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RESEARCH ARTICLE

Organizing a great team with complementary skills: selecting orthogonal vectors with artificial intelligence

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Abstract
It's a well-accepted notion that teams, whose members possess complementary skills, have a higher probability of achieving successful results in science and business. The main task of a leader is to form a compact, high-performing team with such complementary skills, even though no specific formula for this has been provided. The task of selecting `k` members with complementary skills from a pool of `n` candidates is a binomial coefficient complex problem, represented by `C(n,k)`, and the task is one of the most challenging problems in human resource management with uncertainty. Currently, there is no mathematical model or theory capable of quickly selecting a small number of `k` members with `f` complementary skills from a large pool of `n` candidates. This paper proposes a new framework for formulating uncertain members and finding near-optimal solutions in real-time using a pseudorandom inference model with O(1) complexity. A uncertain member i is represented by a vector $S_i(s_{i1},s_{i2},\ldots,s_{if})$ with f skills. Selecting k members among n members with f complementary skills is equivalent to selecting k orthogonal vectors among n vectors. The algorithm suggests that the inclusion of one average or normal member could be beneficial in forming an exceptional team. This framework, along with the theoretical algorithm validated through empirical experiments, holds promising potential for real-world applications across various domains.

Highlights
- A new framework for creating a great team with complementary skills in real-time.
- Complexity of selecting k members among n members is a binomial coefficient: $\binom{n}{k}$.
- Intelligence in the framework for a great team is inferred by pseudorandom numbers.
- A member with f skills of a team can be represented by a vector $S(s_1,s_2,\ldots,s_f)$.
- Selecting complementary skill members is equivalent to selecting orthogonal vectors.

What is known?

The foremost duty of an entrepreneur in business is to build a successful, high-performing team. It's a well-accepted notion that teams, whose members possess complementary skills, have a higher probability of achieving successful results in business. The complexity with the Gram-Schmidt process algorithm for selecting k members from n candidates with f skills and maximizing pairs orthogonality is $O(fk^2 2^n/\mathrm{sqrt}(n))$. In other words, the Gram-Schmidt approach is not feasible for real-time applications, and there is no definitive algorithm for assembling an exceptional team.

What are the new contributions?

This paper proposed a new theory and algorithm, which utilizes pseudorandom numbers, to find near-optimum solutions with an O(1) time complexity. The quality of these solutions was substantiated and validated by empirical simulation results, which provided a distribution of solution quality.

Extended author information available on the last page of the article

Keywords A team with complementary skills · Orthogonal vectors · Artificial intelligence with pseudorandom number · Leadership · Gram-Schmidt process

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1 Introduction

The foremost duty of an entrepreneur in business is to build a successful, high-performing team. A thorough literature review was carried out on the subject of small, high-performance teams. The findings from the review indicate that teams made up of members with complementary skills are generally acknowledged as having a higher likelihood of achieving successful results, but no concrete algorithm has been provided.

The task of selecting `k` members with complementary skills from a pool of `n` candidates is a binomial coefficient problem, represented by `C(n,k) = n!/(k!(n-k)!)`, and the task is one of the most challenging problems in human resource management with uncertainty. This problem of the successful small team is characterized by two types of uncertainties: one concerning the characteristics of the individual members, and the other related to the real-time selection of'k'members from a set of'n'members. The latter is a complex issue involving binomial coefficients.

This paper introduces a novel framework or theory that transforms uncertain elements into a computational model for human resource management. The framework further selects'k'elements from a pool of'n'elements, aiming to maximize the synergy of their skills. This selection process is guided by pseudorandom intelligence and remarkably, it achieves this in constant time, O(1) complexity. The efficacy of the proposed framework is substantiated and validated through extensive simulation results. The notation O(1) is known as Big O notation, In computer science, `O(1)` describes an algorithm that will always execute in the same time (or space) regardless of the size of the input dataset. It's the most efficient time complexity because it doesn't change with the amount of data.

For example, selecting 5 members from 1000 candidates results in $8.25 * 10^{12}$ possible solutions, while selecting 10 members from 1000 candidates results in $2.63 * 10^{23}$ possible solutions. Currently, there is no mathematical model or theory capable of quickly selecting a small number of `k` members with complementary skills from a large pool of `n` candidates with maximizing complementary skills. This paper proposes a new framework and theory for finding near-optimal solutions in real-time using a robust statistical AI model.

