

Strong Low Degree Hardness for the Number Partitioning Problem

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Abstract

Finding good solutions to the *number partitioning problem (NPP)* – that is, finding a partition of a set of N numbers to minimize the discrepancy between the sums of the two subsets – is a well-studied optimization problem, with applications to statistics, physics, and computer science. Along with having numerous practical applications in the design of randomized control trials and processor scheduling, the NPP is famous for possessing a *statistical-to-computational gap*: assuming the N numbers to be partitioned are i.i.d. standard Normal random variables, the optimal discrepancy is $2^{-\Theta(N)}$ with high probability, but the best polynomial-time algorithms only find solutions with a discrepancy of $2^{-\Theta(\log^2 N)}$. This gap is a common feature in optimization problems over random combinatorial structures, and indicates the need for a theory of computational complexity beyond worst-case analysis.

In this thesis, we prove a strong form of algorithmic hardness for the number partitioning problem, aiming to establish that this statistical-to-computational gap is an intrinsic feature of the NPP. We study *low degree algorithms*, as they provide both tunable stability behavior and are tractable models for a broad class of algorithms, under the widely successful *low degree heuristic*. Then, we establish a *brittleness property* on the geometry of the solution set, which ensures that stable algorithms are unable to efficiently traverse this random landscape. By combining these notions, we are able to show *strong low degree hardness*, in that low degree algorithms will fail to find good solutions with high probability. In addition, while we show that low degree polynomial algorithms are structurally ill-suited to the NPP, our results for the more general class of *low coordinate degree algorithms* demonstrate a sharp tradeoff between algorithmic runtime (vis-à-vis algorithmic complexity) and solution discrepancy, which our analysis suggests is optimal.

Finally, we establish a *repulsion property*, giving a precise tradeoff between the discrepancy of a solution to a fixed instance and its distance to other solutions. We then leverage this to show that any algorithm fed through a truly randomized rounding scheme will fail to find solutions with high probability. This work demonstrates the effectiveness of using landscape properties to address questions about algorithmic hardness, and suggests interesting directions for future study.

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1 Introduction

Suppose that we have N items, each with associated weights. How should we divide these items into two groups so that the sum of their weights is as close as possible? Or, is it possible to divide these items into two groups such that the absolute difference of the sums of their weights is below a certain threshold? This question is known as the *number partitioning problem (NPP)*, and has been a subject of fascination in statistics, physics, and computer science since its proposal in 1969 [39].

Formally, let g_1, \dots, g_N be N real numbers. The NPP is the problem of finding the subset A of $[N] := \{1, 2, \dots, N\}$ which minimizes the discrepancy

$$\left| \sum_{i \in A} g_i - \sum_{i \notin A} g_i \right|.$$

Alternatively, identify the instance g_1, \dots, g_N with a point $g \in \mathbf{R}^N$. Then, choosing a subset $A \subseteq [N]$ is equivalent to choosing a point x in the N -dimensional binary hypercube $\Sigma_N := \{\pm 1\}^N$, where $x_i = +1$ is the same as including $i \in A$. The discrepancy of x is now $|\langle g, x \rangle|$, and solving the NPP means finding the x minimizing this discrepancy:

$$\min_{x \in \Sigma_N} |\langle g, x \rangle|. \tag{1.1}$$

Rephrased as a decision problem – whether there exists a subset $A \subseteq [N]$ (or a point $x \in \Sigma_N$) such that the discrepancy is zero, or sufficiently small – the NPP is NP-complete; this can be shown by reduction from the subset sum problem. In fact, the NPP is one of the six basic NP-complete problems of Garey and Johnson, and of those, the only one involving numbers [35, § 3.1].

Finding “good” solutions to this problem has a number of practical applications. For instance,

the NPP and MWNPP¹ were first formulated by Graham, who considered it in the context of multi-processor scheduling: dividing a group of tasks with known runtimes across a pool of processors so as to minimize one core being overworked while others stall [39]. Later work by Coffman, Garey, and Johnson, as well as Tsai, looked at utilizing algorithms for the NPP for designing multiprocessor schedulers or large integrated circuits [22], [88]. Coffman and Lueker also write on how the NPP can be applied as a framework for allocating material stocks, such as steel coils in factories, paintings in museums, or advertisements in newspapers [24].

One particularly important application of the NPP in statistics comes from the design of *randomized controlled trials*. Consider N individuals, each with a set of covariate information $g_i \in \mathbf{R}^d$. Then the problem is to divide them into a treatment group (denoted A_+) and a control group (denoted A_-), subject each to different conditions, and evaluate the responses. In order for such a trial to be accurate, it is necessary to ensure that the covariates across both groups are roughly the same. In our notation, this equates to finding an A_+ (with $A_- := [N] \setminus A_+$) minimizing

$$\min_{A_+ \subseteq [N]} \left\| \sum_{i \in A_+} g_i - \sum_{i \in A_-} g_i \right\|_{\infty}. \quad (1.2)$$

This extension of the NPP is often termed the *vector balancing problem* (VBP), and many algorithms for solving the NPP/VBP come from designing such randomized controlled trials [57], [46].

On the other hand, in 1976, Merkle and Hellman devised one of the earliest public key cryptography schemes, deriving its hardness from their belief that a variant of the NPP was computationally difficult to solve – at the time, it was not yet known whether the NPP was NP-complete or not [75]. Their proposal was for the receiver, say Alice, to generate as a public key N natural numbers (a_1, \dots, a_N) , with N typically around 100 and each a_i around 200 bits long. To encrypt a N -bit message $x = (x_1, \dots, x_N) \in \{0, 1\}^N$, the sender, say Bob, could compute

$$b := \sum_{i \in N} a_i x_i$$

and send the ciphertext b to Alice. Any eavesdropper would know a_1, \dots, a_N , as well as b , and decrypting the message involved finding a subset of the a_i adding up to b . This is known as the *knapsack problem*, which is NP-complete, as can be shown by restriction to the NPP [35, 3.2.1(6)]. However, such NP-completeness is only a worst-case hardness guarantee; Merkle and Hellman’s scheme involved Alice choosing a_1, \dots, a_N by cryptographically scrambling a sequence (a'_1, \dots, a'_N) for which solving the NPP was easy, enabling the receiver to practically decrypt the message x from the ciphertext b . In 1984, Shamir – one of the developers of the RSA cryptosystem still in use today – showed that one could exploit this public key generation process to reduce the “hard” knapsack problem to one which was solvable in polynomial time, rendering the Merkle-Hellman scheme insecure [85]. While today, Merkle-Hellman is but a footnote in the history of cryptography, it demonstrates the importance of looking beyond worst-case hardness and expanding complexity theory to describe the difficulty of the average problem instance.

¹That is, the *multiway number partitioning problem* (MWNPP), in which we want to partition g_1, \dots, g_N into M subsets such that the within-subset sums are mutually close; what “mutually close” means precisely varies across the literature.

Meow moe wmeow. Another major source of interest in the NPP, as well as potential explanations for when it is hard, come from statistical physics. In the 1980s, Derrida introduced the eponymous *random energy model* (REM), a simplified example of a spin glass in which, unlike the Sherrington-Kirkpatrick or other p -spin glass models, the possible energy levels are independent of each other [27], [28], [14]. Despite this simplicity, this model made possible heuristic analyses of the Parisi theory for mean field spin glasses, and it was suspected that arbitrary random discrete systems would locally behave like the REM [15], [60]. The NPP was the first system for which this local REM conjecture was shown [17], [18]. In addition, in the case when the g_i are independently chosen uniformly over $\{1, 2, \dots, 2^M\}$, Gent and Walsh conjectured that the hardness of finding perfect partitions (i.e., with discrepancy zero if $\sum_i g_i$ is even, and one else) was controlled by the parameter $\kappa := \frac{m}{n}$ [42], [41]. Mertens soon gave a nonrigorous statistical mechanics argument suggesting the existence of a phase transition from $\kappa < 1$ to $\kappa > 1$; that is, while solutions exist in the low κ regime, they stop existing in the high κ regime [73]. It was also observed that this phase transition coincided with the empirical onset of computational hardness for typical algorithms, and Borgs, Chayes, and Pittel proved the existence of this phase transition soon after [47], [13].

1.1 The Statistical-to-Computational Gap

Many problems involving searches over random combinatorial structures (i.e., throughout high-dimensional statistics) exhibit a statistical-to-computational gap: the optimal values which are known to exist via non-constructive, probabilistic methods are far better than those achievable by state-of-the-art algorithms. In the pure optimization setting, examples such gaps are found in random constraint satisfaction [77], [1], [66], finding maximal independent sets in sparse random graphs [40], [21], the largest submatrix problem [38], [36], and the p -spin and diluted p -spin models [34], [23]. These gaps also arise in various “planted” models, such as matrix or tensor PCA [20], [68], [69], [53], [50], [3], high-dimensional linear regression [43], [44], or the infamously hard planted clique problem [54], [30], [78], [10], [45]. These indicate that these problems are “hard” in a way that goes beyond being NP; algorithms fail even on average-case instances.

The NPP is no exception: despite its apparent simplicity, its persistent importance in the random optimization literature comes from the shocking width of its associated statistical-to-computational gap. On the statistical side, the landmark result here is by Karmarkar et al., who showed that when the g_i are i.i.d. random variables, with distribution sufficiently nice,² then the minimum discrepancy of (1.1) is $\Theta(\sqrt{N}2^{-N})$ with high probability as $N \rightarrow \infty$ [58]. Their result also extends to *even partitions*, where the sizes of each subset is equal (i.e., for N even), worsening only to $\Theta(N2^{-N})$. Yet the best known algorithms cannot achieve discrepancies close to this in polynomial time.

A first approach to the NPP, often termed the *greedy heuristic*, would be to sort the N inputs, place the largest in one subset, and place the subsequent largest numbers in the subset with the smaller total running sum. This takes $O(N \log N)$ time (due to the sorting step), but achieves a discrepancy of $O(N^{-1})$, extremely far off from the statistical optimum [74]. More recently, Krieger et al. developed an algorithm achieving a discrepancy of $O(N^{-2})$, but in exchange for this poor performance, their algorithm solves for a balanced partition, making it useful for randomized control trials [57].

²Specifically, having bounded density and finite fourth moment.

The true breakthrough towards the statistical optimum came from Karmarkar and Karp, whose algorithm produced a discrepancy of $O(N^{-\alpha \log N}) = 2^{-O(\log^2 N)}$ with high probability. Their algorithm is rather complicated, involving randomization and a resampling step to make their analysis tractable, but their main contribution is the *differencing heuristic* [61]. The idea is as follows: if S is a list of items, then putting $g, g' \in S$ in opposite partitions is the same as removing g and g' and adding $|g - g'|$ back to S . Karmarkar and Karp propose two simpler algorithms based on this heuristic, the *partial differencing method* (PDM) and *largest differencing method* (LDM), which they conjectured could also achieve discrepancies of $O(N^{-\alpha \log N})$. In both, the items are first sorted, and the differencing is performed on the pairs of the largest and second largest items. However, in PDM, the remainders are ignored until all original numbers have been differenced, and then are resorted and repartitioned, while LDM reinserts the remainder in sorted order at each step; in any case, both algorithms are thus polynomial in N . Lueker soon disproved the claim that PDM could achieve the Karmarkar-Karp discrepancy, showing that when g_i were i.i.d. Uniform on $[0, 1]$, then the expected discrepancy was $\Theta(N^{-1})$, no better than the greedy algorithm [72]. However, for g_i i.i.d. Uniform or even Exponential, Yakir confirmed that LDM could achieve the performance of the original differencing algorithm, proving that its expected discrepancy was $N^{-\Theta(\log N)}$ [93]. The constant α was later estimated for LDM to be $\alpha = \frac{1}{2 \ln 2}$, via nonrigorous calculations [16].

