NetSciX2026: International School and Conference on Network Science
February 17^{th}-20^{th}, 2026 - Auckland, New Zealand

Control Spread via Multilayer Network Manipulation

Control Spread, Digital Twins, Influence Maximisation, mABCD, Multilayer Networks

Introduction

Spreading processes in multilayer networks – a class of graphs capable of capturing multiple types of relationships – have attracted growing attention over the recent years. One of the key problems in this space is influence maximisation [1], a form of spread control, which focuses on methods for selecting a set of nodes/actors that, when used as diffusion seeds, contribute to the most effective propagation. Although this topic has been studied from a range of perspectives, many proposed approaches remain case-specific. In practice, improvements over existing methods are often marginal and observed only in a narrow set of graphs and diffusion scenarios.

This work builds on [2], which, after evaluating a range of seed selection strategies, concludes that diffusion outcomes on the same network do not differ substantially across methods. Instead, it is the network topology that has a stronger impact on spreading effectiveness than the specific seeding strategy. This conclusion is supported by theoretical studies, such as those on spread robustness in expander graphs [3]. Following these observations, *this abstract proposes an approach to effectively control spread by modifying the multilayer network structure*.

Methodology

The proposed method is illustrated in Fig. 1 in the form of a conceptual pipeline. It assumes that the analysed real-world multirelational system is encoded into a configuration file for a synthetic graph generator, which can then be used for further modelling. By altering selected parameters of the generator, one can explore a variety of what-if scenarios and construct adjusted "digital twins" that reflect possible modifications of the original system. These can be evaluated under the assumed spreading regime, allowing an assessment of which topology is optimal from the perspective of given influence control task (e.g., maximisation). The methodology adopts `mABCD` [4] as a generator of synthetic multilayer networks, due to its high configurability and computational efficiency. Nonetheless, other tools may be used, but this component is central to the pipeline, as its parameter space define the system's structure.

Another important factor involves three types of errors. Addressing them is essential to ensure the pipeline's correctness, and in this work we aim to resolve them. The first one arises in the configuration retrieval process. For `mABCD`, this task is non-trivial, as some parameters cannot be directly inferred from the network and need to be estimated (e.g., a community division). The second type of error relates to imperfections of the synthetic graph generator, as the produced network may deviate from the specified configuration. This, however, can be mitigated by discarding graphs whose retrieved configuration diverges significantly from the provided one. Finally, the third type of error arises in the simulation of information diffusion, since spreading models remain only approximations of real-world processes. The most direct way of addressing it is to select a model matching the assumed dynamic conditions.

Results and Conclusions

At the time of submission, the work is still ongoing (currently focusing on addressing errors A and B), although preliminary results obtained using a prototype pipeline have been promising. The impact of intercommunity noise level (ξ) on spreading effectiveness under the Multilayer

Independent Cascade Model (parametrised by δ and π) is illustrated in Tab. 1. The importance of this parameter lies in its ability to model how well-defined the communities are, distinguishing pure community structure from random connections. As shown, by manipulating this parameter, diffusion can be slightly enhanced (green cell) or substantially suppressed (red cell).

This work has a strong practical aspect, so ethical considerations regarding potential misuse arise. However, most social systems are subject to oversight by administrative entities, such as social media platform owners or governments. Hence, any interventions following the proposed methodology shall be performed within the rule of law, mitigating the risk of harmful use.

References

[1] D. Kempe et al. “Maximizing the Spread of Influence Through a Social Network”. In: *9th ACM SIGKDD*. 2003, pp. 137–146.

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[3] B. Doerr et al. “Quasirandom Rumor Spreading: Expanders, Push vs. Pull, and Robustness”. In: *Automata, Languages and Programming*. 2009, pp. 366–377.

[4] P. Bródka et al. “The Multilayer Artificial Benchmark for Community Detection (mABCD)”. In: *International Workshop on Modelling and Mining Networks*. 2025, pp. 172–188.

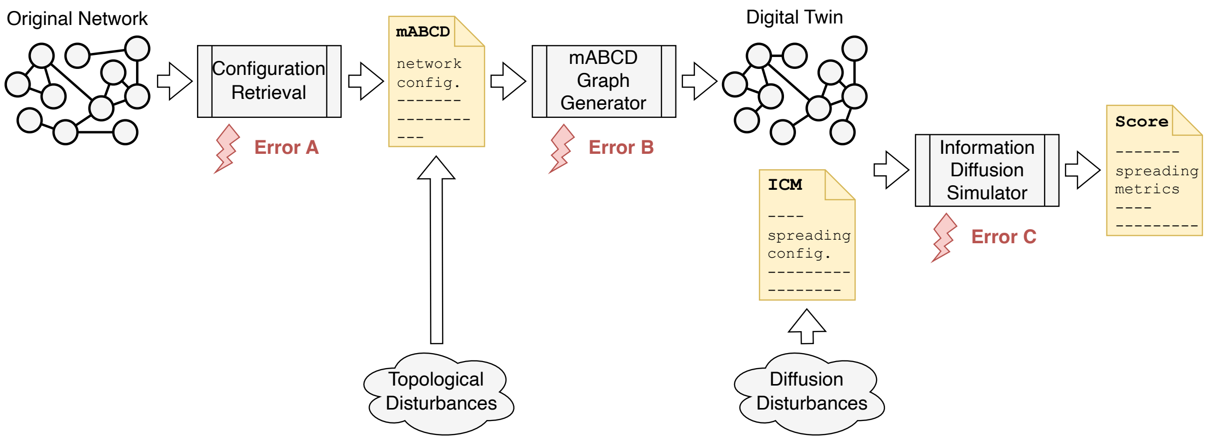

Figure 1: Spread control pipeline. The process begins by retrieving configuration parameters of the real network for the synthetic graph generator. Its digital twin is then generated and evaluated under the appropriate spreading model. Potential perturbations in its configurational model and spreading regime represent the tested what-if scenarios. The pipeline’s efficacy depends on addressing inherent errors arising from imperfections in the employed apparatus.

Table 1: Change in spreading effectiveness $[-1,1]$, where 0 indicates no difference, and positive (negative) values represent improved (reduced) penetration, achieved through MICM-driven spreading in digital twins of a real network with varying inter-community noise levels.

δ	π	ξ				
		0.01	$0.50\xi_{origin.}$	$\xi_{origin.}$	$2.00\xi_{origin.}$	1.00
AND	0.15	-0.1668	-0.0392	0.0000	0.0352	0.0397
	0.20	-0.2440	-0.0450	0.0000	0.0254	0.0290
	0.25	-0.2339	-0.0183	0.0000	0.0049	0.0041
	0.30	-0.1706	-0.0066	0.0000	0.0017	0.0018