

Spiral AI/ML: Co-optimization for High-Performance, Data-Intensive Computing in Resource Constrained Environments

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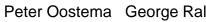


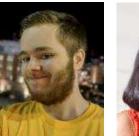
Courtney Rankin



Sandra Sanjeev

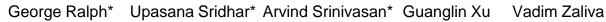












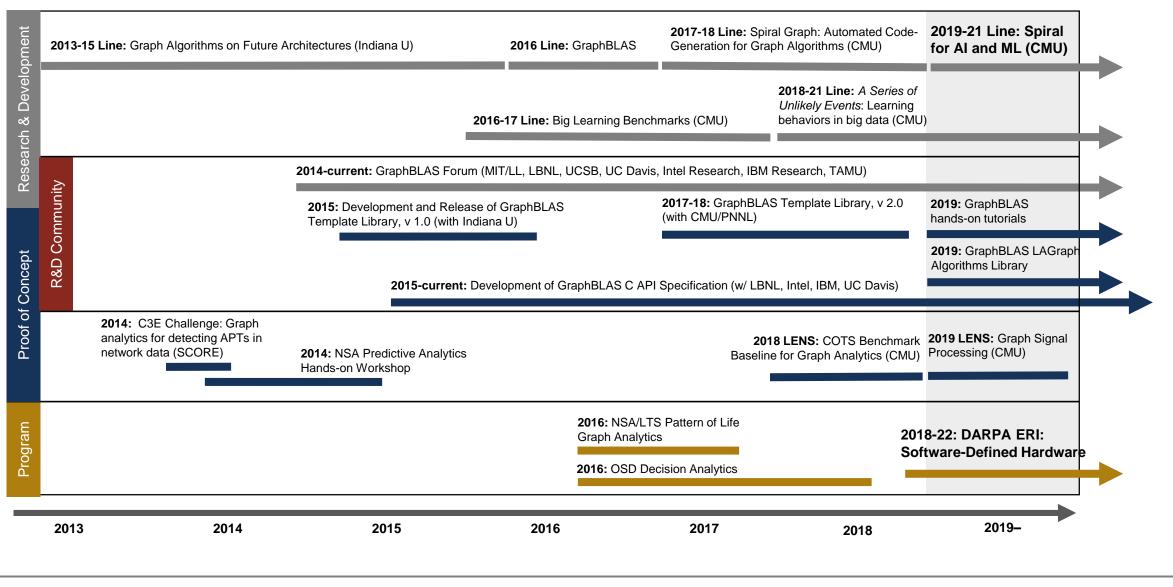




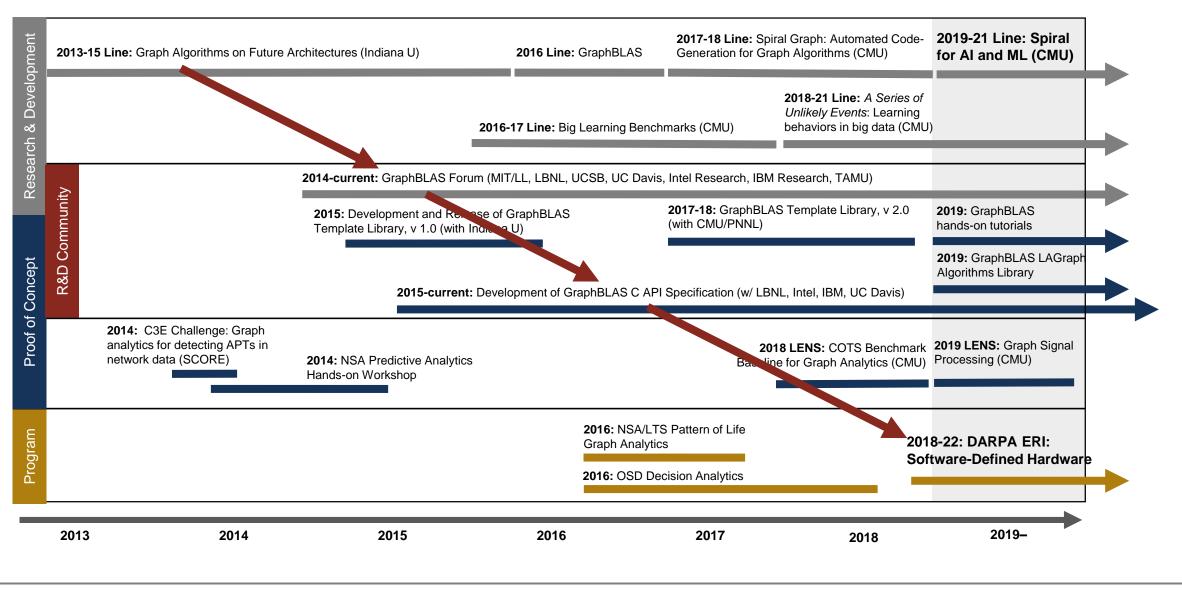
Jiyuan Zhang * unfunded collaborators

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Advanced Computing Efforts: Graphs to Al



Advanced Computing Efforts: Graphs to Al



Spiral/AIML: Co-optimization for High-Performance, Data-Intensive Computing in Resource Constrained Environments



"Rapidly delivering artificial intelligence to a combat zone won't be easy." Col. Drew Cukor, USMC.

Problem(s)

- Increasing complexity in computing architectures.
- Mission cost, size, weight, and power (CSWAP) constraints drive increasing use of FPGAs and ASICs (more complexity).
- Achieving performance from these platforms is hard.
- Achieving performance from data-intensive applications (graphs, ML, AI) is hard.

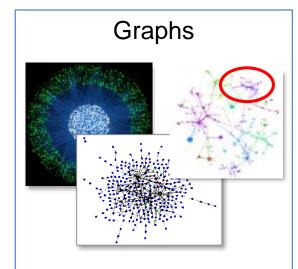
Solution

- Automatic code generation for data-intensive computations.
- Simultaneous, automatic co-optimization of hardware within CSWAP constraints.

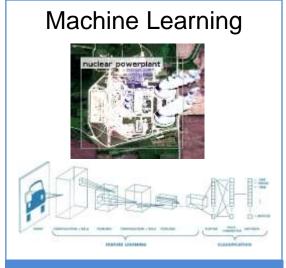
Approach

- Identify common AI/ML/Graph computational primitives.
- Encode knowledge about graph, ML, and AI computational primitives into Spiral code-gen technology.
- Develop hardware performance models allowing Spiral to choose between components satisfying CSWAP requirements.

