Sparse signal recovery and acquisition with graphical models

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<td><a href="http://dx.doi.org/10.1109/MSP.2010.938029">http://dx.doi.org/10.1109/MSP.2010.938029</a></td>
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<tr>
<td>Publisher</td>
<td>Institute of Electrical and Electronics Engineers (IEEE)</td>
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<tr>
<td>Version</td>
<td>Final published version</td>
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<tr>
<td>Accessed</td>
<td>Fri Dec 21 15:50:54 EST 2018</td>
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Many applications in digital signal processing, machine learning, and communications feature a linear regression problem in which unknown data points, hidden variables, or code words are projected into a lower dimensional space via

$$y = \Phi x + n.$$  

(1)

In the signal processing context, we refer to $x \in \mathbb{R}^N$ as the signal, $y \in \mathbb{R}^M$ as measurements with $M < N$, $\Phi \in \mathbb{R}^{M \times N}$ as the measurement matrix, and $n \in \mathbb{R}^N$ as the noise. The measurement matrix $\Phi$ is a matrix with random entries in data streaming, an overcomplete dictionary of features in sparse Bayesian learning, or a code matrix in communications [1]–[3].

Extracting $x$ from $y$ in (1) is ill posed in general since $M < N$ and the measurement matrix $\Phi$ hence has a non-trivial null space; given any vector $v$ in this null space, $x + v$ defines a solution that produces the same observations $y$. Additional information is therefore necessary to distinguish the true $x$ among the infinitely many possible solutions [1], [2], [4], [5]. It is now well known that sparse representations can provide crucial prior information in this dimensionality reduction; we therefore also refer to the problem of determining $x$ in this particular setting as the sparse signal recovery. A signal $x$ has a sparse representation $x = \Psi \alpha$ in a basis $\Psi \in \mathbb{R}^{N \times K}$ when $K \ll N$ coefficients of $\alpha$ can exactly represent or well approximate the signal $x$. Inspired by communications, coding, and information theory problems, we often refer to the application of $\Phi$ on $x$ as the encoding of $x$; the sparse signal recovery problem is then concerned with the decoding of $x$ from $y$ in the presence of noise. In the sequel, we assume the canonical sparsity basis, $\Psi = I$ without loss of generality.

INTRODUCTION

The sparse signal recovery problem has been the subject of extensive research over the last few decades in several different research communities, including applied mathematics, statistics, and theoretical computer science [1]–[3], [6]. The goal of this research has been to obtain higher compression rates; stable recovery schemes; low encoding, update, and decoding times; analytical recovery bounds; and resilience to noise. The momentum behind this research is well justified:
GMs ARE NOT ONLY USEFUL FOR REPRESENTING THE PRIOR INFORMATION ON SPARSE SIGNALS, BUT THEY ALSO LAY THE FOUNDATIONS FOR NEW KINDS OF SYSTEMS FOR THEIR ACQUISITION.

BACKGROUND

GRAPHICAL MODELS

We take a probabilistic, Bayesian approach to sparse signal recovery with GMs. We assume that \( x \) is a realization from a random process with a probability distribution function (pdf) \( f(x) \), which we call as the prior. The information in \( x \) is then transferred to the measurements \( y \) through a conditional pdf \( f(y|x) \). For instance, when the noise \( n \) is independent and identically distributed (i.i.d.) Gaussian with zero mean and variance \( \sigma^2 \), i.e., \( n_i \sim \mathcal{N}(n; 0, \sigma^2) \) for \( i = 1, \ldots, M \), we find that the conditional pdf is yet another Gaussian distribution, given by \( f(y|x) = \mathcal{N}(y; \Phi x, \sigma^2 I_{df \times df}) \), where \( I_{df \times df} \) is the \( M \times M \) identity matrix. To determine \( x \), we exploit Bayes’ rule to form the posterior pdf via \( f(x|y) = f(y|x)f(x)/f(y) \). Then, we can compute various point estimates of \( x \), denoted as \( \hat{x} \), such as the maximum a posteriori (MAP) estimate \( \hat{x} = \text{arg max}_x f(x|y) \), the mean estimate \( \hat{x} = \int x f(x|y) \text{d}x \), etc.

GRAPHICAL REPRESENTATIONS OF PDFs

GMs provide a convenient geometrical representation for describing joint probability distributions of multiple variables [3], [7]–[11]. They have been applied successfully in a wide variety of statistical problems, in fields as diverse as image processing, coding theory, pattern recognition, and artificial intelligence.

Here, we define some notation for GMs. Let \( G = (V, E) \) be a directed/undirected graph formed by a collection of vertices \( V \) and edges \( E \). Each vertex \( v \in V \) represents a random variable \( z_v \) (either discrete or continuous valued). An undirected edge \( e \in E \) indicates dependence between the corresponding pair of
random variables; that is, the conditional density of \( z_v \) given \( z_1, \ldots, z_{v-1}, z_{v+1}, \ldots \) is a function of only the neighbors connected to \( v \). A directed edge indicates that the conditional density of \( z_v \) is a function of only those variables with edges directed towards \( v \). Denote the random variables for any subset \( S \) of the vertices \( V \) as \( z_S \triangleq \{ z_v | v \in S \} \). A clique \( C \) is a fully connected subset of vertices, where there exists an edge \( e \in C \) connecting every pair of vertices in the subgraph.

