

# Exact Methods for VRP

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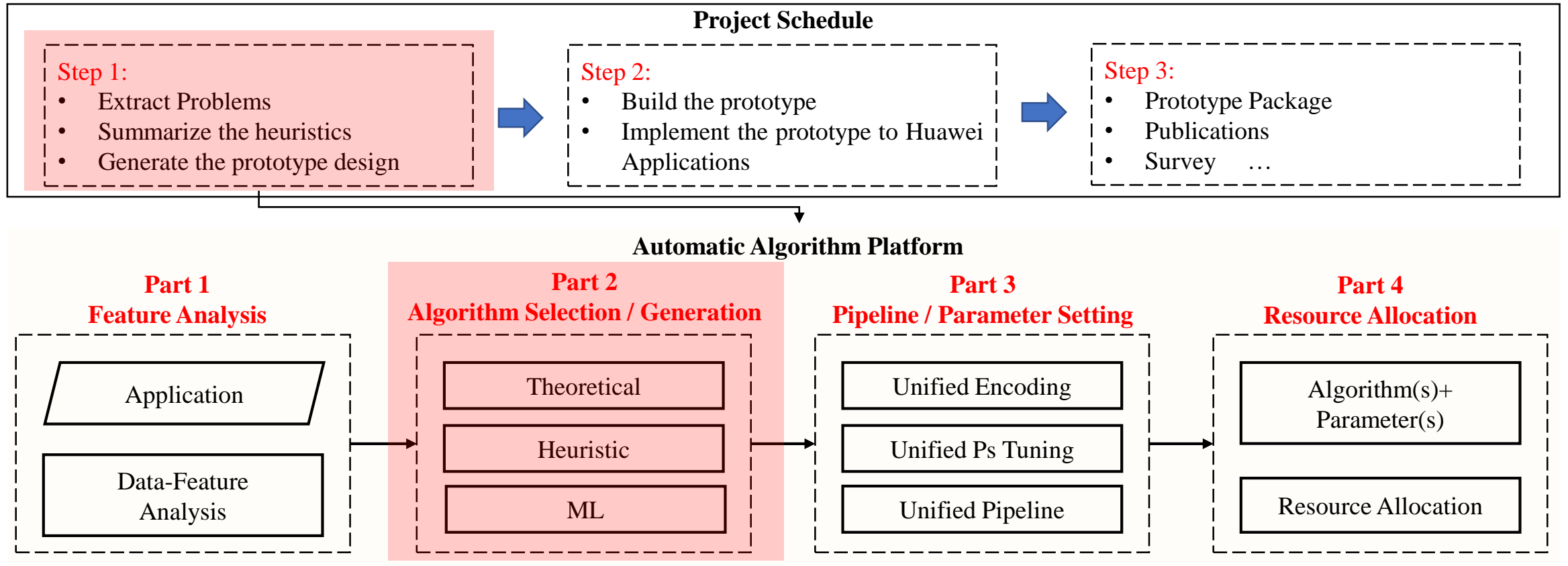
# Outline

1. Roadmap
2. Exact Methods for VRP
3. Conclusion

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# Roadmap

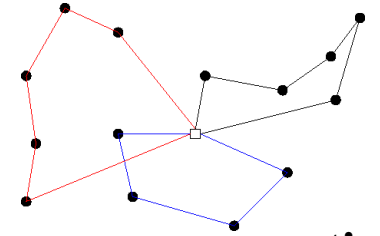


# Methods for VRP

Dantzig and Ramser (1959)  
the first to introduce “**Truck Dispatching Problem**”

Clarke and Wright (1964)  
generalized this problem to a  
linear optimization problem  
“**Vehicle Routing Problem**”

Lenstra and Rinnooy Kan (1981)  
proved VRP is an **NP-hard problem**, exact algorithms are only  
efficient for small problems



## 1. Constructive Heuristics:

Savings heuristic  
Sweep algorithm

## 2. Improvement Heuristics:

K-opt  
 $\lambda$ -interchange

## 3. Exact algorithms:

Branch and Bound  
Cutting Plane  
Network-flows  
Dynamic Programming

## 4. Metaheuristics:

Tabu search  
Simulated Annealing  
Local search methods  
Partical Swarm Optimization  
Ant Colony Algorithm

Genetic Algorithm  
GRASP

## 5. Machine Learning:

Reinforcement Learning  
Pointer network

Perhaps the most famous heuristic of  
this category is the Clarke and Wright  
(1964) savings heuristic

The development of exact algorithms for  
the VRP took off in 1981 with the  
publication of two papers by Christofides

The development of modern heuristics for  
the VRP really started in the 1990s with the  
advent of metaheuristics.

## Topics of previous talks

- 2021.1.19

Metaheuristics for Vehicle Routing Problems

- 2021.3.12

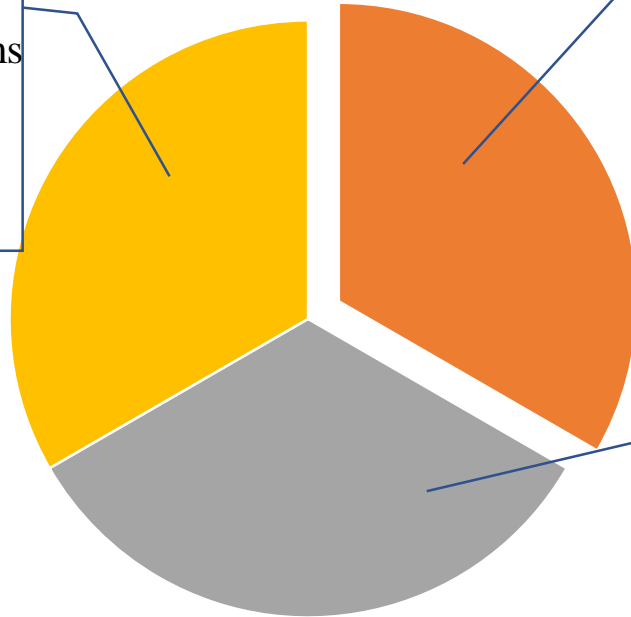
A Metaheuristic Approach for 3L-SDVRP

- 2021.4.7

• Exact Methods for VRP

- 2021.1.31

ML for Combinational Optimization



We are trying to answer following two questions:

1. State-of-the-art exact methods
2. To what scale can the problem be solved by exact methods?

# Outline

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2. Exact Methods for VRP
3. Conclusion



# Notations

For a CVRP problem we give the following notations:

We have a complete directed graph  $G(V, A, c, x)$

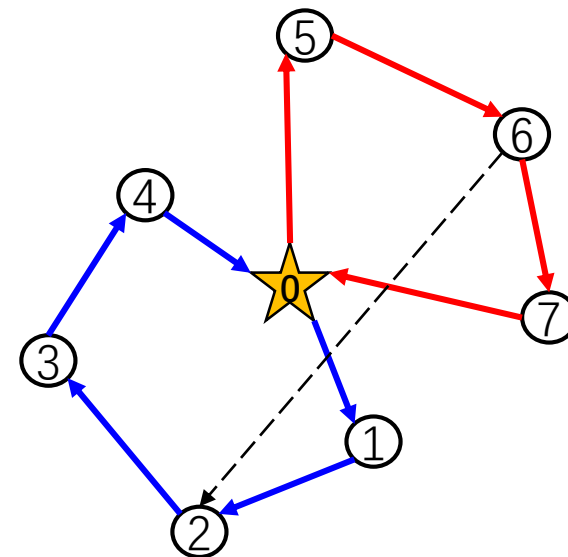
Node set	$V = \{0, 1, \dots, n\}$	$V_C = V / \{0\}$
All arc set	$A$	$A_C$ is the set where $\{i, j\} \in A$ with $i, j \in V_C$
Sub node	$S \in V$	
Sub arc set	$\delta^+(S)$ denotes the set of arcs $(i, j)$ with $i \in S$ and $j \in V / S$ $\delta^-(S)$ denotes the set of arcs $(i, j)$ with $j \in S$ and $i \in V / S$	

$$V = \{0, 1, 2, 3, 4, 5, 6, 7\} \quad A = \{(0, 1), (1, 2), (6, 2), \dots\}$$

$$V_C = \{1, 2, 3, 4, 5, 6, 7\} \quad A_C = \{(1, 2), (6, 2), \dots\}$$

$$S = \{6, 7\} \quad \delta^+(S) = \{(7, 0), \dots\}$$

$$\delta^-(S) = \{(5, 6), \dots\}$$



# Integer programming formulations for VRP

The VRP problems together with its variants are formulated as integer programming formulations in order to implement the exact algorithms. Most existed formulations can be divided into four categories. They are:

1. Two-index, three-index vehicle-flow formulations
2. Set partitioning formulations
3. Single-commodity, two commodity, and multi-commodity flow formulations
4. Arc-packing formulation

## Two-index formulation

$$\min \sum_{(i,j) \in A} c_{ij} x_{ij}$$

s.t.

$$x(\delta^+(i)) = x(\delta^-(i)) = 1 \quad (i \in V_c) \quad (C1)$$

$$x(\delta^+(S)) \geq \lceil q(S) / Q \rceil \quad (S \subseteq V_c) \quad (C2)$$

$$x_{ij} \in \{0,1\} \quad ((i,j) \in A) \quad (C3)$$

- C1 are degree constraints
- C3 are binary constraints
- C2 are called rounded capacity (RC) inequalities

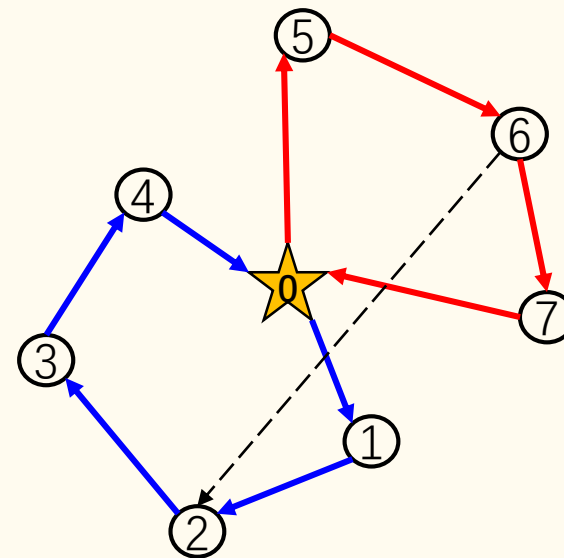
$$V = \{0,1,2,3,4,5,6,7\} \quad A = \{(0,1), (1,2), (6,2), \dots\}$$

$$V_c = \{1,2,3,4,5,6,7\} \quad A_c = \{(1,2), (6,2), \dots\}$$

$$S = \{6,7\}$$

$$\delta^+(S) = \{(7,0), \dots\}$$

$$\delta^-(S) = \{(5,6), \dots\}$$



## Two-index formulation

$$\min \sum_{(i,j) \in A} c_{ij} x_{ij}$$

s.t.

