Flipkart

GRiD 5.0

Problem Statement Title: Personalized Product Recommendations

Institute Name: Indian Institute of Technology (BHU), Varanasi

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

- ❑ Idea is mentioned in below slides and code is submitted in zip file along this pdf

Glossary

- BERT- Bidirectional Encoder Representations from Transformers
- MAML- Model-Agnostic Meta-Learning

Instructions (You Can Delete this Slide)

Dear Team,

Congratulations on reaching this stage - We look forward to some amazing & innovative solutions.

Please find some important instructions before you begin to prepare your submission decks.

Slide Limit : 10 Slides of Content **post (after)** this Slide
Saving Format : Save the file as a PDF to ensure your formatting remains intact
Submission Guide: Only the **'Team Leader'** will be able to submit the Deck.
Only the latest submission will be considered as final
(You can keep updating your deck within the deadline)

Wishing you all the very best !

Team Flipkart GRiD

Use-Cases:

- The model's inherent adaptability, fortified by sentiment analysis and Model-Agnostic Meta-Learning, empowers it to transcend domain boundaries, making it applicable across diverse datasets. This architectural flexibility, rooted in sentiment-driven insights, underpins its capacity to offer robust personalized recommendations in various contexts.

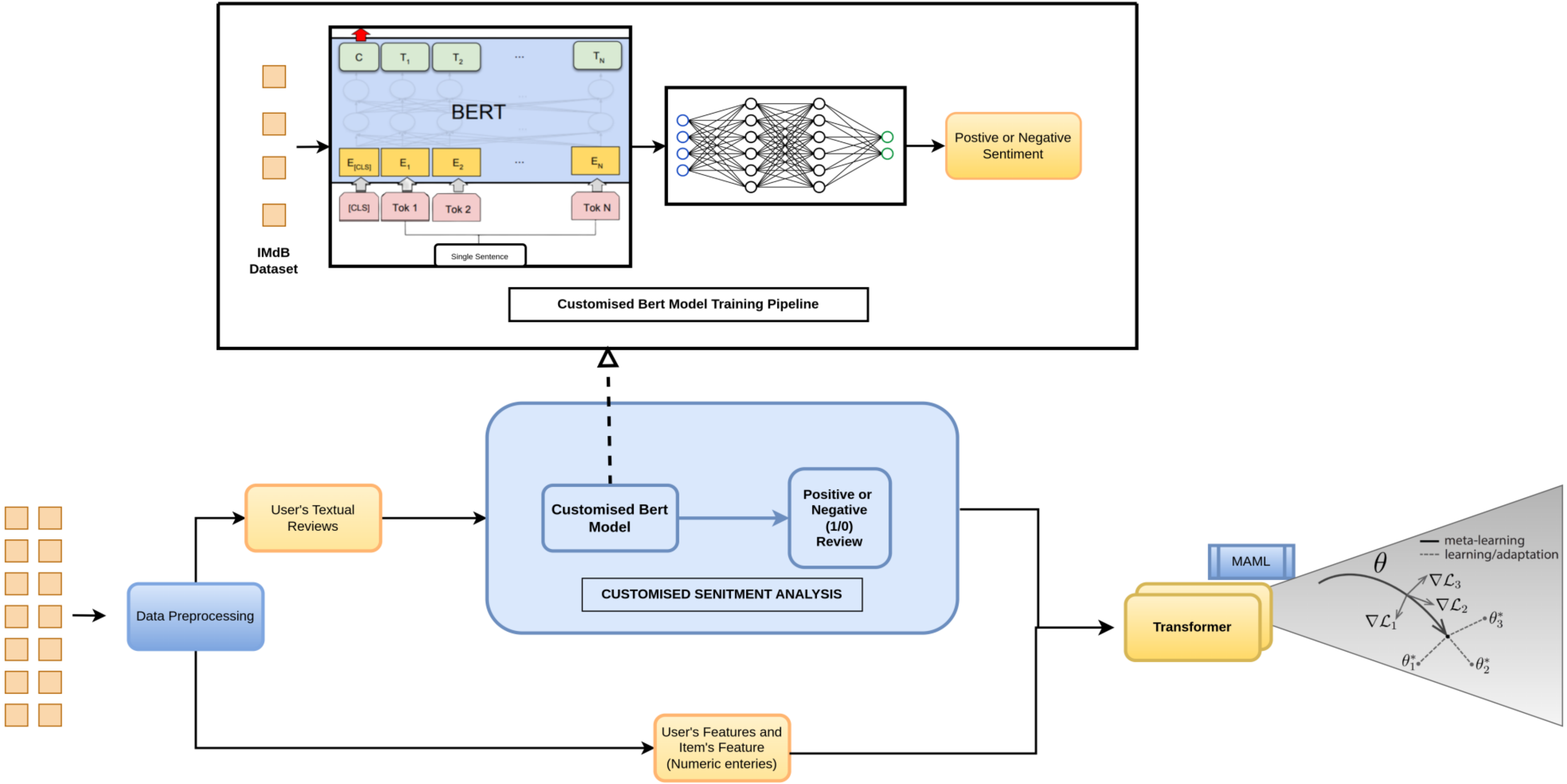
- Utilize sentiment analysis of user reviews and summaries to influence the ranking of products. Positive sentiments can lead to higher rankings, ensuring that products aligned with positive sentiments are prominently featured.

