



---

# Boosting Neural Combinatorial Optimization For Large-Scale Vehicle Routing Problems

---

Fu Luo<sup>1</sup>, Xi Lin<sup>2</sup>, Yaoxin Wu<sup>3</sup>, Zhenkun Wang<sup>1†</sup>, Tong Xialiang<sup>4</sup>, Mingxuan Yuan<sup>4</sup>, Qingfu Zhang<sup>2</sup>

<sup>1</sup> Southern University of Science and Technology,

<sup>2</sup> City University of Hong Kong,

<sup>3</sup> Eindhoven University of Technology,

<sup>4</sup> Huawei Noah's Ark Lab

---

<sup>†</sup>Corresponding author

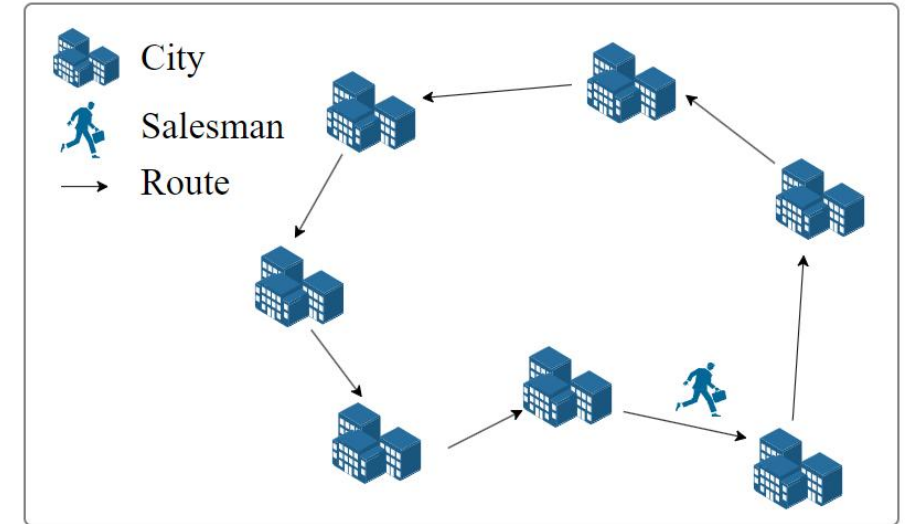
# Vehicle Routing Problem

## ■ Vehicle Routing Problem (VRP)

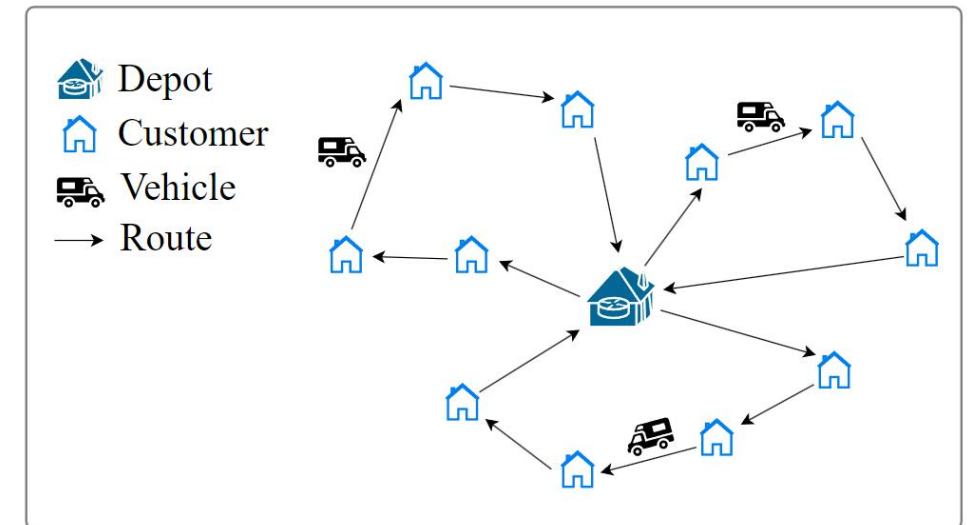
- A classic combinatorial optimization problem
- Has wide applications in logistics, circuit design and other fields.

