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Conceptual Modelling 2014

Proceedings of the Tenth Asia-Pacific Conference on Conceptual Modelling (APCCM 2014),
Auckland, New Zealand,
20 - 23 January 2014

Georg Grossmann and Motoshi Saeki, Eds.

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Preface

The Asia-Pacific Conference on Conceptual Modelling is celebrating its 10th edition! This volume contains the proceedings of the *10th Asia-Pacific Conference on Conceptual Modelling (APCCM 2014)*, held at the Auckland University of Technology, New Zealand from January 20 to 23, 2014 again as part of the Australasian Computer Science Week (ACSW 2014).

The APCCM series focuses on disseminating the results of innovative research in conceptual modelling and related areas, and provides an annual forum for experts from all areas of computer science and information systems with a common interest in the subject. The scope of APCCM 2014 includes areas such as:

- Business, enterprise, process and services modelling;
- Concepts, concept theories and ontologies;
- Conceptual modelling and user participation;
- Conceptual modelling for decision support and expert systems; digital libraries; e-business, e-commerce and e-banking systems; health care systems; knowledge management systems; mobile information systems; user interfaces; and Web-based systems;
- Conceptual modelling of semi-structured data and XML;
- Conceptual modelling of spatial, temporal and biological data;
- Conceptual modelling quality;
- Conceptual models for cloud computing applications;
- Conceptual models for supporting requirement engineering;
- Conceptual models in management science;
- Design patterns and object-oriented design;
- Evolution and change in conceptual models;
- Implementations of information systems;
- Information and schema integration;
- Information customisation and user profiles;
- Information recognition and information modelling;
- Information retrieval, analysis, visualisation and prediction;
- Information systems design methodologies;
- Knowledge discovery, knowledge representation and knowledge management;
- Methods for developing, validating and communicating conceptual models;
- Models for the Semantic Web;
- Philosophical, mathematical and linguistic foundations of conceptual models;
- Reuse, reverse engineering and reengineering; and
- Software engineering and tools for information systems development.

The program committee has selected the contributed papers from 17 submissions. All submitted papers have been refereed by at least three international experts, and have been discussed thoroughly. The six best papers judged by the program committee members have been accepted as full papers and two additional short papers are included in this volume.

The organising committee is honoured that Prof. John Mylopoulos and Prof. Koichiro Ochimizu accepted the invitation to give a talk at APCCM 2014.

Prof. John Mylopoulos holds a distinguished professor position (chiara fama) at the University of Trento, and a professor emeritus position at the University of Toronto. He presented the APCCM 2014 keynote on "Goal-Oriented Requirements Engineering".

Prof. Koichiro Ochimizu is Vice President of Japan Advanced Institute of Science and Technology (JAIST), and Research Professor and Director of Center for Highly Dependable Embedded Systems Technology of JAIST, Japan. The topic of his invited talk was "The Role of Software Models in Developing New Software Systems; A Case Study in Project Management".

The program committee selected the articles *SQL-Sampler: A Tool to Visualize and Consolidate Domain Semantics by Perfect SQL Sample Data* by Van Tran Bao Le, Sebastian Link and Flavio Ferrarotti for the APCCM 2014 Best Student Paper, and *Data-driven Requirements Modeling: Some Initial Results with i** by Aditya Ghose, Metta Santiputri, Ayu Saraswati, and Hoa Khanh Dam for the APCCM 2014 Best Paper Award. The awards includes a cash prize in the amount of NZD 500 for each individual paper. The Best Student Paper was sponsored by the Computing Research and Education Association of Australasia (CORE), and the Best Paper Award was sponsored by the Department of Computer Science, The University of Auckland, New Zealand, and by the Advanced Computing Research Centre, University of South Australia, Adelaide.

We wish to thank all authors who submitted papers and all the conference participants for the fruitful discussions. We are grateful to the members of the program committee and the additional reviewers for their timely expertise in carefully reviewing the papers. We would like to thank the APCCM 2014 Publicity

Chair Dr Markus Kirchberg, Matt Selway and Andreas Jordan for announcing the event. Finally, we wish to express our appreciation to the local organisers at the Auckland University of Technology for preparing the ACSW 2014 event in New Zealand and would like to thank ACSW 2014 for sponsoring the keynote of Prof. John Mylopoulos.

Georg Grossmann
University of South Australia
Motoshi Saeki
Tokyo Institute of Technology
APCCM 2014 Programme Chairs
January 2014

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Welcome from the Organising Committee

On behalf of the Organising Committee, it is our pleasure to welcome you to Auckland and to the 2014 Australasian Computer Science Week (ACSW 2014). Auckland is New Zealand's largest urban area with a population of nearly one and a half million people. As the centre of commerce and industry, Auckland is the most vibrant, bustling and multicultural city in New Zealand. With the largest Polynesian population in the world, this cultural influence is reflected in many different aspects of city life. ACSW 2014 will be hosted at the City Campus of Auckland University of Technology (AUT), which is situated just up from the Town Hall and the Auckland central business district. ACSW is the premier event for Computer Science researchers in Australasia. ACSW2014 consists of conferences covering a wide range of topics in Computer Science and related areas, including:

- Australasian Computer Science Conference (ACSC) (Chaired by Bruce Thomas and Dave Parry)
- Australasian Computing Education Conference (ACE) (Chaired by Jacqueline Whalley and Daryl D'Souza)
- Australasian Information Security Conference (AISC) (Chaired by Udaya Parampalli and Ian Welch)
- Australasian User Interface Conference (AUIC) (Chaired by Burkhard C. Wünsche and Stefan Marks)
- Australasian Symposium on Parallel and Distributed Computing (AusPDC) (Chaired by Bahman Javadi and Saurabh Kumar Garg)
- Australasian Workshop on Health Informatics and Knowledge Management (HIKM) (Chaired by James Warren)
- Asia-Pacific Conference on Conceptual Modelling (APCCM) (Chaired by Georg Grossmann and Motoshi Saeki)
- Australasian Web Conference (AWC) (Chaired by Andrew Trotman)

This year reflects an increased emphasis for ACSW on community building. Complementing these published technical volumes therefore, ACSW also hosts two doctoral consortia and a number of associated workshops, including those for the Heads and Professors of Computer Science, plus for the first time the 'Australasian Women in Computing Celebration'. Naturally in additional to the technical program, there are a range of events, which aim to provide the opportunity for interactions among our participants. A welcome reception will be held in the atrium of the award winning newly built Sir Paul Reeves Building, which has integrated the city campus as a hub for student activity and provides a wonderful showcase for this year's ACSW. The conference banquet will be held on campus in one of the reception rooms in this impressive complex.

Organising a multi-conference event such as ACSW is a challenging process even with many hands helping to distribute the workload, and actively cooperating to bring the events to fruition. This year has been no exception. We would like to share with you our gratitude towards all members of the organising committee for their combined efforts and dedication to the success of ACSW2014. We also thank all conference co-chairs and reviewers, for putting together the conference programs which are the heart of ACSW, and to the organisers of the symposia, workshops, poster sessions and accompanying conferences. Special thanks to Alex Potanin, as the steering committee chair who shared valuable experiences in organising ACSW and to John Grundy as chair of CoRE for his support for the innovations we have introduced this year. We'd also like to thank Hospitality Services from AUT, for their dedication and their efforts in conference registration, venue, catering and event organisation. This year we have secured generous support from several sponsors to help defray the costs of the event and we thank them for their welcome contributions. Last, but not least, we would like to thank all speakers, participants and attendees, and we look forward to several days of stimulating presentations, debates, friendly interactions and thoughtful discussions.

We hope your stay here will be both rewarding and memorable, and encourage you to take the time while in New Zealand to see some more of our beautiful country.

