Tunnel effects in cognition : A new mechanism for scientific discovery and education

Antoine Cornuéjols
Equipe Inférence et Apprentissage
Laboratoire de Recherche en Informatique (LRI)
Université de Paris-Sud, Orsay
91405 Orsay Cedex
(France)
email : antoine@lri.fr

Andrée Tiberghien **Gérard Collet**
UMR GRIC-COAST
CNRS - Université Lyon2
5, Avenue Pierre Mendes France
69976 Bron Cedex 11
(France)
email : Andree.Tiberghien@univ-lyon2.fr, gcollet@ac-grenoble.fr

Abstract

It is quite exceptional, if it ever happens, that a new conceptual domain be built from scratch. Usually, it is developed and mastered in interaction, both positive and negative, with other more operational existing domains. Few reasoning mechanisms have been proposed to account for the interplay of different conceptual domains and the transfer of information from one to another. Analogical reasoning is one, blending is another. This paper presents a new mechanism, called 'tunnel effect', that may explain, in part, how scientists and students reason while constructing a new conceptual domain. One experimental study with high school students and analyses from the history of science, particularly about the birth of classical thermodynamics, provide evidence and illustrate this mechanism. The knowledge organization, processes and conditions for its appearance are detailed and put into the perspective of a computational model. Specifically, we put forward the hypothesis that two levels of knowledge, notional and conceptual, cooperate in the scientific discovery process when a new conceptual domain is being built. The type of conceptual learning that can be associated with tunnel effect is discussed and a thorough comparison is made with analogical reasoning in order to underline the main features of the new proposed mechanism.

Keywords : Conceptual learning. Transfer mechanisms between conceptual domains. Analogical reasoning. Scientific discovery.

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1. Introduction

Conceptual domains are tools that bring both a filter and a magnifying glass on our universe. They select and organize. They segment and predict. They allow to describe, to make predictions and to explain our environment. As such, when they are mature, they offer an operational way of tackling the world. Scientific discovery as well as education is concerned with learning conceptual domains. By "*conceptual domain*", we refer to a vast organization of knowledge, such as the knowledge of Newtonian mechanics, or of the Darwinian theory of evolution.

A conceptual domain has a basic structure of entities and relations at a high level of generality — for example the entity "particle" in physics refers to an abstract concept around which revolves a whole lot of roles (e.g. state, trajectory, and so on) as well as a whole framework of expectations (e.g. a state is completely determinable), theories (e.g. Hamiltonian formulation) and inference and control procedures (e.g. systematic recourse to the least action principle).

Surprisingly few works have directly dealt with how these conceptual domains come to existence, how they are learned, how they develop and how they adapt.

Philosophers have chosen to make a distinction between the context of creation and the context of justification of a theory, focusing almost exclusively on this last problem (see [Popper,1959,1962]). Cognitive scientists on the whole, and machine learning scientists in particular, have mostly centered their work on induction of "simple" and isolated concepts in rather poorly structured hypotheses spaces. This is called the data-driven approach to scientific discovery (see [Langley et al.,1987]). While the results obtained have been spectacular, in many respects they do not bear on the learning of complex conceptual domains and theories. At the same time, the theory-driven approach has concentrated on cases where a strong theory could allow to derive rather precise predictions about the world that could then be tested. Some artificial intelligence work on theory revision have dealt with this situation (e.g. the Revolver system [Rose,1989]) but overall did not touch the problem of building a significant new conceptual domain.

In fact, the relatively few relevant works in machine learning (under the name of constructive induction, theory revision or inductive logic programming) have so far shared a common and mostly tacit assumption in that when learning a conceptual domain, the existing ontology of concepts was supposed to be correct, even if not always operationally efficient. The problem was thus seen as the one of learning new concepts *besides* existing ones, for instance by learning new concepts or predicates within the existing ontology in order to make it more efficient to use or more easy to understand. In this respect, the problem of learning a *new* conceptual domain was not really touched upon. In contrast, we see, in science and education, that one vital problem is to learn new concepts and new ontologies, at once articulated with past ones, but also in competition with them. For instance, learning the concept of "particle" in quantum physics implies keeping some of the aspects of the concept of "particle" in classical mechanics while erasing or deeply modifying some others. This is not to say that the 'old' concept is erroneous or obsolete and must be discarded, but that its range of application must be circumscribed, and that it has to be superseded in some contexts and within some conceptual frameworks.

It is rare, if it ever happens, that a new theory arises from scratch. Rather, it develops within an 'ecology' of other conceptual domains, more or less mature, and more or less operational and activated in the current context. There is therefore a complex interplay of articulation, facilitation, competition and hindrance taking place between various conceptual domains activated at the same time, and, focusing on the learning of a new domain, there are many places and many stages for transfers from one conceptual domain to the one in gestation (figure 1).

This paper reports on a multidisciplinary head-on approach to the problem of learning new ways to interpret the world by relying on (and relating to) old ones. By studying how high school students address problems in conceptual domains that are new to them, we were led to analyze mechanisms that seemed to be at play in their segmenting the world, and constructing models of the situation, as well as the (re)conceptualization efforts that —sometimes— followed. In this paper, we focus on a reasoning mechanism, that we hypothesize, does explain part of the students behavior. We call it 'tunnel effect' for reasons that will be clarified later on. Like analogy, this mechanism allows the transfer of knowledge from one conceptual domain to another one. Unlike analogy however, it does so without having to resort to two situations or cases, but only considers the one at hand, and it does not necessitate to specify beforehand a hierarchy of representation primitives in both domains (one being mostly unknown), nor to define how similarity between the two represented cases must be computed. In fact, it appears so natural that its scope covers a wide range of situations from metaphorical thinking to scientific discovery (See for other descriptions of historical cases of scientific discovery [Holton,1973], [Nerssessian, 1992], [Thagard,1992]).

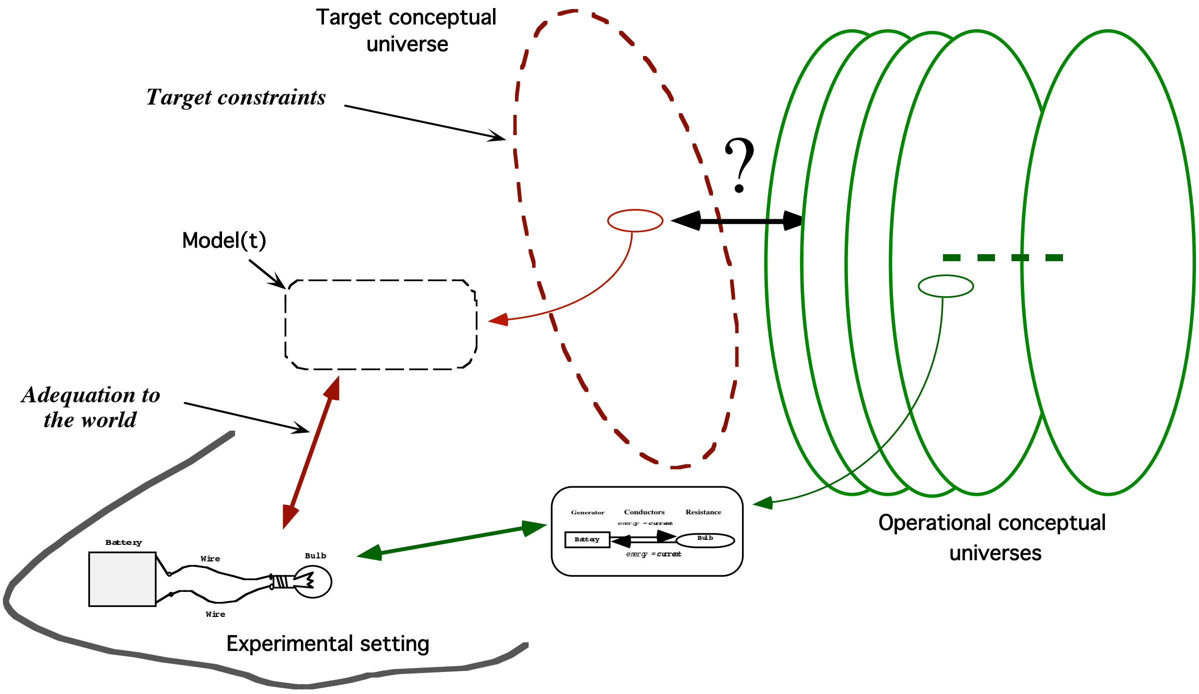

Figure 1. *A view on the problem of learning a new conceptual domain*. A set of phenomena (e.g. a experimental setting) call for interpretation and explanation (some model) within a new target conceptual universe. However, before reaching maturity and efficiency, the new conceptual domain cannot smoothly and forcefully impose its own interpretation. Instead, there is an interplay with more operational conceptual domains that suggest their own viewpoint on the phenomena. In this paper, we study how learning a new domain occurs within the activity of an existing 'ecology' of other conceptual domains.

