Using Data Mining Methods to Build Customer Profiles

G. Adomavicius & A. Tuzhilin. IEEE Computer, vol. 34 no. 2, 2001.

발표자 김형준

Personalization

Collecting Data

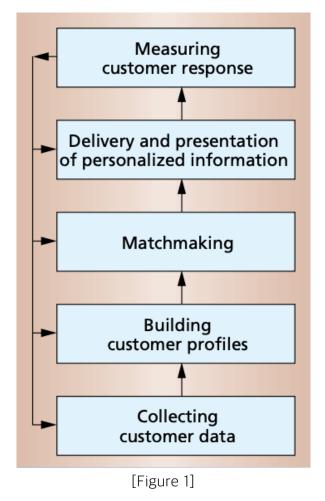
- Collecting customer data from various sources.
- Collected Data must be prepared, cleaned and stored.

Customer Profiling

- Construct accurate customer profiles based on collected data

Matchmaking

- Match appropriate content and service.
 - Content-based : recommending similar items
 - Collaborative filtering : recommend items that similar customer preferred.





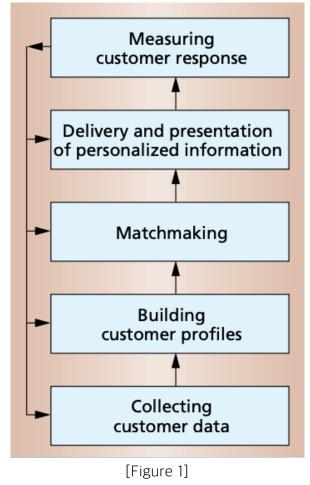
Personalization

Delivery and Presentation

- Pull, push, passive
 - Pull : display information if the customer explicitly requests
 - Push : reach to a customer who is not interacting with the system.
 - Passive : display personalized information in the context of applications.

Measuring Customer Response

- Evaluate the effectiveness of personalization.
 - Time/money spent on the website.
 - Whether the service attracts new customers.
 - Whether the customer loyalty increases.
- This process serves as feedback for possible improvements.
 - Whether to collect additional data
 - Whether to build better user profiles
 - Whether to build better matchmaking algorithms
- Result in providing better understanding of customers, better recommendations and service





Personalization

Collecting Data

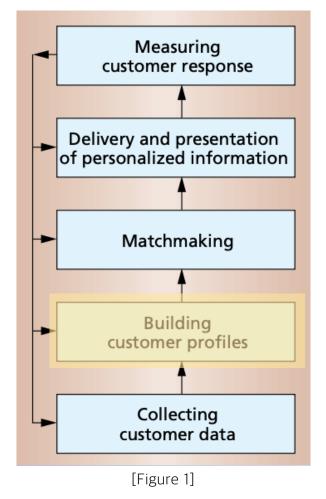
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Customer Profiling < Our topic !

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Motivation

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Personalization has become an important marketing tool.

- e.g. personalized web content presentations to book, CD, stock purchase, etc.

Some important issues of personalization :

- how to extract this knowledge from the available data and store it in customer profiles.
 - We will focus on this issue in this paper!
- how to provide personal recommendations based on a comprehensive knowledge of who customers are, how they behave, and how similar they are to other customers

• To deal with the first issue, this paper developed an approach using information learned from customers' transactional histories.

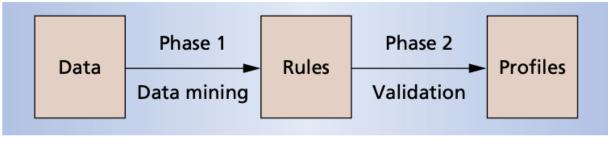
- With these information, we construct accurate, comprehensive individual profiles.
 - Facts
 - Behavioral Rules : describe customers' behaviors
 - Use data mining methods to derive behavioral rules.
 - Developed a method for **validating** customer profiles with help of human domain expert.



