Unifying Web-scale Search and Reasoning from the Viewpoint of Granularity

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Abstract. Considering the time constraints and Web scale data, it is impossible to achieve absolutely complete reasoning results. Plus, the same results may not meet the diversity of user needs since their expectations may differ a lot. One of the major solutions for this problem is to unify search and reasoning. From the perspective of granularity, this paper provides various strategies of unifying search and reasoning for effective problem solving on the Web. We bring the strategies of multilevel, multiperspective, starting point from human problem solving to Web scale reasoning to satisfy a wide variety of user needs and to remove the scalability barriers. Concrete methods such as network statistics based data selection and ontology supervised hierarchical reasoning are applied to these strategies. The experimental results based on an RDF dataset shows that the proposed strategies are potentially effective.

1 Introduction

The assumption of traditional reasoning methods do not fit very well when facing Web scale data. One of the major problems is that acquiring all the relevant data is very hard when the data goes to Web scale. Hence, unifying reasoning and search is proposed [1]. Under this approach, the search will help to gradually select a small set of data (namely, a subset of the original dataset), and provide the searched results for reasoning. If the users are not satisfied with the reasoning results based on the sub dataset, the search process will help to select other parts or larger sub dataset prepared for producing better reasoning results [1]. One detailed problem is that how to search for a good or more relevant subset of data and do reasoning on it. In addition, the same strategy may not meet the diversity of user needs since their backgrounds and expectations may differ a lot. In this paper, we aim at solving this problem.

Granular computing, a field of study that aims at extracting the commonality of human and machine intelligence from the viewpoint of granularity [2, 3], emphasizes that human can always focus on appropriate levels of granularity and views, ignoring irrelevant information in order to achieve effective problem solving [3, 4]. This process contains two major steps, namely, the search of relevant data and problem solving based on searched data. As a concrete approach for problem solving based on Web scale data, the unification of search and reasoning also contains these two steps, namely, the search of relevant facts, and reasoning based on rules and searched facts. A granule is a set of elements that are drawn together by their equality, similarities, indistinguishability from some aspects (e.g. parameter values) [5]. Granules can be grouped into multiple levels to form a hierarchical granular structure, and the hierarchy can also be built from multiple perspectives [3]. Following the above inspirations, the web of data can be grouped together as granules in different levels or under different views for searching of subsets and meeting various user needs. From the perspective of granularity, we provide various strategies for unifying user driven search and reasoning under time constraints. From the multilevel point of view, in order to meet user needs in different levels, unifying search and reasoning with multilevel completeness and multilevel specificity are proposed. Furthermore, from the multiperspective point of view, the unifying process can be investigated based on different perspectives of the knowledge source. We also propose unifying search and reasoning with a starting point, which is inspired by the basic level advantage from cognitive psychology [6], to achieve diversity and scalability.

The rest of this paper focuses on introducing various strategies for unifying search and reasoning from the viewpoint of granularity: Section 2 introduces the multilevel completeness strategy. Section 3 introduces unifying strategy with multilevel specificity. Section 4 discusses the starting point strategy. Section 5 investigates on the multiperspective strategy. For each strategy introduced in this paper, we provide some preliminary experimental results based on a semantic Web dataset SwetoDBLP, an RDF version of the DBLP dataset [7]. Finally, Section 6 discusses some related work and makes concluding remarks.

2 Multilevel Completeness Strategy

Web scale reasoning is very hard to achieve complete results, since the user may not have time to wait for a reasoning system going through the complete dataset. If the user does not have enough time, a conclusion is made through reasoning based on a searched partial dataset, and the completeness is not very high since there are still some sets of data which remain to be unexplored. If more time is allowed, and the reasoning system can get more sub datasets through search, the completeness can migrate to a new level since the datasets cover wider range.

There are two major issues in this kind of unifying process of search and reasoning: (1) Since under time constraint, a reasoning system may just can handle a sub dataset, methods on how to select an appropriate subset need to be developed. (2) Since this unification process require user judges whether the completeness of reasoning results is good enough for their specific needs, a prediction method for completeness is required. We name this kind of strategy as unifying search and reasoning with multilevel completeness, which provides reasoning results in multiple levels of completeness based on the searched sub dataset under time constraints, meanwhile, provides prediction on the completeness value for user judges. In this paper, we develop one possible concrete solution.

