# Arachne: An Arkouda Package for Large-Scale Graph Analytics

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***Abstract*—Due to the emergence of massive real-world graphs, whose sizes may extend to terabytes, new tools must be developed to enable data scientists to handle such graphs efficiently. These graphs may include social networks, computer networks, and genomes. In this paper, we propose a novel graph package Arachne to make large-scale graph analytics more effortless and more efficient based on the open-source Arkouda framework, which has been developed to allow users to perform massively parallel computations on distributed data with an interface similar to NumPy. In this package, we developed a fundamental sparse graph data structure and several useful graph algorithms around our data structure to build a basic algorithmic library. Benchmarks and tools have also been developed to evaluate and demonstrate the provided graph algorithms. The graph algorithms we have implemented thus far include breadth-first search (BFS), connected components (CC), k-Truss (KT), Jaccard coefficients (JC), triangle counting (TC), and triangle centrality (TCE). Their corresponding experimental results based on real-world and synthetic graphs are presented. Arachne is organized as an Arkouda extension package and is publicly available on GitHub (https://github.com/Bears-R-Us/arkouda-njit).**

***Index Terms*—graph analytics, large-scale data, parallel algorithm, open-source framework**

## I. Introduction

Graphs are widely used to represent real-world problems in numerous domains, such as social sciences, biological systems, and information systems. However, the increasing scale of graphs prevents them from being analyzed by popular exploratory data analysis tools, such as Python. Arkouda [20], [21] is an open-source software framework created to be a replacement for NumPy at scale in Python. Arkouda is powered by Chapel [4] at the back-end with a front-end facing Python interface. Chapel is an open source high-level programming language designed for productive parallel computing at scale. It enables the usage of distributed data structures to easily spread data across many computing nodes and their memories. It further provides a global namespace to access all variables without knowing their positions. Finally, Chapel code is typically easier to understand with structures made specifically to facilitate data and task parallelism.

The major objective of this research is to enable data scientists to handle large-scale graphs that can only be held by powerful back-end servers productively. This means we want data scientists to be able to inspect such large data as if they were handling it locally on their personal computing devices. There are many existing graph packages, such as Knowledge Discovery Toolbox (KDT) [19] and GraphBLAS [16]. KDT also has the Python interface, but its back-end compute engine is Combinatorial BLAS. Compared with Combinatorial BLAS, Chapel can support productive and flexible graph algorithm development. GraphBLAS can provide an algebra language for graph operations. However, data scientists may find graph analytics more productive in Python than through a linear algebraic interface.

This work aims to support large-scale graph analysis with high efficiency by developing the Arachne package. More knowledge and insights can be exploited from the graph data easily and efficiently. Without Arachne, data scientists cannot handle real-world graphs productively because of scale, performance, and code complexity.

The major contributions of this research are as follows:

1) A fundamental sparse graph data structure at the core of Arachne is built in Chapel and integrated with Arkouda, accessible through Python.
2) Arachne contains typical graph analytical algorithms to support productive graph analytics in Python, backed by Chapel. These graph algorithms are organized in a cohesive framework with all Chapel and Python code available on GitHub.
3) Experimental results on real-world and synthetic graphs demonstrate the methods in Arachne.

## II. Graph Infrastructure Design and Development

In this section, we introduce the graph data structure of Arachne that help users conduct large-scale graph analytics productively and efficiently.

### A. Graph Data Structure Design

Our graph infrastructure Arachne focuses on large-scale real-world graphs. The compressed sparse row (CSR) format is often and widely used to express sparse graphs. However, CSR is a vertex-centric data structure that cannot efficiently support edge-centric graph algorithms. Therefore, we designed and developed a novel *Double Index* data structure [10] that can efficiently support vertex-centric and edge-centric graph algorithms, and serves as the core data structure in Arachne.

