# PSAIIM: A PARALLEL SOCIAL BEHAVIOR-BASED ALGORITHM FOR IDENTIFYING INFLUENTIAL USERS IN SOCIAL NETWORKS

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#### INTRODUCTION



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- Why do we need to find influence user?
- In order to spread a message quickly through social media we need **influence user**
- What is Influence Maximization (IM)?
- The problem of **influence maximization** can be defined as identification of a set of k network users that maximizes the number of users receiving messages

#### WHY PSAIIM IS BETTER?

#### Older

- 1. Ignored semantics
- 2. Slow and unscalable for large networks
- 3. Treated all actions equally
- 4. Most parallel models ignore semantics

#### **PSAIIM**

- 1. Adds semantics:
  - user interests + interaction behavior
- 2. Uses parallelism for faster execution
- 3. Weighs interactions
- 4. First to combine semantics with parallel processing

#### **BASIC DEFINITIONS**

Community Strongly Connected Community - SCC Connected Acyclic Community - CAC Directed Acyclic Graph - DAG 5

Direct neighbor of a node

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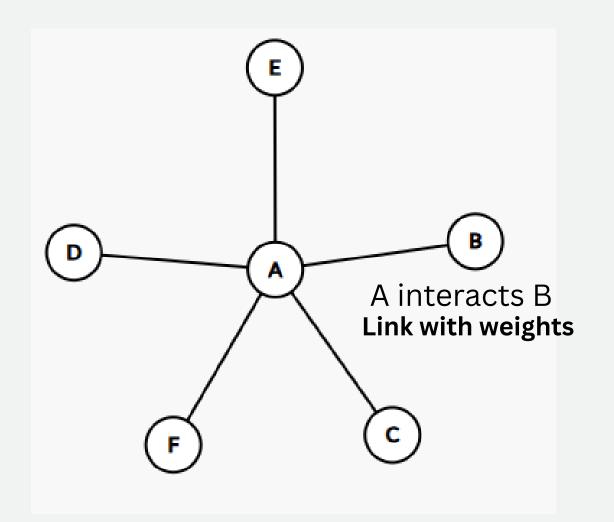
#### **BASIC DEFINITIONS**

- 6 Border of a node
- Semantics of the network
- 8 Vector characteristic of the user
- 9 Active node
- **10** Area of Influence

