# Almost Optimal Distance Oracles for Planar Graphs

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<sup>1</sup>King's College London, UK

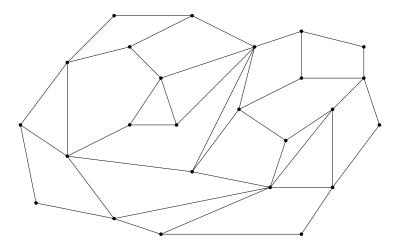
<sup>2</sup>Interdisciplinary Center Herzliya, Israel

<sup>3</sup>University of Wrocław, Poland

<sup>4</sup>University of Haifa, Israel

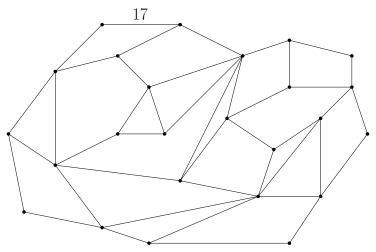
#### STOC 2019

Phoenix, Arizona.



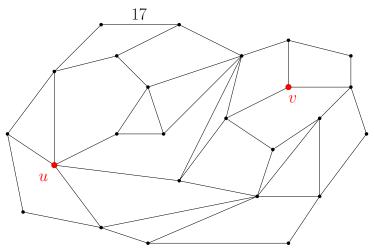
Preprocess an *n*-vertex planar graph G = (V, E) with nonnegative arc lengths, so that given any  $u, v \in V$  we can compute d(u, v) efficiently.

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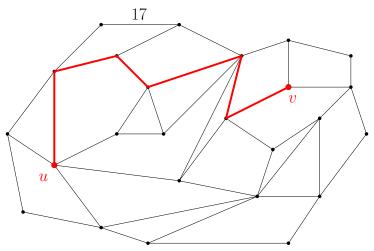
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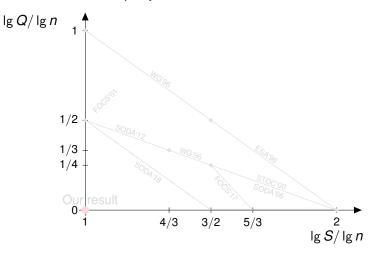
# Goals

Ideally:

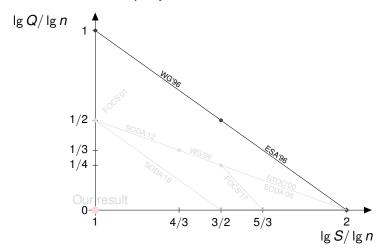
- Fast queries, ideally Q = O(1).
- Small size, ideally S = O(n).
- Fast construction, ideally T = O(n).

The most important tradeoff is between query-time Q and size S.

The tradeoff between the query-time Q and the size S of the structure:

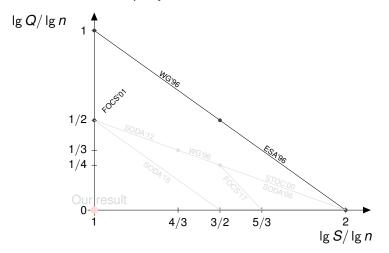


The tradeoff between the query-time Q and the size S of the structure:



Djidjev and Arikati et al. achieved  $Q = O(n^2/S^2)$ .

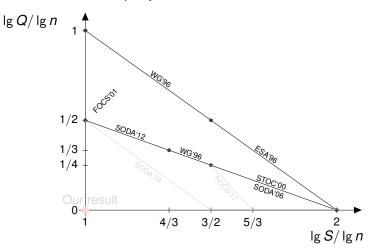
The tradeoff between the query-time Q and the size S of the structure:



Fakcharoenphol and Rao showed that  $S = \tilde{O}(n)$  and  $Q = \tilde{O}(\sqrt{n})$  is possible.

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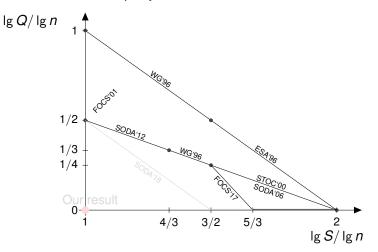
The tradeoff between the query-time Q and the size S of the structure:



This has been extended to  $Q = \tilde{O}(n/\sqrt{S})$  for essentially the whole range of *S* in a series of papers.

