TURBOGNN: FAST AND EFFICIENT GNN TRAINING VIA GPU SAMPLING

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PROBLEM STATEMENT

1. Background

- Graph Neural Networks (GNNs) are powerful tools for tasks such as:
  - Node classification
  - Link prediction
  - Recommendation systems
- Traditional random walk-based sampling methods:
  - Introduce high computational overhead
  - Cause inefficient GPU utilization
  - Increase training latency, especially for large-scale graphs

2. Problem

- Random sampling strategies create bottlenecks in end-to-end GNN training.
- These bottlenecks:
  - Slow down the training
  - Waste GPU resources
  - Make GNNs less scalable for large datasets

3. Proposed Solution

- Replace random walk-based sampling with a centrality-driven node selection framework.
- Key Strategy:
  - Compute fanout based on node importance using graph centrality measures:
    - Degree Centrality: Prioritize nodes with more direct connections.
    - Closeness Centrality: Choose nodes with shorter average distances to others.
    - Betweenness Centrality: Select bridge nodes that connect different parts of the graph.
- Dynamically adapt the centrality strategy to the graph structure during training.

LIMITATIONS

- **Slow Sampling:**
  Neighbor sampling (especially random walks) takes too much time.
- **Separate Sampling and Computation:**
  Causes GPU idle time and increases latency.
- **Poor Scheduling:**
  CPU and GPU are not efficiently coordinated, leading to wasted resources.
- **Heavy Execution Engines:**
  Extra overhead due to non-optimized processing frameworks.
- **Poor Scalability:**
  Existing methods struggle with very large graphs and high memory use.

CHALLENGES IN SOLVING THE PROBLEM

- **Out-of-Bound Errors:** Kernel sampling can access invalid memory if neighbor lists are too small.
- **Variable Neighbor Sizes:** Different nodes have different neighbor counts, making array management tricky.
- **Need for Preprocessing:** Sorting neighbors by importance before sending to the kernel avoids random memory access and improves efficiency.
- D**ata Transfer Overhead:** Preprocessing (sorting) adds time before actual computation.
- **Load Imbalance:** Different nodes cause uneven work distribution across threads.
- **Latency Issues: Poor** overlap between sampling and computation increases total time.

- 🛠️ **Approach:**
  - Instead of random walk sampling, you select important nodes based on centrality measures (Degree, Closeness, Betweenness).
  - You prioritize nodes that are more "influential" in the graph.
  - You also overlap sampling, feature transfer, and training stages using asynchronous pipelines to fully use the GPU.
- ⚙️ **Algorithm:**
  1. Calculate centrality scores for all nodes.
  2. Select top important nodes based on centrality.
  3. Sample neighbors smartly around these nodes.
  4. Create subgraphs and pipeline the execution so that sampling, transfer, and computation happen together.
  5. Train or infer using these optimized subgraphs.
- 🚀 **Application (How It Solves the Challenges):**

