LAGraph Algorithms

LAGraph Working Group

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Abstract

Theoretical documentation for LAGraph.

1 Notation

Table 1 contains the notation of GraphBLAS operations

Additionally, we use $\mathbf{D} = diag(J, n)$ to construct a diagonal matrix $\mathbf{D} \leftarrow \{J, J, [1, 1, \ldots, 1]\}$. The elements of the matrix are $\mathbf{D}(j, j) = 1$ for $j \in J$.

Initializing scalars, vectors, and matrices (GraphBLAS methods):

- let: $s \in \mathbb{Q}_{64}$
- let: $\mathbf{u} \in \mathbb{Q}_{32}^{n}$
- let: $\mathbf{A} \in \mathbb{N}_{16}^{m \times n}$
- let: $\mathbf{A} \in \mathbb{Z}_{64}^{k \times m}$

2 Algorithms

LAGraph [12] implements graph algorithms using the GraphBLAS C API [13].

An incomplete list of GraphBLAS algorithms:

- MSBFS [8], bidirectional BFS [8], pushpull BFS [19]
- DFS [16]
- weakly connected components [21]
- SCC (LAGraph)
- SSSP, delta-stepping [17]
- triangle count [1, 5], triangle enumeration [1], item local clustering coefficient [4]
- k-truss [5]
- betweenness centrality [12]
- closeness centrality [8]
- DNN algorithm [10, 7]
- PageRank variants (at least 2) [4], IISWC paper, ...
- Louvain [11]
- property graphs: incremental TTC case [9], SIGMOD 2014 Contest [8] Roi Lipman's talk[1]
- CFPQs based on a string of GRADES/ADBIS/other papers [2, 3, 14, 18, 15]
- Implementations: GBTL[2], SuiteSparse:GraphBLAS [6], GraphBLAST [20]

[1] `http://wiki.ldbcouncil.org/pages/viewpage.action?pageId=106233859&preview=/106233859/111706128/LDBC-July-2019.pdf`

