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Rapid Data Integration and Analysis for Upstream Oil and Gas Applications

Chung Ming Cheung, Palash Goyal, Greg Harris, Om Patri, Ajitesh Srivastava, Yinuo Zhang, Anand Panangadan, and Charalampos Chelmis, University of Southern California; Randall McKee, Mo Theron, and Tamas Nemeth, Chevron U.S.A. Inc.; Viktor K. Prasanna, University of Southern California

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Abstract

The increasingly large number of sensors and instruments in the oil and gas industry, along with novel means of communication in the enterprise has led to a corresponding increase in the volume of data that is recorded in various information repositories. The variety of information sources is also expanding: from traditional relational databases to time series data, social network communications, collections of unsorted text reports, and linked data available on the Web. Enabling end-to-end optimization considering these diverse types of information requires creating semantic links between them. Though integration of data across silo-ed databases has been recognized as a problem for a long time, it has proven to be difficult to accomplish due to the complexity of the data arrangement within databases, scarcity of metadata that describe the content, lack of a direct mapping between related entities across databases, and the several types of data represented within a database. In addition, there are large amounts of unstructured text data such as text entries in databases and document repositories. These contain valuable information on processes from the field but there is currently no method to convert this raw data to useable information. The Center for Interactive Smart Oilfield Technologies (CiSoft) is a USC-Chevron Center of Excellence for Research and Academic Training on Smart Oilfield Technologies. We describe the Integrated Optimization project at CiSoft which has the goal of developing a framework for automated linking of heterogeneous data sources and analysis of the integrated data in the context of upstream applications.

Introduction

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types of data represented within a database. In addition, there are large amounts of unstructured text data such as text entries in databases and document repositories. These contain valuable information on processes from the field but there is currently no method to convert this raw data to useable information.

The Center for Interactive Smart Oilfield Technologies (CiSoft) is a USC-Chevron Center of Excellence for Research and Academic Training on Smart Oilfield Technologies. We describe the Integrated Optimization project at CiSoft which has the goal of developing a framework for automated linking of heterogeneous data sources and analysis of the integrated data in the context of upstream applications. Our hypothesis is that there is valuable insight to be gained by analyzing large diverse datasets together. In this context, "large" refers to data volume (millions of instances) and "diverse" refers to the variety in data types (such as sensor measurements, work orders, operator text annotations). For example, information related to routine oilwell operations and repairs are recorded in production and maintenance databases respectively. Each of these databases is typically large, has a complex schema, and is updated in independent workflows. Linking these databases, while still retaining their independent operation, enables optimization across both of these databases (such as accounting for planned maintenance activities in production planning). The Integrated Optimization project aims to develop the data abstractions and automation methods for data integration and exploiting the resulting information sources. The project extensively uses pattern recognition techniques to automate data integration. Different methods are being developed to handle the diverse data types encountered in enterprise data stores. State-of-the-art machine learning methods are used to extract only the most discriminative pieces of information from the different types of data (such as abnormal modes of equipment operation). This reflects the growing importance of data mining and machine learning approaches in digital oilfield operations (Burda et al. 2007; Crompton 2008) as they move into the age of Big Data.

The components of the proposed data integration and analysis framework are shown in Figure 1. The Rapid integration framework automatically discovers entries in different databases that are related to each other using lexical, semantic and structural similarities of the data points. In order to accommodate different types of data sources, both structured and unstructured, specific methods are being developed to extract information from each type of data source. The current source types are relational databases, Semantic Web ontologies, social network communications, time-series data, and free-form English text. Together with the data integration component, the framework will enable rapid automatic integration and subsequent analysis of heterogeneous information sources. These components are described in the following sections (specifically, the Rapid Integration Framework for integrating relational databases and ontologies, the Event modeling and management component for time-series analysis and temporal rule mining, Content extraction from text for free-form English text analysis, and the Social network analysis component for modeling enterprise social network interactions). Components of the framework are being evaluated on specific upstream data-driven applications. Descriptions of the evaluation use-cases are included in the corresponding component descriptions.

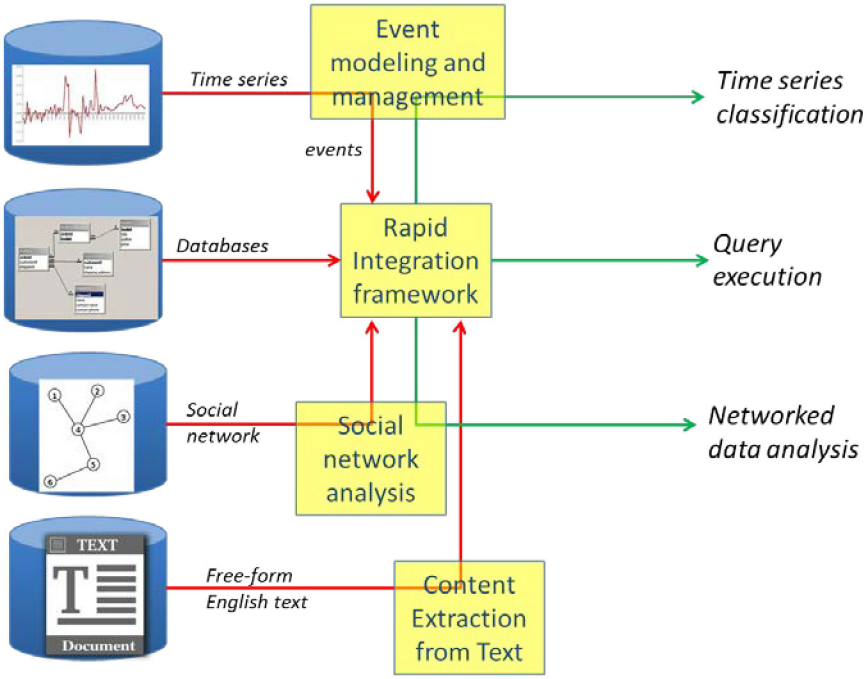


Figure 1—Components of the data integration and analysis framework.

Rapid Integration Framework

The rapid integration component is used to automatically discover correspondences across databases. The first step is to convert relational data into Semantic Web *ontologies.* An ontology represents information as a set of formally defined concepts within a domain. The process of identifying the entities in different ontologies (e.g., columns from different databases) that are related to each other is called *ontology alignment.* We have developed the Unified Fuzzy Ontology Matching (UFOM) framework for automatically detecting linkages between ontologies (Zhang et al. 2014). Unlike other ontology alignment approaches, UFOM is designed to discover linkages of multiple relation types. These linkages can be exploited for efficient querying for similar entities by following relatedness links to discover similar entities instead of evaluating every entity contained in the ontologies. UFOM uses fuzzy logic to compute and represent the relatedness between entities. Each linkage is defined by a *relation score* that represents the degree of the relationship between the entities and the *confidence* in this score. The design of the UFOM framework is illustrated in Figure 2. UFOM takes two ontologies as its input and outputs a fuzzy alignment between them. UFOM consists of four components: Preprocessing Unit, Confidence Generator, Similarity Generator, and Alignment Generator.