## ■ Classical VRPs

- Travelling Salesman Problem (TSP)
- Capacitated Vehicle Routing Problem (CVRP)



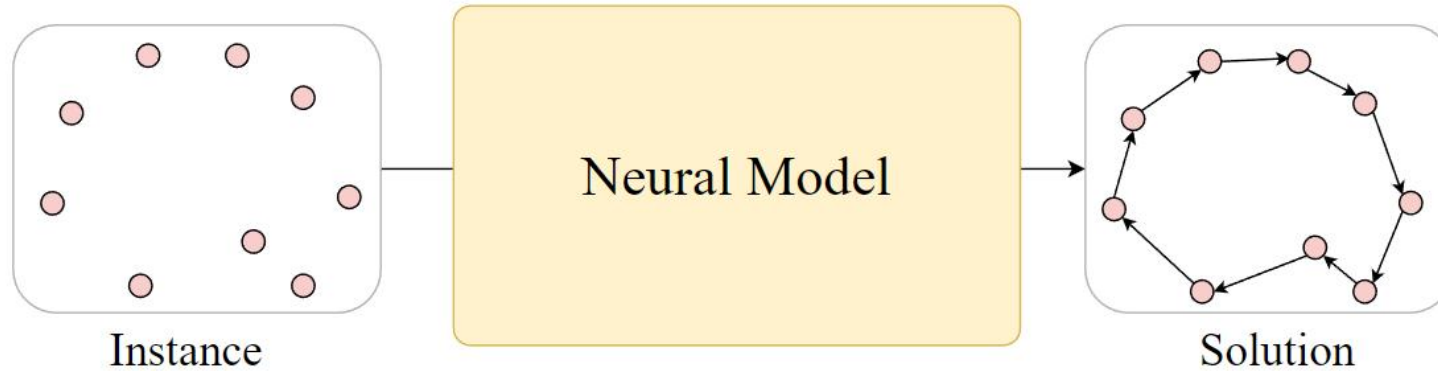
A TSP instance



A CVRP instance

# Neural Combinatorial Optimization

---

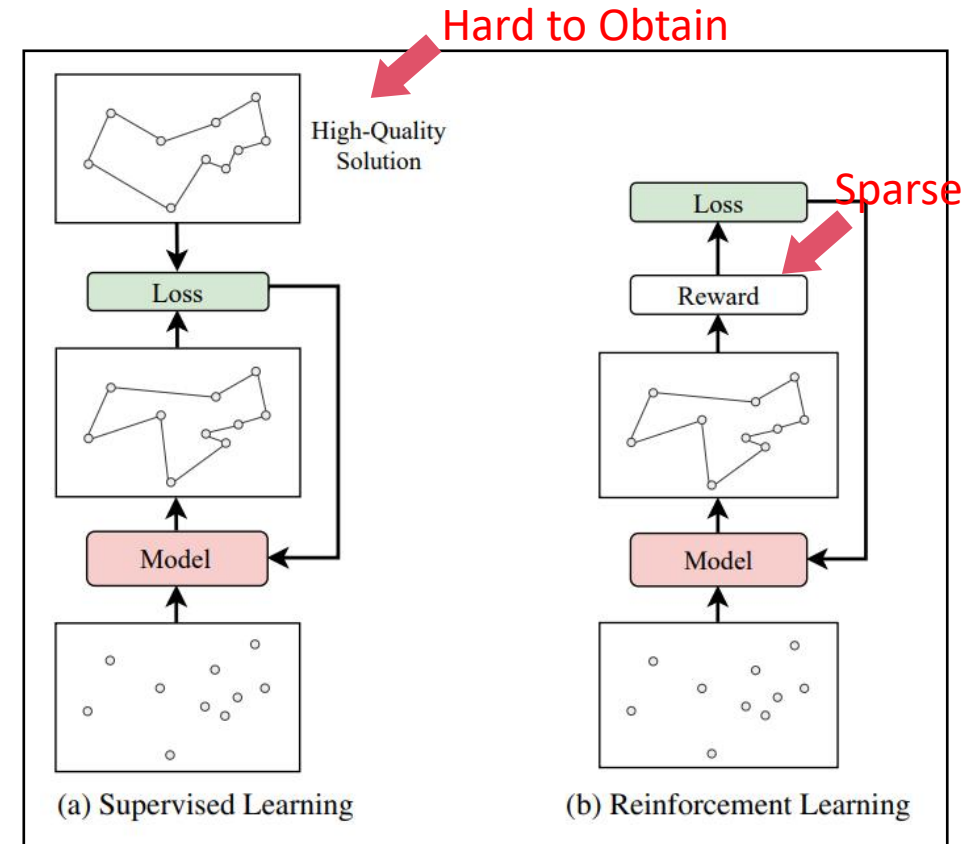
