# Greedy Algorithm for Optimal Team Selection in BanG Dream! Girls Band Party Under Non-Event and Event Conditions

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***Abstract*—Optimal team selection in BanG Dream! Girls Band Party requires choosing five cards from a player's collection to maximize live show performance, a decision complicated by event-specific scoring multipliers that reward cards matching a bonus character or attribute. This paper formalizes this problem as a combinatorial optimization task and proposes a Greedy algorithm that selects cards by their effective value, computed from base stats, a mapped skill score, and an event multiplier. We prove the algorithm's optimality through an exchange argument, and extend the proof to account for the game's character uniqueness constraint by framing the problem as a partition matroid. Using a 20-card dataset curated from Bestdori under a Morfonica/Happy event configuration, the proposed algorithm is validated against brute-force search, achieving identical optimal scores in both non-event and event scenarios while running in $O(n\log n)$time. Results show that four of the five optimal cards change once the event multiplier is applied, with a breakeven analysis quantifying the stat disadvantage a bonus card can absorb while remaining superior to a non-bonus alternative. These findings indicate that effective card team selection cannot rely on stat maximization alone and must account for both event mechanics and structural team constraints.***

***Keywords*—greedy algorithm, combinatorial optimization, partition matroid, BanG Dream! Girls Band Party, mobile game optimization**

## I. Introduction

BanG Dream! Girls Band Party is a mobile rhythm game developed by Craft Egg and published by Bushiroad, in which players form a team of five cards to perform live shows and earn scores based on the combined performance of the selected cards. Each card possesses three core statistics: Power, Technique, and Visual, along with a skill that activates during live performances. The total score of a live show is determined by the sum of these statistics and skill values across all five selected cards, making card selection a critical factor in maximizing performance.

The game operates under two distinct conditions that affect scoring. Under normal (non-event) conditions, the objective is straightforward: maximize the total stat and skill value of the five selected cards. Under event conditions, however, each card is additionally assigned an event multiplier based on whether its character and attribute type match the ongoing event's bonus criteria. A card featuring a bonus character receives a 20% multiplier, a card with a bonus attribute type receives a 10% multiplier, and a card satisfying both conditions receives a 50% multiplier. Since this multiplier applies independently per card, the effective value of each card shifts significantly during events, potentially altering the optimal team composition entirely.

This problem can be formally modeled as a combinatorial optimization problem: given a player's card collection of size $n$, select a subset $S$ of exactly five cards that maximizes the total effective score. Under non-event conditions, the effective value of each card is independent of the others, making the selection problem separable. Under event conditions, the per-card multiplier modifies each card's contribution independently, preserving this separability. This structural property suggests that a Greedy algorithm, which selects the locally optimal card at each step, may produce a globally optimal solution.

This paper makes the following contributions. First, formalize the card selection problem in BanG Dream! Girls Band Party as a combinatorial optimization problem under both non-event and event conditions, where each card's effective value is computed independently using a multiplier $M_i \in \{1.0,1.1,1.2,1.5\}$. Second, implement a Greedy algorithm for this problem and provide a formal justification of its optimality via an exchange argument, given the problem's separable structure. Third, and most significantly, to analyze how event multipliers shift card rankings and derive a quantitative threshold at which a lower-stat bonus card outperforms a higher-stat non-bonus card. Experiments are conducted using card data obtained from Bestdori to validate this threshold analysis across multiple event scenarios.

## II. Theoretical Foundation

### *A. Greedy Algorithm*

A greedy algorithm is an algorithm that solves optimization problems step by step, where at each step, the algorithm takes the best choice that can be obtained at that time without considering the future consequences, following the principle of "take what you can get now" [1]. This algorithm hopes that by choosing a local optimum at each step, the final result will be a global optimum [1].

