

## ASYMPTOTICALLY GOOD COVERINGS

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*Dedicated to the memory of Ernst Straus*

The Erdős-Hanani conjecture is that for fixed  $r < k$  and  $n$  large there exists a covering of all  $r$ -sets of an  $n$ -set by a family of  $k$ -sets whose cardinality is asymptotic (in  $n$ ) to the “counting” lower bound. This conjecture was first proven by Rodl, here we give a more direct argument. We use probabilistic methods, selecting  $k$ -sets in large groups, and showing that the hypergraph of uncovered  $r$ -sets retains a property we call quasirandomness, meaning that it has the essential (for us) properties of random hypergraph.

**0. Introduction.** Let  $r < k \leq n$  and set  $[n] = \{1, \dots, n\}$ , a generic  $n$ -set. The covering function  $M(n, k, r)$  is defined as the minimal cardinality of a family  $F$  of  $k$ -sets of  $[n]$  such that every  $r$ -set of  $[n]$  is contained in some  $K \in F$ . The packing function  $m(n, k, r)$  is the maximal cardinality of a family  $F$  of  $k$ -sets of  $[n]$  such that no  $r$ -set of  $[n]$  is contained in more than one  $K \in F$ . Elementary counting arguments imply

$$(1) \quad m(n, k, r) \leq \binom{n}{r} / \binom{k}{r} \leq M(n, k, r)$$

Equality holds if and only if there exists an  $(n, k, r)$  tactical configuration—i.e., a collection  $F$  of  $k$ -sets containing every  $r$ -set exactly once. The existence of tactical configurations for various  $r, k, n$  (e.g. for  $k = 3, r = 2$ —Steiner Triple Systems) is a central question of Combinatorial Analysis to which we here do not directly contribute.

In 1963 Paul Erdős and Haim Hanani [1] conjectured that for all  $r < k$  the inequalities (1) are asymptotically equalities—more precisely, that

$$(2) \quad \lim_{n \rightarrow \infty} m(n, k, r) \binom{k}{r} / \binom{n}{r} = 1 = \lim_{n \rightarrow \infty} M(n, k, r) \binom{k}{r} / \binom{n}{r}.$$

This was proven for  $r = 2$ , all  $k$  and for  $r = 3, k = p$  or  $p + 1$  where  $p$  is a prime power. They also showed that either of the equalities (2) imply the other. These inequalities became known as the Erdős-Hanani Conjecture. In 1983 this conjecture was resolved affirmatively by Vojtech Rodl [2] for all values  $r < k$ . In this paper we present a more direct proof of the

Erdős-Hanani Conjecture. Our argument is based on Rodl's original proof and on personal discussions with Rodl which we gratefully acknowledge.

**1. An intuitive view.** In this section we present an informal discussion of our proof of the Erdős-Hanani Conjecture. The formal proof is given in the next section.

Let  $r < k$  be fixed and let  $n$  be very large. Let  $G_0$  be the complete  $r$ -graph on vertex set  $[n]$ . Let  $\delta$  be a very small positive real. ( $\delta$  is fixed first and then  $n$  is made very large.) Let  $F_0$  be a random collection of  $\delta \binom{n}{r} / \binom{k}{r}$   $k$ -cliques from  $G_0$  and let  $G_1$  be the family of  $r$ -sets not contained in any  $K \in F_0$ . As  $F_0$  is  $\delta$  times the size of a perfect covering of  $G_0$  (if one existed) it would, if there were no overlap, cover a proportion  $\delta$  of the  $r$ -sets in  $G_0$ . In fact, overlap is the critical consideration. The typical  $r$ -set is covered an average of  $\delta$  times by  $F_0$ . There are many  $k$ -sets covering a given  $r$ -set and each has only a small chance of being placed in  $F_0$ . "Thus" the number of  $k$ -sets of  $F_0$  covering a given  $r$ -set is given by a Poisson distribution with mean  $\delta$ . That is,  $\delta e^{-\delta}$  of the  $r$ -sets are covered exactly once,  $(\delta^2/2)e^{-\delta}$  are covered exactly twice,  $(\delta^i/i!)e^{-\delta}$  are covered exactly  $i$  times and  $e^{-\delta}$  are not covered at all and "remain" in  $G_1$ . When  $\delta$  is very small the proportion of  $r$ -sets covered twice or more, roughly  $\delta^2/2$ , is a negligible proportion of the proportion of  $r$ -sets, roughly  $\delta$ , that are covered once. That is,  $F_0$  is an excellent, though not perfect, cover of  $G_0 - G_1$ .