For issue (1), searching for a more important sub dataset for reasoning may be a practical approach to select the subset effectively [1], and may be an approach to handle the scalability issue, since in most cases, the amount of important data is relatively small. Under the context of the Semantic Web, the semantic dataset can be considered as a graph that contains a set of nodes (subjects and objects in RDF dataset) and a set of relations (predicates in RDF dataset) on these nodes. Hence, in this paper, we borrow the idea of "pivotal node" from network science [8], we propose a network statistics based data selection strategy. Under this strategy, we use the node degree (denoted as $degree(n)$) to evaluate the importance of a node in a dataset. The nodes with relatively high value of node degree are selected as more important nodes and grouped together as a granule for reasoning tasks. There might be many types of predicates which are associated with the nodes in the RDF dataset, and different meanings of the various predicates may meet user needs from different perspectives. According to a specific need from a perspective, (which will be explained in detail in Section 5), we choose one type of predicate to investigate on the importance of a node. When we only consider this type of predicate and neglect other types, a subgraph of the original RDF dataset can be selected out. In this subgraph, the node degree considering a special type of predicate P can be denoted as $degree(n, P)$.

For issue (2), here we give a formula to produce the predicted completeness value ($PC(i)$) when the nodes which satisfy $degree(n, P) \geq i$ (i is a nonnegative integer) have been involved.

$$PC(i) = \frac{|N_{rel(i)}| \times (|N_{sub(i)}| - |N_{sub(i')}|)}{|N_{rel(i)}| \times (|N| - |N_{sub(i')}|) + |N_{rel(i')}| \times (|N_{sub(i)}| - |N|)}, \quad (1)$$

where $|N_{sub(i)}|$ represents the number of nodes which satisfy $degree(n, P) \geq i$, $|N_{rel(i)}|$ is the number of nodes which are relevant to the reasoning task among the involved nodes $N_{sub(i)}$, and $|N|$ is the total number of nodes in the dataset. The basic idea is that, first we can obtain a linear function which go through $(|N_{sub(i)}|, |N_{rel(i)}|)$ and $(|N_{sub(i')}|, |N_{rel(i')}|)$ (i' is the last assigned value of $degree(n, P)$ for stopping the reasoning process before i). Knowing $|N|$ in the dataset ($|N|$ only needs to be acquired once and can be calculated offline), by this linear function, we can predict the number of satisfied nodes in the whole dataset, then the predicted completeness value can be acquired.

As an illustrative example, we take the reasoning task "Who are authors in Artificial Intelligence (AI)?" based on the SwetoDBLP dataset. For the most simple case, following rule can be applied for reasoning to find relevant authors:

$$haspaper(X, Y), contains(Y, \text{"Artificial Intelligence"}) \rightarrow author(X, \text{"AI"})$$

where $haspaper(X, Y)$ denotes that the author X has a paper titled Y, while $contains(Y,$"Artificial Intelligence"$)$ denotes that the title Y contains the term "Artificial Intelligence", and $author(X,$"AI"$)$ denotes that the author X is an author in the field of AI. Since the SwetoDBLP contains too many publications (More than 1,200,000), doing reasoning based on a dataset like this may require an unacceptable period of time, it is better that more important authors could be provided to the user first. Here we choose the predicate that indicate an author has a coauthor (denoted as P_{cn}). Under this perspective, the authors with more coauthors, namely, has a higher value of $degree(n, P_{cn})$, are more important. In order to illustrate the levels of completeness, we randomly choose some $degree(n, P_{cn})$ to stop the reasoning process, as shown in Table 1. The reasoning process will start from the nodes with the biggest value of $degree(n, P_{cn})$, reduce the value gradually as time passed by, and will stop at the chosen $degree(n, P_{cn})$ for user judges. In order to meet users' specific needs on the levels of completeness value, using the proposed completeness prediction method introduced above, the prediction value has also been provided in Figure 1. This prediction value serves as a reference for users to judge whether they are satisfied. If more time is allowed and the user has not been satisfied yet, more nodes are involved, one can get reasoning results with higher levels of completeness. In this way, we provide solutions for the various user needs.

$degree(n, P_{cn})$ value to stop	Satisfied authors	AI authors
70	2885	151
30	17121	579
11	78868	1142
4	277417	1704
1	575447	2225
0	615124	2355

Table 1. Unifying search and reasoning with multilevel completeness and anytime behavior.

