

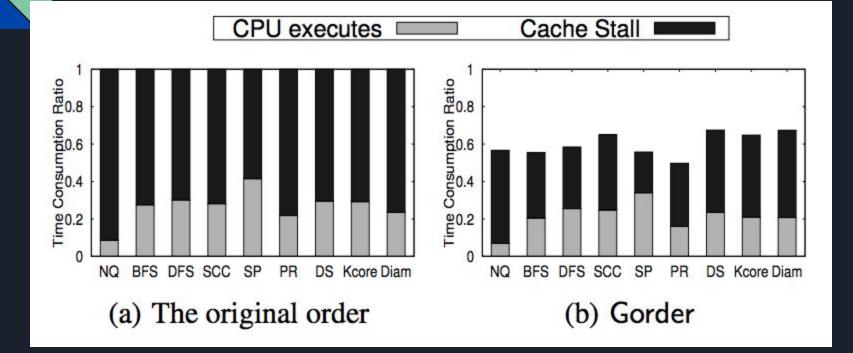
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# Motivation

- Graphs are important
- CPU cache performance is key issue in efficiency in DBS





# Motivation

- Graphs are important
- CPU cache performance is key issue in efficiency in DBS
  - Cache stalls take a large proportion of time
- Can better locality via ordering help?
  - Store frequently accessed nodes close in memory
- How can a generalized solution reduce cache stall rates?



### Graph Access Patterns

• Most common access pattern:

1: for each node  $v \in N_O(u)$  do

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- 2: the program segment to compute/access v
- Locality between neighboring nodes are important
- Locality among sibling nodes even more important

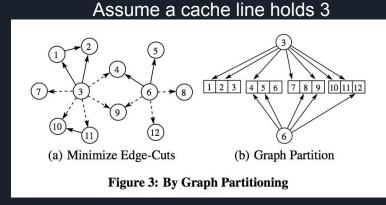
$$\circ \quad {\binom{d_O(u)}{2}} \gg d_O(u)$$

• Let "closeness" heuristic be S(u, v) = S\_s(u, v) + S\_n(u, v)



# Graph Partitioning isn't sufficient

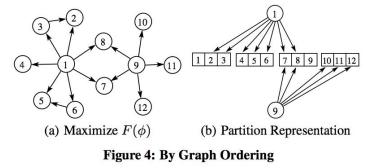
- Real graphs have poor edge cuts b/c power law degree distributions
  - Nodes w/ high degrees
- Fixed sized caches
  - What partition size?
- Data alignment





# Graph Ordering does better

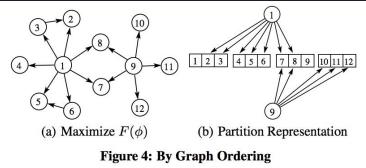
- Optimal permutation  $\phi$  among
- Frequently accessed nodes within window w
- Reorder graph id's
- Sort in all adj. lists





# Graph Ordering does better cont'd

- Locality is continuous for any sliding window
  - Assumes little of data alignment
- Considers sibling and neighbor locality





#### Problem Statement

• Find the optimal permutation  $\phi$  that maximizes aggregate locality defined by  $F(\phi)$  for all sliding windows of size w

$$F(\phi) = \sum_{0 < \phi(v) - \phi(u) \le w} S(u, v)$$
(2)  
= 
$$\sum_{i=1}^{n} \sum_{j=\max\{1, i-w\}}^{i-1} S(v_i, v_j)$$
(3)



# Key Contributions

- Locality scoring function
- Prove NP-hardness of graph ordering
  - Graph ordering is a variant of maximum TSP
    - Maximize reward for sliding windows w
- Propose two algorithms for graph ordering
  - GO
  - GO-PQ
- Evaluation of improved efficiency

# GO algorithm

Algorithm 1 GO (G, w,  $S(\cdot, \cdot)$ )

