Social-Aware Group Display Configuration in VR Conference

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Abstract

Virtual Reality (VR) has emerged due to advancements in hardware and computer graphics. During the pandemic, conferences and exhibitions leveraging VR have gained attention. However, large-scale VR conferences, face a significant problem not yet studied in the literature – displaying too many irrelevant users on the screen which may negatively impact the user experience. To address this issue, we formulate a new research problem, Social-Aware VR Conference Group Display Configuration (SVGD). Accordingly, we design the Social Utility-Aware VR Conference Group Formation (SVC) algorithm, which is a 2-approximation algorithm to SVGD. SVC iteratively selects either the P-Configuration or S-Configuration based on their effective ratios. This ensures that in each iteration, SVC identifies and chooses the solution with the highest current effectiveness. Experiments on real metaverse datasets show that the proposed SVC outperforms 11 baselines by 75% in terms of solution quality.

Introduction

Virtual Reality (VR) has experienced a surge in adoption as industries increasingly utilize it to promote products and enhance services (Mileva 2022; Ning et al. 2021). During the COVID-19 pandemic, VR conferences and exhibitions gained popularity as in-person events are constrained by travel restrictions and social distancing policies. To support virtual gatherings, various metaverse platforms have been exploited. For instance, the ACM SIGKDD 2020 conference used *vFair's 3D platform* for a virtual conference. *Meta Horizon Workrooms* offers advanced features like persistent whiteboards and mixed-reality pass-through functions, enabling users to collaborate in a virtual space (Meta 2023). *Spatial* allows users to customize their 3D virtual space for immersive galleries or exhibitions (Spatial 2023). *Mozilla Hubs* provides spatial audio and media-sharing functions for socializing with custom avatars in a virtual space (Hubs 2023). *Engage* replicates face-to-face interactions, accommodating up to 5,000 live virtual reality users for events, training, and education (ENGAGE 2023). However, these platforms lack the support for *personalized display*, e.g., highlighting important nearby users in Head-Mounted Displays (HMDs), especially in crowded conference environments.

Current VR social apps lack personalization, which displays all users uniformly in the virtual environment and neglects the potential benefits of customization. This curbs the social interactions in VR conferences and diminishes user satisfaction due to three drawbacks. **D1) Obstructed View**. In crowded virtual spaces, users often struggle to find friends or individuals of interest because nearby strangers obstruct their views. **D2) Lack of Customization**. The presence of undesirable strangers in proximity to a target user may lead to undesirable interactions. **D3) Overload**. In large-scale VR exhibitions/conferences, individuals may become overwhelmed by the abundance of participants for interactions or, conversely, become disinterested due to the lack of social connections. These three disadvantages, in combination, lead to *VR-induced Social Isolation*, where users may struggle to connect with individuals they are interested in or socially close to, resulting in reduced interactions and satisfaction. An effective solution to this issue is *Personalized Display*, which allows users to selectively enable or disable the rendering of other users.

In VR environments, different users are not required to view the same set of individuals. Prior studies demonstrate that tailoring user displays in VR enhances social experiences (Pluto 2018). However, existing VR customization research mainly revolves around analyzing factory safety measures in computer vision and data mining, aiming to recommend items to users (Lacko 2020; Ko et al. 2020). These research overlook personalization factors among users. A personalized display enables the VR-based social metaverse with the following advantages. **A1) Social Relationships**. Enabling two users to see each other in the metaverse can enhance their satisfaction, fostering a feeling of shared presence (Bulu 2012). Thus, displaying a group of socially-close friends on an individual's VR screen could be advantageous (Pluto 2018). **A2) Personal Preferences**. Personalized displays, aligning with users' preferences, enhance satisfaction; for example, some users prefer seeing prominent scholars or conference organizers at AAAI, while others anticipate connecting with colleagues sharing their re-

User	Configuration	Ranking					k_u
Andy	Personal preferences	*Bella*	*Carl*	*Faye*	*Eddy*	*Dora*	1
	Social utilities	*Eddy*	*Faye*	*Bella*	*Dora*	*Carl*	
Bella	Personal preferences	*Faye*	*Carl*	*Andy*	*Eddy*	*Dora*	2
	Social utilities	*Eddy*	*Dora*	*Andy*	*Faye*	*Carl*	
Carl	Personal preferences	*Andy*	*Dora*	*Eddy*	*Bella*	*Faye*	1
	Social utilities	*Faye*	*Bella*	*Eddy*	*Andy*	*Dora*	
Dora	Personal preferences	*Andy*	*Eddy*	*Bella*	*Faye*	*Carl*	2
	Social utilities	*Faye*	*Bella*	*Eddy*	*Carl*	*Andy*	
Eddy	Personal preferences	*Faye*	*Carl*	*Dora*	*Bella*	*Andy*	2
	Social utilities	*Andy*	*Bella*	*Carl*	*Faye*	*Dora*	
Faye	Personal preferences	*Dora*	*Andy*	*Carl*	*Eddy*	*Bella*	2
	Social utilities	*Dora*	*Carl*	*Bella*	*Eddy*	*Andy*	

Table 1: Personal preferences ranking, social utilities ranking, and display limitation k_u for each user

search interests. **A3) Limited Display Slots**. To address issues **D2** and **D3**, a limited number of users may be selected for VR displays based on personal preferences and social relationships. Users can specify their preferred number of display slots, enabling them to see those they are interested in or have close social relationships with. Allocating restricted display slots per user efficiently resolves issue **D1** by enabling prioritization of interactions with preferred individuals, thus averting overcrowding. However, achieving a delicate balance between social connections and personal preferences while limiting the number of displayed individuals presents a challenge.

Motivated by the advantages **A1**, **A2**, and **A3**, we propose a new approach, named *Social-Aware VR Conference Group Display Configuration (SVGD)*, to address the issues **D1**, **D2**, and **D3**. Given users' social networks, personal preferences, and social utilities (the likelihood of two users having active and joyful interactions.), SVGD seeks to identify the ideal personalized display configuration for each user within confined slots, maximizing overall user satisfaction.

