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Abstract. Collective intelligence is one major outcome of the digital revolution, but this outcome is hardly evaluated. By implementing a topological knowledge graph (KG) in the metaphor of a brain, the ViewpointS approach attempts to trace and assess the dynamics of collaborative knowledge building. Our approach relies on a bipartite graph of resources (agents, documents, topics) and time stamped "viewpoints" emitted by human or artificial agents. These viewpoints are typed (logical, mining, subjective). User agents feed the graph with resources and viewpoints and exploit maps where resources are linked by "synapses" aggregating the viewpoints. They reversely emit feedback viewpoints which tighten or loosen the synapses along the knowledge paths. Shared knowledge is continuously elicited against the individual "systems of values" along the agents' exploitation/feedback loops. This selection process implements a rudimentary form of collective intelligence, which we assess through innovative metrics.

In this paper, we present the exploitation/feedback loops in detail. We expose the mechanism underlying the reinforcement along the knowledge paths and introduce a new measure called Multi Paths Proximity inspired from the parallel neural circuits in the brain. Then we present the Web prototype VWA implementing the ViewpointS approach and set a small experiment assessing collective knowledge building on top of the exploitation/feedback loops.

Keywords: Collective intelligence · Knowledge graph · Knowledge map · Knowledge paths · Knowledge assessment · Reinforcement · Serendipitous learning · Unsupervised learning

1 Introduction

The so-called digital revolution has been progressively changing our lives in depth since the turn of the millennium, bringing in the hope of a collective intelligence [1]; the World Wide Web together with the internauts has often been compared to a collective brain.

Our previous work implements a topological numeric space where "knowledge shared within a community of agents is continuously elicited against the systems of values of the agents in a selection process." The goal of our approach is twofold: (i) to exploit the metaphor of the brain [2] for improving the collective construction of knowledge and (ii) to better exploit our digital traces in order to refine the understanding of our learning processes. We adopted a tripartite model 'resource/agent'–'resource'–'resource' called ViewpointS by storing and exploiting 'declarations by agents that two resources are close'. Assessing knowledge may seem a hazardous enterprise in such a context characterized by weak semantics. Whereas standard measurements exist in the case of explicit information retrieval, as listed in [3], none of those apply to serendipity: assessing informal learning remains an open issue despite the great deal of research work reviewed in [4]. Our approach is topology driven within the numeric space; it relies on a metric distance which opens the way both for "learning close to what we already know" in agreement with the principle of the "zones of proximal development" [5, 6] and for assessing knowledge acquisition.

This paper is a step forward in deepening the brain metaphor exposed by Edelman in [7]; we implement a feedback mechanism underlying the reinforcement along the knowledge paths and design a new metric taking into account the multiplicity of the knowledge paths.

We start in Sect. 2 by recalling the ViewpointS paradigm, presenting the feedback mechanism and defining a new metric called Multi Paths Distance. In Sect. 3 we briefly present the ViewpointS Web Application implementing the approach. In Sect. 4 we demonstrate the assessment of collective knowledge building through a small experiment using the feedback mechanism. Section 5 starts with a discussion about the results and then presents short term perspectives.

2 The ViewpointS Paradigm

The ViewpointS paradigm previously presented in [8–10] builds up upon trust towards 'peers', would they be humans, databases or mining algorithms. A community of human agents combines in a fully transparent and trackable way their own knowledge and feelings with declarations extracted from the Web. This happens in one single numeric space where:

(i) Inferences of the semantic Web (e.g. “Marguerite Yourcenar was born in 1903”) as well as ‘objective’ declarations of the users (e.g. “I was born in Paris”) provide the *Logical viewpoints*;

(ii) Statistical recommendations due to mining algorithms provide the *Mining viewpoints* (e.g. “https://www.aps.org/publications/apsnews/200207/history.cfm is related to ‘serendipity’”);

(iii) Spontaneous opinions, feelings and feedbacks of the community of agents provide the *Subjective viewpoints* (e.g. “I like this book”; “I think John is the person to contact if you are interested in ‘Serendipity’”).

