

DZIG: Sparsity-Aware Incremental Processing of Streaming Graphs



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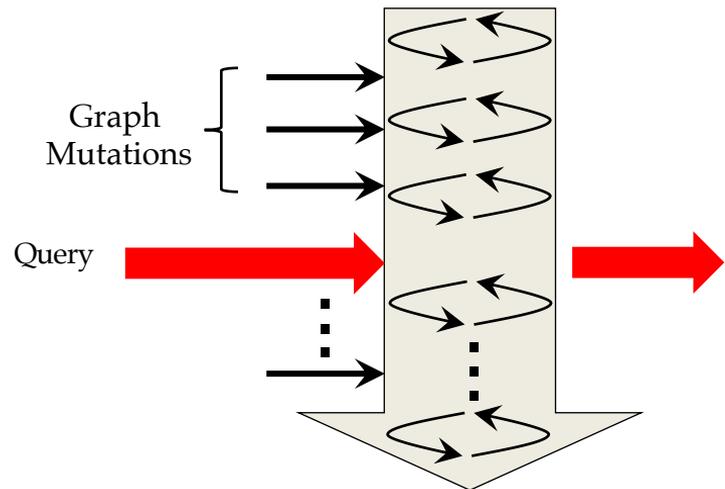
Keval Vora

Simon Fraser University

EuroSys'21
April 28, 2021

Streaming Graph Processing

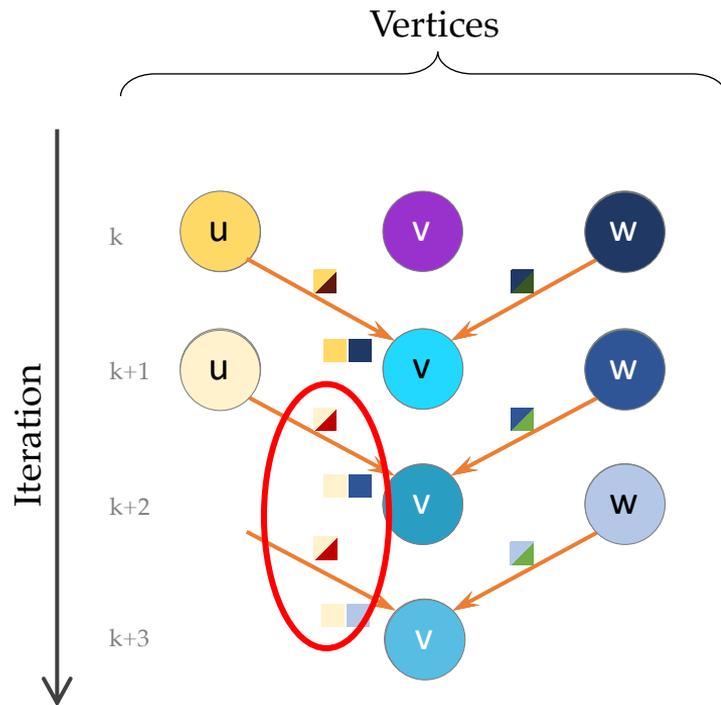
- Graph structure keeps on changing via a stream of edge / vertex updates
- **Incremental Processing**
 - Adjust results incrementally
- Reuse work that has already been done



