ACTA UNIVERSITATIS AGRICULTURAE ET SILVICULTURAE MENDELIANAE BRUNENSIS

Volume LIX 50 Number 7, 2011

VECTORISED SPREADING ACTIVATION ALGORITHM FOR CENTRALITY MEASUREMENT

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Received: February 25, 2011

Abstract

TROUSSOV, A., DAŘENA, F., ŽIŽKA, J., PARRA, D., BRUSILOVSKY, P.: *Vectorised Spreading Activation algorithm for centrality measurement.* Acta univ. agric. et silvic. Mendel. Brun., 2011, LIX, No. 7, pp. 469–476

Spreading Activation is a family of graph-based algorithms widely used in areas such as information retrieval, epidemic models, and recommender systems. In this paper we introduce a novel Spreading Activation (SA) method that we call Vectorised Spreading Activation (VSA). VSA algorithms, like "traditional" SA algorithms, iteratively propagate the activation from the initially activated set of nodes to the other nodes in a network through outward links. The level of the node's activation could be used as a centrality measurement in accordance with dynamic model-based view of centrality that focuses on the outcomes for nodes in a network where something is flowing from node to node across the edges. Representing the activation by vectors allows the use of the information about various dimensionalities of the flow and the dynamic of the flow. In this capacity, VSA algorithms can model multitude of complex multidimensional network flows. We present the results of numerical simulations on small synthetic social networks and multidimensional network models of folksonomies which show that the results of VSA propagation are more sensitive to the positions of the initial seed and to the community structure of the network than the results produced by traditional SA algorithms. We tentatively conclude that the VSA methods could be instrumental to develop scalable and computationally efficient algorithms which could achieve synergy between computation of centrality indexes with detection of community structures in networks. Based on our preliminary results and on improvements made over previous studies, we foresee advances and applications in the current state of the art of this family of algorithms and their applications to centrality measurement.

centrality, network flow, spreading activation, graph-based methods, recommender systems, data mining

Spreading Activation is a family of graph-based algorithms widely used in areas such as information retrieval, epidemic models, and recommender systems (Crestani, 1997; Rocha, Schwabe, Poggi de Aragao, 2004; Troussov *et al.*, 2009; Dařena, Troussov, Žižka, 2010). In this paper we introduce a novel Spreading Activation (SA) method that we call Vectorised Spreading Activation (VSA).

VSA algorithms, like "traditional" SA algorithms, iteratively propagate the activation from the initial set of nodes referred to as the seed, to the other nodes in a network through outward links. The level of the node's activation could be used as a centrality measurement in accordance with dynamic model-based view of centrality in (Borgatti, 2005) "that focuses on the outcomes for nodes in a network where something is flowing from node to node across the edges" (Borgatti, Everett, 2006). Representing the activation by vectors allows us to use of the information about various dimensionalities of the flow and the dynamic of the flow. In this capacity, VSA algorithms can model multitude of complex multidimensional network flows.

In this paper we don't discuss interpretations of the nature of "what is flowing", and we treat the network flow as the process of the propagation of an abstract relevancy measure also called the activation.

The activation is a function on the nodes of the network and spreading activation is an example of the discrete flow process where the activation of a node on the next iteration is explicitly specified as function of the activations at the node and its neighbours. Usually the activation is real-valued or Boolean-valued function. However, a real-valued function on the nodes of the network is not able to describe multiple dimensionalities of the activation, and below we are going to present examples where considering multidimensional flow processes might be useful. Therefore in this paper we assume that the value of the relevancy measure could be represented by vectors of real-valued, Boolean-valued or even other scalar or list (compound) components. We don't assume that vector algebra operations are necessarily meaningful for multidimensional flows; therefore in this paper the term "vector" is used not in a strict mathematical sense, but in a sense frequently assumed in computer sciences: a vector or a "tuple" is a list of components, such as a set of value attributes in relational databases.

The focus of this paper is on "how it is flowing" more than on "what is flowing". Traditional SA algorithms model diffusion-like processes, where on each iteration the future depends only upon the present state – the distribution of relevancy function on the network, and do not depend on the history of how this distribution was achieved. We can provide examples of physical processes, which do not fit into this scheme. For instance, if we consider the system of materials points which oscillate around fixed positions on a regular grid acting by forces of the interaction with neighbour points then knowing positions of the points at a current iteration is not enough to compute the positions on the next iteration. These positions depend not only on the positions of materials points and the interaction between them, but also on the velocity of material points (and approximation of velocities requires knowing at least two previous states of a material point, not one like in diffusion-like processes).

