AI-Driven Box Creation with Budget and Preferences

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*Abstract*—Gofig, it collaborates in developing a Personalized gift hamper recommendation system powered by reinforcement learning. It learns through a user-defined parameter-based gift basket .For example, budget product category includes snacks, sweets, or drinks), and expiry preferences. By using input from users, the recommendation model generates the best basket advice according to the user’s financial and product constraints. A unique aspect This is an interactive feedback loop of this system: after the initial recommendation, users can indicate items they prefer to replace. Then the system will update the hamper and change things that are not liked with other things with the original standards. Successive generations end Interactions, Reinforcement learning trains the model by adjusting its policy and implementing the received feedback to improve recommendation accuracy and personalization. This adaptive learning approach evolves the learner continuously ensuring satisfaction, thus balancing personalization well with cost-effectiveness. It is a testament to the power of Reinforcement learning in building the intelligent recommendation systems adapted to changing user needs.

*Keywords*—Reinforcement Learning, Recommendation System, Personalized Gift Hampers, User Feedback, Adaptive Learning, GoFig, Cost-Effective Personalization, Dynamic Recommendation

# INTRODUCTION

Personalized recommendation systems have arisen as Essential Tools in E-commerce, Digital Media, and More Services-oriented industries that provide the users Personalized experiences appealing to their preference and needs. The development of artificial intelligence and machine learning, especially reinforcement learning, has technologically advanced these systems by enabling them to learn from user interactions and adapt to change preferences. This is a project in an industry prepared in Partnership with Gofig where we have developed Developing a personalized gift basket with reinforcement learning Recommender system. This is a system intended to Dynamically adjusts with feedback from users, aligning closely with satisfaction-driven experience. Gift hampers are versatile and customizable for gifting, but choosing the appropriate mix of commodities which balance the cost, tastes, and shelf life can become demanding. In general, classical recommendation algorithms work based on predefined rules or static models that fail to adapt to the immediate feedback of individual users. Our project addresses this limitation by adopting the reinforcement learning- Based on a recommendation system that iteratively refines its recommendations through a feedback loop. Finally, hampers increasingly get aligned with the user's specific preferences. It operates from three major inputs: the budget, the product category, and date of expiration. Users begin by identifying their budget, pick a category, like snacks or chocolates beverages and any preference towards the product expiry. These inputs feed the recommendation model to produce the best possible basket that is compatible with economic and consumption controls. However, the actual value lies in that feedback mechanism which is itself-interactive. The moment that a recommendation is made, and viewers are invited to review the list of suggested items and provide feedback by checking the items those they want to replace. Then the model changes its real-time recommendations, which would replace unwanted items while satisfying the original user constraints.

This feedback loop allows the model to learn from each interaction, constantly reshaping its recommendations to better fit the user's preferences. Reinforcement learning constitutes a class of machine learning that is particularly well-suited for this project because it can continuously adapt and improve. Unlike the traditional supervised learning, it does not demand support of labeled datasets. Learn about interaction with reinforcement  learning, it is rewarded with regard to the outcome for the environment actions. In our recommendation system, user feedback is the reward signal that for this model to do better recommendations over time. With each user interaction, while learning which, it updates its policy of the items. Therefore, the adaptive learning process allows the model for greater personalization, which is the ultimate goal. growing user frustration. One important consideration in developing this system was scalability and usability within Gofig's business environment. It stores the actual learned policy in a lightweight JSON file. We assure the system to be portable and accessible, and can easily fit into local environments without hitting heavy server or Cloud infrastructure. It is the approach that makes the system manageable, but it is accessible to the users. This means it will be useful in offline or restricted-network conditions.

