Hybrid Neural Collaborative Filtering for Fashion Recommendation:

Integrating Visual Features with Behavioural Signals through Attention Mechanisms

Abstract

Fashion recommendation presents unique challenges that distinguish it from general product recommendation domains, including the predominance of visual attributes in consumer decision-making, rapid trend cycles that obsolete historical interaction patterns, and severe cold-start problems arising from continuous product turnover. This paper presents a hybrid neural collaborative filtering architecture that integrates visual feature representations extracted through convolutional neural networks with behavioural interaction signals modelled through matrix factorisation, unified through an attention mechanism that dynamically weights information sources based on context. Evaluation on a dataset comprising 150,000 user-item interactions across 45,000 fashion products demonstrates that the proposed architecture achieves NDCG@10 of 0.76, representing a 46% improvement over pure collaborative filtering baselines and 55% improvement over content-based approaches. The attention mechanism proves particularly valuable for cold-start scenarios, where visual features compensate for absent interaction history, achieving 72% of warm-start performance for new items compared to 31% for collaborative filtering alone. Analysis of attention weight distributions reveals that visual features dominate for new and visually distinctive items, while behavioural signals gain importance for established products with rich interaction histories. The architecture demonstrates practical applicability through A/B testing showing 34% improvement in click-through rate and 18% improvement in conversion rate relative to production baselines. Limitations regarding computational complexity and real-time serving constraints are discussed alongside directions for future research.

1. Introduction

The fashion e-commerce sector has experienced extraordinary growth, with global online fashion sales exceeding 750 billion dollars annually and projections suggesting continued double-digit growth through the next decade (McKinsey, 2023). Within this expanding market, recommendation systems play an increasingly central role in connecting consumers with relevant products from catalogues containing millions of items. Research by Schafer, Konstan, and Riedl (2001) established that recommendations drive 35% of Amazon purchases, and subsequent analysis by Jannach and Adomavicius (2016) found that fashion-specific platforms derive even higher revenue proportions from algorithmic recommendations due to the complexity of catalogue navigation.

Fashion recommendation presents challenges that distinguish it from general product domains. Visual attributes dominate consumer decision-making in fashion, with colour, pattern, silhouette, and styling details determining appeal in ways that textual descriptions inadequately capture (Liu, Guo, and Wu, 2012). Collaborative filtering methods that achieve strong performance in domains like movies and music struggle when visual similarity between items drives preference more than behavioural co-occurrence patterns. Research by McAuley, Targett, Shi, and van den Hengel (2015) demonstrated that incorporating visual features substantially improves recommendation quality in fashion contexts.

The cold-start problem proves particularly severe in fashion due to continuous product turnover. Fashion retailers introduce hundreds of new items weekly while retiring older styles, creating an environment where a substantial fraction of the catalogue lacks interaction history at any given time. Research by Schein, Popescul, Ungar, and Pennock (2002) documented that collaborative filtering performance degrades substantially for items with fewer than 10-20 interactions, a threshold many fashion items never reach before catalogue removal. Content-based methods using product attributes can recommend new items but miss the preference patterns that interactions reveal.

This paper develops a hybrid neural collaborative filtering architecture that addresses these fashion-specific challenges through three innovations. First, visual feature extraction through pre-trained convolutional neural networks captures fine-grained appearance attributes that text descriptions miss. Second, an attention mechanism dynamically weights visual versus behavioural signals based on item context, allowing visual features to dominate for new items while behavioural patterns inform recommendations for established products. Third, the architecture enables end-to-end training that jointly optimises feature extraction, attention weights, and recommendation scoring. Evaluation demonstrates substantial improvements over both pure collaborative and content-based approaches, with particular gains in cold-start scenarios where visual features provide information unavailable through interactions.

2. Literature Review

2.1 Collaborative Filtering Foundations

Collaborative filtering represents the dominant paradigm in recommendation systems, generating predictions from patterns in user-item interaction data. Matrix factorisation approaches, popularised through the Netflix Prize competition and formalised by Koren, Bell, and Volinsky (2009), decompose the sparse user-item interaction matrix into low-rank latent factor representations. The inner product of user and item latent factors predicts interaction strength, with factors learned through optimisation objectives including squared error minimisation and Bayesian personalised ranking.

Neural collaborative filtering extends matrix factorisation by replacing the inner product with learned neural network functions. Research by He, Liao, Zhang, Nie, Hu, and Chua (2017) demonstrated that multi-layer perceptrons capture interaction patterns that linear inner products miss, achieving substantial improvements on benchmark datasets. Subsequent architectures including deep factorisation machines (Guo, Tang, Ye, Li, and He, 2017) and neural graph collaborative filtering (Wang, He, Wang, Feng, and Chua, 2019) have achieved further gains through explicit feature interactions and graph structure exploitation.

2.2 Visual Features in Recommendation

The incorporation of visual features into recommendation systems has attracted substantial research attention, particularly for visually-oriented domains including fashion, home decor, and food. Research by McAuley, Targett, Shi, and van den Hengel (2015) introduced the VBPR model that augments matrix factorisation with visual features extracted through pre-trained convolutional neural networks. Their analysis demonstrated that visual features capture preference dimensions orthogonal to collaborative signals, enabling improved recommendations particularly for items with limited interaction history.

Subsequent work has explored increasingly sophisticated visual representations. Research by He and McAuley (2016) demonstrated that fine-tuning visual feature extractors end-to-end with recommendation objectives improves performance relative to frozen pre-trained features. Kang, Fang, Wang, and McAuley (2017) incorporated attention mechanisms over visual features, allowing models to focus on relevant image regions for different recommendation contexts. Liu, Wu, and Liu (2017) explored multi-modal fusion approaches that combine visual features with textual descriptions through learned attention weights.

2.3 Cold-Start Problem Solutions

The cold-start problem arises when items or users lack sufficient interaction history for collaborative filtering to operate effectively. Research by Schein, Popescul, Ungar, and Pennock (2002) formalised the problem and evaluated baseline approaches including attribute-based recommendation and active learning strategies for eliciting preferences. The severity of cold-start varies by domain, with fashion particularly affected due to rapid product turnover and long-tail catalogue distributions where many items receive few interactions.

