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SCCD: Social Capital-Driven Career Development Framework

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***Abstract*—Sociological theories of career success provide fundamental principles for the analysis of social links to identify patterns that facilitate career development. Burt's Structural Hole Theory has argued that certain network structures provide career advantage to individuals by facilitating them to access unique information and connecting them with a diverse range of others in different social cliques. The benefits of structural advantages of one's network have been studied extensively in online social networks such as Facebook, Twitter, etc. However, they have not been studied enough in workplace settings for employee career development in the presence of both formal company's hierarchical network and informal enterprise social network. In this paper, we address this problem by proposing a *S*ocial *C*apital-driven *C*areer *D*evelopment framework which leverages enterprise social networks, employee collaboration activity streams and the organizational chart to assess employee's *social capital* across organizational hierarchy levels. We further demonstrate that our framework can enable an employees to reflect on his/her social networking behavior from the collaboration activities and improve on weak aspects for progressing from one hierarchy level to the immediate next level in their respective business units.**

I. Introduction

Online Social Networks (OSNs), e.g. Facebook, Twitter and LikendIn help us in connecting and sharing content with each other in our personal and professional lives. Recently, with the adoption of social networking platforms inside enterprises, known as *Enterprise Social Networks* (ESNs), both employees and employers can benefit from the collaboration and communication data. For example, ESNs can help employees to search for experts [1], share information and gain access to others' expertise for intrapreneurship [2], [3] in the organization, whereas the employer may leverage ESNs for enhancing customer experience, business performance [4] and forming team of experts for a particular task or project [5]. Examples of such ESNs are IBM Connections[1] and Yammer[2].

Social ties are considered to have an effect on an individual's career development [6]. The value derived from social structures (such as social relationships and social grouping) in pursuit of one's goals is known as *Social Capital* (SC) [7] and it has impact on individuals in their career development [6], [8], [9]. A study by [10] found that individuals at bridging positions in their social networks were more likely to be promoted than individuals who were not at the bridging positions.

[1]https://www.ibm.com/uk-en/marketplace/enterprise-social-collaboration
[2]https://www.yammer.com/

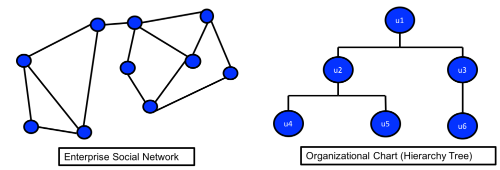


Fig. 1: An example of hybrid aligned enterprise networks

Similarly, [6] examined the social relationships maintained by individuals in the organization and found that having more contacts in other functions and having more weak ties gives access to unique resources relevant for the instrumental objectives of career success. However, most of the existing studies focus on the impact of SC on the career success, instead of highlighting the elements of the social capital that can enable an employee to reflect on his/her social networking behavior. Furthermore, existing research on social capital falls short in considering the formal network of an employee in form of employee's reporting sting structure when analyzing the SC in workplace settings. We address these challenges in our SCCD framework by incorporating employee's social collaboration activities and organizational hierarchy to assess across different hierarchical levels, the aspects that contribute to an employees social capital and raise employees awareness about them. In particular, we our framework contributes in addressing following unique challenges:

- In the workplace settings, there is unique information available related to an individual's business unit and company's organizational chart. Such information can play a crucial role in assessing an employee's social capital for the purpose of employee career development.
- There are multiple sources of social interactions available through employee collaboration which can provide additional patterns of social link formation. Employees could be connected through direct(explicit) as well as indirect(implicit) social relationships based on their common interests and collaboration activities in the organization.
- For an employee's career movement from one level to a higher level of the organization hierarchy, employee needs to be aware of strengths and weaknesses of his/her social capital as well as social capital of others in order to have the social capital similar to others at hierarchy level that is one level immediately above the employee's

current level.

