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Coresets for ℓ_p Regression

- . ℓ_p linear regression problem
 - Let A be an $n \times d$ matrix containing n examples with d features
 - Let \mathbf{b} be a vector of n labels

Solve
$$\min_{\mathbf{x} \in \mathbb{R}^d} \|\mathbf{A}\mathbf{x} - \mathbf{b}\|_p^p = \sum_{i=1}^n |\langle \mathbf{a}_i, \mathbf{x} \rangle - \mathbf{b}_i|^p$$

p = 2: least squares linear regression

. p = 1: least absolute deviations regression

. $p = \infty$: Chebyshev regression

Coresets for ℓ_p Regression

- Coreset: small weighted subset of a dataset
 - Weighted subset \mathbf{S} s.t. $\|\mathbf{S}(\mathbf{A}\mathbf{x} \mathbf{b})\|_p^p = (1 \pm \varepsilon)\|\mathbf{A}\mathbf{x} \mathbf{b}\|_p^p$ for every $\mathbf{x} \in \mathbb{R}^d$
 - Goal: want the coreset size s = nnz(S) to be as small as possible

Coresets for ℓ_p Regression

- . For single response ℓ_p regression, we know how to compute coresets nearly optimally!
 - _ ℓ_p Lewis weight sampling [Cohen—Peng 2015, Woodruff—Yasuda 2023]

- We can guarantee
$$s=\begin{cases} \tilde{O}(\varepsilon^{-2}d^{p/2}) & p>2\\ \tilde{O}(\varepsilon^{-2}d) & p\leq 2 \end{cases}$$

- Question in this work: what if we have multiple responses?
 - m responses specified by a $n \times m$ matrix \mathbf{B}
 - _ Goal: $\|\mathbf{S}(\mathbf{AX} \mathbf{B})\|_{p,p}^p = (1 \pm \varepsilon)\|\mathbf{AX} \mathbf{B}\|_{p,p}^p$ for every $d \times m$ matrix \mathbf{X}
 - Challenge: achieve s independent of m

Coresets for Multiple ℓ_p Regression Main results

Theorem (Strong coreset). Lewis weight sampling gives a sampling matrix **S** such that $\|\mathbf{S}(\mathbf{AX} - \mathbf{B})\|_{p,p}^p = (1 \pm \varepsilon)\|\mathbf{AX} - \mathbf{B}\|_{p,p}^p$ for every $d \times m$ matrix **X** with

$$s = \begin{cases} \tilde{O}(\varepsilon^{-p} d^{p/2}) & p > 2\\ \tilde{O}(\varepsilon^{-2} d) & p \le 2 \end{cases}$$

Furthermore, this is nearly optimal.

Techniques

- _ Generalization of techniques for active ℓ_p regression [Musco—Musco—Woodruff—Yasuda 2022] to achieve a polylogarithmic dependence on m
- Averaging argument to completely remove m dependence

Main results

Theorem (Weak coreset). Lewis weight sampling gives a sampling matrix

S such that $\tilde{\mathbf{X}} = \arg\min_{\mathbf{X}} \|\mathbf{S}(\mathbf{A}\mathbf{X}\mathbf{G} - \mathbf{B})\|_{p,p}^p$ is a $(1 + \varepsilon)$ -approximate minimizer with

Embedding matrix **G**
$$S = \begin{cases} \tilde{O}(\varepsilon^{1-p}d^{p/2}) & p > 2\\ \tilde{O}(\varepsilon^{-1}d) & 1$$

Furthermore, this is nearly optimal.

Coresets for Multiple ℓ_p Regression Applications

- Nearly optimal sublinear algorithms for Euclidean power means
- . Nearly optimal spanning coresets for ℓ_p subspace approximation

Sublinear Euclidean Power Means

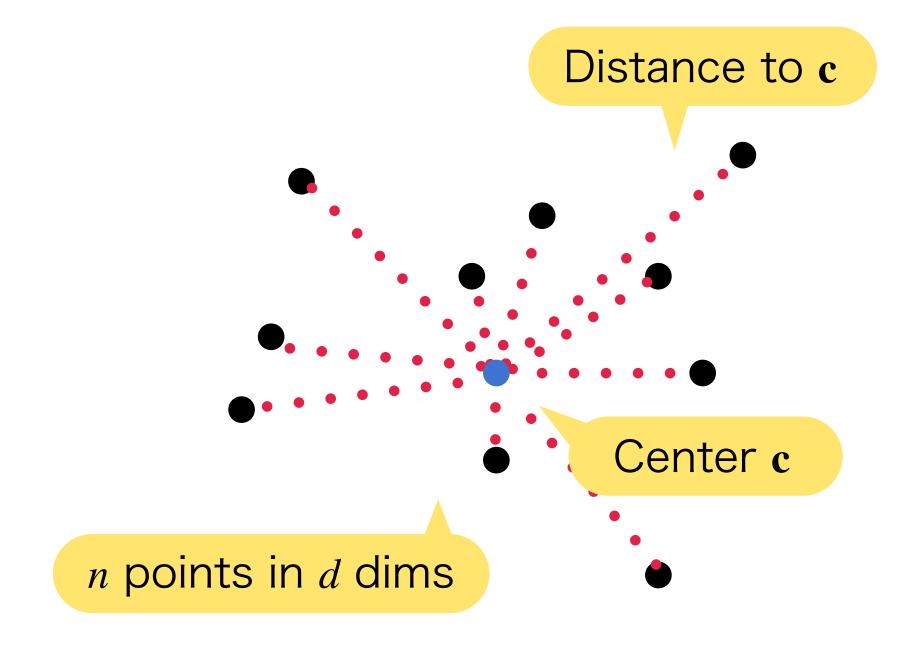
Theorem. In a set of n vectors, a uniform sample of s points is sufficient for a $(1 + \varepsilon)$ -approximate of the Euclidean p-power mean, for

