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Data Mining Techniques for Fashion Outfit Composition : A Review

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ABSTRACT

Composing fashion outfits involves deep understanding of fashion standards while incorporating creativity for choosing multiple fashion items (e.g., Jewelry, Bag, Pants, Dress). In fashion websites, popular or high-quality fashion outfits are usually designed by fashion experts and followed by large audiences. In this paper we provide a brief review on various data mining techniques and algorithms proposed by different authors for implementing proper fashion outfit composition.
Keywords : SVM, Genetic, Composition

I. INTRODUCTION

Fashion style tells a lot about the subject's interests and personality. With the influence of fashion magazines and fashion industries going online, clothing fashions are attracting more and more attention. According to a recent study by Trendex North America1 , the sales of woman's apparel in United States is $111 Billion in 2011 and keeps growing, representing a huge market for garment companies, designers, and e-commerce entities. Different from well-studied fields including object recognition [1], fashion sense is a much more subtle and sophisticated subject, which requires domain expertise in outfit composition. Here an "outfit" refers to a set of clothes worn together, typically for certain desired styles. To find a good outfit composition, we need not only follow the appropriate dressing codes but also be creative in balancing the contrast in colors and styles. Normally people do not pair a fancy dress with a casual backpack, however, once the shoes were in the outfit, it completes the look of a nice and trendy outfit. Although there have been a number of research studies [2] [3] [4] on clothes retrieval and recommendation, none of them considers the problem of fashion outfit composition. This is partially due to the difficulties of modeling outfit composition: On one hand, a fashion concept is often subtle and subjective, and it is nontrivial to get consensus from ordinary labelers if they are not fashion experts. On the other hand, there may be a large number of attributes for describing fashion, for which it is very difficult to obtain exhaustive labels for training. As a result, most of the existing studies are limited to the simple scenario of retrieving similar clothes, or choosing individual clothes for a given event. Fashion plays an increasingly significant role in our society due to its capacity for displaying personality and shaping culture. Recently, the rising demands of online shopping for fashion products motivate techniques that can recommend fashion items effectively in two forms (1) suggesting an item that fits well with an existing set and (2) generating an outfit (a collection of fashion items) given text/image inputs from users. However, these remain challenging problems as they require modeling and inferring the compatibility relationships among different fashion categories that go beyond simply computing visual similarities. Extensive studies have been conducted on automatic fashion analysis in the multimedia community. However, most of them focus on clothing parsing [9, 26], clothing recognition [12], or clothing retrieval [10].

II. LITERATURE REVIEW

Outfit composition has been a recent study of research, many researchers have proposed various techniques for doing the same. In [2], they proposed the enchantment storage room framework which consequently prescribes the most appropriate dress by considering the wearing legitimately and wearing stylishly standards. Restricted by the present execution of human indicator, some attire in the client's apparel photograph collection might be misled. In [3], they presented a new learning framework that can recover a stylized space for clothing items from concurrence Information as well as category labels. The algorithm used in this paper was old and not feasible as compared to our approach. A clothing parsing method based on fashion image retrieval [4]. In which system combines global parse models, nearest neighbor parse models, and transferred parse predictions. This paper did not consider the mixed fashion tradition like ours does. Here the problem is of cross-scenario clothing retrieval given that a daily human photo captured in general environment it [5] only considered the outfit which people are wearing i.e. trending outfit. In [6], they address the issue of cross-area picture recovery, considering the accompanying down to earth application: given a client photograph delineating a dress picture, objective of paper is to recover the same or trait comparable apparel things from web based shopping stores. To address this issue, they proposed a Dual Attribute-mindful Ranking Network (DARN) for recovery include learning. All the more particularly, DARN comprises of two sub- systems, one for every space, whose recovery highlight portrayals are driven by semantic characteristic learning. In [7], they exhibit a viable framework, enchantment wardrobe, for programmed event situated dress matching. Given a client input event, e.g., wedding or shopping, the enchantment storage room shrewdly and naturally combines the client determined reference garments (abdominal area or lower-body) with the most appropriate one from online shops. Limited by the present execution of human finder, some attire in the client's dress photograph collection might be misled. In [8] it depicts the formation of this benchmark dataset and the advances in question acknowledgements that have been conceivable subsequently. We talk about the difficulties of gathering huge scale ground truth comment, feature enter leaps forward in clear cut protest acknowledgement, give a nitty gritty examination of the present state of the field of huge scale picture classification and protest discovery, and analyses the best in class PC vision exactness with human precision. We finish up with lessons learned in the five years of the test, also, propose future headings and enhancements. In [12] they break down and make express the model properties required for such regularities to develop in word vectors. The outcome is another worldwide log-bilinear relapse demonstrates that consolidates the benefits of the two noteworthy model families in the writing: worldwide framework factorization and neighborhood setting window techniques. Our model proficiently influences measurable data via preparing just for the non-zero components in a word-word co-occurrence network, instead of on the whole meager network or on singular setting windows in an extensive corpus. The model produces a vector space with important substructure, as confirm by its execution of 75% on a current word similarity assignment. It likewise beats related models on similitude undertakings and named element acknowledgement.

