Sports team schedule

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Background

There are N teams 1, 2, ..., N that need to be scheduled to play against each other in a round-robin format: each team must meet all the remaining N - 1 teams twice (one at their home stadium and once at their opponents) in a period of 2N - 2 weeks, every week each team must play exactly 1 match. Distance from the stadium of team i to the stadium of team j is d(i, j). Make a schedule for N teams so that the total distance traveled by all teams is the shortest.

Input:

- Line 1: positive even integer N
- Line i + 1 (i = 1, 2, ..., N): i-th row of matrix d

Understanding

Variables:

- N: the number of teams.
- Distance matrix d(i, j): weight matrix of undirected graph. It is a two-dimensional list, in which row i and column j is the distance from the stadium of team i to the stadium of team j.
- Schedule matrix x(i, j): a matrix stored by a two-dimensional list. The index of each row is the index of the home team, and the index of each column is the index of the guest team. Row i and column j is the week that the match between 2 teams is scheduled. The initial states of this matrix (week 0) in an empty matrix, and the final states of this matrix (last week) is the OUTPUT matrix.

Constraints:

- N: the number of teams is a positive even integer. The size of the distance matrix and the schedule matrix is N \times N.
- The distance from the stadium of team i to itself d(i, i) is 0 or the main diagonal of the distance matrix is all 0.
- A team cannot play against itself. We set the week that a team plays against itself x(i, i) is week 0 or the main diagonal of the schedule matrix is all 0.
- Each team must meet all the remaining N 1 teams twice, and every week each team must play exactly one match so the domain of the week in the schedule matrix is {0, 1, 2, ..., 2N 2}. Except week 0, the number of matches each week is N / 2.
- Every week each team must play exactly one match. So all entries in row i (week that team i play at their home stadium) and column i (week that team i play at their opponents) are pairwise different.

Objective function:

Total distance traveled by all teams is minimized

Algorithms

Backtrack:

- Constructing a graph of the states of the tournament. Each node represents the schedule matrix and appropriate information of the tournament (as cost, current position of each team,etc...)
- Define a "get_sub_node" function to get all neighbors of a node. The main idea is we need to construct the schedule for next week of the tournament.

```
def backtrack_solve(input: list):
    N = len(input)
    queue = []
    # tracking the best value in the tree
    best_value = float('inf')

best_config = None
    ##
    # initialize the root of the tree.
```

```
root_matrix = [[None for i in range(N)] for i in range(N)]
for i in range(N):
    root_matrix[i][i] = 0
root_dis = 0
week = 0
root_tracking_pos = [i for i in range(N)]
root = Node(root_matrix, root_dis, week, root_tracking_pos)
queue.append(root)
while queue:
    temp = queue.pop()
    assert isinstance(temp, Node)
    current_week = temp.week
    if current_week == 2*N - 2:
        if temp.dis < best_value:</pre>
            best_config = temp.matrix
            best_value = temp.dis
            print(f"Found better configuration, the new best value is: {best_value}")
            print(f"The new best config is {best_config}")
            print()
    else:
        next_week = current_week + 1
        list_of_nodes = get_sub_node(input, temp)
        for item in list_of_nodes:
            sub_matrix, sub_pos, sub_dis = item
            if sub_dis < best_value:</pre>
                sub_Node = Node(sub_matrix, sub_dis, next_week, sub_pos)
                queue.append(sub_Node)
```

Beam search:

Keeping k lowest nodes in terms of distance cost, and using same model as Backtrack (generalized Greedy)

```
def beam_solve(input,k):
  N = len(input)
  queue = []
  ## tracking the best value in the tree
   c_min = find_min(input)
  ##initialize the root of the tree.
  root_matrix = [[None for i in range(N)] for i in range(N)]
   for i in range(N):
       root_matrix[i][i] = 0
  root_dis = 0
  week = 0
  root_tracking_pos = [i for i in range(N)]
  root = Node(root_matrix,root_dis,week,root_tracking_pos)
   queue.append(root)
  best = None
  while True:
       nodes = copy.deepcopy(queue)
       queue = []
       if nodes[0].week == 2*N - 2:
           for node in nodes:
               if best == None:
                   best = node.matrix,node.dis
               else:
                   if node.dis < best[1]:</pre>
                       best = node.matrix,node.dis
           break
       else:
          next_week = nodes[0].week + 1
           for node in nodes:
               lis = get_sub_node(input, node)
               sub_nodes = [Node(sub_matrix,sub_dis,next_week,sub_pos) for \
                   (sub_matrix,sub_pos,sub_dis) in lis]
               queue += sub_nodes
           queue = sorted(queue,key=lambda x: x.dis)[:k]
   return best
```