Another common property of diffusion-like network flows is that they are usually inherently "linear" as mathematical operators that map the input to the output function on network nodes. For instance, the resulting distribution of the activation initiated in two network nodes is the same as the sum of the resulting distribution of two independent processes initiated in each node from the pair. More formal description of the linearity requires introduction of a black box description of network flow. Black box description of any network flow is the operator H_t which maps the input function on network nodes $x(v)$ to the output function $y(v)$, where t is the continuous or discrete parameter representing time, v – network nodes, $x()$ and $y()$ are real-valued functions (or complex-valued, vector valued, etc. functions). Most of the diffusion-like network flows H_t are linear, i.e. given two initial functions $x_1(v)$ and $x_2(v)$, the result satisfy the properties of superposition and scaling:

$$H_t(\alpha x_1 + \beta x_2) = \alpha H_t(x_1) + \beta H_t(x_2)$$

for any scalar values α and β.

As we outlined above, diffusion-like network flow methods share certain fundamental properties. VSA algorithms could model multitude of complex network flow processes, and in such capacity could be useful to overcome limitations of currently used network flow methods.

The rest of the paper is organized as follows. In section Vectorised Spreading Activation Algorithms we describe the VSA algorithm. In section Applications to User Similarity in Folksonomies we render a formal model of folksonomies as a multidimensional network with four types of nodes corresponding to users, resources, tags and instances of tagging and then we present the results of numerical simulations using VSA. In this section we also present the results of ranking using VSA on small synthetic models of social networks. Section Clustering Behaviour of VSA Results at Different Levels of Analysis demonstrates the behaviour of VSA that is sensitive to clustering structure of networks and section Applications to Centrality Measurement in Large Scale Social Networks shows how the VSA algorithm can be used for calculating various centrality measures in a new way. Finally, the last section describes the conclusions and future work.

Vectorised Spreading Activation Algorithms

Spreading activation algorithms iteratively propagate the activation from the initial set of nodes referred to as the seed, to the other nodes in a network through outward links (Troussov *et al.*, 2009). Usually, this propagation is done until the behaviour of the system stabilizes near the so called the limit distribution or the algorithm is stopped by constraints such as the limitation on the total number of iterations. Representing the activation by vectors (or, more generally, by ordered sequences of non-homogeneous values where components might belong to different universes – numbers, binary and Boolean data types, etc.), allows to store at each node the information about various dimensionalities of the activation as well as the information about dynamics of the process of propagation. We introduce two mechanisms to exploit vector-valued activation to modify the behaviour of the propagation.

The idea behind the first mechanism is to provide the nodes with a kind of "inertia" in terms of changing their activation values according to the progress of previous iterations. In addition, this "inertia" is used to speed up the convergence of the algorithm (i.e. achieving the limit distribution). For instance, if on each iteration the activation at particular node decreases, this mechanism makes this decrease faster.

From the technical point of view, the primary goal of the second mechanism – process dependent constraint on the number of iterations – is to speed

up the convergence of the algorithm without limiting the spread only in the vicinity of the initial seed. Traditional spreading activation algorithms frequently employ constraint on the total number of iterations, so that the process of redistribution of the activation stops independently on the topology of the network and the distribution of the activation achieved (Dařena, Troussov, Žižka, 2010). The new mechanism we propose limits the number of input/output operations for nodes; some nodes (especially those located near the initial seeds), might be removed from the process of redistribution of the activation, while some other nodes (located further from the seed) might continue to participate in the redistribution of the activation. From an application point of view, this mechanism aims to reduce the influence of globally important nodes (hubs) on the activation redistribution on micro level.

Algorithms which propagate real-valued activation function F usually have the following steps (Troussov *et al.*, 2009; Troussov, Parra, Brusilovsky, 2009):

- Initialization – sets the parameters of the algorithm, network, and the initial seed of nodes with non-zero F values.
- Iterations:
  - expansion of the list of nodes with non-zero level of activation,
  - re-computation – the value at each node in the list is recomputed based on the values of the function on nodes which have links to the given node and types of connections,
  - list purging,
  - conditions check to break iterations.
- Normalization – linear scaling up or down the numerical values of the activation level of all nodes in the list of activated nodes to satisfy some conditions of activation conservation.
- Output – the list of nodes ranked according F values.