The graph data structure was developed in the Python front-end and Chapel back-end. We define a graph class at the Python front-end to hold the graph metadata. The metadata includes: (1) the graph name ID, which will be used to access the raw data at the back-end; (2) the number of vertices and edges; (3) and a flag to signify if the graph is directed or weighted. We also define a graph query function *graph_query* to access the different parts of raw data in the given graph. We can query the edge arrays (source/destination of any edge), the vertex array (starting position in the edge array and the number of neighbors of any vertex), and the weight arrays (the weight of any edge). We designed the corresponding graph class in Chapel at the back-end to implement the complete graph in memory. A typical feature is that we define an enumerated Chapel data type *Component* to keep names of different graph parts and build a map between the names and the corresponding data. *Component* is very flexible in expressing different parts of a graph. The specific data organization can be changed in any way, but all graphs can share the same abstract class description. We only need to develop three kinds of functions for each component: (1) Checking if the such component exists. (2) Setting to store the raw data in the component memory. (3) Querying to return the raw data stored in the component memory. We utilize the existing symbol table mechanism and develop a specific graph symbol table entry class *GraphSymEntry* to maintain graph objects. A one-to-one mapping between a graph name ID and a graph object is built in the symbol table, and the Python front-end can query a graph component using a graph name ID based on the symbol table.

Besides the default Chapel data array distribution, we develop another efficient edge-vertex-locale mapping mechanism by providing a *DomArray* data structure, which can customize the array size based on a user-specified Chapel domain, to improve data access locality. The basic idea is shown in Fig. 1. The degree distributions of real-world graphs are often highly skewed. Therefore, edge-centric graph partitions may evenly distribute the edges onto different locales/computing resources. This method will help to achieve near-perfect load balance. Furthermore, for all the edges assigned to a specific locale[1] (a locale is a computing resource in Chapel), we may map the corresponding vertices onto the same locale. This will cause an irregular vertex array distribution. However, it can improve the memory access locality when we employ some edge-centric graph algorithms. We assign the workload based on the edge distribution to improve load balancing and memory access locality for all implemented graph algorithms in the package.

### B. The Arachne Graph Toolkit

We have developed basic graph operations to form a toolkit to support different applications of graph analytics.

The *graph_file_read_mtx()* Python function is used to read an "mtx" format graph file into the back-end. A graph must be built into memory before our toolkit can process it. *graph_file_read()* is a similar Python function with high flexibility. It can skip some head metadata parts to read the real graph data. At the Chapel back-end, we use distributed arrays to keep the graph data when the Arkouda server is started with more than one compute node. When this happens, parallel IO will be employed, and each local array will only keep the data owned by itself. For streaming graphs, we provide the *stream_file_read()* to read a stream as a file and build the corresponding graph sketch in the back-end.

[1]https://chapel-lang.org/docs/primers/locales.html

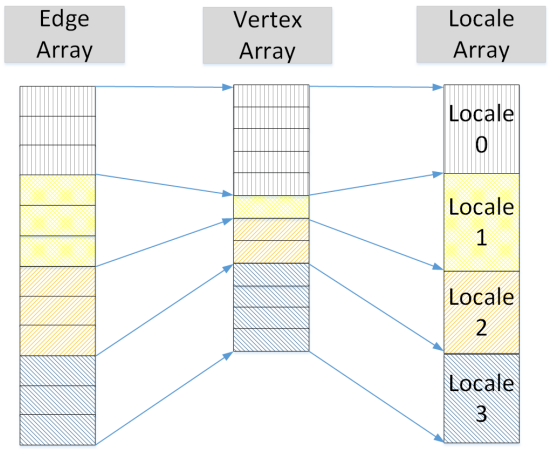


Fig. 1: Edge-centric sparse graph Edge-Vertex-Locale mapping mechanism to improve memory access locality.

Many graph algorithms do not allow duplicated edges or self-loops. Alternatively, the vertex must be labeled starting from 0. We develop the *graph_file_preprocessing()* Python function to clean the original graph. Besides removing the duplicated edges and self-loops, we also have the following operations. (1) If the *Remap* flag is set, we will map all the $N$ vertices in the graph from 0 to $N-1$. (2) If the *DegreeSort* flag is set, we will relabel the vertex based on their degrees. (3) If the *RCM* flag is set, we will preprocess the graph using the *reverse Cuthill–McKee* algorithm. (4) If the *AlignedArray* flag is set, we will further map the vertex arrays employing the Edge-Vertex-Locale mechanism instead of the default distribution.

For benchmarking we also develop the *rmat_gen()* function to generate *R-MAT* graphs [3] based on user-given parameters. When we conduct graph analysis on *R-MAT* graphs, we may use the provided function to generate the required graphs, which all our integrated graph algorithms can then process.