Hill climbing (Local search):

• Starting at a random complete assignment, defining a get_neighbors function to get all neighbor solutions of the current feasible solution, then keep moving if we can find better neighbor assignment

- The all neighbors of a solution is defined by:
 - Swapping the values of any 2 squares in the board, which accord to some teams, and then check for any repetitions in those teams, if there are, fix those repetitions, and keep swapping and checking like that until no repetition is found.
 - Swapping 2 schedules of 2 teams in the board (swapping 2 crosses)

```
def local_solve(input):
  # random initial
  #input: distance matrix
  #return the schedule: matrix , cost
  N = len(input)
  random_matrix = generate(N)
  cost = compute_cost(input,random_matrix)
  initialize = random_matrix,cost
  flag = False
  while flag:
       neighbors = get_neighbors(initialize)
       for neighbor in neighbors:
           #neighbor: matrix:schedule,cost
           schedule,cost = neighbor
          flag = False
           if cost < initialize[1]:</pre>
               initialize = neighbor
               flag = True
   return initialize[0],initialize[1]
```

Iterated local search:

• Applying local search multiple times with random initializations.

```
def iterative_local_solve(input,K):
    best_config = None
    best_cost = float('inf')
    for i in range(K):
        matrix,cost = local_solve(input)
        if cost < best_cost:
            best_cost = cost
            best_config = matrix

return best_config,best_cost</pre>
```

Gibbs sample:

• For each assignment, consider its neighbor assignments, then put the distance cost for the assignment. The higher cost, the lower probability we go into this assignment.

```
def gibb_sampling(input,K,factor):
  best_config = None
  best_cost = float('inf')
  #initialize start position
  mat = generate(len(input))
   current_postion = (mat,compute_cost(distance_matrix,mat))
  for i in range(K):
      #choosing a random number:
      num = random.random()
      list_of_neighs = get_neighbors(current_postion) #mat,cost
       sum_of_cost = sum(1/factor**x[1] for x in list_of_neighs)
       for i in range(len(list_of_neighs)):
          mat,cost = list_of_neighs[i]
          accumulate += 1/factor ** cost
           port = accumulate / sum of cost
          if port > num:
              current_postion = list_of_neighs[i-1]
              break
   return current postion
```

OR-Tools:

- For this problem, we use the CP-SAT solver from OR-Tools. By adding intermediate Boolean variables for computation of the cost function, the function becomes a linear one with constant coefficients.
- In detail, if we use our normal way of computing the cost, that means finding the order of the coordinates in each team schedule that has according incremental values, and then based on this order, calculate the cost, we are hindered from implementing the problem into the ORTools solver. Therefore, we had to change our method of calculating the objective function.

- For each team, we ordered the coordinates (or boxes) in its schedule. The first one will be box (i,i), then all the boxes of the according row, from left to right, and finally all the boxes of the according column, from top to bottom. The first box represents the first week, the row ones represent away weeks, with the destination can be found as the column coordinate, and the column ones represent the home weeks. We indexed these boxes with values from 0 to 2*N 1.
- And then we added in, for each of the teams, (2*N 1)^2 intermediate variables, which can be represented as a square matrix Y with dimension (2*N 1) x (2*N 1). If the week_value of some box i is equal to some week_value of box j + 1, then Y[i][j] = 1, and else, for other cases, Y[i][j] = 0. Because of our coordinate ordering, the meaning of each of the boxes is predetermined, and therefore just by multiplying each intermediate variable with an according coefficient taken from the distance_matrix, and summing all of them, we have our objective function, calculated in a way that is suitable for implementing into the CP-SAT solver.

