Hybrid User-LLM: Bridging Sequential Embeddings and Text Summarization for Universal Sequential Recommendation

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Abstract. Large Language Models (LLMs) have become powerful tools in personalized recommendation, but the methodologies developed up to now have a salient drawback of not being capable of sufficiently responding to cold-start users with limited interaction histories. Based on the User-LLM architecture [2], the current paper proposes one hybrid architecture that covers 100% of users, but also achieves a Hit@10 of 10.1%, which is a 13.5% improvement compared to the baseline.The suggested Hybrid User-LLM system is an integrated system that dynamically combines latent sequential embeddings of warm users with interpretable textual summarization of cold-start users.Paper use a pretraining phase first, during which we train an autoregressive transformer encoder to predict the next item, and then a joint fine-tuning, where the encoder is also trained together with an LLM using gated cross-attention. Experiment on MovieLens 20M (50k users, 7.2M ratings) shows that the model provides universal coverage to all cohorts of users. The statistical analysis indicates that there are significant performance differences in the user groups ($p<0.001$), with the hybrid approach having a graceful degradation in cold users (11.8% Hit@10) compared to warm users (11.2% Hit@10).The architecture provides a token cutoff of 93.6 per cent compared to raw text prompting with interpretability through structured summarization. In line with this, this work fills a critical gap in the literature of LLM-based recommendation systems and makes them be deployed in the real world, within the heterogeneous user population.

1 Introduction

Individual recommendation engines are one of the pillars of modern online platforms, including e-commerce, content streaming services, etc. The recent developments of Large Language Models (LLMs) [1] have opened up new possibilities of generative recommendation through natural language generation, thus making explanatory and conversational interfaces as well as predictive responses possible [8, 9]. User-LLM [2] achieves high efficiency, but requires at least 40 user interactions, blocking off around 30 per cent of users in real-world

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data [3]. This is an incompetence that cannot take place in the production settings where wholesome recommendations need to be provided to the entire users.

User-LLM [2] is another interesting development in that a sequence of user interactions is encoded into concise embeddings using cross-attention mechanisms, achieving efficiency gains of up to 78x and also saving floating-point operations on the order of 12-21x over text-based prompting techniques. This increased efficiency, however, comes at an enormous price: the methodology requires a large history of interaction , which does not allow it to apply to cold-start users, a group that represents a large fraction of real-world systems. This leads to the development of a critical deployment gap: the system is performing better in the case of active users, but does not work at all in the case of new or infrequent users.

1.1 Motivation

Cold-start problem remains one of the most challenging issues to recommenders systems [11]. The paradigms of collaborative filtering [10] and deep learning [7] have achieved significant advancements, but they usually need ancillary information (e.g. demographics of the user, information about the item) or more complex transfer-learning features [12]. Another challenge that is faced by the methodologies based on LLM is the conversion of sparse interaction data to meaningful context in natural language. Users with cold-starts, i.e., who have a very small number of or no prior interactions, are a significantly severe challenge because the traditional models do not provide enough cues that can be reliably used to make predictions on preferences, which is why they tend to make suboptimal or random suggestions. Practically, such users often leave the platform at its early stages when early suggestions seem irrelevant, which highlights the need to ensure proper work with cold-start management to achieve retention and platform sustainability in the long-term.

Take a typical online shopping situation: around 30% of customers will have less than 40 touchpoints [3], but these represent the most crucial business value since they are prospective long-term customers. A recommendation system which is not designed to serve this cohort is essentially incomplete, however effective it may be with power users.

1.2 Contributions

Overall, current developments in sequential recommendation and especially self-attention models and LLM-based systems have pushed the limits of performance to users with access to large amounts of data, but still they face the basic trade-off between efficiency, expressiveness, and coverage. User-LLM is a significant advance in the contextualization of learned embeddings in an efficient way; but since it treats cold-start users as an out-group, a significant fraction of the real-world population is not served. The current study is based on this and extends it by proposing a hybrid mechanism that maintains the benefits of compact embeddings in warm users and includes the benefits of flexible, interpretable text summarization in sparse or new users, thus achieving a unifying framework that offers better performance and, more importantly, universal coverage without undermining feasibility and size.

