Ontology-Based Semantic Interoperability Support in Human-Machine Collective Intelligence Systems

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Abstract. Human-machine collective intelligence systems for decision support are distributed systems involving multiple heterogeneous participants usually represented by services. In order for such systems to function efficiently, the participants have to intensively collaborate, what requires interoperability support. Besides, this support also has to consider auxiliary system elements such as user task description, negotiation protocol, etc. The paper performs a state of the art analysis in the areas of cloud and service-oriented systems and concludes that multi-aspect ontologies that preserve internal aspect ontologies would be the most suitable solution. An example of multi-aspect ontology is presented for a collective intelligence decision support system for the smart city domain.

Keywords: collective intelligence, service-oriented system, heterogeneous community, semantic interoperability, multi-aspect ontology.

1 Introduction

Human-machine collective intelligence is a result of synergy arising due to intensive collaboration between humans and machines aimed at solving a certain task and continuously learning from each other to produce new knowledge. One of the areas that could benefit from collective intelligence is decision making [1]. Due to the distributed nature of such kind of systems and presence of multiple independent participants (community members), they have to self-organise in order to solve the task set. Self-organization stands for mechanisms that enable interactions among community members, which can result in the whole being more than the sum of its parts [2]. That is, self-organization is the mechanism that can help to achieve the main goal of collective intelligence, that is to provide more knowledge than any individual element provides.

However, successful self-organisation can be achieved only if systems the elements (community members) are interoperable with a shared understanding of the task, the context, and each other's perspectives and capabilities [3]. There are four levels of interoperability [4]: technical, semantic, organizational and legislative. Semantic interoperability is understood as shared semantic interpretation of knowledge presented using meta-models. The problem of shared knowledge faces many obstacles in human-machine environments. Namely, different meanings for terms [5], diverse data formats, diverse ontologies reflecting different contexts and area of practice, diverse classification systems, diverse folksonomies emerging from social tagging in various social media [6], and multiple natural languages [7]. All these obstacles exist when heterogeneous teams are aiming at providing collective intelligence.

In 2008, T. Gruber addressed the issue of collective intelligence in the Web, where humans and machines contribute actively to the resulting intelligence, each doing what they do best [5]. Most of the research on the human-machines activities use ontologies as a mechanism enabling interoperability. Ontologies are a mean to represent knowledge about a problem domain in a machine-readable way. They enable obtaining, exchanging and processing information and knowledge based on their semantics rather than just syntax. Ontology is a formal conceptualisation of a particular domain of interest shared among heterogeneous applications [8], [9]. Usually, it consists of concepts existing in the problem domain, relationships between them and axioms. Ontologies are a well-proven tool to solve the interoperability problem,

However, the problem arises due to the independency of the community members. Each of them works within terminology and formalism of own ontology and one cannot make them to agree on that. Besides, solving specific tasks might require certain formalisms of information and knowledge representation. In this case switching to different formalisms would decrease the task solving efficiency and multiple translation of information and knowledge between different formalisms might cause losses of information.

The paper is aimed at answering the question, how to efficiently solve the problem of semantic interoperability support in human-machine collective intelligence systems taking into account the above mentioned limitations. The structure of the paper is as follows. The state of the art review starts with the analysis of ontology usage in cloud computing and service-based systems (Section 2). Then, in Section 3 task-specific ontologies are considered. Finally, the possible solution based on application of the multi-aspect ontologies is proposed in Section 4, which is validated through an example. The results are discussed in the conclusion.

2 Ontologies in Cloud Computing and Service-Based Systems

There is a number of papers that, though looking at cloud-based systems from different perspectives, consider a cloud as a single system (or a class of systems) and propose ontology-based modelling of cloud knowledge. The ontological view of cloud computing [10] as well as the ontology of cloud-based systems [11] do not look into PaaS (Platform as a Service) or IaaS (Infrastructure as a Service) systems and only systematize knowledge about them. The authors of [12] consider an evolution of ontologies for cloud-based systems and discuss ontologies for different types of such systems assuming that all system services use them. Unfortunately, such approaches do not take into account that cloud might consist of multiple independent heterogeneous services and are not aimed to provide for their interoperability.

