Evidential Stochastic Differential Equations for Time-Aware Sequential Recommendation

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Overview

Sequential recommender systems are designed to capture users' evolving interests over time to allow more personalized and timely suggestions. It has following key characteristics:

- **Time-Ordered Interactions:** Capture and analyze users' interactions in a specific sequence to reflect evolving interests.
- **User Behavior Prediction:** Predict the next item a user is likely to engage with, based on previous actions.
- **Dynamic Preference Modeling:** Track and adapt to users' changing preferences over time.
- **Context Awareness:** Often incorporate contextual factors, like time and location, for more relevant recommendations.
- **Personalization:** Tailor suggestions specifically to each user's unique behavior patterns.
- **Real-Time Adaptability:** Update recommendations in real-time as new user interactions occur.

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Key Challenges and Motivation

- Existing sequential recommendation models (e.g., BERT4Rec, SASRec, etc.) often assume uniform time intervals between user interactions, which fails to capture real-world, non-uniform patterns.
- This oversight can lead to inaccurate predictions, as user preferences may change significantly over varying interaction gaps.
- As interaction intervals lengthen, the uncertainty in predicting user behavior grows, making it harder to provide accurate recommendations.

Table: Impact of interaction interval

Interaction	Interval (Seconds)	Ranking ↓	
		BERT4Rec	E-NSDE
$6 \to 7$	44	4	**4**
$13 \to 14$	623,591	24	**16**
$116 \to 117$	62	6	**3**
$150 \to 151$	896,291	56	**18**

- The unrealistic assumption of a uniform interaction interval could significantly impact the model's capability to capture users' continuously evolving behavior and subsequently hurt the recommendation performance as demonstrated in Table 1.

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Solution: E-NSDE Framework

- We propose an **Evidential Neural Stochastic Differential Equation (E-NSDE)** framework as shown in Figure below.

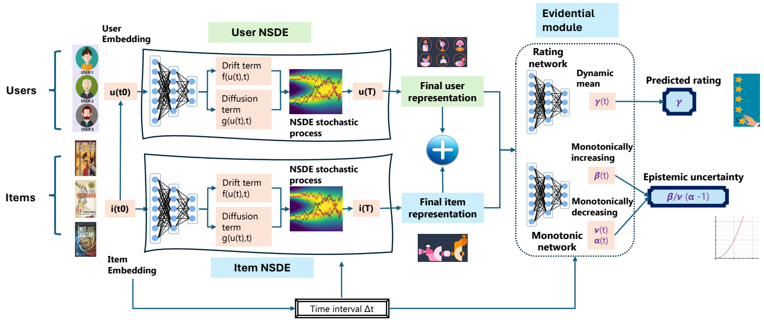
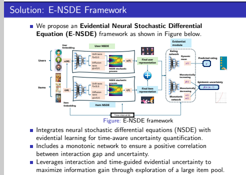


Figure: E-NSDE framework

- Integrates neural stochastic differential equations (NSDE) with evidential learning for time-aware uncertainty quantification.
- Includes a monotonic network to ensure a positive correlation between interaction gap and uncertainty.
- Leverages interaction and time-guided evidential uncertainty to maximize information gain through exploration of a large item pool.



E-NSDE Framework Contd.

- The NSDE module generates fine-grained user and item representations as follows:

$$u(T) = u(t_0) + \int_{t_0}^{T} f(u(t), t; \psi)dt + \int_{t_0}^{T} g(u(t), t; \omega)dB_t \quad (1)$$

  where $u(t_0)$ is the user's initial representation which aggregates a set of initially interacted items: $u(t_0) = \text{agg}(i_1..i_k)$ and T is the final time.

$$i(T) = i(t_0) + \int_{t_0}^{T} f(i(t), t; \psi)dt + \int_{t_0}^{T} g(i(t), t; \omega)dB_t \quad (2)$$

  where, $i(t_0)$ represents item's initial representation
- In Evidential module,
  - The rating network utilizes the fine-grained user u_t and item i_t representations from the NSDE and predicts the score $\gamma_{(u_t, i_t)}$.
  - The monotonic network is designed in such a way that the increase in time interval (Δt), increases the output, i.e., the variance of the predicted rating.

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Training: Evidential and Weighted Bayesian Personalized Ranking Loss

- The regularized EDL loss with negative log-likelihood ($\mathcal{L}^{NLL}[f_\Theta]$) to maximize the marginal likelihood and an evidential regularizer ($\mathcal{L}^{R}[f_\Theta]$) to impose a high penalty on the predicted error with low uncertainty for each sequential update is:

$$\mathcal{L}_{EDL}(u_t, i_t) = \mathcal{L}^{NLL}[f_\Theta(u_t, i_t)] + \lambda\mathcal{L}^{R}[f_\Theta(u_t, i_t)] \tag{3}$$

  where λ is a regularization coefficient.
- To leverage the effective exploration for the long-term, we formulate weighted BPR loss which is computed from non-interacted (negative) that are similar to the user's future interacted items.

$$\mathcal{L}_{\mathrm{WBPR}}(u_t, i_t) = \sum_{(u_t, i_t, j_t \in \mathcal{N}_t)} w_{(i_t, j_t)}\{-\ln[\sigma(\hat{r}_{(i_t, j_t)})]\} \tag{4}$$

  where $\hat{r}_{(i_t, j_t)} = \hat{r}_{(u_t, i_t)} - \hat{r}_{(u_t, j_t)}$, $\sigma(\cdot)$ is the sigmoid.
- The overall loss of the end-to-end model training is obtained by combining the EDL and WBPR loss:

$$\mathcal{L}(u_t, i_t) = \mathcal{L}_{\mathrm{EDL}}(u_t, i_t) + \zeta\mathcal{L}_{\mathrm{BPR}}(u_t, i_t) \tag{5}$$

Recommendation Performance Comparison

- Our experiment setting of sequential recommendation is based on next-item recommendation tasks.
- We split users by 70% into train and 30% in test.
- We leverage the actual time of interactions (in UNIX timestamp) to provide user preference evolution.