In the following, we first describe, in section 2, a simple but telltale experiment in physics teaching. Section 3 describes how the mechanism of tunnel effect could account for it. A key ingredient of this effect lies in the hypothesis of the existence of a notional level in knowledge.

This is analyzed in section 4. How learning can occur as a result of tunnel effects is discussed in section 5, while section 6 contrasts tunnel effect with analogical reasoning with respect to the transfer of knowledge from one conceptual domain to another. Section 7 concludes by underlying key ideas and perspectives.

2. Illustration of the 'tunnel effect' in physics teaching

2.1 Design of the experiments

In order to study learning of new conceptual domains, we set up interpretation tasks in terms of a "new theory". The idea was to force school children to learn a new way to interpret the world, and to study how they tend to do it. More specifically, we performed experiments in physics teaching, and more precisely teaching a qualitative account of the physics of energy taught in high school classes around the age 16-17. The task involved small experimental settings that the students could experiment with, like simple electrical circuits with masses and motors and so on, that were to be interpreted in terms of energy transfers and transformations along an "energy chain" starting and ending with an energy reservoir. The students worked in pairs[1]. This experiment has been done in several classes . We video-recorded several pairs of students and entirely transcribed their verbal productions (for complete details see [Megalakaki & Tiberghien,1995] and [Megalakaki,1995]). (For this paper 6 pairs were thoroughly analyzed).

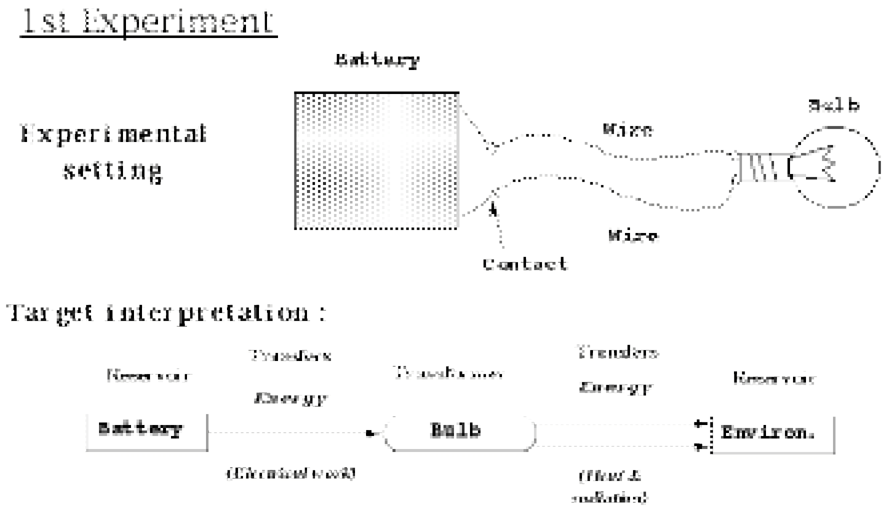

Figure 2. Above : one experimental setting involving a battery connected to a luminous bulb through two wires. Students were to produce an interpretation of this setting in terms of a chain of energy transfers and

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[1] In fact the students are given successively three tasks, only the first task is discussed in the paper. In the first task the experimental material is made up of a bulb, two wires, a battery. In the second task the experiment consists of an object hanging on a string which is completely rolled round the axle of a motor (working as a generator). A bulb is connected to the terminals of the motor. When the object is falling, the bulb shines (figure 3). In the third task the experiments consists in a battery connected to an electrical motor. An object is hanging from a string, attached to the axle of the motor, which is completely unrolled at the beginning. A correct solution is given to the students after the first task.

transformations starting and ending with an energy reservoir. Below : a correct interpretation, called target interpretation.

On one hand, it is important to notice that the interpretation task was not trivial, even in the simplest of the experimental settings shown in figure 2. For instance, there were two wires from the battery to the bulb which satisfied the closed electrical circuit condition, but only one counterpart, corresponding to the transfer of energy under the form of electrical work, in the target interpretation. Likewise, the students had to discover the environment entity while there was no concrete, tangible, counterpart in the experimental setting.

On the other hand, the task facing the students was easier than the one facing the scientists in that they did not have to "invent" the concepts necessary for the task. They were indeed provided beforehand with a declarative account of the target conceptual domain along with a lexicon of the authorized terms and icons that were to be used in their models of the situation (see figure 3). This is one way we were able to control the knowledge brought to bear by the students. The seed target domain also defined integrity rules that specified valid models, as, for instance, the "*a complete energy chain starts and ends with a reservoir*" rule.

Together, the lexical entities used in the definition of the seed conceptual domain and the integrity rules constitute the target constraints for this particular task.

Theory (seed)	**Model (seed)**
Energy can be characterized by:	* ***Symbols*** to be used:
* **its properties** :	$\boxed{\text{res.}}$ for reservoir
- ***Storage***	
- ***Transformation***	$\longrightarrow$ for transfer
- ***Transfer***	
- by ***work*** : mechanical or electrical	(tr.) for transformer
- by ***heat*** ,	
- by ***radiation*** .	* Under the ***constraints***:
***a fundamental principle of conservation**	**- a complete energy chain starts and ends with a reservoir;**
The energy is conserved whatever the transformations, transfer and forms of storage	**- the initial reservoir is different from the final reservoir.**

Figure 3. A simplified version of the seed for the target conceptual domain given to the students. The left part presents the conceptual definitions for the target domain . The right part provides the symbols with which to express the model and the syntactic rules that should be satisfied.

2.2 How the students can solve this problem

Now, we invite the reader to try for a few minutes to specify the reasoning steps that could solve the problem above and others of the same type. Beware that the original description of the experimental setting is in itself a tricky problem. Some students for instance paid attention to details not shown here, like the electrical switch, the fingers, the eyes. Almost none however "perceived" the environment as an entity. While all of them treated the two wires as two distinct entities, most did not single out the filament inside the electrical bulb. All in all, even in this extremely simplified setting, the perception and interpretation of the experiment involve an incredibly large collection of choices, both local and low level and global and strategic. Of course, when the target conceptual domain is well-mastered, as is usually the case for physics teachers, the interpretation task seems so easy that it is done effortlessly and almost unconsciously. It is then obvious that the "correct and unique interpretation" of the experimental setting is the one of figure 2. But for a program to solve this interpretation task, how many choices to face, how much knowledge to have in order to make them efficiently ! Is there any way to help solve problems in an as yet ill-mastered domain ?

One fact that emerged from our study was that out of 6 pairs of students, 5 produced the intermediate model of figure 4 (b) below for the battery-bulb setting. They then departed from it to try to find alternatives, better suited models, meantime laboring over concepts like *energy*, *transfers*, and so on. This, in fact, did not strike us as worthy of interest at first, so much it appeared to be expected. This intermediate model was after all none other than the classical circular electrical interpretation of the setting. Yet, upon reexamination, we were intrigued by the fact that this model, which was so attractive, seemed also pivotal to enable further conceptual elaboration. Could the analysis of the why and how of this particular behavior lead to a better understanding of the processes at play in the learning of new conceptual domains ? The rest of the paper is an answer to this.

