Linear Space Streaming Lower Bounds for Approximating CSPs

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ABSTRACT

We consider the approximability of constraint satisfaction problems in the streaming setting. For every constraint satisfaction problem (CSP) on \( n \) variables taking values in \( \{0, \ldots, q-1\} \), we prove that improving over the trivial approximability by a factor of \( q \) requires \( \Omega(n) \) space even on instances with \( O(n) \) constraints. We also identify a broad subclass of problems for which any improvement over the trivial approximability requires \( \Omega(n) \) space. The key technical core is an optimal, \( q^{-(k-1)} \)-inapproximability for the Max \( k \)-LIN-mod \( q \) problem, which is the Max CSP problem where every constraint is given by a system of \( k = 1 \) linear equations mod \( q \) over \( k \) variables.

Our work builds on and extends the breakthrough work of Kapralov and Krachun (Proc. STOC 2019) who showed a linear lower bound on any non-trivial approximation of the MaxCut problem in graphs. MaxCut corresponds roughly to the case of Max \( k \)-LIN-mod \( q \) with \( k = q = 2 \). For general CSPs in the streaming setting, prior results only yielded \( \Omega(qn) \) space bounds. In particular no linear space lower bound was known for an approximation factor less than 1/2 for any CSP. Extending the work of Kapralov and Krachun to Max \( k \)-LIN-mod \( q \) to \( k > 2 \) and \( q > 2 \) (while getting optimal hardness results) is the main technical contribution of this work. Each one of these extensions provides non-trivial technical challenges that we overcome in this work.

1 INTRODUCTION

In this work we consider the approximability of constraint satisfaction problems (CSPs) by streaming algorithms with sublinear space. We give tight inapproximability results for a broad class of CSPs, while giving somewhat weaker bounds on the approximability of every CSP. We introduce these terms below.

1.1 Background

We consider the general class of constraint satisfaction problems with finite constraints over finite-valued variables. A problem in this class, denoted Max-CSP(\( \mathcal{F} \)), is given by positive integers \( q \) and \( k \) and a family of functions \( \mathcal{F} \subseteq \{ f : \mathbb{Z}_q^k \to \{0, 1\} \} \). An instance of the problem consists of \( m \) constraints placed on \( n \) variables that take values in the set \( \mathbb{Z}_q = \{0, \ldots, q-1\} \), where each constraint is given by a function \( f \in \mathcal{F} \) and \( k \) distinct indices of variables \( j_1, \ldots, j_k \in [n] \). Given an instance \( \Psi \) of Max-CSP(\( \mathcal{F} \)), the goal is to compute the value \( \text{val}_\Psi \) defined to be the maximum, over all assignments to \( n \) variables, of the fraction of constraints satisfied by the assignment. For \( a \in [0, 1] \), the goal of the \( a \)-approximate version of the problem is to compute an estimate \( \hat{\text{val}}_\Psi \) such that \( a \cdot \text{val}_\Psi \leq \hat{\text{val}}_\Psi \leq \text{val}_\Psi \).

In this work we consider the space complexity of approximating Max-CSP(\( \mathcal{F} \)) by a single pass (potentially randomized) streaming algorithm that is presented the instance \( \Psi \) one constraint at a time. We consider "non-trivial" approximation algorithms for Max-CSP(\( \mathcal{F} \)), where we first dismiss two notions of "triviality". First note that since we only consider space restrictions but not
time restrictions, one can sample $O(n)$ constraints of $\Psi$ and solve the Max-CSP($F$) problem on the sampled constraint optimally to get a $(1 - \varepsilon)$-approximation algorithm for every constant $\varepsilon > 0$ in $O(n)$ space. Thus for this paper we view non-trivial algorithms to be those that run in $o(n)$ space.\footnote{We note that there is a gap between the $o(n)$ space we allow and the $O(n \log n)$ space that is trivial, but we are not able to get sharp enough lower bounds to address this gap.} The other form of "triviality" we dismiss is in the approximation factor. Given a family $F$, let $\rho_{\min}(F)$ denote the infimum, over all instances $\Psi$ of Max-CSP($F$), of the value $\val_{\Psi}$. Note that the algorithm that outputs the constant $\rho_{\min}(F)$ is a $(O(1))-space!$ $\rho_{\min}(F)$ approximation algorithm for Max-CSP($F$). Thus we consider $\rho_{\min}(F)$ to be the "trivial" approximation factor for a family $F$. With these two notions of "triviality" in mind, we define Max-CSP($F$) to be $\alpha$-approximable (in the streaming setting) if $\alpha$ is the largest constant such that there exists an $\alpha$-approximation algorithm for Max-CSP($F$) using $o(n)$ space. We say that Max-CSP($F$) is simply approximable (in the streaming setting) if it is $\alpha$-approximable for some $\alpha > \rho_{\min}$. We define a problem to be approximation-resistant (in the streaming setting) otherwise.

1.2 Results

Our first main result in this paper gives a sufficient condition for a problem to be approximation resistant in the streaming setting. We say that $f : \mathbb{Z}_q^k \rightarrow \{0, 1\}$ is a wide constraint if there exists $a \in \mathbb{Z}_q$ such that for every $i \in \mathbb{Z}_q$ we have $f(a + i^k) = 1$ where $i^k = (i, i, \ldots, i)$ and addition is performed in the group $\mathbb{Z}_q$. We say that a family $F$ is wide if every function $f \in F$ is wide.

**Theorem 1.1.** For every $q, k$ and every wide family $F$, Max-CSP($F$) is approximation-resistant.

Many natural CSPs are wide, including Boolean problems such as Max $k$-SAT and Max $q$-colorability. Others, such as Max $k$-LIN($q$) and the "Unique Games" problem, contain wide subfamilies with the same "trivial" approximation factor, and thus Theorem 1.1 implies these are also approximation resistant. We elaborate on some of these examples in Section 4. However, clearly wideness does not capture all CSPs. For general CSPs, while we do not pin down the approximability exactly, we do manage to pin it down up to a multiplicative factor of $q$.

**Theorem 1.2.** For every $q, k$ and every family $F$, if $F$ is $\alpha$-approximable then $\alpha \in \rho_{\min}(F), q \cdot \rho_{\min}(F)$.

Both Theorems 1.1 and 1.2 follow from our more detailed Theorem 4.3. In Section 4 we give a few examples illustrating how our theorems give tight lower bounds for some commonly studied CSPs including Max $q$-coloring, Unique Games, and Max Linear Systems.

1.3 Prior Work

There have been a number of works in the broad area of approximations for streaming constraint satisfaction problems and lower bound techniques for those [1–4, 7–13, 15, 16]. Among these our work is the first work to aim to get tight inapproximability results for a broad class of CSPs for almost linear space single-pass streaming algorithms. Previous works either did not get tight approximation factors or were aimed at specific problems or only got $\Omega(\sqrt{n})$-space lower bounds, though some do target multi-pass streaming algorithms [2, 3] — which we do not do here. We describe the state of the art prior to our work below. (More detailed descriptions of prior works can be found in [4].)

On the front of general lower bounds, Chou, Golovnev, Sudan and Velusamy [4] explored the same set of CSP problems as we do, i.e, Max-CSP($F$) for arbitrary $q, k$ and $F$. Their focus is on looser space lower bounds: specifically, they focus on problems that require $n^{o(1)}$ space vs. those where $n^{o(1)}$ space suffices. They give a complete dichotomy for sketching algorithms, a special class of streaming algorithms. They also give sufficient conditions for approximation resistance with respect to sub-polynomial space general streaming algorithms. Theorem 2.9 in their paper shows that families $F$ where the satisfying assignments of every function in the class support a one-wise independent distribution are approximation resistant. This theorem is incomparable with our Theorem 1.1 in that they give approximation resistance for a broader collection of problems (all wide families support one-wise independence) but the space lower bound is weaker — they give an $\Omega(\sqrt{n})$ lower bound and we get $\Omega(n)$ lower bounds for wide families. [4] does not give an analogue of our Theorem 1.2, though such a result (with the weaker $\Omega(\sqrt{n})$ space lower bound) can be derived from their theorems equally easily. Indeed, our Section 4 is based on their work.

Turning to linear space lower bounds the breakthrough work here is due to Kapralov and Krachun [13], who show that approximating Max Cut (which translates in our setting to Max-CSP($F$) for $F = \{\phi_2\}$ where $\phi_2 : \{0, 1\}^2 \rightarrow \{0, 1\}$ is the binary XOR function) to within a factor $\frac{1}{2} + \varepsilon$ requires $\Omega(n)$ space for every $\varepsilon > 0$. Indeed, our work builds on their work and we compare our techniques later. Prior to the work of Kapralov and Krachun, there was a weaker result due to Kapralov, Khanna, Sudan and Velinker [12] showing that there exists $\varepsilon > 0$ such that $(1 - \varepsilon)$-approximation for Max Cut requires linear space. Finally, Chou, Golovnev and Velusamy [7] get a tight inapproximability for Max Exact 2-SAT (corresponding to the Max-CSP($F$) for $F = \{\phi_2\}$, where $\phi_2 : \{0, 1\}^2 \rightarrow \{0, 1\}$ is the binary OR function) for linear space algorithms, by a reduction from Max Cut.

Thus, prior to our work it was conceivable (though of course extremely unlikely) that every Max-CSP($F$) allowed a $1/2$-approximating streaming algorithm using $o(n)$ space. Our work is the first to prove inapproximability $\alpha \leq 1/2$ for any Max-CSP($F$). Indeed, we get inapproximabilities going to 0 either as $q \rightarrow \infty$ (e.g., for the Unique Games problem) or as $k \rightarrow \infty$ (e.g., for the Max $k$-equality problem with $q = 2$ as defined later in Section 4).

The main contribution of our work is to extend the techniques of [13] to problems beyond Max Cut. Indeed the bulk of our proof takes the tour-de-force proof in [13] and finds the correct replacements in our setting. In the process, we arguably even present cleaner abstractions of their work. We elaborate on this further in the next section but first comment on why we feel the extensions are not straightforward given [13]. First we note that the exact class of problems we are able to deal with in Theorem 1.1 is not the fullest extension one may hope for. At the very least we have not expected to cover the same set of problems as [4, Theorem 2.9], i.e., families supporting one-wise independent distributions, but this
remains open. Indeed to get our extensions we have to formulate a new communication problem which generalizes the one in [13] and is different from the many variations considered in [5] and [4]. In particular we are forced to work with a less expressive set of communication problems that already forces a “linear-algebraic” restriction on the core problems we work with. (We do believe a slight extension of our results to “families containing one-wise independent costs of $\mathbb{Z}_q^k$ should be more feasible.) Having identified the right set of problems, carrying out the proof of Kapralov and Krauthg is still non-trivial. In particular one has to be careful to ensure that the improvement in the exponent of the space bound (from $n^{1/2}$ to $n$) is by a full factor of 2 and not a factor of $k/(k - 1)$, which is what one natural extension would lead to! We comment on these improvements in greater detail in the following.

Finally we point out that an extension of the lower bounds in [4] to $\Omega(n)$ space lower bounds may actually be false. In particular, there is a candidate algorithm for one of the problems (Max 2-AND) that might improve on the approximation factors with $\omega(\sqrt{n})$ space. It certainly works better on the hard instances from previous reductions, but we do not have an improved analysis on all graphs.

### 1.4 Techniques and New Contributions

There are two lines of previous work that seem relevant to this work and we discuss our technical contributions relative to those here. We start with quick comparison with the previous work [4] that gives $\Omega(\sqrt{n})$ lower bounds for a broader subset of problems than those addressed in this paper. We then move on to the work [13] which is much closer to our work and needs more detailed comparison.

