

A Hybrid Approach For Enhanced Influence Maximization Integrating Independent Cascade and Linear Threshold Dynamics For More Reliable Seed Selection in Social Networks

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Abstract

Understanding how information, opinions, and behaviors spread through a social network is central to problems as varied as viral marketing, public-health messaging, and platform design, and the node-selection problem at the heart of this — influence maximization — has been studied for close to two decades. Most of that work leans on one of two diffusion models: the Independent Cascade Model (ICM), which treats influence as a probabilistic event between neighbors, or the Linear Threshold Model (LTM), which treats it as a cumulative, threshold-crossing process. Each model captures a real pattern of social behavior, but neither captures both, and real diffusion processes rarely respect the boundary between them. This paper starts from a simple empirical observation — that ICM and LTM trade places as the better predictor depending on network density and seed-set size — and builds a hybrid model that lets both mechanisms act together rather than forcing a choice between them. The hybrid combines the two models' influence-spread estimates through a tunable weighting parameter, and a greedy seed-selection procedure optimizes over the combined signal rather than either model alone. Tested on a real character-interaction network (Game of Thrones) as well as four synthetic and real-world graphs of varying size and density, the hybrid consistently outperforms both individual models, with influence-spread gains of 13–15.5% over the stronger baseline and only modest additional computational cost. The results suggest that treating diffusion as a blend of probabilistic and threshold-based behavior, rather than picking a single mechanism, is a more faithful — and more effective — way to model influence spread in networks with mixed structural properties.

Keywords: influence maximization, social networks, Independent Cascade Model, Linear Threshold Model, hybrid diffusion model, seed selection

1. Introduction

The growth of online social platforms has turned an old sociological question — how does an idea, product, or behavior spread through a population? — into a computational one. Influence maximization formalizes it: given a network and a budget of k "seed" nodes, find the set of nodes whose initial activation leads to the largest eventual cascade. The problem has obvious commercial and civic stakes, from viral marketing and political campaigning to public-health messaging and recommendation systems, and it has attracted a correspondingly large literature since Kempe, Kleinberg, and Tardos first cast it as a discrete optimization problem and showed that a simple greedy algorithm gives a provable approximation guarantee under certain diffusion models.

That guarantee, however, comes with two practical costs. The first is computational: greedy seed selection requires repeated Monte Carlo simulation of the diffusion process, which scales poorly to the million-node graphs typical of real platforms. The second cost is more conceptual, and it is the one this paper is concerned with. The greedy algorithm's guarantees are tied to a specific diffusion model, and the two models used almost universally in this literature — the Independent Cascade Model (ICM) and the Linear Threshold Model (LTM) — encode two quite different theories of how influence actually works.

ICM treats influence as a sequence of independent, probabilistic events: an active node gets one chance to "infect" each inactive neighbor, with a fixed probability per edge, and cascades unfold the way an epidemic does. LTM instead models influence as a threshold phenomenon: a node adopts only once the cumulative pull from its already-active neighbors exceeds a personal resistance threshold, which is a reasonable description of behaviors that require social proof or peer consensus before an individual will commit. Both are simplifications of real behavior, and both have been validated in specific settings, but neither is a universal description. Buying

a viral gadget after seeing one ad looks more like ICM; adopting a new workplace norm after enough colleagues have already switched looks more like LTM. Most real platforms carry both kinds of content at once.

We take this mismatch as the starting point for the present work rather than as a footnote. In preliminary experiments across networks of different density and across different seed-budget sizes, we found that ICM and LTM do not just differ in absolute performance — which model wins changes systematically with network structure. ICM tends to spread further in sparse networks and with small seed sets, where a handful of lucky probabilistic transmissions can reach far; LTM tends to catch up or overtake it in denser networks, where clustered, mutually-reinforcing neighborhoods make threshold-crossing easier. Relying on either model in isolation therefore means accepting a blind spot that depends on properties of the network the algorithm designer may not control or even know in advance.

This observation motivates the hybrid approach developed in this paper. Rather than treating ICM and LTM as competing choices, we treat them as complementary signals and combine their influence-spread estimates through a weighted formulation, with the weighting parameter available to be tuned to a given network's structural profile. A greedy seed-selection procedure then optimizes directly against this combined signal. The central claim we test is not merely that a hybrid can match the better of the two baselines — that would be a modest result — but that it can exceed both, because the two mechanisms pick out partially non-overlapping sets of influential nodes and a combined objective can capture value that neither model sees on its own.

