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Research Article

The Sparsity of Underdetermined Linear System via l_p Minimization for $0 < p < 1$

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The sparsity problems have attracted a great deal of attention in recent years, which aim to find the sparsest solution of a representation or an equation. In the paper, we mainly study the sparsity of underdetermined linear system via l_p minimization for $0 < p < 1$. We show, for a given underdetermined linear system of equations $A_{m\times n}X = b$, that although it is not certain that the problem (P_p) (i.e., $\min_X \|X\|_p^p$ subject to $AX = b$, where $0 < p < 1$) generates sparser solutions as the value of p decreases and especially the problem (P_p) generates sparser solutions than the problem (P_1) (i.e., $\min_X \|X\|_1$ subject to $AX = b$), there exists a sparse constant $\gamma(A,b) > 0$ such that the following conclusions hold when $p < \gamma(A,b)$: (1) the problem (P_p) generates sparser solution as the value of p decreases; (2) the sparsest optimal solution to the problem (P_p) is unique under the sense of absolute value permutation; (3) let X_1 and X_2 be the sparsest optimal solution to the problems (P_{p_1}) and (P_{p_2}) $(p_1 < p_2)$, respectively, and let X_1 not be the absolute value permutation of X_2. Then there exist $t_1, t_2 \in [p_1, p_2]$ such that X_1 is the sparsest optimal solution to the problem (P_t) $(\forall t \in [p_1, t_1])$ and X_2 is the sparsest optimal solution to the problem (P_t) $(\forall t \in (t_2, p_2])$.

1. Introduction

Recently, considerable attention has been paid to the following sparsity problem. Given a full-rank matrix A of size $m\times n$ with $m \ll n$, m-vector b, and knowing that $b = AX^*$, where $X^* \in \mathbf{R}^n$ is an unknown sparse vector, we expect to recover X^*. Although the system of equations is underdetermined and hence it is not a properly posed problem in linear algebra, sparsity of X^* is a very useful priority that sometimes allows unique solution. Accordingly, one naturally proposes to use the following optimization model (P_0) to obtain the sparsest solutions:

$$(P_0) \quad \min_X \quad \|X\|_0 \qquad \text{s.t.} \quad AX = b, \tag{1}$$

where $\|X\|_0$ denotes the number of nonzero components of X (we call $\|\cdot\|_0$ l_0 norm). This is one of critical problems in compressed sensing research. This problem is motivated by data compression, error correcting codes, n-term approximation, and so forth (see, e.g., [1]). It is known that the problem (P_0) needs nonpolynomial time to solve (cf. [2]). It is crucial to recognize that one natural approach to tackle (P_0) is to solve the following convex minimization problem:

$$(P_1) \quad \min_X \quad \|X\|_1 \qquad \text{s.t.} \quad AX = b, \tag{2}$$

where $\|X\|_1 = \sum_{i=1}^n |x_i|$ is the standard l_1 norm. The study of this problem (P_1) was pioneered by Donoho, Candès, and their collaborators and many researchers have made a lot of contributions related to the existence, uniqueness, and other properties of the sparse solution as well as computational algorithms and their convergence analysis to tackle the problem (P_0) (see survey papers in [3–5]). However, the solutions to the problem (P_1) are often not as sparse as those to the problem (P_0). It is definitely imperative and required for many applications to find solutions which are more sparse than that to the problem (P_1). A natural try for this purpose is to apply the problem (P_p) $(0 < p < 1)$, that is, to solve the following model:

$$\begin{aligned} \left(P_p\right) \ \min_X \quad & \|X\|_p^p \\ \text{s.t.} \quad & AX = b, \end{aligned} \tag{3}$$

where $\|X\|_p^p = \sum_{i=1}^n |x_i|^p$ (we call $\|\cdot\|_p$ l_p-norm, though it is no longer norms for $p < 1$ as the triangle inequality is no longer satisfied). Obviously, the problem (P_p) is no longer a convex optimization problem. This minimization is motivated by the following fact:

$$\lim_{p \to 0_+} \|X\|_p^p = \|X\|_0 . \tag{4}$$

This model was initiated by [6] and many researchers have worked on this direction [1, 2, 7–16]. They demonstrate that (1) for a Gaussian random matrix A, the restricted p-isometry property of order s holds if s is almost proportional to m when $p \to 0_+$ (cf. [8]); (2) when $\delta_{2s} < 1$ (or $\delta_{2s+1} < 1$, $\delta_{2s+2} < 1$), the optimal solution to the problem (P_p) is the same as the optimal solution to the problem (P_0) when $p > 0$ small enough, where $\delta_{2s} < 1$ is the restricted isometry constants of matrix A (similar for $\delta_{2s+1} < 1$, $\delta_{2s+2} < 1$) (cf. [7, 10, 13]); and (3) the l_p minimization can be applied to a wider class of random matrices A (cf. [11]). In addition, in [7, 15], the authors show that the problem (P_p) generates sparser solution than the problem (P_1) and the problem (P_p) generates sparser solution as the value of p decreases by taking phase diagram studies with a set of experiments. Nevertheless, are the conclusions showed by taking phase diagram studies true in theory? In the paper, we will answer this question by studying the sparsity of l_p minimization. Firstly, using Example 2 we show, in general, that the answer to the question above is negative. Secondly, although the answer to the question above is negative, we can prove that, for a given underdetermined linear system of equations $A_{m\times n}X = b$, there exists a constant $\gamma(A, b) > 0$ (we call it sparsity constant) such that the following conclusions hold when $p < \gamma(A, b)$.

(1) The problem (P_p) generates sparser solution as the value of p decreases (Theorem 7).

(2) Let X_p be the sparsest optimal solution to the problem (P_p). Then X_p is the unique sparsest optimal solution to the problem (P_p) under the sense of absolute value permutation (Corollary 6).

(3) Let X_1 and X_2 be the sparsest optimal solution to the problem (P_{p_1}) and problem (P_{p_2}) $(p_1 < p_2)$, respectively, and let X_1 not be the absolute value permutation of X_2. Then there exist $t_1, t_2 \in [p_1, p_2]$ such that X_1 is the sparsest optimal solution to the problem (P_t) $(\forall t \in [p_1, t_1])$ and X_2 is the sparsest optimal solution to the problem (P_t) $(\forall t \in (t_2, p_2])$ (Theorem 8).

2. The Sparsity of Underdetermined Linear System via l_p Minimization

Let $\mathcal{X}$ be the set of all solutions to the underdetermined linear systems $AX = b$. For the convenience of account, we call X_1 the absolute value permutation of X_2, which means that $(|x_{11}|, |x_{12}|, \ldots, |x_{1n}|)$ is the permutation of $(|x_{21}|, |x_{22}|, \ldots, |x_{2n}|)$, where $X_1 = (x_{11}, x_{12}, \ldots, x_{1n})^T$ and $X_2 = (x_{21}, x_{22}, \ldots, x_{2n})^T \in \mathcal{X}$.

Lemma 1 (see [17]). *The problem (P_1) may have more than one solution. Nevertheless, even if there are infinitely many possible solutions to this problem, we can claim that (1) these solutions are gathered in a set that is bounded and convex, and (2) among these solutions, there exists at least one with at most m nonzeros.*

The following example shows that, in general, it is not certain that the problem (P_p) generates sparser solution than the problem (P_1) and the problem (P_p) generates sparser solution as the value of p decreases.

Example 2. We consider the underdetermined linear system of equations $AX = b$, where

$$A = (\alpha_1, \alpha_2, \alpha_3, \alpha_4) = \begin{pmatrix} -\dfrac{20}{29} & 1 & \dfrac{31}{87} & 0 \\ 0 & 1 & \dfrac{8}{15} & 1 \\ \dfrac{60}{29} & 0 & \dfrac{463}{435} & -1 \end{pmatrix}, \tag{5}$$

$b = (1, 2, 3)^T$. By Lemma 1, the l_0-norm of the optimal solutions to the problem (P_1) are not more than 3, and hence the optimal solution is one of the following feasible solutions:

(1) $X_1 = (0, -4/27, 29/9, 58/135)^T$;

(2) $X_2 = (0.1, 0, 3, 0.4)^T$;

(3) $X_3 = (1.45, 2, 0, 0)^T$;

(4) $X_4 = (1.45, 2, 0, 0)^T$.

