Cold Start Solutions For Recommendation Systems

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Chapter 1

Cold Start Solutions For Recommendation Systems

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Abstract

Recommendation systems are essential tools to overcome the choice overload problem by suggesting items of interest to users. However, they suffer from a major challenge which is the so-called cold-start problem. The cold-start problem typically happens when the system does not have any form of data on new users and on new items. In this chapter, we describe the cold start problem in recommendation systems. We mainly focus on Collaborative Filtering (CF) systems which are the most popular approaches to build recommender systems and have been successfully employed in many real-world applications. Moreover, we discuss multiple scenarios that cold-start may happen in these systems and explain different solutions for them.

1.1 Introduction

One of the challenges in everyday life is to make the right decision when purchasing a product. This challenge has been worsen due to the growing *Volume, Variety*, and *Velocity* of data associated with products[3]. Although the massive increase in the number of choices has been an opportunity for consumers to choose the most interesting products, however, this has led to the problem of *Choice Overload*, i.e., the problem of having unlimited number of choices, especially when they do not differ significantly from each other [1, 2].

Recommender Systems (RSs) can mitigate this problem by choosing and suggesting a short list of items for users, based on their personal needs and constraints [3, 4, 5, 6]. These systems, that have been primarily developed and integrated into

[1]Karlsruhe Institute of Technology
[2]Free University of Bozen - Bolzano
[3]https://www.zdnet.com/article/volume-velocity-and-variety-understanding-the-three-vs-of-big-data/

the eCommerce websites, have shown to be effective in supporting users when making decision. However, their application have gone far beyond that as now they have been extensively exploited almost anywhere, from social networks to intelligent personal assistants. Their effectiveness has been proved whenever an enhanced decision support is required in assisting users during their interaction with a system. Such an enhanced support enables the users to expand their experience, e.g., by receiving serendipitous suggestions from a less-explored part of item catalog and allowing the users to experience surprising items that might not be known to them.

For that aim, recommender systems carefully observe the users' behaviors and collect different forms of user preferences, in order to understand the personal tastes of users [7, 8, 9]. These systems then attempt to filter a long list of items and choose a shortlist of suggestions. This capability has made them to become an essential component of any type of commercial information systems that needs to deal with a large catalog of items [10].

1.1.1 Recommendation Approaches

From the mid-90s when early works on recommender systems [11, 12] have been emerged, till now, variety of recommendation approaches have been proposed. These various approaches still share commonalities, based on their underlying algorithms, that makes it possible to classify them into a number of classes [10, 13, 9, 14]. We can briefly describe each of these classes based on the definitions in the literature.

One of the most popular class of recommender systems is **Collaborative Filtering (CF)** [15, 16] which analyzes a set of known ratings and predicts the unknown ratings, expected to be given to the items by the users. A collaborative filtering system, then, recommends to a user the items with the highest predicted ratings. **Content-based (CB)** [17, 18] class of recommender systems analyze the content of the items and recommends items based on their associated content attributes (features). **Utility-based** [19, 20] class of recommender systems predicts the utility scores of users corresponding to the different items (as choice options). This is done by taking into account the needs and constrains of each user when computing the utility scores. The items with the highest predicted utility scores are recommended to the users. **Demographic** [21, 22] class of recommender systems considers the demographic data associated with the users and builds recommendations by taking into account the particular demographic group a user may belong to. **Knowledge-based** [23, 24] class of recommender systems adopts a specific reasoning process which begins by formulating the users' needs and preferences and ends with identifying whether or not an item matches the specific criteria for a target user. **Hybrid** [25, 26] class of recommender systems combines a number of different approaches from a single or multiple class(es) of recommender systems in order to cope with the limitations of each single approach.

