CSCE 689: Special Topics in Modern Algorithms for Data Science

Lecture 24

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## **Presentation Schedule**

- November 27: Chunkai, Jung, Galaxy Al
- November 29: STMI, Anmol, Jason
- December 1: Bokun, Ayesha, Dawei, Lipai

## Previously: Coreset

• Subset X' of representative points of X for a specific clustering objective



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•  $Cost(X, C) \approx Cost(X', C)$ for all sets C with |C| = k

#### Previously: Coreset

• Given a set X and an accuracy parameter  $\varepsilon > 0$ , we say a set X' with weight function w is an  $(1 + \varepsilon)$ -multiplicative coreset for a cost function Cost, if for all queries C with  $|C| \le k$ , we have

 $(1 - \varepsilon)\operatorname{Cost}(X, C) \le \operatorname{Cost}(X', C, w) \le (1 + \varepsilon)\operatorname{Cost}(X, C)$   $(k, z) \text{-clustering: } \operatorname{Cost}(X', C, w) = \sum_{x \in X'} w(x) \cdot \left(\operatorname{dist}(x, C)\right)^{z}$ 

#### Previously: Bernstein's Inequality

• Bernstein's inequality: Let  $X_1, ..., X_n \in [-M, M]$  be independent random variables and let  $X = X_1 + \cdots + X_n$  have mean  $\mu$  and variance  $\sigma^2$ . Then for any  $t \ge 0$ :

 $\Pr[|X - \mu| \ge t] \le 2e^{-\frac{t^2}{2\sigma^2 + \frac{4}{3}Mt}}$ 

• Example: Suppose M = 1 and let  $t = k\sigma$ . Then  $\Pr[|X - \mu| \ge k\sigma] \le 2\exp\left(-\frac{k^2}{4}\right)$ 

#### Last Time: Sampling for Sum Estimation

• Consider a fixed set  $X = \{x_1, ..., x_n\}$  of n numbers

- Suppose we sample each point  $x_i$  with some probability  $p_i$ and rescale by  $\frac{1}{p_i}$
- What is the expected sum?  $E[y_1 + \cdots + y_n] = x_1 + \ldots + x_n$
- What can we say about concentration?

# Last Time: Uniform Sampling for Sum Estimation

- Suppose  $x_1 = \cdots = x_n = 1$
- Suppose  $p_i = p$  for all  $i \in [n]$
- What can we say about concentration?
- Can get a 2-approximation even for  $p = \Theta\left(\frac{1}{n}\right)$
- How many samples do we expect?  $np = \Theta(1)$

# Last Time: Uniform Sampling for Sum Estimation

- Suppose  $x_1, ..., x_n \in [1, 100]$
- Suppose  $p_i = p$  for all  $i \in [n]$
- What can we say about concentration?
- Can get a 2-approximation even for  $p \approx \frac{80000}{n}$
- How many samples do we expect? np is now WAY larger

# Last Time: Uniform Sampling for Sum Estimation

- Suppose  $x_1, \dots, x_n \in [1, n]$
- Suppose  $p_i = p$  for all  $i \in [n]$
- What can we say about concentration?
- Can get a 2-approximation for  $p \approx 1$
- How many samples do we expect? *np* is now *n*

## **Uniform Sampling for Sum Estimation**

- Suppose  $x_1, ..., x_n \in [1, n]$
- Suppose  $p_i = p$  for all  $i \in [n]$
- Do we really need *p* to be a constant? YES!

## 

# Last Time: Importance Sampling for Sum Estimation

- Suppose  $x_1, \dots, x_n \in [1, n]$
- Suppose  $p_i = \frac{x_i}{x}$  for all  $i \in [n]$
- Can get a 2-approximation for importance sampling
- How many samples do we expect?  $\frac{x_1}{x} + \dots + \frac{x_n}{x} = 1$ , so just a constant number of samples!

 Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)



- Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)
- A simple way to obtain X' with  $Cost(X', C) \approx Cost(X, C)$  is to uniformly sample points of X into X'

 Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)

• Suppose all points have the same cost,  $Cost(x, C) = \frac{Cost(X, C)}{n}$ 

How many points do I need to sample to approximate
 Cost(X, C) within a 2-factor?

## Bernstein's Inequality

• Bernstein's inequality: Let  $y_1, ..., y_n \in [-M, M]$  be independent random variables and let  $y = y_1 + \cdots + y_n$  have mean  $\mu$  and variance  $\sigma^2$ . Then for any  $t \ge 0$ :

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• Set 
$$M = \frac{1}{p}$$
,  $t = \frac{1}{2} \cdot \operatorname{Cost}(X, C)$ , and  $\sigma^2 \approx \frac{n}{p}$ . Then for  $x = \operatorname{Cost}(X, C)$ ,  
 $\Pr\left[|y - \mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(4n/p) + (4/3)(x/p)}\right)$ 

 Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)

- Suppose all points have the same cost,  $Cost(x, C) = \frac{Cost(X, C)}{n}$
- Can get a 2-approximation to Cost(X, C) even for  $p = \Theta\left(\frac{1}{n}\right)$
- How many samples do we expect?  $np = \Theta(1)$

- Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)
- Suppose all points have cost between 1 and 100
- Suppose  $p_i = p$  for all  $i \in [n]$