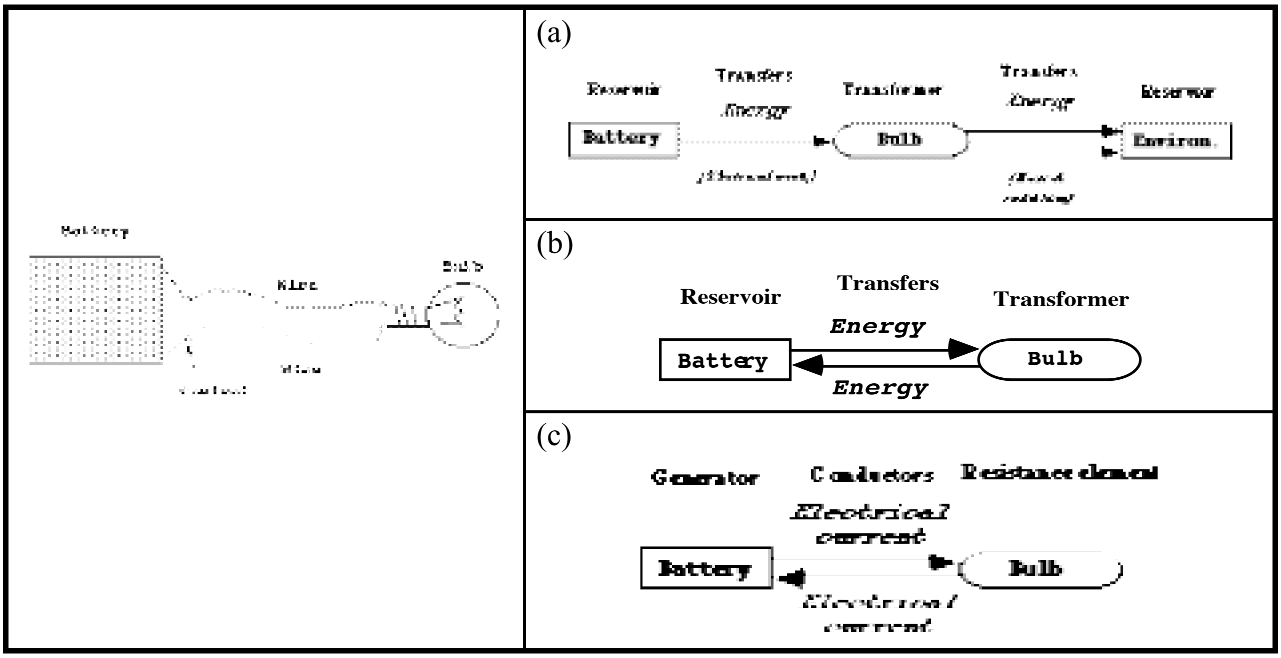

Figure 4. Three interpretations of the experimental setting of the left column.

3. Analysis of the tunnel effect

3.1 Five key ingredients

In this section, we present five key ingredients that concur to the tunnel effect inferencing mechanism. Our description is oriented towards the specification of a computational model.

1. The target conceptual domain is specified by target constraints

It is important to realize that, in scientific discovery as well as in education, even though the target domain may still be unknown, there usually exists some a priori constraints that delimit it. These can be found at two levels.

First, a level concerned with ***metaconstraints.*** In particular :

- *Syntactical constraints.* When mature, a conceptual domain can function entirely as a closed system with entities entertaining relationships with other entities of the same domain and defined only within this domain. These relationships may then be characterized by syntactical constraints that define rules for well-formed formulas and for valid derivations. For instance, in the simplest of cases, these may only consist of dimension equations that have to be satisfied. The right side of the seed theory for the energy domain is another example of such syntactical constraints.
- *General a priori commitments*. It is generally the case that the founders of a new scientific domain are guided by a priori deep beliefs regarding the world (See for instance [Holton,1973] for an interesting discussion on some themata that steer scientific investigation. [Harman,1982] provides also analyses on the underlying philosophical commitments of searchers during the 19th century). These preconceptions may have some repercussions on syntactical constraints. For instance, while developing his theory of electromagnetism, Maxwell was deeply influenced by the concept of continuous action in a medium as opposed to the Newtonian idea of action at a distance that was then the guiding concept in France. Accordingly, Maxwell was naturally looking for a theory expressed using differential equations.

Second, a level corresponding to the ***adequacy to the world***. To be viable, a conceptual domain must possess a good adequacy to the world, that is be able to allow coherent and sufficiently complete descriptions of the world and make predictions that are reasonably confirmed.

Two consequences follow from the existence of these metaconstraints. Indeed, on the one hand, any model or theory must obey them in order to be valid. On the other hand, *any model or theory satisfying, at least at first sight, these metaconstraints may appear to be valid*. This second part is critical for the tunnel effect.

2. Interpretative systems imply active entities

The central task we study in this research is the one of interpreting the physical world according to some conceptual domain given data that can be incomplete and imperfect in various ways. This type of interpretative tasks is far from uncommon and has been one focus of AI research particularly in the field of vision and of natural language processing. Most works have ended up by underlining the role of active structural networks where knowledge is composed of semantic entities organized along relevant semantic links. Each entity, is itself a small organization with pointers to other potential entities and inferencing mechanisms that allow to identify these according to the context. In the language of Minsky (1975), Rumelhart and Norman (1976), and Schank (1982), these entities are called schemata, the pointers slots and the associated inferencing mechanisms demons.

We believe this view to be pertinent as well in the context of the interpretation of the physical world. This is why we envision conceptual domains as composed of schemata, actively engaged in the comprehension of arriving information and guiding the execution of processing operations.

Generic concepts are represented by schemata. These contain variables : references to general classes of concepts that can actually be substituted for the variables in determining the implications of the schema for any particular situation. Inference mechanisms, often local to the schemata are responsible for this. Particular information on the current situation being interpreted is encoded within the memory system when constants _specific values or specific concepts_ are substituted for the variables of a general schema. This is for instance what happens when 'battery' is substituted for the 'initial reservoir' variable of the general schema corresponding to energy chain.

Many of the variables in a schema can have default values associated with them. Their attached demons can also determine potential substitutions. In that way, the whole system is able to encode the situation at hand, to interpret it, and to make predictions about it. This is exactly what we expect from the system.

We will now see what role these schema may play in the tunnel effect mechanism.

3. Candidate entities within the target domain may become associated with known entities (Janus entitites)

During the first attempts to account for sets of phenomena in terms of a conceptual domain in construction, it is natural and usual that ill-known target entities be thought of in terms of known entities from other, more operational, conceptual domains.

Hence, it is remarkable that students incessantly use one term for another (for instance *energy* and (*electrical*) *current*) as if they were interchangeable. This certainly testifies of some underlying confusion regarding these notions. The very same type of confusion seems to be at play in the origin of many scientific domains. For instance, the concept of *heat* was painfully distinguished from the concept of *caloric*, itself associated with hydraulic connotations. Likewise, the concept of *speed* was for a long time intimately associated with the concept of the *force* causing the movement, thus making difficult, if not impossible, to consider changes of referential (see for instance [Viennot,1996] for this and other examples). Any new conceptual domain is learnt in interaction with existing interpretative domains. New concepts can be defined in terms of known concepts, like the concept of mass in General Relativity that Einstein derived from a combination of inertial mass and gravitational mass. They also may be mistaken with concepts from other conceptual domains within a single undifferentiated entity, as when the students associate energy transfers with electrical current, or when Sadi Carnot, in the 1820s, adopted the caloric interpretation of heat. We call these undifferentiated entities *Janus entities*[2] for they are the two faces of a single functioning entity as we now see.

4. Once associated, the entities may share their inference mechanisms

We postulate that entities that are associated within a Janus entity may, if needed, share their inferencing mechanisms. For instance, once Energy_Transfer and Electrical_Current are associated within one Janus entity, for they are used equally by the students, when it becomes necessary to find the direction of Energy_Transfer, this is the inferencing mechanism associated with the direction of Electrical_Current that is triggered. Hence, if this mechanism determines that the directions are -> and <- on account of the + and - terminals of the battery, then these directions are assigned for the Energy_Transfer, even though the underlying reasons are foreign

[2] Roman god represented with two opposite faces. In Roma, he is the guardian of the gates (*januae*) !!

to the energy domain. These inference procedures are not thought upon and pondered while introduced and used in the new conceptual domain, but, on the contrary, they are in a way smuggled in without further immediate checking.

