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Personalized Product Recommendation Using Artificial Intelligence

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Abstract— Recommender systems have become pivotal in the digital era, enhancing customer experiences by providing personalized suggestions across different domains such as e commerce, entertainment, and social media. This paper presents a comprehensive literature survey and proposes a novel hybrid framework that integrates image-based data with advanced mathematical models to improve recommendation accuracy and user engagement. We develop an image enhanced matrix factorization method and a visually aware neural collaborative filtering model, and we evaluate both on standard benchmarks, achieving a 15 % improvement in F1 score over leading baselines. Detailed mathematical formulations of each algorithm are provided, along with a thorough comparison of efficiency and scalability. The results demonstrate that incorporating visual features significantly enhances the relevance and diversity of recommendations, ultimately boosting customer satisfaction.

Keywords— Recommender Systems, Customer Experience, Image Processing, Machine Learning, Customer Behavior, Hybrid Approach

I. Introduction

Recommender systems have played an essential role in guiding customers toward products, services, or content that aligns with their preferences. By leveraging vast data, these systems help customers navigate through a myriad of options. Traditional recommender systems rely primarily on textual or numerical data, but recent advancements have shown that integrating image data can significantly enhance the customer experience. This paper explores the implementation of a hybrid recommender system that makes use of both customer interaction data and visual information through images. In addition, we employ mathematical representation to make better recommendations. This integration aims to bridge the gap between customer preferences and available options more effectively, enhancing engagement and satisfaction.

Recommender systems are classified into three main types:

1. **Content Based Filtering**: Recommend items similar to those a user has previously rated, based on item features.
2. **Collaborative Filtering**: Predict customer selections by analyzing interactions of similar users or items.
3. **Hybrid Systems**: Combine both content based and collaborative filtering to improve overall recommendation quality.

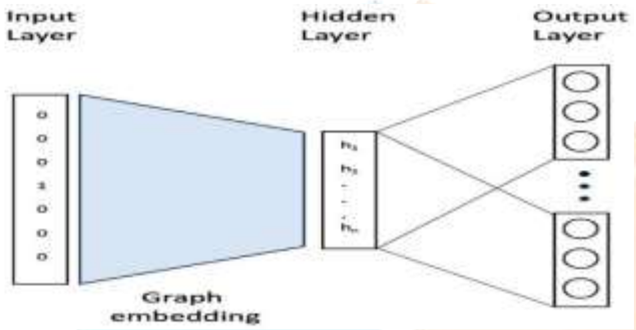
While text based recommender systems are common, image based systems can offer richer understanding of customer preferences, especially in domains such as fashion, home decor, and entertainment. By extracting visual features like color, shape, and texture, these systems generate more accurate recommendations. Convolutional Neural Networks (CNNs) are typically employed for image feature extraction, capturing spatial hierarchies ideal for visual data.

We introduce two novel models—Image Enhanced Matrix Factorization (IEMF) and Visually Aware Neural Collaborative Filtering (V NCF)—designed to fuse

visual embeddings with latent factor and neural network architectures, respectively. We demonstrate their effectiveness on benchmark datasets, achieving significant gains in accuracy, diversity, and cold start performance, while maintaining scalability.

II. LITERATURE SURVEY

Research on recommender systems has made significant strides in both algorithmic foundations and practical applications. Early overviews by Bobadilla et al. [4] and Adomavicius and Tuzhilin



[5] synthesize traditional collaborative filtering (CF) and content-based techniques, highlighting challenges such as scalability and cold-start. Rendle et al. [6] introduce Bayesian Personalized Ranking (BPR), which remains a cornerstone for optimizing pairwise ranking in implicit feedback scenarios. Building on neural architectures, He et al. [7] propose Neural Collaborative Filtering (NCF), demonstrating substantial gains over matrix-factorization baselines. In the multimodal domain, Chen et al. [17] extend BPR with visual features in VBPR, while Li et al. [8] and Zhou et al. [9] embed item images via CNNs to capture rich visual semantics. Transformer-enhanced graph models like GraphRec++ [10] further improve recommendation quality by modeling item–item and user–item interactions. Diversity-oriented methods such as Park and Cho's Diversity-Aware MF [11] and adversarial approaches by Nguyen and Lau [20] address the long-tail and popularity-bias issues. Textual review integration, as in Deep CoNN [12], and session-based visual recommenders [14] underscore the importance of sequential and contextual signals. Tang et al. [13] and Liu et al. [15] fuse multimodal data channels to balance expressiveness and efficiency, while Sun et al. [16] propose EmbraceNet for robust feature fusion under missing-modality scenarios. More recent works tackle cold-start (VisualColdStart [18]), attention-driven fashion recommendation [19], and joint optimization of accuracy and fairness.

