Revisiting Block-Diagonal SDP Relaxations for the Clique Number of the Paley Graphs

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***Abstract*—This work addresses the block-diagonal semidefinite program (SDP) relaxations for the clique number of the Paley graphs. The size of the maximal clique (clique number) of a graph is a classic NP-complete problem; a Paley graph is a deterministic graph where two vertices are connected if their difference is a quadratic residue in a finite field with the number of elements given by certain primes and prime powers. Improving the upper bound for the Paley graph clique number for odd prime powers that are non-squares is an open problem in combinatorics. Moreover, since quadratic residues exhibit pseudorandom properties, Paley graphs are related to the construction of deterministic restricted isometries, an open problem in compressed sensing and sparse recovery. Recent work provides numerical evidence that the current upper bounds can be improved by the sum-of-squares (SOS) relaxations. In particular, the bounds given by the SOS relaxations of degree 4 (SOS-4) have been empirically observed to be growing at an order smaller than square root of the prime. However, computations of SOS-4 appear to be intractable with respect to large graphs. Gvozdenovic et al. introduced a more computationally efficient block-diagonal hierarchy of SDPs and computed the values of these SDPs of degrees 2 and 3 (L2 and L3 respectively) for the Paley graph clique numbers associated with primes p less or equal to 809. These values bound from above the values of the respective SOS-4 and SOS-6 relaxations. We compute the values of the L2 relaxations for p's between 821 and 997. Our results provide some numerical evidence that these relaxations, and therefore also the SOS-4 relaxations, may be scaling at an order smaller than the square root of p. However, due to the size of the SDPs, we have not been able to compute L2 relaxations for p's greater than 997. Therefore, our scaling estimate is not conclusive and presents an interesting open problem for further study.**

I. The Clique Number of the Paley Graphs

A *Paley graph* G_q is a graph with q vertices, where q is a prime power such that $q = 1 \mod 4$;[1] two vertices are connected by an edge $\{i, j\}$ whenever $i-j$ is a quadratic residue in $\mathbb{F}_q$.[2]

The *clique number* $\omega(G)$ of a graph G is the number of vertices in its largest complete subgraph or *clique*. For any Paley graph G_q, this number is bounded above by $\sqrt{q}$ [33].

For a Paley graph with $q = p^{2k}$, the foregoing bound is tight [11]. However, less is known about $\omega(G_q)$ when q is an odd prime power that is a non-square. In particular, if $q = p$, the state-of-the-art lower bounds are scaling as $\log p \cdot \log\log\log p$; the $\log\log\log p$ term can be improved to $\log\log p$ conditional on the Generalized Riemann Hypothesis (see [15] and Theorem 13.5 in [28]). On the other hand, the existing state-of-the-art upper bounds in references [7], [18] improve on $\sqrt{p}$ only by a constant prefactor. We will refer to the upper bound $(\sqrt{2p-1}+1)/2$ in those references as $HP(G_p)$. Numerical experiments appear to suggest that the Paley graph clique number is polylogarithmic in p (see discussion of [13], [31] in [2]). However, proving even a p^ϵ bound for some positive $\epsilon < \frac{1}{2}$ is regarded as a difficult open problem in additive combinatorics [20] (see also [23]).

II. Connections to Deterministic Restricted Isometries

Paley graphs are connected to the construction of deterministic $M \times N$ matrices with the restricted isometry property (RIP), an important problem in compressed sensing and sparse recovery [32]. Random matrix constructions achieve RIP when sparsity is on the order of $M/\text{polylog}(N)$. However, most deterministic constructions, such as equitriangular frames (*ETFs*), are

[1] By the law of quadratic reciprocity, this condition ensures that -1 is a quadratic residue in $\mathbb{F}_q$. Therefore, if $i-j$ is a quadratic residue then so is $j-i$, and the graph is undirected.

[2] See [21] for general background on Paley graphs.

based on controlling a certain *coherence* value, which achieves RIP only when sparsity is on the order of $\sqrt{M}$; this limitation is known as the *square root bottleneck*.[3] The only unconditional construction that overcomes this bottleneck was provided in [9], [10], which leveraged additive combinatorics techniques to achieve RIP for $\Omega(M^{\frac{1}{2}+\epsilon})$ sparsity for small $\epsilon > 0$ (see also [27]).

