

AI-Enabled Intelligent Recommendation Engine for Personalized Digital Services

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ABSTRACT

While the use of recommendation engines to connect users to the service they need is becoming central to the success of digital platforms, the traditional approaches to recommendation engines are faced with a number of challenges in this context: lack of interactions, contextual variation, and rapidly changing preferences. This study aims to suggest an intelligent recommendation engine with AI, which is based on the Attention-based Hybrid Deep Learning Recommendation method based on PyTorch. It brings together embeddings of user information, embeddings of service identities, features characterizing service categories and contextual signals from the surrounding content, and extracts the relative weights of the heterogeneous representations by employing an attention mechanism, to utilize these representations for ranking candidate services. A synthetic benchmark was used to create a reproducible proof-of-concept experiment and contains 360 users, 180 digital services, 12 service categories, 8 contexts, 5,760 training interactions and 1,080 test interactions. The proposed model achieved better ranking quality in all of the overall ranking metric with HR at 10=0.3315, NDCG at 10=0.1694, MRR at 10=0.1208 and AUC=0.6492 compared to popularity, matrix factorization, neural collaborative filtering and non-attentive hybrid model. Results show the usefulness of adaptive feature

fusion to personalize tasks in a context-specific way.

Keywords: Personalization, recommendation, attention, deep learning, context, PyTorch.

Introduction

Digital services are a component of commerce, entertainment, finances, education, communication and public service delivery. With the increasing number of applications and services, users are having to deal with an information overload problem in which they are not able to pinpoint the appropriate selection. Recommendation engines alleviate this by extracting behavioural cues, and then delivering services ranked by their relevance to each user's interest. While effective, conventional collaborative filtering and content-based methods can suffer from ineffectiveness in the presence of little interaction history, new users or services, and when relevance of an option is context-dependent as shown in figure 1.

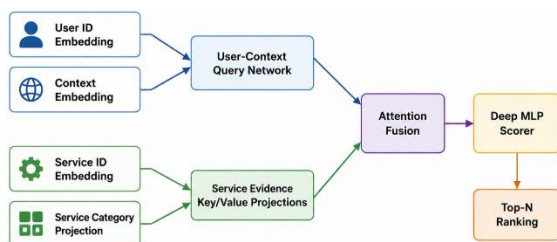


Figure 1. Architecture of the Attention-Based Hybrid Deep Learning Recommendation engine.

The capability of recommender systems has been extended by deep learning to learn the relationship between the service and the user, which is nonlinear and high dimensional. Sequential attention models, like SASRec and BERT4Rec, showed attention to be a useful tool to capture influential behaviors in interaction history [1] [2]. High-order collaborative representations were achieved in two ways: Graph-based methods (NGCF and LightGCN) [3] [4] that used high-order connectivity and neighborhood propagation. Contrastive learning, diffusion models, latent-intent attention, and hybrid architectures are more recent areas of research that have been investigated to boost robustness, representation quality, and personalization [5]-[9]. These

developments do not bridge the divide between models that are very specific and an integrated model that will be able to link between identity, content and context and dynamically manage the role each plays in the recommendations.

In this study, the authors are building an AI-Enabled Intelligent Recommendation Engine for Personalized Digital Services based on Attention-Based Hybrid Deep Learning Recommendation algorithm in PyTorch. Dense representations of user identifiers, service identifiers, service-category descriptors and contextual variables. An attention layer learns adaptive weights for service identity and content signals with respect to the state of the user-context, and a multilayer prediction network estimates preference scores to rank the user-contexts. The architecture is assessed based on its popularity ranking, matrix factorization, neural collaborative filtering and a non-attentive hybrid network. The contribution is a novel, modular and reproducible recommendation framework that boosts the context-awareness of the Top-N recommendation without sacrificing the interpretability of feature importance by means of learned attention weights.

Related Work

Kang and McAuley proposed SASRec which is based on self-attention to capture short- and long-range sequential dependencies while efficiently predicting the next item [1]. Sun et al. took this line one step further by using bidirectional Transformer for encoding and masked-item prediction to obtain more comprehensive behavioral representations (BERT4Rec) [2]. In order to propagate embeddings through the user/item graph, and to explicitly embed higher-order collaborative signals, Wang et al. came up with a new model called NGCF [3]. He et al. demonstrated that linear neighborhood aggregation has the ability to outperform more complex graph transformations in the context of graph recommendation with LightGCN [4].

Table 1. Related work aligned with the proposed recommendation engine.

