Complete The Look

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Business use case

Existing work on Compatible Learning

Implementations

Gaps in current work

Problem Statements

PS1: Indian Compatibility

PS2: Diversity in outfit generation

Beam Search

Diverse Beam Search

DPP-BS

PS3: Style

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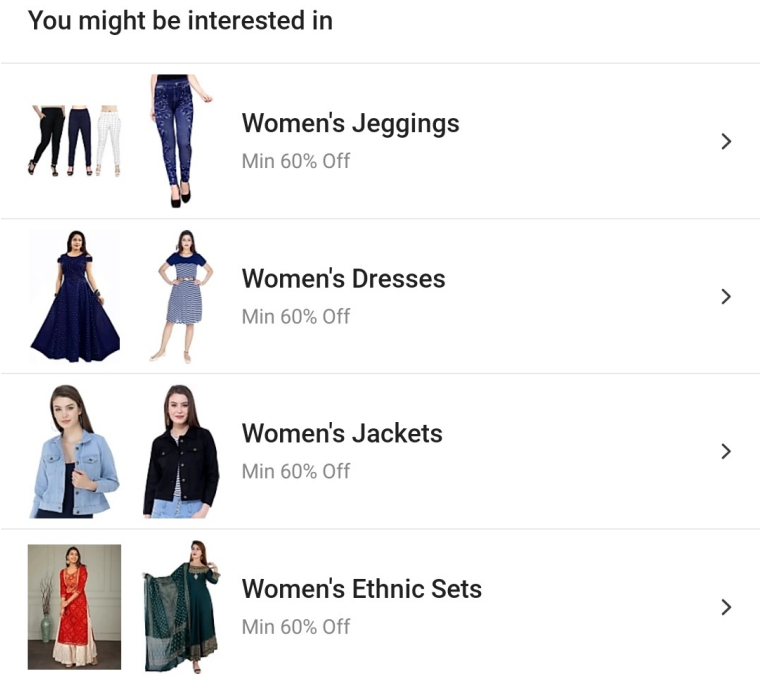
Business Use Case - Importance to Flipkart

- Flipkart - Walmart owned largest E-commerce platform in India; 200M+ users; Largest marketplace for fashion in India
- On Product Page - *Cross* widget does not perform good for Fashion apparels
- Business Problem: Given a product ('hero' product), show a set of products from other categories which 'go well' together to drive purchase in other categories.

