



# ECE 508

## Manycore Parallel Algorithms

### Lecture 8: Triangle Counting for Graph Analytics

# Started Simple: with BFS

- In the last two lectures, we explored BFS,
  - a quick introduction to dynamic extraction and graph problems,
  - but not the most commonly used algorithm
  - (perhaps that might be shortest path?).

# Objective

- to become familiar with parallel graph analytics algorithms
- to understand triangle counting on undirected graphs,
  - a building block for community detection,
  - consider algorithm alternatives, and
  - discuss multi-GPU parallelization
- to understand a use case: truss decomposition

# Graphs Used to Represent Many Things

**Graphs are used to describe a myriad of relationships.**

- computational science relevance (example: bipartite graph between grid points and atoms within cutoff)
- physical path/location connectivity
- temporal relations between road use, movies, products, web pages
- social connections and relationships
- causal relations between events
- and many more...

# Can Obtain Information from Graph Structure

**One can mine a graph to get high-level information.**

- Which communities does an individual X belong to?
- Who are the leaders of community X?
- Which products did people buy after viewing product X?
- Which freeway sections are bottlenecks in X area?

And so forth.

# Graph Analysis Enables Insights

**Graph analysis produces “value”** of many companies.

- “Which web pages include <keyword>?” becomes  
“Which web page about <keyword>  
am I likely to want to read now?”
- “What smartphones are available?” becomes
  - “What’s the best deal on the phones I like?”, and
  - “Which screen protector should I buy,” and
  - “Do I need a portable battery?” and ...

Companies that answer the **transformed questions**  
**attract more customers.**

# Want to Find Communities in Graphs

- Some **graphs** already **have structured data**.
- Social networks, for example,
  - often have groups that individuals can join.
  - Group members are tagged as such.
- But **informal communities** are
  - often **as important or more important**, and
  - these **must be derived** from graph structure.
- Keep in mind that **a community is a set of nodes**—products, roads, movies, or anything else—not just people.

# Triangle Counting is Example and Building Block

We use **triangle counting as an example** of analysis.

- Triangles are the **foundation for finding communities**.
- Show how we can do more work on a graph in order to extract higher-level information.
- And talk about a use case: truss decomposition.



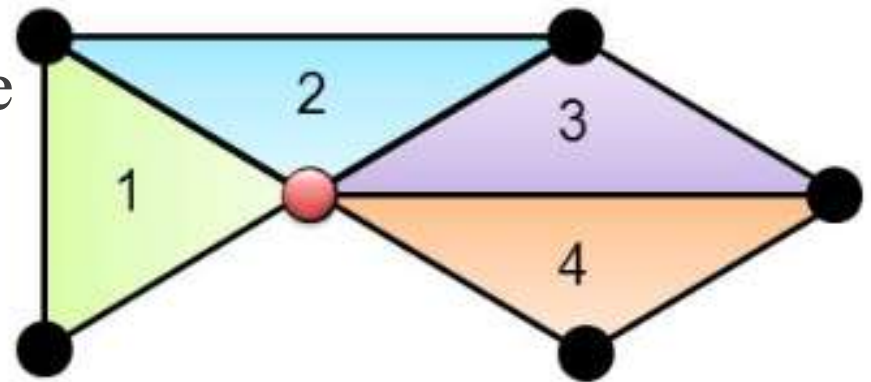
# Count Triangles to Measure Community Strength

- Count the number TC of triangles in a graph.

**What's a triangle?**

**A clique on 3 nodes.**

- A foundational function for community analysis:
  - **small TC means** the **community** is **weak**, while
  - **large TC means** the **community** is **strong**.



# Examine Two Approaches to Counting

**Approaches** to obtaining a graph's TC:

- **linear algebra**: use matrices to count triangles, and
- **neighbor intersection**: measure intersections between edge neighbor lists.

These are **equivalent**, so

- we can **mix** the approaches
- **to find** an **optimal** strategy.

Other approaches exist, such as counting graph isomorphisms, but we discuss only these two.

# Counting on Undirected Graph is Inefficient

Start with a simple, undirected graph.

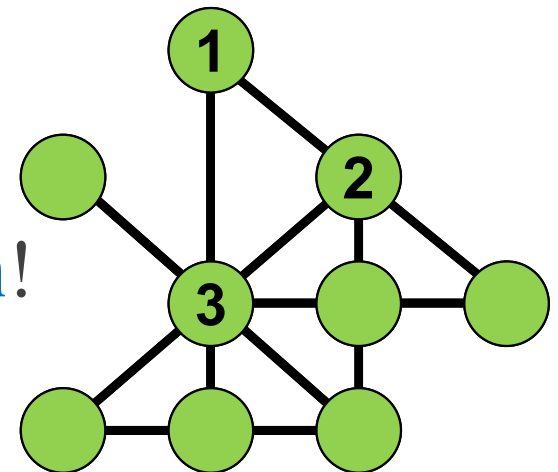
**What happens if we count triangles as discussed?**

Let  $N(n)$  be the set of neighbors of node  $n$ .

For the triangle 1-2-3,

- $3 \in N(1) \cap N(2)$ , so **count** it!
- $2 \in N(1) \cap N(3)$ , so **count ... again!**
- $1 \in N(2) \cap N(3)$ , a **third time!**

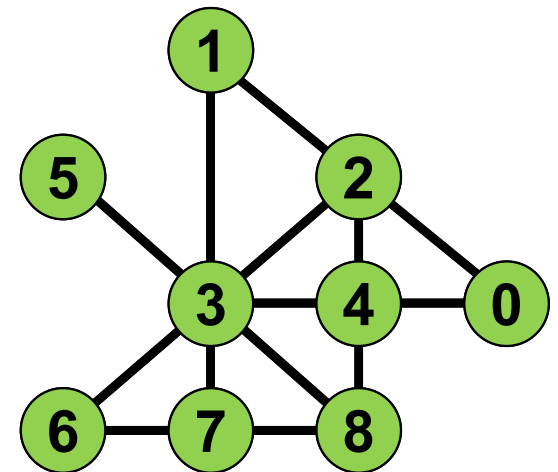
**When done, divide by three.**



# Use Total Order to Transform to Directed

- Instead, **choose a total order** on nodes.
  - Any order will do.
  - For example, node number:
    - $\text{dst} > \text{src}$ .
- **Keep** only **edges that obey the rule**.

**Transform into directed graph.**



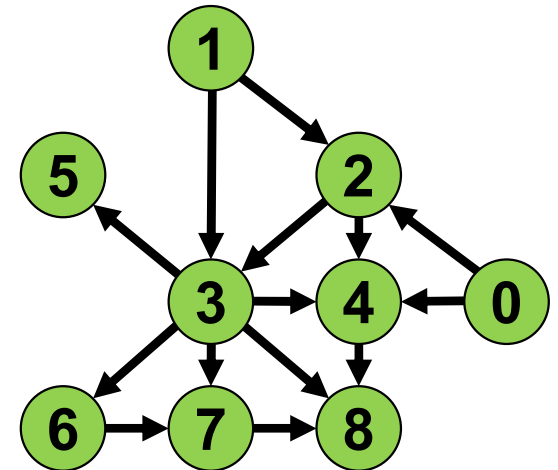
# Resulting Graph Avoids Triple Counting

**Now count triangles again.**

For the triangle 1-2-3,

- $3 \in N(1) \cap N(2)$ , so **count** it!
- $N(1) \cap N(3)$  is now empty.
- And  $N(2) \cap N(3) = \{4\}$  (no 3).

**Each triangle counted once!**



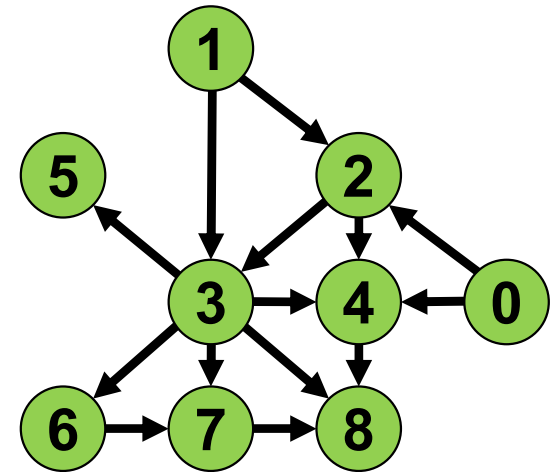
# Graph Rewriting Not Strictly Necessary

Do we need to rewrite the graph?

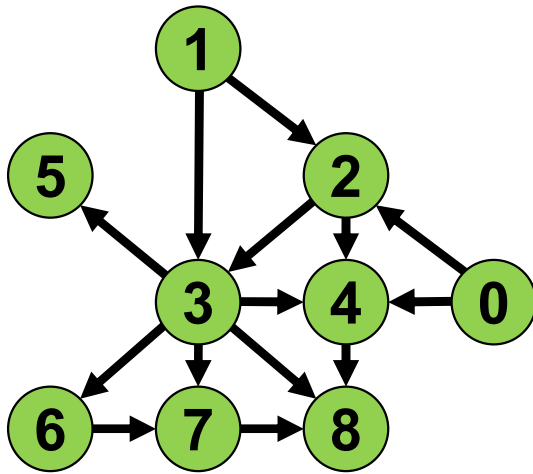
Not necessarily.

For example,

- if we pick node number as the total order,
- we **can ignore edges** with  $\text{dst} < \text{src}$
- **while counting** on the original graph.



# Graphs Represented as Adjacency Matrices



	destination								
	0	1	2	3	4	5	6	7	8
0			1		1				
1			1	1					
2				1	1				
3					1	1	1	1	1
4									1
5									
6								1	
7									1
8									

Practically,

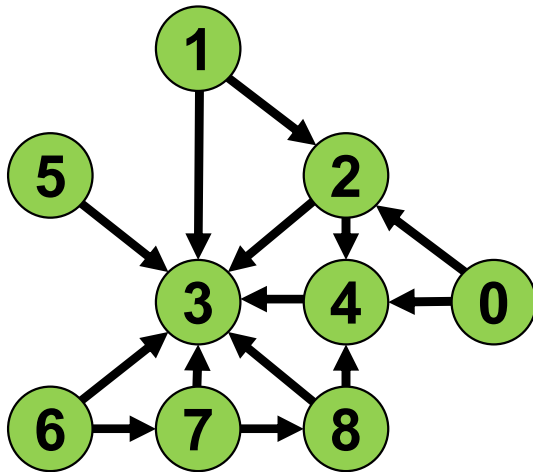
- use the **adjacency matrix**.
- Here it's upper diagonal.

# Many Options Possible for Total Order

- We saw use of node number:
  - $\text{dst} > \text{src}$  : upper-triangular matrix, and
  - $\text{dst} < \text{src}$  : lower-triangular matrix.
- Alternatively, we could use node degree:
  - $d(\text{dst}) > d(\text{src})$ , or by node number for ties.



# Adjacency Matrix with Degree as Total Order



Using node degree,  
we obtain this graph.

		destination								
		0	1	2	3	4	5	6	7	8
source	0			1		1				
	1			1	1					
	2				1	1				
	3									
	4				1					
	5				1					
	6				1				1	
	7				1					1
	8				1	1				

# Side-by-Side Adjacency Matrix Comparison

		destination								
		0	1	2	3	4	5	6	7	8
source	0			1		1				
	1			1	1					
	2				1	1				
	3					1	1	1	1	1
	4									1
	5									
	6								1	
	7									1
	8									

$\text{dst} > \text{src}$

		destination								
		0	1	2	3	4	5	6	7	8
source	0			1		1				
	1			1	1					
	2				1	1				
	3									
	4				1					
	5				1					
	6				1				1	
	7				1					1
	8				1	1				

$d(\text{dst}) > d(\text{src})$

# Different Orders Give Different Properties

- What's the **advantage of** using **node numbers**?
  - No need for graph-wide properties, so can
  - **stream through graph** and write out in one pass.
- What's the **advantage of** using **degree**?
  - **Fewer high-degree nodes**, thus
  - potentially **better load balancing**, but
  - need whole graph to do conversion.

# Counting Triangles with Linear Algebra

Given adjacency matrix  $A$ ,

- **compute  $(A \times A) \cdot A$** , where
- $\times$  is matrix multiplication, and
- $\cdot$  is element-wise multiplication.

Let's do a couple of examples...

# Element (6,3) Counts One Triangle

		1		1				
		1	1					
			1	1				
			1					
			1					
			1				1	
			1	1				

×

		1		1				
		1	1					
			1	1				
			1					
			1					
			1				1	
			1					1
			1	1				

Compute element **(6,3)**.

- Inner product sums to 1.
- **$A(6,3) = 1$** , so per-element multiplication gives **1**.

# Element (0,3) Counts Zero Triangles

		1		1				
		1	1					
			1	1				
			1					
			1					
			1				1	
			1					1
			1	1				

×

		1		1				
		1	1					
			1	1				
			1					
			1					
			1				1	
			1					1
			1	1				

Compute element **(0,3)**.

- Inner product sums to 2.
- **$A(0,3) = 0$** , so per-element multiplication gives **0**.

# How Does the Computation Work?

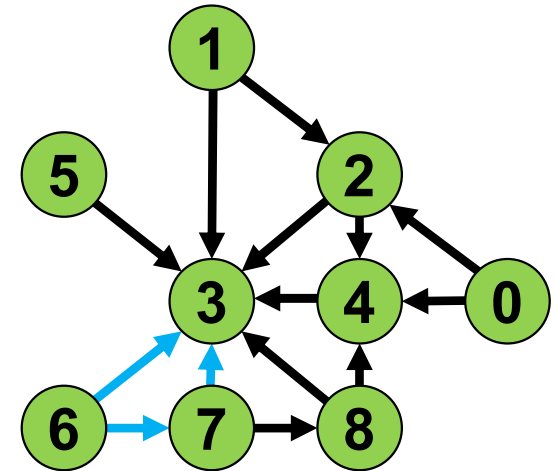
## Element (6,3)

- produced **one triangle**.
- It's shown to the right.

## Element (0,3)

produced **no triangles**.

**Does the computation work?**



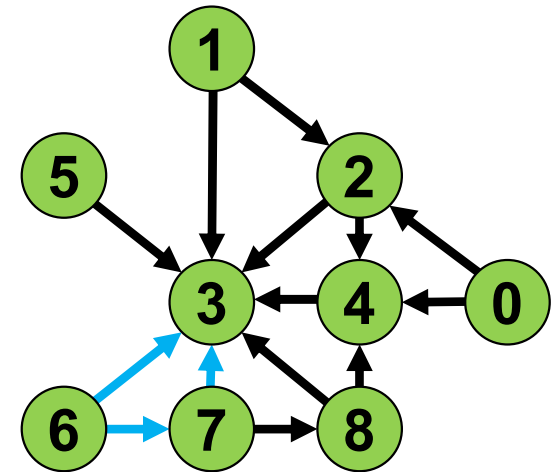
## Combine Two-Hop Paths with Edge Information

Element  $(u,v)$  from matrix multiply

$$P_{uv} = \sum_{w=1}^N A_{uw}A_{wv}$$

**computes** the **number of two-hop paths** from  $u$  to  $v$ .

The **element-wise multiplication** **retains** only those **elements for which  $(u,v)$  is in the graph**.





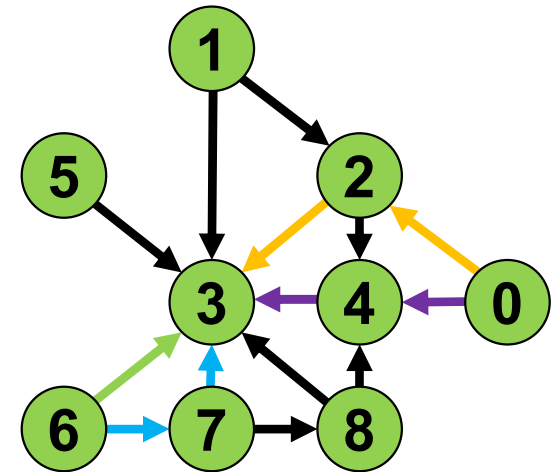
# Each Element Counts One Edge's Triangles

Element (6,3)

- one 2-hop path:  $6 \rightarrow 7 \rightarrow 3$ ,
- and  $(6,3)$  is in graph, so
- one triangle.