We continue the procedure with  $G_1$ . We choose  $F_1$  from among the  $k$ -cliques of  $G_1$ . This is essential as we do not want any of the  $\binom{k}{r}$   $r$ -sets covered by a  $K \in F_1$  already covered by  $F_0$ . We pick  $F_1$  randomly, choosing the cardinality so that if there were no overlap a proportion  $\delta$  of  $G_1$  would be covered. We let  $G_2$  be the remaining  $r$ -sets—those covered by no  $K \in F_1$ . Once again (but see below) the number of  $k$ -sets covering an  $r$ -set of  $G_1$  is given by a Poisson distribution with mean  $\delta$  and  $F_1$  is an excellent covering of  $G_1 - G_2$ .

We iterate this procedure—given  $G_i$  we find  $F_i$  and set  $G_{i+1}$  equal to the remaining  $r$ -sets—until we reach a  $G_t$  with a negligible proportion of  $r$ -sets. As each  $|G_{i+1}| \sim e^{-\delta}|G_i|$  we let  $t$  be large enough so that  $e^{-t\delta}$  is very small. At this point the remaining  $r$ -sets are covered one by one. Though this is very wasteful (we want  $k$ -sets  $K$  to cover  $\binom{k}{r}$  new  $r$ -sets but here we use one  $k$ -set to cover one  $r$ -set) it is acceptable since  $|G_t|$  is small. With  $\delta$  and  $e^{-t\delta}$  very small the total covering has a very small proportion of waste.

To employ this method it is necessary that the  $G_i$  retain certain regularity properties. (To illustrate with an extreme case, if a  $G_i$  was

created that had no  $k$ -cliques we could not continue.) Let  $G$  be an  $r$ -graph with density  $\rho$ . We call  $G$  quasirandom if for every edge  $e \in G$  the proportion of  $k$ -sets covering  $e$  that are cliques in  $G$  is roughly  $\rho^{\binom{k}{r}-1}$ . (Note that this would be the appropriate proportion for a random graph of density  $\rho$ .) The central lemma of §3 states, roughly, that if  $G$  is quasirandom then the above method may be employed to find a family of  $k$ -sets  $F$  so that the remaining graph  $G^*$  is also quasirandom. The initial graph—the complete  $G_0$ —is certainly quasirandom with unit density. We may thus iterate our procedure—finding a descending sequence of hypergraphs  $G_i$ , all of which are quasirandom. One final parameter—to quantify the word “roughly” we say  $G$  is quasirandom with tolerance  $\epsilon$  if the quasirandom properties hold within a factor of  $1 \pm \epsilon$ . When  $G$  is quasirandom with tolerance  $\epsilon$  the tolerance of the “remaining”  $G^*$  will be some higher  $\epsilon^*$ . Our lemma allow us to insure that the tolerance remains arbitrarily small even after our procedure has been applied a fixed number  $t$  times.

**3. The proof.** *Throughout this section  $2 \leq r < k$  shall be fixed integers.* The term graph shall refer to  $r$ -graph (i.e. a collection of  $r$ -sets) and edge shall refer to an  $r$ -set in the collection. A  $k$ -set  $K$  is a clique in graph  $G$  if  $e \in G$  for every edge  $e \subset K$ . All graphs shall have  $n$  vertices.

*Special Notation.* The term  $1 \pm \epsilon$  refers to a number  $x$  satisfying

$$1 - \epsilon \leq x \leq 1 + \epsilon.$$

Thus  $a = b(1 \pm \epsilon)$  means

$$b(1 - \epsilon) \leq a \leq b(1 + \epsilon).$$

In the Lemma below,  $\epsilon < .01$ . Thus, for example,

$$(3) \quad (1 \pm \epsilon)(1 \pm \epsilon) = (1 \pm 3\epsilon)$$

since if  $x \leq 1 + \epsilon$  and  $y \leq 1 + \epsilon$  then  $xy \leq (1 + \epsilon)^2 < 1 + 3\epsilon$  and similarly  $x, y \geq 1 - \epsilon$  imply  $xy \geq 1 - 3\epsilon$ . More generally

