Fashion Recommender Systems in Cold Start

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1 Introduction

Fashion is defined as *"The cultural construction of the embodied identity"* [1]. Fashion is commonly described as the prevailing style of dress or behavior and it can be characterized by the notion of *change*. Fashion encompasses various forms of self-fashioning ranging form street styles to high fashion made by designers [94]. A major challenge in the fashion domain is the increasing *Variety, Volume*, and *Velocity* of fashion production which makes it difficult for the consumers to choose which product to purchase [2]. Shakespeare has -somehow- addressed this issue a long time ago by noting "that the fashion wears out more apparel than the man" [109]. This is not necessarily all negative as the more choices available the better the opportunity for consumers to choose appealing products. However, this phenomenon shall result in 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 [9, 6].

Recommender systems can mitigate this problem by suggesting a personalized selection of items (i.e., fashion products) that are predicted to be the most appealing for a target user (i.e., fashion consumer) [101, 111, 102, 64]. This is done by filtering irrelevant items and recommending a shortlist of the most relevant ones for the users. An effective filtering requires the system to (thoroughly) analyze the user preferences and (deeply) learn the particular taste and affinity of every individual user. A real

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[1] Editorial policy of Fashion Theory: The Journal of Dress, Body & Culture

[2] https://www.zdnet.com/article/volume-velocity-and-variety-understanding-the-three-vs-of-big-data/

world example could be analyzing the purchase history of a customer in Amazon [3] and predicting the interests of the user and ultimately generating recommendation for her. During this process, the recommender system can carefully observe the users' behaviors and elicit different forms of user preferences, in order to understand the personal needs and constrains of the users [104, 97, 114].

User preferences can be elicited in different forms, i.e., in the form of *explicit preference* or *implicit preference* [71, 113]. Explicit preference is a form of user assessment that is explicitly reported by a user (e.g., ratings for items in Zalando [4]) [44, 45]. In spite of its benefits, eliciting explicit preferences requires a certain level of user efforts [39] and may still lack to fully picture the true desires of a user [87]. Implicit preference is another form of preferences which is inferred from the actual observed activities (e.g., clicks on items in Zalando) [91, 59, 49]. Although traditional recommender systems focused on exploiting explicit preferences, however, modern recommendation platforms, particularly in e-commerce, shifted towards techniques that deal with implicit preferences.

Proven capability of recommender systems in learning different forms of user preferences and effectively dealing with choice overload has empowered them to turn to be an essential component of any modern e-commerce that needs to deal with a large catalog of items [15]. Fashion recommender systems have also shown to be effective in supporting users when making choices. Fashion recommendation deals with personalized selection and suggestion of a variety of products ranging from clothing to makeup, including recommendation of individual products or a set of products (outfits). Such a personalized recommendation is commonly generated based on the preferences of a network of consumers and computing the relationships and similarities among their preferences [18, 88, 96, 54, 121]. The effectiveness of fashion recommender systems has been proven in the cases where a decision support tool is needed to assist fashion customer during their interactions with an online shop. Such a support enhances the experiences of the users during the time of shopping, e.g., with surprising recommendation offered to them.

This book chapter addresses the cold start problem in fashion recommender systems. It describes different scenarios of cold start and reviews the potential solutions for this problem proposed so far. The rest of the book chapter is organized as following: section 2 briefly describes the common recommendation techniques in fashion domain. Section 3 explains different scenarios of cold start problem and section 4 reviews solutions for this problem, namely, solutions focused on item-based and user-based side-information (subsection 4.1 and 4.2), solutions based on implicit preferences (subsection 4.3), and potential solutions based on cross-domain and active learning (subsection 4.4 and 4.5). Finally, section 5 provides a conclusion for the book chapter.

