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SYSTEM APPROACH TO MULTICRITERIA EVALUATION OF SESSION-BASED AND SEQUENTIAL RECOMMENDATION SYSTEMS

Background. Recommendation systems have become indispensable components of modern digital platforms, enabling personalised content delivery across diverse domains. Traditional collaborative filtering and content-based approaches often fail to capture temporal dynamics and contextual dependencies inherent in user behaviour patterns. Sequential recommendation systems (SRSs) and session-based recommendation systems (SBRSs) have emerged as new paradigms to capture users' short-term but dynamic preferences for enabling more timely and accurate recommendations.

Objective. The paper aims to propose a system approach for multicriteria evaluation of various SRS and SBRS models – a unified framework for understanding these models, selecting the best recommendation model, and guiding future research directions in temporal-aware recommendation systems, as well as to provide a systematic overview and comprehensive analysis of session-based and sequential recommendation systems, to examine their theoretical foundations, evolution, empirical performance characteristics, and practical deployment considerations.

Methods. A comprehensive analysis of foundational approaches from Markov chain models to modern neural architectures, including attention-based methods, graph neural networks, and state-space models, is conducted. The approaches are systematically categorised based on architectural principles, temporal modelling strategies, and knowledge integration methods. The Analytic Hierarchy Process is applied for the calculation of relative importance of benefits, costs, opportunities and risks in a problem of session-based and sequential recommendation systems synthesis. An experimental study of various SRS and SBRS models was performed on benchmark datasets.

Results. Empirical studies on the temporal benchmark dataset show that combining SASRec and ReCODE improves the Recall@K metric by 9 % over the baseline SASRec model, and combining GRU4Rec with ReCODE improves the metric by 17 % over the baseline GRU4Rec. The SASRec model, which adapts transformer architectures to the sequential recommendation problem, achieved the highest baseline performance in terms of Recall@K and NDCG@K criteria on the benchmark dataset compared to the other examined models, demonstrating the effectiveness of self-attention mechanisms for sequence modelling. ReCODE is a model-independent neural ordinary differential equation framework for recommender systems and an effective framework for studying consumer demand dynamics, has improved the metrics of existing baseline approaches, and has acceptable computational complexity for practical recommender system deployment scenarios.

Conclusions. Session-based and sequential recommendation systems have evolved through several paradigmatic shifts with significant scientific achievements, including establishment of session-based recommendation model as distinct from traditional collaborative filtering, development of attention mechanisms for sequence modelling, and introduction of continuous-time formulations. Future research directions include unified architectures, scalability solutions, improved evaluation methodologies, and extensions to multi-stakeholder scenarios.

Keywords: sequential recommendation; session-based recommendation; temporal modelling; attention mechanisms; graph neural networks; state-space models; deep learning; system analysis; decision making.

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Introduction

Recommendation systems have revolutionised digital content consumption by enabling personalised experiences across e-commerce platforms, streaming services, social media, and news aggregators [1—3]. These systems address the fundamental challenge of information overload by filtering vast content catalogs to present users with relevant items tailored to their preferences and contextual needs.

Traditional recommendation approaches, primarily collaborative filtering and content-based methods, treat user-item interactions as static snapshots, failing to account for the temporal dynamics that characterise real-world user behaviour [2]. However, user preferences evolve continuously over time, influenced by seasonal patterns, trending topics, life events and changing interests. Static models cannot capture preference drift, limiting their ability to provide timely and relevant recommendations [4, 5].

User interactions demonstrate complex sequential patterns where the order, timing and context of actions significantly influence future preferences. For instance, purchasing a camera may increase the likelihood of buying related accessories, but this dependency weakens over time [6, 7].

Also, many modern applications operate with anonymous users or scenarios where long-term user profiles are unavailable due to privacy constraints, cookie limitations or new user cold-start problems. These situations require systems to make accurate recommendations based solely on current session interactions without historical context [4—7].

