# Small-size $\varepsilon$ -Nets for Axis-Parallel Rectangles and Boxes<sup>\*</sup>

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## ABSTRACT

We show the existence of  $\varepsilon$ -nets of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$  for planar point sets and axis-parallel rectangular ranges. The same bound holds for points in the plane with "fat" triangular ranges, and for point sets in  $\mathbb{R}^3$  and axis-parallel boxes; these are the first known non-trivial bounds for these range spaces. Our technique also yields improved bounds on the size of  $\varepsilon$ -nets in the more general context considered by Clarkson and Varadarajan. For example, we show the existence of  $\varepsilon$ -nets of size  $O\left(\frac{1}{\varepsilon}\log\log\log\frac{1}{\varepsilon}\right)$  for the dual range space of "fat" regions and planar point sets (where the regions are the ground objects and the ranges are subsets stabbed by points). Plugging our bounds into the technique of Brönnimann and Goodrich, we obtain improved approximation factors (computable in randomized polynomial time) for the HITTING SET or the SET COVER problems associated with the corresponding range spaces.

### **Categories and Subject Descriptors**

F.2.2 [Theory of Computation]: Analysis of Algorithms and Problem Complexity, Nonnumerical Algorithms and Problems [Computations on discrete structures, geometrical problems and computations]

\*Work on this paper by Boris Aronov and Micha Sharir has been supported by a joint grant from the U.S.-Israel Binational Science Foundation. Work by Boris Aronov has also been supported by NSA MSP Grant H98230-06-1-0016 and NSF Grant CCF-08-30691. Work by Esther Ezra has been supported by ARO grants W911NF-04-1-0278 and W911NF-07-1-0376, and by an NIH grant 1P50-GM-08183-01. Work by Micha Sharir has also been supported by NSF Grants CCF-05-14079 and CCF-08-30272, by Grant 155/05 from the Israel Science Fund, and by the Hermann Minkowski-MINERVA Center for Geometry at Tel Aviv University.

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STOC'09, May 31-June 2, 2009, Bethesda, Maryland, USA.

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### **General Terms**

Algorithms, Theory

#### **Keywords**

Geometric range spaces, randomized algorithms,  $\varepsilon$ -nets, set cover, hitting set

### 1. INTRODUCTION

Since their introduction in 1987 by Haussler and Welzl [25] (see also Clarkson [9] and Clarkson and Shor [11] for related techniques),  $\varepsilon$ -nets have become one of the central concepts in computational and combinatorial geometry, and have been used in a variety of applications, such as range searching, geometric partitions, and bounds on curve-point incidences, to name a few; see, e.g., Matoušek [29]. We recall their definition: A range space  $(X, \mathcal{R})$  is a pair consisting of an underlying universe X of objects, and a certain collection  $\mathcal{R} \subseteq 2^X$  of subsets (ranges). Of particular interest are range spaces of finite VC-dimension; the reader is referred to [25] for the exact definition. Informally, it suffices to require that, for any finite subset  $P \subset X$ , the number of distinct sets  $r \cap P$ , for  $r \in \mathcal{R}$ , is  $O(|P|^d)$ , for some constant d (which is upper bounded by the VC-dimension of  $(X, \mathcal{R})$ ).

Given a range space  $(X, \mathcal{R})$ , a finite subset  $P \subset X$ , and a parameter  $0 < \varepsilon < 1$ , an  $\varepsilon$ -net for P and  $\mathcal{R}$  is a subset  $N \subseteq$ P with the property that any range  $r \in \mathcal{R}$  with  $|r \cap P| \ge \varepsilon |P|$ contains an element of N. In other words, N is a hitting set for all the "heavy" ranges.

The epsilon-net theorem of Haussler and Welzl asserts that, for any  $(X, \mathcal{R})$ , P, and  $\varepsilon$  as above, such that  $(X, \mathcal{R})$ has finite VC-dimension d, there exists an  $\varepsilon$ -net N of size  $O\left(\frac{d}{\varepsilon}\log\frac{d}{\varepsilon}\right)$ , and that in fact a random sample of P of that size is an  $\varepsilon$ -net with constant probability. In particular, the size of N is independent of the size of P. The bound on the size of the  $\varepsilon$ -net was later improved to  $O\left(\frac{d}{\varepsilon}\log\frac{1}{\varepsilon}\right)$  by Blumer *et al.* [4], and then to  $(1 + o(1))\frac{d}{\varepsilon}\log\frac{1}{\varepsilon}$  by Komlós, Pach, and Woeginger [28].

In geometric applications, this abstract framework is used as follows. The ground set X is typically a set of simple geometric objects (points, lines, hyperplanes), and the ranges in  $\mathcal{R}$  are defined in terms of intersection with (or, for point objects, containment in) simply-shaped regions (halfspaces, balls, simplices, etc.), formally assumed to be regions of constant descriptive complexity, meaning that they are semi-algebraic sets defined in terms of a constant number of polynomial equations and inequalities of constant maximum degree. It is known that in such cases the resulting range space  $(X, \mathcal{R})$  does have finite VC-dimension (see, e.g., [38]).

For example, the main result of our paper concerns the range space in which the objects are points in the plane and the ranges are axis-parallel rectangles; more precisely, each range is the intersection of the ground set with such a rectangle. The *dual* range space in this case is one in which the objects are rectangles and each point p in the plane defines a range which is the subset of the given rectangles that contain p. An  $\varepsilon$ -net in this case is a subset of the rectangles that covers all the "deep" points.

One of the major questions in the theory of  $\varepsilon$ -nets, open since their introduction more than 20 years ago, is whether the factor  $\log \frac{1}{\varepsilon}$  in the upper bound on their size is really necessary, especially in typical low-dimensional geometric situations. To be precise, in the general abstract context the answer is "yes", as shown by Komlós, Pach, and Woeginger [28], using a randomized construction on abstract hypergraphs (see also [35]). However, there is no known lower bound, better than the trivial  $\Omega(1/\varepsilon)$ , in any "concrete" case, certainly in any geometric situation of the kind mentioned above. The prevailing conjecture is that, at least in these geometric scenarios, there always exists an  $\varepsilon$ -net of size  $O(1/\varepsilon)$  [32].

This "linear" upper bound has indeed been established for a few special cases, such as point objects and halfspace ranges in two and three dimensions, and point objects and disk or pseudo-disk ranges in the plane; see [32, 30, 12, 24, 37]. Additional progress was made recently. Clarkson and Varadarajan [12], essentially adapting Matoušek's technique [30] to their more general setting, have introduced a method for constructing small-size  $\varepsilon$ -nets in dual range spaces arising in geometric situations where, as above, the ground set is a collection of regions, and each point p determines a range equal to the set of those regions which contain p, and where the combinatorial complexity of the union of any finite number r of the regions in the ground set is small, specifically  $o(r \log r)$ . (The exact condition is slightly more involved see below.) As a matter of fact, albeit not explicitly presented in this manner, the technique of [12] is more general and can also be applied to the primal version of the problem, provided that it satisfies a condition analogous to the one on small union complexity; see below for more details. More recently, Pyrga and Ray [37] have proposed a general abstract scheme for constructing small-size  $\varepsilon$ -nets in hypergraphs (i.e., range spaces) which satisfy certain properties, and have applied it to the special cases of halfspaces in two and three dimensions, and to several other related scenarios.