## III. Implementations of Typical Graph Algorithms

This section introduces useful graph algorithms we have developed and implemented in Arachne. The development of the algorithms take into account their implementation in Chapel. Therefore, the explanations of their parallelism are framed using Chapel's lexical and code structures. Furthermore, each algorithm has a corresponding benchmark file in the Arachne framework that shows how they can be utilized from the Python front-end. More on the benchmarks is in Section III-G.

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### A. Breadth First Search

Since *breadth first search (BFS)* is a very popular method in graph analysis, we developed our *BFS* implementation [9] in Chapel and integrated it in Arkouda at an early stage of Arachne's development.

The major feature of our *BFS* implementation in Chapel is taking advantage of the high-level data structure *DistributedBag*[2] to manage the current frontier and the next frontier. Vertices on different locales can be added into the *DistributedBag* in a parallel-safe manner. This makes parallel programming more efficient because we do not need to implement detailed array insertions or appends at a low level.

The *RCM* preprocessing method provided by our preprocessing function is used to improve the performance of BFS. When using a distributed computing environment, each locale will only work on the vertices whose edges are on that specific locale. This way, we can take advantage of the locality to extend the next frontier in parallel. The irregular memory access pattern of BFS makes its performance in a distributed computing environment often worse than that in a shared-memory counterpart. We believe this is due to many remote fine-grained writes occurring during frontier expansion [14]. This can be mitigated by implementing aggregation when performing remote writes. However, this is out of the scope of this work and will be revisited in later updates to Arachne.

### B. Connected Components

Building a connected components algorithm is easy based on our implemented *BFS* method. However, the *BFS* based method cannot achieve high performance for a large graph with a large diameter. Therefore, we implemented the *FastSV* algorithm [22] in Chapel to improve the performance of the connected components method. *FastSV* involves iterating over all the edges in a graph multiple times until convergence. This edge-centric computational model is attractive for our edge-based distribution data structure. Each locale can process its edges independently to achieve good parallelism.

Furthermore, we simplified the three hooking methods in the *FastSV* algorithm to reduce the total number of synchronizations. At the same time, we designed a simple counter data structure to check the convergence quickly instead of employing two arrays to compute their difference.

### C. K-Truss Analytics

*K-Truss* algorithm must first find triangles in a graph. We developed a novel *Parallel Minimum Search* triangle search kernel for Arachne that can significantly reduce the total triangle search time for any algorithms that rely extensively on it. Compared with the widely used list intersection method, our *Parallel Minimum Search* method can save many operations, and its performance is better than that of the *List Intersection* [7] method, and the directed graph-based method [1]. Based on this triangle search kernel, we have implemented *K-Truss*, *Max-Truss* and *Truss Decomposition* algorithms [8] for different kinds of truss analysis. Furthermore, we employ a binary search-like method in *Max-Truss* to reduce the total number of searches. We employ the results of *K* truss to accelerate the analysis of *K+1* truss in *Truss Decomposition*.

[2]https://chapel-lang.org/docs/modules/packages/DistributedBag.html

### D. Jaccard Coefficient

The *Jaccard Coefficient* [17] is a graph analytic method to expose the similarity between two vertices of a graph in terms of the overlap of their neighboring vertices. For a given vertex $w$, let $Adj(w)$ be the adjacency list of $w$. Then, $\forall u, v \in Adj(w)$, we can increase the number of vertices in common between $u$ and $v$ by 1. This "backwards" method is implemented in Arachne based on our edge-centric graph partition with high memory access locality. Currently, the memory is not optimized for a highly sparse graph because we will use $N \times N$ ($N$ is the total number of vertices) memory to hold all of the coefficients. We are working on significantly reducing the total memory and improving the locality by using a hash-based method to discard most of the zero coefficients.

### E. Triangle Counting

Arachne contains our implementations of the exact triangle counting algorithm for static graphs and approximate triangle counting algorithm for streaming graphs [10]. We built a regression model for real-world graphs whose degrees follow power-law distributions and synthetic graphs whose degrees follow a normal distribution. Employing different regression models for different degree distributions can improve the accuracy of our approximate algorithm. In the Arachne toolkit, based on their practical performance, we employ two triangle counting methods from all the methods implemented in the *triangle centrality* analysis. We chose to highlight the *Parallel Minimum Search*-based and *Path Merge*-based triangle counting algorithms because they are the top 2 methods for most of the graphs.