These challenges have motivated the development of sequential recommendation systems and session-based recommendation systems, representing a paradigmatic shift toward temporal-aware personalisation that adapts to dynamic user contexts and behavioural patterns [8, 9].

The evolution of sequential recommendation systems has been marked by several technological breakthroughs that have progressively addressed the limitations of static approaches:

1. Foundational period (2001—2014). Early work established theoretical foundations through Markov chain models [9, 10] and matrix factorisation extensions [4, 6]. The factorised personalised Markov chain [6] represented a crucial advancement by combining collaborative filtering with Markovian temporal modelling.

2. Deep learning emergence (2015—2017). The introduction of deep learning marked a transformative period. GRU4Rec [11] pioneered neural session-based recommendation, demonstrating superior performance over traditional methods.

3. Attention era (2018—2020). Transformer architectures revolutionised sequential recommendation through SASRec [12], which adapted self-attention for next-item prediction, and BERT4Rec [13], which employed bidirectional attention with masked language modelling training.

4. Post-attention period (2019-present). Graph neural networks enhanced recommendation through SR-GNN [14], which modelled sessions as directed graphs, and knowledge-aware approaches like KGAT [15] that integrated external knowledge graphs. The recent advances in modelling ordinary differential equations as hidden layers functions within deep neural networks enabled the sensitivity of these models to irregularly-sampled data, which became suitable for estimating the consumption trends of goods [16, 17].

However, comprehensive empirical studies [18] have revealed significant methodological concerns and demonstrated that many sophisticated neural approaches fail to consistently outperform simple baselines when evaluated under rigorous conditions with standardised datasets and fair comparison protocols.

Problem Statement

The primary objective is to establish a comprehensive understanding of session-based and sequential recommendation systems through a systematic overview of their theoretical foundations, architectural innovations, empirical performance characteristics, and practical deployment considerations.

The system analysis aims to provide a unified conceptual framework that enables researchers and practitioners to navigate the complex landscape of temporal-aware recommendation approaches and make informed decisions about methodology selection and future research directions.

A system approach

We propose a system approach (Fig. 1) aimed at the evaluation of scenarios for practical deployment of session-based and sequential recommendation systems using the following decision criteria:

1. Performance metrics such as Recall@K — the proportion of model outcomes marked as relevant in the set of ground-truth relevant items; Precision@K — the proportion of relevant elements (items) for user in the set of items, generated by the

model; MAP@K, NDCG@K, MRR@K, which are aimed at assessing the quality of recommendation system to rank items based on their relevance for user.

2. Computational efficiency criteria and metrics, which include:

- model training time;
- computational scalability;
- average time per K inferences (ATI@K) — average computation time for generating top-K item recommendations across user session batches;
- memory usage — peak memory consumption during model inference to assess scalability for production deployment scenarios.

The following opportunities and risks are also taken into account in the process of evaluation of scenarios for the practical deployment of session-based and sequential recommendation systems:

- temporal modelling;
- long-range dependencies;
- knowledge integration complexity;
- discovery of user behavioural patterns (collaborative signals);
- usability of the model that expresses the complexity of the model for the developer, reflecting the number of "change axes" of the algorithm;
- theoretical foundations.

These decision criteria, metrics, opportunities and risks enable comprehensive evaluation of both recommendation quality and computational efficiency, crucial factors for practical deployment of sequential recommendation systems in large-scale e-commerce environments.

Scenarios could, for example, be formed based on hybrid technologies: recurrent neural networks or attention-based models equipped with neural ordinary differential equations framework and other.

Let us consider traditional and modern models and methods for session-based and sequential recommendation systems synthesis.

Markov chain models for sequential recommendations

The theoretical foundations of sequential recommendation were established through probabilistic modelling using Markov chains, which represent user behaviour as stochastic processes over discrete state spaces [9, 10].

