Computing the Closeness Centrality of Evolving Networks on Clusters

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Introduction

Centrality metrics answer questions such as:

- Who controls the flow in a network?
- Who is more important? Who has more influence?
- Whose contribution is significant for connections?

They have various applications:

- Covert network (e.g., terrorist identification).
- Contingency analysis (e.g., weakness/robustness of networks).
- Viral marketing. Traffic analysis. Store locations.

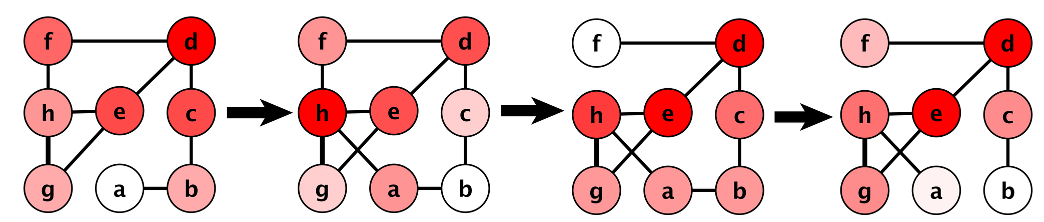
How to maintain an accurate analysis upon graph evolutions?

Closeness Centrality

Let $G = (V, E)$ be an unweighted graph with the vertex set V and edge set E.
The farness of a vertex is $far[u] = \sum_v d(u, v)$.
The closeness of a vertex is $cc[u] = \frac{1}{far[u]}$.
$d(u, v)$ is the length of the shortest path $u \rightsquigarrow v$.

The best known algorithm computes the shortest path graph rooted in each vertex of the graph. The complexity is $O(E)$ per source, $O(VE)$ in total, which makes its computationally expensive.

Variation of Closeness Centrality



The redness of a vertex represents its Closeness.

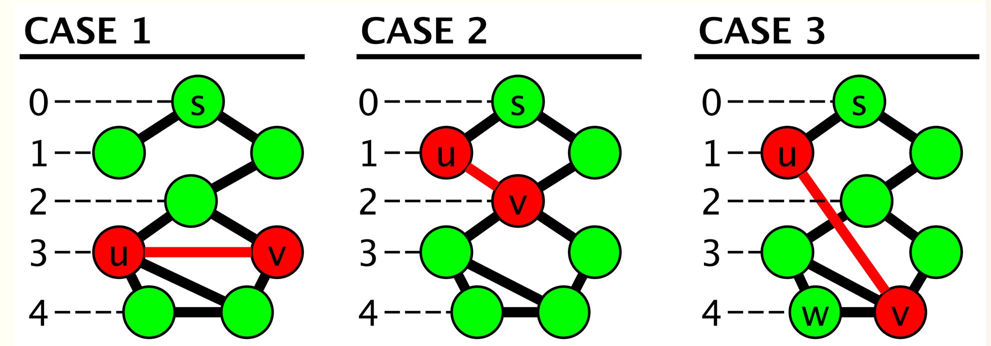
Conclusion

Structural properties of Closeness Centrality lead to an efficient incremental algorithm. The algorithm scales on clusters and enables real-time Centrality analysis.

References

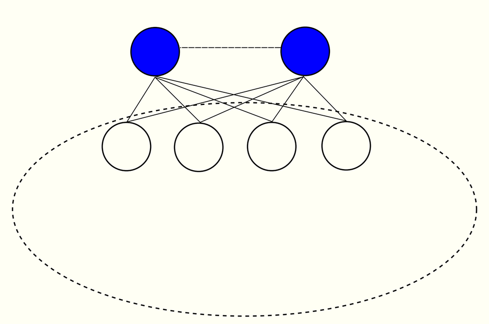
[1] A. E. Sarıyüce, E. Saule, K. Kaya, and Ü. V. Çatalyürek. Hardware/software vectorization for closeness centrality on multi-/many-core architectures. In *Workshop on Multithreaded Architectures and Applications (MTAAP)*, 2014.
[2] A. E. Sarıyüce, E. Saule, K. Kaya, and Ü. V. Çatalyürek. Streamer: a distributed framework for incremental closeness centrality computation. In *IEEE Cluster*, 2013.
[3] A. E. Sarıyüce, E. Saule, K. Kaya, and Ü. V. Çatalyürek. Incremental algorithms for closeness centrality. In *IEEE BigData*, 2013.
[4] A. E. Sarıyüce, E. Saule, K. Kaya, and Ü. V. Çatalyürek. Shattering and compressing networks for betweenness centrality. In *SIAM International Conference on Data Mining, SDM*, 2013.

