

Capacity Analysis of Vector Symbolic Architectures

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Abstract

Hyperdimensional computing (HDC) is a biologically-inspired framework which represents symbols with high-dimensional vectors, and uses vector operations to manipulate them. The ensemble of a particular vector space and a prescribed set of vector operations (including one addition-like for “bundling” and one outer-product-like for “binding”) form a *vector symbolic architecture* (VSA). While VSAs have been employed in numerous applications and have been studied empirically, many theoretical questions about VSAs remain open.

We analyze the *representation capacities* of four common VSAs: MAP-I, MAP-B, and two VSAs based on sparse binary vectors. “Representation capacity” here refers to bounds on the dimensions of the VSA vectors required to perform certain symbolic tasks, such as testing for set membership $i \in S$ and estimating set intersection sizes $|X \cap Y|$ for two sets of symbols X and Y , to a given degree of accuracy. We also analyze the ability of a novel variant of a Hopfield network (a simple model of associative memory) to perform some of the same tasks that are typically asked of VSAs.

In addition to providing new bounds on VSA capacities, our analyses establish and leverage connections between VSAs, “sketching” (dimensionality reduction) algorithms, and Bloom filters.

1 Introduction

Hyperdimensional computing (HDC) is a biologically inspired framework for representing symbolic information. In this framework, we represent different symbols using high-dimensional vectors (hypervectors), called *atomic vectors*, sampled from a natural vector distribution, such as random signed vectors, or sparse binary vectors. We then use standard arithmetic or bit-wise operations on these vectors to perform symbolic operations, like associating or grouping symbols. The distribution over atomic vectors, together with their corresponding operations, form a *vector-symbolic architecture* (VSA).

Many features of VSAs are inspired by aspects of the human brain and memory. They are robust to noise, and the fact that all entries of the vectors are symmetric (i.e. don’t correspond to specific features) allows VSA computations to be highly parallelizable. Most

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VSA vector entries are either 0 or ± 1 , so there is no need for floating point arithmetic, and they admit energy-efficient and low-latency hardware implementations.

In VSA systems, the atomic vectors are typically chosen randomly, with a distribution such that they are highly likely to be pairwise *near-orthogonal*.

While we encounter “the curse of dimensionality” in many algorithmic and machine learning problems, the ability to fit many near-orthogonal vectors into d -dimensional space is a kind of “blessing of dimensionality.”

While VSAs sometimes do not achieve the same performance as neural networks do on certain classification tasks, VSA-based classifiers require much less time and space to train and store. There is also much research at the intersection of VSAs and deep learning; for instance, VSA vector representations could be good neural network inputs, and since all vector representations have the same size, this could be a better way to support inputs with different numbers of features ([1, 2]). In addition, VSAs have found numerous applications outside of learning, including the modeling of sensory-motor systems in smaller organisms ([3, 4]), combining word embeddings to form context embeddings ([5, 6, 7]), and the processing of heart rate respiratory data and other biological times series data ([8, 9, 10]). They are also promising tools for bridging the gap between symbolic data, such as word relationships, and numerical data, such as trained word embeddings ([11]).

In addition to exploring the performance of VSAs in such applications, there have also been several works that study the *representation capacity* of many VSAs. The representation capacity refers to lower bounds on the VSA dimension, needed so that we can reliably perform certain symbolic tasks, such as computing set intersection sizes $|X \cap Y|$ for two sets of symbols X and Y (with possibly different cardinalities). These lower bounds then translate into a design choice (minimum required dimension) for VSA applications. Here we understand reliability in the setting of generating the atomic vectors at random, and asking for good-enough accuracy with high-enough probability. Similarly, another way to quantify representation capacity is the following: if we tolerate a failure probability of δ , can we bound the number of sets or objects we can encode?

The goal of this paper is to provide theoretical analyses of the representation capacities of four particular VSA models. In general, there are far more models that are employed in practice; see [12, 13] for a longer catalog of VSAs. We also assemble a set of tools and frameworks (common to computer scientists) for any future computations and high-probability bounds on VSA capacity.

1.1 Background on VSAs

To define a VSA, we need to first choose a distribution for sampling the atomic vectors. For every individual symbol we want to introduce (that is, excluding associations between multiple symbols), we will independently sample a random m -dimensional vector from a distribution, such as the uniform one over $\{\pm 1\}^m$ (i.e. sign vectors), or a random k -sparse binary ($\{0, 1\}^m$) vector. VSAs are equipped with the following operations; permutation is not always required.

- **Similarity Measurement** ($\langle \cdot, \cdot \rangle$): In almost all VSAs in this paper, we use cosine similarity (i.e. dot product $\langle u, v \rangle$) to measure the similarity between the symbols that u and v represent.

- **Bundling** (\oplus): We use bundling to represent a “union” of several symbols. The goal is for $u \oplus v$ to be similar to both u and v .
- **Binding** (\otimes): Binding is often used to associate symbols as (key, value) pairs. Here, we want $u \otimes v$ to be nearly orthogonal to both u and v .
- **Permutation** (π): If π is a permutation, let $\pi(v)$ be the vector whose i -th entry is $v_{\pi^{-1}(i)}$. We use $[v_1; \pi(v_2); \pi^2(v_3); \dots; \pi^{L-1}(v_L)]$ to encode an *ordered sequence* of symbols or sets.
- **Cleanup:** Let vector x represent a set $X \subseteq \mathcal{X}$, where \mathcal{X} is the universe of all symbols. Given a dictionary of symbols $S \subseteq \mathcal{X}$, we want to compute the elements in $X \cap S$.

Remark 1. *Cleanup will not be a focus of our paper. If we have access to the individual vector representations of elements in S , we can simply execute cleanup as a set of (parallel) membership tests, which use similarity measurement.*

Example 1. *We can represent categorical data using the following bundle of bindings:*

$$\vec{y} = \bigoplus_{i \in \text{features}} \vec{f}_i \otimes \vec{v}_i$$

Here, \vec{f}_i is a VSA vector encoding the concept “feature i ,” while \vec{v}_i is a VSA vector encoding the value of feature i . To train a classifier on the VSA representations $\{\vec{y}\}$, we can average the training vectors over each class to get an exemplar for the class.

$$\vec{c}_i = \frac{1}{\#\{z : \text{label}(z) = i\}} \sum_{z: \text{label}(z)=i} z$$

To classify a new input, we first compute its VSA encoding. We then return the class whose representative vector c_i is closest to it (using similarity measurement).

We will study a few basic predicates on VSAs; one is *membership testing*: given a vector x representing a bundle of atomic vectors, and an atomic vector y , determine if y is in the set represented by x . Another predicate is *set intersection*: if y also represents a set, estimate the size of the intersection of the sets represented by x and y . Here these sets might be sets of vectors bound together, or permuted. Estimation of intersection size is a natural extension of membership testing, and is helpful in applications where VSA represent, for example, sets of properties, where intersection and difference size are rough measure of relatedness.

1.2 Overview of Contributions and Related Work

We focus on four popular VSA families, plus a novel variant of Hopfield networks. The atomic vector initializations of the four, as well as their bundling and binding operators, are shown in Table 1. As surveyed by [12], “MAP” stands for “Multiply-Add-Permute,” while “I” and “B” reference the values that non-atomic vectors take (“integer” and “binary,” respectively).

A key aspect of our analyses is that we translate several VSA operations of interest into the language of sketching matrices (used for dimensionality reduction) or of hashing-based data structures (like Bloom Filters), which are all well-studied objects in computer science. These connections have not been made explicit, or leveraged previously in VSA analysis, though we remark that Sparse-JL was briefly mentioned by [14].

VSA	Atomic Vector	Bundling	Binding
MAP-I	$\{\pm 1\}^m$	Elem.-wise addition	Elem.-wise mult.
MAP-B	$\{\pm 1\}^m$	Elem.-wise add., round to ± 1	Elem.-wise mult
Bloom filters	k -sparse, $\{0, 1\}^m$	Elem.-wise addition, cap at 1	(Out of scope)
Counting Bloom filters	k -sparse, $\{0, 1\}^m$	Elem.-wise addition	(Out of scope)

Table 1: A summary of MAP-I, MAP-B, and Binary Sparse VSAs (which generalize SBDR VSAs). While several binding operators have been proposed for the Binary Sparse VSAs, the study of these operators is outside of the scope of this paper.

1.2.1 Connections to the Broader Computer Science Literature

In several of our analyses, we rely on the Johnson-Lindenstrauss (JL) property, which is foundational to algorithmic matrix sketching, the study of techniques for compressing matrices while approximately preserving key properties, such as least-squares solutions. See [15] for a more detailed treatment of sketching. From the perspective of sketching, our results on permutations, bundles of k -bindings, and Hopfield networks can be regarded as extensions of sketching theory using structured matrices with less randomness than the most direct approaches.

The bundling operator for MAP-B is per-coordinate the *Majority function* in the setting of the analysis of Boolean functions, and is a simple *linear threshold function*. The analysis of the membership test for MAP-B that we give is close to that for analyzing the *influence* of variables for the majority function (cf. [16], Exer. 2.2). Here the influence of a variable on a function is the probability for a random input that the function return value changes when the variable is negated. In comparison, in the analysis of MAP-B bundling, we are interested in the probability that the return value changes when the variable is set to $+1$. Our analysis of MAP-B extends to other operations, including a bundling of bindings, which are related to *polynomial threshold functions* of degree k , where k depends on the maximum number of symbols that are bound together.

Two of the VSAs we analyze are based on Bloom filters, which are space-efficient data structures for testing set membership. They have seen extensive study since their introduction fifty years ago by [17], but we have not found rigorous analyses of their performance in the setting of set intersection (vs membership testing). Our results are novel contributions in this regard.

1.2.2 Other Analyses of VSA Capacity

Some recent works in the VSA literature that have inspired our own work also study the capacity problem, but they analyze more restricted VSA systems and/or use different analysis approaches. To our knowledge, we are the first to formally analyze VSAs in terms of sketching, using tools like the JL property, though [14] does mention the sparse JL transform.

[18] provides a theoretical analysis of VSAs in terms of a measure called “incoherence,” which quantifies the size of the “cross-talk” (dot product) between two independently initialized VSA vectors. They prove results on membership testing and set intersection of bundles, membership testing in key-value pairs (bindings of two symbols, keys and values,

where the set of keys and the set of values are restricted to be disjoint), and show pairwise near-orthogonality of vectors and their coordinate permutations in terms of incoherence. Their work is in the linear setting (which pertains to MAP-I), and extends, as does ours via known results, from sign matrices to matrices of independent sub-Gaussians. We add new bounds that include set intersections for bundles of k -bindings (not restricted to disjoint keys and values), and sequences of sets encoded with rotations (cyclic permutations). Our view of sketching is potentially simpler for understanding capacity bounds on MAP-I, and our hypergraph framework for binding in §4.3 also allows us to extend our analysis for bundlings of bindings beyond only key-value pairs.

Another related work is that of [19], which studies bundling in binary VSA systems, where atomic vectors are controlled by a sparsity parameter. Their model is slightly different from the Bloom-filter inspired binary VSAs that we analyze, and their bundling operator includes a “thinning” step, where the support of the bundle gets reduced to the size of a typical atomic vector. Their analysis of VSA capacity uses Gaussian approximations holding in the limit, and some heuristics to get around the thinning step. We formally analyze the capacity of bundling without thinning, using concentration inequalities. The authors in [19] also conduct several empirical analyses and simulations of sparse binary VSAs, which may be of independent interest.

2 Technical Overview and Statements of Results

In the remainder of the paper, we will present concrete statements of our results, and highlight some of the proof ideas, with an emphasis again on connections to sketching and data structures. Each subsection here (roughly organized by each different VSA we analyze) will have a full section in the appendix where we give their proofs.

Notation and Terminology. We summarize some notation in the following list, for reference.

- $\lfloor a \rfloor$ is the nearest integer to $a \in \mathbb{R}$;
- $\text{sign}(a)$ for $a \in \mathbb{R}$ is 1 if $a > 0$, -1 if $a < 0$ and ± 1 with equal probability if $a = 0$;
- $\text{sign}_{\geq}(a)$ for $a \in \mathbb{R}$ is 1 if $a \geq 0$, and -1 otherwise
- For $a, b \in \mathbb{R}$, $a = b \pm \varepsilon$ means that $|a - b| \leq \varepsilon$, so that $a = b(1 \pm \varepsilon)$ means that $|a - b| \leq b\varepsilon$;
- $v \circ w$ denotes the Hadamard (elementwise) product of two vectors, $(v \circ w)_i = v_i w_i$;
- $v \wedge w$ denotes the elementwise minimum of two vectors v and w , $(v \wedge w)_i = \min\{v_i, w_i\}$; for scalar a and vector v , $a \wedge v$ is the vector with $(a \wedge v)_i = \min\{a, v_i\}$;
- $v \wedge w$ denotes $\sum_i \min\{v_i, w_i\}$;
- $\text{supp}(v) = \{i \in [d] \mid v_i \neq 0\}$, for $v \in \mathbb{R}^d$. For diagonal $V \in \mathbb{R}^{d \times d}$, let $\text{supp}(V) = \{i \in [d] \mid V_{ii} \neq 0\}$;

VSA	Atomic Vector	Bundling
MAP-I	$\bar{S}e_i$	$\bar{S}v$
MAP-B	Se_i	$\text{sign}(Sv)$
Bloom filter	Be_i	$1 \wedge Bv$
Counting Bloom	Be_i	Bv

Table 2: Equivalent to Table 1. Here $e_i \in \{0, 1\}^d$ for $i \in [d]$ has $e_i = 1$, all other coordinates zero, and $v \in \{0, 1\}^d$ represents the set $\text{supp}(v) \subset [d]$. The matrices S , \bar{S} , and B are sign (also called bipolar or Rademacher), scaled sign, and sparse binary, as in Def. 2 and 21.

2.1 Bundling as the output of a linear map.

Our central approach is to cast VSA vectors as the outputs of linear transformations, followed by nonlinear maps for some of the VSAs. Via the linear maps, we can translate between a very simple vector representation for symbols (described below) and the more robust, fault-tolerant, and (in some settings) lower-dimensional ones used in VSAs.

A simple vector representation of elements in a universe \mathcal{X} is their one-hot encoding as unit binary vectors $e_i \in \{0, 1\}^d$, where $d \equiv |\mathcal{X}|$. Then, set union corresponds to adding vectors: a set $X \subset \mathcal{X}$ is a characteristic vector $v \in \{0, 1\}^d$ with $v = \sum_{i \in X} e_i$. The size of $|X|$ corresponds to the squared Euclidean norm $\|v\|^2$. For two sets $X, Y \subseteq \mathcal{X}$ with corresponding characteristic vectors v and w , respectively, $|X \cap Y|$ is simply $v^\top w$; similarly, their symmetric difference $|X \Delta Y|$ is $\|v - w\|^2$.

Thus an embedding of these one-hot encodings, linear or non-linear, that approximately preserves distances and/or dot products of vectors (which is particularly challenging for binary vectors), can be used to maintain sets and the sizes of their intersections and symmetric differences. With this in mind, we can regard the atomic vectors of a VSA as the columns of a random matrix P (so the embedding of vector x is Px , possibly with a non-linearity applied), and for appropriate random P , we will obtain such embeddings.

A correspondence between the VSAs we study and their choice of matrix P is found in Table 2. From this perspective, VSAs perform dimensionality reduction from characteristic vectors in $\{0, 1\}^d$ to an m -dimensional space, for $m \ll d$.

Overview of Tools and Techniques Our analysis of MAP-I establishes the JL property for a variety of random sign matrices, some with dependent entries, that are used to encode bundles, sequences, and bundles of bindings. In the case of sequences and bindings, the entries of the sign matrices we analyze will not be independent, which complicates our analysis; we get around this using standard concentration results like McDiarmid's inequality (Theorem 25) and a version for when the bounded differences hold with high probability (Corollary 27). Our analysis of MAP-B also uses these concentration techniques and also borrows some ideas from Boolean Fourier analysis. For Hopfield nets and our variation Hopfield \pm , we also use standard concentration results like the Hanson-Wright inequality. A Bernstein-like variation of McDiarmid, Theorem 28, is key to our analysis of Bloom filters.

2.2 Analysis of MAP-I Using Johnson-Lindenstrauss

Bundling and Set Intersection For MAP-I, we choose P as a scaled sign matrix \bar{S} .

Definition 2. A sign vector $y \in \{\pm 1\}^m$ (also called a Rademacher vector) is a vector with independent entries, each chosen uniformly from $\{\pm 1\}$. A sign matrix $S \in \{\pm 1\}^{m \times d}$ has columns that are independent sign vectors, and a scaled sign matrix $\bar{S} = \frac{1}{\sqrt{m}}S$ where S is sign matrix.

Thus, Se_i is a random sign vector. For MAP-I, the bundling operator is addition, so a set X can be represented as $\bar{S}v$, with $v = \sum_{i \in X} e_i$. (More typically, MAP-I would use the unscaled sign matrix S , but \bar{S} is convenient for analysis and discussion.) It is known that with high probability, for m sufficiently large, that \bar{S} satisfies the *Johnson-Lindenstrauss (JL) property*, which is the norm-preserving condition in the lemma below.

Lemma 3 ([20, 21], JL). Suppose $\bar{S} \in \frac{1}{\sqrt{m}}\{-1, 1\}^{m \times d}$ is a scaled sign matrix (described in Def. 2). Then for given $\delta, \epsilon > 0$ there is $m = O(\epsilon^{-2} \log(1/\delta))$ such that for given vector $v \in \mathbb{R}^d$, it holds that $\|\bar{S}v\| = \|v\|(1 \pm \epsilon)$, with failure probability at most δ .

This immediately tells us the dimension m required to estimate set sizes up to a multiplicative factor of ϵ , with failure probability δ .

For $X, Y \subseteq \mathcal{X}$, let v and w denote their characteristic vectors. An immediate consequence of the JL lemma is that the symmetric difference size $|X \Delta Y| = \|v - w\|^2$ can be estimated with small relative error as well.

Corollary 4. If random matrix P satisfies the JL property (Lemma 3), then for given $\delta, \epsilon > 0$, and a set $\mathcal{V} \subset \mathbb{R}^d$ of cardinality n , there is $m = O(\epsilon^{-2} \log(n/\delta))$ such that with failure probability δ , for all pairs $v, w \in \mathcal{V}$, $\|P(v - w)\|^2 \in \|v - w\|^2(1 \pm \epsilon)$.

The JL lemma also implies that $(Pv)^\top (Pw) = v^\top P^\top Pw$ concentrates around $|X \cap Y| = v^\top w$.

Corollary 5. Suppose the random matrix P satisfies the JL property (Lemma 3). Then for $v, w \in \mathbb{R}^d$, there is $m = O(\epsilon^{-2} \log(1/\delta))$ so that $v^\top P^\top Pw = v^\top w \pm \epsilon \|v\| \|w\|$ with failure probability δ .

Estimation of the cosine of the angle between v and w , which is $|X \cap Y| / \sqrt{|X| \cdot |Y|}$, up to additive error ϵ , is also now immediate.

The goal of our MAP-I bundling section is to use the above lemmas and corollaries to prove the following theorem.

Theorem 6. Suppose random matrix P satisfies the JL property (Lemma 3). Given M pairs of characteristic vectors $v, w \in \{0, 1\}^d$ such that for every pair v, w , $\|v\|_1 \|w\|_1 \leq N$, then there is $m = O(N \log(M/\delta))$ such that $[v^\top P^\top Pw] = v^\top w$ for all M pairs with probability $\geq 1 - \delta$.

In short, we inherit much of our capacity analysis of bundling in MAP-I through known results about the JL property.

Rotations via JL property. One operation used in VSAs to expand on the number of nearly orthogonal vectors available for use is via permutations of the entries; this is the “P” in the MAP VSA systems introduced by [22]. These can be encoded in permutation matrices $R \in \{0, 1\}^{m \times m}$. We will focus on cyclic permutations.

Definition 7. Let $R \in \mathbb{R}^{m \times m}$ denote the permutation matrix implementing a rotation, so that $R_{m,1} = 1$ and for $i \in [m-1]$, $R_{i,i+1} = 1$, with all other entries equal to zero.

For a random sign vector y , and such a rotation matrix R (or indeed for any permutation matrix with few fixed points), Ry is nearly orthogonal to y , and the vectors $R^\ell y$ for $\ell = 0, 1 \dots L$ are pairwise mutually orthogonal with high probability, if L is not too large. However, the entries of these vectors are not independent, so additional care is needed in analyzing them.

Permutations (and specifically, rotations) can be used to encode a *sequence* of atomic vectors x^ℓ as a sum $\sum_\ell R^\ell x^\ell$. We can also encode a *sequence of sets* with characteristic vectors $v_{(\ell)}$.

