ARTIFICIAL INTELLIGENCE

OFFLINE-3 (MAX-CUT)

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INTRODUCTION:

In GRASP, we must need to follow these steps:
1) partition the nodes into two sets (to simulate a cut between them) . In this step,I used the randomized and semi-greedy algorithm.
2) apply local search in these partitions. In the local search approach, I changed the group of one node per iteration.
I used two methods to choose such a node:
--> choose the first found node suitable for the shift (rewards us with some gain)
--> choose the best found node suitable for the shift (rewards us with the best possible gain)

Also, I used the greedy method to find out the max-cut

ANALYSIS:

1) partition stage:

For the given 54 test cases, the randomized partition performed pretty bad compared to the semi-greedy partition as expected. It is because we are just randomly assigning each node to a partition. But in semi-greedy, we are going with a more rational approach. we partition the nodes such that the cut has the max weighted edges at the choosing time.
the choice may be bad for later choice but considering cases to such an extent would lead us to an NP-COMPLETE solution.

For a randomized partition, it may happen that all nodes went to either the first or second partition using normal rand() function. so I used a distribution function to add some uniformity to the randomization.Same approach was to select alpha for every iteration.
For alpha generation, I used a normal distribution function.

here are the results of partition stage for all 54 test cases---------------------

2) local Search stage:

Here to select the perfect node, my approaches were to select first found suitable node(gain > 0) and best found suitable node (best gain).As expected, when we work with first found suitable node, performance is poor as it is not a greedy approach.
(Here we are referring to the increase in max-cut with gain.)

RESULTS:

Table-1:

Comparison between different partition ways I used.

Observations:

Randomized partition has the worst performance as it doesn't follow the greedy approach. As we become greedier, the max-cut increases in the partition stage.

But better max-cut in the partition stage doesn't ensure better max-cut after the local search stage (explained in later tables) . That is because, when we take a greedier approach we lose randomization and lose the probability of finding global maxima.

# of nodes	# of edges	MinWeight	MaxWeight	Avg. alpha in semi-greedy	Avg. cut in semi-greedy	Avg. Cut in rand	greedy cut
800	19176	1	1	0.493027	11024.2	9585.46	11226
800	19176	1	1	0.487448	11027.1	9576.69	11251
800	19176	1	1	0.508691	11021.1	9590.8	11223
800	19176	1	1	0.486949	11026.1	9581.87	11288
800	19176	1	1	0.493392	11024.2	9591.64	11249
800	19176	-1	1	0.488675	1543.78	77.6707	1797
800	19176	-1	1	0.509038	1385.18	-73.5783	1553
800	19176	-1	1	0.502924	1380.04	-88.051	1636
800	19176	-1	1	0.500968	1431.92	-36.047	1630
800	19176	-1	1	0.520443	1375.69	-84.6293	1666
800	1600	-1	1	0.487506	413.639	18.9689	486
800	1600	-1	1	0.502212	399.854	-1.09711	480
800	1600	-1	1	0.511097	423.112	14.7377	506
800	4694	1	1	0.514237	2895.41	2347.94	2928
800	4661	1	1	0.482004	2875.61	2328.53	2891
800	4672	1	1	0.514085	2882.38	2335.05	2887

800	4667	1	1	0.497464	2876.5	2333.1	2905
800	4694	-1	1	0.50418	729.918	31.0369	840
800	4661	-1	1	0.513044	644.302	-53.9335	757
800	4672	-1	1	0.493462	674.108	-23.7054	778
800	4667	-1	1	0.501805	666.462	-31.7535	794
2000	19990	1	1	0.489748	12355.8	9990.12	12748
2000	19990	1	1	0.488989	12351.6	9994.84	12786
2000	19990	1	1	0.503397	12353.6	9991.92	12812
2000	19990	1	1	0.511754	12360.7	10002.4	12832
2000	19990	1	1	0.511973	12349.1	9989.91	12819
2000	19990	-1	1	0.49841	2313.63	-23.5101	2708
2000	19990	-1	1	0.505796	2286.66	-56.6147	2636
2000	19990	-1	1	0.486761	2377.34	42.3995	2725
2000	19990	-1	1	0.497209	2385.28	52.9858	2719
2000	19990	-1	1	0.487094	2297.42	-45.6397	2669
2000	4000	-1	1	0.50308	1022.41	11.438	1226
2000	4000	-1	1	0.492676	989.108	-12.825	1208
2000	4000	-1	1	0.48563	987.908	-25.5152	1212
2000	11778	1	1	0.499044	7263.19	5891.85	7335
2000	11766	1	1	0.494159	7256.27	5886.47	7274
2000	11785	1	1	0.50045	7265.04	5893.54	7316
2000	11779	1	1	0.509264	7261.32	5889.64	7308
2000	11778	-1	1	0.487518	1749.61	14.679	2035
2000	11766	-1	1	0.512621	1729.41	-53.2943	2043
2000	11785	-1	1	0.487417	1736.13	-9.82973	2053
2000	11779	-1	1	0.503203	1814.1	63.738	2118
1000	9990	1	1	0.493762	6168	4998.67	6385
1000	9990	1	1	0.503036	6170.41	4993.84	6372