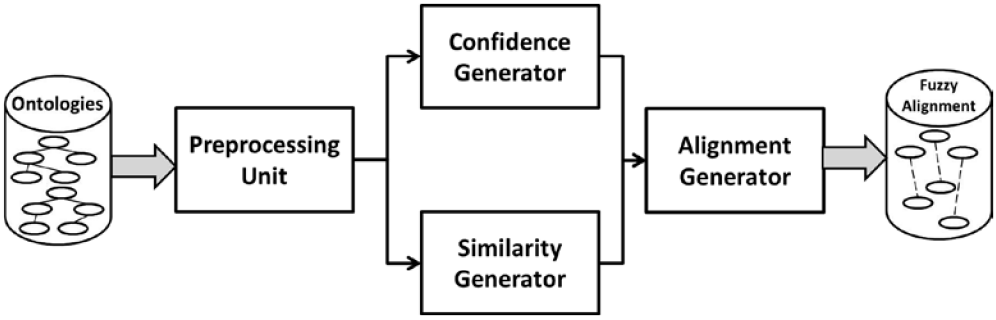


Figure 2—Components of the UFOM system for computing ontology alignment.

The Preprocessing Unit identifies the type of each entity in the ontology and classifies the entities based on their types. Different computation strategies are adopted for matching the entities with the most appropriate type. Specifically, an entity is classified as one of the following types: Class, ObjectProperty, String DatatypeProperty, Datetime DatatypeProperty, and Numerical DatatypeProperty. Confidence Generator quantifies the sufficiency of the resources used to generate a potential match between two entities. It computes a confidence score for each correspondence which reflects if there is sufficient underlying data to generate this correspondence. For correspondence between properties, their instances are the main resources. The more instances that are used for computing similarity, the more confident we can be in the matching process. In order to quantify the sufficiency of the properties, we utilize two metrics — Volume and Variety.

Similarity Generator computes multiple types of similarity for every pair of entities. It generates a vector of similarities between two entities. These similarities form the basis for computing different types of relation correspondences (using their respective fuzzy membership functions). In UFOM, the vector consists of four values: Name-based Similarity, Mutual Information Similarity, Containment Similarity, and Structural Similarity (Figure 3).

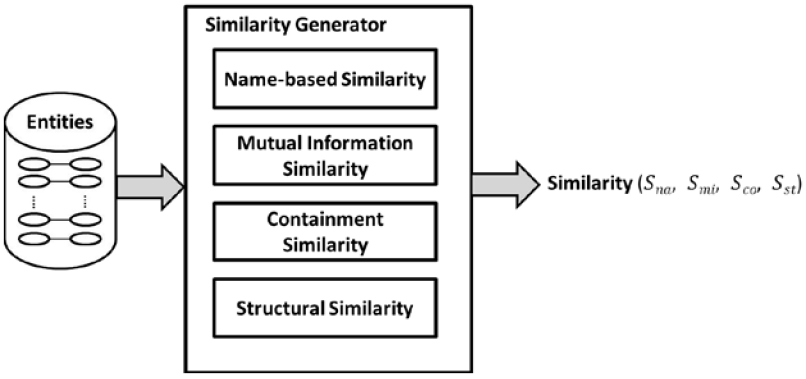


Figure 3—Components of the UFOM Similarity Generator.

Name-based Similarity is calculated based on both the semantic similarity and syntactic similarity between the names of the two entities. The name denoting an entity typically captures the most distinctive characteristic of the instances. Mutual Information Similarity models the mutual information that exists between the individuals of one entity and the domain represented by the second entity. If two properties have a high proportion of instances shared between them, then this is indicative of these properties being highly related. Containment Similarity models the average level of alignment between an instance of an entity and its most similar instance in another entity. It is designed to detect pairs of entities that share a large number of common instances even if the instances themselves are misaligned. The fourth value in the vector of similarities is designed to capture the structural similarity between two properties as they are represented within their ontologies. We represent the ontology as a graph with properties as edges and classes as nodes. If two properties have similar domains and ranges (classes), then they are assigned high similarity. In turn, two classes that have similar properties should have higher similarity.

Alignment Generator calculates a single relation score by combining the vector of similarities using the fuzzy membership functions for each relation type and constructs the correspondence based on both these. The output of Alignment Generator is a set of fuzzy correspondences in the form of relation scores and corresponding confidence scores. The confidence score is obtained from Confidence Generator. In order to calculate the relation score, a set of membership functions are pre-defined in UFOM. Each such membership function corresponds to one type of relation. Once both scores are calculated, AG prunes the correspondences with scores less than pre-defined cutoff thresholds. Different applications will have

different thresholds. For example, a recommendation system may have relatively low thresholds since false positives are tolerated, while a scientific application may have high thresholds.

Query Execution

Fuzzy ontology alignment can be used to speed up query execution over the matched ontologies (Zhang et al. 2015). We consider the following problem: Given two ontologies O1 and O2, return all individuals in O2 which are "relevant" to a given individual *t* in O1. A naïve approach to retrieve all such individuals is to compare each property value of *t* with all property instances in O2. This approach is inefficient in terms of search time. Since we have already discovered the matching between ontology properties, we can improve the query performance using the fuzzy alignment. The query execution has two steps: generating a fuzzy SPARQL query and converting to crisp SPARQL query.

The first step is to identify related properties using the fuzzy alignment. We have developed two approaches for querying related entities: follow only a single alignment link (*direct matching*), and follow multiple alignment links (*indirect matching*). These are illustrated in Figure 4.

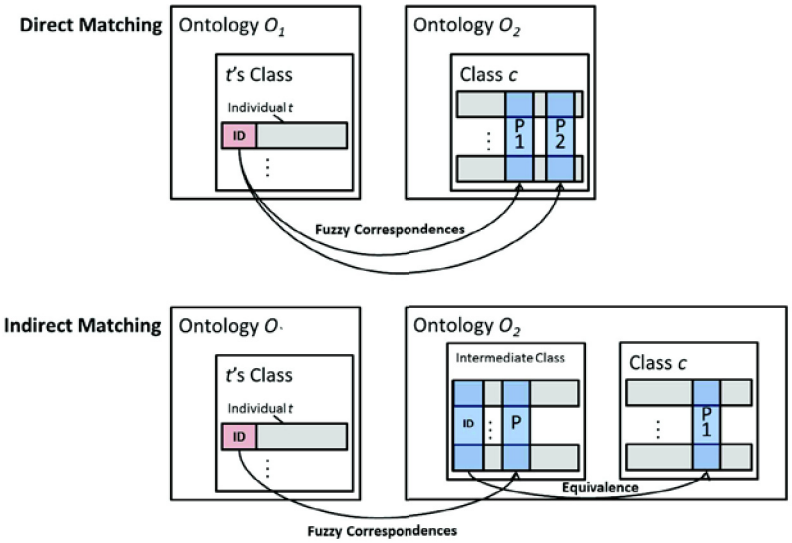


Figure 4—Top: direct matching. Bottom: indirect matching.