The discussion on interoperability in cloud computing [13] argues for semantic models' applicability in such environments. It is claimed that "some parts of the scientific and engineering community weren't impressed by early semantic modelling approaches, especially ones that required large up-front investment". However, the authors note that the situation is changing due to appearance of multiple new applications and technologies using detailed semantic models. Ontologies are pointed out as semantic models that can formalize a great level of details and enable reasoning (making inferences and gaining new knowledge) though they are not often used for overcoming the interoperability problem. For example, an approach to use an ontology for locating services presented in [14] does not consider the issue of interoperability at all.

Multiple works propose usage of one central ontology. The review of cloud computing ontologies [15] among other aims, addresses the interoperability between cloud computing services and mentions several other works but all of them propose a single ontology that has to be accepted by all the services.

The mOSAIC ontology [16] can be considered a step to solving the interoperability problem. It has been developed within the FP7 mOSAIC project aimed at creating and exploiting an open-source Cloud API (Application Programming Interface) and a platform for developing multi-Cloud oriented applications. It does consider that cloud services come from different independent providers, however, it concentrates on the technical issues such as deployment, language, technologies, etc.

The problem of service negotiation through establishing Service-Level Agreements (SLA) is addressed in [17]. The authors consider effects of environment changes to the Quality of Service (QoS) and solve it via introducing context-dependent SLA ontology (called "Cloud SLA Contextual Ontology" or "CSLAC'Onto"). The ontology uses Ontology Web Language (OWL) [18] and specifies the main parties of the SLA process and support Semantic Web Rule Language (SWRL) inference rules [19] to perform reasoning. Though this work does not address the interoperability issue, it can be useful for ontology-based specification of the negotiation process in human-machine collective intelligence systems.

This work is "in-line" with the research aimed at application of the Unified Foundational Ontology for Services (UFO-S) to modelling cloud computing systems with the accent set to SLA [20]. It is concluded that UFO-S by itself only accounts for initial agreement relationships and does not account for the factual relationship. In order to provide such a support an extension is needed. It also lacks the description of the multiple roles that services can perform in a cloud computing system.

The approach in [21] is aimed at building two ontologies (general service ontology and software service ontology) through collecting, specifying and defining relationship between components pertinent within the context of service engineering.

A central ontology proposed in [22] is aimed at low-level description of various cloud services in order for a user to find one that better meets current needs. The authors present an example with nine services of independent providers specifying their characteristics within the ontology manually. However, when dealing with tens or hundreds of services this approach unfortunately will not be efficient since manual description of each service would be too time consuming. The same applies to [23] where an ontology-based information model is proposed to describe properties of entities involved in interactions within an industrial environment that unifies data exchange between these.

An approach to enabling ontology-based web service integration for flexible manufacturing systems is based on building an ontology for the given set of orders, products, industrial equipment, manufacturing processes, events and services [24]. The resulting ontology gives significant benefits to automated decision-making in a manufacturing system but does not help to resolve the interoperability problem.

Works requiring development of an ontology for each particular application give a birth to the ontology as a service concept [25]. Ontology as a service (OaaS) is a service where Cloud vendors provide the application and infrastructure to tailor the source ontology to the users' requirements. The authors of the study reported in elaborated ontology extraction and sub-ontology merging process.

One of the possible solution to support interoperability of heterogeneous independent services can be service encapsulation [26]. The usage of uniform resource expression model is proposed based on the shared cloud ontology. The interoperability between decentralized services is achieved through introduction of virtual resources incapsulating the decentralized ones. Wrappers and annotations can be used in a similar way [27]. These approaches seem to be beneficial for environments with more or less stable set of community members, when new ones do not join too often. In more dynamic environments the necessity to create encapsulating service for each new member could be problematic.

3 Ontologies in Decision Support and Interoperability

There are multiple works offering ontologies in the area of decision support. Domain-specific ontologies are used for inference to support decision making [28, 29] and can be based on different formalisms. Different approaches aimed at decision support are also based on the formalisms that better match used techniques. Thus, ontology-based capturing, representing and documenting knowledge related to decisions in the design of complex engineered systems assumes building a hierarchical structure where Decision Support Problem (DSP) are embedded [30]. Utility-based Decision Support Problem (u-sDSP) templates [30] are aimed at documenting and reuse of the knowledge embedded in earlier made selection decisions. They are described in an ontology based on the Frames formalism [31].

