CPU-Based Shortest Path Algorithms

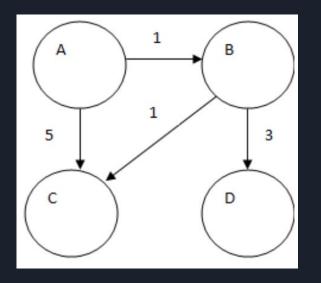
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Definition: Shortest Path

Given a digraph *G* with non-negative weights on its edges, the shortest path from a source node *S*, and a destination node *T* is a directed path from *S* to *T* with the minimum total weight.

- Single-Source Shortest Path: S to V_i , $\forall V_i \subseteq V$
- All-Pairs Shortest Path: V_i to V_j , $\forall V_i$, $V_j \in V$

Example



	А	В	С	D
А	0	1	2	4
В	∞	0	1	3
С	∞	∞	0	∞
D	8	∞	8	0

SSSP: Single-Source Shortest Path

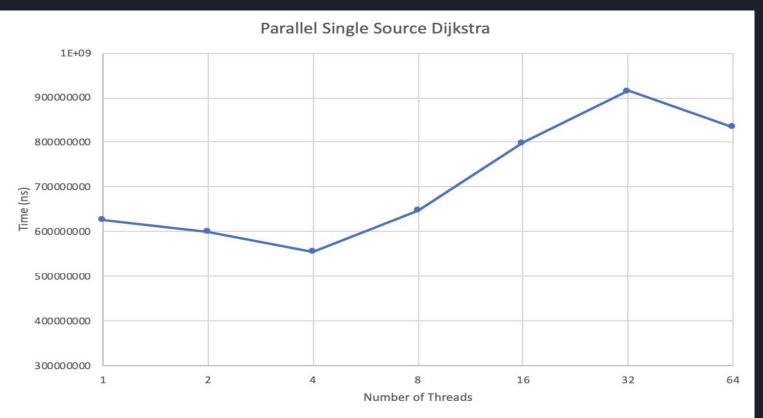
- 1. Mark all nodes as unvisited and set their weights to ∞
- 2. Set current node weight to 0.
- 3. Remove node with smallest weight from unvisited set
- 4. Relax its outgoing edges Given edge (u, v), dist(v) = min(dist(u) + weight(e), dist(v))
- 5. Repeat steps 3 and 4 until the unvisited set is empty.

Dijkstra's Runtime: O(E + VlgV)

Parallel Dijkstra's finds the minimum in parallel with P threads.

Runtime: $O(E + V^2/P) \rightarrow O(E + V)$

SSSP: Single-Source Shortest Path



APSP: All-Pairs Shortest Path

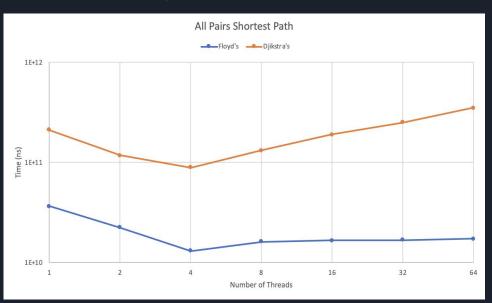
Sequential Floyd-Warshall Algorithm $O(V^3)$:

Lines 7-11 can be parallelized with P threads for runtime $O(V^3/P) \rightarrow O(V)$ with V^2 threads

APSP: All-Pairs Shortest Path

Alternative: Run Djikstra's Algorithm in parallel $\forall V_i \in V$

Runtime: O(E + VlgV)



As expected, Floyd-Warshall's is faster than running Parallel Dijkstra's

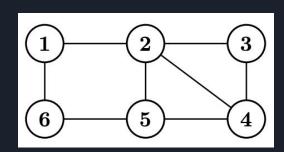
Trade off: Floyd-Warshall needs V^2 threads vs Dijkstra's needs V threads.