# LITERATURE SURVEY

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| **Sl no** | **Methodology** | **Novelty** | **Limitations** |
| 1 | [1] Overview: The paper reviews latest developments in deep learning techniques for recommendation and compares techniques using content and temporal information. Approach: This work extends the classical taxonomy of recommendation systems by trying to include such recent trends, especially those inspired by NLP and CV. Review: This paper consists of the most recurrent approaches found from top conferences, elaborated on goals, novelty, and main evaluation metrics. | Taxonomy Extension: The work extends the taxonomy of recommendation systems up to recent trends, such as content and temporal data. Systematic Review: The work delivers a structured overview of current methods from top conferences on recommendation systems. Standardization Effort: The work will pave the road toward improvement in consistency regarding evaluation protocols and reduce current fragmentation. | The study may only improve some baselines, thus making its results less generalizable. The Research is Fragmented: New methods and lack of standard evaluations blur the clear identification of reference methods creating inconsistencies. Limited Novel Datasets: This experiment relies on existing popular datasets, constraining its ability to test methods on novel or diverse datasets. |
| 2 | [2] It's using content-based filtering where it determines videos with similarities in the following features such as genre, actors, directors, and metadata. Personal preference and rating: it personalizes recommendations based on the past interaction of each individual, hence learning the same to give more suggestions with similarities matching the individual's taste. | Similarity Content: The system is based on content-based filtering where it analyzes their content based on the features of a video, rather than just relying on the behavioral pattern of the user. Personalized Recommendations: It even gives preference and ratings of video results, resulting in a personalized viewing experience, which leads to chances of relevance in recommendations. | Cold Start Problem: Due to the "cold start" problem, the content-based filtering system cannot generate relevant recommendations at all when there isn't enough interaction history coming from new users. This often leads to a very limited number of suggestions, focusing on similar content and ignoring diverse or novel options that the user might like. |
| 3 | [3] Emotion Detection: This model tracks the user's emotions through the use of facial recognition and image processing. The features are extracted, with classification of emotion using Fisher Face Methods. Music Recommendation: After emotion detection has been done, the player selects songs that are a match for it. This process associates the specific songs or playlists with the recognized emotional states on the system. | Emotion-Based Selection of Music: This work innovatively encompasses emotion recognition into a music player for automatically selecting some music that would suit a user's mood. This is much different from the traditional players that still depend on either manual playlists or random tracks. Fisher Face Method: This method is utilized for the real-time emotion-detecting capabilities in music players and introduces a novel approach of recognition. | Limited Emotional Intensity It recognizes only four emotions: Neutral, Sad, Happy and Angry, which is less than the set of human emotions. It depends on Image Format: The system depends on .jpeg photographs; therefore, it will be useful to very few scenarios where dynamic video input a better input would be. Generalization to Diverse Users In the experiment, 80 diverse users were used. However, with a population of this nature, recognition rates may be different, thus reducing its effectiveness. Privacy issues related to storage and processing of facial data were also another issue this technology introduced. |
| 4 | [4] Collaborative Filtering: A collaborative filtering was applied on restaurant recommendations. It relies on other users' judgments and behaviors for suggesting alternative options. Modified CNN Model: The Pearson similarity modified CNN model was used for training the data. This hybrid approach enhances prediction by including collaborative filtering and deep learning. Workflow: this system preprocesses information, trains the model on the split data; it computes errors and sends recommendations for restaurants to the users. | Hybrid Approach: This incorporates Pearson similarity into a modified CNN whose strength in collaborative filtering has been enhanced by improvements between restaurant recommendations. This is the method wherein the traditional filtration strength, in connivance with the advanced neural networks, is adopted. Focus on Madura Island: A study related to Madura Island based on primary data from the local restaurants and, therefore, broadens the specificity and cultural appropriateness of recommendations. | Geographic Limitation: The study is bound within Madura Island, so conclusions drawn here cannot be generalized for others. Data Dependency: The recommendations would receive the influence of quality and quantity of ratings submitted by the users, which deteriorates the accuracy in locations with limited data. Complexity of the Model The complexity of the system has increased due to the modified CNN because more computations are required with a higher implementation and maintenance cost than that of a simple model. |
| 5 | [5] Collaborative Filtering with CNN: This study uses a hybrid recommendation system that integrates collaborative filtering and the CNN model. The method improves further by using embedding architecture in CNN to create vectors for tourism visitor preferences. Process Workflow: The process workflow is divided into several steps, beginning with Data Collection, including data collection through primary data from tourism review surveys in Madura. Data Preprocessing: Clean and Structure data for Training. Models Development and Training: Developing and training the CNN model by collaborative filtering. Cosine Similarity Calculation: Use cosine similarity to evaluate user preferences against tourist destinations. Recommendation Generation: Show personalized tourism recommendations based on similarities.  System Evaluation: The performance of the recommendation system is evaluated with error values. | Hybrid Model: This combines collaborative filtering with CNN and embedding architecture for making accuracy about recommendations and providing insights into user preferences. Focus on Madura Tourism: This research is unique because it promotes tourism in an area that lacks sufficient tourism information and reviews. The objective is education and awareness of hidden treasures on the island. | Data Dependency: the quality of data in the survey determines the performance of the system. Biased or meaningless data will skew some recommendations. Computational Complexity: the combination of CNN and collaborative filtering results in even more computationally intensive systems with great processing requirements, which is somewhat challenging within a limited resource environment.  Generalizability to Other Areas: It is a system developed for Madura but, when transferred to other areas, there might be extreme difficulties in modifying it because varied tourist attraction and user tastes could be involved. |
