An Efficient Local Search Algorithm for Large GD Advertising Inventory Allocation with Multilinear Constraints

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Table 1: Results of LS-IMP for solving real-world ad benchmark under different parameter settings. P0 is the parameter in paper.

Parameter settings	t	ζ	Total #win (60s)	Total #win (300s)	Avg #UR (60s)	Avg #FR (60s)
P0	**100**	**100**	**860**	**764**	**16.4**	**62.8**
P1	50	10	848	755	15.7	61.7
P2	75	10	858	754	15.8	62.2
P3	100	10	854	750	15.5	62.1
P4	125	10	855	748	15.9	61.2
P5	150	10	845	745	15.2	61.8
P6	200	10	846	757	15.1	62.3
P7	50	50	867	759	16.2	64.1
P8	75	50	852	774	16.3	62.8
P9	100	50	857	747	16.3	61.3
P10	125	50	878	745	16.5	64.4
P11	150	50	864	762	16.7	62.1
P12	200	50	859	776	16.0	63.0
P13	50	80	850	759	16.3	62.0
P14	75	80	876	769	16.6	61.9
P15	100	80	847	759	16.2	62.3
P16	125	80	840	764	16.6	62.5
P17	150	80	851	744	16.8	63.1
P18	200	80	848	746	15.8	63.7
P19	50	100	867	784	16.1	62.5
P20	75	100	869	753	16.1	62.4
P21	125	100	873	773	16.1	62.1
P22	150	100	839	788	15.8	63.4
P23	200	100	861	757	16.5	63.8
P24	50	200	861	775	16.4	62.1
P25	75	200	870	759	16.0	62.0
P26	100	200	852	740	16.3	61.2
P27	125	200	852	781	16.2	63.0
P28	150	200	836	769	16.0	61.1
P29	200	200	850	778	16.2	63.3
P30	50	500	855	758	15.1	61.3
P31	75	500	852	750	15.7	62.1
P32	100	500	844	756	15.1	61.6
P33	125	500	852	742	15.4	61.5
P34	150	500	841	752	15.9	61.0
P35	200	500	853	750	15.6	61.7

Table 2: Results of LS-IMP for solving real-world ad benchmark 20 times. P0 is the result in paper.

Parameter settings	Total #win (60s)	Total #win (300s)	Total #win (1000s)	Avg #UR (60s)	Avg #FR (60s)
P0	**860**	**764**	**614**	**16.4**	**62.8**
P1	858	765	616	16.32	62.95
P2	860	762	614	16.4	63.52
P3	861	761	618	16.44	63.80
P4	856	761	616	16.24	62.38
P5	855	768	612	16.2	62.1
P6	861	759	615	16.44	63.81
P7	857	765	610	16.28	62.67
P8	863	766	618	16.52	64.38
P9	857	759	611	16.28	62.67
P10	858	766	614	16.32	62.95
P11	864	761	611	16.56	64.67
P12	863	768	616	16.52	64.38
P13	858	765	610	16.32	62.95
P14	857	768	612	16.28	62.67
P15	856	768	613	16.24	62.38
P16	862	767	613	16.48	64.1
P17	860	759	612	16.4	63.52
P18	861	760	609	16.44	63.83
P19	861	762	611	16.44	63.87
P20	855	765	610	16.2	62.1

Table 3: The numeric comparsion in minlplib instances, all instance is a minimize problem, all solver report the best objective function found within time limit.

Instance	Gurobi-Exact	Gurobi-Heur	LS-IMP
cutoff = 60s			
sonet17v4	1233700	**1182604.5**	**1182604.5**
sonet18v6	3709850	3562770	**3389110**
sonet19v5	2590910	2557780	**2528144**
sonet20v6	3747400	**3311060**	3480810
sonet21v6	8317140	**7701520**	7731250
sonet22v4	2698220	**2386630**	2397132
sonet23v6	8411680	7474600	**7197950**
sonet24v2	5073420	6763260	**5060259**
sonet25v5	7852600	7185020	**7064664**
cutoff = 300s			
sonet17v4	1184730	**1182604.5**	**1182604.5**
sonet18v6	**3389110**	**3389110**	**3389110**
sonet19v5	2590910	2549380	**2528144**
sonet20v6	3658580	**3311060**	3390200
sonet21v6	7908790	**7600750**	**7600750**
sonet22v4	2517840	**2379970**	2387835
sonet23v6	8411680	7150690	**7078810**
sonet24v2	3312580	3312580	**3312579**
sonet25v5	7525050	7093900	**7064664**

Table 4: The number of instances which can find the optimal solution. #opt column is the number where solver can find the optimal solution. #gap is the average gap rate between the best found solution and optimal solution.