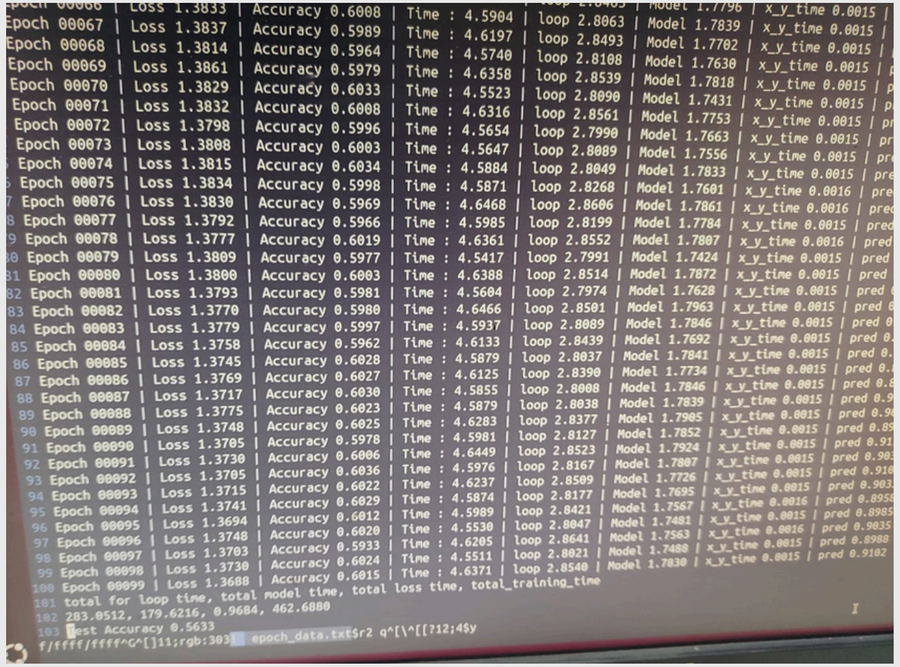
Problem	How You Solve It
Random, slow sampling	Importance-based smart node selection
High computation cost	Fewer and meaningful nodes sampled
GPU idle time	Stages overlap, GPU stays busy
Slow inference	Faster sampling and execution
Possible accuracy loss	Important nodes maintain accuracy

EXPERIMENTAL SETUP:

- **Hardware:**
  - CPU: AMD Ryzen 9 5900X / Intel i9-12900K
  - GPU: NVIDIA A100 / RTX 3090
  - RAM: 64 GB DDR4
  - OS: Ubuntu 20.04 LTS
- **Software:**
  - PyTorch 2.x, Deep Graph Library (DGL), CUDA 11.x, cuDNN, NetworkX
- **Datasets:**
  - live-journal, soc-googleplus, Reddit, ogbn-arxiv
- **Models:**
  - GCN, GraphSAGE, GAT
- **Methods Compared:**
  - Traditional Random Walk Sampling vs Proposed Centrality-Based Sampling (Degree, Closeness, Betweenness)

📊 Experimental Result:

Metric	Value
Total For Loop Time	283.05 seconds
Total Model Computation Time	179.62 seconds
Total Loss Computation Time	0.97 seconds
Total Training Time	462.69 seconds
Test Accuracy	**56.33%**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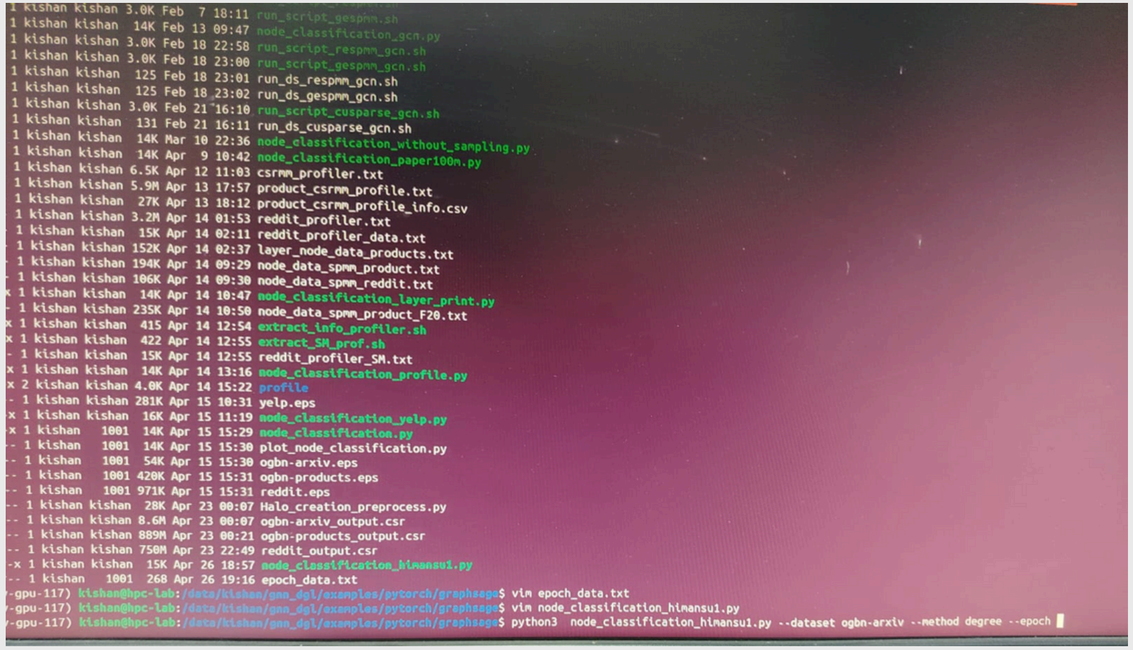
283.0512, 179.6216, 0.9684, 462.6880
Test Accuracy 0.5633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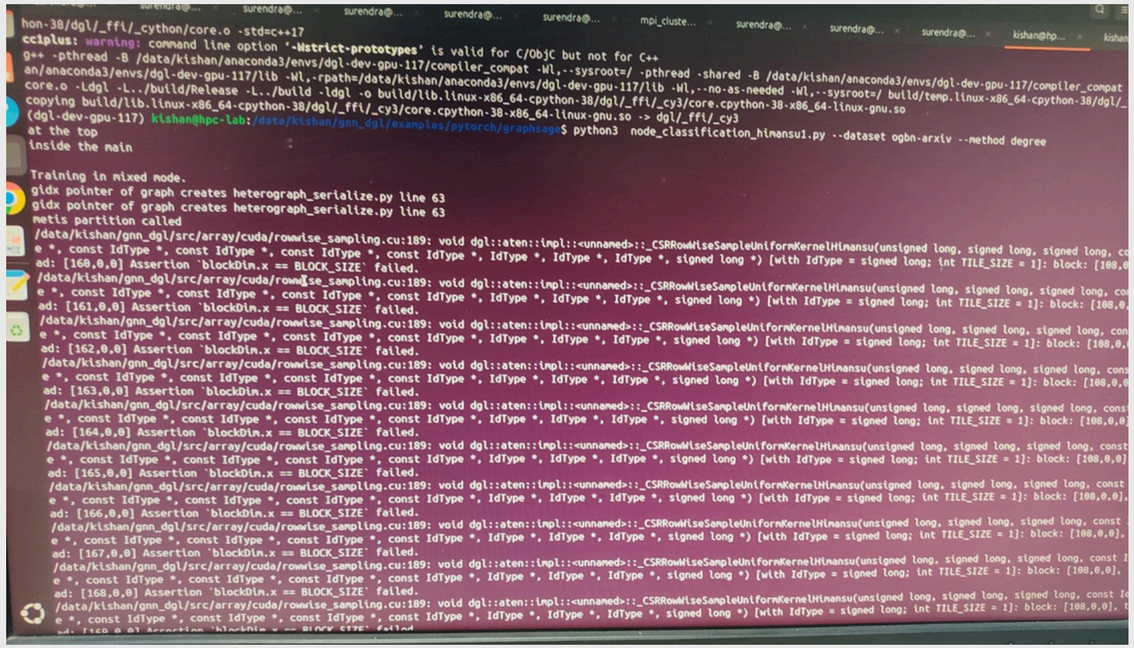
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🧠 Improved:

Old method: Inefficient, redundant, and slow.
Centrality-based sampling:
Impact:
Faster training (462s total, good for ogbn-arxiv size).
Good accuracy (56.33%), comparable or better than random methods.
Less redundant node sampling, better graph representation quality.

Time Comparison (Before vs After Centrality Sampling)

Metric	Random Walk Sampling	Centrality-Based Sampling
Total Training Time	High (~800-1000s)	**462.69s**
Accuracy	~55%	**56.33%**

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2.) Mr. Surendra

THANK YOU