The terminological changes are addressed in different ways. The first one that might come to one's mind is ontology matching. The research presented in [32] is aimed at developing a method based on Linked Data and Semantic Web principles for composing microservices through data integration. It uses matching techniques considering under constraints of resource design. The authors have achieved a successful automatic ontology matching but only for microservices designed as data providers.

The domain-aware matching algorithm aimed at translation between different languages [33] also does not produce results reliable enough for matching ontologies of various services coming into and leaving the community on a continuous basis. As stated by the authors its F-measure reaches the value between 70% and 80%. Application of various techniques such as fuzzy string comparison and dictionaries (e.g., Wikipedia) produces similar level of matching accuracy (up to 80% in [34]).

Ontologies are also used as a tool supporting the integration of heterogeneous sources [35], what improves but does not exclude the manual information processing.

The notion of Semantic Drift has appeared quite recently. It stands for phenomenon of ontology concepts gradually changing as our knowledge of the world evolves, what results in obtaining different meanings, as interpreted by various communities or in different contexts [36]. There are no mechanisms directly aimed at modelling ontological knowledge taking into account the semantic drift. However, for example, the apparatus of temporal logics can be applied for this purpose: the authors of [37] propose to address the problem of terms having different meaning at different PLM stages or different company departments through usage of temporal logics, assigning validity timestamps to the ontology concepts and rules.

Integrating knowledge into multi-domain ontologies works only for specific terminology-related tasks as document processing and analysis [38, 39], but are not efficient for tasks that require strict semantics and inference.

Translations between different ontologies are currently almost not paid attention from the scientific community. A new "distributed ontology language" (DOL) ained at description of translations between terminologies and formalisms of different ontologies is proposed in [40] as a part of the OntoIOp (Ontology Integration and Interoperability), a new international standard proposed in ISO/TC 37/SC 3, aiming at filling this gap. However, if a continuous joint usage of diverse ontologies is required, translation back and forth might likely result in the loss of knowledge.

The most promising approach is to preserve the ontologies of services and build some structure on the top of them. An application of top-level ontology called Basic Formal Ontology (BFO) to facilitate interoperability of multiple engineering-related ontologies [41]. The authors present a system of formal linked ontologies by re-engineering legacy ontologies to be conformant with BFO.

A layered framework is proposed in [42] aimed for integration heterogeneous networked data sources, whose heterogeneity originates from different models (e.g., relational, XML, or RDF), different schemas within the same model, and different terms associated with the same meaning. The authors use metadata representation and global conceptualization with further mapping support in order to provide information translation.

The approach presented in [43] is aimed at description of multi-cloud systems where clouds differ both syntactically and semantically. It is built around an ontology-based abstract model that on the one hand is different from models of the clouds, but on the other hand bridges gaps between them through establishing mappings between own concepts and those of particular clouds.

Viewing a problem domain from different viewpoints has resulted in appearance of Multi-Viewpoints Ontology (MVpOnt) where each viewpoint corresponds to the knowledge representation useful to a particular group of people, which coexists and collaborates with other groups [44]. This approach seems to be the most suitable for the problem set.

4 Multi-Aspect Ontology for Interoperability Support in Human-Machine Collective Intelligence Systems

As it was noted before, the most suitable approach to support interoperability in human-machine collective intelligence systems is multi-viewpoints ontology. However, if we consider different interrelated aspects (facets, constituents) of a complex problem domain we can speak of a multi-aspect ontology that on the one hand provides for the common vocabulary enabling the interoperability between different decision-making processes and ontologies supporting these, and, on the other hand, makes it possible to preserve internal notations and formalisms suitable for efficient support of these processes.

It is generally based on three levels (Fig. 1):

- **Global level:** at this level the concepts and rules related to all aspects are located.
- **Aspect level:** at this level the concepts and rules related to one aspect but accessible from other aspects are located.
- **Local level:** at this level the concepts and rules related to one aspect (both accessible from other aspects and not) and are located.

