Appendix:

Having conducted a series of through experiments, we collect a considerable amount of data to prove the performance benefits achieved by *SLFE*'s redundancy reduction. Due to the page limitation of the paper, we are not able to fit all charts into our paper: **Start Late or Finish Early: A Distributed Graph Processing System with Redundancy Reduction**. Instead, we show those figures and tables in this document as a supplement to our paper. There are seven real word graphs involved in our experiments. To make the charts compact, we refer to those graphs with their short names. However, readers can find their full names and properties in the Table 1.

Table 1: The graph datasets [6, 4, 3] used in experiments.

Real graph	—V—	—E—	AvgDegree	Type
pokec (PK)	1.6M	30.6M	18.8	Social
orkut (OK)	3.1M	117.2M	38.1	Social
livejournal (LJ)	4.8M	69M	14.23	Social
wiki (WK)	12.1M	378.1M	31.1	Hyperlink
delicious (DI)	33.8M	301.2M	8.9	Folksonomy
s-twitter (ST)	11.3M	85.3M	7.5	Social
friendster (FS)	65.6M	1.8B	27.5	Social
Synthetic graph	—V—	—E—	AvgDegree	Type
RMAT1	100M	2B	20	RMAT
RMAT2	300M	6B	20	RMAT
RMAT3	500M	10B	20	RMAT

To give readers a basic idea of what this document has, and help them link back to our paper when looking through those charts, we summaries the contents as follows.

- Figure 1 shows the absolute runtime of intra-machine scalability experiments, as we promised in the end of section 4.2.1 of our paper. We run five applications with seven real graphs that fit in a single machine's memory, while the number of cores varies from 1 to 68. *SLFE* achieves nearly linear scale-up in all cases, besides we draw the runtime of two state-of-art single-machine systems, GraphChi [5] and Ligra [7], as comparison.

- Figure 2 and Figure 3 provide the preprocessing information of PowerGraph [2], PowerLyra [1], and *SLFE* on seven real graphs, as a supplement to the Figure 9 in our paper, which only has preprocessing time of three synthetic graphs. *SLFE* finishes the preprocessing phase (include the RRG generation overhead) faster than PowerGraph and PowerLyra, and shows certain scale-out.

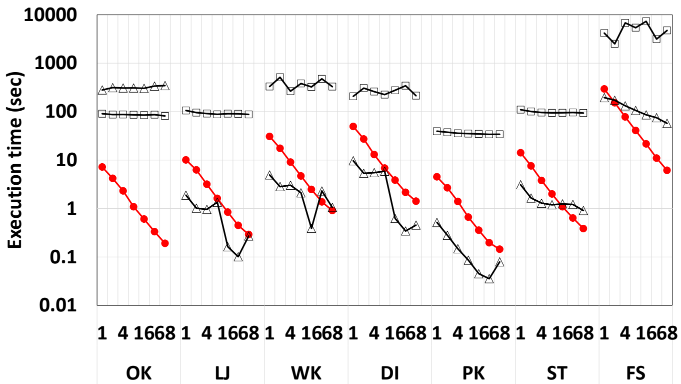
- Figure 4 has the absolute runtime of inter-machine scalability experiments on seven real graphs, as a supplement for the Figure 10 in our paper, where only the data of three synthetic graphs are exhibited. Even considering the RRG generation overhead, *SLFE* outperforms PowerLyra, PowerGraph, and Gemini [8] in almost all the cases. As we pointed in the section 4.2.2 of our paper, execution time does not monotonously decrease when enlarging the cluster size. The reason behind those inflection points is that the communication overhead surpasses the benefits obtained from adding more computation resources.

- Figure 5 reports *SLFE*'s trend lines given seven real graphs as inputs. As the Figure 11 in our paper, Figure 5 is also the result of intra/inter-machine scalability experiments, where we vary the number of cores per machine as well as the number of machines in the cluster. Generally, *SLFE* benefits from more cores all the time, but its performance could degrade as the size of the cluster raises. Especially on those graphs that are relatively small, insufficient computation with more communication overhead leads to the scaling loss.

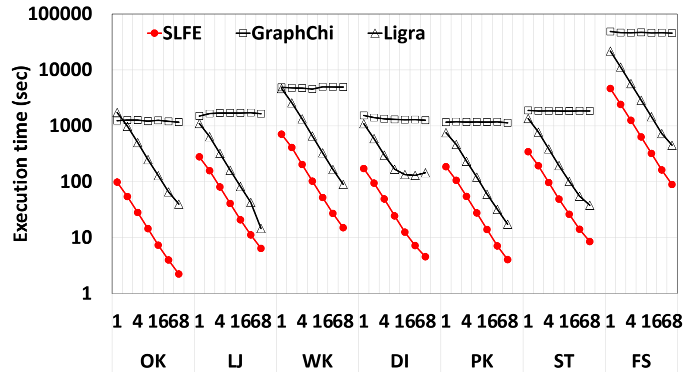
- Figure 6 to Figure 10 demonstrate how the computations reduce during the execution under our principle, that is "start late or finish early". As defined in the section 4.3.1 of our paper, computation refers to an update on a vertex, which includes a min/max or arithmetic operation and its corresponding synchronizations operations. We select six charts as representatives and place them in the Figure 12 of our paper. That is because Widest Path and Single Source Shortest Path have a similar converging trend (see Figure 8 and Figure 9); PageRank and TunkRank are similar to each other in the term of converging trend (see Figure 6 and Figure 7).

- Table 2 lists the memory footprint of *SLFE* and other three distributed graph processing systems. Gemini achieves the highest memory efficiency, while *SLFE* is competitive.

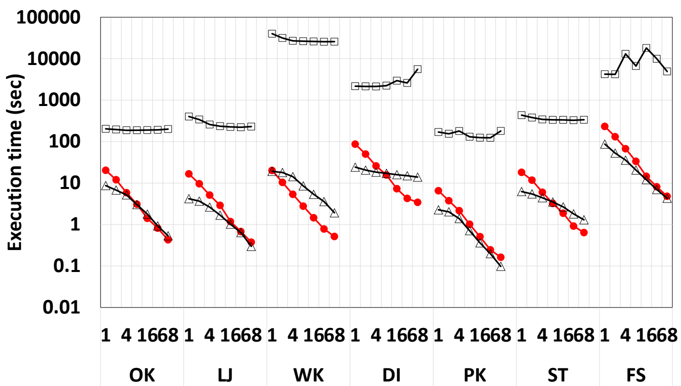
- Table 3 gives out the exact memory cost introduced by our Redundancy Reduction Guidance (RRG).



