http://poloclub.gatech.edu/cse6242

CSE6242 / CX4242: Data & Visual Analytics

MMap (Memory Mapping)

Simple, minimalist approach to scale up computation

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Partly based on materials by
Professors Guy Lebanon, Jeffrey Heer, John Stasko, Christos Faloutsos, Parishit Ram (GT PhD alum; SkyTree), Alex Gray

When should you use Spark/Hadoop, AWS, Azure?

And when should you not?

MMap

Fast Billion-Scale Graph Computation on a PC via Memory Mapping

Lead by

Zhiyuan (Jerry) Lin

Georgia Tech CS Undergrad

Now: Stanford 1st year PhD student

MMap: Fast Billion-Scale Graph Computation on a PC via Memory Mapping. Zhiyuan Lin, Minsuk Kahng, Kaeser Md. Sabrin, Duen Horng Chau, Ho Lee, and U Kang. *Proceedings of IEEE BigData 2014 conference.* Oct 27-30, Washington DC, USA.

Towards Scalable Graph Computation on Mobile Devices. Yiqi Chen, Zhiyuan Lin, Robert Pienta, Minsuk Kahng, Duen Horng (Polo) Chau. *IEEE BigData 2014 Workshop on Scalable Machine Learning: Theory and Applications.*

Graph Computation on Computer Cluster?

Steep learning curve

Cost

Overkill for smaller graphs

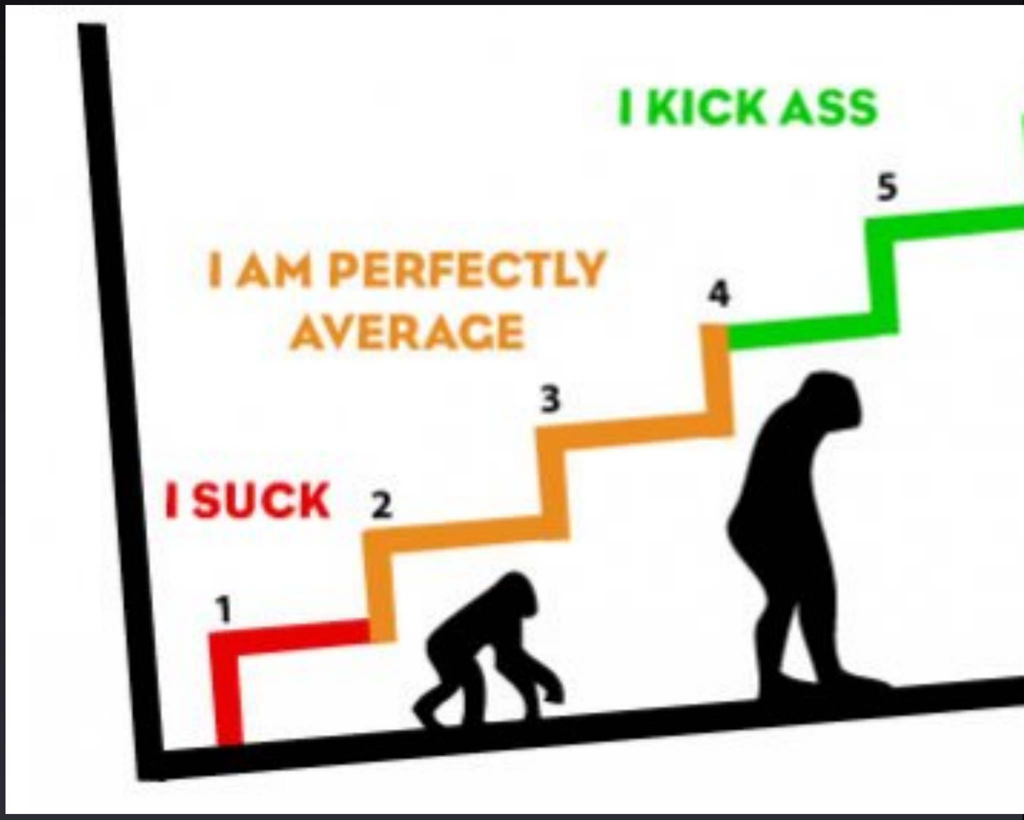


Image source: http://www.drupaltky.org/en/article/20

Best-of-breed Single-PC Approaches

- **GraphChi** – OSDI 2012
- **TurboGraph** – KDD 2013

What do they have in common?

- Sophisticated Data Structures
- Explicit Memory Management

Can We Do Less?