Examples



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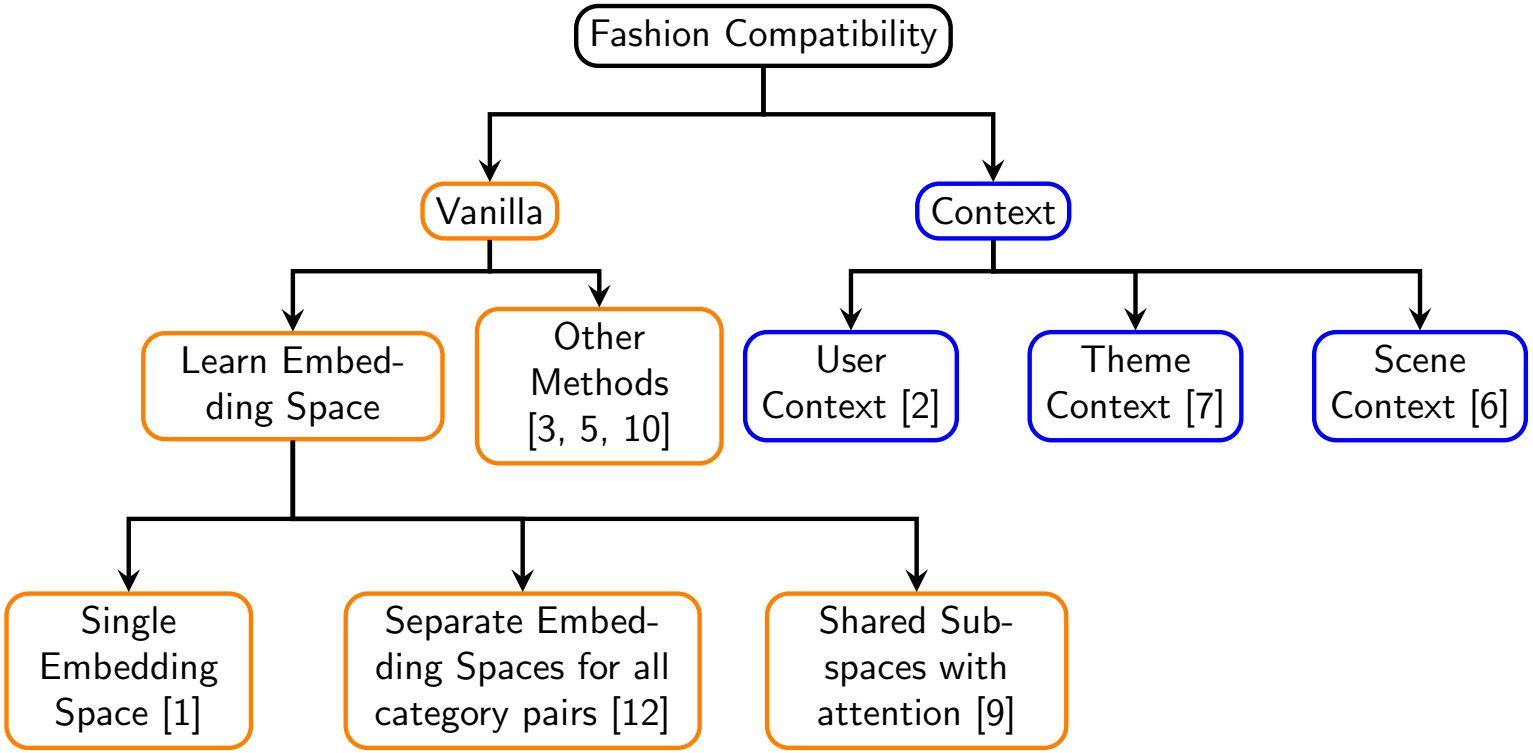
Existing work on Compatible Learning



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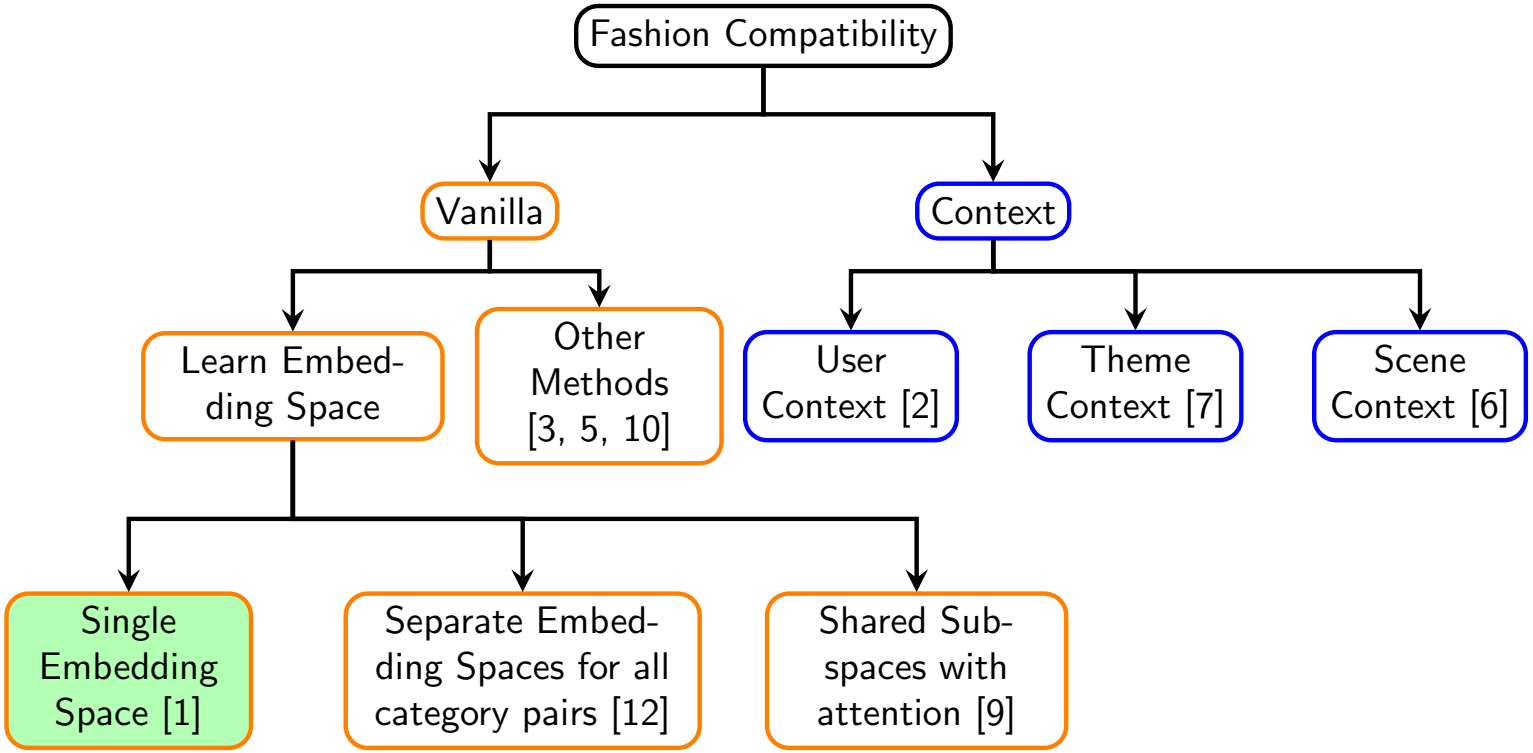

