Ontological Modelling and Social Networks: from expert validation to consolidated domains

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Abstract. Data from Social Networks is a valuable asset within both a scientific and a business world. In the context of this work, ontological modelling from Social Networks is understood as a knowledge building process to generate a shared domain model. Such a technique relies on a balanced co-existence of human intuition/creativity and technological support, referred to as Hybrid Intelligence. Additionally, it assumes collaborative modelling and collective/social intelligence. The method implies a certain degree of uncertainty that is, in principle, inversely proportional to the achieved consensus. There are two clear different convergence points between the proposed process and collective/social intelligence: (*i*) at a data level, because of the nature of the input which is generated by different individuals, communities, stakeholders and actors; and (*ii*) at a modelling level, where human and automatically generated inputs, design decisions and validations are expected to involve several contributors, experts, modellers or analysts. Although looking holistically at the modelling process, this paper concisely focuses mostly on the ontological structure and the associated uncertainty, while resulting systems and studies are object of future work.

Keywords: Ontology · Social Networks · Ontological Modelling · Knowledge Engineering · Uncertainty · Collaborative Modelling · Hybrid Intelligence.

1 Introduction

Social Networks are a massive source of data and, potentially, of information and knowledge. Indeed, it is largely assumed that, if properly exploited, such data is a valuable asset within both a scientific [1] and a business [5] world. This huge amount of information may become extremely effective in a context of data-intensive modelling, where patterns across massive diverse data may be identified by applying sophisticated approaches and methods.

In general terms, Social Networks present an intrinsic complexity [7] that reflects somehow the corresponding complexity of real world systems and human behaviour/interaction. In fact, data from Social Networks present a significant

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level of entropy and noise. Additionally, human or bot-generated malicious activity is a well-known issue within online platforms, with serious social implications (e.g. on democratic elections [29]).

The great availability of complex data is well integrated with the capability of conceptualization in a machine-processable context [16], as well as AI-based technology is providing more and more support for automated classification and analysis, contributing to further increase the scalability of systematic processes.

Ontological modelling assumes the outcome of the knowledge building process to be expressed as a formal ontology [16]. In the context of this work, the mainstream process relies on Social Network data and on Hybrid Intelligence [13], which is understood as a balanced co-existence of human and artificial intelligence.

In this specific case, we assume a broad definition for human intelligence, which is a combination of analytical capabilities and intuition/creativity. Moreover, as the ultimate goal of the aimed process is a shared domain model, a collaborative approach [50] based on collective/social intelligence [25] becomes a driver factor. There are two clear different convergence points between the proposed knowledge-building process and collective/social intelligence: (*i*) at a data level, because of the nature of the input which is generated by different individuals, communities, stakeholders and actors; and (*ii*) at a modelling level, where human inputs, design decisions and validations are expected to involve several contributors, experts, modellers or analysts.

The target process implies a certain degree of uncertainty, which is a key modelling component, critical to establish trust and transparency. In principle, the resulting uncertainty is considered to be inversely proportional to the achieved consensus.

Another relevant aspect is the actual role of AI in collaborative modelling. Pragmatically and at a very theoretical level, AI could be a kind of "special" collaborator, with more or less relevance in a given context. Ideally, it should be in charge to perform the "dirty work", while humans can focus on the most creative and critical aspects. On the other side, an improper use of AI could de facto nullify the hybrid approach by establishing a kind of AI-driven dominant factor. It intrinsically sets up a major challenge to establish effective hybrid environments resulting from the analysis of the actual implications for the cognitive process.

Although looking holistically at the modelling process, this paper concisely focuses on the Ontology and related uncertainty, while resulting systems and studies, as well as the exhaustive discussion of Hybrid Intelligence are object of future work.

Structure of the paper. The introductory part follows with a concise overview of the background concepts and their state of the art (Section 2), while methodological aspects are addressed in Section 3. The core part of the paper includes a conceptual description of the proposed ontology (Section 4), followed by an overview of the current implementation (Section 5) and by a discussion of potential applications (Section 6).