Level Filtering



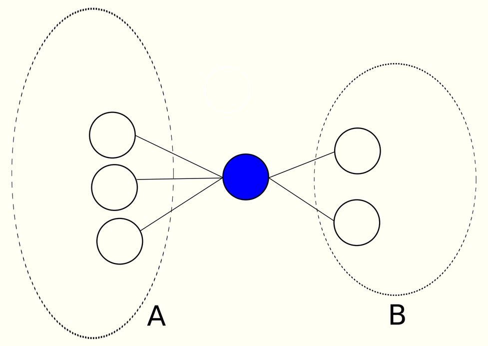
Case 1: No change.
Case 2: Only the structure changes.
Case 3: Some distances change.

Identical Vertices



Vertices identical to each other have the same farness.

Articulation point



When an edge changes in A, all the vertices in B are impacted in the same way as the articulation point.

Incremental Algorithm

- Upon insertion of (u, v)
- Ignore temporarily identical vertices
- Consider (u, v)'s biconnected component
- Compute BFS from u and v (before edge insertion)
- Flag all $s \neq u, v$, s.t. $|d(u, s) - d(v, s)| > 1$,
- Add (u, v) to the graph
- Compute $cc[s]$ for all flagged s
- Change $cc[s]$ in other biconnected components
- Copy $cc[s]$ for identical vertices