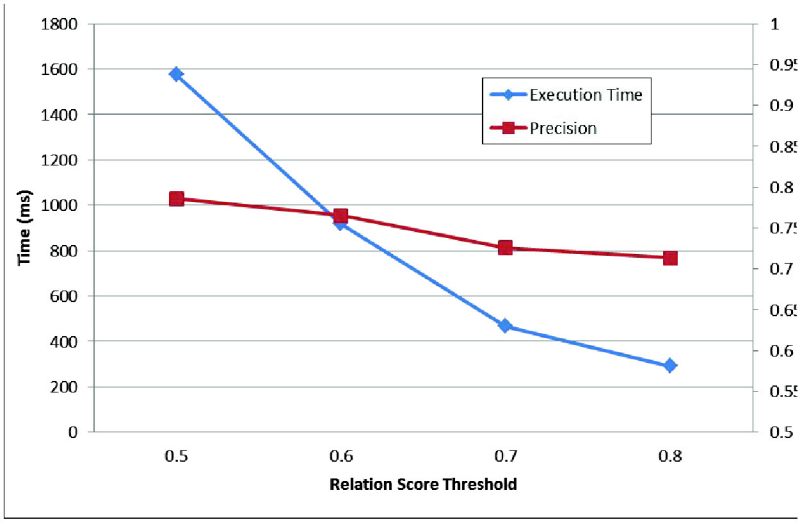
For direct matching, we retrieve properties in O2 having fuzzy relations (such as equivalence and relevance) with *t*'s identifier property using the fuzzy alignment derived by UFOM. For indirect matching, we first identify intermediate classes in O2. Such classes have properties having fuzzy relation with tt's identifier property. Based on the intermediate classes, we discover the properties which are equivalent to the identifier of intermediate class. This equivalent relation usually can be found by checking Object Properties in O2. In contrast to direct matching which outputs a set of properties, indirect matching results in a collection of triples in the form of $(p_1\ p_2, p_3)$, where p_1 is the intermediate class' property having fuzzy relation with *t*'s identifier property, p_2 is the intermediate class' identifier property, and p_3 is the target property equivalent to p_2. Once we have the properties discovered by direct matching and indirect matching, we can build fuzzy SPARQL queries to retrieve the related individuals.

Before converting the fuzzy query to crisp query, we calculate a seed vector for each value pair (v_0, v) where v_0 is the given value and v is the value in the matched properties. The vector considers multiple similarity metrics including syntactic, semantic, and containment similarities. The results are stored in instance ontology. We compute the α-cut of fuzzy terms based on the membership function in order to remove the fuzzy terms. The individuals are ranked based on their membership grade. Once the crisp

SPARQL query is generated, it can be registered on the triple store. As a result, all related individuals are returned. With the help of the fuzzy alignment, the computation burden can be reduced.

Quantitative evaluation

We performed a set of experiments to evaluate query execution components. For datasets, we used publicly available ontologies provided by Ontology Alignment Evaluation Initiative (OAEI) campaigns (Euzenat et al. 2011). The first dataset we use is Instance Matching (IM) ontology from OAEI 2013. It has 5 ontologies and 1744 instances. We initialize 10 individuals from one of the ontologies and retrieve related individuals from other ontologies. The membership grade threshold is set as 0.75. Figure 5(a) shows the performance of our query execution component on the IM ontology. Each data point is generated by averaging the results of 10 individuals.



(a)

Scenario	UFOM(ms)	Baseline(ms)
C_1 to C_3	227	36788
C_2 to C_3	160	25973
C_1 to C_4	431	54302
C_2 to C_4	364	45862

(b)

Figure 5—(a) Precision and execution time on applying UFOM query execution to the Instance Matching Ontology. (b) Query Execution Time (UFOM vs Baseline)

As the relation score threshold increases, both precision and running time for query execution decrease. It is because the number of correspondences decreases when we raise the relation score threshold. As a result, we have fewer correspondences to consider when we generate crisp queries and therefore the computational time is reduced. The reason precision also decreases is that we lose some true correspondences when we increase the relation score threshold. Those correspondences can actually help us to find more related individuals. However, as we can see if we increase the threshold from 0.5 to 0. 8, precision only decreases by 9% while execution time is reduced by 81%. This indicates that the elimination of correspondences caused by increasing threshold do not affect retrieving correct related individuals significantly. This is because the remaining correspondences are still sufficient to find connections between classes. In terms of querying for similar individuals, the correspondences between same pair of classes may have functional overlap.

For the evaluation of querying for related individuals, we considered two ontologies from an enterprise-scale information repository. Due to privacy concerns, we do not reveal the real names of the properties and ontologies. Specifically, we considered two classes, C1 and C2, in O1 and two classes, C3 and C4, in O2. We selected 10 representative individuals from C1 or C2 and retrieve their relevant instances from C3 or C4 using the fuzzy alignment. Both precision and recall are 1.0 when we verified

the results with the ground truth obtained by manually examining the ontologies for each of the automatically retrieved entities.

Computational complexity Indirect matching is capable of discovering entities that are not directly related to the given query entity but it is computationally more intensive than direct matching. We have derived the *computational complexity* of the two approaches. We assume that the cost for comparing a pair of entities is constant. The computation time of the direct matching process is proportional to the number of relevant field pairs, the number of records in the source class that has the specified value, and the number of records in the target class. The computational cost of indirect matching is proportional to the number of records in each indirect class, the size of the set of relevant field pairs between the source class and each indirect class, and the size of the set of primary keys of relevant records identified in a target class. Figure 5(b) shows the average execution time for querying the ontologies from the enterprise-scale information repository. Compared with a baseline approach of traversing the values of all properties in O2, the proposed approach reduces the execution by approximately 99%.

Event Modeling and Management

Time Series Classification using Shapelets

A massive portion of oilfield data today is in the form of sensor streams, which necessitates the use of rapid real-time data analysis techniques (Brule 2013; Abou-Sayed 2012). We have adapted a time-series mining approach that was recently developed in the computer science community, known as time-series shapelets (Le and Keogh 2009), for application to sensor measurements typically collected in the oil and gas industry, in particular to component failure detection and prediction. The streaming time series nature of such data is especially suited to this approach. The shapelets method identifies those time segments ("shapelets") within the available sensor data which are most discriminative for differentiating between two classes, for instance those arising from failed pump components in contrast to those that are working normally. Using discovered shapelets from historical data, predictions about future failures or anomalies can be made such that proactive steps can be taken to mitigate their effects. As an example, a shapelet that was discovered from intake pressure measurements from an electrical submersible pump is overlaid over the full time series in Figure 6 – the short segment shown in red was found to be the most discriminative from this time series and others in the labeled data record for distinguishing failed pumps from normal ones. This shapelet, along with other shapelets, can be used for detecting failures by comparing them with real-time sensor data.