A directed acyclic graph (DAG) is a directed graph without directed loops (so that for any \( v \), there are no directed paths that begin and end with \( v \)). If we denote the set of parents of node \( v \) as \( p(v) \), then it is easy to show that the pdf of a DAG can be factorized as

\[
p(z) = \prod_{v \in V} p(z_v | z_{p(v)}).
\]

An example is shown in Figure 1(a); this can be used to model a quadtree decomposition of radar images [9] or a multiscale wavelet decomposition of natural images [12].

In contrast, Figure 1(b) depicts an undirected graph with loops to represent the Ising model, where the variables \( s \subset z \) represent the latent connections between the signal coefficients \( x \subset z \). Similarly, Figure 1(c) illustrates an extension of the Ising model to the CS measurement setting, which we will revisit in the section “Structured Sparsity via GMs.” By defining an appropriate, nonnegative compatibility function \( \chi_C(z_C) \) for each clique \( C \subset G \), the Hammersley-Clifford theorem [7] enables the pdf of the graph to be written as

\[
p(z) = \frac{1}{Z} \prod_C \chi_C(z_C),
\]

where \( Z \) is the partition function that ensures that \( p(z) \) is properly normalized. The product in (3) is taken over all cliques \( C \) in the graph \( G \).

**INFERENCME MECANISMS**

We refer to the process of estimating local marginal distributions or other summary statistics of \( z \), such as the most probable configuration of \( f(x|y) \), as Bayesian inference.

Inference algorithms on GMs typically exploit the factorization properties (2) and (3) of probability distributions. By manipulating the intermediate factors, it is often possible to compute the likelihood of a particular \( z \) value in an efficient, distributed manner. This strategy is exploited by the sum-product algorithm (also known as belief propagation) and max-product (also known as min-sum) for tree-structured DAGs with rigorous estimation guarantees when the random variables live in a discrete probability space [7]. These algorithms iteratively pass statistical information, denoted as messages, among neighboring vertices and converge in finite number of steps. Such guarantees, unfortunately, do not extend to arbitrary DAGs; inference in DAGs is typically NP-hard [11].

The sum-product and max-product algorithms are routinely applied to GMs with cycles, leading to loopy belief propagation methods, even if their convergence and correctness guarantees for DAGs no longer hold in general [3], [11], [13]. Although there are certain local optimality guarantees associated with the fixed points of loopy belief propagation, there are a number of natural inference problems arising in various applications in which loopy belief propagation either fails to converge, or provides poor results. Loopy belief propagation is therefore an approximate inference method. Surprisingly, state-of-the-art algorithms for decoding certain kinds of error-correcting codes are equivalent to loopy belief propagation. We revisit this topic in the section “Graphical Models for Structured Measurements” to discover a crucial role sparse representations play in providing theoretical guarantees for such algorithms.

Approximate inference is also necessary in cases where the random variables are drawn from a continuous space, since corresponding marginal integrals needed for implementing Bayes’ rule cannot be analytically performed. Monte Carlo Markov chain sampling methods, such as importance sampling, Metropolis-Hastings, and Gibbs sampling, provide computational means of doing approximate inference. The idea is to represent the pdf by a discrete set of samples, which is carefully weighted by some evidence likelihood so that the inference is consistent, with guarantees typically improving with larger sample sizes. See [3] for further background.

Yet another approximate inference method is based on the calculus of variations, also known as variational Bayes (VB) [3], [8]. The quintessential VB example is the mean-field approximation, which exploits the law of large numbers.
to approximate large sums of random variables by their means. In particular, the mean-field approximation essentially decouples all the vertices in the graph, and then introduces a parameter, called a variational parameter, for each vertex. It then iteratively updates these variational parameters so as to minimize the cross-entropy between the approximate and true probability distributions. Updating the variational parameters then facilitates inference in an efficient and principled manner, often also providing bounds on the marginal likelihood to be calculated. Another special case of the VB approach is the well-known expectation-maximization (EM) algorithm for MAP and maximum likelihood estimation, which has been extremely successful in a number of applications [3], [8], [14].

**COMPRESSIVE SENSING**

**SPARSE SIGNAL REPRESENTATIONS**

No non-adaptive dimensionality reducing $\Phi$ can preserve all of the information in all signals. Hence, researchers restrict the application of $\Phi$ to not arbitrary signals $x \in \mathbb{R}^N$ but rather to some subset of $\mathbb{R}^N$, and in particular the set of sparse and compressible signals. A sparsity/compressibility prior is then exploited as a tie-breaker to distinguish the true signal among the infinitely many possible solutions of (1).