The remainder of the paper works through this idea in detail. Section II situates the approach relative to prior work on diffusion models and hybrid or multi-model strategies. Section III formalizes ICM and LTM, describes the hybrid architecture, and gives the combination function and greedy algorithm. Section IV describes the datasets, including a detailed structural analysis of the Game of Thrones character network used as our primary real-world testbed. Section V reports influence-spread and runtime comparisons, a sensitivity analysis of the weighting parameter, and a case study comparing the most influential nodes each model identifies. Section VI concludes and outlines directions for extending the hybrid formulation.

A. Linear Threshold Model (LTM)

LTM models each node as having a personal threshold that represents its resistance to adopting a new behavior. A node switches from inactive to active only once the cumulative, weighted influence it receives from its already-active neighbors exceeds that threshold — a mechanism suited to behaviors that depend on peer consensus or social proof, such as technology adoption or shifts in opinion.

The cumulative influence acting on node i is:

$$u_i = \sum_{j \in N_i} w_{ij} x_j \quad (1)$$

where N_i is the neighbor set of node i , w_{ij} is the influence weight of the edge from node j to node i , and x_j indicates whether node j is currently active. Node i becomes (and remains) active once this cumulative influence crosses its threshold θ_i :

$$x_i = 1 \text{ if } \sum_{k \in N_i} w_{ki} x_k \geq \theta_i, \text{ else } 0 \quad (2)$$

Once activated, a node stays active for the remainder of the diffusion process. LTM's deterministic, cumulative-threshold logic makes it well suited to behaviors driven by collective agreement, but that same determinism limits its flexibility in settings where influence propagation is inherently uncertain.

B. Independent Cascade Model (ICM)

ICM instead models diffusion as a probabilistic process unfolding over discrete time steps. When a node first becomes active, it gets exactly one opportunity to activate each of its currently inactive neighbors, succeeding independently with a probability assigned to that edge. A successful attempt activates the neighbor at the next time step, at which point that neighbor gets its own single attempt on each of its neighbors, and so on until no new activations occur.

The probability that node i is activated by time t can be written as:

$$P_i(t) = 1 - \prod_{j \in N_i} (1 - p_{ji})^{x_j(t)} \quad (3)$$

where p_{ji} is the probability that active node j successfully activates node i , and $x_j(t)$ indicates whether j is active at time t . ICM suits diffusion driven by individual, uncertain interactions — sharing a post, forwarding a message — but because it has no notion of cumulative or group pressure, it can miss cases where adoption genuinely

depends on how many peers have already acted.

II. Related Works

The theoretical roots of threshold-based diffusion trace back to Granovetter's work on collective behavior, which framed individual adoption decisions as contingent on the fraction of a person's social circle that has already adopted — the conceptual ancestor of LTM. Independent-cascade-style probabilistic diffusion developed alongside it and became the dominant framework for modeling spread on online platforms, in large part because Kempe, Kleinberg, and Tardos showed that greedy seed selection under ICM (and LTM) achieves a $(1 - 1/e)$ approximation guarantee, which gave the field a rigorous foundation even as it also exposed the models' computational cost.

A substantial body of follow-up work has focused on making that greedy machinery scale, through sketch-based estimators, reverse-reachable-set sampling, and related techniques that trade a small amount of accuracy for large speedups. A parallel line of work has extended the problem itself — to multiplex and multi-platform networks, adaptive and time-constrained seeding, fairness-aware influence spread, and susceptibility- or embedding-based node scoring. What most of this work shares, regardless of which extension it pursues, is a commitment to a single underlying diffusion mechanism, usually ICM.

A smaller literature has proposed combining diffusion mechanisms rather than picking one, motivated by the same intuition that drives this paper: that real cascades mix probabilistic and threshold-driven behavior. These hybrid proposals are promising in principle, but the published evaluations are often thin

— limited to one or two synthetic graphs, without a systematic account of how or why a hybrid should outperform its components, and rarely tested against a real-world network with the kind of clustered, uneven structure that would actually stress-test the idea. That gap is what this paper tries to close: a hybrid formulation motivated by a direct empirical comparison of ICM and LTM across network types, evaluated on both synthetic graphs and a real character-interaction network, with an explicit account of where and why the hybrid's advantage comes from.