There are two properties inherent in the greedy algorithm:

1. Greedy Choice Property: The optimal solution can be constructed by first selecting the best local decision.
2. Optimal Substructure: The optimal solution to a problem is formed from the optimal solutions of its subproblems. [1]

A greedy algorithm consists of six components:

1. Candidate set (C): contains all candidates that can be selected at each step.
2. Solution set (S): contains the selected candidates.
3. Solution function: determines whether the generated solution set is complete.
4. Selection function: selects candidates from the C set based on a specific heuristic greedy strategy.
5. Feasibility function: checks whether the selected candidate can be included in the solution set without violating the problem constraints.
6. Objective function: maximizes or minimizes the value of the generated solution set.

### B. *Greedy Optimality and Its Proof*

Greedy algorithms do not always produce optimal solutions. There are two main reasons: first, greedy algorithms do not evaluate all possible solutions as thoroughly as exhaustive search [1]; second, there are several different greedy choice functions, so choosing the wrong selection function can result in a non-optimal solution [1]. Therefore, claims of optimality of a greedy algorithm must be proven mathematically, not simply assumed [1].

In the shortest path problem with a naive greedy strategy (choosing the edge with the smallest weight at each step without considering the overall graph structure), a path with weight 13 is obtained, while the optimal solution has weight 11 [2]. This occurs because a local decision that appears profitable at one step may close access to a cheaper path at the next step.

In contrast to the examples above, there are problems where greedy algorithms are mathematically proven to always produce optimal solutions. Dijkstra's algorithm for finding the shortest path in a non-negative weighted graph, which at each step selects the vertex with the smallest temporary distance, is proven to always produce the optimal shortest path [2]. Similarly, Kruskal's algorithm for forming a minimum spanning tree, which at each step selects the edge with the smallest weight that does not form a cycle, is proven to be optimal through a formal proof using the exchange principle [2].

The essence of the exchange argument proof in Kruskal's algorithm is as follows: suppose there is an optimal solution $T$ that does not contain the greedily chosen edge $e$, then adding $e$ to $T$ will form a cycle. Removing any other edge in the cycle with a weight greater than or equal to $e$ will produce a new spanning tree with a total weight no greater than $T$, so that the solution containing $e$ remains optimal [2]. This exchange principle proof method serves as the reference for proving the optimality of the greedy algorithm for the card selection problem in this paper, as will be explained in Section III.

Based on the two categories of examples above, it can be concluded that the optimality of a greedy algorithm depends entirely on the structure of the problem at hand, not on the algorithm itself.

### C. *BanG Dream Card System*

BanG Dream! Girls Band Party is a mobile rhythm game developed by Craft Egg and published by Bushiroad. Players form a team of five cards to perform live shows and earn scores based on the combined performance of their five selected cards. Each card has three core stats: Power, Technique, and Visual, as well as a skill value that is active during the live show. The team's total strength is displayed as the sum of these three stats in the game interface, as shown in Figure II-1.


Figure II-1. The 5-card team selection interface on BanG Dream outside of the event period

Figure II-1 shows a team with a total Power of 168,514, which is the direct sum of Performance (58,510), Technique (51,674), and Visual (58,330). The $Sk_i$ skill value does not have a standard numeric representation in the game and is therefore derived through a custom mapping, which is explained in Section III.

The score in normal conditions (non-event) is formulated as:

$$\text{Score}(S) = \sum_{i \in S} (P_i + T_i + V_i + Sk_i)$$

where $S$ is the set of 5 selected cards, and $P_i, T_i, V_i, Sk_i$ are the Power, Technique, Visual, and Skill values of card *i*, respectively.

The game also holds periodic events in which players can earn additional event points based on their live show performance. During an event, each card receives an additional multiplier if its character or attribute type matches the bonus criteria of the ongoing event:

- A card with a bonus character receives a × 1.2 multiplier
- A card with a bonus attribute type receives a × 1.1 multiplier
- A card satisfying both criteria receives a × 1.5 multiplier
- A card satisfying neither criterion receives a × 1.0 multiplier

Since this multiplier applies independently to each card, the event score is defined as:

$$\text{Score}_{\text{event}}(S) = \sum_{i \in S} (P_i + T_i + V_i + Sk_i) \cdot M_i,$$
$$M_i \in \{1.0,\ 1.1,\ 1.2,\ 1.5\}$$

This independence property of the multiplier $M_i$ is an important foundation for the optimization problem formulation in Section D, since the effective value of each card can be computed without depending on the other cards selected in the team.

