

The Semantic Web identity crisis: in search of the trivialities that never were

Ruben Verborgh* and Miel Vander Sande

Department of Electronics and Information Systems, Ghent University – imec, Belgium

E-mail: ruben.verborgh@ugent.be

Abstract. For a domain with a strong focus on unambiguous identifiers and meaning, the Semantic Web research field itself has a surprisingly ill-defined sense of identity. Started at the end of the 1990s at the intersection of databases, logic, and Web, and influenced along the way by all major tech hypes such as Big Data and machine learning, our research community needs to look in the mirror to understand who we really are. The key question amid all possible directions is pinpointing the important challenges we are uniquely positioned to tackle. In this article, we highlight the community’s unconscious bias toward addressing the Paretonian 80% of problems through research—handwavingly assuming that trivial engineering can solve the remaining 20%. In reality, that overlooked 20% could actually require 80% of the total effort and involve significantly more research than we are inclined to think, because our theoretical experimentation environments are vastly different from the open Web. As it turns out, these formerly neglected “trivialities” might very well harbor those research opportunities that only our community can seize, thereby giving us a clear hint of how we can orient ourselves to maximize our impact on the future.

Keywords: vision, Web, semantics

1. Back to the future

Re-reading the original Semantic Web vision [1] from 2001, we tend to immediately notice where the predictions went wrong. Far less obvious are those that came true; they have become givens in today’s world, part of the *new normal* that now forms our everyday reality. We have forgotten the era ruled by the Nokia 3310, whose monochrome screen’s resolution only covers a fraction of modern app icons, years before many people had Internet access at home—let alone on their *phone*. The crazy thing was imagining that we would be instructing our mobile devices to perform actions for us; the planning and realization of said actions were plausibly explained in the rest of the article. With the unimaginable eventually being solved after a decade of research, the imaginable may have turned out to be the toughest nut to crack.

The roots of the Semantic Web can be traced back to the initial Web proposal [2], whose opening diagram presents what we now refer to as a *knowledge graph*,

an early glimpse into subject–predicate–object triples rather than the URL–HTTP–HTML triad that would ultimately become the Web. That same Web is currently facing severe threats [3–5], having rapidly gone from a utopian harbor of permissionless innovation to a potentially dystopian environment controlled by only a handful of dominant actors. The Semantic Web seems unaffected by most of this, strangely, until we realize that the Web and the Semantic Web have silently split ways not too long after the first RDF specifications appeared.

Nonetheless, semantic technologies are regularly coined as a means of tackling some of the Web’s most pressing challenges, such as combatting disinformation or fueling its re-decentralization movement [6]. Meanwhile, the Semantic Web research community is facing its own battles with the latest technological hypes, doubting between defending its own relevancy next to Big Data, machine learning, and—oh, yes—blockchain, or surfing atop the waves created by those. If you can’t beat them, join them; if you can’t join them, repackage. The days were the keyword “semantics” led to guaranteed project funding have faded faster from our collective memory than the Nokia 3310 ever will.

* Corresponding author. E-mail: ruben.verborgh@ugent.be.

1 Granted, cracks have started creeping into these other
 2 technologies, too. Maybe Big Data is not limitless
 3 in practice if technical capabilities scale faster than the
 4 human and legal processes for ethical data management,
 5 and we do need to link data across distributed sources
 6 instead of unconditionally aggregating them. Perhaps
 7 there are problems that machine learning can never solve
 8 reliably, and the safety provided by first-order logic
 9 proofs is irreplaceable for crucial decisions. And possi-
 10 bly it will turn out that decentralized consensus only
 11 touches a small part of all use cases, that disagreement
 12 under the “anyone can say anything about anything” flag
 13 provides a more workable model of the virtual world.

14 So when we are not riding others’ waves, what is
 15 it that unites the Semantic Web research community?
 16 What makes us truly “us”, what are the semantics we
 17 can attach to our own identity? Having emerged at the
 18 intersection of the Web, databases, and logic, we have
 19 since become disconnected from these domains, our
 20 awareness of which sometimes appears to be frozen
 21 in time. We tend to disregard that the Web from which
 22 we spun off is no longer the same as it was, and that
 23 different approaches are required today. We have held
 24 on to XML and RPC longer than most, confused the ends
 25 with the means that were supposed to achieve them.

26 The main danger within an existential crisis is the
 27 risk of losing our connection to the reality from which
 28 we originate. The philosophy of our community seems
 29 to align with Alan Kay’s quote that “*The best way to*
 30 *predict the future is to invent it.*” We build and we
 31 investigate, expecting the future to wrap its arms around
 32 the creations we are spawning. In this vision article,
 33 we rather embrace John Perry Barlow’s inversion of
 34 the quote, in which “*The best way to invent the future*
 35 *is to predict it.*” Looking back at the dreams from the
 36 past and recombining those with the aspirations of the
 37 present, what are the crucial missing pieces that require
 38 our unique dedication as Semantic Web scholars? As
 39 in the original Semantic Web article, those topics that
 40 have long been considered trivial might very well be
 41 the hardest ones in practice.