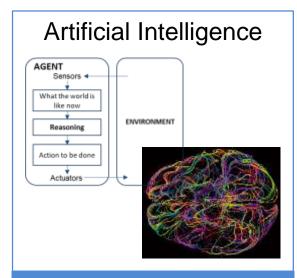
Data Intensive Computing Is Important and Pervasive



- Graphs represent entities and relationships detected through multi-INT sources.
- 1,000s 100,000,000,000s tracks, interactions, events
- GOAL: Find clusters of similar entities or behaviors of interest.



- Machine Learning encompasses techniques that exploit patterns captured in data for a given task.
- 10,000s 1,000,000s labeled and unlabeled data
- GOAL: Provide accurate, datadriven predictions, insights, or models of observed phenomenon.



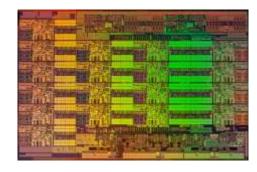
- Al is the collection of computations that make it possible to perceive, reason and act.
- Practically infinite state space and non-deterministic dynamics
- GOAL: Create intelligent agents that achieve target performance in deployed environments.

Common Goal: Timely, accurate, and actionable transformation of **massive amounts of** data into knowledge

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Today's Computing Landscape



Intel Xeon 8180M 2.25 Tflop/s, 205 W

28 cores, 2.5—3.8 GHz 2-way—16-way AVX-512







IBM POWER9 768 Gflop/s, 300 W 24 cores, 4 GHz 4-way VSX-3



Nvidia Tesla V100 7.8 Tflop/s, 300 W 5120 cores, 1.2 GHz 32-way SIMT



Intel Xeon Phi 7290F 1.7 Tflop/s, 260 W 72 cores, 1.5 GHz 8-way/16-way LRBni



Summit 187.7 Pflop/s, 13 MW 9,216 x 22 cores POWER9 + 27,648 V100 GPUs

Slide credit: Franz Franchetti, "18-847G, 2018, Lecture 1: How Big is Big?"

Intel Atom 32 Gflop/s, 2

Intel Atom C3858 32 Gflop/s, 25 W 16 cores, 2.0 GHz 2-way/4-way SSSE3

1 Gflop/s = one billion floating-point operations (additions or multiplications) per second

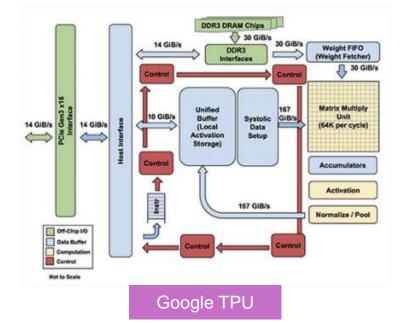


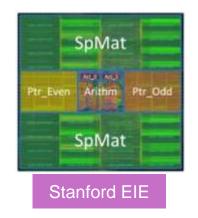
Dell PowerEdge R940 3.2 *Tflop/s, 6 TB, 850 W* 4x 24 cores, 2.1 GHz 4-way/8-way AVX

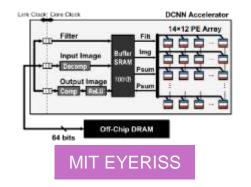
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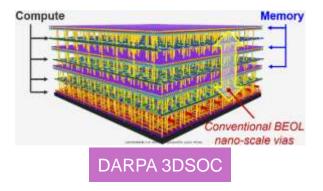
Research Review 2019

Today's Computing Landscape...is not tomorrow's.



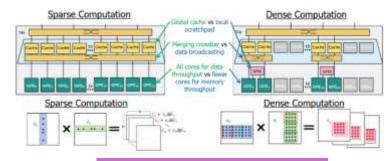




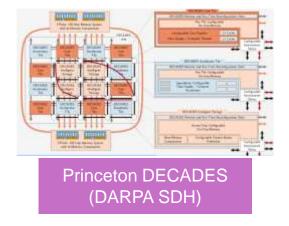




Intel PUMA (DARPA HIVE)



Michigan (DARPA SDH)



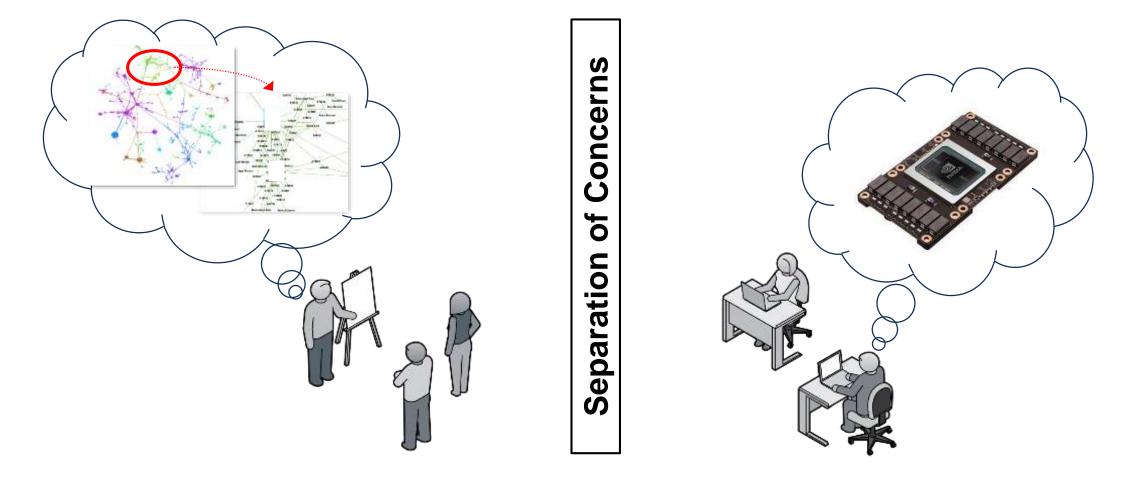
Slide sources: DARPA Electronics Resurgence Initiative (ERI) Summit, July 2019; DARPA ERI Summit, July 2018; DARPA Software Defined Hardware (SDH) Proposers Day, September 2017.