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2 Research background

An exhaustive review of ontology, its current application within computer systems and its role within hybrid systems is out of the scope of this paper. This section rather aims at providing a concise overview of the relationship between Ontology and data and of the application of Ontology related to Social Networks. Moreover, some considerations on Hybrid Intelligence in the context of the current technological momentum are provided.

2.1 Ontology and Data

Within computer systems, ontologies are commonly understood as resources that represent agreed domain semantics [48]. They are rich data models [16], normally characterised by a relative independence from particular applications or tasks [48].

Ontology-based data management [31] is a well-established approach to access and use data in a underlying information system by means of an ontology which provides a conceptual representation of the domain of interest [31]. Additionally, many applications implicitly need to access multiple heterogeneous data sources from internal and/or external databases as an integrated data space. Ontology enables such an abstraction via interoperability [6]. In general terms, linking data to ontologies increases the capabilities of complex systems within a Semantic Web context [4]. Linked Data assumes structured data from different sources linked by semantics [37].

By enabling a semantic knowledge space, ontologies become valuable also at a functional level to enhance and support complex tasks and processes, such as data mining [14] or enrichment [43].

Ontologies are broadly adopted in the different application domains [42], including, among the very many, Medicine [20], Biology [3] and Software Engineering [18]. Sophisticated applications may be developed over the provided semantic infrastructure. For instance, gene Ontology [3] is an ontology-based tool that ambitiously aims to the unification of biology; AmiGO [9] supports the retrieval of gene product data and associated semantics, while [52] converts high-throughput data to clinical relevance.

2.2 Ontology and Social Networks

Looking holistically at the intersection between social and semantics in the Web [39][23], ontologies are largely adopted in different contexts, at a different level of abstraction and as part of different kinds of system.

At a very general level, Social Networks are a huge source of information and of course such data may be used to populate ontologies [17], as well as, according to an opposite perspective, Social Networks may be described or conceptualised by ontologies [10]. Knowledge/information extraction from Social Network is assumed to be a common practice [14] and the role of ontology is often explicit and relevant.

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Within Social Networks, ontologies are normally used to achieve specific goals, such as, for example, collaborative filtering [8], recommendation system [24], access control [35], enhanced user profiling [49] and privacy preservation [11].

Applications that deserve particular attention in perspective because of their relevance, popularity and potential are related to analysis (e.g. [32]) and prediction (e.g. [38]).

2.3 Hybrid Intelligence

Although it is not probably possible to provide a simple, formal, and universally accepted definition of intelligence, "natural intelligence", proper of humans and animals, is commonly associated with the ability to abstract a given reality to generate some kind of mental model. Such models, which may be very subjective, allow the mental simulations that underlay our normal understanding of thinking and reasoning [33]. Our intelligence enables our capability of analysis, of problem solving and decision making in everyday life [27].

Such a definition is often integrated with "Emotional Intelligence" [36], that puts emphasis on emotions (e.g. empathy), with intuition [26], and with creativity. Additionally, the social context affects the way in which a given reality is perceived and, therefore, the associated mental models. Interactions with other individuals contribute to progressively establish a higher level of intelligence, often referred to as "collective intelligence" [30]. Collective Intelligence is an evolving concept that becomes critical in the era of online Social Networks.

On the other side, computers have naturally pointed out the concept of "thinking machines" [34] and so, indirectly, of AI. AI is currently object of an intense discussion given the last advances in the field, which have generated a mixed of excitement and concern both with a generic advice for reflection.

In this specific technological momentum, Hybrid Intelligence is gaining popularity as, in its most modern definition, it focuses on expanding the human intellect with AI, instead of replacing it [19].

3 Methodology and approach

Because of the intrinsic complexity of conceptualization, especially within a computational context, Ontology Engineering is, in general terms, object of research interest. Methodological aspects on ontology design and maintenance with a focus on both knowledge processes and meta- processes have been addressed with a certain degree of generality [51]. While it is largely assumed that ontology design is a creative activity which extensively relies on human intuition from experts and practitioners [2], an engineering approach is required in order to establish an effective and efficient process to generate exploitable outcomes with a focus on usability/re-usability [22]. Moreover, the quality of ontologies may affect, in general, the quality of semantic datasets and structures [21].