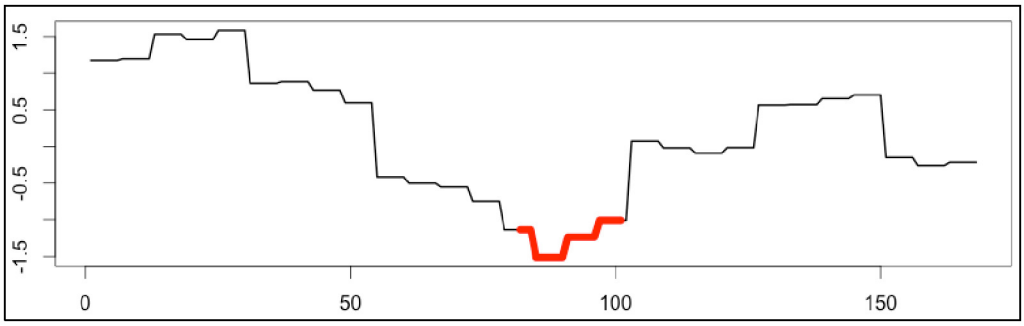


Figure 6—A discriminative segment (shown in red), or shapelet, from a time series as computed by the shapelet mining algorithm. The x-axis shows time (in days) while the y-axis represents normalized values of the intake pressure for a specified ESP.

The shapelets approach is particularly effective for oil and gas enterprise data because it does not need access to the entire historical record of sensor data while making decisions – only the shapelet time segments, identified in an offline step from the historical record, are needed for real-time analysis. This

greatly reduces the amount of data needed to be stored for further data mining. Moreover, this approach does not make any assumptions about the nature of the data, making it practical for real world scenarios. The shapelets found are visually interpretable, making deeper root cause analysis possible. Such time series mining methods are directly related to events in the oilfield, and as described in (Crompton 2008), there are several value propositions for efficient event processing (Patri et al. 2012, 2014b).

Gas Compressor Valve Failure Use Case We coupled feature selection methods with shapelets-based time series classification to address the problem of failure detection of gas compressors (Patri et al. 2015). A regular failure in rotating equipment such as compressors is the breakdown of valves. This issue is of great value to the oil and gas industry because a large portion of production is dependent on rotating equipment. Our goal is to rank sensor dimensions and find signatures in compressor sensor data, which may aid in the prediction of valve failure, and as a result create a path to prioritize and monitor maintenance schedules for compressors, which are often on remote platforms. The data used in our evaluation is from sensors that measure various physical properties of compressors, ranging from compressor vibrations and motor winding temperatures to pressure and temperature for both suction and discharge at the various compression stages.

Our dataset consists of sensor data from four-cylinder gas compressors in an oilfield. Each compressor has approximately fifty sensors. The sensor functions range from measuring compressor vibrations and motor winding temperatures to sensors measuring the pressure and temperature for both suction and discharge at the various compression stages. Data from some of the sensors is shown in Figure 7. We applied feature selection algorithms to automatically rank sensor streams in order of usefulness for the specific prediction tasks.

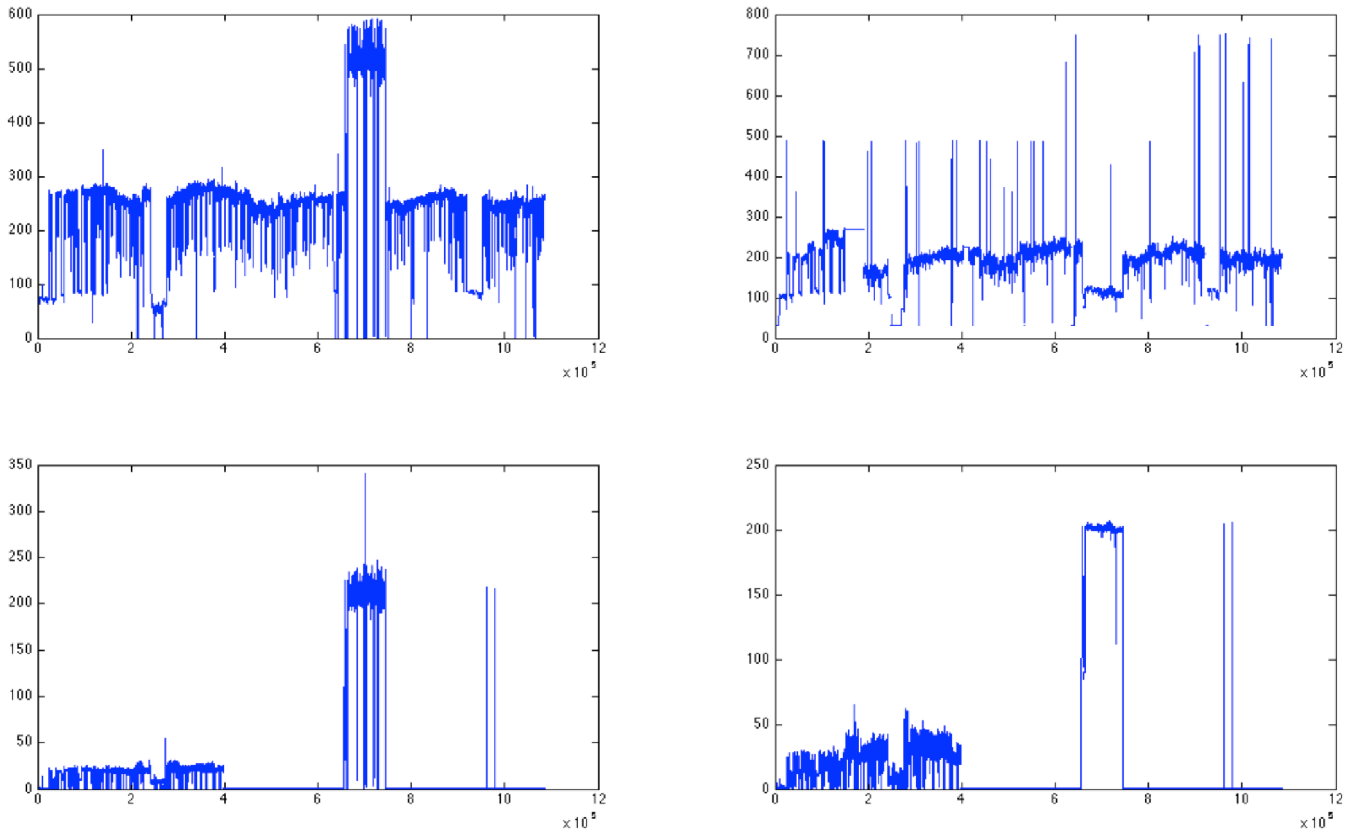


Figure 7—Data from some of the sensors in the gas compressor – discharge temperature of a cylinder (top left), motor winding temperature (top right), motor vibration (bottom left) and cooler vibration (bottom right).

While these sensor measurements are easily accessible, information on past occurrences of abnormal operating conditions is not recorded in a format suitable for use as labels in a machine learning algorithm. We used dates entered as part of maintenance records as labels for the sensor streams in order to apply supervised machine learning algorithms. These were obtained from a subset of work orders on compressor maintenance that focused on issues related to valves. The work orders listed dates of reported failure and completion along with comments for each repair. We used information from the work orders to build our labels, thus framing our failure prediction problem as a time series classification problem.