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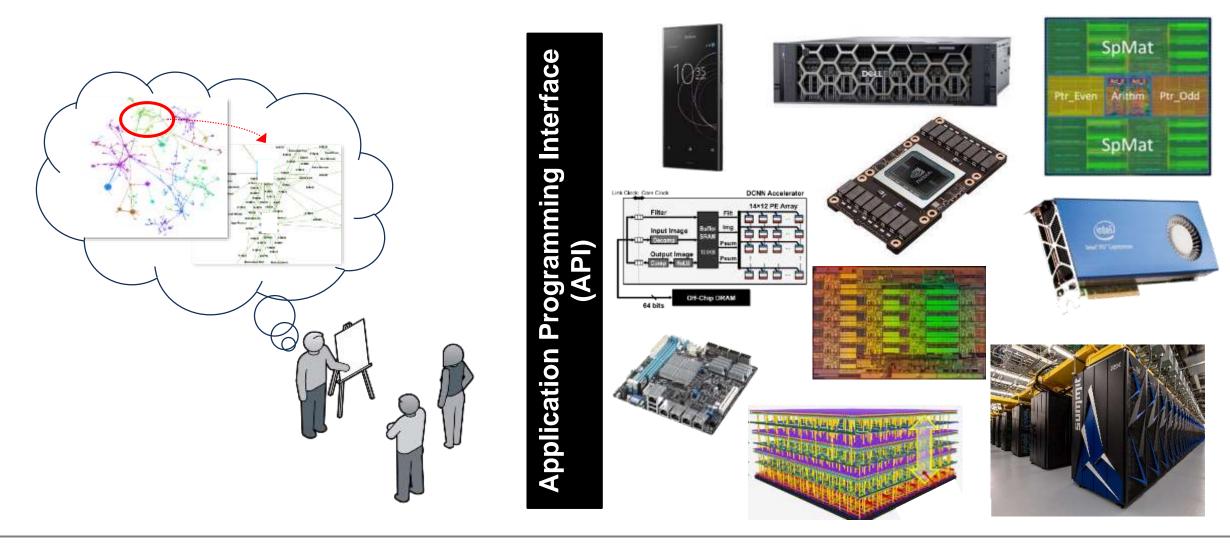
Separation of Concerns

Separate the complexity of algorithms from the complexity of hardware systems:



Separation of Concerns

GOAL: write once, run everywhere...fast (with help from hardware experts).



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Systems for working with Graphs (Irregular Data)

,	RedisGraph Po	owor Owital	Ŭ	GraphQ	∎ HipG	ì	GRACE	Mosai	2	 LigerGraph
Chronos		owerSwitch	Hama	GBT	-	TurboG	rooh		∽ Orie Rock	entDB
Graph	GPS	JCore[OB Graph	GBASE	Julienn	е	•		NUCK	LFGraph
	PICCOIO				GasC	CL Floc	kDB	Sedge	GoFFish	I
Ligi	a Golde		ombBLAS	neo4J	Titan	I	GraphB		BPP	Graphulo
GraphBlast	GraphX	Chaos		tiono for a	roch or			xDGP	TOTEM	Pregelix
Gra	GraphHP GraphMP		Opt	tions for g Dazed ar	•			eaver	Stinger	
GraphMat	Giraph++	Grail		GraphMa	ap	Mosaid		GoDB		AlegroGraph
LCC-Graph		DU	ALSIM	C . of p	- F	WOSak			RASP	Gemini
CuSha	SuiteSparse	Mizan	Horne		Graph	Polymer	Grap	ohIT X-st	ream	GraphX
	XPregel	PathGra	ph H	orton+	Pow	verGraph	Galois	GB /	ArangoDB	cuGraph
Hypergraph	DB Graph	Xstream GraphLab yGBTL GraphChi		pygraphbla		Pregel			pgg aph	raphblas
	PyGBTL			pygraphor	65	Infin		h	Puma	Blogel
Third Party names are the property of their owners. Source: Scalable Graph Processing Frameworks: A Taxonomy and Open Challenges: S. Heidari, Y. Simmhan, R. N. Calheiros, and R. Buyya, ACM Comput. Surv. 51, 3, Article 60 (June 2018); Slide crec										

Third Party names are the property of their owners. Source: Scalable Graph Processing Frameworks: A Taxonomy and Open Challenges: S. Heidari, Y. Simmhan, R. N. Calheiros, and R. Buyya, ACM Comput. Surv. 51, 3, Article 60 (June 2018); Slide credit: Tim Mattson/Intel Labs, "The Growing GraphBLAS community: Progress Report", LPS Workshop on HPC Data Analytics, Sep. 2019.

TigorGraph

Systems for working with Graphs (Irregular Data)

5	RedisGraph			GraphQ		∎ 、	GRAC	E Mos			ligerGraph
Chronos		PowerSwitch	Hama	GBTL		-	Croph			Orient[DB
Grapl	GPS	JCore	JCoreDB Graph		Julier	nne	Graph	G	GunRock		FGraph
Ciupi	Piccolo			GBASE	Ga	asCL Flo	ockDB	Sedge	e Gol	Fish	
Lig	ra Gold	denOrb	ombBLAS	LAS neo4J		an	GraphBLAS		BPP	Graphulo	
GraphBlast	GraphX	Chaos	Crapha					xDG	Р то-	ТЕМ	Pregelix
Gr	GraphHP GraphMP		Graphs	Linear Alge		he Language of bra			Weaver		Stinger
GraphMat	Giraph- CC-Graph	Grail ++ DU	ALSIM	GraphMa	ар	Mosa		GoDB	RASP		legroGraph
CuSha	SuiteSparse	Mizan	Horne		Graph	Polymei	_r Gra	phIT X	-stream	Gerr	ⁱⁱⁿⁱ GraphX
	XPregel	PathGra	ph H	orton+	P	owerGraph	Galoi	s GB	Arango	ЭB	cuGraph
Hypergrapl	nDB Grap	ohLab	Xstream	pygraphblas		Pregel	Kine		pggr ograph		hblas
PyGBTL		Grap	GraphChi			InfiniteGra		ph Puma		ì	Blogel
							han, R. N. Calhe	eiros, and R. Buyy	ya, ACM Comput. S	Surv. 51, 3, Arti	s: A Taxonomy and Open cle 60 (June 2018); Slide credit:

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Tim Mattson/Intel Labs, "The Growing GraphBLAS community: Progress Report", LPS Workshop on HPC Data Analytics, Sep. 2019.