Example 1. (Motivating Example). Fig. 1 presents an illustrative example. Given a social network $G = (V, E)$ of six VR users, as shown in Fig. 1(a), where the hollow user images next to each user indicate the number of slots in her VR display, and a solid user image represents an occupied slot. Table **??** presents the personal preferences rankings, social utilities rankings, and display limitations of each user. The *User* column lists the users. The *Configuration* column outlines the configuration factors, and the *Ranking* column indicates the priority of other users to each individual. The k_u column denotes the number of slots available in each user's VR display. In Figs. 1(b), 1(c), and 1(d), we present three different approaches to configure each user's VR display (called *configuration* hereafter).

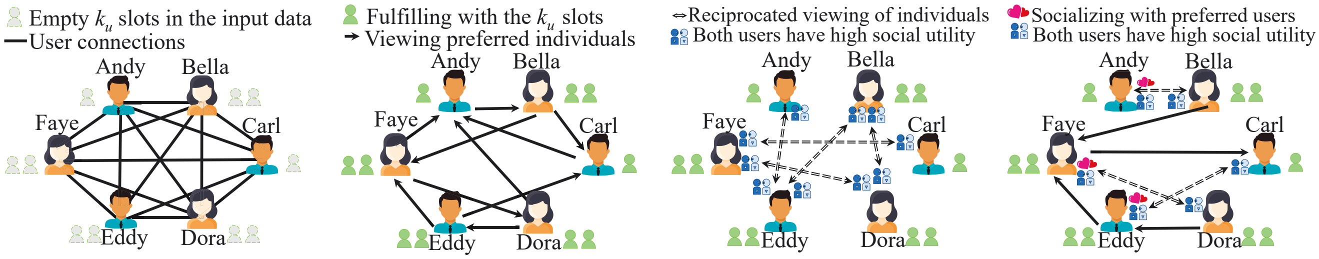
i) **Preference-based configuration (e.g., conventional friend recommendation).** The top-k_u users of interest to each user are configured based on personal preferences. Fig. 1(b) represents the "sees-in-VR" graph of this preference-based configuration, where an arrow from user x to user y indicates that x sees y in her VR display. In an example, Andy has a display slot number k_u of 1. Despite having a high social utility with Eddy, in the preference-based configuration, Andy sees Bella, who is ranked the highest by Andy's personal preferences. Similarly, Bella has a k_u of 2 and sees Faye and Carl, the top-ranked individuals according to her personal preferences. In this configuration, each user sees k_u users during the VR conference, but they do not see each other. This configuration only considers **A2** (personal preferences) and neglects **A1** (social relationships), leading to limited interaction among users during the VR conference and worsening the issue of VR-induced Social Isolation.

ii) **Social-based configuration (e.g., conventional cohesive group extraction).** Fig. 1(c) represents the "sees-in-VR" graph of this social-based configuration. A two-way arrow between two users indicates that they can see each other in the VR display, while a blue user picture indicates that both users have high social utilities. While this configuration promotes social interactions during the VR conference, it comes at the cost of individual preferences. For instance, Andy may desire to see Bella, but due to their significant social distance, Bella is not displayed, despite Andy's interest. Conversely, Bella, with a display slot count of 2 (k_u), can see Dora and Eddy, who are ranked higher according to her social utilities. This social-based configuration primarily considers aspect **A1** (social relationships) but overlooks aspect **A2** (personal preferences), potentially leading to decreased user satisfaction. This reduces users' satisfaction and neglects the crucial purpose of VR conferences: to meet and get acquainted themselves with new people.

iii) **Preferences and socially balanced configuration.** This configuration's "sees-in-VR" graph is presented in Fig. 1(d). For instance, Dora sees Eddy due to her high personal preferences for Eddy, and she also sees Faye since they have a high social utility ranking between them. Likewise, Bella sees Faye as she has a strong personal preference for her, while Bella and Andy see each other due to their relatively high social utility and personal preferences rankings. This configuration, which takes into account **A1**, **A2**, and **A3** (limited display slots), enhances user satisfaction and mitigates VR-induced Social Isolation.

The SVGD problem is distinct from conventional friend recommendation and personalized recommendation approaches (Cheng et al. 2019; Chen et al. 2017; Zhao et al. 2016; Bagci and Karagoz 2016; Lin et al. 2017), as well as cohesive group extraction in social networks (Lu et al. 2022; Al-Baghdadi and Lian 2020; Ma et al. 2022; Sanei-Mehri et al. 2021; Dong et al. 2021; Yang et al. 2021, 2012a). Conventional friend recommendation focuses on suggesting potential friends based on preferences, without considering the impact of other users' configurations in a VR setting. Cohesive group extraction in social networks aims to identify socially-close friends but does not incorporate the inclusion of strangers based on user preferences or interests, which could hinder the formation of new friendships. More importantly, the SVGD problem allows the rendering of different users on individual VR displays, setting it apart from social/preferences group queries and group recommendations.

In summary, conventional research does not consider sev-



(a) Input social network (b) Personal preferences-only (c) Social relationships-only (d) Our idea

Figure 1: An illustrative example of preference-based, social-based, and balanced configuration

eral factors particularly important in VR conferences, including i) personal preferences, ii) the impact of other users' configurations on user satisfaction in VR, iii) co-display among users (two users appear in each other's VR displays), iv) handling over-crowding in VR events, and v) different users to be rendered on different users' VR displays. For instance, the user recommendation approaches maximize individual users' personal preferences and satisfaction, but it neglects ii), iii), iv) . Similarly, group formation and recommendation tend to find socially-close friends, but they do not consider the inclusion of strangers and overlook i), ii), iv), and v). Therefore, previous approaches cannot be applied directly to the SVGD problem studied in this paper.