Element (0,3)

- two 2-hop paths
  - $0 \rightarrow 2 \rightarrow 3$
  - $0 \rightarrow 4 \rightarrow 3$
- but  $(0,3)$  is not in the graph!



# Complete Computation Gives Six Triangles

$$\begin{bmatrix} & & 1 & & 1 & & & & \\ & & 1 & 1 & & & & & \\ & & & 1 & 1 & & & & \\ & & & & & & & & \\ & & & & 1 & & & & \\ & & & & 1 & & & & \\ & & & & 1 & & & 1 & \\ & & & & 1 & & & & 1 \\ & & & & 1 & 1 & & & \end{bmatrix}^2 = \begin{bmatrix} & & & 2 & 1 & & & & \\ & & & 1 & 1 & & & & \\ & & & 1 & & & & & \\ & & & & & & & & \\ & & & & & & & & \\ & & & & & & & & \\ & & & & & & & & \\ & & & & & & & 1 & \\ & & & & 1 & 1 & & & 1 \\ & & & & 1 & & & & \end{bmatrix}$$

Squared adjacency matrix shown on right.

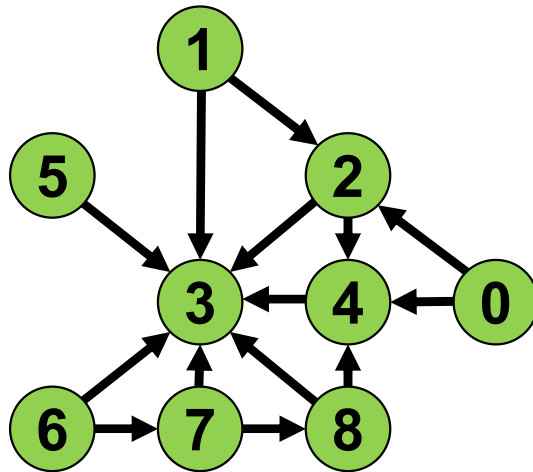
Highlighted terms retained in element-wise multiplication.

**Six triangles total.**

# Algebraic Approach Slow for Sparse Graphs

- The idea is **a starting point**:
  - reasonable for dense matrices, but
  - highly **inefficient for sparse matrices**.
- In practice, for example,
  - only compute matrix elements that matter
  - (no edge, no computation).

## Can Also Count Using Neighbor Set Intersection



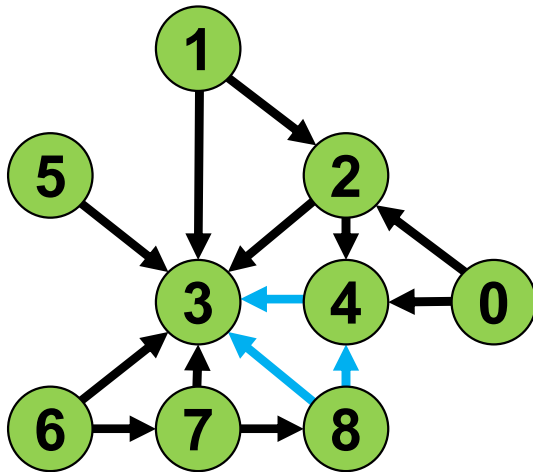
		destination								
		0	1	2	3	4	5	6	7	8
source	0			1		1				
	1			1	1					
	2				1	1				
	3									
	4				1					
	5				1					
	6				1				1	
	7				1					1
	8				1	1				

For each edge  $(u,v)$ ,

**count**  $| N(u) \cap N(v) |$  **triangles**

(cardinality of intersection of neighbors of  $u$  and  $v$ ).

# Edge (8,4) Produces One Triangle



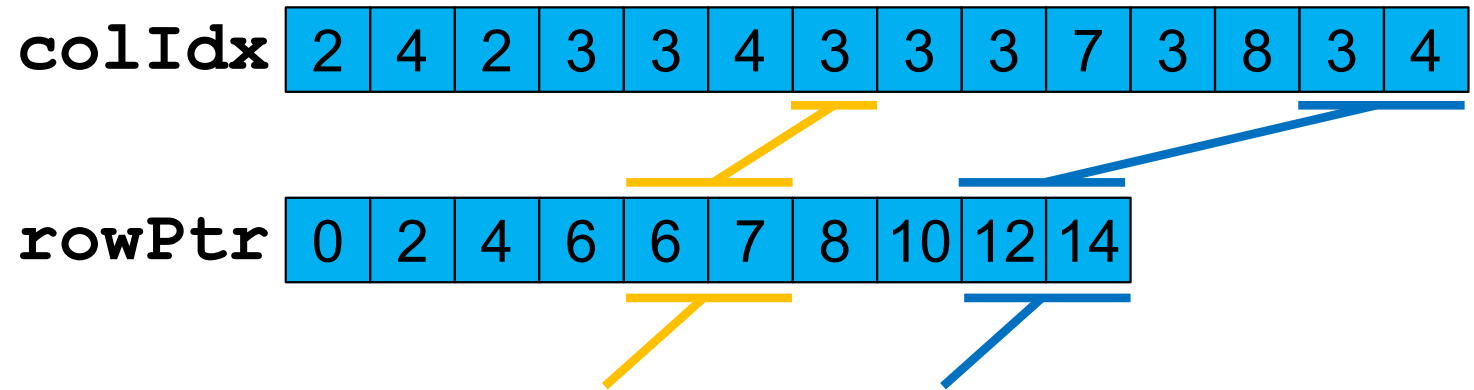
		destination								
		0	1	2	3	4	5	6	7	8
source	0			1		1				
	1			1	1					
	2				1	1				
	3									
	4				1					
	5				1					
	6				1				1	
	7				1					1
	8				1	1				

Consider edge (8,4):

$$N(8) \cap N(4)$$

$$= \{3,4\} \cap \{3\} = \{3\} \text{ (one triangle)}$$

# Execute Intersection on CSR Format



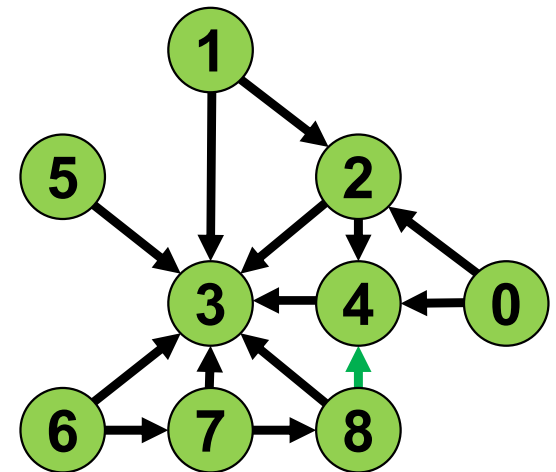
Let's look at our graph in CSR form.

Consider edge (8,4):

**Node 8 ... {3, 4}**

**Node 4 ... {3}**

Intersect to find one triangle.



# Add COO-Style Row Indices to Find Edges

**rowIdx**

0	0	1	1	2	2	4	5	6	6	7	7	8	8
---	---	---	---	---	---	---	---	---	---	---	---	---	---

**colIdx**

2	4	2	3	3	4	3	3	3	7	3	8	3	4
---	---	---	---	---	---	---	---	---	---	---	---	---	---

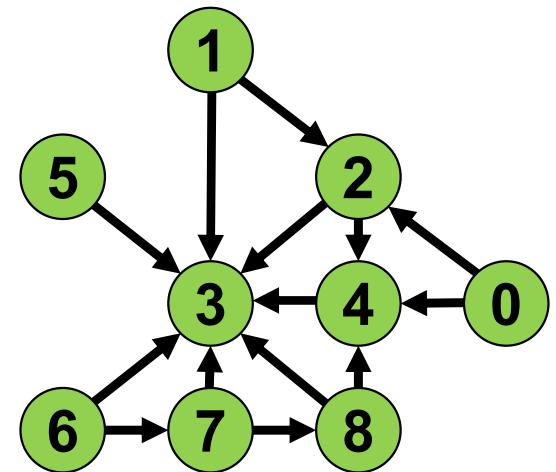
**rowPtr**

0	2	4	6	6	7	8	10	12	14
---	---	---	---	---	---	---	----	----	----

**Parallelize** over **edges** (**colIdx** array),  
but ... **colIdx** gives **v** from **(u,v)**.

**Where is u?**

**Add an array of row indices!**

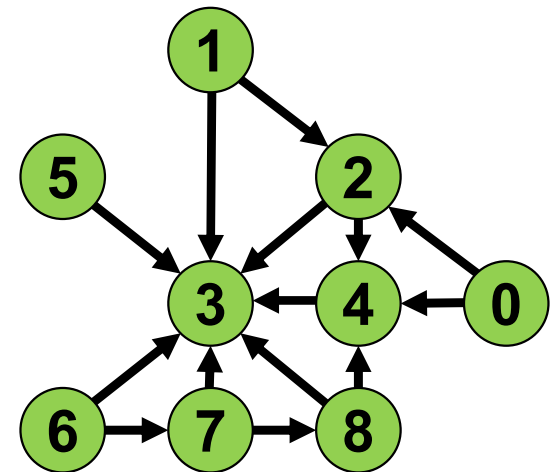


# Still Need rowPtr Array to Find Neighbors

rowIdx	0	0	1	1	2	2	4	5	6	6	7	7	8	8
colIdx	2	4	2	3	3	4	3	3	3	7	3	8	3	4
rowPtr	0	2	4	6	6	7	8	10	12	14				

Why do we still need rowPtr?

To find  $N(u)$  and  $N(v)$ !





# How Does One Find an Intersection?

Now we have two neighbor lists...

**How do we compute set intersection?**

Let  $U \equiv |N(u)|$ ,  $V \equiv |N(v)|$ .

Assume w.l.o.g. that  $U \leq V$ .

**Are the two lists sorted?**

# Intersecting Sorted Lists is Fast

(sorted lists,  $U \leq V$ )

- **linear search**
  - similar to merge sort
  - **complexity**  $O(U + V) = O(V)$
  - parallelization a bit tricky—discussed later
- **binary search** (find elements of  $U$  in  $V$ )
  - **complexity**  $O(U \log V)$
  - parallelizes more easily,  
but better with dynamic parallelism

# Intersecting Unsorted Lists is Less Fast

(**unsorted lists**,  $U \leq V$ )

- **linear search**
  - **complexity**  $O(UV)$
  - easy to parallelize
- **hash**
  - **complexity**  $O(U + V) = O(V)$
  - requires  $O(U)$  **extra memory**
  - easy to parallelize lookups

# Unsorted Lists Can Be Sorted

(unsorted lists,  $U \leq V$ )

- sort both lists first,
  - then use linear search
  - complexity  $O(U \log U + V \log V) = O(V \log V)$
- sort  $(N(U))$  first,
  - then use binary search
  - complexity  $O(U \log U + V \log U) = O(V \log U)$

Sorting is a completely different kernel!

# Pseudo-Code for a Triangle Counting Kernel

(**thread T** executes the following)

**TC**  $\leftarrow$  0

**uPtr**  $\leftarrow$  **rowPtr**[**rowIdx**[**T**]]

**uEnd**  $\leftarrow$  **rowPtr**[**rowIdx**[**T**] + 1]

**vPtr**  $\leftarrow$  **rowPtr**[**colIdx**[**T**]]

**vEnd**  $\leftarrow$  **rowPtr**[**colIdx**[**T**] + 1]

**w**<sub>1</sub>  $\leftarrow$  **colIdx**[**uPtr**]

**w**<sub>2</sub>  $\leftarrow$  **colIdx**[**vPtr**]

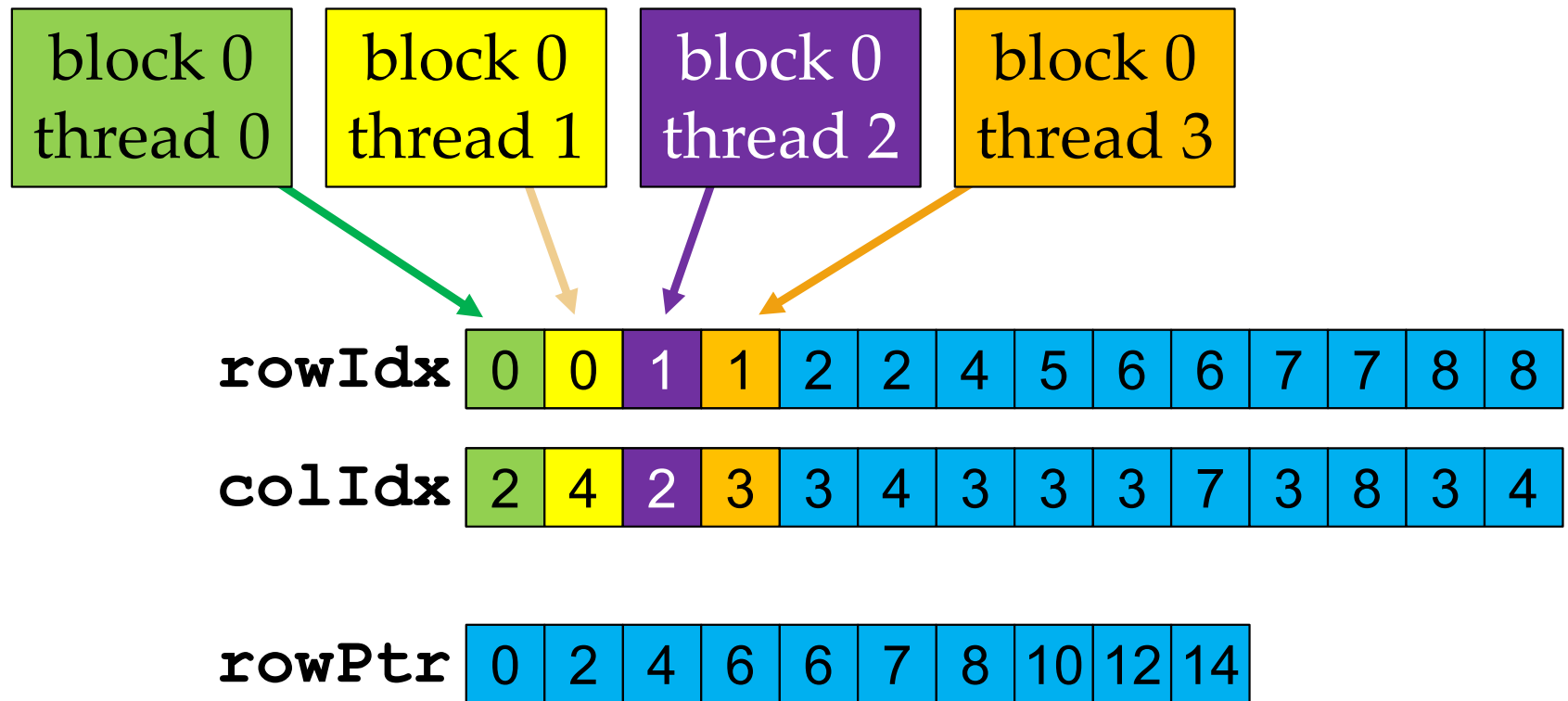
Warning:  
includes a bug.