### F. Triangle Centrality

Triangle centrality [2] is a method to find important vertices based on the concentration of triangles surrounding each vertex. Based on our triangle counting algorithm, when we find a new triangle, we not only update the number of triangles of each vertex but also mark the three edges as true. This lets us know that the vertices connected by a true edge are connected to some triangle.

In Arachne, we reformed the triangle centrality formula so that we only need to calculate two items: (1) the sum of the number of triangles of the given vertex's adjacency list and itself, and (2) the sum of the number of triangles of the given vertex's neighbors that are connected by a triangle. Through this, we can calculate the triangle centrality more efficiently. Of course, all the triangle counting performance optimization methods are also used in the triangle centrality algorithm implementation.

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### G. Benchmarks

We have corresponding benchmarks implemented in Python for all Arachne graph algorithms to evaluate their performance and correctness. These graph benchmarks return the elapsed time of the algorithm and check the correctness for different inputs. For example, to evaluate *K-Truss* algorithms, we developed *truss.py* to evaluate one input graph or a batch of many graphs. After we call the *graph_file_read()* to build the graph in memory, we call the *graph_ktruss(Graph,k)* function to execute different truss analyses. If the parameter value $k > 0$, then *K-Truss* analysis algorithm will be called. If $k$==-1, then the *Max-Truss* analysis algorithm is used. If $k$==-2, then we will call the *Truss Decomposition* analysis algorithm at the back-end to get the truss values of all edges. The proposed benchmarks can also be utilized by a new user as a tutorial on how their Python scripts or Jupyter notebooks should look like if they are using Arkouda for graph analysis.

## IV. Experimental Results

In this section, we provide the performance results of Arachne's algorithms on real-world and synthetic graphs.

### A. Data Sets

The graphs used for experiments can be found in Table I. Columns give the graph name, the number of edges, the number of vertices, the number of connected components in the graph, and the maximum value of *K* in truss analysis. A mix of real-world and synthetic graphs was utilized for the experiments. The real-world graphs represent typical networks that typical data scientists may handle. These real-world graphs consist of authorship, email, and social networks. The largest real-world graph we used for testing with complete results is *com-Youtube* with about three million edges and one million vertices. The largest real-world graph with partial results is *friendster* with about two billion edges and sixty-five million vertices.

Real-world graphs often not only have a different number of edges but different graph properties, such as diameter and power-law exponent. We will measure how those factors can affect the performance of different graph algorithms. If graphs have a similar pattern, we can see how the size of the graphs can affect the algorithm's performance. The Delaunay synthetic graphs will double their number of edges with the same structure. So, Delaunay graphs are an ideal synthetic benchmark to evaluate the algorithm scalability when the number of edges increases.

### B. Experimental Results

Experiments were conducted on a high-performance server with 2 x Intel Xeon E5-2650 v3 @ 2.30GHz CPUs with 10 cores per CPU and a RAM capacity of 512GB.

Results in Table II are an average over ten trials per data set per algorithm. Except for the graph name, each column is the execution time of different operations or algorithms. We list the graph algorithms *BFS*, *Connected Components* (Conn-Comps), *Jaccard Coefficient* (Jaccard), *K-Truss, Max-Truss* and *Truss Decomposition* (Truss-Dec). For *Triangle Counting*, we give the results of two methods, one is the minimum search-based method [8], and another is the merge-path-based method [11]. We use the two methods to measure the *Triangle Counting* (Tricnt-Min for minimum search-based method and Tricnt-Merge for merge-path-based method) and the corresponding *Triangle Centrality* (Trictr-Min for minimum search method and Trictr-Merge for merge-path-based method) algorithms.

TABLE I: Basic information for the graphs used for experimentation.