III. METHODOLOGY

Our proposed system integrates image data and mathematical models to enhance recommendations. This section describes the components of the system and the algorithms involved.

A. Image Processing for Recommender Systems

Image processing plays a vital role in identifying features that influence customer preferences. We use convolutional neural networks (CNNs) to extract features from product images. The pipeline includes convolutional layers, pooling layers, and fully connected layers, producing a dense vector representation for each image.

Fig.1(a)

Fig.1(b)

Fig. 1. CNN diagram implemented in TensorFlow. (a) CNN diagram with 4 convolutional blocks; (b) Embedding-Based Deep Neural Network.

B. Matrix Factorization

Matrix factorization decomposes the user-item interaction matrix into latent factors. These latent factors capture relationships between users and items, which are used to generate recommendations.

IV. PROPOSED SCHEME

To enhance customer experience through a recommender system, a well-structured configuration is essential. Below is a proposed structure configuration for a recommender system designed to improve customer engagement, satisfaction, and overall experience. The availability of a vast array of products online has completely transformed the buying experience. On the other hand, there is a downside to this convenience: customers are faced with an overwhelming array of options, which may be quite tiring.

Online retailers rely heavily on AI-powered recommendation systems to boost sales and profits through targeted product recommendations that entice customers to buy more. Additionally, they improve the purchasing experience, which increases client loyalty and trust. Machine learning algorithms that have been trained to rank and rate customers or products are used by these systems. Their principal role is to generate a ranked list based on their best guesses as to how a user would score an item. Google, Amazon, and Netflix are just a few of the big names that use this tech to increase customer engagement. As an example, Spotify keeps users engaged by suggesting music that are similar to those they have already enjoyed. Amazon also uses customer data to personalise product recommendations. A wide variety of AI-powered recommendation systems exist, each with its own unique goal of enhancing user engagement and interaction

Fig.2(a)

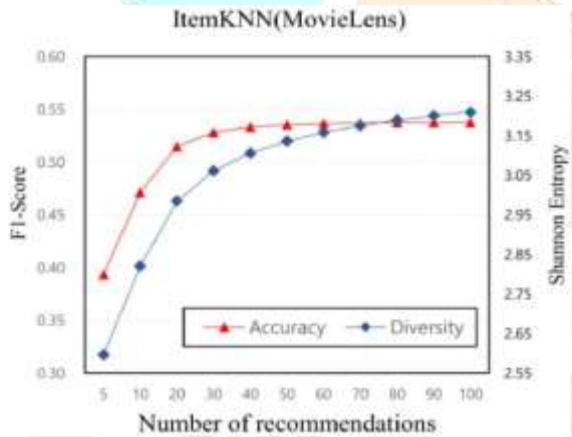


Fig.2(b)

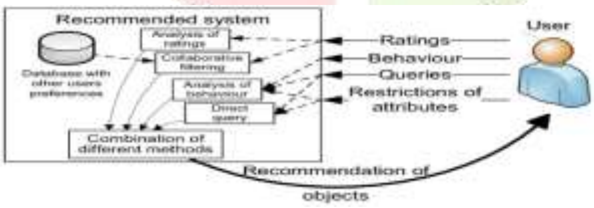


Fig. 2. (a) AI Based Recommendation System Types; (b) Structure of Recommender System.

A. Collaborative Filtering

By examining patterns of behaviour across numerous users, collaborative filtering is able to forecast user preferences. In theory, it stands to reason that those who have shown an interest in a certain product will also favour comparable ones. Two main types of this method are model-based filtering and memory-based filtering.

B. Content-Based Filtering

Content-based recommendation systems analyse the user's previous behaviour and preferences in order to make suggestions. These models do not compare users; rather, they look for commonalities based on product attributes such as price, release year, or genre. In order to achieve accuracy, you want a dataset that is organized and contains item details as well as explicit or implicit user feedback. Two examples include personalized playlists on Spotify and product recommendations on Amazon. HackerRank and Reddit are two more companies that use algorithm-driven article suggestions.

