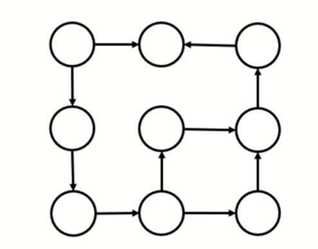
Universidad Rey Juan Carlos

Design and Implementation of Metaheuristic Algorithms for Social Network Influence Problems



Doctoral Thesis

Isaac Lozano Osorio

Advisors:
Prof. Jesús Sánchez-Oro Calvo
Prof. Abraham Duarte Muñoz

grafo RESEARCH

Programa de Doctorado en Tecnologías de la Información y las Comunicaciones.
Escuela Internacional de Doctorado. Universidad Rey Juan Carlos. Móstoles, March 15, 2024.

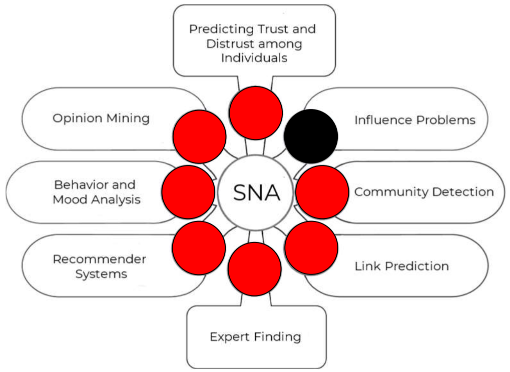
Outline

Outline

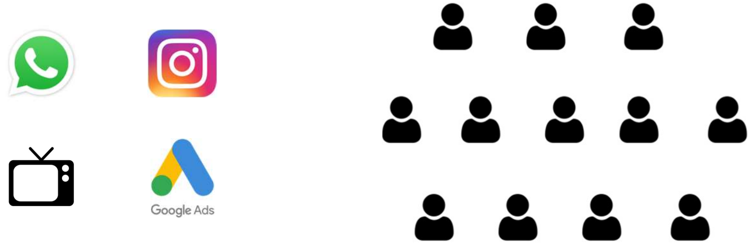
Motivation

Social Network Analysis

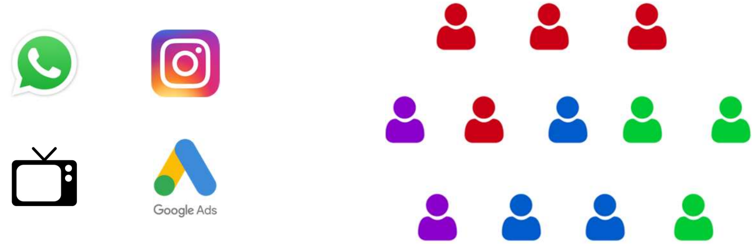
Social Network has become one of the **greatest sources of information** in recent years.