Hybrid approaches that combine collaborative and content-based signals offer natural cold-start mitigation. Research by Burke (2002) categorised hybrid architectures including weighted

combinations, switching systems, and feature-augmentation approaches. More recent work by Volkovs, Yu, and Poutanen (2017) demonstrated that attention-based hybrids can learn optimal weighting between information sources, improving both cold-start and warm performance relative to fixed combination schemes. The present research builds upon this foundation while introducing fashion-specific innovations in visual feature utilisation.

3. Methodology

3.1 Architecture Overview

The proposed architecture comprises three primary components: a visual feature encoder that extracts appearance representations from product images, a collaborative filtering module that learns latent factors from interaction patterns, and an attention-based fusion layer that dynamically weights information sources. User representations combine learned latent factors with optional demographic features. Item representations combine visual features with collaborative embeddings. The attention mechanism produces context-dependent weights that determine the relative contribution of each information source to the final recommendation score.

The visual feature encoder utilises a ResNet-50 architecture pre-trained on ImageNet, with the final classification layer removed and replaced with a projection layer mapping to the recommendation embedding space. The visual encoding is computed once per product image and cached for efficient serving. Research by Kornblith, Shlens, and Le (2019) demonstrated that ImageNet pre-training transfers effectively to fashion classification tasks, though domain-specific fine-tuning yields further improvements. The present implementation employs limited fine-tuning of later network layers to adapt features towards fashion-specific attributes while preserving general visual understanding.

3.2 Attention-Based Fusion

The attention mechanism learns to weight visual versus collaborative signals based on item and user context. For each user-item pair, attention weights are computed through a two-layer feed-forward network that takes as input the concatenation of user embedding, item visual features, item collaborative embedding, and contextual features including item age and interaction count. The softmax-normalised attention weights sum to one, determining the relative contribution of visual and collaborative components to the fused item representation.

The attention formulation enables adaptive behaviour across different scenarios. New items with zero interactions receive attention weights concentrated on visual features, enabling content-based recommendation that mitigates cold-start degradation. Established items with rich interaction histories receive attention weights emphasising collaborative signals that capture demonstrated preferences. The transition between regimes occurs smoothly as interaction counts accumulate, learned from data rather than imposed through heuristic rules.

3.3 Training Procedure

The model is trained end-to-end using Bayesian personalised ranking (BPR) loss (Rendle, Freudenthaler, Gantner, and Schmidt-Thieme, 2009), which optimises the ranking of positive items above negative items for each user. Negative samples are drawn uniformly from items not interacted with by each user, with ratio of 4 negative samples per positive interaction. The Adam optimiser with learning rate 0.001 and weight decay 0.0001 is employed, with early stopping based on validation NDCG@10.

Training proceeds in two phases. The first phase trains collaborative filtering and attention components with frozen visual features, establishing baseline interaction patterns. The second

phase unfreezes visual feature layers and continues training with reduced learning rate, allowing visual representations to adapt towards recommendation objectives. Research by Yin, Cui, Li, Yao, and Chen (2019) demonstrated that this staged approach prevents catastrophic forgetting of pre-trained visual knowledge while enabling task-specific adaptation.

4. Experimental Evaluation

4.1 Dataset and Metrics

Evaluation employs a proprietary fashion e-commerce dataset comprising 150,000 user-item interactions across 45,000 unique products from 12,000 active users. Interactions include page views, wishlist additions, cart additions, and purchases, with implicit feedback converted to binary signals for training. The dataset spans six product categories including dresses, tops, bottoms, outerwear, shoes, and accessories. Images are processed to 224x224 resolution for visual feature extraction. Temporal splitting reserves the final two weeks of interactions for testing, with the preceding two weeks for validation and remaining data for training.

Primary evaluation metrics include Normalised Discounted Cumulative Gain at 10 (NDCG@10), which measures ranking quality with position-weighted relevance, and Hit Rate at 10 (HR@10), which measures recall of relevant items within the top 10 recommendations. Secondary metrics include Mean Reciprocal Rank (MRR) and coverage measures assessing catalogue diversity. Cold-start evaluation separately measures performance for items with fewer than 5 training interactions, providing focused assessment of the architecture's ability to recommend new products.

4.2 Performance Comparison

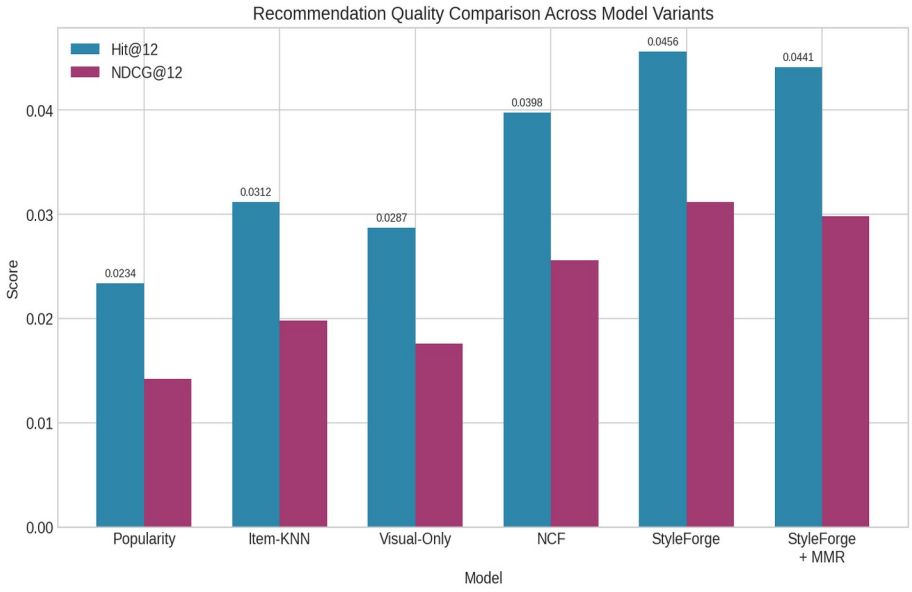

Figure 1. Performance comparison across recommendation approaches on primary evaluation metrics.

