Chapter X

Eliciting Organizational Discourse

A single mind can not study itself, but a collective of minds can certainly study the collective mind.

(Edoardo Boncinelli, 2005)

Abstract

Beginning with this chapter we will describe a methodological approach to identify, represent and model explanatory discourses. In the first part of this chapter we will present the overall methodological framework while in the second part we will focus on the first step of the methodology, that is, the identification and acquisition of explanatory discourses. An interview technique is presented to elicit explanations followed by a detailed example and practical advice.

Investigating Organizational Memory Through Explanatory Discourse

It is time to proceed from theory to practice.

Before confronting the methodological aspects relative to the analysis of explanatory discourses, it is appropriate to sum up the theoretical considerations that have caused us to consider analyzing explanations in organizations from a privileged point of view in order to study the processes of organizational learning. The conceptual pathway followed up to this point can be summarized in the following steps:

a. Organizational memory is made up of a group of *artifacts*, which form the skeleton of the apparatus of persistence, through which organizations make an effort to insure the necessary coordination of individual actions and the achievement of shared objectives. The processes of organizational learning come about when organizations are able to question and to effectively modify organizational memory (Chapters III, IV, and V).
b. By following a constructionist approach, we have analyzed the processes involved in building organizational memory. We have examined the role of organizational actors and explanatory discourse in the *building of collective memory* using the MEP model (Chapters VI, VII, VIII, and IX).
c. We have characterized the "verbal" knowledge contained in explanatory discourse as *grey knowledge*. Individuals construct explanations when they illustrate their discoveries, or, more modestly, justify the outcomes of their actions, both to themselves and to the organizational customers for whom they have acted. The logic of grey knowledge is the logic of argumentation and persuasive discourse (Chapter VIII).

Artifacts, resources, and individual capabilities are the means through which organizational members construct "solutions" for their organizational customers. The rationality of the organizational actors inevitably refer to the constructs of collective memory and to the artifacts, and is consequently reflected in the discourses that organizational actors make in order to justify to themselves and their organizational customers the reasons behind their behavior and that of others.

Therefore, in this and later chapters, we intend to show how the analysis of explanatory discourse can be carried out in practice and used as a tool for observation, analysis, monitoring and management or organizational learning.

A Methodological Proposal for the Analysis of Discourse

In this paragraph we describe a protocol for the elicitation, representation and modeling of explanatory discourse. From the brief summary presented in the preceding paragraphs, some very important methodological indications emerge.

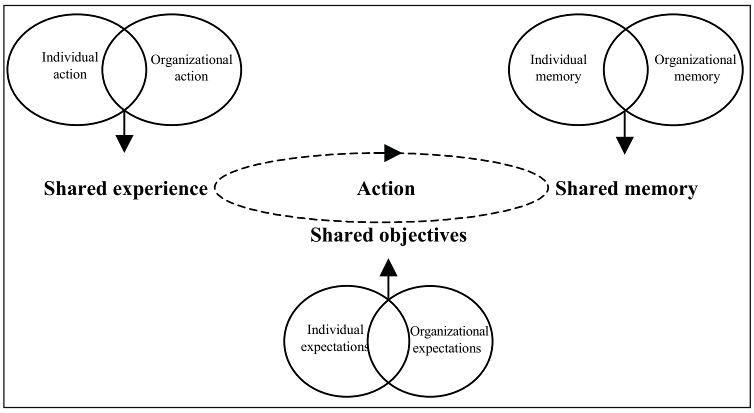
The MEP model (Chapter IX) outlines three temporal coordinates for action: results of past action (memory), current information (experience), intentions (plans). Any explanation will refer to these three coordinates. Furthermore, any of these three temporal dimensions can be referred to both the individual level (my time) and the collective level (others' or organizational time). Consequently all of the three coordinates of action should be analyzed by considering the inevitable overlapping of subjective and collective elements (Figure 1).

According to the logic of the MEP model we need to acknowledge some relevant methodological implications.

In the first place, it will be necessary to point out the experience of the organizational members. Experience is by definition the information coming from the ex-post revision that an individual does in a process of self-observation, in the light of the plan, motivations and memory frames.

In the second place, the constructs of organizational memory should be identified as elements of shared knowledge. Consequently, the analysis must necessarily be

Figure 1. The methodological implications of the MEP model for the elicitation of explanatory discourse



An explanation given by a member of an organization has value for the analysis of organizational memory if it possesses three requirements: (1) It refers to concrete experiences as a result of the comparison between individual and organizational action, (2) assumes an intersection between the expectations of the performer/customers and map (3) it turns to interpretative categories belonging to the collective memory in explaining the facts.

done on a large scale. It is necessary to observe that a necessary condition of the existence of a shared memory is the existence of a shared experience. In terms of methodology, this means taking into account in the identification phase the interactions between the performer and "typical" customers, through the analysis of the minimum web of the most frequent interactions in typical work situations.

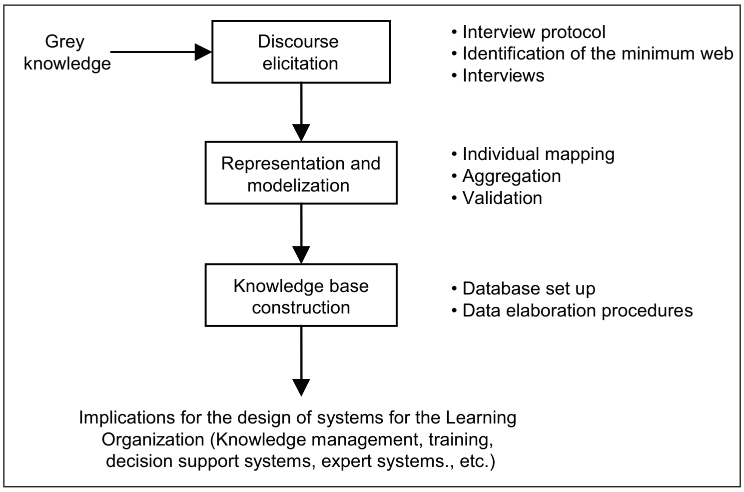
In the third place, given that language represents one of the fundamental mechanisms for the construction of shared memory, it represents for us, as well, the fundamental instrument of analysis through the lens of explanatory discourse. From the whole of these elements we obtain four methodological requisites, which will guide us in the procedure of elicitation and representation of discourses:

- Discourses should be identified from among a *sample* of individuals in the organization that is *as expressive as possible* with respect to the specific task or organizational process that is being investigated (the selection of suppliers, for example).
- Discourses are pertinent to the *ways in which the members of an organization explain* their own behavior and that of others (When is a choice successful? What are the criteria for a "good choice"?, What is meant by "good supplier"?, etc.).
- It is important to identify the explanations made by most of the interlocutors that are part of the *minimum web of interaction* for each of the organizational performer included in the sample in order to identify their shared experiences. In other words, the network of the internal customers should be identified (Who is involved in the selection process? With whom do they interact and why? Who are the typical interlocutors to deal with in the selection process? Who are the customers and the observers of the actions?).
- Discourses should be identified with the *strong involvement of members of the organization*, both in the identification and in the interpretation of the information.

Keeping these assumptions in mind, the methodology is articulated in three phases (Figure 2):

a. **Eliciting explanatory discourses:** Pertinent to the organizational task/process that is being analyzed. The objective is to induce the actors to tell about their significant experiences, asking them in particular to defend the choices made by themselves or others in the realization of specific actions and in pursuing particular objectives.

Figure 2. A methodological proposal for discourse analysis



According to the proposed methodological framework, the analysis of explanation is articulated in three main steps: Elicitation, representation and modeling, and knowledge base construction. The input of the process is the grey knowledge contained in discourse. Each step is in turn articulated in other minor steps. For each step we will provide suggestions about the methodological tools to be used.

b. **Representation and modeling explanatory discourse:** Through content analysis techniques and graphic representation of discourse that are typical of qualitative research.

c. **Construction of the knowledge base:** After validation, discourse models can be archived within a knowledge base that can serve as a starting point for the construction of *support systems for the management of a learning organization* such as, for example, support systems for decisions, knowledge management platforms, and expert systems. Other uses of such knowledge can have to do with training and in general the support for organizational change.

Eliciting Explanatory Discourse

Critical Aspects of the Elicitation of Discourses

In the cases in which the sources are made up of written discourse contained within company documents, the problem of the elicitation of discourse does not appear at all, and it is possible to ignore this phase and go directly to the phases of representation and modeling. Instead, in cases in which it is necessary to isolate discourses, it is possible to use one of the many instruments among those available in the field of qualitative research methodologies for analyzing the belief systems of the actors, both in written and oral forms.[1]

Setting aside the specific technique and the field of application, the objective in any case refers to the attempt to analyze and represent the rationality of the organizational actor, intended as a group of categories of judgment, values, motivations, frameworks, and mental models that guide choices and social behavior.

In the first place, choosing the elicitation depends on considerations of suitability and coherence between the theoretical framework and the methodological instrument used. The choice may also depend on many practical factors, such as the specific goal of the analysis, the characteristics of the organizational context in which the analysis is carried out together with the research approach, the operative constraints, and the costs involved. The management of the trade-off between the depth of analysis and the scale of the investigation is a critical factor in this type of research. Indeed, a common characteristic of the methods based on an interpretative approach is that of being extremely time-consuming and hard to standardize. Moreover, such an approach requires an intense level of involvement and interaction between the researchers and the context. This inevitably creates problems for the management of the research and requires a careful cost/benefit analysis, especially in cases in which the field research must be done on a large scale.

A compromise might be to precede large scale with a pretest phase on a smaller sample, and use the results to plan more structured and standard tools, such as questionnaires and interview protocols to be used on a large scale for the sake of efficiency.

Because grey knowledge is socially constructed, the unit of analysis is not an isolated individual but the *minimum web of organizational interlocutors* who, as observers or customers, are able to describe alternative points of view with respect to the task being analyzed.

Determining an appropriate elicitation protocol can be done by looking at the specific characteristics of the application context, without causing the methodology to lose itself in generalities. For example, for the purpose of application, it is indifferent which sources are used, as long as they involve explanatory discourse. Nevertheless, in general, it is necessary to determine a protocol that can be extended to the different cases of application.

Protocol and Interview Strategies for the Identification of Explanations

It is necessary to create an interview protocol[2] for the elicitation of discourses. The interviews should be done in small teams of two or three analysts to improve the accuracy of the identification and interpretation of the results in the next phase of analysis.

The team of interviewers must interview the entire network that makes up the minimum web of interactions for the performer and his customers (the individual in self-evaluation, direct supervisor, colleagues, clients, etc.).

The interview must be a highly detailed report on the activities actually carried out by the subject in the execution of specific, possibly repeated or typical tasks. The description of the activities will be reinforced and generally more precise if examples are included. It is appropriate to prepare forms containing a questions checklist of the actions to carry out in order to conduct the interview effectively (setting) and possibly, typical questions (framing questions). The form is to be considered a kind of draft that can be adopted in a process that is mostly informal and unstructured.

The general structure of the interview takes shape in the few questions through which the interviewer tries to induce the interviewee to explain the reasons for past choices s/he has made (self-evaluation) or others have made (hetero-evaluation), or the reasons behind a particular evaluation or judgment he has made during the interview. If we call *p* any evaluative proposition (a judgment made to forecast the future such as "*The current unfavorable economic trend will continue until the end of the year*."), very general examples of framing questions are "*Why do you say that p is true?*", "*What made you say that p?*", "*What induced you to sustain that p?*" "*Can you give me an example showing that p?*", "*What causes p?*", etc.

The interview continues dynamically according to the answers given by the interviewee. The task of the interviewer is to attempt to go as deep as possible into the motivations and the rationality behind the explanatory discourse until reaching a satisfactory level (see Box 1 for a practical example).

Eliciting Explanatory Discourse Through Interviews: A Practical Example

A first analysis of the interview presented Box 1 allows us to make some observations:

1. In the first place, the process of interviewing is clearly in the hands of the interviewer, who nevertheless limits himself to soliciting the interlocutor to provide convincing arguments for his/her own evaluations. In other words, to the question "Why r?", where r is any proposition contained in any subjective, unobvious evaluative judgment (*explanandum*) the interviewee can answer by producing possible reasons r1, r2 …rn, (*explanans*) to which the

Box 1. The elicitation of explanatory discourse through interviewing: A practical example

The following text is an excerpt from an interview conducted by one of the authors during a field study, in which an organizational actor was asked to evaluate his own work performance and to justify his evaluation. It is a concrete example of the use of the interview in eliciting explanatory discourse. The aim of the interview was to elicit the theories in use applied by members of an organization in the evaluation of individual competencies for personnel evaluation purpose (see the case study presented in Chapter IX).

