Sublinear GraphApproximation Algorithms

Krzysztof OnakMIT

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Motivation

Want to learn ^a combinatorial parameter of ^a graph:

- the maximum matching size
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- The answer is YES in many cases

The Model

Query access to adjacency list of each node

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Finding ^a Maximal Independent Set Locally

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Oracle for Maximal Independent Set

Construct oracle \mathcal{O} :

- O has query access to $G=(V,E)$
- ${ \mathcal{O} }$ provides query access to maximal independent set $\mathcal{I} \subseteq V$
- $\mathcal I$ is not a function of queries it is a function of G and random bits

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One solution: Luby's maximal independent set algorithm (1986)simulated locally [Marko, Ron 2007]

Here: a method better for sublinear algorithms

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- select maximal independent set greedily
- consider vertices in random order

Random order \equiv random numbers $r(v)$ assigned to each vertex

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 $\mathrm{E}[$ #visited vertices] and query complexity of order $2^{O(d)}$

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Improvement for Random QueryYoshida, Yamamoto, Ito (STOC 2009)

Heuristic:

- Consider neighbors w of v in ascending order of $r(w)$
- Once you find $w \in \mathcal{I},\, v \not\in \mathcal{I}$ (i.e., don't check other neighbors)

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Which gives:

expected query complexity for random vertex = $O(d^2)$ $^2)$

Simplest Application: Vertex Cover

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 $\mathsf{Graph}\; G=(V,E)$

Goal: find smallest set S of nodes such that each edge has endpoint in S

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 Y is an (α,β) -approximation to X if $X\leq Y\leq \alpha\cdot X+\beta$

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 $(2,\epsilon n)$ -approximation: Simulate $\mathcal O$ using our method

Query Complexity

Parnas, Ron (2007):

- o oracles via simulation of local distributed algorithms
- used Kuhn, Moscibroda, Wattenhofer (2006)
- $\forall c>2, \, (c,\epsilon n)$ -approximation with $d^{O(\log(d))}/\epsilon^2$ queries
- $(2,\epsilon n)$ -approximation with $d^{O(\log(d)/\epsilon}$ 3 $^{3)}$ queries

 t communication rounds $\Rightarrow d^{O(t)}$ queries
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Yoshida, Yamamoto, Ito (2009) using our suggestion:

 $(2,\epsilon n)$ -approximation with $O(d^3/\epsilon^2)$ $\mathbf{z})$ queries

Lower Bounds

Trevisan 2007:

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Parnas, Ron 2007:

 $(O(1),\epsilon n)$ -approximation requires $\Omega(d)$ queries

Other Problems

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Maximum Matching Size

- $(1,\epsilon n)$ -approximation for maximum matching size
- Construct an oracle for a matching with no augmenting paths of length $\Theta(1/\epsilon)$
- Can be achieved by ^a sequence of oracles, where eachoracle improves the matching from the previous oracle
- Each improvement corresponds to ^a maximal set of augmenting paths

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Query complexity and running time:

- Our analysis: 2^d $O(1/\epsilon)$
- Yoshida, Yamamoto, Ito (2009): $d^{O(1/\epsilon)}$ 2 $^{2})$

Set Cover:

- **•** Assumption:
	- each element in at most $t=\,$ $O(1)$ of n sets
	- each set has at most $s=\,$ $O(1)$ elements
- Guarantee: $(1 + \ln s, \epsilon n)$ -approximation
- How: use classical greedy algorithm
- Complexity: function of $s,\,t,$ and ϵ

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Dominating Set:

 $(1+\ln(d+1),\epsilon n)$ -approximation in time $\mathrm{function}(d,\epsilon)$

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- Alon: $\Omega(\log n)$ queries to $(o(\log d), \epsilon n)$ -approximate

Maximum Matching

- Maximum Weight Matching:
	- Assumption: degree d and all weights in [0,1]
	- Guarantee: $(1,\epsilon n)$ -approximation
	- How: use Pettie and Sanders (2004)
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	- Guarantee: $(1,\epsilon n)$ -approximation
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	- Complexity: function of d and ϵ
- Maximum Independent Set (Alon):
	- Upper bound:

 $\left(\right)$ $\, O \,$ $\left(\frac{d \cdot \log \log d}{\log d}\right)$ d $\left(\frac{\log\log d}{\log d}\right),\epsilon n\Big)$ -approximation in time $\operatorname{function}(d,\epsilon)$)

Lower bound:

$$
\Omega(\log n) \text{ queries to } \left(o\left(\tfrac{d}{\log d}\right), \epsilon n \right) \text{-approximate}
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Local Graph Partitions[Hassidim, Kelner, Nguyen, O. 2009]

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Hyperfinite Graphs

 (ϵ,δ) -hyperfinite graphs: can remove $\epsilon|V|$ edges and get components of size at most δ