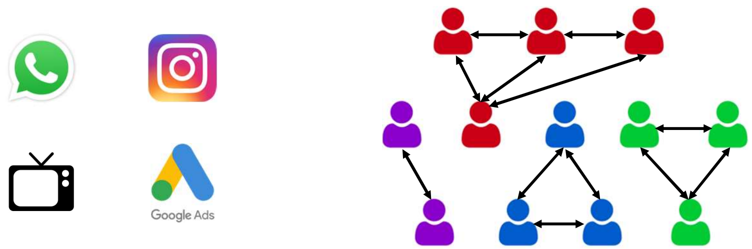
Motivation
Social Network Analysis



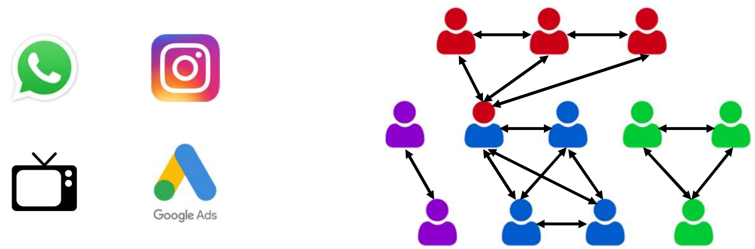
Motivation
Social Network Analysis



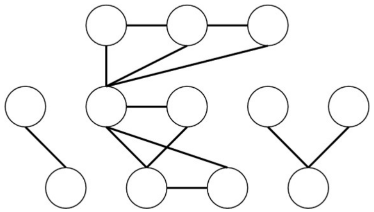
Motivation
Social Network Analysis



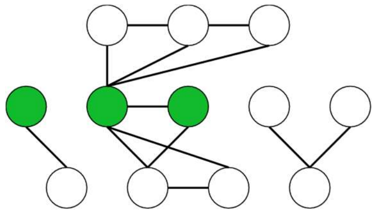
Motivation
Social Network Analysis



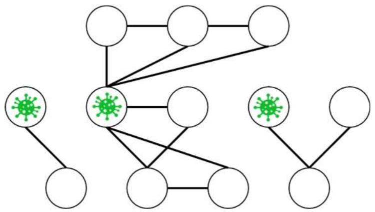
Motivation
Social Network Analysis



Motivation
Social Network Influence Maximization



Motivation
Social Network Influence Minimization



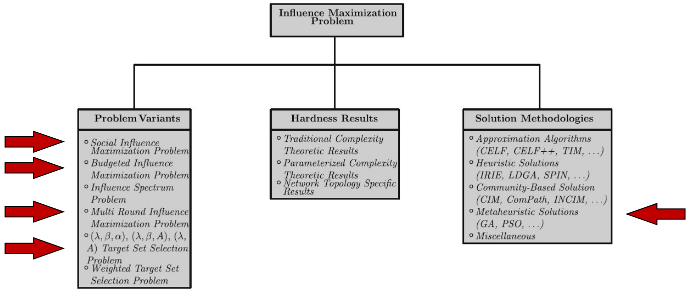
Real world applications
Influence Maximization Problem

Social Network Influence Maximization has been used in several practical applications:

- **Marketing** and advertising campaigns.
- **Eradication** of diseases.
- Product **recommendations**.
- **Emergency response** and crisis management.

Literature review

Influence Maximization Problem



Banerjee, S., Jenamani, M., & Pratihar, D. K. (2020). ***A survey on influence maximization in a social network***. *Knowledge and Information Systems*, *62*, 3417-3455.

Hypothesis and objectives

- Hypothesis:

  Heuristic and metaheuristic techniques can find high-quality solutions to Social Network Influence Problems.

- Objective:

  To design and implement metaheuristic scalable algorithms to address Social Network Influence Maximization Problems.

  - Study the state of the art
  - Identify properties
  - Design an algorithm
  - Implement the algorithm
  - Compare the algorithms
  - Disseminate the results

Outline

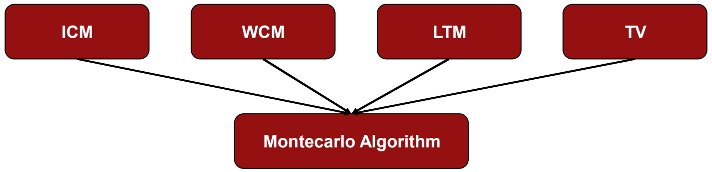
Influence Diffusion Models (IDMs)

Models

Responsible for modeling how the information is transmitted through the network.

Two states: **active** or **not active**.

An IDM assigns an influence probability to each edge.



Influence Diffusion Models (IDMs)

Montecarlo algorithm

Estimate the number of activated users.

4 input parameters:
- Social Network represented as $G = (V, E)$
- Seed of infected/activated users represented as S
- IDM criteria represented by ψ
- Iterations represented as ev

Alternatives:
- Random analysis
- Estimation of variance
- Parallel Montecarlo

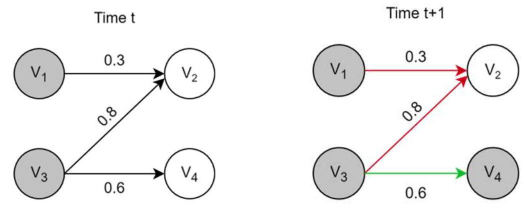
Algorithm 1 $MonteCarlo(G = (V, E), S, \psi, ev)$

```
I ← ∅
for i ∈ 1 ... ev do
    A* ← S
    A ← S
    while A ≠ ∅ do
        B ← ∅
        for v ∈ A do
            for (u, v) ∈ E do
                if ψ then
                    B ← B ∪ {u}
                end if
            end for
        end for
        A* ← A* ∪ B
        A ← B
    end while
    I ← I + |A*|
end for
return I/ev
```


Influence Diffusion Models (IDMs)

Independent Cascade Model (ICM)

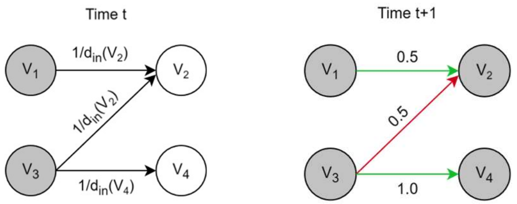
A node (v) that becomes active at time (t), has the chance to activate its neighbor next time ($t + 1$).
Then v generates a random number between $[0, 1]$ for each neighbor u.
If and only if $p_{\{v,u\}} \leq p$, the neighbor u will be activated.



Influence Diffusion Models (IDMs)

Weighted Cascade Model (WCM)

Probability of a user v for being influenced by user u is proportional to the in-degree of user v.
If and only if $\left(1 - \frac{1}{d_{in}(v)}\right) \leq p$, the neighbor u will be activated.