Contributions: Our proposed contributions address the aforementioned challenges. More specifically, we propose a Social Capital-driven Career Development (SCCD) framework to identify strengths and weaknesses of employees social capital based on the employees social activity, their interactions in a an enterprise collaboration platform and their position in the organizational hierarchy. The framework involves three phases:

- **Assessment of employees social capital**, where first we crawl a set of heterogeneous collaboration applications to extract employees social activities as bipartite networks of employees and artifacts (e.g. blogs, wikipages, communities) and construct *implicit affinity networks* among employees such that there is an edge between two employees if they have performed the same activity (e.g., liked/followed/tagged same blog/wikipage/community). The weight of the edges is determined by the frequency of performing the same action by both nodes. Then, we compute a set of measures related to employee social capital.
- **Social capital's correlation analysis with Organization's hierarchy**, where we incorporate organizational structure to learn the importance of social capital elements at various hierarchy levels of the organizational chart. Here, we train a set of machine learning algorithms classify employees into different hierarchical levels using social capital measurements and ground truth positions of employees in the organizational chart.
- **Identification of strengths and weakness**, where strengths and weaknesses of an individual employee are highlighted by comparing employee's social capital with social capital of others at higher level. The comparison highlights how far (or close) an employee is from others at the hierarchy level that is immediate above the employee's current level in terms of the social capital elements.

II. Preliminaries

In this section, we first give preliminary definitions of *implicit affinity networks* and *hierarchy tree* used in this paper as enterprise social network (ESN) and organizational hierarchy respectively. Then we describe the network measurements used as social capital from the perspectives of information benefits.

Implicit Affinity Network: Let $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W})$ be an implicit interactions network which is derived from the enterprise applications (e.g., interactions over a blogging application, Communities application, file sharing application on the enterprise collaboration platform) other than the explicit social networking application, where $\mathcal{V} \subseteq V$ and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is a set of exogenous interactions between employees; $\mathcal{W}$ is an $|\mathcal{E}| \times d$ attribute matrix associated with edges in $\mathcal{E}$ with each row corresponding to an edge, each column an attribute, and an element x_{ij} denoting the j^{th} attribute of edge e_i.

Organizational hierarchy: The *organizational hierarchy* of a company can be represented as a *rooted tree* [11] such that $\mathcal{HT} = (\mathcal{N}, \mathcal{L}, root)$, where $\mathcal{N}$ is the set of employees, $\mathcal{L}$ represents the set of directed links from manager to subordinate in $\mathcal{HT}$ and root represents the head of the business unit.

A. Social capital measurements

In this paper, we exploit the notion of social capital as node's ability to control and access the information in the network. To this end, social capital of a node can be defined from two perspectives: (i) node's global structural embeddedness (centrality) in the overall network which enables a particular node to control the flow of information in the network; and (ii) node's local structural position in the neighborhood which allows a particular node to access unique information. A set of measurements are used to capture both social capital perpectives for individuals in the network

1) Global embeddedness: Global measure of information control for a node is measured using following two basic network global centrality measures for each each node.

- *Closeness Centrality (CC)* - is the distance from an individual to all others in the network and is defined as:

$$CC(u) = \frac{n-1}{\sum_{v=1}^{n-1} d(u,v)} \quad (1)$$

- *Betweenness Centrality (BC)* - indicates a node's role as connector in the shortest paths between any two nodes in the network. It determines the relative importance of the node in terms of other's dependency on the node. The higher the better - More control in the network gives access to more unique information. It is defined as:

$$BC(v) = \sum_{s,t \in V} \frac{\sigma(s,t|v)}{\sigma(s,t)} \quad (2)$$

where $\sigma(s,t|v)$ is the number of shortest paths from node s to t via node v and $\sigma(s,t)$ is the total number of shortest paths from s to t.

2) Local embeddedness: Burt's Structural Hole Theory introduced the concept of "structural hole" which relates to a node's structural position in relatives to it's neighborhood [8]. A node is consider to span a structural hole in the network if it is linked to parts of the network that are otherwise not well connected otherwise [12]. It is argued that nodes with large number of structural hole spanners have advantage of getting access to unique information through friends who do not know each other [8].In this paper, we associate structural hole benefits of having access to unique information with the structural effectiveness of a node's ego network and quantify it with two measures (*Effective Size* and *Constraint*) as proposed by [8]

- *Constraint (CT)* - It is the extent to which a node is constrained by its connections. The lower the better - Low constraint value of a node indicates less dependency of node on its connections. It is defined by [8] as:

$$CT_{ij} = p_{ij} - \sum_{q} p_{iq} m_{qj}, q \neq i, j \quad (3)$$

where m_{jq} is i's interactions with q divided by js strongest relationship with anyone and p_{iq} is the proportion of i's energy invested in relationship with q which is constant as $\frac{1}{N}$, where N is number of nodes in the network.