TigorGraph

GraphBLAS References

Mathematical Foundations of the GraphBLAS

Jeremy Kepner (MIT Lincoln Laboratory Supercomputing Center), Peter Aaltonen (Indiana University), David Bader (Georgia Institute of Technology), Aydın Buluç (Lawrence Berkeley National Laboratory), Franz Franchetti (Carnegie Mellon University), John Gilbert (University of California, Santa Barbara), Dylan Hutchison (University of Washington), Manoj Kumar (IBM), Andrew Lumsdaine (Indiana University), Henning Meyerhenke (Karlsruhe Institute of Technology), Scott McMillan (CMU Software Engineering Institute), Jose Moreira (IBM), John D. Owens (University of California, Davis), Carl Yang (University of California, Davis), Marcin Zalewski (Indiana University), Timothy Mattson (Intel)

Design of the GraphBLAS API for C

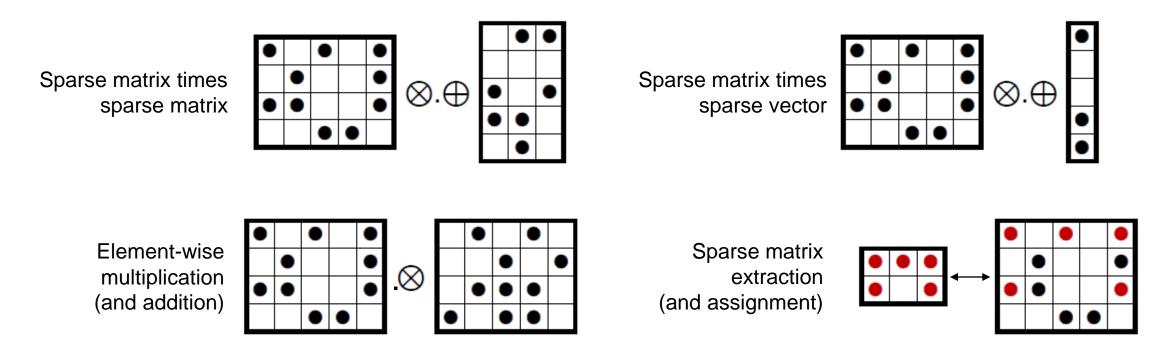
Aydın Buluç[†], Tim Mattson[‡], Scott McMillan[§], José Moreira[¶], Carl Yang^{*,†}

[†]Computational Research Division, Lawrence Berkeley National Laboratory [‡]Intel Corporation §Software Engineering Institute, Carnegie Mellon University ¶IBM Corporation *Electrical and Computer Engineering Department, University of California, Davis, USA

IEEE HPEC 2017

GraphBLAS Primitives

- Basic objects (opaque types)
 - Matrix, vector, algebraic structures, and "control objects"
- Fundamental operations over these objects

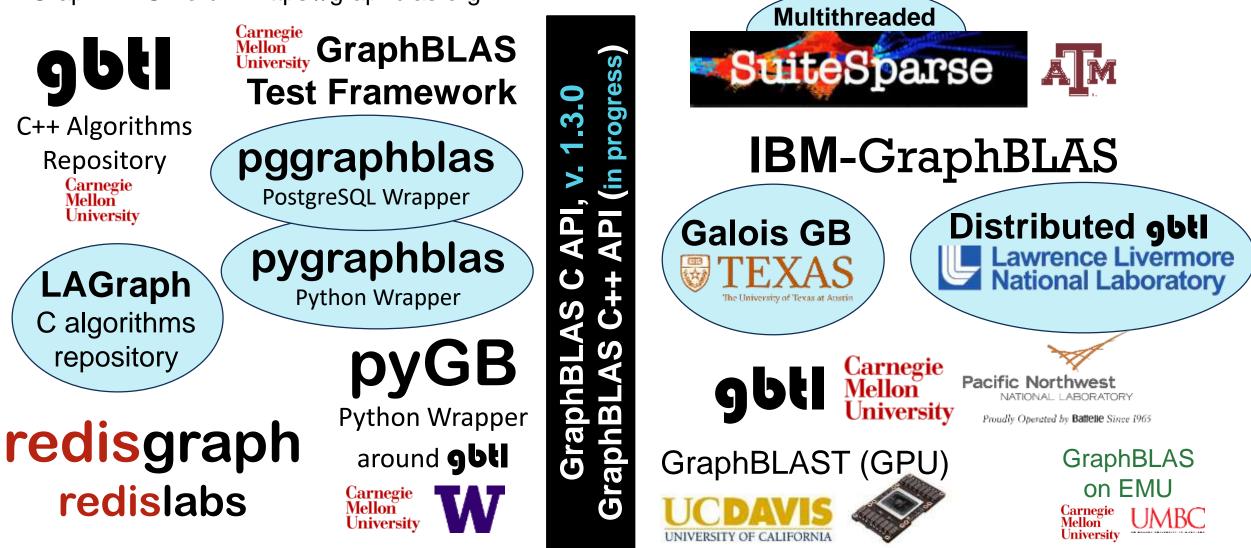


...plus reductions, transpose, and application of a function to each element of a matrix or vector

http://graphblas.org "A. Buluc, T. Mattson, S. McMillan, J. Moreira, C. Yang, "The GraphBLAS C API Specification, v 1.0.0," May 2017, updated May 2018, Sep 2019.

