
Compressed Least-Squares Regression (Supplementary material)

Odalric-Ambrym Maillard and Rémi Munos
 SequeL Project, INRIA Lille - Nord Europe, France
 {odalric.maillard, remi.munos}@inria.fr

1 Proof of Proposition 1

Proposition 1 *Let $(u_k)_{1 \leq k \leq K}$ and v be vectors of \mathbb{R}^N . Let A be a $M \times N$ matrix of i.i.d. elements drawn from one of the previously defined distributions. For any $\varepsilon > 0$, $\delta > 0$, for $M \geq \frac{1}{\frac{\varepsilon^2}{4} - \frac{\varepsilon^3}{6}} \log \frac{4K}{\delta}$, we have, with probability at least $1 - \delta$, for all $k \leq K$,*

$$|Au_k \cdot Av - u_k \cdot v| \leq \varepsilon \|u_k\| \|v\|.$$

Proof: We make use of the following lemma, which states that the random (with respect to the choice of the matrix A) variable $\|Au\|^2$ concentrates around its expectation $\|u\|^2$ when M is large. The proof uses concentration inequalities (Cramer's large deviation Theorem) and may be found e.g. in [1].

Lemma 1 *For any vector u in \mathbb{R}^N and any $\varepsilon \in (0, 1)$, we have*

$$\begin{aligned} \mathbb{P}\left(\|Au\|^2 \geq (1 + \varepsilon)\|u\|^2\right) &\leq e^{-M(\varepsilon^2/4 - \varepsilon^3/6)} \\ \mathbb{P}\left(\|Au\|^2 \leq (1 - \varepsilon)\|u\|^2\right) &\leq e^{-M(\varepsilon^2/4 - \varepsilon^3/6)} \end{aligned}$$

To prove the proposition, we apply the lemma to any couple of vectors $u + w$ and $u - w$, where u and w are vectors of norm 1. From the parallelogram law, we have that

$$\begin{aligned} 4Au \cdot Aw &= \|Au + Aw\|^2 - \|Au - Aw\|^2 \\ &\leq (1 + \varepsilon)\|u + w\|^2 - (1 - \varepsilon)\|u - w\|^2 \\ &= 4u \cdot w + \varepsilon(\|u + w\|^2 + \|u - w\|^2) \\ &= 4u \cdot w + 2\varepsilon(\|u\|^2 + \|w\|^2) = 4u \cdot w + 4\varepsilon. \end{aligned}$$

fails with probability $2e^{-M(\varepsilon^2/4 - \varepsilon^3/6)}$ (we applied the previous lemma twice at line 2).

Thus for each $k \leq K$, we have with same probability:

$$Au_k \cdot Av \leq u_k \cdot v + \varepsilon \|u_k\| \|v\|.$$

Now the symmetric inequality holds with the same probability, and using a union bound for considering all $(u_k)_{k \leq K}$, we have that

$$|Au_k \cdot Av - u_k \cdot v| \leq \varepsilon \|u_k\| \|v\|,$$

holds for all $k \leq K$, with probability $1 - 4Ke^{-M(\varepsilon^2/4 - \varepsilon^3/6)}$, and the proposition follows. \square

2 Proof of Proposition 2

Proposition 2 Assume that f^* is (L, γ) -Lipschitz (i.e. for all $v \in \mathcal{X}$ there exists a polynomial p_v of degree $\lfloor \gamma \rfloor$ such that for all $u \in \mathcal{X}$, $|f(u) - p_v(u)| \leq L|u - v|^\gamma$) with $1/2 < \gamma \leq p$. Then setting $c_h = 2^{h(1-2\gamma)/4}$, we have $\|\alpha^+\| \sup_x \|\varphi(x)\| \leq L \frac{2^\gamma}{1-2^{1/2-\gamma}} \int_0^1 |\varphi_0|$, which is independent of N .

Proof: f^+ decomposes as $f^+ = \sum_{1 \leq h \leq H} \sum_l \alpha_{h,l}^0 \varphi_{h,l}^0 = \sum_{1 \leq h \leq H} \sum_l (\alpha_{h,l}^0 2^{h/2} c_h^{-1}) \varphi_{h,l}$. By Theorem 6.3 of [2], since f^* is (L, γ) -Lipschitz and φ^0 has at least $p \geq \gamma$ vanishing moments, we have $|\alpha_{h,l}^0| \leq L 2^\gamma \int_0^1 |\varphi_0| 2^{-h(\gamma+1/2)}$. Thus we deduce:

$$\|\alpha^+\|^2 = \sum_{1 \leq h \leq H} \sum_l \alpha_{h,l}^2 \leq (L 2^\gamma \int_0^1 |\varphi_0|)^2 \sum_{1 \leq h \leq H} 2^h 2^{-2h\gamma} c_h^{-2}$$

and

$$\|\varphi(x)\|^2 = \sum_{1 \leq h \leq H} \sum_l c_h^2 2^{-h} (\varphi_{h,l}^0(x))^2 \leq \sum_{1 \leq h \leq H} c_h^2$$

Thus, setting $c_h = 2^{(1-2\gamma)h/4}$, we deduce

$$\|\alpha^+\|^2 \sup_x \|\varphi(x)\|^2 \leq (L 2^\gamma \int_0^1 |\varphi_0|)^2 (1 - 2^{1/2-\gamma})^{-2}$$

since $\gamma > 1/2$. □

References

- [1] Dimitris Achlioptas. Database-friendly random projections: Johnson-Lindenstrauss with binary coins. *Journal of Computer and System Sciences*, 66(4):671–687, June 2003.
- [2] Stephane Mallat. *A Wavelet Tour of Signal Processing*. Academic Press, 1999.