The formalism adopted in the ViewpointS paradigm is briefly recalled in Sect. 2.1; for more details the reader might refer to [8, 9]. The feedback mechanism is presented in Sect. 2.2. The metrics governing the exploration of knowledge are presented in Sect. 2.3.

2.1 Interconnected Observation/Action Loops in a Numeric Knowledge Space

In the ViewpointS paradigm, agents, documents and topics constitute the *knowledge resources*; those are interlinked via the *viewpoints*. The *viewpoint* (r_1, {r_2, r_3}, θ, τ) stands for: ‘agent r_1’ (human or artificial) declares at time ‘τ’ that ‘r_2’ and ‘r_3’ are connected in the paradigm θ (*Logical* versus *Mining* versus *Subjective*).

We call Knowledge Graph the bipartite graph consisting of *knowledge resources* and *viewpoints* imported or emitted by the users themselves or by artificial agents. Given two *knowledge resources*, the aggregation of all the *viewpoints* interlinking them is called a *synapse*; it can be quantified and interpreted in terms of proximity by choosing a *perspective*. This is illustrated in Fig. 1.

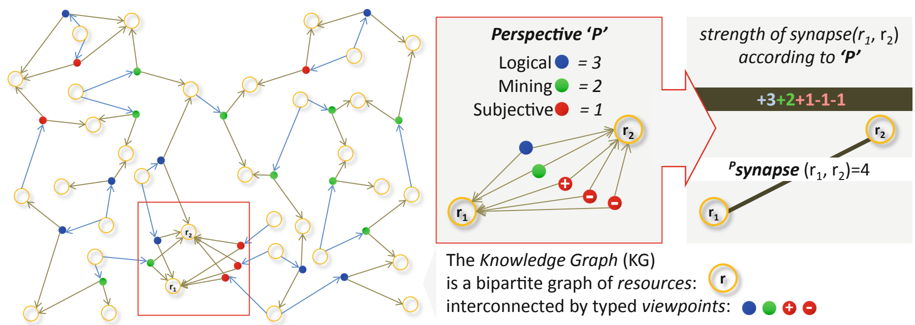

Fig. 1. The bipartite graph of resources and viewpoints is exploited by the user after choosing a perspective ruling the aggregation of viewpoints

The left part of Fig. 1 shows the bipartite graph of resources and viewpoints. When zooming on the two resources r_1 and r_2, we see that five viewpoints (emitted by five distinct agents) interconnect them. These five viewpoints are colored according to their types: blue = *Logical*, green = *Mining* and red = *Subjective*. *Subjective* viewpoints have a polarity: in the example, one is ‘positive’ (declaring proximity according to the subjectivity of the emitter) whereas two are ‘negative’ (denying proximity).

By choosing a *perspective*, any agent can tune the rules aggregating the qualitative *viewpoints* into quantitative *synapses* according to his own preferences with respect to the extraction of the knowledge available on the graph. These rules can integrate any type of IF-THEN predicate filtering the time-stamp, the emitter or the type of the *viewpoints*. In the examples of this paper, choosing the perspective simply consists in tuning the respective weights of the *Logical*, *Mining* and *Subjective viewpoints*, e.g. in Fig. 1 the chosen *perspective* 'P' consists in attributing the weights 3, 2 and 1 respectively for the *Logical*, *Mining* and *Subjective*. As a result, ${}^{P}synapse\,(r_1, r_2) = +3 + 2 + 1 - 1 - 1 = 4$, which is interpreted as "the proximity between r_1 and r_2 is '4'" OR "r_1 and r_2 are at distance ¼".

Given a *perspective* '*P*', we call ^{P}KM (*knowledge map* according to '*P*') the following undirected labelled graph:

- the nodes of ^{P}KM are the *resources* of KG;
- the edges of ^{P}KM are the positive ^{P}*synapses* labelled by their values.

The shared semantics emerge from the dynamics of the intricate observation/action loops among the community of agents interacting with the KG through the ^{P}KM. Agents choose a *perspective*, browse the *knowledge map* ^{P}KM and exploit the shared knowledge issued from the *viewpoints* of the whole community (observation), and reversely update the *knowledge graph* KG by adding new *viewpoints* expressing their feedback (action). Intertwining exploitation of shared resources and feedback on their links enhances collaborative knowledge building; this has been analyzed in [11] and illustrated in [12]. In the ViewpointS paradigm, the shared knowledge is continuously elicited against the individual systems of values of the members of the community in a selection process.