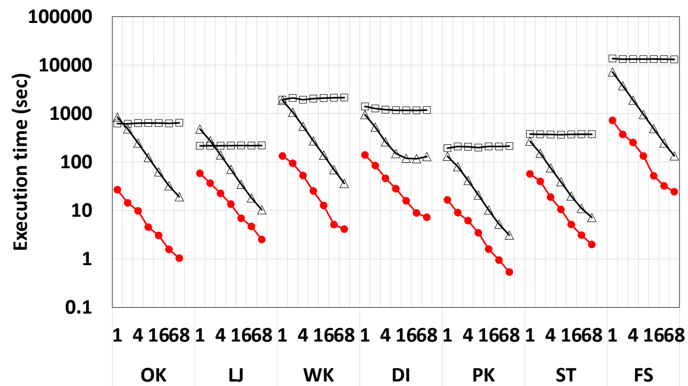
(a) Connected Component



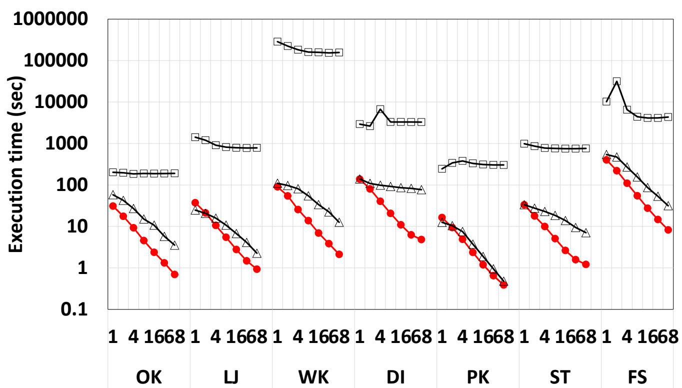
(b) PageRank



(c) Widest Path



(d) TunkRank



(e) Single Source Shortest Path

Figure 1: Intra-machine scalability (1-68 cores) of *SLFE*, GraphChi [5], and Ligra [7] on a single-machine setup.

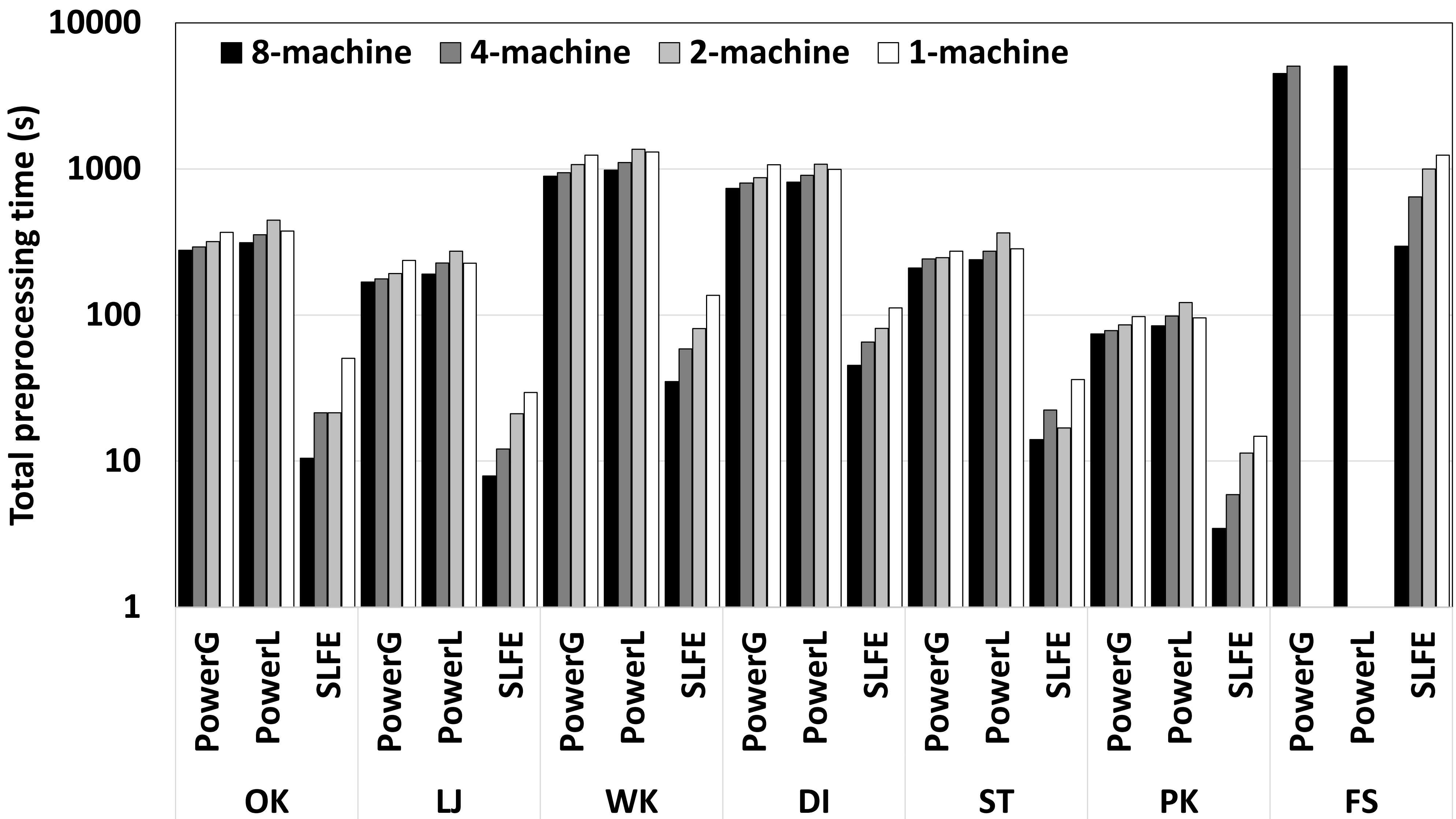


Figure 2: Total preprocessing time for seven real graphs. The preprocessing time consists of loading time, partitioning time (Random partitioner for PowerGraph [2], Ginger partitioner for PowerLyra [1], and Chunking partitioner for *SLFE* and Gemini [8]), formatting time . **Note1:** *SLFE* and Gemini utilize the same preprocessing methodology except for the Redundancy Reduction Guidance (RRG) generation, so the group of bars in the figure labeled by "SLFE" apply for Gemini as well. **Note2:** missing bars of Friendster are due to the failure of exceeding memory capacity.

