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Picturing what others know: towards a dashboard for interdisciplinarity

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Picturing what others know: towards a dashboard for interdisciplinarity

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ABSTRACT

In many complex, multi-faceted, problem-solving situations there is a growing need to pull together various competences and backgrounds, *i.e.* a need to better balance specialisation and interdisciplinarity. But when scientific backgrounds, skills, references, specialized languages and specialized knowledge are too far apart people involved in an interdisciplinary process face a real communication challenge. Communication is here not the best word – it minors the challenge. What actors face is the challenge to reach a common understanding of facts and of pictures of facts, in other words to build a common, unambiguous, knowledge space. Not making this effort often results in misunderstandings, and accordingly in delays and inefficiency. At the end of the day, results may turn out as a nice patchwork rather than as new knowledge. In this contribution we show that it can be worth having actors get aware of distances between them, of overlaps and non-overlaps in terms of methods, specialised language, references and concepts. We present a series of short experiments that are an attempt to “measure” and then visualize the above mentioned distances, and can act as eye openers for a community.

Categories and Subject Descriptors

H.1.2, H.3.1, H.3.7, H.5.2, H.5.3, I.2.4, I.2.8, K.4.3, K.6.1.

General Terms

Measurement, Design, Experimentation, Human Factors.

Keywords

Methodology, Spatio-temporal data, Information visualization, Knowledge management, Interdisciplinary research.

1. GENERAL ISSUE

Back in the early age of enlightenment, or during the renaissance, some scientists could claim they had a global understanding of all scientific fields, and, furthermore, of technologies and philosophy. A sort of “universal knowledge”, as worded by [1], may have

been, at that time, within reach (although soon enough the move for encyclopaedias, *co-written* by several authors, paved the way for modern, collaborative but dispersed science).

This time has obviously more or less passed, and better balancing specialisation and interdisciplinarity appears today as a growing challenge, in the R&D community and more generally in decision making processes. Analysing complex systems – in environmental sciences for instance – is known to require pulling together various competences, encompassing various scientific fields and sub-fields. A good illustration is the analysis of urban particle pollution patterns. Understanding these patterns, deciding on public policies to cope with the inconveniences, requires an observation of the facts (*i.e.* developing real-time survey methods so as to measure amounts of particles in the air) but also requires analysing possible causes (*i.e.* knowing of technologies such as coal-fired plants or diesel engines and catalytic converters) and putting the whole picture into its context (depicting contemporary lifestyles, mobility patterns, commuters, etc.). Hence the introduction of terms such as *multidisciplinary*, *pluridisciplinary*, *interdisciplinary* approaches in the vocabulary of research, and in this of public or private funding calls. But what do these terms refer to? How do they differentiate from one another? Are we talking about slogans, or about practical challenges? Intuitively we would tend to consider that unlike *multidisciplinarity*, that seems to refer to layers of skills added on to the other in order to tackle a multi dimensional problem, *interdisciplinarity* refers to some kind of “in-between”. This is confirmed in [2] with the following definitions:

- *Multidisciplinary*: Juxtaposition of various disciplines, sometimes with no apparent connection [...]

- *Pluridisciplinary*: Juxtaposition of disciplines assumed to be more or less related [...]

- *Crossdisciplinary*: Imposition of the approaches and axioms of one discipline on another [...]

- *Interdisciplinary*: An adjective describing the interaction among two or more different disciplines [...] from simple communication of ideas to the mutual integration of organizing concepts, methodology, procedures, epistemology, terminology [...]

A contribution like [3] where two recent computer technologies are combined in order to back up archaeological research can be considered as a typical *multidisciplinary* experience. Eventually, with time and with the growing introduction of 3D platforms in the enhancement of archaeological findings, it might even turn out to be a *pluridisciplinary* experience. A contribution like [4], where concepts stemming from the field of linguistics structure the creation of a specialised ontology for historic architecture, can be seen as a typical *crossdisciplinary* experience.

An *interdisciplinary* research is something a bit different and [5] says it very clearly: *Interdisciplinary research requires shared models, concepts and terms best developed through incremental working*. A contribution like [6], where the focus is put on the *convergence of user-centered, visually driven analysis methods for time-oriented data*, underlines some of the specific challenges of interdisciplinarity: an ambition to “bridge disciplinary gaps” [7], an ambition to reach some kind of “in-between”. So what exactly is that in-between, supposedly specific to *interdisciplinarity*?

One thing that does bring different actors together is computer-based tools, formalisms and methods such as GIS systems [8], or surveying platforms [9]. But is sharing a tool enough to make something of that in-between? Some languages share an alphabet – does that alphabet constitute an in-between helping people understanding one another in an efficient way? Certainly not: languages remain apart, incomprehensible if one is not taught them. The tool some languages share– an alphabet – cannot be considered as this in-between we expect when we mention interdisciplinarity. Let us take another example. Let us imagine two people driving along the same road. Well the in-between that makes it possible for them to drive on that same road *safely* is not the road itself, a tool, but the Highway Code, a common knowledge.

