Towards Effective Partition Management for Large Graphs

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Motivation
- How to manage large graphs?

- Increasing demand for large graph management on commodity servers
  - ✓ Facebook: 890 million daily active users on average for December 2014

- Achieving fast query response time and high throughput
  - ✓ Partitioning/distributing and parallel processing of graph data
  - ✓ However… It's always easier said than done.

Outline

- Background
- Overview of Sedge
- Techniques of Sedge
  - ✓ Complementary partitioning
  - ✓ On-demand partitioning
  - ✓ Two-level partition management
- A Look Back & Around
- Experimental Evaluations
- Conclusions & Takeaways
- Q & A

Background
- Solutions available

- Memory-based solution
  - ✓ Single-machine: Neo4j, HyperGraphDB
  - ✓ Distributed: Trinity [1]

- General distributed solution
  - ✓ MapReduce-style ill-suited for graph processing

- More specialized solution
  - ✓ Graph partitioning and distribution
  - ✓ Pregel [2], SPAR [3]

Background
- Graph query workload types

- Queries with random access or complete traversal of an entire graph
- Queries with access bounded by partition boundaries
- Queries with access crossing the partition boundaries

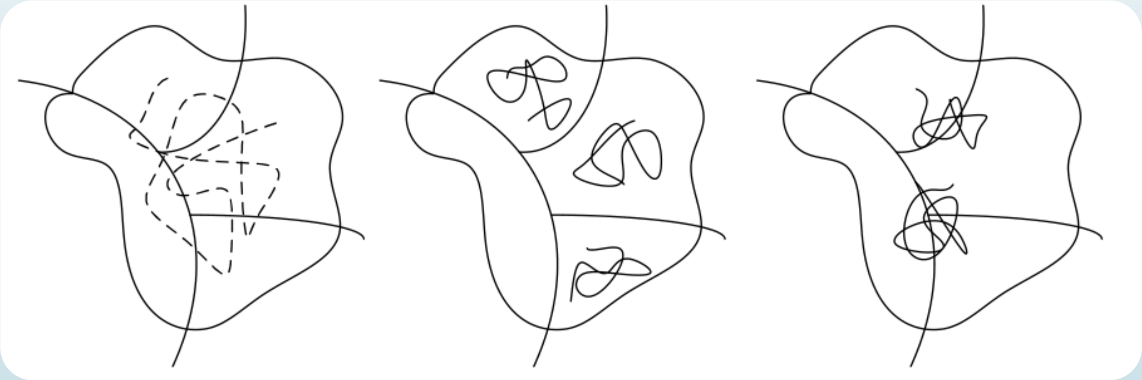
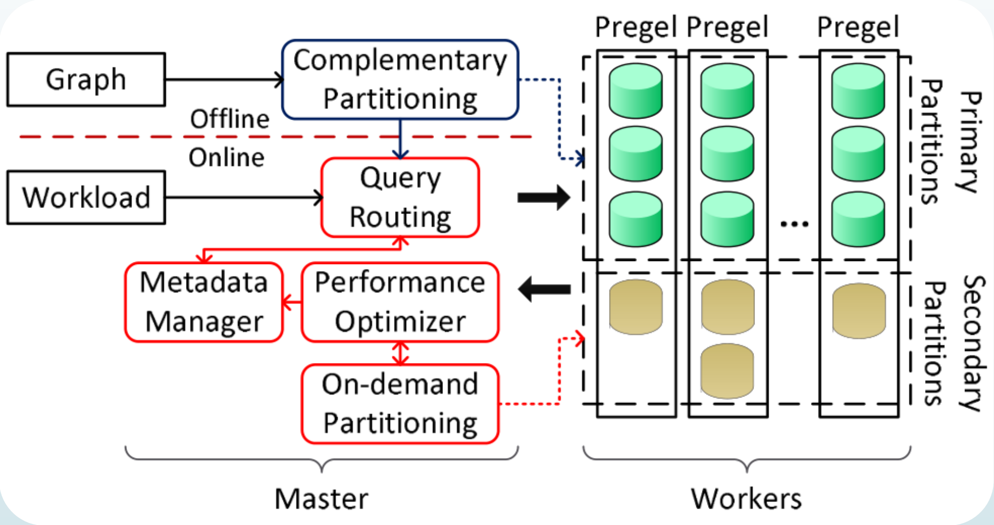


