Graph networks for influence maximization

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Influence Maximization

Presentation

Influence propagation

- Propagate ideas or influence within a network
- Diffusion of medical or technological innovation
- Spread of diseases

How can influence propagation be modeled and estimated ?

Compute the set of maximum expected influence nodes ?

How to solve influence maximization

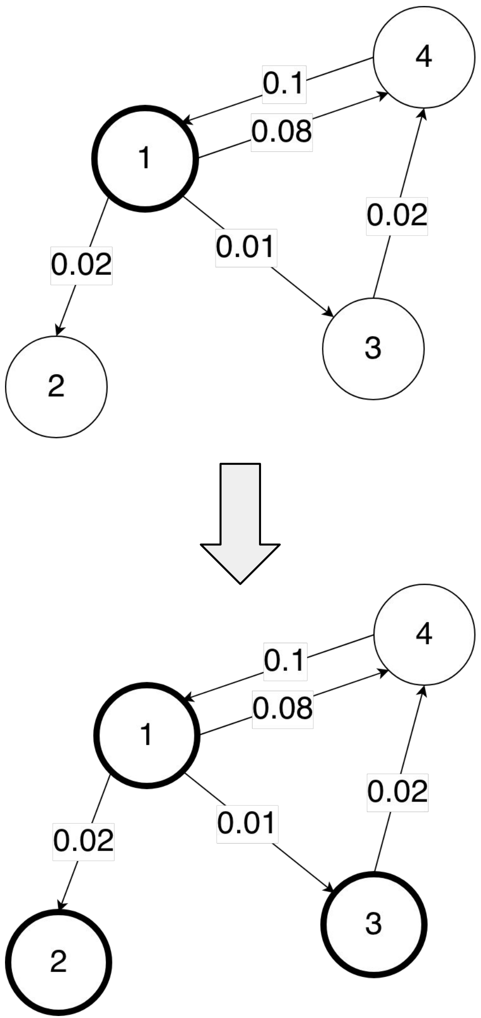
Independent cascade model

- Graph (V, E, w)
- All edges have probability $w(e)$ of propagating influence

Influence maximization

- Select set S of k activated nodes
- $f(S)$ is the expected number of activated nodes

Goal: maximize $f(S)$ with $|S| = k$



Algorithms - Greedy

Algorithm 1 Greedy(k, f)

initialize S = $\emptyset$
for $i = 1$ to k **do**
    select $u = \arg\max_{w \in V-S}(f(S \cup \{w\}) - f(S))$
    $S = S \cup \{U\}$
end for
output S

Complexity is kC with C the complexity of computing the influence spread for a given set.

$\rightarrow$ The problem is intractable but can be approximated by sampling the diffusion process

Trade-off between speed and precision of approximation

This algorithm is very slow in practise.

Algorithms - Faster heuristics

- PMIA [2]: an algorithm based on computing the maximum influence in-out arborescence of the nodes (within a threshold) and estimate the best incremental influence.

- Weighted degree: select every new node as the one with maximum outgoing weights

Graph networks

Presentation

Models that operate on graph-structured data

Graphs can be represented as nodes, edges and global attributes.

Operations are performed sequentially on edges, nodes and global attributes.

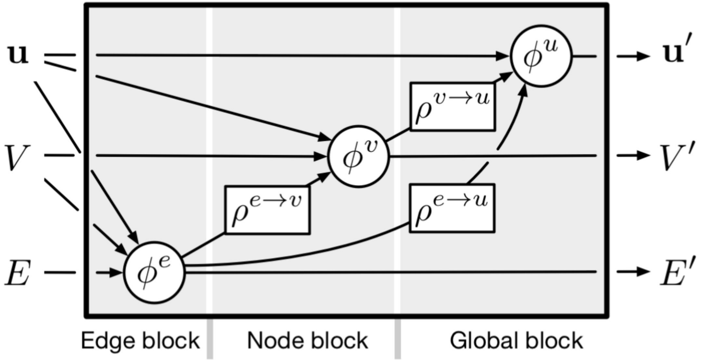


Figure from [3]