Tony Clear
Russel Pears
School of Computer & Mathematical Sciences

ACSW2014 General Co-Chairs
January, 2014

CORE - Computing Research & Education

CORE welcomes all delegates to ACSW2014 in Auckland. CORE, the peak body representing academic computer science in Australia and New Zealand, is responsible for the annual ACSW series of meetings, which are a unique opportunity for our community to network and to discuss research and topics of mutual interest. The component conferences of ACSW have changed over time with additions and subtractions ACSC, ACE, AISC, AUIC, AusPDC, HIKM, ACDC, APCCM, CATS and AWC have now been joined by the Australasian women in computing celebration (AWIC), two doctoral consortia (ACDC and ACE-DC)and an Australasian Early Career Researchers Workshop (AECRW) which reflect the evolving dimensions of ACSW and build on the diversity of the Australasian computing community.

In 2014, we have again chosen to feature a small number of keynote speakers from across the discipline: Anthony Robins (ACE), John Mylopolous (APCCM), and Peter Gutmann (AISC). I thank them for their contributions to ACSW2014. The efforts of the conference chairs and their program committees have led to strong programs in all the conferences, thanks very much for all your efforts. Thanks are particularly due to Tony Clear, Russel Pears and their colleagues for organising what promises to be a vibrant event. Below I outline some of COREs activities in 2012/13.

I welcome feedback on these including other activities you think CORE should be active in.

The major sponsor of Australian Computer Science Week:
- The venue for the annual Heads and Professors meeting
- An opportunity for Australian & NZ computing staff and postgrads to network and help develop their research and teaching
- Substantial discounts for attendees from member departments
- A doctoral consortium at which postgrads can seek external expertise for their research
- An Early Career Research forum to provide ECRs input into their development

Sponsor of several research, teaching and service awards:
- Chris Wallace award for Distinguished Research Contribution
- CORE Teaching Award
- Australasian Distinguished Doctoral Dissertation
- John Hughes Distinguished Service Award
- Various Best Student Paper awards at ACSW

Development, maintenance, and publication of the CORE conference and journal rankings. In 2013 this includes a new portal with a range of holistic venue information and a community update of the CORE 2009 conference rankings.

Input into a number of community resources and issues of interest:
- Development of an agreed national curriculum defining Computer Science, Software Engineering, and Information Technology
- A central point for discussion of community issues such as research standards
- Various submissions on behalf of Computer Science Departments and Academics to relevant government and industry bodies, including recently on Australian Workplace ICT Skills development, the Schools Technology Curriculum and the Mathematics decadal plan

Coordination with other sector groups:
- Work with the ACS on curriculum and accreditation
- Work with groups such as ACDICT and government on issues such as CS staff performance metrics and appraisal, and recruitment of ?students into computing
- A member of CRA (Computing Research Association) and Informatics Europe. These organisations are the North American and European equivalents of CORE.
- A member of Science & Technology Australia, which provides eligibility for Science Meets Parliament and opportunity for input into government policy, and involvement with Science Meets Policymakers

A new Executive Committee from 2013 has been looking at a range of activities that CORE can lead or contribute to, including more developmental activities for CORE members. This has also included a revamp of the mailing lists, creation of discussion forums, identification of key issues for commentary and lobbying, and working with other groups to attract high aptitude students into ICT courses and careers. Again, I welcome your active input into the direction of CORE in order to give our community improved visibility and impact.

CORE's existence is due to the support of the member departments in Australia and New Zealand, and I thank them for their ongoing contributions, in commitment and in financial support. Finally, I am grateful to all those who gave their time to CORE in 2013, and look forward to the continuing shaping and development of CORE in 2014.

John Grundy

President, CORE
January, 2014

ACSW Conferences and the Australian Computer Science Communications

The Australasian Computer Science Week of conferences has been running in some form continuously since 1978. This makes it one of the longest running conferences in computer science. The proceedings of the week have been published as the *Australian Computer Science Communications* since 1979 (with the 1978 proceedings often referred to as *Volume 0*). Thus the sequence number of the Australasian Computer Science Conference is always one greater than the volume of the Communications. Below is a list of the conferences, their locations and hosts.

2015. Volume 37. Host and Venue - University of Western Sydney, NSW.

2014. **Volume 36. Host and Venue - AUT University, Auckland, New Zealand**.

2013. Volume 35. Host and Venue - University of South Australia, Adelaide, SA.
2012. Volume 34. Host and Venue - RMIT University, Melbourne, VIC.
2011. Volume 33. Host and Venue - Curtin University of Technology, Perth, WA.
2010. Volume 32. Host and Venue - Queensland University of Technology, Brisbane, QLD.
2009. Volume 31. Host and Venue - Victoria University, Wellington, New Zealand.
2008. Volume 30. Host and Venue - University of Wollongong, NSW.
2007. Volume 29. Host and Venue - University of Ballarat, VIC. First running of HDKM.
2006. Volume 28. Host and Venue - University of Tasmania, TAS.
2005. Volume 27. Host - University of Newcastle, NSW. APBC held separately from 2005.
2004. Volume 26. Host and Venue - University of Otago, Dunedin, New Zealand. First running of APCCM.
2003. Volume 25. Hosts - Flinders University, University of Adelaide and University of South Australia. Venue - Adelaide Convention Centre, Adelaide, SA. First running of APBC. Incorporation of ACE. ACSAC held separately from 2003.
2002. Volume 24. Host and Venue - Monash University, Melbourne, VIC.
2001. Volume 23. Hosts - Bond University and Griffith University (Gold Coast). Venue - Gold Coast, QLD.
2000. Volume 22. Hosts - Australian National University and University of Canberra. Venue - ANU, Canberra, ACT. First running of AUIC.
1999. Volume 21. Host and Venue - University of Auckland, New Zealand.
1998. Volume 20. Hosts - University of Western Australia, Murdoch University, Edith Cowan University and Curtin University. Venue - Perth, WA.
1997. Volume 19. Hosts - Macquarie University and University of Technology, Sydney. Venue - Sydney, NSW. ADC held with DASFAA (rather than ACSW) in 1997.
1996. Volume 18. Host - University of Melbourne and RMIT University. Venue - Melbourne, Australia. CATS joins ACSW.
1995. Volume 17. Hosts - Flinders University, University of Adelaide and University of South Australia. Venue - Glenelg, SA.
1994. Volume 16. Host and Venue - University of Canterbury, Christchurch, New Zealand. CATS run for the first time separately in Sydney.
1993. Volume 15. Hosts - Griffith University and Queensland University of Technology. Venue - Nathan, QLD.
1992. Volume 14. Host and Venue - University of Tasmania, TAS. (ADC held separately at La Trobe University).
1991. Volume 13. Host and Venue - University of New South Wales, NSW.
1990. Volume 12. Host and Venue - Monash University, Melbourne, VIC. Joined by Database and Information Systems Conference which in 1992 became ADC (which stayed with ACSW) and ACIS (which now operates independently).
1989. Volume 11. Host and Venue - University of Wollongong, NSW.
1988. Volume 10. Host and Venue - University of Queensland, QLD.
1987. Volume 9. Host and Venue - Deakin University, VIC.
1986. Volume 8. Host and Venue - Australian National University, Canberra, ACT.
1985. Volume 7. Hosts - University of Melbourne and Monash University. Venue - Melbourne, VIC.
1984. Volume 6. Host and Venue - University of Adelaide, SA.
1983. Volume 5. Host and Venue - University of Sydney, NSW.
1982. Volume 4. Host and Venue - University of Western Australia, WA.
1981. Volume 3. Host and Venue - University of Queensland, QLD.
1980. Volume 2. Host and Venue - Australian National University, Canberra, ACT.
1979. Volume 1. Host and Venue - University of Tasmania, TAS.
1978. Volume 0. Host and Venue - University of New South Wales, NSW.

Conference Acronyms

ACDC	Australasian Computing Doctoral Consortium
ACE	Australasian Computing Education Conference
ACSC	Australasian Computer Science Conference
ACSW	Australasian Computer Science Week
ADC	Australasian Database Conference
AISC	Australasian Information Security Conference
APCCM	Asia-Pacific Conference on Conceptual Modelling
AUIC	Australasian User Interface Conference
AusPDC	Australasian Symposium on Parallel and Distributed Computing (replaces AusGrid)
AWC	Australasian Web Conference
CATS	Computing: Australasian Theory Symposium
HIKM	Australasian Workshop on Health Informatics and Knowledge Management

Note that various name changes have occurred, which have been indicated in the Conference Acronyms sections in respective CRPIT volumes.