Figure taken from "Towards Effective Partition Management for Large Graphs", SIGMOD 2012

Overview of Sedge
- Self Evolving Distributed Graph Management Environment

- Built upon Pregel, but eliminating constraints and solving problems facing it
  - ✓ Workload balancing, overhead reduction, duplicate vertices…
- Leveraging partitioning techniques to achieve that
  - ✓ 2-level partition architecture supports complementary and on-demand partitioning



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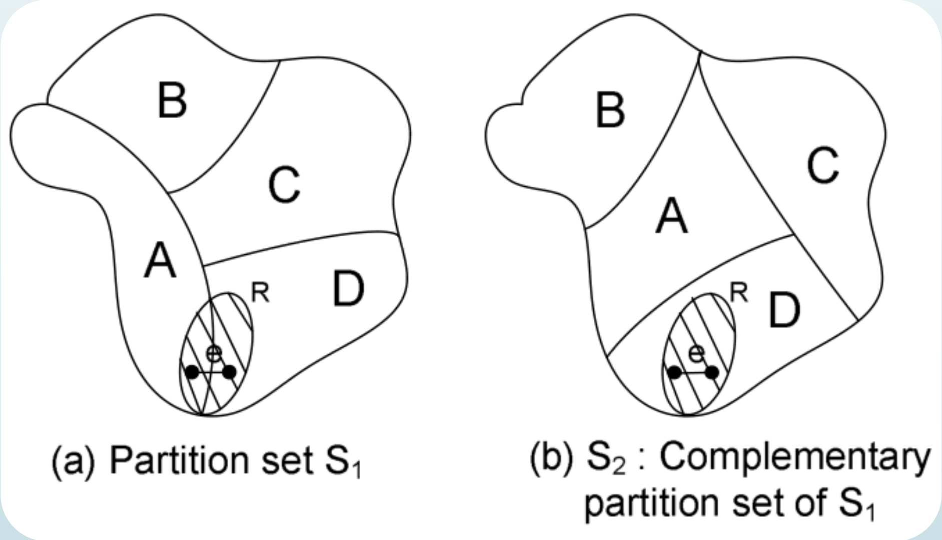
Techniques of Sedge
- Complementary partitioning

- Idea: repartition the graph with region constraint
- Basically, we want to find a new partition set of the same graph so that the originally cross-partition edges become internal ones



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Techniques of Sedge
- Complementary partitioning

- How it's done theoretically?
  - ✓ Formulation to a nonconvex quadratically constrained quadratic integer program (QCQIP) to reuse the existing balanced partitioning algorithms
- How it's done practically?
  - ✓ Solution1: Increase the weight of cut edges by λ then rerun
  - ✓ Solution2: Delete all cut edges first then rerun
- How it works then?
  - ✓ There could be several partitions capable of handling a query to a vertex u
  - ✓ Queries should be routed to a safe partition: u far away from partition boundaries

Techniques of Sedge
- On-demand partitioning

- Hotspot is a real bummer and it comes in two shapes
  - ✓ Internal hotspots located in one partition
  - ✓ Cross-partition hotspots on the boundaries of multiple partitions

Techniques of Sedge
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  - ✓ Internal hotspots located in one partition
  - ✓ Cross-partition hotspots on the boundaries of multiple partitions

- To deal with internal hotspots: Partition Replication
- To deal with cross-partition hotspots: Dynamic Partitioning