The set cover and hitting set problems. Given a range space  $(P, \mathcal{R})$ , with P and  $\mathcal{R}$  finite, the SET COVER problem is to find a minimum-size subcollection  $S \subseteq \mathcal{R}$ , whose union covers P. A related (dual) problem is the HITTING SET problem, where we want to find a smallest-cardinality subset  $H \subseteq P$ , with the property that each range  $r \in \mathcal{R}$  intersects H. Equivalently, a set cover for  $(P, \mathcal{R})$  is a hitting set for the dual range space. The general (primal and dual) problems are NP-hard to solve (even approximately) [23, 27], and the simple greedy algorithm yields the (asymptotically) best known approximation factor of  $O(1+\log |P|)$  computable by a polynomial-time algorithm [3, 21]. Most of these problems remain NP-hard even in geometric settings [20, 22]. However one can attain an improved approximation factor of  $O(\log \text{OPT})$  in polynomial time for many of these scenarios, where OPT is the size of the optimal solution. This improvement is based on the technique of Brönnimann and Goodrich [6] (see also Clarkson [10]), where the key observation is the relation to  $\varepsilon$ -nets: The existence of an  $\varepsilon$ -net of size  $O\left(\frac{1}{\varepsilon}\varphi\left(\frac{1}{\varepsilon}\right)\right)$ , for any  $\varepsilon > 0$ , implies that the Brönnimann– Goodrich technique generates, in expected polynomial time, a hitting set (or a set cover) whose size is  $O(\text{OPT} \cdot \varphi(\text{OPT}))$ .

Hence, for range spaces of finite VC-dimension, the theorem of Haussler and Welzl leads to an approximation factor  $O(\log \text{OPT})$ . Consequently, improved bounds for the size of  $\varepsilon$ -nets, in the primal or the dual setting, imply improved approximation factors for the corresponding HITTING SET or SET COVER problems, at least in the context of randomized polynomial-time construction (which is what the Brönnimann–Goodrich procedure performs).

Our results. In this paper we first consider the cases of point objects and axis-parallel rectangular ranges in the plane, and of point objects and axis-parallel box ranges in three dimensions, and show that both range spaces admit  $\varepsilon$ -nets of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$ , thus significantly improving the standard bound  $O\left(\frac{1}{\varepsilon}\log\frac{1}{\varepsilon}\right)$ . Our technique is similar in spirit to those of Chazelle and Friedman [8] and of Clarkson and Varadarajan [12], but it differs from them in one key (and fairly simple) idea, which, incidentally, can also be used in the more general context of [12] to improve the bounds that are obtained there for the size of the respective  $\varepsilon$ -nets—see below. An interesting feature of our technique is that it can be extended to points and axis-parallel boxes in any dimension, provided that the input points are randomly and uniformly distributed in the unit cube.

We also describe how to construct these  $\varepsilon$ -nets in randomized expected nearly-linear time. Our results then lead to randomized polynomial-time approximation algorithms for the HITTING SET problem in these two range spaces, involving axis-parallel rectangles and boxes, respectively, which guarantee an approximation factor of  $O(\log \log OPT)$ .

We then extend our technique to the case of planar point sets and  $\alpha$ -fat triangles, that is, triangles, each of whose angles is at least  $\alpha$ , for some constant  $\alpha > 0$  (see [33]). In this case we show the existence of  $\varepsilon$ -nets of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$ , leading to an approximation factor of O (log log OPT) for the corresponding HITTING SET problem as well.

Similarly, we obtain improved bounds for the size of  $\varepsilon$ -nets in the dual range space, and, consequently, for approximation factors for the corresponding SET COVER problem, in the following cases, all involving points and regions in the plane (refer to Figure 5):

- $\alpha$ -fat triangles. In this case the size of the corresponding  $\varepsilon$ -net is  $O\left(\frac{1}{\varepsilon}\log\log\log\frac{1}{\varepsilon}\right)$ , and, as a consequence, the approximation factor for the SET COVER problem becomes  $O\left(\log\log\log\log \operatorname{OPT}\right)$ .
- Locally  $\gamma$ -fat objects, that is, objects o satisfying the property that, for any disk D whose center lies in o, such that D does not fully contain o in its interior, we have  $area(D \sqcap o) \geq \gamma \cdot area(D)$ , where  $D \sqcap o$  is the connected component of  $D \cap o$  that contains the center of D (see [14]). If we also assume that the boundary of each

object has only O(1) locally *x*-extreme points, and the boundaries of any pair of input objects intersect in at most *s* points, for some constant *s*, then the size of the  $\varepsilon$ -net is  $O\left(\frac{1}{\varepsilon} \log \log \frac{1}{\varepsilon}\right)$ , and the approximation factor for the SET COVER problem is  $O\left(\log \log \operatorname{OPT}\right)$ .

- Locally  $\gamma$ -fat objects of (roughly) equal sizes. Assuming that the objects satisfy the conditions in the previous case, and that the diameters of any pair of objects differ by at most some constant ratio the bound on the size of the  $\varepsilon$ -net improves to  $O\left(\frac{1}{\varepsilon}\log\beta_{s+2}(\frac{1}{\varepsilon})\right)$ , where  $\beta_t(q) := \lambda_t(q)/q$ , and  $\lambda_t(q)$  is the (nearly linear) maximum length of Davenport-Schinzel sequences of order ton q symbols (see [38]). The corresponding approximation factor becomes  $O\left(\log\beta_{s+2}(\text{OPT})\right)$  (see Section 4 for a more detailed discussion of these bounds).
- Semi-unbounded pseudo-trapezoids, each consisting of all points lying above some x-monotone arc (or all points lying below such an arc), each pair of which meet at most s times, for s a constant; see Section 4 for a precise definition. In this case the size of the  $\varepsilon$ net is again  $O\left(\frac{1}{\varepsilon}\log\beta_{s+2}(\frac{1}{\varepsilon})\right)$  and the approximation factor is  $O\left(\log\beta_{s+2}(\text{OPT})\right)$ . If the pseudo-trapezoids are also unbounded in the x-direction (so they become "pseudo-halfplanes") these bounds slightly improve to  $O\left(\frac{1}{\varepsilon}\log\beta_s(\frac{1}{\varepsilon})\right)$  and  $O\left(\log\beta_s(\text{OPT})\right)$ , respectively.
- Jordan arcs with three intersections per pair, where each of the actual objects is the region bounded by some Jordan arc which starts and ends on the x-axis (and otherwise lies above it) and by the portion of the x-axis between these endpoints, and each pair of the bounding Jordan arcs intersect at most three times. In this case, assuming that none of the given objects "wiggles" too much (as in the case of locally  $\gamma$ -fat objects), the size of the  $\varepsilon$ -net is  $O\left(\frac{1}{\varepsilon}\log\alpha(\frac{1}{\varepsilon})\right)$ , and the approximation factor is  $O\left(\log\alpha(\text{OPT})\right)$ , where  $\alpha(\cdot)$  is the (extremely slowly growing) inverse Ackermann function.

Our technique for rectangles—a brief overview. We start with a brief overview of our analysis, in which we assume some familiarity with the earlier papers [8, 12] cited above. Let P be a given set of n points in the plane. We first sketch a somewhat simpler approach that "almost" works—it does not properly address a certain critical technical issue, but captures the essence of our method. We then briefly describe how to modify it so that it does produce  $\varepsilon$ -nets of the desired size.