Acknowledgment

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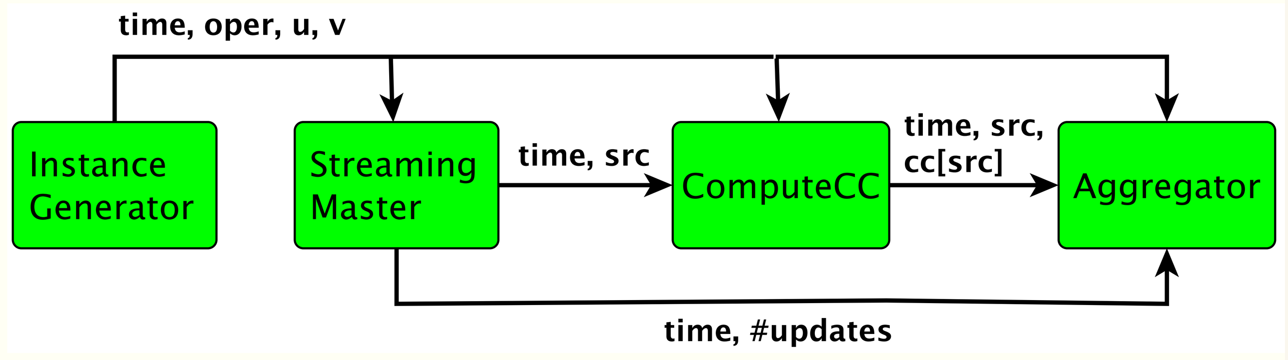
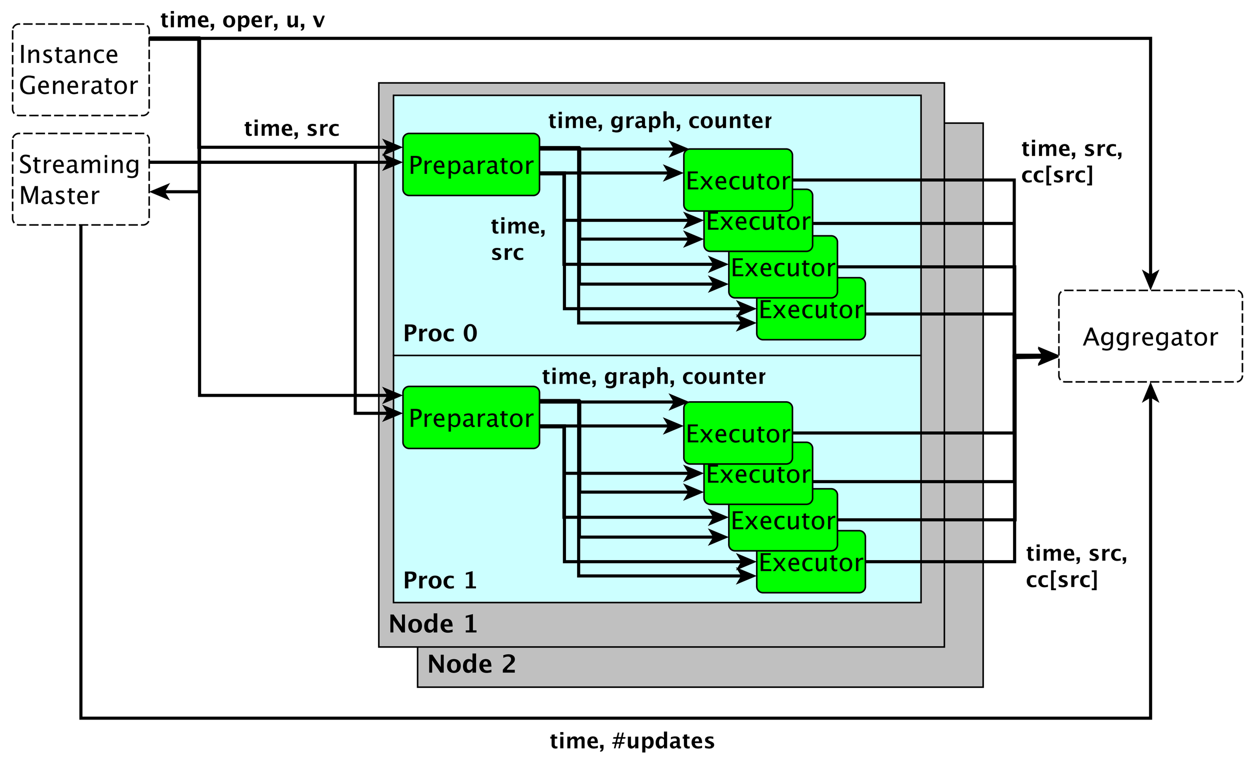
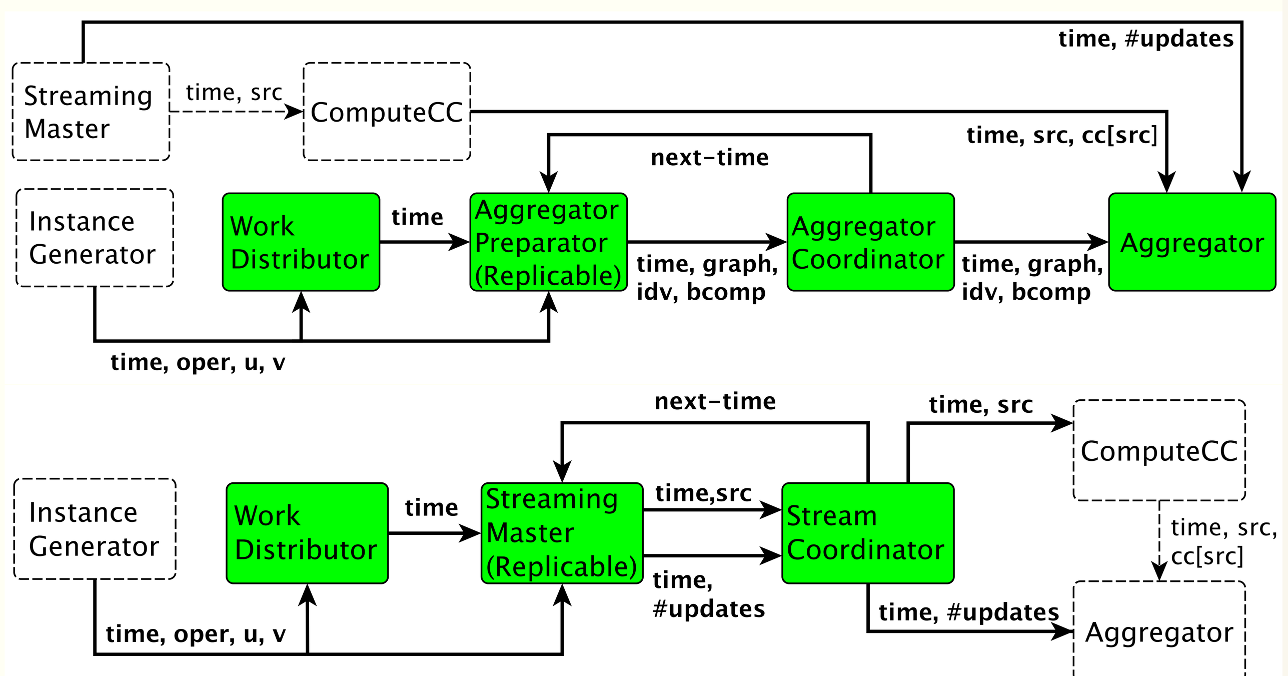
Streamer Layout



