Supplementary Material: Constrained Monotone k-Submodular Function Maximization Using Multi-objective Evolutionary Algorithms with Theoretical Guarantee

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I. Detailed Experimental Results

This part aims to provide the curves of the f value over the running time for MOMS on influence maximization (i.e., Figures 1 and 2) and information coverage maximization (i.e., Figures 3 and 4), which are omitted in our original paper due to space limitation. The value of the budget b is set to 5. The blue dotted line corresponds to the f value of the solution found by the greedy algorithm. Note that one unit on the x-axis corresponds to kbn number of objective function evaluations, i.e., the running time of the greedy algorithm. We can observe that MOMS takes more time to perform as well as the greedy algorithm in most cases, but can find better solutions by performing even more objective function evaluations. The curves of MOMS may decrease at some time, which is because the better solution may be deleted due to the noise in the objective function evaluation. Note that the objective f of influence maximization and information coverage maximization is the expectation of a random variable. We estimate it by the average of 30 simulations in the experiments, and thus we only obtain a noisy f value instead of the exact one.

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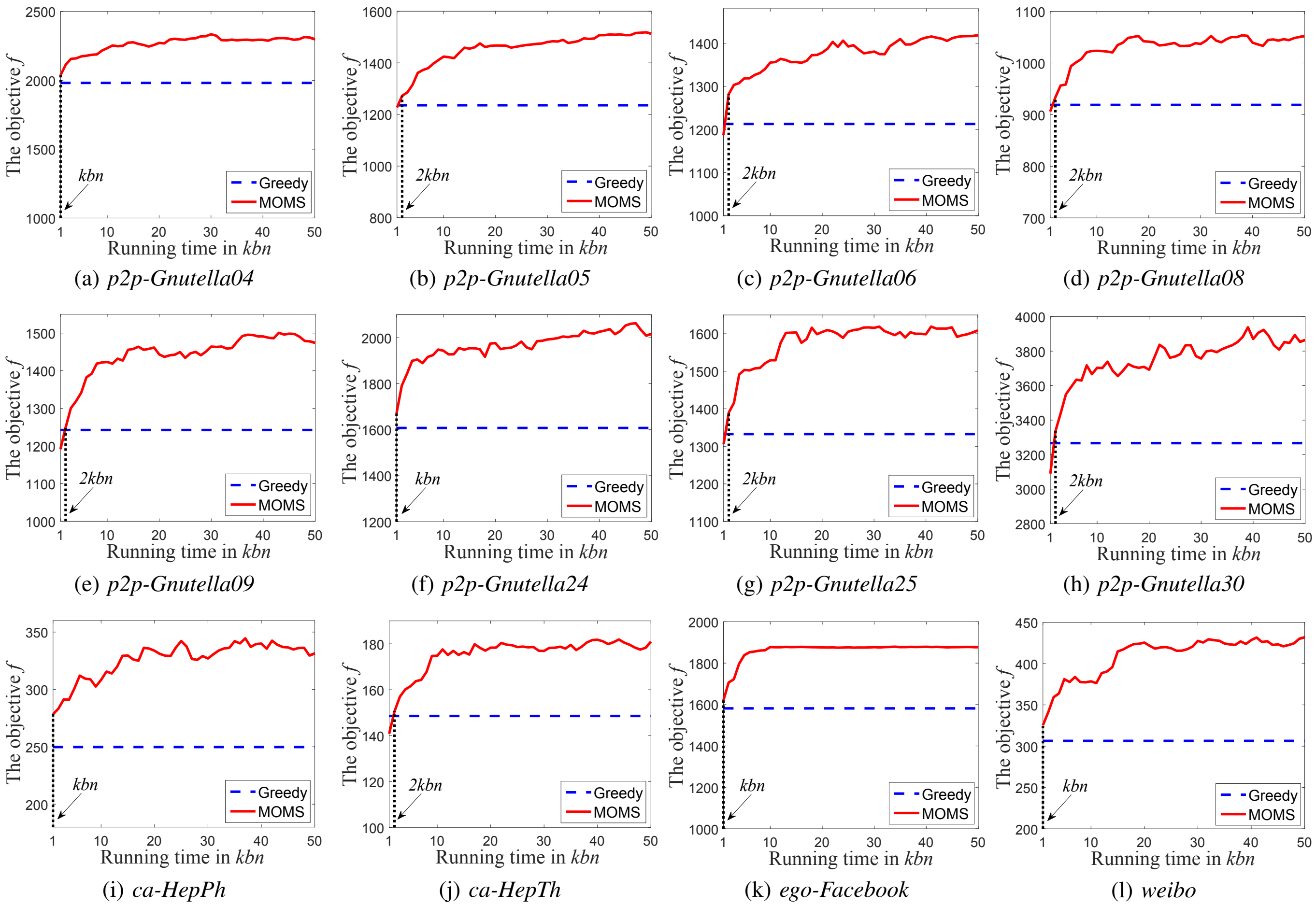
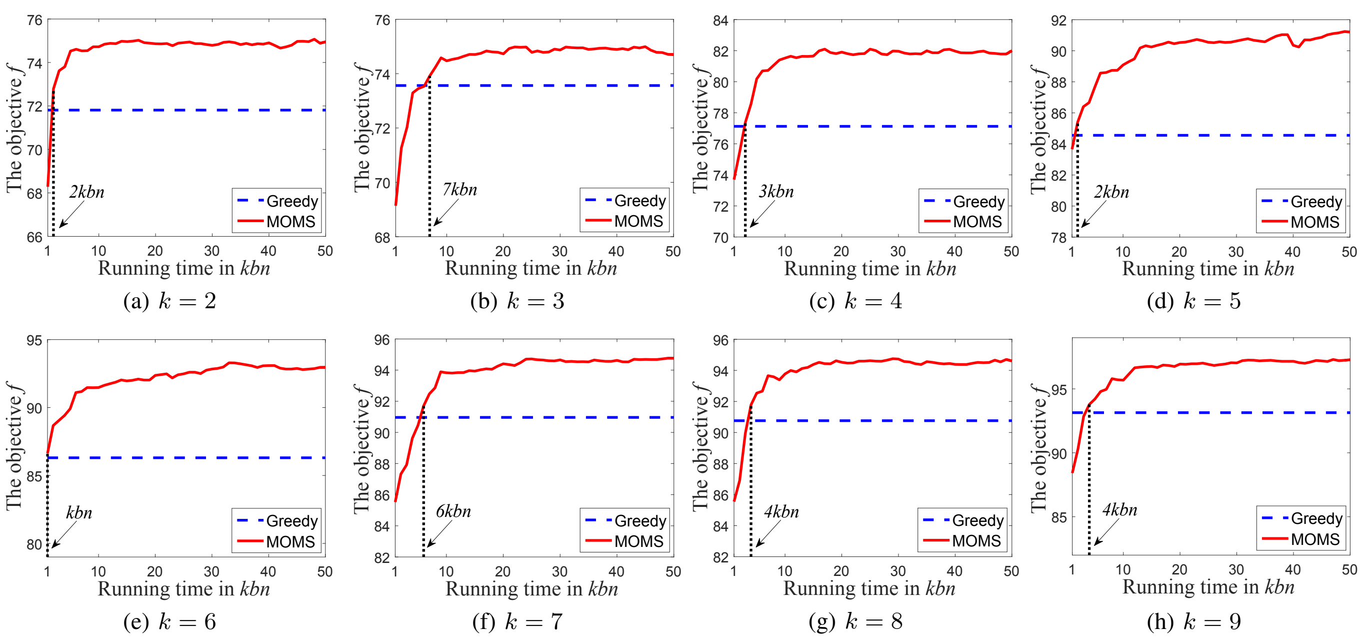


(a) *p2p-Gnutella04* (b) *p2p-Gnutella05* (c) *p2p-Gnutella06* (d) *p2p-Gnutella08*

(e) *p2p-Gnutella09* (f) *p2p-Gnutella24* (g) *p2p-Gnutella25* (h) *p2p-Gnutella30*

