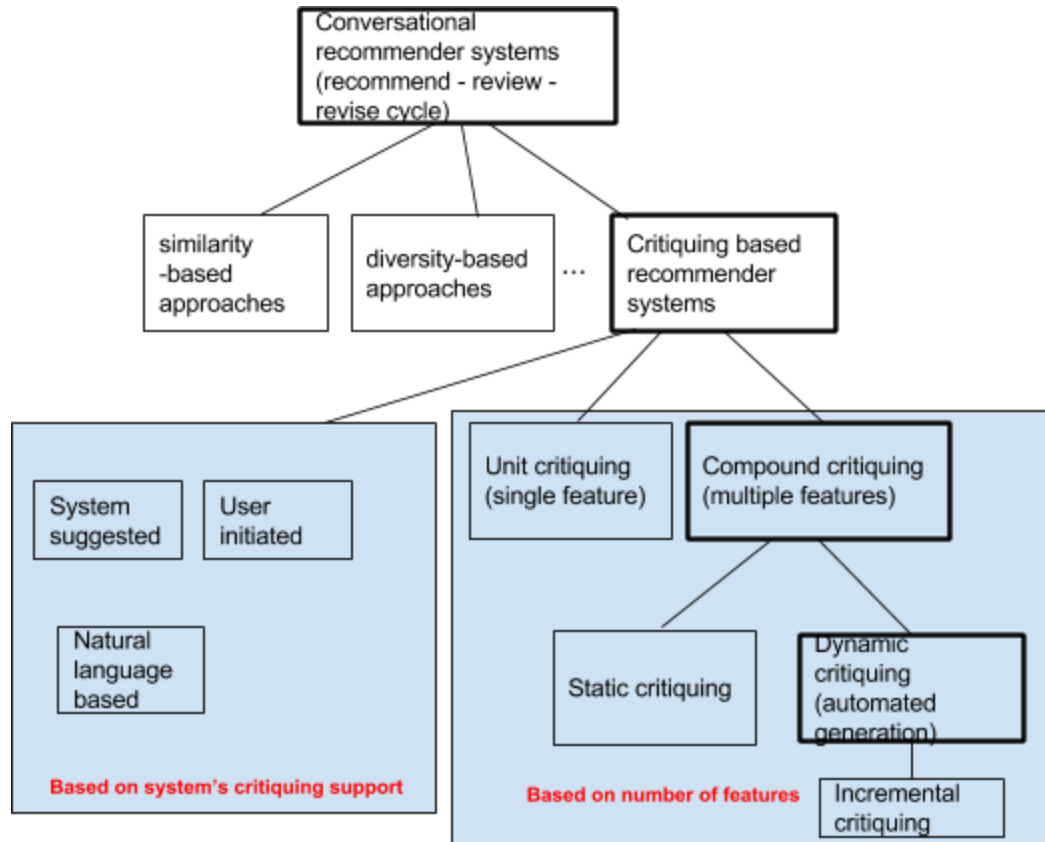
#### **2. New Algorithm for Fast Discovery of Association Rules - M.J.Zaki, S.Parthasarthy, M.Ogihara, and W. Li**

- Single pass over the dataset
- Uses clustering and lattice traversal (bottom up or hybrid)