Definition 8. For $R \in \mathbb{R}^{m \times m}$, $S \in \mathbb{R}^{m \times d}$ and integer $L \geq 0$, let $S_{R,L} \in \mathbb{R}^{m \times Ld}$ denote

$$[S \ R S \ R^2 S \ \dots \ R^{L-1} S].$$

For a sequence of $v_{(0)}, v_{(1)}, \dots, v_{(L-1)} \in \mathbb{R}^d$, let $v \in \mathbb{R}^{Ld}$ denote $v \equiv [v_{(0)} \ v_{(1)} \ \dots \ v_{(L-1)}]$.

The sequence given by v in the definition can be represented in MAP-I as a single vector $\bar{S}_{R,L}v$. We first find m such that $\bar{S}_{R,L}$ satisfies the JL property for general $v \in \mathbb{R}^{Ld}$.

Theorem 9. Given scaled sign matrix $\bar{S} \in \mathbb{R}^{m \times d}$, rotation matrix $R \in \mathbb{R}^{m \times m}$ as in Def. 7, integer $L > 0$, and $\bar{S}_{R,L}$ as in Def. 8. Then for $v \in \mathbb{R}^{Ld}$ as defined above,

$$|\|\bar{S}_{R,L}v\|^2 - \|v\|^2| \leq 3\epsilon\|v\|_{L,1}^2 \leq 3L\epsilon\|v\|^2,$$

with failure probability $6L^2\delta$. It follows that there is $m = O((L/\epsilon)^2 \log(L/\delta))$ such that with failure probability at most δ , $\|\bar{S}_{R,L}v\|^2 = (1 \pm \epsilon)\|v\|^2$.

The proof of Theorem 9 relies on partitioning the rows of \bar{S} so that within the rows of a single partition subset, the corresponding rows of \bar{S} and $R^i\bar{S}$ can be treated independently.

We get tighter bound on m when the $v_{(i)}$ are characteristic vectors: our bound on m depends on K , the maximum number of times that a given symbol appears in v .

Theorem 10. Given scaled sign matrix $\bar{S} \in \mathbb{R}^{m \times d}$, rotation matrix $R \in \mathbb{R}^{m \times m}$ (Def. 7), integer $L > 0$, and $\bar{S}_{R,L}$ as in Def. 8. For a sequence of vectors $v_{(0)}, v_{(1)}, \dots, v_{(L-1)} \in \{0, 1\}^d$, let $K \equiv \|\sum_{0 \leq j < L} v_{(j)}\|_\infty$. There is $m = O(K^2\epsilon^{-2} \log(K/(\epsilon\delta)))$ such that with failure probability δ ,

$$|\|\bar{S}_{R,L}v\|^2 - \|v\|^2| \leq \epsilon\|v\|^2$$

We handle dependences between rows of S using a version of McDiarmid’s inequality (Corollary 27). As noted by Corollary 4 and Corollary 5, satisfying the JL property allows us to find m so we can perform set intersection (dot product) and symmetric difference (subtraction) operations on vectors of form $[v_{(0)} \ v_{(1)} \ \dots \ v_{(L-1)}]$ up to a multiplicative factor of ϵ and failure probability δ .

Bundles of bindings the JL property. In MAP-I, we implement binding using the Hadamard (element-wise) products of atomic vectors. In this setting, we can compactly represent a bundling of k -wise atomic bindings using the matrix $\bar{S}^{\odot k}$.

Definition 11. For sign matrix S , let $S^{\odot k} \in \frac{1}{\sqrt{m}} \mathbb{R}^{m \times \binom{d}{k}}$, where each column of $S^{\odot k}$ is the Hadamard (element-wise) product of k different columns of S . The scaled version $\bar{S}^{\odot k}$ is $\frac{1}{\sqrt{m}} S^{\odot k}$. We clarify that $P^{\odot k \top}$ denotes $(P^{\odot k})^\top$.

With this notation, a bundling of k -wise atomic bindings is $\bar{S}^{\odot k}v$, for $v \in \{0, 1\}^{\binom{d}{k}}$. Note that $\mathbb{E}[\bar{S}^{\odot k} \bar{S}^{\odot k \top}] = \frac{\binom{d}{k}}{m} I_m$, while $\mathbb{E}[\bar{S}^{\odot k \top} \bar{S}^{\odot k}] = I_{\binom{d}{k}}$. In order to reason about intersections over bundles of k -bindings, or about the symmetric difference between the bundles of k -bindings, we again establish the JL property, this time for $\bar{S}^{\odot k}v$. We first present the result for the $k = 2$ case, which captures bundles of key-value bindings.

Theorem 12. For $v \in \{0, 1\}^{\binom{d}{2}}$, there is $m = O(\varepsilon^{-2} \log^3(\|v\|_1 / \varepsilon \delta))$ so that for $\bar{S}^{\odot 2} \in \{\pm \frac{1}{\sqrt{m}}\}^{\binom{d}{2}}$,

$$\Pr[|\|\bar{S}^{\odot 2}v\|^2 - \|v\|^2| > \varepsilon \|v\|^2] \leq \delta.$$

We have a generalized result for all k as well.

Corollary 13. For scaled sign $\bar{S}^{\odot k} \in \{\pm \frac{1}{\sqrt{m}}\}^{\binom{d}{k}}$, $v \in \{0, 1\}^{\binom{d}{k}}$, and $i \in [m]$, there is $C > 0$ and $m = O(\varepsilon^{-2} C^{k \log k} \log^{k+1}(k \|v\|_1 / (\varepsilon \delta)))$ such that

$$\Pr[|\|\bar{S}^{\odot k}v\|^2 - \|v\|^2| > \varepsilon \|v\|^2] \leq \delta.$$

The key challenge of establishing the JL property for bundles of bindings is the fact that the columns of $\bar{S}^{\odot k}$ are not independent; for instance, when $k = 2$, the columns corresponding to $i \otimes j$, $j \otimes k$, and $i \otimes k$ are dependent. To track these dependencies, we can represent $\bar{S}^{\odot k}v$ as a hypergraph when $v \in \{0, 1\}^{\binom{d}{k}}$. Then, if we apply McDiarmid's inequality to the bundling of bindings, we can obtain the constants used in the bounded differences in terms of the degrees in the hypergraph.

Roadmap for Proofs In §4.1, we prove Theorem 6 and discuss how the JL frame extends to the sparse JL and Subsampled Randomized Hadamard Transforms (SRHTs). In §4.2, we prove Theorems 9 and 10. Finally, in §4.3, we prove Theorem 12 and Corollary 13.

2.3 Hopfield Nets and Hopfield \pm

In the early seventies, a simple model of associative memory, based on autocorrelation, was introduced in [23, 24, 25]. In a paper that might be regarded as ushering in the “second age of neural networks,” [26] reformulated that model, and described a dynamic process for memory retrieval.

We analyze the *capacity* of Hopfield’s model, where a collection of vectors constituting the memories is stored. (A survey of autoassociative memories is given in [27].) The capacity problem is to determine the maximum number of such vectors a network can effectively

represent in a model described below, and it is assumed that the vectors to be stored are sign vectors. In our setting, the memories are simply columns of a sign matrix $S \in \{\pm 1\}^{m \times n}$.

Much of our description of the model paraphrases that of [23, 24, 25]. The neural network in Hopfield's model comprises a recurrent collection of neurons with pairwise synaptic connections, with an associated weight matrix $W \in \mathbb{R}^{m \times m}$, such that given input $x \in \{\pm 1\}^m$, a dynamic process ensues with vectors $x[\ell]$, where $x[0] = x$, and $x[\ell+1] = \text{sign}_\geq(Wx[\ell])$. Here, $\text{sign}_\geq(z) = 1$ if $z \geq 0$, and -1 otherwise. When we reach a fixed point, i.e. $x[\ell+1] = x[\ell]$, the process stops, and $x[\ell]$ is output. If a vector x is a fixed point of the network, the network is said to "represent" x . Typically, the goal is to not only show the fixed-point property for some x , but also show that for $y \in \{0, \pm 1\}^m$ close to x (i.e. $y^\top x$ is large), the network output is x given input y , with high probability. The capacity problem is to determine how many vectors are represented by a network, as a function of m and a given lower bound on $y^\top x$.

The weight matrix W in a Hopfield network is $SS^\top - nI_m$, the sum of the outer products of the input vectors with themselves, with the diagonal set to zero. One motivation for this setup is that such a weight matrix can be learned by an appropriately connected neural network via a Hebbian learning process.

In Theorem 14 below, we give a bound on m and $y^\top S_{*j}$ so that $\text{sign}_\geq((SS^\top - nI)y) = S_{*j}$ with bounded failure probability.

Theorem 14. *Given matrix $S \in \{\pm 1\}^{m \times n}$ with uniform independent entries, $j \in [n]$, and $\delta \in (0, 1]$. If $y \in \{0, \pm 1\}^m$ with $y^\top S_{*j}/\|y\| \geq 2\sqrt{n \log(2m/\delta)}$, then with failure probability at most δ , $\text{sign}_\geq((SS^\top - nI_m)y) = S_{*j}$. Here it is assumed that the coordinates i at which $y_i \neq S_{ij}$ are chosen before S , or without knowledge of it.*

The $y^\top S_{*j}/\|y\| = y^\top S_{*j}/\sqrt{\|y\|_1}$ term may seem mysterious. $m - \|y\|_1$ is the number of erasures in y , that is, the number of zero coordinates, and $m - |y^\top S_{*j}|$ is the number of erasures plus twice the number of error coordinates i where $y_i \neq S_{ij}$. When there are only erasures, and $y = S_{*j}$ except for errors, $\|y\|_1 = y^\top S_{*j}$, and $\|y\|_1 \geq 2n \log(2m/\delta)$ suffices.

In §5.1, we discuss the implications of this result for m in various cases. If the coordinates of S_{*j} are split into two blocks, one block can be retrieved given the other. This is an alternative sometimes proposed for VSA cleanup, which otherwise involves multiple membership tests. We also note in the section that the data of a MAP-I bundle of bindings is contained in the Hopfield network, and that robustness under erasures can be used to reduce the size of net.

We also introduce a variant of Hopfield nets, which we call Hopfield \pm , in which the vector outer products yielding W are each multiplied by a random ± 1 value before summing.¹ As described in Theorem 15 below, which establishes a JL-like property for Hopfield \pm , this system can store and recover m^2 (up to log factors) vectors. Considering that it uses $O(m^2)$ space, its storage efficiency for bundling is not far from that of MAP-I.

Theorem 15. *Given $\varepsilon, \delta \in (0, 1]$, scaled sign matrix $\bar{S} \in \frac{1}{\sqrt{m}}\{\pm 1\}^{m \times d}$ with uniform independent entries, diagonal matrix $V \in \mathbb{R}^{d \times d}$, and diagonal matrix $D \in \{0, \pm 1\}^{d \times d}$ with*

¹The name Hopfield \pm references the Rademacher values, and is in homage to the many variants of X called X++.

uniform independent ± 1 diagonal entries. There is $m = O(\varepsilon^{-1} \log(d/\delta)^2)$ such that with failure probability δ , $\|\bar{S}V\bar{D}\bar{S}^\top\|_F^2 = (1 \pm \varepsilon)\|V\|_F^2$.

Roadmap for Proofs Theorem 14 is proven in §5.1. Theorem 15 is discussed in §5.2.

2.4 Analysis of MAP-B

For MAP-B, we write our VSA atomic vectors as Se_i , where S is a random sign matrix (Def. 2). However, we require here that even composite (non-atomic) VSA vectors be sign vectors, so a bundle of atomic vectors is represented as $\text{sign}(Sv)$ for a characteristic vector v .

The nonlinearity of bundling makes analysis more difficult. While we were able to reason about set intersection readily via the JL framework when analyzing MAP-I, our results for MAP-B only hold for testing set membership, which is a specific instance of set intersection. We are able to show that membership testing, to determine if $i \in [d]$ is in $\text{supp}(v)$, as represented by the bundle $x = \text{sign}(Sv)$, can be done by checking if $x^\top S_{*i} \geq \tau$, with threshold τ specified below.

Theorem 16. *For $v \in \{0, 1\}^d$, let $x = \text{sign}(Sv)$ be the MAP-B bundling of $n = \|v\|_1$ atomic vectors. Then for all $i \in [m]$ and $j \in \text{supp}(v)$, $\Pr[x_i S_{ij} = +1] = 1/2 + \Theta(1/\sqrt{n})$, as $n \rightarrow \infty$, and there is $m = O(n \log(d/\delta))$ such that with failure probability δ , $j \in [d]$ has $j \in \text{supp}(v)$ if and only if $x^\top S_{*j} = e_j^\top S \text{sign}(Sv)$ has $x^\top S_{*j} \geq \sqrt{2m \log(2d/\delta)}$.*

The proof borrows (simple) ideas from Boolean Fourier analysis, namely the analysis of the majority function. See [16] for a thorough guide on this topic. In §6.1.3, we also provide a simple extension of Theorem 16 to testing for whether the set intersection between two sets X, Y is empty or not.

We also remark that the bundling operator for MAP-B is *not* associative; while $\text{sign}(Sv)$ is one way that MAP-B might compute a bundle, in a more general setting, there could be a sequence of bundling operations. This would result in a tree of bundle operations of some depth greater than one, in contrast to $\text{sign}(Sv)$, whose tree has depth one. We prove that the reliability of the bundling operation decays exponentially with the depth.

Lemma 17. *Given independent sign vectors $x^{(i)} \in \{\pm 1\}^m, i \in [r]$, construct vector x by setting $x \leftarrow x^{(1)}$, and for $j = 2, \dots, r$, setting $x \leftarrow \text{sign}(x + x^{(j)})$. Then, for $\ell \in [m]$,*

$$\Pr[x_\ell^{(1)} x_\ell = 1] = 1/2 + 1/2^r$$

As a result, great care must be exercised in defining MAP-B bundles for application use.

Rotations and Bundles of Bindings We analyze rotations in the same setting described in Definition 8 and Theorem 9, and bundles of bindings in the setting of Definition 11 and Theorem 12.

Our results for MAP-B rotations and bundles of bindings are more limited than what we are able to prove for MAP-I, again due to the nonlinearities present in the binding operation. As noted before, we only consider single element membership testing. For sequences, this means checking if a single element i is present in the j -th set in a sequence.

Theorem 18. Given a sign matrix $S \in \mathbb{R}^{m \times d}$ and rotation matrix $R \in \mathbb{R}^{m \times m}$, and integer length L . Recall (Def. 8) that $S_{R,L} \equiv [S \ R S \ R^2 S \ \dots \ R^{L-1} S]$. For a sequence of d -vectors $v_{(0)}, v_{(1)}, \dots, v_{(L-1)} \in \{0,1\}^d$, let $v \equiv [v_{(0)} \ v_{(1)} \ \dots \ v_{(L-1)}]$, let $x = \text{sign}(S_{R,L}v)$, and let $n = \|v\|_1$. Then there is $m = O(Ln \log(Ld/\delta))$ such that with failure probability at most δ , $j \in [Ld]$ has $j \in \text{supp}(v)$ if and only if $x^\top S_{*,j \% d} \geq 2\sqrt{m \log(Ld/\delta)}$, where $j \% d \equiv 1 + (j-1) \bmod d$.

The proof of Theorem 10 relies on the MAP-B membership result (Theorem 16) and the same trick of partitioning the rows of $S_{R,L}$ used to prove Theorem 9.

We will analyze MAP-B bundles of bindings in the restricted setting of key-value pairs. We can test whether a single key \otimes value belongs to such a bundle.

Definition 19. A bundle of key-value pairs is here a bundling of bindings $S^{\odot 2}v$, where $S_{*,j}^{\odot 2}$ for $j \in \text{supp}(v)$ is $S_{*,q} \circ S_{*,w}$ with $q \in \mathcal{Q}, w \in \mathcal{W}$, where $\mathcal{Q}, \mathcal{W} \subset [d], \mathcal{Q} \cap \mathcal{W} = \{\}$, and a given q appears in only one binding in such a representation. That is, each $S_{*,q}$ is bound to only one $S_{*,w}$, noting that two q, q' may bind to the same $S_{*,w}$.

Theorem 20. Let $v \in \{0,1\}^{\binom{d}{2}}$ be such that $x = \text{sign}(S^{\odot 2}v)$ is a bundle of key-value pairs, as in Def. 19. Let $n = \|v\|_1$. Then there is $m = O(n \log(d/\delta))$ such that with failure probability at most δ , $j \in [\binom{d}{k}]$ has $j \in \text{supp}(v)$ if and only if $x^\top S_{*,j}^{\odot 2} \geq 2\sqrt{m \log(d/\delta)}$.

The proof of this theorem again leverages Theorem 16.

Roadmap for Proofs In §6.1, we prove Theorem 16. In §6.1.2, we prove Lemma 17. Finally the proofs of Theorems 18 and 20 can be found in §6.2 and §6.3, respectively.

2.5 Sparse Binary Bundling and Bloom Filter Analysis

If we use VSA vectors Bx with B chosen as a sparse binary matrix (defined below), we obtain two new families of VSAs, which we refer to as *Bloom filters* and *Counting Bloom filters*, from their names in the data structures literature.

Definition 21. For given m and $k \leq m$, a k -sparse binary vector $y \in \{0,1\}^m$ has $\|y\|_0 \leq k$, chosen by adding k random natural basis vectors $e_i \in \{0,1\}^m$, with each i chosen independently and uniformly from $[m]$. A k -sparse binary matrix $B \in \{0,1\}^{m \times d}$ has columns that are independent sparse binary vectors, and a scaled k -sparse binary matrix has the form $\bar{B} = \frac{1}{k}B$, where B is a sparse binary matrix. These may be called just sparse, leaving the k implicit.

The Bloom and Counting Bloom filters slightly generalize BSDC-CDT, described in [12]. For more on Bloom filters [17], see e.g. [28]. A Bloom filter represents the set $\text{supp}(v)$ for $v \in \{0,1\}^d$ as $1 \wedge Bv$, recalling that $1 \wedge Bv$ denotes the vector x with $x_i = \min\{1, (Bv)_i\}$.

We give VSA dimension bounds enabling reliable estimation of set intersections; a rigorous version of such an estimator appears to be novel for Bloom filters. We define a function $h_{m,k}(\cdot)$ that maps the expected dot product of the VSA bundles to the dot product of the original vectors.

Theorem 22. Let $v, w \in \{0, 1\}^d$ represent sets X, Y respectively, and define the following counts:

$$n \equiv |X \cap Y| = v \cdot w, \quad n_v \equiv |X \setminus Y| = \|v\|_0 - n, \quad n_w \equiv |Y \setminus X| = \|w\|_0 - n$$

Let $x = 1 \wedge Bv$ and $y = 1 \wedge Bw$, where $B \in \{0, 1\}^{m \times d}$ is a sparse binary matrix.

Assume WLOG $n_w \geq n_v$. Then for $\delta \in (0, 1)$ and $\varepsilon > 0$, there are $k = O(\varepsilon^{-1} \log(1/\delta))$ and $m = O(k\varepsilon^{-1}(n_v n_w + n^2 + \varepsilon(n + n_w)))$ such that $h_{m,k}(x \cdot y) = n \pm \epsilon$ with failure probability δ . Here, $h_{m,k}(z)$ (see Lemma 42) maps the Bloom filter output $1 \wedge Bz$ to an estimate of $\|z\|_0$.

We remark that $h_{m,k}(x \cdot y)$ is not an unbiased estimator of $v \cdot w$; we use a “Bernstein version” of McDiarmid (Theorem 28) to establish concentration of $x \cdot y$ first, and conclude the success of the estimator $h_{m,k}(x \cdot y)$ from there. In our analysis, we also divide $x \cdot y$ into two parts: the 1s contributed by $\text{supp}(v) \cap \text{supp}(w)$ after applying B and the min operation, and the 1s contributed by $\text{supp}(v) \Delta \text{supp}(w)$, which may increment the same index after applying B .

In the *Counting Bloom filter*, the bundle is simply $\bar{B}v$. Here, we want to compute the *generalized* set intersection of two vectors v, w , which refers to the coordinate-wise minimum $v \wedge w$. The generalized set intersection size is $v \wedge w = \|v \wedge w\|_1$. Even though the bundle is a linear map, as was the case with MAP-I, we ultimately analyze a non-linear function for set similarity.