Re-computation step in Iterations includes:

a) computation of Input/Decay/Throughput for links,

b) computation of the new level of activation based on the values of the Current, Input, and Output values of the activation at the node in question.

Straightforward version of Vectorised Spreading Activation algorithm uses vector-valued function F with independent operations for each component of the vector.

Implementation of mechanisms that modify traditional algorithm of propagation of real valued activation, that were mentioned above, requires to store at each node the vector $F(h_1, h_2, \ldots h_n)$, n_{hist}. Values h_i store the history of activation at the node – h_1 is the oldest and h_n most recent value, n_{hist} represents the number of iterations when the node was active.

Re-computation step b) becomes different for such VSA modification and includes:

- If there are enough historical values ($n \geq N_{hist}$, where N_{hist} is a parameter of the algorithm):
  - the "interpolated" value h_R is computed by the linear least square regression (Hastie, Tibshirani, Friedman, 2009) for predicting the next value, h_{n+1}, using the sequence of already known values $h_1, h_2, \ldots h_n$
  - the "transformed" value of the activation h_T is computed based on the current and interpolated values

$$h_T = h_n + (h_R - h_n)/\lambda,$$

where λ is a parameter and h_n the most recent value of the activation

  - reorganisation of the vector with historical values which includes removal of the "oldest" value (h_1) and the use of h_T value

$$\text{new vector} = (h_2, \ldots h_n, h_T).$$

- If there are not enough historical values, new value of the activation h_{new} is calculated based on the actual value and incoming signal, and stored in the history

$$h_{new} = h_{old} + \mu \cdot \text{Input},$$

where μ is a parameter of the algorithm.

- If a node exceeds its limit for input/output operations, it is removed from input/output operations:

$$n_{\text{hist}} = n_{\text{hist}} + 1$$

$$\text{if } n_{\text{hist}} \geq N_{\text{operations\_limit}} \text{ the node is removed}$$

In following sections we show the results of the numerical simulation. Parameters of the algorithm related to the use of vectors are described by the following sequence:

$$\{\lambda, N_{\text{hist}}, N_{\text{operations\_limit}}\}. \quad (1)$$

Other parameters, related to fundamental properties of spreading activation algorithms (see Troussov *et al.*, 2009), such as the use of the number of outgoing links in the redistribution of the activation, signal decay, and aggregation of the input and output activation on each iteration could be described by the following list:

$$\{\beta, \text{decay}, \mu\}. \quad (2)$$

Parameter β defines the portion of activation that is passed by a node to each of its neighbours (on each iteration a node v passes $F(v)*outdegree(v)^{-\beta}$ activation to each of the outgoing links, where $F(v)$ is the activation of the node v, $outdegree(v)$ is the number of nodes adjacent from v (Troussov *et al.*, 2009). When the signal ("activation") passes through a link l, the activation experiences decay by the factor *decay*. Parameter μ is described above in the

re-computation step b). If not specified otherwise, β=0.7, decay=0.8, μ =0.5.

Applications to user similarity in folksonomies

Spreading activation was used by Troussov, Parra, and Brusilovsky (2009) to measure tag aware user similarity in folksonomies (see Wal, 2004) – labelling and tagging usually done in a social a social environment (as such as in del.icio.us). Folksonomies are a popular approach to bottom-up social knowledge management. The process followed an approach of dynamic local ranking: the seed of activation was placed on a node corresponding to the user of interest (like the node A1 in Fig. 1), the algorithm iteratively propagated this "input" through the links between the nodes corresponding to users, tagging instances, resources and tags. Users were ranked according to the "output" – the level of activation at corresponding nodes. Apparently, this method is applicable to other network models of instantiations of socio-technical systems, where links represent relations between people and other artefacts (like resources, tags, etc).