In other words, analysts who wish to conduct an interdisciplinary research should simply **not** take for granted that all they will need is basically to share a goal or a tool. Presumably, and we hope this contribution will back up our claim, they will, prior to the actual co-operation, need to get aware of distances between them in order to **build their in-between**, made of *models, concepts and terms*.

2. OBJECTIVE, CONTEXT, CONTENT

Difficulties of interdisciplinary research are known to many, and convincingly described in [10] who also underlines what is at stake – a *synergy, resulting in enhanced productivity for all participants over the long run*. But in this contribution we shall not discuss interdisciplinarity as such, in general terms: a number of surveys of issues at institutional level have been carried out such as [11] or [12]. Instead, we present a collaborative experiment through which we have tried to measure and visualise distances between actors inside a given community of scientists who analyse spatial dynamics from a variety of points of views (history, archaeology, environment, geography, urban planning, *etc.*). That community does share a concern for spatio temporal data, and quite often a tool – GIS platforms. But a number of misunderstandings between actors and /or of biases needed to be pointed out, proven, and debated so as to have the community go ahead, such as:

- A stronger concern for the space variable than for the time variable.
- polysemous terms that actors interpret differently (“dynamic”, “representation”, “timing”, “accuracy”, “generalisation” for instance).
- Cartographic representations widely privileged over any other visual formalism.
- Scarce integration of infovis-inspired reasoning tools.

It is clear that most actors involved in interdisciplinary research practices are conscious of potential non-overlaps, but our goal was to come out with surveys, numbers, facts, visualisations that would help them go beyond a vague consciousness. Accordingly, we propose *practical* means to assess disciplinary distances so

that actors get a clearer view of overlaps and non-overlaps in terms of methods, specialised language, references and concepts, *etc.*, More precisely, we chose to focus on two prominent potential biases and/or misunderstandings in the above research context:

- *is there today a sort of “spatial bias” in the way we handle such data sets (in other words, a predominance of space-centric concepts and tools, with time seen as a secondary concern)?*

- *are there linguistic biases that prevent actors from understanding one another in a clear-cut way (in other words, do discipline create jargons that result in potential misunderstandings, with the same word corresponding to different notions here and there)?*

Accordingly, we developed two different survey protocols.

The first protocol (section 3.2.1) focuses on analysing a potential *spatial bias*. It results in a visual *measure of impact*, meaning here a measure of how familiar actors are of some classic visual solutions. The hypothesis is that if analysts have a far better knowledge of classic space-oriented visualisations than of classic time-oriented visualisations then it is likely that they do have a bias. Additionally, this first protocol gave us the opportunity to also measure the impact of *infovis* (Information Visualisation) as a discipline, and as a set of practices and solutions, on actors having no or very little implication in that field.

The second protocol (section 3.2.2) focuses on an analysis of similarities and differences in the way actors from various disciplines interpret terms. The hypothesis here is that some terms, or some classes of terms, may have been interpreted in narrow ways here and there, threatening the capacity of actors to get an in-depth understanding of the positions and methods of others.

Both protocols build on methods and practices that are of rather common use: qualitative questionnaires to be filled in by a target group (see for instance [13] and [14]). Some significant differences in terms of practical implementation however need to be pointed out. Accordingly in the next section we present the conditions of the experiment: who was targeted and why, what exactly actors were asked to do, what methods were used, and ultimately how we compared this first “benchmark” experiment with some further surveys. We then focus on the visual results: how the visualisations were designed, and what picture they helped us draw of interdisciplinarity. Finally, conclusions and perspectives underline what we consider was fruitful (or needs to be further developed).

We shall however make no claim that the method we have developed can be used in another context without proper adaptations.

3. EXPERIMENTAL SETUP

3.1 Test group

The experiment was carried out as part of a thematic school (workshop & tutorials) organised by the MoDyS research group, and entitled “Modelling and visualising spatial dynamics : Reasoning on long time spans and uncertainty” [15]. The event’s aim was primarily to identify and measure similarities and differences in the way events, processes, and transformations are handled across various disciplines, and when facing various real cases, datasets and research goals. The MoDyS (Modelling spatial dynamics) research group itself started as a forum where

researchers focused on the intersection of Geomatics and Archaeology. This move followed the massive introduction for more than ten years now of space-oriented concepts and tools both in the acquisition stages (Laser scanning, LIDAR, infra-red, *etc.*) [16] and in the management and post-processing of the data (GIS, CAD, Spatial analysis) [17] [18].

