A personalized and preference-based recommender system using probabilistic relational models

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Recommender systems

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Bayesian Networks

Probabilistic Relational Models

PRM-based personalized recommender system

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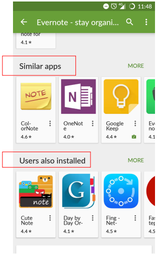

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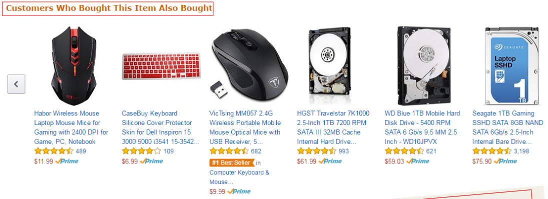

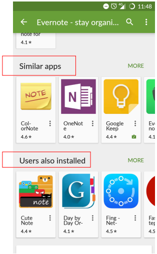

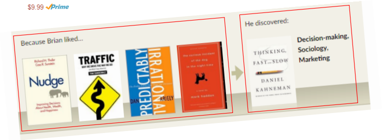

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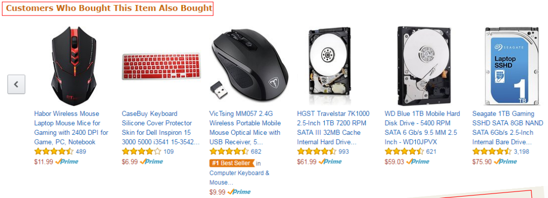

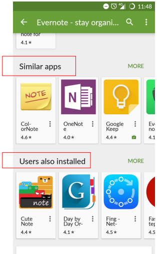

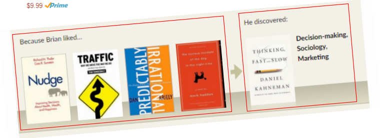

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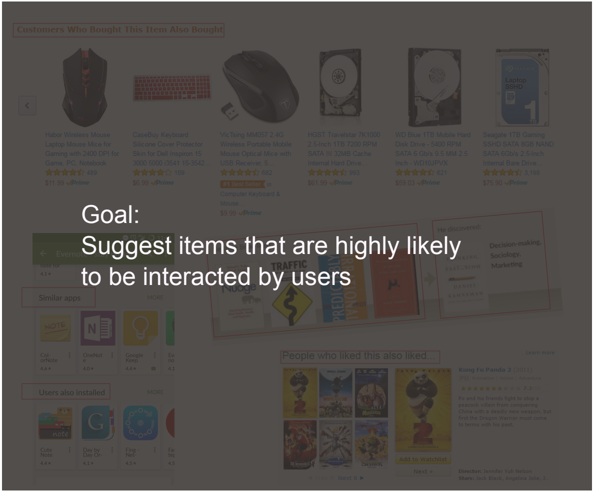

Goal:
Suggest items that are highly likely to be interacted by users

Recommender systems

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Techniques

- Collaborative filtering
  - Assumption: Similar users show similar behaviors

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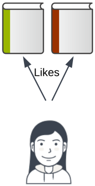

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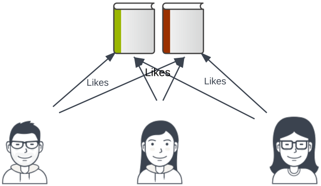

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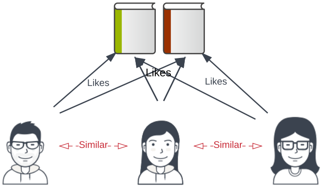

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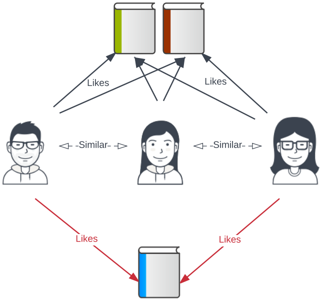

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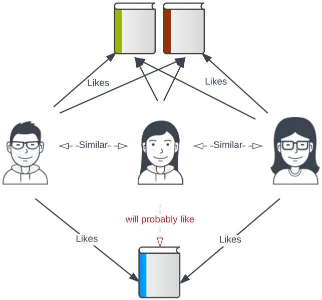

- Collaborative filtering
  - Assumption: Similar users show similar behaviors

Techniques

- Not enough user-item transactions?

- Content-based filtering
  - Assumption: Items with similar features will receive similar ratings by the same user

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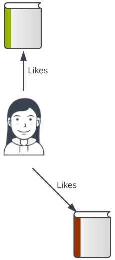
Techniques



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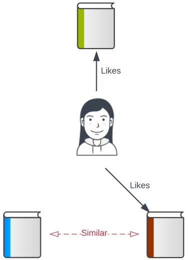

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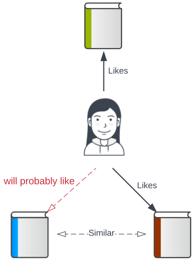

- Content-based filtering
  - Assumption: Items with similar features will receive similar ratings by the same user

Techniques

- No rating/liking history?
- Demographics-based filtering
  - Assumption: Users' interests can depend on their demographics

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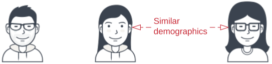
Techniques



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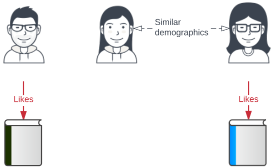

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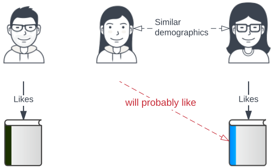

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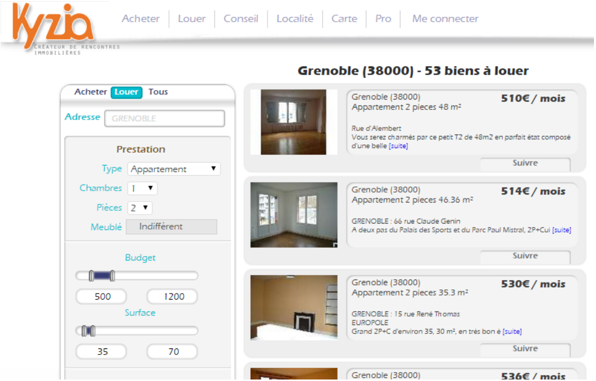
Motivation