While sparse signals live in $\Sigma_K$, the coefficients of a compressible signal $x$, when sorted in order of decreasing magnitude, decay according to the following power law:

$$|x_{(i)}| \leq R i^{-\alpha}, \quad i = 1, \ldots, N,$$

where $I$ indexes the sorted coefficients, and $R > 0$ and $\alpha > 0$ are constants. In the CS setting, we call a signal compressible when $\alpha = 1$. Thanks to the power-law decay of their coefficients, compressible signals are well approximated by $K$-sparse signals in an appropriate norm. For instance, for all $r < 1$ and $0 < \epsilon \ll 1$, $||x - x_{(\epsilon)}||_r \leq \epsilon ||x||_r$ holds independent of $N$ for any $K \geq \lceil (r/\epsilon)^{1/(1-r)} \rceil$, where $||x||_r = (\sum_{i=1}^N |x_i|^r)^{1/r}$ is the $\ell_r$-norm, $x_{(\epsilon)} = \arg \min_{x, ||x||_r \leq K} \|x - x^{(\epsilon)}\|_r$ is the best $K$-sparse approximation of $x$ ($\rho \equiv 1$), and $||x||_0$ is a pseudonorm that counts the number of nonzeros of $x$ [15].

**INFORMATION PRESERVING PROJECTIONS**

The sparsity or compressibility of $x$ is not sufficient alone for distinguishing $x$ among all possible solutions to (1). The projection matrix $\Phi$ must also work in tandem with the signal priors so that recovery algorithms can correctly identify the true signal.

The restricted isometry property (RIP) assumption on $\Phi$ achieves this by requiring $\Phi$ to approximately preserve the distances between all signal pairs in the sparse signal set [5]. More formally, an $M \times N$ matrix $\Phi$ has the $K$-restricted isometry property ($K$-RIP) with constant $\epsilon_K < 1$ if, for all $x \in \Sigma_K$,

$$(1 - \epsilon_K)||x||_2^2 \leq \|\Phi x\|_2^2 \leq (1 + \epsilon_K)||x||_2^2.$$  

An alternative property is the restricted strong convexity (RSC) assumption, which is motivated by convex optimization arguments [16]. In general, the RSC assumption has an explicit dependence on the recovery algorithm’s objective function. For instance, if the recovery algorithm’s objective is to minimize the measurement error (e.g., $||y - \Phi x||_2$), RSC requires $||\Phi^T \Phi||_2$ to be strictly positive for all $x \in \Sigma_K$. In different contexts, other conditions on $\Phi$ are also employed with varying levels of restrictions, such as null space property, spark, and unique representation property [6].

While checking whether a measurement matrix $\Phi$ satisfies the $K$-RIP, RSC, etc., has been running time exponential in $K$ and $N$, random matrices with independent and identically distributed (i.i.d.) sub-Gaussian entries work with high probability provided $M = O(K \log(N/K))$. Random matrices also have a so-called universality property in that, for any choice of orthonormal basis matrix $\Psi$, $\Phi \Psi$ also has the $K$-RIP with high probability. This is useful when the signal is sparse in some basis $\Psi$ other than the canonical basis.

**TRACTABLE RECOVERY ALGORITHMS**

To recover the signal $x$ from $y$ in (1), we exploit our a priori knowledge of its sparsity or compressibility. For example, to recover strictly sparse signals when there is no measurement noise, we can seek the sparsest $x$ that agrees with the measurements $y$. While this optimization can recover a $K$-sparse signal from just $M = 2K$ compressive measurements, it is not a combinatorial, NP-hard problem, but also is not stable in the presence of noise [1].

Tractable recovery algorithms rely on conditions such as the RIP and RSC for stability and correctness and therefore require at least $M = \mathcal{O}(K \log(N/K))$ measurements. They can be grouped into two main camps: convex optimization and greedy approximation. The first camp relies on $\ell_1$-norm minimization as a convex relaxation of seeking sparse solutions

$$\hat{x} = \arg \min_{x} ||x||_1 \text{ s.t. } y = \Phi x.$$  

This optimization problem is known as basis pursuit and corresponds to a linear program that can be solved in polynomial time [1], [4], [5]. Adaptations to deal with additive noise in (1) have also been proposed; examples include basis pursuit with denoising (BPDN) and the least absolute shrinkage and selection operator (LASSO). The second camp finds the sparsest $x$ agreeing with the measurements $y$ through an iterative, greedy search over the coefficients. Example algorithms include iterative hard thresholding (IHT), compressive sampling matching pursuit (CoSaMP), and subspace pursuit (SP) [1].

Currently, convex optimization obtains the best recovery performance in theory, while its greedy counterparts, such as IHT, CoSaMP, and SP, offer desirable computational tradeoffs, e.g., $\mathcal{O}(M \log^2 N)$ versus $\mathcal{O}(M^2 N^{1.5})$ (interior point methods) [1]. Interestingly, algorithms in both camps have similar theoretical recovery guarantees from $M = \mathcal{O}(K \log(N/K))$ when the
measurement matrix $\Phi$ satisfies $K$-RIP with an algorithm dependent $\epsilon_{2K}$ (e.g., $\epsilon_{2K} < \sqrt{2} - 1$ for basis pursuit [5])

$$
\|x - \hat{x}\|_2 \leq C_1(2^{-1/2})\|x - x_K\|_1 + C_2\|n\|_2,
$$

which we refer to as an $\ell_2/\ell_1$ guarantee, where the subscripts are matched to the norms adjacent to the inequality. In (7), $\hat{x}$ is the algorithm output, $C_1$ and $C_2$ are algorithm-dependent constants, and $x_K$ is the signal-dependent best $K$-sparse approximation. The term $\|x - x_K\|_1$ is known as the irrecoverable energy. When the signals are compressible, we can never recover them fully under dimensionality reduction; we can only approximately recover them—and only when $r \leq 1$ in (4).