Reference [4] constructed a family of deterministic ETF matrices using the quadratic residues modulo a prime number p (the *Paley matrices*) which provably achieve RIP when sparsity is on the order of $\sqrt{p}$ by the aforementioned coherence analysis but are *conjectured* to achieve it when sparsity on the order of $p/\text{polylog}(p)$ (which would match the random construction if p is proportional to M). Reference [3] used a matrix construction based on the Legendre symbol (which is closely connected to Paley graphs) to reduce the number of random bits in a random RIP matrix.

Finally, conditioned on a conjecture about the number of edges in any subgraph of a Paley graph, the Paley matrices overcome the square root bottleneck [5].[4] In this conditional construction, a lower bound on $\omega(G_p)$ would lead to a lower bound on the distortion in the sparse recovery (Theorem 2.3 in [5]).

III. SDP RELAXATIONS OF THE CLIQUE NUMBER

The clique number $\omega(G)$ of a graph G is a classical NP-complete problem. It can be formulated as a polynomial optimization over $x \in \mathbb{R}^n$ where n is the number of vertices of $G = (V, E)$:

$$\omega(G) = \left\{ \begin{array}{ll} \max & \sum_{i \in V} x_i \\ \text{s.t.} & x \in \mathbb{R}^n,\ x_i^2 = x_i \text{ for all } i \in V, \\ & x_i x_j = 0 \text{ for all } \{i,j\} \notin E \end{array} \right\}.$$

An extensive body of literature considered upper bounds produced by convex relaxations, which are more computationally efficient. One particular question in this literature is whether semidefinite program (SDP) relaxations would produce upper bounds that are tighter than $O(\sqrt{n})$ where n is the number of vertices of G.

[3]Reference [1] designed deterministic RIP matrices that support the same sparsity $\sqrt{M}$ based on the coherence analysis; however, they are constructed using the adjacency matrix of a Paley graph rather than an ETF.

[4]Using a similar analysis, reference [22] showed an improvement on the *square root bottleneck* by $\epsilon = \frac{9}{40} + \kappa$ for small κ; while this result is not conditioned on any conjectures, it only holds for signals with a certain sparse structure.

Erdos-Renyi graphs $G \sim \mathcal{G}(\frac{1}{2}, n)$ are random graphs where each edge is present independently with probability $\frac{1}{2}$. In this setting, reference [14] showed that the *Lovasz-Schrijver hierarchy* of SDPs attains a nearly $\Omega(\sqrt{n})$ lower bound for clique number relaxations of any constant degree. For any graph G, we denote the values of these relaxations by $N_+^t(G)$ where $t \in \mathbb{N}$ is the degree of the hierarchy.

Another line of work considered the *sum of squares (SOS)* hierarchy of SDPs, also known as the *Lasserre-Parrilo hierarchy*. In the context of the clique number problem, these relaxations, denoted by $SOS_{2t}(G)$ where t is the degree of the hierarchy, are defined as follows. Let $\mathcal{P}(V)$ be the collection of all subsets (power set) of V, and let $\mathcal{P}_t = \{I \in \mathcal{P}(V) \,|\, |I| \leq t\}$ and $\mathcal{P}_{=t} = \{I \in \mathcal{P}(V) \,|\, |I| = t\}$ denote the subsets of V with at most t and exactly t elements, respectively. For $y \in \mathbb{R}^{\mathcal{P}_{2t}}$, we define the *moment matrix* of y $M_t(y) \in \mathbb{R}^{\mathcal{P}_t \times \mathcal{P}_t}$ by $M_t(y)_{IJ} = y_{I \cup J}$ where $I, J \in \mathcal{P}_t(V)$. We also denote by $\mathcal{K}$ the set of all cliques of G. Then the SOS hierarchy is given by

$$SOS_{2t}(G) = \left\{ \begin{array}{ll} \max \sum_{i \in V} y_{i,\emptyset} & \text{(1a)} \\ \text{s.t.} y \in \mathbb{R}^{\mathcal{P}_{2t}},\ y_\emptyset = 1 & \text{(1b)} \\ \quad y_{S,T} = 0 \ \forall\ S \cup T \notin \mathcal{K} & \text{(1c)} \\ \quad M_t(y) \succeq 0 & \text{(1d)} \end{array} \right\}$$

In the average-case setting of $\mathcal{G}(\frac{1}{2}, n)$, reference [6] established a nearly $\Omega(\sqrt{n})$ lower bound for the SOS relaxation of any constant degree for the clique number problem (see also earlier work [12], [19], [30] focusing on the SOS_4 relaxation).