Graph Networks For Influence Maximization

Motivations

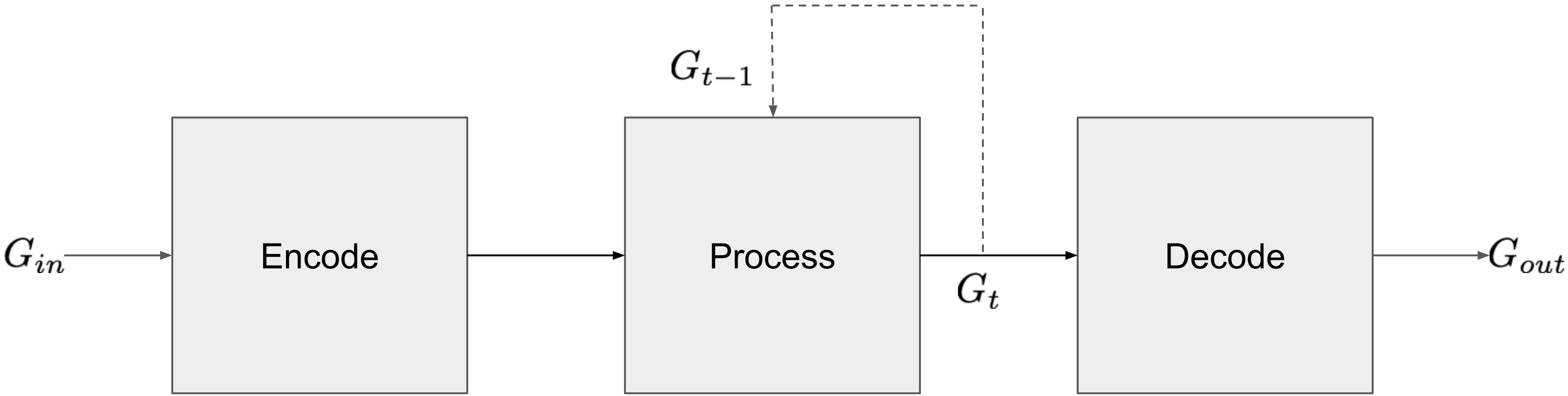
Most algorithms are either computationally very expensive or sub-optimal.

If graph networks can match the performance of these algorithms, it might provide a more scalable alternative for influence maximization.

Experiments

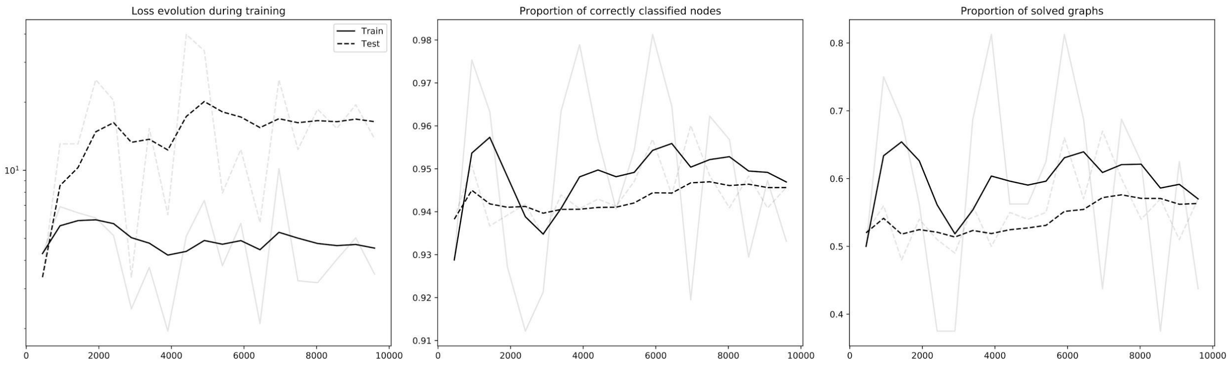
Use a graph network to compute the maximum influence set.