GraphBLAS Ecosystem: This year

GraphBLAS Forum: https://graphblas.org

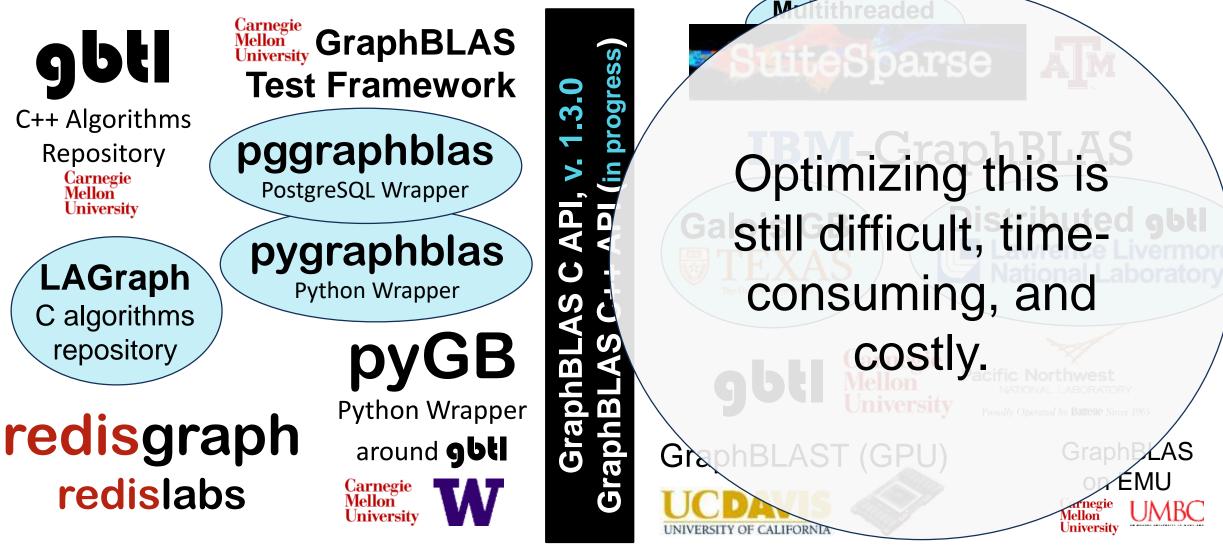


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GraphBLAS Ecosystem: This year

GraphBLAS Forum: https://graphblas.org



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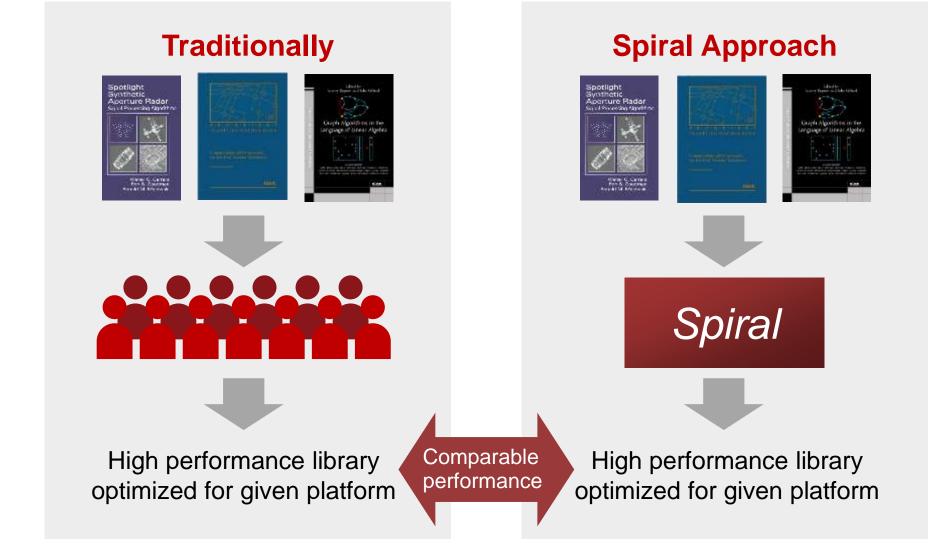
Spiral Code Generation

Prof. Franz Franchetti, CMU ECE



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What is Spiral?



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Spiral: Platform-Aware Formal Program Synthesis

$$#\Delta = \frac{1}{6} tr(A^{3})$$

= ||L.*(L*L^T)||₁

 $\mathbf{C}(\mathbf{L}, \mathbf{z}) = (\mathbf{L} \oplus . \otimes \mathbf{L}^{\mathsf{T}})$

 $#\Delta = \bigoplus_{i,i} \mathbf{C}(i,j)$

$$A = L + U \quad (hi > lo + lo > hi)$$

$$L \times U = B \quad (wedge, low hinge)$$

$$A ^ B = C \quad (closed wedge)$$

$$sum(C)/2 = 4 \text{ triangles}$$

$$B, C$$

$$3 ^ 1 ^ 4$$

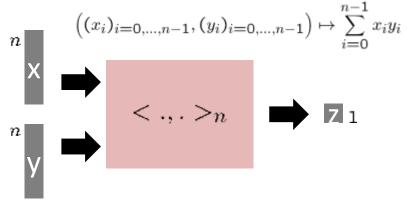
$$2 ^ 1 ^ 4$$

$$1 ^ 2$$

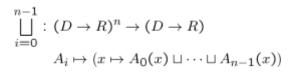
$$1 ^ 2$$

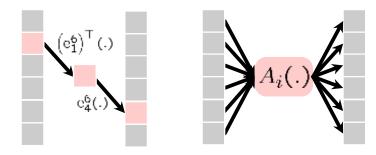
SPIRAL's Math Framework **High Level Operators**

 $< \ldots >_n : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$



Loop Abstraction





Basic Operators

 $\mathsf{Pointwise}_{n,f_i}: \mathbb{R}^n \to \mathbb{R}^n$ $(x_i)_i \mapsto f_0(x_0) \oplus \cdots \oplus f_{n-1}(x_{n-1})$

 $\operatorname{Atomic}_{f(\ldots)} : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ $(x,y) \mapsto f(x,y)$

$$\begin{array}{l} \mathsf{Pointwise}_{n \times n, f_i} : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n \\ \left((x_i)_i, (y_i)_i \right) \mapsto f_0(x_0, y_0) \oplus \cdots \oplus f_{n-1}(x_{n-1}, y_{n-1}) \end{array}$$

 $\mathsf{Reduction}_{n,f_i}:\mathbb{R}^n\to\mathbb{R}$ $(x_i)_i \mapsto f_{n-1}(x_{n-1}, f_{n-2}(x_{n-2}, f_{n-3}(\dots f_0(x_0, \mathsf{id}())\dots))$

