

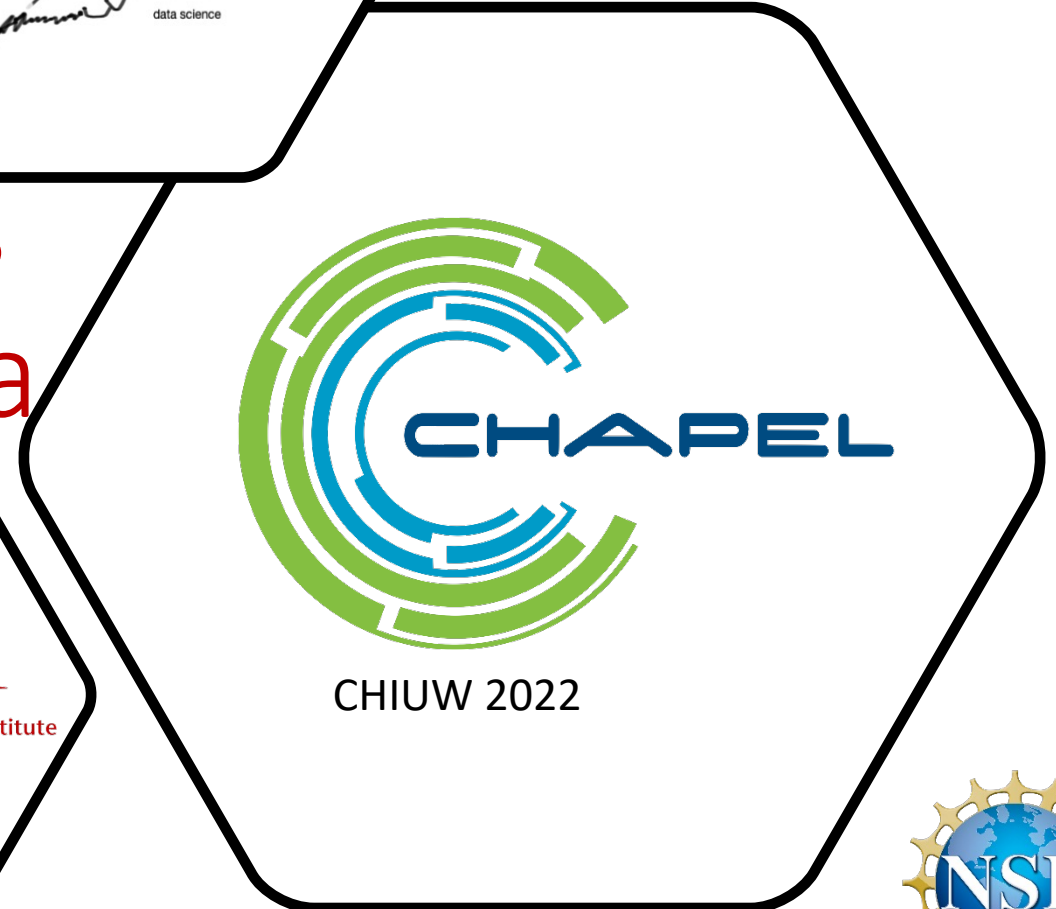
Truss Analytics Algorithms and Integration in Arkouda

Zhihui Du (Presenter)

