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Information Buried in B2B Contracts: Towards Identifying Interdependencies in IT Service Processes

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ABSTRACT

A key aspect of Information Technology Service Management (ITSM) is the monitoring and evaluation of service performance – a task that is complicated by the presence of interrelationships among different service processes in a multi-service contract. While success in the service arrangement requires participant organizations' knowledge about the nature of service dependency and their subsequent effect on performance measures; such information is often *tacitly* present in the service level agreement/contract documents. In this context, the aim of our research is extracting information that might be hidden in the service contracts to assist in better process management and contract (re)negotiation. We propose an information extraction driven framework for analyzing Service Level Agreements (SLA) for IT services. Our framework consists of three stages – 1) Service Entity Recognition, 2) Service Entity Context Recognition, and 3) Service Interdependency Analysis. In this article the focus is on stage 1, where we identify interrelationships by using domain ontology on a set of annotated industry-standard SLAs. Our ongoing research is aimed towards the creation and subsequent validation of process models from the information extracted from SLAs that will help both customer and service provider organizations in contract and compensation formulation, resource allocation, and SLA life cycle management.

Keywords

Information extraction, service level agreements, IT service management, ontology

INTRODUCTION

Information Technology Service Management (ITSM) has become a prevalent practice for delivering infrastructural Information Technology (IT) requirements of an organization. ITSM involves a paradigm shift from managing IT as stacks of individual components to a more process-oriented approach with the aim of aligning a customer's infrastructure with its business needs. The appeal of this approach is evidenced by a rising number of Infrastructure Management Outsourcing (IMO) contracts in various sectors like health care (TMCNet, 2007), financial services, consumer goods sectors (CIO, 2007; FT, 2007), etc.

A significant aspect of ITSM revolves around service metrics – especially measuring and monitoring service performance (Hewlett-Packard, 2006) . Most IMO contracts consist of multiple services that typically include different service components such as network management, desktop support, e-mail services, application services, etc. Each of the services may be measured by multiple performance metrics and may have their own specified quality-of-service (QoS) guarantee. "*This measurement process, while challenging, can be instrumental in protecting the bottom line. It also helps consolidate the alignment of expectations among both customers and service providers, enhancing overall corporate governance and ensuring money is well spent*" – KPMG report (KPMG, 2007). A significant hurdle in the measurement process, however, arises due to inter-relationships among service processes - especially in the context of multi-service contracts which are very typical of IMO arrangements. The interrelationships arise because of the inherently complex nature of IT that performance of a service may often be affected by one or more other services (Deloitte Consulting, 2005; KPMG, 2007). For example, transfer performance of e-mail services not only depends on the configuration of the e-mail servers, but also on the network performance (i.e. by the activities required for managing the internal network). Similarly, the 'availability' dimension of multiple services (e-mail, directory services, file-shared services) may have some correlations, especially if a failure occurs in the internal network. Existence of such interdependence poses risks, both for the customer and the provider of the managed service, as performance evaluation plays a major role in the relationship between the provider and the customer in service outsourcing arrangements. Reported levels of performance are considered indicative of the value the customer obtains from the outsourcing arrangement. Consequently, lack of understanding of the nature of the processes and their dependency structure may lead to wrong set of choices for the performance measure. From the customer's standpoint, such wrong choices may eventually lead to a mismatch between the perceived and actual value obtained from the service contract. From the perspective of the provider, proper understanding of process interrelationships is equally important as it enables better resource allocation and process tracking.

Although trade press and practitioner literature has recognized the presence of service interrelationships and the difficulty they pose in the performance measurement process; so far there has been no systematic effort to capture these interrelationships to the best our knowledge. In this context, the objective of this research is to identify relationships among different service performance measures and process constructs (such as activities and resources) required to perform the services. This is performed by applying information extraction techniques for analysis of sets of Service Level Agreements (SLAs) between customer and service provider organizations. SLAs have commonly accepted standard templates containing details of the service description, performance metrics and the corresponding QoS guarantee as well as (some) description of the activities and resources required to perform a particular service (Open Group, 2004; Padgett, Haji and Djemame, 2005). It can be reasonably argued that such SLAs contain immense information about the different processes constituting a service bundle. Our aim is to extract this information hidden within the contractual documents to identify and establish the dependency structure of different IT service components. This information can then be utilized by both the service provider and customer organizations in the service management life cycle.

