Short Story On A Review of Contemporary Fashion Recommendation System Research

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Introduction

The name of the research review paper is "A Review of Modern Fashion Recommender Systems". Interestingly, the 7 authors of this paper have a variety of industry, academic & cultural backgrounds. For example, Julian McAuley is a professor of computer science at the American university of UC San Diego & Arnau Ramisa is employed at Amazon. However. A majority of the authors of this paper are European. For example, four authors are professors at the Polytechnic University of Bari in Italy (Deldjoo, Nazary, Pelligrini, and Di Noia) and one (Bellogin) is a professor based at the Autonomous University of Madrid in Spain.

The goal of the authors as stated in their abstract is to "identify the most pressing challenges in fashion RS [Recommendation Systems] research […] (and) the most important evaluation goals and perspectives […] and the most commonly used datasets and evaluation metrics." As a consequence of identifying challenges, the authors have identified common patterns in RS architecture. It is also noted that they are trying to identify challenges based on the model's objectives, goals, or tasks and the model's context (the data used as input to the model). Therefore, many of the model challenges may be generalizable to the objective/goal/tasks or context and not the architecture underlying the model itself.

The authors used a survey research method and search strategy to review more than 50 papers in the fashion recommendation system domain within a single research database (DBLP), before collecting the final set of papers to use within the survey. Also, most of the papers were published from the year 2014 to 2023, meaning most of the research is relatively recent work.

Fashion Recommendation Systems by Tasks and Data Input

The authors were able to discover 5 main tasks that the recommendation systems could be classified into:

1. Fashion item recommendation systems (data may be based on user past purchases a.k.a. U-I [User-Item] feedback)
2. Fashion pair and outfit recommendation systems (data may be based on how similar & complementary items are to each other)
3. Size recommendation systems (data may be based on U-I feedback &/or physical measurement questionnaires)
4. Learning explanations for fashion recommendation systems (data may be based on combining tabular and/or image based explanations of machine learning techniques & neural network recommendations)
5. Systems for other fashion prediction tasks

They also further classified the recommendation systems based on 3 types of data used as input by the RS to create the recommendations:

1. RS with data based on user past purchases a.k.a. U-I (User-Item) feedback
2. RS with data based on U-I & Side Information (more information about the user category like gender or age relation to the items brand/color/texture, etc.)
3. RS with data based on CA (Context Awareness such as spatial-temporal or computational environment, multi-media queries, physiological measurements, and information about the users affect or mood)

Among these, the authors found that there are specific challenges given a particular task and data used as input. As there are 5 main abstract tasks and 3 main abstract data type classifications, this implies that there are many combinations of challenges to take into account when considering in implementing a modern recommendation system.

General Pain-points by Task and Data Input

In this section, I will give a rough overview of the general challenges described by the authors according to the type of data and tasks implemented using this data.

User-to-Item Data Based Recommendation Systems

Tabular recommendation systems
The authors mention a big issue in the fashion recommendation systems they reviewed that is specific to capturing the relationships and patterns from users-to-items is the sizing (aka. Fit) of garments. Noted solutions mentioned in the introduction by the authors include recreating the experience of trying on clothes in an online environment (in augmented or virtual reality) or by shipping users clothing recommendations before they commit to purchase to try on as part of a clothing subscription service. However, the issue they mentioned arises from a clothing subscription service is it suffers from a lack of data when a user starts the subscription (a.k.a. the 'cold start' issue), and that user's receiving negative recommendations do not tend to continue purchasing their subscription - leading to a lack of user feedback to the model.

Computer vision recommendation systems
The virtual try-on experience may then be a less cost-intensive solution than the clothing subscription service as users may be able to visualize the clothing without paying for the service, while still contributing valuable user feedback via virtual measurement information that could be used to resolve the cold start issue in the clothing subscription service.

Item-to-Item Data Based Recommendation Systems

Among the item-to-item relationships and patterns being captured by recommendation systems:

Tabular recommendation systems
According to the authors, a noted solution they noticed to increase the accuracy of item-item (previous product purchases or tabular data) recommendation systems in the research they reviewed is matching the product to a style and crafting a "complete outfit" (a.k.a. the fashion item compatibility task) that a user may like based on dimensions such as social group preferences, trends, location, etc.

Computer vision recommendation systems

The authors mention that fashion object detection / localization within images and determining their attributes and similarities to other fashion objects is an issue they noticed in many of the research papers they collected. The authors mention that including images along with tabular data as the types of input to a recommender system (e.g. images taken from social media influencers and normal people) increases the success of a recommendation system when having user accounts having limited tabular product purchase information (a.k.a. the 'cold start' issue).

Conclusion and Final Thoughts

The review paper also discusses the most commonly used evaluation metrics and benchmark datasets according to the task of the recommendation system. The authors noticed that many of the research papers they reviewed mainly evaluate the models in a offline setting without respect to any business metrics. They further describe that a certain “evaluation perspective” can be taken and therefore a model’s performance can be subjective based on the perspective chosen.

For example, the authors describe using standard practice classification or ranking metrics to evaluate a model versus using textual recommendation explanations generated using a combination of machine learning techniques and human feedback to evaluate a model’s performance. For example, simply improving the model metric of accuracy or AUC and not taking into account the explanation of the recommendation could reinforce societal biases learned from the data by the machine learning method or artificially intelligent model.

The authors mention that the diversity of data present within popular datasets and fashion recommendation systems is sourced from a combination of popular social media influencers, street photography images (taken of fashion models for online businesses as if it was an unplanned moment), and fashion blogs and designers. In my opinion, using such sources without careful implementation could reinforce recommendation systems that learn the more glamorized version of style that is used to advertise clothing, rather than that of the general population.