

APPROXIMATE APPROACHES TO THE TRAVELING THIEF PROBLEM

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seek LIGHT

OUTLINE

- Address the multifaceted Traveling Thief Problem (TTP)
- Introduce a new fast basic heuristic method for achieving a good packing of items provided a tour
- Introduce two additional operators, one of which alters a packed tour based on packing
- Compare varying combinations and setups of the heuristic and operators



- n cities, with distances d(i, j) between cities i and j
- *m* items, each with weight *w*_{*ik*} and profit *p*_{*ik*}
- Knapsack capacity W
- Renting rate *R*
- *v_{min}* and *v_{max}* representing the minimal and maximal speed of the traveller



<u>Goal</u>: Visit each city exactly once, maximising the total profit *P* such that the total weight does not exceed the knapsack capacity *W*, where *P* is defined as:

$$P = \sum_{i=1}^{m} p_i x_i - R \sum_{i=1}^{n} t_{i,i+1}$$

where $x_i = \{1|0\}$ depending on whether the item *i* is picked $\{1\}$ or not $\{0\}$, and $t_{i,i}$ is defined as:

$$t_{i,j} = \frac{d(\Pi_i, \Pi_j)}{v_{max} - W_{\Pi_i} \left(\frac{v_{max} - v_{min}}{W}\right)}$$

where Π_i is the city at tour position *i* in tour the Π , and W_{Π_i} is the current weight of the knapsack at city Π_i .

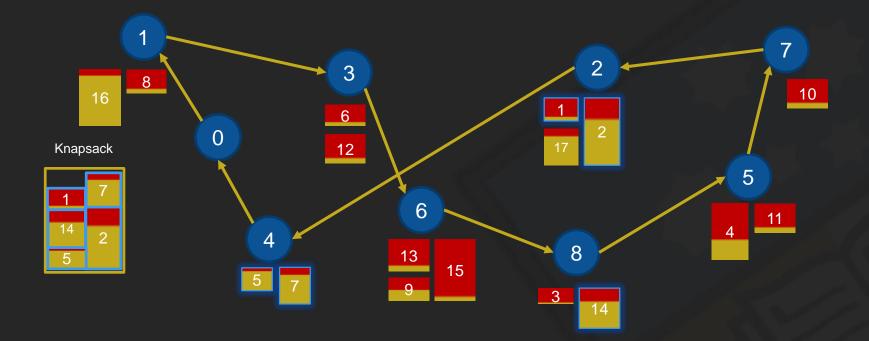


 Composed of the merging of the Traveling Salesman Problem and the Knapsack Problem





 Composed of the merging of the Traveling Salesman Problem and the Knapsack Problem





- Finds a TSP solution using Chained-Lin-Kernighan [1]
- Using the fixed TSP solution, generates a solution for KP problem
- Ignores the interdependency between the individual TSP and KP problems





Calculate heuristic score s_{ik} for each item



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- Sorts items in non-decreasing order based on score s_{ik}



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Once a fixed tour calculated, a score s_{ik} is calculated for each item k in city i:

 $s_{ik} = \frac{p_{ik}}{w_{ik}}$

where p_{ik} and w_{ik} is the profit and weight of item k respectively.



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 $s_{ik} = \frac{p_{ik}}{w_{ik} \times d_i}$

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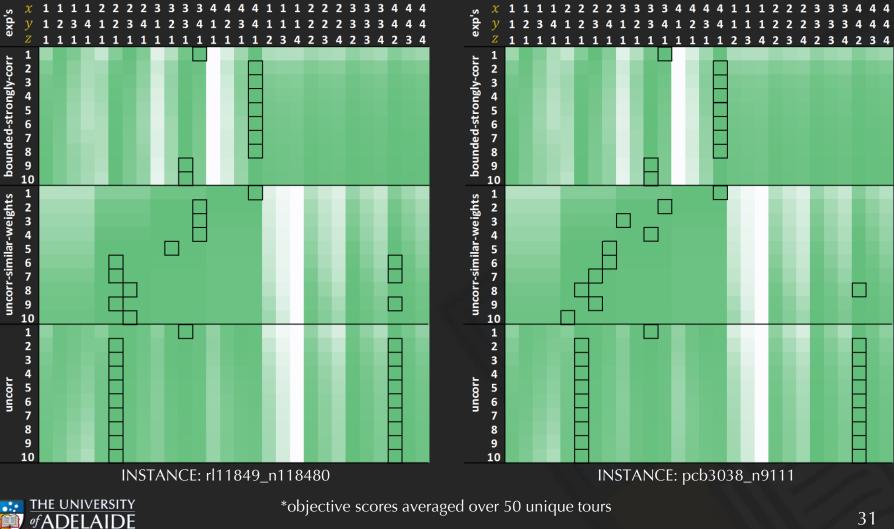
$$s_{ik} = \frac{p_{ik}^{x}}{w_{ik}^{y} \times d_{i}^{z}}$$