**Comparison with [4].** While there is some obvious overlap in the set of problems considered in [4] and this paper (and also in the set of authors) we claim that, beyond this aspect, the overlap in techniques is minimal. Both papers do use lower bounds on communication problems to establish lower bounds on streaming CSPs (which is standard in the context of streaming lower bounds). But the exact set of communication problems is different, and the tools used to establish the lower bounds are also different. In particular, [4] create roughly a new communication problem for every $\gamma$, $\beta$ and $F$ and the main technical contributions there are lower bounds for these problems achieved mainly through a rich set of reductions among these communication problems. In our work we essentially work with one communication problem (once we fix $k$ and $q$) and the core of our work is proving a lower bound for this problem. (This lower bound is based on extending [13] and we will elaborate on this later.) We use this one problem to get hardness for many different $\gamma$, $\beta$ and $F$ — this part is arguably related to the work of [4] but we feel this is the obvious part of their work as well as our work. Finally, turning to the communication problems, the natural communication problems used to analyze streaming complexity involves one way communication among a large constant number of players. The exact problem of this type that we focus on is different from the ones considered in [4] due to a concept we call “folding”. Folding makes our problems too restrictive to work for [4] (i.e., would prevent them for addressing every $(\gamma, \beta) - \text{Max-CSP}(F)$), whereas we do not know how to get our lower bounds without folding. We also note that [4] derive their multiplayer lower bounds from lower bounds for a corresponding 2-player game and all their reductions work only for these 2-player games, which are inherently limited to yielding $\Theta(\sqrt{n})$ space lower bounds.

We now turn to the more significant comparison, with [13]. We start with a quick review of the main steps of [13] and then describe our analysis and conclude with a summary of the differences/new contributions relative to [13].

**Summary of [13].** [13] work with a distributional $T$-player one-way communication game for some constant $T$. The game also has a parameter $\alpha > 0$. In instances of length $n$ of this game, $T$ players $P_1, \ldots, P_T$ get partial matchings $M_1, \ldots, M_T$ on the vertex set $[n]$ along with respective binary labels $z_1, \ldots, z_T$ on the edges of the matchings, i.e., player $t$ receives input $(M_t, z_t)$. Each matching contains $an$ edges, while each corresponding label $z_t$ is an element of $\{0, 1\}^{an}$. In the communication game, the players sequentially broadcast messages as follows. Player $t \in \{T - 1\}$ computes a small message $c_t$ which is a function of $M_t, z_t$ and all “previous messages” $c_1, \ldots, c_{t-1}$ after which the $T$th player outputs a single $0$/$1$ bit that is said to be the output of the communication protocol. The complexity of the protocol is the maximum over $t \in \{T\}$ of the message cost $c_t$, and the goal of the players is to distinguish input instances drawn according to a YES distribution from those drawn according to a NO distribution, defined as follows.

In instances chosen from the NO distribution, the matchings $M_1, \ldots, M_T$ are chosen uniformly and independently from the set of matchings containing $an$ edges on the vertex set $[n]$. Furthermore, the vectors $z_1, \ldots, z_T$ are chosen uniformly and independently from $\{0, 1\}^{an}$. In the YES distribution, the matchings are chosen as in the NO distribution, but in order to generate $z_1, \ldots, z_T$, we choose a common hidden vector $x^* \in \{0, 1\}^n$ uniformly at random and set each $z_t = x^* \oplus x_t^*$ for every edge $e \in \{a, b\}$. Thus, the label $z_t$ can be viewed as specifying which edges of the $t$-th matching cross the cut determined by $x^*$. If $T \gg \frac{1}{\alpha}$ then it can be seen that the YES and NO distributions are very far. The key theorem shows that for every $\alpha > 0$ and $T$, any protocol distinguishing YES instances from NO instances with constant advantage requires $\Omega(n)$ space. With this lower bound a space lower bound on Max Cut is straightforward.

Turning to the communication lower bound, the focus of the analysis are the sets $B_1, \ldots, B_T \subseteq \{0, 1\}^n$ corresponding to the purported hidden vector $x^*$ that are consistent with the messages $c_1, \ldots, c_T$. Specifically for $t \in \{T\}$, $B_t$ is the set of all vectors $x^*$ that are consistent with the first $t$ matchings $M_1: \ldots, M_t$ and the first $t$ messages $c_1: \ldots, c_t$. [13] argue that the sets $B_t$ are not shrinking too fast (in either the YES case or the NO case) using a property that they term “C-boundedness,” defined by the Fourier spectrum of the indicator function of $B_t$ (the function in $\{0, 1\}^n$ to $\{0, 1\}$ that is 1 on $B_t$). We do not give the exact definition of boundedness here but roughly describe it as follows: Given an arbitrary set $B$ of size $S$ and a Fourier weight $w$, the total Fourier mass (strictly the $L_1$-mass) of the wth level Fourier coefficients of $B$ is well-known (by classical Fourier analysis) to be bounded by some amount $U(w) = U_{S,n}(w)$.
For C-bounded sets, the corresponding Fourier mass is required to be at most $C^* \Omega(\frac{\log n}{n})$. The factor of two gained here in the argument of $U$ is the crux to improvement in the space lower bound from $\sqrt{n}$ to $n$. (If the right hand side had been of the form $C^* \Omega(\frac{\log n}{n})$ then the space lower bound would be $\Omega(n^{1/(2a)})$.) This factor of two, in turn, is attributable to the fact that the $z_i$ only contain information about pairs of bits of $x^*$. Their analysis shows that, for every $t$, $B_t$ is $C_t$-bounded for some constant $C_t$. (The proof is inductive on $t$ but the inductive hypothesis is complex and we won’t reproduce it here.) They further show that if $B_T$ is $C$-bounded for some constant $C$, then the distinguishing probability is at most $o(1)$.

Our Analysis. The core of our paper focuses on one problem for every given $q$ and $k$, which we call Max $k$-EQ$(q)$. This is the problem given by Max-$\text{CSP}(F)$ for $F = \{ f_{b_1, \ldots, b_k} : \mathbb{Z}_q^k \rightarrow \{0, 1\} \}$, where $f_{b_1, \ldots, b_k}(a_1, \ldots, a_k) = 1$ if and only if $a_1 = a_1 + b_1 \mod q$ for every $t \in [2, \ldots, k]$. All our lower bounds effectively come from a tight $q^{k-1}$-approximability of this problem for every $q$ and $k$.

To study this problem we introduce a $T$-player communication problem that we call the “Implicit Randomized Mask Detection Problem” (IRMD) described as follows: There are $T$ players each of whom receives an $an$ $k$-hypermatching $M_i$ (i.e., a set of $an$ $k$-uniform hyperedges on $[n]$ that are pairwise disjoint). Additionally, the players receive a label in $\mathbb{Z}_q^k$ for every hyperedge they see. Thus the $t$th player’s input is $(M_t, z_t)$ where $z_t \in (\mathbb{Z}_q^k)^{an}$. In the NO distribution the $z_t$’s are drawn uniformly. In the YES distribution a vector $x^* \in [q]^n$ is drawn uniformly and the label associated with an edge $j = (j_1, \ldots, j_k)$ is $(x^*_{j_1} + a_1, \ldots, x^*_{j_k} + a_k)$ where $a_k \in [q]$ is chosen uniformly and independently for each edge in each matching. The goal of the players is to distinguish between the YES and NO distributions with minimal communication (with one-way communication from the $t-1$th player to the $t$th player, as before).

To lower bound the communication complexity of IRMD we consider a folded version of the problem we call IFRMD where the labels associated with an edge are from $\mathbb{Z}_q^{k-1}$ and obtained by mapping an IRMD label $z = (z^{(1)}, \ldots, z^{(k)}) \in \mathbb{Z}_q^k$ to the label $z' = (z^{(2)} - z^{(1)}, \ldots, z^{(k)} - z^{(1)})$. With this folding we recover the same communication problem as [13] for the case of $k = q = 2$ and the main focus of our work is proving lower bounds for higher $k$ and $q$.

Our analysis of the communication complexity of IFRMD follows the same sequence of steps (with imitation even within the steps) as [13]. In particular we also use the same sets $B_1, \ldots, B_T$ and use the same notion of boundedness.

Turning to the induction and the analysis of boundedness of $B_t$ for general $t$, we are able to extract a clean lemma (Lemma 5.17) that makes the induction completely routine. To explain this contribution note that $B_1$ is the intersection of $B_{t-1}$ with a set say $A_t$ where $A_t$ is of the same type as $B_t$ (both are obtained by looking at the vector $x^*$ projected to a matching followed by some folding). Thus both $B_{t-1}$ and $A_t$ are bounded sets. To complete the induction it would suffice to prove that the intersection of bounded sets is bounded, but alas this is not true! To get that $B_t$ is bounded, we need to use the fact that the matching $M_t$ is random and chosen independently of $B_{t-1}$ but it turns out that that is all that is needed. This is exactly what we show in Lemma 5.17 — and of course this only happens with high probability over the choice of $M_t$.

Incremental contribution over [13]. Given that our result closely follows [13] we now focus on some key differences, and why these contributions are conceptually significant.

(1) The analysis of [13] is intricate and it is not a priori clear what problems it may extend to. Our choice of Max $k$-EQ$(q)$ is not the obvious choice, and was not our first choice. More natural choices would be to go for more general linear systems, or even functions supporting “one-wise independence”, but we are unable to push the analysis to more general cases. Our choice reflects an adequate one to get coarse bounds on the approximability of every problem while getting tight ones for many natural ones.

(2) The choice of the communication problems to work with is also not obvious: Indeed working with both IRMD and IFRMD seems necessary for our approach — the former is more useful for our final inapproximability results whereas the latter is the one we are able to analyze.

(3) The exact notion of boundedness that is necessary and sufficient for our results is also not completely obvious. It is only in hindsight, after carrying out the entire analysis, does it become clear that the notation that works is exactly the same as the one in [13]. Part of the challenge is that in the inductive proof of boundedness even the base case (which is quite simple in [13]) is not obvious in our case, and nor is the inductive step.

• With respect to the base case we note that if we had adopted a weaker notion of boundedness allowing with level Fourier mass to grow roughly as $U((k-1)w/k)$ boundedness would have been easier to prove but the result would not be optimal. Getting a bound of $U(w/2)$ is not technically hard, but involves a non-trivial randomization in the choice of folding purely for analysis purposes. (So there is an implicit passing back and forth between the IRMD and IFRMD problems in this technical step.)

• We also feel that it is important that we are able to extract an induction lemma (Lemma 5.17) that clearly separates the (Fourier and combinatorial) analytic ingredients from the probabilistic setup. We believe the lemma is clarifying even when applied to the proof of [13].

(4) Finally we note that the underlying combinatorics are made significantly more intricate due to the need to work with $k > 2$. A conceptual difference from [13] here is that whereas they explore the distribution of the number of edges in a random matching that intersect with a fixed set of vertices, we have to explore the distribution of edges that have an odd intersection (or non-zero mod $q$ intersection) with a random hypermatching. Indeed this part is clarifying the role of some of the quantities explored in the previous work. Additionally, we note that the number of parameters we have to track is much larger (and indeed it is fortunate that the number of parameters remains a constant independent of $k$), and managing these in our inequalities is a non-trivial technical challenge (even given the heavy lifting in [13]).
Organization of the rest of the paper. We start with some background material in Section 2. We introduce our communication problems (IRMD and IFRMD) in Section 3 and state our lower bounds for these. We use these lower bounds to prove our streaming lower bounds in Section 4. Section 5 introduces the notion of bounded sets and proves our lower bound on the communication problems.

2 PRELIMINARIES
We use the following notations throughout the paper. Let \( \mathbb{N} = \{1, \ldots, n\} \) denote the set of natural numbers and let \( \mathbb{Z}[n] = \{1, 2, \ldots, n\} \). For a discrete set \( X \) and a function \( f : X \to \mathbb{R} \), we denote \( \|f\|_p = (\sum_{x \in X} |f(x)|^p)^{1/p} \) for every \( p > 0 \) and \( \|f\|_0 = \sum_{x \in X} 1_{\{f(x) \neq 0\}} \).

2.1 Total Variation Distance
In our analysis we will use the total variation distance between probability distributions, and several bounds on it presented in this section.

Definition 2.1 (Total variation distance of discrete random variables). Let \( \Omega \) be a finite probability space and \( X, Y \) be random variables with support \( \Omega \). The total variation distance between \( X \) and \( Y \) is defined as follows.

\[
\|X - Y\|_{tv,d} := \frac{1}{2} \sum_{\omega \in \Omega} |\Pr[X = \omega] - \Pr[Y = \omega]|.
\]

We will use the triangle and data processing inequalities for the total variation distance.