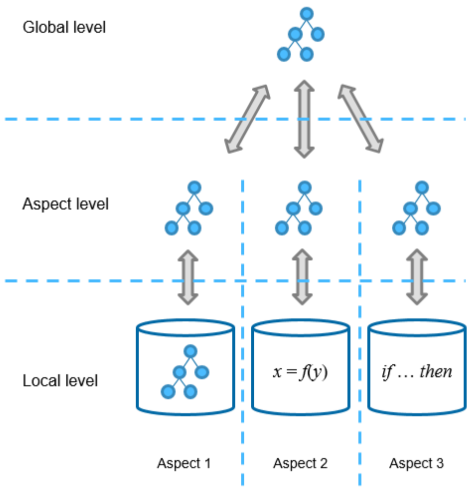

Fig. 1. The main entities of the implemented approach and identified roles

Obviously, the first two aspects have to be described using a formalism, which is global for the system, and the third one – in the internal formalism of the given aspect. There have to be established relationships between the concepts of different levels.

An illustration of a multi-aspect ontology for interoperability support in human-machine collective intelligence systems is based on the domain of decision support in smart city. As the representation formalisms for the first two levels the one proposed in [44] has been used. The illustrative ontology is based on integration of several existing ontologies and considers only three aspects: "*Competences*", "*Negotiation Protocol*", "*User Task*" corresponding to different processes of the decision support based on human-machine collective intelligence. The three aspects are aimed at different tasks and, as a result, they use different formalisms (below, these are described with the most illustrative concepts).

The task considered in the *Negotiation Protocol* aspect is providing an agents with ability to communicate and reach the desired result. Inference rules are defined on top of the negotiation ontology to guide agents' reasoning ability. The negotiation protocol aspect makes agents' negotiation behaviors more adaptive to various negotiation environments utilizing corresponding negotiation knowledge, that does not need to be hard-coded in agents, but it is represented by an ontology [45, 46]. The formalism used in this aspect is OWL, and the example classes are "*Community Member*", "*Human*" (subclass of *Community Member*), "*Agent*" (subclass of *Community Member*), "*Strategy*", "*Utility Function*", "*Parameter*" and "*Role*" (all four are associated with the class *Community Member*).

The *User Task* aspect is aimed at definition of the user tasks in the considered domain (in the given case study the domain is the smart city user information support), their interdependencies and subtasks, as well as functional dependencies between their parameters. The formalism of object-oriented constraint networks makes it possible to define functional dependencies (represented by constraints) between different parameters of the smart city environment then process these via a constraint solver when a particular situation takes place. The internal representation is basically consists of entities, their parameters and constraints defined between them. However, for the interoperability reasons, the following connecting classes are defined at the aspect level: "*Entity*", "*Social*" (subclass of *Entity*), "*Physical*" (subclass of *Entity*) , "*Cyber*" (subclass of *Entity*), "*Parameter*", "*Domain*", subclasses of the *Domain* class (e.g., "*Healthcare*", "*Education*", etc.), "*Rule*".

The third example aspect is *Competences* where competences of the members of the human-machine community. The competences are organized into a hierarchy for facilitating tasks of matching between competences and tasks to be solved. The following classes are considered in this aspect: "*Community member*", "*Competence*", "*Domain*", "*Competence Level*", "*Competence Statement*" (a more detailed description of this ontology can be found in [47]). In this aspect, an OWL ontology is used.

The resulting ontology with all the mentioned classes located at different levels is presented in Fig. 2. The following bridge rules (relationships between concepts) have been introduced:

$Parameter \overset{\equiv}{\leftrightarrow} Parameter_{NegotiationProtocol}$
$Parameter \overset{\equiv}{\leftrightarrow} Parameter_{UserTask}$
$Parameter \overset{\equiv}{\leftrightarrow} CompetenceLevel_{Competences}$
$CommunityMember \overset{\equiv}{\leftrightarrow} CommunityMember_{NegotiationProtocol}$
$CommunityMember \overset{\equiv}{\leftrightarrow} Entity_{UserTask}$
$CommunityMember \overset{\equiv}{\leftrightarrow} CommunityMember_{Competences}$
$Role \overset{\equiv}{\leftrightarrow} Role_{NegotiationProtocol}$
$Role \overset{\equiv}{\leftrightarrow} Role_{UserTask}$
$Domain \overset{\equiv}{\leftrightarrow} Domain_{UserTask}$
$Domain \overset{\equiv}{\leftrightarrow} Domain_{Competences}$

