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How AI-Type Uncertainty Ideas Can Improve Inter-Disciplinary Collaboration and Education: Lessons from a Case Study

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Abstract. In many application areas, there is a need for inter-disciplinary collaboration and education. However, such collaboration and education are not easy. On the example of our participation in a cyberinfrastructure project, we show that many obstacles on the path to successful collaboration and education can be overcome if we take into account that each person's knowledge of a statement is often a matter of *degree* – and that we can therefore use appropriate degree-based ideas and techniques.

Keywords: inter-disciplinary collaboration, degree of expertise, cyberinfrastructure

1. Cyberinfrastructure: A Brief Overview

Before we start explaining the problems of inter-disciplinary communication and our proposed solution to this problem, let us first briefly describe the context of cyberinfrastructure in which our inter-disciplinary communication took place.

Practical problem: need to combine geographically separate computational resources. In different knowledge domains in science and engineering, there is a large amount of data stored in different locations, and there are many software tools for processing this data, also implemented at different locations. Users may be interested in different information about this domain.

Sometimes, the information required by the user is already stored in *one of* the *databases*. For example, if we want to know the geological structure of a certain region in Texas, we can get this information from the geological map stored in Austin. In this case, all we need to do to get an appropriate response from the query is to get this data from the corresponding database.

In other cases, different pieces of the information requested by the user are *stored at different locations*. For example, if we are interested in the geological structure of the Rio Grande Region, then we need to combine data from the geological maps of Texas, New Mexico, and the Mexican state of Chihuahua. In such situations, a correct response to the user's query requires that we access these pieces of information from different databases located at different geographic locations.

In many other situations, the appropriate answer to the user's request requires that we not only collect the relevant data $x_1,\ldots,x_n$, but that we also use some *data processing* algorithms $f(x_1,\ldots,x_n)$ to process this data. For example, if we are interested in the large-scale geological structure of a geographical region, we may also use the gravity measurements from the gravity databases. For that, we need special algorithms to transform the values of gravity at different locations into a map that describes how the density changes with location. The corresponding data processing programs often require a lot of computational resources; as a result, many such programs reside on computers located at supercomputer centers, i.e., on computers which are physically separated from the places where the data is stored.

The need to combine computational resources (data and programs) located at different geographic locations seriously complicates research.

Centralization of computational resources – traditional approach to combining computational resources; its advantages and limitations. Traditionally, a widely used way to make these computational resources more accessible was to move all these resources to a *central location*. For example, in the geosciences, the US Geological Survey (USGS) was trying to become a central repository of all relevant geophysical data. However, this centralization requires a large amount of efforts: data is presented in different formats, the existing programs use specific formats, etc. To make the central data repository efficient, it is necessary:

- to reformat all the data,
- to rewrite all the data processing programs – so that they become fully compatible with the selected formats and with each other, etc.

The amount of work that is needed for this reformatting and rewriting is so large that none of these central repositories really succeeded in becoming an easy-to-use centralized database.

Cyberinfrastructure – a more efficient approach to combining computational resources. Cyberinfrastructure technique is a new approach that provides the users with the efficient way to submit requests without worrying about the geographic locations of different computational resources – and at the same time avoid centralization with its excessive workloads. The main idea behind this approach is that *we keep all (or at least most) the computational resources*

- *at their current locations*,
- *in their current formats*.

To expedite the use of these resources:

- we supplement the local computational resources with the "metadata", i.e., with the information about the formats, algorithms, etc.,
- we "wrap up" the programs and databases with auxiliary programs that provide data compatibility into *web services*,

and, in general, we provide a cyberinfrastructure that uses the metadata to automatically combine different computational resources.

For example, if a user is interested in using the gravity data to uncover the geological structure of the Rio Grande region, then the system should automatically:

- get the gravity data from the UTEP and USGS gravity databases,
- convert them to a single format (if necessary),
- forward this data to the program located at San Diego Supercomputer Center, and
- move the results back to the user.

This example is exactly what we have been designing under the NSF-sponsored Cyberinfrastructure for the Geosciences (GEON) project; see, e.g., [1, 2, 4, 6, 7, 9–15], and what we are currently doing under the NSF-sponsored Cyber-Share project. This is similar to what other cyberinfrastructure projects are trying to achieve.

