Using MapReduce for Impression Allocation in Online Social Networks

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TTLAB

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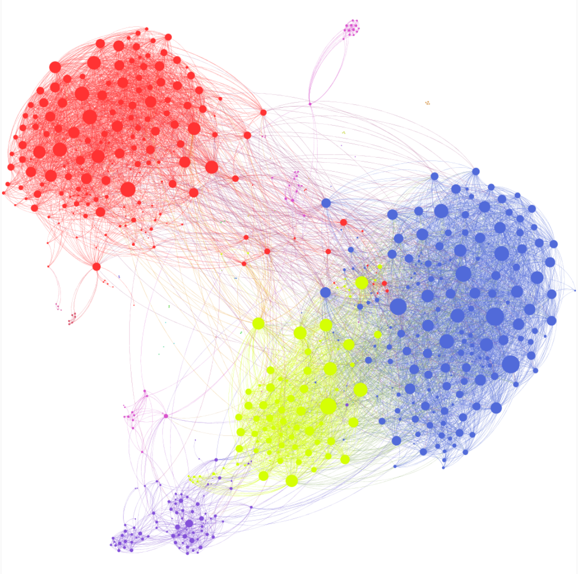
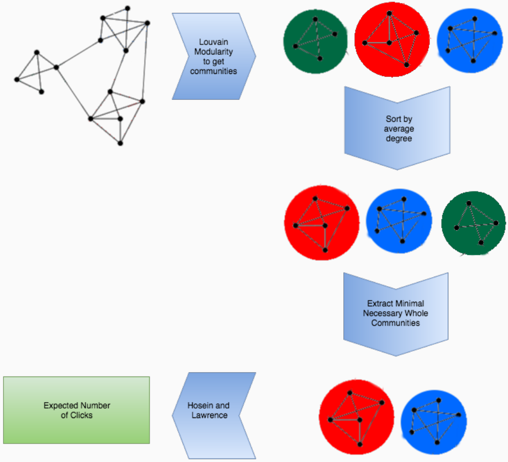
Community Detection Heuristic



Community Detection Heuristic



Performance of Community Detection Heuristic

Table: Performance and Runtime Comparisons

Data	Method	Value	Time (ms)
1	Optimal	1.40	64
	Clustering Heuristic	1.40	66
2	Optimal	1.56	56841
	Clustering Heuristic	1.45	429
3	Optimal	2.03	170967777
	Clustering Heuristic	2.02	52401

$$E\left[\text{clicks in stage k}\right] = \sum_{i=0}^{N} X_{ik} p_k\left[i\right]$$

$$\text{areFriends}(i,j) = I_{(i,j)\in E}\left(i\right)$$

$$p_{ie} = E\left[\text{i's friends who clicked in k}\right] = \sum_{j=0}^{N} \text{areFriends}(i,j) X_{ij} p_j$$

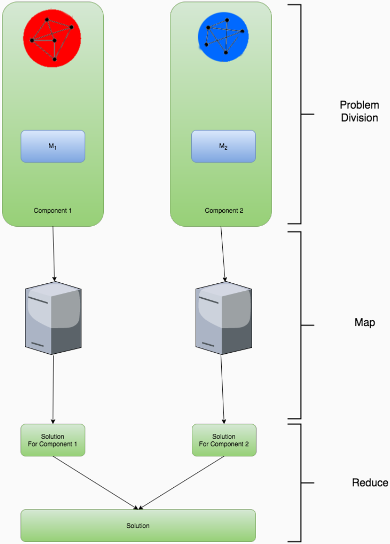
$$E\left[\text{i's probability in k}\right] = min\left\{1,\ max\left\{0,\ p_{k-1} + \alpha\frac{p_{ie}}{n}\right\}\right\}$$

Let $\hat{J}$ be an approximation based on the previous

$$\Delta_j = \hat{J}(X_{+j}) - \hat{J}(X)$$

Let $\Delta_j(c)$ denote the incremental objective function value increase for providing an impression to user j who resides in cluster c.

$$\Delta_j(c) < \kappa$$



M1
M2
Component 1
Component 2
Solution For Component 1
Solution For Component 2
Solution
Problem Division
Map
Reduce

Conclusions

Using community detection to partition the graph, speed up computation time.
There is room for extension and improvement using MapReduce.

