Probabilistic relational models for recommendation systems: review and comparative study

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Motivation

Recommender Systems

- Recommender Systems (RSs) are software tools and techniques providing suggestions for items to be of use to a particular user within a specific domain.
- *Examples :* Amazon, YouTube, etc.

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Recommendation techniques

- Collaborative filtering
- Content-based
- Demographic
- ...

Motivation

Major Challenges

- Scalability - undegraded performance with growing data
- Data sparsity - Sparse User-Item matrix
- Cold start problem - ability to perform recommendation for new user/item or in a new system

Existing techniques drawbacks

Motivation

Major Challenges

Existing techniques drawbacks

- rely on propositional data representation.
- do not exploit all the available information :
  - Collaborative-based approaches are based on the user-item matrix.
  - Content-based approaches are based on the users profiles.
  - ...

Hybrid methods

Motivation

Major Challenges

Existing techniques drawbacks

Hybrid methods

Showed better performance than standard techniques.

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- More expressive classes of directed graphical models have emerged to extract statistical patterns from relational data.

Relational datamining models

Performing recommendation using a relational model :
Probabilistic Relational Models (Koller and Pfeffer 1998)

Outline

Outline...

1. Probabilistic relational models
2. Recommendation using PRMs
3. Implementation
4. Conclusion & perspective

Bayesian networks *(Pearl 1988)*

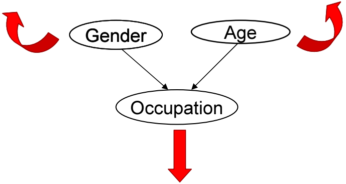
Definition

A BN is composed of 2 components :

- Qualitative : **DAG** over a set of variables.
- Quantitative : set of *CPTs* = *Conditional Probability Table* of each variable given its parents in the graph.

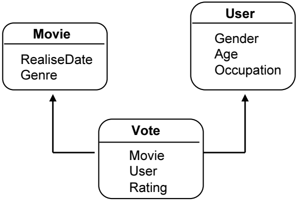
Gender	
M	F
0.4	0.6

Age		
Low	Middle	High
0.4	0.3	0.3



Age / Gender	Occupation		
	Oc1	Oc2	Oc3
Low,F	0.5	0.1	0.4
Low,M	0.3	0.5	0.2
Middle,F	0.2	0.4	0.4
Middle,M	0.9	0.1	0
High,F	0.3	0.5	0.2
High,M	0.2	0.3	0.5

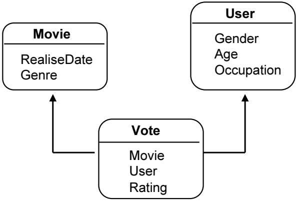
Probabilistic Relational Models *(Koller and Pfeffer 1998)*



An example of a Relational Schema

A relational schema $\mathcal{R}$

Probabilistic Relational Models *(Koller and Pfeffer 1998)*



An example of a Relational Schema

A relational schema $\mathcal{R}$

- Classes + relational variables.

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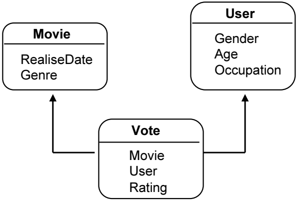

An example of a Relational Schema

A relational schema $\mathcal{R}$

- Classes + relational variables.
- Reference slots (e.g., *Vote.Movie*, *Vote.User*).

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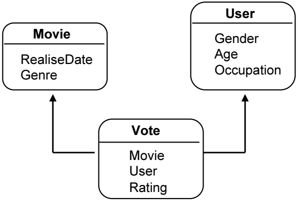


An example of a Relational Schema

A relational schema $\mathcal{R}$

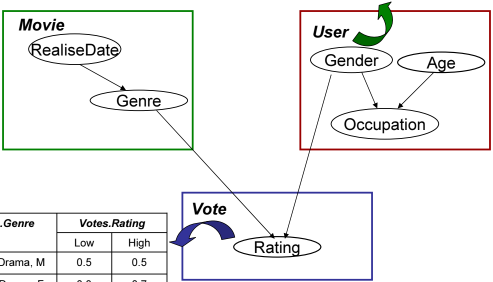
- Classes + relational variables.
- Reference slots (e.g., $Vote.Movie$, $Vote.User$).
- Slot chain = A sequence of reference slots
  - Allow to walk in the relational schema to create new variables (e.g., $Vote.User.User^{-1}.Movie$: all the movies voted by a particular user.)

