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# بسم الله الرحمن الرحيم

مركز الشبكات وتكنولوجيا المعلومات قسم التوثيق الإلكتروني





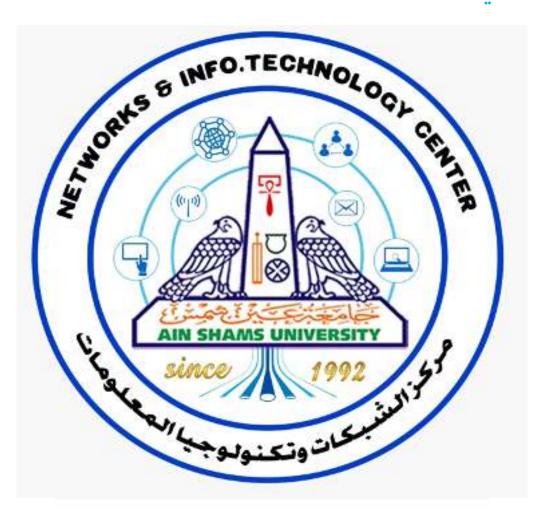


## Mona Maghraby

## جامعة عين شمس

التوثيق الإلكتروني والميكروفيلم قسم

نقسم بالله العظيم أن المادة التي تم توثيقها وتسجيلها على هذه الأقراص المدمجة قد أعدت دون أية تغيرات







## **Effective Approaches for Influence Maximization in Social Networks**

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#### BY

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#### **Abstract**

The detection of the top influential users is well-known scientifically as the social influence maximization. The current existing solutions suffer from several limitations, such as the highly required computations and the running time to find the top influential seed set. Therefore, finding an effective and efficient solution is still a challenging task. In order to solve the current scientific gap, this thesis proposes an effective and scalable community-based approach for the influence maximization problem called Louvain-k-shell Generalization (LKG). LKG is a fast and scalable community-based hybrid approach to detect top influential users in social networks. The LKG hybrid approach consists of three phases: 1) Community detection, in which the complete social network is partitioned into related communities using the Louvain algorithm; 2) Community top nodes detection that applies the k-shell decomposition locally in each portioned community; and finally 3) Selection generalization, in which the prior obtained results are generalized over the whole network for maximizing the global spread of influence. The results of the LKG approach have been shown to achieve better results for the spread of influence using incomplete social networks than the existing related work approaches and with far much less processing time.

An efficient method is presented to enhance the selection criteria for generated communities. The improved community-based approach is called Louvain CRANK-Select (LCS), which is based on CRANK algorithm for better ranking the generated communities that will be used to select the top influential seed set.

The proposed LKG approach has been also applied on a practicable application for the problem of the influence maximization to analyze a sample of Twitter data concerning Covid-19 epidemic. The effective positive influential users' identification is suggested to help health organizations to share and publish a useful and a helpful information about the latest update of the epidemic.

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#### **List of Abbreviations**

ACO-IM Ant Colony Optimization- Influence Maximization

APIs Application programming interfaces

ASIM A Scalable Algorithm for Influence Maximization

CD Credit Distribution

CDIM Continuous-Time Markov Chain into the Independent Cascade Model.

CELF Cost-Effective Lazy Forward

CELF++ Improved Cost-Effective Lazy Forward

CFIN Community Finding Influential Node

CIM Community based Influence Maximization

CoFIM Community based For Influence Maximization

COND-MAT Condense Matter Physics

Covid-19 Coronavirus disease of 2019

CPSP-Tree Community-aware Partial Shortest Path Tree

CRANK Community prioritization model

CTMC-ICM Continuous-Time Markov Chain into the Independent Cascade Model.

DAG Directed Acyclic Graph

DDSE Degree Descending Search Strategy

DSE Descending Search Strategy

DLIM Degree discount and Local Improvement Method

DomIM Dominating Set for Influence Maximization

GNA Genetic New Greedy Algorithm

GRASP Greedy Randomized Adaptive Search Procedure

GWIM Gray Wolf based Influence Maximization

HC Heuristic clustering

IC Independent Cascade

IM Influence Maximization

IMM Influence Maximization via Martingales

IPA parallel algorithm for influence maximization problem

IRIE Influence Ranking (IR) and Influence Estimation (IE)

LCS Louvain CRANK-Select

LDAG Local Directed Acyclic Graph

LGIEM Global and local node influence based community detection

LIE Local Influence Estimation

LKG Louvain K-shell Generalization

LT Linear Threshold

MCDM Multi-Criteria Decision Making

MCS Monte Carlo Simulations

MIA Maximum Influence Arborescence

MLIM Maximum likelihood-based scheme under the Independent

Cascade(IC) model

NAV Node Approximate Influence Value

NP-hard Non-deterministic polynomial-time hardness

PGP Pretty Good Privacy

PMIA Prefix excluding MIA

SA Simulated Annealing

SIMPATH Simple Paths in the neighborhood for influence maximization

SIR Susceptible Infected Recovered

SKIM Sketch-Based Influence Maximization

SLPA Speaker-Listener Label Propagation Algorithm

SNAP Large Net- work Dataset Collections

SPIN Shapley Value-Based Discovery of Influential Nodes

SSA Stop-and-Stare Algorithm

WHO World Health Organization

WIC Weighted Independent Cascade

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#### **List of Publications**

- [1] A. M. Samir, S. Rady, and T. F. Gharib, "LKG: A fast scalable community-based approach for influence maximization problem in social networks," Physica A: Statistical Mechanics and its Applications, vol. 582, p. 126258, July 2021. Elsevier, IF: 3.263.
- [2] A. M. Samir, S. Rady, and T. F. Gharib, "An efficient community-based approach for the influence maximization problem in social networks," IEEE Tenth International Conference on Intelligent Computing and Information Systems (ICICIS), pp. 335-340, 2021.
- [3] A. M. Samir, S. Rady, and T. F. Gharib, "The Identification of the Top Positive Influential Users of the Social Networks to Help in the Control of Covid-19 Spread", Submitted to International Journal of Intelligent Computing and Information Sciences, 2021.