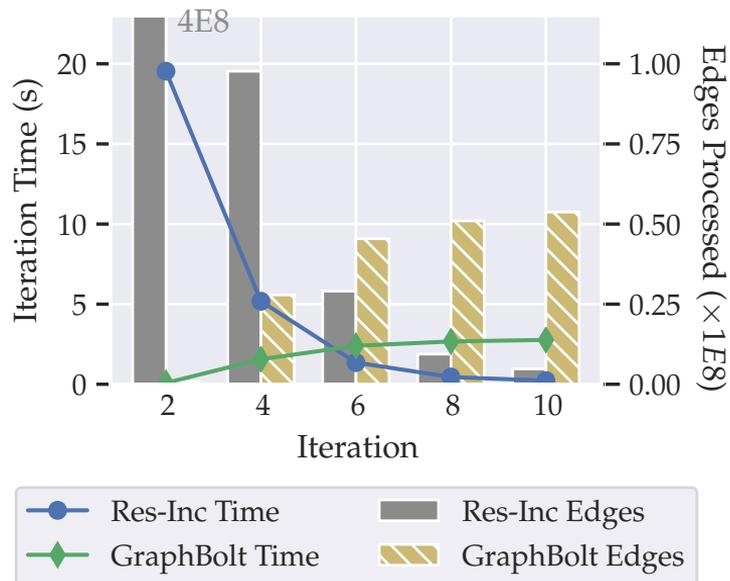
- **Dependency-Driven Incremental Refinement**
- Generates same results at every iteration as a BSP execution from scratch

Dependency-Driven Incremental Refinement

- Upon graph mutation:
 - Identify changes in values
 - Propagate changes step-by-step
- Changes not retained across iterations
- Not friendly to **computation sparsity**



Computation Sparsity



- Hybrid execution
- **Turn off dependency-driven incremental refinement** during sparse iterations

How to **retain high performance** with **dependency-driven incremental processing** during **sparse computations**?

DZIG: Sparsity-Aware Incremental Refinement

- Dependency-driven incremental processing
- Delivers **high performance in presence of sparse computations**
- Generates same results at every iteration as a BSP execution from scratch

How to **identify sparse computations** during incremental refinement?

How to **retain computation sparsity** during incremental refinement?

DelZero: Sparse Updates

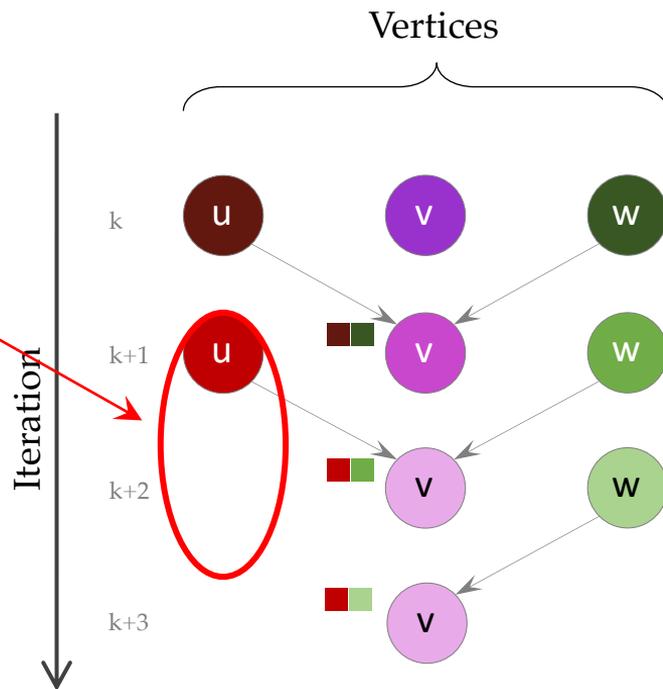
$$\delta_i(v) = \emptyset \quad \text{iff} \quad |v_i - v_{i-1}| \leq \epsilon$$

```

while(curr not empty) {
  parallel_for u in curr {
    float change = (pr[u] - prev_pr[u]) / numOutNbrs(u);
    parallel_for v in outNeighbors(u) {
      atomicAdd(&sum[v], change);
      next.add(v);
    }
  }
  swap(curr, next);
  next.clear();
  parallel_for v in curr {
    float rank = 0.15 + 0.85 * sum[v];
    if(fabs(rank - pr[v]) > epsilon) {
      prev_pr[v] = pr[v];
      pr[v] = rank;
      next.add(v);
    }
  }
}

