Flipkart

GRiD 5.0

Problem Statement Title:

Conversational Fashion Outfit Generator powered by GenAI.

Team Name:

686157-U4DY86T5 (KILLER QUEEN)

Team members details

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Institute Name/Names	BIT MESRA		
Team Members >	1 (Leader)	2	3
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Batch	IT K21 3rd Year	IT K21 3rd Year	IT K21 3rd Year

Deliverables/Expectations for Level 2 (Idea + Code Submission)

We create a Outfit Generator that takes in account:

- User's past preferences
- Occasion
- Locality
- Age
- insights from social media trends to offer tailored and on-trend outfit recommendations

And can also take feedback in a conversational way and edit the outfit accordingly.
We propose the following Solution.

Literature Review and Research Paper Analysis

1905.01866

The paper presents a method called "POG" that generates personalized fashion outfits for online shoppers based on their preferences and compatibility.

1904.00741

The paper addresses the challenge of automatically generating fashion outfits that match a given item, aiming to provide scalable and personalized outfit recommendations.

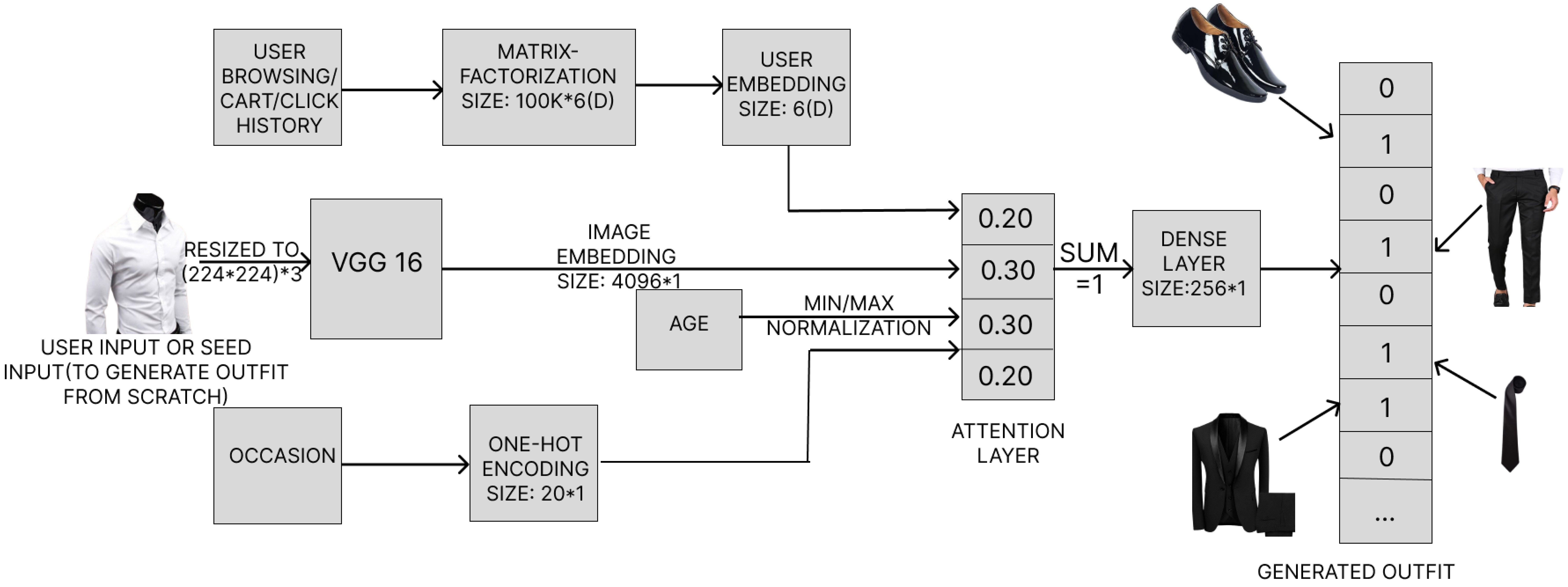
Limitation of the above papers:

- The length of these outfits are fixed. It does not offer flexibility.
- Selects all item in one go and has no Feedback System.
- All use similarity scores which is memory based and hence very slow.