Theorem 23. Let $v, w \in \mathbb{R}_{\geq 0}^d$. Let $K_b \equiv \|v - w\|_\infty \leq \max\{\|v\|_\infty, \|w\|_\infty\}$, and define:

$$n \equiv v \wedge w, \quad n_v \equiv \|v\|_1 - n, \quad n_w \equiv \|w\|_1 - n,$$

Let $x = Bv$ and $y = Bw$, where $B \in \{0, 1\}^{m \times d}$ is a sparse binary matrix. Then, for $\delta \in (0, 1)$ and $\varepsilon > 0$, there are $k = O(K_b \varepsilon^{-1} \log(1/\delta))$ and $m = 12\pi^2 k \varepsilon^{-1} n_v n_w = O(K_b \varepsilon^{-2} n_v n_w \log(1/\delta))$ such that

$$\frac{1}{k}(x \wedge y) - (v \wedge w) \in [0, \epsilon]$$

with failure probability at most δ . Since $n_v + n_w = \|v - w\|_1$, $m = O(K_b \varepsilon^{-2} \|v - w\|_1^2 \log(1/\delta))$ also suffices (using the AM-GM inequality on $n_v n_w$). If $\|v\|_1, \|w\|_1$ are stored, then $\|v - w\|_1$ can be estimated up to additive ε with the same m .

Our theorem helps analyze weighted sets, represented as $v, w \in \mathbb{Z}_{\geq 0}^d$, where $\mathbb{Z}_{\geq 0}$ denotes the nonnegative integers. This also translates to a bound for estimating the ℓ_1 distance between v and w , via $\|v - w\|_1 = \|v\|_1 + \|w\|_1 - 2(v \wedge w)$.

Similarly to our proof of Theorem 22, we split $\frac{1}{k}(x \wedge y)$ into a contribution related to $v \wedge w$, which is $\text{supp}(v) \cap \text{supp}(w)$ for $v, w \in \{0, 1\}^d$, and a contribution from $v - (v \wedge w)$ and $w - (v \wedge w)$, which are the characteristic vectors of $\text{supp}(v) \setminus \text{supp}(w)$ and $\text{supp}(w) \setminus \text{supp}(v)$ for $v, w \in \{0, 1\}^d$. The proof of Theorem 23 also relies on the “Bernstein version” of McDiarmid’s inequality (Theorem 28).

Roadmap for Proofs In §7.1, we prove Theorem 22, and in §7.2, we prove Theorem 23.

2.6 Summary of Contributions

Almost all of our results are summarized in Table 3. A few notable results *not* in the table: an analysis of Hopfield nets using standard concentration results, in §5.1; and an analysis of the decay in “signal” in MAP-B when bundling operation trees have nontrivial depth in §6.1.2.

VSA	Op	Expression	Dimension m	Thm. or Section
MAP-I	S	$\ \bar{S}v\ ^2$	$O(\varepsilon^{-2} \log(1/\delta))$	Lem 3
Sparse JL	S	$\ P_{\text{S JL}}v\ ^2$	$O(\varepsilon^{-2} \log(1/\delta))$	§4.1.1
SRHT	S	$\ P_{\text{SRHT}}v\ ^2$	$O(\varepsilon^{-2} \log(1/\delta) \log^4 d)$	§4.1.1
MAP-I	SS	$\ \bar{S}_{R,L}v\ ^2$	$O(\varepsilon^{-2} L^2 \log(L/\delta))$	Thm 9
MAP-I	SS	$\ \bar{S}_{R,L}v\ ^2$	$O(\varepsilon^{-2} K^2 \log(K/(\varepsilon\delta)))$	Thm 10
MAP-I	BB	$\ \bar{S}^{\odot 2}v\ ^2$	$O(\varepsilon^{-2} \log(\ v\ _1/\varepsilon\delta)^3)$	Thm 12
MAP-I	BB	$\ \bar{S}^{\odot k}v\ ^2$	$O(\varepsilon^{-2} C^{k \log k} \log^{k+1}(k\ v\ _1/(\varepsilon\delta)))$	Cor 13
Hopfield±	S	$\text{tr}(\bar{S}VDS^{\top})$	$O(\varepsilon^{-1} \log(d/\delta)^2)$ (space is m^2)	Thm 15
MAP-B	MS	$\text{sign}(Sv)^{\top} S_{*j} \geq \tau_b$	$O(\ v\ _1 \log(d/\delta))$	Thm 16
MAP-B	MSS	$\text{sign}(S_{R,L}v)^{\top} S_{*,j \leq d} \geq \tau_b$	$O(\ v\ _1 L \log(Ld/\delta))$	Thm. 18
MAP-B	MKV	$\text{sign}(S^{\odot 2}v)^{\top} S_{*j}^{\odot 2} \geq \sqrt{2}\tau_b$	$O(\ v\ _1 \log(d/\delta))$	Thm 20
Bloom	SI	$h_{m,k}(Bv \cdot Bw)$	$O(k\varepsilon^{-1}(n_v n_w + n^2 + \varepsilon(n + n_w)))$ $k = O(\varepsilon^{-1} \log(1/\delta))$	Thm 22
Counting Bloom	GSI	$Bv \wedge Bw$	$O(k\varepsilon^{-1} n_v n_w)$ $k = O(K_b \varepsilon^{-1} \log(1/\delta))$	Thm 23

Table 3: We compile the bounds in this paper for various architectures and operations. Here δ is a bound on the failure probability; m is the VSA dimension; d is the size of the groundset of symbols; S, \bar{S} are defined in Def. 2; L is the sequence length; $\bar{S}_{R,L}$ denotes a sequence, Def. 8; $\bar{S}^{\odot k}$ denotes a bundle of bindings, Def. 11; and $v \in \{0, 1\}^d$ for sets of singletons, $v \in \{0, 1\}^{Ld}$ for sequences, $v \in \{0, 1\}^{\binom{d}{k}}$ for bundles of k bindings.

The **first block of rows** are bounds for norm-preserving *linear* operators, so that relative error ε bound for each in estimating $\|v\|$ translates to an error bound for estimating $\|u - v\|$ for many pairs of vectors u, v , as in Cor. 4; dot products, as in Cor. 5; and in computing set intersection sizes under a variety of conditions on the set sizes, Thm. 6.

First block notation: operation S is estimation of size of a set; SS is size of sequence of sets; BB is size of a Bundle of Bindings (set of bound key-value pairs); matrices $P_{\text{S JL}}, P_{\text{SRHT}}$ are sparse JL matrix and SRHT matrix, as discussed in §4.1.1; K the maximum number of times a symbol appears in a sequence; V is a diagonal matrix version of v ; D is a diagonal sign matrix.

The **second block** are operations with non-linear steps. ε is the *additive* estimation error.

Second block notation: operation MS is set membership test; MSS is membership in a sequence of sets; MKV is membership in a bundle of bindings, where the bindings are key-value pairs; GSI is generalized set intersection (estimation of $v \wedge w = \sum_i \min\{v_i, w_i\}$); matrix B is a sparse binary matrix, Def. 21; $\tau_b = \sqrt{2m \log(2d/\delta)}$; k is the number of nonzeros per column of B ; $h_{m,k}(z) = \frac{1}{k} \log_{1-1/m}(1-z/m)$, defined in Lem. 42; $v, w \in \{0, 1\}^d$ for Bloom filters; $v, w \in \mathbb{Z}_{\geq 0}^d$ for Counting Bloom filters; $K_b = \|v - w\|_{\infty} \leq \max\{\|v\|_{\infty}, \|w\|_{\infty}\}$; finally, $n = v \wedge w$, $n_v = \|v\|_1 - n$, and $n_w = \|w\|_1 - n$, so $n_v + n_w = \|v - w\|_1$.

3 Preliminaries and Concentration Inequalities

In this section, we include a few useful concentration inequalities for functions of random variables that are used throughout our VSA analysis.

Let $f : \Omega_1 \times \dots \times \Omega_n \rightarrow \mathbb{R}$ be an arbitrary function on n variables.

Definition 24. A function $f : \Omega_1 \times \dots \times \Omega_n \rightarrow \mathbb{R}$ has bounded differences with constants $\{c_i\}_{i \in [n]}$ if for all $x_1 \in \Omega_1, \dots, x_n \in \Omega_n$ and all $i \in [n]$,

$$\sup_{y \in \Omega_i} |f(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n) - f(x_1, \dots, x_{i-1}, y, x_{i+1}, \dots, x_n)| \leq c_i$$

When we want to study how f applied to a random variable X concentrates around its mean $\mathbb{E}[f(X)]$, the most standard tool is McDiarmid's inequality. The usual form of McDiarmid's inequality is the following statement:

Theorem 25. Let $X = (X_1, \dots, X_n)$ be a tuple of independent random variables supported on $\Omega_1, \dots, \Omega_n$, respectively. If f has bounded differences with constants c_1, \dots, c_n , then:

$$\begin{aligned} \Pr[f(X) - \mathbb{E}[f(X)] > t] &\leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n c_i^2}\right) \\ \Pr[f(X) - \mathbb{E}[f(X)] < -t] &\leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n c_i^2}\right) \end{aligned}$$

We now derive a standard variant (Corollary 27) of McDiarmid that applies when the bounded differences hold with high probability. This is not a novel modification, but we include it for completeness. The corollary follows from the following lemma, which we will also use throughout our VSA analysis.

Lemma 26. Let X be a random variable taking values in domain D , e.g. $D = \mathbb{R}^n$. Let f and g map from D to \mathbb{R} , such that $\Pr[g(X) \neq f(X)] \leq \delta$, with $g(X) = 0$ when $g(X) \neq f(X)$, and $\sup_{x \in D} f(x) \leq M$ for a value $M \in \mathbb{R}$. Then

$$\begin{aligned} \Pr[f(X) - \mathbb{E}[f(X)] > t + \delta M] &\leq \Pr[g(X) - \mathbb{E}[g(X)] > t] + \delta \\ \Pr[f(X) - \mathbb{E}[f(X)] < -t - \delta M] &\leq \Pr[g(X) - \mathbb{E}[g(X)] < -t] + \delta \end{aligned}$$

Proof. Let B be the “bad subset” of D where $g(X) \neq f(X)$. Here $\mathbb{E}[g(X)]$ is close but not equal to $\mathbb{E}[f(X)]$:

$$\begin{aligned} \mathbb{E}[f(X)] &= \sum_{x \notin B} \Pr[X = x] \cdot f(x) + \sum_{x \in B} \Pr[X = x] \cdot f(x) \\ &\leq \sum_{(x) \notin B} \Pr[X = x] \cdot g(x) + \delta M = \mathbb{E}[g(X)] + \delta M \end{aligned}$$

Similarly, $\mathbb{E}[f(X)] \geq \mathbb{E}[g(X)] - \delta M$

Using this relationship between the means of $f(X)$ and $g(X)$, we have.

$$\Pr[f(X) - \mathbb{E}[f(X)] \geq t'] \leq \Pr[f(X) - \mathbb{E}[f(X)] \geq t' \mid f(X) = g(X)] \cdot \Pr[f(X) = g(X)] + \delta$$

$$\begin{aligned}
&\leq \Pr[g(X) - \mathbb{E}[f(X)] \geq t' | f(X) = g(X)] \cdot \Pr[f(X) = g(X)] + \delta \\
&\leq \Pr[g(X) - \mathbb{E}[f(X)] \geq t'] + \delta \\
&\leq \Pr[g(X) - \mathbb{E}[g(X)] \geq t' - \delta M] + \delta
\end{aligned}$$

The final line comes from the fact that $\mathbb{E}[f(X)] \geq \mathbb{E}[g(X)] - \delta M$. Letting $t' = t + \delta M$ yields the desired bound. The upper bound for $\Pr[f(X) - \mathbb{E}[f(X)] \leq -t']$ is analogous. \square

Corollary 27. *Let X_1, \dots, X_n be independent random variables supported on $\Omega_1, \dots, \Omega_n$, respectively. Define $M := \sup_{x_1, \dots, x_n} |f(x_1, \dots, x_n)|$. If with probability $1 - \delta$ over X_1, \dots, X_n , the function f has bounded differences with constants c_1, \dots, c_n , i.e. there is a set $S \subseteq \Omega$ with $\Pr[X \in S] = 1 - \delta$ such that for all $(x_1, \dots, x_n) \in S$ and $i \in [n]$, we satisfy*

$$\sup_{y \in \Omega_i} |f(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n) - f(x_1, \dots, x_{i-1}, y, x_{i+1}, \dots, x_n)| \leq c_i$$

then both of the following inequalities hold.

$$\begin{aligned}
\Pr[f(X) - \mathbb{E}[f(X)] > t + \delta M] &\leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n c_i^2}\right) + \delta \\
\Pr[f(X) - \mathbb{E}[f(X)] < -t - \delta M] &\leq \exp\left(-\frac{2t^2}{\sum_{i=1}^n c_i^2}\right) + \delta
\end{aligned}$$

Proof. Apply Lemma 26 to f and the function g defined as taking the same value of f for X_1, \dots, X_n such that the bounded differences hold, and zero otherwise. Then, we apply Theorem 25 to g . \square

There is also a version of McDiarmid's inequality that incorporates variances; we refer to it as the "Bernstein form of McDiarmid's Inequality."

Theorem 28 ([29]). *Let $X = (X_1, \dots, X_n)$ be a tuple of independent random variables supported on $\Omega \equiv \prod_{i \in [n]} \Omega_i$. For function $f : \Omega \rightarrow \mathbb{R}$ and $x \in \Omega, i \in [n], y \in \Omega_i$, let $g_i(x, y) \equiv f(x_1, \dots, x_{i-1}, y, x_{i+1}, \dots, x_n)$. (Note that $g_i(x, y)$ does not depend on x_i .) Let*

$$\begin{aligned}
\mathbf{Var}_i(f) &\equiv \sup_{x \in \Omega} \mathbb{E}_{X_i} \left[(g_i(x, X_i) - \mathbb{E}_{X'_i} g_i(x, X'_i))^2 \right] \\
\tilde{\sigma}(f) &\equiv \sum_{i \in [n]} \mathbf{Var}_i(f) \\
B(f) &\equiv \max_{i \in [n]} \sup_{x \in \Omega} |g_i(x, X_i) - \mathbb{E}_{X'_i} g_i(x, X'_i)|
\end{aligned}$$

Then

$$\begin{aligned}
\Pr[f(X) - \mathbb{E}[f(X)] > t] &\leq \exp\left(-\frac{2t^2}{\tilde{\sigma}(f) + tB(f)/3}\right) \\
\Pr[f(X) - \mathbb{E}[f(X)] < -t] &\leq \exp\left(-\frac{2t^2}{\tilde{\sigma}(f) + tB(f)/3}\right)
\end{aligned}$$

We will also need this known concentration bound for Rademacher random variables.

Theorem 29. Let X_1, \dots, X_n be independent Rademacher random variables. Let (a_1, \dots, a_n) be an arbitrary vector in \mathbb{R}^n . Then,

$$\Pr \left[\sum_{i=1}^n a_i X_i \geq t \|a\|_2 \right] \leq \exp \left(-\frac{t^2}{2} \right)$$

4 Analysis of MAP-I Using Johnson-Lindenstrauss

In §4.1, we analyze MAP-I bundling, including the relation of norm estimation to distance, set intersection, and angle estimation, and discuss how the JL perspective extends to the sparse JL and Subsampled Randomized Hadamard Transforms (SRHTs).

Next, in §4.2, we analyze the VSA dimension needed to reliably estimate the intersection of two *sequences* of sets, as encoded using rotations, in both a general and a more restricted setting. This entails proving the JL property for a specific kind of random matrix with dependent entries.

Finally, in §4.3, we analyze intersection of bundles of bound pairs and bundles of k -wise bindings. Again, we establish the JL property for a random matrix with dependent entries. While bundles of key-value bindings have been analyzed before, bundles of k -wise bindings have not.

4.1 Bundling and Set Intersection

The results in this section may apply to VSAs beyond just MAP-I where the bundling operator is addition over the real numbers. Section 3.1 of [30] gives some representational bounds in that setting. Though we provide similar bounds, we frame our results using the Johnson-Lindenstrauss (JL) random projection lemma, which provides a simpler yet powerful lens through which to view the MAP-I VSA. (A connection to JL was briefly mentioned by [31], but it did not factor into any capacity analysis there.)

We first introduce the Johnson-Lindenstrauss (JL) lemma:

Lemma (Restatement of Lemma 3). *Suppose $\bar{S} \in \frac{1}{\sqrt{m}}\{-1, 1\}^{m \times d}$ is a scaled sign matrix (described in Def. 2). Then for given $\delta, \epsilon > 0$ there is $m = O(\epsilon^{-2} \log(1/\delta))$ such that for given vector $v \in \mathbb{R}^d$, it holds that $\|\bar{S}v\| = \|v\|(1 \pm \epsilon)$, with failure probability at most δ .*

Remark 30. We have a similar result for any matrix P with i.i.d. subGaussian entries.

This approximation bound can be easily translated to a bound for multiple differences of vectors. The proof is simply the application of Lemma 3 to the $O(n^2)$ pairs of differences of vectors of \mathcal{V} , and a union bound (yielding the $\log n$ part of the bound).

Corollary (Restatement of Corollary 4). *If random matrix P satisfies the JL property (Lemma 3), then for given $\delta, \epsilon > 0$, and a set $\mathcal{V} \subset \mathbb{R}^d$ of cardinality n , there is $m = O(\epsilon^{-2} \log(n/\delta))$ such that with failure probability δ , for all pairs $v, w \in \mathcal{V}$, $\|P(v - w)\|^2 \in \|v - w\|^2(1 \pm \epsilon)$.*

In other words, the linear mapping P preserves Euclidean distances up to a multiplicative factor of $(1 \pm \epsilon)$. If v and w are characteristic vectors for sets X and Y , then $\|v - w\|^2 = |X \Delta Y|$, the cardinality of the symmetric difference of X and Y . Thus, by taking the difference between their VSA representations Pv and Pw , we can estimate how much the sets X and Y disagree, with small *relative* error ϵ in that estimate, mild dependence on the number of sets we can represent in this way, and no dependence, in the error, on the groundset size n .

However, this doesn't say what the needed dimensionality m is, for accurate estimation of the size of the intersection. We consider this next, using the following standard corollary of Lemma 3.

Corollary (Restatement of Corollary 5). *Suppose the random matrix P satisfies the JL property (Lemma 3). Then for $v, w \in \mathbb{R}^d$, there is $m = O(\epsilon^{-2} \log(1/\delta))$ so that $v^\top P^\top Pw = v^\top w \pm \epsilon \|v\| \|w\|$ with failure probability δ .*

Proof. First, suppose v and w are unit vectors. By Lemma 3 and a union bound, with failure probability at most 3δ we have $v^\top P^\top Pv = v^\top v \pm \epsilon$, $w^\top P^\top Pw = w^\top w \pm \epsilon$, and $(v + w)^\top P^\top P(v + w) = (v + w)^\top (v + w) \pm 2\epsilon$. Since $2v^\top w = (v + w)^\top (v + w) - v^\top v - w^\top w$ and matrix multiplication is an application of a linear operator, an analogous expression holds for $v^\top P^\top Pw$. Then,

$$2(v^\top P^\top Pw - v^\top w) = \pm \epsilon \pm \epsilon \pm 2\epsilon = \pm 4\epsilon,$$

with failure probability 3δ . If v and w are not unit vectors, we apply this reasoning to $v/\|v\|$ and $w/\|w\|$, and then multiply through by $\|v\| \|w\|$, getting $v^\top P^\top Pw = v^\top w \pm 2\epsilon \|v\| \|w\|$. That is, the conclusion holds with relative error parameter 2ϵ and failure probability 3δ . We can fold the factors 2 and 3 into the bound for m , and the result follows. \square

Beyond the approximation condition, the proof only depends on P being a linear operator. Suppose P is a scaled sign matrix \bar{S} , and let $v, w \in \{0, 1\}^d$ be characteristic vectors. We want $v^\top P^\top Pw = v^\top w \pm \epsilon_0$, where $\epsilon_0 < 1/2$. Since $v^\top w$ is an integer, this assures that $v^\top P^\top Pw$ rounds to $v^\top w$. The next lemma gives conditions on ϵ and δ to attain this.

Theorem (Restatement of Theorem 6). *Suppose random matrix P satisfies the JL property (Lemma 3). Given M pairs of characteristic vectors $v, w \in \{0, 1\}^d$ such that for every pair v, w , $\|v\|_1 \|w\|_1 \leq N$, then there is $m = O(N \log(M/\delta))$ such that $\lfloor v^\top P^\top Pw \rfloor = v^\top w$ for all M pairs with probability $\geq 1 - \delta$.*

Remark 31. In particular, this holds for the following special cases.

- **Set membership:** v is a characteristic vector, and w is a standard basis vector e_i for $i \in [d]$. Then, $N = \|v\|_1$, $M = d$, and VSA dimension $m = O(\|v\|_1 \log(d/\delta))$ suffices.
- To get all pairwise intersections among $M^{O(1)}$ vectors v with $\|v\|_1 \leq \sqrt{N}$, we can use $m = O(N \log(M/\delta))$.

Proof. For a given pair of vectors v and w , by Corollary 5 it is enough to choose $\epsilon_0 < 1/2$ and $\epsilon = \epsilon_0 / (\|v\| \|w\|) \geq \epsilon_0 / \sqrt{N}$, to achieve the desired accuracy.