**GRAPHICAL MODELS FOR STRUCTURED SPARSITY**

While CS has the potential to revolutionize data acquisition, encoding, and processing in a number of applications, much work remains before it is ready for real-world deployment. In particular, for CS to truly live up its name, it is crucial that the theory and practice leverage concepts from state-of-the-art transform compression algorithms. In virtually all such algorithms, the key ingredient is a signal model for not just the coefficient sparsity but also the coefficient structure. As we saw in the “Background” section, GMs provide a natural framework for capturing such dependencies among sparse signal coefficients. Hence, we review below some of the GMs that are relevant for structured sparsity and the algorithms that result for sparse signal recovery.

**SPARSITY PRIORS**

Our first departure from the standard, deterministic CS approach is to adopt a more general, Bayesian viewpoint as the algorithm output, while allowing a large range of values with low probabilities to obtain a small number of large coefficients. While this is expected in principle, we also require a generative aspect for such priors to build up structured sparsity models; that is, their statistical realizations result in sparse or compressible signals. This, in turn, is crucial for statistical consistency in high-dimensional scalings of the sparse signal recovery problem.

Two-state mixture models are the canonical i.i.d. models for generating strictly sparse signals. Among mixture models, the spike-and-slab prior stipulates a density with a spike at zero surrounded symmetrically by a uniform distribution with specified boundaries. The mixture probability of the spike at zero approximately determines the percentage of zero coefficients of the signal, and the uniform distribution establishes the distribution of the signal coefficients on the signal support.

To model compressible signals, we can use compressible priors, whose statistical realizations exhibit the power-law decay in (4) [15]. For algorithmic recovery guarantees for CS, we must have $r \leq 1$ for such priors (cf., (4)). For instance, Table 1 demonstrates that $N$-sample i.i.d. realizations of generalized Pareto, Student’s $t$, Fréchet, and log-logistics distributions (each parameterized by a shape parameter $q > 0$ and a scale parameter $\lambda > 0$) are compressible with parameter $r = q$. There also exist non-i.i.d. compressible priors; multivariate Lomax distribution (MLD) provides an elementary example whose pdf is given by MLD \( (x; q, \lambda) \propto (1 + \sum_{i=1}^{N} \lambda^{-1}|x_i|^{-q})^{-q^{-N}} \) [15]. The compressibility parameter MLD is simply $r = 1$, irrespective of its shape parameter.

To illustrate how we can exploit probabilistic priors in sparse signal recovery, we focus on two compressible priors on $x$: MLD and Student’s $t$. While MLD is relatively unknown, the Student’s $t$ distribution has enjoyed tremendous attention in many fundamental problems, such as statistical modeling of natural images, relevance vector machines (RVMs) and automatic relevance determination, and dictionary learning. We consider the case when there is no noise; the observations are then given by $y = \Phi x$ with $M = O(K \log(N/K))$, which has infinitely many solutions for $x$, as discussed in the “Background” section. We know that such projections preserve the information of the largest $K$-coefficients of signal realizations. We will assume that the parameters of MLD and the Student’s $t$ priors are matched (i.e., the shape parameter of Student’s $t$ is one) so that the statistical realizations of both priors have the same decay profile.

**MLD AND BASIS PURSUIT**

We first exploit the MLD likelihood function for sparse signal recovery. For instance, when we ask...
for the solution that maximizes the MLD likelihood given \( y \) for \( \lambda = \lambda_i \), it is easy to see that we obtain the basis pursuit algorithm formulation in (6). In contrast, the conventional probabilistic motivation for the basis pursuit algorithm assumes that \( x \) is i.i.d. Laplacian, e.g., \( f(x) \propto \exp(-||x||/\lambda) \) for some \( \lambda \in \mathbb{R}^+ \). We then face the optimization problem (6), when we seek the most likely signal from the Laplacian prior given \( y \). Unfortunately, i.i.d. Laplacian realizations cannot be approximated as sparse since their compressibility parameter is \( r = \log N \), which is greater than 1 in general (cf. Table 1); it can be shown that \( ||x - x_k||_1 \leq \epsilon ||x||_1 \), requires \( K \geq (1 - \sqrt{\varepsilon})N \) with high probability [15]. Hence, while the \( \ell_1 \) minimization correctly recovers the sparse vectors from \( M = \mathcal{O}(K \log(N/K)) \), it seems that it does not correspond to an i.i.d. Laplacian prior on the sparse signal coefficients in a consistent Bayesian framework and may correspond to the MLD prior as this example demonstrates.