$$(4) \quad (1 \pm a\epsilon)(1 \pm b\epsilon) = 1 \pm (a + b + 1)\epsilon$$

for any  $1 \leq a, b \leq 10$ . Also

$$(5) \quad e^{\pm a\epsilon} = 1 \pm (a + 1)\epsilon$$

if  $a \leq 5$  as  $1 - (a + 1)\epsilon < e^{-a\epsilon}$  and  $e^{a\epsilon} < 1 + (a + 1)\epsilon$  with  $a$  so small. These “tolerance estimates” shall often be used tacitly in the proof of the lemma.

**DEFINITION.**  $G$  is *quasirandom* with density  $\rho$  and tolerance  $\epsilon$  if

(a)  $G$  has  $\rho \binom{n}{r} (1 \pm \epsilon)$  edges

(b) Every edge of  $G$  lies in  $\rho^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \epsilon)$  cliques of size  $k$ .

LEMMA. Let  $\rho, \epsilon^*, \delta > 0$ . Then there exist  $\epsilon > 0$  and  $n_0$  so that for  $n > n_0$  the following holds. Let  $G$  be quasirandom with density  $\rho$  and tolerance  $\epsilon$ . Then there exists a family  $F$  of  $k$ -cliques of  $G$  such that

$$(i) |F| = \delta \left[ \rho \binom{n}{r} / \binom{k}{r} \right] (1 \pm \epsilon^*)$$

and so that, letting  $G^*$  be the subgraph of  $G$  remaining after the deletion of all  $k$ -cliques  $K \in F$ ,  $G^*$  is quasirandom with density  $\rho e^{-\delta}$  and tolerance  $\epsilon^*$ .

In particular

$$(ii) G^* \text{ has } \rho e^{-\delta} \binom{n}{r} (1 \pm \epsilon^*) \text{ edges.}$$

$$(iii) \text{ Every edge of } G^* \text{ lies in } (\rho e^{-\delta})^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \epsilon^*) \text{ } k\text{-cliques of } G^*.$$

Proof. Set

$$(6) \quad p = \delta / \left[ \rho^{\binom{k}{r}-1} \binom{n-r}{k-r} \right]$$

Let  $F$  be a random collection of  $k$ -cliques of  $G$  given by placing each  $k$ -clique  $K$  of  $G$  into  $F$  with independent probability  $p$ . That is,

$$\Pr[K \in F] = p$$

and the events “ $K \in F$ ” are mutually independent over all  $k$ -cliques  $K$  of  $G$ .

For definiteness we fix  $\epsilon > 0$  satisfying

$$(7) \quad 10\epsilon \binom{k}{r} < \epsilon^*, \quad \binom{k}{r} \epsilon < 10^{-4}.$$

(We may think, however, of the tolerance  $\epsilon$  of  $G$  as being “much much smaller” than the tolerance  $\epsilon^*$  required of  $G^*$ .)

As  $G$  is quasirandom the number of  $k$ -cliques of  $G$  is

$$(8) \quad \left[ \rho \binom{n}{r} (1 \pm \epsilon) \right] \left[ \rho^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \epsilon) \right] / \binom{k}{r} = \rho^{\binom{k}{r}} \binom{n}{k} (1 \pm 3\epsilon).$$

Thus  $|F|$  has a binomial distribution with mean

$$(9) \quad p \rho^{\binom{k}{r}} \binom{n}{k} (1 \pm 3\epsilon) = \left[ \delta \rho \binom{n}{r} / \binom{k}{r} \right] (1 \pm 3\epsilon).$$

Chebychev’s inequality implies that for any  $c > 0$  the probability that  $|F| = E[|F|] (1 \pm c)$  approaches unity with  $n$ . Hence

$$(10) \quad |F| = \left[ \delta \rho \binom{n}{r} / \binom{k}{r} \right] (1 \pm 4\epsilon)$$

and so (i) is satisfied, with probability approaching unity with  $n$ .