[2] `https://github.com/cmu-sei/gbtl`

op./method	name	notation
`mxm`	matrix-matrix multiplication	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathbf{A}\oplus.\otimes\mathbf{B}$
`vxm`	vector-matrix multiplication	$\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{u}\oplus.\otimes\mathbf{A}$
`mxv`	matrix-vector multiplication	$\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{A}\oplus.\otimes\mathbf{u}$
`eWiseAdd`	element-wise addition set union of patterns	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathbf{A}\oplus\mathbf{B}$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{u}\oplus\mathbf{v}$
`eWiseMult`	element-wise multiplication set intersection of patterns	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathbf{A}\otimes\mathbf{B}$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{u}\otimes\mathbf{v}$
`extract`	extract submatrix extract column vector extract row vector extract subvector	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathbf{A}(I,J)$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{A}(:,j)$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{A}(i,:)$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathbf{u}(I)$
`assign`	assign matrix to submatrix with mask for $\mathbf{C}$ assign scalar to submatrix with mask for $\mathbf{C}$ assign vector to subvector with mask for $\mathbf{w}$ assign scalar to subvector with mask for $\mathbf{w}$	$\mathbf{C}\langle\mathbf{M}\rangle(I,J)\odot=\mathbf{A}$ $\mathbf{C}\langle\mathbf{M}\rangle(I,J)\odot=s$ $\mathbf{w}\langle\mathbf{m}\rangle(I)\odot=\mathbf{u}$ $\mathbf{w}\langle\mathbf{m}\rangle(I)\odot=s$
`subassign (GxB)`	assign matrix to submatrix with submask for $\mathbf{C}(I,J)$ assign scalar to submatrix with submask for $\mathbf{C}(I,J)$ assign vector to subvector with submask for $\mathbf{w}(I)$ assign scalar to subvector with submask for $\mathbf{w}(I)$	$\mathbf{C}(I,J)\langle\mathbf{M}\rangle\odot=\mathbf{A}$ $\mathbf{C}(I,J)\langle\mathbf{M}\rangle\odot=s$ $\mathbf{w}(I)\langle\mathbf{m}\rangle\odot=\mathbf{u}$ $\mathbf{w}(I)\langle\mathbf{m}\rangle\odot=s$
`apply`	apply unary operator	$\mathbf{C}\langle\mathbf{M}\rangle\odot=f(\mathbf{A})$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=f(\mathbf{u})$
`select (GxB)`	apply select operator	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathit{select}(\mathbf{A},f(k))$ $\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathit{select}(\mathit{low}\leq\mathbf{A}\leq\mathit{up})$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathit{select}(\mathbf{u},f(k))$ $\mathbf{w}\langle\mathbf{m}\rangle\odot=\mathit{select}(\mathit{low}\leq\mathbf{u}\leq\mathit{up})$
`reduce`	reduce matrix to column vector reduce matrix to scalar reduce vector to scalar	$\mathbf{w}\langle\mathbf{m}\rangle\odot=[\oplus_j\mathbf{A}(:,j)]$ $s\odot=[\oplus_{ij}\mathbf{A}(i,j)]$ $s\odot=[\oplus_i\mathbf{u}(i)]$
`transpose`	transpose	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathbf{A}^\top$
`kronecker`	Kronecker multiplication	$\mathbf{C}\langle\mathbf{M}\rangle\odot=\mathit{kron}(\mathbf{A},\mathbf{B})$
`new`	new matrix new vector	let: $\mathbf{A}\in\mathsf{TYPE}^{n\times m}_{\mathsf{PRECISION}}$ let: $\mathbf{u}\in\mathsf{TYPE}^{n}_{\mathsf{PRECISION}}$
`build`	matrix from tuples vector from tuples	$\mathbf{C}\hookleftarrow\{I,J,X\}$ $\mathbf{w}\hookleftarrow\{I,X\}$
`extractTuples`	extract index/value arrays	$\{I,J,X\}\hookleftarrow\mathbf{A}$ $\{I,X\}\hookleftarrow\mathbf{u}$
`dup`	duplicate matrix duplicate vector	$\mathbf{C}\hookleftarrow\mathbf{A}$ $\mathbf{w}\hookleftarrow\mathbf{u}$
`extractElement`	extract scalar element	$s=\mathbf{A}(i,j)$ $s=\mathbf{u}(i)$
`setElement`	set element	$\mathbf{C}(i,j)=s$ $\mathbf{w}(i)=s$

Table 1: GraphBLAS operations and methods based on [6]. *Notation:* Matrices and vectors are typeset in bold, starting with uppercase ($\mathbf{A}$) and lowercase ($\mathbf{u}$) letters, respectively. Scalars including indices are lowercase italic (s, i, j) while arrays are uppercase italic (X, I, J). $\oplus$ and $\otimes$ are the addition and multiplication operators forming a semiring and default to conventional arithmetic $+$ and $\times$ operators. $\odot$ is the apply operator. Masks $\langle\mathbf{M}\rangle$ and $\langle\mathbf{m}\rangle$ are used to selectively write to the result matrix/vector. The complements of masks $\langle\mathbf{M}\rangle$, $\langle\mathbf{m}\rangle$ can be selected with the negation symbol, denoted with $\langle\neg\mathbf{M}\rangle$, $\langle\neg\mathbf{m}\rangle$, respectively. Masks with "replace" semantics (annihilating all elements outside the mask) are denoted with $\langle\!\langle\mathbf{M}\rangle\!\rangle$, $\langle\!\langle\neg\mathbf{M}\rangle\!\rangle$, $\langle\!\langle\mathbf{m}\rangle\!\rangle$, and $\langle\!\langle\neg\mathbf{m}\rangle\!\rangle$, The structure of the mask is denoted with $\langle\{\mathbf{M}\}\rangle$, $\langle\neg\{\mathbf{M}\}\rangle$, $\langle\{\mathbf{m}\}\rangle$, and $\langle\neg\{\mathbf{m}\}\rangle$.