Of course, at its most basic level, the NPP is a search problem over 2^N possible partitions, so given more and more time, an appropriate algorithm could keep improving its partition until it achieved the global optimum. To this degree, Korf developed alternatives known as the *complete greedy* and *complete Karmarkar-Karp* algorithms which, if run for exponentially long time, can find the globally optimal partition [64], [65]. This algorithm was later extended to multiway number partitioning [63]. See also Michiels et al. for extensions to balanced multiway partitioning [76].

For the multidimensional VBP case, Spencer showed in 1985 that the worse-case discrepancy of the VBP was at most $6\sqrt{N}$ for $d = N$ and $\|g_i\|_\infty \leq 1$ for all $1 \leq i \leq N$ [86]. However, his argument is an application of the probabilistic method, and does not construct such a solution. In the average case, Turner et al. proved that, under similar regularity assumptions on the g_i ,² the minimum discrepancy is $\Theta(\sqrt{N}2^{-N/d})$ for all $d \leq o(N)$, with high probability [87]. For the regime $\delta = \Theta(N)$, Aubin et al. conjecture that there exists an explicit function $c(\delta)$ such that for $\delta > 0$, the discrepancy in the $d = \delta N$ regime is $c(\delta)\sqrt{N}$ with high probability [6]. To this end, Turner et al. also showed that for $d \leq \delta N$, one can achieve $O(\sqrt{N}2^{-1/\delta})$ with probability at least 99% [87]. On the algorithmic side, they generalized the Karmarkar-Karp algorithm to VBP, which, for $2 \leq d = O(\sqrt{\log N})$ finds partitions with discrepancy $2^{-\Theta(\log^2 N/d)}$, reproducing the gap of classical Karmarkar-Karp. On the other hand, in the superlinear regime $d \geq 2N$, this average-case discrepancy worsens to $\tilde{O}(\sqrt{N \log(2d/N)})$ [26]. Yet, many proposed algorithms can achieve similar discrepancies, which is believed to be optimal for $d \geq N$ [86], [9], [70], [80].

1.2 Algorithmic Hardness and Landscape Obstructions

Classical algorithmic complexity theory – involving classes such as P, NP, etc. – is poorly suited to describing the hardness of random optimization problems, as these classes are based on the worst-case performance of available algorithms. In many cases, the statistically possible performance of solutions to random instances of these NP-complete problems will be far better than the worst-case analysis would suggest. How then, can we extend complexity theory to describe problems which, like the NPP, are hard on average? Along with the aforementioned statistical-to-computational

gaps, the past two decades of research have shown that many methods can provide evidence of this average-case hardness, such as the failure of Markov chain algorithms [54], [37], [52], the failure of approximate message passing (AMP) algorithms [94], [19], or lower bounding performance against the sum-of-squares hierarchy or the statistical query model [53], [50], [81], [10], [59], [29], [31].

One particularly interesting approach is to prove average-case to worst-case reductions: if one shows that a polynomial-time algorithm for solving random instances could be used to design a polynomial-time algorithm for arbitrary instances, then assuming the problem was known to be in NP, it can be concluded that no such polynomial-time algorithm for the average case can exist [33]. This method has been used to show hardness for sparse PCA, detecting planted independent subgraphs, and more by reducing to the random planted clique problem [20], [11], [12]. To this extent, Hoberg et al. provided such evidence of hardness for the NPP by showing that a polynomial-time approximation oracle achieving discrepancies around $O(2^{\sqrt{N}})$ could give polynomial-time approximations for Minkowski’s problem, the latter of which is known to be hard [49]. More recently, Vafa and Vaikuntanathan showed that the Karmarkar-Karp algorithm’s performance was nearly tight, assuming the worst-case hardness of the shortest vector problem on lattices [90]. Other conjectures suggested that the onset of algorithmic hardness was related to phase transitions in the solution landscapes, something which has been shown for random k -SAT, but this fails to describe hardness for optimization problems.

A more recent and widely successful approach is based on analyzing the geometry of the solution landscape. Many “hard” random optimization problems have a certain disconnectivity property, known as the *overlap gap property (OGP)* [33]. Roughly, this means there exist $0 \leq \nu_1 < \nu_2$ such that, for every two near-optimal states x, x' for a particular instance g of the problem either have $d(x, x') < \nu_1$ or $d(x, x') > \nu_2$. That is, pairs of solutions are either close to each other, or much further away – the condition that $\nu_1 < \nu_2$ ensures that the “diameter” of solution clusters is much smaller than the separation between these clusters.³ Beyond ruling out the existence of pairs of near solutions with $d(x, x') \in [\nu_1, \nu_2]$, a common extension is the *multioverlap OGP* (m -OGP): given an ensemble of m strongly correlated instances, there do not exist m -tuples of near solutions all equidistant from each other. This extension is often useful to lower the “threshold” at which the OGP starts to appear. Once established, the OGP and m -OGP, which is intrinsic to the problem, can be used to rule out the success of wide classes of stable algorithms [7], [1], [77], [40], [82], [91].

For the NPP, it was expected for decades that the “brittleness” of the solution landscape would be a central barrier in finding successful algorithms to close the statistical-to-computational gap. Mertens wrote in 2001 that any local heuristics, which only looked at fractions of the domain, would fail to outperform random search [73, § 4.3]. This was backed up by the failure of many algorithms based on locally refining Karmarkar-Karp-optimal solutions, such as simulated annealing [2], [84], [55], [56], [4]. To that end, more recent approaches for algorithmic development are rooted in more global heuristics [62], [25], [83], and some of the most interesting directions in algorithmic development for the NPP comes from quantum computing: as this is outside our scope, we encourage the interested reader to consult [8], [92]. The main result to this effect comes from Gamarnik and Kızıldağ, who proved that for m of constant order, the m -OGP for NPP held for discrepancies of $2^{-\Theta(N)}$ (i.e., the statistical optimum), but was absent for smaller discrepancies of 2^{-E_N} with $\omega(1) \leq E_N \leq$

³This is called the “overlap” gap property because, in the literature, this is often described in terms of the inner product of the solutions, as opposed to the distance between them.

$o(N)$ [37]. They do show, however, that the m -OGP in for $E_N \geq \omega(\sqrt{N \log N})$ could be recovered for m superconstant. This allowed them to prove that for $\varepsilon \in (0, 1/5)$, no stable algorithm (suitably defined) could find solutions with discrepancy 2^{-E_N} for $\omega(N \log^{-\frac{1}{5}+\varepsilon} N) \leq E_N \leq o(N)$ [37, Thm. 3.2]. These results point to the efficacy of using landscape obstructions to show algorithmic hardness for the NPP, which we will take advantage of in Section 4.4.

1.3 Our Results

In this thesis, we use a variant of the OGP, which we term a *conditional landscape obstruction*, to prove low degree algorithmic hardness guarantees for the NPP at a range of discrepancy scales. Our obstruction is based on the observation that given a solution to one instance of the NPP, it is impossible to pin down the location of any solution to a strongly correlated instance, which prevents suitably stable algorithms from traversing the solution landscape. This is the “brittleness” of the NPP – even small changes in the instance drastically reshape the geometry of the solutions.

To start, let us formalize our terminology for the NPP.

Definition 1.1. Let $g \in \mathbf{R}^N$ be an instance of the NPP, and let $x \in \Sigma_N$. The *energy* of x is

$$E(x; g) := -\log_2 |\langle g, x \rangle|.$$

The *solution set* $S(E; g)$ is the set of all $x \in \Sigma_N$ that have energy at least E , i.e., that satisfy

$$|\langle g, x \rangle| \leq 2^{-E}.$$

Observe here that minimizing the discrepancy $|\langle g, x \rangle|$ corresponds to maximizing the energy $E(x; g)$. This terminology is motivated by the statistical physics literature, wherein random optimization problems are often reframed as energy maximization over a random landscape [73]. We further know that the *statistically optimal energy level* is $E = \Theta(N)$, while the best *computational energy level* (achievable in polynomial time) is $E = \Theta(\log^2 N)$.

For our purposes, an algorithm is a function $\mathcal{A}: \mathbf{R}^N \rightarrow \Sigma_N$ mapping instances g to partitions x . We will discuss extensions to randomized algorithms (which can depend on a random seed ω independent of g) and to \mathbf{R}^N -valued algorithms (which can be forced to give outputs on Σ_N via rounding) in later sections, but for our main analysis, considering deterministic Σ_N -valued algorithms will suffice. In particular, we consider the class of so-called *low degree algorithms*, given by either low degree polynomials or by functions with low *coordinate degree*. Compared to analytically-defined classes of stable algorithms (e.g. Lipschitz, etc.), these algorithms have an algebraic structure making them amenable to precise stability analysis. In addition, the *low degree heuristic* suggests that degree D algorithms (in either sense) are believed to serve as the simplest representatives for the class of $e^{\tilde{O}(D)}$ -time algorithms [51]. This is a reasonable expectation for number partitioning, enabling us to translate our results into heuristic runtime bounds.

Our results show *strong low degree hardness* for the NPP at energy levels between the statistical and computational thresholds, in the sense of Huang and Sellke [52].

Definition 1.2 (Strong Low Degree Hardness [52, Def. 3]). A sequence of random search problems, that is, a N -indexed sequence of random input vectors

$$g_N \in \mathbf{R}^{d_N}$$

and random subsets

$$S_N = S_N(g_N) \subseteq \Sigma_N$$

exhibits *strong low degree hardness (SLDH) up to degree $D \leq o(D_N)$* if, for all sequences of degree $o(D_N)$ algorithms $\mathcal{A}_N: (g, \omega) \mapsto x$ with $\mathbf{E}\|\mathcal{A}(y_N)\|^2 \leq O(N)$, we have

$$\mathbf{P}(\mathcal{A}_N(g_N, \omega) \in S_N) \leq o(1).$$

There are two related notions of degree which we want to consider in [Definition 1.2](#). The first is traditional polynomial degree, applicable for algorithms given in each coordinate by low degree polynomial functions of the inputs. In this case, we show

Theorem 1.3 (Results of [Section 4.5](#)). *The NPP exhibits SLDH for degree D polynomial algorithms, for*

- (a) $D \leq o(\exp_2(\delta N/2))$ when $E = \delta N$ for $\delta > 0$;
- (b) $D \leq o(\exp_2(E/4))$ when $\omega(\log N) \leq E \leq o(N)$.

Under the low degree heuristic, this suggests that polynomial algorithms require double exponential time to achieve the statistical optimal discrepancy; given that brute-force search requires exponential time, this is strong evidence that polynomial algorithms are poor models for the NPP.