- *Effective Size (ES)* - Measure of non-redundancy in the connections of a node. The higher the better - Less number of redundant connections increases employees chance of accessing more unique information. It is defined by [8] as:

$$ES_i = \sum_j \left[1 - \sum_j p_{iq} m_{jq}\right], q \neq i, j \quad (4)$$

III. Related Work

Recent advances in SC theory have started providing a finer-grained analysis of how employees social networks affect their careers in the organization. Studies have utilized social networks to investigate the SC's relationships with job satisfaction [13], [14], job performance [15], and promotion [6], [12]. For example, [6] examined the social relationships maintained by individuals in the organization and found that having more contacts in other functions and having more weak ties give access to unique resources relevant for the instrumental objectives of career success. Similarly, a study by [12] found that individuals at bridging positions in their social networks were more likely to be promoted than the individuals who were not at the bridging positions. However, in workplace environment, social interactions are influenced by employees position in the organizational hierarchy which ultimately can influence their the structural position in the social network. The second limitation of existing research on SC for career development is the use of social network data. A major chunk of previous research on SC have used *Name Generator* and *Position Generator* based methods to gather social network data [13], [16] which may not be the correct representation of today's virtual social network data. The focus of most of the existing studies has been on the impact of SC for career success which may not have much effect on an employee's career development process itself. The SC research needs to be examined in conjunction with the organization hierarchy to highlight the key SC measurements that should be improved for career development, considering the specific workplace settings and the social relationships within enterprise social networks.

IV. Proposed Framework

In this section, we describes the proposed social capital-driven career development framework, SCCD, which mines informal social interactions of employees in a large enterprise in order to identify the weaknesses and strengths of an employee's social capital (SC). SCCD enables employees to reflect on their social networking traits that can benefit them in progressing their career from one level to the next higher level in the organizational hierarchy. Figure 2 illustrates the framework, along with its three main phases, described further below.

The first phase focuses on mining various enterprise applications for employees social interactions and calculating SC measurements described in section II-A. The framework crawls a set of heterogeneous collaboration applications (e.g. blogging,file sharing, community, timeline, Wikipages and Forum) to extract employees social activities as bipartite networks of employees and artifacts (e.g. blogs, wikipages, communities,etc.). One mode projection in performed on the bipartite networks to construct *implicit affinity networks* $IANs = \{\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \ldots, \mathcal{G}_n\}$ among employees such that there is an edge between two employees if they have performed the same activity (e.g., liked/followed/tagged same blog/wikipage/community). The weight of the edges is determined by the frequency of performing the same action by both nodes. All the implicit affinity networks are combined to generate one enterprise social network (ESN) on which SC measurements are calculated (with the help of equations from 1 to 4) for each employee in the network. In our SCCD framework, we use CC, BC measurements to capture the notion of employee being *central* relative to others at his current hierarchy and we use ES,CT and TC to capture the structural position of an employee at that HL.

In the second phase, the SCCD framework incorporates the organizational hierarchy tree and identifies the importance of the social capital measurements for each hierarchy level. A set of supervised machine learning algorithms are trained in this phase where the input features to algorithms consists of a vector of SC measures for each employee and the prediction target is a variable whihc indicates employee's hieararchy level in the organization. The fined tuned algorithm is then used to identify the importance of input features for each hierarchy level. This gives employees an indication of which SC mea-

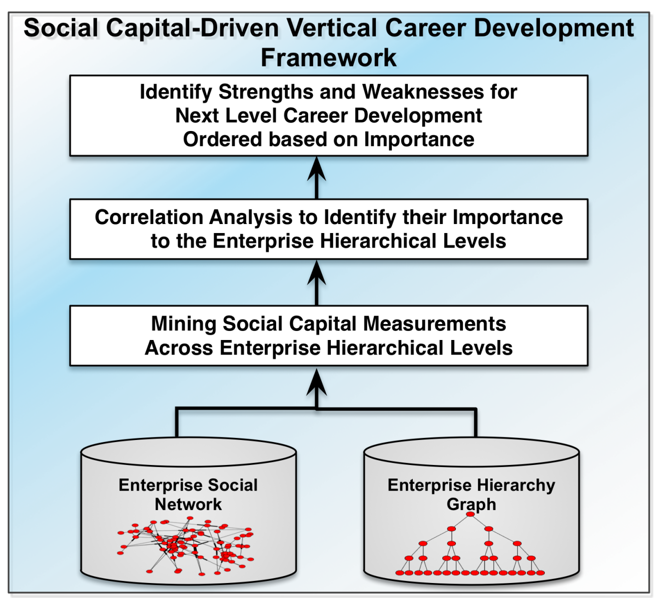


Fig. 2: SCCD: Social Capital Driven Career Development Framework Overview.