*D. Optimization Problem Formulation*

Let $C = \{c_1, c_2, \ldots, c_n\}$ denote a player's card collection of size *n*, where each card $c_i$ is characterized by:

$$c_i = (P_i, T_i, V_i, Sk_i, \text{char}_i, \text{attr}_i)$$

with $P_i, T_i, V_i, Sk_i$ as defined in Section C, and $\text{char}_i, \text{attr}_i$ indicating whether card $i$ matches the bonus character and bonus attribute type of the ongoing event, respectively.

The card team selection problem is defined as follows: given collection $C$, select a subset $S \subseteq C$ with $|S| = 5$ that maximizes the total score $\text{Score}(S)$, under either the non-event or event scoring function defined in Section C.

**Effective value of a card.** For both scoring conditions, define the *effective value* of card $i$ as:

$$w_i = (P_i + T_i + V_i + Sk_i) \cdot M_i$$

where $M_i = 1.0$ under non-event conditions, and $M_i \in \{1.0, 1.1, 1.2, 1.5\}$ under event conditions, depending on $\text{char}_i$ and $\text{attr}_i$ as defined in Section C. Under this definition, the objective function for both conditions can be written uniformly as:

$$\text{Score}(S) = \sum_{i \in S} w_i \text{, subject to } |S| = 5,\ S \subseteq C$$

**Key structural property.** The effective value $w_i$ of each card depends only on that card's own attributes, $P_i, T_i, V_i, Sk_i, \text{char}_i, \text{attr}_i$, and not on which other cards are included in $S$. There is no constraint coupling the selection of one card to another, such as a shared capacity limit (as in the knapsack problem) or a sequencing requirement (as in the traveling salesman problem). This absence of inter-card dependency is what we refer to as the *separability* of the problem.

This structural property has a direct algorithmic implication. Because $w_i$ is independent across cards, selecting the 5 cards with the largest $w_i$ values is guaranteed to maximize $\sum_{i \in S} w_i$. This is formalized through the following exchange argument.

**Claim.** Let $S^* = \{c_{(1)}, c_{(2)}, \ldots, c_{(5)}\}$ be the set of 5 cards with the largest effective values, where $w_{(1)} \geq w_{(2)} \geq \cdots \geq w_{(5)} \geq w_j$ for all $c_j \notin S^*$. Then $S^*$ maximizes $\text{Score}(S)$ over all $S \subseteq C$ with $|S| = 5$.

**Proof.** Suppose, for contradiction, that there exists some $S' \subseteq C$ with $|S'| = 5$ such that $\text{Score}(S') > \text{Score}(S^*)$. Since $|S'| = |S^*| = 5$ and $S' \neq S^*$, there must exist a card $c_a \in S'$ with $c_a \notin S^*$, and a corresponding card $c_b \in S^*$ with $c_b \notin S'$. By the definition of $S^*$, $w_b \geq w_a$, since every card in $S^*$ has an effective value at least as large as any card outside $S^*$. Replacing $c_a$ with $c_b$ in $S'$ therefore yields a set with a total score no smaller than $\text{Score}(S')$. Repeating this exchange for every such pair transforms $S'$ into $S^*$ without decreasing the total score, contradicting the assumption that $\text{Score}(S') > \text{Score}(S^*)$. Therefore, $S^*$ is optimal.

This proof establishes that a Greedy algorithm selecting the 5 cards with the highest effective value $w_i$ is guaranteed to produce the optimal solution, for both the non-event and event scoring conditions. The algorithmic implementation of this strategy is presented in Section III.

**Character uniqueness constraint.** The game enforces an additional restriction: at most one card per character may be selected into a team, i.e., for any two cards $c_i, c_j \in S$ with $i \neq j$, $\text{name}_i \neq \text{name}_j$, even if multiple cards of the same character are owned. Since the dataset used in this study (Section III.D) includes multiple cards belonging to the same Morfonica members under different titles, this constraint is directly active in the primary experiment, not merely a theoretical edge case.

