

PROPAGATION DYNAMICS IN SOCIAL NETWORKS THROUGH RULE-BASED MODELING

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FOREWORD

We are facing the omnipresence of social networks

- Massive amounts of data complexify the analysis of relations among the users (preferences, interests, hobbies...) but allow to search for correlations
- Observation of general tendencies similar to a flock of birds or a swarm of insects
- Attempts to understand the global and specific social network users behaviours (either as a part of a group or as individuals)



The users behaviours have raised the idea of propagation:

- Adoption of an action previously performed by one of your « friend »
- Notions of influence/motivation: common interests or tastes, social cohesion/pressure within a group
- Modelisation and verification: attempts to recreate such behaviour to understand it and anticipate the propagation phenomenon



Normal propagation workflow:



- Direct model and propagation application
- Limited analysis and comparisons

PROPAGATION IN LITERATURE

 Starting with the first mention of influence from one customer to other ones
 Domingos and Richardson (2001)

- Toward marketing orientation with influence maximization in its simplest form Kempe *et al.* (2003)
- Or pluridisciplinary solutions considering social and biological contagion Dodds and Watts (2005)

PROBLEMS AND OPPORTUNITIES

Model comparison:

necessity to compare the many existing models with one another

- Model generalization/unification: improvements to the existing models by detecting the flaws, different options give the possibility to merge different solutions
- Influence maximization/minimization: more than useful for viral marketing and information spreading analysis



We propose to use graph rewriting techniques to:

- Transform existing models into a set of rules: the actual transformation depends of the model complexity, the created rules are non trivials
- Take advantage of the strategy language to manage the rules application to respect the initial model description
- Expend the existing possibilities in model analysis and comparison



Proposed propagation workflow:



- Models transformation
- Computation by steps to ease analysis and comparison





G = (V, E)



G = (V, E)





G = (V, E) $r: L \rightarrow R$



G = (V, E)



 $r: L \rightarrow R$



G = (V, E)

$$r: L \to R$$















Model from Goyal *et al*. (2010) Visualization samples from PORGY, Pinaud *et al*. (2012)





The solution gives some advantages:

- Dividing models in atomic bricks allows easier comparison
- Exchangeable bricks through models to experiment with variable behaviour gives users the opportunity to refine the models
- Keeping track of each atomic operation is essential to understand the missteps met



- Translation of the initial model: considering the many different models, chances are, specificities will be encountered
- Computation power:

historic conservation, rule application or influence maximization are expensive to perform

 Absence of existing comparison methodology: from the best of our knowledge, a tool designed to compare propagation models has never been created before

FUTURE WORK

- Formal methodology for effective model translation and comparison: generalization for the widely used model families (LT and IC)
- Model verification:
 Similar to software model checking, may be used to ensure the results at each step
- Maximization/minimization discovery: automatic comparison responding to specific given criteria

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THANK YOU FOR YOUR ATTENTION.

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APPENDICES

LINEAR THRESHOLD MODEL

- \odot A node v has a set of neighbours S
- A neighbour w can influence v according to a weight $p_{w,v}$ such as

$$\sum_{w \in S} p_{w,v} \le 1$$

- Each v possesses a threshold value θ_v usually picked randomly in [0, 1]
- $\odot v$ activates whenever the combined weight of its neighbours exceeds the threshold value

$$\sum_{active \ w \in S} p_{w,v} \geq \theta_v$$

INDEPENDANT CASCADE MODEL

- \odot A node v has a set of neighbours S
- \odot A neighbour w gets a single chance of activation following the probability $p_{v,w}$
- \odot When v activates, each neighbour is tested:
 - If w succeeds, it becomes active and the cascade will proceed;
 - Otherwise, w stays inactive and no further attempts of activation will be performed.



SUBGRAPH





PROPAGATION - STEP 1











NEXT CANDIDATES





PERPETUATION