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- (ϵ,δ) -hyperfinite graphs: can remove $\epsilon|V|$ edges and get components of size at most δ
- hyperfinite family of graphs: there is ρ such that all graphs are $(\epsilon, \rho(\epsilon))$ -hyperfinite for all $\epsilon >0$

Taxonomy

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If someone gave us a $(\epsilon/2, \delta)$ -partition:

Sample $O(1/\epsilon^2)$ $^{2})$ vertices

- Compute minimum vertex cover for the sampledcomponents
- Return the fraction of the sampled vertices in the covers

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This gives $\pm\epsilon$ approximation to ${\rm VC}(G)/n$ in constant time:

- Cut edges change $\mathrm{VC}(G)$ by at most $\epsilon n/2$
- Can compute vertex cover separately for eachcomponent

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Bad news:

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New Tool: Partitioning Oracles

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	- partition $P(\cdot)$ is not a function of queries, it is ^a function of graph structure and random bits

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- Generic oracle for any hyperfinite class of graphs
	- **Query complexity:** $2^{d^{O(\rho(\epsilon^3/54000))}}$
	- Via local simulation of ^a greedy partitioningprocedure (uses <mark>[Nguyen, O. 2008</mark>])

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- For minor-free graphs:
	- **Query complexity:** $d^{\text{poly}(1/\epsilon)}$
	- Via techniques from distributed algorithms[Czygrinow, Hańćkowiak, Wawrzyniak 2008]

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- For $\rho(\epsilon) \le \text{poly}(1/\epsilon)$:
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	- Via methods from distributed algorithms and partitioning methods of <mark>Andersen</mark> and <mark>Peres (2009)</mark>

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- **•** Time complexity?
	- $Q =$ query complexity
	- $\,k$ $k=$ number of queries
	- Running time $= O(kQ \cdot \log(kQ))$

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- 2. Testing minor-closed properties
	- **Simpler proof of the result of Benjamini,** Schramm, and Shapira (2008)
- 3. Approximating distance to hereditary propertiesin hyperfinite graphs
	- **Earlier only known to be testable** [Czumaj, Shapira, Sohler 2009]
Application 1: Approximation

- For hyperfinite graphs, can get $\pm \epsilon n$ approximation to:
	- **•** minimum vertex cover size (that is also the independence number)
	- minimum dominating set size
	- in time independent of the graph size

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- Earlier/independent proofs of the same results
	- Elek 2009: for graphs with subexponential growth
	- Czygrinow, Hańćkowiak, Wawrzyniak (2008) ⁺ Parnas, Ron (2007): for minor-free graphs

Testing H -minor-freeness in the sparse graph model of Goldreich and Ron (1997)

- Input: query access to constant degree graph G & parameter $\epsilon>0$
- Goal: w.p. $2/3$
	- accept $H\text{-minor-free graphs}$
	- reject graphs far from H -minor-freeness: $\geq \epsilon n$ edges
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- This work: $2^{\mathrm{poly}(1/\epsilon)}$ and simpler proof

Example: Testing planarity(i.e., K_5 - and $K_{3,3}$ -minor-freeness)

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(i.e., K_5 - and $K_{3,3}$ -minor-freeness)

- Algorithm (given partitioning oracle for planar graphsthat usually cuts $\leq \epsilon n/2$ edges):
	- **Estimate the number of cut edges by sampling**
	- If greater than $\epsilon n/2$, reject
	- Check ^a few random components if planar
	- **If any non-planar found, reject** otherwise, accept

Example: Testing planarity

(i.e., K_5 - and $K_{3,3}$ -minor-freeness)

- Algorithm (given partitioning oracle for planar graphsthat usually cuts $\leq \epsilon n/2$ edges):
	- **Estimate the number of cut edges by sampling**
	- If greater than $\epsilon n/2$, reject
	- Check ^a few random components if planar
	- **If any non-planar found, reject** otherwise, accept
- **•** Why it works:
	- planar: few edges cut in the partition
	- ϵ -far: either many edges cut or many copies of $K_{3,3}$ or K_{5}

Simplest Oracle

Global procedure:

Global procedure:

Global procedure:

Global procedure:

Global procedure:

Global procedure:

Global procedure:

Global procedure: \bigcap

Global procedure: $\overline{\bigcap}$

Local simulation

Use technique of Nguyen and O. (2008):

■ Random numbers assigned to vertices generate a random permutation

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Use technique of Nguyen and O. (2008):

- Random numbers assigned to vertices generate a random permutation
- To find a component of $v\colon$
	- recursively check what happened for close verticeswith lower numbers
	- if v still in graph, try to construct a component

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• Tight bounds for vertex cover and maximum matching

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	- This would give ^a polynomial time/query tester forminor-freeness, and resolve an open question of Benjamini, Schramm, Shapira (2008)

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	- This would give ^a polynomial time/query tester forminor-freeness, and resolve an open question of Benjamini, Schramm, Shapira (2008)
- **Good approximation algorithms for other popular** classes of graphs