Undefined 0 (2012) 1–24
IOS Press

The Use of Semantic Web Technologies for Decision Support - A Survey

Editor(s): Krzysztof Janowicz, University of California, Santa Barbara, US
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Abstract. The Semantic Web shares many goals with Decision Support Systems (DSS), e.g., being able to precisely interpret information, in order to deliver relevant, reliable and accurate information to a user when and where it is needed. DSS have in addition more specific goals, since the information need is targeted towards making a particular decision, e.g., making a plan or reacting to a certain situation. When surveying DSS literature, we discover applications ranging from Business Intelligence, via general purpose social networking and collaboration support, Information Retrieval and Knowledge Management, to situation awareness, emergency management, and simulation systems. The unifying element is primarily the purpose of the systems, and their focus on information management and provision, rather than the specific technologies they employ to reach these goals. Semantic Web technologies have been used in DSS during the past decade to solve a number of different tasks, such as information integration and sharing, web service annotation and discovery, and knowledge representation and reasoning. In this survey article, we present the results of a structured literature survey of Semantic Web technologies in DSS, together with the results of interviews with DSS researchers and developers both in industry and research organizations outside the university. The literature survey has been conducted using a structured method, where papers are selected from the publisher databases of some of the most prominent conferences and journals in both fields (Semantic Web and DSS), based on sets of relevant keywords representing the intersection of the two fields. Our main contribution is to analyze the landscape of semantic technologies in DSS, and provide an overview of current research as well as open research areas, trends and new directions. An added value is the conclusions drawn from interviews with DSS practitioners, which give an additional perspective on the potential of Semantic Web technologies in this field; including scenarios for DSS, and requirements for Semantic Web technologies that may attempt to support those scenarios.

Keywords: Decision Support Systems, Semantic Web

1. Introduction

Decision Support (DS) is a field that is classically attributed to the social sciences, e.g., supporting managers to make better decisions. However, since the inception of the IS (Information Systems) field of research in the 60's, part of this community has been devoted to Decision Support Systems (DSS). Under this label we have seen many different kinds of systems presented, e.g., anything from spreadsheet applications for analyzing data, via communication support for group decision making, to Expert Systems and other kinds of "intelligent" approaches. Similar to the Semantic Web, DSS could be viewed more as an application area rather than a basic research field. Nevertheless, in the Semantic Web field a number of fundamental results have emerged, such as logical languages for knowledge representation and their syntactic formats for sharing information on the Web. These

*This work was partly financed by the SecurityLink strategic research center at Linköping University, and the research project Semantic Technologies for Decision Support (funded by CENIIT, Linköping University).

could potentially impact other application fields that also make use of the Web as a medium for sharing information, or simply act as an inspiration for information sharing in general. In this paper we thereby attempt to provide a comprehensive view of the current intersection between the DSS and Semantic Web areas, by (i) performing a structured literature survey, and (ii) presenting the results of a set of interviews with DSS practitioners and comparing them to previous studies, as well as (iii) analyzing the potential future needs of the DSS area where Semantic Web technologies could contribute (based on (i) and (ii)).

Superficially, the Semantic Web shares many goals with DSS, e.g., being able to precisely interpret information, in order to deliver relevant, reliable and accurate information to a user when and where it is needed. DSS have in addition more specific goals, since the information need is targeted towards making a particular decision, e.g., making a plan or reacting to a certain situation. In the following section (Sect. 1.1), we provide a brief background of DSS (the reader is assumed to be familiar with the Semantic Web field, or is referred to surveys on Semantic Web technologies for DSS researchers and practitioners such as [17,24,41,65]). Section 2 describes the setup and results of the structured literature survey, which is used for mapping out the current semantic DSS landscape, and subsequently in Section 3 our interview study with DSS practitioners is presented. In Section 4 we summarize our findings, and discuss the potentials and limits of Semantic Web technologies for DSS, as well as future needs, before we conclude in Section 5.

1.1. Background

DSS research has, ever since first introduced in the 1960's (initially the term was *Management Information Systems* - the DSS term did not become widely used until the early 80's), been a highly diverse field of research, drawing on influences from numerous other areas, including both social sciences and technology development. As already mentioned, one could view DSS more as an application field, rather than a basic research field. Both DSS and the Semantic Web have, for instance, been known to apply technologies originally developed in the context of Artificial Intelligence (AI), as well as general Web technologies, e.g., for so-called Web DSS. DSS have also had a strong focus on models since the start, and today some of the main techniques of Business Intelligence (as a sub-field of DSS) include multidimensional models, data cubes, and OLAP (Online Analytical Processing) [76] - all making heavy use of formal models. Another related field is Information Retrieval (IR), where many early search engines and document indexing approaches were originally targeted at Knowledge Management (KM) or managerial support within enterprises, hence, related to DSS.

The diversity of the field is partly due to the many types of stakeholders involved, i.e., since we are all decision-makers in some context (either personal or professional) different DSS need to target all such types of decision-makers and decision-making contexts respectively. DSS can also be viewed from several different perspectives. For instance, according to [77] DSS can be divided into Model-driven DSS, Data-driven DSS, Communications-driven DSS, Document-driven DSS, and Knowledge-driven DSS.

The *Model-driven DSS* operates on some model of reality, in order to optimize or simulate outcomes of decisions based on data provided. In these systems the model is at focus, and can be accessed and manipulated by the decision maker in order to analyze a certain situation, while the amount of data may not be large. A classical example is a financial decision support system, using financial models to predict the impact of certain managerial decisions on the economical key indicators of the business. *Data-driven DSS* on the other hand focus on the access and manipulation of large amounts of data, e.g., Data Warehousing systems, or even more elementary system such as file systems with search and retrieval capabilities.

While data-driven DSS focus on retrieving and manipulating data, *Document-driven DSS* use text or multimedia document collections as their basis of decision information. Document analysis and IR systems are simple examples from this category. *Communications-driven DSS*, on the other hand, focus on the interaction and collaboration aspects of decision making. Simple examples include groupware and video-conferencing systems that allow distributed and networked decision-making. Finally, *Knowledge-driven DSS* are those that actually recommend or suggest actions to the users, rather than just retrieve information relevant to a certain decision, i.e., these systems try to perform some part of the actual decision making for the user through special-purpose problem-solving capabilities. As can be noted, many of the examples above include systems that we may not consider as particularly "decision-oriented" by today's standards, but which were in many cases originally proposed as DSS tools.

In this paper, however, we choose to refer to an alternative categorization of DSS, which divides DSS into the following (overlapping) categories [11], targeting the purpose of the DSS rather than its internal structure:

- Personal DSS – A DSS supporting individuals in their decision-making.
- Group DSS – A DSS supporting a group of people making a joint decision.
- Negotiation DSS – A DSS supporting negotiation leading up to a decision situation.
- Intelligent DSS – A DSS incorporating some form of "intelligent analysis" functionality, i.e., not only supplying a user with raw (possibly filtered) data, but processing that data in some way as to produce more meaningful information.
- Business Intelligence (BI) – A DSS targeted at data representing the state of an enterprise.
- Data Warehousing – A DSS infrastructure incorporating a set of data sources that are integrated by means of some unifying model.
- Knowledge-management DSS – A DSS targeted at Knowledge Management (KM) in some organization.

Compared to the categorization of [77] we note that BI and Data Warehousing are today most often Data-driven DSS, while Intelligent DSS are more related to Knowledge-driven DSS or in some cases Model-driven DSS. Communication-driven DSS are usually either Group DSS or Negotiation DSS. Personal and Knowledge-management DSS are cross-cutting categories which may be of more or less any of the categories in [77].

2. Literature Survey

In order to characterize the research that has been conducted on Semantic Web technologies for DSS so far, we have performed a structured literature review, which is described in this section.

2.1. Structured Method

To generate a manageable but comprehensive set of articles for our survey, we have chosen to target research publications where the authors explicitly claim to work within this intersection. Later, in Sect. 4 we will discuss the research areas more broadly, and draw on our own knowledge and experience from the Semantic Web field, but in this part of the paper we take a more structured approach. Below we describe first the literature collection method, next, the data collection performed based on the collected literature, and subsequently in the following section we present the results of the structured literature survey.

2.1.1. Literature Collection

In order to make an unbiased selection, and generate a reasonable coverage of all literature that explicitly claims to treat the intersection of DSS and Semantic Web research, we first selected a number of keywords representing each of these fields. The DSS field was here represented by the two keywords *decision support* and *business intelligence*, the second one selected because it is sometimes used as a synonym for decision support in the more business-focused literature. The Semantic Web field was then represented by the keywords *Semantic Web*, *semantic technologies*, *linked data*, and any combination of *ontology* with either *RDF* or *OWL*. Apart from the first two, which are quite obvious, we wanted to capture articles that used some of the more prominent technologies of the field, but without actually mentioning their origin in the Semantic Web. For each source (see further below) articles were retrieved that contained any combination of a DSS keyword and a Semantic Web one, i.e., resulting in up to 10 distinct searches being made within each source.

The sources are of three main types; (i) general online indexing service, (ii) publisher database, and (iii) individual journal or publication series. As a representative of the first category, we used Google Scholar, which indexes a multitude of online publication databases from various publishers. Due to the huge number of articles indexed, we searched for the presence of the 10 combinations of keywords only in article titles and abstracts. Representing the second category, we used the SpringerLink online database, since it covers many of the publications within the Semantic Web field, e.g., proceedings of the most prominent conferences such as ISWC and ESWC. Also in this case, the total number of indexed articles is huge, hence, we restricted the search to articles with any of the 10 keyword combinations in the title or abstract.

