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Specifying Trust-based Community Learning

Dr. Hrushikesha Mohanty[1, 2]
[1]Former Professor, University of Hyderabad, Hyderabad, India
Email: hmcs@uohyd.ac.in
[2]Emeritus Professor, CVR College of Engineering/CSE Department, Hyderabad, India
Email: hmcs@cvr.ac.in

Abstract: **while chatting with neighbours is a social behaviour, trusting a neighbour is a natural tendency. Both play subtle roles in making community knowledge. We propose Trust Based Community Learning, a process that performs asynchronous knowledge transmissions over a neighbour graph implicitly defined in a community. With a formal specification, we have shown community learning as a distributed process and it eventually achieves community knowledge. It's observed that social learning can be facilitated by re-engineering a community neighbour-graph to a small world network.**

Index Terms: **community knowledge, distributed algorithm, asynchronous knowledge transmissions, neighbour-graph.**

I. Introduction

Humans are blessed with knowledge for solving problems of different types ranging from the detection of God's particles to sustainable farming. While research on the human brain is engaged in exploring cognitive processes in human decision making and knowledge formation, the research on Artificial Intelligence is looking for a modeling process that imitates the human learning process. Here we are modeling community learning as a social process for community knowledge. A piece of information useful to the community and mostly known to community members is termed as community knowledge. For example, the concoction of *tulsi* and black pepper is good to treat cold and cough. Sociologists add a usability dimension to knowledge in qualifying it as community knowledge. In the process of transmission, knowledge passes through many individuals. Each may verify usability and authenticity of knowledge and even augment it with further details. This way community knowledge gains trust. The more a person receives knowledge from its neighbours, the more the person updates trust value to the knowledge and informs its neighbours. Thus, community learning is a distributed social process where an individual behaves as an asynchronous autonomic process to receive, process, and forward a piece of knowledge. Social process is a complex process with thousands of variables, non-linear dynamic behaviour, and circularity. That is the reason why many are skeptical about modelling social systems. Nevertheless, there have been active interests in modeling social systems. With increasing computing power and storage capabilities, developing social systems for domain-specific uses is gaining momentum. For that, understanding and specifying social systems are important.

An early work on specifying social phenomenon may be traced to [1]; this paper presents a mathematical framework in explaining social changes. The concept of society-as-a-system has ignited research in Computational Social Science. A bird's eye-view on this area of research may be found in [2]. Currently, society is poised to adopt AI techniques for providing community services and addressing social problems. [3] This has ushered in a trend in studying social phenomena considering society-as-a-system.

While theoretical study includes formal specification of social systems, experimentalists show interest in the development and deployment of such systems. The work presented here is of the former category. It specifies community knowledge-making, a phenomenon that makes knowledge of an individual to a community aware knowledge. The proposed social learning algorithm implements the specification in making use of the social feature trust-thy-neighbour for knowledge sharing. It's seen, social communication is a necessary condition for social learning. By analysis of the algorithm, it is observed that for formation of community knowledge, a society needs to be re-engineered to a small world network.

Including this section, this paper has five sections. The following section positions social science perspectives of the problem referring to the works on community knowledge. The third section presents a formal framework specifying the three entities viz. individual, community and communication. Trust-thy-neighbour, a social aspect is modeled in the fourth section. It also presents a distributed algorithm for trust-based community learning. This is followed by a conclusive remark identifying issues for further research.

II. Community and Community Knowledge

Humans being social share knowledge with their neighbours and acquaintances. A piece of knowledge gained by an individual(s) is termed individual knowledge. The knowledge shared with the community is community knowledge. This process of making community knowledge is termed community learning. The process of learning by an individual is not only based on its capability [4] but also depends on social conditioning. [5] Community learning is a complex process that includes deliberation, argumentation, and affirmation of accrued knowledge that community by large accepts.[6] This process is a reality because community members deliberate, vet, and share a knowledge to form community knowledge. Community knowledge is of two types viz. explicit knowledge and tacit knowledge. Experiences gained by individuals make explicit knowledge whereas tacit knowledge is something one knows but can't explain it. It includes integrated knowledge and heuristics that people use as a thumb's rule. According to sociologists, retrieving tacit knowledge needs interpersonal

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communication. Naturally, interpersonal communication is important for community learning.

In masses, knowledge emanated from an individual(s) propagates across a community making recipients aware of the knowledge. Social Science views community knowledge is subtly learnt for meeting day to day challenges. So, community knowledge is about situated actions, which often turns out specific to people, places, and practices. So, communities may differ in their community knowledge even for the same purpose. For example, practices of paddy cultivation could be different for different communities situated in different places. Still, a common approach may be seen in the generation of community knowledge. Here our interest is in specifying this generic approach. The following section finds such formalization.