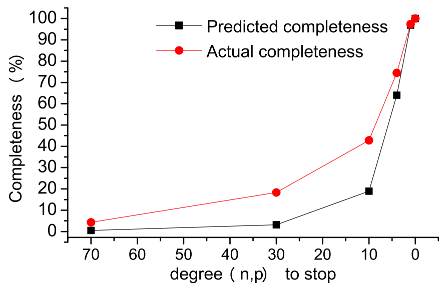

Fig. 1. Comparison of predicted and actual completeness value.

3 Multilevel Specificity Strategy

Reasoning results can be either very general or very specific. If the user has not enough time, the search and reasoning process will just be on a very general level. And if more time is available, this process may go to a more specific level which contains results in a finer level of grain size (granularity). Namely, the unification of search and reasoning can be with multilevel specificity, which provides reasoning results in multiple levels of specificities under time constraints.

The study of the semantic networks emphasizes that knowledge is stored as a system of propositions organized hierarchically in memory [9]. The concepts in various levels are with different levels of specificities. Hence, the hierarchical knowledge structure can be used to supervise the unification of search and reasoning with multilevel specificity. In this process, the search of sub datasets is based on the hierarchical relations (e.g. sub class of, sub property of, instance of, etc.) among the nodes (subjects and objects in RDF) and is forced to be related with the time allowed. Nodes which are not sub classes, instances or sub properties of other nodes will be searched out as the first level for reasoning. If more time is available, more deeper levels of specificity can be acquired according to the transitive property of these hierarchical relations. The specificity will just go deeper for one level each time before the next checking of available time (Nodes are searched out based on direct hierarchical relations with the nodes from the former direct neighborhood level).

Table 2. Answers to "Who are the authors in Artificial Intelligence?" in multiple levels of specificity according to the hierarchical knowledge structure of Artificial Intelligence.

Specificity	Relevant keywords	Number of authors
Level 1	Artificial Intelligence	2355
Level 2	Agents	9157
	Automated Reasoning	222
	Cognition	19775
	Constraints	8744
	Games	3817
	Knowledge Representation	1537
	Natural Language	2939
	Robot	16425
	...	...
Level 3	Analogy	374
	Case-Based Reasoning	1133
	Cognitive Modeling	76
	Decision Trees	1112
	Proof Planning	45
	Search	32079
	Translation	4414
	Web Intelligence	122
	...	...

Table 3. A comparative study on the answers in different levels of specificity.

Specificity	Number of authors	Completeness
Level 1	2355	0.85%
Level 1,2	207468	75.11%
Level 1,2,3	276205	100%

As an illustrative example, we use the same reasoning task in the upper section. For the very general level, the reasoning system will just provide authors whose paper titles contain "Artificial Intelligence", and the reasoning result is

2355 persons (It seems not too many, which is not reasonable.). Since in many cases, the authors in the field of AI do not write papers whose titles include the exact term “Artificial Intelligence”, they may mention more specific terms such as “Agent”, “Machine Learning”, etc. If more time is given, answers with a finer level of specificity according to a hierarchical domain ontology of “Artificial Intelligence” can be provided. Based on all the AI related conferences section and subsection names in the DBLP, we create a “three-level Artificial Intelligence ontology” automatically (This ontology has a hierarchical structure representing “Artificial Intelligence” related topics. Topic relations among levels are represented with “rdfs:subClassOf”), and we utilize this ontology to demonstrate the unification of search and reasoning with multilevel specificity[5]. The rule for this reasoning task is:

$$\begin{gathered} hasResttime, haspaper(X,Y), contains(Y,H), topics(H,\text{“AI”}) \rightarrow \\ author(X,\text{“AI”}) \end{gathered}$$

where *hasResttime* is a dynamic predicate which denotes whether there is some rest time for the reasoning task[6], $topics(H, \text{“AI”})$ denotes that H is a related sub topic from the hierarchical ontology of AI. If the user allows more time, based on the “rdfs:subClassOf” relation, the subtopics of AI in Level 2 of the ontology will be used as H for reasoning to find more authors in the field of AI. Further, if the user wants to get results finer than Level 2, then the subtopics in Level 3 are used as H to produce an even more complete result list. As shown in Tables 2 and 3, based on the hierarchy of Artificial Intelligence, Since Levels 2 and 3 contain more specific sub branches, it is not surprising that one can get more authors when deeper levels of terms are considered, hence, the completeness of the reasoning result also goes to higher levels, as shown in Table 3.