Approach **Data labeling:** To convert the sensor data streams into our required time series training and testing datasets, we partitioned the full sensor stream around the occurrences of failures. A failure report date is available as part of the maintenance records for the gas compressor. However, this report date does not necessarily correspond to the time when the compressor actually failed but rather when a technician created a work order to address a deficiency or respond to a prior open work order. In this work, we label segments as failures if they appear a short while before this failure report date. We expect the actual failure to have occurred before a human operator notices it. Failure windows are set just before these calculated failure times. The size of this window can be set as a parameter in our experiments, but we focused on one-week windows. Since the data in this window is just prior to the failure occurrence, it is likely to be indicative of failure signals before the failure. For each labeled failure occurrence, we obtain the data in this failure window, as shown in Figure 8, and extract shapelets from this window. Each such data segment will have a failure label associated with it.

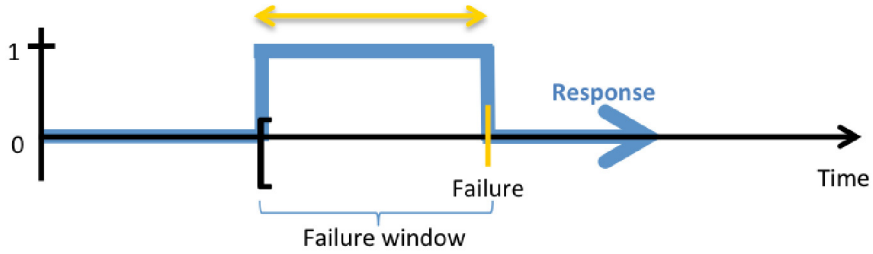


Figure 8—Pre-processing sensor data – a failure window is set just prior to the occurrence of each failure and we use these blocks of data to extract signals indicative of failure

Next, we select normal instances only from those periods that are not close to any failures. Thus, we pick data segments of the same window size from the rest of the data (normal operation) ensuring that there is no intersection between the clean data segments and the failure periods or the pre-failure periods i. e. the failure window. These data segments from normal operation are assigned the "normal" label for classification.

Our approach is presented in the following training and testing algorithms. We have also applied a similar approach for predicting electric submersible pump (ESP) failures in the context of single sensor (univariate) data (Patri et al. 2014).

Training algorithm:

Input: A multivariate time series, time instances known to represent failures

Output: Set of selected sensors; shapelets and decision trees for every selected sensor

1. Pre-processing: Extract equal length (multivariate) segments and assign failure/normal labels to each from the time series based on the distribution of failure instances.

2. Feature selection: Compute a variety of features for each sensor stream in each segment. Specifically, we use the maximum cross-correlation with an exponential decay curve with a pre-defined magnitude and exponent. Correlate the maximum cross-correlation feature for each sensor stream with the

failure/normal labels using a linear classifier. Retain only sensor streams which have > 50% classification accuracy.

3. Apply univariate shapelet mining algorithm (specifically, Fast Shapelets (Rakthanmanon and Keogh 2013)) to only the sensor streams selected in Step 2. This step produces a set of shapelets and a decision tree for each selected sensor stream (much fewer than the total number of sensors).

Testing algorithm:

Input: A single multivariate time series

Output: Class A (Normal) or Class B (Failure)

1. Discard variables from the multivariate time series that correspond to sensors not in the set of selected sensors

2. For every selected sensor stream, compute the Euclidean distance to shapelets in the corresponding decision tree (from Step 3 of the training algorithm).

3. Use the distances to compute a failure/normal label using the decision tree for each selected sensor.

4. Apply majority voting to select a single failure/normal label from the set of labels from selected sensors (from Step 3).

Data mining across heterogeneous data sources

The data integration framework facilitates data mining across heterogeneous data sources and mining the integrated historical data can enable the discovery of temporal patterns. In our work, we identify a class of patterns called classification *rules*, which take the form: "IF *Conditions*, THEN *Class*." The conditions are a conjunction of attributes or features found in the data which identify the target class with high precision. Rules are intended to be concise and interpretable. This comprehensibility relative to "black-box" classifiers facilitates easier adoption by domain experts.

Rule-Learning Features The data integration framework links together both relevant information and non-relevant information to any specific application. Therefore, steps must be taken to restrict the number of features in the search space to reduce the chances of over-fitting the data and finding spurious rules. Preprocessing the data into a smaller set of semantically meaningful features also keeps the rules interpretable.

An example of such preprocessing is the clustering of *pump cards*, which is a series of load-position pairs recorded throughout each pump cycle. Rather than data mining on individual load-position points, we group complete pump cards together into similar clusters. We find that hierarchical agglomerative bottom-up clustering using the Euclidean distance metric works well for grouping similar pump cards. Each cluster is one feature in the search for classification rules. Figure 9 shows some example pump card clusters.

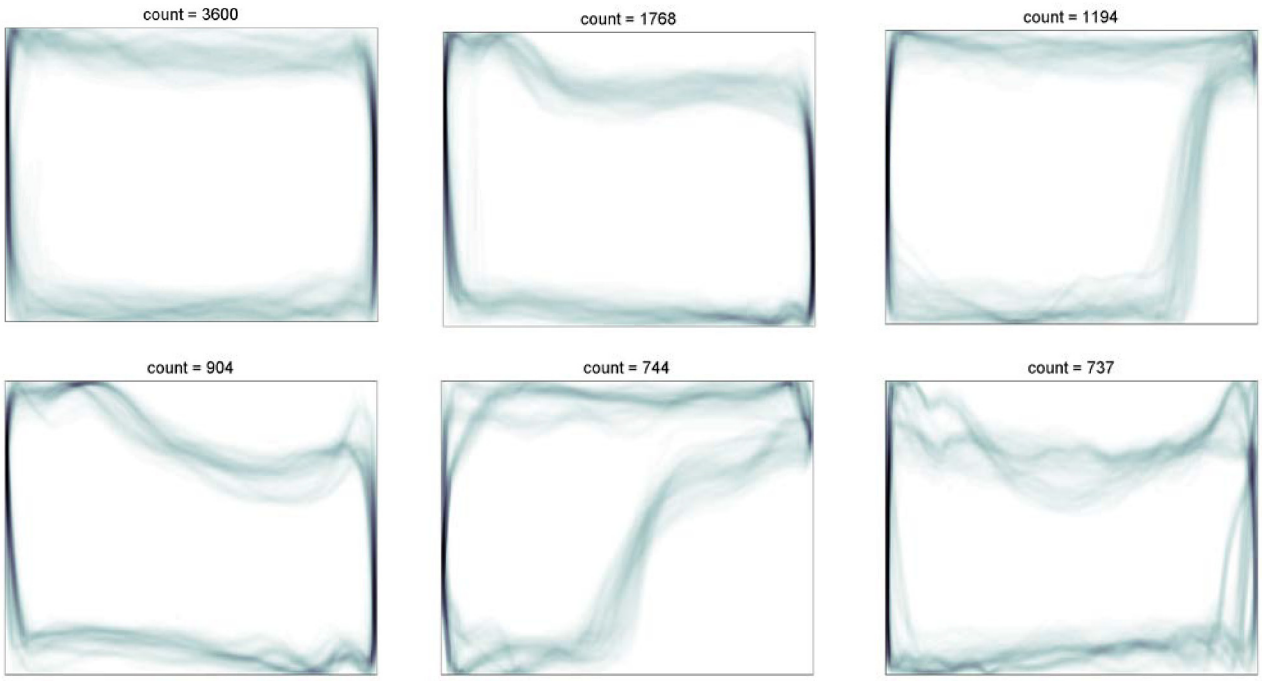


Figure 9—Example pump card clusters. To keep the clusters interpretable, we label each cluster with an image made up of a composition of all member images. This "average" pump card image conveys information to the domain expert.