Finally, representing the third category, we selected a number of journals from both fields. Here the Semantic Web field is being represented through the Journal of Web Semantics (Elsevier) and the Semantic Web Journal (IOS Press). Previous reviews of the DSS field, e.g., [11], have listed the most prominent journals in

DSS research, whereas based on these results we chose to focus on the Decision Support Systems journal (Elsevier), Decision Sciences (Wiley), the International Journal of Information Technology and Decision Making (World Scientific), Information and Management (Elsevier), International Journal of Spatial Data Infrastructures Research (online journal by the Joint Research Centre of the European Commission), and MIS Quarterly (University of Minnesota). The respective online search facilities of the listed journals were used for retrieving articles, by means of the keywords described above. Depending on the facilities provided by the respective sites, if present we included a full-text search of the article content in addition to searching title and abstract. For searching the specific journals we made an additional assumption; all articles of the two Semantic Web journals were assumed to be about the Semantic Web, hence only the two DSS-related keywords were used for retrieval, and the opposite for the clearly DSS-related journals (Decision Support Systems and Decision Sciences), where only the 5 keyword combinations representing Semantic Web concepts were used, while all the remaining IS journals were treated similarly to the general databases. All articles that were either directly available online, or retrievable through library order were collected. A few articles of Google Scholar turned out to constitute "broken links", and hence were not retrieved.

Subsequently, a manual assessment of the articles was made. First, duplicates were removed, e.g., when the same paper had been retrieved based on two separate queries, or when a paper for instance was available both through the authors website, hence indexed by Google Scholar, and through the Journal's own site. Since many of the articles had been retrieved based on a full-text search, it then had to be determined if Semantic Web and DSS technologies and solutions were actually a topic of the paper, or simply mentioned in brief. Articles where Semantic Web or DSS were only mentioned as (i) part of the related work section, (ii) as future work, or (iii) as part of the author bio (present in the template of several of the journals), were discarded. Additionally, a small number of articles were discarded due to the keywords not actually representing the intended meaning, for instance, in one case an article contained the sequence of words "semantic web" but not as a term representing the concept of the Semantic Web but as a part of a sentence mentioning the inherent semantics of the text in web documents. The remaining number of articles is 59, which is the set used for the data collection described below.

2.1.2. Rationale and Method Critique

The above method is by no means the only possible one, nor it is completely without bias. The selection of sources, as well as the use of restrictions on keyword occurrence (i.e., title or abstract), was necessary in order to retrieve a manageable set of articles. However, it also yields a high number of "false negatives" in terms of missed articles. With respect to the source selection, the reason for selecting Google Scholar was mainly due to its high coverage of a wide variety of publisher databases in the computer science field, such as IEEE Xplore and the ACM digital library. In this way we broadened the coverage of the study, but at the same time had to restrict the search to hits only in title or abstract in order for the result to be manageable. One publisher database that was however not covered by Google Scholar is Springer's, SpringerLink. Since many of the most prominent Semantic Web books and conference proceedings are published by Springer, it was natural to add this database to the set of sources. The selection of journals was done both based on the authors experience, but additionally relying on the results from DSS surveys, such as [11], which lists the most influential DSS journals at that time.

The keyword selection is the second large bias of the study. The most obvious terms to use are the ones found already in the title of this article; "Semantic Web" and "Decision Support". However, when it comes to selecting synonyms or other indicators it becomes more tricky. In addition to the keywords actually included, we have tried keywords such as "planning support" (since a large part of planning support systems can be considered as DSS), but without any additional results. Either such a term is not commonly used in the title or abstract of a paper, or planning support systems applying Semantic Web technologies use terms outside our set to describe the semantic technologies they exploit. We have not made an in-dept analysis of this problem, but we merely conclude that the selection of keywords has potentially impacted the result of our study.

A minor source of errors, in particular affecting the reliability of the statistical data for 2011 and 2012 is the fact that some journals publish online preprints of articles before they are actually published in the printed journal. In the case where no publishing date for the printed issue has been found, we have used the online publishing date instead, which means that a few publications initially dated in 2011 should actually be moved to 2012, since they are now officially published in a printed publication with publication date in 2012.

Finally, a remark on the manual assessment of articles (the last step of our literature collection method described above) where a high number of articles were actually discarded due to Semantic Web not being an essential part of the article topic. Originally around 200 articles were collected (including duplicates), hence, the manual assessment removed about 70% of the initial article collection. Apart from duplicate articles, the main problem was with the "Semantic Web" keyword, where numerous articles contained this term in their future work sections or in the author biography. Since there has been a kind of "hype" around the Semantic Web, it seems that (at least until a few years ago) this was a very common term to just "throw in there", possibly just to show that you are aware of the latest developments.

2.1.3. Data Collection

Based on reading the 59 articles in the set, we have then collected information about each one. First of all, a set of metadata elements were collected, according to the following:

– Year of publication
– Number of authors
– Author affiliations
– Author nationality (according to the affiliation)
– Type of publication (i.e., journal article, book chapter, conference paper, or workshop paper)

In addition to these the topics of the articles were classified along three dimensions; (i) theoretical or applied research, (ii) main Semantic Web contribution, and (iii) type of DSS. Here we have chosen to classify something as theoretical research if the paper does not describe a system or other implementation, e.g., use case or empirical study, for the results. The category for applied research thereby represent those contributions consisting of an implementation of some sort, either technical, such as a software system, or organizational in terms of a case study or similar. In addition to these two categories we have singled out survey papers and position papers, which cannot normally be classifies into either of the two previous categories.

The main Semantic Web contribution has been classified according to what Semantic Web technologies or approaches are at focus in the paper. The categories were derived a-priori from the lists of conference topics of the research track of the past four International Semantic Web Conferences. These topics have been quite stable, at least as far back as 2008, where only one new category has appeared (NLP - representing the increased hybridization of NLP and Semantic Web technologies) and one category has been replaced ("Applications of the Semantic Web" is replaced with "Semantic Web Engineering"). The latter is most likely due to the presence of a specific "in use" track where applications are the main focus, hence, the research track now only targets the development rather than the applications themselves. We have chosen not to include the old "applications" category in our categorization, simply because we view the intersection between DSS and Semantic Web technologies as one such application area, hence, all papers could be viewed as belonging to that category. Based on this, we end up with the following 6 categories, where the names and explanations have been slightly tailored to this study:

– Semantic Web data – representation languages, storage, search and querying of Semantic Web data, e.g., RDF data and Semantic Web Services, including approaches for using or producing linked data, as well as quality assurance and provenance tracking of data.
– Ontologies and semantics – representation languages and patterns, engineering, management, retrieval and usage of Semantic Web ontologies and rules, including reasoning services and rule execution engines.
– Semantic Web engineering and development - building of Semantic Web applications, methods, tools and evaluations of applications.
– Natural Language Processing (NLP) – machine learning and information extraction for the Semantic Web, Semantic Web population from text or from exploiting tags and keywords, or using semantic technologies to perform NLP.
– Social Semantic Web – social networks and processes, collaboration and cooperation, context awareness and user modelling, trust, privacy, and security.
– User interfaces – interaction with and creation of Semantic Web data and models, information presentation, visualization and integration, personalization.

To exemplify how these categories have been assigned, assume a paper presenting an approach to use ontologies for information integration and subsequently presenting that information using a novel visualization method exploiting the underlying semantics of the information. Such a paper would be classified as belonging to both the second and final category of the list above, while an application using ontologies for information integration, but using standard user interface components not tailored to the Semantic Web, would be classified as belonging only to the second category of the list. Similarly a paper discussing privacy and security has only been assigned the social Semantic Web category if Semantic Web-related technologies in some way contribute to those issues or their solution. Hence, we have only classified the *contribution of the Semantic Web technologies* used in the paper into these categories, not the overall approach of the paper, and each paper may have multiple classifications.

Finally, we have studied the type of DSS addressed in the paper. For this we have used the categories of DSS listed in [11], as presented in the bullet list of Section 1.1. We have slightly adapted one of the category definitions, compared to [11]; a personal DSS is not restricted to a DSS that is tailored for, or used by, only a small number of users, instead we define a personal DSS as being targeted towards the decision support of a single decision-maker, as opposed to group DSS where decisions are made jointly. Hence, in our view the number of users of a personal DSS can be large, but each user is supported individually in his or her decisions. An example could be a personal online shopping agent; such a system may have millions of users, but each agent supports one single user specifically in his or her shopping decisions. In addition to the above categories, we have added a "general" category, representing approaches that can be used for supporting most of the above DSS categories, e.g., general theories or infrastructure approaches. Also in this case, multiple categories may apply.

2.2. Current State of Semantic DSS Research

Based on the data collected as described above, we can now analyse the nature of the intersection between Semantic Web and DSS research. Figure 1 illustrates the number of publications per year, belonging to the different categories, as well as the yearly total. We note that there has been a steady increase in the total number of publications from 2005 (which is the publication year of the oldest article we found) and onwards, with an exception of 2010 when there was a considerable decrease compared to the year before. We have not been able to find a good motivation for this dip in publication numbers, however it may be due to some external factors, such as conference focus and journal special issues of that year, or be due to some glitch in our data collection, e.g., a missing keyword that was particularly popular at that time. Nevertheless, for 2012 we note that already in the first four months (until April 2012 when the data was collected) a number of articles have been published, hence, we see that if an equal amount is published during the next 8 months we would end up at a level that at least equals 2009, however, it should also be noted that none of the major conferences in the Semantic Web field have yet been held this year. In Figure 2 we note that most articles describe applied research, rather than theoretical work, while there is also a small number of survey articles and position papers in our collection.