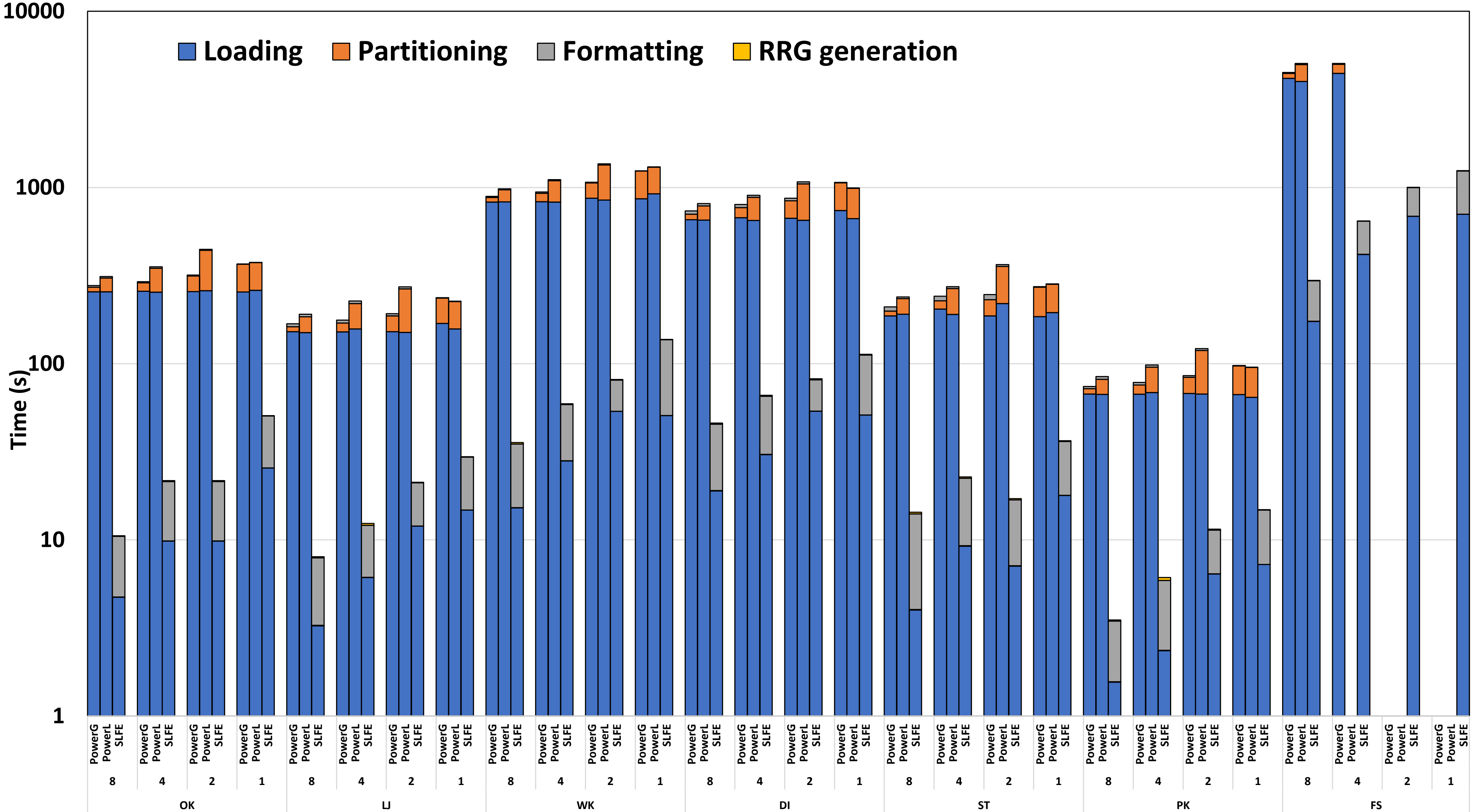
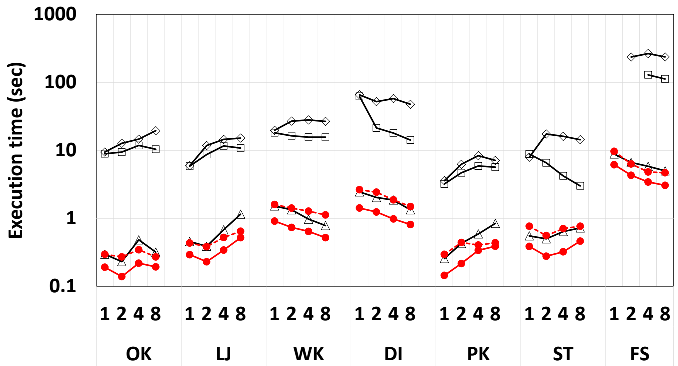
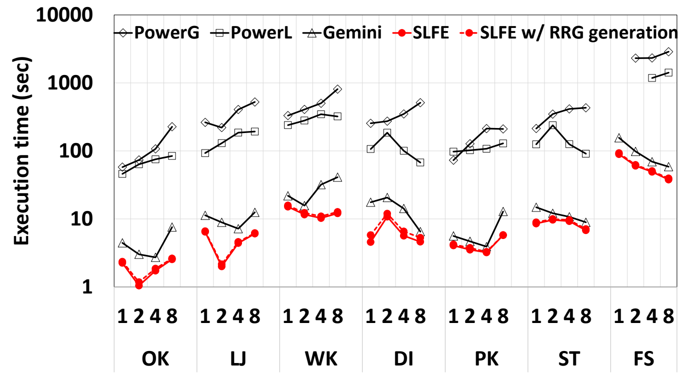