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[3] https://www.Amazon.com

[4] https://www.zalando.no

2 Techniques for Fashion Recommendation

There have been a wide range of recommendation techniques that have been proposed in fashion domain [76, 63]. These techniques can be classified into the following categories:

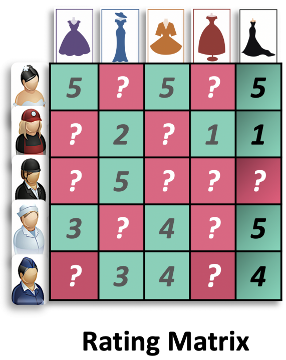

Fig. 1 Schematic figure representing a rating matrix [4]

- Collaborative Filtering (CF) [58, 67, 54] is a popular recommendation technique that aims at learning preferences of users from their ratings for fashion items and predicting the missing ratings that might be given to other products by the users. The user preferences are typically provided to the system in the form of a rating matrix where every entry represents a rating given by a user to an item (see Figure 1). The system then recommends to a user those items that have the highest predicted ratings (i.e., missing entries in the rating matrix).
- Content-based (CB) [10, 18, 122, 76] class of recommendation techniques focuses on adopting the content of the fashion items and generating recommendation based on the content features (e.g., textual description or visual features).
- Hybrid [65, 21, 74] class of recommender systems takes advantage of a combination of techniques from multiple classes of recommender systems in order to deal with the limitations of the individual techniques.
- Machine Leaning class of recommendation techniques adopts a range of computational models with different mechanisms compared to the above-mentioned (classical) techniques. An example is [76] where a *latent* Support Vector Machines (SVM) has been developed for fashion recommendation. Another example is [62] where the authors adopted a probabilistic topic model for learning fashion coordinates that can be used for recommendation. In [63] the authors combined a deterministic and a stochastic machine learning models for recommendation. Another group of approaches implements Learn-to-Rank (L2R) algorithms for recommendation with three alternative variations, i.e., *pointwise, pairwise,* and

listwise [78]. Pointwise variations predict the relevance score of each item independently. Pairwise variations aim at correctly ordering the pairs of items instead of individual items. Hence, the objective is to rank the more relevant items higher than less relevant ones. Listwise variations rely on ranked *lists* as training examples [45]. In [58], the authors proposed a technique based on tensor factorization in order to find the best clothing match. The authors of [55] proposed a technique that extends the Bayesian Personalized Ranking (BPR) by incorporating different item features. A more recent set of works developed recommender systems adopting different variations of the neural networks. An example is [56] where the authors employed Long Short-Term Memory (LSTM) cells [57] to learn temporal correlations between purchases in a fashion shop and to predict the preferred style of each user based on their past purchases.

Although the core recommendation technique plays an important role for the performance, still a recommender system will fail to generate relevant recommendation of fashion products without having certain quantity of quality preference data. This problem is known as *Cold Start* and it happens when the system has not yet acquired sufficient preference data (e.g., user ratings) to build meaningful recommendation for users (see Figure 2). The most common cases of the cold start problem happen when the recommender system is unable to build recommendation for a new user, known as *New User* problem. Another problem happens when the recommender system is unable to recommend a new item to any user, known as *New Item* problem [4, 108, 7, 35]. In severe cases of cold start, both of the new user and new item problems may happen all together. This is a case when an online fashion shop is recently launched and the database does not contain considerable quantity and quality of data portraying the preferences of customers [115, 7, 35].

3 Cold Start

Fashion recommender systems use a dataset of user preferences, typically in the form of ratings, that have been provided by a large community of customers to a catalog of fashion products. The dataset can be defined as a rating matrix where rows show the customers (users) and columns show the fashion products (see Figure 1). Fashion recommender systems then use this dataset and compute prediction for the items that might be interesting to a target user [70, 33]. Recommender systems recognize patterns of relationships within the data and exploit them to build rating predictions that can ultimately be used for generating recommendation.

Predicted ratings are built for each unknown rating for a user-item pair within the defined rating matrix. This leads to computing a ranking list for fashion items, for a particular user. In the ranking list, the items are sorted accordingly to the predicted ratings for that user. Fashion recommender system short-lists the top items of the ranking list with the highest predicted ratings and presents them to a target user in the form of a recommendation list.