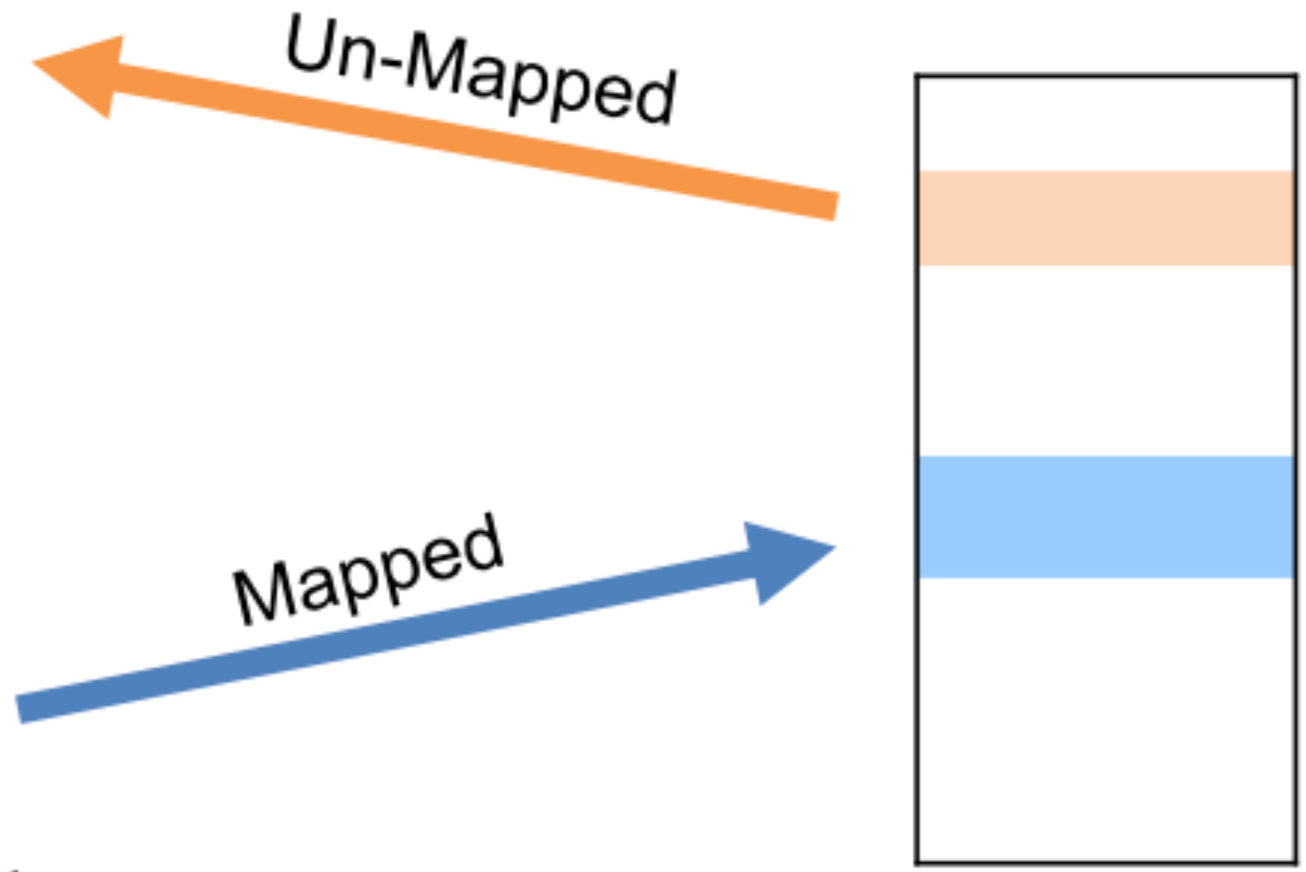
To get same or **better** performance?

e.g., auto memory management, faster, etc.