But the group was then extended to other disciplines or fields of concern – typically History, Computer science, Information visualisation, Architecture, Urban planning, Landscape analysis, *etc.* Accordingly the topics covered evolved, switching from space-centric approaches to broader issues such as understanding and modelling the time variable, dealing with uncertainty, introducing concepts and solutions from the Information visualisation & visual analytics communities, *etc.* As a result, the community knew a significant move, from a face to face situation between two communities, and two competences, to a wider (sort-of) melting pot, thereby opening new communication challenges.

Furthermore, the experiment was carried out as part of an event that was open beyond the research group itself (more than half of the participants were not members of the research group). In other words, possible biases that could have resulted from a test group composed of people having been in contact previously are limited.

The experiment’s target audience should therefore be understood as *the 46 participants of the thematic school*, and not only members of the pre-existing MoDyS community. A majority of that target audience already had opportunities to carry out multidisciplinary research. Profiles were recorded as such, with a “main” disciplinary field corresponding to a participant’s main education or field of competence, and one or several areas of interest corresponding to his other involvements (Figure 1).

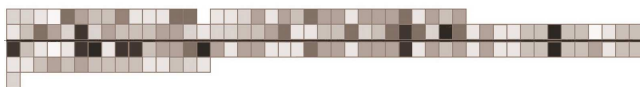


Figure 1: An overview of the profiles of participants. Each column corresponds to a participant. Shades of grey correspond to disciplines or competences. Below the middle horizontal line are squares corresponding to the initial competences or education of participants – several squares, several competences. Above the middle horizontal line are squares corresponding to their current fields of concern or research field. Only 12 participants out of 46 can be said to be “mono-disciplinary” (columns on the right side of the figure).

The experiment’s initial aim was to try and make the target audience aware of potential communication difficulties resulting from divergent terminological habits, to underline unsaid biases, and to illustrate the benefits of infovis-inspired solutions (in assessing the above statements as well as more generally in reasoning on the time variable). The experiment was later prolonged with other groups so as to pull together different benchmarks.

3.2 Tasks

3.2.1 Measure of impact

Here the test group was shown a series of 44 classic visualisations, distributed into three categories:

- visualisations of quantities (ranging from Playfair’s line charts to Mosaic displays [19]),
- visualisations of space-oriented data (ranging from Dupin’s choropleth maps to Galton’s weather maps),

- visualisations of time-oriented data (ranging from M.Homma’s candlestick chart to the spiralGraph display [20]).

Naturally a number of these visualisations bridge several categories: Minard’s flow maps for instance handle both space and time. The test group was not aware of this categorization, used only for the post-processing of their answers.

We chose to combine classic, pre-computer visualisations with more recent solutions since a vast majority of the test group was quite unfamiliar with discipline-specific trends and solutions (notably with infovis formalisms). Each participant was asked to tick, for each of the 44 visualisations, one of the following answers:

- *I know this kind of visualisation and consider myself as concerned.*
- *I know this kind of visualisation and consider myself as not concerned.*
- *I do not know this kind of visualisation.*
- *I do not know this kind of visualisation but I think it could be of use for me.*

In other words, what was tested here was first the impact of a series of visualisations across the test group, and accordingly to some extent across the disciplines the test group corresponded to. But what we were measuring beyond that was on one hand whether or not time-oriented data visualisations differed, in terms of impact, from others; and on the other hand whether recent infovis solutions had crossed disciplinary borders.

3.2.2 Overlaying of concepts and terms

Here the test group was given a sort of lexicon inside which we pulled together 57 terms corresponding to notions that could appear at first glance as straightforward (“process”, “time interval”, “reliability”, “hypothesis”).

For each term, we proposed from 2 to 7 alternative definitions (in French and English) taken from the literature (overall numbers: 250 definitions, 53 references). Terms were distributed in four main categories: phenomenon, time parameter, uncertainty, general vocabulary. Each participant was asked to tick, for each of the 250 definitions, one of the following answers:

- *I use this term in the sense given by that definition.*
- *I use the notion given by that definition, but I use another term for it.*

Participants who felt unconcerned by a term and its definitions were asked to leave the question unanswered. They could also add their own definitions for each term.

A fifth category, called “tabula rasa” was proposed that gave participants the opportunity either to propose a definition for four terms we left definition-less in that category, or to add a new term (result : 11 terms and 21 definitions added).

In other words, we tested here *semantic overlaying*: divergent terminological habits, controversial uses of one term that may refer inside one or another discipline to different notions.

In addition, the density of answers for each term, and each definition, can also be a fruitful indicator, illustrating a strong or weak concern for the notion itself (for instance a notion like “multivocal time”, that one would expect to be a key concept when dealing with uncertain temporal data sets, surprisingly got only 10 votes out of 46 voters).

