

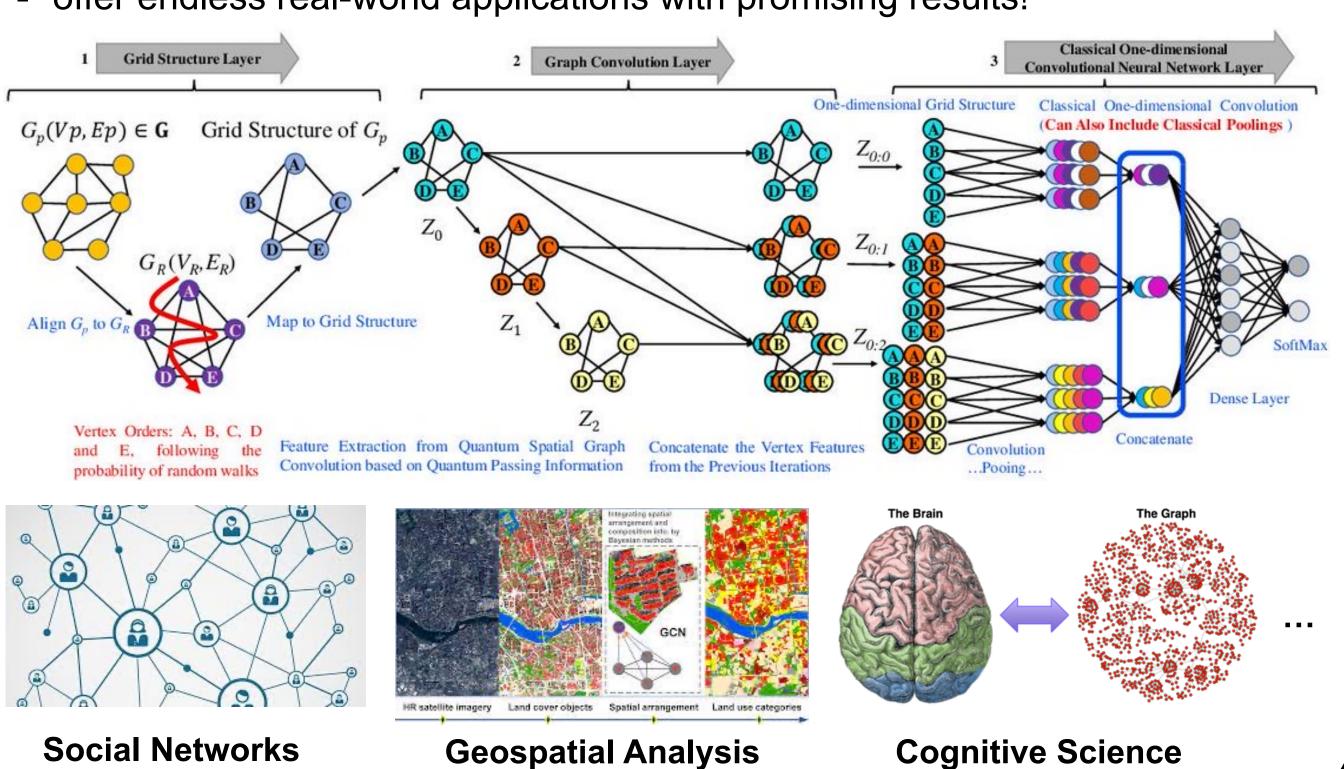
GraphGem: Optimized Scalable System for Graph Convolutional Networks

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1. Background & Motivation

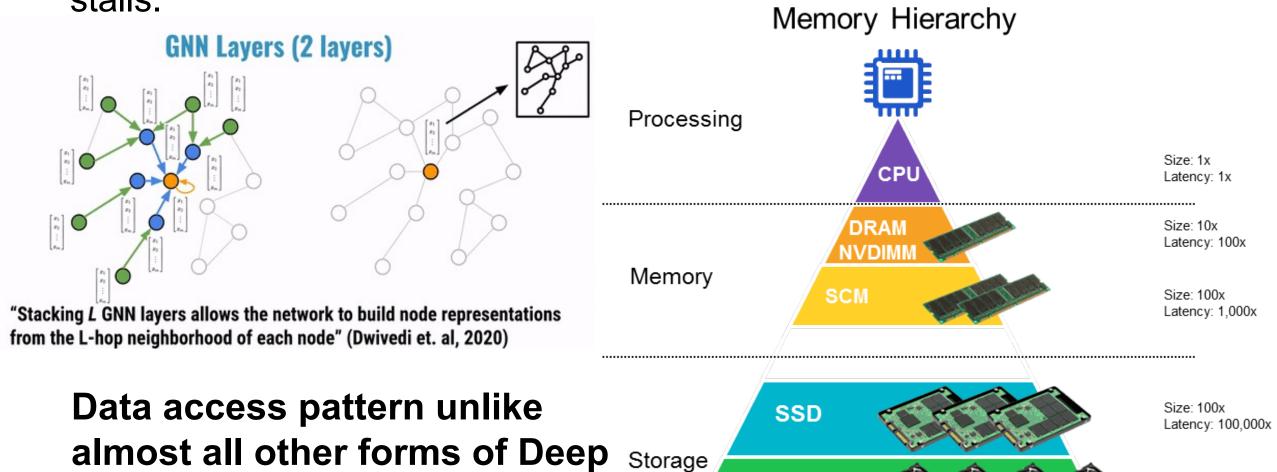
GCNs expand CNN's convolution operation to:

- work with data in non-Euclidean spaces,
- model complex 'long-range' dependencies and network embeddings,
- offer endless real-world applications with promising results!

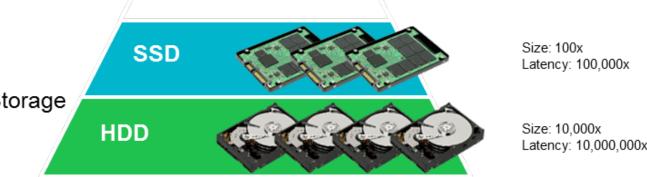


2. Challenges

- Updating a node's value involves I/O cost to read its neighbors (and more I/O for their neighbors..) and write the updated value.
- Large graph and feature matrix forces data reads to go to a lower memory level, resulting in large <u>random access</u>, increasing I/O costs and memory stalls.



Learning!



Time (in seconds)

Most GCN literature utilizes data featurizations which can be easily stored in DRAM / GPU memory!

3. Experiments

Dataset: 89,250 Flickr images | Task: Multi-class image (node) classification | GCN Framework: 2-layer GraphSAINT with Random Walk sampler using TF Featurizations: BoW – 500-dim bag of words of textual captions [341 MB], VGG16 – 100,352-dim block_5_conv_3 layer of image features [34 GB] *VGG16, GPU: OOM!* Machine Hardware: 1 NVIDIA 12GB PCI P100 GPU, 2 Intel Xeon Silver 4114 10-core CPUs, 192 GB RAM