Thus, we turn to the second, more general notion of *coordinate degree*: a function $f: \mathbf{R}^N \rightarrow \mathbf{R}$ has coordinate degree D if it can be expressed as a linear combination of functions depending on combinations of no more than D coordinates. While related to polynomial degree, this enables us to consider a far broader class of algorithms, in which case we show

Theorem 1.4 (Results of [Section 2.4](#)). *The NPP exhibits SLDH for coordinate degree D algorithms, for*

- (a) $D \leq o(N)$ when $E = \delta N$ for $\delta > 0$;
- (b) $D \leq o(E/\log^2 N)$ when $\omega(\log^2 N) \leq E \leq o(N)$.

These results are likely to be the best-possible under the low degree heuristic, which we discuss in [Remark 2.12](#). In particular, the energy-degree tradeoff of $D \leq \tilde{o}(E)$ implies finding solutions with energy E requires time $e^{\tilde{\Omega}(E)}$, and as we'll show, it is possible to achieve such discrepancies via a restricted exponential-time search. Given this, our method produces a sharp energy-runtime tradeoff, indicating there are no nontrivial algorithms that save more than a polylogarithmic factor in the runtime exponent over brute-force search. Overall, our approach towards [Theorem 1.3](#) and [Theorem 1.4](#) suggest that in the case of problems with brittle solution geometry, conditional landscape obstructions are an extremely powerful tool for proving algorithmic hardness.

The rest of the thesis is organized as follows. We review the low degree heuristic and work with low coordinate degree algorithms in [Section 4.1](#). In particular, we provide a self-contained introduction to coordinate degree and related decompositions of L^2 functions in [Section 4.2](#). Our main results then constitute [Section 4.4](#); after giving an overview of our proof strategy, we prove [Theorem 1.3](#) in [Section 4.5](#), and likewise prove [Theorem 1.4](#) in [Section 2.4](#). We conclude in [Section 2.6](#) by extending our results to the case of \mathbf{R}^N -valued algorithms and finish by discussing directions for future research.

1.4 Notations and Preliminaries

We use the standard Bachmann-Landau notations $o(\cdot), O(\cdot), \omega(\cdot), \Omega(\cdot), \Theta(\cdot)$, in the limit $N \rightarrow \infty$. We abbreviate $f(N) \asymp g(N)$, $f(N) \ll g(N)$, or $f(N) \gg g(N)$ when $f(N) = \Theta(g(N))$, $f(N) = o(g(N))$, $f(N) = \omega(g(N))$, respectively. In addition, we write $f(N) \propto g(N)$, $f(N) \lesssim g(N)$, or $f(N) \gtrsim g(N)$ when there exists an N -independent constant C such that $f(N) = Cg(N)$, $f(N) \leq Cg(N)$, or $f(N) \geq Cg(N)$ for all N , respectively.

We write $[N] := \{1, \dots, N\}$. If $S \subseteq [N]$, then we write $\bar{S} := [N] \setminus S$ for the complimentary set of indices. If $x \in \mathbf{R}^N$ and $S \subseteq [N]$, then the *restriction of x to the coordinates in S* is the vector x_S with

$$(x_S)_i := \begin{cases} x_i & i \in S, \\ 0 & \text{else.} \end{cases}$$

In particular, for $x, y \in \mathbf{R}^N$, $\langle x_S, y \rangle = \langle x, y_S \rangle = \langle x_S, y_S \rangle$.

On \mathbf{R}^N , we write $\|\cdot\|$ for the Euclidean norm, and $B(x, r) := \{y \in \mathbf{R}^N : \|y - x\| < r\}$ for the Euclidean ball of radius r around x . In addition, we write

$$B_\Sigma(x, r) := B(x, r) \cap \Sigma_N = \{y \in \Sigma_N : \|y - x\| < r\},$$

to denote points on Σ_N within distance r of x .

We use $\mathcal{N}(\mu, \sigma^2)$ to denote the scalar Normal distribution with given mean and variance. In addition, we write “i.i.d.” to mean independently and identically distributed, and “r.v.” to mean random variable (or random vector, if it is clear from context).

For $p \in [0, 1]$ and a pair (g, g') of N -dimensional standard Normal random vectors, we say (g, g') are *p-correlated* if g' is distributed as

$$g' = pg + \sqrt{1 - p^2} \tilde{g},$$

where \tilde{g} is an independent copy of g .

all 1-dimensional projections $\langle g, x \rangle, \langle g', x \rangle$ have covariance matrix proportional to $\begin{pmatrix} 1 & p \\ p & 1 \end{pmatrix}$; we denote such a pair by $g' \sim_p g$ or, $g' \sim_p g$

We say (g, g') are *p-resampled* if g is a standard Normal random vector and g' is drawn as follows: for each $i \in [N]$ independently,

$$g'_i = \begin{cases} g_i & \text{with probability } p, \\ \text{drawn from } \mathcal{N}(0, 1) & \text{with probability } 1 - p. \end{cases}$$

We denote such a pair by $g' \sim \mathcal{L}_p(g)$.

In both cases, g and g' are marginally multivariate standard Normal and have entrywise correlation p .

— coordinate degree

Let γ_N be the N -dimensional standard Normal measure on \mathbf{R}^N . The *N-dimensional Gaussian space* is the space $L^2(\mathbf{R}^N, \gamma^N)$ of L^2 functions of N i.i.d. standard Normal r.v.s.

For more details, see [67, § 1.3] or [79, § 8.3].

For $g \in \mathbf{R}^N$ and $S \subseteq [N]$.

$$V_S := \{f \in L^2(\gamma_N) : f(g) \text{ depends only on } g_S\},$$

$$V_{\leq D} := \sum_{\substack{J \subseteq [N] \\ |J| \leq D}} V_J.$$

These subsets describe functions which only depend on some subset of coordinates, or on some bounded number of coordinates. Note that $V_{[N]} = V_{\leq N} = L^2(\mathbf{R}^N, \pi^{\otimes N})$.

The *coordinate degree* of a function $f \in L^2(\gamma_N)$ is defined as $\min\{D : f \in V_{\leq D}\}$.

Note that if f is a degree D polynomial, then it has coordinate degree at most D .

Moreover, we have

[79, Exer. 8.18]

$$p^D \mathbf{E}|f(g)|^2 \leq \mathbf{E}_{g' \sim \mathcal{L}_p(g)}[f(g) \cdot f(g')] \leq \mathbf{E}|f(g)|^2$$

Theorem 2.14(a)

— algorithms

For our purposes, a *randomized algorithm* is a measurable function $\mathcal{A}: (g, \omega) \mapsto x \in \Sigma_N$ where $\omega \in \Omega_N$ is an independent random variable in some Polish space Ω_N . Such an \mathcal{A} is *deterministic* if it does not depend on ω . We discuss extensions to when \mathcal{A} is \mathbf{R}^N -valued in [Section 4](#) and [Section 4](#).

We say \mathcal{A} is a *degree D polynomial algorithm* if each output coordinate is given by a degree D polynomial in the N entries of g , for any fixed ω . Similarly, \mathcal{A} is a *coordinate degree D algorithm* if each output coordinate is given by a coordinate degree D function. When the degree is unimportant, we refer to such algorithms as *low degree polynomial (LDP)* or *low coordinate degree (LCD)*, respectively.

1.5 Stability of Low Degree Algorithms

meow

Proposition 1.5 (Low Degree Stability). *Suppose $\mathcal{A}: \mathbf{R}^N \rightarrow \mathbf{R}^N$ is a deterministic algorithm with polynomial degree (resp. coordinate degree) D and norm $\mathbf{E}\|\mathcal{A}(g)\|^2 \leq CN$. Then, for standard Normal r.v.s g and g' which are $(1 - \varepsilon)$ -correlated (resp. $(1 - \varepsilon)$ -resampled),*

$$\mathbf{E}\|\mathcal{A}(g) - \mathcal{A}(g')\|^2 \leq 2CD\varepsilon N, \tag{1.3}$$

and thus for any $\eta > 0$,

$$\mathbf{P}(\|\mathcal{A}(g) - \mathcal{A}(g')\| \geq 2\sqrt{\eta N}) \leq \frac{CD\varepsilon}{2\eta} \asymp \frac{D\varepsilon}{\eta}. \tag{1.4}$$

Proof: We show (1.3) for the case where \mathcal{A} has coordinate degree D and (g, g') are $(1 - \varepsilon)$ -resampled; See [52, Prop. 1.7] for the case where \mathcal{A} is polynomial. In both cases, Markov's inequality gives (1.4).

We follow the proof of [32, Lem. 3.4]. Assume without loss of generality that $\mathbf{E}\|\mathcal{A}(g)\|^2 = 1$. Writing $\mathcal{A} = (\mathcal{A}_1, \dots, \mathcal{A}_N)$, observe that for $g' \sim \mathcal{L}_{1-\varepsilon}(g)$,

$$\mathbf{E}\|\mathcal{A}(g) - \mathcal{A}(g')\|^2 = \mathbf{E}\|\mathcal{A}(g)\|^2 + \mathbf{E}\|\mathcal{A}(g')\|^2 - 2\mathbf{E}\langle \mathcal{A}(g), \mathcal{A}(g') \rangle = 2 - 2\mathbf{E}\langle \mathcal{A}(g), \mathcal{A}(g') \rangle.$$

By [79, Exer. 8.18], we know that for each $\mathcal{A}_i \in V_{\leq D}$ we have

$$(1 - \varepsilon)^D \mathbf{E}|\mathcal{A}_i(g)|^2 \leq \mathbf{E}[\mathcal{A}_i(g)\mathcal{A}_i(g')] \leq \mathbf{E}|\mathcal{A}_i(g)|^2.$$

Summing this over i gives

$$(1 - \varepsilon)^D \leq \mathbf{E}\langle \mathcal{A}(g), \mathcal{A}(g') \rangle \leq 1.$$

Combining this with the above (and the fact that $1 - (1 - \varepsilon)^D \leq \varepsilon D$) yields (1.3). \square

Remark 1.6. Note that Proposition 1.5 also holds for randomized algorithms. Namely, if $\mathcal{A}(g, \omega)$ is a randomized algorithm with polynomial or coordinate degree D and $\mathbf{E}_{g, \omega} \|\mathcal{A}(g, \omega)\|^2 \leq CN$, then applying Markov's inequality to $\omega \mapsto \mathbf{E}[\|\mathcal{A}(g, \omega)\|^2 \mid \omega]$ allows us to reduce to the deterministic case, possibly after adjusting C .

meow Consider algorithm outputting points close to solution

Throughout this section, fix a distance $r = O(1)$.

Note that since r is of constant order, we can convert \mathcal{A} into a Σ_N -valued algorithm by first rounding the $\mathcal{A}(g)$ into the solid binary hypercube and then picking the best corner of Σ_N within constant distance of this output. Such a modification requires additionally calculating the energy of $O(1)$ -many points on Σ_N , adding only $O(N)$ operations.

We can formalize this construction as follows. Let $\text{clip}: \mathbf{R}^N \rightarrow [-1, 1]^N$ be the function which rounds $x \in \mathbf{R}^N$ into the cube $[-1, 1]^N$:

$$\text{clip}(x)_i := \begin{cases} -1 & x_i \leq -1, \\ x_i & -1 < x_i < 1, \\ 1 & x_i \geq 1. \end{cases}$$

Note that clip is 1-Lipschitz with respect to the Euclidean norm.