Techniques of Sedge
- On-demand partitioning

- Partition workload: internal, external (cross-partition)
- Partition Replication starts when internal workload is intensive
  - ✓ Replicate partition P to P'
  - ✓ Send P' to idle machine with free memory space
  - ✓ Else replace a slack partition with P'

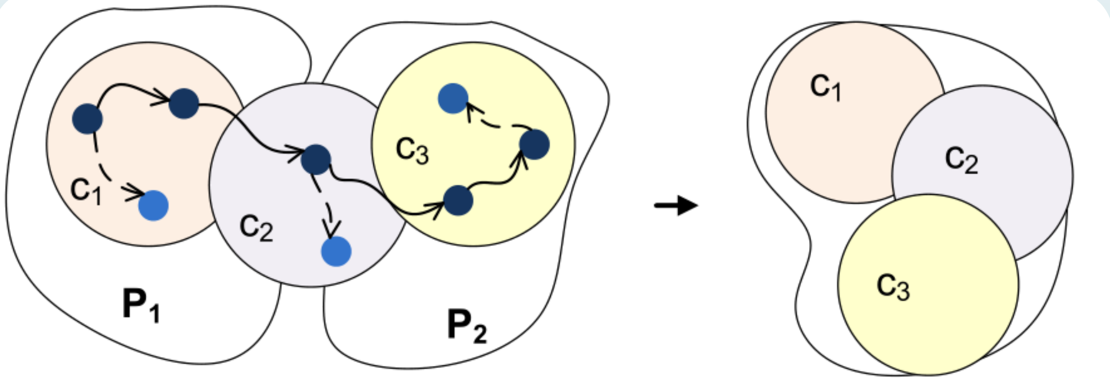
Techniques of Sedge
- On-demand partitioning

- For cross-partition hotspots: Dynamic Partitioning
  - ✓ Better to generate new partitions that only cover these areas
  - ✓ New partitions only share heavy workload while reduce communication

- Step 1: hotspot analysis
  - ✓ Calculate ratio r = $\frac{|W_{ext}(P)|}{|W_{int}(P)|+|W_{ext}(P)|}$ p = $\frac{|E_{ext}(P)|}{|E_{int}(P)|+|E_{ext}(P)|}$
  - ✓ Hypothesis testing: if r is much higher than p, then assume there are cross-partition hotspots in P

Techniques of Sedge
- On-demand partitioning

- Step 2: Track cross-partition queries
  - ✓ Mark the search path with color-blocks
  - ✓ Profile a query to an envelope
  - ✓ Collect the envelopes to form one new partition



(a) Color Block and Query Trace (b) Envelop Collection

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- Color-blocks: coarse-granularity units to trace path of cross-partition queries
- Envelope: a sequence of blocks that covers a cross-partition query
- Envelope Collection: put the maximized # of envelopes into a new partition wrt. space constraint

Figure taken from "Towards Effective Partition Management for Large Graphs", SIGMOD 2012

Techniques of Sedge
- On-demand partitioning

- Envelope collection objective
- ✓ Put the maximized # of envelopes into a new partition wrt. size constraint
- ✓ A classic NP-complete problem: Set-Union Knapsack Problem

- ✓ A greedy algorithm to save the day
- ✓ Intuition: combining similar envelopes consumes less space than combining non-similar ones
- ✓ Metric: Jaccard coefficient $Sim(L_i, L_j) = \frac{|L_i \cap L_j|}{|L_i \cup L_j|}$
- ✓ Solution: Locality-sensitive Hashing

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- On-demand partitioning

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- ✓ Solution: Locality-sensitive Hashing – Min-Hash

Techniques of Sedge
- On-demand partitioning

- Step 2: Track cross-partition queries
  - ✓ Mark the search path with color-blocks
  - ✓ Profile a query to an envelope
  - ✓ Collect the envelopes to form one new partition

- Step 3: Partition Generation
  - ✓ Assign each cluster a benefit score $\rho = \frac{|W(C)|}{|C|}$
  - ✓ Iteratively add the cluster with the highest ρ to an initially empty partition