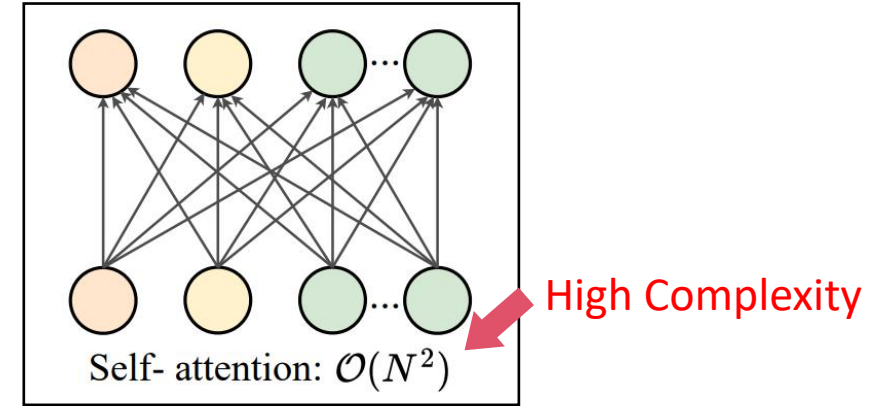


## ■ Neural Combinatorial Optimization (NCO) Methods:

- Advantage: learn problem-solving policies from data, significantly mitigate the need for costly manual algorithm design.
- Limitation: **struggle when applied to large-scale VRPs (limited scalability).**

