The 14^{th} European Conference on Symbolic and Quantitative Approaches to Reasoning with Uncertainty

A Clustering Approach for Collaborative Filtering under the Belief Function Framework

Raoua Abdelkhalek, Imen Boukhris and Zied Elouedi

Lugano, July 12^{th}, 2017

Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Context

- What is the suitable country to visit?
- Which book should I buy for my next vacation?
- Which movie should I watch?
- etc.

Context

How much information can we handle?

A plethora of information

- Confusion.
- Wasting time.
- Reaching unsatisfiable options.

Context

How much information can we handle?

A plethora of information

- Confusion.
- Wasting time.
- Reaching unsatisfiable options.

A plethora of information

- Confusion.
- Wasting time.
- Reaching unsatisfiable options.

Context

How much information can we handle?

A plethora of information

- Confusion.
- Wasting time.
- Reaching unsatisfiable options.

Context

⇒ Recommender systems provide recommendations based on users' preferences.

Context

⇒ Recommender systems provide recommendations based on users' preferences.

Collaborative filtering approach

- The collaborative filtering (CF) is the most widely used recommendation approach.
- The collaboration between users to filter out relevant items.

Collaborative filtering approach

- The collaborative filtering (CF) is the most widely used recommendation approach.
- The collaboration between users to filter out relevant items.

Collaborative filtering approach

- The collaborative filtering (CF) is the most widely used recommendation approach.
- The collaboration between users to filter out relevant items.

Collaborative filtering approach

User-based

- Predicts the active user's preferences based on past ratings from users similar to him.

Item-based

- Computes how similar a set of items the active user has rated, to the target item.

Collaborative filtering approach

User-based

- Predicts the active user's preferences based on past ratings from users similar to him.

Item-based

- Computes how similar a set of items the active user has rated, to the target item.

Collaborative filtering approach

User-based

- Predicts the active user's preferences based on past ratings from users similar to him.

Item-based

- Computes how similar a set of items the active user has rated, to the target item.

Collaborative filtering approach

User-based

- Predicts the active user's preferences based on past ratings from users similar to him.

Item-based

- Computes how similar a set of items the active user has rated, to the target item.

Items: The products on which the recommender system aims to predict the users' preferences.

Collaborative filtering approach

User-based

- Predicts the active user's preferences based on past ratings from users similar to him.

Item-based

- Computes how similar a set of items the active user has rated, to the target item.

Items: The products on which the recommender system aims to predict the users' preferences.

Item-based CF approach

Item-Based CF

Selecting similar items in the system to predict the user's preferences.

Item-based CF approach

Item-Based CF

Selecting similar items in the system to predict the user's preferences.

Item-based CF approach

Example

Similarity ?

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
User 1	2	4	?	3	3	5	3
User 2	5	5	2	4	2	4	?
User 3	?	?	4	2	4	1	5
User 4	3	1	5	1	?	?	2
User 5	1	5	5	3	3	1	?

Item-based CF approach

Example

Similarity ?

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
User 1	2	4	?	3	3	5	3
User 2	5	5	2	4	2	4	?
User 3	?	?	4	2	4	1	5
User 4	3	1	5	1	?	?	2
User 5	1	5	5	3	3	1	?

Similarity ? (Movie 3 — Movie 7)

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
User 1	2	4	?	3	3	5	3
User 2	5	5	2	4	2	4	?
User 3	?	?	4	2	4	1	5
User 4	3	1	5	1	?	?	2
User 5	1	5	5	3	3	1	?

Item-based CF approach

Example

Similarity ?

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
User 1	2	4	?	3	3	5	3
User 2	5	5	2	4	2	4	?
User 3	?	?	4	2	4	1	5
User 4	3	1	5	1	?	?	2
User 5	1	5	5	3	3	1	?

