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StreamBoostE: A Hybrid Boosting-Collaborative Filter Scheme for Adaptive User-Item Recommender for Streaming Services

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ABSTRACT

With home entertainment, selecting the perfect movie is a pervasive challenge, amplified by many streaming platforms like Netflix and Amazon Prime. This study advances a movie recommender system with collaborative filtering approach as implemented in Python titled StreamBoostE. We used the user-based and item-based similarity schemes on feature embedding to aid faster model construction and training for the tree-based gradient boosting ensemble. Employing both user- and item-based collaborative filtering with cosine similarity to ease feature embedding, the system assesses movies inter-relations via personalized user interest and preferences as submitted user titles with a focus on movie genre classification. Results shows the ensemble yields a recommender prediction accuracy of 0.9984 with F1 of 0.996. The major contribution of StreamBoostE is in its capability to expedite the movie selection process when integrated using flask API and streamlit for cross-channel integration in web-based platforms. It presents users with a list of top-10 recommended movies by genre similarity. The XGBoost ensemble performed best with the user-/item-based collaborative filtering scheme fused with feature embedding approach as a sampling method.

Keywords: Random Forest, SMOTE, credit card fraud detection, feature selection, imbalanced dataset

Aims Research Journal Reference Format:
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1. INTRODUCTION

Recommender systems have witnessed widespread adoption across various online platforms in recent years [1]. They are indispensable tools for suggesting personalized contents and products to users [2]. They are fundamentally designed to anticipate a users' interest and preferences so as to facilitate the discovery of relevant and related items [3] that will in turn, enhance a user's engagement with the associated contents [4]. Among the myriad and plethora of techniques adapted in recommender systems, collaborative filtering stands out as the most prominent, most prevalent and effective methodologies [5]. At the crux of these collaborative filtering [6]–[8] – is their capability to generate personalized rating predictions for a particular user simply by analysing patterns of user-item interactions as well as identifying the inherent similarities therein, between a user and the associated web-content items [9]–[11].

To leverage on the collective wisdom of user interactions cum feedback, collaborative filter heuristics infer user preferences and topical interest vis-a-vis recommend related items that tends to align with these associated interests and preferences [12]. This approach – tries to circumvents the need for explicit knowledge about a user or the content/items; And makes it preferably suitable for scenarios where such knowledge cum information may be scarce or incomplete [13]–[15]. In addition, collaborative filters usually offer as accompanying benefit – features such as adaptability, robustness, scalability, flexibility to new knowledge, and accommodation for large volumes of data as it adapts to evolving user interests cum preferences over time [16], [17]. Through techniques such as neighbourhood-based or matrix factorization methods, collaborative filtering algorithms [18]–[20] can effectively capture complex patterns in user-item interactions, enabling them to provide accurate and personalized recommendations across diverse domains and applications [21]–[23].

Summarily, collaborative filters epitomizes the frontier of new and cutting edge recommender systems – as it extrapolates the power of collective user feedback and interactions to deliver personalised, tailored user recommendations about contents (topics) that resonates the individual's interests and preferences [24]–[26]. Many websites, online platforms and portals today – have continued to explore, exploit and proliferate exponentially with the ever-increased growth in user-generated content(s) [27]. With such, the role of collaborative filters to refocus and reshape personalized user-experiences is repositioned and poised to become even more prominent [28]–[30], concretizing its status as a frontier methodology for recommendation systems [31]–[33]. The popularity of collaborative filter is attributed to its domain independence/dominance, scalability, and minimal requirement for additional user or item information beyond historical interactions [34]. But, traditional collaborative filters are degraded by data sparsity, cold start problems, and the difficulty of integrating additional contextual data [35]. To address these concerns in traditional collaborative filtering schemes – we adopt the machine learning scheme with a variety of other heuristics as ensemble feature [36]–[38].

The adoption of machine learning models as low-cost, computational alternatives to tradition schemes – have since yielded successfully trained heuristics and algorithms, which can effectively recognize user interests and preference patterns [39]. Machine learning (ML) models learns these patterns via features of interest, which helps them identify these patterns as signature classification that deviates from the norm [40]. A variety of ML have yielded resultant success with its adoption in collaborative filtering algorithm to include: Logistic Regression [41]–[43], Deep Learning [44]–[46], Bayesian model [47]–[49], Support Vector Machine [50]–[52], Random Forest [53]–[55], K-Nearest Neighbors [56]–[58], and in other models [59]–[61]. Their flexibility and performance is greatly hampered/degraded with the adopted choice in feature selection technique and data-preprocessing scheme [62], [63].