The basic first-order Markov assumption posits that the probability of the next interaction depends solely on the current state:

$$P\left(s_{t+1} \mid s_1, s_2, \ldots, s_t\right) = P\left(s_{t+1} \mid s_t\right)$$

While conceptually appealing for modelling sequential dependencies, these models suffered from severe data sparsity issues due to the exponential growth of transition parameters with vocabulary size, limiting their practical applicability to large-scale systems.

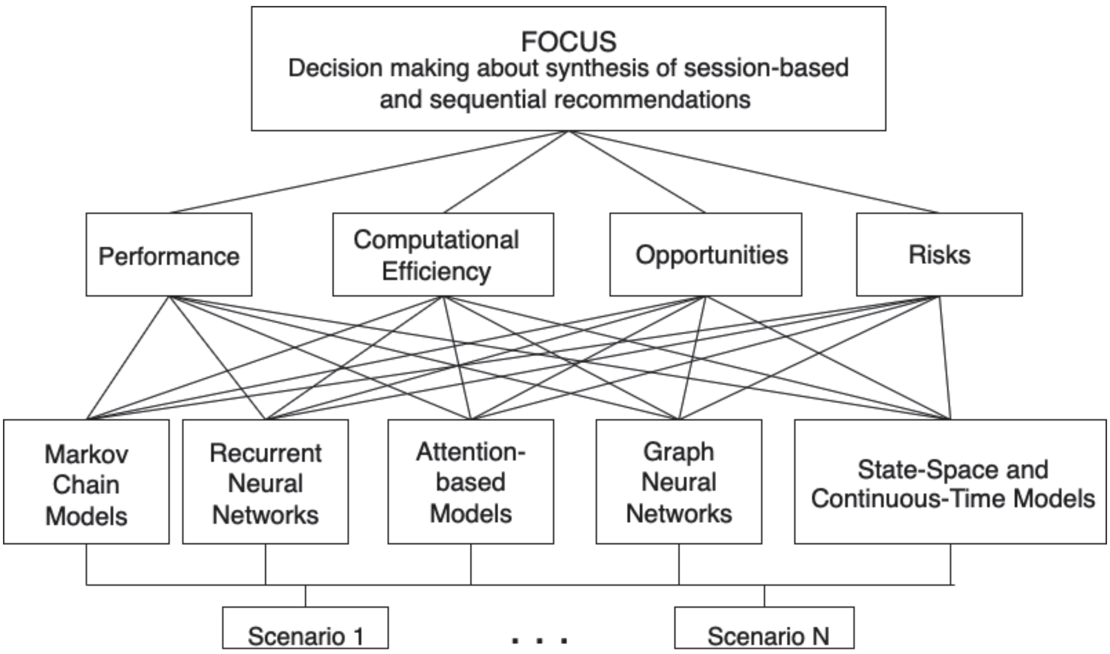

Fig. 1. Scheme of a system approach

The factorized personalized Markov chain addressed sparsity through low-rank matrix factorisation, decomposing the three-way user-item-item tensor into personalised transition matrices [6]:

$$\hat{x}_{uij} = \langle u_u + u_i, v_j \rangle + \langle l_i, r_j \rangle,$$

where u_u, u_i represent user and current item factors, v_j represents the target item factor, and l_i, r_j encompass model item-to-item transitions.

Recurrent neural networks for sequential recommendations

The introduction of recurrent neural networks marked a paradigmatic shift toward end-to-end learning of sequential patterns without explicit state space assumptions.

GRU4Rec model pioneered neural session-based recommendation through gated recurrent units, demonstrating superior performance over traditional collaborative filtering methods [11]:

$$r_t = \sigma(W_r x_t + U_r h_{t-1});$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1});$$

$$\tilde{h}_t = \tanh(W_h x_t + U_h (r_t \otimes h_{t-1}));$$

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \tilde{h}_t.$$

Attention-based models for sequential and session-based recommendations

The transformer revolution in natural language processing motivated its adaptation to sequential recommendation systems through self-attention mechanisms that enable parallel computation and direct modelling of arbitrary-length dependencies.