Joseph Patchett

Oliver Alvarado Rodriguez

David A. Bader

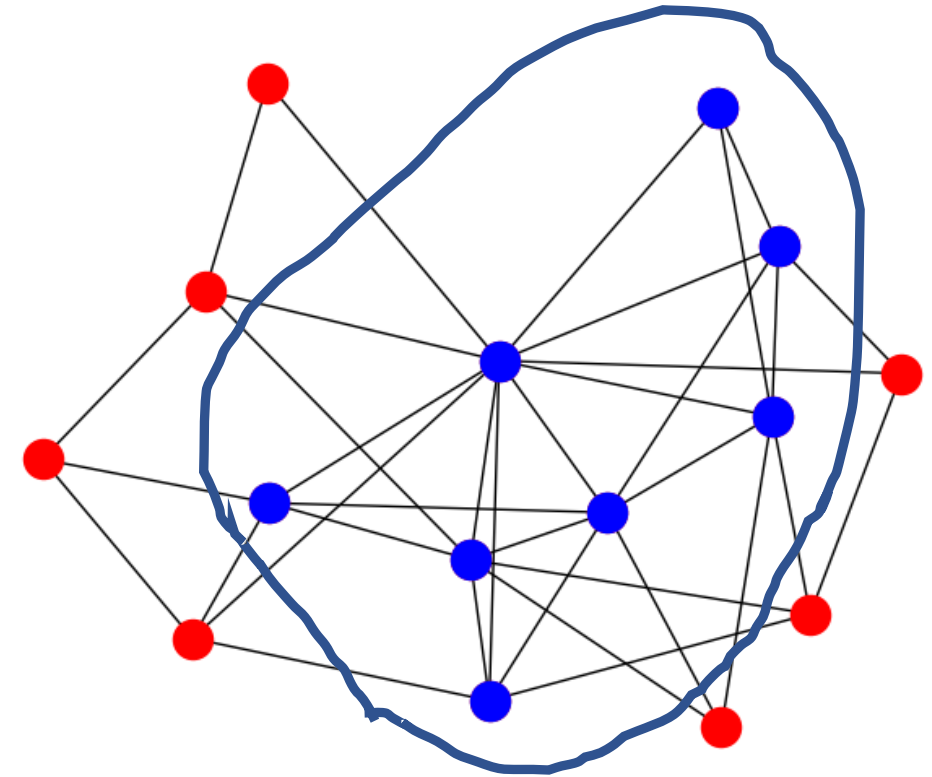


This research is supported by NSF grant CCF-2109988



What is a Truss

- K-Truss
 - a cohesive subgraph to explore **close relationships** in a graph
 - every edge must be part of $k-2$ triangles in the subgraph
 - value K
 - the degree of closeness and the size of the subgraph
 - Larger k means a larger group with a closer connection
 - Widely used
 - polynomial time, a tractable problem (no NP-complete problem) in theory



K=4 truss
Connected by the blue vertices

Why Truss Analytics

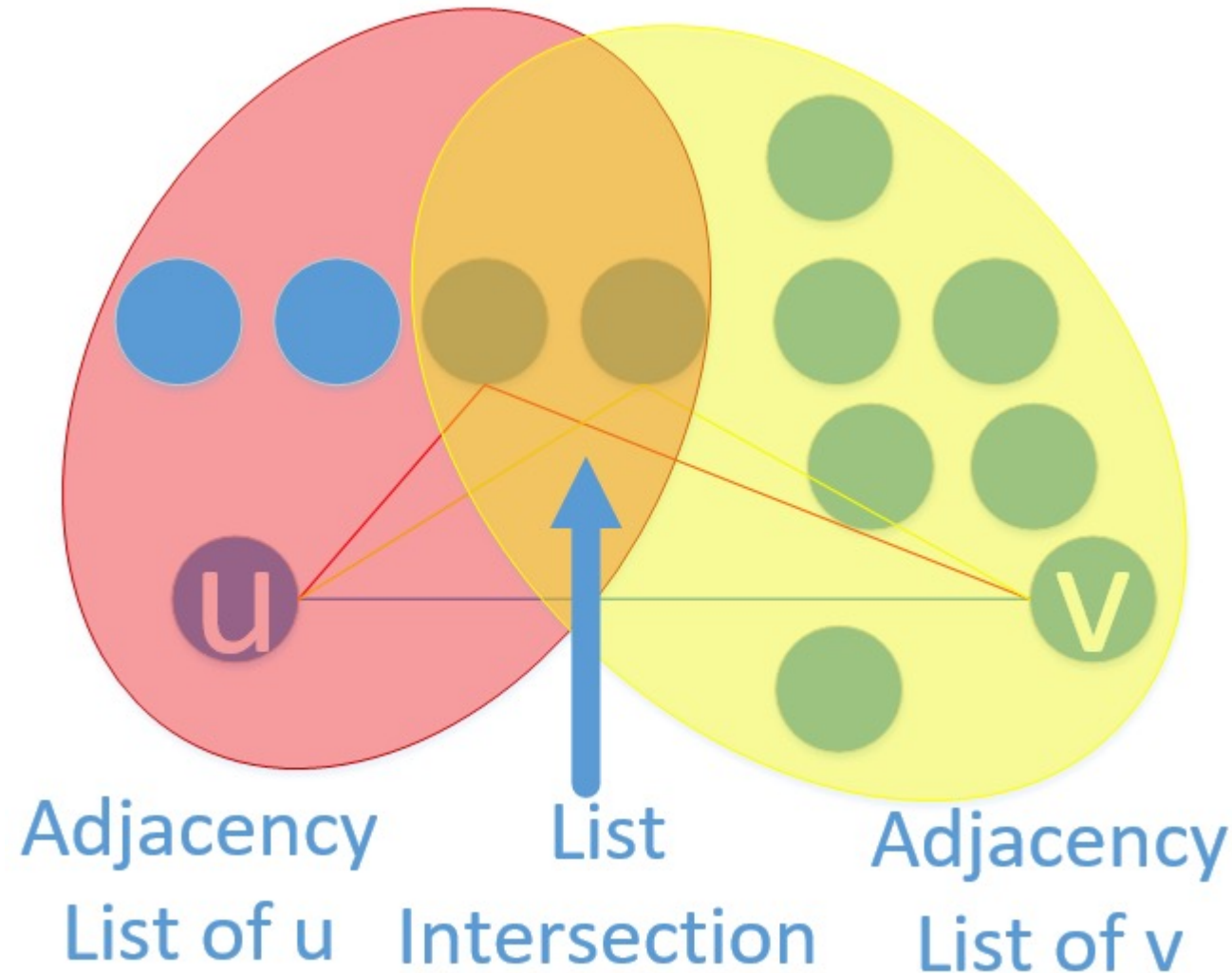
- Answer three questions about a group of elements
 - Who are in the **group** that meets k requirement?
 - K-Truss problem
 - Who are in the **maximal group** that all members have the closest connection?
 - Max K-Truss problem
 - What are all the **different groups** that meet the different degrees of relationships?
 - Truss Decomposition problem
- A typical community detection method
 - Explore insights from a large graph