42 2. A little semantics

43
 44
 45
 46 The term Semantic Web evidently coincides with
 47 adding *semantics* to Web content to improve compre-
 48 hension by machines. However, after two decades of
 49 debate, we still seem uncertain about exactly *how much*
 50 semantics are in fact useful. The writing on the wall is
 51 the disconnect between the data that is published and

1 the applications that should consume them: the call for
 2 Linked Data has brought us the eggs, but the chickens
 3 that were supposed to hatch them are still missing.

4 To intertwine data with meaning, we largely rely on
 5 RDF for exchange and interoperability. But what is really
 6 there is only factual knowledge in a (hyper)graph struc-
 7 ture, with URIs to uniquely identify terms. The intended
 8 meaning of the data is captured through knowledge rep-
 9 resentation ontologies such as RDFS or OWL, and can be
 10 discovered for example through dereferencing. Hence,
 11 data shared as RDF *refers* more to its semantics than it
 12 contains them. And distributing those semantics has
 13 turned out significantly harder than distributing data.

14 Early efforts were heavily devoted to the development
 15 of ontology engineering, and understandably so. Hav-
 16 ing generic software to automatically act on a variety
 17 of independent datasets was what made the Semantic
 18 Web vision so appealing. Once domain knowledge had
 19 been formalized, it could be applied to represent facts,
 20 upon which reasoners could automatically derive new
 21 facts. Yet once we took those endeavors to the Web,
 22 it became apparent we had missed the general practi-
 23 cal implications of the chosen direction. As semantics
 24 are always consensus-based, domain models are only
 25 as valuable as the scope of the underlying consensus.
 26 Hence, its usage cannot be guaranteed by parties that
 27 were not involved or disagree with the consensus. Often,
 28 these parties resort to mitigation strategies that disre-
 29 gard the semantics settled in description logic, such as
 30 selectively reusing properties and classes when publish-
 31 ing data, or freely reinterpreting the semantics through
 32 programming when consuming data.

33 Core frameworks such as RDF and OWL have also
 34 frequently been labeled as “by academics, for academics”
 35 because of their perceived complexity by developers.
 36 Due to a lack of deeper understanding and an inability to
 37 connect with existing development practice, ontologies
 38 are in practice often dumbed down to *vocabularies*—a
 39 term that is used more and more, basically stripping
 40 the data from semantics and once again leaving it up
 41 to individual applications. The major search engines
 42 backing Schema.org is illustrative of this fact, but also
 43 the increasing popularity of the shape languages SHACL
 44 and SHEX. They cover an important gap between data in
 45 the wild and applications: they need to know what data
 46 to expect, which was one of the things neglected by our
 47 fixation on descriptive logic.

48 The paradox between the use of semantics and the
 49 effort to provide it, cultivated a *heterogeneous, SPARQL-*
 50 *based, and underspecified* Web of Data [7]. Practical
 51 implementation and usability has too often been hand-

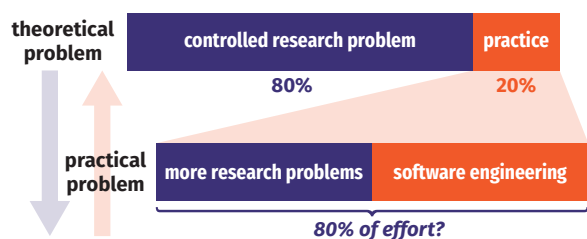


Fig. 1. After having solved the hard 80% of a research problem, we often assume that the remaining 20% are practicalities that can be addressed through trivial engineering. In reality, lifting research from controlled experimental environments to the open Web likely leads to other research problems. In addition to bringing problems from theory to practice, we can let practical problems inspire theory.

wavily address by deep theories. As depicted in Fig. 1, a strong implicit assumption lies dormant in a lot of our work: that solving the hard 80% is where the research happens, and that the remaining 20% is simple engineering to take that research from theory to practice. However, is what we often dismiss as “engineering” really just “engineering”? Given the considerable problems arising when we try to deploy semantics at Web-scale, as scientists, we might want to validate that hypothesis.

What good is inference by reasoning if the ontologies cannot be found or are outdated? What good is having unique identifiers for concepts when stating equality with `owl:sameAs` is inadequate for applications [8]? How realistic is federated query evaluation if queries in practice have to be written for specific endpoints, because reasoning is only ever switched on in theory? Meanwhile, enterprises and common developers start to give up on the formal semantics, and we risk baby being thrown out with the bath water. That is the logical result if we leave the completion of the bigger Semantic Web picture to more pragmatic engineers. Their enthusiastic endorsement of shapes, for instance, could eventually suppress the practice of semantics in data. We as researchers understand that “a little semantics goes a long way” [9] does not necessarily mean that less semantics is better than more. But exactly how much is too much for the Web? Only through research we can find out.