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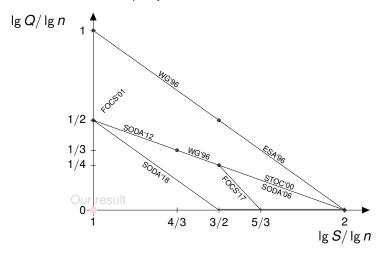
The tradeoff between the query-time Q and the size S of the structure:



In 2017, Cohen-Addad, Dahlgaard, and Wulff-Nilsen showed that this is not optimal, and  $S = O(n^{5/3})$  with  $Q = O(\log n)$  is possible.

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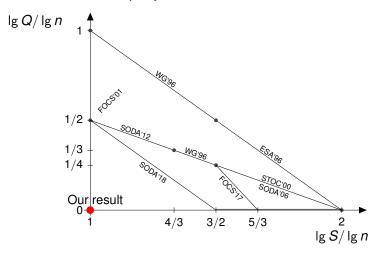
The tradeoff between the query-time Q and the size S of the structure:



In 2018, Gawrychowski et al. improved this to  $S = O(n^{1.5})$  and  $Q = O(\log n)$ .

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The tradeoff between the query-time Q and the size S of the structure:



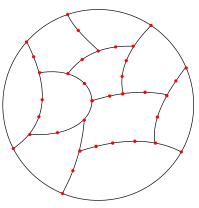
We improve this to  $S = O(n^{1+\epsilon})$  and  $Q = \tilde{O}(1)$  for any  $\epsilon > 0$ .

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# r-divisions

For  $r \in [1, n]$ , a decomposition of the graph into:

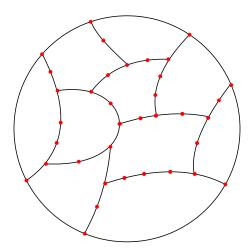
- *O*(*n*/*r*) pieces;
- each piece has O(r) vertices;
- each piece has O(√r) boundary vertices (vertices incident to edges in other pieces).



We denote the boundary of a piece *P* by  $\partial P$  and assume that all such nodes lie on a single face of *P*.

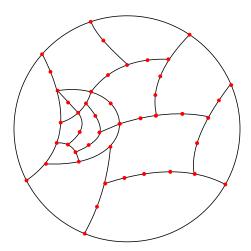
# Recursive *r*-divisions

For  $r_1 < r_2 < \cdots < r_m \in [1, n]$ , we can efficiently compute  $r_i$ -divisions, such that each  $r_i$ -division respects the  $r_{i+1}$ -division.



# Recursive *r*-divisions

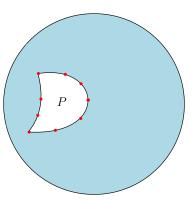
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# Multiple Source Shortest Paths (MSSP)

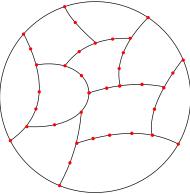
# Klein [SODA'05]

There exists a data structure requiring  $O(n \log n)$  space that can report in  $O(\log n)$  time the distance between any node on the infinite face (boundary node) and any node in the graph.



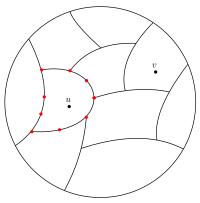
#### • Compute an *r*-division.

- For each piece *P*, for each node  $u \in P$ , store additive weights  $d_G(u, p)$  for  $p \in \partial P$ . Space  $O(n \cdot \sqrt{r})$ .
- For each piece *P*, store an MSSP data structure for the outside of *P* with sources ∂*P*.
  Space Õ(n/r ⋅ n).



#### • Compute an *r*-division.

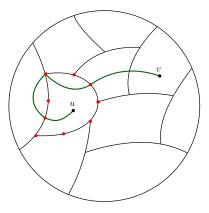
- For each piece *P*, for each node *u* ∈ *P*, store additive weights *d<sub>G</sub>(u, p)* for *p* ∈ ∂*P*.
  Space *O*(*n* · √*r*).
- For each piece *P*, store an MSSP data structure for the outside of *P* with sources ∂*P*.
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Interesting case.

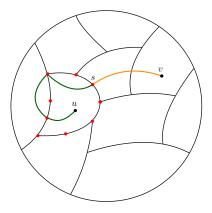
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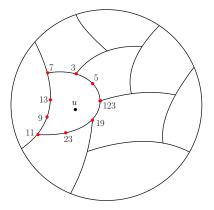
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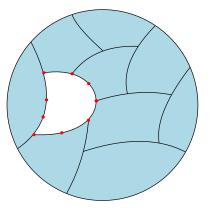


#### We decompose the path on the last boundary node it visits.

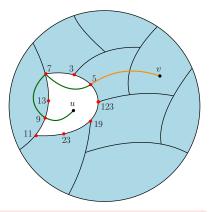
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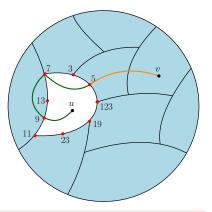


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At query, find node  $p \in \partial P$ , minimizing  $d_G(u, p) + d_{G \setminus (P \setminus \partial P)}(p, v)$ . This is called *point location*.