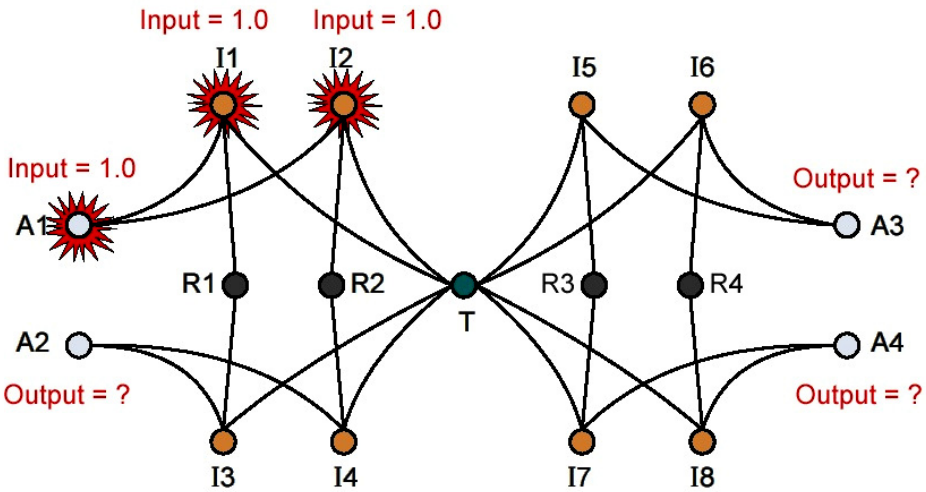
The major finding of Troussov, Parra, and Brusilovsky (2009) is that the number of iterations in constrained SA is a critical factor in ranking: spreading activation allows discriminating between various configurations connecting the users (like tagging the same resources using the same tag) only in a certain range of iterations (around 20 iterations). Since these observations were done on small synthetic configurations, the remaining question is whether the behaviour of such ranking is similar in bigger systems. In other words, applicability of spreading activation to dynamic local ranking hinges upon the feasibility of tuning algorithm's parameters in such a way that the activation initiated in one part of the network will stay within clusters induced by the initial seed (like one or more members of a community of practice in collaborative tagging). The numerical simulation in this and the next section shows that VSA algorithms are capable to keep the activation within a cluster induced by the initial seed.

In our numerical simulation we used the network where two users (A1 and A2) used the same tag for two resources, which were used by another group of users. Fig. 1 presents the network model of the instance of synthetic folksonomy where users A1 and A2 use the same tag T for resources R1 and R2 in four instances of tagging I1, I2, I3, and I4. The same tag T is also used by another group of users – A3 and A4. Ranks of users A2, A3, and A4 according to their relevancy to the user A1 is computed by VSA algorithm using the nodes A1, I1, and I2 as the seed.

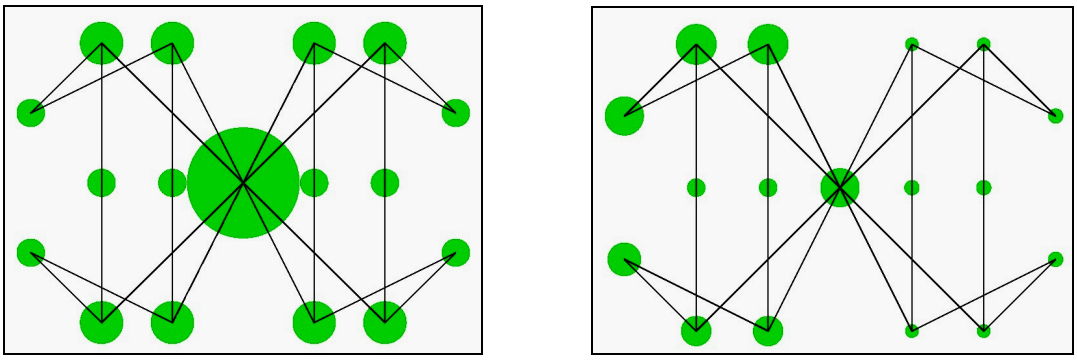
Relevancy of A2 to A1 is higher than relevancy of A3 or A4 to A1 based on tag and resources similarities. Ranks of A2, A3, and A4 based on the length of the shortest path (the simplest graph-based metric) are the same (since the length equals to four in all three cases). However, our common-sense assumption based on clustering structure is that relevancy (or connectivity) of A1 and A2 should be much higher than, e.g. A1 and A3.

Following the method from Troussov, Parra, and Brusilovsky (2009), we computed the ranks of A2, A3, and A4 using VSA with A1, I1, and I2 as the seed.