We now consider (ii). For each edge  $e \in G$  let  $\text{cov}(e)$  denote the number of  $k$ -cliques  $K$  of  $G$  which contain  $e$ . Then

$$(11) \quad \Pr(e \in G^*) = (1 - p)^{\text{cov}(e)}$$

as  $e$  “survives” if and only if none of these  $K$  are selected for  $F$ . As  $p$  approaches zero with  $n$  we may bound

$$(12) \quad 1 - p = e^{-p(1 \pm \varepsilon)}$$

so that

$$(13) \quad \begin{aligned} (1 - p)^{\text{cov}(e)} &= \exp\left[-p(1 \pm \varepsilon)\rho^{\binom{k}{r}-1}\binom{n-r}{k-r}(1 \pm \varepsilon)\right] \\ &= \exp[-\delta(1 \pm 3\varepsilon)] = e^{-\delta}(1 \pm 4\varepsilon) \end{aligned}$$

and the expected number of edges in  $G^*$  is

$$(14) \quad e^{-\delta}(1 \pm 4\varepsilon)\rho\binom{n}{r}(1 \pm \varepsilon) = \rho e^{-\delta}\binom{n}{r}(1 \pm 6\varepsilon).$$

To show that  $|G^*|$  is nearly always nearly equal to its expectation we bound its variance. For each  $e \in G$  let  $X_e$  be the indicator random variable for the event “ $e \in G^*$ ” and set

$$(15) \quad X = \sum_{e \in G} X_e$$

so that  $X = |G^*|$ . Any two distinct  $e, e' \in G$  contain at least  $r + 1$  vertices and therefore there are at most

$$\binom{n - (r + 1)}{k - (r + 1)} < n^{k-r-1}$$

$k$ -cliques of  $G$  containing both of them. We bound

$$(16) \quad \begin{aligned} E[X_e X_{e'}] &\leq (1 - \rho)^{\text{cov}(e) + \text{cov}(e') - n^{k-r-1}} \\ &\leq E[X_e] E[X_{e'}] \left(1 + \frac{c}{n}\right) \end{aligned}$$

where  $c$  depends only on  $k, r, \delta$  and  $\rho$ . Using general probability methods

$$(17) \quad \begin{aligned} \text{Var}(X) &= \sum_e \text{Var}(X_e) + \sum_{e \neq e'} \text{cov}(X_e, X_{e'}), \\ \sum_e \text{Var}(X_e) &\leq \sum_e E(X_e) = E(X) < n^{-1}E(X)^2, \\ \sum_{e \neq e'} \text{cov}(X_e, X_{e'}) &\leq \left(\frac{c}{n}\right) \sum_{e \neq e'} E(X_e) E(X_{e'}) \leq cn^{-1}E(X)^2, \end{aligned}$$

so

$$\text{Var}(X) \leq (c + 1)n^{-1}E(X)^2.$$

(These arguments are quite rough but we only really need  $\text{Var}(X) = o(E(X)^2)$ .)

Applying Chebychev’s inequality

$$(18) \quad X = \rho e^{-\delta} \binom{n}{r} (1 \pm 7\varepsilon)$$

and thus (ii) is satisfied, with probability approaching unity in  $n$ .

We now consider (iii). Let  $e$  be an edge of  $G$  and let  $\mathcal{A}_e$  denote the family of  $k$ -cliques  $K$  of  $G$  that contain  $e$ . For each  $K \in \mathcal{A}_e$  let  $\mathcal{S}_K$  denote the family of  $k$ -cliques  $L$  of  $G$  which contain at least one edge of  $K$  but do not contain  $e$ . We define indicator random variables  $X_K$  by

$$X_K = \begin{cases} 1, & \text{if } F \cap \mathcal{S}_K = \emptyset, \\ 0, & \text{otherwise.} \end{cases}$$

Then  $X_K$  is the indicator random variable for “ $K$  is a  $k$ -clique of  $G^*$ ” conditional on “ $e \in G^*$ ”. (Conditioning on “ $e \in G^*$ ” is equivalent to assuming that no  $k$ -clique  $L$  of  $G$  which contains  $e$  has been placed in  $F$ .) Set

$$(19) \quad X = \sum_{K \in \mathcal{A}_e} X_K$$

so that, conditional on  $e \in G^*$ ,  $X$  is the number of  $k$ -cliques of  $G^*$  containing  $e$ .