Rule Based Compiler

$$\begin{aligned} \operatorname{Code}\left(y = (A \circ B)(x)\right) &\to \left\{ \operatorname{decl}(t), \operatorname{Code}\left(t = B(x)\right), \operatorname{Code}\left(y = A(t)\right) \right\} \\ \operatorname{Code}\left(y = \left(\sum_{i=0}^{n-1} A_i\right)(x)\right) &\to \left\{y := \vec{0}, \operatorname{for}(i = 0..n - 1) \operatorname{Code}\left(y + = A_i(x)\right)\right\} \\ \operatorname{Code}\left(y = (e_i^n)^\top(x)\right) &\to y[0] := x[i] \\ \operatorname{Code}\left(y = e_i^n(x)\right) &\to \left\{y = \vec{0}, y[i] := x[0]\right\} \\ \operatorname{Code}\left(y = \operatorname{Atomic}_f(x)\right) &\to y[0] := f(x[i]) \end{aligned}$$

Leverages DARPA HACMS

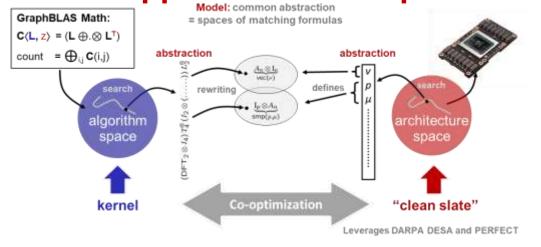
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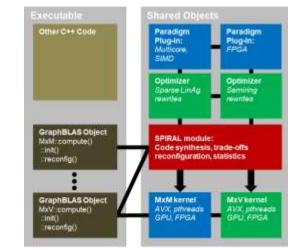
SPIRAL Internals: Autotuning and Code Generation **SPIRAL as JIT and GraphBLAS Optimizer Autotuning in Constraint Space**



 $\left[(L_{s}^{m}\otimes I_{n,lps})\otimes I_{p}\right)\left(I_{p}\otimes_{j}(DPT_{n}\otimes I_{n/ps})\left((L_{p}^{m}\otimes I_{n/ps})\otimes I_{p}\right)\left(\bigoplus_{i=1}^{D-1}T_{n}^{m(i)}\right)\left(I_{p}\otimes_{j}G_{m/p}\otimes DPT_{n}\right)\right)\left(I_{p}\otimes_{i}L_{m/ps}^{m(i)}\right)\left(L_{p}^{m}\otimes I_{m/ps}\right)\otimes I_{p}\right)$

Formal Approach To Co-Optimization





Source Code

- C++, GraphBLAS calls, other supported libraries
- Code = specification, not program

SPIRAL Module

- Acts as JIT, delayed execution engine, Inspector/executor
- Implements telescoping language ideas
- Rewrites code into better algorithms
- Compiles to range of platforms CPU, GPU, FPGA
- Plug-in mechanism for post deployment reconfiguration and update

Leverages DARPA BRASS

Algorithm/Architecture Co-Optimization

Design Space $cost 1/C_m(\xi, \mu)$ algorithm $A(\mu)$

architecture M (»)

"What is the right architecture for my application?" What architecture features are good for my application?

Optimization Problem

 $(\hat{\mathcal{A}}, \hat{\mathcal{M}}) = \operatorname{argmin}_{\theta \in \mathcal{C}_{\mathrm{m}}} (\mathcal{A}(\theta), \mathcal{M}(\xi))$

- Algorithm
- Architecture
- Cost function C_m(ξ, μ)
- Parameters: ξ, μ
- Metric m: power, runtime,...

Task: Find ξ and μ s.t. $C_m(\xi, \mu)$ is minimal

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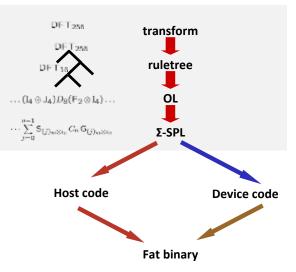
C code