III. Individual, Community, Communication

People, place, and profession are the three important factors for individual livelihood management. Classically, people choose to stay in a place congenial to live, particularly the place offering means to earn. Agrarian families choose a habitat with plenty of natural resources like land and water. Indigenous people choose habitats in forests with natural resources useful for their living. People develop knowledge to make livelihoods utilising the resources available in their habitats. Currently, netizens live in Cyberspace and make use of its resources in many ways. Monetising Cyberspace is a new way to earn a livelihood. Thus, modeling human action, we need to model its habitat because it impacts and impacts human life.

As reported in [7] we model the habitat of a person as a tuple $< K, Q, R, L >$ where K, Q, R, L are knowledge, objective, resource and location respectively. This models the following aspects of a person *p*.

- K:: {k_1, k_2...k_i, ... } : knowledge
- Q :: {q_1, q_2...q_j , ... } : objectives
- R :: {r_1, r_2...r_k, ... } : resources
- L :: { l1, l2, …. lk… } : location

So, habitat of a person p at location l is specified as $H^p =< K^p, Q^p, R^p, L^p >$. A person p in its habitat L^p is endowed with natural resources R^p. A person may have a set of objectives Q^p; of which some could be transactional and some transcendental. Here, we are limited to the former type of objectives. These objectives are to meet individual needs like food, housing, transport, healthcare, safety, education etc.

Materialising objectives needs resources and individual efforts. Naturally, there is a relationship between resources and objectives i.e. $R^p \rightarrow Q^p$. A knowledge of a person p refers to the information that details how to use a resource to materialise an objective. This we label as individual knowledge of a person p situated at L^p and specify as

$$k_L^p = f(r_L^p , q^p) \quad (1)$$

where k_L^p is a knowledge a person p situated at L has and r_L^p *is the resource of p to meet its* objective q^p.

As said before, social learning is achieved by transmission of individual knowledge across the members of a community. Before detailing the social learning process let us define some necessary formalism.

Traditionally community refers to a set of people living in a place exhibiting high degree of homogeneity in their way of life that includes livelihood, cultural, political and religious beliefs. Social scientists' view on community is at times deep and complex. Here for the purpose of this study, it's sufficient to define a community as a set of people with homogeneous habitats. A community C of location L is specified as

$$C_L = \{ (p_L, q_L) | \, H_L^p \equiv H_L^q \} \, \forall \, p, q \in P_L$$

where H_L^p and P_L are respectively a set of habitats and a set of people living in locality L. On varying the degree of similarity, communities of different granularity can be found. On defining *contain-in* relationships, hierarchical community structures can also be defined. Without any compromise, here our discussion limits to a planar community.

In a locality, community members are connected by both situated and functional proximity. For digital society, proximity is defined by friend and *friend-of-friend* relations. Digital communities can be formally represented by a graph. Our discussion here considers traditional society. Still, the proposed idea is applicable to digital society.

Two people in a locality are connected and in communication for their situated or/and functional proximity. A person usually has an opportunity to communicate with neighbours; that is an example of situated proximity. A person communicates with people it meets in its functional worlds viz. workplace, bank, supermarket, temple etc. This is known as transactional proximity. Unlike Cyberspace social platforms, in real world *friend* relation is not transitive in nature. In the real world, a friend of a friend need not be a friend. One may not be in talking terms with its neigbours. Inspite of such possible unfriendliness, society remains connected for far reaching human relationships. So, without loss of generalization we may assume that implicitly people of a locality are connected, maybe directly or indirectly. We formally define this implicit structure by a graph by making use of nbr relation as

$$nbr(p) = \{q \mid q \in (std\_pxmty(p) \cup fnc\_pxmty(p))\}$$

where *std_pxmty(p)* and *fnc_pxmty(p)* are sets of people associated with p by its situated and functional proximity respectively.

The following properties are ascribed to the nbr relation.

- Reflexive : $p \in nbr(p)$
- Commutative : $p \in nbr(q) \implies q \in nbr(p)$
- Transitive: $if \left(\left(q \in nbr(p) \right) \wedge (r \in nbr(q)) \right) \implies (r \in nbr(p))$

With the relation $nbr(p)$, the concept of community graph of a location L i.e. CG_L is defined as

$$CG_L = \{q \mid \forall q \, \exists \, r \wedge r \in nbr(q)\}$$

A community is said to be connected *if and only if* all its members are accessed by nbr relation. For ensuring seamless access between any two members of the community the following condition is applied

$$connected(CG_L) \Leftrightarrow \{\forall \, (p, q) \in CG_L \, \exists \, q \mid q \in nbr^*(p)\}$$

A community is connected when one can reach out to another either directly or through several people in between. Sociologists term this phenomenon as small world problem.[8] Researchers working in networking theory label is as small world network.[9]

The function $nbr^*(p)$ is repetitively applied on neigbours of p to explore all the people connecting to p. A connectivity between p and q is represented by a path $(p \rightarrow q)$ in the graph CG_L. We say, a community is connected when there is a path between any two people of the community. On the basis of the connectivity as defined, the hypothesis follows.