Item-based CF approach
Example

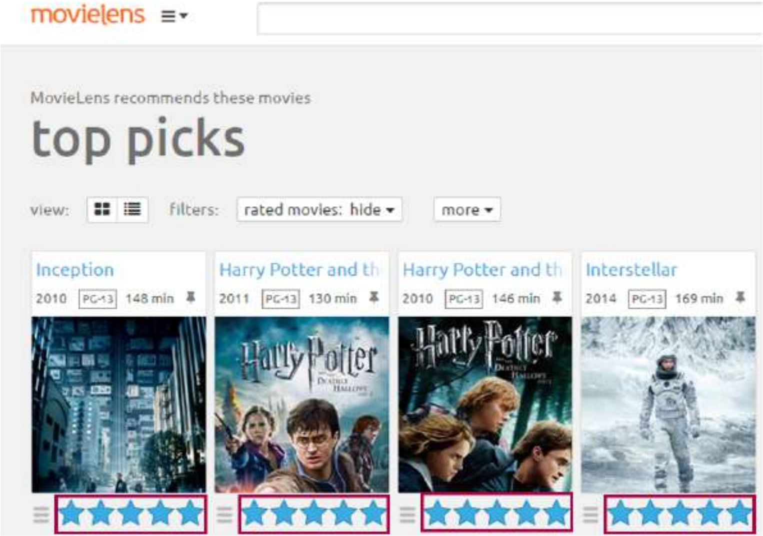
Similarity ?

	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
User 1	2	4	?	3	3	5	3
User 2	5	5	2	4	2	4	?
User 3	?	?	4	2	4	1	5
User 4	3	1	5	1	?	?	2
User 5	1	5	5	3	3	1	?

Item-based CF approach
Example

							Similarity ?
	Movie 1	Movie 2	Movie 3	Movie 4	Movie 5	Movie 6	Movie 7
User 1	2	4	?	3	3	5	3
User 2	5	5	2	4	2	4	?
User 3	?	?	4	2	4	1	5
User 4	3	1	5	1	?	?	2
User 5	1	5	5	3	3	1	?

Item-based CF approach
Example



Motivation

Limitations

- CF needs to search the whole user- item space to compute items similarities.
- This computation leads to poor scalability performance.

⇒ Clustering items to reduce the consuming time.

Motivation

Limitations

- CF needs to search the whole user- item space to compute items similarities.
- This computation leads to poor scalability performance.

$\Rightarrow$ Clustering items to reduce the consuming time.

Motivation

Limitations

- CF needs to search the whole user- item space to compute items similarities.
- This computation leads to poor scalability performance.

$\Rightarrow$ Clustering items to reduce the consuming time.

Motivation

Problem statement

- Does not take into account the uncertainty involved during the clusters assignments.
- An item may potentially belong to more than only one cluster.

⇒ Soft clustering

Motivation

Problem statement

- Does not take into account the uncertainty involved during the clusters assignments.
- An item may potentially belong to more than only one cluster.

$\Rightarrow$ Soft clustering

Motivation

Problem statement

- Does not take into account the uncertainty involved during the clusters assignments.
- An item may potentially belong to more than only one cluster.

$\Rightarrow$ Soft clustering

Objectives

1. Dealing with the **uncertain** aspect of the items' clustering.
2. Improving the **sacalability** of the CF approach under uncertainty.

⇒ Maintaining a good recommendation performance.

Goal

A Clustering Approach for Collaborative Filtering under the Belief Function Framework

Objectives

1. Dealing with the **uncertain** aspect of the items' clustering.
2. Improving the **sacalability** of the CF approach under uncertainty.

⇒ Maintaining a good recommendation performance.

Goal

A Clustering Approach for Collaborative Filtering under the Belief Function Framework

Objectives

1. Dealing with the **uncertain** aspect of the items' clustering.
2. Improving the **sacalability** of the CF approach under uncertainty.

⇒ Maintaining a good recommendation performance.

Goal

A Clustering Approach for Collaborative Filtering under the Belief Function Framework

Objectives

1. Dealing with the **uncertain** aspect of the items' clustering.
2. Improving the **sacalability** of the CF approach under uncertainty.

⇒ Maintaining a good recommendation performance.

Goal

A Clustering Approach for Collaborative Filtering under the Belief Function Framework

Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Definition

- A flexible and rich framework for dealing with imperfect information.