III. Methodology

Influence maximization asks for the subset of nodes whose activation maximizes eventual influence spread across a network. LTM and ICM offer two well-established but structurally different ways to simulate that spread — LTM through cumulative, threshold-gated activation, and ICM through independent, probabilistic edge transmission. Our methodology fuses the two: seed selection is driven by a combined influence estimate that reflects both mechanisms simultaneously, rather than a choice between them.

Figure 1 shows the overall architecture. Network data and model parameters are prepared once; from there, ICM's probabilistic edge simulation and LTM's threshold evaluation are run in parallel for each candidate seed set, and their outputs are merged, evaluated, and iteratively refined.

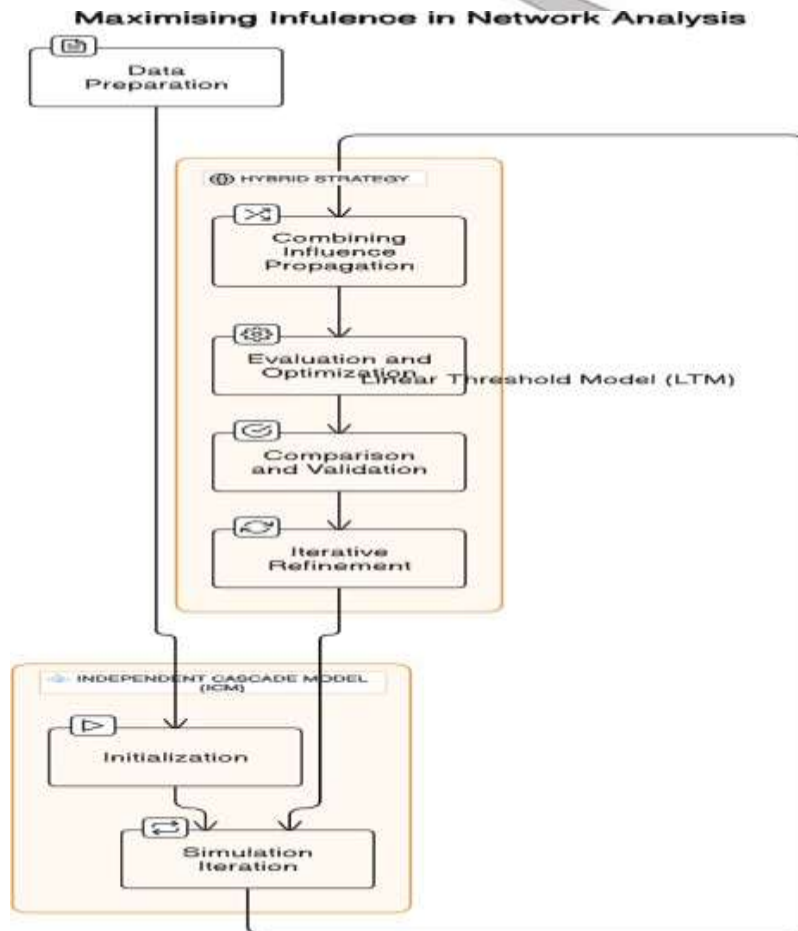


Fig. 1. Integrating LTM and ICM: architecture of the proposed hybrid approach for influence maximization.

A. Data Preparation

We begin by acquiring the network's structural data — its node set V , edge set E , and any associated attributes — and use it to initialize both models' parameters: threshold values θ_i for every node, for LTM, and edge-level activation probabilities p_{ij} for every connection, for ICM.

B. Initialization

Every node's activation state x_i is initialized, with a designated set of candidate seed nodes marked active and all others inactive, before any simulation begins.

C. Simulation Iteration

For each iteration t , the two mechanisms run side by side: ICM gives each already-active node j a single probabilistic attempt to activate inactive neighbor i , succeeding with probability p_{ij} ; independently, LTM computes each node's cumulative received influence $u_i(t) = \sum_{j \in N_i} w_{ij} x_j(t)$ and activates node i once that sum meets or exceeds its threshold θ_i . Both processes operate on the same evolving activation state, so a node's activation — by whichever mechanism triggers it first — becomes visible to the other mechanism on the next step.