In this paper, we prove the NP-hardness of the SVGD problem and propose a 2-approximation algorithm, named *Social Utility-Aware VR Conference Group Formation (SVC)*. This algorithm addresses the challenges posed by personal preferences and social relationships within limited VR display slots. We introduce the concept of *SVD utility* to quantify user satisfaction and propose the *SVD k_u-configuration*, where k_u represents the maximum number of users displayable in a user's VR setup. We evaluate the SVC algorithm on real datasets. The results demonstrate the effectiveness of our approach.

The paper's contributions are summarized as follows.

- We present the new notion of *SVD k_u-configuration* under the context of VR conferences and formulate a new research problem, *Social-Aware VR Conference Group Display Configuration (SVGD)*. SVGD aims to identify an SVD k_u-configuration that facilitates social interactions without sacrificing users' individual preferences.
- We analyze the NP-hardness of SVGD and propose a 2-approximation algorithm, named *Social Utility-Aware VR Conference Group Formation (SVC)*.
- We conducted extensive experiments on 5 real datasets. The results indicate that SVC significantly outperforms other baselines in terms of solution quality and efficiency.

Related Works

VR applications. A wide spectrum of VR applications have emerged recently, such as online VR shopping (Ko et al. 2020), friend-making (Raber, Schommer, and Krüger 2019), social interactions in VR (McVeigh-Schultz, Kolesnichenko, and Isbister 2019), and social VR in edge computing (Wang et al. 2018a). We envisage that the proposed SVGD problem helps users obtain a better VR group conference experience by selecting a suitable set of users for their VR display with the maximum personal preferences and social utilities. To the best of our knowledge, similar functions are not currently available in VR conference products on the market (Meta 2023; Spatial 2023).

Dense subgraph extraction. Extracting dense subgraphs in social networks has been actively studied for decades, e.g., (Shen et al. 2015; Lu et al. 2022; Al-Baghdadi and Lian 2020; Ma et al. 2022; Chen et al. 2018a; Shen et al. 2017; Hsu, Shen, and Yan 2019). However, they cannot be applied directly to our VR conference scenario due to the following reasons. i) The limited number of slots in the VR display (allowed to vary for each user) is not considered, and different users can be rendered on different users' VR displays. ii) The important notion of *co-display* is not incorporated, and many users might suffer from VR-induced Social Isolation. iii) The users' personal preferences and social utilities are not jointly examined, causing poor interactions between the users in the VR conference.

Personalized recommendation. Personalized recommendations are widely used in E-commerce, suggesting products based on user preferences and browsing history (Chen et al. 2017; Liao et al. 2018; Zhao et al. 2022). However, these approaches fail to jointly consider the personal preferences and social interactions. In SVGD, both personal preferences and social interactions are crucially considered, accounting for diverse users displayed on different VR screens. This distinction sets the problem apart from social/preferences group queries (which identify identical users for the entire group)(Yang et al. 2012a) and group recommendations (which suggest the same items for all users).

Problem Formulation and Hardness Result

Given a directed social network $G = (V, E)$, where V represents the set of users and edge set E specifies their social relationships, we first introduce *Social-Aware VR Conference Display with k_u-configuration (SVD k_u-configuration)*, which configures the limited display slots of users in a large-scale VR conference event.

Definition 1. Social-Aware VR Conference Display with k_u-configuration (SVD k_u-configuration). Given k_u display slots specified for user u to display other users in a VR conference, an SVD k_u-configuration is a collection of sets $\mathbb{A} = \{A_u | \forall u \in V\}$, where a set A_u, corresponding to user u, contains at most k_u other users that appear in user u's VR display.

For a large-scale VR conference, each user u sees at most k_u other users to avoid the overcrowded view. As a consequence, some users may not be rendered in a specific user's VR display due to the limited display slots. With the definition of SVD k_u-configuration in hand, we now introduce *co-display* as follows.

Definition 2. Co-display $(u \leftrightarrow v)$ **and** $I(u, v)$**.** Let $u \leftrightarrow v$ denote that users u and v appear in each other's VR display, i.e., $v \in A_u$ and $u \in A_v$. In this case, $u \leftrightarrow v$ is referred to as a *co-display*. We employ a binary indicator function $I(u, v) = 1$ to indicate this co-display relationship, i.e., $I(u, v) = 1$ if $u \leftrightarrow v$, and $I(u, v) = 0$, otherwise.

Since the VR display slot is limited for each user, users u and v might not see each other, i.e., $I(u, v) = 0$, and they cannot have social interactions. Previous studies (Wang et al. 2018b; Gao et al. 2018) indicate that a user's satisfaction in a group activity is affected by two important factors: *personal preferences* and *social utilities*. Therefore, to address the above issue and enhance social interactions, it is important to consider personal preferences and social utilities jointly in our problem formulation.

Specifically, given a pair of users u and v in a social network $G = (V, E)$ with $(u, v) \in E$, let $p(u, v) \geq 0$ denote the personal preference of u on v when v is rendered in u's VR display, and let $\tau(u, v) \geq 0$ denote the social utility for u against v, i.e., how likely u believes that u and v would have active and joyful interactions (Lai et al. 2019; Shuai et al. 2013). Please note that $p(u, v)$ ($\tau(u, v)$) and $p(v, u)$ ($\tau(v, u)$) may be different. The assignment of personal preferences and social utilities can be done either by the user themselves, obtained through the use of social-aware recommendation models (Sankar et al. 2021; Fan et al. 2019), or inferred by event recommendation models (Liao et al. 2018; Yang et al. 2023).

Given the above definitions and following (Ko et al. 2020; Wang et al. 2018b; Chen and Yang 2022; Tong, Meng, and She 2015), we define the *SVD utility*, which integrates personal preferences and social utilities and acts as a metric for a proper configuration of other users appearing on each user's VR display.

