

Push-Relabel Algorithm

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1 The Push-Relabel Algorithm

1.1 Introduction

Unlike augmenting-path algorithms (such as Ford-Fulkerson, Edmonds-Karp, and Capacity Scaling) or blocking-flow algorithms (such as Dinic's), Push-Relabel is a preflow-based algorithm. By relaxing the flow conservation constraint during execution, it maintains a **preflow** rather than a valid flow. This localized approach allows for greater parallelism, as operations on nodes occur independently without global synchronization. Furthermore, it offers superior theoretical time complexity; specifically, the FIFO vertex selection variant achieves $O(V^3)$, outperforming $O(VE^2)$ on dense graphs.

1.2 Theoretical Formulation

1.2.1 Preflow and Excess

A preflow is a function $f : V \times V \rightarrow \mathbb{R}$ that satisfies two fundamental properties:

1. $f(u, v) \leq c(u, v) \quad \forall (u, v) \in V \times V$ (Capacity Constraint)
2. $f(u, v) = -f(v, u) \quad \forall (u, v) \in V \times V$ (Skew Symmetry)

Unlike a standard flow, a preflow relaxes the conservation constraint. For any vertex $u \in V \setminus \{s\}$, the total flow entering u is allowed to exceed the flow leaving it. This difference is defined as the **excess** flow, $e(u)$:

$$e(u) = \sum_{v \in V} f(v, u) - \sum_{v \in V} f(u, v) \geq 0 \quad (2)$$

A vertex u is considered **active** if $e(u) > 0$ and $u \notin \{s, t\}$.

In simple words

Imagine the network as a system of water pipes (edges) and junctions (vertices).

- **Preflow:** A state where water flows into a junction faster than it flows out, creating a temporary buildup. (In a standard flow, inflow must exactly equal outflow).
- **Excess:** The net amount of water currently accumulated at a junction, waiting to be pushed into the next pipe.

1.2.2 Height Function

To direct the flow from the source toward the sink, the algorithm maintains a height function $h : V \rightarrow \mathbb{N}$. A height function is valid if, for all residual edges $(u, v) \in E_f$:

$$h(u) \leq h(v) + 1 \quad (3)$$

Intuitively, flow can only be pushed "downhill" from node u to neighbor v if $h(u) = h(v) + 1$. The source is fixed at $h(s) = |V|$ and the sink at $h(t) = 0$.

1.3 Algorithmic Operations

The algorithm proceeds by iteratively performing two basic operations (from which it's name is also derived!) on active nodes (that is, nodes with a non-zero excess flow):

1. **Push(u, v):** Applies when $e(u) > 0$, residual capacity $c_f(u, v) > 0$, and $h(u) = h(v) + 1$.

$$\Delta = \min(e(u), c_f(u, v))$$

We move Δ units of flow from u to v . If the edge becomes saturated, it is a *saturating push*; otherwise, it is *non-saturating*.

2. **Relabel(u):** Applies when $e(u) > 0$ but no admissible edges exist (i.e., for all neighbors v with residual capacity, $h(u) \leq h(v)$). We increase the height of u :

$$h(u) = 1 + \min\{h(v) \mid (u, v) \in E_f\} \quad (4)$$

1.4 Implementation: FIFO Vertex Selection

To optimize performance and ensure polynomial time termination, we implemented the **FIFO Vertex Selection** rule. Active nodes are maintained in a First-In-First-Out queue. When a node u is removed from the queue, it is "discharged" (Push/Relabel operations are applied repeatedly) until it no longer has excess flow or its height increases.

Algorithm 1 Push-Relabel (FIFO Implementation)

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1: Initialize:  $h(s) \leftarrow |V|$ ,  $h(v) \leftarrow 0$  for others.
2: Saturate all edges  $(s, v)$  leaving source. Update  $e(v)$  and  $e(s)$ .
3: Enqueue all active nodes into Queue  $Q$ .
4: while  $Q$  is not empty do
5:    $u \leftarrow Q.dequeue()$ 
6:   while  $e(u) > 0$  do
7:     if  $\exists v$  such that  $c_f(u, v) > 0$  and  $h(u) == h(v) + 1$  then
8:       Push  $\min(e(u), c_f(u, v))$  from  $u$  to  $v$ 
9:       if  $v \neq s, t$  and  $v$  is not in  $Q$  then
10:         $Q.enqueue(v)$ 
11:       end if
12:     else
13:       Relabel  $u$ :  $h(u) \leftarrow 1 + \min\{h(v)\}$ 
14:     end if
15:   end while
16: end while

```

1.5 Complexity Analysis

The FIFO implementation of Push-Relabel provides a strong theoretical bound suitable for dense graphs:

- **Relabel Operations:** Each vertex can be relabeled at most $2|V|$ times. Total cost: $O(V^2)$.
- **Saturating Pushes:** At most $O(VE)$ operations.
- **Non-Saturating Pushes:** This is the bottleneck. In the FIFO variant, the number of non-saturating pushes is bounded by $O(V^3)$.

Thus, the overall time complexity is $O(V^3)$. This compares favorably to Edmonds-Karp ($O(VE^2)$) on dense networks where $E \approx V^2$.

2 Code and Data Availability

The full C++ implementation of the Push-Relabel algorithm, along with the scripts used to generate the 1,000 synthetic flow networks for validation, is open-source and available online:

<https://github.com/ashdane/push-relabel-implementation>

3 Empirical Validation: Max-Flow Min-Cut Theorem

A core objective of this project is to validate the Max-Flow Min-Cut theorem empirically. The theorem states that the maximum amount of flow possible from source to sink is equal to the capacity of a minimum cut that separates them.

3.1 Min-Cut Extraction Methodology

Upon termination of the Push-Relabel algorithm, we extract the Minimum Cut using the residual graph G_f :

1. Perform a Breadth-First Search (BFS) starting from the source s using only edges with strictly positive residual capacity ($c(u, v) - f(u, v) > 0$).
2. Let S be the set of all vertices reachable from s in G_f .
3. Let T be the set of all vertices not reachable ($V \setminus S$).
4. The Minimum Cut consists of all edges (u, v) in the original graph such that $u \in S$ and $v \in T$.

3.2 Verification Results

We tested the implementation on $N = 1000$ synthetic flow networks. In every instance, the computed Maximum Flow value equaled the sum of the capacities of the edges in the extracted Minimum Cut.

Table 1: Max-Flow vs. Min-Cut Capacity Verification (Sample Data)

Graph Size ($ V $)	Density	Max Flow (Computed)	Min-Cut Capacity	Discrepancy
50	Sparse	450	450	0
50	Dense	12,400	12,400	0
500	Sparse	3,215	3,215	0
500	Dense	89,550	89,550	0

The consistency of these results ($Discrepancy = 0$) confirms the correctness of our Push-Relabel implementation and empirically validates the theorem.