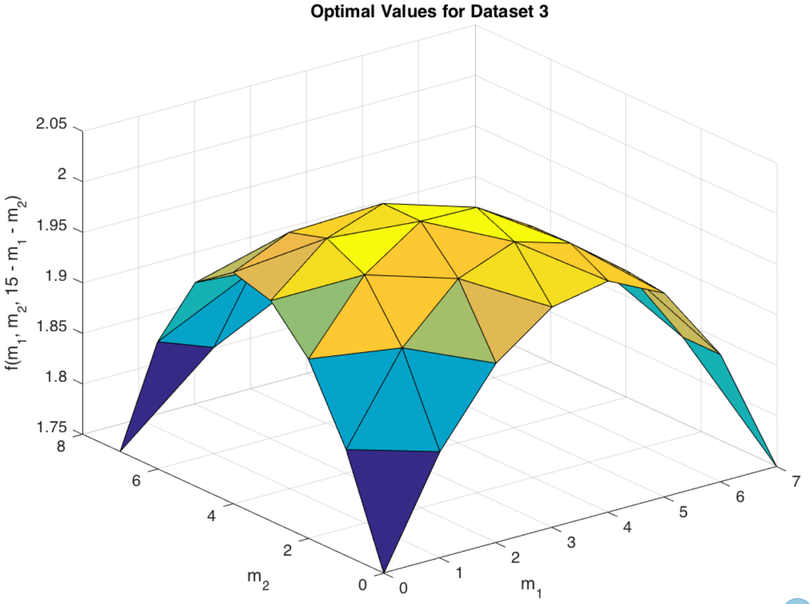
Future and Current Work

1. Developed an algorithm that uses PSO to approximate the allocation of impressions to users
2. Developed an additional greedy approach to approximate the optimal allocation of impressions
3. Currently exploring how distributed computing paradigms such as MapReduce can be used in tandem with community detection to develop more efficient implementations of the aforementioned heuristics
4. Exploring heuristics that can solve the optimal allocation vector
5. Find upperbounds to better characterize the correctness of the solution

