Ninawe and Venkataram *Hum. Cent. Comput. Inf. Sci. (2015) 5:25*
DOI 10.1186/s13673-015-0042-1

Human-centric Computing and Information Sciences
a SpringerOpen Journal

RESEARCH

Open Access

A method of designing a generic actor model for a professional social network

Swapnil S Ninawe and Pallapa Venkataram*

*Correspondence: pallapa@ece.iisc.ernet.in
Protocol Engineering and Technology Unit, Department of Electrical Communication Engineering, Indian Institute of Science, Bangalore, India

Abstract

The emergence of social networks have opened a new paradigm for professional groups to student groups to exchange their information with their contemporaries quickly and efficiently. The social networking enables to set up relations among the people (called actors) who share common interests, activities or connections. An actor or a person plays a predominant role in sharing social networking services, hence optimal modelling of an actor is essential. An actor model must be defined with several issues concerning to interests, activities, devices used, etc. In this paper, we present a generic actor model for a professional social network (GAMPSON) by considering actor's personally identifiable information, professional information, activity, social status, etc. The designed GAMPSON is tested over professional social networks such as agriculture social network and museum social network, where GAMPSON generates unique actors associated with the agriculture and museum social network, and renders relations among the actors. Results demonstrated that it is simple and accurate to generate actors and their relations in any social network along with provision of information over database.

Keywords: Generic actor model, Actor relation, Agriculture social network, Museum social network

Background

With the development of internet technology, a social network [1–4] provides a new way of communication, entertainment and gaining information [5]. Social networks [6–9] have influenced people of different regions and professionals to share the information due to the advancement in the technology [10, 11]. The main goal of a social network is to make the information space [12, 13] where a person can share information like thoughts, personal data, events, etc. It shares the basic purpose of interaction and communication [14], and specifies goals and patterns that vary significantly across different regions of people. Visibility of information [15, 16], structural variations [17, 18] and access [19–22] are the significant characteristics of a social network.

A social network is a social structure [23–27] among individuals known as actors or organisations. The social network also defines a group of actors connected by a set of relationships that are continuously changing. The crucial factor here is relationships among actors that are required for construction of a social network [28]. Hence, as an important research area, developing a social network focuses relationships associated with the actors. Once a social network is constructed, it could be used to analyse knowledge discovery, finding access, searching actors, groups, relations, etc. In general, developing a social network [29] covers the area of any network, and metrics used are based on the mathematics of graph theory [30–32] regardless of the connections. After constructing a social network, its ultimate goal is sharing knowledge [33–36]. In summary, a social network consists of an actor, and its relevant information and association. Thus, an actor model in a social network is essential in precisely determining relation among the actors.

Social networks have gained importance for their functionality enabling people to obtain information based on relationships. This capability comes from a well-defined actor model. Therefore, first thing to architect should be the actor model by which relationships can be build among actors. Formally modelling and analysing an actor model [37] for a social network has deep impact on the development of high quality social network systems. An actor model can have explicit form, meaning that we can determine specific things about an actor model. For example, relations among actors in a social network must be deterministic in nature, meaning that given a set of actors with definitive properties, a model should be able to replicate same relations every time. If an actor model is a good approximation of the real world social network actors, then a definitive assurance about the actor model gives us confidence in the real world realisation. Such certainty is crucial, particularly for social networks, where relation among actors are of utmost importance. A rigorous approach towards formalising and analysing the actor model can help us in determining relations among actors more effectively and efficiently. Studying actor models gives us insight into how social networks are helpful in the real world.

An actor model based on actor's professional information, activity, etc., is difficult to address, and also dynamic data variations, changing relations and varying privileges imposes complexities in actor modelling. The social network simplifies the complexities, and there are few actor models that are currently deployed [37–39] which partially covered professional information, activity, etc. in social networks.

Proposed idea

The main contribution of our work can be summarised as follows. The basic idea is to propose formalism in constructing an actor model based on the characteristic features for modelling and analysing relation among actors in a social network. We propose a generic actor model for a professional social network (GAMPSON) which represents many characteristic features of an actor like personally identifiable information, professional information, activity, etc., and relations among the actors are built based on these characteristic features. The proposed model builds hierarchical and equivalence relations among the actors and is much more compact compared to the other models. The use of the GAMPSON for generating various professional social networks (e.g., agriculture social network) has many advantages. On the one hand, it is a tool for accurately generating distinct actors and relationship among them via simulations. On the other hand, it is possible to analyse variations of the information diffusion process using different settings of the model parameters such as varying the characteristic features of the actors, and determining the relationships at various levels.

Organisation of the paper

The organisation of the rest of the paper is as follows. "Some of the existing actor models of social networks" covers some of the existing actor models for social networks where we discussed different actors models that were built along with their advantages and disadvantages. Design of a GAMPSON was presented in "Generic actor model for a professional social network" along with distinct characteristic features of actors such as personal information, activity, etc. In order to demonstrate the applicability of the model, we designed the actor specifications from the generic model for the professional social networks such as agriculture social network (ASN) and museum social network (MSN) were given in "Design of an actor for the agriculture social network andmuseum social network using the GAMPSON" for provision of information such as seed, soil, crop, etc. to the actors in case of ASN and exhibit information in case of MSN, respectively. Simulation environment of ASN and MSN with the designed actors and testing results were discussed in "Simulation environment" and "Simulation results", respectively. We compared the GAMPSON with other models, and showed results for accuracy of the model and relation among the actors in case of ASN and MSN. At last, we concluded our work in "Conclusions".

Some of the existing actor models of social networks

Several research works exist on actor models for traditional networks but not for social networks, where a generative model for building synthetic human social network graphs was presented [40] reproducing the properties of social relationships accurately, and produced both macroscopic and microscopic structure. In this paper, authors used "triadic closure" and tried to match the properties of human social network. The parameters used were based on graphs properties and not the actual human characteristics that are essential in building a proper social network. Another approach called as heterogeneous actor modelling was studied in [37] and prescribed an approach to a model based on actors, where actors were considered as autonomous reasoning agents. Here, a more formal way of representing an actor as a network element was presented along with UML diagrams, but failed to generate accurate quantifiable relationships. Actor-based slicing techniques for efficient reduction of Rebeca models were proposed [41], and stepwise slicing and bounded slicing were used to approximate the behaviour of the model. This technique was applied to simulation models in formal way in order to reduce for model reduction. They first constructed a controlled flow graph in the model, and then use it to extract the control flow and data flow information of the model. In order to determine relations based on contact, family, friend and comments were found [42], and showed that different types of relationships required different similarity metrics. Here, similarity factors included in metrics were tag frequency, vocabulary overlap, etc. to construct a network, but more basic parameters such as name, occupation, etc. were not considered. Investigation of the social actor model of information systems through an empirical exploration of communication information technology (ICT) was carried out [43] and results suggested that the social actor model can be conceptualised in three dimensions such as interaction, affiliation and environment. Here, parameters such as identity, interaction, affiliation and environment size were used for actor modelling, but failed to show how to construct relation among actors mathematically.

Some of the works on actor model were based on actor profile data, graph structures, connectivity relations, etc. Stochastic actor-based models for dynamics of directed networks were studied [38] and showed an extended form can be used to analyse longitudinal data on social networks with changing attributes of the actors. The model supposed to use minimum mathematics along with some of the properties of graphs such as out-degree, reciprocity, ego, alter,etc., and used directed relations overall, but again did not consider basic properties of actors. In another work, Sudhakara [44] showed how various actors of energy system were making the system worked, and what incentives and constraints each of the actors experienced. This work was more related to household energy consumption and defined energy related actors based on their use. Use of profile data to construct a graph structure was carried out [39] and proposed a simple model to utilise both observable connectivity relation and profile graph. Here, much more rigorous mathematics was used along with similarity measures, and also specified weighted graph model to find relations among the actors. The main disadvantage with this model was its complexity in determining relations. Semantic annotation of abstract models of actor ecosystem [45] could be used to derive executable process models that realise those systems. Here, a partial actor eco system for a transport organisation was proposed with logical operators such as AND, OR and XOR. The advantage of this model was its simplicity in nature but lacked in precision. Other approach in building formal model of social network with rigorous maths along with algorithm were also studied in [46] illustrated the idea and demonstrated the effectiveness of high level Petri nets with channels for formally modelling of social networks and analysed a friend suggestion function in it. Again the disadvantage of such model was its complexity and understandability. In another approach, social relation extraction system using dependency-kernel-based support vector machine was proposed [47], and classified input sentences on the basis of describing social relations between two people. The social relation extraction process was too complex in nature and its applicability was limited.

We have made an attempt to capture the generic model of an actor of a specific professional social network. We have found that our model is complete by drawing a set of characteristic features of an actor based on the type of activities, social status, qualifications, etc. rather than using tag or rule based approach. We also found that an actor can be defined by a set of generic features is more adaptable than using tags or rule based approaches. Our model is simple in nature and its applicability on social networks has produced good results.

Generic actor model for a professional social network

In this section, we present a GAMPSON which initially gathers distinct characteristic features of an actor such as personally identifiable information, professional information, social status, activity, and history (shown in Fig. 1). Depending upon an individual actor these characteristic features vary, and relations among actors can be built based on these characteristics features of the actors. Dynamic change of the characteristic features and varying relations among actors are the key factors in the proposed GAMPSON.

We define the actor of a social network as a five tuple and its structure is as follows.

$$a_i = \{PerI_i, ProfI_i, Act_i, Hist_i, SocS_i\} \tag{1}$$

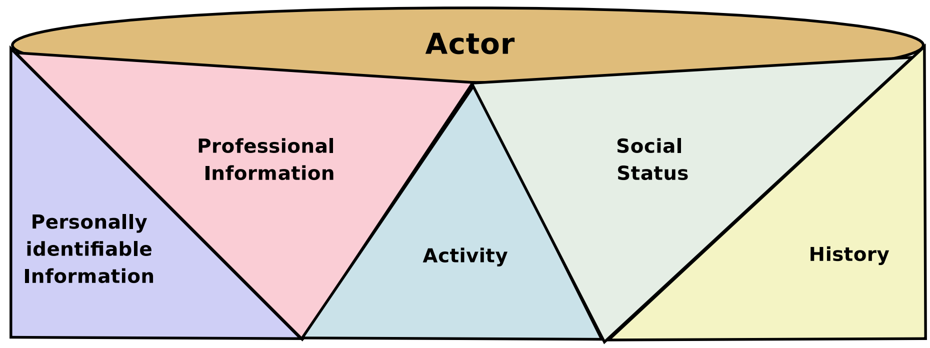

Fig. 1 Generic actor model for a professional social network.

where,

- Personally identifiable Information ($PerI_i$) of the actor a_i : $PerI_i$ is used to identify the actor uniquely. We consider this information as $PerI_i = \{per_i^1, per_i^2, ..., per_i^n\}$. For example, $per_i^1 = Name$, $per_i^2 = address$, $per_i^3 = IP\ address$, $per_i^4 = Telephone\ number$, etc.
- Professional Information ($ProI_i$) of the actor a_i : $ProI_i$ is used to provide profession information of the actor. We recognise this information as $ProI_i = \{pro_i^1, pro_i^2, ..., pro_i^m\}$. For example, $pro_i^1 = education$, $pro_i^2 = occupation$, $pro_i^3 = qualification$, $pro_i^4 = role$, etc.
- Activity (Act_i) of the actor a_i : Act_i is used to provide activity information of the actor. We recognise this information as $Act_i = \{act_i^1, act_i^2, ..., act_i^p\}$. For example, $act_i^1 = research$, $act_i^2 = publications$, etc.
- History ($Hist_i$) of the actor a_i : $Hist_i$ is used to indicate history of the actor. We consider this information as $Hist_i = \{hist_i^1, hist_i^2, ..., hist_i^s\}$. For example, $hist_i^1 = coordination$, $hist_i^2 = interactions$, etc.
- Social Status ($SocS_i$) of the actor a_i : $SocS_i$ is used to indicate social information of the actor. We consider this information as $SocS_i = \{soc_i^1, soc_i^2, ..., soc_i^l\}$. For example, $soc_i^1 = religion$, $soc_i^2 = ethnicity$, $soc_i^3 = class$, $soc_i^4 = position$, etc.
- Thus a typical actor a_i in a social network can be represented as

$$\begin{aligned} a_i = &\{XYZ, 21st\ street\ (NY), 080-86945668, PhD, \\ &Professor, academics, research, publications\} \end{aligned}$$

Weight allocation to the actor's characteristic features

We have considered values (see Table 1) for every characteristic feature to capture the realistic feature of an actor. In education system, if a person is BE (Bachelor of Engineering), then he has supposed to pass 1st to 10th standard, then 2 years in junior college, and later 4 years in Engineering. Hence for BE we have taken $10 + 2 + 4 = 16$. Similarly for BS it is $10 + 2 + 3 = 15$ and for MS it is $10 + 2 + 3$(for BS) $+ 2$(for MS) $= 17$. For ME it is $10 + 2 + 4 + 2 = 18$ and for PhD it is $10 + 2 + 4 + 2 + 5 = 23$. We also have considered type of work done by actors, class of degree, g-index and h-index for education. Hence the total weight of the actor a_i based on education is calculated as

Table 1 Characteristic features and their values used in the GAMPSON

Characteristic features	Sub characteristics	Set	Weights
1. Personally identifiable information (*PerI*)	Name (per_i^1)	{*Name of the actors*}	1 *for common name*
	Address (per_i^2)	{*Home address of the actors*}	1 *for common address*
	IP address (per_i^3)	{*0.0.0.0.0.0 to FF.FF.FF.FF.FF.FF*}	1 *for common IP address*
	Telephone number (per_i^4)	{*Telephone numbers of this actors*}	1 *for common telephone number*
2. Professional Information (*ProI*)	Education (pro_i^1)	{*PhD, ME, MS, BE, BS*}	$15I_{(BS)} + 16\, I_{(BE)}$ $+17\, I_{(MS)} + 18\, I_{(ME)}$ $+23\, I_{(PhD)}$
	Occupation (pro_i^2)	{*Administration, Banking, Finance, Businessman*}	*Exponential weights* (e^{-x})
	Qualification (pro_i^3)	{*Number of years spent n college, equipment handled, courses,conferences*}	*Gaussian weights* ($N(0, 1)$)
	Role (pro_i^4)	{*Provider,collector,manager, security,farmer*}	*Ordered exponential weights*(e^x)
3. Activity (*Act*)	Current (act_i^1)	{*Research activity, course, teaching, session conduction, group seminar, meetings*}	*Priority weights*
	Past (act_i^2)	{*joint number of publications, research topics undertaken, conference attended, positions held*}	*Rank of activity*
4. History (*Hist*)	History of actor ($hist_i$)	{*coordination, interactions, worked on similar project, research similarity, published, papers*}	*Gaussian weights* ($N(0, 1)$)

$$\begin{aligned} Weight\ of\ education\ of\ a_i = {} & (Number\ of\ years\ spent\ the\ college\ by\ a_i) \\ & + (g - index\ of\ a_i) + (h - index\ of\ a_i) \\ & + (class\ of\ degree\ of\ a_i) \end{aligned}$$

For occupation, we have assigned exponential weights because the probability of occurring of an event or activity of an administrator is greater than banker, finance, and businessman. For example, in the agriculture social network, the probability of a scientist (who is administrator) enquiring about soil contents, type of crop, etc. is greater than banker, farmer, and labourer. Also, a professor working in an engineering department will be less interested in the agriculture related activities than a professor in the department of organic chemistry. For history, since history always gets accumulated, hence the Gaussian curve will be formed due to law of large numbers. Consider actors a_i and a_j where if education level of a_i is PhD then it takes value as 23, and education level of a_j is ME then it takes value 18. Also, if an actor a_i has name "Peter Allen" and an actor a_j has name "John Allen", then actors a_i and a_j have common sirname. Hence, the value of the name is given as 1 and same follows for home address, IP address, and telephone number. Activity such as teaching, research activity, session, seminar, publications, research, conference attended, and positions held are assigned weights based on their rank. For example, if number of courses taught are two, then weight of teaching is 2.