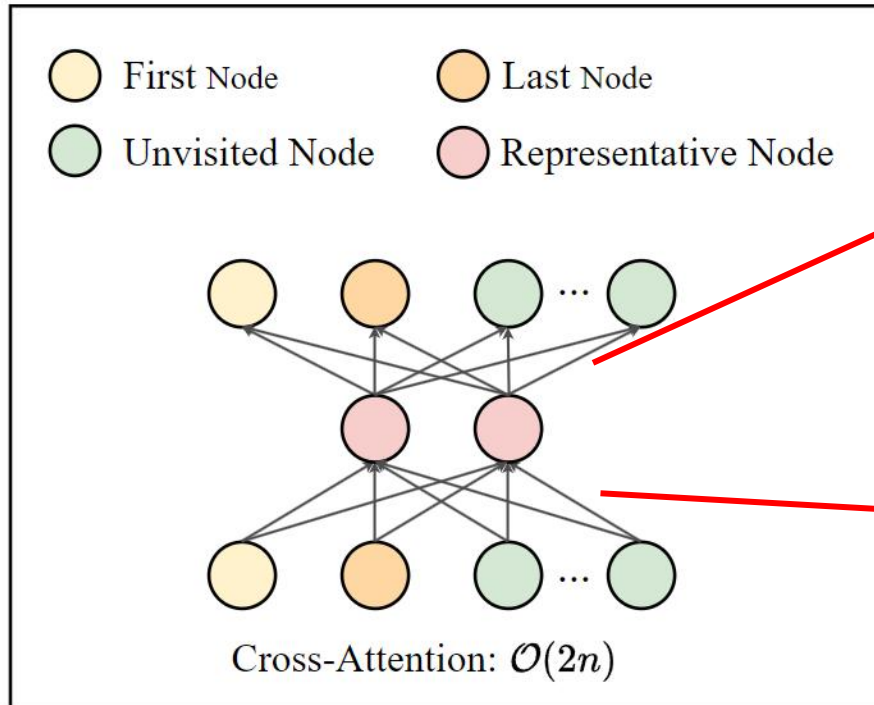
# Obstacles in terms of scalability

- High computational complexity from the self-attention mechanism.
- Difficult to directly train the model on large-scale VRPs
  - Supervised Learning: hard to obtain high-quality labels.
  - Reinforcement Learning: sparse rewards, high GPU memory usage.



# This Work

## ■ Cross-attention mechanism: Linear computational complexity



➤ Step2: update the embeddings of the other nodes by attending them to the representative nodes.

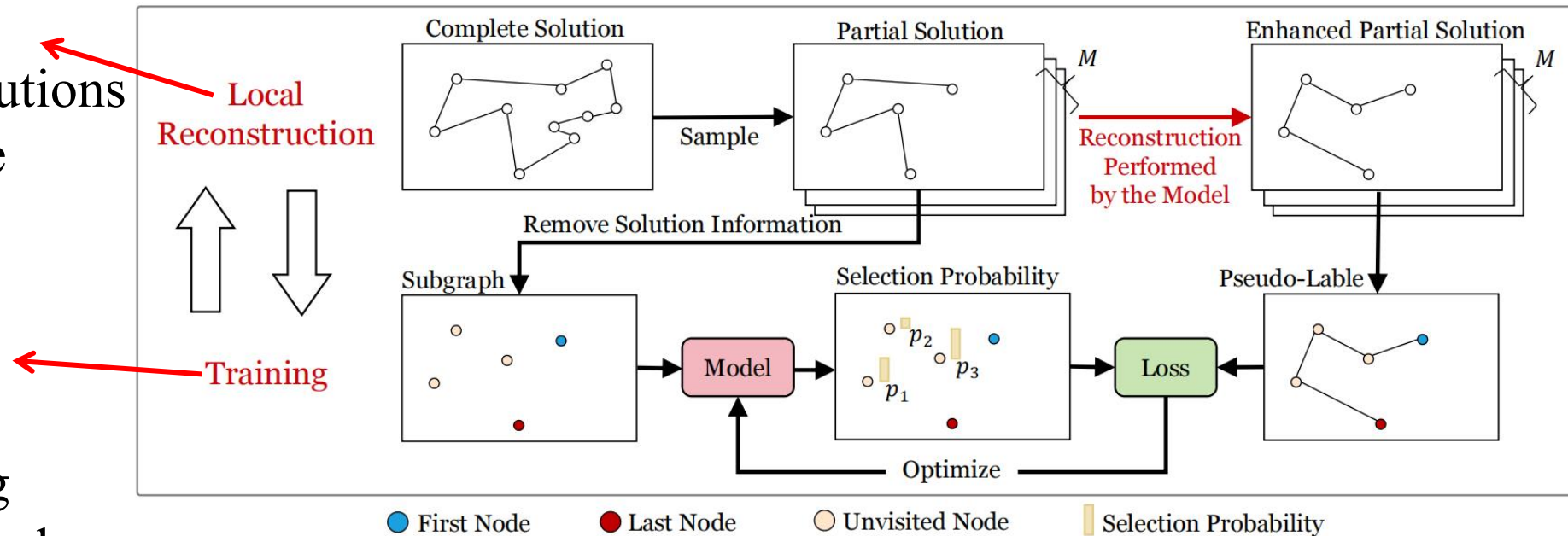
➤ Step1: update the embeddings of the representative nodes by attending them to the other nodes.

# This Work

## ■ Self-Improved Training: Direct model training on large-scale VRP instances

➤ Local Reconstruction:  
Generate enhanced solutions as pseudo-labels by the model itself.

➤ Model Training:  
Improve the model's efficiency in enhancing solutions using the pseudo-labels.