Confidence in inferred production estimates use case *Enhanced Oil Recovery* is a technique used to improve production in fields with highly viscous oil. In this technique, operators inject steam into and around a well that has seen a reduction in flow. The steam heats the oil under the surface, reducing its viscosity. This often leads to an increase in production. The primary indication that a well would benefit from steam stimulation is a decline in production. Inferred production calculations are used as estimates of individual well production in lieu of expensive well gauging. Inferred production is calculated based on an analysis of pump card measurements, in addition to other data. Noise in the inferred production estimates can also lead to sub-optimal wells being flagged for stimulation. For low-producing wells, even well tests measuring actual production can have high variation. This leads to many spurious alerts which obscure the alerts for high-producing wells ready for stimulation.

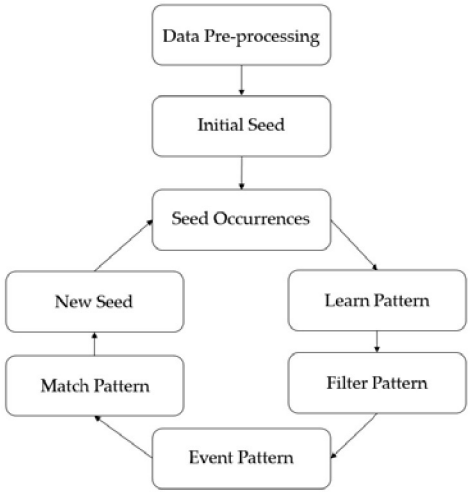
Rule learning can help with Enhanced Oil Recovery by reducing false alarms due to well failures and due to low-confidence inferred production data. For this use-case, the objective for rule learning is to find the best candidate wells based on characteristics of productive wells in the historical record. A good candidate is a well that will benefit most from steam injection. Features can include pump card clusters and temporal information about events, such as the amount of time elapsed since the last steam injection.

Content Extraction from Text

The amount of unstructured text data collected in real-world enterprise applications is increasing with the easy availability of portable computers enabling operators to enter notes in the field. For instance, field engineers record their observations into a Computerized maintenance management system (CMMS) using a mix of natural language and domain-specific terms. Such text instances can number in the hundreds of thousands in an enterprise. In this context, "unstructured" refers to natural language that does not strictly follow the rules of the language. Content extraction from such unstructured text collections is the process of identifying only the key terms in an entry that are relevant to a specific application, i.e., the terms that share a particular relation with each other. Content extraction thus transforms unstructured text to a structured representation. For example, in a maintenance application, the content extraction task could be

to identify terms describing repair actions and parts that were repaired. This transformation helps us understand the data and make use of it in various tasks such as data integration and summarization.

The problem of content extraction has been widely studied in Natural Language Processing but most of these approaches make use of the structure of the text by assuming that it is composed of grammatically correct sentences. Corporate datasets often do not satisfy this criterion. For this reason we applied a bootstrapping based approach to solve the problem (Shang et al. 2015). The approach is illustrated in Figure 10. The method uses an iterative approach where event patterns are used to extract matching sentences and these matches are used to refine the patterns. This approach is adapted from the DIPRE system (Brin 1999) where patterns are used to extract author-book pairs. While DIPRE relied on regular expressions of characters for patterns, we use approximate matching based on the semantic distance between words. We rank patterns in order to ensure that only high precision patterns are retained. We also tokenize the input sentences to extract local features before searching for patterns. The steps are listed in Algorithm 1 (Figure 10). The information extraction part is preceded by set of data pre-processing tasks in which we tokenize the sentences using bigrams, remove stop words, and perform stemming.



Algorithm 1 extractEvents (initial seed events, E; set of sentences, S)

1: Find all occurrences of known events in data: $O \leftarrow \text{findOccurrence}(E, S)$;
2: Generate patterns from occurrences: $P \leftarrow \text{generatePatterns}(O, S)$;
3: Rank patterns: $R \leftarrow \text{rankPatterns}(P, E, S)$;
4: Retain only high ranking patterns: $P^* \subset P, R(p) > \tau, p \in P^*$;
5: Match patterns to sentences to get new events: $E \leftarrow \text{matchPatterns}(P^*, S)$;
6: if E has expanded, then goto Step 1;
7: **return** E;

Figure 10—Illustration of approach and algorithm for event extraction from unstructured data.

We evaluated our approach on the text comments in the database of an enterprise level corporation. The database contained approximately 400,000 lines and represented field notes by engineers. Events in this application correspond to actions taken by engineers and the event parameter represents the object involved in an action. The average length of a line is 13 words.

Welder Repair *PART* on Section `DIGIT` spent *PART* pump `ID DIGIT` suction line install motor valve @ `ID DIGIT`, on `ID NUM`, for well `ID DIGIT`

Figure 11—Examples from enterprise dataset. ID and DIGIT represent alphanumeric characters and numbers respectively that are replaced with type tags before event extraction. PART represents words not shown for privacy concerns.

The lines are a mixture of English words, numbers, and alphanumeric terms. Since variations in numbers and alphanumeric terms between otherwise similar sentences do not typically represent different events, we replaced instances of such terms with a generic tag. Examples of lines in this dataset are shown in Figure 11.

Event and Event parameters	Frequency	Event and Event parameters	Frequency
repair brake	1626	repair *PART*	1024
replace belt	89	new belt	61
repair ppm	56	adjust and	40
brake repair	37	need belt	33
repair water	28	change belt	26
repair belt	20	install ladder	15

Figure 12—Approximate pattern matching: Subset of event and event parameter pairs after first iteration. Pairs in red are considered incorrect in our evaluation.

We selected the following seed Event-Event parameter word pairs for extracting new events from the enterprise dataset: "replace belts", "repair part", "need belts", and "repair break". With these seed pairs and by using approximate matching using WordNet similarity, the patterns found after the first iteration are shown in Figure 12. The false positives are marked in red. The method achieves a precision of 70%.

Learning word relatedness from unstructured text

Given a text dataset, several applications require words in the data to be associated with terms of known significance, i.e., there is a need to learn *word similarity.* Typically, the Distributional Hypothesis, which states that words that occur in the same contexts tend to have similar meanings (Harris 1985), has been used as the basis for association methods in information retrieval (Stiles 1961). However, when the data set contains only short free-form sentences as in the case of field notes in industrial applications, learning similarity based on co-occurrence within the context is not sufficient. Therefore, we need to consider the co-occurrence of a pair of words "across" similar contexts.

