Abstract
Reconciling the ecosystem of semantic Web data with the ecosystem of social Web participation has been a major issue for the Web Science community. To answer this need, we propose an innovative approach called ViewpointS where the knowledge is topologically, rather than logically, explored and assessed. Both social contributions and linked data are represented by triples agent-resource-resource called “viewpoints”. A “viewpoint” is the subjective declaration by an agent (human or artificial) of some semantic proximity between two resources. Knowledge resources and viewpoints form a bipartite graph called “knowledge graph”. Information retrieval is processed on demand by choosing a user’s “perspective” i.e., rules for quantifying and aggregating “viewpoints” which yield a “knowledge map”. This map is equipped with a topology: the more viewpoints between two given resources, the shorter the distance; moreover, the distances between resources evolve along time according to new viewpoints, in the metaphor of synapses’ strengths. Our hypothesis is that these dynamics actualize an adaptive, actionable collective knowledge.

Related work and inspirations
Facing the issue of bridging the gap between social ranking and the semantic Web, (Breslin, Passant, and Vrandečić 2011) distinguish two main options in the literature consisting respectively in “post-formalizing” and “pre-formalizing” the informal content of the social Web. The ViewpointS approach takes a third option: to represent both social contributions and linked data by triples agent-resource-resource. The major consequence of this choice of a memory built upon connections made by agents is to let the collected knowledge evolve continuously along the interactions of the contributors. Another consequence is to ensure trustworthiness, well in line with the recent shift in the Web paradigm bringing the contributor back in the loop (O’Reilly 2015).

In ViewpointS, we started from a tripartite model agent-resource-tag generalizing social networks such as Flickr and proposed as building block the more abstract triple agent-resource-resource, in which agents may themselves
be resources, expressing: “the belief of a resource/agent that two resources are close”. This yields a topological, rather than logical, exploitation of the “wisdom of the crowd” in a manner similar to (Mika 2007; Markines et al. 2009; Specia and Motta 2007). Taking inspiration from the contexts of annotation, disambiguation, concept alignment and information retrieval (Harispe et al. 2014; Lee et al. 2008), we then grouped the triples in order to yield ‘semantic similarity’ or ‘semantic proximity’. We firstly aggregate all the triples connecting two given knowledge resources into a higher level binary link called a synapse. In a second step, we made the hypothesis that any user’s context could be translated into a set of quantification rules for the viewpoints called a perspective; this is in line with (Kim and Scerri 2008) which advice to evaluate ontologies on demand with respect to a specific context. Once a perspective is adopted, the initial heterogeneous semantics carried by the viewpoints are transformed into a knowledge map equipped with a distance. As a consequence, the agents can use the proximities resulting from the existing viewpoints when browsing knowledge maps and reversely update the knowledge through new viewpoints expressing their feedback e.g., “I believe this agent matches/does-not-match the topic of my query” or “I deny concept-a/ instance-1 and concept-b/ instance-2 are connected through relation-r”.

Along these exploitation/feedback cycles, the shared knowledge is continuously elicited against the beliefs of the agents in a selection process supported by the evolving strength of synapses. Here comes the metaphor of the brain. According to the Theory of Neuronal Group Selection (Edelman and Tononi 2000), which recently reappeared in the front scene under the name of connectome (Seung 2012), knowledge results from a process of continual re-categorization. In our approach, the dynamics of synapses aim at yielding an evolving topology where knowledge is constantly reorganized\(^1\).

The next section firstly presents the formalism supporting the ViewpointS “Knowledge graph”, then goes through some aspects exploring its topology in order to assess collective knowledge on top of heterogeneous semantics.

**A topological, unified view on heterogeneous semantics**

In the ViewpointS approach, all the resources (identified by a URI) contributing to knowledge are grouped in a single class: Knowledge resource. Figure 1 illustrates five mutually exclusive subclasses of knowledge resources covering most of the practical cases:

- Human Agent or Legal person: entity “performing acts and undertaking obligations” \(^{[32]}\) such as humans or organizations, by emitting connections between resources.
- Artificial Agent: numeric entity emitting connections between resources.
- Physical document: document of the real world such as a book.
- Numeric document: numeric entity such as a Web page.
- Descriptor: meaningful linguistic expression, playing the role of tag.

Knowledge resources participate to connections called viewpoints: each viewpoint is a subjective connection established by an agent (Human or Artificial) between two knowledge resources; each viewpoint implicitly brings in the specific semantics of its emitter. However, these semantics do not need to be shared by the agents that will further exploit the knowledge, as it will be explained when describing the “knowledge maps”. The formalization of these heterogeneous semantics is illustrated in Figure 2:

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\(^1\) This point requires a real-life scenario and cannot be demonstrated in this paper; setting such a scenario is our next objective.
of average interest\(^2\); in that example, \(\theta=\text{vp:rating}\) is a transcription of the MovieLens linked data.