If δ' is the failure probability of Corollary 5, then the overall failure probability is at most $M\delta'$, by a union bound. Thus for $\delta' = \delta/M$ and ϵ from the JL property equal to ϵ_0/\sqrt{N} , the dimension m of Corollary 5 is $m = O(N \log(M/\delta))$, and every dot product estimate is accurate to within additive ϵ_0 with failure probability at most δ . The result follows. \square

Angle estimation Let $\Theta_{v,w}$ denote the angle between vectors v and w .

Lemma 32. *Under the conditions of Lemma 3, for $v, w \in \mathbb{R}^d$, there is $m = O(\epsilon^{-2} \log(1/\delta))$ so that $\cos \Theta_{\bar{S}v, \bar{S}w} = \cos \Theta_{v,w} \pm \epsilon$ with failure probability δ .*

Proof. This follows from $\cos \Theta_{v,w} = \frac{v^\top w}{\|v\|\|w\|}$, and similarly for $\Theta_{\bar{S}v, \bar{S}w}$; applying Corollary 5 to the estimation of $v^\top w$, $\|v\|$, and $\|w\|$, and finally folding constant-factor increases in ϵ and δ into m . \square

4.1.1 Variations Using Alternative Sketching Matrices

Using sparse JL The sparse JL transform has ϵm nonzero entries per column of P , each entry an independent sign (that is, ± 1). Such a matrix, multiplied by a scaling factor, also satisfies Lemma 3, as shown in [32, 33], and therefore could be used in VSAs with the same performance, at least as far as bundling goes. However, element-wise product does not seem to be enough to do binding effectively for such a representation, as the element-wise product of sparse vectors is likely to be all zeros.

Using Subsampled Randomized Hadamard Transform (SRHT) The SRHT, described in [34], is multiplication by a matrix ZHD , where D is a random sign diagonal matrix (random sign flips on the diagonal), H is a Hadamard matrix (an orthogonal sign matrix), and Z simply selects a uniform random subset of the rows (a diagonal binary matrix). This operation, along with a scaling factor, is shown by [35] to satisfy the conditions of Lemma 3, up to needing the larger target dimension $m = O(\epsilon^{-2} \log(1/\delta) \log^4 d)$, that is, with an additional factor of $\log^4 d$. While for many applications, a useful property of SRHT is that $ZHDv$ is rapidly computed, here the main attraction is that the generation or storage of random sign values is greatly reduced; entries of the H matrix are readily computed using bitwise operations on the entry indices.

4.2 Rotations for Encoding Sequences

For scaled sign matrices, using a rotation (i.e. a permutation that is a single large cycle), we can store length- L sequences of vectors with an error bound that grows quadratically with L . It is possible that there is a better general bound than this; we found better performance in a special case. If the vectors are, in particular, characteristic vectors, so that a sequence of symbols is being stored (and not e.g. a sequence of embeddings), then better error behavior (that depends on how much the vectors overlap, rather than naively on L) typically occurs.

Before further definition and analysis, we have some lemmas useful for the analysis.

Lemma 33. *Say we sample independent scaled random sign matrices $P_1, P_2 \in \{\pm 1\}^{m \times d}$ with m large enough to satisfy the JL property, i.e. for given $v \in \mathbb{R}^d$, with failure probability δ , it holds that $\|P_i v\|^2 = (1 \pm \epsilon) \|v\|^2$. If the block matrix $[P_1 \ P_2]$ also satisfies the JL property, then for given unit vectors $x_1, x_2 \in \mathbb{R}^d$, with failure probability at most 3δ , $|x_1^\top P_1^\top P_2 x_2| \leq 2\epsilon$.*

Proof. Since P_1 and P_2 were sampled independently, the block matrix $[P_1 P_2]$ itself is a larger random sign matrix, and it satisfies the JL property for ε with probability $\leq \delta$. We have

$$\|P_1 x_1 + P_2 x_2\|^2 = \|[P_1 P_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}\|^2 = (\|x_1\|^2 + \|x_2\|^2)(1 \pm \epsilon) = 2(1 \pm \epsilon)$$

with failure probability δ , since $[P_1 P_2]$ satisfies the same conditions as P_1, P_2 . With failure probability at most 3δ , the embedding conditions hold for $[P_1 P_2]$, P_1 , and P_2 . Assuming they do,

$$\begin{aligned} |x_1^\top P_1^\top P_2 x_2| &= \left| \frac{1}{2} [\|P_1 x_1 + P_2 x_2\|^2 - \|P_1 x_1\|^2 - \|P_2 x_2\|^2] \right| \\ &\leq \frac{1}{2} [2(1 + \epsilon) - (1 - \epsilon) - (1 - \epsilon)] \leq 2\epsilon. \end{aligned}$$

The result follows. \square

Lemma 34. Let $R \in \mathbb{R}^{m \times m}$ denote a rotation matrix, as in Def. 8. Let $\bar{S} \in \mathbb{R}^{m \times d}$ be a scaled sign matrix such that for given $x \in \mathbb{R}^d$, $\|\bar{S}x\|^2 = \|x\|^2(1 \pm \epsilon)$ with failure probability δ . Then for unit vectors $x, y \in \mathbb{R}^d$ and $r \leq m/2$, we have $|x^\top \bar{S}^\top R^r \bar{S} y| \leq 4\epsilon$, with failure probability 6δ . If x and y are not unit vectors, then $|x^\top \bar{S}^\top R^r \bar{S} y| \leq 4\epsilon \|x\| \|y\|$.

Proof. We have $(R^r \bar{S})_{i*} = \bar{S}_{[(i+r-1)\%m+1]*}$, where $j \% m$ denotes j modulo m . Consider the division of the rows of \bar{S} and of $R^r \bar{S}$ into blocks of size r . The first r rows of \bar{S} and the first r rows of $R^r \bar{S}$ comprise together the first and second blocks of \bar{S} , since $\{(i+r-1)\%m+1 | i \in [r]\} = \{1+r, 2+r, \dots, r+r\}$. The second block of r rows of \bar{S} and of $R^r \bar{S}$ comprise together the second and third block of rows of \bar{S} , and so on.

As a consequence, \bar{S} and $R^r \bar{S}$ can each be split into two matrices \bar{S}_1, \bar{S}_2 and $(R^r \bar{S})_1, (R^r \bar{S})_2$, where \bar{S}_1 comprises the odd-numbered blocks of \bar{S} , and $(R^r \bar{S})_1$ comprises the corresponding blocks of $R^r \bar{S}$, such that the rows of \bar{S}_1 and the rows of $(R^r \bar{S})_1$ are chosen from disjoint sets of rows of \bar{S} , and similarly for \bar{S}_2 comprising the even-numbered blocks of \bar{S} , and $(R^r \bar{S})_2$ comprising the corresponding blocks of $R^r \bar{S}$. That is, splitting the entries of x and y in the same way into vectors x_1, x_2, y_1, y_2 , we have that

$$x^\top \bar{S}^\top R^r \bar{S} y = x_1^\top \bar{S}_1^\top (R^r \bar{S})_1 y_1 + x_2^\top \bar{S}_2^\top (R^r \bar{S})_2 y_2.$$

Since the entries of \bar{S}_1 were chosen independently from those of $(R^r \bar{S})_1$, we can apply Lemma 33 to have that $|x_1^\top \bar{S}_1^\top (R^r \bar{S})_1 y_1| \leq 2\epsilon$, with failure probability $C\delta$, with a similar statement for $x_2^\top \bar{S}_2^\top (R^r \bar{S})_2 y_2$. Adding these bounds, and taking a union bound on the failure probability, yields the result for unit vectors. The claim about non-unit vectors follows immediately. \square

Definition 35. For $v \in \mathbb{R}^{Ld}$ encoding a sequence $v_{(0)}, v_{(1)}, \dots, v_{(L-1)} \in \mathbb{R}^d$, as in Def. 8, define

$$\|v\|_{L,1} \equiv \sum_{0 \leq j < L} \|v_{(j)}\|$$

Theorem (Restatement of Theorem 9). *Given scaled sign matrix $\bar{S} \in \mathbb{R}^{m \times d}$, rotation matrix $R \in \mathbb{R}^{m \times m}$ as in Def. 7, integer $L > 0$, and $\bar{S}_{R,L}$ as in Def. 8. Then for $v \in \mathbb{R}^{Ld}$ as defined above,*

$$|\|\bar{S}_{R,L}v\|^2 - \|v\|^2| \leq 3\epsilon\|v\|_{L,1}^2 \leq 3L\epsilon\|v\|^2,$$

with failure probability $6L^2\delta$. It follows that there is $m = O((L/\epsilon)^2 \log(L/\delta))$ such that with failure probability at most δ , $\|\bar{S}_{R,L}v\|^2 = (1 \pm \epsilon)\|v\|^2$.

Note that bounds for set difference and intersection follow by slight variation of Corollaries 4 and 5, and sharper ones using $\|v\|_{L,1}$ instead of $\|v\|$.

Proof. Recall that $R^\top R = I$ and $R^\top = R^{-1}$. Assuming the approximation bounds of Lemma 34 hold for several instances, we have that

$$\begin{aligned} \|\bar{S}_{R,L}v\|^2 &= \left\| \sum_{0 \leq j < L} R^j \bar{S} v_{(j)} \right\|^2 \\ &= \sum_{0 \leq j, j' < L} v_{(j')}^\top \bar{S}^\top (R^\top)^{j'} R^j \bar{S} v_{(j)} \\ &= \sum_{0 \leq j < L} v_{(j)}^\top \bar{S}^\top \bar{S} v_{(j)} + 2 \sum_{0 \leq j' < j < L} v_{(j')}^\top \bar{S}^\top R^{j-j'} \bar{S} v_{(j)} \\ &\leq \|v\|^2(1 \pm \epsilon) + 2 \sum_{0 \leq j' < j < L} \epsilon \|v_{(j')}\| * \|v_{(j)}\| \\ &\leq \|v\|^2 + 3\epsilon \left(\sum_{0 \leq j < L} \|v_{(j)}\| \right)^2, \end{aligned}$$

as claimed. Here we use that for vector $z \in \mathbb{R}^L$, $\|z\|_2 \leq \|z\|_1 \leq \|z\|_2 \sqrt{L}$. This also implies the last inequality of the theorem statement. The failure probabilities of Corollary 5 for the diagonal terms, and Lemma 34 for the off-diagonal terms, imply the overall bound via a union bound. The last line follows using Lemma 3. \square

4.2.1 Tighter Bounds for Characteristic Vectors

The above theorem applies to any sequence of vectors, but better bounds are obtainable for characteristic vectors, in some cases: consider v and w the characteristic vectors of distinct symbols. Then $\bar{S}v$ and $R\bar{S}w$ are entry-wise independent, because v and w select different columns of \bar{S} , and the rotation $R\bar{S}$ doesn't change this. Next we apply this idea more generally.

Theorem (Restatement of Theorem 10). *Given scaled sign matrix $\bar{S} \in \mathbb{R}^{m \times d}$, rotation matrix $R \in \mathbb{R}^{m \times m}$ (Def. 7), integer $L > 0$, and $\bar{S}_{R,L}$ as in Def. 8. For a sequence of vectors $v_{(0)}, v_{(1)}, \dots, v_{(L-1)} \in \{0, 1\}^d$, let $K \equiv \|\sum_{0 \leq j < L} v_{(j)}\|_\infty$. There is $m = O(K^2 \epsilon^{-2} \log(K/(\epsilon\delta)))$ such that with failure probability δ ,*

$$|\|\bar{S}_{R,L}v\|^2 - \|v\|^2| \leq \epsilon\|v\|^2$$

Note that here, each $v_{(j)}$ is the characteristic vector of a collection of symbols, and K is the maximum number of times that some symbol is represented, adding up appearances over the given vectors. Bounds for set difference and intersection follow by slight variation of Corollaries 4 and 5.

Proof. Our proof of this lemma uses a corollary of McDiarmid's Inequality (Theorem 25). The product $\bar{S}_{R,L}v$ is a sum of vectors of the form $R^j \bar{S}_{*i}$, for entries i of $v_{(j)}$ equal to one. Recall that $v_{(j)} \in \mathbb{R}^d$ is the j -th block of v , and that we defined $K = \|\sum_{0 \leq j < L} v_{(j)}\|_\infty$. We can decompose v into a sum $v = \sum_{k \in [K]} x^k$, where each $x^k \in \{0, 1\}^{Ld}$, such that no $j, j' \in \text{supp}(x^k)$ has $j \bmod d = j' \bmod d$. For each $k \in K$, the vector $\sqrt{m}\bar{S}_{R,L}x^k$ is a sum of independent sign vectors, since each entry of 1 in x^k will select a different column of \bar{S} , and so Lemma 3 applies, and $\|\bar{S}_{R,L}x^k\|^2 = (1 \pm \epsilon)\|x^k\|^2$ with failure probability δ .

We will show next for $k, k' \in [K]$ with $k \neq k'$, that $D_{k,k'} \equiv x^{k'}^\top \bar{S}_{R,L}^\top \bar{S}_{R,L} x^k$ concentrates around its expectation $x^{k'}^\top x^k$. To do this, we will apply McDiarmid's Inequality, (Corollary 27). First, we note that each entry $(\bar{S}_{R,L}x^k)_i$ is a sum of independent Rademacher values, scaled by $1/\sqrt{m}$, and so by Theorem 29 its square is at most $\frac{1}{m}\|x^k\|^2 \log(2/\delta_1)$ with failure probability δ_1 , for δ_1 to be determined.

Let \mathcal{E} be the event that all entries of $\bar{S}_{R,L}x^k$ and $\bar{S}_{R,L}x^{k'}$ satisfy this bound; this holds with failure probability at most $2\delta_1 m$. To apply Theorem 25, we need to bound, for each entry of \bar{S} , the change in $D_{k,k'}$ that can occur when the entry takes one of its values $+1$ or -1 . Due to the construction of x^k and $x^{k'}$, the entry affects only at most one entry $(\bar{S}_{R,L}x^k)_i$ and at most one entry $(\bar{S}_{R,L}x^{k'})_{i'}$.

The difference in $D_{k,k'}$ due to a change in an entry of \bar{S} contributing to $(\bar{S}_{R,L}x^k)_i$ is at most $\frac{2}{\sqrt{m}}(\bar{S}_{R,L}x^{k'})_i$; if event \mathcal{E} holds, its square is at most $\frac{4}{m^2}\|x^{k'}\|^2 \log(2/\delta_1)$. Similarly, the difference due to a change in an entry contributing to $\bar{S}_{R,L}x^{k'}$ is at most $\frac{4}{m^2}\|x^k\|^2 \log(2/\delta_1)$. Putting these together, the squared change in $D_{k,k'}$ due to an entry that appears on both sides is at most

$$\begin{aligned} & (2|(\bar{S}_{R,L}x^{k'})_i| + 2|(\bar{S}_{R,L}x^k)_{i'}|)^2 \\ &= 4 \left(|(\bar{S}_{R,L}x^{k'})_i|^2 + 2|(\bar{S}_{R,L}x^{k'})_i \cdot (\bar{S}_{R,L}x^k)_{i'}| + |(\bar{S}_{R,L}x^k)_{i'}|^2 \right) \\ &\leq 8|(\bar{S}_{R,L}x^{k'})_i|^2 + 8|(\bar{S}_{R,L}x^k)_{i'}|^2 \\ &= \frac{8}{m^2} \cdot \log(2/\delta_1)(\|x^{k'}\|^2 + \|x^k\|^2). \end{aligned}$$

The third line follows from the AM-GM inequality.

To obtain the total of the squared difference bounds, as needed in Corollary 27, note that a given entry of \bar{S} may be one of $m\|x^k\|^2$ relevant entries of \bar{S} on one side, and may be one of $m\|x^{k'}\|^2$ relevant entries on the other. Suppose we "charge" an appearance of an entry among the $m\|x^k\|^2$ entries contributing to $\bar{S}_{R,L}x^k$ an amount of $\frac{8}{m^2} \log(2/\delta_1)\|x^{k'}\|^2$, and an appearance of an entry among the $m\|x^{k'}\|^2$ contributing to $\bar{S}_{R,L}x^{k'}$ an amount of $\frac{8}{m^2} \log(2/\delta_1)\|x^k\|^2$. Then from the above, the contribution of every entry, and its one or two appearances, to the sum of squares of per-entry changes to $D_{k,k'}$, is accounted for. That sum of squares, as needed for Cor. 27, is therefore at most

$$\frac{16}{m} \log(2/\delta_1) \|x^k\|^2 \|x^{k'}\|^2,$$

assuming still event \mathcal{E} .

To apply Cor. 27, we have upper bound $M = \|x^k\|^2\|x^{k'}\|^2$, and δ of that corollary at most $2\delta_1 m$. We note that since $k \neq k'$, we have $\mathbb{E}[D_{k,k'}] = 0$. So

$$\Pr(D_{k,k'} \geq t + 2\delta_1 m \|x^k\|^2\|x^{k'}\|^2) \leq 2 \exp\left(-\frac{t^2 m}{16 \log(2/\delta_1) \|x^k\|^2\|x^{k'}\|^2}\right) + 2\delta_1 m.$$

Setting $\delta_1 \leq \varepsilon\delta/4K^2m$ for target failure probability δ , and $t = \frac{1}{2}\varepsilon\|x^k\|\|x^{k'}\|$, we get

$$\Pr(D_{k,k'} \geq \varepsilon\|x^k\|^2\|x^{k'}\|^2) \leq 2 \exp\left(-\frac{\varepsilon^2 m}{16 \log(2/\delta_1)}\right) + \varepsilon\delta/2K^2,$$

so the failure probability is less than δ/K^2 for $m = O(\varepsilon^{-2} \log(K/\varepsilon\delta))$. (As is not hard to verify.)

Suppose we have this bound for all $k \neq k'$, which by union bound holds with failure probability at most δ . We have

$$\begin{aligned} \|\bar{S}_{R,L}v\|^2 &= \sum_k (1 \pm \varepsilon)\|x^k\|^2 \pm \frac{1}{2}\varepsilon \sum_{k \neq k'} \|x^k\|\|x^{k'}\| \\ &= \|v\|^2(1 \pm \varepsilon) \pm \varepsilon \left(\sum_k \|x^k\|\right)^2 = \|v\|^2(1 \pm \varepsilon) \pm K\varepsilon\|v\|^2, \end{aligned}$$

and the theorem follows, after folding K into ε and adjusting constants. \square

4.3 Binding

4.3.1 Bundles of pair-wise bindings

As discussed in the introduction, a bundle of pairwise bindings can be given as a vector $\bar{S}^{\odot 2}v$, where $v \in \{0, 1\}^{\binom{d}{2}}$, and $\bar{S}^{\odot 2} \in \{\pm \frac{1}{\sqrt{m}}\}^{m \times \binom{d}{2}}$ is defined in Def. 11. We have $\mathbb{E}[\|\bar{S}^{\odot 2}v\|^2] = \|v\|^2$, and need to show that $\|\bar{S}^{\odot 2}v\|^2 \in \|v\|^2(1 \pm \varepsilon)$ with high probability.

Theorem (Restatement of Theorem 12). *For $v \in \{0, 1\}^{\binom{d}{2}}$, there is $m = O(\varepsilon^{-2} \log^3(\|v\|_1/\varepsilon\delta))$ so that for $\bar{S}^{\odot 2} \in \{\pm \frac{1}{\sqrt{m}}\}^{\binom{d}{2}}$,*

$$\Pr[|\|\bar{S}^{\odot 2}v\|^2 - \|v\|^2| > \varepsilon\|v\|^2] \leq \delta.$$

For our analysis we will use a graph $G(V, E)$ of interactions in $\bar{S}^{\odot k}$ of columns in \bar{S} . Index the columns of $\bar{S}^{\odot k}$ by the columns of \bar{S} from which they came, so $\bar{S}_{*,\{i_1, i_2, \dots, i_k\}}^{\odot k}$ denotes the column of $\bar{S}^{\odot k}$ that is the binding of columns $\bar{S}_{*,i_1}, \bar{S}_{*,i_2}, \dots, \bar{S}_{*,i_k}$ of \bar{S} . Also use this indexing scheme for $v \in \mathbb{R}^{\binom{d}{k}}$. Now for given $v \in \mathbb{R}^{\binom{d}{k}}$, the graph (or hyper-graph, for $k > 2$) G has edges $E = \{e \subset [\binom{d}{k}] \mid v_e \neq 0\}$, and vertices $V = \{i \mid i \in e \in E\}$.

We can also include singleton atomic vectors in the bundling, by including the all-ones vector $\vec{1}_m$ as an atomic vector, bound to each singleton. Note that approximate orthogonality holds also for these bindings, and the dimension is $\binom{d+1}{2}$, within a constant factor of $\binom{d}{2}$.