Despite a significant number of contributions [44] and different possible approaches (e.g. human-centred [28], collaborative [46]), as far as the author knows,

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there is no consensus on a reference methodological framework as well as on a relatively systematic process. However, a number of principles have progressively emerged and are commonly accepted [12]. OBO Foundry principles for ontology engineering [47] are commonly adopted within the biomedical domain and may be reasonable applied more in general [45].

In line with this set of principles, the development of the proposed ontology re-iterates the importance of:

- open and public-ally available source
- implementation in a standard formal language
- global identifiers
- annotations and meta-data as part of the implementation
- unambiguous definition of concepts and relationships
- orthogonality and link to other vocabularies

A conceptual description of the ontology is provided in the next section, while some details of major interest on its implementation are proposed later on in the paper.

4 Ontology in concept

A simplified view of the aimed knowledge building process is proposed in Fig. 1a. Such a conceptualization doesn't reflect a fine-grained process but rather a theoretical holistic architecture.

Ideally, three different phases (and associated architectural components) can be identified as follows:

- *Integration.* It aims to systematically establish a knowledge space from input datasets and knowledge/information sources. Such a purpose overcomes data integration as it requires a semantic approach.
- *Analysis.* The knowledge-space is processed as a whole to generate an additional level of knowledge, eventually also including human inputs. Automated capabilities become determinant to approach scalable analysis and modelling.
- *Synthesis.* Final outputs, including analytics and models, are generated from the previous step.

A conceptual representation of *SS-Dom* ontology is proposed in Fig. 1b. Despite the ontology presents a seamless structure at an implementation level (see Section 5), from a logical perspective it is possible to ideally distinguish among at least three different modules (or sub-ontologies): *Data*, *CORE* and *Application*. Such a logical structure results from the underlining process and reflects a focus on usability and flexibility along different possible applications and systems. While *Data* and *CORE* support in close synergy the knowledge-space enabling, *Domain* supports the modelling phase.

Each semantic module is discussed separately in the following sub-sections.

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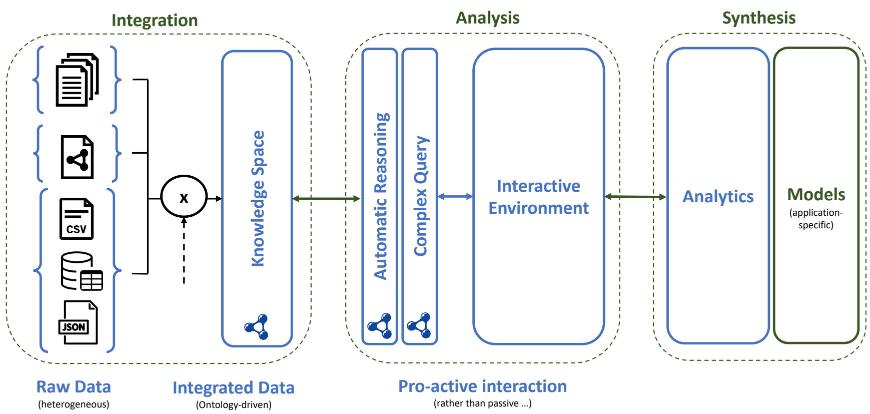
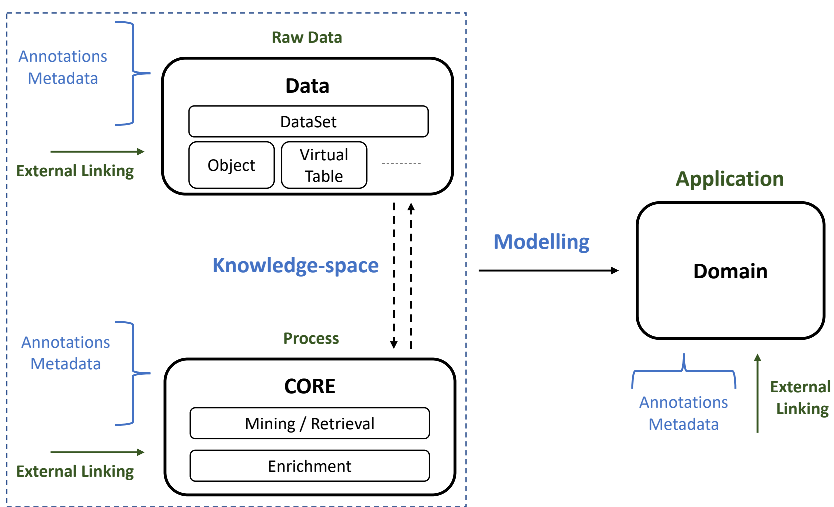