The rest of the paper is organized as follows. In the following section, we provide a background discussion and briefly review related research. This is followed by an overview of the research approach, where the proposed framework for SLA interdependency analysis is presented. Next, we detail the stage 1 of the framework, which is the focus of this article. A case study is used to illustrate the feasibility of ideas mentioned here. Finally, we conclude with an outline of the future work pertaining to this research project.

BACKGROUND

Interdependencies in service processes and their subsequent effect on service performance often lead to sub-optimal outcomes (KPMG, 2007). Although practitioner literature and trade press articles (Hayes, 2005; Munk, 2006) acknowledge the complications in both service delivery and performance monitoring arising from interrelated processes, so far there is no systematic way to capture and model such interrelationships. While formal business process modeling methodologies – especially workflow modeling – may be used to capture these relationships; the existence of a detailed model encompassing every aspect of a multi-component service contract often do not exist. Since Service Level Agreements (containing enormous textual information) are now an integral part of IT services, we adopt a relatively new approach (following Li, Wang, Zhang, and Zhao (2007)) where process level information can be extracted from policy level documents (SLAs in our context).

In recent years, significant progress in research has been made where process-related information is mined from various forms of organizational records. A notable effort is in the area of process mining which aims at analyzing process, control, data, etc. based on event logs produced by various information system applications (van der Aalst, 2005). A related approach is business process intelligence (Grigori, Casati, Castellanos, Dayal, Sayal and Shan, 2004), where data mining techniques are employed on performance indicators as a means of identifying problematic areas in business processes. These methods, while provide us with conceptual direction, are not directly applicable for our research as our aim is to gain knowledge of process interdependencies *before* service delivery, so event logs and actual performance measures might not be available and/or applicable. We utilize Information Extraction (IE) technologies. Information Extraction technologies are already being used for gathering business intelligence (e.g. (Saggion, Funk and Maynard, 2007)). This technology seems appropriate for the task in hand as IE is based on Natural Language Processing concepts where textual input is used to produce *relevant* information automatically from text and other sources and (Cunningham, 2005). Also, the existence of text information will help us utilize the context around the IT service area, which can then be used to identify non-obvious relationships between activities (task) and performance.

OVERVIEW OF APPROACH

In order to derive and explicate meaningful information buried in service contracts, we propose an information extraction driven approach for analyzing service level agreements. Figure 1 shows the conceptual framework that outlines the overall research goals of this project. The framework involves three stages, namely: service entity recognition, service entity context information, and service interdependency analysis. These stages are discussed below in greater detail.

Stage 1. Service Entity Recognition

Stage 1 consists of analyzing service level agreements in order to extract key components that characterize the service and also provide information from a business process perspective. Of particular interest are elements such as service performance measures, their frequency of measures, tasks and resources associated with performing the concerned service, and so forth. The goal of identifying these elements is to provide a starting point to find relevant information about these entities in the following stages. The relevance of the information extracted from the following stages would be governed by how precisely these entities are revealed in the first place. This problem of identifying specific domain entities – in this case, IT service domain related – is termed as named entity recognition (NER) in the information extraction or text mining terminology. In this article, we use an ontology-based approach to addressing this problem, which is discussed later in the article.