ACSW and APCCM 2014 Sponsors

We wish to thank the following sponsors for their contribution towards this conference.

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Keynote Talk

Data-driven Requirements Modeling: Some Initial Results with i*

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Abstract

Requirements acquisition is widely recognized as a hard problem, requiring significant investments in time and effort. Given the availability of large volumes of data and of relatively cheap instrumentation for data acquisition, this paper explores the prospect of data-driven model extraction in the context of i* models. The paper presents techniques for extracting dependencies from message logs, and for extracting task-dependency correlations from process logs. The preliminary empirical results are encouraging.

Keywords: Requirements acquisition, data-driven model extraction, i* model

1 Introduction

The connection between requirements and the data that might be used to generate, understand and analyze requirements has been largely ignored in the literature. Yet the growing ubiquity of data, the ability to access large-scale sensor instrumentation and the availability of "big data" tools has thrown up significant opportunities for developing a new generation of data-driven requirements engineering (RE) tools. These opportunities come in many forms.

First, data can alleviate the well-known challenges associated with requirements acquisition/elicitation [15]. Organizations are often unable to leverage the benefits of conceptual modeling and the principled use of enterprise architecture because of the (often steep) investment required. The phenomenon is an instance of the *knowledge acquisition bottleneck* - a problem with an even longer pedigree [1]. Conceptual modeling is a time consuming human task of considerable complexity. We will argue in this paper that developing a capability to "mine"' requirements from data can pay rich dividends. Earlier work [4] suggests that tools that extract "snippets" of models (or *proto-models*) by mining legacy text and model artefacts (these latter being in different notations) can significantly improve modeler productivity (with some empirical results pointing to about a two-thirds reduction in modeler effort).

Second, data-driven requirements monitoring provides the ability to improve the quality of requirements specifications, which in turn lead to improvements in the quality of the systems delivered. Execution data provides the basis for extracting requirements (which may be viewed as abstract descriptions of the data that these are mined from). Deviations between the mined requirements and those originally specified by stakeholders can flag problems. Similarly, we might cluster data associated with the particularly "desirable" (as determined by stakeholders) parts of execution histories, and extract requirements from these. The requirements thus obtained would represent more accurate encodings of stakeholder intent.

Third, clustering data associated with "undesirable" instances of execution histories (again, determined by stakeholders) can help us mine requirements anti-patterns. Within the context of a given RE exercise, these anti-patterns would identify "no-go" areas (i.e., requirements that lead to undesirable consequences).

Finally, the ability to establish an online, real-time correlation between requirements and data can help us use requirements models as dashboards.

What we have outlined above are effectively four distinct hypotheses about how data (specifically, behaviour histories) can deliver value in the requirements engineering exercise. In this paper, we put the first two of these hypotheses to the test. We focus on a well-regarded early-phase requirements modeling language of long standing - the i* notation [20]. The use of i* makes the case for data-driven requirements engineering more compelling, for several reasons. i* is particularly effective in modeling high-level strategic requirements, and also supports distributed goal modeling. Consequently i* serves as a natural representation of complex organizational contexts. This paper presents some initial steps toward an evaluation, by devising and evaluating techniques that permit us to (partially) "mine" i* models from execution data. We restrict our attention to mining dependencies and the tasks within the depender and dependee actors that each dependency is associated with. We present two techniques: the *Dependency Extraction (DE)* technique which mines dependencies from message logs and the *Task-Dependency Correlation Extraction (TDCE)* technique which mines the tasks/-goals in an i* SR model that are associated with each dependency from process logs.

Our focus on message logs and process logs is realistic. Message logs are routinely maintained within the enterprise context. Sometimes, these manifest as email repositories, but our current work does not address the deployment of sophisticated NLP techniques that would be required to mine these. Instead, we use an abstract, generalized messaging format that resembles a number of industry-standard electronic messaging formats such as RosettaNet [17], ebXML [5] and a host of EDI formats. These are clearly easier to mine

than natural language message logs, but nonetheless provide a useful basis for a proof-of-concept tool. Process logs are also routinely maintained by firms. A variety of business process management tools as well as bespoke process logging tools can be leveraged to obtain these. Unlike process mining tools, however, we do not seek to extract process designs from process logs, but instead mine for patterns of task activations that point to the existence of a dependency.

We also simplify matters by assuming that the only i* models of interest are those that involve only goal dependencies. We keep softgoals entirely outside the purview of our current discussion. Techniques for mining other types of dependencies represent an important direction for future work.

These techniques only support the mining of *partial* i* models, specifically inter-actor dependencies, and tasks/goals associated with each dependency.We present two different evaluations of these techniques. First, we evaluate their effectiveness (in terms of precision and recall) in mining partial i* models from behaviour histories that simulate the execution of an initial complete i* model. Second, we validate the hypothesis that it is possible to generate better quality (i.e., more accurate) models by mining behaviour histories of imperfect "as-is" contexts that have been filtered by stakeholders (to remove behaviour traces that are undesirable). Much more detailed evaluation is possible, and is the focus of future work, but our preliminary results are encouraging.

The rest of this paper is organized as follows. The next section provides background on the i* notation. The following two sections describe the DE and the TDCE techniques respectively, in detail. We then provide an evaluation of this approach, in which we separately evaluate the DE and TDCE techniques and then bring them together in evaluating how user input into filtering behaviour histories can lead to more accurate models. We then provide a brief discussion of related work before presenting concluding comments and directions for future work.

2 Background

i* [20] is a well-known requirements modelling language which describes the organizational context of an information system based on the notion of intentional actors. In modeling an actor in i*, we specify its goals, the means available to achieve these goals and how other actors depend on it to achieve their goals. Actors depend on each other for goals to be achieved, tasks to be performed, resources to be furnished and performance measures to be optimized. Such dependencies are described in an i* strategic dependency (SD) model. There are four types of strategic dependencies that may be specified in an i* model. A goal dependency models situations where an actor depends on another actor to achieve a goal. A resource dependency exists when an actor relies on another actor to provide a resource. A task dependency suggests that an actor needs another actor to carry out a task. Finally, softgoal dependencies capture the non-functional properties of a model. As noted above, we will focus only on goal dependencies in this paper (and argue that all other dependencies, except softgoal dependencies, can be reduced goal dependencies in form or another).

An i* strategic rationale (SR) model describes internal interactions between goals and tasks within each actor. Specifically, it shows how a task can be decomposed into subtasks, subgoals, resources and softgoals (i.e. they need to be performed or satisfied in order for the task to succeed). In addition, it describes means-ends links, which describe alternative ways to achieve a goal. It may also describe how tasks contribute to achieving softgoals (positively or negatively). Figure 1 shows an example of an i* SR model for a meeting scheduler system which we adapted from [20]. There are three actors here: *Meeting Initiator*, *Meeting Participant* and *Meeting Scheduler*. There are a number of dependencies between the actors. For example, the Meeting Initiator depends on the Meeting Participant to achieve the goal of *Attends Meeting*. The SR model also shows the exact tasks that are involved in a dependency (these are of particular interest in this paper). For example, the task Obtain AvailDate of actor Meeting Scheduler depends on the task Find Agreeable Date Using Scheduler to attain goal EnterAvailDate. In the next sections, we will describe how we mine existing message logs and process logs to extract those dependencies between actors and their tasks.

3 The Dependency Extraction (DE) Technique

The Dependency Extraction (DE) technique is intended to mine message logs for i* dependencies, and is based on the following intuitive observations. All dependencies manifest themselves in messages, such as a request from the depender to the dependee at the creation of a dependency, and a message in the reverse direction when the dependency is fulfilled. Hence, a message log that maintains a record of all messages (over a certain period) between the actors of interest represents a rich repository of clues about these dependencies. Message logs are ubiquitous. A corporate email repository can be viewed as a message log, although the messages are entirely unstructured. In many cases, messages are structured such as in a variety of Electronic Data Exchange (EDI) languages, or in more recent standards such as RosettaNet and ebXML. Our current approach assumes a structured message log. We use a generalized message format in our evaluation, inspired by (and representing the common core of) the messaging standards discussed above. For our purposes, a message log is a sequence of messages consisting, at a minimum, the following components:

- An *interaction ID*, which is used to identify a conversation or *interaction*, but not an individual message.
- *Sender ID*
- *Receiver ID*
- A *timestamp* which describes the time when a message is sent or received (we assume message transmission to be instantaneous).
- A *message type*, which would involve types such as requests, responses etc.
- A *message payload*, consisting of the semantic content of the message (which might be imperative or descriptive or a variety of other speech acts).