Definition 1.7. Let $r > 0$ and \mathcal{A} be an algorithm. Define the $[-1, 1]^N$ -valued algorithm $\hat{\mathcal{A}}_r$ by

$$\hat{\mathcal{A}}_r(g) := \begin{cases} \underset{x' \in B_\Sigma(\text{clip}(\mathcal{A}(g)), r)}{\text{argmin}} |\langle g, x' \rangle| & B_\Sigma(\text{clip}(\mathcal{A}(g)), r) \neq \emptyset, \\ \text{clip}(\mathcal{A}(g)) & \text{else.} \end{cases} \quad (1.5)$$

If \mathcal{A} is low degree, then this modification $\hat{\mathcal{A}}_r$ of \mathcal{A} is also stable.

Lemma 1.8. Suppose $\mathcal{A}: \mathbf{R}^N \rightarrow \mathbf{R}^N$ is a deterministic algorithm with polynomial degree (resp. coordinate degree) D and norm $\mathbf{E}\|\mathcal{A}(g)\|^2 \leq CN$. Then, for $r = O(1)$ and standard Normal r.v.s g and g' which are $(1 - \varepsilon)$ -correlated (resp. $(1 - \varepsilon)$ -resampled), $\hat{\mathcal{A}}_r$ as in Definition 1.7 satisfies,

$$\mathbf{E}\|\hat{\mathcal{A}}_r(g) - \hat{\mathcal{A}}_r(g')\|^2 \leq 4CD\varepsilon N + 8r^2. \quad (1.6)$$

Thus for any $\eta > 0$.

$$\mathbf{P}(\|\hat{\mathcal{A}}_r(g) - \hat{\mathcal{A}}_r(g')\| \geq 2\sqrt{\eta N}) \leq \frac{CD\varepsilon}{\eta} + \frac{2r^2}{\eta N}. \quad (1.7)$$

Proof: Observe that by the triangle inequality, $\|\hat{\mathcal{A}}_r(g) - \hat{\mathcal{A}}_r(g')\|$ is bounded by

$$\begin{aligned} & \|\hat{\mathcal{A}}_r(g) - \text{clip}(\mathcal{A}(g))\| + \|\text{clip}(\mathcal{A}(g)) - \text{clip}(\mathcal{A}(g'))\| + \|\text{clip}(\mathcal{A}(g')) - \hat{\mathcal{A}}_r(g')\| \\ & \leq 2r + \|\mathcal{A}(g) - \mathcal{A}(g')\|. \end{aligned}$$

This follows as clip is 1-Lipschitz and the corner-picking step in (1.5) only moves $\hat{\mathcal{A}}_r(g)$ from $\text{clip}(\mathcal{A}(r))$ by at most r . By Jensen's inequality, squaring this gives

$$\|\hat{\mathcal{A}}_r(g) - \hat{\mathcal{A}}_r(g')\|^2 \leq 2(4r^2 + \|\mathcal{A}(g) - \mathcal{A}(g')\|^2).$$

Combining this with Proposition 1.5 gives (1.6), and (1.7) follows from Markov's inequality. \square

meow Of course, our construction of $\hat{\mathcal{A}}_r$ is certainly never polynomial and does not preserve coordinate degree in a controllable way. Thus, we cannot directly hope for Theorem 4.4, Theorem 4.5, Theorem 4.7, or Theorem 4.8 to hold. However, because this rounding does not drastically alter the stability analysis, we are still able to show that for any \mathbf{R}^N -valued low coordinate degree algorithm \mathcal{A} and $r = O(1)$, strong low degree hardness holds for $\hat{\mathcal{A}}_r$. The same argument proves hardness when \mathcal{A} is a low degree polynomial algorithm; this is omitted for brevity.

2 Hardness for Low Degree Algorithms

meow determinisitc Sigma_N valued assumption

Theorem 2.1 (Hardness for LDP Algorithms). *Let g and g' be $(1 - \varepsilon)$ -correlated standard Normal random vectors. Let \mathcal{A} be any degree D polynomial algorithm with $\mathbf{E}\|\mathcal{A}(g)\|^2 \leq CN$. Assume that*

- (a) *if $E = \delta N$ for $\delta > 0$, then $D \leq o(2^{\delta N/2})$;*
- (b) *if $\omega(\log N) \leq E \leq o(N)$, then $D \leq o(2^{E/4})$.*

Then there exist $\varepsilon = \varepsilon(N, E) > 0$ and $\eta = \eta(N, E) > 0$ such that

$$\mathbf{P}(\mathcal{A}(g) \in S(E; g)) = o(1).$$

Theorem 2.2 (Hardness for LCD Algorithms). *Let g and g' be $(1 - \varepsilon)$ -resampled standard Normal random vectors. Let \mathcal{A} be any coordinate degree D algorithm with $\mathbf{E}\|\mathcal{A}(g)\|^2 \leq CN$. Assume that*

- (a) *if $E = \delta N$ for $\delta > 0$, then $D \leq o(N)$;*
- (b) *if $\omega(\log N) \leq E \leq o(N)$, then $D \leq o(E/\log^2 E)$.*

Then there exist $\varepsilon = \varepsilon(N, D) > 0$ and $\eta = \eta(N, E) > 0$ such that

$$\mathbf{P}(\mathcal{A}(g) \in S(E; g)) = o(1).$$

2.1 Preliminary Estimates

Lemma 2.3 (Normal Small-Probability Estimate). *Let $E, \sigma^2 > 0$, and suppose $Z \mid \mu \sim \mathcal{N}(\mu, \sigma^2)$. Then*

$$\mathbf{P}(|Z| \leq 2^{-E} \mid \mu) \leq \exp_2\left(-E - \frac{1}{2} \log_2(\sigma^2) + O(1)\right). \quad (2.1)$$

Proof: Observe that conditional on μ , the distribution of Z is bounded as

$$\varphi_{Z|\mu}(z) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \leq (2\pi\sigma^2)^{-1/2}.$$

Integrating over $|z| \leq 2^{-E}$ then gives (2.1), via

$$\mathbf{P}(|Z| \leq 2^{-E}) = \int_{|z| \leq 2^{-E}} (2\pi\sigma^2)^{-1/2} dz \leq 2^{-E - \frac{1}{2} \log_2(2\pi\sigma^2) + 1}. \quad \square$$

Note that (2.1) is a decreasing function of σ^2 . Thus, if there exists γ with $\sigma^2 \geq \gamma > 0$, then (2.1) is bounded by $\exp_2(-E - \log_2(\gamma)/2 + O(1))$.

Lemma 2.4 (Chernoff-Hoeffding). *Suppose that $K \leq N/2$, and let $h(x) = -x \log_2(x) - (1-x) \log_2(x)$ be the binary entropy function. Then, for $p := K/N$,*

$$\sum_{k \leq K} \binom{N}{k} \leq \exp_2(Nh(p)) \leq \exp_2\left(2Np \log_2\left(\frac{1}{p}\right)\right).$$

Proof: Consider a $\text{Bin}(N, p)$ random variable S . Summing its PMF from 0 to K , we have

$$1 \geq \mathbf{P}(S \leq K) = \sum_{k \leq K} \binom{N}{k} p^k (1-p)^{N-k} \geq \sum_{k \leq K} \binom{N}{k} p^K (1-p)^{N-K}.$$

The last inequality follows by multiplying each term by $(p/(1-p))^{K-k} \leq 1$. Rearranging gives

$$\begin{aligned} \sum_{k \leq K} \binom{N}{k} &\leq p^{-K} (1-p)^{-(N-K)} \\ &= \exp_2(-K \log_2(p) - (N-K) \log_2(1-p)) \\ &= \exp_2\left(N \cdot \left(-\frac{K}{N} \log_2(p) - \left(\frac{N-K}{N}\right) \log_2(1-p)\right)\right) \\ &= \exp_2(N \cdot (-p \log_2(p) - (1-p) \log_2(1-p))) = \exp_2(Nh(p)). \end{aligned}$$

The final equality then follows from the bound $h(p) \leq 2p \log_2(1/p)$ for $p \leq 1/2$. \square

Proposition 2.5. *For all $E \leq O(N)$, there exists $\eta = \eta(N, E) \in (0, 1/2)$ such that for N sufficiently large,*

$$2\eta \log_2 \left(\frac{1}{\eta} \right) < \frac{E}{4N}.$$

In addition

- (a) if $E = \Theta(N)$, this η is $O(1)$;
- (b) if $E \leq o(N)$, this η satisfies $\eta \gtrsim E/N \log_2(N)$.

Proof: (a) For $E = \Theta(N)$, E/N is bounded by an N -independent constant $\delta > 0$. It is thus possible to find some $\eta = O(1)$ such that $-2\eta \log_2 \eta < \delta/4$, as desired.

(b) Heuristically, if $0 < \eta, E/N \ll 1$ and $-\eta \log \eta \sim E/N$, then $E/N = \eta^{\pm o(1)}$. Therefore, $\log E/N \sim (1 \pm o(1)) \log \eta$, whence $\eta \sim E/(N \log N/E)$. On these grounds, for $E \leq o(N)$ we choose

$$\eta := \frac{E}{16N \log_2(N/E)} \gtrsim \frac{E}{N \log_2 N}$$

where the 16 is an arbitrary universal constant. We can verify numerically that for N sufficiently large (hence E/N sufficiently small) this choice gives $2\eta \log_2(1/\eta) < E/4N$. \square

2.2 Conditional obstruction

Thus, within a small neighborhood of any $x \in \Sigma_N$, the number of nearby points is exponential in N , with a more nontrivial dependence on η . The question is then how many of these are solutions to the correlated instance g' . This forms the heart of our conditional landscape obstruction.

