Recommendation System

Personalized, Multi-Stakeholder, Multi-Criteria and Multi-Objective Recommendation System

By

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Introduction

Recommender System (RS) is a Software tool and technique that maximizes the consumer satisfaction by tailoring the suggestions according to their personalized preferences.

- Recommender system (S) can be defined as a function f that maps from a user, an item, and the interaction data to a score that will be used to rank items for recommendation to the user.

$$\boxed{S: f(u, \mathrm{i}, R)}$$

Let $\boldsymbol{U}$ be a collection of users and their associated data.
$\boldsymbol{I}$ be a collection of items plus data, and
$\boldsymbol{R}$ be a collection of data about the interactions between users and items, such as ratings, denoted as $r_{u,i}$

- Majority of the e-commerce applications and commercial online applications such as NetFlix, Amazon, YouTube, TripAdvisor social networking websites are employing RS to filter personalized information from large source of data.

Introduction: Abstract view of the RS

Traditionally Recommender System (RS) Utilizes the historical user-item interaction or the content-based information (either visual or textual) to learn user preferences.

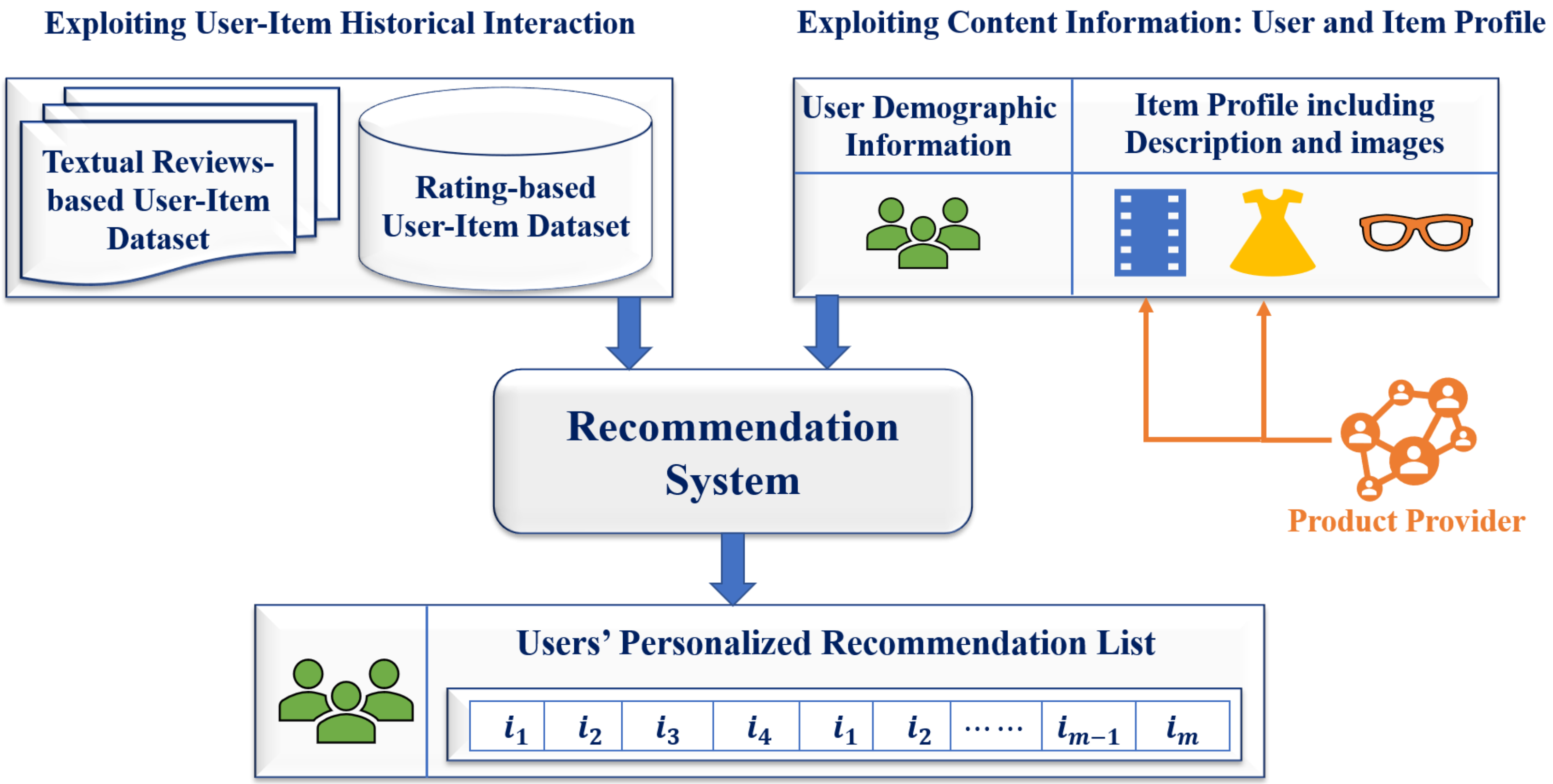

Fig. 1: Traditional RS

Introduction: Types of the RS

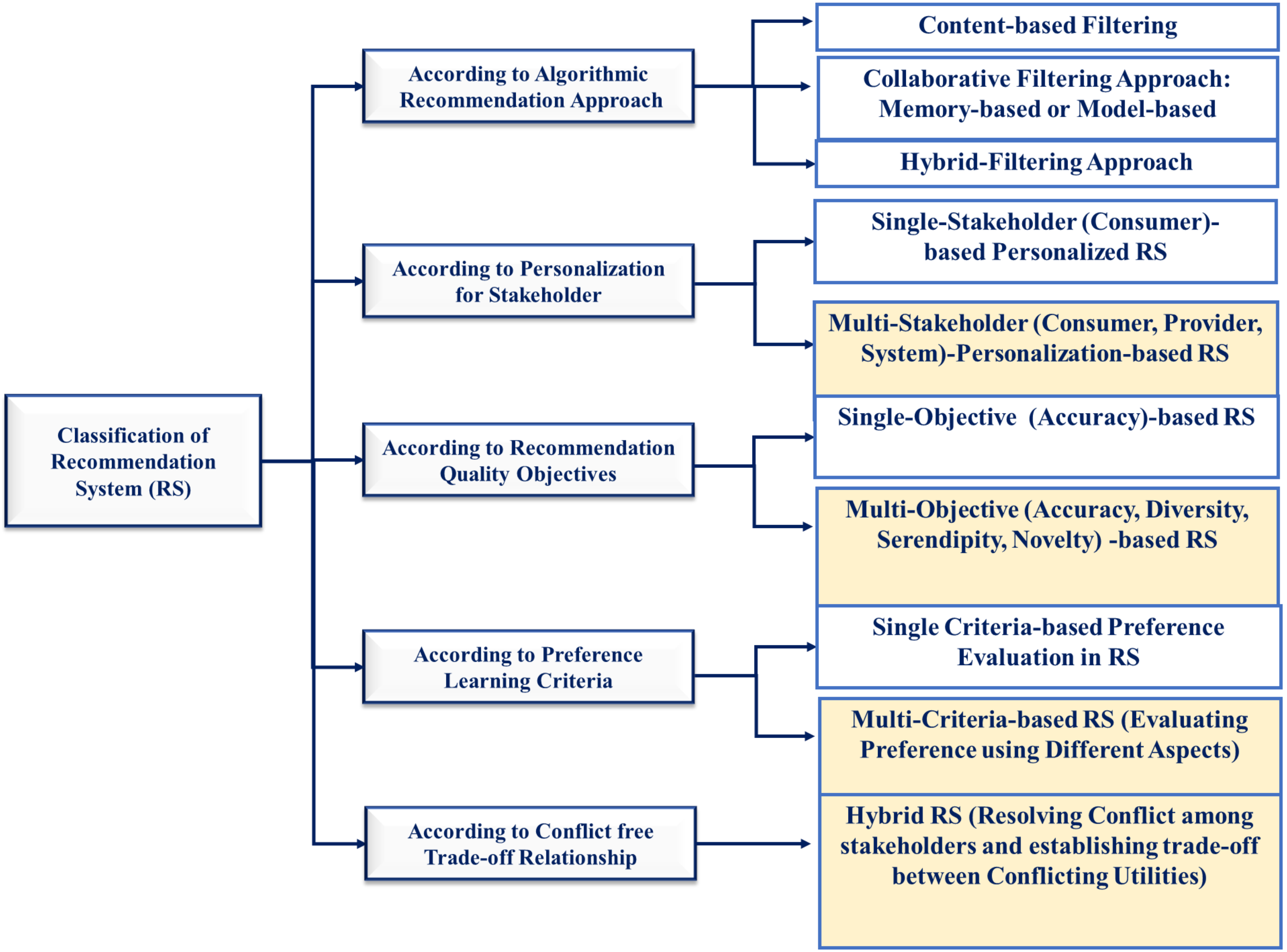

Fig. 2: Traditional RS

Collaborative filtering models use the collaborative power of the ratings provided by multiple users to make recommendations.