Proposition 2.2 (E.g.,[11, Claim 6.5]). For random variables \( X, Y \) and \( W \):

- (Triangle inequality) \( \|X - Y\|_{tv,d} \leq \|X - W\|_{tv,d} - \|Y - W\|_{tv,d} \).
- (Data processing inequality) If \( W \) is independent of both \( X \) and \( Y \), and \( f \) is a function, then \( \|f(X, W) - f(Y, W)\|_{tv,d} \leq \|X - Y\|_{tv,d} \).

Lemma 2.3. Let \( X, Y, W \) be random variables and let \( f \) be a function. If there exists \( \delta > 0 \) such that for every fixed \( x \) in the support of \( X \), we have

\[
\|f(x, Y) - f(x, W)\|_{tv,d} \leq \delta ,
\]

then the following holds:

\[
\|(X, f(X, Y)) - (X, f(X, W))\|_{tv,d} \leq \delta .
\]

Proof. Proof is given in the full version [6]. \( \square \)

We will also need the following lemma from [13].

Lemma 2.4 ([13] Lemma B.2). Let \( X^1, X^2 \) be random variables taking values on finite sample space \( \Omega_1 \). Let \( Z^1, Z^2 \) be random variables taking values on sample space \( \Omega_2 \), and suppose that \( Z^2 \) is independent of \( X^1, X^2 \). Let \( f : \Omega_1 \times \Omega_2 \to \Omega \) be a function. Then

\[
\|f(X^1, f(X^1, Z^2)) - (X^2, f(X^2, Z^2))\|_{tv,d} \leq \|(X^1, f(X^1, Z^2)) - (X^1, f(X^1, Z^2))\|_{tv,d} + \|X^1 - X^2\|_{tv,d} .
\]

2.2 Concentration Inequality
We will use the following concentration inequality from [13] which is essentially an Azuma-Hoeffding style inequality for submartingales.

Lemma 2.5 ([13, Lemma 2.5]). Let \( X = \sum_{i \in [N]} X_i \) where \( X_i \) are Bernoulli random variables such that for every \( k \in [N] \),

\[
\mathbb{E}[X_k | X_1, \ldots, X_{k-1}] \leq p ,
\]

for some \( p \in (0, 1) \). Let \( \mu = Np \). For every \( \Delta > 0 \), we have:

\[
\Pr \{ X \geq \mu + \Delta \} \leq \exp \left( -\frac{\Delta^2}{2\mu + 2\Delta} \right) .
\]

2.3 Fourier Analysis
In this paper, we will use Fourier analysis over \( \mathbb{Z}_q \) (see, for instance, [9, 14]). For a function \( f : \mathbb{Z}_q^n \to \mathbb{C} \), its Fourier coefficients are defined by \( \hat{f}(u) = \frac{1}{q^n} \sum_{a \in \mathbb{Z}_q^n} f(a) \cdot \omega^{u \cdot a} \), where \( u \in \mathbb{Z}_q^n \) and \( \omega = e^{2\pi i/q} \) is the primitive \( q \)-th root of unity. In particular, for every \( a, f(a) = \sum_{u \in \mathbb{Z}_q^n} \hat{f}(u) \cdot \omega^{u \cdot a} \).

Later we will use the three following important tools. Note that we define the \( p \)-norm of \( f \) as \( \|f\|_p = \sum_{x \in \mathbb{Z}_q^n} |f(x)|^p \) rather than the standard definition which uses expectation. This is for future notational convenience.

Lemma 2.6 (Parseval’s identity). For every function \( f : \mathbb{Z}_q^n \to \mathbb{C} \),

\[
\|f\|_2^2 = \sum_{a \in \mathbb{Z}_q^n} |f(a)|^2 = q^n \sum_{u \in \mathbb{Z}_q^n} \hat{f}(u)^2 .
\]

Note that for every distribution \( U \) on \( \mathbb{Z}_q^n \), \( \hat{U}(0^n) = q^{-n} \). For the uniform distribution \( U \) on \( \mathbb{Z}_q^n \), \( \hat{U}(u) = 0 \) for every \( u \neq 0^n \). Thus, by Lemma 2.6, for any distribution \( f \) on \( \mathbb{Z}_q^n \),

\[
\|f - U\|_2^2 = q^n \sum_{u \in \mathbb{Z}_q^n} \left( \hat{f}(u) - \hat{U}(u) \right)^2 = q^n \sum_{u \in \mathbb{Z}_q^n \setminus \{0^n\}} \hat{f}(u)^2 . \tag{2.7}
\]

We now introduce some standard facts about how convolutions interact with the Fourier transform operation. For functions \( f, g : \mathbb{Z}_q^n \to \mathbb{C} \), their convolution \( * \\ f \circ g : \mathbb{Z}_q^n \to \mathbb{C} \) is defined as \( f \circ g(a) = \sum_{v \in \mathbb{Z}_q^n} f(v) \cdot g(a - v) \). The first lemma is the so-called “convolution theorem,” which essentially states that, up to normalization factors, the Fourier transform of the convolution of two functions is equal to the product of the individual Fourier transforms.

Lemma 2.8 (Convolution Theorem). For \( f, g : \mathbb{Z}_q^n \to \mathbb{C} \), we have

\[
\hat{f} \ast \hat{g}(u) = q^n \cdot \hat{f}(u) \cdot \hat{g}(u) .
\]

for all \( u \in \mathbb{Z}_q^n \).

Proof. Proof is given in the full version [6]. \( \square \)

We will also need the following lemma, which states that the Fourier transform of the product of two functions is given by the convolution of the individual Fourier transforms.

Lemma 2.9 (Fourier transform of product of functions). For every \( f, g : \mathbb{Z}_q^n \to \mathbb{C} \), and \( u \in \mathbb{Z}_q^n \), we have

\[
\hat{f} \cdot \hat{g}(u) = \sum_{u' \in \mathbb{Z}_q^n} \hat{f}(u') \cdot \hat{g}(u - u') .
\]
Furthermore, for every $h \in [n]$, 
\[ \sum_{u \in \mathbb{Z}_q^n, \|u\|_2 = h} \tilde{f}(u) \cdot \tilde{g}(u') = \sum_{u \in \mathbb{Z}_q^n, \|u\|_2 = h} \tilde{f}(u) \cdot \tilde{g}(u'). \]

Proof. Proof is given in the full version [6]. \hfill \Box

The hypercontractivity theorem states that the 2-norm of a function after the application of a noise operator can be nicely upper bounded.

**Lemma 2.10** (Hypercontractivity Theorem [14, Page 278]). Let $f : \mathbb{Z}_q^n \to \mathbb{C}$ be a square-integrable function and let $1 \leq p < 2$, 
\[ 0 \leq \rho \leq \frac{1}{\sqrt{q^2 - 1}}(1/q)^{1/2-1/p}, \]
we have 
\[ \|T_\rho f\|_2 \leq \|f\|_p, \]
where $T_\rho$ is the noise operator defined by $T_\rho f(x) = \sum_{u \in \mathbb{Z}_q^n} \tilde{f}(u)\rho^{|u||u|_0}u^*x$.

Next, we present the following consequence of the hypercontractivity theorem.

**Lemma 2.11.** There exists $\zeta > 0$ such that for every $q, \forall f : \mathbb{Z}_q^n \to \{\pm 1\}$ and $\mathcal{B} = \{a \in \mathbb{Z}_q^n \mid f(a) = 0\}$ the following holds: if $|\mathcal{B}| \geq q^{-n^{\alpha}}$ for some $b \in \mathbb{N}$, then for every $v \in \mathbb{Z}_q^n$ and every $h \in \{1, \ldots, 4b\}$, we have 
\[ \frac{q^2n}{|\mathcal{B}|^2} \sum_{u \in \mathbb{Z}_q^n, \|u+v\|_2 = h} |\tilde{f}(u)|^2 \leq \left(\frac{\zeta \cdot b}{h}\right)^h. \]

Proof. Proof is given in the full version [6]. \hfill \Box

### 3 COMMUNICATION PROBLEMS

Throughout this paper, we will be dealing with $k$-hypermatchings on vertices from the set $[n]$, i.e., a set of edges $e_1, \ldots, e_m$ where $e_i \subseteq [n], |e_i| = k$ and $e_i \cap e_j = \emptyset$ for every $i \neq j \in [m]$.

We let $e_i = \{e_{i1}, \ldots, e_{i\ell}\}$. The direct encoding of a matching $M = \{e_1, \ldots, e_m\}$ will be given by a hypermatching matrix $A \in \{0, 1\}^{km \times \ell n}$ where $A_{\ell k}(i_{\ell k}) = 1$ if and only if $j = e_{i\ell}$. (Thus, $A$ is a matrix with row sums being 1 and column sums being at most $k$.)

We will also find it convenient to refer to edges by their indicator vectors in $\mathbb{Z}_q^n$. For an edge $e_i$, we will use the boldface notation $e_i \in \mathbb{Z}_q^n$ to refer to this vector, i.e., $(e_{i\ell})_j = 1$ if $j = e_{i\ell}$ for some $\ell$ and $(e_{i\ell})_j = 0$ otherwise.

We are now ready to define the communication game, which we term the Implicit Randomized Mask Detection (IRMD) problem:

**Definition 3.1** (Implicit Randomized Mask Detection (IRMD) Problem). Let $q, k, n, T \in \mathbb{N}$ and $\alpha \in (0, 1/k)$ be parameters. Let $D_T$ and $D_N$ be distributions over $\mathbb{Z}_q^n$. The $(D_T, D_N)$-IRMD$_{\alpha, T}$ game, there are $T$ players and a hidden $q$-coloring encoded by a random $x^\ast \in \mathbb{Z}_q^n$. The $t$-th player has two inputs: (a) $A_T \in \{0, 1\}^{ak n \times \ell n}$, the hypermatching matrix (see above) corresponding to a random hypermatching $M_t$ of size $an$ and (b) a vector $z_t \in \mathbb{Z}_q^{ak n}$ that can be generated from one of two different distributions:

- (Yes) $z_t = A_T x^\ast + b_t$ where $b_t \in \mathbb{Z}_q^{ak n}$ is of the form $b_t = (b_{t1}, \ldots, b_{t\ell \cdot an})$ and each $b_{ti} \in \mathbb{Z}_q^n$ is sampled from $D_T$.
- (No) $z_t = A_T x^\ast + b_t$ where $b_t \in \mathbb{Z}_q^{ak n}$ is of the form $b_t = (b_{t1}, \ldots, b_{t\ell \cdot an})$ and each $b_{ti} \in \mathbb{Z}_q^n$ is sampled from $D_N$.

This is a one-way game where the $t$-th player can send a private message to the $(t+1)$-th player after receiving a message from the previous player. The goal is for the $T$-th player to be able to decide whether the $(z_t)$ have been chosen from the “Yes” distribution or “No” distribution. The advantage of a protocol (in which the $T$-th player outputs either “Yes” or “No”) is defined as $|Pr_{D_T}[\text{the $T$-th player outputs Yes}] - Pr_{D_N}[\text{the $T$-th player outputs Yes}]|$. \hfill \Box

**Remark 3.2.** We remark that the inputs to the $T$ players in the IRMD problem can be viewed as a stream $\sigma = \sigma(1) \cdots \sigma(T)$, where the $t$-th player’s input $(A_t, z_t)$ is converted to a stream $\sigma(t) = \sigma(1)(i) \in [n\ell])$ where the elements of the stream are of the form $\sigma(t)(i) = j(t)(i), z(t)(i)$ with $j(t)(i) \in [n\ell]$ is a sequence of $k$ distinct elements of $[n]$ and $z(t)(i) \in \mathbb{Z}_q^n$. This “streaming” representation will be used when we relate the complexity of IRMD to the approximability of various Max-CSP($F$) problems in Theorem 4.3.

