

A map without a legend

The semantic web and knowledge evolution

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Abstract. The current state of the semantic web is focused on data. This is a worthwhile progress in web content processing and interoperability. However, this does only marginally contribute to knowledge improvement and evolution. Understanding the world, and interpreting data, requires knowledge. Not knowledge cast in stone for ever, but knowledge that can seamlessly evolve; not knowledge from one single authority, but diverse knowledge sources which stimulate confrontation and robustness; not consistent knowledge at web scale, but local theories that can be combined. We discuss two different ways in which semantic web technologies can greatly contribute to the advancement of knowledge: semantic eScience and cultural knowledge evolution.

Keywords: semantic web, linked data, big data, open data, knowledge, knowledge representation, ontology, machine learning, web of data, reproducible research, eScience, cultural evolution

1. Life before the semantic web

Many animals are able to learn from their environment. This can be achieved through perceiving the environment and experimenting with it: acting and learning from the results of actions. Some of these animals learn from others. Most of them do it by mere imitations, such as birds learning songs [1]. However, it is known that some monkeys are able to signal danger and even that some other species can learn the signal from others [2].

The resulting behaviour shared among a population is called culture. Culture encompasses know-how, knowledge, languages, traditions, among other things, and does not have to be explicitly expressed.

Human beings are special among these species because they can express the knowledge¹ that they learn and communicate it to other human beings.

¹In this paper, knowledge is not opposed to belief, but to data, as customary in the field of knowledge representation. Thus, we are

Bees can communicate how to reach food sources in an articulated language, but this stunning capability seems to be fixed. Direct knowledge communication is a very powerful mechanism because it leads to transmit knowledge without having to relearn it from experience. This capability grew slowly and led to teaching, monasteries, universities, and conferences.

Besides articulated expression, written expression and communication have allowed to get rid of time and space in knowledge transmission. Through tablets, rolls, books, libraries, or scholar journals it is possible to build on someone else knowledge without even meeting.

This led to a variety of ways to acquire knowledge: by observing and experimenting, by imitating, by communicating (talking, writing, reading). These key fea-

not focusing on the epistemological status of statements, but on their form. Knowledge is concerned with general statements; data with particular statements.

tures have provided a selective advantage to the human species. This has been more eloquently storytold [3].

The worldwide web, facilitating cultural exchange, is a culminating point in this story, so far. One initial achievement of the web has been to make knowledge more easily and readily accessible across the planet. Knowledge was expressed in a not-very different way than before: through natural language texts and pictures, later through movies, interpretable by human beings. Those who have experienced the transition of the world before and after the web can only be grateful. The ease of use of the web pushed knowledgeable people all over the world to provide worldwide access to their knowledge. In this respect, wikipedia and stackoverflow in which millions of individuals care about articulating what they know for others, are just two but wonderful and precious successes.

Hence, a semantic web [4, 5], allowing machines to grasp this knowledge, is a tremendous idea.

2. The data advent: a little semantics went a long way... but may remain stuck here

The semantic web could be characterised by one of its early slogans: a web for machines. Not only for humans, but also for machines. The web was already processed by machine, but its content was aimed at being interpreted by human beings. More precisely it meant that the *content* of the web would be more machine processable.

However, there may be various understanding of ‘content’. It could be metadata: a set of attributes that help web search and classification. It could be precise data that is interpreted by specific programs, e.g. calendars or software dependencies. It could be relatively general knowledge representations of the content, such as causal relations or universal statements. Technologies developed by the W3C Semantic web activity covered these three aspects.

The semantic web did not immediately took off. This is not particularly surprising, but in our world in which everything has to change fast, this is considered a shortcoming. In particular, though enthusiastic scholars had been eager to develop sophisticated representations or ontologies, these were instantiated with little data. Hence of little *practical* use.

It was necessary to provide data to this semantic web because no one was interested by a bunch of theorem provers. Fortunately, by that time, the web was not short of data. Linked data [6], building on semantic

web technologies, was welcome to benefit from these data and semantic web technologies. The linked data trend was spot on as it met other trends such as openness, big data, and later, data flow from the internet of things. Governments supported the process to connect data sources of administrations. Companies competed to acquire giant meshes of data on which they could run cleverly engineered pieces of software to learn what was there.