Kyzia – A real estate search system



Motivation

	Usual Recommender Systems	Kyzia
Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive

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Motivation

	Usual Recommender Systems	Kyzia
Items	‣ Frequently purchased ‣ Not expensive	‣ Not frequently purchased ‣ Expensive
User-Item Transactions	‣ Many transactions from many users as well as from the same user	‣ Very few transactions

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Motivation

	Usual Recommender Systems	Kyzia
Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive
User-Item Transactions	▸ Many transactions from many users as well as from the same user	▸ Very few transactions
Users	▸ Demographics information	▸ No user profile

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Motivation

	Usual Recommender Systems	Kyzia
Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive
User-Item Transactions	▸ Many transactions from many users as well as from the same user	▸ Very few transactions
Users	▸ Demographics information	▸ No user profile
User preferences	▸ Rating ▸ Likes ▸ Preferred values of items' features	▸ Preferred values of items' features ▸ Preferences for features

Motivation

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	Usual Recommender Systems	Kyzia
Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive
User-Item Transactions	▸ Many transactions from many users as well as from the same user	▸ Very few transactions
Users	▸ Demographics information	▸ No user profile
User preferences	▸ Rating ▸ Likes ▸ Preferred values of items' features	▸ Preferred values of items' features ▸ Preferences for features

PRM-based Personalized Recommender System

Motivation

	Usual Recommender Systems	Kyzia
Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive
User-Item Transactions	▸ Many transactions from many users as well as from the same user	▸ Very few transactions
Users	▸ Demographics information	▸ No user profile
User preferences	▸ Rating ▸ Likes ▸ Preferred values of items' features	▸ Preferred values of items' features ▸ Preferences for features
Contextual Information		▸ Spatial information

PRM-based Personalized Recommender System

Motivation

	Usual Recommender Systems	Kyzia
Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive
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Contextual Information		▸ Spatial

PRM-based Personalized Recommender System

PRM-SA

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Items	▸ Frequently purchased ▸ Not expensive	▸ Not frequently purchased ▸ Expensive
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User preferences	▸ Rating ▸ Likes ▸ Preferred values of items' features	▸ Preferred values of items' features ▸ Preferences for features
Contextual Information		▸ Spatial

PRM-based Personalized Recommender System

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Items	Frequently purchased Not expensive	
User-Item Transactions	Many transactions from many users as well as from the same user	
Users	Demographics information	
User preferences	Rating Likes Preferred values of items' features	
Contextual Information		Spatial

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PRM

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Contextual Information		Spatial

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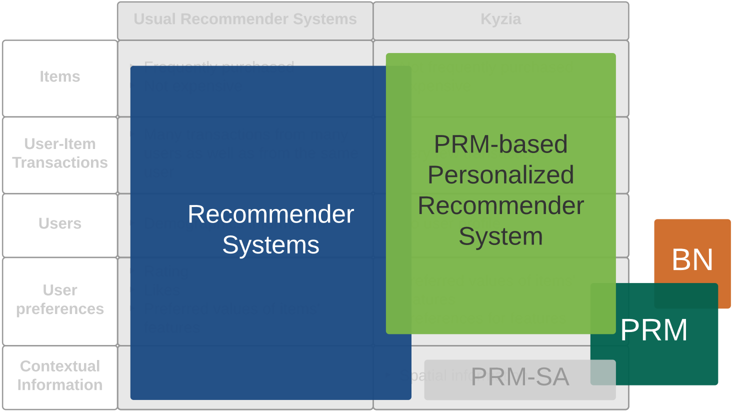

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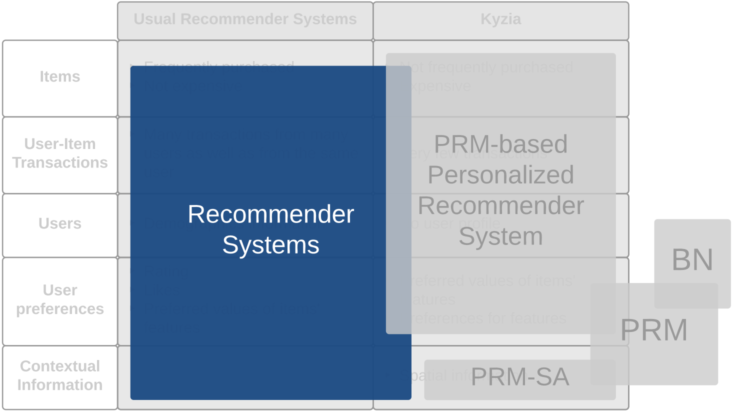

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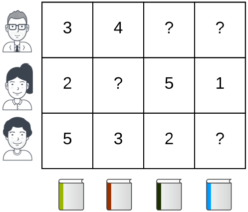
Data

- Multidimensional array
  - User-item matrix
- Relational data



3	4	?	?
2	?	5	1
5	3	2	?