Furthermore, we can show that the optimal solution to the problem (P_p) $(p = 0.8, 0.95)$ is one of above feasible solutions. It is easy to calculate that

$$\|X_1\|_{0.8}^{0.8} = 3.2756,$$

$$\|X_2\|_{0.8}^{0.8} = 3.0472,$$

$$\|X_3\|_{0.8}^{0.8} = \|X_4\|_{0.8}^{0.8} = 3.0873,$$

$$\begin{aligned}
\|X_1\|_{0.95}^{0.95} &= 3.6502, \\
\|X_2\|_{0.95}^{0.95} &= 3.3706, \\
\|X_3\|_{0.95}^{0.95} = \|X_4\|_{0.95}^{0.95} &= 3.3552, \\
\|X_1\|_1 &= 3.7999, \\
\|X\|_1 &= 3.5, \\
\|X_3\|_1 = \|X_4\|_1 &= 3.45.
\end{aligned} \tag{6}$$

Thus X_2 is the optimal solution when $p = 0.8$ and X_3 is the optimal solution when $p = 0.95$ and $p = 1$. However, $\|X_2\|_0 = 3$, $\|X_3\|_0 = 2$. Therefore, the problem (P_p) does not generate sparser solution than the problem (P_1) and the problem (P_p) does not generate sparser solution as the value of p decreases.

In the following, we will prove the conclusions mentioned in Introduction.

We define two functions $f(t) = \|X\|_t = (|x_1|^t + \cdots + |x_k|^t)^{1/t}$ $(t > 0)$ and $g(t) = \|X\|_t^t = |x_1|^t + \cdots + |x_k|^t$ $(t > 0)$, where $X = (x_1, \ldots, x_k)$ and $x_i \neq 0$. Then $f(t) = (g(t))^{1/t}$.

Theorem 3. *$f(t)$ is a monotone decreasing convex function and*

$$f'(t) = \frac{f(t)}{t}\left(\frac{g'(t)}{g(t)} - \ln f(t)\right). \tag{7}$$

Proof. It is easy to show that (7) holds. Without loss of generality, we assume that $|x_1| \le |x_2| \le \cdots \le |x_k|$. Because

$$\begin{aligned}
f'(t) &= \frac{f(t)}{t}\left(\frac{g'(t)}{g(t)} - \ln f(t)\right) \\
&= \frac{f(t)}{t^2}\left(\frac{\sum_{i=1}^k |x_i|^t \ln |x_i|^t}{g(t)} - \ln g(t)\right) \\
&\le \frac{f(t)}{t^2}\left(\ln |x_k|^t - \ln g(t)\right) \le 0,
\end{aligned} \tag{8}$$

$f(t)$ is monotone decreasing.

Furthermore, $f(t)$ is a convex function. In fact, we have, by the convexity of function $f(x) = x^2$,

$$\left(\frac{\sum_{i=1}^k |x_i|^t \ln |x_i|}{\sum_{i=1}^k |x_i|^t}\right)^2 \le \frac{\sum_{i=1}^k |x_i|^t \ln^2 |x_i|}{\sum_{i=1}^k |x_i|^t}. \tag{9}$$

That is,

$$\left(\frac{g'(t)}{g(t)}\right)^2 \le \frac{g''(t)}{g(t)}. \tag{10}$$

Thus

$$\left(\frac{g'(t)}{g(t)}\right)' = \frac{g''(t)}{g(t)} - \left(\frac{g'(t)}{g(t)}\right)^2 \ge 0 \tag{11}$$

and hence $g'(t)/g(t)$ is monotone increasing. Since $f(t)$ is monotone decreasing, we know that $g'(t)/g(t) - \ln f(t)$ is monotone increasing. Because $f(t)/t$ is monotone decreasing, $g'(t)/g(t)$ is monotone increasing and $g'(t)/g(t) - \ln f(t) \le 0$,

$$\begin{aligned}
f''(t) &= \left(\frac{f(t)}{t}\right)'\left(\frac{g'(t)}{g(t)} - \ln f(t)\right) \\
&\quad + \frac{f(t)}{t}\left(\frac{g'(t)}{g(t)} - \ln f(t)\right)' \ge 0
\end{aligned} \tag{12}$$

which implies that $f(t)$ is convex function. □

Theorem 4. *For a given underdetermined linear system of equations $A_{m\times n}X = b$, there exists a constant $\gamma > 0$ such that, for any $X_1, X_2 \in \mathcal{X}$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$ when $0 < t < \gamma$.*

Proof. Let $X^k = \{X \mid \|X\|_0 = k, X \in \mathcal{X}\}$ and $X_\beta^k = \{X \in X^k \mid$; there exists β such that $\prod_{i=1}^k |x_i| = \beta\}$. Clearly, we have $X^k = \cup_\beta X_\beta^k$, $\mathcal{X} = \cup_{k=1}^n X^k$.