Algorithm Core and Contributions

- Algorithm Core
 - Triangle Counting
- Contributions
 - A parallel triangle counting core with $O(\log n)$ instead of $O(n)$ time
 - Productive and High-Performance Tool for truss analytics
 - Use Chaple to implement the algorithm and Use Python as the Interface (Arkouda)

Core Algorithm Description

- Existing Methods
 - List Intersection
 - Binary Search ($O(n \log(n))$), two adjacency lists
 - Path Merge ($O(n)$), two adjacency lists
- Proposed Method
 - Minimum Search (three adjacency lists)
 - Time complexity $O(\log n)$
 - $\text{degree}(u) < \text{degree}(v)$, w in adjacency of u
 - If $\text{degree}(w) < \text{degree}(v)$
 - Search v in the adjacency of w
 - If $\text{degree}(w) \geq \text{degree}(v)$
 - Search w in the adjacency of v
 - $\text{degree}(u)$ parallel threads
 - Significant time savings for real-world graphs



Building Parallel k-Truss Algorithms

Algorithm 1: Naive K-Truss Parallel Algorithm

```
1 NaiveKTruss( $G, k$ )  
   /*  $G = \langle E, V \rangle$  is the input graph with edge set  $E$  and vertex set  $V$ .  $k$  is the given K-Truss value.  
2  $EdgeDel[] = -1$  // initialize all edges as not deleted  
3 while there is any edge can be deleted do  
4    $sup[] = 0$  // initialize the triangle counting array  
5   forall (undeleted edge  $e = \langle u, v \rangle \in E$ ) && ( $e$  is local) do  
6     calculate  $sup(e, G)$  using list intersection or minimum search method  
7      $sup[e] = sup(e, G)$   
8   end  
9   forall ( $e = \langle u, v \rangle \in E$ ) && ( $e$  is local) do  
10    if ( $EdgeDel[e] == -1$ ) && ( $sup[e] < k - 2$ ) then  
11       $EdgeDel[e] = k - 1$   
12    end  
13  end  
14 end  
15 return  $EdgeDel$ 
```

Calculate # Triangles
in parallel

Remove Edges that cannot
Support $k-2$ Triangles

Building Optimized Parallel K-Truss Algorithms

- Calculate Triangles in Parallel
- Remove edges that cannot support $k-2$ triangles using minimum search method
- LOOP (search affected edges)
 - Use minimum search method to identify affected edges and update triangle supports
 - Remove edges that cannot support $k-2$ triangles