surements they should focus on first for career development. Furthermore, a correlation is performed between hierarchy levels and SC measurements to ensure the importance inferred from machine learning algorithms are correct. An ordered list of SC measurements is further retrieved based on the correlation values, where a higher correlated measurement has a stronger influence on the hierarchy level.

The third phase retrieves for a given employee based on the current level occupied in the hierarchical chart, what are the weaknesses and strengths in order to reach the next level based on the mined information from the first phase, ordered SC measures based on importance retrieved from the second phase. For this purpose, the SCCD framework compares the vertical SC of an employee with the horizontal SC of the level desired (e.g., manager level) to highlight the difference and a further analysis of difference will indicate particular SC measurements that employee to focus on. In particular, the horizontal SC for a HL is calculated as the range of values between the first and third quartile (i.e., 25% to 75% percentile) for each measurement. Further, considering the higher the better, anything lower than the first quartile would be considered a *Weakness* and placed in the ordered list of weaknesses based on its importance to be highlighted to the employee. In contrast, if the measurement is within the defined range it is considered as *Normal* and if exceeding this range in a positive way it is added to the *Strengths* list ordered by its importance.

V. Experiments

To evaluate our SCCD framework, we conducted extensive experiments on a number of real-world implicit affinity networks obtained from an enterprise social and collaboration platform called IBM Connections [3] which was deployed in a large organization for internal use of employees. The platform consists of a number of different applications that supports employee networking and facilitates collaboration among employees. The social networking application allows employees to reciprocally connect (e.g. become friends), tag, mention and follow each other. In addition to direct interactions, the platform also supports employees collaboration through following social applications: a **blogging** application which allows employees to create blog posts, ‘like’, or comment on others’ posts; a **file sharing** application; a **tagging** application that allows employees to tag each other with a descriptive label; and an application to create **wikis** where content can be co-authored by multiple employees. In a way, IBM Connections supports “explicit” and “implicit” social networks through direct and indirect interactions respectively.

A. Data

We leveraged implicit social networks from IBM Connections. More specifically, we used following datasets to evaluate our framework. An irreversible MD5-hashing technique was used to anonymize and align the records across all the datasets.

[3]https://www.ibm.com/us-en/marketplace/ibm-connections

TABLE I: The basic topology features of implicit ESNs. N denotes total number of nodes in the network. M is the number of links in the network. $<k>$ represents the mean value of node degrees, C indicates mean clustering coefficient of the network.

Network	**N**	**M**	**<k>**	**C**
Blogging	67898	4134607	121.78	0.597
Community	51130	1063503	41.6	0.034
File Sharing	1300995	6221974	9.56	0.023
Wiki-Pages	62831	2642472	84.11	0.412
Forum	47506	3230957	136.02	0.587
Timeline	72383	1483368	40.98	0.434

1) *Collaboration activity streams as ESN* - ESN dataset contains a large number of activities performed by employees on an *Enterprise collaboration platform - IBM Connections*, for a period of over 2.5 years (Jan 2014 - June 2016). Collaboration activities include “creating/commenting/linking” a blog, “joining/following” a community, “tagging/following” others, “creating/commenting/linking” someone’s status update.
2) *Organizational Chart as HT* - In addition to social network and the collaboration data, we also had access to employee’s organizational chart(*HT*) from the company’s Human Resources department which contained all active employees in the organization till June 2016.

B. Evaluation Metrics

In order to evaluate the prediction results in the phase two where SC measurements are used to predict hierarchy level of the employee and identify the importance of SC measures, we used following measures to evaluate our machine learning models:

- **Precision:** It is the number of true-positives in relation to all positive classifications.