2.2 Reinforcing Versus Weakening Knowledge Paths in the Loops

Subjective viewpoints have a polarity. Positive (resp. negative) *viewpoints* are used for declaring (resp. denying) proximity between *resources*. Through *subjective viewpoints*, an agent may create direct connections: (i) between him/her and a given *resource*, e.g. "like/dislike" OR (ii) between two given *resources*, e.g. "match/mismatch".

A complementary mechanism involves a special category of *subjective viewpoints* called *feedback viewpoints*; it is illustrated in this paper. *Feedback viewpoints* allow agents to strengthen OR weaken the shortest path[1] between two distant *resources*, by distributing fragments of a subjective viewpoint along the shortest path in the metaphor of the reinforcement of synapses in our neural circuits. We illustrate this by an imaginary use case based on the following KG:

- *documents* have been connected via *Mining viewpoints* to *topics*, e.g. 'saying92' has been connected to 'topic-A';
- *human agents* (*Marguerite Yourcenar*, *Voltaire*…) have been connected via *Logical viewpoints* to *topics* (topic-G, topic-S …);
- by transitivity, the *agents* are connected to the *documents* by paths where the proximities are computable.

[1] The computation of the shortest path distance bounded by 'b' is explained in Sect. 2.3.

Three human agents (HA_1, HA_2 and HA_3) exploit the knowledge through the perspective P_0 where the weights of the *Logical*, *Mining* and *Subjective viewpoints* are all equal to ‘1’; the corresponding knowledge map is denoted ^{P0}KM. They react to the proximities by emitting the *Subjective feedback viewpoints* illustrated in Fig. 2.

Fig. 2. The human agents HA_1, HA_2 and HA_3 update the proximities between *Marguerite Yourcenar* and *saying*$_{94}$, *saying*$_{92}$ and *saying*$_{91}$ respectively.

Figure 3A below illustrates the initial state of ^{P0}KM. The *Subjective feedback viewpoints* yield the final state illustrated in Fig. 3B.

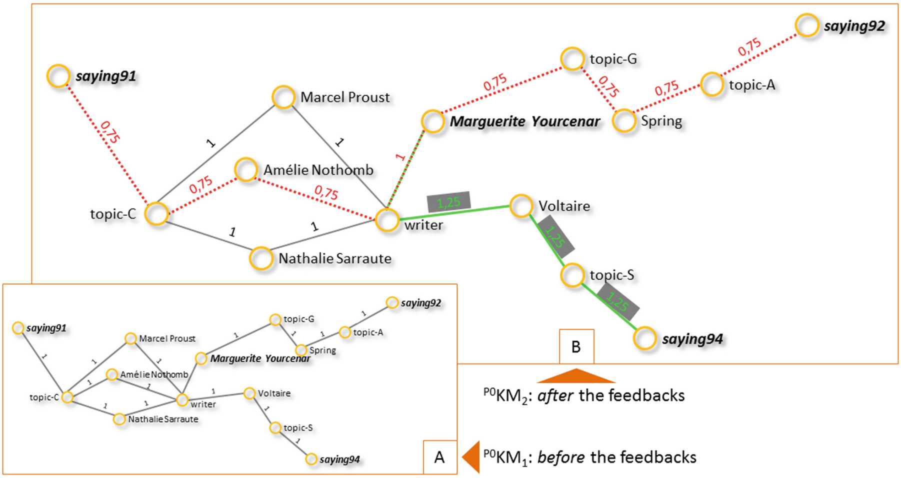

Fig. 3. Evolution A → B of the ^{P0}KM as a consequence of the TIGHTENING and LOOSENING; the labels are the strengths of the synapses (Color figure online)

- The shortest path between *Marguerite Yourcenar* and *saying*$_{94}$ counts ‘n = 4’ edges and goes through ‘writer’, ‘Voltaire’ and ‘topic-S’. HA_1 TIGHTENS the path through a *positive feedback viewpoint* by adding a subjective viewpoint of ‘+1/(n = 4)’ on each edge; each corresponding ^{P}*synapse* evolves from ‘1’ (grey lines in image A) to ‘1,25’ (green lines in image B).