Year	Study	Methodology	Key contribution	Limitation
2018	Kang & McAuley, SASRec [1]	Self-attentive sequential modeling	Balances recent and long-range behavior efficiently	Relies mainly on interaction sequences; limited side/context features
2019	Sun et al., BERT4Rec [2]	Bidirectional Transformer with masked-item prediction	Learns richer sequential preference representations	Higher training cost and dependence on sufficient behavior history
2019	Wang et al., NGCF [3]	Graph neural collaborative filtering	Captures high-order user-item connectivity	Graph propagation can be costly; weak use of content/context
2020	He et al., LightGCN [4]	Simplified graph convolution for collaborative filtering	Improves graph recommendation with linear propagation	Does not directly model contextual states or service metadata
2021	Zhao et al., RecBole [5]	PyTorch recommendation framework	Standardizes datasets, models, tuning, and evaluation	Framework contribution rather than a new personalization mechanism
2022	Xie et al., CL4SRec [6]	Contrastive sequential learning	Uses self-supervision to improve sparse sequence representations	Sensitive to augmentation design and still sequence-centered
2022	Qiu et al., DuoRec [7]	Contrastive regularization with semantic positives	Reduces representation degeneration	Primarily optimized for sequential item recommendation
2023	Wang et al., DiffRec [8]	Diffusion-based denoising recommender	Models noisy interactions and temporal preference shifts	Diffusion training and inference add computational complexity
2025	Zhang et al., ANTM [9]	Neural topic model + BPR + attention	Captures latent user intents with adaptive weighting	Intent modeling adds complexity and depends on interaction evidence
2025	Alrashidi et al., DHSRS [10]	Deep hybrid model using social and textual traits	Addresses sparsity, cold start, and contextual information	Requires auxiliary social/text data and may be domain dependent

Reproducibility and the uniform evaluation of different recommendation models gained importance with RecBole, a PyTorch-based framework that encompasses general, sequential, context-aware and knowledge-based recommendation models [5]. To solve the lack

of supervision problem, Xie et al. proposed to use next-item learning in conjunction with contrastive objectives, called CL4SRec [6]. To alleviate the representation degeneration, Qiu et al. proposed a regularization method called contrastive regularization and a positive

sampling method called semantically consistent positive sampling, and added them together to form a new method called DuoRec [7]. Later, Wang et al. introduced DiffRec, which used diffusion-based denoising to enhance the generation of interactions and further refined the model by introducing an efficient latent space and a time change of preference [8].

Recent studies confirm the importance of paying attention and feature fusion. Zhang et al. combined a neural topic model, with Bayesian personalized ranking and attention to capture the latent user intents which led to improvements in hit rate and NDCG [9]. Alrashidi et al. proposed deep neural processing along with social and textual characteristics to address sparsity, cold start and contextual issues [10]. Overall, the literature indicates significant advances, but there are a number of strategies that focus on a single signal family. This work thus entails fusing user identity, service identity, content, and context in a single attention controlled PyTorch architecture to rank digital services and services more personalized[01-09]. This design is not designed to have fixed feature weights that do not change over time or with each user, but instead change the evidence used according to the context and user.

Research Methodology

The research method adopts a design and evaluation manner and is based on a model of Attention-Based Hybrid Deep Learning Recommendation, which is fully realized using PyTorch. There are four sources of information in the input space: user identifiers, digital-service identifiers, service-category metadata and contextual states. User and service identifiers are associated to learnable embedding vectors and service descriptors are converted to a linear projection and then a nonlinear activation. A trainable embedding that describes the situation of the interaction, is regarded as context. This representation offers collaborative, content and situational evidence in one model, thereby decreasing reliance on one information source.

A. Research Design

We use a design-and-evaluation approach with a completely PyTorch-based Attention-Based Hybrid Deep Learning Recommendation model.

It is a collaborative and content and contextual evidence that is integrated in a single integrated framework. The following four types of information were used: user identifiers, identifiers of digital-services, metadata of the service-categories and contextual states. This design aims to provide less reliance on a single information source, and to enable recommendations to be based on both long-term preferences and behavior in specific contexts.

B. Input Representation

Identifiers of the users and services are integer encoded and converted to trainable embedding vectors. The service-category descriptors are one-hot encoded and projected and then activated by a nonlinear transformation. Trainable embeddings of the interaction situation (contextual states). The user and context embeddings for each tuple of user-service-context are combined and fed into a query network to get a user-context conditioned representation of the user. The two candidate evidence-vectors are generated by independently transforming the two sets of service identity and service-content representations.

Table 2. Experimental configuration of the PyTorch proof-of-concept.