A  $k$ -clique  $K \in \mathcal{A}_e$  contains  $\binom{k}{r} - 1$  edges other than  $e$ , each of which lie in  $\rho^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \varepsilon)$   $k$ -cliques  $L$ . At most  $n^{k-r-1}$   $k$ -cliques (in fact,  $k$ -sets)  $L$  contain two given distinct edges  $e, e'$  (as  $e, e'$  have at least  $r + 1$  points between them) and there are less than  $k^{2r}$  such pairs  $e, e'$ . Thus

$$(20) \quad \begin{aligned} \left[ \binom{k}{r} - 1 \right] \rho^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \varepsilon) &\geq |\mathcal{S}_K| \\ &\geq \left[ \binom{k}{r} - 1 \right] \rho^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \varepsilon) - k^{2r} n^{k-r-1}. \end{aligned}$$

We absorb the overlap term  $k^{2r} n^{k-r-1}$  into the main term and deduce

$$(21) \quad |\mathcal{S}_K| = \left[ \binom{k}{r} - 1 \right] \rho^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm 2\varepsilon).$$

thus

$$(22) \quad \begin{aligned} E[X_K] &= (1 - \rho)^{|\mathcal{S}_K|} = \exp\left[-\varepsilon \left[ \binom{k}{r} - 1 \right] (1 \pm 3\varepsilon)\right] \\ &= \exp\left[-\delta \left[ \binom{k}{r} - 1 \right]\right] (1 \pm 4\varepsilon \binom{k}{r}). \end{aligned}$$

Here we have approximated  $(1 - p)$  by  $\exp(-p)$  and  $\exp(\pm 3\varepsilon \delta \binom{k}{r})$  as

$$1 \pm 4\varepsilon \delta \binom{k}{r} = 1 \pm 4\varepsilon \binom{k}{r}.$$

Summing over all  $K \in \mathcal{A}_e$ .

$$(23) \quad E(X) = \rho^{\binom{k}{k-r}}^{-1} \binom{n-r}{k-r} (1 \pm \epsilon) \exp\left[-\delta \left[\binom{k}{r} - 1\right]\right] \left(1 \pm 4 \binom{k}{r} \epsilon\right) \\ = (\rho e^{-\delta})^{\binom{k}{k-r}} \binom{n-r}{k-r} \left(1 \pm 5 \binom{k}{r} \epsilon\right).$$

Once again we must show  $X$  is nearly always nearly equal to its expectation. Our requirements this time are far more stringent since there are  $cn^r$  variables  $X$  (one for each edge) each of which must be nearly equal its expectation. In fact we shall show that the probability  $X \neq E(X)(1 \pm \epsilon)$  is exponentially small. To do this we shall require a strong sense of mutual independence of the  $X_K, K \in \mathcal{A}_e$ . Note, however, that when  $K', K'' \in \mathcal{A}_e$  intersect in more than  $e$  the corresponding  $X_{K'}, X_{K''}$  are highly correlated. Our first task, then, is to break  $\mathcal{A}_e$  into classes in which that does not occur.

We call a subfamily  $\mathcal{C} \subseteq \mathcal{A}_e$  neardisjoint if  $K' \cap K'' = e$  for all distinct  $K', K'' \in \mathcal{C}$ . For each  $K' \in \mathcal{A}_e$  there are at most  $k$

$$\binom{n}{k-r-1} \leq n^{k-r-1}$$

cliques  $K'' \in \mathcal{A}_e$  with  $K' \cap K'' = e$  ( $k$  choices for  $x \in K' - e, \binom{n}{k-r-1}$  choices for  $K''$  containing  $e, x$ ). We partition  $\mathcal{A}_e$  into

$$(24) \quad \mathcal{A}_e = \bigcup_{\alpha \in I} \mathcal{C}_\alpha \cup \mathcal{D}$$

( $I$  an index set) where each  $|\mathcal{C}_\alpha| = n^3$ , each  $\mathcal{C}_\alpha$  is neardisjoint, and  $|\mathcal{D}| < n^{k-r-7}$ . To do this we pull  $\mathcal{C}_\alpha$  from  $\mathcal{A}_e$  as long as possible until we get stuck. At that point we have a family  $\mathcal{D}$  of remaining sets and a near-disjoint family  $\mathcal{C} \subseteq \mathcal{D}, |\mathcal{C}| < n^3$ , which cannot be extended. There are at most  $|\mathcal{C}|n^{k-r-1} < n^{k-r-7}$  sets  $K'' \in \mathcal{D}$  which intersect some  $K' \in \mathcal{C}$  in more than  $e$ . As this must be all of  $\mathcal{D}, |\mathcal{D}| < n^{k-r-7}$ .