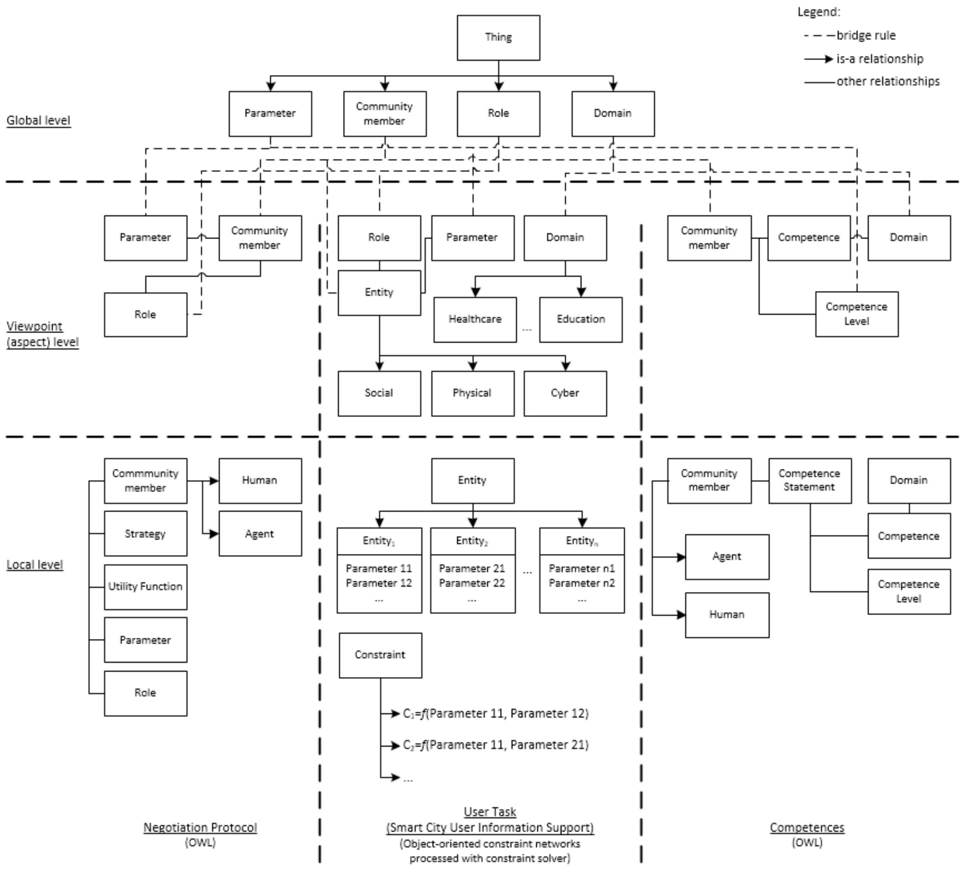

Fig. 2. Multi-aspect ontology for three viewpoints.

i.e., the *Roles* from different aspects are the same roles, and *Entity* from the *User Task* aspect is *Community Member* from the *Negotiation Protocol* aspect. Only the bidirectional inclusion bridge rule indicated with the symbol $\overset{\equiv}{\leftrightarrow}$ is shown in the example that states that two concepts under different viewpoints are equal).

Conclusions

The paper investigates the problem of providing for semantic interoperability in human-machine collective intelligence systems, that are distributed systems involving multiple heterogeneous participants. A state of the art in the areas of cloud and service-oriented systems has been carried out. As a result, it was concluded that multi-aspect ontologies that preserve internal aspect ontologies would be the most suitable solution. An example of multi-aspect ontology is presented for a collective intelligence decision support system for the smart city domain.

The research is currently at an early stage, and building a full size multi-aspect ontology together with prototyping and experimenting are planned as future work. The main limitation visible at the moment is the limited number of aspect ontologies that can be integrated since the building the global and aspect levels is a manual work.

