Social Capital Accounting
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Abstract
To better understand and improve the quality of our lives, there has been a need for measuring non-economic capital such as social capital and natural capital in addition to economic capital. Quantifying non-economic capital, however, is not easy and has not been widespread. In this paper, we will propose a system where any individual can start measuring their social capital, turning them into a real-world asset that enables improving their economic well-being, while preserving individual privacy and security.

1. Background
In order to quantify and improve the quality of our lives, we have long been dependent upon economic metrics at a national level. The Gross Domestic Product (GDP) created in 1937 has been a major metric for our society and helped to drive our economy. In 2009, Stiglitz, Sen, and Fitoussi \cite{1} pointed out that GDP had not accurately represented citizen well-being. They also made recommendations on measuring a society in three angles; economic capital, non-economic capital, and sustainability. Since then, new ways to measure non-economic capital, combined with an increase in digital technology, have been explored. The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems categorize those emerging metrics into four areas; Positive Psychology Well-Being Metrics, International Governmental Well-being Metrics, Business Well-being Metrics and Social Media Well-being Metrics \cite{2}. While these metrics have relied upon a long list of survey questions or social network data, there is another new approach that captures real-life data by utilizing various sensor devices including smartphones, wearable devices, and cameras. Mood Meter Project is one of the examples of utilizing advanced technology to quantify emotion \cite{3}. However, the novel metrics that have been developed are not widely deployed or accepted.

2. Introduction
In this paper, we will propose a mechanism to digitize social capital based on solid research in computational social science, the study of human behavior by means of large-scale operational data from digital systems data and machine learning analytics methods. The reason to choose to measure social capital is that some studies have shown that social connections, among various non-economic factors, are among the most influential factors on human well-being. For instance, a study that tracks the life activities of hundreds of people for 90 years found that the primary determinant of individual well-being is the quality of their social connections with people they trust \cite{4}. Digital non-economic capital (our “digital identities”) is also an essential part of the system when it comes to improving the quality of our lives.

3. Design Principles

3.1 General
The system needs to have the following properties.

1) A model to quantify human interactions.
First, the system needs a model to quantify human interactions. The recent advances in computational social science have provided a number of methods to quantify social connections. For instance, mobile phone data including proximity, time and location allows accurate inference of friendship network structure \cite{5}. The structure, reciprocity and directionality of friendship plays an important role in the spread of new behaviors and norm enforcement \cite{6}. Moreover, trust, a central component of social and economic interactions among humans,
can be accurately predicted using passive sensing and network analysis [7]. We can combine these ideas in order to quantify the social capital created by human interactions by use of passively sensed signals.

2) A mechanism to convert human interactions to a real asset.
The second essential part of the system is a mechanism to convert human interactions to a useful asset. Our model considers that each time a reciprocal human interaction happens, an asset is created as a proof of her/his contribution to the relationship. This asset may be considered to be a kind of credit score, and could act as a potentiating or gating factor for economic capital in many ways. The more contributions you make to building a reciprocal relationship means the higher the social credit score you gain, which in may be used to help you in financial interactions requiring interpersonal trust.

3) A total amount of asset within the network.
Third, the system needs to have the capability of calculating an individual asset as well as the total amount of social assets in the network. If the system can measure the total amount of assets, we can then begin to quantify the social capital within a community.

4) Diversity, transparency, and consensus concerning models to quantify human interactions.
Human relationships are diverse and differ depending on contexts in nature. Therefore, if a single model dominates the determination of how much social capital people have, that would be catastrophic to society. To avoid this scenario, it is critical to ensure that the system has multiple and diverse models, with models selected in a democratic manner. In order to insure transparency and accountability it is also necessary to record which model is being used each time an asset is generated, and the circumstances of that generation event.

5) A low entry barrier.
A practical system needs to have a low entry barrier to be able to start the system quickly and easily for individuals, thus driving wider adoption. For this study, we chose a smartphone and smartphone application to capture the data since smartphones are one of the most prevalent devices, and they can capture data passively and continuously.

6) Privacy and security.
With the recent increase in the number security breaches to corporate databases (e.g. Equifax breach [8]) there is the strong concern on the part of the citizen for the security and privacy of their personal data. It is with this backdrop of concern that we have adopted the Open Algorithms (OPAL) architecture [9] as the basis for our data privacy approach.

There are several key design aspects of the OPAL architecture:

- Data remains in personal data stores: Instead of collecting data from each Personal Data Store (PDS) of individuals, it is the algorithm that is sent to each PDS for local execution. Thus, each PDS must observe the OPAL principles, where raw data cannot be accessed directly but only through local safe execution of algorithms.

- Vetted algorithms: Algorithms that are sent to each PDS must be vetted by experts in the domain to ensure that the algorithms preserve persona privacy. That is, the algorithms themselves must not inadvertently “leak” private information, and must not lead to re-identification of individuals.

- Local use of data encryption: Encryption should be employed to protect data while it is in storage. New types of encryption schemes that allow for computations on encrypted data (homomorphic encryption, secure multiparty computation) provide a promising direction for data security.

- Legal foundation for communities of PDS: The group of personal data stores should collectively operate under the Open Algorithms scheme, defining legal agreements under which the system should operate. New legal constructs such as the Personal Information Protection Company (PIPC) legislation in Vermont, US, provide a good start at such a foundation.
3.2 System Architecture
We employ OPAL system developed by MIT [9]. Figure 1 summarizes the high-level architecture. Two users (User#1 and User#2) have a social relationship and an ongoing interaction, both online and face-to-face. In these interactions, both users generate data (e.g. common geolocation data points), and each user stores these interaction-generated data on their respective personal data repositories. This is shown in Step 1 and Steps 2 and 3 in Figure 1. When a Querier entity seeks to obtain insights from these interactions data, it employs the OPAL system to perform privacy-preserving queries to the respective user repositories.

