QPIN: A Quantum-inspired Preference Interactive Network for E-commerce Recommendation

Panpan Wang
panpan_tju@tju.edu.cn
Tianjin University
Tianjin, China

Zhao Li
lizhao.lz@alibaba-inc.com
Alibaba Group
Hang Zhou, China

Yazhou Zhang
yzhou_zhang@tju.edu.cn
Tianjin University
Tianjin, China

Yuexian Hou*
yxhou@tju.edu.cn
Tianjin University
Tianjin, China

Liangzhu Ge
geliangzhu123@tju.edu.cn
Tianjin University
Tianjin, China

ABSTRACT

Recently, recurrent neural networks (RNNs) based methods have achieved profitable performance on mining temporal characteristics in user behavior. However, user preferences are changing over time and have not been fully exploited in e-commerce scenarios. To fill in the gap, we propose an approach, called quantum inspired preference interactive networks (QPIN), which leverages the mathematical formalism of quantum theory (QT) and the long short term memory (LSTM) network, to interactively learn user preferences. Specifically, the tensor product operation is used to model the interaction among a single user's own preferences, i.e. individual preferences. A quantum many-body wave function (QMWF) is employed to model interaction among all users' preferences, i.e. group preferences. Further, we bridge them by deriving a rigorous projection, and thus take the interplay between them into account. Experiments on an Amazon dataset as well as a real-world e-commerce dataset demonstrate the effectiveness of QPIN, which achieves superior performances compared with the state-of-the-art methods in terms of AUC and F1-score.

CCS CONCEPTS

• **Information systems → Personalization**; **Recommender systems**; *Temporal data*; • **Applied computing → Online shopping**.

KEYWORDS

E-commerce Recommendation; Recurrent Neural Networks; Quantum Theory

ACM Reference Format:
Panpan Wang, Zhao Li, Yazhou Zhang, Yuexian Hou, and Liangzhu Ge. 2019. QPIN: A Quantum-inspired Preference Interactive Network for E-commerce Recommendation. In *The 28th ACM International Conference on Information and Knowledge Management (CIKM '19), November 3–7, 2019, Beijing, China.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3357384.3358076

*This is the corresponding author.

CIKM '19, November 3–7, 2019, Beijing, China

ACM ISBN 978-1-4503-6976-3/19/11…$15.00
https://doi.org/10.1145/3357384.3358076

1 INTRODUCTION

Temporal dynamic is a typical feature of one's shopping behavior in the e-commerce platform. For example, as the time is changing from summer to winter, user's shopping characteristics shift from cool to warm. In order to capture the temporal characteristics, recurrent neural networks (RNNs) based methods have been recently proposed and demonstrated their competitive capabilities to recommend proper items for users at the right time [4, 8, 9]. The existing methods mainly focus on mining the transformation of temporal characteristics of user preferences, while the interaction information is largely neglected.

In the course of shopping online, a user's own preferences, such as category, brand and seller, would affect each other. We posit that is the interaction among individual preferences. Correspondingly, there also exists interaction among the overall users' preferences (i.e., group preferences). Since the need of considering more information, it is natural that modelling the interaction among group preferences is a more complex task. However, factorization machine [2], which is one kind of popular interaction modelling method, is insufficient for capturing the interaction among group preferences. Further, the interplay between individual and group preferences is also ignored. For example, a user wants to buy a mechanical watch. But he finds that smart watch is popular now, which may cause the transformation of his current preference. In addition, product consumed by Hollywood stars often leads a fashion, which shows that individual preferences have an effect on the group preferences.