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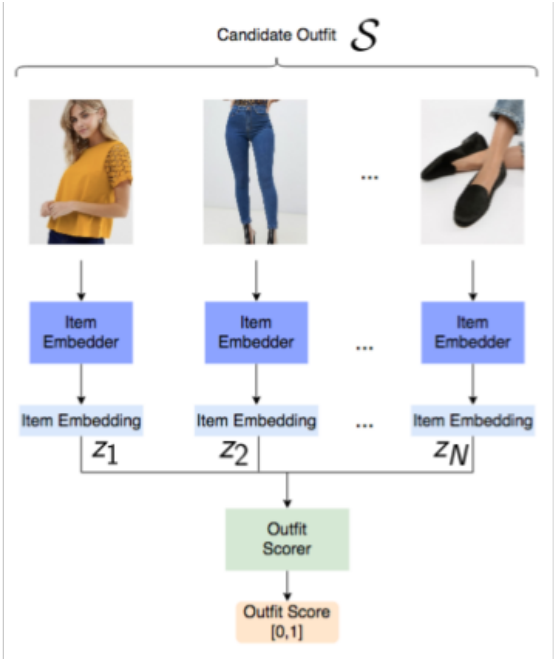
Implementations

Single Embedding Space [1]



$$y(\mathcal{S}) = \sigma\left(\frac{1}{N(N-1)}\sum_{\substack{i,j=1\\ i<j}}^{N} \mathbf{z}_i \cdot \mathbf{z}_j\right)$$

$$l(y(\mathcal{S}), t) = -t log(y(\mathcal{S})) - (1-t) log(1 - y(\mathcal{S}))$$