1:1 Pro System

• Building customer profiles

- Two main phases : rule discovery, validation

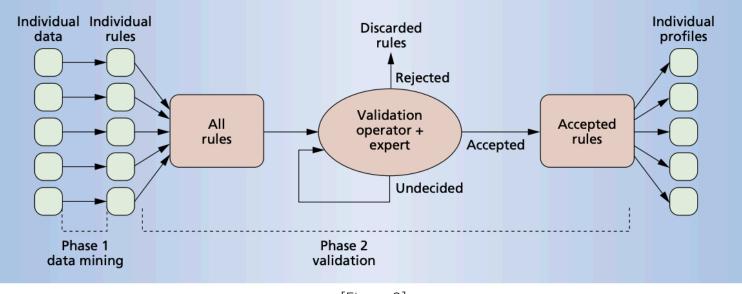


[Figure 2]



Building customer profiles

- Two main phases : rule discovery, validation

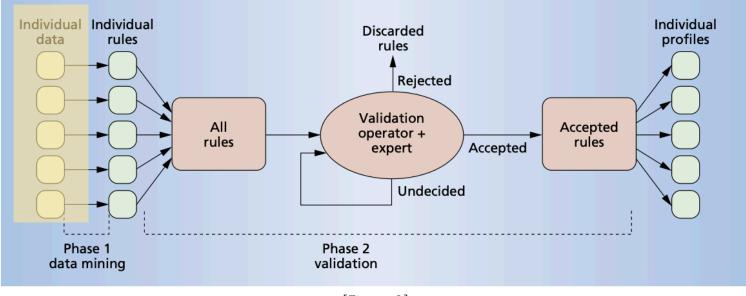






• Building customer profiles

- Two main phases : rule discovery, validation
- The whole process begins with **collecting the data.**

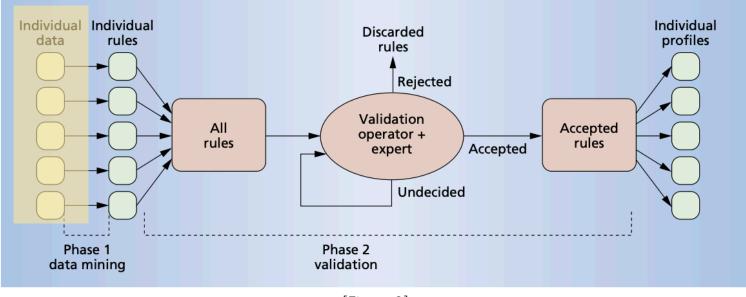






Data Model

- Factual : who the customer is.
 - e.g. name, gender, birth date, address, etc.
- Transactional : what the customer does.
 - e.g. purchase date, purchased product, paid amount, coupon use, etc.







Data Model

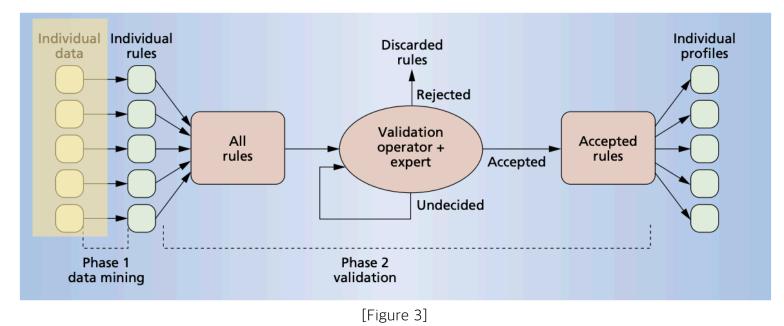
- Factual : who the customer is.
 - e.g. name, gender, birth date, address, etc.
- Transactional : what the customer does.
 - e.g. purchase date, purchased product, paid amount, coupon use, etc.

