

3-2013

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Technical Report: UTEP-CS-13-18

To appear in *Journal of Uncertain Systems*, 2013, Vol. 7.

Recommended Citation

Ramirez, Carlos; Kreinovich, Vladik; and Argaez, Miguel, "Why ℓ_1 Is a Good Approximation to ℓ_0 : A Geometric Explanation" (2013). *Departmental Technical Reports (CS)*. 758.

https://scholarworks.utep.edu/cs_techrep/758

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Why ℓ_1 Is a Good Approximation to ℓ_0 : A Geometric Explanation

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Received 1 April 2012; Revised 16 April 2012

Abstract

In practice, we usually have partial information; as a result, we have several different possibilities consistent with the given measurements and the given knowledge. For example, in geosciences, several possible density distributions are consistent with the measurement results. It is reasonable to select the simplest among such distributions. A general solution can be described, e.g., as a linear combination of basic functions. A natural way to define the simplest solution is to select one for which the number of the non-zero coefficients c_i is the smallest. The corresponding “ ℓ_0 -optimization” problem is non-convex and therefore, difficult to solve. As a good approximation to this problem, Candès and Tao proposed to use a solution to the convex ℓ_1 optimization problem $\sum |c_i| \rightarrow \min$. In this paper, we provide a geometric explanation of why ℓ_1 is indeed the best convex approximation to ℓ_0 .

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Keywords: ℓ_0 -norm, ℓ_1 -norm, sparse representation, Ockham razor

1 Formulation of the Problem

Need to select a solution from all solutions consistent with the observations. In each practical situations, we usually have partial information; as a result, we have several different possibilities consistent with the given measurements and the given knowledge.

For example, in many practical situations, we want to find out how a certain quantity changes from one spatial location to another: in geophysics, we want to find out the density $\rho(x)$ at different spatial locations x ; in meteorology, we want to find out the temperature, wind speed and wind direction at different spatial locations, etc. From the mathematical viewpoint, what we want to find out is a function.

To exactly describe a general function, we need to know the values of infinitely many parameters. For example, functions can be represented as a linear combination $\sum c_i \cdot e_i(x)$ of functions from some basis $\{e_i(x)\}$. Elements of this basis can be monomials (in Taylor series), sines and cosines (in Fourier series), etc. So, to determine a function, we must find all these parameters c_i from the results of measurements and observations. At any given moment of time, we only have finitely many measurement and observation results. So, we only have finitely many constraints on infinitely many parameters. In general, when we have a system of equations in which there are more unknown than equations, this system allows multiple solutions; this is a well-known fact for generic linear systems, it is a known fact for generic non-linear systems as well. So, several different solutions are consistent with all the measurement results.

For example, in geosciences, several possible density distributions are consistent with the measurement results. Scientists usually want us not only to present them with the set of all possible solutions, but also want us to select one of these solutions as the most “reasonable” one – in some natural sense.

Occam’s razor: idea. One of the ways to select a solution is to select the solution which is, in some reasonable sense, the simplest among all possible solutions consistent with all the observations.

ℓ_0 -solutions as a natural formalization of Occam’s razor. As we have mentioned, a general function can be described, e.g., as a linear combination of basic functions. In this representation, a natural way to

define the simplest solution is to select one for which the number of the non-zero coefficients c_i is the smallest. This number is known as the ℓ_0 -norm $\|c\|_0 \stackrel{\text{def}}{=} \#\{i : c_i \neq 0\}$.

ℓ_0 -solutions are difficult to compute. The ℓ_0 -norm is non-convex. It is known that non-convex optimization problems are computationally difficult to solve exactly; see, e.g., [8]. Not surprisingly, the ℓ_0 -optimization problem is also computationally difficult: it is known to be NP-hard; see, e.g., [2, 3, 4, 6].

How to solve non-convex optimization problems. The difficulty of solving non-convex optimization problems is caused by the non-convexity of the corresponding objective function. For convex objective function, there exist feasible optimization algorithms; see, e.g., [8]. Because of this, one of the possible ways to solve a non-convex optimization is to solve a similar *convex* optimization problem. This idea is known as *convex relaxation*.

