Multi-Source Knowledge Bases and Ontologies with Multiple Individual and Social Viewpoints

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Abstract

In open environments like the Web, and open Multiagent and Peer2Peer systems, consent among the autonomous, self-interested knowledge sources and users very often cannot be established, and the estimation of trustability and truthfulness of knowledge sources may not be possible. Moreover, competing viewpoints and their communicative contexts even provide valuable meta-knowledge about the intentions of the participants and their social relationships. As a foundational approach to semantically heterogeneous knowledge perspectives, we introduce a formal framework for the computational representation and integration of multi-source knowledge, which makes explicit heterogeneous viewpoints, and conflicting opinions and their social contexts, and allows for the rating, generalization and optional fusion of knowledge by social choice.

Keywords: Semantic Web, Knowledge and Ontology Aggregation and Ranking, Knowledge Provenance, Ontology Merging

1. Introduction

Open environments like the (Semantic) Web, and Multiagent and Peer2Peer systems are characterized by properties like *openness*, *opaqueness of true intentions and true beliefs* of the participants (trustability might not be given or known), high *dynamics* and *complexity*, and the *absence of consented and authoritative knowledge* in general (especially using media like discussion forums, Wikis or Blogs, and in regard to topics like politics, culture, and the assessment of products, other opinions and people). These issues have in common that they rise mainly from the *autonomy* of knowledge sources and users, being black- or gray-box actors with more or less opaque goals and heterogeneous world views. The way such autonomous entities exchange information is *communication*. Information on the web can already be considered as communicative, because it is generated in order to influence its recipients and its intentionality and reliability is often unknown. This is even true if knowledge is exchanged indirectly, tacitly or asynchronously using, e.g., static web sites. Like ordinary communication, web knowledge is also contextualized with other knowledge, and it can be agreed as well as denied by other knowledge on the web. Starting from these observations, we pursue the goal to represent knowledge contributions in regard to their communicative (i.e., social) origin, acceptance and use, not their "degree of being true" or reliable as in most related approaches from multi-party knowledge acquisition and belief revision (e.g., [2, 7]). Thereby, we do not restrict ourselves to a specific formal logic, and do for the purpose of this work also not separate assertive knowledge about individuals and ontological knowledge about concepts.

2. Semantical Perspectives

As an approach to the described issues, our setting consists of autonomous, self-interested *knowledge sources* (KSs) and *knowledge users* (KUs), being, e.g., documents, web sites, data bases, or peers in a Peer2Peer network. We rely on the assumption that both a knowledge source and a knowledge user (and sets like social groups or communities thereof) can be described exhaustively (for our purposes) by her *expected* more or less uncertain *communication attitudes* [8] towards arbitrary pieces of knowledge in terms of *agreement* and *contribution*. These expectations are maintained and, if necessary, revised dynamically by an *observer*, who trails communication processes (e.g., observing web sites or agents).

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"Agreement" is simply the attitude of a KU or KS being *allegedly* in consent (resp. dissent) with a logical statement, and "contribution" states whether the KS is expected to contribute pro-actively a certain statement or type of statement, which means inter alia that the contribution is adequate from the point of view of the contributor in a certain situation, in terms of, e.g., state of argumentation, communication topic and social norms. For example, during a discourse about a certain theme, a KS is expected to agree even with off-topic statements if these are true in her opinion (e.g., when being asked), but contributes only on-topic statements pro-actively. Both attitudes can depend heavily from the respective social context the KS/KU is situated in, including the set of addresses of a knowledge contribution (KC) and the state of the communication process when uttering the KC. E.g., since KSs are autonomous, self-interested entities, and thus need not to be honest or sincere, a certain KS can express opinion a facing knowledge user ku_1 and almost simultaneously assert $\neg a$ facing knowledge user ku_2, even without changing her true beliefs. We represent both attitudes as logical modalities, namely $Agrees$ and $Cont$(-ributes).