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References

1. Glenn, J.C.: Collective Intelligence and an Application by The Millennium Project. World Futur. Rev. 5, 235–243 (2013). https://doi.org/10.1177/1946756713497331.
2. Bonabeau, E.: Decisions 2.0: The power of collective intelligence. MIT Sloan Manag. Rev. 50, 44–53 (2009).
3. van den Bosch, K., Bronkhorst, A.: Human-AI cooperation to benefit military decision making. In: Proceedings of Specialist Meeting Big Data & Artificial Intelligence for Military Decision Making (2018). https://doi.org/10.14339/STO-MP-IST-160.
4. European Commission: New European Interoperability Framework: Promoting seamless services and data flows for European public administrations, https://ec.europa.eu/isa2/sites/isa/files/eif_brochure_final.pdf.
5. Gruber, T.: Collective knowledge systems: Where the Social Web meets the Semantic Web. J. Web Semant. 6, 4–13 (2008). https://doi.org/10.1016/j.websem.2007.11.011.
6. Harry, H., Valentin, R., Shepherd, H.: The complex dynamics of collaborative tagging. In: Proceedings of the 16th International WWW Conference (2007).
7. Lévy, P.: From social computing to reflexive collective intelligence: The IEML research program. Inf. Sci. (Ny). 180, 71–94 (2010). https://doi.org/10.1016/j.ins.2009.08.001.
8. Gruber, T.R.: A translation approach to portable ontology specifications. Knowl. Acquis. 5, 199–220 (1993). https://doi.org/10.1006/knac.1993.1008.
9. Staab, S., Studer, R. eds: Handbook on Ontologies. Springer Berlin Heidelberg, Berlin, Heidelberg (2009). https://doi.org/10.1007/978-3-540-92673-3.
10. Katzan, Jr., H.: On An Ontological View Of Cloud Computing. J. Serv. Sci. 3, 1–6 (2010). https://doi.org/10.19030/jss.v3i1.795.
11. Youseff, L., Butrico, M., Da Silva, D.: Toward a Unified Ontology of Cloud Computing. In: 2008 Grid Computing Environments Workshop. pp. 1–10. IEEE (2008). https://doi.org/10.1109/GCE.2008.4738443.
12. Bellini, P., Cenni, D., Nesi, P.: Cloud Knowledge Modeling and Management. In: Murugesan, S. and Bojanova, I. (eds.) Encyclopedia of Cloud Computing. pp. 640–651. John Wiley & Sons, Ltd, Chichester, UK (2016). https://doi.org/10.1002/9781118821930.ch52.
13. Sheth, A., Ranabahu, A.: Semantic Modeling for Cloud Computing, Part 1. IEEE Internet Comput. 14, 81–84 (2010). https://doi.org/10.1109/MIC.2010.98.
14. Deng, L., Liu, X.: Cloud ontology semantically improves cloud computing services. In: Liu, H.-C., Sung, W.-P., and Yao, W. (eds.) Management, Information and Educational Engineering. pp. 171–175. CRC Press (2015). https://doi.org/10.1201/b18558-38.
15. Androcec, D., Vrcek, N., Seva, J.: Cloud computing ontologies: A systematic review. In: MOPAS 2012 : The Third International Conference on Models and Ontology-based Design of Protocols, Architectures and Services. pp. 9–14 (2012).