Frame of discernment: Θ

$$\Theta = \{\theta_1, \theta_2 \ldots .. \theta_n\}$$

$$2^\Theta = \{A : A \subseteq \Theta\}$$

Basic belief assignment: *bba*

$$m : 2^\Theta \rightarrow [0, 1]$$
$$\sum_{A \subseteq \Theta} m(A) = 1$$

Belief function theory

Basic Concepts

Definition

- A flexible and rich framework for dealing with imperfect information.

Frame of discernment: Θ

$$\Theta = \{\theta_1, \theta_2 .....\theta_n\}$$

$$2^{\Theta} = \{A : A \subseteq \Theta\}$$

Basic belief assignment: *bba*

$$m : 2^{\Theta} \rightarrow [0, 1]$$
$$\sum_{A \subseteq \Theta} m(A) = 1$$

Definition

- A flexible and rich framework for dealing with imperfect information.

Frame of discernment: Θ

$$\Theta = \{\theta_1, \theta_2 .....\theta_n\}$$

$$2^\Theta = \{A : A \subseteq \Theta\}$$

Basic belief assignment: *bba*

$$m : 2^\Theta \rightarrow [0, 1]$$
$$\sum_{A \subseteq \Theta} m(A) = 1$$

- The combination rules combine the *bba*'s induced from independent information sources into a unique one.

Dempster's rule of combination

$$(m_1 \oplus m_2)(A) = k. \sum_{B,C \subseteq \Theta : B \cap C = A} m_1(B) \cdot m_2(C)$$

$$k^{-1} = 1 - \sum_{B,C \subseteq \Theta : B \cap C = A} m_1(B) \cdot m_2(C) \text{ and } (m_1 \oplus m_2)(\varnothing) = 0$$

- The combination rules combine the *bba*'s induced from independent information sources into a unique one.

Dempster's rule of combination

$$(m_1 \oplus m_2)(A) = k. \sum_{B,C \subseteq \Theta : B \cap C = A} m_1(B) \cdot m_2(C)$$

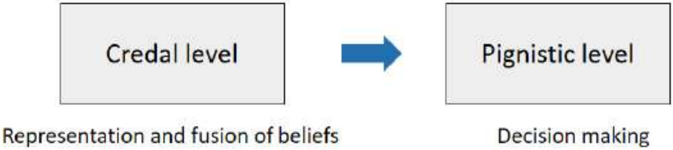
$$k^{-1} = 1 - \sum_{B,C \subseteq \Theta : B \cap C = A} m_1(B) \cdot m_2(C) \text{ and } (m_1 \oplus m_2)(\varnothing) = 0$$

Belief function theory

Decision making

Pignistic probability

$$BetP(A) = \sum_{B \subseteq \Theta} \frac{|A \cap B|}{|B|} \frac{m(B)}{(1 - m(\emptyset))} \; for \; all \; A \in \Theta$$



Examples

- Belief K-modes: Dealing with uncertainty in the attribute values.
- Evidential C-means: Handling uncertainty for objects' assignment.
- ...

Examples

- Belief K-modes: Dealing with uncertainty in the attribute values.
- Evidential C-means: Handling uncertainty for objects' assignment.
- ...

Examples

- Belief K-modes: Dealing with uncertainty in the attribute values.
- **Evidential C-means:** Handling uncertainty for objects' assignment.
- ...

Evidential C-means

- **Allows a credal partition of the objects.**

Principle

- Determining the mass m_i representing partial knowledge regarding the cluster membership to any subset of Θ.
- $\Theta = \{\omega_1, \omega_2, \ldots, \omega_n\}$.
- n is the number of clusters.

Evidential C-means

- **Allows a credal partition of the objects.**

Principle

- Determining the mass m_i representing partial knowledge regarding the cluster membership to any subset of Θ.
- $\Theta = \{\omega_1, \omega_2, \ldots, \omega_n\}$.
- n is the number of clusters.