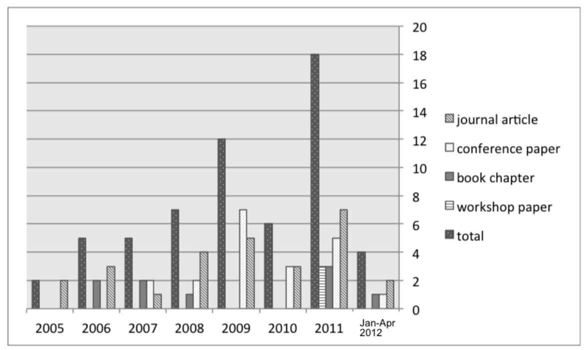

Fig. 1. Number of articles of each category, as well as the summed total for each year.

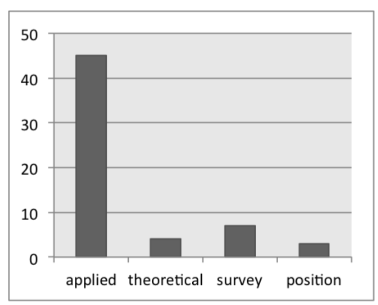

Fig. 2. Type of study reported.

With respect to where this research is being conducted, we have plotted the number of publications based on the country of origin of its authors (a paper with several authors could thus belong to two categories) in Figure 3. Here we can see that a small number of papers include authors from Central and South America, and those have all appeared in the last few years. There is a steady participation from both Asia (only one paper comes from the Pacific region) and North America (US and Canada), while the large increase in publications is mainly due to an increased number of contributions from European countries, in particular for 2011. On average each paper has about 3.5 authors, from an average of 2.2 different institutions, and 30% of the papers have at least one author coming from outside academia (besides universities, we include univeristy hospitals, and publicly funded research centers and institutes in the notion of "academia"), e.g., a company or a private healthcare facility. These numbers indicate that most research is done jointly between several parties, and that there is a healthy involvement of industry actors, although it could be discussed if the latter should futher increase.

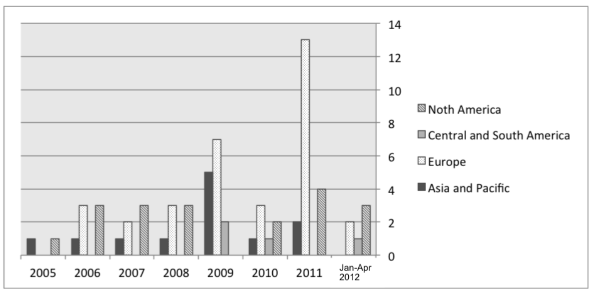

Fig. 3. Geographical distribution of affiliations.

When studying the contribution of Semantic Web technologies to the DSS field, as illustrated by Figure 4, we note that the two high-impact areas have been *ontologies and semantics* and *Semantic Web data*, with particular emphasis on the former. Many DSS applications use ontologies and rules as a means for making the DSS "intelligent" in some data analytics sense. The same phenomenon can be seen in Figure 5 where Intelligent DSS has been one of the main categories of Semantic Web-supported DSS throughout the years. An explanation for this is also the fact that DSS and Semantic Web share a common ancestry in early AI technologies, which are still acknowledged as a part of DSS legacy for data analysis.

While many Semantic Web applications use rather light-weight solutions and ontologies, DSS on the other hand have often been used in more closed scenarios than the Web and have many times utilized quite complex ontological reasoning and rule bases, more similar to Expert Systems of AI than today's Semantic Web applications. Much of the Semantic Web-related work in DSS, especially in the medical and health care domains, could be viewed as a direct continuation of the Expert Systems tradition, e.g., [8,26,27,28,32,34,47,51,52,75,79,80,82,84,92], simply adopting the emerging Semantic Web standards (RDF, OWL etc.) for knowledge representation, replacing older representation conventions or special-purpose languages. Since Expert Systems have traditionally been ontology- or rule-based, it is easy to see how they can quickly assimilate novelties in terms of new logical formalisms and modelling languages, while adopting such technologies has proved much more difficult in the general Web scenario.

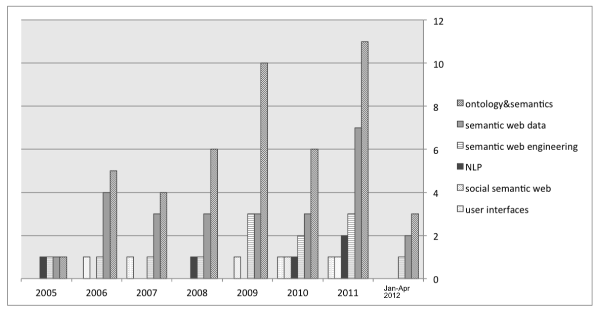

Fig. 4. Number of publications reporting the use of specific Semantic Web technologies.

This also becomes evident when studying the application domains of Semantic Web-supported DSS, as seen in Figure 6, where traditional Expert Systems domains such as the health care and biomedical domains have been among the most prominent, e.g., as illustrated by applications in Clinical Decision Support (CDS)[28,32,79,80,82], medical training [46], and biomedical research [32,81]. Legal knowledge management is another field where Expert System approaches have classically been applied, and this domain is represented in our article collection as well, i.e., through the modelling and automatic monitoring of Service Level Agreement compliance [74] and general modelling of legal ontologies [90] for DS. Another context where the common AI tradition is visible is the use of agent architectures, e.g., e-Commerce scenarios such as intelligent shopping agents [50,58,60].

Semantic Web data can be utilized for DSS in several ways. Some approaches use formats such as RDF and OWL to integrate and allow access to data from existing data sources [8,12,16,18,25,56], e.g., Data Warehousing-like approaches to database integration but with new formats, while others focus on extracting Web data [15] or even utilizing Semantic Web data, already in RDF, as an entirely new data source [33,69,85,86], e.g., by incorporating Linked Data (LD) in their DSS application, or simply proposing to move from current data publishing principles to LD [70].

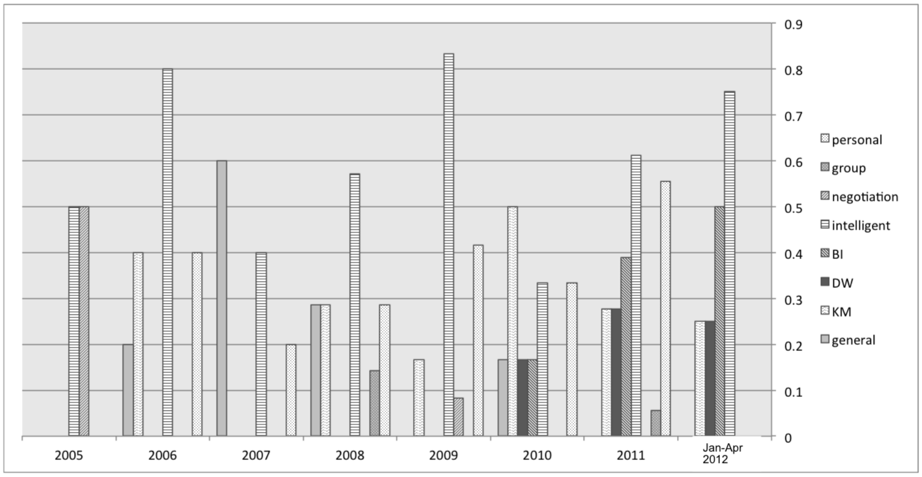

Fig. 5. Fraction of the publications each year treating different types of DSS.

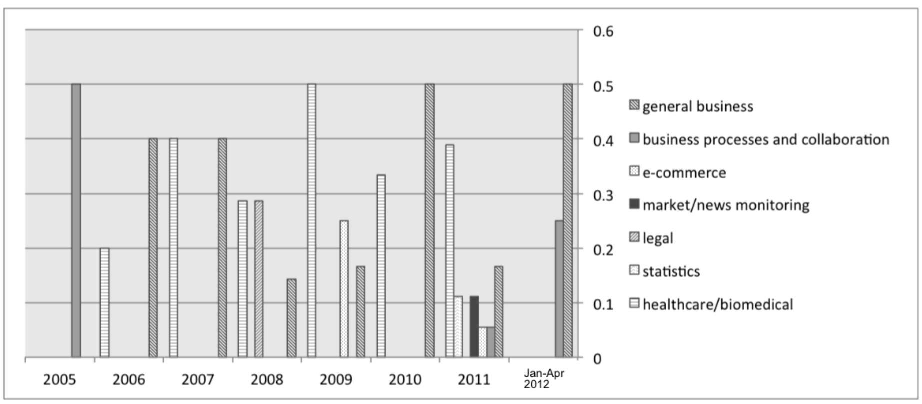

Fig. 6. Fraction of the publications each year applying Semantic Web technologies to specific domains (only domains with more than one paper appear in the graph).

Still, more often than not, some form of ontology is used on top of this data, to allow for integrated querying and reasoning, as in [12,16]. This high interest in ontologies is most likely due to the DSS domain already being highly focused on models, not only through the Expert Systems tradition but through approaches such as multidimensional modelling, data cubes, and OLAP (although these primarily utilize mathematical models rather than logical ones), which are common especially in the BI area. This, as opposed to the Semantic Web community where data rather than models has been the main focus of practitioners the past few years. In our paper collection we even find approaches for annotating and integrating models themselves, based on OWL ontologies, e.g., annotation of general data analysis and decision models [40,19,18] or business process models [78,39], as well as interest in model integration and matching [57], and transformation between models, e.g., from topic maps to ontologies [67].