Dataset	Gurobi						LS-IMP			LS-IMP + Gurobi 30s + remaining time		
	Exact			Heur								
	#opt	#feas	#gap	#opt	#feas	#gap	#opt	#feas	#gap	#opt	#feas	#gap
cutoff = 60s												
$\mathcal{D}_1$	8	12	95.3%	10	12	95.5%	**85**	**179**	**17.5%**	84	**179**	17.6%
$\mathcal{D}_2$	2	4	98.5%	9	26	90.1%	**92**	**166**	**18.3%**	89	**166**	18.4%
$\mathcal{D}_3$	0	0	100%	13	43	85.0%	**79**	**178**	**19.8%**	77	**178**	19.9%
$\mathcal{D}_4$	0	0	100%	4	29	95.0%	**82**	**171**	**18.7%**	78	**171**	18.9%
$\mathcal{D}_5$	0	0	100%	8	41	84.5%	**97**	**176**	**15.4%**	94	**176**	15.6%
Total/Avg	10	16	98.7%	44	151	90.2%	**435**	**870**	**17.9%**	422	**870**	18.0%
cutoff = 300s												
$\mathcal{D}_1$	50	96	61.5%	12	17	91.6%	86	**180**	17.3%	**90**	**180**	**16.5%**
$\mathcal{D}_2$	51	82	57.8%	18	44	85.5%	94	**167**	18.2%	**101**	**167**	**17.7%**
$\mathcal{D}_3$	35	66	73.8%	13	56	76.0%	80	**179**	19.6%	**85**	**179**	**18.9%**
$\mathcal{D}_4$	32	74	69.6%	12	43	82.5%	83	**172**	18.5%	**87**	**172**	**18.0%**
$\mathcal{D}_5$	31	67	75.8%	15	53	79.1%	99	**176**	15.2%	**103**	**176**	**15.0%**
Total	199	385	67.8%	70	213	82.9%	442	**874**	17.7%	**466**	**874**	**17.2%**
cutoff = 1000s												
$\mathcal{D}_1$	100	150	30.5%	30	81	65.8%	87	**180**	17.2%	**113**	**180**	**13.5%**
$\mathcal{D}_2$	99	151	29.1%	32	91	63.2%	96	**167**	18.1%	**110**	**167**	**16.5%**
$\mathcal{D}_3$	79	124	36.9%	28	87	67.2%	80	**179**	19.6%	**95**	**179**	**15.5%**
$\mathcal{D}_4$	83	132	33.3%	31	71	70.5%	84	**172**	18.4%	**90**	**172**	**17.5%**
$\mathcal{D}_5$	95	141	31.2%	28	90	63.5%	100	**176**	15.2%	**106**	**176**	**14.3%**
Total	456	698	32.2%	149	420	63.5%	447	**874**	17.7%	**514**	**874**	**15.4%**

Table 5: Continuous experiment. #feas_round is the number of continuous feasible instance after rounding solution. #vio_rate is the average constraint violated rate when rounding continuous solution to integer solution.

Dataset	Gurobi	Gurobi-Continuous			LS-IMP
	#feas	#feas	#feas_round	#vio_rate	#feas
cutoff = 60s					
$\mathcal{D}_1$	12	14	13	4.5%	**179**
$\mathcal{D}_2$	4	6	5	3.1%	**164**
$\mathcal{D}_3$	0	0	0	0	**172**
$\mathcal{D}_4$	0	0	0	0	**170**
$\mathcal{D}_5$	0	0	0	0	**175**
Total	16	20	18	1.5%	**860**
cutoff = 300s					
$\mathcal{D}_1$	96	98	79	4.6%	**180**
$\mathcal{D}_2$	82	85	70	4.2%	**167**
$\mathcal{D}_3$	66	66	56	3.3%	**179**
$\mathcal{D}_4$	74	75	63	5.3%	**172**
$\mathcal{D}_5$	67	68	55	6.3%	**176**
Total	385	392	323	4.7%	**874**
cutoff = 1000s					
$\mathcal{D}_1$	150	157	135	4.3%	**180**
$\mathcal{D}_2$	151	158	135	4.1%	**167**
$\mathcal{D}_3$	124	133	116	3.1%	**179**
$\mathcal{D}_4$	132	141	124	4.9%	**172**
$\mathcal{D}_5$	141	149	135	5.8%	**176**
Total	698	738	646	4.4%	**874**