To model preference characteristics mentioned above, we propose an approach, called **Quantum inspired Preference Interactive Network** (QPIN), which leverages the mathematical formalism of quantum theory (QT) and the long short term memory (LSTM) network, to learn user preferences. Each preference is described by the superposition of multiple basis state vectors. To improve processing efficiency of QPIN, individual preferences are analogous to a basic composite system that are described by a **tensor product** of different basis vectors. In quantum theory, a **quantum many-body wave function** (QMWF) is used to describe a composite system containing more complex correlations and quantum entanglement [1]. We use QMWF to describe group preferences. Then, we make a projection from tensor product based representation to QMWF based representation to model the interplay between group preferences and individual preferences. The basic idea and formulation of our method is inspired by [7], which apples the tensor product and QMWF into language model. We evaluate our proposed QPIN on an Amazon dataset and a real-world dataset collected from Taobao website. A series of systematic experiments show that QPIN significantly outperforms the state-of-the-art methods in terms of **Area Under the Curve** (AUC) and **F1 score**.

2 QUANTUM PRELIMINARIES

In quantum theory, a quantum system is residing in a Hilbert space $\mathcal{H}_i$, which is a complex vector space with the dimension of M_i. For simplicity and in line with previous quantum inspired models [7], we restrict our model to vectors spaces over real values of space $\mathbb{R}$. A quantum state is a unit vector $\vec{u}$. With the Dirac's notation, $\vec{u}$ is expressed as a ket $|u\rangle$, and its transpose is expressed as a bra $\langle u|$. A projection from a state vector $|u\rangle$ to a state vector $|v\rangle$ is computed by an inner product, denoted as $\langle u|v\rangle$. It is obvious that $\langle u|v\rangle = \langle v|u\rangle$. For a composite system consisting of N quantum systems, its Hilbert space is a tensor product of the spaces, i.e. $\mathcal{H} := \otimes_{i=1}^{N}\mathcal{H}_i$.

3 LEARNING INTERACTION DYNAMICS WITH QUANTUM INSPIRED PREFERENCES INTERACTIVE NETWORK

In this work, we target recommending items for users by mining preferences from history behavior records. Suppose we have users' behavior sequences, for each sequence $\{u_1, ..., u_{T-1}\}$, u_t contains K items, and each item in u_t consists of N type of preferences, i.e. $\{f_1, f_2, \ldots, f_N\}$, that affect user's choice of items. To correctly recommend the items appeared at the last time stamp u_T, we now introduce our proposed **Quantum inspired Preference Interactive Network (QPIN)**.

3.1 Quantum inspired Preference Representation and Projection

In this paper, each type of preference f_i is residing in a finite dimensional Hilbert space $\mathcal{H}_i$. Its state vector is defined as $|f_i\rangle = \sum_{h_i=1}^{M_i} \alpha_{i,h_i}|\phi_{h_i}\rangle$, where each basis vector $|\phi_{h_i}\rangle$ corresponds to a specific sub-preference. α_{i,h_i} is probability amplitude of each sub-preference, satisfying $\sum_{h_i=1}^{M_i} \alpha_{i,h_i}^2 = 1$. Taking an example illustrates preference and its sub-preferences. If f_i refers to 'smart phone', its sub-preferences can be color, CPU, RAM, etc..

Individual preferences refer to a single user's preferences, and are represented with a **tensor product state**. The tensor product models the interaction among individual preferences. Its representation is described as follows:

$$
\begin{aligned}
|\Phi^{individual}\rangle &= |f_1\rangle \otimes \cdots \otimes |f_N\rangle \\
&= \sum_{h_1=1}^{M_1} \cdots \sum_{h_N=1}^{M_N} \mathcal{F}_{h_1 \ldots h_N} |\phi_{h_1}\rangle \otimes \cdots \otimes |\phi_{h_N}\rangle
\end{aligned} \tag{1}
$$

where $|\Phi^{individual}\rangle$ is residing in a new Hilbert space with $M_1 \times \cdots \times M_N$ dimension, and describes the individual preferences. $|\phi_{h_1}\rangle \otimes \cdots \otimes |\phi_{h_N}\rangle$ is the basis vector. $\mathcal{F}_{h_1 \ldots h_N}$ is an entry in tensor $\mathcal{F} \in \mathbb{R}^{M_1 \times \cdots \times M_N}$, and represents the probability amplitude of the corresponding compound sub-preferences. With the tensor product operation, $\mathcal{F}_{h_1 \ldots h_N} = \prod_{i=1}^{N} \alpha_{i,h_i}$ deriving that $\mathcal{F}$ contains $M_1 + M_1 + \cdots + M_N$ free parameters.