Definition 3. SVD utility ($w_{A_u}(u, v)$). Given an SVD k_u-configuration $\mathbb{A} = \{A_1, A_2, ..., A_{|V|}\}$, the SVD utility of user u on user $v \in A_u$ combines personal preference and social utility,

$$w_{A_u}(u, v) = (1 - \lambda) \cdot p(u, v) + \lambda \cdot \tau(u, v) \cdot I(u, v), \quad (1)$$

where $\lambda \in [0, 1]$ is a weighting factor, which can be directly set by a user or implicitly learned from existing models (Zhao, McAuley, and King 2014; Liao et al. 2018).

An alternative approach for incorporating preferential and social factors is to employ an end-to-end machine learning approach, generating user and item representations and using a neural network aggregator to compute overall user satisfaction (Cao et al. 2018). However, this approach demands an algorithm to generate potential configurations for ranking and relies heavily on substantial training data to fine-tune the aggregator's parameters. In contrast, prior research (Wang et al. 2018b; Liao et al. 2018; Zhao, McAuley, and King 2014) has shown that a blend of preferential and social factors, combined with assigned or learned weights, can effectively evaluate user satisfaction. Various objective functions, such as $w_{A_u}(u, v) = min(p(u, v), \tau(u, v))$, $w_{A_u}(u, v) = max(p(u, v), \tau(u, v))$, and $w_{A_u}(u, v) = p(u, v) \cdot \tau(u, v)$, yield subpar solutions and user satisfaction. In specific contexts, min and max solely consider personal or social factors. Moreover, when either min or product is exceedingly low for either p or τ, the outcomes might not favor a particular individual despite deserving consideration in real scenarios. Hence, akin to (Wang et al. 2018b; Ko et al. 2020), we frame the SVD utility as a weighted fusion of aggregated personal preferences and social utilities, governed by the parameter λ.

Here, $w_{A_u}(u, v)$ is a directional utility from user u to a user v in her configuration, $\forall u \in V$. The users selected in user u's configuration appear in user u's VR display, but user u may not be in their configurations. Hence, SVD utility $w_{A_u}(u, v)$ is a directional utility. The SVD utility $w_{A_u}(u, v)$ incorporates both the personal preference $p(u, v)$ and social utility $\tau(u, v)$. The social utility $\tau(u, v)$ takes effect only when the co-display condition holds, i.e., $u \leftrightarrow v$ holds ($I(u, v) = 1$). This is because users u and v can interact only when they see each other in their own VR displays.

In this paper, we formulate the *S̲ocial-Aware V̲R Conference G̲roup D̲isplay Configuration (SVGD) problem* to configure suitable users in every user's VR display by identifying the best SVD k_u-configuration. Here, SVGD includes two additional constraints: i) *Personal preference constraint* θ, which requires that for a user u, any user v rendered in u's VR display must have a personal preference at least θ, i.e., $p(u, v) \geq \theta, \forall u \in V, v \in A_u$. Following (Hsu, Shen, and Chang 2020; Hsu, Lan, and Shen 2018), the above constraint aims to meet the minimum required personal preferences to prevent users from becoming extremely dissatisfied. In SVGD, this personal preference constraint (referred to as *preference constraint* hereafter) avoids rendering users that receive a low personal preference; ii) Display slot k_u for all $u \in V$, which specifies the maximum number of other users that can be rendered on user u's VR display, to prevent too many people being rendered on users' VR displays, making the displays too crowded[1]. Here, even if two users' social utilities are low, e.g., previously unknown to each other, they may still want to see each other on their VR displays if they have a high preference. Therefore, we do not set the social utility constraint in our problem. Please note that SVGD allows each user to see different surrounding

[1]The constraint k_u can be modified to a weighted constraint to account for users' varying weights based on their proximity to each other such that the sum of the weights of all the users in a given user's configuration does not exceed k_u.

users, which makes the problem different from traditional group query and group recommendation problems. As mentioned in Section , there are three disadvantages, **D1**, **D2**, and **D3** in current VR, and it is not feasible to let everyone see each other. Therefore, we employ **A1** and **A2** to customize the display for each user (addressing **D2** and **D3**), and use **A3** to avoid the user's display being overcrowded (addressing **D1**). Moreover, we define the *total SVD utility of* $\mathbb{A}$ as $\sum_{u \in V} \sum_{v \in A_u} w_{A_u}(u, v)$, which is the summation of the utility values of each user u and the other users in u's VR display, i.e., A_u. Here, $w_{A_u}(u, v)$ is the SVD utility defined in Definition 3.

Specifically, the SVGD problem is formulated as follows.

Problem.: *Social-Aware VR Conference Group Display Configuration (SVGD).*
Given: A social network $G = (V, E)$, personal preference $p(u, v)$ for all $u, v \in V$, social utility $\tau(u, v)$ for each directed edge $(u, v) \in E$, weighting parameter λ, personal preference constraint θ, and display slot $k_u, \forall u \in V$.
Objective: To find an SVD k_u-configuration $\mathbb{A}^*$ that maximizes the total SVD utility: $\sum_{u \in V} \sum_{v \in A_u} w_{A_u}(u, v)$, where each set $A_u \in \mathbb{A}^*$ contains at most k_u other users (k_u can vary for each individual), and for each v in A_u, its personal preference for u is at least θ.

An alternative objective is to maximize users' *exposure*, aiming for each user to appear in the displays of the largest possible number of other users on average. However, this objective does not consider the preferences factor, leading to poor potential interactions. Another potential problem formulation is to maximize the social utilities while requiring the personal preferences to be at least θ (the personal preference constraint). However, this formulation lacks the flexibility to cover various VR conference scenarios and cater to varying user intentions. Our problem formulation permits adjusting these two trade-off parameters to fit different scenarios.

Theorem 1. SVGD is NP-hard.

Proof. We prove this theorem by reducing it from the *Exact Cover by Three Sets problem* (Cormen et al. 2022). The complete proof is shown in Appendix A. □

Approximation Algorithm For SVGD

In this section, we present the *Social Utility-Aware VR Conference Group Formation (SVC)* algorithm, a 2-approximation algorithm for SVGD. A simple greedy approach falls short of achieving a guaranteed performance bound. For instance, the preference-based configuration (illustrated in Fig. 1) solely accounts for **A2** (personal preferences), while the social-based setup only considers **A1** (social relationships), leading to compromised user satisfaction.

