# Analysis Algorithms for Large-Scale Networks 

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Algorithm Analysis Overview

## Asymptotic Complexity

- Algorithms measured on time complexity and space complexity
- Time complexity - how long an algorithm takes to complete
- Space complexity - how much memory is needed for computation

| $O(n)$ | $\Omega(n)$ | $\Theta(n)$ |
| :--- | :--- | :--- |
| Run time grows at <br> least as fast as $n$ | Run time grows at <br> most as fast as $n$ | Run time grows <br> exactly as fast as $n$ |

## Graph Representations

- Adjacency matrix
- Space: $\Theta\left(V^{2}\right)$
- Element query: $\Theta(1)$

| 0 | 0 | 0 | 1 | 0 |
| :--- | :--- | :--- | :--- | :--- |
| 0 | 0 | 1 | 1 | 0 |
| 0 | 1 | 0 | 1 | 1 |
| 1 | 1 | 1 | 0 | 1 |
| 0 | 0 | 1 | 1 | 0 |

- Adjacency list
- Space: $\Theta(V+E)$
- Element query: $\Theta$ (degree(V))

| 0 | 3 |  |  |  |
| :--- | :--- | :--- | :--- | :---: |
| 1 | 2 | 3 |  |  |
| 2 | 1 | 3 | 4 |  |
|  |  |  |  |  |
| 3 | 0 | 1 | 2 |  | 4

Degree Distribution

## Degree Distribution

- Set of all degrees in a network [5]
- Mean degree used as a measure of density of the network



## Degree Distribution

- Intuitively, will need to visit each vertex vand count edges incident on v
- Can be performed in $\mathrm{O}(\mathrm{V}+\mathrm{E})$ with an adjacency list
- Loop through adjacency list
- At each vertex, count the number of edges
- Alternatively, use a variant of breadth-first or depth-first search, both of which are $\mathrm{O}(\mathrm{V}+\mathrm{E})$


## Degree Distribution

- Intuitive approach


Characteristic Path Length

## Characteristic Path Length

- Average length of shortest paths between all pairs of vertices in a graph [7]
- Can also look at diameter - longest shortest path


| $V$ | 0 | 1 | 2 | 3 | 4 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0 | 0 | 2 | 2 | 1 | 2 |
| 1 | 2 | 0 | 1 | 1 | 2 |
| 2 | 2 | 1 | 0 | 1 | 1 |
| 3 | 1 | 1 | 1 | 0 | 1 |
| 4 | 2 | 2 | 1 | 1 | 0 |

$L=1.12$

## Characteristic Path Length

- Need to solve all-pairs-shortest-path problem with an unweighted graph
- Given a graph $G$, find the minimum distance $d_{G}(s, t)$ for all $s, t \in V$

| 1 |
| :--- |
| 4 | | $0 \rightarrow 3 \rightarrow 1$ | $1 \rightarrow 3 \rightarrow 0$ | $2 \rightarrow 3 \rightarrow 0$ | $3 \rightarrow 0$ | $4 \rightarrow 3 \rightarrow 0$ |
| :--- | :--- | :--- | :--- | :--- |
| $0 \rightarrow 3 \rightarrow 2$ | $1 \rightarrow 2$ | $2 \rightarrow 1$ | $3 \rightarrow 1$ | $4 \rightarrow 2 \rightarrow 1$ |
| $0 \rightarrow 3$ | $1 \rightarrow 3$ | $2 \rightarrow 3$ | $3 \rightarrow 2$ | $4 \rightarrow 3 \rightarrow 1$ |
| $0 \rightarrow 3 \rightarrow 4$ | $1 \rightarrow 2 \rightarrow 4$ | $2 \rightarrow 4$ | $3 \rightarrow 4$ | $4 \rightarrow 2$ |
|  | $1 \rightarrow 3 \rightarrow 4$ |  |  | $4 \rightarrow 3$ |

## Characteristic Path Length

- Naive approach
- Breadth-first search repeated for each vertex
- BFS runs in $O(E+V)$ for one source node, so overall runtime is $O\left(E V+V^{2}\right)$
- If graph is dense, this approaches $\mathrm{O}\left(\mathrm{V}^{3}\right)$
- Faster method
- Reduce to matrix multiplication [6]
- Runtime: $\mathrm{O}\left(\mathrm{V}^{2.376} \mathrm{log} \mathrm{V}\right)$
- Even better method
- dynamic programming - iteratively optimize a $\mathrm{V}^{*} \mathrm{~V}$ matrix of shortest path lengths [3]
- Runtime: $\mathrm{O}\left(\mathrm{V}^{2} \log \mathrm{~V}\right)$
- Space: $O\left(V^{2}\right)$