Q: All things considered, if you had to express your opinion on how satisfied you are of your own performance, how would you judge yourself?

A: I am generally satisfied, conscious of having strengths and weaknesses that I am obviously trying to work on, and I believe that especially in the past year I have been able to improve.

Q: Can you explain what you mean by strengths and weaknesses? What do you base your evaluation of strengths and weaknesses on?

A: My strengths come from my long experience in the Personnel Office and so they refer to the consistent results I am able to obtain regarding certain circumstances at work. By now I have accumulated a historic memory of my past performances that have produced certain outcomes and confirmation from colleagues I work closely with and the ones I don't work with everyday, but fairly frequently, such as in the provincial offices, which have given me positive feedback regarding my efficiency at work […]

Q: About feedback, can you illustrate how internal and external contacts in the company have shown their approval? What types of things have they mentioned in particular? You can give me examples, if you would like.

A: Both from my current director and the ones I have worked with in the past, since I began doing my new job in the personnel office, because I entered as an administrative employee, and later when Personnel Development Unit was set up, I was immediately involved in it with the current director. Then from union representatives in the management of some situations in reference to single dependents, colleagues or groups of employees, because I was involved in the evaluation of the professional performance for the career advancement and on that occasion I received positive feedback from the union on how I dealt with colleagues.

Q: What aspects of your work do you think have been particularly appreciated, for example by the union representatives?

A: Well, certainly the objectivity that I don't think they expected from a representative of the personnel office, because, in practice, shall we say, we are on opposite sides. Objectivity and fast answers when my colleagues needed them. These are the two main factors: the importance that I gave to their requests and the care I gave in providing a response. So, even when the answer was no, they were appreciative in that they accepted the reasons for the refusal and didn't consider them as being specious, or a simple contradiction to their position, because the response was the result of careful, in-depth research done to determine the validity of the colleagues' observation in contrast with a first decision that was made by the administration.

Q: When you speak of careful research, what type of research do you mean? What informational channels do you usually use, for example?

A: I use very few channels of information, because we haven't computerized our personnel records yet, and so all of the information we have is on paper. I think I have a good technique for finding information, especially because I know where to find it and I use my experience and historical memory for this.

Q: How long have you had your current job?

A: Actually, I have done my current job for about five years, even though I have also held other positions in the same company. I think I can say that in some ways I have become a point of reference within the company, in that many colleagues contact me, even informally, to ask me for information or advice. One of my strengths is certainly my ability to provide the needed information quickly, that is based on my memory of past events, episodes, precedents, data retrieval and rules...In addition to the ability to find information, another strength is in my ability to get to the heart of the problem and provide a response.

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Box 1. continued

Q: It seems as if this ability comes above all from experience...or has it also been developed through specific training?

A: I think, in the first place, that it is a personal characteristic that has been developed in the field with experience supported only partially by training. Obviously, I tend to be quick but at the same time, analytical. I never stop at the first thing I see; I always check for the possibility of more confirmation. I always try to dig a little. Generally, the main complaint among colleagues in the local offices is that they feel cut off from the central office, when they call they are not satisfied because they get evasive responses. Instead, if they deal with me they are generally satisfied. So I have a sort of internal visibility that makes me happy, even though I have always experienced it not at the personal level but as visibility for the work we have done - that is what made me feel satisfied. Visibility that came from all the activities that we have been involved with in the past few years, of the sensibility that we are trying to instill in this company with respect to questions of development and professional growth, of competencies, and then perhaps cemented in the ability to provide effective answers to management and organizational problems that these changes have inevitably brought about. We have made the effort to contextualize and put into action, operationally so that there is an effective process of change in the company, discourses and projects that otherwise both the top management and lower level employees would think of as a marketing ploy.

Q: Looking back over our interview and returning to your strengths, other than the meticulousness, depth, precision and rapidity with which you do your research, being exhaustive when someone comes to you with a problem, correct me if I have misunderstood what you said, which other positive characteristics do you have, perhaps making reference, if you wish, to particular circumstances at work?

A: I could say that one of my personal characteristics, which is also a strength, is my intuition. That's what I call it, anyway, I don't know if there is a more appropriate term...

Q: Can you try to explain what you mean by intuition, in detail?

A: I would try to translate it like this. It often happens that new facts presented themselves that we have to deal with, for example, a new rule or problem with the management of contracts, etc.. Often they are problems that we did not notice in time, for example during the conception phase before starting a project. Intuition, for me, is anticipating these problems, understanding beforehand where they might lead. I am, perhaps with respect to my other colleagues, better able to anticipate unexpected consequences. This characteristic probably comes from a capacity for connecting several aspects of the life of the company, that in its turn is the result of more knowledge about the company's activities thanks to my previous experience, so that, when it is time to write a report, a document, a memorandum, I think I am better at evaluating what will be the positive or negative impact of what we are writing. My weak point is that I am not able to manage the other side of this ability. Which is a limit. As a matter of fact, I tend to radicalize my position because of an excess of confidence, and I don't accept that others are not able to see it or that I need to tolerate some inefficiencies that there may be for political motives or opportunities at a given moment. Sometimes my reaction is to become too rigid when something cannot be done the way it should be.

interviewer can respond with more questions like "Why r1?", "Can you give me an example in which r1?", etc. The *explanans* are in their turn evaluative judgments that, in the eyes of the interviewee, are acceptable reasons sustaining his own argument. Naturally, some of the *explanans* r1, r2 ...rn, can represent for the interviewer reasons that are not obvious, that must be justified by more detailed explanations. The level of depth is discretional, in the sense that the optimum level is the one that is sufficient for the interviewer to affirm that s/he *has understood* the reasons given by the interviewee.

2. Through the analysis of the relationships between explanandum/explanans it is possible to describe theories of action (theories-in-use, see Chapter III) identified through the interview both in the form of rules such as:

   If r1, r2 …rn then r
   If r11, r12 …rn1 then r1

   and in the form of "indemonstrable" propositions, or those that do not need to be demonstrated, which assume for the interviewee the value of "axioms," "laws," points of reference," "fundamental values," rules of thumb," etc.

   For example, from the excerpt of the interview in the box, it is possible to identify some rules:

   - The positive evaluation of own capabilities depends on the availability of objective feedback from other organizational actors.
   - The negative response to a request is accepted if it is the result of meticulous and documented research.
   - The ability to find useful information is the result of "historical memory," the ability to analyze, and speed in providing accurate answers.

   Naturally, these rules reflect personal opinions and convictions, so they are not necessarily shared, normatively correct or generalizable.
3. Interviewees find it very natural to make reference to specific and concrete "work situations" and to organizational artifacts and values in order to argue in favor of their judgment, possibly giving examples relative to past events often in the form of anecdotes and stories; it is the job of the interviewer to explore this type of construct and analyze it in depth both during the interview, and later in the mapping of the content (see Chapter XI).
4. Behavior and events should be described with respect to concrete situations and the activities that an individual carries out in these situations in order to satisfy the expectations of someone, who assumes the role of customer and behaves as an organizational observer. The number of customers and observers may require the elicitation of all the explanatory discourse made by all of the individuals involved in the same object of investigation. The analysis of discourses developed by the individuals that are part of the same microweb of organizational relationships allows us to identify the presence of constructs and shared interpretative categories, as well as the possible cognitive discrepancies and categories between the actors. These webs also often contain references to resources which are accessible to members of the web and organizational artifacts that mediate the relationships between the members.

5. The style of the interviewee is almost always retrospective; behavior and events are interpreted again as the result of experience rather than described in objective terms and remote from the context and from the circumstances in which they took place; often the interviewee dwells upon critical episodes in her own working life. The observer must examine these "critical incidents" closely (Flanagan, 1954; McClelland, 1971), noting behaviors and theories of action carried out in those circumstances.

Conclusion

These considerations, together with the example reported in Box 1, offer some practical suggestions to the reader for the identification of explanatory discourse through interviews. After the interview, the available output is given by the meticulous transcription of the interview itself and by the collection of notes and observations in the field.

There is a wealth of informational material, but it is still rough and unformed. In the next chapter we will describe some techniques for the systematic analysis and mapping of the content of the interview. By 'mapping the interview' we mean following a procedure for representing the synthesis of the content, in a graphic representation (maps), through which it is possible to highlight the most relevant concepts and the relationships between them contained in the interview.

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Endnotes

1 Among possible techniques that can be used to elicit individual belief systems there are *content analysis* techniques (Erdner & Dunn, 1990), the *repertory grid technique* (Kelly, 1955), interview techniques such as the *Self Q* (Bougon, 1983), *Focus Group*, the *Critical Incident Iinterview* (Flanagan, 1954), the *Behavioral Event Interview* (McClelland, 1978), narrative methods and *Semiotic Analysis* (Eco, 1979). Such techniques, originally developed in sociological and psychological research, have been largely applied in organizational and management studies (Coffey & Atkinson, 1996; Huff, 1990; Wright et al., 2000). A comprehensive book on qualitative research methods is the one edited by Lincoln and Denzin (2005).

2 Here we will provide a set of coherent methodological indications for the methodology presented in this volume. For the more operational aspects and more in-depth methodological studies the reader can refer to one of the many available manuals available for conducting qualitative research in companies (Denzin & Lincoln, 2005).

Chapter XI

Mapping Discourses

La tua loquela ti fa manifesto.[1]

(Dante, Inferno, X, 25)

Abstract

This chapter deals with the issue of discourse representation. A possible way to represent discourse is by mapping its contents (concepts) and its structure (i.e., showing the relationships between concepts). In particular, we give a detailed presentation of the argument analysis technique, a mapping approach developed to elicit and represent argumentative discourse. Later in the chapter we also provide some references to a wider set of techniques that can be used to build cognitive maps, which is a way of represent the belief systems of an individual through which he/she interprets a specific problem or situation.

Analyzing and Modeling Explanatory Discourse

The objective of representing discourses collected through interviews is to arrive at a semi-formal representation of their contents and structure. These maps allow us to underline the essential elements of discourse and to represent the system of shared beliefs and meanings contained in discourses. (Eden & Ackerman, 1992; Huff, 1990; Weick, 1979). The structured nature of explanatory discourse facilitates both the process of analyzing the content of discourse and representing it.

The representation of explanatory discourses is accomplished in three phases: *mapping, aggregation and validation* (Coffey & Atkinson, 1996; Huberman & Miles, 1994).

The operation of mapping usually consists in the construction of a graphic representation of discourse. According to the approach described in Chapter X, Figure 2, the mapping step is usually preceded by an analysis of the contents of the discourse, in which recurrent terms, key expressions, and significant declarations are highlighted. To point out the internal structure of explanations a technique called *argument analysis is proposed* (Fletcher & Huff, 1990; Toulmin, 1957; Toulmin et al., 1979).

Explanatory discourse is intrinsically structured. It consists of a set of interrelated arguments, statements and facts provided by a speaker to persuade others about the validity of a nonobvious claim (see Chapter VIII). Many approaches have been proposed to describe the characteristics of such a structure, beginning with the rhetorical and ending with the applications found in organizational and managerial literature (Fletcher & Huff, 1990; Mason & Mitroff, 1983; Sillince, 2001).

Among the various approaches, *argument analysis* seems particularly appropriate because of its congruence with the theoretical assumptions of the methodological approach proposed in this book and for practical reasons tied to the relative ease of application. According to Toulmin (1959), Toulmin, Rieke, and Janik (1979), an argumentation is a sequence of interconnected affirmations (*claim*) that establish the content and the strength of the position of the orator. As a consequence, explanatory discourse can be broken down into a series of claims. The claims can be *designative* (they establish the existence of an event), *definitory* (they define the characteristics of an event), *evaluative* (they assign value to a given event), or *invocative* (they invoke the execution of an action). Claims can be classified into the following categories, with respect to the functions that they have in the discourse:

1. The *key claim*, or conclusion of an argumentation.
2. *Common claims* corresponding to facts, common sense, and the opinions of influential people.

3. The *grounds*, meaning the facts offered to support a claim. In argument analysis, the ground maybe: (a) shared and personal opinions offered as facts; (b) objective data.
4. *Warrants*, meaning the rules that demonstrate how the *grounds* support the *claims*; they can be *substantive* (justified through logic), *authoritative* (justified through authority), and *motivational* (justified through values).
5. *Qualifiers*, expressions or terms that limit the validity of the claims, such as "usually," "rarely," "according to what we know," etc.