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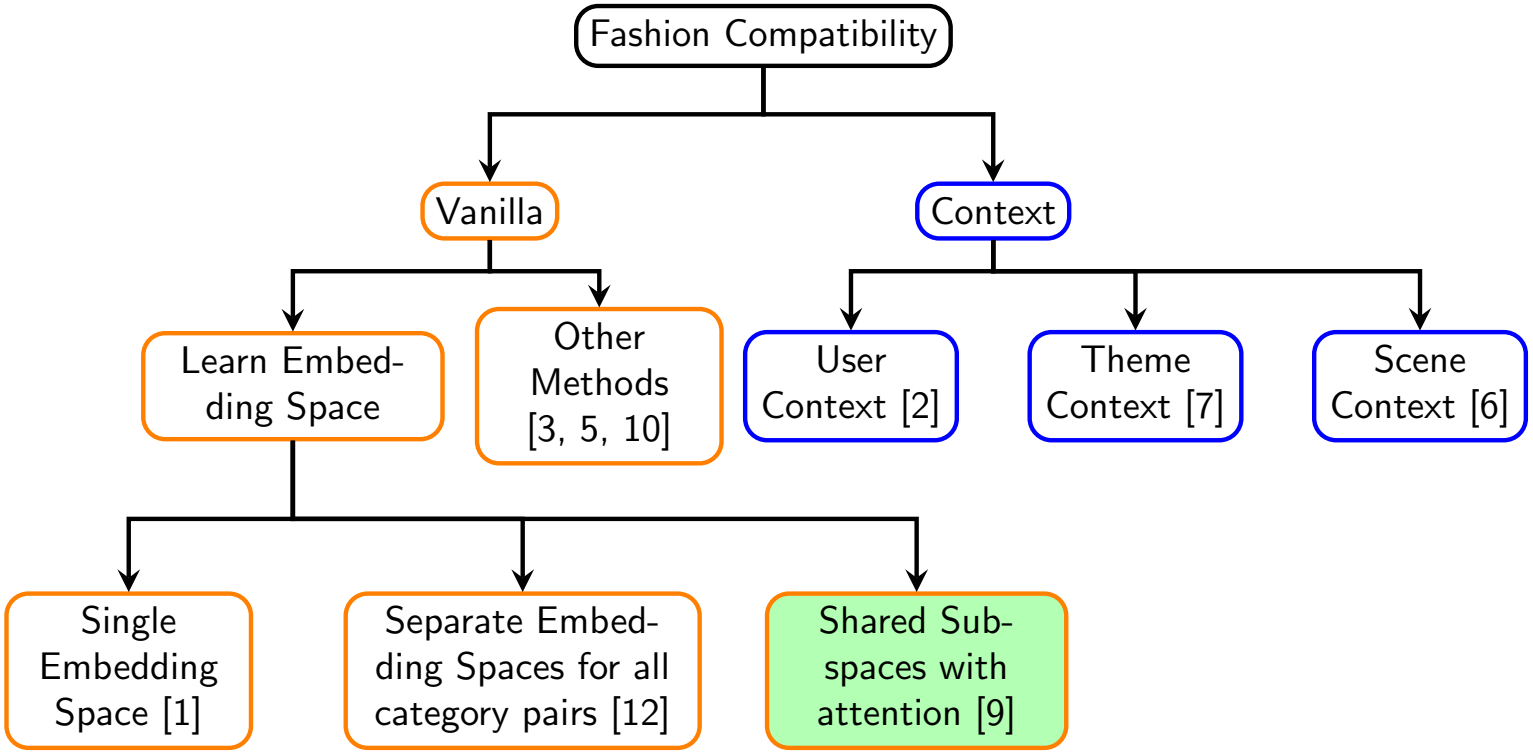

