

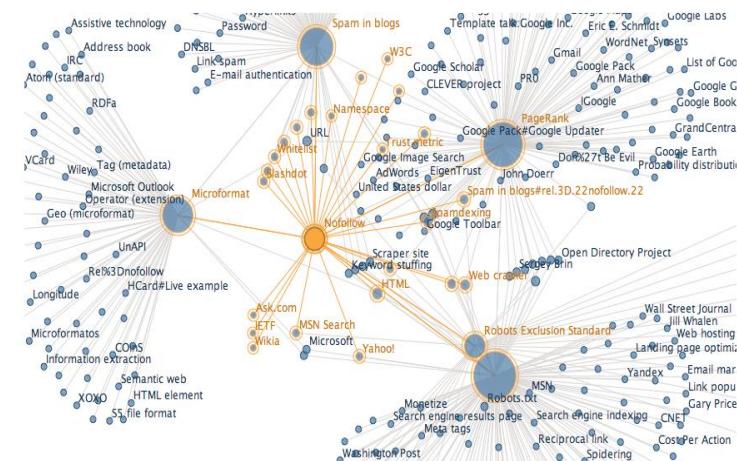
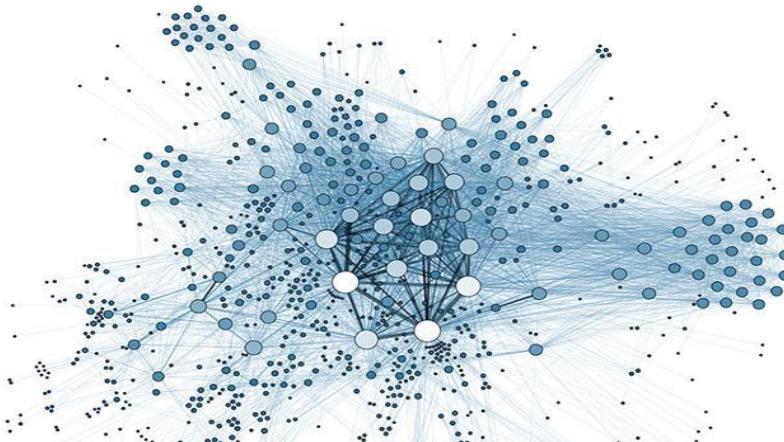
# Heterogeneous Computing for Graph Algorithms

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# Introduction

- Graph processing has been prevalent
- Real world graphs large in size
- Processing such real world graphs requires effective harnessing of multiple nodes of CPU and GPU devices



# GPUs

- Graphical Processing Units (GPUs)
- A single CPU can consist of 2, 4, 8 or 12 cores
- GPUs consist of a large number of light-weight cores
- Typically GPU and CPU coexist in a heterogeneous setting
- “Less” computationally intensive part runs on CPU (coarse-grained parallelism), and more intensive parts run on GPU (fine-grained parallelism)



# Challenges

- Irregular memory access, hence poor locality.
- Poor computation-to-communication ratio.
- Varying parallelism while execution.
- Frequent need of synchronization.
- Load Balancing across computing units.
- **Most important: To be able to use all the heterogeneous resources**

# Divide and Conquer

- Partition and run the algorithm independently on the devices
- Three cases
  - **Case 1:** Control the independent algorithmic computations – MST
  - **Case 2:** Split into batches and different pipeline stages on the devices – Betweenness centrality
  - **Case 3:** Let loose and correct – Community Detection

# Case 1: Minimum Spanning Tree (MST)

- MST one of the important graph applications
- Large scale MST requires multiple nodes with distributed memory parallelism