Thus, if an actor a_i is PhD, administrator, and teaching, and an actor a_j is ME, administrator, and teaching, then

$$\begin{aligned}&\textit{Weight of an actor } a_i \textit{ based on common characteristic features}\\&= W_{a_i} = \frac{23 + e^{-1} + 2}{4} = 6.3419\end{aligned}$$

$$\begin{aligned}&\textit{Weight of an actor } a_j \textit{ based on common characteristic features}\\&= W_{a_j} = \frac{18 + e^{-1} + 2}{4} = 5.0919\end{aligned}$$

Relation among actors in a social network

A relation ($R_{ij} = R(a_i, a_j)$) defines the way in which two actors a_i and a_j are connected in a social network. A relation R_{ij} can be defined as an expression involving one or more characteristic features of actors a_i and a_j. Relation among actors a_i and a_j is set up based on their characteristic features as

$$\begin{aligned}R_{ij} = R(a_i, a_j) = &\left\{PerI_i \cap PerI_j\right\} + \{ProI_i \cap ProI_j\} + \{Act_i \cap Act_j\}\\&+ \{SocS_i \cap SocS_j\} + \{Hist_i \cap Hist_j\}\end{aligned} \tag{2}$$

The categorisation of the relation (R_{ij}) among actors a_i and a_j is given by

$$R(a_i, a_j) = \begin{cases} \textit{hierarchical} & \text{if } (W_{a_i} - W_{a_j}) > 0 \\ \textit{equivalence} & \text{if } (W_{a_i} - W_{a_j}) = 0 \\ \textit{no relation} & \text{otherwise} \end{cases}$$

Hierarchical relation among actors

Consider actors a_i, a_j, and a_k as shown in Fig. 2, where a_i and a_j have common features such as ($ProI_i \cap ProI_j \neq \phi$ and $Act_i \cap Act_j \neq \phi$) PhD and ME, administrator, and teaching, i.e., the actor a_i is PhD $= 23$, administrator $= e^{-1}$, and teaching $= 2$, and the actor a_j is ME $= 18$, administrator $= e^{-1}$, and teaching $= 2$.

$$W_{a_i} = \frac{pro_i^1 + pro_i^2 + act_i^1}{4} = \frac{23 + e^{-1} + 2}{4} = 6.3419$$

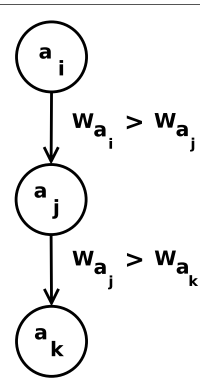

Fig. 2 Hierarchical relation among actors a_i, a_j, and a_k.

$$W_{a_j} = \frac{pro_j^1 + pro_j^2 + act_j^1}{4} = \frac{18 + e^{-1} + 2}{4} = 5.0919$$

Since $W_{a_i} > W_{a_j}$, the hierarchical relation exists among the actors a_i and a_j.

Also, actors a_j and a_k have common feature such as ($ProI_j \cap ProI_k \neq \phi$) ME and BE, and provider.

$$W_{a_j} = \frac{pro_j^1 + pro_j^4}{4} = \frac{18 + e^1}{4} = 5.1795$$

$$W_{a_k} = \frac{pro_k^1 + pro_k^4}{4} = \frac{16 + e^1}{4} = 4.6795$$

Since $W_{a_j} > W_{a_k}$, the hierarchical relation exists among the actors a_j and a_k.

Equivalence relation among actors

Consider actors a_i, a_j, and a_k as shown in Fig. 3, where a_i and a_j have common features such as ($ProI_i \cap ProI_j \neq \phi$ and $Act_i \cap Act_j \neq \phi$) PhD and MS, courses, and research. Similarly, actors a_i and a_k have common features such as ($ProI_i \cap ProI_k \neq \phi$ and $Act_i \cap Act_k \neq \phi$) PhD and MS, courses, and research.

$$W_{a_i} = \frac{pro_i^1 + pro_i^3 + act_i^1}{4} = \frac{23 + 0.6352 + 1}{4} = 6.1588$$

$$W_{a_j} = \frac{pro_j^1 + pro_j^3 + act_j^1}{4} = \frac{17 + 0.6352 + 1}{4} = 4.6588$$

$$W_{a_k} = \frac{pro_k^1 + pro_k^3 + act_k^1}{4} = \frac{17 + 0.6352 + 1}{4} = 4.6588$$

Since $W_{a_i} > W_{a_j}$, $W_{a_i} > W_{a_k}$, and $W_{a_j} = W_{a_k}$, the equivalence relation exists among the actors a_j and a_k.

Design of an actor for the agriculture social network and museum social network using the GAMPSON

We have considered the ASN for study because $32 billion was spent in developed and developing countries (in 2008) on agriculture research [48]. Despite of spending such a

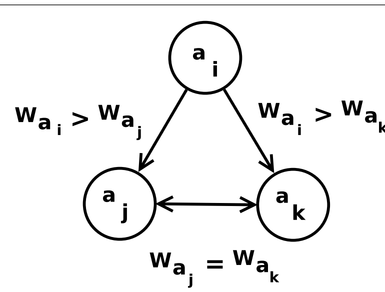

Fig. 3 Equivalence relation among actors a_j and a_k.

huge ammount on the agriculture research, the relation among the participants remains oblivious. We wanted to show a mathematical way in which these participant can come together so as to share their knowledge based on the relations. Also, for comparison purpose, we have studied MSN because information provisioning to actors of museum [49] is crucial based on relations among the actors. Hence, in this section, we demonstrate applications such as the ASN and MSN using the GAMPSON. We have considered a typical 25 actors based ASN and MSN as shown in Figs. 4 and 5, respectively. Dynamic acquisition and updation of actors' characteristic features such as personally identifiable information, professional information, social status, activity, and history is the key to define an actor for the ASN and MSN. We have explicitly defined characteristic features such as personally identifiable information, professional information, activity, history, and social status of actors related to the ASN and MSN. Actors and their characteristic features used in the ASN and MSN are shown in Tables 2 and 3, respectively.

Relation among actors in the agriculture social network

Some of the actors along with their common characteristic features, weights, and relations used in the ASN are shown in Table 4. The relation among the actors in the agriculture social network can be given as follows.

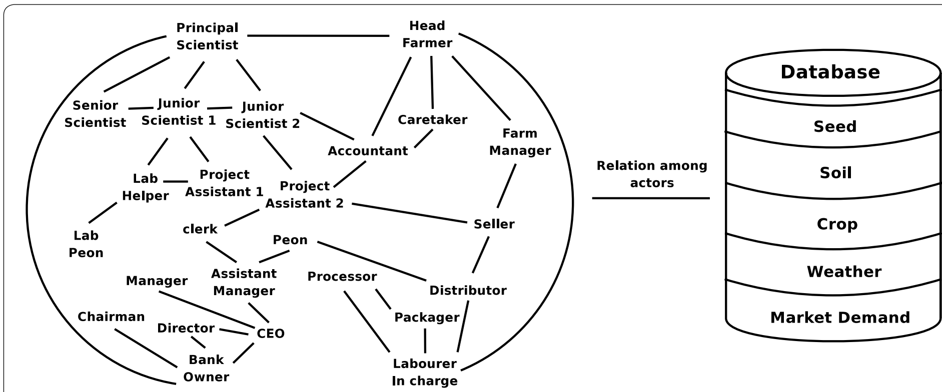

Fig. 4 A typical application for the agriculture social network.

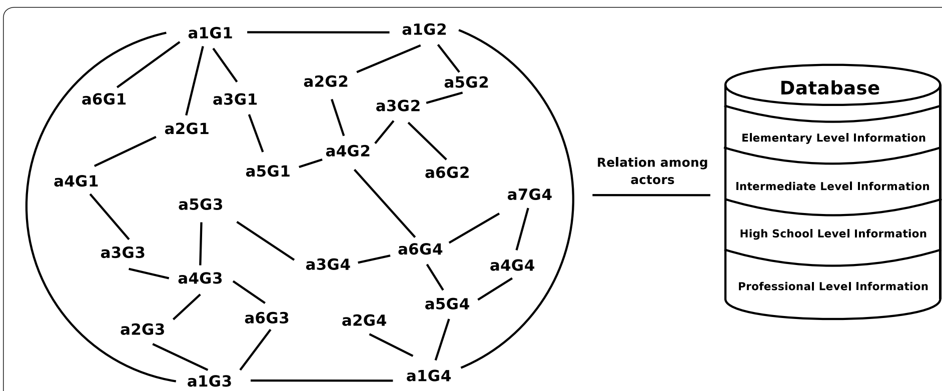

Fig. 5 A typical application for the museum social network.

Table 2 Actors and their characteristic features used in the agriculture social network

Group	Actor	Characteristic features
Scientist (S)	Principal scientist (PS)	{*EFG, No.23(BR), 127.36.14.25, 080—4625, PhD and ME, administrator, collector, publications*}
	Junior scientist 1 (JS1)	{*ABC, No.29(BR), 128.336.12.1, 080—2247, ME, conference, collector, publications*}
	Junior scientist 2 (JS2)	{*FGI, No.17(BR), 182.693.25.78, ME, collector, publications*}
	Project assistant 1 (PA1)	{*XYZ, 22nd street(BR), 128.258.6.4, 080—5698, BE, conference*}
	Project assistant 2 (PA2)	{*HIK, No.102(BR), BE, collector, publications*}
	Senior scientist	{*BCD, No.12(BR), PhD, 103.25.16.12, 080—4631, academic, courses, provider, meetings, interaction*}
	Lab helper	{*GHI,No.66(BR),interactions,coordination*}
	Lab peon	{*ABD, No.130(BR), coordination,*}
Banker (B)	Bank owner	{*CDE, 144th street(DC, 169.48.63.17, 066—4562, banking, administrator, conferences*}
	Chairman	{*EFL, 132th street(DC), 456.289.27.36, 066—4532, banking, meetings, coordination*}
	Director	{*YPR, 122th street(DC), 465.236.59.45, 060—6421, banking, meetings, interactions*}
	CEO	{*GPL, 103th street(DC), 456.13.465.44, 060—8456, banking, meetings, interactions*}
	Manager	{*NDK, 102th street(DC), 146.23.256.14, 060—4452, banking, manager, coordination*}
	Assistant manager	{*AST, 82th street(DC), 198.63.25.163, 060—7896, banking, manager, interactions*}
	Clerk (CL)	{*CLK, 12th street(DC), 156.32.256.23, 060—4861, banking, collector, coordination*}
	Peon	{*PEO, No.3 block2(DC), provider, interactions*}
Farmer (F)	Head farmer	{*HEF, 15th street(LA), 456.12.354.36, collector, finance*}
	Accountant	{*CDF, 21st block(LA), 18.25.36.12,080—4697, collector, courses, coordination, hindu*}
	Caretaker	{*JFK, 55th street(LA), 080—4972, collector, equipment, handling*}
	Farm manager	{*IJK, 43rdavenue(LA), 19.26.55.12,080—7895, finance, meeting,session conduction*}
Labour (L)	Labourer in charge	{*VWX,45th(BR), 080—6348, businessman, coordination, christian*}
	Packager	{*STU,25th(BR), 080—4589, businessman, interaction*}
	Processor	{*LMN, 25th(BR), 080—4561,BE, equipment handling, interactions, christian*}
	Distributor	{*ABL, 23rd(BR), 080—1523, businessman, provider, interactions*}
	Seller	{*DEF, 55 street(LA), 080—4563, finance, session, conduction, interaction, christian*}

Hierarchical relation among actors in the agriculture social network

Consider actors PS, $JS1$, and $PA1$, where PS and $JS1$ have common professional information ($ProI_{PS} \cap ProI_{JS1} \neq \phi$ and activity $Act_{PS} \cap Act_{JS1} \neq \phi$) such as PhD and ME, collector, and publications.

$$W_{PS} = \frac{pro^1_{PS} + pro^4_{PS} + act^2_{PS}}{4} = \frac{23 + e^2 + 2}{4} = 8.0972$$

$$W_{JS1} = \frac{pro^1_{JS1} + pro^4_{JS1} + act^2_{JS1}}{4} = \frac{18 + e^2 + 2}{4} = 6.8472$$

Since $W_{PS} > W_{JS1}$, the hierarchical relation exists among the actors PS and $JS1$.

Table 3 Actors and their characteristic features used in the museum social network

Group	Actor	Characteristic features
Group 1 (G1)	a_1G_1	$\{ABCD, No.1135(NJ), 168.15.16.13, 084-4562, PhD\ and\ ME, christian\}$
	a_2G_1	$\{BCDE, No.4568(BR), 166.28.64.211, 097-1541, ME, hindu\}$
	a_3G_1	$\{CDEF, No.8954(NJ), 186.54.36.12, 145-4569, ME, sikh\}$
	a_4G_1	$\{DEFG, 44nd\ street(DC), 187.36.56.79, 986-4568, BE, christian\}$
	a_5G_1	$\{EFGH, No.51(NJ), 142.25.63.78, 965-4512, BE, sikh\}$
	a_6G_1	$\{FGHI, No.57(BR), 155.36.45.89, 789-4563, PhD, christian\}$
Group 2 (G2)	a_1G_2	$\{GHIJ, No.77(NJ), 146.35.32.14, 147-6932, 8th\ std.\ 1st\ class, hindu\}$
	a_2G_2	$\{HIJK, No.76(BR), 165.89.7.36, 489-1254, 10th\ std.\ 2nd\ class, christian\}$
	a_3G_2	$\{IJKL, 148th\ street(DC), 145.69.85.64, 189-1234, 4th\ std.\ 2nd\ class, hindu\}$
	a_4G_2	$\{JKLM, 139th\ street(BR), 136.28.36.14, 478-0258, 10th\ std.\ 1st\ class, christian\}$
	a_5G_2	$\{KLMN, 127th\ street(NJ), 168.69.54.36, 741-1234, 12th\ std.\ 2nd\ class, christian\}$
	a_6G_2	$\{LMNO, 104th\ street(BR), 178.56.48.97, 982-4568, 10th\ std.\ 1st\ class, christian\}$
Group 3 (G3)	a_1G_3	$\{MNOP, 118th\ street(NJ), 189.64.85.26, 698-4782, 9th\ std.\ 2nd\ class, hindu\}$
	a_2G_3	$\{NOPQ, 87th\ street(BR), 17.95.68.145, 634-7451, 6th\ std.\ 1st\ class, christian\}$
	a_3G_3	$\{OPQR, 82th\ street(DC), 173.59.86.124, 742-1453, 11th\ std.\ 3rd\ class, christian\}$
	a_4G_3	$\{PQRS, No.31\ block2(DC), 148.56.42.29, 486-1287, 4th\ std.\ 1st\ class, hindu\}$
	a_5G_3	$\{QRST, 19th\ street(LA), 147.65.35.42, 489-1784, 3rd\ std.\ 1st\ class, christian\}$
	a_6G_3	$\{RSTU, 53st\ block(LA), 376.45.25.41, 965-1854, BE, sikh\}$
Group 4 (G4)	a_1G_4	$\{STUV, 47th\ street(LA), 192.36.54.89, 789-9856, 12th\ std.\ 2nd\ class, christian\}$
	a_2G_4	$\{TUVW, 23rdavenue(NJ), 193.45.68.25, 863-1789, 8th\ std.\ 1st\ class, christian\}$
	a_3G_4	$\{UVWX, 44th(BR), 183.63.25.15, 983-4856, ME, hindu\}$
	a_4G_4	$\{VWXY, 88th(DC), 178.69.58.46, 489-6523, 5th\ std.\ 1st\ class, hindu\}$
	a_5G_4	$\{WXYZ, 47th(BR), 178.64.25.14, 685-2645, BE, christian\}$
	a_6G_4	$\{XYZA, 63rd(DC), 179.45.68.25, 698-7845, 12th\ std.\ 2nd\ class, christian\}$
	a_7G_4	$\{YZAB, 41\ street(LA), 188.68.56.57, 687-1512, 10th\ std.\ 1st\ class, hindu\}$