In addition to these fundamental components, we need to consider the *subclaims*, that is the set of claims through which the interviewee articulates analytically a key claim and two basic rhetorical mechanisms: *reiteration*, and *elaboration*. Reiteration is the technique through which the interviewee reproposes a claim (or warrant or grounds), for example, at the beginning and at the end through a summary. Elaboration is a kind of parentheses of the discourse in which the interviewee dwells upon the illustration of a claim through examples, often in the attempt to circumstantiate and limit the field of reasoning, rather than as a communicative expedient.

The logic underlying argumentative reasoning is abductive (see Box 1 in Chapter II). It can explain an outcome, support a decision, and sustain an evaluation. It begins with the conclusion and goes back along a kind of logical chain until it finds plausible causes, like a tree develops from the top to its roots. When the tree of explanation is complete, then it is reversed. Through this reversion, the speaker can present his argument as if it were a logical argument by using the classic model of logical deduction (*modus ponens*): given the condition A, and given the rule *if A then B*, then B.

For example this is the technique that the famous character in Sir Conan Doyle's novels, the detective Sherlock Holmes, uses to solve his puzzling cases. But what Holmes defines as a chain of deduction[2] is actually a mix of deductive and abductive reasoning. The main difference between these two kinds of reasoning is that in deductive reasoning the consequence *B* necessarily comes from the rule *if A then B* and the acceptance of the assumption *A*; while in abduction, given *B*, for example from the observation of available evidence, Holmes finds a possible explanation in the form of a rule: *If A then B,* and concludes that it must (or at least could) be *A*. So there is no necessity in abductive argumentation but only knowledge in the form of wit or commonsense, and an explanation can rich of observations and objective facts but also of assumptions that are taken for granted, implicit or instrumental, which would have no place in the kingdom of traditional logic.

Apart from this clarification about the starting assumptions, the argumentative reasoning can develop similarly to a deductive reasoning. The mechanism that links claims, warrants and grounds is demonstrated in the following example (Fletcher & Huff, 1990):

GROUND	(GIVEN THAT) *The barometric pressure has decreased and the wind has begun to blow in the past hour.*
WARRANT	(AND BECAUSE) *Usually, decreasing barometric pressure and an increasing intensity of wind can signal the arrival of a low pressure system that will bring rain.*
CLAIM	(I AFFIRM THAT) *It will probably rain.*

In the example above, qualifiers such as *usually* and *probably* are immediately identifiable. Moreover, there is no difference between the ground and claim from the syntactical point of view. Both are assertions, but the claim is by nature potentially more controversial than the ground, which instead is offered by those who explain it as an acceptable fact supporting a Claim. Warrants, in the end, link the grounds and the claim through a quasi-logic reasoning.

The example cited above, as simple and uncomplicated as it seems, in which it is otherwise possible to take objective measure of the variables in question, underlines that in cases like this, language can be deeply ambiguous and inaccurate. How much does the pressure have to decrease? How hard does the wind have to blow? How much do the qualifiers such as *usually* and *probably* weaken the conclusion? How willing are we to bet that it will rain if we only have the information contained in the example?

Mapping Explanatory Discourse

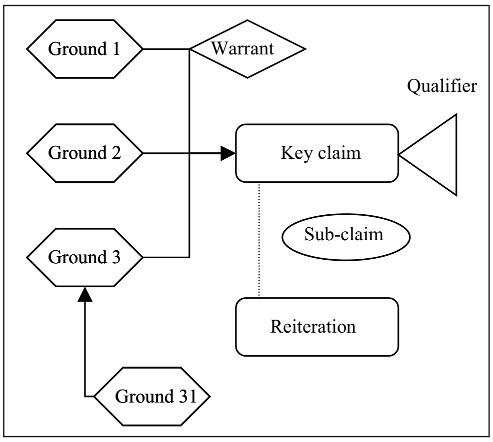
A map is a graphic representation of concepts revealing the contents of discourse and their reciprocal relationships. The objective of mapping is to represent the relationships between the concepts through graphics and some formal rules.[3]

The characteristic of explanatory discourse of having a "rational" structure with the aim of persuading the interlocutor and the possibility, through argument analysis, of separating discourse into constitutive elements, greatly facilitates the identification of a graphic representation of the structure of discourse in which the principle components of the argumentation and their reciprocal relationships are easily recognizable (Figure 1).

It is clear that mapping loses some of the wealth of meaning through the reduction of ambiguity contained in discourse. For this reason, the operation of mapping should be done with the utmost care and the knowledge that "*the map is not the territory*."

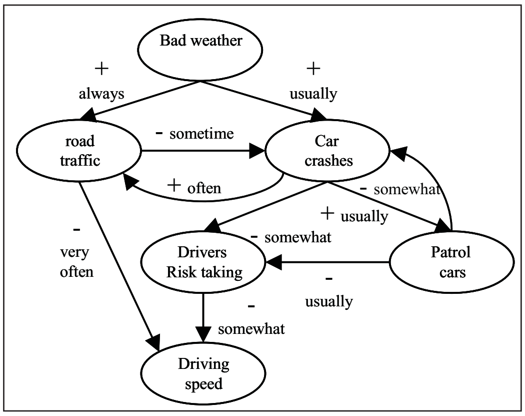
Box 1 and Figure 3 describe the application of argument analysis to the example interview reported in Chapter X.

Figure 1. Example of a graphic representation of explanatory discourse



Argument analysis allows us to classify the speech acts contained in an explanation analytically according to their function in the context of the discourse. The graphic representation shown here is the visual representation of the structure of the discourse.

Figure 2. An example of a causal map (Adapted from Kosko, 1992)



This figure contains an example of a cognitive (causal) map representing the theory of action of the driver of a car in bad driving conditions. Maps are a set of nodes (concepts) and arcs (relationships). In causal maps, the sign "+" and "-" between nodes i and j Mean, resprectively, positive and negative causal links betweens the connected concepts.

Box 1. Analysis of content and mapping

In Figure 4 an example is shown of the mapping process relative to the interview reported in Chapter X in which the interviewee is asked to evaluate his own work performance and his own level of professional development.

Step 1: Analyzing the content, compiling the dictionary of concepts, codifying the relationships between concepts.

The transcription of the interview reported in Chapter X was analyzed through the technique of argument analysis. The objective is to identify and isolate the various components of explanatory discourse, and to assemble them so that they reproduce the structure of an argument. To facilitate the analysis it is helpful to have a coding sheet available, like the one in Figure 3, which shows a subset of the elements the have come out of the interview.

With reference to the codes used in Figure 3, CG stands for Ground Claim, meaning a claim used as a ground by an interviewee, for which the interviewer usually asks further justification. The simple ground is instead a fact that supports a claim in a way that is obvious to both the interlocutors. Warrants are also not reported when they are obvious. For each ground it is necessary to show the line of text in which it appears, the type (evaluative, designative, etc.) and a progressive code for identification. (n°).

The self-evaluation shown in the text of the tree in Figure 3 ("I am fairly satisfied..") is explained on the base of two subclaims (SC1: knowledge of his own strengths, and SC2; knowledge of his own weaknesses). The evaluation relative to his strengths is justified on the basis of a series of further affirmations, classifiable as ground-claims (GC), such as: "By now I have accumulated a historic memory of my past performances […]", "that have produced certain outcomes and confirmation from colleagues I work closely with and the ones I don't work with everyday, but fairly frequently, such as in the provincial offices, who have given me positive feedback regarding my efficiency at work", etc.

Step 2: Plotting the Map. The objective of mapping is to represent the structure of the argumentation through a graphic description. In this example, the form of representation used is that of a tree; the interviews are conducted so that the discourse assumes an almost hierarchical structure. Nevertheless, it is not a pure hierarchy because of the presence of horizontal relationships between the variables such as feedback, interactions and returns of various types. Therefore, we will speak in general of the tree of explanations even though it will actually be an oriented graph. In Figure 4 a map relative to the interview extract in Chapter X is shown.

The results of the discourse analysis should be used appropriately in the mapping phase. Indeed, the literature on qualitative research methodologies recognizes that the two typologies of techniques (content analysis and mapping) must be used in a substantially complementary way in order to avoid a situation in which the operation of synthesis that is obtained through mapping becomes excessively reductive. The phases illustrated in Chapter X Figure 2 should be implemented regardless of the specific technique of analysis of the content and mapping used. As the example also demonstrates, in the cases in which argument analysis is used, it is necessary to take into account the following ulterior indications:

In the text analysis phase, the results of the argument analysis must be taken into account through the identification not only of the relationships and concepts, but also the role of the concept in the discourse, specifying, for example, if a given affirmation is a claim (that is, a relationship that will be "demonstrated"), a ground (that

Figure 3. Example of a coding sheet

Coder: Luca Iandoli		Coding date:					
Interviewee: Mr XXX		Interviewee position: XYZ					
Line	*n°*	*Grounds*	*Type*	*Line*		*Key claim*	*Type*
11	**CG1**	By now I have accumulated a historic memory of my past performances that have produced certain outcomes […]	Ev	3	**KC1**	I am generally satisfied	Ev
10	**CG2**	and confirmation from colleagues I work closely with and the ones I don't work with everyday, but fairly frequently	Ev	*Subclaim (SC) – elaboration (EL) – reiteration (RE)*			
9	**CG3**	long experience in the Personnel office	Ev	3 3	**SC1** **SC2**	conscious of having strengths and weaknesses	
Warrants				**Qualifiers**			
12	**W1**	*If* feedback *then* outcomes and visibility					

continued on following page

Box 1. continued

is, a "demonstrated or demonstrable affirmation or one that will be demonstrated as promised"), or a warrant (that is, a rule of acceptable inference), as shown in Figure 3. Moreover, in argumentative discourses the rules can be made only partially explicit, in particular this is often true for the premises. It is necessary, finally, to try and point out the use of possible artificial rhetoric with which the interviewee has used to particularly underline certain aspects or to define the environment and the validity of his reasoning (elaborations, reiterations).

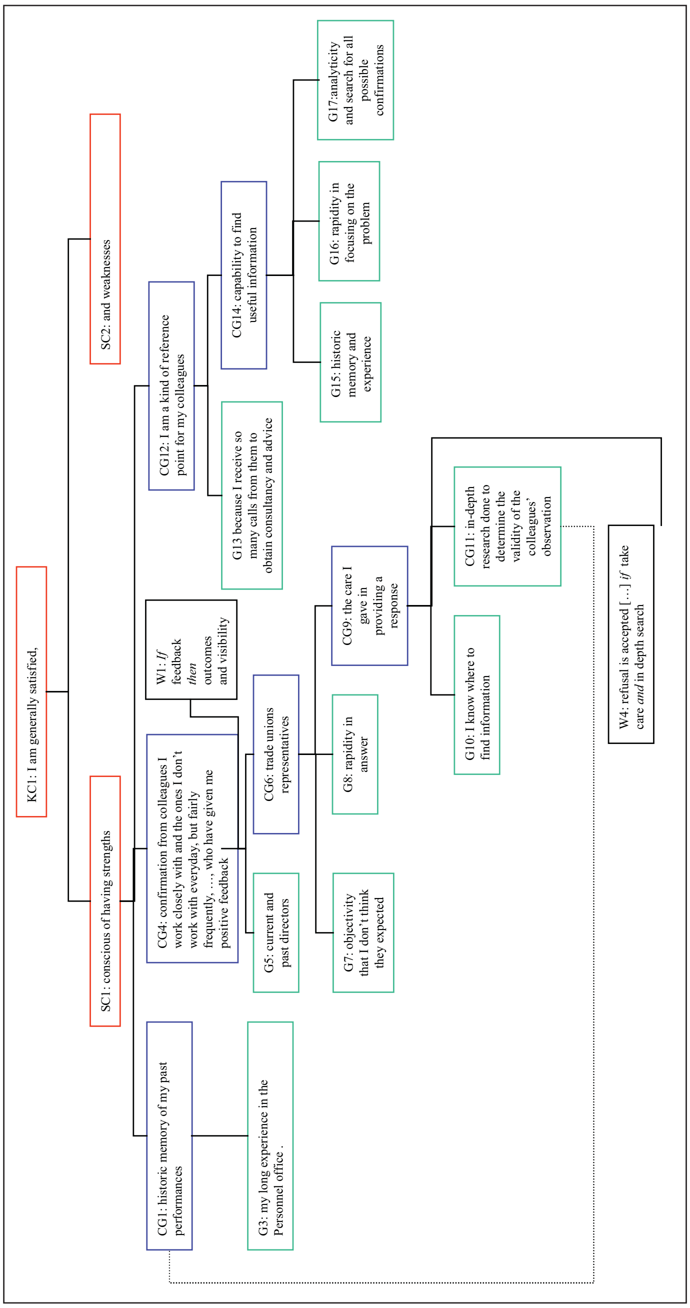
In the phase in which relationships are codified, it is important to avoid limiting the process to the identification of cause and effect relationships, and to find information on the intensity and the limitations expressed by the interviewee regarding these relationships, such as "A has a positive influence on B", A makes it possible for B to happen", A facilitates B", etc. Moreover, it is also important to point out relationships that are of a different nature to cause/effect, such as "A is (is not) the equivalent of B", "A is (is not) an example of/belongs to/ a member of B", etc. For each type of relationship, it is important to show the relationships in the table that are possible qualifiers that limit the validity of the relationships, such as "often", "a fair amount", "always", "in most cases", etc.