Group preferences refer to the overall users' preferences. Since the interaction among group preferences is more complex than the interaction among individual preferences, a **quantum many-body wave function** (QMWF) is employed to represent group preferences, which the representation is described as:

$$
|\Phi^{group}\rangle = \sum_{h_1=1}^{M_1} \cdots \sum_{h_N=1}^{M_N} \mathcal{G}_{h_1 \ldots h_N} |\phi_{h_1}\rangle \otimes \cdots \otimes |\phi_{h_N}\rangle \tag{2}
$$

where $|\Phi^{group}\rangle$ is residing in a Hilbert space with $M_1 \times \cdots \times M_N$ dimension, and represents the group preferences. $|\phi_{h_1}\rangle \otimes \cdots \otimes |\phi_{h_N}\rangle$ is the basis vector. $\mathcal{G}_{h_1 \ldots h_N}$ is a specific entry in a tensor $\mathcal{G} \in \mathbb{R}^{M_1 \times \cdots \times M_N}$ holding all the probability amplitude. Since there are entanglements within a composite system described by QMWF, the tensor $\mathcal{G}$ contains $M_1 \times M_2 \times \cdots \times M_N$ parameters. Besides, solving $\mathcal{G}$ is an intractable problem which is referred as a quantum many-body problem [1, 7].

To further model the interplay between group preferences and individual preferences, we make a projection from a tensor product based individual representation to a QMWF based group representation, i.e. $\langle\Phi^{individual}|\Phi^{group}\rangle$. According to the quantum computation rules, this projection will eliminate the high-dimensional basis vectors in Eq.(2) and Eq.(1) to get the following equation:

$$
\langle\Phi^{individual}|\Phi^{group}\rangle = \sum_{h_1=1}^{M_1} \cdots \sum_{h_N=1}^{M_N} \mathcal{G}_{h_1 \ldots h_N} \times \mathcal{F}_{h_1 \ldots h_N} \tag{3}
$$

Since $\langle\Phi^{individual}|\Phi^{group}\rangle = \langle\Phi^{group}|\Phi^{individual}\rangle$, it reveals the interplay between group preferences and individual preferences. More detail about inferring Eq.(3) can refer to a recent work [7].

Considering the computational complexity issue of $\mathcal{G}$, a common solution used in practice to approximate this high-dimensional tensor is the tensor decomposition method. Specifically, we use Canonical Polyadic Decomposition (CP decomposition [5]) in this paper. Then, $\mathcal{G}$ can be decomposed as:

$$
\mathcal{G} \approx \sum_{r=1}^{N_r} c_r \cdot g_{r,1} \otimes g_{r,2} \otimes \cdots \otimes g_{r,N} \tag{4}
$$

where $g_{r,i} = (g_{r,i,1}, ..., g_{r,i,M_i})^T$, (i=1,...,N) is a unit vector with M_i-dimension, and $g_{r,1} \otimes g_{r,2} \otimes \cdots \otimes g_{r,N}$ is called a rank-1 tensor. c_r is the weight coefficient for each rank-1 tensor. N_r is the rank of $\mathcal{G}$, which is defined as the smallest number of rank-1 tensors that generate $\mathcal{G}$ as their sum. We further make CP decomposition of $\mathcal{G}$ in Eq.(4), then put it into Eq.(3) and obtain:

$$
\langle\Phi^{individual}|\Phi^{group}\rangle = \sum_{r=1}^{N_r} c_r \prod_{i=1}^{N} (\sum_{h_1=1}^{M_1} \cdots \sum_{h_N=1}^{M_N} g_{r,i,h_i} \cdot \alpha_{i,h_i}) \tag{5}
$$

The interaction among preferences and the interplay between individual preferences and group preferences are both contained in such a projection. We will adopt the embedding space to represent preferences, then the probability amplitude α_{i,h_i} corresponds to the value (after normalization) of h_i^{th} dimension of preference f_i on the embedding space.