Table: Recommendation performance comparison

Category	Model	MovieLens-100K		Movielens-1M		Netflix		Amazon Book	
		P@5	nDCG@5	P@5	nDCG@5	P@5	nDCG@5	P@5	nDCG@5
Dynamic MF	timeSVD++	0.3842±0.015	0.3420±0.013	0.3917±0.016	0.3508±0.013	0.3756±0.016	0.2951±0.013	0.3601±0.014	0.3128±0.012
	CKF	0.3916±0.017	0.3620±0.013	0.3928±0.016	0.3552±0.015	0.3600 ±0.017	0.2986±0.014	0.3823±0.016	0.3214±0.015
Graph	NGCF	0.3859±0.014	0.3662±0.012	0.3978±0.016	0.3587 ±0.018	0.3574±0.015	0.3167±0.017	0.3574±0.012	0.3321±0.011
	LightGCN	0.4103±0.014	0.3702±0.013	0.4028±0.017	0.3632±0.015	0.3617±0.013	0.3204±0.016	0.3678±0.013	0.3382±0.012
Sequential	CASER	0.4096 ±0.012	0.3663±0.015	0.4021±0.014	0.3626±0.016	0.3658 ±0.013	0.3189±0.012	0.3722±0.012	0.3414±0.012
	SASRec	0.4105±0.013	0.3740 ±0.011	0.4112±0.015	0.3708±0.017	0.3746±0.012	0.3257±0.014	0.3812±0.014	0.3445±0.012
	BERT4Rec	0.4149±0.014	0.3781±0.011	0.4163±0.012	0.3754 ±0.013	0.3793±0.011	0.3295±0.013	0.3846±0.013	0.3463±0.013
	S^3-Rec	0.4124 ±0.012	0.3755±0.014	0.4134±0.013	0.3715 ±0.014	0.3786±0.016	0.3274±0.013	0.3725±0.014	0.3350±0.012
	CL4SRec	0.4210±0.016	0.3821±0.017	0.4205±0.013	0.3781 ±0.015	0.3814 ±0.016	0.3318±0.012	0.3858±0.014	0.3313±0.011
	SAR	0.4034±0.012	0.3741±0.012	0.4023±0.014	0.3747±0.014	0.3711±0.012	0.3224±0.013	0.3658±0.012	0.3320±0.014
	ResAct	0.4366±0.014	0.3948±0.012	0.4286±0.014	0.3814±0.011	0.3867±0.012	0.3360±0.011	0.3884±0.013	0.3472±0.013
ODE	LT-OCF	0.4267±0.013	0.3785±0.015	0.4141±0.016	0.3673 ±0.014	0.3848±0.012	0.3313±0.013	0.3841±0.014	0.3416±0.012
	GRU-ODE	0.4398±0.014	0.3902 ±0.017	0.4275±0.013	0.3792±0.013	0.3994±0.013	0.3417±0.015	0.3856±0.014	0.3455±0.012
Proposed	**E-NSDE**	**0.4711±0.015**	**0.4112±0.013**	**0.4551±0.011**	**0.3982±0.016**	**0.4194±0.013**	**0.3637±0.015**	**0.4021±0.014**	**0.3621±0.012**

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Ablation Study

- **Uncertainty vs. Interaction gap:** We further investigate the impact of the user-item interaction gap and the corresponding uncertainty in providing important and diverse items in Table (a).

- Further, ablation study on key components of the E-NSDE model in Table (b).

Table: (a) Diverse recommendations by E-NSDE; (b) Ablation of key components

Model	Important Movies (Genre)	Future Movie's Genre
GRU-ODE	Dead Man Walking ('Drama') Richard III ('Drama') Mad Love ('Romance')	'Thriller' 'Drama' 'Mystery'
E-NSDE	GoldenEye ('Thriller') Taxi Driver ('Drama') Twelve Monkeys ('Sci_Fi')	'Crime' 'Sci_Fi'

(a)

NSDE	EDL	WBPR	Performance	
			P@5	nDCG@5
✓			0.4065	0.3677
✓	✓		0.4523	0.3962
✓		✓	0.4120	0.3715
✓	✓	✓	**0.4711**	**0.4112**

(b)

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└Ablation Study

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Conclusions

- We propose a novel time-aware sequential recommendation model called E-NSDE.
- It includes NSDE module that enables continuous, time-aware modeling of user preferences, without requiring uniform time intervals.
- Further, monotonic network ensures the relationship between time intervals and uncertainty is properly reflected—longer time intervals increase model uncertainty.
- Provides SOTA performance in multiple real-world datasets.

Poster

More detailed information will be in the Poster with **ID: 96864 (Poster Session 2)**.

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