Factual	CustomerId	LastName	FirstName	BirthDate	Gender	
	0721134 0721168 0730021	Doe Brown Adams	John Jane Robert	11/17/1945 05/20/1963 06/02/1959	Male Female Male	
Transactional	CustomerId	Date	Time	Store	Product	CouponUsed
	0721134 0721134 0721168 0721134 0730021 0730021 0721168 0730021	07/09/1993 07/09/1993 07/10/1993 07/10/1993 07/10/1993 07/10/1993 07/12/1993 07/12/1993	10:18am 10:18am 10:29am 07:02pm 08:34pm 08:34pm 01:13pm 01:13pm	GrandUnion GrandUnion Edwards RiteAid Edwards Edwards GrandUnion GrandUnion	WheatBread AppleJuice SourCream LemonJuice SkimMilk AppleJuice BabyDiapers WheatBread	No Yes No No No Yes No



Customer profile : What we want to build!

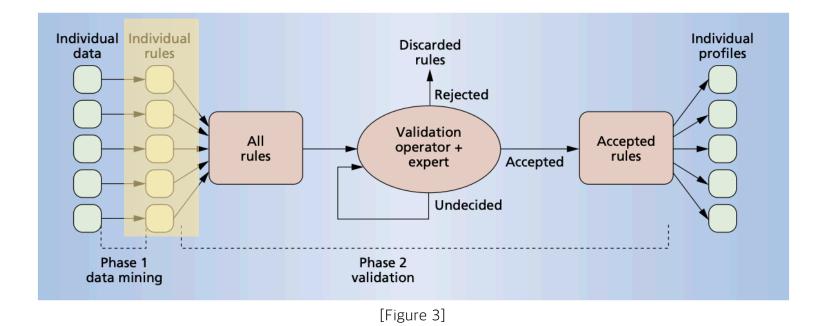
- **Factual profile** : obtained from customer's factual data + some transactional data.
 - e.g. name, gender, etc. + customer's favorite beer is Heineken, customer's biggest purchase, etc.
- **Behavioral profile(rules)** : customer's actions mostly derived from transactional data.
 - Use rules to describe customer behavior.
 - e.g. when purchasing cereal, the customer usually buys milk, etc.
- Other profiling methods does not include behavioral profiles(rules)





Rule discovery

- Apply rule discovery methods individually to every customer's data.
 - Rule discovery methods may vary
- Methods work well for applications with **many transactions.**
 - Applications with less transactions, rules tend to be less reliable.
 - e.g., car purchase, vacation planning, etc.



Rule discovery

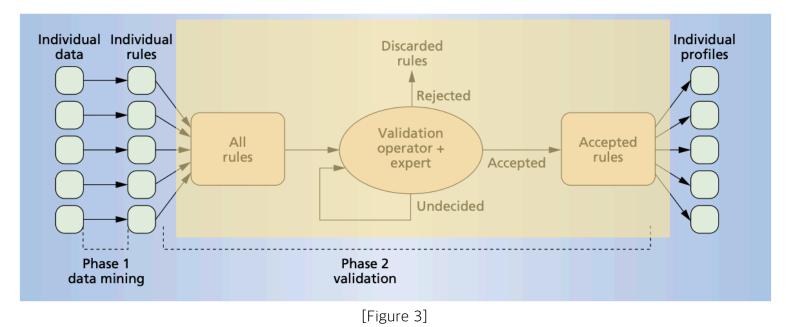
- Example (Figure 5.)
 - 95 percent of the cases when he buys lemon juice, he buys it at RiteAid.
 - 2.4 percent of all John Doe's shopping transactions include purchasing lemon juice at RiteAid.