Table 4 Actors along with their common characteristic features, weights, and relations used in the ASN

Actors	Common characteristic features	Weight of actors	Relation among actors
1. *PS and JS*1	$pro^1_{PS} = PhD = 23$, $pro^1_{JS1} = ME = 18$, $pro^4_{PS} = pro^4_{JS1} = collector = e^2$, $act^2_{PS} = act^2_{JS1} = publications = 2$	$W_{PS} = 8.0972$, $W_{JS1} = 6.8472$	$W_{PS} > W_{JS1}$ Hierarchical relation
2. *PS and JS*2	$pro^1_{PS} = PhD = 23$, $pro^1_{JS2} = ME = 18$, $pro^4_{PS} = pro^4_{JS2} = collector = e^2$, $act^2_{PS} = act^2_{JS2} = publications = 2$	$W_{PS} = 8.0972, W_{JS2} = 6.8472$	$W_{PS} > W_{JS2}$ Hierarchical relation
3. *JS*1 *and JS*2	$pro^1_{JS1} = pro^1_{JS2} = ME = 18, pro^4_{JS1} = pro^4_{JS2} = collector = e^2, act^2_{JS1} = act^2_{JS2} = publications = 2$	$W_{JS1} = 6.8472, W_{JS2} = 6.8472$	$W_{JS1} = W_{JS2}$ Equivalence relation
4. *JS*1 *and PA*1	$pro^1_{JS1} = ME = 18$, $pro^1_{PA1} = BE = 16, pro^3_{JS1} = pro^3_{PA1} = conference = 0.8632$	$W_{JS1} = 4.7158, W_{PA1} = 4.2158$	$W_{JS1} > W_{PA1}$ Hierarchical relation
5. *JS*2 *and PA*2	$pro^1_{JS2} = ME = 18$, $pro^1_{PA2} = BE = 16, pro^4_{JS2} = pro^4_{PA2} = collector = e^2, act^2_{JS2} = act^2_{PA2} = publications = 2$	$W_{JS2} = 6.4097, W_{PA2} = 6.3472$	$W_{JS2} > W_{PA2}$ Hierarchical relation

Also, $JS1$ and $PA1$ have common professional information ($ProI_{JS1} \cap ProI_{PA1} \neq \phi$) such as ME and BE, and conference.

$$W_{JS1} = \frac{pro^1_{JS1} + pro^3_{JS1}}{4} = \frac{18 + 0.8632}{4} = 4.7158$$

$$W_{PA1} = \frac{pro^1_{PA1} + pro^3_{PA1}}{4} = \frac{16 + 0.8632}{4} = 4.2158$$

Since, $W_{JS1} > W_{PA1}$, the hierarchical relation exists among the actors JS and $PA1$. Hence, the hierarchical relation exists among the actors PS, $JS1$, and $PA1$ as shown in Fig. 6.

Equivalence relation among actors in the agriculture social network

Consider actors PS, $JS1$, and $JS2$, where PS and $JS1$ have common professional information ($ProI_{PS} \cap ProI_{JS1} \neq \phi$ and activity $Act_{PS} \cap Act_{JS1} \neq \phi$) such as PhD and ME, collector, and publications. Similarly PS and $JS2$ have common professional information ($ProI_{PS} \cap ProI_{JS2} \neq \phi$ and activity $Act_{PS} \cap Act_{JS2} \neq \phi$) such as PhD and ME, collector, and publications.

$$W_{PS} = \frac{pro^1_{PS} + pro^4_{PS} + act^2_{PS}}{4} = \frac{23 + e^2 + 2}{4} = 8.0972$$

$$W_{JS1} = \frac{pro^1_{JS1} + pro^4_{JS1} + act^2_{JS1}}{4} = \frac{18 + e^2 + 2}{4} = 6.8472$$

$$W_{JS2} = \frac{pro^1_{JS2} + pro^4_{JS2} + act^2_{JS2}}{4} = \frac{18 + e^2 + 2}{4} = 6.8472$$

$$W_{PA2} = \frac{pro^1_{PA2} + pro^4_{PA2} + act^2_{PA2}}{4} = \frac{16 + e^2 + 2}{4} = 6.3472$$

Since, $W_{PS} > W_{JS1}, W_{PS} > W_{JS2}$, and $W_{JS1} = W_{JS2}$, the equivalence relation exists among the actors $JS1$ and $JS2$ as shown in Fig. 6. Also, $W_{PA1} \neq W_{PA2}$, hence the equivalence relation doesn't exists among the actors $PA1$ and $PA2$.

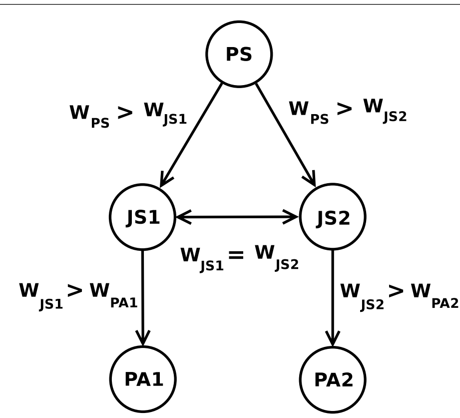

Fig. 6 Hierarchical and equivalence relation among the actors in the agriculture social network.

Relation among actors in the museum social network

We consider the MSN as another example (see Fig. 5), where some of the actors along with their common characteristic features, weights, and relations used in the MSN are shown in Table 5.

Simulation environment

We have considered characteristic features of actors and four groups of actors of agriculture and museum social network as shown in Fig. 7 to simulate the GAMPSON. Initially all actors are assigned their respective personally identifiable information, professional information, activity, history, and social status. As actors enter the system randomly, the GAMPSON dynamically monitors different characteristic features depending upon circumstances of actors, and corresponding relations among actors are formed. We also provided access to actors over databases based on the relation among the actors.

Simulation Results

We have created profiles of actors of ASN and MSN based on actors characteristic features, and calculated weights of actors theoretically. Later, using the GAMPSON, the variation of weights of actors is observed over time through simulations (on Java platform). We have varied characteristic features of the actors of ASN and MSN considering Eq. 2 and taken the average of values (we call it theoretical value). Later, we observe characteristic features for one path, and compare with the average value (we call it observed). The results are shown in Figs. 8 and 9, where the graphs are plotted as the percentage of accuracy (obtained from Eq. 3) of the model for a set of actors of a group against time for ASN and MSN, respectively, and show that the theoretical and observed weights of actors matches closely.

$$Accuracy = \frac{True\ value\ of\ relation - Variation\ in\ true\ value\ of\ relation}{True\ value\ of\ relation} \tag{3}$$

Other graphs are plotted in Figs. 10 and 11 for the percentage of accuracy of the model for a set of actors of four groups against time for ASN and MSN, respectively, and show

Table 5 Actors along with their common characteristic features, weights, and relations used in the MSN

Actors	Common characteristic features	Weight of actors	Relation among actors
1. a_1G_1 and a_2G_1	$pro^1_{a_1G_1} = PhD = 23$, $pro^1_{a_2G_1} = ME = 18$	$W_{a_1G_1} = 5.75,\ W_{a_2G_1} = 4.5$	$W_{a_1G_1} > W_{a_2G_1}$ Hierarchical relation
2. a_1G_1 and a_3G_1	$pro^1_{a_1G_1} = PhD = 23$, $pro^1_{a_3G_1} = ME = 18$	$W_{a_1G_1} = 5.75,\ W_{a_3G_1} = 4.5$	$W_{a_1G_1} > W_{a_3G_1}$ Hierarchical relation
3. a_2G_1 and a_3G_1	$pro^1_{a_2G_1} = pro^1_{a_3G_1} = ME = 18$	$W_{a_2G_1} = 4.5,\ W_{a_3G_1} = 4.5$	$W_{a_2G_1} = W_{a_3G_1}$ Equivalence relation
4. a_2G_1 and a_4G_1	$pro^1_{a_2G_1} = ME = 18$, $pro^1_{a_4G_1} = BE = 16$	$W_{a_2G_1} = 4.5,\ W_{a_4G_1} = 4$	$W_{a_2G_1} > W_{a_4G_1}$ Hierarchical relation
5. a_3G_1 and a_5G1	$pro^1_{a_3G_1} = ME = 18$, $pro^1_{a_5G1} = BE = 16$	$W_{a_3G_1} = 4.5,\ W_{a_5G1} = 4$	$W_{a_3G_1} > W_{a_5G1}$ Hierarchical relation

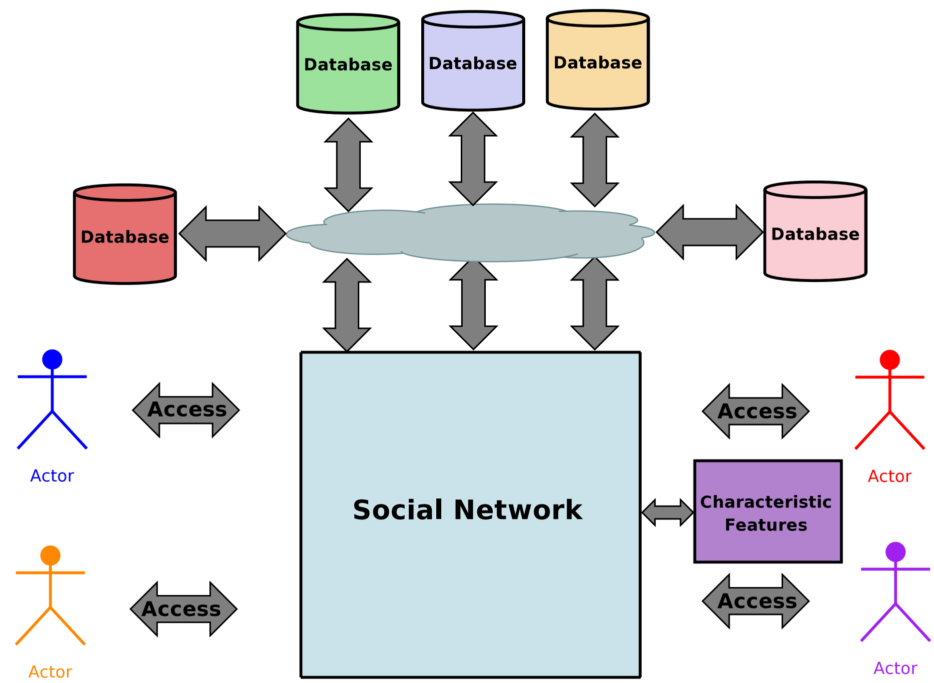

Fig. 7 Simulation environment.

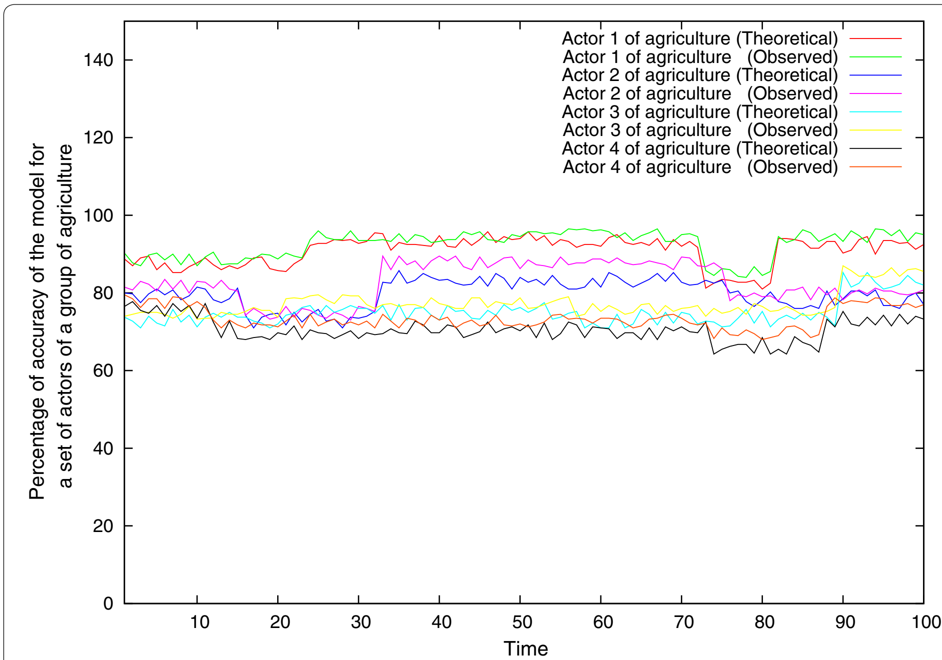

Fig. 8 Percentage of accuracy of the model for a set of actors of a group of agriculture vs time. Here, we have considered a set of actors of a group of agriculture social network and varied their characteristic features over time.

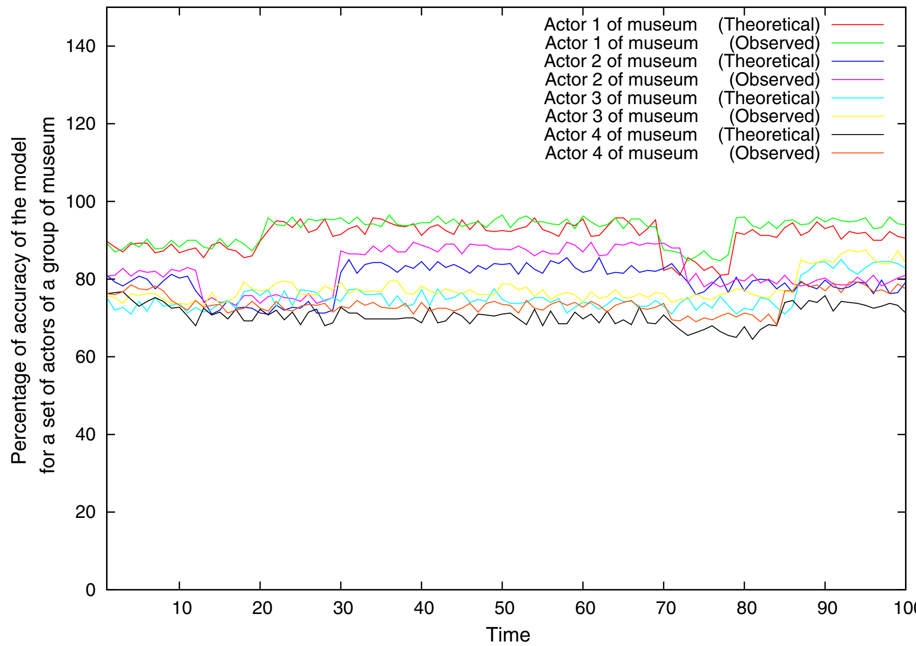

Fig. 9 Percentage of accuracy of the model for a set of actors of a group of museum vs time. Here, we have considered a set of actors of a group of museum social network and varied their characteristic features over time.