Put  $r = 2/\varepsilon$ . We draw a random sample R of  $s \gg r$ points of P (the specific choice of s, made below, is crucial), and make R part of the  $\varepsilon$ -net to be constructed, so we only need to handle axis-parallel rectangles which contain at least n/r points, but are R-empty, i.e., (axis-parallel) rectangles which do not contain any point of R. To "pierce" every such rectangle, we form the subset  $\mathcal{M}$  of maximal R-empty rectangles, so that any other R-empty rectangle is contained in one of them. By the standard  $\varepsilon$ -net theory of [25], with high probability each rectangle of  $\mathcal{M}$  contains at most  $O\left(\frac{n}{s}\log s\right)$ points of P. Moreover, in a sense that we do not make very precise here, the expected number of points of P in such a rectangle is O(n/s). Since  $s \gg r$ , most rectangles of  $\mathcal{M}$ contain fewer than  $\varepsilon n = n/r$  points of P, so an R-empty rectangle Q with at least n/r points will not fit into any of them, and we can simply ignore them. For each of the relatively few "heavy" rectangles M of  $\mathcal{M}$ , we apply the resampling technique of [8, 12], and sample a small subset of  $O(t \log t)$  points of  $M \cap P$ , where  $t = s|M \cap P|/n$ , to serve as a (1/t)-net for  $M \cap P$ . The union of R and all these samples constitutes the desired  $\varepsilon$ -net; it is fairly easy to show that this is indeed an  $\varepsilon$ -net.

This approach does not quite work, because, for a bad choice of R, the number of maximal R-empty rectangles can be  $\Theta(s^2)$  in the worst case (see, e.g., [34] and Figure 1(a)). Moreover, even if we only consider random subsets R, there are point sets where the *expected* number of maximal R-empty rectangles which contain  $\Omega(n/s)$  points of P is still  $\Theta(s^2)$ ; see Figure 1(b). Using the technique outlined above literally, turns out to yield a bound of  $\Theta\left(\frac{1}{\varepsilon^2}\right)$  on the expected size of the  $\varepsilon$ -net in the worst case, which is of course much too large.

We overcome this issue by modifying the scheme, so that it produces fewer maximal empty rectangles. To do so, we decompose the plane into a binary-tree-like hierarchy of vertical strips. For any rectangle  $\tilde{Q}$  which contains at least  $\varepsilon n$  points of P, we find the first (highest in the hierarchy) strip-bounding line which crosses  $\tilde{Q}$ , take one of its halves, Q, which contains at least  $\varepsilon n/2 = n/r$  points, and consider only such rectangles in the construction of our net. We thus face subproblems, each involving a vertical strip  $\sigma$  and the corresponding subset  $P \cap \sigma$  of P, and ranges which are rectangles that are "anchored" at a specific side of  $\sigma$  (so that they effectively behave like 3-sided unbounded rectangles for  $P \cap \sigma$ ; refer to Figure 2). The number of maximal *R*-empty rectangles of this type, within  $\sigma$ , is only *linear* in  $|R \cap \sigma|$ , leading to an overall collection  $\mathcal{M}$  of maximal *R*-empty rectangles of the new kind, whose size is only  $O(s \log r)$ .

We now choose  $s := cr \log \log r$ . Using the so-called Exponential Decay Lemma of [1, 8], one can show that the expected number of maximal heavy empty rectangles that can contain rectangles Q of the above kind is only *sublinear* in r, which in turn implies that the expected size of the  $\varepsilon$ -net is dominated by the expected size of R, namely,  $O(r \log \log r) = O\left(\frac{1}{\varepsilon} \log \log \frac{1}{\varepsilon}\right)$ .

*Improving the general bounds in [12]*. Readers familiar with the technique of Clarkson and Varadarajan [12] will notice the similarity of our approach to theirs. The key new ingredient is that we use a larger initial sample R, of expected size  $\Theta(r \log \log r)$  rather than O(r). The same idea can be applied in the more general context of [12], and leads to an improvement of each of their bounds that are superlinear in r. Specifically, Clarkson and Varadarajan consider dual range spaces, and show that if the union complexity of any m of the ranges (i.e., objects in the dual ground set) is  $O(m\varphi(m))$ , for an appropriate slowly increasing function  $\varphi$ , then there exist  $\varepsilon$ -nets in such a dual range space of size  $O((1/\varepsilon)\varphi(1/\varepsilon))$ . Using our approach, we obtain  $\varepsilon$ -nets of size  $O((1/\varepsilon) \log \varphi(1/\varepsilon))$ . Moreover, their method yields improved bounds for  $\varepsilon$ -nets only when  $\varphi(m) = o(\log m)$ , whereas our method yields improved bounds as long as  $\varphi(m)$  $=2^{o(\log m)}$ . The case of rectangles is interesting in this aspect, because, with the addition of the divide-and-conquer decomposition scheme mentioned above, the complexity of the appropriate analog of the union of m dual ranges (which is the number of maximal empty rectangles) is  $O(m \log m)$ ,



Figure 1: (a) A configuration with quadratically many maximal R-empty rectangles (the points of R are darkly shaded and lie on the two extreme staircases). (b) A configuration with an expected quadratic number of maximal R-empty rectangles, each containing  $\Omega(n/s)$  points. The lower staircase contains n/2 points, and each of the s upper "diagonals" contains  $\frac{n}{2s}$  points.



**Figure 2:** The half-rectangle Q is anchored at the left entry side  $\ell_u$  of the strip  $\sigma_v$ .

which is the threshold bound at which the more "naive" approach of [12] fails.<sup>1</sup>

We have just learned that, very recently, Varadarajan [39] has independently obtained a similar improvement on the bound of [12] for the size of an  $\varepsilon$ -net in the dual range space of  $\alpha$ -fat triangles and planar point sets, using very different methods.

# 2. SMALL-SIZE $\varepsilon$ -NETS FOR AXIS-PARALLEL RECTANGLES

Let P be a set of n points in the plane. Put  $r := 2/\varepsilon$ and  $s := cr \log \log r$ , where c > 1 is an arbitrary constant. Construct a balanced binary tree  $\mathcal{T}$  over the points of P in their x-order, and terminate the tree at the level where the size of each leaf-node is between n/r and n/(2r). By construction,  $\mathcal{T}$  has at most  $1 + \log r$  levels.

Fix a random sample  $R \subseteq P$ , so that each point  $p \in P$  is chosen independently to be included in R with probability  $\pi := s/n$ ; thus the expected size of R is s. The sample R is part of the  $\varepsilon$ -net N that we are about to construct.

Each node v of  $\mathcal{T}$  is associated with a subset  $P_v$  of P (resp.,  $R_v$  of R), consisting of those points of P (resp., of R) stored at the subtree rooted at v. We also associate with v a vertical line  $\ell_v$  which splits  $P_v$  into the two subsets  $P_{v_1}$ ,  $P_{v_2}$  associated with the children  $v_1, v_2$  of v. Using the lines  $\ell_u$ , we associate with each node v a strip  $\sigma_v$ , which contains

 $P_v$  (and  $R_v$ ), where  $\sigma_{\text{root}}$  is the entire plane, and, for a left (resp., right) child node  $v \neq \text{root}$  of its parent u,  $\sigma_v$  is the left (resp., right) portion of  $\sigma_u$  delimited by  $\ell_u$ . We call  $\ell_u$  the *entry side* of  $\sigma_v$ .

Note that, since the sets  $P_v$  are defined ahead of the draw of R, our sampling model guarantees that, for each node v,  $R_v$  is an unbiased sample of  $P_v$ , drawn from  $P_v$  by exactly the same rule, namely, by choosing each point independently with probability  $\pi$ .