Regardless of the class of the implemented recommendation approach, a prerequisite to any recommender system is the availability of the data that may indicate the needs and preferences of the users. Indeed, in spite of the fact that the algorithm performance plays an important role, however, the quality of recommendations based on any class of recommender systems may become poor if no or low quality data has

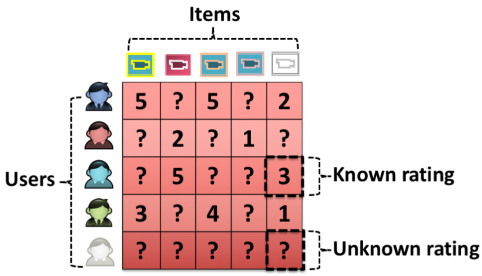

Figure 1.1 Rating Matrix: rows represent users and columns represent items. The entries of the matrix contain the " known" ratings, users have provided to items. The "unknown" ratings are represented with question marks.

been provided by users [27, 28]. This is a situation known as *Cold Start* problem, which typically happens when a new user registers to the system and no preference data is available for that user. This is a major problem in recommender systems specially with large number of users.

In this book chapter, we address the cold start problem in recommender system. We mainly focus on Collaborative Filtering (CF) systems as they are very popular type of the real-world recommender systems. We describe different scenarios that cold start may happen in these systems and survey the solutions for the problem that have been proposed by the literature.

1.2 Collaborative Filtering

Collaborative filtering based recommender systems exploit a dataset of user feedbacks, mainly in the form of *ratings*, that have been provided by a network of users to a catalog of items. The dataset is typically represented as matrix where rows represent users and columns represent items (see figure 1.1). Collaborative filtering systems then use this dataset and predict which items could be interesting to a target user [15, 16]. For that, these systems mine patterns of relationships and similarities among the users and use them to learn predictive models that can generate recommendations.

Such predictions are computed for every unknown rating for a pair of user-item within the rating matrix. This results in a rank list of items, computed for a target user, where items are sorted accordingly to their predicted ratings. Collaborative filtering system selects a short list of items with the highest predicted ratings and recommends it to the target user.

While recommender systems based on collaborative filtering approach have presented promising performance, however, they can largely suffer from cold start problem due to the lack of data for certain users or certain items [13, 29]. The main form of cold start problem is the *New User* problem which occurs when a new user registers to the system and requests to receive recommendations before she has provided

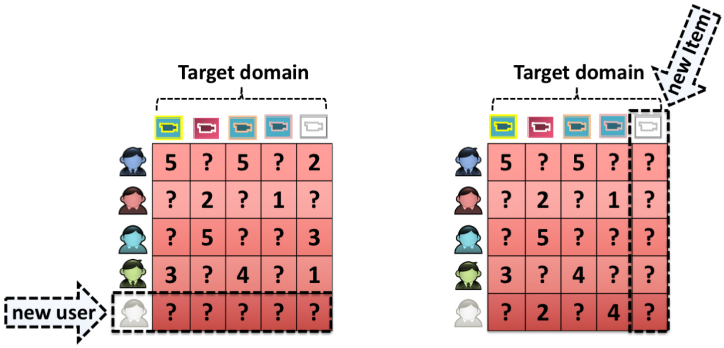

Figure 1.2 Illustration of Cold Start problem in recommender systems: New user problem (left) and New item problem (right)

any rating to any item (see figure 1.2). Another type of cold start is the *New Item* problem which occurs when a new item is added to the item catalog and none of the users has yet rated that new item (see figure 1.2). The *Sparsity* of the data can be also considered as relevant issue to the cold start problem. In severe cases of data sparsity, the performance of the collaborative filtering systems can be seriously damaged leading to a very poor quality of recommendation. This is a situation where the number of *known* ratings is extremely smaller than the number of *unknown* ratings and the system has to compute predictions for the unknown ratings [13, 30].

The remaining sections, discuss a set of solutions, that have been proposed by the literature, in addressing the cold start problem.