As we want to reason about uncertain attitudes also, we allow for probabilistic weights $Pr(...) \in [0;1]$, that is, for probabilistic modalities of the form $Pr(Agrees_{id}(f))$ and $Pr(Cont_{id}(f))$. At this, id denotes a knowledge source (in case of $Agrees$ and $Cont$) or a knowledge user (for $Agrees$ only), and f denotes a logical formula from a language denoted as F. For lack of space, we focus on the $Agrees$ modality mainly. Other attitudes, like *LacksInformation* for KUs are also reasonably, but are not investigated in this paper. *Social contexts* (besides the resp. knowledge targets) are expressed as parts of probability conditions. Precisely, we denote probabilities which depend from a certain social context as $Pr(Agrees_{ks_i}(f) \longleftarrow context)$ and $Pr(Cont_{ks_i}(f) \longleftarrow context)$, with $context = (kt_i, socialState)$, kt_i being a (set of) identifiers of knowledge user(-s) (e.g., agents, web bots, web surfers...) the agreement (resp. contribution) is addressed to, and $socialState$ denoting a social situation. The latter can comprise many kinds of circumstances, like process states, or logical conditions, or time intervals of the form $timePoint_{start}..timePoint_{end}$. For the introductional purpose of this work, we use either logical conditions (conditioning the occurrence of communications, not content truth) or topical state names (e.g., $Cont_{seller}(statement) \longleftarrow (customer, SellingTalk)$). A social state can denote past, present and future situations. In case of past and present states, the respective probability becomes 1 or 0 provided the agreement (contribution) is observable. Observe that the social context might be only a part of the (expected) evidence the maintainer of the probability has. Previous knowledge about the KSs/KUs, e.g. obtained from trust networks, might contribute additionally to these probabilities.

We can now model viewpoints and opinions of autonomous entities (KSs and KUs) in a unified way in terms of their respective communication attitudes towards knowledge, which we unite under the term *perspective* (θ). The $\theta[F']^A$ we are focusing on are called *assertive perspectives*.

$$\theta[F']^A, \theta[F']^C : Id \times Context \times F' \rightarrow [0;1]$$
$$\theta[F'] : Id \times Context \times F' \rightarrow [0;1] \times [0;1]$$

$$\theta[F']^A_{id}(f \longleftarrow context) = Pr(Agrees_{id}(f) \longleftarrow context)) \quad (1)$$

$$\theta[F']^C_{id}(f \longleftarrow context) = Pr(Cont_{id}(f) \longleftarrow context)) \quad (2)$$

$$\theta[F']_{id}(f \longleftarrow context) = (\theta[F']^A_{id}(f \longleftarrow context), \theta[F']^C_{id}(f \longleftarrow context)) \quad (3)$$

At this, $F' \subseteq F$ is a set of formulas the perspective is restricted to. $[F']$ is most times omitted in this paper for simplicity. $id \in Id$ is an unambiguous identifier within a set Id of identifiers of entities currently present in the respective application, denoting either a KS or/and KU (of course, a KU can be a KS also, and vice versa), or simply identifying the respective perspective (i.e., a perspective need not to be explicitly bound to a KU/KS, but can be self-contained also). Technically, e.g. URIs could be used as identifiers. The context is the situation of the entity id when he expresses his opinion with the respective probability. $\longleftarrow context$ can be omitted in order to obtain the probability in absence of any contextual information. If, e.g., $\theta^A_{sellerAgent}(heavy(camera) \longleftarrow (customer_1, ...)) = 1$ and $\theta^A_{sellerAgent}(\neg heavy(camera) \longleftarrow (customer_2, ...)) = 1$, an observer can conclude $\theta^A_{sellerAgent}(heavy(camera)) = 0.5$ if no context is given.

In case the entity id can be queried (i.e., acts in a collaboratively manner upon questions), or has a publicly visible content (like a web page), θ^A can be derived from θ^C using
$\theta^A_{id}(f \longleftarrow context) =$
$\theta^C_{id}(f \longleftarrow (observer, Queries_{observer}(f) \cup context))$, with $Queries_{observer}(f)$ denoting a situation in which entity id is asked iff he agrees with f.