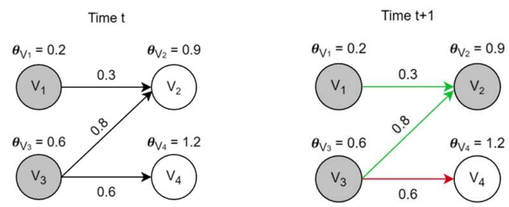


Influence Diffusion Models (IDMs)

Linear Threshold Model (LTM)

A weight $\omega(u, v)$ is associated to each edge (u, v) and a threshold θ_u is associated to each node u.
A node u will be activated if the total weight between itself and its activated neighbors is, at least, θ_u.

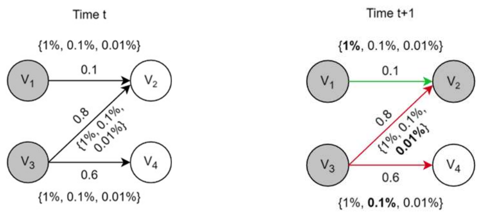
$$\sum_{v} \omega(u, v) \geq \theta_u$$



Influence Diffusion Models (IDMs)

Tri-Valency Model (TV)

Randomly selects the edge probability from $\boldsymbol{p} = \{1\%, 0.1\%, 0.01\%\}$.
The activated node v then generates a random number between $[0,1]$ for each neighbor u.
If and only if $\boldsymbol{p}_{\{v,u\}} \leq \boldsymbol{p}$, the neighbor u will be activated.



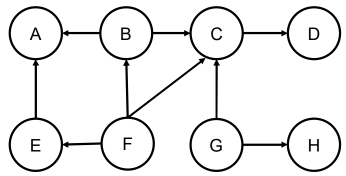
Social Network Influence Maximization Problem

Objective

To maximize the number of nodes in the network that are influenced by the seed set S.

Math. Definition

$$S^* \leftarrow \underset{s \in SS}{\operatorname{argmax}}\ MC(G, S, IDM, ev)$$



p = 1 and $|S|$ = 2

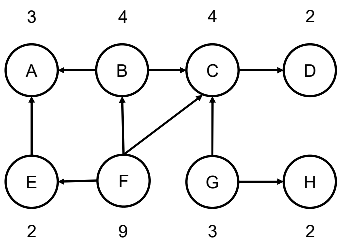
Budgeted Influence Maximization Problem

Objective

To find a set of seed nodes that maximizes the activated users without exceeding a given budget B.

Math. Definition

$$S^* \leftarrow \underset{s \in SS}{\operatorname{argmax}}\ MC(G, S, IDM, ev) : \sum_{u \in S} C(u) \leq B$$



p = 1 and B = 10

Target Set Selection Problem

Objective

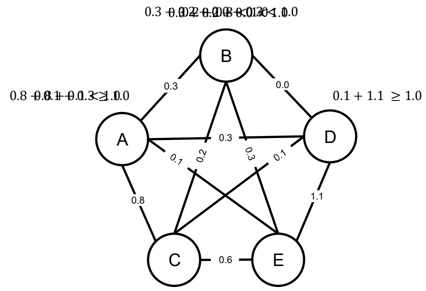
To find a set of seed nodes that maximizes the activated users without exceeding a given budget K.

Math. Definition

$$x_v^{t-1} \leq x_v^t \ \ \forall v \in V, 1 \leq t \leq T \qquad \alpha, \beta : V \rightarrow \mathbb{Z}^+$$

$$TSS(S) = \sum_{v \in V} \beta(v) \cdot x_v^T \qquad \sum_{v \in V} \alpha(v) \cdot x_v^0 \leq K$$

$$S^* \leftarrow \underset{s \in SS}{\operatorname{argmax}}\ TSS(S)$$



Outline

1. Introduction
2. Social Network Influence Problems
3. Methodology
   - 3.1 Constructive procedures
   - 3.2 Improving procedures
   - 3.3 Metaheuristics
   - 3.4 Advanced strategies
4. Discussion of results
5. Conclusions and future work

Methodology
Motivation

1. Exact algorithms require high-computing times when the size of the problems grows.
2. Heuristic algorithms emerge as a good alternative.
3. Metaheuristic algorithms guide heuristics.

"A metaheuristic is a high-level problem-independent algorithmic framework that provides a set of guidelines or strategies to develop heuristic optimization algorithms."

K. Sörensen and F. Glover.

Methodology
General Scheme

1. Generate an initial solution through a **constructive** procedure.
2. Improve the initial solution through a **local search** procedure.
3. Escape from local optima traps using **metaheuristic** techniques.

Methodology
Constructive procedures

Proposed constructive procedures to solve SNIM problems:

1. Based on the **objective function** ($g_{of}(u)$).

   SNIMP and TSS

2. According to the neighbor **out-degree** ($g_{de}(u)$).

   SNIMP, BIMP and TSS

3. Heuristic based on the **first and second neighbors out-degree** ($g_{ne}(u)$).

   SNIMP and BIMP

4. **Prioritizes** nodes that **do not** have **selected** neighbors as a seed node ($g_{dist}(u)$).

