Good morning!

CS 744: POWERGRAPH

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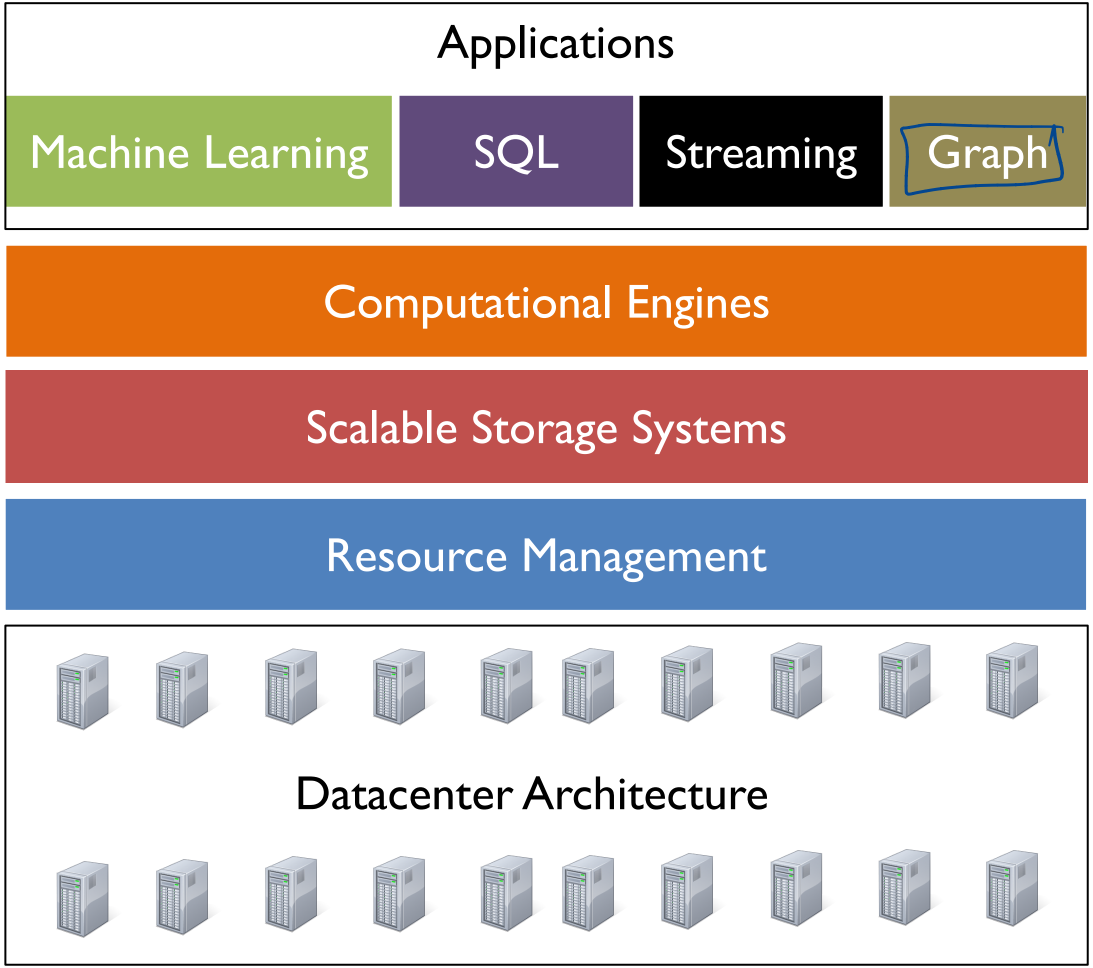
Fall 2021

ADMINISTRIVIA

- Midterm grading in progress
- Course Project

↳ checkpoint. update ≃ end of Nov

↳ office hours / setup meetings



Applications

Machine Learning

SQL

Streaming

Graph

Computational Engines

Scalable Storage Systems

Resource Management

Datacenter Architecture

GRAPH DATA

Datasets

Twitter / Social network

graph of follows / friends

Web graph

links between pages

Maps

locations connected by streets

Facts about entities [wikipedia]

→ Knowledge

Application

Recommendation

"You might know"