where p_{ik} and w_{ik} is the profit and weight of item k respectively, and d_i is the distance from city i to the end of the tour.



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*objective scores averaged over 50 unique tours

Once a fixed tour calculated, a score s_{ik} is calculated for each item k in city i:

$$s_{ik} = \frac{p_{ik}^{\alpha}}{w_{ik}^{\alpha} \times d_i}$$

where p_{ik} and w_{ik} is the profit and weight of item k respectively, and d_i is the distance from city i to the end of the tour.



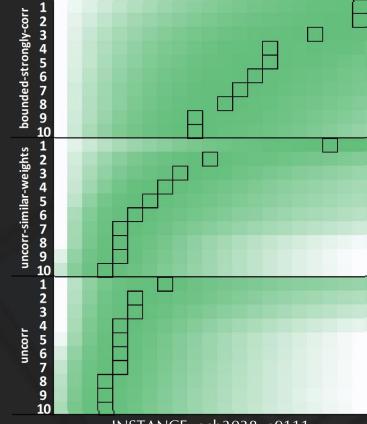
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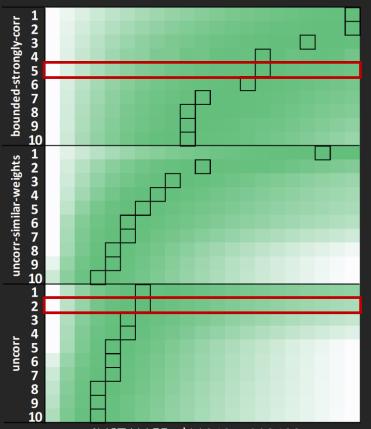


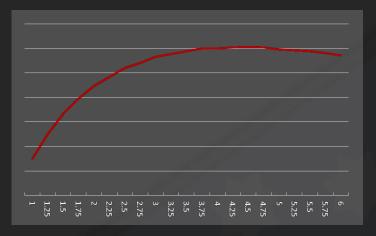
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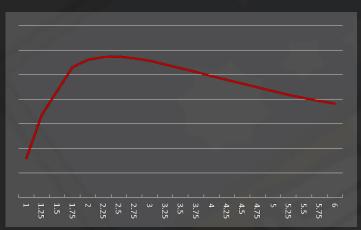
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*objective scores averaged over 50 unique tours