| Graphs | Edges | Vertices | CCs | Triangles | Max K |
|---|---|---|---|---|---|
| **ca-GrQc** | 14484 | 5242 | 354 | 48260 | 44 |
| **ca-HepTh** | 25973 | 9877 | 427 | 28339 | 32 |
| **as-caida20071105** | 53381 | 26475 | 1 | 36365 | 16 |
| **facebook_combined** | 88234 | 4039 | 1 | 1612010 | 97 |
| **ca-CondMat** | 93439 | 23133 | 567 | 173361 | 26 |
| **ca-HepPh** | 118489 | 12008 | 276 | 3358499 | 239 |
| **email-Enron** | 183831 | 36692 | 1065 | 727044 | 22 |
| **ca-AstroPh** | 198050 | 18772 | 289 | 1351441 | 57 |
| **loc-brightkite_edges** | 214078 | 58228 | 547 | 494728 | 43 |
| **soc-Epinions1** | 405740 | 75879 | 2 | 1624481 | 33 |
| **amazon0601** | 2443408 | 403394 | 7 | 3986507 | 11 |
| **com-Youtube** | 2987624 | 1134890 | 1 | 3056386 | 19 |
| **friendster** | 1806067135 | 65608366 | 1 | 4173724142 | 129 |
| **delaunayn10** | 3056 | 1024 | 1 | 2047 | 4 |
| **delaunayn11** | 6127 | 2048 | 1 | 4104 | 4 |
| **delaunayn12** | 12264 | 4096 | 1 | 8215 | 4 |
| **delaunayn13** | 24547 | 8192 | 1 | 16442 | 4 |
| **delaunayn14** | 49122 | 16384 | 1 | 32921 | 4 |
| **delaunayn15** | 98274 | 32768 | 1 | 65872 | 4 |
| **delaunayn16** | 196575 | 65536 | 1 | 131842 | 4 |
| **delaunayn17** | 393176 | 131072 | 1 | 263620 | 4 |
| **delaunayn18** | 786396 | 262144 | 1 | 527234 | 4 |
| **delaunayn19** | 1572823 | 524288 | 1 | 1054626 | 4 |
| **delaunayn20** | 3145686 | 1048576 | 1 | 2109090 | 4 |
| **delaunayn21** | 6291408 | 2097152 | 1 | 4218386 | 4 |
| **delaunayn22** | 12582869 | 4194304 | 1 | 8436672 | 4 |
| **delaunayn23** | 25165784 | 8388608 | 1 | 16873359 | 4 |
| **delaunayn24** | 50331601 | 16777216 | 1 | 33746670 | 4 |

*1) Graph Construction Time:* First, we can see in Table II that the time of building the graphs in Arachne is generally much larger than the execution time of different algorithms. However, once a graph is built in memory, the graph data can be shared by all algorithms of Arachne. So, the cost of the graph construction can be amortized by all the following analyses and quering operations on the graph.

*2) Execution time of Different Algorithms:* For each graph, in general, the execution time of *Connected Components* is the smallest. However, the execution time of *Jaccard Coefficients* is often the largest. This is expected because our highly optimized *Connected Components* can work on all the edges in parallel to quickly propagate the root vertex IDs of all the components. The workload is balanced, and no idle threads exist in this procedure. It will need at most $log(\frac{M}{P})$ iterations on all the edges to converge, where $M$ is the total number of edges and $P$ is the total number of parallel processors or cores. However, calculating the *Jaccard Coefficients* will need $\frac{N \times N}{2}$ memory (if we keep all the coefficients) and about $(\frac{N}{P})^2 \times \frac{M}{P}$ calculations to get all the *Jaccard Coefficients*, where $N$ is the number of vertices. Triangle counting is the dominant part of triangle centrality calculations, so most of triangle centrality's time goes towards triangle counting. The performance of *BFS* is highly related to the graph's diameter. A larger diameter

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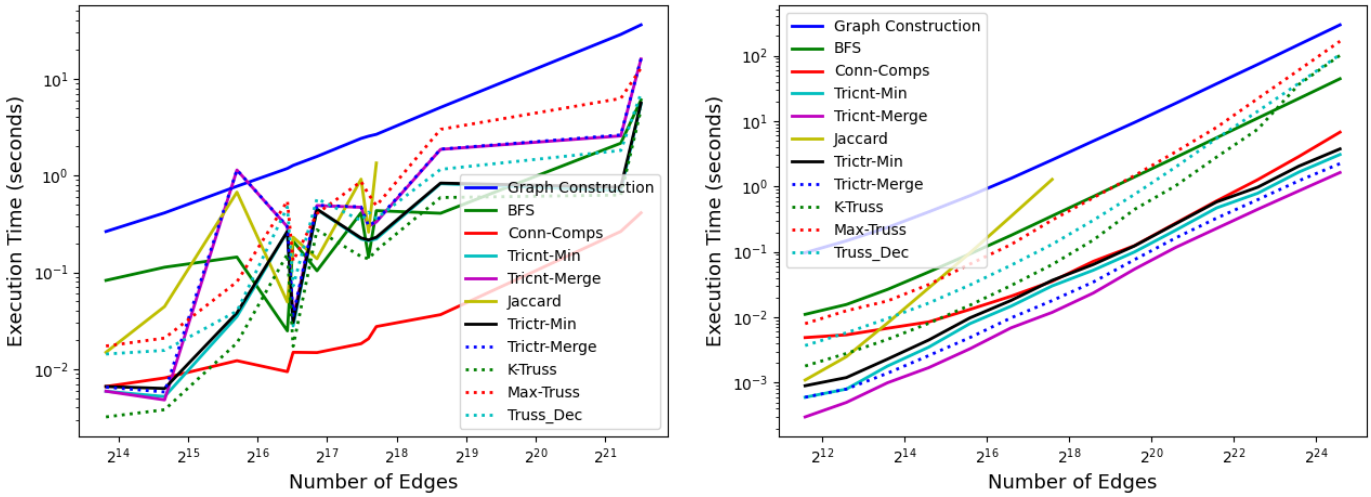
TABLE II: Execution time (seconds) of different graph algorithms on real-world and synthetic graphs ('-' means that the graph cannot be held by current memory).