Main Idea: **Memory-mapped** the Graph

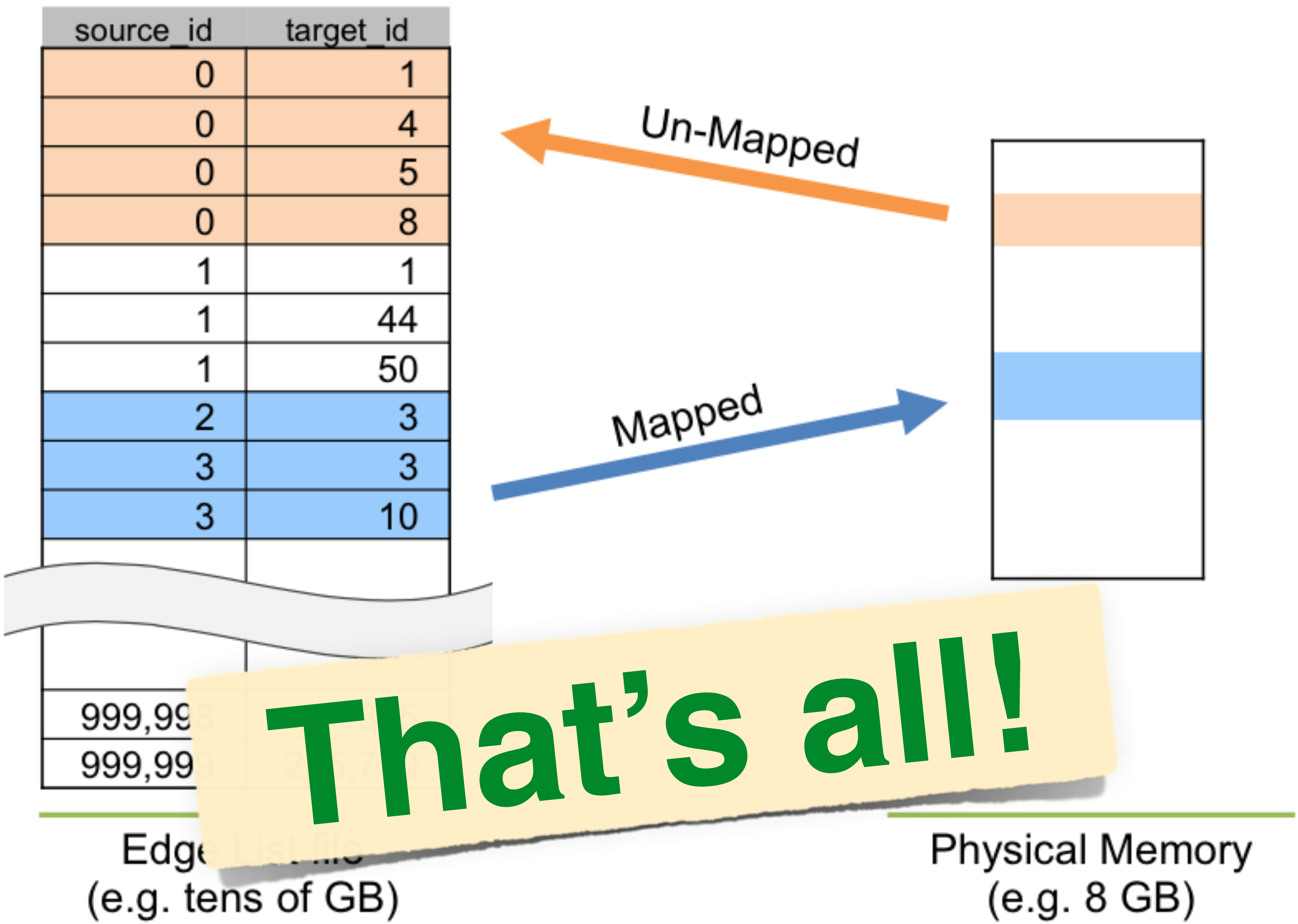
source_id	target_id
0	1
0	4
0	5
0	8
1	1
1	44
1	50
2	3
3	3
3	10
999,998	875
999,999	255,750

Edge List file
(e.g. tens of GB)

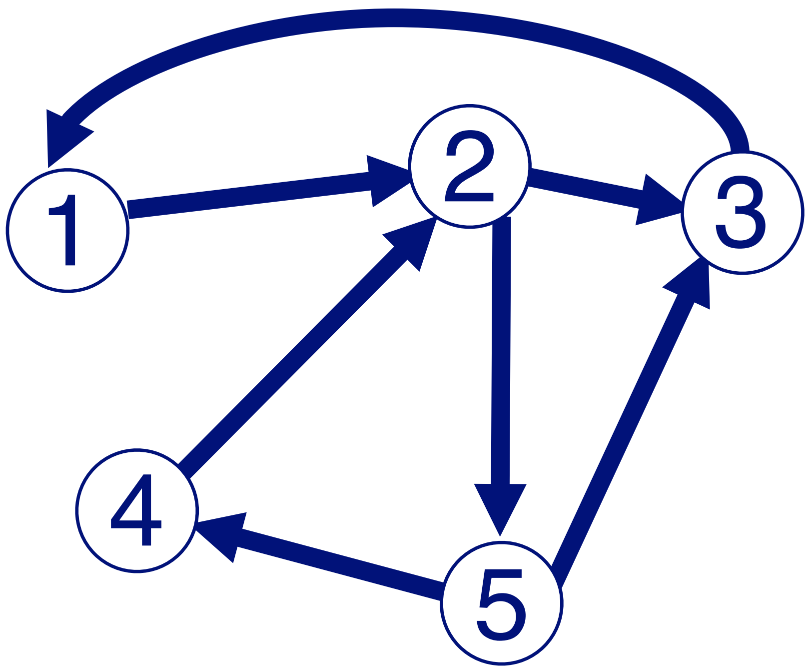


Physical Memory
(e.g. 8 GB)

Main Idea: **Memory-mapped** the Graph



How to compute PageRank for huge matrix?



Reminder

Use the power iteration method

http://en.wikipedia.org/wiki/Power_iteration

$$\mathbf{p} = c\,\mathbf{B}\,\mathbf{p} + \frac{(1-c)}{n}\,\mathbf{1}$$

$$\underbrace{\begin{bmatrix} p1 \\ p2 \\ p3 \\ p4 \\ p5 \end{bmatrix}}_{\mathbf{p'}} = c \underbrace{\begin{bmatrix} & & 1 & & \\ 1 & & & 1 & \\ & 1/2 & & & 1/2 \\ & & & & 1/2 \\ & 1/2 & & & \end{bmatrix}}_{\mathbf{B}} \underbrace{\begin{bmatrix} p1 \\ p2 \\ p3 \\ p4 \\ p5 \end{bmatrix}}_{\mathbf{p}} + \frac{(1-c)}{n} \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix}$$