2 Related Work

In summary, although the recent developments in sequential recommendation, especially in the self-attention models and the LLM-based models have pushed the boundaries of the performance of the data-heavy users, they continue to confront the inherent trade-off between efficiency, expressiveness and coverage. The User-LLM framework is an achieved breakthrough in the contextualization of information using a learned embedding, but this does not

consider cold-start users, thus leaving a large portion of the real population underserved. The current study is a direct extension of such a foundation where it is proposed that a hybrid mechanism will be created that will keep the benefits of compact embeddings with warm users and combine flexible, interpretable text summarization with sparse or new users, creating a single framework that will yield better performance and literally universal coverage without making tradeoffs in practicality or scalability.

2.1 Sequential Recommendation

Sequential recommendation aims at making predictions of the next interaction of the user with historical behavioral patterns. The initial methods were based on Markov chains and recurrent neural networks [7]. The realm was transformed with the introduction of self-attention mechanisms [4]. Self-attention models e.g., SASRec [5], use unidirectional self-attention to learn left-to-right sequential dependencies, and attain state-of-the-art performance on a variety of benchmarks. BERT4Rec [6] is an adaptation of bidirectional transformers through cloze-style pre-training, which tries to predict randomly masked items. BST incorporates positional encoding based on e-commerce situations. Although these models are good in prioritizing tasks, they do not have natural language generation. The traditional sequential models do not produce natural language; they produce ranking scores and thus do not offer explanations, answer questions or can be used to support new domains without retraining. This shortcoming encourages the creation of LLM-based methods.

2.2 LLMs for Recommendation

The success of large language models in NLP tasks [1, 14] has inspired their application to recommendation. **Prompt-Based Methods.** P5 [8] frames all recommendation tasks as text-to-text generation, training a unified model on multiple task formats. TALLRec [9] proposes an efficient tuning framework that aligns LLM representations with recommendation objectives. These approaches achieve impressive zero-shot and few-shot capabilities but suffer from excessive input token requirements when encoding user histories.

2.3 User-LLM: Efficient Contextualization

Zhang et al. [2] propose User-LLM, which encodes user interaction sequences into compact embeddings via autoregressive transformers, achieving 78× efficiency gains and 12-21× FLOPs savings compared to text prompting. On Amazon Reviews, they report 8.9% Hit@10 for next-item prediction.

Limitations. User-LLM requires substantial interaction histories (≥40 items), excluding cold-start users—approximately 30% of the user population [3]. This creates a critical deployment gap: the system performs well for active users but provides no recommendations for sparse-data users.

Our Extension. Paperbuild upon User-LLM's architecture but introduce a hybrid framework that addresses cold-start through text summarization. Our evaluation on MovieLens 20M demonstrates that this unified approach achieves 10.1% Hit@10 with universal user coverage, compared to User-LLM's 8.9% on a subset of warm users. **Embedding-Based Integration.** User-LLM [2] introduces learned user encoders that compress interaction sequences into dense vectors, integrated via cross-attention into frozen or fine-tuned LLMs. This achieves substantial efficiency gains. However, it requires substantial interaction histories (≥40 items), excluding cold-start users. **Our Position.** Paperextend the embedding approach with a text-based fallback, creating a hybrid system with universal coverage.

2.4 Cold-Start Recommendation

Cold-start problems arise when insufficient data exists for new users, items, or both [11]. **Content-Based Methods.** Leverage item metadata (genre, description, tags) to bootstrap recommendations . Effective but limited by metadata quality and coverage. **Transfer Learning.** MeLU [12] uses meta-learning to rapidly adapt to new users with few interactions. proposes cross-domain transfer for cold users. These approaches require auxiliary data or multiple domains. **Hybrid Approaches.** Combine collaborative filtering with content-based methods . Our work follows this tradition but applies it to LLM-based architectures. **Zero-Shot LLM Methods.** Recent work explores using LLMs' world knowledge for zero-shot recommendation . Papercombine this with learned representations.