   BIMP

Methodology

Constructive procedures

Proposed greedy methods to solve SNIM problems:

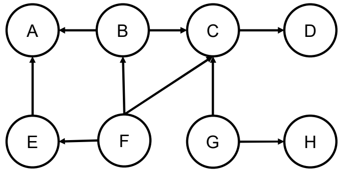
1. $g_{of}(u) = MonteCarlo(G, S \cup u, IDM, ev)$
2. $g_{de}(u) = d_u^+ = N_u^+ \ where \ N_u^+ = \{w \in V : (u,w) \in E\}$
3. $g_{ne}(u) = d_u^+ + \sum_{v \in N_u^+} d_v^+$
4. $\boldsymbol{g_{dist}(u)} = \begin{cases} d_u^+ & if \ v \notin S, \forall v \in N_u^+ \\ \frac{d_u^+}{2} & otherwise \end{cases}$

$g_{of}(F) = 6 \quad g_{of}(H) = 5$

$g_{de}(F) = 3 \quad g_{de}(H) = 0$

$g_{ne}(F) = 7 \quad g_{ne}(H) = 0$

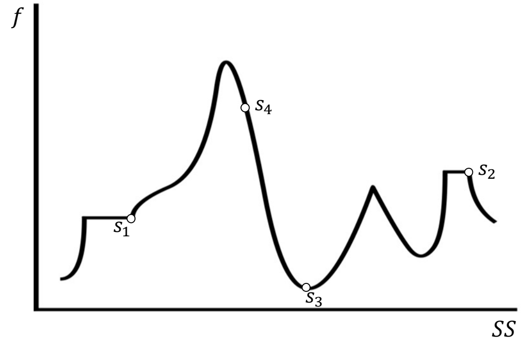
$g_{dist}(F) = 1.5 \quad g_{dist}(H) = 0$



$p = 1$

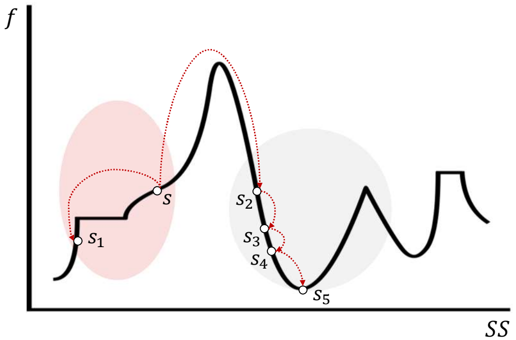
Methodology

Single vs Multi-Start



Methodology

Improving procedures – Neighborhood and moves



Methodology

Improving procedures – Local search

Local search procedures start with a feasible solution and at each iteration try make **moves** from a **neighborhood** to find **better solutions**.

Proposed neighborhoods:

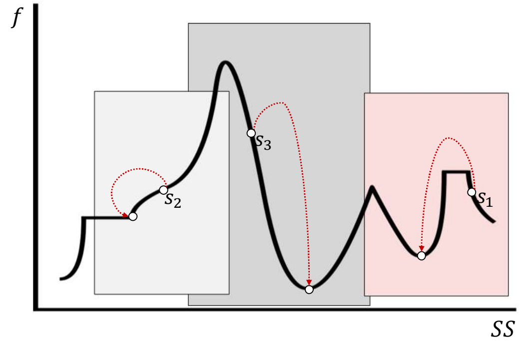
- Swap neighborhood – SNIMP
- Replace neighborhood – TSS and BIMP

Exploration strategies:

- *First improvement*
- *Best improvement*

Methodology

Improving procedures – Neighborhood local optima



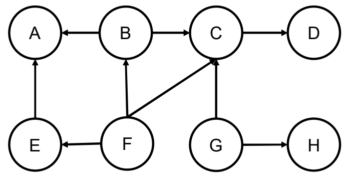
Methodology

Improving procedures – Swap neighborhood

Main idea:

- Exchange with a seed node to a non-activated node.

$N_S(S) = \{Swap(S, u, v)\ \forall\, u \in S \wedge \forall v \in V \backslash S\}.$



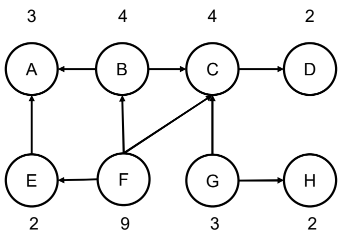
p = 1

Methodology

Improving procedures – Replace neighborhood

Main idea:

- Exchange a seed node to a not activated node (one or more).



p = 1 and B = 10

$Replace(S, u, P) = S\ \{u\} \cup P$

$N_R(S) = \{S' \leftarrow Replace(S, u, P)\ \ \forall_u \in S\ \wedge \forall P \in V \backslash S\text{:}\ \sum_{p \in P} C(p) \leq B + C(u)\}$

Methodology

Greedy Randomized Adaptive Search Procedure (GRASP)

Main contributions:

1. **Diverse** starting solutions.
2. **Strategically** sampling the solution space.
3. **Scalable** algorithm in terms of quality.