Moreover, data is the fuel for the knowledge mill. The availability of data, and computing power, unleashed the amazing capabilities of data analytics and machine learning from these data. This made some sense on top of raw data, that which can lead to impressive applications. Hence, it effectively contributes to make the web more intelligible to machines [7].

Nowadays, web users are not expected to provide knowledge, nor to access it. It seems that they are mere data provider, mostly through their actions, e.g. click, buy, like. These data are machine processable, but not open. They are kept secret, in silos, to the exclusive exploitation of a single organisation. They are processed by corporations which eventually learn knowledge from that data. But this knowledge, in turn, is not shared nor even prone to be communicated because not necessarily expressed in an articulated language. Instead, it is directly actioned. Hence, knowledge does not improve.

3. For knowledge!

After twenty years, the semantic web field is mostly focused on data, even when it is made of so-called knowledge graphs.

Of course, schemata and vocabularies are used. But, they are most of the time used for helping machines to parse data. Most of them simply express the structure and eventual relations between entities, but not what we know about them. Hence, the interpretation of data relies on the system after parsing. Knowledge is not made explicit nor shared; it is not available for scrutiny, reuse or evolution.

A semantic web without knowledge is for machines like a map without a legend for humans. The lack of a legend does not prevent to distinguish a road from a river, a bridge from a boat shuttle. But it does not help understanding how these can be used to travel. It does not enable the explorer to plan her trip, by reasoning on elevation or humidity.

1 Hence, this seems like a regression which brings us
2 down the knowledge evolution ladder: humanity may
3 eventually be fed with data, but any knowledge will
4 have to be learnt again and again.

5 This is why the grand goal of formally expressing
6 knowledge on the web must be rehabilitated. One am-
7 bition of the semantic web was to make knowledge
8 available to machines, so that at least they can help
9 us work with this knowledge, not only to find it out
10 but to process it, to improve it and to communicate it
11 to the world [7], as the next knowledge medium [8].
12 This could have led to a further knowledge ecosys-
13 tem in which knowledge is elaborated while it is used
14 for providing services. Like the web can be seen as
15 a data washing machine [9], all the knowledge of the
16 web, may be used to clean up and to improve knowl-
17 edge. Reconsidering knowledge sharing and evolution
18 at web scale would empower humans and machines
19 alike with knowledge that can be both used to provide
20 services and jointly refined and elaborated.

21 The goal is not to build the all-encompassing ontol-
22 ogy with which everyone will agree. Knowledge does
23 not have to be centralised: diversity is source of dispu-
24 tation and robustness. Knowledge is not cast in stone
25 for ever, but it has to seamlessly evolve. Knowledge
26 need not be consistent at web scale, it can come in lo-
27 cal theories that can be combined.

28 The semantic web initiative has already provided
29 a good basis for expressing and sharing knowledge.
30 First, universal and well-defined languages such as
31 RDF, RDFS, OWL, or SPARQL have been designed
32 and reliable implementations exist. Then many spe-
33 cialised ontologies using these technologies have been
34 developed from the most abstract, e.g. work, prove-
35 nance, to the more concrete, e.g. proteins, scientific ar-
36 ticles.

37 In the remainder, two different aspects are con-
38 sidered: how explicitly sharing formalised knowledge
39 contributes to improve scientific practices, hence our
40 shared knowledge; how knowledge, shared or not, may
41 be seamlessly evolved and how this can be studied in
42 an effective way. Of course, these directions are not
43 without connection and not the only possible ones.
44 However, they are in a totally different position with
45 respect to the current state of the semantic web.

46 4. eScience: an example of web of knowledge

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50 Let us take a typical example of collaborative
51 knowledge elaboration, sharing and evolution: scien-

1 tific research. eScience is a paramount example of
2 knowledge expression and evolution.

3 Science has not been left aside of the professional
4 computerisation: it has been very active from this
5 standpoint. Statistical packages, plotting and editing
6 notebooks are now commonplace and *in silico* sim-
7 ulations are accepted. This facilitates the production,
8 analysis and dissemination of knowledge by and for
9 humans helped by machines. Meanwhile, little is made
10 for helping machines to have a grasp at the content.