Maps that are made to represent a system of beliefs of an individual are known as cognitive maps and there are various methodologies and approaches for information gathering and map construction. In Figure 2 an example of a causal cognitive map is shown. Causal maps are represented through graphs made up of nodes (concepts) and arcs (causal relationships). An arc is a bridge between two concepts, A and B in the direction of A toward B occurrence.

Further and more detailed examples of cognitive and causal maps will be provided in Chapters XIV and XV. Regardless of the specific technique used in the graphic representation, the methodology for the graphic representation of a discourse through mapping is articulated in six phases:

a. **Analysis of the content:** It is necessary to reread the transcription of the interview carefully in order to identify the most relevant passages, the salient concepts present in the discourse, marking them directly on the original document (*documentary coding method*, Wrightson, 1976);
b. **Composition of a "dictionary" of concepts:** A list of relevant concepts must be written as well as the meaning ascribed to them by the interviewee, assigning a code to each concept and trying to eliminate possible redundancies. In this phase, it is important to note the shades of meaning that are behind the labels used by the interviewee that will be used as names of concepts, paying particular attention to the frequency with which the most important terms are used in the text.
c. **Codification of the relationships between the concepts:** In this step a list of the relationships between the concepts is created. The list should report the kind of relationship and the position in the text.[4]
d. **Composition of the map:** Finally, the list of relationships and concepts is assembled into visual map.

Figure 4. An example of mapping of explanatory discourse through argument analysis approach



e. **Aggregation:** Given a collection of individual maps, it is possible, if needed, to obtain a group map by merging the single maps. An alternative option is to building the collective map directly, together with the group members in ad hoc meeting.

f. **Validation:** Validating the map consists of reaching a satisfactory level of reliability in the output of the interview data, considering that it will grow with the level of interpretative convergence between the analysts and the interviewee. The analysts must reach an adequate level of agreement in the interpretation of data and the information contained in the discourses. This agreement must include both the concepts (their identification and meaning) and the relationships between them. It is highly important that the interviewee confirm the results, by "recognizing himself in the map." We will analyze the validity issue in depth in Chapter XVI.

Conclusion: Toward Modeling Discourses

The representation of discourses is an attempt to capture and to structure the grey knowledge contained in explanation. This allows us to investigate and identify shared belief systems, mental models used by organizational members that influence choices and behavior, and possible changes that such cognitive systems undergo in the processes of organizational learning.

The proposed methodology constitutes just a first step toward a modeling of discourses, meaning the construction of formal systems that allow for the true elaboration of discourses through logical-mathematic models. This attempt, still at he embryonic stage, aims at the simulation of decisional models contained in discourses through appropriate algorithms. Which techniques can help us to reach our objectives? What use can be derived for the organization from the availability of "verbal machines" that implement formal models of discourse?"

The next two chapters will be dedicated to exploring some possible answers. These are complementary to the present chapter. They are meant to supply another methodological instrument for organizational analysts who intend to make an in-depth study of discourse modeling.

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Endnotes

1 Thy mode of speaking makes thee manifest.

2 See the second chapter, "The science of deduction," in "A study in scarlet," the first Sherlock Holmes novel published in 1887.

3 Mapping the concepts and rules expressed in natural language through formal systems of representation has been widely used in some artificial intelligence applications, in particular in the development of expert (computer) systems that, by reproducing the reasoning of a human expert, are used to support the analysis and diagnosis of complex problems, the diagnosis and more generally support for decisions. The development of techniques for identifying and mapping the knowledge of experts is the objective of the so-called "knowledge engineering." In this field, the "reliability" of the representation has a strong

impact on the reliability and on the performance of the system. The approach to mapping proposed in this book, though methodologically similar to that of knowledge engineering, differs in that the aims are above all descriptive. The objective of the map is not, at least for now, to support diagnoses and decisions, but to identify the constructs of organizational memory in order to describe action theories in use, tacit constructs, and promote more awareness and wider knowledge of the organization in organizational actors.

4 A taxonomy of the typologies of relationships is effectively described in Huff (1990).

Chapter XII

Modeling Discourses

Marcel Benabou (Un aphorisme peut en cacher un autre, Bibliotèque Oulipienne, n.13, 1980) has designed a machine to create aphorismes. It is made up by two parts: A grammar and a lexicon. The grammar is formed by a certain number of general rules that are used by most of the aphorisms; such as: A is the shortest way from B to C, A is another way of doing B, the little A's make the important B's, A would not be A if there were not B, Happiness is in A and not in B, A is a sickness that can be treated with B, etc. The lexicon contains couples (or tuples) of words that can be false synonyms (love/friendness, word/language), antonyms (life/death, form/content, memory/oblivion), words with similar spelling, words used often together (crime/punishment, sickle/hammer, science/life), etc. The injection of the lexicon into the grammar produces ad libitum a series almost infinite of aphorisms, all sense makers, some more than others. A computer program created by Paul Braffort is able to produce on demand several dozens in a few seconds: Memory is a sickness that can be treated with oblivion; memory would not be memory if it were not oblivion […].

(Georges Perec, Penser/Classer)

Abstract

In this chapter we introduce the concept of verbal model. A verbal model is a mathematical modeling of the variables contained in a discourse and of the relationships among them. A discourse may contain linguistic variables, i.e., variables assuming linguistic values. For instance the variable "performance" can assume values such as poor, satisfying, above average, excellent, etc. Verbal models can accept linguistic inputs as well as quantitative variables and can be implemented starting from the discourse map through fuzzy logic algorithms. Such algorithms can simulate to a certain degree the theories of action contained in explanations. This chapter presents an introduction to fuzzy logic and to some possible ways of constructing verbal models, while we provide several examples in Chapters XIII and XIV.

Systems for Learning Organizations: Rhetoric Machines

A logical machine can be thought of as of a device able to produce conclusions given some input by carrying out a process of logical reasoning. Personal computers are examples of logical machines. A logical machine can be very efficient and it produces objective and often unquestionable results. Let us consider a different kind of reasoning machine, a machine that is capable of producing (sometimes involuntarily) new meanings like the one described by Perec at the beginning of this chapter.

The *experiment* cited by Perec shows how it is possible to create meaning involuntarily through very simple, formal algorithms. Naturally, the meaning does not lie in the algorithm, but in those who interpret the aphorisms that are generated automatically. Benabou's machine is an example of an open artifact. An important part of the memory of a learning organization should be made up of the artifacts with the capacity to generate scenarios that have multiple or unexpected meanings.

As outlined in Chapter IV, one of the most common ways for an organization to guarantee the continuity of action is to transform itself into a machine through the adoption of closed artifacts that imply impersonal and prescriptive theories of action. This way, the organization can be compared to a software program, made up of libraries and programs, functions, databases, protocols, mass memory, and events of synchronization. The technical apparatus of persistence of an organization machine, consisting of procedures, bureaucracy, planning, and control systems, has many defects, which are often highlighted by organizational literature and recalled in this text (an excess of optimism, inertia to change, reductionism, etc.) but it has one positive aspect. For better or worse, it never stops working until someone, or something stops the engine. This is enough to keep managers occupied and placate their anxiety (and, rest assured, that is no small thing).

However, as we have discussed in Chapter V, a closed memory can prevent the organization from learning by revising its memory.

What systems should replace the procedures and closed artifacts of the organization machine? The problem for the learning organization is not to do without the artifacts in the name of a destructuralization of organizational processes. The problem is how to obtain open artifacts that support and structure action but at the same time are able to tolerate and solicit various interpretations, creativity, and a multiplicity of uses.

One possible suggestion is to build verbal models, through which it is possible to elaborate the information contained in the discourse, in order to simulate the theories of action described in the discourse itself.

Verbal models are an example of *rhetoric machines*. While the logic machines such as calculators, automatons, or more generally, algorithms (see Box 1), aim at resolving, through logic or computation, specific problems efficiently and quickly, rhetoric machines simulate the possible effects of theories of action contained in discourses, preserving the adaptability and the imprecision of verbal expressions.

Rhetoric machines, however, are still formal systems. The challenge is to build such formal systems overcoming the rigidity of algorithms and traditional machines. To do so we must use a new kind of logic.

Box 1. A very brief history of logic machines

The creation of "thinking" machines, those capable of imitating man and possibly replacing him in carrying out complex tasks that require the ability to reason, has been the goal of scientists and scholars over the centuries, not to mention the literary inventions of the same type: Praga's Golem, Asimov's robots, the humanoids of Blade Runner, by Philip Dick, and Kubrick's HAL, the super-computer in 2001: A Space Odyssey.

Aristotelian logic comes from an attempt to describe human reasoning in a formal way. The first attempts to assign a computational base to human thought were brought forward by Descartes and then by Leibniz. However, it was not until the 19th century that the first calculating machines began to be widely used. These machines included the mechanical calculator invented in England by the Babbages, who attempted, among other things, to commercialize it, without success. Mechanical calculators finally gained commercial success between the end of 19th and the first half of the twentieth century. Among the most surprising models was the Curta (http://www.vcalc.net/cu.htm), a formidable example of a pocket-sized mechanical calculator (Figure 1).

Mechanical calculators have two major limits: The first is that they are complex machines that are cumbersome and very expensive to make, since they are made up of complicated metallic parts; the second is that the functioning logic of these machines is incorporated into their physical structure. In other words, mechanical calculators are invented and built in order to carry out a few operations and they are only slightly reconfigurable or, as we would say today, programmable.

There are two fundamental innovations underlying all of the current "thinking" machines: a mathematical logic (Boolean logic) and a new technology (electronic circuits). Boolean logic uses mathematical formalism to describe logical operations of propositional logic through mathematical logical functions that assume true

continued on following page

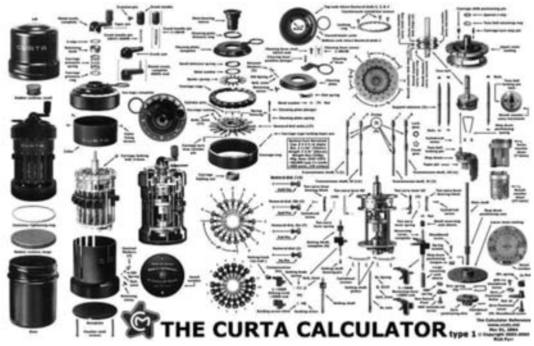
Box 1. continued

or false values (0 and 1 in the binary system). The Turing machine (1950), made up of a memory-tape and a reading and writing system of binary data that allows for the implementation of formal algorithms and contains the logical framework upon which all computers are now based.

Fundamentally, it was Claude Shannon, as a PhD student at MIT in Boston in the 1930s, who understood intuitively that an electronic circuit could be used to physically carry out the logical operations that are typical of all the existing machines that process digital information.

As outlined in Chapter I, Shannon's circuits and the Cybernetics revolutionized the concept of machine and gave birth to the era of the intelligent devices.

Figure 1. Assembly of the Curta, a pocket-sized mechanical calculator . http://www.vcalc.net/cu.htm



From Discourses to Rhetoric Machines

The techniques identified in Chapters X and XI allow us to describe the contents and the structure of an explanation as a static picture. The goal of the verbal model is to provide a dynamic model of a discourse in order to derive the consequences contained within it. Our point of view is that of simulation, which produce scenarios as result of the theory of action described by the verbal model. Our questions are: What are the consequences of our verbal model? What are the effects?