    (as long as the total size ≤ the default partition size M)

Techniques of Sedge - On-demand partitioning

- Step 2: Track cross-partition queries
  - ✓ Mark the search path with color-blocks
  - ✓ Profile a query to an envelope
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- Step 3: Partition Generation
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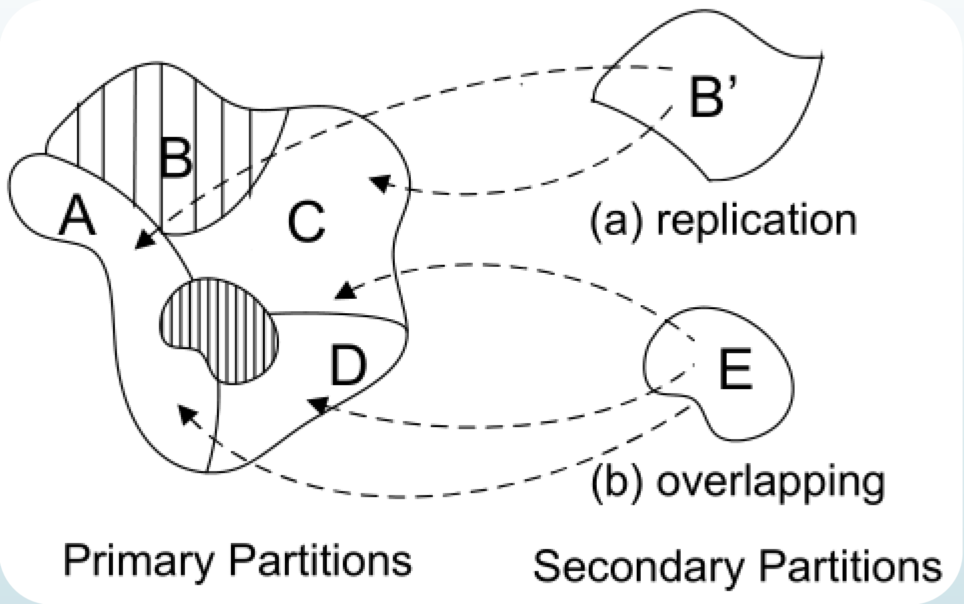
  - ✓ Iteratively add the cluster with the highest ρ to an initially empty partition (as long as the total size ≤ the default partition size M)
- Discussion: too good to be true?

Techniques of Sedge
- Two-level partition management

- Two-level partition architecture
  - ✓ Primary partitions: A, B, C and D inter-connected in two-way
  - ✓ Secondary partitions: B’ and E connected with primary ones in one-way



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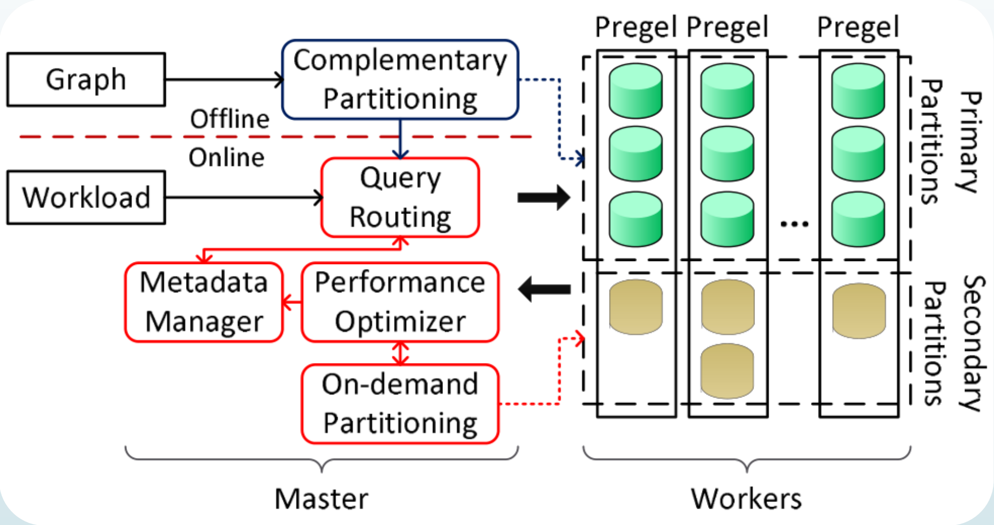
A Look Back & Around
- Other modules of Sedge