ℓ_1 -solutions as a good approximation to ℓ_0 . For ℓ_0 -problems, as a good convex approximation, Candès and Tao proposed to use a solution to the corresponding convex ℓ_1 optimization problem, i.e., to find the values of all the coefficients c_i for which the ℓ_1 -norm $\|c\|_1 \stackrel{\text{def}}{=} \sum |c_i|$ is the smallest possible; see, e.g., [1, 2, 3, 4, 5, 7].

Challenge. The idea of replacing the original ℓ_0 -problem with the corresponding ℓ_1 -problem was based on the result – described in [2, 3, 4] – that under certain conditions, ℓ_1 -optimization provides us with the solution to the original ℓ_0 -problem.

However, in practice, the ℓ_1 -approximation to the original ℓ_0 -problem is used way beyond these conditions. As a result, we often get a solution which is not exactly minimizing the original ℓ_0 -norm, but which provides much smaller values of the ℓ_0 -norm than other known techniques.

In such situations, the use of ℓ_1 norm is purely heuristic, not justified by any proven results. It is therefore desirable to provide a mathematical explanation for the success of ℓ_1 -approximation to ℓ_0 -optimization.

What we do in this paper. In this paper, we provide a geometric explanation for the empirical success of ℓ_1 -approximation to the ℓ_0 -problems.

2 Geometric Justification of ℓ_1 -Norm

Important observation: we need ℓ_ε , not ℓ_0 . Intuitively, if we can decrease the absolute value $|c_i|$ of one of the coefficients without changing other coefficients, we get a simpler sequence. The original ℓ_0 -norm does not capture this difference, since, e.g., sequences $(10, 10, 0, \dots, 0)$ and $(10, 1, 0, \dots, 0)$ have the exact same ℓ_0 -norm equal to 2. To capture this difference, it is reasonable to use an ℓ_ε -norm $\|c\|_\varepsilon \stackrel{\text{def}}{=} \sum |c_i|^\varepsilon$ for some small $\varepsilon > 0$.

This new norm captures the above difference: e.g., $\|(10, 1, 0, \dots, 0)\|_\varepsilon = 10^\varepsilon + 1 < \|(10, 10, 0, \dots, 0)\|_\varepsilon = 2 \cdot 10^\varepsilon$. On the other hand, when $\varepsilon \rightarrow 0$, we have $|c_i|^\varepsilon \rightarrow 0$ when $c_i = 0$ and $|c_i|^\varepsilon \rightarrow 1$ when $c_i \neq 0$, so $\|c\|_\varepsilon \rightarrow \|c\|_0$. Thus, for sufficiently small ε , the value $\|c\|_\varepsilon$ is practically indistinguishable from $\|c\|_0$. Because of this, in practice, instead of the ℓ_0 -norm, a ℓ_ε -norm corresponding to some small $\varepsilon > 0$ is actually used.

Towards formalizing the problem. Our objective is to select, among all possible combinations $c = (c_1, \dots, c_n)$ which are consistent with observations, the one which is, in some sense, most reasonable. In other words, we need to be able, given any two combinations $c = (c_1, \dots, c_n)$ and $c' = (c'_1, \dots, c'_n)$, to decide which combination is better. In precise terms, we need to describe a total (= linear) *pre-ordering* relation \leq on the set \mathbb{R}^n of possible combinations, i.e., a transitive relation for which for every c and c' , either $c \leq c'$ (c is better or of the same quality as c') or $c' \leq c$. As usual, we will use the notation $c < c'$ when $c \leq c'$ and $c' \not\leq c$, and $c \equiv c'$ when $c \leq c'$ and $c' \leq c$.

If we use an objective function $f(c_1, \dots, c_n)$, then the relation $(c_1, \dots, c_n) \leq (c'_1, \dots, c'_n)$ takes the form $f(c_1, \dots, c_n) \leq f(c'_1, \dots, c'_n)$.