- Edges are represented by the transition probability and log-transition probability
- Nodes have a binary indicator of whether or not they belong to the MI set

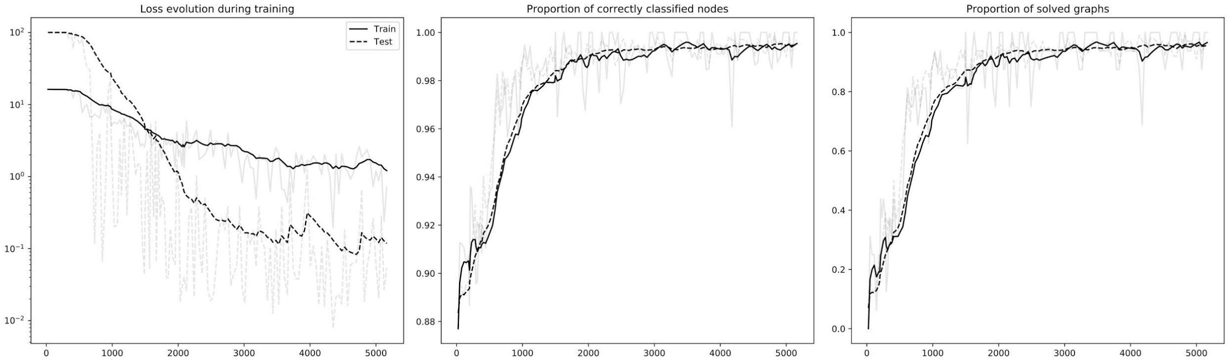


Results - 1 node - Training

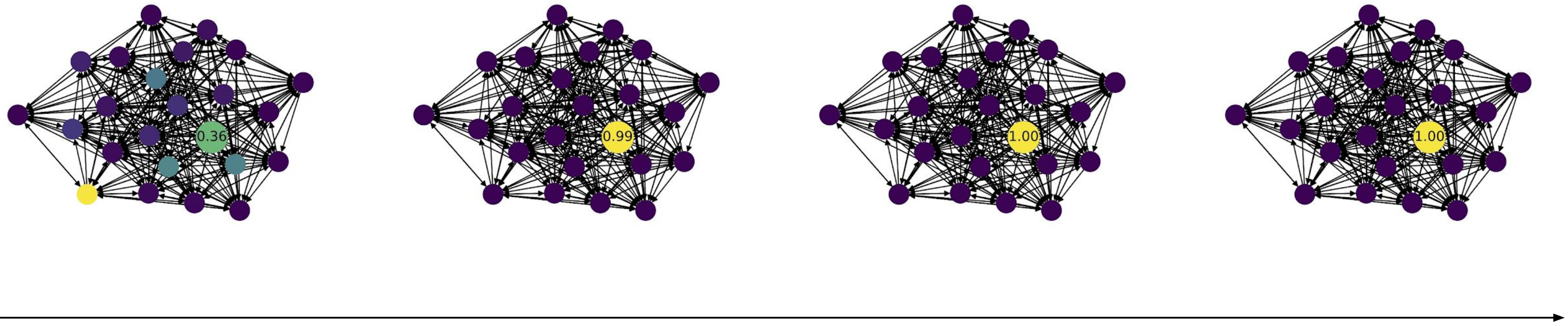
- Weighted degree



- PMIA

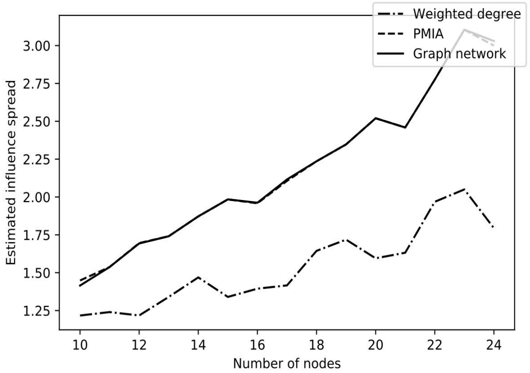


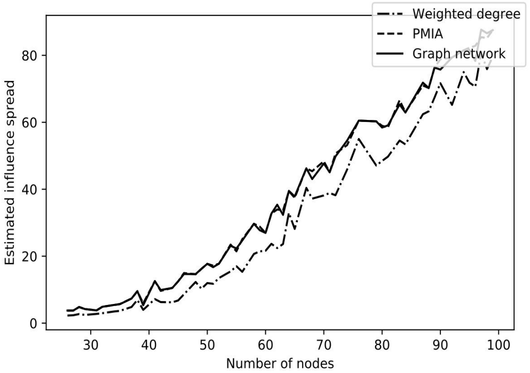
