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# بسم الله الرحمن الرحيم

مركز الشبكات وتكنولوجيا المعلومات

قسم التوثيق الإلكتروني



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# جامعة عين شمس

التوثيق الإلكتروني والميكروفيلم

## قسم

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





Ain Shams University  
Faculty of Computer and Information Sciences  
Information Systems Department

# Effective Approaches for Influence Maximization in Social Networks

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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.
CELLF	Cost-Effective Lazy Forward
CELLF++	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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- [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.