Natural requirements. As we have mentioned, if we decrease one of the absolute values c_i , we should get a better solution. It also makes sense to require that the quality does not depend on permutations and that the relative quality of two combination does not change if we simply use different measuring units (i.e., replace $c = (c_1, \dots, c_n)$ with $\lambda \cdot c = (\lambda \cdot c_1, \dots, \lambda \cdot c_n)$).

It is also reasonable to require that the relation is *Archimedean* in the sense that for every two combinations $c \neq 0$ and $c' \neq 0$, there exists a $\lambda > 0$ for which $\lambda \cdot c \equiv c'$. Indeed, when $\lambda = 0$, we have $\lambda \cdot c = 0 \leq c'$; for very large λ , we have $c' \leq \lambda \cdot c$; thus, intuitively, there should be an intermediate value λ for which $\lambda \cdot c$ and c' are equivalent.

Definition 1. A linear pre-ordering relation \leq on \mathbb{R}^n is called:

- natural if for all values $c_1, \dots, c_{i-1}, c_i, c'_i, c_{i+1}, \dots, c_n$, if $|c_i| < |c'_i|$, then

$$(c_1, \dots, c_{i-1}, c_i, c_{i+1}, \dots, c_n) < (c_1, \dots, c_{i-1}, c'_i, c_{i+1}, \dots, c_n).$$

- permutation-invariant if $(c_1, \dots, c_n) \equiv (c_{\pi(1)}, \dots, c_{\pi(n)})$ for every c and for every permutation π ;
- scale-invariant if $c \leq c'$ implies $\lambda \cdot c \leq \lambda \cdot c'$.
- Archimedean if for every $c \neq 0$ and $c' \neq 0$, there exist a real number $\lambda > 0$ for which $\lambda \cdot c \equiv c'$.

It turns out that to describe each such pre-order can be uniquely determined by a set:

Proposition 1. A natural Archimedean pre-order \leq is uniquely determined by the set

$$B_{\leq} \stackrel{\text{def}}{=} \{c : c \leq (1, 0, \dots, 0)\}.$$

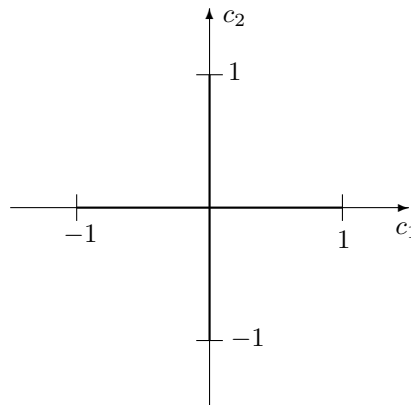
Proof. Indeed, since \leq is Archimedean, for every vector c , there exists a value $\lambda(c)$ for which

$$c \equiv \lambda(c) \cdot (1, 0, \dots, 0) = (\lambda(c), 0, \dots, 0).$$

Due to the naturalness property, the smaller $\lambda(c)$, the better the corresponding vector $(\lambda(c), 0, \dots, 0)$ and thus, the better the combination c : $c \leq c' \Leftrightarrow \lambda(c) \leq \lambda(c')$. Thus, to determine the pre-order \leq , it is sufficient to know the value $\lambda(c)$ for all c . One can easily see that this value, in turn, can be uniquely determined from the set B_{\leq} , as $\min\{k : c/k \in B_{\leq}\}$. The proposition is proven.

Proposition 2. For a natural permutation-invariant scale-invariant Archimedean pre-order \leq , the set B_{\leq} contains the set

$$B_0 \stackrel{\text{def}}{=} \{(c_1, 0, \dots, 0) : |c_1| \leq 1\} \cup \dots \cup \{(0, \dots, 0, c_i, 0, \dots, 0) : |c_i| \leq 1\} \cup \dots \cup \{(0, \dots, 0, c_n) : |c_n| \leq 1\}.$$



Proof. Let us show that every element of the set B_0 indeed belongs to B_{\leq} .