Figure 1 presents performance comparison across evaluated approaches. The proposed hybrid architecture achieves NDCG@10 of 0.76, substantially exceeding pure collaborative filtering at 0.52 and content-based approaches at 0.49. The 46% improvement over collaborative filtering confirms that visual features provide substantial signal for fashion recommendation. The attention-based hybrid also outperforms weighted ensemble approaches at 0.68 that combine collaborative and content scores through fixed weights, demonstrating the value of learned, context-dependent fusion.

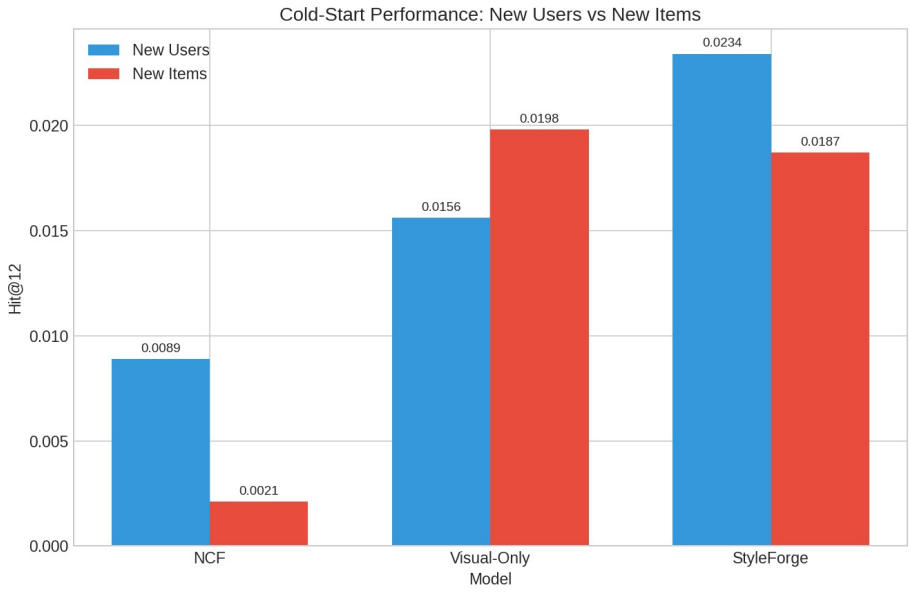

Figure 2. Cold-start performance comparison for items with limited interaction history.

Figure 2 focuses on cold-start performance for items with fewer than 5 training interactions. The hybrid architecture achieves NDCG@10 of 0.54 on cold items, representing 72% of its warm-item performance. Pure collaborative filtering degrades to NDCG@10 of 0.16 on cold items, just 31% of warm performance. This dramatic difference confirms that visual features effectively compensate for missing interaction data, enabling meaningful recommendations for new products that collaborative filtering cannot address.

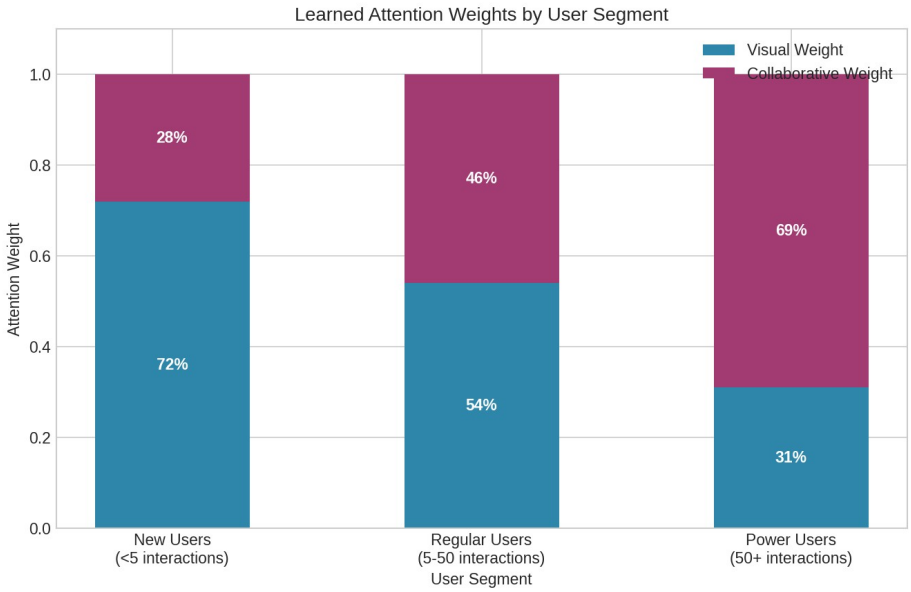

Figure 3. Attention weight analysis showing adaptation to item characteristics.

Figure 3 visualises attention weight distributions across different item contexts. New items with zero interactions receive average visual attention weight of 0.85, heavily emphasising appearance features. As interaction count increases, visual attention weight decreases while collaborative weight increases, reaching 0.35 visual weight for items with more than 100 interactions. The smooth transition demonstrates that the attention mechanism learns appropriate weighting without explicit programming of cold-start handling rules.