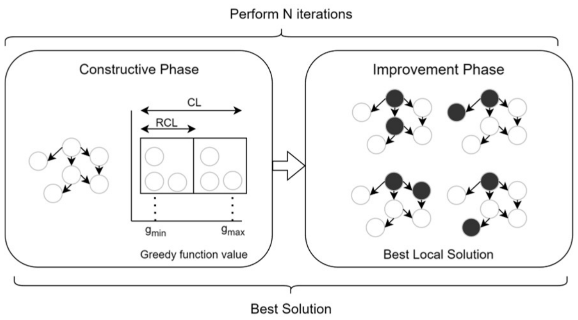
Main variants:

1. Reactive GRASP.
2. Parallel GRASP.
3. Path Relinking + GRASP.

Used in SNIMP, BIMP and TSS

Methodology

Greedy Randomized Adaptive Search Procedure (GRASP)

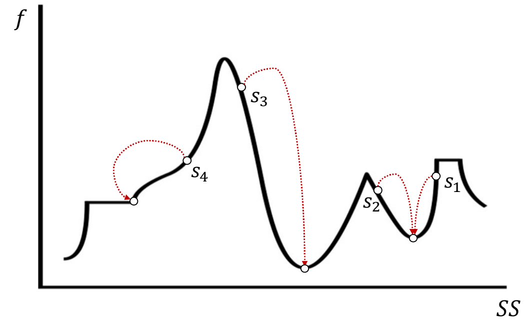


Methodology

Greedy Randomized Adaptive Search Procedure (GRASP)

Main steps:

1. Generate an initial solution.
2. Improve it through an improvement method.
3. Restart the procedure (step 1).



Methodology

Path Relinking

Main contributions:

1. **Combines solutions** of similar quality to generate new, potentially better solutions.
2. Combines different search methods into a single structure, being **flexible** and **adaptable** to a wide range of optimization problems.
3. It uses information from previous solutions to **guide the search**, allowing it to target **promising** regions of the search space.

Main variants that determine how to explore the search space:

1. Static Path Relinking.
2. Dynamic Path Relinking.
3. Adaptive Path Relinking.

Used in TSS

Methodology

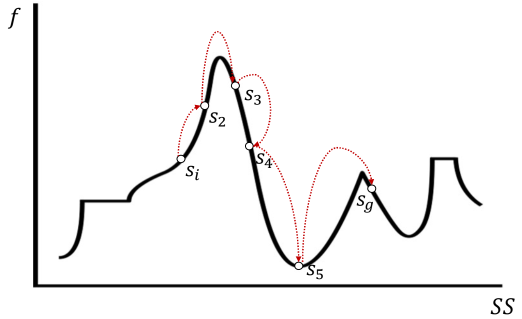
Path Relinking

Strategies:

1. **Interior Path Relinking** (**IPR**): connect two high-quality solutions replacing non-existing nodes in both solutions, the fact if that two good solutions could find new good solutions.
2. **Exterior Path Relinking** (**EPR**): follows the opposite idea of IPR, removal nodes that are in both solutions, the main idea is **diversify**.
3. **Reactive Path Relinking** (**RPR**): combines IPR and EPR **according solution similarity**. If high similarity, then IPR to favor intensification else EPR to favor diversification. **It is a related work from this doctoral thesis**.

Methodology

Path Relinking



Advanced strategies

Overview

- Propose ideas for improving local search **efficiency**:
  - Find better **quality** solutions.
  - Reduce computing **time**.
  - Scalability.
- Strategies of **general applicability**, not only for a specific problem or for the SNIMP family, but also for other optimization problems.

Advanced strategies

Objective function factorization

- **Motivation:** to reduce the computational time of the Montecarlo.
- **Objective:** to avoid recalculating metrics that can be stored in cache.
- **Strategies:**
  - Store influence given by seed sets.
  - Parallel Montecarlo execution.
  - Random performance.
  - Use profiler to analyze the performance and improve it.
  - Reduce number of Montecarlo simulations.

Advanced strategies

Neighborhood reduction

- **Motivation**: to reduce the computational time of the local search.
- **Objective**: to avoid exploring lower-quality solutions.
- **Strategies:**
  - Restrict moves by selecting a subset of promising nodes.
  - Discard nodes that do not met the budget.
  - Detect promising nodes without Montecarlo.

Outline

1. Introduction
2. Social Network Influence Problems
3. Methodology
4. Discussion of results
   - 4.1 Results for the SNIMP
   - 4.2 Results for the BIMP
   - 4.3 Results for the TSS
5. Conclusions and future work

Discussion of results

Methodology

1. Instances & Preliminary experimentation.
   - Request instances.
   - Generate instances.
   - Preliminary analysis.
   - Generate test set.
2. Competitive Testing.
   - Obtain state-of-the-art source code.
   - Execute the algorithms.
   - Numerical analysis.
   - Statistical testing: nonparametric tests.
3. Conclusions & Contribution.