| 6 | [6] The research utilizes content-based filtering as a food recommendation approach. It considers what users have consumed earlier and the dietary preferences of the users. User-Item Matrix: This matrix stores ratings on different food items, and those ratings are the foundation for personalized recommendation. | It uses an item-item similarity matrix for computing item-to-item similarities; it identifies and recommends items similar to the ones liked before by the user. The model indicates that the content-based food recommender system is much more accurate and personalized compared to traditional systems because it increases the level of relevance and user experience since recommendations are made customizing to the past preferences of a given user. | Cold Start Problem: This recommender does not work so well on new users because it simply doesn't have data available to have a good recommendation for those. Limited Exploration: It tends to exaggerate the same sorts of food items, losing out on diverse choices beyond what they've been frequently exploring. Dependence on Appropriate Data: For the system to be successful, the ratings and the attributes of food must be proper. Additionally, any gap or error in the data decreases the quality of recommendations. |
| 7 | [7] In this study, the recommendation system is constructed based on IBCF and through the study of similarities between items by analyzing user ratings. Algorithm for K-Nearest Neighbor: The KNN is utilized through the IBCF algorithm. It provides recommendations to the products by finding and ranking the five closest neighbors along with their similarity scores.  Web Interface with Flask : It integrates the recommendation model into a Python Flask user interface, enabling users to interact with it and request product suggestions. | Beauty product Focus: The system focuses on body care products on the sociolla platform that will make the recommendations much more precise. Social Trends Influence: The paper outlines the influence of social media trends on the purchase of beauty products, especially concerning Indonesian beauty standards. The recommendation system aids users in managing countless options with curated suggestions based on their preferences. | Cold Start Problem: IBCF does not make a recommendation for newly signed-up users with no ratings. It cannot make accurate recommendations since there are no ratings. Moderate Prediction Accuracy: An RMSE of 0.69193 indicates decent accuracy but can improve further. The lower the RMSE, the closer the actual rating versus the predicted rating is. The system may end up being too obsessed with similar types of products, and users lose access to new or diverse options outside of their preferences. |
| 8 | [8] Owing to the fact that meal-scenario generated is unique and that it raises a privacy concern of users, real-world collection of the data was tough. Thus, simulation is used to generate all the required data by simulating affiliations of the meal-course from user-course interaction data, thus generating the user-meal interaction. The method produces comprehensive data, yet maintains privacy for users. Healthiness Scores: The paper computes meal healthiness scores using two nutritional standards, thereby ensuring the recommendations made are according to the user's choices and his or her requirements as far as nutrition is concerned. Baseline Models: The experiment tested a set of baseline models, in which disjoint as well as co-operative interaction learning methods were concentrated upon:.  Then, models were tested with the aim of determining meal recommendation quality for user-meal and user-course interactions. | Introducing the MealRec^+ Dataset. The MealRec^+ dataset is an important contribution to this field that provides a publicly available resource with meal-course affiliations and two levels of user interaction for better research about meal recommendation systems.  Simulation Method: With this new approach, complex interaction data become available that otherwise could not be obtained; especially when real-world data is not feasible due to privacy issues as in the context of recommending meals. | Simulated Data Dependence: Simulated data is successful for experimentations but fails to represent the complexity real users may introduce into behavior. The models need to be tested on real applications to validate their effectiveness. Issues of Privacy: Artificial data assists in privacy but the lack of real user data may constrain findings from translating to actual user preferences and behavior. Complexity in Model Size: Cooperative interaction learning introduces complexity, requiring additional computational resources and thus the problem with the deployment is greater in highly resource-intensive settings. |
| 9 | [9] The framework applies interactions of a user with the food content on Instagram; therefore, it analyses likes, comments, shares, and follows for inferential inferences concerning the preferences of foods. Image Recognition Methodologies: In this study, it explores the use of methodologies for image recognition in the analysis of pictures of foodstuffs on Instagram, possibly applying deep learning models in identification and classification. Deep Learning Models: This framework uses deep learning to analyze behavioral data and images of food toward giving personalized food recommendations. Validations and Deployments: It validates a comparison between the models with traditional food surveys to show the effectiveness of social media data. | The study uses Instagram data to fetch food recommendations, which is not a very explored area in traditional systems. Interdisciplinary Approach: Social media analysis integrated with food recommendation systems, image recognition, and deep learning, through which this system shall address both technical and behavioral issues. | Privacy Issues: The social media data might raise issues of privacy especially regarding personal preferences and behavior. Noisy Data: The social media data might contain noisy data, having irrelevant interactions that may distort the food preferences of the user and then degrade the quality of the recommendation. Data Bias : The architecture likely suffers from bias propagated from social media: the evolving trends that are currently led by influencers or commercial policies: recommendations biased towards food types that might not reflect user preferences. |
| 10 | [10] It computes the matrix density by discovering the food and service rating distribution, and analyzes rating with what kind of restaurants they like to make a sparse dataset to be filled in. Popularity-Based Model: It uses a popularity-based model to be their selection method for recommendation on restaurants. The model ranks restaurants according to their popularity through user ratings and how often they go there. It uses a scoring system of the top-ranked eateries and most popular dishes to assist users in finding highly rated options in new locations. SVD and Collaborative Filtering The model applies singular value decomposition and collaborative filtering to predict the user's preferences through their relationships with items in order to enhance the accuracy of recommendations, hence improving the recommendation process. | The sparsity problem of the recommendation systems will be diminished using the matrix density approach since it utilizes the calculation of the matrix density using both food and service ratings to enhance the performance. Hybridized Techniques: This work has combined the popularity-based recommendation technique and SVD and collaborative filtering techniques to allow better recommendations on restaurants. | Cold Start Problem: There is a significant limitation on Collaborative Filtering. Recommendations fail for new users or restaurants with a few ratings because there is too little data from them to generate accurate recommendations. Dependence on Popularity: Popularity models tend to recommend restaurants that are well-known, whereas some relatively unknown or niche places may be of great quality. This is due to the quality of the dataset being used in recommendation accuracy of "Kaggle". Poor data quality or data bias can negatively impact model performance, impairing the reliability of recommendations. |
