RepeatNet: A Repeat Aware Neural Recommendation Machine for Session-based Recommendation

Pengjie Ren[1,2], Zhumin Chen[1], Jing Li[1], Zhaochun Ren[3], Jun Ma[1], Maarten de Rijke[2]
[1] Shandong University, Jinan, China
[2] University of Amsterdam, Amsterdam, The Netherlands
[3] Data Science Lab, JD.com, Beijing, China

Motivation

Table 1: Repeat ratio (%) on three benchmark datasets.

Datasets	Train	Validation	Test
YOOCHOOSE 1/4	25.52	25.51	26.02
DIGINETICA	19.94	20.06	20.49
LASTFM	20.72	20.42	20.95

- ***Repeat consumption*:** the patterns by which a user consumes the same item repeatedly over time, in a wide variety of domains, ranging from check-ins at the same business location to re-watches of the same video and the recency of consumption is the strongest predictor of repeat consumption.
- A repeat-explore mechanism for session-based recommendation to automatically learn the switch probabilities between repeat and explore modes.

Overview of RepeatNet

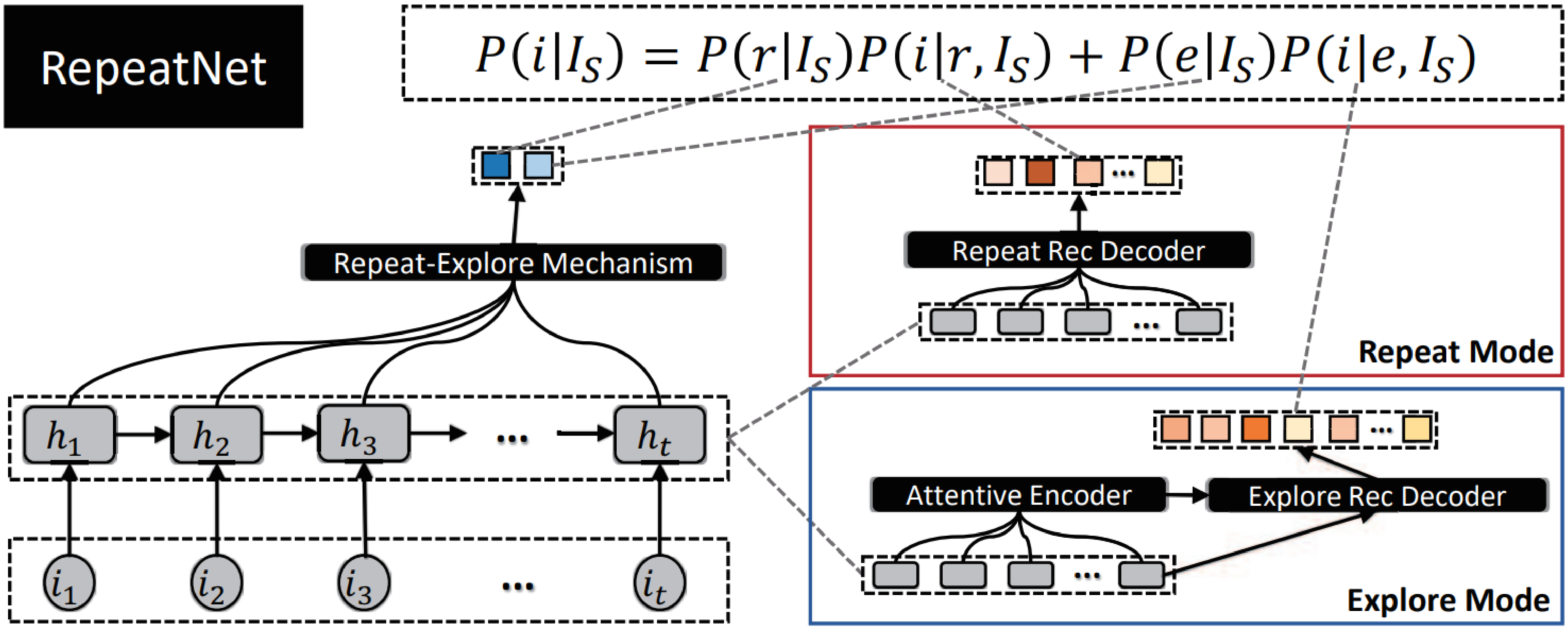

Figure 1: Overview of RepeatNet.