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$$x(\delta^+(S)) \geq \lceil q(S) / Q \rceil \quad (S \subseteq V_c) \quad (C2)$$

$$x_{ij} \in \{0,1\} \quad ((i,j) \in A) \quad (C3)$$

- Subtour elimination (SE) inequalities<sup>[1]</sup>

$$x(\delta^+(S)) \geq 1 \quad (S \subseteq V_c)$$

- Fractional capacity (RC) inequalities<sup>[1]</sup>

$$x(\delta^+(S)) \geq q(S) / Q \quad (S \subseteq V_c)$$

- Rounded capacity (RC) inequalities<sup>[1]</sup>

$$x(\delta^+(S)) \geq \lceil q(S) / Q \rceil \quad (S \subseteq V_c)$$

- Generalized large multistar (GLM) inequalities<sup>[2]</sup>

$$x(\delta^+(S)) \geq \frac{1}{Q} \sum_{i \in S} (q_i + \sum_{j \in V_c \setminus S} q_j (x_{ij} + x_{ji})) \quad (S \subseteq V_c)$$

- Knapsack large multistar (KLM) inequalities<sup>[3]</sup>

$$x(\delta^+(S)) \geq \frac{1}{\beta} \sum_{i \in S} (\alpha_i + \sum_{j \in V_c \setminus S} \alpha_j (x_{ij} + x_{ji})) \quad (S \subseteq V_c)$$

$$\alpha^T y \leq \beta$$

$$\text{conv} \left\{ y \in \{0,1\}^n : \sum_{i \in V_c} q_i y_i \leq Q \right\}$$

[1] Naddef, Denis, and Giovanni Rinaldi. "Branch-and-cut algorithms for the capacitated VRP." *The vehicle routing problem*. Society for Industrial and Applied Mathematics, 2002. 53-84.

[2] Gouveia, Luis. "A result on projection for the vehicle routing problem." *European Journal of Operational Research* 85.3 (1995): 610-624.

[3] Letchford, Adam N., Richard W. Eglese, and Jens Lysgaard. "Multistars, partial multistars and the capacitated vehicle routing problem." *Mathematical Programming* 94.1 (2002): 21-40.

## Set partitioning formulations

$$\min \sum_{r \in \Omega} c_r z_r$$

s.t.

$$\sum_{r \in \Omega} a_{ir} z_r = 1 \quad (i \in V_c) \quad (C1)$$

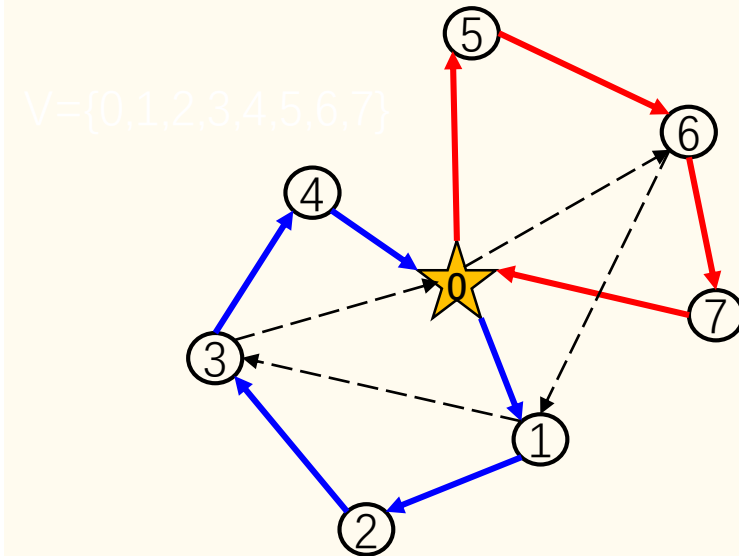
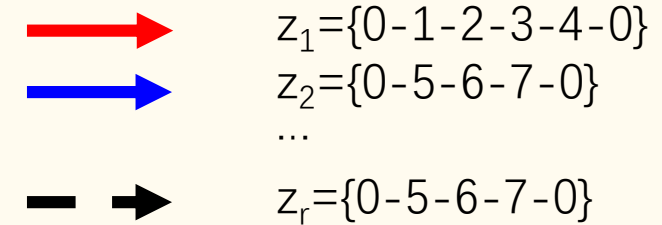
$$z_r \in \{0,1\} \quad (r \in \Omega) \quad (C2)$$

$\Omega$  denote the set of possible routes

$z_r$  is a binary variable, it takes 1 if route  $r$  is used

$c_r$  denote the cost of route  $r$

$a_{ir}$  is a binary variable, it takes 1 if customer  $i$  is used in route  $r$



## Multi-commodity flow formulations (MCF2b)

$$\min \sum_{(i,j) \in A} c_{ij} x_{ij}$$

s.t.

$$x(\delta^+(i)) = x(\delta^-(i)) = 1 \quad (i \in V_c)$$

$$x_{ij} \in \{0,1\} \quad ((i,j) \in A)$$

$$f^k(\delta^+(0)) = f^k(\delta^-(k)) = g^k(\delta^+(k)) = g^k(\delta^-(0)) = 1 \quad (k \in V_c)$$

$$f^k(\delta^-(0)) = f^k(\delta^+(k)) = g^k(\delta^-(k)) = g^k(\delta^+(0)) = 0 \quad (k \in V_c)$$

$$f^k(\delta^-(l)) = f^k(\delta^+(l)) = g^l(\delta^-(k)) = g^l(\delta^+(k)) \quad (k, l \in V_c : l \neq k)$$

