ITERATIVE LOG THRESHOLDING

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ABSTRACT
Sparse reconstruction approaches using the re-weighted $\ell_1$-penalty have been shown, both empirically and theoretically, to provide a significant improvement in recovering sparse signals in comparison to the $\ell_1$-relaxation. However, numerical optimization of such penalties involves solving problems with $\ell_1$-norms in the objective many times. Using the direct link of reweighted $\ell_1$-penalties to the concave log-regularizer for sparsity, we derive a simple prox-like algorithm for the log-regularized formulation. The proximal splitting step of the algorithm has a closed form solution, and we call the algorithm log-thresholding in analogy to soft thresholding for the $\ell_1$-penalty. We establish convergence results, and demonstrate that log-thresholding provides more accurate sparse reconstructions compared to both soft and hard thresholding. Furthermore, the approach can be directly extended to optimization over matrices with penalty for rank (i.e. the nuclear norm penalty and its re-weighted version), where we suggest a singular-value log-thresholding approach.

Index Terms— sparsity, reweighted $\ell_1$, non-convex formulations, proximal methods

1. INTRODUCTION
We consider sparse reconstruction problems which attempt to find sparse solutions to over-determined systems of equations. A basic example of such a problem is to recover a sparse vector $x \in \mathbb{R}^N$ from measurements $y = Ax + n$, where $y \in \mathbb{R}^M$ with $M < N$, and $n$ captures corruption by noise. Attempting to find maximally sparse solutions is known to be NP-hard, so convex relaxations involving $\ell_1$-norms have gained unprecedented popularity. Basis pursuit (or LASSO in statistics literature) minimizes the following objective:

$$
\min \|y - Ax\|_2^2 + \lambda \|x\|_1
$$

(1)

Here $\lambda$ is a parameter that balances sparsity versus the norm of the residual error. There is a myriad of algorithms for solving (1) (see e.g. [1, 2, 3]), and for large-scale instances, variations of iterative soft thresholding have become very popular:

$$
x^{(n+1)} = S_\lambda \left(x^{(n)} + A^T(y - x^{(n)})\right)
$$

(2)

where $S_\lambda(z)$ applies soft-thresholding for each entry:

$$
S_\lambda(z) = \text{sign}(z) \max(0, |z| - \lambda).
$$

(3)

Based on operator splitting and proximal projection theories, the algorithm in (2) converges if the spectral norm $\|A\| < 1$ [4, 5]. This can be achieved simply by rescaling $A$. Accelerated versions of iterative thresholding have appeared [6].

An exciting albeit simple improvement over $\ell_1$-norms for approximating sparsity involves weighting the $\ell_1$-norm: $\sum_i w_i |x_i|$ with $w_i > 0$. Ideal weights require knowledge of the sparse solution, but a practical idea is to use weights based on solutions of previous iterations [7, 8]:

$$
w_i^{(n+1)} = \frac{1}{\delta + |x_i^{(n)}|}
$$

(4)

This approach can be motivated as a local linearization of the log-heuristic for sparsity [7]. There is strong empirical [8] and recent theoretical evidence that reweighted $\ell_1$ approaches improve recovery of sparse signals, in the sense of enabling recovery from fewer measurements [9, 10].

In this paper, we consider the log-regularized formulation that gives rise to the re-weighting schemes mentioned above, and propose a simple prox-like optimization algorithm for its optimization. We derive a closed-form solution for the proximal step, which we call log-thresholding. We establish monotone convergence of iterative log-thresholding (ILT) to its fixed points, and derive conditions under which these fixed points are local minima of the log-regularized objective. Sparse recovery performance of the method on numerical examples surpasses both soft and hard iterative thresholding (IST and IHT). We also extend the approach to minimizing rank for matrix functions via singular value log-thresholding.

