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Advancements in Meaning Negotiation for Enhanced Semantic Collaboration in Information Systems

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Abstract

Pragmatic Web emerges from Semantic Web to empower human-computer collaboration. The majority of methods rely on knowledge exchange and reuse through ontologies and rules, leading to the development of interactive systems through distributed multiagent systems over the web. Meaning negotiation becomes crucial for agents to reach a consensus on the meaning of concepts within a domain. Various approaches have been suggested to enhance the pragmatics of the web through meaning negotiation. In this scope, Aldo de Moor's pragmatic web model integrates contextual and domain ontologies in a case study. The model explores the potential of ontology merging to enhance the meaning of negotiation. Ontology merging streamlines communication by reducing negotiation steps, and fostering more efficient collaboration across diverse domains. This paper explores the potential of Aldo de Moor's pragmatic web model to improve the meaning negotiation process in multiple domains. To assess the efficacy of merging ontologies in meaning negotiation, the authors designed 123 scenarios applicable to 30 different domain ontologies. These scenarios encompassed various contextual situations, simulating real-world interactions between agents. The effectiveness of our approach is demonstrated in this paper through an example in the e-recruitment domain. The result demonstrated a statistically significant reduction in negotiation steps when using the merged ontology compared to traditional methods. The Kolmogorov-Smirnov test revealed an 87% reduction (p-value $<$ 0.05), highlighting the effectiveness of the approach.

Keywords

Meaning Negotiation; Multi-agent Systems; Web 4.0, Pragmatic Web; Ontologies Merging.

1. Introduction

In today's distributed communities, seamless cooperation, coordination, and communication have become crucial aspects of successful online interactions. The evolution of the web, from Web 1.0 to Web 3.0 (Semantic Web), has transformed information-sharing paradigms. However, despite these advancements, challenges such as semantic heterogeneity (variations in meaning) and the nuances of human language persist (Singh, 2002).

This article explores the Pragmatic Web as a strategic approach to address the limitations encountered by the Semantic Web. It emphasizes human collaboration through a process called ontology negotiation, with a specific focus on meaning negotiation (Van Diggelen, et al., 2007). This crucial process involves harmonizing interpretations of terminology within a semantic framework, essentially bridging the gap between Artificial Intelligence (AI) and the field of Knowledge Representation (KR) (Keskes & Rahmoun, 2017; Schoop, et al. 2006).

This article delves into the intersection of three critical domains: the Pragmatic Web, Artificial Intelligence (AI) and Knowledge Representation (KR), and the negotiation process. Knowledge Representation (KR) deals with how knowledge is formalized and represented for computers to understand and manipulate. In the context of the Semantic Web, ontologies act as formal specifications of knowledge within a specific domain. Meaning negotiation within the Pragmatic Web fosters alignment between the ontologies, ensuring consistent interpretation of data across different systems and applications.

Introducing a streamlined conceptual model inspired by prior research (Keskes & Rahmoun, 2017; De Moor, 2005), our proposed methodology seeks to mitigate complexities within the pragmatic web, introducing a contextual dimension to meaning negotiation. The study contributes practical insights, offering a refined scenario applicable to diverse domain ontologies within the Semantic Web. The comparative analysis, supported by statistical tests, validates the significant impact of ontology merging on the meaning negotiation process.

In the corporate landscape, negotiation, especially meaning negotiation, is vital for establishing customer trust. It ensures alignment with customer understanding and preemptively addresses potential misunderstandings. In e-commerce, negotiation influences discrete transactions and customer relationships, vital for online commerce success. For example, AI-powered chatbots, like Sephora's, utilize negotiation techniques to tailor product recommendations, enhancing sales and customer satisfaction through personalized interactions.

Meaning negotiation within the Pragmatic Web is a crucial community learning process, fostering collective outcomes through verbal or textual discourses on specific objects (Mustapha, 2010). This involves agents converging on agreements via communication mediums, starting with a preferred conceptual representation of an object or concept (Warglien, & Gärdenfors, 2015).

In summary, meaning negotiation in the Pragmatic Web is the process through which agents reach agreements, seeking correspondence between terms in different contextual domains to disambiguate their meanings. The utility of meaning negotiation can be illustrated in different professional contexts.

- Legal Contracts and Agreements: establishing precise meanings, fostering clarity in contracts.

