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# KNOWLEDGE TRANSFER DYNAMICS: HOW TO MODEL KNOWLEDGE IN THE FIRST PLACE?

**Widad Guechtouli***
HEC Alger, Laboratoire MARKETIC (Algeria)
guechtouli.widad@gmail.com

**Amel Kasmi**
HEC Alger, Laboratoire PERMANAN (Algéria)
kasmiamel@yahoo.fr

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**Abstract:**
In this paper, we study both processes of direct and indirect knowledge transfer, from a modelling perspective, using agent-based models. In fact, there are several ways to model knowledge. We choose to study three different representations, and try to determine which one allows to better capture the dynamics of knowledge diffusion within a social network. Results show that when knowledge is modelled as a binary vector, and not cumulated, this enables us to observe some heterogeneity in agents' learning and interactions, in both types of knowledge transfer.

**Keywords:** knowledge modelling, knowledge transfer, social networks.

**Résumé :**
Dans cet article, nous étudions les processus de transfert de connaissances direct et indirect, du point de vue de la modélisation, en utilisant des modèles à base d'agents. En fait, il existe plusieurs façons de modéliser les connaissances. Nous choisissons d'étudier trois représentations différentes, et nous essayons de déterminer laquelle permet de mieux saisir la dynamique de diffusion des connaissances au sein d'un réseau social. Les résultats montrent que lorsque la connaissance est modélisée comme un vecteur binaire, et non cumulé, cela permet d'observer une certaine hétérogénéité dans l'apprentissage et les interactions des agents, dans les deux types de transfert de connaissances.

**Mots clés** : Modélisation des connaissances, transfert de connaissances, réseaux sociaux.

***Author Corresponding**

## 1- Introduction:

Upstream of any innovation activity, individuals implied in the process of innovation must be able tointeract and exchange knowledge under satisfying conditions. In this context, Foray and Zimmermann (2001) talk about the “good properties” of knowledge distribution. They write on this matter « *only fast and widened knowledge circulation makes it possible to profit from the single potential of a great number of qualified individuals*” (ibid, p.7). The speed with which knowledge is transmitted between various individuals thus makes it possible for them to coordinate in an easier way. Besides, the distribution of knowledge within a network offers a “guaranty of quality” (ibid.) of the produced knowledge, as it is checked by a certain number of individuals, who had to deal with. Hence, the sharing of knowledge between several individuals is a complex process that seems relevant to study.
The process of knowledge transfer is often studied in the context of a social network (Cowan and Jonard, 1999; Cowan and Jonard, 2006; Morone and Taylor, 2004a; etc). as it allows repeated interactions between various individuals. Besides, the frequency of interactions can constitute a key element in the transfer of certain knowledge, especially tacit knowledge (Nonaka and Takeuchi, 1995).

In this perspective, agent-based modelling (ABM) can be considered as a suitable tool to study the problems of knowledge transferwithin social networks (see for example works of Cowan and Jonard, 1999; Morone and Taylor, 2004a; Cataldo *et al.*, 2001).Indeed, they enable to study dynamic phenomena and to capture complexity within a model (Phan, 2003; Gilbert *et al.*, 2001). Moreover, they enable to test different scenarios of simulations. But before studying knowledge transfer, one seeks to know how to model knowledge in the first place, in a way that enables us to study knowledge transfer within a social network. As Walliser states, knowledge « is frequently incorporated into agents and cannot be encoded in an explicit way” (Walliser, 2004, p. 194).

According to Cowan and Jonard (1999), models presenting knowledge as a scalar cannot apprehend the process of knowledge diffusion, while models presenting knowledge ad a vector can. In addition, the representation of knowledge as a stockpile was highly criticized in the literature (Morone and Taylor, 2003). “… *Cognition follows* *combinatory rules and not additive rules"*(*ibid*., p 9), and does not allow to capture the way that knowledge is diffused between various individuals, as a knowledge vector would (Cowan and Jonard, 1999). Indeed, knowledge is not accumulated, but rather is articulated with knowledge already held by an individual. This argument finds its origin in the distinction made between the economy of knowledge and the economy of information (Ancori *et al.*, 2000).Thus, the question that we raise here is *how knowledge should be modelled in order to capture the dynamics of knowledge diffusion within a social network?*

To answer this question, we will go through the existing literature around knowledge, and try to identify different kinds of knowledge and how they can be transferred. This will allow us to build agent-based models featuring three different representations of knowledge, where we will observe the dynamics of knowledge transfer. The last section of this paper will present the results, discussion and concluding remarks.