Discovered rules (for John Doe)	 (1) Product = LemonJuice => Store = RiteAid (2.4%, 95%) (2) Product = WheatBread => Store = GrandUnion (3%, 88%) (3) Product = AppleJuice => CouponUsed = YES (2%, 60%) (4) TimeOfDay = Morning => DayOfWeek = Saturday (4%, 77%)
	 (5) TimeOfWeek = Weekend & Product = OrangeJuice => Quantity = Big (2%, 75%) (6) Product = BabyDiapers => DayOfWeek = Monday (0.8%, 61%) (7) Product = BabyDiapers & CouponUsed = YES => Quantity = Big (2.5%, 67%)



Rule validation

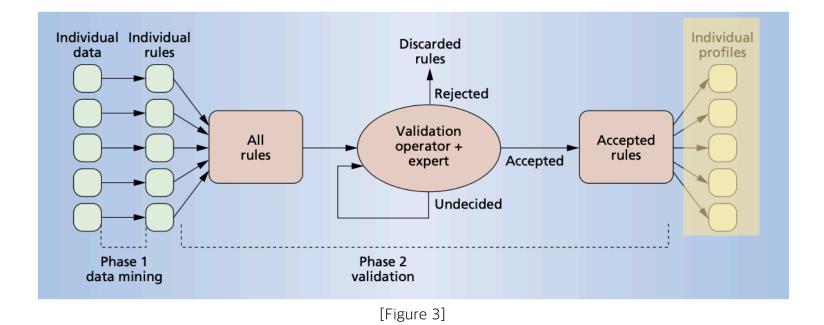
- Data mining methods generate large numbers of rules -> validation is necessary!
- Domain expert inspect the rules -> Accept or reject rules
 - Accepted rules form the behavioral profiles.
- **Scalability** is a big issue! It's impossible for the expert to validate all the rules one by one.
 - 1:1 Pro System uses **validation operators** that let a human expert validate large numbers of rules at a time with relatively **little input** from the expert.





Profile building process

- After rule validation, the system places the accepted rules in the customer's profile.





Rule validation process (Notations)

- *R*_{all} : **all rules** discovered during Phase 1.
- O_{acc} : **accepted** rules for a single validation operator.
- O_{rej} : **rejected** rules for a single validation operator.
- *R_{unv}* : remaining **unvalidated** rules.

Input: Set of all discovered rules R_{all}.

- Output: Mutually disjoint sets of rules R_{acc} , R_{rej} , R_{unv} , such that $R_{all} = R_{acc} \cup R_{rej} \cup R_{unv}$.
- (1) $R_{unv} := R_{all}, R_{acc} := \emptyset, R_{rej} := \emptyset$.
- (2) while (not TerminateValidationProcess()) begin
- (3) Expert picks a validation operator (say, O) from the set of available validation operators.
- (4) O is applied to R_{unv} . Result: disjoint sets O_{acc} and O_{rej} .

(5)
$$R_{unv} := R_{unv} - O_{acc} - O_{rej}, R_{acc} := R_{acc} \cup O_{acc}, R_{rej} := R_{rej} \cup O_{rej}.$$



Rule validation process

- All rules are considered unvalidated. ($R_{unv} = R_{all}$)
- Expert chooses various *validation operators* and applies them to the unvalidated rule set.
 - For all the validated rules, some are **accepted**(**O**_{acc}) and some are **rejected**(**O**_{rej})
- The remaining unvalidated rules (R_{unv}) go through the same process.
- The process stops then the *TerminateValidationProcess* condition is met.

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Rule validation process

- Validation operators
 - Similarity-based rule grouping
 - Put similar rules into groups.
 - Template-based rule filtering
 - Filters rules that match expert-specified rule templates (accepting templates / rejecting templates)
 - Redundant-rule elimination
 - Eliminates rules that can be derived from other facts = rules that by themselves carry no information.
- Input: Set of all discovered rules R_{all}.

Output: Mutually disjoint sets of rules R_{acc} , R_{rej} , R_{unv} , such that $R_{all} = R_{acc} \cup R_{rej} \cup R_{unv}$.