# Pseudo-Code for a Triangle Counting Kernel

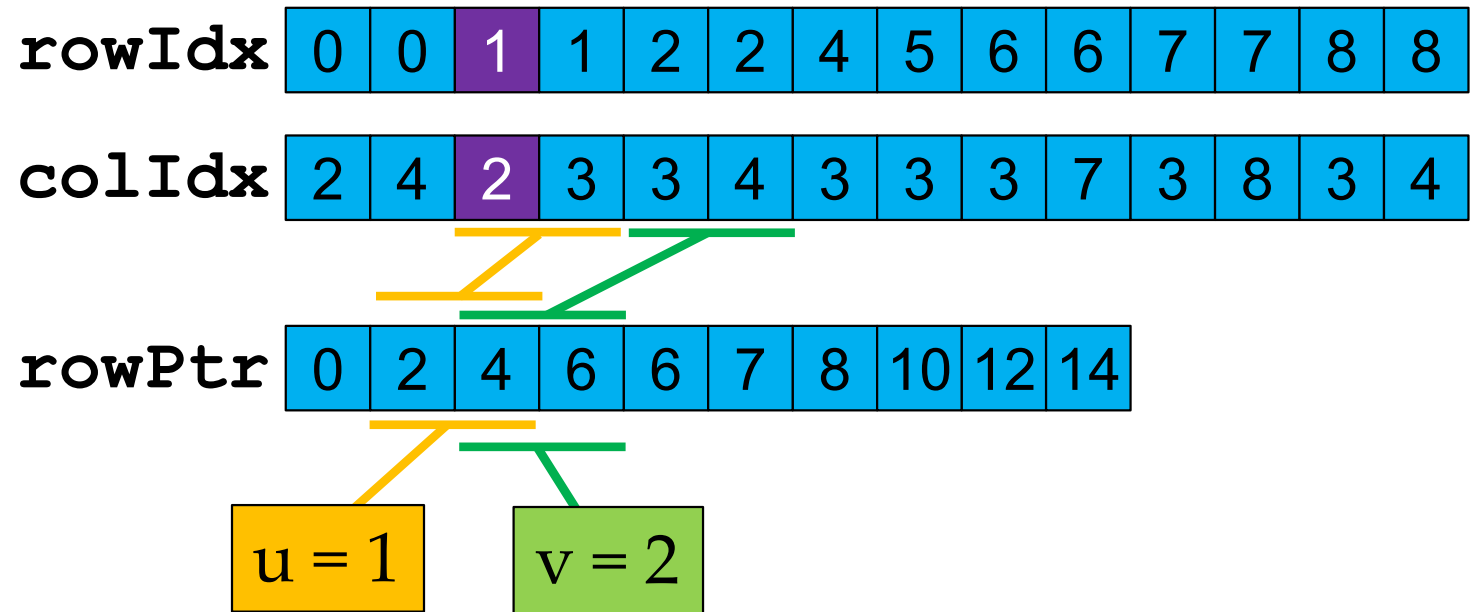
(**thread T** executes the following)

```
while (uPtr < uEnd) ^ (vPtr < vEnd)
  if  $w_1 < w_2$  then  $w_1 \leftarrow \text{colIdx}[++uPtr]$ 
  else if  $w_1 > w_2$  then  $w_2 \leftarrow \text{colIdx}[++vPtr]$ 
  else if  $w_1 = w_2$  then
     $w_1 \leftarrow \text{colIdx}[++uPtr]$ 
     $w_2 \leftarrow \text{colIdx}[++vPtr]$ 
    ++TC
  end if
end while
```

# Each Thread Handles One Edge

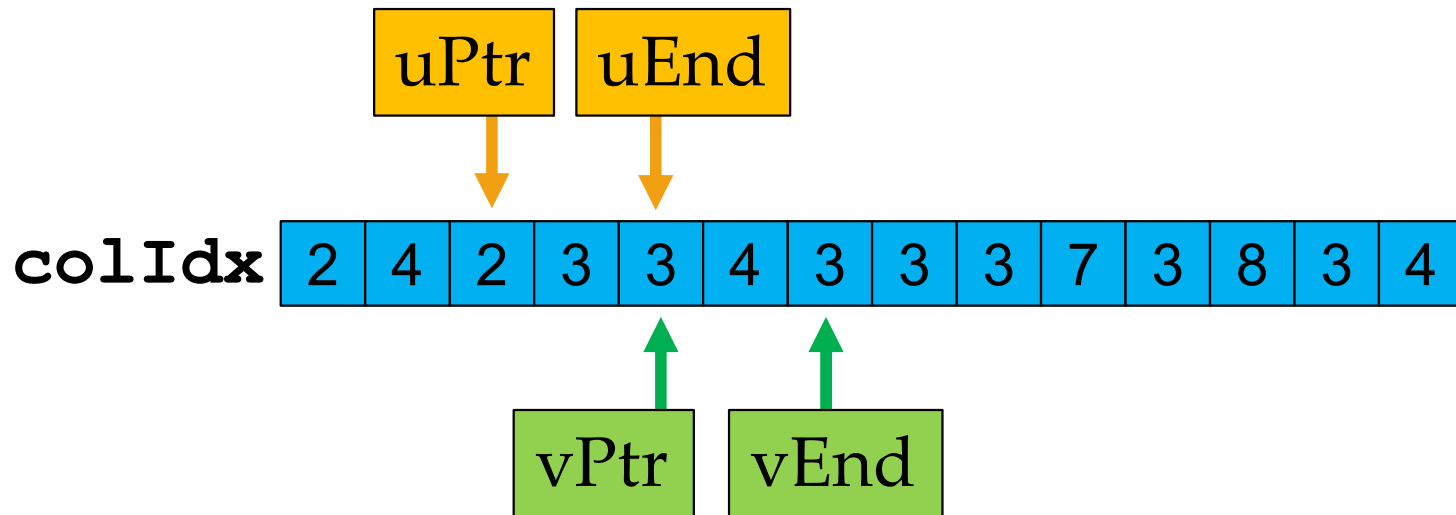


# Thread 2 Looks Up Neighbor List Indices





## Thread 2 Executes the Search Loop (Iter. #1)

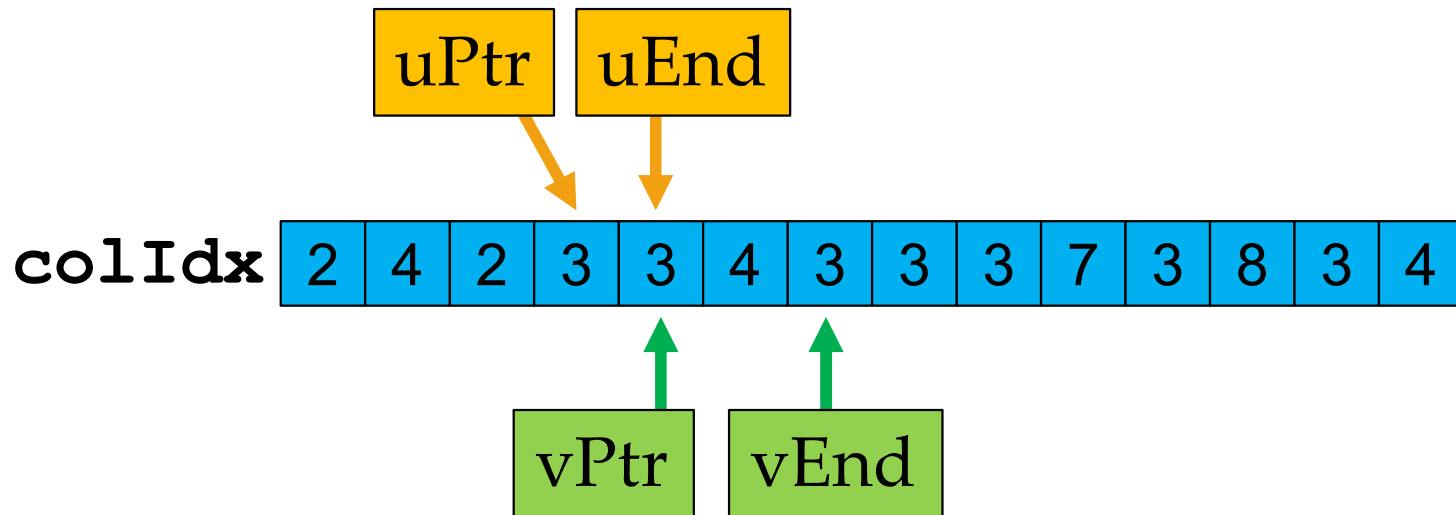


$$TC = 0, w_1 = 2, w_2 = 3$$

$$w_1 < w_2$$

Advance `uPtr` and set  $w_1$  to 3.

## Thread 2 Executes the Search Loop (Iter. #2)

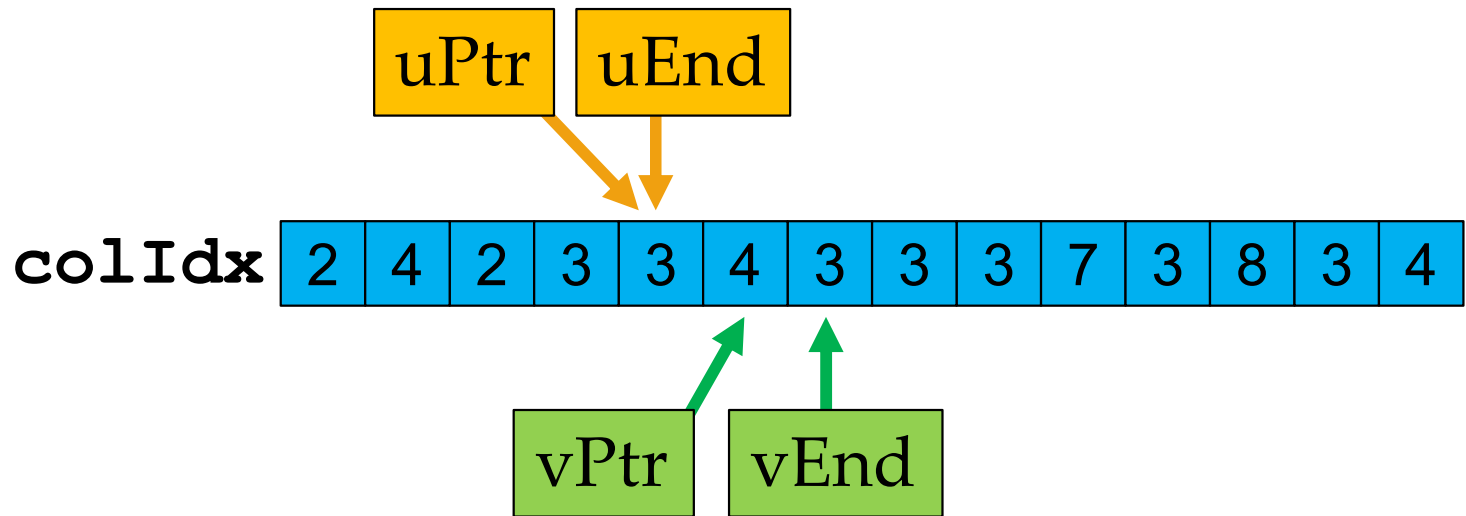


**TC = 0,  $w_1 = 3$ ,  $w_2 = 3$**

**A match!**

**Advance `uPtr` and `vPtr`, and increment TC.**

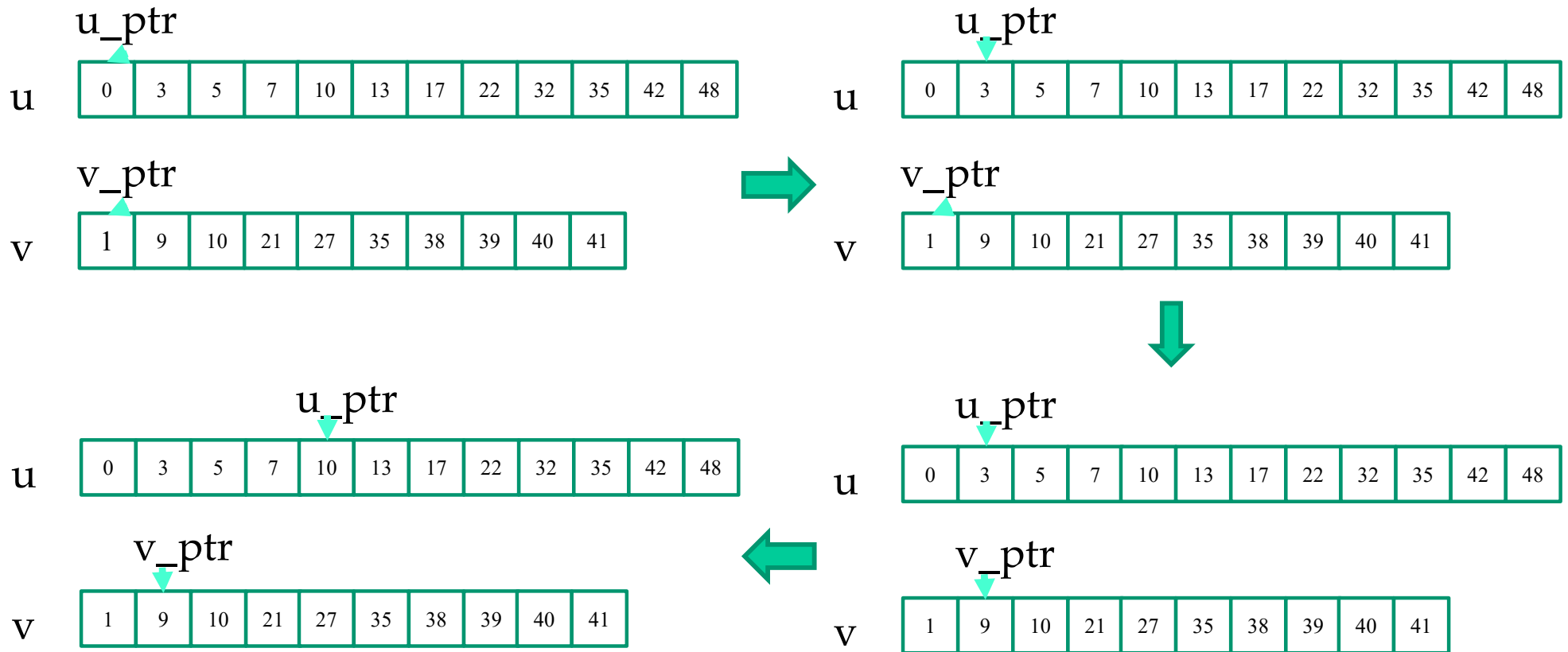
## Thread 2 Executes the Search Loop (Ends)



