# Unsplittable Euclidean Capacitated Vehicle Routing

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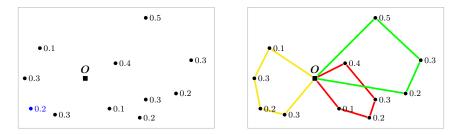
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# Capacitated vehicle routing problem (CVRP)

Input:

- depot O
- n terminals with unsplittable demands in (0,1]

Minimize total length of tours s.t. each tour has total demand  $\leq 1$ 



Fundamental problem in operations research

## **Equal demands**



# **Unequal demands**

1981	Golden and Wong
1987	
1991	Labbé, Laporte, and Mercure
2021	Blauth, Traub, and Vygen
2022	Friggstad, Mousavi, Rahgoshay, and Salavatipour
2023	Mathieu and Zhou

• general metrics
• Euclidean plane
• planar graphs
• trees
graphs of bounded treewidth
• graphs of bounded highway dimension
graphic metrics

## Arbitrary demands

- 1.5-hard [folklore]
- 2.694-approximation [Friggstad et al. 2022]
- $(2+\epsilon)$ -approximation for any  $\epsilon>0$  [our result]

### Big demands only

- NP-hard [folklore]
- 2.694-approximation [Friggstad et al. 2022]
- $(1+\epsilon)$ -approximation for any  $\epsilon > 0$  [our result]

Note: Both our results **match the best known approximation factors** in the corresponding equal demand settings.

# Big demands only

#### Our result

 $(1+\epsilon)$ -approximation for any  $\epsilon>0$ 

#### Definition

Let  $\epsilon > 0$ . A demand is **big** if it is at least  $\epsilon$ , and is **small** otherwise.

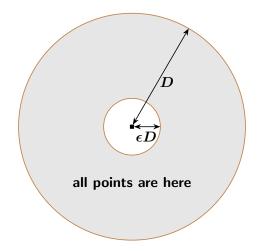
## Polynomial time exact algorithm for big demands only, assuming:

- $O_{\epsilon}(1)$  locations
- **2**  $O_{\epsilon}(1)$  distinct demands at each location

#### Q: How to achieve both assumptions?

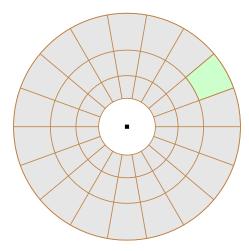
## Reducing the number of locations (1/3)

## Step 1: Reduce to bounded distance



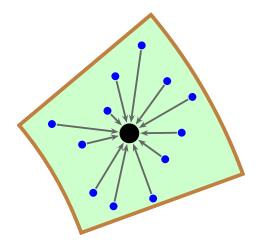
## Reducing the number of locations (2/3)

Step 2: Decompose the gray area into  $O_{\epsilon}(1)$  cells



## Reducing the number of locations (3/3)

Step 3: Move each terminal to the center of its cell



## Reducing the number of distinct demands

# Adaptive rounding

(a) Sort all demands at a center



(b) Make groups of equal cardinality

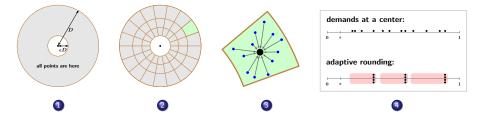


### (c) Round up to maximum demand in group



### Algorithm for big demands only

- Reduce to **bounded distance**
- Occompose into cells
- Move each big terminal to the center of its cell
- Apply adaptive rounding on the demands at each center
- Solve the resulting instance in **polynomial time**



# **Arbitrary demands**

#### Our result

 $(2+\epsilon)$ -approximation for any  $\epsilon>0$ 

## Algorithm for big demands only (revisited)

- Reduce to **bounded distance**
- Oecompose into cells
- Move each big terminal to the center of its cell
- Apply adaptive rounding on the demands at each center
- Solve the resulting instance in **polynomial time**
- Q: How to deal with small demands?
- A: Insert one step between ② and ③ : Cluster the small terminals in each cell into big terminals

Case 1: Optimal solution has sufficiently many tours (2/5)

### Cluster the small terminals in each cell into big terminals:

(a) Compute a TSP tour on the small terminals in the cell

- (b) Partition the tour into segments, each of total demand  $\approx \epsilon$
- (c) For each segment, connect its endpoints to the center of the cell

a big terminal at the center of the cell



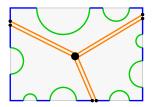


# Case 1: Optimal solution has sufficiently many tours (3/5)

 $\mathbf{opt}\,$  : cost of an optimal solution to the initial instance

#### Lemma 1

The cost within cells is at most  $(1+2\epsilon) \cdot \text{opt.}$ 





- green is the optimal solution
- blue ≤ 1.5 · cell boundaries ≤ ε · opt, by Karp and since the optimal solution has many tours
- orange  $\leq \epsilon \cdot \operatorname{opt}$ , since each segment has total demand  $\approx \epsilon$

# Case 1: Optimal solution has sufficiently many tours (4/5)

**opt** : cost of an optimal solution to the initial instance **opt'** : cost of an optimal solution to the clustered instance

#### Lemma 2

The cost between cells is at most  $(1 + \epsilon) \cdot \operatorname{opt}' \leq (1 + 4\epsilon) \cdot \operatorname{opt}$ .

#### Construction of a near-optimal solution to the clustered instance:

- Compute a set of tours each of capacity  $1 + \epsilon$  [Becker and Paul] cost  $\leq (1 + \epsilon) \cdot opt$
- Remove one **cluster** (of demand  $\epsilon$ ) from each tour
- Connect the removed clusters by a TSP tour
  cost ≤ ε ⋅ opt, since the optimal solution has many tours
- Iterated tour partitioning on the TSP tour
  cost ≤ ε opt, since only ε demand is removed from each tour

# Case 1: Optimal solution has sufficiently many tours (5/5)

**opt** : cost of an optimal solution to the initial instance **opt'** : cost of an optimal solution to the clustered instance

#### Lemma 1

The cost within cells is at most  $(1+2\epsilon) \cdot \text{opt.}$ 

#### Lemma 2

The cost between cells is at most  $(1+4\epsilon) \cdot \text{opt.}$ 

Conclusion: Overall cost is at most  $(2+6\epsilon) \cdot \text{opt.}$ 

### Algorithm

- **Q** Round down each demand to an integer multiple of  $\frac{1}{2n}$
- **②** Compute a  $(1 + \epsilon)$ -approximation to the rounded instance [Arora]
- Split each tour into two tours, each within the capacity

#### Cost analysis:

- **2** : at most  $(1 + \epsilon) \cdot \text{opt}$
- I doubling the cost

Conclusion: Overall cost is at most  $(2+2\epsilon) \cdot \text{opt.}$ 

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Thank you!