Targeting FPGAs With SPIRAL

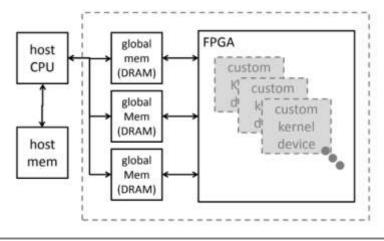
Range of Platforms



FPGAs in SPIRAL Flow



Execution Layer: OpenCL



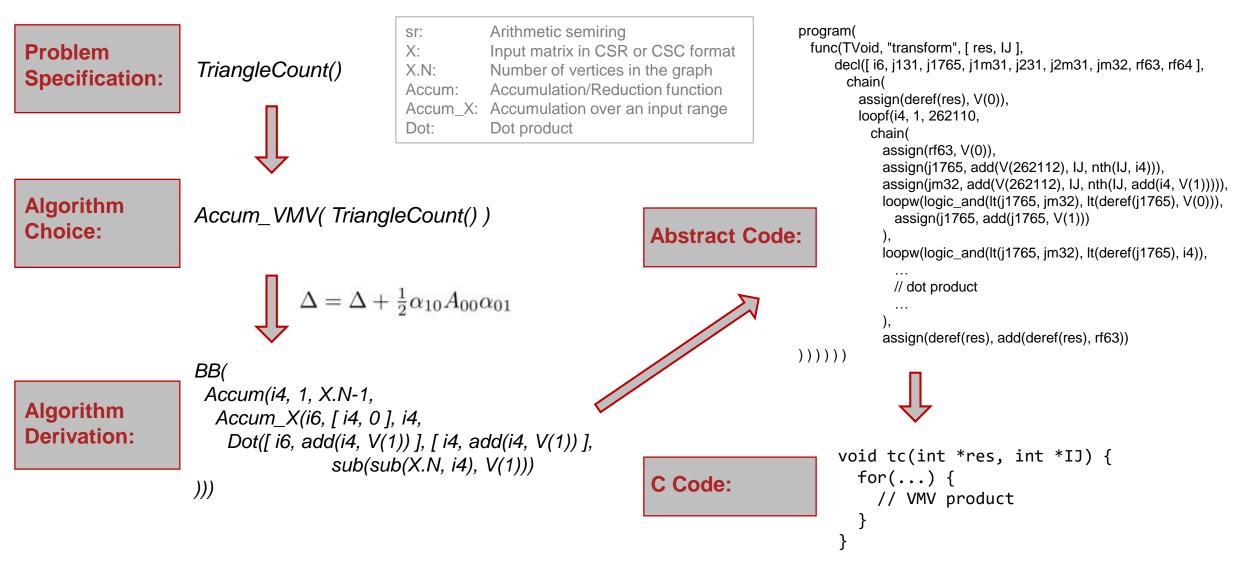
BUT: Not standard OpenCL Code

- _kernel mmm(__global float *A, ... *B, ... *C) {
 for(int i=0; i<N; i++)
 for(int j=0; j<N; j++)
 for(in k=0; k<N; k++)
 C[i*N+j]=C[i*N+j]+A[i*N+k]*B[k*N+j]</pre>
- NDRange=(1, 1, 1)
 never do this on GPU!!
- · Arbitrary control flow (loops, if's) and dependencies
- · Becomes just "regular" C-to-HW synthesis
 - pipeline and parallelize loops
 - schedule for initiation-interval, resource, etc.

Only want OpenCL's platform model and API; "work-group" & "work-item" not too meaningful

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Graph Algorithms in Spiral



```
Research Review 2019
```

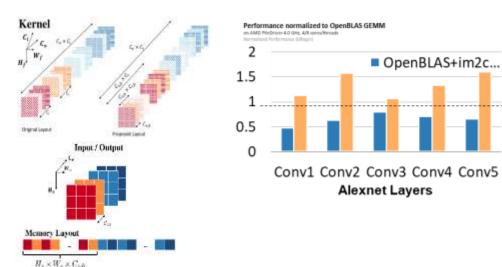
It Works for Triangle Counting and K-TRUSS

```
spiral> t := TriangleCount();
TriangleCount()
spiral> rt := RandomRuleTree(t, opts);
Accum VMV FLAME2( TriangleCount() )
spiral> srt := SumsRuleTree(rt, opts);
BB(
 Accum(i1, 1, 262110,
   Accum X(i3, [ i1, 0 ], i1,
     Dot([ i3, add(i1, V(1)) ], [ i1, add(i1, V(1)) ], sub(sub(V(262111), i1), V(1)))
spiral> cs := CodeSums(srt, opts);
program(
  chain(
     func(TVoid, "init", [ ],
        chain()
     ),
     func(TVoid, "transform", [ res, IJ ],
        decl([ i3, j1, j11, j1m1, j21, j2m1, jm1, rf1, rf2 ],
           chain(
              assign(deref(res), V(0.0)),
              loopf(i1, 1, 262110,
                 chain(
                    assign(rf1, V(0.0)),
                    assign(j1, add(V(262112), IJ, nth(IJ, i1))),
                    assign(jm1, add(V(262112), IJ, nth(IJ, add(i1, V(1))))),
                    loopw(logic_and(lt(j1, jm1), lt(deref(j1), V(0))),
                       assign(j1, add(j1, V(1)))
                    loopw(logic_and(lt(j1, jm1), lt(deref(j1), i1)),
                       chain(
                          assign(i3, deref(j1)),
                          assign(rf2, V(0.0)),
                          assign(j11, add(V(262112), IJ, nth(IJ, i3))),
                          assign(j1m1, add(V(262112), IJ, nth(IJ, add(i3, V(1))))),
                          assign(j21, add(V(262112), IJ, nth(IJ, i1))),
                          assign(j2m1, add(V(262112), IJ, nth(IJ, add(i1, V(1))))),
                          loopw(logic_and(lt(j11, j1m1), lt(deref(j11), add(i1, V(1)))),
                             assign(j11, add(j11, V(1)))
```

```
void ktruss(int *dEk, int k) {
 int *S = (int*)malloc(E * sizeof(int));
 int *IAk = (int*)malloc((V+1) * sizeof(int));
 int *JAk = (int*)malloc(E * sizeof(int));
 int Ek = E;
  for (int i = 0; i < V+1; i++) IAk[i] = IA CSR[i];</pre>
 for (int i = 0; i < E; i++) JAk[i] = JA CSR[i];
 int iter = 1;
 while (1) {
   int row = 0;
   for (int i = 0; i < Ek; i++) {
     while (IAk[row+1] == i) row++;
     int i0 = IAk[row]; int b0 = IAk[row + 1];
     int i1 = IAk[JAk[i]];
     int b1 = IAk[JAk[i] + 1];
     int res = 0;
     while (i0 < b0 \&\& i1 < b1) {
       int v0 = JAk[i0]; int v1 = JAk[i1];
       if (v0 == v1)
         res++;
       if (v0 \le v1)
         i0++;
       if (v1 <= v0)
         i1++;
      }
     S[i] = res;
 500 lines generated C code
```

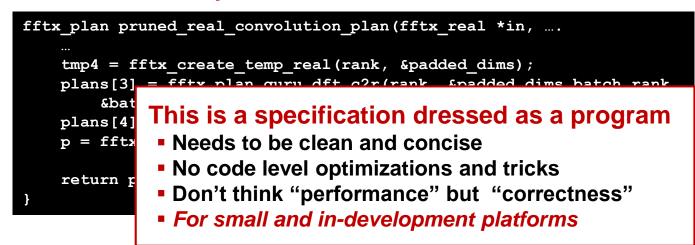
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Current Efforts Feeding Into SPIRAL AI/ML SPIRAL CUDA/OpenACC GPU Target

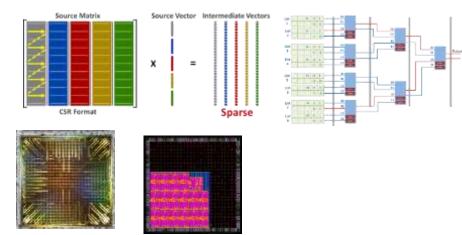


void ioprunedconv_130_0_62_72_130(double *Y, double *X, double * S) {
 ...
for(int i18899 = 0; i18899 <= 1; i18899++) {
 for(int i18912 = 0; i18912 <= 4; i18912++) {
 a9807 = ((2*i18899) + (4*i18912));
 a9808 = (a9807 + 1);
 a9809 = (a9807 + 52);
 a9810 = (a9807 + 53);
 ...
 *((104 + Y + a12569)) = ((s3983 - s3987)
 + (0.80901699437494745*t6537)
 + (0.58778525229247314*t6538));
 *((105 + Y + a12569)) = (((s3984 - s3988)
 + (0.80901699437494745*t6538));
 - (0.58778525229247314*t6537));
 }
</pre>

