

ence maximization problem. In [8], the authors look at the special case of the voter model and design efficient algorithms in this setting.

Our two-stage model for influence maximization is related to the field of stochastic optimization where problems are commonly solved using the *sample average approximation* method [16]. Golovin and Krause [11] study a stochastic sequential submodular maximization problem where at each step an element is chosen, its realization is revealed and the next decision is made. We note that contrary to adaptive seeding, the decision made at a given stage does not affect the following stages as the entire set of nodes is available as potential seeds at every stage.

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7. REFERENCES

- [1] <https://projects.coin-or.org/Clp>.
- [2] A. A. Ageev and M. Sviridenko. Pipage rounding: A new method of constructing algorithms with proven performance guarantee. *J. Comb. Optim.*, 8(3):307–328, 2004.
- [3] E. Bakshy, J. M. Hofman, W. A. Mason, and D. J. Watts. Everyone’s an influencer: quantifying influence on twitter. In *WSDM*, 2011.
- [4] C. Borgs, M. Brautbar, J. Chayes, and B. Lucier. Maximizing social influence in nearly optimal time. In *SODA*, volume 14. SIAM, 2014.
- [5] N. Chen. On the approximability of influence in social networks. In *SODA*, pages 1029–1037, 2008.
- [6] J. Cheng, L. Adamic, P. A. Dow, J. M. Kleinberg, and J. Leskovec. Can cascades be predicted? WWW ’14, pages 925–936, New York, NY, USA, 2014. ACM.
- [7] P. Domingos and M. Richardson. Mining the network value of customers. In *KDD*, pages 57–66, 2001.
- [8] E. Even-Dar and A. Shapira. A note on maximizing the spread of influence in social networks. In *WINE*, pages 281–286, 2007.
- [9] S. L. Feld. Why your friends have more friends than you do. *American Journal of Sociology*, pages 1464–1477, 1991.
- [10] S. Goel, D. J. Watts, and D. G. Goldstein. The structure of online diffusion networks. In *EC ’12, Valencia, Spain, June 4-8, 2012*, pages 623–638, 2012.
- [11] D. Golovin and A. Krause. Adaptive submodularity: Theory and applications in active learning and stochastic optimization. *Journal of Artificial Intelligence Research*, 42(1):427–486, 2011.
- [12] R. A. Holley and T. M. Liggett. Ergodic theorems for weakly interacting infinite systems and the voter model. *The annals of probability*, pages 643–663, 1975.
- [13] T. Horel and Y. Singer. Scalable methods for adaptively seeding a social network. *CoRR*, abs/1503.01438, 2015.
- [14] D. Kempe, J. M. Kleinberg, and É. Tardos. Maximizing the spread of influence through a social network. In *KDD*, pages 137–146, 2003.
- [15] D. Kempe, J. M. Kleinberg, and É. Tardos. Influential nodes in a diffusion model for social networks. In *ICALP*, pages 1127–1138, 2005.
- [16] A. J. Kleywegt, A. Shapiro, and T. Homem-de Mello. The sample average approximation method for stochastic discrete optimization. *SIAM Journal on Optimization*, 12(2):479–502, 2002.
- [17] R. Kumar, B. Moseley, S. Vassilvitskii, and A. Vattani. Fast greedy algorithms in mapreduce and streaming. In G. E. Blueloch and B. Vöcking, editors, *SPAA 2013*, pages 1–10. ACM, 2013.
- [18] S. Lattanzi and Y. Singer. The power of random neighbors in social networks. *WSDM*, 2015.
- [19] J. Leskovec, D. Chakrabarti, J. M. Kleinberg, and C. Faloutsos. Realistic, mathematically tractable graph generation and evolution, using kronecker multiplication. In *PKDD 2005*, volume 3721 of *Lecture Notes in Computer Science*, pages 133–145. Springer, 2005.
- [20] J. Leskovec, A. Krause, C. Guestrin, C. Faloutsos, J. M. VanBriesen, and N. S. Glance. Cost-effective outbreak detection in networks. In *KDD*, pages 420–429, 2007.
- [21] J. Leskovec and A. Krevl. SNAP Datasets: Stanford large network dataset collection. <http://snap.stanford.edu/data>, June 2014.
- [22] M. Mathioudakis, F. Bonchi, C. Castillo, A. Gionis, and A. Ukkonen. Sparsification of influence networks. In *KDD*, 2011.
- [23] E. Mossel and S. Roch. On the submodularity of influence in social networks. In *STOC*, pages 128–134, 2007.
- [24] G. L. Nemhauser, L. A. Wolsey, and M. L. Fisher. An analysis of approximations for maximizing submodular set functions—i. *Mathematical Programming*, 14(1):265–294, 1978.
- [25] M. Richardson and P. Domingos. Mining knowledge-sharing sites for viral marketing. In *KDD*, pages 61–70, 2002.
- [26] M. Richardson and P. Domingos. Mining knowledge-sharing sites for viral marketing. In *KDD*, pages 61–70. ACM, 2002.
- [27] L. Seeman and Y. Singer. Adaptive seeding in social networks. In *FOCS*, 2013.
- [28] J. Vondrák, C. Chekuri, and R. Zenklusen. Submodular function maximization via the multilinear relaxation and contention resolution schemes. In *STOC*, pages 783–792. ACM, 2011.
- [29] J. Yang and S. Counts. Predicting the speed, scale, and range of information diffusion in twitter. In *ICWSM*, 2010.
- [30] T. R. Zaman, R. Herbrich, J. V. Gael, and D. Stern. Predicting information spreading in twitter, 2010.