- Address the cold start problem for new users by leveraging sentiment analysis and user demographics to generate accurate recommendations from the outset.

- Use sentiment analysis on user feedback to understand areas of improvement, enabling continuous refinement of the recommendation system based on user sentiments.

- Detect emerging clothing trends by analyzing sentiment patterns associated with specific products or styles, allowing the system to identify and promote trends favored by users.

BLOCK DIAGRAM:



Solution Statement(Proposed Approach):

Here we use the dataset of the clothing industry. In the context of the clothing industry, the present study addresses the challenge of personalised product recommendations by devising **a multi-stage algorithmic approach**. The proposed system employs sentiment analysis in conjunction with **a transformer-based recommendation model**, coupled with the utilisation of **the Model-Agnostic Meta-Learning (MAML) algorithm**. Our primary objective is to enhance the user experience by tailoring product rankings based on individual preferences, historical interactions, sentiment, and product attributes.

In this model, we present a comprehensive approach that amalgamates sentiment analysis with **a customised BERT model**, **transformer-based modelling**, and **meta-learning** to devise an innovative personalised product ranking system for the clothing industry(taken dataset). We have started with the following points, which are mentioned below:

1) Sentiment Analysis with Customized BERT Model:

The Categorical features, encompassing review text and summary, were subjected to sentiment analysis using a customised **BERT (Bidirectional Encoder Representations from Transformers) model**. This facilitated the extraction of nuanced sentiment information from user-generated content, thereby helps in contributing to a holistic understanding of user preferences. BERT is pretrained on IMdB movie review dataset and finally used in training for sentiment based inputs.

2) Transformer Model for Personalized Recommendations:

We used a transformer-based recommendation model because it was adopted as the core of the personalised product ranking system. Transformers, renowned for their proficiency in processing sequential data, were leveraged to analyse review text, summary, and numerical features. The model exhibited an aptitude for generating personalised product rankings by encapsulating intricate patterns and interdependencies.

Solution Statement(Proposed Approach):

4. Model-Agnostic Meta-Learning (MAML):

We use the **Model-Agnostic Meta-Learning (MAML) algorithm** because it was incorporated to enable rapid adaptation of the recommendation model to individual user preferences. MAML's unique meta-learning capabilities empower the model to adapt quickly to new user profiles and preferences, enhancing the system's responsiveness.