## Betweenness Centrality

## Betweenness Centrality

- Probability that a given vertex falls on a randomly-selected shortest path between two other vertices in the network [2]


$$
C_{B}(3)=4 / 7
$$

## Betweenness Centrality - exact

- Basic approach [1]

1. Compute length and number of shortest paths between all pairs

- Variation of all-pairs-shortest-path problem

2. Sum all pair-dependencies

- Pair-dependency - ratio of shortest paths between $s$ and $t$ containing $v$
- Takes $\mathrm{O}\left(\mathrm{V}^{3}\right)$ time to sum all pair-dependencies, and $\mathrm{O}\left(\mathrm{V}^{2}\right)$ space to store shortest paths


## Betweenness Centrality - exact

- Faster method [1]
- Runtime: O(VE) on unweighted graphs

$$
\mathrm{O}\left(\mathrm{VE}+\mathrm{V}^{2} \log \mathrm{~V}\right) \text { on weighted graphs }
$$

- Space: O(V + E)
- Based on BFS for unweighted graphs or Djikstra's algorithm for weighted graphs
- Use the fact that $v$ is a predecessor of $w$ to calculate a partial sum for dependency of $s$ on $v$
- Adding these partial sums together over all predecessors of w yields the pair-dependencies needed to calculate betweenness centrality



## Betweenness Centrality - exact

Algorithm 1: Betweenness centrality in unweighted graphs
$C_{B}[v] \leftarrow 0, v \in V$
for $s \in V$ do
$S \leftarrow$ empty stack;
$S \leftarrow$ empty stack;
$P[w] \leftarrow$ empty list, $w \in V ;$
$P[w] \leftarrow$ empty list, $w \in V ;$
$\sigma[t] \leftarrow 0, t \in V ; \quad \sigma[s] \leftarrow 1 ;$
$\sigma[t] \leftarrow 0, t \in V ; \quad \sigma[s] \leftarrow 1 ;$
$d[t] \leftarrow-1, t \in V ; \quad d[s] \leftarrow 0 ;$
$d[t] \leftarrow-1, t \in V ;$
$Q \leftarrow$ empty queue;
enqueue $s \rightarrow Q$;
while $Q$ not empty do
dequeue $v \leftarrow Q$;
push $v \rightarrow S$;
foreach neighbor $w$ of $v$ do
// $w$ found for the first time?
if $d[w]<0$ then
enqueue $w \rightarrow Q ;$
$d[w] \leftarrow d[v]+1$;
end
// shortest path to $w$ via $v$ ?
if $d[w]=d[v]+1$ then
$\begin{aligned} & \text { f } \\ & d[w]=d[v]+1 \text { then } \\ & \sigma[w] \leftarrow \sigma[w]+\sigma[v] ;\end{aligned}$
append $v \rightarrow P[w]$; end
end
end
$\delta[v] \leftarrow 0, v \in V ;$
// $S$ returns vertices in order of non-increasing distance from $s$ while $S$ not empty do
pop $w \leftarrow S$;
for $v \in P[w]$ do $\delta[v] \leftarrow \delta[v]+\frac{\sigma[v]}{\sigma(w)} \cdot(1+\delta[w])$;
if $w \neq s$ then $C_{B}[w] \leftarrow C_{B}[w]+\delta[w]$;
end

- Run modified BFS from source s

1. Compute shortest path lengths and predecessor lists from $s$ to $v \in V$
2. Update betweenness centrality values for all $v$ $\in \mathrm{V}$ based on dependency of s on V

- Repeat for all $s \in V$


## Betweenness Centrality - exact



- Results on random, undirected, unweighted graphs for size 100-2000 vertices and density 10\%-90\% of all possible edges


## Betweenness Centrality - approximate

- LINERANK algorithm [4]
- Measure the importance of a node by summing the importance score of its incident edges
- Importance score of an edge is the probability that a random walker traversing edges via nodes (with random restarts) will stay at the edge
- Defined using a directed line graph


Original graph


Directed line graph

## Betweenness Centrality - approximate

- LINERANK runtime: $\mathrm{O}(\mathrm{kE})$
- Run for kiterations
- Each iteration improves the accuracy of the estimate, but reasonable accuracy can be achieved after only a few iterations
- LINERANK space: O(E)
- Algorithm uses two incidence matrices, which hold only non-zero elements of the directed line graph, of which there are E elements

Questions?

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