

#### **Differential Privacy**



Note: preserve privacy of entire stream of T outputs

#### Sublinear Sp Process Edge Update N Graph sparsification computes a smaller subgraph of input graph 1. Keep or discard *e* usi sparsification proce Determine property of sparsified 2. If <u>value</u> of optimal graph as approximate answer of original graph not change signific 3. Else use static priv solution in <u>sparsif</u> 4. Return last compu

## The Power of Graph Sparsification in the Continual Release Model

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		Res	ults	for Inserti	on-O	nly Graph	
<image/> <section-header><text><text></text></text></section-header>		Problem		Previous Results		Our Resu	
		Densest Subgraph	Error	$\left(1+\eta,\frac{\log^2}{\varepsilon}\right)$ (value only)	$\frac{n}{2}$	$\left(1+\eta, \frac{\log^2}{\varepsilon}\right)$	
			Space	$\Theta(m)$		$\widetilde{O}\left(\frac{n}{\epsilon}\right)$	
		Maximum Matching	Error	$\left(1+\eta, \frac{\log^2}{\varepsilon}\right)$	$\frac{n}{2}$	$\left( (1 + \boldsymbol{\eta})(2 + \widetilde{\boldsymbol{\alpha}}) \right)$	
		Size	Space	<b>Θ</b> ( <b>m</b> )		$O\left(\frac{\text{poly}(\log \theta)}{\epsilon}\right)$	
el	Prior Work						
<ul> <li>Continual release of numerical graph statistics</li> <li>ual release</li> <li>Song Little Mehta Vinterbo Chaudhuri '18; Fichtenberger Henzinger Ost. '21;</li> <li>Jain Smith Wagaman '24]</li> </ul>						istics Prior cc works con	
o], tes e	<ul> <li>Online streaming algorithms (non-private)</li> <li>Independent set [Halldorrsson Halldorsson Losievkaja Sze '16; Cormode Dark Konrad '18]</li> <li>Dominating set, matching [Chen Chitnus Eades Wirth '23]</li> <li>Edge coloring [Ghosh Stoeckl '23]</li> <li>Static private algorithms</li> <li>Densest subgraph, <i>k</i>-Core decomposition [Dhulipala Liu Raskhodnikova Shi Shun Yu '22; Dhulipala Li Liu '23; Dini Lattanzi Vassilvitskii '24; Henzinger Sricharan Zhu '24]</li> </ul>						
ace	via Spars	ification					
				Snarsific	ation	needs to	

leta-Algorithm (Input: edge e)	Sparsification needs to approximately preserve					
ing problem specific (randomized)	(coupled) edge edit distance between neighboring graphs					
uure						
solution in <u>sparsified</u> graph did	d Lazy updates to avoid $O(T)$ error from releasing					
cantly, skip to 4.	new solution per update					
vate algorithm to compute new						
	Need to ensure error from					
<u>ied</u> graph	static private algorithm does					
	not blowup in original grap					
ated solution						

![](_page_0_Picture_9.jpeg)

![](_page_0_Picture_10.jpeg)

1@colur	nbia.edu					
IS		Sublinear Spa	ce Densest			
$\frac{lts}{n}$	<ul> <li>Uses uniform sampling [McGregor Tench Vorotnikova Va &gt; Sample each edge with p ≈ n log n/m, obtain O(n log n) s     </li> <li>Need to adaptively choose sampling probability p to releve Use Sparse Vector Technique (SVT) to halve sampline         <ul> <li>Ensure O (log n/ε) additive error from static private algorite</li> <li>Ensure returned subgraph has sufficiently high density</li> </ul> </li> <li>Approximation guarantee follows from intricate Chernof accounts for SVT / static algorithm errors</li> <li>ε-DP guarantee from DP of SVT, edge edit distance being</li> </ul>					
ontinual in pute ex ind requ tire grad egedy	<pre>release act graph ire storing oh</pre> P<					
	Fully Dynamic Lower Bounds					
	Problems Matching size, triangle count, connected components	Previous Results $(1, \Omega(\log T))$	Our R $\left(1,\Omega\left(\min\left(\right.\right.\right)\right)$			
<ul> <li>Based on reduction to inner product queries</li> <li>Encode secret dataset within initial graph</li> </ul>						

Use eage addition/deletions to simulate multiple inner pr secret database

# Google Research

### **COLUMBIA UNIVERSITY** IN THE CITY OF NEW YORK

#### Subgraph (DSG)

- /u '15; Esfandiari Hajiaghayi Woodruff '16] sized sample, rescale sampled solution by  $\frac{1}{n}$
- lease answer after every update ng probability when edge count doubles
- ithm does not compound when rescaling
- y, absorb additive error as multiplicative error

#### f bound argument

#### ng preserved, and composition

![](_page_0_Picture_22.jpeg)

#### **Cover via Sparsification**

#### edge updates adjacent to a single vertex h streams to output values of solutions er Henzinger Ost '21; Jain Smith Wagaman '24]

		Our Result		
$\leq \boldsymbol{0}(\widetilde{\boldsymbol{lpha}})$	Error	$\left(3+\eta+O\left(\frac{\widetilde{lpha}}{arepsilon} ight),O\left(\frac{\widetilde{lpha}\log n}{arepsilon} ight) ight)$		
ex Cover				
ows which vers it	Space	$O(n\widetilde{\alpha})$ (arboricity $\widetilde{\alpha}$ )		
S				
Results				
$\left(\sqrt{\frac{n}{\epsilon}}, \frac{T^{1/4}}{\epsilon^{3/4}}\right)\right)$				
aduct quaria	e of the			
ouuci querie		SCAN ME		