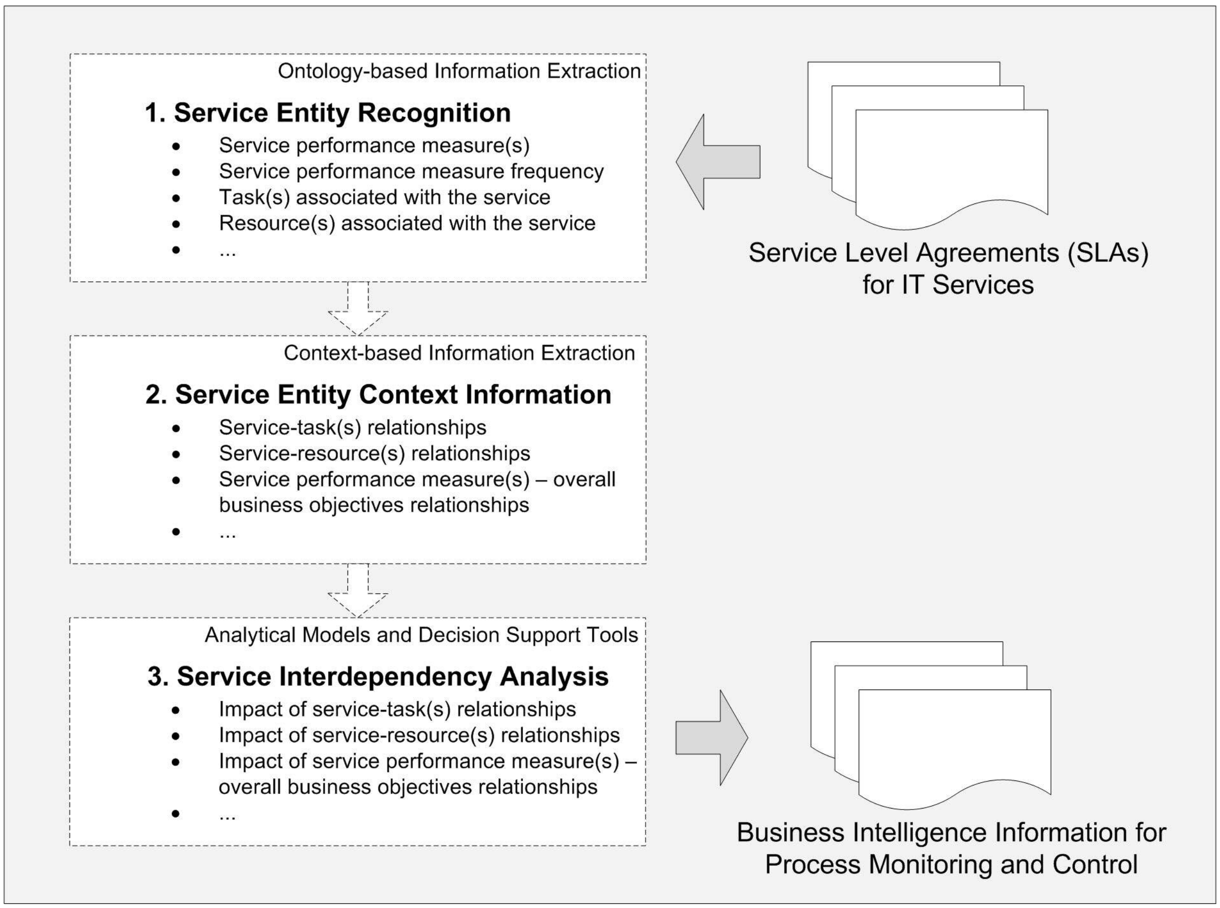

Figure 1. A Service Interdependency Analysis Framework

Stage 2. Service Entity Context Information

Stage 2 involves identifying relationships between the entities recognized in the earlier stage. Some of the relationships that would be of interest here include studying the association that service performance measures have with tasks in different IT service processes, resources in those processes and overall business objectives. This is certainly a complex problem given that the relationships are defined across different sentences in the contract documents. Current approach to tackling this problem is governed by using rule-based methods and statistical learning methods. This presents an opportunity to investigate novel algorithms and techniques that can facilitate revealing such context information in service level agreements.