Discussion of results

Methodology - Experimental environment

- Programming Language: Java 9 – 17.
- *Metaheuristic Optimization frameworRK* (MORK) 10-13.
- Experimental machine: AMD EPYC 7282 16 cores CPU with 32Gb of RAM & Intel Core i7 (2.6 GHz) with 8GB RAM.
- Performance metrics:
  - **Avg.**: objective function value.
  - **Time (s)**: run time measured in seconds.
  - **Dev (%)**: average deviation from the best-known solution.
  - **Gap (%)**: average deviation from the optimal solution.
  - **Best**: times that the algorithm is able to reach the best solution in the experiment.
  - **Optimal**: number of times that the algorithm is able to reach the optimal solution in the experiment.

Results for the **SNIMP**

Instances & Preliminary experimentation

Instance	Nodes	Edges
WikiVote	7115	103689
ca-AstroPh	18772	198110
ca-CondMat	23133	93497
cit-HepPh	34546	421578
email-Enron	36692	183831
p2p-Gnutella31	62586	147892
email-EuAll	265214	420045

Total: 7·|K| = 35

SNAP

https://snap.stanford.edu/

https://grafo.etsii.urjc.es/SNIMP

- Adjust α **parameter** = Random.
- Determine the number of explored nodes in the neighborhood for the local search phase = 20.
- IDM = ICM.
- K = [10, 20, 30, 40, 50].

Results for the **SNIMP**

Competitive testing

Algorithm	Avg.	Time (s)	Dev (%)	Best
CELF	208.33	**5.55**	6.59	0
CELF++	221.49	60.09	4.25	0
PSO	195.54	1146.71	18.93	0
GRASP	**236.37**	39.04	**0.00**	**35**

Results for the **SNIMP**

Conclusions & Contribution

- A **novel metaheuristic** approach for dealing with the SNIMP.
- Two **constructive** procedures are **proposed**.
- Intelligent neighborhood exploration strategy is parameterized being **highly scalable**.
- Results are **supported** by **Friedman** test and then the pairwise **Wilcoxon** test.

Results for the **BIMP**

Instances & Preliminary experimentation

Instance	Nodes	Edges
Ca-HepT	9877	25998
Ca-CondMat	23133	93497
HC Twitter	54836	89059
soc-Epinions1	75879	405740

Total: 4·|Budget|·|IDM| = 84.

- Adjust α parameter = Random.
- Maximum number of iterations Ψ in the local search phase = 500.
- IDM = [ICM (1%), ICM (2%), WCM, TV].
- Budgets = [2000, 2600, 6000, 10000, 140000, 180000, 22000].

https://snap.stanford.edu/

https://grafo.etsii.urjc.es/BIMP

Results for the **BIMP**

Competitive testing

IDM	Algorithm	Avg.	Time (s)	Dev (%)	Best
ICM (1%)	ComBIM	8319.68	214.97	17.64	0
	GRASP	**8872.61**	**117.06**	**0.00**	**21**
ICM (2%)	ComBIM	14467.65	215.31	6.49	3
	GRASP	**14828.77**	**146.21**	**0.07**	**18**
WCM	ComBIM	2277.79	214.04	57.49	0
	GRASP	**10087.08**	**97.80**	**0.00**	**21**
TV	ComBIM	1976.11	214.68	39.01	0
	GRASP	**2677.58**	**69.65**	**0.00**	**21**
Summary	ComBIM	6760.31	214.75	30.18	3
	GRASP	**9116.51**	**107.68**	**0.02**	**81**

Results for the **BIMP**

Conclusions & Contribution

- **Robust comparison** with four influence diffusion models.
- A **scalable algorithm** for solving BIMP.
- A **real-life instance** generated based on tweets in the Healthcare area.
- Results are **supported by Friedman** test and then the pairwise **Wilcoxon** test.

Results for the **TSS**

Instances & Preliminary experimentation

Instance	Nodes	Edges
Optimal value is known (82)	10-58	100-3364
Prison*	67	4489
email-Eu-core	1005	25571
ego-Facebook	4039	88234
ca-GrQc	5242	14496
Twitch EN	7126	35324
LastFM Asia	7624	27806
ca-HepTh	9877	25998
BlogCatalog3	10312	333983

Total: 90

- Adjust α parameter = Random.
- Select greedy function = Based on degree.
- Local search = Advanced local search.

https://snap.stanford.edu/
https://grafo.etsii.urjc.es/TSS
http://vlado.fmf.uni-lj.si/pub/networks/data/UciNet/UciData.htm
http://datasets.syr.edu/datasets/BlogCatalog3.html