Algorithm 2: Optimized K-Truss Parallel Algorithm

```
1  OptKTruss( $G, k$ )
   /*  $G = \langle E, V \rangle$  is the input graph with edges set  $E$  and vertices set  $V$ .  $k$  is the given K-Truss value.
2   $EdgeDel[] = -1$  // initialize all edges as undeleted
3   $sup[] = 0$  // initialize the support array of each edge
4   $SetDel = \phi; SetAff = \phi$ 
5  forall ( $e \in E$ ) && ( $e$  is local) do
6     $sup[e] = sup(e, G)$  using minimum search method
7  end
8  forall ( $e \in E$ ) && ( $e$  is local) do
9    if ( $EdgeDel[e] == -1$ ) && ( $sup[e] < k - 2$ ) then
10      $EdgeDel[e] = 1 - k$ 
11     Add  $e$  into  $SetDel$ 
12   end
13 end
14 while ( $SetDel$  is not empty) do
15   forall ( $e_1 \in SetDel$ ) && ( $e_1$  is local) do
16     using minimum search method to find  $e_2$  and  $e_3$  that can form a triangle with  $e_1$ 
17     reduce the support of  $e_2$  and  $e_3$  if they are undeleted edges
18     add the affected edges into  $SetAff$  if their supports are less than  $k - 2$ 
19   end
20   forall ( $e \in SetDel$ ) && ( $e$  is local) do
21     if ( $EdgeDel[e] == 1 - k$ ) then
22        $EdgeDel[e] = k - 1$ 
23     end
24   end
25    $SetDel.clear()$ 
26    $SetDel \Leftarrow SetAff$  // switch the values of the two sets.
27 end
28 return  $EdgeDel$ 
```

Building Parallel Max K-Truss Algorithms

- Estimate the upper bound value of k_{up}
- Modified Binary Search in $[3, k_{up}]$
 - The k -truss is not empty but $(k+1)$ truss is
 - If k_{low} is not empty then check k_{up}
 - If k_{up} is empty then check k_{mid}
 - While k_{mid} is empty then update k_{mid} and check again
 - If k_{mid} is not empty then update k_{low} and search recursively

Algorithm 3: Max K-Truss Parallel Algorithm

```
1  MaxKTruss( $G$ )
   /*  $G = \langle E, V \rangle$  is the input graph with edges set  $E$  and vertices set  $V$ .
2  Let  $k_{low} = 3$  and set  $k_{up}$  based on the proposed analysis method
3  return DownWardSearch( $G, k_{low}, k_{up}$ )
4  function DownWardSearch( $G, k_{low}, k_{up}$ )
5  EdgeDel = kTruss( $G, k_{low}$ )
6  if (All edges have been deleted) then
7  |   return ( $k_{low} - 1$ , EdgeDel)
8  end
9  else
10 |   EdgeDel = kTruss( $G, k_{up}$ )
11 |   if (there are undeleted edges in EdgeDel) then
12 |   |   return ( $k_{up}$ , EdgeDel)
13 |   end
14 |   else
15 |   |    $k_{mid} = (k_{low} + k_{up}) / 2$ 
16 |   |   EdgeDel = kTruss( $G, k_{mid}$ )
17 |   |   while (All edges have been deleted in EdgeDel) do
18 |   |   |    $k_{up} = k_{mid} - 1$ 
19 |   |   |    $k_{mid} = (k_{low} + k_{up}) / 2$ 
20 |   |   |   EdgeDel = kTruss( $G, k_{mid}$ )
21 |   |   end
22 |   |   if ( $k_{mid} == k_{up} - 1$ ) then
23 |   |   |   return ( $k_{mid}$ , EdgeDel)
24 |   |   end
25 |   |   else
26 |   |   |    $k_{low} = k_{mid} + 1$ 
27 |   |   |   return DownWardSearch( $G, k_{low}, k_{up}$ )
28 |   |   end
29 |   end
30 end
```


Data Structure Design and Selection

- High-level Set/DistBag and Low-level Arrays
 - Easy \leftrightarrow Performance
 - List intersection using set.contains operation is expensive
- Atomic Variables
 - The number of triangles updated by multiple removed edges
 - The total number of removed edges updated by multiple removed edges
- ForAll/CoForAll
 - Implicit synchronization among different parallel threads