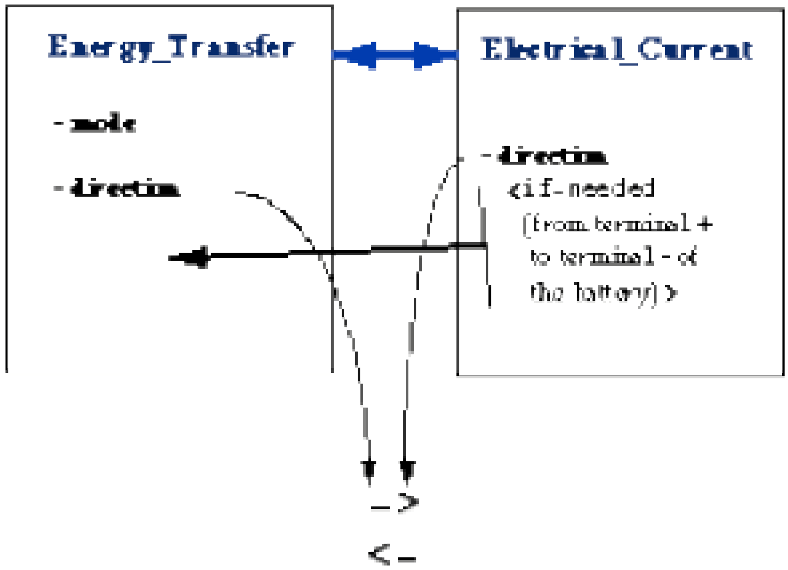

Figure 5. When two entities, shown here as conceptual schemata with attached slots or aspects and inferencing mechanisms, are associated within a Janus entity, they can share aspects and methods. For instance here, when there is a need for the determination of the direction aspect of Energy_Transfer, the method from the corresponding aspect of Electrical_Current can be used in place of the missing one.

It is important to realize that this phenomenon, which is central in what we call the tunnel effect in cognition, is ordinary. It happened when Carnot was equating the "caloric" with heat, thereby introducing —smuggling in— its conservative property and thence its cyclic character. This model, formalized by Clapeyron and later thought upon prominently by Thomson and Clausius, is completely unexplainable devoid of this underlying commitment, that is unthinkable in a world where, thanks to Joule, heat and work are two forms of energy, interchangeable in part. It happened to Maxwell when he equated the ether (incompressible fluid) with a model for electromagnetic interactions, smuggling in the seeds for the difficulties faced in physics until Einstein's special relativity theory got rid of them (and of most of the smuggled in properties of ether). It happens all the time, and it happens unconsciously. This smuggling might turn out to be genial when it brings with it unexpected solutions to outstanding problems. There is no reason why it might not also hinder further solution.

To sum up, each time entities from two different interpretation domains are matched or associated within one Janus entity, they can bring with them :

(i) *inferencing mechanisms* corresponding to common aspects of the associated entities. For instance, the demon attached to the direction aspect of Electrical_Current can be used in place of the _missing_ corresponding demon for the direction aspect of Energy_Transfer.

(ii) *new aspects*. For instance in another task not detailed here, one student made the association between Energy_Reservoir and weight. This in turn allowed him to show how to "fill up the weight" by rising it ! This is one clear instance of a property _to be fillable_ originally absent from the weight concept, but brought over by the association with Reservoir.

5. *The reinterpretation of the built model entirely within the target domain may produce unforeseen and unpredictable consequences.*

The mechanism described above that is responsible for the sharing of aspects and inferencing procedures may lead to *a true transfer of information from one conceptual domain to another* when the interpretative model of the world built in part thanks to the former is then reinterpreted entirely within the target domain.

For instance, in the task described in §2, the students built the circular model shown in figure 4(b) using inferencing mechanisms from the electrical face of the Electrical_Current/Energy_Transfer Janus entity. They then undertook to interpret this model in order to make predictions : for instance they predicted that the energy goes back to the battery, or better still that all of the light coming out from the bulb goes back entirely to the battery, which is in fact what the model expresses. There is therefore no doubt that this interpretative activity took place entirely within the target domain, that is the energy domain.

Besides, it must be realized that the circular nature of the model of figure 4(b) could not be obtained within the energy conceptual domain. There simply would be no reason for it. It had to be built using some information from other domains. We have already stressed the same point regarding the Carnot's model in thermodynamics, which, stemming from foreign preconceptions (heat viewed as an imponderable and conservative substance), was reinterpreted within the new thermodynamics yielding the concept of entropy, a strange state function defined with respect to the ideal cycle of Carnot. Harman (1982), Locqueneux (1996) and Stenghers (1997) among others have excellently shown how the circular model of Carnot would have been impossible to conceive of in the new thermodynamics of Joule. This is a clear example of a transfer from one conceptual domain to another. The genius of Carnot lies in part in having proposed a model, that even though was founded on erroneous postulates (the caloric hypothesis), could be reinterpreted fruitfully in the new domain. This transfer of a model from one conceptual domain to another was possible because the metaconstraints were compatible. In particular the syntactic ones (pressure, volume, temperature and so on regarded as relevant variables) were the same. And, at a deeper level, Carnot's model was a way to express and test the principle according to which the cause was conserved in the effect, cause and effect being either some matter (the caloric) or some force (the so-called living force, later called kinetic energy).

In *summary*, the tunnel effect transfer mechanism relies on the following elements :

- Each conceptual domain, be it in gestation, is specified by *metaconstraints* that set in particular how a valid model should look like as a syntactical construct.
- Conceptual domains are made of active conceptual entities that can be modeled as *schemata* in a semantic network.
- Target conceptual entities can in a first stage be intimately associated (confused) with entities belonging to other conceptual domains. These associations are called *Janus entities*.
- Janus entities allow each of the associated entity to *borrow aspects and inferencing mechanisms* from their twin face when needed. This may help the building of a model of the situation to be interpreted.

- If and when the build model is *reinterpreted* within the target conceptual domain, which is made possible if and only if the metaconstraints of the target domain are satisfied, then unexpected conclusions may ensue. In this case, it can be said that a transfer of information has occurred between some source domain(s) and the target domain.

3.2 Why call it tunnel effect ?

The cognitive mechanism described above has been named tunnel effect because of an analogy with a phenomenon in quantum physics whereby sometimes a particle may apparently jump over a barrier between two potential wells without being endowed with the necessary energy to do so (see figure 6). We feel that, in a way, it is possible to envision each conceptual domain as a different potential well. A situation (for instance a experimental setting) may be interpreted within one or another conceptual domain. But to reinterpret the situation in terms of a different conceptual domain should require to abandon the initial interpretation (expressed as a model in the initial domain), to go back to the situation itself and then to build a new interpretation in the new domain. The transfer mechanism we call tunnel effect acts as if there was no barrier between the wells. The original model built inside the first domain is thus taken and imported in the new domain disguised as if it was a licit model. This is possible when the metaconstraints specifying the two domains are compatible. The thus transferred model might bring with it unchecked aspects and information that are foreign to the target domain. As we have seen, this in turn opens the possibility for unpredictable consequences when reinterpretation occurs in the new domain.

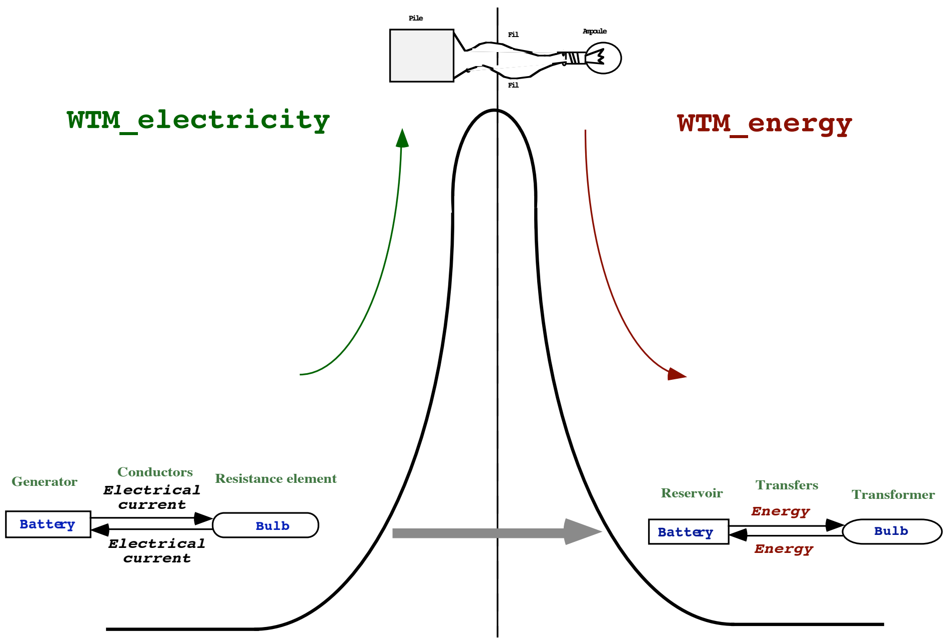

Figure 6. The way a situation should be reinterpreted when going from one conceptual domain to another is to abandon the first interpretation, come back to the original situation and build a new interpretation in the new domain (as indicated by the curved arrows above the barrier). In the *cognitive tunnel effect*, as in the quantum tunnel effect, the interpretative model built in one conceptual domain may be directly imported from the original domain to the new one (gray arrow). In this way, it is possible that some information properly belonging to the original domain are smuggled into the new one without checking. This is all the more feasible that the metaconstraints corresponding to each conceptual domains

are similar, thus making possible that the original interpretation be mistaken for a valid one into the new domain.