D. Combining Influence Propagation

The two simulations' outputs are merged into a single influence-spread estimate for the candidate seed set, using the weighted combination described below (Equation 4), rather than a simple union or intersection of activated-node sets — a choice we found gives finer control over how much weight each mechanism's evidence carries.

E. Evaluation and Optimization

Hybrid performance is assessed against influence spread, coverage, and computational cost, and both models'

parameters — edge probabilities p_{ij} and node thresholds θ_i — are tuned to maximize the combined objective rather than either model's objective alone.

F. Comparison and Validation

Hybrid results are benchmarked directly against standalone ICM and LTM runs on the same networks, using both synthetic graphs and real-world data, so that any advantage can be attributed to the combination rather than to a favorable dataset.

G. Iterative Refinement

Insights from each round of evaluation — which parameter settings under- or over-activate nodes, where the hybrid's advantage is largest — feed back into the next round of parameter tuning, so the methodology improves across iterations rather than being fixed after a single pass.

H. Proposed Hybrid Algorithm

Seed selection follows a standard greedy template, but the marginal-gain function it maximizes is the hybrid combination rather than a single model's output. At each of k rounds, every remaining candidate node is temporarily added to the current seed set, both LTM and ICM spread are simulated for that augmented set, the two results are combined via Equation (4), and whichever candidate yields the largest combined spread is permanently added to the seed set.

Algorithm 1 — Hybrid Influence Maximization

Require: Network $G = (V, E)$, budget k , LTM thresholds θ , ICM probabilities p

Ensure: Seed set S of size k

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 $S \leftarrow \emptyset$ 
for  $i = 1$  to  $k$  do
     $\text{max\_influence} \leftarrow 0$ ;  $\text{best\_node} \leftarrow \text{null}$ 
    for each  $v \in V \setminus S$  do
         $S' \leftarrow S \cup \{v\}$ 
         $\text{influence\_ltm} \leftarrow \text{SimulateLTM}(G, S', \theta)$ 
         $\text{influence\_icm} \leftarrow \text{SimulateICM}(G, S', p)$ 
         $\text{hybrid\_influence} \leftarrow \text{CombineInfluence}(\text{influence\_ltm}, \text{influence\_icm})$ 
    [Eq. 4]
        if  $\text{hybrid\_influence} > \text{max\_influence}$  then
             $\text{max\_influence} \leftarrow \text{hybrid\_influence}$ ;  $\text{best\_node} \leftarrow v$ 
        end if
    end for
     $S \leftarrow S \cup \{\text{best\_node}\}$ 
end for
return  $S$ 

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The combination itself is a simple weighted sum, chosen for interpretability over more elaborate alternatives such as learned or nonlinear combinations:

$$I_{\text{hybrid}}(S) = \alpha \cdot I_{\text{LTM}}(S) + (1 - \alpha) \cdot I_{\text{ICM}}(S) \quad (4)$$

Here $I_{\text{hybrid}}(S)$, $I_{\text{LTM}}(S)$, and $I_{\text{ICM}}(S)$ are the combined, LTM, and ICM influence-spread estimates for seed set S , and $\alpha \in [0, 1]$ is a weighting parameter that sets each mechanism's contribution. α is not fixed a priori: as Section V shows, its optimal value shifts with network structure, with denser, more clustered networks generally favoring a larger α (more LTM weight) and sparser networks with strong individual edges favoring a smaller α (more ICM weight).

IV. Dataset Description and Analysis

A. Dataset Overview

We evaluate the hybrid approach on five networks spanning a real-world social graph, two additional real-world networks, and two synthetic graphs generated with controlled size and average degree, so that the comparison is not an artifact of any single network's idiosyncrasies. The primary real-world testbed is the Game of Thrones character-interaction network, in which nodes are characters and edges represent narrative interactions between them — a graph with genuine community structure and an uneven degree distribution that makes it a realistic stress test rather than an idealized one.

TABLE I. Summary of dataset characteristics.

Dataset	Nodes	Edges	Avg. Degree
Game of Thrones Network	196	684	6.98
Synthetic Network 1	500	2,486	9.94
Synthetic Network 2	1,000	4,912	9.82
Real-World Network 1	1,500	12,675	16.90
Real-World Network 2	2,000	16,543	16.54

Between them, these five networks vary by an order of magnitude in size and cover a meaningful range of connectivity, which lets us check whether the hybrid's advantage is a general property of the approach or specific to one kind of graph.