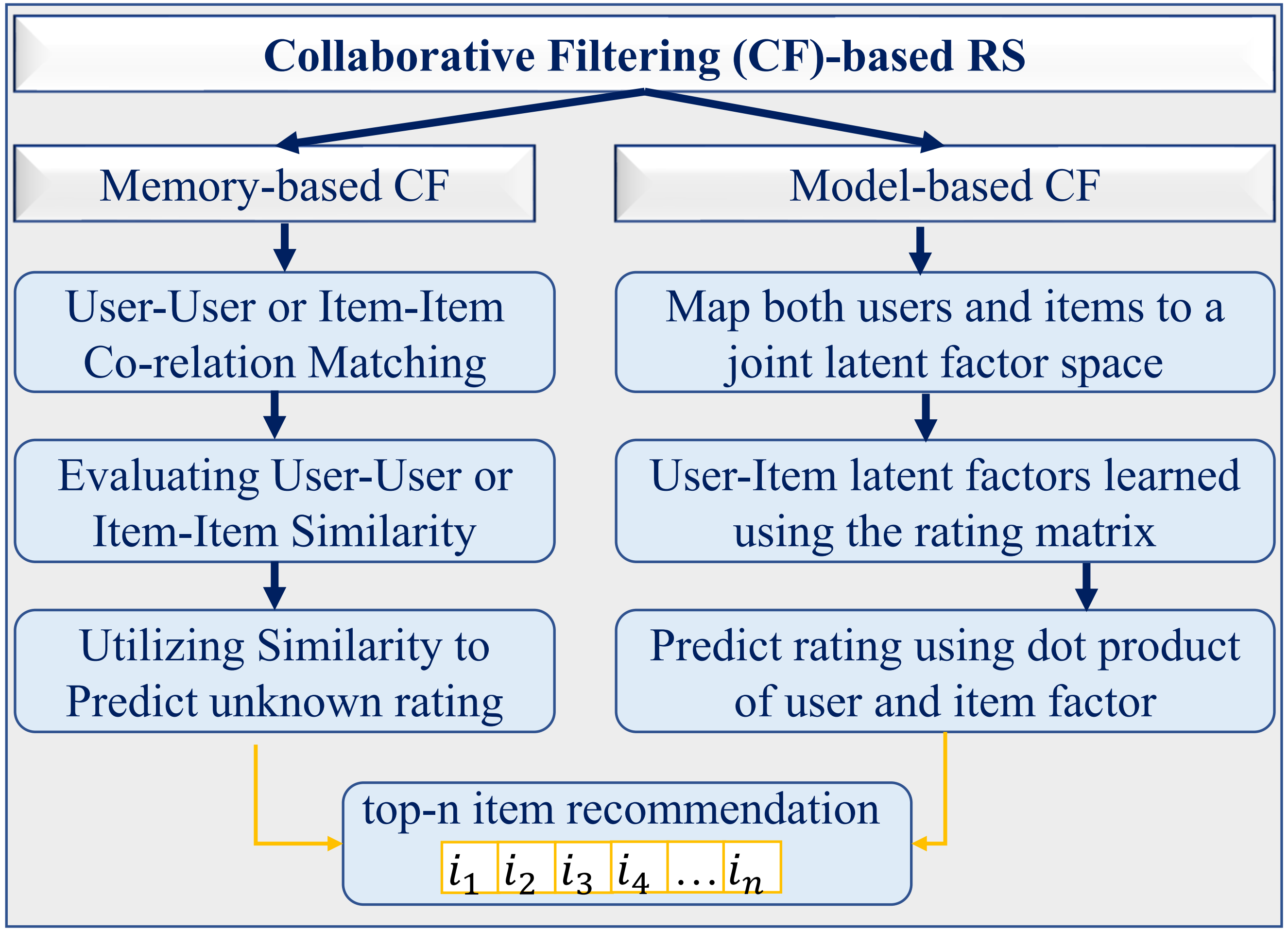

Fig. 3: Collaborative Filtering (CF)-based RS

In content-based recommender systems, the descriptive attributes (visual or textual) of items are used to make recommendations.

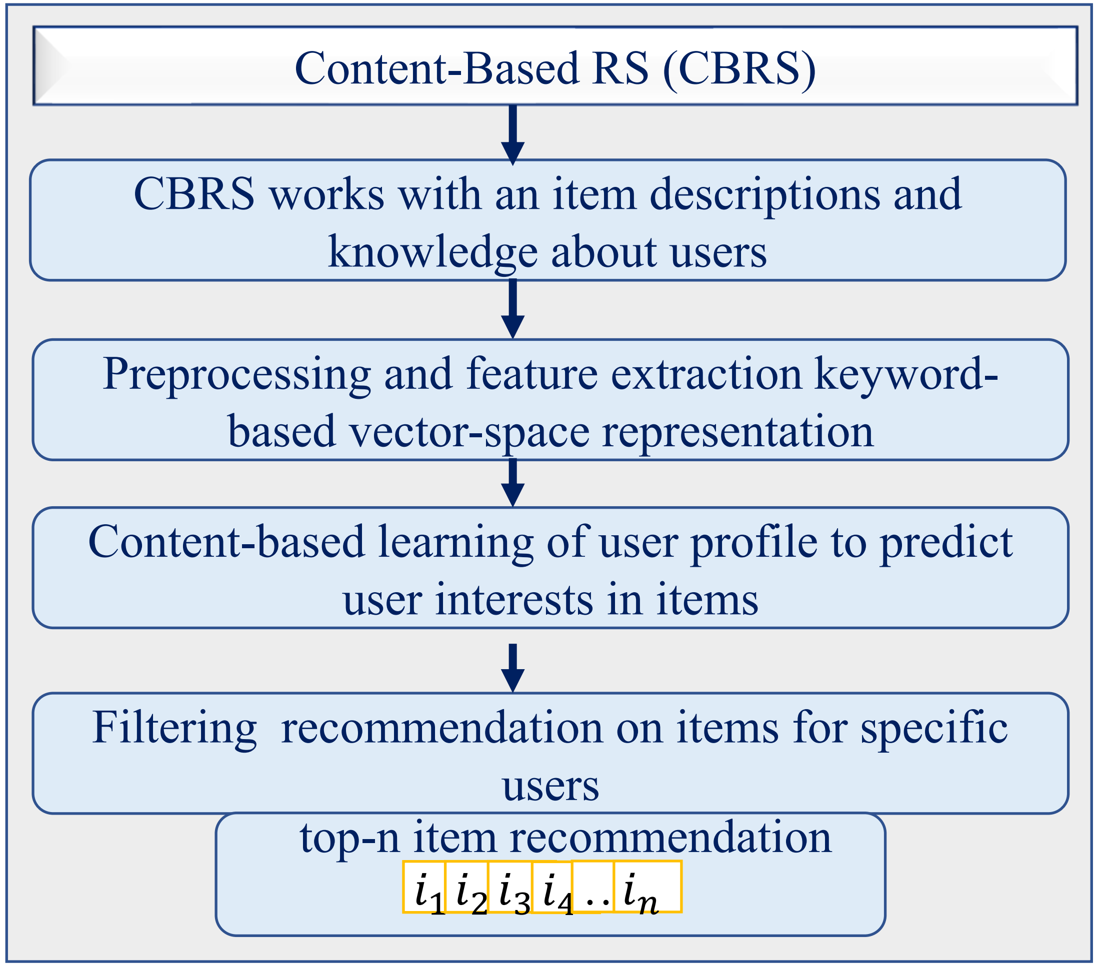

Fig. 4: Content-based RS

Introduction: Multi-Objective RS (MORS)- Need of MORS

Collaborative Filtering or CBRS-based Traditional Recommendation Methods

User (U) Item (I)

