Travelling Salesperson

1. Code

** See Appendix for Code

2. Time and Space Complexity

Priority Queue: sort, insert, pop. Time: O(nlogn) Space: O(n^2 n!)

My Priority Queue takes O(nlogn) time because both insertion and popping are constant time. However, when I'm sorting my list, this will take O(nlogn) time because python uses TimSort which is a hybrid of insertion sort and merge sort.

Search States: tuples Time: O(1) Space: O(n^2)

I use tuples, which do not take any time to manipulate. They require $O(n^2)$ space however to store the matrix for the related decision/state.

Reduce Cost Matrix and updating it: reduce function.

Time: O(n^2) Space: O(n^2)

This takes $O(n^2)$ time because when checking the row/column lowest value to update and checking to see if each row has a 0. Afterwards checking each column for 0's.

BSSF Initialization: Greedy. Time: O(n^3) Space: O(n^2)

Started with an initial Greedy Algorithm which takes $O(n^3)$. The reason for it being n^3 is I choose the best Greedy BSSF using each city as a starting city. This helps the Branch and Bound algorithm when deciding to trim or not trim a solution. Therefore, decreasing the chances of O(n!) time.

Expanding one Search State into others:

This will be constant time and space because upon expanding, a new search state will be created. Therefore, see above "Search States" for Time and Space.

The full Branch and Bound algorithm:

Time: O(n^2 n!) Space O(n^2 n!)

The full Branch and Bound algorithm will take O(n^2 n!) time and space because worst case scenario, the while loop which empties the priority queue will run for n! time. This can be shortened due to pruning, however at most it will run n! times. Then for each run of the while loop. The matrix will have to be reduced based upon the decision. Each reduction has O(n^2) time complexity. Therefore, in all this portion will take O(n^2 n!) time. Other actions occur in the Branch and Bound, greedy for example. But due to the max rule, these are negligible.

3. State Data Structures

I represented each state as a tuple that was inserted into the priority queue. Each tuple contained the matrix related to the decision, the route so far, the route names so far, the score of decision, the column of chosen destination (this is used for future computations once expanded), the level (how deep the decision is in the tree), calculated score based on lowerBound – (level * offset).

4. Priority Queue Data Structure

For my priority queue, I inserted tuples (as described above in #3) which contained the needed data for each state. The priority queue was sorted in descending order based off a "score" that was assigned to each state. This score was calculated by subtracting from the lowerBound of the state by the level/deepness of the state multiplied by a constant level multiplier. The reason for this was to prioritize deeper states that were closer to a solution rather than states near the top of the tree which needed many more computations to find an answer. This helped with speed improvements and finding a BSSF better than the initial BSSF in better time. Each iteration I would pop() from the Priority Queue and use that tuple as the current decision to be expanded. If the expanded decision deserved to be inserted into the queue, it was simply appended. Sorting would occur at each iteration to make sure that the queue was in the proper order so the right state would become expanded.

Approach for initial BSSF

For my initial BSSF I used a form of greedy algorithm to calculate a BSSF which was used for initial trimming and calculation. This greedy algorithm would start at the first node and calculate a greedy solution, then continue that process calculating greedy solutions from each node in the list. Finally, the lowest of all these solutions is returned. This allows for less error to occur during the "Hard" difficulty.

6. Table							
# Cities	Seed	Running	Cost of	Max # of	# of BSSF	Total # of	Total # of
		time	best tour	stored	updates	states	states
		(sec.)	found	states at		created	pruned
			(*=optimal)	a given			
				time			
15	20	0.18309	8781	76	1	3330	3108
16	902	2.588	8059	74	2	36400	34124
17	968	27.204	10192	417	7	295936	278522
15	947	1.002	7891	33	0	15915	14855
16	120	8.028	9207	150	0	99872	93631
18	542	60	10684	838	7	786366	742673
20	295	60	11081	277	4	551380	523808
22	626	60	12462	373	9	556116	530830
26	829	60	13234	970	0	491166	472276
50	363	60	23133	2031	2	229150	224566

7. Results of Table

A couple of observations I made while gathering the data for the table above:

- The more cities that had infinite routes to them, the more likely it was that the original greedy BSSF was the most optimal one.
- As problem size increased, the total number of states increased similarly the number of pruned states would increase. This was expected. The number of infinite distanced cities also contributed to this.
- It seemed that the moment I went above 17 cities that the time taken jumped up to 60 seconds for most every case. I think this has to do with my LVL_MULTIPLIER variable. I think that if I increased this offset that the threshold where solutions took the 60 seconds would increase.
- I noticed that the max # of stored states seems to also be correlated to # of BSSF updates as well. An odd case is for 26 cities. There were a lot of max states, however no better solution was found. (I think that the infinite distance cities could have contributed to this).

8. Mechanisms for finding solutions early and to dig deeper

As mentioned above in #4, I used a form of "score" for each state that was calculated using the equation: 'lowerBound – (IvI * LVL_MULTIPLIER)'. My Priority Queue was sorted based upon this calculated score. This caused my queue to prioritize states that were "deeper" and were closer to finding solutions rather than states that had just begun, which would require much more calculation to find an answer. I adjusted this LVL_MULTIPLIER until I found a balance and solution finding time that I liked.

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Appendix
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tempRouteNames = currentDecision[2].copy()
tempMatrix[col][currentDecision[4]] = math.inf
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