## 2- Information, knowledge and transferability

### 2-1. Knowledge vs. Information: convergence or complementarity?

It is not possible anymore to consider knowledge as partitions of information held by individuals, the only difference between different knowledge being the composition of these partitions (Lazaric and Lorenz, 2000). In fact, the definition of knowledge held by an individual is rather an issue of articulation and treatment of information. They state: "*The idea is that knowing something requires active interpretation of information, and this knowing may be highly unevenly distributed despite the fact that access to information is symmetric or equal*".

Hence, knowledge appears much more complex than information. If it is not interpreted to be used in a particular context, information does not have a value as such (Cohendet *et al*, 2006). If, on the other hand, it is interpreted and contextualized, then it is transformed into knowledge. Knowledge is then built from information that is processed and interpreted in a given context. An existing knowledge can also be supplemented by new knowledge. Knowledge "is nourished" by information (Créplet, 2001).

The difference between knowledge and information can be tempered as Andriessen *et al*(2004) do it. Indeed, one can represent these two concepts like two ends of the same continuum with various zones of gray. For example, a list of names cannot represent anything more but information, while data on the manner of solving a problem can represent knowledge.

Zacklad (2004) offers a definition of it which joined this argument and which we adopt in what follows. He defines knowledge as "*a potential of action given to an individual or collective actor in the context of a situation within which he pursues a project* ».

According to this definition, knowledge transfer is different from information transfer. Complexity inherent to the concept of knowledge also implies a certain complexity in its diffusion. In fact, the transfer depends on processes determining the definition of knowledge. Thus, transferring knowledge depends on the cognitive capacities of the individuals involved in the transfer (comprehension and interpretation), as on the context in which this process is. These two parameters relate to the epistemological approach of knowledge.

## 2-2. An epistemological approach of knowledge

This dimension, which originates with the work of Polanyi (1958), is largely used in the literature and classifies knowledge as tacit or implicit knowledge, and explicit knowledge.

### 2-2-1.Explicit knowledge:

Explicit knowledge is a knowledge which can be transmitted without taking the risk that it loses whole or part of its meaning. That is ensured through a process of codification, because explicit knowledge is a codifiable or codified knowledge. As stated by Foray (2000), explicit knowledge is placed on a knowledge store, it is not linked to a specific person. Explicit knowledge can be handled like information (Cowan and Foray, 1997). We draw the reader's attention not to confuse these two concepts, which are certainly closely dependent, but that we consider as completely distinct. Explicit knowledge and information do share an important characteristic which is the facility of circulation, but as we specified previously knowledge is *built from* information. The latter must still be interpreted by the actors to become knowledge. Information as such has only little value; what makes it valuable is the interpretation that individuals make of it in a particular context.

Explicit knowledge is often transcribed in a codebook (Cowan *et al.*, 2000). The process of codifying knowledge brings some fundamental changes in the economic aspect of the creation and the diffusion of knowledge. The principal change lies in the costs of access to knowledge. Knowledge codification can indeed generate important fixed costs, relating to the various stages of the process of codification. However, once this process is done, the transmission of this codified knowledge can be done at lower cost (Cowan and Foray, 1997). Knowledge is stored on a knowledge store which facilitate their access and which preserve the integrity of its meaning. It can be consulted an infinite number of times, without deteriorating its quality or its quantity. Moreover, knowledge codification brings changes relating to the economic activities and the process of innovation in particular. It allows the externalization of the processes of knowledge creation. Certain knowledge can be bought, instead of being produced within the firm (*ibid*.).

2-2-2. Tacit knowledge:

To define this concept, we will relate to the work of Cowan *et al.* (2000), which offers a synthesis of work treating of the tacit character of knowledge. The tacit term was popularized by work of Polanyi (1958), which considered tacit knowledge as a component of human knowledge distinct from but complementary to explicit knowledge in the conscious cognitive processes. Polanyi illustrated this concept in reference to the fact that the individual is conscious of certain objects, without its attention being necessarily focused on these objects. This did not make them less important, because they constituted the context which made possible the focusing of the individual's attention (Cowan *et al.*, 2000). Andriessen *et al.* (2004) define tacit knowledge as often implicit and unconsciously articulated. Following this, the concept of "tacit knowledge" was largely applied to personal knowledge that was **not easily transmitted** between individuals.
In the literature, the two concepts of explicit and tacit knowledge are often opposite. One could then try to define tacit knowledge, while basing oneself on the definition of explicit knowledge. Explicit

knowledge being defined like a codified knowledge, a tacit knowledge could be defined as non codified knowledge or non codifiable (Witt *et al,* 2007). It is expressed through action and defies any verbal expression (*ibid*), and can be classified in the category of non codifiable and non articulable knowledge. It is a knowledge which can be acquired only by action, and falls under the "learning by doing" or the behavioral learning processes (Leroy, 1998). Hence, this kind of knowledge translates "know-how".