(i) *ca-HepPh* (j) *ca-HepTh* (k) *ego-Facebook* (l) *weibo*

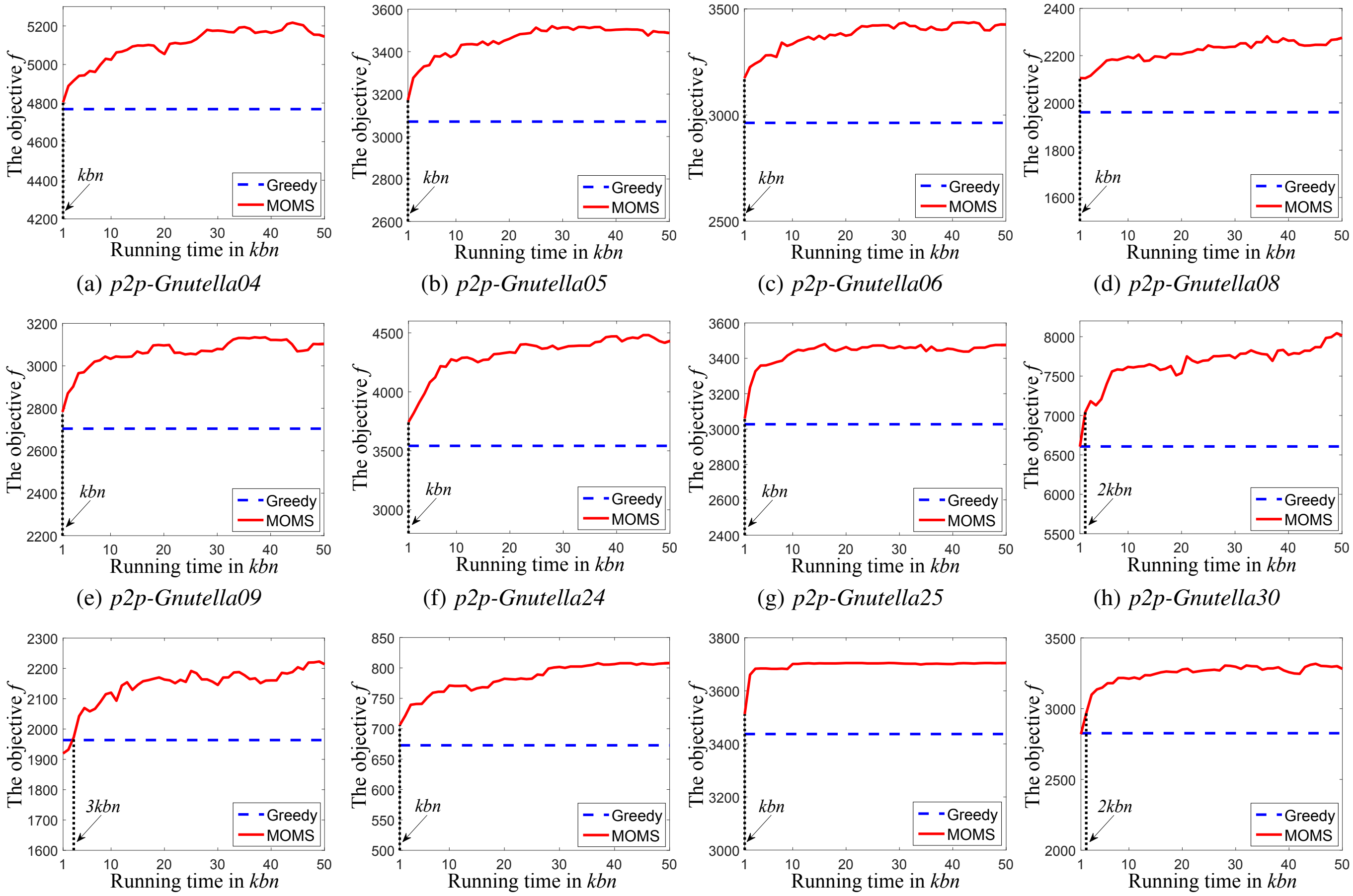
Figure 1. The objective f v.s. the running time for MOMS on influence maximization with $k = 1$ and $b = 5$. The objective f: the average number of active nodes (the larger the better).