A comprehensive literature review was undertaken to validate the premise that teams, composed of members with complementary skills, are more likely to achieve successful outcomes. Miles and Watkins wrote an influential article entitled "The leadership team: complementary strengths or conflicting agendas?" (Miles and Watkins 2007). They emphasized how to organize a great team with complementary skills or strengths for successful outcomes. However, they did not demonstrate how to construct a computational mathematical model, nor how to select members with complementary skills from a large pool of candidates in a way that maximizes the synergy of these skills.

Katzenbach and Smith proposed the original ideas on the complementary skills in the discipline of teams for successful outcomes (Katzenbach and Smith 1993a). High-performance organizations leverage the collective wisdom of teams composed of members with complementary skills (Katzenbach and Smith 1993b). However, they did not formulate and propose a computational mathematical model or theory.

The real team experiment took place in a medical team called the PDSA (Plan, Do, Study, Act) team, which consisted of anesthesiologists, nurses, nurse practitioners, and surgical technicians with complementary skills (Cunningham et al. 2018). Their successful experiment was based on three studies (Deneckere et al. 2012; Schmutz et al. 2015; Hina-Syeda et al. 2013). Their studies fell short in formulating and quantifying the complementary skills in a manner that would allow their application in other contexts.

From safety viewpoints, Thomas L et al. presented successful studies on complementary skills in team training and engagement (Thomas and Galla 2013). Similarly, the role of the principal designer is best served by a team with complementary skills that are needed at different stages of the construction projects (Issaka Ndekugri et al. 2022). While both studies categorized member skills, they did not formulate and propose a computational mathematical model or theory.

From neuroscience viewpoint, Du, M. et al. suggested that like physical space, social knowledge is encoded as a cognitive map in the human brain and represented with a grid-like code so that the cognitive map can be used as complementary skills for successful outcomes (Du and Parkinson 2021). However, they did not formulate and propose a computational mathematical model or theory on complementally skills.

Baran proposed an idea on building a competitive village based on complementary skills for successful outcomes (Baran 2021). However, Baran did not formulate and propose a computational mathematical model or theory.

Angela Foerster and Jon Links depicted that a key to successful collaborative research is the assembly of team members with complementary skills (Foerster and Links 2019). They emphasized the importance of complementary skills, but they did not formulate and propose a computational mathematical model or theory on complementally skills.

Xie et al. showed that skill complementarity can enhance heterophily in collaboration networks (Xie et al. 2016). They showed and analyzed the importance of complementary skills, but they did not formulate complementary skills.

Linderman et al. revealed that complementary skills can advance healthcare technology education and innovation in academia (Linderman et al. 2020). However, they did not formulate and propose a computational mathematical model or theory on complementally skills.

Xu, W. et al. presented that for those with complementary skills, technology can increase their productivity, and hence the wages their skills are likely to command (Xu et al. 2021). Disclosure of preliminary results may be necessary to find collaborators with complementary skills since early feedback can improve the quality of eventual journal submission (Thursby et al. 2018). Both studies did not formulate and propose a computational mathematical model or theory on complementally skills.

Saghatelian et al. employed a complementary skill strategy and formed a "hormone team" consisting of covalently bound glucagon and triiodothyronine. Together, the unexpected teammates create a remarkable compound that improves key metabolic parameters in a mouse model of metabolic syndrome (Saghatelian and Cravatt 2016). However, they did not formulate a computational mathematical model or theory on complementally skills.

The literature review results suggested that teams composed of members with complementary skills are more likely to achieve successful outcomes in many areas in general. However, there is no general model, theory or algorithm that shows how to scientifically create a great team with complementary skills and maximize their complementary skills. First, the proposed framework is to convert uncertain members to a computational model to maximize complementary skills. Second, the pseudorandom method is used for selecting k members from a pool of n members in O(1) time complexity with the aim of maximizing complementary skills. As far as we are aware, the current studies on constructing exceptional teams have not utilized theories, data, or datasets grounded in a solid mathematical framework.