Probabilistic Relational Models *(Koller and Pfeffer 1998)*

Definition

Aggregators

User.Gender	
M	F
0.4	0.6



Movie.Genre / *User.Gender*	*Votes.Rating* Low	High
Drama, M	0.5	0.5
Drama, F	0.3	0.7
Horror, M	0.2	0.8
Horror, F	0.9	0.1
Comedy, M	0.5	0.5
Comedy, F	0.6	0.4

Probabilistic Relational Models *(Koller and Pfeffer 1998)*

Definition

A PRM Π for a relational schema R :

- A qualitative dependency structure $\mathcal{S}$ (with possible long **slot chains** and **aggregation functions**).
- A set of parameters $\theta_{\mathcal{S}}$.

Aggregators

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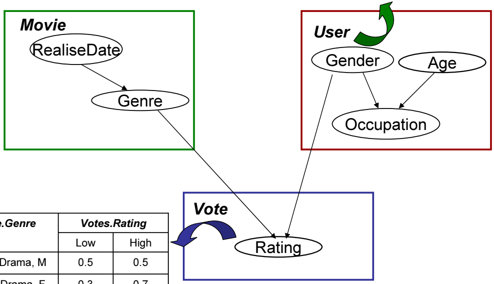

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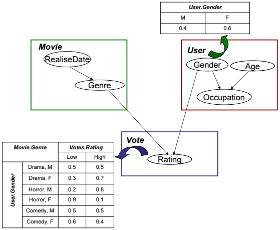

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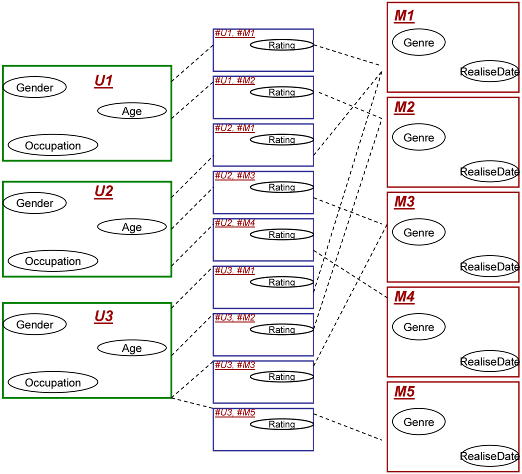
Aggregators

- $\gamma(\mathit{Vote.User.User}^{-1}.\mathit{Movie.genre}) \rightarrow \mathit{Vote.rating}$: All the gender of movies voted by a particular user
  - A finite set, not known in advance to create the conditional probability table.
  - Has to be substitute by an aggregated value (e.g. ($\gamma = \mathit{MODE}$).

Ground Bayesian Network (1/2)

GBN

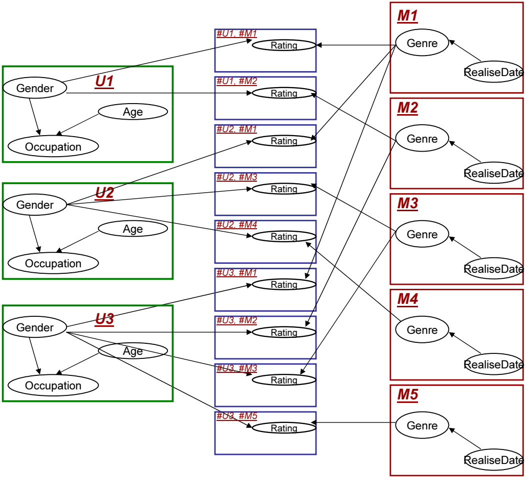
Varies with the relational skeleton that instantiates the model.



Ground Bayesian Network (2/2)

GBN

Varies with the relational skeleton that instantiates the model.



PRMs learning

Close to BN learning.

PRMs learning

Close to BN learning.

- Parameters learning

PRMs learning

Close to BN learning.

- Parameters learning
- Structure learning NP-Hard
  - Probabilistic dependencies may be between two attributes from either the same class or the classes reachable through reference slots.
  - Constraint on slot chain length for adding dependencies.

PRMs learning

Existing methods

Only few works have focused on PRMs structure learning [*RGS (Getoor et al. 2001), RPC, RCD (Maier et al. 2010, 2013)*].