Can initialize this vector to any non-zero vector, e.g., all “1”s

Example: PageRank (implemented using MMap)

http://www.cc.gatech.edu/~dchau/papers/14-bigdata-mmap.pdf

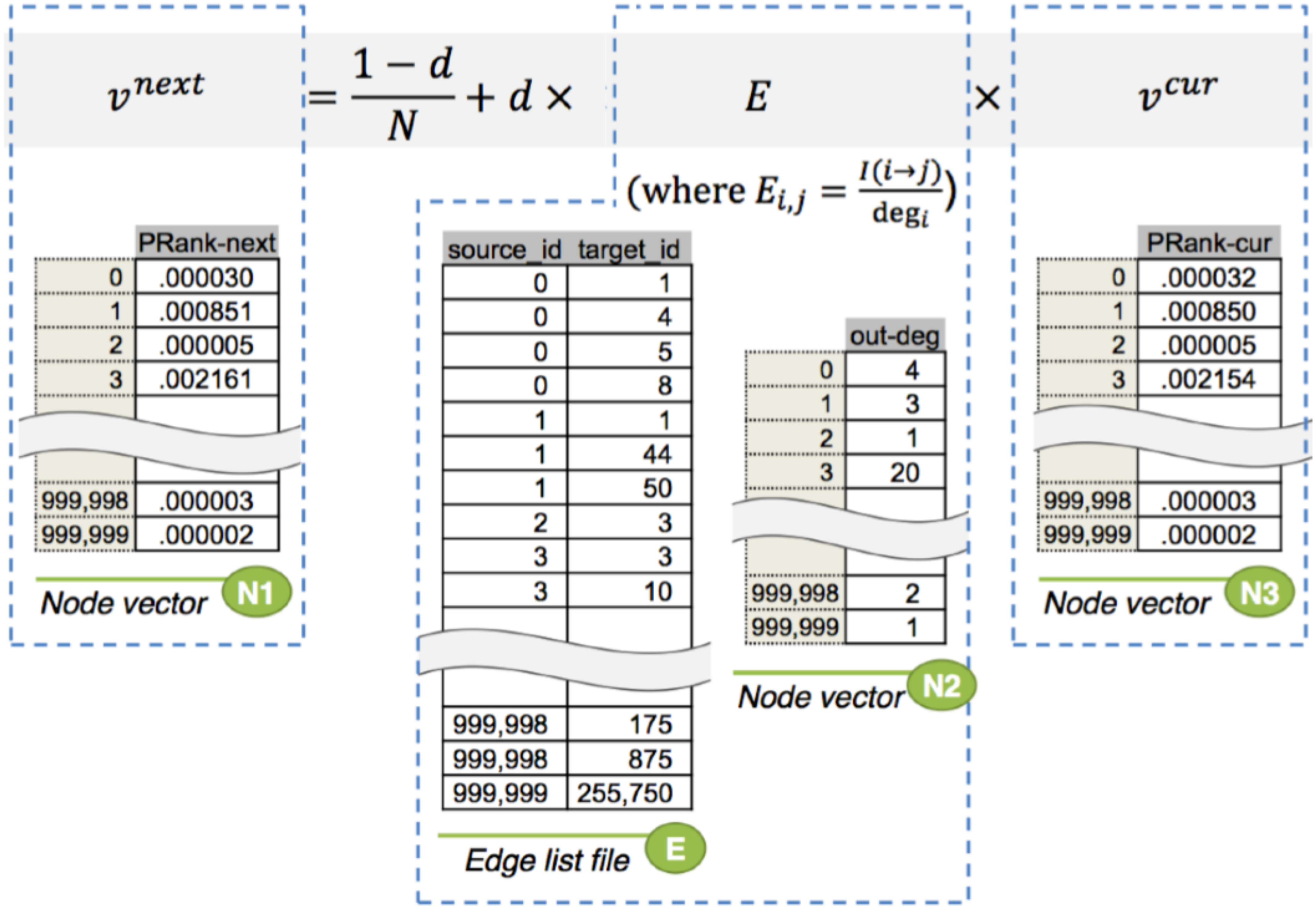
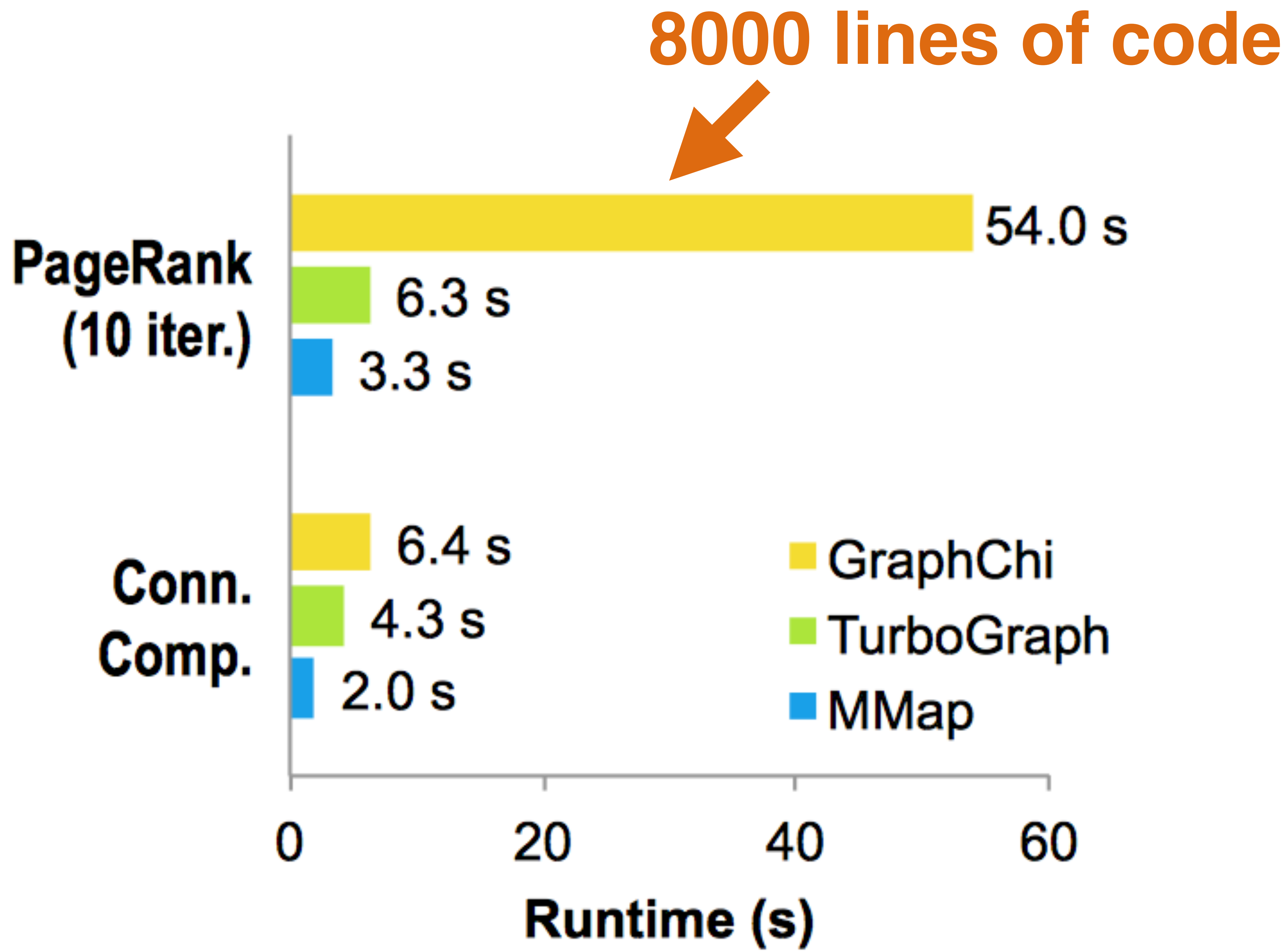
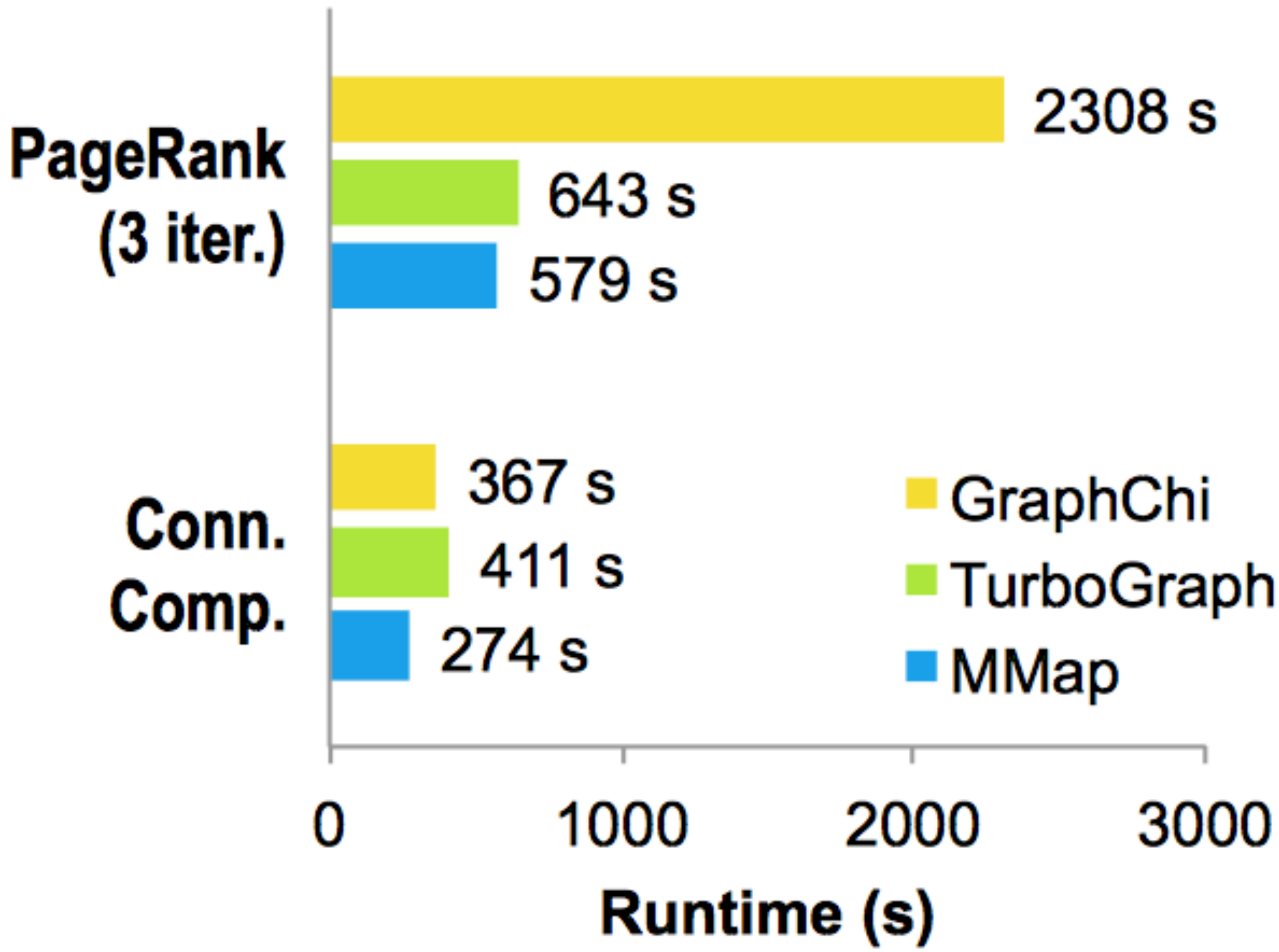