Returning to Figure 4, we note that in addition to a steady interest in ontologies and Semantic Web data, the other areas are also represented, even if only by a few papers each. Examples of where *Semantic Web engineering* has impacted DSS are the use of triple stores as part of the DSS infrastructure [9,16,17,41,69,81], and the deployment of Service Oriented Architectures (SOA) enhanced by Semantic Web technologies [24,42,56,60,68,83] for sharing and accessing data. Some approaches even take this one step further and apply Semantic Web technologies in peer-to-peer networks, for interpreting messages, e.g., facilitating offers in a negotiation scenario [43].

The increased interest of hybridization between *NLP* and Semantic Web technologies that has been observed in general Semantic Web research recently, has also been taken advantage of for DSS, e.g., by exploiting Information Extraction (IE) to populate Semantic Web datasets for later analysis by a DSS [33,65,81], and through various kinds of ontology and rule learning approaches [44,50,55,90] for bootstrapping semantic models.

The intersection between DSS and the *social Semantic Web* is in our paper collection mainly focused on contextualizing data [16,23], utilizing social annotations such as tags [45], and providing better decision support through advanced user modelling [23,30]. Finally, with respect to *user interfaces*, a few DSS approaches have actively exploited data semantics and ontologies to personalize and contextualize user interfaces [71,24], as well as describing graphical elements by means of semantic models, e.g., statistical charts [45], or 3D models [14].

As already mentioned, Figure 5 shows the high fraction of articles focused on Intelligent DSS, however, also Personal DSS is a recurring topic throughout the dataset. This result is consistent with the earlier study of the complete DSS domain in [11], which concluded that personal DSS is one of the major focus areas of DSS in general. Knowledge-management (KM) focused DSS is another common topic, which is not very surprising considering that one focus of the Semantic Web in general is improved information management, hence, it is quite straight forward to transfer those technologies to KM within organizations as well. One prominent example of this category is health care KM [8], as also mentioned above, but our paper sample additionally includes KM in other areas, such as management of railway knowledge [64], and transfer of empiric (tacit) knowledge [35].

Another interesting aspect is that papers discussing Semantic Web in relation to general aspects of DSS, rather than specific solutions, have dropped in numbers, while two new types of DSS have emerged only in the past three years; Business Intelligence and Data Warehousing. This illustrates how Semantic Web technologies and ideas have gone from being something mainly for Intelligent DSS, i.e., a continuation of the AI tradition, or something discussed in general terms in a survey article, to being applied in almost every area of DSS research. A similar trend can be spotted in Figure 6, where Semantic Web-related DSS have gone from being applied in two or three domains (e.g., medicine, general business scenarios, and legal DSS) to now having a much broader field of application (e.g., in 2011). This is in line with the Semantic Web field in general, where techniques are today applied to numerous industry domains, and for numerous types of business use cases, as envisioned already by [61].

One classic DSS field is military command and control, but in our collection we only find one single article treating this topic [88]; a bit more surprising is that this is also one of only three papers [33,68,88] mentioning the more general concept of "situation awareness". In Figure 6 we have additionally omitted the "long tail" of application areas (only categories with more than one paper have been included). However, if considering the "long tail" it actually shows that we have gone from between 2 and 5 distinct application areas per year between 2005 and 2010 to as many as 9 distinct areas in 2011 (in addition to the ones listed in Figure 6 we have noted applications for environmental data analysis, project planning, and command and control).

3. Interview Study

In order to additionally capture a snapshot of viewpoints from non-university research and industry today, we decided to conduct a small set of interviews. The main aim of the interviews is to survey what challenges are perceived by DSS researchers and practitioners today, and what requirements, typically addressed by Semantic Web technologies, are highlighted by those challenges. Larger interview studies have been conducted in various projects during the past years, e.g., such as in the Value-IT project [73]. We start by giving a brief summary of their findings in the next section, nevertheless, we see an additional need for presenting a more detailed analysis of industry needs through examples scenarios, which is then provided by our own interview results in Section 3.3.

3.1. Related Studies

With respect to mapping out industrial needs and current state, there exist several studies that also include aspects of DSS. The Value-IT project[1] studied the application of semantic technologies in enterprises, in particular from a business perspective. In their Deliverable 3.2 [73] they present the results of an extensive survey, consisting of both literature surveys of use

[1] http://www.value-it.eu/

case reports as well as interviews with 675 decision-makers around Europe, from a variety of industry sectors. One important class of applications mentioned is DSS, which is actually presented as one of the areas that currently has the largest gap between existing applications and perceived needs, in particular for larger companies. In that survey, interoperability is found to be the overall top priority need for enterprises, with searching and linking of information, and collaboration support as runners-up. They also note that database interoperability is one of the most commonly addressed problems in enterprise projects today, i.e., an area where most enterprises already have ongoing efforts. Despite pointing at the need for better solutions in most application areas where semantic technologies could indeed help, many enterprises still showed relatively low interest in semantic technologies, which according to the report authors may be due to a lack of understanding of such technologies and their benefits, and lack of trust in their maturity.

Another survey that comes to similar conclusions is the SAP report by Dau [38], which studies the benefits and costs of semantic technologies in enterprise applications. He lists data integration, separation of schema from data, schema evolution, semantic search, and semantically supported collaboration as the key areas where benefits arise when using semantic technologies. On the downside, he sees technical challenges such as scalability and immaturity of currently available frameworks, the cost of modelling and creating good ontologies, especially considering the lack of experience most enterprises have with the languages involved, subsequent education costs for enterprise personnel, as well as the difficulty of measuring actual quantitative improvements that the technologies provide. Nevertheless, the author concludes by noting that semantic technologies come with a number of clear benefits, and it is only a matter of time until they become a mainstream technology in enterprise systems. While this report is not directly targeted at DSS, the conclusions most likely hold for this category of applications as well.

Given this broader picture of enterprise needs, we now proceed to report on the views of our sample enterprise DSS experts, which largely confirms but additionally further detail the above conclusions.

3.2. Interview Setup

In this section we summarize the interview setup.

3.2.1. Participants

In our research project Semantic Technologies for Decision Support, at Linköping University, we have two industrial partners as well as two partners constituting research institutes, each of which are working with different aspects of DSS. One industrial partner is a large Swedish corporation providing security and defence solutions, ranging from aviation to military training and support systems for civil security and crisis management. The interviewee (*a*) from this partner is a project manager and solutions developer with background mainly in systems for situational awareness in security and crisis management, as well as for monitoring of societal functions by citizens and decision makers. Examples of DSS of this partner include Web applications for traffic monitoring, both land and sea traffic, citizen-driven fault reporting systems for municipalities, and DSS applications for customs officers tracking goods and vessels.

The second industrial partner is a small Swedish company providing systems and consultancy for professional training, e.g., training decision-makers for day-to-day activities or crisis situations focusing on core functions of society such as nuclear power plants, water and electricity supply, airports and harbours etc. The interviewee (*b*) from this partner is co-founder of the company, but also an active consultant and project manager who has been involved in developing the company's training management software. Examples of DSS of this partner include tools for planning and monitoring large scale training scenarios, in addition the interviewee has experience from a multitude of DSS belonging to their trainees that are usually integrated into the training scenarios.

The third partner is a large Swedish research institute, targeted at research for security and defence applications. The two interviewees (*c* and *d*) are researchers and system developers, involved in projects related to simulation and prediction systems for real-time decision support, mainly based on sensor information integration and formal models. Examples of DSS of this partner include simulation systems for predicting individual and population behaviour, from single units in a battlefield up to simulations of national and global scenarios.

The fourth partner is a US research center, focused on DSS research and applications for the US Navy. The interviewee (*e*) is a researcher and project manager involved in applications for situation awareness and information sharing and integration, mainly for emergency management and space situation awareness. Examples of DSS of this partner include information integration applications for message passing and information sharing between emergency managers, e.g., police, fire departments, medical personnel, logistics, etc., in a crisis situation, as well as situation awareness applications with map-based interfaces for plotting events of interest.

Since the project involving these four partners is slightly biased towards the security field we decided, for the sake of broadening the scope of this paper, to include two additional interviews. The first interviewee (*f*) being a clinical practitioner and researcher, with long experience in medical decision support applications, e.g., clinical decision support and systems supporting drug prescription, who is currently the head of a government-funded foundation for supporting medical drug research, epidemiology, and drug economy issues. The interviewee was previously responsible for the national project of implementing electronic health records in Sweden. Examples of DSS in the experience of the interviewee are the Clinical DSS (CDSS) applied today in Swedish primary and specialist care, e.g., related to the electronic health records, and DSS used by medical practitioners and farmacies for drug prescription.

The second additional interviewee (*g*) being a Business Intelligence (BI) consultant with long experience of a multitude of different BI applications and scenarios. This interviewee is currently head of the BI department of his consultancy firm, and has mainly experience with large-scale data warehousing, OLAP, and different kinds of model-based BI applications.