Recall in this respect that of course a perspective does not need to reflect the true (mental) belief of the agreeing/contributing entity. It is also important to see that a perspective is only a more or less uncertain model even of the communication stance of such entities, obtained by an observer from past experience and background knowledge.

If the observer has no knowledge about the attitude of id towards a formula f, a way to express this is to set $\theta_{id}(f \longleftarrow$

$context) = (0.5, 0.5)$, denoting a uniform distribution of such unknown attitudes.

Perspectives show some resemblance to *logical views* [3] and *contexts* (as in *context logic*) (e.g., [6]), and assumably the latter could be modeled as a special case of an assertive perspectives without probabilities and without social contexts (which provide in general no truth conditions for formulas, but pragmatic conditions for their communicative support, usage etc.). We demand that

$$(\theta_{id}^{A}(f \leftarrowtail c) = 1 \wedge \theta_{id}^{A}(f \rightarrow f' \leftarrowtail c) = 1) \rightarrow \theta_{id}^{A}(f' \leftarrowtail c) = 1 \quad (4)$$

$$\theta_{id}^{A}(f \leftarrowtail c) \geq \theta_{id}^{C}(f \leftarrowtail c) \quad (5)$$

and

$$(\theta_{id}^{A}(f \leftarrowtail c) = p) \rightarrow (\theta_{id}^{A}(\neg f \leftarrowtail c) = 1 - p) \quad (6)$$

In order to model *social* perspectives, each of multiple agents, we also allow for sets of KSs and KUs (cf. 3.1 and 3.2 also for the fusion of multiple individual perspectives): $\theta_{\{id_1,...,id_n\}}^{A}(f \leftarrowtail context) =$

$$\frac{\sum_{i=1}^{n} \theta_{id_i}^{A}(f \leftarrowtail context)}{n} \quad (7)$$

$\theta_{\{id_1,...,id_n\}}^{C}$ is lifted analogously.

3. Perspective Generation and Taking

An observer aiming at modeling knowledge sources or users might faces the situation that only a subset of formulas is given as positive or negative evidence for the respective perspective (e.g., explicitly given as a technical KB, or from a voting process). In this case, the observer needs to generate missing information from the given core set of explicit examples. A set of such examples is given in the form of a so-called *quoted knowledge base* (QKB):

A *quoted knowledge base* is a set of formulas annotated with KS/KU identifiers, i.e., $\{(id_1, f_1), ... : id_i \in Id, f_i \in F\}$.

The generation of a perspective (without considering its contexts) from such a QKB *qkb* can be done as follows: $\forall f \in F', \theta[F']_{id}^{A} = gen_{id}^{A}(qkb)$, with

$$gen_{id}^{A}(qkb, f) = 1 \leftrightarrow \exists (id, f') \in qkb : f' \vdash f \quad (8)$$

$$gen_{id}^{A}(qkb, f) = 0 \leftrightarrow \exists (id, f') \in qkb : \neg f' \vdash f \quad (9)$$

$$gen_{id}^{A}(qkb, f) = 0.5 \leftrightarrow (\neg \exists (id, f') \in qkb : f' \vdash f) \quad (10)$$

$$\wedge (\neg \exists (id, f') \in qkb : \neg f' \vdash f) \quad (11)$$

or alternatively:

$$gen_{id}^{A}(qkb, f) = semanticDist(f, \{f' : (f', id) \in qkb\}) \quad (12)$$

The KB content is treated as being non-monotonic, since it is used as evidence for a perspective, and not as an exhaustive description of it. $semanticDist$ measures the semantic distance of a formula and other formulas. Being out of the scope of this paper, please refer to [4] for details.

The inverse way (obtaining a QKB or a KB from perspectives) is covered at the end of this section in the context of *socially reified knowledge bases*.