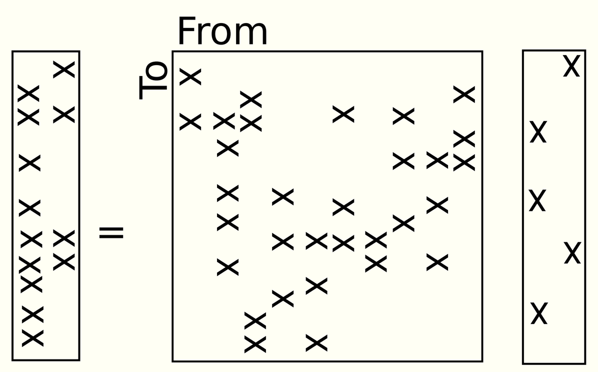
Leveraging the NUMA Hierarchy



Making Aggregator and StreamingMaster Replicable



Vectorized Bottom-Up Traversal



Multiple traversals can be executed simultaneously to leverage the large vector registers of modern processors.

Test Machine

64 nodes computational cluster:

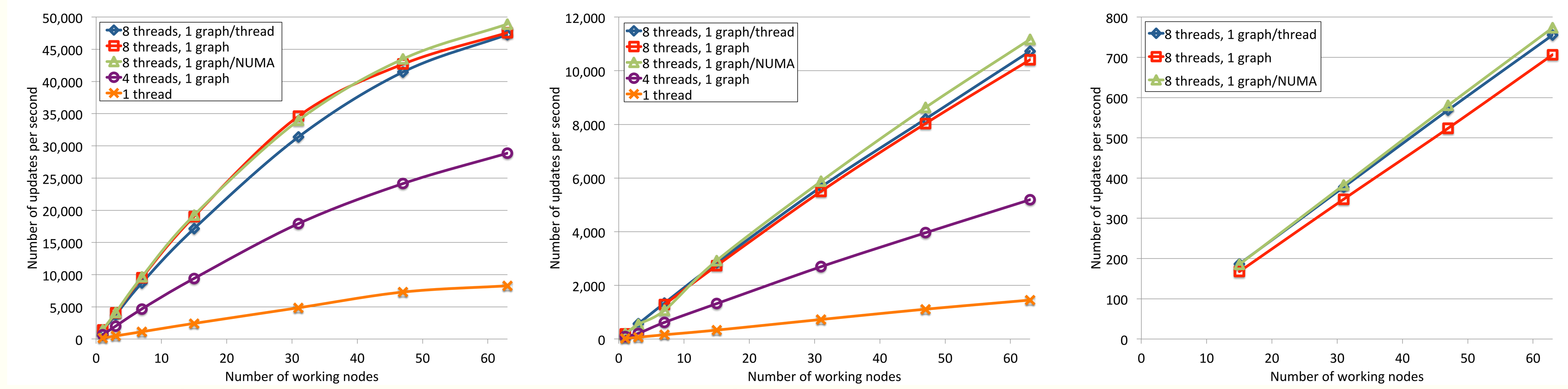
- 2 Intel Xeon E5520 @2.27Ghz
  - 4 cores (8 cores per node)
  - 2-way SMT (16 threads per node)
  - 8MB L3 cache (shared per proc)
- 48 GB of main memory
- 20 Gbps InfiniBand

Test Instances

Incrementally inserting 50 initially removed edges on different graphs. It leads to different number of updates in centrality.

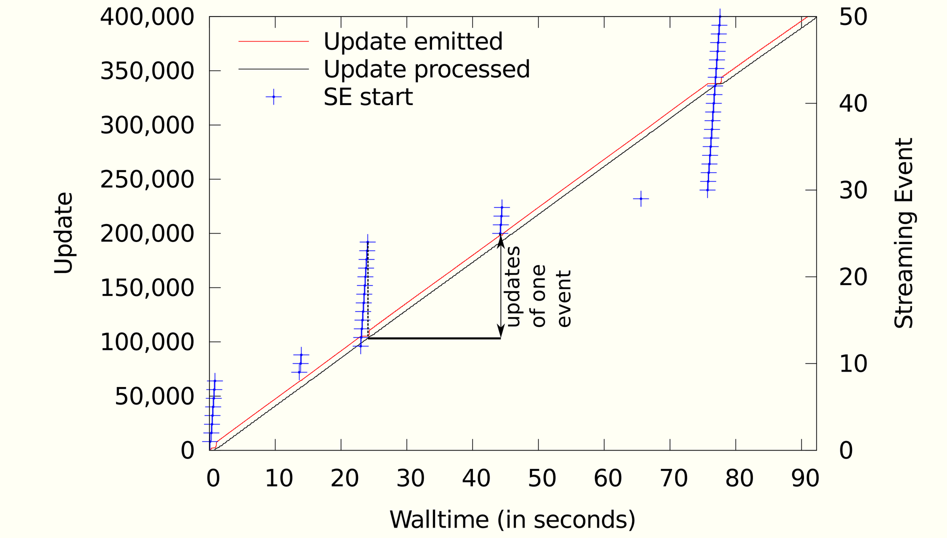
Name	$\|V\|$	$\|E\|$	# updates
`web-NotreDame`	325,729	1,090,008	399,420
`web-Google`	916,428	4,321,958	2,527,088
`soc-pokec`	1,632,804	30,622,464	4,924,759