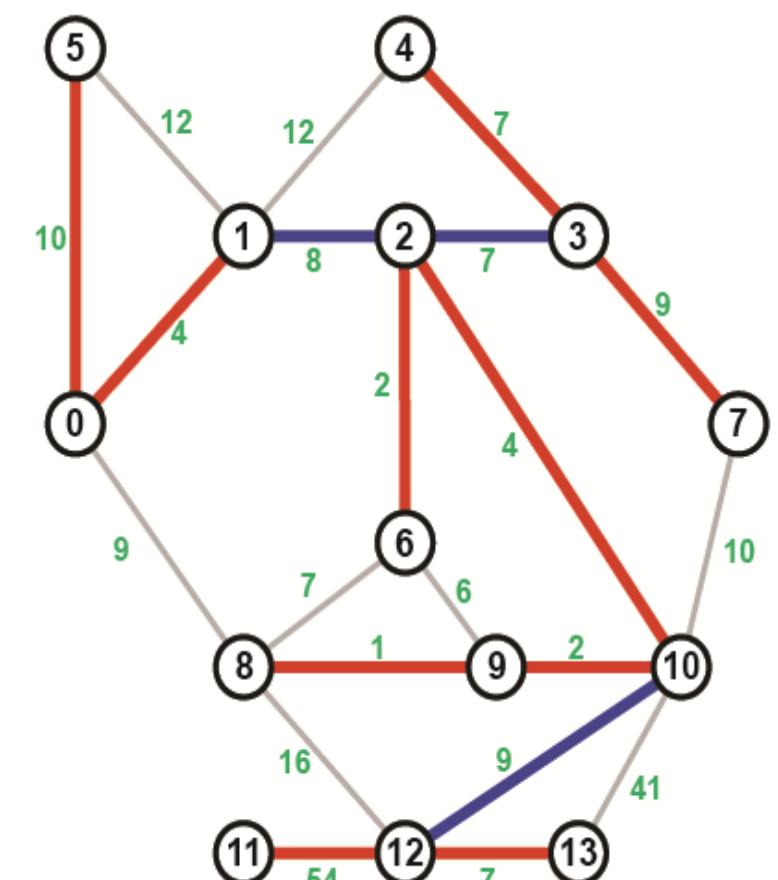
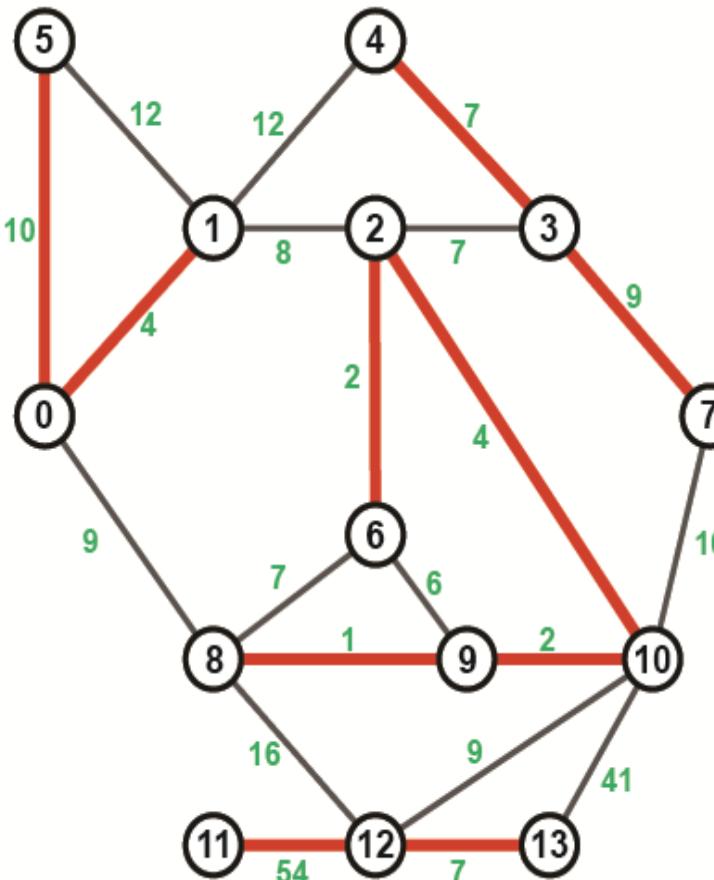
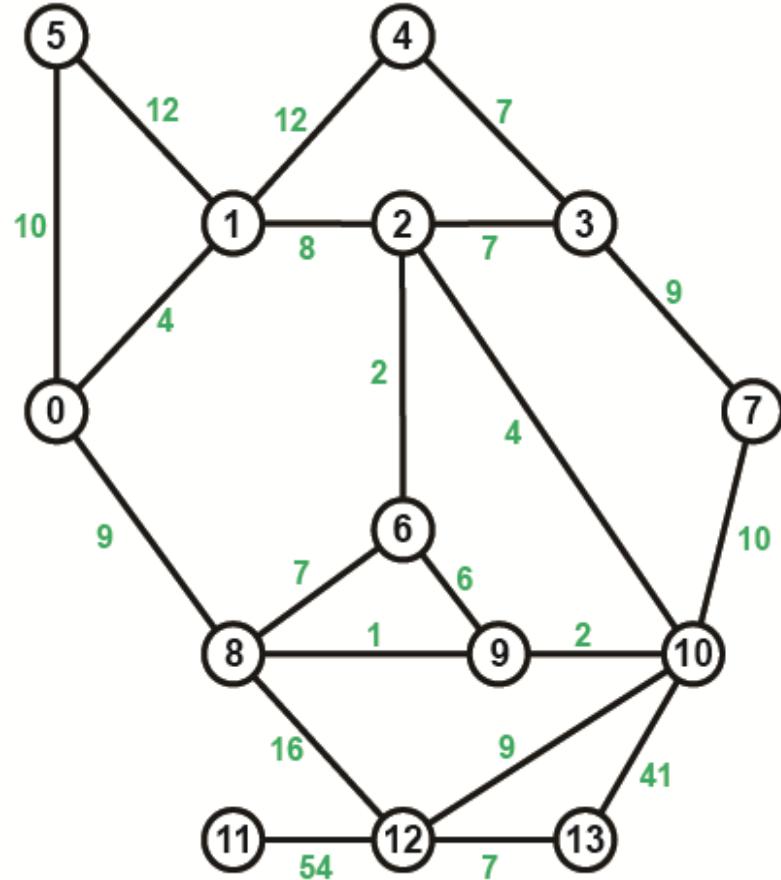
# Multi-node multi-device MST