The SVC algorithm efficiently tackles the SVGD problem by assigning near-optimal configurations to users to maximize SVD utility. It employs a *Quantified Social Benefit Network* (QSB network) to accommodate two selection strategies: *Personal Preference Attention Configuration* (P-Configuration) and *Social utilities Aware Configuration* (S-Configuration). During the configuration, the QSB network integrates social utilities and personal preferences into the original graph, using directed edges for P-Configurations and undirected edges for S-Configurations.

Next, in the *Configuration Comparison* stage, the effective SVD utility ratio between the two configurations is compared in order to determine the sequence of users to be included in the configuration. A superlative sequence is created for each user's configuration, ensuring that the utility obtained by each user's choice of the configuration decreases iteratively. This ensures a better utility to be extracted earlier.

Detailed Algorithm Design

Effective SVD utility with P/S-Configuration. To facilitate the effective design of P-Configuration and S-Configuration, we first extend the SVD utility defined in Equation (1), and propose the concept of *effective SVD utility* to capture the increment of SVD utility when executing P-Configuration or S-Configuration. For a user u in a P-Configuration, when user v is added to A_u, the *effective SVD utility with P-Configuration* of user u is denoted as $\Delta(u \to v)$. Similarly, the concept of *effective SVD utility with S-Configuration* of users u and v is denoted as $\Delta(u \leftrightarrow v)$. The S-Configuration involves two users u and v, i.e., SVC selects user u into A_v and selects user v into A_u simultaneously.

Effective SVD utility ratio with P/S-Configuration (Effective P/S ratio). To enable SVC to identify appropriate users to include in a user u's VR display set A_u, we first present the *effective SVD utility* mentioned above. We define the *effective SVD utility ratio with P/S-Configuration*, the *effective SVD utility* normalized by the number of selected users whose k_u are not full, in order to find the *effective SVD utility* increment when adding a user to another user's display slots under both configurations. The *effective SVD utility ratio with P-Configuration* (referred to as *effective P-Configuration ratio* for short) of users u on v is denoted as $\rho(u \to v)$. The *effective SVD utility ratio with S-Configuration* (referred to as *effective S-Configuration ratio* for short) of users u and v is denoted as $\rho(u \leftrightarrow v)$. The two effective ratios are critical because the display slots are limited. By measuring the normalized increment of SVD utility in user selections, SVC effectively identifies the candidates that result in better solutions with limited display slots.

Construction of Quantified Social Benefit Network. Given the input social network $G = (V, E)$, with i) personal preference constraint θ, ii) display slot $k_u, \forall u \in V$, SVC embeds the social utilities and personal preferences into the original graph and constructs the QSB network. The SVD utility containing only personal preferences is embedded in the two weighted directed edges between each pair of users, and the sum of SVD utilities between two users with personal preferences and social utilities is embedded as a weighted undirected edge between users. We present an example in Appendix C. Upon performing the configuration, the edge weights between the selected users are updated to preserve the approximation ratio.

SVC maintains a collection $\mathbb{S} = \{S_u \mid u \in V\}$ of user sets. Each set $S_u \in \mathbb{S}$ represents the users selected by SVC to appear in the VR display of user u. Initially, SVC generates a collection $A^\theta = \{A^\theta_u \mid u \in V\}$ of potential sets. Each set $A^\theta_u \in A^\theta$ contains only the users who satisfy the preference constraint, i.e., $A^\theta_u = \{v \mid p(u,v) \geq \theta, \forall v \in V\}$, to filter out impossible user selections. Subsequently, SVC iteratively selects the P-Configuration or S-Configuration with the greater effective ratio. This approach ensures that the user selected in each iteration represents the current best solution. After each selection, SVC updates the corresponding $\rho(\cdot)$ accordingly.

Specifically, if $\rho(x \leftrightarrow y) < \rho(u \to v)$, SVC performs a P-Configuration and identifies the user $v \in A^\theta_u$ and the corresponding S_u that maximizes the *effective P-Configuration ratio* $\rho(u \to v)$. SVC then adds user v to S_u. To find $\rho(u \to v)$, i) if user u is not in A_v, then $\Delta(u \to v) = (1 - \lambda) \cdot p(u,v)$, because in this case $I(u,v) = 0$, indicating that user u does not appear in user v's VR display. ii) Otherwise, if user u is already in A_v, then $\Delta(u \to v) = (1-\lambda) \cdot p(u,v) + \lambda \cdot (\tau(u,v) + \tau(v,u))$, because users u and v establish the co-display relationship and $I(u,v) = 1$, and thus $\lambda \cdot (\tau(u,v) + \tau(v,u))$ is included in $\Delta(u \to v)$. Please note that $p(v,u)$ is excluded here as it has previously been introduced in a P-Configuration $\Delta(v \to u)$. Then, the *effective P-Configuration ratio* $\rho(u \to v)$, which is $\frac{\Delta(u \to v)}{1}$, where the 1 in the denominator indicates that only 1 user, i.e., user v, is selected at this iteration. Next, after a P-Configuration that adds v to S_u, SVC updates $\rho(v \to u)$ to $(1-\lambda) \cdot p(v,u) + \lambda \cdot (\tau(u,v) + \tau(v,u))$ and sets $\rho(u \leftrightarrow v)$ to 0, because the SVD utility of v on u increases and v can no longer be selected for u by an S-Configuration.

In previous iterations, a user may have chosen another user based on a high *effective P-Configuration ratio*. However, it is possible that the social utilities between these two users are greater than other users' P-Configuration. Therefore, the social utilities between the users who have previously made a P-Configuration needs to be examined to ensure that the current selection is still the best option, i.e., the largest ratio. In addition, the process of edge update is also important, since it involves one-way and opposite selections to partition the globally optimal solution. One-way selection refers to the situation whether a user u chooses another user v, whereas the opposite selection refers to user v selecting user u. With one-way selection, we partition the global optimal solution into two segments, with one segment chosen by SVC, while the other is not.