- Medical Diagnosis and Treatment: enabling shared understanding of medical terms, diagnoses, and treatment options.

- **Education:** clarifying of concepts and instructions, improving learning outcomes.

- Marketing and Advertising: Marketers often need to negotiate the meaning of slogans, brand messages, and product descriptions to ensure resonance with the target audience.

These examples highlight the meaning of negotiation's crucial role in achieving effective communication and collaboration across professional domains. Professionals can enhance successful outcomes by embracing meaningful negotiation strategies.

Ontologies serve as crucial components in various domains such as artificial intelligence, Semantic Web, and natural language processing, effectively managing knowledge by providing a structure for sharing and reusing information. This not only facilitates meaningful negotiation but also enhances communication among agents, promoting effectiveness and interoperability within the community.

However, the diversity of ontologies can lead to challenges, resulting in an information overload issue, particularly in common domains. The process of individually querying ontologies for information from diverse sources can be inefficient and time-consuming.

To address these challenges, ontology merging emerges as a crucial process. By consolidating multiple ontologies within the same domain, the process produces a unified and coherent ontology. This merging process proves essential when agents collaborate to understand the context of their group or domain, facilitating the accomplishment of their activities.

Several challenges are associated with ontology merging, including heterogeneity, conflicts, and potential loss of information. Techniques such as vocabulary alignment, schema alignment, and conflict resolution are employed to address these challenges, making ontology merging a valuable tool for integrating and combining knowledge from multiple sources.

2. Literature Review

In meaning negotiation, three key classes—ontological (Keskes & Rahmoun, 2017; De Moor, 2005; Van Diggelen, 2007; Burato, 2011; Maarif, 2020; Zhu, et al., 2021), logical (Burato, 2011), cognitive (Lindh-Knuutila, 2006) and non-structured (Jones, 2020; Schenker, 2021; Myrendal, 2019)—define contextual representation. Ontological representation is widely used for information sharing, and structured domain knowledge, though finding an optimal granularity remains a challenge.

Intelligent agents, acting on behalf of community members, engage in negotiation within distributed environments. Auctions (Keskes & Rahmoun, 2017; De Moor, 2005), as open distributed systems, facilitate competition without altering agents' knowledge. In contrast, argument-based negotiation (Burato, 2011; Van Diggelen, 2007) allows agents to adapt knowledge based on opposing arguments.

A negotiation protocol, governed by a set of rules, enhances intelligent interaction among agents, defining participants, legal proposals, declarations, and negotiation outcomes (Van Diggelen, 2007; Zhu, et al., 2021; Lindh-Knuutila, 2006). Strategies guide agents on task-specific behaviors (Burato, 2011; Myrendal, 2019; Jones, 2020).

The pragmatic model introduces pragmatic constraints to solve problems, offering explicit flexible knowledge in context. In meaning negotiation, it improves communication and retrieves contextually relevant information, crucial for efficient problem-solving. The commercial sector stands out in web-based meaning negotiation (Keskes & Rahmoun, 2017; De Moor, 2005), with the potential for generalization across diverse domains.

The pragmatic model applies specific constraints to address distinct problems, offering precise interpretations within a given context. It serves as a contextual framework for meaning negotiation, enhancing communication, and information retrieval. However, dispersed pattern solutions across various contexts complicate knowledge gathering. To streamline the process, centralizing or integrating solutions becomes crucial.

To integrate heterogeneous information, the paper presents merging methods classified into semi-automatic (Schenker, 2021; Vidyarthi, et al., 2014; Fu, 2016; Negi & Malik, 2018; Makwana & Ganatra, 2018) and automatic (Lindh-Knuutila, 2006; Robin & Uma, 2010; Maree & Belkhatir, 2015; Guo, et al., 2022; Ocker, et al., 2022; Chen, et al., 2022). Generally, all approaches are based on terminological and structural similarity. Semantic similarities (Robin & Uma, 2010; Vidyarthi, et al., 2014; Maree & Belkhatir, 2015), enriched by external resources like WordNet and Power Thesaurus, disambiguate concepts, eliminate redundancies, and resolve inconsistencies.

A pre-treatment step, eliminating stop words and aiding lexical database search, proves essential for effective label relation merge (Vidyarthi, et al., 2014). In summary, understanding the meaning of negotiation and ontology merging approaches is crucial for advancing intelligent interaction and knowledge integration in diverse domains.