4 Starting Point Strategy

Psychological experiments support that during problem solving, in most cases, people try to investigate the problem starting from a “basic level” (where people find convenient to start according to their own background knowledge), in order to solve the the problem more efficiently [6]. In addition, concepts in a basic level are used more frequently than others [10]. Following this idea, we define that during the unification of search and reasoning process on the Web for a specified user, there is a starting point (denoted as SP), which consists of a user identity (e.g. a user name, a URI, etc.) and a set of nodes which serve as the background for the user (e.g. user interests, friends of the user, or other

[5] Here we ignore the soundness of this ontology, which is not the focus of this paper (Supporting materials on how we build the ontology can be found from : http://www.iwici.org/user-g.). One can choose other similar ontologies instead.

[6] For implementation, logic programming languages such as Prolog does not allow a dynamic predicate like *hasResttime*. But we can consider $resttime(T)$ as a counter which would return a number. Then, we can check the number to know whether there is any rest time left. Namely: $resttime(T), T > 0 \rightarrow hasResttime$.

Table 4. A comparative study of the multilevel completeness strategy without and with a starting point. (User name: John McCarthy)

Completeness	Authors (coauthor numbers) without a starting point	Authors (coauthor numbers) with a starting point
Level 1 $degree(n, P_{cn})$ ≥ 70	Carl Kesselman (312) Thomas S. Huang (271) Edward A. Fox (269) Lei Wang (250) John Mylopoulos (245) Ewa Deelman (237) ...	Hans W. Guesgen (117) * Carl Kesselman (312) Thomas S. Huang (271) Edward A. Fox (269) Lei Wang (250) John Mylopoulos (245) ...
Level 2 $degree(n, P_{cn})$ $\in [30, 70)$	Claudio Moraga (69) Virginia Dignum (69) Ralph Grishman (69) Biplav Srivastava (69) Ralph M. Weischedel (69) Andrew Lim (69) ...	Virginia Dignum (69) * John McCarthy (65) * Aaron Sloman (36) * Claudio Moraga (69) Ralph Grishman (69) Biplav Srivastava (69) ...
...	...	...

user familiar or related information). A starting point is used for refining the unification of search and reasoning process in the form that the user may prefer.

Following the idea of starting point, the search of important nodes for reasoning can be based on the following strategies:

- Strategy 1 (Familiarity-Driven): The search process firstly select out the nodes which are directly related to the SP for the later reasoning process, and SP related results are ranked to the front of others.
- Strategy 2 (Novelty-Driven): The search process firstly select out the nodes which are not directly related to the SP, then they are transferred to the reasoning process, and SP related nodes are pushed to the end of others.

Strategy 1 is designed to meet the user needs who want to get more familiar results first. Strategy 2 is designed to meet the needs who want to get unfamiliar results first. One example for strategy 2 is that in news search on the Web, in most cases the users always want to find the relevant news webpages which have not been visited. Here we give an example using strategy 1, and this example is a synergy of the multilevel completeness strategy and the starting point strategy. Following the same reasoning task in the above sections, "John McCarthy", is taken as a concrete user name in a SP, and his coauthors[7] whom he definitely knows (with * after the names) are ranked into the top ones in every level of the

[7] In this study, we represent the coauthor information for each author in an RDF file using the FOAF vocabulary "foaf:knows". The coauthor network RDF dataset created based on the SwetoDBLP dataset can be acquired from http://www.iwici.org/dblp-sse. One can utilize this dataset to create a starting point for refining the reasoning process.

"Artificial Intelligence" author lists when the user tries to stop while an arbitrary $degree(n, P_{cn})$ of the relevant nodes has been involved (Since the coauthors are all persons whom the author should know. These information helps users get more convenient reasoning results.). Some partial output in some levels is shown in Table 4. The strategy of multilevel specificity and starting point can also be integrated together, which provide reasoning results based on starting point in every level of specificity to produce a more user-preferred form of results.

5 Multiperspective Strategy

User needs may differ from each other when they expect answers from different perspectives. In order to avoid the failure of understanding in one way, knowledge needs to be represented in different points of view [11]. If the knowledge source is investigated in different perspectives, it is natural that the search and reasoning results might be organized differently. Each perspective satisfies user needs in a unique way. As another key strategy, unifying search and reasoning from multiperspective aims at satisfying user needs in multiple views.