We suppress the subscripts $\alpha$ and $T$ when they are clear from context. Furthermore, we simply use IRMD to refer to $(D_T, D_N)$-IRMD with $D_T$ being the uniform distribution over $\{0, 1, k, \ldots, (q-1 \cdot k)\}$ and $D_N$ being the uniform distribution over $\mathbb{Z}_q^n$. The following theorem shows that in this special case, the IRMD problem requires linear communication. We remark that the theorem could hold for other pairs of distributions and leave the question of whether such a lower bound holds as an interesting open problem.

**Theorem 3.3** (Linear lower bound for IRMD). For every $q, k, n \in \mathbb{N}$ and $\delta \in (0, 1/2)$, $\alpha \in (0, 1/k)$, $T \in \mathbb{N}$ there exists $n_0 \in \mathbb{N}$ and $r \in (0, 1)$ such that the following holds. If $D_T, D_N$ are the uniform distributions over $\{0, 1, \ldots, (q-1 \cdot k)\}$ and $\mathbb{Z}_q^n$ respectively and $n \geq n_0$ then every protocol for $(D_T, D_N)$-IRMD$_{\alpha, T}$ with advantage $\delta$ requires $\tau n$ bits of communication.

We prove the hardness of IRMD by first proving the hardness of a folded version of IRMD. In the folded version of the communication problem, we augment each hyperedge with an associated center $c \in e$. Given a $k$-hypermatching $M = (e_1, \ldots, e_m)$ and a sequence of centers $c = (c_1, \ldots, c_m)$ with $e_i = ((e_{i1}), \ldots, (e_{i\ell}) = c_i)$, the $c$-centered folded encoding of $M$ is the matrix $A_c \in \mathbb{Z}_q^{(k-1)m \times \ell n}$

given by 
\[ (A_c)_{(k-1)i}(j, \ell) = \begin{cases} 1 & \text{if } j = (e_i)_{\ell} \text{ and } \ell \in [k-1] \\ -1 & \text{if } j = c_i \text{ and } \ell \in [k-1] \\ 0 & \text{otherwise} \end{cases} \]

We define the folded version of the IRMD problem below (note that all the arithmetic is over $\mathbb{Z}_q$):

**Definition 3.4** (Implicit Folded Randomized Mask Detection (IFRMDEX) Problem). Let $q, k, n, T \in \mathbb{N}$ and $\alpha \in (0, 1/k)$ be parameters. In the IFRMDEX game, there are $T$ players and a hidden $q$-coloring encoded by a random $x^\ast \in \mathbb{Z}_q^n$. The $t$-th player has a pair of inputs $(A_T, x^\ast, w_t)$ given as follows. $A_T, x^\ast \in \mathbb{Z}_q^{(k-1)m \times \ell n}$ gives a $c_i$-centered folded encoding of a random hypermatching $M_t$ of size $an$, $w_t$ gives a sequence of centers $c_1, \ldots, c_m$.

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and \( w_t \in \mathbb{Z}_q^{\pi(k-1)n} \) is a vector that can be generated from two different distributions:

- (YES) \( w_t = A_t,c_t,x^t \).
- (NO) \( w_t \) is uniform over \( \mathbb{Z}_q^{\pi(k-1)n} \).

This is a one-way game where the \( t \)-th player can send a private message to the \((t + 1)\)-th player after receiving message from the previous player. The goal is to decide (by the \((T - 1)\)-th player) whether the \( \{w_t\} \) are coming from the YES distribution or the NO distribution. The advantage of a protocol is defined as the absolute value of

\[
\Pr_{(A_t,c_t,w_t) \in \text{YES}} \left[ \text{the } T\text{-th player outputs Yes} \right] - \Pr_{(A_t,c_t,w_t) \in \text{NO}} \left[ \text{the } T\text{-th player outputs Yes} \right].
\]

The main technical theorem of this paper is the following \( \Omega(n) \) communication lower bound for IFRMD.

**Theorem 3.5** (Linear lower bound for IFRMD). For every \( q,k \in \mathbb{N} \) and \( \delta \in (0,1/2) \), there exists \( n_0 \in (0,1/k) \) such that for every \( \alpha \in (0,\alpha_0) \) and every \( T \in \mathbb{N} \) and every \( \delta \in (0,1) \), there exists \( \tau \in (0,1) \) such that the following holds. When \( n \geq n_0 \) is large enough, any protocol for IFRMD with advantage \( \delta \) requires \( \tau n \) bits of communication.

The proof of Theorem 3.5 is given in the beginning of section 5. We now prove a lemma establishing a reduction from IFRMD to IRMD that preserves the communication complexity. Note that by this lemma, Theorem 3.3 will be an immediate corollary of Theorem 3.5.

**Lemma 3.6.** Let \( n,k,\alpha \) be the parameters. Suppose there exists a protocol for IRMD using at most \( s \) bits communication with advantage \( \delta \), then there exists a protocol for IFRMD using at most \( s \) bits communication with advantage \( \delta \).

**Proof.** Suppose we have an instance of IFRMD with input \((A_t,c_t,w_t)\) to the \( t \)-th player. We show how to transform this into an instance of IRMD. For each \( t \), the \( t \)-th player performs the following computations on his/her input:

1. Use \( A_t,c_t \) to compute the underlying hypermatching \( M_t \) by identifying the set of nonzero columns for each block of \( k - 1 \) rows of \( A_t,c_t \) and compute the corresponding matrix \( \Pi_t \).
2. For each \( i \in [an] \), sample \( x_{t,i} \) uniformly at random. Let \( z_t \in \mathbb{Z}_q^{\pi kn} \) be defined by \( (z_t)_{(i-1)k+j} = (w_t)_{(i-1)k+j} + a_{t,i} \) for each \( j = 1,2, \ldots ,k-1 \) and \( (z_t)_{ik} = a_{t,i} \). We claim that the inputs \((A_t,z_t)\) correspond to an instance of IRMD. It suffices to show that if \((\{A_t,c_t,w_t\})_{t \in [T]} \) follows the YES (resp. NO) distribution of IFRMD, then \((\{A_t,z_t\})_{t \in [T]} \) follows the YES (resp. NO) distribution of IRMD.

Let \( m = an \). For each \( t \), let \( \epsilon_1(t), \epsilon_2(t), \ldots , \epsilon_{m}(t) \) be the hyperedges corresponding to \( A_t,c_t \) (in order), with \( (\epsilon_{(j)})_k = c_{t,i} \).

We first focus on the YES case. Then, note that for \( j = 1,2, \ldots ,k-1 \), we have

\[
(z_t)_{(i-1)k+j} = (w_t)_{(i-1)k+j} + a_{t,i} = (x^*_{\epsilon_{(j)}})_i + (x_{\epsilon_{(j)}})_i + a_{t,i} = x^*_{(z_t)} + a_{t,i},
\]

Moreover,

\[
(z_t)_{ik} = a_{t,i} = x^*_{(c_t)} + (x^*_{\epsilon_{(j)}})_i + a_{t,i} = x^*_{(z_t)} + (x_{\epsilon_{(j)}})_i + a_{t,i}.
\]

Thus, it follows that \( z_t = \Pi_t x^* + b_t \), where \( b_t = (b_t,1, \ldots ,b_t,an) \) is given by \( b_t,1 = (x^*_{\epsilon_{(j)}})_i + a_{t,i} \cdot I_k \) where \( I_k \) is the all 1 vector of length \( k \).

Since \( a_{t,i} \) is uniform over \( \mathbb{Z}_q \), this takes care of the YES case. The NO case is easier to see: \( \Pi_t \) encodes a random \( k \)-hypermatching of size \( an \) and \( z_t \) is uniform over \( \mathbb{Z}_q an \). □

**Proof of Theorem 3.3 using Theorem 3.5.** For the sake of contradiction, suppose there exists a protocol for IFRMD with advantage \( \delta \) using fewer than \( n \) bits of communication. Then by Lemma 3.6 there exists a protocol for IRMD with advantage \( \delta \) using fewer than \( n \) bits of communication, which contradicts Theorem 3.5. This completes the proof of Theorem 3.3. □

In the following section we show how Theorem 3.3 yields the claimed hardness of streaming problems. In the rest of this paper, we focus on the proof of Theorem 3.5, i.e., the linear communication lower bound for IFRMD.

### 4 STREAMING PROBLEMS AND HARDNESS

In this section we state and prove our main technical theorem establishing linear space lower bounds for the approximability of many CSPs.

Below we define the two crucial constants associated with a family \( \mathcal{F} \) which lay out the "trivial" approximability, and the inapproximability that we prove. In particular we define the notion of a width \( \omega(\mathcal{F}) \in [1/q,1] \) for every family \( \mathcal{F} \). The notion of a wide family from Theorem 1.1 corresponds to a family with maximum width, i.e., \( \omega(\mathcal{F}) = 1 \).

**Definition 4.1** (Minimum value, Width of \( \mathcal{F} \)). For a family \( \mathcal{F} \), we define its minimum value \( \rho_{\min}(\mathcal{F}) \) to be the infimum over all instances \( \Psi \) of Max-CSP(\( \mathcal{F} \)) of \( v.\,, \). For \( b \in \mathbb{Z}_q \) and \( f : \mathbb{Z}_q \to [0,1] \) we define \( b \)-width of \( f \), denoted \( \omega(b,f) \) to be the quantity

\[
\left| \{ \mu \in \mathbb{Z}_q : (b+\mu) \in \Psi \} \right|.
\]

The width \( f \) is defined by \( \omega(f) \), is given by \( \omega(f) = \max_{b \in \mathbb{Z}_q} \omega(b,f) \). Finally for a family \( \mathcal{F} \), we define its width to be \( \omega(\mathcal{F}) = \min f_{\in \mathcal{F}} \omega(f) \). We say that a family \( \mathcal{F} \) is wide if \( \omega(\mathcal{F}) = 1 \).

As described above \( \rho_{\min}(\mathcal{F}) \) may not even be computable given \( \mathcal{F} \), but as pointed out in [4] it is a computable function. Key to this assertion is the following equivalent definition of \( \rho_{\min}(\mathcal{F}) \) which follows from Definition 2.4 and Proposition 2.5 of [4].

**Proposition 4.2** ([4, Proposition 2.4]). For every \( k,q,\mathcal{F} \subseteq \{ f : \mathbb{Z}_q^k \to \{0,1\} \} \) and every \( \epsilon \in (0,1/10) \) we have

\[
\rho_{\min}(\mathcal{F}) = \rho(\mathcal{F}) = \min_{D \subseteq \Delta(\mathcal{F})} \left\{ \max_{a \in \Delta(\mathcal{F})} \left\{ \frac{1}{|D|} \sum_{a \in D} \left[ f(a) \right] \right\} \right\}.
\]

We are now ready to prove the main theorem of the paper on the approximability of CSPs by applying Theorem 3.3.

**Theorem 4.3** (Linear Space Inapproximability of CSPs). For every \( k,q,\mathcal{F} \subseteq \{ f : \mathbb{Z}_q^k \to \{0,1\} \} \) and every \( \epsilon \in (0,1/10) \) we have the
following: Every randomized single-pass streaming \((1 + \epsilon) \cdot \frac{\rho(\mathcal{F})}{\epsilon \cdot \text{IRMD}(\mathcal{F})}\) approximation algorithm for Max-CSP(\(\mathcal{F}\)) requires \(\Omega(n)\) space.

**Proof.** Given \(\mathcal{F}\) and \(\epsilon \in (0, 1/10)\), let \(a = \epsilon/(100k^2q)\) and \(T\) be some large enough constant that only depends on \(k, q, F, \epsilon, a\). Let ALG be a space distinguishing algorithm that returns an instance \(\mathcal{F}\) from instances from the set \(\{\mathcal{F} \mid \text{val} \leq (1 + \epsilon/3)\rho(\mathcal{F})\}\) with success probability at least \(2/3\). We show how to use ALG to devise an \(o(1)\)-bit communication protocol for IRMD = IRMD_{a,T} with advantage at least \(1/6\).