This constraint partitions the candidate set $C$into disjoint groups $C_1, C_2, \ldots, C_m$ by character name, with the restriction that at most one card may be selected from each group. This structure is known in combinatorial optimization as a **partition matroid** [4]. For a partition matroid, the Greedy algorithm, which processes candidates in non-increasing order of $w_i$ and skips any candidate whose group already has a selected representative, is known to always produce an optimal solution [4].

Consequently, the optimality result established above must be restated under this constraint: $S^*$is optimal not necessarily as the unconstrained top-5 cards by $w_i$, but as the top-5 *feasible* cards by $w_i$, where feasibility requires at most one card per character. The Greedy procedure in Section III.E (Algorithm 1) implements this through the feasibility check on line 9, which is therefore not a redundant safeguard but an essential component of correctness for the dataset used in this study. Section IV presents empirical cases in which this feasibility check causes a higher-$w_i$ card to be skipped in favor of a lower-$w_i$ card from an unused character.

## III. Methodology

*A. Card Data Representation*

Each card in the dataset is represented using the following attributes:

TABLE I. Card Data Representation

| ***Field*** | ***Description*** |
|---|---|
| card_id | Unique identifier for the card |
| name | Character's full name (e.g., "Mashiro Kurata", "Rui Yashio") |
| title | Card title as it appears in-game |
| band | The character's band |
| attribute | Pure, Cool, Powerful, or Happy |
| rarity | 3★, 4★, or 5★ |
| power, technique, visual | Base stats obtained directly from Bestdori |
| skill_description | Original in-game skill text |
| is_event_char | Whether the card's character matches the event's bonus character |
| is_event_attr | Whether the card's attribute matches the event's bonus attribute |

### *B. Skill Value Mapping*

Unlike Power, Technique, and Visual, skill effects in BanG Dream do not have a standardized numerical value provided by the game. To enable quantitative comparison, this study restricts the dataset to cards with a single skill category, namely $Score\ Up$, and defines a discrete mapping $Sk_i$ based on the skill's score percentage as follows:

- Skill description: Score increased by 130% for 7 seconds, $Sk_i = 3$
- Skill description: Score increased by 100% for 7 seconds, $Sk_i = 2$
- Skill description: Score increased by 60% for 7 seconds, $Sk_i = 1$

This restriction limits skill variation to three discrete tiers, ensuring that differences in team score are primarily driven by Power, Technique, Visual, and the event multiplier $M_i$, rather than by an uncontrolled diversity of skill effects. The duration is held constant at 7 seconds across all mapped skills, so that the mapping depends solely on the score percentage.

### *C. Event Bonus Criteria*

For the event scenario, the bonus character is set to the **Morfonica** band, and the bonus attribute is set to **Happy**. Under this configuration, each card in the dataset receives a multiplier $M_i$according to Section II.C, depending on whether its band matches Morfonica ($\mathrm{char}_i$) and/or its attribute matches Happy ($\mathrm{attr}_i$).

### *D. Dataset Construction*

A sample of $n = 20$cards is curated from Bestdori, an open BanG Dream! card database, satisfying the following criteria:

1. At least 5 cards belong to the Morfonica band (candidates for the bonus character multiplier).
2. At least 5 cards have the Happy attribute (candidates for the bonus attribute multiplier).
3. Rarity is distributed across 3★, 4★, and 5★, allowing the analysis to examine whether lower-rarity bonus cards can outperform higher-rarity non-bonus cards under event conditions.
4. Each character is represented by at most two cards in the dataset (one with the Happy attribute, one without), resulting in 15 distinct characters across 20 cards. This deliberately exercises the character uniqueness constraint described in Section II.D within the primary experiment, rather than treating it as a theoretical edge case.
5. All cards carry a Score Up skill, mapped according to the scheme described in Section III.B.

### *E. Greedy Algorithm for Card Team Selection*

Following the Greedy framework defined in Section II.A, the algorithm is specified as:

1. Candidate set ($C$): the 20-card dataset.
2. Selection function: select the candidate with the highest effective value $w_i = (P_i + T_i + V_i + Sk_i) \cdot M_i$.
3. Feasibility function: a candidate is feasible if its name has not already been selected into $S$.
4. Solution function: $S$is complete when $|\ S\ | = 5$.
5. Objective function: maximize $\sum_{i \in S} w_i$.