| Graphs | Graph Construction | BFS | Conn-Comps | Tricnt-Min | Tricnt-Merge | Jaccard | Trictr-Min | Trictr-Merge | K-Truss | Max-Truss | Truss-Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **ca-GrQc** | 0.2641 | 0.0825 | 0.0066 | 0.0059 | 0.0059 | 0.0149 | 0.0066 | 0.0065 | 0.0032 | 0.0173 | 0.0143 |
| **ca-HepTh** | 0.4114 | 0.1128 | 0.0081 | 0.0052 | 0.0048 | 0.0443 | 0.0063 | 0.0058 | 0.0038 | 0.0209 | 0.0156 |
| **as-caida20071105** | 0.7743 | 0.1437 | 0.0122 | 0.0349 | 1.1407 | 0.6731 | 0.0381 | 1.1439 | 0.0186 | 0.0797 | 0.0397 |
| **facebook_combined** | 1.1833 | 0.0248 | 0.0094 | 0.2632 | 0.2954 | 0.0493 | 0.2645 | 0.2968 | 0.1539 | 0.5461 | 0.4720 |
| **ca-CondMat** | 1.2727 | 0.2101 | 0.0149 | 0.0279 | 0.0333 | 0.2309 | 0.0304 | 0.0358 | 0.0172 | 0.1311 | 0.0722 |
| **ca-HepPh** | 1.5751 | 0.1037 | 0.0148 | 0.4462 | 0.4898 | 0.1382 | 0.4489 | 0.4924 | 0.2748 | 0.4040 | 0.5768 |
| **email-Enron** | 2.4186 | 0.4124 | 0.0183 | 0.2207 | 0.4696 | 0.9165 | 0.2264 | 0.4746 | 0.1456 | 0.8673 | 0.3427 |
| **ca-AstroPh** | 2.5489 | 0.1431 | 0.0206 | 0.2122 | 0.2983 | 0.2599 | 0.2159 | 0.3021 | 0.1378 | 0.6402 | 0.4182 |
| **loc-brightkite_edges** | 2.6647 | 0.4336 | 0.0275 | 0.2213 | 0.3315 | 1.3466 | 0.2301 | 0.3400 | 0.1687 | 0.4883 | 0.3600 |
| **soc-Epinions1** | 5.0575 | 0.4074 | 0.0365 | 0.8237 | 1.8627 | 3.4277 | 0.8353 | 1.8745 | 0.5923 | 2.9999 | 1.1582 |
| **amazon0601** | 28.7435 | 2.1594 | 0.2645 | 0.6977 | 2.5684 | – | 0.7587 | 2.6287 | 0.6284 | 6.2614 | 1.8164 |
| **com-Youtube** | 36.0688 | 6.0387 | 0.4118 | 5.5000 | 16.0007 | – | 5.6162 | 16.1142 | 4.8273 | 12.8802 | 7.0787 |
| **friendster** | 12023.7931 | 362.7490 | 168.2291 | 19499.3154 | 34238.1467 | – | 19529.4456 | 34268.2398 | 21155.3487 | – | 31356.5000 |
| **delaunayn10** | 0.0973 | 0.0111 | 0.0049 | 0.0006 | 0.0003 | 0.0011 | 0.0009 | 0.0006 | 0.0018 | 0.0080 | 0.0037 |
| **delaunayn11** | 0.1476 | 0.0157 | 0.0054 | 0.0008 | 0.0005 | 0.0025 | 0.0012 | 0.0008 | 0.0028 | 0.0126 | 0.0058 |
| **delaunayn12** | 0.2365 | 0.0267 | 0.0068 | 0.0018 | 0.0010 | 0.0082 | 0.0023 | 0.0014 | 0.0046 | 0.0178 | 0.0096 |
| **delaunayn13** | 0.4092 | 0.0493 | 0.0085 | 0.0035 | 0.0017 | 0.0281 | 0.0045 | 0.0026 | 0.0081 | 0.0317 | 0.0165 |
| **delaunayn14** | 0.7222 | 0.0931 | 0.0132 | 0.0080 | 0.0033 | 0.0963 | 0.0098 | 0.0049 | 0.0153 | 0.0651 | 0.0312 |
| **delaunayn15** | 1.3312 | 0.1791 | 0.0210 | 0.0148 | 0.0069 | 0.3496 | 0.0181 | 0.0098 | 0.0306 | 0.1296 | 0.0625 |
| **delaunayn16** | 2.5501 | 0.3546 | 0.0355 | 0.0302 | 0.0119 | 1.2826 | 0.0367 | 0.0180 | 0.0640 | 0.3067 | 0.1306 |
| **delaunayn17** | 4.9490 | 0.7023 | 0.0717 | 0.0525 | 0.0235 | 5.0781 | 0.0642 | 0.0346 | 0.1518 | 0.6710 | 0.3046 |
| **delaunayn18** | 9.5101 | 1.3968 | 0.1244 | 0.0997 | 0.0544 | – | 0.1233 | 0.0760 | 0.4452 | 1.4655 | 0.7552 |
| **delaunayn19** | 18.6501 | 2.7768 | 0.2744 | 0.2140 | 0.1168 | – | 0.2681 | 0.1631 | 1.0228 | 3.3737 | 1.9792 |
| **delaunayn20** | 37.1980 | 5.5629 | 0.6024 | 0.4709 | 0.2289 | – | 0.5809 | 0.3286 | 2.8205 | 8.0215 | 5.4189 |
| **delaunayn21** | 73.5252 | 11.1037 | 1.2717 | 0.7893 | 0.4484 | – | 0.9756 | 0.6288 | 7.5073 | 22.0953 | 14.1159 |
| **delaunayn22** | 147.7980 | 22.1427 | 2.8730 | 1.6619 | 0.8573 | – | 2.0468 | 1.2239 | 36.4061 | 60.4223 | 37.8495 |
| **delaunayn23** | 295.7184 | 44.3626 | 6.7721 | 3.0825 | 1.6348 | – | 3.7533 | 2.2393 | 101.1284 | 166.3325 | 104.1138 |
| **delaunayn24** | 598.9867 | 88.3603 | 13.9053 | 6.7230 | 3.0720 | – | 8.1737 | 4.4086 | 306.1790 | 456.9431 | 315.1510 |