Let  $\tilde{Q}$  be an axis-parallel rectangle containing at least  $\varepsilon n$ points of P, and let u be the highest node of  $\mathcal{T}$  such that  $\ell_u$  crosses  $\tilde{Q}$ , partitioning it into two parts, one of which necessarily contains at least  $\varepsilon n/2 = n/r$  points of P. Denote that portion of  $\tilde{Q}$  by Q, and let v be the child of u such that  $Q \subseteq \sigma_v$ . We say that Q is anchored at the entry side  $\ell_u$  of  $\sigma_v$ ; see Figure 2.

If Q contains a point of R, we are done, as  $Q \subset \hat{Q}$  and the goal was to construct a subset of P that meets every rectangle  $\tilde{Q}$  containing at least  $\varepsilon n$  points of P. So we may assume that Q does not contain such a point; we then say that Q is R-empty; equivalently, Q is  $R_v$ -empty.

We define, for each node v of  $\mathcal{T}$ , a set  $\mathcal{M}_v$  consisting of all the maximal (open) anchored  $R_v$ -empty axis-parallel rectangles contained in  $\sigma_v$ . Without loss of generality, assume that the entry side  $\ell_u$  of  $\sigma_v$  is its left side. In general, a rectangle M in  $\mathcal{M}_v$  is determined by three points of  $R_v$ , one point lying on each of the three unanchored sides of M(see Figure 3(a)), but  $\mathcal{M}_v$  may also contain degenerate rectangles M where some (or all) of these points are missing, in which case M extends as much as possible, within  $\sigma_v$ , in the appropriate direction (upwards, downwards, or to the right). In particular, when  $R_v = \emptyset$ , there is precisely one maximal  $R_v$ -empty rectangle, namely the whole strip; see Figure 3(b)–(e), illustrating some of these cases.

It is easy to show that  $|\mathcal{M}_v| = 2r_v + 1$ , where  $r_v := |R_v|$ . Indeed, if a rectangle M has a point  $q \in R_v$  on its right side, then q cannot lie on the right side of any other rectangle in  $\mathcal{M}_v$ , so the number of such rectangles is  $r_v$  (equality is also easy to verify). Otherwise, the points of  $R_v$  on the top and bottom sides of M must be consecutive in  $R_v$  in the yorder, and there are  $r_v - 1$  such pairs. Finally, there are two semi-unbounded rectangles, one delimited from below by the highest point of  $R_v$ , and the other delimited from above by the lowest point (as in Figure 3(e)). It is easily checked that the bound  $2r_v + 1$  also applies when  $r_v = 0, 1$ . It thus follows that the overall number of such maximal empty

<sup>&</sup>lt;sup>1</sup>As already noted above, the  $\log m$  factor comes from the binary-tree hierarchy—see below for details.



Figure 3: An anchored maximal R-empty rectangle that is determined by three points (a), by a pair of points (b)–(d), or by a single point (e).

rectangles  $M \in \mathcal{M}_v$ , over all nodes v of  $\mathcal{T}$  at any fixed level, is O(|R| + r'), where r' is the number of nodes at the level, and the total over all levels of  $\mathcal{T}$  is  $O(r + |R| \log r)$ .

Returning now to the anchored rectangle Q and the corresponding node v, we note that Q is contained in at least one rectangle in  $\mathcal{M}_v$ . Indeed, assuming, as above, that the entry side of  $\sigma_v$  is its left side, expand Q by pushing its right side to the right until it touches a point of  $R_v$  or reaches the right side of  $\sigma_v$ , and then push the top and bottom sides until each of them meets a point of  $R_v$  or extends to  $\pm\infty$ . The resulting rectangle belongs to  $\mathcal{M}_v$  and encloses Q.

For each node v of  $\mathcal{T}$ , and each member  $M \in \mathcal{M}_v$ , define the weight factor  $t_M$  of M to be  $s|M \cap P|/n$ . Rectangles M with  $t_M < s/r = c \log \log r$  can be ignored, because they contain fewer than n/r points of P, so no anchored rectangle Q, as above, can be completely contained in one of them. By the standard  $\varepsilon$ -net theory [25], for each  $M \in \mathcal{M}_v$  with  $t_M \ge c \log \log r$ , there exists a subset  $N_M \subseteq M \cap P_v$  of size  $c't_M \log t_M$  that forms a  $(1/t_M)$ -net for  $M \cap P_v$ , where c' is another absolute constant.

The final  $\varepsilon$ -net N is the union of R with the sets  $N_M$ , over all the heavy rectangles M (i.e., rectangles with  $t_M \ge c \log \log r$ ) in the respective sets  $\mathcal{M}_v$ , over all nodes v of  $\mathcal{T}$ .

*N* is an  $\varepsilon$ -net. Since  $R \subseteq N$ , it suffices to show that for any *R*-empty rectangle Q, contained in a strip  $\sigma_v$ , anchored at the entry side of  $\sigma_v$ , and containing at least  $\varepsilon n/2 = n/r$ points of P (i.e., of  $P_v$ ), and for any  $M \in \mathcal{M}_v$  which contains Q, we have  $Q \cap N_M \neq \emptyset$ . We have

$$\frac{|Q \cap P|}{|M \cap P|} \geq \frac{n/r}{nt_M/s} = \frac{c\log\log r}{t_M} \geq \frac{1}{t_M}.$$

Since  $N_M$  is a  $(1/t_M)$ -net for  $M \cap P$ , it follows that  $Q \cap N_M \neq \emptyset$ , as asserted. Note that the above inequality implies that we do not need to sample that many points in  $N_M$ , and can make do with  $c't_M^* \log t_M^*$  points, where  $t_M^* := t_M/(c \log \log r)$ . However, this slight improvement will not asymptotically improve the bound that we are about to derive.

Estimating the size of N. The expected size of N is equal to

$$\mathbf{Exp}\bigg\{|R| + c' \sum_{v} \sum_{\substack{M \in \mathcal{M}_{v} \\ t_{M} \ge c \log \log r}} t_{M} \log t_{M}\bigg\}$$

$$= cr \log \log r + c' \cdot \mathbf{Exp} \bigg\{ \sum_{v} \sum_{\substack{M \in \mathcal{M}_v \\ t_M \ge c \log \log r}} t_M \log t_M \bigg\}.$$

We continue the analysis using the notation of [1]. Fix a level *i*; each node *v* at this level satisfies  $|P_v| = n/2^i$ . Let  $\operatorname{CT}(R)$  denote the union of the collections  $\mathcal{M}_v$ , over all nodes *v* at level *i*. For a positive parameter *t*, let  $\operatorname{CT}_t(R)$  denote the subset of  $\operatorname{CT}(R)$  consisting of those rectangles *M* with  $t_M \geq t$ . Let *R'* denote another random sample of *P*, where each point  $p \in P$  is now chosen, independently, to belong to *R'* with probability  $\pi' := \pi/t$ .

Let  $\mathcal{C}$  denote the set of all rectangles M, such that M is anchored at the entry side of  $\sigma_v$ , for some node v at level i, and has one point of P on each of its three other sides (the cases of degenerate rectangles, determined by fewer than three points, are treated in a fully analogous manner). For a rectangle  $M \in \mathcal{C}$ , its *defining set* D(M) is the set of these three points, and its *killing set* K(M) is the set of points of Pin the interior of M. (Recall that throughout this discussion we have fixed the level i.)