Evidential C-means

- **Allows a credal partition of the objects.**

Principle

- Determining the mass m_i representing partial knowledge regarding the cluster membership to any subset of Θ.
- $\Theta = \{\omega_1, \omega_2, \ldots, \omega_n\}$.
- n is the number of clusters.

Evidential C-means

- **Allows a credal partition of the objects.**

Principle

- Determining the mass m_i representing partial knowledge regarding the cluster membership to any subset of Θ.
- $\Theta = \{\omega_1, \omega_2, \ldots, \omega_n\}$.
- n is the number of clusters.

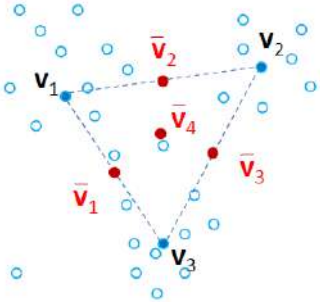
Evidential C-means

- **Allows a credal partition of the objects.**

Principle

- Determining the mass m_i representing partial knowledge regarding the cluster membership to any subset of Θ.
- $\Theta = \{\omega_1, \omega_2, \ldots, \omega_n\}$.
- n is the number of clusters.

Evidential C-means
ECM



Principle

- Every partition is represented by a prototype $v_k \in \mathbb{R}^p$.
- Each subset A_j of Θ is represented by the barycenter $\bar{v}_j$ of the centers v_k.

Objective Criterion

- The credal partition is determined by minimizing the following objective function:

$$J_{ECM} = \sum_{i=1}^{n} \sum_{\{j/A_j \neq \emptyset, A_j \subseteq \Theta\}} \mid A_j^{\alpha} \mid m_{ij}^{\beta} d_{ij}^{2} + \sum_{i=1}^{n} \delta^2 m_{i\emptyset}^{\beta}$$

- $\alpha \geq 0$ is a weighting exponent for cardinality.
- $\beta > 1$ is a weighting exponent controlling the hardness of the partition.
- δ represents the distance between all instances and the empty set.

Evidential C-means
ECM

Objective Criterion

- The credal partition is determined by minimizing the following objective function:

$$J_{ECM} = \sum_{i=1}^{n} \sum_{\{j/A_j \neq \emptyset, A_j \subseteq \Theta\}} \mid A_j^{\alpha} \mid m_{ij}^{\beta} d_{ij}^{2} + \sum_{i=1}^{n} \delta^2 m_{i\emptyset}^{\beta}$$

- $\alpha \geq 0$ is a weighting exponent for cardinality.
- $\beta > 1$ is a weighting exponent controlling the hardness of the partition.
- δ represents the distance between all instances and the empty set.

Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Collaborative Filtering

Basic concepts

- Target item: The current item for which we would like to predict users' preferences
- Active user: The user for whom the task is to find items' suggestions.
- Rating $r_{u,i}$: The preference expressed by the user u for the item i in the system.
- User-item matrix: The set of all rating triples (User, Item, Rating).

Collaborative Filtering

Basic concepts

- Target item: The current item for which we would like to predict users' preferences
- Active user: The user for whom the task is to find items' suggestions.
- Rating $r_{u,i}$: The preference expressed by the user u for the item i in the system.
- User-item matrix: The set of all rating triples (User, Item, Rating).

Collaborative Filtering

Basic concepts

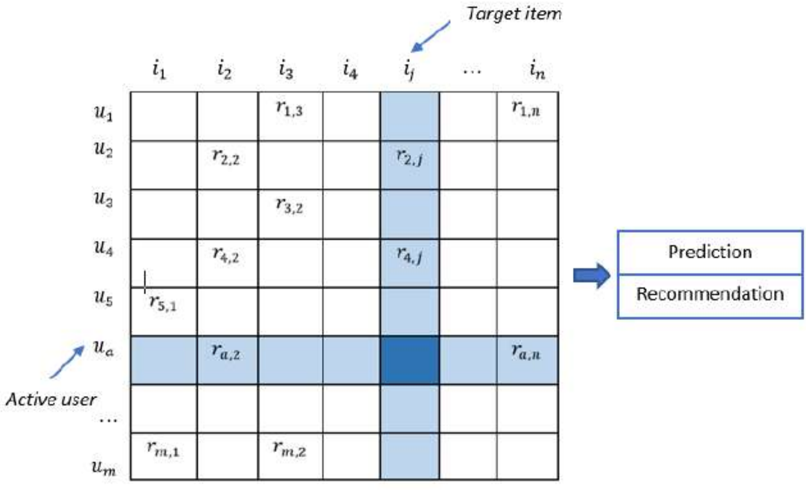
- Target item: The current item for which we would like to predict users' preferences
- Active user: The user for whom the task is to find items' suggestions.
- Rating $r_{u,i}$: The preference expressed by the user u for the item i in the system.
- User-item matrix: The set of all rating triples (User, Item, Rating).