3. Ontology Merging Techniques for Enhanced Meaning Negotiation

The Pragmatic Web emphasizes meaning negotiation to reduce communication ambiguities through the use of ontologies. The basic model involves two layers: a semantic layer with domain ontologies and a data dictionary, and a pragmatic layer with contextual ontologies for specific domains. In a commercial scenario, a seller initiates a product proposal to a buyer, adjusting details based on feedback until agreement. The negotiation process involves referencing domain ontologies and a dictionary to disambiguate concepts across different domains and contexts. Successful negotiations contribute to a common pragmatic pattern stored in a shared ontology for future use.

Authors (De Moor, 2005) simplified this model by merging domain and contextual ontologies using the prompt method, reducing steps from 13 to 9. However, this approach has only been studied in a single domain.

This paper focuses on the e-recruitment domain, implementing the meaning negotiation of (Keskes & Rahmoun, 2017) and (De Moor, 2005) using a merging ontology method. Power Thesaurus is employed for merging, facilitating expert collaboration, and eliminating the need for a separate dictionary call. The merged ontology enhances the negotiation process, allowing experts to add new concepts and meanings as needed.

The scenario involves an industrial company and a doctoral researcher. The process involves presenting CV details, comparing profiles, and utilizing ontologies.

The scenario starts with the researcher presenting their CV to the industrial company, which lacks academic domain knowledge. The company seeks assistance from university domain ontology. At the beginning of the process, the researcher initiates the search for a position within the R&D department of the company by sending an initial request that conforms to the specified pattern in their ontology (Step 1). The intermediate agent (broker) receives this request and projects it onto the individual context ontologies of the industrial company (Step 2). However, the company cannot find an exact match in its contextual ontology for the researcher's profile due to its specificity (Step 3).

Consequently, the negotiation process generalizes the initial query and forwards the query back to the intermediate agent (Step 4- generalization of the query). This generalized query now seeks a Faculty_Member as a potential recruit. The intermediate agent then projects this generalized query onto the individual context ontologies of the industrial company (Step 5). The process continues to generalize the initial pattern until it either finds answers or reaches the most generalized pattern possible. This principle can also be applied to queries projected onto the Semantic Web.