Technical advantages of cyberinfrastructure: a brief summary. In different knowledge domains, there is a large amount of data stored in different locations; algorithms for processing this data are also implemented at different locations. Web services – and, more generally, cyberinfrastructure – provide the users with an efficient way to submit requests without worrying about the geographic locations of different computational resources (databases and programs) – and avoid centralization with its excessive workloads [8]. Web services enable the user to receive the desired data $x_1,\ldots,x_n$ and the results $y = f(x_1,\ldots,x_n)$ of processing this data.

Main advantage of cyberinfrastructure: the official NSF viewpoint. Up to now, we concentrated on the technical advantages of cyberinfrastructure. However, its advantages (real and potential) go beyond technical. According to the final report of the National Science Foundation (NSF) Blue Ribbon Advisory Panel on Cyberinfrastructure, "a new age has dawned in scientific and engineering research, pushed by continuing progress in computing, information, and communication technology, and pulled by the expanding complexity, scope, and scale of today's challenges. The capacity of this technology has crossed thresholds that now make possible a comprehensive 'cyberinfrastructure' on which to build new types of scientific and engineering knowledge environments and organizations and to pursue research in new ways and with increased efficacy.

Such environments and organizations, enabled by cyberinfrastructure, are increasingly required to address national and global priorities, such as understanding global climate change, protecting our natural environment, applying genomics-proteomics to human health, maintaining national security, mastering the world of nanotechnology, and predicting and protecting against natural and human disasters, as well as to address some of our most fundamental intellectual questions such as the formation of the universe and the fundamental character of matter."

Main advantage of cyberinfrastructure: in short. Cyberinfrastructure greatly enhances the ability of scientists to discover, reuse and combine a large number of resources, including data and services.

2. Towards Cyberinfrastructure-Related Interdisciplinary Collaboration and Education

Need for inter-disciplinary collaboration. A successful cyberinfrastructure requires an intensive collaboration between

- domain scientists – who provide the necessary information and metadata, and
- computer scientists who provide the corresponding cyberinfrastructure.

Moreover, since we combine data obtained by different subdomains, we also need collaboration between representatives of these subdomains.

Need for inter-disciplinary education. For the collaboration between researchers from different disciplines (even different sub-disciplines) to be successful, we need to *educate* collaborating researchers in the basics of each others' disciplines.

Inter-disciplinary collaboration and education: a typical communication situation. Let us give an example of a typical problem that we encountered when we started collaboration within our Cyber-ShARE Center.

- Suppose that a computer science has an interesting idea on how to better organize the geosciences' data and/or metadata. This is a typical *collaboration* problem.
- Alternatively, a computer scientist may simply want to teach, to a geosciences colleague, a few existing computer science ideas on how to organize data and/or metadata. This is a typical *education* problem.

How to convey a computer science idea to a geoscientist?

First possibility: just convey this idea. One possibility is simply to describe this idea in Computer Science terms.

Alas, many of these terms are usually very specific. Even many computer scientists – those whose research is unrelated to cyberinfrastructure – are not very familiar with these terms and with the ideas behind them.

The only serious way for a geoscientist to understand and learn these terms, notions, ideas is to learn the material of several relevant computer science courses – i.e., in effect, to get a second degree in computer science. A few heroes may end up doing this, but it is unrealistic to expect such deep immersion in a normal inter-disciplinary collaboration.

Second possibility: try to illustrate this idea in the domain science terms. Alternatively, to make it clearer, a computer scientist can try to explain his or her ideas on the example of a toy geosciences problem.

The limitation of this approach is that the computer scientist is usually not a specialist in the domain science (in our case, in geosciences). As a result, his or her description of the toy problem is, inevitably, flawed: e.g., oversimplified. Hence, the problem that the new idea is trying to solve in this example is often not meaningful to a geoscientist – and since the motivation is missing, it is difficult to understand the idea.

Conveying a problem: a similar situation. A similar situation occurs when instead of communicating an *idea*, we try to communicate a *problem*. Specifically, suppose that a geoscientist (or, more generally, a domain scientist) has a real problem in which, he believes, cyberinfrastructure can help.

Comment. There are such problems – otherwise, the geoscientist would not seek collaboration with a computer scientist.

First possibility: just convey this problem. One possibility is simply to describe this idea in the geosciences terms.

Alas, these terms are usually very specific: even many geoscientists – those whose research is unrelated to the specific sub-domain – may be not very familiar with these terms and with the ideas behind them.

The only serious way for a computer scientist to understand and learn these terms, notions, ideas is to learn the material of several relevant geosciences courses – i.e., in effect, to get a second degree in the domain science. A few heroes may end up doing this, but, as we have mentioned earlier, it is unrealistic to expect such deep immersion in a normal inter-disciplinary collaboration.