Collaborative Filtering

Basic concepts

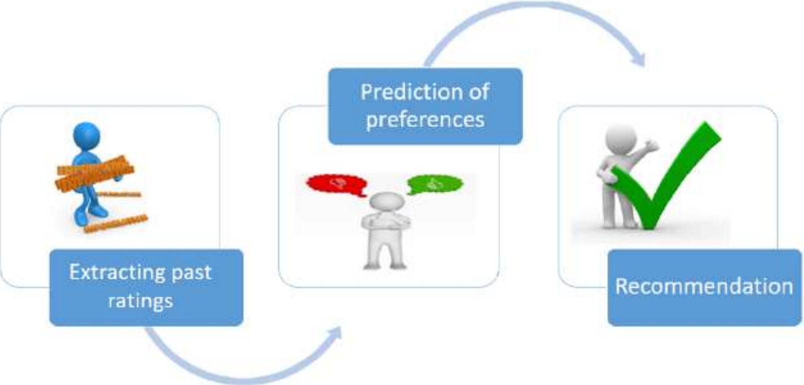
- Target item: The current item for which we would like to predict users' preferences
- Active user: The user for whom the task is to find items' suggestions.
- Rating $r_{u,i}$: The preference expressed by the user u for the item i in the system.
- User-item matrix: The set of all rating triples (User, Item, Rating).

Collaborative Filtering



User-Item matrix

Collaborative Filtering



Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Evidential Clustering CF

Step1

Items Clustering

Step2

Clusters Selection

Step3

Ratings Prediction

Evidential Clustering CF

Step1

Items Clustering

Step2

Clusters Selection

Step3

Ratings Prediction

Evidential Clustering CF

Step1

Items Clustering

Step2

Clusters Selection

Step3

Ratings Prediction

Step1: Items Clustering

Principle

1. Exploiting the user-item matrix and randomly initializing the cluster centers.
2. Computing the euclidean distance between the items and the non empty subsets of Θ.
3. Allocating for each item in the matrix a mass of belief to any subsets of the Θ.
   $\Rightarrow$ Credal partition.

Step1: Items Clustering

Principle

1. Exploiting the user-item matrix and randomly initializing the cluster centers.
2. Computing the euclidean distance between the items and the non empty subsets of Θ.
3. Allocating for each item in the matrix a mass of belief to any subsets of the Θ.
   $\Rightarrow$ Credal partition.

Step1: Items Clustering

Principle

1. Exploiting the user-item matrix and randomly initializing the cluster centers.
2. Computing the euclidean distance between the items and the non empty subsets of Θ.
3. Allocating for each item in the matrix a mass of belief to any subsets of the Θ.

   $\Rightarrow$ Credal partition.

Step1: Items Clustering

Principle

1. Exploiting the user-item matrix and randomly initializing the cluster centers.
2. Computing the euclidean distance between the items and the non empty subsets of Θ.
3. Allocating for each item in the matrix a mass of belief to any subsets of the Θ.
   $\Rightarrow$ Credal partition.

Step1: Items Clustering
Example

User-item matrix

	$Movie_1$	$Movie_2$	$Movie_3$	$Movie_4$	$Movie_5$
$User_1$	3	?	4	1	2
$User_2$	4	4	2	?	?
$User_3$	3	2	4	3	2
$User_4$	?	1	5	2	3
$User_5$	5	2	0	2	5

- The clustering process consists of providing a credal partition for the 5 movies.