We have developed the notion of **cross-context similarity** (CCS) to relate similarity *between sentences* (more generally, denoted "contexts") to *similarity between the individual words* that comprise the context. Our approach makes use of a simple bag-of-words model relating terms to their contexts and the similarity is calculated using only the information provided in a labeled sentence corpus. In the case, where the sentences (contexts) are not labeled and similarity between them is not known, we can use established sentence similarity measures (e.g., cosine similarity) to compute context similarity. Our hypothesis is that the more often two terms occur in similar contexts, the greater the cross-context similarity between them. The idea is especially advantageous in short texts, where the contexts are short sentences. In this case there may not be enough information in the same context to find similar terms. For instance consider the sentences:

1. *"Two-Face has appeared in multiple Batman media forms."*
2. *"The character of Joker has undergone many revisions."*

Co-occurrence alone does not provide any relationship between (*Joker, Two-Face*). However, if it is known that the sentences are related (both describe Batman villains), one can infer that there is some similarity between (*Joker, Two-Face*).

The CCS model is based on computing cross-occurrence which is defined as a measure of the weighted co-occurrence between terms in similar contexts. The weights in the cross occurrence are calculated based on context similarity over all pairs of contexts and the membership score of words in the corresponding contexts. This membership score may be a binary value representing presence/absence, frequency, or TF-IDF score. Cross-occurrence is appropriately normalized to get CCS so that it is bounded between 0 and 1.

We use CCS to automatically obtain the relatedness between cataloged (English) and uncatalogued (non-English codes such as part numbers) words from text data in an enterprise dataset. A sample of results obtained using CCS is shown in Figure 13. In this graph, low relatedness links were removed, preserving only meaningful relationships. The cataloged words such as *flats, tires*, and *vehicle* can be together considered to form a description of the codes.

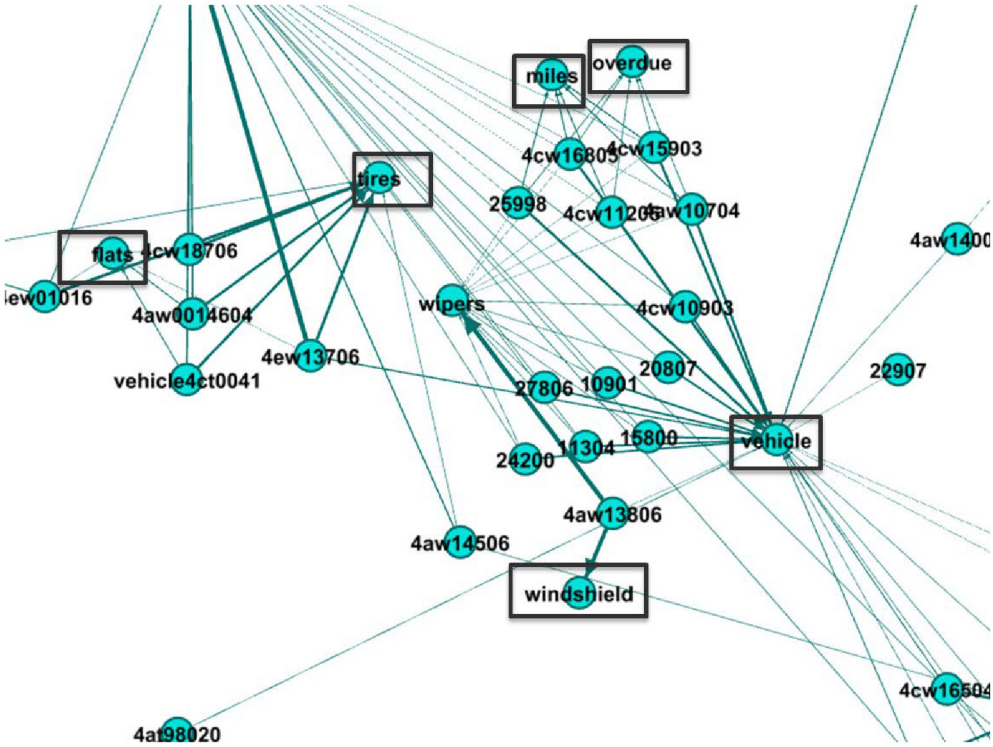


Figure 13—Relatedness between cataloged (English) and uncatalogued (non-English codes such as part numbers) words using CCS.

Figure 14 shows another snapshot of the relatedness measure, where all the codes related to wells gather around the term *wells*. Thus, CCS not only finds the relatedness but also helps in interpreting the meaning of unknown terms.

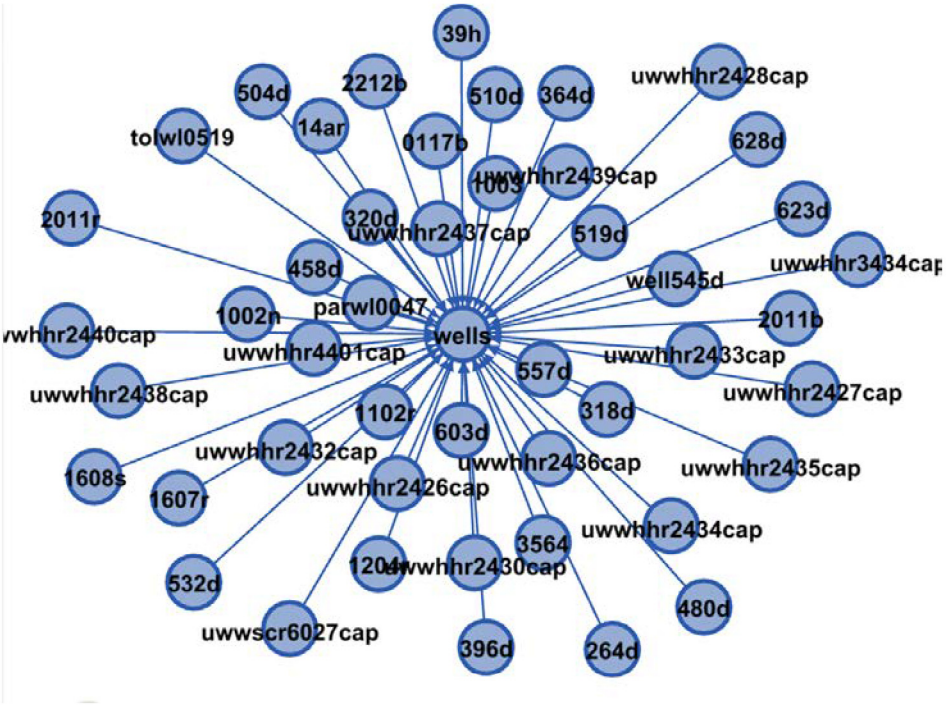


Figure 14—Relatedness between known word (*well*) and non-English codes (part numbers) as computed using CCS.