**STUDENT'S \( t \) AND ITERATIVE REWEIGHTED LEAST SQUARES**

We now exploit the Student's \( t \) likelihood function for sparse signal recovery, similar to MLD likelihood function above

\[
\hat{x} = \max_{x'} f(x) = \min_{x'} \sum_j \log(1 + \lambda^{-2}x_j^2), \text{ s.t. } y = \Phi x'.
\]  

Unfortunately, (8) is a nonconvex problem. However, we can circumvent the nonconvexity in (8) using a simple variational Bayes idea where we iteratively obtain a tractable upperbound on the log-term in (8) using the following inequality: \( \forall u, v \in (0, \infty), \log u \leq \log v + u/v - 1 \). After some straightforward calculus, we obtain the iterative algorithm below, indexed by \( k \), where \( \hat{x}_{(k)} \) is the \( k \)th iteration estimate (\( \hat{x}_{(0)} = 0 \))

\[
\hat{x}_{(k)} = \min_{x'} \sum_j w_{(k)} x_j^2, \text{ s.t. } y = \Phi x'; \text{ where } w_{(k)} = (\lambda^2 + x_j^2)^{-1}.
\]  

The decoding scheme in (9) is well known as iterative reweighted least squares (IRLS), where each iteration has an analytical solution [19].

Both priors in the above algorithms are trying to approximate their signal realizations, which have the same decay profile, and yet result in radically different algorithms. Both schemes have provable recovery guarantees; however, they differ in terms of their computational costs: \( \mathcal{O}(M^2N) \) (IRLS) versus \( \mathcal{O}(M^2N^{1.5}) \) (BP).

**STRUCTURED SPARSITY VIA GMs**

Compressible priors provide a natural launching point for incorporating further structure among the sparse signal coefficients. Here, by structure, we specifically mean the probabilistic dependence and independence relationships among sparse signal coefficients as summarized by directed and undirected graphs. Such relationships are abundant in many diverse problems, such as speech recognition, computer vision, decoding of low-density parity-check codes, modeling of gene regulatory networks, gene finding, and diagnosis of diseases. GMs also provide powerful tools for automatically learning these interactions from data. While learning GMs is an active research area, it is beyond the scope of this article.

**TREE GRAPHS**

Wavelet transforms sparsify piecewise smooth phenomena, including many natural and man-made signals and images. However, the significant discrete wavelet transform (DWT) coefficients do not occur in arbitrary positions for such signals. Instead they exhibit a characteristic signal-dependent structure, with the large and small wavelet coefficients clustering along the branches of the wavelet tree. We highlight the persistence of the parent child relationship for several large DWT coefficients on the wavelet image in Figure 2.

Hidden Markov tree (HMT) models and Gaussian scale mixtures (GSMs) on steerable pyramids succinctly and accurately captures this statistical structure [12], [20], [21]. The HMT models the probability density function of each wavelet coefficient as a mixture density with a hidden binary state that determines whether the coefficient is large or small. Wavelet coefficient persistence along the tree branches is captured by a tree-based Markov model that correlates the states of parent and children coefficients. GSMs exploit the Student's \( t \) prior or its variants. Both models have been successfully applied to improve the performance of denoising, classification, and segmentation algorithms for wavelet sparse signals. For an explanation of the EM algorithm applied to GSMs, see the original EM paper [14].

Another Bayesian approach leverages the clustering of the DWT coefficients using the spike-and-slab prior along with VB inference. The main idea is to construct a tree-structured, conjugate-exponential family sparse model for wavelet coefficients where the mixture probability of the spike at an individual sparse coefficient on the wavelet tree is controlled by the size of its parent on the tree. Then, the VB updates can be efficiently calculated with convergence guarantees. For instance, [17] demonstrates that the VB approach simultaneously improves both the recovery speed and performance over the state-of-the-art greedy and convex optimization-based CS recovery approaches, discussed in the section “Background.” Moreover, as opposed to providing single point estimates, probabilistic predictions are made within the VB framework; for instance, the precision of each sparse coefficient can be inferred.
MARKOV RANDOM FIELDS

Background-subtracted images play a fundamental role in making inferences about objects and activities in a scene in computer vision and, by nature, have structured spatial sparsity corresponding to the foreground innovations. That is, compared to the scale of the scene, the foreground innovations are usually not only sparse, but they are also clustered in a distinct way, corresponding to the silhouettes of moving humans and vehicles; see Figure 3. Such clustering behavior is also encountered in neuroscience problems that are involved with decoding of natural images in the primary visual cortex (V1) or understanding the statistical behavior of groups of neurons in the retina [1].

Markov random fields (MRFs) can capture interactivity and produce collective effects among sparse signal coefficients; previous applications have included sonar image segmentation, scene geometry estimation using multiple sensors, and designing discriminative classifiers. To enforce clustered sparse behavior, we use a special MRF, called the Ising model, with latent support variables \( s_i \) such that \( s_i = -1 \) when \( x_i \) is small and \( s_i = 1 \) when \( x_i \) is large; the support variables thus have the following pdf:

\[
f(s) = \exp \left\{ \sum_{\ell, j \in E} \lambda_{\ell j} s_\ell s_j + \sum_{j \in V} \lambda_j s_j \right\},
\]

where prior parameters consist of the edge interaction parameters \( \lambda_{\ell j} \) and the vertex bias parameters \( \lambda_j \); cf., the “Background” section. Interestingly, when the underlying graph of support variables in the Ising model is tree structured or chordal (i.e., each cycles in the graph of four or more nodes has a chord, which is an edge joining two nodes that are not adjacent in the cycle), the pdf in (10) can be equivalently represented by HMTs since, for instance, the set of distributions parameterized by directed trees is exactly the same as the set of distributions parameterized by undirected trees (cf., [11, Sect. 4.5.3]).