Let us now see how these types of knowledge can be transferred.

## 3- Knowledge transferability

The major differences between tacit and explicit knowledge involve important differences in the way of transferring them from an individual to another. Witt *et al*(2007) present two types of knowledge transfer which we decide to adopt here.

### 3-1. Direct knowledge transfer

Direct knowledge transfer is done thanks to means of communication used between two individuals, such as verbal communication, which require face-to-face contact. Witt *et al* (ibid) talk about knowledge transfer in terms of communication between individuals. *"Knowledge is communicated directly only in oral or visual transmissions requiring face-to-face contact between transmitter and recipient – the communication technology that humans are naturally endowed with*" (*ibid*, p. 3).

We choose to extend this definition to all the means of communication which enable two individuals to communicate instantaneously and without intermediary. Thus, we include there all the technological means available which fulfill these functions. For instance, we can think of means like telephone, videoconferences, etc.

We supplement the definition offered by Witt *et al* (2007) and we define direct knowledge transfer as any knowledge transfer which allows two individuals to communicate without intermediary.

### 3-2. Indirect knowledge transfer

In a similar way, indirect knowledge transfer is a transfer which is done thanks to means of indirect communication. Knowledge must initially be explicited by the transmitter then transmitted or stored by means of an artificial medium which will allow the recipient to consult it later on, an unlimited number of times. "*Indirect knowledge transmission relies on optical, acoustic, or electronic signals. Examples of communication by means of intermediate knowledge storage are written documents and visual and acoustic displays*" (*ibid*., 2007, p. 3).

This type of transfer thus supposes a preliminary codification of non-codified and codifiable knowledge. It enables the recipient to consult knowledge as many times as he wishes to, without time constraint. These authors consider this type of transfer more interesting in terms of knowledge transfer than the direct transfer, because once knowledge is codified and sent to the recipient, it is stored on a knowledge store that is accessible by the recipient, who can consult it instantaneously or later on. "*Indirect communication making use of technical media enables a more powerful knowledge transfer than direct communication*" (*ibid*). This for the following reasons:

This type of transfer is not restricted to only two individuals; knowledge can have several recipients, and thus be diffused more widely, unconstrained, provided that all the recipients understand the code used to codify it;

Codified knowledge is transmitted independently of the physical presence of the individual who holds it. The technological medium can be improved by the various individuals implied in the transfer process.To this definition of the process of indirect transfer, we can bring the following examples: knowledge posted on an electronic forum, knowledge codified and transcribed on paper or electronic documents, etc.

### 3-3. How knowledge can be transferred?

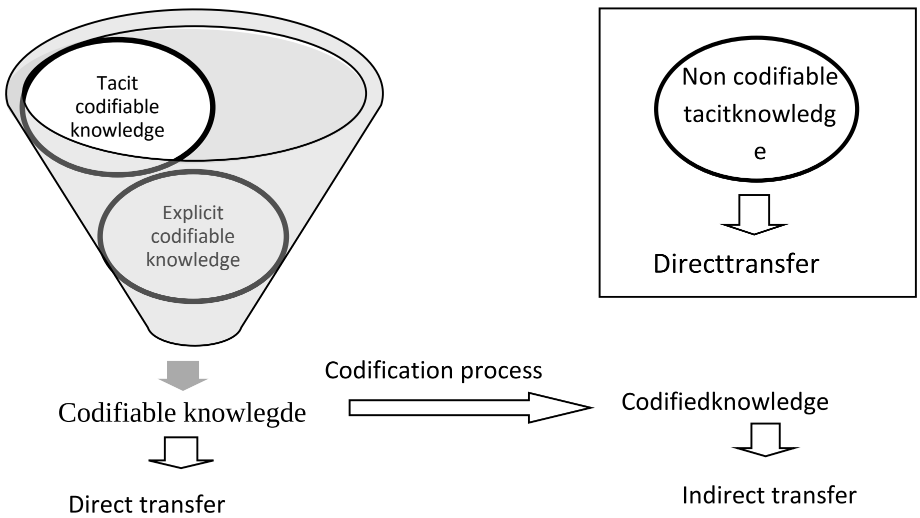
According to the definition of the two types of transfer previously mentioned, it seems that what determines the type of transfer to use is not the explicit/tacit character of knowledge. In fact, this very widespread classification in the literature is not very relevant in making such a decision. Indeed, what determines that knowledge has to be transferred in a direct or indirect way is its codifiable/non codifiable character. Hence, we propose an alternative classification based on this condition.