We prove Theorem 12 using this graphical view of $\bar{S}_\ell^{\odot 2}v$ in the following way. For given $\ell \in [m]$ we can write the Rademacher variables contributing to nonzero summands of $\bar{S}_\ell^{\odot 2}v$ as $X_\ell = (x_1, x_2, \dots, x_{|V|})$, for V the vertex set of the associated graph G . Also, we can express $\bar{S}_\ell^{\odot 2}v$ as a function

$$\sqrt{m} \cdot \bar{S}_{\ell,*}^{\odot 2}v = f(X_\ell), \text{ where } f(x) = \sum_{\{i,j\} \in E} x_i x_j. \quad (1)$$

Proof of Theorem 12. For $i \in [|V|]$, let function $g_i(x_1, \dots, x_{|V|})$ take value $x_i(1_{\{i\} \in E} + \sum_{j: (i,j) \in E} x_j)$. (Here $1_{\{i\} \in E}$ equals one when $\{i\} \in E$, and zero otherwise.) Then, for any $\ell \in [m]$, flipping the sign of x_i changes any $f(X_\ell)$ by no more than $2|g_i(X_\ell)|$. By Theorem 29, with $a_1, \dots, a_{\deg_G(i)} = 1$ and $t = \sqrt{6 \log(|E|m/\delta)}$, we have

$$\Pr \left[2|g_i(X_\ell)| > 2\sqrt{6 \deg_G(i) \cdot \log(2|E|m/\delta)} \right] < \frac{\delta^3}{8|E|^3 m^3}. \quad (2)$$

Let \mathcal{E} be the event that these upper bounds hold for all $\ell \in [m], i \in V$. Then taking the union bound over all $m|V|$ such $g_i(X_\ell)$, event \mathcal{E} occurs with failure probability at most

$$\delta_{\mathcal{E}} \equiv \frac{\delta^3}{4|E|^2 m^2},$$

noting that $2|E| \geq |V|$, since each vertex occurs in some edge, and at most two vertices occur in one edge.

For $\ell \in [m]$, let function $\check{f}(X_\ell)$ be equal to $f(X_\ell)$ when \mathcal{E} holds, and be zero otherwise. By McDiarmid's Inequality, Theorem 25,

$$\begin{aligned} \Pr[|\check{f}(X_\ell) - \mathbb{E}[\check{f}(X_\ell)]| \geq t] &\leq 2 \exp \left(\frac{-2t^2}{\sum_{i \in [|V|]} (2\sqrt{6 \deg_G(i) \cdot \log(|E|m/\delta)})^2} \right) \\ &= 2 \exp \left(-\frac{t^2}{12|E| \log(|E|m/\delta)} \right). \end{aligned}$$

From Proposition 2.5.2 of [36], therefore, for all $\ell \in [m]$, $\check{f}(X_\ell) - \mathbb{E}[\check{f}(X_\ell)]$ is a sub-Gaussian random variable, with proxy variance within a constant factor of at most

$$\sigma_{\check{f}}^2 \equiv 12|E| \log(|E|m/\delta).$$

Let $\bar{f} \equiv \mathbb{E}[\check{f}(X)]$, for Rademacher X . Since $\mathbb{E}[f(X)] = 0$, we have

$$\begin{aligned} |\bar{f}| &= |\mathbb{E}[\check{f}(X) \mid \mathcal{E}] \Pr[\mathcal{E}] + \mathbb{E}[\check{f}(X) \mid \neg \mathcal{E}] \Pr[\neg \mathcal{E}]| \\ &= |\mathbb{E}[f(X) \mid \mathcal{E}] \Pr[\mathcal{E}] + 0| \\ &= |\mathbb{E}[f(X)] - \mathbb{E}[f(X) \mid \neg \mathcal{E}] \Pr[\neg \mathcal{E}]| \\ &\leq |0 - \mathbb{E}[f(X) \mid \neg \mathcal{E}] \delta_{\mathcal{E}}| \\ &\leq |E| \delta_{\mathcal{E}}, \end{aligned} \quad (3)$$

since $|f(X)| \leq |E|$.

Let $\check{F} \equiv \frac{1}{m} \sum_{\ell} \check{f}(X_{\ell})^2$, and $\check{F}_c \equiv \frac{1}{m} \sum_{\ell} (\check{f}(X_{\ell}) - \bar{f})^2$. Using Exercise 2.7.10 and Corollary 2.8.3 of [36], it follows that

$$\Pr[|\check{F}_c - \mathbb{E}[\check{F}_c]| > t] \leq 2 \exp \left(-cm \min \left(\frac{t^2}{\sigma_f^4}, \frac{t}{\sigma_f^2} \right) \right).$$

For $t = \varepsilon|E|/2 < \sigma_f^2$, the upper bound is $2 \exp(-cm\varepsilon^2 / \log(|E|m/\delta)^2)$, for a different constant c , so there is $m = O(\varepsilon^{-2} \log(|E|/\varepsilon\delta)^3)$ such that

$$\Pr[|\check{F}_c - \mathbb{E}[\check{F}_c]| > \varepsilon|E|/2] \leq \delta/2. \quad (4)$$

We have a tail estimate for \check{F}_c , but not for \check{F} or $\|P^{\odot 2}v\|^2 = \frac{1}{m} \sum_{\ell} f(X_{\ell})^2$. We have

$$\begin{aligned} \check{F}_c - \mathbb{E}[\check{F}_c] &= \frac{1}{m} \sum_{\ell} (\check{f}(X_{\ell}) - \bar{f})^2 - \mathbb{E}[\check{f}(X_{\ell}) - \bar{f}]^2 \\ &= \check{F} - \mathbb{E}[\check{F}] + \frac{1}{m} \sum_{\ell} -2\check{f}(X_{\ell})\bar{f} + \bar{f}^2 + 2\mathbb{E}[\check{f}(X_{\ell})\bar{f}] - \bar{f}^2 \\ &= \check{F} - \mathbb{E}[\check{F}] + 2\bar{f}^2 - \frac{2}{m}\bar{f} \sum_{\ell} \check{f}(X_{\ell}). \end{aligned}$$

Using (3) and $|f(X)| \leq |E|$, we have

$$|\check{F} - \mathbb{E}[\check{F}]| \leq |\check{F}_c - \mathbb{E}[\check{F}_c]| + 4\delta_{\mathcal{E}}|E|^2. \quad (5)$$

We can apply Lemma 26 to $\bar{S}^{\odot 2}v$ and \check{F} , as f and g in that lemma, using that $\check{F} = \|\bar{S}^{\odot 2}v\|^2$ with failure probability at most $\delta_{\mathcal{E}}$, and that $\|\bar{S}^{\odot 2}v\|^2 \leq |E|^2$. Using $t = \varepsilon\|v\|^2/2 + 4\delta_{\mathcal{E}}|E|^2$ in that lemma, together with (5) and (4), we have

$$\begin{aligned} \Pr[|\|\bar{S}^{\odot 2}v\|^2 - \|v\|^2| > \varepsilon\|v\|^2/2 + 4\delta_{\mathcal{E}}|E|^2 + \delta_{\mathcal{E}}|E|^2] &\leq \Pr[|\check{F} - \mathbb{E}[\check{F}]| > \varepsilon\|v\|^2/2 + 4\delta_{\mathcal{E}}|E|^2] \\ &\leq \Pr[|\check{F}_c - \mathbb{E}[\check{F}_c]| > \varepsilon\|v\|^2/2] + \delta_{\mathcal{E}} \\ &\leq \delta/2 + \delta_{\mathcal{E}} \leq \delta. \end{aligned}$$

The theorem follows, using $5\delta_{\mathcal{E}}|E|^2 = 5\delta^3/4m^2 < \varepsilon\|v\|^2/2$, possibly adjusting m by a constant factor. □

4.3.2 Bundles of Bindings of Multiple Vectors

We can again hope to use Corollary 27 in this setting. However, to obtain the appropriate constants c_1, \dots, c_n to use in Corollary 27, we cannot directly apply Theorem 29; it is only a base case, for when $k = 2$. We proceed via induction on the maximum binding size.

Lemma 36. *Given hypergraph $G = (V, E)$, let $f(x_1, \dots, x_{|V|}) = \sum_{e \in E} \prod_{i \in e} x_i$, and let k be the maximum hyperedge size. Let $X = (X_1, \dots, X_{|V|})$ be a tuple of independent random Rademacher variables, i.e., each takes values $\{\pm 1\}$ with probability $\frac{1}{2}$. For $\delta_0 \leq O\left(1/\sqrt{|E|}\right)$:*

$$\Pr \left[|f(X)| \geq 2\sqrt{k! \cdot |E|} \log^{k/2} (k/\delta_0) \right] \leq \delta_0$$

Proof. We proceed by induction on k . When $k = 2$, we are done by Theorem 12.

To handle general k , we again apply the version of McDiarmid in Corollary 27. If we fix $(x_1, \dots, x_{|V|})$, changing the value of x_i again changes f by at most $\sum_{e \in E: i \in E} \prod_{j \in E: j \neq i} x_j$. The expression $\sum_{e \in E: i \in E} \prod_{j \in E: j \neq i} x_j$ encodes a hypergraph $G_i = (V_i, E_i)$ with maximum edge size $k - 1$, so by induction, we may assume:

$$\Pr \left[\left| \sum_{e \in E: i \in E} \prod_{j \in E: j \neq i} x_j \right| \geq 2\sqrt{(k-1)!|E_i|} \log^{(k-1)/2}(k/\delta_0) \right] \leq \frac{(k-1)\delta_0}{k}$$

Now, we invoke Corollary 27 with $c_i = 2\sqrt{(k-1)!|E_i|} \log^{(k-1)/2}(k/\delta_0)$.

$$\begin{aligned} \sum_{i=1}^{|V|} c_i^2 &= \sum_{i=1}^{|V|} 4(k-1)!|E_i| \log^{k-1}(k/\delta_0) \\ &= 4(k-1)! \log^{k-1}(k/\delta_0) \sum_{i=1}^{|V|} |E_i| \\ &\leq 4(k-1)! (\log^{k-1}(k/\delta_0)) \cdot k|E| \\ &= 4k! \cdot |E| \log^{k-1}(k/\delta_0) \end{aligned}$$

We can also set $t = \sqrt{2}\sqrt{k! \cdot |E|} \log^{k/2}(k/\delta_0)$. Then,

$$t^2 = 2k! \cdot |E| \log^k(k/\delta_0) \geq \frac{1}{2} \log(k/\delta_0) \sum_{i=1}^{|V|} c_i^2$$

Finally, setting $\delta = \frac{(k-1)\delta_0}{k}$, $M = |E|$, Corollary 27 implies:

$$\Pr \left[|f(X)| \geq \sqrt{2}\sqrt{k! \cdot |E|} \log^{k/2}(k/\delta_0) + \frac{(k-1) \cdot |E| \cdot \delta_0}{k} \right] \leq \frac{\delta_0}{k} + \frac{(k-1)\delta_0}{k} \leq \delta_0$$

To complete the proof, it suffices to show

$$\frac{(k-1) \cdot |E| \cdot \delta_0}{k} \leq (2 - \sqrt{2})\sqrt{k! \cdot |E|} \log^{k/2}(k/\delta_0)$$

However, given our upper bound on δ_0 , this holds for all values of k . \square

Corollary (Restatement of Corollary 13). *For scaled sign $\bar{S}^{\odot k} \in \{\pm \frac{1}{\sqrt{m}}\}^{\binom{d}{k}}$, $v \in \{0, 1\}^{\binom{d}{k}}$, and $i \in [m]$, there is $C > 0$ and $m = O(\varepsilon^{-2} C^k \log^k(k \|v\|_1 / (\varepsilon \delta)))$ such that*

$$\Pr[|\|\bar{S}^{\odot k} v\|^2 - \|v\|^2| > \varepsilon \|v\|^2] \leq \delta.$$

Just as there was a graphical view of $\bar{S}^{\odot 2} v$, we have a natural way to view $\bar{S}^{\odot k} v$ as a hypergraph $H = (V, E)$. For each $\ell \in [m]$, let $X_\ell = (x_1, x_2, \dots, x_{|V|})$ be the Rademacher variables contributing to the summands of $\bar{S}_\ell^{\odot k}, *v$, the ℓ -th entry of $\bar{S}^{\odot k} v$, and we can write

$$f(X_\ell) \equiv \sqrt{m} \bar{S}_\ell^{\odot k} = \sum_{(i_1, \dots, i_k) \in E} x_{i_1} x_{i_2} \cdots x_{i_k}$$

Proof. We will follow the same approach to the proof of Theorem 12. Due to the similarity of the proofs, we will omit steps here, but we will keep track of the parameters and calculations that differ.

Fix $i \in [|V|]$, and define $g_i(x_1, \dots, x_{|V|}) = x_i \sum_{e \in E: i \in e} \prod_{j \in e, j \neq i} x_j$. For each coordinate $\ell \in [m]$, flipping the sign of x_i will change $f(X_\ell)$ by at most $\sum_{e \in E: i \in e} \prod_{j \in e, j \neq i} x_j$. Lemma 36 gives us a high probability bound on the magnitude of $\sum_{e \in E: i \in e} \prod_{j \in e, j \neq i} x_j$:

$$\Pr \left[2|g_i(X_\ell)| > 2\sqrt{(k-1)! \cdot 3^{k-1} \cdot \deg_G(i) \cdot \log^{(k-1)}(k|E|m/\delta)} \right] \leq \frac{\delta^3}{4k|E|^3m^3}$$

Choosing this upper bound on the probability ensures that we obtain the same δ_ε as we do in Theorem 12. Defining $\check{f}(X_\ell)$ as before, Theorem 25 says

$$\Pr [| \check{f}(X_\ell) - \mathbb{E}[\check{f}(X_\ell)] | \geq t] \leq 2 \exp \left(- \frac{t^2}{k! \cdot 3^{k-1} \cdot |E| \log^{(k-1)}(k|E|m/\delta)} \right)$$

The proxy variance of $\check{f}(X_\ell) - \mathbb{E}[\check{f}(X_\ell)]$ is now

$$\sigma_{\check{f}}^2 \equiv k! \cdot 3^{k-1} \cdot |E| \log^{(k-1)}(k|E|m/\delta)$$

Defining \check{F} and \check{F}_c the same way, and choosing large enough $m = O(\varepsilon^{-2} \cdot k!^2 \cdot 3^{2k} \cdot \log^{k+1}(k|E|/(\varepsilon\delta)))$, we have

$$\Pr [| \check{F}_c - \mathbb{E}[\check{F}_c] | > \varepsilon|E|/2] \leq \delta/2$$

The remainder of the proof follows without changes after we fix the value of m . Regarding the dependence on k ,

$$\log(k!^2 3^{2k}) \leq \log(2\pi k(k/e)^{2k} e^{1/6k} 3^{2k}) = 2k \log(3k/e) + O(\log k) = O(k \log k),$$

using an inequality form of Stirling's approximation. The corollary follows. \square

5 Autocorrelation Associative Memories as Bundles of Robust Bindings

As discussed in §2.3, this section provides a new analysis of Hopfield networks, and proposes a Hopfield variant that is a space-efficient VSA bundling operation.

5.1 Analysis of Hopfield Networks via Concentration Bounds

Our analysis is akin to that of [37], but uses concentration bounds instead of large deviation bounds holding in the limit. The results are similar, in leading terms.

Theorem (Restatement of Theorem 14). *Given matrix $S \in \{\pm 1\}^{m \times n}$ with uniform independent entries, $j \in [n]$, and $\delta \in (0, 1]$. If $y \in \{0, \pm 1\}^m$ with $y^\top S_{*j} / \|y\| \geq 2\sqrt{n \log(2m/\delta)}$, then with failure probability at most δ , $\text{sign}_\geq((SS^\top - nI_m)y) = S_{*j}$. Here it is assumed that the coordinates i at which $y_i \neq S_{ij}$ are chosen before S , or without knowledge of it.*

Since $m \geq (y^\top S_{*j})^2 / \|y\|_1$, a necessary condition here is that $m \geq 4n \log(2m/\delta)$. When $y = S_{*j}$, $y^\top S_{*j} = m = \|y\|_1$, and $m \geq 4n \log(2m/\delta)$ suffices. There is

$$m = (1 + o(1))4n \log(2n/\delta) \text{ as } n/\delta \rightarrow \infty$$

such that $m \geq 4n \log(2m/\delta)$.

Proof. Let $I_{-j} \in \mathbb{R}^{n \times n}$ denote the identity matrix with its j 'th diagonal entry set to zero. We have

$$(SS^\top - nI_m)y = S_{*j}S_{*j}^\top y - y + (SI_{-j}S^\top - (n-1)I)y.$$

The first coordinate of $(SI_{-j}S^\top - (n-1)I)y$ is $\sum_{j' \in [n]} \sum_{\substack{1 < j'' \leq m \\ j' \neq j}} S_{1j'}S_{j'j''}y_{j''}$, which is a sum of at most $(n-1)(\|y\|_1 - 1) \leq n\|y\|_1$ independent ± 1 values. By Theorem 29, with failure probability at most $2\exp(-\alpha)$, this sum is bounded by $\sqrt{2\alpha n\|y\|_1}$ in magnitude. For $\alpha = \log(2m/\delta)$, with failure probability δ , every coordinate of $(SI_{-j}S^\top - (n-1)I)y$ is at most $\sqrt{2\alpha n\|y\|_1}$.

Assuming this bound, if $S_{*j}^\top y - 1 > \sqrt{2\alpha n\|y\|_1}$, then $S_{ij}S_{*j}^\top y - y_i$ agree in sign with S_{ij} , and will exceed $((SI_{-j}S^\top - (n-1)I)y)_i$ in magnitude, for all $i \in [m]$, and therefore $\text{sign}_\geq(SS^\top y) = S_{*j}$. For this it is enough if $S_{*j}^\top y / \sqrt{\|y\|_1} > 2\sqrt{\alpha n} = 2\sqrt{n \log(2m/\delta)}$, as claimed. \square

Relation to VSA: bundling of bindings Suppose m is even, and we can write $S_{*j} = [\begin{smallmatrix} x \\ y \end{smallmatrix}]$, for $x, y \in \{\pm 1\}^{m/2}$. Then assuming the above conditions, there is $m = O(n \log(n/\delta))$ so that the Hopfield output on input $[\begin{smallmatrix} x \\ 0 \end{smallmatrix}]$ or $[\begin{smallmatrix} 0 \\ y \end{smallmatrix}]$ will be S_{*j} . In this special case, the Hopfield network does a bit more than a bundle of pairwise bindings can do: it returns the other vector of a binding, without performing membership tests over a dictionary of vectors (cleanup). This should not be entirely surprising, since $[\begin{smallmatrix} x \\ y \end{smallmatrix}] [\begin{smallmatrix} x \\ y \end{smallmatrix}]^\top = [\begin{smallmatrix} xx^\top & xy^\top \\ yx^\top & yy^\top \end{smallmatrix}]$, and the diagonal entries of xy^\top and yx^\top form the Hadamard product vector (i.e. element-wise product vector) $x \circ y$, which is the MAP-I binding of x and y .

Looking at the weight matrix $W = \sum_{j=1}^n S_{*j}S_{*j}^\top$, the two particular diagonals observed above contain exactly the MAP-I bundling of pairwise bindings of MAP-I atomic vectors, of dimension equal to half the net size. Also, the outer product xy^\top is the binding operator for x and y proposed by [38], and the relation of this binding operator to the MAP-I binding as a reduced representation is well-known via [39].

As mentioned in the introduction, much of this discussion, including the weight matrix as a sum of outer products of the input vectors, the fixed-point condition for representation, the mapping to neural networks, and reconstruction from erasures, goes back at least to [23, 24, 25].

Thinning the weight matrix By Theorem 14, it suffices if $\|y\|_1 \geq 2n \log(2m/\delta)$ for the theorem's conclusion to apply, so that the S_{*j} matching y can be reconstructed. That is, for diagonal matrix $V \in \{0, 1\}^{m \times m}$, if $\|V y\|_1 \geq 2n \log(2m/\delta)$ is large enough, $\text{sign}_\geq(SS^\top V y) = S_{*j}$. We could regard this, for given V, y , as $\text{sign}_\geq(W y)$ for a matrix $W \equiv SS^\top V$ with $\|V\|_F^2$ nonzero columns: we erase columns of SS^\top , not entries of y . That is, if n vectors are to be stored, but the vector dimension is fixed at larger than $m \gg 2n \log(2m/\delta)$, the necessary number of stored entries is smaller than m^2 .