The viewpoints\(^*\) types are grouped into 7 meta-types: \{author, like, similar, onto-match, social-match, algo-match, preview\}.

The knowledge graph

Knowledge resources and viewpoints together form a bipartite Knowledge graph\(^2\) denoted KG, where the knowledge is persistently stored. By contrast, retrieving information happens in transient maps computed on demand.

The knowledge maps

A preliminary step for retrieving knowledge consists in reifying the querying context by use of a perspective \(\mathcal{U}\) i.e., a set of quantification rules applied to the viewpoints. It may be default rules adopted by a group of users in a recurrent context, or specific rules filtering KG according to preferences such as: ignoring the viewpoints anterior to a given date, privileging the viewpoints emitted by some agents or privileging viewpoints of a given meta-type.

Given a KG, computing the knowledge map associated to a context \(\mathcal{U}\) involves three steps: i) grouping all the viewpoints connecting any given pair of knowledge resources into higher level link called synapses and then ii) choosing the rules for valuating the synapses i.e., setting the perspective \(\mathcal{U}\) as a map-reduce process. This is illustrated in Figure 3.

![Figure 3: Building a knowledge map $\mathcal{U}^\text{KM}$](image)

We call knowledge map and denote $\mathcal{U}^\text{KM}$ the undirected labelled graph interpreting KG through the perspective \(\mathcal{U}\). Depending on the perspective adopted, one single KG may therefore be interpreted into several distinct $\mathcal{U}^\text{KM}$, the topology of which can be exploited with standard graph algorithms in order to exhibit knowledge. In practice, $\mathcal{U}^\text{KM}$ is never built exhaustively! Instead, the synapses are computed on demand along a Dijkstra-inspired exploration bounded by a parameter \(\mathcal{m}\). We denote $\mathcal{U}^\text{m}$ \(\Psi\)-neighbours\((r)\) the neighborhood of a target \(r\) resulting from an exploration bounded by \(\mathcal{m}\) in the perspective \(\mathcal{U}\). This can be compared to the semantic similarity of (Zhu and Iglesias 2017); however using the perspective \(\mathcal{U}\) only requires knowledge about meta-types i.e., the user does not need any preliminary knowledge about the ontologies source of the viewpoints of meta-type "onto-match".

Two things should be noted: i) the bigger the synapse the shorter the distance and ii) as long as \(\mathcal{m}\) is small compared to the size of KG, the exploration of new branches quickly stops; therefore the worst-case complexity is never reached in practical cases. The practical complexity does not depend on the size of KG but on its local density.

The topological assessment of the knowledge

(Adomavicius and Tuzhilin 2005; Yamaba, Tanoue, and Takatsuka 2013) write that powerful recommender systems will exploit more and more the underlying topologies. Taking inspiration from this, our objective is to provide a means to characterize the underlying topology in KG in terms of information. For example, if when browsing through a given movie dataset the uncertainty about genres is reduced by its topology, we may say according to (Klir 2005) that the dataset embeds information about 'genres'.

Let us consider in KG a collection \(\mathcal{O}\) of objects (e.g., 'movies') and a collection \(\mathcal{D}\) of descriptors (e.g., 'genres'), we measure whether close elements of \(\mathcal{O}\) have similar elements of \(\mathcal{D}\) in their respective neighborhoods. We call "local homogeneity" (of \(\mathcal{O}\) with respect to \(\mathcal{D}\) the probability to find similar elements of \(\mathcal{D}\) in the neighborhoods of close elements of \(\mathcal{O}\). Let \(|\mathcal{D}|\) be the cardinal of \(\mathcal{D}\), in order to compute the "local homogeneity" we use a \(|\mathcal{D}|\)-dimensional vector space.

Let \(\mathcal{U}\) be a perspective, let \(\mathcal{m}\) be the parameter for computing neighborhoods, let \(\mathcal{O} = \{o_j\}_{j \in |\mathcal{O}|}\) and \(\mathcal{D} = \{d_j\}_{j \in |\mathcal{D}|}\) be two collections of knowledge resources, we denote \(\mathcal{D}(o_j)\) the vector of dimension \(|\mathcal{D}|\) \(\{d^2(o_j)\}_{j \in |\mathcal{D}|}\) such that \(d^2(o_j)\) is the number of occurrences of \(d_j\) in the neighborhoods of \(o_j\). Let \(|\mathcal{D}|\) be the cardinal of \(\mathcal{D}\), in order to compute the "local homogeneity" we use a \(|\mathcal{D}|\)-dimensional vector space.

\[ \text{localHomogeneity}(\mathcal{O}) = \text{average value of cosine similarity } (\mathcal{D}(o_1), \mathcal{D}(o_2)) \text{ computed upon all the pairs } (o_1, o_2) \text{ verifying } \sum_{d_j} \Psi(o_1, o_2) \leq m. \]

This will be denoted: \(\mathcal{U}^\text{m} \Psi \cap \mathbb{H}(\mathcal{O})\).