At this stage, we think that it is necessary to bring some details, as for the codified character of knowledge. If it is codified, it can as well be transmitted via oral communication as through a written knowledge store for example. In some cases, it is easier to transmit codifiable knowledge in an indirect way. For example, to solve a mathematical problem, it is easier to transmit the solution by writing down the mathematical demonstration, than by transferring it in an oral way. Thus, it would be more interesting to codify this knowledge in order to transcribe it, *and* it can be stored easily. This represents a considerable advantage if knowledge is intended for several individuals.

On the other hand, a non codified and non codifiable knowledge cannot be transmitted by means of a written knowledge store. If one takes the example of the knowledge which enables to ride bicycle, it cannot be transcribed or transmitted by means of any support. It is a tacit knowledge, which is not articulable and which can be expressed only in the action of the individual who holds it. Thus, to transmit such knowledge, "the transmitter" must *show* to the "recipient" what to do. This is know-how. For this type of knowledge, the only type of possible transfer is the process of direct transfer.

Let us summarize in what follows the types of transfers corresponding to the various kinds of knowledge, classified according to their codifiable character.

**Figure N°1 : An alternative classification of knowledge**



## 4- Agent-based models

We will use ABM to study knowledge diffusion within a social network. We will model both direct and indirect knowledge transfer within a population composed of a pool of experts and new comers who seek to acquire knowledge. Both models will feature 3 representation of knowledge, and we will try to observe the dynamics of knowledge diffusion for each representation. This is described in what follows.

### 4-1. Definition the agents' and the population's features

We have a population composed of 110 agents[1]: a pool of 10 experts and 100 new comers. The goal of each new comer is to acquire knowledge, by asking questions. Each agent is characterized by the following features:

4-1-1. An initial endowment in knowledge:

For each model, we propose to test three different representations of knowledge; two of them present the cognitive endowment of an individual as a stockpile of various knowledge, while the third is a binary vector.

a. *Knowledge as a binary vector*:

Each agent in endowed with a knowledge vector, composed of 100 types of knowledge[2]. An endowment of 0 in a knowledge *k* means that an agent doesn't have that particular knowledge; whereas, an endowment of 1 means that he does.

| | | | | | |
|---|---|---|---|---|---|
| Knowledge → | 1 | 2 | … | 99 | 100 |
| Knowledgeendowments → | 1 | 0 | … | 1 | 1 |

*Fig. 2Example 1: This agent has knowledge 1, 99, and 100, but does not have knowledge 2.*

[1] We studied the effect of the size of the population on the learning of agents. Results show that the size of the population has no effect on the results of the simulations.

[2]We deliberately chose these values because they enable us to keep certain coherence in terms of knowledge to be acquired for an agent. In each of the three representations, an agent has to acquire 100 elements (knowledge or degrees of expertise).

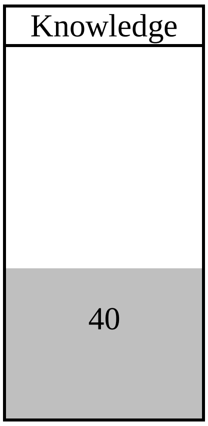
We draw the attention of the reader to the fact that this vector consists of binary values only. There is no accumulation of knowledge here. It is different from the one used by Cowan and Jonard (1999)as they cumulate knowledge.

*b. Knowledge as a stockpile*

- *One knowledge with 100 degrees of expertise*

Here, agents only have one type of knowledge. However, they have different degrees of expertise in this knowledge, ranging from 0 to 100. This knowledge can be illustrated in the following way:

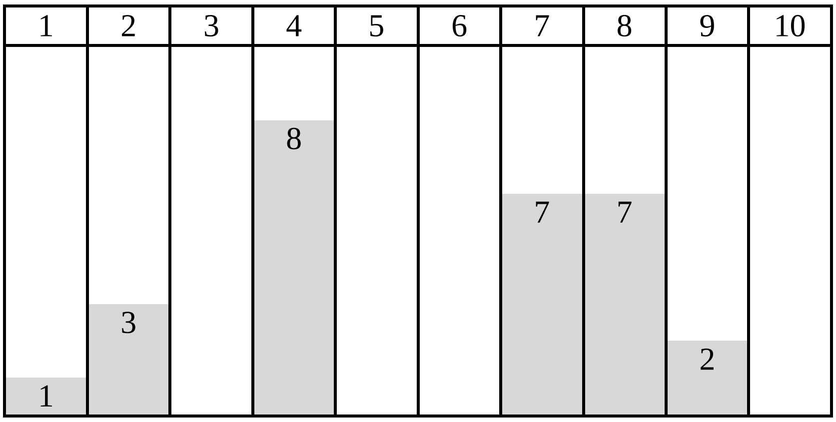
**Figure N°2: An agent has a degree of expertise of 40**




- *10 different knowledge with 10 degrees of expertise*

An agent can have 10 different types of knowledge with different degrees of expertise ranging from 0 to 10 in each one of them.