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Validation operator Examples

- Similarity-based rule grouping
 - Put similar rules into groups.
 - Put rules 1 and 2 in the same group.
 - Same structure : **Product => Store**
 - Rule 3 would not be grouped together because the structure is : **Product => CouponUsed**

Discovered rules (for John Doe)	 (1) Product = LemonJuice => Store = RiteAid (2.4%, 95%) (2) Product = WheatBread => Store = GrandUnion (3%, 88%) (3) Product = AppleJuice => CouponUsed = YES (2%, 60%) (4) TimeOfDay = Morning => DayOfWeek = Saturday (4%, 77%) (5) TimeOfWeek = Weekend & Product = OrangeJuice => Quantity = Big (2%, 75%) (6) Product = BabyDiapers => DayOfWeek = Monday (0.8%, 61%) (7) Product = BabyDiapers & CouponUsed = YES => Quantity = Big (2.5%, 67%)
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Validation operator Examples

- Template-based rule filtering
 - Filters rules that match expert-specified rule templates (accepting templates / rejecting templates)
 - For a rule template : *REJECT HEAD* **= {Store = RiteAid**}
 - Reject all rules that have **Store = RiteAid** in their heads.

Discovered rules (for John Doe)	<pre>(1) Product = LemonJuice => Store = RiteAid (2.4%, 95%) < RULE REJECTED ! (2) Product = WheatBread => Store = GrandUnion (3%, 88%)</pre>
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Validation operator Examples

- Redundant-rule elimination
 - Eliminates rules that can be derived from other facts = rules that by themselves carry no information.
 - For a rule : **Product = AppleJuice => Store = GrandUnion(2%, 100%)**
 - Buys apple juice only at Grand Union. -> is this a meaningful rule?
 - If the customer shops exclusively at Grand Union, this rule becomes meaningless.



Rule validation process

- Other validation operators
 - Visualization
 - view subsets of unvalidated rules in visual representations such as histograms and pie charts.
 - Statistical analysis
 - computes various statistical characteristics of unvalidated rules
 - Browsing
 - inspect individual rules or groups of rules directly by viewing them on the screen.

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Rule validation process

- TerminateValidationProcess()
 - Experts can specify the criterion in several ways.
 - Validation continues until some **predetermined percentage** of rules is validated.
 - e.g., 95% of the rules.
 - Validation terminates when the validation operators validate only a **few rules** at a time.

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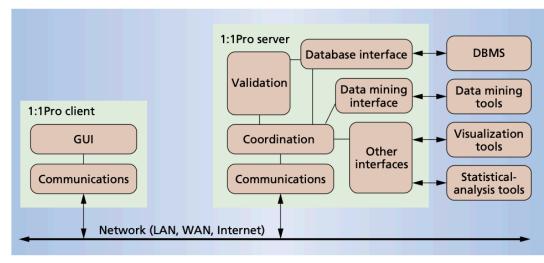
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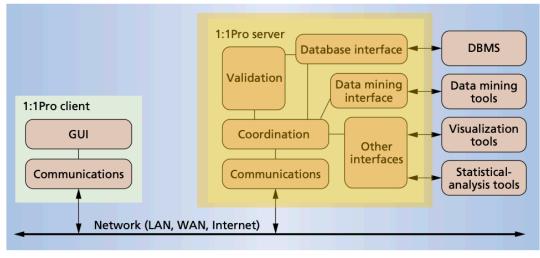
- Takes **factual** data and **transactional** data as input.
- Follows the **client-server model**.



[Figure 7]



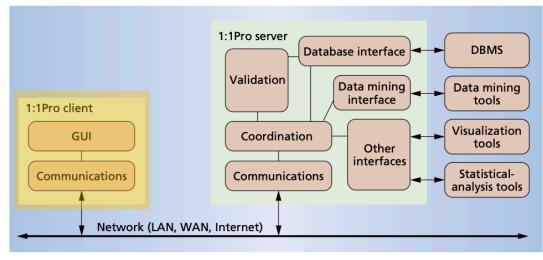
- Server component
 - Coordination module : coordinates profile construction (rule generation, validation process)
 - Validation module : validates the rules.
 - Supports similarity-based grouping, template-based filtering, redundant-rule elimination, and browsing operators.
 - Communications module : handles all communications with the client component.
 - Separate interface to external modules
 - e.g., DBMS, data mining tools, and visualization tools