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- Multidimensional array
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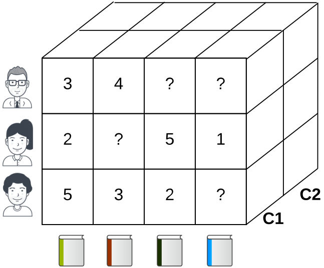


Data

- Multidimensional array
  - User-item matrix
- Relational data
  - Database

User

user_id	gender	age_group
user_1	Male	20-30
user_2	Female	15-20
user_3	Female	30-45

Book

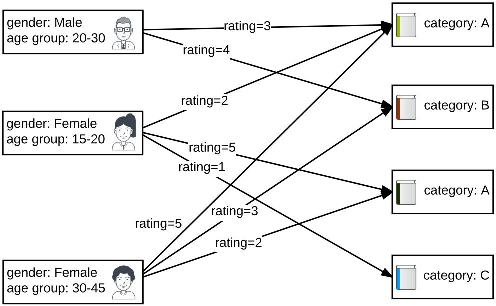
book_id	category
book_1	A
book_2	B
book_3	A
book_4	C

Rating

book_id	user_id	rating
book_1	user_1	3
book_1	user_2	2
book_1	user_3	4
...	...	...
book_4	user_2	1

Data

- Multidimensional array
  - User-item matrix
- Relational data
  - Graph



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Bayesian Networks

- Directed acyclic graph
  - Nodes = random variables
  - Edges = direct probabilistic dependencies
  - No edge = conditional independency
- Full joint distribution

$$\prod_i P(X_i \mid Pa(X_i)) \quad (1)$$

(2)

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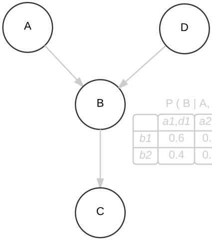
P(A)

a1	0.35
a2	0.65

P(D)

d1	0.2
d2	0.8



P (B | A, D)

	a1,d1	*a2,d1*	*a1,d2*	*a2,d2*
b1	0.6	0.25	0.7	0.15
b2	0.4	0.75	0.3	0.85

P (C | B)

	b1	*b2*
c1	0.2	0.15
c2	0.4	0.45
c3	0.4	0.4

(2)

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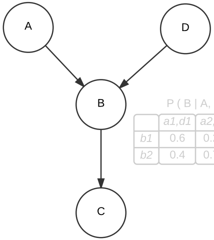

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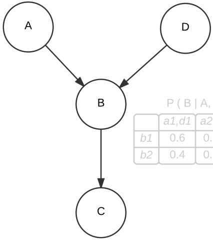

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P (B | A, D)

	a1,d1	a2,d1	a1,d2	a2,d2
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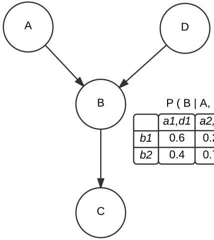

P(A)

a1	0.35
a2	0.65

P(D)

d1	0.2
d2	0.8

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	a1,d1	*a2,d1*	*a1,d2*	*a2,d2*
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P (C | B)

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c2	0.4	0.45
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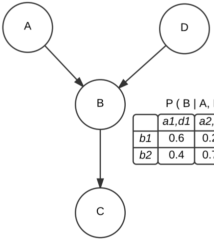
d1	0.2
d2	0.8



P (B | A, D)

	a1,d1	*a2,d1*	*a1,d2*	*a2,d2*
b1	0.6	0.25	0.7	0.15
b2	0.4	0.75	0.3	0.85

P (C | B)

	b1	*b2*
c1	0.2	0.15
c2	0.4	0.45
c3	0.4	0.4

(2)

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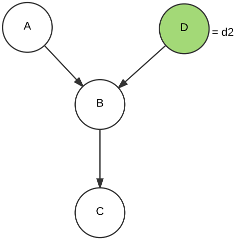
Querying

$P(\text{variable} \mid \text{evidence about others})$



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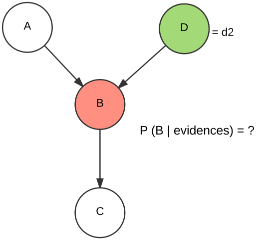
Querying

P(variable | evidence about others)



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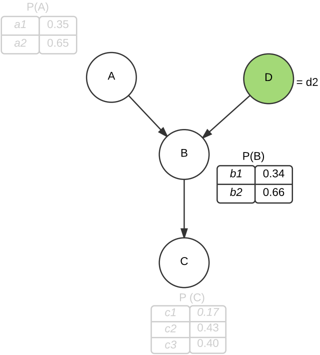

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Querying

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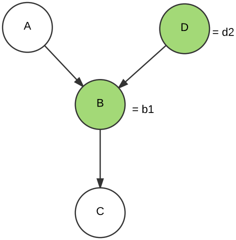

A personalized and preference-based recommender system using probabilistic relational models

Rajani Chulyadyo

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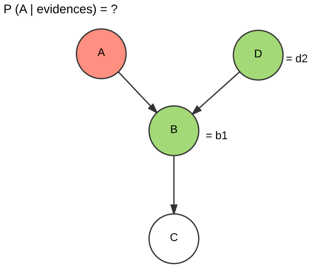
Querying

P(variable | evidence about others)



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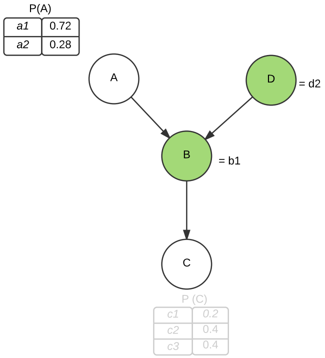

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Bayesian Networks

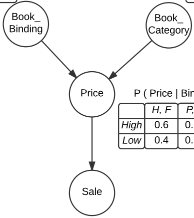
Example

P(Book_Binding)

Hard	0.35
Paperback	0.65

P(Book_Category)

Fiction	0.2
Non-Fiction	0.8



P (Price | Binding, Category)

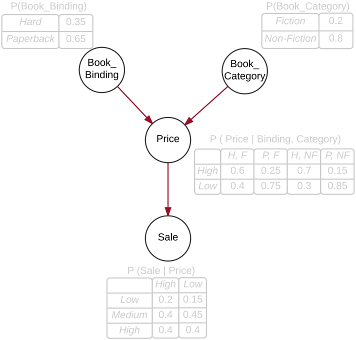
	H, F	*P, F*	*H, NF*	*P, NF*
High	0.6	0.25	0.7	0.15
Low	0.4	0.75	0.3	0.85

P (Sale | Price)