3. Where is the Web?

What arguably sets us apart besides semantics is, well, the Web. In contrast to relational or other databases, our domain of discourse is infinite and unpredictable on multiple levels. Because of the open-world assumption, no single RDF document contains the full truth. Even worse, any sufficiently large collection of Web docu-

ments will contain contradictions that, under classical logic, allows us to derive *any* truth—henceforth to be referred to as *ex Tela quodlibet*. Not only can anything be proven from a contradiction, in these days of fake news and dubious political advertising, it has never been easier to find self-consistent documents online in support of virtually any given conclusion or its opposite.

The Web is what we deliver as an answer to any Linked Data skeptic, as an irrefutable argument that all of our perceived or actual complexity is justified, because we are dealing with problems that span the entire virtual address space of the globe and in fact the entire universe. The Web is the reason why our ontologies are spread all over the place, why the prefix expansion for the OWL ontology counts 30 characters, why FOAF is forever stuck at version 0.9, the Dublin Core vocabulary at 3 different ones, and why we cannot all just use *Schema.org*. The Web is why Open Data exists, why our public SPARQL endpoints are down 1.5 days a month [10], why stable vocabularies suddenly disappear. Everything we do, we do it the way we do it, because the Web sets the rules such that anything more simple or logical would *not* do. If the Web is such a self-explanatory answer to the existence of our discipline—then why are so afraid to put our work on top of it?

We are not even talking here about taking our scholarly communication to the Web; let that be the crusade of the dogfooders [11], to whom we dedicate Section 7. We mean to say that “*it works in our university basement*” has become an acceptable and applauded narrative—and to be fair to both the innocent and the guilty, impressive efforts undertaken in such basements have rightly been awarded scientific stamps of excellence through rigorous non-Web peer review processes. However, we cannot claim the Web as the sole source of our intricacies, while simultaneously ignoring all of the Web’s difficulties by conducting all of our experiments in hermetically controlled environments. By doing so, we pretend that the comfortable 80% cannot significantly be affected by the unpredictable impurities of the 20%, that an n -fold performance gain in our basements can implicitly be extrapolated to the same gain for Linked Data in general. As Goodhart’s law states: “*When a measure becomes a target, it ceases to be a good measure*”, except that we can strongly question whether non-Web environments, however pure and controlled, have ever fulfilled the role of good measure providers in the first place.

No, we cannot safely assume that the `owl:sameAs` predicate has consistently been used in accordance with at least one of its several meanings [12]. No, we cannot assume that SPARQL endpoints will be available or even

1 return valid `RDF`. Yes, people will use the same `URL` to
 2 refer to *different* things, and obviously different `URLS`
 3 to point to the *same* things—without even throwing in
 4 as little as a semantically ambiguous `schema:sameAs`.
 5 Yes, our precious data sets unnecessarily use different
 6 ontologies, so we have to switch on reasoning, even
 7 though that makes our results suddenly *worse* than
 8 the state of the art—and did we mention that one of
 9 those ontologies no longer dereferences but, even back
 10 when it still did, was not linked to the others anyway?
 11 Upon closer reflection, our fears about the Web are
 12 probably justified; our scientific conclusions and their
 13 presumed external validity perhaps a little less.

14 We are all aware that the Web is a good platform
 15 for data publication, but a pretty bad platform for data
 16 consumption [13]. Yet that exactly is *the* reason to not
 17 ignore the 20% any longer, but to embrace the unique
 18 challenges and opportunities it brings. Crucial and some-
 19 times counterintuitive insights arise when Web-based
 20 techniques are applied to research problems previously
 21 only studied in isolation. As an example, link-traversal-
 22 based query execution [14] taught us that `SPARQL` queries
 23 can exist separately from specific interfaces to evaluate
 24 them, which in turn are independent from back-ends.
 25 Understanding that some of our standardized protocols
 26 do not adhere to the constraints of the Web’s underlying
 27 `REST` architectural style, allows us to design interfaces
 28 with better scalability properties, which might perform
 29 worse in closed environments but yield desirable prop-
 30 erties on the public Web [15]. Taking this even further,
 31 we can wonder whether the default semantics of simple
 32 `SPARQL` queries are tailored too much to closed databases
 33 as opposed to the Web we publicly claim to target.

34 We should, however, not become too puristic in our
 35 judgment; an important aspect of scientific studies is
 36 their ability to zoom in on the isolated contribution of
 37 specific factors. Several valid use cases for non-Web `RDF`
 38 applications exist, so not every single undertaking has
 39 to embody the omnipotent role ascribed to the mythical
 40 Semantic Web agent. Nonetheless, as a community,
 41 we want to ensure we combine the 80% sufficiently
 42 often with the 20%, such that we obtain at least a more
 43 adequate impression of the potentially huge number of
 44 research questions hiding in plain sight.