1.3 Active Learning in Recommender Systems

One of the main solutions to the cold start problem in recommender systems, is *Active Learning*. Generally, active learning is part of a broader research topic of *Machine Learning*, a well-known research area which focuses on design and development of novel algorithms in solving a large variety of tasks such as regression and classification tasks [31, 32, 33, 34]. These algorithms typically need big datasets to learn patterns behind data and build models that can be used to predict unprecedented data [35]. This is a form of learning process that is called *Passive Learning* [36]. However, the availability of such big data can not be always presumed as there are realistic cases where the data is (e.g.,) partially available. In such cases, the system may not be able to achieve a certain level of accuracy unless more data is collected. While this could be beneficial, however, collecting more data can be an expensive process and may require extensive human involvement. Therefor, the system has to focus on collecting only high quality data by carefully controlling the data collection process. This will help the system to minimize the cost of data collec-

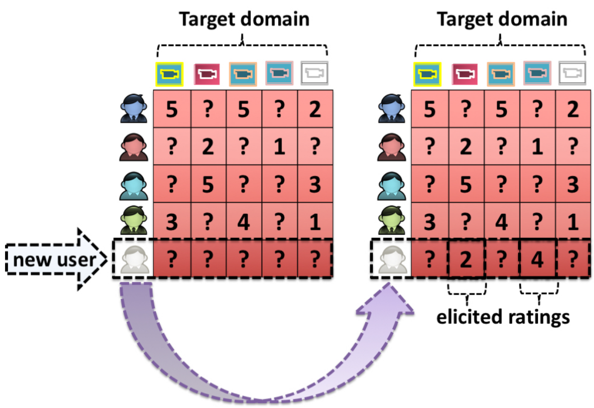

Figure 1.3 *Active Learning in recommender systems: a new user registers to the system, where active learner proposes her to rate a selection of items, and elicits the ratings.*

tion while maximizing the expected benefit. This form of learning process is called *Active Learning* [36, 37, 28].

In comparison to the passive learning, there can be two big advantageous, brought by the active learning. The first advantage is that, in active learning, the system does not need to have access to the entire data and instead, it can iteratively obtain further data. The second advantage is that, active learning allows the system to carefully analyze the available data and decide which data to be collected. This process will disallow the noisy data to be collected and may improve the quality of the input data.

In the context of recommender systems, active learning can bring similar advantageous, and hence, it can be a natural solution to the cold start problem. This can be the reason why the initial interaction of new users with recommender systems begins with active learning where the system requests the new users to provide ratings for a set of *selected* items [38]. This allows the system to obtain a minimum amount of data that can describe the preference of a new user (see figure 1.3). Hence, an active learner follows a set of defined rules that is used to automatically regulate the *item selection* process. By applying these rules, the system *elicits* ratings from the (new) users and use them to build or update their profiles. The very precise definition for selecting items to propose to a user to rate is called active learning *Strategy* [8, 39, 40, 28].

While there has been a broad range of active learning strategies, proposed in the literature, however, according to [38, 28], these strategies can be classified into few classes, listed below:

- **Uncertainty Reduction** [8, 39] strategies try to select items with more diverse ratings as the system is less certain about them. Suppose that a lot of users have given high ratings to an item, while many users have given low ratings to the same item. In such a case, it will be difficult for the system to predict whether or not to recommend that item. Conversely, an item that has received low ratings from nearly all users can be easily excluded from the recommendation. Hence, collecting the ratings of items with diverse ratings may be very informative and may decrease the uncertainty of the system when computing predictions [8, 39].