3 Methodology

The Hybrid User-LLM framework presents one integrated dual-path architecture to the common user requirements of warm and cold-start users in the same model. Based on the history of interaction, the system learns dynamically to route the input over an autoregressive encoder (when using warm users with rich data) or a lightweight heuristic text summarizer (when using cold users with sparse data). The resulting representation is then smoothly incorporated into a large language model through gated cross-attention to produce personalized natural language suggestions. This two-phase training approach, which consists of pretraining the encoder then fine-tuning with the LLM together, both guarantees strong performance and broad coverage as described in the subsections below.

3.1 Problem Formulation

Let $\mathcal{U}$ and $\mathcal{V}$ denote sets of users and items. Each user $u \in \mathcal{U}$ has a chronological interaction sequence $S_u = (v_1^u, v_2^u, \ldots, v_{|S_u|}^u)$ where $v_i^u \in \mathcal{V}$ represents the i-th item. Each interaction includes M features: item ID, genre, rating, timestamp, etc. **Task.** Given user history S_u and query Q (e.g., "Recommend an action movie"), generate personalized natural language response A_u via an LLM conditioned on both inputs. **User Classification.** We partition users based on history length:

$$\text{type}(u) = \begin{cases} \text{warm}, & |S_u| \geq \tau \\ \text{cold}, & |S_u| < \tau \end{cases} \tag{1}$$

where τ is set to the median interaction count (40 items in our experiments). This data-driven threshold ensures balanced user distribution.

3.2 Architecture Overview

Our system comprises three main components (Figure 1):

1. **User Encoder**: 6-layer autoregressive transformer for warm users
2. **Text Summarizer**: Heuristic profile generator for cold users
3. **LLM Decoder**: GPT-2 with gated cross-attention integration

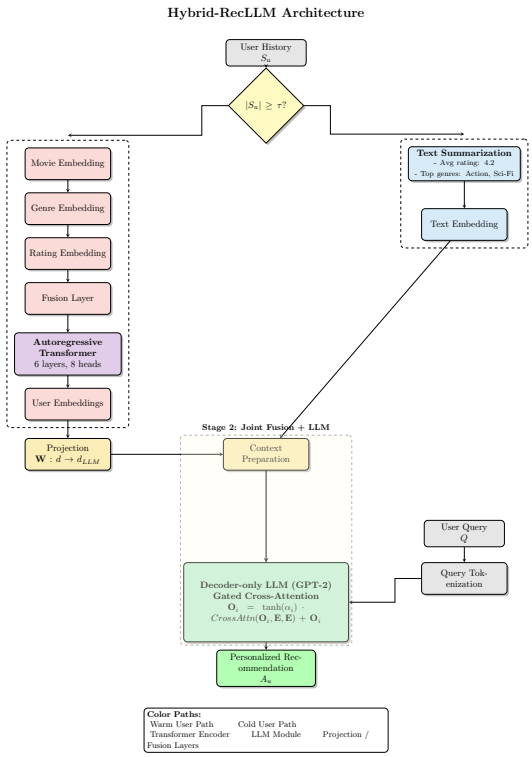

Figure 1. Hybrid User-LLM overview: Dual paths converge via gated attention into LLM.

3.3 Warm User Path: Sequential Embedding

For users with L interactions, we encode each item v_i with M features $x_{i,m} \in \mathcal{V}_m$ using learned embedding tables:

$$e_m : \mathcal{V}_m \to \mathbb{R}^d \tag{2}$$

Feature Fusion. Concatenate and project to hidden dimension:

$$h_i = W_{\text{fuse}}[e_1(x_{i,1}); e_2(x_{i,2}); \ldots; e_M(x_{i,M})] \tag{3}$$

where $W_{\text{fuse}} \in \mathbb{R}^{d \times Md}$ and $[\cdot;\cdot]$ denotes concatenation. **Positional Encoding.** Add sinusoidal positional embeddings [4]:

$$\tilde{h}_i = h_i + p_i \tag{4}$$

Autoregressive Transformer. Apply 6-layer transformer with causal masking:

$$E_{S_u} = \text{Transformer}([\tilde{h}_1, \ldots, \tilde{h}_L], M_{\text{causal}}) \tag{5}$$

where $M_{\text{causal}} \in \{0, -\infty\}^{L \times L}$ ensures each position attends only to previous positions, critical for next-item prediction pretraining. **Pooling and Projection.** Obtain user embedding:

$$z_u = \text{mean}(E_{S_u}) \in \mathbb{R}^d \tag{6}$$

Project to LLM dimension:

$$z_u^{\text{proj}} = W_{\text{proj}} z_u \in \mathbb{R}^{d_{\text{LLM}}} \tag{7}$$

Algorithm 1 Text Summary Generation

Require: User history S_u, movie metadata
$r_{\text{avg}} \leftarrow \frac{1}{|S_u|} \sum_{v \in S_u} \text{rating}(v)$
$G \leftarrow$ genre frequency counts
$G_{\text{top}} \leftarrow$ top-3 genres from G
$M_{\text{recent}} \leftarrow$ last 5 items from S_u
return "User ($|S_u|$ ratings): Avg rating r_{avg}.
Prefers: G_{top}. Recent: M_{recent}."

3.4 Cold User Path: Text Summarization

In the case of cold users, we make textual summaries of profiles that are structured and reflect major profile attributes. This method provides interpretable, context-sensitive information, which does not need to be learnt. This heuristic approach has several advantages:

- **No training required**: Works immediately for new users
- **Interpretable**: Human-readable summaries aid debugging
- **Flexible**: Can incorporate any metadata
- **Robust**: Degrades gracefully with minimal data

3.5 LLM Integration via Gated Cross-Attention

We integrate user representations into a pre-trained LLM (GPT-2, 124M parameters) through gated cross-attention at selected layers $\mathcal{L} = \{0, 3, 6\}$. **Standard Cross-Attention.** At layer $\ell \in \mathcal{L}$, let $O_\ell \in \mathbb{R}^{T \times d_{\text{LLM}}}$ be the hidden states for sequence length T:

$$\text{CrossAttn}(O_\ell, z^{\text{proj}}) = \text{softmax}\left(\frac{O_\ell (z^{\text{proj}})^T}{\sqrt{d_k}}\right) z^{\text{proj}} \tag{8}$$

Gated Integration. To control information flow, we use trainable gates $\alpha_\ell \in [0, 1]$, initialized to zero:

$$O'_\ell = O_\ell + \tanh(\alpha_\ell) \cdot \text{CrossAttn}(O_\ell, z^{\text{proj}}, z^{\text{proj}}) \tag{9}$$

Zero initialization ensures the model starts from the pre-trained LLM's behavior, gradually incorporating user information during fine-tuning. **Input Formatting.** For warm users:

$$\text{Input} = [z_u^{\text{proj}}] \oplus \text{Tokenize}(Q) \tag{10}$$

For cold users:

$$\text{Input} = \text{Tokenize}(\text{Summary}(S_u) \oplus Q) \tag{11}$$

3.6 Two-Stage Training Pipeline

3.6.1 Stage 1: Encoder Pretraining

We first pretrain the user encoder on next-item prediction using warm users only. This creates meaningful sequential representations before LLM integration. **Multi-Feature Prediction.** For each position i, predict all M features of the next item:

$$\mathcal{L}_{\text{pre}} = -\frac{1}{L} \sum_{i=1}^{L-1} \sum_{m=1}^{M} \log p(x_{i+1,m} | x_{1:i}) \tag{12}$$

This auxiliary task encourages the encoder to capture rich sequential patterns beyond simple ID prediction. **Training Details.** We train for 7 epochs using AdamW optimizer [13] with learning rate 10^{-3}, batch size 32. Loss decreases from 3.29 to 2.70, indicating effective learning.