The results of numerical simulation in Fig. 2-a demonstrate that the unconstrained spread of activation provides exactly the same ranking for highly relevant node A2 and less relevant nodes A3 and A4. After 24 iterations the activation at all nodes is within 5% from the values of the limit distribution shown in Fig. 2-a. We conclude that small number of SA iterations is not sufficient for fine-grained analysis of nodes' connectivity and large number of iterations makes the computation more expensive and quickly leads to the activation "crawling away". Fig. 2-b shows the results of VSA with parameters {5.0, 3, ∞} defined by the formula (1). This version of VSA is "unconstrained – i.e. $N_{operations\_limit}=\infty$, and



1: *The network model of the instance of synthetic folksonomy where users A1 and A2 use the same tag T for resources R1 and R2. The same tag T is also used by another group of users – A3 and A4.*



(a) Unconstrained SA *(b) Vectorised SA*

2: *The initial seed at nodes A2, I1, and I2 in Fig. 1 is propagated by unconstrained SA algorithm (the iterations continue until the distribution is settled) and by VSA.*

after 7 iterations the values of activation at each node were within 5% margin of the limit distribution values.

In experiments shown in Fig. 1 and in all other experiments with running unconstrained SA on undirected graphs the ranking order of nodes did not depend on the position of the initials seed, and ranking order had high positive correlation with outdegree of nodes – the more links a node had, the higher was the rank (like the highest ranking for the node T in Fig. 2-a). Ranking provided by unconstrained VSA in Fig 2-b is less dependent of the outdegree and gives higher ranks for the nodes highly relevant to the initial seed (such as nodes A2, I3, and I4).

Clustering behaviour of VSA results at different levels of analysis

One of the leading approaches in recommender systems is using communities as an entity to create a way to provide recommendations. We tentatively assume that the multidimensional network model of folksonomies (Cattut *et al.*, 2007) could exhibit properties of "small world" networks and exhibit high degree of clustering and a user of collaborative tagging systems could be classified as a "member" of several "communities", defined for instance as groups with tight connections (Girvan, Newman, 2002). These communities can overlap and some of the micro-level communities might be the part of the "mezzo-level" communities. For instance, users interested in collaborative filtering could also have wider interests in computer science, a geographic community may contain a number of ethnic communities (Tropman, Erlich, Rothman, 2006). Therefore community based recommendation could be based on the detection of "micro-level" or "mezzo-level communities" and the results of community-based recommendation could depend on the scale of the communities and development of "scale-aware" algorithms could be a promising approach.

The following experiments show that VSA could be tuned to be "scale-aware" to provide ranking on different levels. In Fig. 3 we show the results of numerical simulations on a network with four strong "micro level" clusters interconnected in such a way that mezzo-level clusters emerge.

Parameters of the VSA algorithm used, given by formulas (1) and (2) are: b) – {5, 3, 3} and {0.5, 0.8, 0.5}; c) – {50, 3, ∞} and {0.5, 0.8, 2}; d) {5, 3, ∞} and {0.7, 0.8, 2}.

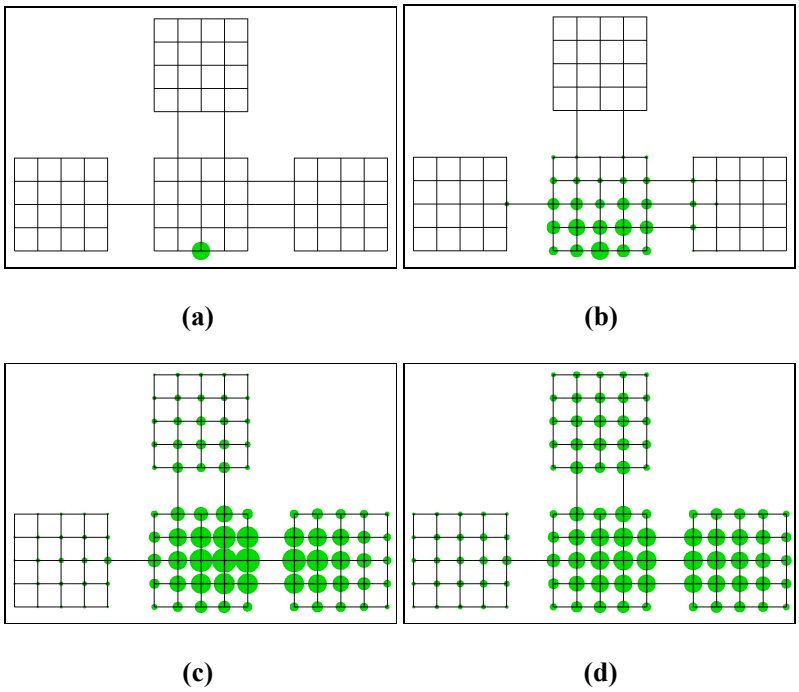
This network exhibits such properties of small world phenomena, typical for network models of socio-technical systems, as short distances between nodes and high degree of clustering. Under different parameters of the algorithm, the limit distribution could stay locally (Fig. 3-b) mainly within the micro-level cluster induced by the initial seed, or propagate further to another most connected cluster, which together form what might be considered as a mezzo-level cluster induced by the initial seed (Fig. 3-c). Changing parameters further lead to the results that the limit distribution (Fig. 3-d) reflects the topology of the network, being almost insensitive to the position of the initial seed.

