gSketch:
On Query Estimation in Graph Streams

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Synopsis

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3. A Naïve Solution: Global Sketching
4. A Better Sketch Partitioning Solution: gSketch
5. Experimental Evaluation
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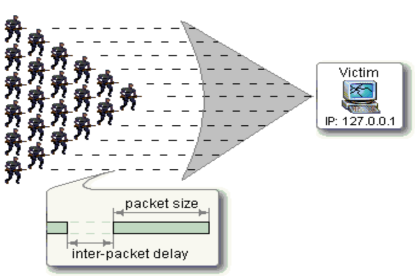
Introduction

- **Graph stream = Graph + Data stream**
  - The edge set is massive
  - Edges are received and updated rapidly in a form of a stream
- **Most existing network applications can be naturally modeled as graph streams**
  - Representative applications
    - Intrusion detection on Internet
    - Social networks
    - Telecommunications



Challenges

- **Graph streams**
  - In a very large scale, the data cannot be stored explicitly in main memory, or even on disk
  - The arriving rate of graph streams is fast
    - "*You can never step in the same stream twice*" --- Heraclitus
- **Graph** streams
  - The universe we are keeping track of is extremely large
  - The dynamic nature hampers a direct application of many algorithms for static memory-resident graphs

Problem Formulation

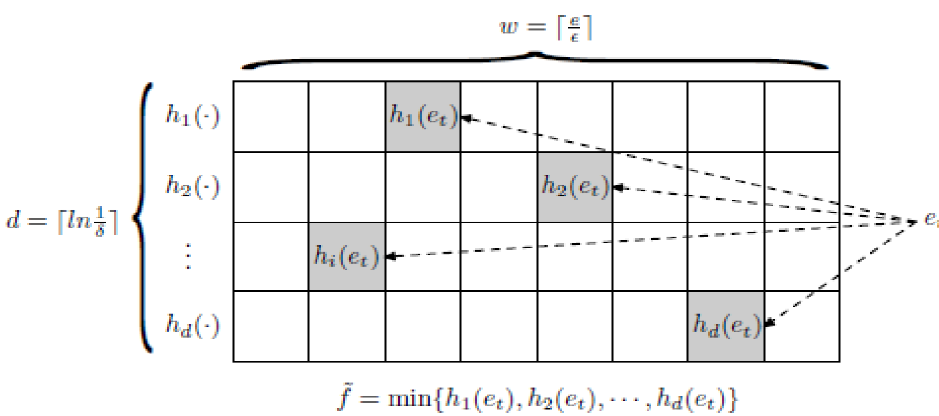
- **Graph streams**
  - $G = (V, E)$ a labeled, directed graph
    - $|V| = N$;
    - $E = \{<u_{t1}, v_{t1}>: f_{t1}; <u_{t2}, v_{t2}>: f_{t2}; \ldots\ldots; <u_{ti}, v_{ti}>: f_{ti}; \ldots\ldots\}$
- **Queries to be estimated**

1. **Edge query**
   - Determine the frequency of the edge $<X, Y>$: $f(X, Y) = \sum_{ti \in T} f(X, Y; t_i)$
2. **Aggregate subgraph query**
   - Determine the aggregate frequency behavior of the edges in a subgraph

A Naïve Solution: Global Sketching

- **Global sketching**
  - A direct application of any existing sketch method for data streams
    - AMS[STOC'96], Lossy-Count[VLDB'02], CountMin[J.Alg'05,SIGMOD'11], Bottom-k[VLDB'08], ……
  - **CountMin** sketch
    - Given a data stream with *N* arrivals till the time-stamp *t*, the estimated frequency $\tilde{f}$ is bounded up *w.h.p.* $(1 - e^{-d})$

$$f \leq \tilde{f} \leq f + e * N/w$$



A Naïve Solution: Global Sketching

- **The vulnerabilities of global sketching**
  - The relative error of query estimation on edge i is $\frac{e}{w}N/f_i$, which is proportional to N/f_i !
  - Such an estimation error incurred can be **extremely high**
    - Edge frequencies of a graph stream are distributed quite unevenly
    - “Low-frequency" edges are quite relevant for querying, and may show up repeatedly in the workload