## **BASIC STRUCTURE OF GRAPH**

#### **Vector characteristic of the user**

```
User A: {
  interests: ["sports", "memes", "tech"]
}
```

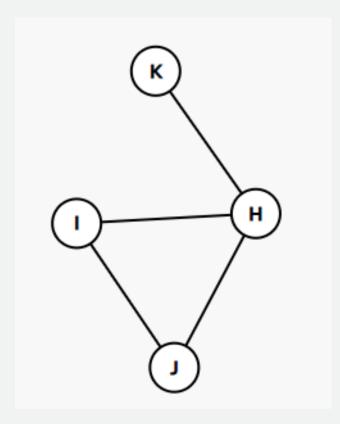


#### Border of a node

Direct Neighbor of A B, C, D, E, F

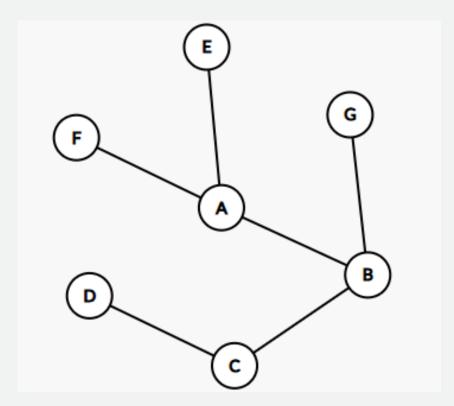


#### **COMMUNITIES**



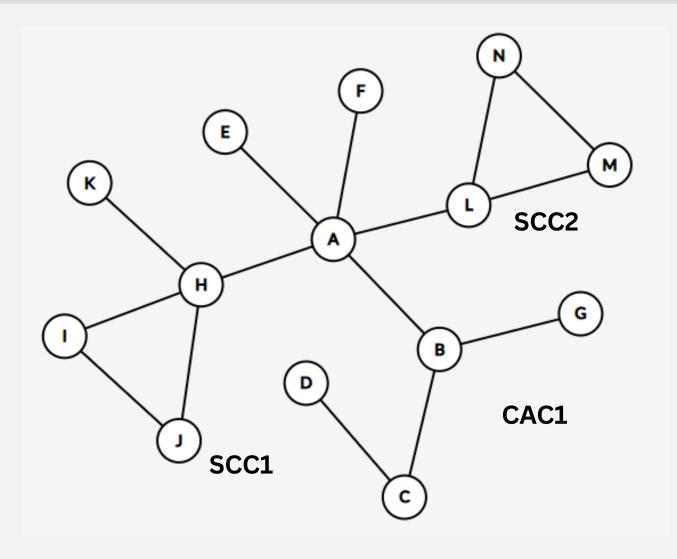
Strongly Connected Community
Every Node can reach every other Node

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**Connected Acyclic Community** 

#### DIRECTED ACYCLIC GRAPH



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#### TWO MAIN PHASES OF PSAIIM

Phase I

Influence Power Calculation

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Phase II

Influential Node Selection



#### PHASE I - INFLUENCE POWER CALCULATION

- Combine user behavior + interests to understand influence.
- Use PageRank to assign influence scores to each user.
- But PageRank is slow for big graphs!

#### PROBLEMS WITH PAGERANK

- To calculate a node's score, you need other node scores.
- Creates dependency: A needs B, B needs C, etc.
- Not easy to parallelize.

## **SOLUTION - GRAPH PARTIONING**

- Break graph into smaller parts:
  - SCC (Strongly Connected Components)
  - CAC (Connected Acyclic Components)
- These groups are easier to compute separately.

#### **ASSIGN LEVELS WITH DFS**

- Use Depth First Search to give levels to each group:
  - Level 0: No dependency
  - Level 1: Depends on level 0
  - Level 2: Depends on level 1, and so on...
- Compute PageRank level by level in parallel.

#### SEED CANDIDATES SELECTION

After computing influence scores using PageRank:

- For each node v, define its Influence Zone area where it can spread influence.
- Calculate the Local Average Influence in that zone  $\rightarrow$  IL(v).
- A node becomes a candidate if:
- IP(v) > IL<sub>0</sub>(v)  $\rightarrow$  Meaning it's more influential than its surroundings.

#### PHASE II - INFLUENTIAL NODE SELECTION

- Build an Influence-BFS Tree from each user.
- This tree shows how far & fast a user's influence spreads.

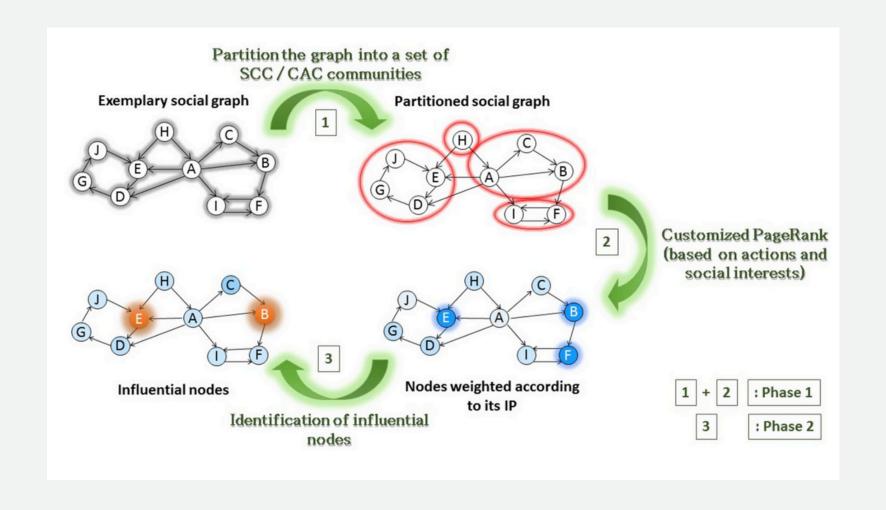
#### **Choosing the Top Influencers**

- Pick users with:
  - Highest influence score
  - Largest reach
  - Minimal overlap (so each spreads to a different audience)
- Stop when you have k best users.