For \(f \in \mathcal{F}\), let \(b_f \in 2^k\) be a sequence maximizing \(\omega_f(b_f)\) and let \(S_f = \{b_f + a^k \mid a \in \mathbb{Z}_q\}\). Further let \(D_f = \Delta(\mathcal{F})\) be a distribution achieving the minimum in the equivalent definition of \(\rho(\mathcal{F})\) from Proposition 4.2. Let \(\sigma = (\sigma_1, \ldots, \sigma_m)\) be an instance of IRMD with \(m = \text{Tail}(\mathcal{F})\) players, so that \(m = \text{Tail}(\mathcal{F})\) and \(\sigma_i = (j(i), z(i))\) where \(j(i)\) is a sequence of \(k\) distinct elements of \(N\) and \(z(i) \in 2^k\). For each \(\sigma_i\) we either generate 0 or 1 constraint of Max-CSP(\(\mathcal{F}\)) as follows: We sample \(f(i) \sim D_f\) and output the constraint \((f(i), j(i))\) if \(z(i) \in S_f(i)\) and output no constraint otherwise. Applying this step independently to each \(\sigma_i\) generates an instance \(\Psi\) of Max-CSP(\(\mathcal{F}\)) with \(m \leq m\) constraints on \(n\) variables. We make the following claims about \(\Psi\).

1. \(\text{Pr}_{\text{YES}}(\tilde{m} > (1 + \epsilon/10) \cdot q^{-(k-1) \cdot m} \mid m = o(1)\text{ and } \text{Pr}_{\text{NO}}(\tilde{m} < (1 - \epsilon/10) \cdot q^{-(k-1) \cdot m} \mid m = o(1))\text{, i.e., the number of constraints } \tilde{m} \text{ does not deviate in the wrong direction from its expectation } q^{-(k-1) \cdot m} \text{ with high a probability.}

2. If \(\sigma\) is generated from the YES distribution with hidden vector \(x\) then with high probability the number of constraints of \(\Psi \) satisfied by \(x\) is at least \((\omega(\mathcal{F}) - \epsilon/10) \cdot q^{-(k-1) \cdot m}\).

3. If \(\sigma\) is generated from the NO distribution with hidden vector \(x\) then with high probability every \(\mathcal{F}\) the number of constraints of \(\Psi \) satisfied by \(x\) is at most \((\rho(\mathcal{F}) + \epsilon/10) \cdot q^{-(k-1) \cdot m} \). In particular, \(\text{Pr}_{\text{YES}}(\text{val} \geq (1 + \epsilon/3) \cdot \rho(\mathcal{F}) \mid m = o(1))\).

With the above claims in hand, it is straightforward to convert ALG into an \(O(1)\)-bit communication protocol for IRMD with advantage at least \(1/6\) between the \((t-1)\)-th player, generates the constraints corresponding to the \(t\)-th block of the stream \(\sigma\), and simulates ALG on this part of the stream corresponding to \(\Psi\), and output the resulting protocol achieving advantage at least \(1/3 - o(1)\) at least \(1/6\) on IRMD. Finally, we invoke Theorem 3.3 and conclude that \(s = \Omega(n)\).

We thus turn to proving claims (1)-(3). Given \(\sigma_1, \ldots, \sigma_m\) and \(v \in \mathbb{Z}_q^m\), we create a collection of related variables as follows: For \(i \in [m]\), let \(X_i = 1\) if \(\sigma_i\) results in a constraint and \(0\) otherwise.

Further, let \(Y_1(v) = 1\) if \(X_i = 1\) and the resulting constraint is satisfied by the assignment \(v\). (Note that all these are random variables depending on \(\sigma\).) Below, we bound the expectations of the sums of these random variables in the YES and NO cases, and also argue that these variables are close to their expectations (or at least give bounds on deviating from the expectation in one direction). This will suffice to prove claims (1)-(3) and thus the theorem.

**Proof of Claim (1).** We start with \(\tilde{m} = \sum_{i=1}^m X_i\) in the NO case: In this case we have \(\mathbb{E}[X_i] = |S_f|/q = q^{-(k-1)}\) (note that \(|S_f| = q \text{ for every } f\)). Furthermore the \(X_i\)'s are independent since \(z(i)\)'s are uniform and independent of each other. Thus \(X_i\) is sharply concentrated around \(q^{-(k-1)}\), and we get that \(\text{Pr}_{\text{NO}}(\tilde{m} \leq (1 + \epsilon/10) \cdot q^{-(k-1)} \mid m = o(1))\).

Turning to the YES case, since \(z(i)\)'s are no longer independent, the \(X_i\)'s are correlated. To enable the analysis, we define a vector \(x^*\) to be \(\gamma\)-good for \(\gamma > 0\) if for every \(R \in \mathbb{Z}_q\) we have \(\text{Pr}_{\sigma \in \mathcal{F}}(X_i = R \mid m = o(1)) \leq (1 + \gamma)(1/q)\). Note that for every constant \(\gamma > 0\), the probability that \(x^*\) is not \(\gamma\)-good is \(o(1))\). Fix \(x^*\) that is \(\gamma\)-good. We claim that in this case, \(\mathbb{E}[X_i | X_{i+1} = 1] \leq q^{-(k-1)} \cdot (1 + \gamma + a\gamma q^{k})\). (See this note that the effect of conditioning on \(X_{i+1} = 1\) only affects \(X_i\) due to the fact that \(z(i)\)'s are chosen from a smaller set of variables and not all of \(N\).)

Let \(t \in [T]\) denote the block containing \(i, i = (1-1/t)\). Then \(S_t\) denote the set of variables that do not participate in the edges \((j(t-1) + 1), \ldots, j(t-1)\) \(S_t\) does not participate in the edges \((j(t-1) + 1), \ldots, j(t-1)\) for every \(T \in \mathbb{Z}_q\) we have \(\text{Pr}_{\mathcal{F}}(X^*_i = R \mid m = o(1)) \leq (1 + \gamma + a\gamma q^{k})\).

With these notes in hand, it is straightforward to prove Claim (1) and (3) and thus the theorem.
uniform and independent of all other random variables. We conclude that $\mathbb{E}[Y(v) | Y_{1:L-1}(v)] \leq (1 + \epsilon/10) \cdot \rho(\mathcal{F}) \cdot q^{-(k-1)}$. Finally, we apply Lemma 2.5 again to conclude that 

$$\Pr(Y(v) = \sum_{i=1}^{m} Y_{i}(v) > (1 + \epsilon/10) \cdot \rho(\mathcal{F}) \cdot q^{-(k-1)} \cdot m) \leq c^{-m}$$

where $c > 1$ depends on $q, k, \mathcal{F}, \alpha, \epsilon$ but not on $T$ or $n$. Thus by setting $T$ large enough, we can bound $c^{-m} \leq q^{-2n}$. This allows us to use the union bound to conclude that the probability that there exists $v \in \mathbb{Z}_q^n$ such that $Y(v) > (1 + \epsilon/10) \cdot \rho(\mathcal{F}) \cdot q^{-(k-1)} \cdot m$ is at most $q^{-n} = o(1)$. Combining with the lower bound on $m$ from Claim (1) we get that with probability $1 - o(1)$ we have $\text{val}_\mathcal{F} \leq (1 + \epsilon/3) \cdot \rho(\mathcal{F})$ in this case.

This concludes the proofs of the claims and thus the proof of Theorem 4.3.

Theorems 1.1 and 1.2 follow immediately from Theorem 4.3 as we show below.

Proof of Theorem 1.1. The theorem follows from the fact that for a wide family $\omega(\mathcal{F}) = 1$ and in this case Theorem 4.3 asserts that a $\rho(\mathcal{F}) + \epsilon$ approximation requires linear space.

Proof of Theorem 1.1. The theorem follows from the fact that for every non-zero function $f$ we have $\omega(f) \geq 1/q$ and so for every family $\mathcal{F}$ also we have $\omega(\mathcal{F}) \geq 1/q$. Thus Theorem 4.3 asserts that a $\rho(\mathcal{F}) \cdot q + \epsilon$ approximation requires linear space, where $\rho(\mathcal{F})$ approximation is trivial.

Some examples. We now give some examples illustrating the power of Theorem 4.3. Our first example is the familiar $q$-coloring problem.

Example 1 (Max-$q$Col).

Let $k = 2$ and $q \geq 2$. Let $\mathcal{F} = \{f: \mathbb{Z}_q^2 \to \{0,1\}\}$ where $f(u,v) = 1$ if and only if $u \neq v$. The “Max $q$-Coloring” problem is defined to be Max-$q$Col = Max-CSP($\mathcal{F}$). It is easy to verify $\rho(\mathcal{F}) = 1 - 1/q$ and $\omega(\mathcal{F}) = 1$. We thus conclude by Theorem 1.1 that Max-$q$Col is approximation resistant.

Next we turn to the Unique Games Problem.

Example 2 (Max-$q$UG).

Let $k = 2$ and $q \geq 2$. Let $\mathcal{F} = \{f: \mathbb{Z}_q^2 \to \{0,1\}\}$ where $f^{-1}(1)$ is a bijection. The “$q$-ary Unique Games” problem is defined to be Max-$q$UG = Max-CSP($\mathcal{F}$). We show below that $\rho(\mathcal{F}) = 1/q$. We also show that there exists $\mathcal{F}' \subseteq \mathcal{F}$ such that $\rho(\mathcal{F}') = 1/q$ and $\omega(\mathcal{F}') = 1$. Applying Theorem 1.1 to $\mathcal{F}'$ we get that $1/q + \epsilon$ approximating Max-CSP($\mathcal{F}'$) requires linear space and the same holds for Max-$q$UG = Max-CSP($\mathcal{F}$) by monotonicity.

We define the family $\mathcal{F}'$ to be $\mathcal{F}' = \{f_{a}[u \in \mathbb{Z}_q] \}$ where $f_{a}(u,v) = 1$ if and only if $u = v + a$. Let $\mathcal{D} = \text{Unif}(\mathbb{Z}_q)$. For every $f \in \mathcal{F}$ we have that $\mathbb{E}_{(u,v) \sim \mathcal{D}}[f(u,v)] = 1/q$. So for every $\mathcal{D}_f \in \Delta(\mathcal{F})$ we have $\mathbb{E}_{(u,v) \sim \mathcal{D}}[f(u,v)] = 1/q$. This proves $\rho(\mathcal{F})$, $\rho(\mathcal{F}') \geq 1/q$. To get the upper bound we let $\mathcal{D}_f$ be uniform over $\mathcal{F}'$. For every $(u,v) \in \mathbb{Z}_q^2$ we have $\mathbb{E}_{(u,v) \sim \mathcal{D}}[f(u,v)] = 1/q$ and so for every distribution $\mathcal{D} \in \Delta(\mathcal{Z}_q^2)$ (which is more than we need) we have $\mathbb{E}_{(u,v) \sim \mathcal{D}}[f(u,v)] \leq 1/q$. This proves $\rho(\mathcal{F}')$, $\rho(\mathcal{F}) = 1/q$ (since $\mathcal{D}_f$ is supported on $\mathcal{F}'$).

Now turning to $\omega(\mathcal{F}')$, note that for every $f_a \in \mathcal{F}'$ we have $\{b + a, b \in \mathbb{Z}_q\} \in f_a^{-1}(1)$. Thus $\omega(f_a) \geq \omega_{(a,0)}(f_{a}) = 1$. It follows that $\omega(\mathcal{F}') = 1$.

Our third example talks about constraints that are general linear systems.

Example 3 (Max-Lin$_{k,r,q}$).

For $k \geq 2$ and prime $q$ and $0 \leq r < k$, we define Max-Lin$_{k,r,q}$ = Max-CSP($\mathcal{F}$) for $\mathcal{F} = \mathcal{T}_{k,r,q} = \{f_{A,b} : \mathbb{Z}_q^k \to \{0,1\}, A \in \mathbb{Z}_q^{k \times r}, b \in \mathbb{Z}_q^r\}$ where $f_{A,b}(x) = 1$ if and only if $Ax = Ab$. (Thus constraints are systems of satisfiable linear equations with solutions of dimension at least $k - r$.)

