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Worst-case Conditional Hardness and Fast Algorithms with Random Inputs for Non-dominated Sorting *

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ABSTRACT

We study the computational complexity of the non-dominated sorting problem (NDS): Given a set P of n points in \mathbb{R}^m , for each point $p \in P$, compute ℓ , the length of longest domination chain $p_1 \succ p_2 \succ \dots \succ p_\ell = p$, where x dominates y (denoted as $x \succ y$) if x is not larger than y in every coordinate. A special case of NDS, which we label as NDS1, is to find all the non-dominated points in P . NDS has emerged as a critical component for multi-objective optimization problems (MOPs). For $m \leq 3$, $\Theta(n \log n)$ -time is known. For a fixed small $m > 3$, the best bound is $O(n \log^{m-2} n \log \log n)$. For larger m , the best result is an $O(mn^2)$ -time algorithm.

We show that the $O(mn^2)$ running time is nearly optimal by proving an almost matching conditional lower bound: for any $\epsilon > 0$, and $\omega(\log n) \leq m \leq (\log n)^{O(1)}$, there is no $O(mn^{2-\epsilon})$ -time algorithm for NDS or NDS1 unless a popular conjecture in fine-grained complexity theory is false. To complete our results, we present an algorithm for NDS with an expected running time $O(mn + n^2/m + n \log^2 n)$ on uniform random inputs.

CCS CONCEPTS

• **Theory of computation** → **Algorithm design techniques**;

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1 INTRODUCTION AND RELATED WORK

We study the computational complexity of the non-dominated sorting problem (NDS). Let P be a set of n points in \mathbb{R}^m . We say that a point p dominates¹ another point q , denoted by $p \succ q$, if $p_i \leq q_i$ for positive $i \leq m$, i.e., p is no larger than q in every coordinate and $p \neq q$. Note that it is possible that neither p nor q dominates the other point. A point p is *non-dominated* w.r.t. P if p is not dominated by any other points in P . Given a set of P points, the non-dominated sorting problem asks to compute the *rank function* $R : P \rightarrow \mathbb{N}$ defined as follows: $R(p) = 1$ if p is a non-dominated point, and $R(p) = 1 + \max\{R(q) : q \succ p\}$, otherwise. A widely used variant of NDS, which we label NDS1, is to find all $p \in P$ such that $R(p) = 1$.

Non-dominated sorting has emerged as a critical component for multi-objective optimization problems (MOPs). In contrast to single objective optimization where we try to find the best possible solution, the desired result of an MOP is typically a set of Pareto-optimal solutions that reflect the trade-offs among different objectives. An NDS algorithm is a computational bottleneck for multi- and many-objective evolutionary algorithms (MOEAs). NDS1 has broader applications beyond MOEAs, notably including skyline query in database [6].

The non-dominated sorting problem is completely solved when $m = 2$ or 3 with a worst-case time complexity of $\Theta(n \log n)$ [7, 9]. For a fixed $m > 2$, $O(n \log^{m-1} n)$ -time algorithms are known using divide-and-conquer (D&C), often referred to as Jensen's sort [5], and the best known running time for this approach is $O(n \log^{m-2} n \log \log n)$ -time algorithm [1]. For general m , the first $O(mn^2)$ -time algorithm is due to Deb *et al.* [2]. Since then there have been several algorithms achieving the same worst-case bounds, but focusing on practical running time [3, 4, 8, 10, 11, 13]. Until now, the $O(mn^2)$ -time bound has stood for almost two decades. Further note that NDS1 does not have a known faster solution.

1.1 Our Results

We show that the running time $O(mn^2)$ is essentially optimal assuming the *Hitting Set Conjecture* (HSC) is true. The Hitting Set Problem (HS) is defined as follows: Given two families of sets A and B containing n sets each over the universe $\{1, \dots, m\}$ where

¹we use notion of $p_i \leq q_i$ to be consistent with the MOEA community where, in the context of minimization, the point p is better when every coordinate is smaller than q .

$m = \omega(\log n)$, decide if there exists a set $a \in A$ that intersects (hits) every set $b \in B$ in at least one element. If we use binary vectors to represent sets, the HS problem is equivalently defined as follows: Given two sets A and B of vectors over $\{0, 1\}^m$ where $m = \omega(\log n)$, decide if there exists a vector $a \in A$ such that for all $b \in B$, $\sum_{i=1}^m a_i \cdot b_i > 0$.

Hitting Set Conjecture (HSC). For any constant $\epsilon > 0$, and m where $\omega(\log n) \leq m < (\log n)^{O(1)}$, there is no $O(mn^{2-\epsilon})$ -time algorithm for the Hitting Set Problem.