(a) Conceptualization of the aimed knowledge building process.



(b) Ontology overview from a conceptual perspective.

Fig. 1: The knowledge engineering process and its ontological view.

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4.1 Data sub-ontology: dataset & atomic data

The *Data* sub-set deals with a semantic representation of the raw data, understood as the input for the process. This lower semantic level is designed to meet some key requirements for dataset and atomic data specification.

The datasets that take part to the knowledge building process need to be formally specified and semantically characterised [40]. It assures transparency, traceability, as well as enhanced analysis capabilities. The definition of a dataset can vary from case to case and it is not necessarily the traditional one. For instance, a very common case working with data sourced from Social Networks is to consider a data endpoint isolated by a specific retrieval query as a dataset. It allows a further degree of analysis as results may be produced or interpreted as a function of the retrieval method.

The holistic specification of datasets is one of the key requirements at a data level but it is not a sufficient condition by itself to assure a functional semantic environment. Indeed, in order to fully enable an ontology-based process, including internal inference and co-ordination/support for external computations, in general terms data has to be available within the semantic space at an atomic level or a proper access method to external data has to be established. For example, a given dataset from Twitter is semantically specified but also the single objects - i.e. posts and or authors - are described at an ontological level. At an atomic level, typical approaches are based on the mapping of relational models or object-oriented representations into semantic formats.

In summary, the sub-ontology provides two key assets to higher layers:

- Semantically-enriched holistic specification of datasets
- Integrated specification of raw data to support semantic data management

4.2 CORE sub-ontology: retrieving & processing raw data

The sub-ontology previously described provides a relatively static view of raw data and eventual semantic enrichments. The CORE sub-ontology may be considered its natural complement as it focuses on relevant related processes.

Typical examples, where applicable, are the data retrieval process and unstructured text analysis. In the former case, it is important to formally specify the logic adopted to isolate a given dataset, for instance the keywords adopted within a given query. The latter case normally relies on NLP techniques and may typically include, among others, text, topic and sentiment analysis.

At a more semantic level, semantic linking, equivalence and other relationships may be established to generate an enhanced knowledge space. Many recent studies and developments shows how the capability to effectively adopt cutting-edge technology may affect in a determinant way the quality of the final outcome. Therefore this phase may be considered as critical to establish Hybrid Intelligence. While boundaries are assumed to be blurred, an effective approach should take into account the complexity of a cognitive process that largely relies on AI technology.

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4.3 Domain sub-ontology: from expert validation to consolidated domains

This is the most abstracted and, in a way, most application-specific ontological subset. It includes the characterising aspects of the target domain resulting from the knowledge space.

Such a synthesis effort may include different aspects and aim to different interrelated components. A relatively common understanding includes (*i*) the definition of the domain taxonomy, (*ii*) the classification of domain elements according to that taxonomy, (*iii*) relationships among the different domain elements and (*iv*) semantic enrichments, annotations and linking.