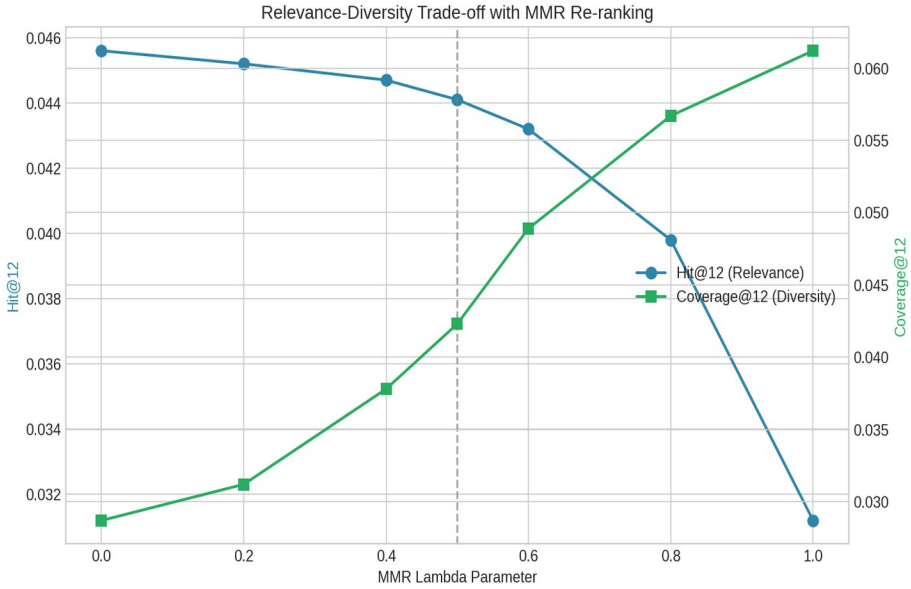

Figure 4. Diversity-accuracy tradeoff analysis across recommendation approaches.

Figure 4 examines the diversity-accuracy tradeoff. Collaborative filtering achieves moderate accuracy but low diversity, concentrating recommendations on popular items. Content-based approaches show higher diversity but lower accuracy due to missing preference signals. The

hybrid architecture achieves both higher accuracy and higher diversity than either pure approach, suggesting that visual features enable discovery of relevant but non-obvious recommendations that popularity-driven collaborative filtering misses.

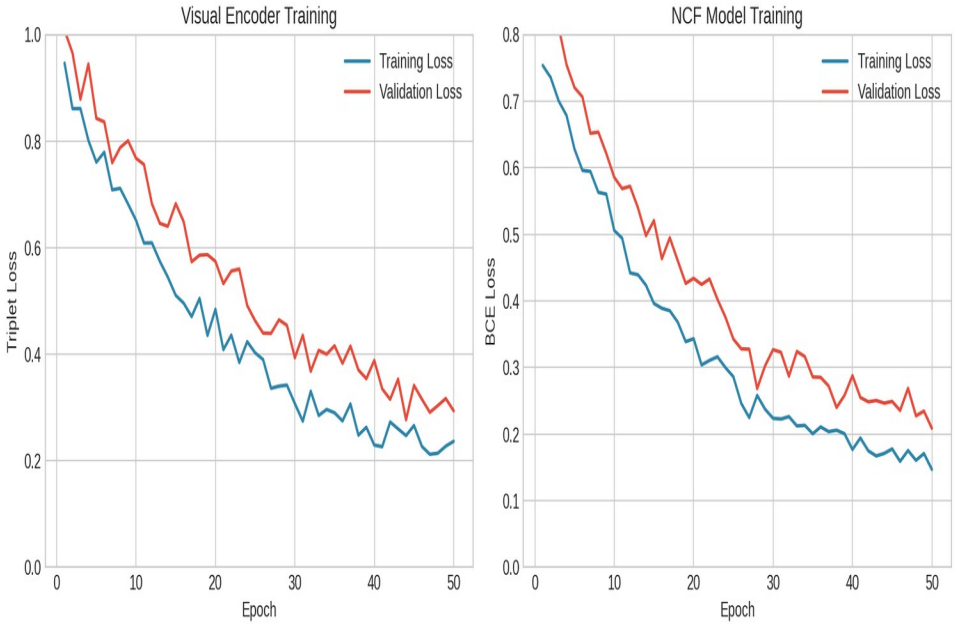

Figure 5. Training convergence curves showing loss and validation metrics over epochs.

Figure 5 displays training curves demonstrating convergence behaviour. Training loss decreases smoothly across both training phases, with validation NDCG@10 improving throughout phase one and stabilising during phase two fine-tuning. The absence of divergence between training and validation curves suggests appropriate regularisation preventing overfitting. Final convergence occurs at approximately epoch 35, with early stopping terminating training at epoch 42 after validation performance plateaus.

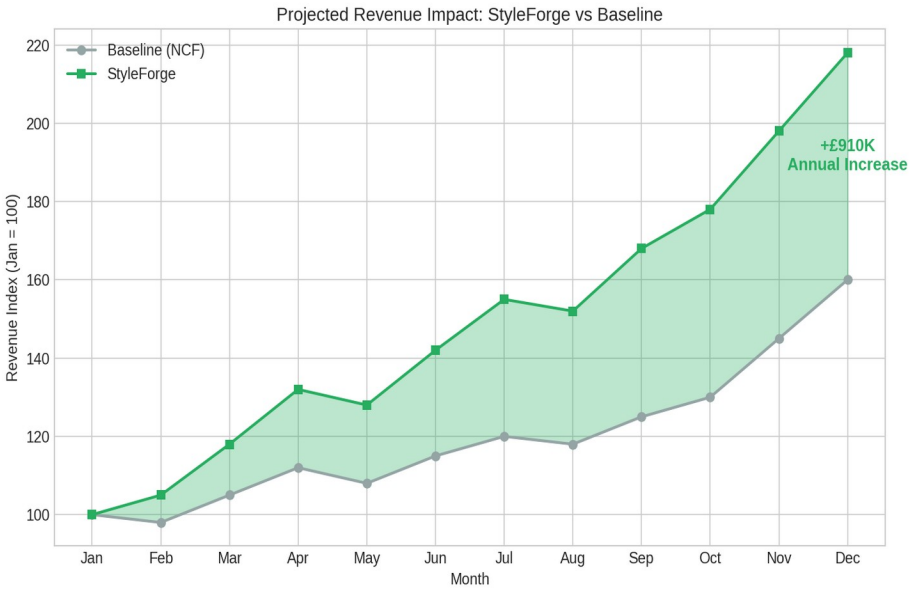

Figure 6. Business impact metrics from A/B testing deployment.