- meta-data manager
  - ✓ Meta-data maintained by master and Pregel instances (PI)
  - ✓ **In master**: info about each PI and a table mapping vertices to PI
  - ✓ (Instance Workload Table, Vertex-Instance Fitness List)
  - ✓ **In PIs**: an index mapping vertices to partitions in each PI
  - ✓ (Partition Workload Table, Vertex-Primary Partition Table, Partition-Replicates Table, Vertex-Dynamic Partitions Table)



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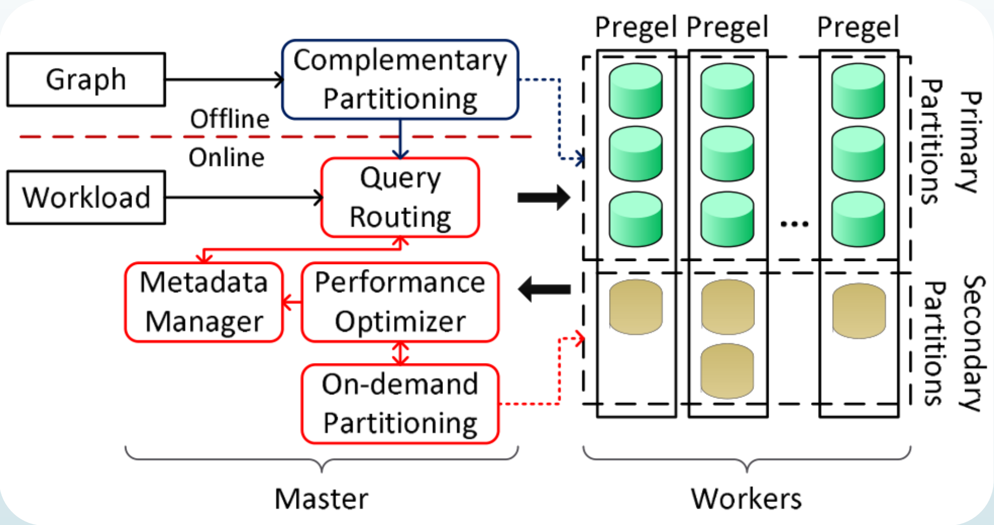
A Look Back & Around
- Other modules of Sedge

- Performance Optimizer
  - ✓ Continuously collects run-time information from all the PIs and characterizes the execution of the query workload
  - ✓ The master updates IWT while PIs maintain the PWTs



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A Look Back & Around - Other related works

- Large-scale graph partitioning tools
  - ✓ METIS, Chaco, SCOTCH
- Graph platforms
  - ✓ SHS, PEGASUS, COSI, SPAR
- Distributed query processing
  - ✓ Semi-structured, relational, RDF data