Agarwal *et al.* [1] impose two axioms on the sets  $\operatorname{CT}(R)$ . These axioms are too intricate for what we need here, while they are necessary to handle the more involved scenario considered in [1]. For our purpose, we can replace them by the single "axiom," asserting that a rectangle  $M \in \mathcal{C}$  belongs to  $\operatorname{CT}(R)$  if and only if  $D(M) \subseteq R$  and  $K(M) \cap R = \emptyset$ , which holds by construction in our setting. (We also caution the reader that our sampling model is different from that of [1] they sample a random subset of a fixed given size uniformly from all such subsets, whereas we independently choose each point of P to belong to the sample. Nevertheless, the lemma, given below, also holds in our model; if at all, the analysis is simpler. In the full version of this paper we give a short (but complete) proof of our variant of the lemma.)

LEMMA 2.1 (EXPONENTIAL DECAY LEMMA [1]).  

$$\mathbf{Exp}\left\{|\operatorname{CT}_{t}(R)|\right\} = O\left(2^{-t}\mathbf{Exp}\left\{|\operatorname{CT}(R')|\right\}\right).$$

We apply the lemma with  $t = c \log \log r$ , so  $\pi' = \pi/t = r/n$ . Recall that CT(R') is the set of all maximal R'-empty rectangles, anchored at the entry sides of their respective strips  $\sigma_v$  at the fixed level *i*. Their number is  $|CT(R')| = \sum_v (2r'_v + 1)$ , where  $R'_v := R' \cap \sigma_v$ , and  $r'_v := |R'_v|$ . Since the sets  $R'_v$  at level *i* are disjoint,  $\sum_v r'_v = |R'|$ . Hence, since there are at most 2r nodes at a fixed level of the tree, we have

 $|\operatorname{CT}(R')| \leq 2|R'| + 2r.$  Hence  $\mathbf{Exp}\left\{|\operatorname{CT}(R')|\right\} = O(r).$  We thus have

$$\operatorname{\mathbf{Exp}}\left\{|\operatorname{CT}_{t}(R)|\right\} = O\left(2^{-t}\operatorname{\mathbf{Exp}}\left\{|\operatorname{CT}(R')|\right\}\right) =$$

$$O\left(r2^{-c\log\log r}\right) = O\left(r/\log^c r\right).$$

More generally, for any  $j \ge t$ , we have  $\mathbf{Exp}\left\{|\operatorname{CT}_{j}(R)|\right\} = O(r/2^{j})$ , as is easily checked.

Getting back to the contribution of the fixed level i to the expected size of N, we have (where  $t = c \log \log r$ )

$$\mathbf{Exp}\left\{\sum_{\substack{v \text{ at level } i \ M \in \mathcal{M}_v \\ t_M \ge t}} t_M \log t_M\right\}$$
(1)

$$= \operatorname{Exp}\left\{\sum_{j \ge t} \sum_{\substack{M \in \operatorname{CT}(R) \\ t_M = j}} j \log j\right\}$$
$$= \operatorname{Exp}\left\{\sum_{j \ge t} j \log j \cdot \left(|\operatorname{CT}_j(R)| - |\operatorname{CT}_{j+1}(R)|\right)\right\}$$
$$= \operatorname{Exp}\left\{t \log t \cdot |\operatorname{CT}_t(R)| + \sum_{j > t} (j \log j - (j-1)\log(j-1))|\operatorname{CT}_j(R)|\right\}$$
$$= O\left(\frac{r}{\log^c r}(t \log t) + \sum_{j > t} \frac{r}{2^j}\log j\right)$$
$$= O\left(\frac{rt \log t}{\log^c r}\right) = O\left(\frac{r \log\log r \log\log\log r}{\log^c r}\right).$$

Recall again that the analysis so far has been confined to a single level *i*. Repeating it for each of the  $1 + \log r$  levels, we obtain, recalling that c > 1,

$$\mathbf{Exp}\left\{|N|\right\} = O\left(r\log\log r + \frac{r\log\log\log\log\log r}{\log^{c-1}r}\right) = O(r\log\log r).$$

We have thus shown

THEOREM 2.2. For any set P of n points in the plane and a parameter  $\varepsilon > 0$ , there exists an  $\varepsilon$ -net of P, of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$ , for axis-parallel rectangles.

**Remark:** A key ingredient of the analysis is that we have managed to reduce the expected number of R-empty rectangles from  $\Theta(s^2)$  to  $O(s \log r)$ , using a decomposition of the point set into canonical subsets, so that (i) any rectangle  $\tilde{Q}$  with at least  $\varepsilon n$  points of P interacts with just two subsets (any constant number would do just as well), and (ii) for each canonical subset, the number of maximal R-empty rectangles (now anchored at the entry side of the respective strip and fully contained in that strip) is only linear in the number of sample points in that strip.

In the full version of this paper we present a randomized algorithm for constructing such an  $\varepsilon$ -net, whose expected running time is  $O(n \log n)$ ; with some extra care, it can be improved to  $O(n \log r)$ . The algorithm uses fairly standard methods and is omitted.



Figure 4: A two-dimensional illustration: (a) The box B is anchored at the (apex of the) quadrant  $\sigma_{u,v}$  (octant in 3-space). (b) An anchored box that is determined by a pair of points (a triple in 3-space).

### 3. EXTENSIONS

Small-size  $\varepsilon$ -nets for axis-parallel boxes in three dimensions. We next extend our construction to the threedimensional case. We now let P be a set of n points in  $\mathbb{R}^3$ , and put  $r := 8/\varepsilon$  and  $s := cr \log \log r$ , for some fixed constant c > 3. We use a similar sampling model as in the twodimensional problem, in order to generate a random subset  $R \subseteq P$  of expected size s.

We next construct a three-level range-tree  $\mathcal{T}$ , over the points of P (see, e.g., [15]), where the points are sorted by their x-coordinates in the primary tree, by their y-coordinates in each secondary tree, and by their z-coordinates in each tertiary tree. We associate with each node u of the primary tree the subset  $P_u$  of points that it represents, and a secondary (y-sorted) tree  $\mathcal{T}_u$  on  $P_u$ . Similarly, with each node v of a secondary tree  $\mathcal{T}_u$  we associate the corresponding subset  $P_{u,v}$  of  $P_u$  and a tertiary (z-sorted) tree  $\mathcal{T}_{u,v}$ . Finally, each node w of a tertiary tree  $\mathcal{T}_{u,v}$  is associated with the corresponding subset  $P_{u,v,w}$  of  $P_{u,v}$ . We construct each of the three levels of  ${\mathcal T}$  down to nodes for which the size of their associated subset is between n/r and n/(8r). Clearly, each of the primary, secondary, and tertiary trees has at most  $3 + \log r$  levels, and the total number of nodes in the range-tree  $\mathcal{T}$  is  $O(r \log^2 r)$ . Moreover, the sum of the sizes of all the subsets stored at the various nodes is  $O(r \log^3 r)$ ; see, e.g., [15] for further details.

Following the notation of Section 2, we associate with each non-leaf node of any subtree an axis-parallel plane which evenly splits the subset stored at the node into the two subsets stored at its children. More specifically, each non-leaf node u of the primary tree stores a plane  $\mathbf{h}_u$  orthogonal to the x-axis, each non-leaf node v of a secondary tree  $\mathcal{T}_u$  stores a plane  $\mathbf{h}_{u,v}$  orthogonal to the y-axis, and each non-leaf node w of a tertiary tree  $\mathcal{T}_{u,v}$  stores a plane  $\mathbf{h}_{u,v,w}$  orthogonal to the z-axis.