Thus, for our machine learning approach – we adopt/adapt the eXtreme Gradient Boost (XGBoost) ensemble with user- and item-based similarity collaborative filter technique, as fused with feature embedding for the chosen Kaggle dataset. Our choice for XGBoost is due to its ability to reduce overfitting, to address imbalanced datasets, and yield a vigorous prediction accuracy [64]–[66].

2. LITERATURE REVIEW

Many studies have advanced the applications of personalized rating recommendations using collaborative filter techniques in many various domain tasks. For example, Murad et al. [67] adopted an enhanced collaborative filtering technique for e-commerce, which enabled the online (web) platform to provision users with more targeted, tailored product recommendations; Thus, facilitated the discovery of new (web-based) items cum products that near-perfectly aligned with the user's interests and preferences. Nassar et al. [68] explored its adoption and adaption in media streaming platforms noting that platforms such as Netflix and YouTube have continued to benefit from improved media-streaming recommendations for user tailored preference via the creation of user-targeted, interest profiles that further enhances user satisfaction, improves user-trust and engagement levels.

Newer search engines today – have also continued to leverage on the processing prowess of collaborative filtering fused with content analysis, as means to deliver more pertinent results for ambiguous queries; And thus, enhances the overall user search experience and their requisite relevance to a user [69]–[72]. Collaborative filter recommender system capabilities can also be extended to significantly enhance user experiences across various online platforms, advanced more user engagement, improve user satisfaction, enhance user-trust level and in time, ensure more monetization [73]–[75]. Studies have continued to provision and yield insightful knowledge that are gleaned to potentially, revolutionize the landscape for recommender systems as they become frontrunner to pave way for more personalized and effective user experience across a variety of domain tasks and applications [76]–[78].

It is crystal that the potential applications of collaborative filtering extend beyond traditional online (web-based) platforms, as it can be expanded/extended to financial portfolios, healthcare, education, and tourism, with its range of benefits. Ibor et al. [79] exploited collaborative filtering with blockchain in electronic healthcare records to assist in personalized treatment options tailored to specific individuals and/or patient profiles. Thus, it helped to optimizing healthcare delivery and patient outcomes and agreed by [80]. Also, Ejeh et al. [81] investigated its adoption on the pharmaceutical chain with drug records to assist in personalized treatment and assessment of fitness of drugs targeted to yield optimal resolution effects, tailored to specific patient profiles; And in turn, helped to optimize healthcare delivery.

Singh et al. [82] explored and employed collaborative filtering technique as recommender heuristic in financial portfolio for investment opportunities. They investigated how the provisioned data will help align forecasts with investors risk profiles and financial goals. While, they had insightful results – they proved that recommender system enhanced portfolio management and wealth generation strategies. Ajaegbu et al. [83] extended collaborative filtering technique as adapted to aid travellers' discovery of personalized 'anticipated' travel destinations and experiences based on their location interest reviews and preferences, targeted user travel history, and budget constraints. This can be useful in enhancing an overall travel planning, coordination and sojourn implementation process as means to yield a profound and enriched tailored travel experience for which proffered recommendations were found to have aligned with individual preferences and interests [84].

Malasowe et al. [33] extended Ojugo et al. [41] by investigating the use of collaborative filtering technique to recommend an adaptive personalized learning schemes, which provided users with a learner-centered educational resources tailored to a specific student learning style; And in turn yielded improved academic goals outcome with personalized subject interests and topics. It agreed with [85] that results provided insight to facilitate personalized learning experiences as well as in formative testing skills [86] as was requisite for blended-learning approach [87] for adoption explosion during covid-19 era [88]–[91]. These were accounted for to have provisioned improve learning outcome [87], [92]–[94], and promote lifelong learning initiatives [95]–[98].