Stage 3.Service Interdependency Analysis

Stage 3 involves a systematic impact analysis of the task-resource-performance relationships identified in Stage 2. In a sense, this step will enable looking at the IT service management process beyond mere measurement, compliance, and performance tracking. Few example questions are given below that might provide unique insights into the process

- What are the *general* patterns of processes/activities overlap in IT service?
    - Are there any causal relationships between these intersections? If so, can the identified causal relationships be helpful in root-cause analysis of repeated failures?
- How does the causal relationships affect (multiple) performance measure(s)?
    - This knowledge is very important in formulating the right incentive-based compensation structure. For example, if higher incentives are placed on the speed of problem resolution than on resolving/preventing the root cause; the provider organization may not make its staffing and effort allocation decisions in the best interest of the customer.
- Are there any idiosyncratic patterns of service interrelationships based on size/industry/IT sophistication of the customer organization? If so, how do they affect the overall performance of the service arrangement?

Essentially, the purpose of the final phase is to exploit the richness of the information gathered from the first two stages to assist in dynamic SLA management – especially in helping the participants in enhancing the service experience through the continuous improvement of service activities, functions, and processes.

SERVICE ENTITY RECOGNITION

In this article we focus on stage 1 of the proposed framework. As mentioned earlier, the focus of this stage is on identifying a feature set that can provide process specific information for the concerned service mentioned in the service contract. Several related approaches are plausible. Some such approaches are discussed briefly followed by discussing the approach followed for this study.

Text mining approaches based on feature set extraction have been studied in the past. Ingvaldsen , Gulla, Su, and Ronneber (2005) propose one such approach for entity extraction from governing documents in relation to business process models. The approach is based on ranking feature vectors for fragments of documents, such as sections and paragraphs, based on cosine similarity measures. Tools such as GATE-ANNIE (Cunningham, Maynard, Bontcheva and Tablan, 2002) and LingPipe (2008) provide generic NER capabilities where names, organizations, dates can be extracted from text descriptions. Typically, these tools employ statistical models or linguistic grammar-based techniques that are commonly designed with a "one size fits all" philosophy. In this regard, some novel tools such as ESpotter are noteworthy. ESpotter is based on the idea of adapting lexicons and patterns on the Web to specific domains, and also providing users the ability to customize the lexicon and patterns for NER (Zhu, Uren and Motta, 2005).

Ontologies-based information extraction approaches have received much attention in recent years, especially with increasing research on the semantic web (Gomez-Perez, Corcho and Fernandez-Lopez, 2004). In the context of SLA analysis, two possibilities are noted. One involves using SLAs in the construction of domain ontologies, while the other involves using domain ontologies to annotate SLAs. The former is referred to as ontology learning (Maedche and Staab, 2001), while the later is referred to as ontology annotation (Handschuh and Staab, 2003).

The goal in ontology learning is to automatically create IT service ontologies using SLAs that broadly captures the terminology used in the IT service industry. For example, typical IT services use the term "office automation software" to refer to word processing and spreadsheet applications. Some organizations may use the term "desktop applications" for these applications, and use "office automation software" to refer to "workflow management systems". Both the terms are relevant in the broader context of IT services, but the usage of particular terms will determine which of these are more useful for any given organization. Machine learning and automated language processing techniques are used to facilitate the task of ontology construction. For example, the OntoLearn system extracts relevant domain terms from a corpus of text, relates them to appropriate concepts in a general-purpose ontology, and detects semantic relationships among the concepts (Navigli, Velardi and Gangemi, 2003). Several other approaches for this have been noted in the literature. See Engels and Lech (2003), Missikoff, Navigli, and Velardi (2002), Maedche and Staab (2000).