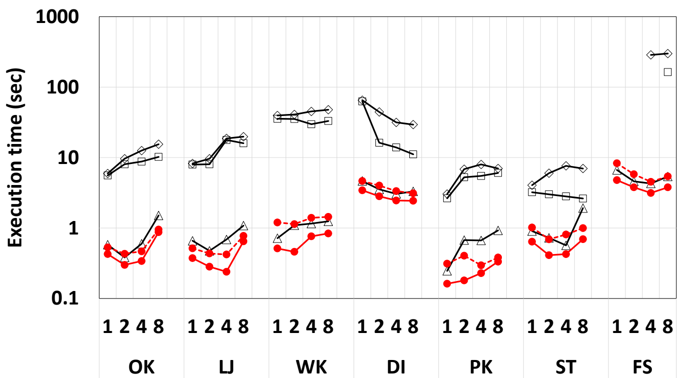
Figure 3: Breakdown of preprocessing time for seven real graphs, into loading time, partitioning time (Random partitioner for PowerGraph [2], Ginger partitioner for PowerLyra [1], and Chunking partitioner for *SLFE* and Gemini [8]), formatting time, and the Redundancy Reduction Guidance (RRG) generation time (only *SLFE* has but so little that need to zoom in to observe). **Note1:** *SLFE* and Gemini utilize the same preprocessing methodology except for the Redundancy Reduction Guidance (RRG) generation, so the group of bars in the figure labeled by "SLFE" apply for Gemini as well. **Note2:** missing bars of Friendster are due to the failure of exceeding memory capacity.



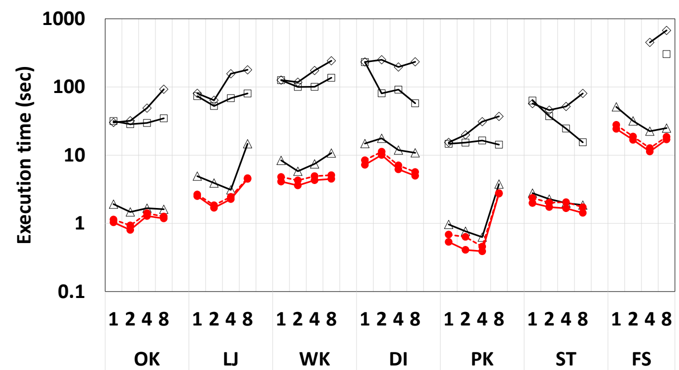
(a) Connected Component



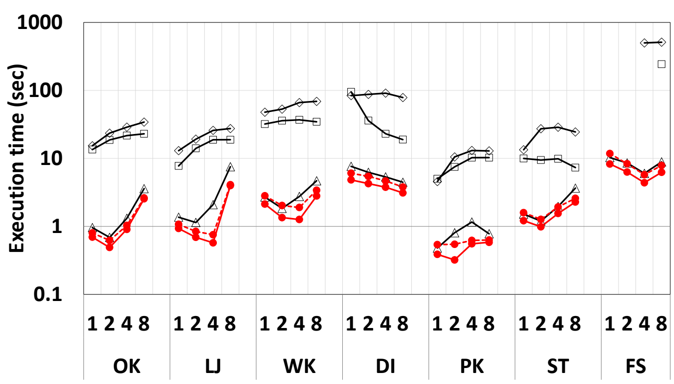
(b) PageRank



(c) Widest Path

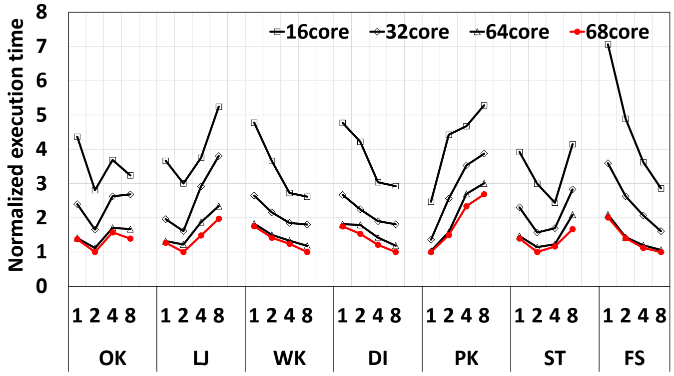


(d) TunkRank

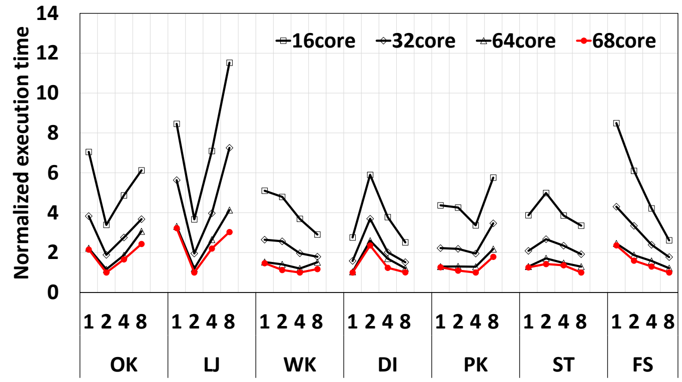


(e) Single Source Shortest Path

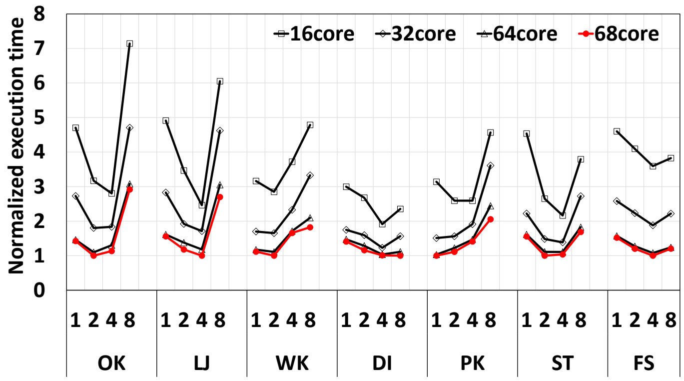
Figure 4: Inter-machine scalability (1-8 machines) of PowerGraph [2], PowerLyra [1], Gemini [8] and *SLFE*. Execution time does not include preprocessing time, and *SLFE* has two series, one includes the Redundancy Reduction Guidance (RRG) generation overhead, another not. **Note:** missing points are due to the failure of execution.