The procedure is given in Algorithm 1.

```
Algorithm 1: GREEDY_CARD_SELECT(C, k=5, is_event)
Input:  C (candidate cards), k (team size), is_event (boolean)
Output: S (selected team)
for each card in C:
    compute w[card] = (P+T+V+Sk) × M(card, is_event)
sort C in descending order of w
S ← ∅
used_names ← ∅
for card in C:
    if |S| = k: break
    if card.name ∉ used_names:
        S ← S ∪ {card}
        used_names ← used_names ∪ {card.name}
return S
```

This procedure runs in $O(n\log\ n)$ time due to the sorting step, followed by a single $O(n)$ pass through the sorted candidates.

### *F. Experimental Scenarios*

Three scenarios are evaluated using the dataset described in Section III.D:

1. Non-event scenario: $M_i = 1.0$for all cards; the team is selected purely based on $P_i + T_i + V_i + Sk_i$.
2. Event scenario: $M_i$is computed per Section III.C, using the Morfonica/Happy bonus configuration.
3. Threshold scenario: pairs of bonus and non-bonus cards with varying stat differences are compared to determine the minimum stat advantage required for a

non-bonus card to outperform a bonus card, as derived in Section IV.

For each scenario, the Greedy algorithm's output is validated against a brute-force exhaustive search over all $\binom{20}{5}$ combinations to confirm optimality.

Unlike the dataset configuration discussed in Section II.D's general formulation, the dataset used in this study (Section III.D) deliberately includes multiple cards sharing the same character name, specifically among the Morfonica members, in order to satisfy the event bonus criteria for both character and attribute multipliers. As a result, the feasibility check on line 9 of Algorithm 1 is expected to be triggered during execution: whenever two cards of the same character both rank among the top candidates by $w_i$, only the higher-ranked one is admitted into $S$, while the lower-ranked one is skipped regardless of its $w_i$value. This behavior is essential for producing a valid team composition, since the underlying game mechanics do not permit two cards of the same character to be selected simultaneously. The specific instances in which this skip occurs, and their effect on the resulting team's total score, are reported in Section IV.

## IV. Results and Analysis

### A. Dataset Overview

The experiment uses a 20-card dataset obtained from Bestdori, configured with **Morfonica** as the bonus character and **Happy** as the bonus attribute for the event scenario. The dataset deliberately includes two cards for each of the five Morfonica members (one under the Happy attribute, one under a different attribute), so that the character uniqueness constraint described in Section II.D is directly exercised. As a result, the 20 cards span only **15 distinct characters**, not 20. The full dataset and source code are available in the GitHub repository referenced in the Appendix.