The following optimization problem emerges as result of the MAP formulation of (1) over a lattice graph on the image pixels, as illustrated in Figure 3, when the observations are corrupted by i.i.d. Gaussian noise with variance \( \sigma^2 \):

\[
[\hat{x}, \hat{s}] = \arg \max_{x, s} \sum_{\ell, j \in E} \lambda_{\ell j} s_\ell s_j + \sum_{j \in V} \lambda_j s_j + \log(p(x_j | s_j)) \frac{1}{2\sigma^2} \| y - \Phi x \|^2.
\]

For the compressibility of the structured sparse signal \( x \) as signal dimensions vary, the pdfs \( p(x_j | s_j) \) should be chosen to result in a compressible prior for the signal coefficients, such as Student’s \( t \), with proper scale parameters to differentiate the small and large coefficients. Although the objective function is nonconvex, a local optimum can be efficiently obtained via variational methods and alternating minimization techniques over the support and the signal coefficients.
In the context of sparse signal recovery, recent work [18] exploits the Ising model and demonstrates that it naturally motivates a greedy search algorithm for background subtraction with clustered sparsity, dubbed Lattice matching pursuit (LAMP). Enabled by the Ising model, the LAMP algorithm converges significantly faster due to the reduction in the search space and recovers sparse signals from a much smaller number of measurements without sacrificing stability. Similar optimization formulations can also be seen in applications involving face recognition in the presence of occlusions, where the occlusions are not only sparse but also contiguous.

To solve (11), the LAMP algorithm relies on an approach inspired by the RIP assumption on the measurement matrices. The key observation for this iterative recovery scheme is that when the sampling matrix $\mathbf{F}$ has $K$-RIP with constant $\varepsilon_K \ll 1$ in (5), then the vector $\mathbf{b} = \mathbf{F}^T \mathbf{y}$ can serve as a rough approximation of the original signal $\mathbf{x}$. In particular, the largest $K$ entries of $\mathbf{b}$ point toward the largest $K$ entries of the $K$-sparse signal $\mathbf{x}$. Then, given the signal coefficient estimates, LAMP uses graph cuts to obtain the MAP estimates of the latent support variables $s$. By clever bookkeeping of the data residual along with the auxiliary support estimates, LAMP iteratively refines its signal estimates until convergence; see Figure 3 for a robust recovery example from $M = 2K$, where the signal-to-noise ratio (SNR) in measurements is 10 dB.

**STRUCTURED POWER-LAW PROCESSES**

In many sparse signal recovery problems, the appropriate signal sparsifying basis or dictionary $\mathbf{C}$ is oftentimes unknown and must be determined for each individual problem. In dictionary learning problems, researchers develop algorithms to learn a sparsifying dictionary directly from data using techniques where a set of signals are compressible in particular with nonparametric Bayesian priors. By nonparametric, we mean that the number of parameters within the prior distribution is beforehand unspecified. Recent work in this area focused on vision applications and developed structured random processes to capture the power-law distribution of the image patch frequencies and segment sizes. Such distributions lay the foundations of a scale, resolution independent inference mechanism, which is key for compressible structured sparse models.

We highlight two examples. Indian buffet processes (IBPs), which provide exchangeable distributions over binary matrices, exploit hierarchical probability models and can be used to infer the dictionary size and its composition for natural images. Recent work exploits the IBP formalism for sparse signal recovery by jointly learning the sparsifying dictionary and demonstrates that significant improvements can be achieved in sparse recovery, denoising, and inpainting of natural images [22]; see Figure 4. Similarly, Pitman-Yor processes provide a statistical framework for unsupervised discovery and segmentation of visual object categories with power-law properties. Further applications of such power-law priors to the sparse signal recovery problem have yet to emerge [23].

**GRAPHICAL MODELS FOR STRUCTURED MEASUREMENTS**

While random matrices have information preserving guarantees for the set of sparse signals, they are difficult to store,
Graphs are an expander if any “small” subset $S$ of $A$ has “many” neighbors $\Gamma(S)$ in $B$.

An example of a bipartite graph $G = (A, B, E)$ over the “left” set $A$ of size $N$ and the “right” set $B$ of size $M$. A graph is an expander if any “small” subset $S$ of $A$ has “many” neighbors $\Gamma(S)$ in $B$.

Natural images exhibit significant self-similarities that can be leveraged using the Indian buffet processes (IBP) in sparse signal recovery even if a large number of pixels are missing. The IBP mechanism automatically infers a dictionary, in which the image patches are sparse, and the composition of these patches on the image to significantly improve the recovery performance over linear interpolation. (a) Target. (b) Incomplete. (c) Lin. interp. (27.6 dB). (d) IBP (35.2 dB). (e) Learned dictionary.