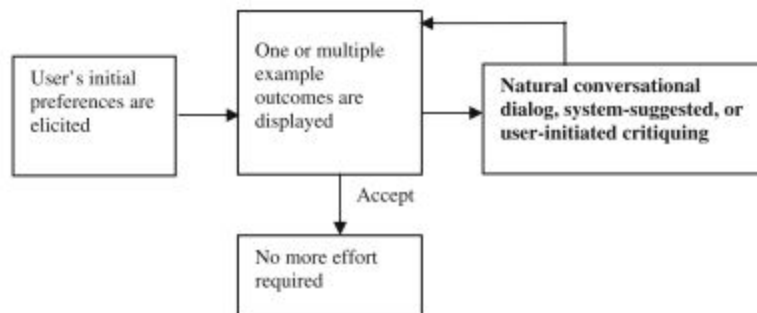
### Critiquing

#### **1. Dynamic Critiquing - James Reilly, Kevin McCarthy, Lorraine McGinty, and Barry Smyth [2004]**

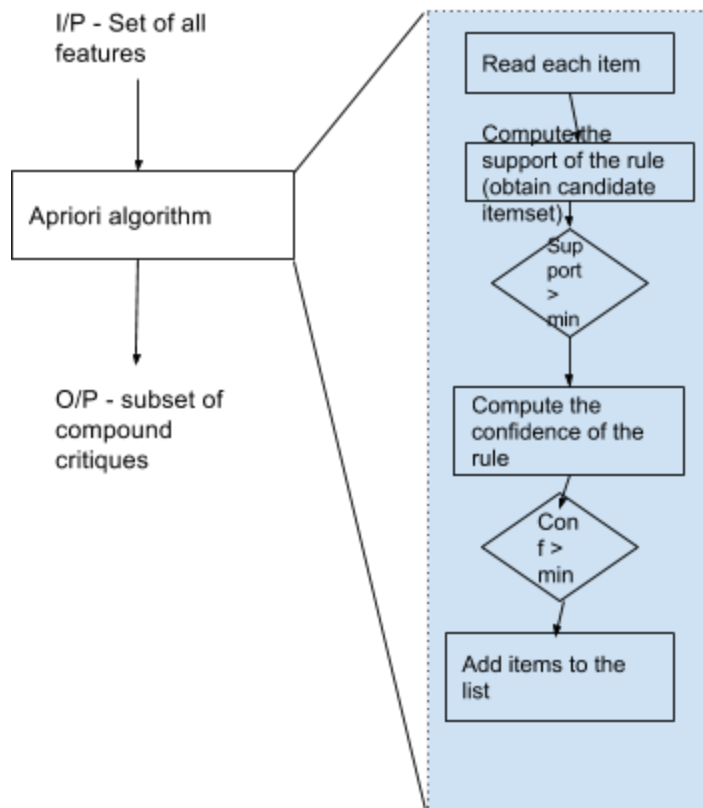
- Conversational recommender system - follows *recommend-review-revise* cycle (tweaking, critiquing).
- In case-based recommender systems (also, conversational recommender systems, knowledge based recommender systems), users provide a direct preference for a feature - eg. a camera that is "cheaper". Here "cheaper" is a critiquing over the price value. This is single-feature critique (since critiquing is done over a single feature "price"). When critiquing is done over multiple features it is called **compound critiques**.
- Aim - To provide a technique for **automatically** generating compound critiques for recommender systems (offers explanatory benefits)



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- Discovering compound critiques - choose feature pairs that are useful and recurring from all possible critiquing combinations (pattern base) . Main problem is “how to recognize these recurring patterns?” . One solution is to use **Apriori algorithm** which uses **association rules** ( $a \rightarrow b$ ) in order to restrict the search space.



(taken from 2)



- Advantages : explanatory benefits, performance advantages

## 2. Critiquing based recommenders : Survey and emerging trends

- Advantages of critiquing : cold start problem
- Three types of critiquing - Natural language dialogue based, user initiated, system initiated

	Natural language based	User-initiated critiquing	System-suggested critiquing
What is it ?	> Engages users in a conversational dialog and prompts them to provide preference feedback to the current recommendation	> simulating users to make self-motivates critiques	Pre-defined tweaking features 1. Dynamic critiquing (later incremental critiquing to include user's history) 2. Multi attribute utility theory based

			critiquing
example	Expertclerk (converts natural language to SQL queries), Adaptive place advisor	Example critiquing agent (MAUT based) , Flat finder (pareto-optimality) <b>EC performed better than dynamic critiquing (chen and Pu 2006)</b>	1.FindMe, ATA (Automated travel agent) - static critiques
pros	1. Suitable for speech interfaces (eg. while driving)	1. High level user control 2. Less perceived cognitive effort	1. Takes user's preference into consideration
cons	1. Requires precise NLP	1. Not easy to grab at first sight (a warm-up period is required)	1. Still unable to precisely match user's needs

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- MAUT - based compound critiquing (they generate compound critiques based on differences from top candidate) and visual critiquing provide better results than dynamic critiquing; **preference-based organization interface** is a combination of MAUT and dynamic critiquing and it performs better than the rest.
- 2 more factors to consider : **critiquing coverage** - the number of items returned after each critiquing, **critiquing modality** - types of critiques users can give to a product. Further classified into *similarity-based* (find a product similar to this one), *quality-based* (find similar but cheaper product) and *quantity-based* (find similar but atleast \$100 cheaper).
- **Hybrid critiquing** : version 1 combines EC and Dynamic critiquing; version 2 combines preference-based organization interface and example critiquing. (with version 2, users quickly find their preferred item)

#### Visualization techniques

1. Social network visualization: can we go beyond the graph by f.Viegas, J.Donath - <http://wiki.commres.org/pds/CommunicationTheory/SocialNetworkVisualization.pdf>
- 2.

#### Evaluation metric (for lit survey)

#### Filter bubble methods (for lit)