The DSS exemplified by the interviewees consist mainly of Personal DSS, in combination with Intelligent DSS, BI, Data Warehousing, and KM-focused DSS (see Section 1.1 for an explanation of the categories). While none have particular support targeted at collaboration, some still support group decision-making in some sense, e.g., through information sharing and delegation:

- Personal DSS - The situation awareness applications of interviewees (a) and (e), the training management systems of interviewee (b), the CDSS of interviewee (f), and the BI systems of interviewee (g).
- Group DSS - Partly implemented in the training management systems of (b), and the emergency management systems of (e).
- Intelligent DSS - Simulation systems of (c) and (d), as well as the CDSS for drug prescription of (f).
- BI and Data Warehousing - Main target of interviewee (g).
- KM DSS - Partly the target of the CDSS of interviewee (f).

3.2.2. *Interview Script*

The interviews were carried out in a semi-structured manner, using open questions where the interviewees were always free to add comments and reflections to their answers. The interviews were divided into three parts; the first part (i) being devoted to the background of the interviewee and their experience in DSS and potentially with Semantic Web technologies, the second part (ii) being devoted to a number of themes, representing certain features or functionalities of a DSS, where the interviewees were asked to either reject the presence or need of such features in DSS of their field of expertise, or to confirm the presence or the future need of such functionalities by describing scenarios where such features would be needed, or are currently used, and finally the third part (iii) being devoted to recording the opinion of the interviewee with respect to where the most urgent challenges of DSS within their field of expertise lie, and (if known to them) where they believe that semantic technologies could give the most benefit. All but one of the interviews were conducted in Swedish, whereby their responses have been translated and are here interpreted and explained in English. The answers of part (i) are reported as part of Sect. 3.2.1, while the two latter parts are reported in Sect. 3.3.

The themes used for the second part of the interviews, were based on a list of system feature categories for which we believe that Semantic Web technologies and approaches could be particularly useful. For each such feature category, we have listed a number of indicators, which if present could indicate the need for solutions related to that particular category (sets are overlapping, i.e., the same indicator can support several feature categories, and several indicators may be needed in orders to deduce the need of one feature). Before the interviews we listed 40 distinct indicators, which in different constellations point at the need for the 7 hypothetical feature categories below. For instance, the feature category "information integration" is supported by indicators such as the presence of several datasources, with different formats, some of which may be "external" and hence are not under our own control, may change frequently, etc. The list of feature categories and conditions consist of (main features, with a sample of indicators in parenthesis):

- Information integration (several data sources, different formats, external data sources, high change rate, exchangeable data sources)
- Information filtering and selection (several large data sources, different tasks and roles of users, abstraction)
- Information extension, exploration, and explanation (data may be missing in internal sources, user explanations, browsing relations between data, drill-down of information)
- Information interpretation, event detection, and prediction (large data sources, high change rate of data, abstraction and aggregation, situation detection, "real-time" data, data analysis)
- Information tracking and post-event analysis (large data sources, abstraction and aggregation, situation detection, post-session evaluation and session follow-up, provenance)
- Models and model evolution (different changing data formats, external data sources, changing user tasks and views, model-based analysis, relations between information, browsing and linking)
- Sharing decisions (trust, provenance, accountability, user created data, interaction between users, delegation)

When asking the interviewees to give examples of (or reject) the need for the detailed indicators they were asked to describe example scenarios taken from the projects and systems they have been involved with, and within those scenario descriptions we recorded their mentions of the detailed feature indicators. In Sect. 3.3 their responses are described, and compared, in particular to find common system scenarios that apply to several fields, and thereby might constitute particularly important features to support. Finally, their answers to the open questions of part (iii) constitute an indication of the needs and priorities of DSS practitioners today.

3.3. Interview Results

In this section we summarize their responses, presented by feature category.

3.3.1. Information Integration

All of the interviewees recognized the need for some form of information integration in their respective fields. Interviewees (a), (b), and (e) all exemplified this through scenarios of integrating sensor information with reports from human actors, as well as external information from the web.

For the training scenarios of (b) this may mean to integrate sensor data from a training field, with observer reports entered by human observers as text in a dedicated software, while (a) exemplified through scenarios of monitoring a municipality, where sensor information such as weather and state of important infrastructures (e.g., water and energy supply, traffic etc.) should be integrated with reports from inhabitants regarding disturbances and problems. Interviewee (e) exemplified this through an emergency management scenario where human and machine communication between emergency managers from different organizations, e.g., fire department, police, and medical personnel, need to be integrated with sensor information and background knowledge, such as maps of the area. Interviewees (c) and (d) took examples from integration of simulation outcomes from several simulators, as well as integration of spatial data, e.g., map layers, expressed using different standards and from several sources as input to simulations. In health care, information integration is needed for combining the information in electronic health records with background knowledge about drugs and health conditions, according to interviewee (f). For the BI scenarios of interviewee (g) information usually comes from within the same organization, but from different source systems that collect that data, and since a BI system usually is not tightly integrated with those systems, it has to react to constant changes in the original sources and their schemas.

Although the need for information integration exists, several interviewees, e.g., (a) and (f), confirm that there is not a good solution for this in their systems at the moment. Most often static connections between systems are set up including tailored transformation software, which has to be constantly maintained as schemas or technologies of data sources change.

Those that today are not using external data sources for direct input, also confirm the need for doing this in the future, e.g., to incorporate information from the support systems of the trainees' own organization to monitor what they do during training (b), and to incorporate web sources into BI systems, for monitoring the environment of an enterprise (g). The only difference in needs that can be noted is with respect to the integration of user-created data, where interviewees (c) and (d) do not see this need in their simulation systems, and interviewee (g) currently do not see the integration of user-created data on the BI side, but certainly on the side of the enterprise information and management systems where the BI software gets its data.

3.3.2. Information Filtering and Selection

With respect to filtering, all interviewees acknowledge the presence of large amounts of data, more than a user can cope with without some sort of filtering. Several of the interviewees also exemplify limitations in today's systems (e.g., interviewees (a) and (e)) where the systems claim to perform some "intelligent analysis" but in fact are only plotting the data on a map - which is more about "moving data around" (according to interviewee (e)) than actually filtering out the interesting things.

In all systems, except the simulation and prediction systems of interviewees (c) and (d), there are several types of users with different roles and motivations for using the DSS, which results in the presence of different views (based either on the login category of the user, or selected manually through preferences). Today, these views are most often generated by a fixed set of filtering rules that are decided at design time, e.g., as in the BI applications of (g) where predefined "reports" are the representations of such tailored views.

Usually, as a user you can also select among a predefined set of filters, or perform some kind of free text search over data. However, all interviewees (except the BI specialist (g)) acknowledge an urgent need for better and more flexible information filtering and selection methods.

3.3.3. Information Extension, Exploration, and Explanation

Information extension in this context means to be able to incorporate new data and data sources if needed, e.g., to find related information on the web, or to generate explanations or drill-down of information presented, all based on a user's need for more information related to the current data elements in focus. Most DSS today seem not to have an "open world view" but seem rather static, where the sources are determined at design time and data is not usually linked or browsable, e.g., through some kind of drill-down with increased levels of detail in data, or through associative relations. The only concrete example of "drill-down" we get is the ability to click on an icon on a map, as explained by interviewee (a), to see the data values associated to that icon, or the display of metadata or provenance information related to the data being viewed. In BI scenarios interviewee (g) mentions that it is important to include specific views on information tailored to "power users" who want to explore the raw data items and create their own analyses and filters, however, in other types of interfaces the opportunity to see the underlying data is not present.

The only example of a system that actually explains to the user how something was derived, is the CDSS of interviewee (f), where warning flags are raised if a patient is at risk of getting prescribed a medicine he or she is allergic to, or a medicine that can interact in an unwanted way with another of their prescribed drugs. Such flags can be examined further by the healthcare professional, to see what the reason is for the warning being raised, and even get suggestions for suitable actions, such as changing the dose of a medicine. The same system also allows for browsing the data about medical conditions and drugs in such a way that the user may end up retrieving information from external sources, such as the drug providing company or a patient association.

None of the other interviewees could give any examples of such scenarios, while it seems rather common to have a static "link collection" available for the users, so that they can proceed to investigate external web sources on their own, which could be interpreted as a need for retrieving and extending information in the system in some cases. Explanations of derived information, and drill-down in terms of exploring the underlying data or its sources, seems uncommon, however, this may simply be due to the very simple forms of aggregation and analysis that is currently performed (as mentioned previously).

3.3.4. Information Aggregation, Event Detection, and Prediction

Only a few of the interviewees claim that their systems today perform some kind of data aggregation. The BI area has a long tradition of data aggregation, and has developed specialized methods for pre-aggregation to improve system performance, e.g., through OLAP cubes (as also explained by interviewee (g)). However, in other DSS areas such aggregation seems to be done sparsely or not at all. Interviewee (f) explains that in their medical decision support today, the focus is mainly on individuals, and the only aggregation is on the level of collecting all the data about that particular patient, while one could imagine interesting opportunities, e.g., for research, if data were to be aggregated also over the health records of a population. Here there is also a problem of legislation largely forbidding the aggregation of health data in Sweden, however, if appropriately aggregated and anonymized it could provide a highly valuable research basis.

Both interviewees (a) and (b) point at the graphical user interface of their system as the point where filtering and data selection or aggregation happens, mainly through fixed views over data. Interviewee (a) explains this through an example from their situation awareness systems using map interfaces, where data about certain places are aggregated based on the zoom level of the map, i.e., by zooming out, more and more events are considered to happen "in the same place" (in relation to the granularity of the map) and are thereby shown through one single icon rather than individual ones. Hence, we note that aggregation, if present, is usually done along very elementary dimensions.