Results for the **TSS**

Competitive testing

Optimal value is known

Algorithm	Avg.	Time (s)	Gap (%)	Optimal
Gurobi	**45.38**	117.14	**0.00**	**82**
SA	46.31	**0.01**	4.86	76
CELF	42.07	**0.01**	12.19	61
SPR	44.54	**0.01**	1.82	79
DPR	44.34	**0.01**	2.58	76

Large instances

Algorithm	Avg.	Time (s)	Dev (%)	Best
SA	23302.00	4534.97	1.71	5
CELF	23514.13	33652.97	2.23	3
SPR	23629.00	**715.71**	0.44	3
DPR	**23716.63**	3025.87	**0.12**	**6**

Results for the **TSS**

Conclusions & Contribution

- **SPR** and **DPR** are able to provide high-quality solutions. If the computing time is a hard constraint **SPR** else **DPR**.
- Proposed **local search** is **optimized** by reducing the evaluation of the objective function.
- **Dataset** of instances has been **extended** with real-life networks.
- Results are **supported** by **Friedman** test and then the pairwise **Wilcoxon** test.

Outline

General conclusions

Hypothesis:

✓ *Heuristic and metaheuristic techniques can find high-quality solutions to Social Network Influence Problems.*

Achieved objectives:

✓ Review and analyze the current **state of the art**.

✓ Obtain **properties** and structural **characteristics** of the problem.

✓ Propose a **heuristic algorithm** to solve each problem and **compare** it with state-of-the-art algorithms.

✓ **Document** and **disseminate** the research results through this dissertation and publications in scientific forums.

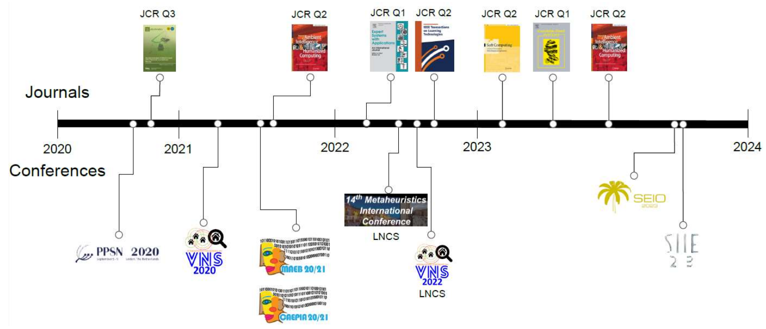
✓ **Make publicly available** the **source code** and instances to ease further comparison.

Future lines of research

- **Dynamic social networks** in real time marketing campaigns in **real time**.
- **Robust Influence Diffusion Models** to evaluate influence propagation.
- **Influence minimization:** fake news and the spread of rumors are on the rise.

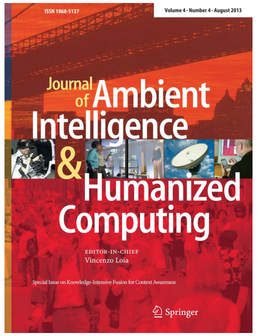
Main contributions

Timeline



Main contributions

3 JCR publications

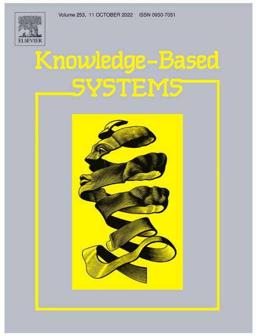


Isaac Lozano-Osorio, Jesús Sánchez-Oro, Oscar Cordón and Abraham Duarte. A quick GRASP-based method for influence maximization in social networks. ***Journal of Ambient Intelligence and Humanized Computing***, 14, 3767-3779, 2023 (**JCR**, **Q2, 2021**).

Constructive: Based on first and second neighbor out-degree.
Local Search: First Improvement & Swap neighborhood.
Metaheuristic: GRASP.

Main contributions

3 JCR publications

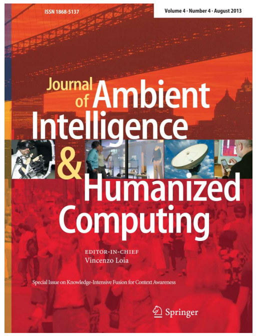


Isaac Lozano-Osorio, Andrea Oliva García and Jesús Sánchez-Oro. Dynamic Path Relinking for the Target Set Selection problem. ***Knowledge-Based Systems***, 278:110827, 2023 (**JCR**, **Q1, 2022**).

Constructive: Based on degree.
Local Search: First Improvement & Replace neighborhood.
Metaheuristic: GRASP + Path Relinking.

Main contributions

3 JCR publications



Isaac Lozano-Osorio, Jesús Sánchez-Oro and Abraham Duarte. An efficient and effective GRASP algorithm for the Budget Influence Maximization Problem. ***Journal of Ambient Intelligence and Humanized Computing***, -, -, 2024 (**JCR**, **Q2, 2021**).