Algorithm 1: Breadth-first search.

```
Function BFS
    frontier(s) = TRUE
    for level = 1 to n − 1 do
        seen⟨frontier⟩ = level
        frontier⟨⟨¬seen⟩⟩ = frontier any.pair A
```

Algorithm 2: Breadth-first search (push/pull).

```
Function BFS
    frontier(s) = TRUE
    for level = 1 to n − 1 do
        seen⟨frontier⟩ = level
        push = use some heuristics to determine whether to push/pull
        if push then
            frontier⟨⟨¬seen⟩⟩ = frontier any.pair A
        else
            frontier⟨⟨¬seen⟩⟩ = A any.pair frontier
```

Algorithm 3: Multi-source breadth-first search.

```
Data: ...
Result: ...
Function MSBFS
    Frontier ↤ diag(S, n)
    for level = 1 to n − 1 do
        Seen⟨Frontier⟩ = level
        Frontier⟨⟨¬Seen⟩⟩ = Frontier any.pair A
```

Algorithm 4: Betweenness centrality.

Function *MSBFS*

// The **NumSp** structure holds the number of shortest paths for each node and starting vertex discovered so far.
// Initialized to source vertices.
$\mathbf{NumSp} \hookleftarrow \{s, [1, 1, \ldots, 1]\}$
// The **Frontier** holds the number of shortest paths for each node and starting vertex discovered so far.
// Initialized to source vertices.
$\mathbf{Frontier}\langle\mathbf{NumSp}\rangle = \mathbf{A}(s, :)$
$d = 0$
// The **Sigmas** matrices store frontier information for each level of the BFS phase.
// BFS phase (forward sweep)
do
  // $\mathbf{Sigmas}[d](:, s) = d^{\mathrm{th}}$ level frontier from source vertex s
  let: $\mathbf{Sigmas}[d] \in \mathbb{B}^{n \times nsver}$
  $\mathbf{Sigmas}[d](:, :) = \mathbf{Frontier}$ // Convert matrix to Boolean
  $\mathbf{NumSp} = \mathbf{NumSp} \oplus \mathbf{Frontier}$ // Accumulate path counts
  $\mathbf{Frontier}\langle\!\langle\mathbf{NumSp}\rangle\!\rangle = \mathbf{A}^\top \oplus.\otimes\, \mathbf{Frontier}$ // Update frontier
while $nvals(\mathbf{Frontier}) > 0$
let: $\mathbf{NumSpInv} \in \mathbb{Q}_{32}^{n \times nsver}$
$\mathbf{NumSpInv} = 1.0 \oslash \mathbf{NumSp}$
let: $\mathbf{BCU} \in \mathbb{Q}_{32}^{n \times nsver}$
$\mathbf{BCU}(:) = 1.0$ // Make **BCU** dense, initialize all elements to 1.0
let: $\mathbf{W} \in \mathbb{Q}_{32}^{n \times nsver}$
// Tally phase (backward sweep)
for $i = d - 1$ **downto** 0 **do**
  $\mathbf{W}\langle\!\langle\mathbf{Sigmas}[i]\rangle\!\rangle = \mathbf{NumSpInv} \oslash \mathbf{BCU}$
  $\mathbf{W}\langle\!\langle\mathbf{Sigmas}[i-1]\rangle\!\rangle = \mathbf{A} \oplus.\otimes\, \mathbf{W}$ // Add contributions by successors and mask with that BFS level's frontier.
  $\mathbf{BCU} \mathrel{\oplus}= \mathbf{W} \otimes \mathbf{NumSp}$
// Row reduce **BCU** and subtract $nsver$ from every entry to account for 1 extra value per **BCU** row element
$\mathbf{delta} = [\oplus_j \mathbf{BCU}(:, j)]$
$\mathbf{delta} \mathrel{\ominus}= nsver$

Algorithm 5: PageRank (used in Graphalytics).