(a) Real-Wrold Graphs

(b) Synthetic Graphs

Fig. 2: Execution Time vs Number of Edges for Real-World and Synthetic Graphs

often means poor performance because limited parallelism can be exploited. For *Truss Analysis*, *K-Truss* analysis is part of *Truss Decomposition*. This means the execution time of *K-Truss* will be smaller than that of *Truss Decomposition*. We use estimated upper bound and binary search to find the maximum $K$ value. Since the estimated upper bound is often larger than the exact maximum $K$, there will be some additional operations for *Max-Truss* analysis. However, for a very large maximum $K$ value, the execution time of *Truss Decomposition* will be larger than that of *Max-Truss*. The experimental results show that when the estimated maximum $K$ value is not very large, we may choose *Truss Decomposition* to get the maximum $K$ value with better performance.

For the same algorithm on different real-world graphs, a larger number of edges is not necessarily indicative of a longer execution time. For example, *facebook_combined* has more edges than *as-caida20071105*. However, it has shorter execution time for most graph algorithms (except the truss analysis algorithms). This is due to *facebook_combined* having much fewer vertices, and the access for different edges may have higher locality. Arachne can take advantage of such properties to improve performance. This example shows that not only the scale but also the topology of a given graph can greatly affect the performance of the same algorithm.