Results

We experiment our algorithms with cases of N = 4 to N = 18. Our results are shown below:

		Exact Algorithms							Heuristic Algorithms														
N = 4 No. Input (distance matrix)		_															Meta-heuristic Algorithms) Gibb Sampling (K = 20, factor = 10)				\		
		Ba- Cost	cktracki	ng ime	Beam Se Cost	earch (K = 10) Time	OR-Tools (tin	ne_limit = 30 Time	,	Cost max	Local Search		Time av			rch (K = 20) Time	Cost min Cost						
	[[0, 14, 8, 10], [14, 0, 2, 16		130 1.3			30 0.022821		0.2525334			161.5					0.116170112					543 0.075056		
	[[0, 11, 6, 8], [11, 0, 13, 15		120 1.0			20 0.015474		0.3265458			142.3	6.9720	0.006046	<u> </u>		0.110396001			172		557 0.075752		
	[[0, 2, 10, 3], [2, 0, 1, 1], [1		46 0.3			55 0.016643		0.1303708			76.8		41 0.006147			0.115875799			109		0.075326		
	[[0, 6, 19, 6], [6, 0, 6, 6], [1		115 0.6			45 0.015848		0.2248786			145.3		0.006464		121	0.11391803					0.1 0.074667		
	[[0, 8, 11, 18], [8, 0, 6, 12] [[0, 19, 0, 3], [19, 0, 15, 19		106 0.6			08 0.016006 35 0.015913		0.2900109			141.9 137.4		.13 0.00684 3			0.122274279 0.118231739					503 0.074361 715 0.073388		
	[[0, 6, 19, 17], [6, 0, 14, 0]		115 0.6			49 0.016072		0.2918910					95 0.006413		121	0.11198837				172.3 14.21			
8	[[0, 7, 13, 4], [7, 0, 3, 3], [1		77 0.5	82724	9	94 0.015744	77	0.4859941			100.2		85 0.00623 !			0.200260892					164 0.073296		
	[[0, 8, 11, 10], [8, 0, 5, 7],	1	125 0.8			27 0.015564		0.1423313					.51 0.006063			0.198194362			188		0.076564		
10	[[0, 14, 7, 0], [14, 0, 10, 0]	54 0.6			77 0.01556	54	0.2612139	93 65	87	75.4		7.2 0.00574	2 0.005745 57 0.204744692 54 88 76.8 8.930845 0.0757										
	N = 6		Exact Algorithm											Heuristic Algorithms Meta houristic Algorithms									
	eam Search (K = 10) OR-Tools (t				ne limit - 30\			ocal Search			Meta-heuristic Algorithms Iterative Local Search (K = 20) Gibb Sampling (K = 20, factor = 2)								. 2)				
No.	Input (distance_matr		Cost	Tin		Cost	Time	Cost min	Cost_max		SD	Time		Cost	Tim	,		Cost_ma:			Time_avg		
	[[0, 14, 11, 16, 0, 6], [1	_	248			209	30.10935119				21.32422			289		435296	311	378			37 0.817953		
	[[0, 12, 8, 5, 5, 9], [12,		247	0.92	3515	239	30.10478216	312	402	368.8	24.25238	8 0.056	6628	330	1.831	483955	345	420	6 38	6.9 24.596	52 0.838233		
3	[[0, 2, 11, 19, 4, 5], [2,	0, 1	187			154				284.1	21.2208			245		985274	276	34		2.9 24.428			
	[[0, 15, 3, 4, 3, 3], [15,		180	_			30.11800174				20.66021			237		083146	262	31			15 0.832203		
	[[0, 19, 4, 11, 17, 3], [1		197	_		161					33.67244			260		359646	281	350			36 0.830625		
	[[0, 3, 19, 6, 10, 1], [3,		253 241	_	_	234 239	30.11793164 30.09339636				23.00845 24.97465			304 329		068501 587156	310 360	37: 50:			06 0.838203 01 0.838135		
	[[0, 17, 5, 18, 6, 9], [17] [[0, 12, 16, 14, 3, 15], [338				30.10977547				24.97465 24.37576			414		045844	438	523			13 0.808251		
	[[0, 9, 6, 7, 12, 6], [9, 0		150	_			30.11102091				12.34864			206		445335	225	27			38 0.827346		
	[[0, 0, 5, 19, 17, 16], [0		204				30.12871928				17.86244			310		102484	310				71 0.816618		
					xact Al	gorithms						•		Heuristic A	lgorithms	<u> </u>			•	-			
	N = 8		LAGE AIGOTETINIS												Meta-h	neuristi	c Algorith	ms					
		Be	am Sea	rch (K =	: 10) O	R-Tools (tim	ne_limit = 60)			ocal Search	ı		Itera	tive Local S	ocal Search (K = 20)				oling (K = 20, facto		2)		
No.	Input (distance_matr		Cost	Tin		Cost	Time		Cost_max		SD		e_avg	Cost	Time			ost_max		_	Time_avg		
	[[0, 0, 2, 0, 15, 14, 17,		313			362	60.2479353	564	640		27.4471		46815		6.61348		537	652	60				
	[[0, 15, 14, 1, 6, 18, 7, 6]		444		-	449	60.2686597	678	765	727.2	29.7089		51719		7.65740		672	829	732				