# Performance On Uniformly Distributed Instances

Table 1: Comparative results on synthetic TSP and CVRP instances. \*: results are cited directly from original publications. N/A: the method exceeds the time limit (e.g., seven days) or produces infeasible solutions. OOM: the method exceeded memory limits.

Method	TSP1K		TSP5K		TSP10K		TSP50K		TSP100K	
	Obj. (Gap)	Time	Obj. (Gap)	Time	Obj. (Gap)	Time	Obj. (Gap)	Time	Obj. (Gap)	Time
LKH3	23.12 (0.00%)	1.7m	50.97 (0.00%)	12m	71.78 (0.00%)	33m	159.93 (0.00%)	10h	225.99 (0.00%)	25h
Concorde	23.12 (0.00%)	1m	50.95 (-0.05%)	31m	72.00 (0.15%)	1.4h	N/A	N/A	N/A	N/A
Random Insertion	26.11 (12.9%)	<1s	58.06 (13.9%)	<1s	81.82 (13.9%)	<1s	182.65 (14.2%)	15.4s	258.13 (14.2%)	1.7m
DIFUSCO*	23.39 (1.17%)	11.5s	—	—	73.62 (2.58%)	3.0m	—	—	—	—
H-TSP	24.66 (6.66%)	48s	55.16 (8.21%)	1.2m	77.75 (8.38%)	2.2m	OOM		OOM	
GLOP	23.78 (2.85%)	10.2s	53.15 (4.26%)	1.0m	75.04 (4.39%)	1.9m	168.09 (5.10%)	1.5m	237.61 (5.14%)	3.9m
POMO aug×8	32.51 (40.6%)	4.1s	87.72 (72.1%)	8.6m	OOM		OOM		OOM	
ELG aug×8	25.738 (11.33%)	0.8s	60.19 (18.08%)	21s	OOM		OOM		OOM	
LEHD RRC1,000	23.29 (0.72%)	3.3m	54.43 (6.79%)	8.6m	80.90 (12.5%)	18.6m	OOM		OOM	
BQ bs16	23.43 (1.37%)	13s	58.27 (10.7%)	24s	OOM		OOM		OOM	
SIGD bs16	23.36 (1.03%)	17.3s	55.77 (9.42%)	30.5m	OOM		OOM		OOM	
INViT-3V greedy	24.66 (6.66%)	9.0s	54.49 (6.90%)	1.2m	76.85 (7.07%)	3.7m	171.42 (7.18%)	1.3h	242.26 (7.20%)	5.0h
LEHD greedy	23.84 (3.11%)	0.8s	58.85 (15.46%)	1.5m	91.33 (27.24%)	11.7m	OOM		OOM	
BQ greedy	23.65 (2.30%)	0.9s	58.27 (14.31%)	22.5s	89.73 (25.02%)	1.0m	OOM		OOM	
SIGD greedy	23.573 (1.96%)	1.2s	57.19 (12.20%)	1.8m	93.80 (30.68%)	15.5m	OOM		OOM	
Ours greedy	23.569 (1.95%)	0.2s	52.59 (3.17%)	5.2s	74.69 (4.05%)	20.1s	168.50 (5.36%)	7.7m	239.84 (6.13%)	33.0m
Ours PRC10	23.396 (1.20%)	0.9s	52.36 (2.73%)	5.1s	73.99 (3.08%)	10.0s	166.69 (4.22%)	1.33m	235.38 (4.16%)	3.0m
Ours PRC50	23.279 (0.69%)	4.6s	51.92 (1.85%)	23.4s	73.41 (2.27%)	49.0s	165.01 (3.17%)	4.9m	233.13 (3.16%)	9.2m
Ours PRC100	23.254 (0.58%)	9.4s	51.82 (1.67%)	52.0s	73.29 (2.11%)	1.7m	164.59 (2.91%)	8.6m	232.55 (2.90%)	17m
Ours PRC500	23.217 (0.43%)	46s	51.70 (1.43%)	4.6m	73.12 (1.87%)	8.5m	164.09 (2.60%)	42.2m	231.75 (2.55%)	1.4h
Ours PRC1,000	<b>23.207 (0.38%)</b>	1.5m	<b>51.67 (1.36%)</b>	9.4m	<b>73.08 (1.81%)</b>	17.0m	<b>163.95 (2.51%)</b>	1.38h	<b>231.52 (2.45%)</b>	2.6h