Sparse measurement matrices have several desirable features: i) matrix-vector products during the encoding of the vector $x$ into $\Phi x$ can be performed very efficiently, in time proportional to the number of nonzeros in $\Phi$; ii) the measurement vector $\Phi x$ can be quickly updated if one or a few of its coordinates are modified—crucial for processing massive data streams; iii) the recovery process is quite efficient as well, since it relies on the matrix-vector product as a subroutine. Moreover, the graphical interpretation of such matrices enabled designing recovery algorithms using the belief propagation approach, leading to highly accurate recovery methods. Because of these reasons, various forms of sparse recovery using sparse matrices has been recently a subject of extensive research; see the recent survey [2] and the references therein.

To complement the above, we also point out some disadvantages of sparse matrices. One of them is that they are directly applicable only to the case where the signal $x$ is approximately sparse in the canonical basis, i.e., $x = \alpha$ (see the “Introduction” section for the notation). If the signal (as it is often the case) is sparse only after applying a linear transformation $\Psi$, then the actual measurement matrix is equal to $\Phi \Psi$. This requires that the matrix $\Psi$ is known before the measurements are taken. Note that the product matrix $\Phi \Psi$ might not be sparse in general, and the encoding therefore must perform extra computation, corresponding to matrix multiplication; the order of these computations is $O(NM)$ for general matrices, but it is much lower for special bases, such as discrete Fourier and wavelet transforms.

**INTUITION AND THE RANDOMIZED CASE**

We start from an intuitive overview of why properly chosen sparse matrices are capable of preserving enough information about sparse signals to enable their recovery. We focus on the case where $x$ is exactly $K$-sparse, the matrix $\Phi$ is random, and the goal is to exactly recover $x$ from $y = \Phi x$ with “high” probability.

Consider first a particularly simple distribution over sparse matrices, where the $i$th column of $\Phi$ contains exactly single 1, at a position, indexed by $h(i)$, chosen independently and uniformly at random among the rows $\{1 \ldots M\}$. Multiplying $\Phi$ by $x$ has then a natural message-passing interpretation; each coordinate $x_i$ is sent to the $h(i)$th coordinate of the measurement vector $y$, and all coordinates sent to a given entry of $y$ are added together. Assuming that $M$ is sufficiently larger than $K$, we make the following observation: since the vector $x$ is $K$-sparse and the indices $h(i)$ are chosen randomly from $\{1 \ldots M\}$, there is only a small probability that any particular matrix $\Phi$ is not sufficiently sparse.
coordinate $x_i$ will collide with any other nonzero entry $x_j$ (where by collision we mean $h(i) = h(j)$). Therefore, $x_i = y_{h(i)}$ and we can recover sparse coefficients by inverse mapping from the measurement vector.

Unfortunately, the above procedure also creates many erroneous entries over the entire vector $x$. In short, we note that each zero entry $x_i$ has approximately $K/M$ chance of colliding with some nonzero entry. Each such collision results in a erroneous nonzero entry in the recovered vector. As a result, a recovered vector can have $K/M \times (N-K) \gg K$ erroneous entries, and therefore becomes a poor approximation of a $K$-sparse signal $x$.

To improve the quality of recovery, we reduce the probability of such erroneous entries via repetition. Specifically, instead of having only one per column of the measurement matrix $\Phi$, we can select $D$ random entries of each column and set them to 1. There are several different distributions of $D$-tuples from $\{1\ldots M\}$ than can be used, leading to essentially identical recovery results; see the survey [2]. In the graph representation, this means that each node $i \in A$ has a set of $D$ neighbors in $B$; we denote this set by $\Gamma(i)$. On one hand, this increases the probability of a collision, since now $y$ can contain up to $DK$ nonzero entries. However, if we set $M = CDK$ for some constant $C > 1$, then for any fixed node $i \in A$, each of the $D$ neighbors of $i$ has at most $DK/M = 1/C$ chance of colliding with another nonzero entry. Therefore, the probability that all neighbors of $i$ collide with other nonzero entries is very small, at most $1/C^D$.

Therefore, a sparse matrix $\Phi$ can potentially preserve information for an overwhelming fraction of the coordinates of $x$ by encoding it into $y$. Then, how can we recover $x$ from $y$? If $C > 2$ and $D = d \log N$ for large enough constant $d$, then one can show that, with high probability, less than half of the neighbors of each node $i \in A$ collide with other nonzero entries. In that case, taking the median of the (most frequently occurring value) of the entries $\{y_j : j \in \Gamma(i)\}$ returns the correct value of $x_i$. This is the basic idea behind Count-Median [25] and Count-Sketch [24] algorithms, which further extend this approach to general vectors $x$. For this case, however, we need to use the median estimator; the mode estimator does not work in this setting. In fact, the “small” entries of $x$ can make all coordinates of $y$ distinct, in which case the mode estimator can report an arbitrary value. The resulting algorithms require $M = O(K \log N)$, and the recovery is performed in time proportional to $O(N \log N)$.

To reduce the number of measurements, researchers have developed more elaborate algorithms, based on loopy belief propagation [26], [27] and related message-passing approaches [28]. Here, we sketch the Counter Braids algorithms of [27]. That algorithm works assuming that the vector $x$ is $K$-sparse and nonnegative.