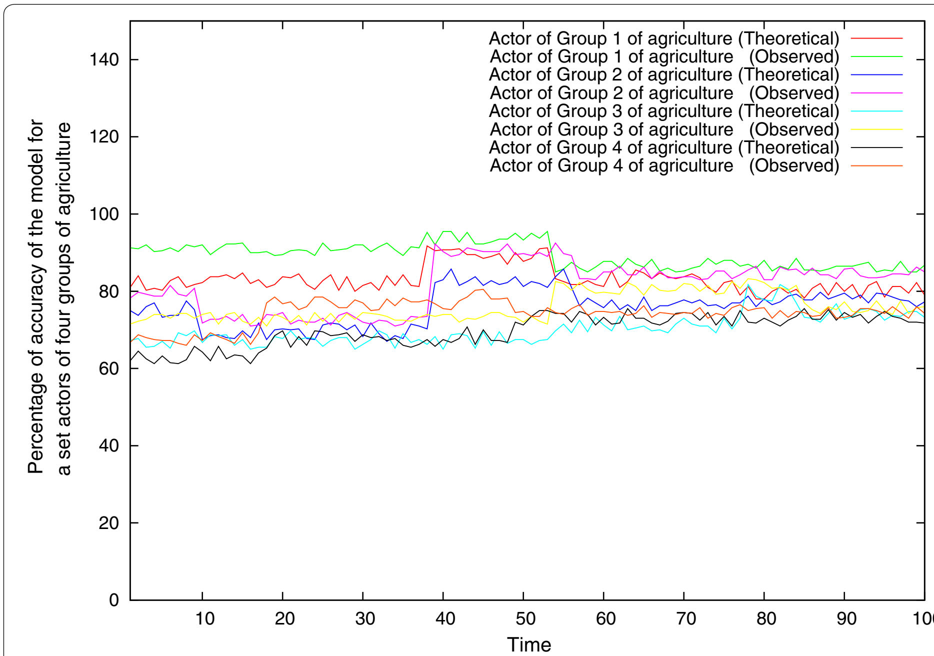

Fig. 10 Percentage of accuracy of the model for a set actors of four groups of agriculture vs Time. Here, we have considered a set of actors of four groups of agriculture social network and varied their characteristic features over time.

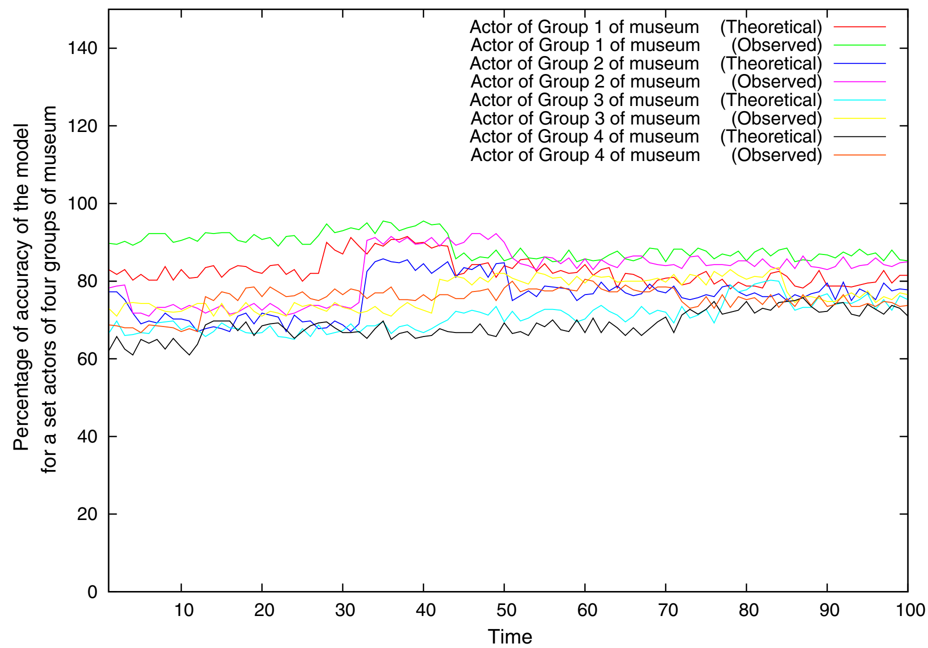

Fig. 11 Percentage of accuracy of the model for a set actors of four groups of museum vs time. Here, we have considered a set of actors of a group of museum social network and varied their characteristic features over time.

initially significant variation in the weights of the actors, but as time increases, the weights of the actors tend to match closely.

In order to determine the variation of relation for a set of actors over neighbourhood of an actor, we first set up relation among actors theoretically. Later using the GAMPSON, the variation of relation for a set of actors is observed over neighbourhood of an actor through simulations (on Java platform). We have plotted variation of relation for a set of actors against neighbourhood of the actors. Here, we have considered a path from 1st neighbourhood till 6th neighbourhood and plotted the normalised weight with each actor along the path. Neighbourhood of an actor can be easily seen from Fig. 2, where an actor a_j is at first neighbourhood of an actor a_i, an actor a_k is at second neighbourhood, and so on. Graphs are plotted as the variation of relation for a set of actors of a group against neighbourhood of an actor (Figs. 12, 13) for ASN and MSN, respectively, and show that the relation for a set of actors of a group is approximately same up to first neighbourhood for without and with actor model. But as more neighbourhood of an actor is considered, there is significant improvement in the relation for actors with our actor model than without actor model (from first neighbourhood up to fourth neighbourhood).

Other graphs are plotted in Figs. 14 and 15 for the variation of relation for a set of actors of four groups against neighbourhood of an actor for ASN and MSN, respectively, and again show significant improvement in the relation for actors with our actor model than without actor model (from second neighbourhood up to fourth neighbourhood).

In order to determine accuracy of the model for various actors, we have plotted calculated weights of various actors of a group and also of four different groups. Bar graphs in

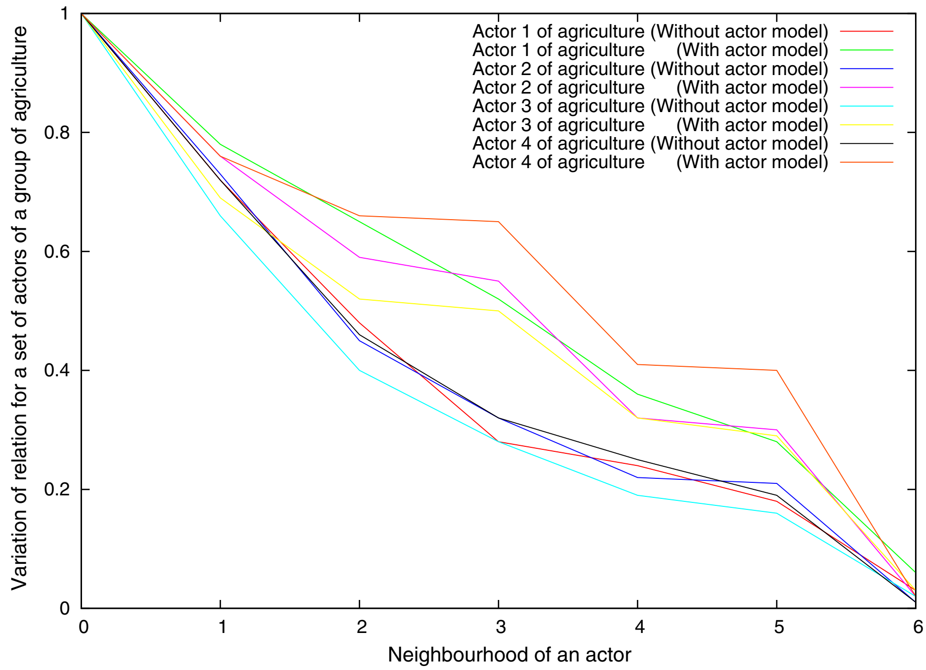

Fig. 12 Variation of relation for a set of actors of a group of agriculture vs neighbourhood of an actor. Here, we have considered a set of actors of a group of agriculture social network and observed the relationship values up to six levels.

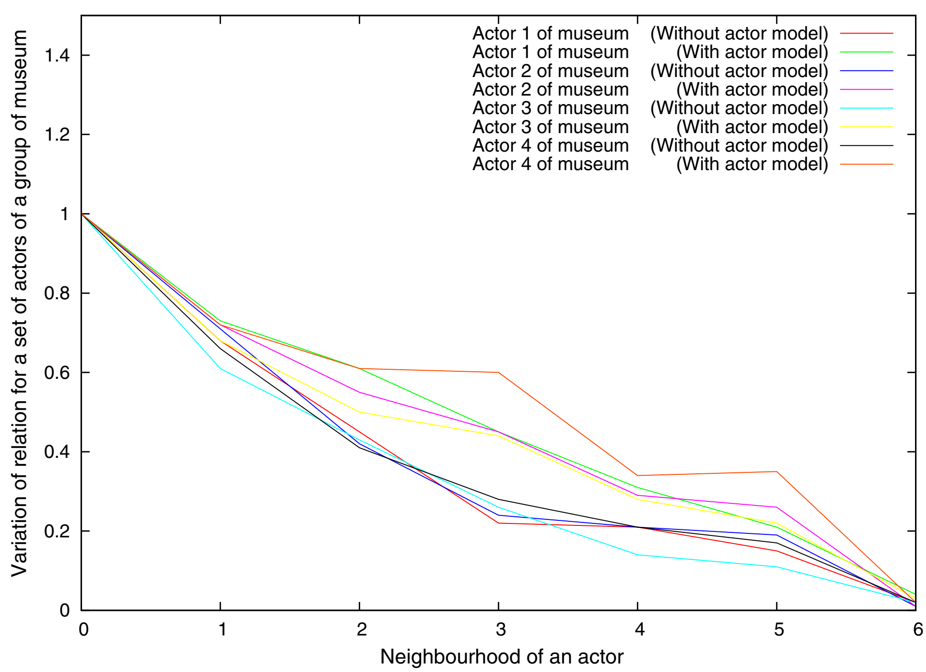

Fig. 13 Variation of relation for a set of actors of a group of museum vs neighbourhood of an actor. Here, we have considered a set of actors of a group of museum social network and observed the relationship values up to six levels.

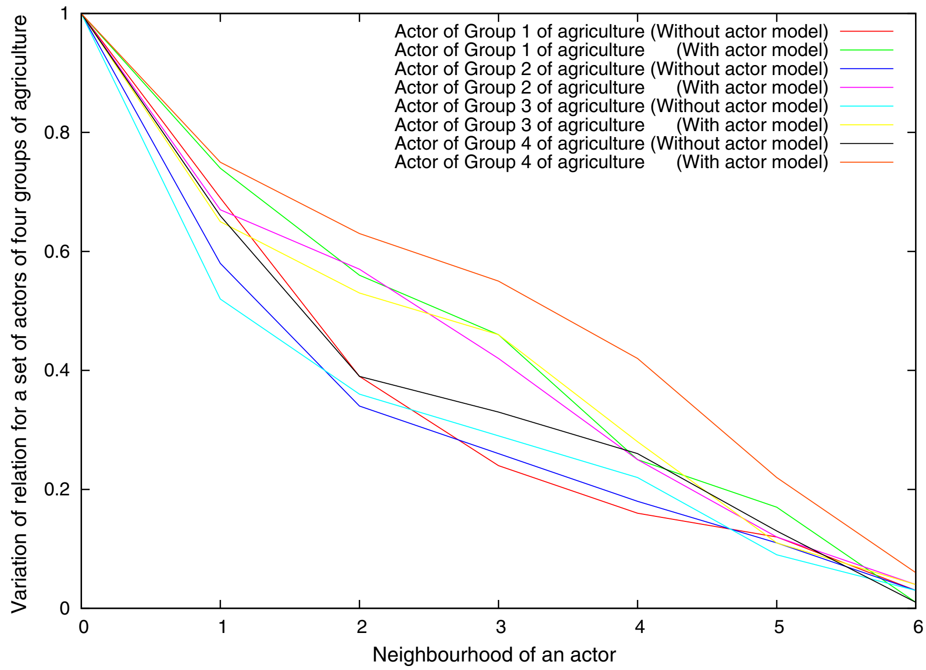

Fig. 14 Variation of relation for a set of actors of four groups of agriculture vs neighbourhood of an actor. Here, we have considered a set of actors of four groups of agriculture social network and observed the relationship values up to six levels.

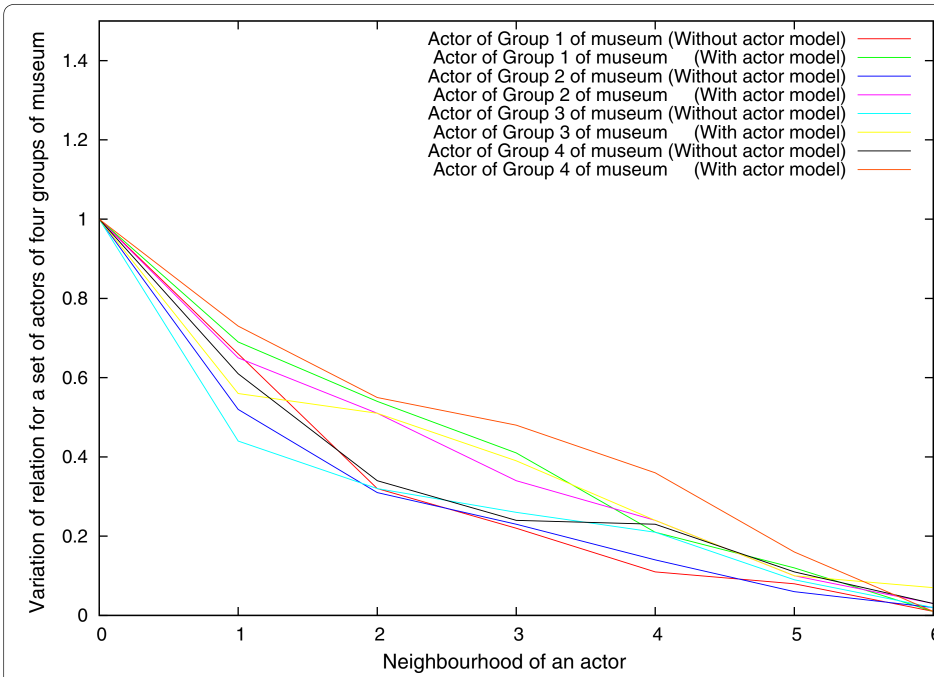

Fig. 15 Variation of relation for a set of actors of four groups of museum vs neighbourhood of an actor. Here, we have considered a set of actors of four groups of museum social network and observed the relationship values up to six levels.

Figs. 16 and 17 show the comparison of the normalised percentage of the accuracy of the model for a set of actors of a group and indicates that the normalised accuracy values for actors of ASN and MSN varies between 18 to 86% and 10 to 82%, respectively.

The comparison for the normalised percentage of accuracy of the model for a set of actors of four groups are shown in bar graphs Figs. 18 and 19 for ASN and MSN, respectively, and also explains that the maximum accuracy values for group 1, group 2, group 3 and group 4 are 82, 80, 68 and 62%, respectively for ASN and the maximum accuracy values for group 1, group 2, group 3 and group 4 are 83, 80, 66 and 64%, respectively for MSN.

In order to determine accuracy of the model for a set of actors of a group for cross social networks, we have taken actors of ASN and applied to MSN, and vice versa. The graph is plotted in Fig. 20 as percentage of accuracy of the model for a set of actors of a group of agriculture applied to museum against time, and shows large variation in theoretical and observed values over time. Another graph is plotted in Fig. 21 as percentage of accuracy of the model for a set of actors of a group of museum applied to agriculture against time, and also shows significant variation in theoretical and observed values over time.

The graph is plotted in Fig. 22 as percentage of accuracy of the model for a set actors of four groups of agriculture applied to museum against time, and shows large variation in theoretical and observed values over time. Another graph is plotted in Fig. 23 as percentage of accuracy of the model for a set actors of four groups of museum applied to agriculture against time, and also again shows large variation in theoretical and observed values over time.

