

Parallelizing PageRank Algorithm using OpenMP

Background and Motivation

- PageRank is a core algorithm in web-scale information retrieval
- Models the Web as a large directed graph
- Characteristics:
 - Iterative computation
 - Memory-bandwidth intensive
 - Highly irregular graph structure (cache miss)

Project Goal:

Design parallelized PageRank implementations using OpenMP.

PageRank: Random Surfer Model

- A user repeatedly:
 - Follows an outgoing hyperlink with probability d
 - Jumps to a random page with probability $(1 - d)$
- The PageRank value represents the stationary probability of visiting a page
- Importance is defined recursively

A page is important if it is pointed to by other important pages

Formula

$$PR^{(t+1)}(u) = \frac{1-d}{N} + \frac{d}{N} \sum_{k \in D} PR^{(t)}(k) + d \sum_{v \in In(u)} \frac{w_{v,u} \cdot PR^{(t)}(v)}{\sum_{z \in Out(v)} w_{v,z}}$$

- t : The number of iterations.
- N : total number of nodes
- d : damping factor (typically 0.85)
- D : set of dangling nodes (nodes with no outgoing edges)
- $In(u)$: in-neighbors of node u
- $Out(v)$: out-neighbors of node v
- $w_{v,u}$: weight of edge $(v \rightarrow u)$

Graph Representation: CSR Format

- Graph stored using **Compressed Sparse Row (CSR)**
- Arrays:
 - `offset[]` : starting index of edges of nodes
 - `struct Edge m[]` : edges - destination node and weight

Advantages:

- Compact memory layout
- Efficient sequential edge traversal
- Well-suited for shared-memory systems

Push vs Pull Traversal

Push (Source-Centric)

- Iterate over outgoing edges
- Update destination nodes with new PageRank
- Parallel writes to shared memory (critical)
- Requires atomic operations or locks

Pull (Destination-Centric)

- Iterate over destination nodes
- Read from incoming neighbors
- Each thread writes to a private location (lock-free)
- I will basically use this strategy

Strategy 1: Dynamic Scheduling

```
#pragma omp parallel
{
    // Pre-calculate normalized values to avoid an irregular memory access
    // Also collect the dangling nodes
    #pragma omp for schedule(static) reduction(+: dangling_sum)
    for (int i = 0; i < n; ++i) {
        if (out_w[i] != 0) {
            pr_normalized[i] = pr[i] * damping / (double) out_w[i];
        } else {
            dangling_sum += pr[i];
        }
    }
}

#pragma omp single
    base_score = (1.0 - damping + damping * dangling_sum) / n;

// Scheduling overhead
#pragma omp for schedule(dynamic, 64) reduction(+: diff)
for (int u = 0; u < n; ++u) {
    double sum = base_score;
    const int start = converse->offset[u], end = converse->offset[u + 1];
    for (int i = start; i < end; ++i) {
        const int v = converse->m[i].v;
        const int w = converse->m[i].w;
        // Here we have one irregular memory access (also bottleneck)
        sum += w * pr_normalized[v];
    }
    pr_new[u] = sum;
    diff += fabs(sum - pr[u]);
}
}
```

Strategy 2: Edge-Balanced Static Partitioning

Distribute work based on number of edges

```
// Calculate partition boundaries based on edge counts
int *start_v = malloc(sizeof(int) * (num_threads + 1));
start_v[num_threads] = n;
#pragma omp parallel for schedule(static)
for (int i = 0; i < num_threads; i++) {
    // Find the node index where the cumulative edge count reaches i * (total_edges / threads)
    start_v[i] = lower_bound(converse->offset, 0, n + 1, i * e / num_threads);
}
// ...
// Distribute the nodes
#pragma omp parallel reduction(+: diff)
{
    const int tid = omp_get_thread_num();
    const int end_v = start_v[tid + 1];
    for (int u = start_v[tid]; u < end_v; u++) {
        // ...
    }
}
```


Advantages and Limitations of Strategy 2

Advantages:

- Minimal scheduling overhead than dynamic scheduling
- Theoretically good load balance
- Improved cache locality

Limitations:

- Static partitioning cannot adapt at runtime
- Performance sensitive to the CPU Architecture
- Slowest thread determines total time (I will introduce this later.)