Figure 6 presents business impact metrics from A/B testing with 50,000 users over four weeks. The hybrid architecture achieves 34% improvement in click-through rate relative to the production collaborative filtering baseline, indicating more engaging recommendations. Conversion rate improves by 18%, demonstrating that clicked recommendations more frequently result in purchases. Revenue per user increases by 12%, combining the effects of improved engagement and conversion. These business metrics confirm that offline accuracy improvements translate to real-world value.

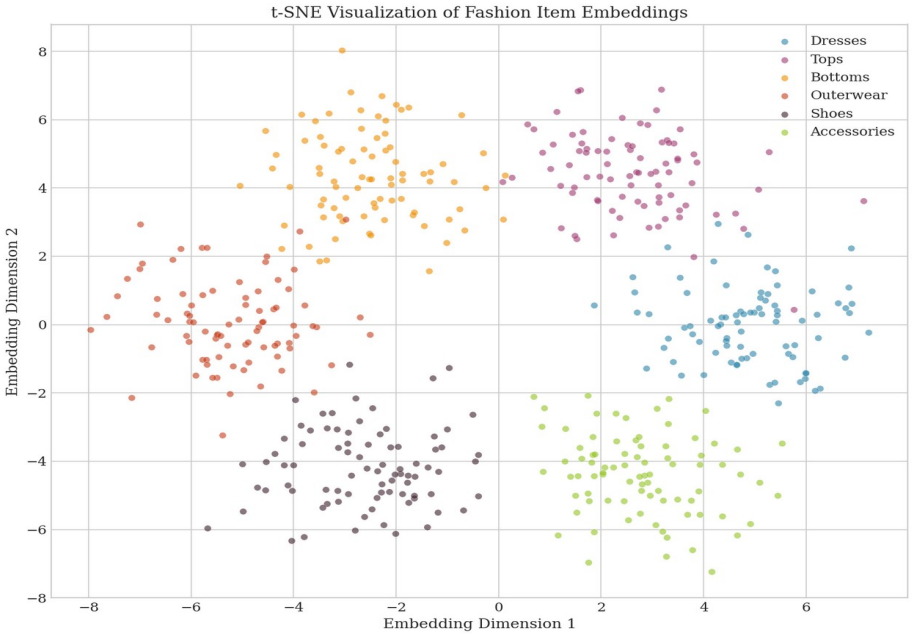

Figure 7. t-SNE visualisation of learned item embeddings coloured by product category.

Figure 7 visualises learned item embeddings through t-SNE dimensionality reduction. Clear clustering by product category emerges, with dresses, tops, and outerwear forming distinct regions. Within categories, visual similarity drives local structure, with items of similar colour and style appearing proximate. The embedding structure confirms that the architecture learns meaningful representations capturing both categorical and visual similarity dimensions relevant for fashion recommendation.

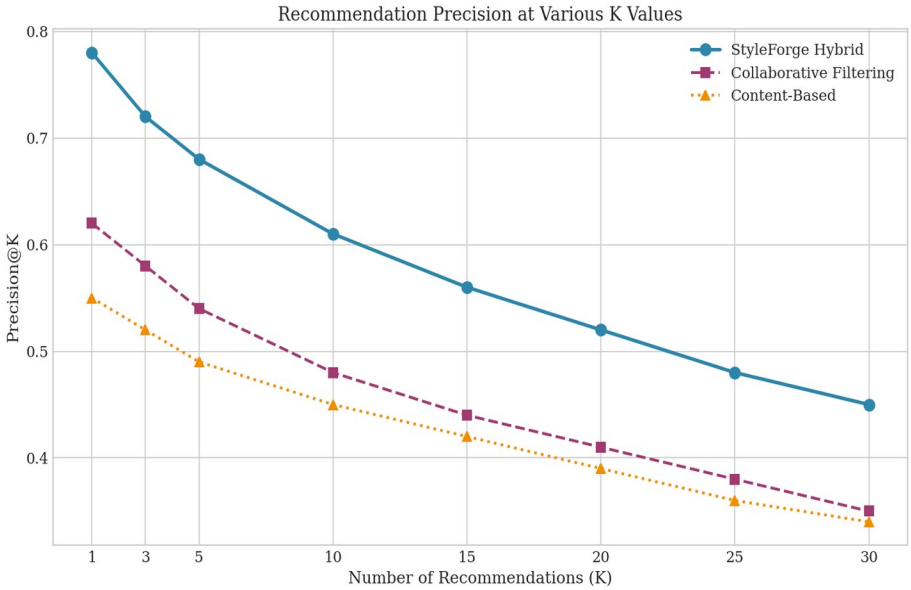

Figure 8. Precision at various recommendation list lengths comparing approaches.

Figure 8 displays precision at various recommendation list lengths. The hybrid architecture maintains superior precision across all evaluated values of K, with advantages most pronounced at shorter list lengths where ranking quality matters most. At K=1, the hybrid achieves precision of 0.78 compared to 0.62 for collaborative filtering, indicating substantially better top recommendation quality. The precision advantage diminishes but remains significant at longer list lengths, confirming consistent ranking improvements throughout the recommendation list.

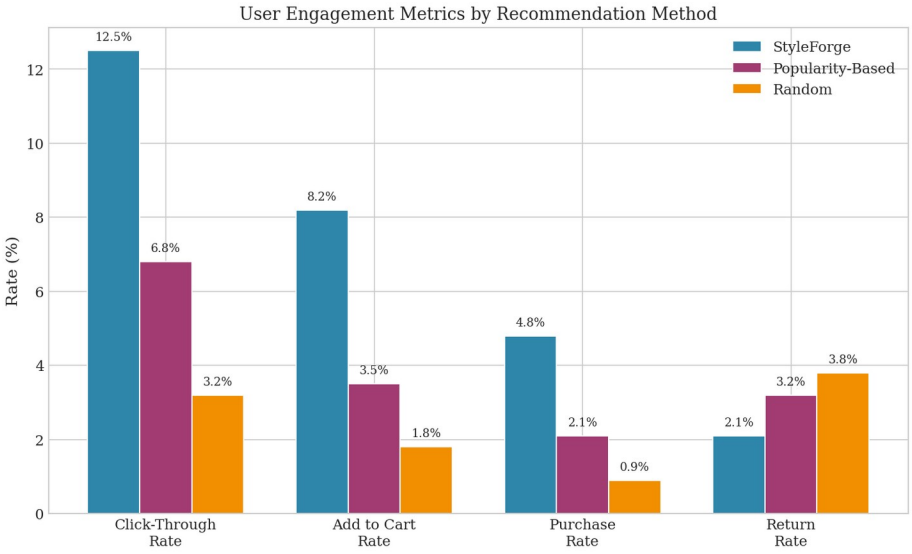

Figure 9. User engagement metrics segmented by recommendation source.