When moving from more or less static datasets to data flows, even more challenging scenarios arise, i.e., making sense of large amounts of rapidly changing information (from a user perspective) through scalable intelligent analysis over large datasets. Filtering could be seen as a prerequisite to this kind of analysis, while the features we discuss here target more challenging scenarios with near real-time data, such as Complex Event Processing (CEP) or anomaly detection.

Several of the interviewees exemplify the use of some form of data representing the "current situation", e.g., traffic situation on land or at sea (a), situation of a municipality or region (a), situation of an emergency or crisis (a,e), situation in a training scenario (b), situation in an enterprise (g). Today this data is commonly analysed manually, e.g., by plotting the data on a map, in a table, or as a graph, and then letting the user analyse it by simply viewing it, such as manually detecting traffic jams from sensor data and roadside cameras (a), or a limited rule-based analysis is made, such as detecting the presence of two interfering drugs prescribed to a patient (f).

Very few systems perform more advanced analysis of data, however in closed simulation settings, where agents represent humans to simulate the actions of a population under certain conditions, more advanced models are used to specify how those agents detect certain conditions (situations) in their environment (c,d). Despite the overall lack of support for this kind of "situation detection", several of the interviewees mention this as one of the most important challenges, e.g., interviewee (e) emphasizes that just "shuffling data around" is pretty useless, unless the system also helps users to detect the important things that are going on, and presents those in a high-level view so that the situation is immediately understandable by the user.

Interviewee (e) emphasizes the time aspect of decision-making, especially in a crisis situation, where managers have to make split-second decisions in order to save lives. In such cases, they rely on long experience rather than careful analysis of data for making the right decision, however, this is also a requirement for faster and more accurate event detection in data, to provide the decision-makers with an accurate information to base decisions on. In particular, detecting unwanted situations or anomalies in data seems to have a high priority.

The systems of interviewee (c) and (d) are the only ones targeted at performing predictions based on the current situation, in this case through simulation models, hence, the prediction is the outcome of the complete execution session. The BI systems of interviewee (g) are also to some extent used to find trends in data and to make suggestions on future actions, and so are the CDSS systems of interviewee (f). Although both acknowledge that these capabilities are usually very basic, e.g., restricted to analyzing the effects of one single action of the user, such as prescribing a certain drug in the medical case, or changing some business parameter in the BI case. Predictions are on the other hand not something explicitly mentioned by the interviewees, possibly since a more imminent need is still to be able to analyze the current situation in a better manner.

3.3.5. Information Tracking and Post-Event Analysis

While the previous feature category dealt with near "real time" data, tracking of large data flows is concerned with historical data, and related to issues such as data provenance, post-analysis of how a situation has unfolded etc. Rather than focusing on single events, here we need to analyze the complete scenario.

Probably the most self-evident situation when this is needed is the follow-up of training situations, as exemplified by interviewee (b), where there is a plan of the training scenario, and a number of goals to achieve, which are all to be evaluated after the training session, in order to explain the outcome as well as to learn from it. Similar follow-ups are conducted in medical DSS (f), which are not only used for follow-up of the patients and their treatment, but also for conducting research (so-called evidence based medicine).

The need for this kind of follow-up and tracking of situations was not acknowledged by all the interviewees, e.g., interviewee (a) pointed at the fact that some kinds of data are not legally allowed to be stored more than a certain amount of time, and many open systems on the web are targeted at giving users an accurate picture of the current situation rather than being able to evaluate the past, e.g., the current traffic monitoring systems by interviewee (a). Nevertheless, interviewee (a) acknowledges that interesting conclusions could also be drawn from statistics and past situations, e.g., road and harbour conditions and capacity in the land and sea traffic cases, as well as frequencies of certain disturbances or emergencies in the case of municipal monitoring, although this is not being done today. In the BI case, historical data is often used to analyze the outcome of managerial decisions (g), however, this is rarely performed in an automated fashion, rather reports are printed and manually analysed.

In summary, all the interviewees acknowledge the need for tracing data and user actions, e.g., related to issues of security, provenance, and individual responsibility, but rarely see the need for advanced analysis capabilities related to such tracked sessions or situations.

3.3.6. Models and Decision Sharing

The last two feature categories, i.e., *models and model evolution* and *decision sharing*, are related to a meta-perspective since these features concern specific ways of supporting solutions discussed previously. This makes the need for these solution categories harder to derive and exemplify based on the interviews. Nevertheless, it is clear that several interviewees already today exploit some kind of models, while the need for providing dynamically evolving models rather than static ones is present but not currently met. Evidence for the need of models is also quite clear from the discussion of information integration, since most interviewees claim to be having problems with changing information schemas, exchange of data sources, and incorporating external information. Additionally, they all mention the lack of flexibility as a severe problem, whereby also models need to be dynamic and change along with evolving data, schemas and technologies in general. Similarly, the storing of meta-level information, i.e., information about decisions themselves, appear in example scenarios from emergency management (e), e.g., how to convey a decision by an incident manager to the agencies involved, and BI (g), e.g., how to express the information that a certain managerial decision was based on certain BI information, are expressed by the interviewees.

3.3.7. Challenges

When asked for the main challenges of their respective DSS fields, five of the interviewees directly mention the need for better data aggregation, abstraction, and analysis in order to provide more "intelligent" and user-relevant analysis of data, to detect the interesting situations (or events), in the vast amount of data available. As expressed by interviewee (a), we have spent a lot of time and effort in recent years on getting access to data in the first place, but now that we have it we are not sure how to treat data and extract the truly interesting things hidden within it. This largely confirms the top-ranked issues for enterprise systems found in the surveys presented in Sect. 3.1.

Interviewee (e) explains this issue further by exemplifying the need for data at several levels of aggregation and abstraction, drawing on a newspaper analogy; in a newspaper we can read the front page to get the main headlines, if we are interested in a specific topic we flip to that page, and get a more detailed headline and short summary, only if we really find that interesting we have to go further and read the whole text. In the opinion of interviewee (e) this kind of "data summarization" and drill-down constitutes and important feature, together with concise descriptions of the information at all these levels, tailored to the user needs. The remaining two interviewees mention this issue indirectly, by asking for better access to data, through better user interfaces that point the user to the relevant parts of the data.

Other important challenges are to handle huge amounts of data (so called "big data" (g)), handling flows of data rather than static data in a store (b), providing true interoperability of data sources, i.e., not only on a syntactic level (c, d, and f), and letting DSS affect our organizations by integrating the tools closer into our work processes (g) and finding new ways of collaborating that incorporate these services (e).

3.3.8. Potential Contribution of Semantic Web Technologies

All the interviewees had some previous idea of what "semantic technologies" might be (we did not check if these ideas were "correct" or not, and to what extent they were familiar with specific aspects), and were asked if they were able to envision where they think such technologies would create the most value for DSS users.

Several of the interviewees considered the use of semantic representations as a prerequisite to remedy the current problems in interoperability and information sharing and integration, as well as a means for creating more flexible system, e.g., mirroring the changing environment around them, as well as a means of creating more "intelligent" detection models for spotting interesting events in data. Again, this is in line with the expectations on semantic technologies for enterprise systems reported in previous studies (see Sect. 3.1).

Some also saw an opportunity to create more abstract models, for reusability in DSS design, and sharing solutions between different DSS. The opportunity to standardize descriptions, e.g., vocabularies, for describing data was mentioned, as well as modelling non-hierarchical relations between concepts, to improve the information structures and models used within DSS. Finally, one interviewee (g) also pointed at some possible drawbacks, in that Semantic Web representation languages, e.g., their XML-serialization, add too much overhead when dealing with "big data" and hence a lot more work on scalability and efficiency of semantic data management is needed.

In relation to the Semantic Web technology categories explained in Section 2.1.3, we can conclude that the use of Semantic Web data, ontologies, and the software frameworks supporting these are confirmed to be important prerequisites to future cross-fertilization of DSS and Semantic Web. A particular limitation today, is related to the Semantic Web engineering and Semantic Web data categories, i.e., efficiency of the formats and algorithms in order to be able to handle "big data". The remaining categories, i.e., NLP, social aspects, and user interfaces, are not mentioned explicitly in relation to Semantic Web technologies. This is not highly surprising, it is to be expected that if the tasks considered as basic prerequisites by the interviewees, e.g., information integration, are not satisfactory solved yet, then it is difficult to envision the use of more advanced technologies. However, when surveying the problems and challenges as listed in the previous sections, we note that several of the interviewees mention the integration of sensor data with unstructured information provided by users, the need for better contextualized and individually tailored data analysis methods, as well as better data access through special-purpose user interfaces (which are issues related to the NLP, social Semantic Web, and user interfaces categories respectively).

4. Discussion and Future Challenges

In this section we proceed to analyze the intersection between DSS and Semantic Web research, by drawing on the previous sections, i.e., the current state of research and applications in the area and the expressed needs of the sample DSS specialists that have been interviewed, together with general Semantic Web approaches or research directions that has the potential to influence DSS research in the future.

4.1. Semantic Web data

One of the most important basic needs of DSS, which cuts across all the application domains of the interviewees, is the need for easier and more flexible information integration methods. To some extent this need has already been addressed by research as presented in Section 2.2, e.g., by exploring RDF/OWL and Linked Data as a formal data representation in DSS [69,70,86], and analysing the feasibility and qualities of different ontology alignment methods [57]. Nevertheless, using Semantic Web technologies does not necessarily imply the use of (or existence of) standardized vocabularies for describing your data, nor the reuse of URI:s for data linking. The Web of Data today is a true bottom-up effort, where de-facto standards are growing out of use rather than set by standardization organizations. If such de-facto standards are present and used, linking and integration often becomes quite straight forward, while in other cases data integration can still require a large effort, consisting of URI-mapping and vocabulary reconciliation.

