

# Message Passing Algorithms for Compressed Sensing: II. Analysis and Validation

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**Abstract**—In a recent paper, the authors proposed a new class of low-complexity iterative thresholding algorithms for reconstructing sparse signals from a small set of linear measurements [1]. The new algorithms are broadly referred to as AMP, for *approximate message passing*. This is the second of two conference papers describing the derivation of these algorithms, connection with related literature, extensions of original framework, and new empirical evidence.

This paper describes the state evolution formalism for analyzing these algorithms, and some of the conclusions that can be drawn from this formalism. We carried out extensive numerical simulations to confirm these predictions. We present here a few representative results.

## I. GENERAL AMP AND STATE EVOLUTION

We consider the model

$$y = A s_o + w_o, \quad s_o \in \mathbb{R}^N, \quad y, w_o \in \mathbb{R}^n, \quad (1)$$

with  $s_o$  a vector that is ‘compressible’ and  $w_o$  a noise vector. We will assume that the entries of  $w_o$  are centered independent gaussian random variables with variance  $v$ .

The general AMP (approximate message passing) algorithm reads

$$x^{t+1} = \eta_t(x^t + A^* z^t), \quad (2)$$

$$z^t = y - A x^t + \frac{1}{\delta} z^{t-1} \langle \eta'_{t-1}(x^{t-1} + A^* z^{t-1}) \rangle, \quad (3)$$

with initial condition  $x_0 = 0$ . Here, for a vector  $u = (u_1, \dots, u_N)$  we write  $\langle u \rangle \equiv \sum_{i=1}^N u_i / N$ , and  $\eta'(\cdot; \cdot)$  indicates the derivative of  $\eta$  with respect to its first argument. Further  $\delta \equiv n/N$  and  $\{\eta_i(\cdot)\}_{t \geq 0}$  is a sequence of scalar non-linearities (see Section III), a typical example being soft thresholding, which contracts its argument towards zero.

### A. Structure of the Algorithm

This algorithm is interesting for its low complexity: its implementation is dominated at each step by the cost of applying  $A$  and  $A^*$  to appropriate vectors. In some important settings, matrices  $A$  of interest can be applied to a vector implicitly by a pipeline of operators requiring  $N \log(N)$  flops; an example would be  $A$  whose rows are randomly chosen from among the rows of a Fourier matrix; then  $Ax$  can be computed by FFT and subsampling.

Even more, the algorithm is interesting for the message passing term  $\frac{1}{\delta} z^{t-1} \langle \eta'_{t-1}(x^{t-1} + A^* z^{t-1}) \rangle$ . Similar algorithms

without this term are common in the literature of so-called iterative thresholding algorithms. As discussed in the companion paper, the message passing term approximates the combined effect on the reconstruction of the passing of  $nN$  messages in the the full message passing algorithm.

The message passing term completely changes the statistical properties of the reconstruction, and it also makes the algorithm amenable to analysis by a technique we call State Evolution. Such analysis shows that the algorithm converges rapidly, much more rapidly than any known result for the IST algorithm. Furthermore, it allows us to make a variety of theoretical predictions about performance characteristics of the algorithm which are much stronger than any predictions available for competing methods.

### B. State Evolution

In the following we will assume that the columns of  $A$  are normalized to unit Euclidean length. We define the *effective variance*

$$\sigma(x_t)^2 \equiv v + \frac{1}{N\delta} \|x_t - s_o\|_2^2. \quad (4)$$

The effective variance combines the observational variance  $v$  with an additional term  $\frac{1}{N\delta} \|x_t - s_o\|_2^2$  that we call the interference term. Notice that  $v$  is merely the squared reconstruction error of the naive ‘matched filter’ for the case where  $s_o$  contains all zeros and a single nonzero in a given position  $i$  and the matched filter is just the  $i$ -th column of  $A$ .

The interference term measures the additional error in estimating a single component of  $s_{o,i}$  that is caused by the many small errors in *other components*  $j \neq i$ . The formula states that the effective variance at iteration  $t$  is caused by the observational noise (invariant across iteration) and the current errors at iteration  $t$  (changing from iteration to iteration). The interference concept is well known in digital communications, where phrases like *mutual access interference* are used for what is algebraically the same phenomenon.