5. Ranking system:

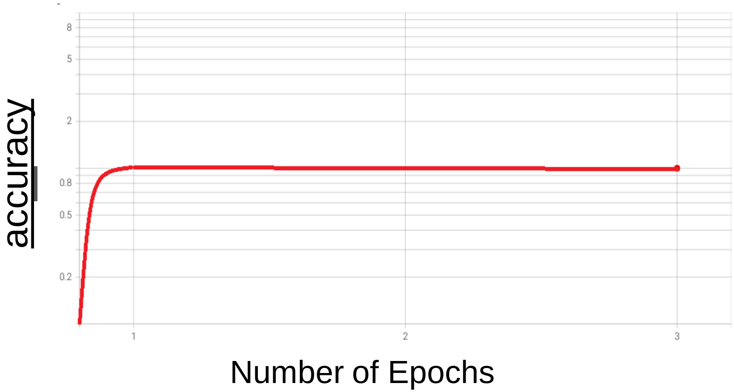
The model's ranking system employs a composite equation: **Ranking Score = 5 * (review_rating) + Quality**. Review_rating, generated by the **BERT model**(as shown in Block Diagram), encapsulates sentiment (0-1), while Quality, a dataset attribute, adds an intrinsic product dimension. This amalgamation integrates sentiment and quality for comprehensive product ranking.

- **Conclusion:**

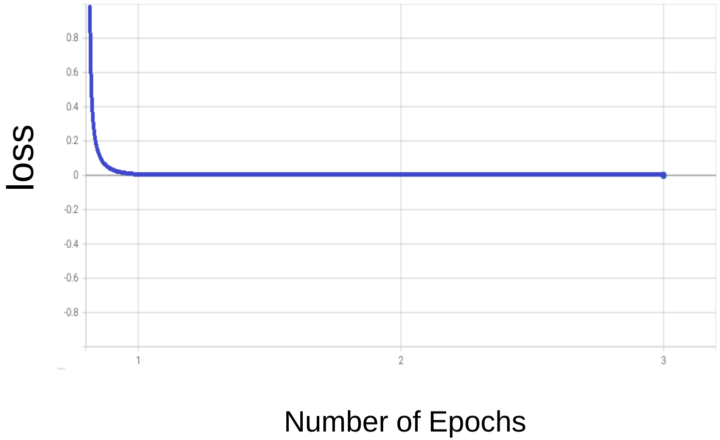
  The proposed approach, intertwining sentiment analysis, transformer-based modelling, and MAML showcases promise in achieving personalized product recommendations within the clothing industry(as we have taken the dataset of the clothing industry). By harnessing sentiment insights and adapting swiftly to user preferences, the system holds the potential for revolutionizing the e-commerce user experience.

Solution Statement(Proposed Approach):

- **RESULTS:**



Mean of total number of logits is equal to target in an Epoch



Cross Entropy
loss between logits and labels

Limitations

- The success of our recommendation system hinges on the caliber and comprehensiveness of our dataset. Here, we lack a substantial dataset that encompasses user sentiments, product characteristics, and past interactions within the realm of the clothing industry, it curtails the system's potential to uncover intricate trends and furnish accurate, tailored recommendations. The big and diverse datasets were found to be of 80 GB in compressed form !, this was beyond our access computation limits.

Future Scope

- The adoption of cutting-edge transformer architectures, such as T5 (Text-to-Text Transfer Transformer), could infuse the recommendation system with even more sophisticated language modeling capabilities, potentially yielding improved recommendations

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- Increasing the **diversification of datase**t to make it universal recommender system which supports **all products** which are on **Flipkart online shopping platform**.

- Incorporating multiple modalities beyond text, such as images or audio, could provide a comprehensive user profile. Combining sentiment cues from diverse modalities could offer richer insights into user preferences, leading to more accurate and holistic recommendations.

- Evolving user modeling strategies that consider temporal dynamics and evolving preferences could enhance the system's predictive accuracy, particularly in scenarios with rapidly changing trends or user behaviours.

- Designing mechanisms like Trend Tracker and User Feedback Loop for real-time adaptation to sudden shifts in user sentiment or preferences can elevate the system's agility and responsiveness, ensuring optimal recommendations in dynamic environments.

- Exploring the transferability of sentiment analysis and recommendation models across different domains could extend the solution's applicability to various industries beyond clothing, contributing to a broader spectrum of personalized experiences.

Thank You