A *stable set* of a graph $G = (V, E)$ is a subset $S \subset V$ such that no two nodes in S have an edge between them. The size $\alpha(G)$ of the largest stable set of G is called the independence or stability number of G. The *Lovász* ϑ *function*, which can be also formulated as an SDP, is a convex relaxation of $\alpha(G)$. Note that for a complement graph $\bar{G}$, $\alpha(G) = \omega(\bar{G})$, and Lovász ϑ represents the first and weakest degree of the SOS hierarchy, i.e., $\vartheta(G) = SOS_2(\bar{G})$ (see, e.g., Section 4.1.3 in [16]).

Since the Paley graphs are self-complementary, $\omega(G_p) = \alpha(G_p)$. The classic upper bound $\alpha(G_p) \leq \sqrt{p}$ is realized by the $SOS_2(G_p)$ relaxation of the Paley graph clique problem (Theorem 13.14 in [8] and Theorem 8 in [25]), but the current state-of-the-art upper bound $HP(G_p)$ in [7], [18] has a tighter constant prefactor. Numerical ex-

periments in [26] show that the Lovasz ϑ relaxation with additional nonnegativity constraints sometimes improves on $HP(G_p)$.

Recent work revisited the higher-degree SOS relaxations in the deterministic worst-case context of the Paley graphs. Specifically, for $q = p$ prime, reference [24] presented numerical experiments suggesting that $SOS_4(G_p)$ may scale as $O(p^{\frac{1}{2}-\epsilon})$ for some $\epsilon > 0$ and proved that these values are at least $\Omega(p^{\frac{1}{3}})$; see also [23].

For large graphs, the SOS relaxations appear to be computationally intractable, especially for higher degree t of the hierarchy, which entail optimization over $\mathbb{R}^{\mathcal{P}_t \times \mathcal{P}_t}$ matrices. For example, the SOS_4 relaxations do not appear to be currently computationally feasible for $p > 250$ (Section 6 and Figure 1 in [24]).

IV. Block-diagonal SDP hierarchy

References [16], [17] introduced a new hierarchy of SDPs, denoted by L^t, which is nested between the Lovasz-Schrijver and SOS hierarchies, and in particular the optimal values of this new hierarchy L^t bound from above the corresponding SOS-$2t$ values. This new hierarchy is more computationally tractable that the SOS hierarchy because it is based on the block-diagonal submatrices of the moment matrix. In the context of the Paley graph clique number, the size of the block-diagonal relaxations can be reduced further by leveraging graph symmetries. This section provides an exposition of the L^2 relaxations in [16], [17].

For $y \in \mathbb{R}^{\mathcal{P}_{t+1}}$ and a subset of vertices $T \subset V$ of size $|T| = t-1$, let $M(T;y) \in \mathbb{R}^{\mathcal{P}_{t-1} \times (n+1)}$ be a principal submatrix of $M_t(y)$ whose rows and columns are indexed by $\mathcal{A}(T) = \bigcup_{S \subseteq T} \mathcal{A}_S$ where $\mathcal{A}_S = \{S\} \cup \{S \cup \{i\} \,|\, i \in V\}$. Following [17], we consider $\mathcal{A}_S$ as a multiset, i.e., we keep possible repeated occurrences, e.g., S and $S \cup \{i\}$ if $i \in S$.[5] Let $A_S(y)$ denote the principal submatrix of $M(T;y)$ indexed by the set $\mathcal{A}_S$: it is a symmetric $(n+1) \times (n+1)$ matrix with entries

$$A_S(y)_{00} = y_S, A_S(y)_{0i} = y_{S \cup \{i\}}, \;\; A_S(y)_{ij} = y_{S \cup \{i,j\}}$$

for $i, j \in V$. We will index matrix and vector entries by $[0, \ldots, n-1]$, the elements of a finite field $\mathbb{F}_n$ to simplify our subsequent discussion of the Paley graph relaxations.

[5]Therefore, $|\mathcal{A}_S| = 2^{t-1}(n+1)$ and $M(T;y) \in \mathbb{R}^{2^{t-1}(n+1) \times 2^{t-1}(n+1)}$. Technically $M(T;y)$ is a submatrix of $M_t(y)$ after removing the repeating rows of the latter.

By Lemma 2.2 in [17] $M(T;y)$ is positive semidefinite (PSD) if and only if for all $S \subseteq T$ the matrix

$$A(S,T)(y) := \sum_{S' : S \subseteq S' \subseteq T} (-1)^{|S' \setminus S|} A_{S'}(y)$$

is PSD.