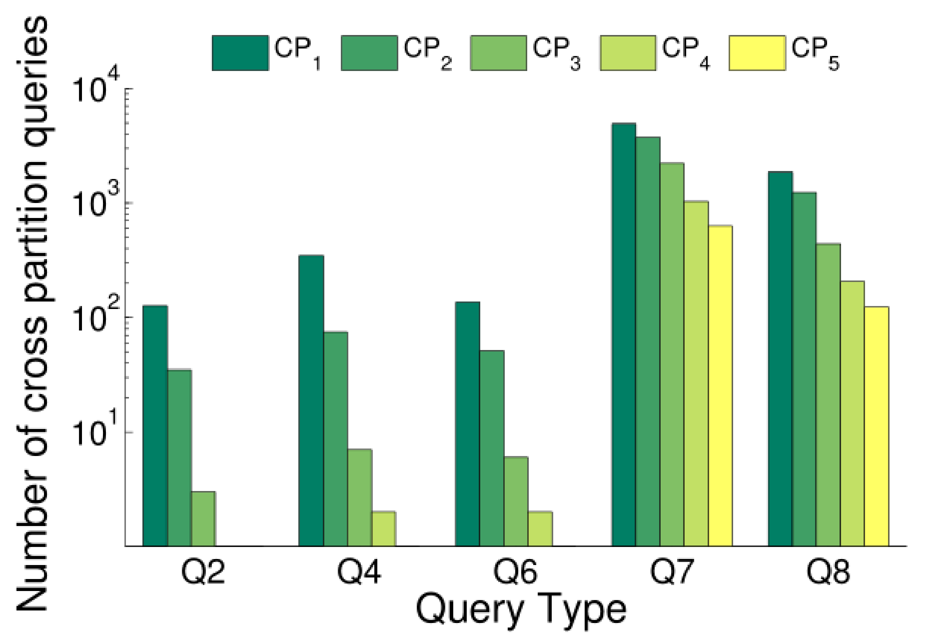
Experimental Evaluations -With RDF Benchmark

- Hardware setting
  - ✓ 31 computing nodes
  - ✓ One serves as the master and the rest workers

- SP^2Bench
  - ✓ Choose the DBLP library as its simulation basis
  - ✓ 100M edges with 5 Queries: Q2, Q4, Q6, Q7, Q8

Experimental Evaluations -With RDF Benchmark

- Experiment setting
  - ✓ Partition configuration: CP1 to CP5
  - ✓ Workload: 10,000 random queries with random starts
- Results
  - ✓ Significant cross-partition query reduction
  - ✓ Cross-partition query vanishes for Q2,Q4 and Q6



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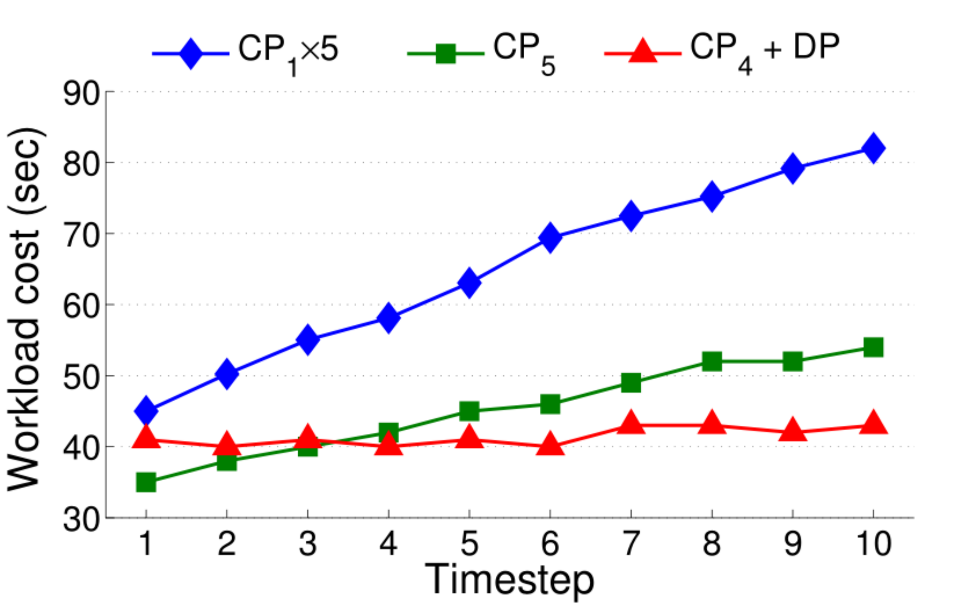
Experimental Evaluations -With RDF Benchmark