11 Semantic eScience is a further step in that direction
12 [10]. It exploits semantic web technologies to provide
13 an interoperable and machine-interpretable infrastruc-
14 ture for scientific enquiry. Within the past 10 years, it
15 has been a continuing source of attention.

16 Necessary technologies are already in place for
17 metadata and identification: IRIs provide a natural way
18 to identify entities such as researchers (ORCID) or
19 documents (DOI). Support has been provided to ex-
20 press bibliographic data in RDF [11]. This allows ex-
21 pressing metadata about scientific literature.

22 On the content side, i.e. the objects of scientific
23 statements, there are already many resources to ex-
24 press these with semantic web technologies. In life and
25 health sciences, Gene ontology, OBO Foundry, bio-
26 portal, and Bio2RDF were already there 10 years ago
27 and continuously improved [12]. On the mathematical
28 side, efforts have been made to provide ways to offer a
29 semantic encoding [13].

30 It is also possible to deal with the methodological
31 aspect of research. Some work have proposed the ex-
32 pression of hypotheses [14]. On the experimental side:
33 researchobject has provided a way to describe proto-
34 cols [15]. Attempts are made to describe evaluation
35 methods [16]. Finally, efforts have been made to ad-
36 dress open science requirements to publish data sets.
37 Google dataset search [17] offers search among data
38 sets described with schema.org dataset and DCAT. Re-
39 lations between such elements—which process pro-
40 duced which data, what hypothesis is it supposed to
41 support, in which paper this has been published— can
42 be kept track of through provenance assertions [18].

43 All this allows for expressing scientific knowledge
44 on the web, not only the results of scientific enquiry
45 but the whole process that led to establish such results.
46 Hence, ingredients for semantic scientific research are
47 available. What is missing is that scientific practices
48 embrace semantic web technologies. This can come
49 from more integration in work habits and new appli-
50 cations providing benefits. Here are a few example of
51 these.

1 Scientific knowledge expressed with semantic web
2 technologies would clearly facilitate searching results
3 [19]. However, more can be obtained from it with the
4 help of machines. Knowledge expressed formally on
5 the web could lead to formal scientific collaboratories
6 [20]. For instance, data analysis workflows can be ex-
7 ploited for continuous reevaluation of hypotheses by
8 updating data analyses when new data is available [21].
9 It may be checked, beforehand, that an experiment is
10 prone to refute a claim. Papers whose results contra-
11 dict one another could be identified. On the mathemat-
12 ical side, proof checking, now performed at the scale
13 of one theory may be attempted at larger scales. Exper-
14 iments testing a particular hypothesis, or a more spec-
15 ific one, can be found to avoid duplication. A protocol
16 may be analysed to pinpoint what should be changed
17 to affect the results of experiments. Literature can be
18 exploited to predict averse effects [22]. More simply,
19 machine learning could help cleaning and mining re-
20 sult as well as suggesting interesting tracks. These ap-
21 plications require knowledge and cannot rely on data
22 alone.

23 In addition to contributing to open research, seman-
24 tic expression of research processes may help address-
25 ing reproducibility issues. Providing accurate descrip-
26 tions of computer-based experiments can allow a com-
27 puter to reproduce them. Tools may be developed to
28 help (debugging and) peer-reviewing experiment pre-
29 registrations. They may also help to identify missing
30 information in descriptions and so even facilitate off-
31 line reproducibility.

32 This is where full knowledge can play its role, by
33 enabling machines to help us improving our knowl-
34 edge by confronting it to existing data, by finding con-
35 tradiction with other pieces of knowledge, by learn-
36 ing from data and knowledge. Machines could then
37 join the course of knowledge evolution adding value to
38 knowledge and massively confronting it.

39 5. Evolving knowledge

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43 Knowledge, whether expressed on the web or not,
44 whether generated through eScience or not, must
45 evolve. Knowledge that does not evolve, and systems
46 based on it, are at risk of obsolescence. If the seman-
47 tic web is to be more than a parenthesis in supporting
48 the knowledge of humanity, efforts should be made for
49 ensuring its smooth and continuous evolution.