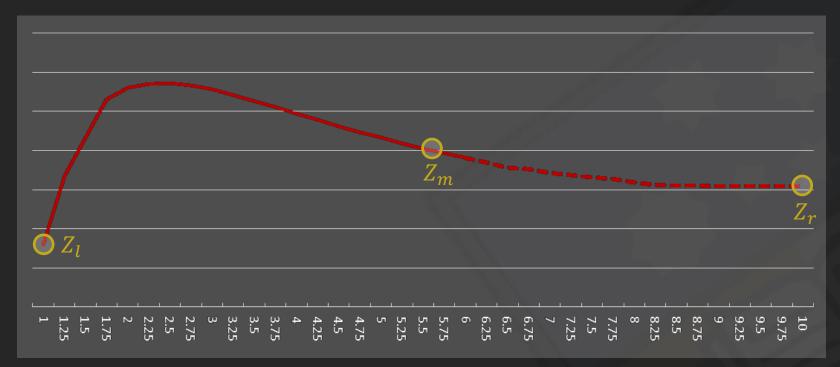


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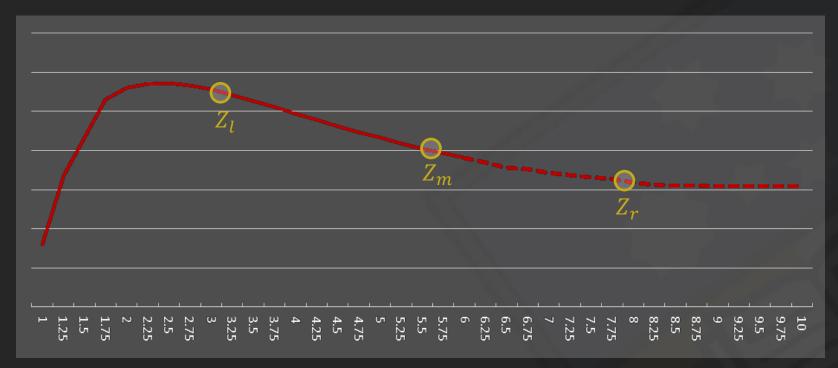
*objective scores averaged over 50 unique tours

- Sample different α values and compare the objective scores
- Narrow in on the best α value quickly