[Figure 6]



- Client component
 - Graphical user interface (GUI)
 - Specify validation operations and view the results of the iterative validation process.
 - Communications modules
 - Sends the expert-specified validation request to the server.
 - Server receives validation operators and passes to the **coordination** module
 - The coordination module passes to the validation component for processing



[Figure 7]



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📕 Filter Rules				
BODY	Season DayOfWee Gender	[<=] Age Product [*] Store	Enter	Clear
ACCEPT BODY [>=] Da	vyOfWeek HEAD [<=] Pro	duct,Store,TotalPrice		
	OK	C	ANCEL	

[Figure 8]



- Log files
 - Log file records the **entire validation process**.
 - ResultId : the instance of the validation operator used.
 - Operator : operator's type (grouping, browsing, filtering)
 - SourceId : the instance of the previously applied validation operator
 - Date/Time : time stamp
 - Notes : expert's comments.

ResultId	Operator	Sourceld	Date/Time	Notes
6	Filter	5	11/23/1998 5:26pm	Rejecting: demogr. in the body
7	Group	3	11/23/1998 5:37pm	Used attribute-level setting here
8	Browse	7	11/23/1998 5:51pm	Accepted: 7 groups, rejected: 11
9	Filter	3	11/23/1998 6:28pm	Rejecting: 'age' in the head



Experiments

Experiments

• Experiment 1

- Seasonality analysis : Finding rules describing **season-related** customer behaviors.
- Settings:
 - 1,903 households purchasing various nonalcoholic **beverages** over **a one-year period**.
 - 21 fields characterizing the purchase transactions and 353,421 records
 - 186 records per household
 - Validated rules themselves.
- Results:
 - Data mining module generated 1,022,812 association rules
 - About 537 rules per household.
 - Many rules capture **specific behavior** of individual households
 - most rules represent a very small number of households.
 - 40 percent of the 407,716 discovered rules are about 5 or fewer of the 1,903 households.
 - Of that 40 percent, nearly half apply to only **1 household.**
 - One hour to perform the whole process
 - Validated 97.2 percent of the rules : 4.0 percent accepted / 93.2 percent rejected
 - reduced the average customer profile size from **537** unvalidated rules to **21 accepted rules**.



• Experiment 1

Table 1. A validation process for the seasonality analysis of market research data.					
Validation operator	Accepted rules	Rejected rules	Unvalidated rules		
Redundancy elimination	0	186,727	836,085		
Filtering	0	285,528	550,557		
Filtering	0	424,214	126,343		
Filtering	0	48,682	77,661		
Filtering	10,052	0	67,609		
Grouping (652 groups)	23,417	6,822	37,370		
Grouping (4,765 groups)	7,181	1,533	28,656		
Total	40,650	953,506	1,724,281		

[Figure 10]



Experiments

• Experiment 2

- Seasonality analysis : Finding rules describing **season-related** customer behaviors.
- Settings:
 - Help of a marketing expert
 - Apply **redundant-rule** elimination
 - Apply several template-based filtering rejection operators
 - e.g., reject all rules not referring to the Season or DayOfWeek attributes
 - grouped the remaining unvalidated rules
- Results:
 - Accepted 42,496 rules.
 - 4.2 percent of all discovered rules
 - About 40 minutes on the entire process



Problems

Problems of 1:1 Pro

- The rule evaluation process is **subjective**
 - Different experts can arrive at **different evaluation results** using the same validation process.
- Problem of generating many **irrelevant rules**.
 - Mostly are rejected during the validation process.
 - Solution : specify **constraints** on the types of rules.
- Ideal solution is to combine the **constraint specification**, **data mining**, and rule **validation** stages in one system.
 - Currently working on integrating the stages.



Thank you