In the spirit of RosettaNet, we assume that all messages that involve responses to an initial message (that starts a conversation, such as a service request) refer to a unique ID generated by the initial message. We shall refer to the set of all messages pertaining to such a unique ID as an *interaction*, the unique ID as the *interaction ID*.

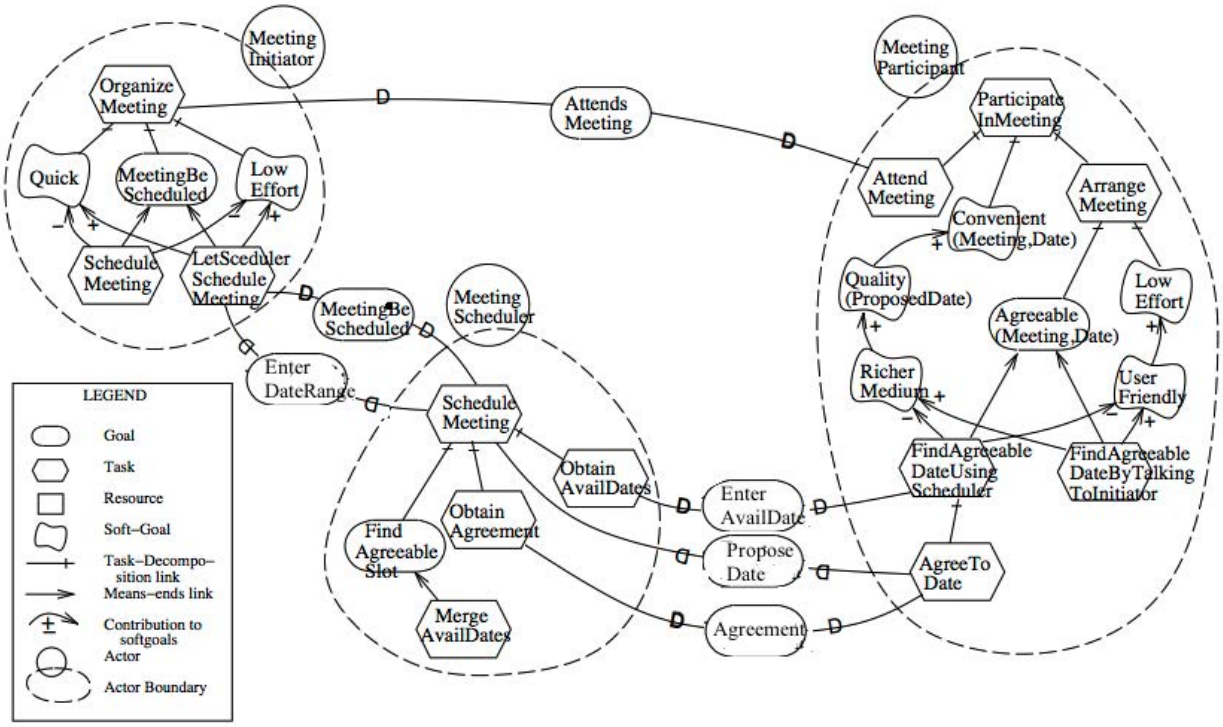


Figure 1: An i* SR model for a meeting scheduler system (adapted from [20])

Given the availability of unique interaction IDs, it is easy to extract complete interactions from a noisy message log where multiple interactions might be interleaved. Our next task is to extract the goal (e.g., the service request or product order) that is the object of the conversation. Goals are often represented in natural language using verb phrases. The information extraction techniques used for extracting verb phrases admit considerable complexity. For the purposes of our proof-of-concept evaluation, we assume an even simpler textual format, consisting of ⟨verb, noun⟩ pairs (such as buy book, supply product, assess claim etc.). Our technique for extracting these is as follows:

- We extract the set of all ⟨verb, noun⟩ pairs that appear in a given interaction.
- We annotate each element of this set with the number of messages that it appears in.
- We identify the element with the highest frequency and if it passes the threshold $k_{message}$, it referred to as the *goal designator* associated with the dependency.

We use the following procedure to identify dependencies from message logs:

- We partition the set of all interactions extracted from a message log into sets the share the same goal designator.
- We assume that a *significance threshold* $k_{interaction}$ is provided by the user. If a cluster of interactions (with the same goal designator) represents $k_{interaction}\%$ or higher of the set of all interactions, we treat that cluster as *significant* and indicative of a dependency.

4 The Task-Dependency Correlation Extraction (TDCE) Technique

In this section, we will present the the Task-Dependency Correlation Extraction (TDCE) technique that identifies the task in the depender actor and the task in the dependee actor that are associated with a given dependency. This information will be mined from the process logs.

The mining of task dependency correlations starts with process logs from different actors where the execution of each actor generates a distinct log. A process log consists of a list of tasks executed by an actor over time. Multiple process logs from different actors could be combined into one process log, as shown in the example in Table 1. This process log lists all tasks executed by all actors (either as the depender or as the dependee). By examining this log, we can observe that when actor i activates task a at time t_x, within some n units of time in the future, at time $t_x + n$, actor j activates task b. When this particular pattern of task activation become frequent (or satisfies a certain threshold), then there is an indication of a dependency between task a in actor i as the depender and task b in actor j as the dependee.

Each entry in the process log consists of:

- a $taskID$, which is used to identify certain task in an actor.
- a *timestamp* which describes the time when a task is activated by the actor. The timestamp of the first entry is t_0 which indicates the initial time - the timestamps of subsequent entries is increased each by one unit time.

The list of these entries will comprise a process log.

In this example, from the first row, we can observe that at the initial time t_0, there are three different actors, each of which activates a task, i.e. actor A activates task a_0, actor B activates task b_1, and actor

C activates task c_0. In the second row, the time is increased by one time unit to become $t_0 + 1$. At time $t_0 + 1$, actor A does nothing, actor B activates task b_4, and actor c activates task c_1, and so on.

In the process log shown in the example above, we can generate a good guess of which tasks participate in a dependency by examining the task sequence patterns that occurs in the process log. We adapt the GSP (Generalised Sequential Patterns) algorithm in order to mine this sequence pattern. It generates pairs of tasks sequences where the first task is from the depender actor and the second task is from the dependee actor. For example a pair $<(a_0)(c_2)>$means that there is a pattern between $<(a_0)>$and $<(c_2)>$which indicates that there is a dependency between those two tasks with task $<(a_0)>$as the depender and task $<(c_2)>$as the dependee. Then it will determine how frequent this pattern is in the log by counting the number of occurrence of each pair. This number of occurrence of each pair is called its support and the predetermined threshold is the minimum support.

The GSP (Generalised Sequential Patterns) algorithm was proposed by Srikant and Agrawal (1996). The algorithm takes as input a process log which consists of set of tasks ordered by time. It finds all sequences of tasks whose support is greater than the minimum support threshold specified by the user. In addition to the minimum support threshold, there are timing constraints that must satisfied, namely the maximum time difference between the earliest and latest task activation and the minimum and maximum gaps between adjacent task. We leverage this algorithm, providing as input a process log ordered by time and obtaining as output all sequential patterns in the log.

The algorithm makes multiple passes over the log. The initial constraint for this part is that we are only interested in results that consist of two tasks, because our aim is to discover dependencies that relates pairs of tasks. Therefore we limit the pass to $k = 2$. The first pass of the algorithm finds all sequences with a single task in it along with their occurrence count (support). The output is 1-task long sequences or L_1. On the second pass, the algorithm generates 2-tasks-long candidate sequences C_2 with L_1 as its seed. This is motivated by the fact that for a sequence to be frequent, all of its subsequences must also be frequent. As the support counts are determined, the sequences with support greater than the determined threshold are included in L_2.