1000	9990	1	1	0.504832	6169.14	4990.39	6424
1000	9990	1	1	0.505204	6172.9	4992.98	6411
1000	9990	1	1	0.487549	6174.71	4994.19	6331
3000	6000	1	1	0.50237	5038.12	3001.06	6000
3000	6000	1	1	0.499198	5067.87	3000.12	6000
3000	6000	1	1	0.50294	5077.23	2998.32	5880
1000	5909	1	1	0.513865	3635.77	2956.65	3660
1000	5916	1	1	0.506038	3640.96	2960.5	3665
1000	5914	1	1	0.505293	3638.09	2958.87	3635
1000	5916	1	1	0.489363	3638.58	2957.47	3665

Table-2:

Explains the number of iterations in local search stage has been taken on average for each of the partition ways

Observations:

1) When we randomly partitioned, iteration count in the local search stage hugely increased but the result is not good. Whereas, in the semi-greedy stage, we get better results with fewer number of iterations in the local search stage.

# of nodes	# of edges	MinWeight	MaxWeight	Itr count for rand	Avg.result for rand	Itr count for greedy	result for greedy	Itr count for semi-greedy	Avg.result for semi-greedy
800	19176	1	1	143.04	10426.3	47.1314	11330.4	59.6385	11188.5
800	19176	1	1	144.414	10432.1	32	11324.5	61.1189	11196.7
800	19176	1	1	146.031	10446.4	36.7934	11308.7	58.3631	11181.8
800	19176	1	1	146.204	10440.5	28.1875	11343.8	61.9095	11197.4
800	19176	1	1	149.769	10465.1	23.2353	11313.1	60.7368	11192.7
800	19176	-1	1	141.943	915.605	26.9658	1859.4	61.279	1717.02
800	19176	-1	1	142.313	777.148	39.7037	1651.8	60.8704	1556.09
800	19176	-1	1	158.646	855.739	31.2703	1715.21	59.7826	1550.8
800	19176	-1	1	147.911	851.775	32.377	1701.79	56.3712	1590.37

800	19176	-1	1	165.261	903.29	26.6239	1726.69	59.1454	1543.4
800	1600	-1	1	82.6347	225.482	1.46721	486.934	8.81647	429.639
800	1600	-1	1	75.2467	187.664	2.97015	483.94	8.84672	415.956
800	1600	-1	1	81.1366	218.579	1.92035	507.841	9.35645	440.416
800	4694	1	1	82.203	2595.73	14.7886	2947.39	22.0162	2926.33
800	4661	1	1	97.3049	2618.88	23.7907	2921.39	20.2023	2903.48
800	4672	1	1	96.8129	2625.46	21.6541	2915.21	19.1862	2908.76
800	4667	1	1	103.162	2637.88	19.9194	2932.82	19.3914	2902.78
800	4694	-1	1	120.472	430.489	18.271	864.075	31.7085	783.479
800	4661	-1	1	124.817	353.416	17.6299	780.906	32.9031	700.246
800	4672	-1	1	124.812	384.018	16.2308	801.077	31.905	728.076
800	4667	-1	1	119.079	355.405	13.5952	812.071	34.1012	723.81
2000	19990	1	1	327.199	11350.3	43.6667	12838.1	106.722	12578.4
2000	19990	1	1	309.591	11284.4	35.8545	12860.6	113.72	12590.4
2000	19990	1	1	328.544	11362.4	40.5966	12883.9	112.417	12588.8
2000	19990	1	1	321.332	11340.6	31.8857	12885.3	103.145	12576.7
2000	19990	1	1	322.665	11331.2	40.252	12894.6	109.133	12576
2000	19990	-1	1	343.867	1408.9	72.8421	2831.24	117.475	2561.8
2000	19990	-1	1	365.745	1479.42	56.5887	2742.75	112.87	2526.3
2000	19990	-1	1	345.31	1480	48.5472	2819.25	116.675	2624.12
2000	19990	-1	1	343.034	1481.78	42.9515	2799.31	107.188	2612.04
2000	19990	-1	1	362.123	1470.26	75.3448	2805.62	118.448	2548.01
2000	4000	-1	1	199.705	516.992	8.65891	1241.32	20.3517	1062.31
2000	4000	-1	1	202.134	498.512	4.36232	1214.72	21.6658	1031.68
2000	4000	-1	1	241.127	584.37	5.93701	1221.87	22.9085	1033.05
2000	11778	1	1	233.774	6591.07	37.2727	7386.55	46.89	7329.89
2000	11766	1	1	228.844	6571.74	48.5044	7342.02	49.7755	7326.88
2000	11785	1	1	239.814	6618.34	43.3529	7381.55	48.8019	7334.79