Interaction (Rating/Review)

$R \leftarrow U * I$

Exclusive focus on

Improving Recommendation Accuracy by recommending highly rated & popular items

Highly Accurate Recommendation May not be Interesting and Useful

Uncertainty in learning user preferences

Whether the generated recommendation is **Relevant** to user ?

Whether the recommendation covers items' of **Diverse** categories ?

Whether the recommendation Includes **Novel** Items ?

What about low rated and unpopular **(long-tail)** items ?

Recommendation Community moved beyond the conventional accuracy metrics through the inclusion of multiple recommendation objectives

Using

Multi-Objective RS (MORS)

Introduction: Multi-Objective RS (MORS) (Contd.)

- MORS aims to learn user preferences in multiple dimensions to ensure the balanced inclusion of diverse, novel, pleasantly surprising, yet relevant items in the recommendation list.

$$\boldsymbol{L_u} \leftarrow \boldsymbol{f}[(\boldsymbol{R} \leftarrow \boldsymbol{U} * \boldsymbol{I}), (\boldsymbol{max}\, \boldsymbol{\theta}(\boldsymbol{Obj_i})\ \forall \boldsymbol{Obj_i}),\ (\boldsymbol{EM})] \quad (1)$$

Where $\boldsymbol{L_u}$: *Recommendation List*, $\theta(Obj_i)$: objectives' (Obj_i) value, Obj_i: Objective that may belong to various objective functions, EM: Evaluation Metrics.

