## **Expanders via Local Edge Flips**

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#### Outline

- How can we construct an expander locally? Problem motivation and related works
- A simple distributed protocol The switch and the flip protocols
- A new analysis for the two protocols Obstacles in the analysis and new approach for the problem
- Conclusions and future directions Open problems

# How can we construct an expander locally?

## Why is it interesting?

#### Distributed system P2P networks Sensor networks Asynchronous system



- Benefits Efficient
  - Robust



#### New challenges

Important to construct quickly good network structure

Only local communication

### Local graph algorithms

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Algorithms based on *local* message passing among nodes



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#### Advantages

Applicable to large scale graphs

Fast, easy to implement in parallel (MapReduce, Hadoop, Pregel...)



## Starting from any connected graph is it possible to construct an expander locally?

#### **Previous work**

SKIP+: A Self-Stabilizing Skip Graph. R. Jacob, A. W. Richa, C. Scheideler, S. Schmid and H. Täubig. J. ACM 61(6): 36:1-36:26 (2014)

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#### Limitations:

- Using this technique it is not possible to obtain an algebraic expander
- In any round nodes can exchange arbitrary large messages
- Memory needed by a single node in any round is not bounded
- Synchronous model, complex algorithm



#### Starting from any connected graph is it possible to define a simple rule to construct an expander locally?

# A simple distributed protocol

[McKay, *Congressus Numerantium* 1981] **A simple protocol:** 

Pick two edges at random and invert their endpoints



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Limitation

It is not local It may disconnect the graph

[Mahlmann and Schindelhauer, SPAA 2005] Pick a random length 3 path and invert its endpoints



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Experimentally it seems to be really fast

#### What is known about them?

[Cooper, Dyer and Greenhill, SODA 2005] For d-regular graph the switch protocol converges to the configuration model in  $\tilde{O}(n^8d^{15})$  steps.

[Greenhill, SODA 2015]

For non regular graph with max degree in  $O(\sqrt{m})$  the switch protocol converges to the configuration model in  $\tilde{O}(m^{10}d_{max}^{14})$  steps.

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[Mahlmann and Schindelhauer, SPAA 2005]

For d-regular graph the flip protocol converges to the configuration model.

[Feder, Guetz, Mihail, and Saberi, FOCS 2006]

For d-regular graph the flip protocol converges to the configuration model in  $\tilde{O}(d^{34}n^{36})$  steps.

[Cooper and Dyer, PODC 2009] For d-regular graph the flip protocol converges to the configuration model in  $\tilde{O}(d^{23}n^{17})$  steps.

#### How do they perform in practice?

[Mahlmann and Schindelhauer, SPAA 2005] Experimentally switch and flips protocol t

Experimentally switch and flips protocol transform any graph in an expander very quickly.

Conjectures:

Switch converges on d-regular graph in O(nd) steps.

Flip converges on d-regular graph in  $O(nd \log n)$  steps.

A new analysis for the two protocols

Starting from any d-regular graph, with  $d \in \Omega(\log n)$ ,

the switch protocol transforms the graph in an algebraic expander in  $O\left(nd\right)$  steps.

the flip protocol transforms the graph in an algebraic expander in  $O\left(n^2 d^2 \sqrt{\log n}\right)$  steps.

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Small cuts may first become smaller and only later increase.



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#### **Expected change of laplacian**

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Let 
$$\Delta^{(t)} = L\left(G^{(t+1)}\right) - L\left(G^{(t)}\right)$$
  
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Big Data and Sublinear Algorithms Workshop, DIMACS

Nice term

Unfortunately we cannot argue directly on the expectation of the matrix after t step.

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We use a classic potential used for matrix concentration:

$$\Phi^{(t)} = \hat{tr} \left( e^{-\frac{20\log n}{d} L^{(t)}} \right)$$

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Note that in order to have  $\Phi^{(t)}$  very small all the eigenvalues need to be large.

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Taking expectation:

$$E\left[\Phi^{(t+1)}|G^{t}\right] = \Phi^{(t)} - \frac{4\log n}{d^{3}n}\hat{tr}\left(e^{-\frac{20\log n}{d}L^{(t)}}\left(L^{(t)}\left(\frac{d}{2}\hat{I} - L^{(t)}\right)\right)\right)$$

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Using common diagonalization

$$\sum_{1 \le i \le n} e^{-\frac{20 \log n}{d} \lambda_i} \lambda_i (d/2 - \lambda_i)$$

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Two interesting cases:

$$\forall i : \lambda_i \ge \frac{d}{4}$$
$$\sum_{1 \le i \le n} e^{-\frac{20 \log n}{d} \lambda_i} \lambda_i (d/2 - \lambda_i) \in O(n^{-3})$$

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Two interesting cases:

$$\exists i : \lambda_i < \frac{d}{4}$$

We look at:

$$\frac{\sum_{1 \le i \le n} e^{-\frac{20 \log n}{d} \lambda_i} \lambda_i (d/2 - \lambda_i)}{\Phi^{(t)}} = \frac{\sum_{1 \le i \le n} e^{-\frac{20 \log n}{d} \lambda_i} \lambda_i (d/2 - \lambda_i)}{\sum_{1 \le i \le n} e^{-\frac{20 \log n}{d} \lambda_i}}$$

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Thus:

$$E\left[\Phi^{(t+1)}|G^{(t)}\right] = \left(1 - \Omega\left(\frac{\sqrt{\log n}}{n^2 d^2}\right)\right)\Phi^{(t)} + O(n^{-3})$$

So in expectation  $\Phi^{(t)}$  is in  $O(n^{-3})$  after  $O(n^2 d^2 \log n)$  steps, hence using Markov inequality we get the result.

#### Limit of our analysis

Expected additive improvement in a round can be  $O\left(\frac{1}{n^2d^2}\right)$ 



## Conclusions and future directions

New technique to analyze distribute protocol

New convergence time analysis for flip and switch protocol Improve analysis of the flip

Study parallelized version of the protocol

Study node addition or deletion

## Thanks!