| 11 | [11] Predicting treatments, OTC vs. doctor, using patient data: demographics and medical histories. It will lead to improved guidance regarding the management of antibiotic resistance by accurately predicting what the correct treatment is, diminishing both cost in healthcare and improving care. | Machine learning for differentiating OTC medicine usage from doctor consultations for treatments against antibiotic resistance: In pursuit of predictions on appropriate treatments and a cutting down on antibiotic misuse and bacteria drug-resistant microbes. | The effectiveness of the model might only apply to the CMED healthcare system and the people of Bangladesh, possibly restricting its applicability to different areas or groups. Needs a lot of information about patients, which might not be easily accessible all the time. It could be difficult for medical staff to understand the reasoning behind the model's choices because of the complicated nature of combining different models. |
| 12 | [12] This paper goes into more detail about a deep learning approach that combines unstructured data in the form of resource descriptions with structured knowledge graphs in an academic resource recommendation system. Current limitations from other methods are addressed, as those generally depend on only one type of information, and this model is probably using neural networks in processing to feature both textual and graph data. | It presents the research study on deep learning models for academic resource recommendations, unifying unstructured and structured data-a method heavily used in e-commerce and entertainment but hardly ever used within academia-that are presented here as capable of showing these techniques applied in an educational space through specially curated datasets on online learning and citation networks. | Model performance will depend on data quality and availability. - Deep learning models are computationally intensive, leading to the possibility of not working in real-time. - Generalization may suffer if the MOOCCubeX and DBLPv12 datasets are not representative. |
| 13 | [13] Using the adversarial attack framework SAVAGE, the paper explores how path length variance between sources and targets affects attacks on recommendations in social network recommendation systems-such as friend/follower recommendations on social media. | It analyzes how the path lengths of source-target can influence adversarial attacks on social recommendation systems and offer insights into friend/follower suggestions in compromised social networks. | Limited path length effects explored in smaller or non-Twitter networks; results may vary by platform structure and user interactions. |
| 14 | [14] This research uses a Club Recommendation System that is based on the Factorization Machines model, preferring to personalize recommendations for club membership and using matrix factorization in the analysis of student data to enhance group recommendations. | This study applies the factorization technique from commercial recommendation systems to gather club recommendations in an academic setting, hence overcoming coeducational learning challenges through personalization of counselling around a broad array of student preferences. | Failure in managing multivarious preferences of students effectively  Obscurity in structure of a dataset and performance of CRS. Performance applies across diverse academic settings - Possible privacy issues arise from using student preference data for suggestions. |
| 15 | [15] It employs federated learning in the research of the tourism recommender system, which allows for cross-domain recommendation with protected data. Each domain will process the data and contribute to global model training but will not share the data directly. | Federated learning combined with cross-domain recommendations in tourism enables collaborative training while maintaining the user's privacy simultaneously. | Variability in the performance of the model depends on the quality of data. Federating learning across heterogeneous datasets is very hard. Non-standardized data formats across domains are challenging. |
| 16 | [16] This research applied the FC-DNN to crop recommendation models of soil and weather variables. The study compared the FC-DNN against some specific models, which are decision trees, logistic regression, gradient boosting, random forests, K-Nearest Neighbors, SVMs, and Naïve Bayes in different regards to assess the accuracy of each crop. | It takes agricultural recommendations and incorporates them with a Fully Connected Deep Neural Network in an analysis of varied influential factors for crop yield suggestions as a novel approach to agriculture, typically relying on much simpler models. | These FC-DNN models may be resource-intensive, therefore limiting access to smaller farms. There is not an indication of what the dataset size is and how regional applicability might influence generalization of results. These models may be harder to interpret than simpler models. |
| 17 | [17] This work developed a crop recommendation system using a Random Forest classifier with Artificial Neural Networks. The work used soil, climatic, and temperature data with K-Fold Crossvalidation in Keras to optimize it for higher accuracy during the training on precision agriculture. | This model integrates precision agriculture with Random Forest classifiers and ANN for improved crop recommendations with a new method in agriculture, often dominated by less complex algorithms. | ANN's complexity may need more resources, limiting access for some farmers. - Effectiveness relies on data quality and regional relevance, which could impact generalization across various agricultural areas. - Dataset details and scalability limitations are unclear. |
| 18 | [18] It uses AI and data analytics in the study, making it capable of developing algorithms that predict house prices and market trends. Examining varying real estate data points, it seeks to clarify investment choices in order to promote better outcomes for buyers. | Incorporating AI in real-time property evaluation and price prediction introduces one-stop-shop real estate that allows a buyer to make savvy investments into property with speed. | Model accuracy depends on data quality and real estate record availability. - Challenges arise from rapidly changing market conditions in dynamic property markets. - Limited use if real estate data is unavailable or restricted. |
| 19 | [19] Using a survey from 429 tourists to generate this recommendation system, the analysis preprocessed the data with three feature selection methods and built four models for prediction: Decision Tree, Random Forest, k-NN, MLP, with appropriate metrics such as hit rate and NDCG for recommendations. | It is an exclusive approach which uses varying machine learning models and feature selection for recommending a tourist destination that suits the individual needs of tourists across regions of Thailand. | Limitation-Small data base, only 429 respondents. Regional recommendations may not be applicable to the kinds of tourists interested in some particular things-for example, Paris for the romantic. Accuracy would vary depending on the seasonal changes in tourist preferences. |
| 20 | [20] A textbook recommendation model would be developed using the ISODATA algorithm in grouping practices from teachers aimed at optimizing resource allocation and enhancing learning for students. | This study therefore displays unique usage of ISODATA in textbook recommendations with outcomes that improvise students' learning outcomes and aid resource optimization in education management. | Dataset size and features are limited, potentially affecting generalizability. Effectiveness may vary by academic discipline or region. There's little insight on how the ISODATA algorithm compares to other clustering methods for recommendations. |
