A Resource Planning Model for Professional Services Organizations

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***Abstract*— Professional services firms are project based. Execution of these projects involve identifying and planning for the right skills. In this paper, we model the problem of predicting the skills requirement for the projects in the pipeline of a professional services firm from the bill of resources of some similar projects that had been executed in the past by the firm. This tactical decision problem is modeled as a graph clustering problem by representing the projects as nodes of the graph. Agglomerative clustering heuristic is applied for optimally clustering the nodes of the graph. The proposed model is analyzed for a simple case in which there are five projects in the history of a professional services firm.**

***Index Terms*— Services supply chain, professional services automation, resource planning, bill of resources.**

I. Introduction

Professional services organizations enable professionals to complement one another to offer a broad range of services, achieve scale and scope economies, and jointly develop a shared reputation that leverage their collective efforts. Unlike other businesses, they have unique ways of working with unique challenges and opportunities. They operate through projects, that is, through discrete engagements for external and internal clients, delivered according to an agreed-upon scope, schedule, fee, and a set of deliverables. Their projects, contracts and engagements often follow a familiar course for one job to the next, with standard phases and tasks. Examples of professional services firms, include IT services businesses, architectural and engineering firms, design and planning firms, management consulting firms, systems integrators, accounting firms, research organizations, and government contractors. Professional services are studied in [2], [4], [5], [6], [12], [16], and [18]. Improving the performance of professional services suppliers is critical to a company′s business performance. In a professional services supply chain people and time are important resources. A multinational company could save millions of dollars by strategically selecting the service partners for its requirements at various part of the globe. Just as the effective management of the goods supply chain transformed vast sector of the manufacturing and retail industries, effective management of the professional services will transform the professional services industries and services industries, in general.

The rapid growth of professional services and consulting firms brings about new challenges and a new reality to the industry. To meet these challenges, we need to understand real views of costs and capabilities, and then develop proper technology to track and manage the services business. Given the lumpy demand of the business, professional services organizations are ridden with inefficient processes and behavior. Resources are not utilized at their optimal capacities, collaboration is less than ideal, billing cycles are lengthy, project status is based on outdated information, and project costs are not managed or known with certainty, all of which lead to a less-than-productive organization and decreased profitability. Professional services automation (PSA) solutions address these inefficiencies in much the same way that ERP solutions address the business processes for more traditional industries [6],[16]. By automating the business processes involved in professional services firms, its processes would be much more streamlined.

Many types of services organizations are beginning to use, or are using PSA solutions. These include the following: IT related services firms, management consulting, architectural engineering, construction, legal, and accounting firms, as well as other firms not typically

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considered in the services vertical market. The benefits reaped from PSA solutions have significant impact on the bottom line of these organizations. From increased staff utilization and employee productivity to reduced personnel turnover and higher customer satisfaction. PSA solutions show a positive return on investment for services organizations. Already, SAP reports 22% internal rate of return (IRR) for some of its clients$'$ of mySAP CRM.

In a professional services supply chain people and time are important resources. To thrive in the global market, professional service organizations have to optimize their resources to deliver on customer commitments, increase utilization and minimize costs. A global service delivery model that utilizes a consistent methodology no matter where the customer or the consultants are located is critical to the company$'$s success. One needs to better manage the pipeline to determine which efforts will yield the greatest commercial benefit to prove business value over low-cost competitors. At present, in the context of professional services organizations, there is as yet no proven methodology for optimally using a firm$'$s global resources for service delivery. In this paper, we address the problem of optimally managing the resources of a professional services firm based on the estimated skills requirements for the projects in its pipeline.

A. Contribution and organization

The skills requirement for the projects in the pipeline of a professional services firm is obtained from the bill of resources of its past projects. A pipeline project$'$s requirement is predicted based on the bill of resources of some similar projects that were executed in the past. The similarity between the new project and other past projects is established by clustering them based on the various project characteristics.

Clustering problems arise in many different applications, such as data mining and knowledge discovery, data compression and vector quantization, pattern recognition and pattern classification [9], [10], [11]. The notion of what constitutes a good cluster depends on the application and there are many methods for finding clusters subject to various criteria, both ad hoc and systematic.

One class of clustering problems is the k-means problem. A popular heuristic for solving the k-means problem is based on a simple iterative scheme for finding a locally minimal solution. This algorithm is often called the k-means algorithm [1], [9], [13]. However, the result is not necessarily a global minimum. In most of the variants of k-means clustering, it is NP-hard [8]. Clustering based on k-means is closely related to a number of other clustering and location problems. There are no efficient solutions known to any of these problems and some formulations are NP-hard [8]. Statistical convergence of k-means and several of its variants had been discussed in [3], [14], [17], and [19].

