Which Matters Most in Making Fund Investment Decisions? A Multi-granularity Graph Disentangled Learning Framework

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ABSTRACT

In this paper, we highlight that both conformity and risk preference matter in making fund investment decisions beyond personal interest and seek to jointly characterize these aspects in a disentangled manner. Consequently, we develop a novel Multi-granularity Graph Disentangled Learning framework named MGDL to effectively perform intelligent matching of fund investment products. Benefiting from the well-established fund graph and the attention module, multi-granularity user representations are derived from historical behaviors to separately express personal interest, conformity and risk preference in a fine-grained way. To attain stronger disentangled representations with specific semantics, MGDL explicitly involve two self-supervised signals, *i.e.,* fund type based contrasts and fund popularity. Extensive experiments in offline and online environments verify the effectiveness of MGDL.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Graph Learning, Intelligent Matching, Disentangled Learning

ACM Reference Format:
Chunjing Gan, Binbin Hu, Bo Huang, Tianyu Zhao, Yingru Lin, Wenliang Zhong, Zhiqiang Zhang, Jun Zhou, and Chuan Shi. 2023. Which Matters Most in Making Fund Investment Decisions? A Multi-granularity Graph Disentangled Learning Framework. In *Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '23), July 23–27, 2023, Taipei, Taiwan.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3539618.3592088

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SIGIR '23, July 23–27, 2023, Taipei, Taiwan

ACM ISBN 978-1-4503-9408-6/23/07…$15.00
https://doi.org/10.1145/3539618.3592088

1 INTRODUCTION

The beginning of the economic era centered on "personal finance" encourages the flourishing of online investment platforms(*e.g.,* Wealthfront and Alipay). To help individual investors make fund investment decisions, current financial platforms strive to provide intelligent matching of fund products among a large number of choices, which can be naturally abstracted as a classical matching or recommendation problem [7, 16, 26] with great interest-oriented efforts [15, 20] based on sequential [4, 10, 17] and graph learning [2, 3, 6, 8, 12, 21, 25, 28] based modelling. Despite considerable success in various traditional recommendation scenarios, *e.g.,* E-commerce, intelligent fund matching may be unlikely to benefit since personal interest may lose its leading role in the decision of financial products.

Comprehensive facts have shed light on the question "Which matters most in making fund investment decisions beyond personal interest", lying in the following two aspects related to the fairly unique financial scenarios (as shown in Fig. 1): (1) *Conformity* widely exists among individual investors. In the current fund market, a wealth of investment products have sprung up. Unfortunately, most users' financial knowledge could not meet their increasing investment needs, resulting in the common phenomenon that a large number of users buy fund products with the crowd. (2) *Risk Preference* is of crucial importance for making investment decisions. Different fund products refer to different risk levels. Therefore, users' risk preference derived from historical behavior, as a decisive signal, deserves more attention for discovering desired funds.

Intuitively, the idea of injecting both conformity and risk preference is impressive, while the solution is non-trivial, facing the following challenges. (**C1**): Users' investment decisions are attributed to multiple aspects, *i.e.,* personal interest, conformity and risk preference. Therefore, it is desired to develop a multi-granularity framework for disentanglement since a unified user representation is insufficient to capture such differences. (**C2**): The interactivity

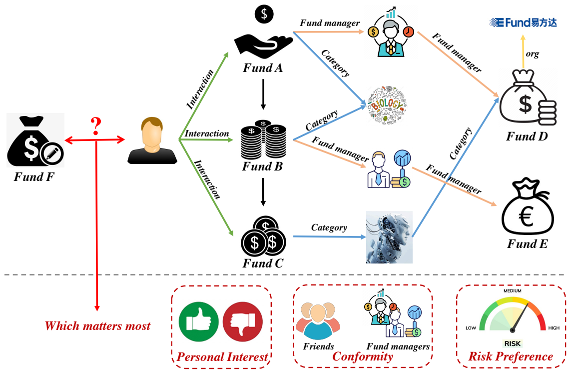


Figure 1: A toy example of graph based intelligent fund matching in practical financial platforms.