3.3 A “no computer” survey method

After some debate, and despite its cost at post-processing time, we decided for an “old times” survey method, based on printed material rather than on interactive platforms - and this for several reasons:

- If most of the participants had a good or very good knowledge of computer platforms, some were by contrast less at ease with such environments, possibly biasing the results.
- Since the experiment was carried out during a continuing education event, we wished to foster discussions in small workgroups, in informal contexts.
- Filling in forms pages long on a computer screen often goes with a good deal of boredom. Since the amount of questions we asked testers was rather high we considered necessary to provide a more playful, and debate-enhancing survey modality.

As a result, both the above experiments were conducted basing on a comparable scenario. The data – may it be lists of visualisations or of terms and definitions- was presented inside A3 format leaflets, left for use on a large table for the whole duration of the event (4 days). Participants could come and go around that table anytime during the whole period, fill in leaflets in one go or little by little. In order to “vote”, each participant was given a specific inked stamp pad (two colours of ink were used to differentiate the meanings of the vote). Beyond the somewhat playful aspect, the idea was to have votes kept anonymous.

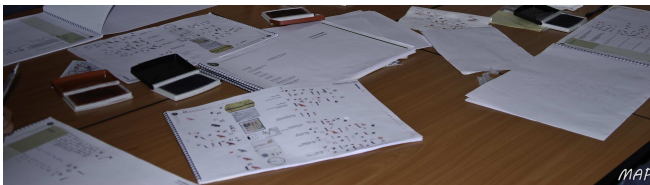


Figure 2: The survey material - printed material and inked stamp pads.

3.3.1 Further surveys

This experimental setup was reused in later experiences in order to try and compare results obtained on the initial test group with others, and to identify possible biases. These additional surveys were however only conducted on the *measure of impact* test. Groups targeted were last-year students in specific courses preparing them for a PhD. These groups were this time consistent in terms of education –students in mechanical engineering or in architecture. The same method was applied (except timing constraints, stronger here) and results are discussed in the conclusion section.

4. ANALYSIS OF THE RESULTS

Following the survey, we analysed the results through four graphics aimed at having actors get aware, through visual means, of distances between them, of overlaps and non-overlaps. The paper-based survey was transferred in an RDBMS structure that is queried on the fly in order to output SVG (Scalable Vector Graphics) interactive visualisations. For didactic purposes (illustrating the potential and variety of infovis-inspired solutions), we chose to use two classic, easy to read visualisations (BubbleViz and sparklines) and to develop two specific visual displays, with strong interaction modalities. It is clear that alternative designs could (and probably should) be tested, with possibly better results. However the four solutions were duly

decoded and commented by actors during post-event meetings - and accordingly played their expected role.

4.1 Measure of impact

The first visualisation we developed was aimed at analysing globally the “quantities” of votes. It builds on the classic “bubbleviz chart” formalism, with each line corresponding to one of the four possible answers (Figure 3, from top to bottom, *do not know but could be concerned*, *do not know*, *know and not concerned*, *know and concerned*). Each column corresponds to one of the 44 visualisations in the survey, and the size of circles or bubbles corresponds to the number of votes.

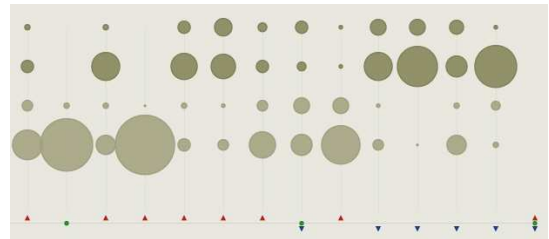


Figure 3: Partial view of the bubbleviz chart, with the four lines of votes. Bottom glyphs correspond to categories (from top to bottom, quantities, space, and time).

Categories (quantities, space-oriented data, time-oriented data) to which each visualisation corresponds are shown as coloured glyphs in a bottom line, and some interaction added. The visualisation does reveal some interesting patterns (Figure 4):

- Voters are clearly more familiar with visualisations of quantities or of space-oriented data (left and middle parts of the figure) than with visualisations of time-oriented data (right side of the figure).
- What is more, when voters claim they know visualisations dedicated to time-oriented data these solutions are all derivatives of the traditional timeline paradigm (1, 2, 3, 4).
- Some interesting exceptions strike out – milestones in the history of data visualisation that seem forgotten (a')
- Finally, some poorly known concepts are pointed out as potentially interesting (a', b').

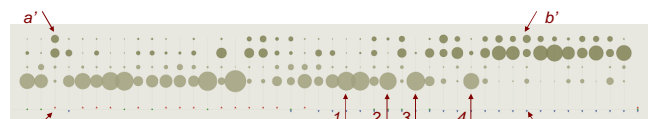


Figure 4: The bubbleviz chart showing votes per visualisation.