```

PageRank



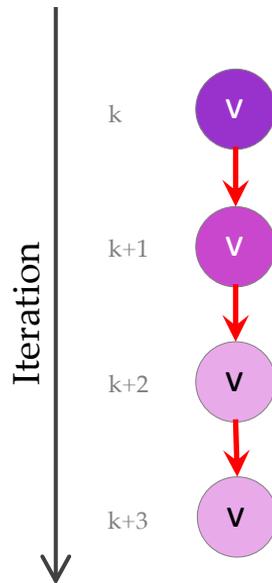
DelZero-Aware Incremental Refinement

- Express **incremental refinement recursively**

$$g_i^T(v) = g_i(v) \oplus \Delta_i^T(v)$$

$$\Delta_i^T(v) = \Delta_{i-1}^T(v) \left[\begin{array}{l} \bigcup_{\substack{\forall e=(u,v) \in E_a \\ s.t. \delta_{i-1}(u) \neq \emptyset}} \delta_{i-1}(u) \\ \bigcup_{\substack{\forall e=(u,v) \in E_d \\ s.t. \delta_{i-1}(u) \neq \emptyset}} \delta_{i-1}(u) \end{array} \right]$$

$$\left[\begin{array}{l} \bigcup_{\substack{\forall e=(u,v) \in E^c \\ s.t. \delta_{i-1}(u) \neq \emptyset}} \delta_{i-1}(u) \\ \bigcup_{\substack{\forall e=(u,v) \in E^c \\ s.t. \delta_{i-1}^T(u) \neq \emptyset}} \delta_{i-1}^T(u) \end{array} \right]$$



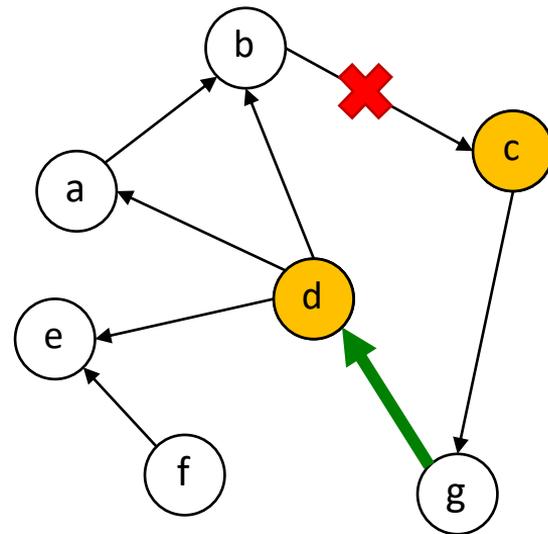
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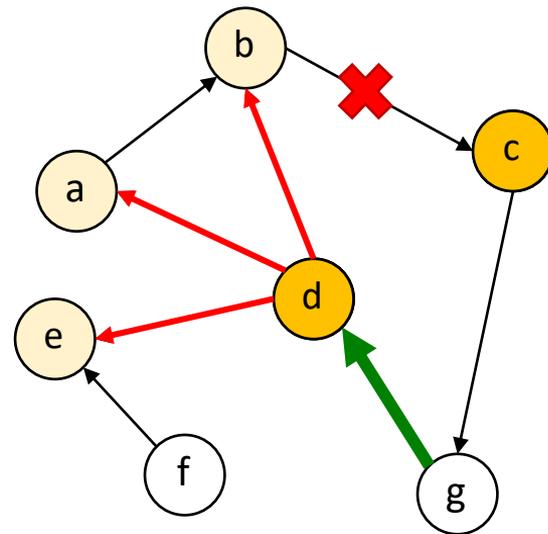
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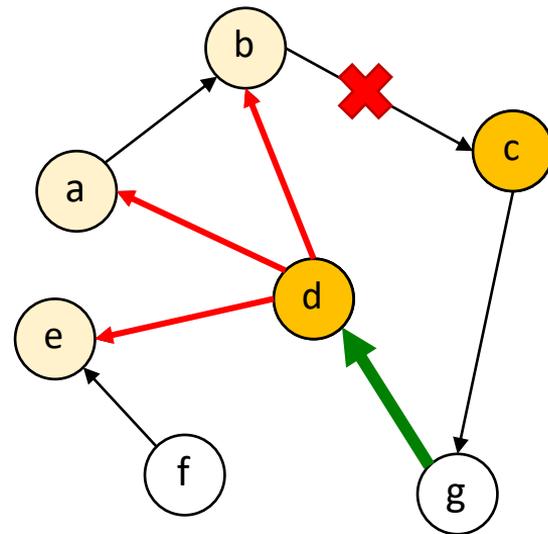
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DelZero-Aware Incremental Refinement