We will let  $\hat{\sigma}_t$  denote any estimate of  $\sigma_t$ , and we will assume that  $\hat{\sigma}_t \approx \sigma_t$ ; see [1] for more careful discussion. Suppose that the nonlinearity takes the form  $\eta_t(\cdot) = \eta(\cdot; \theta_t)$  where  $\theta$  is a tuning parameter, possibly depending on  $\hat{\sigma}_t$ ; see below for more. Let  $\mathcal{F}$  denote the collection of CDFs on  $\mathbb{R}$  and  $F$  be the CDF of  $s_o(i)$ . Define the MSE map  $\Psi : \mathbb{R}^+ \times \mathbb{R}^3 \times \mathcal{F} \mapsto \mathbb{R}^+$

by

$$\Psi(\sigma; v, \delta, \theta_t, F) = v + \frac{1}{\delta} \mathbb{E} \left\{ \left[ \eta_t(X + \sigma Z) - X \right]^2 \right\}$$

where  $X$  has distribution  $F$  and  $Z \sim \mathcal{N}(0, 1)$  is independent of  $X$ . We suppose that a rule  $\Theta(\sigma; v, \delta, \theta, F)$  for the update of  $\theta_t$  is also known.

**Definition I.1.** *The state is a 5-tuple  $S = (\sigma; v, \delta, \theta, F)$ ; state evolution is the evolution of the state by the rule*

$$\begin{aligned} (\sigma_t^2; v, \delta, \theta_t, F) &\mapsto (\Psi(\sigma_t^2); v, \delta, \theta_{t+1}, F) \\ t &\mapsto t + 1 \end{aligned}$$

As the parameters  $(v, \delta, F)$  remain fixed during evolution, we usually omit mention of them and think of state evolution simply as the iterated application of  $\Psi$  and  $\Theta$ :

$$\begin{aligned} \sigma_t^2 &\mapsto \sigma_{t+1}^2 \equiv \Psi(\sigma_t^2) \\ \theta_t &\mapsto \theta_{t+1} \equiv \Theta(S_t) \\ t &\mapsto t + 1 \end{aligned}$$

The initial state is taken to have  $\sigma_0^2 = v + \|s_0\|_2^2/N\delta$ .

As described, State Evolution is a purely analytical construct, involving sequential application of rules  $\Psi$  and  $\Theta$ . The crucial point is to know whether this converges to a fixed point, and to exploit the properties of the fixed point. We expect that such properties are reflected in the properties of the algorithm. To make this precise, we need further notation.

**Definition I.2. State-Conditional Expectation.** *Given a function  $\zeta : \mathbb{R}^4 \mapsto \mathbb{R}$ , its expectation in state  $S_t$  is*

$$\mathcal{E}(\zeta|S_t) = \mathbb{E} \left\{ \zeta(U, V, W, \eta(U + V + W)) \right\},$$

where  $U \sim F$ ,  $V \sim N(0, v)$  and  $W \sim N(0, \sigma_t^2 - v)$ .

Different choices of  $\zeta$  allow to monitor the evolution of different metrics under the AMP algorithm. For instance,  $\zeta = (u - x)^2$  corresponds to the mean square error (MSE). The False Alarm Rate is tracked by  $\zeta = 1_{\{\eta(v+w) \neq 0\}}$  and the Detection Rate by  $\zeta = 1_{\{\eta(u+v+w) \neq 0\}}$ .

**Definition I.3. Large-System Limits.** *Let  $\zeta : \mathbb{R}^4 \mapsto \mathbb{R}$  be a function of real 4-tuples  $(s, u, w, x)$ . Suppose we run the iterative algorithm  $\mathcal{A}$  for a sequence of problem sizes  $(n, N)$  at a the value  $(v, \delta, F)$  of underlying implicit parameters, getting outputs  $x_t$ ,  $t = 1, 2, 3, \dots$ . The large-system limit  $\text{ls.lim}(\zeta, t, \mathcal{A})$  of  $\zeta$  at iteration  $t$  is*

$$\text{ls.lim}(\zeta, t, \mathcal{A}) = \text{p.lim}_{N \rightarrow \infty} \langle \zeta(s_{o,i}, u_{t,i}, w_{o,i}, x_{t,i}) \rangle_N,$$

where  $\langle \cdot \rangle_N$  denotes the uniform average over  $i \in \{1, \dots, N\} \equiv [N]$ , and  $\text{p.lim}$  denotes limit in probability.