Firstly, for any $X_1, X_2 \in X_\beta^k$, there exists a constant $\gamma_\beta^k > 0$ such that when $0 < t < \gamma_\beta^k$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$.

Obviously, for any given $X_1, X_2 \in X_\beta^k$, there is a positive number $\{\gamma_\beta^k\}_j$ such that when $0 < t < \{\gamma_\beta^k\}_j$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$. Hence, it suffices to show $\inf_j\{\gamma_\beta^k\}_j = \gamma_\beta^k \neq 0$. Otherwise, for an arbitrarily small positive number ε, there exists t with $0 < t < \varepsilon$, $Y_1 \in X_\beta^k$, and $Y_2 \in X_\beta^k$ such that

$$f_1'(t) = (\|Y_1\|_t)' = f_2'(t) = (\|Y_2\|_t)'. \tag{13}$$

Using (7) we obtain

$$\begin{aligned}
&\frac{f_1(t)}{t}\left(\frac{g_1'(t)}{g_1(t)} - \ln f_1(t)\right) \\
&= \frac{f_2(t)}{t}\left(\frac{g_2'(t)}{g_2(t)} - \ln f_2(t)\right).
\end{aligned} \tag{14}$$

That is,

$$\frac{g_1'(t)/g_1(t) - \ln f_1(t)}{g_2'(t)/g_2(t) - \ln f_2(t)} = \frac{f_2(t)}{f_1(t)}. \tag{15}$$

Since $Y_1, Y_2 \in X_\beta^k$, we have $\prod_{i=1}^k |y_{1i}| = \prod_{i=1}^k |y_{2i}| = \beta$.

Hence

$$\sum_{i=1}^k \ln |y_{1i}| = \sum_{i=1}^k \ln |y_{2i}|. \tag{16}$$

Therefore, there is a positive integer M such that

$$\sum_{i=1}^k \ln^M |y_{1i}| \neq \sum_{i=1}^k \ln^M |y_{2i}| \tag{17}$$

and, for any positive integer N with $N < M$,

$$\sum_{i=1}^{k} \ln^{N} |y_{1i}| = \sum_{i=1}^{k} \ln^{N} |y_{2i}|. \quad (18)$$

Since, for any positive integer K,

$$g_1^{(K)}(0) = \left(|y_{11}|^t + \cdots + |y_{1k}|^t\right)^{(K)}\Big|_{t=0} = \sum_{i=1}^{k} \ln^{K} |y_{1i}|,$$
$$g_2^{(K)}(0) = \left(|y_{21}|^t + \cdots + |y_{2k}|^t\right)^{(K)}\Big|_{t=0} = \sum_{i=1}^{k} \ln^{K} |y_{2i}|, \quad (19)$$

we obtain, for M and N mentioned above,

$$g_1^{(M)}(0) \neq g_2^{(M)}(0),$$
$$g_1^{(N)}(0) = g_2^{(N)}(0). \quad (20)$$

We assume, without loss of generality, that $g_1^{(M)}(0) < g_2^{(M)}(0)$. For the M mentioned above, (15) becomes

$$\left[\frac{g_1'(t)/g_1(t) - \ln f_1(t)}{g_2'(t)/g_2(t) - \ln f_2(t)}\right]^{1/t^{M-1}} = \left[\frac{f_2(t)}{f_1(t)}\right]^{1/t^{M-1}} = \left[\frac{g_2(t)}{g_1(t)}\right]^{1/t^{M}}. \quad (21)$$

For the right of (21), we obtain

$$\begin{aligned}\lim_{t\to 0}\left[\frac{g_2(t)}{g_1(t)}\right]^{1/t^{M}} &= \exp\left\{\lim_{t\to 0}\frac{\ln g_2(t) - \ln g_1(t)}{t^{M}}\right\} = \exp\left\{\lim_{t\to 0}\frac{g_2'(t)/g_2(t) - g_1'(t)/g_1(t)}{Mt^{M-1}}\right\} \\ &= \exp\left\{\lim_{t\to 0}\frac{g_2''(t)/g_2(t) - g_1''(t)/g_1(t) - g_2'^2(t)/g_2^2(t) + g_2'^2(t)/g_1^2(t)}{Mt^{M-1}}\right\} = \cdots \\ &= \exp\left\{\frac{g_2^{(M)}(0) - g_1^{(M)}(0)}{k}\right\} > 1.\end{aligned} \quad (22)$$