Second possibility: try to illustrate this idea in terms understandable to a computer scientist. Alternatively, to make it clearer, a geoscientist can try to explain his or her problem by using terms understandable to a computer scientist.

A limitation of this approach is that the geoscientist is usually not a specialist in computer science. As a result, his or her description of the problem is, inevitably, flawed: e.g., oversimplified. Hence, the problem is difficult to understand.

Consequences. As a result of the above problems, our weekly meetings – in which we tried to understand domain science problems and explain possible solutions – were, for a while, not very productive. For a while, they turned into what we called "fight club", when

- a geoscientist would find (and explain) flaws in a toy geosciences model that a computer scientist uses to describe his or her ideas, while
- a computer scientist would find (and explain) flaws in the way a geoscientist would describe his or her problem.

And then we succeeded. And then we – serendipitously – found a solution to our struggles. After we found this solution, we started thinking why it worked – and discovered an explanation – via the matter-of-degree ideology.

Our solution may be known, but our explanation seems to be new. While our approach is probably known – at least there exist other successful inter-disciplinary collaborations, so some solutions have been found – we could not find a theoretical explanation for its success. To the best of our knowledge, our explanation is new.

What we would like to do: our main objective. Our main goal is to explain to others how this problem can be solved – and thus, make other inter-disciplinary collaborations more productive. This is what we plan to do in this paper.

The fact that we are not simply proposing an empirical solution, that we have a theoretical justification for our successful strategy, hopefully makes our case more convincing – so we hope that others will follow our strategy.

An additional objective. Since we have a theoretical explanation in terms of degrees (numbers), we hope to transform our original *qualitative* idea into a more precise *quantitative* strategy.

This is mostly the subject of future work: since it is desirable not only to propose formulas, but also to show that these formulas – based on an inevitably simplified description of the communication situation – really work. To convincingly test whether this idea works or not, we need to have numerous examples of using this idea – and to have these examples, we must first convince others to use our strategy.

Thus, the convincing is still the main objective of this paper.

3. Our Successful Empirical Approach to the Inter-Disciplinary Collaboration Problem

Main idea: let us use examples of successful cyberinfrastructure collaborations. The above problems may sound unsolvable if we restrict ourselves to a specific domain science. However, the very fact that we are not starting from scratch, that there are already examples of successful inter-disciplinary collaborations – shows that these communication problems are solvable.

Describing these successful examples is a way to convince scientists that collaboration is possible and potentially beneficial.

It turns out that, moreover, these outside examples themselves helped us to solve our communication problem.

What we did. Instead of trying to describe his ideas in purely computer science terms or on a toy geosciences example, a computer scientist described these ideas on the example of his applying similar ideas to a complete different area: solar astronomy.

What happened. This description was inevitably less technical – since none of us is a specialist in solar astronomy – and therefore, much more understandable.

Positive results. As a result, we got a much better understanding of the original computer science idea.

Recommendation. When a communication problem occurs because of the different areas of expertise of the describer and the respondent, try to convey the message on the example on a *different* domain, a domain in which both the describer and the respondent have a similar level of sophistication.

4. Explanation in Terms of Degrees

Idea of degrees. Every person has different degrees of knowledge in different areas.

There are many potential ways to measure these degrees. A natural way is to gauge the degree of expertise the way we gauge the student's knowledge: by counting the proportion of correct answers on some test describing the knowledge. In this case, the degree is a number between 0 and 1, with 0 representing no knowledge at all and 1 meaning perfect knowledge.

Comment. This may sound like a probabilistic definition, but it is important to notice that when the knowledge is imperfect, the resulting knowledge is not a random selection. Usually, in every discipline, we have:

- the simplest facts that practically everyone knows,
- somewhat more sophisticated facts and results that fewer people know,
- etc.,
- all the way to subtle technical details that only true experts know.

An imperfect knowledge usually means that a person knows all the facts and results of limited sophistication level: from very basic when this knowledge is small to very deep when the knowledge is greater.

For example, when a person has a basic level of understanding, this person knows the basic facts, but lacks knowledge about more sophisticated details – so this person's idea of these details will be most probably wrong.

In general, the body of knowledge contains statements of different degree of sophistication. Our definition of the degree of expertise as simply a proportion means, crudely speaking, that this body of knowledge contains an equal number of statements at different levels of sophistication.

Similarly, it is reasonable to conclude that an individual body of knowledge of a person in a certain area is equally distributed between different levels – from the simplest to the level of sophistication of this person.