1: select a node v as the start node,  $P[1] \leftarrow v$ ; 2:  $V_R \leftarrow V(G) \setminus \{v\}, i \leftarrow 2;$ 3: while i < n do 4:  $v_{max} \leftarrow \emptyset, k_{max} \leftarrow -\infty;$ 5: for each node  $v \in V_R$  do i-1 $k_v \leftarrow \sum S(P[j], v);$ 6:  $j = \max\{1, i-w\}$ 7: if  $k_v > k_{max}$  then 8:  $v_{max} \leftarrow v, k_{max} \leftarrow k_v;$ 9:  $P[i] \leftarrow v_{max}, i \leftarrow i+1;$ 10:  $V_R \leftarrow V_R \setminus \{v_{max}\};$ 



# GO algorithm

Fgo is Fw is bound locality

Greedily maximize  $F(\phi)$  by inserting v with the largest  $\bullet$ 

aggregate S() in previous window w

Randomly select starting node 

Eq. 4
$$k_v = \sum_{j=\max\{1,i-w\}}^{i-1} S(v_j,v)$$

- Redundantly computes eq. 4 w-times for same pair  $(v_j,$  $\bullet$ v) while in same window
- Scans through even nodes w/o neighbor/sibling  $\bullet$

rolationshing								
relationships		w = 3		<i>w</i> =	= 5	w = 7		
		$F_{go}$	$\overline{F}_w$	$F_{go}$	$F_w$	$F_{go}$	$F_w$	
Fgo is GO result Fw is upper pound of optimal ocality score	Facebook	149,073	172,526	231,710	275,974	308,091	373,685	
	AirTraffic	2,420	3,468	2,993	4,697	3,465	5,545	
	Table 1: $F_{ao}$ and $\overline{F}_{w}$							

# GO-PQ algorithm

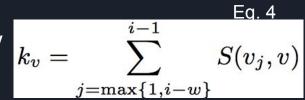
Algorithm 2 GO-PQ  $(G, w, S(\cdot, \cdot))$ 