To date, several hypotheses have been used to prove conditional lower bounds of “easy” problems, e.g., the *All-Pairs Shortest Paths* (APSP) conjecture, the *Orthogonal Vectors* (OV) conjecture, and the *Hitting Set* (HS) conjecture; please see [12] and references therein. We add to this growing body of fine-grained complexity results by using the HSC to prove our main result.

THEOREM 1.1. *For any constant $\epsilon > 0$, and m where $\omega(\log n) < m < (\log n)^{O(1)}$, there is no $O(mn^{2-\epsilon})$ -time algorithm for NDS or NDS1 unless the HSC is false.*

While our result, assuming the HSC is true, rules out any chance of significantly improving the $O(mn^2)$ worst case bound, there are ways to get better results. We list two here. First, there may exist an algorithm with worst case running time $O(mn^2 / \log^{O(1)} n)$. Second, algorithms may perform better on restricted input instances. We now give our second result which exploits the second option.

THEOREM 1.2. *Under the uniform random input assumption, there is an algorithm that takes as input a set of points P in \mathbb{R}^m , and outputs the rank function (as defined in the NDS problem) in expected time $O(n^2/m + mn + n \log^2 n)$.*

PROOF SKETCH. The algorithm is a variant of the Best Order Sort (BOS) algorithm from [10]. The key intuition is that for random inputs, the expected running time of BOS improves by roughly an m^2 factor for two reasons. First, most points are mutually non-dominated, and verifying this takes only $O(1)$ (instead of m) expected time. Second, all points are ranked after exploring $O(n/m)$ (instead of n) expected points. \square

2 CONDITIONAL HARDNESS OF NON-DOMINATED SORTING

To prove Theorem 1.1, we introduce the following problem.

Bichromatic Binary Non-Dominating Problem (BBND).

Given two sets of points A and B where (i) $|A| = |B| = n$ and (ii) each point is a vector over $\{0, 1\}^m$ where $m = \omega(\log n)$, decide if there exists a point $a \in A$ that is not dominated (i.e., there exists a positive $i \leq m$ such that $a_i < b_i$) by any point $b \in B$.

LEMMA 2.1 (REDUCTION FROM HS TO BBND). *If BBND can be solved in time $T(m, n)$, then HS can be solved in time $O(T(m, n) + mn)$.*

PROOF. We define a reduction $R(A, B) = (A', B)$ from HS to BBND using the binary vector formulation of the HS problem as follows. Set $A' := \{a' : a \in A\}$ where $a'_i = 1$ if $a_i = 0$, and $a'_i = 0$ if $a_i = 1$ for $i \leq m$. Clearly R runs in time $O(mn)$.

We now prove the completeness of R . Assume that (A, B) is a yes-instance to HS. That is, there exists $a \in A$ such that for all $b \in B$,

$\sum_{i=1}^m a_i \cdot b_i > 0$. This means there is a positive $i \leq m$ such that $a_i = b_i = 1$. By construction (since we flip bitwise from a to a'), for the same i , we have $a'_i = 0$ and $b_i = 1$, so $a'_i < b_i$. This holds for every $b \in B$. Therefore, this particular vector $a' \in A'$ is not dominated by any $b \in B$, so (A', B) is a yes-instance for BBND.

We now prove the soundness of R . Assume that (A', B) is a yes-instance to BBND. So, there is a point $a' \in A'$ that is not dominated by any point $b \in B$. This means for each $b \in B$, there is a positive $i \leq m$ such that $a'_i < b_i$. Since a' and b are binary vectors, this implies $a'_i = 0$ and $b_i = 1$. By construction, we have $a_i = 1$ and $b_i = 1$ for the same i . This holds for every $b \in B$. Hence, this vector a has the property that $\sum_{i=1}^m a_i \cdot b_i > 0$ for all $b \in B$, so (A, B) is a yes-instance for HS. \square

Next we solve BBND using an NDS1 algorithm. The following lemma is obvious.

LEMMA 2.2. *The input (A, B) for BBND is a yes-instance if and only if there exists $a \in A$ such that $R_{A \cup B}(a) = 1$ in the solution population $A \cup B$ where $R_{A \cup B}(p)$ is the rank of a solution p in the population $A \cup B$.*

We now prove Theorem 1.1.

PROOF OF THEOREM 1.1. By Lemma 2.1, it is enough to solve the BBND problem in time $O(mn^{2-\epsilon})$. If there is an $O(mn^{2-\epsilon})$ -time algorithm for NDS1, we solve BBND in time $O(mn^{2-\epsilon})$ as follows: Given an instance (A, B) , we find all the elements of $A \cup B$ with rank 1 and output yes if there is an $a \in A$ in this set and no otherwise. The correctness follows immediately from Lemma 2.2. \square

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