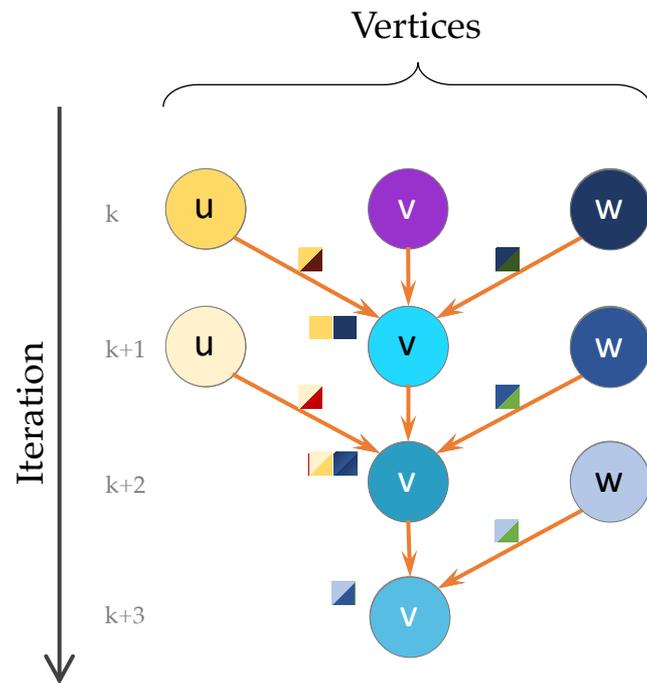
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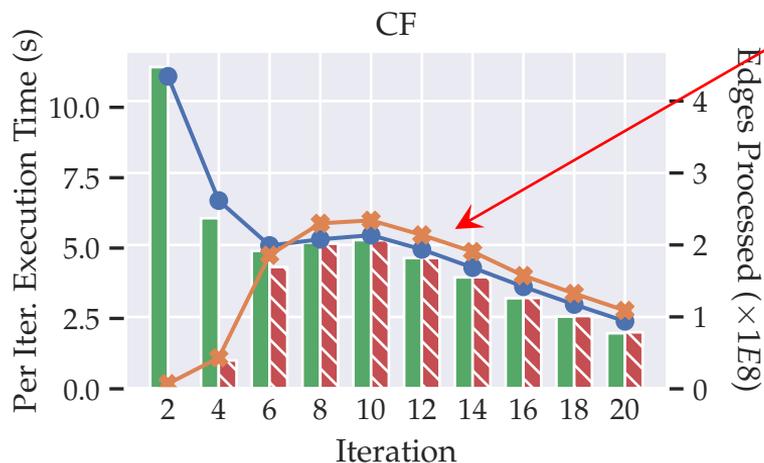
$$\Delta_i^T(v) = \Delta_{i-1}^T(v) \bigcup_{\substack{\forall e=(u,v) \in E_a \\ \text{s.t. } \delta_{i-1}(u) \neq \emptyset}}^{+} \delta_{i-1}(u) \bigcup_{\substack{\forall e=(u,v) \in E_d \\ \text{s.t. } \delta_{i-1}(u) \neq \emptyset}}^{-} \delta_{i-1}(u)$$

Correctness Proof
in Paper!

$$\bigcup_{\substack{\forall e=(u,v) \in E^c \\ \text{s.t. } \delta_{i-1}(u) \neq \emptyset}}^{-} \delta_{i-1}(u) \bigcup_{\substack{\forall e=(u,v) \in E^c \\ \text{s.t. } \delta_{i-1}^T(u) \neq \emptyset}}^{+} \delta_{i-1}^T(u)$$