46 47 **4. “Linked” as bigger than “Big”**

48
 49 When Big Data became mainstream around 2010,
 50 the Semantic Web community was listening with great
 51 attention. After all, we had already been working with

1 staggering numbers of facts, hundreds of millions of
 2 triples not being an exception. Furthermore, when con-
 3 sidering all data on the Web as a whole, we would surely
 4 reach the threshold at which Linked Data should be
 5 considered Big Data in its own right.

6 However, Big Data and Linked Data are not nec-
 7 essarily structurally compatible. A main advantage of
 8 the `RDF` data model is that it allows for flexibility, en-
 9 abling people to capture data that does not lend itself
 10 well to the rigid structures of spreadsheets or relational
 11 databases. Big Data solutions derive their strength from
 12 a rigorous, extensive schema, which strongly contrasts
 13 with `RDF`’s highly normalized triple format. While there
 14 have been solutions that leverage Big Data technologies
 15 to address `RDF` use cases such as querying [16], they
 16 require reformatting data to fit the Big Data paradigm.

17 A conceptual issue with the Big Data vision, at least
 18 for our purposes, is that it takes the path of the lowest
 19 common denominator, as a natural result of an aggrega-
 20 tion process. While aggregation definitely has its merits
 21 for discovery and analysis, it also flattens unique charac-
 22 teristics and attributes of individual datasets, dissolving
 23 them into a much larger and more homogeneous space.
 24 An example of how this unintentionally can become trou-
 25 blesome is found within the Europeana initiative [17],
 26 which serves the noble cause of aggregating highly
 27 diverse metadata from cultural institutions all across
 28 Europe. However, several individual institutions felt
 29 wronged when they had to send their data set—which
 30 they knew so well and had taken care of for so many
 31 years—only for it to be mingled with those of *others*
 32 who surely would have different accents and inferior
 33 quality thresholds [18]. What gives Big Data its attrac-
 34 tiveness and efficiency might thus be removing what
 35 differentiates us. Time will tell if similar arguments can
 36 be made about the Wikidata project [19], which aims
 37 to be a global knowledge base.

38 For some time, we have been mildly apologetic about
 39 not doing Big Data, at one point hastily rebranding our-
 40 selves as “Semantics and Big Data” [20] before realizing
 41 that, indeed, there is another research community out
 42 there that is better positioned to tackle those challenges.
 43 Considering the 2001 article [1] as the official birth date
 44 of the Semantic Web, let us conveniently ignore those
 45 teenage years during which we should be forgiven for
 46 going through different phases that were all just part of
 47 constructing our own identity. We should not aspire to
 48 be that popular kid from high school, who, as it turned
 49 out later, had merely peaked early in life. Nearing our
 50 twenties now, let us stop apologizing already for just
 51 being ourselves.

1 If we conceptually think about Big Data versus what
2 we are aiming to achieve with Linked Data, our chal-
3 lenges might very well be the harder ones. Notwith-
4 standing impressive research and engineering efforts to
5 scale up Big Data solutions the way they do, harvesting
6 an enormous amount of homogeneous data in a single
7 place creates ideal conditions for processing and anal-
8 ysis. A small number of very large data sets is easier
9 to manage than a very large number of small data sets.
10 Size does matter, just not always in the way others think:
11 the heterogeneity and distribution of Linked Data is
12 currently at a level that cannot be adequately tackled
13 with Big Data techniques. Instead of being ashamed
14 about practicing Small Data, we should proudly flaunt
15 its multitude and diversity. In times of increasing calls
16 for inclusion, let this be a good thing.

17 Because even if we technically would be able to
18 centralize everything in one place, we could only serve
19 the relatively small space of public data, not all of
20 the private data that is the focus point of Big Data
21 applications. After all, there are very good reasons for
22 data to live in different places, not in the least legal or
23 privacy concerns. Those needs are only becoming more
24 pressing, given important drivers such as the GDPR legal
25 framework in Europe, and a strong world-wide call for
26 more privacy and control over personal data. By keeping
27 data in millions of small personal data stores close to
28 people, we are in a much better position to safeguard
29 people’s most precious digital assets. The challenge
30 then of course is in connecting these distributed pieces
31 of data at runtime, which the Solid project [21] does
32 through Linked Data.

33 In a distributed future, there will not be less data,
34 but more; if it cannot reside in one place for whatever
35 reason, it will have to be linked. This is yet another
36 reason why we need to be prepared for Web-scale dis-
37 covery and querying over federations that are magni-
38 tudes more challenging than our current experimental
39 environments.