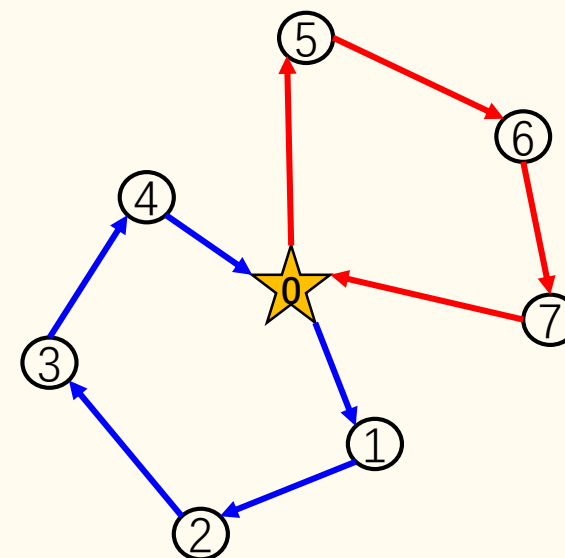
$$\sum_{k \in V_c \setminus \{i,j\}} q_k (f_{ij}^k + g_{ij}^k) \leq (Q - q_i - q_j) x_{ij} \quad ((i,j) \in A)$$

$$f_{ij}^k + g_{ij}^k \leq x_{ij} \quad (k \in V_c, (i,j) \in A)$$

$$f_{ij}^k, g_{ij}^k \in \{0,1\} \quad (k \in V_c, (i,j) \in A)$$

$f_{ij}^k$  and  $g_{ij}^k$  indicate whether a vehicle traverses the arc  $(i, j)$  on the way to customer  $k$  or after visiting customer  $k$ , respectively.

$$\begin{aligned} f^6(\delta^+(0)) &= f^6(\delta^-(6)) = g^6(\delta^+(6)) = g^6(\delta^-(0)) = 1 \\ f^6(\delta^-(0)) &= f^6(\delta^+(6)) = g^6(\delta^-(6)) = g^6(\delta^+(0)) = 0 \\ f^6(\delta^-(7)) &= f^6(\delta^+(7)) = g^7(\delta^-(6)) = g^7(\delta^+(6)) \\ f_{56}^6 + g_{56}^6 &\leq x_{56} \end{aligned}$$



# Arc-packing formulation

$$\min \sum_{(i,j) \in A} c_{ij} x_{ij}$$

s.t.

$$x(\delta^+(i)) = x(\delta^-(i)) = 1 \quad (i \in V_c)$$

$$x_{ij} \in \{0,1\} \quad ((i,j) \in A)$$

$$f^k(\delta^-(0)) = f^k(\delta^+(0)) = g^k(\delta^-(0)) = g^k(\delta^+(0)) = 0 \quad (k \in V_c)$$

$$f^k(\delta^-(l)) = f^k(\delta^+(l)) = g^l(\delta^-(k)) = g^l(\delta^+(k)) \quad (k, l \in V_c : l \neq k)$$

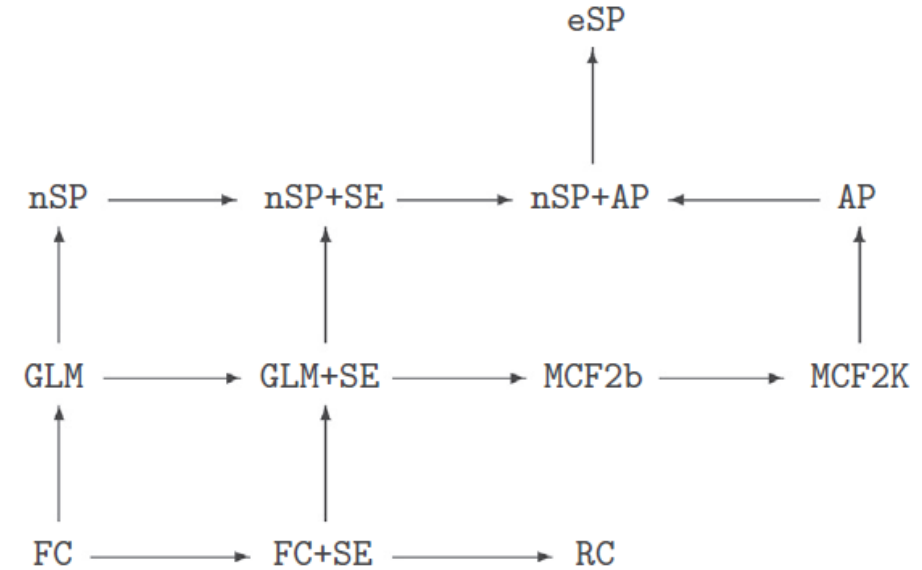
$$\sum_{k \in V_c \setminus \{i,j\}} q_k (f_{ij}^k + g_{ij}^k) \leq (Q - q_i - q_j) x_{ij} \quad ((i,j) \in A)$$