- The shortest path between *Marguerite Yourcenar* and *saying*$_{91}$ counts ‘4’ edges and goes through ‘topic-G’, ‘spring’ and ‘topic-A’. HA$_2$ LOOSENS the path through a *negative feedback viewpoint* by adding a subjective viewpoint of ‘−1/4’ on each edge; each corresponding ^{P}*synapse* evolves from ‘1’ (grey lines in A) to ‘0,75’ (red dotted lines in B).
- The shortest path between *Marguerite Yourcenar* and *saying*$_{91}$ counts ‘4’ edges and goes through ‘writer’, ‘Amélie Nothomb’ and ‘topic-C’. HA$_3$ LOOSENS the path through a *negative feedback viewpoint* by adding in the KG a subjective viewpoint of ‘−1/4’ on each edge; each corresponding ^{P}*synapse* evolves from ‘1’ (grey lines in A) to ‘0,75’ (red dotted lines in B).

2.3 The Metrics Sustaining the Exploitation of Knowledge

In our previous work [9], the metric in use was the “shortest path distance bounded by ‘b’”, denoted ^{b}SPD, an adaptation of Dijkstra’s algorithm with acceptable complexity[2] which: (i) scans all the paths respecting the threshold ‘b’ between two given resources and (ii) computes the shortest path. Given a ^{P}KM, the length of an edge $r_i - r_j$ is defined as $1/^{P}$*synapse* (r_i, r_j); the length of a path $r_i - \ldots - r_j \ldots - r_k$ is the sum of the edges’ lengths. ^{b}SPD(r_i, r_j) returns ‘NA’ if no path of length <= b link r_i to r_j; it returns d <= b otherwise. ^{b}SPD has been illustrated in the imaginary case developed in [8].

In this paper, we wish to consider multiple parallel paths when computing proximities in ^{P}KM. We characterize an “equivalent synapse” expressing a proximity between two given resources by taking into account all the possible paths; we call it “multi paths proximity bounded by ‘b’” and denote it ^{b}MPP. The computation of ^{b}MPP requires two preliminary definitions:

- we call ^{b}Neighbours(r_0) the set of resources r_x such that ^{b}SPD(r_0, r_x) is available;
- we call ^{b}Paths(r_0, r_x) the set of all paths $(r_0, \ldots, r_x)$ of length <= b between r_0 and resources belonging to ^{b}Neighbours(r_0).

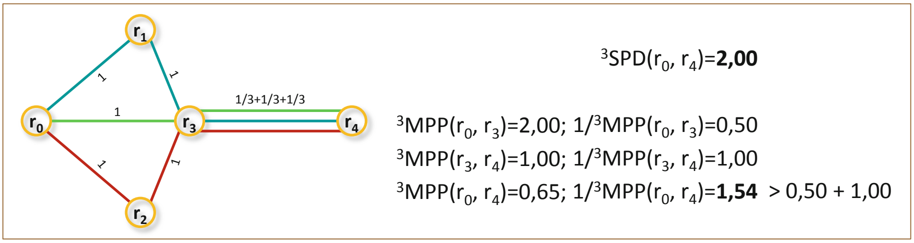

Fig. 4. Computation of ^{3}MPP(r_0, r_4). The label “1/3 + 1/3 + 1/3” between r_3 and r_4 indicates that *synapse*(r_3, r_4) participates to three paths linking r_3 to r_4, each of these paths using a channel capacity of 1/3 of the strength of the synapse.

[2] The worst case complexity of Dijkstra’s algorithm is O $(N_W^2\ N_R^2)$, where N_W is the number of viewpoints in KG and N_R is the number of resources in KG. In ^{b}SPD, the worst case complexity is practically never reached because of the bound ‘b’.