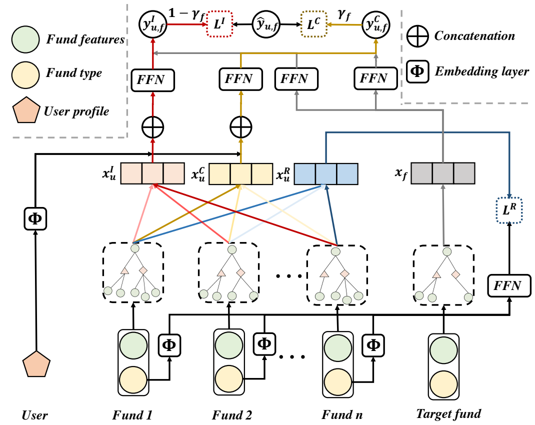


Figure 2: Overall architecture of the proposed MGDL.

between funds is powerful to capture users' disentangled representations, since fund products with similar categories or fund managers always show similar representations through interaction. Subsequently, high-order correlations between fund products are encouraged to be incorporated. (**C3**): In the practical scenarios, only implicit feedback (*e.g.,* click) could be collected for guiding the overall learning procedure (*i.e.,* personal interest). Hence, it is hard to obtain external labeled data to distinguish the remaining aspects (*i.e.,* conformity and risk preference) with explicit supervision.

To tackle these challenges, we propose **MGDL**, a Multi-granularity Graph Disentangled Learning framework to help users discover the most proper fund products. To distinguish multiple aspects of user representations, we seek to build MGDL upon recently emerging disentangled procedure with historical behaviors, where multi-granularity representation could be obtained based on the attention mechanism in a fine-grained manner (**C1**). By introducing the fund knowledge graph (Fig. 1), we inject graph learning into sequential learning based on the well-designed fund graph, whose goal is to pull similar funds closer in the disentangled process while dynamic preference could be also summarized simultaneously (**C2**). Aiming at alleviating the dependency on labeled data for learning multi-granularity user representations, we creatively explore and explicitly exploit two parts of self-supervised signals: fund type based contrasts and fund popularity. (**C3**). Multifaceted experiments show the superiority of MGDL across offline and online settings.

2 THE PROPOSED APPROACH

In this section, we present MGDL, for intelligent matching of fund investment products, as shown in Fig. 2.

Incorporating Fund Graph Learning into Disentanglement. Actually, disentangled learning has been widely applied in traditional recommendation scenarios for multi-interest extraction [1, 11, 18], which could be viewed as a soft clustering process between historical behaviors. As a promising way, the message passing procedure of GNNs could enlarge the similarities of neighbor funds in the graph [24], and thus potentially facilitating such a clustering process. On the other hand, financial products in practical platforms essentially form a graph in nature, connected via common organizations, fund managers, types and heavyweight stocks.

i) *Fund Graph Learning*. We briefly review the well-established fund graph, which potentially enhances the fund representations and the following disentangled process. We consider five relations: a) $\underline{\textit{fund} \overset{manage}{\longleftrightarrow} \textit{fund manager}}$, b) $\underline{\textit{fund} \overset{belong\ to}{\longleftrightarrow} \textit{organization}}$, c) $\underline{\textit{fund} \overset{heavyweight}{\longleftrightarrow} \textit{stock}}$, d) $\underline{\textit{fund} \overset{track}{\longleftrightarrow} \textit{stock index}}$, e) $\underline{\textit{fund} \overset{belong\ to}{\longleftrightarrow} \textit{type}}$. The fund graph serves as a bridge between non-adjacent funds in historical behaviors with external knowledge for enhancing fund representations in the following disentanglement.

Given the fund graph $\mathcal{G} = \{\mathcal{E}, \mathcal{R}\}$ with the entity set $\mathcal{E}$ and the relation set $\mathcal{R}$, following the common practice, we perform graph convolution operation $\mathrm{Conv}(\mathcal{G}; \Theta)$ to summarize the fund graph structural information. Note that the above operation could be easily implemented as an attention [19] or a SAGE [5] convolution.