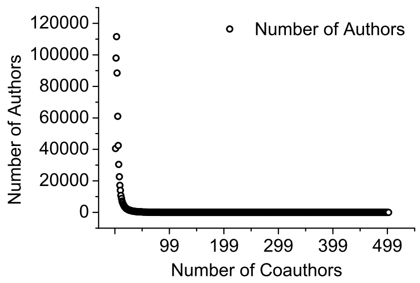

Fig. 2. Coauthor number distribution in the SwetoDBLP dataset.

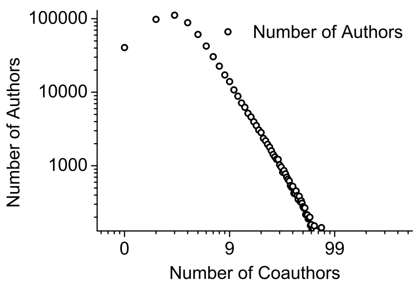

Fig. 3. log-log diagram of Figure 2.

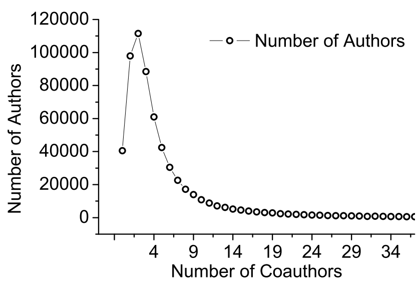

Fig. 4. A zoomed in version of Figure 2.

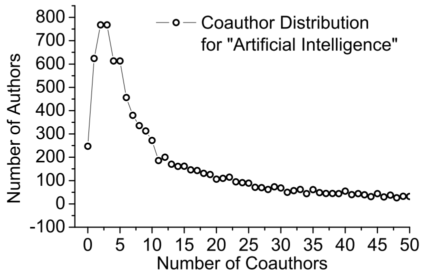

Fig. 5. A zoomed in version of coauthor distribution for "Artificial Intelligence".

We continue the reasoning task of "Who are authors in Artificial Intelligence ?". As proposed in the above sections, we use node degree under a perspective

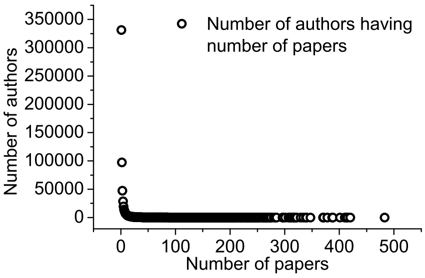

Fig. 6. Publication number distribution in the SwetoDBLP dataset.

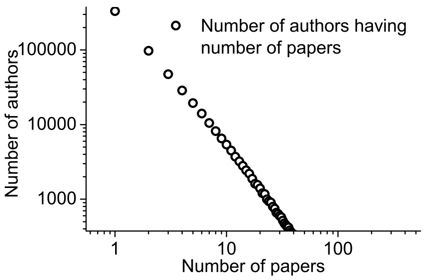

Fig. 7. log-log diagram of Figure 6.

($degree(n, P)$) to search for a subset of the original data for reasoning. Here we consider following perspectives: the number of coauthors, and the number of publications. Firstly, We choose the perspective of the number of coauthors. From this perspective, we find following characteristics of the SwetoDBLP dataset: Coauthor number distribution is shown as in Figure 2. In the left side of Figure 3, there is a peak value in the distribution, and it does not appear at the point of 0 or 1 coauthor number (as shown in Figure 4). Hence, the shape of the distribution is very much like a log-normal distribution. These phenomena are not special cases that just happen to all the authors, we also observed the same phenomenon for authors in many sub-fields in computer science, such as Artificial Intelligence (as shown in Figure 5, Software Engineering, Data Mining, Machine Learning, the World Wide Web, Quantum Computing, etc. As a comparison of the coauthor number view, we provide some partial results from the view point of publication number. We observe that, different from the perspective of coauthor number distribution, the publication number distribution follows very much like a power law distribution, without a peak value in the middle of the distribution curve, as shown in Figures 6 and 7.

It is clear that since the distribution of node degree under the above two perspectives are different, and for the same node, the node degree under these two perspectives are different, we can conclude that using different perspectives, both of the sequence of nodes provided for reasoning and the reasoning results are organized differently. In this way, various user needs can be satisfied.

6 Discussion and Conclusion

The study of unifying reasoning and search at Web scale [1] is the framework that this paper is based on. The strategies introduced in this paper aim at providing some possible solutions for how the unification can be done in a more user-oriented way from the viewpoint of granularity. They are developed based on many existing studies. Here we introduce two major related areas, namely, variable precision logic and previous studies on reasoning with granularity.