The computation of ${}^{b}MPP\ (r_1, r_2)$ illustrated in Fig. 4 obeys four rules:

- rule 1: given 'b', we restrict the computation to the following subgraph of KG: ${}^{b}Paths(r_1, r_2)$;
- rule 2: when 'n' paths of ${}^{b}Paths(r_1, r_2)$ share a ${}^{P}synapse$, we consider a channel capacity '$cc = {}^{P}synapse/n$' for each path, and a pseudo-length '$L_{edge} = 1/cc$' for this edge in each path;
- rule 3: for each $path_i$ between r_1 and r_2, we consider the pseudo-length $LL(path_i) = \sum_{edges\ in\ path} L_{edge}(path_i)$);
- rule 4: ${}^{b}MPP\ (r_1, r_2) = \sum_{i=1,\ n} 1/LL(path_i)$.

$1/{}^{b}MPP(r_0, r_0) = 0$. $1/{}^{b}MPP$ satisfies the symmetry condition: $1/{}^{b}MPP(r_1, r_2) = 1/{}^{b}MPP(r_2, r_1)$. However $1/{}^{b}MPP$ DOES NOT satisfy the triangle inequality: $1/{}^{b}MPP(r_0, r_4) > 1/{}^{b}MPP(r_0, r_3) + 1/{}^{b}MPP(r_3, r_4)$. It is NOT a metric distance.

3 VWA, the ViewpointS Web Application

The ViewpointS Web Application (VWA) has been implemented in the Spring Web MVC framework providing Model-View-Controller (MVC) architecture; the KG is stored in a Postgresql database exploited through a Java API. Once logged in, any user can create *resources* and emit *viewpoints* shared by the community.

The web based graphical user interface presents 7 significant zones marked in red in Fig. 5 below.

Zone 1 lists the menu commands:

- New resource: Knowledge graphs (KGs) are populated with different classes of *resources*: "artificial agent", "human agent", "numeric document", "physical document", or "topic". Every resource class has a distinct color when appearing in the draw area (*Zone 3*). Only in case of a Numeric document, an additional option of attaching (uploading) an URL is presented. All resources are identified based on their name. It must be noted that the set of *resources* is shared by all the KGs; on the contrary, each *viewpoints* belongs to one and only one KG.
- New Logical Viewpoint: Two resources are to be selected before a logical viewpoint can be emitted (by the current user) to interconnect them. A radio-button (containing '+' sign) is preselected.
- New Subjective Viewpoint: Similar to the previous option, two resources are to be mentioned. Four radio buttons allow the user to tune the polarity and strength of the emitted viewpoint. Choosing '−', '0', '+' and '++' signs create a 'negative', 'neutral', 'positive' and 'double positive' *viewpoint* respectively.
- New Feedback: A feedback between two resources can either be positive (TIGHTEN) or negative (LOOSEN) as depicted by the '−' and '+' signs respectively[3].

[3] In either case, the result is the emission of a series of fragmented viewpoints along the shortest path between the two resources, as explained in Sect. 2.2.