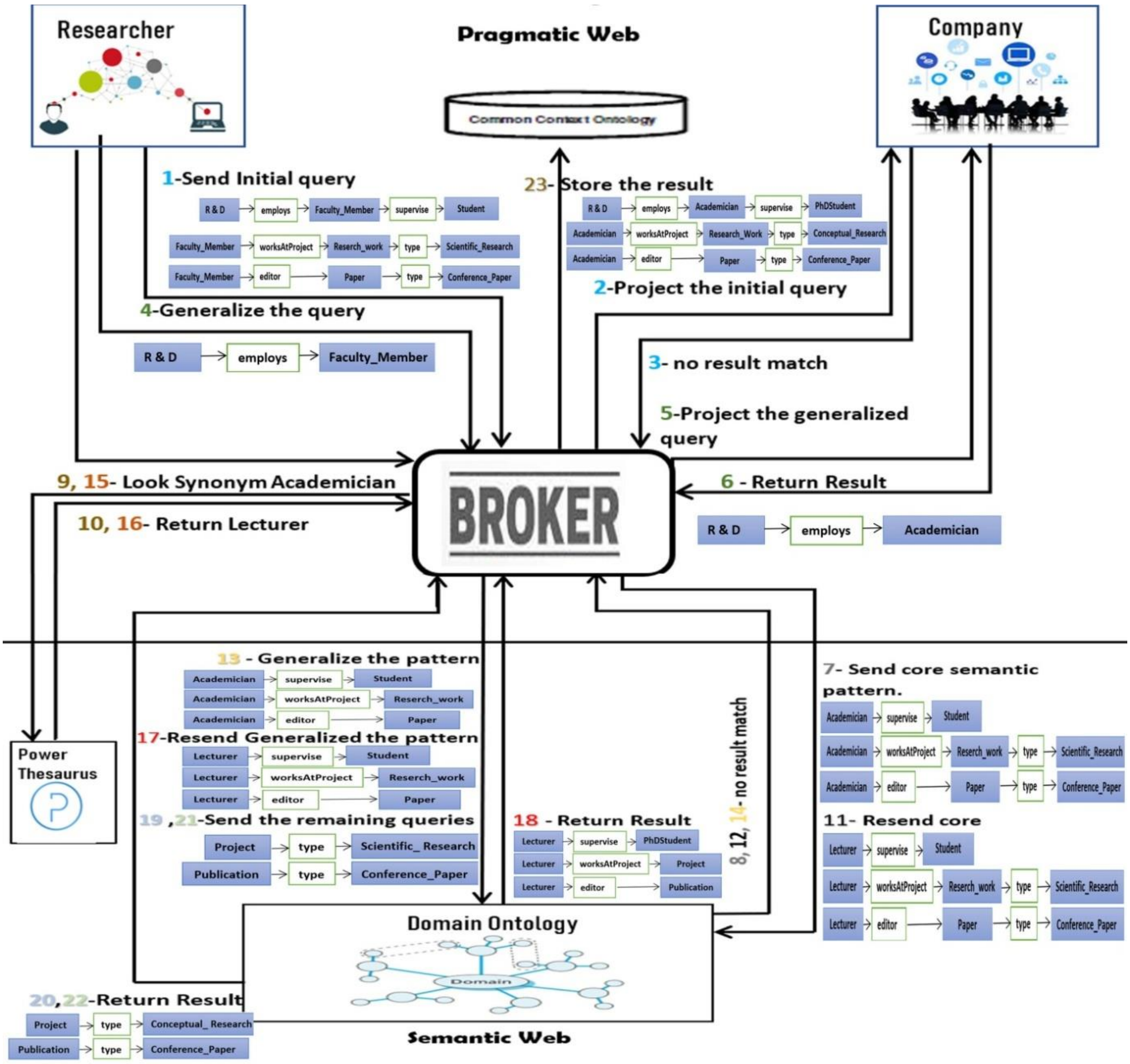

Figure 1: Meaning negotiation process before merging.

After generalization, the company communicates its intention to recruit an academician back to the intermediate agent (Step 6). To ensure alignment with the researcher's profile, the company enriches its knowledge by consulting the domain ontology to match the required pattern. This involves focusing on the semantic pattern, especially the portion following the employs-relation. The intermediate agent then sends this core semantic pattern to a selected domain ontology on the Semantic Web (Step 7).

If no match is found (Step 8), the intermediate agent automatically seeks similar concepts to the academician concept in the Power Thesaurus dictionary (Step 9). Subsequently, the query is resent to the domain ontology (Step 11), replacing the original concept with synonyms retrieved from the dictionary (Step 10 & 16).

If the domain ontologies still fail to produce a matching result (Steps 12 & 14), the intermediate agent proceeds to further generalize the query and resends it for consideration (Steps 13 & 17). These steps are iterated until a corresponding result is obtained (Step 18). The remaining segment of the core semantic pattern, post-generalization, follows a similar treatment process as the preceding steps (Steps 19 & 21), and the final results are returned to the intermediate agent (Steps 20 & 22). Finally, the obtained results are stored in the comment contextual ontology (Step 23).

