CS 744: MARIUS

Shivaram Venkataraman Fall 2022

ADMINISTRIVIA

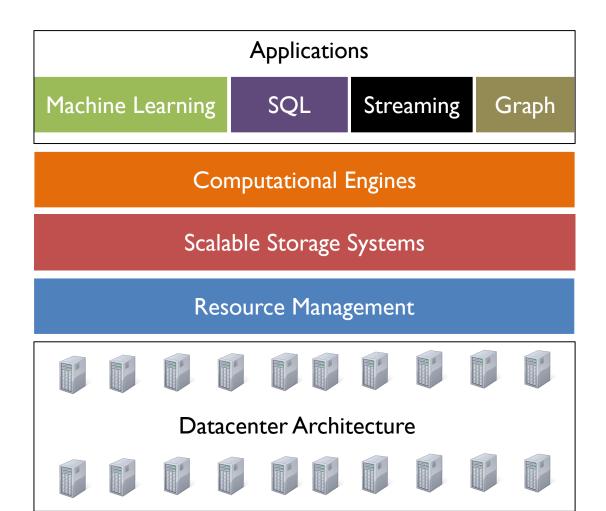
- Midterm grades out!
- Regrade requests: In-person (strongly preferred)
 - Thu: After class, Roger's OH
 - Mon: Shivaram's OH, Roger's OH
 - Tue: After class

Course Project: Check in by Nov 23th

PROJECT CHECK-INS

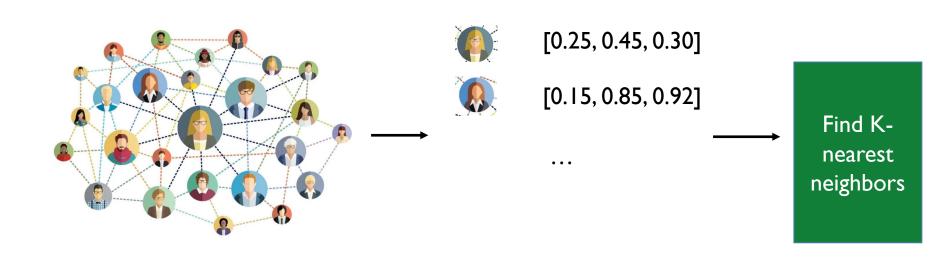
One page document that includes the following

- What have you done so far
- Any challenges that you have faced so far
- Your timeline (from now till end of the semester)
- Things you need help from the course staff
- Any other comments/remarks



EXAMPLE: LINK PREDICTION

Task: Predict potential connections in a social network



BACKGROUND: GRAPH EMBEDDING MODELS

Score function

Capture structure of the graph given source, destination embedding

Loss function

Maximize score for edges in graph

Minimize for others (negative edges)

$$\mathcal{L} = \sum_{e \in G} \sum_{e' \in S'_e} \max(f(e) - f(e') + \lambda, 0))$$

TRAINING ALGORITHM

SGD/AdaGrad optimizer

Sample positive, negative edges

Access source, dest embeddings for each edge in batch

```
for i in range(num_batches)
```

B = getBatchEdges(i)

E = getEmbeddingParams(B)

G = computeGrad(E, B)

updateEmbeddingParams(G)

CHALLENGE: LARGE GRAPHS

Large graphs → Large model sizes

Example

3 Billion vertices, d = 400

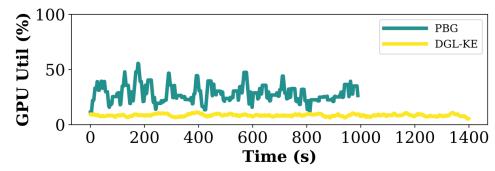
Model size = 3 billion * 400 * 4 = 4.8 TB!

Need to scale beyond GPU memory, CPU memory!

CHALLENGE: DATA MOVEMENT

DGL-KE: Sample edges, embeddings from CPU memory

Pytorch-BigGraph: Partition embeddings so that one partition fits on GPU memory. Load sequentially



One epoch on the Freebase86m knowledge graph

MARIUS

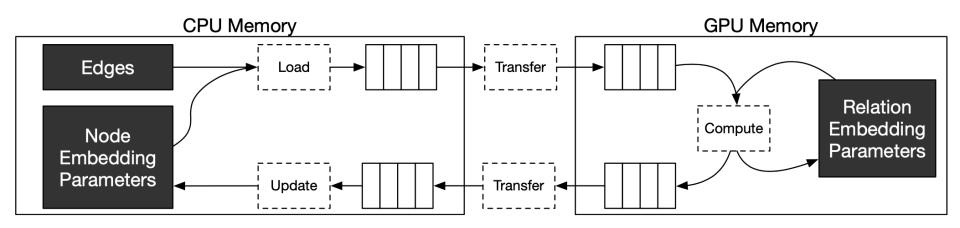
I/O efficient system for learning graph embeddings

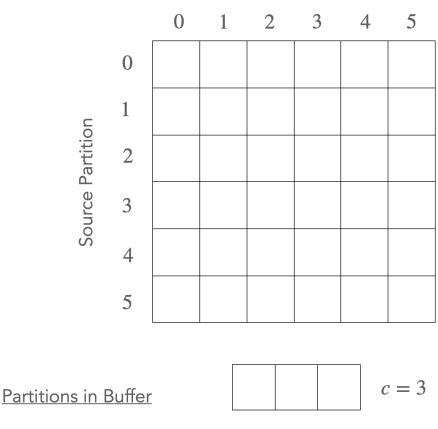
Marius Design

- Pipelined training
- Partition ordering



PIPELINED TRAINING





Destination Partition

OUT OF MEMORY TRAINING

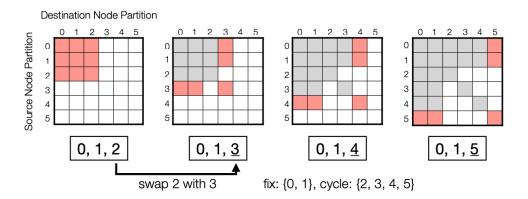
Key idea: Maintain a cache of partitions in **CPU** memory

Questions

Order of partition traversal?

How to perform eviction?

BETA ORDERING



Initialize cache with c partitions

Swap in partition that leads to highest number of unseen pairs

Achieved by fixing c-I partitions and swap remaining in any order

SUMMARY

Graph Embeddings: Learn embeddings from graph data for ML

Marius: Efficient single-machine training

Pipelining to use CPU, GPU

Partition buffer, BETA ordering

DISCUSSION

https://forms.gle/uNAKsPsZp56CcIVz9

How does the partitioning scheme used in this paper differ from partitioning schemes used in PowerGraph and why?

| System | Deployment | Epoch Time (s) | Per Epoch Cost (\$) |
|--------|-------------|----------------|---------------------|
| Marius | 1-GPU | 727 | .61 |
| DGL-KE | 2-GPUs | 1068 | 1.81 |
| DGL-KE | 4-GPUs | 542 | 1.84 |
| DGL-KE | 8-GPUs | 277 | 1.88 |
| DGL-KE | Distributed | 1622 | 2.22 |
| PBG | 1-GPU | 3060 | 2.6 |
| PBG | 2-GPUs | 1400 | 2.38 |
| PBG | 4-GPUs | 515 | 1.75 |
| PBG | 8-GPUs | 419 | 2.84 |
| PBG | Distributed | 1474 | 2.02 |

What are some shortcomings of Marius? What could the authors do to further improve the system?

NEXT STEPS

Next class: Distributed GNNs

Project check-ins by Nov 23th