	High	*Low*
Low	0.2	0.15
Medium	0.4	0.45
High	0.4	0.4

Learning from Data

Book_Binding	Book_Category	Price	Sale
Hard	Non_Fiction	Low	Medium
Hard	Non_Fiction	High	Low
Paperback	Non_Fiction	High	Medium
Paperback	Non_Fiction	Low	High
Paperback	Non_Fiction	Low	Medium
Hard	Non_Fiction	High	Low
Paperback	Fiction	Low	High
Paperback	Non_Fiction	High	High
Paperback	Non_Fiction	Low	Medium



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Learning from Data

Book_Binding	Book_Category	Price	Sale
Hard	Non_Fiction	Low	Medium
Hard	Non_Fiction	High	Low
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Paperback	Non_Fiction	Low	High
Paperback	Non_Fiction	Low	Medium
Hard	Non_Fiction	High	Low
Paperback	Fiction	Low	High
Paperback	Non_Fiction	High	High
Paperback	Non_Fiction	Low	Medium

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Fiction	0.2
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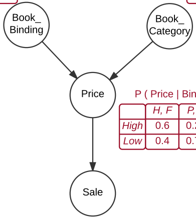

P (Price | Binding, Category)

	H, F	*P, F*	*H, NF*	*P, NF*
High	0.6	0.25	0.7	0.15
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Bayesian Networks

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- Designed for modeling attribute-based domains (a single table of IID instances)
- The IID assumption is often violated in relational data

Agenda

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	Usual Recommender Systems	Kyzia
Items	Frequently purchased Not expensive	Not frequently purchased Expensive
User-Item Transactions	Many transactions from many users as well as from the same user	Very few transactions
Users	Demographics information	No user profile
User preferences	Rating Likes Preferred values of items' features	Preferred values of items' features Preferences for features
Contextual Information		Spatial information

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PRM-based Personalized Recommender System

PRM-SA

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PRM

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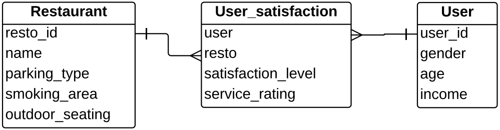
Basic terminologies [Getoor, 2001]



Relational schema = Database schema

Class = Database table

Restaurant, User, User_satisfaction

Attribute = Column

e.g., Restaurant.smoking_area, User.income

Object = Row in a table

$\langle 1, F, 21, Low \rangle$ in User table

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Probabilistic Relational Models (PRM)

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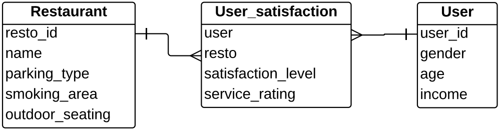
Basic terminologies [Getoor, 2001]



Relationship between objects ≈ Foreign key constraint between tables

Reference slot = Foreign key column

e.g., User_satisfaction.resto

Probabilistic Relational Models (PRM)

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Basic terminologies [Getoor, 2001]

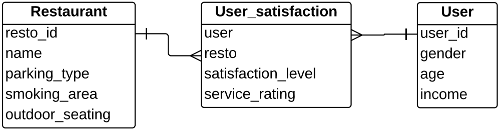
- Inverse slot: Inverse of a reference slot
  e.g., User_satisfaction.resto^{-1}

  All User_satisfaction objects for a particular Restaurant object
- Slot chain: A sequence of reference and inverse slots
  Examples:

  User_satisfaction.resto^{-1}.user

  All users who have rated (User_satisfaction object) a particular restaurant

  User_satisfaction.resto^{-1}.user.user^{-1}.resto
  All restaurants that have been rated by the users who have rated a particular restaurant



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Probabilistic Relational Models (PRM)

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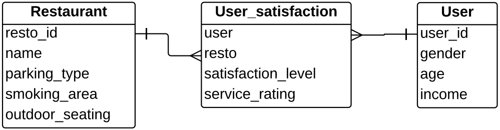

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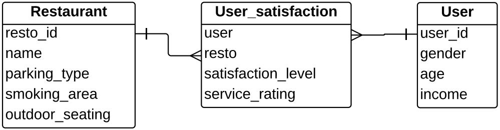

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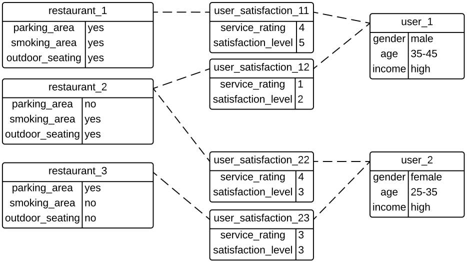
Instantiation of a relational schema

- Complete instantiation
- Relational skeleton
- Uncertain attributes
- Uncertain references
- Uncertain existence of relationships



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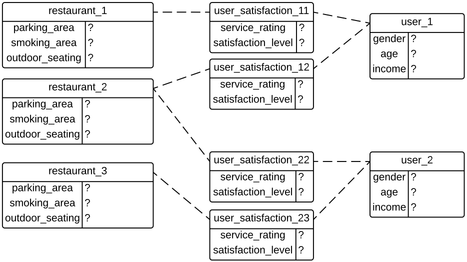

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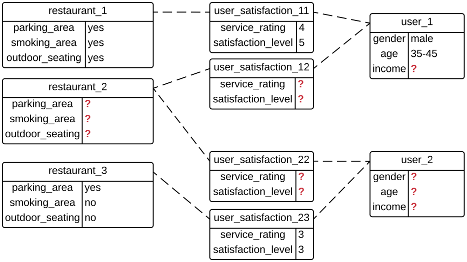

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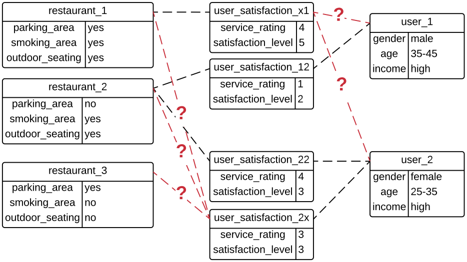

A personalized and preference-based recommender system using probabilistic relational models