But at this stage the disciplinary field of voters is still not taken into consideration. This is done through another visual formalism (Figure 5) in which what is observed is, for each of the 44 classic visualisations, whether there is a relation of the votes to the discipline of voters. In the centre of this concentric graphics two pieces of information are encoded: the category (or categories) to which the classic visualisation corresponds, and its date of creation (Figure 5, a, b). Each angular sector then corresponds to a given voter, and the main discipline of voters is represented by the coloured exterior rings (Figure 5, c). Some interaction is added (on/off switches for textual data or links to in-depth descriptions of the visualisation). The visual formalism helps pointing out differences in terms of background, of references, of expectations, inside the target group. Figure 5 represents votes corresponding to a mediaeval map that appears in Matthew Paris's 'Book Of Additions', a typical ribbon map building on the notion of ordinal time. Naturally here archaeologists and historians do know, if not this specific map, at least this type of representation.

By contrast, a majority of geographers and computer scientists apparently never came across such graphics. But a more intriguing observation can be made: almost one archaeologist or historian out of two declares he feels unconcerned by such ribbon maps.

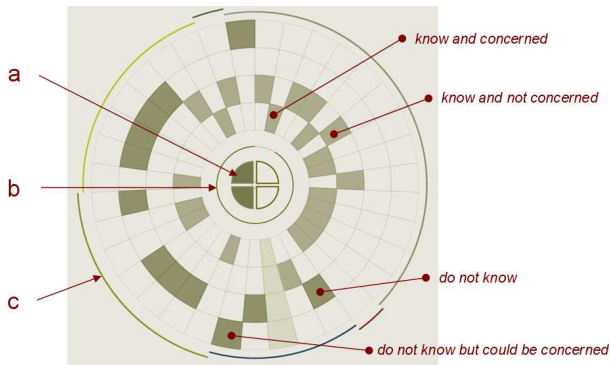


Figure 5: Votes and profiles of voters for a given visualisation. Left, results for W.Paris’s London-Jerusalem itinerary, Right, legend of the graphics.

The formalism can also be used to compare answers collected for several visualisations. At times the result is nothing like a surprise (Figure 6) - some classics *are* known by a vast majority of voters. But this result still gives a useful indication, since it ultimately corresponds to *what references people have in common*.

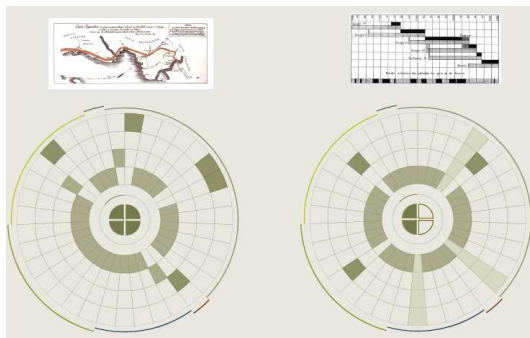


Figure 6: Comparison of votes for two classic solutions – Minard’s flow maps and Marey’s chronological chart. Unsurprisingly, both are familiar to the whole test group.

The result can also be hard to analyse, with rather chaotic answers (Figure 7) and **no** real discipline-specific behaviours striking out (except in the computer scientists group - bottom, blue ring).

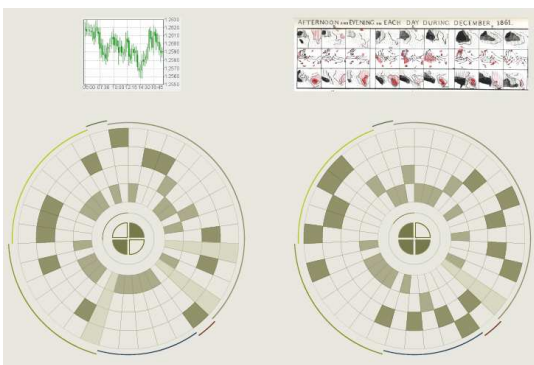


Figure 7: Comparison of votes for M.Homma’s candlestick charts and F.Galton’s weather maps.

However one clear indication is given: inconsistencies inside each group, and a rather poor impact of classic infovis solutions in the test group. In short this concentric visual formalism helps reading behaviours and backgrounds, notably:

- Discipline-specific knowledge patterns
- Common references across the group
- Discipline-specific behaviours (fields of concern that are privileged, solutions that raise an interest).

But in many test groups some people are likely to give fast, and somewhat untrustworthy answers – typically here possibly a systematic “I know that kind of visualisation” answer. This is detected through a third visual formalism (Figure 8), inspired by E.R Tufte’s sparklines [21].

Each line corresponds to a voter (a coloured dot on the left identifies the discipline), each column corresponds to one the 44 visualisations. Read horizontally, the visual formalism helps spotting individual behaviours – voters who often abstain from giving a vote, voters who almost always give the same answer, etc.