Table 6: Continuous experiment using the heuristic version with Gurobi

Dataset	Gurobi		Gurobi-Continuous						LS-IMP
	Exact	Heur	Exact			Heur			
	#feas	#feas	#feas	#feas_round	#vio_rate	#feas	#feas_round	#vio_rate	#feas
cutoff = 60s									
$\mathcal{D}_1$	12	12	14	13	4.5%	99	80	4.3%	**179**
$\mathcal{D}_2$	4	11	6	5	3.1%	96	78	3.8%	**164**
$\mathcal{D}_3$	0	16	0	0	0	96	74	6.7%	**172**
$\mathcal{D}_4$	0	5	0	0	0	84	67	3.2%	**170**
$\mathcal{D}_5$	0	10	0	0	0	95	79	6.2%	**175**
Total	16	54	20	18	1.8%	470	378	5.0%	**860**
cutoff = 300s									
$\mathcal{D}_1$	96	17	98	79	4.6%	**189**	168	7.6%	180
$\mathcal{D}_2$	82	44	85	70	4.2%	**193**	157	6.5%	167
$\mathcal{D}_3$	66	56	66	56	3.3%	**192**	164	7.2%	179
$\mathcal{D}_4$	74	43	75	63	5.3%	**191**	165	7.0%	172
$\mathcal{D}_5$	67	53	68	55	6.3%	**191**	164	6.8%	176
Total	385	213	392	323	4.7%	**956**	808	7.0%	874
cutoff = 1000s									
$\mathcal{D}_1$	150	81	157	135	4.3%	**189**	158	7.6%	180
$\mathcal{D}_2$	151	91	158	135	4.1%	**193**	157	6.5%	167
$\mathcal{D}_3$	124	87	133	116	3.1%	**192**	164	7.2%	179
$\mathcal{D}_4$	132	71	141	124	4.9%	**191**	165	7.0%	172
$\mathcal{D}_5$	141	90	149	135	5.8%	**191**	164	6.8%	176
Total	698	420	738	646	4.4%	**956**	808	7.0%	874

Table 7: The metric comparsion in the paper using Gurobi with continuous variable.