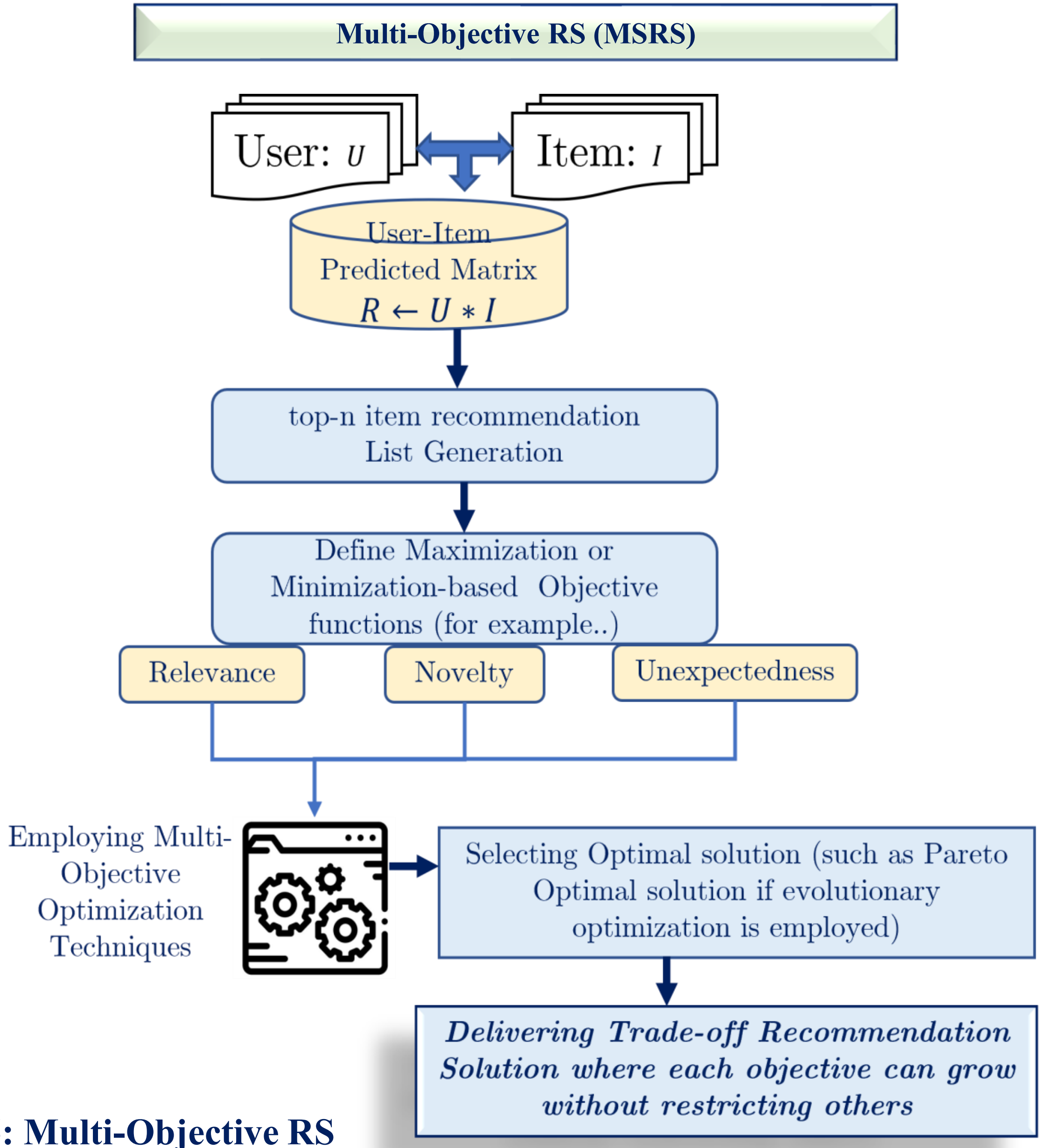

Fig. 5: Multi-Objective RS

Introduction: Multi-Stakeholder RS (MSRS)- Need of MSRS

Collaborative Filtering or CBRS-based Traditional Recommendation Methods

User (U) Item (I)

Interaction (Rating/Review)

$R \leftarrow U * I$

Exclusive focus on

Improving and Personalizing the recommendation for **end-user (Consumer)** only

Resulting in lower utility gain for other stakeholders including product provider and RS itself

Uncertainty in learning multi-stakeholder preferences

Personalizing RS for **Product Providers'** Preferences and goals ?

Personalizing RS for **System-level** Preferences and goals ?

Trade-off fair recommendation by satisfying Consumer, Provider and System objectives simultaneously?

Personalized Utility Functions for each stakeholder ?

Recommendation Community moved beyond consumer preferences by including Multi-stakeholder preferences

Using

Multi-Stakeholder RS (MSRS)

Introduction: Multi-Stakeholder RS (MSRS)- (Contd.)

MSRS incorporates the perceptions and utilities of the various parties participating in the recommendation process

$$\boldsymbol{C^+, P^+, Sy^+ \leftarrow f\{(R_{S'} \leftarrow' S * I), (CBF_S), \theta_{MS}, S_{EM}\}} \qquad (2)$$

Where C^+: Consumer Personalization, P^+: Provider Personalization, Sy^+: System Personalization, R_S: Stakeholder ($S \in (C, P, Sy)$ interaction with an item (I), CBF_S: content-based features of stakeholder, θ_{MS}: Learning model