- We propose a multi-node multi-device algorithm following a divide-and-conquer paradigm
- Graph is partitioned across multiple nodes and further across multiple devices
- Boruvka's MST invoked independently on each partition/device
- Results merged using a novel hierarchical merging algorithm

# Boruvka's MST

- Iteratively finds lightest edges from a component and merges two components connected by a lightest edge – called edge contraction
- Process repeated until a single component formed
- Edges contracted across all the iterations form the minimum spanning tree

# Boruvka's MST



# Hybrid CPU-GPU MST

- Consists of:
  - Partitioning
  - Independent computations:
    - Run the Bouruvka's algorithm on each device
    - But **don't run** the algorithm on the border vertices
  - Merging
  - Post processing

# Implementation: HyPar Divide-and-conquer API

Function	Remarks
partGraph	Partitions the graph into number of processing units.
indComp	Performs independent computations of a graph kernel, given by an <i>appName</i> , on each partitions independently with <b>excpCond</b> and returns the result.
mergeParts	Merges the results from the independent computations on the devices and communicates ghost vertices.
postProcess	Performs postprocessing by executing the kernel given by <i>postProcessKernelName</i> with updated graph as the input.

# HyPar Runtime Optimizations

## 1. Ratio for Graph Partitioning:

- To find the ratio for partitioning we use a heuristic approach. We choose 5-10 random induced subgraphs with 5% of the total number of nodes and run the application on both the CPU and GPU devices simultaneously to find the partitioning ratio.

## 2. Threshold for Independent Computation

- While performing independent computation in each partition, the amount of parallelism may drop significantly after few iterations.
- HyPar automatically find the threshold by observing trend in execution times, and switches to the merging step at the threshold

## 3. Recursive Invocation of Partitioning-Independent Computations-Merging

- After mergeStep in many applications the remaining graph size may be large.
- HyPar framework again partitions the reduced graphs using the same partitioning ratio, followed by invocation of indComp and mergeStep if the size of the graph is more than a threshold

# Case 2: Betweenness Centrality

- Betweenness Centrality is a shortest path metric used to give a score to each vertex in a graph or network based on how many shortest paths it lies on.
- Definition:-
  - For a graph  $G = (V, E)$ , where  $V$  is the set of vertices and  $E$ , the set of edges. Let  $\sigma_{st}(v)$  denotes the number of shortest path from vertex 's' to vertex 't', where  $s \neq t$ , passing through vertex  $v$ .
  - Based on above, we find  $\delta_{st}(v) = \sigma_{st}(v) / \sigma_{st}$  , where  $\delta_{st}(v)$  denotes the pair-wise dependency between of the pair 's' and 't' on 'v'.
  - The Betweenness Centrality score of the vertex is given by
- One way to find BC for all vertices is to perform an APSP and aggregate the pair-wise dependencies for all vertices. Its costly,  $O(n^3)$  and infeasible for larger graphs.