ii) *Multi-granularity Representation Learning with Disentanglement.* After extracting graph enhanced fund representation $\mathbf{H}^{(L)} \in \mathbb{R}^{|\mathcal{E}| \times d}$ with $\mathrm{Conv}(\mathcal{G}; \Theta)$, given target user u's historical behaviors $S = \left\{f_1, \cdots f_{|S|}\right\}$, we retrieve corresponding fund representations to express user's behavior sequence as $\mathbf{X}_u^S \in \mathbb{R}^{|S| \times d}$. Next, we employ the self-attention mechanism to perform disentanglement with the d-dimensional vector set $\{\boldsymbol{w}^{\mathcal{I}}, \boldsymbol{w}^{\mathcal{R}}, \boldsymbol{w}^{C}\}$ that focus on different aspects (*i.e.,* personal Interest, Risk preference and Conformity).

$$
\begin{aligned}
\hat{\boldsymbol{\beta}}_u &= \sigma(\mathbf{X}_u^S \mathbf{W}^D), \\
\{\boldsymbol{\beta}_u^{\mathcal{I}}, \boldsymbol{\beta}_u^{\mathcal{R}}, \boldsymbol{\beta}_u^{C}\} &= \{\hat{\boldsymbol{\beta}}_u \boldsymbol{w}^{\mathcal{I}}, \hat{\boldsymbol{\beta}}_u \boldsymbol{w}^{\mathcal{R}}, \hat{\boldsymbol{\beta}}_u \boldsymbol{w}^{C}\}, \\
\{\mathbf{x}_u^{\mathcal{I}}, \mathbf{x}_u^{\mathcal{R}}, \mathbf{x}_u^{C}\} &= \{\mathbf{X}_u^{S\top} f(\boldsymbol{\beta}_u^{\mathcal{I}}), \mathbf{X}_u^{S\top} f(\boldsymbol{\beta}_u^{\mathcal{R}}), \mathbf{X}_u^{S\top} f(\boldsymbol{\beta}_u^{C})\}.
\end{aligned} \tag{1}
$$

Here, $\sigma(\cdot)$ is a non-linear function, $f(\cdot)$ is the softmax function and $\mathbf{W}^D \in \mathbb{R}^{d \times d}$ is the base weight matrix. Although the above self-attention model has a strong capability of separating multiple aspects of user representations, disentanglement among them is not guaranteed in such an unsupervised manner [13].

Supervising Risk Preference with Fund Type based Contrasts. In fact, the entire historical behaviors related to funds provide a holistic view of user risk preference. On the other hand, we notice that the fund type is a vital factor for characterizing the risk level of funds. In light of these observations, we can abstract useful priors for risk preference from the historical fund type sequences to supervise the representation of risk preference. Formally, we denote the historical fund type sequence of user u as $\mathcal{S}_u^{\mathcal{T}} = \{t_1, \cdots, t_{|\mathcal{S}_u^{\mathcal{T}}|}\}$, and then we calculate the unifying representation of the entire interaction history as the self-supervised signal for risk preference.

$$\mathbf{x}_u^{\mathcal{T}} = \mathrm{FFN}(g(\{\Phi(t) | t \in \mathcal{S}_u^{\mathcal{T}}\})), \tag{2}$$

where $\Phi(\cdot)$ denotes the "Embedding" operation, $g(\cdot)$ is the pooling function and FFN$(\cdot)$ represents the feed forward neural networks.

Inspired by the success of contrastive learning in various applications [9], we construct our self-supervised loss as follows,

$$\begin{aligned} \mathcal{L}^{\mathcal{R}} = &- \sum_{\mathcal{B}} \sum_{u \in \mathcal{B}} log \frac{exp(sim(\mathbf{x}_u^{\mathcal{R}}, \mathbf{x}_u^{\mathcal{T}})/\tau)}{\sum_{u' \sim P_{neg}^{\mathcal{B}}} exp(sim(\mathbf{x}_u^{\mathcal{R}}, \mathbf{x}_{u'}^{\mathcal{T}})/\tau)} \\ &- \sum_{\mathcal{B}} \sum_{u \in \mathcal{B}} log \frac{exp(\mathbf{x}_u^{\mathcal{T}}, \mathbf{x}_u^{\mathcal{R}})/\tau)}{\sum_{u' \sim P_{neg}^{\mathcal{B}}} exp(sim(\mathbf{x}_u^{\mathcal{T}}, \mathbf{x}_{u'}^{\mathcal{R}})/\tau)}, \end{aligned} \tag{3}$$

where τ is the temperature parameter, and negative samples are drawn from the uniform distribution $P_{neg}^{\mathcal{B}}$ under batch $\mathcal{B}$.