16. Moscato, F., Aversa, R., Martino, B. Di, Fortis, T.-F., Munteanu, V.: An analysis of mOSAIC ontology for Cloud resources annotation. 2011 Fed. Conf. Comput. Sci. Inf. Syst. 973–980 (2011).
17. Labidi, T., Mtibaa, A., Gargouri, F.: Ontology-Based Context-Aware SLA Management for Cloud Computing. In: Lecture Notes in Computer Science. pp. 193–208. Springer (2014). https://doi.org/10.1007/978-3-319-11587-0_19.
18. W3C: Web Ontology Language (OWL), https://www.w3.org/OWL/.
19. W3C: SWRL: A Semantic Web Rule Language Combining OWL and RuleML, https://www.w3.org/Submission/SWRL/.
20. Livieri, B., Guarino, N., Zappatore, M.S., Guizzardi, G., Longo, A., Bochicchio, M., Nardi, J.C., Barcellos, M.P., Quirino, G.K., Falbo, R.A.: Ontology-based modeling of cloud services: Challenges and perspectives. In: PoEM (Short Papers) CEUR Workshop Proceedings. pp. 61–70 (2015).
21. Yustianto, P., Doss, R., Suhardi, Kurniawan, N.B.: Consolidating Service Engineering Ontologies : Building Service Ontology from SOA Modeling Language (SoaML). In: 2018 International Conference on Information Technology Systems and Innovation (ICITSI). pp. 555–561. IEEE (2018). https://doi.org/10.1109/ICITSI.2018.8695936.
22. Nepal, S., Zhang, M., Ranjan, R., Haller, A., Georgakopoulos, D.: An Ontology-based System for Cloud Infrastructure Services' Discovery. In: Proceedings of the 8th IEEE International Conference on Collaborative Computing: Networking, Applications and Worksharing. pp. 524–530. IEEE (2012). https://doi.org/10.4108/icst.collaboratecom.2012.250650.
23. Pullmann, J., Petersen, N., Mader, C., Lohmann, S., Kemeny, Z.: Ontology-based information modelling in the industrial data space. In: 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA). pp. 1–8. IEEE (2017). https://doi.org/10.1109/ETFA.2017.8247688.
24. Cheng, H., Xue, L., Wang, P., Zeng, P., Yu, H.: Ontology-based web service integration for flexible manufacturing systems. In: 2017 IEEE 15th International Conference on Industrial Informatics (INDIN). pp. 351–356. IEEE (2017). https://doi.org/10.1109/INDIN.2017.8104797.
25. Flahive, A., Taniar, D., Rahayu, W.: Ontology as a Service (OaaS): a case for sub-ontology merging on the cloud. J. Supercomput. October, 1–32 (2011).
26. Zhong, Y., Li, W., Guo, W., Gong, L., Lodewijks, G.: A method of modeling and service encapsulation on cloud logistics resources. In: 2015 IEEE 19th International Conference on Computer Supported Cooperative Work in Design (CSCWD). pp. 383–388. IEEE (2015). https://doi.org/10.1109/CSCWD.2015.7230990.
27. Buitelaar, P., Cimiano, P., Frank, A., Hartung, M., Racioppa, S.: Ontology-based information extraction and integration from heterogeneous data sources. Int. J. Hum. Comput. Stud. 66, 759–788 (2008). https://doi.org/10.1016/j.ijhcs.2008.07.007.
28. Ranjbar Kermany, N., Alizadeh, S.H.: A hybrid multi-criteria recommender system using ontology and neuro-fuzzy techniques. Electron. Commer. Res. Appl. 21, 50–64 (2017). https://doi.org/10.1016/j.elerap.2016.12.005.
29. Dustdar, S., Nastić, S., Šćekić, O.: Smart Cities. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-60030-7.
30. Ming, Z., Wang, G., Yan, Y., Dal Santo, J., Allen, J.K., Mistree, F.: An Ontology for Reusable and Executable Decision Templates. J. Comput. Inf. Sci. Eng. 17, 031008 (2017). https://doi.org/10.1115/1.4034436.
31. Wang, H., Noy, N., Rector, A., Musen, M., Redmond, T., Rubin, D., Tu, S., Tudorache, T., Drummond, N., Horridge, M.: Frames and OWL Side by Side. In: 9th International Protege Conference. p. 54 (2006).
32. Salvadori, I.L., Huf, A., Oliveira, B.C.N., dos Santos Mello, R., Siqueira, F.: Improving entity linking with ontology alignment for semantic microservices composition. Int. J. Web Inf. Syst. 13, 302–323 (2017). https://doi.org/10.1108/IJWIS-04-2017-0029.