- Experiment setting
  - ✓ Partition Configuration: CP1*5, CP5 and CP4+DP
  - ✓ Evolving query workload: evolving 10,000 queries with 10 timestamps
- Results
  - ✓ Blue vs. green: effect of complementary partitioning
  - ✓ Green vs. red: effect of on-demand partitioning



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Experimental Evaluations -With Real Graph Datasets

- Datasets

Graph	Size (GB)	Partition (s)	VFL (MB)	VPT (MB)
Web	14.8	120	81.5	35.3
Twitter	24	180	109.0	45.4
Bio	13	40	135.9	55.3
Syn.	17	800	543.7	205

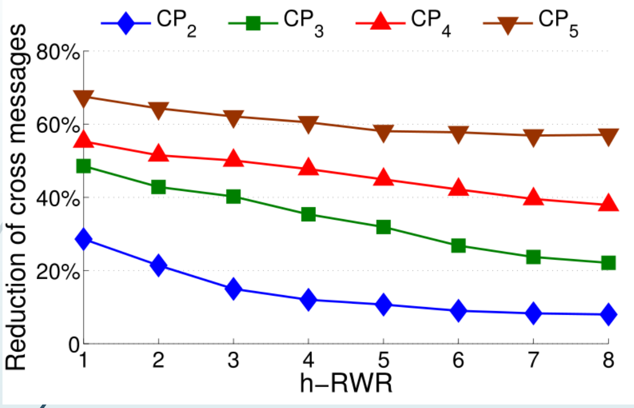
- Query workload

✓ neighbor search

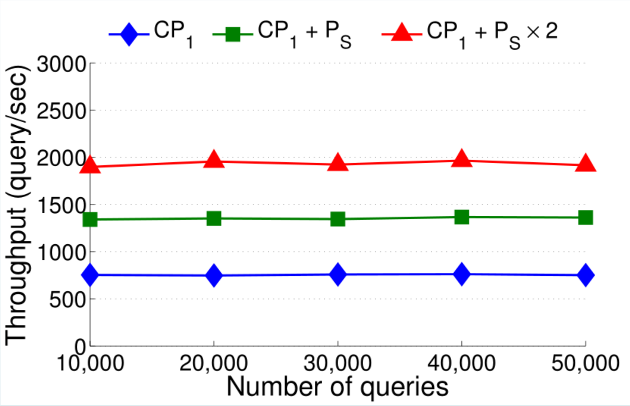
✓ random walk

✓ random walk with restart

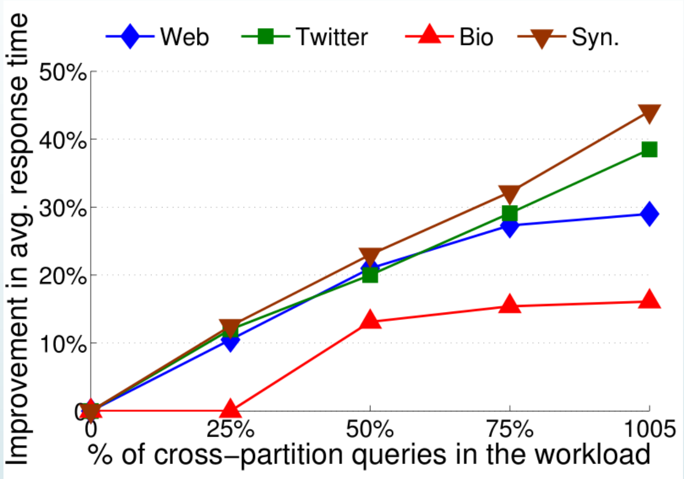
Experimental Evaluations -With Real Graph Datasets