(a) $k = 2$ (b) $k = 3$ (c) $k = 4$ (d) $k = 5$

(e) $k = 6$ (f) $k = 7$ (g) $k = 8$ (h) $k = 9$

Figure 2. The objective f v.s. the running time for MOMS on influence maximization with $k \geq 2$ and $b = 5$. The objective f: the average number of active nodes (the larger the better).



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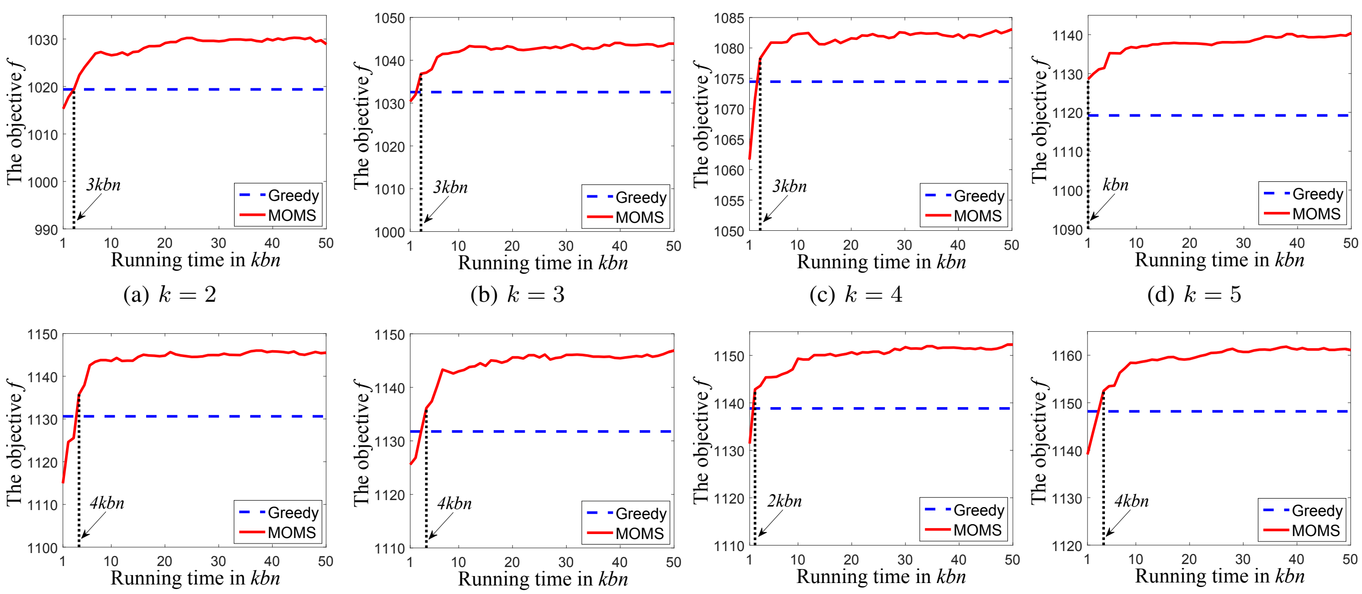
(i) *ca-HepPh* (j) *ca-HepTh* (k) *ego-Facebook* (l) *weibo*

Figure 3. The objective f v.s. the running time for MOMS on information coverage maximization with $k = 1$ and $b = 5$. The objective f: the average number of active nodes and informed nodes (the larger the better).



(a) $k = 2$ (b) $k = 3$ (c) $k = 4$ (d) $k = 5$

(e) $k = 6$ (f) $k = 7$ (g) $k = 8$ (h) $k = 9$

Figure 4. The objective f v.s. the running time for MOMS on information coverage maximization with $k \geq 2$ and $b = 5$. The objective f: the average number of active nodes and informed nodes (the larger the better).