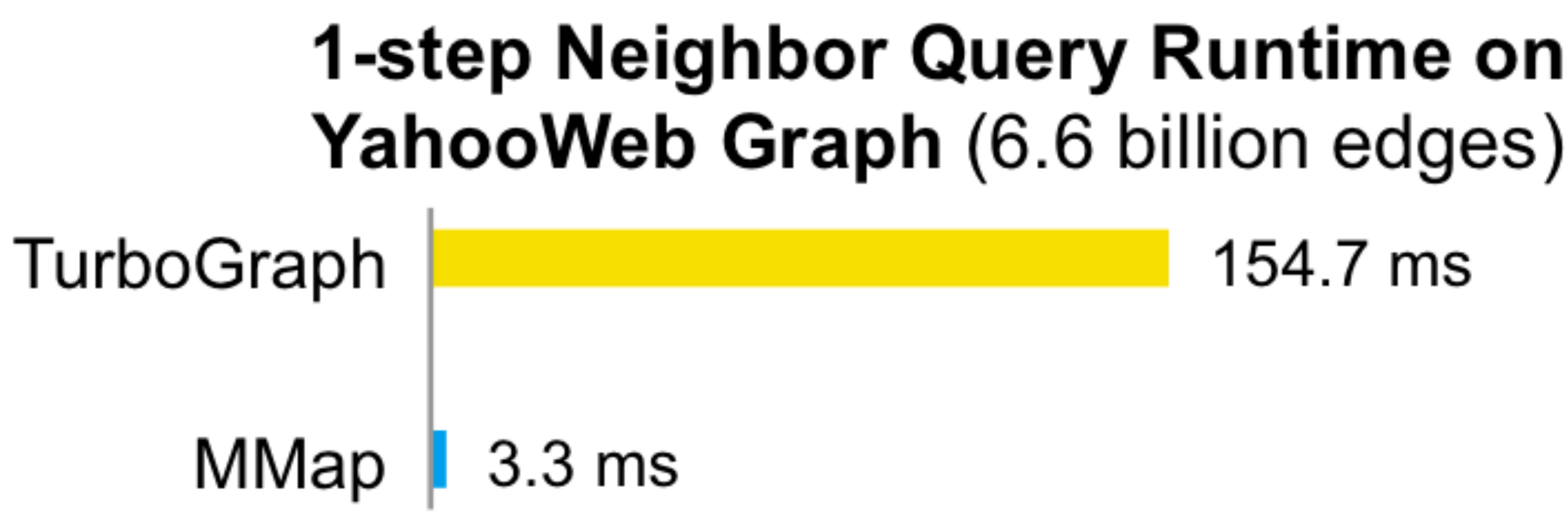
Fig. 3: **Data structures used for computing PageRank.** In



(a) LiveJournal graph (69M edges)



(c) YahooWeb graph (6.6B edges)



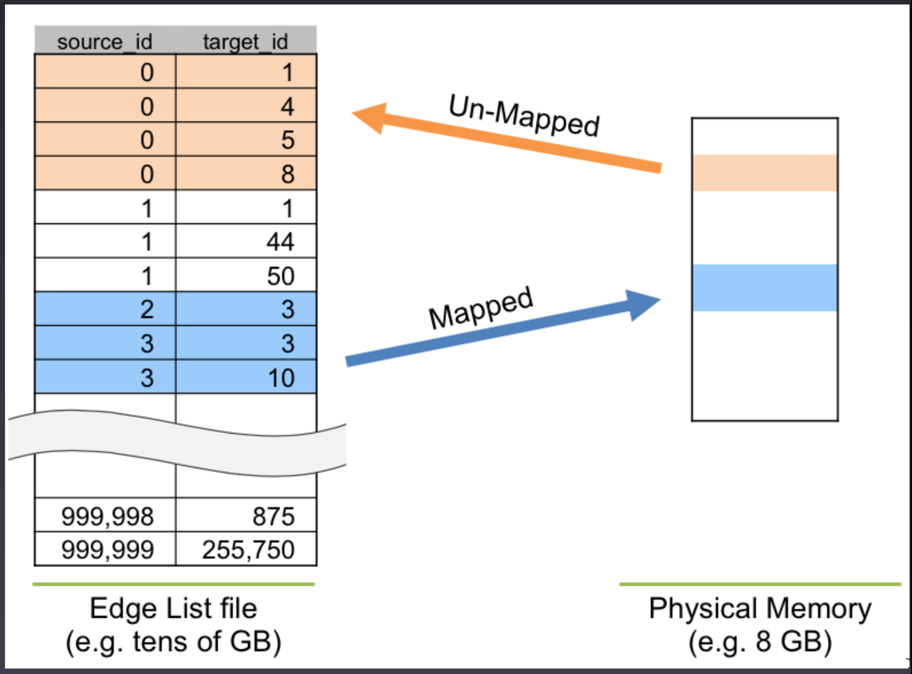
Why Memory Mapping Works?