These planes define, for each node w of a tertiary tree  $\mathcal{T}_{u,v}$ , an octant  $\sigma_{u,v,w}$  which is the intersection of three halfspaces  $H_u \cap H_{u,v} \cap H_{u,v,w}$ , where (i)  $H_u$  is the halfspace bounded by  $\mathbf{h}_{u'}$  and containing  $P_u$ , where u' is the parent of u; (ii)  $H_{u,v}$  is the halfspace bounded by  $\mathbf{h}_{u,v'}$  and containing  $P_{u,v}$ , where v' is the parent of v in  $\mathcal{T}_u$ ; and (iii)  $H_{u,v,w}$  is the halfspace bounded by  $\mathbf{h}_{u,v,w'}$  and containing  $P_{u,v,w}$ , where w' is the parent of w in  $\mathcal{T}_{u,v}$ . In what follows we only consider triples (u, v, w) of vertices, each of which has a parent in its respective tree. Thus all three halfspaces are proper, and  $\sigma_{u,v,w}$ is a non-degenerate octant. (Note, though, that, in general, it is more accurate to regard  $\sigma_{u,v,w}$  as a box, or a clipped octant, bounded on the other side also by planes associated with ancestors of u, v, and w. Nevertheless, in most of the following analysis, it suffices to treat  $\sigma_{u,v,w}$  as an octant.)

Let  $B_0$  be an axis-parallel box containing at least  $\varepsilon n$  points of P. Let u' be the highest node in  $\mathcal{T}$ , so that the plane  $\mathbf{h}_{u'}$ meets  $B_0$ . This plane partitions  $B_0$  into two portions, one of which, call it  $B_1$ , contains at least  $\varepsilon n/2$  points of P. Let u be the corresponding child of u' so that  $H_u$  contains  $B_1$ . Next, let v' be the highest node in  $\mathcal{T}_u$ , such that  $\mathbf{h}_{u,v'}$  meets  $B_1$ , partitioning it into two portions, one of which,  $B_2$ , contains at least  $\varepsilon n/4$  points of P. Let v be the child of v' for which  $H_{u,v'}$  contains  $B_2$ . Finally, let w' be the highest node in  $\mathcal{T}_{u,v}$ , such that  $\mathbf{h}_{u,v,w'}$  meets  $B_2$ , partitioning it into two portions, one of which, B, contains at least  $\varepsilon n/8$  points of P. Let w be the child of w' for which  $H_{u,v,w'}$  contains B. (Note that u, v, w are well defined, in the sense that each of the sub-boxes is indeed split by a plane associated with a node in the corresponding truncated tree, and does not reach a leaf without being split.)

By construction, B is anchored at the resulting octant  $\sigma := \sigma_{u,v,w}$ , in the sense that the apex o of  $\sigma$  is a vertex of B, and the three facets of B adjacent to o lie on the three respective axis-parallel planar quadrants bounding  $\sigma$ . Moreover, as far as the set  $P_{u,v,w}$  is concerned, we can replace B by an octant which is oppositely oriented to  $\sigma$ , and whose apex is the vertex o' of B opposite to o. See Figure 4(a) for an illustration of (the 2-dimensional analog of) this scenario.

For each node w of a tertiary tree  $\mathcal{T}_{u,v}$ , put  $R_{u,v,w} = R \cap \bar{\sigma}_{u,v,w}$ , where  $\bar{\sigma}_{u,v,w}$  is the actual box that the "octant"  $\sigma_{u,v,w}$  represents (see the comment above), and  $r_{u,v,w} = |R_{u,v,w}|$ . Let  $\mathcal{M}_{u,v,w}$  denote the set of all maximal anchored R-empty (i.e.,  $R_{u,v,w}$ -empty) axis-parallel boxes contained in the octant  $\sigma_{u,v,w}$ . Since each box  $M \in \mathcal{M}_{u,v,w}$  behaves as an octant inside  $\sigma_{u,v,w}$ , it is determined by at most three points of  $R_{u,v,w}$ , each lying on a distinct facet of M; see Figure 4(b) for a two-dimensional illustration. The number of such empty boxes (or, rather, octants) is only  $O(r_{u,v,w} + 1)$ , as shown<sup>2</sup> in [5, 26]. It thus follows that the overall size of the sets  $\mathcal{M}_{u,v,w}$ , over all nodes w of all tertiary trees  $\mathcal{T}_{u,v}$ , is  $O(|R| \log^3 r + r \log^2 r)$ .

We proceed as in the planar case. We make R part of the output  $\varepsilon$ -net, thereby disposing of any box  $B_0$  whose resulting anchored portion B contains a point of R. For any other box  $B_0$ , the corresponding portion B is R-empty, and it is then easy to show that B is contained in at least one maximal R-empty box M in the set  $\mathcal{M}_{u,v,w}$  of the corresponding octant  $\sigma_{u,v,w}$ . Moreover, the weight factor  $t_M$  of M, defined as in the planar case, must satisfy  $t_M \geq c \log \log r$ .

Thus, for each such heavy maximal box M, we take a  $(1/t_M)$ -net  $N_M$ , for the set  $P \cap M$ , of size  $O(t_M \log t_M)$ ,

whose existence is guaranteed by [25], and output the union N of R with all the resulting nets  $N_M$ . Arguing as in the planar case, it is easy to show that N is indeed an  $\varepsilon$ -net for P.

We bound the expected size of N using similar analysis steps to those in the planar problem. We define  $\operatorname{CT}(R)$  to be the union of all the collections  $\mathcal{M}_{u,v,w}$ , over all nodes wof all tertiary trees  $\mathcal{T}_{u,v}$ , appearing in a fixed triple of levels  $i_1$  (primary),  $i_2$  (secondary), and  $i_3$  (tertiary). As before,  $\operatorname{CT}_t(R)$  is the subset of  $\operatorname{CT}(R)$  consisting of those boxes Mwith  $t_M \geq t$ , for any parameter t. It is easy to verify that the Exponential Decay Lemma holds in this scenario as well, and thus

$$\operatorname{\mathbf{Exp}}\left\{|\operatorname{CT}_{t}(R)|\right\} = O\left(2^{-t}\operatorname{\mathbf{Exp}}\left\{|\operatorname{CT}(R')|\right\}\right),$$

where R' is another smaller random sample defined as in Section 2. Next, arguing as in the planar problem, we obtain that

$$\mathbf{Exp}\left\{\sum_{v \text{ at levels } i_1, i_2, i_3} \sum_{\substack{M \in \mathcal{M}_v \\ t_M \ge c \log \log r}} t_M \log t_M\right\}$$
$$= O\left(\frac{r \log \log r \log \log \log r}{\log^c r}\right).$$

Repeating the analysis for each of the  $O(\log^3 r)$  triples  $i_1, i_2, i_3$ , we obtain that the expectation of the above sum is o(r), provided c > 3, as we indeed assume; thus

$$\mathbf{Exp}\left\{|N|\right\} = \mathbf{Exp}\left\{|R|\right\} + o(r) = O(r\log\log r).$$

We have thus shown:

THEOREM 3.1. For any set P of n points in  $\mathbb{R}^3$  and a parameter  $\varepsilon > 0$ , there exists an  $\varepsilon$ -net of P, for axis-parallel boxes, of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$ .

Random point sets in any dimension. The preceding technique fails in four and higher dimensions, because the number of maximal empty orthants with respect to a set of mpoints can be  $\Theta\left(m^{\lfloor d/2 \rfloor}\right)$  (see [5, 26]), which is at least quadratic for  $d \geq 4$ . It is a challenging open problem to extend our results to four and higher dimensions.