3.2 Quantum inspired Preferences Interactive Network

In user sequence, each item x_k^t in u_t consists of N features, i.e. $x_k^t = [f_k^{t,1}, f_k^{t,2}, ..., f_k^{t,N}]$, which are considered as a single user's preferences. From Eq.5, we need to construct preferences' embeddings. We first initialize an embedding matrix for each type of preference, denoted as $F_i \in \mathbb{R}^{|V_i| \times M_i}$, where $|V_i|$ is the length of F_i, and M_i refers to embedding dimension. The i^{th} preference for item x_k^t is denoted as $f_k^{t,i} = [\alpha_{i,1}^k, \alpha_{i,2}^k, ..., \alpha_{i,M_i}^k] \in F_i$. The representation of x_k^t is formed by concatenating all the preferences' embeddings. In this paper, we utilize LSTM [6] to model each behavior sequence. Since there are more than one item in u_t, we sum up $\{x_1^t, \dots, x_K^t\}$ as the input x_t of LSTM.

To obtain Eq.5, we initialize a tensor $\mathcal{G} \in \mathbb{R}^{N_r \times (1+M_1+\cdots+M_N)}$ with a decomposition form, where N_r is the rank size. For each item, its preferences' embeddings x_k^t and the initialized $\mathcal{G}$ are put into Eq.(5), and the projection result is denoted as p_k^t. We sum up $\{p_1^t, \dots, p_k^t\}$ at time stamp t, i.e. $\sum_{k=1}^{K} p_k^t$, and multiply it with the hidden state h_t of LSTM. With the last input of recommended item $x_{recommended}^T$, we obtain the last hidden state h_T. Next, we sum up all of the history weighted hidden states and concatenate it with h_T as $x_{feature}$:

$$x_{feature} = \left[\sum_{t=1}^{T-1} \sum_{k=1}^{K} p_k^t \cdot h_t, h_T \right] \tag{6}$$

It is finally put into softmax function for determining whether the recommended item is user preferred. The back propagation is trained with the cross entropy loss:

$$\boldsymbol{L} = -\sum_{i}^{N} [y_i \log p(x_{feature}) + (1 - y_i) \log(1 - p(x_{feature}))] \tag{7}$$

where $p(x_{feature})$ is probability of positive label output by softmax, and y_i represents the target label.

4 EXPERIMENTS

4.1 Datasets

Amazon Dataset. It contains product reviews and meta-data from Amazon[1], which is used as benchmark dataset [3]. We conduct experiments on a subset named "Clothing, Shoes and Jewelry". Each item in this dataset contains three features: item_id, categories and brand. Both categories and brands are indexed and replaced with "category_ids" and "brand_ids". We extract two adjacent subsequences with equal length of 30 days from each user's behavior sequence as training data and testing data, respectively. A day refers to one time stamp. We take items at the last day in each subsequence as user preferred items (i.e. positive samples). Negative samples are randomly selected from an item pool without positive samples, and they are equal to the number of positive samples. If there is no record of the last day, the sub-sequence will be removed from both training set and testing set. This dataset finally obtains 16592 training samples and 166 testing samples.

Taobao Dataset. It is collected from Taobao[2] website. We randomly select 100,000 users from a user pool and extract user behavior logs from November, 14 to January, 12 on 2018. Each item in this dataset owns four features: item_id, category_id, brand_id, and seller_id. The data preprocessing is the same with the Amazon dataset, and get 389316 training samples and 263292 testing samples at last.