With advances in the evolution of collaborative filtering, its scope of potential application domain is also poised to expand with key opportunities that are characterized by diverse user interests and preference – yielding a variety of options that may otherwise not be feasible to be evaluated, manually [40]. Thus, profiling user preferences and matching them against the most relevant choices will continue to yield a wide variety and array of real-world recommender tasks. And with the system implemented, will provision users with a plethora of user-targeted, tailored recommenders; That in turn, holds immense potentials with tangible deliverables and benefits for enhanced user experiences and improved engagement, across the various sectors.

1.2. Study Motivations

Despite its widespread adoption – the inherent gaps and persistent challenges that often degrades the performance and efficacy of collaborative filtering heuristics in practical applications are as below [99]–[103]. These include (but not limited to):

a. Data sparsity – traditional collaborative filter algorithms encounter difficulties in scenarios where user-item interaction data is both sparse and rarely available. The sparseness of dataset does lead to degraded accuracy, lowered user-trust and reliability with the generated recommendations; which in turn – impacts user engagement, satisfaction and yields degraded system/model performance. Related issues to sparseness can include:
   - Finding the right-formatted dataset is crucial in machine learning task as it will improve model construction, generalization, training and performance evaluation.
   - If the right-format dataset is available, it is often limited and un-balanced data, which often yield poor generalization, model over-train and overfit [104].
   - Studies are found to use the dataset as retrieved without data balancing applied – as fraud dataset is found as imbalanced in their class-distribution [37], [105], to enhance the overall accuracy [106]–[108] as traditional recommenders may yield limited performance and its adaption to new emergent collaborative patterns.

b. Cold-start issue arises when a recommender system encounters new users/items with insufficient historical interaction data. Thus, algorithm fails to provide insightful data or

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knowledge as the lack of data impeded and hampers the system's capability to cater to a diverse user-base,

c. Contextual knowledge adaption results if the algorithm fails to seamlessly integrate contextual data like user preference, interest and environmental conditions. Without such inclusion, its absence yields generic results and less-relevant recommendations – implying the limited adaptability of the algorithm to provide meaningful insights and knowledge.

d. Previous Successful Knowledge: Despite the many potentials with hybrid collaborative filter schemes and algorithms using context-aware enhancements to improved their inherent performance, there is a dearth of comprehensive comparative studies to aid effective and efficient comparison of study performance on standard datasets [109]–[111]. This absence and the lack thereof, with limited available and empirical evidence has been found to hamper many practitioners' capability for informed decision support about the most effective approaches for their specific recommender system requirements.

2. MATERIAL AND METHOD

2.1. Data Gathering

Dataset used was obtained from [web]: www.kaggle.com/datasets/netflix_prize/mediastreaming". Dataset contains Netflix records of streaming contents with their respective genre for 2022. It consists of 284,807-recorded contents classifications. Input is transformed using the principal component analysis (PCA) [4]. A description is seen as in table 2 as thus:

2.2. Feature Embeddign with User-/Item-based collaborative Filter Approach

With collaborative Filtering recommendation systems, user similarity was determined using the widely utilized cosine similarity technique. If a user does not review items, the user's ratings are assigned to 0. This method would find the similarities between the movie items and suggest the movie is like the valid movie title entered by the user regarding the movie genre and similarity based on the movie from the datasets.

The rating prediction was computed on an unrated user item obtained from the active user's neighbors K items. In rating prediction, it wanted to forecast the implicit and interacting information elements simultaneously [41]. It can be measured by the degree of resemblance between users. Then, based on user similarity values, a set for the first k users near the active user will be generated [112]. Rating prediction was under the Memory-Based Collaborative Filtering method; users store the entire grouping of previously rated things. This data was saved as a user-item matrix. This method will recommend movies depending on the dataset's movie rating information.