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*3) Algorithm Scalability:* We use the Delaunay graphs to show the scalability of our algorithms on the same structure but for differently scaled graphs. We can see that when the number of edges (workload) is doubled, the execution time of our algorithms in Arachne are approximately also doubled for most of the cases. The execution time increases almost linearly when the workload increases. This means that no idle computing resources can be used to further improve the performance, or our algorithms have already fully taken advantage of the parallel resources. However, when the given graph becomes very large, the execution time will increase faster because memory becomes the major performance bottleneck instead of computing resources.

*4) Most Edges Processed Per Second For Each Algorithm:* To finalize the discussion of our results, we will now list the highest value of edges processed per second for each of our algorithms. In Fig.2, we give the relationship between execution time and the number of edges for both real-world graphs and synthetic graphs. We can clearly see that the execution time will increase linearly with the number of edges for the same structure Delaunay synthetic graphs. However, for real-world graphs, the relationship is often very irregular because the topology and number of edges can both affect the performance of a graph. The best edges/second performance is as follows. **Graph Construction:** 150,208 edges per second were processed for the friendster graph. (2) **BFS:** 4,978,834 edges per second were processed for the friendster graph. (3) **Conn-Comps:** 11,107,035 edges per second were processed for the soc-Epinions1 graph. (4) **Tricnt-Min:** 8,164,161 edges per second were processed for the delaunayn23 graph. (5) **Tricnt-Merge:** 16,759,420 edges per second were processed for the delaunayn17 graph. (6) **Jaccard:** 2,829,629 edges per second were processed for the delaunayn10 graph. (7) **Trictr-Min:** 6,704,921 edges per second were processed for the delaunayn23 graph. (8) **Trictr-Merge:** 11,416,582 edges per second were processed for the delaunayn24 graph. (9) **K-Truss:** 6,889,389 edges per second were processed for the ca-HepTh graph. (10) **Max-Truss:** 1,242,132 edges per second were processed for the ca-HepTh graph. (11) **Truss-Dec:** 1,663,869 edges per second were processed for the ca-HepTh graph.

## V. Related Work

One of the earliest works that mimic a productive front-end with a highly parallel and compute-intensive back-end is Matlab*P (2.0) [5], [6]. It aimed to provide a user-friendly interface for massive computations in the back-end in an embarrassingly parallel manner. Another approach that aims to provide similar graph functionality is the Knowledge Discovery Toolbox (KDT), which uses a combinatorial BLAS back-end with MPI that communicates with a Python front-end [19]. Our Arachne toolbox provides a few more options than theirs, such as the ability to perform truss analytics and compute the Jaccard coefficient of graphs.

GraphBLAS [16] is an application programming interface (API) to express graph algorithms in the language of linear algebra. It can be supported by different packages, such as SuitSparse [18]. Compared to our toolbox, we do not require a data scientist to be aware of underlying linear algebra or mathematical methods; all they need to know is how they can use graph algorithms for their data analyses.

There are also graph packages in Chapel, such as the Chapel Graph Library (CGL) [15] and the Chapel Hypergraph Library (CHGL) [13]. In these packages, graphs are represented as hypergraphs, allowing constant time conversion between them. They use both the regular graph and hypergraph representations to drive their graph analytical algorithms. Our work in Arachne differs by focusing on graph analytics and not requiring some conversions to hypergraphs to fully carry out graph algorithmic steps.

Of course, there are also graph toolboxes that are coded solely in Python, such as NetworkX [12]. However, such packages cannot handle very large graphs and the performance is limited.

## VI. Conclusion

A highly productive graph package and environment are essential for data scientists to efficiently exploit the value from big graph data. Thus, we present the Arachne toolkit for interactive graph analytics at scale. On the one hand, we hope data scientists can use simple tools such as general programming in Python. On the other hand, we hope this package can provide very high performance to handle large graphs. We take advantage of the open-source framework Arkouda to build Arachne and integrate it into Arkouda to achieve the above two essential and often conflicting objectives.

For the next steps, we are going to integrate more graph algorithms into Arachne and improve their performance through Chapel-based code and general algorithmic optimizations. Further, this paper highlights the performance of our algorithms in a shared-memory computational environment. However, to truly handle massive file sizes, we need to further explore the optimization methods of these algorithms in a distributed (memory) computing environment.

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