SASRec model adapted transformer architectures for sequential recommendation through unidirectional self-attention with causal masking [12]:

$$\text{Attention}(Q, K, V) = \\ = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}} \otimes M\right) V,$$

where Q, K, V are linear projections of input embeddings, and $M \in \{0,1\}^{n \times n}$ is a lower triangular mask also known as casual mask preventing future information leakage.

BERT4Rec model extended this approach through bidirectional attention with masked language modelling training [13]:

$$L_{MLM} = -\sum_{i \in M} \log P\left(s_i^* \mid s_i\right),$$

where M denotes masked positions and s_i represents the sequence with position i masked.

Recent developments address attention mechanism limitations through computational efficiency improvements and temporal awareness enhancements.

LightSANs reduces computational requirements through simplified attention mechanisms, while TiSASRec incorporates temporal information through time-aware positional encodings:

$$\text{Attention}_{\text{time}}(Q, K, V, T) = \\ = \text{softmax}\left(\frac{Q(K + T_K)^T}{\sqrt{d_k}}\right)(V + T_V),$$

where T_V, T_K encode temporal intervals between interactions.

Graph neural network models

Graph neural networks (GNNs) provide a natural framework for modelling structural relationships within user sessions and between items in recommendation scenarios.

SR-GNN [14] represents sessions as directed graphs where nodes correspond to items and edges capture transition relationships. The gated graph neural network updates node representations through iterative message passing:

$$a_v^{(t)} = A_v \left[h_1^{(t-1)}, \ldots, h_n^{(t-1)} \right]^T W + b;$$

$$z_v^{(t)} = \sigma\left(W_z a_v^{(t)} + U_z h_v^{(t-1)}\right);$$

$$h_v^{(t)} = \left(1 - z_v^{(t)}\right) \otimes h_v^{(t-1)} + z_v^{(t)} \otimes \tilde{h}_v^{(t)},$$

where A is the adjacency matrix encoding session graph structure.

Knowledge graph integration enhances recommendation through external structured information incorporation.

KGAT model employs attention-based information propagation over collaborative knowledge graphs [15]:

$$e_u^{(l+1)} = \text{LeakyReLU} \times \\ \times \left(W^{(l)} \sum_{(h,r,t) \in N_u} \pi(h, r, t)\, m_{h,r,t}^{(l)} \right),$$

where $\pi(h, r, t)$ represents attention weights for relation-specific message aggregation.

State-space and continuous-time models

Neural ordinary differential equations (Neural ODEs) formulate hidden state evolution as a continuous-time dynamical system rather than a discrete layer-wise transformation [16]:

$$\frac{dh(t)}{dt} = f_\theta\left(h(t), t\right);$$

$$h(t_1) = h(t_0) + \int_{t_0}^{t_1} f_\theta\left(h(t), t\right) dt,$$

where f_θ is a neural network parameterisation. Solutions are computed with numerical ODE solvers; gradients are obtained via the adjoint method. Core advantages for recommendation systems based on Neural ODEs include natural handling of irregular time intervals between interactions, continuous preference evolution, principled temporal modelling, and interpretability through explicit dynamics.

Among the applications of Neural ODEs for recommendation systems, ReCODE model stands out and proves to be an efficient framework for studying users' consumption dynamics [17]. ReCODE is a model-agnostic framework that decomposes recommendation into:

$$\mathrm{Score}(u, i, t) = \alpha \times$$

$$\times \mathrm{Static}\ (u, i) + (1 - \alpha) \cdot \mathrm{Dynamic}\ (u, i, t),$$

where the dynamic component is a Neural ODE capturing repeat-intent over time.