- **Error Reduction** [40, 28] strategies attempt to select items that collecting their ratings may directly reduce the prediction error. This is due to the fact that there are items with highly diverse ratings where the ratings are poorly correlated with the ratings of the other items (e.g., *Napoleon Dynamite* movie in *Netflix* dataset) [40]. While selection of such items for active learning may not contribute to the predictive power of the system, still uncertainty reduction strategies may select them for active learning. Instead, error reduction strategies may ignore these items and focus more on items with ratings that can positively improve the prediction accuracy [28].
- **User Adaptation** [41, 39] strategies try to personalize the active learning process to the particular characteristics of the users by selecting and proposing different items for different users to rate. This is due to the fact that different users may have different knowledge, familiarity and preferences towards different category of items and hence it is not very convenient to select a similar set of items for these different types of users. Accordingly, taking into account such differences among users in active learning process could lead to collecting higher quality and quantity of ratings.
- **Acquisition Probability** [28, 42] strategies try to maximize the chance that a user can rate an item and hence they select items that are more likely to be known by a user. Suppose that a user has not been in a restaurant while the system requests her to rate that restaurant. The rating of that user may not be so informative and instead may increase the level of noise within the data. Hence, it is crucial for the active learner to take into account the likelihood that a user is familiar with an item when requesting her to rate the item.
- **Decision Tree-based** [39, 43] strategies adopt decision tree algorithms in order to identify informative items to be selected for active learning. Each node of such decision tree, contains a candidate item to be proposed to a new user to rate. Therefore, the node somehow represents a group of like-minded users who has rated that candidate item similarly. Accordingly, each node splits the users into 3 groups, i.e., those who have given that candidate item (i) high rating, (ii) low ratings, or (iii) no rating. The active learner builds this decision tree based on an optimization term that leads to the reduction of the prediction error. Once the decision tree is built, the system can use it to iteratively select items to propose to a new user, hence traversing from root node of the tree to the leaf nodes, depending on the ratings provided by the user.
- **Prediction based** [37, 44] strategies build prediction models that are used to decide which items to be selected for active learning. The prediction-based strategies rank items according to the predicted ratings and select the top items with highest predicted ratings. The adopted predictive models may vary from *Probabilistic* models [45, 41, 28] to *Matrix Factorization* models [46, 47]. An advantageous of these strategies is that they select items that are likely to be in-

teresting for users and hence the users are not bothered during the active learning process. Indeed, the users may even enjoy checking and rating the selected items. It is also highly probable that the proposed items are familiar to the users, and hence, the chance to actually obtain the ratings by these strategies is high.

- **Hybrid** [48, 49] strategies combine a number of individual strategies in order to take advantages of multiple ones. This may allow the hybrid strategies to simultaneously optimize different metrics, such as *accuracy*, *diversity*, and *user satisfaction*. Moreover, there are situations that an individual strategy may fail to properly select items to propose to a target user to rate. However, in such particular situations, hybridizing the individual strategies can tackle the problem and lead to improving the performance of the individual strategies.

1.4 Semantic-based Recommender Systems

The traditional solutions for the cold start problem are based on the popular Content-based Filtering (CBF) approaches. These approaches build user profiles by associating their preferences with the semantic attributes of the item content [50, 51, 52, 6, 53, 54]. Exploiting the content of the items has been used to address the new item problem. When a new item is added to the catalog, the item profile is built by various types of semantic attributes (see figure 1.4). The recommender can use such profiles to compute similarity or built machine learning models to generate relevant recommendations.

In early recommender systems, semantic attributes were based on less-structured form of semantic content such as item category or item description. These attributes are exploited by the recommender systems to establish *Vector Space Model (VSM)* [18], where, each item is represented by a multi-dimensional vector of content attributes [55].

More novel class recommender systems has been emerged after the famous article of Tim Berners-Lee [4] (as known as the father of the Semantic Web) [56]. He proposed to formulate a set of rules to create the Web of data, known as *Linked Data* principles [57]. In order to better understand Linked Data, the following brief description of content architecture in Web could be beneficial.

Current Web, as known as *Web of Document*, contains billions of documents which are related to each other by *hyperlinks*. This architecture makes it possible for users to traverse the Web by visiting hyperlinks. While the content of the Web is human-readable, however, it still suffers from massive ambiguity originated from the lack of a proper structure with respect to the *representation* of information. This ambiguity in information consequently makes it incapable for machines to understand the provided information. Linked Data principles [57] are indeed proposed in addressing this problem.

According to the noted proposal, the knowledge is modeled by *Resource Description Framework (RDF)* which provides a generic graph-based data model for describing *resources*, including their relationships with other resources [58]. By

[4] https://en.wikipedia.org/wiki/Tim_Berners-Lee

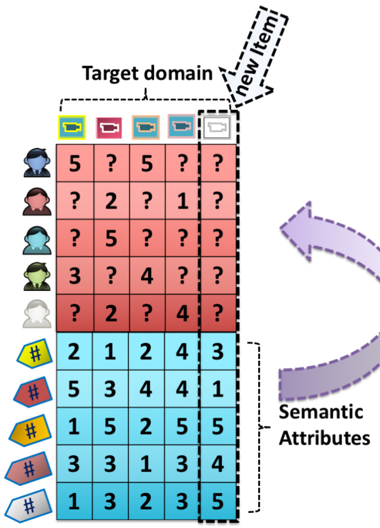

Figure 1.4 *Recommendation based on semantic attributes, in addressing the New Item problem as part of Cold Start problem*

interlinking some publicly available linked data dataset such as DBpedia[5] and Wikidata[6], *Linked Open Data* has been emerged as a network of interconnected datasets, accessible via endpoints. It is possible to query Linked Open Data by query languages such as *RDF Query Language* [59].