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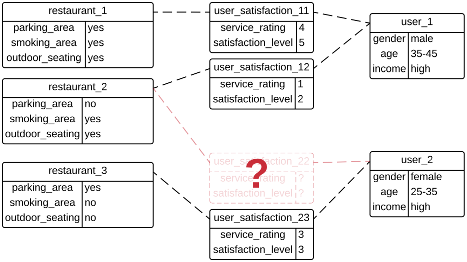
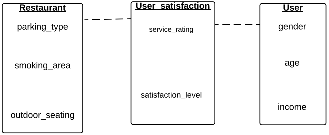


Probabilistic Relational Models

- A PRM [Getoor, 2001] of a **relational schema** consists of
  - A qualitative dependency structure
  - A set of parameters



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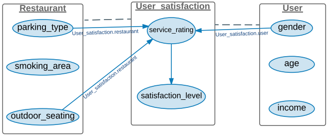

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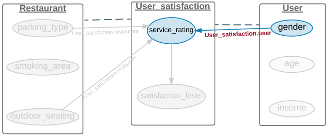

Probabilistic Relational Models

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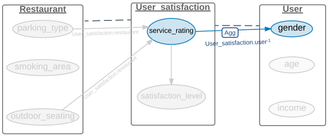

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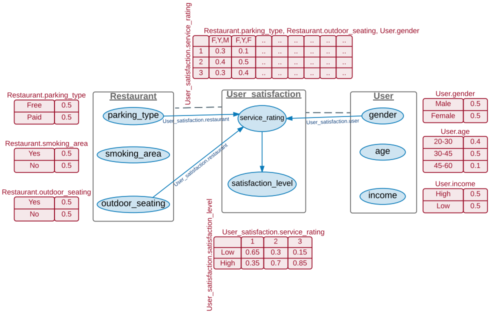

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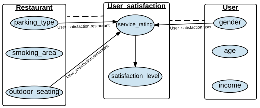
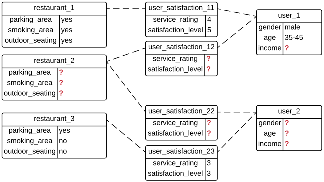
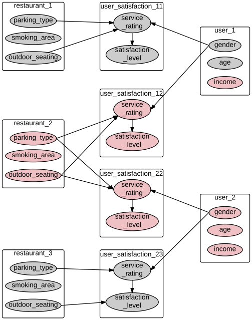
Ground Bayesian network

- Applying the probabilistic dependency template on all objects in a relational skeleton results in a Bayesian Network
- Inference is performed on this network







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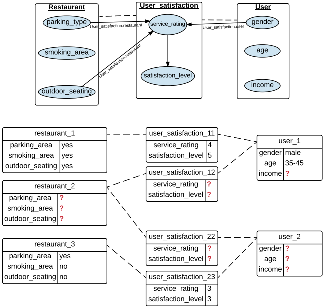

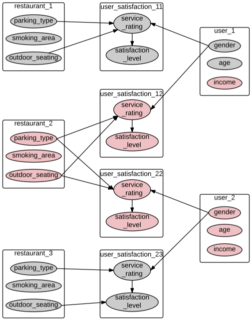

Probabilistic Relational Models

Extensions [Getoor, 2001]

- PRM with Reference Uncertainty (PRM-RU)
- PRM with Existence Uncertainty (PRM-EU)

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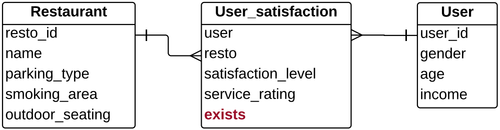
Probabilistic Relational Models

Extensions [Getoor, 2001]

- PRM with Reference Uncertainty (PRM-RU)
- PRM with Existence Uncertainty (PRM-EU)

PRM-EU

- Introduces a binary attribute ‘exists’ in the relationship class



- Goal: Predict ‘exists’ attribute
- Suitable for recommendation systems
  - Recommendation = Predicting whether a relationship can exist between a user and an item
  - Applied by [Huang et al., 2004] in their PRM-based unified recommendation framework

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Items	Frequently purchased Not expensive	
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PRM-based personalized RS

- Based on PRM-EU
- Personalizes recommendations from two types of preferences of users
  - Preferences for feature values
  - Preferences for features

PRM-based personalized RS

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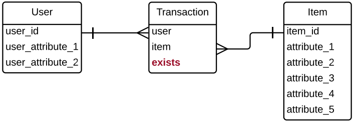
Common RS

- Predicts links between users and items



Our RS

- Assumption:
  - A user states his preferred feature values or search criteria in a search session
  - In a particular search session, a user visits the page of properties if he finds them interesting

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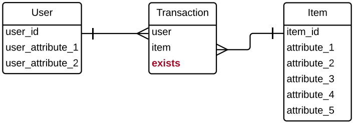
Common RS

- Predicts links between users and items



Our RS

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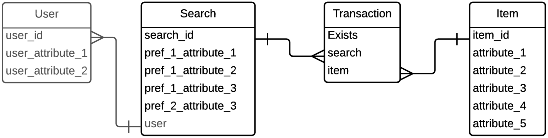
  - A user states his preferred feature values or search criteria in a search session
  - In a particular search session, a user visits the page of properties if he finds them interesting

PRM-based personalized RS

Schema

- Item is directly related to Search (instead of User)
- Transaction indicates if an item is visited in a particular search session
- The goal is to predict links between users' search criteria and items



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PRM-based personalized RS

Two components

1. PRM for Preference-based Recommenders (PRM-PrefReco)
   - Generic structure
   - Partially personalized parameters
2. Bayesian network
   - Obtained by instantiating PRM-PrefReco over database applying users' preferences for items' characteristics

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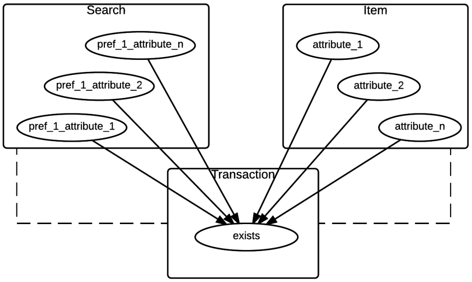
PRM-PrefReco

