Fraud Detection by Dense Subgraph Detection



Fraud Detection

- Text-based methods
- Graph-based methods
 - Unexpected spectral patterns
 - [1] Prakash, B. Aditya, et al. "Eigenspokes: Surprising patterns and scalable community chipping in large graphs." *Data Mining Workshops, 2009. ICDMW'09. IEEE International Conference on*. IEEE, 2009.
 - Dense subgraphs
 - [2] Hooi, Bryan, et al. "Fraudar: Bounding graph fraud in the face of camouflage." *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2016.

Dense Subgraph Detection

- Given a graph G = (V, E) with vertices V and edges $E \subseteq V \times V$.
- Find a subgraph S such that d(S) is maximized.
- GoldBerg's algorithm (1984)
 - Transferred to a min-cut problem which can be solved as a max-flow problem. [3] Goldberg, Andrew V. *Finding a maximum density subgraph*. Berkeley, CA: University of California, 1984.
- Charikar's algorithm (2000)
 - Approximation algorithm by greedy approach.
 - Provable 2-approximation guarantee.

[4] Charikar, Moses. "Greedy approximation algorithms for finding dense components in a graph." *International Workshop on Approximation Algorithms for Combinatorial Optimization*. Springer, Berlin, Heidelberg, 2000.

Charikar's algorithm on Undirected Graph



International Conference on Knowledge Discovery and Data Mining. ACM,

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Charikar's algorithm on Undirected Graph



Figure from:

[5] Gionis, Aristides, and Charalampos E. Tsourakakis. "Dense subgraph discovery: Kdd 2015 tutorial." *Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2015.

Charikar's algorithm on Undirected Graph

- input: undirected graph G = (V, E)output: S, a dense subgraph of G
- 1 set $G_n \leftarrow G$
- 2 for $k \leftarrow n$ downto 1
- 2.1 let v be the smallest degree vertex in G_k
- 2.2 $G_{k-1} \leftarrow G_k \setminus \{v\}$
- 3 output the densest subgraph among $G_n, G_{n-1}, \ldots, G_1$

On Directed Graph

- Duplicate the vertices.
- Make G into a bipartite graph.



Fraudar

Require: Bipartite $G = (\mathcal{U} \cup \mathcal{W}, \mathcal{E})$; density metric g of the form in (1)

- 1: procedure FRAUDAR (G, g)
- 2: Construct priority tree T from $\mathcal{U} \cup \mathcal{W}$

3:
$$\mathcal{X}_0 \leftarrow \mathcal{U} \cup \mathcal{W}$$

4: **for**
$$t = 1, ..., (m+n)$$
 do

5:
$$i^* \leftarrow \arg \max_{i \in \mathcal{X}_i} g(\mathcal{X}_i \setminus \{i\})$$

6: Update priorities in T for all neighbors of i^*

7:
$$\mathcal{X}_t \leftarrow \mathcal{X}_{t-1} \setminus \{i^*\}$$

- 8: end for
- 9: **return** $\arg \max_{\mathcal{X}_i \in \{\mathcal{X}_0, ..., \mathcal{X}_{m+n}\}} g(\mathcal{X}_i)$

10: end procedure

[2] Hooi, Bryan, et al. "Fraudar: Bounding graph fraud in the face of camouflage." *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2016.

Runtime

- Utilized a priority tree
 - Fast minimum retrieval ($O(\log |V|)$)
 - Fast updating ($O(\log |V|)$)
- Total runtime: $O((|V| + |E|)\log |V|)$

Dataset

- Twitter data extracted in July 2009.
- 41.7 million users.
- 1.47 billion follows.
- Fraudar detected a 4031 followers by 4313 followees subgraph with density 68%.
- Human labeling: 57% of the detected followers are were labelled as fraudulent, deleted or suspended accounts.