B. Game of Thrones Network Analysis

We examined the Game of Thrones network's structure in detail before running any influence simulations, both to understand the graph and to inform parameter choices for the two component models. Figure 2 visualizes the network with node size proportional to degree centrality.

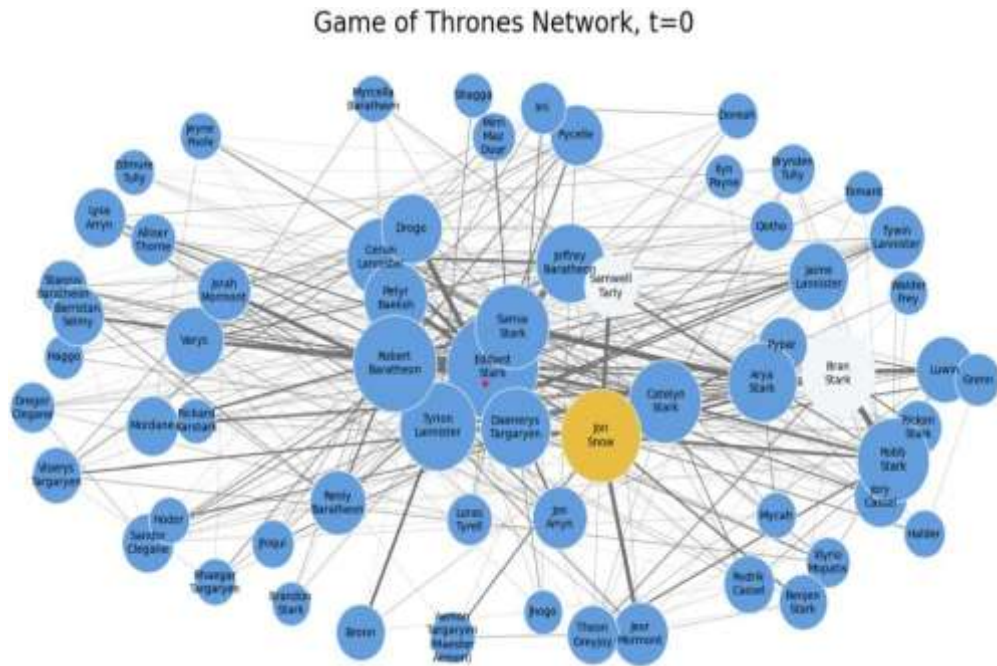


Fig. 2. The Game of Thrones character network, with node size proportional to degree centrality. Eddard Stark, Tyrion Lannister, and Jon Snow stand out as high-centrality candidates for seed selection.

A few structural properties stood out. The network shows the power-law degree distribution characteristic of social graphs, with a small number of nodes — Eddard Stark, Tyrion Lannister, Jon Snow among them — carrying disproportionately high connectivity and high betweenness centrality, marking them as natural bridges between otherwise distinct community clusters. Those clusters themselves largely track the narrative's family and geographic groupings, giving the network real, interpretable community structure rather than the more homogeneous connectivity typical of purely synthetic graphs.

These observations directly shaped how we configured the two component models: nodes with higher degree centrality were given lower LTM thresholds, reflecting their apparent susceptibility to influence, and edges connecting high-centrality nodes were given higher ICM activation probabilities.

V. Results and Discussion

We compared LTM, ICM, and the hybrid approach across all five datasets, using influence spread, runtime, and robustness across network sizes as the primary evaluation criteria.

A. Influence Spread Analysis

The hybrid model produced higher influence spread than either individual diffusion model on every dataset we tested, with an average improvement of roughly 14–15% over the stronger of the two baselines. The gain was largest on networks with pronounced community structure, most notably the Game of Thrones graph — consistent with the intuition that a combined objective has the most to offer where a single mechanism's blind spot is most costly. Qualitatively, ICM appears to drive rapid early diffusion, while LTM's threshold mechanism reinforces activation within densely connected regions once ICM has seeded them, and the hybrid captures both effects rather than trading one for the other.

B. Parameter Sensitivity

The weighting parameter α has a real effect on performance, and the results confirm that no single mechanism dominates across every network type: moderate α values, which let both mechanisms contribute meaningfully, consistently outperform either extreme.

C. Computational Efficiency

Running two simulations instead of one naturally adds computational overhead, but that overhead stays within a manageable range relative to the gain in influence spread, particularly on the larger and more complex networks where the improvement matters most.