4.2 Compared Methods and Setup

In this paper, we compare the following methods: (1) **LSTM** [6] is used as baseline method. (2) **DeepFM** [2] utilizes the factorization machines to model the interaction among features. We set all features' embedding dimension to 50. All of the history embeddings are summed up and concatenated with the recommended item's embedding as the input. (3) **Session-RNN** [4] exploits RNN to capture user's short-term preferences based on sequential actions within a session. In this paper, we consider a user record as a session, and use the publicly available implementation[3]. (4) **Attention-GRU-3M** [9] is designed for a brand-level ranking system in e-commerce platform, and has achieved three modifications based on Attention-GRU model. The dimension of attention cell and dense layer are set to 10 and 128 by default, respectively. (5) **Time-LSTM** equips LSTM with time gates to model real time interval feature [8]. Since real time interval is not taken into consideration in our proposed method, for a fair comparison, time interval of each user record is set to 1. **QPIN** is our proposed method in this paper. N_r is ranging from [50, 200] with interval of 10 .

All methods are implemented based on TensorFlow framework. We set the hidden state dimension of RNNs utilized in compared methods of 128. For both datasets, the embedding dimension of item_id, brand_id, and category_id are set to 100, 30, and 20 respectively. And the embedding dimension of seller_id on Taobao dataset is set to 50. We use Adam [7] as the optimizer with an initial learning rate of 0.001. We set the mini-batch size to 50 and the epoch to 20.

Area Under ROC Curve (**AUC**) and **F1-score** [9] are used to evaluate the recommendation performance of different methods.

4.3 Experimental Analysis

4.3.1 Model Comparison. Based on the above parameter settings, we report the performance of all compared methods in Table 1. For QPIN, we report the results of $N_r = 180$ on Amazon dataset and $N_r = 60$ on Taobao dataset. It is obvious that our proposed method significantly outperforms other methods of AUC and F1-score across two datasets. In comparison, deepFM achieves the worst performance. Session-RNN captured short-term preferences performs worse than LSTM. Time-LSTM has a similar architecture

[1] http://jmcauley.ucsd.edu/data/amazon/

[2] https://www.taobao.com/

[3] https://github.com/Songweiping/GRU4Rec_TensorFlow

Table 1: Model Comparison on Amazon and Taobao Datasets. (Bold typeset indicates the best performance. † indicates statistical significance at $p < 0.05$ compared with the baseline method.)

Methods	Amazon Dataset		Taobao Dataset	
	AUC	F1	AUC	F1
LSTM (Baseline)	0.60946	0.57325	0.74698	0.66642
DeepFM	0.52090	0.56299	0.65981	0.60685
Time-LSTM	0.60427	0.54769	0.74871	0.67022
Session-RNN	0.59856	0.53979	0.72382	0.65732
Attention-GRU-3M	0.59492	0.54692	0.7022	0.62611
QPIN	**0.68624**†	**0.61279**†	**0.75446**†	**0.67217**†

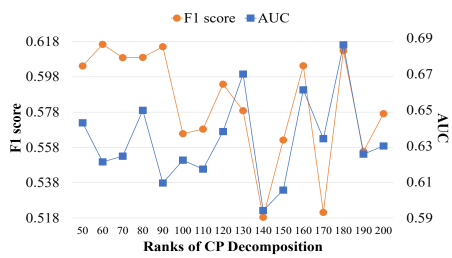

Figure 1: AUC and F1-score of QPIN with different ranks on Amazon dataset

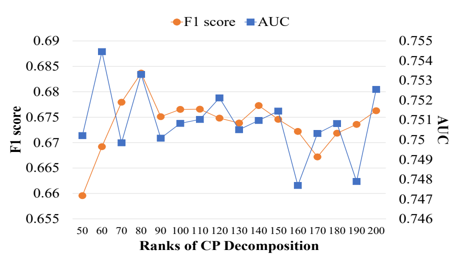

Figure 2: AUC and F1-score of QPIN with different ranks on Taobao dataset

with LSTM, and achieves almost the same performances. Attention-GRU-3M has modifications of GRU but still has a poor performance. These methods fail to model the interaction among preferences and the interplay between group preferences and individual preferences, which are captured by QPIN and can improve the accuracy of recommendation.