$$f_{ij}^k + g_{ij}^k \leq x_{ij} \quad (k \in V_c, (i,j) \in A)$$

$$f_{ij}^k, g_{ij}^k \in \{0,1\} \quad (k \in V_c, (i,j) \in A)$$

$$x_{ij} = f_{ij}^j \quad (j \in V_c, i \in V \setminus \{j\})$$

$$x_{ij} = g_{ij}^i \quad (i \in V_c, j \in V \setminus \{i\})$$

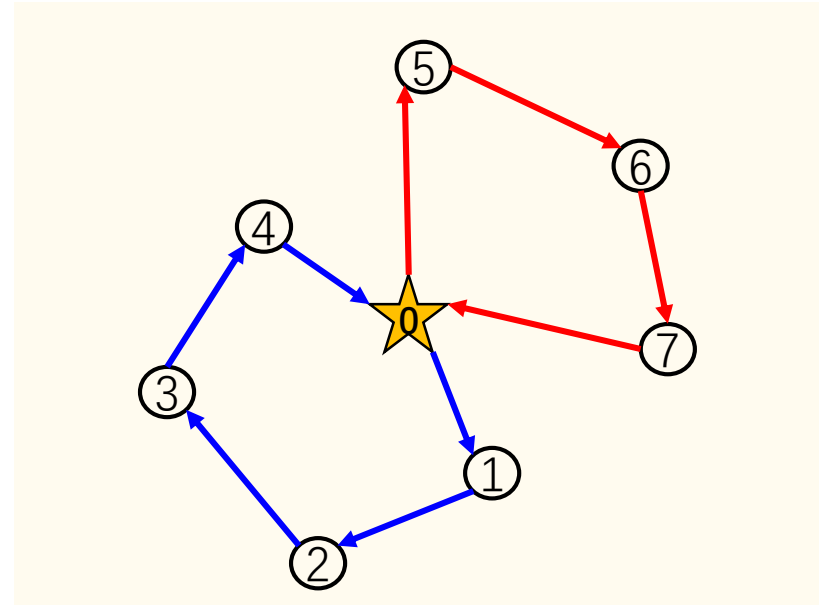


**Fig. 1.** Hierarchy of CVRP formulations.

[1] Letchford, Adam N., and Juan-José Salazar-González. "The capacitated vehicle routing problem: Stronger bounds in pseudo-polynomial time." *European Journal of Operational Research* 272.1 (2019): 24-31.


# Exact algorithms

1. Integer linear programming
2. Dynamic programming
3. Branch-and-Bound
4. Branch-and-Cut
5. Branch-Cut-and-Price
6. ...





## Key works about branch-cut-and-price (BCP)

- 
- [Balinski and Quandt, 1964] Set-partitioning formulation for CVRP
  - [Laporte and Nobert, 1983] Branch-and-bound
  - [Desrochers et al., 1992] First branch-and-price
  - [Lysgaard et al., 2004] Best branch-and-cut algorithm
  - [Fukasawa et al., 2006] Robust branch-cut-and-price
  - [Baldacci et al., 2008] Enumeration technique
  - [Jepsen et al., 2008] (non-robust) subset-row cuts
  - [Baldacci et al., 2011b] Ng-route relaxation
  - [Pecin et al., 2017b] Best branch-cut-and-price
  - [Costa et al., 2019] Recent surveys

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  - [Fukasawa et al., 2006]
  - [Baldacci et al., 2008]
  - [Jepsen et al., 2008]
  - [Baldacci et al., 2011b]
  - [Pecin et al., 2017b]
  - [Costa et al., 2019]

Set-partitioning formulation for CVRP

$$\min \sum_{r \in \Omega} c_r z_r$$

s.t.

$$\sum_{r \in \Omega} a_{ir} z_r = 1 \quad (i \in V_c) \quad (\text{C1})$$

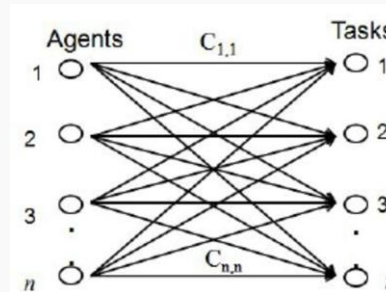
$$z_r \in \{0,1\} \quad (r \in \Omega) \quad (\text{C2})$$

## Key works about branch-cut-and-price (BCP)

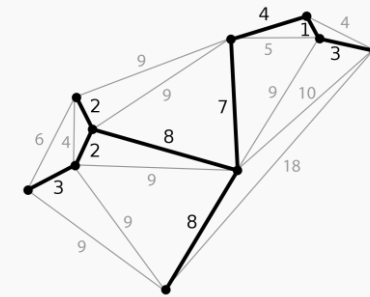
- [Balinski and Quandt, 1964]
- [Laporte and Nobert, 1983]
- [Desrochers et al., 1992]
- [Lysgaard et al., 2004]
- [Fukasawa et al., 2006]
- [Baldacci et al., 2008]
- [Jepsen et al., 2008]
- [Baldacci et al., 2011b]
- [Pecin et al., 2017b]
- [Costa et al., 2019]

MIP formulation with edge variables, rounded capacity cuts, and branch-and-bound

Assignment problem



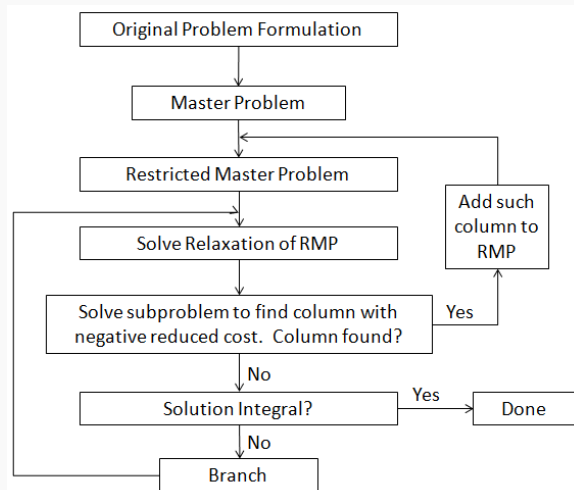
Shortest spanning tree



# Key works about branch-cut-and-price (BCP)

- [Balinski and Quandt, 1964]
- [Laporte and Nobert, 1983]
- [Desrochers et al., 1992]
- [Lysgaard et al., 2004]
- [Fukasawa et al., 2006]
- [Baldacci et al., 2008]
- [Jepsen et al., 2008]
- [Baldacci et al., 2011b]
- [Pecin et al., 2017b]
- [Costa et al., 2019]