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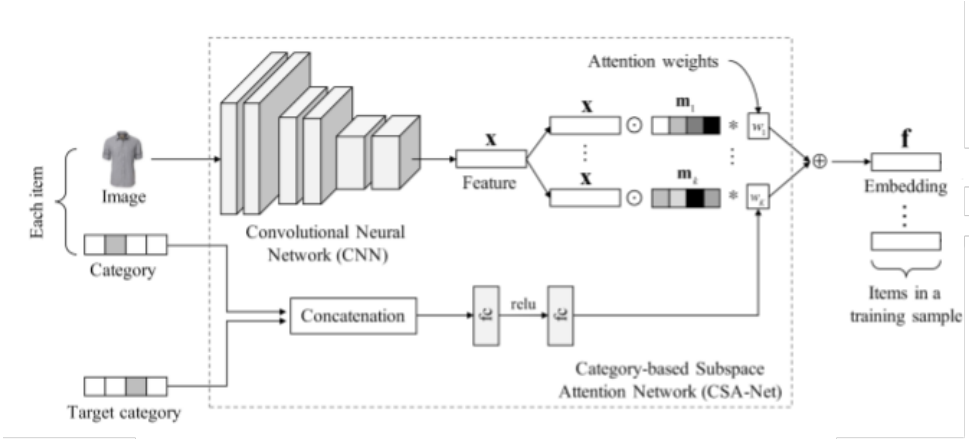
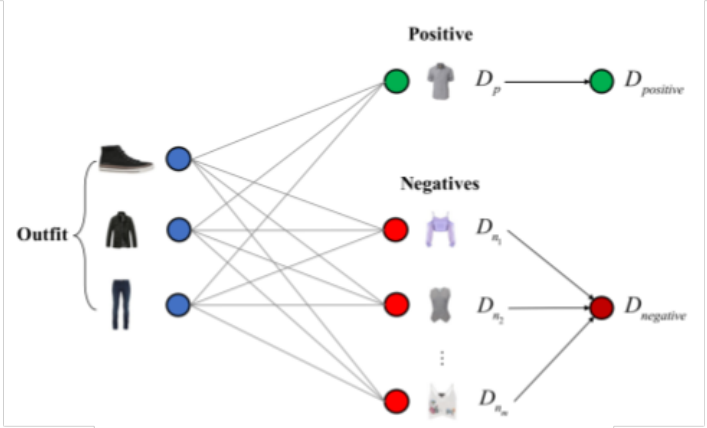
Implementations

Shared Subspaces with attention [9]





$$l(O, p, N) = \max(0, D_p - D_N + m)$$

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Indian Compatibility	Diversity in Outfit generation	Style
Indian preferences are different from the people in the west	E-commerce platforms need diverse outfits for diverse users	How to deal with different Styles?

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PS1: Indian Compatibility

a Difference in *compatibility* notion - color heavy matching

Western Dataset

Indian example

b Negative Sampling is hard for some categories, e.g. jeans

c Ethnic/Indian categories are not present in existing datasets

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PS1: Indian Compatibility

Problem Statement: Learn *Indian-compatibility* between fashion items.

Data Generation

a Feedback App - Manual annotations for to get positives and negatives

b Fashion Apparel Segmentation and Localisation

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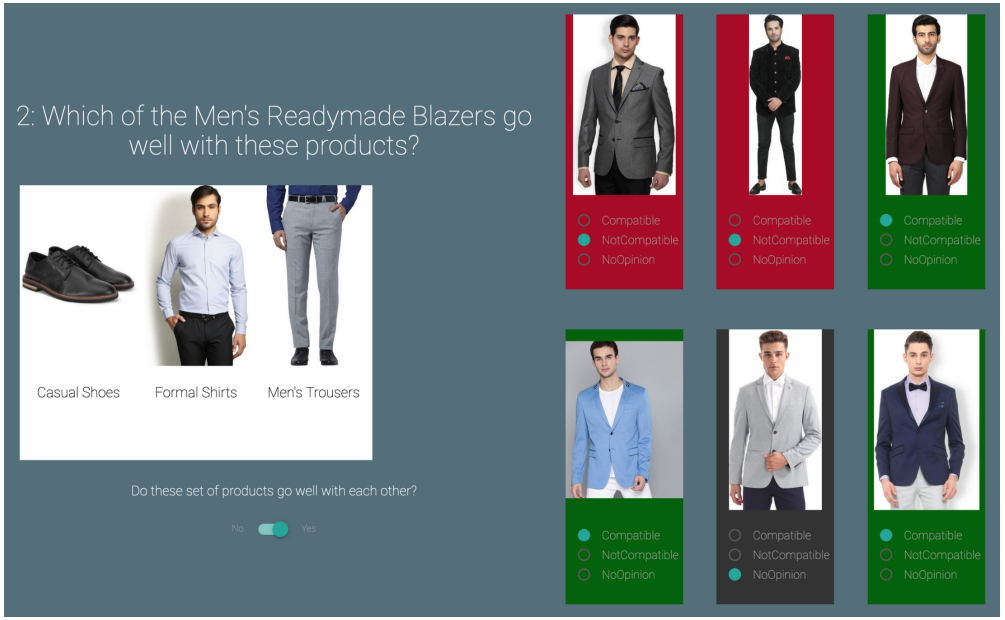