**Figure N° 3 : Knowledge and degrees of expertise of an agent**



4-1-2. An agent's competence

It is defined according to the representation of knowledge used:

For knowledge as a binary vector, we define an agent’s competence by the number of knowledge he possesses. Technically, an agent’s competence is the sum of ones in his knowledge vector. This definition follows the work of Cataldo*et al* (2001). In their model, these authors model each agent’s knowledge as a mask composed of 0 and 1 for different types of knowledge. They state: *“The increasing number of pieces of information of a particular type, the more experienced the individual will be in that area. In addition, experience is represented in the number of ones that the knowledge mask has”.*

With regard to the situation where the agents have only one type of knowledge with 100 degrees of expertise, the competence of an agent is simply equal to its degree of expertise.

Lastly, when agents have 10 different types of knowledge with 10 degrees of expertise, the competence of an agent will be equal to the sum of its degrees of expertise in the various knowledge it possesses. For example, the competence of the agent whose knowledge is illustrated in Fig.4will be equal to 28.

4-1-3. Rules of interaction: The selection of an knowledge-provider

The choice a knowledge-provider will depend on the type of simulations which we use.

- In simulation with direct knowledge transfer: agents always choose the most competent agent in the population.
- In simulation with indirect knowledge transfer: agents don’t choose a particular agent, but post a question on a forum. It is a mode of communication that is often used in knowledge intensive communities (see for instance the work of (Guechtouli *et al,* 2013); Marquois-Ogez (2006), Conein and Delsalle (2005)). Here, individuals do not interact in a direct way, with a targeted individual.

4-1-4. Other features:

*Availability*: defined by the number of questions that an agent is able to answer per time-step.

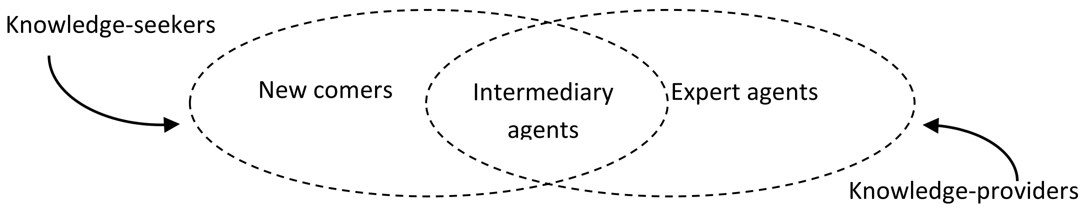
*Tolerance threshold*: defined as follows:

- In direct knowledge transfer: it is defined as the number of unanswered questions that an agent is willing to accept from another agent, before deciding not to ask this agent anymore.
- In indirect knowledge transfer: it is it is defined as the number of unanswered questions that an agent is willing to accept before deciding not to ask questions anymore and leaving the network.

In terms of answering questions and providing knowledge, we consider that the population of agents is divided in two parts: priority knowledge-providers (pkp) and secondary knowledge-providers (skp). *Pkp* have a competence equal to 100, whereas *skp* have a competence greater than or equal to a competence threshold (CompMin) defined as the minimal competence required in order to be able to answer questions. This threshold is set to 75[3].

Agents with competence lower than 100 will be calledknowledge-seekers.

**Figure N° 4 : Agents and their functions**




### 4-2. Definition of interactions:

Each agent interacts once per time step. According to the way in which knowledge is modelled, the question asked differs.

[3]We led simulations for several values for CompMin and 75 is the value where the largest number of agents is able to increase their individual competencies.

If knowledge is modeled as a binary vector, the question raised by agent *a* will concern a knowledge chosen randomly among all those which it does not have.

If knowledge is represented as a stockpile, then the question asked will relate to the smallest degree of expertise which the agent does not have. In order to better understand this, let us take the examples presented in the figures Fig. 3and Fig.4.

If an agent has only one type of knowledge with 100 degrees of expertise, as it is illustrated in Fig.3,its next question will relate to a degree of expertise equal to 41.