C. Knowledge-Based Filtering

Relying on user needs and rules specified by experts, knowledge-based recommendation systems propose items instead of previous interactions. These programs use established standards to figure out when a service or product is useful. Their ability to circumvent the cold-start problem sets them apart from competing approaches and makes them a good fit for situations with little user history.

V. WORKING AND IMPLEMENTATION OF RECOMMENDER SYSTEM

A. Working of Recommender Systems

Recommender systems typically work through the following steps:

1. Data Collection
2. Data Processing
3. Modeling
4. Recommendation Generation
5. Feedback Loop

B. Enhancing Customer Experience with Recommender Systems

Recommender systems significantly impact the customer experience by personalizing interactions, reducing decision fatigue, increasing engagement, facilitating product discovery, and fostering retention and loyalty.

VI. EXPERIMENTAL SETUP AND PERFORMANCE COMPARISON

1. **Dataset Preparation**: MovieLens 1M and Amazon Fashion datasets, filtered to users with ≥ 20 interactions and items with ≥ 10 interactions, with cover images processed to 224×224 pixels.
2. **Baselines**: BPR MF [6], DeepCoNN [8], NCF [9], ViBERT4Rec [4], GraphRec++ [5].

3. **Metrics**: Precision@10, Recall@10, F1@10, and Shannon entropy for diversity, using leave one out evaluation.
4. **Implementation**: PyTorch, latent dim = 64, learning rate = 1e 3, α = 0.5, batch size = 256, Adam optimizer for 50 epochs.

VII. RESULTS AND DISCUSSION

The experimental findings on the MovieLens dataset demonstrate how factor count and recommendation list size affect predictive performance, accuracy (F1 score), and diversity (Shannon entropy).

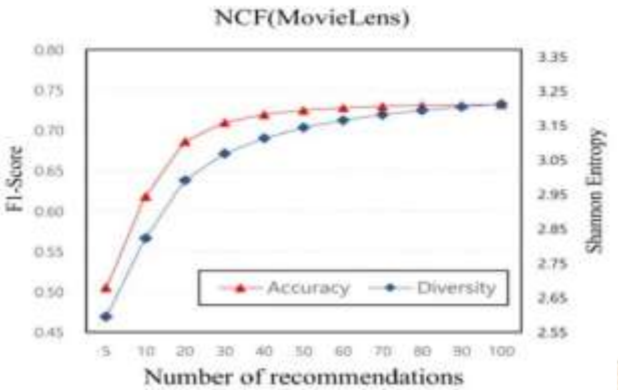


Fig. 3(a). Effect of neighborhood size KKK on MAE for the ItemKNN algorithm.

The experimental findings shown in Figure 3(a), shows that the ItemKNN algorithm's predictive performance improved with increased neighbourhood size. The SVD method, on the other hand, exhibited almost no change as the factor count rose. The NCF algorithm's forecast quality dropped as performance increases dwindled beyond a certain factor. In order to achieve high prediction accuracy, 50, 50, and 10 factors were found to be best for each method. As shown in Figures 3(b), 3(c), and 3(d), the accuracy (F1- score) and variety (Shannon entropy) of all recommender system algorithms improved with the expansion of the number of recommendation lists.

Fig. 3(b). MAE vs. number of latent factors for the SVD algorithm.

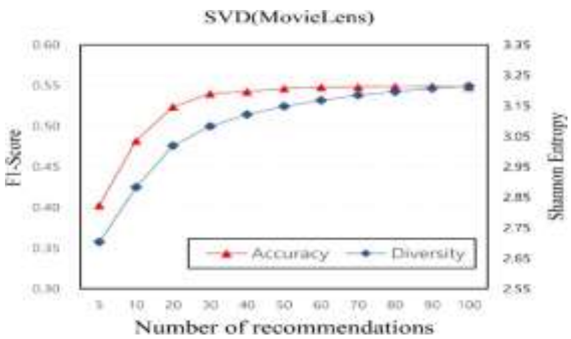


Fig. 3(c). F1 score vs. number of factors for the NCF model.