4.3.2 Parameter Analysis. We analyze the influence of different ranks N_r in CP decomposition on both datasets, as shown in Fig.1 and Fig.2. Due to the sparsity of Amazon dataset, QPIN is slightly sensitive to the choice of N_r. However, results from the evaluation of F1-score are almost larger than 0.55, which outperform Time-LSTM, Session-RNN, and Attention-GRU-3M. And most of these results from AUC are higher than 0.62, which is obviously better than all the other compared methods. For Taobao dataset, performance of QPIN under AUC and F1-score are stably larger than 0.75 and 0.67, respectively. These performances demonstrate that our model is stably superior to the state-of-the-art methods.

Table 2: Ablated QPIN for both Amazon and Taobao datasets

Methods	Amazon Dataset		Taobao Dataset	
	AUC	F1	AUC	F1
Hidden-Sum	0.61257	0.57119	0.74335	0.66055
QPIN	0.68624	0.61279	0.75446	0.67217

4.3.3 Ablation Study. We design a sub-model for a comprehensive study on the impact of interplay between group preferences and individual preferences of the QPIN model: Hidden-Sum, which $x_{feature}$ in Eq.6 does not contain the projection p_k^t, but only sums up the history hidden states from h_1 to h_{T-1}. From Table 2, we observe that QPIN stably outperforms Hidden-Sum. The results verify that the interplay between group preferences and individual preferences make a positive contribution to correctly recommend user preferred items.

5 CONCLUSION

In this paper, we propose a novel method to model the interaction among preferences and the interplay between group preferences and individual preferences with inspiration of quantum theory. We integrate these characteristics into LSTM, which correctly recommend items for users. Experiments on a public dataset and a real-world dataset show the significant improvement on our approach compared with the state-of-the-art methods. In future work, we will explore the effectiveness of applying quantum theory into solving the problem about recommendation task.

ACKNOWLEDGMENTS

This work is funded in part by the National Key R&D Program of China (2017YFE0111900), the National Natural Science Foundation of China (61876129), the Alibaba Innovation Research Foundation 2017 and the European Unions Horizon 2020 research and innovation program under the Marie Skodowska-Curie grant agreement No. 721321.

REFERENCES

[1] Giuseppe Carleo and Matthias Troyer. 2017. Solving the quantum many-body problem with artificial neural networks. *Science* 355, 6325 (2017), 602–606.
[2] Huifeng Guo, Ruiming Tang, Yunming Ye, Zhenguo Li, and Xiuqiang He. 2017. DeepFM: a factorization-machine based neural network for CTR prediction. *arXiv preprint arXiv:1703.04247* (2017).
[3] Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In *proceedings of the 25th international conference on world wide web*. International World Wide Web Conferences Steering Committee, 507–517.
[4] Balázs Hidasi, Alexandros Karatzoglou, Linas Baltrunas, and Domonkos Tikk. 2016. Session-based recommendations with recurrent neural networks. (2016).
[5] Frank L Hitchcock. 1927. The expression of a tensor or a polyadic as a sum of products. *Journal of Mathematics and Physics* 6, 1-4 (1927), 164–189.
[6] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation* 9, 8 (1997), 1735–1780.
[7] Peng Zhang, Zhan Su, Lipeng Zhang, Benyou Wang, and Dawei Song. 2018. A quantum many-body wave function inspired language modeling approach. In *Proceedings of the 27th International Conference on Information and Knowledge Management*. ACM, 1303–1312.
[8] Yu Zhu, Hao Li, Yikang Liao, Beidou Wang, Ziyu Guan, Haifeng Liu, and Deng Cai. 2017. What to do next: Modeling user behaviors by time-lstm. In *Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence, IJCAI-17*. 3602–3608.
[9] Yu Zhu, Junxiong Zhu, Jie Hou, Yongliang Li, Beidou Wang, Ziyu Guan, and Deng Cai. 2018. A Brand-level Ranking System with the Customized Attention-GRU Model. In *Proceedings of the Twenty-Seven International Joint Conference on Artificial Intelligence, IJCAI-18*.