Such database has been used by novel class of recommender systems that are relied on the new form of semantic data that can better represent the *knowledge* of human. These novel semantic recommender systems focused on exploiting the *semantic* content information rather than the *raw* content data based on the *Web of data* [60]. This has brought variety of advantages to recommender systems, such as, mitigating the new item cold start problem, as well as, empowering recommender systems to provide semantic-aware explanations for recommendations.

1.5 Recommendation based on Visual Features

Another group of recommendation approaches, that can address the cold-start problem, implements the idea of enriching the item profiles with additional source of data. The enriching mechanism allows them to be capable of coping with the *New Item* problem. A representative technique within this group of recommender systems is proposed by [61] where the authors exploited a set of visual features in a multimedia recommender system (see figure 1.5). The proposed features are called

[5] https://wiki.dbpedia.org/
[6] https://www.wikidata.org/wiki/Wikidata:Main_Page

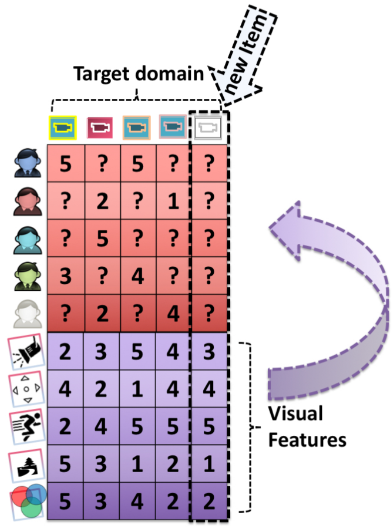

Figure 1.5 Recommendation based on visual features, in addressing the New Item problem as part of Cold Start problem

Mise-en-scene features and they are based on variation of colours, camera and object motions, and lighting within the multimedia items. The results of the experiments have shown that these automatically extracted features can solve the new item cold start problem [62, 61, 63]. The same authors have extended that work and proposed another recommendation technique based on exploiting *MPEG7* and *Deep Learning* visual features [64]. Again, the results have shown the substantial power of visual features in solving the new item problem in recommender systems. There have been many recent related works that have used visual features in recommender systems, but mainly focused on deep learning features [65, 66, 67, 68].

There have been also earlier works that have studied the potential of building *style-aware* recommender systems based on visual features [69, 70, 71, 72, 73, 74]. As an example, the authors of [72] introduced *VideoReach* which is a recommender system that can extend the semantic item profile with visual features. The results of their experiments have shown that this extension has positively affected the click-through-rate. The work in [73] presented an algorithm that can integrates different ranking lists, generated based on visual features and none-visual attributes. The results have shown improvement.

A limitation of these works is that they have typically assumed that there are already a set of semantic attributes collected and the visual features are used in combination with these semantic attributes. Therefore, further studies is needed in investigating the actual power of visual features, mainly when traditional semantic attributes are not available.

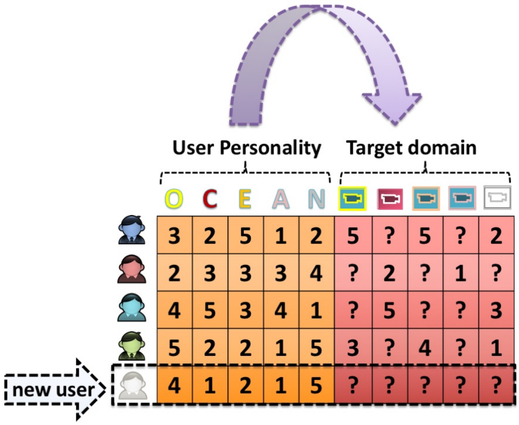

Figure 1.6 Personality based recommender systems, in addressing the New User problem as part of Cold Start problem