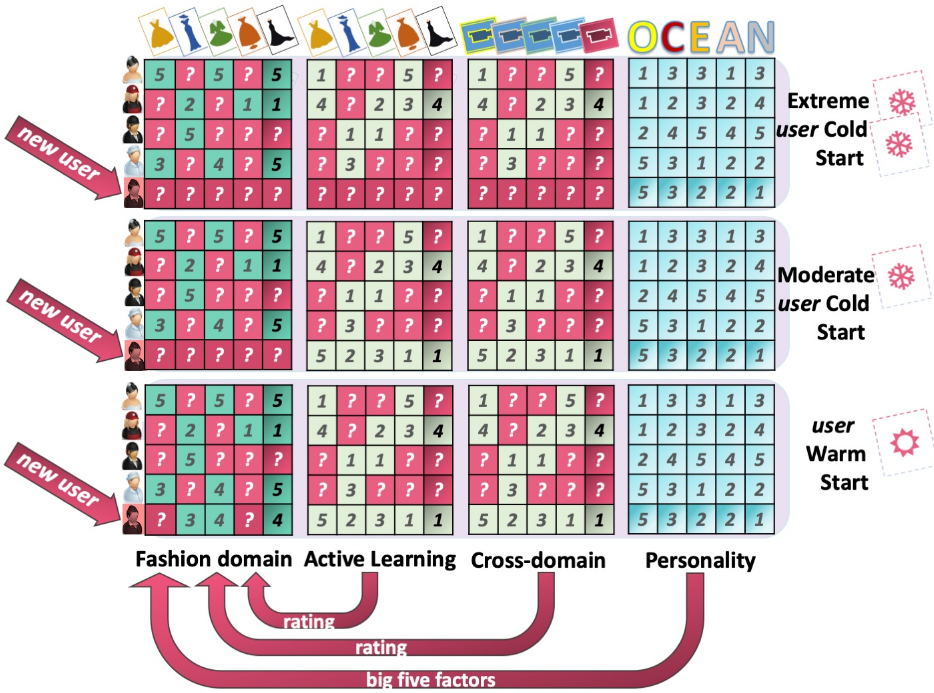

Fig. 2 User Cold Start scenarios: (i) Extreme User Cold Start, (ii) Moderate User Cold Start, and (iii) User Warm Start. Within each scenario, certain values of user-annotated features can be unknown to the recommender system. These missing features are indicated with “?" mark.

It is a fact that fashion recommender systems have already shown promising performance in dealing with particularities of this domain. However, they may still suffer from a number of challenges due to the lack of data for certain users or certain items [4, 108]. These challenges are mainly related to the cold start problem. One of the main challenges is defined as the *New User* problem which may happen when a new user enters to the fashion recommender system and requests recommendations before she has provided any preferences to any item (see figure 2). Another form of this challenge is defined as the *New Item* problem which happens when a new fashion product is added into the item catalog and none of the users has yet rated that new product (see figure 3). Similarly, the *Sparsity* of the rating dataset is known to be another related challenge. In extreme cases of sparsity problem, the performance of the fashion recommender systems will be damaged resulting in a very low quality of recommendation. In such a situation, the number of *known* ratings is extremely lower than the number of *unknown* ratings and still the fashion recommender system has to make predictions for the large number of unknown ratings [4, 11].

In real-world fashion recommender systems, different scenarios may happen, i.e., *Extreme* cold start, *Moderate* cold start, *Warm* start scenario.