There are two main phases that are explained in detail below, in terms of how candidates are generated and how their support are counted.

1. *Join phase.* In this phase, we generates all candidates starting from candidates of length 1. The process is straightforward as all the tasks that were in the process log are placed in this set of candidates L_1. To generate candidates of length 2, L_2, a task from L_1 is joined with another that is also in the L_1. If i and j are tasks belonging to L_1, then task j is added to i. But for all candidates of length 2, there is one more constraint i.e. any two tasks in a dependency must not happen at the same time. Therefore any candidate dependency relating two tasks that activate at the same time must be excluded from the result. Initially task j should be added as a task-set ($<(i\ j)>$) and as a separate task ($<(i)(j)>$), but because of this constraint, we only add j as a separate task.

   In our example from Table 1, we start with all candidates of length 1, L_1. It would consists of $<(a_0)>$, $<(a_1)>$, $<(a_2)>$, $<(b_0)>$, $<(b_1)>$, $<(b_2)>$, $<(b_3)>$, $<(c_0)>$, $<(c_1)>$, $<(c_2)>$, and $<(c_3)>$.

   Next we need to eliminate these candidates according to the value of minimum support in the prune phase.

2. *Prune phase.* We eliminate candidates according to our constraints:

   (a) Since dependencies relate pairs of tasks from two different actors, any pattern that contains tasks from the same actor must be excluded from the result.

   (b) All the candidates with a support value lower than minimum support is excluded from the result.

   Note that constraint (a) is only applied to 2-task-long candidates and is not applied to 1-task-long candidates. On the other hand, constraint (b) is applied in both cases.

   Returning to our example, we have generated L_1, and now all tasks in the L_1 must be examined against constraint (b). For this example, we set the minimum support as 2, which means that for any task or set of tasks to be classified as frequent, it must occur at least two times. In the log in Table 1, for actor A there are three different tasks (a_0, a_1, and a_2). The support for these tasks are 3, 1, and 1 respectively. Because the support for a_1 and a_2 are less than the minimum support, they do not included in the sequence of 1-tasks. We repeat this for all tasks and the result is shown in the first column of Table 2.

Actor / Time	*actor* A	*actor* B	*actor* C
t_0	a_0	b_1	c_0
$t_0 + 1$	–	b_3	c_1
$t_0 + 2$	a_0	b_2	c_2
$t_0 + 3$	a_2	b_0	–
$t_0 + 4$	a_1	b_1	c_3
$t_0 + 5$	a_0	b_3	c_2

Table 1: Example of process log

We continue to search for all candidates of length 2 by repeating the join and prune phases. This step is illustrated in Table 2. In the join phase, we start with the first candidate $<(a_0)>$in the first column. Thus, all sequences of form $<(a_0)(\mathrm{X})>$, where X is any task, are searched. Recall that we do not search for $<(a_0, \mathrm{X})>$because it implies that the two tasks occurs at the same time. By combining $<(a_0)>$with the second candidate $<(b_1)>$, we find 2-task-candidate $<(a_0)(b_1)>$. A similar procedure is repeated for all sequences of the first column. All 2-task-long candidate sequences generated in the join phase are shown in the second column.

Next, according to constraint (a) in the pruning phase, we begin by determining whether the two events are executed by the same actor (if they do, then the sequence is eliminated). For example, in the second row, in sequence $<(b_1)(b_3)>$, both tasks are executed by the same actor, namely actor B. Therefore the sequence is eliminated by applying constraint (a). Thus the remaining candidates for the second row are

Frequent sequences of length 1	Candidates of length 2	
	after join	after pruning
$<(a_0)>$	$<(a_0)(b_1)>$, $<(a_0)(b_3)>$, $<(a_0)(c_2)>$	$<(a_0)(c_2)>$
$<(b_1)>$	$<(b_1)(a_0)>$, $<(b_1)(b_3)>$, $<(b_1)(c_2)>$	$<(b_1)(a_0)>$, $<(b_1)(c_2)>$
$<(b_3)>$	$<(b_3)(a_0)>$, $<(b_3)(b_1)>$, $<(b_3)(c_2)>$	–
$<(c_2)>$	$<(c_2)(a_0)>$, $<(c_2)(b_1)>$, $<(c_2)(b_3)>$	–

Table 2: Candidate generation

$<(b_1)(a_0)>$and $<(b_1)(c_2)>$. The same also applies to sequence $<(b_3)(b_1)>$in the third row. We then determine the support count for each of the remaining candidates. The first candidate $<(a_0)(b_1)>$has support count 1, which is less than the minimum support - it is therefore eliminated. Next candidate, $<(a_0)(b_3)>$, also has support count of 1, and is also eliminated. Candidate $<(a_0)(c_2)>$has support count of 2 - it is therefore included in the result. In the second row, we have two remaining candidates, $<(b_1)(a_0)>$, and $<(b_1)(c_2)>$. Both have a support count of 2 and are thus included in the result. We repeat this procedure for the rest of the candidates. The result is shown in the third column of Table 2.

The result patterns of this algorithm are all sequential patterns that occur between two tasks in the process log. For our process log example in Table 1, these are $<(a_0)(c_2)>$, $<(b_1)(a_0)>$, and $<(b_1)(c_2)>$.

5 Evaluation

The purpose of the evaluation exercise is to establish the following:

- The Dependency Extraction (DE) technique and the Task-Dependency Correlation Extraction (TDCE) technique generate reasonably reliable results.
- Both these techniques can be leveraged to improve the quality of i* models (assessed in terms of how closely a model corresponds to the "ideal" model, and hence to the reality being modeled) by leveraging user tagging (or filtering) of the logs recording the behaviour of an "as-is" system or process that the target system is intended to replace. Since i* is also particularly effective as a domain modeling tool, an improvement in model quality might also entail obtaining a better representation of the context in which the target system is to be situated (or even more generally, a better model of the organizational context).

Our evaluation involved the generation of simulated behaviour histories (message logs plus process logs) given an i* model. To achieve this, we *randomly executed* these models, the sense described below. For each distinct dependency in an i* model, we generated a large number of *interactions* (specific numbers in the following subsections), with configurable levels of noise (thus we had noisy messages within interactions, and we had entirely noisy interactions that would not point to any reasonable goal dependency). The non-noise components involves messages and interactions that were deliberately constructed to conform to the i* model at hand. The sum total of these interactions provided the message log that we mined. We similarly generated process logs by randomly selecting tasks/goals from the i* model and allocating random timestamps to them. We, however, ensured that each dependency in the model was reflected at least once in the process log. In other words, if there was a dependency relating task a_i in actor A to talk b_j in actor B in the model, we would ensure that the process log contained at least one entry for task b_j at a time point after that for task a_i.

5.1 Evaluation of the DE technique

We started with the i* model shown in Figure 1, originally used in [20]. The model consists of 3 actors and 6 dependencies.

To simplify the process of obtaining *goal designators*, we assume that they consist of ⟨verb, noun⟩ pairs. We permit *goal designators* to also consist of ⟨verb, verb⟩ since some verbs in the past tense resemble nouns (participle adjectives or normalizing an adjective). When processing the payload, we extracted the pair by getting the first ⟨verb⟩ in the payload and the first ⟨noun⟩ following said verb.

We used the Stanford Log-linear Part-Of-Speech Tagger v3.2.0 [8] for tagging message payloads. The tagger takes a sentence such as *This is a sample sentence* and assign parts of speech, e.g., noun ver, adjective,etc, like so $This\_DT is\_VBZ a_D T sample\_NN sentence\_NN$. These tags conform to the Penn Treebank Tagset [14] where tag starting with $\_V$ is verb and tag $\_N$ is noun. So we can parse our payload with these tags to find the ⟨verb, noun⟩ pattern.