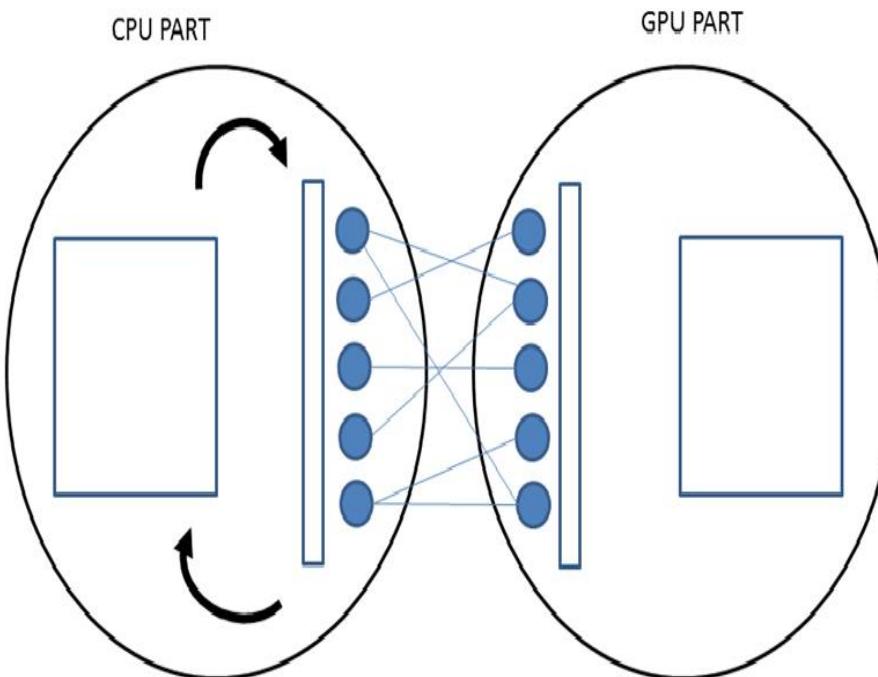
# Brandes Algorithm for Betweenness Centrality

- The algorithm by Brandes [JMS-2001] consists of two phases: a **forward** and a **backward** phase.
- The forward phase consists of a BFS traversal or SSSP calculation with  $s$  as the source. For each vertex the #shortest paths and predecessor list is calculated.
- The backward phase traverses the vertices in descending order of their distance from  $s$ .

## DISTANCE CALCULATIONS IN FORWARD PHASE.

- In an iteration a source  $s$  is selected
- Distance values of all nodes in  $G$ , except  $s$  are set to  $\infty$ , which is set to 0.
- **Step 1.**
  - BFS/SSSP from  $s$  in  $Pr(s)$ .
  - $d_C[s, v], \forall v \in Pr(s)$ .
  - **Initial step.**
- **Step 2.**
  - Update  $B_{G-Pr(s)}$  using edge cuts.
  - Using  $d_C$  values of  $B_{Pr(s)}$ , relaxing the values of  $B_{G-Pr(s)}$ .
- **Step 3.**
  - Updating the  $B_{G-Pr(s)}$  in the same partition.
  - Using  $BM_{G-Pr(s)}$  for further relaxing the values of  $B_{G-Pr(s)}$ .
- **Step 4.**
  - Update  $B_{Pr(s)}$  using edge cuts.
  - Using  $d_C$  values of  $B_{G-Pr(s)}$ , relaxing the  $d_C$  values of  $B_{Pr(s)}$ .
- **Step 5.**
  - Updating the  $B_{Pr(s)}$  in the same partition.
  - Using  $BM_{Pr(s)}$  for relaxing the  $d_C$  values of  $B_{Pr(s)}$ .