Similarly, to carry out an S-Configuration, SVC identifies two users x and y that maximize the *effective S-Configuration ratio* $\rho(x \leftrightarrow y)$ so as to add users x and y to S_y and S_x, respectively. The calculation of $\rho(x \leftrightarrow y)$ is based on the *effective SVD utility with S-Configuration* $\Delta(u \leftrightarrow v)$, which is the SVD utility increment when user u is selected into A_v and user v is selected into A_u simultaneously. Therefore, $\Delta(u \leftrightarrow v) = (1-\lambda) \cdot (p(u,v) + p(v,u)) + \lambda \cdot ((\tau(u,v) + \tau(v,u)))$. In this case, $I(u,v) = 1$, and the co-display relationship between users u and v thereby holds. Then, $\rho(u \leftrightarrow v) = \frac{\Delta(u \leftrightarrow v)}{2}$ because 2 users (i.e., users u and v) are chosen for A_v and A_u, respectively. After performing an S-Configuration of x and y, SVC also needs to update the effective SVD utility. In this case, SVC sets $\rho(x \to y)$ and $\rho(y \to x)$ to 0, as x and y can no longer be selected for each other. The updating of edge weights in the S-Configuration is used to prevent redundant selection. Since x and y are already in the configuration of each other, if the weights are not updated in time, redundant P-Configurations may be executed in the future, which impacts the efficiency.

Next, in each iteration, SVC adds new users to the collection $\mathbb{S}$ by performing either a P-Configuration or S-Configuration with the greater effective ratio. If the number of users in a set S_u for a user u reaches the limit of k_u display slots, SVC stops adding users to that set. If all the sets in $\mathbb{S}$ are full or no more users can be selected, SVC stops and returns $\mathbb{S}$ as the final solution $\mathbb{A}^*$. We present a running example and the pseudocode in Appendix D.

Analysis of Approximation Ratio of SVC

In this section, we prove that SVC is a 2-approximation algorithm. The core idea is that, given any optimal solution $\mathbb{O}$, the selected users can be viewed as a sequence of single-user selections with a descending order based on the effective SVD utility, i.e., $\{u^{\mathbb{O}}_1, u^{\mathbb{O}}_2, ...\}$. This is because the optimal solution is the result with the highest total SVD utility, the configuration with a high SVD utility must be selected firstly. For the proposed SVC, it also selects a sequence of users $\{u_1, u_2, ...\}$ with P/S-Configurations. We prove that the effective SVD utility of $u^{\mathbb{O}}_i$ being less or equal to two times the effective SVD utility for each user u_i must hold. In other words, the effective SVD utility ratio with P/S-Configuration is bounded by two on the selected users of SVC. The time complexity of SVC is $O(max_{\forall u}(k_u) \cdot |V| \cdot log(|E|))$.

Theorem 2. SVC is a 2-approximation algorithm to SVGD with a time complexity $O(max_{\forall u}(k_u)|V| \cdot log(|E|))$.

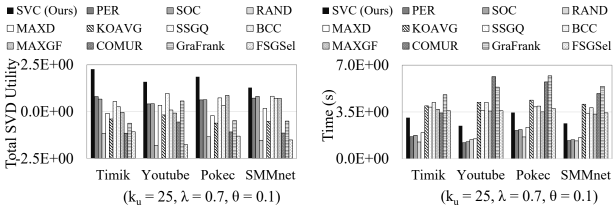
Proof. The detailed proof is presented in Appendix E. □

In real applications, k_u is usually small, e.g., $k_u < 100$, enabling SVC to find the solution efficiently. Moreover, the size of users V in the VR scenarios is much smaller than the number of users V in each dataset in Section , because it only encompasses the individuals participating in the VR event. Therefore, SVC is very efficient in practical scenarios.

Experimental Results

Performance Evaluation

The detailed experiment setup is presented in Appendix I. To evaluate the effectiveness and the efficiency of the proposed SVC, we compare SVC with 12 various baselines on 5 real datasets. i) *Timik* (Jankowski, Michalski, and Bródka 2017), ii) *Pokec* (Takac and Zabovsky 2012), iii) *Youtube* (Yang and Leskovec 2012), iv) *SMMnet* (Moraes and Cordeiro 2019), and v) *Facebook* (McAuley and Leskovec 2012). The specifics of these datasets are described in Appendix I. While there is no existing algorithm for the SVGD problem, we implement 12 baseline approaches. i) PER (Yang



(a) Total SVD utility on diff. datasets (b) Time on diff. datasets

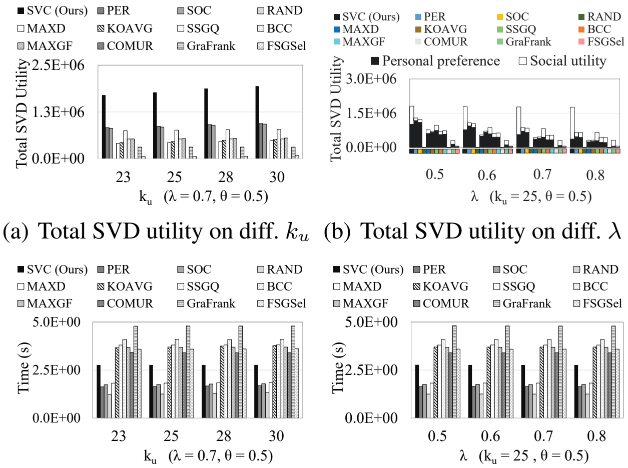
Figure 2: Results on four large-scale datasets

et al. 2012b), ii) SOC (Yang et al. 2012b), iii) RAND, iv) MAXD (Behnezhad and Derakhshan 2020), v) KOAVG (Ko et al. 2020), vi) SSGQ (Chen et al. 2018b), vii) BCC (Dong et al. 2021), viii) COMUR (Chen and Yang 2022), ix) GraFrank (Sankar et al. 2021), x) FSGSel (Shen et al. 2022), xi) MAXGF (Shen et al. 2020), and xii) BF, which enumerates all combinations to find the optimal solution. The baselines are introduced in Appendix H. We evaluate them by the following metrics: i) total SVD utility, and ii) total execution time. All algorithms are implemented in a server with an Intel Xeon W-2245 CPU with 128 GB RAM. Personal preferences and social utilities are assigned according to (Ko et al. 2020; Chen and Yang 2022).