SiameseNet [24]. SiameseNet utilizes a Siamese CNN to project two clothing items into a latent space to estimate their compatibility. To compare with SiameseNet, we train a network with the same structure by considering fashion items in the same outfit as positive compatible pairs and items from two different outfits as negative pairs. The compatibility of an outfit is obtained by averaging pairwise compatibility, in the form of cosine distance in the learned embedding, of all pairs in the collection. For fair comparisons, the embedding size is also set to 512. We also normalize the embedding with $\ell 2$ norm before calculating the Siamese loss, and set the margin parameter to 0.8. SetRNN [8]. Given a sequence of fashion images, SetRNN predicts the fashion set popularity using an RNN model. We use the popularity prediction of SetRNN as the set compatibility score. Visual-semantic Embedding (VSE). We only learn a VSE by minimizing Ee in Eqn. 5 without training any LSTM model. The resulting embeddings are used to measure the compatibility of an outfit, similar to SiameseNet. Bi-LSTM. Only a bidirectional LSTM is trained without incorporating any semantic information. F-LSTM+VSE. Jointly training the forward LSTM with visualsemantic embedding, i.e., minimizing Ef + Ee . B-LSTM+VSE. Similarly, only a backward LSTM is trained with visual-semantic embedding, i.e. minimizing Eb + Ee . Bi-LSTM+VSE. Our full model by jointly learning the bidirectional LSTM and the visual-semantic embedding. The first two approaches are recent works in this line of research and the remaining methods are used for ablation studies to analyze the contribution of each component in our proposed framework. The hyper-parameters in these methods are chosen using the validation set.

Patterns are commonly used to capture knowledge and experience about proven solutions for recurring problems (Reiners, 2013). In the past, patterns and pattern languages have been used in various di↵erent research domains (Alexander et al, 1977; Hohpe and Woolf, 2003). In literature, discovering patterns is described as a generative process and is referred as pattern mining (Dearden and Finlay, 2006; Appleton, 1997), which is a metaphor for discovering patterns from existing designs (Dearden and Finlay, 2006). Reiners et al. propose di↵erent pattern mining methods (Reiners, 2013; Reiners et al, 2015). A pattern mining process in their perspective is a manual assessment of existing solutions with domain experts, e.g., in workshops, and relies heavily on the experts' experience. In addition to workshops, a community-based platform with online discussions, commenting, rating, and voting is used to share knowledge and to assess existing solutions. Fehling et al (2015) propose a pattern research methodology where pattern candidates shall be identified from concrete solutions, which are then linked to the abstracted patterns (Falkenthal et al, 2014a,b). In another research, Fehling et al (2014) published a general pattern identification, authoring, and application process, which is applicable for several research domains. The iteration-based process consists of three phases: (i) pattern identification, (ii) pattern authoring, and (iii) pattern application. Each phase is broken down into a separate cycle that consists of multiple sub-activities. Our work applies to the phase pattern identification, which is the structuring, collection, and analysis of information in a domain in which patterns shall be identi- fied. Following this method, we build upon a Costume Repository that contains a large number of documented concrete solutions. Moreover, this repository provides a machine-accessible interface that can be used for analyzing the contained data. We provide details about these approaches in Section 3. Fayyad et al (1996) introduce the process of Knowledge Discovery in Databases (KDD). KDD refers to the overall process of discovering useful knowledge from data. This process incorporates the concepts of data mining and proposes a comprehensive approach to identify potential coherences in data. Our approach bases on the KDD process in order to analyze existing documented solutions for potential pattern indicators in the area of costumes in films. Data mining can be used to "discover hidden, previously unknown and usable information from a large amount of data" (ISO, 2006). Data mining techniques are used to gather knowledge from an underlying data set for a better understanding usually without any expectation on the outcome (ISO, 2006). The Apriori algorithm, as proposed by Agrawal and Srikant (1994), is one well-known algorithm in the area of data mining. It is used for discovering association rules between items in a database of sales transactions (Agrawal and Srikant, 1994). As a prominent example, consider the market basket analysis, helping retailers to find out, which of their offered products are typically sold in combination with other products. The resulting association rules can be used, for example, to optimize the store layout or to adapt the advertising strategy of the retailer.

III. CONCLUSION

In this paper, we consider the challenging problem of fashion outfit composition, which reflects the difficulties of matching domain expert knowledge and modeling the diversity in fashion. We studied the work done by various authors in their studies and evaluated as Genetic algorithm is most suitable for performing composition for fashion outfits.

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