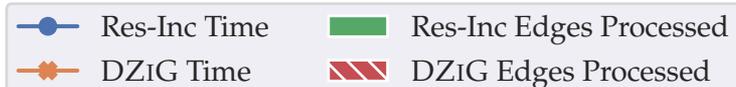


Adaptive Sparse Incremental Processing

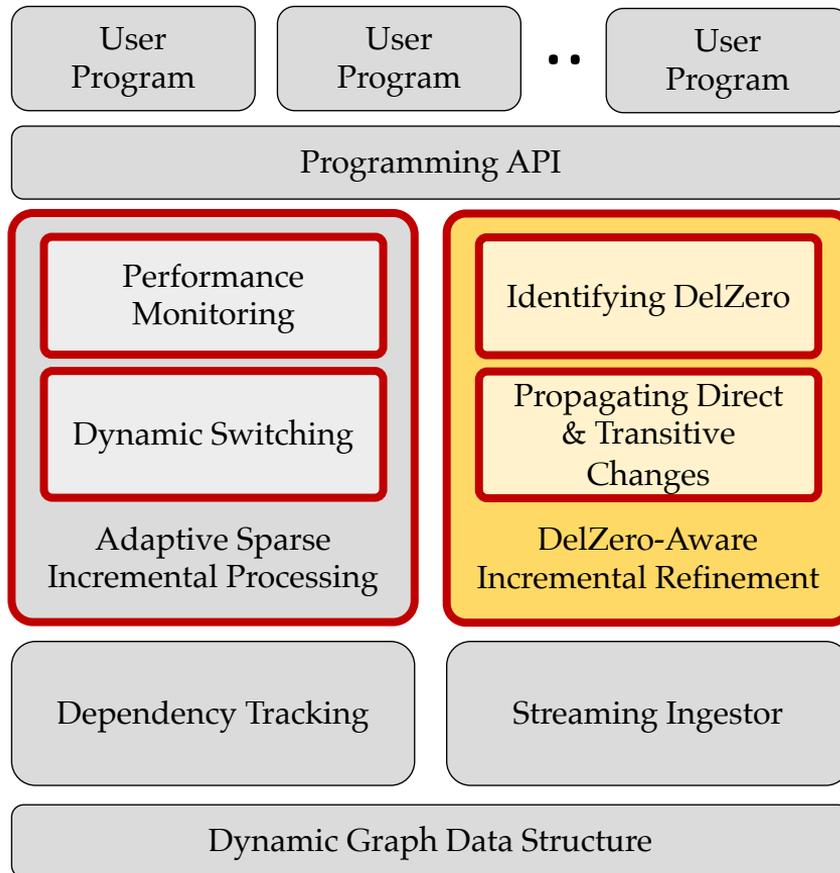


- Minor overhead due to **two ops per edge** (retract old value & propagate new value)

