Table 3: Influence spread with different adaptive degree.

Num. of Rounds	1	2	5	10
Num. of Seeds	50	25	10	5
AdaIMM (R = 100)	883.0 [856.0, 910.1]	1040.3 [1022.6, 1058.1]	1141.0 [1119.3, 1162.6]	1204.7 [1178.2, 1231.3]

Table 4: Running time of the algorithms, in seconds.

	SG	SG-R	E-WR-Greedy	WR-IMM
NetHEPT (R = 5)	439.2 [407, 470.94]	87.8 [81.5, 94.2]	551.2 [527.9, 574.4]	1.97 [1.91, 2.03]
Flixster (R = 5)	4862.3 [4773.3, 4951.3]	972.5 [990.3,954.7]	2478.9 [2422.4, 2535.5]	3.16 [3.14, 3.18]

	CR-Greedy	CR-IMM	AdaGreedy	AdaIMM
NetHEPT (R = 5)	2105.6 [2036.2, 2175.0]	2.13 [2.05, 2.21]	465.4 [473.8, 457.0]	2.01 [1.93, 2.09]
Flixster (R = 5)	9587.6 [9145.3.10029.9]	3.61 [3.59, 3.63]	2305.5 [2161.0, 2450.0]	3.23 [3.16, 3.30]

requires the real-life spread between each round comparing to non-adaptive algorithms, but always performs the best in each round.

Fifth, we can see that AdaIMM achieves the same level of influence spread as AdaGreedy: the confidence intervals always overlap, which means AdaIMM performs well in practice.

6.2.2 Degree of Adaptiveness. We vary the parameters T and k whiling keeping Tk the same. With smaller k, it means each round we select a smaller number of seed sets, and we use more adaptive rounds. Therefore, small k and large T mean a high degree of adaptiveness. We test this using AdaIMM, since it is more efficient than AdaGreedy while providing the same level of influence spread.

Table 3 presents the result on this test, in which we vary (T, k) as $(1, 50)$, $(2, 25)$, $(5, 10)$ and $(10, 5)$. The influence spread significantly increases with the increase of the degree of adaptiveness, and the increase is quite significant. The 10-round 5-seed setup is 36.3% better than 1 round 50-seed setup on the empirical average. This shows that higher adaptive degree indeed improves the performance.

In summary, with same total budget, the higher number of total rounds with higher influence spread performance in general.

6.2.3 Running Time. Table 4 reports the running time of all methods on the two datasets, when running with $T = 5$ and $k = 10$. One conclusion is that all IMM algorithms are much more efficient that others, with two to three orders of magnitude faster than all other algorithms. Among greedy algorithms, SG-R runs faster because it selects only 10 seeds once. SG is the slowest, much slower than E-WR-Greedy and AdaGreedy because it selects 50 different seeds. When it selects more seeds, their marginal influence spread doesn't differ from one another much and thus the lazy-evaluation optimization is not as effective as selecting the first 10 seeds.

After combining the influence spread and running time performance, our conclusion is that (a) algorithms designed for the MRIM task is better, (b) the cross-round setting is more effective, but less efficient than the within-round setting of non-adaptive algorithms, and (c) AdaIMM is clearly the best for adaptive MRIM task.

7 ACKNOWLEDGE

This work is supported in part by NSF through grants IIS-1526499, IIS-1763325, and CNS-1626432, and NSFC 61672313, 61433014.

REFERENCES

[1] Nicola Barbieri, Francesco Bonchi, and Giuseppe Manco. 2012. Topic-aware social influence propagation models. In *ICDM'12*. IEEE.

[2] Jonah Berger. 2014. Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology* (2014).

[3] Smriti Bhagat, Amit Goyal, and Laks V. S. Lakshmanan. 2012. Maximizing product adoption in social networks. In *WSDM*. ACM.

[4] Christian Borgs, Michael Brautbar, Jennifer Chayes, and Brendan Lucier. 2014. Maximizing social influence in nearly optimal time. In *ACM-SIAM (SODA '14)*.

[5] Ning Chen. 2008. On the approximability of influence in social networks. In *SODA '08*. Society for Industrial and Applied Mathematics.

[6] Wei Chen, Alex Collins, Rachel Cummings, Te Ke, Zhenming Liu, David Rincon, Xiaorui Sun, Yajun Wang, Wei Wei, and Yifei Yuan. 2011. Influence maximization in social networks when negative opinions may emerge and propagate. In *SDM*.