We performed experiments with 4 parameters. $n_{message}$ describes the proportion of noise messages in the complete message log (all non-noise messages permitted the extraction of the correct goal designator). $n_{interaction}$ describes the proportion of noisy interaction in the set of all interactions in the message log, where a noisy interaction is one which does not lead to any single identifiable goal designator. $k_{message}$ and $k_{interaction}$ are as defined in Section 4. We initially created a message log with no noise (i.e., neither noisy messages nor noisy interactions) consisting of 7381 interactions. Setting $k_{interaction} = 10\%$ and $k_{message} = 10$, we were able to extract all of the dependencies, as shown in Table 3.

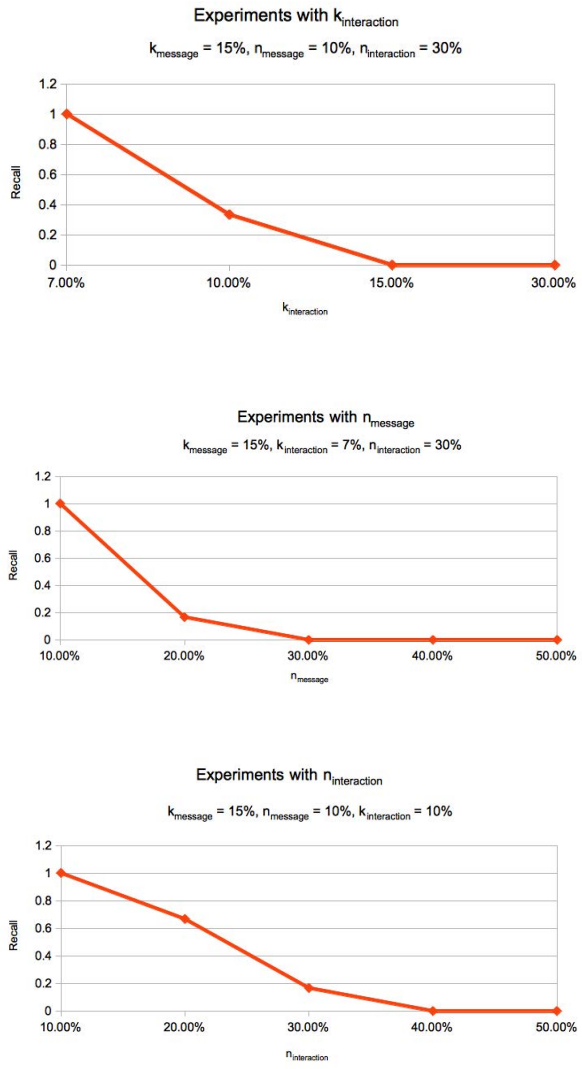
We plotted the performance of the DE technique (in terms of recall - there were no false positives and hence precision was always 1) against each of these parameters. We show 3 of the 4 results below (the final graph was omitted due to space considerations). As expected, recall decreases as the amount of noise increases (i.e., as $n_{message}$ and $n_{interaction}$ increase). Similarly, recall decreases as we get more selective in identifying dependencies (i.e., as $k_{interaction}$ increases). These results were generated using message logs that were between 25000 to 30000 messages long, with about 2000 interactions. The results were consistently the same.

5.2 Evaluation of the TDCE technique

Given a set of tasks as the input of our tool, we use two sets: the set of expected dependencies which were in the input model and the set of dependencies actually discovered in the result. Recall is defined by the number of correct dependencies discovered by our

Depender	Dependee	Goal Designator	Interaction Percentage
Meeting Scheduler	Meeting ParticipantA	Enter AvailDates	15.13%
Meeting Scheduler	Meeting ParticipantA	Agreement	18.02%
Meeting Initiator	Meeting ParticipantA	Attends Meeting	17.18%
Meeting Scheduler	Meeting ParticipantA	Propose Date	15.76%
Meeting Initiator	Meeting Scheduler	Meeting BeScheduled	17.55%
Meeting Initiator	Meeting Scheduler	Enter DateRange	16.37%
		total interaction	7381

Table 3: Results using non-noisy logs with $k_{interaction} = 10\%$ and $k_{message} = 10\%$



technique divided by the total number of expected dependencies in the result.

In this evaluation, we execute the input model including all of the dependencies. The task activation log will be created with the depender, dependee, the tasks and the dependencies from the input i* model as the expected result along with other tasks from the input model as noise. The task activation log for each actor was created randomly but we deliberately input the execution of every dependency. Then we ran this log against our tool.

There are two inputs that we will use as variable in this evaluation of the TDCE technique: (a) the number of entries in the task activation log; and (b) the minimum support. We performed separate experiments for each of those variable by varying the value of one variable and keeping the other fixed.

From the result, the recall is 1.0 indicating that every dependency in the expected result set is discovered. This can be explained by the fact that if there is a dependency between two tasks, there are frequent patterns between those two tasks in the log and it will be detected.

On the other hand, in addition to the expected dependencies, there are other dependencies that were discovered in the actual result but were not in the input model. This might happen because one factor that might affects the result is the interleaved of the entries in the task activation log. For example lets assume that we have a log consisting of two actors (let say actor A and actor B) with one dependency between these two actors (between task a_0 of actor A and task b_0 of actor B). Since the algorithm will find all the sequence in the log, there can be two different dependency discovered depends on the order of the entry in the log. This is illustrated below.

Actor / Time	*actor* A	*actor* B
t_0	a_0	
$t_0 + 1$		b_0
$t_0 + 2$	a_0	
$t_0 + 3$		b_0

Table 4: Example 1

Actor / Time	*actor* A	*actor* B
t_0	a_0	
$t_0 + 1$	a_0	
$t_0 + 2$		b_0
$t_0 + 3$		b_0

Table 5: Example 2

In example 1, the result would be two dependencies $<(a_0,b_0)>$and $<(b_0,a_0)>$, while the second example the dependency would be $<(a_0,b_0)>$. Therefore there are possibilities that any dependency might show up in the log although it was not in the model

The minimum support count for our evaluation in the first scenario is fixed at 1.0 which means that support count = 1.0 * the number of execution. For example if we execute 10 times, then the support count is 10, so that any pattern that occurs 10 times or more is included in the result. For the second scenario, we use a task activation log with 2000 entries. The two graphs in Figure 3 show the precision of our technique in two different scenarios. As can be seen in Figure

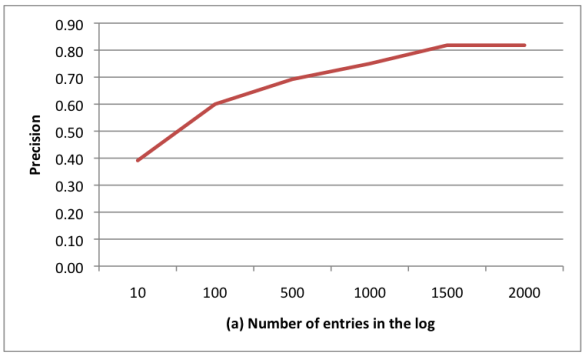


Figure 2: Precision relative to log size

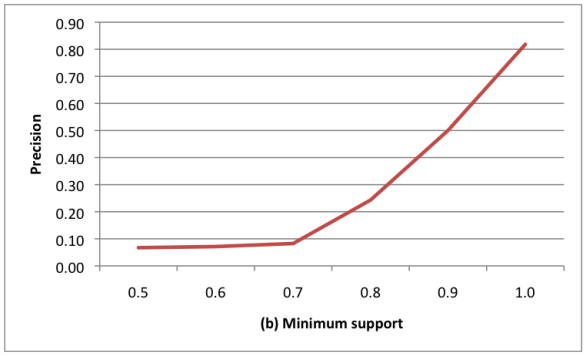


Figure 3: Precision relative to min support

3(a), with small log, the precision is not very accurate (given just ten entries, precision is only 0.39). But with a larger log, the precision is increasing up to 0.82. Precision remains relatively constant at 0.82 when the log reach 1500 entries or more. While in Figure 3(b), the higher minimum support will give more accurate result. For example, given the support of 1.0, precision reach up to 0.82 but precision drop to 0.5 when support is set to 0.9 and keep decreasing until under 0.1 with support of 0.7 or less. Hence the result suggest that both the number of the entries in the task activation log and the minimum support are very influential to the accuracy of the result. Therefore if we want to get more accurate result, we can do two things, either increase the volume of the data or increase the minimum support count.