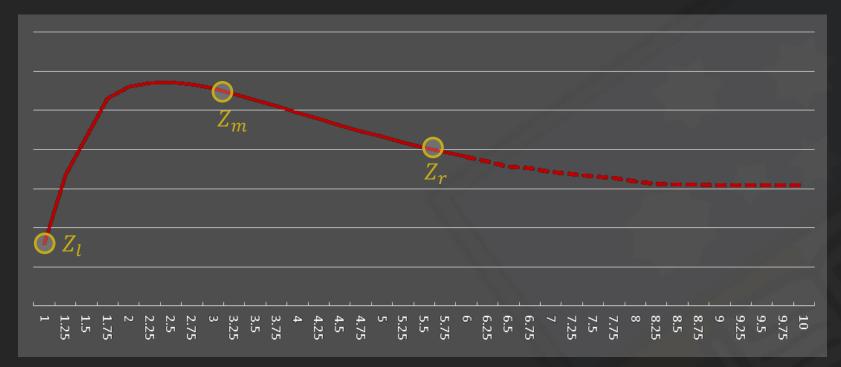
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- Sample different *α* values and compare the objective scores
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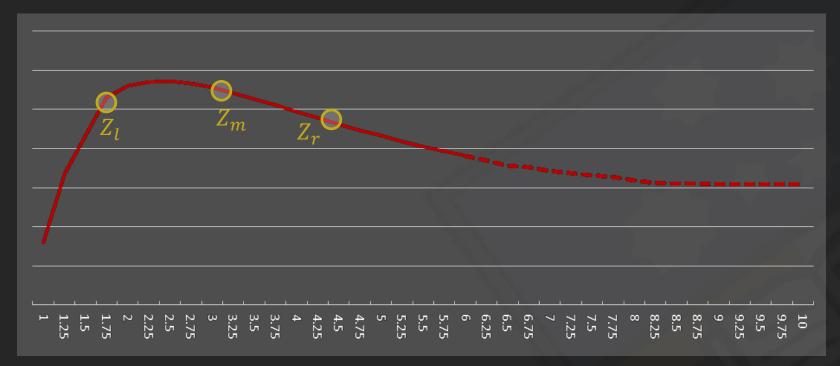
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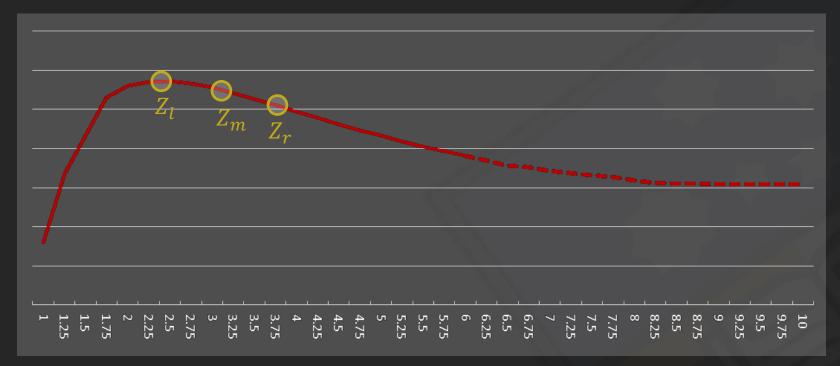
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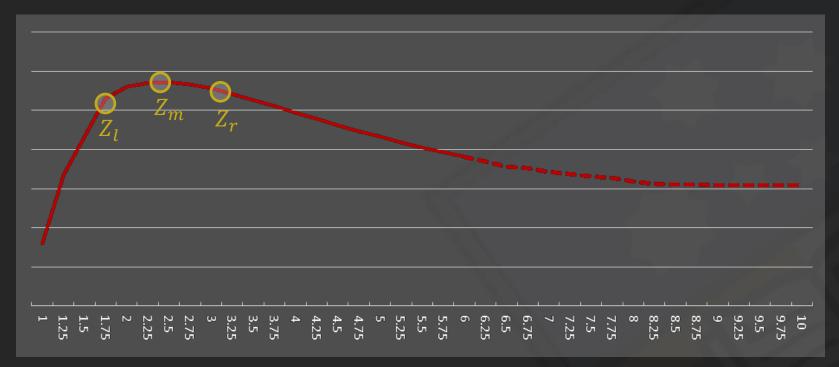
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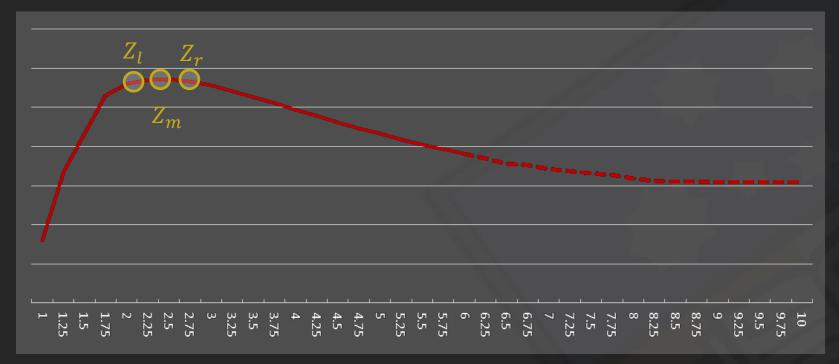
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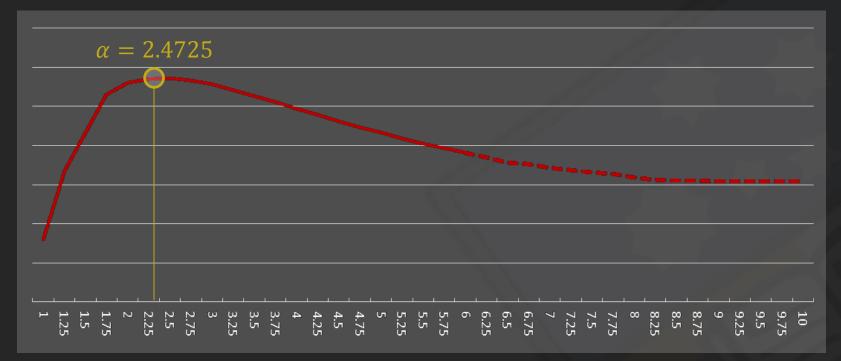
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ADDITIONAL OPERATORS

- The fast basic packing approach is not guaranteed to find globally optimal TTP solution:
 - 1. Doesn't modify tours based on items
 - 2. The packing plan it finds may not be optimal for a given tour
- Introduce two local search operations to slightly improve on a given tour and packing plan:
 - 1. BitFlip Only modifies packing plan
 - 2. Insertion Modifies tour based on provided packing plan