These reductions lead to the following relaxation of the independence set problem of an arbitrary graph with n vertices:[6] $L^t(G) =$

$$\left\{ \begin{array}{l} \max \sum_{i \in V} y_{\{i\}} \\ \text{s.t.} y \in \mathbb{R}^{\mathcal{P}_{t+1}}, \; y_\emptyset = 1 \\ \quad y_{\{i,j\}} = 0 \;\forall\; (i,j) \in E \\ \quad A(S,T)(y) \succeq 0 \text{ for all } S \subset T \text{ and } T \in \mathcal{P}_{=t-1} \end{array} \right\}$$

This optimization problem has $\binom{n}{t-1} 2^{t-1}$ PSD constraints with respect to $n+1 \times n+1$ matrices $A(S,T)(y)$.

In the remainder of this section, for consistency with [16], [17], we will consider the independent set problem rather than the equivalent maximal clique problem.

In the context of a Paley graph G_p, references [16], [17] exploit its symmetries to reduce the number of the PSD constraints. Using the vertex-transitivity of the graph and Lemma 2.4.5 in [16], the PSD constraints in $L^2(G_p)$ is reformulated in terms of two $(p+1) \times (p+1)$ matrices using just one arbitrary vertex $h \in V$, e.g., $\{0\}$; the resulting matrices $A_\emptyset(y)$ and $A_{\{0\}}(y)$ used in the constraints are given below. Furthermore, a Paley graph is edge-transitive - this symmetry allows to reduce the number of optimization variables corresponding to non-edges to one variable, $y_{\{0,k\}}$ for some $\{0,k\} \notin E$.

The triples without edges (triangle) form orbits under the graph automorphism group of affine mappings $\phi_{ab} : \mathbb{F}_p \to \mathbb{F}_p$ given by $\phi_{ab}(u) = au + b$ where $u \in \mathbb{F}_p$, $a, b \in \mathbb{F}_p$ and $a \neq 0$ is a square in $\mathbb{F}_p$. Therefore, the number of optimization variables corresponding to triangles without edges, can be reduced to the number of the orbits of the triangles of the form $\{0, \alpha, \beta\}$ under ϕ_{ab}.

Since a Paley graph is edge-transitive, the representatives of the orbits of fully connected triangles are given by $\{0, 1, \beta\}$ where both β and $\beta - 1$ are squares in $\mathbb{F}_p$. The representatives of the orbits of triangles without edges

[6]The independence set formulation leads more naturally than the equivalent clique number formulation to further simplifications of the L^t program discussed here in the context of Paley graphs.

can be expressly computed as well. Lemma 6.2.1 in [29] explicitly sets forth the orbits of the latter triangles; there are approximately $(p-5)/24$ orbits. Let Ω be the set of representatives of the orbits of ϕ_{ab} acting on the set of triangles without any edges. We denote $m := |\Omega|$. Then $L_2(G_p) =$

$$\left\{\begin{array}{ll} \max\ p \cdot y_{\{0\}} & \text{(3a)} \\ \text{s.t. } y_{\{0\}}, y_{\{0,k\}} \in \mathbb{R},\ y \in \mathbb{R}^m & \text{(3b)} \\ A_\emptyset(y) - A_{\{0\}}(y) \succeq 0 & \text{(3c)} \\ A_{\{0\}}(y) \succeq 0 & \text{(3d)} \end{array}\right\}$$

where

$$A_\emptyset(y) = \left(\begin{array}{c|c} 1 & y_{\{0\}}\mathbb{1}^\intercal \\ \hline y_{\{0\}}\mathbb{1} & y_{\{0\}}I + y_{\{0,k\}}A(\bar{G}_p) \end{array}\right)$$

encodes the vertices by $y_{\{0\}}$ and nonedges by $y_{\{0,k\}}$, both scalars, and $A(\bar{G}_p)$ is the adjacency matrix of the complement graph $\bar{G}_p$. Furthermore, $A_{\{0\}}(y) =$

$$\left(\begin{array}{c|c|c} y_{\{0\}} & y_{\{0\}} & y_{\{0,k\}}A(\bar{G}_p)_{0,1:\text{end}} \\ \hline y_{\{0\}} & y_{\{0\}} & y_{\{0,k\}}A(\bar{G}_p)_{0,1:\text{end}} \\ \hline y_{\{0,k\}} \times A(\bar{G}_p)_{1:\text{end},0} & y_{\{0,k\}} \times A(\bar{G}_p)_{1:\text{end},0} & M \end{array}\right)$$

where

$$M = \text{diag}(A(\bar{G}_p)_{1:\text{end},0}) + \sum_{\alpha,\beta\in\Omega} X^{\alpha\beta} y_{\{0,\alpha,\beta\}}.$$

The matrix $X^{\alpha\beta} \in \mathbb{R}^{p-1\times p-1}$ encodes each orbit of ϕ_{ab} acting on the set of triangles without any edges: $X^{\alpha\beta}_{ij} = 0$ if $\{i,j\} \in E$ for any ϕ_{ab} acting on $(0,\alpha,\beta)$ and 1 otherwise. (Note $X^{\alpha\beta}_{ii} = 0$ for all $\alpha,\beta \in \Omega$.)