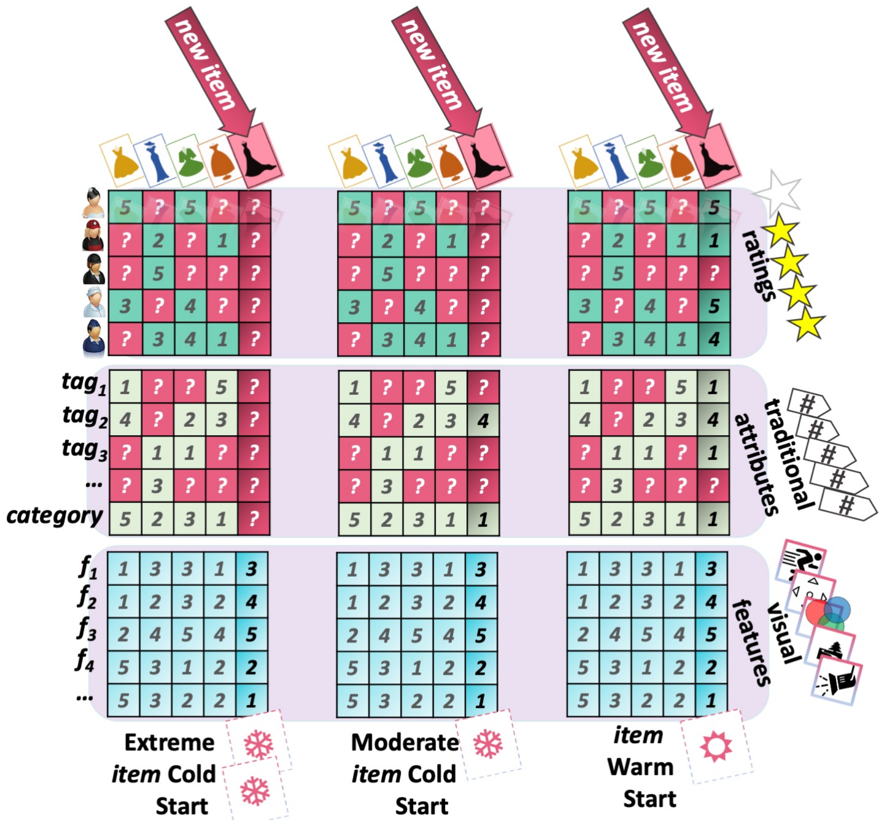

Fig. 3 Item Cold Start scenarios: (i) Extreme item Cold Start, (ii) Moderate item Cold Start, and (iii) item Warm Start. Within each scenario, certain values of user-annotated features can be unknown to the recommender system. These missing features are indicated with "?" mark.

- **Extreme Cold Start** in fashion recommender systems occurs when a new user registers to the system and requests recommendation before providing any data about her preferences (extreme new user problem). This scenario is illustrated in Figure 2 (top row). This problem also occurs when a new product is added to the catalog without holding any data that can describe that item. Consequently, the system would fail to recommend that item to any user (extreme new item problem). This scenario is shown in Figure 3 (left column). This is a serious problem and has to be tackled promptly.
- **Moderate Cold Start** occurs when a limited amount of preference data is provided by a user or a certain form of side information is collected to be used by the system for recommendation (Moderate New User Problem). This scenario is illustrated in Figure 2 (middle row). It could also happen for a new item when some sort of semantic features are partially available (Moderate New Item Prob-

lem). This scenario is shown in Figure 3 (middle column). Moderate cold start can happen as a mixed scenario of extreme cold start for some items and warm start for other items. Hence, it can be seen as an intermediate situation when a recommender system is in a transition phase from extreme cold start to warm start situation. However, this still means that the system has a serious problem as the user and items in the extreme cold start situation may not be well served by recommender system. This is the most common scenario and related literatures typically refer to this scenario as a cold start.

- **Warm Start** can be considered as the best possible scenario for fashion recommender systems as significant information provided by users (User Warm Start). This scenario is illustrated in Figure 2 (bottom row). In the case of items, it refers to the situation when fashion products have already obtained considerable preference data that can be well exploited for recommendation (Item Warm Start). This scenario is presented in Figure 3 (right column). There could be also considerable quantity of user-annotated semantic features (i.e., tags and reviews) in the dataset.

The rest of the book chapter, reviews the potential solutions to tackle the cold start problem.

4 Potential Solutions

4.1 Item Side Information Approaches

Content-based Filtering (CBF) has been one of the most popular approaches for recommendation in different application domains [63, 122, 64, 76, 47]. CBF relies on content features of items (as known as *side information*) in order to effectively mitigate the cold start problem in recommender systems [29, 13, 36, 30]. In fashion recommender systems, when a new product is added to the item catalog, an initial profile of the item is made by using different sources of content features (see figure 3)[65, 52]. These content features are exploited by the system to form a *Vector Space Model (VSM)* [93], where items are represented by a multi-dimensional vector [80, 27, 31]. The system adopts machine learning models that can learn from item vectors and recognize patterns among them and ultimately generate relevant recommendation [84, 103].

