

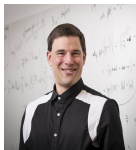
# Parallel Breadth-First Search and Exact Shortest Paths and Stronger Notions for Approximate Distances

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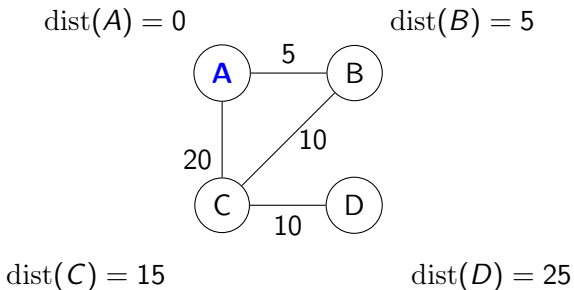
Christoph  
Grunau

# Today's Topic: The Shortest Path Problem.

- Undirected graph with non-negative weights  $w(e)$ .
  - Single source.
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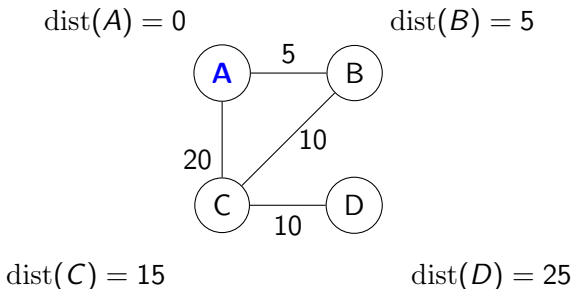
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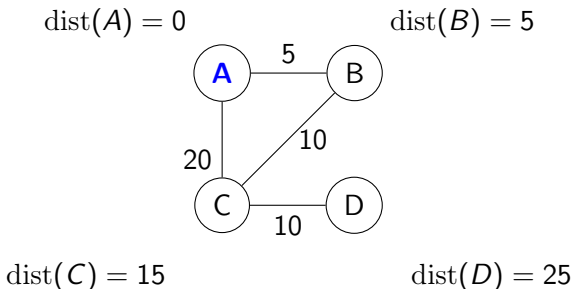
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We assume some source  $A$  is clear from context. We define:

- **Exact distances:**  $\text{dist}(B)$ . Sometimes  $\text{dist}(A, B)$ .

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## Definition

We assume some source  $A$  is clear from context. We define:

- **Exact distances:**  $\text{dist}(B)$ . Sometimes  $\text{dist}(A, B)$ .
- **Approximate distances:**  $\tilde{d}(B)$ .

# Approximate distances.

Distance estimate = any function  $\tilde{d} : V \rightarrow \mathbb{R}_{\geq 0}$ .

## Definition

A function  $\tilde{d} : V \rightarrow \mathbb{R}_{\geq 0}$  is a **weak  $(1 + \varepsilon)$ -approximation** (with respect to some source  $s \in V$ ) if:

$$\forall v \in V \quad \text{dist}(v) \leq \tilde{d}(v) \leq (1 + \varepsilon)\text{dist}(v).$$

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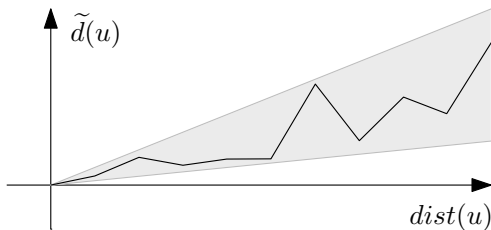
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**Example:**  $G =$  a path graph (from left to right). Source = leftmost node.



weak approximate distances

Shortest path (i.e., distance computation) is an important building block. For example:

- Maximum flows [Edmonds-Karp'72] [Dinitz'70],
- Embeddings (embedding a graph into L1 [Bourgain'85]),
- Clustering (doing low-diameter decompositions [MPX'13]),
- Etc.



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But these algorithms typically assume **exact** distance computations. This is easy in the sequential model (e.g., Dijkstra = simple and near linear).

But in other models (parallel, distributed, streaming, etc.) exact distances are notoriously hard to compute. **Approximate** distances are much easier. But the above applications **typically fail** with (weak) approximations.

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- 2 **Main Result:** Find efficient algorithms to construct them from weak (usual) distance approximations.
- 3 **Consequence:** Give the first  $\widehat{O}(m)$ -work sublinear-depth parallel exact SSSP algorithm.
  - Not in this talk!
  - Our result:  $\widehat{O}(m)$  work and  $\widehat{O}(\sqrt{n})$  depth.
  - Same result achieved independently by [Cao, Fineman'23].