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives} \quad (5)$$

- **Recall:** It is the true-positive rate. It is also known as *Sensitivity* and is defined as:

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \quad (6)$$

- **F-measure:** It is the harmonic mean of precision and recall. It is defined as

$$F = 2 * (precision * recall)/(precision + recall) \quad (7)$$

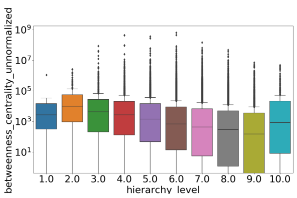
VI. Results

In this section, we report on results for each phase of our SCCD framework. We first statistically present four social capital (SC) measurements Closeness centrality (CC), Betweenness Centrality (BC), Ego Network constraint (CT) and Ego network’s Effective Size (ES). Then from phase two, we present SC measures across all the hierarchy levels (HL), machine learning algorithm results in terms of precision, recall and f1 scores as well as important SC measures for each HL.

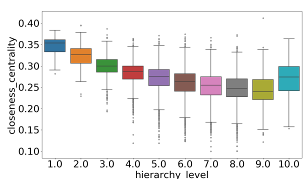
TABLE II: Summary statistics for SC measures

SC measure	mean	min	max	std	25%	50%	75%
CC	0.255290	0.099792	0.412353	0.031084	0.233647	0.258326	0.278389
BC	2.161265e-06	0.0	1.762505e-02	9.083579e-05	2.245342e-10	1.566021e-08	2.211076e-07
ES	19.4	-1.0	13414.9	91.8	1.0	4.7	16.6
CT	0.269254	0.000285	1.0	0.308784	0.055668	0.137144	0.342402

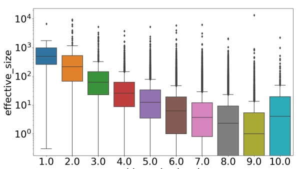
Table II gives summary statistics of four SC measurements across all the hierarchy levels. Important measures are the min, max and mean for each measurement. We also present in Fig 3, the results for four SC measurements out of all the node level network measurements calculated, as they are the most significant representation of an employee's control and access to information in the network. It is important to highlight here that HLs are in decreasing order which means larger HLs actually corresponds to lower-level employees.



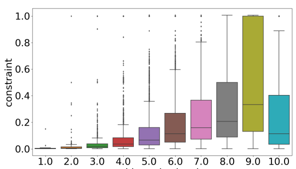
(a) Betweenness Centrality (BC)



(b) Closeness Centrality (CC)



(c) Effective Size (ES)

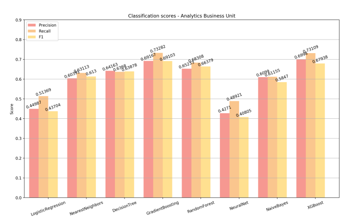


(d) Constraint (CT)

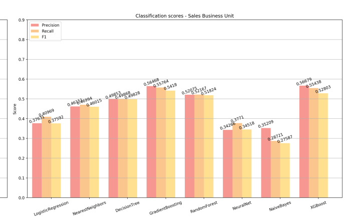
Fig. 3: Closeness Centrality, Betweenness Centrality and Effective Size and Constraint results.

As it can be observed in Fig 3a, the median value of BC varies little as we move from HL 1 to 10. An approximate consistent BC across HLs suggests that BC does not impact too much on HL of the employee which can be observed from its low correlation, i.e., 0.02, to HL in Table III. The median values of CC have a downward trend from top to bottom of the hierarchy as shown in Fig 3b and is an indication that geodesic distance among individuals gets larger with the hierarchy. Furthermore, Pearson's correlation of CC with HL is higher than compared to other SC measurements. It is expected for CC to be higher correlated with HL as it indicates the extent of employees reachability within their HL. We discussed in section II-A that higher ES and lower CT lead to having better social capital for career development. We also observe ES and CT trend for each HL in Fig 3c 3d. ES has downward a trend whereas CT has an upward trend from top of the hierarchy to the bottom which indicates that individuals at higher levels have less redundancy in their connections which can be observed from high EF values (0.9 and 0.86 for level 1 and level 2 respectively) for top hierarchy levels compared to low EF values (0.34 for level 9 and 0.33 for level 10) for lower levels.