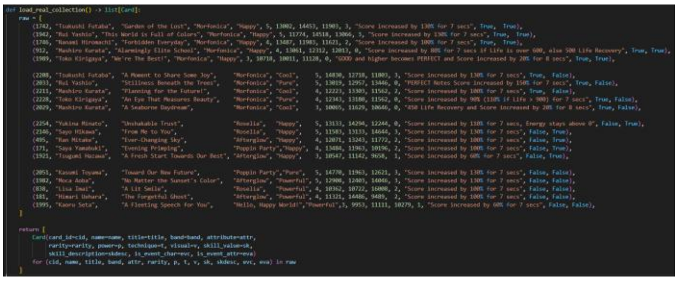

Figure IV-1. Band Dream Card Dataset Definition

### B. Non-Event Scenario

Table II shows the team selected by Algorithm 1 under non-event conditions ($M_i = 1.0$ for all cards).

```
==============================================================================
  [SKIP] 'This World is Full of Colors' (Rui Yashio) - slot already filled, w_i=39361

==============================================================================
  GREEDY TEAM [NON-EVENT]
==============================================================================
  #  Name             Title                             Stat  Mult      w_i
  ----------------------------------------------------------------------------
  1  Yukina Minato    Unshakable Trust                 39671   1.0    39671
  2  Rui Yashio       Stillness Beneath the Trees      39422   1.0    39422
  3  Sayo Hikawa      From Me to You                   39363   1.0    39363
  4  Tsukushi Futaba  Garden of the Lost               39361   1.0    39361
  5  Moca Aoba        No Matter the Sunset's Colo...   39360   1.0    39360
  ----------------------------------------------------------------------------
  TOTAL SCORE                                                        197177

  Cards SKIPPED (character slot already filled):
    - 'This World is Full of Colors' (Rui Yashio), w_i=39361

  [VALIDATION NON-EVENT] Greedy=197177  BruteForce=197177  -> MATCH (Greedy optimal)
```

Figure IV-2. program output for the non-event scenario

TABLE II. Greedy Team Non-Event

| ***No*** | ***Name*** | ***Title*** | ***Stat*** | $w_i$ |
|---|---|---|---|---|
| 1 | Yukina Minato | Unshakable Trust | 39,671 | 39,671 |
| 2 | Rui Yashio | Stillness Beneath the Trees | 39,422 | 39,422 |
| 3 | Sayo Hikawa | From Me to You | 39,363 | 39,363 |
| 4 | Tsukushi Futaba | Garden of the Lost | 39,361 | 39,361 |
| 5 | Moca Aoba | No Matter the Sunset's Color | 39,360 | 39,360 |
| | | ***Total*** | | ***197,177*** |

Brute-force search over all valid combinations confirms this result is optimal (197,177 = 197,177).

**Character constraint in effect.** Prior to applying the feasibility check, the unconstrained ranking placed a second Rui Yashio card, *"This World is Full of Colors"* ($w_i = 39{,}361$), at rank 5. Since Rui Yashio's character slot was already filled by *"Stillness Beneath the Trees"* at rank 2, this card was skipped, and *"No Matter the Sunset's Color"* ($w_i = 39{,}360$) was selected instead. This confirms that the feasibility check on line 9 of Algorithm 1 is not a redundant safeguard: it actively alters the outcome, even though the score difference between the skipped and selected card is marginal (1 point).

```
for card in candidates:
    if len(selected) >= team_size:
        break
    if card.name not in used_names:
        selected.append(card)
        used_names.add(card.name)
    else:
        skipped.append(card)
        if verbose:
            print(f"  [SKIP] '{card.title}' ({card.name}) - "
                  f"slot already filled, w_i={card.effective_value(is_event):.0f}")

total_score = sum(c.effective_value(is_event) for c in selected)
return selected, total_score, skipped
```

Figure IV-3. the feasibility-check segment of Algorithm 1's implementation

### C. Event Scenario

Table III shows the team selected under event conditions, using the Morfonica/Happy bonus configuration.

```
==========================================================================
 GREEDY TEAM [EVENT]
==========================================================================
 #  Name              Title                          Stat  Mult     w_i
 ------------------------------------------------------------------------
 1  Tsukushi Futaba   Garden of the Lost             39361   1.5   59042
 2  Rui Yashio        This World is Full of Color...  39361   1.5   59042
 3  Mashiro Kurata    Alarmingly Elite School        37386   1.5   56079
 4  Nanami Hiromachi  Forbidden Everyday             37093   1.5   55640
 5  Toko Kirigaya     We're The Best!                31857   1.5   47786
 ------------------------------------------------------------------------
 TOTAL SCORE                                                      277587

 No cards skipped due to character uniqueness constraint.

 [VALIDATION EVENT] Greedy=277587  BruteForce=277587  -> MATCH (Greedy optimal)
```

Figure IV-4. program output for the event scenario

TABLE III. Greedy Team Event (Bonus: Morfonica × Happy)

| *No* | *Name* | *Title* | *Stat* | $M_i$ | $w_i$ |
|---|---|---|---|---|---|
| 1 | Tsukushi Futaba | Garden of the Lost | 39,361 | 1.5 | 59,042 |
| 2 | Rui Yashio | This World is Full of Colors | 39,361 | 1.5 | 59,042 |
| 3 | Mashiro Kurata | Alarmingly Elite School | 37,386 | 1.5 | 56,079 |
| 4 | Nanami Hiromachi | Forbidden Everyday | 37,093 | 1.5 | 55,640 |
| 5 | Toko Kirigaya | We're The Best! | 31,857 | 1.5 | 47,786 |
| | | ***Total*** | | | ***277,587*** |

Brute-force search again confirms optimality (277,587 = 277,587). Notably, all five selected cards belong to the five Morfonica members under the Happy attribute, each receiving the maximum 1.5× multiplier. No skip occurs in this scenario, since each character contributes at most one bonus-eligible card.