33. Bella, G., Giunchiglia, F., McNeill, F.: Language and domain aware lightweight ontology matching. J. Web Semant. 43, 1–17 (2017). https://doi.org/10.1016/j.websem.2017.03.003.
34. Song, S., Zhang, X., Qin, G.: Multi-domain ontology mapping based on semantics. Cluster Comput. 20, 3379–3391 (2017). https://doi.org/10.1007/s10586-017-1087-x.
35. Partridge, C.: The role of ontology in integrating semantically heterogeneous databases. , Padova (2002).
36. Stavropoulos, T.G., Kontopoulos, E., Meroño-Peñuela, A., Tachos, S., Andreadis, S., Kompatsiaris, I.: Cross-domain Semantic Drift Measurement in Ontologies Using the SemaDrift Tool and Metrics. In: Joint proceedings of the 3rd Workshop on Managing the Evolution and Preservation of the Data Web (MEPDaW 2017) and the 4th Workshop on Linked Data Quality (LDQ 2017) co-located with 14th European Semantic Web Conference (ESWC 2017). pp. 59–72 (2017).
37. Tarassov, V., Fedotova, A., Stark, R., Karabekov, B.: Granular Meta-Ontology and Extended Allen's logic: Some Theoretical Background and Application to Intelligent Product Lifecycle Management Systems Valery. In: Schwab, I., van Moergestel, L., and Gonçalves, G. (eds.) INTELLI 2015 : The Fourth International Conference on Intelligent Systems and Applications. pp. 86–93. , St. Julians, Malta (2015).
38. Liu, J., Zhou, M., Lin, L., Kim, H. jin, Wang, J.: Rank web documents based on multi-domain ontology. J. Ambient Intell. Humaniz. Comput. 1–10 (2017). https://doi.org/10.1007/s12652-017-0566-5.
39. Kureychik, V., Semenova, A.: Combined Method for Integration of Heterogeneous Ontology Models for Big Data Processing and Analysis. In: CSOC 2017: Artificial Intelligence Trends in Intelligent Systems. Advances in Intelligent Systems and Computing. pp. 302–311 (2017). https://doi.org/10.1007/978-3-319-57261-1_30.
40. Kutz, O., Mossakowski, T., Galinski, C., Lange, C.: Towards a Standard for Heterogeneous Ontology Integration and Interoperability. In: International Conference on Terminology, Language and Content Resources (LaRC). pp. 1–10 (2011).
41. Hagedorn, T.J., Smith, B., Krishnamurty, S., Grosse, I.: Interoperability of disparate engineering domain ontologies using basic formal ontology. J. Eng. Des. 1–30 (2019). https://doi.org/10.1080/09544828.2019.1630805.
42. Cruz, I.F., Xiao, H.: Ontology Driven Data Integration in Heterogeneous Networks. In: Complex Systems in Knowledge-based Environments: Theory, Models and Applications. Studies in Computational Intelligence. pp. 75–98. Springer Berlin Heidelberg, Berlin, Heidelberg (2009). https://doi.org/10.1007/978-3-540-88075-2_4.
43. Quinton, C., Haderer, N., Rouvoy, R., Duchien, L.: Towards multi-cloud configurations using feature models and ontologies. In: Proceedings of the 2013 international workshop on Multi-cloud applications and federated clouds - MultiCloud '13. p. 21. ACM Press, New York, New York, USA (2013). https://doi.org/10.1145/2462326.2462332.
44. Hemam, M., Boufaïda, Z.: MVP-OWL: a multi-viewpoints ontology language for the Semantic Web. Int. J. Reason. Intell. Syst. 3, 147 (2011). https://doi.org/10.1504/IJRIS.2011.043539.
45. Wang, G., Wong, T.N., Wang, X.: An ontology based approach to organize multi-agent assisted supply chain negotiations. Comput. Ind. Eng. 65, 2–15 (2013). https://doi.org/10.1016/j.cie.2012.06.018.
46. Tamma, V., Phelps, S., Dickinson, I., Wooldridge, M.: Ontologies for supporting negotiation in e-commerce. Eng. Appl. Artif. Intell. 18, 223–236 (2005). https://doi.org/10.1016/j.engappai.2004.11.011.
47. Brandmeier, M., Neubert, C., Brossog, M., Franke, J.: Development of an ontology-based competence management system. In: 2017 IEEE 15th International Conference on Industrial Informatics (INDIN). pp. 601–608. IEEE (2017). https://doi.org/10.1109/INDIN.2017.8104840.