

Intro skeleton

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May 5, 2023

Introduction

Group-based research is ubiquitous and becoming increasingly large-scale with the popularization of online recruitment systems. Empirical research using small and large groups can be found in fields as diverse as behavioural game theory (Hawkins, 2015), evidence-based social policy (Balafoutas and Sutter, 2012; Hauser et al., 2014; Janssen et al., 2010; Nishi et al., 2015), cumulative cultural evolution (Dereux et al., 2013), psychotherapy (Joyce et al., 2010; Rebok et al., 2014), education (Osborne and Collins, 2001; Yeager et al., 2019), and organizational psychology (Spoon et al., 2021). Furthermore, focus groups are an extremely popular method most large, consumer-facing enterprises employ to derive insights about their products and services, meaning group-based research is also widely practiced outside of academia (Krueger, 2014). As online participant recruitment systems become increasingly popular with both industrial and academic researchers (Sauter et al., 2020), social scientists can quickly recruit large numbers of people which then have to be organized into group units for further study. When the research design is complex (e.g., where multiple sessions or a screening process is involved), scheduling all these participants for appointments in a manner which is resource-conscious becomes highly challenging.

Interestingly, contemporary tools researchers use to address these scheduling problems lack the sophistication to solve this problem adequately. It appears the vast majority of social scientists employ one of two methods to resolve participant scheduling. The first common method includes tools such as Sona (Sauter et al., 2020), where each individual in the pool of interested participants self-selects a single appointment to undertake the study from a set of appointments the researcher specified in advance. This method was primarily designed with individual-based research projects in mind and is both effective and pragmatic in this context. For individual lab sessions, participants can select the first appointment that suits their schedule, keeping the cognitive exertion required by the participant at this stage minimal. However, this method of self-selecting single appointments can become highly inefficient in group-research contexts. The unsuitability arises from the fact that most group-research seeks to recruit groups whose member count falls into a particular range. Since a group, by definition, must have at least three members, there are three broad categories of

desirable group member ranges in group research: 1) precise group sizes (e.g., groups of exactly four), 2) groups with some leeway (e.g., groups of three to five), and open-ended groups (e.g., three or more people). In appointment self-selection contexts where 1) or 2) applies, some participants are bound to find their desired appointment already at capacity. In any case, they may inadvertently select an appointment which is not popular enough to be feasible. Signing up to an appointment which ends up being infeasible and thus cancelled with a plea by the researcher to attempt scheduling another one can be a frustrating experience for participants and therefore likely increases the propensity of such participants to disengage entirely. Thus, while appearing pragmatic at face value, self-selection of singular appointments results in researchers having too little information and flexibility to accommodate at least a portion of their sample, risking a laborious allocation process which may negatively impact participant retention. The second popular method involves participants indicating their availability to attend each timeslot in the set of timeslots the researcher defined a priori, as is the case with Doodle poll (Alrawi et al., 2016). Once participants have indicated their availabilities, the researcher invites eligible participants to the single most popular session. This method places more initial cognitive labour on the participant but ensures participants will not have to be repeatedly rescheduled since invitations will only be sent for viable sessions. This approach to allocation is most useful when seeking to host a single session with a maximal number of attendees, as can be the case for single-occurrence events. However, like the first method, it conflicts with the researcher’s needs for groups of specific sizes, while also discarding every participant who did not select the most popular session. This is primarily due to these tools’ specific focus on identifying the single best event, rather than a set of events. Since the event proposed by these tools is the single most popular one, there is no in-built consideration of the group sizes which poses problems to group research that does not want to recruit a single, large group of people.

There is a strong case for an allocation system that maximizes the number of groups across sessions. As a toy example, consider a hypothetical scenario where we have four interested participants (A, B, C, D), want to recruit pairs, and running multiple sessions is possible. The researcher provided exactly three timeslots for the participants to choose from (T1, T2, T3) and the participants’ choices are as follows: A: T1, T3; B: T1, T3; C: T1, T2; D: T2. In this case, the single most popular timeslot had three signups. Since we can only run dyads, running T1 would only grant us one group, and will render both other timeslots infeasible if we do not carefully consider whether to run the session with A and B over A and C. This conundrum arises since running A and C will mean no other timeslot will have at least two eligible people. Suppose we had an algorithm which instead proposed a context-sensitive solution, where A, B are allocated to T3; and C, D to T2. This set-based solution makes perfect use of our sample, allocating all four individuals to give rise to two dyads. It should also be noted that the likelihood of erroneously making inefficient allocations is only exacerbated in larger samples due to their vastly greater combinatoric space. Thus, prioritizing single slots without considering the rest of the sam-

ple risks inefficient allocations, which can lead to underpowered research and unnecessary frustration.

Given the obligation to make efficient use of participant resources, there is a growing need for systems that are purpose-built for group allocations which do not suffer from the aforementioned drawbacks. To reiterate, an ideal system would find the set of timeslots (rather than a single timeslot) which are expected to achieve the optimal number of attendees. If the sessions are costly to run (e.g., social cognitive neuroscience experiments similar to Bevilacqua et al., 2019), this might be the smallest set of slots that satisfy size criteria maximally well. Should the researcher instead be more concerned with the statistical power of planned group-level analyses, they alternatively may be seeking the largest possible set of viable timeslots. Unlike the aforementioned methods, finding an optimal set of slots poses a computational challenge, since there is no obvious analytical method to derive the optimal allocation. In fact, one may have to try every combination of participants and their selected timeslots to verify that one has found the best solution.

Instead of seeking mathematically optimal algorithms, our aim with this paper was to provide initial, empirically-informed solutions which are accessible enough for researchers to utilize in their own practice. We first propose a methodology which allows us to study this set of allocation problems through simulation. Secondly, we present metrics with which the quality of an allocation can be evaluated in the context of the researcher’s specific needs. Thirdly, we developed a set of heuristics to make allocation decisions. We apply each meta-heuristic to a wide array of different simulated research scenarios, and make relative comparisons of their performance in these contexts. We conclude by demonstrating how our code can be applied to a real-world dataset.

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