| 21 | [21] A paper for a path of personalized learning based on AI suitable for vocational college students, gathering data about the students and conducting competency assessments to provide the students with accurate suggestions. For every student, customized resources and courses are provided based on his or her needs and progress. | The study explores the integration of this new AI in vocational education through the personalization of learning paths for improved skill development with independent selection of student resources. | There may be limited details in the dataset, which may affect generalization. The adaptation of the system to other fields of vocational professions or other levels of skills among students is hard. The future work requires much adaptability, accuracy, and the incorporation of real project applications. |
| 22 | [22] Here, it provided a model integrating an attention mechanism with an MLP for better suggestions of courses. Unlike the former that learns complex data representations in the process, the attention mechanism balances recommendations with the learning state of the student, enhancing personalization as well as precision. | So, the course recommendation system presented by the MLP with an attention mechanism is more hybrid in the sense that it gives personal recommendations better than other methods because it aligns with the learning states of students and their preferences. | The dataset under study is of an unspecified size with unspecified diversity so that results cannot be generalized. - This design might not be valid across all educational contexts due to differences in the data or design. - Further evaluation is needed for the scalability of this model with larger datasets or varied systems. |
| 23 | [23] This paper present Tencent's ads recommendation system design and implementation. The main methods involved are: Feature encoding towards embeddings, sequence, numeric, pretraining Dimensional collapse and interest entanglement on feature representation Model optimization via training technique that removes biases and enhances exploration. | The paper resolves key challenges within recommendations systems, such as dimensional collapse and interest entanglement, and in addition to that, it can demonstrate Tencent's ads recommendation team's tools and approaches toward optimizing feature representations for model performance in online advertising. | Very small amount of information on performance metrics, or comparison with other systems. The methodology seems to be highly specific to Tencent and then can't be generalized at all. Few techniques are brought out in a very thinly underpinned or general sense at theory. |
| 24 | [15] The paper introduces a novel approach towards VFL for recommender systems with the Fully-Vertical Federated Recommendation, called Fully-VFR. It includes key methodologies like retrieval-enhanced Vertical Federated recommender, better representations among parties, or ReFer. The "retrieval-and-utilization" algorithm. Federated retrieval augmentation either Cross-RA for missing fields or Local-RA for improving the comprehension of user groups. | This paper advances VFR to a Full-VFR model that exhaustively takes advantage of all the information coming from the data, and not only from overlapping groups of users. ReFer brings improvement to federated learning from retrieval-based augmentation and applies the retrieval-enhanced machine learning paradigm to the private setting. | There is no information on the computational complexity or scalability of the approach. The methodology might require additional infrastructure to incorporate the platforms. For instance, more studies can be done for recommendation tasks that do not relate to CTR prediction. |
| 25 | [24] Knowledge graph-based recommendation system with data modules, graph embedding, and clustering for personalized suggestions. | Uses knowledge graphs for scalability and cold-start problems. | Depends on exact community clustering and graph embeddings |
| 26 | [25] Federated knowledge graphs hybrid ML large language models for adaptive learning. | Federated Knowledge Graphs: Federating large language models for educational purposes. | Issues about privacy and data integrity in dynamic systems. |
| 27 | [26] Real-time emotion detection and music recommendation using graph convolutional networks. | Music recommendation personalized through real-time physiological signals. | Limited real-time physiological data and privacy concerns. |
| 28 | [27] This system will integrate NCF, GloVe, and DNN with personalized recommendation. | Both GloVe-DNN and NCF address sparsity and cold-start problems. | Computational complexity may depend on high-quality item profiles. |
| 29 | [28] Performance Analysis of ML Algorithms: Decision Trees, Random Forest, SVM, KNN, Naive Bayes, LightGBM, Logistic Regression. | Analysis of different ML algorithms for crop advisement. | Depends on soil and environmental factors; needs extensive data. |
| 30 | [29] Deep learning recommendation algorithm for personalized E-mirror settings using user behavior data. | E-mirror settings according to the driver. | Improves driving, reduces changes. |
| 31 | [30] Comparison between traditional techniques and deep learning techniques for recommending books, such as embedding layers, MLP, and attention mechanisms. | Deep learning in smart libraries. | No definite boundaries, focus is on response time. |
| 32 | [31] Pre-trains multilingual encoder using unsupervised learning on co-occurrence of skills and job titles, fine-tuned via contrastive learning using ESCO taxonomy | Multilingual job title encoder based on sequential learning. | Failure to accommodate non-ESCO datasets or languages. |
| 33 | [32] Content-based filtering, collaborative filtering, and hybrid methods are combined with specific recommendations. | Hybrids that integrate different algorithms for music recommendation | User history dependency for precise recommendations may prevent new users - the cold start problem. |
| 34 | [33] Yoga Pose Recommendations based on Medical History, Current Condition, and Week Using Hartigan-Wong k-Means clustering. | This is ML-based pregnancy-focused recommendation system. | Based on clinical information, only forecast asanas. |
| 35 | [34] Literature Review on Techniques, Roles, Applications, and Future of Recommender Systems in Education. | Review of education recommendation system | Lack of empirical data, theory review without experimentation. |
| 36 | [35] Movie recommendations using TF-IDF and KNN. | This combines content-based filtering with KNN. | Limited by reliance on genre similarity and TF-IDF analysis. |
| 37 | [36] MARDPG: Cooperative Partial Observation Planning. | MARDPG introduces multi-scenario optimization. | Very few details on specific scenarios or scalability issues. |
| 38 | [37] It uses Euclidean distance for calculating similarity of films and recommends based on genre as well as normalized rating. | Used over cosine similarity: Euclidean distance. | Not really able to compare performance metrics or with any other methods. |
| 39 | [38] Machine learning models such as Random Forest and Support Vector Machine offer career recommendations based on skill, interest, and personality. Dynamic tests and an interactive mobile app are featured. | Custom, responsive career forecasting with feedback. Little about their performance evaluation or comparison with other models. An ML-based recommendation system for surplus item sharing Model-Based Collaborative Filtering (MBCF) via Matrix Factorization This suggests a product through user behavior and shares surplus with the needy. | MBCF makes product recommendations through matrix factorization, on the basis of user behavior patterns, and allows for excess items to be shared with those who need it. It does not contain sufficient system evaluation, dataset, and model comparison information. |
| 40 | [39] Model-Based Collaborative Filtering (MBCF) through Matrix Factorization is used for product recommendations based on user behavior. The system allows people to share excess items with those in need. | Model-Based Collaborative Filtering (MBCF) through Matrix Factorization is used for product recommendations based on user behavior. The system allows people to share excess items with those in need. | Limited details on system evaluation, dataset used, and comparison with other models |