Hypothesis-1: A message sent by a community member eventually reaches all in the community.

This is achieved with the assumption that a person on receiving a message from a neighbour passes it to its other neighbours. This is viewed as a breadth-first graph traversal and can be simulated by a distributed breadth-first search algorithm. [10]. In the worst case, that is for very sparingly connected community this path length could be $(N-1)$ where $(N = |CG_L|)$, N the total population of the community. Making a community aware of individual knowledge by communication among community members is a process of community learning. The next section presents a trust-based model for community learning.

IV. Community Learning

Primarily, knowledge transmission among community members takes place while they meet in. homes, workplaces, and social spaces like in streets and markets. Here to model the knowledge transmission process, we propose the trust-thy-neighbour principle.

Prnciple-1: A person shares its knowledge with neighbours it trusts enough.

Principle-2: A person reassess trust of the knowledge received from its neigbours.

Hearsays have their social bearing because it conditions community members. A community member usually trusts another, and the degree of trust depends on many parameters like social identity, proximity and transaction history. Among the people one knows, a person at its workplace is more trusted than a person it meets in a supermarket. Further a person with good transaction history is more credible than the one with not good or unknown history. An individual p's trust assessment on its neighbour q i.e. $trust_q^p$ depends on two factors viz. trust by own experience, trust by community image. The second one is a gross trust value of q, as p finds from its neighbourhoods.

$$trust_q^p = sts_q^p + cts_q^C \,; \left(trust_q^p\right) = 1 \qquad (2)$$

where $(sts_q^p \in (0,1))$ and $(cts_q^C \in (0,1))$ are respectively the self-test-score of p on q and the community-test-score of C on q. It is assumed that cts_q^C is available centrally and the score is computed making use of transactional history of q. Thus, trust in community is computed following the principle of trust-thy-neighbour.

An individual p on receiving a piece of knowledge k from q with trust value $(trust_q^k \in (0,1))$, updates trust as

$$trust_{p,q}^k = trust_q^p + \left(1 - trust_q^p\right) \times trust_q^k \,;$$

$$\left(trust_{p,q}^k\right) = 1 \qquad (3)$$

An individual p's trust on k received from q i.e. $trust_{p,q}^k$ has a base-trust i.e. trust p has on q $(trust_q^p)$. Further receiving a trust value $trust_q^k$ from q, the trust of p on q is upgraded by $trust_q^k$ times. It's to be noted, distrust is modeled by zero trust value.

Thus, an individual p receives trust values of a knowledge k from its neighbour q then p's trust on k i.e. $trust_k^p \in (0,1)$

$$trust_p^k = trust_p^k + \left(1 - trust_p^k\right) \times trust_{p,q}^k \,;$$

$$\left(trust_k^p\right) = 1 \qquad (4)$$

Below we present an algorithm TBCL (Trust Based Community Learning)

Algorithm 1 TBCL: Executed forever at an individual p

```
begin
∀ k=(1 ··· K) trust_p^k = own.trust_p^k ;
∀ q ∈ nbr(p) compute(trust_q^p);
for () { // wait to receive a message
rcv(trust_q^k) from q ∈ nbr(p) { // on receiving a message
old.trust_p^k = trust_p^k
compute trust_{p,q}^k; // apply eqn.3.
compute trust_p^k } // apply eqn.4;
if (old.trust_p^k ≠ trust_p^k) ∧ ( trust_p^k ≥ δ_p^k ) then {
∀ q ∈ nbr(p) send(trust_p^k) } // inform neighbours.
}
end
```

A. Observations

Some of the observations due to TBCL are as follows. These observations are argued upon with reference to the line numbers of the algorithm.

Observation 1. Community learning is asynchronous.

With reference to the lines 9-10 in TBCL, whenever there is an update of trust on knowledge k at an individual p then it informs the change to its neigbours. On receiving this update message, each of these neighbours update the knowledge trust at their ends. If a person finds knowledge trust equal or greater than the threshold trust value then the neighbours are informed about the knowledge with its latest trust value. This transmission causes a domino-effect and eventually all in the community are aware of the knowledge (assuming the knowledge qualifies at each vertex for transmission i.e. knowledge trust is greater or equal to the knowledge trust threshold at the vertex.) By design of the proposed distributed algorithm, each vertex asynchronously executes the algorithm. Let us assume, at each vertex trust threshold condition is satisfied, so the knowledge k eventually reaches all the vertices. This makes a community aware of the knowledge k. Thus, community learning is asynchronous in nature. Please note that the previous section formalises community as a graph.