A Better Solution: Sketch Partitioning

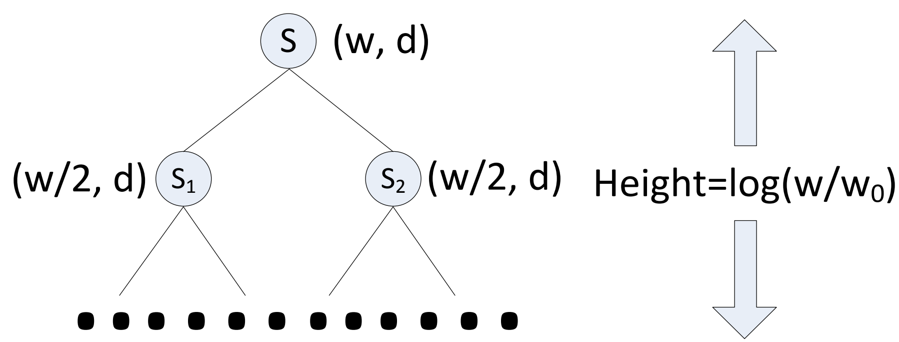
- **Broad intuition**
  - Common characteristics of real graph streams
    - Global Heterogeneity and Skews: the relative frequencies of different edges are very uneven
    - Local Similarity: within structurally localized regions of the graph, relative frequencies of edges are often correlated
  - **(Data/workload) samples** are always available
- **Key idea:**
  - Partitioning the global sketch, so that edges with similar frequencies are maintained and queried in **localized sketches** in order to achieve better estimation accuracy

gSketch: Overview

- **Objective**
  - Given a space limit S, to partition the global sketch over different regions of the graph
    - Partition based on vertices toward counting edges with sufficient frequency uniformity within a sketch
- **Sampling-based partitioning**
  - A sample of the original stream is available
  - Both a sample of the stream and a sample of the query workload are available

Sketching Partitioning with Data Sample

- **Recursive partitioning in a top-down fashion as in a decision tree**
  - Data Samples are used to estimate edge frequencies based on local similarity of **edges emanating from different vertices**
  - Optimize the partitioning of S into S_1 and S_2



$$min\ E = min\left(\sum_{m \in S_1} \frac{\tilde{d}(m) * \tilde{F}(S_1)}{\frac{\tilde{f}_v(m)}{\tilde{d}(m)}} + \sum_{m \in S_2} \frac{\tilde{d}(m) * \tilde{F}(S_2)}{\frac{\tilde{f}_v(m)}{\tilde{d}(m)}}\right)$$

Sketching Partitioning with Data/Workload Samples

- **Recursive partitioning in a top-down fashion as in a decision tree**
  - **Workload Samples** are used to estimate "**relative weights**" of different edges

$$min\ E = min\left(\sum_{m \in S_1} \frac{\widetilde{w}(m) * \tilde{F}(S_1)}{\frac{\widetilde{f_v}(m)}{\tilde{d}(m)}} + \sum_{m \in S_2} \frac{\widetilde{w}(m) * \tilde{F}(S_2)}{\frac{\widetilde{f_v}(m)}{\tilde{d}(m)}}\right)$$

Early Termination of the Recursive Partition

1. **The width of a partitioned sketch** at a given level is less than a particular threshold w_0: $Width(S_i) \leq w_0$
2. **The number of distinct edges** being counted in a sketch is less than a given factor of the sketch table width: $\sum_{m \in S} \tilde{d}(m) < C * Width(S_i)$
   - The probability of any collision in a particular cell in S can be bounded by C