With the advent of generative AI, computational ethics must be seriously considered. From a computational ethics perspective, leaders must show why and how members are selected based on scientific evidence where fairness, accountability and transparency play a key role in ensuring the evidence in computational ethics. This paper can contribute to computational ethics.

This paper proposes a new framework or theory that utilizes an artificial intelligence algorithm to efficiently select a high-performing team from a large pool of members in real-time with O(1) time complexity. The proposed framework can provide scientific evidence from a computational ethics perspective, and the quality of the team composed of selected members can be evaluated based on orthogonal vectors to maximize complementary skills.

The goal of this paper is to propose a mathematical model and theory for quickly selecting a team with complementary skills within a few seconds. Many studies on complementary skills show remarkable achievements in creating a great small team. However, there is no general model or theory for this purpose.

There is the Gram-Schmidt process algorithm, but it takes a very long time since the algorithm can find all orthogonal vectors with $O(fk^2)$ floating point operations, where f is the number of the skills and k is the number of vectors or members (Golub and Loan 1996). $O(fk^2)$ is complexity notation used to describe the time and space complexity of an algorithm. $O(fk^2)$ represents a quadratic relationship between the size of the input 'k' and the time or space required by the algorithm. This means that as the size of the input 'k' increases, the time or space required by the algorithm increases quadratically. Since selecting k members among n members with the complexity of C(n,k), the total complexity is $O(C(n,k)\, fk^2)$ where C(n,k) is the binomial coefficient. With the recursive algorithm, C(n,k) is nearly equivalent to $O(2^n/\mathrm{sqrt}(n))$. Therefore, the complexity with the Gram-Schmidt process algorithm for selecting k members from m members with f skills is $O(fk^2 2^n/\mathrm{sqrt}(n))$. In other words, the Gram-Schmidt process algorithm is not applicable to this intractable problem.

On the other hand, the proposed algorithm with a time or space complexity of O(1) has a constant relationship between the size of the input n and the resources required. This means that the time or space required by near-optimum solutions remains constant, regardless of how large the input n becomes. The simulation results are set to demonstrate the quality of the solutions, thereby validating their proximity to optimal solutions.

First, this paper proposes a mathematical model or theory. Second, in the proposed algorithm, selecting members with complementary skills can be translated into the mathematical model. Third, selection mechanism of artificial intelligence using pseudorandom numbers will be described. Finally, the proposed algorithm will be evaluated from the viewpoint of the orthogonality distribution. Note that the proposed algorithm is based on O(1) computation complexity.

Artificial intelligence has been playing a key role in solving a variety of problems (LeCun et al. 2015; Yamada et al. 2016). The most important core of artificial intelligence lies in using pseudorandom numbers (Takefuji and Yamada 2020). They demonstrated the example using the constrained pseudorandom numbers for solving coin-weighing puzzles using a balance. In classic 12-coin-3-weighing puzzle, twelve coins are given where eleven of which are identical. If one is different, we don't know whether it is heavier or lighter than the others. The balance may be used three times to determine if there is a unique (counterfeit or fake) coin to isolate it and determine its weight relative to the others. Therefore, in the 12-coin-3-weighing puzzle, we have to isolate a single counterfeit coin by three weighings using the balance.

In their algorithm, solution candidates are generated by pseudorandom number with the simple deductive method. They showed that constrained pseudorandom numbers can solve classic coin-weighing puzzles faster than existing human-expert-devised algorithms (Takefuji and Yamada 2020). In other words, it is demonstrated that intelligence is truly inferred by pseudorandom numbers in artificial intelligence to reinforce the state of the system in near-optimum solutions.

To clarify the achievement of constant time complexity O(1), the proposed approach leverages heuristic computing techniques to effectively promote convergence toward optimum or near-optimal solutions. By systematically evaluating orthogonal values for minimization, the method harnesses the power of pseudorandom numbers, guiding the system's state toward increasingly optimal configurations, independent of the problem's size. As a result, computation times remain effectively constant, regardless of the inherent complexity of the problem.

The proposed approach is grounded in the well-established principles of Lyapunov function minimization, which is a fundamental aspect of many neural computing optimization methods. The significant contributions of Takefuji and Lee (1989) are also recognized; his groundbreaking research on neural computing for graph planarization has considerably advanced the field. This historical context highlights both the effectiveness of the proposed algorithm and its adaptability in addressing a wide variety of combinatorial challenges, including team formation.