Supervising Conformity with Fund Popularity. Actually, conformity encourages users with limited financial knowledge to pick popular funds, which are always highly recommended by fund managers and even the public. Hence, it inspires that the *fund popularity* is a critical factor to capture conformity. Formally, we define the popularity of target fund f as follows,

$$\gamma_f = \frac{\log C_f - \log C_{min}}{\log C_{max} - \log C_{min}}. \tag{4}$$

Here, C_f denotes the number of user interactions *w.r.t.* fund f while $C_{max} = \max_{f \in \mathcal{F}} C_f$ and $C_{min} = \min_{f \in \mathcal{F}} C_f$ respectively represent the maximum and the minimum, where $\mathcal{F}$ is the fund set. Meanwhile, given target user u and fund f, we can obtain the conformity based score as follows,

$$y_{u,f}^{C} = \sigma(\mathrm{FFN}^{C}(\mathbf{x}_u^{\mathcal{P}} || \mathbf{x}_u^{C})^{\top} \cdot \mathrm{FFN}^{C}(\mathbf{x}_f)), \tag{5}$$

where $\mathbf{x}_u^{\mathcal{P}}$ is the feature vector of user basic profile, $\mathbf{x}_f$ is the fund representation retrieved from $\mathbf{H}^{(L)}$, "||" is the concatenation operation and $\sigma(\cdot)$ is the sigmoid function. Considering the positive correlation between conformity score and fund popularity, we formulate the conformity-side loss function in the following supervised way,

$$\mathcal{L}^{C} = \gamma_f \cdot \text{C-E}(y_{u,f}^{C}, \hat{y}_{u,f}), \tag{6}$$

where $\hat{y}_{u,f}$ is the ground truth and C-E$(\cdot)$ represents the cross entropy loss. Analogously, personal interest can be modelled in the above similar way where funds with low popularity are the core.

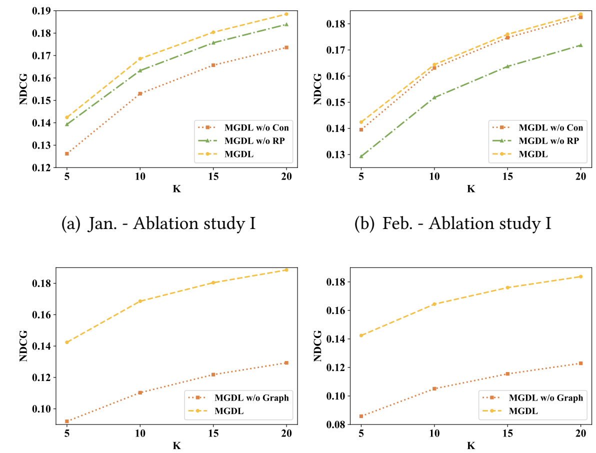
$$\begin{aligned} y_{u,f}^{\mathcal{I}} &= \sigma(\mathrm{FFN}^{\mathcal{I}}(\mathbf{x}_u^{\mathcal{P}} || \mathbf{x}_u^{\mathcal{I}})^{\top} \cdot \mathrm{FFN}^{\mathcal{I}}(\mathbf{x}_f)), \\ \mathcal{L}^{\mathcal{I}} &= (1 - \gamma_f) \cdot \text{C-E}(y_{u,f}^{\mathcal{I}}, \hat{y}_{u,f}). \end{aligned} \tag{7}$$

Putting All Together and Making Prediction. By integrating all the above loss functions, the overall objective function for the proposed MGDL is defined as follows,

$$\mathcal{L} = \mathcal{L}^{\mathcal{I}} + \mathcal{L}^{C} + \epsilon \cdot \mathcal{L}^{\mathcal{R}}, \tag{8}$$

where $\epsilon \geq 0$ controls the risk preference term $\mathcal{L}^{\mathcal{R}}$. At last, MGDL considers both conformity and interest for the final prediction,

$$y_{u,f} = \gamma_f \cdot y_{u,f}^{C} + (1 - \gamma_f) \cdot y_{u,f}^{\mathcal{I}}. \tag{9}$$



(a) Jan. - Ablation study I (b) Feb. - Ablation study I

(c) Jan. - Ablation study II (d) Feb. - Ablation study II

Figure 3: Ablation studies *w.r.t.* NDCG. Similar trends could also be observed on Mar. and Apr. datasets.