RepeatNet

- **Framework**

Given an action (e.g., clicking, shopping) session $I_S = \{i_1, i_2, \dots, i_\tau, \dots, i_t\}$, where i_τ refers to an item, session-based recommendation tries to predict what the next event would be,

$$P(i_{t+1}|I_S) = P(r|I_S)P(i_{t+1}|r, I_S) + \mathrm{P}(e|I_S)P(i_{t+1}|e, I_S)$$

where r and e denote repeat mode and explore mode, respectively. Here, $P(r|I_S)$ and $\mathrm{P}(e|I_S)$ represent the probabilities of executing in *repeat mode* and *explore mode*, respectively. $P(i_{t+1}|r, I_S)$ and $P(i_{t+1}|e, I_S)$ refer to the probabilities of recommending i_{t+1} in *repeat mode* and in *explore mode*, respectively, given I_S.

RepeatNet

- **Session encoder (GRU)**

$$z_\tau = \sigma(W_z[emb(i_\tau), h_{\tau-1}])$$
$$r_\tau = \sigma(W_r[emb(i_\tau), h_{\tau-1}])$$
$$\widetilde{h_\tau} = \tanh(W_h[emb(i_\tau), r_\tau \odot h_{\tau-1}])$$
$$h_\tau = (1 - z_\tau) \odot h_{\tau-1} + z_\tau \odot \widetilde{h_\tau},$$

After the session encoder, each session I_S is encoded into $H = \{h_1, h_2, \dots, h_\tau, \dots, h_t\}$.

- **Repeat-explore mechanism (soft-attention)**

$$[P(r|I_S), P(e|I_S)] = \mathrm{softmax}\left(W_{re}^c c_{I_S}^{re}\right)$$

$$c_{I_S}^{re} = \sum_{\tau=1}^{t} \alpha_\tau^{re} h_\tau, \qquad \alpha_\tau^{re} = \frac{\exp(e_\tau^{re})}{\sum_{\tau=1}^{t} \exp(e_\tau^{re})}, \qquad e_\tau^{re} = v_{re}^T \tanh(W_{re} h_t + U_{re} h_\tau)$$

where h_t is the last hidden state.

RepeatNet

- **Repeat recommendation decoder**

$$e_\tau^r = v_r^\top \tanh(W_r h_t + U_r h_\tau)$$

$$P(i \mid r, I_S) = \begin{cases} \frac{\sum_i \exp(e_\tau^r)}{\sum_{\tau=1}^{t} \exp(e_\tau^r)} & \text{if } i \in I_S \\ 0 & \text{if } i \in I - I_S \end{cases}$$

- **Explore recommendation decoder**

$$f_i = \begin{cases} -\infty & \text{if } i \in I_S \\ W_e^c c_{I_S} & \text{if } i \in I - I_S \end{cases}$$

$$P(i \mid e, I_S) = \frac{\exp(f_i)}{\sum_{\tau=1}^{t} \exp(f_\tau)},$$

$$c_{I_S} = [h_t, c_{I_S}^e], \qquad c_{I_S}^e = \sum_{\tau=1}^{t} \alpha_\tau^e h_\tau, \qquad \alpha_\tau^e = \frac{\exp(e_\tau^e)}{\sum_{\tau=1}^{t} \exp(e_\tau^e)}, \qquad e_\tau^e = v_e^T \tanh(W_e h_t + U_e h_\tau)$$

where c_{I_S} is a hybrid representation of session I_S, which combines with the last hidden state and attentive state.

RepeatNet

- **Repeat recommendation decoder**

$$e^r_\tau = v_r^\top \tanh(W_r h_t + U_r h_\tau)$$

$$P(i \mid r, I_S) = \begin{cases} \frac{\sum_i \exp(e^r_\tau)}{\sum_{\tau=1}^{t} \exp(e^r_\tau)} & \text{if } i \in I_S \\ 0 & \text{if } i \in I - I_S \end{cases}$$

- **Explore recommendation decoder**

$$f_i = \begin{cases} -\infty & \text{if } i \in I_S \\ W_e^c c_{I_S} & \text{if } i \in I - I_S \end{cases}$$

$$P(i \mid e, I_S) = \frac{\exp(f_i)}{\sum_{\tau=1}^{t} \exp(f_\tau)},$$

$$c_{I_S} = [h_t, c^e_{I_S}], \qquad c^e_{I_S} = \sum_{\tau=1}^{t} \alpha^e_\tau h_\tau, \qquad \alpha^e_\tau = \frac{\exp(e^e_\tau)}{\sum_{\tau=1}^{t} \exp(e^e_\tau)}, \qquad e^e_\tau = v_e^T \tanh(W_e h_t + U_e h_\tau)$$

where c_{I_S} is a hybrid representation of session I_S, which combines with the last hidden state and attentive state.