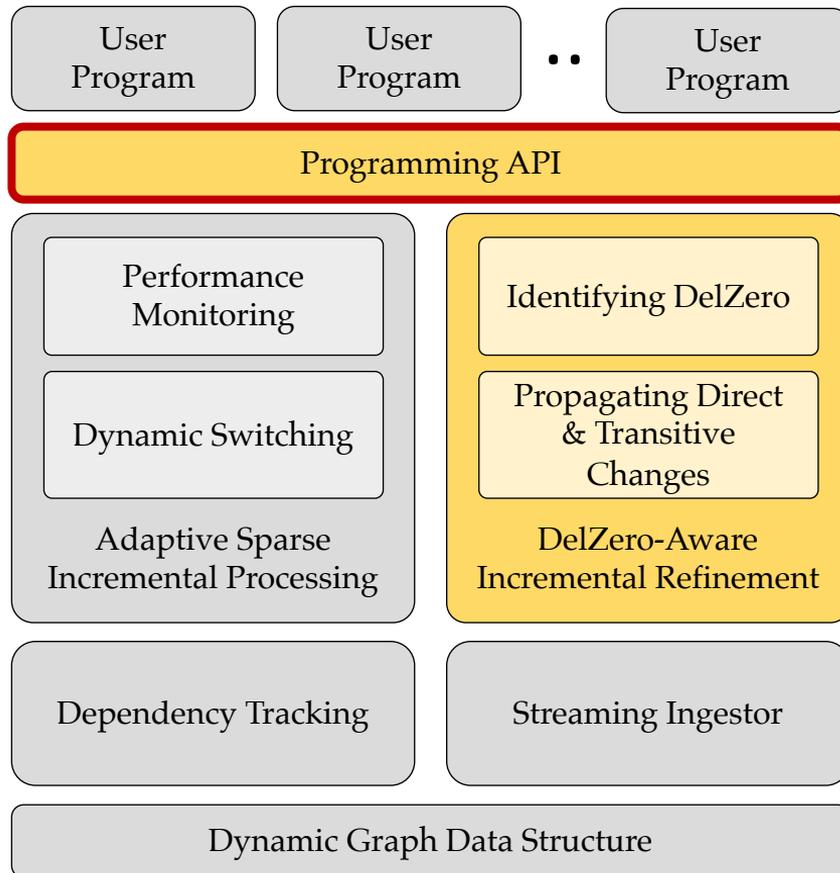
- **Automatically switch** to traditional incremental processing
- **Linear regression** to estimate iteration time



DZIG System



DZIG System



Extracting DelZeros

PageRank:

$$PR(u) = 0.15 + 0.85 \times \sum_{(u,v) \in G} \frac{PR(v) \times W(u,v)}{N(v)}$$

```

bool notDelZero(VValueType oldVal, VValueType newVal) {
    return fabs(newVal - oldVal) > epsilon;
}
DeltaType vertexChange(VId v, VValueType oldVal,
                       VValueType newVal, Graph G) {
    return (newVal - oldVal) / G.out_degree[v];
}
DeltaType edgeChange(Edge e, DeltaType change,
                     VValueType oldVal, VValueType newVal, Graph G) {
    return change * G.edge_weight[e];
}
void addChange(AggregationType* aggr, DeltaType delta) {
    atomicAdd(aggr, delta);
}
void removeChange(AggregationType* aggr, DeltaType delta){
    atomicSubtract(aggr, delta);
}
VValueType computeVertex(VId v, AggregationType aggr,
                          VValueType oldVal, Graph G) {
    return 0.15 + (0.85 * aggr);
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DeltaType edgeChange(Edge e, DeltaType change,
                     VValueType oldVal, VValueType newVal, Graph G) {
    return change * G.edge_weight[e];
}

void addRemoveChange(AggregationType aggr,
                     DeltaType oldDelta, DeltaType newDelta)
    atomicAdd(&aggr, newDelta - oldDelta);
}

VValueType computeVertex(VId v, AggregationType aggr,
                         VValueType oldVal, Graph G) {
    return 0.15 + (0.85 * aggr);
}

```

Experimental Setup

- **Graph Benchmarks:**

PageRank (PR), Belief Propagation (BP), Collaborative Filtering (CF),
Co-Training Expectation Maximization (CoEM), Label Propagation (LP)

Graph	Edges	Vertices
UKDomain (UK) [7]	1.0B	39.5M
Twitter (TW) [28]	1.5B	41.7M
TwitterMPI (TT) [10]	2.0B	52.6M
Friendster (FT) [16]	2.5B	68.3M
Yahoo (YH) [62]	6.6B	1.4B