**Hypothesis I.4. Correctness of State Evolution for AMP.** *Run an AMP algorithm for  $t$  iterations with implicit state variables  $v, \delta, F$ . Run state evolution, obtaining the state  $S_t$  at time  $t$ . Then for any bounded continuous function  $\zeta : \mathbb{R}^4 \mapsto \mathbb{R}$  of the real 4-tuples  $(s, u, w, x)$ , and any number of iterations  $t$ ,*

- 1) *The large-system limit  $\text{ls.lim}(\zeta, t, \mathcal{A})$  exists for the observable  $\zeta$  at iteration  $t$ .*
- 2) *This limit coincides with the expectation  $\mathcal{E}(\zeta|S_t)$  computed at state  $S_t$ .*

State evolution, where correct, allows us to predict the performance of AMP algorithms and tune them for optimal performance. In particular, SE can help us to choose the nonlinearities  $\{\eta_t\}$  and their tuning. The objective of the rest of this paper is twofold: (1) Provide evidence for state evolution; (2) Describe some guidelines towards the choice of the nonlinearities  $\{\eta_t\}$ .

## II. AMP-BASED ALGORITHMS

Already in [1] we showed that a variety of algorithms can be generated by varying the choice of  $\eta$ . We begin with algorithms based on soft thresholding. Here  $\eta_t(x) = \eta(x; \theta_t)$  is given by the soft threshold function

$$\eta(x; \theta) = \begin{cases} x - \theta & \text{if } \theta < x, \\ 0 & \text{if } -\theta \leq x \leq \theta, \\ x + \theta & \text{if } x < -\theta. \end{cases} \quad (5)$$

This function shrinks its argument towards the origin. Several interesting AMP-Based algorithms are obtained by varying the choice of the sequence  $\{\theta_t\}_{t \in \mathbb{N}}$ .

### A. AMP.M( $\delta$ )

The paper [1] considered the noiseless case  $v = 0$  where the components of  $s_o$  are iid with common distribution  $F$  that places all but perhaps a fraction  $\epsilon = \rho(\delta) \cdot \delta$ ,  $\rho \in (0, 1)$  of its mass at zero. That paper proposed the choice

$$\theta_t = \tau(\delta) \widehat{\sigma}_t. \quad (6)$$

where an explicit formula for  $\tau(\delta)$  is derived in the online supplement [2]. As explained in that supplement, this rule has a minimax interpretation, namely, to give the smallest MSE guaranteed across all distributions  $F$  with mass at zero larger than or equal to  $1 - \epsilon$ .

### B. AMP.T( $\tau$ )

Instead of taking a worst case viewpoint, we can think of specifically tuning for the case at hand. Consider general rules of the form:

$$\theta_t = \tau \widehat{\sigma}_t. \quad (7)$$

Such rules have a very convenient property for state evolution; namely, if we suppose that  $\widehat{\sigma}_t \equiv \sigma_t$ , we can redefine the state as  $(\sigma_t^2; v, \delta, \tau, F)$ , with  $(v, \delta, \tau, F)$  invariant during the iteration, and then the evolution is effectively one-dimensional:  $\sigma_t^2 \mapsto \sigma_{t+1}^2 \equiv \Psi(\sigma_t^2)$ . The dynamics are then very easy to study, just by looking for fixed points of a scalar function  $\Psi$ . (This advantage is also shared by AMP.M( $\delta$ ), of course).

While the assumption  $\widehat{\sigma}_t \equiv \sigma_t$  does not hold, strictly speaking, at any finite size, it will hold asymptotically in the large system limit for many good estimators of the effective variance.