To put this into context of related work, [11] has considered iterative thresholding based on non-convex $\ell_p$-norm penalties for sparsity. However, these penalties do not have a connection to re-weighted $\ell_1$ optimization. Also, [12] have investigated coordinate descent based solutions for non-convex penalties including the log-penalized penalty, but their approach does not use closed form log-thresholding. Finally, general classes of non-convex penalties, their benefits for sparse recovery, and reweighted convex-type methods for their optimization are studied in [13]. This class of methods is different from the log-thresholding we propose.
2. ISTA AS PROXIMAL SPLITTING

We briefly review how soft-thresholding can be used to solve the sparse reconstruction problem in (1). Functions of the form \( f(x) = h(x) + g(x) \) where \( h(x) \) is convex differentiable with a Lipschitz gradient, and \( g(x) \) is general convex can be solved by a general proximal splitting method [5]:

\[
\hat{x}^{(n+1)} = \text{prox}_g \left( x^{(n)} - \nabla h(x^{(n)}) \right).
\] (5)

The prox-operation is a generalization of projection onto a set to general convex functions:

\[
\text{prox}_h(x) = \arg \min_z h(z) + \frac{1}{2} \|x - z\|^2.
\] (6)

If \( h(x) \) is an indicator function for a convex set, then the prox-operation is equivalent to the projection onto the set, and ISTA itself is equivalent to the projected gradient approach.

Forward-backward splitting can be applied to the sparse recovery problem (1) by deriving the proximal operator for \( h \). If \( h \) is an indicator function of the set \( \{ x : \|A^T(x - y)\|_2 < \varepsilon \} \), then the proximal operator is given by \( x^{(n+1)} = \text{Proj}_{S_\varepsilon}(x^{(n)}) \) where \( S_\varepsilon \) is the set defined in (2). The convergence of ISTA in (2) thus follows directly from the theory derived for forward-backward splitting [5].

3. LOG-THRESHOLDING

The reweighted-\( \ell_1 \) approach can be justified as an iterative upper bounding by a linear approximation to the concave log-heuristic for sparsity (here \( \delta \) is a small positive constant) [7].

\[
\min f(x) = \min \|y - Ax\|^2 + \lambda \sum_i \log(\delta + |x_i|).
\] (7)

While the log-penalty is concave rather than convex, we still consider the scalar proximal objective around a fixed \( x \):

\[
g_\lambda(z) \triangleq (z - x)^2 + \lambda \log(\delta + |z|).
\] (8)

We note that for \( \delta \) small enough, the global minimum of \( g_\lambda(z) \) over \( z \) (with \( x \) held constant) is always 0. However, when \( |x| > x_0 \triangleq \sqrt{2\lambda} - \delta \), the function also exhibits a local minimum, which disappears for small \( x \). We show that it is the local, rather than the global minimum, that provides the link to re-weighted \( \ell_1 \) minimization and is key to the log-prox algorithm we propose. Indeed, it is also the local (and not global) minimum that provides the link to iteratively re-weighted \( \ell_1 \) algorithms.

Our algorithm arises directly from first order necessary conditions for optimality. For \( |x| > x_0 \), we solve the equation \( \nabla g_\lambda = 0 \) to find the local minimum in closed-form. We call this operation log-thresholding , \( L_\lambda(x) \):

\[
L_\lambda(x) = \begin{cases} 
\frac{1}{2} \left( (x_i - \delta) + \sqrt{(x_i + \delta)^2 - 2\lambda} \right), & x > x_0 \\
\frac{1}{2} \left( (x_i + \delta) - \sqrt{(x_i - \delta)^2 - 2\lambda} \right), & x < -x_0 \\
0, & \text{otherwise}
\end{cases}
\] (9)

where \( x_0 = \sqrt{2\lambda} - \delta \). We illustrate log-thresholding in Figure 1. The left plot shows \( g_\lambda(z) \) as a function of \( z \) for several values of \( x \). For large \( x \) the function has a local minimum, but for small \( x \) the local minimum disappears. For log-thresholding we are specifically interested in the local minimum: an iterative re-weighted \( \ell_1 \) approach with small enough step size starting at \( x \), i.e., beyond the local minimum, will converge to the local minimum, avoiding the global one. The right plot in Figure 1 shows the log-thresholding operation \( L_\lambda(x) \) with \( x_0 = 1 \) as a function of \( x \). It can be seen as a smooth alternative falling between hard and soft thresholding.