VSA_s, Autocorrelation Associative Memories, and modern Hopfield nets. A different neural network model was proposed in recent years by [40], sometimes called a *modern* Hopfield network, which also uses a dynamic process to produce its output. Here the output of an iteration is more “peaked;” for example, a version by [41] uses softmax when computing the next iterate. This model has a higher capacity than classical associative memories using sums of outer products. However, it stores all its input vectors explicitly, so that the main question is not whether the given vectors are *represented* (since they are stored), but under what circumstances the dynamic process *converges*. The number of entries stored in this model is $\Theta(mn)$, where (classic) associative networks store $\Theta(m^2)$, and VSAs store $\Theta(m)$. The different amounts of storage imply different capabilities:

- The modern Hopfield model gives a high-capacity way to do maximum inner product search on a set of vectors, using a neural network formalism.
- The associatron/original Hopfield model supports the reconstruction of a vector in a stored set of vectors from an erased or noisy version.
- VSAs support membership tests, telling us whether two given vectors are present as a bound pair in a set.

5.2 Hopfield±: Autocorrelation Associative Memories as VSAs

We can also use an AAM/Hopfield model (a sum of vector outer products) to do set intersection estimation, as in VSAs. Here we represent a bundle as the sum of outer products of a vector with itself, as in [38]. The key theorem, proven below, is the following.

Theorem (Restatement of Theorem 15). *Given $\varepsilon, \delta \in (0, 1]$, scaled sign matrix $\bar{S} \in \frac{1}{\sqrt{m}}\{\pm 1\}^{m \times d}$ with uniform independent entries, diagonal matrix $V \in \mathbb{R}^{d \times d}$, and diagonal matrix $D \in \{0, \pm 1\}^{d \times d}$ with uniform independent ± 1 diagonal entries. There is $m = O(\varepsilon^{-1} \log(d/\delta)^2)$ such that with failure probability δ , $\|\bar{S}VDS^\top\|_F^2 = (1 \pm \varepsilon)\|V\|_F^2$.*

Since \bar{S} is a JL projection matrix, it will, with high probability, preserve the norms of the columns of V , and multiplying by \bar{S}^\top on the right will preserve the norms of the rows of $\bar{S}V$. We can think of this as \bar{S} satisfying the JL property with respect to the operation $\bar{S}VDS^\top$. The novelty here is that the dependence of m on ε is ε^{-1} , not ε^{-2} ; on the other hand, $\bar{S}VDS^\top$ comprises m^2 values, not m . This is yet another route to preserving the norm of a vector, stored as the diagonal of V , using the same storage and speed of computation (up to log factors) as that of simply using a larger projection matrix on one side, as in MAP-I. In other words, we obtain a bundling operator with performance characteristics similar to those of MAP-I, but using fewer random bits.

This theorem is analogous to Lemma 3. The following is analogous to Corollary 5, and can be proven in exactly the same way. It implies in particular that for diagonal matrices X, Y representing sets, with 0/1 diagonal entries encoding element membership, the size of their intersection can be estimated accurately using their “Hopfield net” representations.

We have a direct analog of Corollary 5, stated below. Analogs of Corollary 4 and Theorem 6 also follow directly; we omit the proofs.

Corollary 37. *Under the conditions of Theorem 15 (the JL property for $\bar{S}VDS\bar{S}^\top$), for diagonal $X, Y \in \mathbb{R}^{d \times d}$, there is $m = O(\varepsilon^{-2} \log(d/\delta)^2)$ so that $\text{tr}((\bar{S}XDS\bar{S}^\top)(\bar{S}YDS\bar{S}^\top)) = \text{tr}(XY) \pm \epsilon \|X\|_F \|Y\|_F$ with failure probability δ .*

Note that $\text{tr}(XY)$ is here the Frobenius product of X and Y . We omit the proof; it is isomorphic to the proof of Corollary 5.

To prove Theorem 15, we will use the Hanson-Wright inequality. In its statement,

$$\|X\|_{\psi_2} = \inf\{K \mid \mathbb{E}(\exp(X^2/K^2)) \leq 2\}$$

is the sub-Gaussian norm of random variable X , which in our case, for a Rademacher variable, will be $1/\sqrt{\log 2}$.

Theorem 38 (Hanson-Wright inequality, [42]). *Let $x \in \mathbb{R}^d$ be a random vector with independent entries, $\mathbb{E}[x] = 0$, and $\|x_i\|_{\psi_2} \leq K$ for some positive constant K . Let A be an $n \times n$ matrix. Then for every $t \geq 0$,*

$$\Pr\{|x^\top Ax - \mathbb{E}[x^\top Ax]| > t\} \leq 2 \exp\left[-c \min\left(\frac{t^2}{K^4 \|A\|_F^2}, \frac{t}{K^2 \|A\|}\right)\right],$$

where c is some positive constant. In particular, $t = \frac{K^2}{c} \|A\|_F \log(2/\delta)$ yields a failure probability bound of at most δ , when $\log(1/\delta) \geq c$.

Proof of Theorem 15. Let $E = \bar{S}^\top \bar{S} - I$; since the diagonal entries of E are zero, we have

$$\begin{aligned} \|\bar{S}VDS\bar{S}^\top\|_F^2 &= \text{tr}(\bar{S}VDS\bar{S}^\top \bar{S}VDS\bar{S}^\top) = \text{tr}(VD(I+E)VD(I+E)) \\ &= \text{tr}(V^2 D^2) + 2 \text{tr}(V^2 D^2 E) + \text{tr}(VDEVDE) \\ &= \|V\|_F^2 + 0 + \text{tr}(VDEVDE) \\ &= \|V\|_F^2 + 0 + \sum_{i \in [d]} (VDE)_{i*} (VDE)_{*i} \\ &= \|V\|_F^2 + 0 + \sum_{i,j \in [d]} V_{ii} D_{ii} E_{ij} V_{jj} D_{jj} E_{ji} \\ &= \|V\|_F^2 + b^\top V(E \circ E)Vb, \end{aligned} \tag{6}$$

where in the last step $b \in \{\pm 1\}^d$ comprises the diagonal entries of D , and we use the symmetry of E . The simplifications also use the fact that V and D commute and D^2 is a projection matrix.

We will apply the Hanson-Wright inequality, for which we need to bound $\|V(E \circ E)V\|_F^2$. First, we bound the entries of E : each such entry is $\frac{1}{m}$ times a sum of m independent Rademacher values, and therefore from Theorem 29 is at most $\frac{1}{\sqrt{m}} \sqrt{2 \log(2/\delta_1)}$ with failure probability δ_1 . By applying a union bound to all $d(d-1)$ off-diagonal entries of E , we have that all such entries are at most $\frac{2}{\sqrt{m}} \sqrt{\log(2d/\delta_1)}$ with failure probability δ_1 . Assuming this event, the square of each entry is at most $\frac{4}{m} \log(2d/\delta_1)$. We have

$$\|V(E \circ E)V\|_F^2 = \sum_{i,j \in [d]} V_{ii}^2 V_{jj}^2 E_{ij}^4 \leq \frac{16 \log(2d/\delta_1)^2}{m^2} \sum_{i,j \in [d]} V_{ii}^2 V_{jj}^2 = \frac{16 \log(2d/\delta_1)^2}{m^2} \cdot \|V\|_F^4.$$

We will apply Theorem 38 with x and A of the theorem mapping to b and $V(E \circ E)V$. We have $\mathbb{E}_b[b^\top V(E \circ E)Vb] = 0$, since off-diagonal terms with $\mathbb{E}_b[b_i b_j \dots]$, $i \neq j$ are zero, and the diagonal entries of E are zero. The value of t in the last line of Theorem 38 translates here to

$$b^\top V(E \circ E)Vb \leq \frac{c}{\log(2)} \cdot \frac{4 \log(2d/\delta_1)}{m} \cdot \|V\|_F^2 \log(1/\delta_2)$$

with failure probability δ_2 , using $\|X\|_{\psi_2} = 1/\sqrt{2}$, for $X \sim \{\pm 1\}$. Putting this together with (6), using a union bound for the events with failure probabilities δ_1 and δ_2 , and reducing the precise bound above to $O()$ notation, yields the result. \square

6 Analysis of MAP-B

We will analyze membership testing for MAP-B, for bundles (§6.1), sequences of sets as encoded with rotations (§6.2), and bundles of bound key-value pairs (§6.3). Here being a key-value pair means that some restrictions are placed on members of a bound pair, in particular that the keys come from a set that is disjoint from the set of values, and so there is greater independence among the relevant random variables.

Recall that the MAP-B bundling operator is $\text{sign}(Sv)$, where S is a sign matrix, Def. 2, and the sign function takes a random ± 1 value when its argument is zero.

6.1 Bundling

6.1.1 Membership Test

We first consider testing membership in a MAP-B bundling of n atomic vectors.

Theorem (Restatement of Theorem 16). *For $v \in \{0, 1\}^d$, let $x = \text{sign}(Sv)$ be the MAP-B bundling of $n = \|v\|_1$ atomic vectors. Then for all $i \in [m]$ and $j \in \text{supp}(v)$, $\Pr[x_i S_{ij} = +1] = 1/2 + \Theta(1/\sqrt{n})$, as $n \rightarrow \infty$, and there is $m = O(n \log(d/\delta))$ such that with failure probability δ , $j \in [d]$ has $j \in \text{supp}(v)$ if and only if $x^\top S_{*j} = e_j^\top S \text{sign}(Sv)$ has $x^\top S_{*j} \geq \sqrt{2m \log(2d/\delta)}$.*

Note that MAP-B bundling is not associative, so analysis of this bundling operation is not the end of the story, as discussed in §6.1.2.

Proof. We consider $S_{*j}^\top x$ in the two cases where j is, and is not, in $\text{supp}(v)$. Fix some $\hat{j} \in \text{supp}(v)$, and let $a = S_{1\hat{j}}$ and $b = (Sv)_1 - a$, so that $x_1 = \text{sign}(a+b)$, and $a \text{sign}((a+b)) = \text{sign}(a(a+b))$ is a summand of $S_{*\hat{j}}^\top x$. We consider the cases where $n-1$ is even vs. odd. Let \mathcal{E} denote the event $\text{sign}(a(a+b)) > 0$.

Since the $n-1$ summands of $b = (Sv)_1 - a$ are i.i.d. Rademacher variables, the probability that $b = 0$ is, for $n-1$ even, equal to $\binom{2p}{p} \frac{1}{2^{2p}} = \frac{1}{\sqrt{\pi p}} (1 + O(1/p)) = \sqrt{\frac{2}{\pi n}} (1 + O(1/n))$, where $p = (n-1)/2$, using Stirling's approximation, or the related expression for the Catalan numbers. For $n-1$ even, when $b \neq 0$, $|b| \geq 2$, so $a+b > 0$, and $\Pr[\mathcal{E}|b \neq 0] = 1/2$. We have

$$\Pr[\mathcal{E}] = \Pr[\mathcal{E} | b = 0] \Pr[b = 0] + \Pr[\mathcal{E} | b \neq 0] \Pr[b \neq 0]$$

$$\begin{aligned}
&= \Pr[b = 0] + \frac{1}{2}(1 - \Pr[b = 0]) \\
&= \frac{1}{2} + \frac{1}{2}\sqrt{\frac{2}{\pi n}}(1 + O(1/n)) = \frac{1}{2} + \sqrt{\frac{1}{2\pi n}}(1 + O(1/n)).
\end{aligned}$$

When $n - 1$ is odd, b cannot be zero, while

$$\Pr[b = 1] = \Pr[b = -1] = \binom{n-1}{n/2-1} \frac{1}{2^{n-1}} = \frac{n/2}{n} \binom{n}{n/2} \frac{2}{2^n} = \frac{1}{\sqrt{\pi(n/2)}}(1 + O(1/n)).$$

Considering the rounding for the case $a + b = 0$, we have $\Pr[\mathcal{E} \mid b = \pm 1] = 3/2$. Therefore,

$$\begin{aligned}
\Pr[\mathcal{E}] &= \frac{3}{2} \Pr[b = \pm 1] + \frac{1}{2} \Pr[b \neq \pm 1] \\
&= \frac{1}{2} + \Pr[b = \pm 1] \\
&= \frac{1}{2} + \sqrt{\frac{2}{\pi n}}(1 + O(1/n)).
\end{aligned}$$

So

$$\begin{aligned}
\Pr[x_1^{(1)} x_1 = 1] &= \Pr[\text{sign}(a(a+b)) > 0] \\
&= \Pr[\mathcal{E}] \geq 1/2 + \sqrt{1/2\pi n}(1 + O(1/n)) \\
&> 1/\sqrt{7n} \text{ for large enough } n.
\end{aligned}$$

This applies to all coordinates of all vectors $S_{i,j}$ for $j \in \text{supp}(v)$, and inspection of the expressions shows the first claim of the theorem, $\Pr[x_i S_{ij} = +1] = 1/2 + \Theta(1/\sqrt{n})$ for such i, j .

For the remaining claim: we have that $x^\top S_{*j}$ for $j \in \text{supp}(v)$ is a sum of ± 1 independent values, with $+1$ having probability $1/2 + \Theta(1/\sqrt{n})$, and at least $1/2 + \sqrt{1/7n}$, for large enough n ; this implies expectation at least $m/\sqrt{7n}$. Hoeffding's inequality implies that $\Pr[x^\top S_{*j} - m/\sqrt{7n} < -\sqrt{2m \log(2d/\delta)}] \leq \delta/2d$. Now suppose $j \notin \text{supp}(v)$. Then using Hoeffding again, we obtain:

$$\Pr[x^\top S_{*j} > \sqrt{2m \log(2d/\delta)}] \leq \delta/2d.$$

Thus, there is $m = O(n \log(d/\delta))$ such that $m/\sqrt{7n} > 2\sqrt{2m \log(2d/\delta)}$, and therefore by a union bound for all $j \in [d]$, with failure probability at most δ , $x^\top S_{*j} > \sqrt{2m \log(2d/\delta)}$ if and only if $j \in \text{supp}(v)$. \square

6.1.2 Dependence on Depth

Instead of bundling a set of elements all at once, suppose instead that bundling is done as a sequence of operations. We will see that for some such sequences, with high depth, so much information is lost that accurate membership tests become impossible.

Lemma (Restatement of Lemma 17). *Given independent sign vectors $x^{(i)} \in \{\pm 1\}^m, i \in [r]$, construct vector x by setting $x \leftarrow x^{(1)}$, and for $j = 2, \dots, r$, setting $x \leftarrow \text{sign}(x + x^{(j)})$. Then, for $\ell \in [m]$,*

$$\Pr[x_\ell^{(1)} x_\ell = 1] = 1/2 + 1/2^r$$

Proof. We consider $x_1^{(1)} x_1$; the same analysis applies to $x_\ell^{(1)} x_\ell$ for $\ell > 1$. Let a denote $x_1^{(1)}$, and let $z_{(j)}$ denote the value of x_1 just after the assignment $x \leftarrow \text{sign}(x + x^{(j)})$ in computing x . Since $b \text{sign}(c + e) = \text{sign}(bc + be)$ for $b = \pm 1$, we have that

$$x_1 x_1^{(1)} = az_{(r)} = \text{sign}(az_{(r-1)}) + ax^{(r)}.$$

By induction on j with this base case, $az_{(r-j)} = \text{sign}(az_{(r-(j+1))}) + ax^{(r-j)}$, ending with $az_{(1)} = a^2 = 1$. Suppose inductively on j (in the other direction) that $az_{(j)}$ is $+1$ with probability $1/2 + 1/2^j$, respectively; this is true for $j = 1$, as noted. We have $az_{(j)} = \text{sign}(az_{(j-1)}) + ax^{(j)}$, and $ax^{(j)} = \pm 1$ with equal probability independent of $az_{(j-1)}$. Analysis of the four combinations $az_{(j-1)} = \pm 1, ax^{(j)} = \pm 1$ and their probabilities shows that the inductive step holds, that is, $az_{(j+1)}$ is $+1$ with probability $1/2 + 1/2^{j+1}$. In particular, $\Pr[x_1 x_1^{(1)} = az_{(r)} = +1] = 1/2 + 1/2^r$, as claimed. \square

Note that this property of $x_\ell x_\ell^{(1)}$ does not require the $x^{(i)}$ to be atomic vectors of the VSA. Considering such summands for $x^\top x^{(1)}$ leads to $\mathbb{E}[x^\top x^{(1)}] \approx m/2^r$, as compared to at least $m/\sqrt{7n}$ as in Theorem 16, with a corresponding change in m needed to obtain effective membership testing. Suppose all the $x^{(i)}$ are bundles, and x is the root of a tree of bundlings of a total of n vectors. Then $x^{(1)}$ is a leaf of a tree of bundling operations of depth at least r , with possibly $n = r$, when all $x^{(i)}$ involved with $x^{(1)}$ are atomic; $n = 2^r$, when x is the root of a complete binary tree of depth r ; or $n > 2^r$, when $x^{(1)}$ is not at the maximum depth, or when a single bundling operation involves more than two vectors. Thus for membership testing to be effective, m might need to be at large as 4^n , or as small as $\tilde{O}(n)$, depending on operation depth in computing x .

The following lemma puts $x^{(1)}$ in a more general bundle.

Corollary 39. *Given independent sign vectors $x^{(i)} \in \{\pm 1\}^m$ for $i \in [n']$ and $y^{(j)} \in \{\pm 1\}^m$ for $j \in [r]$, construct vector x by setting $x \leftarrow \text{sign}(\sum_{i \in n'} x^{(i)})$, and then for $j = 1, \dots, r$, setting $x \leftarrow \text{sign}(x + y^{(j)})$. Then, for $\ell \in [m]$,*

$$\Pr[x_\ell^{(1)} x_\ell = 1] = \frac{1}{2} + \frac{1}{2^r} \Theta\left(\frac{1}{\sqrt{n}}\right)$$

Proof. Combine the analysis of Theorem 16 with the lemma just above. \square

Note that this corollary covers any sequence of operations yielding a vector of the form $x^{(1)} \oplus y$, that is $x^{(1)}$ bundled with y , regardless of how y was computed in the MAP-B algebra.

6.1.3 Testing for Empty Intersection

In this section, rather than estimating set intersection size, we aim for bounds on m so that we can distinguish between nonempty and empty set intersections. Estimating the set intersection *size* will depend on a rather complicated convolution of Rademacher random variable; the question of distinguishing emptiness has a much cleaner analysis.

Throughout this section, we assume that the elements comprising X and Y were all bundled during the same operation. In other words, they correspond to a depth-1 bundling tree, in the language of the previous section.

Lemma 40. *Let $X, Y \subseteq [d]$, and use x and y to denote their respective MAP-B vectors. If we choose dimension $m \geq \Omega(\log(1/\delta) \cdot |X||Y|)$, we can distinguish between the cases $|X \cap Y| = 0$ and $|X \cap Y| \geq 1$, using the criterion of whether $x^T y$ is smaller or greater than $\sqrt{2m \log(2/\delta)}$.*

Proof. Let $v, w \in \{0, 1\}^d$ be characteristic vectors for the sets $X, Y \subseteq [d]$. First, if $|X \cap Y| = 0$, their MAP-B bundles $x = \text{sign}(Sv)$ and $y = \text{sign}(Sw)$ are independent, and for any coordinate $\ell \in [m]$:

$$\mathbb{E}[x_\ell y_\ell] = \Pr[x_\ell y_\ell = 1] - \Pr[x_\ell y_\ell = -1] = 0$$

Using Theorem 29, we conclude that with probability $1 - \frac{\delta}{2}$, we satisfy $x^T y \leq \sqrt{2 \log(2/\delta)} \cdot m$.

Now, suppose $|X \cap Y| = 1$. Then, we can use e^* to denote the standard basis vector that represents the element in their intersection. Let $x = \text{sign}(Sv)$ and $y = \text{sign}(Sw)$ be the MAP-B bundles representing X and Y . (Here, S is a random sign matrix; see Definition 2.)

Since all coordinates within x are independent of each other (and likewise for y), it suffices to understand the distribution of a single coordinate. Fix $\ell \in [m]$. We will study the quantities $\Pr[x_\ell y_\ell = 1]$ and $\Pr[x_\ell y_\ell = -1]$ to eventually obtain a concentration bound for $x^T y$.

Let $Z^{(X)} = (Se^*)_\ell + \sum_{i \in X \setminus Y} Z_i^{(X)}$, where the $\{Z_i^{(X)}\}_{i=1}^m$ are independent Rademacher variables coming from the ℓ -th coordinates of the atomic vectors that were bundled to form X . Define $Z^{(Y)}$ similarly for Y , and let $X' = Z^{(X)} - (Se^*)_\ell$ and $Y' = Z^{(Y)} - (Se^*)_\ell$.