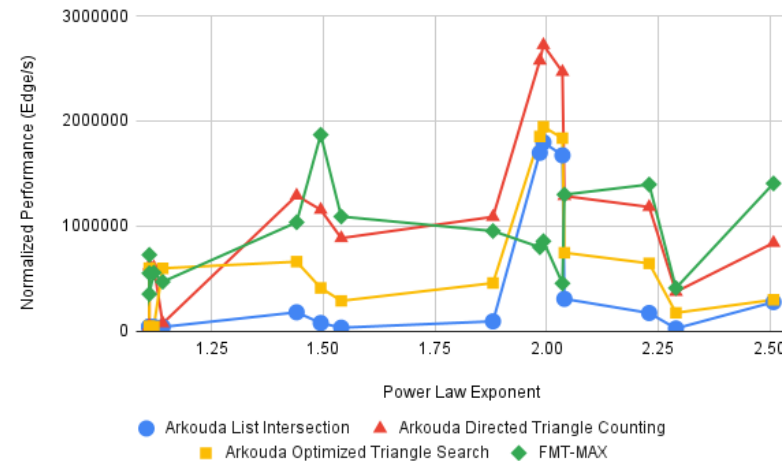
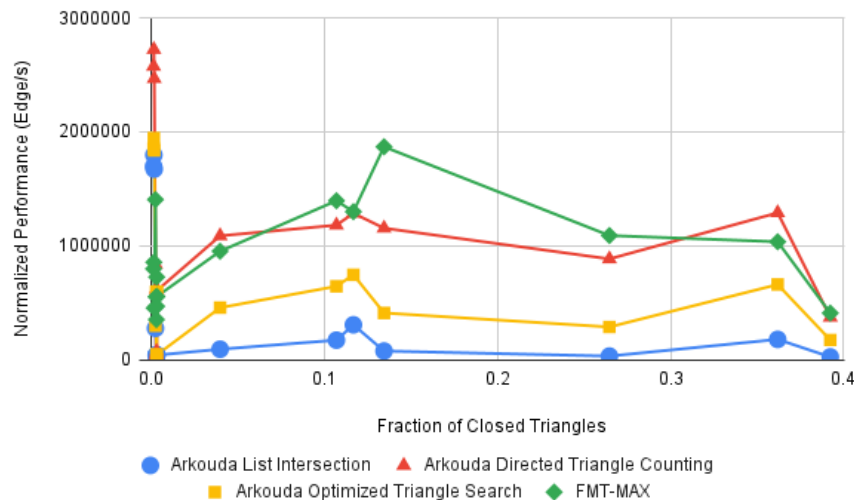
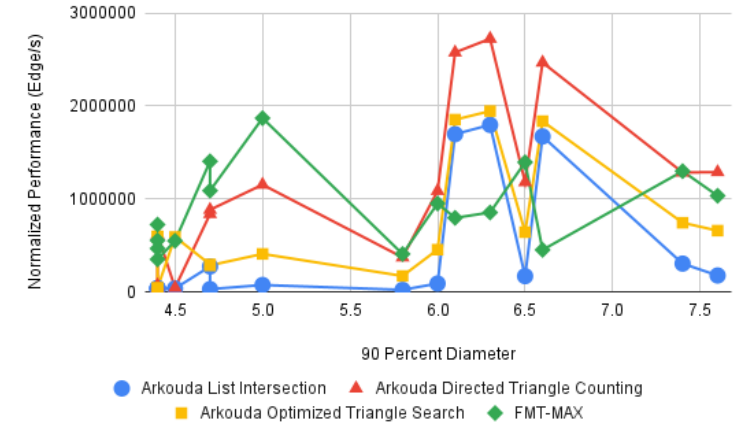
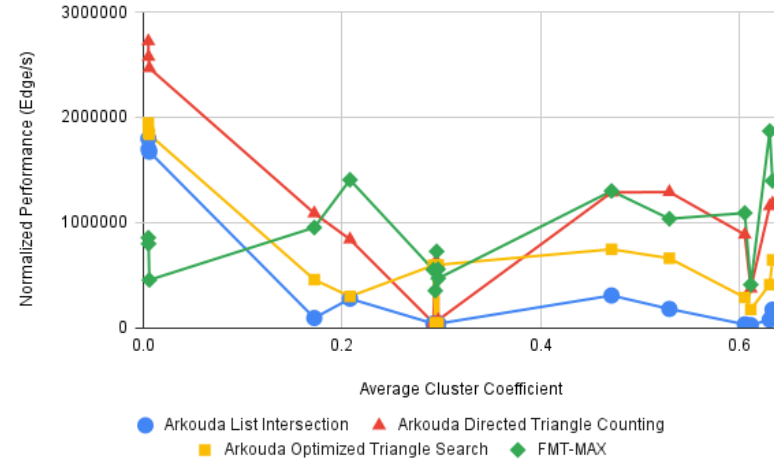
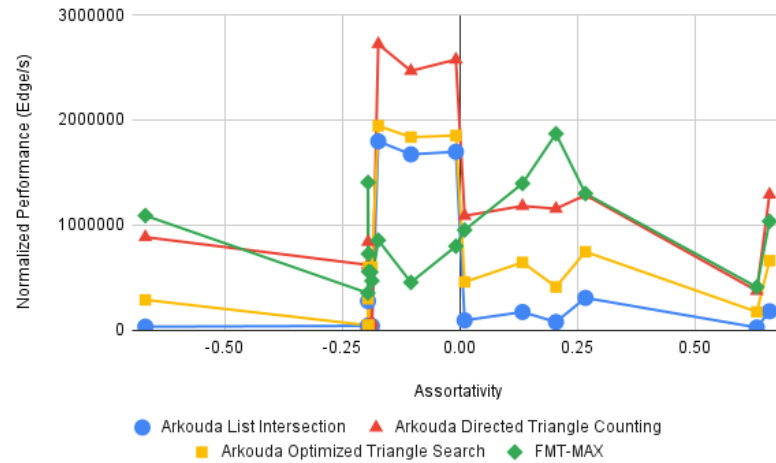
Experimental Setup