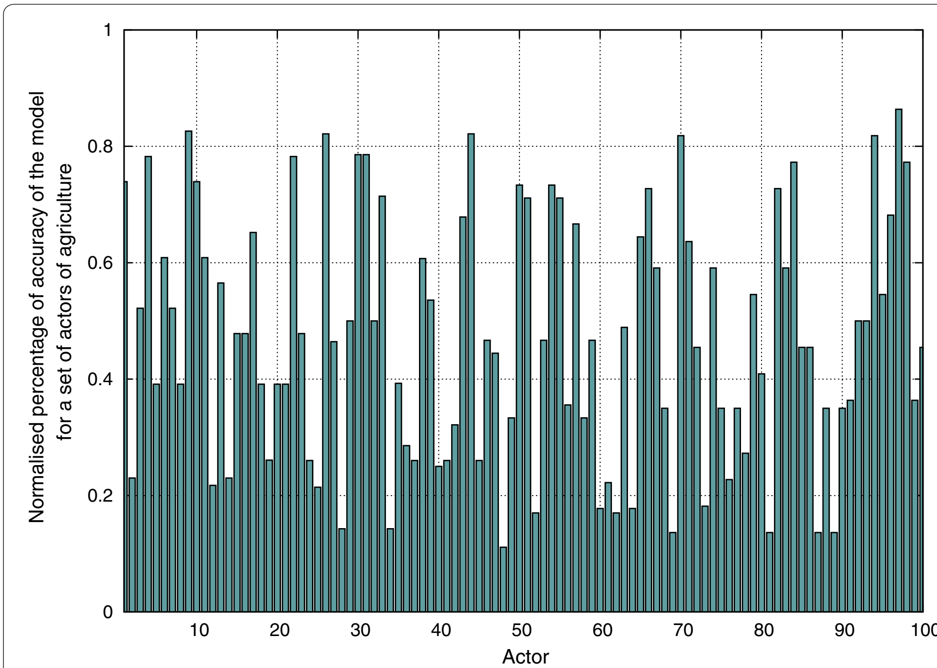

Fig. 16 Normalised percentage of accuracy of the model for a set of actors of agriculture vs actor. Here, we have considered a set of actors of agriculture social network and observed percentage of accuracy of our model for hundred actors.

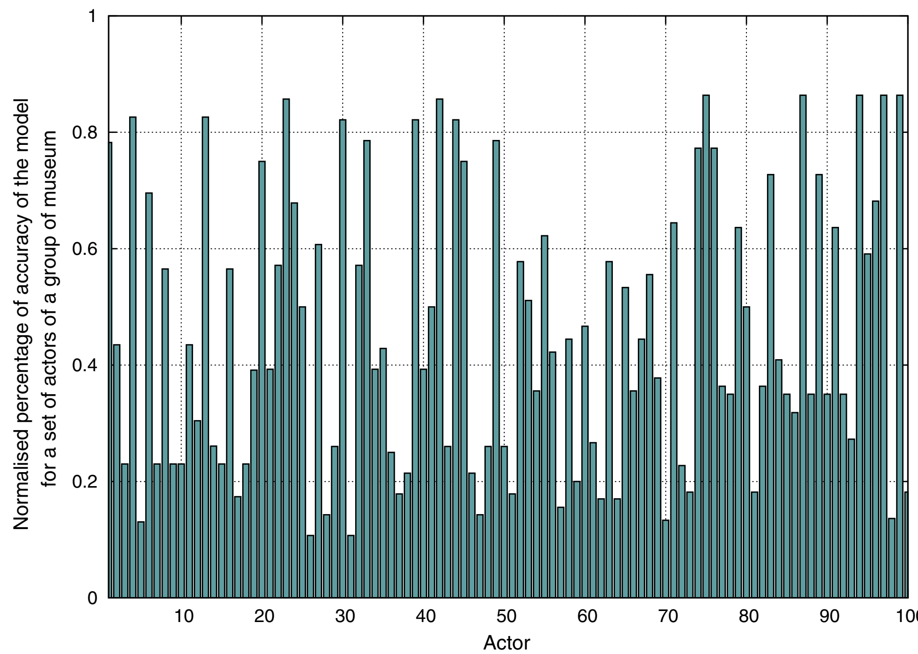

Fig. 17 Normalised percentage of accuracy of the model for a set of actors of a group of museum vs actor. Here, we have considered a set of actors of museum social network and observed percentage of accuracy of our model for hundred actors.

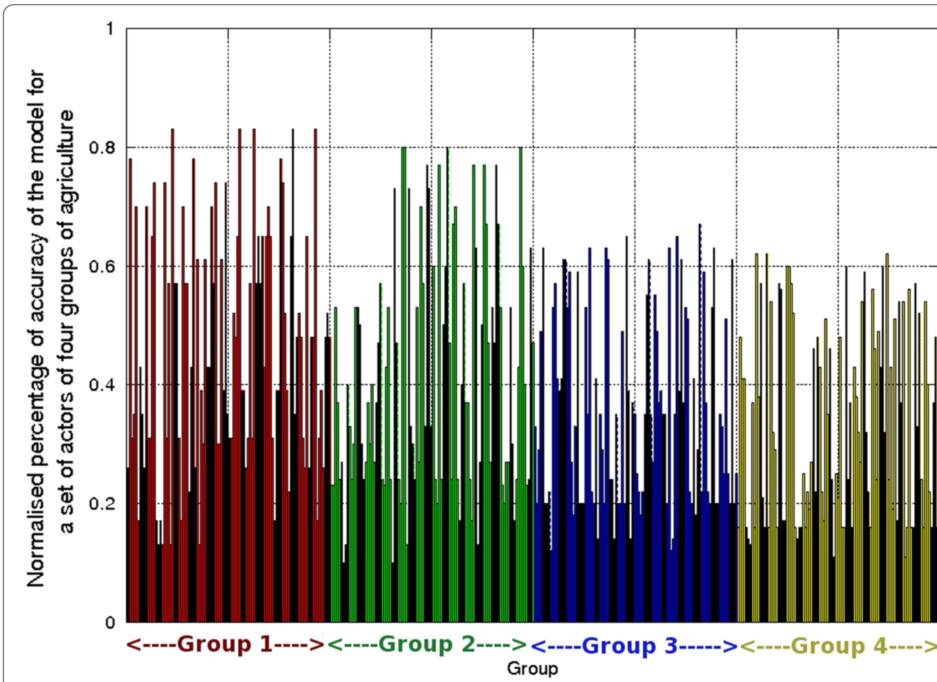

Fig. 18 Normalised percentage of accuracy of the model for a set of actors of four groups of agriculture vs actor. Here, we have considered a set of actors of four groups of agriculture social network and observed percentage of accuracy of our model for actors.

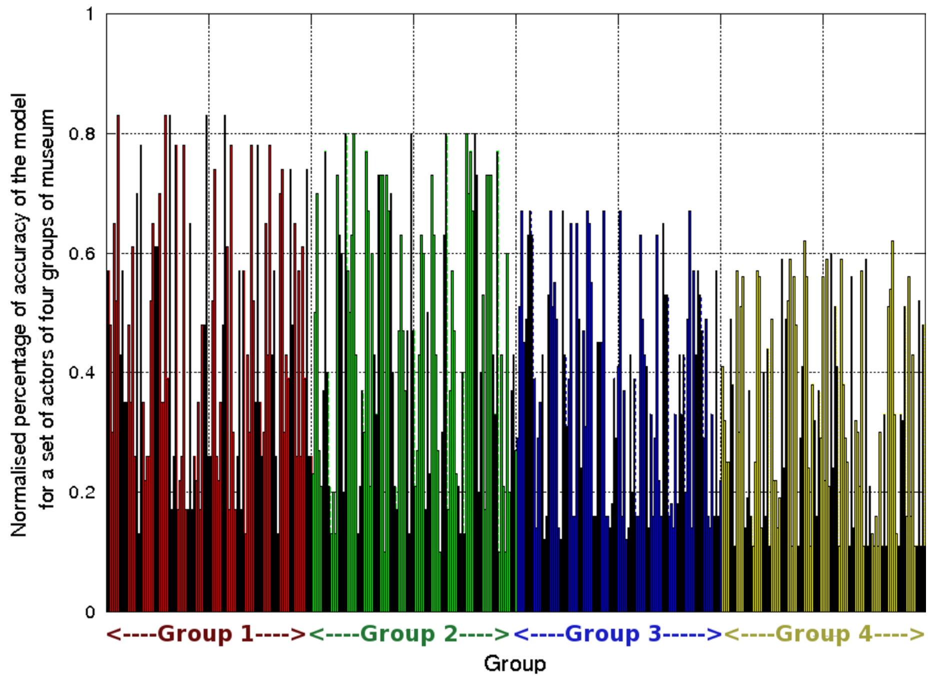

Fig. 19 Normalised percentage of accuracy of the model for a set of actors of four groups of museum vs actor. Here, we have considered a set of actors of four groups of museum social network and observed percentage of accuracy of our model for actors.

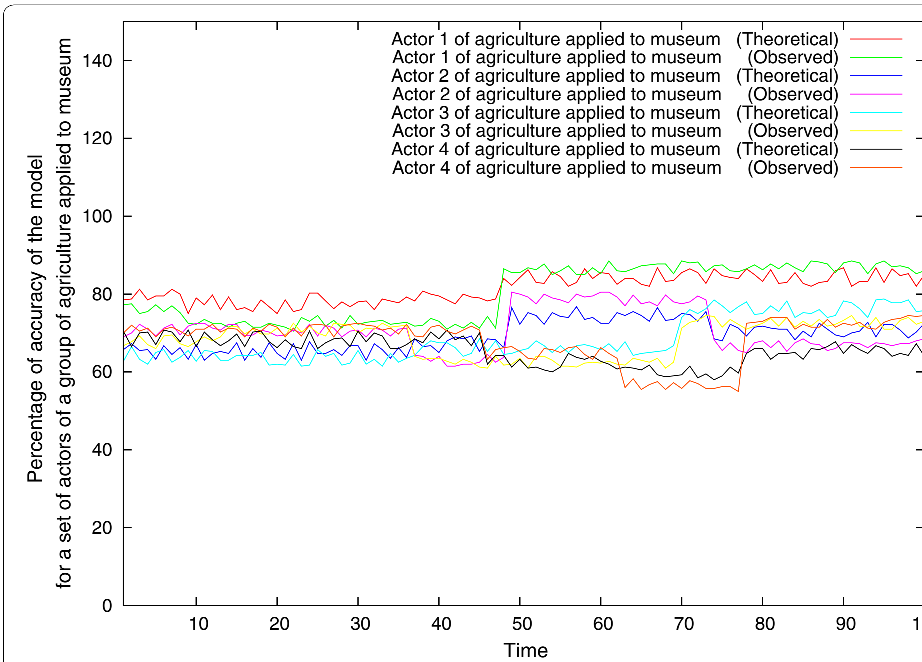

Fig. 20 Percentage of accuracy of the model for a set of actors of a group of agriculture applied to museum vs time. Here, we have varied characteristic features of a set of actors of a group of agriculture social network and applied them over museum social network in order to observe accuracy over time.

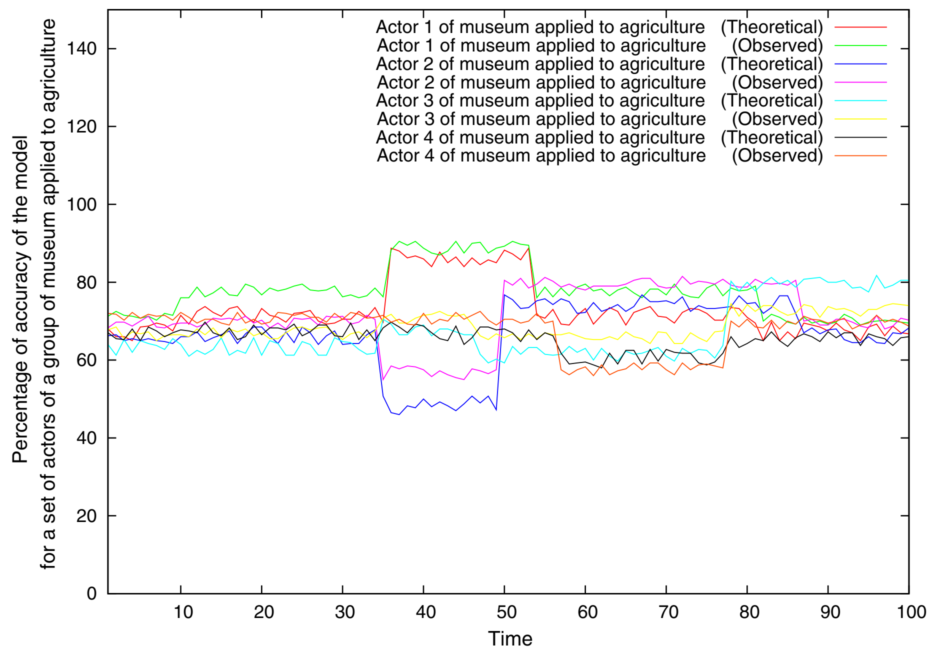

Fig. 21 Percentage of accuracy of the model for a set of actors of a group of museum applied to agriculture vs Time. Here, we have varied characteristic features of a set of actors of a group of museum social network and applied them over agriculture social network in order to observe accuracy over time.

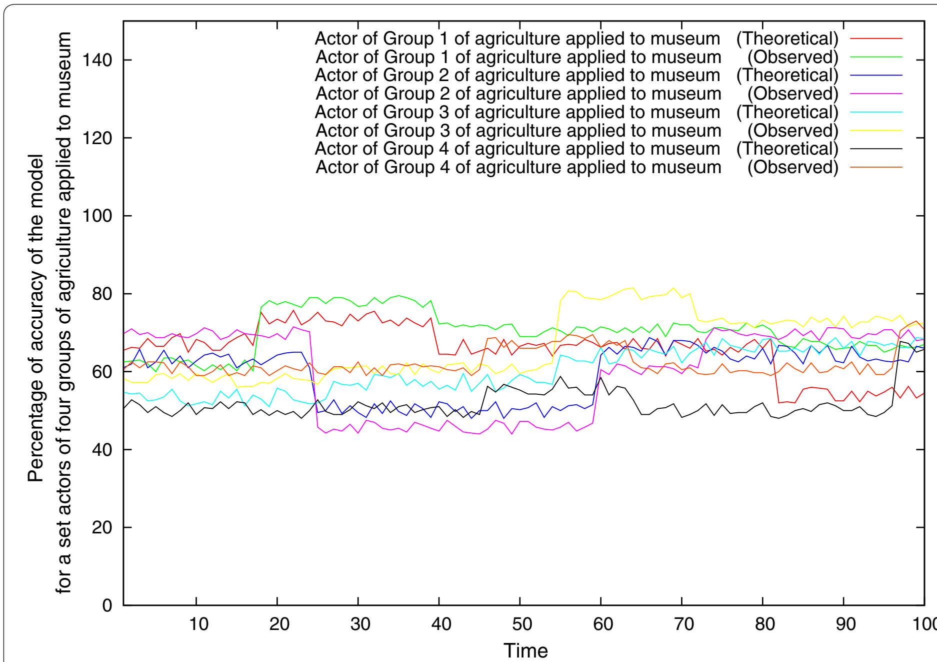

Fig. 22 Percentage of accuracy of the model for a set actors of four groups of agriculture applied to museum vs time. Here, we have varied characteristic features of a set of actors of four groups of agriculture social network and applied them over museum social network in order to observe accuracy over time.