Results - 1 node - Processing

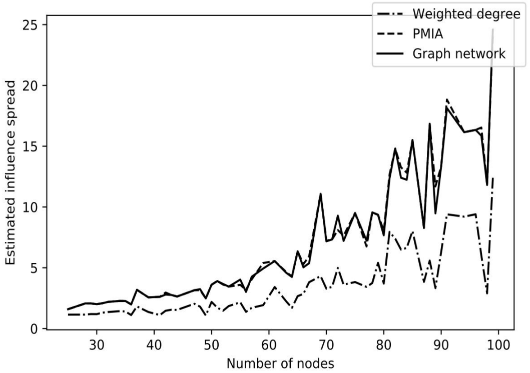


Step 1 Step 3 Step 7 Step 10

Results - 1 node - Expected influence spread



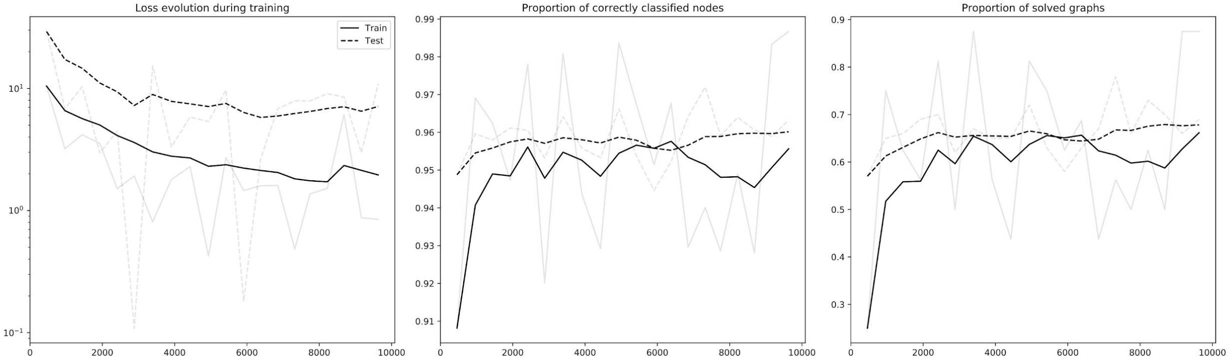




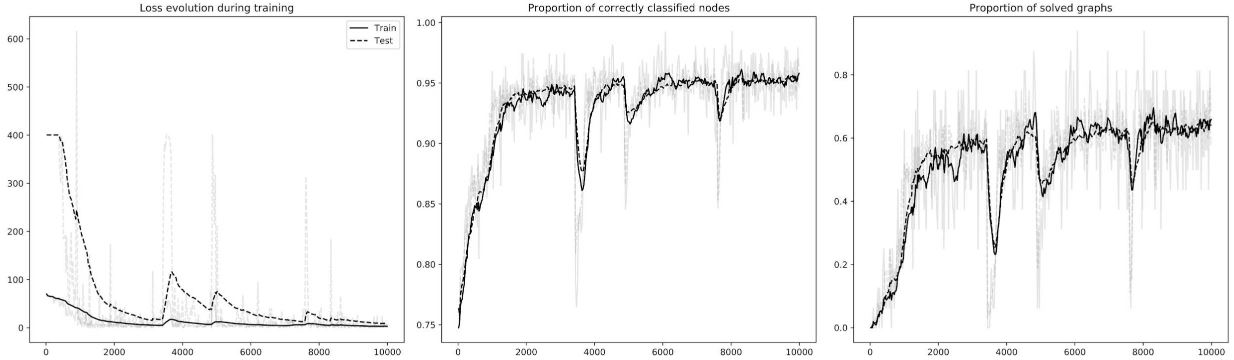
- Graph network generalizes very well (bigger and shallower graphs)
- Approximately the same expected influence spread as PMIA, even on graphs never seen