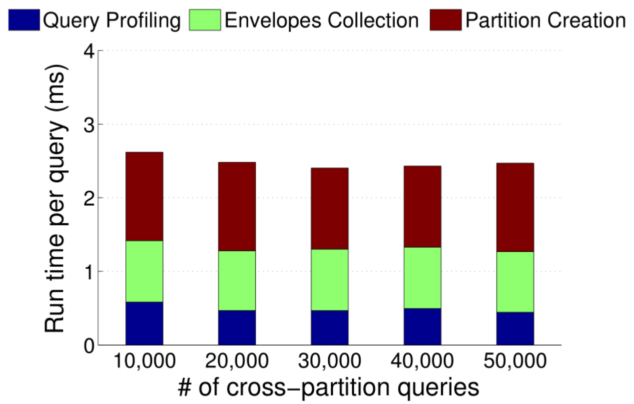
Complementary Partitioning



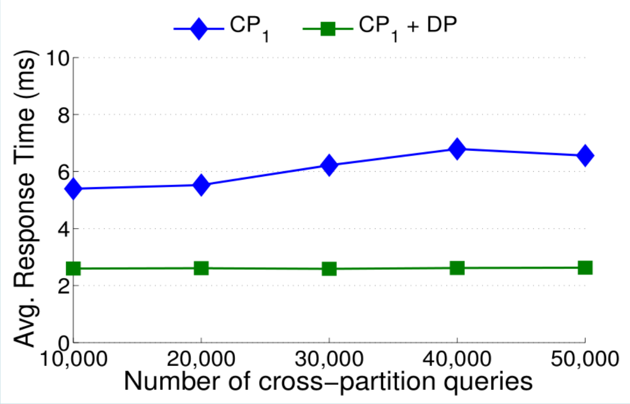
Partition replication: throughput



Cross-partition queries vs. Improvement ratio in avg. response time



Dynamic Partitioning: runtime cost



Dynamic partitioning: response time

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Conclusions & Takeaways

- Partitioning techniques with two level partition management
  - ✓ Complementary partitioning
  - ✓ On-demand partitioning
- Greedy algorithm for dynamic partitioning
- Available at http://grafia.cs.ucsb.edu/sedge/index.html

- Takeaways:
  - ✓ One partition scheme cannot fit all
  - ✓ Always a tradeoff between data locality and load balancing
  - ✓ Future work can be done regarding efficient distributed RDF data storage management, distributed query processing over RDF, etc.

Q & A

- 1. In this work, a major assumption is that the network bandwidth is consistent for each pair of nodes. But in reality, it's often not the case. How to efficiently manage partitions in a distributed setting with network bandwidth unevenness?

- 2. Metadata are becoming big data as well. In this design, the VPT is a few GB for each node. In estimation, metadata is 0.1% - 1% of the data space [4]. How to efficiently manage these tables? More generally, how to efficiently manage graph metadata?

- 3. How to compare or extend Sedge to other settings and partition metrics:

✓ Setting: multi-processors?

✓ Data model: hyper-graph?

✓ Metrics: Query makespan or boundary cut?

References

- [1] Shao, Bin, Haixun Wang, and Yatao Li. "Trinity: A distributed graph engine on a memory cloud." *Proceedings of the 2013 ACM SIGMOD International Conference on Management of Data*. ACM, 2013.
- [2] Malewicz, Grzegorz, et al. "Pregel: a system for large-scale graph processing." *Proceedings of the 2010 ACM SIGMOD International Conference on Management of data*. ACM, 2010.
- [3] Pujol, Josep M., et al. "The little engine (s) that could: scaling online social networks." *ACM SIGCOMM Computer Communication Review* 41.4 (2011): 375-386.
- [4] E. L. Miller, K. Greenan, A. Leung, D. Long, and A. Wildani. (2008) Reliable and efficient metadata storage and indexing using nvram. [Online]. Available: dcslab.hanyang.ac.kr/nvramos08/EthanMiller.pdf

Backup
- Duplicate sensitive graph query

- Use UNION instead of SUM.