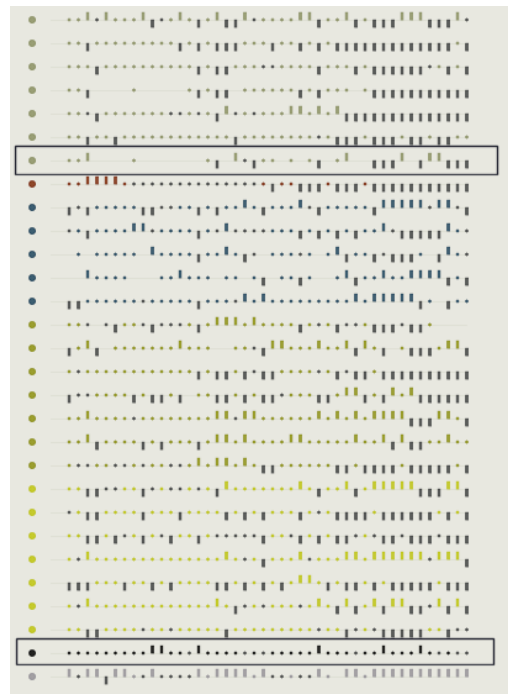


Figure 8: The sparklines visual formalism – two individual, specific behaviours are spotted.

This last visual formalism also has an additional role, this of assessing “how thirsty to know or use” voters are. An interactive menu allows to remove all answers from the sparklines except one (Figure 9). On the left part of Figure 9 only the “I do not know this type of visualisation (and do not want to)” answers are shown. On the right part of Figure 9 only the “I do not know this type of visualisation but I think it could be of use for me” answers are shown. The contrast is striking – with some voters definitely not convinced of the potential of the collection of visualisations, and others clearly willing to go further. This visual formalism also underlines a rather weak interest by the test group for time-oriented visualisations (right columns of the sparklines) – once again an eye-opener for the community, and a point we definitely needed to check.

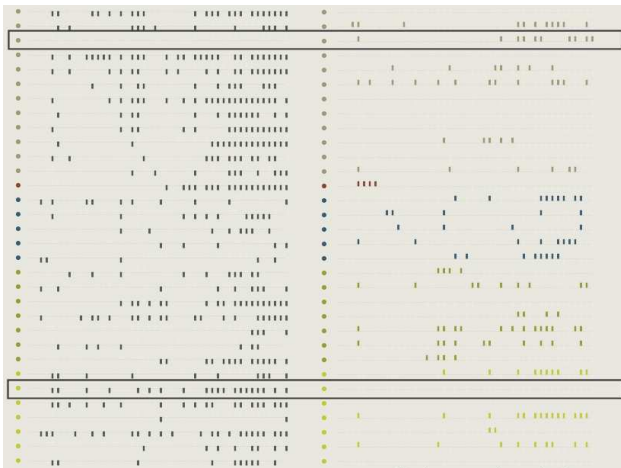


Figure 9: Sparklines showing (left) only the “I do not know” answer and (right) only the “I do not know but want” answer (partial view, two opposite behaviours spotted).

The tendency is confirmed in a variant of the sparklines formalism where the 44 classic visualisations are distributed in three groups (categories quantities, space and time). A visual solution like the peopleGarden metaphor [22] for instance apparently raised very little interest. This is an indication that infovis as such remains something like a *terra incognita* for the test group.

To sum it up, the bubbleviz formalism is used to point out a common trend inside the whole group of testers (space privileged over time); and the concentric visual display underlines biases of sub-groups of testers (discipline-specific behaviours). Both can be used to share a common understanding, as unveilers (more than as statistical indicators, naturally).

Finally, the sparklines formalism is used to detect individual, specific behaviours and therefore rather corresponds to an “expert” view of the survey’s results.

4.2 Overlaying of concepts and terms

The above measure of impact is supposed to help measuring *what tools for visual reasoning actors have in common*. In an interdisciplinary problem-solving situation there are earlier stages when what is at stake is reaching a common understanding of concepts, notions, terms that will form the basis of the common investigation.

This is precisely what we have tried to analyse in this second experiment. The resulting visualisation is loosely inspired both by the *franco-polish mnemonic method* [23] and by the *postHistory* visual formalism [24]. It combines a reading of the collection of terms and definitions, a reading of votes, and a reading of votes per discipline.

The collection of terms and definitions is what is presented to users by default. Terms are distributed into categories (phenomenon, time parameter, uncertainty, general vocabulary, tabula rasa), forming sort-of tiles (Figure 10). Inside a category, each term is presented as a smaller, square tile inside which definitions for the term are presented as even smaller tiles. A different outline colour is used to differentiate definitions in French or in English. Basic interactions allow users to read the definitions. At this stage the collection itself is analysed, with for instance a rather high density of definitions in some categories.