1. METHODOLOGY

The proposed solution is a reinforcement learning customized-based recommendation system to produce individually customized gift baskets. This would no longer depend on static data or pre-existing patterns of user behavior, the way most classic recommendation systems do. It would adjust dynamically to the real-time feedback through reinforcement learning.. The adaptive and user-centeredness feature would be at the top.

A diagram of a product

Description automatically generated

Fig.1

1. User Input and Generation of First Recommendation

Generation of recommendation starts with the statement of requirements. Requirements include budget, type of item to be purchased (e.g. biscuits, Chocolates, candies, and an expiration date to splurge on consumed goods. It then computes a possible basket, best fitting with the constraints of the chosen budget and item category. The technique applied here has every selected item falling within the time span the user requires, within the budget of the user and within the category of items that the user wants.

*Algorithm:* *Generate Hamper*

*Input: budget, selected\_categories, expiry\_days, policy\_data*

*Output: hamper (list of items)*

*1. Filter items by selected\_categories and expiry\_days.*

*2. For each item:*

*- Calculate item score from policy\_data.*

*3. Sort items by score in descending order.*

*4. Initialize total\_cost = 0, hamper = []*

*5. For each item in sorted items:*

*- If total\_cost + item.price <= budget:*

*- Add item to hamper.*

*- Update total\_cost += item.price*

*6. Return hamper*

2. Collection and Continuous Substitution of Feedback

Once the suggestion of items comes, it asks the user to see the proposed hamper and let him describe what he likes and dislikes. This will allow the customers to tweak the proposed recommendation. This process will allow the customers to select items they desire and create a hamper of their choice.

*Algorithm: Process Feedback*

*Input: hamper, feedback\_list, policy\_data*

*Output: updated\_hamper*

*1. For each item in hamper:*

*- If feedback is 'disliked':*

*- Call Update Policy(item\_id, 'disliked', policy\_data)*

*- Replace item with the next highest scored item within category and budget.*

*2. For each liked item:*

*- Call Update Policy(item\_id, 'liked', policy\_data)*

*3. Return updated\_hamper*

3. Policy Reinforcement Learning for Revising and Optimizing the Policy

The solution essentially describes the design of a reinforcement learning model. One that learns by interaction with the user and learns from the feedback given by users and then informs the model’s policy, thus updating it. The updating of the policy allows the model to "learn" from the user preferences over time and become more accurate with every round of proposal.

*Algorithm: Update Policy*

*Input: item\_id, feedback, policy\_data*

*Output: updated policy\_data*

*1. Load policy\_data from JSON file.*

*2. If feedback is 'liked':*

*- Increase item’s score by increment value.*

*3. If feedback is 'disliked':*

*- Decrease item’s score by decrement value.*

*4. Save updated policy\_data to JSON.*

*5. Return updated policy\_data*

4. Optimization for long-term user satisfaction

Using reinforcement learning, the model will optimize not only for short-term but also long-term user satisfaction. This

Adaptive policy always reserves room for amendment in case, and therefore improves over time the relevance and personalization of each successive recommendation.

5. Local Interface for User Interaction

The program supports a simple, local user interface where people can set their input preferences and view advice, besides giving them the critiques. This is a local set-up and this, of course, also ensures that user data prevents leaving the premises. It does not require a server or cloud deployment, thereby making it accessible and manageable without much infrastructure. This will make the adaptive recommendation system more and more effective and personal over time through interactions. Considering that reinforcement learning was combined with the user-centered feedback approach, this approach will fill the gaps of traditional recommendation systems: They focus on adaptability, learning continuously in real-time. Response to changes based on users' preferences makes it a fulfilling and even more engaging user experience.

1. RESULTS

The general objective of the project was to design and develop a reinforcement-learning-based recommendation system that can offer gift hampers based on users: budget, expiration date and product category. It may update their suggested streams every time with regard to the user’s choices and may shape them closer by adapting the selection policy accordingly to user preference. Below are some of the anticipated results in detail:

1.Personalized Hamper Generation Based on User Inputs

*Planned Outcome:*

So, let's create the mechanism through which a user can define his budget, choose from predefined categories like breakfast items, chocolates or snacks, and then set priority over the items that expire. All items should be filtered by their expiry dates and the system must retain only the ones having a shelf life that falls within the threshold defined by the user. This must be selected in conjunction with the budget constraint so that the products in the basket are relevant enough to fulfill the categories of the user.