3 EXPERIMENTS

Dataset Description. We collect a real-world large-scale dataset[1] from one of the biggest financial platforms in China, and extract four sub-datasets by month for performance evaluation, namely **Jan.**, **Feb.**, **Mar.** and **Apr.**. Specifically, for each month, we leave out interactions on the last day as the test set and utilize the remaining data for training. Moreover, we hold out a part of the training data as the validation set for parameter tuning. Due to the huge volume of real-world interaction records, the daily sampling strategy is applied in each sub-dataset. Finally, each sub-dataset includes about **one million** users and about **ten thousand** funds, with about **fifty million** records for training, about **half a million** records for validation and about **eight million** records for testing. Meanwhile, we organize the fund graph with about **ten thousand** entities and about **half a million** relations.

Overall Performance. We report the overall comparison results in Table 1. Note that the fund graph is adopted in MGDL, thus we extend LightGCN and DisenGCN to adapt to the mixed graph consisting of the user-item bipartite graph and the fund graph for a fair comparison. Besides, we find NGCF [22] , KGAT [21] and DGCF [23] achieve relatively poor performance when compared to above selected baselines, and thus we omit them in our experimental results. We find that MGDL outperforms all baselines by a large margin in all cases, indicating the superiority of supplementing the fund recommendation issue with both conformity and risk preference modelling via the multi-granularity graph disentangled learning. Moreover, the performance gain of DisenGCN *w.r.t.* ComiRec reveals the usefulness of fund graph structure for pulling similar funds closer in the disentangled process, while SASRec works remarkably well among these baselines, intuitively attributed to the powerful ability of Transformer architecture.

[1]The dataset does not contain any Personalized Identifiable Information.

Datasets	Methods	Recall@5	Recall@10	Recall@15	Recall@20	NDCG@5	NDCG@10	NDCG@15	NDCG@20
Jan.	SASRec [10]	0.1805	0.2537	0.2985	0.3313	0.1192	0.1428	0.1547	0.1624
	ComiRec [1]	0.1324	0.1846	0.2185	0.2519	0.0813	0.0978	0.1068	0.1147
	LightGCN [6]	0.1148	0.1755	0.2068	0.2330	0.0729	0.0927	0.1010	0.1071
	DisenGCN [14, 27]	0.1363	0.1869	0.2240	0.2545	0.0924	0.1086	0.1184	0.1256
	MGDL	**0.2088**	**0.2892**	**0.3338**	**0.3680**	**0.1424**	**0.1686**	**0.1804**	**0.1885**
Feb.	SASRec [10]	0.1861	0.2471	0.2910	0.3251	0.1253	0.1450	0.1565	0.1646
	ComiRec [1]	0.1282	0.1830	0.2306	0.2556	0.0838	0.1014	0.1140	0.1199
	LightGCN [6]	0.1399	0.1932	0.2281	0.2566	0.0891	0.1063	0.1156	0.1223
	DisenGCN [14, 27]	0.1389	0.2017	0.2369	0.2630	0.0866	0.1070	0.1163	0.1224
	MGDL	**0.2069**	**0.2752**	**0.3188**	**0.3514**	**0.1424**	**0.1644**	**0.1760**	**0.1837**
Mar.	SASRec [10]	0.2054	0.2720	0.3138	0.3480	0.1489	0.1703	0.1814	0.1895
	ComiRec [1]	0.1231	0.1840	0.2165	0.2438	0.0802	0.0998	0.1085	0.1149
	LightGCN [6]	0.1258	0.1767	0.2173	0.2533	0.0856	0.1019	0.1126	0.1211
	DisenGCN [14, 27]	0.1441	0.2068	0.2536	0.2895	0.0934	0.1136	0.1260	0.1344
	MGDL	**0.2423**	**0.3131**	**0.3591**	**0.3935**	**0.1646**	**0.1875**	**0.1997**	**0.2078**
Apr.	SASRec [10]	0.2113	0.2734	0.3110	0.3380	0.1452	0.1653	0.1752	0.1816
	ComiRec [1]	0.1129	0.1871	0.2204	0.2434	0.0809	0.1042	0.1130	0.1184
	LightGCN [6]	0.1243	0.1782	0.2130	0.2402	0.0814	0.0989	0.1081	0.1145
	DisenGCN [14, 27]	0.1607	0.2192	0.2543	0.2836	0.1056	0.1247	0.1340	0.1409
	MGDL	**0.2295**	**0.2924**	**0.3313**	**0.3614**	**0.1636**	**0.1839**	**0.1942**	**0.2014**

