Exceeding Historical Exposure

in Session-based Recommender Systems

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Session-based Recommender Systems

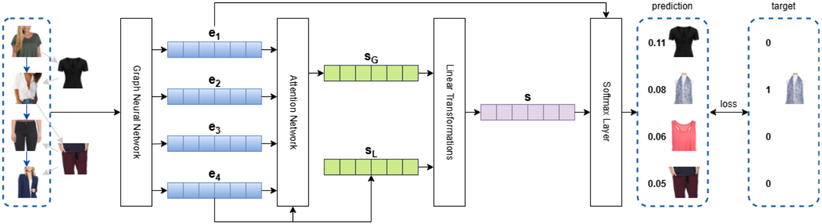
- $\mathcal{I} = \{i_1, i_2, \ldots, i_N\}$ – a set of N items;
- $\mathcal{S} = \{S_1, S_2, \ldots, S_M\}$ – a set of M anonymous sessions;
- $S_m = (s_{m,1}, s_{m,2}, \ldots, s_{m,L_m})$ – a list of items of length L_m (mth session);
- $R_m = (r_{m,1}, \ldots, r_{m,K})$ – a list of K recommended items for mth session;

Session-based Recommender System Task:

$$(s_{m,1}, s_{m,2}, \ldots, s_{m,L_m-1}) \xrightarrow{RS} R_m, \text{ preferably } s_{m,L_m} \in R_m.$$

Session-based Recommender Systems

Session-based Recommendations with Graph Neural Network



Shu Wu, Yuyuan Tang, Yanqiao Zhu, Liang Wang, Xing Xie, and Tieniu Tan. 2019. Session-based recommendation with graph neural networks. In Proceedings of the Thirty-Third AAAI Conference on Artificial Intelligence and Thirty-First Innovative Applications of Artificial Intelligence Conference and Ninth AAAI Symposium on Educational Advances in Artificial Intelligence (AAAI'19/IAAI'19/EAAI'19). AAAI Press, Article 43, 346–353. https://doi.org/10.1609/aaai.v33i01.3301346

Challenges Related to Uncertainty

- **Implicit feedback:**

$$\text{interaction} \neq \text{satisfaction}$$

- **Exposure bias:**

$$\text{selected} \neq \text{most wanted}$$

- **Popularity bias:**

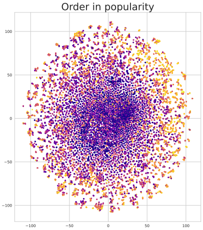
$$\text{popular} \Rightarrow \text{visible}$$

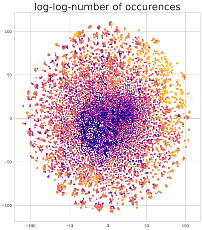
- **Data Sparsity:**

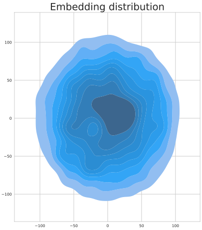
$$\text{no interaction} \neq \text{no interest}$$

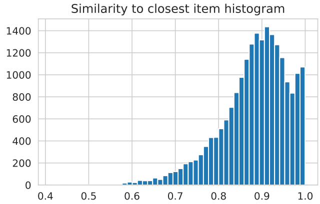
Symptoms of bias

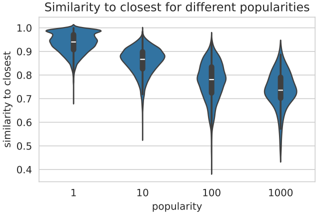
Symptomes of Bias







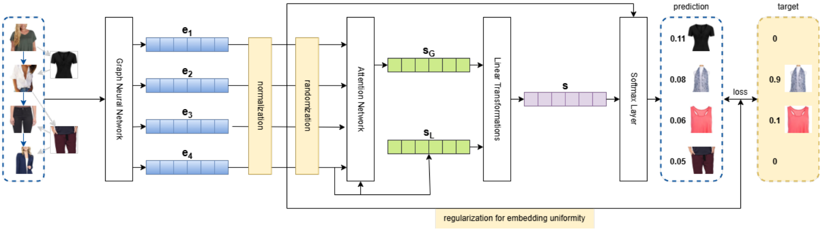




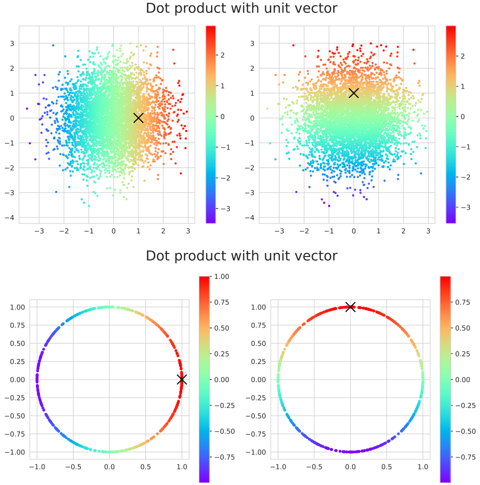
average item popularity: 17, average target popularity: 136, average recommendation popularity: 134 (train) / 137 (test)