And for the left of (21), we obtain

$$\begin{aligned}&\lim_{t\to 0}\left[\frac{g_1'(t)/g_1(t) - \ln f_1(t)}{g_2'/g_2(t) - \ln f_2(t)}\right]^{1/t^{M-1}} \\ &= \exp\left\{\lim_{t\to 0}\frac{\ln\left(\ln g_1(t) - \left(g_1'(t)/g_1(t)\right)\times t\right) - \ln\left(\ln g_2(t) - \left(g_2'(t)/g_2(t)\right)\times t\right)}{t^{M-1}}\right\} = 1.\end{aligned} \quad (23)$$

This is a contradiction and thus when $0 < t < \gamma_\beta^k$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$.

Secondly, for any $X_1, X_2 \in X^k$, there exists a constant $\gamma^k > 0$ such that when $0 < t < \gamma^k$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$.

It suffices to show that $\inf_\beta \gamma_\beta^k = \gamma^k \neq 0$. Otherwise, for an arbitrarily small positive number ε, there is t with $0 < t < \varepsilon$, $Y_1 \in X_{\beta_1}^k$ and $Y_2 \in X_{\beta_2}^k$ $(\beta_1 \neq \beta_2)$ such that

$$f_1'(t) = \left(\|Y_1\|_t\right)' = f_2'(t) = \left(\|Y_2\|_t\right)'. \quad (24)$$

Using (7) again, we also obtain (15).

For the right of (15), we have

$$\lim_{t\to 0}\frac{f_2(t)}{f_1(t)} = \exp\left\{\lim_{t\to 0}\frac{\ln g_2(t) - \ln g_1(t)}{t}\right\} = \frac{\prod_i |y_{1i}|}{\prod_i |y_{2i}|} \neq 1. \quad (25)$$

And for the left of (15), we have

$$\lim_{t\to 0}\frac{g_1'(t)/g_1(t) - \ln f_1(t)}{g_2'(t)/g_2(t) - \ln f_2(t)} = \lim_{t\to 0}\frac{\left(g_1'(t)/g_1(t)\right)\times t - \ln g_1(t)}{\left(g_2'(t)/g_2(t)\right)\times t - \ln g_2(t)} = 1. \quad (26)$$

This is a contradiction and thus $\inf_\beta \gamma_\beta^k = \gamma^k \neq 0$.

Thirdly, for any $X_1 \in X^k$, $X_2 \in X^s$, $k \neq s$, there exists a constant $\gamma^{k,s} > 0$ such that when $0 < t < \gamma^{k,s}$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$.

We assume, without loss of generality, that $\|X_1\|_0 = k < s = \|X_2\|_0$. Then

$$\lim_{t\to 0}\frac{g_1'(t)/g_1(t) - \ln f_1(t)}{g_2'(t)/g_2(t) - \ln f_2(t)} = \lim_{t\to 0}\frac{\left(g_1'(t)/g_1(t)\right)\times t - \ln g_1(t)}{\left(g_2'(t)/g_2(t)\right)\times t - \ln g_2(t)} = \frac{\ln k}{\ln s} < 1, \quad (27)$$

$$\lim_{t\to 0}\frac{f_2(t)}{f_1(t)} = \exp\left\{\lim_{t\to 0}\frac{\ln g_2(t) - \ln g_1(t)}{t}\right\} = \infty.$$

So there is a positive number $\gamma^{k,s}$ such that when $t < \gamma^{k,s}$,

$$\frac{g_1'(t)/g_1(t) - \ln f_1(t)}{g_2'(t)/g_2(t) - \ln f_2(t)} < \frac{f_2(t)}{f_1(t)}, \quad (28)$$

which implies that

$$f_2'(t) = \left(\|X_2\|_t\right)' < f_1'(t) = \left(\|X_1\|_t\right)'. \quad (29)$$