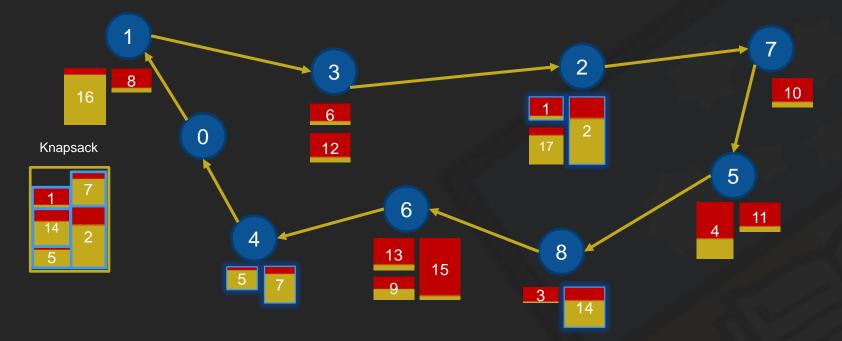
BITFLIP

- Iteratively evaluates the outcome of flipping each bit position corresponding to each item $I_m \in M$ in the packing plan P
- If flipping the bit improves the objective value then the change is kept, otherwise the packing plan is restored
- Can be time consuming on instances with a large number of items as <u>every</u> item is checked
- Can be run consecutively a number of times to increase improvements



INSERTION

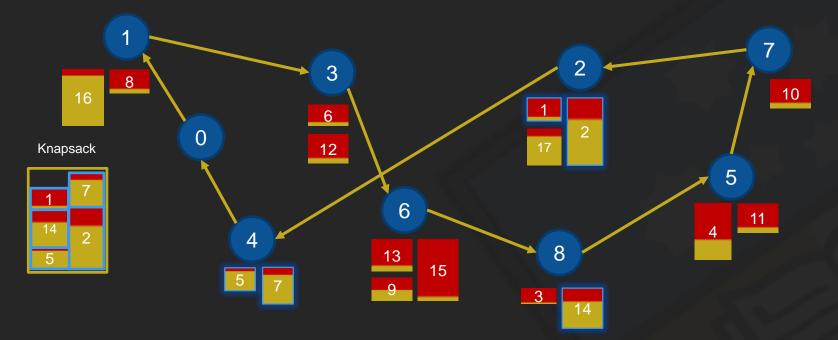
 Takes advantage of situation where valuable item is picked up at a particular city early in the tour and is worth visiting the city later in the tour





INSERTION

 Takes advantage of situation where valuable item is picked up at a particular city early in the tour and is worth visiting the city later in the tour





INSERTION

- Searches over cities in reverse tour order evaluating the effect of inserting each city at all positions before its own in the tour
- If one or more positions are found, the one that achieves the highest objective score is chosen
- Typical good TTP solutions, and solutions constructed by the fast basic heuristic, have many items picked up towards the end of the tours, hence the time consuming **Insertion** operator begins at the end of the tour
- Experiments show Insertion makes rare and minor improvements to a TTP solution provided by the fast basic heuristic



ALGORITHM COMBINATIONS

S1: CLK > Fast Packing

S2: CLK > Fast Packing > BitFlip until convergence or time expired
S3: CLK > Fast Packing > (1+1)-EA until convergence or time expired
S4: CLK > Fast Packing > Insertion until convergence or time expired
S5: repeat S1 until time expired

[1] (1+1)-EA is similar to BitFlip however instead of changing every bit which improves the objective score, each bit is changed with a probability $\frac{1}{m}$ CLK: Chained Lin-Kernighan



ALGORITHM COMBINATIONS

- C1: CLK > Fast Packing > repeat one BitFlip then one Insertion until convergence or time expired
- C2: CLK > Fast Packing > repeat one BitFlip then one (1+1)-EA then one Insertion until convergence or time expired
- C3: Repeat CLK then Fast Packing until 10% of time expired pick best > one BitFlip then one Insertion until time expired
- C4: Repeat CLK then Fast Packing until 10% of time expired pick best > one BitFlip then one (1+1)-EA then one Insertion until time expired
- C5: repeat C1 until time expired
- C6: repeat C2 until time expired

CLK: Chained Lin-Kernighan



MIP APPROACH

MIP (Mixed Integer Programming) approach of Polyakovskiy, Neumann (2014):

- Given tour able to solve optimal packing plan exactly or approximately
- Very costly in regard to runtimes as it uses a linearization technique to handle non-linear terms in the objective function



EXPERIMENTS

- Compare our algorithm combinations S1-S5 and C1-C6 with the MIP and the MATLS (Memetic Algorithm with the Two-stage Local Search) approach of Mei, Li, Yao (2014)
- Use comprehensive set of benchmark instances from [1,4]:
 - 51 85900 cities
 - three types: *uncorrelated, uncorrelated with similar weights,* and *bounded strongly correlated*
 - 1,3,5, or 10 items per city for each TSP and KP combination
 - For each TTP configuration there is 10 different instances with varying knapsack capacities