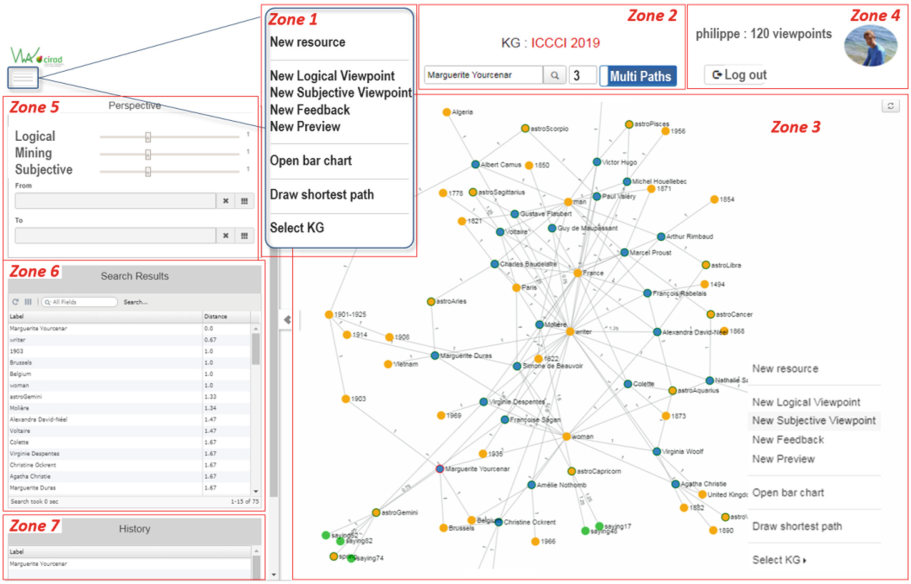

Fig. 5. The graphical user interface of VWA as it appears after user authentication and log in (Color figure online)

- New Preview: A *resource* ‘x’ can be connected to a Numeric document that will appear on right click on ‘x’ in the draw area. Nota: preview viewpoints do not contribute to the *synapses.*
- Open bar chart: This function calculates all the proximities (according to the metrics selected in zone 2) between (i) a given *resource* ‘x’ and (ii) a vector ‘Z’ of selected *resources* playing the role of referential. The result is a bar chart drawing the Z-profile of ‘x’.
- Draw shortest path: Operates on two resources selected from “Search results” *(Zone 6)* and/or “History” *(Zone 7).* The shortest path between them according to the current *perspective* is computed and drawn in the draw area (*Zone 3*).
- Select KG: A list of knowledge graphs (created by the administrator) is provided to the user.

Zone 2 is the area for activating a search, on the basis of the parameters defined in the *perspective* (*Zone 5*). The results are shown graphically in the draw area (*Zone 3*) and also listed in “search results” (*Zone 6*). The search is conducted on the basis of resource name (auto completion is available). The neighborhood radius (‘b’ for ^{b}SPD and ^{b}MPP as mentioned in Sect. 2.2) tunes the depth of the search. A toggle between “shortest-path” and “multi-paths” metrics is available[4].

Zone 3 is the draw area where the neighborhood of the target in ^{P}KM is edited with *resources* interlinked by *‘synapses’* with labels corresponding to their weights.

[4] These metrics have been described in Sect. 2.2.

The target of the search is circled in red. The graph can be resized and reshaped with simple mouse drag operations. Right clicking on a resource circled in green shows its preview in a tiny dialogue box. They can be further elaborated with a left click. The edition is cumulative until a change of *perspective* or a "clean visu" (up-right button)

Zone 4 is self-explanatory as shown in the Fig. 5. The picture of the agent and the number of viewpoints emitted by the agent are displayed. The logout button is also present in this zone.

Zone 5 is the perspective pane that monitors the aggregation of viewpoints into *synapses* as explained in Sect. 2.1. In the current state of the prototype, only simple tuning of perspectives is available: the *synapses* of the knowledge graph can be revaluated according to the three sliders corresponding to the *viewpoints* types (*Logical, Mining* and *Subjective*). Besides, *viewpoints* can be filtered according to time 'τ'.

Zone 6 contains the search results. These results are ranked according to their proximities from the selected resource. Double clicking on a resource can select the resource and copy it in the search area.

Zone 7 keeps track of every resource that has been successfully searched and selected.

The ViewpointS Web Application (VWA) is regularly enriched with new functionalities; a demo version, where the sessions are not persistent, is available at url: viewpoints.cirad.fr/vwademo.

4 Assessing Collective Knowledge

In order to assess the collective knowledge with the metrics presented in Sect. 2.3, we have set a toy experiment where three VWA users express knowledge about a panel of writers. The knowledge graph (KG) is initially populated by *Logical viewpoints* and *Mining viewpoints*; the three VWA users express their own opinions about the writers by adding subjective *feedback* viewpoints. Then we use the metrics presented in Sect. 2.3 to measure the reinforcement versus weakening of the knowledge paths.