40 5. AI beyond ML

41
42
43
44 There is no question the age of *Deep Learning* is very
45 much upon us. As the last one to mature, deep learning
46 has spawned numerous research efforts, techniques,
47 and even production-ready applications with machine
48 learning, elevating the state of AI once again. Semantic
49 Web research has not been resilient to the siren song,
50 and started exploiting RDF knowledge bases as fertile
51 soil for Deep Learning and other machine learning

1 approaches. The popular topics that emerged, such
2 as *embeddings* [22] and *concept learning* [23] enable
3 model training from description logics to complete and
4 extend any semantic information present. Developing
5 such approaches is crucial to reduce the high manual
6 currently required for participating in the Semantic Web.

7 Semantic technologies were originally considered
8 part of the AI family and in essence still are [24]. In-
9 ference of logical consequences from data can drive a
10 machine’s autonomy. Yet in the shadow of advanced
11 machine learning, the “cool kids” perceive us as apostles
12 of an old, inflexible, and outdated rule-based approach.
13 However, maturity in the machine learning field also un-
14 covered the gaps where semantic technology can prove
15 its relevance. Use cases prone to *decision accuracy*,
16 such as healthcare or privacy enforcement, profit from
17 the exact outcomes of first-order logic. Furthermore,
18 the ability of some semantic reasoners to *explain* their
19 actions through proofs [25] is a much desired trait by
20 the primarily black-box machine learning methods.

21 As both angles have their merits, the future is very
22 likely *hybrid*, and we need to further explore compli-
23 mentary roles. For instance, semantics and inference
24 can pre-label data that improve the accuracy of models.
25 Or, post-execution explainability could be achieved by
26 reasoning over semantic descriptions of nodes. In the
27 area of digital assistants, such as the promising work
28 with Almond [26] and Snips [27], declarative AI can
29 append a human representation of the world to represen-
30 tations trained on raw data. This would fill knowledge
31 gaps of current assistants such as Siri and Alexa, in-
32 crease their associative ability, and eventually improve
33 the *authenticity* of their interactions. Some more funda-
34 mental questions also need to be answered, such as train-
35 ing a model under the open world assumption. Fitting
36 strategies exist, but there are many more unknowns.

37 Semantic inference and first-order logic might lead to
38 less spectacular conclusions, but they will be nonethe-
39 less crucial to advanced machine learning systems. Also
40 here, it is important to solve the engineering side of
41 things. Almond and Snips are directly usable to devel-
42 opers, who, through testing, discover further challenges.
43 When machine learning solutions “just work” develop-
44 ers do not need to know what is inside, that is the result
45 of research, not just engineering. Getting rid of the “triv-
46 ial” problems with semantic inference hopefully means
47 providing these more spectacular results, on the Web.
48 Maybe this is the better way to position ourselves in one
49 of the next waves to come: reinforcement learning.
50
51

6. Challenging until proven trivial

Ultimately, all of this shows that we need to guard ourselves from conducting research in a vacuum. Not all science requires practical purposes, but if we would only design solutions for problems that will never even exist if the Semantic Web does not take off any further, then we should at least *consider* prioritizing those urgent problems that are blockers to adoption. Part of our hesitance might be that, having fought hard for recognition as a scientific domain, we are afraid to be pushed back into the corner of engineering. Our conferences and journals tend to have a high threshold for what qualifies as research, with a strong focus on qualitative experimentation. While high thresholds in general are commendable, they also result in a higher percentage of false negatives, both in submitted works that never get accepted, and in stellar research ideas that never materialize because fear of such rejections encourages safer bets.

We tend to zoom in on very focused, often incremental research problems, which tend to bring us progress. Again Pareto's law from Fig. 1 lures around the corner: we consider the core 80% of a hard problem and assume that the remaining 20% is a non-issue. Converting technological research into digestible chunks for developers is considered trivial and outside of our scientific duty. Everything that reeks of pure engineering is shunned.

However, most researchers in our community have not built a single Semantic Web app, so we cannot pretend to understand the insides of that 20%. It is impossible to tell whether the remainder is trivial or not; and many of the experiences above reveal that some of the most complex research problems appear exactly there. But how would we know? We do not get in touch with some of the most pressing issues, because we already ruled them out as trivial, and then wonder about the low adoption of the otherwise excellent 80% research.

Since the Semantic Web started, Web development has massively changed. Many apps are now built by front-end developers, for whom Semantic Web technologies are inaccessible, explaining the success of substantially less powerful but far more developer-friendly technologies such as GraphQL. We compensate by drawing those back into the research domain [28], but gloss over a crucial point: bringing SPARQL levels of expressivity to front-end developers is in fact a *research* problem.