*Achieved Outcome:*

It makes a basket from the input by the users; items are selected within the budget besides filtered for the expiry; therefore, every item in the basket satisfies the freshness and category constraints. I applied a recommendation policy which would essentially determine what one should look for in each category to balance quality, relevance, and budget.

2. Dynamic Feedback-Driven Recommendation System

*Planned Outcome:*

Feedback from end-users would now be gathered by this system design about the items in their hampers. Depending upon whether a user "likes" or "dislikes" an item, the selection policy of the system would now favor liked items and degrade disliked items in its selection process for future recommendations. Allow substitution of items for the ones disliked, where the system must repeat over the selection process several times until satisfactory items are included.

*Achieved Outcome:*

It collects feedback toward every item and up-dates the recommendation policy according to such feedback that improves future selection by favoring those items that get positive feedback. Implemented item replacement functionality that instructs the system to find other items if the chosen product has no liking. From this feedback loop, the system will not stop unless it finds the liked item exhausts all the possible replacements, thus ensuring that a recommendation process is centered around the user. Construct a reinforcement learning policy that will keep on storing and updating selection values for every item so that, in time, the system moves towards alignment with the user's preference.

3.Policy Update and Continuous Learning

*Planned Outcome:*

The policy will introduce new items with exploitation in exploration and explore already liked items that produce much better recommendation experience.

*Achieved Outcome:*

Implemented a JSON-based policy storage system, so the policy values assigned to every item would be presented and updatable. This policy uses a learning rate, which changes the preference values of items by taking feedback from users. Due to the randomness incorporated into the item selection mechanism, the system, therefore, made use of the exploration and exploitation tradeoff; it introduced some new items while always preferring better-rated ones. Indeed, it gradually attains enough capacity to supply baskets that closely approach the taste of the person showing evidence of learning intent.

4. Real-world Application and Scalability Potential

*Planned Outcome:*

The model should, therefore, be scalable with large item datasets and adaptable according to differences of user preferences, so that there will be a real use case when a person is to create a personalized gift hamper.

*Achieved Outcome:*

Then, it may be customized for the real-world requirements with different budgets, categories, and even tailored based on feedback. Since the architecture of the system is based on reinforcement learning with JSON files, it easily allows capacity for a more extensive inventory and further dimensions for customization to be added. Both can be implemented small and scaled up, like a combination of an e-commerce platform or cloud-based services.

A black screen with white text

Description automatically generated

Fig.2

1. FUTURE SCOPE

* Personalization Enhancements:

Incorporated user profiles and preferences at a more granular level to improve the model's personalization capabilities while supporting recommendations of a particular character around past behavior, demographics, or shifting tastes. Relevance and satisfaction in the long term.

* Dynamic Context Awareness:

Introduce contextual awareness, be it seasonal trends or event-based recommendations. This might mean that the model starts recommending certain items during holiday seasons or festivals -basically getting the model's recommendations in line with market trends and user expectations.

* Advanced User Feedback Mechanisms:

Perhaps the most engaged feedback mechanisms - sentiment analysis or rating systems - give more information than simple feedback regarding user preference. Then recommendations could both be superior to nuances and better adaptive.

* Scaling for Larger Inventories:

Scale up the model for a huge and diversified product inventory, which may even extend across various product categories beyond hampers. This could mean finding an optimal policy for a more intricate selection and budgeting of products.

* Real-Time Adaptation and Deployment:

Implement a real-time adaptive learning system whereby the model updates its policy based on recent user interactions. This might require real-time data handling and potentially even cloud or server deployment, depending on the dimension of the project that transcends local deployment.

1. CONCLUSION

Using reinforcement learning embedded within the project, the gift hamper recommendation system made significant strides in personalizing the process of creating gift hampers. This has been one of the more robust illustration potentials of reinforcement learning in dynamic recommendation systems considering budget, category preferences, and preferences for item expiration all within one. Because the model unifies a feedback system with an opportunity to have input in real time given by the users over each recommended item, the system gradually learns to make its recommendations fit the user-centric and adaptive hold.

Two significant things the system derived were explanations about the applicability of RL in satisfying user satisfaction for a gift hamper selection system. The traditional task practiced either engages in manual operations or algorithms that do not recognize changing user preferences. Our system applies RL with a policy feeding on feedback from the user's likes and dislikes. This system is self-contained, lightweight, and portable because the policy is maintained and updated in a JSON file. Having a learning rate, it allows the model to balance positive and negative feedback; therefore, it may change its selections of items in order to show both short-term and long-term preferences by the users. The system, therefore, provides a local user interface so that the user may communicate to that user and take feedback from that user without requiring any server or cloud infrastructure.

It makes the local interface only the truly stand-alone experience which is more accessible and more secure without dependency on network connectivity-this would help in making it more usable in places where cloud solutions may not be possible or necessary. The results obtained in this research are meaningful, as they represent real success.