While CS has the potential to revolutionize data acquisition, encoding, and processing in a number of applications, much work remains before it is ready for real-world deployment.

First, observe that for nonnegative signals $x$, the median-based approach of estimating $x_i$ can be further simplified. Specifically, one can observe that for any neighbor $j$ of $i$ in $G$, we have $y_j \geq x_i$, since collisions with nonnegative entries of $x$ can only increase the values of $y_i$. Therefore, we can estimate $x_i$ by taking the minimum—instead of the median—of the set $\{y_j : j \in \Gamma(i)\}$. Note that this can only lead to an overestimation of $x_i$. This variant of the one-shot approach, called Count-Min, has been discovered in [25] and [29].

The Counter Braids algorithm can be now described as an iterative refinement of Count-Min. Consider the estimation vector $x'$ obtained above, i.e., $x_i' = \min\{y_j : j \in \Gamma(i)\}$. From the discussion, we have $x_i' \geq x_i$. The key idea is that we can now use $x'$ to obtain an underestimation of $x$. Consider any edge $i - j$. Since $y_j = \sum_{i \in \Gamma(j) \setminus \Gamma(i)} x_i$ and $x_i \geq x_i'$, it follows that for $x_i'' = y_j - \sum_{i \in \Gamma(j) \setminus \Gamma(i)} x_i'$ we have $x_i'' \leq x_i$. Thus, we obtained a refined bound for $x$, this time from below. We can now iterate this approach, alternating between upper and lower bounds on $x$, until they are equal, in which case the recovery is exact, or some other stopping condition is satisfied.

The analysis given in [27] shows that, for a proper distribution over matrices $\Phi$, one can give the following guarantee. Let $x$ be any $K$-sparse signal. Then, the Counter Braids algorithm, when given a random matrix $\Phi$ and the measurement vector $\Phi x$, recovers $x$ with high probability, as long as $K/N$ is small enough and $M \geq \kappa K \log(N/K)$ for $\kappa \approx 2.08$.

In a very recent work [28], the authors present a message-passing scheme (for general sparse vectors $x$) that achieves a bound for $M$ matching that of $\ell_1$ minimization. Unlike other algorithms described in this section, the algorithm of [28] uses dense random matrices.

**Deterministic Case**

The above discussion provides an intuition why multiplying a fixed vector $x$ by a randomly chosen sparse matrix $\Phi$ should preserve sufficient information about $K$-sparse approximation to $x$. To be able to construct one (deterministic) matrix $\Phi$ that works for all vectors $x$, we need concrete matrices that behave in a semirandom fashion. For sparse matrices such property is encapsulated by the notion of graph expansion. For any set $S \subseteq A$, we let $\Gamma(S)$ be the set of neighbors of nodes in $S$, i.e., $\Gamma(S) = \cup_{i \in S} \Gamma(i)$. We say that the graph $G$ is an $(s, \alpha)$-expander if for any $S \subseteq A$, $|S| \leq s$, we have $|\Gamma(S)| \geq \alpha |S|$. Note that the expansion factor $\alpha$ is always at least $D$, since each node can have at most $D$ neighbors. However, there exist graphs that achieve $\alpha = (1 - \epsilon)D$ for any constant $\epsilon > 0$; such graphs require $D = O(\log(N/s))$ and $M = |B| = O(s \log(N/s))$. See Figure 5 for an illustration.

To see why expansion is desirable for sparse recovery, consider the case when $\epsilon$ is very close to 0 and $s = K$. Let $x$ be a
surprisingly to date, the sparse signal acquisition and recovery problems have been studied largely in isolation.

conclusions

A great deal of theoretic and algorithmic research has revolved around sparsity view of signals over the last decade to characterize new, sub-Nyquist sampling limits as well as tractable algorithms for signal recovery from dimensionality reduced measurements. Despite the promising advances made, real-life applications require more realistic signal models that can capture the underlying, application-dependent order of sparse coefficients, better sampling matrices with information preserving properties that can be implemented in practical systems, and ever faster algorithms with provable recovery guarantees for real-time operation.

On this front, we have seen that GMs are emerging to effectively address the core of many of these desiderata. GMs provide a broad scaffold for automatically encoding the probabilistic dependencies of sparse coefficients for sparse signal recovery. By exploiting the GM structure of signals beyond simple sparsity, we can radically reduce the number of measurements, increase noise robustness, and decrease recovery artifacts in signal acquisition. GMs are instrumental in constructing measurement matrices based on expander graphs. These matrices not only stably embed sparse signals into lower dimensions but also lead to faster recovery algorithms with rigorous guarantees. Moreover, the GM-based inference tools, such as variational methods, can estimate a posterior distribution for the sparse signal coefficients, providing confidence bounds that are critical in many applications.

Surprisingly to date, the sparse signal acquisition and recovery problems have been studied largely in isolation. Real progress in efficient signal recovery, processing, and analysis requires that we unify probabilistic, structured sparsity models with sparse measurement matrices to simultaneously reduce sampling requirements and the computational complexity of recovery without compromising the recovery guarantees. This will in turn entail investigation of streaming algorithms, coding theory, and learning theory with a common, connecting element, which we expect to be GMs.

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