Ranking / Scoring

- PageRank

Directions / Traffic analysis

GRAPH ANALYTICS

Perform computations on graph-structured data

Examples

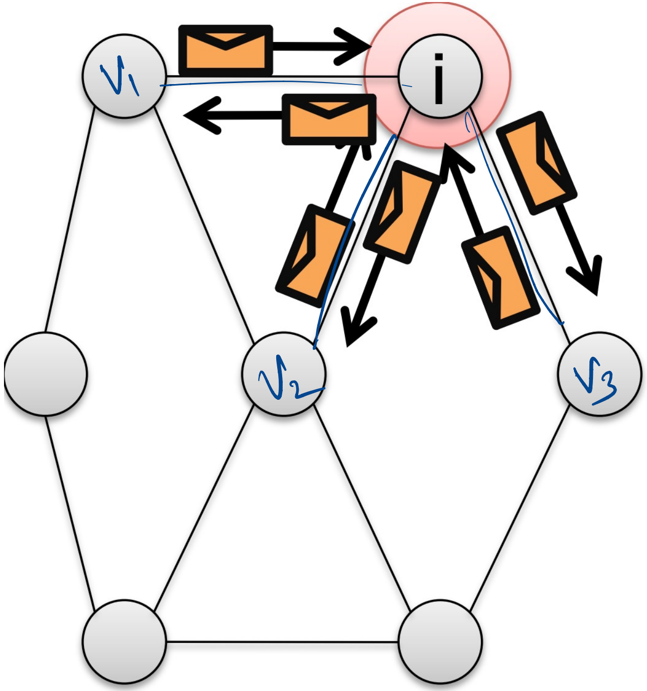
- PageRank
- Shortest path
- Connected components
- …

Online graph serving
- low latency traversals
- Graph updates

Analytics
- Batch job
- large graph and you want to analyze it

PREGEL: PROGRAMMING MODEL

~ 2008



```
Message combiner(Message m1, Message m2):
    return Message(m1.value() + m2.value());

void PregelPageRank(Message msg):
    float total = msg.value();

    vertex.val = 0.15 + 0.85*total;

    foreach(nbr in out_neighbors):
        SendMsg(nbr, vertex.val/num_out_nbrs);
```

Combined or Accumulated message

"think - like - a - vertex"

→ Vertex Program that operates on messages over Edges

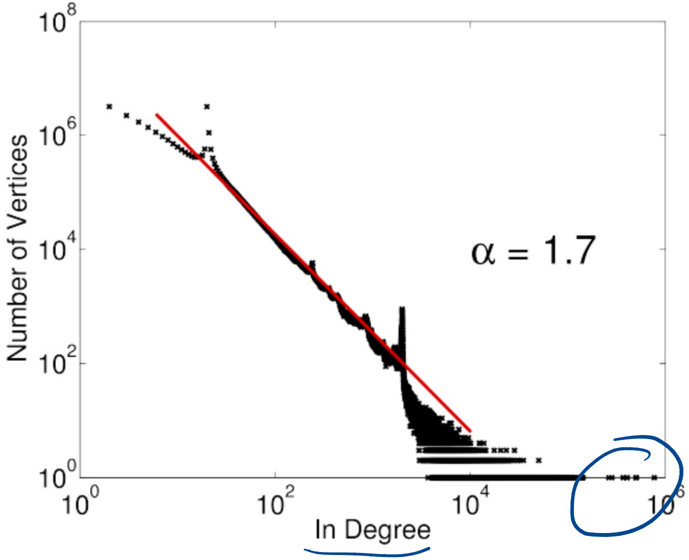
NATURAL GRAPHS

- Skew in the "in-degree"
  so very few users have lots of followers

- Some vertices have lots of messages come in

  - Work Imbalance → "Compute"
  - Storage / Network →

Stragglers / Low utilization / Increased time for 1 iteration



(a) Twitter In-Degree

POWERGRAPH

Programming Model:
Gather-Apply-Scatter

→ Vertex based programming model

Sync / Async execution

Better Graph Partitioning
with vertex cuts

GATHER-APPLY-SCATTER

Gather: Accumulate info from nbrs

Apply: Accumulated value to vertex

Scatter: Update adjacent edges

Gather returns an accumulator

- Sum aggregates accumulators

Apply - updates vertex state

Scatter - updates edge state

state of vertex

state of edge

```
// gather_nbrs: IN_NBRS
gather(Du, D(u,v), Dv):
    return Dv.rank / #outNbrs(v)

sum(a, b): return a+b
```

= Combiner

```
apply(Du, acc):
    rnew = 0.15 + 0.85 * acc
    Du.delta = (rnew - Du.rank)/
        #outNbrs(u)
    Du.rank = rnew
```