We conclude this subsection by noting that the results of numerical simulation suggest that VSA provides sensible redistribution of the activation needed for local ranking.

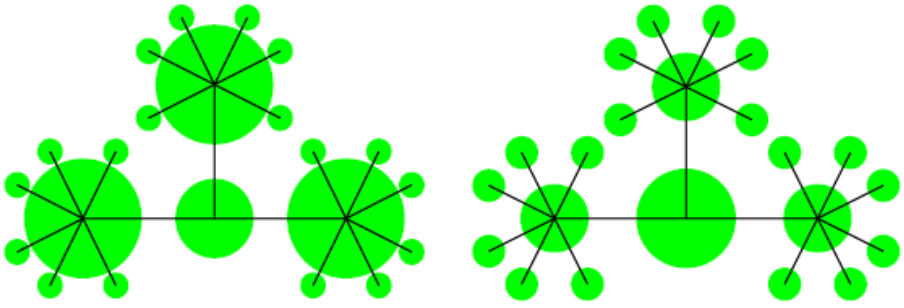
Applications to centrality measurement in large scale social networks

Using analogy with physical processes, one can describe SA algorithms (as well as random walk processes) as models of diffusion. Despite the differences between different versions of such models, they might have some common properties, limiting their applications.

One of such properties might be described as follows. Directed links, such as hyperlinks between Web pages, might be interpreted as "positive" votes confirming the prominence of nodes in the network, and the direction of links could be successfully used for nodes' ranking by the algorithms like PageRank.



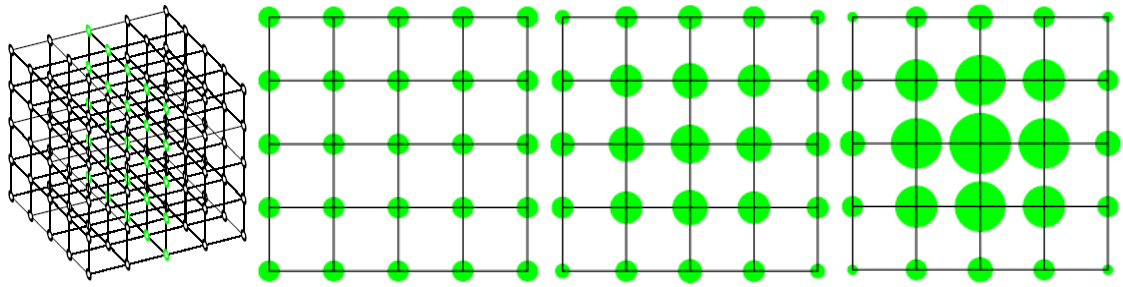
3: *The results of VSA propagation on a synthetic network with four strong clusters. Fig. a) shows the initial seed; while figures b), c), and d) show the limit distribution using different parameters of the algorithm.*



4: *VSA propagation on a star-shaped network with parameters according formulas 1 a 2: a – {∞, 3, ∞} and {0.5, 0.8, 1}, b – {∞, 3, ∞} and {–0.5, 0.8, 1}*

On the contrary, network models of instantiations of socio-technical systems are usually inherently "undirected" and are rendered as undirected graphs. When a diffusion-like process works on such structures, the activation from a node propagated trough outwards links flashes back through reciprocal links (see Hotho *et al.*, 2006) and when the level of activation is used for ranking, nodes with many links might be "overrated". For instance, if a diffusion-like process is used for ranking in social networks, the results of ranking might have strong positive correlation with the ranking according to degree centrality (see e.g. Wasserman, Faust, 1994), while for many application of social network analysis people should be ranked to the prominence of their position in the network, for instance according to their so called betweenness centrality – a measure of the extent to which an actor has control over information flowing between others. Degree of a node is a property of local topology, i.e. it depends only on a node and its neighbours. Therefore degree centrality does not reflect the global position of a node in the network as opposed to such centrality measurements as betweenness and closeness centrality.