Structure

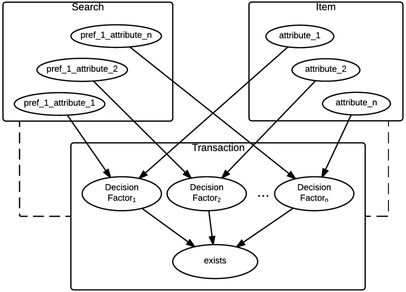
- Transaction.exists depends on user's search criteria and item's attributes



PRM-PrefReco

Structure

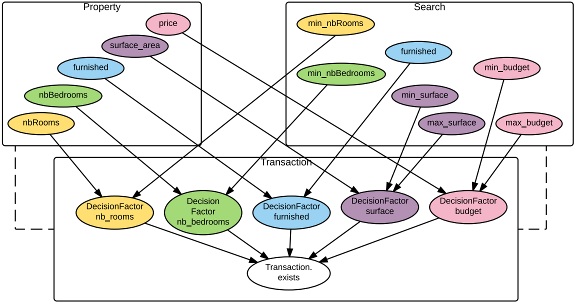
- Introduce a *Decision Factor* for each attribute of Item class and its corresponding attribute(s) from Search class.



PRM-PrefReco

Structure

- Example



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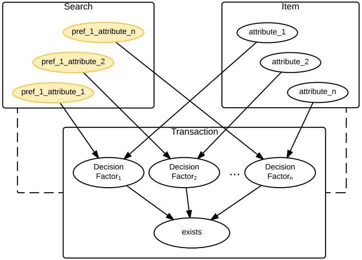
Parameters

Uniform distribution

P(Search.pref_i_attribute_1)	
$state_{11}$	$state_{12}$
..	..

.
.
.

P(Search.pref_i_attribute_n)	
$state_{n1}$	$state_{n2}$
..	..



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PRM-PrefReco

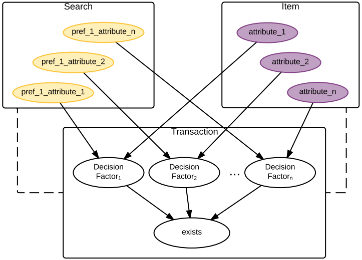
Parameters

Uniform distribution

P(Search.pref_i_attribute_1)	
$state_{11}$	$state_{12}$
..	..

.
.
.

P(Search.pref_i_attribute_n)	
$state_{n1}$	$state_{n2}$
..	..



Learn them from data

P(Item.attribute_1)	
$state_{11}$	$state_{12}$
..	..

.
.
.

P(Item.attribute_n)	
$state_{n1}$	$state_{n2}$
..	..

PRM-PrefReco

Parameters

Uniform distribution

P(Search.pref_i_attribute_1)	
$state_{11}$	$state_{12}$
..	..

.
.
.

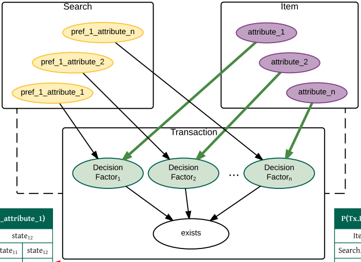
P(Search.pref_i_attribute_n)	
$state_{n1}$	$state_{n2}$
..	..

Learn them from data

P(Item.attribute_1)	
$state_{11}$	$state_{12}$
..	..

.
.
.

P(Item.attribute_n)	
$state_{n1}$	$state_{n2}$
..	..

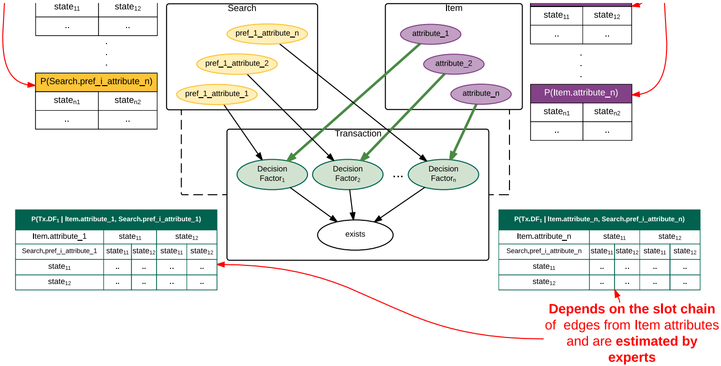


P($Tx.DF_1$ | Item.attribute_1, Search.pref_i_attribute_1)				
Item.attribute_1	$state_{11}$		$state_{12}$	
Search.pref_i_attribute_1	$state_{11}$	$state_{12}$	$state_{11}$	$state_{12}$
$state_{11}$	..	..	..	..
$state_{12}$	..	..	..	..

P($Tx.DF_1$ | Item.attribute_n, Search.pref_i_attribute_n)				
Item.attribute_n	$state_{11}$		$state_{12}$	
Search.pref_i_attribute_n	$state_{11}$	$state_{12}$	$state_{11}$	$state_{12}$
$state_{11}$	..	..	..	..
$state_{12}$	..	..	..	..

Depends on the slot chain of edges from Item attributes and are **estimated by experts**

Parameters



- Decision factor ≈ Similarity between attributes of Search and target item and/or items related to target item

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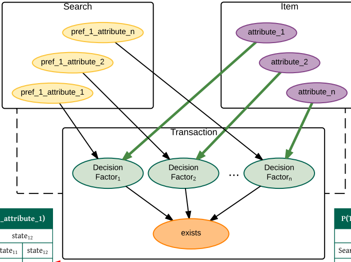
Parameters

Uniform distribution

P(Search.pref_i_attribute_1)	
state$_{11}$	state$_{12}$
..	..

.
.
.

P(Search.pref_i_attribute_n)	
state$_{n1}$	state$_{n2}$
..	..



Learn them from data

P(Item.attribute_1)	
state$_{11}$	state$_{12}$
..	..

.
.
.