Strategy 3: Approximate PageRank with Active Frontier

Observation:

- Many nodes converge early
- Updating them repeatedly wastes memory bandwidth

Method:

- Maintain a frontier of active nodes
- Only update nodes with significant change

Introduces larger approximation error but somehow preserves ranking quality by choosing a smaller error ϵ

```

// 1. Compute updates only for nodes in current 'frontier'
#pragma omp parallel for schedule(static)
for (int i = 0; i < frontier_size; i++) {
    const int u = frontier[i];
    // ... compute sum ...
    pr_new[u] = sum;
    // Mark if this node needs to be active next time
    next_idx_prefix[i] = fabs(sum - pr[u]) > eps;
}

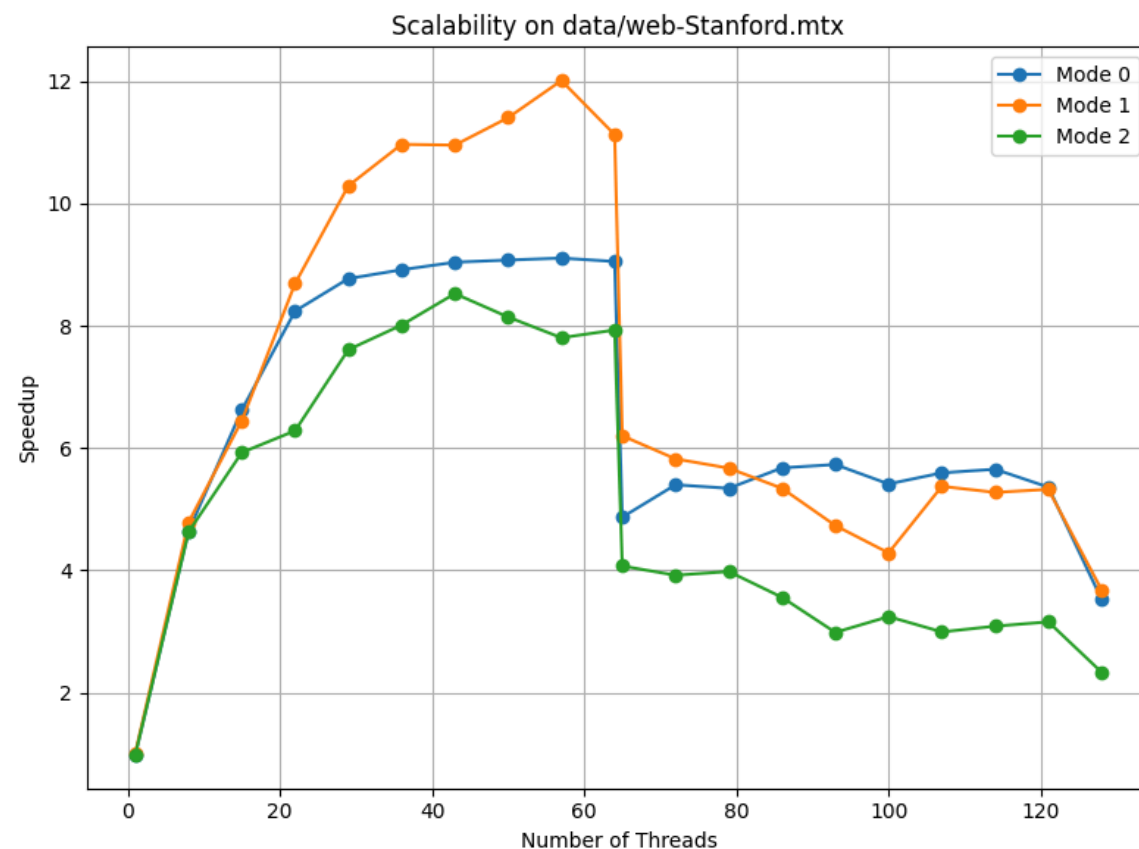
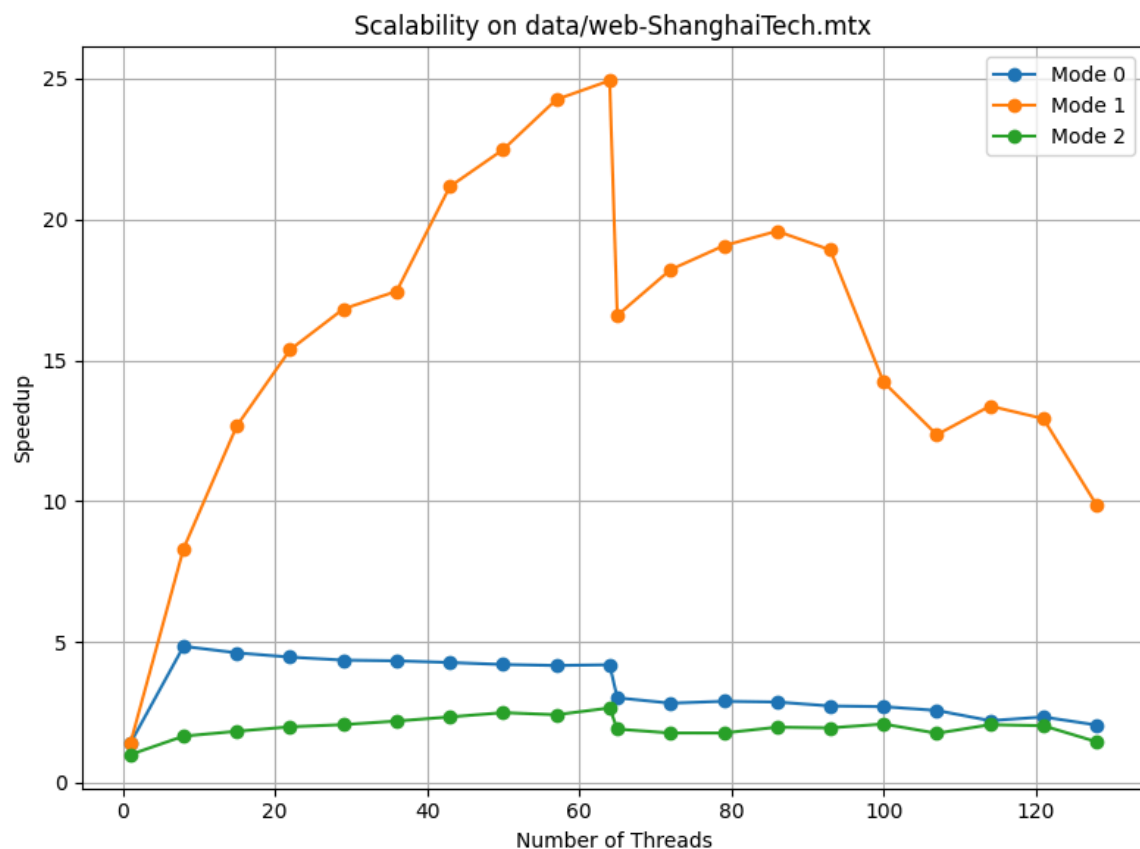
// 2. Parallel prefix sum to calculate write positions (each thread calculates a block)