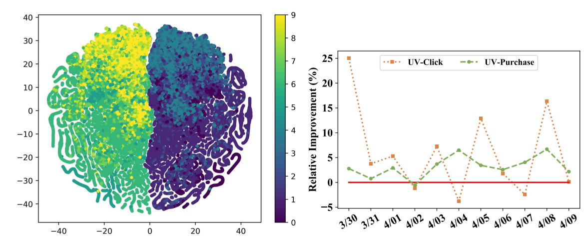
Table 1: Overall performance evaluation across four offline datasets. The best results are highlighted in boldface.

Ablation I: Impact of Multi-granularity Disentangled Learning. We prepare two variants of MGDL, namely i) **MGDL w/o Con**, which removes the conformity part and ii) **MGDL w/o RP**, which removes the risk preference modelling. From Fig. 3 (a) and (b) we observe that the complete MGDL achieves the best performance in all cases across evaluation metrics. It indicates that both conformity and risk preference are indispensable to the fund recommendation task, and the well-designed disentangled component with self-supervision endows MGDL with more meaningful representations.

Ablation II: Effectiveness Analysis of Fund Graph Learning. Next, we zoom into the effectiveness of the fund graph learning towards MGDL, and specifically denote the variant removing the fund graph learning as **MGDL w/o Graph**. Not surprisingly, we observe that the performance of MGDL drops a lot without fund graph learning in Fig. 3 (c) and (d), revealing that the fund graph structure, as a critical prior, could greatly contribute to MGDL.

Visualization Analysis. To examine the capability of MGDL intuitively, we visualize the conformity- and personal interest-side user representations (*i.e.,* $\mathbf{x}_u^C$ and $\mathbf{x}_u^I$) using *t*-SNE, since they are used for the final predictions. We label each user according to his/her fund holding level: 0∼4 for $\mathbf{x}_u^C$ and 5∼9 for $\mathbf{x}_u^I$, *e.g.,* users hold 0∼100 in our platform would be labeled as 0 for $\mathbf{x}_u^C$ and 5 for $\mathbf{x}_u^I$.

From Fig. 4 (a), we find that: i) MGDL can reasonably separate the conformity- and personal interest-side representations and learn a relatively crisp boundary. It depicts that user conformity is well distinguished by MGDL through our proposed self-supervised signal, *i.e.,* fund popularity. ii) Both of the conformity- and personal interest-side representations are well layered *w.r.t.* the user holding level, which shows that MGDL could well reflect the risk preference even though no relevant label (*i.e.,* user holding level) is available.



(a) (b)

Figure 4: (a) Visualization of predictive user embeddings learned by MGDL. (b) Online performance.

Online Performance. We deploy MGDL on our platform for A/B test against a baseline model based on FM and Transformer. We perform online evaluation from "2022/3/30" to "2022/4/09" via metrics **UV-Click** and **UV-Purchase** [2], and show the experimental results in Fig. 4 (b). Compared to the baseline (*i.e.,* the red solid line in the Fig. 4 (b)), MGDL gains the overall improvements of 3.12% and 6.92% *w.r.t.* UV-Click and UV-Purchase, which are both statistically significant with a significance level of 95%. This practice-oriented experiment further demonstrates the superiority of MGDL.

4 CONCLUSION

In this paper, we propose MGDL to perform effective intelligent matching of fund investment products, where both conformity and risk preference are emphasized in making fund investment decisions beyond personal interest. Comprehensive experiments in offline/online environments demonstrate the superiority of MGDL.

[2] UV means unique visitor

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