	[[0, 1, 8, 12, 17, 17, 13] [[0, 15, 18, 19, 4, 0, 16]		344 425			390 392	60.270849 60.4682847	611 560	711 748	661.7 675.9	35.2264 51.7245	_	37301 27517	617 642	6.86799 7.84873		639 679	738 760	686 724				
	[[0, 9, 4, 4, 10, 0, 17, 1]	_	378	_		392	60.4871099	656	748	697.4	26.7756		47123	595	6.98763		635	744	699				
	[[0, 13, 2, 3, 14, 4, 6, 2]		337			342	60.2801782	601	724	666.3	34.5126	_	69154	584	7.06886		617	778	662				
	[[0, 3, 13, 4, 19, 1, 5, 1		366			440	60.273295	770	820	792.7	15.8888	_	29167	726	8.19560		724	880	803				
	[[0, 0, 0, 8, 3, 11, 7, 14]		437	125.0	0109	453	60.2498519	679	797	732.7	32.5168	33 0.3 6	65796	697	6.94498	9925	689	801	758	.5 33.2306	8 4.698643		
	[[0, 13, 17, 4, 5, 18, 9,		338			412	60.5750086	715	829	782.4	37.0531	_	35498	686	7.81587		701	834	753				
10	[[0, 19, 8, 2, 5, 3, 1, 1],	[19]	402	122.4	1059	366	60.2692796	619	705	670	26.812	21 0.	51653	579	6.58829	4417	620	704	662	.4 31.2203	6 4.920971		
				Exact A	Algorith	hms							Heuristic Algorithms										
	N = 10											L	Meta-heuristic Algorithms										
			OR-Tools (time_			-			ocal Search				erative Loc			-			Sampling (K = 20, faction Cost_avg				
No.	Input (distance_m		(ost			Cost_min C			SD	Time_a		Cost		me					SD	Time_avg		
	1 [[0, 19, 6, 12, 14, 0,		1			.5396489	1191	1330		44.22669			120		744615	1248			1313.2				
	2 [[0, 17, 17, 8, 0, 18,		<u> </u>			.5897861	1107	1210	1150.4	28.9029			10		160708	1054				54.86195			
	3 [[0, 15, 13, 11, 11, 1					0.5168863	1419	1596		57.88773			14:		.292845	1430			1530.7				
	4 [[0, 13, 12, 2, 14, 18					0.6480511	1283	1448		48.47783			120		.208624	1278			1347.1				
	5 [[0, 13, 17, 0, 1, 14,		 	71		0.525107	1032	1240		67.79126 49.25489			103		659101	1097		_	1201.1	66.39854			
	6 [[0, 4, 6, 12, 5, 5, 8, 7 [[0, 7, 15, 0, 19, 4, 1		1			0.9153499	1308 1320	1458 1427	1370.4 1385.3	49.25489 35.8486		_	129		893219 134089	1362			1419.8 1349.3				
			-			0.5460515	1343	1562	1441.1				130		538163	1256 1322			1409.5				
	8 [[0, 0, 18, 5, 8, 15, 7 9 [[0, 19, 5, 9, 13, 14,		\vdash			0.5844218	1224	1349	1279.9				110		218277	1227			1303.1	43.44972			
	0 [[0, 2, 13, 6, 11, 18,		1			0.528994	1223	1349		40.47564	_	_	120			1207							
	· [110, 2, 13, 0, 11, 10,	-2, /,					1223	1343	1275.5	70.77304	1.323	JJ,									10.33370		
	N = 12	Exact Algorithms											ic Algorith		Mata to	intic *1							
	N = 12		OR-Tools (time_limit = 150)			mit = 150)			ocal Case-	ral Search		-	Iterative Local Search (K = 20			Meta-heuri		Algorithms ampling (K = 20, facto		20tor - 1.2	<u> </u>		
No	No. Input (distance_matrix					Time	Cost_min C		ocal Searc	n SD	Time_		Cost		<u> </u>			st_max Cost_avg		SD			
	1 [[0, 3, 4, 13, 9, 11, 2		_			0.9121057	1582	.ost_max 1847	1733		9 4.27 4			94 136.1		1643			1791.3		Time_avg 58.98845		
	2 [[0, 17, 9, 18, 17, 5,		1			0.9121057	1795	1970	1882.6						913341	1808		2029	1873	66.9245			
	3 [[0, 8, 16, 6, 3, 14, 1		1			0.9176916	1795	1840	1760.5				16		3.66995	1740			1815.5				
	4 [[0, 10, 6, 14, 17, 1,		1			0.9684659	1824	2059	1961.6		_			44 128.4		1889			1998.1	70.30955			
	5 [[0, 13, 5, 16, 12, 7,		1			1.6469485	1495	1684	1584.9					18 129.0		1472			1626.3	105.8438			
	6 [[0, 0, 17, 2, 3, 11, 1					1.6277501	1838	2049	1931.7					50 129.3		1789		-	1892.4	60.34199			
	7 [[0, 7, 3, 16, 1, 0, 7,		1			1.5670786	1768	2049	1869					99 130.3		1762			1832.5	63.03835			
	8 [[0, 3, 12, 10, 5, 1, 5		}			0.9558213	1525	1664	1607					46 128.1		1572		-	1643.2		59.03462		
	9 [[0, 14, 1, 1, 6, 10, 1		1	143		151.70122	1889	2098	1985.9					35 130.1		1840			1958.9	63.63167			
	0 [[0, 16, 10, 3, 0, 18,			124		50.959891	1656	1898	1772.4						177093	1750			1826.7	62.33966			
	1-2 / // -/-/-/-	-,	1															- 1	*	- 3230			