$$s = \begin{cases} \tilde{O}(\varepsilon^{-2}) & p = 1\\ \tilde{O}(\varepsilon^{-1}) & p \in (1,2)\\ \tilde{O}(\varepsilon^{1-p}) & p \in (2,\infty) \end{cases}$$

Furthermore, these bounds are nearly optimal.



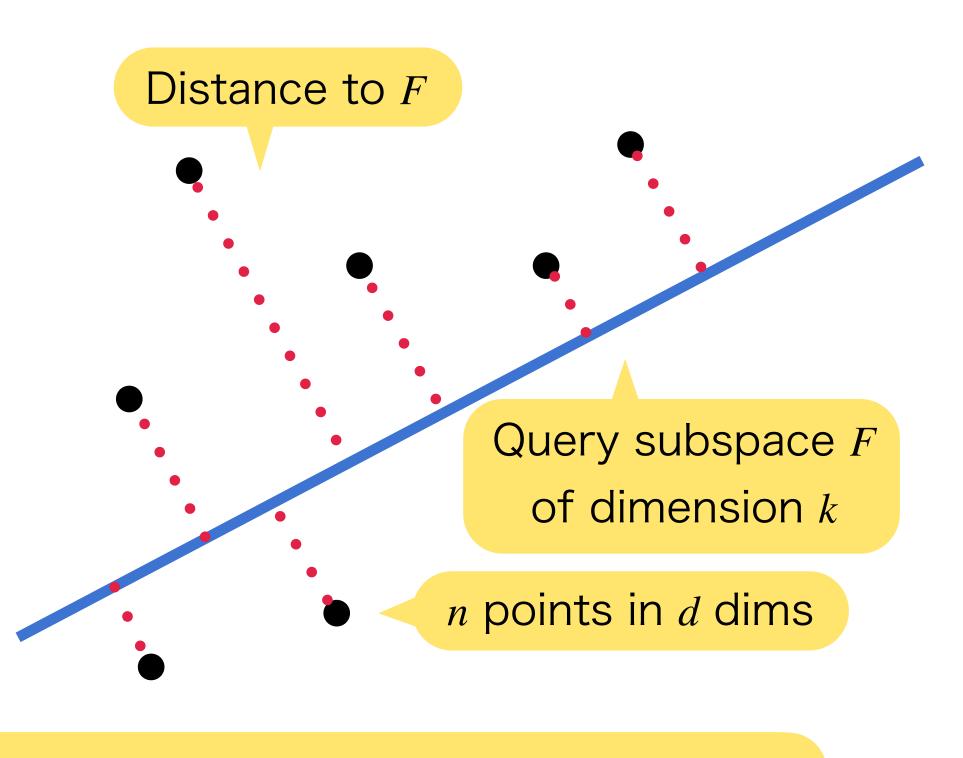
- Think of ${\bf B}$ as the n vectors, ${\bf A}$ as all ones
- . Dvoretzky's theorem to embed ℓ_2 into ℓ_p



Power mean cost: ℓ_p norm of the distances

How many uniform samples do we need?

Spanning Coresets for ℓ_p Subspace Approximation



Projection cost: ℓ_p norm of the distances

Theorem. For $p \in (1,2)$, there is always a subset of s points that spans a $(1 + \varepsilon)$ -approximate solution, where $s = \tilde{O}(\varepsilon^{-1}k)$. Furthermore, these bounds are nearly optimal.

- . Improves a $s = \tilde{O}(\varepsilon^{-1}k^2)$ bound of Shyamalkumar Varadarajan
- Compute a coreset to the optimal solution

How many input points are needed to span a $(1 + \varepsilon)$ -approximate solution?

Coresets for Multiple ℓ_p Regression Conclusion

- . We study the problem of constructing coresets for multiple ℓ_p regression
- We construct coresets with nearly optimal size independent of the # responses
- Two applications:
 - Nearly optimal sublinear algorithms for Euclidean power means
 - _ Nearly optimal spanning coresets for ℓ_p subspace approximation