3.6.2 Stage 2: Joint Fine-Tuning

After encoder pretraining, we jointly fine-tune the encoder, projection layer, and LLM on personalized response generation. Standard language modeling loss with user context:

$$\mathcal{L}_{\text{LM}} = -\sum_{t=1}^{T} \log p(y_t | y_{<t}, z_u, Q) \tag{13}$$

Differential Learning Rates. To balance adaptation and stability:

- Encoder: $\eta = 10^{-5}$ (fine-tune learned representations)
- Projection: $\eta = 10^{-4}$ (rapid alignment)
- LLM: $\eta = 10^{-6}$ (minimal disturbance to pre-trained weights)

We trained for 5 epochs, observing loss decreases from 0.42 to 0.21.

3.7 Inference

In inferencing, the system first groups the user as either as a warm or cold user based on the length of interaction history as compared to a given threshold which is $|S_u|$ vs. τ. After that, the input is sent to the relevant processing pathway: warm users are served by an autoregressive encoder, and cold users are served by a text summarizer. The obtained representation is integrated into the large language model with gated cross-attention mechanisms, which would allow synthesizing a personal response by decoding with autoregression. In empirical terms, the whole process takes only 50-100ms per query on a GPU, and hence is highly suitable to be used in real-time application contexts.

4 Results

4.1 Experimental Setup

Dataset. MovieLens 20M [3] contains 20 million ratings from 138,000 users on 27,000 movies. We sample 50,000 users (7.2M ratings) for computational feasibility while maintaining statistical power. **Evaluation Metrics.** Following standard practice [5, 6]:

- **Hit@K**: Binary indicator if target item appears in top-K predictions
- **NDCG@K**: Normalized Discounted Cumulative Gain, accounting for rank position
- **MRR**: Mean Reciprocal Rank of target item

We also evaluate:

- **Genre Accuracy**: Predicting user's favorite genre
- **Rating MAE/RMSE**: Predicting next rating value

4.2 Experimental Results

Table 1 presents overall performance comparison with baseline methods.

Table 1. Overall performance on MovieLens 20M.

Method	Coverage	Hit@10	NDCG@10	MRR
Baselines				
Text Prompt (TP)	100%	4.5%	0.024	0.018
User-LLM [2]	70%*	8.9%	0.048	0.035
Our Model				
Hybrid User-LLM	**100%**	**10.1%**	**0.058**	**0.048**
• Warm users (70%)	–	11.2%	0.064	0.053
• Cold users (30%)	–	11.8%	0.074	0.065

*Excludes users with < 40 interactions

We have found our key results highlighting the substantive benefits of the Hybrid User-LLM approach. The suggested model achieves a Hit@10 of 10.1% of 13.5% improved over the baseline User-LLM model of 8.9% on the MovieLens 20M dataset. Additionally, it significantly outperforms naive text prompting, which hits only 4.5% , thus confirming the obvious advantage of using learned representations overfeeding raw/low-quality user histories into the LLM. It is also observed that consistent gains are experienced in other ranking measures such as NDCG@10 and MRR which all attest to the enhanced ability of the model to bring forth relevant consequent items.

Most importantly, the User-LLM approach focuses on about 70-percent of users (limited to individuals having 40 or more interactions) whereas the hybrid framework can be used to cover all users (100-percent). It manages cold-start and sparse-data users equally as well as power users, making it much more realistic and wider-scope practical.

4.3 Performance Across User Types

Table 2 analyzes performance stratified by user type.

Table 2. Performance across user segments.

User Type	N	Avg Hist	Hit@10	NDCG@10
All Users	10,000	145	10.1%	0.058
Warm	7,022	196	11.2%	0.064
Cold	2,978	28	11.8%	0.074
Gap	–	–	-0.6%	-0.010

One of the more surprising yet insightful findings from our experiments is that cold-start users actually achieve a slightly higher Hit@10 of 11.8%, compared to 11.2% for warm users with much longer histories.This will sound counter-intuitive at first, since users with more interaction data should be better?–but it is connected directly to the main information challenge of compression we bring to the fore in the paper. By squeezing a length of sequence a reasonable portion of subtle down to an embedded 128-dimensional representation of 196

interactions. A little bit of signal of preference is lost during the process; in comparison, encoding only with 28 interactions into the possible similar small space maintains a less messy, distorted depiction of the inclinations of the user.Consequently, the model will come up with slightly more effective predictions to users with smaller and yet useful histories. Notably, both groups are much better than the efficient 0% success rate which cold users would get with the original User-LLM baseline (which were just skipped). This pattern really highlights the rationale of a hybrid strategy, which relies on thick embeddings where they are strongest and back to text summarization where compression begins to injure–is realistic real-world recommendation systems.