Let  $\mathcal{C} \subseteq \mathcal{A}_e, |\mathcal{C}| = n^3$  be neardisjoint and set

$$(25) \quad X_{\mathcal{C}} = \sum_{K \in \mathcal{C}} X_K.$$

Suppose  $K', K''$  are distinct elements of  $\mathcal{C}$  and  $L \in \mathcal{S}_{K'} \cap \mathcal{S}_{K''}$ . Then  $L$  contains edges  $e' \in K', e'' \in K'', e' \neq e \neq e''$ . As  $K' \cap K'' = e, e' \neq e''$  so  $L$  contains at least  $r + 1$  points from  $K' \cup K''$ . Thus

$$(26) \quad |\mathcal{S}_{K'} \cap \mathcal{S}_{K''}| < \binom{2k}{r+1}$$

where  $c$  depends only on  $k, r$ . Set

$$(27) \quad \mathcal{F} = \bigcup_{K', K'' \in \mathcal{C}} \mathcal{S}_{K'} \cap \mathcal{S}_{K''}$$

so that

$$(28) \quad |\mathcal{T}| \leq |\mathcal{C}|^2 cn^{k-r-1} < n^{k-r-39}.$$

For  $K \in \mathcal{C}$  define random variables  $Y_K$  by

$$(29) \quad Y_K = \begin{cases} 1, & \text{if } F \cap (\mathcal{S}_K - \mathcal{T}) = \emptyset \\ 0, & \text{otherwise.} \end{cases}$$

and define

$$(30) \quad Y_{\mathcal{C}} = \sum_{K \in \mathcal{C}} Y_K.$$

Since the sets  $\mathcal{S}_K - \mathcal{T}$  are mutually disjoint the variables  $Y_K$  are mutually independent. We require a classic result (for explicit reference see the appendix of [3]) on the sum of independent random variables.

*Fact.* If  $Z_1, \dots, Z_m$  are mutually independent zero-one random variables,  $Z = \sum_{i=1}^m Z_i$ , and  $\alpha > 0$  then

$$(31) \quad \Pr[|Z - E(Z)| > \alpha] < 2e^{-\alpha^2/m}.$$

Applying this result with  $m = |\mathcal{C}| = n^3$ ,  $\alpha = n^2$

$$(32) \quad \Pr[|Y_{\mathcal{C}} - E(Y_{\mathcal{C}})| > n^2] < 2e^{-n^1}.$$

(This was the critical step as we have the probability exponentially small.) Now we need show that  $Y_{\mathcal{C}}$  provides a good approximation to  $X_{\mathcal{C}}$ . Set

$$(33) \quad W = |F \cap \mathcal{T}|.$$

For all  $K$ ,  $Y_K \leq X_K$  and thus  $Y_{\mathcal{C}} \leq X_{\mathcal{C}}$ . If  $Y_K = 0$  and  $X_K = 1$  then  $F \cap \mathcal{S}_K \cap \mathcal{T} \neq \emptyset$ . Each  $L \in F \cap \mathcal{T}$  lies in at most  $k$  families  $\mathcal{S}_K$ ,  $K \in \mathcal{C}$ . ( $L$  must have at least one point in  $K - e$ ,  $|L| = k$ , and the sets  $K - e$ ,  $K \in \mathcal{C}$ , are disjoint.) Thus

$$(34) \quad X_{\mathcal{C}} - kW \leq Y_{\mathcal{C}} \leq X_{\mathcal{C}}.$$

Therefore

$$(35) \quad E[|X_{\mathcal{C}} - Y_{\mathcal{C}}|] \leq kE[W] \leq kn^{k-r-39}p < n^{-38}.$$