Sensitivity tests and comparisons with optimal solutions on the small dataset. To understand the performance gap between the proposed approach and the optimal solution, we first compare the results on the small dataset, *Facebook*. The results demonstrate that our algorithm outperforms other baselines. Moreover, we conduct additional sensitivity tests on dataset *Facebook* with different λ, θ, k_u, and different inputs generated by Random, RevGNN (Li et al. 2021), GraphRec (Fan et al. 2019), and DGRec (Yang et al. 2023). Details of the experiments are shown in Appendix J.

Scalability and sensitivity tests on large networks. Fig. 2 compares the total SVD utility on the four large social networks, *Timik*, *Youtube*, *Pokec*, and *SMMnet*. We set $\lambda = 0.7$, $\theta = 0.1$, and all users' display slots $k_u = 25$ by default. Figs. 2(a) and 2(b) present the objective values and execution time of the proposed SVC and other baselines. Because the numbers of users in these datasets are different, we performed Z-Score Normalization (Patro and Sahu 2015) on the results. The results illustrate that the proposed SVC outperforms the other baselines in terms of solution quality and efficiency.

Fig. 3 presents the sensitivity tests on the 3D VR metaverse social network dataset, *Timik*. In Figs. 3(a) and 3(b), we compare the results with different values of $k_u = \{23, 25, 28, 30\}$ and values of $\lambda = \{0.5, 0.6, 0.7, 0.8\}$. SVC achieves the best performance over all the baselines. PER and SOC do not perform well because they consider either personal or social aspect only. MAXD employs the degree of edges to create the configuration and thereby is difficult to ensure that the chosen edges have a higher personal preference or social utility. KOAVG is designed to recommend items to a group of users, and thereby ignoring users' personal preferences. BCC and SSGQ do not pay special attention to personal preferences and do not guarantee that users can see each other, leading to high social utility limitations. GraFrank, COMUR, FSGSel, and MAXGF establish configurations based on different factors, which might disregard the important personal preferences and social utilities in the process. Moreover, SVC outperforms other baselines by 75% on average, while the p-values of SVC to the baselines are all less than 0.05, indicating that the SVD utility of SVC is statistically greater than other baselines. Figs. 3(c) and 3(d) present the execution time of the sensitivity test. The value of λ only influences the calculation of the total SVD utility, does not affect the execution time.



(a) Total SVD utility on diff. k_u (b) Total SVD utility on diff. λ

(c) Time on diff. k_u (d) Time on diff. λ

Figure 3: Sensitivity tests on the large-scale *Timik* dataset

Conclusion

This paper explores the new research problem, SVGD, to configure display slots for users in VR conferences by jointly considering three important factors. We analyze the hardness of SVGD and propose a 2-approximation algorithm, named SVC, to tackle SVGD. In our experiments with 5 real datasets manifest that SVC surpasses other baseline methods in both solution quality and efficiency. In our future research, we plan to extend SVC for more generalized scenarios, such as the user's view being obstructed.

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References

Al-Baghdadi, A.; and Lian, X. 2020. Topic-based community search over spatial-social networks. *VLDB*.

Bagci, H.; and Karagoz, P. 2016. Context-Aware Friend Recommendation for Location Based Social Networks Using Random Walk. In *WWW*.

Behnezhad, S.; and Derakhshan, M. 2020. Stochastic Weighted Matching:(1-ϵ) Approximation. In *FOCS*.

Bulu, S. T. 2012. Place presence, social presence, co-presence, and satisfaction in virtual worlds. *Computers & Education*.

Cao, D.; et al. 2018. Attentive Group Recommendation. In *SIGIR*.

Chen, B.-J.; and Yang, D.-N. 2022. User Recommendation in Social Metaverse with VR. In *CIKM*.

Chen, J.; et al. 2017. Attentive Collaborative Filtering: Multimedia Recommendation with Item- and Component-Level Attention. In *SIGIR*.

Chen, L.; et al. 2018a. Maximum Co-Located Community Search in Large Scale Social Networks. *VLDB*.

Chen, Y.-L.; et al. 2018b. On efficient processing of group and subsequent queries for social activity planning. *TKDE*.

Cheng, S.; et al. 2019. Friend recommendation in social networks based on multi-source information fusion. *IJMLC*.

Cormen, T. H.; et al. 2022. *Introduction to algorithms*. MIT press.

Dong, Z.; et al. 2021. Butterfly-Core Community Search over Labeled Graphs. *VLDB*.

ENGAGE. 2023. ENGAGE. https://engagevr.io/. Accessed:2023-1-15.

Fan, W.; et al. 2019. Graph Neural Networks for Social Recommendation. In *WWW*.

Gao, S.; et al. 2018. Multi-role event organization in social networks. *Information Sciences*.

Hsu, B.-Y.; Lan, Y.-F.; and Shen, C.-Y. 2018. On automatic formation of effective therapy groups in social networks. *TCSS*.

Hsu, B.-Y.; Shen, C.-Y.; and Chang, M.-Y. 2020. WMEgo: Willingness Maximization for Ego Network Data Extraction in Online Social Networks. In *CIKM*.

Hsu, B.-Y.; Shen, C.-Y.; and Yan, X. 2019. Network intervention for mental disorders with minimum small dense subgroups. *IEEE Transactions on Knowledge and Data Engineering*, 33(5): 2121–2136.