Feedback App used by the annotators to get Indian Compatibility Data

Segmentation Modules for Upperbody, Wholebody, Lowerbody

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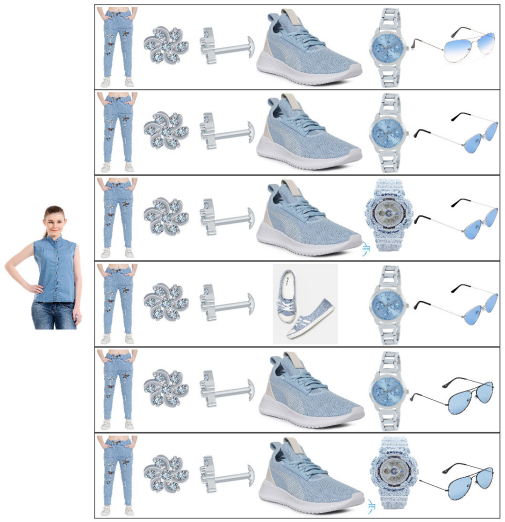
PS2: Diversity in outfit generation - Beam Search

Once a compatibility space is learnt, how to produce outfit for a given 'hero' product? - Answer from text generation methods - Beam Search



Problem with Beam Search: Very similar outputs at the end.

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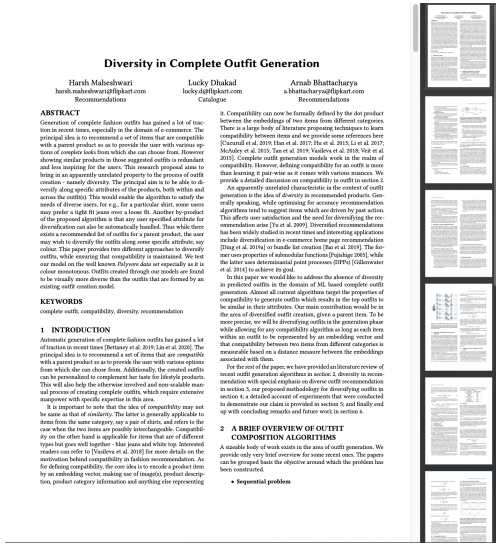
PS2: Diversity in outfit generation - Diverse BS

Diverse Beam Search [13] - Solves this problem by penalising similarity during beam selection.

PS2: Diversity in outfit generation - DPP-BS

- Determinantal Point Process: Popular algorithm in the recommendations domain to sample diverse points.
- We propose Beam Search where beams at each step are sampled using DPP.
- WIP

We submitted our work on Diversity in Outfit Generation in Flipkart's internal Data Science Annual Conference 2021.



Diversity in Complete Outfit Generation

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ABSTRACT

Generation of complete fashion outfits has gained a lot of traction in recent times, especially in the domain of e-commerce. The principal idea is to recommend a set of items that are compatible with a parent product so as to provide the user with various options of complete looks from which she can choose from. However showing similar products in those suggested outfits is redundant and less inspiring for the users. This research proposal aims to bring in an apparently unrelated property to the process of outfit creation - namely diversity. The principal aim is to be able to diversify along specific attributes of the products, both within and across the outfit(s). This would enable the algorithm to satisfy the needs of diverse users, for e.g., for a particular shirt, some users may prefer a tight fit jeans over a loose fit. Another by-product of the proposed algorithm is that any user specified attribute for diversification can also be automatically handled. Thus while there exists a recommended list of outfits for a parent product, the user may wish to diversify the outfits along some specific attribute, say colour. This paper provides two different approaches to diversify outfits, while ensuring that compatibility is maintained. We test our model on the well known *Polyvore data set* especially as it is colour monotonous. Outfits created through our models are found to be visually more diverse than the outfits that are formed by an existing outfit creation model.