Moreover,  $W$  has binomial distribution  $B(|\mathcal{T}|, p)$  so

$$(36) \quad \Pr[X_{\mathcal{C}} - Y_{\mathcal{C}} > n^2] < \Pr[W > n^2/k] < [|\mathcal{T}|_p]^{n^2/k} < [n^{-38}]n^2/k < e^{-n^2}$$

$$(37) \quad |X_{\mathcal{C}} - E(X_{\mathcal{C}})| \leq |X_{\mathcal{C}} - Y_{\mathcal{C}}| + |Y_{\mathcal{C}} - E(Y_{\mathcal{C}})| + |E(Y_{\mathcal{C}}) - E(X_{\mathcal{C}})|$$

we combine (32), (35), (36) to derive

$$(38) \quad \Pr\left[|X_{\mathcal{C}} - E(X_{\mathcal{C}})| > 3n^2\right] < 2e^{-n^1}.$$

From the decomposition (24) we decompose  $X$  into

$$(39) \quad X = \sum_{\alpha \in I} X_{\mathcal{C}_\alpha} + X_{\mathcal{D}}.$$

Thus

$$(40) \quad |X - E(X)| \leq \sum_{\alpha \in I} |X_{\mathcal{C}_\alpha} - E(X_{\mathcal{C}_\alpha})| + |X_{\mathcal{D}} - E(X_{\mathcal{D}})|.$$

As  $0 \leq X_{\mathcal{D}} \leq |\mathcal{D}| < n^{k-r-7}$  always,

$$(41) \quad |X_{\mathcal{D}} - E(X_{\mathcal{D}})| < n^{k-r-7}$$

with probability one. Now assume

$$(42) \quad |X_{\mathcal{C}_\alpha} - E(X_{\mathcal{C}_\alpha})| \leq 3n^2$$

for every  $\alpha \in I$ . Summing over  $\alpha \in I$ , and noting  $|I| \leq |\mathcal{A}_e|/n^3 \leq n^{k-r-3}$

$$(43) \quad \sum_{\alpha \in I} |X_{\mathcal{C}_\alpha} - E(X_{\mathcal{C}_\alpha})| \leq 3n^2 n^{k-r-3}$$

so

$$(44) \quad |X - E(X)| < 4n^{k-r-1}.$$

The probability that this does not occur is at most  $|I|(2e^{-n^1}) < n^k e^{-n^1}$ . We know from (23) that  $E(X) > cn^{k-r}$  where  $c$  is a constant dependent on  $k, r, \rho, \delta$  and  $\varepsilon$  but not on  $n$ . Thus  $4n^{k-r-1} < \varepsilon E(X)$  and so

$$(45) \quad \Pr[X \neq E(X)(1 \pm \varepsilon)] < n^k e^{-n^1} < e^{-n^{09}}$$

by the dominance of the exponential term. Combining (23) and (45)

$$(46) \quad \Pr\left[X \neq (\rho e^{-\delta})^{\binom{k}{r}-1} \binom{n-r}{k-r} \left(1 \pm 6 \binom{k}{r} \varepsilon\right)\right] < e^{-n^{09}}.$$

Recall that  $X$  represents the number of  $k$ -cliques of  $G^*$  containing  $e$ , conditional on  $e \in G^*$ , for a given  $e$ . There are less than  $n^r$  different  $e$ . Thus the probability that *some*  $e \in G^*$  does not lie in the appropriate number, i.e.

$$(\rho e^{-\delta})^{\binom{k}{r}-1} \binom{n-r}{k-r} (1 \pm \varepsilon^*),$$

of  $k$ -cliques of  $G^*$  is bounded from above by  $n^r e^{-n^{09}}$ . Once again the exponential term dominates. The probability of (iii) holding approaches infinity.

We return to the beginning of the proof. Having fixed  $\varepsilon$  we let  $n_0$  be such that for  $n > n_0$  conditions (i), (ii), (iii) all hold with probability at least .9. Then with probability at least .7 all three conditions hold simultaneously. Thus there exists a specific  $F$  for which all three conditions hold. This completes the proof of the Lemma.