Configuration	Value
Users	360
Digital services	180
Service categories	12
Context states	8
Training interactions	5,760
Validation interactions	720
Test interactions	1,080
Embedding dimension	32
Batch size	2,048
Optimizer	AdamW
Loss	Binary cross-entropy with logits
Training epochs	10
Random seed	2026
Candidate set per test event	1 positive + 59 negatives

C. Attention-Based Hybrid Model

A part of the attention mechanism is designed to compute the similarity between the user-context query and the learned key representations of service identities and service contents. Normance with softmax function is used to get two data-dependent attention weights. These weights give a relative weight to the identity-based and content-based evidence for each prediction. The vector of values of services being fused, which results in a weighted representation of the services. This fused service vector, query vector, element-wise interaction terms and attention weights are then concatenated and passed through fully connected layers using a ReLU activation and dropout. An unbounded preference logit is generated by output layer for each candidate service.

$$\text{Attention: } \alpha = \text{softmax}((q \cdot k) / \sqrt{d}), \quad \text{fused} \\ \text{service vector} = \sum \alpha_i v_i$$

$$\text{Preference score: } \hat{y}(u,s,c) = \text{MLP}[q, z, q \odot z, u \\ \odot c, \alpha]$$

D. Training Procedure

The model is trained using implicit feedback in the form of a binary classification problem. Interacted services are considered examples of the positive and unobserved ones are considered as a sampled example of the negative. Hard negative sampling focusses on services that are reasonable to consider in the same user in other situations, resulting in a harder discrimination problem than random negative sampling. AdamW is the algorithm that minimises logits and binary cross entropy. The embedding dimension is 32, mini-batch size is 2,048 and training is done for 10 epochs. The experiments are conducted on the CPU version of PyTorch, with the results being reproducible with the following random number seed: 2026 The model can be directly used on the GPU.

E. Synthetic Benchmark and Data Split

The proof-of-concept benchmark is a synthetic proof, and not a claim to deployment evidence from a commercial platform. It serves 360 users and 180 services, 12 service categories and eight contextual states. A category and a latent representation are attributed to each service, a category, a latent preference vector are

attributed to each user, and the quality component is attributed to each service-user pair depending on the context. Context and user's preference, together with characteristic of services, impact on service selections, which happen probabilistically through interactions. If the split is done temporally, then the number of interactions in the training set is 5760, the number for validation is 720, and the number for test is 1080. For each test event, one service is used and 59 candidate negatives are used, the majority of which are from the user's preferred categories, but in other settings.

F. Evaluation and Implementation

Hit Rate at 10 (HR@10), normalized discounted cumulative gain at 10 (NDCG@10), mean reciprocal rank at 10 (MRR@10) and area under the receiver operating characteristic curve (AUC) are used to evaluate performance. There are four types of metrics: HR@10 (has the desired service in the top ten results), NDCG@10 (higher ranking of the desired service), MRR@10 (reciprocal rank of the first relevant result), and AUC (how much discrimination there is between positive and negative candidates). The following four baseline methods are evaluated: Popularity Ranking, Matrix Factorization, Neural Collaborative Filtering and a Hybrid multilayer perceptron without attention. The weights of the learned attentions are also averaged across test interactions to explore the relative use of service identity and service-content evidence. The data in the interaction table is sorted by time, and the loss from the validation of the interactions is monitored during training; the final performance statistics are computed for the test split.

Results And Discussion

The results on the proof of concept evaluation showed that the attention-based hybrid model was the most effective model in terms of overall ranking results gained by five models used. The proposed model obtained HR@10 of 0.3315, NDCG@10 of 0.1694, MRR@10 of 0.1208, and AUC of 0.6492. The non-attentive Hybrid-MLP reached 0.3204, 0.1600, 0.1116, and 0.6277 on the same metrics. Compared to the nearest one in architecture, the attention resulted in a

3.47% increase in HR@10, 5.84% increase in NDCG@10, 8.22% increase in MRR@10 and 3.43% increase in AUC. The improvements

indicate that adaptive fusion not only increased the probability of being in the top-10 set but also their position in the set as shown in table 3.

Table 3. Comparative ranking results.

