# **FASCIA:** Fast Approximate Subgraph Counting and Enumeration

# Abstract

We present a new shared-memory parallel implementation of Alon et al.'s color-coding technique called FASCIA for the problems of approximate subgraph counting and subgraph enumeration.

- Subgraph counting is used in multiple domains, inlcuding bioinformatics, chemoinformatics, social network analysis, among many others
- We present multiple algorithmic improvements to the baseline color-coding technique for subgraph counting targeted at improving runtime, parallelization, and memory usage
- Our method allows real-time count estimates of subgraphs up to seven vertices on networks with tens of millions of edges. Count estimates of up to twelve vertice subgraphs are obtained in minutes.

# **Color-Coding Technique**

Color-coding allows an approximation algorithm for subgraph counting that runs in about  $O(m \cdot 2^k \cdot$  $e^k$ .) instead of  $O(n^k)$  for the exact naïve algorithm, where m is the number of edges in the graph, n is the number of vertices, and k is the number of vertices in the subgraph.

The procedure for the algorithm is as follows:

- Randomly color every vertice in the graph with at least k colors
- Use a dynamic programming scheme to count the number of *colorful* subgraph embeddings, where colorful means each subgraph vertice has a distinct color
- Scale this count by the probability that any given embedding will be colorful
- Repeat the first three steps some number of times
- Average all determined counts and output result

# Acknowledgements

George M. Slota and Kamesh Madduri

Department of Computer Science and Engineering The Pennsylvania State University

#### Test Environment

Figure 3 demonstrates how FASCIA can produce Reported runtimes were retrieved from a single node of Gordon at the San Diego Supercomputing Center. real-time count estimates for templates up to 7 nodes The graphs used came from the SNAP database, in size on a large 33 million edge network. Template Virginia Tech Network Dynamics and Simulation up to 12 nodes complete in a matter of minutes. Science Laboratory.



Figure 1: Templates used in experiments

#### **Algorithmic Optimizations**

- Multiple parallelization strategies
- Representation of subgraph colorings as single integers using a combinatorial indexing system
- Pre-computation of complex operations stored in cache-resident table
- Template partitioning scheme that allows up to <sup>1</sup> reduction in total work performed

#### Memory Optimizations

<ul> <li>Smart st</li> </ul>	orage and dyna	mic programming t	table p
initializa	tion		
<ul> <li>Careful t</li> </ul>	cemplate partiti	oning and organization	tion
• Fast has	h table which e	xploits random grap	oh
coloring	to reduce collisi	lons	
• These	memory opti	mizations can	Г
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Figure 2: Memory usage of the naïve and improved table and hash table on the (a) Portland and (b) PA road networks

Using a 12 node template on a large network, we achieve  $12 \times$  parallel speedup. On a smaller network we can parallelize multiple simultaneous counts, and achieve over a  $6.5 \times$  parallel speedup.

Figure 4: Parallel scaling of (a) inner loop with U12-2 temlate on Portland and (b) both inner and outer loop with U7-2 emplate on Enron email network (n=33K, m=180K)

#### **Runtimes and Parallel Scaling**



Motif finding is determining frequently occurring subgraphs by comparing counts between networks, and has found importance within the field of bioinformatics. Below we domonstrate counts for all 11 possible 7 vertice templates on 4 biological networks. All counts were calculated in a few minutes with under 1% error.

Figure 3: Runtimes on Portland network (n=1.6M, m=33M)



#### **Error Bounds**

Festing demonstrates that for even a modest sized network, error is very small after few iterations. Eror decreases with increasing network size but increase with increasing template size.



Figure 5: Error on the Enron email network

Figure 6: Motif finding on E. coli, S. cerevisiae, H. pylori, and C. elegans

Similar to a regular degree distribution, a graphlet degree distribution is the number of vertices have a distinct number of subgraph embeddings. This distribution can be used to compare networks on the basis of local structural similatiry.



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## Motif Finding



# Graphlet Degree Distributions





Figure 7: Graphlet degree distribution for template U5-2 on the Enron network and a random G(n, p) graph of the same size and average degree

### Conclusions

nrough algorithmic optimizations, FASCIA nieves considerable speedup compared to or work while reducing memory nsumption and parallel overhead ASCIA is especially useful for motif finding a calculating graphlet degree distributions