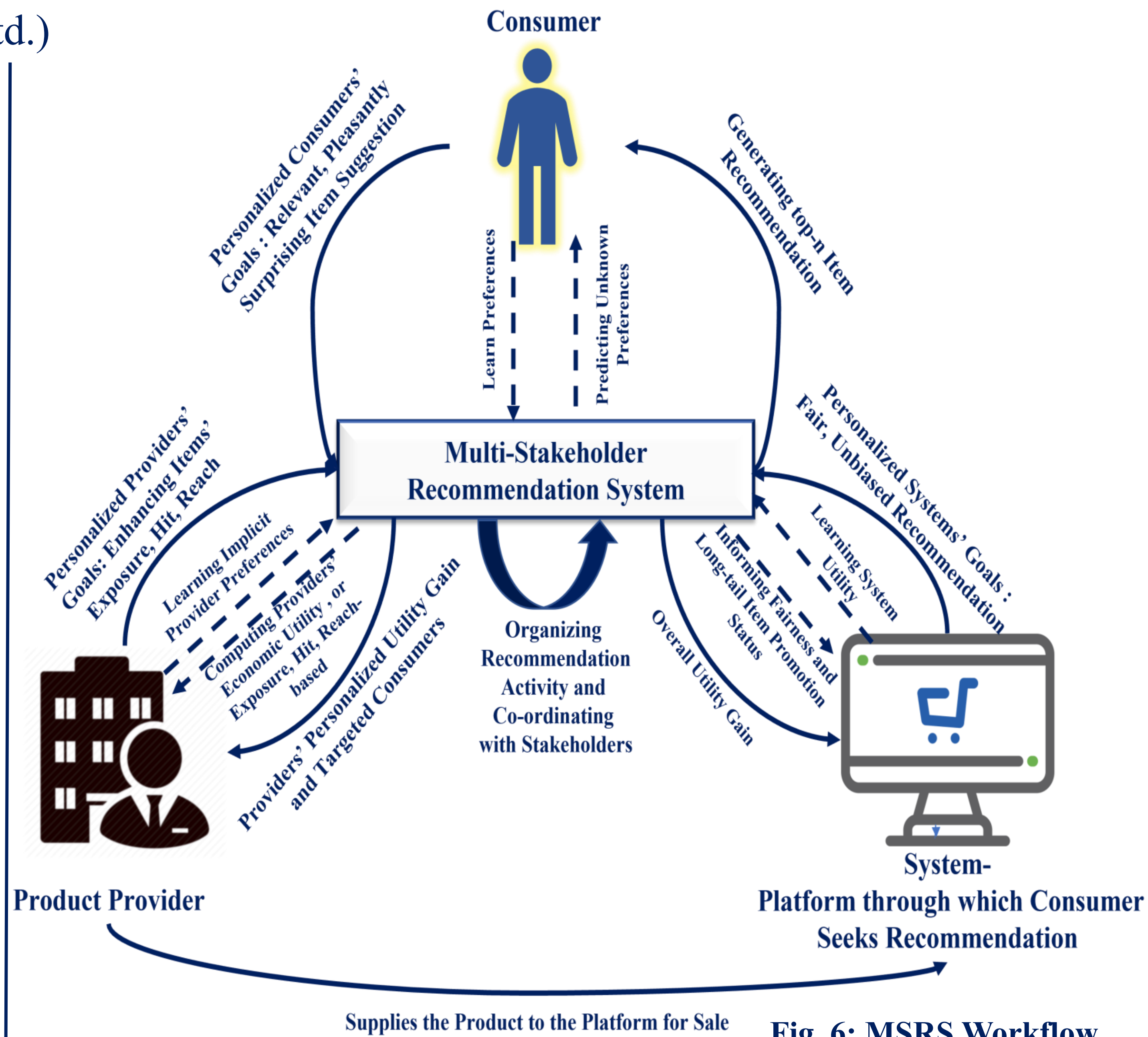

Fig. 6: MSRS Workflow

Introduction: Multi-Criteria RS (MCRS)- Need of MCRS

Collaborative Filtering or CBRS-based Traditional Recommendation Methods

User (U) Item (I)

Interaction (Rating/Review)

$R \leftarrow U * I$

Exclusive focus on

Single-Criteria-based overall Rating system to evaluate user preferences

Users' implicit preferences-based on different aspects of an item are still unexplored

Uncertainty in Single-Criteria-rating-based evaluation

Evaluating Stakeholders' preference on various item characteristics (such as Movie story, cast and action) ?

Personalizing Recommendation by **learning preferences on each aspects (criteria)** of an item ?

Incorporating **Multi-Criteria Preference learning in MSRS domain for fair personalization**?

Recommendation Community focuses on Predicting user preferences on each aspect (criteria) of an item and aggregating criteria-wise preference

Using

Multi-Criteria RS (MCRS)

Introduction: Multi-Criteria RS (MCRS)- (Contd.)

MCRS analyzes users' implicit preferences-based on different aspects of an item using multi-criteria rating.

$$L_u \leftarrow f\left[\left(R_{c_k} \leftarrow U * I\right), (\theta_{MC}), (EM)\right] \quad (3)$$

Where R_{C_k}: Criteria-wise user-item rating θ_{MC}: Multi-criteria learning model