Traditionally, content features exploited by recommender systems were *semantic* features based on semantic content (e.g., item description, tags, and category) [27, 80, 106, 32, 7]. However, recent approaches for fashion recommendation implement the novel idea of further enriching the item description with visual features [28]. Such visual features encapsulate the aesthetic form of the fashion products and represent the *style*. Such visual features are typically extracted from the product images based on the methodologies brought from Computer Vision and multimedia retrieval and recommendation [116, 53, 72, 105, 103].

A variety of research works have been performed on investigating usage of visual features for user and item modeling in fashion domain, e.g., for clothing matching [58, 83] and visually-aware recommendation [54, 55, 62]. Different forms of visual features have been proposed for extraction that can be classified into two big classes, i.e., (i) Hand-crafted features and (ii) Deep Learning (DL) based features [65, 125, 77, 63, 54, 55, 62].

While hand-crafted features [65] may still offer promising performance, recently, deep learning based approaches have achieved superior accuracy in comparison to them [19]. Adopting Convolutional Neural Networks (CNN) is an example of approaches based on deep learning that builds discriminative representation of fashion products [79]. Another work that pioneered this research is [76] where the authors proposed a clothing recommender system based on human body parsing detectors and latent Support Vector Machine (SVM) model. The authors in [58] proposed a technique called Functional Pairwise Interaction Tensor Factorization (FPITF) that is capable of using tensor factorization in order to predict the clothing match.

Regardless of the type of features, several works developed methodologies to exploit the content features when dealing with cold start problem. In [26], the authors proposed a content-based recommender system that constructs detailed clothing features to build up item profiles. The recommender algorithm is based on K-Nearest Neighbors (KNN) which is commonly used to make similarity-based recommendation for new items. Authors of [52] extended Collaborative Filtering and enabled it to recommend groups of fashion products (instead of individual products). The groups are formed based on certain type of features such as product category. This allowed their recommender system to tackle the new item problem. The approach has been deployed in a fashion retailer called *Rue La La*. In [56] the authors employed Long Short-Term Memory (LSTM) cells [57] that can handle cold start while learning temporal correlations between purchases in a fashion shop and ultimately to generate recommendation based on their past purchases.

In addition, there exists other works that go beyond recommendation and extend usage of visual features by performing recognition, parsing, and style extraction of clothing [65]. By common definition, clothing recognition focuses on matching clothing with clothing in an online shop and retrieving similar clothing from their photos. Clothing parsing methods aim at decomposing and labeling semantically meaningful parts of the clothing photo. Style extraction methods aim to learn the style of a product by extracting descriptive features from its visual content [65]. Among these tasks, the extracted style of clothing can be the most relevant for the fashion recommendation. For instance, the clothing style will enable the recommender systems to tackle the new item problem. Examples of approaches within this group of recommender systems are [68, 20]. Even collaborative filtering based techniques can be extended to be capable of using visual features. As an example, authors [55] proposed Visual Bayesian Personalized Ranking (VBPR) that extends the Bayesian Personalized Ranking (BPR) by incorporating the visual features. VBPR can be further extended to model the evolution of fashion trends in visually-aware recommendation [54].

4.2 User Side Information Approaches

A potential approach to deal with the cold start problem focuses on exploiting additional user attributes (as known as *side information*). A number of works have adopted this approach to build a customer profile not only in fashion domain [85, 17] but also other domains [12, 86, 86, 82]. Different forms of user attributes has been proposed in the recommender system literature. One of the important forms of side information represents the psychological characteristics of user and can be modeled by *Personality Traits*. The personality traits are defined as predictable and stable characteristics of individuals which can explain the "consistent behavior pattern and interpersonal processes originating within the individuals" [14]. Personality traits can represent the differences of individuals with respect to *emotional, interpersonal, experiential, attitudinal* and *motivational* dimensions [66].