It turns out that, depending on  $F$  and  $\delta$ , different values of  $\tau$  lead to very different performance characteristics. It is natural to ask for the fixed value  $\tau = \tau^*(v, \delta, F)$  which, under state evolution gives the smallest equilibrium MSE. We have developed software to compute such optimal tuning; results are discussed in [5].

### C. AMP.A( $\lambda$ )

In much current work on compressed sensing, it is desired to solve the  $\ell_1$ -penalized least squares problem

$$\text{minimize } \frac{1}{2} \|y - Ax\|_2^2 + \lambda \|x\|_1. \quad (8)$$

In different fields this has been called Basis Pursuit denoising [6] or Lasso [7]. Large scale use of general convex solvers is impractical when  $A$  is of the type interesting from compressed sensing, but AMP-style iterations *are* practical. And, surprisingly an AMP-based algorithm can effectively compute the solution by letting the threshold ‘float’ to find the right level for solution of the above problem. The threshold recursion is:

$$\theta_{t+1} = \lambda + \frac{\theta_t}{\delta} \langle \eta'(x^t + A^* z^t; \theta_t) \rangle. \quad (9)$$

### D. AMP.0

It can also be of interest to solve the  $\ell_1$ -minimization problem

$$\min_x \|x\|_1 \text{ subject to } y = Ax. \quad (10)$$

This has been called Basis Pursuit [6] in the signal processing literature. While formally it can be solved by linear programming, standard linear program codes are far too slow for many of the applications interesting to us.

This is formally the  $\lambda = 0$  case of AMP.A( $\lambda$ ). In fact it can be advantageous to allow  $\lambda$  to decay with the iteration number

$$\theta_{t+1} = \lambda_t + \frac{\theta_t}{\delta} \langle \eta'(x^t + A^* z^t; \theta_t) \rangle. \quad (11)$$

Here, we let  $\lambda_t \downarrow 0$  as  $t \rightarrow \infty$ .

### E. Other Nonlinearities

The discussion above has focused entirely on soft thresholding, but both the AMP algorithm and SE formalism make perfect sense with many other nonlinearities. Some case of specific interest include

- The Bayesian conditional mean:  $\eta(x) = \mathbb{E}\{s_0 | s_0 + U + V = x\}$ , where  $U$  and  $V$  are just as in Definition I.2. This is indeed discussed in the companion paper [3], Section V.
- Scalar nonlinearities associated to various nonconvex optimization problems, such as minimizing  $\ell_p$  pseudonorms for  $p < 1$ .

## III. CONSEQUENCES OF STATE EVOLUTION

### A. Exponential Convergence of the Algorithm

When State Evolution is correct for an AMP-type algorithm, we can be sure that the algorithm converges rapidly to its limiting value – exponentially fast. The basic point was shown in [1]. Suppose we are considering either AMP.M( $\delta$ ) or AMP.T( $\tau$ ). In either case, as explained above, the state evolution is effectively one-dimensional. Then the following is relevant.

**Definition III.1. Stable Fixed Point.** *The Highest Fixed Point of the continuous function  $\Psi$  is*

$$\text{HFP}(\Psi) = \sup\{m : \Psi(m) \geq m\}.$$

*The stability coefficient of the continuously differentiable function  $\Psi$  is*

$$\text{SC}(\Psi) = \left. \frac{d}{dm} \Psi(m) \right|_{m=\text{HFP}(\Psi)}.$$

*We say that  $\text{HFP}(\Psi)$  is a stable fixed point if  $0 \leq \text{SC}(\Psi) < 1$ .*

Let  $\mu_2(F) = \int x^2 dF$  denote the second-moment functional of the CDF  $F$ .

**Lemma III.2.** *Let  $\Psi(\cdot) = \Psi(\cdot; v, \delta, F)$ . Suppose that  $\mu_2(F) > \text{HFP}(\Psi)$ . The sequence of iterates  $\sigma_t^2$  defined by starting from  $\sigma_0^2 = \mu_2(F)$  and  $\sigma_{t+1}^2 = \Psi(\sigma_t^2)$  converges:*

$$\sigma_t^2 \rightarrow \text{HFP}(\Psi), \quad t \rightarrow \infty.$$

*Suppose that the stability coefficient  $0 < \text{SC}(\Psi) < 1$ . Then*

$$(\sigma_t^2 - \text{HFP}(\Psi))^t \leq \text{SC}(\Psi)^t \cdot (\mu_2(F) - \text{HFP}(\Psi)).$$

In short, when  $F$  and  $v$  are such that the highest fixed point is stable, state evolution converges exponentially fast to that fixed point.