Experimental Results

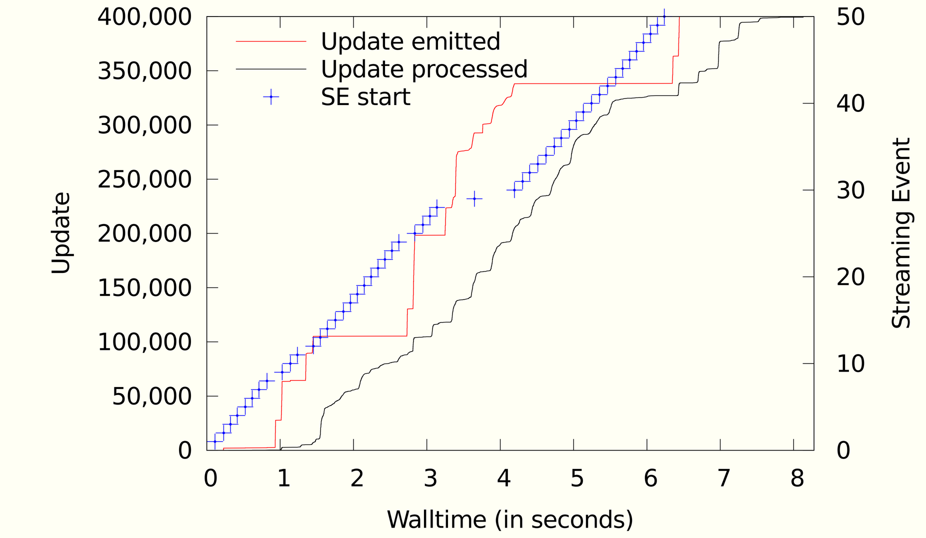


`web-NotreDame` `web-Google` `soc-pokec`

Log Analysis of `web-NotreDame`

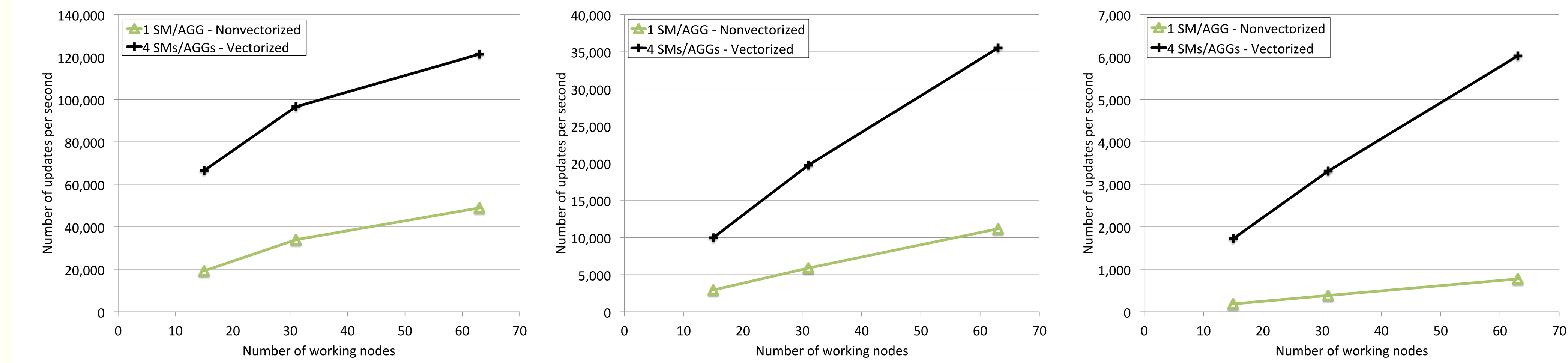


3 worker nodes



63 worker nodes

Using Replicable StreamingMaster and Aggregator (and Vectorization)



`web-NotreDame` `web-Google` `soc-pokec`