Once such integration is done, however, Linked Data enables many new opportunities. One which is highlighted by [70,81], namely that using Semantic Web technologies for data integration also enables new research opportunities, by allowing the linking and federated use of datasets from different researchers and even different fields of research. In addition, this does not only apply to research data, but data in general, as shown by numerous use cases of the Linking Open Data (LOD) project [20], although few have so far had a DSS focus.

Naturally, trust, provenance and data quality become important aspects when incorporating Web data in DSS, and unfortunately these aspects are only beginning to be researched in the context of the Semantic Web, e.g., as illustrated by the W3C Provenance Working Group started only last year [6]. In particular, Semantic Web approaches and available frameworks have so far largely overlooked security issues, such as data confidentiality or intellectual property rights. Although the semantic technologies as such cannot be expected to in themselves handle such issues, the frameworks where they are embedded need to address this problem. Since many such frameworks have so far been more of research prototypes rather than commercial tools, there is generally a low level of trust in that security and confidentiality of data can be ensured when applying Semantic Web approaches.

So far Linked Data has been mostly discussed in an open Web setting, however, the same techniques and principles can be applied to closed scenarios, such as enterprise data. Numerous software tools exist for performing so called "triplification" of data, e.g., starting from relational databases or XML schemas [49,3], as well as for transforming data and aligning it to one or more vocabularies (e.g., [72]), and even automated link discovery has been proposed [91]. Hence, by expressing appropriate transformation rules in a high level rule language the bulk transformation of data, and possibly even some linking, can then be performed without much human intervention – letting the human engineers focus on data quality rather than syntactic issues. Once linked data has been produced, the links between data and datasets can be utilized in several ways, both for information integration and aggregation, as well as using links to browse data through associative relationships, which was another need expressed by the interviewees. Linked enterprise data, i.e., combining LOD with enterprise-internal information, has the potential to revolutionize the way enterprises view their data and build DSS for both BI and other scenarios.

An obstacle to this development is efficiency, as one of the interviewees note: if you have really large amounts of data, and in particular when concerned with lots of literal values, it can create a huge overhead to transfer and manipulate URIs and formats such as RDF/XML, rather than raw data in a streamlined format. Scalability problems have lately received much attention in the Semantic Web community, e.g., by development of efficient triple stores [2] and scalable Web reasoning methods (e.g., see the LARKC project [1] and the series of NeFoRS workshops [5]). Nevertheless, relational database systems and Data Warehousing methods have had a few decades of head start, while we are still to see the bulk of research on optimization of Semantic Web technologies. Additionally, few studies have been made on the overhead and possible streamlining of the formats themselves (although several syntaxes are available for most languages), rather most research targets the procedures for manipulating data and ontologies using their formal semantics. A important path is also the continued hybridization between classic techniques, e.g., relational databases and Data Warehousing, and Semantic Web technologies, both in order to make use of the more efficient methods from other areas as well as taking into account the multitude of legacy data sources that exist.

The fact that DSS are often domain-specific and potentially even organization-internal also affects the data filtering and selection methods that should be used. Traditional approaches, such as statistical methods and other kinds of free text search (e.g.,using Google-like methods, primarily operating on the syntactical level), might not work as well as in the general case since keywords are highly specialized and alone may not be enough to discriminate between documents. In most DSS tasks it is also important to find data elements relevant to an information need, rather than documents. In particular in time critical scenarios, such as emergency management, browsing through documents to find the right information is not feasible. This is one of the main drivers for using Semantic Web technologies in the DSS field, since the Semantic Web has boosted the development of data-centric rather than document-centric retrieval methods. On the other hand, general Semantic Web methods operate in a more unstructured and open scenario than relational databases and their query languages, which are also highly data-centric.

Recently the notion of *semantic search* has been discussed in the Semantic Web community, which could be seen as ways to query Semantic Web data rather than "search" in the classic Information Retrieval sense (e.g., see [87]), and where user interaction is usually more similar to Question Answering rather than keyword search (e.g., as in [63]). In the field of DSS the situation is different from the general Web setting, for instance, DSS users are already used to getting tailored reports and data elements related to their needs, hence, keyword search is not the main mode of interaction as on the Web. This means that semantic search is a highly relevant paradigm, which might even be easier to develop and more easily adopted by users in the DSS domain than in an open Web setting. However, we need to provide easy-to use interfaces and efficient solutions that provide accurate answers for time-critical decisions if semantic search is to be adopted for DSS on a large scale.

4.2. Ontologies and Semantics

In order to make sense of Linked Data, and enable views and queries over datasets, ontologies are commonly used as vocabularies for the data. In the set of papers we have studied, ontologies are likely the most common Semantic Web technology that is applied to DSS, and some ontologies are quite complex. This is a little bit surprising, since this is usually not the case on the Semantic Web in general, where much research is simply about utilizing data while using only a very simple data model (or no ontology at all). We have already proposed one explanation for this, i.e., it may be due to the common AI origin of the two fields, which means that the use of ontologies for DSS was common already before the Semantic Web, and the contribution has thereby mainly been new languages, and to some extent reusable ontologies on the Web.

This is visible through the numerous Expert System-like applications proposed in our paper collection, e.g., in the CDSS area [8,28,32,34,47,51,52,79,80,82,84, 92]. A recent study from the ONTORULES project [59] even proposes Expert System as a near-synonym to what they call "decision support type systems", claiming that many DSS carry on the Expert Systems tradition, although they are today called by different names. However, constructing and using application-specific ontologies in this way suffers from the same well-known problems as in the Expert Systems tradition, possibly the most prominent being the so-called "knowledge acquisition bottleneck". While automatic ontology construction has been tried both for DSS, e.g., by [44,50,90], an in the general case for the Semantic Web (sometimes called Ontology Learning [31,36]), it has so far not been considered as highly successful in practice, while ontology evolution approaches, in particular user-assisted ones such as [93], may prove more feasible.

Other approaches for reducing the effort in ontology engineering have also been proposed, e.g., reuse of general top-level ontologies, and reuse of smaller ontological components such as Content Ontology Design Patterns (CPs) [48,21]. An advantage of DSS scenarios is that they often focus on particular domains, or even more or less closed sets of data sources, as opposed to the general open Web scenario. This might imply that both automatic methods, such as Ontology Learning, and component based modelling, such as using catalogs of CPs (possibly domain-specific), potentially could become quite successful in this restricted setting. Similarly, the Semantic Web today is also a huge source of reusable ontologies. Not all of them are of high quality nor of high complexity, but some are actually widely used, e.g., the FOAF ontology[2], SKOS[3], Semantic Web versions of the Dublin Core vocabulary[4], the DBPedia ontology[5] etc. The mere fact that ontologies are shared and reused, supports easier information integration in all fields, including DSS. However, in our paper collection we note that most ontologies described are tailor-made and do not refer to any of these common vocabularies, which shows an area of possible improvement.

One area that has received quite some focus in the LOD community is spatial data, e.g., datasets such as GeoNames, for adding a spatial aspect to data, and for instance, being able to link events and objects to places, and use a map interface to visualize data. Although there were no such papers in our collection, there exists approaches for spatial decisions support (e.g., recent examples in [53,54,94]), in particular approaches for using ontologies, which could potentially make use of the large amount of spatial data available in the LOD cloud, as well as efforts in using ontologies to organize and better access spatial decision support resources (data, models, tools) [62]. The emerging interest in Semantic Web technologies in this community is also evident when looking at the program of the past few year's conferences of the Global Spatial Data Infrastructure Association[6].

Once basic information access, integration, and selection processes are in place, requirements move towards intelligent data aggregation and analysis - or as expressed by one of the interviewees: we now know how to retrieve and integrate data, but it is not equally clear what to *do* with data. In DSS scenarios the focus is often on large amounts of highly dynamic data, e.g., data streams. In the Semantic Web community there has recently been a shift in focus from more static datasets towards handling RDF data streams [89], e.g., of sensor data, and performing intelligent analysis, such as event detection and processing (sometimes called Complex Event Processing - CEP) [10,13,66]. However, there may be another underlying issue that hampers the combination of current DSS technologies for data analysis and Semantic Web approaches, namely the different types of models used. Apart from the DSS that actually already use ontologies, many model-based DSS rely on mathematical models, e.g., statistical models, rather than "symbolic" ones such as ontologies. It may not be straight forward to use such models together, as have been seen also on the Web, where despite recent developments there is still a

[2] http://xmlns.com/foaf/0.1/
[3] http://www.w3.org/2008/05/skos
[4] http://purl.org/dc/terms/
[5] http://dbpedia.org/ontology/
[6] http://www.gsdi.org/gsdiConferences

wide chasm between statistical search techniques and semantic search, and between statistical and fuzzy approaches on one side and crisp logical approaches on the other, for instance.

When considering scale, projects such as LARKC [1] have attempted to address scalability issues of Semantic Web technologies, in particular complex tasks such as reasoning, and plug-ins for the LARKC software platform provides support for stream reasoning and CEP. Nevertheless, these approaches mainly rely on expressing event detection rules as SPARQL queries, hence, they do no incorporate the use of standard reasoners or declarative pattern descriptions, e.g., through OWL ontologies, but rather lets the user express detection mechanisms implicitly as queries. In addition, streams are usually assumed to be expressed in known vocabularies, rather than interpreted at runtime, and systems are set up with a predefined number of streams.