The proposed algorithm distinguishes itself by employing an evaluation of orthogonal values instead of relying on constrained forces, thereby enhancing its ability to achieve optimal or near-optimal solutions. Additionally, the strategic use of pseudorandom numbers is essential for generating team members and updating orthogonal values at each iteration, maintaining a constant time complexity of O(1). In contrast to existing algorithms that may struggle with the quality of the initial state or the updating process, the incorporation of pseudorandomness effectively mitigates these challenges, improving the overall robustness of the solution.

Furthermore, the methodology has demonstrated significant promise in classic coin-weighing puzzles, outperforming traditional algorithms (Takefuji, 2020), thereby providing further empirical evidence of its efficacy. Notably, the quality of solutions generated by the proposed method is directly proportional to the number of trials conducted, rather than the complexity of the problem itself. These clarifications aim to reinforce both the theoretical underpinnings and practical applicability of the work presented, thereby adding depth to its contribution to the field.

This paper introduces an O(1) time algorithm that evaluates the frequency of high-quality solutions relative to the number of trials conducted. It is important to emphasize that the proposed method is based on heuristic computing techniques rather than machine learning. The quality of the solutions is assessed by analyzing both their frequency and the corresponding orthogonal values, where lower orthogonal values indicate superior solutions. Additionally, a higher frequency of high-quality solutions correlates with better overall outcomes. To further illustrate the distribution of orthogonal solutions, this paper presents results from three sets of experiments consisting of 2,000 trials, 20,000 trials, and 200,000 trials respectively. These findings provide empirical support for the effectiveness of the proposed algorithm.

2 Methods

This paper shows how to represent uncertain individual members with complementary skills. In a mathematical model, a member i with f skills can be represented by an f-dimensional vector $S_i(s_{i1},s_{i2},\ldots,s_{if})$. Consider two vectors ($S_1$ and S_2). Two members or vectors (S_1 and S_2) are orthogonal if they are perpendicular to each other. In other words, two vectors are orthogonal if and only if their *dot product* is zero. The dot product can be calculated as follows:

$$\mathrm{S1}\cdot\mathrm{S2}=\begin{pmatrix} s_{11} \\ s_{12} \\ \vdots \\ s_{1f} \end{pmatrix}\cdot\begin{pmatrix} s_{21} \\ s_{22} \\ \vdots \\ s_{2f} \end{pmatrix}=\mathrm{s11}*\mathrm{s21}+\mathrm{s12}*\mathrm{s22}+\cdots+\mathrm{s1f}*\mathrm{s2f}$$

If we have five members to be selected as a team, $\binom{5}{2}=$ 10 pairs exist. A sum of 10 pairs orthogonality can be checked. If the sum orthogonality is zero, five vectors are mutually orthogonal. The larger the sum of pairs orthogonality, the less orthogonal the vectors are to each other. In other words, the quality of selected members can be checked by the sum of possible pairs orthogonality. The less the sum of pairs orthogonality, the better the team. In other words, sum orthogonality can show the quality of a team.

The proposed algorithm is based on pseudorandom numbers so that the computation time is determined by the number of trials. In other words, the proposed algorithm has a constant computation time, denoted as O(1).

The algorithm can be investigated by the fixed number of trials instead of large candidates such as a binomial coefficient. Generally, the inference quality can be improved by increasing the number of trials (pseudorandom samples).

The drawback of the proposed framework is that it requires scoring the skills of all members and the number of skills should be identified and determined to represent complementary skills. However, once the scores are made for individual members, the best or near best members can be selected in real time. The simulation results are used to substantiate the quality of the solutions.

The proposed Python program is flexible and modifiable to change important parameters (n, k, f) for selecting k members from n member with f skills. Each of f skills has a range of integer low and high value. The quality of orthogonality can be determined by a given threshold. In the Python program, pseudorandom number range can be determined by:

random.range(low,high)
Let low be - and high be 2 in a skill. random.range(- 1,2) can generate three classes of each skill: - 1, 0, and 1.
random.range(- 2,3) generates five classes of each skill: - 2, - 1, 0, 1, 2.