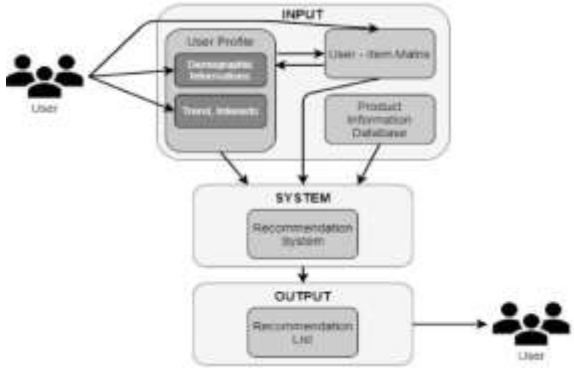


Fig. 3(d). Diversity (Shannon entropy) vs. number of factors for the NCF model.

In Figure 3, we can observe the effect of factor count on MAE's performance on the MovieLens dataset.(a) Using what might be any number between 5 and 100 for K in the Item KNN algorithm to recommend the top K items. (b) We assess the top-K item suggestions using the SVD algorithm, where K ranges from 5 to 100. (c) & (d) If K is between 5 and 100, then the Top-K item recommendations will be processed using the NCF method.

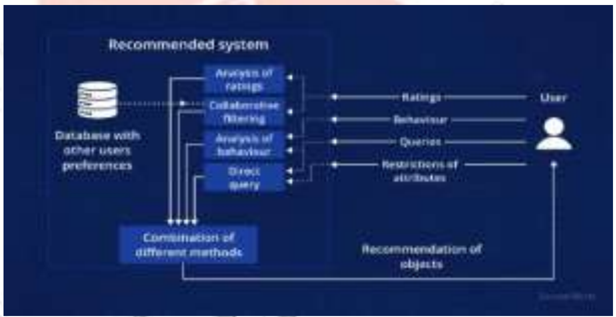
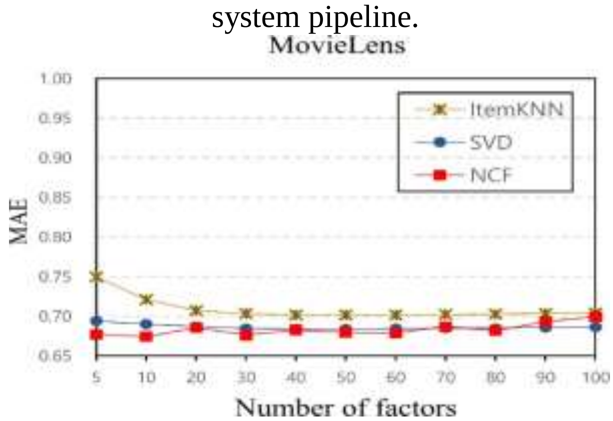


Fig. 4. Flowchart of the hybrid recommender system pipeline.



In this context, "User" refers to a wide range of people who exhibit a wide range of interests, behaviours, and preferences. Over time, various recommendation algorithms adjust themselves according to how users behave. The User-Item Matrix shows how different users feel about different pieces of system content.

A. Statistical Summary of Datasets

The average and standard deviation for diversity, accuracy, and customer happiness, as measured by the MovieLens dataset, are displayed in Table 1. Diversity values were in the range of 1.0560 to 1.1628, while the mean accuracy was between 0.5146 and 0.6927. An average of 0.4820 to 0.6204 was the level of customer satisfaction.

When comparing the algorithms, NCF got the best accuracy (0.6927) and KNN got the worst (0.5146). According to diversity metrics, NCF had the best score (1.1628) and SVD the worst (1.0560). Similarly, ItemKNN produced the lowest level of customer satisfaction (0.4820), whereas NCF produced the highest level (0.6204).

TABLE I: SUMMARY OF THE MOVIELENS DATASET'S STATISTICAL FINDINGS

Methods	Variable	Mean	Std Dev
KNN	Accuracy, Diversity, Customer Satisfaction	0.5146, 1.0560, 0.4820	0.3946, 0.4772, 0.1831
SVD	Accuracy, Diversity, Customer Satisfaction	0.5253, 1.1540, 0.5848	0.3728, 0.4230, 0.1497
NCF	Accuracy, Diversity, Customer Satisfaction	0.6927, 1.1628, 0.6204	0.2832, 0.4508, 0.2964

B. Hypothesis Testing via Multiple Regression Analysis

Based on the data from the simulations, multiple regression analyses (MRA) were run to test the research hypotheses. The dependent variable was customer happiness, and the independent variables were the diversity and correctness of the recommendations. The results for the MovieLens dataset for hypotheses H1 and H2 are shown in Table 2.