We can create a set of possibly heterogeneous perspectives $\{\theta_1, ..., \theta_n\}$ from a single possibly inconsistent unquoted knowledge bases $kb = \{f_i : f_i \in F\}$ using some perspective grouping function. This can be considered as some kind of "reverse engineering" of a multi-source knowledge base. *group* might take into account the degree of inconsistency and/or the topical distances within the KB. We restrict ourselves here to a simple case where the grouping function creates so-called *maximally-consistent* subsets of KBs [5]:

$$\{\theta_{id1}^{A}, ..., \theta_{idn}^{A}\} = \{gen_{id1}^{A}(\{(ks_1, id1), ..., (ks_{1_1 m}, id1)\}) ... gen_{idn}^{A}(\{(ks_n, idn), ..., (ks_{n_n m}, idn)\}) : \{ks_i, ..., ks_{i_i m}\} \in con(kb) \wedge \forall ce \in con(kb) : \neg(\{ks_i, ..., ks_{i_i m}\} \subset ce)\} \quad (13)$$

using $con(kb) = \{ks \subseteq kb : ks \nvdash \perp\}$ (i.e., all consistent subsets in kb).

A *single* perspective can be obtained from a possibly inconsistent KB using learning techniques from, e.g., *Stochastic Logic Programming*, given that the KB consists of ground formulas. The *merging of perspectives* (cf. below) is also a way to obtain probabilistically consistent perspectives from inconsistent knowledge bases, given that this knowledge base is given indirectly as a set of perspectives.

Grouping can also be done with a QKB instead of a KB in order to retrieve "knowledge communities", i.e., sets of virtual perspectives corresponding to sets of KUs/KSs (resp. their identifiers) assumably sharing certain knowledge and thus forming social groups emergent from communicated opinions. Again, with the simple consistency criterium:

$$\{\theta_{id_{1_1} \sqcup ... \sqcup id_{1_1 m}}^{A}, ..., \theta_{id_{n_1} \sqcup ... \sqcup id_{n_n m}}^{A}\} = \{gen_{id_{1_1} \sqcup ... \sqcup id_{1_1 m}}^{A}(\{(ks_1, id_{1_1} \sqcup ... \sqcup id_{1_1 m}), ...\}) ... gen_{id_{n_1} \sqcup ... \sqcup id_{n_n m}}^{A}(\{(ks_n, id_{n_1} \sqcup ... \sqcup id_{n_n m}), ...\}) : \{(ks_i, id_{i_1}), ..., (ks_{i_i m}, id_{i_i m})\} \in con'(qkb) \wedge \forall ce \in con'(qkb) : \neg(\{ks_i, ..., ks_{i_i m}\} \subset dropId(ce))\} \quad (14)$$

using $con'(qkb) = \{qks \subseteq qkb : dropId(qks) \nvdash \perp\}$ (i.e., all consistent subsets in qkb ignoring quotation) and $dropId(\{(f_1, id_1)...\}) = \{f_1...\}$.

The $id_{j_1} \sqcup ... \sqcup id_{j_j m}$ denote composite "community" identifiers, consisting of multiple identifiers of KS contributing consistent sets of formula within the qkb. Note that such "communities" can overlap. Topical grouping using θ^C instead of θ^A would work analogously again, but would require a grouping function which groups those formulas contributing to the same topic (e.g., the identifiers of contributors of inconsistent formulas like a and $\neg a$, but also $fast(digicam_1)$, $slow(digicam_1)$ and $camera(digicam)$ would be considered to be within the same topical community).

Given a set of multiple perspectives, we can state easily how the elements of a certain knowledge base (including ontologies) are "viewed" (agreed, liked...) from these perspectives. This leads to a *socially reified* knowledge base (SRKB):

A *socially reified knowledge base* $srkb(p)$ over a set of pairs of perspectives and social contexts $p = \{(id_i, c_j), ..., (id_n, c_n)\}$ is defined by

$$srkb(p) = \{(f_i, \{id_1 \leftarrowtail c_1\text{':'}\theta_{id_1}(f_i \leftarrowtail c_1), ..., id_n \leftarrowtail c_n\text{':'}\theta_{id_n}(f_i \leftarrowtail c_i)\}) : f_i \in F\} \quad (15)$$

Example:
$\{(fast(digicam), \{buyer \leftarrowtail (\{...\}, Testing) : (0.4, 0), seller \leftarrowtail (\{buyer\}, Selling) : (1, 1)\}), seller \leftarrowtail (\{...\}, Testing) : (0.3, 0)\})\}$. Here, KU $buyer$ is expected to approve that a certain digital camera is fast with probability 0.4 when testing it, but is not expected to utter this opinion pro-actively. KS $seller$ approves that the camera is fast with probability 1 in a selling talk (context $Selling$), and with probability 0.3 when testing it by himself.