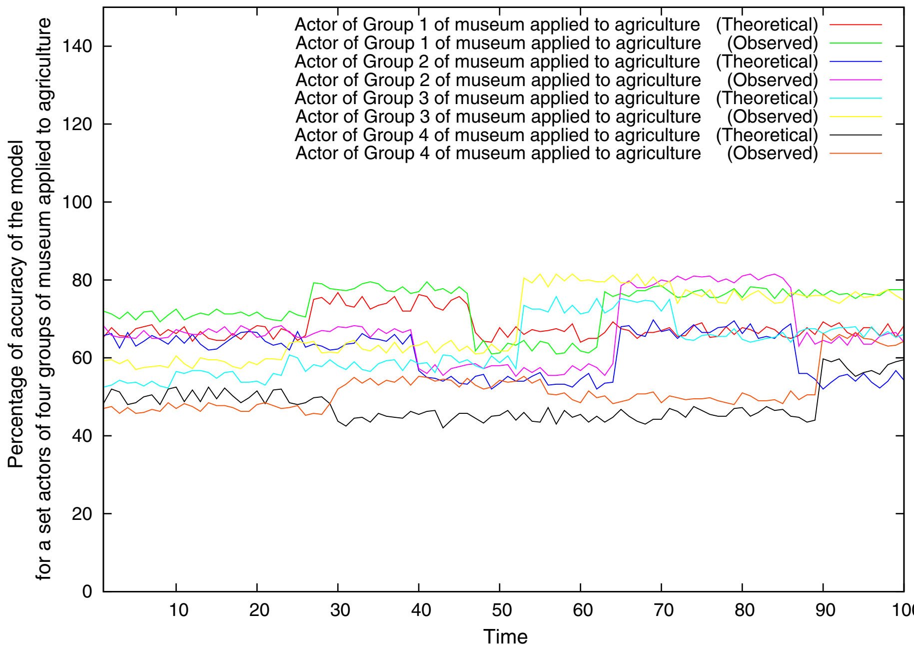

Fig. 23 Percentage of accuracy of the model for a set actors of four groups of museum applied to agriculture vs time. Here, we have varied characteristic features of a set of actors of four groups of museum social network and applied them over agriculture social network in order to observe accuracy over time.

In order to observe accuracy of the model for various actors for cross social networks, we have plotted calculated weights of various actors of a group and also of four different groups. Bar graphs in Figs. 24 and 25 show the comparison of the normalised percentage of accuracy of the model for a set of actors of a group, and indicates that the normalised accuracy values for actors of ASN and MSN varies between 18 and 92% and 10 and 85%, respectively.

The comparison for the normalised percentage of accuracy for a set of actors of four groups for cross social networks are shown in bar graphs Figs. 26 and 27, respectively, and also explains that the maximum accuracy values for group 1, group 2, group 3 and group 4 are 78, 72, 52 and 46%, respectively for actors of ASN applied to MSN and the maximum accuracy values for group 1, group 2, group 3 and group 4 are 66, 56, 50 and 38%, respectively for actors of MSN applied to ASN.

Comparison of percentage of accuracy of the GAMPSON, ICT [43], and Stochastic model [38] over actors of agriculture social network and museum social network is shown in Figs. 28 and 29, and comparison of cross social networks is shown in Figs. 30 and 31. In all the cases, GAMPSON accuracy is better (see Table 6) than ICT and Stochastic model. Average accuracy for the GAMPSON, ICT, and Stochastic model is 71–82%, 56–66%, and 49–64%, respectively.

Comparison of variation of relation for the GAMPSON, ICT, and Stochastic model over actors of agriculture social network and museum social network is shown in Figs. 32 and 33, and comparison of cross social networks is shown in Figs. 34 and 35. In all the cases, GAMPSON is efficient in finding relations better (see Table 7) than ICT and Stochastic model.

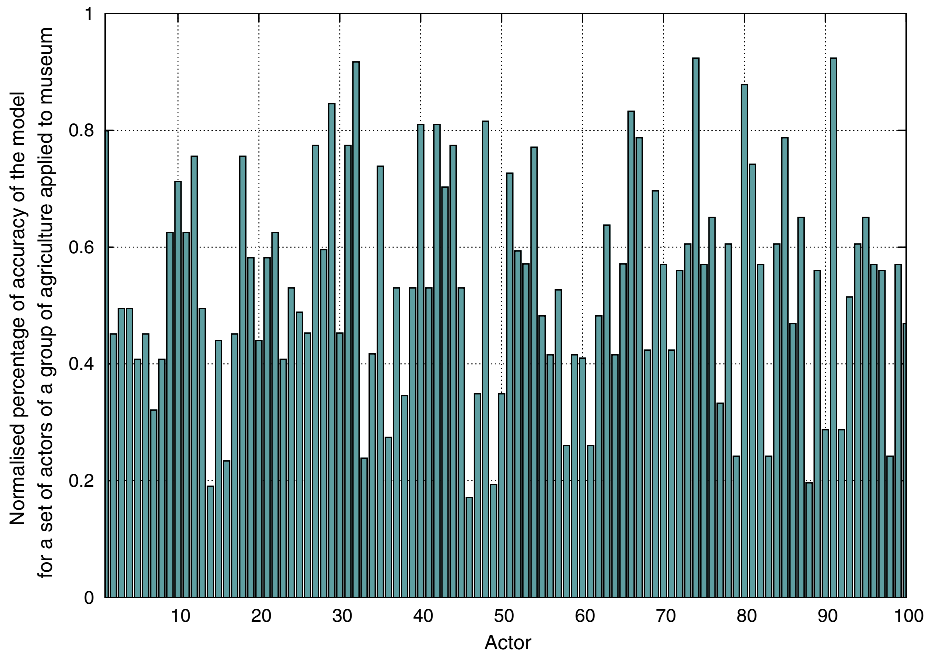

Fig. 24 Normalised percentage of accuracy of the model for a set of actors of a group of agriculture applied to museum vs actor. Here, we have considered a set of actors of agriculture social network and applied them over museum social network in order to observe percentage of accuracy of our model for hundred actors.

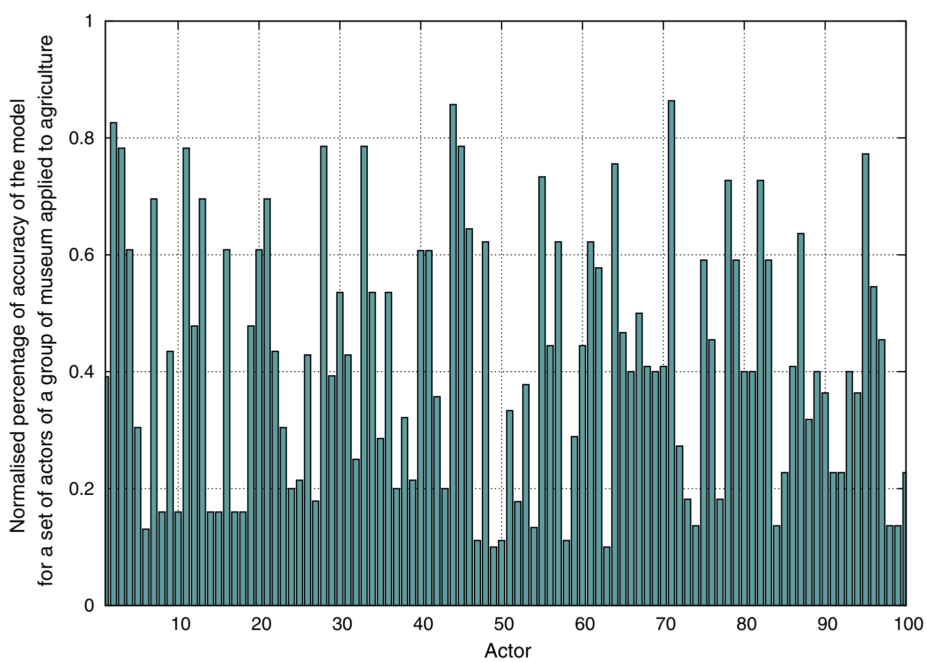

Fig. 25 Normalised percentage of accuracy of the model for a set of actors of a group of museum applied to agriculture vs actor. Here, we have considered a set of actors of museum social network and applied them over agriculture social network in order to observe percentage of accuracy of our model for hundred actors.

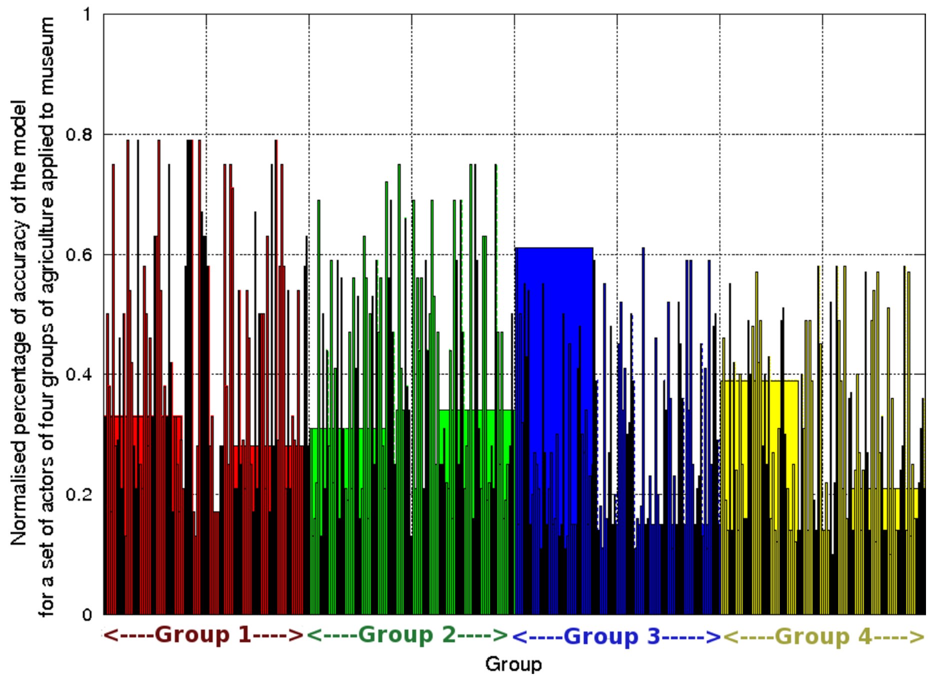

Fig. 26 Normalised percentage of accuracy of the model for a set of actors of four groups of agriculture applied to museum vs group. Here, we have considered a set of actors of four groups of agriculture social network and applied them over museum social network in order to observe percentage of accuracy of our model.

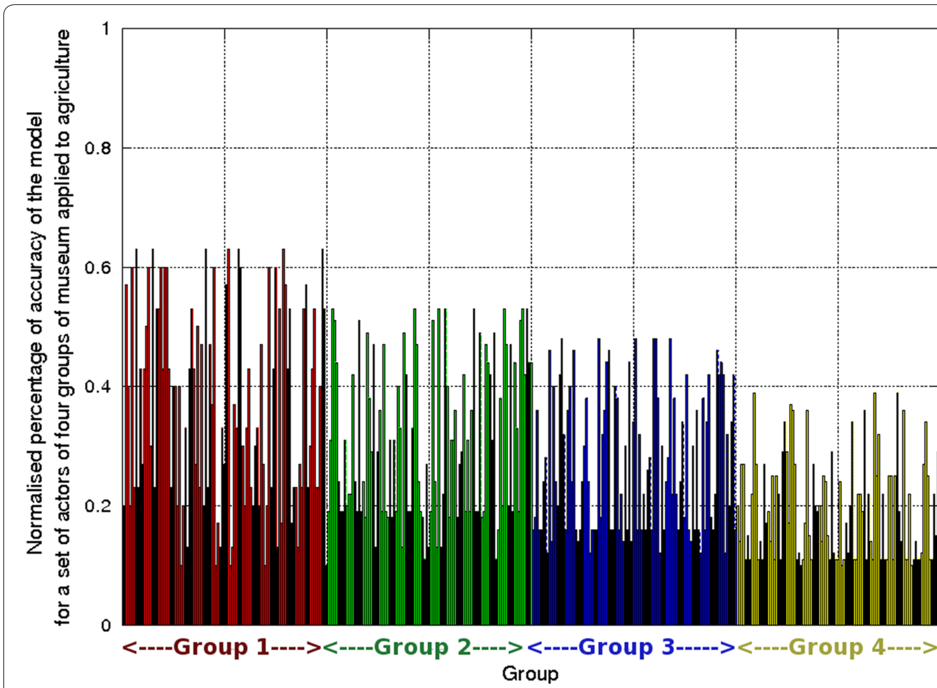

Fig. 27 Normalised percentage of accuracy of the model for a set of actors of four groups of museum applied to agriculture vs group. Here, we have considered a set of actors of museum social network and applied them over museum social network in order to observe percentage of accuracy of our model.

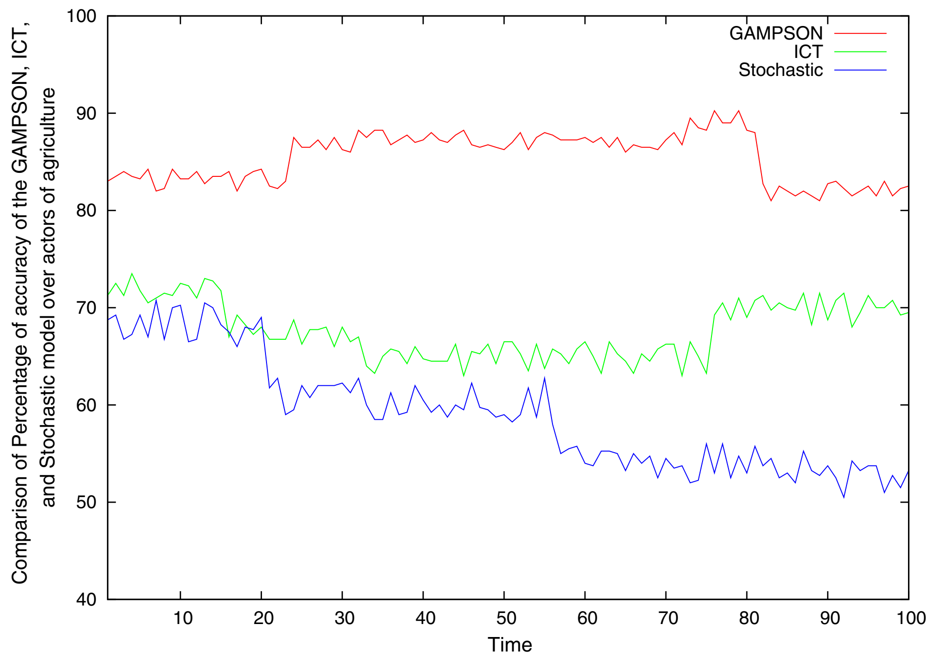

Fig. 28 Comparison of percentage of accuracy of the GAMPSON, ICT, and Stochastic model over actors of agriculture vs time. Here, we have considered a set of actors of agriculture social network and varied their characteristic features over time, and compared percentage of accuracy of the GAMPSON, ICT, and Stochastic model.