When we have large, sparse graphs with limited cores,

$$O(V/P * (E + V \lg V)) \cong O(V^2 \lg V / P) \leq O(V^3 / P)$$

Matrix Multiplication Based Implementations: Distance Products

Given W, a nxn matrix containing the edge weights of the graph, W^k gives the distances realized by paths that use at most k edges.



2.

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

 $\mathsf{B} = \begin{pmatrix} 0 & 1 & 1 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 \\ 1 & 1 & 0 & 1 & 1 & 0 \end{pmatrix}$

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$$(\mathbf{A} \star \mathbf{B})_{ij} = \min_{k=1}^{n} \{a_{ik} + b_{kj}\}, 1 \le i, j \le n.$$

$$A^{2} = \begin{pmatrix} 2 & 0 & 1 & 1 & 2 & 0 \\ 0 & 4 & 1 & 2 & 1 & 2 \\ 1 & 1 & 2 & 1 & 2 & 0 \\ 1 & 2 & 1 & 3 & 1 & 1 \\ 2 & 1 & 2 & 1 & 3 & 0 \\ 0 & 2 & 0 & 1 & 0 & 2 \end{pmatrix}$$

Seidel's Algorithm

- APSP Algorithm for unweighted, undirected graphs
- Computes logarithmic number of distance matrices
- O(M(n)*log(n)), where M(n) is the cost of multiplying 2 matrices
 - \circ Sequential: $O(n^{2.375477}\log(n))$
 - Parallel: O(log²(n))

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Seidel(A)
       Let Z = A \cdot A
       Let B be an n \times n 0-1 matrix,
          where b_{ij} = \begin{cases} 1 & \text{if } i \neq j \text{ and } (a_{ij} = 1 \text{ or } z_{ij} > 0) \\ 0 & \text{otherwise} \end{cases}
       IF \forall i, j, i \neq j \ b_{ii} = 1 then
              Return D = 2B-A
       Let T = Seidel(B)
       Let X = T \cdot A
       Return n \times n matrix D,
          where d_{ij} = \begin{cases} 2t_{ij} & \text{if } x_{ij} \geq t_{ij} \cdot degree(j) \\ 2t_{ii} - 1 & \text{if } x_{ii} < t_{ij} \cdot degree(j) \end{cases}
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Shoshan-Zwick Algorithm

- APSP algorithm that works on weighted, undirected graphs where existing edge weights are integers in the range of $\{1, 2, ..., N\}$
- Computes a logarithmic number of distance products in order to determine shortest paths
- Algorithm is based on not allowing the range of elements in the matrix it is uses to increase
- Stores distance matrices as it iterates in order to recover the shortest path
- O(log(N*n)*N*M(n))
 - \circ Sequential: O(N*n^{2.375477*}log(N*n))
 - \circ Parallel: O(N*log(n)log²N*n))

Function SHOSHAN-ZWICK-APSP(**D**)

- 1: $l = \lceil \log_2 n \rceil$.
- 2: $m = \log_2 M$.
- 3: **for** (k = 1 to m + 1) **do**
- 4: $\mathbf{D} = clip(\mathbf{D} \star \mathbf{D}, 0, 2 \cdot M).$
- 5: end for
- 6: $A_0 = D M$.
- 7: **for** (k = 1 to l) **do**
- 8: $\mathbf{A}_k = clip(\mathbf{A}_{k-1} \star \mathbf{A}_{k-1}, -M, M).$
- 9: end for
- 10: $\mathbf{C}_l = -M$.
- 11: $\mathbf{P}_l = clip(\mathbf{D}, 0, M)$.
- 12: $\mathbf{Q}_l = +\infty$.
- 13: **for** (k = l 1 down to 0) **do**
- 14: $\mathbf{C}_k = [clip(\mathbf{P}_{k+1} \star \mathbf{A}_k, -M, M) \wedge \mathbf{C}_{k+1}] \vee [clip(\mathbf{Q}_{k+1} \star \mathbf{A}_k, -M, M) \wedge \mathbf{C}_{k+1}].$
- 15: $\mathbf{P}_k = \mathbf{P}_{k+1} \bigvee \mathbf{Q}_{k+1}.$
- 16: $\mathbf{Q}_k = chop(\mathbf{C}_k, 1 M, M).$
- 17: **end for**
- 18: **for** (k = 1 to l) **do**
- 19: $\mathbf{B}_k = (\mathbf{C}_k \ge 0).$
- 20: **end for**
- 21: $\hat{\mathbf{B}}_0 = (-M < \mathbf{P}_0 < 0)$.
- 22: $\hat{\mathbf{R}} = \mathbf{P}_0$.
- 23: $\Delta = M \cdot \sum_{k=0}^{\infty} 2^k \cdot \mathbf{B}_k + 2 \cdot M \cdot \hat{\mathbf{B}}_0 + \hat{\mathbf{R}}.$
- 24: **return** Δ .