Designing an appropriate Linked Data *developer experience* [29] is so challenging because, while regular apps are hard-coded against one specific well-known back-end, Linked Data apps need to expect the unex-

pected as they interface with heterogeneous data from all over the Web. Building such complex behavior involves a sophisticated integration of many branches of our research, which requires designing and implementing complex program code. Exposing such complex behavior into simple primitives, as is needed for front-end developers, requires *automating* the generation of that complex code, likely at runtime. Such endeavours have not been attempted at the research level, let alone they would be ready for implementation by skilled engineers.

This research gap between current research solutions and practice means that much of our work cannot be directly applied. We could deem it acceptable that nothing works in practice yet. Unfortunately, such a lax attitude leaves us with an all too comfortable hiding spot: why would my research have to work in the real world if others' does not? As a direct consequence of this line of thought, we cannot meaningfully distinguish research that could eventually work from research that never will.

Until we have examined whether or not something is trivial, we should not make any implicit assumptions. We have been wrong before. Perhaps we should consider scoring research works on the 80/20 Pareto scale, and ensure that we have enough of both sides at our conferences and in our journals. By also judging applicability, we abandon our filter bubbles and extend our action radius to urgent problems in the way of adoption—which will only enlarge our research community.

7. Practice what we preach

Not only do many of us lack Semantic Web experience as app developers, our even bigger gap is experience as users. Although a significant amount of our communication (not in the least toward funding bodies) consists of technological evangelism, we rarely succeed in leveraging our own technologies. If we keep on finding excuses for not using our own research outcomes, how can we convince others? The logicians among us will undoubtedly recognize the previous statement as a *tu quoque* fallacy: our reluctance to dogfood is factually independent of our technology's claim to fame. Yet if all adoption were solely based on sound reasoning, our planet would look very different today. Credibility and fairness aside, we are not in the luxury position to tell others to "do as I say, not as I do." The burden of proof is entirely upon ourselves, and the required evidence extends beyond the scientific.

1 In addition to being an instrument of persuasion,
 2 dogfooding addresses a more fundamental question:
 3 which parts of our technology are ready for prime time,
 4 and which parts are not? By becoming users of our own
 5 technologies, we will gain a better understanding of the
 6 elusive 20% that clearly, had it actually been so trivial,
 7 would already have been there. Never underestimate the
 8 power of frustration: feeling frustrated about unlocked
 9 potential is what prompted Tim Berners-Lee to invent
 10 the Web [30]. Only by managing almost his entire life
 11 with Linked Data, he is able to keep a finger on the
 12 Semantic Web's pulse, and his eyes on its Achilles' heel.

13 If we similarly had a deeper understanding of real-
 14 world Linked Data flows and obstacles, would we not
 15 be in a better position to make a difference? We might
 16 want to address concrete problems happening today, in
 17 addition to targeting those that will hopefully arise—
 18 conditional on today's problems ending up solved—after
 19 several more years.

20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51

8. In conclusion

After almost two decades, the Semantic Web should
 step out of its identity crisis into adolescence. In search
 of a target market for adoption, research in semantic
 technologies has ridden others' waves all too often, in
 an attempt to assimilate with all use cases but our own.
 This brought us as a community into a disconnect with
 the place where we can make a difference: the Web.
 There, new technologies still emerge every day—just
 not ours. Investing in theoretically interesting problems
 without also delivering the necessary research to achieve
 practical implementations seems to have singled us out.

A Semantic Web has data and semantics intertwined,
 yet distributing those semantics has been proven to be
 harder than sharing data. Can we focus on the practice
 and implications of sharing and preserving semantics? If
 not, we might leave the original vision to die in the hands
 of a more short-term and pragmatic agenda. No doubt,
 the need for full-scale data integration will eventually
 reappear, possibly reinventing the solutions and methods
 we are working on today. But that realization might take
 another decade to surface.

The Web might not be our only target market, but it
 is the one that sets us apart. Yet it does not pop up in
 the average “treats to validity” section—if there even is
 one. The rules are set in a unique way, which requires
 overcoming specific hurdles to make things work. To
 really test the external validity of our work, we should
 submerge in the practical side of things and thus make

the Web a better suited place for data consumption.
 Our experimental environment should not be that of
 Big Data. We should thrive with a lot of small datasets
 instead of a few large ones, and in heterogeneity instead
 of homogeneity. We could differentiate ourselves as the
 main driver for the much needed re-decentralization of
 the Web, where, backed by privacy and data legislation,
 Web-scale federation is the next Big thing. To this end,
 positioning semantic technologies as complement to ma-
 chine learning is a necessity. The future of AI is hybrid:
 descriptive logic can bring accuracy, explainability and,
 of course, meaningful data to the table.