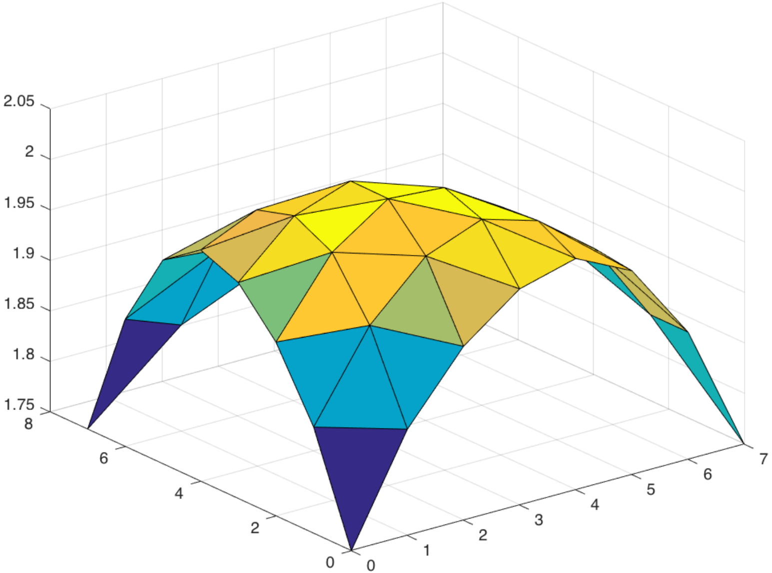
References

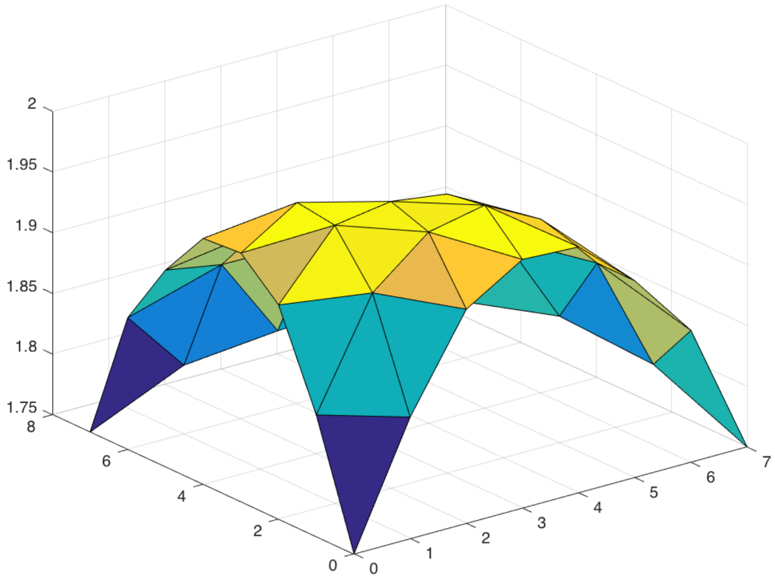
1 P. Hosein and T. Lawrence, “Stochastic dynamic programming model for revenue optimization in social networks,” in Wireless and Mobile Computing, Networking and Communications (WiMob), 2015 IEEE 11th International Conference on, Oct 2015, pp. 378–383.
2 Abbassi, Zeinab and Bhaskara, Aditya and Misra, Vishal, “Optimizing Display Advertising in Online Social Networks,” in Proceedings of the 24th International Conference on World Wide Web, WWW ’15. Florence, Italy: ACM, 2015, pp. 1-11.
3 E. Bakshy, D. Eckles, R. Yan, and I. Rosenn, “Social influence in social advertising: Evidence from field experiments,” in Proceedings of the 13th ACM Conference on Electronic Commerce. ACM, 2012, pp. 146– 161.
4 H. Bao and E. Y. Chang, “Adheat: An influence-based diffusion model for propagating hints to match ads,” in Proceedings of the 19th International Conference on World Wide Web, ser. WWW ’10. New York, NY, USA: ACM, 2010, pp. 71–80. [Online]. Available: http://doi.acm.org/10.1145/1772690.1772699
5 S. Bhagat, A. Goyal, and L. V. Lakshmanan, “Maximizing product adoption in social networks,” in Proceedings of the Fifth ACM International Conference on Web Search and Data Mining, ser. WSDM ’12. New York, NY, USA: ACM, 2012, pp. 603–612. [Online]. Available: http://doi.acm.org/10.1145/2124295.2124368
6 J. Hartline, V. Mirrokni, and M. Sundararajan, “Optimal marketing strategies over social networks,” in Proceedings of the 17th International Conference on World Wide Web, ser. WWW ’08. New York, NY, USA: ACM, 2008, pp. 189–198. [Online]. Available: http://doi.acm.org/10.1145/1367497.1367524
7 S. Lei, S. Maniu, L. Mo, R. Cheng, and P. Senellart, “Online influence maximization,” in Proc. KDD, Sydney, Australia, Aug. 2015.

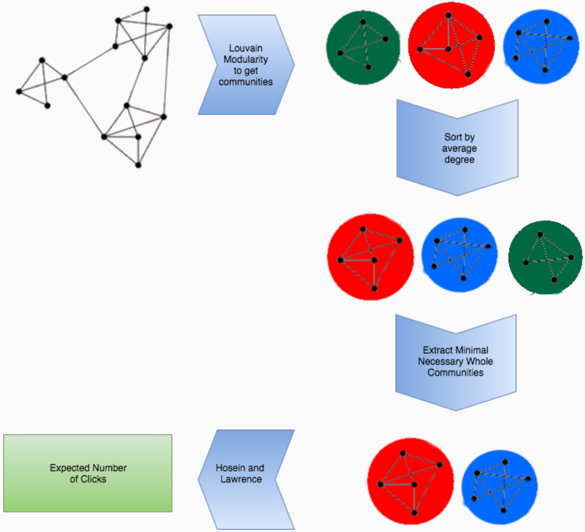
Thank You!

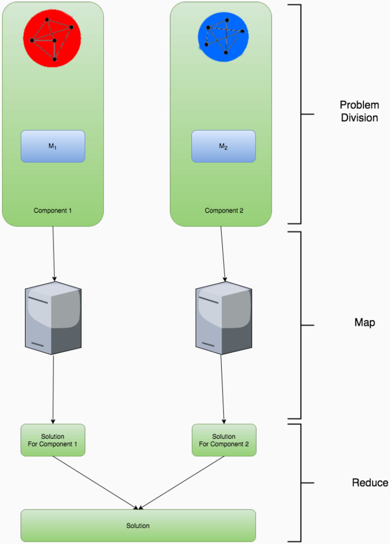

Optimal Values for Dataset 3
f(m1, m2, 15 - m1 - m2)
2.05
2
1.95
1.9
1.85
1.8
1.75
8
6
4
2
0
m2
0
1
2
3
4
5
6
7
m1

Expected Number of Clicks as Computed Using Heuristic 1 for Dataset 3




2
1.95
1.9
1.85
1.8
1.75
8
6
4
2
0
0
1
2
3
4
5
6
7


Louvain Modularity to get communities
Sort by average degree
Extract Minimal Necessary Whole Communities
Hosein and Lawrence
Expected Number of Clicks


M1
M2
Component 1
Component 2
Problem
Division
Map
Solution
For Component 1
Solution
For Component 2
Reduce
Solution