$$(clip(\mathbf{A}, a, b))_{ij} = \begin{cases} a & \text{if } a_{ij} < a \\ a_{ij} & \text{if } a \le a_{ij} \le b \\ +\infty & \text{if } a_{ij} > b \end{cases}$$
$$(chop(\mathbf{A}, a, b))_{ij} = \begin{cases} a_{ij} & \text{if } a \le a_{ij} \le b \\ +\infty & \text{otherwise} \end{cases}$$

$$\begin{split} \left(\mathbf{A} \bigwedge \mathbf{B}\right)_{ij} &= \left\{ \begin{array}{ll} a_{ij} & \text{if } b_{ij} < 0 \\ +\infty & \text{otherwise} \end{array} \right. \\ \left(\mathbf{A} \bigwedge \mathbf{B}\right)_{ij} &= \left\{ \begin{array}{ll} a_{ij} & \text{if } b_{ij} \geq 0 \\ +\infty & \text{otherwise} \end{array} \right. \\ \left(\mathbf{A} \bigvee \mathbf{B}\right)_{ij} &= \left\{ \begin{array}{ll} a_{ij} & \text{if } a_{ij} \neq +\infty \\ b_{ij} & \text{if } a_{ij} = +\infty, b_{ij} \neq +\infty \\ +\infty & \text{if } a_{ij} = b_{ij} = +\infty \end{array} \right. \end{aligned}$$

$$\begin{aligned} \left(\mathbf{C} \geq 0\right)_{ij} &= \left\{ \begin{array}{ll} 1 & \text{if } c_{ij} \geq 0 \\ 0 & \text{otherwise} \end{array} \right. \\ \left(0 \leq \mathbf{P} \leq M\right)_{ij} &= \left\{ \begin{array}{ll} 1 & \text{if } 0 \leq p_{ij} \leq M \\ 0 & \text{otherwise} \end{array} \right. \end{aligned}$$



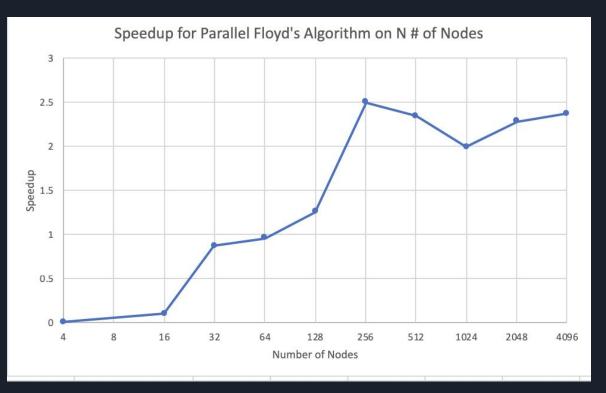
Analysis of Matrix Based Implementations

Conclusion

- Shortest Path Algorithms can be improved using parallelization on CPU
- CPU-based implementations efficiency capped by number of available processors
 - Maximum speedup when num of threads = number of available processors (4)
- Speedups are only realized for larger number of nodes
 - For smaller inputs, benefits of parallelization are negligible and cost of setting up parallelization too high
- Matrix-based algorithms do not perform well in practice on CPU

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Parallelization is not helpful for smaller graphs