Lemma 2.6. *Let (g, g') be a pair of either $(1 - \varepsilon)$ -correlated or $(1 - \varepsilon)$ -resampled instances. Let $x \in \Sigma_N$ be conditionally independent of g' given g . Then for any $\eta \in (0, 1/2)$,*

$$\begin{aligned} & \mathbf{P}_{g' \sim_{1-\varepsilon} g} \left(\begin{array}{l} \exists x' \in S(E; g') \text{ such that} \\ \|x - x'\| \leq 2\sqrt{\eta N} \end{array} \right) \\ & \leq \exp_2 \left(-E - \frac{1}{2} \log_2(\varepsilon) + 2\eta \log_2 \left(\frac{1}{\eta} \right) N + O(\log N) \right), \end{aligned} \quad (2.2)$$

and

$$\begin{aligned} & \mathbf{P}_{g' \sim \mathcal{L}_{1-\varepsilon}(g)} \left(\begin{array}{l} \exists x' \in S(E; g') \text{ such that} \\ \|x - x'\| \leq 2\sqrt{\eta N} \end{array} \middle| g \neq g' \right) \\ & \leq \exp_2 \left(-E + 2\eta \log_2 \left(\frac{1}{\eta} \right) N + O(1) \right). \end{aligned} \quad (2.3)$$

Proof: Throughout, abbreviate $\eta_N := 2\sqrt{\eta N}$. We first show (2.2), by bounding the probability that

$$|B(x, \eta_N) \cap S(E; g')| = \sum_{x' \in B_\Sigma(x, \eta_N)} I\{x' \in S(E; g')\}$$

is nonzero. By Markov's inequality, this is upper bounded by

$$\begin{aligned}
\mathbf{E} \left[\sum_{x' \in B_\Sigma(x, \eta_N)} I\{x' \in S(E; g')\} \right] &= \mathbf{E} \left[\sum_{x' \in B_\Sigma(x, \eta_N)} \mathbf{E}[I\{x' \in S(E; g')\} \mid g] \right] \\
&= \mathbf{E} \left[\sum_{x' \in B_\Sigma(x, \eta_N)} \mathbf{P}(|\langle g', x' \rangle| \leq 2^{-E} \mid g) \right].
\end{aligned} \tag{2.4}$$

Note in particular that the range of this sum is independent of the inner probability, as g' and x are conditionally independent. To bound the number of terms in (2.4), let k is the number of coordinates which differ between x and x' (i.e., the Hamming distance), so that $\|x - x'\|^2 = 4k$. Thus $\|x - x'\| \leq 2\sqrt{\eta N}$ if and only if $k \leq N\eta < N/2$, so by [Lemma 2.4](#),

$$|B_\Sigma(x, \eta_N)| = \sum_{k \leq N\eta} \binom{N}{k} \leq \exp_2(2\eta \log_2(1/\eta)N). \tag{2.5}$$

To bound the inner probability under $g' \sim_{1-\varepsilon} g$, fix any $x' \in \Sigma_N$ and write

$$g' = pg + \sqrt{1-p^2}\tilde{g}$$

for $p := 1 - \varepsilon$ and \tilde{g} an independent copy of g . We know $\langle \tilde{g}, x' \rangle \sim \mathcal{N}(0, N)$, so this gives

$$\langle g', x' \rangle \mid g \sim \mathcal{N}(p\langle g, x' \rangle, (1-p^2)N).$$

This is nondegenerate for $(1-p^2)N \geq \varepsilon N > 0$; by [Lemma 2.3](#), we get

$$\mathbf{P}_{g' \sim_{1-\varepsilon} g}(|\langle g', x' \rangle| \leq 2^{-E} \mid g) \leq \exp_2\left(-E - \frac{1}{2} \log_2(\varepsilon) + O(\log N)\right).$$

Combining with (2.5), this gives (2.2) by

Alternatively, for (2.3), we know that if $g = g'$, then the $B(x, \eta_N) \cap S(E; g')$ will be nonempty if x is chosen to be a solution to g ; we thus condition on $g \neq g'$ throughout (2.4). To bound the corresponding inner term, again fix any $x' \in \Sigma_N$ and let \tilde{g} be an independent copy of g . Let $J \subseteq [N]$ be a random subset where each $i \in J$ independently with probability $1 - \varepsilon$, so g' can be represented as

$$g' = g_J + \tilde{g}_{\bar{J}}.$$

Conditional on (g, J) , we know that $\langle \tilde{g}_{\bar{J}}, x' \rangle$ is $\mathcal{N}(0, N - |J|)$ and $\langle g_J, x' \rangle$ is deterministic, so that

$$\langle g', x' \rangle \mid (g, J) \sim \mathcal{N}(\langle g_J, x' \rangle, N - |J|).$$

As $\{g \neq g'\} = \{|J| < N\}$, we have $N - |J| \geq 1$ conditional on $g \neq g'$. Thus, [Lemma 2.3](#) gives

$$\mathbf{P}_{g' \sim_{1-\varepsilon} g}(|\langle g', x' \rangle| \leq 2^{-E} \mid g, g \neq g') \leq \exp_2(-E + O(1)),$$

and we conclude (2.3) as in the previous case. □

meow correlated pairs

Lemma 2.7 (Adapted from [52, Lem. 2.7]). *Let (g, g') be a pair of either p -correlated or p -resampled instances. Then for any set $S \subseteq \mathbf{R}^N$ and $p > 0$, with $q := \mathbf{P}(g \in S)$,*

$$\mathbf{P}_{g' \sim_p g}(g \in S, g' \in S) \geq q^2 \quad \text{and} \quad \mathbf{P}_{g' \sim \mathcal{L}_p(g)}(g \in S, g' \in S) \geq q^2.$$

Proof: First, let $\tilde{g}, g^{(0)}, g^{(1)}$ be three i.i.d. copies of g , and observe $g' \sim_p g$ are jointly representable as

$$g = \sqrt{1 - \varepsilon} \tilde{g} + \sqrt{\varepsilon} g^{(0)}, \quad g' = \sqrt{1 - \varepsilon} \tilde{g} + \sqrt{\varepsilon} g^{(1)}.$$

Since g, g' are conditionally independent given \tilde{g} , we have by Jensen's inequality that

$$\mathbf{P}_{g' \sim_p g}(g \in S, g' \in S) = \mathbf{E}[\mathbf{P}(g \in S, g' \in S \mid \tilde{g})] = \mathbf{E}[\mathbf{P}(g \in S \mid \tilde{g})^2] \geq \mathbf{E}[\mathbf{P}(g \in S \mid \tilde{g})]^2 = q^2.$$

Likewise, when $g' \sim \mathcal{L}_p(g)$, let J be a random subset of $[N]$ where each $i \in J$ independently with probability p , so that (g, g') are jointly representable as

$$g = \tilde{g}_J + g_J^{(0)}, \quad g' = \tilde{g}_J + g_J^{(1)}.$$

Thus g and g' are conditionally independent given (\tilde{g}, J) , and we conclude in the same way. \square

Remark 2.8. Note that **Lemma 2.7** also holds in the case where $\mathcal{A}(g, \omega)$ is randomized, in the sense of **Definition 4.1**. meow Namely, write

$$\begin{aligned} p &= \mathbf{P}(\mathcal{A}(g, \omega) \in S(E; g)), & P &= \mathbf{P}(\mathcal{A}(g, \omega) \in S(E; g), \mathcal{A}(g', \omega) \in S(E; g')), \\ p(\omega) &= \mathbf{P}(\mathcal{A}(g, \omega) \in S(E; g) \mid \omega), & P(\omega) &= \mathbf{P}(\mathcal{A}(g, \omega) \in S(E; g), \mathcal{A}(g', \omega) \in S(E; g') \mid \omega). \end{aligned}$$

Lemma 2.7 shows that for any $\omega \in \Omega_N$, $P(\omega) \geq p(\omega)^2$. Then, by Jensen's inequality,

$$P = \mathbf{E}[P(\omega)] \geq \mathbf{E}[p(\omega)^2] \geq \mathbf{E}[p(\omega)]^2 = p^2.$$

Thus, in combination with **Remark 1.6**, the remainder of the proof also applies when \mathcal{A} depends on an independent random seed ω .

2.3 Proof of Hardness for LDP Algorithms

We consider the case where \mathcal{A} is a polynomial algorithm with degree D .

Consider a pair of $(1 - \varepsilon)$ -correlated instances (g, g') . Let $x := \mathcal{A}(g)$ and $x' := \mathcal{A}(g')$.

We define the events

$$\begin{aligned} S_{\text{solve}} &:= \{\mathcal{A}(g) \in S(E; g), \mathcal{A}(g') \in S(E; g')\}, \\ S_{\text{stable}} &:= \{\|\mathcal{A}(g) - \mathcal{A}(g')\| \leq 2\sqrt{\eta N}\}, \\ S_{\text{cond}}(x) &:= \left\{ \nexists x' \in S(E; g') \text{ such that } \begin{aligned} &\|x - x'\| \leq 2\sqrt{\eta N} \end{aligned} \right\}. \end{aligned} \tag{2.6}$$

Intuitively, the first two events ask that the algorithm solves both instances and is stable, respectively. The last event, which depends on x , corresponds to the conditional landscape obstruction: for an x depending only on g , there is no solution to g' which is close to x .

Lemma 2.9. *For $x := \mathcal{A}(g)$, we have $S_{\text{solve}} \cap S_{\text{stable}} \cap S_{\text{cond}}(x) = \emptyset$.*

Proof: Suppose that S_{solve} and S_{stable} both occur. Letting $x := \mathcal{A}(g)$ (which only depends on g) and $x' := \mathcal{A}(g')$, we know $x' \in S(E; g')$ and is within distance $2\sqrt{\eta N}$ of x , contradicting $S_{\text{cond}}(x)$. \square

Proof of Theorem 2.1: Let $p_{\text{solve}} := \mathbf{P}(\mathcal{A}(g) \in S(E; g))$ be the probability that \mathcal{A} solves one instance. By Lemma 2.7, $\mathbf{P}_{g' \sim_{1-\varepsilon} g}(S_{\text{solve}}) \geq p_{\text{solve}}^2$.

In addition, let

$$p_{\text{cond}} := \max_{x \in \Sigma_N} 1 - \mathbf{P}_{g' \sim_{1-\varepsilon} g}(S_{\text{cond}}(x)). \quad p_{\text{unstable}} := 1 - \mathbf{P}_{g' \sim_{1-\varepsilon} g}(S_{\text{stable}}),$$

Set $\varepsilon := 2^{-E/2}$ and set η as in Proposition 2.5. By Lemma 2.6, for N sufficiently large,

$$\begin{aligned} p_{\text{cond}} &\leq \exp_2 \left(-E - \frac{1}{2} \log_2(\varepsilon) + 2\eta \log_2 \left(\frac{1}{\eta} \right) N + O(\log N) \right) \\ &\leq \exp_2 \left(-E + \frac{E}{4} + \frac{E}{4} + O(\log N) \right) = \exp_2 \left(-\frac{E}{2} + O(\log N) \right) = o(1). \end{aligned}$$

Next, (a) for $E = \delta N$ and $D = o(\exp_2(\delta N/2))$, Proposition 1.5 gives

$$p_{\text{unstable}} \lesssim D\varepsilon = D \exp_2 \left(-\frac{\delta N}{2} \right) = o(1),$$

and (b) for $\log N \ll E \ll N$ and $D = o(\exp_2(E/4))$,

$$\begin{aligned} p_{\text{unstable}} &\lesssim \frac{D\varepsilon}{\eta} \lesssim \frac{D \exp_2(-E/2) N \log_2(N)}{E} \\ &\leq D \exp_2 \left(-\frac{E}{2} + O(\log N) \right) \\ &\leq o(1) \cdot \exp_2 \left(-\frac{E}{4} + O(\log N) \right) = o(1). \end{aligned}$$

That is, both p_{cond} and p_{unstable} vanish for large N .

To conclude, Lemma 2.9 gives (for $\mathbf{P} = \mathbf{P}_{g' \sim_{1-\varepsilon} g}$)

$$\mathbf{P}(S_{\text{solve}}) + \mathbf{P}(S_{\text{stable}}) + \mathbf{P}(S_{\text{cond}}(x)) \leq 2,$$

and rearranging yields

$$(p_{\text{solve}})^2 \leq p_{\text{unstable}} + (1 - \mathbf{P}(S_{\text{cond}}(x))) \leq p_{\text{unstable}} + p_{\text{cond}} = o(1). \quad \square$$

Discussion meow

2.4 Hardness for Low Coordinate Degree Algorithms

Next, let \mathcal{A} have coordinate degree D . Now consider a pair of $(1 - \varepsilon)$ -resampled instances (g, g') . Let $x := \mathcal{A}(g)$ and $x' := \mathcal{A}(g')$.

$$\begin{aligned} S_{\text{diff}} &:= \{g \neq g'\}, \\ S_{\text{solve}} &:= \{\mathcal{A}(g) \in S(E; g), \mathcal{A}(g') \in S(E; g')\}, \\ S_{\text{stable}} &:= \{\|\mathcal{A}(g) - \mathcal{A}(g')\| \leq 2\sqrt{\eta N}\}, \\ S_{\text{cond}}(x) &:= \left\{ \nexists x' \in S(E; g') \text{ such that } \|x - x'\| \leq 2\sqrt{\eta N} \right\}. \end{aligned} \tag{2.7}$$

Note that these are the same events as (2.6), plus the event that g' is nontrivially resampled from g .