The initial state $h(t_0)$ is encoded from user-item interaction history; the ODE

$$\frac{dh(t)}{dt} = f_\theta\left(h(t), t, c\right)$$

evolves the latent state given context c; a decoder yields the repeat probability $p(u, i, t)$. ReCODE model integrates with matrix factorisation, neural collaborative filtering, GRU4Rec and SASRec models as the static branch.

Recent work applies Neural ODEs to recommendation by modelling repeat consumption and time-aware intensities with continuous dynamics.

A decision support tool in a problem of making session-based and sequential recommendations

The Analytic Hierarchy Process (AHP) is a decision-making method based on a system approach of structuring a complex problem in the form of a hierarchy creating pairwise comparison matrices of decision criteria, checking and increasing the consistency of judgments. AHP includes calculation of local priorities (weights), aggregation of priorities, and sensitive analysis of results. AHP combines mathematical and psychological principles for multi-criteria decision-making involving both quantitative and qualitative factors.

We propose to apply AHP for calculation of relative importance of benefits, costs, opportunities and risks (hereinafter decision criteria) in a problem of evaluation of scenarios for practical deployment of session-based and sequential recommendation systems.

Hierarchy of decision criteria is presented on Fig. 2. Let us consider the criteria in more detail. Recommendation system quality is assessed by using a special class of metrics – ranking quality metrics. Let $R_u@K$ denote the top-K recommendations for user/session u; G_u is the set or graded vector of relevant items.

1. Recall@K or HitRatio@K metric reflects the coverage of relevant items found in the first K positions (not rank-aware) and is defined as follows:

$$\mathrm{Recall@}K = \frac{1}{|U|}\sum_u \frac{|R_u@K \cap G_u|}{|G_u|}.$$

The metric is good for measuring how many of the truly relevant items are retrieved when G_u is known.

2. Precision@K metric denotes how many of the top-K are relevant:

$$\mathrm{Precision@}K = \frac{1}{|U|}\sum_u \frac{|R_u@K \cap G_u|}{\min\left(K, |G_u|\right)}.$$

3. MRR@K (mean reciprocal rank) metric emphasizes placing the first relevant item as high as possible and is defined as:

$$\mathrm{MRR@}K = \frac{1}{|U|}\times$$

$$\times \sum_u \frac{1}{\min\left(r \le K \mid \text{item at rank } r \in G_u\right)}.$$