For this study – we also adapt the feature embedding approach since we can measure the semantic data/knowledge of either users or items, based on a meta-path by the similarities of the homogeneous objects. To unify the extracted similarities of objects (with both the user-based and item-based filtering scheme), we use a nonlinear mapping function to compress the numerical similarities to domain 0-1 and is defined as in Equation 1 as thus:

$$f(x) = \frac{1 - e^x}{1 + e^x} \qquad (1)$$

Given the similarity of the information between different objects, the paper utilizes the traditional matrix factorization [30], [113], [114] to map the similarity into a low-dimensional feature space and extracts the feature representation of each object. The objective function *L* is formulated as such that *Q* is a set including the similarity relationships of users, I*uv* is an indication function that equals 1 if *Q* includes the relationship between user(s) u and user(s) v; Else, *Q* is set as 0. Also, we have that the function S*uv* is the similarity between user u and user v converted by mapping function *f* - whereas *r* is represents an object in a low-dimensional space and d is the dimension of a feature space to yield the Equation 2 [115], [116]:

$$L = \frac{1}{2} \sum_{(u,v)\in Q} I_{uv} \left(S_{uv} - \sum_{k=1}^{d} r_{uk} r_{vk} \right)^2 + \frac{\delta}{2} \|r\|^2 \qquad (2)$$

To minimize the loss function in this approach, we will adapt the tree-based eXtreme Gradient Boosting (XGBoost) ensemble approach.

2.3. The Proposed XGBoost Classifier

The XGBoost is a decision tree-based ensemble, which leverages on scalable Gradient Boost model [117] to classify data-points. As a strong classifier, it explores boosting scheme to combine weak learners over a series of iteration on data-points to yield optimal fit solution [118]. It expands its objective function by minimizing its loss function as in Equation 3 so as to yield an improved ensemble variant that manages its trees' complexity more effectively and efficiently [119]. Its optimal leverages on the predictive processing power of its weak base-learners, accounting for their weak performance that contributes knowledge about the task, to its final outcome [120].

Thus, with each candidate data (x_i, y_i) trained, we expand the objective function via loss function *l*($Y_i^t, \hat{Y}_i^t$) and its regularization term $\Omega(f_t)$ – which ensures ensemble does not overfit and is devoid of poor generalization. This feat ensures training dataset fits with re-calibrated solution that remains within the set bounds of the solution. This regularization term ensures our tree complexity, appropriately fits – and also, tunes the loss function for higher accuracy.

$$L^t = \sum_{i=1}^{n} l\left(Y_i^t, \hat{Y}_i^{t-1} + f_k(x_i)\right) + \Omega(f_t) \qquad (3)$$

2.3. Training Phase

Ensemble learns from scratch via training set as expanded data-points. The iterative tree construction feat allows bootstrap training of each tree to enhance training data. Trees' collective knowledge is enhanced by this, and helped ensemble identify the intricate patterns present in each transaction.

Training set blends synthetic and actual samples to guarantees XGBoost comprehensive learning; And thus, improves its flexibility.

1. Step 1 - Hyper-Parameter Tuning controls how much of the tree complexity and its corresponding nodal weights need to be adjusted in place of gradient loss. The lower the value, the slower we travel on a downward slope. It also ensures how quickly a tree abandons old beliefs for new ones during the training. Thus, as tree learns – it quickly differentiates between important feats and otherwise. A higher learning rate implies that the tree can change, learn newer features as well as adapts flexibly, and more easily.

The ensemble uses the regularization term to ensure the model changes quickly, only to values that are within the lower and upper bounds. The ensemble does this to ensure that it adequately adjusts its learning rate to avoid over-fitting and overtraining. Hyper-parameters tuned includes max_depth, learning_rate and n_estimator. For best performance, the XGBoost ensemble must carefully tune these parameters [121].

2. Step 2 – Retraining is an applied ML scheme that estimates the learned skills of a heuristic technique on unseen data. It also seeks to evaluate model's performance about its accuracy on how well it has learned the underlying feats of interest via the resampling technique. To retrain – modelers choose several data folds (partitions) to ensure model is devoid of overfitting. We use stratified k-fold (rearranges the data to ensure that each fold is a good representation of the entire dataset) [98], [122]–[124].

The resultant ensemble was deploying as an application program interface (API) to help effectively test the system. Thus, it is utilized as web-application, mobile apps and ported onto a variety of platforms as embedded system using automated teller machine. point-of-sale unit etc [125], [126]. We achieved this feature using the flask API to simulate its integration into a web-based app, and we used the Streamlit interface – to test the ensemble [127] as embedded with other web-based apps.