After the description of the tunnel effect mechanism, two questions immediately arise. First, where do Janus entities come from ? How do different entities can become associated ? Second, how the tunnel effect can affect subsequent learning ? Is tunnel effect associated with a special form of learning ? In the following, we study these questions in turn.

4. The notional level hypothesis

4.1 The hypothesis

Gentilhomme (1994), a linguist interested in the "techno-dialects", has proposed that a distinction be made between *notions* and *concepts*.

The hypothesis put forth by Gentilhomme is that there is a difference between an informal, common sense use of language, and a rigid formal one used in scientific discourses. He argued that a scientist, in his professional activity, is always playing back and forth between these two extremes, ordinarily happily using the scientific concepts of his trade, with all their precision and attached apparatus of constraints and methods, but sometimes going back to the fluid common sense notions when dealing with ill-mastered domains. For instance, a physicist would naturally resort to the *notion* of *twisting* when trying to understand how the *concept* of *torsion* could apply in a new domain. In this way, the notional core attached to each concept would provide a bridge for migrating from one conceptual domain to another.

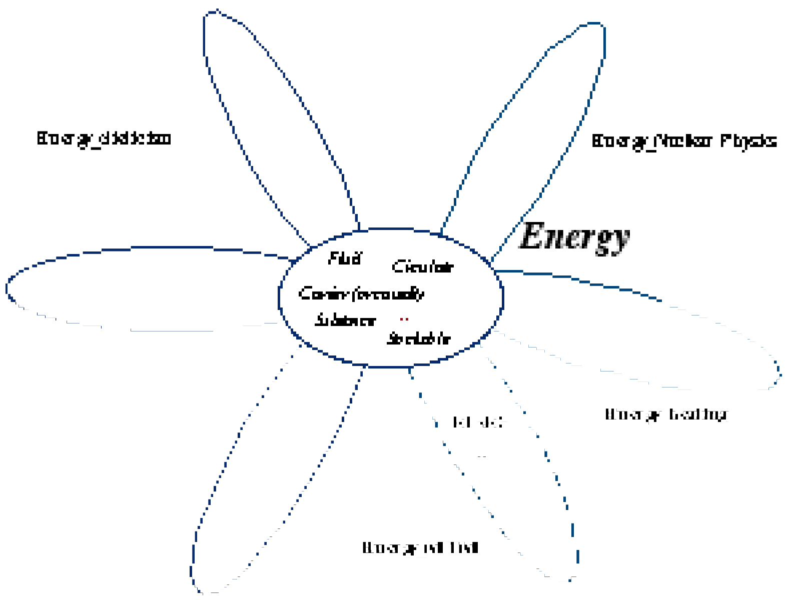

Figure 7. The notion and concepts associated with *energy*. Energy_MTM is the target domain.

Figure 7 above tries to give a qualitative picture of this idea. For each linguistic entity, there would be a notional core made up of the common sense notions associated with it. For instance, the notion associated with “energy” would include beliefs (represented as schemata in our model, §4.3, with energy as a role) such as : energy is a kind of fluid or substance that can circulate, be stored (e.g. the expression “I am full of energy this morning”), and is often linked with causality.

Around this notional core, there would be several "petals", each one corresponding to some specific conceptual domain resulting from a deliberative conceptual work. In the energy example, petals could be associated with the definition and properties of energy as elaborated in nuclear physics, or in dietetics, and so on.

Following this line of investigation, we introduce the hypothesis that two levels of description co-operate while constructing a new conceptual domain. In the context of this study, the relevance of this idea is threefold :

- It explains how conceptual entities, each properly belonging to closed conceptual systems, can be associated.
- It supplies a possible source for the origin of candidate target entities, that are otherwise difficult to account for. We submit that this is how popularization accounts of scientific disciplines may inseminate other scientific disciplines.
- It provides a flexible basis for learning concepts : by specializing notions.

4.2 Criteria for characterizing notional and conceptual levels

Notions and concepts can be distinguished from a linguistic point of view, considering the properties of the linguistic items themselves, and their behavior pattern within verbal productions. Though everyday language and scientific language cannot easily be separated from each other, some criteria are still fit for use[3]. We list here a short list of *distinguishing characteristics for notions and concepts.*

***Notions** :*

- Their meaning is fixed by the social communication requirement, and shared by all speakers.
- Their meaning is flexible. Figures of speech are possible and quite frequent, such as metaphor, metonymy, play on words, that can alter the meaning in various and gradual ways. Notions can also evolve by adjunction of modalities.
- Notion can be reformulated. The notional level allows the use of synonyms and various re-formulations

  The following extract of a dialog proceeding from the energy task, points out a metaphoric use of the word "energy":

  F Energy is moving, what would you say ?
  [...]
  F Energy just goes through...
  [...]
  F Energy comes back from the bulb.
  [...]
  F You see, energy leaves from there. It goes "ttssouiii" through the wires, and gets there.

- Notions can be altered when translated from one language to another.

3 For further details, see [Lerat, 1995], and [Kocourek, 1991].

Concepts :

- They do not necessarily possess an a priori meaning, nor one that is definitive, but, once a conventional meaning has been fixed, it must be completely enforced.
- The referent is not only one object, but also the result of a thorough conceptual and deliberative work around classes of objects : either concrete or abstract.
- The information attached to a concept is entirely determined by its conceptual definition.
  - Any adaptation or change is impossible.
  - The meaning is independent from the context.
  - Any variation amounts to designate a different class of objects.
- Concepts cannot be reformulated using approximate definition. Therefore, any attempt to grasp the meaning of a given term by way of paraphrases can be seen as a symptom that the agent is staying at the notional level.

  For example, searching for an energy transfer, a student states:

  F The *transport* modes {instead of transfer modes}, it's not only heat ...
- Concepts are to be translated in a one-to-one way.
- The definition of concepts can evolve, but only through discrete changes, excluding gradual slippages.

4.3 Notions and concepts : an artificial intelligence perspective

Many studies have centered on concepts in complex domains, what they represent, how they function and how they can be learnt (e.g. [Cassirer,1977], [Reif & Allen,1992]). For our purpose, it is enough to retain the following description.

A ***concept*** is a node in a relational graph. Leaving aside its semantic content (its links with the world of phenomena), a concept can be entirely defined and considered at this level, that is within the graph. This is what a scientist does when he/she manipulates symbols (e.g. radiation energy, cross section, Q, X, ...) using relations (e.g. differential equations linking symbols, ...) staying completely at a technical level without any further thought –for a while– for the meaning of the syntactical operations performed. As such, a concept can only be modified through a change of relation(s) in the graph, something which nicely accounts for the discrete nature of conceptual change in contrast with the continuous transformations possible at the notional level.

In addition, a concept gets its semantic content at least partly thanks to a set of recognition procedures that allow to identify positive instances in the world, a set of inference procedures responsible for completion of missing data and prediction, and a store of previously encountered cases, possibly including prototypes.

If the characterization of the conceptual level is a rather well-explored territory in cognitive science, this is far from being the case with regard to the notional level. We are therefore very cautious about the following depiction that we offer as a tentative proposal open to criticisms as well as, we hope, positive contributions. Our aim here is to provide a characterization for the lack of differentiation between two entities, as well as a possible mechanism for the learning of concepts in connection with the notional level.

We submit that the notional level consists of a set of schemata that are easy to activate when trying to make sense of the world. Let us first consider some instances of notions.