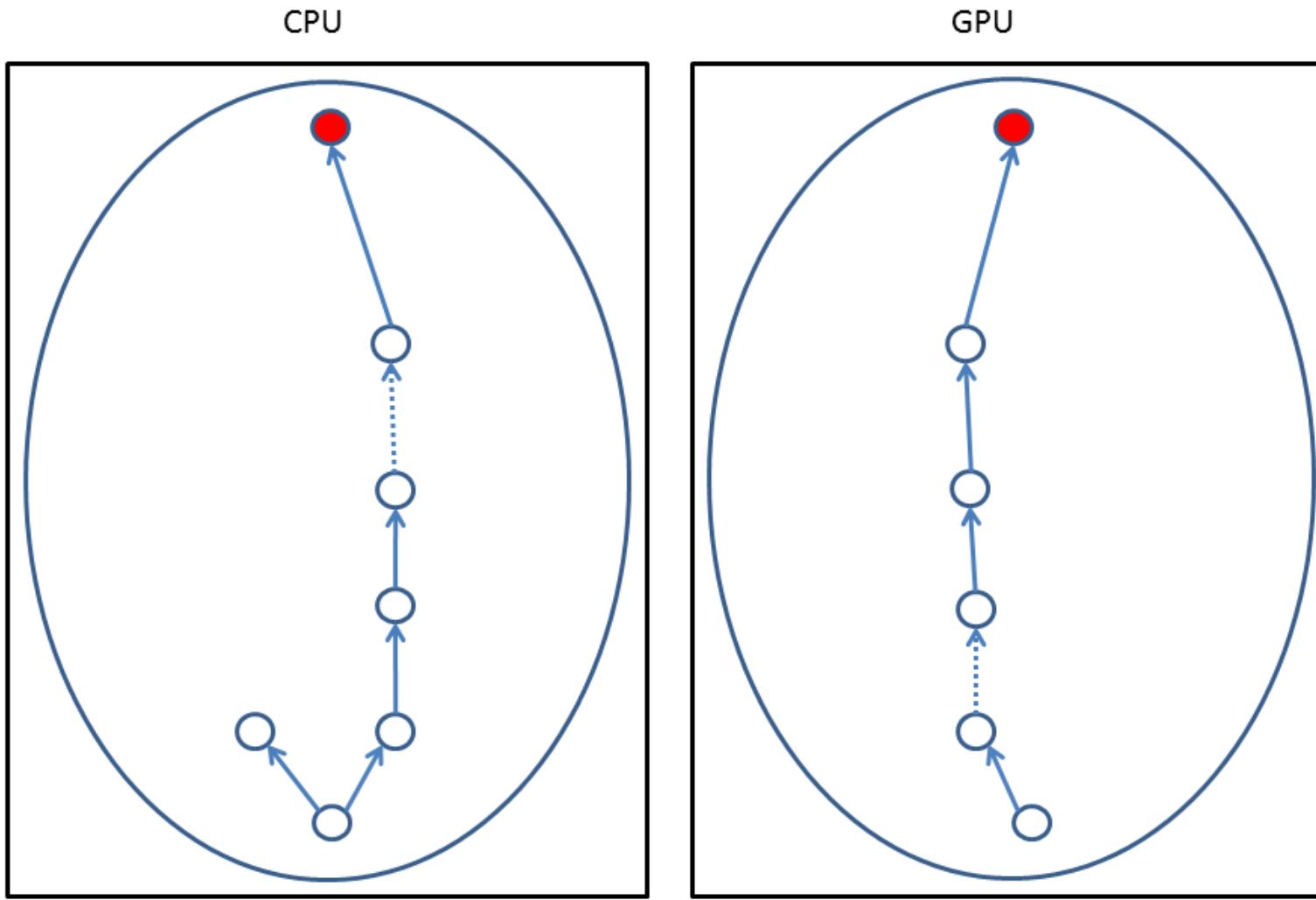
ILLUSTRATION ITERATIVE STEP



## ASYNCHRONOUS AND HYBRID BACKWARD PHASE

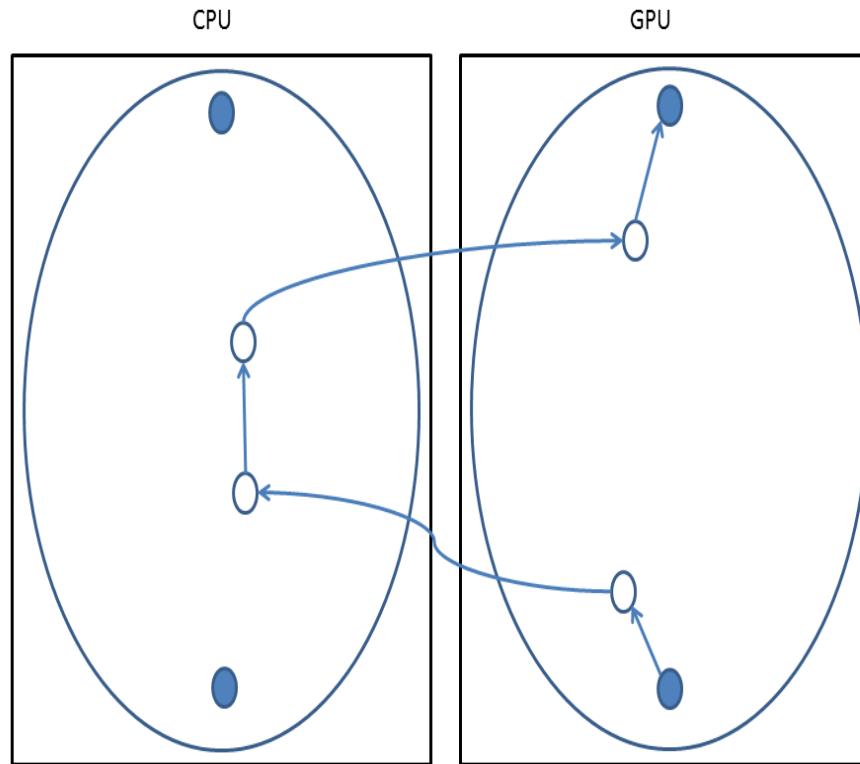
- The non-zero  $edge\sigma$  characterizes the dependency information.
- The execution is launched simultaneously on CPU and GPU.
- CPU computation threads.
  - In CPU partition.
  - For each  $dist$  level starting from max till the min.
  - Set  **$borderNodeinLevel$**  if current level has a border node in GPU.