This paper proposes a graph based model for clustering the projects of a professional services firm.

This paper is organized as follows. In section II, we state the problem of building a tactical decision model for predicting the skills requirement for the projects in pipeline of a professional services firm. The problem is modeled as a graph in Section III. A method based on single-linkage hierarchical clustering is used for solving the graph model, in Section IV. The proposed model is analyzed and validated on a professional services firm in which the prediction is made based on five projects in its history. Finally, in Section VI we conclude.

II. Problem Statement

Professional services firms are project based. Each project execution would involve a set of skills. In this research, we propose a tactical decision model to determine skills requirement for a professional services project based on the skills requirement of similar projects that were executed previously. The decision manager of a firm wants to plan the resource requirement for the projects in the pipeline. The manager inputs the project specifications into the system. The system recommends the skills requirement for the project based on the bill of resources of similar projects in the firm$'$s history. For example consider SAP industry solutions deployment project of a firm. The skills requirement for the mining and oil industry specific solutions may have similar skills requirement, over the projects that were executed in the past by the firm. Based on the bill of resources for the projects on mining and oil specific industry solutions, the skills requirement for a project on mining, which is in the pipeline, could be estimated.

Let P be a project of a professional services firm. Let T be the total estimated time (in days) for executing P. Let $S_1, S_2, \ldots, S_n$, be the set of skills available within the firm. For project P, let $r_1, r_2, \ldots, r_n$, be the requirement of skills (in percentage) $S_1, S_2, \ldots, S_n$, respectively. That is $r_i = \frac{T_i}{T}$, where T_i corresponds to the time (in days) required for skill S_i of P. The percentage skills requirement or bill of resources could be expressed as an n-tuple, $(r_1, r_2, \ldots, r_n)$. Let P^* be a project in the pipeline for which the bill of resources is to be estimated by the firm. Assuming that the projects executed in the past by the firm are clustered, based on the percentage skills requirement, the best estimate for $(r_1^*, r_2^*, \ldots, r_n^*)$, is the center of the cluster corresponding to similar projects as that of P^*. If similar projects corresponding to P^* are distributed over different clusters, then the best estimate is the mean of the centers of those clusters. With this observation, the problem boils down to clustering the projects that were executed over the past by the firm.

III. Modeling

In this section we model the problem of optimal clustering of projects as a graph clustering problem. This problem is NP-hard as this can be reduced to k-means clustering problems which are known to be NP-hard in the literature [8]. For graph theoretic terminologies we refer to [7], [15].

The projects of a firm are represented by a node in a graph G. Every node of G has an n-tuple $(r_1, r_2, \ldots, r_n)$ corresponding to it, which denotes the bill of resources corresponding to the project. We interchangeably use the term node, for a project and its bill of resources, depending on the case. Any two nodes of G is connected by an undirected edge. This makes the graph G totally connected. We note that G would have $\frac{p(p-1)}{2}$ edges, if G has p nodes. With respect to each edge, we associate a non-negative real number which denotes the distance between the two nodes that the edge is incident on. The distance between two nodes is computed using a distance measure, such as Euclidean, Manhattan and so on [9]. Clustering a graph G is to group the nodes of G into $C_1, C_2, \ldots, C_N$, such that every node of G is in exactly one of the C_i's. For cluster C_i, its center or centroid, $d_i = (d_{i1}, d_{i2}, \ldots, d_{in})$, is defined as $d_{ik} = \frac{\sum_{j=1}^{p} r_{jk}\delta_{ij}}{\sum_{j=1}^{p} \delta_{ij}}$, where, (i) p denotes the number of nodes of G, (ii) for a node j, r_{jk} denotes the k-th component of its bill of resources, and (iii) $\delta_{ij} = 1$ if node j belongs to the i-th cluster, and 0, otherwise. An optimal clustering of a graph G, is clustering the nodes of G, that minimizes, $\sum_{i=1}^{N}\sum_{j=1}^{p}\sum_{k=1}^{n}(r_{jk} - d_{ik})^2\delta_{ij}$. To optimally cluster the projects is to optimally cluster the nodes of G.

For a clustering of G, we define its cluster center graph G' as follows. Let the clusters be $C_1, C_2, \ldots, C_N$, and their corresponding centers be $d_1, d_2, \ldots, d_N$. The cluster center graph has $d_1, d_2, \ldots, d_N$ as its nodes. Any two nodes of the cluster center graph would be joined by an edge. The distance associated with an edge incident on the nodes i and j would now correspond to the distance between the centers d_i and d_j.