A number of previous researches have investigated the impact of clothing attribute on the impression of personality. The results have shown that clothing (as part of fashion) can communicate comprehensive pieces of information about differences among people [123]. For instance, clothing can represent the favor, society level, attitude toward life, and personality. In fact, clothing is a language of signs, a nonverbal system of communication [81]. The authors of [25] modified the clothing colour for job applicants and changed it from light to dark. The results have shown certain level of differences in judgments of applicants.

A range of psychological models have been proposed to model the personality traits of an individual. A popular model is the *Big Five Factor model (FFM)* [22] which explains the personality of an individual in terms of five dimensions called big five traits. The list of these traits is: *Openness, Conscientiousness, Extroversion, Agreeableness* and *Neuroticism* (as known as *OCEAN*). Figure 2 (right column) illustrates how the personality traits can be represented in a user profile.

A number of reviewed works have shown that individuals with dissimilar personality traits follow dissimilar choice making processes [90, 41]. Hence, individuals with similar personality traits are more likely to share similar choices and preferences [107, 100]. Prior works have also developed the idea of using personality traits in recommender systems to mitigate the cold start problem [11, 107]. When a new user registers in a recommender system and has not given any information about herself, personality traits can be an alternative source of information in order to build relevant recommendation (see Figure 2). This can be done to compute the user-based similarity using personality traits or building computational (latent) models based on personality traits [41]. As an example of works within this area, the authors of [118] 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 fashion domain, limited attempts have been done on learning from effective signals obtained from people (i.e., short-term emotions as well as long-term moods and personality traits) for the potential of making recommendation. For instance, [95] integrated emotion signal of consumers for building recommendation of fashion products in the cold start situation. The work aimed at investigating the potential power of peoples' affective characteristics in predicting their preferences for fashion products. In [40] the authors proposed a recommender system that can use different forms of information, including user persona (personality) and social connections to recommend clothing. The authors of [123] has made analysis on exploring the potential relationship of personality type and how people make choices of wearing.

4.3 Approaches based on Implicit Preferences

An alternative type of cold start solutions focuses on collecting the implicit preferences (feedback) from the users and utilizing them for generating recommendation. When a customer enters to an online shop, the system can monitor her activities and try to infer her preferences from the activities. As an example, the system can log the browsing history or purchase records and learn the actual preferences of the user which are then exploited for recommendation. In modern recommender systems, even facial expressions of the users can be used to identify emotions and ultimately the preferences and choices [1, 119, 120].

A wide range of recommender systems are capable of leveraging implicit preferences, some of which are specifically designed for that goal [59, 99, 98, 50] and the others adopt hybrid models that use both of the implicit and explicit preferences. As an example, the authors of [69] extend the standard Singular Value Decomposition (SVD) model which originally leverages only explicit preferences. The extended model is called SVD++ and it can exploit implicit preferences in order to generate recommendation.

In fashion domain, a number of works have proposed a recommendation framework based on the implicit preferences. For example, in [55], a recommendation model has been developed that can tackle the cold start problem by incorporating both implicit preferences from users together with visual features from items. In [88], the authors assumed that no explicit preferences are available and hence developed a fashion recommendation framework that can learn from implicit preferences of users collected by a fashion app. The collected data includes user actions ranging from scrolling in the app to purchasing a product. In addition to user related data, the system also uses item price and popularity in order to generate recommendation. Also visual Bayesian personalized ranking [54], introduced before, is capable of incorporating the implicit preferences for improving the performance of fashion recommendation in cold start.

4.4 Cross-domain Approaches

Alternative class of approaches for fashion recommender systems focuses on using cross-domain methodology [65]. This recommendation class is also referred to as *transfer learning* where a (data-driven) function is learnt to link the target domain (fashion) and auxiliary domains. This can be done by projecting the representations of the target and auxiliary domains into a common feature space.