As previously introduced, in the context of this work we are assuming a human effort supported by advanced technology to fully exploit the potential of hybrid approach. In order to effectively model shared domains, a collaborative approach reflecting expert and collaborative intelligence becomes critical. While it is reasonable to assume that such a philosophy ultimately increases the quality of the outcome, it also generates in fact a certain degree of uncertainty, which is, in principle, inversely proportional to the achieved consensus. Additionally, collaboration may be one of the key issue to establish a real balanced coexistence of human and artificial intelligence.

5 Current implementation

A detailed description of the Ontology implementation is out of the paper scope. This section rather aims to overview the evolving implementation, which is currently adopted in the different experiments and studies. Such empirical experimentation is providing valuable feedback that is contributing to a progressive consolidation and generalization of the resulting system.

Additionally, the second part of the section addresses the uncertainty model, with a focus on concept classification. Such uncertainty is addressed at an holistic level to reflect an extended collaboration model that involve humans and machines.

5.1 Ontological modelling

The current prototype is based on a formal specification of datasets [40]. The original model has been adapted to import social content from Twitter in a JSON format. Most semantic descriptions and enrichments adopt the PERSWADE-CORE vocabulary [41], which also provides a generic relationship model among ontological elements to be particularised as a part of the modelling process.

A simplified example of ontological model for a given domain is represented in Fig. 2. Such a conceptualization shows an example of class hierarchy at a very small scale, for instance resulting from a preliminary phase. It is composed of two parts, one of which is fully inferred from the other by automatic rules. The taxonomy overall represents the domain model as perceived by final users. However, outputs are generated from the inferred part of the ontology.

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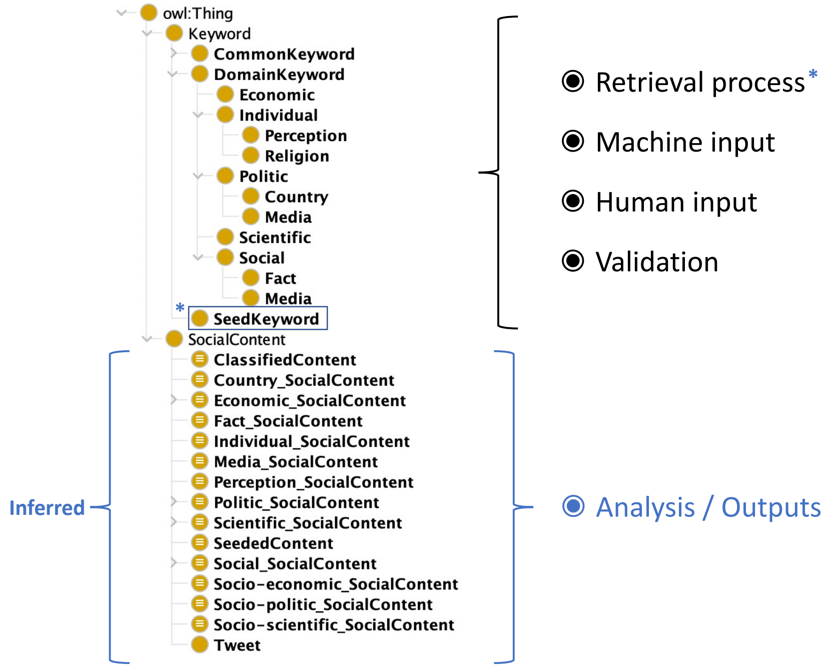

Fig. 2: Example of class hierarchy in Protege [15] and its interpretation.

The ontological model results from a combination of machine inputs, which are expected to be predominant given the amount of data, and human inputs, typically validations or structural modifications. In addition, the retrieval strategy plays a key role as it determines the data endpoints, that are the actual input for the process. There are a number of mechanisms in the system to explicit the retrieval process and to make it part of the final ontological model. For instance, as shown in Fig. 2, the keywords used in the retrieval process are classified under the category *SeedKeyword*; it may facilitate the design of specific filters, if requested at an application level.