In order to succeed, we will need to hold ourselves to
 a new, significantly higher, standard. For too many years,
 we have expected engineers and software developers
 to take up the remaining 20%, as if *they* were the ones
 needing to catch up with *us*. Our fallacy has been our
 insistence that the remaining part of the road solely
 consisted of code to be written. We have been blind
 to the substantial research challenges we would surely
 face if we would only take our experiments out of our
 safe environments into the open Web. Turns out that the
 engineers and developers have moved on and created
 their own solutions, bypassing many of the lessons
 we have learned, because we stubbornly refused to
 acknowledge the amount of research needed to turn our
 theories into practice. Since we seemingly did not want
 the Web, more pragmatic people took over.

And if we are honest, can we blame them? Clearly, the
 world will not wait for us. Let us not wait for the world.

References

- [1] T. Berners-Lee, J. Hendler and O. Lassila, The Semantic Web, *Scientific American* **284**(5) (2001), 34–43.
- [2] T. Berners-Lee, Information Management: A Proposal, Technical Report, CERN, 1989. <https://www.w3.org/History/1989/proposal.html>.
- [3] T. Berners-Lee, Three challenges for the Web, according to its inventor, 2017. <https://webfoundation.org/2017/03/web-turns-28-letter/>.
- [4] T. Berners-Lee, The Web is under threat. Join us and fight for it., 2018. <https://webfoundation.org/2018/03/web-birthday-29/>.
- [5] T. Berners-Lee, 30 years on, what's next #ForTheWeb?, 2019. <https://webfoundation.org/2019/03/web-birthday-30/>.
- [6] R. Verborgh, Re-decentralizing the Web, for good this time, in: *Linking the World's Information: Tim Berners-Lee's Invention of the World Wide Web*, O. Seneviratne and J. Hendler, eds, ACM, 2019. <https://ruben.verborgh.org/articles/redecentralizing-the-web/>.
- [7] M. Schmachtenberg, C. Bizer and H. Paulheim, Adoption of the Linked Data Best Practices in Different Topical Domains, in: *The Semantic Web – ISWC 2014*, P. Mika, T. Tudorache,