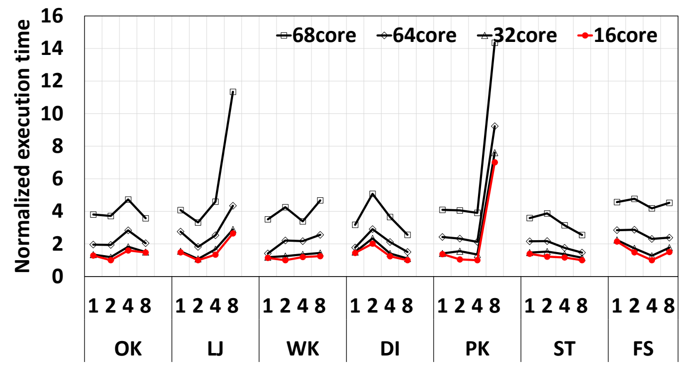
(a) Connected Component



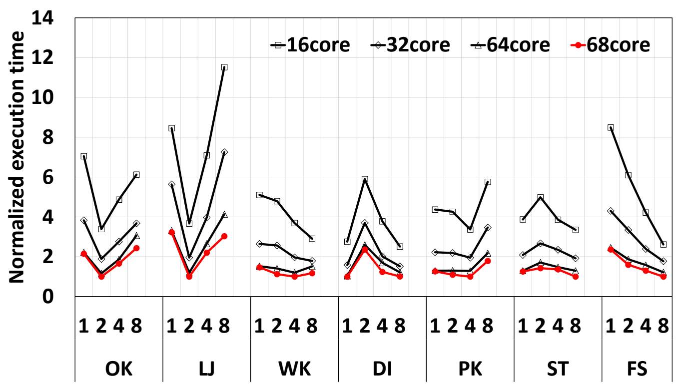
(b) PageRank



(c) Widest Path

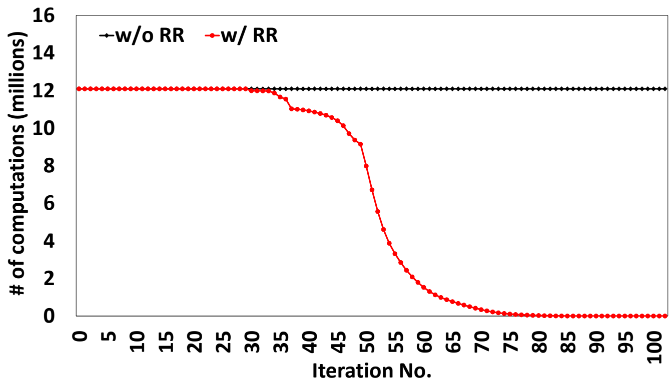


(d) TunkRank

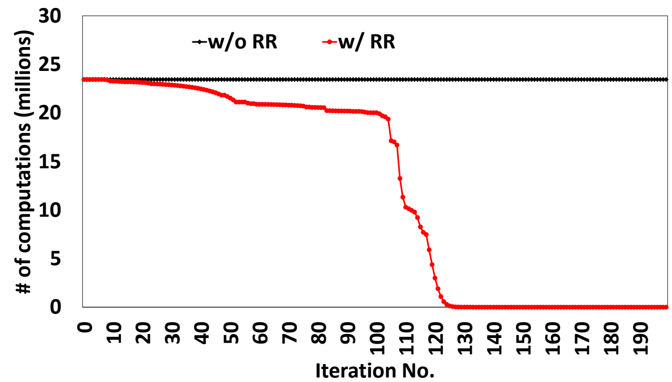


(e) Single Source Shortest Path

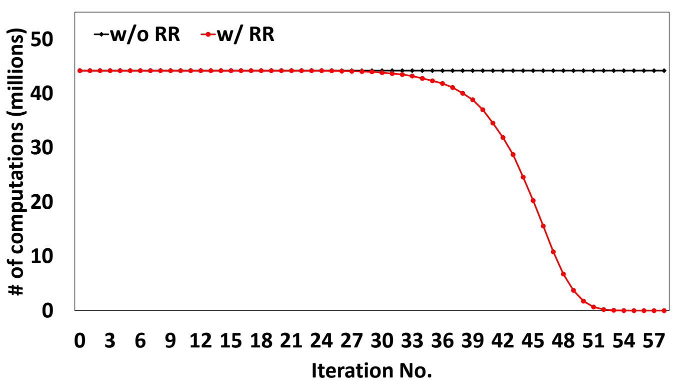
Figure 5: Trend-line analysis of *SLFE* (1-8 machines with 16, 32, 64, and 68 cores per machine) on seven real graphs.