First, assume $|X \setminus Y|$ and $|Y \setminus X|$ are both even. The other cases follow similarly; the only change to track is that when $|X \setminus Y|$ (or $|Y \setminus X|$) is odd, $Z^{(X)}$ (resp. $Z^{(Y)}$) could be 0, and we have a $\frac{1}{2}$ chance of $Z^{(X)}$ (resp. $Z^{(Y)}$) being positive and a $\frac{1}{2}$ chance it is negative.

$$\begin{aligned} \Pr[x_\ell = y_\ell = 1] &= \Pr[Z^{(X)} = Z^{(Y)} = 1] \\ &= \Pr[X' \geq 0, Y' \geq 0] \cdot \Pr[(Se^*)_\ell = 1] + \Pr[X' \leq 0, Y' \leq 0] \cdot \Pr[(Se^*)_\ell = -1] \\ &= \Pr[X' \geq 0] \cdot \Pr[Y' \geq 0] \end{aligned}$$

We obtain the following equations similarly, again when $|X \setminus Y|$ and $|Y \setminus X|$ are even.

$$\begin{aligned} \Pr[x_\ell = 1, y_\ell = -1] &= \Pr[X' \geq 0] \cdot \Pr[Y' < 0] \\ \Pr[x_\ell = -1, y_\ell = 1] &= \Pr[X' < 0] \cdot \Pr[Y' \geq 0] \\ \Pr[x_\ell = y_\ell = -1] &= \Pr[X' < 0] \cdot \Pr[Y' < 0] \end{aligned}$$

Combining these terms, the quantity $\Pr[x_\ell y_\ell = 1] - \Pr[x_\ell y_\ell = -1]$ is equal to:

$$(\Pr[X' \geq 0] - \Pr[X' < 0]) \cdot (\Pr[Y' \geq 0] - \Pr[Y' < 0]) = \Pr[X' = 0] \cdot \Pr[Y' = 0] \quad (7)$$

Again using the fact that $\binom{2p}{p} \frac{1}{2^{2p}} = \frac{1}{\sqrt{\pi p}}(1 + O(1/p)) = \sqrt{\frac{2}{\pi n}}(1 + O(1/n))$ (which was also used in the membership test), we have $\Pr[x_\ell y_\ell = 1] - \Pr[x_\ell y_\ell = -1] \geq \Omega\left(\frac{1}{\sqrt{|X| \cdot |Y|}}\right)$.

Define $p \equiv C' \cdot \frac{1}{\sqrt{|X| \cdot |Y|}}$, so $\Pr[x_\ell y_\ell = 1] \geq \frac{1+p}{2}$. Applying the Chernoff bound for a sum of m Rademachers, we have:

$$\Pr\left[(x^\top y \geq \frac{m}{2} + \frac{pm}{2} - \sqrt{2 \log(2/\delta) \cdot m}\right] \geq 1 - \frac{\delta}{2}$$

In order to distinguish between the two cases, we require $\frac{pm}{2} \geq 2\sqrt{2 \log(2/\delta) \cdot m}$, so we need to choose $m \geq \Omega\left(\frac{\log(2/\delta)}{p^2}\right)$. \square

Remark 41. If we have $|X| = n$ and $|Y| = 1$, and enforce a failure probability of $\frac{\delta}{d}$ (so that we can union bound over all atomic vectors that represent $[d]$), we recover the result of Lemma 6.1.

6.2 Rotations

Here we consider membership testing, leveraging Theorem 16 in a simple way.

Theorem (Restatement of Theorem 18). *Given a sign matrix $S \in \mathbb{R}^{m \times d}$ and rotation matrix $R \in \mathbb{R}^{m \times m}$, and integer length L . Recall (Def. 8) that $S_{R,L} \equiv [S \ R S \ R^2 S \ \dots \ R^{L-1} S]$. For a sequence of d -vectors $v_{(0)}, v_{(1)}, \dots, v_{(L-1)} \in \{0, 1\}^d$, let $v \equiv [v_{(0)} \ v_{(1)} \ \dots \ v_{(L-1)}]$, let $x = \text{sign}(S_{R,L}v)$, and let $n = \|v\|_1$. Then there is $m = O(Ln \log(Ld/\delta))$ such that with failure probability at most δ , $j \in [Ld]$ has $j \in \text{supp}(v)$ if and only if $x^\top S_{*,j \% d} \geq 2\sqrt{m \log(Ld/\delta)}$, where $j \% d \equiv 1 + (j-1) \bmod d$.*

Proof. Consider

$$x^\top S_{*,j \% d} = \sum_{i \in [m]} x_i S_{i,j \% d} = \sum_{i \in [m]} S_{i,j \% d} (S_{R,L})_{i,*} v = 1 + \sum_{i \in [m]} S_{i,j \% d} ((S_{R,L})_{i,*} v - S_{i,j \% d}).$$

The random variables of S that appear in $S_{i,j \% d} ((S_{R,L})_{i,*} v - S_{i,j \% d})$ cannot appear in

$$S_{i+L,j \% d} ((S_{R,L})_{i+L,*} v - S_{i+L,j \% d}),$$

since the appearances of a given $S_{i,j}$ due to shifting in $S_{R,L}$ only span L rows. That is, there are at most L blocks of at least $(m/L) - 1$ rows such that each block can be analyzed as in Theorem 16. We obtain, for a given block of rows, and after taking into account that only $(m/L) - 1$ rows are in a block, that there is $m = O(Ln \log(d/\delta))$ such that with failure probability δ , $j \in [d]$ has $j \in \text{supp}(v)$ if and only if the vectors \tilde{x} and \tilde{S}_{*j} corresponding to the block of rows have $\tilde{x}^\top \tilde{S}_{*j} \geq 2\sqrt{(m/L) \log(d/\delta)}$. By requiring failure probability at most δ/L , satisfied by $m = O(Ln \log(dL/\delta))$, the result follows. \square

6.3 Binding

Binding is done in MAP-B the same as in MAP-I, namely, as coordinate-wise product. Here we also consider membership test in a bundle of bindings, where again we assume that the bundling is done in one step, that is, a sum over the integers followed by the sign function.

6.3.1 Membership in Key-Value Pairs

We will show the following.

Theorem (Restatement of Theorem 20). *Let $v \in \{0, 1\}^{\binom{d}{2}}$ be such that $x = \text{sign}(S^{\odot 2}v)$ is a bundle of key-value pairs, as in Def. 19. Let $n = \|v\|_1$. Then there is $m = O(n \log(d/\delta))$ such that with failure probability at most δ , $j \in [\binom{d}{k}]$ has $j \in \text{supp}(v)$ if and only if $x^\top S_{*j}^{\odot 2} \geq 2\sqrt{m \log(d/\delta)}$.*

The conclusion of the theorem is much the same as that of Theorem 16. This is not a coincidence: the analysis of key-value pairs reduces to the same setting as that earlier lemma.

Proof. For $j \in [\binom{d}{2}]$, let $w(j) \in W, q(j) \in Q$ be the indices such that $S_{*,j}^{\odot 2} = S_{*,w(j)} \circ S_{*,q(j)}$. Let $\hat{j} \in \text{supp}(v)$. We have $\text{sign}(x^\top S_{*\hat{j}}^{\odot 2}) = \text{sign}(1 + (S^{\odot 2}v - S_{*,\hat{j}}^{\odot 2})^\top S_{*\hat{j}}^{\odot 2})$, and

$$S^{\odot 2}v - S_{*,\hat{j}}^{\odot 2} = \sum_{j \neq \hat{j}} S_{*,q(j)} \circ S_{*,w(j)}.$$

Since each $S_{*,q(j)}$ appears only once in the sum, the summands are independent sign vectors. (Whatever the relations among the $w(j)$.) So $x^\top S_{*,\hat{j}}^{\odot 2}$ satisfies the same conditions as does the same expression in the proof of Theorem 16, as does $x^\top S_{*,j'}^{\odot 2}$ for $j' \notin \text{supp}(v)$. Therefore the same conditions on m imply the same results on failure probability as in Theorem 16, and the lemma follows. \square

7 Sparse Binary Bundling and Bloom Filter Analysis via Concentration

We will analyze the VSA dimension needed for reliably estimating the size of the intersection of sets represented by Bloom filters (§7.1) and Counting Bloom filters (§7.2). In the latter, we actually consider a generalization to weighted sets.

7.1 Bloom Filters

In the VSA model described in this section, the atomic vectors are $x \in \{0, 1\}^m$ where for some k , $\|x\|_1 \leq k$, with the nonzero entries chosen randomly. As discussed in Def. 21, an atomic vector B_{*j} is created by performing k trials, in each trial picking $i \in [m]$ uniformly at random and setting $B_{ij} \leftarrow 1$. (It is possible to pick the same $i \in [m]$ twice, in which case we only perform the update once.) Bundling will be done with disjunction, so a set with characteristic vector $v \in \{0, 1\}^d$ is represented as $1 \wedge Bv$, meaning that the coordinate-wise minimum of Bv with 1 is taken.

This representation, and the resulting membership testing, has long been studied as used as *Bloom filters*, with many variations, including applications to *private* set intersection estimation. However, the narrow question of how to use dot products of Bloom filter representations (or other simple vector operations) to estimate set intersection size, is less well developed. It is outlined briefly in [28], and discussed in [43]. An analysis is given in [44],

where the assumption is made that the entries of Bv are independent of each other.² We will bound the error in estimating set intersections using Bloom filters in Theorem 22.

A key quantity for our analysis is the number of nonzeros in Bv as a function of $\|v\|_0$, when $v \in \{0, 1\}^d$. We will let $\|x\|_0$ denote the number of nonzeros of x , so $\|1 \wedge Bv\|_1 = \|Bv\|_0$. This includes real numbers y , so $\|y\|_0$ is one when $y \neq 0$, and 0 otherwise.

Lemma 42. *For $v \in \{0, 1\}^d$, let $n \equiv \|v\|_0$. Define $\kappa \equiv \|Bv\|_0$, and let $p_\ell \equiv (1 - 1/m)^{k\ell}$. Then $\mathbb{E}[\kappa] = m(1 - p_n)$. Moreover, letting $\tilde{m} \equiv -1/\log(1 - 1/m)$,*

$$1 - \frac{k\ell}{m-1} \leq p_\ell = \exp(-k\ell/\tilde{m}) \leq \exp(-k\ell/m) \quad (8)$$

Letting $h_{m,k}(z) \equiv \frac{-\tilde{m}}{k} \log(1 - \frac{z}{m})$, we have $h_{m,k}(\mathbb{E}[\kappa]) = h_{m,k}(m(1 - p_n)) = n$.

Here, we can think of $h_{m,k}$ as an estimator for $\|v\|_0$, accounting for collisions in Bv . It is not unbiased, as we do not have $\mathbb{E}[h_{m,k}(\kappa)] = n$, but $h_{m,k}(\kappa)$ will still be a *good* estimator if κ concentrates; luckily for us, it does, as shown below.

The definitions of \tilde{m} may also seem a bit curious; we use the following well-known inequalities.

$$\begin{aligned} \log(1+x) &\leq x \text{ for all } x \\ -\log(1-x) &\leq \frac{x}{1-x} \text{ for } x < 1 \end{aligned} \quad (9)$$

These imply

$$\frac{1}{m} \leq -\log(1 - \frac{1}{m}) \leq \frac{1/m}{1 - 1/m} = \frac{1}{m-1}, \text{ and so} \quad (10)$$

$$m-1 \leq \tilde{m} \leq m \quad (11)$$

of Lemma 42. Observe that for each of n vectors B_{*j} , there will be k independent trials generating random $i \in [m]$, so for $(Bv)_i$ to be zero, all kn independent trials need to miss index i . This happens for a single trial with probability $1 - 1/m$, and so the probability that all kn trials miss i is $(1 - 1/m)^{kn}$. It follows that the expected number of nonzeros

$$\mathbb{E}[\kappa] = \mathbb{E}[\|Bv\|_0] = \mathbb{E}\left[\sum_{i \in [m]} \|B_{i*}v\|_0\right] = \sum_{i \in [m]} \mathbb{E}[\|B_{i*}v\|_0] = m(1 - (1 - 1/m)^{kn}) = m(1 - p_n),$$

as claimed. To show (8), we use (9) and (10), which imply

$$1 - \frac{k\ell}{m-1} \leq \exp(-k\ell/(m-1)) \leq \left(1 - \frac{1}{m}\right)^{k\ell} = p_\ell \leq \exp(-k\ell/m),$$

as claimed. The last claim is immediate. \square

²This is a good approximation, but the approximation is not rigorously substantiated, so the results are correct only up to that assumption. See also [45] regarding difficulties in the analysis of Bloom filters.

Theorem (Restatement of Theorem 22). *Let $v, w \in \{0, 1\}^d$ represent sets X, Y respectively, and define the following counts:*

$$n \equiv |X \cap Y| = v \cdot w, \quad n_v \equiv |X \setminus Y| = \|v\|_0 - n, \quad n_w \equiv |Y \setminus X| = \|w\|_0 - n$$

Let $x = 1 \wedge Bv$ and $y = 1 \wedge Bw$, where $B \in \{0, 1\}^{m \times d}$ is a sparse binary matrix.

Assume WLOG $n_w \geq n_v$. Then for $\delta \in (0, 1)$ and $\varepsilon > 0$, there are $k = O(\varepsilon^{-1} \log(1/\delta))$ and $m = O(k\varepsilon^{-1}(n_v n_w + n^2 + \varepsilon(n + n_w)))$ such that $h_{m,k}(x \cdot y) = n \pm \epsilon$ with failure probability δ . Here, $h_{m,k}(z)$ (see Lemma 42) maps the Bloom filter output $1 \wedge Bz$ to an estimate of $\|z\|_0$.

When $\varepsilon < 1/2$, the integrality of n implies an exact result. Thus, the theorem implies that when n and n_v are $O(1)$, $m = O(kn_w)$ and $k = O(\log(1/\delta))$ suffice. This includes the case of membership testing, where $n_v = 1$.

The theorem also allows $\varepsilon > 1$, including $\varepsilon = \tilde{\varepsilon}n$, which allows us to estimate n up to relative error ε rather than additive error ε . In this case, $m = O(k\tilde{\varepsilon}^{-1}(n_v n_w/n + n) + kn_w)$ and $k = O(\max\{1, \tilde{\varepsilon}^{-1}n^{-1} \log(1/\delta)\})$ suffice.

Proof. Let $v^c = v \circ w$, where \circ denotes element-wise product, so $n = \|v^c\|_0$, and let

$$\kappa_\cap = \|Bv^c\|_0.$$

Let $x^c = 1 \wedge Bv^c$, $\tilde{x} = x - x^c$, $\tilde{y} = y - x^c$, and let

$$\kappa_\Delta \equiv \tilde{x} \cdot \tilde{y} = x \cdot y - \kappa_\cap,$$

noting that $\tilde{x} \cdot x^c = 0$ and $\tilde{y} \cdot x^c = 0$,

$$\begin{aligned} \tilde{x} \cdot \tilde{y} &= x \cdot y - x^c \cdot x - x^c \cdot y + x^c \cdot x^c \\ &= x \cdot y - (x^c \cdot \tilde{x} + x^c \cdot x^c) - (x^c \cdot \tilde{y} + x^c \cdot x^c) + x^c \cdot x^c \\ &= x \cdot y - x^c \cdot x^c \end{aligned}$$

In other words, we can rewrite $x \cdot y = \kappa \equiv \kappa_\cap + \kappa_\Delta$, where κ_\cap counts the 1s that x and y have in common due to elements in $\text{supp}(v) \cap \text{supp}(w)$, while κ_Δ counts the 1s common to x, y due to elements corresponding to the symmetric difference $\text{supp}(|v - w|) = \text{supp}(v) \Delta \text{supp}(w)$, that are not already counted in κ_\cap .

Recall that we defined $p_\ell \equiv (1 - 1/m)^{k\ell}$ in Lemma 42. Then,

$$p_n \equiv 1 - \frac{1}{m} \mathbb{E}[\kappa_\cap] = 1 - \frac{1}{m} \mathbb{E}[\|Bv\|_0], \quad p_{nv} \equiv 1 - \frac{1}{m} \mathbb{E}[\|Bv\|_0], \quad p_{nw} \equiv 1 - \frac{1}{m} \mathbb{E}[\|Bw\|_0]$$

Using Lemma 42 and (8), and letting $p_{vw} \equiv (1 - p_{nv})(1 - p_{nw})$,

$$\begin{aligned} \mathbb{E}[\kappa_\cap] &= m(1 - p_n) \\ \mathbb{E}[\kappa_\Delta] &= mp_n p_{vw}, \text{ and } p_{vw} \leq \frac{kn_v}{m-1} \cdot \frac{kn_w}{m-1} = \frac{k^2 n_v n_w}{m^2} (1 + O(1/m)). \end{aligned} \tag{12}$$

where the latter is due to the fact that the probability that given entries \tilde{x}_i and \tilde{y}_i contribute to $\tilde{x} \cdot \tilde{y}$ is the probability that (a) the n entries of v^c yield $B_{i*}v^c = 0$, and (b) that both

entries \tilde{x}_i and \tilde{y}_i are nonzero. Note that the three events in (a) and (b) are independent, since $\text{supp}(v^c)$, $\text{supp}(v - v^c)$, and $\text{supp}(w - v^c)$ are disjoint.

Suppose, for some $\varepsilon_\cap, \varepsilon_T > 0$,

$$\begin{aligned}\kappa_\cap &\geq \mathbb{E}[\kappa_\cap] - \varepsilon_\cap \\ \kappa &\leq \mathbb{E}[\kappa] + \varepsilon_T,\end{aligned}\tag{13}$$

which holds with small failure probability, as shown below.

First, using these assumptions on κ_\cap and κ , we establish a lower bound on $h_{m,k}(\kappa)$. Since $\kappa_\Delta \geq 0$,

$$\begin{aligned}-\frac{k}{\tilde{m}} h_{m,k}(\kappa) &= \log\left(1 - \frac{\kappa}{m}\right) = \log\left(1 - \frac{\kappa_\cap + \kappa_\Delta}{m}\right) \\ &\leq \log\left(1 - \frac{\kappa_\cap}{m}\right) \\ &\leq \log\left(1 - \frac{\mathbb{E}[\kappa_\cap] - \varepsilon_\cap}{m}\right) \\ &= \log\left(p_n + \frac{\varepsilon_\cap}{m}\right) \\ &= \log(p_n) + \log\left(1 + \frac{\varepsilon_\cap}{mp_n}\right) \\ &\leq \log(p_n) + \frac{\varepsilon_\cap}{mp_n} \\ &\leq -\frac{k}{\tilde{m}}\left(n - \frac{\varepsilon_\cap}{kp_n}\right), \text{ using (11) and the definition of } p_\ell, \text{ and so} \\ h_{m,k}(\kappa) &\geq n - \frac{\varepsilon_\cap}{kp_n}.\end{aligned}$$

If we assume that $m \geq 2kn + 1$, then $p_n \geq 1/2$. We have

$$h_{m,k}(\kappa) - n \geq -\frac{\varepsilon_\cap}{kp_n} \geq -\frac{2\varepsilon_\cap}{k},\tag{14}$$

Again, using our assumptions on the sizes of κ_\cap and κ , we can obtain an upper bound on $h_{m,k}(\kappa)$

$$\begin{aligned}h_{m,k}(\kappa) &= \frac{-\tilde{m}}{k} \log\left(1 - \frac{\kappa}{m}\right) \\ &\leq \frac{-\tilde{m}}{k} \log\left(1 - \frac{\mathbb{E}[\kappa] + \varepsilon_T}{m}\right) \\ &= \frac{-\tilde{m}}{k} \log\left(p_n - p_n p_{vw} - \frac{\varepsilon_T}{m}\right) \\ &= n - \frac{\tilde{m}}{k} \log\left(1 - p_{vw} - \frac{\varepsilon_T}{mp_n}\right) \\ &\leq n - \frac{m}{k} \log\left(1 - p_{vw} - \frac{\varepsilon_T}{mp_n}\right) \text{ using (11)} \\ &\leq n + \frac{m}{k} p_{vw} + \frac{m}{k} \frac{\varepsilon_T}{mp_n(1 - p_{vw})}, \text{ using (9)}\end{aligned}\tag{15}$$

Assume that

$$m \geq \max\{k\sqrt{2n_v n_w} + 1, 2kn + 1\}. \quad (16)$$

which includes the prior assumption on m . Then using (8) and (12),

$$1 - p_{vw} \geq 1 - \frac{kn_v}{m-1} \cdot \frac{kn_w}{m-1} \geq 1/2$$

so $p_n(1 - p_{vw}) \geq 1/4$. Therefore, from (15),

$$\frac{k}{m}(h_{m,k}(\kappa) - n) \leq p_{vw} + \frac{\varepsilon_T}{mp_n(1 - p_{vw})} \leq p_{vw} + \frac{4\varepsilon_T}{m},$$

and so

$$h_{m,k}(\kappa) - n \leq \left[\frac{kn_v n_w}{m} + \frac{4\varepsilon_T}{k} \right] (1 + O(1/m)), \text{ using (12).} \quad (17)$$

Both (14) and (17) control how close $h_{m,k}(\kappa)$ is to n , but they rely on the assumptions in (13). We now need to bound $\Pr[\kappa_\cap - \mathbb{E}[\kappa_\cap] \leq -\varepsilon_\cap]$ and $\Pr[\kappa - \mathbb{E}[\kappa] \geq \varepsilon_T]$, so that (13) holds with high probability.