Cross-domain recommendation has been well-studied not only in the field of recommender systems, but also in related research areas for a situation where only a limited quantity of data might be available in the target domain [61]. 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 enable it to perform *cross-selling* or coping with the cold start problem in its target domain.

There have been various algorithms developed for cross-domain recommendation [42, 124, 92]. While these algorithms may implement different mechanisms for the cross-domain recommendation, they share commonalities which enable us to classify them into two major classes, i.e., *Knowledge Aggregation* approaches [2, 8, 110, 16] and *Knowledge Transfer* approaches [24, 117, 46, 73].

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 and transferring 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 knowledge in order to support the recommendation for the target domain [24, 35].

A representative example is the work of [51] where authors proposed a deep learning technique to compute the similarity among the photos taken from streets and shops. The technique is based on Convolutional Neural Networks (CNN). Transfer learning has been also adopted to mitigate the complexity of training deep learning techniques in the fashion domain. As an example, [75] proposed adopting GoogleNet architecture [116] for their training set for that task of feature extraction from clothing [65].

4.5 Rating Elicitation Approaches

An alternative set of approaches that can remedy the cold start problem are based on the idea of rating elicitation in recommender systems. These approaches are called *Active Learning*, a notion that traditionally has origin in theory of machine learning [43, 39]. This set of approaches has been adopted for designing algorithms in solving problems with scarce resources [112, 5, 3]. Active learning can be applied when a machine learning algorithm needs a large dataset for training [48] while such data is limited or expensive to acquire.

Active learning can offer a number of advantages specially in the initial phase of interaction of new users with recommender systems. It can be used to request the new users to reveal their preferences by rating a set of items [38, 37, 34], enabling the recommender system to bootstrap its knowledge about the taste and affinity of the new user (see figure 2). Active learner adopts a number of heuristics or rules to coordinate the process of rating elicitation. Those heuristics (as known as *strategies*) will allow the system to concentrate on eliciting the ratings that are more informative for the system to learn the user profile [97, 104]. This can be done in a single domain or multi-domain scenario [92].

In fashion domain, a minor attention has been drawn by active learning strategies. As an example, [60] presents an active learning strategy as part of clothing image retrieval and recommendation framework. The strategy is enabled to learn the preferences of users and use them for generating personalized recommendation. The proposed framework can also utilize a content-based algorithm and employ a user interaction to elicit the user feedback. The evaluation has shown the effectiveness of the developed strategy.

5 Conclusion

This book chapter discusses several scenarios related to the cold start problem in fashion recommender systems. The challenges that may happen in each of these scenarios can largely damage the performance of fashion recommender systems regardless of the quality of the core algorithm. The chapter reviews potential solutions that can be utilized to remedy these challenges.

The solutions can be classified into a number of categories, namely approaches based on *item side information* and *user side information*, approaches based on *implicit preferences*, *cross-domain* approaches, and *active learning*. Most of these approaches have been well-integrated in fashion domain while some may still have potential to be used due to their promising results in the other related domains. It is important to note that none of the approaches can necessarily offer the ultimate and conclusive solution to all of the above-mentioned cold start scenarios. In fact, every approach has a set of advantages and disadvantages which make it a unique solution that may better suit to a specific cold start scenario.

Moreover, many of the surveyed literatures have mainly viewed the fashion recommender systems from a narrow lens of classical rating-based systems with the matrix representation of users and items. Hence, the subject of the recommendation is reduced to mainly suggesting outfit to a potential fashion shopper. This is while the task of fashion recommendation may go beyond that traditional view of only finding the right outfit for a shopper and become more of modelling fashion products along with dimensions of style, design, size and fit.

Finally, it shall be noted that, additional to an efficient solution that can deal with cold start problem, a recommender system requires effective usage of interface and interaction design [23] to well serve its users and to fulfill their needs and constrains. This makes the research on cold start to be a cross-disciplinary area where various disciplines are involved, e.g., Interaction Design, Data Science, Databases and Psychology. This chapter may hopefully open up and offer a bird eye view of the cold start in fashion domain which shall be beneficial for researchers in the academia and practitioners in the industry, and as a result, advancing the knowledge in the recommender systems area.

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