Fig. 4 shows that with a particular set of parameters VSA ranks the nodes according to the degree centrality (Fig. 4-a), while with another set of parameters ranking is the same as provided by betweenness and closeness centrality (the most activated node, the centre of the star, gets the most activation on Fig. 4-b).



5: *VSA propagation on 5×5×5 grid: a) 5×5×5 grid; the initial activation, which is set 1.0 for all the nodes, is not shown on this figure; b) the central layer of the grid and the initial activation 1.0 shown by balls; c) the limit distribution of the activation at the central layer for parameters {∞, 3, ∞} and {0.5, 0.8, 1}, d) the limit distribution of the activation at the central layer for parameters {∞, 3, ∞} and {–0.5, 0.8, 1}*

Fig. 5-a gives and example of an undirected network where most of the nodes have the same degree. Still VSA robustly ranks nodes according to closeness centrality.

From the results of the experiments shown on Fig. 4 and Fig. 5 we tentatively conclude that VSA is capable to compute various centrality metrics which do not "overrate" nodes with high degree centrality. We also tentatively conclude that VSA could be used for efficient computing of centrality metrics which take into account the clustering properties of the network.

CONCLUSIONS AND FUTURE WORK

We presented applications of a VSA algorithm to tag-aware recommender systems using multidimensional network models of folksonomies. In particular we showed that the results of propagation – the distribution of the activation when the process converges – are more sensitive to the positions of the initial seed and to the clustering structure of the network than results produced by traditional spreading activation. Combined with findings of Troussov, Para, Brusilovsky (2009), we tentatively assume that VSA algorithms are a promising approach to ranking on micro- and mezzo-level needed for the construction of high-performance graph-based recommender systems.

Numerical simulation on synthetic networks shows that the results of VSA propagation are more sensitive to the positions of the initial seed and to the community structure of the network than the results produced by traditional SA algorithms. For instance, the nodes at the core of a community (the set of network nodes "which are joined together in tightly-knit groups between which there are only looser connections", see Girvan, Newman, 2002), get more activation than the nodes at the periphery of the community.

We theorize that the future development of VSA methods might be driven by "physics-inspired" and "logic-inspired" algorithms. SA algorithms have roots in numerical simulation of various physics phenomena, particularly by finite-difference methods (Rübenkönig, 2006). From the other hand, the iterative procedure of SA is essentially the same as the procedure that determines the new state of a cell in cellular automata (Shiff, 2008) such as Conway's Game of Life. Actually, finite difference approximations to differential equations were one of precursors of cellular automata (Wolfram, 2002). The major difference is that cellular automata usually perform on rectangular (cubic, etc.) grids, but the extensions to arbitrary networks are feasible. Another difference is that cellular automata use "logical operations" while traditional SA use arithmetic operation. Agglomerative types of clustering, such as the MajorClust algorithm in Stein, Nigemman (1999), or Chinese whispers algorithm (Biemann, 2006) provide partitioning of the network into clusters using operations similar to used in cellular automata.

The identity of the computational procedures allows us to conclude that developing of VSA algorithms with hybrid operations over the components of the activation vector. For instance, "physical" operations could be responsible for the propagation of the activation around the initial seed and the level of the activation indicates the relevancy of nodes to the initial seeds. "Logical" operations could propagate Boolean markers, which indicate potential belongings of nodes to clusters. Such a hybrid propagation will combine ranking with clustering; and it is computationally efficient on massive networks since the major time consuming operations – retrieval of nodes – serve both "physical" and "logical" operations. The clustering does not involve partitioning of the whole network.

Based on our preliminary results and on improvements made over previous studies, we foresee advances and applications in the current state of the art of this family of algorithms and their applications to centrality measurement.

Acknowledgements

This paper is supported by the Research program of Czech Ministry of Education number VZ MSM 6215648904/03/03/05.

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