Other iterative thresholding algorithms have theoretical guarantees which are far weaker. For example, FISTA [8] has a theoretical guarantee of  $O(1/t^2)$ , while SE evolution implies  $O(\exp(-ct))$ .

### B. Phase Transitions For $\ell_1$ minimization

Consider the special setting where the noise is absent  $w_o = 0$  and the object  $s_o$  obeys a strict sparsity condition; namely the distribution  $F$  places a fraction  $\geq 1 - \epsilon$  of its mass at the origin; and thus, if  $s_o$  is iid  $F$ , approximately  $N \cdot (1 - \epsilon)$  of its entries are exactly zero.

A phase transition occurs in this setting when using  $\ell_1$  minimization for reconstruction. Namely, if we write  $\epsilon = \rho \cdot \delta$  then there is a critical value  $\rho(\delta)$  such that, for  $\epsilon < \rho(\delta) \cdot \delta$ ,  $\ell_1$  minimization correctly recovers  $s_o$ , while for  $\epsilon > \rho(\delta) \cdot \delta$ ,  $\ell_1$  minimization fails to correctly recover  $s_o$ , with probability approaching one in the large size limit. State Evolution predicts this phenomenon, because, for  $\epsilon < \rho_{\text{SE}}(\delta) \cdot \delta$ , the highest fixed point is at  $\sigma_t^2 = 0$ , while above this value, the highest fixed point is at  $\sigma_t^2 > 0$ . Previously, the exact critical value  $\rho(\delta)$  at which this transition occurs was computed by combinatorial geometry, with a rigorous proof; however, it was shown in [1] that the algorithm AMP.M( $\delta$ ) has  $\rho(\delta) = \rho_{\text{SE}}(\delta)$ , validating the correctness of SE.

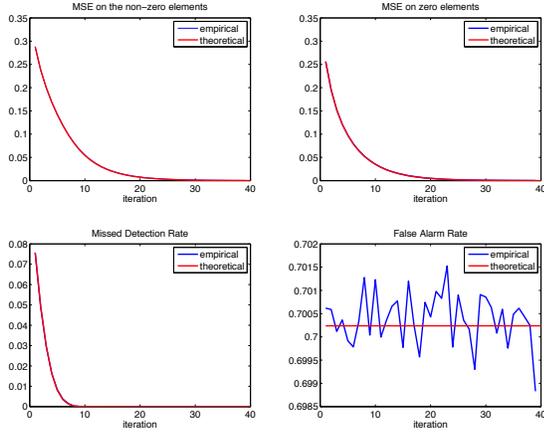


Fig. 1. Observables versus iteration, and predictions by state evolution. Panels (a)-(d): MSENZ, MSE, MDR, FAR. Curve in red: theoretical prediction. Curve in blue: mean observable. For this experiment,  $N = 5000$ ,  $\delta = n/N = .3$ .  $F = 0.955\delta_0 + 0.045\delta_1$

### C. Operating Characteristics of $\ell_1$ penalized Least-squares.

State evolution predicts the following relationships between  $\text{AMP.T}(\tau)$  and  $\text{BPDN}(\lambda)$ .  $\text{AMP.T}(\tau)$  has, according to SE, for its large- $t$  limit an *equilibrium state* characterized by its equilibrium noise plus interference level  $\sigma_\infty(\tau)$ . In that state  $\text{AMP.T}(\tau)$  uses an equilibrium threshold  $\theta_\infty(\tau)$ . Associated to this equilibrium NPI and Threshold, there is an equilibrium detection rate