Results - 2 nodes - Training

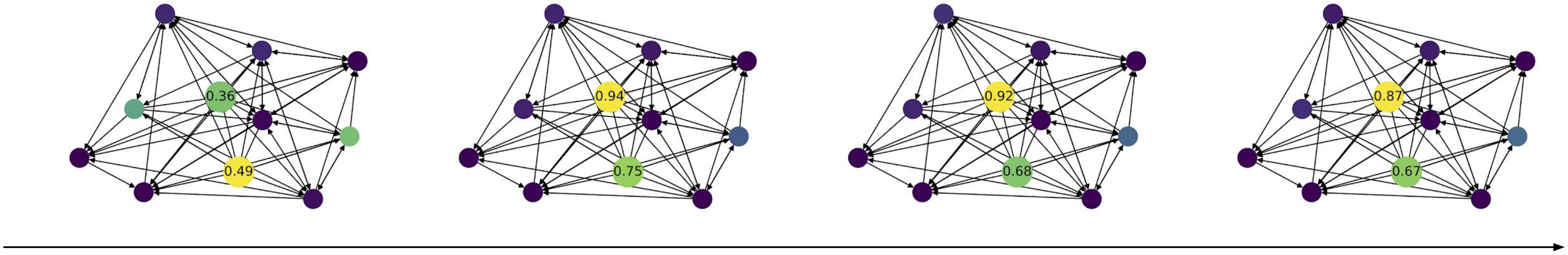
- Weighted degree



- PMIA

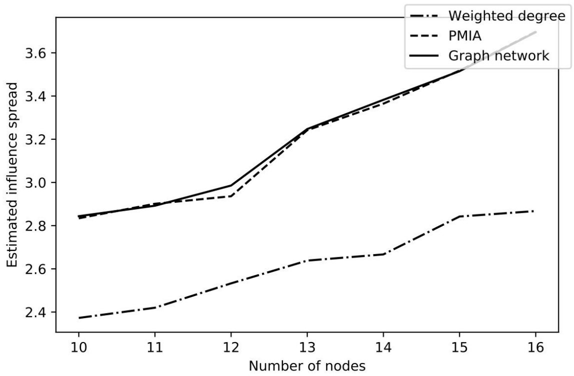


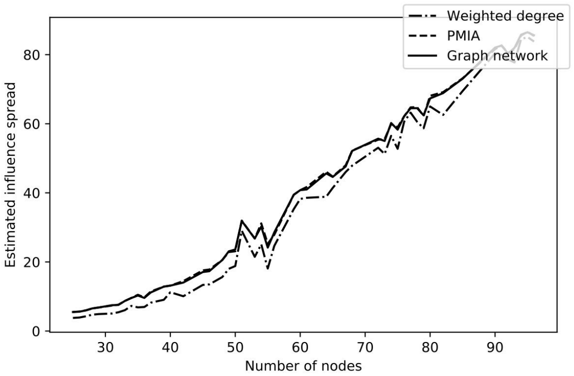
Results - 2 nodes - Processing



Step 1 Step 3 Step 7 Step 10