    - Wait till GPU has completed the current level.
- GPU handler thread.
  - A CPU thread.
  - Invokes the GPU kernel.
  - For each  $dist$  level starting from max till the min.
  - If  **$borderNodeinLevel$**  is set then copy the border node values to CPU.
  - If there is a border node in current partition.
    - Wait till CPU has completed the current level.
    - Copy border values from CPU to GPU.

## ILLUSTRATION BACKWARD STEP



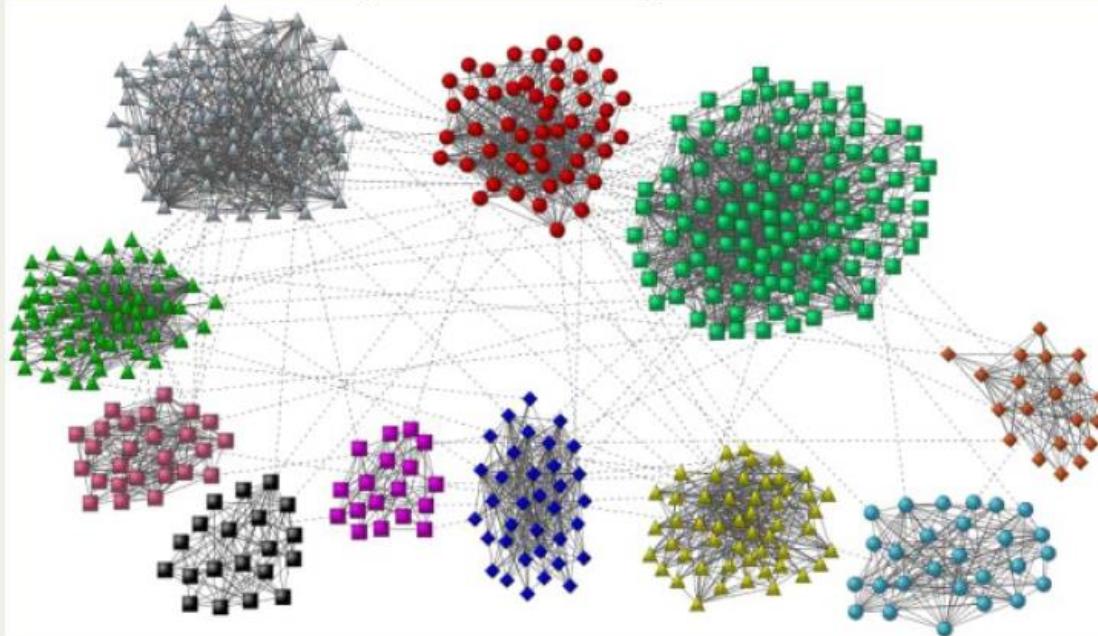
## CONTINUED...