1.6 Personality-based Recommender Systems

One of natural solutions to tackle with the cold start problem is to use additional user attributes (as known as *side information*), in order to build the initial profile of a new user [75, 76]. There have been already different types of such attributes, proposed in the literature. However, one of the most representative forms of attributes is the psychological ones related to the *Personality Traits* of users. These personal traits are based on predictable and stable characteristics of users, and they describe the "consistent behavior pattern and interpersonal processes originating within the individuals" [77]. Personality traits can portray the differences of users in terms of *emotional, interpersonal, experiential, attitudinal* and *motivational* aspects [78].

Psychology literature is already mature in the personality field and various psychological models are available on how to represent the personality aspects of an individual person. One of the most well-known models is the *Five Factor model (FFM)* [79], which is commonly adopted in different research disciplines [80]. This model describes the personality of a person with respect to five dimensions as known as *Big Five* traits: *Openness, Conscientiousness, Extroversion, Agreeableness* and *Neuroticism* (as known as *OCEAN*).

It has been shown that users with different personality traits express differences in their decision making process [81, 82]. Accordingly, users with similar personality traits are more likely to share similar preferences [83]. Authors of [84] have studied the correlation of personality traits with musical preferences and showed that users with high openness trait typically share similar preferences for jazz, blues and classical musical genres, and users with high extroversion and agreeableness traits are likely to enjoy rap, hip-hop, funk and electronic musical genres. The authors of [85] have conducted an experiment that showed a strong relation between the preferences of users for certain web applications and their particular personality traits. In [86], the relation of personality traits and emotional expressions have been investigated for users who were watching movies in different social contexts. The results have showed that different patterns of emotional expressions can be observed for different users with their unique personality traits.

The promising results of the above-described works, showing the correlation of personality and preferences of users, has motivated further studies on the idea of exploiting personality in recommender systems, e.g., in addressing the cold start scenario [44, 30, 87, 82, 83]. Hence, when a new user enters the system and has not provided any data associated with her preferences, personality traits can be used to profile her and generate personalized recommendation (see figure 1.6). Hence, the personality can be used either to compute the similarity among users for *similarity*-based recommender systems, or as additional user attributes, in *model* based recommender systems.

As an example of works within this area, the authors of [88] adopted different recommendation approaches and showed that incorporation of personality may lead to a better recommendation quality in cold-start scenario. [89] has investigated the potential of using personality and showed that personality characteristics can lead to improvement in the performance of recommender systems. In [90, 80] the relation of personality of musical tastes is exploited in order to generate relevant recommendation for users. Finally, [91] has developed a recommender system that uses personality profiles of users to generate recommendations for them. This is done by first analyzing the hotel reviews written by users. Then using the correlations among the reviews and the personality traits, the system extracts the personality profiles of the users and compute similarities among the users in order to build similarity-based recommendations.

A limitation of personality-based approaches is that, before the personality data is used, the users should complete a personality questionnaire, which can be a time consuming process. This is why there are recent machine learning techniques that are built to extract the personality traits from other sources such as social network profiles of the users.

1.7 Cross Domain Recommender Systems

Another solution for the cold start problem in recommender systems is based on exploitation of axillary domains in order to generate recommendations in a target domain. This is called *Cross-domain Recommendation* and it is one of the research topics that have been well-studied in the community of recommender systems. The reason can be due to the fact that current e-commerce web applications typically operate in multiple domains and they use mechanisms to aggregate multiple types of data from multiple domains. Availability of such data can bring benefits to a recommender system and enables it to perform (e.g.,) *cross-selling* or coping with the cold start problem in its target domain.