Let $\mathcal{T}'_{k,r,q} = \{f_{A,b} \in \mathcal{T}_{k,r,q} : \mathbb{A} = 0\}$. It is easy to verify that for every $k, r, q$, $\rho(\mathcal{T}'_{k,r,q}) \geq \rho(\mathcal{T}_{k,r,q}) \geq q^{-r}$. By choosing $\mathcal{T}'_{k,r,q}$ to be uniform over $f_{A,b}$ with full rank matrices $A$ satisfying $A = 0$, we get $\rho(\mathcal{T}_{k,r,q})$, $\rho(\mathcal{T}'_{k,r,q}) = q^{-r}$. For $r < k$, we also get $\omega(\mathcal{T}') = 1$ and thus applying Theorem 1.1 to $\mathcal{T}'$ we get that Max-CSP($\mathcal{T}'$) is approximation resistant. The same holds for Max-$q$UG = Max-CSP($\mathcal{F}$) by monotonicity.a

Finally we mention one more problem. This problem arises in the work of Singer, Sudan and Velusamy [15] who use it to show the approximation resistance of the “maximum acyclic subgraph” problem.

Example 4 (Max-Less-Than$_{q}$).

For $k = 2$ and $q \geq 2$ define $\mathcal{F} = \{<q : \mathbb{Z}_q^2 \to \{0,1\}\}$ where $<q$ is given by $<q(u, v) = 1$ if and only if $u < v$. It is possible to show $\rho(\mathcal{F}) = \frac{1}{2}(1 - 1/q)$. Also $\omega_{(0,0)}(<q) = 1 - 1/q$ and this can be used to show that $\omega(\mathcal{F}) = 1 - 1/q$. By Theorem 4.3 it follows that $1/2 + \epsilon$-approximating Max-CSP($\mathcal{F}$) requires linear space.

5 LOWER BOUND ON THE COMMUNICATION COMPLEXITY

In this section we prove a linear lower bound on the communication complexity of IFRMD (Theorem 3.5). Our proof is via a hybrid
argument which starts with all players receiving inputs from the NO distribution, and switching the players’ input distribution one at a time starting with Player 1 to the YES distribution. We state a key “hybrid lemma” (Lemma 5.1) which asserts that any one step of switching does not alter the distribution of the message output by the switched player.

To state our lemma we recall some notations and set up a few new ones. Let \( a, n, k, q, T, m = an \in \mathbb{N} \) denote the usual parameters of IFRMD. Recall that the player \( t \) gets as input a matrix \( A_t \in \mathbb{Z}_q^{(k-1)m \times m} \) corresponding to a \( k \)-uniform hypermatching \( M_t \) consisting of \( m \) hyperedges folded over the center vector \( e_t \) and a vector \( w_t \in \mathbb{Z}_q^{(k-1)m} \). For notational convenience, we will separate the input \( A_t, e_t, w_t \) into a matrix \( A_t \in \mathbb{Z}_q^{(k-1)m \times m} \) and the center \( e_t \). For a sequence of objects \( O_1, O_2, \ldots, O_T \), we denote \( O_{1:T} = \{O_1, O_2, \ldots, O_T\} \) for every \( t \in [T] \). With this notation we have that the message \( S_t \) sent by the \( t \)-th player is a function of \( A_{1:t}, e_{1:t}, w_t, e_{1:t-1} \) and \( S_{1:t-1} \). Next, note that by Yao’s principle, we may assume that the messages sent by the players in IFRMD are all deterministic.

Namely, a protocol for IFRMD can be specified by deterministic message functions \( r_1, r_2, \ldots, r_T \) so that \( S_t = r_t(A_{1:t}, e_{1:t}, S_{1:t-1}, w_t) \) denotes the message sent by the \( t \)-th player. The communication complexity of a protocol is defined as the largest output length of \( r_t \).

When \((A_{1:T}, e_{1:T}, w_{1:T})\) is drawn from the YES distribution (resp. the NO distribution), we denote \( S^Y_{1:T} \) (resp. \( S^N_{1:T} \)) to be the resulting messages. Without loss of generality \( S_T \) is just a bit “Yes/No” indicating the output of the protocol. Thus, to prove Theorem 3.5 we need to show that \( S^Y_T \) and \( S^N_T \) are close in total variation distance. For the induction we prove the much stronger statement that \((A_{1:t}, e_{1:t}, S^Y_{1:t}, S^N_{1:t})\) are close in total variation distance, i.e.,

\[
\| (A_{1:T}, e_{1:T}, S^Y_{1:T}) - (A_{1:T}, e_{1:T}, S^N_{1:T}) \|_{TV} \leq \delta.
\]

The following lemma provides the key step in this analysis. Roughly it says that if the first \( t-1 \) players’ inputs are according to the YES distribution then the \( t \)-th player’s output on the YES input is typically distributed very similarly to the output on the NO distribution (even conditioned on all previously announced hypermatchings, centers and messages). Formally, the lemma identifies a sequence of events \( E_1 \supseteq E_2 \supseteq \cdots \supseteq E_T \) such that (i) \( E_t \) enforces a “typicality” restriction on the messages and inputs that the \( t \)-th player receives and (ii) if the messages and input received by the \( t \)-th player are typical then the player cannot distinguish whether its input is sampled from the YES distribution or the NO distribution (assuming all previous players’ inputs were from the YES distribution).

**Lemma 5.1 (Hybrid lemma).** For every \( q, k \in \mathbb{N} \), there exists \( a_0 \in (0, 1/k) \) such that for every \( \alpha \in (0, a_0) \), \( T \in \mathbb{N} \), and \( \delta \in (0, 1) \), there exist \( n_0 \in \mathbb{N} \) and \( t \in (0, 1) \) such that for every \( n \geq n_0 \) the following holds:

Let \( \Pi = (r_1, \ldots, r_T) \) be a deterministic protocol for IFRMD where each message function \( r_t \) outputs a message of at most \( tn \) bits. Let \( x \sim \text{Unif}(\mathbb{Z}_q^n) \) and let \( M_1, \ldots, M_T \) be independent random hypermatching

\[ \text{of size an over } [n]. \]

Let \((A_t, e_t)\) be an independent random folded encoding of \( M_t \) for all \( t \in [T] \). Let \( S^Y_t \) and \( S^N_t \) be the Yes and No message of the \( t \)-th player defined previously for message function \( r_t \) for all \( t \in [T] \). Then there exists a sequence of events \( E_1 \supseteq E_2 \supseteq \cdots \supseteq E_T \) such that (i) \( E_t \) only depends on \((A_{1:t}, e_{1:t})\) and \( S^Y_{1:t-1}, S^N_{1:t-1} \), (ii) \( \Pr[E_t] \geq 1 - \delta/T \), (iii) \( \Pr[E_t \mid S_{1:t-1}] \leq \delta/T \) for all \( t = 2, 3, \ldots, T \), and (iv) for every fixed \((A_{1:T}, e_{1:T})\) and \( S^Y_{1:t-1} \) satisfying \( E_t \), one has

\[
\| S^Y_t - r_t(A_{1:t}, e_{1:t}, S^Y_{1:t-1}, U_t) \|_{TV} \leq \delta/T,
\]

where \( U_t \sim \text{Unif}(\mathbb{Z}_q^{(k-1)n^a}) \).

The proof of Lemma 5.1 will be provided in Section 5.4. Theorem 3.5 follows almost immediately from Lemma 5.1 as shown in Section 5.1. In the rest of this section and the following sections we prove Lemma 5.1. Here we give an overview of this part of the proof.

The general idea behind the proof of Lemma 5.1 is to argue that information about \( x^t \) “leaked” by the messages of the first \( t-1 \) players (i.e., \( S_{1:t-1} \)) is not sufficient for the \( t \)-th player to distinguish between the case where \( w_t = A_t, e_t \) (the YES case) and the case where \( w_t \) is uniform. The earlier proofs of this type (in particular as in [11]) simply counted the total information gleaned about \( x^t \) which is bounded by the total communication. Such proofs are inherently limited to achieving only a \( \sqrt{n} \) lower bound. To go further, as in [13], one needs to argue about the structure of the information learned about \( x^t \), and in particular note that no player sees \( x^t \) directly, and the \( t \)-th player only sees \( A_t, e_t \). In particular no coordinate of \( x^t \) is revealed directly, though the sum of many pairs of coordinates are directly revealed.) Thus the information about \( x^t \) comes from a “reduced space” and we would like to capture and exploit the structural restriction imposed by this restriction. Information-theoretic tools seem to fail to capture this restriction and the key to the work of [13] is to give a Fourier analytic condition, that they call “boundedness”, that captures this restriction.

The boundedness condition applies to what we call the “posterior distribution” of \( x^t \), i.e., the distribution of \( x^t \) conditioned on the first \( t \) messages. This distribution turns out to be the uniform distribution over a set \( B_t \subseteq \mathbb{Z}_q^n \) (see Lemma 5.6). The boundedness condition places restrictions on the Fourier spectrum of the indicator function of this set. (See Definition 5.11.) To use this condition we need three ingredients elaborated below, which we abstract as lemma statements in this section and prove in later section. Given these three lemmas the proof of Lemma 5.1 follows and is given in Section 5.4.

The first ingredient we need is that boundedness of \( B_{t-1} \) implies that the \( t \)-th player is unable to distinguish between its input being from the YES distribution or the NO distribution. This is stated as Lemma 5.16. Next we need to show that given information about \( A_t, e_t \), the posterior distribution of \( x^t \) is indeed bounded, and we assert this in Lemma 5.15. Note that this also serves as the base case of our induction. Finally we argue that if \( B_{t-1} \) is bounded, then for most matchings \( A_t \) (and every center \( e_t \) of \( A_t \)) the resulting set \( B_t \) is bounded. This is asserted in Lemma 5.17. In the rest of this section, after showing that Lemma 5.1 implies Theorem 3.5 in Section 5.1, we introduce the posterior sets and discuss their basic properties in Section 5.2, we introduce boundedness and state the
three lemmas above in Section 5.3, and finally conclude with the proof of Lemma 5.1 in Section 5.4.

5.1 Proof of Theorem 3.5

We now show how the lemma suffices to prove Theorem 3.5. The proof is analogous to the proof of Lemma 6.3 in [13]. We remark that the lemma is not immediate and effectively depends on the fact that players can jointly sample from the YES distribution since these samples are correlated by the hidden vector $\mathbf{x}^0$. So the proof is inherently asymmetric visavis the treatment of the YES and NO distributions.

Proof of Theorem 3.5. For the sake of contradiction, assume that there exists a protocol $T = (r_1, \ldots, r_T)$ that solves IFMRD with advantage more than $\delta$ and less than $\tau n$ bits of communication for some $n \geq n_0$. In what follows, we will show that $\|A_{1:T}, c_{1:T}, S_{1:T}^Y - A_{1:T}, c_{1:T}, S_{1:T}^N\|_{\text{tvd}}, \delta \leq \delta$, which implies that the advantage of the protocol cannot be greater than $\delta$, hence producing a contradiction.

For every $q, k \in \mathbb{N}$, we set $a_0 \in (0, 1/k)$ and $r_0 \in (0, 1)$ as in Lemma 5.1. For every $\alpha \in (0, \alpha_0)$, $T \in \mathbb{N}$, and $\delta' = \delta/2$, we set $n_0 \in \mathbb{N}$ and $r \in (0, 1)$ as in Lemma 5.1.