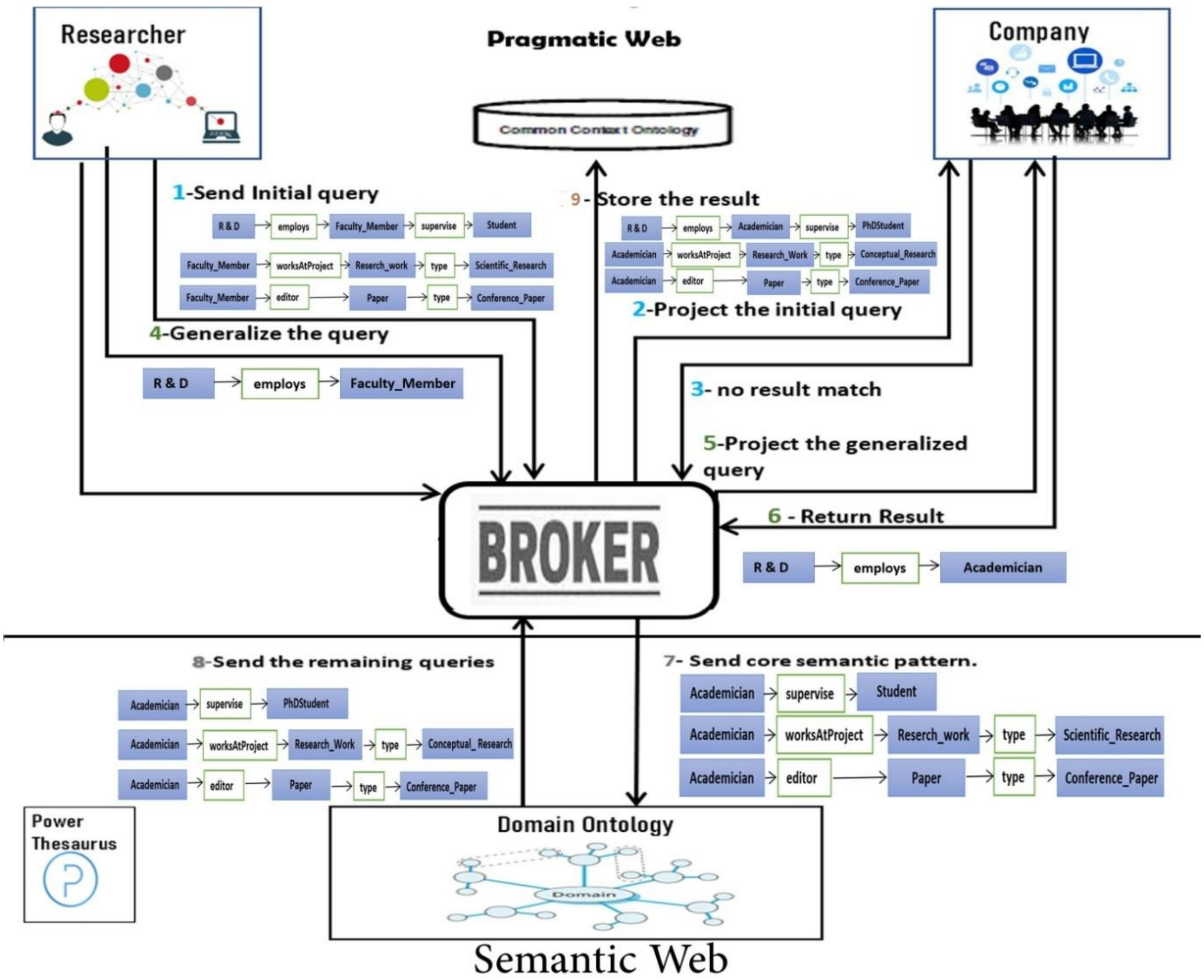

Figure 2: Meaning negotiation process after merging.

The meaning negotiation process, illustrated in Figure 1, comprises 23 steps. The result is added to a common ontology between the researcher and the company as a pragmatic pattern. Implementing the process with merged ontologies reduces the steps to 9, eliminating the need for dictionary calls.

In the merged ontology case, the core semantic pattern query is directly answered by the domain ontology, eliminating the need for generalization or dictionary calls. The overall negotiation process improves by reducing the number of steps from 23 to 9, enhancing cooperation between experts through the dictionary (See Figure 2).

4. Result

In this section, we present the results using frequency tables to highlight information, assessing the achievement of research objectives in comparing the meaning of negotiation process steps with and without ontology merging. The sample size is crucial for statistical tests; a minimum of 30 samples is necessary to establish that a variable follows a probability law.

The sample size of 123 exceeds the minimum requirement of 30 for relying on the normality assumption, validating statistical test results through the Central Limit Theorem for datasets larger than or equal to 30. The variables are qualitative, with estimated theoretical numbers surpassing five. A larger sample size enhances the reliability and robustness of statistical analyses, providing more precise estimates and stronger evidence for drawing conclusions. This comprehensive sample size reflects the execution of various scenarios across diverse domains and contextual situations, showcasing a thorough data collection effort.

Table 1 represents the number of gaining steps according to the number of scenarios. The heading of the table exposes the difference between steps in the negotiation process without and with merging ontologies. It illustrates the decrease in the steps that bring the merging ontologies to the meaning negotiation process. The maximum number of steps gained is 44 (Step numbers of scenario before merging – Step numbers of scenario after merging).