Lemma 2.10. *For g, g' being $(1 - \varepsilon)$ -resampled, $\mathbf{P}(S_{\text{diff}}) = 1 - (1 - \varepsilon)^N$.*

Proof: This follows from the calculation

$$\mathbf{P}(g = g') = \prod_{i=1}^N \mathbf{P}(g_i = g_{i'}) = (1 - \varepsilon)^N. \quad \square$$

Given this meow This is necessary as when $g = g'$, S_{stable} always holds and $S_{\text{cond}}(x)$ always fails. Note however that if we knew that $\mathbf{P}(S_{\text{diff}}) = 1$ (which is always the case for g, g' being $(1 - \varepsilon)$ -correlated), then these definitions agree with what we had in . Again, we can define $p_{\text{cond}}^{\text{res}}$ via

As before, our proof follows from showing that for appropriate choices of ε and η (depending on D, E , and N), $p_{\text{unstable}}^{\text{res}}$ and $p_{\text{cond}}^{\text{res}}$ are $o(1)$. However, we are also required us to choose $\varepsilon \gg \frac{1}{N}$, so as to ensure that $g \neq g'$, as otherwise (a) $p_{\text{cond}}^{\text{res}}$ would be too large and (b) the $1 - \mathbf{P}(S_{\text{diff}})$ term would fail to vanish. This restriction on ε stops us from showing hardness for algorithms with degree larger than $o(N)$, as we will see shortly.

Lemma 2.11. *For $x := \mathcal{A}(g)$, we have $S_{\text{diff}} \cap S_{\text{solve}} \cap S_{\text{stable}} \cap S_{\text{cond}}(x) = \emptyset$.*

Proof: This follows from Lemma 2.9, noting that the proof did not use that $g \neq g'$ almost surely. \square

We can interpret this as saying $S_{\text{solve}}, S_{\text{stable}}, S_{\text{cond}}$ are all mutually exclusive, conditional on $g \neq g'$.

Proof of Theorem 2.2: Again let $p_{\text{solve}} := \mathbf{P}(\mathcal{A}(g) \in S(E; g))$ be the probability that \mathcal{A} solves one instance. By Lemma 2.7, $\mathbf{P}_{g' \sim \mathcal{L}_{1-\varepsilon}(g)}(S_{\text{solve}}) \geq p_{\text{solve}}^2$. We now redefine p_{cond} and p_{unstable} via

$$p_{\text{cond}} := \max_{x \in \Sigma_N} 1 - \mathbf{P}_{g' \sim \mathcal{L}_{1-\varepsilon}(g)}(S_{\text{cond}}(x) \mid S_{\text{diff}}), \quad p_{\text{unstable}} := 1 - \mathbf{P}_{g' \sim \mathcal{L}_{1-\varepsilon}(g)}(S_{\text{stable}} \mid S_{\text{diff}}).$$

Setting η as in Proposition 2.5, we have by Lemma 2.6 that

$$p_{\text{cond}} \leq \exp_2 \left(-E + 2\eta \log_2 \left(\frac{1}{\eta} \right) N + O(1) \right) \leq \exp_2 \left(-\frac{3E}{4} + O(1) \right) = o(1).$$

Next, set $\varepsilon := \log_2 \frac{N/D}{N}$. This clearly has $N\varepsilon \gg 1$, so

$$\mathbf{P}(S_{\text{diff}}) = 1 - (1 - \varepsilon)^N \geq 1 - e^{-\varepsilon N} \rightarrow 1. \quad (2.8)$$

By [Proposition 1.5](#), we have for (a) $E = \delta N$ and $D = o(N)$ that

$$p_{\text{unstable}} \lesssim D\varepsilon = \frac{D}{N} \log_2 \left(\frac{N}{D} \right) = o(1).$$

Likewise, for (b) $\log^2 N \ll E \ll N$ and $D = o(E/\log^2 N)$ we get

$$p_{\text{unstable}} \lesssim \frac{D\varepsilon}{\eta} \lesssim \frac{D \log_2(N/D) \log_2(N)}{E} \leq \frac{D \log_2^2 N}{E} = o(1).$$

Again, these choices of ε and η ensure both p_{cond} and p_{unstable} vanish for large N .

To conclude, [Lemma 2.11](#) gives, for $x = \mathcal{A}(g)$, that $\mathbf{P}_{g' \sim \mathcal{L}_{1-\varepsilon}(g)}(S_{\text{solve}}, S_{\text{stable}}, S_{\text{cond}}(x) \mid S_{\text{diff}}) = 0$, so

$$\mathbf{P}(S_{\text{solve}} \mid S_{\text{diff}}) + \mathbf{P}(S_{\text{stable}} \mid S_{\text{diff}}) + \mathbf{P}(S_{\text{cond}}(x) \mid S_{\text{diff}}) \leq 2.$$

Thus, rearranging and multiplying by $\mathbf{P}(S_{\text{diff}})$ gives

$$\mathbf{P}(S_{\text{solve}}, S_{\text{diff}}) \leq \mathbf{P}(S_{\text{diff}}) \cdot (p_{\text{unstable}} + p_{\text{cond}}) \leq p_{\text{unstable}} + p_{\text{cond}}.$$

Finally, adding $\mathbf{P}(S_{\text{solve}}, \neg S_{\text{diff}}) \leq 1 - \mathbf{P}(S_{\text{diff}})$, which is $o(1)$ by our choice of ε , to both sides (so as to apply [Lemma 2.7](#)) lets us conclude

$$p_{\text{solve}}^2 \leq \mathbf{P}(S_{\text{solve}}) \leq p_{\text{unstable}} + p_{\text{cond}} + (1 - \mathbf{P}(S_{\text{diff}})) = o(1). \quad \square$$

With this, we can show strong low degree hardness for low coordinate degree algorithms at linear energy levels $E = \Theta(N)$. As before, this corresponds to hardness at the statistically optimal energy regime, but now applies to an extremely broad category of algorithms.

Finally, combining the ideas behind [Theorem 4.5](#) and our conditional landscape obstruction for $(1 - \varepsilon)$ -resampled Normal random variables, we can show hardness for algorithms with low coordinate degree at sublinear energy levels, ranging from $\log^2 N \ll E \ll N$. Here we have to increase our lower bound to $\log^2 N$ as opposed to $\log N$ from [Theorem 4.5](#), to address the requirement that $\varepsilon = \omega(1/N)$, but this still enables us to “close” the statistical-to-computational gap by proving hardness in this range. Note also that our method also allows us to derive a clear tradeoff between solution energy and algorithm degree.

Remark 2.12 (Tightness of Coordinate Degree Bounds). For any $E \leq \Theta(N)$, there is an easy method to achieve a discrepancy of 2^{-E} in $e^{O(E)}$ time.

- (a) Pick a subset $J \subseteq [N]$ of E coordinates.
- (b) Run LDM on the restricted NPP $g_{\bar{J}}$ to find a partition $x_{\bar{J}}$ with $\langle g_{\bar{J}}, x_{\bar{J}} \rangle \leq 1$.
- (c) If we fix the values of $x_{\bar{J}}$, the NPP given by g turns into finding x_J minimizing $|\langle g, x \rangle| = |\langle g_J, x_J \rangle + \langle g_{\bar{J}}, x_{\bar{J}} \rangle|$. Note here that $\langle g, x \rangle \mid (g_{\bar{J}}, x_{\bar{J}}) \sim \mathcal{N}(\mu, E)$, for $\mu = \langle g_{\bar{J}}, x_{\bar{J}} \rangle$.
- (d) Given the statistical energy threshold is $\Theta(N)$, we know g has a solution with energy E with high probability. Moreover, by the proof of [Lemma 2.3](#), the probability of any x_J solving g_J is

independent of $O(1)$ constant shifts to the instance, so we can conclude that this restricted NPP also has an energy E solution.

- (e) Thus, at this stage, we can brute force search over the remaining J coordinates, which gives a solution with energy E with high probability, in $e^{O(E)}$ time.

In particular, this suggests that our results [Theorem 4.7](#) and [Theorem 4.8](#) are optimal under the low degree heuristic. Namely, low degree hardness of finding solutions with energy E holds up to degree $\tilde{o}(E)$, which implies finding such solutions requires at least time $e^{\tilde{\Omega}(E)}$. This restricted brute force strategy shows that it is indeed possible to find these solutions in time $e^{\tilde{O}(E)}$, implying that our method gives the optimal energy-runtime tradeoff.

It is worthwhile asking whether the low degree heuristic is truly appropriate in our brittle setting. For instance, in most cases where it has been applied to a random optimization problem (e.g., by Huang and Sellke [\[52\]](#)), the objective under consideration has been fairly stable. However, the NPP has a very one-dimensional landscape, lacking the “depth” which foils the low degree heuristic for, e.g., broadcasting on trees [\[48\]](#). Moreover, the sharp energy-runtime tradeoff in [Remark 2.12](#) is suggestive of the strength of this heuristic in this case.

As a final remark, consider that an algorithm with coordinate degree $\Omega(N)$ (equivalently, $\Theta(N)$) is one which considers nonlinear interactions between some constant fraction of all the coordinates as N gets large. Intuitively, such an algorithm is forced to look at how a large number of instance elements balance against each other, giving further evidence to the claim that any sufficiently local algorithm for the NPP will be no better than random search. The good algorithms must be global, which reflects recent developments in heuristics for computing solutions to the NPP [\[62\]](#), [\[25\]](#), [\[83\]](#).

2.5 Extensions to Close Algorithms

In [Section 4.4](#), we have established strong low degree hardness for both low degree polynomial and low coordinate degree algorithms. However, our stability analysis assumed that the algorithms in question were Σ_N -valued. In this section, we show that this assumption is not in fact as restrictive as it might appear.

Throughout, let \mathcal{A} denote a \mathbf{R}^N -valued algorithm. We want to show that:

- (a) no low degree \mathcal{A} can reliably output points *close* – within constant distance – to a solution;
- (b) no Σ_N -valued algorithm $\tilde{\mathcal{A}}$ coming from randomly rounding the output of \mathcal{A} , which changes an $\omega(1)$ number of coordinates, can find a solution with nonvanishing probability.

In principle, the first possibility fails via the same analysis as in [Section 4.4](#), while the second fails because the landscape of solutions to any given NPP instance is sparse.

Why are these the only two possibilities? For \mathcal{A} to provide a way to actually solve the NPP, we must be able to turn its outputs on \mathbf{R}^N into points on Σ_N . If \mathcal{A} could output points within a constant distance (independent of the instance) of a solution, then we could convert \mathcal{A} into a Σ_N -valued algorithm by manually computing the energy of all points close to its output and returning the energy-maximizing point.