$$\text{EqDR}(\tau) = \mathbb{P}\{\eta(U + V + W; \theta_\infty) \neq 0\}$$

where  $U \sim F$ ,  $V$  is  $N(0, v)$  and  $W$  is  $N(0, \sigma_\infty^2 - v)$ , with  $U, V, W$  independent. Namely, for all sufficiently large  $\tau$  (i.e.  $\tau > \tau_0(\delta, F, v)$ ) we have

$$\lambda = (1 - \text{EqDR}(\tau)/\delta) \cdot \theta_\infty(\tau);$$

this creates a one-one relationship  $\lambda \leftrightarrow \tau(\lambda; v, \delta, F)$  calibrating the two families of procedures. SE predicts that observables of the  $\ell_1$ -penalized least squares estimator with penalty  $\lambda$  will agree with the calculations of expectations for  $\text{AMP.T}(\tau(\lambda; v, \delta, F))$  made by state evolution.

## IV. EMPIRICAL VALIDATION

The above-mentioned consequences of State Evolution can be tested as follows. In each case, we can use SE to make a fixed prediction in advance of an experiment and then we can run a simulation experiment to test the accuracy of the prediction.

### A. SE Predictions of Dynamics of Observables

Exponential convergence of AMP-based algorithms is equivalent to saying that a certain observable – Mean-squared error of reconstruction – decays exponentially in  $t$ . This is but one observable of the algorithm’s output; and we have tested not only the SE predictions of MSE but also the SE predictions of many other quantities.

In Figure 1 we present results from an experiment with signal length  $N = 5000$ , noise level  $v = 0$ , indeterminacy  $\delta = n/N = 0.30$  and sparsity level  $\epsilon = 0.045$ . The distribution  $F$  places 95.5% of its mass at zero and 4.5% of its mass at 1. the fit between predictions and observations is extremely good – so much so that it is hard to tell the two curves apart. For more details, see [2].

### B. Phase Transition Calculations

Empirical observations of Phase transitions of  $\ell_1$  minimization and other algorithms have been made in [4], [9], and we follow a similar procedure. Specifically, to observe a phase transition in the performance of a sparsity-seeking algorithm, we perform 200 reconstructions on randomly-generated problem instances with the same underlying situation ( $v = 0$ ,  $\delta$ ,  $F$ ) and we record the fraction of successful reconstructions in that situation. We do this for each member of a large set of situations by varying the undersampling ratio  $\delta$  and varying sparsity of  $F$ . More specifically, we define a  $(\delta, \rho)$  phase diagram  $[0, 1]$  and consider a grid of sites in this domain with  $\delta = .05, .10, \dots$  and  $\rho = .03, .06, \dots, .99$ . For each  $\delta, \rho$  pair in this grid, we generate random problem instances having a  $k$ -sparse solution  $s_0$ , i.e. a vector having  $k$  ones and  $n - k$  zeros; here  $k = \rho \cdot \delta \cdot N$ .

Defining success as exact recovery of  $s_0$  to within a small fixed error tolerance, we define the empirical phase transition as occurring at the  $\rho$  value where the success fraction drops below 50%. For more details, see [2].

Figure 2 depicts the theoretical phase transition predicted by State Evolution as well as the empirical phase transition of  $\text{AMP.M}(\delta)$  and a traditional iterative soft thresholding algorithm. In this figure  $N = 1000$ , and  $\text{AMP.M}(\delta)$  was run for  $T = 1,000$  iterations. One can see that empirical phase transition of  $\text{AMP.M}(\delta)$  matches closely the state evolution prediction. One can also see that the empirical phase transition of iterative soft thresholding, without the message passing term, is substantially worse than that for the AMP-based method with the message passing term.

### C. Operating Characteristics of $\ell_1$ penalized Least-squares

The phase transition study gives an example of SE’s accuracy in predicting AMP-based algorithms in a *strictly* sparse setting, i.e. where only a small fraction of entries in  $s_0$  are nonzero. For a somewhat different example, we consider the generalized Gaussian family, i.e. distribution functions  $F_\alpha$  with densities

$$f_\alpha(x) = \exp(-|x|^\alpha)/Z_\alpha.$$

In the case  $\alpha = 1$  there is a very natural connection with  $\ell_1$ -minimization algorithms, which then become MAP estimation schemes. In the case  $\alpha = 1$ , an iid realization from  $f_\alpha$ , properly rescaled to unit  $\ell_1$  norm, will be uniformly distributed on the surface of the  $\ell_1$  ball, and in that sense this distribution samples all of the  $\ell_1$  ball, unlike the highly sparse distributions used in the phase transition study, which sample only the low-dimensional faces. When  $\alpha < 1$ , the sequence is in a sense