N = 14										Meta-heuristic Algorithms										
			OR-Tools (tim							Iterative Local Search (K = 20) Gibb Sampling (K = 20, factor = 1.125)										
No.		distance_matrix)	Cost	Time	_	Cost_max		SD	Time_avg			Time	Cost_min			SD	Time_avg			
		5, 19, 13, 6, 10, 15,	1604	151.52007		2309	2186.9		11.20461			347.2234184		2324		85.98714	153.5752			
		9, 19, 0, 3, 19, 3, 4, 13, 13, 4, 7, 0, 18,	1844 1436	65.77477764 151.513077		2627 2117	2455 2065.6	45.4024	11.24238 11.10672		2287 1828	343.413633 346.3244733	2229 1950	2610 210		121.2055 47.20887	151.4988 151.8805			
		6, 15, 15, 14, 5, 2,	1810			2569	2497.2	61.52109	11.1866			343.9190943	2372	264		90.70832	153.9645			
		13, 14, 1, 10, 6, 11,	1518			2381	2288.7	63.97925	11.23335			343.3807498	2179	2398		71.25354	154.7751			
		5, 19, 9, 0, 3, 10, 3,	1866	151.5089474	2513	2732	2606.3	74.80798	11.0537		2377	344.119521	2381	2690	0 2520	88.56009	155.5073			
		5, 4, 6, 11, 3, 3, 2, (1815	151.9208296		2498	2414.5	64.83698	11.22015			342.1507165	2298	2542		72.93688	157.0348			
		9, 13, 10, 11, 13,	1635	151.570418		2369 2716	2220.6	90.33788	11.2178			343.0403545	2101	2410		106.569				
		7, 2, 7, 7, 19, 6, 0, 3, 4, 8, 9, 5, 12, 1, 8	1972 1962	151.9373676 151.5614681		2657	2640.1 2560.3	57.54892 70.79242	11.08803			345.0125803 342.3906829	2501 2396	268: 265:		58.39606 86.74644	151.7655			
10	110, 10,	3, 4, 0, 3, 3, 12, 1, 4	1302	131.301100.					T		_ ,					00.7 10 11	131.0127			
				L	Exact Algorithms					Heuristic Algorithms										
		N = 16																		
	N - 10				OD Tools (times limit 150)					Local Search										
					OR-Tools (time_limit = 150)							L(ocai se	arcn						
No	No. Input (distance_matrix)					st	Time		Cost_min		Cost_max		Cost_avg		SD	Time	Time_avg			
	1	[[0, 16, 2, 3	19, 10, 0,	10, 11,		2578	152.2	288767	'	3230		3536	336	2.9 1	L07.1743	26.	34445			
	2	[[0, 11, 12,	, 5, 17, 15	5, 15, 1		2372	152	.77251		3040		3268	313	0.8	75.54807	7 2	26.338			
	3	[[0, 16, 3, 3	10, 9, 5, 1	l, 4, 14,		2482	152.4	439697		3259		3449	334	6.6	57.92562	2 25	.5058			
	4	[[0, 17, 14,	, 17, 2, 6,	14, 4, :		2731	152.3	320037		3365		3701	347	1.4	112.1202	2 25.4	49031			
	5	[[0, 17, 12,	, 14, 6, 1,	2, 7, 1:		2270	153.2	297634		2814		3003	291	3.7	55.54227	25. !	51691			
	6	[[0, 11, 6, 3	12, 7, 12,	2, 0, 10		2277	152.2	292395		2778		3185	299	7.5 1	L24.8699	25.	50795			
	7	[[0, 13, 8,	7, 2, 3, 13	L, 4, 9, 8		2458	152.3	322567	'	3139		3355	326	4.8	70.39697	25.	51071			
	8	[[0, 11, 15,	, 0, 14, 17	7, 13, 1		2657	153	.44855		3188		3533	332	2.8 1	105.1188	25.	50811			
	9	[[0, 7, 4, 15	5, 4, 12, (), 7, 12,		2716	152.2	254155	•	3227		3432	329	2.5	52.99956	25.	39263			
	10	[[0, 17, 1,	4, 15, 11,	12, 19,		2425	152.2	259414		3118		3416	32	230 8	35.18216	25.	49691			
	N = 18				Ex	าร	Heuristic Algorithms													
					OR-Tools (time_limit = 150)				Local Search											
No).	Input (dis	tance_m	atrix)	Cos	st	Ti	me	Cost	_min	Cos	t_max	Cost_a	avg	SD	Time	e_avg			
	1	[[0, 1, 19, 5				3345	154.4	567192	2	3917		4190	406	9.8	99.68261	_	82674			
	2	[[0, 0, 7, 5,	5, 8, 10,	1, 1, 1		3522	153.8	324763	3	3900		4203	408	4.6	95.81951	87.	72683			
	3 [[0, 18, 6, 6, 18, 15,			0, 7, 1			153.312624		·	4238		4618	4424.8		125.7933	87.	47296			
	4	[[0, 4, 7, 17	7, 13, 16,	19, 13,		3908	153.2	661388	3	4320		4732	452	9.5	140.4685	87.	82188			
	5	[[0, 6, 11, 1	15, 10, 8,	11, 6,		3174	154.4	719492	2	3820		4053	39	930 6	58.75237	87.	27406			
	6	[[0, 14, 0, 7	7, 13, 1, 1	19, 19, (3525	154.4	091918	3	4020		4277	4:	149 8	33.36799	87.	25857			
									_					-		_				