In analogy to ISTA, we can now formally define the iterative log-thresholding algorithm:

\[
\hat{x}^{n+1} = L_\lambda \left( x^n + A^T(y - Ax^n) \right)
\] (10)

where \( L_\lambda(x) \) applied the element-wise log-thresholding operation we obtained in (9). We establish its convergence next.

3.1. Convergence of iterative log-thresholding

The theory of forward-backward splitting does not allow an analysis of log-thresholding, because the log is non-convex, and log-thresholding is not a contraction (in particular, it is not firmly non-expansive). Therefore, for the analysis we use an approach based on optimization transfer using surrogate functions [14] to prove convergence of ILT to its fixed points. At a high-level the analysis follows the program for IHT in [15], but some of the steps are notably different, and in particular some assumptions on the operator action are necessary to establish that fixed points correspond to local minima of our formulation. In the appendix we establish:

**Proposition 1** Under the assumption \( \|A\|_2 < 1 \), the ILT algorithm in (10) monotonically decreases the objective \( f(x) \) in (7), and converges to fixed points. A sufficient condition for these fixed points to be local minima is that \( A \) restricted to the non-zero coefficients is well-conditioned, specifically that the lowest singular values of the restriction are greater than \( \frac{1}{2} \).
4. SINGULAR VALUE LOG-THRESHOLDING

A closely related problem to finding sparse solutions to systems of linear equations is finding low-rank matrices from sparse observations, known as matrix completion:

$$\min \text{rank}(X) \text{ such that } X_{i,j} = Y_{i,j}, \{(i,j) \in \Omega\}$$

(11)

Similar to sparsity, rank is a combinatorial objective which is typically intractable to optimize directly. However, the nuclear norm $\|X\|_*$ is defined as $\sum \sigma_i(X)$, where $\sigma_i(X)$ are the singular values of $X$, serves as the tightest convex relaxation of rank, analogous to $\ell_1$-norm being the convex relaxation of the $\ell_0$-norm. In fact, the nuclear norm is exactly the $\ell_1$-norm of the singular value spectrum of a matrix. This connection enables the application of various singular value thresholding algorithms: for instance, the SVT algorithm of [16] alternates soft-thresholding of the singular value spectrum with gradient steps. In the experimental section we investigate a simplified singular-value log-thresholding algorithm for matrix completion, where we replace soft thresholding with hard and log-thresholdings. We present very promising empirical results of singular value log-thresholding in Section 5 and a full convergence analysis will appear in a later publication.

5. EXPERIMENTS

We investigate the performance of iterative log thresholding via numerical experiments on noiseless and noisy sparse recovery. Intuitively we expect ILT to recover sparser solution than soft-thresholding due to the connection to re-weighted-$\ell_1$ norms, and also to behave better than the non-smooth iterative hard thresholding.

First we consider sparse recovery without noise, i.e. we would like to find the sparsest solution that satisfies $y = Ax$ exactly. One could in principle solve a sequence of problems \(^1\) with decreasing $\lambda$, i.e. increasing penalty on $\|y - Ax\|^2_2$ via IST, IHT, ILT. However, when we know an upper bound $K$ on the desired number of non-zero coefficients, a more successful approach is to adaptively change $\lambda$ to eliminate all except the top-$K$ coefficients in each iteration, as used e.g. in [17]. We compare the performance of IST, IHT, and the proposed ILT in Figure 2. We have $N = 200, M = 100$ and we vary $K$. Apart from changing the thresholding operator, all the algorithms are exactly the same. The top plot shows the average reconstruction error from the true sparse solution $\|\hat{x} - x^*\|_2$. It is averaged over 1000 trials allowing IST, IHT and ILT to run for up-to 250 iterations. The bottom plot shows probability of recovering the true sparse solution. We can see that ILT is superior in both probability of recovery (higher probability of recovery) and in reconstruction error (lower reconstruction error) over both IST and IHT.