EXPERIMENTS

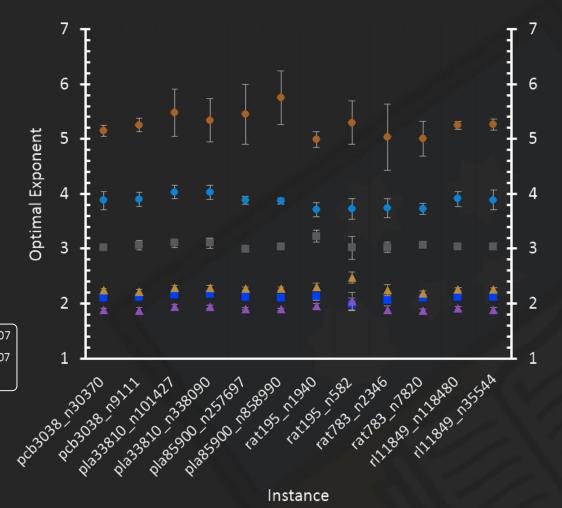
- From the 9720 benchmark instances 72 representative cases were selected:
 - six different number of cities: *195, 783, 3038, 11849, 33810, 85900*
 - all types: *uncorrelated, uncorrelated with similar weights,* and *bounded strongly correlated*
 - Two different items per city: *3* and *10*
 - Two different knapsack capacities: *3* and *7* times the size of the smallest knapsack
- All algorithms run for 10 minutes per instance, except MIP which ran for 8 hours on instances where $n \in \{33810, 85900\}$
- 30 independent repetitions of algorithms on each instance



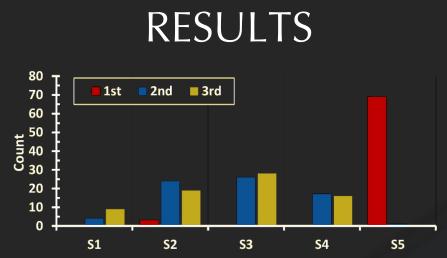
RESULTS

- *α* is relatively equal for similar types of instances no matter instance size
- Bounded-strongly have highest and most variable *α*
- As knapsack capacity W increases, α decreases

bounded-strongly-corr_03	bounded-strongly-corr_07
uncorr-similar-weights_03	uncorr-similar-weights_07
▲ uncorr_03	▲ uncorr_07



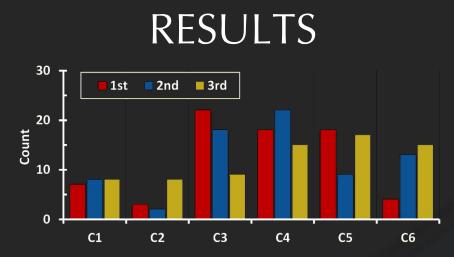




Comparison of the number of first, second, and third placings of S algorithms across the 72 instances

- S5 clearly outperforms the others, showing the importance of a good initial tour
- S2-S4 relatively equal runners up showing they perform on instances where the others do not
- The placings of S4 highlight the necessity to consider modifications to the tour of a TTP solution

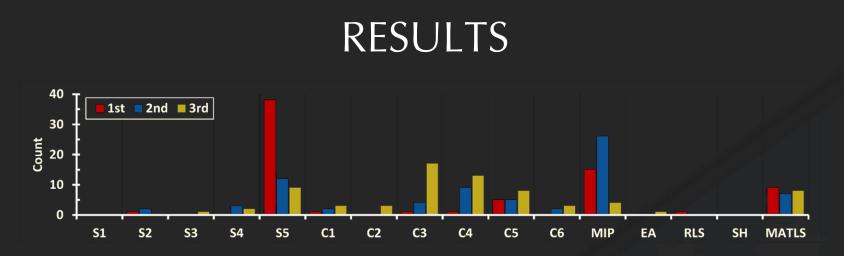




Comparison of the number of first, second, and third placings of C algorithms across the 72 instances

- Recall that C3 and C4 sample several starting tour options, compared to C1 and C2, and that C5 and C6 are the restart variants of C1 and C2
- The dominance C3 and C4 again suggest the importance of finding a good initial TSP tour solution
- C5 and C6 perform better than the single iteration C1 and C2 methods, however they do not perform as well as C3 and C4 which have more time to sample a greater number of initial tours





Comparison of the number of first, second, and third placings of all algorithms across the 72 instances

EA: Evolutionary Algorithm, RLS: Random Local Search, SH: Simple Heuristic. All from [1].