P(Item.attribute_n)	
state$_{n1}$	state$_{n2}$
..	..

P(Tx.DF$_1$ | Item.attribute_1, Search.pref_i_attribute_1)				
Item.attribute_1	state$_{11}$		state$_{12}$	
Search.pref_i_attribute_1	state$_{11}$	state$_{12}$	state$_{11}$	state$_{12}$
state$_{11}$	..	..	..	..
state$_{12}$	..	..	..	..

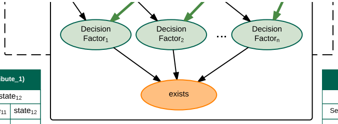
P(Tx.DF$_1$ | Item.attribute_n, Search.pref_i_attribute_n)				
Item.attribute_n	state$_{11}$		state$_{12}$	
Search.pref_i_attribute_n	state$_{11}$	state$_{12}$	state$_{11}$	state$_{12}$
state$_{11}$	..	..	..	..
state$_{12}$	..	..	..	..

Depends on the slot chain of edges from Item attributes and are **estimated by experts**

P(Tx.exists | Tx.DF$_1$, ..., Tx.DF$_n$)				
Tx.DF$_1$	state$_{11}$		state$_{12}$	
..	..	..	..	..
Tx.DF$_n$	state$_{n1}$	state$_{n2}$	state$_{n1}$	state$_{n2}$
state$_{11}$	..	..	..	..
state$_{12}$	..	..	..	..

User-specific

Parameters



P(Tx.DF$_1$ | Item.attribute_1, Search.pref_i_attribute_1)				
Item.attribute_1	state$_{11}$		state$_{12}$	
Search.pref_i_attribute_1	state$_{11}$	state$_{12}$	state$_{11}$	state$_{12}$
state$_{11}$	..	..	..	..
state$_{12}$	..	..	..	..

P(Tx.exists | Tx.DF$_1$, ..., Tx.DF$_n$)				
Tx.DF$_1$	state$_{11}$		state$_{12}$	
..	..	..	..	..
Tx.DF$_n$	state$_{n1}$	state$_{n2}$	state$_{n1}$	state$_{n2}$
state$_{11}$	..	..	..	..
state$_{12}$	..	..	..	..

User-specific

P(Tx.DF$_1$ | Item.attribute_n, Search.pref_i_attribute_n)				
Item.attribute_n	state$_{11}$		state$_{12}$	
Search.pref_i_attribute_n	state$_{11}$	state$_{12}$	state$_{11}$	state$_{12}$
state$_{11}$	..	..	..	..
state$_{12}$	..	..	..	..

- Apply MCDA methods, e.g., AHP [Saaty, 2008], to rank decision factors based on users' preferences
- Assign a weight to each decision factor
- Apply approximation heuristics, e.g., Weighted Sum Method (WSM) [Fishburn, 1967], Noisy-OR [Pearl, 1988] etc., to generate the CPD of the target variable

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Types of recommendation models

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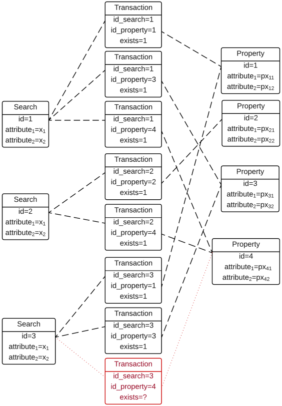
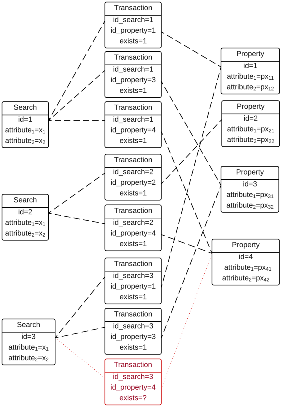
Example database

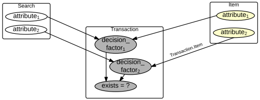


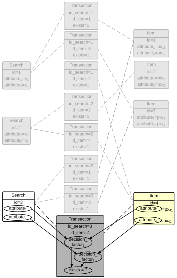
Types of recommendation models

Example database



- Type I: Feature matching





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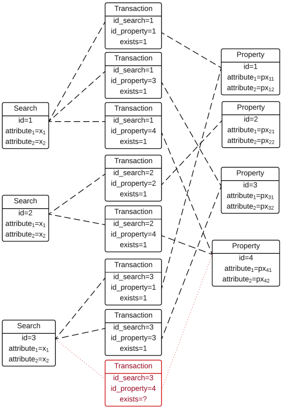
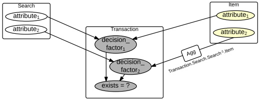
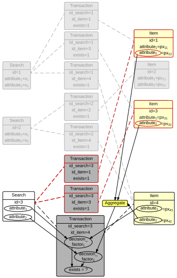
Example database



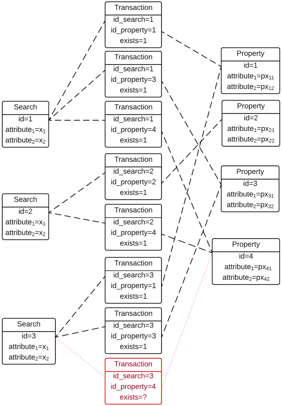
- Type II: Content-based filtering



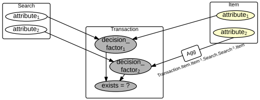


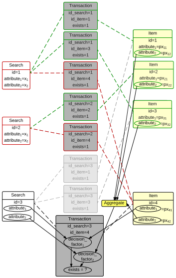
Types of recommendation models

Example database



- Type III: Collaborative filtering





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Experiments

- Dataset:
  - Kyzia dataset with very few search sessions and a small number of transactions in each session
  - Not enough data to build Type III models
- Personalization:
  - Users' preferences for feature values: collected from website
  - Users' preferences for feature: collected manually
  - Analytic Hierarchy Process (AHP) for ranking decision factors
- Objectives:
  - Comparison of two heuristics – Noisy-OR , and Weighted Sum Method (WSM)
  - Comparison of Type I and Type II models
- Evaluation method: offline