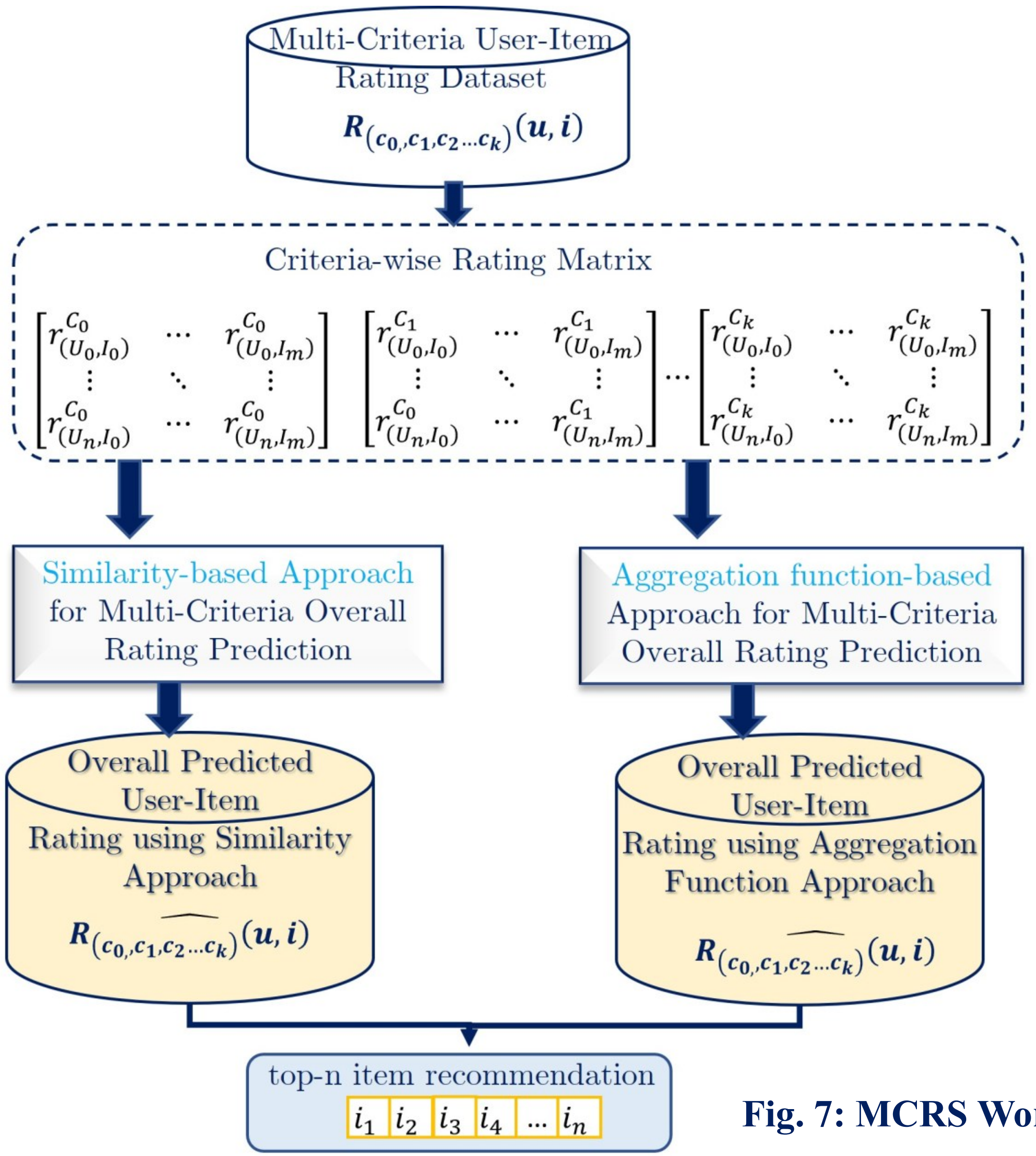

Fig. 7: MCRS Workflow

Consumer/User Accuracy-based Measures

- Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE): evaluation of the error between the predicted and actual rating

$$\boldsymbol{MAE} = \frac{1}{|R_t|} \sum_{\substack{u \in U_{R_t} \\ i \in I_{R_t}}} |r_{u,i} - \hat{r}_{u,i}| \quad (4)$$

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{|R_t|} \sum_{u,i \in R_t} (r_{u,i} - \hat{r}_{u,i})^2} \quad (5)$$

Where R_t: Test dataset of the rating, U_{R_t}: Users in the test dataset, I_{R_t}: Items in the test dataset, $r_{u,i}$: actual rating information, $\hat{r}_{u,i}$: predicted rating, $|R_t|$: length of the testing.

- $Precision@n$ measures the proportion of the top-n items in the RL that are relevant to the users (Rel_u) and $recall@n$ metrics evaluate the relevant items included in the RL.

$$\boldsymbol{Precision@(n)_u} = 1/|U| \sum_{u \in U} |L_u \cap Rel_u| / |L_u| \quad (6)$$

$$\boldsymbol{Recall@(n)_u} = 1/|U| \sum_{u \in U} |L_u \cap Rel_u| / |Rel_u| \quad (7)$$

- Normalized Discounted Cumulative Utility Gain ($NDCG@t$) assess how well RS models rank items on a recommendation list.

$$\boldsymbol{NDCG@t} = \frac{DCG@t}{IDCG@t} \quad (8)$$

Where $DCG@t = \sum_{i=1}^{t} \frac{2^{REL_i - 1}}{log_2(i+1)}$: Discounted Cumulative Gain, $IDCG[t] = \sum_{i=1}^{|REL|} \frac{2^{REL_i - 1}}{log_2(i+1)}$: Ideal Discounted Cumulative Gain

Provider/ Producer Evaluation Measures

- **Exposure** metrics count the inclusion of the providers' item in the recommendation list.

$$\boldsymbol{Exposure} = \frac{1}{|P|}\sum_{L_i \in RL}\sum_{i \in L_i} \mathbb{1}\ iff(i \in P(i)) \quad (9)$$

- The **Hit provider metrics** count includes highly rated providers' items in the recommendation list.

$$\boldsymbol{Hit} = \frac{1}{|P|}\sum_{L_i \in RL}\sum_{i \in L_i} \mathbb{1}\ iff(i \in P(i)\ and\ r_{u,i} \in R) \quad (10)$$

- The **reach metrics** measures the total number of users receiving the recommendation of the provider's products.

$$\boldsymbol{Reach} = \frac{1}{|P|}\sum_{L_i \in RL} \mathbb{1}\ iff(\,|P(i) \cap L_i| > 0) \quad (11)$$

- The **Target Reach** metrics track how many of the providers' targeted customers receive the suggestion for one of the providers' products.

$$\boldsymbol{Target\ Reach} = \frac{1}{|P|}\sum_{L_i \in RL} \mathbb{1}\ iff\big(\,|P(i) \cap L_i| > 0\ \wedge u \in T(U_p)\big) \quad (12)$$

Where $|P|$: Number of providers, RL: Recommendation List, $P(i)$: Providers' produced item set, $\mathbb{1}$: indicator function denotes the updating, $r_{u,i}$: user (u)-item (i) rating information, $T(U_p)$: Target users of the provider.

Introduction: Evaluation Measures for System Stakeholder

System Stakeholder Evaluation Measures

- The novelty metrics track the recommendation of the items new to the user and have not been rated earlier.

$$\boldsymbol{Novelty}\,(\boldsymbol{u},\boldsymbol{i}) = \frac{1}{|L|}\sum_{j\in L}(1 - Sim(i,j)) \qquad (13)$$

- The long-tail metrics satisfy the systems' goal of fairly incorporating unpopular items in the recommendation list with

$$\boldsymbol{long - tail} = \sum_{i\in L}\frac{1}{m_i(v_i+1)^2} \qquad (14)$$

Where m_i and v_i : represents the mean and variance of the rating information.

- Satisfied providers (SAT_{pro}) with greater Exposure Utility (EU_p) than the mean exposure of the provider($\overline{Exp}$).

$$\boldsymbol{SAT_{pro}} = 1/|P|\sum_{p\in P}\mathbb{1}_{[(EU_p>\overline{Exp})]} \qquad (15)$$

- Satisfied consumers with higher Consumer Utility (CU_u) with mean Consumption ($Cons$) of the user.

$$\boldsymbol{SAT_{con}} = 1/|C|\sum_{c\in C}\mathbb{1}_{[(CU_u>\overline{Cons})]} \qquad (16)$$

Where $|P|$: number of providers, $|C|$: number of consumers, $\overline{Cons}$: mean consumption (average proportion of the items highly rated by the consumer),

Need of Recommender System

Research Gaps

1. Most MORS models lacks in evaluating or examining consumers' acceptance and preferences.
2. Relying exclusively on sparse user-item rating interaction and poorly analyze latent user preferences.
3. Focusing on consumers' preferences and completely ignoring the provider and system preferences.
4. Existing MSRS models do not have personalized utility functions to address specific goals of the stakeholders.