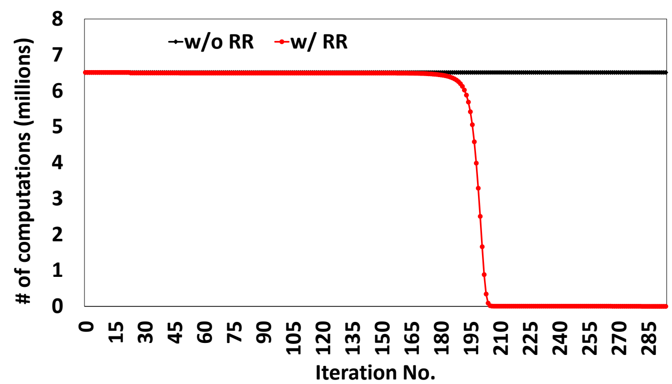
(a) Orkut



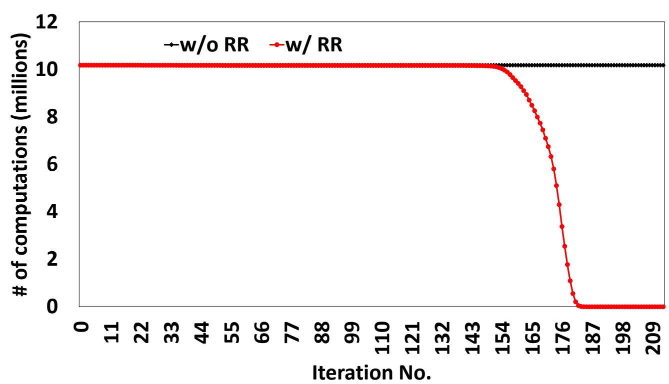
(b) Wiki



(c) Delitags

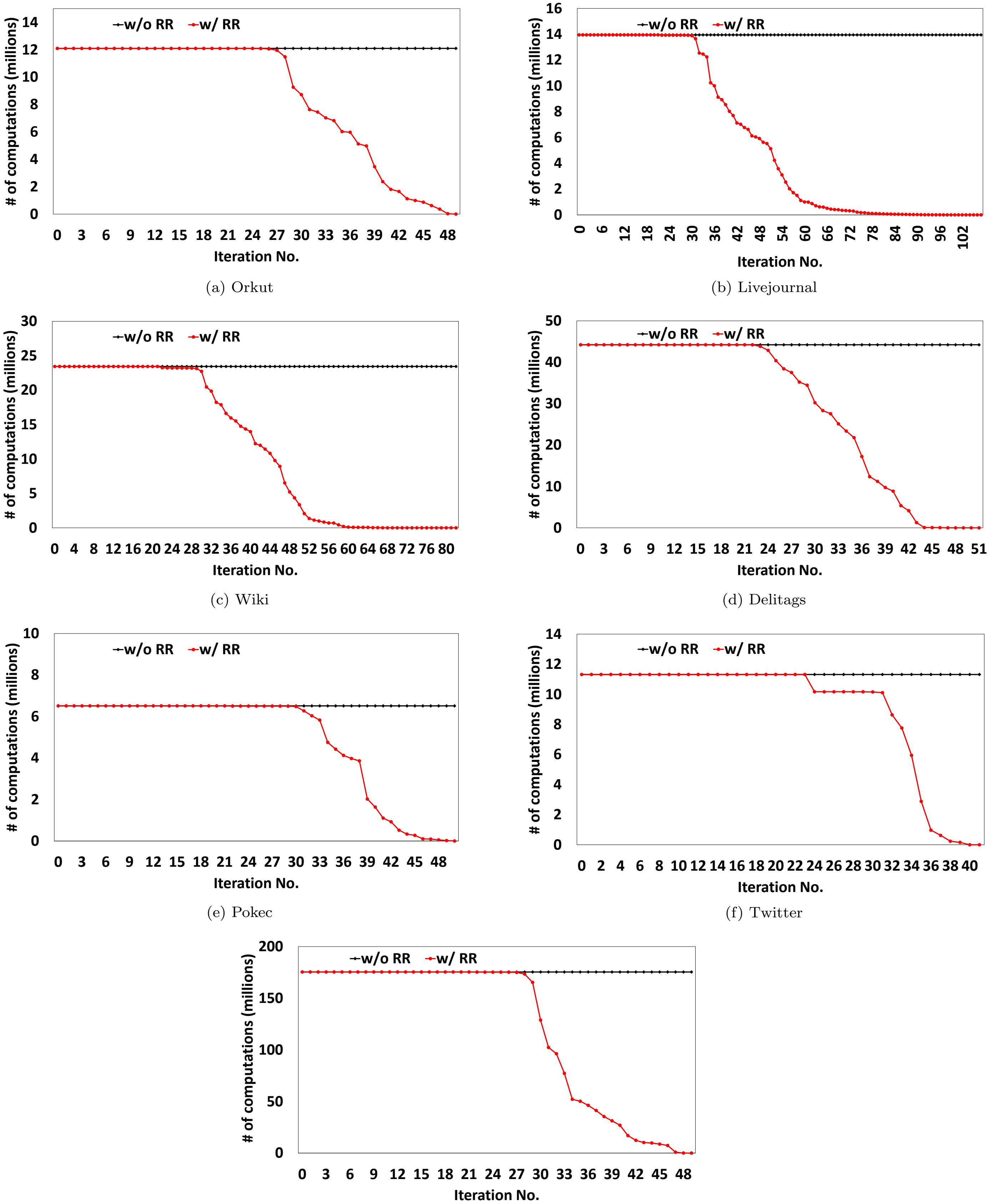


(d) Pokec



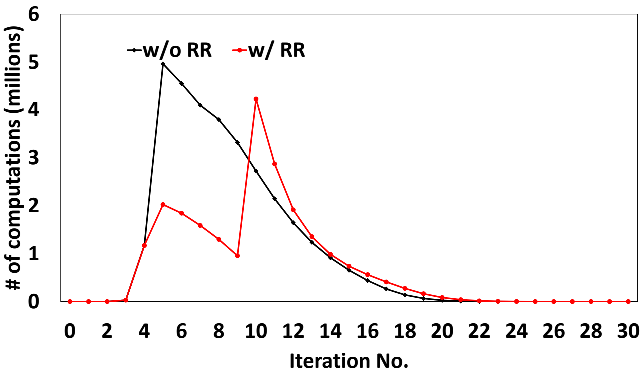
(e) Twitter

Figure 6: Dynamic counts of computations in each iteration of PageRank (charts for Liverjournal and Friendster are in the paper). The gap between those two curves indicates the amount of computations reduced by our Redundancy Reduction (RR) technique.

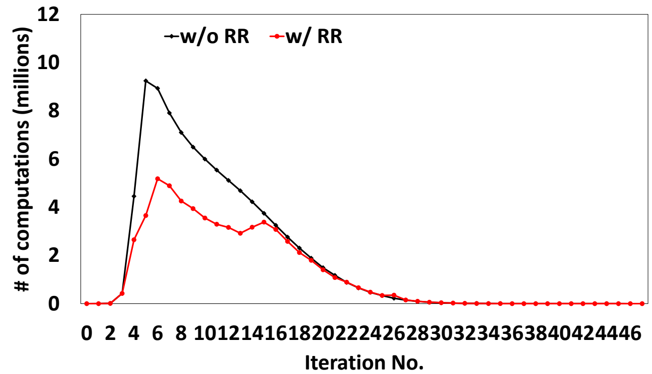


(a) Orkut (b) Livejournal (c) Wiki (d) Delitags (e) Pokec (f) Twitter (g) Friendster

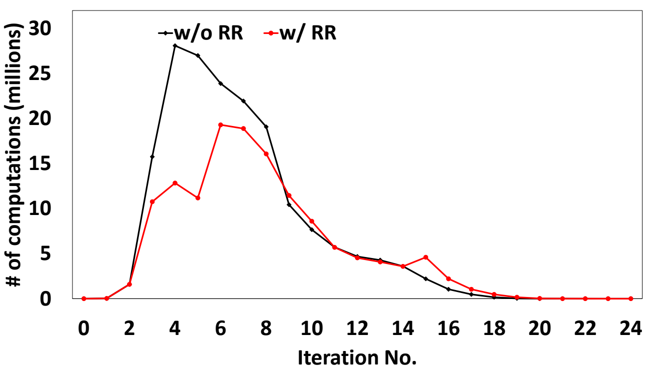
Figure 7: Dynamic counts of computations in each iteration of TunkRank. The gap between those two curves indicates the amount of computations reduced by our Redundancy Reduction (RR) technique.