• S5, MIP, and MATLS are the best performing algorithms overall



RESULTS

n	m	t	\mathbf{F}	S1	S5	C3	C4	C5	C6	MIP	MATLS
		\mathbf{bsc}	3	88.1	99.6	99.4	99.4	99.6	99.5	100	96.3
			7	88.0	99.2	99.2	99.2	99.2	99.2	99.2	95.6
	582	unc	3	98.2	99.2	99.3	99.3	99.3	99.3	99.3	99.5
	ñ		7	99.2	99.9	100	100	100	100	100	99.8
		msn	3	96.1	98.6	99.0	98.9	99.3	99.0	99.5	98.5
195		m	7	98.2	99.1	99.2	99.2	99.3	99.2	99.3	99.2
		\mathbf{bsc}	3	89.6	99.9	99.9	99.9	99.9	99.9	100	98.3
			7	89.2	97.7	97.1	97.5	97.7	97.6	98.1	97.0
	1940	unc	3	96.0	99.1	98.7	98.7	99.3	99.1	99.1	99.0
	19	m	7	96.3	98.6	97.7	97.7	98.7	98.5	98.8	99.2
		usw	3	88.4	91.3	91.3	91.6	91.5	91.7	91.4	97.0
			7	92.6	96.3	95.6	95.6	96.4	96.0	96.9	99.4
ĺ		bsc	3	97.8	99.7	99.4	99.4	99.6	99.4	99.7	96.6
			7	95.5	99.3	98.7	98.6	99.1	98.8	99.0	96.6
	2346	unc	3	95.9	98.9	98.5	98.5	98.8	98.5	98.7	98.8
			7	96.3	97.9	97.6	97.7	97.9	97.7	97.8	98.6
		nsn	3	95.3	99.1	99.2	99.2	99.5	99.3	99.5	98.7
783			7	96.0	99.7	99.6	99.5	99.8	99.5	99.7	98.7
2		\mathbf{bsc}	3	98.0	99.7	99.6	99.7	99.4	99.5	99.8	94.8
	_		7	97.0	99.5	99.4	99.4	99.3	99.1	99.5	94.5
	7820	unc	3	96.8	99.3	99.2	99.1	99.2	98.7	99.3	98.5
			7	97.9	99.5	99.4	99.3	99.3	99.1	99.4	99.0
		мsп	3	96.0	99.3	99.6	99.6	99.4	99.0	99.6	97.7
			7	95.9	99.3	99.2	99.2	99.2	98.4	99.4	98.1
		bsc	3	97.9	99.5	99.1	99.1	98.1	98.0	99.1	93.9
			7	97.6	99.4	99.0	99.0	97.7	97.4	98.8	94.4
	9111		3	98.0	99.7	99.4	99.4	98.5	98.0	99.5	99.0
			7	98.3	99.7	99.5	99.4	98.9	98.5	99.6	99.4
		nsw	3	97.0	99.1	99.2	99.1	97.2	97.2	99.2	98.2
3038			7	97.6	99.6	99.3	99.2	98.4	97.7	99.3	99.0
	30370	\mathbf{bsc}	3	98.1	99.6	99.3	99.3	99.0	99.0	99.3	96.7
			7	97.0	99.2	98.7	98.8	98.6	98.2	98.9	95.8
		unc	3	97.1	99.6	99.2	99.1	98.9	98.8	99.3	99.0
			7	97.8	99.5	99.3	99.3	99.2	98.9	99.3	99.2
		usn	3	94.8	98.9	98.2	98.3	97.6	97.6	98.6	98.3
		ä	7	96.2	99.1	98.6	98.4	98.5	97.9	98.6	98.6

