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| S.no | Journal name | Algorithms | Parameters | Advantages | Future Enhancements |
| 1 | “Explainable Outfit Recommendation with Joint Outfit Matching and Comment Generation” , Yujie Lin, Pengjie Ren, Zhumin Chen, Zhaochun Ren, Jun Ma, and Maarten de Rijke, 2020 | Neural Outfit Recommendation (NOR)  Convolutional Neural Network  Recurrent Neural Network | NOR has 2 parts - Outfit Matching and Comment generation  Convolutional Neural Network - Outfit matching  Recurrent Neural Network - Comment generation | Overcomes the following problems  -compatibility of fashion factors  -transformation of visual and textual information | Identify negative sentiments along with the positive ones  Generate longer comments  Incorporate auto-encoder to improve further performance  Build a personalized outfit recommendation system |
| 2 | “EPYNET: Efficient Pyramidal Network for Clothing Segmentation”, Andrei De Souza Inacio and Heitor Silverio Lopes, 2020 | Single Shot MultiBox Detector (SSD)  Feature Pyramid Network (FPN) | Integrates data augmentation methods and noise reduction techniques to increase accuracy  Propose a new dataset named UTFPR-SBD3, consisting of 4500 manually annotated images  Introduce a new measure of dataset imbalance | Possible to detect the influence of background, classes with small items, or classes with a too high or too low number of instances | Handle illumination changes better to enhance the discrimination between similar objects |
| 3 | “Aspect-Based Fashion Recommendation With Attention Mechanism”, Weiqian Li and Bugao Xu, 2020 | Aspect-based fashion recommendation model with attention mechanism (AFRAM) has two parallel paths  - Convolutional Neural Networks  - Long short-term memory networks (LSTM) | One path processes user reviews and other copes with item reviews | With real-world customer reviews and ratings collected from two renowned business websites, AFRAM outperformed the five state-of-the-art recommenders in terms of accuracy of predicting customer ratings |  |
| 4 | “Modeling Instant User Intent and Content-Level Transition for Sequential Fashion Recommendation”, Yujuan Ding, Yunshun Ma, Wai Keung Wong and Tat-Seng Chua, 2022 | Attentional Content-level Translation-based Recommender (ACTR) that simultaneously uses instant user intent of each translation and the intent-specific transition probability | Define instant relationships between adjacent items that the user interacted, which are the three fundamental domain-specific relationships of: match, substitute and others  Augment item-level transition modelling with multiple sub-transitions | First work that specifies the implicit user actions in online fashion shopping with explicit instant intent | Focus on long-term intent or intent in certain session  Appying ACTR to other variety of E-commerce categories, rather than just fashion |
| 5 | “A3-FKG: Attentive Attribute-Aware Fashion Knowledge Graph for Outfit Preference Prediction”, Huijing Zhan, Jie Lin, Kenan Emir Ak, Boxin Shi, Ling-Yu Duan and Alex C. Kot, 2021 | Knowledge Graph Embedding (KGE) algorithm to encode KG into low-dimensional entity and relation embedding  Graph Convolutional Networks (GCNs)  Graph Attention Networks (GATs)  Relational Graph Convolutional Network (R-GCN) | Two-level attention mechanism  - User-specific relation-aware attention layer which captures the user’s fine-grained preferences  - Target-aware attention layer which characterizes the user’s latent diverse interests | Estimates the user’s preference towards the outfit | Attempt to borrow the domain knowledge of clothing matching rules into the construction of fashion-aware knowledge graph |
| 6 | “Tripartite Graph Regularized Latent Low-rank Representation for Fashion Compatibility Prediction”, Peiguang Jing, Jing Zhang, Liqiang Nie, Shu, Ye, Jing Liu, Yuting Su, 2021 | Compositional Network (Comp-Net)  Graph Reasoning Network (GRNet)  Laplacian model  With Low-rank Representation Learning (LLR) in hand, an improved version of (LatLLR) Latent LLR was proposed | In TGRLLR, the latent low-rank representation is considered by decomposing the original feature matrix in both column and row directions to tackle the problem of insufficient observation | Tackles insufficient training samples and sparsity problems | Improve generalization ability when used for large-scale scenarios  Focus on developing an end-to-end convolutional neural network to better deal with fashion compatibility prediction tasks |
| 7 | “Visual and Textual Jointly Enhanced Interpretable Fashion Recommendation”, Qianqian Wu, Pengpeng Zhao, and Zhiming Cui, 2020 | Bi-directional two-layer adaptive attention review model  Review-driven visual attention model | Capture the user’s visible and invisible preferences to the target product and provide textual explanations by highlighting some words  Get personalized image representation driven by user’s preference obtained from historical review | Highlights on the invisible features as material and quality of the clothes  Offers both visual and textual explanations | Focus on how to further dig more accurate and effective user preference information in the review information  Consider effectively mining the internal connection between user reviews and product images |