Dataset	Gurobi						Gurobi-Continuous						LS-IMP		
	Exact			Heur			Exact			Heur					
	#win	#UR	#FR	#win	#UR	#FR	#win	#UR	#FR	#win	#UR	#FR	#win	#UR	#FR
cutoff = 60s															
$\mathcal{D}_1$	12	1.7%	5.8%	12	1.7%	5.8%	13	1.9%	6.0%	32	5.5%	15.7%	**179**	**15.5%**	**64.7%**
$\mathcal{D}_2$	4	0.6%	1.9%	11	1.7%	5.7%	5	0.6%	1.9%	26	3.0%	9.6%	**164**	**16.4%**	**60.7%**
$\mathcal{D}_3$	0	0	0	16	2.3%	9.0%	0	0	0	30	15.0%	36.0%	**172**	**16.7%**	**62.0%**
$\mathcal{D}_4$	0	0	0	5	1.2%	5.0%	0	0	0	21	14.0%	35.0%	**170**	**16.3%**	**61.6%**
$\mathcal{D}_5$	0	0	0	10	1.8%	4.8%	0	0	0	19	3.0%	9.8%	**175**	**17.0%**	**62.8%**
Total/Avg	16	0.4%	1.9%	54	1.4%	4.9%	18	0.5%	1.6%	128	8.1%	21.2%	**860**	**16.4%**	**62.8%**
cutoff = 300s															
$\mathcal{D}_1$	69	7.7%	39.6%	13	1.8%	7.0%	67	7.5%	36.7%	40	5.9%	20.3%	**146**	**17.7%**	**68.8%**
$\mathcal{D}_2$	61	6.0%	35.5%	24	2.6%	13.9%	66	6.3%	38.5%	35	3.7%	10.9%	**141**	**17.7%**	**62.8%**
$\mathcal{D}_3$	42	5.1%	22.8%	17	4.3%	14.7%	39	4.7%	20.6%	37	16.3%	38.7%	**159**	**18.1%**	**64.3%**
$\mathcal{D}_4$	47	5.9%	28.8%	17	2.4%	11.7%	53	6.9%	30.8%	29	15.4%	37.7%	**153**	**16.6%**	**62.5%**
$\mathcal{D}_5$	42	5.3%	24.7%	21	3.4%	11.2%	46	5.7%	24.7%	31	6.4%	11.1%	**165**	**17.3%**	**65.7%**
Total/Avg	261	6.0%	30.3%	92	2.7%	11.7%	271	6.2%	30.2%	144	9.5%	23.7%	**764**	**17.5%**	**64.8%**
cutoff = 1000s															
$\mathcal{D}_1$	115	15.3%	62.3%	34	6.6%	24.1%	**123**	**18.5%**	66.7%	40	5.9%	20.3%	117	17.7%	**68.9%**
$\mathcal{D}_2$	109	14.7%	61.3%	40	6.3%	28.4%	**116**	15.3%	64.5%	35	3.7%	10.9%	112	**17.7%**	**62.9%**
$\mathcal{D}_3$	87	11.4%	46.8%	30	7.0%	25.2%	89	12.7%	50.6%	37	16.3%	38.7%	**131**	**18.1%**	**64.4%**
$\mathcal{D}_4$	92	12.1%	52.6%	35	4.2%	22.2%	95	13.9%	55.8%	29	15.4%	37.7%	**124**	**16.6%**	**62.6%**
$\mathcal{D}_5$	105	14.6%	55.6%	33	6.8%	23.8%	107	15.7%	56.7%	31	6.4%	11.1%	**130**	**17.4%**	**66.0%**
Total/Avg	508	13.6%	55.7%	172	6.2%	24.7%	530	14.8%	58.8%	172	9.5%	23.7%	**614**	**17.5%**	**65.0%**

Table 8: The metric using Lagrange multiple method

Dataset	Lagrange multiple method				LS-IMP			
	#feas	#win	#UR	#FR	#feas	#win	#UR	#FR
cutoff = 60s								
$\mathcal{D}_1$	4	0	0.4%	2.1%	**179**	**179**	**15.5%**	**64.7%**
$\mathcal{D}_2$	4	0	0.4%	2.0%	**166**	**166**	**16.4%**	**60.7%**
$\mathcal{D}_3$	0	0	0	0	**178**	**178**	**16.7%**	**62.0%**
$\mathcal{D}_4$	0	0	0	0	**171**	**171**	**16.3%**	**61.6%**
$\mathcal{D}_5$	0	0	0	0	**176**	**176**	**17.0%**	**62.8%**
Total/Avg	8	0	0.08%	0.1%	**870**	**870**	**16.4%**	**62.8%**
cutoff = 300s								
$\mathcal{D}_1$	5	1	0.5%	2.5%	**180**	**180**	**17.7%**	**68.8%**
$\mathcal{D}_2$	7	2	0.7%	3.6%	**167**	**167**	**17.7%**	**62.8%**
$\mathcal{D}_3$	0	0	0	0	**179**	**179**	**18.1%**	**64.3%**
$\mathcal{D}_4$	0	0	0	0	**172**	**172**	**16.6%**	**62.5%**
$\mathcal{D}_5$	0	0	0	0	**176**	**176**	**17.3%**	**65.7%**
Total/Avg	12	3	0.3%	1.2%	**874**	**874**	**17.5%**	**64.8%**
cutoff = 1000s								
$\mathcal{D}_1$	6	2	0.6%	3.2%	**180**	**180**	**17.7%**	**68.9%**
$\mathcal{D}_2$	9	3	1.0%	6.2%	**167**	**167**	**17.7%**	**62.9%**
$\mathcal{D}_3$	1	0	0.1%	0.4%	**179**	**179**	**18.1%**	**64.4%**
$\mathcal{D}_4$	0	0	0	0	**172**	**172**	**16.6%**	**62.6%**
$\mathcal{D}_5$	1	0	0.1%	0.5%	**176**	**176**	**17.4%**	**66.0%**
Total/Avg	17	5	0.3%	2.2%	**874**	**874**	**17.5%**	**65.0%**