Results - 2 nodes - Expected influence spread



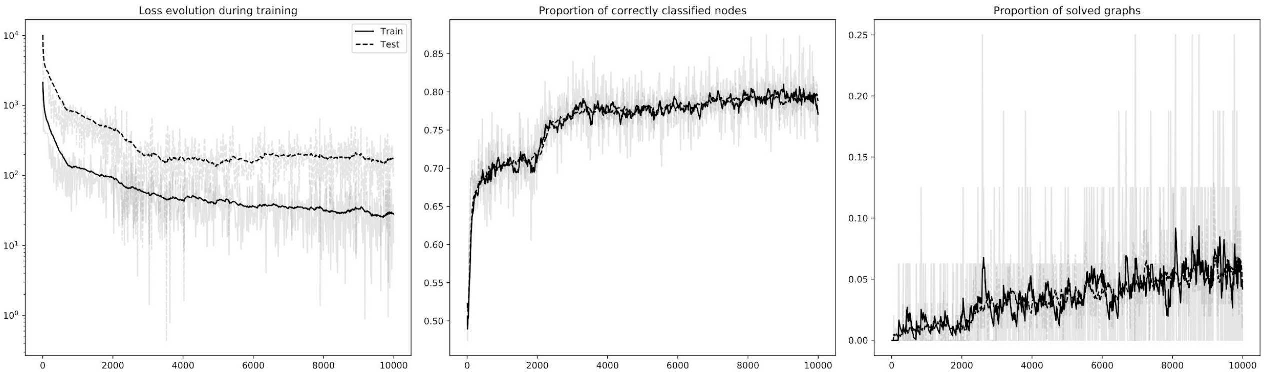


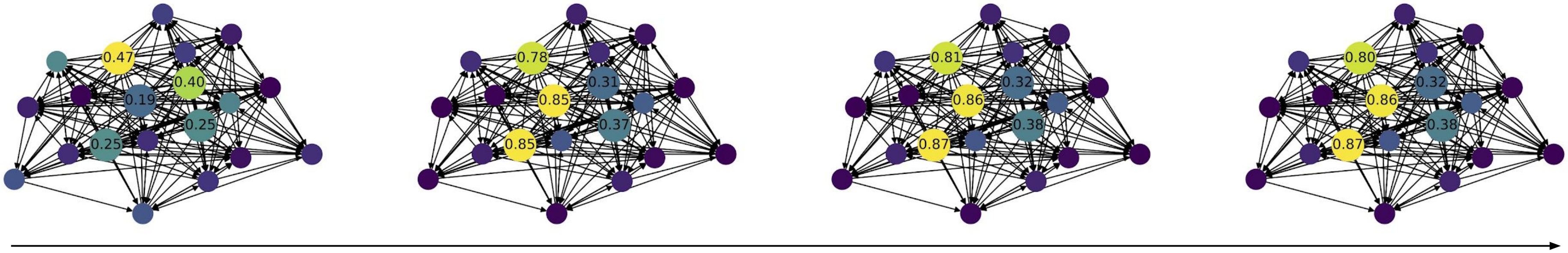
- Task were GN did not match PMIA’s output as accurately
- Still high expected IS (slightly higher than PMIA)

→ Does GN learn its own better/equal IM solver ?