From the experience achieved so far, the benefits of ontology and ontological modelling can be informally summarised as follows:

- reduce the gap between humans and machine within hybrid environments
- help to address the complexity of the process
- foster transparency (potentially)

5.2 Modelling uncertainty

As previously addressed, the hybrid approach and the need for automated processing of massive data, intrinsically generate an uncertainty. In general terms,

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because of the collaborative approach, we distinguish between individual (e.g. one user or expert) and shared or collective view of the ontological model.

Given an individual view of a classification for the keyword k from the contributor m, $k|_{u_m}$, a collective view associated with M participants ($K|_M$) may be generated from individual views by union or intersection as in eq. 1 and eq. 2 respectively.

$$k|_M = \cup\, k|_{u_m} \qquad u_m \in M \tag{1}$$

$$k|_M = \cap\, k|_{u_m} \qquad u_m \in M \tag{2}$$

As an example, we assume to aim at modelling a generic COVID-19 domain from Social Networks data. Given the genericness of the topic, it is expected to have a very diversified taxonomy that may include concepts at a different level of abstraction.

Let's assume a collaborative approach for keyword classification involving 3 independent participants. Looking at two specific keywords, $Sweden$ and $Italy$, two contributors provide the same individual view ($Sweden/Italy|_{u_1} = \{Country\}$ and $Sweden/Italy|_{u_2} = \{Country\}$) according to a generic-purpose classification, while the third participant assumes a more contextual interpretation by providing an additional association ($Sweden/Italy|_{u_3} = \{Country, Politics\}$). Depending on the intent and extent of the model, a collective view $Sweden/Italy|_{u_1,u_2,u_3}$ may be generated by union (eq. 3) or intersection (eq. 4).

$$\begin{aligned} &Sweden/Italy|_{u_1,u_2,u_3} = \\ &\quad = Sweden/Italy|_{u_1} \cup Sweden/Italy|_{u_2} \cup Sweden/Italy|_{u_3} = \\ &\qquad = \{Country\} \cup \{Country\} \cup \{Country, Politics\} = \\ &\qquad\qquad = \{Country, Politics\} \end{aligned} \tag{3}$$

$$\begin{aligned} &Sweden/Italy|_{u_1,u_2,u_3} = \\ &\quad = Sweden/Italy|_{u_1} \cap Sweden/Italy|_{u_2} \cap Sweden/Italy|_{u_3} = \\ &\qquad = \{Country\} \cap \{Country\} \cap \{Country, Politics\} = \\ &\qquad\qquad = \{Country\} \end{aligned} \tag{4}$$

The uncertainty p associated with the collective view (k_M^p) is a function of the dis-alignment among individual views and, therefore, may be computed by estimating the distance between the collective view and the individual views. The size of a view is the number of associations that it includes.

Assuming the maximum size of the collective view S computed according to eq. 5 and s_m to be the size of the difference between S and the individual view from the contributor m (eq. 6), uncertainty can be computed as in eq. 7.

$$S = sizeOf\ \{\cup\, k|_{u_m}\} \tag{5}$$

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$$s_m = sizeOf\ \{S - k|_{u_m}\} \tag{6}$$

$$p \ = \ \sum^{m}(S - s_m) \ \ / \ \ M \tag{7}$$

Regardless of the method adopted to generate the collective view - i.e. eq. 3 or 4 - from a uncertainty point of view, the partial dis-alignment may be computed for the example provided as per eq. 7, where $S = 2$ (maximum size of the collective view), $M = 3$ (number of contributors), while the size of individual views is $s_{u_1} = 1$, $s_{u_2} = 1$ and $s_{u_3} = 0$. It results in $p = 0.67$.

This simple model intuitively reflects the idea that a higher consensus - i.e. averagely smaller s_m - is synonymous with a lower uncertainty. There is no clear understanding of the relationship between uncertainty and the number of contributors in a given context. We prefer, therefore, to do not consider the number of participants explicitly in the uncertainty quantification.

In general terms, the same model can be adopted to express (i) the uncertainty associated with a given concept classification (ii) a holistic understanding of the uncertainty (example in Fig. 3).