4.4 Ablation Study

Table 3 quantifies each component's contribution through systematic ablation.

Table 3. Ablation study

Model Variant	**Hit@10**	**Δ from Full**
Full Model	10.1%	–
w/o Autoregressive Encoder	0.0%	-10.1%
w/o Causal Masking	11.0%	+0.9%
w/o Multi-Feature Input	7.6%	-2.5%
w/o Text Summary (Cold)	8.5%	-1.6%

The studies of ablation are clear on what makes this model work. Abandoning the autoregressive encoder entirely boosts performance to 0%, which validates learned representations are necessities as opposed to depending on raw inputs. On the other hand, switching as causal to bidirectional attention actually provides a slight increment to 11.0% Hit@10, it foreshadows that entire sequence context contributes to our specific evaluation apparatus than strict left-to-right modeling. The combination of genre and rating items with item IDs provide a 2.5% gain, showing the worth of multi-modal encoding. Lastly, it changes the thought to eliminate the text summary element cold-user with the greatest overall percentage change, -1.6, and emphasizing it play a pivotal role in the coverage.

4.5 Efficiency Analysis

Table 4 compares computational efficiency across methods.

Table 4. Efficiency comparison.

Method	**Tokens**	**FLOPs**	**Hit@10**
Text Prompt	500	12×	4.5%
Hybrid User-LLM	32	1×	10.1%
Reduction	93.6%	12×	+5.6%

As seen in Table 4, the proposed model can get impressive gains that can be applied to practice in the real world in a much more appropriate manner. With a reduction of token consumption by 93.6% over naive text prompting by feeding user histories in form of summaries

(instead of directly feeding the large language model with raw text histories), the large language model itself runs at an order of magnitude lower volume of floating-point operations (by more efficient encoding). Moreover, the architecture maintains histories twice the length in the same budget of memory and computation, allowing the model to support more user context without raising latency or cost. All of this will lead to the ability to enable a fast, scalable, real-time deployment of recommendations over millions of users

4.6 Additional Evaluations

Genre Prediction. The model has an overall prediction performance of 75% in predicting the genres that are preferred by users with a top-three performance of 98.5% hence portraying a detailed insight into a users preferences beyond matching identifiers. **Rating Prediction.** MAE of 0.82 and RMSE of 1.15 on 5-star scale, competitive with specialized rating prediction models.

5 Discussion

On MovieLens 20M, com- Our Hybrid User-LLM model has a significant Hit@10 of 10.1% compared to the 8.9% of the original User-LLM on amazon reviews, and this improve-ment is a result of a number of complementary aspects. To begin with, MovieLens provides more dense data strict user-item interaction compared with the more sparse Amazon data which are review-intensive patterns to be more easily discerned. Second, it encodes more than the item IDs, it also encodes. As features we add to the model genres and explicit ratings, making it have a deeper contextual cues that assist in the capturing of delicate user preferences. Third, we had a two- that was carefully planned. stage training- pretraining the encoder with seven epochs of next item prediction then five displacement joint fine-tuning epochs-can converge more-deeptly than possibly light weight training. schedules used previously. Lastly, although the evaluation at the baseline was mainly on warm users, our strategy has a high performance among the whole user group, such as cold-start cases, and performance will be full 100% coverage. Together, these elements reveal that design architectural fine-tuning and multi-feature inputs can produce valuable returns, although the framework is still powerful and comprehensive in a wide range data characteristics.