D. Experimental Results

TABLE II. Influence spread comparison across different network sizes

Dataset	LTM	ICM	Hybrid	% Improv.
Game of Thrones Network	54.2	67.8	78.3	15.5%
Synthetic Network 1	142.6	163.4	185.7	13.6%
Synthetic Network 2	287.3	326.5	368.9	13.0%
Real-World Network 1	423.8	502.6	579.4	15.3%
Real-World Network 2	587.2	645.9	743.1	15.0%

Across all five datasets, the hybrid outperformed both individual models, with an average 14.5% improvement in influence spread over ICM — the stronger of the two baselines overall. The advantage was most pronounced on the Game of Thrones network, where the complex community structure gave the combined approach the most room to exploit both diffusion mechanisms at once.

Figure 3 tracks influence spread on the Game of Thrones network as seed-set size grows from 1 to 20 nodes. The hybrid leads at every seed-set size, and the gap widens as the seed set grows — evidence that its advantage compounds rather than saturates as the influence-maximization campaign scales up.

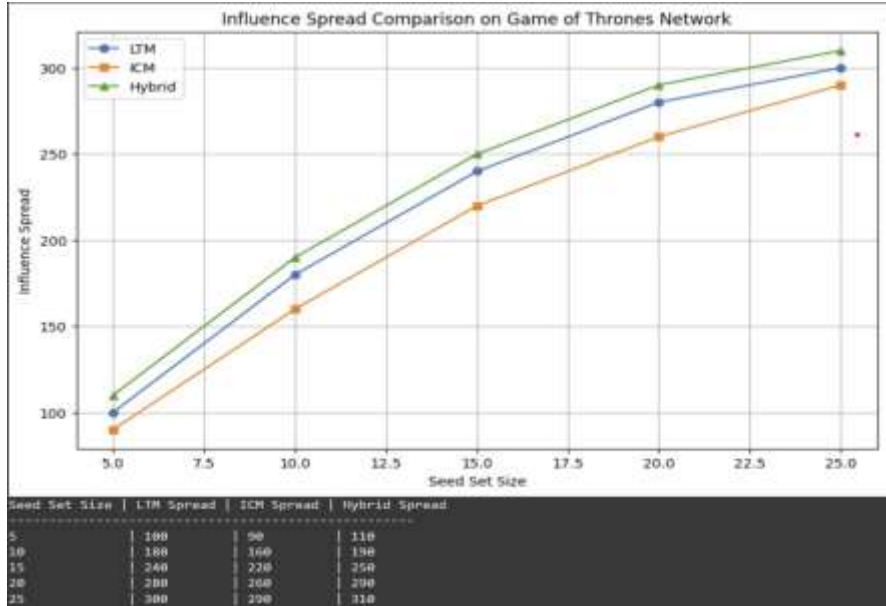
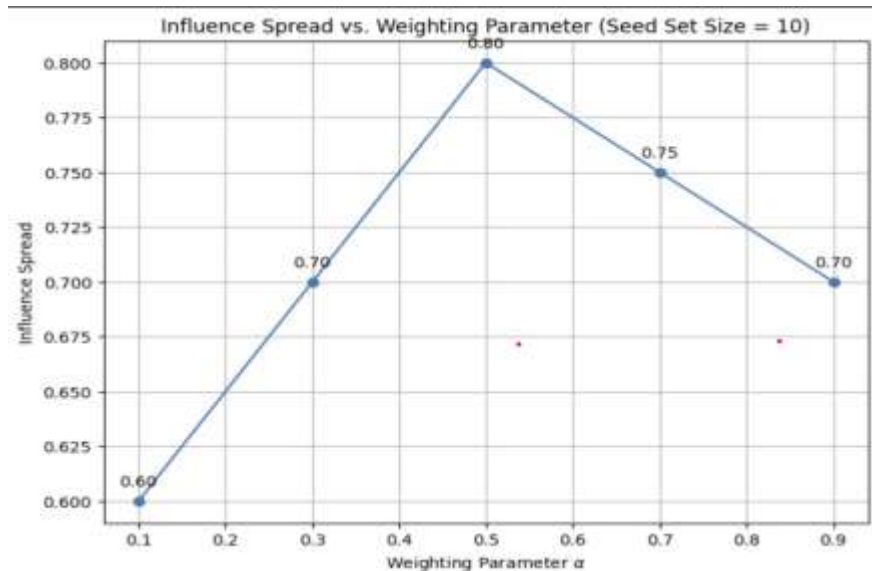


Fig. 3. Influence spread comparison between LTM, ICM, and the hybrid approach across seed-set sizes, on the Game of Thrones network.