# Performance On Uniformly Distributed Instances

Method	CVRP1K		CVRP5K		CVRP10K		CVRP50K		CVRP100K	
	Obj. (Gap)	Time	Obj. (Gap)	Time	Obj. (Gap)	Time	Obj. (Gap)	Time	Obj. (Gap)	Time
HGS	36.29 (0.00%)	2.5m	89.74 (0.00%)	2.0h	107.40 (0.00%)	5.0h	267.73 (0.00%)	8.1h	476.11 (0.00%)	24h
LKH3	37.09 (2.21%)	3.3m	93.71 (5.19%)	1.33h	118.76 (10.6%)	1.74h	399.12 (49.1%)	15.8h	N/A	N/A
Random Insertion	57.42 (58.2%)	<1s	154.38 (72.0%)	<1s	191.80 (78.6%)	<1s	490.56 (83.2%)	<1s	943.87 (98.3%)	2s
GLOP-G (LKH3)	39.50 (8.83%)	1.3s	98.90 (10.2%)	6.8s	116.28 (8.27%)	11.2s	OOM		OOM	
POMO aug $\times$ 8	84.89 (134%)	4.8s	393.27 (338%)	11m	OOM		OOM		OOM	
ELG aug $\times$ 8	41.57 (14.56%)	1.1s	109.54 (22.06%)	30s	OOM		OOM		OOM	
LEHD RRC1,000	37.43 (3.15%)	3.4m	101.07 (12.6%)	31m	138.73 (29.2%)	41m	OOM		OOM	
BQ bs16	38.17 (5.17%)	14s	104.40 (16.3%)	2.6m	OOM		OOM		OOM	
SIGD bs16	39.15 (7.91%)	17.3s	103.46 (15.3%)	1.91m	131.48 (22.4%)	3.97m	477.43 (78.3%)	25.9m	OOM	
INViT-3V greedy	42.75 (17.8%)	11.4s	109.85 (22.41%)	1.4m	141.41 (31.66%)	4.2m	402.05 (50.17%)	2.9h	688.80 (44.67%)	8.3h
LEHD greedy	38.91 (7.23%)	0.8s	105.61 (17.69%)	1.56m	146.24 (36.16%)	11.85m	OOM		OOM	
BQ greedy	39.28 (8.23%)	1.03s	108.09 (20.48%)	8.1s	196.44 (82.9%)	1.2m	OOM		OOM	
SIGD greedy	40.18 (10.7%)	1.2s	106.14 (18.3%)	7.9s	135.12 (25.8%)	45s	493.64 (84.4%)	4.3m	OOM	
Ours greedy	38.11 (5.01%)	0.2s	92.44 (3.01%)	5.49s	109.02 (1.50%)	20.62s	269.34 (0.60%)	8.06m	475.06 (-0.22%)	33.1m
Ours PRC10	37.93 (4.52%)	0.7s	93.92 (4.65%)	3.9s	112.17 (4.43%)	6.8s	285.20 (6.52%)	28s	496.24 (4.23%)	59s
Ours PRC50	37.57 (3.54%)	3.5s	92.06 (2.58%)	19.9s	108.79 (1.29%)	34s	271.77 (1.51%)	2.3m	476.71 (0.13%)	4.8m
Ours PRC100	37.49 (3.31%)	8.0s	91.58 (2.05%)	46s	108.04 (0.59%)	1.3m	268.02 (0.11%)	5.49m	471.35 (-1.00%)	11.5m
Ours PRC500	37.33 (2.88%)	44.6s	91.00 (1.41%)	4.4m	106.85 (-0.51%)	7.6m	263.56 (-1.56%)	31.1m	465.18 (-2.30%)	1.1h
Ours PRC1,000	<b>37.28 (2.72%)</b>	1.5m	<b>90.81 (1.19%)</b>	8.8m	<b>106.69 (-0.66%)</b>	15.2m	<b>262.82 (-1.83%)</b>	1.04h	<b>463.95 (-2.55%)</b>	2.17h