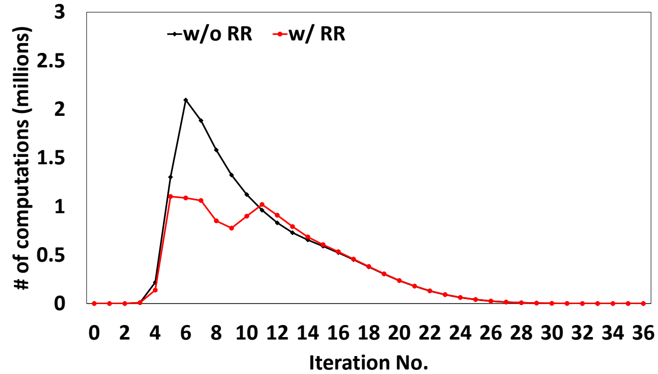
(a) Orkut



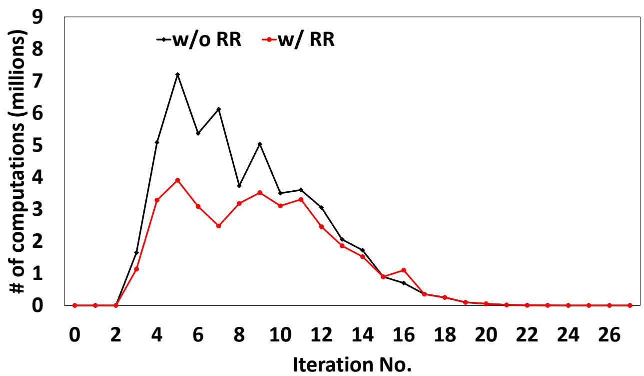
(b) Wiki



(c) Delitags



(d) Pokec



(e) Twitter

Figure 8: Dynamic counts of computations in each iteration of Single Source Shortest Path (charts for Liverjournal and Friendster are in the paper). The gap between those two curves indicates the amount of computations reduced by our Redundancy Reduction (RR) technique.

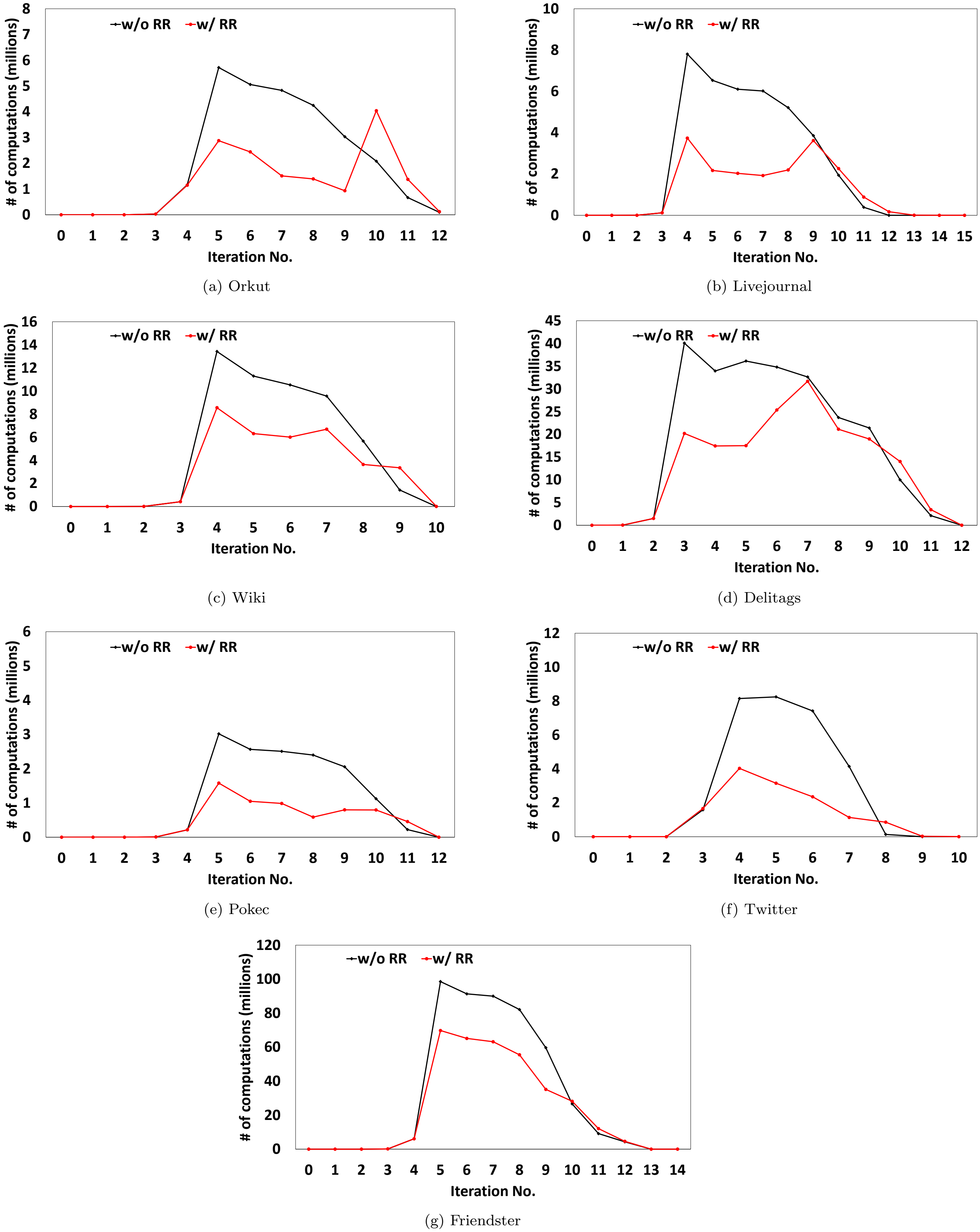
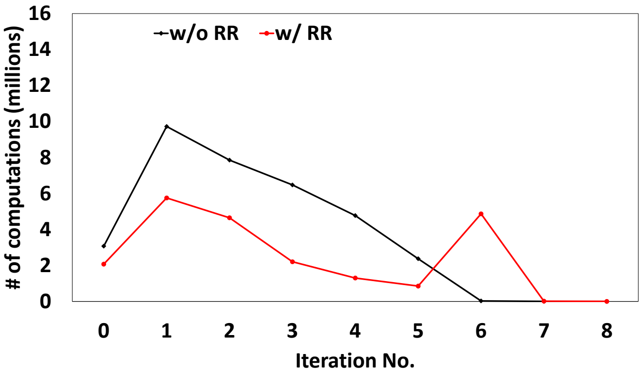
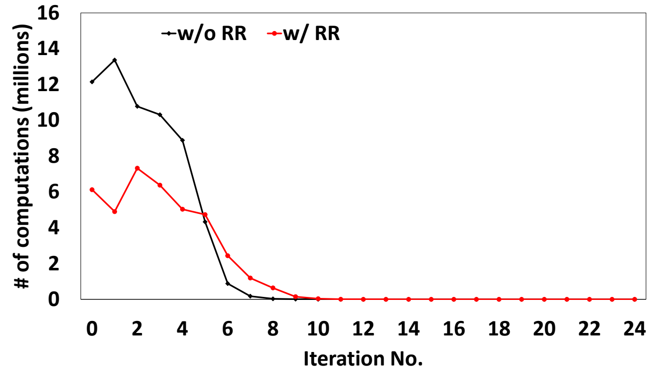


