POSTER: An Efficient Uncertain Graph Processing Framework for Heterogeneous Architectures

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Abstract

Uncertain or probabilistic graphs have been ubiquitously used in many emerging applications. Previously CPU based techniques were proposed to use sampling but suffer from (1) low computation efficiency and large memory overhead, (2) low degree of parallelism, and (3) nonexistent general framework to effectively support programming uncertain graph applications. To tackle these challenges, we propose a general uncertain graph processing framework for multi-GPU systems, named `BPGraph`. Integrated with our highly-efficient path sampling method, `BPGraph` can support a wide range of uncertain graph algorithms' development and optimization. Extensive evaluation demonstrates a significant performance improvement from `BPGraph` over the state-of-the-art uncertain graph sampling techniques.

CCS Concepts: • **Computing methodologies** → **Parallel programming languages**; • **Computer systems organization** → *Parallel architectures.*

Keywords: uncertain graph, path sampling, GPU

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1 Introduction

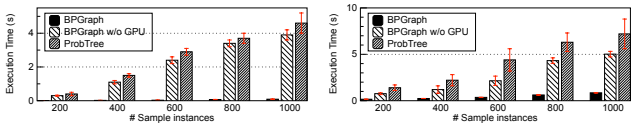
Uncertainty is intrinsic to a wide spectrum of applications, which inevitably applies to graph data such as noisy measurement in bio-informatics [2, 9], connection probability in peer-to-peer network [8], congestion prediction in traffic network [7], etc. In the literature, uncertain graphs have been widely utilized to represent these uncertainties, in which, the existence of the connection is supposed to be independently indeterminate, and is formulated as a probabilistic edge. Solving an uncertain graph problem requires to iterate through all its instances, a.k.a., possible worlds. As the number of possible worlds grows exponentially to the number of edges, it is unrealistic to get exact solutions.

Previous works on uncertain graph analysis have sought to sampling based methods to get approximate solutions on uncertain graphs [4, 5, 11, 14]. With a reasonable amount of samples, an approximate solution can be estimated with an accuracy guarantee. The three main limitations of these existing approaches are as follows.

First, *poor computation and memory efficiency caused by unnecessary edge sampling*. Our evaluation shows that the existing approaches suffer from significant performance and memory overhead, especially for large uncertain graphs.

Table 1. *Uncertain graph datasets.*

Dataset	*Vertices*	*Edges*	*Size*	*Edge Prob*
netHept[1]	15,233	62,774	921KB	0.04±0.04
gnutellaP2P[1]	62,586	147,892	1.8MB	0.23±0.20
coauthor-DBLP[1]	540,486	15,245,729	331MB	0.11±0.09
soc-twitter[10]	28,504,110	531,000,244	14GB	0.46±0.28
uk-2005[1]	39,454,748	936,364,284	20GB	0.32±0.25



(a) *netHept* **(b)** *gnutellaP2P*

Figure 1. *GPU-accelerated performance comparison.*

Second, *lack of utilization for modern general-purpose accelerators* (e.g., GPUs) that are widely available in high performance systems. Packed with massive parallelism and high-bandwidth memory, modern GPU is an attractive computing platform for uncertain graph processing [3, 6, 12, 13, 15].

Third, *lack of a general support for developing efficient uncertain graph applications*. Previous uncertain graph processing solutions only provide ad-hoc optimizations on one or several applications, while do not provide a general programmable interface for users to effectively implement a wide-range of applications. In summary, an efficient, scalable, and programmable uncertain graph processing framework is desirable.

2 Contributions

Our *novel path sampling method* aims to eliminate unnecessary edge sampling at runtime and improve computation and memory efficiency. It can effectively identify useless edges before performing sampling, and only considers edges that are on a path between the source and target vertices to be useful.

Centered around this sampling method, we present `BPGraph`, an efficient, scalable, and programmable uncertain graph processing framework that helps implement path sampling on GPUs. `BPGraph` provides a general programming interface so that users can implement various uncertain graph processing applications with ease. Additionally, it optimizes the data organization and computation patterns to better map uncertain graph processing onto GPUs, and is able to scale on multi-GPU systems.