2000	11779	1	1	244	6622.56	34.8761	7357.06	51.3361	7334.89
2000	11778	-1	1	323.164	1072.36	42.3333	2092.53	81.8497	1891.98
2000	11766	-1	1	309.299	971.604	25.7379	2081.53	76.9271	1863.01
2000	11785	-1	1	314.497	1027.72	24.5	2087	79.5112	1874.57
2000	11779	-1	1	275.254	969.031	22.9085	2148.07	78.1991	1950.79
1000	9990	1	1	166.618	5686.13	18.1909	6414.39	57.73	6287.34
1000	9990	1	1	163.602	5669.9	25.6557	6409.77	53.7458	6281.32
1000	9990	1	1	166.195	5683.62	15.2692	6452.54	55.8372	6285.7
1000	9990	1	1	168.814	5693.21	26.4583	6460.83	54.1973	6284.42
1000	9990	1	1	183.455	5752.92	25.1579	6381.21	54.3159	6286.76
3000	6000	1	1	391.688	4003.32	1	6000	35.0471	5122.24
3000	6000	1	1	387.898	3991.5	1	6000	31.7641	5143.57
3000	6000	1	1	362.708	3926.39	1	5880	33.9886	5158.46
1000	5909	1	1	113.712	3295.28	30.4643	3699.64	25.9387	3671.79
1000	5916	1	1	124.731	3332.51	28.265	3708.13	26.3892	3677.7
1000	5914	1	1	125.838	3337.91	26.8976	3681.03	25.5956	3673.92
1000	5916	1	1	115.499	3306.51	26.0182	3703.98	23.4812	3671.23

Table-3:

We used two types of local search algo (best choose and first choose). This table shows the comparison between them on the basis of the number of iterations taken by each of them and their performance.

Also, we placed our GRASP solution, the iteration for which we got the solution, the partition type we used for that solution(randomized, greedy or semi-greedy).

(0 for randomized, 1 for greedy, 2 for semi-greedy)

Observations:

1) First choose local search ends in very few iterations and has poor performance.
2) For solutions, the semi-greedy partition mostly contributes.