Observation 2. Community learning is a non-terminating process.

In practice an individual hears from its neigbours and thus learns a new knowledge or updates it with new information with trust. There may be a change in trust value. By Observation 1, an update on k propagates to all the connected community members. This process continues forever in a community. This notion of non-terminating social learning is implemented in lines 4-11 in algorithm TBCL.

Observation 3. Community Learning is trust-based learning.

The observation follows directly from the TBSL lines 9-10. An individual informs its neigbours when its trust on a knowledge k is greater or equal to the threshold trust value i.e δ_p^k. (case.1) A conservative person may have a high threshold value whereas (case.2) a diabolically opposite type of individual may have zero threshold i.e. it unconditionally passes on all messages to its neighbours. (case.3) By agreement, a common trust threshold can be fixed for everybody. This case ensures a level of trust across the community. This conditionality (line 9 of TBCL) may inhibit a person from transmitting knowledge. For this, the next observation follows.

Observation 4. An individual can never know everything that others know.

There is a chance of no transmission of knowledge because of many reasons. For example, a person may not trust the knowledge and does not transmit it to its neighbours. (line 9) There could be another cause, that's social factors. Neighbours may miss chatting or meeting for their preoccupations. Another social scenario could be due to highly heterogeneous communities where the loss of message transmission is a reality for people practicing individualistic lifestyles. In such a community people used to live in self-isolation. For both the reasons i.e. deficit of trust and social lifestyle, community knowledge is not an all-aware knowledge.

For this reason, we redefine the concept of community knowledge, A knowledge is community knowledge when the knowledge is available with a neighbour at a given distance say *d.* Small world network concept corroborates this definition. A network is of small world nature when distance between any two vertices in the network is less than equal to log of the total number of vertices present in the network. According to sociologists, a society is inherently a small world. [8] Network theorists, intending to establish small network, propose network rewiring technique to make a network connected by a given distance, say d (any two vertices in network is at the distance less than or equal to d) .[11]

Obesrvation 5. As knowledge transmission is context and trust dependent, success in reengineering a people network depends on knowledge and its relevance to community members.

A community goes on continuous trust revision, because social behaviour of a community varies with time; so people to people trust also varies. Erosion of mutual trust may impact on sustainability of community knowledge. This could be a reason why in the course of time the community forgets its past knowledge.

V. CONCLUSION

On specifying a human habitat, individual knowledge and community knowledge, this work proposes TBCL: Trust Based Community Learning algorithm. Each community executes this algorithm on receiving knowledge from its neighbour. The proposed asynchronous non-terminating distributed algorithm supports trust-based community learning. The working of the algorithm is explained with five observations. It shows the need of social reengineering to promote small world community networking to facilitate the making of community knowledge.

The work reported here is an attempt to understand and formalise the community learning process so a community can be reengineered for making community aware of a knowledge. However, the proposed algorithm needs to be validated by field experiments. These may add more social aspects to the idea of community knowledge formation process. Community knowledge is undeniably important to enable people with knowledge for sustainable livelihood management.

Some fundamental issues listed below invite further research.

1. While a relation between communication and trust building is apparent, still it needs a computational model

to estimate influence of different social parameters viz. community size, frequency of communication, personal habitats etc, in community learning.

2. A computational model for adaptive social re-engineering is an interesting topic for further research. Adaptive TBCL algorithm online reengineers community network to a required small world network for achieving community knowledge.
3. Making a community resilient to social changes is necessary so that community knowledge is not a loss of social inheritance. For this purpose, TBCL is to be integrated into social memory so loss of community knowledge can be prevented.

Graph federated learning as reported in [12] provides a mechanism for finding a foundation model on learning from multiple clients so that information access for individual needs is improved. This problem has a similarity with community learning that needs to honour privacy of individuals and at the same time supports propagation of individual knowledge of interests to community members. While application of AI techniques in modeling social phenomena is interesting, the promise of AI in empowering local communities is welcome. This technology mediated community is better structured for governance and sustainable development. [13] In corroboration to this idea, research on small world network says, in general a community is self-configured to assume a structure that's neither random nor regular. [14] This trend promises a new vista in multi-disciplinary research bringing Social Science, Computer Science and Artificial Intelligence together for modeling social phenomena and provisioning community services.

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