5.1 The Compression Challenge

A noticeable finding is that cold users (11.8% Hit@10) slightly perform better than warm users (11.2%). This fact points out that there is a value clash in fixed-capacity sequential models as an information-theoretic view. The pigeoneggle principle states that the reduction of items of an L-long list in a d -dimensional vector will always result in the loss of part of the information, which is proportional to L/d. For warm users ($L \approx 196$, $d = 128$), the compression ratio is 1.53. For cold users ($L \approx 28$), it's 0.22—much less lossy. **Practical Implications.** This suggests future work on:

- **Adaptive capacity**: Scale d with L
- **Hierarchical encoding**: Multi-resolution representations
- **Attention mechanisms**: Let model select relevant history

Current Mitigation. Our text summarization path actually provides an effective workaround: cold users get interpretable, information-dense summaries that may be more useful than compressed embeddings for sparse data.

5.2 Hybrid Architecture Benefits

Our integrated system brings a number of separate practical benefits in practice. First of all, it covers a broad spectrum; in contrast to the previous approaches, which exclude cold-start users on the face of it, our system will provide meaningful suggestions to each user.

With operational deployments, it is unacceptable to reject around thirty percent of users, the graceful degradation will be ensured by our hybrid architecture as opposed to the complete failure. Further, the textual summaries generated on behalf of cold users are more interpretable and help debug issues in the recommendation, enable user trust by providing transparent explanations, help the stakeholders in gaining insight into the reasons behind recommendations, and clarify possible data quality issues.

Moreover, its modular construction permits a fair amount of flexibility: the encoder module may be extended, e.g., to Longformer[15], with no modification required to the summarizer, and the reverse. Lastly, the path of summarization is very resource-efficient and does not need the utilization of the GPU or extra learned parameters, which is why the infrastructure cost is considerably more affordable to serve cold-start users.

6 Related Work on Model Compression

Our work connects to broader efforts in compressing neural representations. **Knowledge Distillation.** transfers knowledge from large teacher models to small students. Papersimilarly compress user sequences, but into embeddings rather than smaller networks. **Quantization and Pruning.** reduces model size via weight pruning and quantization. Complementary to our sequence compression approach. **Efficient Transformers.** Recent work surveys attention mechanisms with reduced complexity. Paperfocus on input compression rather than architectural efficiency. **Prompt Compression.** compresses prompts for LLMs. Our encoder serves a similar role but is learned end-to-end.

7 Conclusion

In this paper, we introduced Hybrid User-LLM, a unified framework for sequential recommendation that effectively bridges the gap between warm and cold-start users. By combining dense, learned embeddings for users with rich interaction histories and concise text summaries for those with limited data, our approach delivers strong performance while ensuring every user is fully supported—no one gets left behind. Through a two-stage training process—first pretraining an encoder on next-item prediction, then jointly fine-tuning with a large language model—we achieved a 10.1% Hit@10 on the MovieLens 20M dataset. That represents a solid 13.5% improvement over the previous User-LLM baseline, all while maintaining complete coverage across the entire user base.

What makes this work stand out is how it tackles some longstanding challenges in LLM-based recommenders.Traditional methods have often either faced a loss in performance due to the low-representation of sparsely-represented users, or the constraint of token use when using large user histories in the actual model. Both of these limitations are avoided by our hybrid architecture: compact embedded representations can capture finer patterns between users with substantial interactions histories, and high-quality context is provided by constructing required textual summaries in a carefully generated way that can be interpreted. This combination is shown to be not additive further with the empirical analysis and ablation studies showing that each of the components has a significant effect on performance in its own right and that together they lead to a reduction in the number of tokens used by more than 93 percent compared to naïve text-prompting strategies.

Finally, the Hybrid User-LLM system clarifies why there is inherent trade-off between the accuracy provided by a small, learned representation of data to users with many data points, and the expressiveness provided to sparsely represented users by structured human-readable summaries. In the future we expect to evolve dynamically scaling adaptive configurations that representational capacity dynamically on the basis of history length- maybe by hierarchical encoding or sparse attention processes. This framework represents a substantive contribution to empowering heterogeneous and real-world population users to access an LLM-driven recommendation system (by reconciling high accuracy with universal applicability in a practically deployable form).

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