Since in this evaluation we artificially created the task activation log and deliberately executed all dependencies in the input model, we acknowledge that they would not be representative for all possibilities of task activation log in practice. For instance, there might be a case where a dependency in the input model was not executed at all or was executed but in a number of times which was lower that the minimal support. In such cases, our technique might not be able to detect it.

Another limitation of this technique involves settings where multiple dependencies exist between the same pair of actors. Our current approach works well if we have a guarantee that only one dependency would exist between a given pair of actors. Thus, when we determine that a pair of tasks are related via a dependency, we are able to leverage the DE technique to identify what the goal designator for that dependency is. In the case of multiple dependencies between the same two actors, the DE technique would suggest multiple goal designators, while the TDCE technique would suggest multiple task pairs, but we would not have the wherewhithal to associate the task pairs with the goal dependencies identified by the DE technique.

5.3 Improving requirements quality: Evaluation

A key contribution of this work is the ability to achieve data-driven improvements in the quality of requirements models. There are two approaches to this that we explore. In the first, we explore settings where the user is able to describe the ideal *behaviour* (for our purposes, a *behaviour* will be described via a combination of a *message log* and a *process log*) of the system in question. We extract models from these idealized behaviours, as opposed to the noisy behaviours that have been the focus of the previous parts of the evaluation. In the second approach, we explore settings where the requirements engineering exercise is conducted in the context of an existing, "as-is" system or process(es), the behaviour of which we are able to log. The user filters this (potentially imperfect) behaviour generated by the existing system/process (by removing entries from the message and process logs that (in the perception of the user) represent manifestations of imperfect bahviour, and our machinery extracts models from these filtered logs. The evaluation involved a trained i* modeler, who was asked to generate a model (Figure 4) which was not revealed to the research team. This model played the role of the "ideal" model against which the quality of the extracted models was evaluated. The quality of an extracted model was evaluated by either: (1) assessing how closely it conformed to the user's "ideal" model (which was revealed to the research team after the model extraction phase was completed) or (2) obtaining input from the user suggesting that some dependencies that existed in the user's intuitive understanding of the domain (and had been manifested in the idealized behaviours supplied by the user, but not in the "ideal" model) has been discovered by our machinery.

User-generated idealized behaviours: With the model in Figure 4 in mind, the i* modeler gave us a message log with 12 entries (each of which was a request message) and a process log with 35 entries. Our machinery then extracted a partial i* model with the following characteristics. Of the 23 dependencies in the original user model, we discovered 19 dependencies (relating the correct pairs of actors and tasks). We also extracted 9 new dependencies that were not part of the user's original model. Figure 5 shows the model that was extracted. The bold lines denote false positives and the dashed lines denote false negatives.

User-filtered "as-is" behaviours: In this part of the evaluation, the i* modeler revealed the idealized model to the research team. This was used to generate 5 behaviours (i.e., 5 sets of ⟨ message-log, process-log ⟩ pairs). The message logs varied in length from 2 to 10 messages per log. The process logs varied in length from 9 to 13 entries. We additionally generated 5 incorrect behaviours, by randomly selecting 1 dependency in each case and randomly changing either the depender or dependee actor, or the source or target task. We then interleaved the 5 correct and 5 incorrect behaviours and presented these to the i* modeler. Our intent was to simulate the execution of an imperfect system/process, whose behaviour would be represented by the interleaved logs. The i* modeler was then asked to remove from the message and process logs entries that did not correspond to the intuitions that were represented in the idealized model. We then applied our machinery to extract a partial i* model from the filtered logs. We discovered 19 of

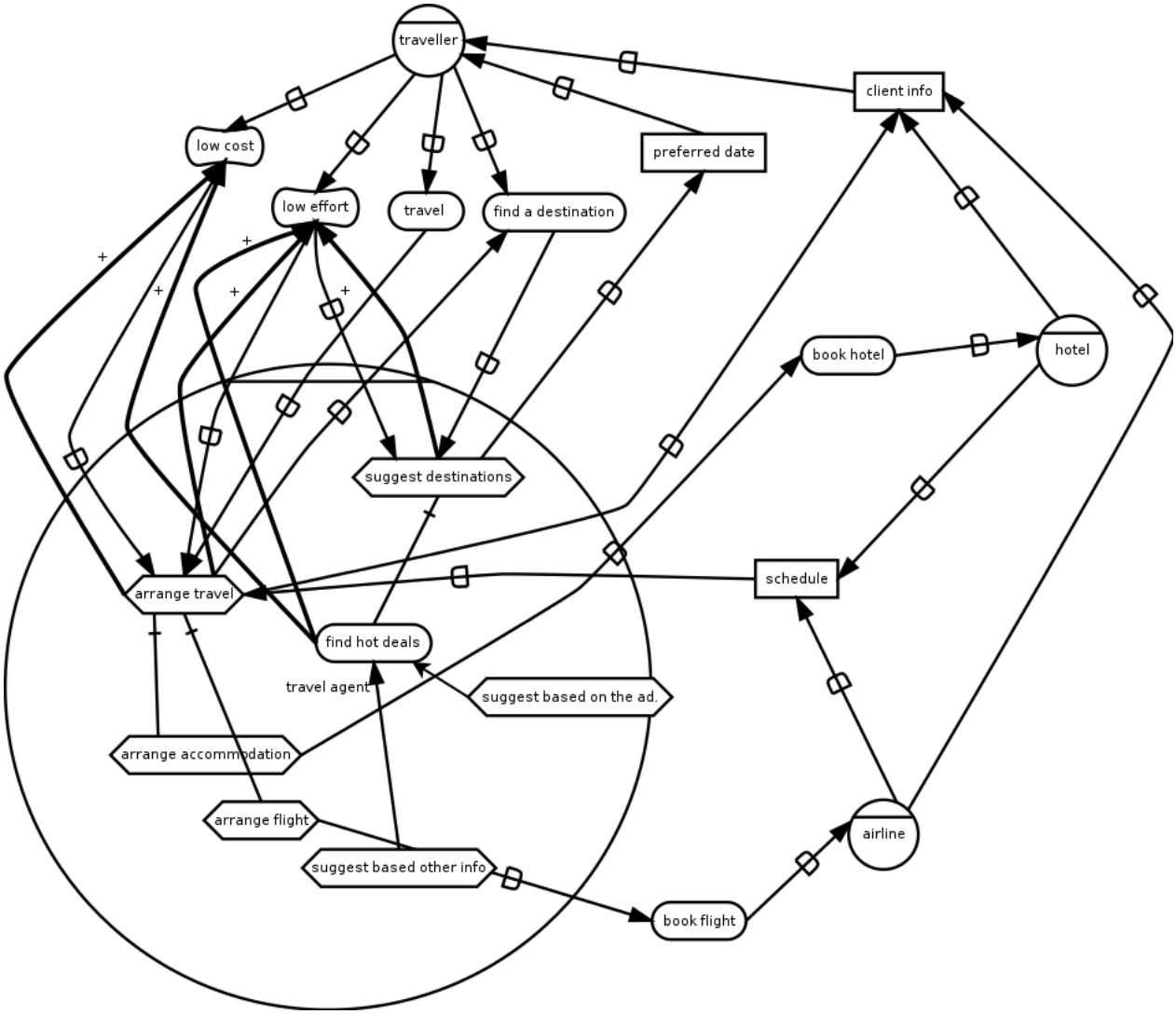


Figure 4: Model from user

the original 23 dependencies in the idealized model (this was an identical result to the evluation using user-generated idealized behaviours) and 10 new dependencies. Of these 10 new dependencies, 6 were distinct to the dependencies extracted in the evluation using user-generated idealized behaviours. The i* modeler also suggested that 9 of the new dependencies discovered were largely in accord with his intuitions about the domain being modeled, but had not been reflected in the idealized model that he had initially generated. This suggests that this approach can help surface implicit requirements via the filtering of noisy behaviours. The extracted model is shown in Fingure 6 below. As before, the bold lines denote false positives and the dashed lines denote false negatives.