Data: α constant (damping factor)
Result: ...

Function *PageRank*

$\mathbf{pr}(:) = 1/n$
$\mathbf{outdegrees} = [\oplus_j \mathbf{A}(:, j)]$
for $k = 1$ **to** $numIterations$ **do**
  $\mathbf{importance} = \mathbf{pr} \oslash \mathbf{outdegrees}$
  $\mathbf{importance} = times(\mathbf{importance}, \alpha)$ // apply the $times(x, s) = x \cdot s$ operator
  $\mathbf{importance} = \mathbf{importance} \oplus.\otimes\, \mathbf{A}$
  $\mathbf{danglingVertexRanks}\langle\neg\mathbf{outdegrees}\rangle = \mathbf{pr}(:)$
  $totalDanglingRank = [\oplus_i \mathbf{danglingVertexRanks}(i)(\otimes)]\frac{\alpha}{n}$
  $\mathbf{pr}(:) = \frac{1-\alpha}{n} \oplus totalDanglingRank$
  $\mathbf{pr}\langle\mathbf{importance}\rangle = \mathbf{pr} \oplus \mathbf{importance}$

Algorithm 6: Algebraic Bellman-Ford for SSSP.

Function *SSSP*
  $\mathbf{d}(s) = 0$
  for $k = 1$ **to** $n - 1$ **do**
    $\mathbf{dtmp} = \mathbf{d}$ min.plus $\mathbf{A}$
    if $\mathbf{dtmp} = \mathbf{d}$ **then**
      break
    $\mathbf{d} \leftarrowtail \mathbf{dtmp}$

Algorithm 7: Delta-stepping SSSP.

Data:
$\mathbf{A}, \mathbf{A_H}, \mathbf{A_L} \in \mathbb{Q}^{|V| \times |V|}$
$s, i \in \mathbb{N}$
$\Delta \in \mathbb{Q}$
$\mathbf{t}, \mathbf{t_{Req}} \in \mathbb{Q}^{|V|}$
$\mathbf{t_{B_i}}, \mathbf{e} \in \mathbb{N}^{|V|}$

Function *DeltaStepping*
  $\mathbf{A_L} = select(0 < \mathbf{A} \leq \Delta)$
  $\mathbf{A_H} = select(\Delta < \mathbf{A})$
  $\mathbf{t}(:) = \infty$
  $\mathbf{t}(s) = 0$
  while $nvals(select(i\Delta \leq \mathbf{t})) \neq 0$ **do**
    $s = 0$
    $\mathbf{t_{B_i}} = select(i\Delta \leq \mathbf{t} < (i + 1)\Delta)$
    while $\mathbf{t_{B_i}} \neq 0$ **do**
      $\mathbf{t_{Req}} = \mathbf{A_L}^\top \oplus.\otimes (\mathbf{t} \otimes \mathbf{t_{B_i}})$
      $\mathbf{e} = select(0 < \mathbf{e} \oplus \mathbf{t_{B_i}})$
      $\mathbf{t_{B_i}} = select(i\Delta \leq \mathbf{t_{Req}} < (i + 1)\Delta) \otimes (\mathbf{t_{Req}} \underset{\oplus}{\text{min}}\, \mathbf{t})$
    $\mathbf{t_{Req}} = \mathbf{A_H}^\top \oplus.\otimes (\mathbf{t} \otimes \mathbf{e})$
    $\mathbf{t} = \mathbf{t}$ min $\mathbf{t_{Req}}$
    $i = i + 1$

Algorithm 8: All-pairs shortest path (Floyd–Warshall algorithm).