Solution

1. The RS must assess the stakeholders' acceptance and the item's suitability to their profile.
2. Integrating reviews and side information about an item, helps RS to analyze user preferences better.
3. Incorporating competing utilities of various stakeholders through suitable utility functions.
4. Defining Personalized utility functions for satisfying provider and system-level goals.

Research Gaps

Research Gaps

5. The MSRS model still rely on user-item ratings to analyze provider and system preferences.

6. MCRS techniques employ statistical averaging and ignores the criteria-wise relationship, similarity

7. Existing hybrid RS model ignores the system-level goals, and it still needs to establish the trade-off.

Solution

5. The exclusive provider-item interaction matrix, may better represent their preferences.

6. Learn the implicit user preferences and ensembled similarity and aggregation function approach.

7. Developing the Hybrid RS to preserve the stakeholders' preferences and optimize the competing utilities.

Need of a Equitable RS through Multi-Pronged Utility Function Approach

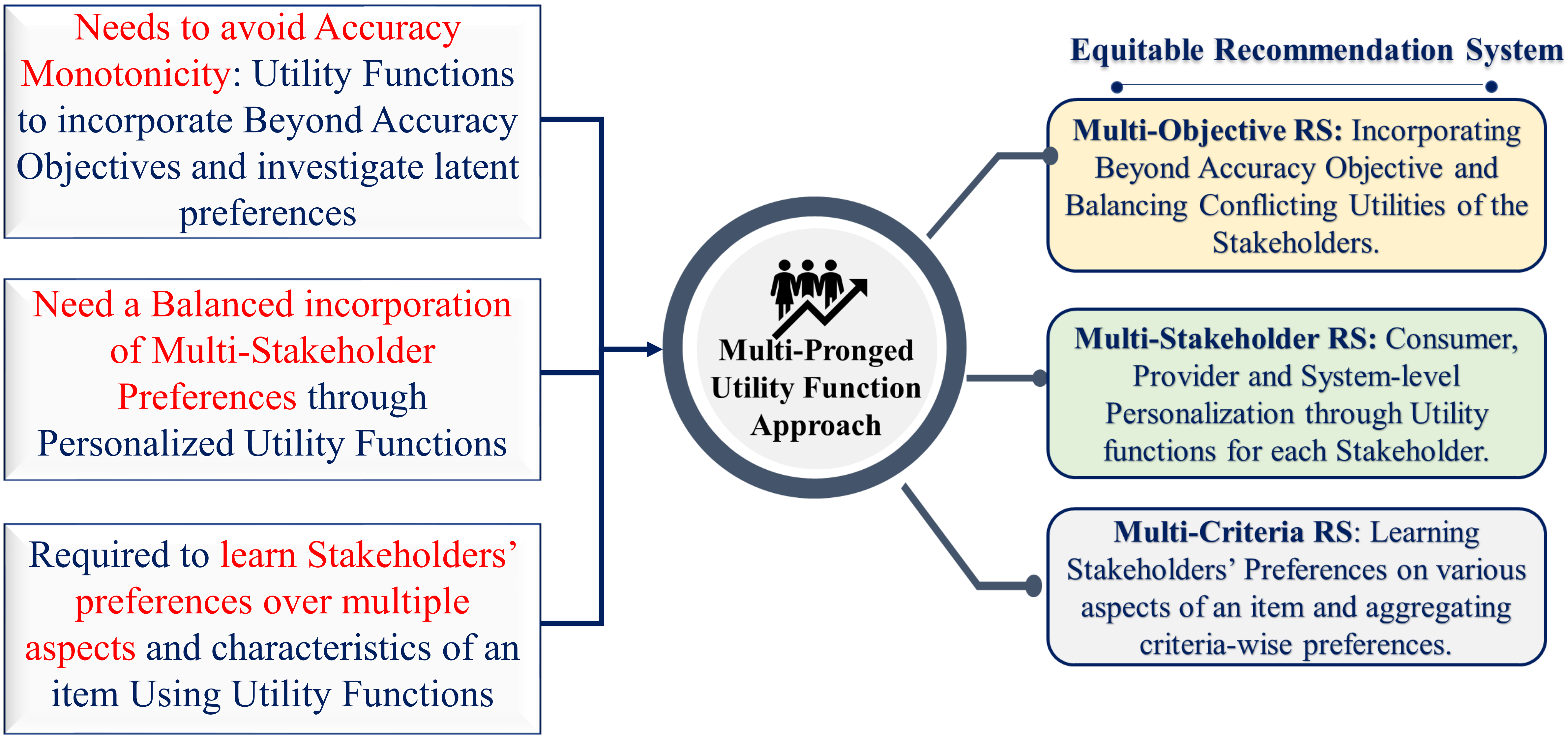

Fig. 5: Multi-Pronged Utility Function Approach-based Equitable RS