ε/degree

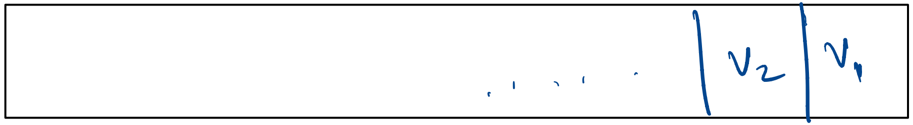
```
// scatter_nbrs: OUT_NBRS
scatter(Du,D(u,v),Dv):
    if(|Du.delta|> ε) Activate(v)
    return delta
```

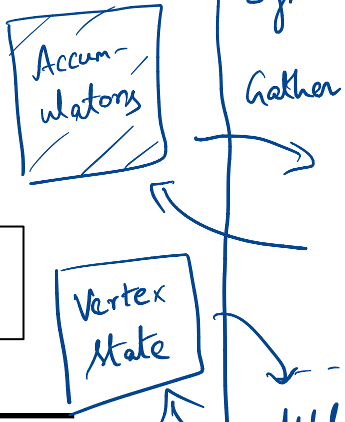
EXECUTION MODEL, CACHING

1. Activate all vertices

not all active in every iteration

Active Queue





Delta caching

Cache accumulator value for vertex → Prev iteration

Optionally scatter returns a delta

Accumulate deltas

↳ Saves a lot of gather calls

Synchronous exec mode

Gather phase

→ Run gather + sum for all active vertices

Apply

→ Run apply phase

Scatter

→ Will activate vertices for next iteration

SYNC VS ASYNC

Sync Execution

Gather for all active vertices, followed by Apply, Scatter

Barrier after each minor-step

$G(V_1)$

$A(V_1)$ → update V_1 state

$G(V_2)$ ← reads updated state

Async Execution

Execute active vertices, as cores become available

No Barriers! Optionally serializable

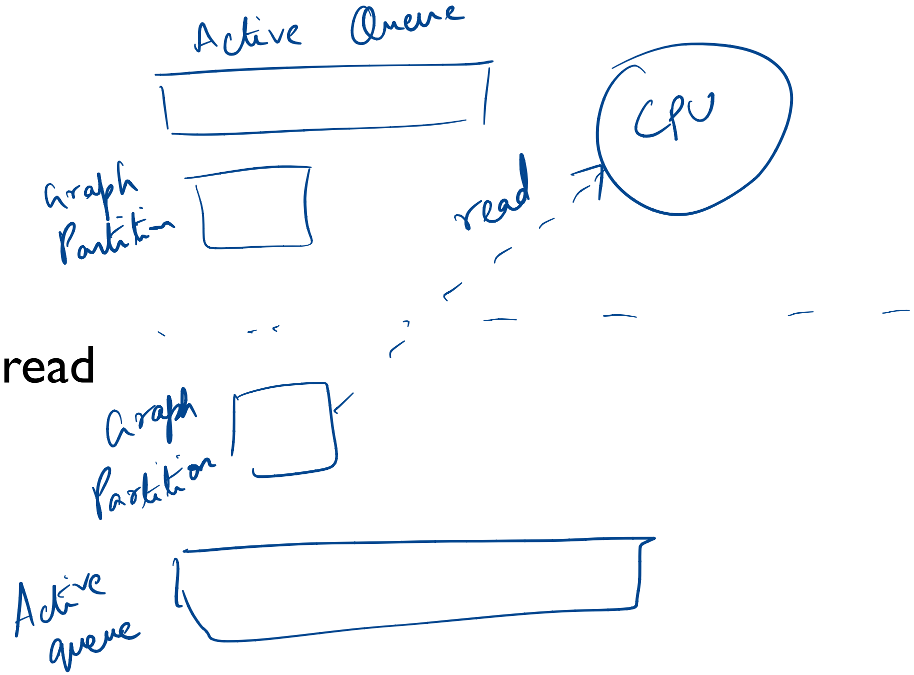
- Update vertex & edge state "eagerly"
- Some algorithms accelerates
- no guarantees on convergence