Use-cases

(a) Everyday Outfit Inspiration
(b) Special Occasions
(c) Feedback Loop
(d) Travel Wardrobe Planning
(e) Fashion Confidence (emotional aspect)
(f) Seasonal Updates
(g) Discovery of New Brands
(h) Personal Style Exploration.
(i) Incorporating Social Media Trends

Solution statement/ Proposed approach



OUTFIT GENERATOR USING MULTILEVEL CLASSIFICATION

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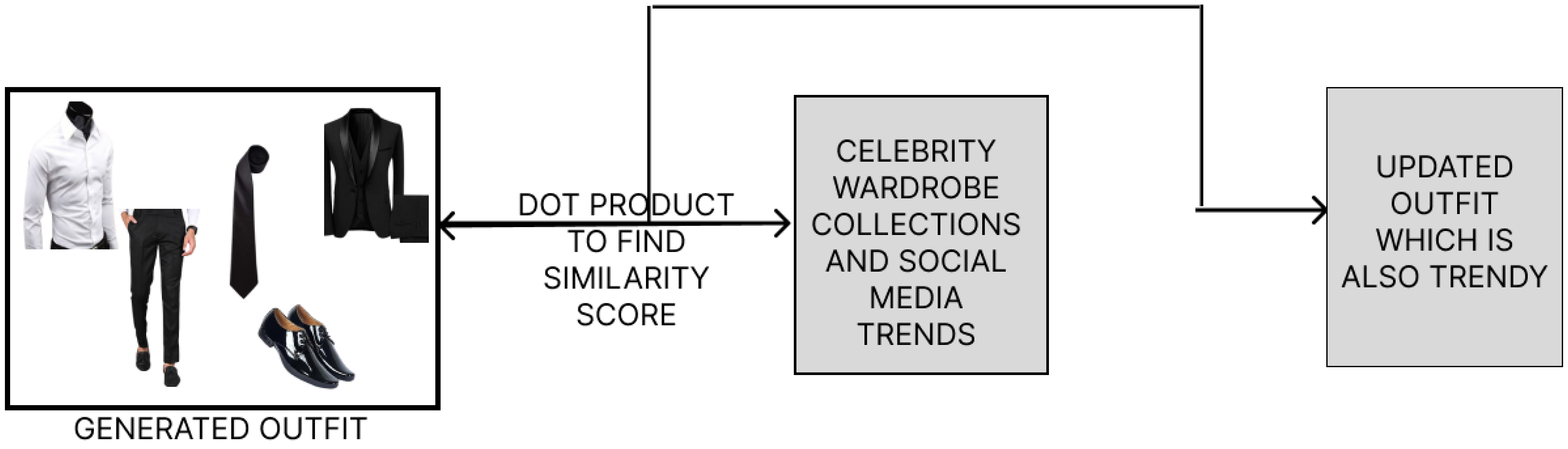
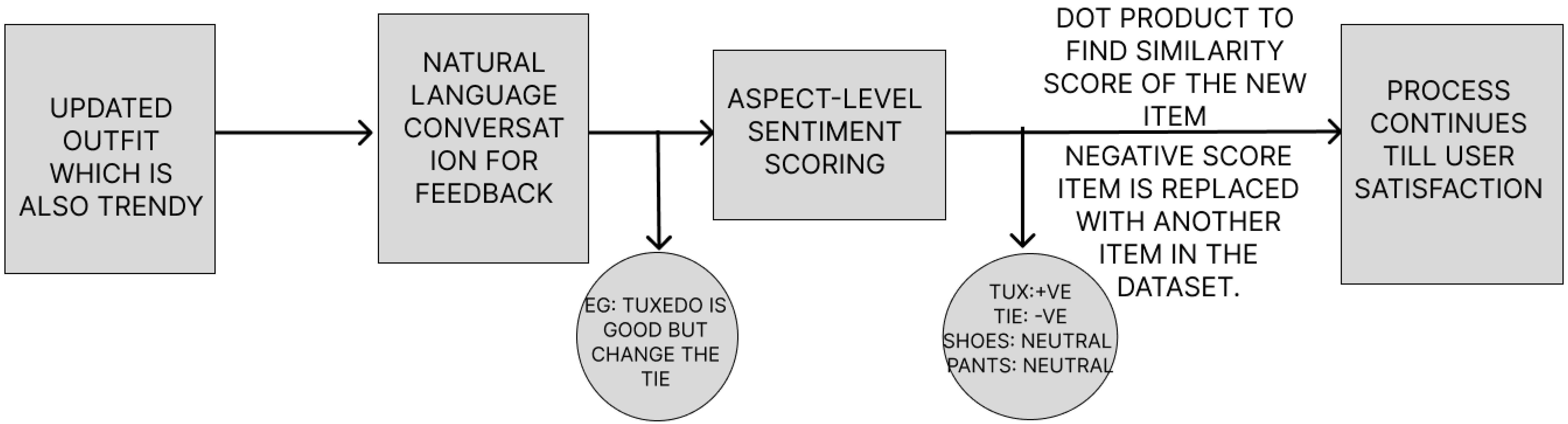