Hybrid Deep-Stochastic Approach

Model Schema



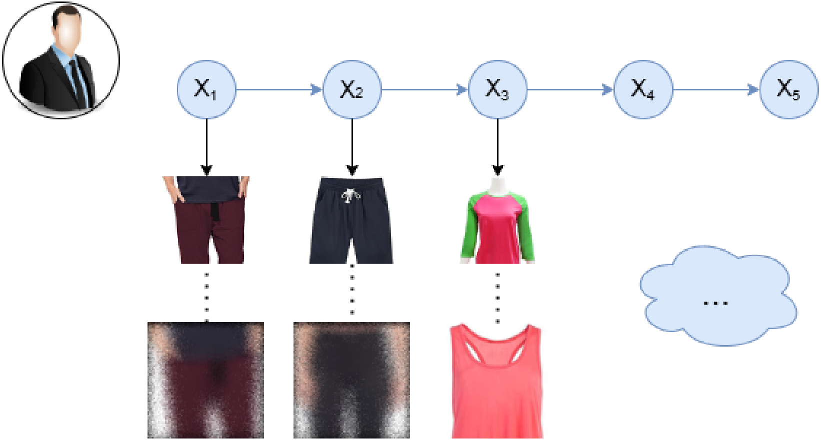
Unbiased Representation



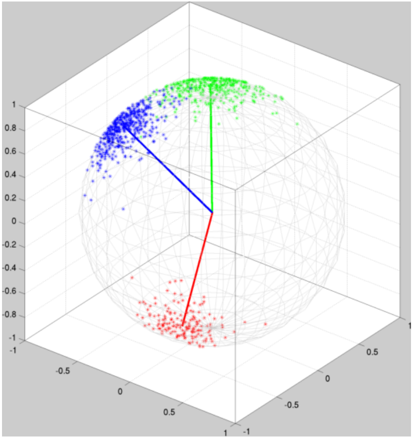
$$\mathrm{RBF}_{\tau}(\mathbf{v}, \mathbf{v}') = e^{-\tau \|\mathbf{v}-\mathbf{v}'\|_2^2}.$$

Uncertain User Interest

User Interest as Stochastic Process



Dense User Interest



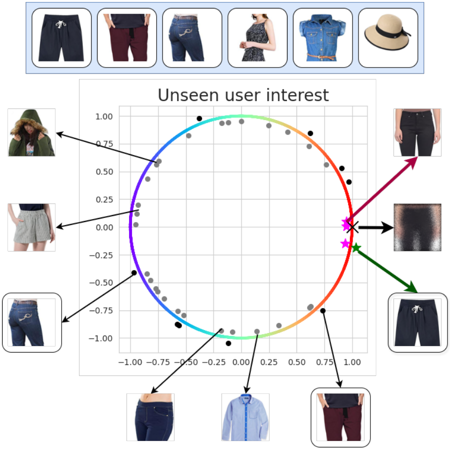
$$X_{m,j} \sim \text{vMF}(., e_{m,j}, \kappa), \text{ for a fixed } \kappa$$

$$\text{vMF}(x, \mu, \kappa) \propto \exp\{\kappa x^T \mu\}$$

$$\text{vMF}(x, \mu, \kappa) \sim \mathcal{N}(\mu, \kappa^{-1}) | \|x\|_2 = 1$$

Image source: https://github.com/isrish/VMM/blob/master/transparent.png

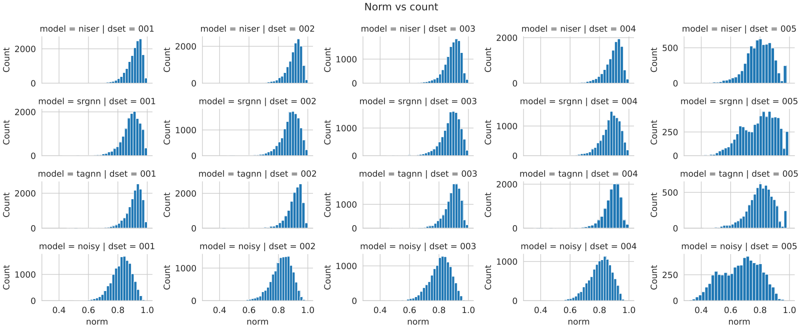
Target Uncertainty



$$
y_j^* = \begin{cases} \dfrac{\exp\{\kappa \mathbf{v}_j^T \mathbf{v}_{m,L_m}\}}{\sum_{p=1}^{P} \exp\{\kappa \mathbf{v}_p^T \mathbf{v}_{m,L_m}\}} \cdot \gamma & \text{if } i_j \in F_m \text{ (fake target)} \\ 1 - \sum_{p=1}^{P} y^*_{f_{m,p}} & \text{if } s_{m,L_m} = i_j \text{ (true target)} \\ 0 & \text{otherwise} \end{cases}
$$