Our next experiment compares the three iterative thresholding algorithms on noisy data. Since regularization parameters have a different meaning for the different penalties, we plot the whole solution path of squared residual error vs. sparsity for the three algorithms in Figure 3. We compute the average residual norm for a given level of sparsity for all three algorithms, averaged over 100 runs. We have $M = 100, N = 200, K = 10$ and a small amount of noise is added. We can see that the iterative log thresholding consistently achieves the smallest error for each level of sparsity.

In our final experiment we consider singular value log-thresholding for matrix completion. We study a simplified algorithm that parallels the noiseless sparse recovery algorithm with known number of nonzero-elements $K$. We alternate gradient steps with steps of eliminating all but the first $K$ singular values by soft, hard and log-thresholding. We have an $N \times N$ matrix with 30% observed entries, $N = 100$ and rank, $K = 2$. We show the average error in Frobenius norm from the true underlying solution as a function of iteration number over 100 random runs in Figure 4. We see that the convergence of log-SV-thresholding to the correct solution is consistently faster. We expect similar improvements to hold for other algorithms involving soft-thresholding, and to other problems beyond matrix completion, e.g. robust PCA.

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\(^1\) This is easy for IST and IHT by sorting $|x|$ in descending order. Let $s = \text{sort}(|x|)$ then $\lambda = s_{K+1}$. For ILT we have $\lambda = \frac{(s_{K+1} + s_{K+2})^2}{4}$ from [16].

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Fig. 2. Noiseless sparse recovery: (a) average error-norm (b) probability of exact recovery after 250 iterations over 1000 random trials. $M = 100, N = 200$.

Fig. 3. Sparse recovery with noise. Average error vs. sparsity over 100 trials, after 250 iterations.
where

\[
\text{Proposition 2}
\]

gence to fixed points of \( f \) to iterative log-thresholding. We can see that finding local minima over \( i \), i.e., can be done independently for each coordinate. We can independent of \( n \).

Note that \( n \).

\[
\text{Proposition 3}
\]

In other words, if \(|\bar{x}_i| > x_0\), then the corresponding gradient component satisfies local stationarity conditions for problem \( f \), and if \(|\bar{x}_i| < x_0\), the gradient is bounded.

\[
\text{Proposition 4}
\]

Next, we have:

\[
\text{Proof:}
\]

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\text{Proof:}
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\text{Proof:}
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Moreover, if the singular values of the restriction of $A$ are monotonically increasing and bounded, so the iterates $\{x_i\}$ must converge. Finally, we have
\[
\eta \lambda + \eta_i \lambda - \frac{1}{2} \left( \frac{2 \lambda}{|x_i| + \delta} \right)^2 \geq -\frac{1}{4} \eta \|\delta\|_2^2
\]
where the last inequality comes from the fact that for any $i \in \Gamma_1$, we have $\frac{\sum_{i=1}^{n} |x_i|^2}{2\lambda} \geq 1$.

**Proposition 5** ILT converges to its fixed points if $\|A\|_2 < 1$. Moreover, if the singular values of the restriction of $A$ to the $\Gamma_1$ columns are greater than $\frac{1}{2}$, these fixed points must be the local minima of (7).

The result follows from the proof technique of [15] (Theorem 3); in particular the sums $\sum_{n=1}^{\infty} \|x^{n+1} - x^n\|^2$ are monotonically increasing and bounded, so the iterates $\{x_i\}$ must converge. Finally, we have
\[
Q(\tilde{x} + \eta) = Q(\tilde{x} + \eta, \tilde{x}) - \frac{1}{4} \|\mathcal{P}_1 \eta\|^2 + \|A \mathcal{P}_1 \eta\|^2,
\]
This quantity is non-negative provided that the singular values of the restriction of $A$ to $\Gamma_1$ are greater than $\frac{1}{2}$.

\[
\square
\]

7. REFERENCES

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