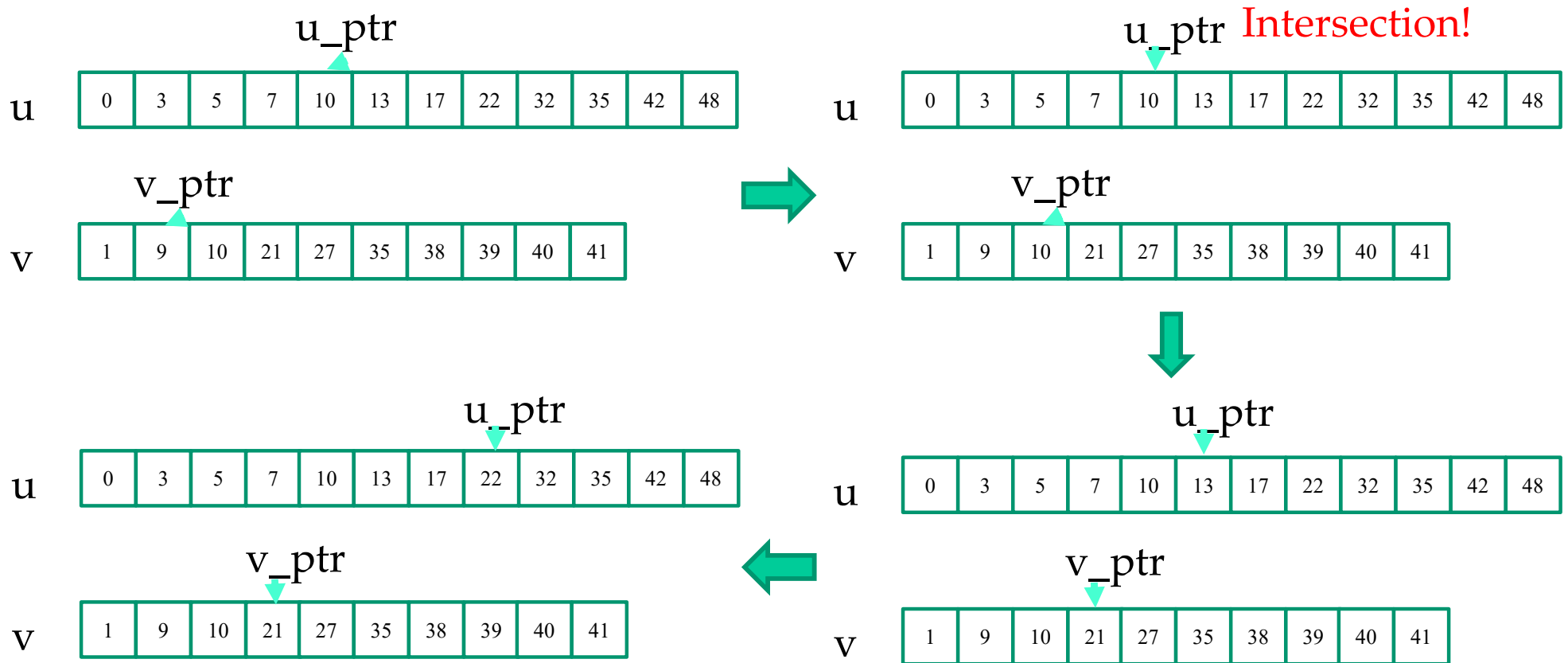
**TC = 1, uPtr = uEnd**

**All done! Found 1 triangle.**

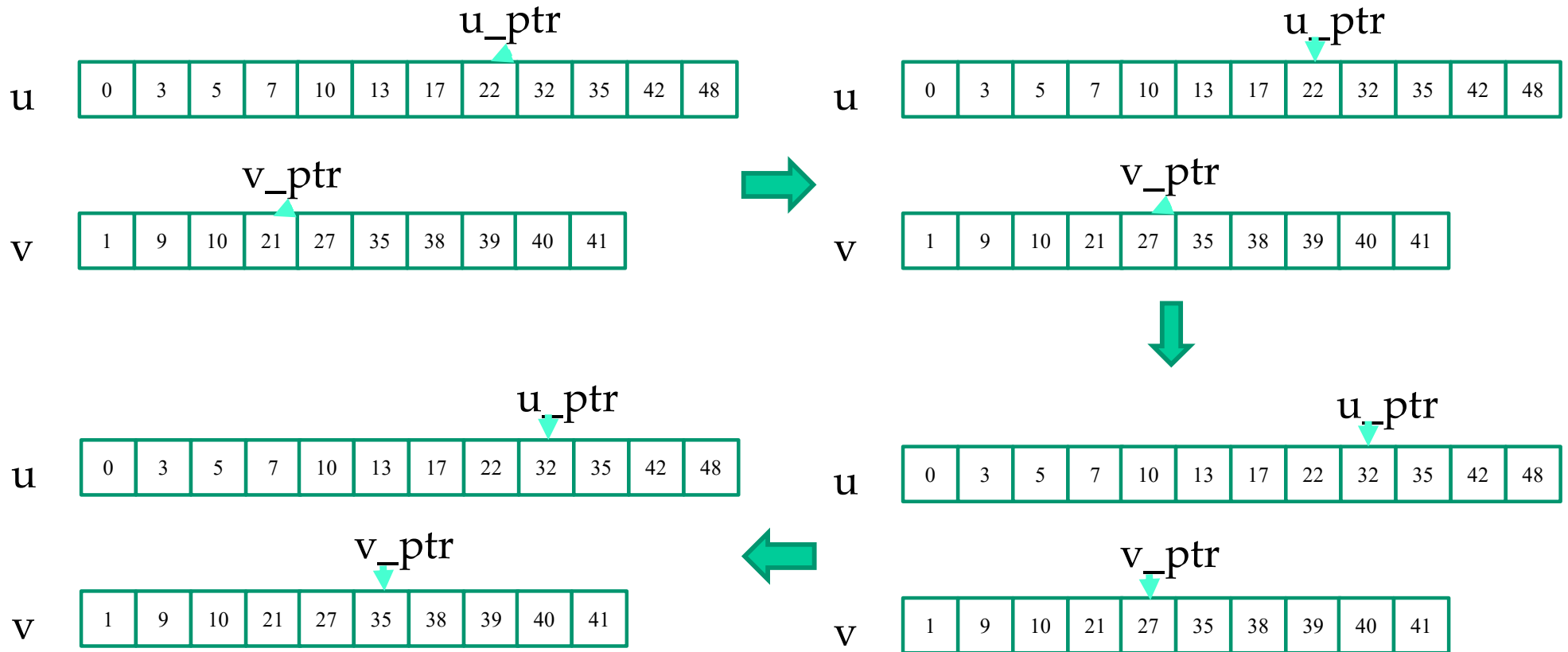
# Longer Example of Intersection (1 of 4)



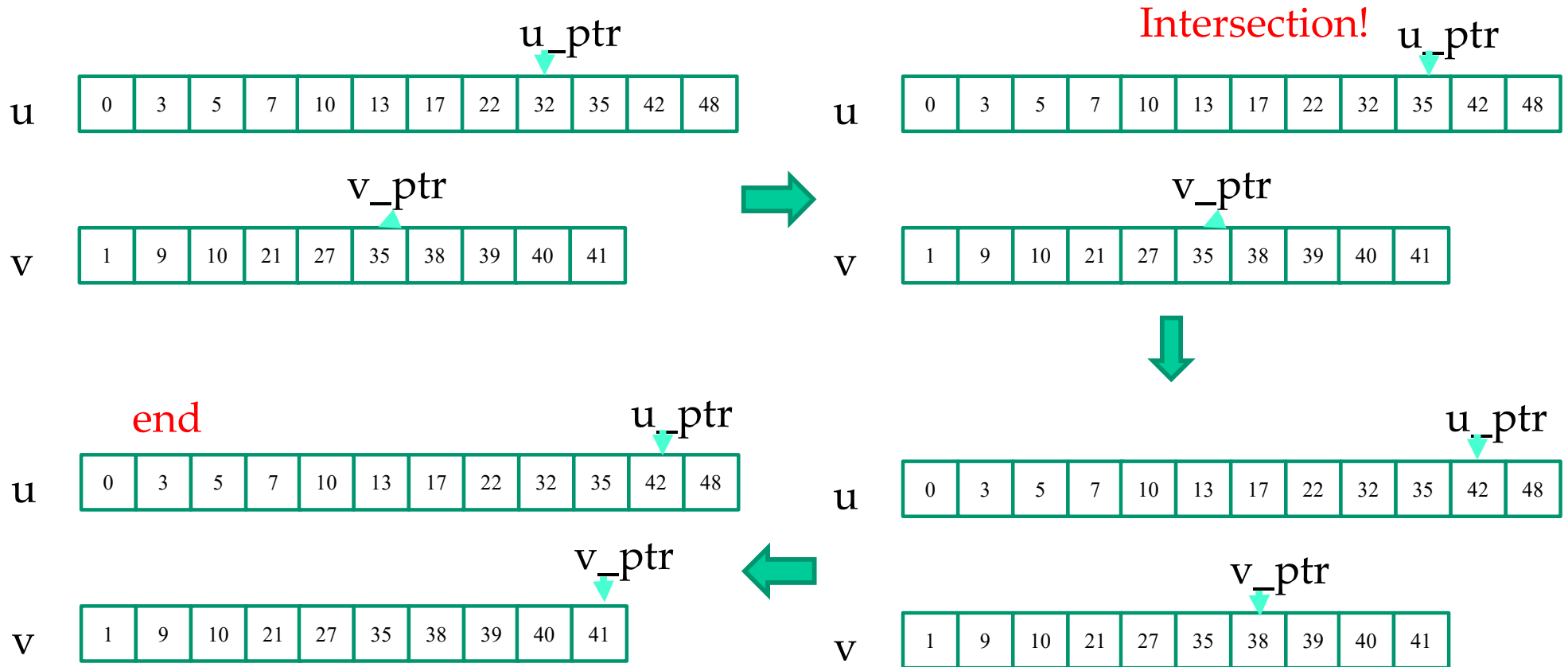
# Longer Example of Intersection (2 of 4)



# Longer Example of Intersection (3 of 4)

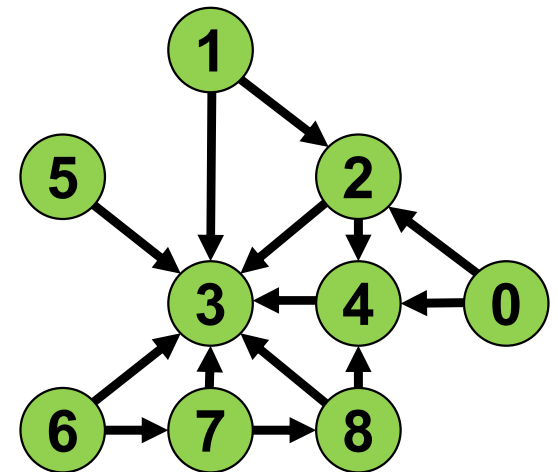


# Longer Example of Intersection (4 of 4)



# Need to Reduce Per-Thread TC to Graph TC

- When done,
  - **reduce TC over threads and blocks**
  - to find total TC for graph.
- **Works reasonably well** for small, balanced neighbor lists.
- That's the basic **approach for Lab 6.**





# Control Divergence May be a Problem

Each thread

- ping-pongs between
- advancing uPtr and
- advancing vPtr.

May lead to **significant branch divergence!**\*

\*Take a look at the `__syncwarp` function,  
which may be useful on Titan V (Volta) GPUs.

# Load Imbalance Also a Problem

Neighbor list **intersection parallelized** across edges.

- **Variable** neighbor **list length creates load imbalance.**
- Some threads take much more time to finish.

Thread 1



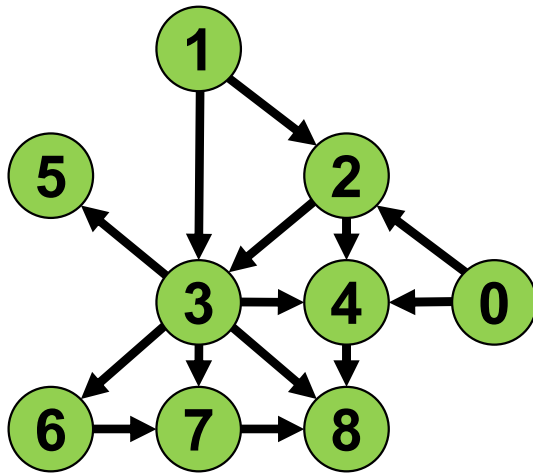
Thread 2



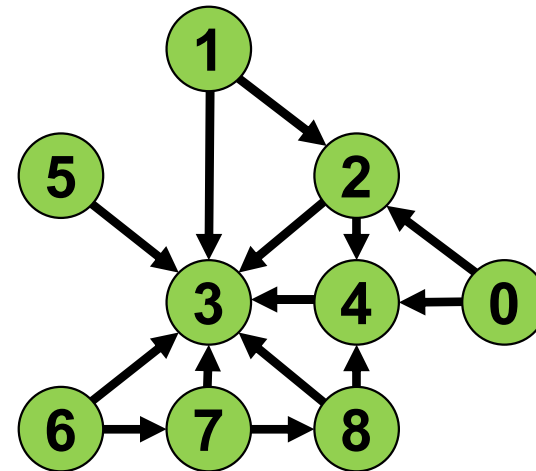
# Total Order Selection Affects Load Balance

Load imbalance is why the total order chosen can matter.

Remember our two versions?



Node degrees are  
2,2,2,**5**,1,0,1,1,0



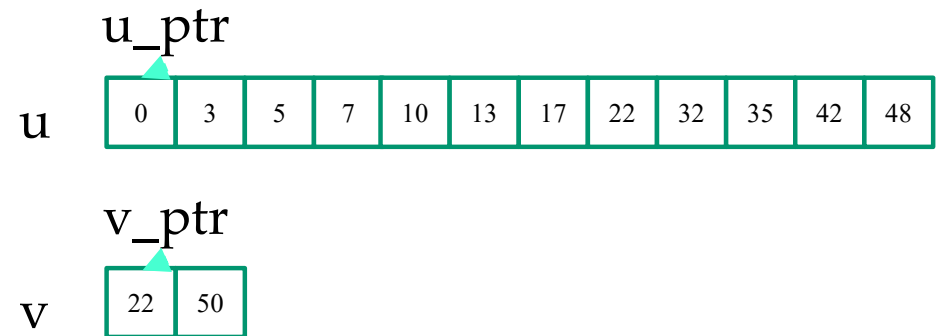
Node degrees are  
2,2,2,0,1,1,2,2,2

# Complexity $O(U+V)$ Requires TWO Short Lists

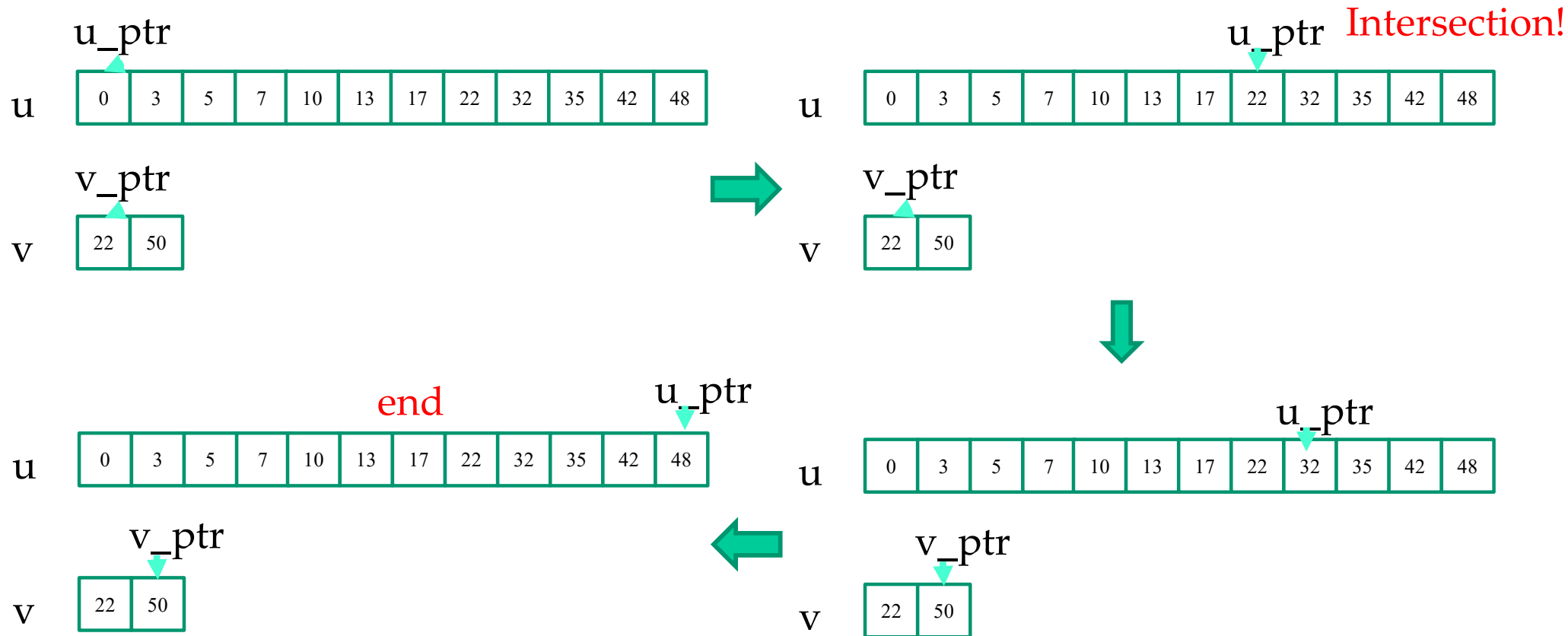
## One short list

- **does not** imply that
- a thread **finishes quickly**.