Hubs. 2023. Hubs Mozilla. https://hubs.mozilla.com/?utm_medium=referral&utm_source=xr4work.com. Accessed:2021-11-3.

Jankowski, J.; Michalski, R.; and Bródka, P. 2017. A multi-layer network dataset of interaction and influence spreading in a virtual world. *Scientific data*.

Ko, S.-H.; et al. 2020. Optimizing Item and Subgroup Configurations for Social-Aware VR Shopping. *VLDB*.

Lacko, J. 2020. Health Safety Training for Industry in Virtual Reality. In *Cybernetics & Informatics (K&I)*.

Lai, H.-C.; et al. 2019. Social-Aware VR Configuration Recommendation via Multi-Feedback Coupled Tensor Factorization. In *CIKM*.

Li, G.; et al. 2021. Training Graph Neural Networks with 1000 Layers. In *ICML*.

Liao, Y.; et al. 2018. Joint Modeling of Participant Influence and Latent Topics for Recommendation in Event-Based Social Networks. *ACM Trans. Inf. Syst.*

Lin, K.-P.; Shen, C.-Y.; Chang, T.-L.; and Chang, T.-M. 2017. A consumer review-driven recommender service for web e-commerce. In *2017 IEEE 10th Conference on Service-Oriented Computing and Applications (SOCA)*, 206–210. IEEE.

Lu, Z.; et al. 2022. On Time-optimal (k, p)-core Community Search in Dynamic Graphs. In *ICDE*.

Ma, C.; et al. 2022. Finding Locally Densest Subgraphs: A Convex Programming Approach. *VLDB*.

McAuley, J.; and Leskovec, J. 2012. Learning to Discover Social Circles in Ego Networks. In *NIPS*.

McVeigh-Schultz, J.; Kolesnichenko, A.; and Isbister, K. 2019. Shaping Pro-Social Interaction in VR: An Emerging Design Framework. In *CHI*.

Meta. 2023. Workrooms. https://www.oculus.com/workrooms/?utm_medium=referral&utm_source=xr4work.com. Accessed:2021-11-3.

Mileva, G. 2022. 50+ metaverse statistics. https://influencermarketinghub.com/metaverse-stats/.

Moraes, L. M. P.; and Cordeiro, R. L. F. 2019. SMMnet: A Social Network of Games Dataset. In *SBBD*.

Ning, H.; et al. 2021. A Survey on Metaverse: the State-of-the-art, Technologies, Applications, and Challenges.

Patro, S.; and Sahu, K. K. 2015. Normalization: A preprocessing stage. *arXiv preprint arXiv:1503.06462*.

Pluto. 2018. A 2018 survey by Pluto VR and The Extended Mind. https://www.extendedmind.io/2018-survey-of-social-vr-users. Accessed: 2022-9-25.

Raber, F.; Schommer, C.; and Krüger, A. 2019. Friend-GroupVR: Design Concepts Using Virtual Reality to Organize Social Network Friends. In *INTERACT*.

Sanei-Mehri, S.-V.; et al. 2021. Mining largest maximal quasi-cliques. *TKDD*.

Sankar, A.; et al. 2021. Graph Neural Networks for Friend Ranking in Large-Scale Social Platforms. In *WWW*.

Shen, C.-Y.; Shuai, H.-H.; Hsu, K.-F.; and Chen, M.-S. 2017. Task-Optimized Group Search for Social Internet of Things. In *EDBT*, 108–119.

Shen, C.-Y.; et al. 2015. Socio-spatial group queries for impromptu activity planning. *TKDE*.

Shen, C.-Y.; et al. 2020. Activity organization for friend-making optimization in online social networks. *TKDE*.

Shen, C.-Y.; et al. 2022. Density Personalized Group Query. *VLDB*.

Shuai, H.-H.; et al. 2013. Willingness Optimization for Social Group Activity. *VLDB*.

Spatial. 2023. Spatial. https://spatial.io/?utm_medium=referral&utm_source=xr4work.com. Accessed:2021-11-3.

Takac, L.; and Zabovsky, M. 2012. Data analysis in public social networks. *International Scientific Conference and International Workshop Present Day Trends of Innovations*.

Tong, Y.; Meng, R.; and She, J. 2015. On bottleneck-aware arrangement for event-based social networks. In *ICDE Workshops*.

Wang, L.; et al. 2018a. Service Entity Placement for Social Virtual Reality Applications in Edge Computing. In *INFOCOM*.

Wang, X.; et al. 2018b. Joint User- and Event- Driven Stable Social Event Organization. In *WWW*.

Yang, C.-H.; Shuai, H.-H.; Shen, C.-Y.; and Chen, M.-S. 2021. Learning to solve task-optimized group search for social Internet of Things. *IEEE Transactions on Knowledge and Data Engineering*, 34(11): 5429–5445.

Yang, D.-N.; Shen, C.-Y.; Lee, W.-C.; and Chen, M.-S. 2012a. On Socio-Spatial Group Query for Location-Based Social Networks. In *KDD*, 949–957.

Yang, J.; and Leskovec, J. 2012. Defining and Evaluating Network Communities Based on Ground-Truth. In *ICDM*.

Yang, L.; et al. 2023. DGRec: Graph Neural Network for Recommendation with Diversified Embedding Generation. In *WSDM*.

Yang, X.; et al. 2012b. On Top-k Recommendation Using Social Networks. In *RecSys*.

Zhao, K.; et al. 2022. Joint Learning of E-Commerce Search and Recommendation with a Unified Graph Neural Network. In *WSDM*.

Zhao, T.; McAuley, J.; and King, I. 2014. Leveraging Social Connections to Improve Personalized Ranking for Collaborative Filtering. In *CIKM*.

Zhao, W. X.; et al. 2016. Connecting Social Media to E-Commerce: Cold-Start Product Recommendation Using Microblogging Information. *TKDE*.