3. RESULTS AND DISCUSSION

3.1. Training Performance Evaluation

Training allows decision tree's adjustment via the loss and regularization function(s). We tune tree's hyper-parameters via a trial-n-error mode for: max_depth, learning_rate, and n_estimators respectively during training to yield an optimal solution [128]. Tuned values for each parameter is as in Table 1, and it improves our proposed ensemble's fitness in lieu of performance generalization. It is observed that the best-fit results in learning_rate of 0.251, max_depth of 5, and n_estimators of 250 respectively.

Table 1. Hyper-parameter Values

Hyper-Parameters	Definition	Trial-n-Error	Best Value
Max-Depths	Max. number of trees depth	[1, 2, 4, 5, 6, 8, 10]	5
Learning Rate	Step-size for learning	[0.05, 0.1, 0.2, 0.3, 0.5, 0.75]	0.25
N_Estimators	Number of trees in ensemble	[50, 100, 150, 200, 250, 300, 350, 400, 450, 500]	250

Using the hyper-parameters as in table 1, the ensemble yields the metrics in table 2 below – which notes that the cues and lures for the negative sentiments were detected and effectively classified with an 87-percent accuracy (0.87); while the cues and lures for positive sentiments were also detected with a prediction accuracy of 97-percent (0.97).

Such disparities in the accuracy of prediction may have been expected and are normal – due to errors of false-positives, true-negatives, false-negatives, and true-negatives in agreement with [61], [129]–[131] as in Table 2 and figure 1.

Table 2. Stratified k-Fold Evaluation Metric for F1

Iterations	1	2	3	4	5	6	7	8	9	10	11	12
F1-Score	0.972	0.981	0.979	0.978	0.983	0.996	0.989	0.984	0.990	0.989	0.986	0.987

The ensemble during the retraining or cross-validation phase – over a series of iterations (movement) yields an accuracy prediction of 99.6 percent (i.e. 0.996) in predicting streaming multi-media.

3.2. Discussion of Findings

It provides insights into which characteristics have a bigger influence on overall performance and aids in identifying the most important aspects influencing the model's predictions [89], [132].

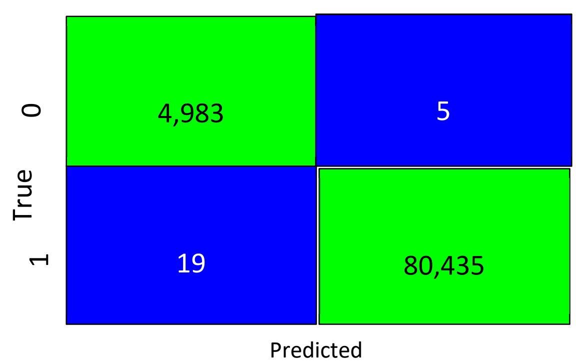

Figure 1. XGBoost Confusion matrix using SMOTE

The ensemble yields an Accuracy of 0.9984, F1-score of 0.996, Precision of 0.9616 and a Recall of 0.9890 respectively. Figure 1 shows the confusion matrix for the evaluated ensemble's performance [38] that XGBoost correctly classifies test-set instances with over 99.84% accuracy with only 24-incorrect classifications and 85,418 correctly classified instances, which agrees with [133], [134]. The XGBoost ensemble performed best with the user-/item-based collaborative filtering scheme fused with feature embedding approach as a sampling method as adapted [112], [135].

4. CONCLUSIONS

With the current surge in technological development and the widespread adoption of new technology-driven business strategies, businesses can now operate more efficiently, productively, and profitably.

Despite the enormous amount of data generated daily, we have observed that media streaming is keeping up in developing cutting-edge technologies to aid data analytics. This, can be improved [133], [134].

The ensemble has benefits [136]: (a) it yields more features via user-based and item-based collaborative filtering approach that ensures faster hybrid model construction and training [137], (b) the adapted collaborative filtering approach ensured lessened training time for the XGBoost ensemble especially its fusion with streamlit and flask to yield further integration over web-contents, where quick response is critical [138], [139], (c) it yielded faster implementation with robust and effective cross-channel apps/platforms integration [140], (d) XGBoost yields enhanced accuracy in that adapted feats did not degrade performance compared to [46], [135]. Our ensemble successfully predicted and recommended targeted-user items for streaming media contents transactions for the Netflix multi-media streaming platforms [141], [142] with minimal false-positives. This will in turn, provision an improved user-trust experience, interest and preference.

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