#### FINAL OUTPUT

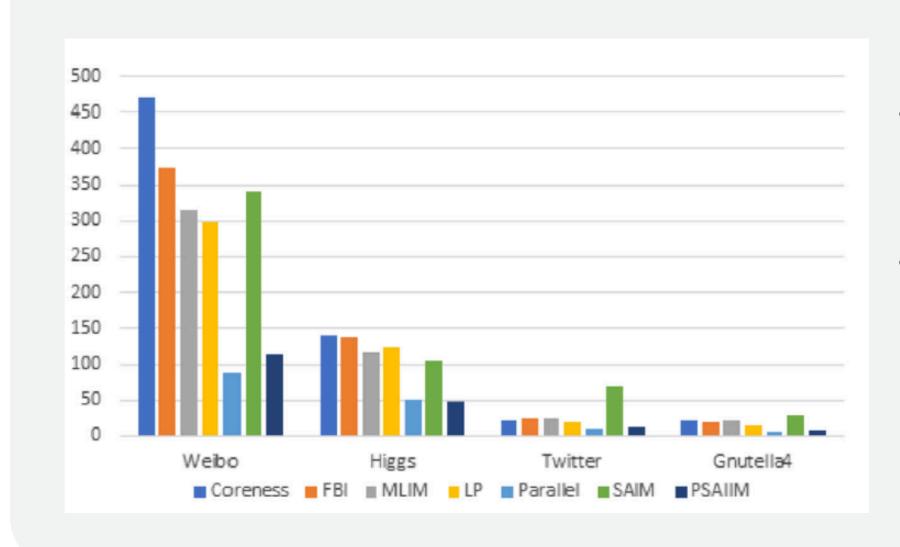
- A list of top-k users who can spread information effectively.
- Fast and efficient thanks to:
  - Semantic data (interests, behavior)
  - Graph partitioning
  - Parallel processing

#### FLOW CHART OF THE PSAIIM ALGORITHM



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#### RESULT



- Higher influence spread across small and midsized datasets due to its use of both social structure and semantic information
- On large datasets, its performance slightly declined as meaningful user interaction data diminished, but parallel speedup is more noticeable.

#### **OUR IMPLEMENTATION**

- We will be applying distributed computing by using virtual machines, they will communicate using MPI
- We will be using METIS for graph partitioning, and
- OpenMP for parallelization

#### **USE OF METIS AND MPI**

- The graph shall be subdivided into smaller graphs using METIS
- Each process on each virtual machine will apply PSAIIM algorithm on its subgraph
- The master node will send subgraphs to each of the processes
- After the processes on the machines have completed their processing, the results are gathered at master

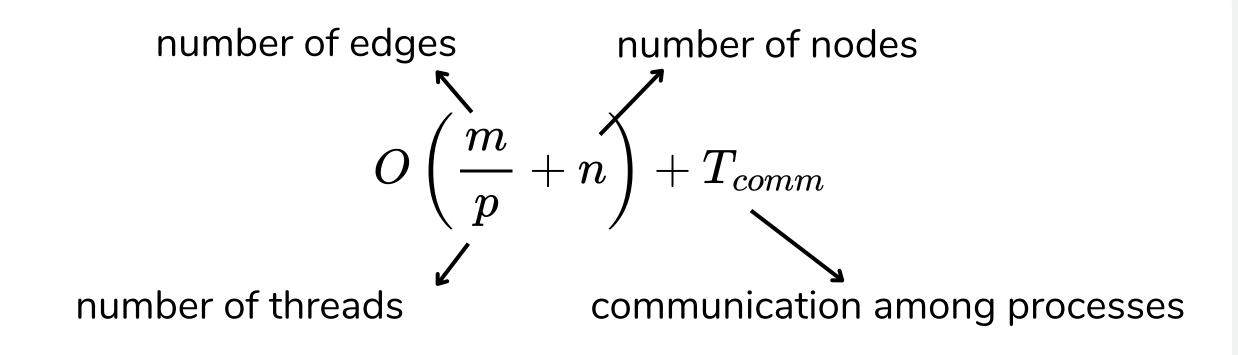
#### **USE OF OPENMP**

- In each process, the influence power calculation phase takes place
- This is implemented using the PageRank algorithm, which is parallelized
- This parallelization is achieved using OpenMP-each thread is assigned a community

#### WHY OPENMP?

- OpenMP is optimized for CPU-based parallelism, which fits well for running on clusters with multi-core CPUs
- Since PSAIIM is graph-based and involves recursive structures like BFS trees, OpenMP allows you to parallelize loops easily without porting the entire algorithm to a GPU programming model (which OpenCL requires).

## TEMPORAL COMPLEXITY ANALYSIS OF OUR IMPLEMENTATION





# THANK YOU