Social Network Analysis

The wealth of information available in the modern enterprise is not limited to formal interactions and silos containing structured data. As social media have become phenomenally popular, enterprises have adopted light-weight tools such as on-line forums and microblogging services for internal communication. Employees have been using social network sites and microblogging services to stay in touch with close colleagues or to reach out to employees they do not know, to connect on a personal level or to establish strong professional relationships (Wu et al. 2010). Analysis of enterprise social interactions analysis can lead to insights, both at the atomic (micro) and collective (macro) level. Micro analysis is intended to provide better tools for communication, search and productivity, whereas macro analysis is be used for strategic decision making and informed planning. Examples of micro analysis include recommendation services that can connect employees to "interesting" people, suggest "interesting" discussions for employees to contribute, or projects to get involved in. Macro analysis can enable enterprises to utilize the results stemming out of informal interactions analysis, to better understand how their employees work together to complete tasks or produce innovative ideas, reveal trends, identify experts and influential individuals, so as to evaluate and adjust their management strategy, team building and resource allocation policies (Chelmis et al. 2013).

In prior work, we have designed and built the Semantic Social Network Analysis for the Enterprise (rESONAtE) model (Chelmis et al. 2013). rESONAtE is a formal model that abstracts the semantics of social network communication into an integrated, context-aware, time-sensitive, multi-dimensional space, with the goal of enabling the correlation across different domains (Chelmis et al. 2013). The social graph representation, shown in Figure 15, represents both social links between users and maintains integrated information regarding users dynamically changing interests and activities, across collaboration tools used in the work environments. The *Social Layer* captures users' contextual and temporal interactions. Nodes represent users and arcs represent explicit relationships (links) between them. An edge between users is defined by the context under which it was created and has an associated timestamp. The *Content Layer* captures published content from all available sources, including but not limited to resources shared by

users (e.g. photos or videos), bookmarked and/or tagged resources (e.g. URLs), users' generated content (e.g. status updates in Facebook), e-mails, chat messages, and blog posts. The *Semantic Layer* contains meta-information about content, and can be broken down into several constituting layers, each containing different metadata about the content.

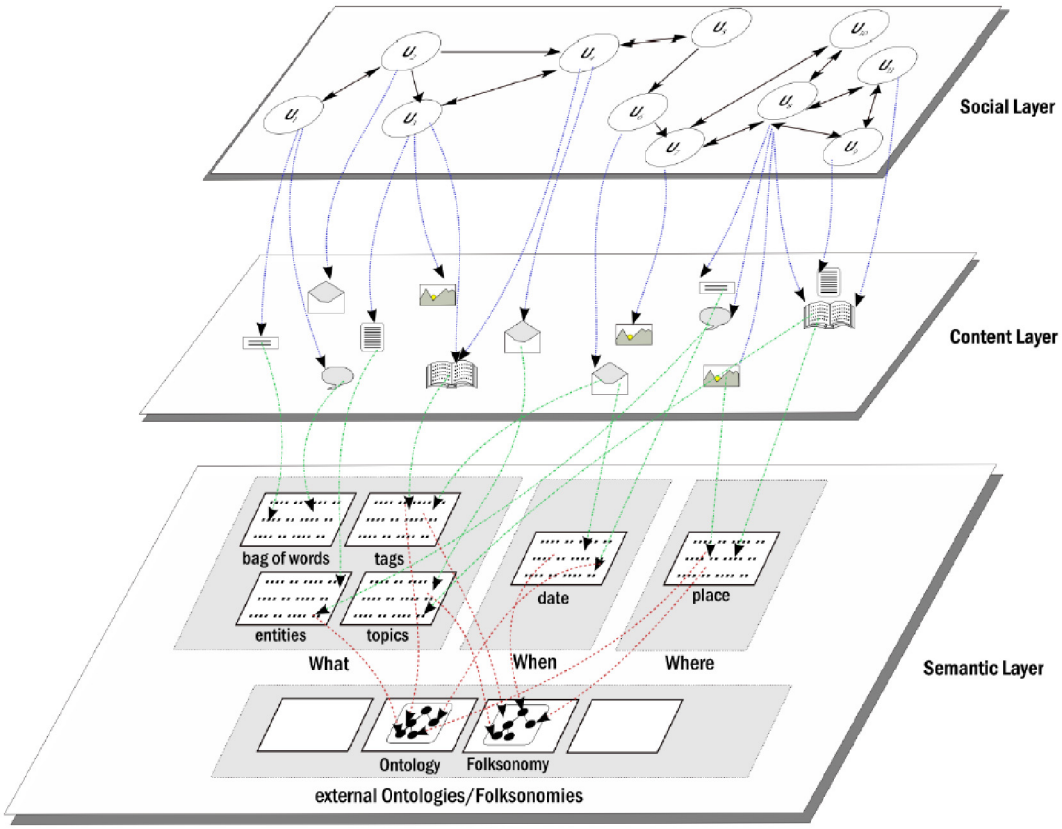


Figure 15—Layers of the rESONAtE model for representing social network communications (Chelmis et al. 2013).

Organizational Hierarchy vs. Social Network Interactions

Organizational hierarchy is relatively static whereas communication may reflect "shortcuts," i.e. collaboration that spans hierarchical levels when seeking for help, or offering guidance. Studying communication patterns may reveal hidden organizational dynamics such as employees belonging to the same team according to the organizational hierarchy, but rarely actually interact due to having diverse responsibilities. Social network analysis can enable better understanding of how information propagation works between corporate borders. As a specific use-case of such analysis, we have analytically examined the impact of organizational hierarchy in adopting new technologies in the enterprise (Chelmis et al. 2014).

For our study, we acquired the organizational hierarchy of a Fortune 500 multinational company. In addition, we gathered adoption logs of the internal microblogging service, which resembles Twitter, during the first two years of adoption of the service in the enterprise. This dataset allows us to empirically characterize individual dynamics and influence and examine the spread of adoption through the hierarchy. To characterize the adoption mechanism of the internal microblogging service, we developed two agent-based computational models with the least possible number of parameters. The model emphasizes modeling the cumulative number of adoptions over time, rather than trying to predict which specific node in the network will infect which other nodes. The model represents the influence that each node has on the spread of influence (microscopic modeling) and uses this to provide an analytical framework by which

changes in the adoption rate over time can be predicted (macroscopic dynamics). This study suggested that middle-level managers are most successful in influencing employees into adopting the new microblogging service. The analysis was further extended to model a wide variety of social network influence (Srivastava 2014).

Conclusions

The Integrated Optimization project is developing a suite of technologies to enable rapid integration and analysis of large heterogeneous data sources in the oil and gas industry. The Rapid Integration Framework provides a semantic layer for integrating relational databases and ontologies without affecting the underlying data recording workflows. The Event Modeling and Management component develops machine learning-based methods for classifying sensor measurements and has applications in predicting equipment (electric submersible pumps and compressors) failures and for optimizing enhanced oil recovery operations. Methods for content extraction from text enable automatic identification of key terms in large quantities of free-form English text. The models for social network analysis can provide insights to oil and gas enterprises seeking to realize the dynamics of adoption of new technologies in their organization and could assist in designing better strategies for rapid and efficient technology adoption and information dissemination at the workplace. These methods are currently evaluated in specific upstream applications.

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