Function *FloydWarshall*
  $\mathbf{D} \leftarrowtail \mathbf{A}$
  for $k = 1$ **to** n **do**
    $\mathbf{D} = \mathbf{D}$ min$[\mathbf{D}(:, k)$ min.plus $(\mathbf{D}(k, :)]$

Algorithm 9: FastSV algorithm.

```
Function FastSV
    n = nrows(A)
    gf = f
    dup = gf
    mngf = gf
    {I, X} ↤ f
    repeat
        // Step 1: Stochastic hooking
        mngf = mngf min A
        mngf = mngf second.min gf
        f(X) = f min mngf
        // Step 2: Aggressive hooking
        f = f min mngf
        // Step 3: Shortcutting
        f = f min gf
        // Step 4: Calculate grandparents
        {I, X} ↤ f
        gf = f(X)
        // Step 5: Check termination
        diff = dup ≠ gf
        sum = [⊕_i diff(i)]
        dup = gf
    until sum == 0
```

Algorithm 10: Triangle count (Cohen's algorithm).

```
Function TriangleCount
    L = tril(A)
    U = triu(A)
    B = L ⊕.⊗ U
    C = B ⊗ A
    t = [⊕_ij C(i, j)]/2
```

Algorithm 11: Triangle count (Sandia).

```
Function TriangleCount
    L = tril(A)
    C⟨L⟩ = L ⊕.⊗ L
    t = [⊕_ij C(i, j)]
```

Algorithm 12: Triangle count (FLAME).

```
Function TriangleCountFlame
    for i = 2 to n − 1 do
        A_20 = A(i + 1 : n, 0 : i − 1)
        a_10 = A(0 : i − 1, i)
        a_12 = A(i, i + 1 : n)
        t ⊕= a_10 ⊕.⊗ A_20 ⊕.⊗ a_12
```

Algorithm 13: Local clustering coefficient.

```
Function PageRank
    Tri⟨A⟩ = A ⊕.⊗ A          // compute triangle count matrix
    tri = [⊕_j Tri(:, j)]      // reduce to triangle count vector
    deg = [⊕_j A(:, j)]        // reduce to vertex degree vector
    wed = perm2(deg)           // apply perm2(x) = x · (x − 1) to get wedge count vector
    lcc = tri ⊘ wed            // LCC vector
```

Algorithm 14: k-truss algorithm.

```
Function KTruss
    C ↤ A
    nonzeros ↤ nvals(C)
    for i = 1 to n − 1 do
        C⟨C⟩ = C ⊕.land C
        C = select(C ≥ k − 2)
        if nonzeros == nvals(C) then
            break
        nonzeros ↤ nvals(C)
```

Algorithm 15: Louvain algorithm (WIP).

```
Function Louvain
    G ⊕= Gᵀ
    k = [⊕_j A(:, j)]
    m = ½[⊕_i k(i)]
    S ↤ I

    vertices_changed ↤ nvals(k)
    while vertices_changed > 0 do
        for j ∈ range(|V|) do
            v = G(j, :)
            t_q = v any.pair S
            sr = S(j, :)
            S(j, :) = empty

            q ↤ k
            q⟨k⟩ ⊗= −k(j)/m
            q ⊕= v
            q_1⟨t_q⟩ = q ⊕.⊗ S

            t = (q_1 == [max_i q_1(i)])
            while nvals(t) ≠ 1 do
                p = random() ⊗ t
                t = (p == [max_i p(i)])
            S(j, :) = t

            if nvals(sr ⊗ t) == 0 then
                vertices_changed = nvals(k)
            vertices_changed = vertices_changed − 1
```

Algorithm 16: Community detection using label propagation (for undirected graphs).

```
Function CDLP
    L ↤ diag([0, 1, ..., n − 1])
    for k = 1 to t do
        F = A any.second L                                    // Frequency matrix
        {I, ␣, X} ↤ F
        merge_sort_pairs(I, X)
        labels = for each row in I, select min mode value from X
```

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