As discussed in the previous section, the existence of multiple dependencies between the same pair of actors in this model prevented us from correlating the task pairs generated by the TDCE technique with the dependencies generated by the DE technique. The net upshot was that we had several "unnamed" dependencies. Nonetheless, discovering the existence of dependencies, even in the absence of goal designators, provides valuable insights.

Overall, this part of the evaluation suggests that there is merit in the general idea of using this machinery to improve the quality of requirements extracted, although the machinery missed some dependencies and generated some false positives.

6 Related Work

The research reported in this paper is related in some ways to the existing body of work on *process mining* [18] [19], in that we also use process logs as one of several data sources. However, what we do with process logs is entirely different. Unlike process mining, we generate task-dependency correlations from this data. A proposal to leverage web logs to support non-functional requirements elicitation [16] shares some intuitions with our work (but uses different techniques as well as different inputs and outputs). A body of existing work on extracting requirements from natural language can inform the extraction of goal designators (see, for instance, [2] [3]), although our current evaluation uses a simpler proof-of-concept implementation. The Business Intelligence Model (BIM) [11] bears some relation to our proposal in its ability to serve as a data-driven dashboard for the enterprise. Approaches to run-time adaptation, such as in [6], concept discovery [12], ontology extraction [9] and model-based diagnosis [7] are relevant. The literature on requirements change (e.g., [10]) is also relevant. We expect that the literature on social network analysis [13] might provide techniques of relevance to this

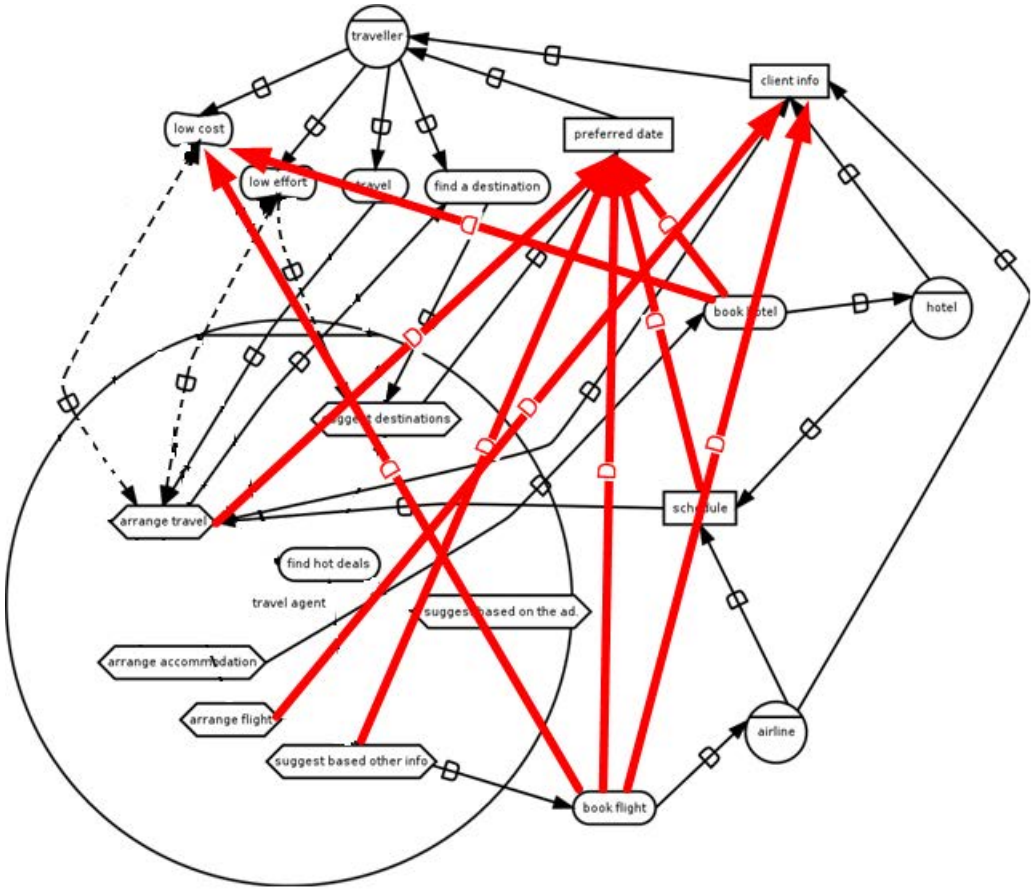


Figure 5: Extracted model-1

research.

7 Conclusions and future work

In this paper, we have provided preliminary evidence to support the hypotheses that data-driven extraction of requirements models can be effective, and that this approach, coupled with user involvement in identifying undesirable behaviour traces, can lead to more accurate models. We have performed this evaluation in the context of i* models, and have further simplified the problem by focusing not on extracting complete i* models, but only the dependencies and the task dependency correlations. We believe that this is a first step in a much larger program of research that considers the problem of data-driven extraction of models in a range of notations. We have also offered some innovative approaches to the evaluation of these techniques, but much deeper and careful evaluation remains to be done. Future work will also involve leveraging results from a range of other areas, including social network analysis.

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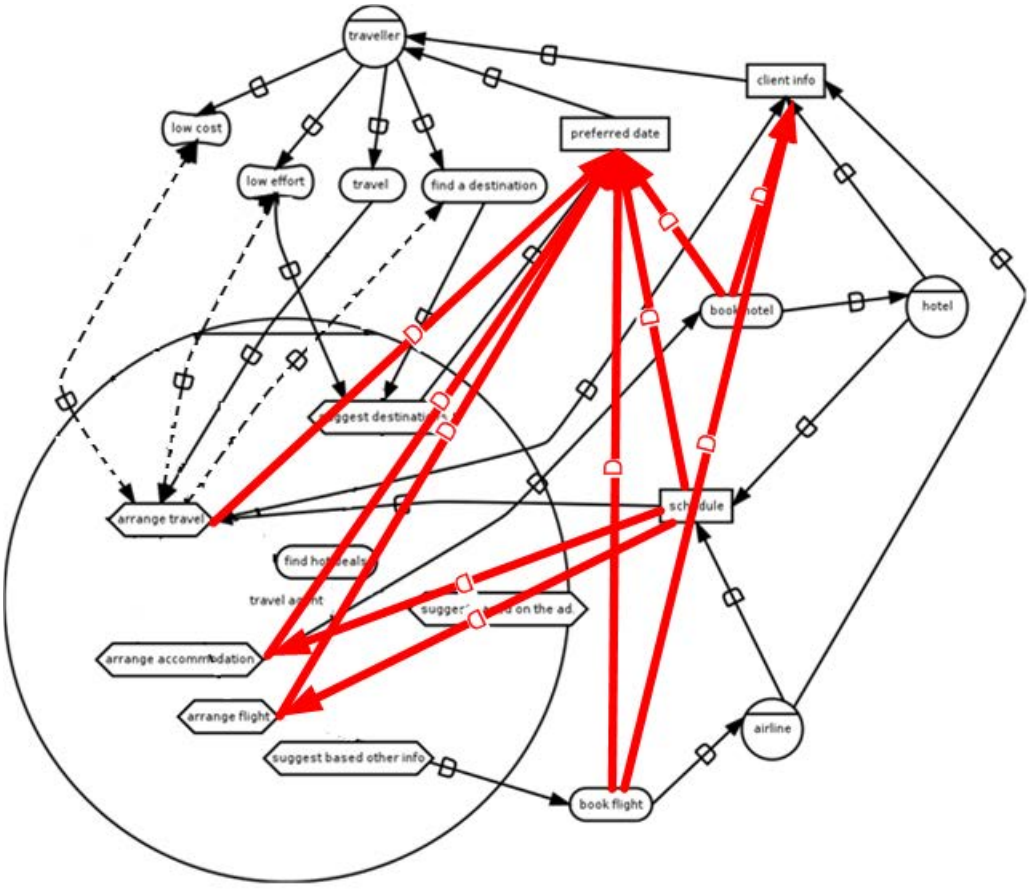

Figure 6: Extracted model-2

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