However, another common way to convert a \mathbf{R}^N -valued algorithm into a Σ_N -valued one is by rounding the outputs, as in [\[5\]](#), [\[52\]](#). Doing this directly can lead to difficulties in performing the

stability analysis. In our case, if we know that no \mathcal{A} can reliably output points within constant distance of a solution, then any rounding scheme which only flips $O(1)$ many coordinates will assuredly fail. Thus, the only rounding schemes worth considering must flip $\omega(1)$ many coordinates.

We first show that no low degree \mathcal{A} can find points within constant distance of a solution, effectively by reproducing the argument of [Section 2.4](#). We then turn to describing a landscape obstruction to randomized rounding, relying on what we term the *solution repulsion property*: solutions to any NPP instance are far away from each other, with this distance tradeoff controlled by the energy level of the solution set in consideration. This can then be leveraged to show that any sufficiently randomized rounding scheme will always fail to find solutions at energies higher than the computational threshold.

Throughout this section, fix a distance $r = O(1)$. Consider the event that the \mathbf{R}^N -valued algorithm \mathcal{A} outputs a point close to a solution for an instance g :

$$S_{\text{close}}(r) = \left\{ \begin{array}{l} \exists \hat{x} \in S(E; g) \text{ s.t.} \\ \mathcal{A}(g) \in B(\hat{x}, r) \end{array} \right\} = \{B(\mathcal{A}(g), r) \cap S(E; g) \neq \emptyset\}.$$

2.6 Extensions to Real-Valued Algorithms

In [Section 4.4](#), we have established strong low degree hardness for both low degree polynomial and low coordinate degree algorithms. However, our stability analysis assumed that the algorithms in question were Σ_N -valued. In this section, we show that this assumption is not in fact as restrictive as it might appear.

Throughout, let \mathcal{A} denote a \mathbf{R}^N -valued algorithm. We want to show that:

- (a) no low degree \mathcal{A} can reliably output points *close* – within constant distance – to a solution;
- (b) no Σ_N -valued algorithm $\tilde{\mathcal{A}}$ coming from randomly rounding the output of \mathcal{A} , which changes an $\omega(1)$ number of coordinates, can find a solution with nonvanishing probability.

In principle, the first possibility fails via the same analysis as in [Section 4.4](#), while the second fails because the landscape of solutions to any given NPP instance is sparse.

Why are these the only two possibilities? For \mathcal{A} to provide a way to actually solve the NPP, we must be able to turn its outputs on \mathbf{R}^N into points on Σ_N . If \mathcal{A} could output points within an constant distance (independent of the instance) of a solution, then we could convert \mathcal{A} into a Σ_N -valued algorithm by manually computing the energy of all points close to its output and returning the energy-maximizing point.

However, another common way to convert a \mathbf{R}^N -valued algorithm into a Σ_N -valued one is by rounding the outputs, as in [\[5\]](#), [\[52\]](#). Doing this directly can lead to difficulties in performing the stability analysis. In our case, if we know that no \mathcal{A} can reliably output points within constant distance of a solution, then any rounding scheme which only flips $O(1)$ many coordinates will assuredly fail. Thus, the only rounding schemes worth considering must flip $\omega(1)$ many coordinates.

We first show that no low degree \mathcal{A} can find points within constant distance of a solution, effectively by reproducing the argument of [Section 2.4](#). We then turn to describing a landscape

obstruction to randomized rounding, relying on what we term the *solution repulsion property*: solutions to any NPP instance are far away from each other, with this distance tradeoff controlled by the energy level of the solution set in consideration. This can then be leveraged to show that any sufficiently randomized rounding scheme will always fail to find solutions at energies higher than the computational threshold.

2.7 Hardness for Close Algorithms

Throughout this section, fix a distance $r = O(1)$. Consider the event that the \mathbf{R}^N -valued algorithm \mathcal{A} outputs a point close to a solution for an instance g :

$$S_{\text{close}}(r) = \left\{ \begin{array}{l} \exists \hat{x} \in S(E; g) \text{ s.t.} \\ \mathcal{A}(g) \in B(\hat{x}, r) \end{array} \right\} = \{B(\mathcal{A}(g), r) \cap S(E; g) \neq \emptyset\}.$$

We recall the setup from [Section 2.4](#). Let g, g' be $(1 - \varepsilon)$ -resampled standard Normal vectors and define the events

$$\begin{aligned} S_{\text{diff}} &:= \{g \neq g'\}, \\ S_{\text{solve}} &:= \{\hat{\mathcal{A}}_r(g) \in S(E; g), \hat{\mathcal{A}}_r(g') \in S(E; g')\}, \\ S_{\text{stable}} &:= \{\|\hat{\mathcal{A}}_r(g) - \hat{\mathcal{A}}_r(g')\| \leq 2\sqrt{\eta N}\}, \\ S_{\text{cond}}(x) &:= \left\{ \begin{array}{l} \nexists x' \in S(E; g') \text{ such that} \\ \|x - x'\| \leq 2\sqrt{\eta N} \end{array} \right\}. \end{aligned} \tag{2.9}$$

These are the same events as in [\(2.7\)](#), just adapted to $\hat{\mathcal{A}}_r$. In particular, [Lemma 2.11](#) holds unchanged.

Moreover, we define

$$\hat{p}_{\text{solve}}^{\text{cor}} := \mathbf{P}(\hat{\mathcal{A}}_r(g) \in S(E; g)) \geq \mathbf{P}(S_{\text{close}}(r)), \tag{2.10}$$

$$\hat{p}_{\text{unstable}}^{\text{cor}} := 1 - \mathbf{P}(S_{\text{stable}} \mid S_{\text{diff}}), \quad \hat{p}_{\text{cond}}^{\text{cor}}(x) := 1 - \mathbf{P}(S_{\text{cond}}(x) \mid S_{\text{diff}}),$$

along with $\hat{p}_{\text{cond}}^{\text{cor}} := \max_{x \in \Sigma_N} \hat{p}_{\text{cond}}^{\text{cor}}(x)$, echoing [\(4.3\)](#). Observe that since $\hat{p}_{\text{cond}}^{\text{cor}}$ makes no reference to any algorithm, the bound in [Proposition 4.3](#) holds without change. Moreover, [Lemma 1.8](#) lets us control $\hat{p}_{\text{unstable}}^{\text{cor}}$. The final piece needed is an appropriate analog of [Theorem 4.6](#).

Lemma 2.13. *For g, g' being $(1 - \varepsilon)$ -resampled, we have*

$$\mathbf{P}(S_{\text{solve}}) = \mathbf{P}(\hat{\mathcal{A}}_r(g) \in S(E; g), \hat{\mathcal{A}}_r(g') \in S(E; g')) \geq (\hat{p}_{\text{solve}}^{\text{cor}})^2.$$

Proof: Observe that, letting $+$ denote Minkowski sum, we have

$$\{\hat{\mathcal{A}}_r(g) \in S(E; g)\} = \{\text{clip}(\mathcal{A}(g)) \in S(E; g) + B(0, r)\}.$$

Expanding $S(E; g)$, the proof proceeds as in [Theorem 4.6](#). □

Theorem 2.14. Let $\omega(\log^2 N) \leq E \leq \Theta(N)$, and let g, g' be $(1 - \varepsilon)$ -resampled standard Normal r.v.s. Consider any $r = O(1)$ and \mathbf{R}^N -valued \mathcal{A} with $\mathbf{E}\|\mathcal{A}(g)\|^2 \leq CN$, and assume in addition that

- (a) if $E = \delta N = \Theta(N)$ for $\delta > 0$, then \mathcal{A} has coordinate degree $D \leq o(N)$;
- (b) if $\log^2 N \ll E \ll N$, then \mathcal{A} has coordinate degree $D \leq o(E/\log^2 N)$.

Let $\hat{\mathcal{A}}_r$ be as in [Definition 1.7](#). Then there exist $\varepsilon, \eta > 0$ such that

$$\hat{p}_{\text{solve}}^{\text{cor}} = \mathbf{P}(\hat{\mathcal{A}}_r(g) \in S(E; g)) = o(1).$$

Proof: First, by [Lemma 2.11](#), the appropriate adjustment of (4.2) holds, namely that

$$(\hat{p}_{\text{solve}}^{\text{cor}})^2 \leq \hat{p}_{\text{unstable}}^{\text{cor}} + \hat{p}_{\text{cond}}^{\text{cor}} + (1 - \mathbf{P}(S_{\text{diff}})). \quad (2.11)$$

To ensure $\mathbf{P}(S_{\text{diff}}) \rightarrow 1$, we begin by following (4.1) and choosing $\varepsilon = \log_2(N/D)/N$. Moreover, following the proof of [Theorem 4.7](#) and [Theorem 4.8](#), we know that choosing

$$\eta = \begin{cases} O(1) \text{ s.t. } 2\eta \log_2(1/\eta) < \delta/4 & E = \delta N, \\ \frac{E}{16N \log_2(N/E)} & E \leq o(N), \end{cases}$$

in conjunction with [Proposition 4.3](#), guarantees that

$$\hat{p}_{\text{cond}}^{\text{cor}} \leq \exp_2\left(-\frac{3E}{4} + O(1)\right) = o(1).$$

Finally, note that in the linear case, when $\eta = O(1)$, we trivially have $\frac{r^2}{\eta N} = o(1)$. In the sublinear case, for $\eta = E/(16N \log_2(N/E))$, we instead get

$$\eta N = \frac{E}{16 \log_2(N/E)} \geq \frac{E}{16 \log_2 N} = \omega(1),$$

since $E \gg \log^2 N$. Thus, applying the properly modified [Lemma 1.8](#) with these choices of ε and η , we see that $\hat{p}_{\text{unstable}}^{\text{cor}} = o(1)$. By (2.11), we conclude that $\hat{p}_{\text{solve}}^{\text{cor}} = o(1)$. \square

Note that as $\hat{p}_{\text{solve}}^{\text{cor}}$ upper bounds $\mathbf{P}(S_{\text{close}}(r))$, this argument shows algorithmic hardness for low degree \mathbf{R}^N -valued algorithms aiming to output points within constant distance of a solution.

3 Truly Random Rounding

While deterministic algorithms fail to get close to NPP solutions, perhaps a randomized rounding scheme could work instead. As discussed above, the failure of algorithms finding outputs within a constant distance of a solution motivates considering rounding schemes which are “truly random,” in that they change a superconstant number of coordinates. However, this approach is blunted by the same brittleness of the NPP landscape that established the conditional obstruction of [Proposition 4.2](#) and [Proposition 4.3](#). In particular, [Theorem 3.4](#) shows that if one has a subcube of Σ_N with dimension growing slowly with N , then at most only one of those points will be a solution.

For this section, again let \mathcal{A} be a deterministic \mathbf{R}^N -valued algorithm. Moreover, assume we are searching for solutions with energy between $\log^2 N \ll E \leq N$; note that for lower values, the Kar-markar-Karp algorithm can already achieve discrepancies of $N^{-\Theta(\log N)}$ energy in polynomial time.

To start, for any $x \in \mathbf{R}^N$, we write x^* for the coordinate-wise signs of x , i.e.,

$$x_i^* := \begin{cases} +1 & x_i > 0, \\ -1 & x_i \leq 0. \end{cases}$$

We can then define the deterministically rounded algorithm $\mathcal{A}^*(g) := \mathcal{A}(g)^*$.