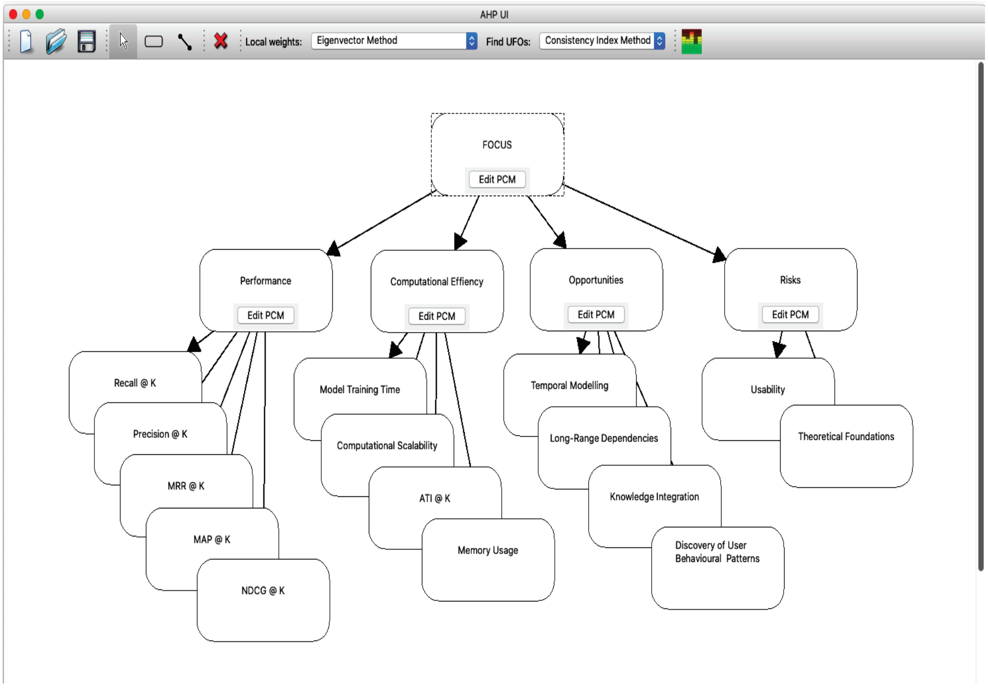

Fig. 2. Hierarchy of the criteria in a problem of evaluation of scenarios for practical deployment of session-based and sequential recommendation models

4. MAP@K (mean average precision) averages precision at every relevant hit, rewarding both finding many relevant items and ranking them early:

$$\mathrm{MAP@}K=\frac{1}{|U|}\sum_{u}\mathrm{AP@}K(u),$$

where

$$\mathrm{AP@}K=\frac{1}{\min\left(K,|G_u|\right)}\times$$

$$\times\sum_{r\le K}\mathrm{Precision@}r(u)\cdot 1\left(r\le K\,|\,\text{item at rank } r\in G_u\right).$$

5. NDCG@K (normalised discounted cumulative gain) is a rank-aware metric, it penalties putting elements lower or higher their true relevance score (rating):

$$\mathrm{NDCG@}K(u)=\frac{1}{|U|}\sum_{u}\frac{\mathrm{DCG@}K(u)}{\mathrm{IDCG@}K(u)},$$

where $\mathrm{DCG@}K(u)=\sum_{r\le K}\frac{g_{u,r}}{\log_2(r+1)}$; $g_{u,r}$ is graded relevance at rank r, and IDCG is the maximum achievable DCG for u.

Pairwise comparisons between decision criteria and sub-criteria are usually performed by an expert (Fig. 3) in a special fundamental scale. Priorities (weights) of decision criteria and sub-criteria are than calculated based on pairwise compari son matrices using the eigenvector method and other [19]. In a case of strong inconsistency of expert judgements, the most inconsistent elements of pairwise comparison matrices are found automatically [20] without participation of an expert (Fig. 4).

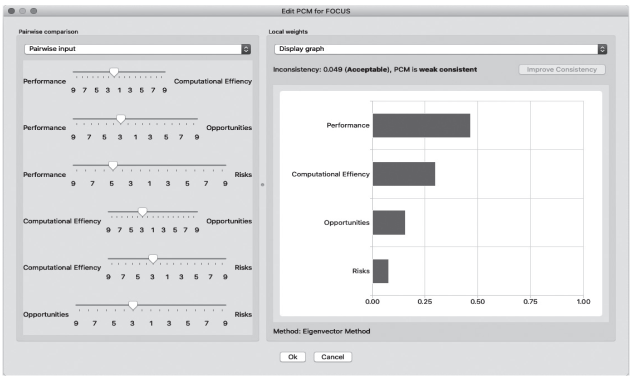

Fig. 3. Pairwise comparisons between criteria (left) and resulting local priorities (right)

Experimental evaluation and benchmarking analysis

Sequential recommendation systems, presented in this research, were evaluated on Million Musical Tweets Dataset (MMTD) — an established bench-