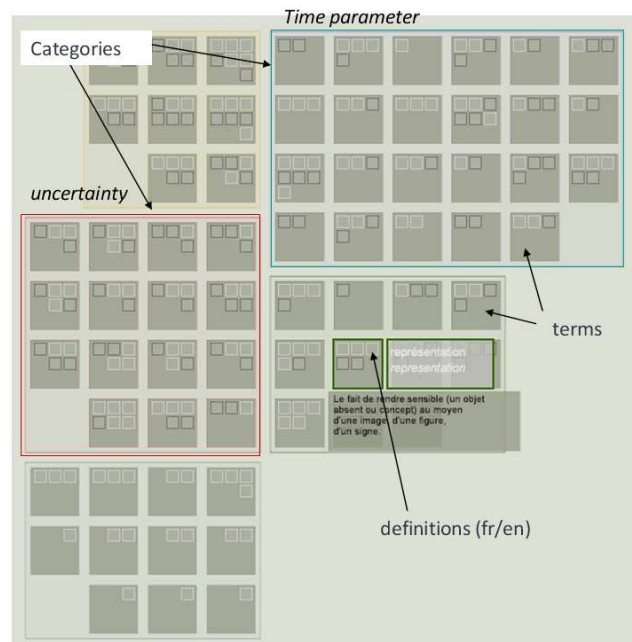


Figure 10: Visualisation of the collection of terms and definitions, distributed by categories.

Votes are introduced on user demand, as an additional layer composed of small red or green squares for each definition (Figure 11). The surface of those squares is indicative of the number of votes. Colours correspond to the meaning of the vote:

Green: *I use this term in the sense given by that definition.*

Red: *I use the notion given by that definition, but I use another term for it.*

The visualisation can be analysed term by term, with for instance cases when one definition is privileged by voters (a large, dominating green square for one of the term’s definitions, see Figure 11, a, “cyclic time”). In other cases several definitions are considered as equally relevant (green squares of similar sizes for several definitions of a term, see Figure 11, b, “phenomenon”). As a consequence actors are made aware of an overlaying challenge (If the definitions all agree then the notion behind the term is a shared one, but if they differ then various interpretations of the term are present in the test group).

Controversy is clearly assessed (red squares) and some definitions are rejected by a large majority of voters (red square bigger than green square, see Figure 11, c, “dynamics”, “duration”, “event”). What is shown here is a sort of common interdisciplinary behaviour: the notion depicted by the rejected definition is used, but another term is used for it.

Finally there are cases when one definition is equally rejected and agreed with (see Figure 11, d, “generalisation”, “subjectivity”, “representation”, “information”). Now this is typically the notions an interdisciplinary community will indeed have to discuss: not making that effort would most probably result in misunderstandings, and accordingly in delays and inefficiency.

The amounts of votes for each definition, and each term, also give an indication. The number of votes in the “time parameter” category (top right, blue outlined tile) is visibly small, at least smaller than in the other categories: the test group seems to pay less attention to time than to space, and as a consequence feels unfamiliar or unconcerned with a wide range of terms such as

“chronon”, “temporal operator”, “branching time”, etc. In addition, categories can be observed as such, and Figure 11 shows that the uncertainty category (black outline) concentrates a high number of definitions that are questioned – an indicator that the community would need a thorough debate if it was to co-act in an interdisciplinary analysis process where such notions are key.

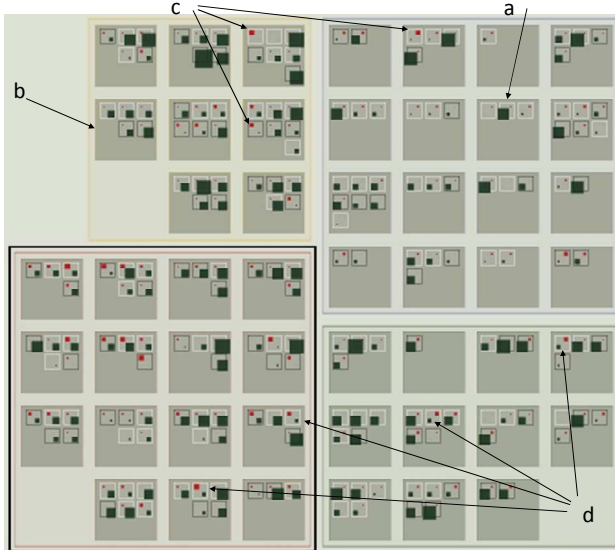


Figure 11: Visualisation of votes – definitions in the “uncertainty” category, outlined in black, appear as quite often controversial.

At this stage what the visualisation shows is a global picture of where controversies are. But the discipline of voters is not visible. This is done though a third level of interaction, allowing users to read for each term, and each definition, each individual vote represented by a coloured vertical bar (Figure 12).