Whereas if an agent has 10 knowledge with 10 degrees of expertise for each one of them as presented for instance in Fig. 4, then the question will relate to a knowledge chosen randomly among the 10 knowledge of the agent. As for the degree of expertise, it corresponds to the smallest degree that an agent lacks in the selected knowledge. For example, if the question is about knowledge 4, then the degree of expertise required will be 9.

### 4-2-1. The process of response of a knowledge-provider

Once he receives a question, a knowledge-provider provides an answer if he is available and if he can answer the question. For thathe carries out two tests:

*Test of availability:*

If the number of questions that the knowledge-provider received is lower than the value of his availability, the he is available and carries out the second test.

If not, he ignores the question.

*Test of competence*:

This test is different according to whether knowledge is represented as a binary vector or as a stockpile.

<u>For knowledge as a binary vector:</u> the test of competence is summarized in what follows:

- If the knowledge-provider has the requested knowledge, he answers the question.

- If not, he ignores it.

For knowledge in the form of a stockpile: (one knowledge with 100 degrees of expertise or 10 knowledge with 10 degrees of expertise), here the question asked by each knowledge-seeker corresponds to a degree of expertise concerning a given knowledge. The test of competence is as follows:

- If the degree of expertise required is lower than or equal to the degree of expertise of the knowledge-provider that receives the question, then this agent can answer the question;
- If it is higher than the degree of expertise of the knowledge-provider in the requested knowledge, then it cannot answer the question and ignores it.

A knowledge-provider carries out the two tests of availability and competence to answer (or not) each question he receives.

Each knowledge-seeker asks a question per time step, as long as its competence is lower than the maximum competence.

4-2-2. Learning process

Each time an agent gets an answer to a question; it raises its knowledge of that particular subject to 1, and won't ask questions about this knowledge anymore. Following example 1 (cf. Fig. 2), an agent increases her knowledge of subject 2, as shown below.

**Figure N°5: An agent learns and acquires knowledge about subject 2**

| | | | | | |
|---|---|---|---|---|---|
| Subjects → | 1 | 2 | … | 99 | 100 |
| Knowledgevector → | 1 | **1** | … | 1 | 1 |

For the two other representations of knowledge, the process of learning is as follows: each time an agent receives an answer concerning a particular knowledge, his degree of expertise in this knowledge increases with 1 point.

# 5- Results of simulations:

## 5-1. Simulations with direct knowledge transfer

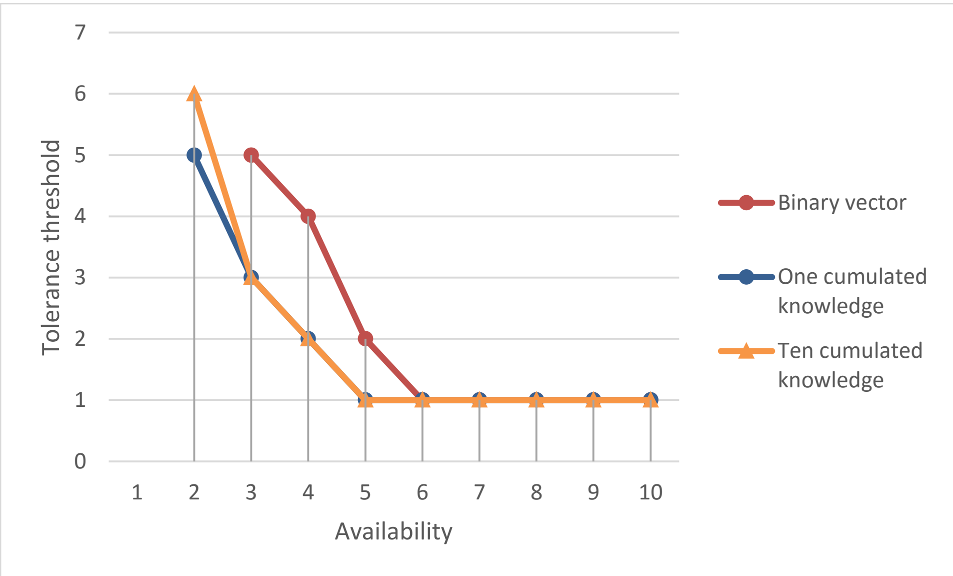
The objective of these simulations is to see how a different representation of knowledge can influence the process of knowledge transfer. This is why the results obtained following these simulations will be presented in the form of a comparison between the three representations of knowledge.We chose to observe only one indicator, which summarizes well the way in which knowledge is transferred. This indicator is agents' coordination for optimal learning, that is the matching values of availability and tolerance threshold that are necessary for all agents to become experts.