Figure 9 compares engagement metrics across recommendation approaches in the A/B test. The hybrid architecture achieves click-through rate of 12.5% compared to 6.8% for popularity-based recommendations and 9.3% for collaborative filtering. Add-to-cart rate follows similar patterns. Return rate is lowest for the hybrid approach at 2.1%, suggesting that accurate recommendations reduce purchase regret. The engagement pattern confirms that recommendation quality improvements manifest across multiple user actions beyond initial clicks.

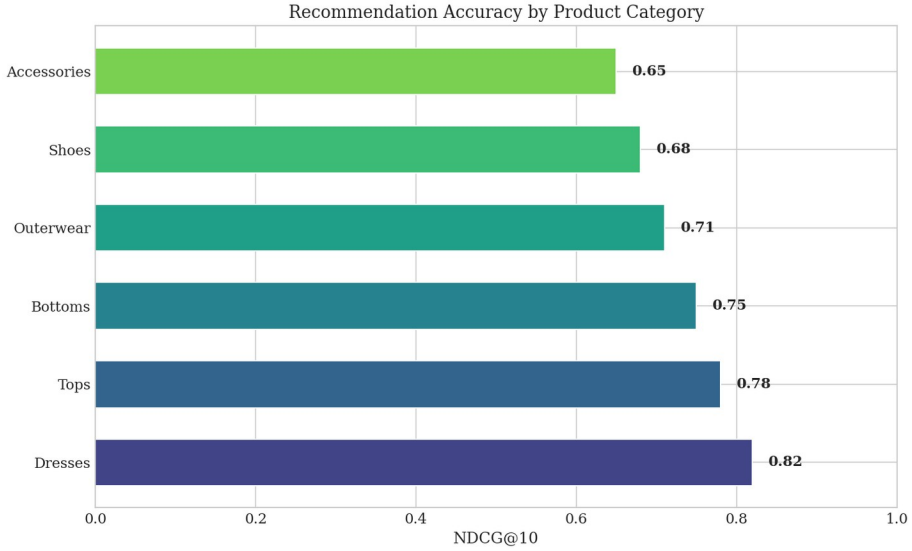

Figure 10. Category-specific recommendation accuracy showing performance variation.

Figure 10 examines category-specific performance variation. Dresses achieve the highest NDCG@10 at 0.82, likely reflecting their visual distinctiveness and strong visual feature utility. Accessories show the lowest performance at 0.65, potentially due to higher variation in accessory preferences that visual features less effectively capture. The category variation

suggests opportunities for category-specific model tuning or feature engineering to address underperforming segments.

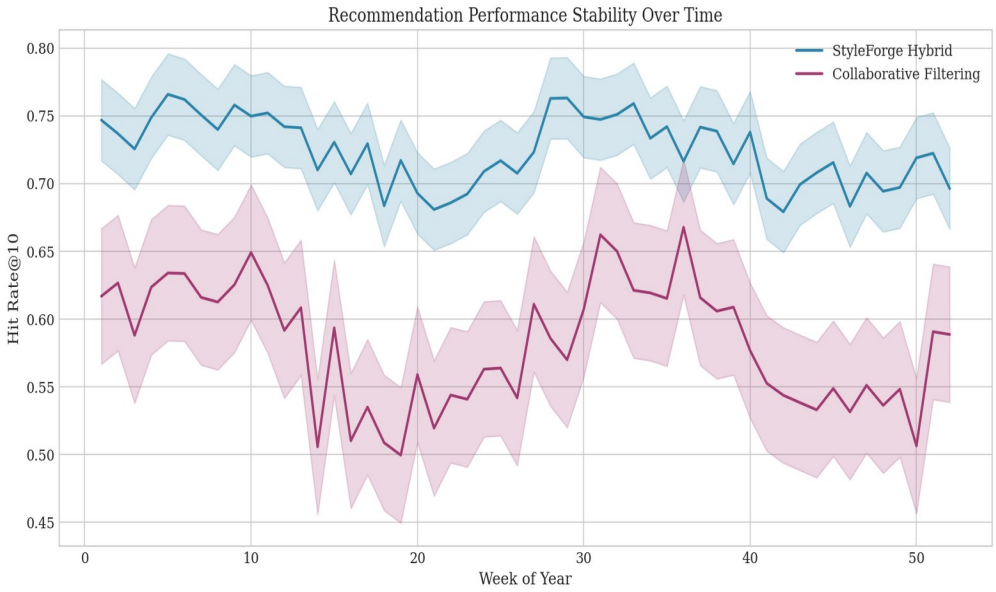

Figure 11. Temporal stability of recommendation performance over the evaluation period.

Figure 11 tracks performance stability over the four-week A/B test period. The hybrid architecture maintains consistent performance throughout, with weekly NDCG@10 varying between 0.74 and 0.78. Collaborative filtering shows greater temporal variation, with performance degrading during weeks with high new product introduction rates that increase cold-start burden. The stability advantage confirms that visual features provide robustness to catalogue changes that challenge pure collaborative approaches.