- **Server:** 32-cores @ 2 GHz, 231 GB RAM

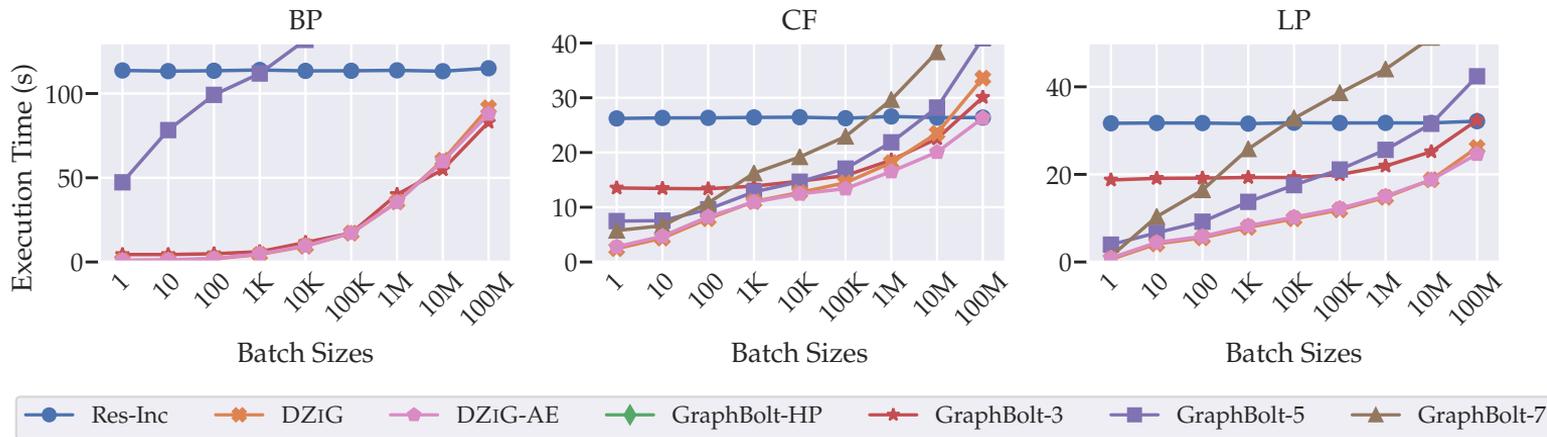
DZiG Performance

	PR-1K			BP-1K			CF-1K			CoEM-1K			LP-1K		
	UK	TT	FT	UK	TT	FT	UK	TT	FT	UK	TT	FT	UK	TT	FT
DZiG	0.578	11.2	21	1.4	4.77	1.23	4.71	11.1	4.25	0.73	7.64	5.43	0.609	8.05	6.03
Res-Inc	4.38	15.8	29.6	35.8	114	164	10.2	26.5	43.1	5.5	22.9	31.9	9.11	31.6	49.8
GraphBolt	1.5	11.7	21.4	2.7	6.37	5	7.83	12.9	8.39	0.983	7.52	5.63	3.18	12.3	9.25

Execution time (in seconds)

- Up to **133x faster** than restarting from scratch
- Comparable performance with the best hand-picked GraphBolt switching
- Up to **5.22x faster** than GraphBolt

DZiG Performance



- **Pushes scale** of dependency-driven incremental processing
- Adaptive Sparse Incremental Processing helps for large batch sizes
- **Better & consistent performance**

Comparison with Other Frameworks

	Graph Update			PageRank			SSSP		
	1	100	10K	1	100	10K	1	100	10K
DZiG	0.06	0.09	0.33	8.62	10.56	11.20	0.05	0.05	0.09
GraphBolt	1.15	1.17	1.42	9.04	11.14	12.25	0.05	0.05	0.09
Aspen	1E-4	2E-3	7E-3	29.48	29.29	29.68	3.31	3.31	3.27
GraphOne	4E-3	0.09	1.64	19.91	19.73	20.02	13.24	13.09	18.41
LLAMA	x	x	x	20.55	20.55	20.55	2.77	2.77	2.77
Stinger	0.02	2.88	7.06	431.18	437.11	488.78	145.15	145.12	147.17

Execution time (in seconds)

- **Significantly lower end-to-end processing times** (update + analytics time)
- Up to **3.39x/30.1x faster than Aspen** on PageRank/SSSP
- Up to **2.2x/120x faster than GraphOne** on PageRank/SSSP