3.3 Ownership of metadata and data
There are several subtle points summarized in Figure 1:

- Joint-ownership of data: Both User#1 and User#2 claim joint-ownership on their personal data, as generated through their interactions. This is because the two users created the relationship, and therefore own the context metadata (identifying that the relationship exist). This is akin to jointly owning an edge between two nodes in a relationship graph.

- Data never leaves the repositories: The OPAL principles dictate that (i) data never leaves repository and that (ii) vetted algorithms are sent to the repository endpoints.

- Authorization required from both users: In order for the Querier entity to request the execution of vetted algorithms (at the relevant repositories), authorization permission and consent must be obtained by both users.

4. Simulation
For the purpose of simulating how social capital is created in a real-world community, we constructed a simplified model and applied it to a real-world community of young families, as documented in the Friends and Family dataset [10].

Friends and Family dataset was first introduced by Aharony [11]. The dataset is based on a yearlong study and participants of the study consisted of 130 adult members within a young-family residential living community adjacent to a major research university in North America. All members of the community are couples, and at least one of the members is affiliated with the university. Among the 130+ adult members, 55 were added in the experiment in the spring of 2010 and the rest in the fall of 2010. Their interactions were passively sensed through mobile phones, with signals including Call log, SMS log, Bluetooth devices nearby, GPS, WiFi access points and so forth. The benefit of using this dataset is that, because of its richness and density, it is possible to utilize results from a number of previous research efforts (such as [5] [6] [7]) that have been conducted upon the dataset.

Our model quantifies social capital by specifying that each reciprocal interaction between two persons generates one unit of social capital for each of them, as a proof of their contribution to the relationship. Although a way to identify an interaction differs by signals, we selected call logs since operational measures of trust are most accurately predicted through call logs [7].
The results of this measurement of social capital accumulation throughout the experimental period is shown in Figure 2, illustrating a network graph as well as the distribution of social capital in the community. In the network graph, each node represents a participant and the size of a node shows how much social capital each participant holds. Each edge represents a connection and the width of an edge represents the volume of interactions between two participants.

In this experiment we ask each participant 3 "trust" questions about every other participant:
1) Would you ask person X for help in sickness?
2) Would you ask person X for a hundred-dollar loan?
3) Would you ask person X for babysitting?
where "X" is the other experiment participant. Using our social capital measure, we were able to predict answers to these trust questions with an average 94% accuracy.

5. Discussion

The design of this system could be scalable with other devices, signals, models. That is, there are a number of possibilities to quantify human interactions. Although a smartphone was selected as a sensor device in this research, wearable devices or other media that connect people could be employed depending on data to capture as each device or media has its own advantages and disadvantages. As for signals, this study chose call logs as a signal. However, other types of signals such as email logs, SMS logs and application logs are all possible predictors for trust among humans and in addition have been shown to be useful predictors of interpersonal trust.

Moreover, the idea of being able to digitize human relationship is not limited to the number of interactions as we demonstrated in this study but can include multiple types of models in order to better quantify human interactions. If models include multiple contexts such as friends, family members and, co-workers, it could represent more diverse human interactions, giving users the freedom to choose a model from various options.
depending on contexts or needs. One of the examples of other models involves measuring the extent to which people have diverse connections. It was shown that there is a strong correlation between the diversity of individual relationship and the economic development of communities [12], which means city planners could introduce the system to stimulate the economy of a city by enhancing the diversity of individual relationships.

From the users' perspective, a number of applications can be enabled by measuring social capital. At an individual level, users can utilize their social capital in order to borrow money at lower interest rates or without collateral, gaining access to better jobs, or receiving a discount for purchasing goods and services. Combining such a measure of social capital with other types of non-economic capital can also open up more opportunities.

In addition, if widely accepted, social capital can become a means of enhancing human-to-human exchanges. At a local level, managers in any organizations can monitor and improve their groups' performance by referring to the total amount of social capital within the group or total social capital across organizations, without endangering individual privacy. At a national or global level, the total amount of social capital could act as a new economic indicator for factors that have never been quantified on such a wide scale.

6. Social Networks and Digital Trust

In human societies, the reputation of a person within a community is a function of not only the network of community interactions, but it is also influenced by the degree and frequency of interactions. Networks that are "dense" – where everyone is connected – are the traditional source of local trust regarding an individual. For example, if Carol is close friends with Alice and with Bob independently, it will be less risky for Alice to trust Bob even though they may have only transacted infrequently. It is in Bob’s self-interest to remain honest in dealing with Alice due to their respective strong connectivity with Carol.

Similarly, a person’s digital identity credentials -- data about them that is used in digital transactions -- becomes trusted within a human community because the reputation of the person is attested to by the human members of the community. Consequently accurate data regarding individuals and their network of connections is crucial to the establishment of digital trust among members of a group or a community. A community with a dense, accurate digital network representation of their interpersonal interactions can potentially create a digital “Trust Network” consisting of assertions between community members, and this could provide a trustworthy foundation for digital exchanges between the members. The bedrock of digital trust, just like human-to-human trust, is a human community with frequent positive interactions [13].

7. Conclusion

We have shown a system where any individual can start measuring their social capital and turning this capital into a real-world asset that improves their well-being, while preserving individual privacy and security.

References