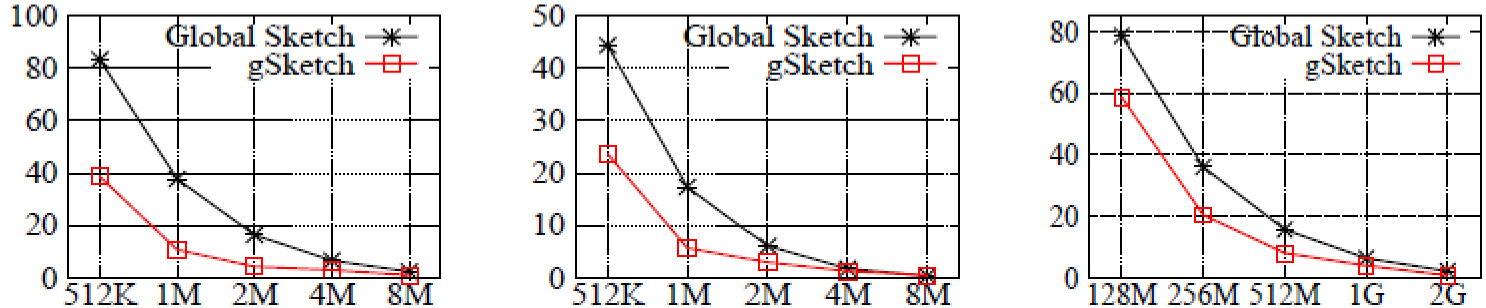
gSketch: Query Processing

- **Sketch partitioning is performed on the sample data as a preprocessing step**
  - Data samples only
  - Data and query workload samples
- **After sketch partitioning, graph streams are maintained and queried by a set of partitioned localized sketches**
  - Each edge is dispatched to its corresponding local sketch for frequency maintenance and query processing
  - Edges not in the data sample are uniformed dispatched to an **outlier sketch**

Experimental Evaluation

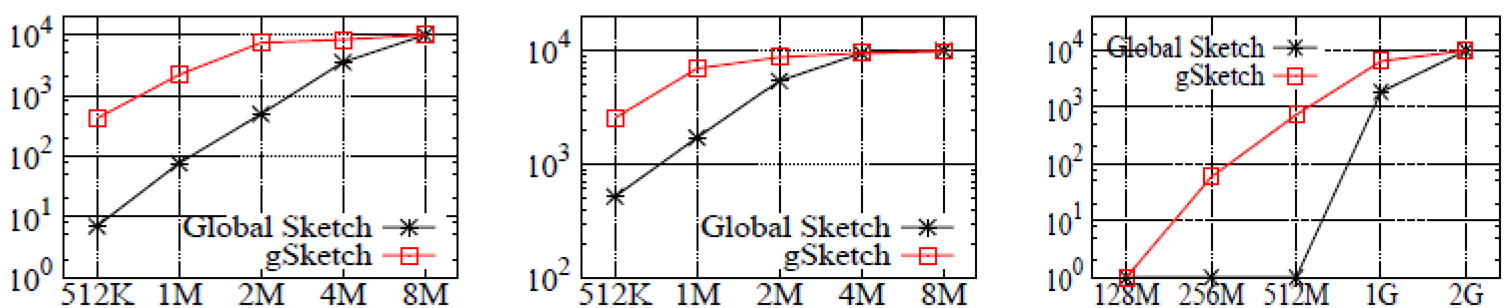
- **gSketch vs. Global sketching**
- **Evaluation methods**
  - Average relative error
  - Number of effective queries
- **Two real data sets and one synthetic data set**
  - DBLP (1,954,776 edges)
  - IBM-Attack Sensor Streaming Data (3,781,471 edges)
  - GTGraph (10^8 vertices and 10^9 edges)

Query Estimation Accuracy of Edge Queries (Data Sample Only)