Objective Function

- **Prediction loss function**

$$L_{rec}(\theta) = -\frac{1}{|\mathbb{I}_{\mathbb{S}}|} \sum_{I_S \in \mathbb{I}_{\mathbb{S}}} \sum_{\tau=1}^{|I_S|} \log P(i_\tau \mid I_S)$$

- **Prediction loss function**

$$L_{mode}(\theta) = -\frac{1}{|\mathbb{I}_{\mathbb{S}}|} \sum_{I_S \in \mathbb{I}_{\mathbb{S}}} \sum_{\tau=1}^{|I_S|} \mathbb{1}(i_\tau \in I_S) log P(r|I_S) + \big(1 - \mathbb{1}(i_\tau \in I_S)\big) P(e|I_S)$$

where $\mathbb{1}(i_\tau \in I_S)$ is an indicator function that equals 1 if $i_\tau \in I_S$ and 0 otherwise.

- **Joint training**

$$L(\theta) = L_{rec}(\theta) + L_{mode}(\theta)$$

Experiments

Table 3: Experimental results (%) on the three datasets.

Methods	YOOCHOOSE				DIGINETICA				LASTFM			
	MRR		Recall		MRR		Recall		MRR		Recall	
	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20	@10	@20
POP	0.26	0.30	0.81	1.33	0.18	0.20	0.53	0.89	1.09	1.26	2.90	5.26
S-POP	17.70	17.79	25.96	27.11	13.64	13.68	20.56	21.06	8.36	8.71	18.08	22.59
Item-KNN	20.89	21.72	41.56	52.35	10.77	11.57	25.04	35.75	4.48	4.85	9.77	14.84
BPR-MF	1.90	1.97	3.07	4.05	1.86	1.98	3.60	5.24	4.88	5.19	9.87	14.05
FPMC	16.59	17.50	38.87	51.86	6.30	6.95	17.07	26.53	4.58	4.99	11.67	17.68
PDP	18.44	19.15	40.03	52.98	6.75	7.24	19.57	28.77	4.86	5.05	12.11	18.09
GRU4REC	21.64	22.60	46.67	59.56	7.59	8.33	19.09	29.45	4.92	5.39	11.56	17.90
Improved-GRU4REC	28.36	29.15	57.91	69.20	13.63	14.69	33.48	46.16	9.60	10.15	20.98	29.04
GRU4REC-TOPK	29.76	30.69	58.15	70.30	13.14	14.16	31.54	45.23	7.44	7.95	15.73	22.61
NARM	28.52	29.23	58.70	69.73	15.25	16.17	33.62	**49.70**	10.31	10.85	22.04	29.94
RepeatNet (no repeat)	30.02	30.76	59.62	70.21	12.71	13.52	30.96	42.56	9.92	10.47	21.81	29.96
RepeatNet	**30.50**†	**31.03**†	**59.76**†	**70.71**	**16.90**†	**17.66**†	**36.86**†	47.79	**11.46**†	**12.03**†	**24.18**†	**32.38**†

Bold face indicates the best result in terms of the corresponding metric. Significant improvements over the best baseline results are marked with † (t-test, $p < .05$). The scores reported in (Li et al. 2017b) on the DIGINETICA dataset differ because they did not sort the session items according to the "timeframe" field, which ignores the sequential information. We run the code released by (Hidasi et al. 2016a; Tan, Xu, and Liu 2016; Hidasi and Karatzoglou 2017; Li et al. 2017b) to obtain the results of GRU4REC, Improved-GRU4REC, GRU4REC-TOPK, and NARM.

Experiments

Table 4: MRR@20 (%) of RepeatNet (with and without repeat mechanism) on repeat and non-repeat sessions.

RepeatNet		With repeat	No repeat
YOOCHOOSE	Rep	58.78	**60.18**
	Non-Rep	**21.60**	20.42
DIGINTICA	Rep	**56.27**	29.20
	Non-Rep	7.71	**9.48**
LASTFM	Rep	**41.63**	32.68
	Non-Rep	4.18	**5.06**

Rep: repeat sessions; *Non-Rep*: non-repeat sessions.

Table 5: Recall@20 (%) of RepeatNet (with and without repeat mechanism) on repeat and non-repeat sessions.

RepeatNet		With repeat	No repeat
YOOCHOOSE	Rep	**97.41**	93.70
	Non-Rep	61.32	**61.95**
DIGINTICA	Rep	**99.09**	65.18
	Non-Rep	34.58	**36.73**
LASTFM	Rep	**91.22**	67.06
	Non-Rep	16.79	**20.10**

Table 8: MRR@20 and Recall@20 (%) of RepeatNet with and without joint learning.

Loss	YOOCHOOSE		LASTFM	
	MRR	Recall	MRR	Recall
L_{rec}	**31.03**	**70.71**	**12.03**	**32.38**
$L_{rec} + L_{mode}$	28.99	69.64	11.58	31.94