High-degree nodes' info automatically cached/kept in memory for future frequent access

Read-ahead paging preemptively loads edges from disk.

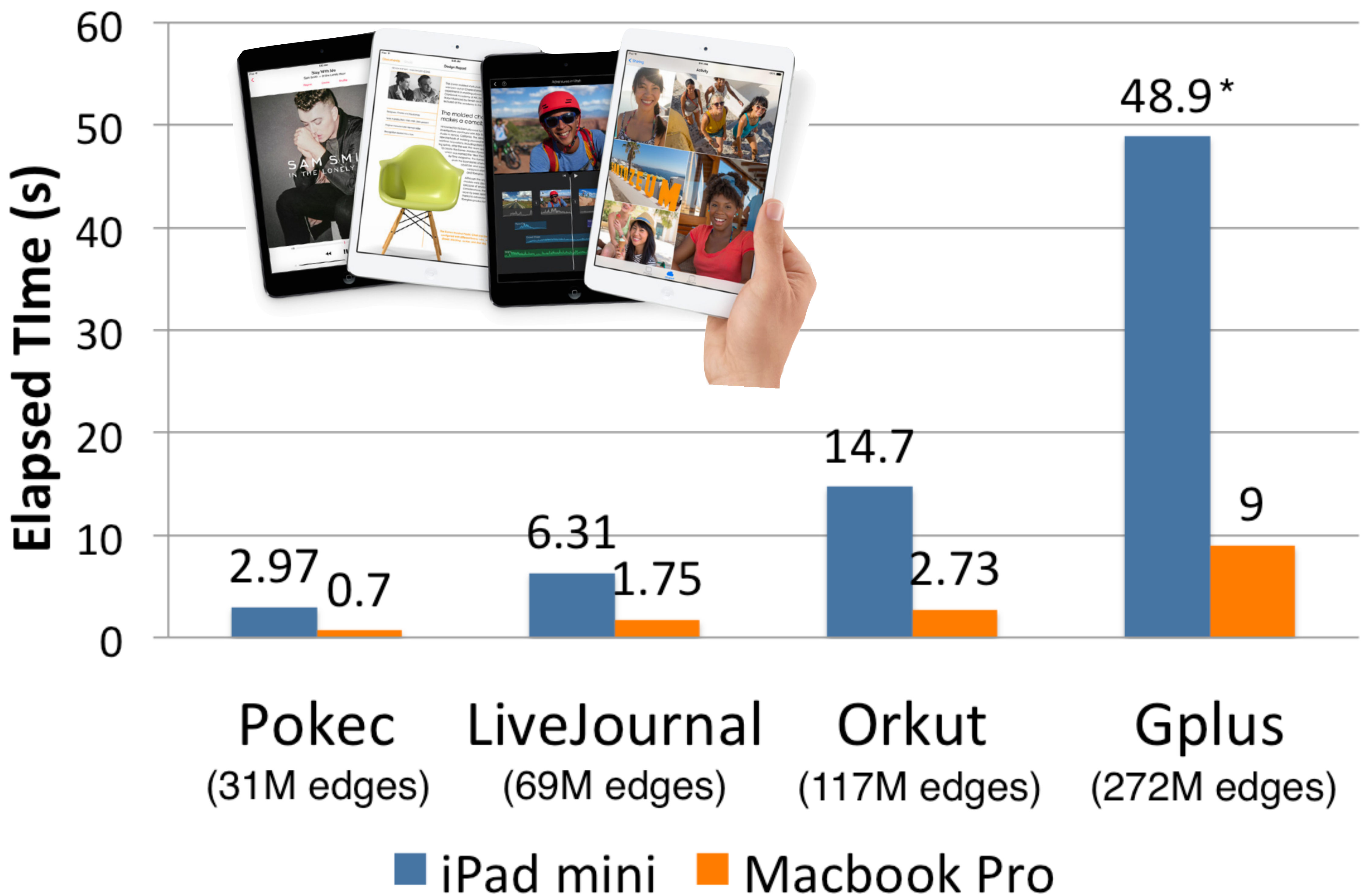
Highly-optimized by the OS

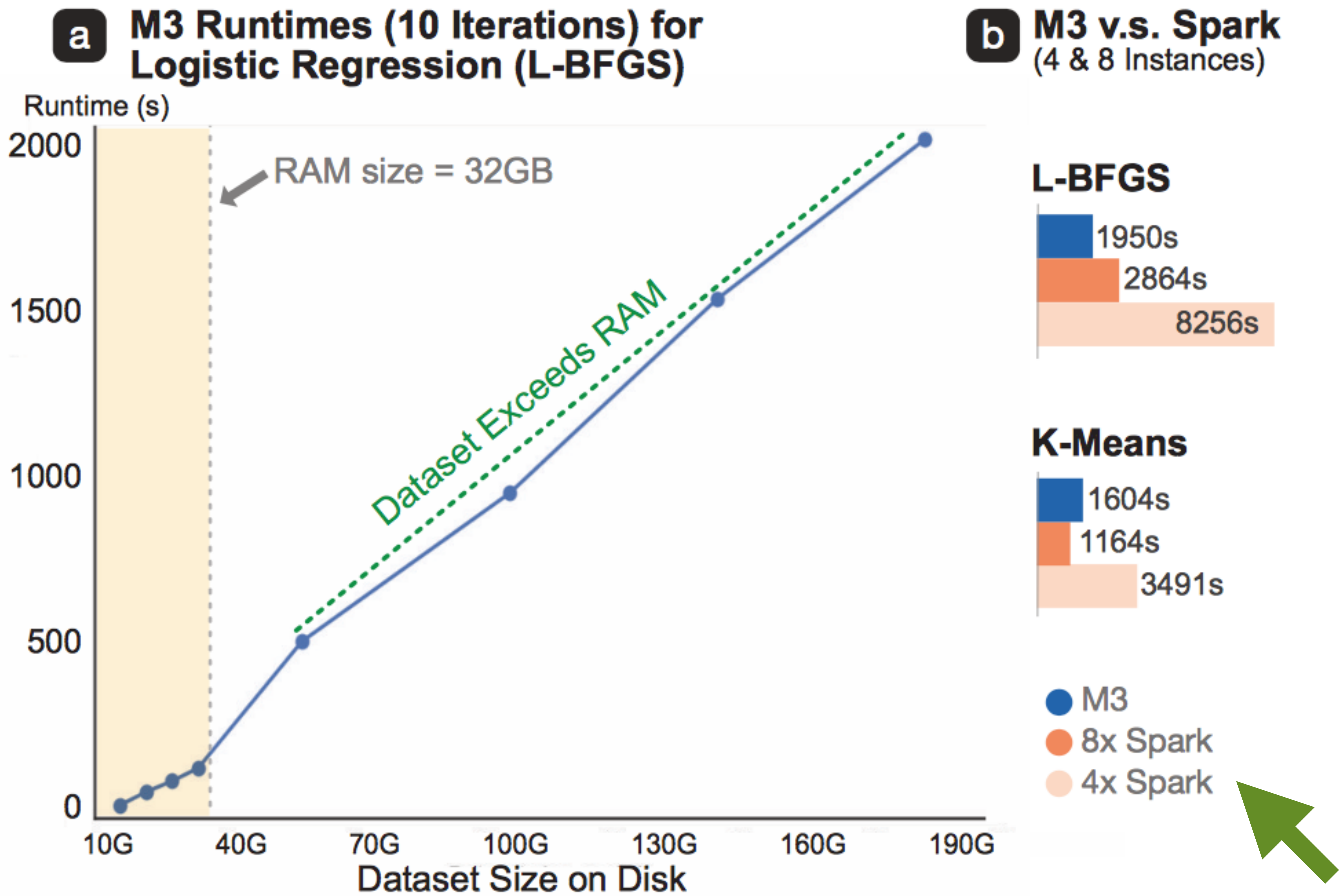
No need to explicitly manage memory (less book-keeping)



Also works on tablets! (If you want.)

Big Data on Small Devices (270M+ Edges)




a
M3 Runtimes (10 Iterations) for Logistic Regression (L-BFGS)
Runtime (s)
2000
1500
1000
500
0
RAM size = 32GB
Dataset Exceeds RAM
10G
40G
70G
100G
130G
160G
190G
Dataset Size on Disk
b
M3 v.s. Spark
(4 & 8 Instances)
L-BFGS
1950s
2864s
8256s
K-Means
1604s
1164s
3491s
M3
8x Spark
4x Spark

MMap project website http://poloclub.gatech.edu/mmap/

MMap Publications Code Datasets People

Scalable Machine Learning & Graph Mining via Virtual Memory

`Memory Mapping` based computation is a minimalist approach that forgoes sophisticated data structures, explicit memory management, and optimization techniques but still achieve high speed and scalability, by leveraging the fundamental memory mapping (MMap) capability found on operating systems.

Broader Impacts of this Project

Large datasets in terabytes or petabytes are increasingly common, calling for new kinds of scalable machine learning approaches. While state-of-the-art techniques often use complex designs, specialized methods to store and work with large datasets, this project proposes a minimalist approach that forgoes such complexities, by leveraging the fundamental virtual memory capability found on all modern operating systems, to load into the virtual memory space the large datasets

Faster I/O Operations

Less Overhead