\(^2\) Although our approach has not yet addressed large datasets such as DBPedia, it has been thought to do so.

\(^3\) The worst case complexity of the algorithm is \(O(|\mathcal{W}|^2|\mathcal{P}|^2)\).
The value of local homogeneity varies between ‘0’ and ‘1’. A local homogeneity of ‘0’ corresponds to the absence of information expressed by D with respect to O. A local homogeneity of ‘1’ corresponds to the maximal information expressed by D with respect to O. Since the computation of “local homogeneity” only comes into play for remotely assessing the evolution of collective knowledge, we do not worry about the complexity resulting from the size of |D|.

The MovieLens Experiment

To prove the concept of ViewpointS, we take a Web dataset where explicit knowledge expressed by linked data is mixed with implicit knowledge issued from social contributions: MovieLens. The complete dataset consists of 100,000 movies and 1,000,000 ratings which have been collected by the GroupLens Research Project at the University of Minnesota. Their data have played the role of experimental matter for many authors (Peralta 2007; Harpale and Yang 2008; Jung 2012). In the following, we take an extract of the original dataset: 1682 movies rated by 943 commenters providing 5,000 ratings. We aim at illustrating:

a) how a Web dataset involving linked data from the semantic Web together with individual opinions issued from social ranking can be transcribed into a unique knowledge graph;

b) how the implicit knowledge associated to ‘ratings’ and the explicit knowledge issued from linked data can be both (and yet distinctly) topologically assessed.

The ViewpointS model for MovieLens

To transcribe the explicit information embedded in MovieLens into ViewpointS, we firstly create knowledge resources:

- MovieId stands for movies as Physical documents
- UserId stands for users as Legal persons
- AA-MovieLens is the Artificial agent corresponding to the MovieLens Ontology
- Age, genderId, gender, Occupation, Year are considered as Descriptors

We then consider that AA-MovieLens is the emitter of viewpoints with meta-type “onto-match”:

- the viewpoint (AA-MovieLens, [movieX, genreY], mo:genre, τ) stands for: the artificial agent ‘AA-MovieLens’ connects the object ‘movieX’ to the descriptor ‘genreY’

We then consider that each userId emits self-describing viewpoints with meta-type “onto-match”:

- the viewpoint (userId, [userId, occupationX], cv:jobType, τ)

We finally consider that each userId rate movies through viewpoints with meta-type “social-match”:

- the viewpoint (userX, [movieY, ** *], vp:rating, τ) stands for: the legal person ‘userId’ considers the object ‘movieY’ as ‘of average interest’

Protocol and measurements

We initialize the knowledge graph by transcribing the movies descriptions and users profiles as explained upper. Each movie is linked to one or more of the 18 ‘genres’ by viewpoints of type mo:genre and to one ‘year’ by a viewpoint of type mo:releaseDate. Each user is linked to one ‘class of age’ by a viewpoint of type foaf:member, one ‘gender’ by a viewpoint of type foaf:gender, and one ‘occupation’ by a viewpoint of type cv:jobType. All these viewpoints are time-stamped \( \tau_0 \); this is called cycle 0. We then arbitrary split the ratings into 5 subsets of 1000 ratings each (called cycle 1, cycles), using viewpoints of type vp:rating time-stamped \( \tau_i \) where \( 'i' \) is the cycle number.

We consider 3 perspectives:

- \( U_1 \) reflects priority given to explicit knowledge, i.e., viewpoints of meta-type “social-match” are weighted 1 whereas viewpoints of meta-type “onto-match” are weighted 3. In this perspective, the distance between a ‘movie’ and its ‘genre’ is 1/3, so that consequence two movies of same ‘genre’ are at distance \( <= 2/3 \); we therefore expect \( 'm=1' \) to be relevant for measuring the local homogeneity in ‘genres’ through this perspective.
- \( U_2 \) reflects balanced importance of explicit versus implicit knowledge, i.e., all viewpoints are weighted 1.
- \( U_3 \) reflects priority given to implicit knowledge, i.e., viewpoints of meta-type “social-match” are weighted 3 whereas viewpoints of meta-type “onto-match” are weighted 1.

In the perspectives \( U_2 \) and \( U_3 \), viewpoints of type mo:genre are valued ‘1’, so that two movies connected to the same ‘genre’ are at distance \( <= 2 \); we therefore expect \( 'm=2' \) to be relevant for measuring the local homogeneity in ‘genres’ through these two perspectives.

Besides, the multiplicity of ratings by different users in the dataset will yield strong synapses and in consequence short distances. As a consequence, both ‘m=1’ and ‘m=2’
are expected suitable for measuring the local homogeneity in ‘ratings’, whatever the perspective.