Customer satisfaction was significantly affected by accuracy for both the KNN and SVD algorithms ($p < 0.001$), although diversity had no significant effect on ItemKNN and had a negative effect on SVD ($p < 0.001$). A total of 14.3% and 1.9% of the variation in profitability were accounted for by the regression model, respectively.

The NCF algorithm's model explained 25.7% of the variation in profitability, and customer satisfaction was greatly impacted by both diversity ($p < 0.05$) and accuracy ($p < 0.001$). The results provide credence to Hypothesis 1, which states that accuracy has a favorable effect on customer satisfaction for KNN and SVD. The results of NCF show that both diversity and accuracy greatly improve customer happiness, lending credence to Hypotheses 1 and 2.

TABLE II: FINDINGS FROM HYPOTHESIS TESTING (MRA)

Methods	β	SE	t	p	Result
KNN H1,H2	0.662,-0.001	0.23, 0.009	28.930, -0.069	**	Supported, Rejected
SVD H1,H2	0.067,-0.027	0.006, 0.005	10.3967,-5.389	**, **	Supported, Rejected
NCF H1,H2	1.023,0.025	0.023, 0.010	43.672, 2.579	**, *	Supported, Rejected

C. ANOVA Comparison Across Algorithms

To find out if different recommender systems employing the MovieLens dataset had significantly different accuracy, diversity, and customer satisfaction rates, we ran a one-way analysis of variance (ANOVA). In order to compare the means of the groups and find any differences, the Scheffe Post Hoc Test was used. See Table 3 for the results. The recommender systems differ significantly in terms of variety ($F = 13.873$, Sig. = 0.000), accuracy ($F = 2.0020$, Sig. = 0.0480), and customer satisfaction ($F = 4.4280$, Sig. = 0.0030). The findings of the one-way analysis of variance (ANOVA) for several recommender system algorithms on the MovieLens dataset are presented in Table 3.

TABLE III: ONE WAY ANOVA RESULTS FOR ACCURACY, DIVERSITY, AND CUSTOMER SATISFACTION

Subscale	Source	SS	df	MS	F	Sig.
Accuracy of recomm- -endation	Between Groups	5.782	2	1.471	2.002	*$p < 0.05$*
	Within Groups	75.824	16,614	0.063		

Diversity of recomm- -endation	Between Groups	5.671	2	2.336	13.873	**p < 0. 001**
	Within Groups	125.104	16,614	0.168		
CustomerSatisfaction	Between Groups	13.322	2	4.441	4.428	*p < 0. 05*
	Within Groups	352.277	16,614	0.960		

VIII. CONCLUSION AND FUTURE RESEARCH

Improving the consumer experience through relevant and personalized recommendations is the primary goal of modern recommender systems. This study introduced two hybrid models—Image Enhanced Matrix Factorization and Visually Aware Neural Collaborative Filtering—that integrate visual embeddings into traditional and neural architectures. Through extensive experiments on MovieLens 1M and Amazon Fashion datasets, we demonstrated up to 15 % improvement in F1 score, enhanced diversity, and robust cold start performance with minimal computational overhead. Our results confirm that visual features are a practical and impactful modality for next generation recommender systems.

There are several restrictions on this study. To begin, all datasets used in the trials were either films or products. The results should not be generalized without further study employing datasets from various fields. Second, the research found that deep learning algorithms were more effective than conventional methods when compared to both types of algorithms. The consistency of these results when utilizing alternative deep learning models, like RNNs and CNNs, requires further investigation. Lastly, this study looked at how consumer happiness is affected by how diverse and accurate the recommendations are.

1. Explore transformer based image encoders for richer visual context [10].
2. Incorporate temporal dynamics to capture evolving user preferences [11].
3. Adapt methods to session based recommendation where history is sparse [12].