SPIRAL Library as DSL Frontend



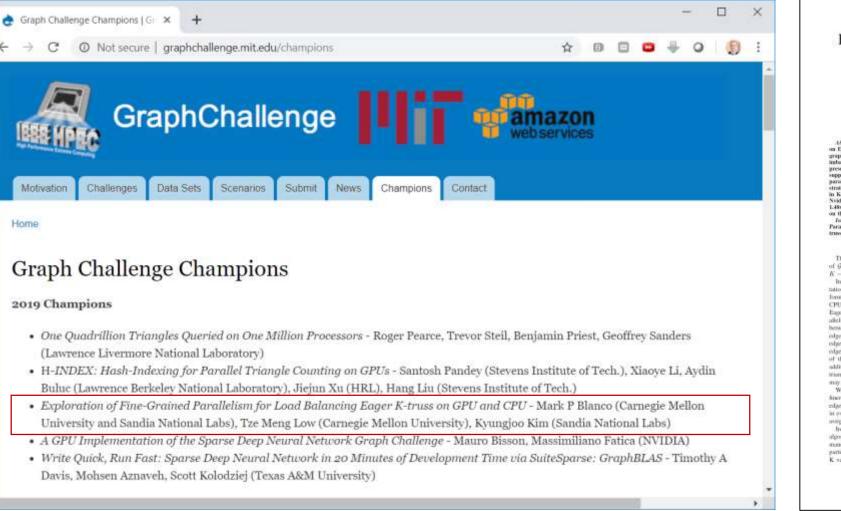
A SPIRAL/SEI Chip in 2020/2021



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4

Result: Graph Challenge Champions



Exploration of Fine-Grained Parallelism for Load Balancing Eager K-truss on GPU and CPU

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Adotuct-In this work we present a performance exploration on Easer K-irnos, a Incar-absobraic formulation of the K-irnos graph planetthm. We address performance issues related to land instalance of parallel tasks in commetric, triangular graphs for presenting a fine-grained perallel approach to executing the support computation. This approach also increases available parallelism, making it amenable in GPU execution. We deponitsie eer hie-grateel parallel approach using implementations in Kokkos and exaluate them on an Intel Medala: CPU and an Nidia Teda V100 GPU, Overall, we observe between a 1.26-1.48x improvement on the CPU and a 9.97-16.92x improvement on the GPU due to our fine-grained parallel forigulation. Juder Termi-Graph Alcorithms, K-truss, Linner Alcohra, Paralleliun, High Performance, GPU, CPU, Kokkos, Eager Ktrates, Performance Periodulity

Algorithm 1: Linear algebraic K-mass algorithm. Lowercase letters are vectors and capital letters are matrices. Input: A is the adjavency restric of logist graph Output: S represents the superit of edges in A i corresponde la fulai while and opportunge the $S = A^T A + A^{-//}$ Step 1) computeSupports $M \mapsto S \geq (k-2)^{-//}$ Step 2: prineEdges $A \mapsto A \in M$ converge - inf netwograf(M)

1. INTROOPCTION

The K-transes of a graph G ore highly connected satigraphs in milliseconds for specific configuration. of G where each edge in a submark is an edge in at least

K = 2 distinct triangles in the subgraph [1]. In this work, we present a fine-grained parallel implemennation of the Eager K-truss algorithm [2], a linear algebraic CPU and the GPU. The key observation is that the existing Eager K-itree algorithm inex a course-grained approach to pat-

allelism by dividing the edges into blocks that are distributed of this approach suffers from potential load initialance. In most edges can be removed addition, the Easter K-trues algorithm computer with an upper These two steps of the K-trues algorithm can generally may be skewed significantly as the algorithm proceeds.

assignment to a processing element. he Sections II and III, we present details of our proposal

sigorithm. For an efficient implementation, we use a perform # Euger K-mass Algorithm

We report our results in millions of edges processed per second for each graph, and also provide a strengary table with firmings

II. BACKORGEND

To keep this paper self-contained, we pervide a brief description of the Eager K-trust algorithm in this section. For formulation of an edge-centric K-tours algorithm, on both the the detailed algorithmic derivation, we refer to Low et al. [2]

A. Linear Algebraic K-reast Algorithm

retara S

Similar to many other K-tress implementations, Eager Kbetween parallel workers based on the common series that the truss takes a two-step approach. Specifically, the first step edges are commoned to; typically the 'source' vertex. As each - computes the support of all edges, and the second step primes edges may be connected to different number of neighboring edges whose support are below a specifical diseshold. This twoedges (i.e. edges that share the same vertex), the performance step approach is then repeated on the prused graphes) until no

triangelar adjacency matrix, which means this load indulance - be expressed using finane algebraic notation as described in Algorithm 1, where A is given as the adjacency matrix of the We result the load initializer problem by introducing + input graph, and M is a binary matrix where M[i, j] = 1 when finer-grained task unit epon which parallel workers compute $|S(t, j)| \ge (k - 2)$ [4]. The z-operator representation elementadge membership in wareads - the edge support values. This, wise multiplication of the input operands. Note that Step 1 in essence, introduces parallelism within each Nock of edges - computes matrix 8, where each ratio at S[i, j] is the number of triangles containing the edge between nodes i and j.

stunce postable garafiel programming model. Kokkos [3]. In The Eager K-truss algorithm derives its name for the enger particular, we report our K-spos performance for several fixed monoer in which is updates the support values of all edges K values on NVIDEA V100 and hand Skylake architectures. His each manufar that has been identified. Specifically, the

Open Source Spiral: CMU/ECE and SEI Partnership

- Open Source SPIRAL available
 - non-viral license (BSD)
 - Initial version, effort ongoing to open source whole system
 - Commercial support via SpiralGen, Inc.
- Developed over 20 years
 - Funding: DARPA (OPAL, DESA, HACMS, PERFECT, BRASS), NSF, ONR, DoD HPC, JPL, DOE, CMU SEI, Intel, Nvidia, Mercury
- Open sourced under DARPA PERFECT
- Ongoing Partnership between SEI and ECE





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