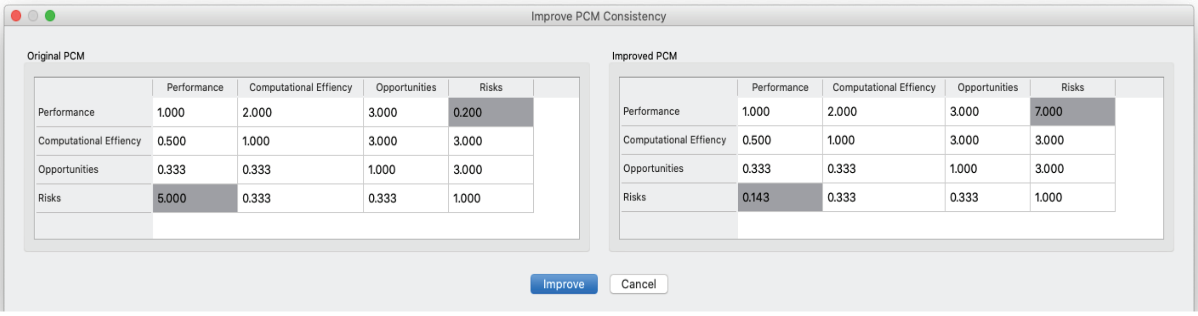

Fig. 4. The most inconsistent elements of a pairwise comparison matrix (left) and suggested automatic adjustment (right)

mark dataset. Million Musical Tweets Dataset [21] is a music listening history dataset with high-frequency interactions suitable for evaluating fine-grained temporal modelling approaches.

Results of evaluation of KGAT, GRU4Rec and SASRec models, as well as the proposed GRU4Rec&ReCODE and SASRec&ReCODE, equipped with ReCODE framework are displayed in Table 1 for $K = 50$.

The experimental results demonstrate that SASRec model achieves the strongest baseline performance, showing the effectiveness of self-attention mechanisms for sequential modelling, while Neural ODE-based ReCODE framework demonstrates consistent improvements when integrated with sequential baseline model. However, the impact of knowledge graph modelling on NDCG metric suggests the hypothesis that models equipped with this data structure learns to rank relevant models more efficiently.

The overall evidence supports the value of Neural ODE-based continuous-time modelling for sequential recommendation, with ReCODE providing meaningful enhancements to established baseline approaches while maintaining computational feasibility for practical deployment scenarios.

Table 1. Models' evaluation results on MMTD dataset

Model	Metric	
	Recall@K	NDCG@K
KGAT	0.1489	0.1006
GRU4Rec	0.1974	0.0841
SASRec	0.2274	0.1043
Proposed GRU4Rec&ReCODE	0.2307	0.0926
Proposed SASRec&ReCODE	0.2486	0.0994

Conclusions

A comprehensive system analysis of session-based and sequential recommendation systems has been provided, examining their evolution from foundational probabilistic approaches to modern neural architectures, with particular emphasis on emerging Neural ODE-based continuous-time modelling approaches. Our analysis reveals several fundamental achievements in sequential recommendation research. The field has progressed through distinct paradigmatic phases from Markov chain foundations establishing probabilistic frameworks, through neural recurrent approaches, which demonstrate deep learning effectiveness, to attention-based methods, which achieve state-of-the-art performance, and finally to emerging continuous-time formulations, which offer both theoretical rigor and computational efficiency.

The experimental evidence demonstrates that Neural Ordinary Differential Equations provide principled continuous-time modelling capabilities for sequential recommendation. The ReCODE framework achieves consistent performance improvements with respect to Recall@K metric across the considered base models GRU4Rec and SASRec, and validates the model-agnostic effectiveness of continuous-time approaches for capturing temporal dynamics in user behaviour.

The empirical analysis of benchmark datasets LastFM and Nowplaying-RS in terms of evaluation metrics reveals critical methodological considerations. The rich contextual features and temporal precision of datasets like Nowplaying-RS prove particularly valuable for evaluating sophisticated continuous-time models, while standardized evaluation protocols remain essential for reliable comparison across approaches.

Neural ODE-based approaches excel in scenarios with irregular temporal intervals and significant repeat consumption patterns, making them particularly suitable for music streaming, e-commerce, and content platforms where temporal dynamics significantly influence user preferences. While Neural ODEs introduce computational overhead through ODE solvers and adjoint gradient computation, the consistent performance gains and linear complexity advantages for long sequences justify their deployment in scenarios requiring sophisticated temporal modelling.