Usually, the operation of formalizing an explanatory discourse is a *reduction,* in which the ambiguity of the natural language is sacrificed in favor of the consistency of internal logic. Even the example presented in this chapter is a simplified representation of the complexity of discourse. Nevertheless, verbal models try to keep the loss of information due to formalization to a minimum. Verbal models reproduce the structure of the argumentation by turning to a set of mathematical techniques that allow us to model the ambiguity of linguistic expressions (Bonissone, 1980; Chen & Hwang, 1991; Herrera et al., 2000; Saaty, 1979; Wenstøp, 1975a, b; Zadeh, 1973).[1]

There are three assumptions underlying this approach:

a. The first, theoretical in nature, according to which preserving the ambiguity of discourses contributes to the growth of flexibility and the degree of openness of organizational systems.
b. The second, methodological in nature, according to which the verbal knowledge, though ambiguous, may contain useful information that should not be considered as noise.
c. The third, applicative in nature, according to which, in all the cases where it is necessary to evaluate qualitative variables, nor is there any effective or low-cost proxy, it is appropriate to elaborate directly linguistic information.

Now is the time to define what we mean by *linguistic information*. Chen and Hwang (1992) suggest that we consider *linguistic* when dealing with the information characterized by at least one of the following attributes:

a. **Unquantifiable information:** Intrinsically qualitative variable for which there are no reliable proxies or it is costly/arbitrary to identify them (e.g., the comfort of a vehicle is usually expressed in linguistic terms such as good, fair, poor, etc. They are qualitative data).
b. **Incomplete information:** The information is approximate and the precision of the instrument is unknown (e.g., that car was going "a*bout 50 miles per hour*").
c. **Unobtainable information:** An evaluation is possible but data are not available, so it is necessary to make estimates indirectly and qualitatively (e.g., an individual's bank account or age, if it is not to be revealed; in these cases one can estimate wealth or age by evaluating lifestyle choices or appearance).
d. **Partial ignorance:** Imprecision can be derived from an awareness of an intrinsic ignorance of the phenomenon being described, due to the impossibility of gathering the necessary information (e.g., "*It is plausible that the stock market will not rise significantly in a short time.*").

It is not difficult to recognize the presence of such characteristics in the information that organizational actors face every day when taking action and making decisions.

Codifying the Uncertainty and the Ambiguity of Verbal Language Through Fuzzy Logic

The theory of fuzzy sets[2] (Zadeh, 1965) allows us to represent the ambiguity contained in linguistic information. The original paper on fuzzy logic encountered skepticism and occasional hostility. Forty years later many international journals have been published which include the word "fuzzy" in their title and thousands of patents have been applied. By 1973, Zadeh had stated the principle of incompatibility on which the fuzzy approach is based: "*As the complexity of a system increases, our ability to make precise and significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics. It is in this sense that precise quantitative analyses of the behavior of humanistic systems are not likely to have much relevance to the real world societal, political, economic, and other types of problems which involve humans either as individuals or in groups*" [Zadeh, 1973].

The most important concept of the fuzzy sets theory is the partial belonging in a set, whose power is clearly illustrated by the following example: Say you park your car in a parking lot with 100 painted parking spaces. The probability approach assumes you park in one parking space and each space has some probability that you will park in it. All these parking space probabilities add up to 100%. If the parking lot is full, there is zero probability that you will park in it. If there is only one empty parking space, say the thirty-fourth space, you will park there with 100% probability. If the parking lot is empty, and if we know nothing else about the parking lot, you have the same slim chance, 1%, of parking in any one of the parking spaces.

The probability approach assumes parking in a space is a neat and bivalent affair. You park in the space or not, all or none, in or out. A walk through a real parking lot shows otherwise. Cars crowd into narrow spaces and at angles. One car hogs a space and a half and sets a precedent for the cars that follow. To apply the probability model we have to round off and say one car per space.

Up close things are fuzzy. Borders are inexact and things coexist with nonthings. You may park your car 90% in the 34th space and 10% in the space to the right of it, the 35th space. Then the statement "*I parked in the 34th parking space*" is not all true and the statement "*I did not park in the 34th parking space*" is not all false. To a large degree you parked in the 34th space and to a lesser degree you did not. To some degree you parked in all the spaces. But, most of those were zero degrees. This claim is fuzzy and yet more accurate. It better approximates the "fact" that "*you parked in the 34th parking space*" [Kosko, 1993, pp. 12-13].

The partial belonging in a fuzzy set is represented in mathematical terms by the *membership function*. The following is the mathematical definition of a fuzzy set:

Given a universe of the discourse U, a fuzzy set A in U is defined by a membership function that assigns to each element u in U a value between 0 and 1. When a value 0 is assigned to u then u does not belong with the set A. When it assumes the value 1 then it completely belongs to set A. When it has an intermediate value between 0 and 1 then the element will partially belong to A.

Many phenomena can be effectively represented through the membership function. Practically all phenomena where there is a variable graduality and intensity. Moreover, dynamic phenomena can be grouped, with values that change over time. Finally, ambiguous phenomena, which can belong to two or more interpretative categories.

For instance, *U* is the universe of discourse of admissible values of height for an adult person (e.g., [140 cm, 200 cm]) and *A* is the set of "tall people" that naturally constitutes a sub-set of *U*.

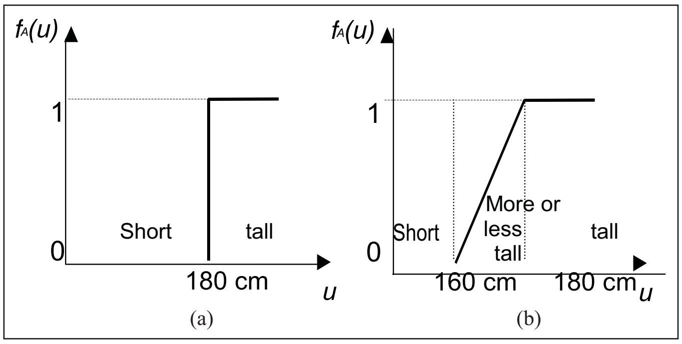
The set, "tall people" does not have well-defined borders; it is a fuzzy set, with a gradual passage between belonging and not belonging to the set. A dividing line at 180 cm that separates tall people from people who are not tall is unnatural. There is no justification for the exclusion of people with a height of 179 cm from the set of tall people. The membership function reproduced in Figure 2(a) is therefore far from common sense and not ideal for reproducing verbal judgments.

However, we could also think of it in a different way. We can distinguish between individuals that certainly belong to the set of tall people A (for example people taller than 180 cm), individuals that do not belong at all (for example people shorter than 160 cm and individuals that only partly belong (all individuals with a height between 160 ad 180 cm). This produces the membership function in Figure 2(b) that foresees a diagonal line that allows us to represent the concept of "more or less tall." Moreover, the degree of membership of the individual *u* in the set *A* can be interpreted as the degree of truth of the proposition "The individual *u* is tall.*"*

For example, for u = 130 cm the degree of membership of u in A is zero. This implies that truth of the proposition "the individual u is tall" is zero. That is, the proposition is false. For u = 190 cm the membership degree of u in A is one. Then the truth of the proposition "the individual u is tall" is one, meaning the proposition is true. The most interesting case is with u = 170 cm. In this case the membership of u in A is 0.5. Thus, the truth-value of the proposition "the individual u is tall" is 0.5. We can interpret this result as *'*u is *neither* tall *nor* short.

Thanks to the possibility of applying fuzzy theory to already existing models and methodologies, fuzzy logic has provided significant innovative contributions in the field of automatic controls, advanced calculus, artificial intelligence and support for decisions.[3] The enormous potential offered by fuzzy logic can be found in the fascinating possibility to use the rigor of logic and mathematics in modeling

Figure 2. An example of membership functions for a fuzzy set and a canonical set



In the case of the canonic set, illustrated in the figure on the left, it is easy to distinguish objects that belong to the set from those that do not, through the introduction of an arbitrary limit (1,8 m). In the fuzzy case, it is impossible to draw a net line between the set and the external context. One possible way to consider this characteristic is to associate to different elements different intensities of membership in the fuzzy set. The people of medium height belong and do not belong to the set of tall people; the passage from being tall to not being tall is smooth.

linguistic expressions and forms of approximate reasoning. To represent, therefore, knowledge in many areas in which the complexity of phenomena allows above all for the imprecise linguistic descriptions, in particular for those systems that Zadeh (1973) defines as *humanistic systems*, setting them against inanimate of the natural sciences and engineering (*mechanistic systems*).

Zadeh states that the two main motivations that cause researcher to turn to this type of computational techniques are:

In the first place, computing with words can be a necessity when available information is too imprecise to justify the use of numbers, and, second, when a certain level of imprecision can be tolerated and exploited to achieve computational efficiency, robustness, low cost solutions, and a better correspondence with reality. (Zadeh, 1996, p. 105)

Zadeh's intuition comes out of the fact that individuals, when effectively completing even very complex tasks seem to tolerate acceptable levels of imprecision, thanks to their ability to describe a task in an approximate way, that is *linguistically*. In other words, in the execution of a task, individuals do not rely upon precise analytical models, like mathematical, but upon imprecise but adequate verbal models in the various situations they are involved in.

Methods for "computing with words" have been developed through concepts such as *linguistic variables, fuzzy relations*, *approximate reasoning, linguistic qualifiers, and linguistic modifiers*. More recently, the entire set of these techniques applied in the field of decisional support have been classified under the label of *linguistic decision analysis* (LDA) (Herrera & Herrera-Viedma, 2000).

In this approach, the concept of linguistic variables (i.e., variables assuming verbal values) is central assume linguistic values. For example, the variable "height" can assume a value of the set {very short, short, medium height, tall, very tall}. LDA provides a set of techniques for the representation, combination and aggregation of linguistic variables. It can be understood as a kind of linguistic arithmetic, in which the input of certain fundamental operations are not whole or real numbers, but linguistic expressions represented through fuzzy sets.

Although fuzzy logic is not in itself sufficient to represent the complexity and the shades of meaning contained in linguistic expressions, it is undeniable that it allows us to model many characteristics of these expressions; first of all, their fuzziness and their ambiguity, as we will explain through examples shown in the next two chapters.

Components of a Verbal Model

Usually, to obtain a model of a verbal discourse, we need to reduce it to a set of logical propositions and apply the inference mechanism to these in order to logically deduct the consequences of given assumptions.

Alternatively, verbal models can be transformed into a mathematical form. In this case as well, a reduction of the variables and the relationships between them is carried out to define measurable approximations (indicators) and a model, as a set of equations. The limits of both attempts at modeling the discourse are immediately apparent. Both the logical model and the algebraic model drastically reduce the shades of meaning and the wealth of information contained in the discourse. An example of logical and algebraic modeling is shown in Table 1.

Regarding the ability to effectively simulate the results of reasoning, the logical model, at least in the ingenuous representation in Table 1 is not stable in that, assuming the initial values of knowledge = 1 and forgetting = 0, the model fluctuates.

The incapacity of two-valued logic to take the intensity of the variables into account is in some ways resolved by the algebraic formulation of the model. But there is a price to pay, since one must identify: (a) procedures for the measurement of the variables (e.g., amount of learning, amount of forgetting, etc.); (b) meanings of parameters, often determined heuristically, but that do not have clear correspondence in the discourse (coefficients α, β e δ).

Fuzzy logic allows for a further way to implement a verbal model, since it provides the operative tools for "computing with words."

To illustrate some of the possible ways to represent and manipulate linguistic variables and connectives within *verbal model*, we will refer to the general model of the argumentative discourse shown in Chapter XI described according to the rules of argument analysis. In this model, we see the following fundamental components:

1. **Verbal judgments:** In this category we include any verbal assertion that is classifiable as a *key claim* (conclusion of an argumentation), a *sub claim* (judgment in which the claim is articulated), *common claim* (facts, common sense, opinions of influential people), *ground* (facts offered in support of the claim).
2. **The rules of argumentation:** In this category we group all of the rules of reasoning through which an individual "deduces" conclusions beginning with certain judgments used as premises; *warrants* (rules that demonstrate how the grounds support the claim) belong in this category.
3. **Linguistic connectives** such as *qualifiers*, that limit the validity of the claim.

Modeling an explanatory discourse means having a methodology that allows for the formal representation of these three fundamental components.

In the following, we will show how it is possible to reach this objective through the computational and technical methods of *linguistic decision analysis.* We show how such methods allow us to attenuate the problem of meaning reductions that are typical of the formal modeling process with respect to the use of traditional quantitative techniques for the representation of verbal judgments.