KEYWORDS

complete outfit, compatibility, diversity, recommendation

1 INTRODUCTION

Automatic generation of complete fashion outfits has gained a lot of traction in recent times [Bettaney et al. 2019; Lin et al. 2020]. The principal idea is to recommend a set of items that are compatible with a parent product so as to provide the user with various options from which she can choose from. Additionally, the created outfits can be personalized to complement her taste for lifestyle products. This will also help the otherwise involved and non-scalable manual process of creating complete outfits, which require extensive manpower with specific expertise in this area.

It is important to note that the idea of *compatibility* may not be same as that of *similarity*. The latter is generally applicable to items from the same category, say a pair of shirts, and refers to the case when the two items are possibly interchangeable. Compatibility on the other hand is applicable for items that are of different types but goes well together - blue jeans and white top. Interested readers can refer to [Vasileva et al. 2018] for more details on the motivation behind compatibility in fashion recommendation. As for defining compatibility, the core idea is to encode a product item by an embedding vector, making use of image(s), product description, product category information and anything else representing it. Compatibility can now be formally defined by the dot product between the embeddings of two items from different categories. There is a large body of literature proposing techniques to learn compatibility between items and we provide some references here [Cucurull et al. 2019; Han et al. 2017; Hu et al. 2015; Li et al. 2017; McAuley et al. 2015; Tan et al. 2019; Vasileva et al. 2018; Veit et al. 2015]. Complete outfit generation models work in the realm of compatibility. However, defining compatibility for an outfit is more than learning it pair-wise as it comes with various nuances. We provide a detailed discussion on compatibility in outfit in section 2.

An apparently unrelated characteristic in the context of outfit generation is the idea of *diversity* in recommended products. Generally speaking, while optimizing for accuracy recommendation algorithms tend to suggest items which are driven by past action. This affects user satisfaction and the need for diversifying the recommendation arise [Yu et al. 2009]. Diversified recommendations has been widely studied in recent times and interesting applications include diversification in e-commerce home page recommendation [Ding et al. 2019a] or bundle list creation [Bai et al. 2019]. The former uses properties of submodular functions [Fujishige 2005], while the latter uses determinantal point processes (DPPs) [Gillenwater et al. 2014] to achieve its goal.

In this paper we would like to address the absence of diversity in predicted outfits in the domain of ML based complete outfit generation. Almost all current algorithms target the properties of compatibility to generate outfits which results in the top-outfits to be similar in their attributes. Our main contribution would be in the area of diversified outfit creation, given a parent item. To be more precise, we will be diversifying outfits in the generation phase while allowing for any compatibility algorithm as long as each item within an outfit to be represented by an embedding vector and that compatibility between two items from different categories is measurable based on a distance measure between the embeddings associated with them.

For the rest of the paper, we have provided an literature review of recent outfit generation algorithms in section 2, diversity in recommendation with special emphasis on diverse outfit recommendation in section 3, our proposed methodology for diversifying outfits in section 4, a detailed account of experiments that were conducted to demonstrate our claim is provided in section 5, and finally end up with concluding remarks and future work in section 6.

2 A BRIEF OVERVIEW OF OUTFIT COMPOSITION ALGORITHMS

A sizeable body of work exists in the area of outfit generation. We provide only very brief overview for some recent ones. The papers can be grouped basis the objective around which the problem has been constructed.

- **Sequential problem**

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PS3: Dealing with *Style*

- How to define *Style*?
  - a Product Level - Can be based on attributes [4] or latent [8]
  - b Outfit Level - Could be themes like Formal, Casual; Could be occasions like Dating, Travel etc.[7, 11]

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- How to define *Style*?
  - a Product Level - Can be based on attributes [4] or latent [8]
  - b Outfit Level - Could be themes like Formal, Casual; Could be occasions like Dating, Travel etc.[7, 11]
- Problem Statement: Reference Style guided outfit creation - Given a 'hero' product and a catalogue, generate an outfit 'inspired' by the *style* of a reference outfit. The inspiration is constrained to known *styles*.