Consider the lists below.



# Long vs. Short List Can Run Long



# Overheads May Outweigh Gains in Balancing Load

## What can we do about long-running threads?

- Analogous to exam grading:
  - 5 staff, 5 problems
  - One problem per staff
  - But one problem is hard to grade...
- Can other staff help? Fairly and consistently?
- Or does the time to “train” them (coordinate, launch kernels, change algorithm, and so forth) cost more than just waiting for the thread to finish?

# First Option: Switch to Binary Search

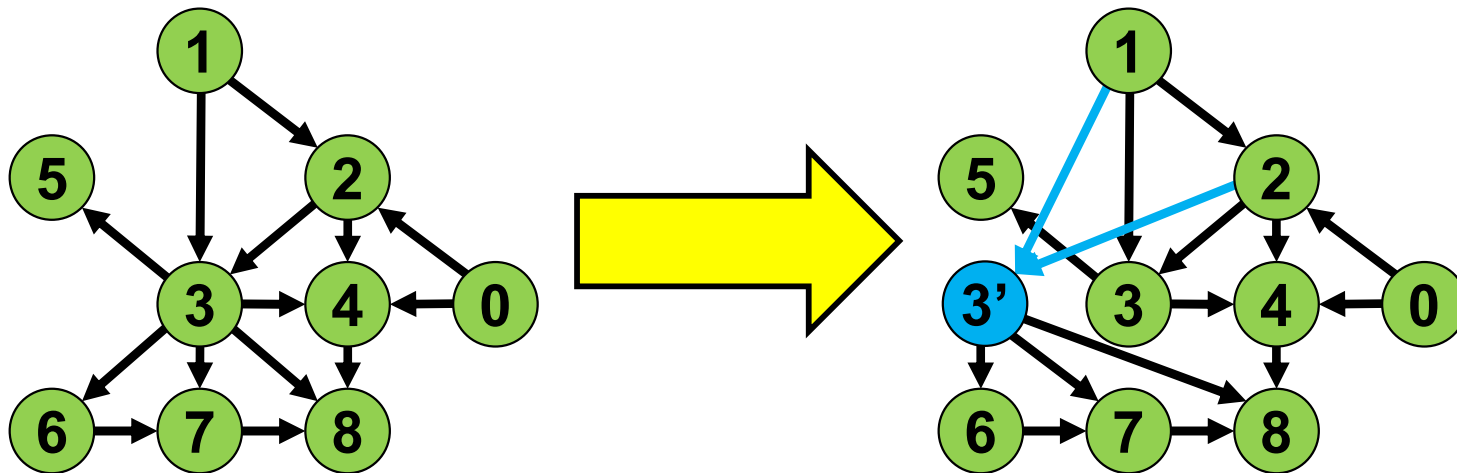
**One option: switch to binary search.**

- **Find** elements of **short list (U)** in **long list (V)**
- Be careful:
  - complexity  **$O(U \log V)$**  instead of  **$O(V)$** , so
  - **need  $U < V / \log V$**  to be competitive.
  - But remember that one thread running by itself means 31 other resources unused.
- **Can parallelize  $N(u)$  across threads;**  
doing so does not reduce complexity.

## Second Option: Break into Pieces

**Alternatively, break long list into pieces.**

- Can **parallelize** search **over pieces**.
- Be careful: **complexity is  $O(UV)$ !**
- Equivalently, can split nodes statically.



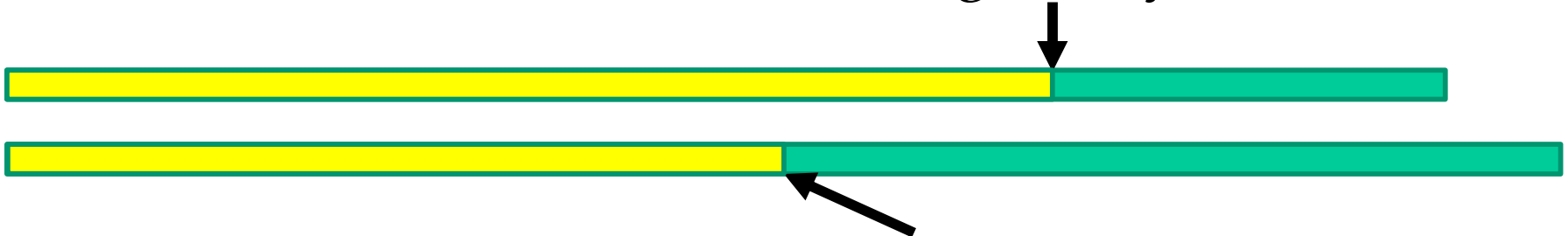


# Use Binary Search to Partition

## What if both lists are long?

- **Splitting both** lists can be **expensive!**
- But maybe **not so bad if done thoughtfully...**

3. Repeat as necessary.      2. Find where splitter should go (may not be even).



4. Compare sections.      1. Pick midpoint as splitter.

# Lots of Room for Tuning and Techniques

Lots of Ph.Ds written (and more available!) trying to optimize graph representations and algorithms.

The **solutions discussed**

- **require new kernels** (to get more threads).
- **Next week**, we'll talk about **dynamic parallelism** in CUDA, which allows one to launch kernels from kernels.

# Performance Depends on Input Graph

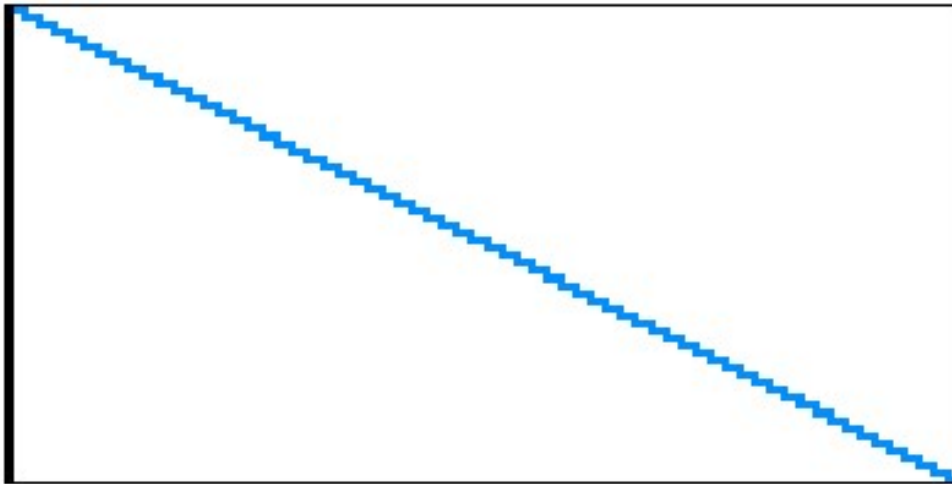
- Let's take a look at some examples:
  - SuiteSparse Matrix Collection\*  
(<https://sparse.tamu.edu/>).
  - Many types, many irregular connections.
- One architecture does not fit all.

\*T.A. Davis, Y. Hu, “The University of Florida Sparse Matrix Collection,”  
ACM Transactions on Mathematical Software 38(1), Article 1, Dec. 2011.

# Example 1: Linear Programming

A linear programming problem:

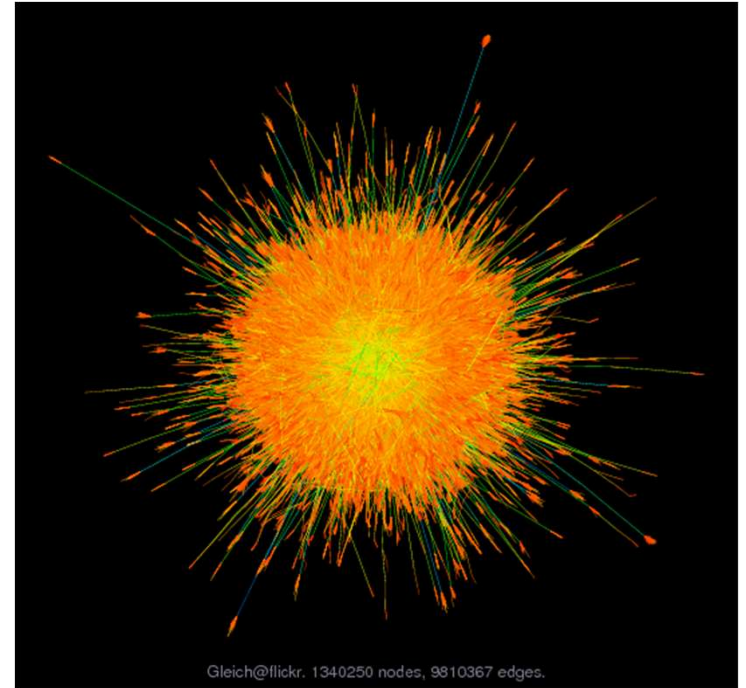
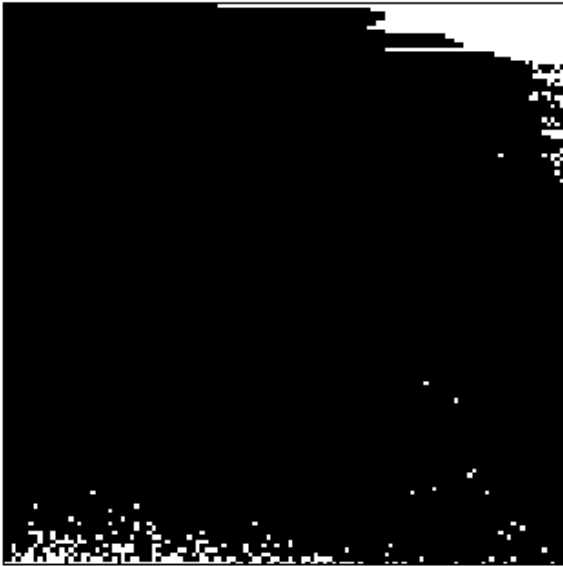
- C. Mészáros' test set
- ID: Mészáros/aircraft



## Example 2: Photo Management

Photo management app:

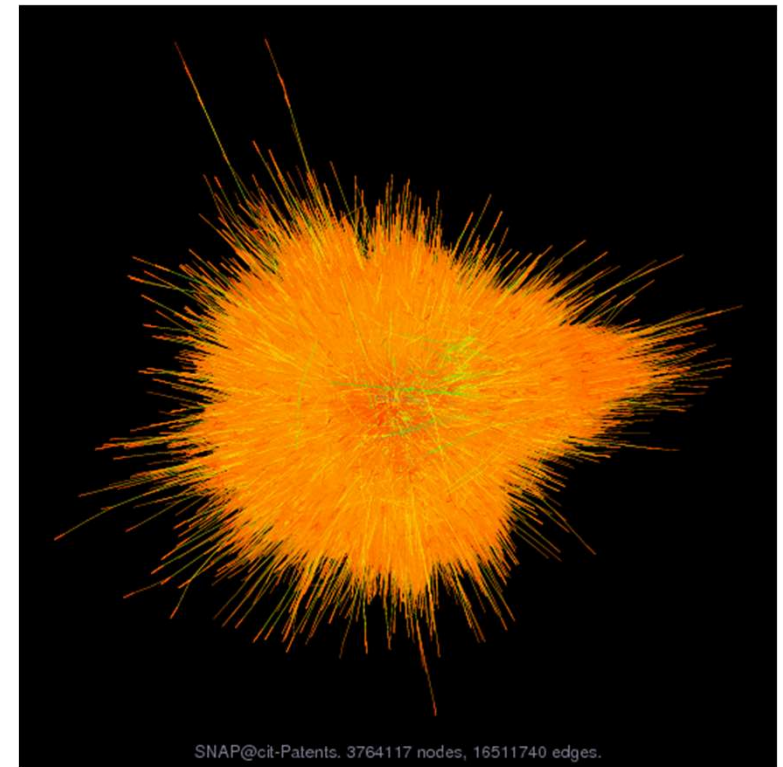
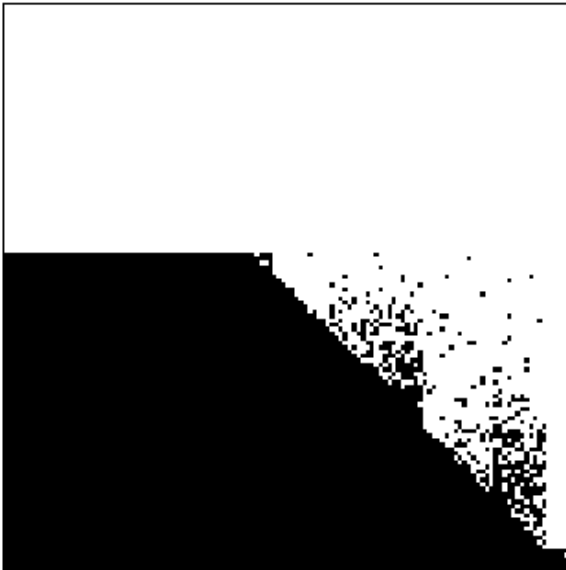
- David Gleich's 2005 crawl of flickr.com
- ID: Gleich/flickr.html



## Example 3: Patent Citations

Relationships between patents:

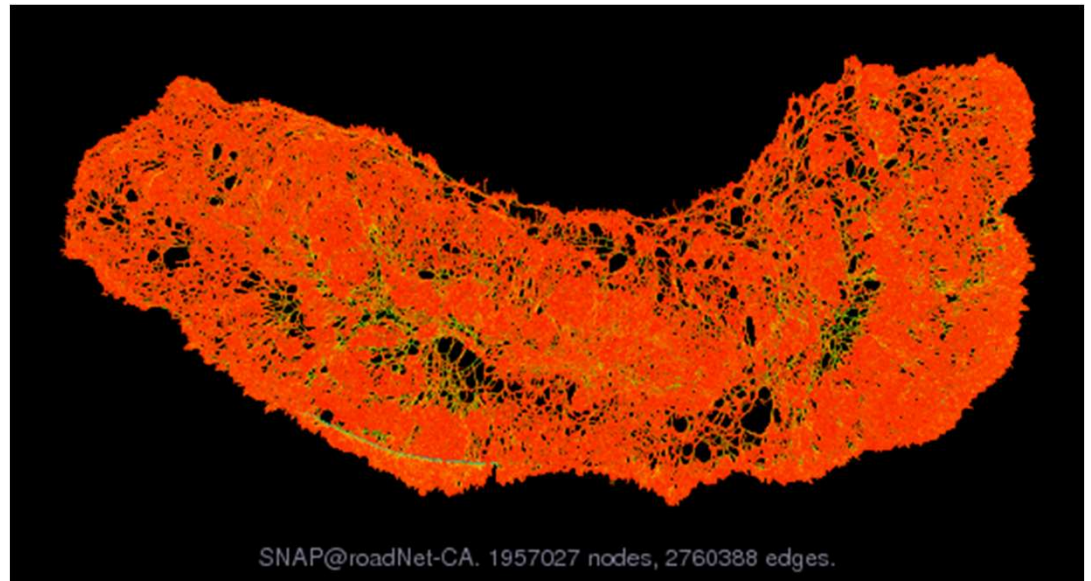
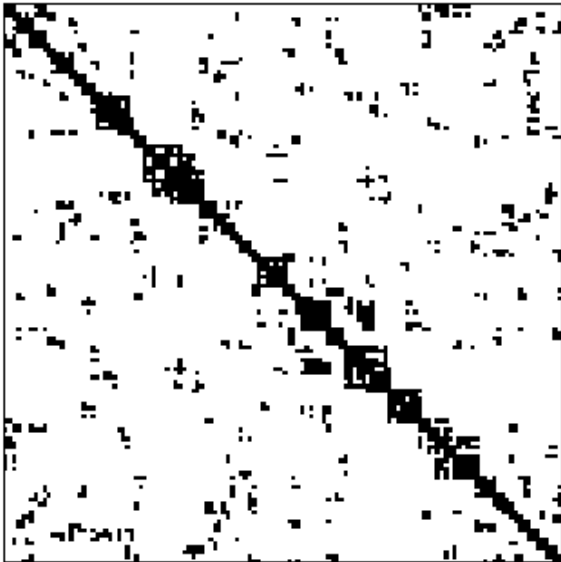
- citations amongst US patents
- ID: SNAP/cit-Patents.html