DISTRIBUTED EXECUTION

Symmetric system, no coordinator → Similar to Naiad

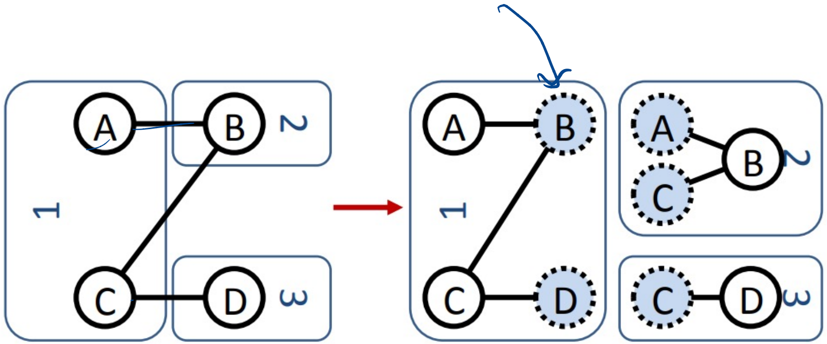
Load graph into each machine

Communicate across machines to spread updates, read state



GRAPH PARTITIONING

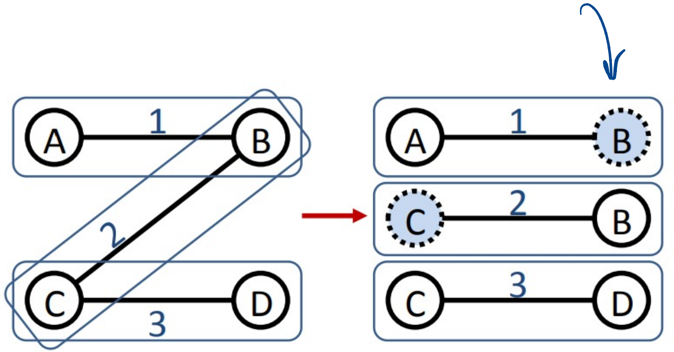
ghost vertices



(a) Edge-Cut

- Place a vertex on a machine
  - Minimize number of edges that cross machines
- Can lead to imbalance

ghost vertices



(b) Vertex-Cut

- Place an edge on a machine
- Replicas of vertex state when edges are on diff machines
- One primary replica!

RANDOM, GREEDY OBLIVIOUS

Three distributed approaches:

Random Placement

↳ stream through edges, pick a random machine

Coordinated Greedy Placement

↳ check which machine already has this vertex and place edge there

Oblivious Greedy Placement

↳ Only know local set of vertices. Not global

OTHER FEATURES

Async Serializable engine

- Preventing adjacent vertex from running simultaneously
- Acquire locks for all adjacent vertices

Fault Tolerance

- Checkpoint at the end of super-step for sync

SUMMARY

Gather-Apply-Scatter programming model

Vertex cuts to handle power-law graphs

Balance computation, minimize communication

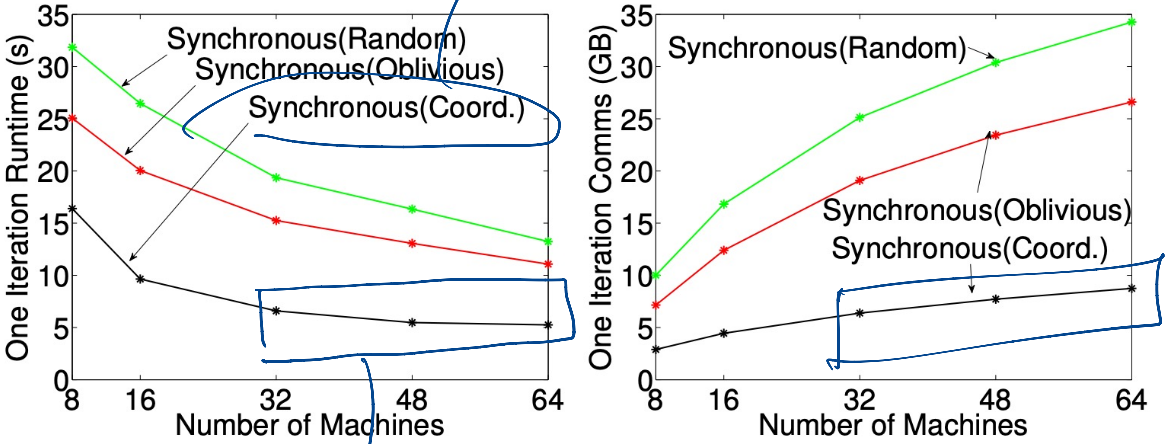
DISCUSSION

https://forms.gle/Xs3ibsUCdjynBv7u8

Consider the PageRank implementation in Spark vs synchronous PageRank in PowerGraph. What are some reasons why PowerGraph might be faster?

- Delta caching
  - → Communication, computation might be lower
  - → Join between edge list and Page Rank
- Vertex Cuts
  - → Edge cuts in Spark. Imbalance / more communication
    ↓
    Join step
- Fault tolerance
  - → Partial recovery can be faster?

Coord has best iteration time



(a) Twitter PageRank Runtime

(b) Twitter PageRank Comms

Comm keeps going up!

wins are not big after 32 machines

NEXT STEPS

Next class: GraphX / COST

which sections of which papers