(a) DBLP (b) IP Attack Network (c) GTGraph

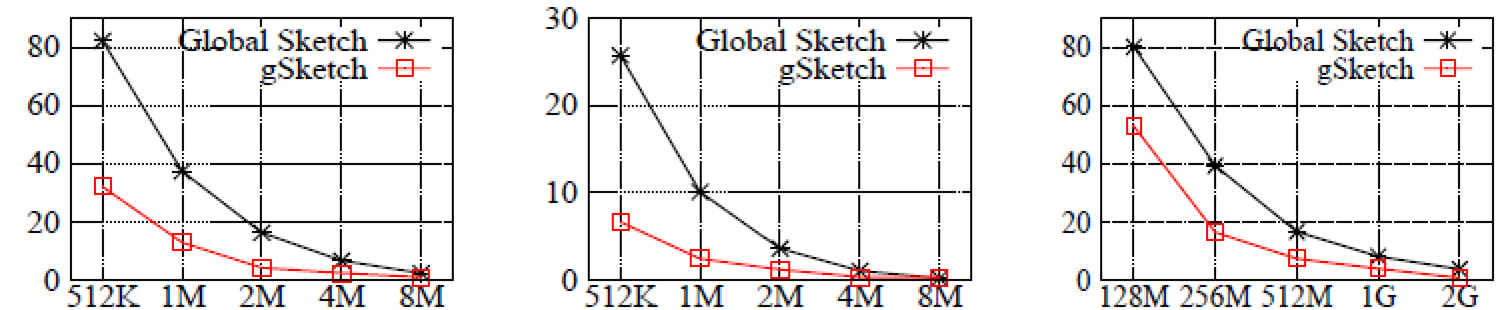
Figure: Average Relative Error



(a) DBLP (b) IP Attack Network (c) GTGraph

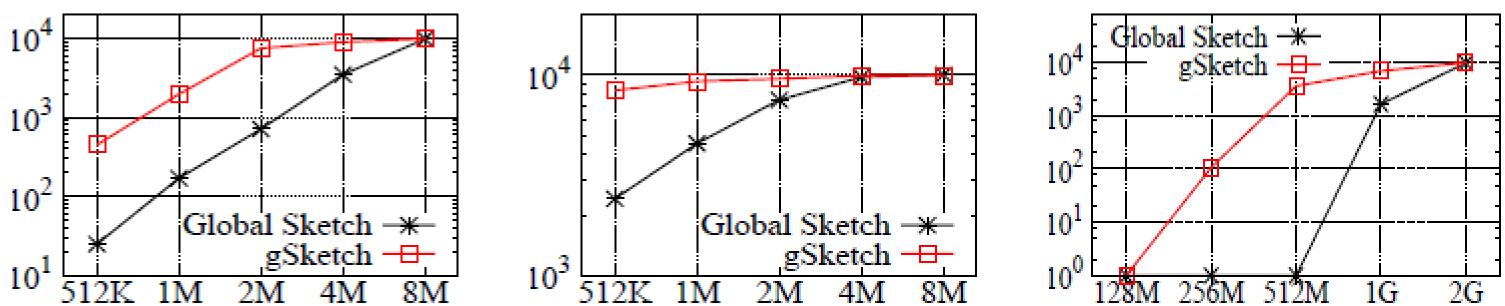
Figure: Number of Effective Queries

Query Estimation Accuracy of Edge Queries (Data and Query Workload Samples)



(a) DBLP (b) IP Attack Network (c) GTGraph

Figure: Average Relative Error (Zipf Skewness $\alpha = 1.5$)



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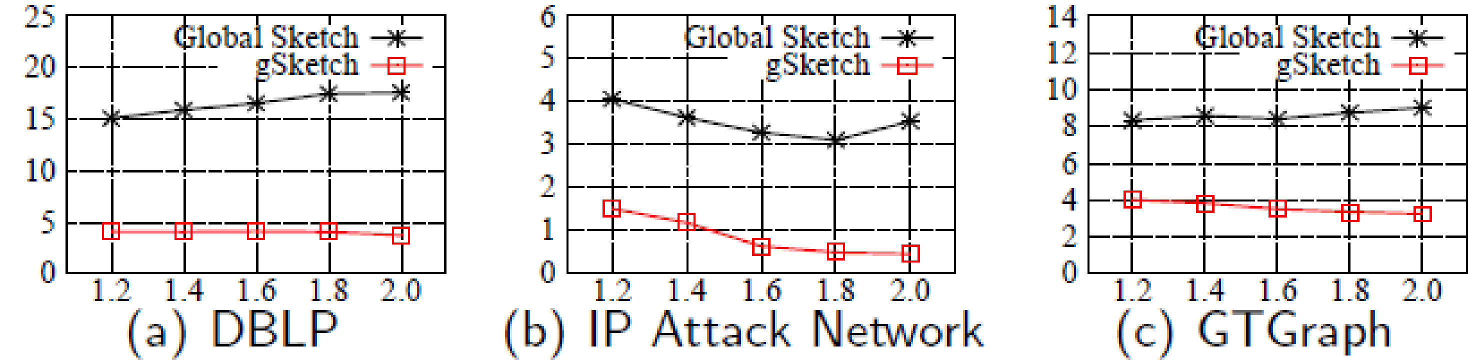


Figure: Average Relative Error (1G Memory)