- CPU and GPU both traverse asynchronously, until a border node is found.
  - If there is a border node then either processor has to wait for the other to reach current level.
  - Only when required.
- The synchronizations in the backward phase.
  - Depend on the structure of the graphs.
    - Number of border nodes in either partitions.
    - Relation of border nodes among the partitions.
  - Its equal to the number of iterative steps in the forward phase.
- Communication is minimized
  - Only copy the border data structures.
    - delta values.



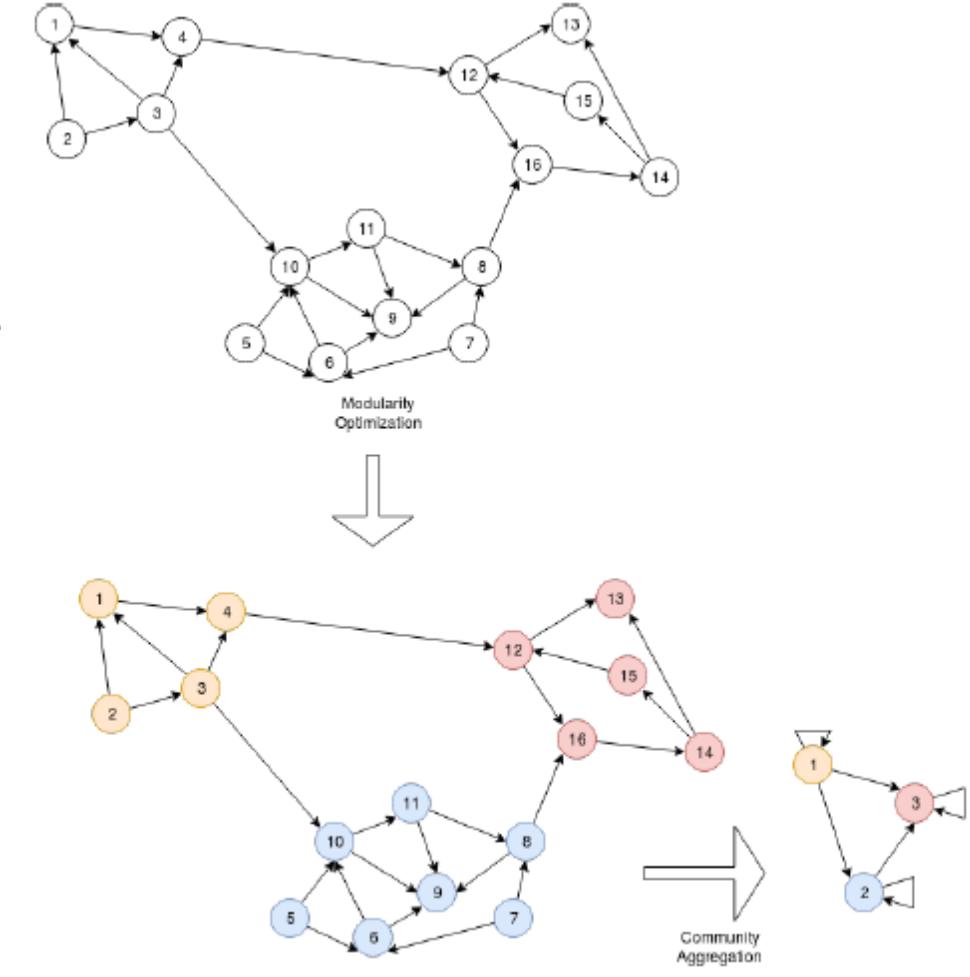
# Case 3: Community Detection

- Attempts to identify modules or connected components in a graph
- Used in various fields such as biological science and health care