Experiments

Distance to Closest



Overall Results

model	Hit-Rate Train	Hit-Rate Test	Coverage Train	Coverage Test	ARP Train	ARP Test	RBF
			Diginetica				
random	0.0005	0.0004	100.0000	100.0000	16.9196	16.8887	-
bigram	0.8516	0.3480	100.0000	99.9977	55.1153	53.5065	-
NISER	0.7369	0.4831	98.7302	91.0161	61.9805	**59.7067**	0.0606
SR-GNN	0.7794	0.4656	98.1883	91.9719	**61.3056**	60.8660	0.0633
TAGNN	0.7399	0.4869	98.7744	90.7533	62.7503	61.0402	0.0642
noisy	**0.7448**	**0.5109**	**99.9372**	**93.2650**	64.8328	64.4680	0.0632
			YooChoose 1/64				
random	0.0013	0.0011	100.0000	100.0000	22.7245	22.7522	-
bigram	0.8214	0.6496	100.0000	99.9815	541.5820	422.3570	-
NISER	0.7839	**0.7154**	90.5194	68.9828	577.5689	452.8599	0.0630
SR-GNN	**0.7922**	0.7020	92.9343	71.8053	570.2716	440.6263	0.0584
TAGNN	0.7848	0.7142	90.6800	68.9828	573.5134	450.1954	0.0654
noisy	0.7809	0.7083	**99.6418**	**76.0917**	**548.8170**	**432.2718**	**0.0551**

Variants of YooChoose

dataset	model	Hit-Rate Train	Hit-Rate Test	Coverage Train	Coverage Test	ARP Train	ARP Test	RBF
001	NISER	0.7931	0.7161	93.3728	69.4859	507.2249	375.9715	0.0633
	SR-GNN	0.8029	0.7055	95.6232	71.6744	501.7716	368.0752	0.0584
	TAGNN	0.7948	0.7174	93.6618	69.9608	506.6953	371.1567	0.0622
	noisy	0.7923	0.7140	99.7591	76.2439	479.1834	353.9358	0.0522
002	NISER	0.7995	0.7274	95.2478	71.6670	443.3394	367.6830	0.0596
	SR-GNN	0.8083	0.7160	96.9171	72.3438	442.8813	362.1181	0.0584
	TAGNN	0.7994	0.7274	95.0297	71.2685	438.5160	365.4440	0.0561
	noisy	0.7975	0.7225	99.7368	76.2087	417.8626	349.0806	0.0531
003	NISER	0.8244	0.7315	95.6840	69.5603	380.1184	321.6723	0.0609
	SR-GNN	0.8321	0.7237	97.3828	71.1290	377.3208	317.0184	0.0583
	TAGNN	0.8249	0.7313	95.7571	70.3975	378.3776	320.0574	0.0604
	noisy	0.8226	0.7285	99.4798	75.0792	363.6459	307.6846	0.0546
004	NISER	0.8257	0.7256	95.8043	68.4054	346.6219	242.4871	0.0612
	SR-GNN	0.8411	0.7232	97.6971	69.3214	343.6278	241.2055	0.0588
	TAGNN	0.8306	0.7255	96.2055	69.7052	343.8487	244.2331	0.0625
	noisy	0.8293	0.7255	99.3545	74.7819	329.8606	230.7884	0.0563
005	NISER	0.8337	0.7051	86.1694	52.2745	15.1847	37.0339	0.0576
	SR-GNN	0.9481	0.7318	96.2169	54.3728	15.5628	36.9127	0.0594
	TAGNN	0.8328	0.7130	87.0271	49.7779	15.2988	36.7836	0.0573
	noisy	0.9353	0.7336	96.7529	61.0354	16.1653	37.6747	0.0603

Results

- Two datasets with different levels of popularity bias (and preparation of in-between levels).
- **Hit-rate** improvement for less biased data (Diginetica):
  0.4656 (SRGNN) $\rightarrow 0.4869$ (TAGNN) $\rightarrow 0.5109$ (our) .
- **Average recommendation popularity** decreased for more biased data (YooChoose):
  453 (NISER) $\rightarrow 441$ (SRGNN) $\rightarrow 432$ (our) .
- **Coverage** improved for both datasets:
  91.9719 (SRGNN) $\rightarrow 93.2650$ (our) – Diginetica;
  71.8053 (SRGNN) $\rightarrow 76.0917$ (our) – YooChoose.

Conclusion

Take-home Messages

- Recommender Systems are a crucial **business** tool and a vivid field of **research**.
- Data is always associated with a degree of **uncertainty**. It can be directly addressed with **stochastic** methods.
- Recommender Systems have specific challenges like **popularity** and **exposure bias**. Those are learned by the model and **encoded** in the items' **latent space**.
- The proposed approach uses **deep** learning and **stochastic** modelling. It allows for bias reduction and **better model generalization**.

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