4.1 Settings

The following *resources* initially populate the KG:

- 'HA_1', 'HA_2' and 'HA_3': human agents sources of the *Subjective* knowledge in VWA; other "human agents", e.g. 'Marguerite Yourcenar'
- 'Authors Database': artificial agent source of the *Logical* knowledge
- 'Astrological Statistics': artificial agent source of the *Mining* knowledge
- a few "topics": 'solar year', 'spring', 'astroCancer', 'astroSagittarius', …
- numeric documents called "sayings" that the users may read by right-clicking on them in the KM, e.g. '$saying_{81}$: The person does not look into her past: she dives into it, she bathes there. She does not make plans for the future; she makes plans for the past.'

The following *viewpoints* initially populate the KG:

- Logical *viewpoints* emitted by ‘AUTHORS DATABASE’ interlink the writers, their astrological signs and the seasons of the solar year, e.g. ‘Marguerite Yourcenar LINKEDTO astroGemini’
- *Mining viewpoints* emitted by ‘ASTROLOGICAL STATISTICS’ interlink the sayings and the astrological signs, e.g. ‘saying_{81} LINKEDTO astroGemini’.

The three users ‘HA_1’, ‘HA_2’ and ‘HA_3’ are invited to browse the knowledge graph under the *perspective* P_1 illustrated in Fig. 6. They benefit in real time from the contributions of the others BUT are deprived from the *Mining viewpoints*, i.e. they are not influenced by the knowledge of ‘ASTROLOGICAL STATISTICS’. During this browsing, they are invited to express in feedback their own opinions about the proximities between the “sayings” and the writers by exclusively using the TIGHTEN and LOOSEN facilities exposed in Sect. 2.2.

4.2 Results

The first result is a proof of concept: we have implemented the mechanism described in Sect. 2.2 and proven the reinforcement versus weakening of some knowledge paths: Fig. 6 (directly issued from VWA) is a perfect match of Fig. 3 (drawn at design phase) through the following translations: topic-A → astroAries; topic-C → astroCancer; topic-G → astroGemini; topic-S → astroSagittarius. After the experiment, the probability to reach *saying_{94}* from *Marguerite Yourcenar* when browsing along the paths has become stronger than the probability to reach *saying_{91}* or *saying_{92}*; in other words, the communities of agents have collectively declared that *saying_{94}* fits her better than by the two other sayings.

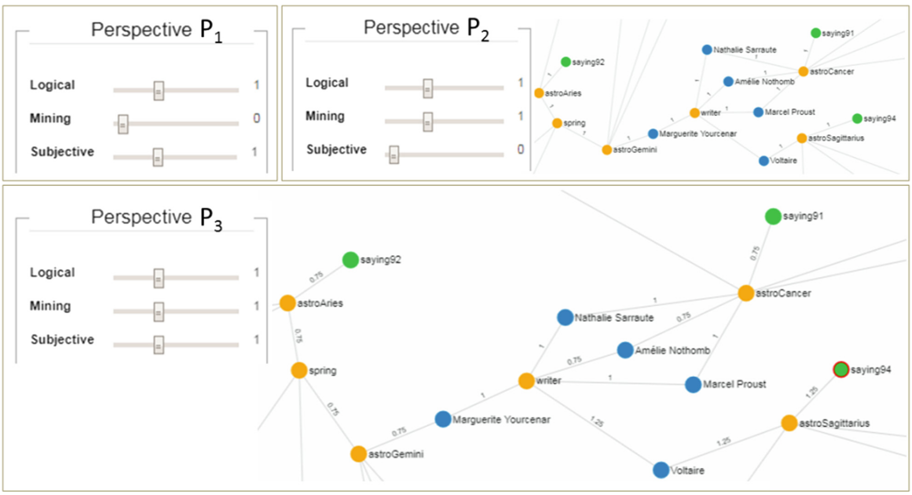

Fig. 6. *Perspectives* and corresponding *knowledge maps*: P_1 considers *Logical+Subjective viewpoints*, P_2 considers *Logical+Mining* and P_3 considers *Logical+Mining+Subjective*

The results presented in Fig. 7 illustrate a search where the target is ‘Marguerite Yourcenar’.