A QKB or SRKB can be obtained via the annotation of an ordinary KB, or (trivially) from a set of perspectives directly. Since a perspective might generate attitudes (Agrees, Contributes) for every possible formula f (0.5 denoting maximal uncertainty), restricting the inclusions using a filter function appears to be reasonable, e.g. filtering out formulas and perspective annotations using a condition like $\varepsilon \leq \theta_{id}^{A/C}(f) \leq 1 - \varepsilon$.
We denote QKBs/SRKBs obtained from perspectives as $srkb(\{\theta_{idi}\})$ (resp. qkb).

An un-quoted KB $kb(pset, context)$ obtained from a set of perspectives $pset$ is defined as $\{f : \exists \theta_{id}^A \in pset : \theta_{id}^A(f' \leftarrowtail context) = 1 \wedge f' \vdash f\} \cup \{\neg f : \exists \theta_{id}^A \in pset : \theta_{id}^A(f' \leftarrowtail context) = 0 \wedge \neg f' \vdash \neg f\}$. Obviously, such a KB can be inconsistent.

How a set of perspectives can be retrieved from a QKB has been shown already. Analogously, we define the set of perspectives obtained from a subset $srkb'$ of some socially reified knowledge base to be $pset(srkb')$. This is done basically in the same way as in the QKB case (details omitted for lack of space).

3.1. Perspective Merging and Generalization

Perspectives can be merged using social choice techniques. For our purpose, we outline several methods to form a single merged perspective from a set of other perspectives (for lack of space for the merger of pairs of assertive perspectives only). Of course, these approaches can be combined and extended in various ways.

Majority voting Given a set of (assertive) perspectives $\{\theta_{idi}^A : idi \in Id\}$ and a formula f, for the resulting perspectives the following holds in this case: $\theta_{merger}^A(f \leftarrowtail c) = max(min(|\{\theta_{idi}^A : \theta_{idi}^A(f \leftarrowtail c) \geq \gamma\}| - |\{\theta_{idi}^A : \theta_{idi}^A(f \leftarrowtail c) < \gamma\}|, 1), 0)$, with γ being some trigger value for approval (e.g., 1).

Social power or reputation In case there is a linear order $id_1 \succ id_2 \succ ...id_n$ or values $rep(id_i) \in [0; 1]$ given (obtained e.g. from a *Social Network*), denoting the social power or the reputation (resp. trustability, credibility...) of some KS, it can be used to weight perspectives, for example using $\theta_{merger}^A(f \leftarrowtail c) = \frac{\sum_{i=1}^n \theta_{id_i}^A(f \leftarrowtail c) \cdot rep(id_i)}{n}$. In [2], a similar approach has been used in the context of dynamic knowledge bases.

Averaging This is simply achieved with $\theta_{merger}^A = \theta_{\{idi:idi \in Id\}}^A$. We consider this to be the "purest" method to determine the social support for some assertion, for our purpose even in favor of commonly used "biased" ways like majority voting or the consideration of KS reputation. Our kind of averaging is related to *Bayesian Aggregation* (e.g., [1]), but aggregates and retrieves, as described in section 2, the context-depended probabilities of communicative actions supporting formulas instead.