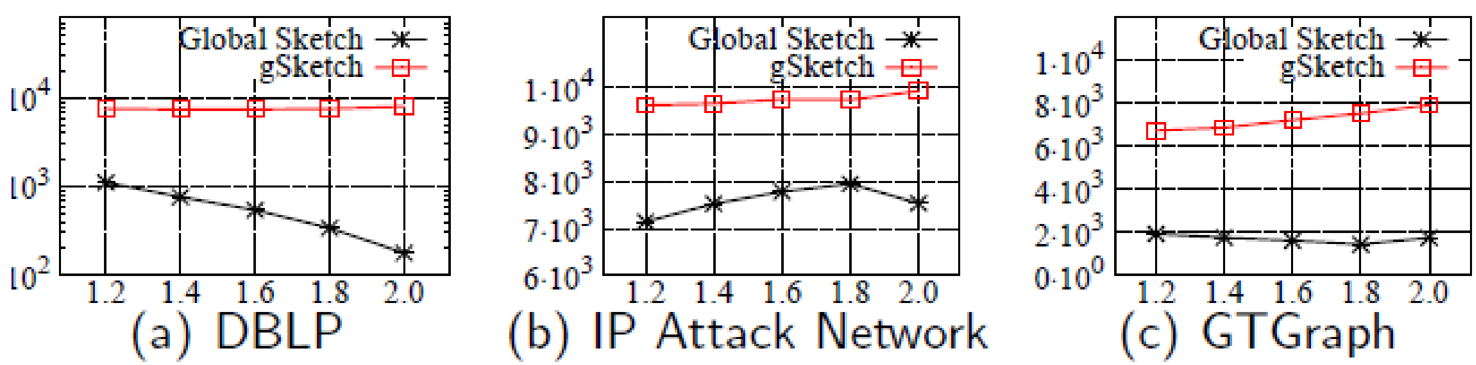
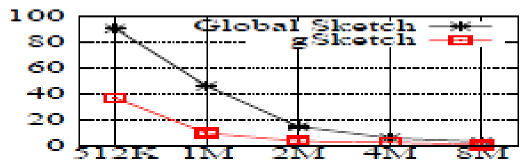
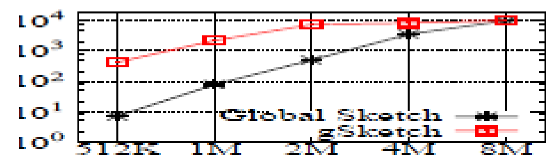


Figure: Number of Effective Queries (1G Memory)

Query Estimation Accuracy of Aggregate Subgraph Queries

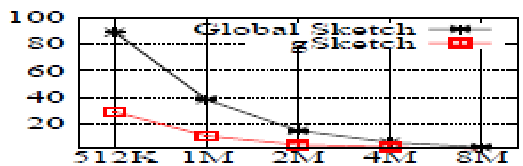


(a) Avg. Relative Error

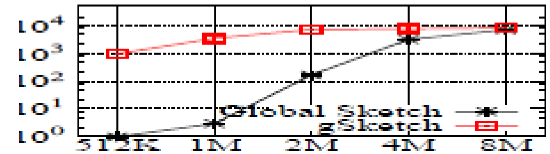


(b) # Effective Query

Figure: Data Sample Only

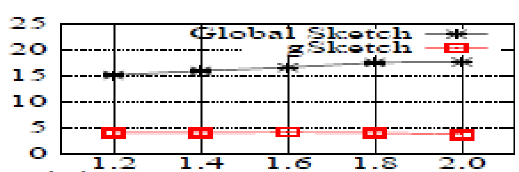


(a) Avg. Relative Error

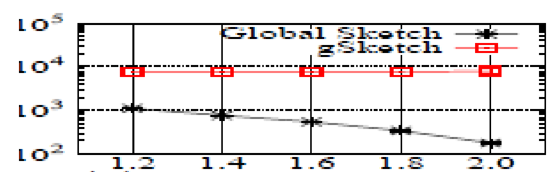


(b) # Effective Query

Figure: Data & Workload Samples ($\alpha = 1.5$)



(a) Avg. Relative Error



(b) # Effective Query

Figure: Data & Workload Samples (Memory = 1G)