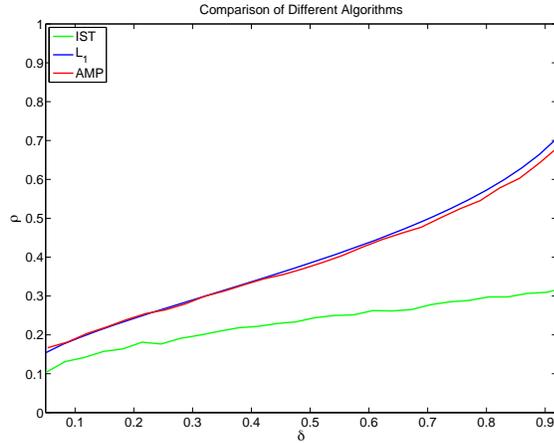


Fig. 2. Phase transitions of reconstruction algorithms. Blue Curve: Phase Transition predicted by SE; Red Curve empirical phase transition for  $AMP(\delta)$  as observed in simulation; Green Curve, empirical phase transition for Iterative Soft Thresholding as observed in simulation.

more sparse than when  $\alpha = 1$ . The case  $\alpha = .7$  has been found useful in modelling wavelet coefficients of natural images.

We considered exponents  $\alpha \in \{0.35, 0.50, 0.65, 0.75, 1.0\}$ . At each such case we considered incompleteness ratios  $\delta \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$ . The set of resulting  $(\alpha, \delta)$  pairs gives a collection of 25 experimental conditions. At each such experimental condition, we considered 5 or so different values of  $\lambda$  for which SE-predicted MSE's were available. In total, simulations were run for 147 different combinations of  $\alpha$ ,  $\delta$  and  $\lambda$ . At each such combination, we randomly generated 200 problem instances using the problem specification, and then computed more than 50 observables of the solution. In this subsection, we used  $N = 500$ .

To solve an instance of problem (8) we had numerous options. Rather than a general convex optimizer, we opted to use the LARS/LASSO algorithm.

Figure 3 shows a scatterplot comparing MSE values for the LARS/LASSO solution of (8) with predictions by State Evolution, as described in section III.C. Each data point corresponds to one experimental combination of  $\alpha$ ,  $\delta$ ,  $\lambda$ , and the datapoint presents the median MSE across 200 simulations under that combination of circumstances. Even though the observed MSE's vary by more than an order of magnitude, it will be seen that the SE predictions track them accurately. It should be recalled that the problem size here is only  $N = 500$ , and that only 200 replications were made at each experimental situation. In contrast, the SE prediction is designed to match large-system limit. In a longer paper, we will consider a much wider range of observables and demonstrate that, at larger problem sizes  $N$ , we get successively better fits between observables and their SE predictions.

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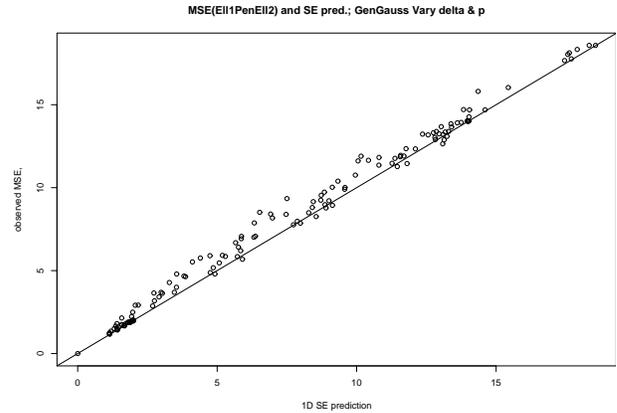


Fig. 3. Mean-squared Error for  $\ell_1$ -penalized Least-squares estimate versus predicted error according to State Evolution.

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