Indeed, due to naturalness, when $|c_1| \leq 1$, we have $(c_1, 0, \dots, 0) \leq (1, 0, \dots, 0)$ and thus, $(c_1, 0, \dots, 0) \in B_{\leq}$. Due to permutation-invariance, for every i and for every c_i with $|c_i| \leq 1$, we have $(0, \dots, 0, c_i, 0, \dots, 0) \equiv (c_i, 0, \dots, 0)$. So, from $(c_i, 0, \dots, 0) \leq (1, 0, \dots, 0)$, we conclude that $(0, \dots, 0, c_i, 0, \dots, 0) \leq (1, 0, \dots, 0)$ and thus, $(c_1, 0, \dots, 0) \in B_{\leq}$. The proposition is proven.

How to describe approximation accuracy? The ℓ_0 -norm is not convex, and we want to approximate it by a convex one, i.e., by a convex objective function $f(c_1, \dots, c_n)$ which is, in some reasonable sense, the “most accurate” approximation to the ℓ_0 -norm. How can we describe approximation accuracy? According to Proposition 1, each pre-order \leq is uniquely determined by the corresponding set B_{\leq} . Thus, it is reasonable to use the difference between the corresponding sets to gauge the approximation accuracy.

One can see that when $\varepsilon \rightarrow 0$, the set $\{c : \|c\|_{\varepsilon} \leq \|(1, 0, \dots, 0)\|_{\varepsilon} = 1\}$ tends to the above-defined set B_0 . For the relation \leq corresponding to a convex function, the set

$$B_{\leq} = \{c : c \leq (1, 0, \dots, 0)\} = \{c : f(c_1, \dots, c_n) \leq f(1, 0, \dots, 0)\}$$

is also convex. In these terms, our goal is to find a convex set B approximating the set B_0 .

In general, the sets S and S' are equal when each element of the set S belongs to S' and each element of S' belongs to S . Thus, the difference between two sets S and S' comes from elements which belong to S but not to S' (these elements form the difference $S - S'$) and the elements which belong to S' but not to S (these elements form the difference $S' - S$).

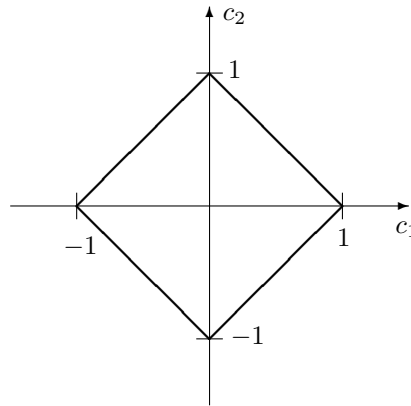
In our case, due to Proposition 2, each element of the set B_0 belongs to B_{\leq} . Thus, the only difference between the sets B_0 (corresponding to ℓ_0 -norm) and the desired convex approximation B is the difference $B - B_0$. So, we arrive at the following definition.

Definition 2. We say that a convex set $B \supseteq B_0$ is a better approximation of the set B_0 than a convex set $B' \supseteq B_0$ if $B - B_0 \subset B' - B_0$ (and $B - B_0 \neq B' - B_0$).

Discussion. The relation defined in Definition 2 is only a partial order, so it is not a priori clear that there is a convex set which is the best according to this criterion. However, the following result shows that such an optimal approximation does exist.

Proposition 3. Out of all convex sets B containing the set B_0 , the best approximation to B_0 is the convex hull of B_0 :

$$B_1 = \text{Conv}(B_0) = \{(c_1, \dots, c_n) : \sum_{i=1}^n |c_i| = 1\}.$$



Proof is straightforward: every convex set containing B_0 contains its convex hull, so the convex hull is indeed the best approximation in the sense of Definition 2.

Discussion. Using the technique described in the proof of Proposition 1, we can see that the pre-order corresponding to the set B_1 is equivalent to minimizing the ℓ^1 -norm. Thus, ℓ_1 -norm is indeed the best convex approximation to the ℓ_0 -norm.

Acknowledgments

This work was supported in part by the National Science Foundation grants HRD-0734825 and HRD-1242122 (Cyber-ShARE Center of Excellence) and DUE-0926721, by Grants 1 T36 GM078000-01 and 1R43TR000173-01 from the National Institutes of Health, and by a grant on F-transforms from the Office of Naval Research.

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