IV. Solving Methodology

In this section, we propose a heuristic method for optimally clustering the past projects of a professional services firm to predict the skills requirement for future projects of the firm. This heuristic method is analogous to the single linkage aggregate hierarchical clustering [9].

Heuristic for optimal clustering of projects:

(i) Initialize the number of clusters to be p (the total number of past projects). Let the clusters be $C_1, C_2, \ldots, C_p$. Assign project P_i to cluster C_i.

(ii) Compute the center of each cluster. Let $d_1, d_2, \ldots, d_p$ be the centers corresponding to $C_1, C_2, \ldots, C_p$, respectively.

(iii) Compute the cluster center graph, G'.

(iv) For each pair of nodes d_i and d_j of G', compute the distance.

(v) Select a minimum distance edge from G' (randomly, if there are many).

(vi) Let the minimum distance edge be incident on the nodes d_l and d_k of G'. Merge clusters l and k.

(vii) Repeat steps (ii)-(vi), till stopping criteria is reached.

The stopping criteria of the algorithm could be: (i) when the number of clusters reduces to a fixed number, k, or (ii) when all the edges in the cluster center graph, G', has its distance more than a threshold, T, that is set apriori.

Each iteration of the heuristic takes $O(k)$ time, where k is the number of edges of the initial cluster center graph. For each iteration atleast two clusters are merged. Merging all the initial clusters takes $O(l)$ time, where l is the number of nodes of the initial cluster center graph. Therefore, in the worst case the heuristic takes $O(kl)$ time.

V. Analysis

For example consider SAP retail projects which need the following skills: (i) Skill 1 - skills for understanding the business processes, (ii) Skill 2 - skills for understanding the retail module of SAP, (iii) Skill 3 - system skills such as Windows and Unix. Let the projects in the history be $P1$, $P2$,$P3$,$P4$ and $P5$. Projects P_i, that are executed by the firm for different companies, A, B, C, D, and E, have bill of resources (0.9,0.05,0.05), (0.6,0.3,0.1), (0.5,0.4,0.1), (0.5,0.3,0.2) and (0.4,0.3,0.3) respectively. The projects graph corresponding to them would be as shown in Figure 1.

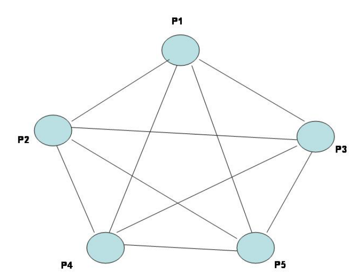

Fig. 1. Example of professional services projects graph

Initially, there are five clusters and each node is in a separate cluster. Since, each cluster has a single node, they are the centers of their respective clusters. Next, the distance between the centers of the clusters are computed. The edges and (P2,P3), (P2,P4), (P3,P4), and (P4,P5), qualify as minimum edges. The algorithm arbitrarily chooses the minimum edge (P2,P4), and merge the clusters corresponding to them. This reduces the number of clusters to 4. The resulting clusters would be $cluster1 = \{P1\}, cluster2 = \{P2, P4\}, cluster3 = \{P3\}, cluster4 = \{P5\}$. If the algorithm is terminated when the number of clusters reduces to 2, the resulting clusters would be $cluster1 = \{P1\}, cluster2 = \{P2, P3, P4, P5\}$.

Intutively, it is quite clear that the projects P2,P3,P4, and P5, have more similarity in their bills of resources than project P1. So, the algorithm has clustered projects P2,P3,P4, and P5, in the same cluster and project P1, in a different cluster at termination.

In this case, the proposed algorithm and the k-means algorithm [9] obtains an optimal cluster.

VI. Conclusion

Every professional services firm needs to estimate the skills requirement for the projects in its pipeline to pre-plan for the resources ahead before all or some of the projects in the pipeline take off. This tactical decision making would help the manager of the firm to source internally or externally based on the resource requirement for these projects. In this paper, we have addressed this tactical decision problem. First, we stated the problem and modeled the problem by representing the projects as nodes in a graph. We have also proposed a heuristic algorithm to obtain an optimal clustering of the projects in the firm′s history, which in turn is used to estimate the demand for the projects in the pipeline. We analyzed the proposed model and algorithm, on a simple case in which the history had five projects. This analysis validates some intution that one would have on this case. In future, we plan to extend the study to the scenarios′ in which the firms would have more projects in its history. We also plan to compare the proposed model with the popular k-means clustering.

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