In order to support DSS in closed scenarios, the latter assumptions are probably reasonable, however, we envision the need for more flexible ways to interpret data and express patterns in data. For instance, currently there is a lack of research on modelling incomplete and uncertain event patterns, as well as the evolution and extension of detection patterns at runtime (c.f. the discussion on Ontology Learning and Evolution previously). Using SPARQL for event detection also suffers from some clear limitations with respect to performing temporal reasoning over the RDF streams, while a multi-layer approach using cascaded SPARQL queries can potentially assist in data aggregation.

Subsequently, these approaches may need to be combined with statistical approaches for tracking general event trends, or prediction models for analysis of decision consequences, which are already quite common in the DSS field. In fact, when considering the use of models for data analysis, the Semantic Web field may actually benefit from studying well-established models in the DSS field, for improving data analysis in the general Semantic Web setting. Such cross-fertilization is already underway, where for instance vocabularies have been proposed for expressing multi dimensional data in RDF [37], and applying well-known DS analysis methods on top of RDF data [69].

4.3. NLP, Social Semantic Web, and User Interfaces

The previous two general topics have been the backbone of Semantic Web research, hence, they are also the areas with the most mature and well-known approaches. However, during the past few years the Semantic Web community has acknowledged the need for broadening research to also incorporate more user-oriented research topics, e.g., social and interaction aspects, as well as the need for utilizing and/or producing natural language in addition to data in order to leverage the use of the human readable Web and other legacy systems and data sources. As could be seen, this has also been a focus of some DSS-related Semantic Web approaches. Although, similarly to within the the general Semantic Web area, such approaches and publications constitute a minority of the total body of research.

Important aspects, related to DSS, include the ability to personalize and contextualize data, in order to create tailored filters, views and analysis mechanisms on data. Such approaches have already been proposed, e.g., for personal shopping agents as noted previously. Nevertheless, other areas of DS could benefit from more flexible views and analysis mechanisms, as for instance suggested by the BI expert we have interviewed.

Several of the interviewees also express the need for further integration between text sources and data, e.g., in order to incorporate human communication as a data source in areas such as emergency management and monitoring of municipal communities. Today, the NLP community has developed stable and scalable entity recognition methods, Information Extraction (IE) methods, and even to some extent deep parsing techniques, which will enable the detailed analysis of text sources in DSS. However, the integration between Semantic Web and NLP is still in its infancy.

The development of novel user interfaces for the Semantic Web has contributed to tie together the so-called Social Web with the Semantic Web and the classical “human readable” Web [29], for instance by providing user interfaces for contributing and editing Semantic Web data directly in a Web browser [7]. The Semantic Web can be utilized for numerous different purposes, including support for developers and “power users” with in-depth knowledge of semantic formalisms, however, when applied to DSS the users are most often decision-makers in some organization, who may not even be very used to computers or the Web. In such cases it is of essence that intuitive user interfaces hide all the underlying complexity of algorithms and data formalisms, while still being flexible and providing “intelligent” yet transparent support for user tasks.

This is a user interaction challenge that is still not sufficiently researched in the Semantic Web community. Considering these types of users, also the requirements for proper explanations and drill-down of information become essential, i.e., for a user to trust an “intelligent” system, that system must be able to explain how something was derived and what the user should potentially do about the situation. As we have seen, this is done in a few DSS today, but in a quite crude fashion. Since current research in the Semantic Web field is addressing similar issues, a suitable use case for explanation and trust scenarios could be to investigate their application in DSS.

Finally, taking a metalevel perspective, Semantic Web technologies could also support the sharing of information about decision-making processes and decisions themselves. Such information is rarely made explicit in DSS, and even more rarely shared between DSS or published for later use (whether internally or externally). In the context of consumer products and e-Commerce, there is a tradition of storing information about user behaviour, e.g., “buying decisions”, in order to provide better services to similar kinds of users, c.f. the “other users who purchased this item also bought. . . ” suggestions provided by many large e-Commerce sites. In a similar manner one could imagine DSS in the general case storing information about decision behaviour, and learning from such behaviour to in the future provide even better DS services, or being able to later follow-up and present the decision process history and relevant decisions to a user. In line with this there have been attempts to analyze the needs of a semantic decision vocabulary [22], e.g., for reasoning on decision consequences, tracking past decisions and their motivations etc., and this is currently being investigated by a W3C Community Group [4].

5. Summary and Conclusions

In this paper we have provided an overview of the area of Semantic Web-related DSS research, through a structured literature survey. It turns out that the amount of research publications has boomed during the past three to four years (except for an unexplained dip in 2010), and the main increase can be attributed to research in European institutions. During the past 2-3 years we also noted a significant broadening of the scope, both in terms of the Semantic Web technologies that are applied, the type of DSS applications, as well as in the industry domains that are targeted – in our opinion most likely due to the increased maturity and increased business interest within the Semantic Web field itself.

Confirming the results of similar surveys of the DSS field as a whole, we find that the most common type of DSS is the Personal DSS, supporting individual decision-making. For natural reasons, also Intelligent DSS is a prominent category, relying on the Semantic Web providing means for “intelligent” knowledge representation and reasoning. The latter also points at the common legacy of the two fields, i.e., technologies developed within AI research, which is for instance visible in the high amount of approaches using ontologies and rules for Expert System-like functionalities (in particular within the CDSS domain). Nevertheless, there are also approaches that propose more specific uses of Semantic Web ontologies, such as for annotating DSS models, or providing background knowledge to the use of such models on top of data. Other prominent usages of Semantic Web technologies include the exploitation of Semantic Web data formats, both for integrating existing data sources in legacy formats, and for extending current sources with data from the Semantic Web.

Our interview study, where 7 DSS researchers and practitioners from 6 different organizations (4 none research-oriented) were interviewed, shows that the state of DSS practice today differs from the state reported in our collection of papers, which is not very surprising. There is usually a gap between research and industry practice, and only 30% of our collected papers actually had industry participants as co-authors, which still leaves room for improvement. The interviewees note two kinds of challenges; (i) areas where technologies should be made more flexible and effective, and (ii) areas where they do not yet have good solutions and where new technologies and ideas are needed. For (i) the main challenges relate to better and more flexible information integration, sharing, and improved data filtering, while related to (ii) there are numerous challenges concerning data aggregation, abstraction, and analysis, and the scalable management of big and dynamic datasets. For the latter, we would like to point at this as a great opportunity for Semantic Web researchers to use DSS as a testbed for calability and efficiency experiments, in order to optimize and streamline the technologies. Despite possible challenges, these are all areas where Semantic Web approaches may be able to improve current DSS solutions, and we emphasize that information interoperability and integration seems to be a key facilitator for most DSS scenarios, as also noted by previous studies of semantic technologies for enterprise systems in general.

In addition to the more well-researched areas of Semantic Web research we also see a clear need in DSS for NLP-related approaches, improved user interfaces for visualizing and interacting with semantic data, as well as approaches for incorporating the social aspects of the Web. Here DSS could provide the use cases for advancing Semantic Web research in these areas. A number of limitations of current Semantic Web technologies relate to their lack of support for trust, provenance and assurance of data quality, together with scalability and efficiency problems related to the formalisms used. While the latter has been a hot topic for several years in the Semantic Web community, the remaining topics still need an increased focus.

Areas where surprisingly little cross-fertilization has so far taken place (at least judging from our literature survey) include spatial decision support and planning support, e-government, and applications related to the natural sciences (e.g., environmental applications and life sciences, except for CDSS). These are areas where a lot of Semantic Web data and ontologies exist, but has so far not been utilized for DSS to a large extent.

Although some approaches for Semantic Web-supported BI have been proposed, this is still the area the Semantic Web has probably influenced the least – in our opinion mainly due to the high requirements of BI with respect to both trust, security, and efficiency, but also the difference in current technologies and models used. Once these obstacle can be overcome, Semantic Web can greatly contribute to BI, for instance, by not only letting an enterprise analyze its internal state, but to integrate that information with external data and analyze the situation in relation to the outside world, e.g., including competitors, events reported in the news, etc. As is also noted by [11], BI is a field where a lot of money is made and spent, hence, a focus of many IT companies, which should make this an interesting focus also for Semantic Web-related research.

In summary, Semantic Web technologies have been used to support DSS since 2005, when the first paper in our collection appeared. However, it is not until the last 2-3 years that technologies from the Semantic Web have been applied to a broader range of DSS applications and domains. An obstacle to the adoption of Semantic Web technologies is still their scalability and immaturity with respect to optimization and efficiency, compared to classic data management solutions, but not all DSS fields have strict efficiency requirements. On one hand, Semantic Web technologies can help to solve basic DSS needs such as information interoperability, integration and linking, while additionally potentially continuing to support the development of "Intelligent DSS", but in a new and more open manner than what was traditionally possible with AI technologies. An interesting aspect is also the potential of DSS providing data for the Semantic Web, e.g., by providing Semantic Web vocabularies for expressing metadata about decisions and decision-making, which can then be shared with others.

Acknowledgements

This work was partly financed by the SecurityLink strategic research center at Linköping University, and the research project Semantic Technologies for Decision Support (funded by CENIIT, Linköping University). Furthermore, we would like to thank Naicong Li, Olivier Bodenreider, Eva Maria Kiss, and the additional anonymous reviewer for their valuable comments on how to improve this paper, as well as Marie Gustafsson Friberger at Malmö högskola for valuable comments during the writing process.

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