Model	HR@10	NDCG@10	MRR@10	AUC
Popularity	0.3111	0.1590	0.1134	0.6443
MF	0.1741	0.0833	0.0564	0.5058
NCF	0.3009	0.1523	0.1075	0.6177
Hybrid-MLP	0.3204	0.1600	0.1116	0.6277
Attention-Hybrid	0.3315	0.1694	0.1208	0.6492

Neural collaborative filtering achieved HR@10 of 0.3009, NDCG@10 of 0.1523, MRR@10 of 0.1075, and AUC of 0.6177. The proposed model, thus, increased the above measures by 10.15%, 11.22%, 12.41% and 5.11%, respectively. The HR metric at rank 10 (HR@10) and AUC values were 0.3111 and 0.6443, respectively, which were competitive since there was repeat exposure of categories in the synthetic service inventory. It achieved a better score than the robust non-personalized baseline on HR@10, NDCG@10 and MRR@10 by 6.55%, 6.56% and 6.57% respectively while having an equal score on AUC. The weak context-confusable negatives setting was best achieved by the matrix factorization which achieved HR@10=0.1741 and NDCG@10=0.0833. The weakest hard context confusables was achieved by HR@10=0.1741 and NDCG@10=0.0833 matrix factorization as shown in figure 2.

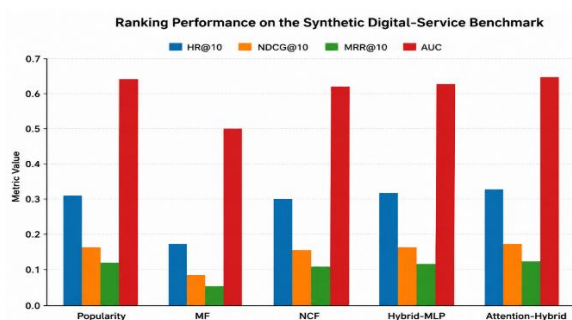


Figure 2. Comparative ranking metrics for the tested recommendation approaches.

The trained loss in the attention architecture was constant from the first epoch (0.5581) till the 10th epoch (0.4685). On average 59,47% of the attention was given to the service-identity evidence while 40,53% was given to the service

content evidence. The distribution suggests that collaborative identity signals are still the most significant ones and content information had some impact on the context-conditioned ranking. This is in line with the study design, which provides service categories that provide useful information, but maintains interactions with individual service users as shown in figure 3.

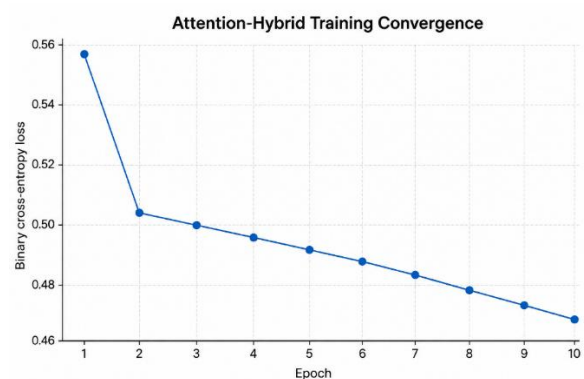


Figure 3. Training loss of the Attention-Hybrid model across ten epochs.

The results obtained numerically demonstrate the internal feasibility of the benchmark, and are not the results of an external deployment benchmark. Here are some of the more real-world platform effects, delayed feedback, exposure bias, missing context, and changing service catalogs that can have more significant impacts on actual platform data. The idea of attention-controlled hybrid fusion to improve the quality of the result of the ranking in the comparative experiment presented the main hypothesis, which suggests that attention-controlled hybrid fusion can improve ranking results quality when relevance depends on various factors including user, service, content and context. The pattern of the metric, however,

is different: better for NDCG and MRR than AUC – the majority of the gains are in the top of the ranked list where users will go to services. This is the appropriate behaviour to have for digital interfaces with limited display space. The comparison with Hybrid-MLP demonstrates that there is this additional context information that the learned weighting should be based upon, other than feature concatenation.

Conclusion

In this study, an AI-Enabled Intelligent Recommendation Engine for Personalized Digital Services was proposed based on Attention-Based Hybrid Deep Learning Recommendation method and its features in PyTorch. The architecture takes the user identity, the service identity, the service-category information, and the contextual state, applies adaptive attention, and scores user preferences. The performance of the model was then

evaluated by using a reproducible synthetic benchmark and the model outperformed the other models with HR@10 of 0.3315, NDCG@10 of 0.1694, MRR@10 of 0.1208 and AUC of 0.6492. The highest relative improvement was 8.22% for MRR@10, which shows better positioning of relevant services towards the top of the ranking list compared to non-attentive hybrid baseline. Content evidence was also found to be used meaningfully with identity evidence, as revealed by attention analysis. The results agree with the feasibility of attention-controlled hybrid fusion as a practical approach for personalization in a context-specific manner. The framework can be extended to real digital-service logs, temporal drift, cold-start cohorts, fairness analysis, privacy-preserving learning and online user experiments in various service domains and realistic deployment settings in the future.

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