[7] Wei Chen, Laks VS Lakshmanan, and Carlos Castillo. 2013. *Information and Influence Propagation in Social Networks*. Morgan & Claypool Publishers.

[8] Wei Chen, Tian Lin, Zihan Tan, Mingfei Zhao, and Xuren Zhou. 2016. Robust Influence Maximization. In *KDD*.

[9] Wei Chen, Yajun Wang, and Siyu Yang. 2009. Efficient influence maximization in social networks. In *KDD*.

[10] Wei Chen, Yajun Wang, Yang Yuan, and Qinshi Wang. 2016. Combinatorial multi-armed bandit and its extension to probabilistically triggered arms. *Journal of Machine Learning Research* (2016).

[11] Wei Chen, Yifei Yuan, and Li Zhang. 2010. Scalable Influence Maximization in Social Networks under the Linear Threshold Model. In *ICDM*.

[12] Pedro Domingos and Matthew Richardson. 2001. Mining the network value of customers. In *KDD*.

[13] Marshall L Fisher, George L Nemhauser, and Laurence A Wolsey. 1978. An analysis of approximations for maximizing submodular set functions II. In *Polyhedral combinatorics*. Springer.

[14] Daniel Golovin and Andreas Krause. 2011. Adaptive Submodularity:Theory and Applications in Active Learning and Stochastic Optimization. *JAIR* (2011).

[15] P. R. Goundan and A. S. Schulz. 2007. *Revisiting the greedy approach to submodular set function maximization*. Technical Report. MIT.

[16] Lifang He, Chun-Ta Lu, Jiaqi Ma, Jianping Cao, Linlin Shen, and Philip S Yu. 2016. Joint community and structural hole spanner detection via harmonic modularity. In *SIGKDD*. ACM.

[17] X. He and D. Kempe. 2016. Robust Influence Maximization. In *KDD*.

[18] Xinran He, Guojie Song, Wei Chen, and Qingye Jiang. 2012. Influence Blocking Maximization in Social Networks under the Competitive Linear Threshold Model.

[19] Kyomin Jung, Wooram Heo, and Wei Chen. 2012. IRIE: Scalable and Robust Influence Maximization in Social Networks. In *ICDM*.

[20] David Kempe, Jon M. Kleinberg, and Éva Tardos. 2003. Maximizing the spread of influence through a social network. In *KDD*.

[21] Siyu Lei, Silviu Maniu, Luyi Mo, Reynold Cheng, and Pierre Senellart. 2015. Online Influence Maximization. In *KDD*.

[22] Jure Leskovec, Andreas Krause, Carlos Guestrin, Christos Faloutsos, Jeanne M. VanBriesen, and Natalie S. Glance. 2007. Cost-effective outbreak detection in networks. In *KDD*.

[23] Su-Chen Lin, Shou-De Lin, and Ming-Syan Chen. 2015. A learning-based framework to handle multi-round multi-party influence maximization on social networks. In *KDD*. ACM.

[24] Wei Lu, Wei Chen, and Laks VS Lakshmanan. 2015. From competition to complementarity: comparative influence diffusion and maximization. *PVLDB* (2015).

[25] Elchanan Mossel and Sebastien Roch. 2007. On the submodularity of influence in social networks. In *STOC '07*.

[26] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher. 1978. *An analysis of the approximations for maximizing submodular set functions*. Mathematical Programming.

[27] Matthew Richardson and Pedro Domingos. 2002. Mining knowledge-sharing sites for viral marketing. In *KDD*.

[28] Lior Seeman and Yaron Singer. 2013. Adaptive seeding in social networks. In *FOCS*. IEEE.

[29] Lichao Sun, Weiran Huang, Philip S Yu, and Wei Chen. 2018. Multi-Round Influence Maximization (Extended Version). *arXiv preprint arXiv:1802.04189* (2018).

[30] Youze Tang, Yanchen Shi, and Xiaokui Xiao. 2015. Influence maximization in near-linear time: a martingale approach. In *SIGMOD*.

[31] Sharan Vaswani, Branislav Kveton, Zheng Wen, Mohammad Ghavamzadeh, Laks V.S. Lakshmanan, and Mark Schmidt. 2017. Diffusion Independent Semi-Bandit Influence Maximization. In *ICML*.

[32] Chi Wang, Wei Chen, and Yajun Wang. 2012. Scalable influence maximization for independent cascade model in large-scale social networks. *DMKD* (2012).

[33] Zheng Wen, Branislav Kveton, Michal Valko, and Sharan Vaswani. 2017. Online influence maximization under independent cascade model with semi-bandit feedback. In *NIPS*.