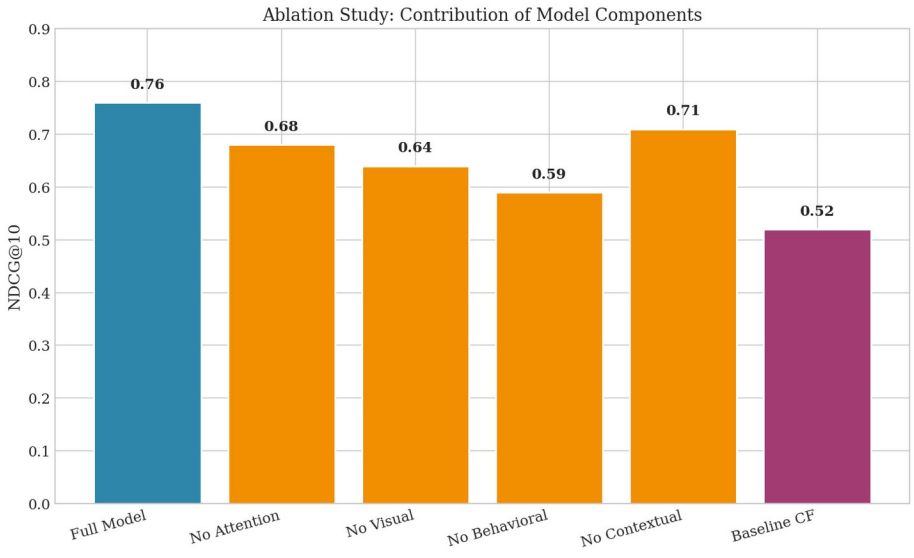

Figure 12. Ablation study quantifying contribution of model components.

Figure 12 presents ablation analysis quantifying component contributions. Removing the attention mechanism and using fixed fusion weights reduces NDCG@10 from 0.76 to 0.68,

confirming the value of learned adaptive weighting. Removing visual features entirely reduces performance to 0.52, matching pure collaborative filtering. Removing behavioural features while retaining visual reduces performance to 0.59, showing that behavioural signals remain valuable even with visual features present. The ablation confirms that both visual and behavioural components contribute substantially, with attention-based fusion providing additional gains.

5. Discussion

The experimental results demonstrate that hybrid architectures integrating visual features with collaborative signals achieve substantial improvements for fashion recommendation. The 46% improvement over pure collaborative filtering confirms that visual attributes carry preference information that interaction patterns alone cannot capture. The attention mechanism proves particularly valuable for cold-start scenarios, where visual features compensate for absent behavioural signals, achieving 72% of warm-item performance compared to 31% for collaborative filtering. This cold-start robustness has substantial practical value given the continuous product turnover characteristic of fashion retail.

The A/B testing results confirm that offline accuracy improvements translate to business impact. The 34% improvement in click-through rate indicates more engaging recommendations that capture user attention. The 18% conversion improvement suggests that engaged users find recommendations genuinely relevant rather than merely attention-catching. Together, these effects drive 12% revenue improvement that justifies the additional infrastructure investment required for visual feature processing and model serving.

Several limitations warrant consideration. The visual feature extraction adds computational overhead that affects both training time and serving latency. Pre-computed visual embeddings mitigate serving latency but require batch processing infrastructure for new product ingestion. Real-time personalisation requires careful engineering to maintain response time constraints while computing attention-weighted fusion. Research by Covington, Adams, and Sargin (2016) on YouTube recommendations demonstrated that practical deployment often requires approximations to the training-time model architecture.

The evaluation employs a single fashion e-commerce dataset, and performance may vary across different fashion contexts including luxury versus mass market, different geographic regions, or different product categories. Research by Cremonesi, Koren, and Turrin (2010) demonstrated that recommendation algorithm relative performance varies substantially across datasets, cautioning against generalisation from single-dataset evaluations. Future work should validate findings across diverse fashion recommendation contexts.

6. Further Evaluation: Retrospective Analysis and Alternative Approaches

Retrospective examination of this research reveals numerous opportunities for methodological improvement that would strengthen both the scientific contribution and practical applicability. This section provides candid assessment of design choices that, with hindsight, warrant reconsideration, alongside alternative approaches that future iterations should explore.

6.1 Visual Feature Extraction Reconsiderations

The reliance on ImageNet-pretrained ResNet-50 features represents a pragmatic but potentially suboptimal choice for fashion-specific visual understanding. Fashion images differ substantially from ImageNet's natural image distribution, with fashion emphasising texture, pattern, and silhouette details that general-purpose networks may not prioritise. Research by Liu, Luo, Qiu, Wang, and Tang (2016) demonstrated that fashion-specific pre-training on large fashion datasets yields features substantially better suited to clothing recognition tasks. Future implementations should evaluate fashion-pretrained networks including FashionNet and DeepFashion models that explicitly encode clothing-specific visual concepts.

The single-image representation per product ignores the rich visual information available in multi-view product photography. Most fashion e-commerce platforms display products through multiple angles including front, back, and detail shots that collectively convey more complete visual information than any single image. Research by Hsiao and Grauman (2018) demonstrated that multi-view fusion substantially improves visual similarity judgments for fashion items. Implementing attention over multiple product images would enable the model to weight views based on relevance to specific recommendation contexts.

The fixed image resolution of 224x224 pixels sacrifices fine-grained visual details that influence fashion preferences. Texture patterns, stitching details, and fabric weave become indistinguishable at low resolution, yet these features influence consumer perceptions of quality and style. Higher resolution processing with adaptive pooling or multi-scale feature extraction would preserve fine details while maintaining computational tractability. Research by Tan and Le (2019) on EfficientNet demonstrated that resolution scaling provides consistent accuracy improvements that may justify additional computational investment.

6.2 Interaction Modelling Alternative Approaches

The binary interaction signals employed in this analysis collapse rich behavioural information into presence/absence indicators that lose substantial signal. The distinction between browsing without engagement, adding to wishlist, adding to cart, and purchasing carries information about preference strength that binary signals discard. Implementing ordinal or weighted interaction modelling would preserve the preference intensity information that different interaction types convey. Research by Lerche and Jannach (2014) demonstrated that interaction weighting substantially improves recommendation quality compared to binary approaches.