Variable precision logic is a major method for reasoning under time constraints, which provides two reasoning strategies, namely, variable certainty and variable specificity reasoning [12]. Concerning time constraint, given more time, a system with variable specificity can provide a more specific answer, while a system with variable certainty can provide a more certain answer [12]. Some strategies on unifying search and reasoning introduced in this paper, for example, the multilevel specificity strategy is inspired by variable specificity reasoning. The major difference is that: variable specificity reasoning uses "if-then-unless" rule, while multilevel specificity strategy uses hierarchical knowledge structure to supervise the unification process of search and reasoning. In this paper, we did not investigate on the idea of variable certainty. Since it belongs to non-monotonic reasoning, and the certainty won't necessarily go higher as more data is involved (since there might be contradictions [13] or inconsistency [14] on the facts, especially in the dynamic changing context of the Web). How it can be applied to a more user-centric environment still needs further investigations.

The study of reasoning with granularity starts from the logic approaches for granular computing [15–17], etc. Under the term of granular reasoning, it has also been studied from the perspectives of propositional reasoning [18], Aristotle's categorial syllogism [19], and granular space [20]. These studies concentrate on the logic foundations for reasoning under multi-granularity (mainly on zoom-in and zoom-out). In this paper, our focus is on how to unify the search and reasoning process from the viewpoint of granularity, namely, how to search for a good subset of the original dataset, and do reasoning on the selected dataset based on the idea of granularity. Besides the inspiration from granular computing [3, 4], especially granular structures [3]. The strategies proposed in this paper are also inspired from Cognitive Psychology studies on human problem solving (e.g. starting point) [6, 21]. Further, we concentrate on how granularity related strategies can help to effectively solve Web scale reasoning problems according to different user context and time constraints.

We also need to point out that although the strategies introduced in this paper are inspired by some basic strategies in granular computing, the granular structures, more specifically granular knowledge structures that are mentioned in this paper are different from previous studies [3, 22]. In granular computing, granules are organized hierarchically from larger grain sizes to smaller ones (or the other way around), and the granules in coarser levels contain the ones in finer levels. In this study, although granules are still in a hierarchy, the granules does not contain each other. In the multilevel completeness strategy, granules are organized into different levels by the node degree under a perspective, granules with higher value of $degree(n, P)$ do not contain those with lower values. In the multilevel specificity strategy, although the hierarchical knowledge structures of Artificial Intelligence has a typical granular structure (All the subtopics are covered under the terms one level coarser than them.), the granular structure of the reasoning results based on this hierarchy is different from the granular structures studied previously [3, 22], since the results which were got from the coarser levels cannot cover finer levels (The reason is that if the user does not have enough time, nodes in finer levels, such as authors of "Decision Trees", will not be selected for the reasoning task whether they are AI authors.).

As an approach for incomplete reasoning at Web scale, unifying search and reasoning from the viewpoint of granularity provides some strategies which aim at removing the diversity and scalability barriers for Web reasoning.

For the diversity issue: The strategy of starting point focuses on user specific background and the unification process is familiarity driven or novelty driven, and is obviously user oriented. Multilevel completeness strategy is with anytime behavior [23], and provides predictions of completeness for user judges when the user interact with the system. Multilevel specificity strategy emphasizes on reasoning with multiple levels of specificity and users can choose whether to go into more specific or more general levels. Multiperspective strategy attempts to meet various user needs from multiple perspectives.

For the scalability issue: In the multilevel completeness strategy, although the partial results may have low completeness, more important results have been searched out and ranked to the top ones for reasoning based on their higher values of $degree(n, P)$. In other words, more important results are provided as a possible way to solve the scalability problems. The starting point strategy also provides two methods to select important nodes for reasoning. The multilevel specificity strategy concentrates on the appropriate levels of specificity controlled by the knowledge hierarchy and does not get into unnecessary levels of data. Hence, under limited time, the reasoning task and time is reduced.

Since user needs are very related to the satisfaction of reasoning results, in future studies, we would provide a comparison from the user perspective on the effects of multiple strategies mentioned in this paper. We would also like to investigate in great details on how these strategies can be combined together to produce better solutions[8]. Since the unification of Web scale search and reasoning from the viewpoint of granularity brings many human problem solving strategies to Web reasoning, it can be considered as an effort towards Web intelligence [24].

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