Г	n	m	t	F	S1	S5	C3	C4	C5	C6	MIP	MATLS
			bsc	3	97.1	99.2	98.4	98.6	97.3	97.4	97.5	93.5
				$\overline{7}$	96.7	98.9	97.9	98.1	96.6	96.7	96.7	93.9
		544	unc	3	97.4	99.0	98.4	98.5	97.6	97.8	98.0	98.4
		35544 35544		$\overline{7}$	97.9	99.5	98.9	99.0	98.0	98.3	98.4	99.3
	<u> </u>		мsп	3	96.3	98.6	97.8	98.0	96.2	96.5	97.2	97.6
	346			7	97.1	99.0	98.5	98.5	97.0	97.3	97.3	98.7
	11849		\mathbf{bsc}	3	96.7	99.0	98.4	98.3	96.9	97.0	97.9	93.6
				7	96.2	99.2	98.1	98.3	96.2	96.4	97.4	94.0
			unc	3	97.2	99.2	98.6	98.7	97.4	97.6	98.3	98.4
				7	97.4	99.2	98.6	98.4	97.9	97.8	98.5	98.8
			nsw	3	95.3	98.3	97.8	97.8	95.6	95.9	97.1	97.6
				7	96.2	98.9	98.1	98.0	96.7	96.7	97.9	98.5
			unc bsc	3	91.3	97.9	95.5	94.0	93.9	92.0	98.3	94.4
		23	q	7	91.0	97.9	94.2	95.3	93.8	91.7	96.5	94.1
		42	nc	3	70.6	73.5	71.4	71.5	71.2	70.9	73.3	75.8
		101427		7	95.1	98.2	96.4	96.0	95.3	95.5	99.9	-98.4
	0	Π	msn	3	90.4	97.5	93.7	93.3	92.5	91.8	96.2	95.9
	33810		n	7	92.2	98.0	94.7	93.9	93.9	93.5	98.1	97.4
	ŝ	338090	\mathbf{bsc}	3	92.2	97.3	93.8	93.3	92.5	92.4	99.1	93.9
			д	7	92.6	97.1	94.9	94.3	92.6	93.3	96.9	94.6
			unc	3	94.7	98.3	95.3	95.5	95.8	95.0	97.8	98.0
			n	7	95.0	98.4	96.0	96.1	96.2	95.7	98.5	98.7
			nsw	3	91.3	97.7	93.5	92.8	92.1	92.3	98.3	96.4
				7	93.9	98.3	94.4	95.1	94.1	94.6	99.5	98.3
			\mathbf{bsc}	3	95.8	98.3	96.3	95.8	95.9	96.4	97.6	-
		Q	-0	7	96.1	97.8	96.8	95.9	96.3	97.1	98.4	
		858990 338090	unc	3	97.4	98.9	94.2	94.1	97.8	97.7	-	
			n Si	7	97.6	98.6	95.6	95.4	98.0	98.2	98.1	
	0		msn	3	95.1	97.6	92.6	92.3	96.1	95.2	-	- 74
	85900			7	95.8	97.4	93.4	93.3	96.4	96.0	97.9	-
	85		\mathbf{bsc}	3	95.9	96.8	96.2	97.1	95.6	96.3		-
				7	96.6	97.2	97.0	97.6	96.6	96.3		94.1
			unc	3	97.6	97.5	92.1	92.0	97.6	97.3		-
			n msn	7	97.9	97.9	94.6	94.5	97.8	97.7		98.5
				3	95.7	97.5	91.8	92.7	96.3	95.3		-
		ਸੋਂ 7		96.6	96.9	93.2	93.2	96.5	96.3	-	97.9	
	avg				95.2	98.2	97.0	96.9	96.9	96.8	87.2	84.9
	\mathbf{avg}^{-85900}				95.0	98.3	97.5	97.4	97.0	96.8	98.1	97.0



Objective value ratios compared to maximum found across all algorithms and iterations

CONCLUSIONS

- The strength of our fast basic packing heuristic is its speed, allowing more initial Lin-Kernighan tours to be sampled (15-60 milliseconds for 195 cities, and 18-110 seconds for 85,900 cities)
- Local search operators such as BitFlip and Insertion have positive yet limited effect due to their computational complexity
- Even MIP approach only just achieves comparable performance with the limited time availability



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