- 1 A. Bernstein, C. Welty, C. Knoblock, D. Vrandečić, P. Groth,
2 N. Noy, K. Janowicz and C. Goble, eds, Springer International
3 Publishing, Cham, 2014, pp. 245–260. ISBN 978-3-319-11964-
4 9.
- [8] W. Beek, J. Raad, J. Wielemaker and F. van Harmelen,
5 sameAs.cc: The Closure of 500M owl:sameAs Statements, in:
6 *The Semantic Web*, A. Gangemi, R. Navigli, M.-E. Vidal, P. Hitzler,
7 R. Troncy, L. Hollink, A. Tordai and M. Alam, eds, Springer
8 International Publishing, Cham, 2018, pp. 65–80. ISBN 978-3-
9 319-93417-4.
- [9] J. Hendler, The dark side of the semantic web, *IEEE Intelligent
10 Systems* **22**(1) (2007), 2–4.
- [10] C. Buil-Aranda, A. Hogan, J. Umbrich and P.-Y. Vandenbussche,
11 SPARQL Web-Querying Infrastructure: Ready for Action?, in:
12 *Proceedings of the 12th International Semantic Web Conference*,
13 2013.
- [11] S. Capadisli, Decentralised and Socially-Aware Scholarly
14 Communication, PhD thesis, University of Bonn, 2019,
15 In preparation. [https://linkedresearch.org/article/csarven.ca/
16 decentralised-socially-aware-scholarly-communication](https://linkedresearch.org/article/csarven.ca/decentralised-socially-aware-scholarly-communication).
- [12] H. Halpin, P.J. Hayes, J.P. McCusker, D.L. McGuinness and
17 H.S. Thompson, When owl:sameAs Isn't the Same: An Analysis
18 of Identity in Linked Data, in: *The Semantic Web – ISWC 2010*,
19 P.F. Patel-Schneider, Y. Pan, P. Hitzler, P. Mika, L. Zhang,
20 J.Z. Pan, I. Horrocks and B. Glimm, eds, Springer, 2010, pp. 305–
21 320. ISBN 978-3-642-17746-0.
- [13] F. van Harmelen, 10 Years of Semantic Web: does it
22 work in theory?, 2011. [https://www.cs.vu.nl/~frankh/spool/
23 ISWC2011Keynote/](https://www.cs.vu.nl/~frankh/spool/ISWC2011Keynote/).
- [14] O. Hartig, C. Bizer and J.-C. Freytag, Executing SPARQL
24 Queries over the Web of Linked Data, in: *The Semantic Web -
25 ISWC 2009*, A. Bernstein, D.R. Karger, T. Heath, L. Feigenbaum,
26 D. Maynard, E. Motta and K. Thirunarayan, eds, Springer Berlin
27 Heidelberg, Berlin, Heidelberg, 2009, pp. 293–309. ISBN 978-
28 3-642-04930-9.
- [15] R. Verborgh, M. Vander Sande, O. Hartig, J. Van Herwegen,
29 L. De Vocht, B. De Meester, G. Haesendonck and
30 P. Colpaert, Triple Pattern Fragments: a Low-cost Knowl-
31 edge Graph Interface for the Web, *Journal of Web Semantics*
32 **37–38** (2016), 184–206. doi:10.1016/j.websem.2016.03.003.
33 <http://linkeddatafragments.org/publications/jws2016.pdf>.
- [16] A. Schätzle, M. Przyjaciół-Zablocki, A. Neu and G. Lausen,
34 Sempala: Interactive SPARQL Query Processing on Hadoop,
35 in: *The Semantic Web – ISWC 2014*, P. Mika, T. Tudorache,
36 A. Bernstein, C. Welty, C. Knoblock, D. Vrandečić, P. Groth,
37 N. Noy, K. Janowicz and C. Goble, eds, Springer International
38 Publishing, Cham, 2014, pp. 164–179. ISBN 978-3-319-11964-
39 9.
- [17] A. Isaac and B. Haslhofer, Europeana Linked Open Data –
40 data.europeana.eu, *Semantic Web Journal* **4**(3) (2013), 291–297.
41 doi:10.3233/SW-120092.
- [18] R. Verborgh, One flew over the cuckoo's nest – The role of
42 aggregation on a decentralized Web, 2018. [https://rubenverborgh.
43 github.io/EuropeanaTech-2018/](https://rubenverborgh.github.io/EuropeanaTech-2018/).
- [19] D. Vrandečić and M. Krötzsch, Wikidata: A Free Collaborative
44 Knowledge Base, *Communications of the ACM* **57** (2014), 78–
45 85.
- [20] P. Cimiano, O. Corcho, V. Presutti, L. Hollink and S. Rudolph
46 (eds), *The Semantic Web: Semantics and Big Data*, Springer,
47 2013. ISBN 978-3-642-38287-1. doi:10.1007/978-3-642-38288-
48 8.
- [21] E. Mansour, A.V. Sambra, S. Hawke, M. Zereba, S. Capadisli,
49 A. Ghanem, A. Abounaga and T. Berners-Lee, A Demonstration
50 of the Solid Platform for Social Web Applications, in: *Compan-
51 ion Proceedings of the 25th International Conference on World
Wide Web*, 2016, pp. 223–226. doi:10.1145/2872518.2890529.
- [22] Q. Wang, Z. Mao, B. Wang and L. Guo, Knowledge graph
embedding: A survey of approaches and applications, *IEEE
Transactions on Knowledge and Data Engineering* **29**(12) (2017),
2724–2743.
- [23] L. Bühmann, J. Lehmann and P. Westphal, DL-Learner—A
framework for inductive learning on the Semantic Web, *Journal
of Web Semantics* **39** (2016), 15–24.
- [24] H. Halpin, The semantic web: The origins of artificial intelli-
gence redux, in: *Third international workshop on the history and
philosophy of logic, mathematics, and computation (HPLMC-04
2005)*, Citeseer, 2004.
- [25] R. Verborgh, D. Arndt, S. Van Hoecke, J. De Roo, G. Mels,
T. Steiner and J. Gabarro, The pragmatic proof: Hypermedia
API composition and execution, *Theory and Practice of Logic
Programming* **17**(1) (2017), 1–48.
- [26] G. Campagna, R. Ramesh, S. Xu, M. Fischer and M.S. Lam,
Almond: The Architecture of an Open, Crowdsourced,
Privacy-Preserving, Programmable Virtual Assistant, in: *Pro-
ceedings of the 26th International Conference on World
Wide Web*, 2017, pp. 341–350. ISBN 978-1-4503-4913-0.
doi:10.1145/3038912.3052562.
- [27] A. Coucke, A. Saade, A. Ball, T. Bluche, A. Caulier, D. Leroy,
C. Doumouro, T. Gisselbrecht, F. Caltagirone, T. Lavril,
M. Primet and J. Dureau, Snips Voice Platform: an embedded
Spoken Language Understanding system for private-by-design
voice interfaces, *CoRR* (2018). <http://arxiv.org/abs/1805.10190>.
- [28] O. Hartig and J. Pérez, Semantics and Complexity of
GraphQL, in: *Proceedings of the 2018 World Wide Web
Conference*, 2018, pp. 1155–1164. ISBN 978-1-4503-5639-8.
doi:10.1145/3178876.3186014.
- [29] R. Verborgh, Designing a Linked Data developer ex-
perience, 2018. [https://ruben.verborgh.org/blog/2018/12/28/
designing-a-linked-data-developer-experience/](https://ruben.verborgh.org/blog/2018/12/28/designing-a-linked-data-developer-experience/).
- [30] T. Berners-Lee, The next Web, 2009. [https://www.ted.com/talks/
tim_berners_lee_on_the_next_web](https://www.ted.com/talks/tim_berners_lee_on_the_next_web).