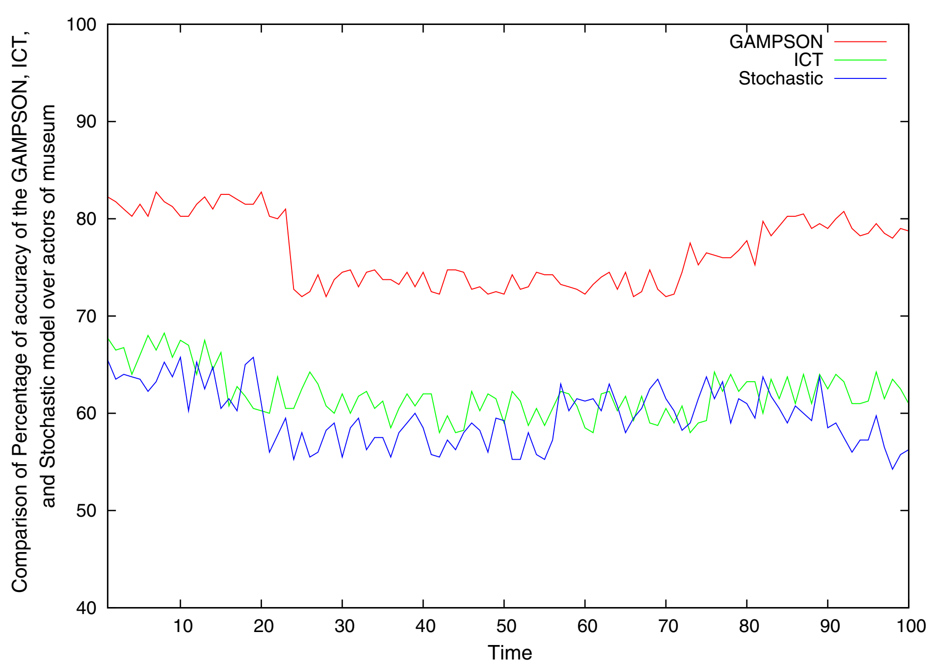

Fig. 29 Comparison of percentage of accuracy of the GAMPSON, ICT, and stochastic model over actors of museum vs time. Here, we have considered a set of actors of museum social network and varied their characteristic features over time, and compared percentage of accuracy of the GAMPSON, ICT, and stochastic model.

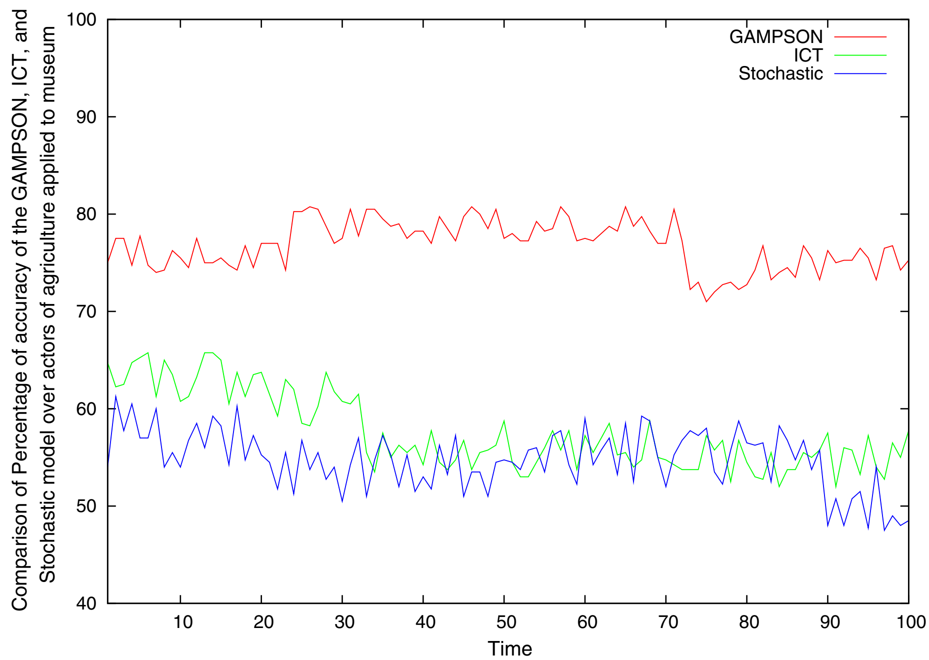

Fig. 30 Comparison of percentage of accuracy of the GAMPSON, ICT, and stochastic model over actors of agriculture applied to museum vs time. Here, we have varied characteristic features of a set of actors of agriculture social network and applied them over museum social network in order to observe accuracy of the GAMPSON, ICT, and stochastic model over time.

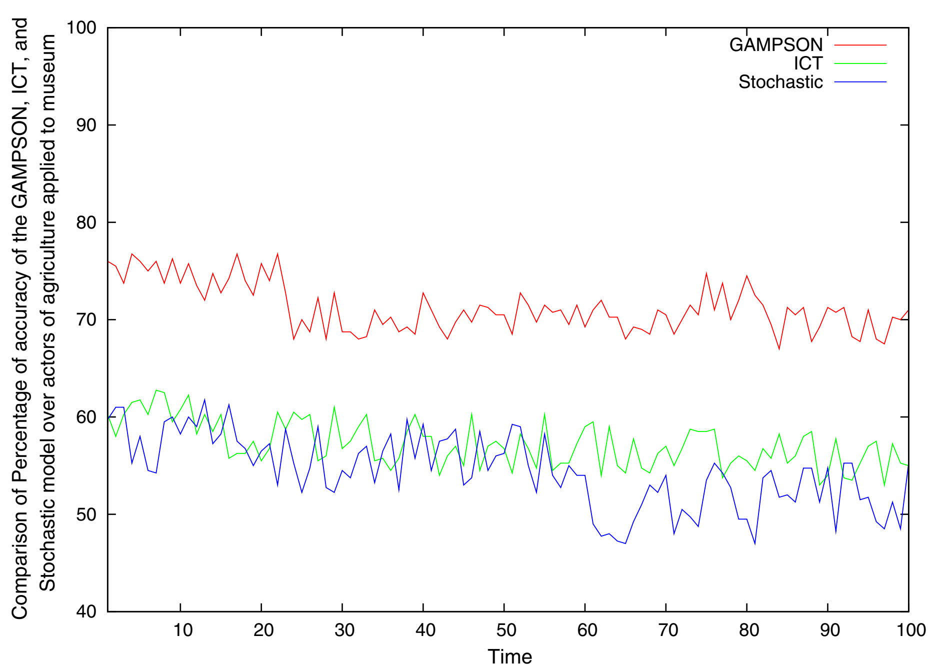

Fig. 31 Comparison of percentage of accuracy of the GAMPSON, ICT, and Stochastic model over actors of agriculture applied to museum vs time. Here, we have varied characteristic features of a set of actors of museum social network and applied them over agriculture social network in order to observe accuracy of the GAMPSON, ICT, and Stochastic model over time.

Table 6 Comparison of the GAMPSON, ICT and Stochastic model with respect to accuracy

	GAMPSON (%)	ICT (%)	Stochastic (%)
1. % of accuracy (for ASN)	83–89	6–72	50–68
2. % of accuracy (for MSN)	71–82	58–68	54 –65
3. % of accuracy (for ASN to MSN)	71– 82	51– 64	48 –61
4. % of accuracy (for MSN to ASN)	58–77	52– 62	45 –61

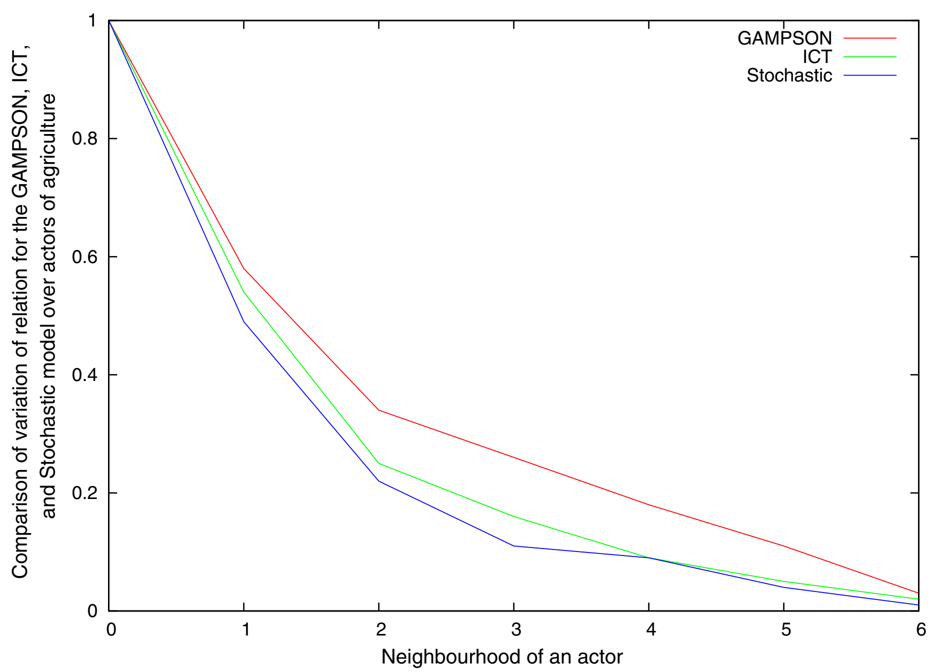

Fig. 32 Comparison of variation of relation for the GAMPSON, ICT, and Stochastic model over actors of agriculture vs neighbourhood of an actor. Here, we have considered a set of actors of agriculture social network and observed the relationship values up to six levels, and compared variation of relation for the GAMPSON, ICT, and Stochastic model.

Conclusions

We considered the problem of building an actor model for a professional social network by exploiting the characteristic features. The main theme of the paper was to address a method of designing a GAMPSON, which facilitated creation of actors by utilising characteristic features such as personally identifiable information, professional information, activity, history, and social status. Further more, instead of traditional approach that utilises matrix of data, the proposed system first classified actors into different groups. Secondly, it utilised various characteristics of actors, and relations such as hierarchical and equivalence are built among actors. At last, the GAMPSON was designed for the professional social networks such as ASN and MSN, where the acquisition of the characteristic features of actors related to the agriculture and museum were carried out. Relation among actors of the ASN and MSN were dynamically formed and updated. Our simulations demonstrated that the graphs obtained were consistent with the generalised

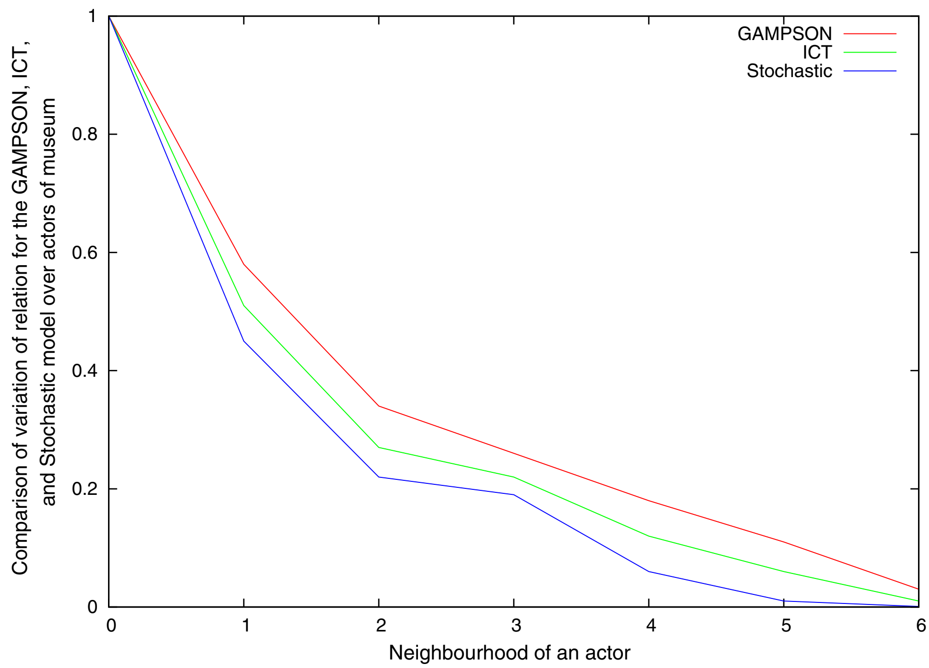

Fig. 33 Comparison of variation of relation for the GAMPSON, ICT, and Stochastic model over actors of museum vs neighbourhood of an actor. Here, we have considered a set of actors of museum social network and observed the relationship values up to six levels, and compared variation of relation for the GAMPSON, ICT, and Stochastic model.

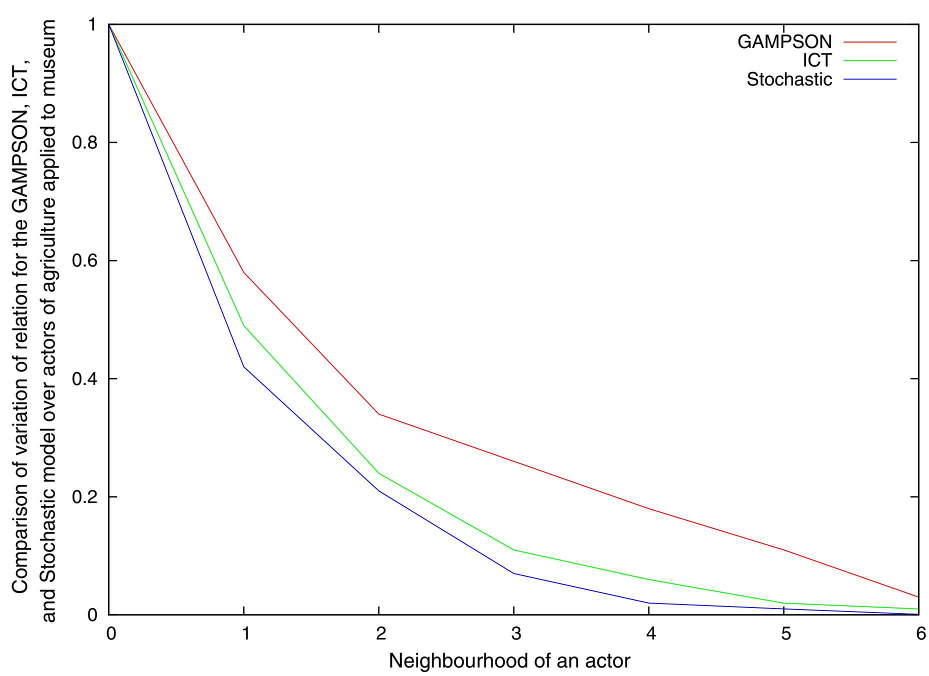

Fig. 34 Comparison of variation of relation for the GAMPSON, ICT, and Stochastic model over actors of agriculture applied to museum vs neighbourhood of an actor. Here, we have considered a set of actors of agriculture social network and applied them over museum social network in order to observed the relationship values up to six levels for the GAMPSON, ICT, and Stochastic model.

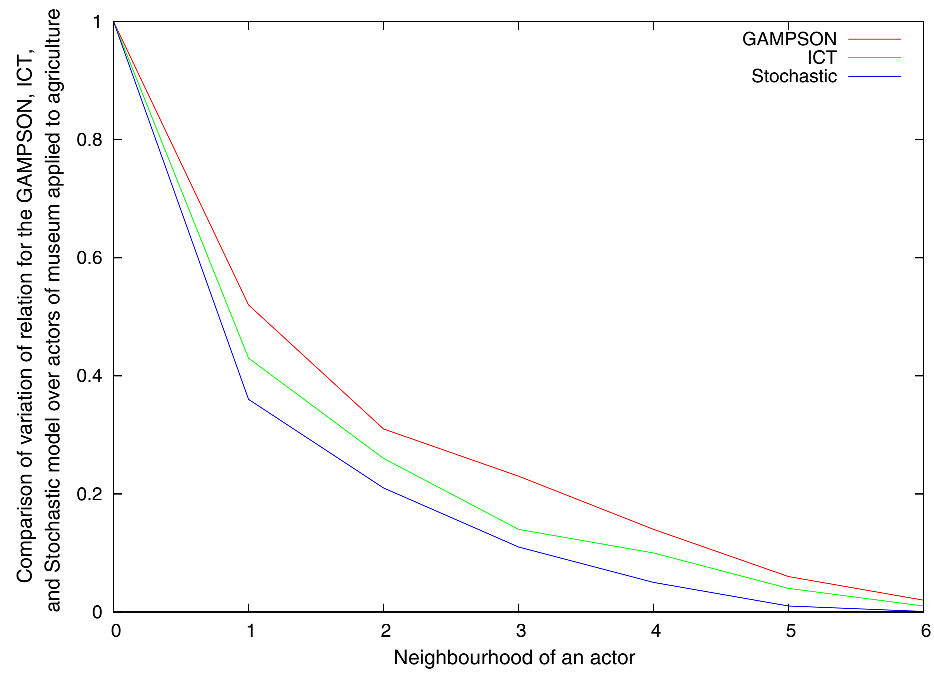

Fig. 35 Comparison of variation of relation for the GAMPSON, ICT, and stochastic model over actors of museum applied to agriculture vs Neighbourhood of an actor. Here, we have considered a set of actors of museum social network and applied them over agriculture social network in order to observed the relationship values up to six levels for the GAMPSON, ICT, and Stochastic model.

