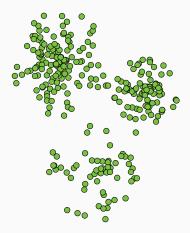
### Improved Coresets for Euclidean k-Means

Vincent Cohen-Addad, Kasper Green Larsen, David Saulpic Chris Schwiegelshohn, Omar Ali Sheikh-Omar

# k-Means Clustering

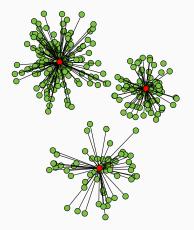


#### Problem Definition

Let A be a set of n points in d dimensional Euclidean space and let k be a positive integer. The objective consists of finding a set of k centers S minimizing

$$cost(A, S) := \sum_{p \in A} \min_{c \in S} \|p - c\|^2.$$

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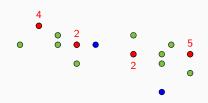
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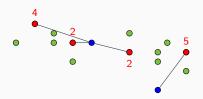






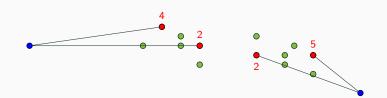












## Theoretical Results on Coresets for Euclidean k-Means

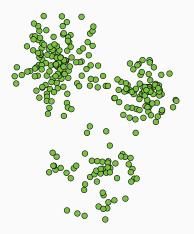
Upper Bounds		
Har-Peled, Mazumdar (STOC'04)	$O(k\epsilon^{-d+2}\log n)$	
Chen (Sicomp'09)	$O(dk^2\epsilon^{-2}\log n)$	
Langberg, Schulman (SODA'10)	$O(d^2k^3\epsilon^{-2})$	
Feldman, Langberg (STOC'11)	$O(dk\epsilon^{-4})$	
Feldman, Schmidt, Sohler (Sicomp'20)	$O(k^3\epsilon^{-4})$	
Becchetti, Bury, Cohen-Addad, Grandoni, S. (STOC'19)	$O(k\epsilon^{-8})$	
Huang, Vishnoi (STOC'20)	$O(k\epsilon^{-6})$	
Braverman, Jiang, Krauthgamer, Wu (SODA'21)	$O(k^2\epsilon^{-4})$	
Cohen-Addad, Saulpic, S. (STOC'21)	$O(k\epsilon^{-4})$	
Cohen-Addad, Larsen, Saulpic, S. (STOC'22)	$O(k^2\epsilon^{-2})$	
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Cohen-Addad, Larsen, Saulpic, S., Sheikh-Omar (NeurIPS'22)	$O(k^{1.5}\epsilon^{-2})$	
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- Weigh each point inversely proportionate to the sampling probability



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$$\begin{tabular}{|c|c|c|c|c|} \hline First Step & Second Step & Overall \\ \hline \hline \Theta(\varepsilon^{-2}\min(k,\varepsilon^{-2})) & \Theta(k) & O(k\varepsilon^{-2}\min(k,\varepsilon^{-2})) \\ \hline \end{tabular}$$

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First Step	Second Step	Overall
$\Theta(\varepsilon^{-2}\min(k,\varepsilon^{-2}))$	$\Theta(k)$	$O(k\varepsilon^{-2}\min(k,\varepsilon^{-2}))$
$\Theta(\varepsilon^{-2})$	$O(k \cdot \sqrt{k})$	$O(k^{1.5} \varepsilon^{-2})$