# Hybrid CPU-GPU Algorithm

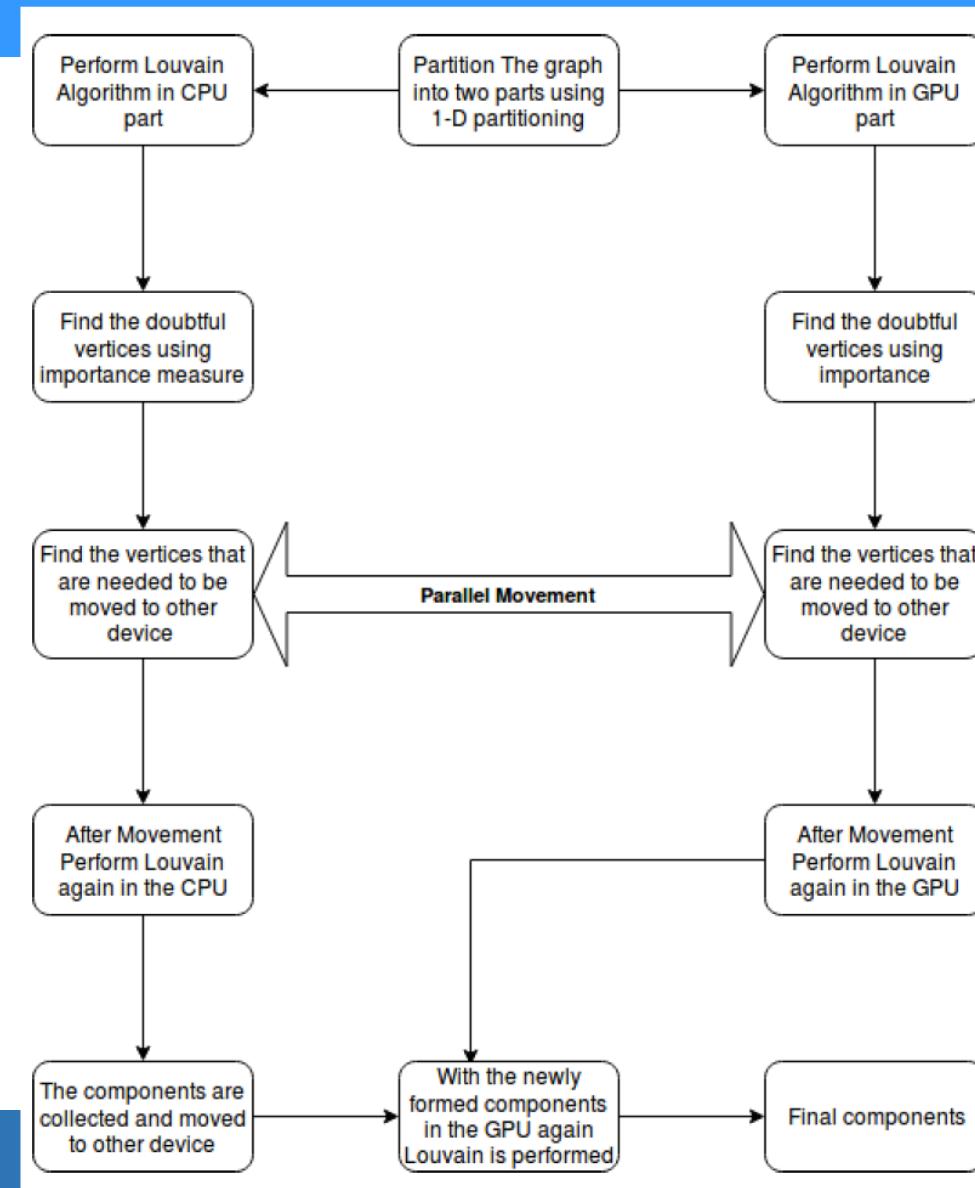
- Once again, partition for CPU and GPU
- Perform independent communities in the devices using a community detection algorithm (e.g., Louvain's)



# Hybrid algorithm

- This will form *pseudo communities*
- In the next step, *doubtful vertices* are identified, separated and exchanged
- Independent communities formed again
- Process repeated until components become small

# Hybrid Algorithm



# Some Lessons

- Take up simple algorithms
  - Simple graph algorithms (e.g., graph coloring), matrix computations
- Try to let it loose across the different devices
- See what needs to be done to get correct answers

# Thank You Questions?