The line represents the number of scenarios in which merging ontologies brought gained steps. For example, thirty-nine scenarios of merging ontologies have reduced the process of negotiation by four steps. The authors found 15 scenarios from 123 where merging ontologies brought no gain to the process.

Table 1. The Result Table.

Number of gained steps	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**20**	**24**	**28**	**44**
Scenario numbers	15	1	39	2	27	3	13	1	8	6	4	2	2

The Kolmogorov-Smirnov (KS) test serves to validate the previous findings by comparing the distribution of a sample to a reference distribution. This non-parametric statistical test computes the KS distance (D) by evaluating the empirical cumulative distribution function (CDF) of the sample dataset (Fobs) against the theoretical CDF of the reference distribution (Fexp). In this context, Fobs represents the observed distribution of scenario numbers according to the number of gained steps, while Fexp embodies the expected distribution derived from a theoretical probability distribution. The theoretical probability distribution is established under the null hypothesis, which posits that ontology merging exerts no influence on meaning negotiation across all 123 scenarios (no gained steps).

The KS statistic (D) quantifies the maximal vertical deviation between Fobs and Fexp, computed as the absolute difference between corresponding values of the two CDFs (D = |Fexp - Fobs|). This statistic reflects the most significant vertical distance between the two cumulative distribution functions, thereby offering insight into the extent of disparity between the sample dataset and the expected distribution. Two hypotheses are defined:

- H0 posits that the ontologies merging process does not impact meaning negotiation, with the assumption that the ontologies merging process exerts no influence across all 123 scenarios of meaning negotiation.

- Conversely, H1 asserts that merging ontologies indeed exerts influence on the meaning negotiation process.

After calculating the KS statistic, the critical value is ascertained based on the sample size and significance level. If the computed statistic surpasses this critical value, the null hypothesis is rejected, signifying a substantial distinction between the observed and expected distributions. Conversely, if the computed statistic falls below the critical value, the null hypothesis is accepted, indicating no notable deviation between the distributions. This decision-making process allows for evaluating if the ontology merging process affects meaning negotiation across diverse scenarios.

Table 2. Kolmogorov-Smirnov Test.

Number of gained steps	**0**	**2**	**4**	**6**	**8**	**10**	**12**	**14**	**16**	**20**	**24**	**28**	**44**
Observed Effective	15	1	39	2	27	3	13	1	8	6	4	2	2

Theoretical effective	123	0	0	0	0	0	0	0	0	0	0	0	0
$\mathbf{F_{obs}}$	0.122	0.130	0.447	0.463	0.683	0.707	0.813	0.821	0.886	0.935	0.967	0.984	1
$\mathbf{F_{exp}}$	1	1	1	1	1	1	1	1	1	1	1	1	1
D	**0.878**	0.870	0.553	0.537	0.317	0.293	0.187	0.179	0.114	0.065	0.033	0.016	0

The highest distance in Table 2 is 0.8780. The Kolmogorov-Smirnov test for n = 123 and a risk threshold of 5% gives the critical value equal to 0.1226. Since 0.8780 > 0.1226, the authors reject the hypothesis H0. The authors conclude that merging the contextual with the domain ontologies affects the meaning negotiation process in several domains positively.

5. Conclusion

In summary, this study addresses the challenge of information overload on the web and highlights the significance of meaning negotiation in the pragmatic web for accessing relevant information. Despite advancements in the Semantic Web, issues like information overload persist.

This paper focuses on pragmatic web development, specifically meaning negotiation via ontology merging. We introduce a simplified meaning negotiation process using a power Thesaurus dictionary, fostering collaboration in the expert domain community and clarifying concept meanings.

Building on the model in (De Moor, 2005) and innovations in (Keskes & Rahmoun, 2017), our work optimizes the negotiation process in multiple domains through ontology merging. Using a benchmark of diverse domain ontologies, we aim to validate the efficacy of this approach, emphasizing run-time efficiency.

Our research demonstrates the impact of merging ontologies on the meaning negotiation process through comparative studies, showcasing improved efficiency. The work contributes to advancing the meaning of negotiation in the pragmatic web, particularly in overcoming challenges of information overload and ambiguity, making the process more efficient across diverse domains.

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Ethics approval

Not applicable.

Conflict of interest

The authors declare that there is no competing interest.

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