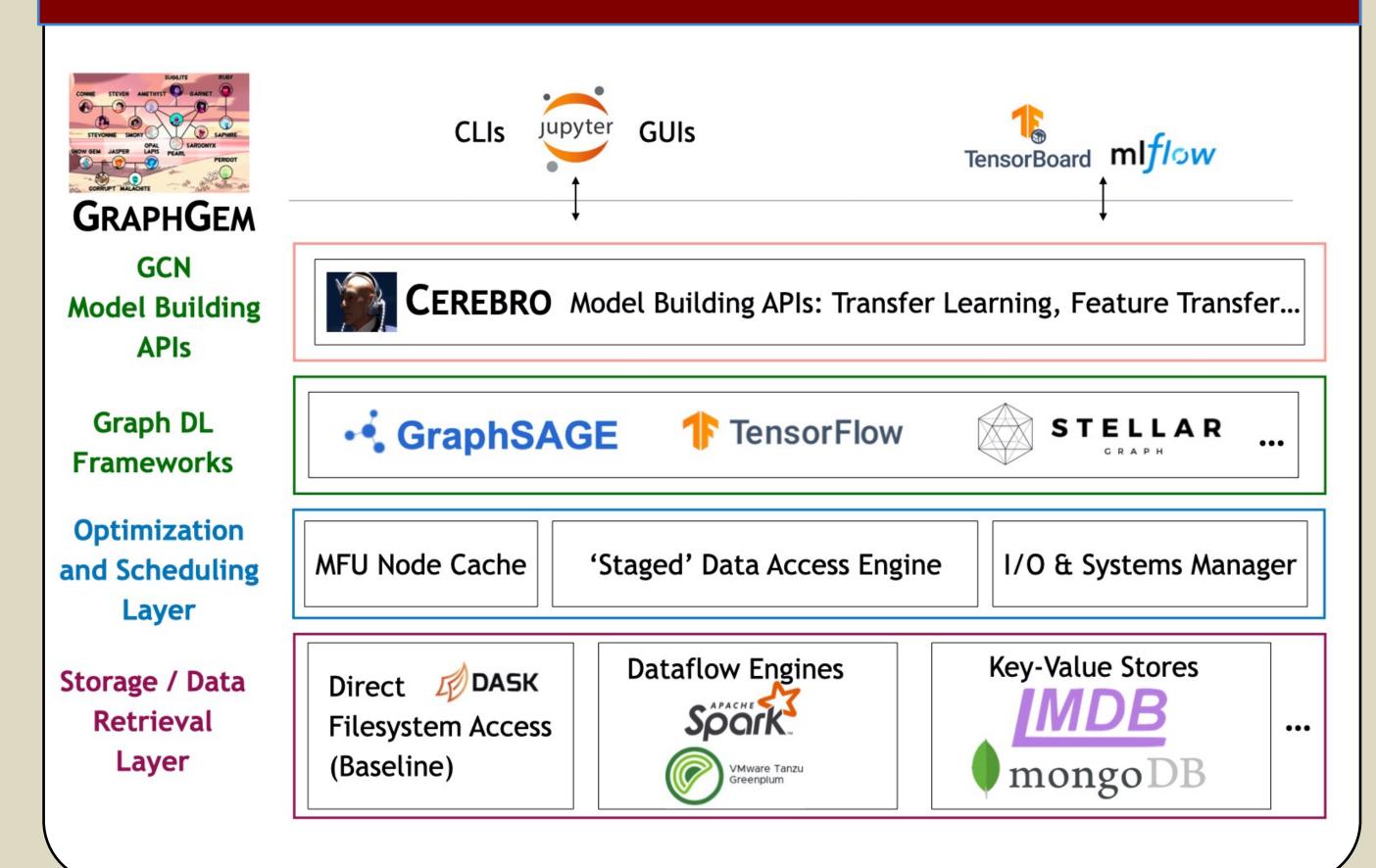
Graphs: Processor Utilization (top graphs) & Main-Memory Utilization (bottom graphs), plotted over time (bottom x-axis) and epoch end-times (top x-axis) **BoW. CPU** BoW, GPU VGG16, CPU 22.4 23.4 24.1 25.2 25.9 27.0 Time (in seconds) Time (in seconds) (140 (D) 130 RAM Utilization (in GB) RAM Utilization (in moderate of the moderate o

Time (in seconds)

4. Proposed Architectural Stack

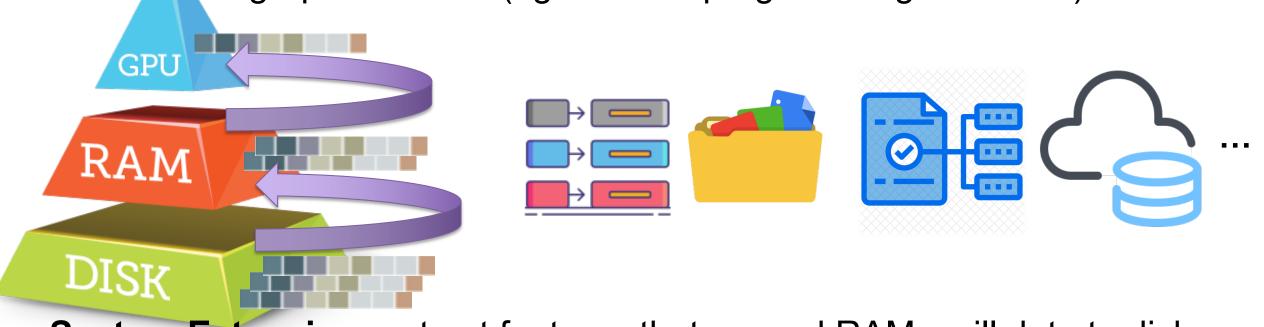
Time (in seconds)

GPU Memory



5. Future Work

- Baseline: Make the VGG16 feature variant work on GPU by spilling data to DRAM and reading it to GPU as needed
- **Additional Metrics:** *DRAM-to-GPU* network and I/O *traffic*
- Optimization Layer: optimally 'stage' mini-batches to processor based on the inherent graph structure (eg – CUDA programming for GPUs)



- System Extension: extract features that exceed RAM, spill data to disk, and monitor performance across multiple memory levels
- Storage Extensions: Diversify experimentation with key-value stores, multiple GPUs, distributed set-ups etc.

References: Arun Kumar et al. 2021. "Cerebro: A Layered Data Platform for Scalable Deep Learning." In CIDR.; Zeng, Hanqing et al. "GraphSAINT: Graph Sampling Based Inductive Learning Method." ArXiv abs/1907.04931 (2020): n. pag.