# of nodes	# of edges	Min Weight	Max Weight	Avg. itr for best chose	Avg. cut for best chose	Avg. itr for first chose	Avg. cut for first chose	# of Itr in GRASP	solution	solution Itr	partition Type in solution
800	19176	1	1	161.995	11352.9	1.21115	10599.2	1200	11454	400	2
800	19176	1	1	160.969	11352.3	1.16865	10598.4	1200	11497	1033	0
800	19176	1	1	163.958	11344.5	1.20661	10619.3	1200	11459	200	2
800	19176	1	1	163.111	11360.3	1.16221	10630.5	1200	11483	250	2
800	19176	1	1	161.382	11346.8	1.17759	10597.3	1200	11483	1118	1
800	19176	-1	1	166.494	1896.3	1.1648	1150.47	1200	2009	528	0
800	19176	-1	1	166.603	1726.44	1.17763	957.536	1200	1851	1005	2
800	19176	-1	1	172.094	1737.06	1.21559	989.769	1200	1848	888	2
800	19176	-1	1	173.457	1772.55	1.16693	996.868	1200	1891	616	2
800	19176	-1	1	173.355	1727.95	1.1495	1023.23	1200	1850	501	2
800	1600	-1	1	61.7155	441.385	1.10473	296.267	1200	488	3	1
800	1600	-1	1	58.853	433.125	1.13496	273.008	1200	488	31	2
800	1600	-1	1	61.182	455.714	1.11765	305.5	1200	510	31	2
800	4694	1	1	75.3836	2947.48	1.14262	2726.02	1200	2981	690	1
800	4661	1	1	86.3781	2925.71	1.1474	2711.37	1200	2963	751	2
800	4672	1	1	83.9403	2930.37	1.15798	2731.74	1200	2973	813	2
800	4667	1	1	91.577	2927.84	1.16749	2721.03	1200	2966	1128	2
800	4694	-1	1	111.762	839.696	1.14858	534.038	1200	907	789	2
800	4661	-1	1	113.541	754.123	1.14923	446.036	1200	810	250	2
800	4672	-1	1	112.386	782.117	1.13742	497.495	1200	838	572	1
800	4667	-1	1	111.637	778.554	1.14983	467.747	1200	846	390	0
2000	19990	1	1	343.242	12815.5	1.19672	11646.8	1200	12939	640	2
2000	19990	1	1	316.554	12814.6	1.18519	11686.3	1200	12941	1015	2
2000	19990	1	1	334.982	12821.1	1.16102	11651.5	1200	12950	46	2
2000	19990	1	1	334.597	12813.9	1.14035	11723.5	1200	12966	997	2
2000	19990	1	1	326.02	12814.6	1.21717	11654.6	1200	12950	27	2
2000	19990	-1	1	348.171	2813.14	1.1314	1668.17	1200	2931	27	2

2000	19990	-1	1	355.169	2776.59	1.22581	1684.81	1200	2909	713	2
2000	19990	-1	1	358.584	2864.57	1.17253	1710.64	1200	2979	1033	2
2000	19990	-1	1	360.41	2867.72	1.26025	1788.46	1200	3023	226	1
2000	19990	-1	1	358.463	2792.17	1.20139	1665.53	1200	2952	4	1
2000	4000	-1	1	147.042	1107.64	1.11551	729.337	1200	1252	15	2
2000	4000	-1	1	139.11	1075.19	1.09194	756.545	1200	1224	23	2
2000	4000	-1	1	152.351	1073.72	1.06903	767.724	1200	1234	27	0
2000	11778	1	1	203.115	7386.31	1.1567	6882.01	1200	7474	817	2
2000	11766	1	1	202.54	7376.88	1.15385	6834.91	1200	7452	652	2
2000	11785	1	1	209.272	7390.57	1.13158	6878.37	1200	7465	740	2
2000	11779	1	1	214.587	7381.17	1.20169	6840.94	1200	7458	296	0
2000	11778	-1	1	293.692	2027.89	1.15881	1242.84	1200	2140	679	2
2000	11766	-1	1	296.569	2004.07	1.15461	1199.69	1200	2126	846	2
2000	11785	-1	1	290.035	2010.92	1.15101	1252.72	1200	2121	48	0
2000	11779	-1	1	273.732	2093.35	1.16272	1316.76	1200	2195	224	0
1000	9990	1	1	166.714	6398.58	1.21144	5812.18	1200	6483	970	2
1000	9990	1	1	168.525	6396.32	1.20792	5829.22	1200	6515	161	2
1000	9990	1	1	165.426	6397.26	1.14017	5828.61	1200	6480	11	2
1000	9990	1	1	168.438	6401.08	1.19056	5840.64	1200	6503	10	2
1000	9990	1	1	180.703	6400.17	1.18475	5843.93	1200	6499	93	0
3000	6000	1	1	259.607	5237.59	1.10562	4549.84	1200	6000	8	2
3000	6000	1	1	274.081	5221.98	1.09724	4576.44	1200	6000	19	2
3000	6000	1	1	259.151	5221.96	1.11318	4477.99	1200	5880	3	0
1000	5909	1	1	101.706	3701.65	1.15372	3437.86	1200	3749	158	2
1000	5916	1	1	108.313	3705.69	1.14212	3440.89	1200	3756	719	2
1000	5914	1	1	106.589	3699.39	1.2368	3447.94	1200	3745	26	2
1000	5916	1	1	105.739	3700.04	1.15824	3427.6	1200	3739	1	2