- The notion attached to the term energy seems to refer to qualities like being a fluid, being a vector for causality, being consumable, and so on.
- The notion of torsion refers to processes that allow thought experiments, and make possible qualitative predictions.
- Physicists often mention the kind of mental tinkering they do before any computation in order to get a feeling for what is to be expected with regard to some experiment. For instance, they can play with various qualitative models of quantum particles (e.g. some of corpuscular nature and some of wave nature) in order to predict the behaviour of some quantum system.

The first example above seems to involve mostly properties, while the others imply inferencing procedures suitable for qualitative reasoning. In our view, ***notions are schemata*** that can belong to a very wide scope of nature, ranging from the very abstract, like the schema for *linear causality*, to the very low-level and concrete, like the schema for *transformation* (which involves four roles : the transformer, the transformee, the initial state and the final state) (see [Collet,1996] for further details). Like the usual schemata, the notional ones have variables (often of a linguistic nature, that is referred by names like 'the cause', 'the agent', 'the initial state', and so on). But these variables are associated with loose constraints that allow them to be substituted by a wide range of possible entities with various degrees of fitness and various degrees of necessity. For instance, in the transform notional schema (see figure 12 below), the final state does not have to be identified, and the only constraint is that it is different from the initial state. In addition, the inference procedures, or demons, attached to the variables are of a fuzzy nature (close to the sense of fuzzy logic), providing only trends and qualitative dependencies between the variables (see for instance figure 11 below about the linear causality schema).

In a given context, only a set of the notional schemata, deemed to be relevant, would be considered. For instance, in the energy-chain task, some schemata are implied by the seed theory (e.g. transformer, reservoir, ...) and others are activated by the context of a physics class like the one of linear causality.

At this point, it is interesting to discuss the resemblance and differences between what we call *notions* and the *Informal Qualitative Models* (IQMs) introduced by Sleeman et al. (1989) and further refined notably by Gordon (1995). IQMs were introduced in order to bridge the gap between the data-driven and the theory-driven approaches of scientific discovery computational models. They are basically structural models of actual or hypothetical physical systems that should help to construct qualitative predictive theories or laws which describe or explain the behaviour of a phenomenon in nature. It is our opinion that while the overall organization and functioning of notions and IQMs are similar, there is a distinction as regard to their scope and intent. IQMs are intended to act as kinds of general patterns for the specific laws (generally thought of in terms of numerical dependencies) to be found. As such they are organized in hierarchies and describe the whole phenomenon at hand. In contrast, notions can be of different levels of granularity, sometimes describing local aspects of the phenomena to be interpreted, and sometimes deep underlying principles (as "the cause is conserved in the effect"). In addition, notions are not primarily intended to provide potential and qualitative dependencies between variables of interest, but are more aimed at supplying explanations in terms of processes taking place in the physical phenomena. All in all, though, IQMs and notions share a lot of assumptions about the role of qualitative and informal knowledge in the scientific discovery process., and their relationship deserves further study.

4.4 How entities from different domains can be associated : Janus entities

There is plenty of evidence that human subjects smoothly associate entities belonging to different and in some sense incommensurate domains. Considering only the dialogs registered during the energy chain task described in §2, we get instances like the one of figure 8, where different entities are matched or used as if they were equivalent.

(1)

Lionel (163) : ... the reservoir what is it ? Stores the energy. It is the battery, it is the battery that we put here ...

----

(2)

(The students try to put a name to an arrow)

Fabien (423) : ... what do we write ?
Peggy (424) : It is ... hum ... we write energy, do we ? If not ...
Fabien (425) : Yeah
Peggy (426) : The movement of electrons

----

(3)

Lionel (125) : ... But may be we have to draw the arrows to show where the energy ... the current goes
Fulvia (126) : But we do not know where it goes
Lionel (127) : From the terminal + to the terminal -

Figure 8. Some instances of dialogs between pairs of students during the task (from Megalakaki & Tiberghien (1995) and Megalakaki (1995).

On one hand, students readily match RESERVOIR with *battery*, while, properly speaking, RESERVOIR is a concept in the energy domain under construction and *battery* is a word used in everyday life language independently from considerations for the physics of energy. On the other hand, students associate TRANSFER OF ENERGY with ELECTRICAL CURRENT which belong to two different conceptual domains. How are these associations between disparate entities from different worlds possible ?

The hypothesis of an underlying always available notional level provides an answer. The idea is that many concepts are denoted using lexical entities, such as “heat”, “work”, “radiation”, “reservoir”. These entities are themselves associated with a set of notional properties. When entities from different domains are compared, the comparison would be done at the notional level. In that way, RESERVOIR and *battery* can be matched on the ground that, at the notional level, both can be empty or filled, both keep some kind of fluid that is often associated with some causal properties. Likewise, at the notional level, ENERGY TRANSFER and ELECTRICAL CURRENT share attributes like being fluids that circulate and are carriers of causality. Therefore, at the notional level, they can be mistaken one for the other.

Figure 9 depicts the association in one Janus entity of *electrical current* and *energy* considered at the notional level. In the tunnel effect considered throughout this paper, the model of the experimental setting viewed within the conceptual domain of electricity is imported without checking as a valid model viewed within the domain for energy, where it is then reinterpreted. This transposition is automatically done because of the Janus entity of which electrical current and energy are two faces.

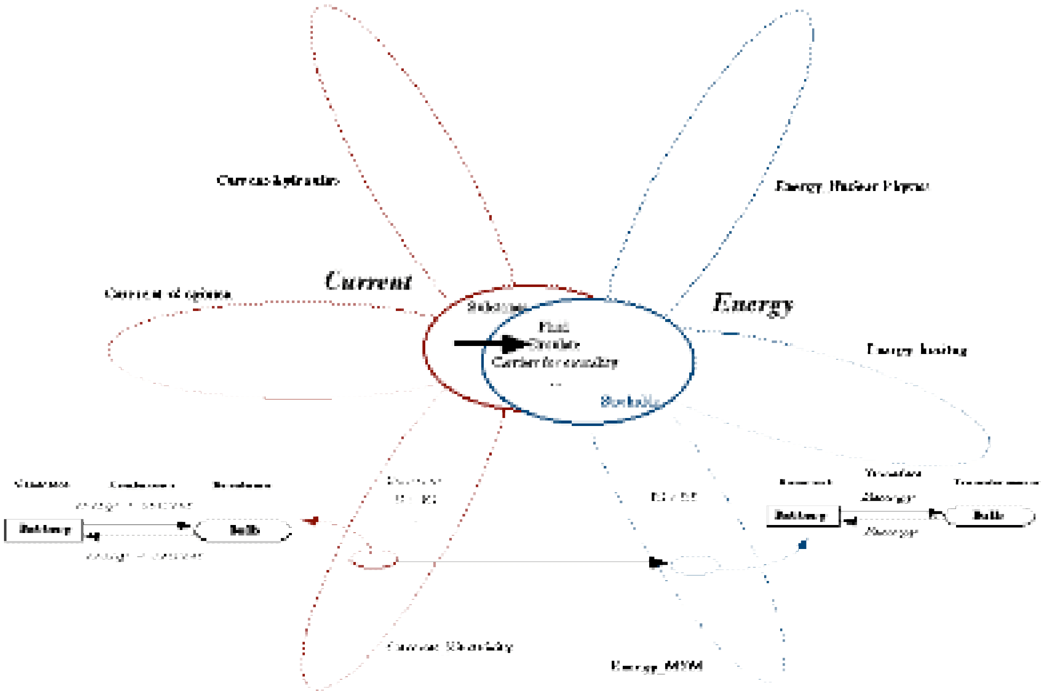

Figure 9. An example of a Janus entity. How the equivalence at the notional level between the notions associated with *energy* and *current* can lead to a confusion of conceptual domains for problem-solving.

5. How tunnel effect activates further adaptation and conceptual learning

Two cases must be examined with respect to the opportunities for learning opened when a model has been obtained using tunnel effect :

1. The model obtained remains valid even after being re-interpreted in the target domain under construction.
2. The model turns out to be erroneous either when confronted with the world or because internal inconsistencies are discovered within the target interpretation domain.

We study these two cases in turn.