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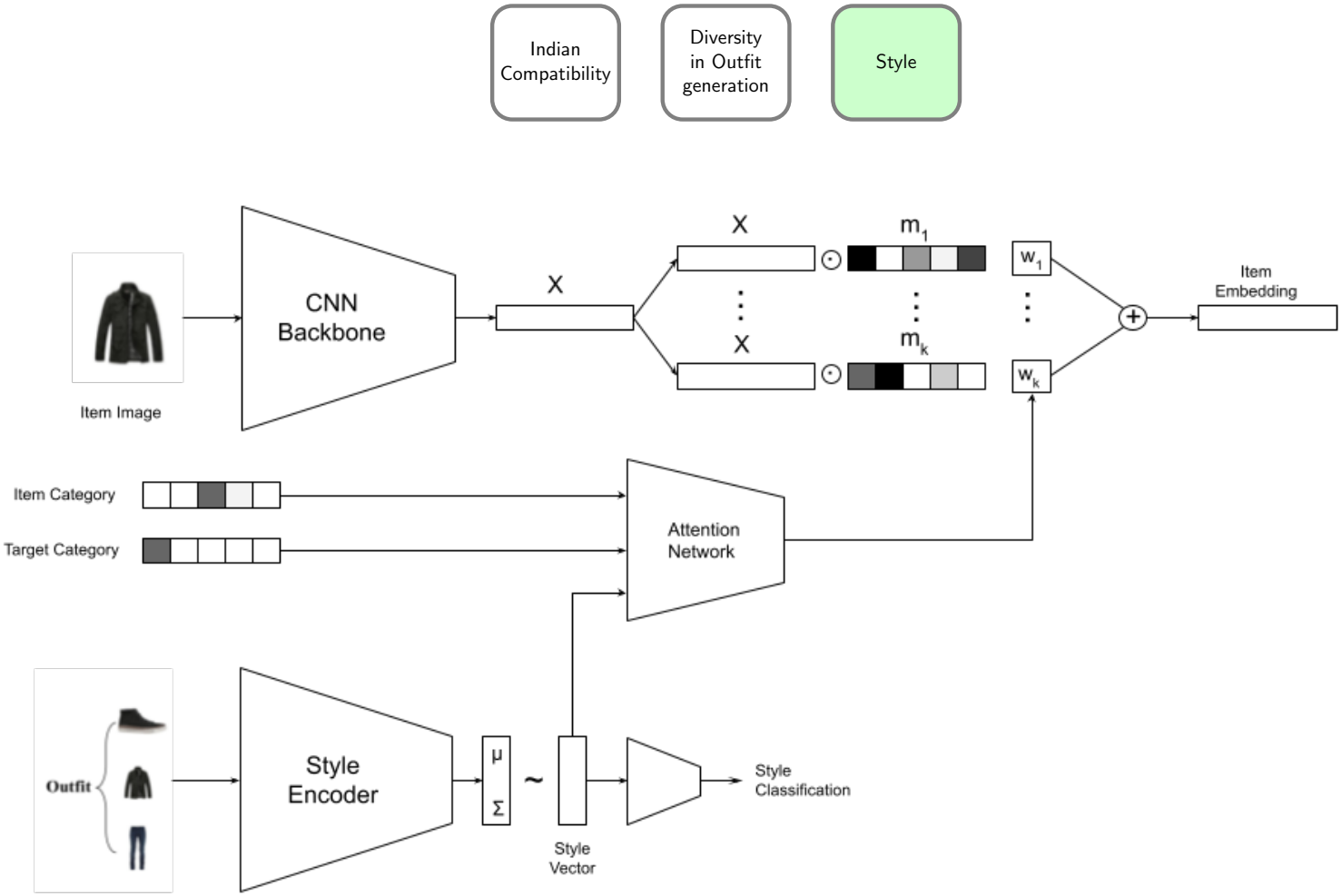

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