Constructive: Prioritizes nodes that do not have selected.
Local Search: First Improvement & Replace neighborhood.
Metaheuristic: GRASP.

Main contributions

6 Workshops

- 3 Workshops **GRAFO**.
- 1 **Escuela de Invierno** organized by Red HEUR.
- 1 Workshop **Optimad**.
- 1 Workshop in International Conference on Parallel Problem Solving from Nature (**PPSN 2020**).
- Participation in the **5th "Thesis in 3 Minutes" contest**.

Main contributions
3 National Conferences

Isaac Lozano-Osorio, Jesús Sánchez-Oro, Oscar Cordón and Abraham Duarte. Nuevos algoritmos metaheurísticos para el análisis de la influencia de los usuarios en las redes sociales. ***XIX Conferencia de la Asociación Española para la Inteligencia Artificial***, Málaga, 2021.

Isaac Lozano-Osorio, Jesús Sánchez-Oro and Abraham Duarte. Optimización heurística de problemas relacionados con redes sociales. ***XIX Conferencia de la Asociación Española para la Inteligencia Artificial***, Málaga, 2021.

Isaac Lozano-Osorio, Andrea Oliva García and Jesús Sánchez-Oro. Path Relinking Dinámico para el problema Target Set Selection. ***XL Congreso Nacional de Estadística e Investigación Operativa***, Elche, 2023.

Main contributions
4 International Conferences

Isaac Lozano-Osorio, Jesús Sánchez-Oro, Oscar Cordón and Abraham Duarte. Measuring the influence of users in social networks using Variable Neighborhood Search. ***ICVNS 2021***, Abu Dhabi, U.A.E.

Isaac Lozano-Osorio, Jesús Sánchez-Oro and Abraham Duarte. Multi-Round Influence Maximization: A Variable Neighborhood Search Approach. ***Lecture Notes in Computer Science***, *vol 13863*, 2023.

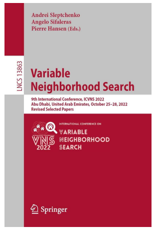
Anna Martínez-Gavara, **Isaac Lozano-Osorio**, Rafael Martí and Abraham Duarte. Multi-start variable neighborhood search for the dispersion problem with capacity and cost constraints, ***ICVNS 2022***, Abu Dhabi, U.A.E.

Main contributions
4 International Conferences

Isaac Lozano-Osorio, Jesús Sánchez-Oro, Anna Martínez-Gavara, Ana D. López-Sánchez and Abraham Duarte. An Efficient Fixed Set Search for the Covering Location with Interconnected Facilities Problem. ***14th Metaheuristics International Conference***, *Ortigia-Syracuse, Italy.*

Isaac Lozano-Osorio, Jesús Sánchez-Oro, Abraham Duarte and Kenneth Sörensen. What characteristics define a Good Solution in Social Influence Minimization Problems? ***15th Metaheuristics International Conference***, *Lorient, France.*

Main contributions
2 Related SJR publications

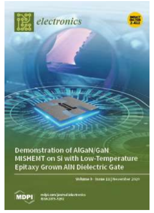


Isaac Lozano-Osorio, Jesús Sánchez-Oro and Abraham Duarte. Multi-Round Influence Maximization: A Variable Neighborhood Search Approach. ***Lecture Notes in Computer Science***, *vol 13863*, 2023.

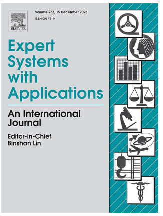
Isaac Lozano-Osorio, Jesús Sánchez-Oro, Anna Martínez-Gavara, Ana D. López-Sánchez and Abraham Duarte. An Efficient Fixed Set Search for the Covering Location with Interconnected Facilities Problem. ***Lecture Notes in Computer Science***, *vol 13838*, 2023.

Related contributions

4 Related JCR publications



Isaac Lozano-Osorio, et al. Optimizing Computer Networks Communication with the Band Collocation Problem: A Variable Neighborhood Search Approach. ***Electronics***, 9:1860, 2020 (**JCR**, **Q3**).



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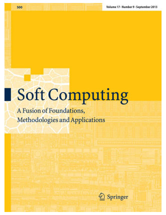

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Funding & Projects

- Project “**Cybersecurity, Network Analysis and Monitoring for the Next Generation Internet.**”, Comunidad de Madrid y Fondos Estructurales de la Unión Europea with grant ref. P2018/TCS-4566.
- Project “**Metaheurísticas eficientes para la optimización en grafos**”, funded by Spanish Ministerio de Ciencia, Innovación y Universidades under grant ref. PGC2018-095322-B-C22.
- Project “**Nueva metodología holística para la configuración, comparación y evaluación de metaheurísticas.**”, grant ref PID2021-126605NB-I00.
- Universidad Rey Juan Carlos “contratos Predoctorales de Personal en Formación en Departamentos de la Universidad”, grant ref 2021/PREDOC21-007-2145.

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