Query Efficiency

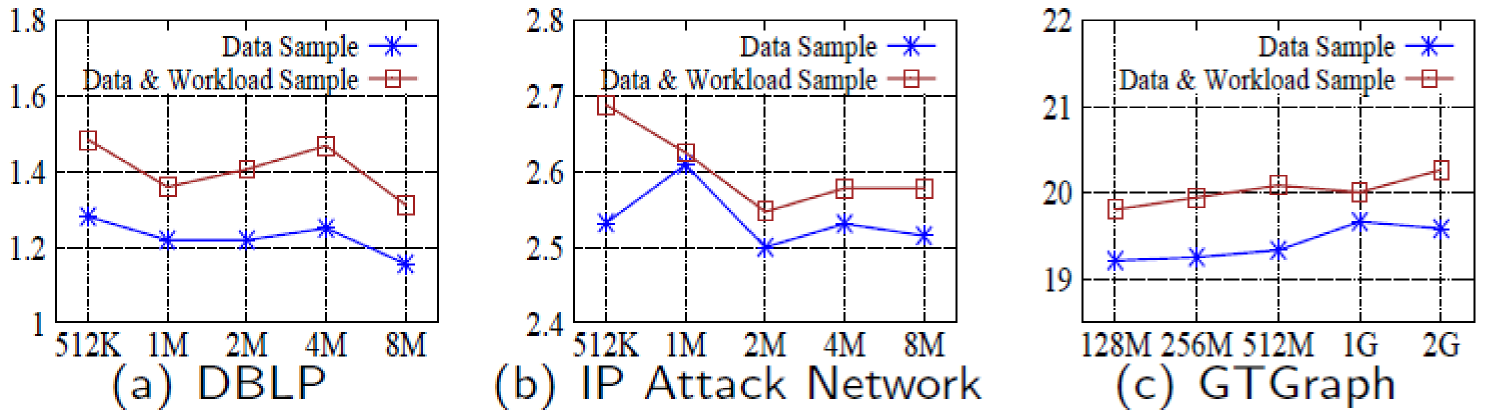


Figure: Sketch Construction Time (Seconds)

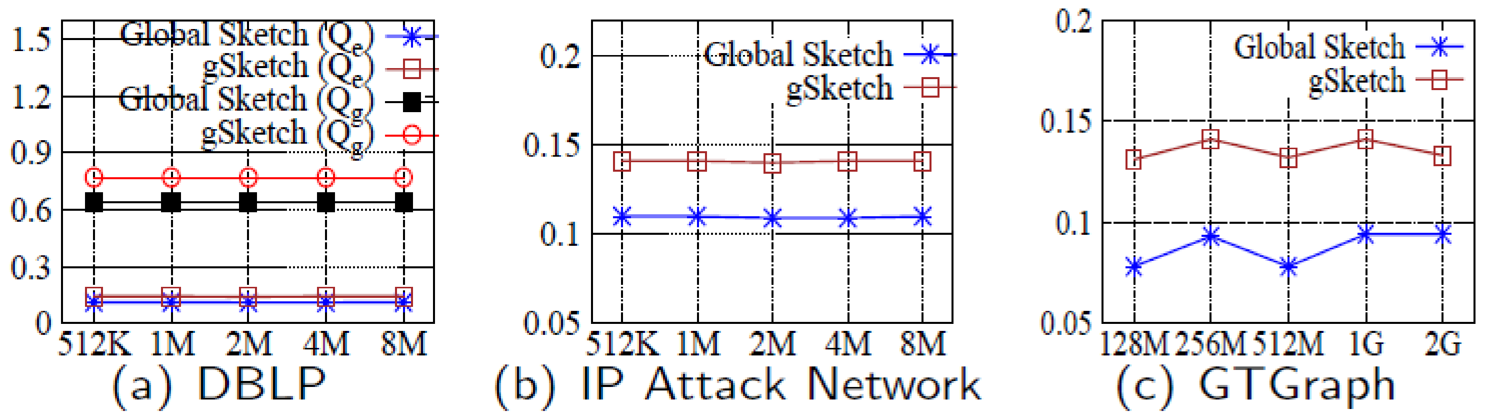


Figure: Query Processing Time (Seconds)

Effects of New Vertices/Edges

		Memory		Size		
		128M	256M	512M	1G	2G
Average relative error	gSketch	58.5968	20.381	8.0068	3.9345	0.7257
	Outlier sketch	58.5971	20.392	8.0081	3.9557	0.7837

Table: Average Relative Error of gSketch and Outlier Sketch in GTGraph

Conclusions

- **gSketch: a Partition-based sketch method for better query estimation in massive graph streams**
  - Adaptation of well-known sketching methods in conventional data streams
  - Leveraging common structural characteristics of massive graphs
  - Achieving up to an order of magnitude improvement in estimation accuracy
- **Future directions**
  - Computation of complex functions of edge frequencies in subgraph queries
  - Structural queries

Thank you!

Q & A

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