## *D. Team Composition Shift*

Table IV compares the two scenarios directly.

```
========================================================================
 TEAM COMPOSITION CHANGE: NON-EVENT -> EVENT
========================================================================
 Cards unchanged : 1
 Cards replaced  : 4
   OUT: 'Unshakable Trust' (Yukina Minato), stat=39671, mult=1.0, w_i=39671
   IN : 'This World is Full of Colors' (Rui Yashio), stat=39361, mult=1.5, w_i=59042
   OUT: 'Stillness Beneath the Trees' (Rui Yashio), stat=39422, mult=1.0, w_i=39422
   IN : 'Alarmingly Elite School' (Mashiro Kurata), stat=37386, mult=1.5, w_i=56079
   OUT: 'From Me to You' (Sayo Hikawa), stat=39363, mult=1.0, w_i=39363
   IN : 'Forbidden Everyday' (Nanami Hiromachi), stat=37093, mult=1.5, w_i=55640
   OUT: 'No Matter the Sunset's Color' (Moca Aoba), stat=39360, mult=1.0, w_i=39360
   IN : 'We're The Best!' (Toko Kirigaya), stat=31857, mult=1.5, w_i=47786
```

Figure IV-5. program output showing which cards were replaced when transitioning from non-event to event scenario

TABLE IV. Cards Replaced Between Non-Event and Event Teams

| *Removed (non-event)* | *Stat* | *Added (event)* | *Stat* | $M_i$ | $w_i$ |
|---|---|---|---|---|---|
| Yukina Minato, "*Unshakable Trust*" | 39,671 | Rui Yashio, "*This World is Full of Colors*" | 39,361 | 1.5 | 59,042 |
| Rui Yashio, "*Stillness Beneath the Trees*" | 39,422 | Mashiro Kurata, "*Alarmingly Elite School*" | 37,386 | 1.5 | 56,079 |
| Sayo Hikawa, "*From Me to You*" | 39,363 | Nanami Hiromachi, "*Forbidden Everyday*" | 37,093 | 1.5 | 55,640 |
| Moca Aoba, "*No Matter the Sunset's Color*" | 39,360 | Toko Kirigaya, "*We're The Best!*" | 31,857 | 1.5 | 47,786 |

This result illustrates the central claim of this paper: under event conditions, cards with substantially lower base stats can outrank cards with higher base stats once the multiplier is applied. The most extreme case is Toko Kirigaya's *"We're The Best!"* (stat 31,857), which replaces Moca Aoba's *"No Matter the Sunset's Color"* (stat 39,360), a stat disadvantage of 7,503 points, fully compensated by the 1.5× event multiplier ($31{,}857 \times 1.5 = 47{,}786 > 39{,}360$).

## *E. Breakeven Threshold Analysis*

```
========================================================================
 BREAKEVEN ANALYSIS (minimum non-bonus stat to outperform a bonus card)
========================================================================
   Bonus card base_stat |  1.5x threshold |  1.2x threshold |  1.1x threshold
  ---------------------------------------------------------------------------
                38,000 |          57,000 |          45,600 |          41,800
                40,000 |          60,000 |          48,000 |          44,000
                42,000 |          63,000 |          50,400 |          46,200
                44,000 |          66,000 |          52,800 |          48,400
```

Figure IV-6. output for the breakeven threshold analysis

To quantify this trade-off more generally, Table V reports the minimum base stat a non-bonus card ($M_i = 1.0$) must have to outperform a bonus card of a given base stat, for each multiplier tier, computed as threshold = bonus_stat × $M_i$.