TO FIND CLOSEST MATCH IN CELEBRITY WARDROBE COLLECTIONS. THE ITEMS THAT CLOSELY RESEMBLE ANY ITEM FROM THE COLLECTION IS SWAPPED. HENCE OUTFIT ADHERES TO MODERN TRENDS



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Explanation

As the given problem statement is quite feature demanding, our solution is an amalgamation of different components which are briefly described below:

1. Initial Outfit Generation->

a. Attention Layer: This pre-trained model which is responsible for assigning weights to the multiple inputs based on their importance in selecting the outfit. It’s output is directed to the dense layer. The inputs of the attention layer are as explained below-:

i. User input/Seed input – This item initiates the generation of the entire outfit. This seed m be given by the user or generated based on the other inputs (occasion, past history, etc) given the user. This image is then processed through a pre-trained model “Resnet -50” (or “VGG -16”) whi generates an image embedding.

ii. Occasion – This is the occasion as specified by the user which is then ‘one-hot encoded’ into a binary vector.

iii. User browsing/cart/purchased items- This includes converting 3 matrices containing user browsing(clicks) history matrix, purchase history matrix & cart history matrix, into 3 user embeddings using ‘Matrix Factorization’ method.

iv. Age – This involves normalization of the user’s age using ‘min/max normalization’

b. Dense Layer – This is an interconnected network of neurons trained on our dataset, which helps the network learn and make predictions.

c. Initial Generated outfit – This is output of the dense layer and includes 1 complete outfit based on the inputs given.

2. Social Media Trend

a. Takes initial outfit generated as input.

b. Uses celebrities’ wardrobe items as a representative of current social media trends/fads.

c. Find out the similarity score between the generated outfit and wardrobe items.

d. If similarity is quite high, then that item is swapped with the corresponding wardrobe item.

e. Now this final outfit is presented to the user for their feedback.

3. User feedback & outfit modification

a. Feedback from the user is passed through a Natural Language Processing (NLP) model, which extracts useful information from the sentence and presents it in a form understandable by the next layer.

b. Now ‘aspect level sentiment analysis’ is done which interprets whether to modify certain outfit items or finalize the current outfit. It then scores items, where a higher score means replacement is wanted by the user.

c. If modification is required, items with high score are sent back to the dense layer to processed again according to the feedback inputs.

d. This process repeats until no further modifications are required by the user.

4. Final outfit is presented to the user.

Evaluation of the Model

Accuracy:

- Formula: (True Positives + True Negatives) / Total Samples
- Description: tells you how often your model's predictions are correct overall.

Precision:

- Formula: True Positives / (True Positives + False Positives)
- Description: tells you how many of the items your model predicted as positive are actually positive.

Recall:

- Formula: True Positives / (True Positives + False Negatives)
- Description: tells you how many of the actual positive items your model was able to predict.

F1 Score:

- Formula: 2 * (Precision * Recall) / (Precision + Recall)
- Description: provides a balance between Precision and Recall, especially in scenarios where the class distribution is imbalanced.

Limitations

- Cold start
- inaccurate output of attention layer due to unaccounted factors ,i.e., weights assigned are not accurate according to real world.
- As we aren’t taking INPUT in a conversational way, users might not be able to convey what they desire.

Future Scope

(a) Sustainable Fashion Choices.

(b) Augmented Reality Integration (lenskart tryon)

(c) Cultural and Historical Styles.

(d) Collaborative Outfit Planning.

(e) AI-Personalized Fashion Blogs:

Thank You