Since the second row and columns of $A_{\{0\}}(y)$ will match those of $A_\emptyset(y)$, we can remove the first row and column in each matrix for purposes of the (3c) constraint. This leads to a $p \times p$ rather than $p+1 \times p+1$ matrix in that constraint. Lastly for purposes of the other constraint (3d), we can remove the rows and columns with edges (which are indexed by the nonresidues) leading to a $(p+1)/2 \times (p+1)/2$ matrix.

V. New Computations

We replicated the $L^2(G_p)$ computations reported in [16], [17] using Matlab/CVX for primes $p \leq 809$ as well as extended them for all $p < 1000$.[7] These resulting new values are shown in Table I. Figure 1 shows that $L^2(G_p) \sim p^{0.456}$ which is tighter than $HP(G_p) = (\sqrt{2p-1}+1)/2$, the upper bound on $\omega(G_p)$ established in [7], [18]. Moreover, since $SOS_4(G_p) \leq L^2(G_p)$, our results provide some numerical evidence that the SOS_4 relaxations of the Paley graph clique number may be asymptotically growing at an order smaller than square root of p. However, due to the size of the SDPs, we have not been able to compute the $L^2(G_p)$ values for $p > 997$. Therefore, our scaling estimate is not conclusive and presents an interesting open problem for further study.

[7]The code is available at http://vladkobzar.com/.

p	$\vartheta(G_p)$	$L^2(G_p)$	$\omega(G_p)$
821	28.653	18.673	12
829	28.792	18.105	11
853	29.206	18.909	13
857	29.275	18.429	13
877	29.614	19.711	13
881	29.682	18.689	11
929	30.48	19.292	13
937	30.61	19.248	11
941	30.676	19.34	11
953	30.871	19.199	11
977	31.257	19.737	13
997	31.575	20.058	13

TABLE I: The $L^2(G_p)$ values for $809 < p < 1000$ determined in this paper, together with the values of $\omega(G_p)$ obtained from [31].

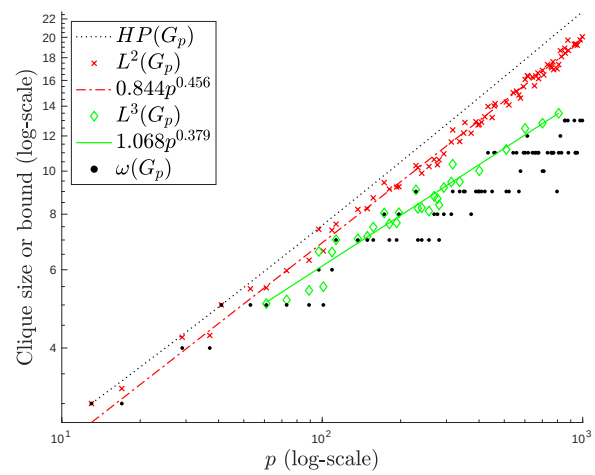

Fig. 1: The $L^2(G_p)$ values for $809 < p < 1000$ determined in this paper, and the $L^2(G_p)$ and $L^3(G_p)$ values for $p \leq 809$ determined in [16], [17] are fitted to power models of the form ap^b. The values of $\omega(G_p)$ were obtained from [31] and $HP(G_p) = (\sqrt{2p-1}+1)/2$ represents the upper bound on $\omega(G_p)$ established in [18].

VI. Potential extensions

As mentioned above, we have not been able to compute the $L^2(G_p)$ values for $p > 997$, and therefore, our scaling estimate is not conclusive. We hope that these values for larger problems can be computed to obtain a scaling estimate of the $L^2(G_p)$ values with higher confidence. We also hope that the higher degree L^t relaxations can be computed and used to upper bound the corresponding SOS_{2t} values in the context of the Paley graph clique number and beyond. For these purposes, it may be advantageous to decompose the $A_S(y)$ matrices in terms of smaller matrices that could be used in the positive semidefinite constraints. A similar result was achieved in [29] with respect to the Lovasz ϑ by decomposing the moment matrix in terms of the so-called "zonal" matrices. We leave these potential extensions for future work.

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