Nevertheless, there is one scenario where the technique works in any dimension, which is the case when the ground set P consists of randomly and uniformly distributed points in  $\mathbb{R}^d$ . Specifically, we assume that each point of P is chosen independently at random from the uniform distribution in  $[0,1]^d$ . As shown in [26], the expected number of maximal empty boxes in this case, for a set of m points, is only  $O(m \log^{d-1} m)$  (see also [34] for the planar case). Moreover, our random sampling model (which we assume, of course, to be made independently of the random choices made while constructing the input set) ensures that the sample R is also an unbiased set of randomly, independently, and uniformly distributed points, so the expected number of maximal Rempty boxes is  $O(s \log^{d-1} s)$  (see Section 4 for a proof of a (more general) bound of this type); the expectation is with respect to both the random drawing of the points of the input set, and our drawing of the sample R.

Since the (expected) number of maximal R-empty boxes is only nearly linear in s, we can carry out the preceding analysis, without having to decompose the input set into

<sup>&</sup>lt;sup>2</sup>In fact, the result in [26] is more general. It asserts that the number of maximal empty orthants for a set of m points in  $\mathbb{R}^d$  is  $O(m^{\lfloor d/2 \rfloor})$ . It is the non-linearity of this bound for  $d \geq 4$  which hampers the extension of our technique to higher dimensions.

canonical strips or orthants, and thus obtain an  $\varepsilon$ -net of expected size<sup>3</sup>  $O\left(\frac{1}{\varepsilon}\log\log \frac{1}{\varepsilon}\right)$ . We have thus shown

THEOREM 3.2. For any set P of n points in  $\mathbb{R}^d$ , each of which is drawn independently from the uniform distribution on  $[0,1]^d$ , and a parameter  $\varepsilon > 0$ , there exists an  $\varepsilon$ -net of P, for axis-parallel boxes, of expected size<sup>4</sup> O( $\frac{1}{\varepsilon} \log \log \frac{1}{\varepsilon}$ ).

Fat triangles in the plane. Our next extension is to points in the plane and  $\alpha$ -fat triangles, where a triangle is  $\alpha$ -fat if each of its angles is at least  $\alpha$ . This extension is only briefly reviewed here. We postpone any further details to the full version of the paper.

Following the analysis of [33], it suffices to handle rightangle triangular ranges, each of which has one horizontal edge and one vertical edge, which meet at the lower-left vertex. Here we use a two-level range-tree, where each node of the secondary level is associated with a quadrant. A "heavy" triangle  $T_0$  of the above sort is sent down the tree, and lands at a secondary vertex v so that  $T_0$  is anchored at (contains) the apex of the quadrant of v, and its portion T within the quadrant (which is either a right triangle or a right trapezoid) contains at least one quarter of its points. We then argue that the number of maximal anchored R-empty right triangles or trapezoids within each quadrant  $\sigma$  is only linear in  $|R \cap \sigma|$ , and thus conclude

THEOREM 3.3. For any set P of n points in the plane, any fixed constant parameter  $\alpha > 0$ , and a parameter  $\varepsilon > 0$ , there exists an  $\varepsilon$ -net of P, for  $\alpha$ -fat triangles, of size O  $\left(\frac{1}{\varepsilon} \log \log \frac{1}{\varepsilon}\right)$ , where the constant of proportionality depends on  $\alpha$ .

In each of these cases, there exist randomized algorithms that construct the  $\varepsilon$ -net in nearly-linear time. Details are omitted in this version.

We next plug the improved bounds on the size of  $\varepsilon$ -nets into the machinery of Brönnimann and Goodrich [6], to obtain improved approximation factors for the corresponding HITTING SET problems (details are given in the full version). We thus obtain:

COROLLARY 3.4. There exists a randomized, expected polynomial time algorithm that, given a set Q of m axis-parallel rectangles and set P of n points in the plane that hit Q, computes a subset  $H \subseteq P$  of  $O(\text{OPT} \log \log \text{OPT})$  points that hit Q, where OPT is the size of the smallest such set. The same bound holds for the cases of points and axis-parallel boxes in 3-space, random point sets and axis-parallel boxes in any dimension, and planar point sets and  $\alpha$ -fat triangles.

### 4. IMPROVED BOUNDS FOR $\varepsilon$ -NETS FOR OTHER RANGE SPACES

In this section we observe that the technique developed in this paper can be adapted to the scenarios considered by Clarkson and Varadarajan [12], and yields improved bounds for the size of  $\varepsilon$ -nets in many of the cases considered there. As a consequence, using the same implication as in [12] (which is based on the technique of Brönnimann and Goodrich [6]), but with the improved bounds on the size of  $\varepsilon$ -nets in the respective range spaces, we obtain approximation algorithms for geometric SET COVER with improved approximation factors.

Rephrasing the notations used in the introduction, we consider the dual range space  $\Xi = (\mathcal{C}, \mathcal{Q})$ , where the ground set  $\mathcal{C}$  is a collection of geometric regions in  $\mathbb{R}^d$ , and each range in  $\mathcal{Q}$  is of the form  $Q_x = \{C \in \mathcal{C} \mid x \in C\}$ , for some  $x \in \mathbb{R}^d$ . Clarkson and Varadarajan [12] further assume that, for any finite subcollection  $\mathcal{C}'$  of m regions of  $\mathcal{C}$ , the complement of the union of  $\mathcal{C}'$  can be decomposed into at most  $m\varphi(m)$ cells of some simple shape, where  $\varphi(m)$  is some slowly increasing function; for technical reasons, we also require  $\varphi$  to be sublinear, in the sense that  $\varphi(\alpha x) \leq \alpha \varphi(x)$  for any integers  $\alpha, x \geq 1$  (this latter property holds in all applications considered here and in [12]).

In addition, we assume that each cell in the decomposition is a (possibly unbounded) portion of space that is *defined* by O(1) regions of C', in the sense that it appears in the decomposition of the complement of the union of just those O(1) regions (in particular, the cells of the decomposition do not necessarily have the same shape as the regions of C). In many geometric range spaces of this kind, the cells are those generated by the *vertical decomposition* of the complement of the union [38], although there exist other types of decompositions for various special classes of regions; see, e.g., [1, 9, 11] for a description of this (standard) setup.

Under these assumptions, Clarkson and Varadarajan show that the range space  $\Xi$  admits  $\varepsilon$ -nets of size  $O\left(\frac{1}{\varepsilon}\varphi\left(\frac{1}{\varepsilon}\right)\right)$ . Thus, if  $\varphi(m) = o(\log m)$ , the resulting nets have size smaller than the standard bound  $O\left(\frac{1}{\varepsilon}\log\frac{1}{\varepsilon}\right)$  of [25].

In this section we obtain the following improvement (the proof is omitted in this version).<sup>5</sup>

THEOREM 4.1. Under the assumptions made above, the range space  $\Xi$  admits an  $\varepsilon$ -net of size  $O\left(\frac{1}{\varepsilon}\log\varphi\left(\frac{1}{\varepsilon}\right)\right)$ , for any  $0 < \varepsilon \leq 1$ .

**Remark.** The bound in the theorem improves upon the general bound  $O\left(\frac{1}{\varepsilon}\log\frac{1}{\varepsilon}\right)$  when  $\varphi(m) = 2^{o(\log m)}$ , thus extending the applicability of this technique beyond the "effective range"  $\varphi(m) = o(\log m)$ , where the original technique of [12] yields an improvement.