Step1: Items Clustering
Example

User-item matrix

	$Movie_1$	$Movie_2$	$Movie_3$	$Movie_4$	$Movie_5$
$User_1$	3	?	4	1	2
$User_2$	4	4	2	?	?
$User_3$	3	2	4	3	2
$User_4$	?	1	5	2	3
$User_5$	5	2	0	2	5

- The clustering process consists of providing a credal partition for the 5 movies.

The credal partition corresponding to the five movies (c=3)

	$\emptyset$	$\{C_1\}$	$\{C_2\}$	$\{C_1, C_2\}$	$\{C_3\}$	$\{C_1, C_3\}$	$\{C_2, C_3\}$	Θ
M_1	0.002	0.968	0.009	0.007	0.004	0.004	0.001	0.001
M_2	0.046	0.294	0.271	0.110	0.113	0.073	0.051	0.038
M_3	0.005	0.001	0.001	0.004	0.993	0.009	0.001	0.004
M_4	0.006	0.021	0.885	0.017	0.024	0.010	0.024	0.009
M_5	0.036	0.148	0.493	0.090	0.094	0.047	0.055	0.032

Step2: Clusters Selection

Principle

- Computing the pignistic probability *BetPi* induced by each *bba*.
- Assigning each item to the cluster with the highest pignistic probability.

Step2: Clusters Selection

Principle

- Computing the pignistic probability *BetPi* induced by each *bba*.
- Assigning each item to the cluster with the highest pignistic probability.

Step2: Clusters Selection

Example

The pignistic probabilities corresponding to the five movies

Movies	C_1	C_2	C_3	Selected cluster
$Movie_1$	0.9773	0.0144	0.0083	?
$Movie_2$	0.4188	0.3833	0.1979	?
$Movie_3$	0.0017	0.0029	0.9953	?
$Movie_4$	0.0387	0.9155	0.0458	?
$Movie_5$	0.2374	0.5992	0.1633	?

- Making a final decision about the cluster of each movie.

Step2: Clusters Selection

Example

The pignistic probabilities corresponding to the five movies

Movies	C_1	C_2	C_3	Selected cluster
$Movie_1$	**0.9773**	0.0144	0.0083	C_1
$Movie_2$	**0.4188**	0.3833	0.1979	C_1
$Movie_3$	0.0017	0.0029	**0.9953**	C_3
$Movie_4$	0.0387	**0.9155**	0.0458	C_2
$Movie_5$	0.2374	**0.5992**	0.1633	C_2

- Selecting the corresponding cluster having the highest value.

Principle

- Extracting the items belonging to the same cluster as the target item.
- Computing the average of the ratings corresponding to the same clusters members.

Principle

- Extracting the items belonging to the same cluster as the target item.
- Computing the average of the ratings corresponding to the same clusters members.

Step3: Ratings Prediction

Rating Computation

- The rating prediction is performed as follows:

$$\widehat{R}_{u,i} = \frac{\sum_{j \in C_i(u)} R_{uj}}{|C_i(u)|}$$

- $C_i(u)$ is the set of items $\in$ to the cluster of the item i and rated by the user u.
- R_{uj} is the rating given by user u to item j.
- $|C_i(u)|$ is the number of items rated by user u in cluster C_i.

Step3: Ratings Prediction

Rating Computation

- The rating prediction is performed as follows:

$$\widehat{R}_{u,i} = \frac{\sum_{j \in C_i(u)} R_{uj}}{|C_i(u)|}$$

- $C_i(u)$ is the set of items $\in$ to the cluster of the item i and rated by the user u.
- R_{uj} is the rating given by user u to item j.
- $|C_i(u)|$ is the number of items rated by user u in cluster C_i.

Step1: Items Clustering

Example

User-item matrix

	$Movie_1$	$Movie_2$	$Movie_3$	$Movie_4$	$Movie_5$
$User_1$	3	?	4	1	2
$User_2$	4	4	2	?	?
$User_3$	3	2	4	3	2
$User_4$	?	1	5	2	3
$User_5$	5	2	0	2	5
Clusters	C_1	C_1	C_3	C_2	C_2

- The rating $\widehat{R}_{1,2}$ given by $User_1$ to $Movie_2$?