In order to guarantee reproducibility, random.seed() needs to be fixed such as random.seed(8). In the program, default total_members, n = 1000 and default selected_members, k = 5 can be modifiable.

Let total number = 30 and selected members = 5. The proposed program with 30 members from ‘0’ to ‘29’ can generate the following 8 skills with 3 skill classes.

$$\{'0':'-100-1-11-1-1','1':'-1-11-101-10','2':'00001-10-1','3':'0-1-110100','4':'01-110-1-10','5':'10-11-10-11','6':'-1011-11-11','7':'-11-101-1-11','8':'01100100','9':'-1-11-11101','10':'01011-10-1','11':'01011-111','12':'1-10-1-100-1','13':'0-1000010','14':'-110-1-11-1-1','15':'-10-1-100-11','16':'0-1-101000','17':'-11-101-1-1-1','18':'1-1110-110','19':'1-11-1-1-1-10','20':'011-11000','21':'0-110-1-11-1','22':'1-1-1000-1-1','23':'-11-100-10-1','24':'-11101-110','25':'11-110100','26':'0-1-1-1-10-1-1','27':'-11-1111-11','28':'001-11111','29':'1-11-10101'\}$$

Consider a business team composed of five members, each bringing a unique set of eight complementary skills to the table. It's worth noting that in leading business or management schools, the range of business skills taught can vary, typically falling between five and twelve.

8 business skills are commonly defined as follows: management skill, team-building skill, analytical skill, negotiation skill, problem-solving skill, sales and marketing skill, financial management skill, and transferable skill.

Therefore, a member can be represented by an 8-dimensional vector. In other words, 8 skills can be represented by an 8-dimensional vector:

(0,0,- 1,1,0,- 1,0,0) which can be expressed by '00–110 - 100' in the Python program.

There are three levels of each skill (1, 0, - 1):

1: I am good at this skill.
0: I am normal at this skill.
− 1: I am not good at this skill.

The vector of '00–110 - 100' indicates that management skill is normal, team-building skill is normal, analytical skill is not good, negotiation skill is good, problem-solving skill is normal, sales and marketing skill is not good, financial management skill is normal, and transferable skill is normal respectively.

The goal is to create a great team by selecting 5 members from 1000 members with 8 complementary skills. A team with complementary skills means that 5 members (vectors) are mutually orthogonal.

For example, the vector of '100010–1 - 1' is orthogonal to that of '00–110 - 100' since a dot product of two vectors can be used to identify whether the two vectors are orthogonal or not: 1 * 0 + 0 * 0 + 0*(− 1) + 0 * 1 + 1 * 0 + 0*(− 1) + (− 1)* 0 + (− 1)* 0 = 0.

The vector of '− 100–1–111 - 1' is not orthogonal to that of'10001,011':

$$(-1) * 1 + 0 * 0 + 0 * 0 + (-1) * 0 + (-1) * 1 + 1 * 0 + (-1) * (1) + (-1) * (1) = -4$$

In calculating a sum of possible pairs orthogonality, absolute value of a pair orthogonality is commonly used. The proposed method employs a straightforward heuristic algorithm. This algorithm randomly selects five members from a pool of 1000, then calculates the sum of pair orthogonality, consistently retaining the highest score with each update. In the proposed experiments, all scores along with their frequencies are meticulously recorded to facilitate the observation of distribution statistics to substantiate the quality of solutions.

3 Results

In the experiments, the goal is to create a great business team of 5 members with 8 complementary skills from 1000 members. 8 business complementary skills are defined such as management skill, team-building skill, analytical skill, negotiation skill, problem-solving skill, sales and marketing skill, financial management skill, and transferable skill.

We have tested the proposed algorithm with randomly generated 1000 members, 5 selected members, 8 skills and 3 skill classes. With 2000 trials or 20000 trials, we cannot find an orthogonal set with 8 complementary skills. With 200000 trials, one solution was discovered in 4 s:

$$\begin{aligned} &\text{selected memebers} = [166,\ 377,\ 714,\ 767,\ 520] \\ &= '00000000',\ '101101-11',\ '01-10-10-10',\ '010-10111',\ '-1101110-1' \end{aligned}$$

Figures 1, 2 and 3 display the distribution of orthogonality scores where X-axis shows the sum orthogonality while Y-axis indicates the number of occurrences. Figure 1 shows that the best sum orthogonality is 3 with 1922 trials. Figure 2 shows that the best sum orthogonality is 2 with 3759 trials. Figure 3 shows that the best sum orthogonality is 0 with 134277 trials. In other words, the perfect complementary members are found.