3 Experiments

We perform the experiments on a NVIDIA DGX server with 8 NVIDIA V100 GPUs. Each GPU has 80 Streaming Multiprocessors, 32GB global memory and 768KB L2 cache. The system also consists of two 10-core Intel(R) Xeon(R) CPU E5-2698 v4, and 504GB DDR4 main memory, running with Ubuntu 18.04 (kernel v4.15.0) and CUDA 10.0.

Datasets. Table 1 shows the real-world graphs with a broad range of sizes and features. The edge probabilities in datasets come from real-world application criteria or are assigned uniformly and randomly within a specified value range.

Parameter Setting. For query pairs, we select 10 different source vertices, uniformly at random from the datasets. Next, the target vertices are chosen from n hops from the source vertices, uniformly at random, in which n is randomly selected from 2 to the diameter. The reported results of s-t query are calculated by averaging those of pairs. Initially, the value K, i.e., # samples, is 100. It increases at a step of 200 till the results converge.

State-of-the-arts. We evaluate our system by comparing with four state-of-the-art methods: *MC-Sampling (MC)* [14], *BitEdge-Aware Sampling (BA)* [16], *ProbTree (PT)* [11], *DistR (DR)* [4]. We compare their performance for three applications: source-to-target reliability query, k-nearest neighbor (KNN), and any-pair shortest path.

Performance Comparison. Compared to multi-CPU versions of *MC*, *BA*, *PT*, and *DR*, *BPGraph* significantly outperforms them in all applications. For the s-t query, *BPGraph* is on average 39× and 30× faster than entirety sampling methods, i.e., MC sampling and BA Sampling, respectively. Compared to the partition sampling method (ProbTree), *BPGraph* is 26× faster. For KNN and shortest path, *BPGraph* presents even higher speedups, e.g., it achieves an average speedup of 69× and 43× compared to MC sampling and ProbTree respectively. It is because these two applications have much larger workloads due to recursive traversal and sampling. For the reason of *BPGraph*'s superior performance, it is because 1) *BPGraph* only traverses the graph once and also samples useful edges only, 2) the high-parallelism computing capability of GPU over multi-core CPUs, and 3) the high memory bandwidth of the NVIDIA V100 GPU over the CPU.

Moreover, to show the benefits of path sampling, we implement a version of CPU-based *BPGraph* without utilizing GPUs. Figure 1 compares the performance of *BPGraph* on GPU, *BPGraph* on CPU, and ProbTree, which performs best among four state-of-the-art methods. Even without GPU acceleration, *BPGraph* on CPU still achieves better performance than ProbTree, which indicates the effectiveness and efficiency of our proposed path sampling method. Also, we observe that the performance of *BPGraph* on GPU achieves over 20× improvement compared with *BPGraph* on CPU.

Scalability over Multiple GPUs. We evaluate the scalability of *BPGraph* with 2 large graphs, i.e., *soc-twitter* and *uk-2005*, on 8 GPUs. The performance does scale well as we add more GPUs. Specifically, the performance of multi-GPU execution on *soc-twitter* achieves average 1.4×, 3.0× speedup

from 1 GPU to 2 GPUs, 8 GPUs. *BPGraph* reduces the communication overhead by using the vertex status array to mark the master/slave vertices for value synchronization, which minimizes unnecessary GPU communication. On the *uk-2005* datase, *BPGraph* achieves almost 4.2× speedup using 8 GPUs (6207s) over using 1 GPU (1498s). This is because the comparatively peer-to-peer communication gives us a benefit of scalability on larger uncertain graph datasets on multi-GPU servers.

4 Conclusion

In this work, we develop *BPGraph*, a novel GPU-based uncertain graph analytic system. It produces over 58× speedup over the state-of-the-art multi-core CPU-based uncertain graph algorithms, and 20× over a GPU-implementation of MC-sampling. This is achieved thanks to our proposed *path sampling* methodology and its efficient GPU implementation. For future work, we plan to extend *BPGraph* with distributed configuration based on high-speed storage and networks, to enable for even larger-scale uncertain graph processing.

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