Results - 5 nodes

PMIA



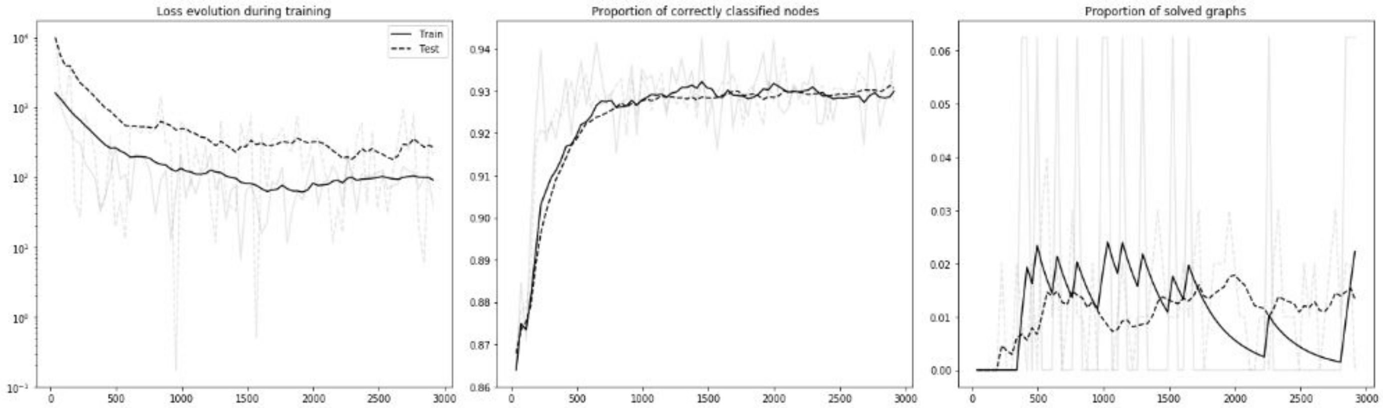


Step 1 Step 8 Step 16 Step 30

Results - 5 nodes

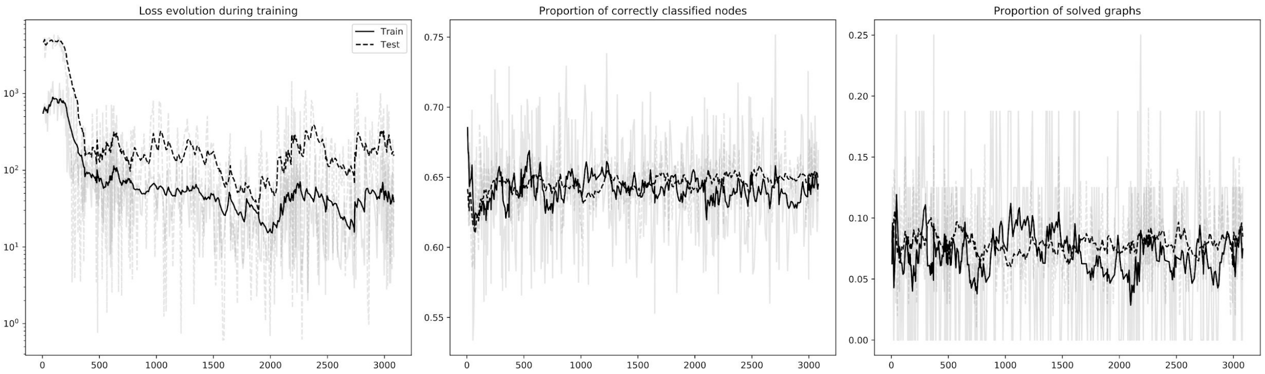
Weighted

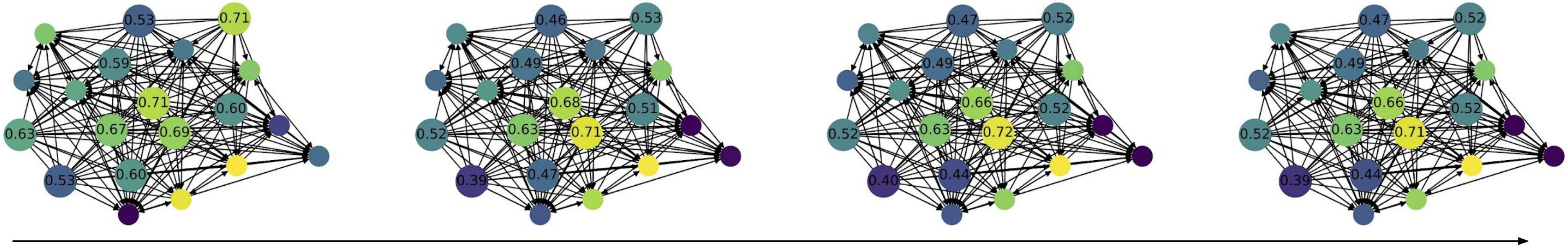
Degree



Results - 10 nodes

PMIA





Step 1 Step 8 Step 16 Step 30

Conclusion & Perspectives

- Extension to larger scale results : more nodes/edges and larger seed sets.
- Investigate the generalization properties that were observed on small sets of seed nodes.
- See how it compares in a more challenging setting such as online IM against IMLinUCB [1].

Graph networks seem like a very promising way of tackling the IM problem but suffer from the constraints of currently existing algorithms to effectively learn.

References

1. Wen, Z., Kveton, B., Valko, M. & Vaswani, S. Online Influence Maximization under Independent Cascade Model with Semi-Bandit Feedback. NIPS 2016
2. Chen, W., Wang, C. & Wang, Y. Scalable influence maximization for prevalent viral marketing in large-scale social networks. *KDD ’10*
3. Battaglia, P. W. *et al.* Relational inductive biases, deep learning, and graph networks. *arXiv:1806.01261 [cs, stat]* (2018).