omp_prefix_sum(next_idx_prefix, frontier_size, prefix_block_sum);

// 3. Culling
#pragma omp parallel for schedule(static)
for (int i = 0; i < frontier_size; i++) {
    const int prev_val = (i == 0) ? 0 : next_idx_prefix[i - 1];
    if (next_idx_prefix[i] > prev_val) {
        next_frontier[next_idx_prefix[i] - 1] = frontier[i];
    }
}

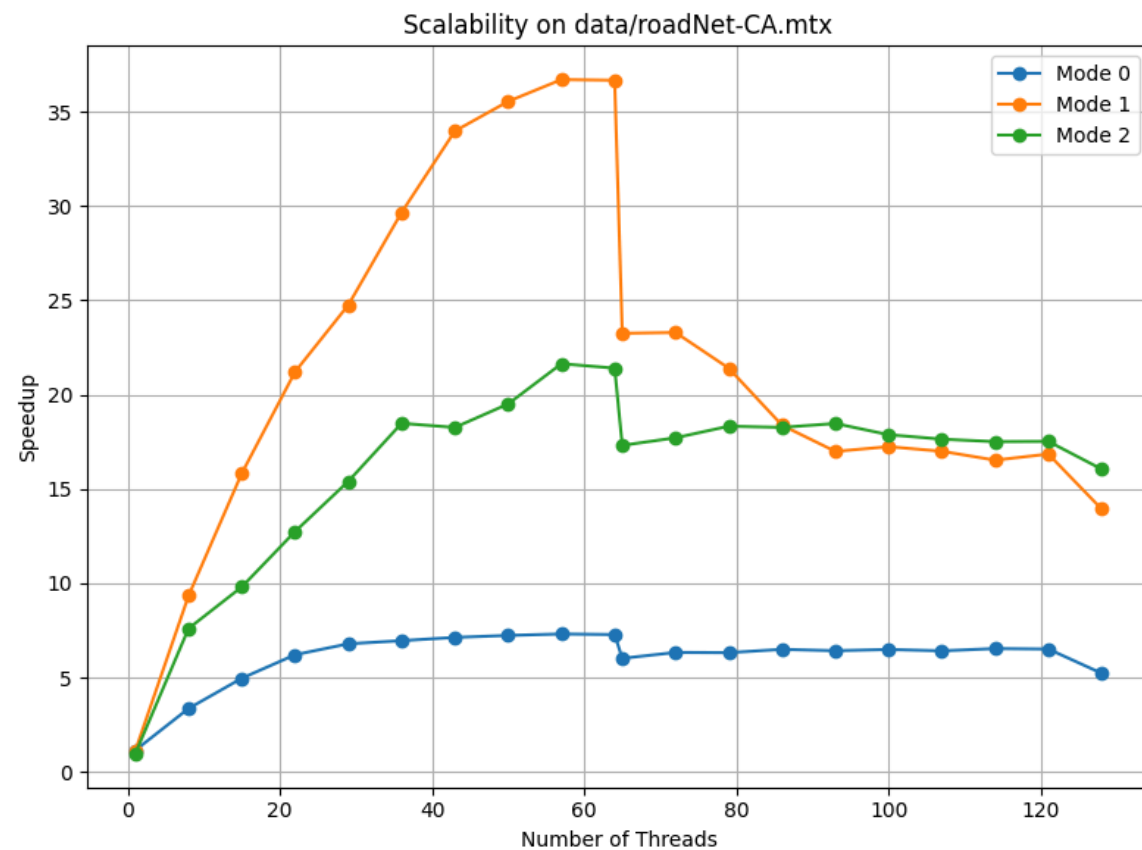
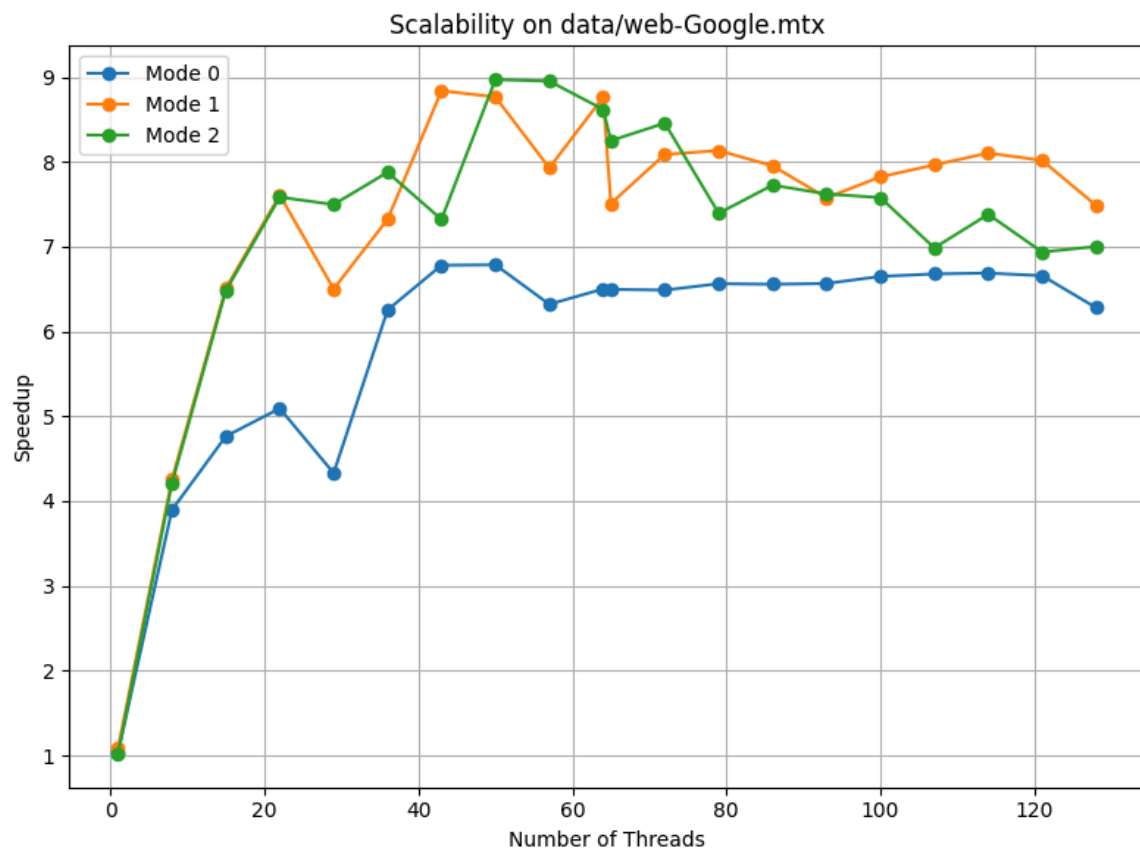
```