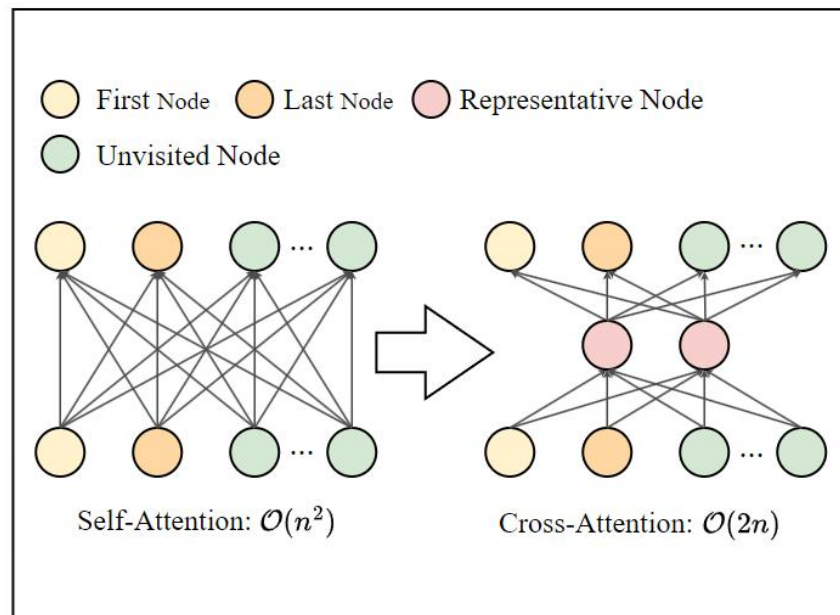
# Performance On Real-World Instances

Table 2: Results on TSPLIB and CVRPLIB. OOM: The method is inapplicable due to the memory limit. <sup>†</sup>: There exist instances that are not solvable by the NCO method due to the OOM issue.

	TSPLIB				CVRPLIB			
Method	$1K < n \leq 5K$	$n > 5K$	All	Solved #	$1K < n \leq 7K$	$n > 7K$	All	Solved #
GLOP	5.017%	6.870% <sup>†</sup>	5.495%	31/33	15.335%	21.317%	17.898%	14/14
ELG aug $\times 8$	11.34%	OOM	11.34%	23/33	10.57% <sup>†</sup>	OOM	10.57%	6/14
BQ bs16	10.648%	30.579% <sup>†</sup>	12.948%	26/33	13.918%	OOM	13.918%	8/14
LEHD RRC1,000	3.996%	18.458% <sup>†</sup>	7.371%	30/33	8.423%	21.525% <sup>†</sup>	11.043%	10/14
SIGD greedy	12.369%	152.879% <sup>†</sup>	48.630%	31/33	14.733%	49.491%	29.629%	14/14
BQ greedy	11.640%	162.116% <sup>†</sup>	64.649%	32/33	16.923%	52.267%	32.071%	14/14
INViT greedy	11.492%	9.996%	11.038%	33/33	15.873%	26.637%	20.486%	14/14
LEHD greedy	11.139%	39.343% <sup>†</sup>	17.720%	30/33	15.203%	32.797% <sup>†</sup>	18.722%	10/14
Ours greedy	6.767%	10.697%	8.244%	33/33	15.806%	15.504%	15.677%	14/14
Ours PRC1,000	<b>1.576%</b>	<b>4.043%</b>	<b>2.556%</b>	33/33	<b>8.347%</b>	<b>11.209%</b>	<b>9.574%</b>	14/14

# Summary

- Cross-Attention:  
Linear complexity



- Self-Improved Training:  
Direct model training on large-scale VRP instances