Supporters vs. Opponents Similar to averaging, but under consideration of those perspective only which certainly have a determined opinion about the formula: $\theta_{merger}^A(f \leftarrowtail c) = \frac{|supporters_f|}{|supporters_f| + |opponents_f|}$, with $supporters_f = \{\theta_{id_i}^A(f \leftarrowtail c) : \theta_{id_i}^A(f \leftarrowtail c) = 1\}$, $opponents_f = \{\theta_{id_i}^A(f \leftarrowtail c) : \theta_{id_i}^A(f \leftarrowtail c) = 0\}$.

Strictly common ground
$\theta_{merger}^A(f \leftarrowtail c) = 1 - min(|\{\theta_{idi}^A : \theta_{idi}^A(f \leftarrowtail c) < 1\}|, 1)$

In addition to the merging of multiple perspectives, *generalization* is also concerned with the preceding selection of which perspectives to be merged. We will need this in 3.2 to combine perspectives according various criteria in order to reduce the complexity of the possibly very large number of individual perspectives in environments like the internet (e.g., one user of a socially reified KB might be interested in the viewpoint of "the average contributor" only, whereas other might want to know the opinions of all single contributors). This is achieved by selecting and subsequently merging subsets of perspectives from a larger set $pset$. The specific technique proposed here is derived from the simple observation, that a (plain) knowledge base obtained from a single perspective should be consistent, whereas a KB obtained from the union of multiple such KBs is maximal inconsistent, compared to the union of every subset of such KBs. We use this for a leveled generalization, where each generalization step obtains mergers from mutually "rather consistent" perspectives obtained recursively by the preceding step. The idea thereby is that having multiple consistent perspectives annotating a KB is assumably uninteresting (because these perspectives a likely similar anyways), and thus such perspectives should be merged earlier than rather inconsistent perspectives (surely an assumption that might be not adequate for every application).

$$generalize(pset, merge, steps, context) = \begin{cases} \{merge(set_j) : set_j \in 2^{pset}\} \text{ if } steps = 0 \\ generalize(\{merge(set_j) : set_j \in (2^{pset} \setminus ls)\}, \\ \quad merge, steps - 1) \text{ otherwise} \end{cases} \tag{16}$$

with $ls = set'_0, kb_0 \preceq kb_1 \preceq ... \preceq kb_n$,
$kb_i = kb(set'_i, context), \{set'_i\} = 2^{pset}$.

At this, $merge$ is a merging function, and $\preceq$ is a inconsistency *score ordering* [5] (intuitively, kb_1 is less inconsistent that kb_1 if $kb_1 \preceq kb_2$). Observe that ls is determined non-deterministically (a score ordering is not unequivocal), so there is a choice of which element of the power set should be dropped at each generalization step.

3.2. Opinion Bases

Opinion bases (OB) are a basic kind of *Open Knowledge Bases* [9], defined upon socially reified knowledge bases, with special features making them more easy to use and to display. Specifically, i) the perspectives used to reify knowledge are obtained from the KB itself (making the KB *reflective*), ii) a number of generalization steps is applied to the KB, and iii) the KB is presented as a table. Formally, an *opinion base* is a tuple

$OpBase(srkb, cset, generalize, step, merge, rows)$, with

- $srkb$ being a subset of a socially reified knowledge base,
- $cset$ being a set of social contexts the creator of the OB is interested in,
- $generalize$ being a generalization function (cf. previous section),
- $step \in \mathbb{N}_0$ being the generalization step of the opinion base,
- $merge$ being a merger function such that $merge(\{\theta_{idin_j} : idin_j \in Id\}) = \theta_{idout}$, and
- $rows = \{rowcluster_i\}$ being a set of row clusters (the "output" of the OB), each corresponding to a different formula within $srkb$. Hereby, each $rowcluster_i$ is a set $\{(id_j, c_k, \theta_{id_j}(f_l \longleftarrow c_k)) : id_j \in ids(generalize(pset(srkb), merge, step, c_k)), c_k \in cset, f_l \in formulas(srkb))\}$.
  Recall that $pset(srkb)$ retrieves a set of perspectives from a SRKB. $formulas$ shall obtain the plain KB from a SRKB (i.e., stripped from perspective annotations), and id shall retrieve the identifiers in a set of perspectives.

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