1. *The model remains valid.*

This is what happened during the construction of thermodynamics by Carnot, Clapeyron, Thomson, Joule, Clausius and others (Longair, 1984; Science & Vie, 1994). Even though the cyclic model of Carnot was obtained in and tightly tied to a conceptual domain where heat was equated to caloric (an imponderable fluid with the property of being conserved), its expression as the cyclic diagram of Carnot/Clapeyron, once re-interpreted within the new thermodynamics of Joule, Thomson and Clausius, where heat is no longer a conservative property, lead to no contradiction or erroneous predictions. On the contrary, the model remained a very helpful tool for thought experiments, one which eventually lead to the discovery by Clausius of a special state function called entropy.

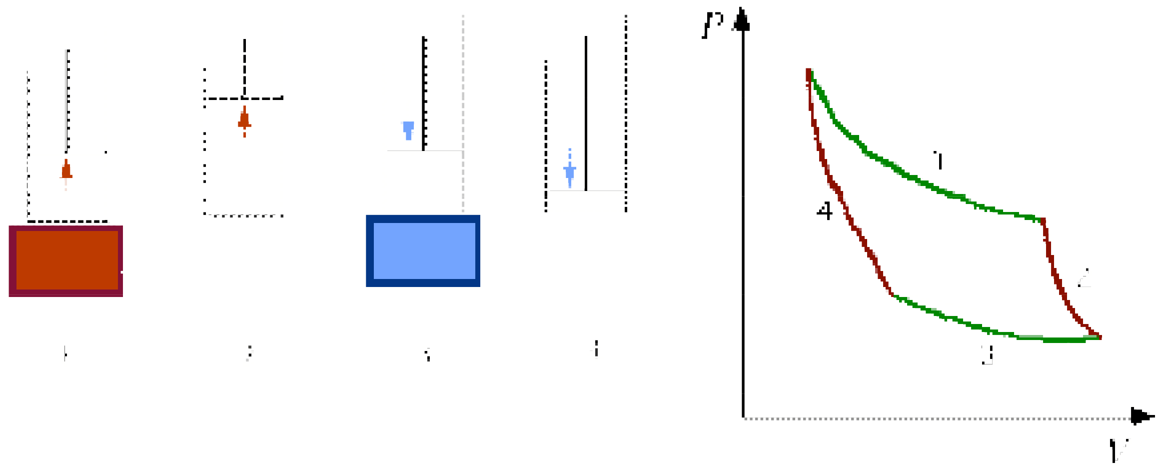

Figure 10. A sketch of the four stages of the Carnot's cycle and its formal depiction by Clapeyron in a pressure-volume diagram.

In this context, conceptual learning occurred not because of an overt contradiction manifested by the re-interpreted model, but because the model had to be thought upon in order to find new justifications for it once it became clear that it deeply rested on the obsolete caloric hypothesis.

It would certainly be interesting to study if some general form of Explanation-Based Learning (Mitchell,1997) could be proposed in order to account for this type of situations. This is as yet an open area for research.

2. *The model turns out to be erroneous when re-interpreted.*

In our energy chain experiments, this happened either when students realized that the model implied that the energy was flowing back to the battery (which they knew was incorrect), or when they discovered an inconsistency with the target integrity rule stating that the initial energy reservoir should be different from the final one. In both cases, the students resumed their reasoning steps to check if they did not make a mistake. The subsequent learning process, if it ever took place, involved two stages. In the first one, the students had to prove that the faces of the Janus entities were indeed different, i.e. they could not be identical even though they appeared to be so. In the second one, they had to specialize their concept of energy in order that it could no longer be mixed up with the notion of electrical current.

Since the energy chain experiment was set for a duration of two hours at most, any conceptual learning was at best merely hinted at in the students' dialogs. We therefore are not ready yet to provide a full account of these two steps which involve complex interactions between schemata (Cauzinille-Marmèche et al. (1997) provide an analysis of some simple “repair mechanisms” used by students to adapt their model). We will merely describe one instance of each step in order to illustrate the nature of the mechanisms at play.

1. *How to detect that two entities cannot play the same role : an example*

   Section 3.1 showed that most pairs of students did not, at first, differentiate energy from electrical current, and therefore, through tunnel effect, produced a circular model for the energy circulation. The model thus obtained was then interpreted within the energy domain with predictions that the energy will flow back to the battery which, they say, cannot be the case. Since this is the point where a difference between the properties of energy and of electrical current are uncovered, it is interesting to further investigate it.

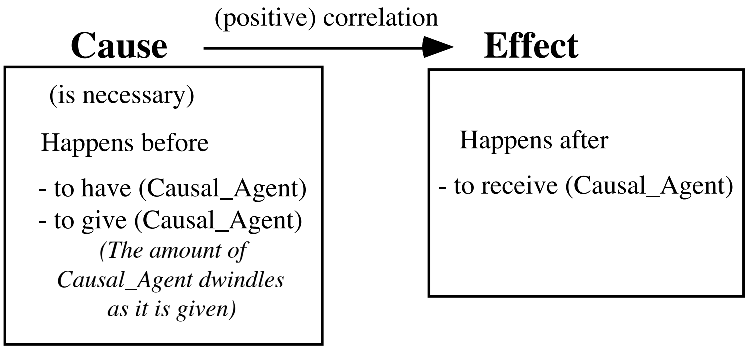

Figure 11. A sketch for the linear causality schema at the notional level.

Energy is considered by students as a Causal_Agent. The battery is known to be a reservoir of energy, that is a source of Causal_Agent, and the state of the lamp as being a kind of Effect. Therefore, according to the linear causality schema (see [Tiberghien,1984]), the source of energy must increasingly wear out as it gives away energy. That would not be the case if energy was flowing back to it, which is exactly what the model predicts. Ad absurdio, then, energy cannot flow back to the battery, and therefore it cannot be identical to electrical current which is known, by definition, to return to the battery.

We have an example here of a reasoning process involving several schemata at the notional level (linear causality, reasoning by reducing to the absurd, giving, receiving, diminishing, and so on). While it is not really complex, it still requires a not trivial coordination, and a complete and precise artificial intelligence modeling has yet to be realized. It is however displayed naturally and apparently effortlessly by most students. Its only output is to point out the impossibility of maintaining an identification of *energy* and *electrical current* at the conceptual level. At this stage, a new and more precise characterization of energy is yet to be learned. We believe the subsequent learning process to act on the schemata that were activated in the previous reasoning, but we so far lack a better description. The following sub-section shows how learning can occur in a simpler context.

2. *Learning through specialization of schemata : from notions to concepts*

We describe here how the schema for *transformation* at the notional level could be specialized to become a schema within the conceptual domain for energy.

At the notional level, the schema for Transform would involve 4 roles with rather loose specifications allowing many various arguments to satisfy them (see figure 11). One way to specialize this schema is to take its instantiation in the case of some phenomena as a positive example for the target conceptual schema, and to specialize the constraints attached to each role as tightly as possible to fit the positive instance (bottom-up generalization). This could give a schema such as the one in figure 12.

- **Transform$_{\text{–Notionnal}}$**
  - Agent : (3) ∈ {Human, Causal_Agent, ...}
  - Subtance : (4) ∈ Everything , keeps the same essence
  - **Initial State**: (1)
  - **Final State** : (2)

  $\}$ *Opposite Superficial characteristics*

- **Transform$_{\text{–U_Energy}}$**
  - Agent : **(1) ∈ Object_from_the_experiment (e.g. bulb)**
  - Subtance : **(1) ∈ Energy**
  - Initial State : **(1) ∈ Transfer mode = Energy (e.g. Electrical work)**
  - Final State : **(1) ∈ Transfer mode = Energy (e.g. Heat, radiation)**

  & **Mesure(Final State) = Mesure(Initial State)** /*Invariance*/

Figure 12. An example of a specialization of a notional description of one entity into a conceptual description obtained through bottom-up generalization of an experimental instance (here the battery-bulb experimental setting in which we have added an hypothetical mean to measure that the energy is the same before and after the transformation, hence the invariance condition). Notice the numbers attached to each role or slot. Their meaning is the following : (1) necessary, (2) optional, (3) possible, (4) rare, (5) sufficient. In the conceptual schema, all roles become necessary.

6. The tunnel effect vs. analogical reasoning

Very few inference mechanisms have been proposed that deal with the transfer of information between different conceptual domains. *Analogical reasoning* is one of them —the most famous—, *blending* is another one (Fauconnier & Turner, 1998), and, we submit, *tunnel effect* is a contender too. A full comparative study of the three of them would be more than interesting, but is beyond the scope of this paper. However, we believe that a comparison with analogical reasoning might help to enlighten some characteristics of the tunnel effect as an inferencing mechanism. We will concentrate in each case on the conditions for a transfer between interpretation domains to occur, and on the information content that is transferred.