In conclusion, we take $\gamma = \min\{\gamma^k, \gamma^{k,s} \mid k, s = 1, 2, \ldots, n\}$ and thus when $0 < t < \gamma$, for any $X_1, X_2 \in \mathcal{X}$, either $f_1'(t) = (\|X_1\|_t)' < f_2'(t) = (\|X_2\|_t)'$ or $f_2'(t) = (\|X_2\|_t)' < f_1'(t) = (\|X_1\|_t)'$. □

Obviously, for a given underdetermined linear system of equations $A_{m\times n}X = b$, there are infinitely many constants $\gamma_i > 0$ such that when $0 < t < \gamma_i$ Theorem 7 holds. The supremum of γ_i is called the sparse constant of underdetermined linear system of equations $A_{m\times n}X = b$ and denoted $\gamma(A, b)$.

Corollary 5. *Let equations $A_{m\times n}X = b$ be an underdetermined linear system. Then $f_1(t) = \|X_1\|_t$ and $f_2(t) = \|X_2\|_t$ have at most one intersection in $(0, \gamma(A, b))$, where $X_1, X_2 \in \mathcal{X}$ and X_1 is not the absolute value permutation of X_2.*

Proof. It is easy to prove that the conclusion holds by Theorems 4 and 7. □

Corollary 6. *Let X_p be the sparsest optimal solution to the problem (P_p) $(p < \gamma(A, b))$. Then X_p is the unique sparsest optimal solution to the problem (P_p) under the sense of absolute value permutation.*

Proof. Suppose that X_{p^*} is another sparsest optimal solution to the problem (P_p) and X_{p^*} is not the absolute value permutation of X_p. By Theorem 7, $\forall t \in (0, p)$, either $f_1'(t) = (\|X_p\|_t)' < f_2'(t) = (\|X_{p^*}\|_t)'$ or $f_1'(t) = (\|X_p\|_t)' > f_2'(t) = (\|X_{p^*}\|_t)'$. We suppose that $f_1'(t) = (\|X_p\|_t)' < f_2'(t) = (\|X_{p^*}\|_t)'$ and hence $\forall t \in (0, p)$ we have $f_1(t) > f_2(t)$, which implies that $\|X_p\|_0 > \|X_{p^*}\|_0$. This is a contradiction. □

Theorem 7. *The problem (P_p) generates sparser solution as the value of p decrease when $p < \gamma(A, b)$.*

Proof. If the conclusion does not hold, then there exists the optimal solutions X_1 to the problems (P_{p_1}) and the optimal solutions X_2 to the problems (P_{p_2}) satisfying $p_1 < p_2 < \gamma(A, b)$ and $\|X_1\|_0 = s > k = \|X_2\|_0$. We consider the following two cases.

(1) If $\|X_1\|_{p_1} = \|X_2\|_{p_1}$, then $\|X_1\|_{p_2} < \|X_2\|_{p_2}$ because of Corollary 5 and $s > k$. This contradicts with the fact that X_2 is the optimal solutions to (P_{p_2}).

(2) If $\|X_1\|_{p_1} < \|X_2\|_{p_1}$, then $\|X_1\|_t$ and $\|X_2\|_t$ have at least one intersection in $(0, p_1)$ because of $s > k$. Since $\|X_2\|_{p_2} \le \|X_1\|_{p_2}$, $\|X_1\|_t$, and $\|X_2\|_t$ have at least one intersection in $(p_1, p_2]$. This is contradictory to Corollary 5.

□

Theorem 8. *Let X_1 and X_2 be the sparsest optimal solution to the problem (P_{p_1}) and problem (P_{p_2}) $(p_1 < p_2 < \gamma(A, b))$, respectively, and X_1 is not the absolute value permutation of X_2. Then there exist $t_1, t_2 \in [p_1, p_2]$ such that when $p_1 \le t \le t_1$, X_1 is the sparsest optimal solution to the problem (P_t) and when $t_2 < t \le p_2$, X_2 is the sparsest optimal solution to the problem (P_t).*

Proof. Firstly, X_1 is not the optimal solution to P_{p_2} and hence $\|X_1\|_{p_2} > \|X_2\|_{p_2}$. In fact, if $\|X_1\|_{p_2} = \|X_2\|_{p_2}$, then $\|X_1\|_{p_1} < \|X_2\|_{p_1}$ by Corollary 5 and X_1 is the optimal solution to the problem (P_{p_1}). By Corollary 5 again, we have $\|X_1\|_0 < \|X_2\|_0$ which contradicts with the fact that X_2 is the sparsest optimal solutions to (P_{p_2}).