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Д.В. Андросов, Н.І. Недашківська

СИСТЕМНИЙ ПІДХІД ДО БАГАТОКРИТЕРІАЛЬНОГО ОЦІНЮВАННЯ СЕАНСОВИХ І ПОСЛІДОВНИХ РЕКОМЕНДАЦІЙНИХ СИСТЕМ

Проблематика. Рекомендаційні системи стали незамінними компонентами сучасних цифрових платформ, забезпечуючи персоналізацію контенту в різних сферах. Традиційна колаборативна фільтрація та підходи на основі вмісту часто не в змозі охопити часову динаміку та контекстні залежності властиві моделям поведінки користувачів. Системи послідовних рекомендацій (sequential recommendation systems, SRSs) і системи рекомендацій на основі сеансів (session-based recommendation systems, SBRSs) з’явилися як нові парадигми для охоплення короткострокових динамічних уподобань користувачів для надання більш своєчасних і точних рекомендацій.

Мета дослідження. Запропонувати системний підхід до багатокритеріального оцінювання різних моделей SRS і SBRS – уніфіковану структуру для розуміння цих моделей, вибору найкращої моделі та спрямування майбутніх напрямів досліджень у системах рекомендацій з урахуванням часу. Виконати систематичний огляд і всебічний аналіз сеансових і послідовних систем рекомендацій, їх теоретичних основ, еволюції, емпіричних характеристик продуктивності й аспектів практичного розгортання.

Методика реалізації. Проаналізовано фундаментальні підходи від моделей ланцюгів Маркова до сучасних нейронних архітектур, включаючи методи на основі уваги, графові нейронні мережі і моделі простору станів. Систематично класифіковано підходи, ґрунтуючись на архітектурних принципах, стратегіях часового моделювання та методах інтеграції знань. Метод аналізу ієрархій застосовано для розрахунку відносної важливості доходів, витрат, можливостей і ризиків у задачі синтезу сеансових і послідовних систем рекомендацій. Проведено експериментальне дослідження різних моделей SRS і SBRS на контрольних наборах даних.

Результати дослідження. Емпіричні дослідження на еталонному для часового моделювання наборі даних показали, що поєднання SASRec та ReCODE покращило значення метрики Recall@K на 9 % порівняно з базовою моделлю SASRec, а поєднання GRU4Rec з ReCODE покращило цю метрику на 17 % порівняно з базовою GRU4Rec. Модель SASRec, яка адаптує архітектуру трансформера до задачі надання послідовних рекомендацій, досягла найвищої базової продуктивності за критеріями Recall@K і NDCG@K на еталонному наборі даних порівняно з іншими розглянутими моделями, демонструючи ефективність механізмів самоуваги для моделювання послідовностей. Незалежна від моделі структура ReCODE нейронних звичайних диференціальних рівнянь для рекомендаційних систем – ефективна основа для вивчення динаміки споживчого попиту, покращила метрики наявних базових підходів і має прийнятну обчислювальну складність для практичних сценаріїв розгортання рекомендаційних систем.

Висновки. Рекомендаційні системи на основі сеансів і послідовностей еволюціонували через зміну кількох парадигм із значними науковими досягненнями, включаючи становлення рекомендаційних моделей на основі сеансів відмінних від традиційної колаборативної фільтрації, розробку механізмів уваги для моделювання послідовностей і впровадження моделей неперервного часу. Майбутні напрями досліджень включають уніфіковані архітектури, рішення для масштабування, вдосконалені методології оцінювання та розширення для сценаріїв з багатьма зацікавленими сторонами.

Ключові слова: послідовна рекомендація; сеансова рекомендація; часове моделювання; механізми уваги; графові нейронні мережі; моделі простору станів; глибоке навчання; системний аналіз; прийняття рішень.

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