The experiment consists in going through cycle₀ to cycle₅ in 3 successive runs and measuring “local homogeneities” at the end of each cycle of each run.
- RUN₁,₁ corresponds to the perspective U₁ with m=1
- RUN₂,₂ corresponds to the perspective U₂ with m=2
- RUN₃,₂ corresponds to the perspective U₃ with m=2

Denotations
- M is the population of 1682 movies
- Genres is the collection of 18 genres
- Ratings is the collection \{*, **, ***, ****, *****\}
- \( U_{1,m,Genres} ≤ H( M ) \) is the local homogeneity of movies with respect to genres
- \( U_{1,m,Ratings} ≤ H( M ) \) is the local homogeneity of movies with respect to ratings

Results and interpretation
The 3 runs corresponding to the three perspectives associated with the suitable ‘m’ parameters (namely RUN₁,₁, RUN₂,₂ and RUN₃,₂) are presented in Figure 4.

![Figure 4: Assessment of explicit knowledge (genres) and implicit knowledge (ratings) along the interaction cycles](image-url)

We firstly observe that \( U_{1,m,Genres} ≤ H( M ) \) always takes significant values (between 0.30 and 0.55), whatever the cycle and the perspective. We interpret it as “genres provide information about movies, despite the noise due to other informational dimensions”.

We then observe that \( U_{1,m,Ratings} ≤ H( M ) \) always increases along the cycles (between 0.00 and 0.45), whatever the cycle and the perspective. We interpret it as “ratings provide information about movies, roughly in proportion with their number, despite the noise due to other informational dimensions”.

The major output of the experiment is that the value of \( U_{1,m,Genres} ≤ H( M ) \) decreases while \( U_{1,m,Ratings} ≤ H( M ) \) increases along the cycles, whatever the run. This illustrates concurrence and complementarity between the topological assessments respectively associated to ‘genres’ and to ‘ratings’. We interpret it as “genres and ratings are independent informational dimensions”.

Moreover, the intersection of the curves corresponding to these two dimensions occurs after cycle₁ i.e., after 3000 viewpoints ‘rating’, to be compared with 2893 viewpoints ‘genre’. We interpret it as: “ratings and genres are equally powerful informational dimensions”.

Finally, the curves intersect at a point quite independent from the perspective. This reinforces the hypothesis that “local homogeneity” proves information within the hidden topology of KG, whatever the map. A close look shows that the highest local homogeneity at intersection point appears in the perspective U₂: 0.32 for RUN₁,₁, 0.35 for RUN₂,₂, 0.34 for RUN₃,₂. We interpret it as “the balanced perspective U₂ is the best suited for observing simultaneously genres and ratings”.

Discussion
The MovieLens dataset has fulfilled our demonstration objectives:

a) we have transcribed all the information stored in the MovieLens dataset (social ranking and explicit semantics) into a unique knowledge graph.

b) we have topologically assessed the progressive dissemination of the implicit knowledge associated to ‘ratings’, in a knowledge graph initially embedding only the explicit knowledge of linked data.

Let us discuss these two points more in detail. Our formalism seems suitable for capturing both explicit knowledge delivered by linked data and implicit knowledge available in the Social Web. We cannot pretend however to capture all the richness of the semantic Web: for instance, the viewpoints fail in expressing the conceptual ‘parent-child’ relationship or ‘composition-component’ relationships, usually known as ‘is a’ and ‘is part of’ respectively. We capture only flat descriptions, not the conceptual verticality of ontologies. This built-in limitation rules out the possibility of logical assessment, but allows the topological assessment of proximity in a context of heterogeneous semantics.

Moreover our unified characterization of the collective knowledge seems well suited for observing the Web dynamics: we have provided topological arguments for assessing that “genres and ratings are complementary dimensions competing for providing information about movies recommendation, with comparable power”.

Another important aspect of the approach is the disconnection between the storage of the knowledge events (the viewpoints), and their delayed interpretations through knowledge maps responding to distinct perspectives. The viewpoints are purely qualitative; interpreting them in terms of quantities entirely depends on the perspective taken by the final user. Perspectives can be seen as a kind of global social ranking occurring “at exploration time”. This might be a response to the usual biases in social net-
works resulting from self-promotion or dishonest recommendation, since untrusted viewpoints emitters can easily be discarded when tuning the perspective.

**Future work**

We are currently developing an API offering intuitive input, easy browsing of the knowledge and one-click feedback. The next step in our agenda is to prove the concept in real life scenarios, i.e., to invite users to elicit knowledge collectively by using the ViewpointS approach through the API mentioned above. Two use cases have been planned, both oriented towards cross-disciplinary discoveries: one in the biomedical domain, in the context of the SIFR project, the other in the agronomic domain will be hosted by Cirad.

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**References**