* User-specific Hamper Generation: The user can choose a budget and category or specification of expiry constraints to generate an appropriate hamper suitable for his/her own needs. System responses: it filters items based on their dates of expiry and makes the best selection based on policy-driven priorities.
* Dynamic Feedback: Another highlight of the system is its dynamic ability to change recommendations on the fly based upon real-time feedback received from users. In this regard, it supports functionality for liking or disliking an item with instant invocation updates the policy values for that item. The disliked items are then replaced with similar alternatives to make sure that the hamper reflects the vision of the user. This is one of the reinforcement learning features wherein a system learns from user interactions and increases its chances to yield user satisfaction with successive uses.
* Adaptive policy with sequential improvement: Adaptive policy with online improvement continuously learns to maximize preferred items by a user given policy values adjusted through feedback; one balancing exploration-news introduction with exploitation-item recommendation with the highest preference value, so that every basket is fresh and personalized.
* Scalability and Real-World Application Potential: Scalability and Real-World Application Potential: The system could be scalable. Thus, if this storage-based architecture in JSON policy were to be extended further, the number of items or categories could go on even more without rebuilding much of the system. Therefore, the sort of reinforcement learning taken into this experiment lays a good foundation for further scalability; one would envision that the system could handle more and more items or get hitched into a platform like eBay or Amazon to present personalized gift proposals. It opens up major avenues in retail and application to personal service through the development of this project itself - the strength-driven reinforcement learning-based recommendation system and therefore an enhanced possibility of strengthening recommendations due to changes in user preferences based on exposing systems like these directly into real-world domains in the form of personal shopping assistants and marketing tools implemented to identify user interest. In summary, therefore, this project proved adaptivity and efficiency in reinforcement learning for adaptive recommendation systems. Carefully designing and incorporating feedback from customizing, we have designed a dynamic system that meets preferences and learns continuously. These steps form a foundation toward further exploration into broader applications of reinforcement learning in recommendation systems as proof of concept toward AI-driven personalization for retail, e-commerce, and more. The above results thus indicate a good basis for further research and development of reinforcement learning principles within the given domain, in that they indicate that successful integration within this context appears possible.

The gift hamper recommendation system, built within this project using reinforcement learning, achieved significant milestones toward personalizing the process of creating gift hampers.

Designed keeping in mind budget, category preferences, and item expiration preferences, it has been one of the representation potential of reinforcement learning in the dynamic recommendation systems. As the model integrates a

feedback system with the opportunity to have real-time input

given by the users over each recommended item, the system

gradually learns to make its recommendations fit the user-centric and adaptive hold.

The two major successes of this project are the explanations on the applicability of RL toward improving user satisfaction for a gift hamper selection system. The task traditionally practiced is based on either manual operations or algorithms that fail to recognize changing user preferences. Our system applies RL on a policy feeding on the feedback from the user's likes and dislikes.

The policy is maintained and updated in a JSON file, which makes the system self-contained, lightweight, and portable. With a learning rate, it lets the model balance positive and negative feedback; as such, it may adjust its selections of items to show both short-term and long-term preferences by the users.

With a local user interface, the system enables the user to interact with the user and to collect feedback from this user, without any dependency on server or cloud infrastructure. It makes the local interface only the truly stand-alone experience which is more accessible and also more secure without dependency on network connectivity-this would help make it more usable in places where cloud solutions may not be possible or necessary. The results obtained in this research are meaningful, as they represent real success in:

* User-specific Hamper Creation: The user can specify budget and category preferences, along with expiry constraints to generate a hamper tailored to his/her needs. The system appropriately responds to user inputs by filtering items by their expiry dates and making the best selection based on policy-driven priorities.
* Dynamic Feedback Incorporation: Dynamic Feedback Incorporation: Another advantage of the system is its adaptability to change recommendations on the fly according to real-time feedback from users. It does this by allowing users to "like" or "dislike" an item, and its instant invocation updates its policy values for that item. The disliked items are then replaced with similar alternatives so that the hamper reflects the user's vision. This feature represents a type of reinforcement learning where a system learns from user interactions and thereby increases the chances of yielding user satisfaction with successive uses.

* Adaptable Policy with Continuous Improvement: Adaptive policy with online improvement: it learns continuously to maximize the items preferred by the user, given feedback-adjusted policy values; it balances exploration (introduction of news) with exploitation (recommendation of items with the highest preference value) so that every basket is fresh and personalized.
* Scalability and Real-World Application Potential: Scalability and Real-World Application Potential: This system has demonstrated the scalability potential. Extending from this architecture based on storage in JSON-based policy means that the number of items or categories may grow without reconstructing much of the system. Therefore, the type of reinforcement learning accepted in this experiment lays a good foundation for further scalabilities; one would envision that the system would handle greater numbers of items or get hooked into a platform such as eBay or Amazon to present personalized gift proposals.

It opens up major avenues in retail and application to personal service through the development of this project itself - the strength-driven reinforcement learning-based recommendation system and therefore an enhanced possibility of strengthening recommendations due to changes in user preferences based on exposing systems like these directly into real-world domains in the form of personal shopping assistants and marketing tools implemented to identify user interest. In summary, therefore, this project proved adaptivity and efficiency in reinforcement learning for adaptive recommendation systems. Carefully designing and incorporating feedback from customizing, we have designed a dynamic system that meets preferences and learns continuously. These steps form a foundation toward further exploration into broader applications of reinforcement learning in recommendation systems as proof of concept toward AI-driven personalization for retail, e-commerce, and more. The above results thus indicate a good basis for further research and development of reinforcement learning principles within the given domain, in that they indicate that successful integration within this context appears possible.

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