Table 1. Example of modeling a discourse (Our adaptation from Wenstøp, 1975b)

Discourse
"Learning is based on reading good books, added to the ability to assimilate and not forget what has been read. Knowledge grows and is nourished by proper reading and by the knowledge itself. Unfortunately, it is also natural for human beings to forget more if too many things are learned at the same time and as the amount of knowledge accumulates, although it is more difficult to forget what is truly known."
Logical Model
If you read a lot and *do not* forget *then* you learn *If* you know *and* you learn *then* you increase what you know *If* you know *and* you learn *then* you tend to forget
Algebraic Model
Knowledge = Knowledge – forgetting Knowledge = Knowledge + learning Forgetting = δ exp (β learning) + α knowledge

Fuzzy Reasoning

One of the main uses of fuzzy logic is the modeling of so-called *approximate reasoning*. For approximate reasoning we mean the reasoning described through linguistic rules such as *if...then*, as in the following example:

If the price of petroleum rises a lot, the rate of inflation tends to increase.

If inflation is high, there will probably be an increase in social conflict due to the rise in the cost of living.

It is well known that the first attempt to model reasoning was Aristotelian or bivalent logic. In Aristotelian logic, the basic rules of inference are *modus ponens, the modus tollens and syllogism,* which can be expressed in the following way:

If *a* and (*a* implies *b*) then *b*	(modus ponens)
If *not* (*b*) and (*a* implies *b*) then *not* (*a*)	(modus tollens)
If (*a* implies *b*) *and* (*b* implies *c*) then (*a* implies *c*)	(syllogism)

where *a, b* and *c* are propositions. The rule of *modus ponens* has been extended to fuzzy logic through the *compositional rule of inference* introduced by Zadeh (1973), in which the classic *modus ponens* makes up the particular case in which the logical values assumed in the propositions are limited to *true* and *false*.

The compositional rule of inference is based on the fundamental idea that a speech act, such as '*if x is A, then y is B*' (in which *A* and *B* are generally two linguistic labels) is the expression of a fuzzy link between the fuzzy sets *A* and *B*. In fuzzy terms, *A* and *B* are verbal labels that correspond to values of the linguistic variables x and y. Through speech acts, we define fuzzy functions, for example in table form (see Table 2), where A_i and B_i are labels that identify the values assumed by the linguistic variables x and y. It follows that speech acts of this type describe a relationship between two fuzzy variables. For example, the speech act "*If x is tall, y is heavy"* identifies the relationship between the variable *height* and *weight.*

What distinguishes the compositional rules of inference from the *modus ponens* of classical logic is in the fact that, given the rule *If A then B* and given the observation *A',* different from *A*, the compositional rule of inference allows us to infer a conclusion *B,'* similar to *B, from A'* similar to *A*. While with classical logic it is not possible to deduce anything. For example, given the rule *If a tomato is red then it is ripe*, and given the observation that a *given tomato* is *more or less red*, the compositional rule of inference produces a fuzzy label *B'* next to *ripe*, that we can call *more or less ripe*. The choice of an appropriate operator for fuzzy implication also guarantees that other intuitive properties of reasoning are satisfied (Baldwin & Pilsworth, 1980; Fukami et al., 1980; Klir & Yuan, 1995).[4]

Thanks to the fact that the compositional rules of inference satisfy intuitive properties and that linguistic labels can be given to assumptions and conclusions, we can define systems of rules in verbal form.[5] Although there is no direct proof of the fact that a human being reasons effectively in a fuzzy way, nevertheless the simplicity of the method, if nothing else, leads us to make a hypothesis: when faced with complex tasks, human beings "simplify" the problem, tolerating acceptable levels of uncertainty and accepting an approximate, but satisfying execution of a task that can be improved with experience.[6]

Fuzzy Multiattribute Techniques

In problems where the number of variables is high, a fuzzy system of rule-based system becomes computationally inefficient. In such cases, or when simpler solutions are needed for the problem of aggregation of *n* fuzzy verbal judgments, it is possible to turn to fuzzy multiattribute techniques of aggregation.

Often, classic multiattribute techniques and the fuzzy set theory are used jointly (in such case it is also said that a preexisting method has been fuzzified). For example, it is possible to define fuzzy linear programming models (Zimmermann, 1991), in which constraints and objectives are defined in fuzzy of linguistic forms, or fuzzy models of regression in which the variables and the weights are fuzzy functions instead of simple numbers. In all cases, in which fuzzification has been done, normally there are computational complications as the object of the elaborations are not simple numeric values, but memberships functions.[7]

In general, for a multiattribute decision-making problem, a formulation can be done in the following way. A finite set of alternatives is considered $R = \{R_1, R_2, \ldots, R_m\}$, (for example, *m* candidates for a job interview), a set of finite criteria or attributes that such alternatives must satisfy $C = \{C_1, C_2, \ldots, C_n\}$ (for example, education,

Table 2. An example of linguistic function

X (height)	=>	y (weight)
A_1 = very short	=>	B_1 = very light
A_2= short	=>	B_2 = light
A_3= tall	=>	B_3 = heavy
A_4= very tall	=>	B_4 = very heavy

Box 2. Linguistic decision analysis

The algorithms of fuzzy approximate reasoning are the foundation of the commercial success of fuzzy logic, which has been usefully employed in the resolution of problems of nonlinear system control with a very low cost/performance ratio.

Fuzzy technologies are largely employed in the construction of intelligent mechanisms incorporated into consumer products in which it is not necessary to achieve elevated levels of precision: Washing machines, automatic transmissions, and focus mechanisms in cameras and movie cameras. The control systems of these mechanisms use algorithms based on *If-then* rules such as *If the air cool then slow down the air conditioner*.

By translating verbal rules into mathematical models, fuzzy rule systems can simulate verbal discourses. This is the specific area of *linguistic decision analysis*.

While in the field of automatic controls there is a vast amount of literature in the area of linguistic decision analysis we can say that the problem is still on the forefront. Nevertheless, it is highly relevant to a series of applicative areas, generally tied to the interaction between man and machines. Pushed by the enormous success in the filed of automatic controls, fuzzy logic has partly abandoned that which, in the intentions of its inventor Lotfi Zadeh, was supposed to be its primary objective: To identify a new way to model natural language that allows us to "compute with words" (Zadeh, 1996).

In recent years, scholars of fuzzy decision-making have given new energy to the research (Godo & Torra, 2000; Herrera & Herrera-Viedma, 1996, 2000; Torra, 1997; Yager, 1998; Zadeh, 2002). In any case, these studies focus on a formal and mathematical level and ignore interactions with linguistics and cognitive psychology. The sensation of many scholars is that it would be necessary to investigate more closely the possibility that fuzzy logic may have some cognitive foundations[7].

experience, motivation, technical competence, etc.). We can assign to each alternative R_i n scores x_{ij}, each expressing the degree to which the alternative R_i satisfies the criterion C_j (for instance, the x_{ij}'s could be the assessment of education level for the j-th candidate). In Chapter XIV we will discuss a fuzzy rule-based verbal model to analyze organizational behavior.

The problem is to identify, among the *m* available, the best alternative, which satisfies the criteria most closely. The process of determining the best alternative can be described in the following phases:

a. **Scoring:** Assign a value x_{ij} to each couple (R_i, C_j)
b. **Weighting:** Assign to each criteria C_j a weight w_j that represents its importance
c. **Criteria Aggregation:** Calculate for every R_i an overall score $x_i = f_c(x_{i1}, x_{i2}, \ldots, x_{in}, w_1, \ldots, w_n)$ that represents the global score achieved by R_i through an appropriate function of multiattribute aggregation f_c
d. **Ranking:** Given the set of points X = $\{x_1, x_2, \ldots, x_m\}$, choose the alternative that corresponds to the highest number of points

In order to resolve the problem of determining the global score for each alternative, starting with *n* elementary evaluations, it is necessary to establish how to represent the values x_{ij}, how to estimate the weights w_i, how to choose f and how to order the values x_i.

For each of these steps, many solutions have been proposed in the literature (Chen & Hwang, 1991), and there is a general consensus around the fact that a perfect solution, in general, does not exist, but that the choice of the method must be made according to the characteristics of the problem to be resolved.

In a fuzzy multiple attribute decision making (MADM) problem the values x_{ij}, x_i, w_i and the functions of aggregation f_c and f_p can be fuzzy, or expressable through linguistic labels. Therefore, in the presence of linguistic information, the MADM method, with respect to approximate reasoning models, allows us to "compute with words," although in a less transparent way. It can be said the fuzzy MADM method allows us to model very simple reasoning, such as:

If the attribute of $\boldsymbol{C}_1$ *of* $\boldsymbol{R}_i$ *has a value* $\boldsymbol{V}_{i1}$*, ..., and the attribute* $\boldsymbol{C}_m$ *has a value* $\boldsymbol{V}_{im}$*, and taking into account that* $\boldsymbol{C}_1$ *has an importance of* $\boldsymbol{w}_1$ *... and* $\boldsymbol{C}_m$ *has an importance of* $\boldsymbol{w}_m$*, then* $\boldsymbol{R}_i$ *has a value of* $\boldsymbol{V}_i$*,*

where V_{ij}, w_1 and V_i are linguistic values that are representable through fuzzy sets.

An Example of a Linguistic Connective: The Fuzzy Quantifier

In classic logic two quantifiers are introduced, existential quantifiers of *x* (*there is at least one x*), and the universal quantifiers of *x* (*for every x*). For example, it can be said that a given property is true for all of the elements of a certain set or for at least one element of a given set. Sometimes, in daily language we use logic quantifiers imprecisely, such as when we say that *all birds fly*, while it would be more correct to say that *most* birds fly. Traditional logic does not admit this type of compromise.

However, in daily language we often use imprecise quantifiers, such as *few, many, almost all*, etc. Fuzzy logic allows for the representation of these linguistic expressions, generalizing the classic concept of quantifier. It is possible to demonstrate that an unlimited number of quantifiers can be defined that fall between the two extreme cases of traditional logic.

Fuzzy quantifiers are classifiable into two categories: *Absolute* fuzzy quantifiers, defined in *R,* such as *around ten, at least five, more than one hundred,* and *relative* fuzzy quantifiers, defined in the interval [0,1], such as *almost all*, *about half, most, etc*.

Fuzzy quantifiers are actually fuzzy sets. They can be represented through a membership function Q defined on a numeric interval R, which associates to every element r a value $Q(r)$ between zero and one. In Figure 3 two representations of the absolute quantifier "*about ten*" are shown, as well as the one relative to "*most*."

Fuzzy quantifiers can be used to represent the qualifiers (see Chapter XI), i.e., linguistic connectives that have the task of limiting or circumscribing the validity of a judgment in a discourse, as in the expression bad weather usually creates traffic jams.

In the applications, fuzzy quantifiers are used in the modeling of the rules of approximate reasoning (Zadeh, 1996) and in multicriteria and multiperson aggregation (Herrera et al., 1996; Yager, 1988, 1993). For example, given a number of criteria (for example, those used for personnel recruitment of a certain professional figure in a company) it is possible to identify those candidates that meet most of the criteria (or many of the criteria, at least half, etc.).

From Theory to Practice

Up to this point, a quick overview has been provided for the reader on the set of possible approaches for modeling the verbal information contained in discourses through fuzzy logic.

The joint use of fuzzy techniques, of qualitative research methodologies and discourse mapping represents a possible answer to the need for learning organizations to have "soft" models that do not sacrifice information to the meaning, precision to flexibility of use, certainty of results to the exploration of multiple scenarios. This last characteristic will be explained more clearly through applicative examples presented in the next chapters.

One of the new things that must characterize the methodological apparatus of the learning organization is in the heterogeneity of techniques, in the eclecticism of methods, and in the strength of synthesis to join the effectiveness of qualitative techniques to the rigor and efficiency of quantitative ones.