The parameters which we varied are the following:

- Knowledge-providers' availability between 1 and 10 questions per time step;
- Knowledge-seekers' tolerance threshold between 1 and 10 unanswered questions per agent;

Results are as follows:

**Figure N° 6: Agents' coordination for optimal learning in direct knowledge transfer**




We can notice, fromthe results presented in Fig. 7, that agents' coordination is much easier in simulations with one and ten knowledge that in simulations where knowledge is modelled as a vector. Optimal learning is in fact observed for all the values of availability, even if knowledge-seekers are not tolerant. Whereas when knowledge is represented as a binary vector, it is necessary to wait for availability equal to 3 questions per time step and a tolerance threshold equal to 5 to observe optimal learning.

5-1-1. Discussion of the results:

By modelling knowledge as a vector, there is no particular bond between the different types of knowledge that compose this vector. Knowledge is not ordered according to any degree of difficulty; they are thus not cumulated. An agent may have knowledge located at the beginning of the vector and not possess some other located a little further on the vector.

That is not the case when one speaks about knowledge as a stockpile. If a question relating to a degree of expertise *n* is asked to an agent which has a degree of expertise *m* equal to or higher than *n*, then this agent can obligatorily answer this question. The only element which conditions its answer is its availability. This is illustrated in the following figures:

**Figure N°7 : Knowledge as a stockpile**

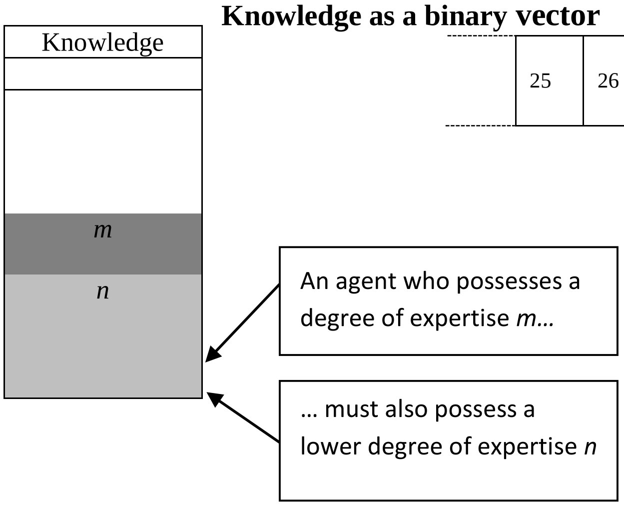
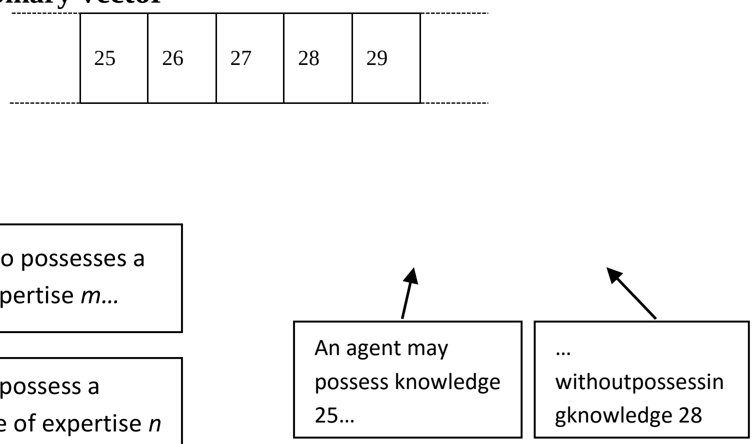