Let us use these degrees in our communication problem. Let us re-formulate the above communication situations in terms of the corresponding degrees.

First situation: a specialist conveys an idea or a problem in the terms of his/her discipline. Let us start with a situation in which a computer scientist describes his/her ideas in computer science terms – or a geoscientist describes his or her problem in geoscience terms.

The first person, the person who describes the idea or the problem is an expert in his or her area, so this person's degree d_1 is close to 1: $d_1 \approx 1$. The original idea (or problem) is therefore described on this persons' level of expertise.

The second person, the person to whom this idea (or this problem) needs to be conveyed is not a specialist in the corresponding terms, so his or her degree of expertise d_2 in the describer's domain is much smaller: $d_2 \approx 0$.

By definition of the degree of expertise, this means that only the d_2-th part of the original idea – the part corresponding to the sophistication level below this person's degree of expertise – will be properly understood. So, the result degree of understanding d is equal to the respondent's degree of expertise $d_2 \approx 0$ in the describer's domain.

Second situation: a specialist translates an idea or a problem into the terms of the other discipline. Let us now describe a situation in which a computer scientist tries to describe his/her ideas in geoscience terms – or a geoscientist tries to describe his or her problem in computer science terms.

The first person, the person who describes the idea or the problem, is not an expert in the domain in which this person is trying to describe, so this person's degree of expertise d_1 in this domain is close to 0: $d_1 \approx 0$. So, when this person translates his or her idea (problem) into this new domain, this translation is absolutely correct only at the sophistication level d_1.

In other words, while the main idea may be correct, most technical details will be wrong – since the describer is not an expert in the new domain.

The second person, the person to whom this idea (or this problem) needs to be conveyed is a specialist in the corresponding terms, so he or she will see all the errors – and thus, will be unable to understand all the details beyond the very basic, at the level d_1.

Thus, the resulting degree of understanding is equal to the describer's degree of expertise $d_1 \approx 0$ in the respondent's domain.

General case. Let us now consider a general case, when the describer translates his or her idea (or problem) into a domain in which he or she has a degree of expertise d_1 and the respondent has a degree of expertise d_2.

In general, similar to the above two situations, there are two problems that prevent us from perfect understanding:

- first, the describer's level may be too low, so his or her presentation has a lot of inaccuracies that prevent understanding;
- second, the describer's level may be too high, so his or her presentation may be too sophisticated for the responder to understand – which also prevents understanding.

Because of these two possible problems, let us consider two subcases corresponding to the above two situations:

- when the new domain is closer to the describer's area of expertise, i.e., when $d_2 \le d_1$, and
- when the new domain is closer to the respondent's area of expertise, i.e., when $d_1 \le d_2$.

Case when $d_2 \le d_1$. In this case, the describer's degree of sophistication in the new domain is higher than the respondent's, so the respondent will not be able to detect inaccuracies in the describer's presentation. The only problem here is that since the describer's level of sophistication d_1 may be higher than the respondent's level d_2, the corresponding part of the presentation will not be clear to the respondent.

From all the knowledge corresponding to the levels of sophistication from 0 to d_1, only the parts corresponding to levels from 0 to $d_2 \le d_1$ will be properly understood. We have argued above that the knowledge is more or less uniformly distributed across different levels of sophistication. Out of d_1 different levels, only d_2 levels lead to understanding.

As a result, the proportion d of properly understood message is approximately equal to the ratio d_2/d_1.

Case when $d_1 \le d_2$. In this case, the describer's degree of sophistication in the new domain is smaller than the respondent's, so the respondent will be able to understand all the terms that the describer is using. However, because of the possible difference of the levels of expertise, the respondent will be able to detect inaccuracies in all the levels of sophistication beyond d_1.

Thus, from all the knowledge corresponding to the levels of sophistication from 0 to d_2, only the parts corresponding to levels from 0 to $d_1 \le d_2$ will be properly understood. We have argued above that the knowledge is more or less uniformly distributed across different levels of sophistication. Out of d_2 different levels on which the recipient receives information, only d_1 levels lead to understanding.

As a result, the proportion d of property understood message is approximately equal to the ratio d_2/d_1.

General formula. In both cases, the degree of understanding d can be obtained by dividing the smallest of the degrees d_1 and d_2 by the largest of these two degrees:

$$d = \frac{\min(d_1, d_2)}{\max(d_1, d_2)}. \qquad (1)$$

This indeed explain the success of our empirical strategy. When the describer formulates his or message either in his or her own domain terms or in terms of the respondent's domain, we have $\min(d_1, d_2) \approx 0$ and $\max(d_1, d_2) \approx 1$, so $d \approx 0$.