The results of all three distributions indicate a normal distribution and demonstrate the consistency of the proposed heuristic algorithm. This experiment found that the threshold in the Python program forces the search to restrict less than its threshold for mitigating the computation time by three times. On average, it takes 1.9 million trials to obtain a single orthogonal set. The simulation results indicated that the quality of the solution can be assured to be in close proximity to the optimum.

4 Discussion

The Gram-Schmidt process is a systematic way of finding a whole set of orthogonal vectors that form a basis for a space spanned by given vectors. The cost of Gram-Schmidt algorithm is asymptotically O(fk^2) floating point operations, where f is the number of the skills and k is the number of vectors. However, Gram-Schmidt algorithm is extremely slow because of a large number of floating-point operations.

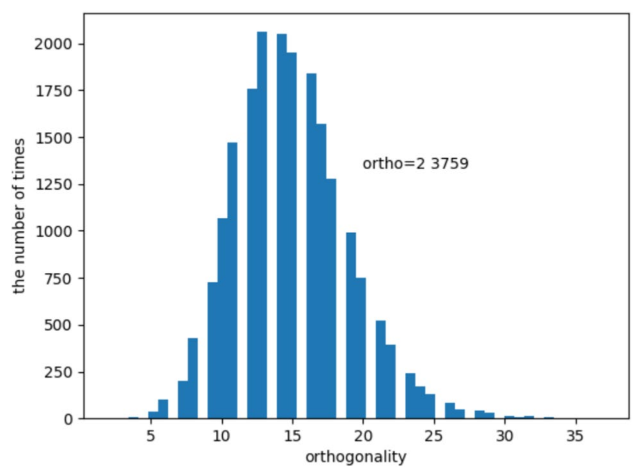

Fig. 2 Orthogonality distribution with 20000 trials

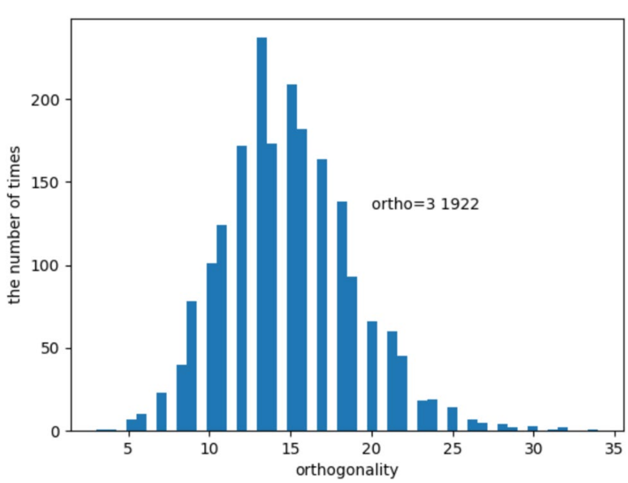

Fig. 1 Orthogonality distribution with 2000 trials

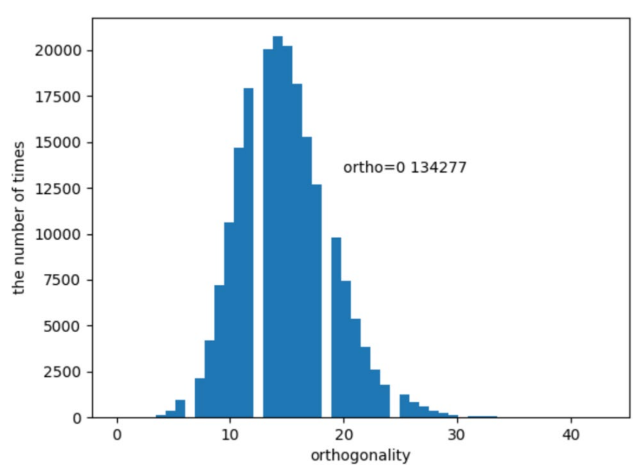

Fig. 3 Orthogonality distribution with 200000 trials

The complexity with the Gram-Schmidt process algorithm for selecting k members from n candidates with f skills is $O(fk^2 2^n/\mathrm{sqrt}(n))$. In other words, it is not practical for real-time applications.