- Data sets
 - 9 real-world graphs
 - 7 synthetic graphs
- Comparison algorithms
 - Naïve List Intersection (set)
 - Naïve Min Search (set)
 - Optimized Min Search (array)
 - Path Merge (not given in the paper)

Performance Comparison

Graph	LI Naive K-Truss	MS Naive K-Truss	MS Opt K-Truss	MS Max K Truss	MS Truss Decomposition	Speedup 1	Speedup 2
amazon0601	1008.58	509.29	60.61	93.22	66.22	2.0	16.6
as-caida20071105	16.70	2.98	1.00	1.73	0.88	5.6	16.7
ca-AstroPh	113.28	56.11	9.64	11.16	5.17	2.0	11.7
ca-CondMat	23.52	11.58	2.11	2.58	2.21	2.0	11.2
ca-GrQc	2.49	1.24	0.29	0.35	0.36	2.0	8.6
ca-HepPh	29.33	14.69	3.07	3.22	3.45	2.0	9.6
ca-HepTh	3.88	1.93	0.50	0.61	0.61	2.0	7.7
com-Youtube	4885.27	302.37	55.72	71.89	61.94	16.2	87.7
delaunay_n10	2.04	1.05	0.08	0.09	0.08	1.9	25.5
delaunay_n11	5.50	2.81	0.16	0.18	0.16	2.0	34.2
delaunay_n12	14.00	7.15	0.32	0.36	0.31	2.0	44.3
delaunay_n13	36.69	18.74	0.62	0.70	0.61	2.0	58.9
delaunay_n14	98.61	50.46	1.23	1.46	1.22	2.0	79.9
delaunay_n15	266.96	136.52	2.49	2.93	2.45	2.0	107.3
delaunay_n16	735.75	378.16	4.91	5.83	4.87	1.9	149.8

Preliminary Graph topology and Normalized Performance Analysis



Conclusion

- Algorithm
 - The novel parallel **minimum search**-based method can really improve the performance Truss Analytics Algorithms compared with the widely used existing list intersection methods.
- Language
 - Chapel's high-level data structure (set/distbag...), atomic variables and parallel structure forall/coforall are very helpful to implement the parallel truss algorithms **productively**
- Data Science Environment
 - Arkouda can help **Python users** to employ the provided large-scale truss analytics with high performance

Acknowledgement

We appreciate the help from Michael Merrill, William Reus, Brad Chamberlain, Elliot Joseph Ronaghan, Engin Kayraklioglu, David Longnecker and the Chapel and Arkouda community when we integrated the algorithms into Arkouda. This research was funded in part by NSF grant number CCF-2109988.

Thank You!

Q&A