# A Technique For Choosing the Weights for Weighted $\ell_1$-minimization.

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A prominent approach to the problem of recovering a *sparse* vector $x_0 \in \mathbb{R}^d$ (meaning that only few coefficients $x_0(i)$ are non-vanishing) from *underdetermined linear measurements* $b = Ax_0$ is $\ell_1$-minimization:

$$\min \|x\|_1 \text{ subject to } Ax = b. \tag{$\mathcal{P}_1$}$$

For many different types of measurement matrices $A \in \mathbb{R}^{m,d}$, it can be shown that the solution to $(\mathcal{P}_1)$ is equal to an $s$-sparse ground truth signal $x_0$ with high probability provided $m \gtrsim s \log(d)$.
Sometimes, one knows more about $x_0$ than that it is sparse. Concretely, one might know that certain sets of indices $S_i \subseteq \{1, \ldots, d\}$ are more likely to contain non-zero indices. A proposed method for taking advantage of this additional knowledge is to use a *weighted* $\ell_1$*-norm* in the minimization program:

$$\min \|x\|_{1,w} = \min \sum_{i=1}^{d} w_i |x(i)| \text{ subject to } Ax = b.$$

Choosing the weights is a subtle issue. The general idea is to put lower weights on indices which are likely to be non-zero, but choosing the weights in a clever manner can lead to significantly better results. In this talk, we will describe a simple and efficient method of finding weights which in a certain sense are optimal for the case of $A$ being Gaussian. The talk is based on the paper [1].

## Références

[1] A. Flinth. Choice of Weights for Sparse Recovery With Prior Information. *IEEE Trans. Inf. Theory.* 62(7):4276 - 4284, 2016.

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