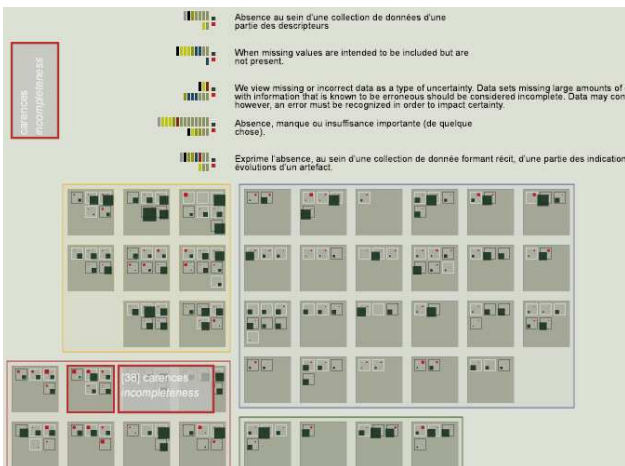


Figure 12: Visualisation of individual votes for a given term. To each definition (written above the tiles) correspond lines of vertical bars – each bar is a voter, and the bar’s colour represents the main discipline of the voter. “Green” votes are aligned in the top row, “red” votes in the bottom row.

This visualisation is used in a fine grain analysis in order to try and spot discipline-specific interpretations of terms. It helped us uncover patterns we would not have expected – for instance controversy over the term “information”. One would imagine

there is no need to have a debate over what it means, but one of the definitions we provided “*information [is the] result of the interpretation of raw data in a specific context*” was rejected by geographers and geographers only – an indication that debate is needed so as to have the notion clarified inside the community.

5. LIMITATIONS AND PERSPECTIVES

We have presented an approach aimed at an awakening by actors to the *practical and partly avoidable* difficulties of an interdisciplinary research. The protocol includes two major steps:

- A survey method highlighting overlaps and non-overlaps in terms of background, references, terms and notions (a method willingly undemanding in terms of learning curve, or of familiarity with computer platforms).
- A series of visualisations helping to pinpoint discipline-specific behaviours, and more generally to analyse the survey’s results from a variety of standpoints.

It has to be stated clearly that a number of biases were introduced. The first and prominent one is the data set itself: both the collection of classic visualisations and the collection of terms are *subjective* collections. Other samples may have resulted in different observations. Another bias to point out is the survey method: we privileged a (supposedly) playful and debate-enhancing survey modality – but we acknowledge answers given by participants may have been influenced by the fact that some chose to go through the survey with a friend or colleague, and accordingly may have changed their intuitive vote following a debate.

But in parallel, it should also be said that our goal was nothing like reaching general conclusions. Our intent was but to encourage debate, a debate we nourished by numbers and facts, and additionally to publicize infovis-inspired solutions in a community where they are not that influential. We make no claim on the generic aspect of the survey protocols we have implemented, of the visualisations we propose, or of how representative the target groups are. Yet we tend to consider that the very approach – having people, if they are to co-act in an investigation process, say out where they stand, in practical terms, through concrete and structured interrogations – can be a plus in the context of complex, multi-faceted, problem-solving situations.

Following this first experiment, where can we go next? One thing we did is compare results with a second target group on the measure of impact experiment (see section 3.3.1). Globally behaviours remain consistent and somehow expected: the second group are pre-PhD students, not directly involved in the handling of spatio-temporal data sets, and accordingly are less familiar with many of the visualisations we had selected. There are some more interesting differences though, such as the “thirst for knowledge” indicator – significantly higher in the second group on some specific visualisations (TimeWheel formalism or peopleGarden metaphor for instance). A further enlargement of the target group, notably through the development of a crowdsourcing platform, is one of the directions we investigate. This would call for a significant rethinking of the technical platform and would require in particular more interactivity, and more updatability.

6. CONCLUSION

Our intent with this experiment was to use a survey protocol and a set of visualisations as eye-openers for a community. The outcome of this experiment is therefore neither a protocol nor a set of

visualisations, but the influence they had on participants, *i.e.* a greater awareness of:

- unthought-of biases in the community (predominance of space-centric solutions),
- lacks in the handling of the time parameter,
- potential support of infovis-birthered formalisms in the handling of spatio-temporal data.

In short, the experiment shows that in an interdisciplinary investigation process, or in a problem-solving situation, actors will better and faster communicate with one another if they have been given practical means to assess disciplinary distances. But this can only occur if a scenario of interaction has been designed, here consisting of a survey + a set of visualisations. The scenario we propose is certainly questionable, but a lack of scenario simply results in an ignorance of disciplinary distances.

Accordingly, this paper calls for the emergence of sort-of *dashboards for interdisciplinarity*, consisting of *statements of distances* between actors, prior to their actual co-acting. Such dashboards can be seen as tools to initiate a move from interdisciplinarity to what [1] calls *transdisciplinarity*, *i.e.* [...] *a common system of axioms for a set of disciplines*.

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8. REFERENCES

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