Initially, it is not necessary to spend a significant amount of time searching for all vectors. Instead, our goal is to quickly obtain a few optimal or near-optimal solutions in real-time. The proposed algorithm is based on statistical inference with pseudorandom numbers and can find a subset of orthogonal vectors using O(1) integer operations. The quality of the inference can be improved by increasing the number of attempts or trials, resulting in better reasoning.

The proposed algorithm demonstrated creating a great business team of 5 members with 8 complementary skills with 3 skill classes from 1000 members. By 100 million trials with the proposed algorithm, 52 orthogonal sets were discovered as shown in APPENDIX.

An intriguing observation is that the same member, denoted as '00000000', is included in 39 orthogonal sets. This finding implies that to construct a high-performing team of five members, it could be advantageous to incorporate one member who is deemed average or normal, and not particularly distinguished.

This phenomenon could potentially be attributed to the impact of diversity. A comprehensive literature review was conducted to substantiate the hypothesis concerning the performance of diverse teams.

Gomez et al. emphasized the importance of diversity in helping organizations improve both patient care quality and financial results (Gomez and Bernet 2019). A diversity-friendly environment can help to ensure that everyone has a voice in the change process, which can lead to better outcomes for everyone.

Turi et al. studied diversity's impact on organizational performance (Turi et al. 2022). They found that age diversity, diversity beliefs, and leadership expertise have a significant impact on organizational performance. Leadership expertise plays a significant mediating role in organizational performance.

Liu et al. investigated our kinds of team diversity, including status capital diversity, decision capital diversity, online reputation diversity, and professional knowledge diversity (Liu et al. 2019). They found that diversity in status capital and decision capital negatively impacts team performance, while diversity in online reputation and professional knowledge positively impacts team performance. The impact of status capital diversity and online reputation on team performance is moderated by the leader's reputation.

There is currently no existing research related to our new finding on the role of including one member who is deemed average or normal, and not particularly distinguished in a high-performing team. This suggests that further research is necessary to explore this topic.

This paper only proposed the framework and theoretical algorithm with empirical experiments for creating a great team with complementary skills, but it can be used for real-world applications such as staffing services, temporary staffing, recruiting, outplacement, and others in the near future. The Python programs will be available upon the acceptance of this manuscript.

In conclusion, the experiments successfully showcased the creation of an effective business team, comprising five members each with eight complementary skills, from a pool of 1000 candidates. The process yielded near-optimum solutions in real-time, boasting an impressive O(1) time complexity.

When tested with randomly generated data, the algorithm was able to identify a solution within four seconds, after conducting 200,000 trials. The Gram-Schmidt process, while systematic, is not practical for real-time applications due to the complexity of $O(fk^2 2^n/\mathrm{sqrt}(n))$ where f is the number of skills, and k members are selected from a pool of n candidates respectively.

The proposed algorithm, on the other hand, is based on statistical inference with pseudorandom numbers and can find near-optimum solutions in real-time with O(1) integer operations. The results indicated that the quality of inference can be enhanced by augmenting the number of trials. A fascinating insight from the experiment was that 39 out of the 52 orthogonal sets identified included the same member, denoted as '00000000'. This finding suggests that incorporating a member who is considered average or typical—rather than exceptionally distinguished—may be advantageous when constructing a high-performing team of five members. This perspective prompts a reevaluation of the criteria for team composition, emphasizing the potential value of balance over individual distinction.

This algorithm is fundamentally a heuristic computing method, distinguishing it from traditional machine learning models. At each step, the objective is to minimize orthogonal values in an efficient manner, leveraging an O(1) time complexity. The algorithm utilizes pseudorandom numbers, which play a crucial role in the random generation of team members and in updating solutions towards optimal configurations.