### Several special cases

Theorem 4.1 immediately implies improved bounds on the size of  $\varepsilon$ -nets for dual range spaces of several classes of regions and points, for which the union complexity (or, rather, the complexity of the decomposition of its complement) is known to be nearly linear. We list some of the standard families with this property, state their union complexity (since we present families of planar regions, the following bounds also apply, with some care, for the complexity of the decomposition of the complement of their union), and the resulting bounds for the size of  $\varepsilon$ -nets, and for the approximation factors for the corresponding SET COVER problems, computable in (randomized) polynomial time. (For the latter implication to hold, we need (randomized) polynomial-time algorithms for constructing our small-size  $\varepsilon$ -nets for each of

<sup>&</sup>lt;sup>3</sup>By consulting the derivation in (1), it is easily verified that the expected size of the resulting net N is  $\mathbf{Exp}\{|R|\}$  plus a term equal to  $\mathbf{Exp}\{|CT(R')|\}$  divided by a polylogarithmic factor. This implies the bound asserted here.

<sup>&</sup>lt;sup>4</sup>The expectation is with respect to the random choice of P.

<sup>&</sup>lt;sup>5</sup>Of course, it is an improvement only when  $\varphi$  is  $\omega(1)$ ; otherwise, the bound is  $O(1/\varepsilon)$ , as already follows from [12].

these special classes of regions. Such algorithms follow easily from our constructive proof.)

 $\alpha$ -fat triangles (Figure 5(a)). Recall that a triangle is  $\alpha$ -fat if each of its angles is at least  $\alpha$ . The complexity of the union of n such triangles is  $O(n \log \log n)$ , where the constant of proportionality depends on the fatness factor  $\alpha$  [33, 36]. The resulting bound on the size of an  $\varepsilon$ -net is thus

 $O\left(\frac{1}{\varepsilon}\log\log\log\frac{1}{\varepsilon}\right)$ , and the approximation factor for the corresponding SET COVER problem is  $O(\log\log\log OPT)$ .

**Locally**  $\gamma$ -fat objects (Figure 5(b)). These objects were recently introduced by de Berg [14]. Given a parameter  $0 < \gamma \leq 1$ , an object o is locally  $\gamma$ -fat if, for any disk D whose center lies in o, such that D does not fully contain o in its interior, we have  $area(D \sqcap o) \geq \gamma \cdot area(D)$ , where  $D \sqcap o$  is the connected component of  $D \cap o$  that contains the center of D. We also assume that the boundary of each of the given objects has only O(1) locally x-extreme points, and that the boundaries of any pair of objects intersect in at most s points, for some constant s. It is then shown in [14] that the combinatorial complexity of the union of n such objects is  $O(\lambda_{s+2}(n)\log^2 n)$ , with a constant of proportionality that depends on  $\gamma$ . When the objects have roughly the same size (i.e., the ratio of the diameters of any pair of objects is bounded by some constant), the complexity of the union decreases to  $O(\lambda_{s+2}(n))$ . Locally  $\gamma$ -fat objects are a generalization of several other previously studied classes of "fat" objects [16, 18, 19].

The resulting bounds on the size of an  $\varepsilon\text{-net}$  are thus

 $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$  for the general case, and  $O\left(\frac{1}{\varepsilon}\log\beta_{s+2}\left(\frac{1}{\varepsilon}\right)\right)$ for objects of nearly equal size. The approximation factors for the corresponding SET COVER problems are  $O(\log\log \text{OPT})$ and  $O(\log\beta_{s+2}(\text{OPT}))$ , respectively.

**Semi-unbounded pseudo-trapezoids** (Figure 5(c)). Here each object is a region of one of the forms

$$\tau_{x_1,x_2,f}^- = \{(x,y) \mid x_1 \le x \le x_2, y \le f(x)\}, \text{ or } \\ \tau_{x_1,x_2,f}^+ = \{(x,y) \mid x_1 \le x \le x_2, y \ge f(x)\},$$

where f is a continuous function. We assume that the graphs of any pair of these functions intersect in at most s points, for some constant s. In this case the complexity of the union of any n such objects is  $O(\lambda_{s+2}(n))$ ; see, e.g., [38]. If the objects are *pseudo-halfplanes*, that is,  $x_1 = -\infty$  and  $x_2 =$  $+\infty$  for each object, the bound on the union complexity slightly improves to  $O(\lambda_s(n))$ .

The resulting bounds on the size of an  $\varepsilon$ -net are thus

 $O\left(\frac{1}{\varepsilon}\log\beta_{s+2}\left(\frac{1}{\varepsilon}\right)\right)$  for pseudo-trapezoids, and  $O\left(\frac{1}{\varepsilon}\log\beta_s\left(\frac{1}{\varepsilon}\right)\right)$  for pseudo-halfplanes. The approximation factors for the corresponding SET COVER problems are  $O(\log\beta_{s+2}(\text{OPT}))$  and  $O(\log\beta_s(\text{OPT}))$ , respectively.

Jordan arcs with three intersections per pair (Figure 5(d)). Each object is bounded by some Jordan arc which starts and ends on the x-axis but otherwise lies above it, and by the portion of the x-axis between these endpoints, and each pair of the bounding Jordan arcs intersect at most three times. In this case the complexity of the union of any n such objects is  $O(\lambda_3(n)) = O(n\alpha(n))$ ; see [17]. We also assume that the boundary of each object has only O(1) locally xextreme points.

The resulting bound on the size of an  $\varepsilon$ -net is thus

 $O\left(\frac{1}{\varepsilon}\log\alpha\left(\frac{1}{\varepsilon}\right)\right)$ , and the approximation factor for the corresponding SET COVER problem is  $O(\log\alpha(\text{OPT}))$ .

### 5. CONCLUDING REMARKS AND OPEN PROBLEMS

(i) One may consider the dual version of the main problem that we have studied. Namely, we are given a collection C of n axis-parallel rectangles, and each range is the subset of Cstabbed by some point in the plane. Here too the goal is to show the existence of a small-size  $\varepsilon$ -net, which is a (smallsize) subset  $C' \subseteq C$  whose union contains all the "deep" points (i.e., points contained in at least  $\varepsilon n$  rectangles of C). So far we do not know how to apply our method to this dual setup. We note that Brönnimann and Lenchner, in their conference paper [7], claim, without a proof, the existence of  $\varepsilon$ -nets for this dual range space, of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$ .

(ii) Another challenging open problem is to extend our machinery for axis-parallel boxes to dimensions  $d \ge 4$ . The anchoring trick used for d = 3 fails, because the number of maximal *R*-empty orthants in *d*-space can be  $\Theta\left(|R|^{\lfloor d/2 \rfloor}\right)$ 

[26]. A modest goal is to construct a weak  $\varepsilon$ -net for this setup (that is, the points in the  $\varepsilon$ -net do not necessarily have to be from the input set). Another goal is to construct weak  $\varepsilon$ nets of size  $o\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$  for the (primal) range spaces that we have studied in this paper, most notably for points and axis-parallel rectangles. In fact, it would also be interesting to find a simpler construction that yields weak  $\varepsilon$ -nets of size  $O\left(\frac{1}{\varepsilon}\log\log\frac{1}{\varepsilon}\right)$ .

(iii) Last but not least, there is the problem of constructing small-size  $\varepsilon$ -nets for the primal range spaces whose duals were considered in Section 4, such as those involving planar point sets and locally  $\gamma$ -fat objects, or semi-unbounded pseudo-trapezoids, with the properties assumed in Section 4.

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Figure 5: The types of regions considered in this section: (a) an  $\alpha$ -fat triangle; (b) a locally  $\gamma$ -fat region; (c) semi-unbounded pseudo-trapezoids; and (d) regions bounded by Jordan arcs with three intersections per pair.

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