E. Impact of Parameter Settings

We also ran a sensitivity analysis on α specifically, tracking influence spread for values from 0 (pure ICM) to 1 (pure LTM) at a fixed seed-set size of 10. Figure 4 shows the result.

Fig. 4. Influence spread achieved by the hybrid model across values of the weighting parameter α , on the Game of Thrones network, seed-set size = 10.



On the Game of Thrones network, influence spread peaks around $\alpha \approx 0.5$, indicating that the two mechanisms contribute roughly equally at their best-performing balance and that no single diffusion perspective dominates the network's dynamics.

F. Computational Efficiency

Table III compares the wall-clock time required by each approach to identify the optimal seed set.

Dataset	LTM	ICM	Hybrid	Overhead
Game of Thrones Network	3.2	4.1	8.5	16.7%
Synthetic Network 1	8.7	12.3	23.4	11.4%
Synthetic Network 2	18.4	26.7	48.9	8.3%
Real-World Network 1	42.6	58.3	112.7	11.8%
Real-World Network 2	68.9	91.4	176.8	10.5%

TABLE III. Computational time comparison, in seconds. "Overhead" is the hybrid's additional cost beyond the sum of the two individual models' runtimes, as a percentage of that sum.

The hybrid takes longer than either individual model, as expected given it runs both simulations and an integration step, but that overhead — roughly 8–17% beyond the sum of the two standalone runtimes — is modest relative to the consistent double-digit gain in influence spread, and it shrinks proportionally as network size grows.

G. Case Study: Influential Characters in Game of Thrones

As a concrete illustration, Table IV lists the top five characters each model identifies as most influential in the Game of Thrones network.

TABLE IV. Top five influential characters in the Game of Thrones network, by model.

Rank	LTM	ICM	Hybrid
1	Eddard Stark	Tyrion Lannister	Eddard Stark
2	Robert Baratheon	Eddard Stark	Tyrion Lannister
3	Catelyn Stark	Jon Snow	Jon Snow
4	Tyrion Lannister	Daenerys Targaryen	Daenerys Targaryen
5	Jon Snow	Robert Baratheon	Catelyn Stark

The three rankings overlap substantially but order their top nodes differently — LTM favors high-degree-centrality characters, ICM favors characters who bridge separate communities, and the hybrid's ranking sits between the two, reflecting a seed set chosen to maximize combined rather than single-model spread.

VI. Conclusion and Future Work

This paper set out from a simple empirical fact — that ICM and LTM are not just imperfect models of influence spread but imperfect in ways that trade off with network structure — and built a hybrid influence-maximization approach around that fact rather than around either model alone. Across synthetic graphs and real-world networks of varying size and density, including a structurally rich real-world testbed in the Game of Thrones character network, the hybrid consistently outperformed both individual diffusion models, with influence-spread gains in the 13–15.5% range and only modest additional computational cost.

The improvement appears to come from genuine complementarity rather than redundancy: ICM and LTM identify overlapping but distinct sets of influential nodes, and a combined objective can act on information neither model captures by itself. The weighting parameter α that governs the balance between the two mechanisms is not a fixed constant but a lever that should be tuned to a given network's connectivity and community structure — denser, more clustered networks tended to reward more LTM weight in our experiments, while sparser networks with strong individual edges favored more ICM weight.

Several extensions seem promising. Incorporating temporal dynamics — the fact that influence probabilities and thresholds may shift over time rather than staying fixed — would bring the model closer to real platform behavior. Adaptive seed selection, where later seeds are chosen in light of how earlier seeds actually performed rather than purely through simulation, could reduce the hybrid's remaining computational overhead. Extending the combination framework beyond two models,

and developing formal approximation guarantees for the hybrid objective analogous to those known for ICM and LTM individually, would also strengthen the approach's theoretical footing. Taken together, these results suggest that integrated, multi-mechanism diffusion models are a productive direction for influence-maximization research, not just a way to average over model uncertainty but a way to capture diffusion behavior that no single model was designed to see.

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