## Example 4: California Road Network

Relationships between roads:

- road network in California
- ID: SNAP/roadNet-CA.html

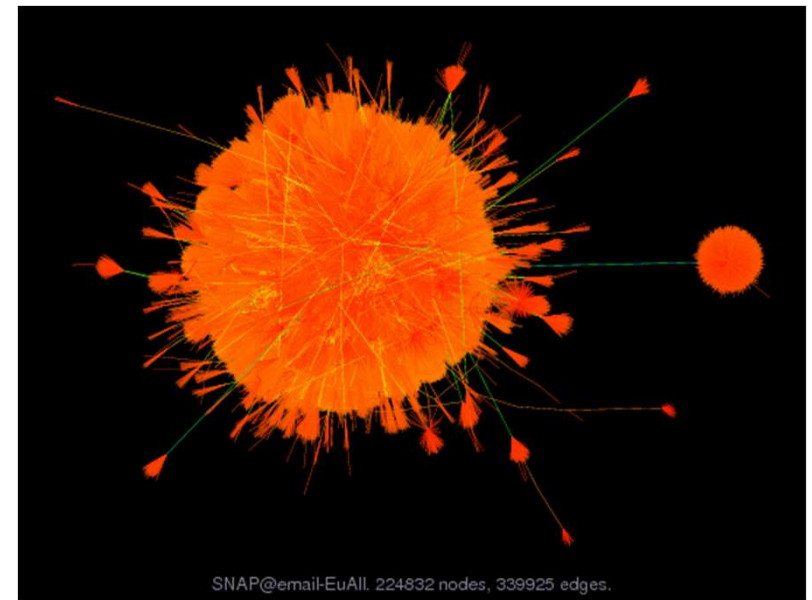
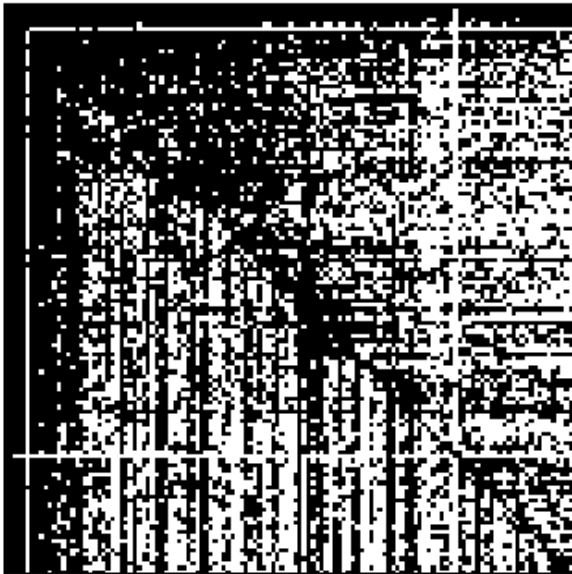




## Example 5: E-Mail Social Network

Relationships between e-mail correspondents:

- E-mail network from an EU research institution
- ID: SNAP/email-EuAll.html



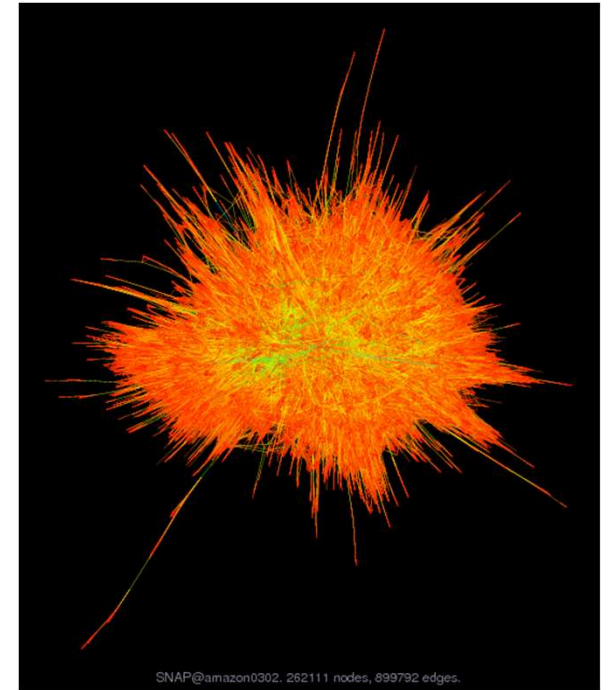
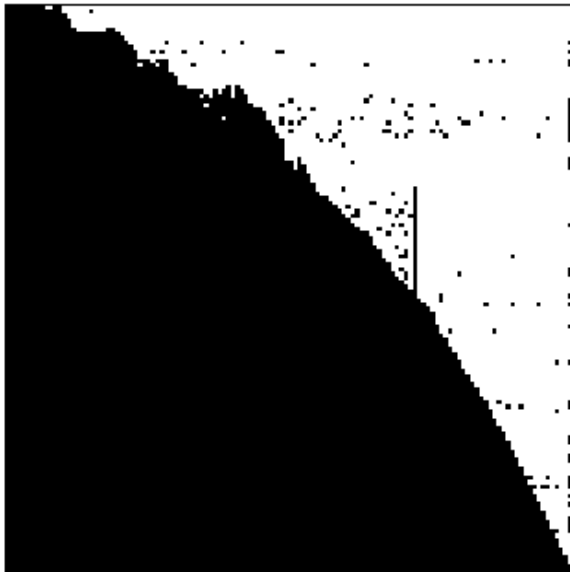
SNAP@email-EuAll. 224832 nodes, 339925 edges.



## Example 6: Online Shopping!

Relationships between purchases:

- Amazon co-purchasing product network from 2003
- ID: SNAP/amazon0302.html



# GPUs Set the Record for Triangle Counting

An example from 2012:\*

- Twitter graph: 41M nodes, 1.4B edges, 34.8B triangles
- Hadoop: 1536 machines → 423 minutes (7 hours)
- GraphLab on 64 machines (1024 cores) → 1.5 minutes

**Achieving that speed requires multiple GPUs.**

**How do we do that?**

\*J.E. Gonzalez, Y. Low, H. Hu, D. Bickson, C. Guestrin, “PowerGraph: Distributed Graph-Parallel Computation on Natural Graphs,” OSDI, 2012.

# cudaMemcpy Copies Data Across PCIe

## Why use multiple GPUs?

In 2012, Twitter graph

- did not fit in a GPU's memory, but
- today it would.
- Bigger graphs exist, but
- didn't need 64 GPUs in 2012.

Sometimes, **need more throughput.**

That's why we want **data scalability**, remember?

# cudaMemcpy Copies Data Across PCIe

Let's review CPU-GPU system architecture.

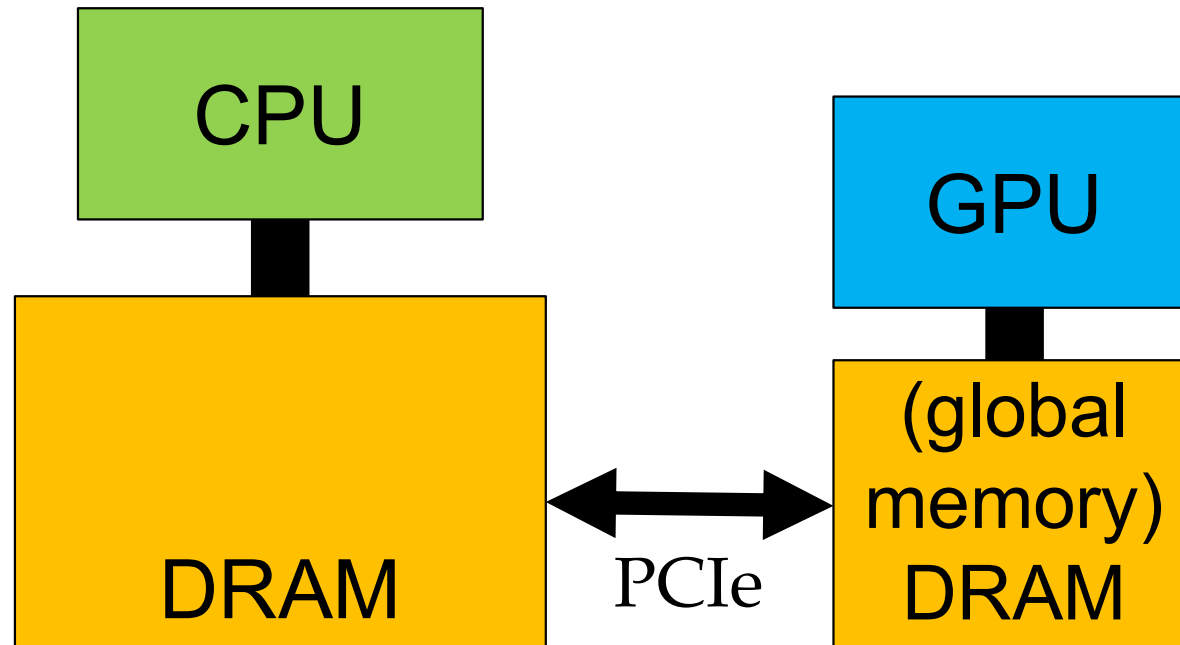
**Host** (CPU) **and device** (GPU)

- **have** associated **DRAM memories**,
- which are separate.

**cudaMemcpy** uses

- Direct Memory Access (**DMA**) **engines** on GPU to
- **move data between** these **memories** (over PCIe).

# Illustration of System Architecture



**cudaMemcpy** used to move data back and forth.

# Pinned Host Memory Makes Copying Faster

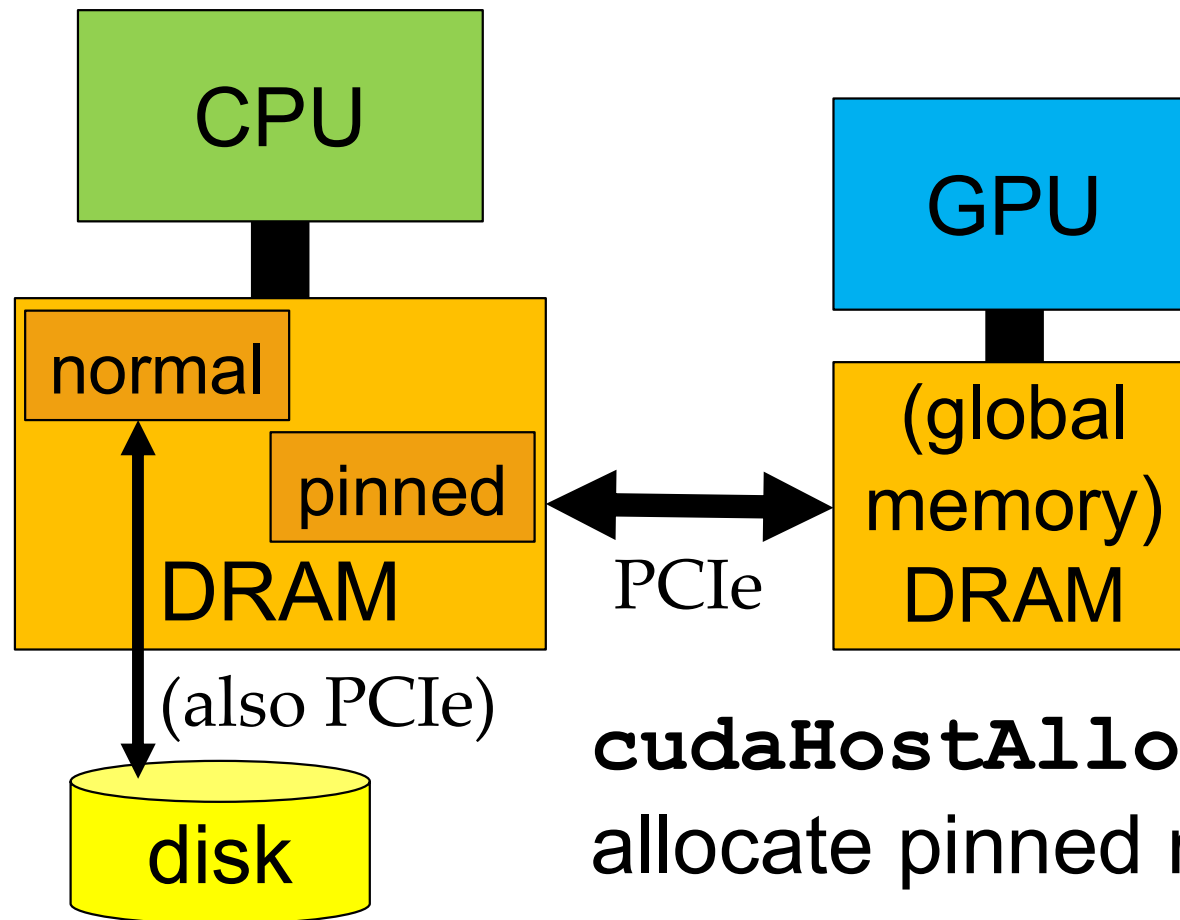
**CPU memory** managed by OS:

- **virtualized, and** sometimes
- **swapped** transparently **onto disk**.

DMA engines require non-virtualized addresses.

- Can **“pin” memory** in OS to avoid swapping.
- **Use `cudaHostAlloc`** to allocate pinned memory,
- but **be careful**: too much pinned memory makes system extremely slow!
- Pinned memory is **faster to copy** to device memory.