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Experiments

- Dataset:
  - Kyzia dataset with very few search sessions and a small number of transactions in each session
  - Not enough data to build Type III models
- Personalization:
  - Users' preferences for feature values: collected from website
  - Users' preferences for feature: collected manually
  - Analytic Hierarchy Process (AHP) for ranking decision factors
- Objectives:
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Experiments

- Dataset:
  - Kyzia dataset with very few search sessions and a small number of transactions in each session
  - Not enough data to build Type III models
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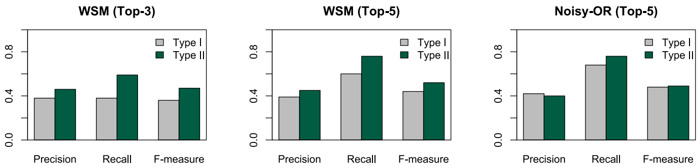
  - Users' preferences for feature values: collected from website
  - Users' preferences for feature: collected manually
  - Analytic Hierarchy Process (AHP) for ranking decision factors
- Objectives:
  - Comparison of two heuristics – Noisy-OR , and Weighted Sum Method (WSM)
  - Comparison of Type I and Type II models
- Evaluation method: offline

Results

- Choice of approximation heuristics did not seem to have big impact on the result
- Type II models performed better than Type I models did



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PRM-based personalized RS

- Capable of performing recommendations from users' preferences even in less data – suitable for systems in cold-start situation
- Applicable in domains where items are expensive and less frequently purchased, e.g. flights, hotels etc.

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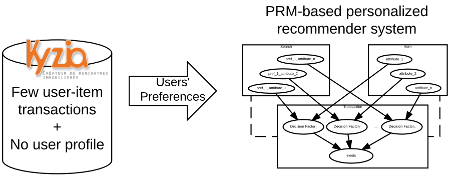

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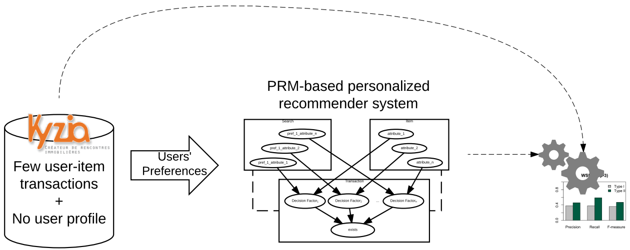

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PRM-based Recommender System

- **Short-term**
  - Offline testing with bigger datasets
  - Combining different types of recommendation models
  - Application of MCDA methods other than AHP
- **Mid-term**
  - Online testing
- **Long-term**
  - Exploring other relational learning methods, such as hinge-loss Markov random fields [Kouki et al., 2015], [Fakhraei et al., 2015]

Thank you for your attention!

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Part I

Appendix

References I

[Ben Ishak, 2015] Ben Ishak, M. (2015).
Probabilistic relational models: learning and evaluation.
PhD thesis, Université de Nantes; Université de Tunis, Institut Supérieur de Gestion de Tunis.

[Bollobás et al., 2003] Bollobás, B., Borgs, C., Chayes, J., and Riordan, O. (2003).
Directed scale-free graphs.
In *Proceedings of the fourteenth annual ACM-SIAM symposium on Discrete algorithms*, pages 132–139. Society for Industrial and Applied Mathematics.

[Cooper and Herskovits, 1992] Cooper, G. F. and Herskovits, E. (1992).
A bayesian method for the induction of probabilistic networks from data.
Machine learning, 9(4):309–347.

[Delcroix and Ben Mrad, 2016] Delcroix, V. and Ben Mrad, A. (2016).
Modéliser un critère par un réseau bayésien : V-structure et observations probabilistes fixes.
In *Proceedings of the 8th Journées Francophones sur les Réseaux Bayésiens et les Modèles Graphiques Probabilistes*, JFRB 2016, pages 1–18, Clermont-Ferrand, France.

[Fakhraei et al., 2015] Fakhraei, S., Foulds, J., Shashanka, M., and Getoor, L. (2015).
Collective spammer detection in evolving multi-relational social networks.
In *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1769–1778. ACM.

References II

[Fishburn, 1967] Fishburn, P. C. (1967).
Additive utilities with incomplete product sets: Application to priorities and assignments.
Operations Research, 15(3):537–542.

[Getoor, 2001] Getoor, L. (2001).
Learning statistical models from relational data.
PhD thesis, Stanford University.

[Huang et al., 2004] Huang, Z., Zeng, D., and Chen, H. (2004).
A unified recommendation framework based on probabilistic relational models.
In *Fourteenth Annual Workshop on Information Technologies and Systems (WITS)*, pages 8–13.

[Kouki et al., 2015] Kouki, P., Fakhraei, S., Foulds, J., Eirinaki, M., and Getoor, L. (2015).
Hyper: A flexible and extensible probabilistic framework for hybrid recommender systems.
In *Proceedings of the 9th ACM Conference on Recommender Systems*, pages 99–106. ACM.

[Lee and Honavar, 2016] Lee, S. and Honavar, V. (2016).
On learning causal models from relational data.
In Schuurmans, D. and Wellman, M. P., editors, *Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence*, pages 3263–3270, Phoenix, Arizona, USA. AAAI Press.

References III

[Maier et al., 2013] Maier, M., Marazopoulou, K., Arbour, D., and Jensen, D. (2013).
A sound and complete algorithm for learning causal models from relational data.
In *Proceedings of the Twenty-Ninth Conference on Uncertainty in Artificial Intelligence*, UAI 2013, pages 371–380, Bellevue, WA, USA.

[Pearl, 1988] Pearl, J. (1988).
Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference.
Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

[Pitman, 2002] Pitman, J. (2002).
Combinatorial stochastic processes.
Lecture Notes for St. Flour Summer School.

[Saaty, 2008] Saaty, T. L. (2008).
Decision making with the analytic hierarchy process.
International journal of services sciences, 1(1):83–98.