We consider the following two cases.

(1) If $\|X_1\|_{p_1} = \|X_2\|_{p_1}$, then, for any $p_2 \ge t > p_1$, X_2 is the sparsest optimal solution to the problem (P_t). Otherwise, there exists X_3 such that $\|X_3\|_t < \|X_2\|_t$ or $\|X_3\|_t = \|X_2\|_t$ and $\|X_3\|_0 < \|X_2\|_0$. If $\|X_3\|_t < \|X_2\|_t$, then $\|X_3\|_0 > \|X_2\|_0$ by Corollary 5 and $\|X_3\|_{p_1} \ge \|X_1\|_{p_1} = \|X_2\|_{p_1}$, which is contradictory to Theorem 8. If $\|X_3\|_t = \|X_2\|_t$ and $\|X_3\|_0 < \|X_2\|_0$, then $\|X_3\|_{p_1} < \|X_2\|_{p_1} = \|X_1\|_{p_1}$ by Corollary 5, which contradicts the fact that X_1 is the optimal solutions to (P_{p_1}). Therefore, we pick $t_1 = t_2 = p_1$.

(2) If $\|X_1\|_{p_1} < \|X_2\|_{p_1}$, then, by $\|X_1\|_{p_2} > \|X_2\|_{p_2}$, $\|X_1\|_t$ and $\|X_2\|_t$ have one intersection t_0 in (p_1, p_2), and hence $\|X_1\|_0 < \|X_2\|_0$. We assume, without loss of generality, that $\|X_1\|_0 + 2 = \|X_2\|_0$. Let X_3 be the sparsest optimal solution to the problem P_{t_0}. Then X_3 is not the absolute value permutation of X_2. Otherwise, we have $\|X_3\|_{t_0} = \|X_2\|_{t_0} = \|X_1\|_{t_0}$, that is, X_1 is the optimal solution to the problem P_{t_0}. Since $\|X_1\|_{p_1} < \|X_2\|_{p_1} = \|X_3\|_{p_1}$, we have $\|X_1\|_0 < \|X_3\|_0$ which contradicts the fact that X_3 is the sparsest optimal solution to the problem P_{t_0}.

If X_3 is the absolute value permutation of X_1, then $\|X_3\|_{t_0} = \|X_1\|_{t_0} = \|X_2\|_{t_0}$ and thus, by the proof of case (1), for any $p_2 \geq t > t_0$, X_2 is the sparsest optimal solution to the problem (P_t). Obviously, for any $p_1 \leq t \leq t_0$, X_1 is the sparsest optimal solution to the problem (P_t). Therefore, we pick $t_1 = t_2 = t_0$.

If X_3 is not the absolute value permutation of X_1, then $\|X_3\|_0 = \|X_1\|_0 + 1$ by Corollary 6, and there exist $t_1 \in (p_1, t_0)$, $t_2 \in (t_0, p_2)$ such that t_1 is the intersection of $\|X_3\|_t$ and $\|X_1\|_t$ and t_2 is the intersection of $\|X_3\|_t$ and $\|X_2\|_t$. By the proof above, we have that, for any $t \leq t_1$, X_1 is the sparsest optimal solution to the problem (P_t) and for any $t > t_2$, X_2 is the sparsest optimal solution to the problem (P_t). □

3. Conclusion

In this paper, the sparsity of underdetermined linear system via l_p minimization for $0 < p < 1$ has been studied. Our research reveals that for a given underdetermined linear system of equations $A_{m\times n}X = b$ there exists a sparse constant $\gamma(A, b) > 0$ such that when $p < \gamma(A, b)$, the problem (P_p) generates sparser solution as the value of p decreases and the sparsest optimal solution to the problem (P_p) is unique under the sense of absolute value permutation and if X_1 is not the absolute value permutation of X_2 where X_1 and X_2 are the sparsest optimal solution to the problems (P_{p_1}) and (P_{p_2}) $(p_1 < p_2)$, respectively, then there exist $t_1, t_2 \in [p_1, p_2]$ such that X_1 is the sparsest optimal solution to the problem (P_t) $(\forall t \in [p_1, t_1])$ and X_2 is the the sparsest optimal solution to the problem (P_t) $(\forall t \in (t_2, p_2])$.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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