Table 7 Comparison of the GAMPSON, ICT and stochastic model with respect to relation

	Neighbourhood					
	1	**2**	**3**	**4**	**5**	**6**
1. Variation of relation over neighbourhood (for ASN)						
GAMPSON	0.58	0.34	0.26	0.18	0.11	0.03
ICT	0.54	0.25	0.16	0.09	0.05	0.02
Stochastic	0.49	0.22	0.11	0.09	0.04	0.01
2. Variation of relation over neighbourhood (for MSN)						
GAMPSON	0.56	0.33	0.25	0.16	0.10	0.02
ICT	0.51	0.27	0.22	0.12	0.06	0.01
Stochastic	0.45	0.22	0.19	0.06	0.01	0.001
3. Variation of relation over neighbourhood (ASN to MSN)						
GAMPSON	0.53	0.33	0.23	0.15	0.08	0.01
ICT	0.49	0.24	0.11	0.06	0.02	0.01
Stochastic	0.42	0.21	0.07	0.02	0.01	0.001
4. Variation of relation over neighbourhood (MSN to ASN)						
GAMPSON	0.52	0.31	0.23	0.14	0.06	0.01
ICT	0.43	0.26	0.14	0.10	0.04	0.01
Stochastic	0.36	0.21	0.11	0.05	0.01	0.001

formulation and the applications. The results are encouraging when we compared the proposed model with the ICT and Stochastic model, and showed that our model performed better in terms of finding relations more accurately. We consider that the proposed actor model can be used as a tool for automatically constructing a professional social network, and can be easily deployed to find relations among actors meticulously.

The use of actor-oriented approach can change the way in which social networks are constructed and relations among the actors are formed. It can provide practical way to precisely generate actors of any professional social network. The only parameters required are the basic once that can be easily acquired through profiles, websites, friends, etc. In the future, we would like to extend our model to find the main characteristic features that reflects the model most and can be used in quick construction of any social network.

Abbreviations

GAMPSON: generic actor model for a professional social network; ASN: agriculture social network; MSN: museum social network; CF: characteristic feature; $PerI_i$: personally identifiable information of the actor a_i; $ProI_i$: professional information of the actor a_i; Act_i: activity of the actor a_i; $Hist_i$: history of the actor a_i; $SocS_i$: social status of the actor a_i; W_{a_i}: weight of the actor a_i; $R(a_i, a_j)$: relation among the actors a_i and a_j.

Authors' contributions

PV conceived the study of the actor model, and participated in its design and coordination and helped to draft the manuscript. SSN carried out the actor model studies, participated in the simulation and drafted the manuscript. All authors read and approved the final manuscript.

Acknowledgements

The authors would like to acknowledge the support and helpful comments of the research scholars of Protocol Engineering and Technology Unit, which made the overall presentation better.

Compliance with ethical guidelines

Competing interests

The authors declare that they have no competing interests.

Received: 9 February 2015 Accepted: 24 July 2015
Published online: 12 August 2015

References

1. Heidemann J, Klier M, Probst F (2012) Online social networks: a survey of a global phenomenon. Comp Netw 56(18):3866. doi:10.1016/S1389128612003088
2. Greetham DV, Hurling R, Osborne G, Linley A (2011) Social networks and positive and negative affect. Procedias Soc Behav Sci 22(0):4. doi:10.1016/S1877042811013747
3. Qiu J, Lin Z, Tang C, Qiao S (2009) Discovering organizational structure in dynamic social network. In: Ninth IEEE international conference on data mining, ICDM '09, pp 932–937. doi:10.1109/ICDM.2009.86
4. Ninawe SS, Venkataram P (2013) A method of developing a generic social network. Int J Inf Educ Technol 3:488–493. doi:10.7763/IJIET.2013.V3.323
5. Chen Y, Xu X, Wang Z (2012) Family-oriented social network and services. In: International joint conference on service sciences, IJCSS, pp 217–221. doi:10.1109/IJCSS.2012.25
6. Brodka P, Saganowski S, Kazienko P (2009) GED: the method for group evolution discovery in social networks. Soc Net Anal Min 1–14. doi: 10.1007/s13278-012-0058-8
7. Toivonen R, Kovanen L, Kivel M, Onnela JP, Saramki J, Kaski K (2009) A comparative study of social network models: network evolution models and nodal attribute models. Soc Netw 31(4):240. doi:10.1016/S0378873309000331
8. Jiajin Z, Lichang C, Qingsong D, Haidong Z, Yonghua Z (2014) A social networks integrated sensor platform for precision agriculture. In: 4th IEEE international conference on network infrastructure and digital content, IC-NIDC, pp 131–136. doi:10.1109/ICNIDC.2014.7000280
9. Huatao P (2010) Path selection for social network evolution map formation of start-up enterprises. In: International conference on computer and communication technologies in agriculture engineering, CCTAE, vol 1, pp 47–50. doi:10.1109/CCTAE.2010.5543709
10. Nunez MM, Aguiar WSP (2014) Efficiency analysis of information technology and online social networks management: an integrated DEA-model assessment. Inform Manag 51(6):712. doi:10.1016/j.im.2014.05.009.http://www.sciencedirect.com/science/article/pii/S0378720614000627
11. Martin D, Allan J, Newton J, Jones D, Mikulak S, Mayorga E et al (2011) Using web-based and social networking technologies to disseminate coastal hazard mitigation information within the Pacific Northwest component of the integrated ocean observing system, IOOS. In: OCEANS 2011, pp 1–9

12. Chen N, Zhang X, Wang C (2015) Integrated open geospatial web service enabled cyber-physical information infrastructure for precision agriculture monitoring. Comp Elect Agri 111(0):7. doi:10.1016/j.compag.2014.12.009.http://www.sciencedirect.com/science/article/pii/S0168169914003196
13. Wang Y, Wang Y, Qi X, Xu L (2009) OPAIMS: open architecture precision agriculture information monitoring system. In: Proceedings of the 2009 international conference on compilers, architecture, and synthesis for embedded systems. ACM, New York, NY, CASES '09, pp 233–240. 10.1145/1629395.1629428.http://doi.acm.org/10.1145/1629395.1629428
14. Wilson C, Sala A, Puttaswamy KPN, Zhao BY (2012) Beyond social graphs: user interactions in online social networks and their implications. ACM Trans Web 6(4):17. doi:10.1145/2382616.2382620.http://doi.acm.org/10.1145/2382616.2382620
15. Iribarren JL, Moro E (2011) Affinity paths and information diffusion in social networks. Soc Netw 33(2):134. doi:10.1016/S0378873310000596
16. Lee H, Kwon J (2011) Improving context awareness information retrieval with online social networks. In: First ACIS/JNU international conference on computers, networks, systems and industrial engineering, CNSI, pp 391–395. doi:10.1109/CNSI.2011.54
17. Valente TW, Fujimoto K, Unger JB, Soto DW, Meeker D (2013) Variations in network boundary and type: a study of adolescent peer influences. Soc Netw 35(3):309. doi:10.1016/S0378873313000154
18. Lin CC, Kang JR, Chen JY (2015) An integer programming approach and visual analysis for detecting hierarchical community structures in social networks. Inform Sci 299(0):296. doi:10.1016/j.ins.2014.12.009.http://www.sciencedirect.com/science/article/pii/S0020025514011463
19. Ninawe SS, Venkataram P (2013) A method of designing an access mechanism for social networks. In: Nineteenth IEEE national conference on communications, NCC, pp 1–5. doi:10.1109/NCC.2013.6488048
20. Carminati B, Ferrari E, Perego A (2006) Rule-based access control for social networks. In: On the move to meaningful internet systems 2006: OTM 2006 workshops, Lecture Notes. In: Meersman R, Tari Z, Herrero P (eds) Computer Science, vol 4278. Springer, Heidelberg, pp 1734–1744
21. Carminati B, Ferrari E, Perego A (2009) Rule-based access control for social networks. ACM Trans Inf Syst Secur 13(1):6. doi:10.1145/1609956.1609962
22. Matharu GS, Mishra A, Chhikara P (2014) A framework to leverage cloud for modernization of Indian agricultural produce marketing system. In: Proceedings of the 2014 international conference on information and communication technology for competitive strategies, ICTCS '14. ACM, New York, NY, pp 7:1–7:7. doi:10.1145/2677855.2677862. http://doi.acm.org/10.1145/2677855.2677862
23. Peng G, Mu J (2011) Network structures and online technology adoption. IEEE Trans Eng Manag 58(2):323. doi:10.1109/TEM.2010.2090045
24. Schoenebeck G (2013) Potential networks, contagious communities, and understanding social network structure. In: Proceedings of the 22nd international conference on world wide web (International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, Switzerland, 2013), WWW '13, pp 1123–1132
25. Wasserman S, Faust K (1994) Social network analysis: methods and applications, vol. 8, Cambridge University Press, Cambridge
26. Lesure RG, Wake TA, Borejsza A, Carballo J, Carballo DM, Lpez IR et al (2013) Swidden agriculture, village longevity, and social relations in formative central Tlaxcala: towards an understanding of macroregional structure. J Anthropol Archaeol 32(2):224. doi: 10.1016/j.jaa.2013.02.002. http://www.sciencedirect.com/science/article/pii/S0278416513000159
27. Armbruster W, Ahearn M (2014) Encyclopedia of agriculture and food Systems. In: Alfen NKV (ed), Academic Press, Oxford, pp 201–219. doi:10.1016/B978-0-444-52512-3.00116-9. http://www.sciencedirect.com/science/article/pii/B9780444525123001169
28. Chang WL, Lin TH (2010) A cluster-based approach for automatic social network construction. In: IEEE second international conference on social computing, SocialCom, pp 601–606. doi:10.1109/SocialCom.2010.94
29. Malik H, Malik AS (2011) Towards identifying the challenges associated with emerging large scale social networks. Procedia Computer Science. In: The 8th international conference on mobile web information systems, MobiWIS 2011, vol 5, p 58. doi:10.1016/S187705091100384X
30. Daraghmi EY, Ming YS (2012) Using graph theory to re-verify the small world theory in an online social network word. In: Proceedings of the 14th international conference on information integration and web-based applications and services, IIWAS '12. ACM, New York, NY, pp 407–410. doi:10.1145/2428736.2428811
31. West DB (2000) Introduction to graph theory, 2nd edn. Prentice Hall, London
32. Cutillo L, Molva R, Onen M (2011) Analysis of privacy in online social networks from the graph theory perspective. In: global telecommunications conference, GLOBECOM 2011, IEEE, pp 1–5. doi:10.1109/GLOCOM.2011.6133517
33. Sato I, Yoshida M, Nakagawa H (2008) Knowledge discovery of semantic relationships between words using nonparametric bayesian graph model. In: Proceedings of the 14th ACM SIGKDD international conference on knowledge discovery and data mining, KDD '08. ACM, New York, NY, pp 587–595. doi:10.1145/1401890.1401962
34. Jalalimanesh A (2012) Knowledge discovery in scientific databases using text mining and social network analysis. In: IEEE conference on control, systems industrial Informatics, ICCSII, pp 46–49. doi:10.1109/CCSII.2012.6470471
35. Vangala RNK, Hiremath BN, Banerjee A (2014) A theoretical framework for knowledge management in Indian agricultural organizations. In: Proceedings of the 2014 international conference on information and communication technology for competitive strategies, ICTCS '14. ACM, New York, NY, pp 6:1–6:7. doi:10.1145/2677855.2677861.http://doi.acm.org/10.1145/2677855.2677861
36. Yongyuth P, Prada R, Nakasone A, Kawtrakul A, Prendinger H (2010) AgriVillage: 3D multi-language internet game for fostering agriculture environmental awareness. In: Proceedings of the international conference on management of emergent digital ecosystems, MEDES '10. ACM, New York, NY, pp 145–152. doi:10.1145/1936254.1936280.http://doi.acm.org/10.1145/1936254.1936280
37. Lee E (2011) Heterogeneous actor modeling. In: Proceedings of the international conference on embedded software, EMSOFT, pp 3–12

38. Snijders TA, van de Bunt GG, Steglich CE (2010) Introduction to stochastic actor-based models for network dynamics. Dynamics of Social Networks. Soc Netw 32(1):44. doi:10.1016/S0378873309000069
39. Yoshida T (2010) Toward finding hidden communities based on user profile. In: IEEE international conference on data mining workshops, ICDMW, pp 380–387. doi:10.1109/ICDMW.2010.20
40. Conti M, Passarella A, Pezzoni F (2012) A model to represent human social relationships in social network graphs, in social informatics, Lecture notes. In: Aberer K, Flache A, Jager W, Liu L, Tang J, Guret C (eds) Computer Science, vol 7710. Springer, Heidelberg, pp 174–187
41. Sabouri H, Sirjani M (2010) Actor-based slicing techniques for efficient reduction of Rebeca models. Selected papers of the 5th international workshop on formal aspects of component software. Sci Comput Program 75(10):811. doi:10.1016/S0167642310000304
42. Lipczak M, Sigurbjornsson B, Jaimes A (2012) Understanding and leveraging tag-based relations in on-line social networks. In: Proceedings of the 23rd ACM conference on hypertext and social media, HT'12. ACM, New York, NY, pp 229–238. doi:10.1145/2309996.2310035
43. Wong I, Steinhoff P (2009) Investigate the social actor model of ICT use in organizations. In: 42nd Hawaii international conference on system sciences, HICSS '09, pp 1–8. doi:10.1109/HICSS.2009.274
44. Reddy BS, Srinivas T (2009) Energy use in Indian household sector—an actor-oriented approach. Energy and its sustainable development for India energy and its sustainable development for India. Energy 34(8): 992. doi:10.1016/S0360544209000437
45. Ghose A, Koliadis G (2007) Actor eco-systems: from high-level agent models to executable processes via semantic annotations. In: 31st annual international computer software and applications conference, COMPSAC 2007. vol. 2, pp 177–184. doi:10.1109/COMPSAC.2007.50
46. Ding J, Cruz I, Li C (2011) A formal model for building a social network. In: IEEE international conference on service operations, logistics, and informatics, SOLI, pp 237–242. doi: 10.1109/SOLI.2011.5986562
47. Choi M, Kim H (2013) Social relation extraction from texts using a support-vector-machine-based dependency trigram kernel. Inform Process Manag 49(1):303. doi:10.1016/S0306457312000544
48. George WAM, Norton N, Alwang J (2015) Economics of agricultural development: world food systems and resource use, 3rd edn. Routledge, Abingdon
49. Chen KTN (2013) Motivations of visitors to visit museums: a comparison study of museum visitors in the West and in Thailand. In: Recent trends in social and behaviour sciences: proceedings of the international congress on interdisciplinary behaviour and social sciences, pp 355–363