Step1: Items Clustering
Example

User-item matrix

	$Movie_1$	$Movie_2$	$Movie_3$	$Movie_4$	$Movie_5$
$User_1$	3	?	4	1	2
$User_2$	4	4	2	?	?
$User_3$	3	2	4	3	2
$User_4$	?	1	5	2	3
$User_5$	5	2	0	2	5
Clusters	C_1	C_1	C_3	C_2	C_2

- The rating $\widehat{R}_{1,2}$ given by $User_1$ to $Movie_2$?
- $Movie_2$ and $Movie_1 \in C_1$.
- $\widehat{R}_{1,2} = \frac{3}{1} = 3$.

Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Experimental study

MoviesLens

- 943 users
- 1682 movies
- 100 000 ratings
- Ratings scale: [1,5]

Evaluation metrics

Mean Absolute Error (MAE)

- Evaluating the prediction accuracy.

$$MAE = \frac{\sum_{u,i} |\widehat{R}_{u,i} - R_{u,i}|}{\|\widehat{R}_{u,i}\|}$$

- $R_{u,i}$: Real rating for the user u on the item i
- $\widehat{R}_{u,i}$: Predicted rating
- $\|\widehat{R}_{u,i}\|$: Total number of the predicted ratings.

$\Rightarrow$ Lower values of MAE = Better prediction accuracy

Evaluation metrics

Mean Absolute Error (MAE)

- Evaluating the prediction accuracy.

$$MAE = \frac{\sum_{u,i} |\widehat{R}_{u,i} - R_{u,i}|}{\|\widehat{R}_{u,i}\|}$$

- $R_{u,i}$: Real rating for the user u on the item i
- $\widehat{R}_{u,i}$: Predicted rating
- $\|\widehat{R}_{u,i}\|$: Total number of the predicted ratings.

$\Rightarrow$ Lower values of MAE = Better prediction accuracy

Evaluation metrics

Mean Absolute Error (MAE)

- Evaluating the prediction accuracy.

$$MAE = \frac{\sum_{u,i} |\widehat{R}_{u,i} - R_{u,i}|}{\|\widehat{R}_{u,i}\|}$$

- $R_{u,i}$: Real rating for the user u on the item i
- $\widehat{R}_{u,i}$: Predicted rating
- $\|\widehat{R}_{u,i}\|$: Total number of the predicted ratings.

$\Rightarrow$ Lower values of MAE = Better prediction accuracy

Evaluation metrics

Mean Absolute Error (MAE)

- Evaluating the prediction accuracy.

$$MAE = \frac{\sum_{u,i} |\widehat{R}_{u,i} - R_{u,i}|}{\|\widehat{R}_{u,i}\|}$$

- $R_{u,i}$: Real rating for the user u on the item i
- $\widehat{R}_{u,i}$: Predicted rating
- $\|\widehat{R}_{u,i}\|$: Total number of the predicted ratings.

$\Rightarrow$ Lower values of MAE = Better prediction accuracy

Evaluation metrics

Precision

- Evaluating the quality of recommendations.

$$Precision = \frac{IR}{IR + UR}$$

- IR: Interesting item has been correctly recommended
- UR: Uninteresting item has been incorrectly recommended

$\Rightarrow$ Higher precision values = Better performance

Evaluation metrics

Precision

- Evaluating the quality of recommendations.

$$Precision = \frac{IR}{IR + UR}$$

- *IR*: Interesting item has been correctly recommended
- *UR*: Uninteresting item has been incorrectly recommended

$\Rightarrow$ Higher precision values = Better performance

Evaluation metrics

Precision

- Evaluating the quality of recommendations.

$$Precision = \frac{IR}{IR + UR}$$

- *IR*: Interesting item has been correctly recommended
- *UR*: Uninteresting item has been incorrectly recommended

$\Rightarrow$ Higher precision values = Better performance

Evaluation metrics

Precision

- Evaluating the quality of recommendations.

$$Precision = \frac{IR}{IR + UR}$$

- *IR*: Interesting item has been correctly recommended
- *UR*: Uninteresting item has been incorrectly recommended

$\Rightarrow$ Higher precision values = Better performance

Evaluation metrics

Scalability Performance

- The ability of the recommendation approach to be run quickly.