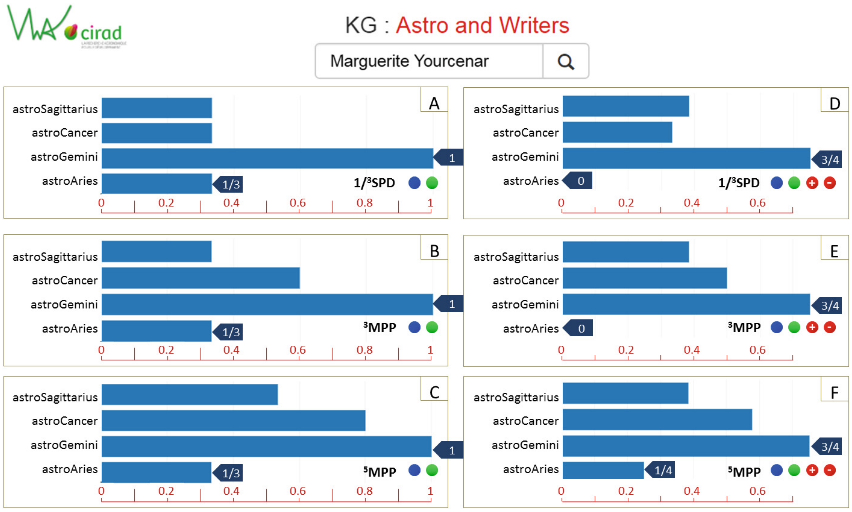

Fig. 7. Impact of the feedbacks on the "astrological profile" of Marguerite Yourcenar (M. Y.); the bar charts reflect proximities according to two distinct perspectives, 'WITH subjective viewpoints' in the right diagrams) and various metrics (1/SPD versus MPP) (Color figure online)

By comparing left to right we assess the reinforcement mechanism. The left diagrams A, B, C give proximities according to *perspective* P_2: WITHOUT subjective viewpoints (only blue and green viewpoints), i.e. with all viewpoints BEFORE the feedback by the users. The right diagrams D, E, F give proximities according to *perspective* P_3: WITH the subjective viewpoints, i.e. with all viewpoints INCLUDING the feedback by the users (blue, green, red+ and red− viewpoints).

By comparing up to down, we compare the metrics: A&D use the shortest path proximity $1/^3$SPD; B&C use the multi paths proximity ^{3}MPP; E&F use the multi paths proximity ^{5}MPP.

The measures displayed in the six diagrams open to the following comments:

- given a *perspective* (either P_2 or P_3), proximities computed by MPP are equal or bigger than proximities computed by 1/SPD: the proximities in 'B' are bigger than in 'A'; the proximities in 'E' are bigger than in 'D'.
- ^{b}MPP increases when 'b' increases: the proximities in 'C' are bigger than in 'B'; the proximities in 'F' are bigger than in 'E'.
- both TIGHTEN and LOOSEN operate independently from the metric or the bound 'b' chosen: by comparing successively A&D, B&C and E&F, we can see that the respective proximity between: (i) 'M. Y.' and 'astroAries' decreases, (ii) 'M. Y.' and 'astroGemini' decreases, (iii) 'M. Y.' and 'astroCancer' decreases, (iv) 'M. Y.' and 'astroSagittarius' increases.

5 Discussion

In this paper, we have put the focus on the exploitation/feedback loops of a community of agents sharing knowledge resources. We have provided features and metrics aimed at aggregating individual viewpoints into measurable proximities and presented the ViewpointS Web Application (VWA), working online.

We have proved the concept of a feedback mechanism impacting the topology of the knowledge graph in the metaphor of a collective brain by setting an experiment where users were specifically required to feedback. We have described and operated a new measure called "multi paths proximity (MPP)". MPP does not respect the triangle inequality. MPP yields greater proximities than 1/SPD and these proximities increase with the bound 'b' reflecting the depth of the search. We have opened the way to the assessment of collective knowledge: (i) perspective-dependent knowledge paths appear through Knowledge Maps and (ii) these paths are strengthened or weakened depending on the dynamics of the interactions.

Our next step will consist in setting a more ambitious real-life experiment in order to better analyze MPP in comparison with 1/SPD, especially by comparing their respective stabilities along the dynamics of the interactions, and better explicit the benefits driven from the brain metaphor in assessing collective knowledge.

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