Let $\mathcal{E}_t \supseteq \mathcal{E}_2 \supseteq \cdots \supseteq \mathcal{E}_T$ be the sequence of events guaranteed by Lemma 5.1 such that $\Pr[\mathcal{E}_t | \mathcal{E}_{t-1}] \leq \delta'/T$ for $t = 2, 3, \ldots, T$. Note that by the properties of these events, with probability at least $1 - \delta'$, we have $\|S_t^Y - r_t(A_{1:T}, c_{1:T}, S_{1:t-1}^Y, U_t)\|_{\text{tvd}} \leq \delta'/T$ for all $t \in [T]$. We use $\|\cdot\|_{\text{tvd}}, \mathcal{E}_t$ to denote the total variation distance of distributions conditioned on $\mathcal{E}_t$. We inductively show that for every $t \in [T]$,

$$\|(A_{1:t}, c_{1:t}, S_{1:t}^Y) - (A_{1:t}, c_{1:t}, S_{1:t}^N)\|_{\text{tvd}}, \mathcal{E}_t \leq \frac{t \delta'}{T}.$$ (Induction hypothesis)

First, we prove the base case $t = 1$. Recalling that $S_0^Y = S_0^N$, we have

$$\|S_0^Y - r_1(A_{1:T}, c_{1:T}, S_0^Y, U_1)\|_{\text{tvd}}, \mathcal{E}_1 = \|(A_{1:T}, c_{1:T}, (M_1, c_1, S_0^N, U_1))\|_{\text{tvd}}, \mathcal{E}_1 = \|S_1^Y - r_1(M_1, c_1, S_0^N, U_1)\|_{\text{tvd}}, \mathcal{E}_1 \leq \delta'/T,$$

Observe that for every fixed $A_1$ and $c_1$ and $S_0^Y$ satisfying $\mathcal{E}_1$, we have $\|S_0^Y - r_1(M_1, c_1, S_0^N, U_1)\|_{\text{tvd}}, \mathcal{E}_1 \leq \delta'/T$, where the randomness is over $S_0^Y$ and $U_1$. It follows from Lemma 2.3 that

$$\|(A_{1:T}, c_{1:T}, S_{1:t}^Y) - (A_{1:T}, c_{1:T}, S_{1:t}^N)\|_{\text{tvd}}, \mathcal{E}_t \leq \frac{t \delta'}{T},$$

which completes the base case.

Next, we tackle the induction step. For every $t = 2, \ldots, T$, we have

$$\|(A_{1:t}, c_{1:t}, S_{1:t}^Y) - (A_{1:t}, c_{1:t}, S_{1:t}^N)\|_{\text{tvd}}, \mathcal{E}_t = \|(A_{1:t}, c_{1:t}, S_{1:t-1}^Y, r_t(A_{1:t}, c_{1:t}, S_{1:t-1}^Y, A_t, c_t, x^t))\|_{\text{tvd}}, \mathcal{E}_t - (A_{1:t}, c_{1:t}, S_{1:t-1}^N, r_t(A_{1:t}, c_{1:t}, S_{1:t-1}^N, U_t))\|_{\text{tvd}}, \mathcal{E}_t.$$

Let us define $Q_{t-1}^Y = (A_{1:t-1}, c_{1:t-1}, S_{1:t-1}^Y)$ and $Q_{t-1}^N = (A_{1:t-1}, c_{1:t-1}, S_{1:t-1}^N)$. Then, we can rewrite the above expression for total variation distance in terms of the new notation as follows:

$$\|(A_{1:t}, c_{1:t}, S_{1:t}^Y, r_t(A_{1:t}, c_{1:t}, S_{1:t}^N, A_t, c_t, x^t))\|_{\text{tvd}}, \mathcal{E}_t - (A_{1:t}, c_{1:t}, S_{1:t}^N, r_t(A_{1:t}, c_{1:t}, S_{1:t}^N, U_t))\|_{\text{tvd}}, \mathcal{E}_t \leq \|Q_{t-1}^Y - Q_{t-1}^N\|_{\text{tvd}}, \mathcal{E}_t,$$

We now apply Lemma 2.4. Applying this lemma with $X^1 = Q_{t-1}^Y$, $X^2 = Q_{t-1}^N$, $Z^1 = (A_t, c_t, A_t, c_t, x^t)$, $Z^2 = ((A_t, c_t, U_t))$, and $f$ as the function that maps the tuple $(X, (B, C))$ to $(B, r_t(X, B, C))$, we get

$$\|Q_{t-1}^Y - Q_{t-1}^N\|_{\text{tvd}}, \mathcal{E}_t \leq \Pr[\mathcal{E}_T] + \|Q_{t-1}^Y - Q_{t-1}^N\|_{\text{tvd}}, \mathcal{E}_t + \|Q_{t-1}^Y - Q_{t-1}^N\|_{\text{tvd}}, \mathcal{E}_t.$$
This implies that \( \Pi \) cannot have advantage more than \( \delta \), which contradicts the assumptions of the theorem statement. Therefore, we conclude that any protocol for IFRMD with advantage \( \delta \) requires \( r n \) bits of communication, as desired.

\[ \square \]

5.2 Posterior Sets and Functions

The main challenge in proving Lemma 5.1 lies in the condition (iv), i.e., requiring the closeness of the Yes message (i.e., \( S_Y = r_l(A_{1:t}, c_{1:t}, S^Y_{1:t-1}, A_{t+1}, x^*) \)) and the hybrid No message (i.e., \( S^N = r_l(A_{1:t}, c_{1:t}, S^N_{1:t-1}, U_1) \)). Intuitively, if \( x^* \sim \text{Unif}(\mathbb{Z}_q^n) \) and is independent of the other arguments, then \( A_{t+1}, x^* \) is uniformly distributed over \( \mathbb{Z}_q^{(k-1)\alpha n} \) and hence \( S^Y \) follows the same distribution as \( r_l(A_{1:t}, c_{1:t}, S^Y_{1:t-1}, U_1) \). However, \( x^* \) is correlated with the previous messages \( S_{1:t-1} \), so the above ideal situation would not happen in general. Nevertheless, we are able to analyze the conditional distribution of \( A_{t+1}, x^* \) on the previous messages by explicitly characterizing the posterior distribution of \( x^* \) after receiving the messages from the first \( t-1 \) players. That is, the conditional distribution of \( A_{t+1}, x^* \) can be described by first sampling \( x^* \) from the posterior distribution and then applying \( A_{t+1} \).

For every fixed \( A_{1:t}, c_{1:t} \), and \( S_{1:t} \), we would like to identify a distribution \( D_t \) over \( \mathbb{Z}_q^n \) such that \( D_t \) is the conditional distribution of \( x^* \) given messages \( S_{1:t} \). Note that by the choice of the No case, the conditional distribution of \( x^* \) given messages \( S_{1:t} \) is simply the uniform distribution over \( \mathbb{Z}_q^n \). Thus, we only need to worry about the Yes case.

**Definition 5.5** (Posterior sets and functions). Under the setting described above, for each \( t \) and fixed \( A_{1:t}, c_{1:t}, \) and \( S_{1:t} \), define

- (Reduced posterior set) \( B_{r:t} \leq \frac{n(k-1)m}{q} \) be the set of possible values of \( z_t = A_{t+1}, x \) that leads to message \( S_t \); Note that \( B_{r:t} \) should be thought of as a function on \( A_{1:t}, c_{1:t}, \) and \( S_t \) in the sense that \( B_{r:t} = g_{r:t}^{-1}(S_t) \) where \( g_{r:t} = r_l(A_{1:t}, c_{1:t}, S_{1:t-1}) \).
- Let \( q \) be the indicator function of \( B_{r:t} \).
- (Aggregated posterior set and function) Let
  \[
  B_{1:t} := \{ x \in \mathbb{Z}_q^n | A_{t+1}, c_{t+1}, x \in B_{r:t} \}.
  \]
  Also, let \( 1_{B_{1:t}} : \mathbb{Z}_q^n \to \{0, 1\} \) be the indicator function of \( B_{1:t} \).

5.3 Fourier Analytic Conditions

In this subsection, we define and analyze Fourier-analytic properties of the posterior set \( B \) and show that these properties are sufficient for the condition (iv) (i.e., Corollary 5.7) of Lemma 5.1. Note that we have a characterization of the posterior distribution of \( x^* \), the following corollary shows that Equation 5.2 (i.e., the condition (iv) of Lemma 5.1) can be simplified to bounding the total variation distance between the posterior distribution and the uniform distribution.

**Corollary 5.7** (Reducing Equation 5.2). Let \( r_1, S^Y_{1:t-1}, A_{1:t}, c_{1:t}, B_{1:t}, U_1 \) be defined as before, we have

\[
\| r_l(A_{1:t}, c_{1:t}, S^Y_{1:t-1}, A_{t+1}, x^*) - r_l(A_{1:t}, c_{1:t}, S^N_{1:t-1}, U_1) \|_{TVd} \leq \| (A_{t+1}, x^*) - U_1 \|_{TVd}
\]

where \( x^* \sim \text{Unif}(B_{1:t}) \).

**Proof.** By Lemma 5.6, we have

\[
S^Y = r_l(A_{1:t}, c_{1:t}, S^Y_{1:t-1}, A_{t+1}, x^*)
\]

where \( x^* \sim \text{Unif}(B_{1:t}) \). Note that when we fix \( A_{1:t}, c_{1:t}, \) and \( S^Y_{1:t-1} \) (hence \( B_{1:t} \) is also fixed), by data processing inequality (see item 2 of Proposition 2.2) we have

\[
\| r_l(A_{1:t}, c_{1:t}, S^Y_{1:t-1}, A_{t+1}, x^*) - r_l(A_{1:t}, c_{1:t}, S^N_{1:t-1}, U_1) \|_{TVd} \leq \| (A_{t+1}, x^*) - U_1 \|_{TVd}.
\]

Namely, Equation 5.2 (i.e., the condition (iv) of Lemma 5.1) can be replaced with \( \| (A_{t+1}, x^*) - U_1 \|_{TVd} \leq \gamma / T \), i.e., after applying a random folded hypermatching matrix \( A_{t+1} \) to the posterior distribution \( \text{Unif}(B_{1:t}) \), the distribution of the resulting string is close to the uniform distribution \( \text{Unif}(\mathbb{Z}_q^{(k-1)\alpha n}) \).

Finally, the following lemma shows that when the amount of communication is small, the posterior set is large with high probability.

**Lemma 5.8** (Posterior set is large). Let \( \Pi = (r_1, \ldots, r_T) \) be a deterministic protocol for IFRMD where each message function \( r_t \) outputs a message of length at most \( s \) bits for some \( 1 \leq s \leq n \). Let \( B_t \) be the posterior set defined in Definition 5.5 for every \( t \in [T] \). For every \( \delta \in (0, 1) \) and \( t \in [T] \), we have \( |B_t| \geq \delta \cdot 4^t \cdot q^{-3} \) with probability at least \( 1 - \delta \) over the randomness of \( x \in \mathbb{Z}_q^n \).

**Proof.** Fix a hypermatching \( M \) and centers \( e \), the \( t \)-th message function induces a partition \( P_{1} \cup \cdots \cup P_{2^s} \) of \( \mathbb{Z}_q^n \). For each \( x \in \mathbb{Z}_q^n \), we define \( P(x) \) to be the part that contains \( x \), i.e., if \( x \in P_{i} \), then \( P(x) = P_{i} \). Note that

\[
\frac{1}{|P(x)|} = \frac{\sum_{i=1}^{2^s} \Pr_{x \in \mathbb{Z}_q^n} \left[ x \in P_i \right]}{|P(x)|} = \sum_{i=1}^{2^s} \frac{|P_{i}| \cdot q^{-n}}{|P_{i}|} = \frac{2^s}{2^s q^n} \leq q^{-3n}.
\]

By Markov’s inequality, we have \( |P(x)| < \delta \cdot 4^t \cdot q^{-3} \) with probability at most \( \delta \) as desired.

5.3 Fourier Analytic Conditions

In this subsection, we define and analyze Fourier-analytic properties of the posterior set \( B \) and show that these properties are sufficient for the condition (iv) (i.e., Corollary 5.7) of Lemma 5.1.