- 1 Introduction
- 2 New Stronger Notions of Distance Approximations.
  - Stronger Notion: Smoothness
  - Stronger Notion: Tree-likeness
  - Smoothness + Tree-likeness =  $<3$
- 3 Efficient Constructions: Lifting Weak Approximations to Smooth Ones
- 4 Conclusion

# Stronger Notion: Smoothness

## Definition

A function (called “distance estimate”)  $\tilde{d} : V \rightarrow \mathbb{R}_{\geq 0}$  is a **smooth  $(1 + \varepsilon)$ -approximation** (with respect to a source  $s \in V$ ) if:

$$\begin{aligned} & \tilde{d}(s) = 0 \text{ and} \\ \forall u, v \in V \quad & |\tilde{d}(u) - \tilde{d}(v)| \leq (1 + \varepsilon)\text{dist}(u, v). \end{aligned}$$

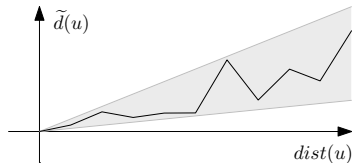


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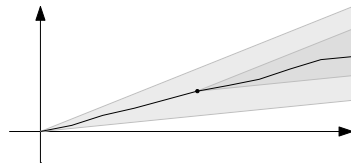
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weak approximate distances



smooth approximate distances

# Stronger Notion: Tree-likeness

## Definition (Informal)

$\tilde{d} : V \rightarrow \mathbb{R}_{\geq 0}$  is **tree-like** if:

- $\tilde{d}(s) = 0$ , and
- every other node  $v$  has a neighbor  $u$  whose estimate  $\tilde{d}$  is smaller by at least  $w(u, v)$ .

(Check the full talk for formal details.)

# Smoothness + Tree-likeness = $< 3$

## Theorem

*The following two are equivalent:*

- *$\tilde{d}$  is a smooth and tree-like  $(1 + \varepsilon)$  approximation (from source  $s$ ).*

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- *$\tilde{d}$  is a smooth and tree-like  $(1 + \varepsilon)$  approximation (from source  $s$ ).*
- *Given weights  $w : E \rightarrow \mathbb{R}_{\geq 0}$ , there exists a perturbation  $w'(e) \in [w(e), (1 + \varepsilon)w(e)]$  such that  $\tilde{d}(v) = \text{dist}_{w'}(\text{source} = s, v)$ .*

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# Efficient Constructions: Lifting Weak Approximations to Smooth Ones

## Theorem

Suppose we have an oracle that computes *weak*  $(1 + \varepsilon)$ -approximate distances.

There is an efficient algorithm that calls the oracle  $O(\log n)$  times, asks for weak  $(1 + \varepsilon/O(\log n))$ -approximations on different graphs, and computes  $(1 + \varepsilon)$ -approximate *smooth* distances.

- Same for *tree-likeness*.
- I will only the main ideas behind efficiently turning weak  $\rightarrow$  smooth.



# Efficient Constructions: Lifting Weak Approximations to Smooth Ones

Goal:  $\forall u, v \in V \quad |\tilde{d}(u) - \tilde{d}(v)| \leq (1 + \varepsilon)\text{dist}(u, v)$ .

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A function  $\tilde{d}$  is  $(\alpha, \delta)$ -smooth if:

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I will present an efficient algorithm that will transform  $\tilde{d}$  from

$$(\alpha, \delta) \rightarrow \left(\alpha \cdot \left(1 + \frac{\varepsilon}{O(\log n)}\right), \delta/2\right).$$

Then we would be done!  $(1, n^{100}) \rightarrow \dots \rightarrow (1 + \varepsilon, \frac{1}{n^{100}})$ .

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---

**Algorithm** Slow Partial Smoothing algorithm ( $n$  oracle calls)

---

- 1: Let  $G'$  be the graph  $G$  with distances multiplied by  $(1 + \frac{\epsilon}{2 \log n})\alpha$ .
  - 2:  $\tilde{d} \leftarrow O(G, \text{source} = s, \text{approx} = 1 + \frac{\epsilon}{\log n})$
  - 3: **for** each  $u \in V(G)$  **do**
  - 4:      $\tilde{d}_u \leftarrow O(G', \text{source} = u, \text{approx} = \frac{\epsilon}{10 \log n})$
  - 5:      $\tilde{d}_u(\cdot) \leftarrow \tilde{d}(u) + \tilde{d}_u(\cdot)$
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**Intuition**

*When looking at nodes at most  $\frac{\delta \log n}{\epsilon}$  close to  $u$ , they are already  $(\alpha \cdot (1 + \frac{\epsilon}{O(\log n)}), \delta/2)$ -smooth.*

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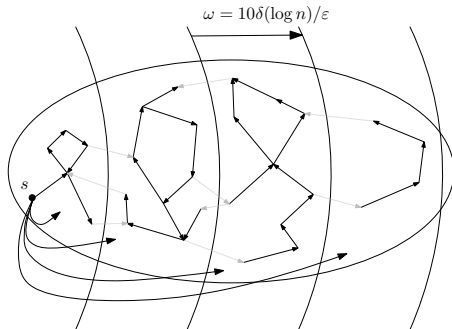
**Intuition**

When  $\text{dist}(u, v) > \frac{\delta \log n}{\epsilon}$ , then  $\tilde{d}_u(v) > \tilde{d}(v)$ .

$$(\alpha, \delta) \rightarrow (\alpha \cdot (1 + \frac{\epsilon}{O(\log n)}), \delta/2)$$

**Q:** How to reduce the number of oracle calls from  $n$  to  $O(1)$ ?

**A:** (Carefully) carve out the graph into strips of width  $\omega := \frac{10\delta \log n}{\epsilon}$ . Connect all nodes to the source. Call the oracle. (And fix certain kind of mistakes.)



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Thank you!