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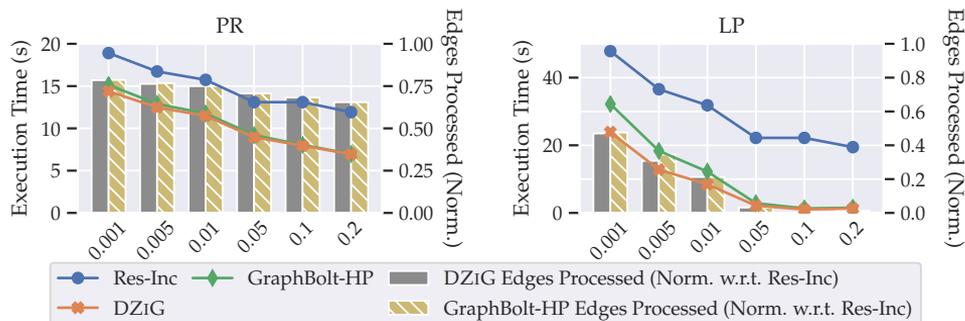
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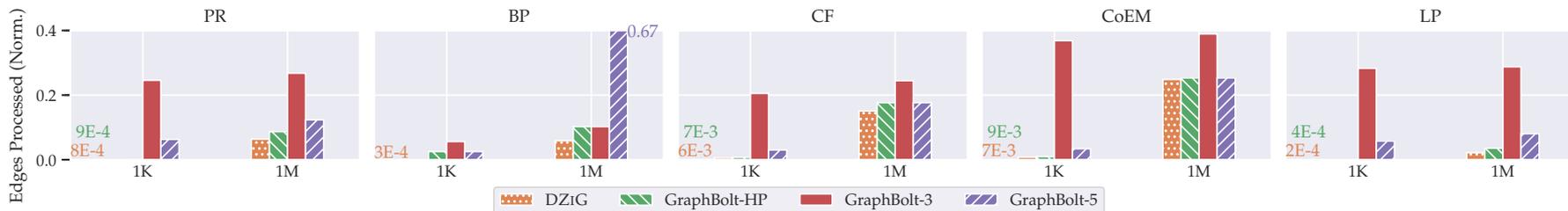
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Other Experiments

	PR	BP	1K CF	CoEM	LP	PR	BP	1M CF	CoEM	LP
DZiG	1.21	4.51	6.89	3.54	2.46	1.71	10.2	9.45	4.2	2.82
GraphBolt-HP	3.73	14.1	12.3	3.05	3.68	4.49	84.2	15.3	5.47	4.34
GraphBolt-3	5.35	14.4	16.7	6.29	9.31	5.45	84.2	16.4	6.56	9.14
GraphBolt-5	4.54	14.7	13.5	3.05	5.41	4.66	87.6	15.6	5.47	5.96
Res-Inc	4.97	70.6	17.7	13.2	13.2	5.27	68.1	17.4	13	12.7



	UK		TW		TT		FT	
	DZiG	GB	DZiG	GB	DZiG	GB	DZiG	GB
PR	4.8%	5.4%	3.8%	6.1%	3.9%	4.3%	4.1%	4.7%
BP	10.3%	10.3%	9.0%	8.9%	10.0%	9.1%	9.6%	8.8%
CF	12.9%	19.0%	11.4%	15.7%	11.4%	17.1%	12.1%	18.3%
CoEM	5.4%	7.7%	4.5%	4.4%	4.5%	4.4%	4.9%	4.9%
LP	7.9%	7.6%	6.7%	6.5%	5.6%	6.5%	7.0%	6.0%



Conclusion



github.com/pdclab/graphbolt

- Dependency-Driven incremental processing important to process dynamic graphs
- **DelZero-Aware incremental refinement** crucial to retain high performance
 - Pushes the scale of dependency-driven incremental processing to **high mutation rates**
- **Adaptive sparse incremental** processing
 - **Automatic switching** based on **performance monitoring**
- Efficient programming model **naturally exposes DelZeros**
 - **Merged edge updates** for performance
- Efficient **dynamic graph data structure**
- DZiG outperforms state-of-the-art solutions