Recall that $\kappa_\cap = \|Bv^c\|_0$. We can express κ_\cap as $\kappa_\cap(X_1, X_2, \dots, X_{kn})$, where each X_ℓ makes a random choice $i \in [m]$ and sets $B_{i*}v^c$ to one; such choices are made k times for each of the n entries of v^c that are equal to one. To apply Theorem 28, bounds on $B(\kappa_\cap)$ and the $\mathbf{Var}_i(\kappa_\cap)$ are needed.

Given choices for all other X_ℓ , a choice i for X_ℓ changes κ_\cap if and only if given those other choices, $B_{i*}v$ is equal to zero. The only effect of these other choices is the number of bins already with ones, that is, the number of i' with $B_{i'*}v^c = 1$. Given that r bins have ones, the expected value of κ_\cap with respect to the random choice X_ℓ is $1 - r/m$, and the most κ_\cap can differ from this is $1 - r/m \leq 1$, since it can hit one of those r bins that are already one. The variance $\mathbf{Var}_\ell(\kappa_\cap)$ is $r/m - (r/m)^2 \leq r/m \leq (kn - 1)/m$, the variance of a Bernoulli random variable with probability $1 - r/m$ of being one, and zero otherwise. Thus $\tilde{\sigma}(\kappa_\cap) \leq (kn)^2/m$.³ From Theorem 28, if $\varepsilon_\cap = k\varepsilon/4$ for given $\varepsilon > 0$, then

$$\begin{aligned} \Pr[\kappa_\cap - \mathbb{E}[\kappa_\cap] \leq -\varepsilon_\cap] &\leq \exp\left(-\frac{2\varepsilon_\cap^2}{\tilde{\sigma}(\kappa_\cap) + \varepsilon_\cap B(\kappa_\cap)/3}\right) \leq \exp\left(-\frac{2\varepsilon_\cap^2}{(kn)^2/m + \varepsilon_\cap/3}\right) \\ &= \exp\left(-\frac{2(k\varepsilon/4)^2}{(kn)^2/m + (k\varepsilon/4)/3}\right) = \exp\left(-\frac{\varepsilon^2}{8n^2/m + 2\varepsilon/3k}\right). \end{aligned} \quad (18)$$

Leaving aside for the moment the values needed for m and k , we consider next $\Pr[\kappa - \mathbb{E}[\kappa] \geq \varepsilon_T]$. Here from $\kappa = \kappa_\cap + \kappa_\Delta$, we can regard κ as the function of $2kn + 2kn_v + 2kn_w$ random variables, of which the first $2kn$, from κ_\cap , have $\tilde{\sigma}$ contribution at most $(kn)^2/m$ and $B \leq 1$. The next $2kn_v$, representing the choices made that result in \tilde{x} , each have the property that their mean and variance, as a function of the choices of all the other variables, depend only on the number of ones in \tilde{y} : the minimum mean is $1 - kn_w$, so the contribution

³Put in a common setting, the bound of [28] corresponds to putting into the tail estimate denominator a value of $kn \geq (kn)^2/m$ for $m \geq kn$, and the bound of [46] quoted in [45] corresponds to $m \geq (kn)^2/m$ for $m \geq kn$.

to B is at most $1 - kn_w \leq 1$; the maximum variance is $(kn_w/m)(1 - (kn_w/m)) \leq kn_w/m$. There are kn_v such variables, so the contribution to $\tilde{\sigma}$ is $(kn_v)(kn_w/m)$. Similarly, the last kn_w random choices have $B \leq 1$ and contribution to $\tilde{\sigma}$ of $(kn_w)(kn_v/m)$. So $B(\kappa) \leq 1$, and $\tilde{\sigma}(\kappa) \leq k^2(n^2 + 2n_v n_w)/m$. If $\varepsilon_T = k\varepsilon/4$, we have

$$\begin{aligned}\Pr[\kappa - \mathbb{E}[\kappa] \geq \varepsilon_T] &\leq \exp\left(-\frac{2\varepsilon_T^2}{\tilde{\sigma}(\kappa) + \varepsilon_T B(\kappa)/3}\right) \leq \exp\left(-\frac{2\varepsilon_T^2}{k^2(n^2 + 2n_v n_w)/m + \varepsilon_T/3}\right) \\ &= \exp\left(-\frac{2(k\varepsilon/4)^2}{k^2(n^2 + 2n_v n_w)/m + (k\varepsilon/4)/3}\right) \\ &= \exp\left(-\frac{\varepsilon^2}{8(n^2 + 2n_v n_w)/m + 2\varepsilon/3k}\right).\end{aligned}\tag{19}$$

If (19) yields a bound of $\delta/2$, (18) will too, and the total failure probability will be at most δ .

Assume WLOG that $n_w \geq n_v$. From (17), for the mean of κ to be at most ε , we must have $m \geq kn_v n_w / 2\varepsilon$. This implies that in (19), $8(n^2 + 2n_v n_w)/m + 2\varepsilon/3k \leq 8n^2/m + c_1\varepsilon/k$, for $c_1 = 32 + \frac{2}{3}$. For $8n^2/m$ to not dominate $c_1\varepsilon/k$ in the sum $8n^2/m + c_1\varepsilon/k$, we need $m \geq 8kc_1n^2/\varepsilon$, yielding $2c_1\varepsilon/k$ in the denominator, so that under these assumptions regarding m ,

$$\begin{aligned}\Pr[\kappa_\Delta - \mathbb{E}[\kappa_\Delta] \geq \varepsilon] &\leq \exp\left(-\frac{\varepsilon^2}{8(n^2 + 2n_v n_w)/m + 2\varepsilon/3k}\right) \\ &\leq \exp\left(-\frac{\varepsilon^2}{2c_1\varepsilon/k}\right) = \exp(-k\varepsilon/2c_1) \leq \delta/2 \text{ for } k = 2c_1 \log(2/\delta)/\varepsilon.\end{aligned}$$

With a similar bound for $\Pr[\kappa - \mathbb{E}[\kappa] \leq -\varepsilon]$, via (14), we have that $m \geq \frac{k}{\varepsilon}(n_v n_w/2 + 8c_1 n^2 + \varepsilon(n_v + n_w))$ with $k = 2c_1 \log(2/\delta)/\varepsilon$ suffices to obtain $h_{m,k}(x \cdot y) = n \pm \varepsilon$ with failure probability δ . The result follows. \square

7.2 Counting Bloom Filters

In another sparse binary model, bundling is done by addition instead of disjunction, so a bundle is simply Bv instead of $1 \wedge Bv$. In the data structures literature, this is a *counting* variant of a Bloom filter. Here B is chosen to be sparse in a slightly different way than for Bloom filters: each atomic vector B_{*j} for $j \in [m]$ has all vectors with k ones equally likely, or equivalently, is created by starting from a vector of all zeros, in each trial picking $i \in [m]$ uniformly at random, setting $B_{ij} \rightarrow 1$, until there are k nonzeros.

When the sparsity is block-structured, that is, an atomic m -vector has m divisible by k , and there are k blocks each with exactly one nonzero entry, then the resulting bundling is called a *count-min sketch* in the data structures literature, and the Sparse Block Codes model in the VSA literature. See [47] and [48] respectively for more information.

[47] showed that dot product estimation for two bundles can be done as a nonlinear operation: taking dot products of corresponding blocks and then the minimum of these k dot products. The resulting estimate X of $v \cdot w$ using Bv and Bw has $v \cdot w \leq X \leq v \cdot w + \varepsilon$ with failure probability δ , for $m = km'$ where $k = O(\log(1/\delta))$ and $m' = O(\|v\|_1 \|w\|_1 / \varepsilon)$. For $v, w \in \{0, 1\}^d$, the dimension m needed for estimating set intersection size has a smaller

dependence on ε , but possibly worse dependence on $\|v\|_1$, $\|w\|_1$, and $v \cdot w$ than what we showed for Bloom filters. This is because $\|v\|_1\|w\|_1 = (n_v + n)(n_w + n) \geq n_v n_w + n^2$, where n , n_v , and n_w are defined in Theorem 22.

Beyond the setting above, v and w may have entries that are nonnegative integers, corresponding to multi-sets (sets where each element appears with some multiplicity). Dot products for such multi-sets have applications in database operations. However, one could also consider an analog of set intersection for multi-sets where the multiplicity of an element in the intersection is the minimum of its multiplicities in the two intersected multi-sets. The size of the intersection, defined in this way, can also be estimated using bundles of sparse binary atomic vectors. This operation will be analyzed next. For $x, y \in \mathbb{R}^m$, let $x \wedge y$ denote the vector z with $z_i = \min\{x_i, y_i\}$. As discussed, on nonnegative vectors, we define the operation $x \wedge y \equiv \|x \wedge y\|_1 = \sum_{i \in [m]} \min\{x_i, y_i\}$. Note that $\|x - y\|_1 = \|x\|_1 + \|y\|_1 - 2(x \wedge y)$, analogous to $\|x - y\|_2^2 = \|x\|_2^2 + \|y\|_2^2 - 2(x \cdot y)$.

Theorem (Restatement of Theorem 23). *Let $v, w \in \mathbb{R}_{\geq 0}^d$. Let $K_b \equiv \|v - w\|_\infty \leq \max\{\|v\|_\infty, \|w\|_\infty\}$, and define:*

$$n \equiv v \wedge w, \quad n_v \equiv \|v\|_1 - n, \quad n_w \equiv \|w\|_1 - n,$$

Let $x = Bv$ and $y = Bw$, where $B \in \{0, 1\}^{m \times d}$ is a sparse binary matrix. Then, for $\delta \in (0, 1)$ and $\varepsilon > 0$, there are $k = O(K_b \varepsilon^{-1} \log(1/\delta))$ and $m = 12\pi^2 k \varepsilon^{-1} n_v n_w = O(K_b \varepsilon^{-2} n_v n_w \log(1/\delta))$ such that

$$\frac{1}{k}(x \wedge y) - (v \wedge w) \in [0, \epsilon)$$

with failure probability at most δ . Since $n_v + n_w = \|v - w\|_1$, $m = O(K_b \varepsilon^{-2} \|v - w\|_1^2 \log(1/\delta))$ also suffices (using the AM-GM inequality on $n_v n_w$). If $\|v\|_1, \|w\|_1$ are stored, then $\|v - w\|_1$ can be estimated up to additive ε with the same m .

Proof. Let $\tilde{v} \equiv v - (v \wedge w)$, $\tilde{w} \equiv w - (v \wedge w)$ and $\tilde{x} \equiv B\tilde{v}$, $\tilde{y} \equiv B\tilde{w}$. Note that $n_v = \|\tilde{v}\|_1$, $n_w = \|\tilde{w}\|_1$. Using $\min\{c + a, c + b\} = c + \min\{a, b\}$, we have

$$\begin{aligned} \frac{1}{k}(x \wedge y) &= \frac{1}{k}(Bv \wedge Bw) \\ &= \frac{1}{k}(B(v \wedge w) + B\tilde{v}) \wedge (B(v \wedge w) + B\tilde{w}) \\ &= \frac{1}{k}\vec{1}_m^\top B(v \wedge w) + \frac{1}{k}(B\tilde{v} \wedge B\tilde{w}) \\ &= v \wedge w + \frac{1}{k}(\tilde{x} \wedge \tilde{y}). \end{aligned} \tag{20}$$

It remains to bound $\frac{1}{k}(\tilde{x} \wedge \tilde{y})$. We have $\tilde{v} \circ \tilde{w} = 0$, so for every $i \in [m]$, $B_{i*}\tilde{v}$ is independent of $B_{i*}\tilde{w}$. Therefore,

$$\Pr[\tilde{x}_i \wedge \tilde{y}_i \geq z] = \Pr[\tilde{x}_i \geq z] \Pr[\tilde{y}_i \geq z]$$

Since $\|\tilde{v}\|_1 = n_v$, $\mathbb{E}[\tilde{x}_i] = kn_v/m$, and so by Markov's inequality $\Pr[\tilde{x}_i \geq z] \leq kn_v/(zm)$. Similarly, $\Pr[\tilde{y}_i \geq z] \leq kn_w/(zm)$. Using the identity $\mathbb{E}[Y] = \sum_{z \geq 1} \Pr[Y \geq z]$,

$$\mathbb{E}[\tilde{x}_i \wedge \tilde{y}_i] = \sum_{z \geq 1} \Pr[\tilde{x}_i \wedge \tilde{y}_i \geq z] = \sum_{z \geq 1} \Pr[\tilde{x}_i \geq z] \Pr[\tilde{y}_i \geq z]$$

$$\leq \sum_{z \geq 1} (kn_v/(mz))(kn_w/(mz)) = \zeta(2) \cdot \frac{k^2 n_v n_w}{m^2} = \frac{\pi^2}{6} \cdot \frac{k^2 n_v n_w}{m^2},$$

where $\zeta(2) = \sum_{z \geq 1} 1/z^2$ is the Riemann zeta function. Thus

$$\mathbb{E}[\tilde{x} \wedge \tilde{y}] \leq \frac{\pi^2}{6} \cdot \frac{k^2 n_v n_w}{m}. \quad (21)$$

It remains to show that $\tilde{x} \wedge \tilde{y}$ concentrates. We will use the Bernstein form of McDiarmid's inequality (Theorem 28), showing concentration of a function $f(X)$. Here $X \in [m]^{n_t}$ for $n_t \equiv k\|\tilde{v} + \tilde{w}\|_0 \leq k(n_v + n_w)$, and each X_r , for $r \in [n_t]$, maps to a column j of B where $\tilde{v}_j + \tilde{w}_j > 0$, and for random $i = X_r \in [m]$, B_{ij} is incremented by one. The function $f(X)$ is then $f(X) = B\tilde{v} \wedge B\tilde{w}$, where B is determined by X . To use Theorem 28, we need to bound $\tilde{\sigma}(f)$ and $B(f)$ of that theorem, bounding the effects of changes of single entries of X .

Suppose B' is the result of the choices of X , for all entries except for entry X_r , where X_r maps to column j , and to a random $I \in [m]$. Then the resulting $B = B' + e_I e_j^\top$, where $e_j \in \{0, 1\}^d$ (with the 1 in the j position) and $e_I \in \{0, 1\}^m$ (with the 1 in the I position) are natural basis vectors, and $Bv = B'v + e_I e_j^\top v = B'v + v_j e_I$.

Here $g_i(X, y)$ of Theorem 28 corresponds to $g(B', j, I) = (B' + e_I e_j^\top)\tilde{v} \wedge (B' + e_I e_j^\top)\tilde{w}$, and we need to bound, over all B' and j , $\mathbf{Var}_i[g(B', j, i)]$ and $\max_i |g(B', j, i) - \mathbb{E}_{i'} g(B', j, i')|$. Again noting that because addition distributes over minimization, we can let $x' \equiv B'\tilde{v} - (B'\tilde{v} \wedge B'\tilde{w})$ and $y' \equiv B'\tilde{w} - (B'\tilde{v} \wedge B'\tilde{w})$, and write

$$\begin{aligned} g(B', j, I) &= (B'\tilde{v} + e_I \tilde{v}_j) \wedge (B'\tilde{w} + e_I \tilde{w}_j) \\ &= [(B'\tilde{v})_I + \tilde{v}_j] \wedge [(B'\tilde{w})_I - \tilde{w}_j] + \sum_{i \neq I} (B'\tilde{v} \wedge B'\tilde{w})_i \\ &= [(B'\tilde{v})_I + \tilde{v}_j - ((B'\tilde{v})_I \wedge (B'\tilde{w})_I)] \\ &\quad \wedge [(B'\tilde{w})_I + \tilde{w}_j - ((B'\tilde{v})_I \wedge (B'\tilde{w})_I)] \\ &\quad + ((B'\tilde{v})_I \wedge (B'\tilde{w})_I) + \sum_{i \neq I} (B'\tilde{v} \wedge B'\tilde{w})_i \\ &= (x'_I + \tilde{v}_j) \wedge (y'_I + \tilde{w}_j) + (B'\tilde{v} \wedge B'\tilde{w}) \\ &= (B'\tilde{v} \wedge B'\tilde{w}) + \beta_{Ij}, \end{aligned} \quad (22)$$

where $\beta_{Ij} \equiv (x'_I + \tilde{v}_j) \wedge (y'_I + \tilde{w}_j)$.

Since the choices of I and j don't affect $(B'\tilde{v} \wedge B'\tilde{w})$, only β_{Ij} affects $\tilde{\sigma}(f)$ and $B(f)$. As $\tilde{v} \circ \tilde{w} = 0$, we first assume that $\tilde{v}_j > \tilde{w}_j = 0$. Under that assumption, since $x' \circ y' = 0$, either $\beta_{Ij} = 0$ or $\beta_{Ij} = y'_I \wedge \tilde{v}_j$, and so $\|\beta_{*j}\|_\infty \leq \|\tilde{v}\|_\infty$ for all j .

Allowing for the possibility that $\tilde{w}_j > \tilde{v}_j = 0$ and that sometimes $\beta_{ij} = 0$, we have

$$\begin{aligned} B(f) &= \max_{B', j, i} |g(B', j, i) - \mathbb{E}_{I'} g(B', j, I')| \\ &= \max_{B', j, i} |\beta_{ij} - \mathbb{E}_{I'} \beta_{I'j}| \quad \text{from (22)} \\ &\leq \max\{\|\tilde{v}\|_\infty, \|\tilde{w}\|_\infty\} = \|v - w\|_\infty = K_b. \end{aligned} \quad (23)$$

Also, under the assumption for given $j \in [d]$ that $\tilde{v}_j > \tilde{w}_j = 0$,

$$\begin{aligned}\mathbf{Var}_r(f) &= \sup_{B'} \mathbb{E}_I[(\beta_{Ij} - \mathbb{E}_{I'}\beta_{I'j})]^2 \leq \sup_{B'} \mathbb{E}_I[\beta_{Ij}^2] \leq \sup_{B'} \mathbb{E}_I[(y'_I \wedge \tilde{v}_j)^2] \text{ using } \tilde{v}_j > \tilde{w}_j = 0 \\ &\leq \sup_{B'} \tilde{v}_j \mathbb{E}_I[y'_I \wedge \tilde{v}_j] \leq \sup_{B'} \tilde{v}_j \mathbb{E}_I[y'_I] = \sup_{B'} \tilde{v}_j \|y'\|_1/m \\ &\leq k\tilde{v}_j \|\tilde{w}\|_1/m.\end{aligned}$$

Combining this with an analogous expression when $\tilde{w}_j > \tilde{v}_j = 0$, and summing over all X_r ,

$$\tilde{\sigma}(f) \leq 2k^2 \|\tilde{v}\|_1 \|\tilde{w}\|_1/m = 2k^2 n_v n_w/m. \quad (24)$$

We can now apply Theorem 28, scaling by k as in the theorem, and using $k = \frac{2K_b}{3}\varepsilon^{-1} \log(1/\delta)$ and $m = 12\pi^2 k\varepsilon^{-1} n_v n_w = 8\pi^2 \varepsilon^{-2} n_v n_w \log(1/\delta)$, to obtain

$$\begin{aligned}\Pr[\tilde{x} \wedge \tilde{y} > \mathbb{E}[\tilde{x} \wedge \tilde{y}] + k\varepsilon/2] &\leq \exp\left(-\frac{2(k^2\varepsilon^2/4)}{\tilde{\sigma}(f) + k\varepsilon B(f)/6}\right) \\ &\leq \exp\left(-\frac{k^2\varepsilon^2/2}{(2k^2 n_v n_w/m) + k\varepsilon K_b/6}\right) \quad \text{from (24), (23)} \\ &= \exp\left(-\frac{\varepsilon^2}{4n_v n_w/m + k^{-1}\varepsilon K_b/3}\right) = \exp\left(-\frac{\varepsilon^2}{n_v n_w/(3\pi^2 \varepsilon^{-2} n_v n_w \log(1/\delta)) + \varepsilon^2/2 \log(1/\delta)}\right) \\ &\leq \exp\left(-\frac{\varepsilon^2}{\varepsilon^2/2 \log(1/\delta) + \varepsilon^2/2 \log(1/\delta)}\right) = \delta.\end{aligned}$$

We also need (21) to bound

$$\mathbb{E}[\tilde{x} \wedge \tilde{y}] \leq \frac{\pi^2}{6} \cdot \frac{k^2 n_v n_w}{m} = \frac{\pi^2}{6} \cdot \frac{k^2 n_v n_w}{12\pi^2 k\varepsilon^{-1} n_v n_w} = k\varepsilon/2.$$

Putting these together,

$$\Pr[\tilde{x} \wedge \tilde{y} \geq k\varepsilon] \leq \delta,$$

which with (20) implies the result. \square

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