The goal in ontology annotation is to use existing IT service ontologies to annotate SLAs with the objective of obtaining rich information that can provide a foundation for further semantic analysis. Several tools have been developed in the context of the Semantic Web initiative that can be extended for such application. For example, Magpie tool supports semantic markup of web documents on-the-fly based on a particular ontology of concepts and relations (Dzbor, Domingue and Motta, 2003). Earlier, Erdmann, Maedche, Schnurr, and Staab (2000) proposed a manual ontology-based semantic annotation approach for a knowledge portal application. This is based on the idea of decentralized manual annotation of a set of web pages in a portal, and then automatic aggregation and presentation of this information.

We have adopted the later approach, namely ontology-based semantic annotation, for service entity recognition. A number of issues guided this choice. First, ontologies exist in many IT service organizations in a number of forms (Hill, 2006). Use of such ontologies can provide better entity recognition through the use of targeted feature comparison (e.g., "desktop applications" in the above mentioned example). Second, use of well-defined ontologies to automatically annotate SLAs with key entity information (followed by manual verification and augmentation) can serve as a starting point for further application of ontology learning based approach, which can then be used iteratively with this approach. Moreover, this approach will not be hindered by the lack of availability of large corpus of SLAs for training and testing purposes, as may be the case in small to medium enterprises. Last, wide availability of tools such as Apolda (Wartena, Brussee, Gazendam and Huijsen, 2007), and OBIE plugin for GATE (Bontcheva, Tablan, Maynard and Cunningham, 2004) provided adequate software support for this research.

In performing this analysis, Apolda (Automated Processing of Ontologies with Lexical Denotations for Annotation) processing resource plugin for GATE was used (Wartena et al., 2007). This is because the built-in gazetteer processing resource in GATE is not very feasible for recognition of a large number of different concepts with only a few textual representations available per concept. Rather, it is more suited for the extracting large number of few concepts from a very large list of documents. Apolda plugin annotates a text document by taking terms from an OWL ontology. Apolda searches the document for OWL annotation properties associated with the ontology classes and instances. The annotation consists of the name of the matched class and the URL of the ontology. Predefined or user defined properties consisting of textual representations of the ontology concepts may be used to annotate the document. Two such annotation properties can be specified during the analysis. However, more than two annotation properties can also be accommodated by introducing a common super property for all types of annotations. If matching with lemmas is used, arbitrary sequences of lemmas and token strings can be matched.

Case Study

The ontology-based information extraction approach adopted for service entity recognition is illustrated here. Representative SLA templates for typical IT services such as desktop hardware and operation system service, standard office automation software service, e-mail service, directory services, web access service, user training service, and such were drawn from SLA Management Handbook (2004) and ITIL (2007). SLAs used at the authors' local institutions were also referred to. Figure 2 shows two sample SLAs, SLA1 for desktop hardware and operation system service (Service 1) and SLA2 for standard office automation software service (Service 2). Selected performance measures have been shown here to indicate interdependencies between and within services.

An IT service ontology was developed based on typical concepts and activities found in ITSM. This OWL ontology was augmented with annotation properties to provide commonly used textual representations for the concepts in the ontology. Such textual representations are typically phrases consisting of two to four words. For example, "hardware installation", "software configuration", and so forth. Using the Apolda processing resource for GATE (Wartena et al., 2007), the SLAs were annotated following typical tokenization, stemming processing.

In Figure 2, the highlighted annotations of service entities have been overlaid with arrows depicting the results of the interdependency analysis that was conducted manually. Arrow 1 indicates that the installation accuracy in Service 1 affects the installation accuracy in Service 2. This is due the fact that the office software installation service assumes that the hardware and operating system installation is done correctly (mentioned in SLA2). Both services are also affected by network services, as shown by arrow 2. It is mentioned though that network related failures will not be included in the measurement installation accuracy of those services. However, it would not have been possible to know about this buried information, without a careful manual analysis of the service contracts. Arrow 3 indicates the association of the customer satisfaction performance measures between the two services. Interdependencies between performance measures within the same service may also be revealed by such analysis. For example, arrow 4 indicates that the software currency affects the interoperability measure for service 2.