According to the dominant view on analogy (e.g. (Falkenheimer et al., 1989; Greiner, 1988)), **analogical reasoning** involves the interpretation of two cases, —called the source case for the supposedly well-known one, and the target case for the one to be completed—, that may be interpreted within two different interpretation domains (e.g. the solar system as a source case and the supposedly ill-understood atom system as a target one). Each case is supposed to be represented as a graph of relations and nodes standing for primitive concepts. Analogical reasoning implies then that a best partial match be found between the two graphs, and, in a second step, that the part of the graph representing the source case with no counterpart in the target case representation be copied, translated and added to the target representation in order to fill the missing part. Many questions arise as to the principles that should govern both the matching operation, the translation and the transfer, not to speak about subsequent verification and adaptation. Deep concerns have also been expressed about the interpretation process of the two cases during analogy and the ensuing representation of the cases (e.g. (Hosftädter, 1995; Mitchell, 1993)). It is important to note that both domains —the source and target— must be sufficiently well understood in order that the respective conceptual primitives be identified, put in hierarchy and potentially matched. This view of analogical reasoning thus prevents the consideration of a target domain that would be in gestation and of which conceptual primitives would be very uncertain.

If we consider then the analogical inferencing mechanism as a kind of black box with inputs and outputs, the *inputs* consist of the source and target conceptual domains (the conceptual primitives and their relationships (including the said over-important hierarchies) and in the two cases (be they already represented as some would pretend is realistic, or be they interpreted in the context of the analogy as others would insist is unavoidable). The *black box* then searches for one satisfying matching between the two cases (given as rigid representations or not) and computes the completion of the target case representation. The *output or information gained* in the operation consists therefore in the added features and properties of the target case.

Analogy	Tunnel effect
• Two experimental settings or situations that are posited as analogs to each other	• One experimental setting or situation only
• Interpretation takes place both in the source domain and in the target domain (there are two situations to be interpreted).	• Interpretation takes place in the source domain subject to the target constraints and adequacy to the world criterion.
• Relies heavily on **comparisons** :	• **No comparison** is involved, only interpretation
• Implies complex pattern matching between the two case representations	• Involves associations at the notional level between target entities and source ones
• Tightly associated with the notion of similarity *between* structures. One problem is to explain how this similarity is computed	• Associated with confusion at the notional level. No notion of similarity *between* constructs
• There is **transfer** by matching, alignment and completion from the source to the target	• There is transfer by reinterpretation of the model of which some aspects have been automatically filled-in within the source interpretation domain(s). The built model gains **autonomy** and is **reinterpreted** in the target domain
• *New information* is produced through the completion of the target case representation	• *New information* is produced through automatic completion of the model within the source domain
• Does not explain how the source is chosen	• The source domain(s) is(are) the most operational for interpretation in the current situation
• **Learning** is supposed to arise as : - learning of indexing scheme - generalization and abstraction from analog cases - not really new conceptualization, except by generalization	• **Learning** : - Reconceptualization focuses on associated entities that led to inconsistencies in order to differentiate them - Progressive operationalization of the new conceptual domain - Articulation with primitive perceptions about the world and with the source conceptual domain

Table 1. A summary of the main features of analogical reasoning versus features of tunnel effect.

In contrast, **tunnel effect** only involves the interpretation of a *single situation or case* (e.g. an experimental setting or a set of phenomena). The *input* of the tunnel effect black box consists of the operational source interpretation domain(s), the target criteria that specifies the target interpretation domain (including preconceptions about some target entities, their properties and relationships), and the case (situation or set of phenomena) to be interpreted and understood in the target interpretation domain (e.g. the battery-lamp experiment to be interpreted in terms of energy exchanges, the electromagnetic interactions as measured in Faraday's experiments in terms of a theory in germ in Maxwell's head, or the steam engines in terms of heat and work and other related variables in the nascent thermodynamics). The *black box* then searches for a model of the case satisfying the target criteria. Because most target entities are not yet operational and interpretable directly in the world, they have to be transformed in terms of the more operational interpretation domains given as inputs. In this transformation process, submitted to the target criteria, and during model building, some aspects of the model may be automatically filled up through automatic inferencing within the source domain(s) (as is the case when the arrows for transfers are automatically specified when it is decided to translate `energy transfer` from the notion of electrical current). The *output or information gained* in the operation consists of the unexpected (because not planned) consequences of the model when interpreted within the target interpretation domain, or in the experimental setting if some target entities are already partially interpretable in the world (as is the case for "energy" for 16-17 years old students).

In both analogical reasoning and tunnel effect, the detection of discrepancies between the resulting model and the world or of other inconsistencies opens opportunities for learning. The difference lies in the fact that tunnel effect is intrinsically intended towards the process of building the domain interpretation domain (through the setting up of connections between this domain, the operational ones in the context and the world) whereas analogical reasoning is oriented towards the completion of some specific case with the help of another 'similar' one. While failed analogies may lead to reconceptualisation in the target interpretation domain, this is much less direct than the learning that may occur when a tunnel effect has produced an unfit model of the world in the interpretation domain.

7. Conclusion

This paper takes seriously the idea that cognition may imply the existence (and coexistence) of several different interpretation universes, and that a specially important type of learning consists of acquiring new ways of interpreting the world or some aspects of it. In our study we focused on the learning of a new target conceptual domain from the currently operational interpretation one(s) when the attention of the cognitive agent is driven towards the interpretation and understanding of some phenomenon or set of phenomena.

In studying the type of conceptual learning at play when students are learning a new conceptual domain or when scientists are struggling to find new ways to account for the world, we discovered the important role that one, so far never mentioned, mechanism can play in transferring knowledge from one conceptual domain to another. This mechanism, that we call tunnel effect, facilitates the discovery of interpretations of the world in terms of a new and still ill-known conceptual domain. Its main features are the following :

1. It implies a *lack of differentiation between entities* belonging to different domains
2. While building an expressed model of the phenomena, there might be *illicit transfers of inference processes from one source entity to an associated target one*. This eases the construction of models by providing inference mechanisms from the source domain(s) that make up for the as yet non-existent inference mechanisms of the target domain.

3. If the thus obtained model is then reinterpreted entirely within the target domain, the results of the illicit inferencing processes may bring out unforeseen consequences that may satisfy or not the target constraints defining the target domain.
4. It is then possible that reconceptualisation occurs, either to evolve conceptual definitions that help establish differentiation with other concepts and notions, or to make target entities more operational by articulating them more directly to the experimental world.

The essential ingredient in this transfer mechanism lies in the a priori lack of differentiation between would-be conceptual entities. To account for this, we appealed to the idea of a notional level of knowledge and discourse. While tackling situations in terms of ill-mastered conceptual domains, the natural tendency would be to reason at the notional level. This would allow flexible matching or association between otherwise ill-known entities.

Much remains to be done in order to precisely characterize the notional level and the learning that can take place as a result of tunnel effects. However, we believe that our attempt at modeling the learning of new conceptual domains through a mechanism like tunnel effect has some important philosophical implication in that it deeply changes the classical viewpoint according to which learning new conceptual systems must necessarily be accompanied by conscious and painful confrontations with some contradiction between the 'old' theory and facts. Our approach, by contrast, underlines the *constructive role* that existing conceptual domains can play in learning a new one. Furthermore, tunnel effect is inherently cognitively cheap. It demands for confusion to take place at the notional level, and for reinterpretation within the target domain. This is easier by far than analogical reasoning, as classically presented in artificial intelligence, which implies costly optimization of complex graph matching. Thanks to it, inferencing procedures can be used automatically to fill missing aspects where they should not if a cautious and systematic search was performed. This facilitates obtaining candidate interpretations of the world, a process that otherwise could be lengthy and costly. In addition, tunnel effect provides more than a somewhat blind exploration process in that it supplies a focus for attention and reconceptualisation in case the candidate solution turns out not to satisfy the target constraints. Reasoning and learning can then bear on the discovery of distinguishing properties of the erroneously confused entities. Tunnel effect thus provides an economical way of transferring knowledge from one conceptual domain to another and it offers a focus for subsequent conceptual learning.

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