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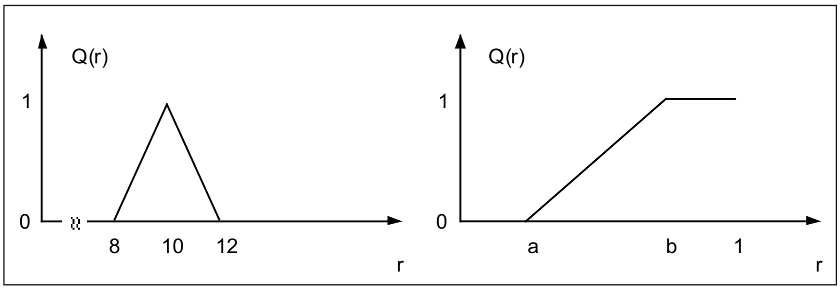
Figure 3. Absolute and relative fuzzy quantifiers



For a given number r, the value Q(r) represents the degree to which the value of r satisfies the concept expressed by the linguistic expression associated to Q. In the figure on the left we have the absolute quantifier about ten to which values between 8 and 12 units belong with a certain degree. On the right side we have the relative quantifier most, which is defined on the interval R = [0,1]. Here r is a percentage. If r = 60% we get Q(r) = 0.8, which means that a 60% percentage can be assumed to represent the concept most with a rather high degree of truth.

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Endnotes

[1] These techniques actually combine a set of tools (multiattribute and multiobjective decision making, fuzzy set theory) whose joint use represents an attempt to model the uncertainty contained in verbal expressions.

[2] The attribute *fuzzy* was introduced by Lotfi Zadeh in his 1965 paper. It is synonymous with blurred, not clear, distinct or precise. However, none of these alternative connotations possess the provocative meaning deliberately introduced by Zadeh (1965). Previous attempts to formulate multivalues logic

were by Luckasiewicz in the thirties. The concept of vague set was introduced for the fisrt time by Max Black in 1937.

3 A bibliography of introduction to fuzzy logic, as important as it is, would be impossible given the huge corpus of pubblication on the subject. We will limit ourselves to suggesting two manuals that have been widely circulated as educational publications: Zimmermann (1991); Klir and Yuan (1995). Another interesting, though less rigorous, text is the one by Kosko (1993). For their historical importance, we suggest reading two articles by Zadeh (1965, 1973).

Many scientific magazines are dedicated to fuzzy logic, above all in the field of artificial intelligence and engineering. Among the more "general" ones we would like to remind the reader of *Fuzzy Sets and Systems*, *IEEE Transactions on Fuzzy Systems*, *Journal of Intelligent Systems*. Among the magazines dedicated to the application of fuzzy logic in the field of economics and managerial science we suggest the *Fuzzy Economic Review*.

4 Among the main properties that fuzzy inference must satisfy, we remind the reader of the following:

- **Fundamental property:** The consequence B' should never be more restrictive than the observation A' (for example, give the implication *x is tall -> y is heavy* and the observation *x is tall* it should not be possible to infer that *y is very heavy*).
- **Property of regularity:** More A implies more B;
- **Propagation of fuzziness:** In a chain of implications, the later inferences should be more and more vague; for example, considering the following chain of implications ' x is tall' -> 'y is heavy' -> 'z is obese' -> 'w is at risk for a heart attack' ->'v is at risk of a premature death,' given the observation 'x_1 is taller than 1.9m', it is clear that any consideration on the possibility of a premature death of x_1 should be much more vague on the inference on his weight.
- **Consistency:** Given the rule *if A then B* and given the observation A' = A (not B), the inference must produce the outcome B' = B (not A)

5 It is possible to demonstrate (Kosko, 1992) that a system like this is a *universal approximator* in the sense that it can approximate any continuous function defined or desired on a compact interval. The precision of the system grows with the number of rules adopted; the rules grow exponentially with the number of variables and the desired precision, which renders this type of model usable for smaller problems only (few variables, according to the precision required), unless the system that must be modeled does not admit a hierarchical decomposition. It is possible to demonstrate that given a function $f: R^n \rightarrow R^p$, a number of k^{n+p-1} rules are needed to approximate the function, where *k* is

the number of the fuzzy relationships necessary to "cover" the function *f* in a given hypercube.

6 And it is just that which is verified in hybrid systems obtained through the combination of fuzzy rules and neural networks in the operation of fine tuning the rules according to training data (Kosko, 1992).

7 Zadeh and Zimmermann, personal communication.

8 In quite simple terms, if it can be straightforward to say that 3 + 2 = 5, it is not as easy to say that *more or less 3* + *about 2*= *about 5*, because we have to add two functions (*more or less 3* + *about 2*) to determine the shape of the function *about 5*.

Chapter XIII

Modeling Verbal Judgements

Squareness may be succinctly and yet thoroughly defined as the inability to see quality before it's been intellectually defined, that is before it gets all chopped up into words …We have proved that quality, though undefined, exists. Its existence can be seen empirically in the classroom, and can be demonstrated logically by showing that a world without it cannot exist as we know it. What remains to be seen, the thing to be analyzed, is not quality, but those peculiar habits of thought called 'squareness' that sometimes prevent us from seeing it.

(Robert M. Pirsig, *Zen and the Art of Motorcycle Maintenance: An Inquiry into Values*)

Abstract

In the previous chapter we have outlined the basic structure of a verbal model and its main components: Judgments, rules and qualifiers. This chapter proposes a model, called the dual truth model, to represent verbal judgments through fuzzy logic. Furthermore, the dual truth model permits us to examine more in depth and

quantitatively assess the vagueness and ambiguity contained in a verbal judgment. An application of the model to the definition of assessment scale for personnel appraisal is also provided.

The Fuzziness of Verbal Judgments

One of the factors which makes natural language such a flexible and efficient tool is its inherent imprecision. It is surprising, in fact, how even a fairly limited vocabulary (it is estimated that the average educated person knows only a few thousand words) is enough to enable a person to carry out even very complex tasks.

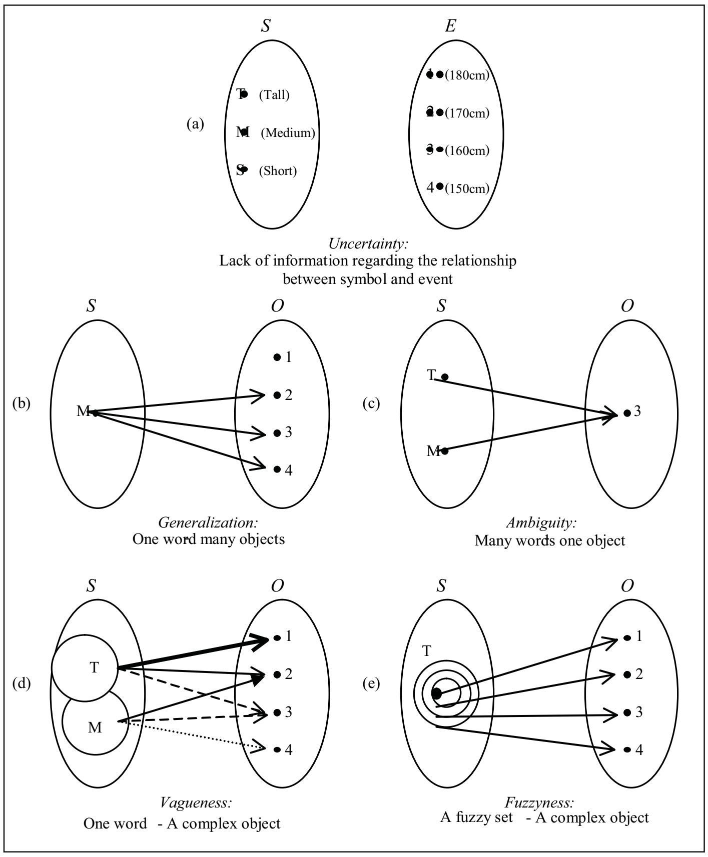
The set of symbols which we use to denote events and circumstances is therefore relatively limited. It is also true that if there were enough symbols to allow for a one-to-one relationship with all possible events our brains would not be able to handle such a vast amount of information. How does a person manage to identify a potentially enormous number of events using a finite number of symbols?

Let's consider the example in Figure 1[1], where there are two sets: The set S of symbols {T, M, S} and the set *O* of objects {1, 2, 3, 4}. Let's assume, for example, that the symbols are three words {Tall, Medium, Short} and the objects are four different heights {180 cm, 170 cm, 160 cm, 150 cm}. The observer's task is to associate the symbols with the events. In a situation like this, one of the following three outcomes is possible:

1. *Uncertainty* (Figure 1a), where the observer is unable to identify a link between symbols and events because of lack of knowledge;
2. *Generalization* (Figure 1b), where the observer tries to use the same symbol to classify events which are different but in some way similar;
3. *Ambiguity* (Figure 1c), where the observer does not have the right symbol for the event so tries to use two others in combination to explain it.

With a given set of symbols whose total number is necessarily lower than that of possible events, the problem arises of how to deal with uncertainty, generalization and ambiguity. If we use the symbols as labels to denote objects it would be impossible to solve this problem, but fortunately language does not work like this. If we think, for example, of the adjective *tall* to indicate a person's height, we know that a person who measures 190 cm is definitely *tall* and that someone who is 150 cm definitely isn't, and also that someone who is about 170 cm is *tall* to a certain extent. At the same time we can still refer to someone of 160 cm as *tall* depending on the context, for example if we are talking about children or pygmies.

Figure 1. Uncertainty, ambiguity, vagueness, fuzziness



The concept of linguistic uncertainty derives from the difficulty in establishing a certain relationship between a limited number of verbal expressions and a large number of facts or events (Figure 1a). Generalization occurs when one word is used to indicate many things (Figure1b). Ambiguity instead results from using several different words to indicate the same thing (Figure 1c). The combination of generalization and ambiguity leads to vagueness (Figure 1d). In this case words are used in a rather indistinct way to denote categories of objects or events which partially overlap (vagueness). Fuzziness is a measure of the concept of vagueness, which we get by applying specific mathematical techniques (Figure 1e).

This example aims to show how we can use words as symbols of an uncertain significance and that it is this very uncertainty of language which enables us to adapt the same word to different events in different situations. As Russell reminds us, there are many possible facts which can go to prove a vague assertion.

In general, the vagueness of words, which is closely linked to the process of categorization of experience, means that many events can be labeled in the same way. The meaning which is then attached to the word is situated and socially constructed, making language use even more context-based and specific.

Language therefore enables us to adapt words to situations. Figure 1(d) represents the relationship between the imprecise word *tall* and four different values of height that can be applied to it, whereby the thickness of the line is proportional to how opportune or possible it is to use the word in each of the four cases. We could say that each of the four events can be thought of as elements belonging to a set which we can label *tall*, but each element belongs with a different intensity. Since height values only belong partially to the set *tall* we might think of these values as belonging to different sets simultaneously even if in varying degrees. For example, a person who is 175cm tall could be considered either *medium* or *tall*.

The fuzzy sets theory enables us to represent the vagueness of verbal expressions using a concept of partial membership. In other words, we can use a linguistic label to denote different events only if we accept that the boundaries of that label are not rigidly fixed.

A Model for the Representation of Verbal Judgment: Logical and Linguistic Truth

Usually, the representation of linguistic evaluations in a logical framework underestimates how different the concept of truth is in linguistic and logical propositions (Strawson, 1952). Roughly speaking, the truth of a linguistic proposition is mainly a matter of social consensus, while the truth of a logical proposition is mainly a matter of coherence with other propositions. We are interested in two questions related to the relationship between these concepts of truth. First question: Given an event, what is the truth of a linguistic proposition describing that event? Second question: Given a true linguistic proposition, what is the logical truth, which corresponds to that linguistic proposition? In order to attempt to answer those questions we consider two cases. In the first case, we know that the height of John is 178 cm and we want to know the truth-value of the linguistic proposition "John is tall." In the second case, given the verbal proposition "John is tall," we want to know what the logical truth hidden in this proposition is, if no additional information is given. Let us look more closely at those two cases.

CASE A: What is the truth of the statement "John is tall," given that the height of John is 178 cm?

The proposition "The height of John is 178 cm" identifies a point in the interval [150 cm, 190 cm], while the term "tall" is an element of a set of terms used by the evaluator to explicit his or her evaluation. We can suppose that the term "tall" is the third term of the term set TS3 = {short, medium, tall}. According to the fuzzy set theory we can represent this term set as a family of membership functions, as represented in Figure 2. Thus, the truth of the proposition "John is tall" is given by the value of the membership function "tall" in the term set TS3. We can easily see that, for the value of height equal to 178, the value if tall is equal to 0.80. In formal terms:

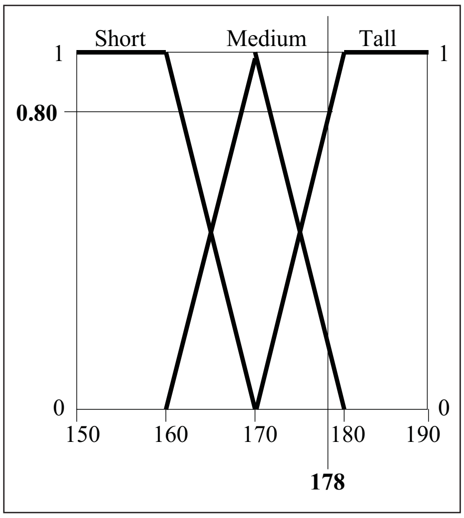
truth ("John is tall" | (Height(John) = 178) AND TS3) = 0.80

CASE B: What is the truth of the statement "John is tall," no more information given?