Recall that given a matching \( M = (e_1, \ldots, e_m) \) and centers \( c = (c_1, \ldots, c_m) \), \( A_k \) is the \( c \)-centered folded encoding of \( M \). We are going to define three properties for sets \( B \) in \( \mathbb{Z}_q^n \). First, we say a set
As we keep track of posterior sets that are induc-

\[ U_{C,s}(h) := \begin{cases} 1, & h = 0 \\ \left( \frac{C\sqrt{n}}{h} \right)^{h/2}, & 1 \leq h \leq s. \end{cases} \]  

(5.10)

**Definition 5.11 (Bounded set).** Let \( n, q \in \mathbb{N} \), \( 0 \leq s \leq n \), \( C > 0 \), and \( B \subset \mathbb{Z}_q^n \). We say \( B \) (as well as its indicator function \( I_B \)) is \((C, s)\)-bounded if, for every \( h \in \mathbb{N} \),

\[ \sum_{u \in \mathbb{Z}_q^n} \frac{q^n}{|B|} |I_B(u)| \leq U_{C,s}(h). \]  

(5.12)

**Remark 13.** As we keep track of posterior sets that are inductively refined, we will need the entire Fourier spectrum of the corresponding indicator functions to be bounded from above by the function \( U_{C,s} \) (for appropriate \( C, s > 0 \)), which is defined piecewise on the low, medium, and high regimes. This allows us to show that \( A_\varepsilon x \) is close to the uniform distribution on \( \mathbb{Z}_q^{(k-1)an} \) when \( x \) is drawn from such a posterior set \( B \subset \mathbb{Z}_q^n \) (see **Lemma 5.16**). However, the upper bound given by \( U_{C,s}(h) \) in the high regime \( h > s \) is guaranteed automatically as long as \( B \) is large enough. Thus, we only need to keep track of the Fourier spectrum for weights in the middle regime; hence, the \((C, s)\)-boundedness property that we maintain inductively only concerns Fourier weights in this regime.

More specifically, if a set \( B \subset \mathbb{Z}_q^n \) is \((C, s)\)-bounded and satisfies \(|B| \geq q^{n-s}\), then we have that

\[ \sum_{u \in \mathbb{Z}_q^n} \frac{q^n}{|B|} |I_B(u)| \leq U_{C,s}(h) \]

for all \( 0 \leq h \leq n \).

Finally, in what follows we will show that the intersection of a "restricted set" is also bounded and this will be the core of our induction. To do this we need to understand the Fourier behavior of restricted sets. It turns out that restricted sets satisfy a property stronger than being bounded, which we term "reduced"-ness below.

**Definition 5.14 (Reduced set).** Let \( n, q \in \mathbb{N} \), \( 0 \leq s \leq n \), \( C > 0 \), and \( B \subset \mathbb{Z}_q^n \). Let \( M \) be a \( k \)-hypermatching. We say \( B \) (as well as its indicator function \( I_B \)) is \((M, C, s)\)-reduced if the following hold.

- For every \( u \in \mathbb{Z}_q^n \) if there exists \( i \in [n] \) such that \( u_i = 1 \) but \( i \) is not contained in \( M \), then \( I_B(u) = 0 \).
- For every \( u \in \mathbb{Z}_q^n \), if there exists a hyperedge \( e_i \) of \( M \) such that \( (u, e_i) \neq 0 \) mod \( q \), then \( I_B(u) = 0 \).
- For every \( h \in \{1, \ldots, s\} \) and \( v \in \mathbb{Z}_q^n \),

\[ \sum_{u \in \mathbb{Z}_q^n, \text{ } |u+v|=h} \frac{q^n}{|B|} I_B(u) \leq U_{C,s}(h). \]

There are two key lemmas about these Fourier analytic conditions. The first lemma establishes the base case of the induction toward showing the aggregated posterior set being \((C, s)\)-bounded (for some \( C = O(1) \) and \( s = \Omega(n) \)). In fact, we show a stronger guarantee in which every posterior set \( B_t \) is \((M_t, C, s)\)-reduced.

**Lemma 5.15 (Base case).** For every \( q, k \geq 2 \), \( a \in (0,1/k) \), there exists a constant \( C \) such that for every \( k \)-hypermatching \( M \) on \([n]\) of size \( m \leq an \), suppose \( n \in \mathbb{N} \) is large enough and \( 0 < b \leq s \leq n/32 \), then the following holds. Let \( B \subset \mathbb{Z}_q^n \). If (i) there exists a sequence of centers \( s \) such that \( B \) is \((M, C, s)\)-reduced and (ii) \(|B| \geq q^{n-b} \), then \( B \) is \((M, C, s)\)-reduced.

The proof of **Lemma 5.15** is given in the full version [6]. (We note that the proof yields that \( C \geq 2\delta^2 ek^{2/3} \delta^3 \) where \( \delta \) is the constant from **Lemma 2.11**.)

Recall from **Corollary 5.7** that the condition (iv) in **Lemma 5.1** implies by showing \( A_\varepsilon x \) is close to the uniform distribution over \( \mathbb{Z}_q^{(k-1)an} \) with high probability over to choice of \( A_\varepsilon \) where \( x \) is sampled uniformly from the posterior set \( B_t \). The second key lemma shows that \( A_\varepsilon x \) is indeed close to uniform when the posterior set is bounded.

**Lemma 5.16 (Boundedness implies closeness to uniformity).** For every \( q, k \geq 2 \) and \( 0 < \delta \leq 1/2 \), there exists \( a_0 = a_0(k, q, \delta) \) such that for every \( \alpha \in (0, a_0) \), \( C > 0 \), there exists \( t_0 = t_0(q, k, \alpha, \delta) \) such that the following holds for any \( \tau \in (0, t_0) \) and sufficiently large \( n \):

Let \( B \subset \mathbb{Z}_q^n \) be a \((C, s)\)-bounded set with \(|B| \geq q^{n-b} \), for \( 4 \log(3)/\delta \leq b \leq s \leq t_n \). Let \( M \) be a random \( k \)-hypermatching of size \( an \) and \( \varepsilon \) be a sequence of centers for \( M \) and let \( A_\varepsilon \) denote the centered folded encoding and \( M \). Then, with probability at least \( 1 - \delta \) over the choice of \( M \), we have that for every \( z \in \mathbb{Z}_q^{(k-1)an} \), we have

\[ 1 - \delta < \langle A_\varepsilon x, z \rangle < 1 + \delta. \]

As a consequence, we also have

1. \( \|A_\varepsilon x - U\|_{\ell^1} \leq \delta \) where \( x \sim \text{Unif}(B) \) and \( U \sim \text{Unif}(\mathbb{Z}_q^{(k-1)an}) \).
2. For every non-negative function \( f \) over \( \mathbb{Z}_q^{(k-1)an} \),

\[ (1 - \delta) \leq \frac{E_{x \sim \text{Unif}(B)} [f(A_\varepsilon x)]}{E_{z \sim \text{Unif}(\mathbb{Z}_q^{(k-1)an})} [f(z)]} \leq (1 + \delta). \]

The proof of **Lemma 5.16** is given in the full version [6].

Our final lemma of this section asserts that if \( I_B(x) \) is \((C, s)\)-bounded, then \( f_{t+1} \) is \((O(C), s)\)-bounded with high probability.

**Lemma 5.17 (Induction step).** For every \( q, k \in \mathbb{N} \) there exist \( a_0 \in (0,1/k) \) and \( C_0 > 0 \) such that for every \( \alpha \in (0, a_0), C > C_0 \), and \( \delta \in (0,1/2) \), there exist \( C_t > 0, a_0 \in \mathbb{N} \), and \( t_0 \in (0,1) \) such that the following holds. For every \( n \geq n_0, \) every \( 0 < b, b', s < t_0n \),
and every $B \subset \mathbb{Z}_q^n$ that satisfies $|B| \geq q^{-b}$ and is $(C,s)$-bounded, let $M$ be a uniformly random $k$-hypermatching of size at most $an$, with probability at least $1 - 4\delta$ over the randomness of $M$, for every $(M, C, s)$-reduced set $B' \subset \mathbb{Z}_q^n$ with $|B'| \geq q^{-b'}$ and $|B \cap B'| \geq (1 - \delta) \cdot |B|$, $|B'|/q^a \geq q^{-a}$, we have $B \cap B'$ is $(C', s)$-bounded.

Lemma 5.17 is proved in the full version [6]. In our inductive application of the lemma above, we set $B \leftarrow B_{t-1}$ and $B' \leftarrow B_t$ for every $t \in \{2, 3, \ldots, T\}$ to get that all the $B_i$’s are bounded and this is the core of the proof of Lemma 5.1.

5.4 Proof of Lemma 5.1

Proof of Lemma 5.1. For every $q, k \in \mathbb{N}$, we choose $a_0^q$ to be the minimum of the $a_q$’s from the induction step (i.e., Lemma 5.17) and the “boundedness implies uniformity” lemma (i.e., Lemma 5.16). We set $C_0$ according to Lemma 5.17 and for every $a \in (0, a_0^q)$, $T \in \mathbb{N}$, and $\delta \in (0, 1)$, we invoke Lemma 5.16 with $\delta' = \delta/10T$ and $C = C_0$ to get $\tau_0 = \tau_0(q,k,a,\delta', C_0) > 0$ and set $\tau = \tau_0n$. Let $\tau > 0$ be a small constant. We will explicitly fix this quantity later.) Let $b = \tau n + \log_2(10/\delta')$. We choose $\tau$ such that $27b < s = \tau_0n$. Let $C_1 = C_0$. We define $E_1$ to be the event that $|B_1| \geq q^{-2b}$ and $B_1$ is $(C_1,s)$-bounded, where $B_1$ refers to the posterior set defined in Definition 5.5. By the “posterior set is large” lemma (i.e., Lemma 5.8) and the “base case” lemma (i.e., Lemma 5.15) we have $\Pr[\overline{E_1}] \leq \delta'/10 \leq \delta/T$ as desired. This satisfies condition (ii) of Lemma 5.1.

Next, for each $i \in \{2, 3, \ldots, T\}$, let $E_i = E_{i-1} \cap \cdots \cap E_{1}$ and $E'_i$, where $E'_i$ denotes the event that the aggregate posterior set $B_i$ is large, i.e., $|B_i| \geq q^{-2b}$ and $B_i$ is $(C_i,s)$-bounded, where $C_i > 0$ is a constant that will be inductively chosen later. Note that by construction $E_0$ only depends on $(A_1, c_1, s_1)$ and $\delta_1^T$, and hence satisfies condition (i) of the lemma. To show that $E_i$ happens with high probability conditioned on $E_{i-1}$, note that the “posterior set is large” lemma (i.e., Lemma 5.8) and the “base case” lemma (i.e., Lemma 5.15), we have $|B_i| \geq q^{-a}$ and $B_i$ is $(M_i, C_i, s)$-reduced with probability at least $1 - \delta$. Moreover, the event $E_{i-1}$ implies that $B_{i-1}$ is $(C_{i-1}, s)$-bounded and hence if we set $\tau' = \tau_0(q,k,a,\delta', C_{i-1})$, by the “boundedness implies uniformity” lemma (i.e., Lemma 5.16), $\exists \mathbb{Z}_q^{(k-1)an}$, we have the following claim.

Claim 5.18. When $27b < s$, conditioned on $E_{t-1}$, with probability at least $(1 - \delta')$ over the choice of $M_t$, the set $B_{t+1}$ satisfies

$|B_{t+1}| \geq (1 - \delta') \cdot |B_{t-1}| \cdot |B_t|/q^n$.

Proof. Proof is given in the full version [6].

Finally, for every $t \in \{T\}$, if we set $\tau < \tau_0(q,k,a,\delta', C_{t-1})$, by the “boundedness implies uniformity” lemma (i.e., Lemma 5.16), we know that $\|A_1x \|_1 - \|U_t\|_{l_1} \leq \delta'$ where $x^* \sim \text{Unif}(B_1)$, $U_t \sim \text{Unif}(\mathbb{Z}_q^{(k-1)an})$. As $SY = r_1(A_1, c_1, s_1, Y_{T-1}, A_Tx)$ where $x^* \sim \text{Unif}(B_1)$, by the data processing inequality we have $\|SY - r_1(A_1, c_1, s_1, Y_{T-1}, U_t)\|_{l_1} \leq \delta/T$ as desired. This satisfied condition (iv).

To conclude, we set $\tau > 0$ to be a small constant that satisfies $27b < \tau_0n$ and $\tau < \tau_0(q,k,a,\delta', C_{t-1})$ for all $t \in \{T\}$ where $C_t$ is inductively chosen as described above. This completes the proof of Lemma 5.1.

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