Given that this analysis was conducted manually, the next step would be to provide (semi)automatic support tools for such analysis. Stages 2 and 3 in the proposed framework highlight the steps needed in order to provide such support, which is part of our future research agenda.

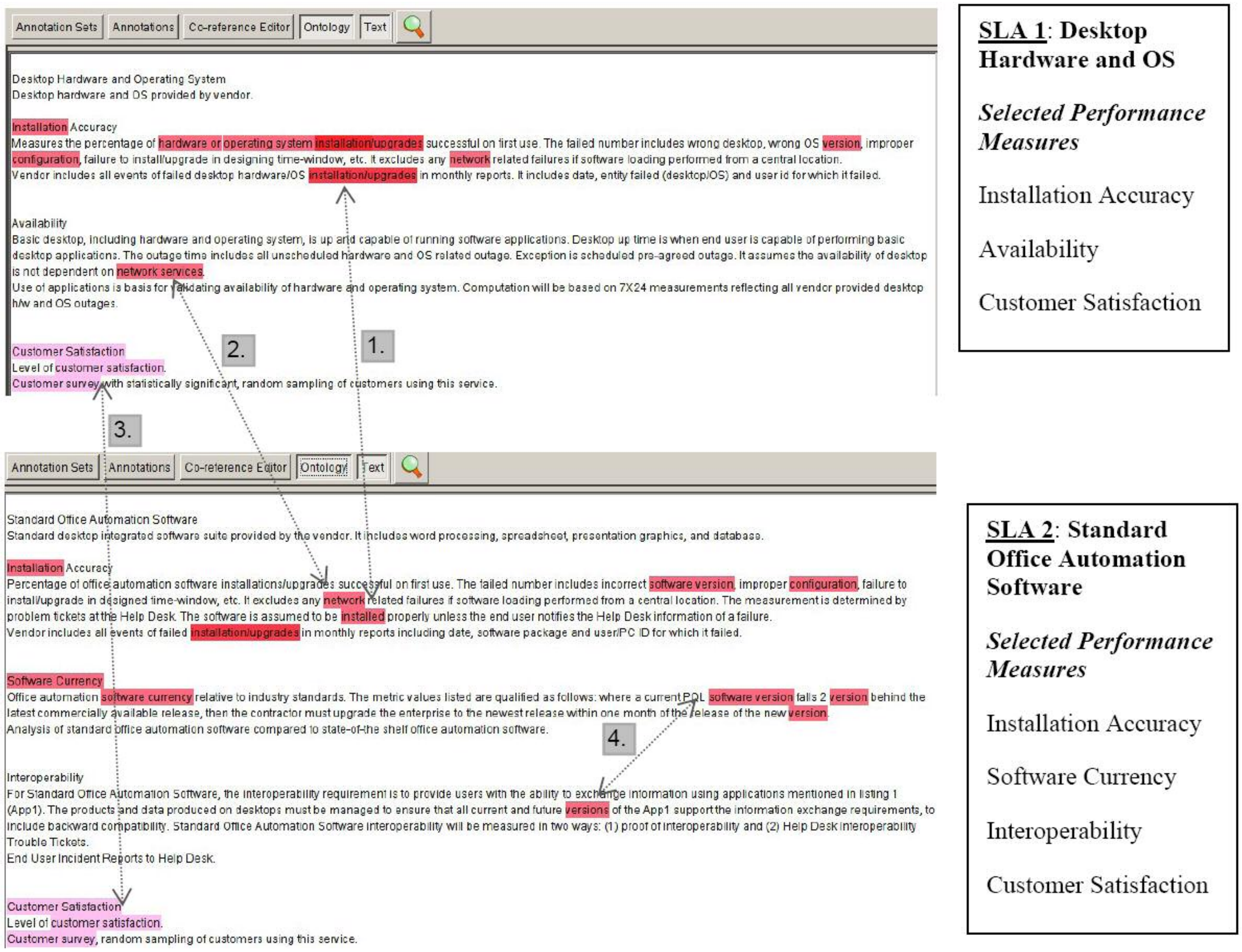

Figure 2. Illustration of Service Interdependencies Revealed Through Service Entity Recognition