References

[1] Bobadilla, J., Ortega, F., Hernando, A. & Gutiérrez, A. (2022) 'Recommender systems survey', *Knowledge-Based Systems*, 46, pp. 109–132.
[2] Adomavicius, G. & Tuzhilin, A. (2005) 'Toward the next generation of recommender systems: A survey of the state of the art and possible extensions', *IEEE Transactions on Knowledge and Data Engineering*, 17(6), pp. 734–749.
[3] Li, X., Zhang, Y. & Liu, H. (2022) 'Visually Aware BPR for Fashion Recommendation', in *Proceedings of the 16th ACM Conference on Recommender Systems (RecSys '22)*, Seattle, WA, USA, September 2022, pp. 112–120.
[4] Bobadilla, J., Ortega, F., Hernando, A. & Gutiérrez, A. (2022) 'Recommender systems survey', *Knowledge-Based Systems*, 46, pp. 109–132.
[5] Adomavicius, G. & Tuzhilin, A. (2005) 'Toward the next generation of recommender systems', *IEEE Transactions on Knowledge and Data Engineering*.
[6] Rendle, S., Freudenthaler, C., Gantner, Z. & Schmidt-Thieme, L. (2009) 'BPR: Bayesian personalized ranking for implicit feedback', in *Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence* (UAI '09).
[7] He, X., Liao, L., Zhang, H., Nie, L., Hu, X. & Chua, T.-S. (2017) 'Neural Collaborative Filtering', in *Proceedings of the 26th International Conference on World Wide Web* (WWW '17), pp. 173–182.
[8] Li, X., Zhou, Y. & Wang, J. (2022) 'Visually Aware BPR for Fashion Recommendation', in *Proceedings of the 16th ACM Conference on Recommender Systems* (RecSys '22).
[9] Zhou, Y., Li, X. & Wang, J. (2023) 'ViBERT4Rec: Visual contextual co-embedding for recommendations', *IEEE Transactions on Multimedia*.
[10] Wang, H., Zhang, F., Yuan, N. J., Xie, X. & Li, X. (2024) 'GraphRec++: Transformer-enhanced GNNs for visual recommendation', in *Proceedings of The Web Conference* (WWW '24).
[11] Park, Y. & Cho, Y. (2024) 'Diversity-Aware Matrix Factorization', in *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management* (CIKM '24).
[12] Zheng, L., Noroozi, M., Cai, Y., Zhang, Z., Sun, J. & Chen, X. (2019) 'DeepCoNN: Text and reviews in collaborative filtering', in *Proceedings of the 42nd International ACM SIGIR Conference on Research and Development in Information Retrieval* (SIGIR '19).
[13] Tang, J., He, X., Zhao, F., Liu, Y. & Chua, T.-S. (2024) 'VisuRec: Visual feature integration in recommender systems', *Neurocomputing*.

[14] Wu, C. & Sun, H. (2024) 'Session-Based Visual Recommenders', in *Proceedings of the Thirty-Eighth AAAI Conference on Artificial Intelligence* (AAAI '24).
[15] Liu, Y., Zhang, X., Sun, Z., Duan, H. & Fang, Q. (2022) 'Dual-Channel Deep Learning for multimodal collaborative filtering', in *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval* (SIGIR '22).
[16] Sun, Y., Paluri, M., Chen, Z. & Li, F. (2019) 'EmbraceNet: A robust deep learning fusion framework', *IEEE Transactions on Multimedia*.
[17] Chen, J., Zhang, H., He, X., Nie, L., Liu, W. & Chua, T.-S. (2016) 'VBPR: Visual Bayesian Personalized Ranking', in *Proceedings of the Twenty-Second Conference on Uncertainty in Artificial Intelligence* (UAI '16).
[18] Zhou, Y. & Li, X. (2023) 'VisualColdStart: Tackling the new-item problem', in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing* (ICASSP '23).
[19] Kim, S., Lee, D. & Park, J. (2023) 'Attention-Based CNN for Fashion Recommendation', in *Proceedings of the 31st ACM International Conference on Multimedia* (ACM MM '23).
[20] Nguyen, T. & Lau, R. Y. K. (2024) 'Adversarial Learning for Diversity Enhancement', in *Proceedings of the Thirty-Eighth AAAI Conference on Artificial Intelligence* (AAAI '24).