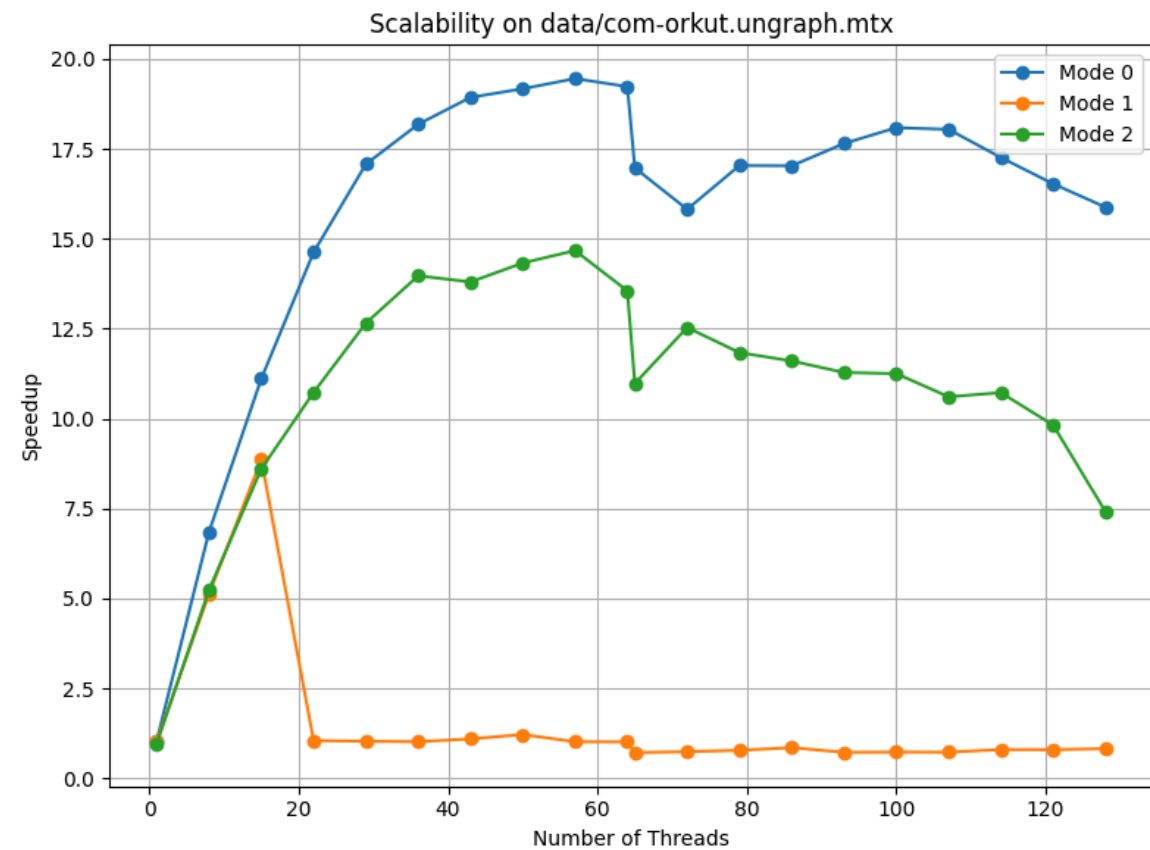
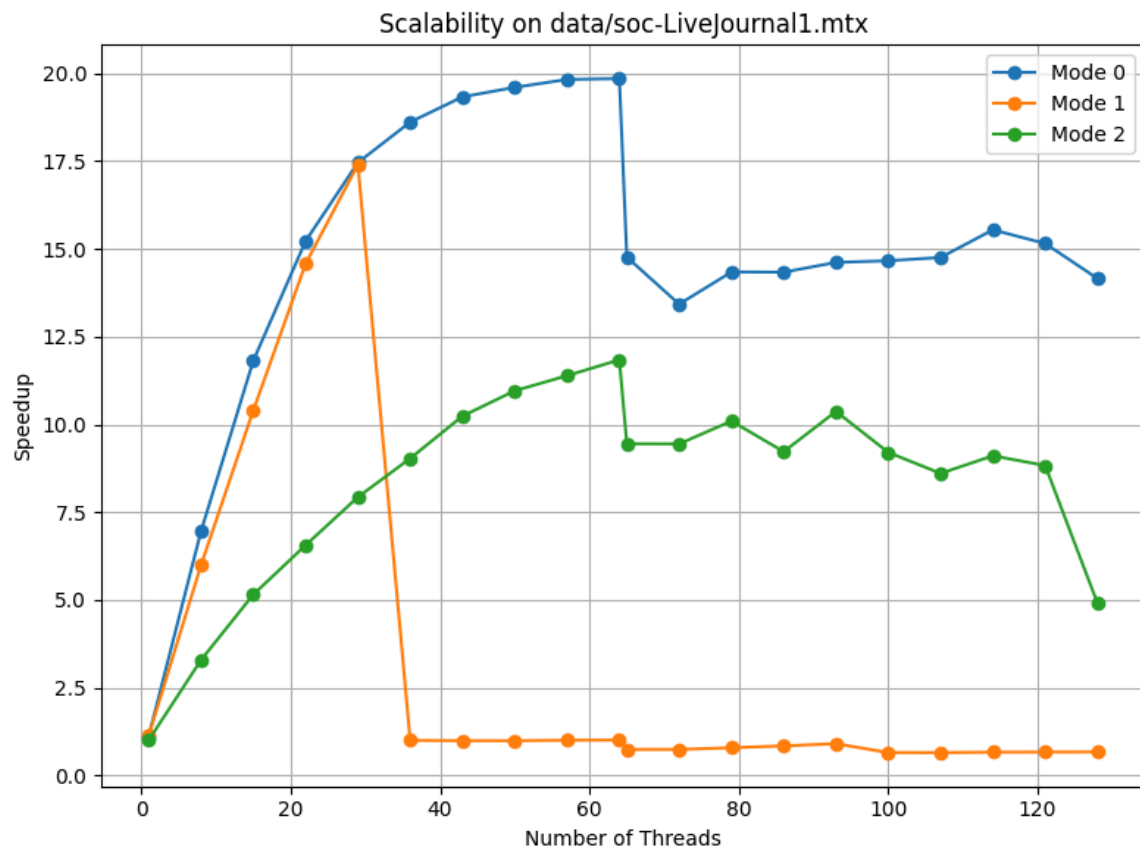
AMD EPYC 7742 64-Core Processor (2250 MHz, 128 Threads, 2 NUMA Nodes)

Strategy 1 & 2: $\epsilon = 10^{-6}$; Strategy 3: $\epsilon = 10^{-8}$



Strategy 2 works well since almost all pages will link to the homepage
(i.e. <https://www.shanghaitech.edu.cn/>)





Both are social networks (friends). The neighbors are highly randomized.

Sharply declines at thread number 15~16 and 32~33.

Dynamic scheduling hides memory latency

Conclusions

- Strategy 2 works better on the graphs of real Webs.
- No single parallel strategy is universally optimal (tradeoffs)
- Strategy selection depends on:
 - Degree distribution
 - Graph size
 - CPU/NUMA topology
- Approximation can significantly reduce runtime with acceptable error

Thank you!