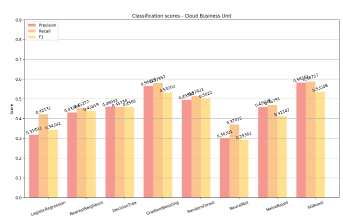
For phase two of the SCCD framework, we trained a set of linear and non-linear supervised machine learning models to categorize employees of different business unit in the organization into their levels of hierarchy. We divided our dataset into training and test sets with a test size of 30%. To further evaluate performance of the algorithms, a k-fold cross validation approach was adopted, which randomly divides all links into k subsets and models are trained with $k-1$ subsets while tested with the one remaining set. This process is repeated k times, with each of subset used exactly once as the testing set. In this paper, we used 10-fold cross validation and the trained models are Logistic Regression (LR), Linear Discriminant Analysis (LDA), Nearest Neighbours (KNN), Gradient Boosting(GB), Decision Tree (CART), Random Forest (RF), eXtrem Gradient Boosting (XGB), Naïve Bayes (NB), and Multi-layer Perceptrons (NN). Input to models was feature vector consisting of SC measures and prediction target was a multi-class variable representing hierarchy levels in the business unit. level in the hierarchy. Precision, recall and f1 scores comparison of trained algorithms with the test dataset is shown in Figure 4. It can be observed from the bar plots that Boosting based models such as GB nad XGB performed best across precision, recall and f1 performance measures compared to all trained models. The best score achieved with xgb classification model is precision of 0.699 , recall of 0.731 and f1 of 0.679 under the parameters of *learning rate* equal to 0.1, *max depth* equal to 5, and the *number of estimators* equal to 1000.



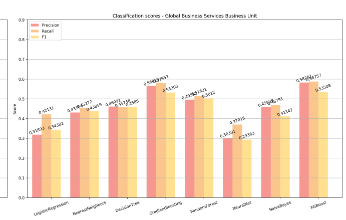
(a) Analytics



(b) Sales



(c) Cloud



(d) Global Business Services

Fig. 4: Prediction of employees into their HLs using SC measures

To identify the weaknesses and strengths of an employee, we further expand on the horizontal SC. Let us consider CT at level 8, where the lower the better, we observe that the normal SC interval for CT at level 8 is between (0.25, 0.45) (i.e., first to third quartile). Beyond this range, for individuals with CT higher than 0.45, CT would be highlighted *strength*, while a

TABLE III: Pearson Correlation of SC measurements with HLs

SC Measurement	CC	BC	ES	CT
Pearson Correlation with hierarchy level	0.32	0.02	0.15	0.25

CT lower than 0.25 would be a *weakness*. The order of the weaknesses and strengths depends on the importance of SC measurement to the HL. We deduce this importance from the Pearson correlation of each SC measurement with the HL as shown in Table III. From the Table III, we observe that CC,and CT are the most correlated SC measurements with HL. Thus, these measurements were identified as most important structural SC measurements for the employees' career development for the considered dataset. The reason behind is that CC indicates the measure of social cohesion within that hierarchy level, CT indicates the employees' dependency on their direct social connections and TC indicates the extent to which an employee tends to create triadic closures in the network. A similar methodology is adopted to identify the weaknesses and strengths of a given employee for each measurement.

VII. Conclusion and Future Work

This paper proposed a SCCD framework which highlights the weaknesses and strengths of an employee's social networking traits relative to hierarchy level in the organization. Our results contribute to the analysis of social capital factors at work and their importance to hierarchy levels for employee career development by incorporating formal hierarchy structure with informal social networks. Our framework demonstrated that employee's collaboration activity data can be leveraged to derive insights that can support an employee in adopting a social networking behavior of others at the higher hierarchical level in the organization.

There are two key limitations to the current study, use of network measurements as social capital, and the evaluation of predicting hierarchy levels with social capital measurements. Most of the sociologists agree with the definition of social capital as the value an individual can derive from his/her social network but there is no consensus between sociologists on measurements for the social capital. Hence, it's measurements are subjective to context of the problem being studies.

In future work, we plan to expand our framework with additional social capital measurements reaching higher correlations values with the hierarchy level across bonding, bridging and linking social capital dimensions as well as identifying the different ranges for strengths and weakness of the existing measurements. We further plan to improve our classification models by incorporating *explicit* friendship network of employees and further tuning the models.

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