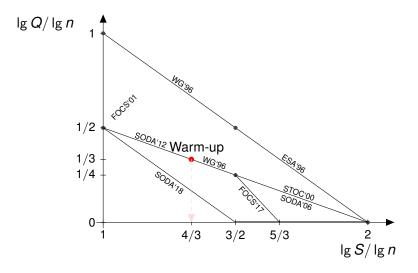
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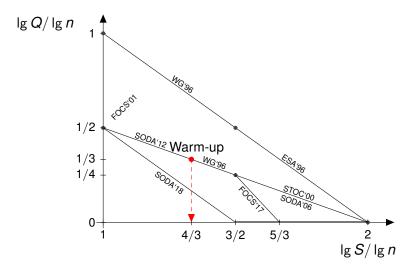


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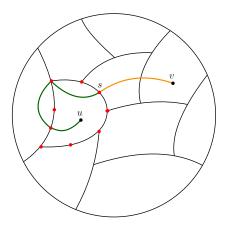
Perform point location by trying all  $O(\sqrt{r})$  boundary nodes.

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# First goal

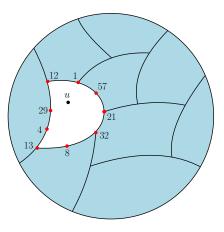


Instead of trying all possible  $O(\sqrt{r}) = O(n^{1/3})$  candidate boundary nodes, we want to compute the last boundary node *s* visited by the shortest path in  $\tilde{O}(1)$  time.

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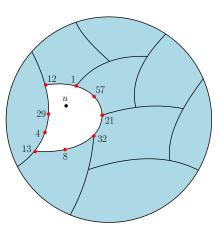
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# Each node *u* defines a set of additive weights $d_G(u, p)$ for $p \in \partial P$ .



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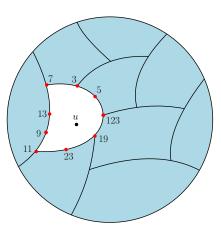


#### Gawrychowski et. al. [SODA'18]

Given an MSSP data structure for the outside of P, with sources  $\partial P$ , there exists an  $\tilde{O}(|\partial P|)$ -sized data structure for each set of additive weights for  $\partial P$  that answers point location queries in  $\tilde{O}(1)$  time.

# **Point location**

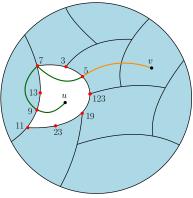
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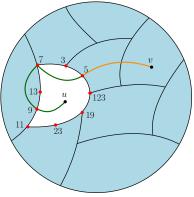
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- Compute an *r*-division.
- For each piece *P*, for each node *u* ∈ *P*, store additive weights *d<sub>G</sub>(u, p)* for *p* ∈ ∂*P*.
  Space *O*(*n* ⋅ √*r*).
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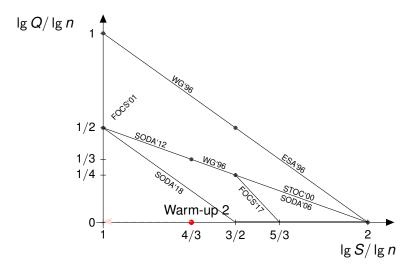


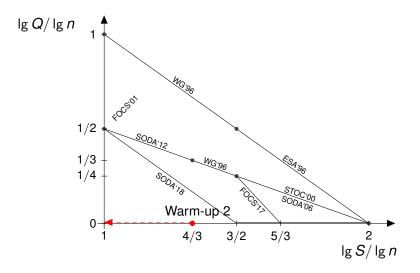
At query, perform point location by trying all possible  $O(\sqrt{r})$  candidate boundary nodes.

- Compute an *r*-division.
- For each piece *P*, for each node  $u \in P$ , store additive weights  $d_G(u, p)$  for  $p \in \partial P$ . Preprocess these for point location. Space  $\tilde{O}(n \cdot \sqrt{r})$ .
- For each piece *P*, store an MSSP data structure for the outside of *P* with sources ∂*P*.
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At query, perform point location in  $\tilde{O}(1)$  time!