## First branch-and-price



1. For a subset of paths  $P' \subset P$ , define a **Restricted Master Problem (RMP)**, containing subset  $P'$  of variables  $\lambda$
2. Solve RMP by an LP solver, obtain an optimal primal solution  $(\bar{x}, \bar{\lambda})$  and dual solution  $(\bar{\pi}, \bar{\mu})$ .
3. Solve the **pricing problem** to verify whether there is a variable  $\lambda_p$  with a negative reduced cost:

$$\min_{p \in P} \sum_{a \in A} \bar{\pi}_a h_a^p - \bar{\mu}. \quad (1)$$

4. If solution value of (1) is negative, add one or several variables  $\lambda_p$  to (RMP) and go to stage 2
5. Otherwise, run a **separation algorithm** to find constraints  $Bx \leq b$  violated by  $\bar{x}$ . If violated inequalities are found, add them to (RMP) and go to stage 2, otherwise stop.

## Key works about branch-cut-and-price (BCP)

- [Balinski and Quandt, 1964]
- [Laporte and Nobert, 1983]
- [Desrochers et al., 1992]
- [Lysgaard et al., 2004]
- [Fukasawa et al., 2006]
- [Baldacci et al., 2008]
- [Jepsen et al., 2008]
- [Baldacci et al., 2011b]
- [Pecin et al., 2017b]
- [Costa et al., 2019]

### Best branch-and-cut algorithm

- Uses capacity, framed capacity, generalized capacity, strengthened comb, multistar, partial multistar, extended hypotour inequalities, and classical Gomory mixed integer cuts.

$$\min \sum_{(i,j) \in A} c_{ij} x_{ij}$$

s.t.

$$x(\delta^+(i)) = x(\delta^-(i)) = 1 \quad (i \in V_c) \quad (C1)$$

$$x(\delta^+(i)) \geq \lceil q(S)/Q \rceil \quad (S \subseteq V_c) \quad (C2)$$

$$x_{ij} \in \{0,1\} \quad ((i,j) \in A) \quad (C3)$$

- At present, the **most promising solution** technique appears to be *branch-and-cut*. They **all based on** the so-called *two-index formulation*.

## Key works about branch-cut-and-price (BCP)

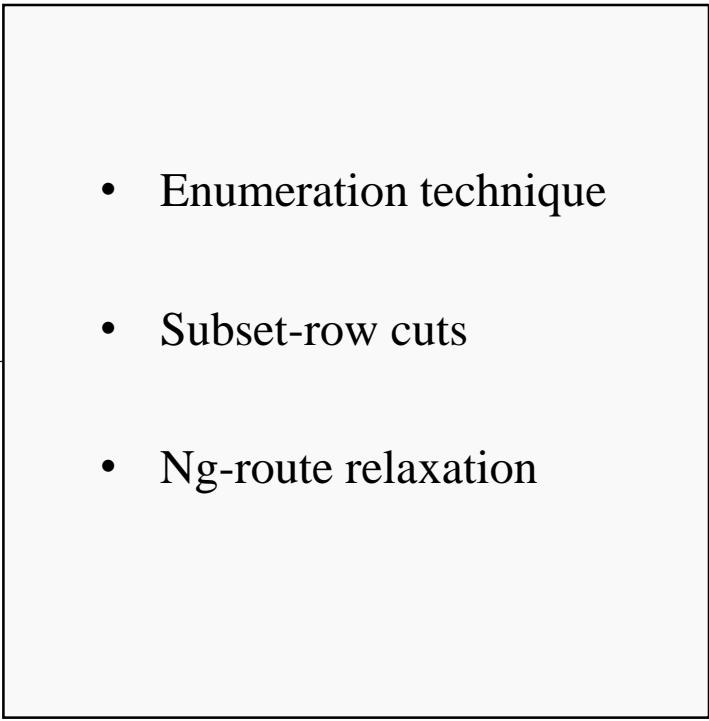
- 
- [Balinski and Quandt, 1964]
  - [Laporte and Nobert, 1983]
  - [Desrochers et al., 1992]
  - [Lysgaard et al., 2004]
  - [Fukasawa et al., 2006]
  - [Baldacci et al., 2008]
  - [Jepsen et al., 2008]
  - [Baldacci et al., 2011b]
  - [Pecin et al., 2017b]
  - [Costa et al., 2019]

### Robust branch-cut-and-price

- Combines branch-and-cut and branch-and-price
- The **best exact algorithms** for CVRP have been based on **either** branch-and-cut **or** Lagrangean relaxation/column generation
- The resulting branch-and-cut-and-price algorithm can solve to optimality **all instances** from the literature with **up to 135 vertices**