# Illustration of Pinning Host Memory



**`cudaHostAlloc`** used to allocate pinned memory.

# Zero-Copy Access from GPU to Host Memory

Since CUDA 2.2 (2009),

- **GPU** has been **able to access pinned host memory**
- **directly** over PCIe!\*

To do so, translate pinned host address to GPU with

```
cudaError_t cudaHostGetDevicePointer
```

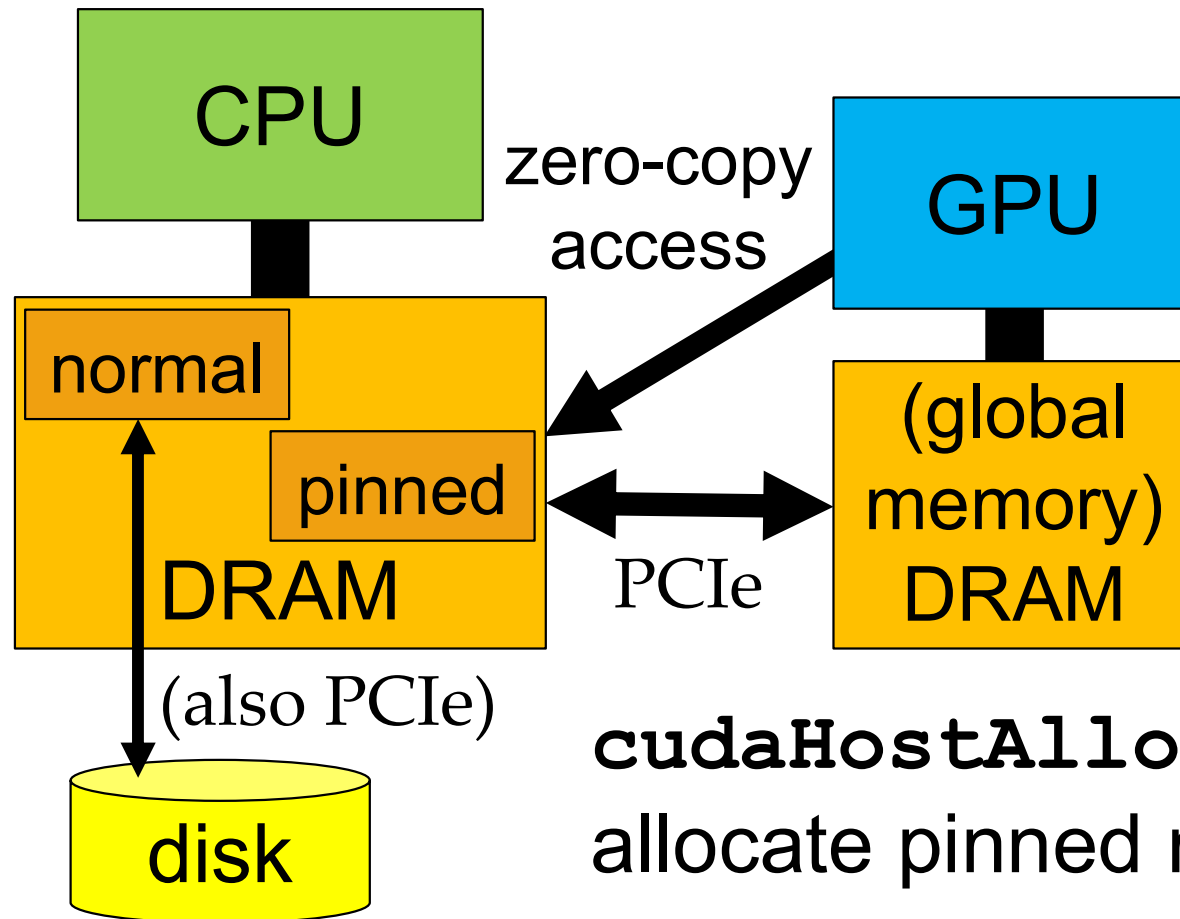
```
(void** devPtr, void* hostPtr, unsigned int flags);
```

- (flags should be 0).
- GPU can then **use zero-copy access** to **\*devPtr**.

\*See Section 9.1.3 of <https://docs.nvidia.com/cuda/cuda-c-best-practices-guide/> for more detail.



# Illustration of Zero-Copy Access



**cudaHostAlloc** used to allocate pinned memory.

## Zero-Copy Access Also Works GPU to GPU

In early 2014, NVIDIA announced **NVLink**,

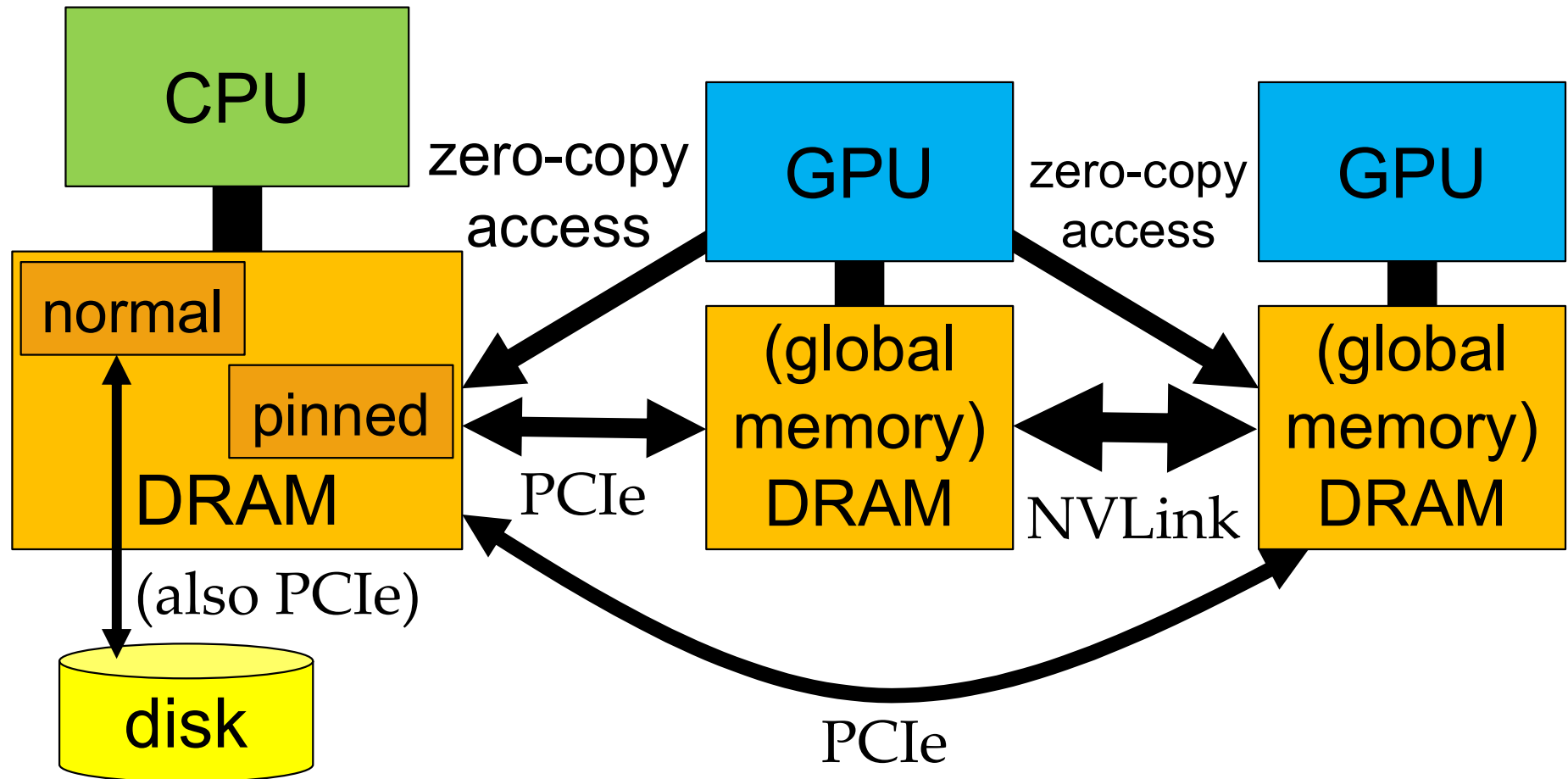
- a **proprietary GPU-GPU interconnect**
- for multi-GPU systems.

NVLink provides

- **lower latency and higher throughput than PCIe**
- for GPUs in the same system to move data between device memories.

In GPU kernel, **use zero-copy access!**

# Illustration of Multi-GPU Connectivity



# Set Device Context with `cudaSetDevice`

**How? Takes some setting up...\***

Remember this function?

```
cudaError_t cudaGetDeviceCount (int* count);
```

- Turns out it might not always return 1!
- **Device IDs are 0 to N-1** where **N** is **\*count**.

To switch contexts

- (per “host thread”—consider using Posix),
- **call `cudaSetDevice`** with the desired ID.

\*Managing multiple devices is covered in Section 6.1  
of <https://docs.nvidia.com/cuda/cuda-runtime-api/>.

# CUDA Calls Use Selected Device

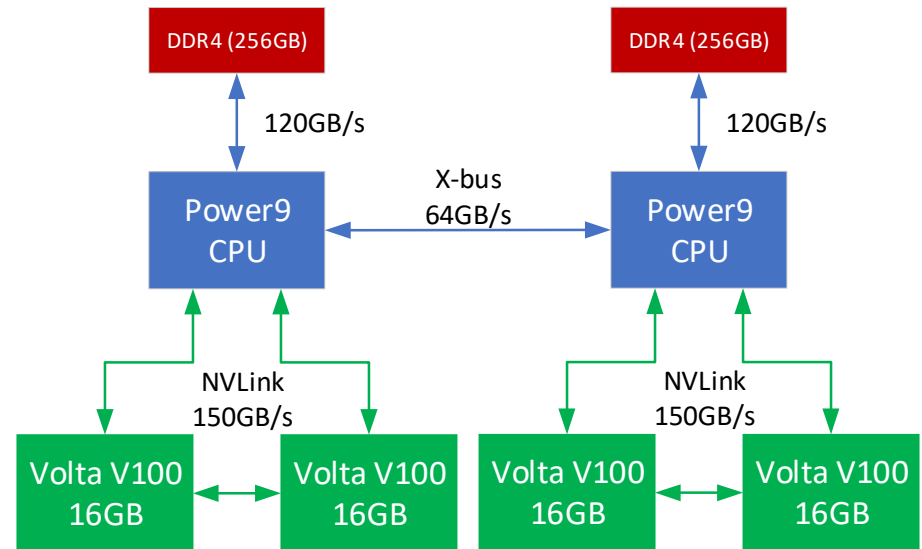
**CUDA calls occur in a context.**

- Allocate memory ... on the selected device.
- Copy memory ... to/from the selected device.
- Launch a kernel ... on the selected device.

# Bigger Systems May Have $>1$ CPU and $>1$ GPU

You may have access to more powerful machines!

- For example, in Spring 2019, IBM provided the Newell machine:
- 2 IBM Power9 CPUs,  
each 10 cores/80 threads@4.02GHz, 256GB RAM.
- 4 NVIDIA Volta V100 GPUs (16GB)



## NUMA Machines May Not Give Full Accessibility

Be warned: typically, **GPUs cannot use**

- **zero-copy access** to another GPU's memory
- **if the other GPU** is “**connected**”
- **to a different CPU**, even in a NUMA system like the Newell machine.

To check accessibility, use (on a CPU)

```
cudaError_t cudaDeviceCanAccessPeer  
(int* canAccessPeer, int device, int peerDevice);
```

If the CPU can't see the target GPU to  
make this call, the answer is “no.”

## Zero-Copy Access Still a Distributed Memory Model

**Zero-copy access does require programmer effort.**

Allocations

- separate for each GPU,
- so **pointers are separate.**

Can we **split** an “**array**” **across** GPU **memories**? Yes ...

1. Use indirection: `float* arr[numGPU];`  
Extra instructions and a **little complexity; or**
2. use different names: `float* arr1, * arr2;`

**Much more complicated.**



# Unified Memory Simplifies Data Structures

In **CUDA 6.0** (also 2014), NVIDIA released

- a primitive version of Distributed Shared Memory\*
- called “**unified memory**.”

Allocate with **cudaMallocManaged**.

- CPU and GPUs can access.
- GPUs leverage zero-copy access if available.

\*K. Li, P. Hudak, “Memory Coherence in Shared Virtual Memory Systems,” 5th Annual Symposium on Principles of Distributed Computing, pp. 229-239, 1986.

# Still Need to Think About Access Patterns

Unified memory keeps **one copy of data** (only)

- **Coherence** is **not supported**,
- so be careful with write accesses.

**Kernel-level synchronization does work,**

- so CPU can read GPU results safely
- after a kernel completes.

# Unified Memory Moves Pages Automatically

## Unified memory

- **uses page migration** from memory to memory.
- similar to that used in Sun Enterprise servers in early 2000s.

## Pages

- matching OS page size,
- typically **4 kB** to **64 kB**.
- **migrate on-demand**.

# Unified Memory Tricky to Use Well

Latency of migration has a huge performance impact.\*

- **Prefetching is supported**, but
- be sure that kernels have high data locality and reuse.

**Poorly-designed access** patterns

- **lead to pages thrashing** between GPUs.
- Unified memory also **suffers from false sharing**:
  - threads making **independent use** of data
  - that are mapped to the **same page**.

\*N. Sakharnykh, "Maximizing Unified Memory Performance in CUDA,"  
“<https://developer.nvidia.com/blog/maximizing-unified-memory-performance-cuda/>”

# My Take: Same Old DSM

## Uniform memory

- is a lot like the 28 previous years
- of SVM/DSM systems:
- looks great at first, but
- can be **really hard to use** in practice
- **if you care about performance.**

# Partitioning Strategies: Edge List Partition

## What about our approach?

Each thread:

1. Looks up **u** and **v**.

	GPU0			GPU1			...	
rowIdx	0	0	1	1	1	2	2	3
colIdx	1	2	2	3	4	3	4	4

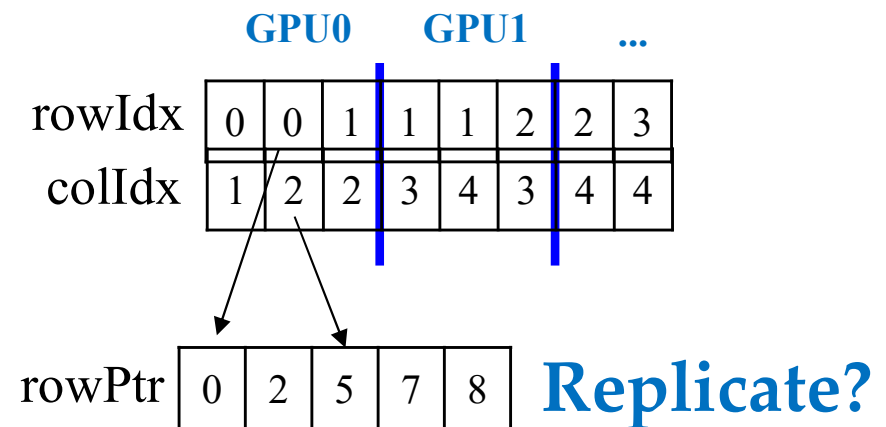
**Easy to partition** across GPUs!

# Partitioning Strategies: Edge List Partition

## What about our approach?

Each thread:

1. Looks up **u** and **v**.
2. Retrieves neighbor indices.



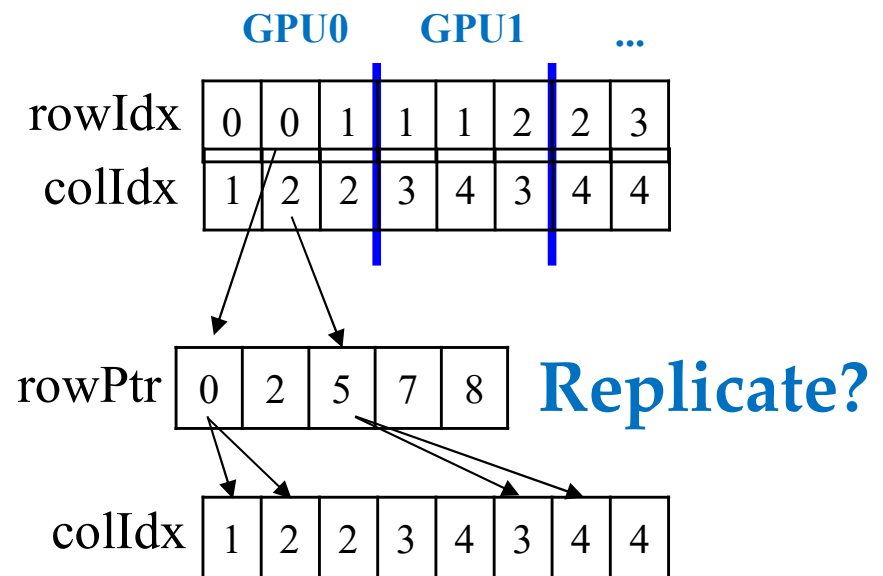
# Partitioning Strategies: Edge List Partition

## What about our approach?

Each thread:

1. Looks up **u** and **v**.
2. Retrieves neighbor indices.
3. Accesses neighbor lists.

Also **replicate colIdx**?