While the Gram-Schmidt process method is known for consistently providing optimal solutions, it often demands an impractical amount of computation time. This presents a significant challenge, as many users are unwilling to wait extended periods for solutions. In contrast, the proposed method delivers optimum or near-optimal solutions in real time, leveraging its O(1) time complexity to efficiently address even complex problems. By prioritizing speed without sacrificing solution quality, this innovative approach is particularly well-suited for dynamic environments where timely decision-making is essential. This combination of efficiency and effectiveness marks a substantial advancement in heuristic computing strategies.

This paper acknowledges that accurately representing complementary skills is crucial and requires careful consideration. The example provided in this paper is based on a traditional business team comprising eight distinct skills. However, the framework is flexible, allowing for the expansion and adaptation of both the number of skills and their features to suit various team configurations. This adaptability ensures that the proposed approach remains relevant and applicable across different organizational contexts. The proposed method can be extended from a vector to a matrix, as a matrix is comprised of multiple vectors.

The matrix must be closely aligned with the foundational concepts in social psychology and organizational behavior. By integrating insights from these fields, the matrix can more effectively capture the complex interactions and dynamics that influence team performance and collaboration. This strong connection to the relevant literature will enhance the matrix's relevance and applicability in understanding organizational structures and behaviors.

To strengthen the understanding of how a matrix can be effectively coupled with the foundations of literature from social psychology and organizational behavior, it is essential to explore several key themes supported by relevant citations. First, group dynamics and team formation are crucial; Forsyth (2018) emphasizes the impact of cohesion, communication, and interpersonal relationships within teams. A matrix that incorporates these dynamics can map skill complementarities and identify optimal team configurations. Additionally, the work of Belbin (2010) on team roles illustrates how different skill sets can complement each other to enhance overall team effectiveness. Thus, integrating a matrix reflecting these roles can provide valuable insights into how various skills contribute to team success.

Social identity theory, articulated by Tajfel and Turner (2010), further elaborates on how group identity influences behavior and interactions within teams. By employing concepts from social identity within the matrix, it can better represent individual perceptions of roles and the dynamics at play. In the realm of motivation and leadership, Robbins and Judge (2019) highlight the importance of these elements within organizational structures, suggesting that grounding the matrix in established organizational principles will enhance its utility in understanding skill interactions and their impact on motivation and performance.

Moreover, psychological safety, as discussed by Edmondson (1999), plays a significant role in team functioning, allowing members to take risks and share ideas without fear of negative repercussions. Designing the matrix with these psychological principles in mind can foster a supportive team environment, ultimately enhancing performance. By integrating insights from social psychology and organizational behavior, the matrix will provide a holistic perspective on team interactions and dynamics, enabling a robust representation of the complexities involved in organizational settings and leading to improved outcomes for team formation and performance.

5 Conclusion

The proposed algorithm swiftly creates high-performing teams by finding optimal solutions in real-time. It proved its efficacy by forming a business team with diverse skills from a large pool. The inclusion of an average member in successful teams hints at diversity's role in team performance. The algorithm, while theoretical, has potential for staffing and recruiting applications. Further research is needed on the role of average members in high-performing teams. The Python programs will be available upon manuscript acceptance. The experiments showcased the creation of an effective business team in real-time, with an impressive O(1) time complexity. The algorithm identified a solution within four seconds in tests, suggesting its practicality over the Gram-Schmidt process. The results indicated that increasing the number of trials enhances the quality of inference. The recurring inclusion of an average member in successful teams suggests its potential benefit in team formation. This framework and algorithm, validated through experiments, hold promise for real-world applications.

Appendix

(52 orthogonal sets by 100 million trials).

(52 orthogonal sets by 100 million trials)

[166, 377, 714, 767, 520]= ['00000000', '101101-11', '01-10-10-10', '010-10111', '-1101110-1']
[704, 166, 766, 861, 380]= ['011-11101', '00000000', '10-111100', '01-1-11-10-1', '-1-10010-10']
[703, 190, 166, 816, 896]= ['00-10010-1', '00-10-1-110', '00000000', '100-1-10-10', '-1000-1101']
[809, 166, 892, 805, 259]=['10-110110', '00000000', '1-10000-10', '0-1-1-10-11-1', '-10-1011-1-1']
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[182, 315, 71, 498, 251]= ['-1-100-1-100', '-11-110001', '0010-1111', '0-1-1-11011', '10010-110']

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