TABLE V. Breakeven Thresholds

| *Bonus card base stat* | *1.5× threshold* | *1.2× threshold* | *1.1× threshold* |
|---|---|---|---|
| 38,000 | 57,000 | 45,600 | 41,800 |
| 40,000 | 60,000 | 48,000 | 44,000 |
| 42,000 | 63,000 | 50,400 | 46,200 |
| 44,000 | 66,000 | 52,800 | 48,400 |

Within the observed stat range of this dataset (approximately 30,000-40,000), no non-bonus card can realistically reach the 57,000-66,000 threshold required to outperform a fully-bonused (1.5×) card. This explains why the event-optimal team in Table III consists entirely of Morfonica/Happy cards: at the 1.5× tier, the multiplier advantage is large enough that no available non-bonus card in the dataset can compensate for it. The 1.1× and 1.2× thresholds are comparatively closer to the dataset's stat range, suggesting that for single-criterion bonuses, a high-stat non-bonus card has a more realistic chance of remaining competitive.

## *F. Algorithm Efficiency*

For $n = 20$ candidate cards, brute-force search evaluates $\binom{20}{5} = 15{,}504$ combinations (before filtering combinations that violate the character constraint), whereas Algorithm 1 requires only a single $O(n\log n)$ sort followed by an $O(n)$ feasibility pass. Both approaches produced identical optimal scores in both scenarios (Sections IV.B and IV.C), empirically confirming the optimality result formalized in Section II.D.

## V. CONCLUSION

This paper formalized the team selection problem in BanG Dream! Girls Band Party as a combinatorial optimization problem under both non-event and event scoring conditions, and implemented a Greedy algorithm to solve it. Three main conclusions can be drawn from this study.

First, the card selection problem exhibits a separable structure: the effective value $w_i$ of each card depends only on that card's own attributes and not on which other cards are selected, which allows the optimal team to be obtained through a simple exchange argument (Section II.D). When combined with the game's character uniqueness constraint, the problem forms a partition matroid, for which the Greedy algorithm remains provably optimal. This was empirically confirmed in Section IV.B, where the feasibility check skipped a higher-ranked card in favor of a lower-ranked one from an unused character, and validated against brute-force search across both scenarios (Sections IV.B and IV.C), with identical optimal scores obtained in each case.

Second, the event multiplier significantly reshapes the optimal team composition. Four of the five cards selected under non-event conditions were replaced once the Morfonica/Happy bonus was applied (Section IV.D), with the most extreme case showing a card with a 7,503-point stat disadvantage outperforming a higher-stat non-bonus card once the 1.5× multiplier was applied. This demonstrates that maximizing raw stats alone is an event-blind strategy that can lead to substantially suboptimal team choices.

Third, the breakeven threshold analysis (Section IV.E) quantified this trade-off: within the dataset's observed stat range, no non-bonus card could realistically compensate for the 1.5× multiplier, whereas the 1.1× and 1.2× thresholds were comparatively more attainable. This indicates that the practical impact of event bonuses is highly tier-dependent, with dual-criterion bonuses (matching both character and attribute) creating a substantially larger competitive gap than single-criterion bonuses.

Overall, these results show that optimal card team selection in BanG Dream! Girls Band Party cannot be reduced to a static stat-maximization problem; it requires accounting for both the game's structural constraints and its event-driven scoring mechanics. The Greedy algorithm proposed in this paper handles both requirements efficiently, running in $O(n\log n)$time, in contrast to the combinatorial cost of brute-force search.

Future work may extend this study by incorporating a wider range of skill types beyond Score Up, by modeling team-wide skill interactions rather than treating skill values independently, or by validating the breakeven thresholds derived in Section IV.E against a larger and more diverse card collection.

## APPENDIX

The complete program implementation code can be seen at the following link: https://github.com/Minaqu28/Greedy-BangDream


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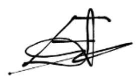
## STATEMENT

I hereby declare that the paper I wrote is my own writing, not an adaptation or translation of someone else's paper, and is not plagiarized.

Bandung, 19 Juni 2026



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