# Big Data Require Distribution

**That strategy replicates more than half of the data.**

Not much room for problem growth.

**For throughput, that's fine.**

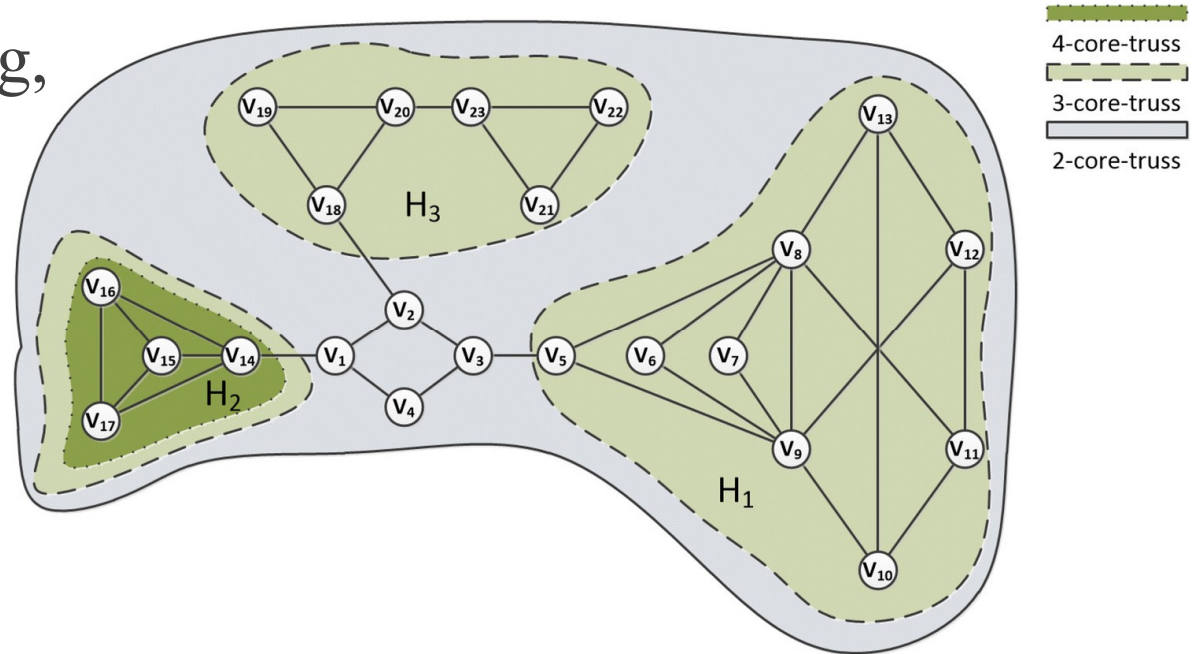
**For bigger graphs,**

- need to use zero-copy access
- or unified memory.

Eventually need to **write as distributed memory** code (using MPI, for example).

# Use Case: Truss Decomposition

From triangle counting,  
we can keep building  
up to **find trusses in  
graphs.**

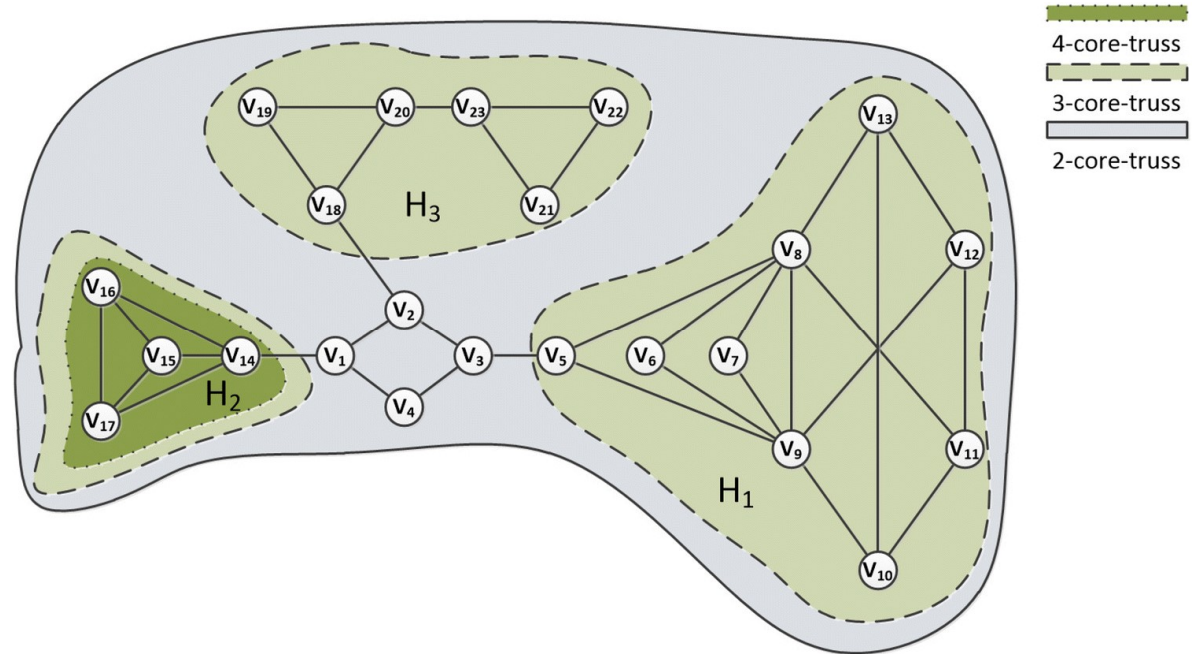


[ Image taken from Z. Li, Y. Lu, W.-P. Zhang, R.-H. Li, J. Guo, X. Huang, R. Mao, “Discovering Hierarchical Subgraphs of K-Core-Truss,” Data Science and Engineering, 3, pp. 136–149, 2018. ]

# Trusses Measure Community Strength

## What's a truss?

An **N**-truss is a subgraph in which **each edge** is **part of at least  $(N - 2)$  triangles**.



[ Image taken from Z. Li, Y. Lu, W.-P. Zhang, R.-H. Li, J. Guo, X. Huang, R. Mao, “Discovering Hierarchical Subgraphs of K-Core-Truss,” Data Science and Engineering, 3, pp. 136–149, 2018. ]

# Trusses are Not Cliques

Is a truss a clique?

Not quite.

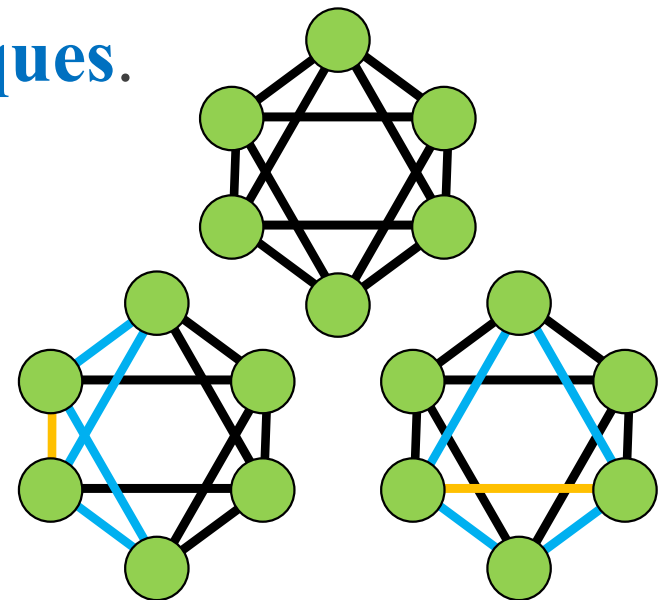
The smallest **N**-truss is the clique on **N** elements.

But **larger N-trusses need not be cliques**.

For example, this graph is a **4**-truss...

It's fully symmetric, but easier to see as two cases:

- side edges (two triangles), and
- middle edges (two triangles).



# Finding 3-Trusses is Just a Triangle Count

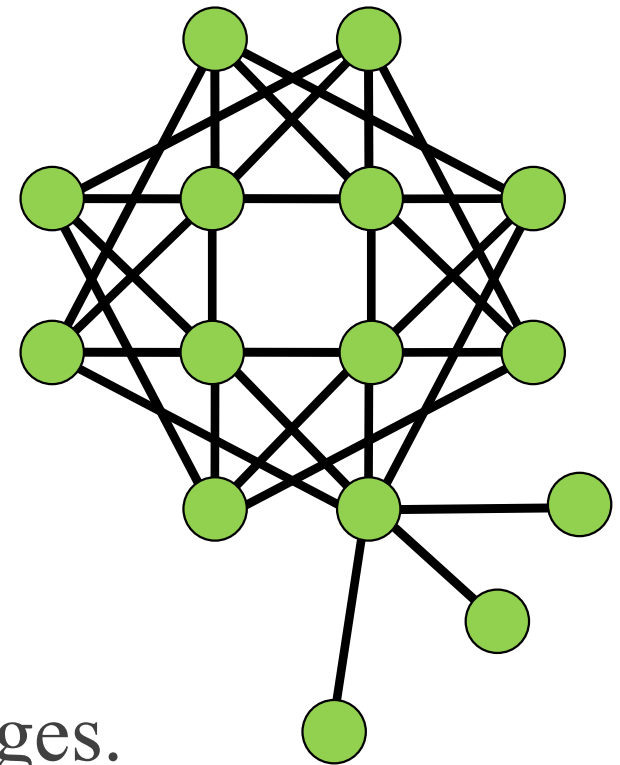
## How can we find N-trusses?

For  $N=3$ , it's easy:

- **find the triangles**, then
- **get rid of non-triangle edges.**

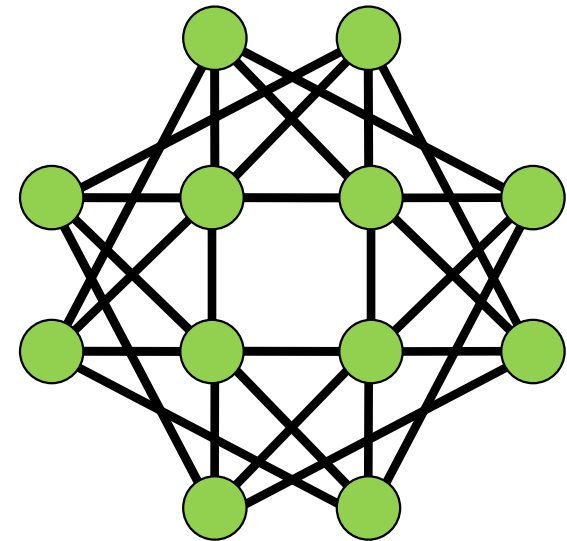
Since edges not in triangles ...

- aren't in triangles ...
- the triangle count per edge is unaffected by removing those edges.



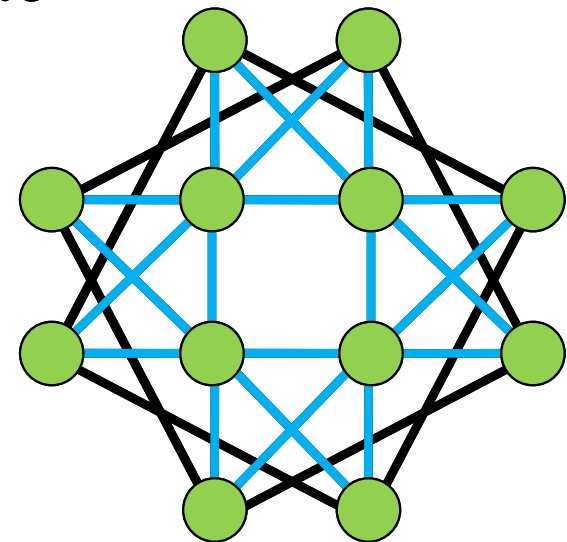
# Stronger Trusses Require Iteration

- **For**  $N$ -truss with  $N > 3$ , must **iteratively remove** until all remaining edges are part of at least  $N - 2$  triangles.
- Consider the graph to the right, for example...  
**any 4-truss parts?**



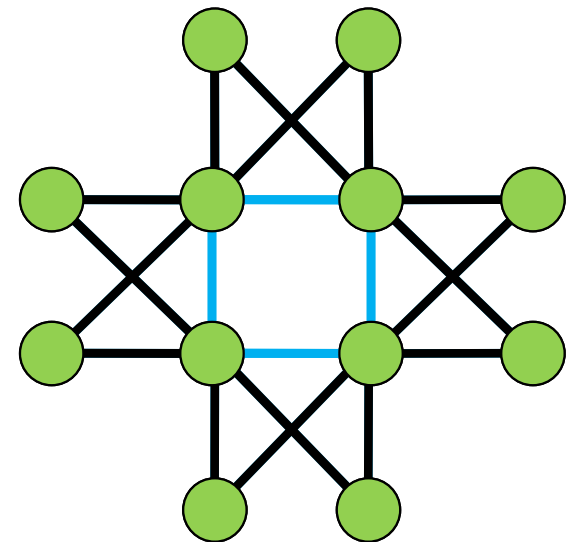
# Start with a Triangle Count

- All edges in this graph contribute to triangles, but no edge contributes to more than 2 triangles.
- Let's mark the edges in 2 triangles in blue.
- Black edges contribute to only one triangle.
- Next, let's remove all edges that are not in 2 triangles.



# Removing Edges Removes Triangles

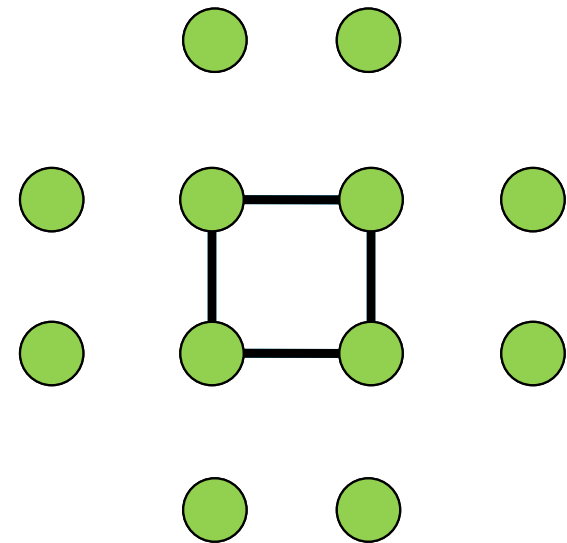
- But now some of the edges are no longer in 2 triangles!
- Let's make those edges black.
- Now we can remove more black edges, as they do not contribute to enough triangles.





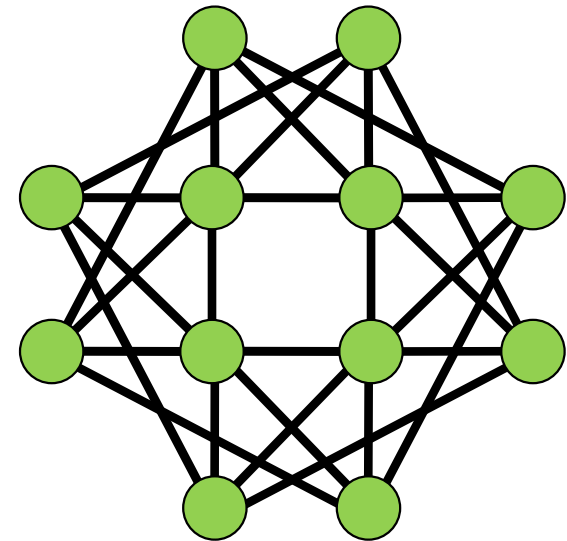
# Each Removal Leads to More Removals

- Again, some of the edges are no longer in 2 triangles!
- Let's make those edges black.
- Finally, all edges are black!



# Example Graph has no 4-Truss Portions

So the graph shown has  
no 4-truss portions!





# ANY QUESTIONS?