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Critics

- Lack of evaluation process, in a common framework.
- Absence of relational benchmarks to evaluate the effectiveness of the proposed approaches.
- Non-existence of random generation process for generating synthetic data.

Outline...

PRM for recommendation

- Recommendation = predicting the relationships between users and items.

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- Once learnt, PRM can be used to predict new relations without going through existing relations. Makes it scalable.

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- Recommendation = predicting the relationships between users and items.
- Once learnt, PRM can be used to predict new relations without going through existing relations. Makes it scalable.
- Learns a model directly from relational data. Data sparsity is not an issue.

Related work

Existing approaches

- *Getoor et al., 1999* proposed the idea of parameter learning from incomplete data.
- *Newton et al., 2004* defined hPRMs and used it to perform recommendation.
- *Huang et al., 2005* proposed a unified recommender system based on PRM.
- *Gao et al., 2007* Combine PRMs with other machine learning method.

Critics

Related work

Existing approaches

Critics

- PRMs are either designed for a specific recommendation task or used in a highly basic form due to the intensive computation required by the model estimation process.

Our objective

Related work

Existing approaches

Critics

Our objective

Provide efficient PRMs learning techniques : illustrate our development on the recommendation task.

Steps of our recommendation Process

Adaptation to *Huang et al.'s* Unified Recommendation Framework

- Combines Collaborative, content-based and demographic filtering into a single framework.
- Our focus on rating data.

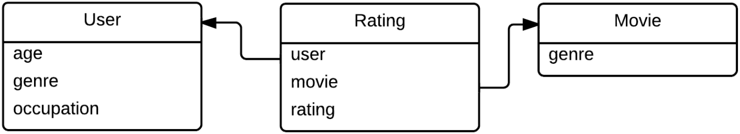

FIGURE : A relational schema for MovieLens dataset

Steps of our recommendation Process

- Relational attributes generation

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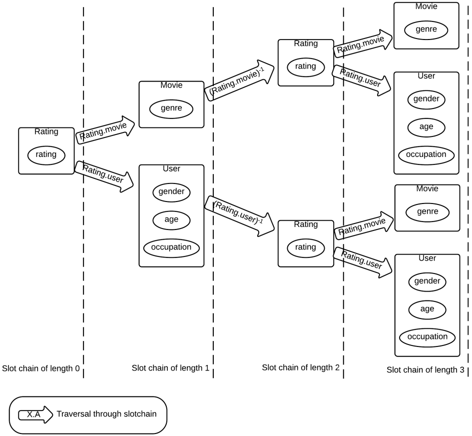

FIGURE : Slot chain traversal

Steps of our recommendation Process

- Relational attributes generation : Multiset operation

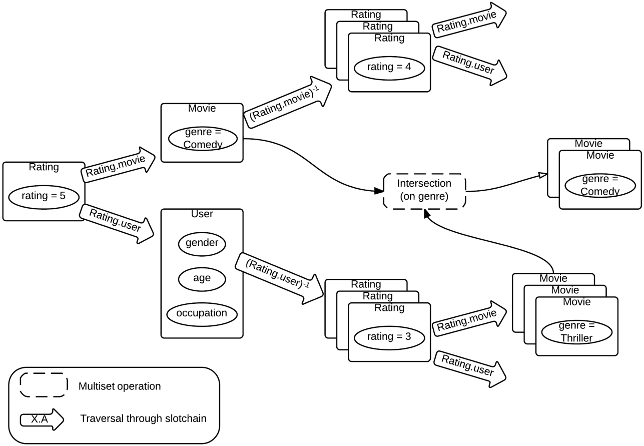

FIGURE : Illustration for multi-set operation

Steps of our recommendation Process

- Markov Blanket detection
  - Identify the attributes within *Markov Blanket* of the target attribute
  - We are using *IAMB (Incremental Association Markov Blanket, [Tsamardinos et al., 2003])* algorithm with *Mutual Information* as the association measure
- Model creation
  - Heuristic search approach can be used to find the exact structure of the attributes
  - We build a Naïve Bayesian classifier
  - Parameters learning
    - Maximum Likelihood Estimation when enough data
    - Experts' knowledge when insufficient data (new system)