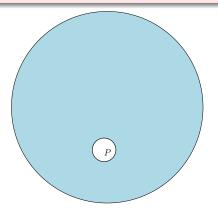


# Second goal

#### Shrink pieces.

#### • Compute an $n^{\epsilon}$ -division.

- For each node *u* ∈ *P*, store additive weights *d<sub>G</sub>(u, p)* for *p* ∈ ∂*P*. Preprocess these for point location.
- For each piece *P*, store the required information to support:
  - ► distance queries from ∂P to nodes outside P;
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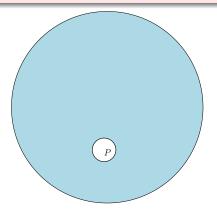


## Second goal

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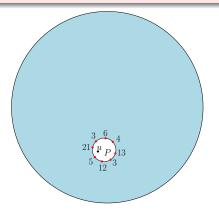
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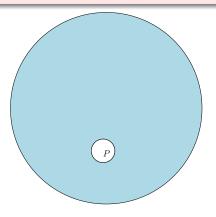
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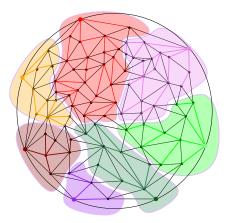


## Additively weighted Voronoi diagrams

Internals of point location.

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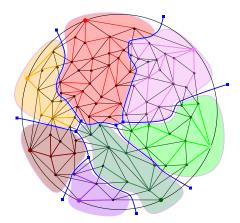
## Additively weighted Voronoi diagrams



The Voronoi cell of each site consists of all nodes closer to it with respect to the additive distances.

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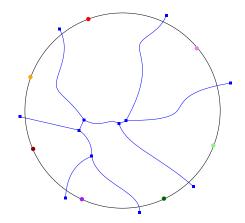
## Additively weighted Voronoi diagrams



Because all sites are adjacent to one face, the diagram can be described by a tree on  $O(|\partial P|) = O(\sqrt{r})$  nodes (independent of *n*!).

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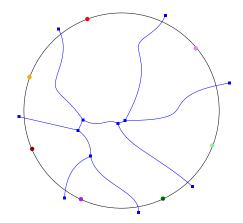
## **Point location**



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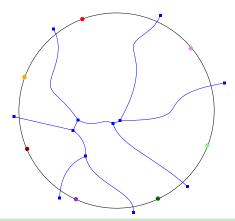
## **Point location**

Point locating *v* essentially reduces to  $O(\log r)$  distance queries from the sites to *v*.



## **Point location**

Point locating v essentially reduces to  $O(\log r)$  distance queries from the sites to v.

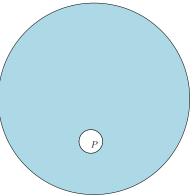


### Idea

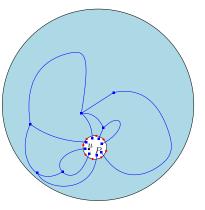
Handle such distance queries recursively

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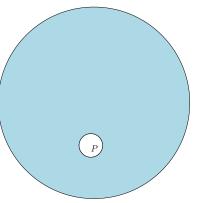
- Compute a recursive *r*-division for  $r_i = n^{i \cdot \epsilon}$ .
- For each piece *P* of the  $n^{\epsilon}$ -division, for each node  $u \in P$ , store a Voronoi diagram for the outside of *P* with sites  $\partial P$  and additive weight  $d_G(u, p)$  for  $p \in \partial P$ . Space  $\tilde{O}(n \cdot \sqrt{r_1})$ .
- For each piece *P*, store the required information to answer distance queries from  $\partial P$  to nodes outside *P*.



- Compute a recursive *r*-division for  $r_i = n^{i \cdot \epsilon}$ .
- For each piece *P* of the *n*<sup>ϵ</sup>-division, for each node *u* ∈ *P*, store a Voronoi diagram for the outside of *P* with sites ∂*P* and additive weight *d*<sub>G</sub>(*u*, *p*) for *p* ∈ ∂*P*. Space Õ(*n* ⋅ √*r*<sub>1</sub>).
- For each piece *P*, store the required information to answer distance queries from  $\partial P$  to nodes outside *P*.