## Key works about branch-cut-and-price (BCP)

- 
- [Balinski and Quandt, 1964]
  - [Laporte and Nobert, 1983]
  - [Desrochers et al., 1992]
  - [Lysgaard et al., 2004]
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  - [Jepsen et al., 2008]
  - [Baldacci et al., 2011b]
  - [Pecin et al., 2017b]
  - [Costa et al., 2019]

- 
- Enumeration technique
  - Subset-row cuts
  - Ng-route relaxation

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- [Balinski and Quandt, 1964]
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  - [Baldacci et al., 2008]
  - [Jepsen et al., 2008]
  - [Baldacci et al., 2011b]
  - [Pecin et al., 2017b]
  - [Costa et al., 2019]

### Best branch-cut-and-price

- Limit-memory method

### branch-cut-and-price (BCP)

- The best performing exact algorithms for CVRP developed in the **last 10 years** are based in the combination of **cut and column generation**



# How big a VRP problem can exact methods solve

- Measuring it by the size where instances can be consistently solved, We observe an increase from 50 to 200 customers.<sup>[1]</sup> (2014)
- All the instances used for benchmarking exact algorithms, with up to 199 customers, were solved to optimality. <sup>[2]</sup> (2017)
- Sophisticated branch-cut-and-price (BCP) algorithms for some of the most classical VRP variants now solve many instances with up to a few hundreds of customers.<sup>[3]</sup> (2020)
- Now most instances of the most classic VRPs with up to 200 customers can be solved, some of them in a long time. More importantly, instances with up to 100 customers can often be solved in less than 1 minute.<sup>[3]</sup> (2020)

[1] Toth, Paolo, and Daniele Vigo, eds. Vehicle routing: problems, methods, and applications. Society for Industrial and Applied Mathematics, 2014.

[2] Pecin, Diego, et al. "Improved branch-cut-and-price for capacitated vehicle routing." Mathematical Programming Computation 9.1 (2017): 61-100.

[3] Pessoa, Artur, et al. "A generic exact solver for vehicle routing and related problems." Mathematical Programming 183.1 (2020): 483-523.

# How big a VRP problem can (hybrid) heuristics (probably) solve

- It is safe to say that current metaheuristics are capable of producing high quality solutions for instances with up to 500 customers.<sup>[1]</sup> **(2014)**
- Two heuristics are tested on newly proposed instances with 100-1000 customers.<sup>[2]</sup> **(2017)**
- Two-stage tabu search used on VRPTW with 100-1000 customers.<sup>[3]</sup> **(1999)**
- Local search method tested on new instances with 3000-30000 customers.<sup>[4]</sup> **(2019)**

[1] Toth, Paolo, and Daniele Vigo, eds. Vehicle routing: problems, methods, and applications. Society for Industrial and Applied Mathematics, 2014.

[2] Uchoa, Eduardo, et al. "New benchmark instances for the capacitated vehicle routing problem." European Journal of Operational Research 257.3 (2017): 845-858.

[3] Gehring, Hermann, and Jörg Homberger. "A parallel hybrid evolutionary metaheuristic for the vehicle routing problem with time windows." Proceedings of EUROGEN99. Vol. 2. Springer Berlin, 1999.

[4] Arnold, Florian, Michel Gendreau, and Kenneth Sörensen. "Efficiently solving very large-scale routing problems." Computers & Operations Research 107 (2019): 32-42.

# Time cost comparison<sup>[1]</sup>

## Exact method (BCP)

**Table 5**  
BCP median times for each configuration.

	Hours	Days	Ratio		Hours	Days	Ratio
<i>n</i>				Demand			
100	0.26	0.01	0.03	U	0.19	0.01	0.02
125	0.2	0.01	0.02	1-10	4.41	0.18	0.45
150	1.36	0.06	0.14	5-10	9.73	0.41	1
175	2.99	0.12	0.31	1-100	99.51	4.15	10.23
200	9.73	0.41	1	50-100	183.01	7.63	18.81
225	40.85	1.7	4.2	Q	>312	>13	>32.07
250	34.77	1.45	3.57	SL	286.5	11.94	29.45
Dep				<i>r</i>			
C	1.42	0.06	0.15	[3,5]	1.37	0.06	0.14
E	53.15	2.21	5.46	[6,8]	2.03	0.08	0.21
R	9.73	0.41	1	[9,11]	9.73	0.41	1
				[12,14]	24.14	1.01	2.48
Cust				[15,16]	86.67	3.61	8.91
R	9.92	0.41	1.02	[17,18]	139.9	5.83	14.38
C	7.1	0.3	0.73	[21,23]	143.32	5.97	14.73
RC	9.73	0.41	1				

## Heuristics

n	mins	hours
100-200	<10	/
200-500	10-60	<1
500-1000	60-800	1-13.3

[1] Uchoa, Eduardo, et al. "New benchmark instances for the capacitated vehicle routing problem." European Journal of Operational Research 257.3 (2017): 845-858.

Budget

MIP

BB

BCP

BC

GA

ACO

SS

Next stage



ML

100-1000

~100

100-1000

~100

**MIP:** Mixed integer programming

**BB:** Branch-and-Bound

**BC:** Branch-and-Cut

**BCP:** Branch-and-Cut-and-Price

**TS:** Tabu Search

**SA:** Simulated Anneal

**ACO:** Ant Colony Optimization

**GA:** Generic Algorithm

**SS:** Scatter Search

**GRASP:**

Greedy randomized adaptive search procedure

**ILS:** Iterated Local Search

**ALNS:** Adaptive Large Neighbourhood Search

**VNS:** Variable Neighbourhood Search

Heading

?