Remark 3.1. Observe that if \mathcal{A} was a low coordinate degree algorithm, then \mathcal{A}^* has the same coordinate degree, so strong low degree hardness as proved in [Section 2.4](#) still applies. On the other hand, if \mathcal{A} was a low polynomial degree algorithm, then \mathcal{A}^* will not be polynomial, but as coordinate degree bounds polynomial degree, we can recover strong low degree hardness, albeit with worse bounds on D .

In contrast to deterministically rounding of the outputs of \mathcal{A} by taking signs, we can consider passing the output of \mathcal{A} through a randomized rounding scheme. Let $\text{round}(x, \omega): \mathbf{R}^N \times \Omega \rightarrow \Sigma_N$ denote any randomized rounding function, with randomness ω independent of the input. We will often suppress the ω in the notation, and treat $\text{round}(x)$ as a Σ_N -valued random variable. We can describe such a randomized rounding function in the following way. Define $p_1(x), \dots, p_N(x)$ by

$$p_i(x) := \max\left(\mathbf{P}(\text{round}(x)_i \neq x_i^*), \frac{1}{2}\right). \quad (3.1)$$

We need to guarantee that each $p_i(x) \leq 1/2$ for the following alternative description of $\text{round}(x)$.

Lemma 3.2. Fix $x \in \mathbf{R}^N$. Draw N coin flips $I_{x,i} \sim \text{Bern}(2p_i(x))$ as well as N signs $S_i \sim \text{Unif}\{\pm 1\}$, all mutually independent; define the random variable $\tilde{x} \in \Sigma_N$ by

$$\tilde{x}_i := S_i I_{x,i} + (1 - I_{x,i}) x_i^*.$$

Then $\tilde{x} \sim \text{round}(x)$.

Proof: Conditioning on $I_{x,i}$, we can check that

$$\mathbf{P}(\tilde{x}_i \neq x_i) = 2p_i(x) \cdot \mathbf{P}(\tilde{x}_i = x_i \mid I_{x,i} = 1) + (1 - 2p_i(x)) \cdot \mathbf{P}(\tilde{x}_i \neq x_i \mid I_{x,i} = 0) = p_i(x).$$

Thus, $\mathbf{P}(\tilde{x}_i = x_i^*) = \mathbf{P}(\text{round}(x)_i = x_i^*)$. □

By [Lemma 3.2](#), we can redefine $\text{round}(x)$ to be \tilde{x} as constructed above without loss of generality.

It thus makes sense to define $\tilde{\mathcal{A}}(g) := \text{round}(\mathcal{A}(g))$, which is now (a) Σ_N -valued and (b) randomized only in the transition from \mathbf{R}^N to Σ_N (i.e., the rounding does not depend directly on g , but only on the output $x = \mathcal{A}(g)$). We should expect that if $\tilde{\mathcal{A}} = \mathcal{A}^*$ (e.g., if \mathcal{A} outputs values far outside the cube $[-1, 1]^N$) with high probability, then low degree hardness will still apply, since \mathcal{A}^* is deterministic. However, in general, any $\tilde{\mathcal{A}}$ which differs from \mathcal{A}^* will fail to solve g with high probability. This is independent of any assumptions on \mathcal{A} : any rounding scheme will introduce so

much randomness that \tilde{x} will effectively be a random point, which has a vanishing probability of being a solution because of how sparse and disconnected the NPP landscape is.

To see this, we first show that any randomized rounding scheme as in [Lemma 3.2](#) which differs almost surely from simply picking the signs will resample a diverging number of coordinates.

Lemma 3.3. *Fix $x \in \mathbb{R}^N$, and let $p_1(x), \dots, p_N(x)$ be defined as in (3.1). Then $\tilde{x} \neq x^*$ with high probability if and only if $\sum_i p_i(x) = \omega(1)$. Moreover, assuming that $\sum_i p_i(x) = \omega(1)$, the number of coordinates in which \tilde{x} is resampled diverges almost surely.*

Proof: Recall that for $x \in [0, 1/2]$, $\log_2(1 - x) = \Theta(x)$. Thus, as each coordinate of x is rounded independently, we can compute

$$\mathbf{P}(\tilde{x} = x^*) = \prod_i (1 - p_i(x)) = \exp_2 \left(\sum_i \log_2(1 - p_i(x)) \right) \leq \exp_2 \left(-\Theta \left(\sum_i p_i(x) \right) \right).$$

Thus, $\mathbf{P}(\tilde{x} = x^*) = o(1)$ if and only if $\sum_i p_i(x) = \omega(1)$.

Next, following the construction of \tilde{x} in [Lemma 3.2](#), let $E_i = \{I_{x,i} = 1\}$ be the event that \tilde{x}_i is resampled from $\text{Unif}\{\pm 1\}$, independently of x_i^* . The E_i are independent, so by Borel-Cantelli, $\sum_i \mathbf{P}(E_i) = 2 \sum_i p_i(x) = \omega(1)$ implies that \tilde{x}_i is resampled infinitely often with probability 1. \square

To take advantage of the above construction, we show [Theorem 3.4](#): this is a landscape obstruction for single instances of the NPP which shows that solutions resist clustering at a rate related to their energy level (i.e., higher energy solutions push each other further apart). This will let us conclude that any $\tilde{\mathcal{A}}$ which is not equal to \mathcal{A}^* with high probability fails to find solutions.

Theorem 3.4 (Solutions Repel). *Consider any distances $k = \Omega(1)$ and energy levels $E \gg k \log N$. With high probability, there are no pairs of distinct solutions $x, x' \in S(E; g)$ to an instance g with $\|x - x'\| \leq 2\sqrt{k}$ (i.e., within k sign flips of each other):*

$$\mathbf{P} \left(\exists (x, x') \in S(E; g) \text{ s.t. } \|x - x'\| \leq 2\sqrt{k} \right) \leq \exp_2(-E + O(k \log N)) = o(1). \quad (3.2)$$

Proof: Consider any $x \neq x'$, and let $J \subseteq [N]$ denote the coordinates in which x, x' differ. Then

$$x = x_{\bar{J}} + x_J, \quad x' = x_{\bar{J}} - x_J.$$

Assuming both $x, x' \in S(E; g)$, we can expand the inequalities $-2^{-E} \leq \langle g, x \rangle, \langle g, x' \rangle \leq 2^{-E}$ into

$$\begin{aligned} -2^{-E} &\leq \langle g, x_{\bar{J}} \rangle + \langle g, x_J \rangle \leq 2^{-E}, \\ -2^{-E} &\leq \langle g, x_{\bar{J}} \rangle - \langle g, x_J \rangle \leq 2^{-E}. \end{aligned}$$

Multiplying the lower equation by -1 and adding the resulting inequalities gives $|\langle g, x_J \rangle| \leq 2^{-E}$.

Thus, finding pairs of distinct solutions within distance $2\sqrt{k}$ implies finding a subset $J \subseteq [N]$ of at most k coordinates and $|J|$ signs x_J such that $|\langle g, x_J \rangle| \leq 2^{-E}$. By [\[89, Exer. 0.0.5\]](#), there are

$$\sum_{1 \leq k' \leq k} \binom{N}{k'} \leq \left(\frac{eN}{k} \right)^k \leq (eN)^k = 2^{O(k \log N)}$$

choices of such subsets, and at most 2^k choices of signs. Now, $\langle g_J, x_J \rangle \sim \mathcal{N}(0, |J|)$, and as $|J| \geq 1$, [Lemma 2.3](#) and the following remark implies $\mathbf{P}(|\langle g_J, x_J \rangle| \leq 2^{-E}) \leq \exp_2(-E + O(1))$. Union bounding this over the $2^{O(k \log N)}$ possibilities gives [\(3.2\)](#). \square

Here, our technique of converting pairs of solutions into subvectors of g which must have small sum enables us to reduce the size of the set we union bound over from $2^{O(N)}$ to $2^{O(k \log N)}$. Moreover, observe that this proof can be adapted to show that for a fixed $x \in S(E; g)$, there are no other solutions within k sign flips with high probability.

Finally, we exhibit strong hardness for truly randomized algorithms. Roughly, this holds because if enough coordinates are resampled, the resulting point is random within a subcube of dimension growing slowly with Σ_N , which overwhelms the brittleness in [Theorem 3.4](#).

Theorem 3.5. *Let $x = \mathcal{A}(g)$, and define x^*, \tilde{x} , etc., as previously. Moreover, assume that for any x in the possible outputs of \mathcal{A} , we have $\sum_i p_i(x) = \omega(1)$. Then, for any $E \geq \omega(\log^2 N)$, we have*

$$\mathbf{P}(\tilde{\mathcal{A}}(g) \in S(E; g)) = \mathbf{P}(\tilde{x} \in S(E; g)) \leq o(1).$$

Proof: Following the characterization of \tilde{x} in [Lemma 3.2](#), let $K := \max(\log_2 N, \sum_i I_{x,i})$. By the assumptions on $\sum_i p_i(x)$ and [Lemma 3.3](#), we know K , which is at least the number of coordinates which are resampled, is bounded as $1 \ll K \leq \log_2 N$, for any possible $x = \mathcal{A}(g)$. Now, let $J \subseteq [N]$ denote the set of the first K coordinates to be resampled, so that $K = |J|$, and consider

$$\mathbf{P}(\tilde{x} \in S(E; g) \mid \tilde{x}_{\bar{J}}),$$

where we fix the coordinates outside of J and let \tilde{x} be uniformly sampled from a K -dimensional subcube of Σ_N . All such \tilde{x} are within distance $2\sqrt{K}$ of each other, so by [Theorem 3.4](#), the probability that there is more than one such $\tilde{x} \in S(E; g)$ is bounded by

$$\exp_2(-E + O(K \log N)) \leq \exp_2(-E + O(\log^2 N)) = o(1),$$

by assumption on E . Thus, the probability that any of the \tilde{x} is in $S(E; g)$ is bounded by 2^{-K} , whence

$$\mathbf{P}(\tilde{x} \in S(E; g)) = \mathbf{E}[\mathbf{P}(\tilde{x} \in S(E; g) \mid \tilde{x}_{\bar{J}})] \leq 2^{-K} \leq o(1). \quad \square$$

While this rules out many possible randomized rounding schemes, there is still the potential for rounding in a way that depends on both g and x to find solutions with nonvanishing probability. More generally, recent work by Li and Schramm has pointed out that the presence of an OGP or a conditional landscape obstruction is itself evidence of the brittleness of a random optimization problem [\[71\]](#). Thus, stable algorithms (e.g., Lipschitz, smooth, etc.) are intrinsically ill-suited for such tasks. In light of this, low (coordinate) degree algorithms, which can be stable but are not required to be continuous or smooth, provide better intrinsic models. Given that, new approaches on algorithms for the NPP could focus on non-stable algorithms, such as linear or semidefinite programming. We invite these as interesting directions for potential future work.

4 Section meow

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4.1 a

4.2 b

4.3 c

4.4 d

4.5 f

Definition 4.1. meow

Proposition 4.2.

Proposition 4.3.

Theorem 4.4.

Theorem 4.5.

Theorem 4.6.

Theorem 4.7.

Theorem 4.8.

$$i \tag{4.1}$$

$$i \tag{4.2}$$

$$i \tag{4.3}$$

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