**Figure N°8: Knowledge as a binary vector**

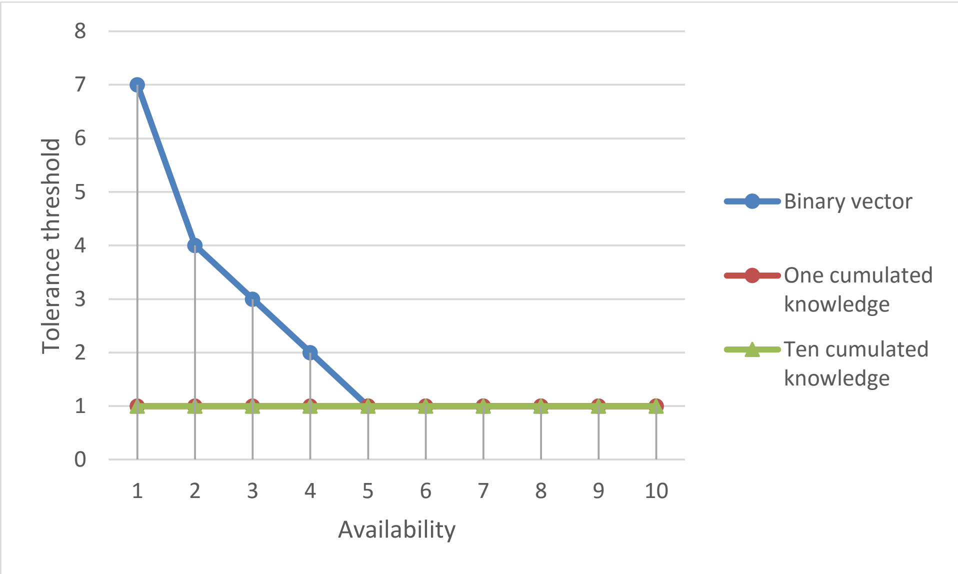



Thus, if we compare the three types of knowledge modelling, all things being equal, an agent gets more answers when knowledge is cumulated (cf. two preceding figures). It is this difference which induces great changes in terms of agents' coordination.

### 5-2. Simulations with indirect knowledge transfer

In indirect transfer of knowledge, results show a clear difference between the three representations of knowledge. Here, all the agents become experts for all the values of availability and tolerance when knowledge is treated as a stockpile (one or ten knowledge with various degrees of expertise). This result is only due to this way of modeling knowledge. When one models knowledge in the form of degrees of expertise, agents receive more quickly answers to their questions. These answers being stored on a forum, all the agents have access to knowledge before deciding to leave the social network.

**Figure N°9: Agents' coordination for optimal learning in indirect transfer: three structures of knowledge**




### 5-3. Discussion of the results

The results observed in Fig. 10show that there is a difference in terms of transfer in knowledge, if it is modelled as a binary vector or as a stockpile. In these simulations, it seems that, thanks to the mechanism described in the Fig. 8and Fig. 9, agents receive answers sufficiently quickly so they do not have to leave the network.

In fact, given the mechanism of interaction describes previously, all knowledge-seekers ask the same question at the beginning. The interactions occurring on a forum, all the individuals receive the answer given by one of the knowledge-providers. All the knowledge-seekers then increase their individual competences on the first time step. The same procedure is repeated with the following time steps. Consequently, they all systematically obtain answers to their questions. They never leave the network.

We had chosen this mechanism of interaction to maintain a plausible character for the interactions within asocial network. A new comer cannot ask a question requiring a high degree of expertise without having a certain expertise first. The process of learning is done gradually by asking questions requiring a higher degree of expertise as the individual competence of the agent increases. However, it proves that this modeling of knowledge as a stockpile does not enable us to have a real heterogeneity in the interactions. Thus, this representation of knowledge does not enable us to capture the way in which knowledge is diffused.

## 6- Concluding remarks:

In this work, we aimed to study the processes of knowledge transfer within social networks, and more precisely, we wished to know which representation of knowledge would enable us to better capture the dynamics of knowledge diffusion.

In order to do so, we chose to use agent-based modelling, this methodology seeming particularly adapted to our purpose.Simulations which we carried out related to two types of transfer: indirect and direct transfer of knowledge. We tested two types of representations of knowledge: knowledge as a stockpile, and as a binary vector.

Our results show that the transfer of knowledge is facilitated when knowledge has a cumulated form that when it is represented by a binary vector. This result concerns both types of knowledge transfer studied in this paper. That is due to the fact that, when knowledge is represented as a stockpile, various knowledge which an individual possesses are connected to each other. They are ordered (cf. Fig. 8), and an individual cannot have a knowledge requiring a certain degree of expertise without having some other requiring a lower degree of expertise. However, since knowledge is ordered following an order which requires ascending degrees of expertise, this representation of knowledge does not enable to observe a great heterogeneity in the interactions, and does not allow to capture the way in which knowledge is diffused within a social network.

On the opposite, when knowledge is modelled as a binary vector, i.e. when knowledge is not cumulated, simulations enables us to observe some heterogeneity in agents' learning and interactions. This modelling of knowledge thus allows for a better capturing of knowledge transfer dynamics within a social network.

In our future research, we would like to extend the work presented in this paper to the process of knowledge creation. Following the models developed by Cowan et *al.*(2006) and Cowan *et al*. (2007), we could observe how knowledge creation dynamics can be captured according to the chosen knowledge representation.

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