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$$\Pr[|y - \mu| \ge t] \le 2e^{-\frac{2\sigma^2 + \frac{4}{3}Mt}{3}}$$

• Set 
$$M = \frac{100}{p}$$
,  $t = \frac{1}{2} \cdot \text{Cost}(X, C)$ , and  $\sigma^2 \approx \frac{10000n}{p}$ . Then for  $x = \text{Cost}(X, C)$ ,  
 $\Pr\left[|y - \mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(100n/p) + (4/3)(50x/p)}\right)$ 

- Suppose  $x_1, ..., x_n \in [1, 100]$
- Suppose  $p_i = p$  for all  $i \in [n]$

• For 
$$\Pr\left[|y-\mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(10000n/p)+(4/3)(100x/p)}\right)$$
,  
we require  $\frac{20000n}{p} \approx \left(\frac{x}{2}\right)^2$  and  $x$  can be as small as  $n$ , so we  
need  $p \approx \frac{80000}{n}$ 

 Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)

- Suppose all points have cost between 1 and 100
- Can get a 2-approximation even for  $p \approx \frac{80000}{n}$
- How many samples do we expect? np is now WAY larger

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• Set 
$$M = \frac{n}{p}$$
,  $t = \frac{1}{2} \cdot \text{Cost}(X, C)$ , and  $\sigma^2 \approx \frac{n^3}{p}$ . Then for  $x = \text{Cost}(X, C)$ ,  
 $\Pr\left[|y - \mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(n^2/p) + (4/3)(nx/2p)}\right)$ 

- Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)
- $\bullet$  Suppose all points have cost between 1 and 100
- Suppose  $p_i = p$  for all  $i \in [n]$
- For  $\Pr\left[|y-\mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(10000n/p)+(4/3)(100x/p)}\right)$ , we require  $\frac{20000n}{p} \approx \left(\frac{x}{2}\right)^2$  and x can be as small as n, so  $p \approx \frac{80000}{2}$

- Suppose  $p_i = p$  for all  $i \in [n]$
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 Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)

• Suppose all points have cost between 1 and *n* 

• How many points do I need to sample to approximate Cost(X, C) within a  $(1 + \varepsilon)$ -factor?

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• Set 
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 $\Pr\left[|y - \mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(n^2/p) + (4/3)(nx/2p)}\right)$ 

## Uniform Sampling for Sum Estimation

- Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)
- Suppose all points have cost between 1 and *n*
- Suppose  $p_i = p$  for all  $i \in [n]$
- For  $\Pr\left[|y \mu| \ge \frac{x}{2}\right] \le 2\exp\left(-\frac{(x/2)^2}{2(n^2/p) + (4/3)(nx/2p)}\right)$ , we require  $\frac{2n^2}{p} \approx \left(\frac{x}{2}\right)^2$  and x can be as small as n, so we need  $p \approx 1$

- Consider a fixed set X and a fixed set C of k centers, which induces a fixed cost Cost(X, C)
- Uniform sampling needs a lot of samples if there is a single point that greatly contributes to Cost(X, C)



• Fix: Importance sampling, sample each point  $x \in X$  into X' with probability proportional Cost(x, C), i.e., Cost(x, C)/Cost(X, C)



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## Importance Sampling for Coreset Construction

• What is the variance for each  $y_i$ ?

• 
$$\operatorname{Var}[y_i] \leq \frac{1}{p_i} \cdot \left(\operatorname{Cost}(x_i, C)\right)^2 \leq \operatorname{Cost}(x_i, C) \cdot \operatorname{Cost}(X, C)$$
  
•  $\operatorname{Var}[y] = \operatorname{Var}[y_1] + \dots + \operatorname{Var}[y_n] \leq \left(\operatorname{Cost}(X, C)\right)^2$ 

• Fix: Importance sampling, sample each point  $x \in X$  into X' with probability proportional Cost(x, C), i.e., Cost(x, C)/Cost(X, C)

• Importance sampling only needs X' to have size  $O\left(\frac{1}{\epsilon^2}\right)$  to achieve  $(1 + \epsilon)$ -approximation to Cost(X, C)

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- What about a different choice *C* of *k* centers?



- Importance sampling only needs X' to have size  $O\left(\frac{1}{\epsilon^2}\right)$  to achieve  $(1 + \epsilon)$ -approximation to Cost(X, C)
- To handle all possible sets of *k* centers:
  - Need to sample each point x with probability  $\max_{C} \frac{\operatorname{Cost}(x,C)}{\operatorname{Cost}(X,C)}$ instead of  $\frac{\operatorname{Cost}(x,C)}{\operatorname{Cost}(X,C)}$
  - Need to union bound over a net of all possible sets of k centers

#### Nets

• A net *N* is a set of sets *C* of *k* centers such that accuracy on *N* implies accuracy everywhere

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  - Need to union bound over a net of all possible sets of k centers

Net with size 
$$\left(\frac{n\Delta}{\varepsilon}\right)^{O(kd)}$$

## Sensitivity Sampling

• The quantity  $s(x) = \max_{C} \frac{Cost(x,C)}{Cost(X,C)}$  is called the *sensitivity* of *x* and intuitively measures how "important" the point *x* is

• The *total sensitivity* of X is  $\sum_{x \in X} s(x)$  and quantifies how many points will be sampled into X' through importance/sensitivity sampling (before the union bound)