Heuristic Algorithms

Exact Algorithms

7 [[0, 9, 1, 10, 3, 15, 16, 1, 1

8 [[0, 5, 19, 18, 14, 2, 18, 3,

9 [[0, 15, 8, 6, 19, 14, 6, 16,

10 [[0, 11, 2, 8, 10, 4, 17, 6, 1

Because the solving time for backtracking, iterative local search, and gibb sampling wasn't feasible, so accordingly, we only tested for $N \le 4$; $N \le 14$.

4019

4448

3899

3782

4382

4681

4173

4155

4188.3

4014.4

4587

3962

119.0267

80.65427

96.7611

119.4534

87.62574

87.26774

83.39593

83.23291

3302 153.2680487

3776 153.3741745

3386

3393

154.3056025

154.3556985

As shown, for N = 4, OR-Tools and backtracking do always give the optimal solution, while beam-search occasionally does. For N >= 6, no algorithm of these could find the optimal solution.

In terms of cost, for N = 6, OR-Tools outperforms the other algorithms on most of the tests, with some exceptions from beam-search finding a better solution. As N increases, solutions from the heuristic algorithms, compared to OR-Tools feasible solution with a time_limit (as shown), are mostly bad, and worse over time.

In terms of solving time, local search did best, but its cost is not acceptable compared to OR-Tools' or Iterative local search's ones. However, as we could see, the time it takes for our local search algorithm to solve with different data are comparatively the same, so we think our get_neighbors function has some flaws, and therefore could be improved in the future.

So, based on the collected data, we recommend using OR-Tools for getting a feasible solution to this problem.

Future works

Improve the performance of backtracking and beam search by optimizing the get_sub_node function. Improve our heuristic algorithms by improving our get_neighbors function. Implement Integer programming solver of OR-Tools.

List of tasks

Group 20 - Topic 19

1. **Trần Quốc Đệ 20210179** <u>de.tq210179@sis.hust.edu.vn</u>

- Code (50%)
- Presentation (70%)
- Report (15%)

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- Report (45%)
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