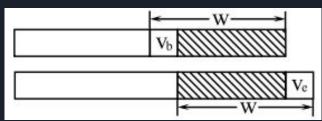
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1: for each node v \in V(G) do
2:
        insert v into Q such that key(v) \leftarrow 0;
3: select a node v as the start node, P[1] \leftarrow v, delete v from Q;
4: i \leftarrow 2;
5: while i < n do
6:
       v_e \leftarrow P[i-1];
7:
       for each node u \in N_O(v_e) do
8:
           if u \in \mathcal{Q} then \mathcal{Q}.incKey(u);
9:
        for each node u \in N_I(v_e) do
10:
            if u \in \mathcal{Q} then \mathcal{Q}.incKey(u);
11:
            for each node v \in N_O(u) do
12:
               if v \in Q then Q.incKey(v);
13:
        if i > w + 1 then
14:
            v_b \leftarrow P[i-w-1];
15:
            for each node u \in N_O(v_b) do
16:
               if u \in \mathcal{Q} then \mathcal{Q}.decKey(u);
17:
            for each node u \in N_I(v_b) do
18:
               if u \in \mathcal{Q} then \mathcal{Q}.decKey(u);
19:
               for each node v \in N_O(u) do
20:
                   if v \in Q then Q.decKey(v);
21:
        v_{max} \leftarrow \mathcal{Q}.\mathsf{pop}();
22:
         P[i] \leftarrow v_{max}, i \leftarrow i+1;
```



# GO-PQ algorithm

- Similar to GO
- Uses PQ to maintain sliding window
- $Q[v] = k_v as computed by Eq. 4$
- When V\_e joins, v in W increment their keys if there is a neighbor and/or sibling relation
- V\_b leaves, v w/ relations decrements key
- Pops largest key as V\_b





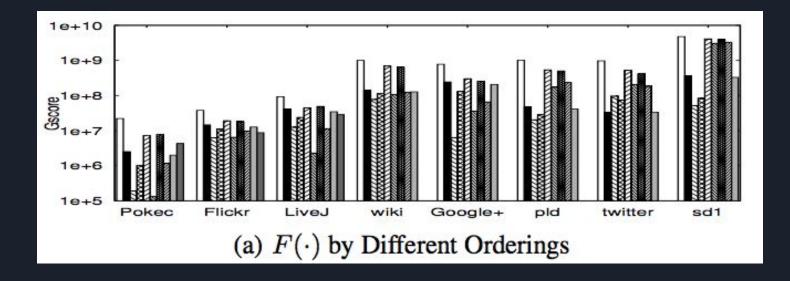


# Time complexities

**Theorem 3.2:** The GO Algorithm 1 is in  $O(w \cdot d_{max} \cdot n^2)$ , where  $d_{max}$  denotes the maximum in-degree of the graph G.

**Theorem 3.3:** The time complexity of the GO-PQ algorithm is  $O(\mu \cdot \sum_{u \in V} (d_O(u))^2 + n \cdot \varrho)$ , where  $\mu$  denotes the time complexity for the updates (incKey(·) and decKey(·)) and  $\varrho$  denotes the time complexity for finding the max node (pop()).







Order	L1-ref	L1-mr	L3-ref	L3-r	Cache-mr
Original	11,109M	52.1%	2,195M	19.7%	5.1%
MINLA	11,110M	58.1%	2,121M	19.0%	4.5%
MLOGA	11,119M	53.1%	1,685M	15.1%	4.1%
RCM	11,102M	49.8%	1,834M	16.5%	4.1%
DegSort	11,121M	58.3%	2,597M	23.3%	5.3%
CHDFS	11,107M	49.9%	1,850M	16.7%	4.4%
SlashBurn	11,096M	55.0%	2,466M	22.2%	4.3%
LDG	11,112M	52.9%	2,256M	20.3%	5.4%
METIS	11,105M	50.3%	2,235M	20.1%	5.2%
Gorder	11,101M	37.9%	1,280M	11.5%	3.4%

#### Table 3: Cache Statistics by PR over Flickr (M = Millions)



Order	NQ	BFS	DFS	SCC	SP	PR	DS	Kcore	Diam
Original	76.5	20.0	9.4	13.0	17.5	58.4	21.7	20.0	17.5
MINLA	76.0	22.7	10.2	12.8	20.7	62.5	21.8	20.5	18.3
MLOGA	76.0	21.7	9.4	12.3	19.8	62.1	21.8	20.6	18.5
RCM	61.6	14.4	7.5	8.7	8.9	44.9	18.2	17.5	11.7
DegSort	59.3	18.7	8.0	12.1	16.6	55.1	21.9	16.9	15.5
CHDFS	50.0	14.2	5.1	8.3	13.2	38.0	18.4	16.1	10.4
SlashBurn	56.6	16.8	6.7	9.3	10.2	44.5	18.9	16.8	13.5
LDG	74.7	22.7	10.0	13.6	18.7	58.4	22.0	20.3	17.9
Gorder	40.0	12.1	4.6	7.2	10.8	31.5	16.9	14.5	9.5

Table 7: L1 Cache Miss Ratio on sd1-arc (in percentage %)



 Applying Gorder to distributed graph systems is complicated b/c unclear how graph partitioning happens

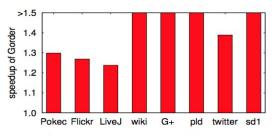


Figure 12: PageRank (4 threads)

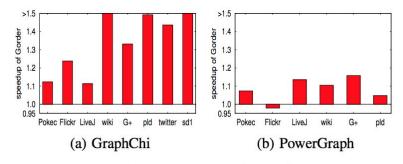


Figure 13: PageRank on Graph Systems



# Conclusion

- CPU stalling is important barrier to efficiency
- This paper presents a generalized optimization for graph algorithms with the common access pattern
  - 1: for each node  $v \in N_O(u)$  do
  - 2: the program segment to compute/access v



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#### References

• Hao Wei, Jeffrey Xu Yu, Can Lu, Xuemin Lin Speedup Graph Processing by Graph Ordering