CONCLUSION AND FUTURE WORK

In this paper, we propose an information extraction driven framework to identify process interdependencies in bundled IT service arrangements from narrative Service Level Agreements. In large B2B IT service agreements consisting of multiple components, activities pertaining to a particular service may impact the efficiency, effectiveness, and/or performance of other related services. Such interdependent nature of the service(s) and corresponding performance measure poses significant challenge in the measurement and monitoring phases of the service management life cycle and is often the cause of tension between service provider and customer organizations. The purpose of our research is to assist the participants of an IT service arrangement in obtaining a better appreciation of the interrelationships among different service components so that measurement, monitoring, and subsequent compensation schemes are more effective for both organizations. In this paper, we present the framework of our research along with some initial results and provide an outline of our ongoing research agenda.

SLAs, usually being very detailed in nature, are a treasure trove of information that can be utilized to gain insights into several aspects of service processes (that might not be easily available or documented otherwise) such as activities, resource requirements, performance measures, and so forth. At the current stage of the research, we applied semantic annotation based information extraction technologies to a set of industry standard SLAs. Our preliminary results demonstrate that this technique is able to indicate interrelationships among different process components – especially service activities and performance measure sets.

Our research is a first step towards a systematic effort to identify and categorize process interrelationships from a set of textual process-related documents. Our ongoing research will contribute to the recent body of knowledge in the area of business intelligence generation from process mining (e.g. van der Aalst and Weijters 2004, Wang et al. 2006). The value proposition of our work is the fact that systematic extraction of such process related information will help both the customer and provider organizations to improve the process of service delivery and management. For the customer organization, knowledge about performance measure interrelationships will enable the customers to negotiate better contracts and, more specifically, compensation schemes that most often have a performance-contingent part. For the provider organization, identification of process dependencies will assist in better process management and resource allocation tools. This knowledge will also assist in the monitoring phase activities such as fine tuning of the SLAs and performance measures, root-cause analysis, etc. Finally, as part of our research is involved in context based information extraction, a by-product of our research is the creation of an industry standard ontology for IT infrastructure services, that can be incorporated in the ITIL (Information Technology Infrastructure Library, http://www.itil-officialsite.com/home/home.asp) framework, which is currently the most widely accepted approach for IT service management.

At this point, we must also acknowledge the challenges and limitations of our research. Our approach to information extraction depends on textual information, and as such, the quality of the extracted information is a function of the quality of the text itself. More importantly, it must be mentioned that only those information, that are *explicitly* mentioned in the service ontologies through textual descriptions for annotation properties will be extracted using the current methodology. For example, the speed of problem resolution for different services through the help desk (e.g. e-mail, directory services) may be interrelated as staffing levels and traffic volume would determine the responsiveness. However, this information is implicit in the sense that it requires the knowledge that help desk resources may be shared among the different services. As long as this information is not explicit in the text document, it poses a challenge to the extraction technique. Another difficulty in achieving our goals is that this information extraction mechanism requires a domain ontology. Currently, we have a limited set of SLAs, from which the ontology in the example is created. As such, the results obtained so far, are too some extent idiosyncratic to the set of SLAs. In future, we will need a wider set to use the ontology learning mechanism discussed earlier, in order to automatically construct more detailed ontologies and thus improve the annotation results while achieving results with superior generalizability.

Our ongoing research agenda involves the creation and subsequent validation of process models from the information extracted from SLAs. We are currently in the process of gathering several IT service levels agreement from different organizations so that we have a comprehensive base to create an industry standard IT Service ontology. This ontology can then be utilized in identifying process and performance inter-relationships in each constituent SLA. Cross-comparison of the results thus obtained, will provide significant insights about interdependencies in IT service processes at two levels – at individual organizational level and at a more general industry level.

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