There have been various algorithms developed for cross-domain recommendation [92, 93, 94]. While these algorithms may implement different mechanisms for the cross-domain recommendation, they share commonalities which enables us

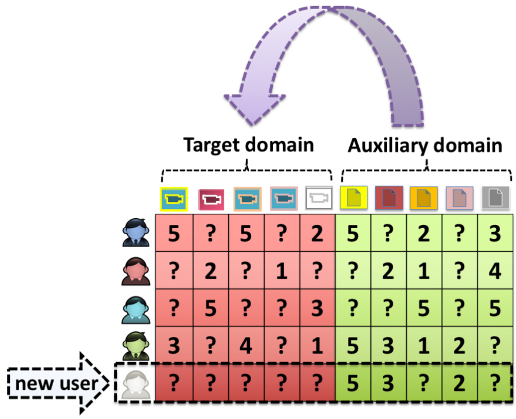

Figure 1.7 Cross-domain recommender systems, in addressing the New User problem as part of Cold Start problem

to classify them into two major classes, i.e., *Knowledge Aggregation* approaches [95, 96, 97, 98] and *Knowledge Transfer* approaches [99, 100, 101, 102].

The former approach aims to *aggregate* the knowledge from different auxiliary domains in order to generate recommendations in the target domain. The latter approach is based on the idea of eliciting the user ratings from auxiliary domains and *transfer* this knowledge to the target domain. In this sense, the latter approach attempts to *link* different domain knowledges in order to support the recommendation for the target domain [99].

As an example of former approach can be the work in [103], that proposed various knowledge aggregation mechanisms that have proved to be effective in improving the accuracy of target domain recommendations in cold start. An example of the latter approach is presented in [104] where the authors propose leveraging the preference knowledge transfer from an auxiliary domain to the target domain. The results of evaluation have shown that the proposed recommendation method overtakes the classical recommendation methods.

A limitation of the cross-domain recommendation is that, there has to be considerable overlap among the adopted datasets in different domains. Hence, without the having axillary domain and the target domain overlap, it would be not feasible to apply the techniques described in this section.

1.8 Conclusion

In this book chapter, we addressed the cold start problem in recommender systems. This problem happens when the system is not able to recommend relevant items to a *new user* or to recommend a *new item* to the existing users.

Table 1.1 Summary of the solutions for the Cold Start problem

Solution	**Cold start**		**Methods**
	New User	**New Item**	
Active Learning	✓	✓	• Uncertainty Reduction [105, 8, 39] • Error Reduction [40, 106] • User Adaptation [107, 40, 8] • Acquisition Probability [108, 109, 110] • Decision Tree-based [39, 43, 47] • Prediction-based [41, 46, 37] • Hybrid [48, 111, 37]
Semantic Attributes		✓	• Graph-based [112, 113] • Machine Learning [114, 115, 116]
Personality Traits	✓		• Similarity based on personality [103] • Personality traits in the model [104]
Visual Features		✓	• Mise-en-scene features [61, 62, 117] • MPEG7 features [63] • Deep Learning features [66, 67, 68]
Cross-domain	✓		• Knowledge Aggregation [103] • Knowledge Transfer [104]

We discussed various solutions that have been proposed in the literature. These solutions are summarized in table 1.1. These solutions can be classified into 5 classes, i.e., *Active Learning*, *Semantic Attributes*, *Visual Features*, *Personality Traits*, and *Cross-domain Recommendation*. Although all of these solutions have been successfully applied and evaluated in prior works, however, none of these solutions can be seen as a conclusive remedy to the cold start as a generic problem. Indeed, each of these solutions can be effective in a particular situation of cold start. Some of these solutions (semantic attributes and visual features) can address the new item problem while some others (personality traits and cross-domain) can address the new user problem. Active learning techniques can address both of these problems.

It is worth noting that, the cold start research area in recommender systems is a multi-disciplinary field of research, and involves disciplines of Machine Learning, Psychology, and Human Computer Interaction (HCI). For instance, each of the cold start solutions need proper adoption of the interface design patterns [118] when obtaining user preferences or presenting a recommended item. Therefore, collaboration among researchers within these disciplines can surely be useful in improving the quality of current the state-of-the-art approaches.

In conclusion, this chapter shall hopefully provide an overall overview of the research on cold start and can be a useful source of guidelines for researchers in the academia and practitioners in the industry. It can hopefully advances the knowledge in this area, as well as, the related areas.

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