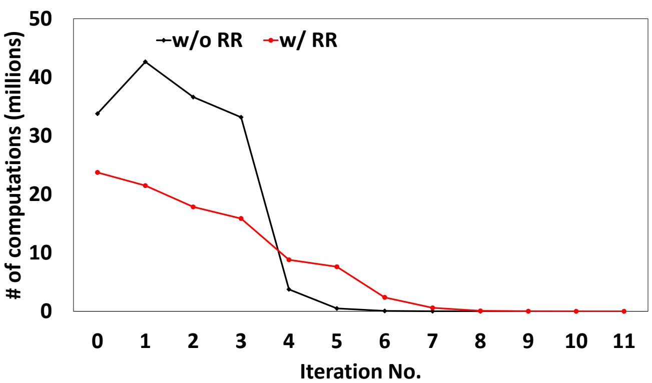
Figure 9: Dynamic counts of computations in each iteration of Widest Path. The gap between those two curves indicates the amount of computations reduced by our Redundancy Reduction (RR) technique.



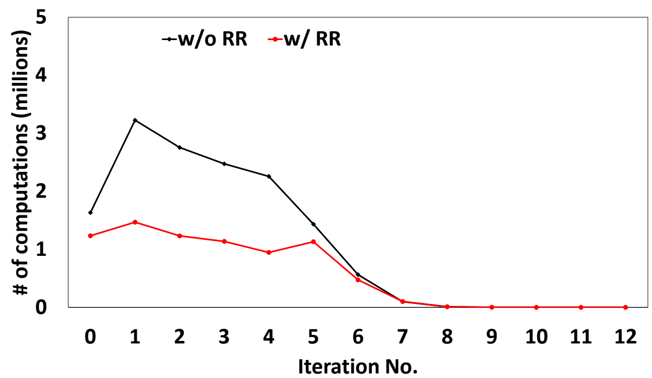
(a) Orkut



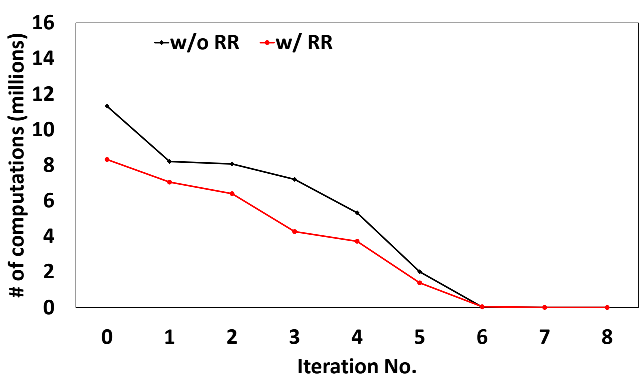
(b) Wiki



(c) Delitags



(d) Pokec



(e) Twitter

Figure 10: Dynamic counts of computations in each iteration of Connected Component (charts for Liverjournal and Friendster are in the paper). The gap between those two curves indicates the amount of computations reduced by our Redundancy Reduction (RR) technique.

Table 2: Memory footprint of *SLFE*, PowerLyra [1], PowerGraph [2], and Gemini [8] on seven real graphs. "-" denotes the execution failure due to exceeding memory capacity.

		Orkut(OK)	Livejournal(LJ)	Wiki(WK)	Delitags(DI)	Pokec(PK)	Twitter(ST)	Friendster(FS)
SLFE	1-machine(GB)	1.57	1.16	4.98	5.18	0.51	1.67	26.42
	8-machine(GB)	3.36	3.57	8.41	8.66	2.1	4.5	43.82
PowerL	1-machine(GB)	15.33	9.19	45.61	38.91	4	11.37	-
	8-machine(GB)	22.18	16.06	63.14	61.7	6.76	17.25	305.38
PowerG	1-machine(GB)	10.58	6.55	33.96	29.72	2.87	8.5	-
	8-machine(GB)	13.05	11.24	39.17	46.47	5.26	14.85	203.96
Gemini	1-machine(GB)	1.54	1.14	4.9	5	0.5	1.61	25.78
	8-machine(GB)	3.24	3.38	7.9	7.31	2.03	4.04	38.8

Table 3: Redundancy Reduction Guidance (RRG) memory cost on seven real graphs.

	Orkut(OK)	Livejournal(LJ)	Wiki(WK)	Delitags(DI)	Pokec(PK)	Twitter(ST)	Friendster(FS)
RRG space on 1-machine(GB)	0.012	0.019	0.049	0.14	0.006	0.046	0.49
RRG/total memory footprint on 1-machine	0.76%	1.63%	0.98%	2.7%	1.17%	2.75%	1.85%
RRG space on 8-machine(GB)	0.096	0.15	0.39	1.08	0.051	0.36	3.99
RRG/total memory footprint on 8-machine	2.86%	4.2%	4.64%	12.47%	2.43%	7.99%	9.11%

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