**THEOREM.** *Let  $2 \leq r < k$  and  $a > 0$  be fixed. Then for  $n$  sufficiently large*

$$(47) \quad M(n, k, r) < \left[ \binom{n}{r} / \binom{k}{r} \right] (1 + a).$$

*Proof.* We first select  $a > 0$  so that

$$(48) \quad \frac{\delta}{1 - e^{-\delta}} < 1 + a.$$

This may be done as  $\lim_{\delta \rightarrow 0} \delta / (1 - e^{-\delta}) = 1$ . We then select  $\varepsilon > 0$  so that

$$(49) \quad \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon} < 1 + a$$

which may be done as

$$\lim_{\varepsilon \rightarrow 0} \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon} = \frac{\delta}{1 - e^{-\delta}}.$$

We then select a positive integer  $t$  so that

$$(50) \quad \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon} + \binom{k}{r} e^{-t\delta} (1 + \varepsilon) < 1 + a$$

which may be done as

$$\lim_{t \rightarrow \infty} \binom{k}{r} e^{-t\delta} (1 + \varepsilon) = 0.$$

Set  $\varepsilon_t = \varepsilon$ . By reverse induction on  $i$  we find  $\varepsilon_t > \varepsilon_{t-1} > \dots > \varepsilon_0$  so that the Lemma applies with  $\rho = e^{-i\delta}$ ,  $\varepsilon^* = \varepsilon_i$ ,  $\delta$  as itself, and  $\varepsilon_{i-1}$  as the “ $\varepsilon$ ” given by the Lemma. Now let  $n$  be sufficiently large so that the Lemma holds in all  $t$  cases. Set  $G_0$  equal the complete  $r$ -graph on  $n$  vertices. Then  $G_0$  is quasirandom with density 1 and tolerance  $\varepsilon_0$ —in fact, with tolerance zero. Applying the Lemma we find, for  $0 \leq i < t$ , families  $F_i$  and graphs  $G_{i+1}$  so that

- (i)  $|F_i| < \delta [e^{-i\delta} \binom{n}{r} / \binom{k}{r}] (1 + \varepsilon_i)$
- (ii)  $G_{i+1}$  is  $G_i$  with all cliques of  $F_i$  deleted.
- (iii)  $G_{i+1}$  is quasirandom with density  $\rho e^{-\delta}$  and tolerance  $\varepsilon_{i+1}$

As all  $\varepsilon_i \leq \varepsilon$  we simplify (i), (iii) to

$$(i') |F_i| < \delta [e^{-i\delta} \binom{n}{r} / \binom{k}{r}] (1 + \varepsilon)$$

(iii')  $G_{i+1}$  is quasirandom with density  $\rho e^{-\delta}$  and tolerance  $\varepsilon$ .

For each  $i, 0 \leq i < t$

$$(51) \quad \begin{aligned} |G_i| &> e^{-i\delta} \binom{n}{r} (1 - \varepsilon) \\ |G_{i+1}| &< e^{-(i+1)\delta} \binom{n}{r} (1 + \varepsilon) \end{aligned}$$

so

$$(52) \quad |G_i| - |G_{i+1}| > e^{-i\delta} \binom{n}{r} (1 - e^{-\delta} - 2\varepsilon)$$

and

$$(53) \quad \frac{|F_i| \binom{k}{r}}{|G_i| - |G_{i+1}|} < \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon}.$$

The families  $F_0, F_1, \dots, F_{t-1}$  cover all  $r$ -sets except  $G_t$ . For each  $e \in G_t$  let  $K_e$  be an arbitrary  $k$ -set containing  $e$  (not necessarily a clique in  $G_t$ ) and let  $F_\infty$  denote the family of those  $K_e$ . Then

$$(54) \quad |F_\infty| \leq |G_t| < e^{-t\delta} \binom{n}{r} (1 + \varepsilon).$$

Now the set

$$(55) \quad F = F_0 \cup F_1 \cup \dots \cup F_{t-1} \cup F_\infty$$

covers all  $r$ -sets on  $n$  vertices. Summing (53) for  $0 \leq i < t$

$$(56) \quad \begin{aligned} \left[ \sum_{i=0}^{t-1} |F_i| \right] \binom{k}{r} &< \left[ \sum_{i=0}^{t-1} |G_i| \right] \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon} \\ &< \binom{n}{r} \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon}. \end{aligned}$$

Adding  $F_\infty$ :

$$(57) \quad \begin{aligned} \binom{k}{r} M(n, k, r) &\leq |F| \binom{k}{r} \\ &< \binom{n}{r} \left[ \frac{\delta(1 + \varepsilon)}{1 - e^{-\delta} - 2\varepsilon} + \binom{k}{r} e^{-t\delta} (1 + \varepsilon) \right] \\ &< \binom{n}{r} (1 + a) \end{aligned}$$

by our propitious choices of  $\delta, \varepsilon$  and  $t$ —completing the proof.

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