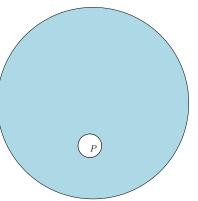


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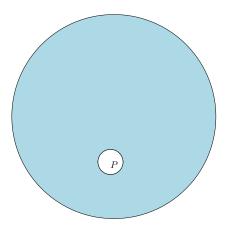


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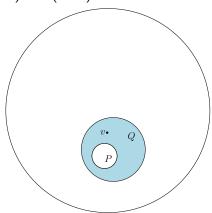
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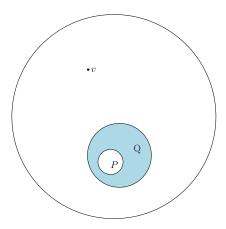


We can not afford to store an  $\Omega(n)$ -sized MSSP for each of the  $n^{1-\epsilon}$  pieces.



Store an MSSP for piece *Q* of the  $n^{2\cdot\epsilon}$ -division that contains *P*. This handles the case  $v \in Q$ . Space:  $\tilde{O}(n^{1-\epsilon} \cdot n^{2\epsilon}) = \tilde{O}(n^{1+\epsilon})$ .

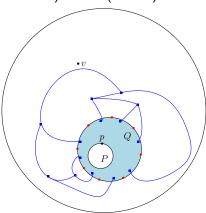




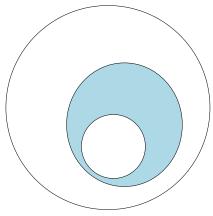
P. Charalampopoulos et al.

Case  $v \notin Q$ : each  $p \in \partial P$  stores a Voronoi diagram for the outside of Q with sites  $\partial Q$ .

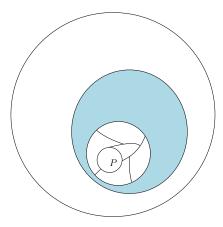
Space:  $\tilde{O}(n^{1-\epsilon} \cdot n^{\epsilon/2} \cdot n^{2\epsilon/2}) = = \tilde{O}(n^{1+\epsilon/2}).$ 



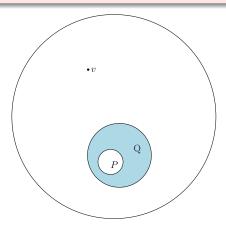
Repeat the same reasoning for increasingly larger pieces of sizes  $n^{i\cdot\epsilon}$ , for  $i = 1, ..., 1/\epsilon$ . There are  $n^{1-i\epsilon}$  pieces at level *i*, each stores MSSP and Voronoi diagrams of size  $\tilde{O}(n^{(i+1)\epsilon})$ . Total space is  $\tilde{O}(\frac{1}{\epsilon}n^{1+\epsilon})$ .



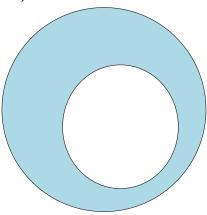
Smaller pieces share the MSSP data structures at higher levels.



Each point location query, either gets answered at the current level, or reduces to  $O(\log n)$  point location queries at a higher level.



If not earlier, then in the top level we answer the point location query in  $O(\log^2 n)$  time. Query time:  $O(\log^{1/\epsilon} n)$ .



## Tradeoffs and construction time

We show the following tradeoffs for  $\langle S, Q \rangle$ :

(Õ(n<sup>1+ϵ</sup>), O(log<sup>1/ϵ</sup> n)), for any constant 1/2 ≥ ϵ > 0;
 (O(n log<sup>2+1/ϵ</sup> n), Õ(n<sup>ϵ</sup>)), for any constant ϵ > 0;
 (n<sup>1+o(1)</sup>, n<sup>o(1)</sup>).

Some of the issues I shoved under the rug:

- details of point location;
- $\partial P$  is not a single face of P (holes);
- constructing these oracles in  $O(n^{3/2+\epsilon})$  time.

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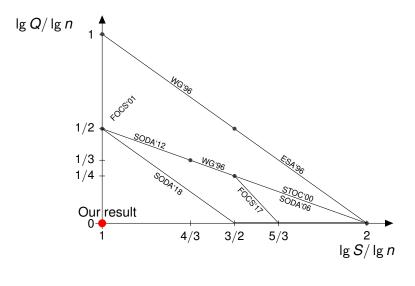
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## Open problems

• Can we get  $\tilde{O}(n)$  space and  $\tilde{O}(1)$  query time?

• Can we get the construction time to be  $\tilde{O}(n)$ ?

- Improvements on dynamic distance oracles? Currently:
  - exact: UB  $\tilde{O}(n^{2/3})$ ; LB  $\tilde{O}(n^{1/2})$  (conditioned on APSP)
  - 2 approx.: UB  $\tilde{O}(n^{1/2})$  (undirected) ; no LB.



## **Questions?**