Comparative protocol

Proposed Approach

- Evidential clustering item-based CF (EC-IBCF)

VS

Traditional Approach

- Evidential item-based CF (EV-IBCF)

Comparative protocol

Proposed Approach

- Evidential clustering item-based CF (EC-IBCF)

VS

Traditional Approach

- Evidential item-based CF (EV-IBCF)

Comparative protocol

Proposed Approach

- Evidential clustering item-based CF (EC-IBCF)

VS

Traditional Approach

- Evidential item-based CF (EV-IBCF)

Experimental results

- Performance in terms of prediction and recommendation

	Traditional approach	Proposed aproach
Metric	EV-IBCF	EC-IBCE
Mean_MAE	0.809	**0.793**
Mean_Precision	0.733	**0.75**

⇒ EC-IBCE has the lowest error values in terms of Mean_MAE.

⇒ EC-IBCE achieves better results in terms of Mean_Precision.

Experimental results

- Performance in terms of prediction and recommendation

	Traditional approach	Proposed aproach
Metric	EV-IBCF	EC-IBCE
Mean_MAE	0.809	**0.793**
Mean_Precision	0.733	**0.75**

⇒ EC-IBCE has the lowest error values in terms of Mean_MAE.

⇒ EC-IBCE achieves better results in terms of Mean_Precision.

Experimental results

- Performance in terms of prediction and recommendation

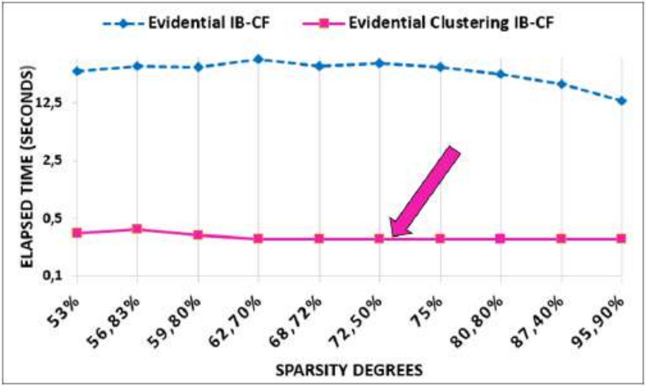
	Traditional approach	Proposed aproach
Metric	EV-IBCF	EC-IBCE
Mean_MAE	0.809	**0.793**
Mean_Precision	0.733	**0.75**

⇒ EC-IBCE has the lowest error values in terms of Mean_MAE.

⇒ EC-IBCE achieves better results in terms of Mean_Precision.

Experimental results

- Scalability Performance



$\Rightarrow$ The execution time of the clustering CF approach is substantially lower than the basic evidential CF.

Outline

1 Introduction

2 Belief Function Theory

3 Collaborative Filtering Recommender

4 Evidential Clustering Collaborative Filtering

5 Experimental Study

6 Conclusion and Future Works

Conclusion and future works

Conclusion

- A new clustering CF approach based on the Evidential C-Means method.
- Maintaining a good scalability and recommendation performance.

Future works

- Relying on the different *bba's* corresponding to the different clusters rather that the most significant one.

Conclusion and future works

Conclusion

- A new clustering CF approach based on the Evidential C-Means method.
- Maintaining a good scalability and recommendation performance.

Future works

- Relying on the different *bba's* corresponding to the different clusters rather that the most significant one.

Conclusion and future works

Conclusion

- A new clustering CF approach based on the Evidential C-Means method.
- Maintaining a good scalability and recommendation performance.

Future works

- Relying on the different $bba's$ corresponding to the different clusters rather that the most significant one.

Thank you