50 Semantic eScience can contribute to this, but is not
51 sufficient. Human knowledge evolves independently

1 from scientific research, which is a relatively recent
2 way to deal with knowledge. Contrary to science, peo-
3 ple do not necessarily elaborate knowledge for itself,
4 but evolve it through its use. However, both processes
5 contribute to ‘improve’ knowledge and evolutionary
6 interpretations of science are not new [23].

7 Natural selection can be thought of as a simple con-
8 trol mechanism based on variation, selection and trans-
9 mission [24]. This can be implemented in comput-
10 ers as had already been done for genetic program-
11 ming [25]. Concerning human knowledge, anthropol-
12 ogy identified and studied cultural evolution [26]. Thus
13 one way of addressing the problem of knowledge evo-
14 lution is through understanding how cultural evolution
15 techniques may be adapted to the semantic web.

16 Experimental cultural evolution has been success-
17 fully applied to natural language [27]. It is perfectly
18 reasonable to apply experimental cultural evolution to
19 knowledge [28]. Knowledge generates individual be-
20 haviour, which is subject to selective pressure from the
21 environment and thus spreads differentially. Knowl-
22 edge evolution can indeed be implemented as a mech-
23 anism that makes knowledge evolve seamlessly while
24 it is used.

25 Experiments have been performed with knowledge-
26 carrying agents adapting minimally their knowledge
27 when it reveals inadequate. The behaviour of such
28 agents becomes more coherent as more interactions
29 are performed. Like in cultural evolution, knowledge
30 transmission does not necessarily happen through in-
31 heritance. On the contrary, agents may transmit knowl-
32 edge by cooperating or by directly exchanging it. Such
33 minimal distributed social mechanisms for evolving
34 and shaping knowledge are desirable features for so-
35 cial machines [29].

36 Experimental cultural evolution has been adapted to
37 evolve abstract cultures [30], natural language features
38 [27], and, closer to the semantic web, ontology align-
39 ments. In particular, it can be used to repair align-
40 ments better than blind logical repair [31], to create align-
41 ments based on entity descriptions [32], to learn align-
42 ments from dialogues framed in interaction protocols
43 [33, 34], or to correct alignments until no error re-
44 mains and to start with no alignment [35, 36]. Each
45 study provides new insights and opens directions on
46 the effects of local reactive adaptation on the resulting
47 knowledge.

48 There are two important challenges to provide
49 evolvability to the semantic web knowledge: under-
50 standing cultural knowledge evolution and embedding
51 it within the semantic web. Contrary to the situation

described for eScience: the task is not to merely use and spread semantic web technologies, but to properly extend them.

Cultural knowledge evolution principles may be studied by following the path of experimental cultural evolution presented above or developing more theoretical approaches. Many challenging questions are yet unanswered. For instance, the formation and evolution of common knowledge, i.e. proper culture, must be studied. Another relevant issue is the co-evolution of knowledge learnt from the environment and knowledge acquired through communication.

Concerning web integration, we are back in the read-write web debate: as long as agents are reduced to knowledge consumers, only top-down evolution is possible; as soon as they become proper learners, i.e. able to evolve and communicate the knowledge they learn, a more lively evolution is possible. This requires these agents, human or software applications, to expose and adapt the knowledge they use.

6. Conclusions

The semantic web endeavour has so far provided impressive outcomes in terms of linked data, which can be interpreted by machines, as well as representation languages and ontologies. This is only the beginning of the journey towards a semantic web contributing to the knowledge of humanity. A solid basis is available that should be pushed further.

Human beings shape their culture and knowledge progressively through evolution. The current emphasis of the semantic web towards data undermines this enterprise. Knowledge learnt from data is not made explicit nor communicated. Hence, it cannot properly evolve, but has to be relearnt.

For the semantic web to take its full part in knowledge advancement, it has to be complemented by explicit knowledge expression and sharing. This would unleash the capability to properly evolve knowledge as illustrated by work on two directions: (a) scientific knowledge elaboration processes may be improved by expressing them semantically, and (b) knowledge on the web may be evolved smoothly through evolutionary techniques.

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