Steps of our recommendation Process

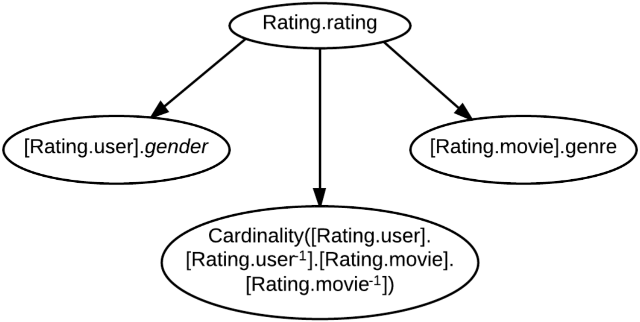

FIGURE : A simple classifier for recommendation

- Recommendation
  - Predict $Pr(V|X)$ where V is the target attribute (Rating.*rating* in our example) and X are the Markov Blanket attributes

Outline...

Incurred difficulties

Existing tools

- Almost there is no software tools for manipulating PRMs :
  - Unbbayes : limited to simple PRM models creation and transformation to GBN. No learning methods have been implemented.
  - Proximity : allow the creation and evaluation of some probabilistic models designed for relational knowledge discovery, not PRMs.
  - RCD/RPC : provide only DAPER learning.

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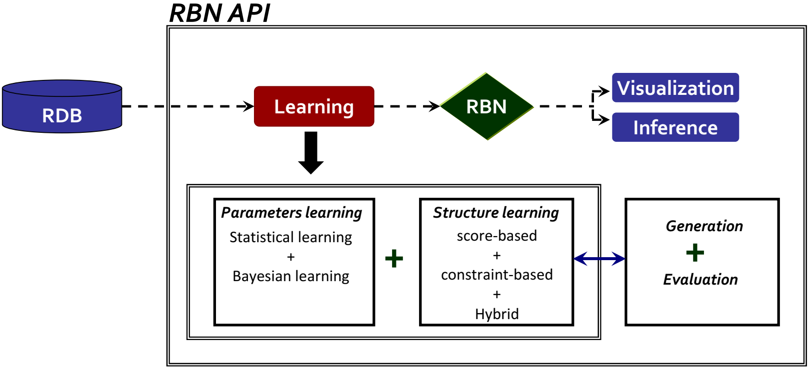
Solution

Need to develop all from scratch.

PILGRIM platform

- Implemented in C++ language
- ProBT API for BN basic creation / parameter learning / inference
- Boost graph library

PILGRIM platform



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Conclusion

- Use PRM to combine simple models – Demographics / Items' features.
- Capable of providing recommendations for new users.
- Can be made capable of providing recommendations in a new system.
- Longer slot chains for collaborative filtering.
- Multiset operations for better attributes.

Perspective

- Use of long slot chains and integration with multiset operators.
- Evaluation on multiple datasets.
- Comparison based on performance metrics.

THANK YOU !

Any question ?

Outline...

Evaluation

- Top-N recommendation method
  - Items are ranked on the basis of the probability of getting high ratings
  - Top N items are recommended and compared with the user's actual preference
  - Average metrics over all users

Evaluation

- Metrics :

$$\text{Precision}(P) = \frac{\text{Number of } \textit{hits}}{N} \tag{1a}$$

$$\text{Recall}(R) = \frac{\text{Number of } \textit{hits}}{\text{Number of high rated movies in the test set}} \tag{1b}$$

$$\text{F-measure}(F) = \frac{2 \times P \times R}{P + R} \tag{1c}$$

where *hits* is the number of actual preferences that appear in the top-N recommendations.

Evaluation

- Dataset – MovieLens dataset
    - 80% train set, 20% test set
    - 2 type of test sets – General test set and test data for coldstart situation

Result

- 2 models
  - *Rating.user.gender*, *Rating.user.age*, *Rating.movie.genre*
  - *Rating.user.gender*, *Rating.user.age*, *Rating.user.occupation*,*Rating.movie.genre*

Test set	Model	N = 10			N = 20		
		P	R	F-M	P	R	F-M
General	Model 1	0.0176	0.0203	0.0186	0.0245	0.0376	0.0279
Coldstart	Model 1	0.0200	0.0200	0.0200	0.0250	0.0268	0.0258
General	Model 2	0.0588	0.0247	0.0213	0.0735	0.0551	0.0393
Coldstart	Model 2	0.0200	0.0200	0.0200	0.0350	0.0350	0.0350