Gap

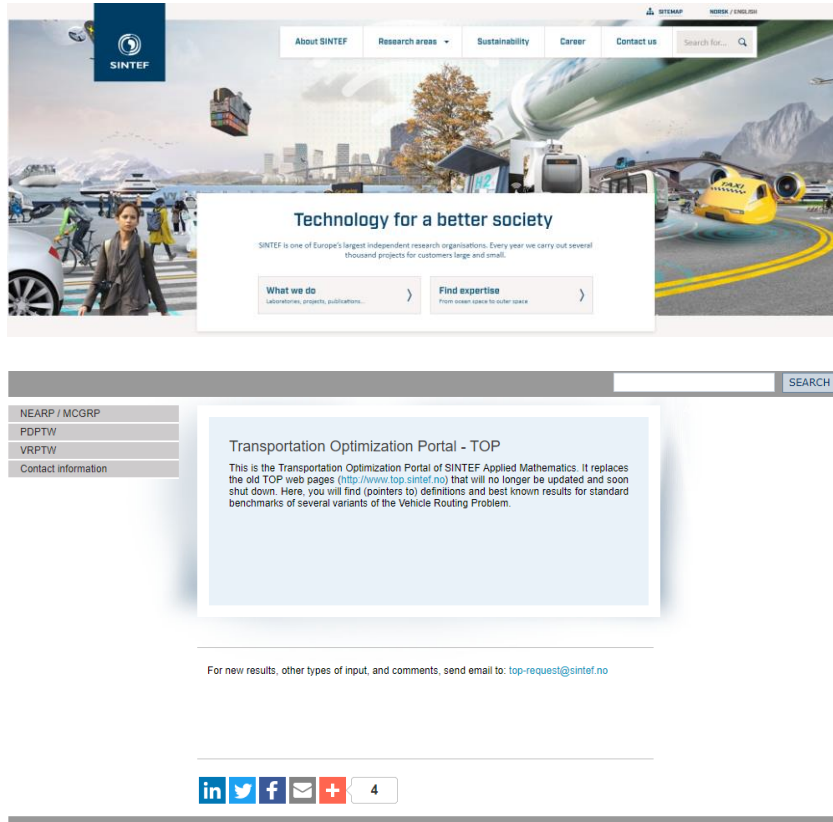
<https://baijiahao.baidu.com/s?id=1685417905897714864&wfr=spider&for=pc>

ALNS, Tabu, GLS

<https://blog.csdn.net/yunqiinsight/article/details/89178260>

ALNS, ML

# Best known solution of SINTEF Benchmark



lrc1_10_1	82	49111.78	SB	30-Jan-19
lrc1_10_2	71	45547.38	HW	30-Nov-20
lrc1_10_3	53	35620.73	HW	30-Nov-20
lrc1_10_4	40	27213.93	HW	30-Nov-20
lrc1_10_5	72	50323.04	HW	26-Feb-21
lrc1_10_6	67	45115.22	HW	30-Nov-20
lrc1_10_7	60	41560.52	HW	23-Dec-20
lrc1_10_8	55	41063.60	HW	15-Jan-21
lrc1_10_9	53	39182.15	HW	30-Nov-20
lrc1_10_10	47	36552.46	HW	23-Dec-20
lrc2_10_1	22	34463.46	SCR	05-Nov-19
lrc2_10_2	19	38619.13	HW	10-Dec-20
lrc2_10_3	16	27218.08	HW	23-Dec-20
lrc2_10_4	11	23220.38	HW	26-Feb-21
lrc2_10_5	16	40848.54	HW	30-Nov-20
lrc2_10_6	17	30910.65	SCR	05-Nov-19
lrc2_10_7	15	33275.24	SCR	31-Dec-19
lrc2_10_8	-	-	-	-
lrc2_10_9	-	-	-	-
lrc2_10_10	11	29100.28	HW	23-Dec-20

PDPTW



rc1_10_1	90	45830.62	CAINIAO	Dec-19
rc1_10_2	90	43718.84	SCR	Apr-19
rc1_10_3	90	42163.46	SCR	Apr-19
rc1_10_4	90	41397.81	SCR	Feb-20
rc1_10_5	90	45069.37	SCR	Jun-19
rc1_10_6	90	44844.95	SCR	Sep-19
rc1_10_7	90	44457.79	SCR	Feb-20
rc1_10_8	90	43956.91	SCR	Jan-20
rc1_10_9	90	43899.45	SCR	Apr-19
rc1_10_10	90	43573.95	SCR	Jan-20
rc2_10_1	20	30276.27	CAINIAO	Nov-18
rc2_10_2	18	26104.09	SCR	Oct-18
rc2_10_3	18	19911.48	SCR	Jan-20
rc2_10_4	18	15693.28	CAINIAO	Feb-19
rc2_10_5	18	27067.04	SCR	Jul-19
rc2_10_6	18	26741.27	CAINIAO	27-sep-18
rc2_10_7	18	24999.66	SCR	Jan-20
rc2_10_8	18	23595.33	SCR	Mar-19
rc2_10_9	18	22943.42	SCR	Mar-19
rc2_10_10	18	21834.94	SCR	Jul-19

VRPTW

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# Outline

1. Roadmap
2. Exact Methods for VRP
3. Conclusion

## Conclusion

1. Branch-cut-and-price (BCP) is one of the state-of-the-art exact method
2. Exact methods can solve many instances with up to a few hundreds of customers
3. Use hybrid approach and ML techniques

# Exact Methods for VRP

Thanks!

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