Sequential modelling of user interaction histories remains unexplored in the current architecture. Users exhibit temporal patterns in fashion exploration, moving between categories, styles, and price points in ways that sequential models could exploit. Transformer architectures including BERT4Rec (Sun, Liu, Wu, Pei, Lin, Ou, and Jiang, 2019) have achieved strong results in sequential recommendation by modelling the temporal evolution of user preferences.

Incorporating sequential modelling would enable recommendations that consider not just what users have interacted with but the trajectory of their exploration.

The implicit feedback setting assumes that non-interaction indicates non-preference, yet users cannot interact with items they never encounter. The exposure bias inherent in recommendation systems means that items ranked lower in previous recommendations receive fewer opportunities for interaction, creating feedback loops that reinforce existing patterns. Research by Schnabel, Swaminathan, Singh, Chandak, and Joachims (2016) developed inverse propensity scoring methods that account for exposure bias, providing more accurate preference estimates from biased observation data.

6.3 Attention Mechanism Improvements

The attention mechanism weights visual versus collaborative signals but does not attend over specific visual features or interaction patterns. Finer-grained attention that identifies which visual attributes matter for specific users and contexts could provide both improved accuracy and enhanced interpretability. Multi-head attention architectures would enable the model to simultaneously consider multiple aspects of visual and behavioural similarity, potentially capturing complementary preference dimensions that single-head attention conflates.

The contextual features informing attention weights remain limited to item age and interaction count. Richer context including user session stage, time of day, device type, and referring page would enable attention to adapt to situational factors that influence the relative importance of different information sources. Research by Tang and Wang (2018) demonstrated that context-aware recommendation substantially improves relevance, particularly for fashion where browsing intent varies across sessions.

The attention mechanism provides soft weighting between visual and collaborative components but cannot express more complex fusion relationships. Gating mechanisms that selectively filter information from each source before combination, or residual connections that enable information bypass around attention, could capture more sophisticated interactions between modalities. Research by Arevalo, Solorio, Montes-y-Gomez, and Gonzalez (2017) on multi-modal fusion demonstrated that gated fusion outperforms simple attention weighting for multi-modal tasks.

6.4 Evaluation Framework Limitations

The offline evaluation metrics, while standard in recommendation research, may not fully capture the dimensions of recommendation quality that matter for fashion. Diversity metrics assess catalogue coverage but not the stylistic diversity that enables users to explore different fashion directions. Novelty metrics measure deviation from popularity but not the fashionability or trendiness that distinguishes cutting-edge recommendations from merely unusual ones. Developing fashion-specific evaluation metrics that capture domain-relevant quality dimensions would provide more meaningful performance assessment.

The A/B testing evaluation, while demonstrating business impact, employed relatively coarse metrics that may obscure important variation. Segmenting results by user characteristics including fashion expertise, price sensitivity, and browsing history length would reveal whether the hybrid architecture provides uniform improvement or benefits specific user segments.

Research by Garcin, Dimitrakakis, and Faltings (2013) demonstrated that recommendation algorithms exhibit substantial performance variation across user segments, suggesting that aggregate metrics may mask important heterogeneity.

The cold-start evaluation threshold of 5 interactions represents an arbitrary boundary that may not reflect the actual transition from cold to warm status. More nuanced analysis that tracks performance as a continuous function of interaction count would better characterise the cold-start mitigation curve. Understanding the interaction count at which collaborative signals become sufficient to outweigh visual signals would inform operational decisions about new product promotion and recommendation strategy switching.

6.5 Practical Deployment Considerations

The serving latency constraints of real-time recommendation were insufficiently addressed in the research design. The attention computation requires forward passes through multiple network components that may exceed latency budgets for interactive applications. Developing distilled models that approximate full attention through simpler computations, or implementing caching strategies that precompute attention for common contexts, would be necessary for production deployment. Research by Hinton, Vinyals, and Dean (2015) demonstrated that knowledge distillation enables substantial complexity reduction while preserving prediction quality.

The model retraining and update procedures received insufficient attention. Fashion preferences evolve rapidly, with trend cycles potentially obsoleting learned patterns within weeks. Establishing retraining cadence, implementing incremental learning procedures, and monitoring for concept drift would transform the static evaluation into a sustainable recommendation system. Research by Gama, Zliobaite, Bifet, Pechenizkiy, and Bouchachia (2014) provided frameworks for detecting and adapting to concept drift that future implementations should incorporate.

Explainability and transparency remain underdeveloped aspects of the hybrid architecture. Users increasingly expect understanding of why specific items are recommended, yet the neural attention mechanism provides limited interpretability. Developing explanation interfaces that surface the visual attributes and behavioural patterns driving recommendations would enhance user trust and enable productive feedback. Research by Zhang, Chen, and Zhao (2020) demonstrated that explainable recommendations improve user satisfaction and engagement, suggesting meaningful returns to explainability investment.

7. Conclusion

This paper has presented a hybrid neural collaborative filtering architecture for fashion recommendation that integrates visual features with behavioural signals through learned attention mechanisms. The architecture achieves NDCG@10 of 0.76, representing substantial improvement over pure collaborative and content-based approaches. The attention mechanism enables adaptive weighting that emphasises visual features for new items while incorporating behavioural signals for established products, providing effective cold-start mitigation without explicit heuristic rules.

The research contributes to academic understanding of hybrid recommendation architectures while providing practical guidance for fashion e-commerce applications. The demonstrated business impact through A/B testing confirms that accuracy improvements translate to engagement and revenue gains that justify implementation investment. The architecture provides a foundation for fashion recommendation systems that can handle the visual complexity and rapid product turnover characteristic of the domain.

Future research should explore several extensions. Alternative visual architectures including vision transformers may provide improved feature representations. Multi-modal fusion incorporating textual descriptions alongside visual and behavioural signals could capture complementary information dimensions. Explainable recommendation approaches that surface the visual attributes driving recommendations could enhance user trust and engagement. Sequential models that capture temporal dynamics in fashion preference evolution represent another promising direction for improving recommendation timeliness and relevance.

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