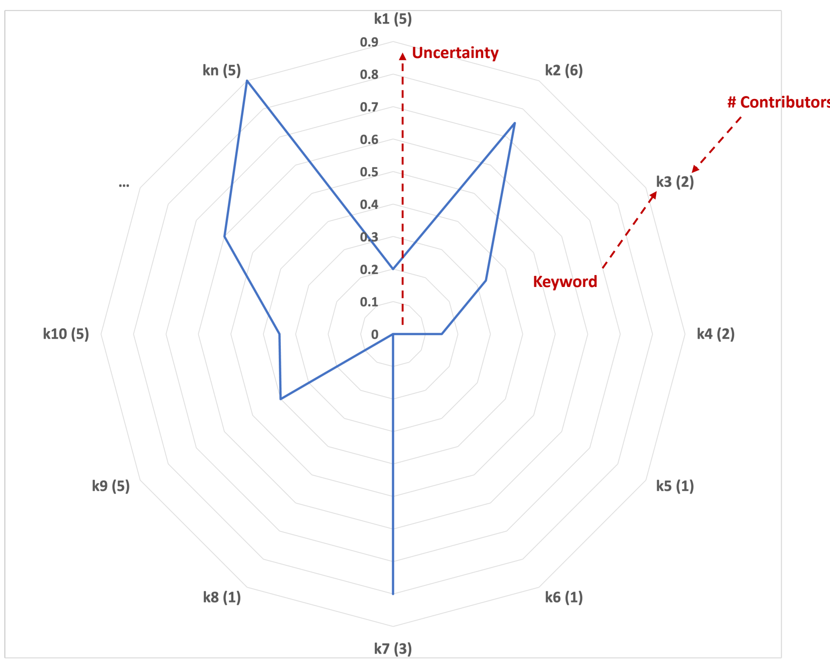

Fig. 3: Holistic visualization of the uncertainty associated with a given classification. This is a mock-up generated from fake data as an example.

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6 Applications

The concept of ontological model from Social Networks implicitly presents a certain generality. Its effective exploitation depends mostly on the quality of the achieved outcome against the intent/scope of the aimed model.

Ontological modelling becomes valuable where conceptualization plays (or may play) a key role, especially when the conceptual model is expected to be machine-processable and adopted within sophisticated computer systems. The benefits emerged from empirical experimentations have been briefly discussed in the previous section.

As previously discussed, Social Networks are a massive source of data, although it is not always easy to convert such a huge amount of data into information or knowledge. It applies also to ontological modelling that requires human intuition, expertise and capability to be integrated with sophisticated computer-based techniques to assure an effective and scalable process along the different stages.

Because of the nature of data from Social Networks, which is mostly human-generated, applications with a social focus may be extremely relevant in this context, as well as those in which collaborative modelling or collective intelligence provide an effective value. Additionally, ontological modelling may contribute to address entropic data at a significant scale.

Ongoing studies adopting the techniques and models addressed in the paper focuses on hybrid technology, situation awareness, controversial (e.g. NO-Vax) and socio-scientific (e.g. Climate Change) issues.

7 Conclusions and Future Work

This paper has discussed ontological modelling from Social Networks in context by concisely summarizing the related body of knowledge. The approach proposed aims to generate a consolidated shared conceptualization of a target domain in an ontological format by applying hybrid techniques resulting from a balanced integration of human intuition/creativity with cutting-edge technology. The collaborative approach considerably increases the quality of the outcome but also introduces a potential uncertainty that is inversely proportional to the achieved consensus.

Although the paper presents a holistic foci on the process, it puts emphasis on ontological structures. Such a semantic infrastructure is expected to be applied within different systems and studies, mostly in the social science domain.

The current implementation as presented in the paper is supporting the initial design of system, the analysis technique, and the integration of the different functional components of the associated research prototype. The ontology is expected to evolve accordingly, in line to an agile philosophy which prioritises effective application, usability and re-usability.

The empirical experimentation conducted so far has allowed to informally identify possible benefits of ontological models within hybrid environments to

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reduce the gap between humans and machine, help to address the complexity of the process, and potentially foster transparency.

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