When the describer instead formulates his or her own message in the language of the third domain, in which $d_1 \approx d_2$, we have $\min(d_1, d_2) \approx \max(d_1, d_2)$ and therefore, $d \approx 1$.

5. Towards Precise Quantitative Recommendations

What will be the ideal case. According to the above formula (1), the degree of understanding d attains the largest possible value 1 when $\min(d_1, d_2) = \max(d_1, d_2)$, i.e., when both degrees of expertise coincide: $d_1 = d_2$. So, to maximize the degree of understanding, we must find a common domain in which both the describer and the respondent have the same level of expertise.

Dependence on the domain. In general, the further the area a from the person's main area of expertise a_0, the smaller this person's degree of sophistication $d(a)$ in this area a.

Let $\rho(a, a_0)$ describe the "distance" between different domains. Thus, the degree $d(a)$ should be a decreasing function of this distance: $d(a) = f(\rho(a, a_0))$ for some decreasing function $f(\rho)$.

Dependence on the expert. This function $f(\rho)$ is, in general, different for different experts:

- Some experts are more "narrow", for them this decrease is more steep: for such experts, even for reasonably close areas $a \approx a_0$, the level of expertise $d(a)$ is very low.
- Some experts are more "broad", they retain some level of expertise even in sufficiently distant domains a.

To take this difference into account, let us describe the expert's "radius" of possible expertise by r – we can define it, e.g., as the distance $\rho(a, a_0)$ at which the corresponding degree of expertise $d(a)$ drops to a certain threshold d_0. The broader the expert, the larger this radius.

Resulting formula. We can then reasonably conjecture that for all experts, we have

$$d(a) = f_0\left(\frac{\rho(a,a_0)}{r}\right) \quad (2)$$

for some universal monotonically decreasing function $f_0(\rho)$.

Towards recommendations. We want to select a domain a for which $d_1(a) = d_2$. Due to formula (2), this means that

$$f_0\left(\frac{\rho(a,a_{01})}{r_1}\right) = f_0\left(\frac{\rho(a,a_{02})}{r_2}\right). \quad (3)$$

Since the function $f(\rho)$ is monotonic, this means that

$$\frac{\rho(a,a_{01})}{r_1} = \frac{\rho(a,a_{02})}{r_2}. \quad (4)$$

Resulting recommendation. Select an area a for which the equality (4) holds.

Example. Let us consider the case when the domains are represented by points in a usual Euclidean space, with a standard metric $\rho(a,a_0)$. In this case, it is reasonable to look for the location of a on the straight line

$$\{\alpha \cdot a_{01} + (1-\alpha)\cdot a_{02} : 0 \le \alpha \le 1\} \quad (5)$$

connecting the describer's and the respondent's areas of expertise a_{01} and a_{02}. For a point

$$a = \alpha \cdot a_{01} + (1-\alpha)\cdot a_{02} \quad (6)$$

on this line, the formula (3) takes the form

$$\frac{\alpha \cdot \rho(a_{01},a_{02})}{r_1} = \frac{(1-\alpha)\cdot \rho(a_{01},a_{02})}{r_2}. \quad (7)$$

Dividing both sides of this equality by the distance $\rho(a_{01},a_{02})$ and multiplying both sides by $r_1 \cdot r_2$, we conclude that

$$\alpha \cdot r_2 = (1-\alpha)\cdot r_1, \quad (8)$$

hence

$$\alpha = \frac{r_1}{r_1+r_2} \quad (9)$$

and

$$a = \frac{r_1}{r_1+r_2}\cdot a_{01} + \frac{r_2}{r_1+r_2}\cdot a_{02}. \quad (10)$$

An alternative recommendation. An alternative recommendation is to use an "interpreter", i.e., a person who has a reasonable (although not perfect) understanding in both fields.

Here, a describer first use the terms of his or her domain to convey the idea (or problem) to the interpreter. In this transaction, because of the interpreter's knowledge, the degree of understanding $d = \dfrac{\min(d_1,d_2)}{\max(d_1,d_2)}$ is reasonably high.

The interpreter then translates the message into the respondent's domain and conveys thus translated message to the respondent. Here, also, the degree of understanding is reasonably high.

Comment. This strategy, by the way, works well too. We hope that the above formulas will help to optimize this approach as well.

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