In natural language the proposition "John is tall" means, for any possible listener, that in most situations John could be considered "tall" and only in few situations he could be considered short. Both for the speaker and the listener the word "tall" always includes the opposite concepts of TALLNESS and SHORTNESS. In other words we assume that the linguistic proposition "John is tall" can be broken down into two logical propositions, "John is SHORT" and "John is TALL," where antonyms TALL and SHORT (written in capital letters) denote "absolutely short" and "absolutely tall." Consequently, the truth of the linguistic proposition:

P = "John is tall"

Figure 2. The truth value of 'tall', given the height of 178 cm



is broken down into the pair of truths related to propositions:

PL = "John is SHORT;"
PR = "John is TALL."

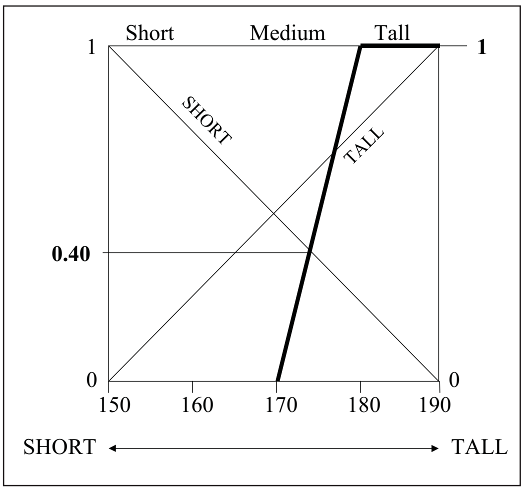
The linguistic proposition P = "John is tall" corresponds to a piece of information of the form "X is V," where the term X is a linguistic variable, and V is an element of the term set TS3 {short, medium, tall}. The terms of the term set are in an ordinal scale and each term V defines part of the universe of discourse whose extremes are the couple of antonyms SHORT and TALL. Figure 3 represents membership function of the term "tall" in the term set TS3.

In the same figure the functions of "SHORT" and "TALL" are represented. These functions correspond to the two diagonals of the square. Simply, they mean that the truth-value of TALL increases linearly from 0 to 1, and, vice-versa, the truth-value of SHORT decreases. Given these functions, the truth of the proposition P is equivalent to the determination of the degree of consistency (*cons*) of both the propositions PL and PR with P. If the evaluative sentence is the proposition:

P = "John is tall"

and the pair of related logical assertions is:

Figure 3. The truth value of 'tall', no more information given



PL = "John is SHORT"
PR = "John is TALL"

the truth of the proposition P is a couple of values (a,b), such as:

truth ("John is tall") =
= (cons {"John is SHORT" | "John is tall"}, cons{"John is TALL" | "John is tall" }) =
= (sup {min(SHORT, tall)}, sup{min{TALL, tall)}) = (a,b)

Table 1. Truth couples per term set varying from 1 to 11 values

	number of verbal terms in the term set										
Verbal values	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
VVL Very very low										0.92 0.17	0.92 0.15
VL Very low					0.86 0.29	0.88 0.25	0.89 0.22	0.9 0.2	0.91 0.18	0.83 0,25	0.85 0.23
L Low		0.75 0.5	0.8 0.4	0.83 0.33	0.71 0.43	0.75 0.38	0.78 0.33	0.8 0.3	0.82 0.27	0.75 0.33	0.77 0.31
MLL Moreless low							0.67 0.44	0.7 0.4	0.73 0.36	0.67 0.42	0.69 0.38
A^- Lower average				0.67 0.5		0.63 0.5		0.6 0.5	0.64 0.45	0.58 0.5	0.62 0.46
A Average	0.67 0.67		0.6 0.6		0.57 0.57		0.56 0.56		0.55 0.55		0.54 0.54
A^+ Upper average				0.5 0.67		0.5 0.63		0.4 0.7	0.36 0.73	0.42 0.67	0.46 0.62
MLH Moreless high							0.44 0.67	0.4 0.7	0.36 0.73	0.42 0.67	0.38 0.69
H High		0.5 0.75	0.4 0.8	0.33 0.83	0.43 0.71	0.38 0.75	0.33 0.78	0.3 0.8	0.27 0.82	0.33 0.75	0.31 0.77
VH Very high					0.29 0.86	0.25 0.88	0.22 0.89	0.2 0.9	0.18 0.91	0.25 0.83	0.23 0.85
VVH Very very high										0.17 0.92	0.15 0.92

In the case depicted in Figure 3, the pair of truth-values of the proposition "John is tall" is (0.40, 1.00). The pair can be interpreted as answers to the following questions: "What is the possibility that John is considered absolutely short, knowing that someone said that he is tall? What is the possibility that John is considered absolutely tall, knowing that someone said that he is tall?" Or, more simply, "What is the truth degree of the assertion 'John is tall'? And what is its falsity degree?" The fuzzy model answers to those questions with a couple of values, which, according to the viewpoint of Sainsbury (1988), express the fact that the linguistic assertions are neither definitely true nor definitely false.

The pair of values represents a bridge between linguistic and logical propositions. We named as *dual truth model* this representation of how linguistic evaluations embody paradoxical truths.

We can generalize from this to calculate the truth couple per term set of any number of items. If we imagine that the items in a term set can be represented by triangular functions we get the truth couple (a, b) as shown in Table 1. The pairs show the following relationship:

$$a = (j + 2 - i)/(j + 2) \qquad b = (i + 1)/(j + 2)$$

where j is the number of verbal terms in the term set size and i the position the verbal values holds on the verbal scale.

It is interesting to note how as j increases, the two values tend to complement each other. Following this simple observation, it can easily be demonstrated that if j were infinite we would have no need to characterize the assessment P with a couple of values. One would be enough because each is the complement of the other (the negation, in the dual logic).

Properties of the Dual Truth Model

Although natural language is quite varied, we don't normally use many verbal terms to express our opinions. This means that they are often rather ambiguous. We ask a limited number of signs to represent a much larger number of events.

If we start with the truth couples we can find measures to assess precision, ambivalence and ambiguity in verbal judgments. The truth couples define a two-dimensional space known as the dual truth space as shown in Figure 4.

Any verbal judgment is represented by a point V whose coordinates are the values of the truth couple. A precision line can be identified in this plane. The proximity of the point to this precision line increases as the number of elements in the term set increases. The points which are actually on the line have the greatest degree of precision, just in this case we need a term set with infinite values. The point with coordinates (1,1) denotes a complete inability to express a judgment (degree of precision equals 0, e.g., an individual is tall and short at the same time with the highest degree of possibility).

The complement of precision is vagueness. For any given point on the plane we can find an associated measure of vagueness in the judgment which is defined as follows:

Vagueness = (right value + left value - 1)

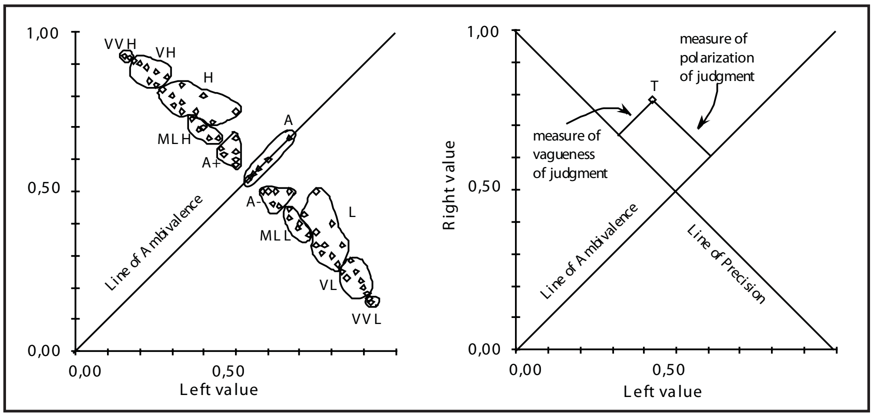
The vagueness of V is proportional to its distance from the precision line.

The second diagonal in the dual truth space defines what is called an *ambivalence line*. Polarization is a measure to assess how sharp is a judgment. Ambivalence is the negation of polarization:

Polarization = abs(right value – left value)

Ambivalence = 1 – Polarization

Figure 4. Measures of precision, ambivalence and ambiguity in verbal evaluation



The verbal judgments shown in Table 1 can be positioned on a left value/right value plane thus determining how close they are to the lines of ambivalence and precision without actually being part of either (left side picture). The points are always located above the precision line. It is thus possible to introduce ambiguity measures into the judgement depending on its coordinates. On the right side figures, verbal judgments belonging to different term sets are shown.

where abs indicates the absolute value of the difference. The evaluation is more ambivalent the closer to the line of ambivalence it is. It is easy to prove that more polarized judgments like *very very low* or *very high* have low degrees of ambivalence whereas the term *average* has the highest degree of ambivalence. Even the measure of ambivalence, if the verbal judgment is equal, depends on the size of term set adopted.

We finally introduce the measure of ambiguity defined as:

$$Ambiguity = \frac{\sqrt{Vagueness^2 + Ambivalence^2}}{\sqrt{2}}$$

A judgment is ambiguous if it is vague and ambivalent. Once the term set is fixed, the most ambiguous judgment is *average*. However, as we might expect, the ambiguity related to *average* decreases as the number j of the elements in the term set increases.

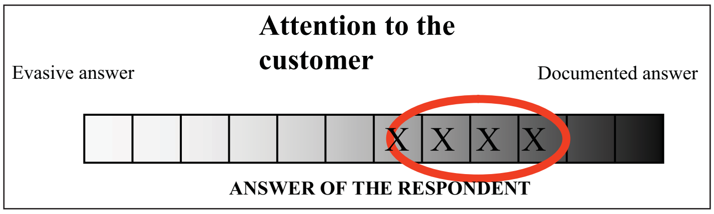
The Representation of Judgment Through Fuzzy Scales

The dual truth model provides a framework for a more comprehensive use of the informational content of verbal judgment. It enables us to formulate an assessment scale whereby the assessor can choose the most suitable degree of precision for expressing his or her judgment.

The model presented below dispenses with the traditional concept of a scale as a successive ordinal scale of values each with its own label. The verbal scale is simply a bar with *n* number of boxes which represents a continuum going from a totally negative assessment to a totally positive one. There are no labels on the scale apart from those of the two opposites. The assessor can choose a box or a whole section of the continuum as illustrated in Figure 5.

The two antonyms, as well as representing the two opposite poles of an assessment, also represent two poles of meaning. For example, an assessment of the attention given to the customer is measured on a continuum from *evasive answer* to *documented answer*. The two poles thus act as a guide for interpreting the linguistic variable *attention to customer* within the context in which it is used and constructed. An answer like the one given in Figure 5 is the equivalent of a verbal assessment of the type: "*for the most part, X shows a high level of sensitivity to client needs.*"

Figure 5. Uncertainty scale



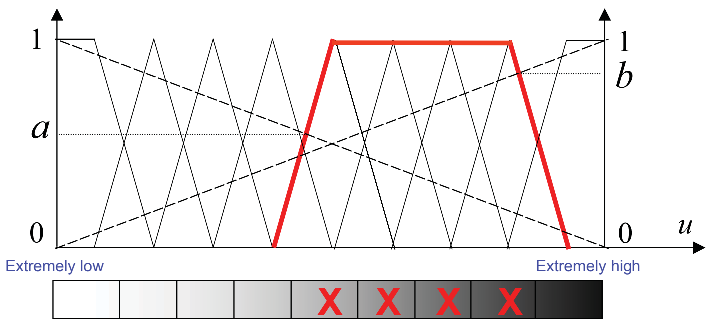
If we combine the scale model and the dual truth model we can measure the ambiguity inherent in the assessment, or give it a numerical value as shown in Figure 6.

If we divide the bar into *n* boxes a triangular function can be associated with the judgment expressed in anyone box. If the judgment is expressed in more than one box then it is vaguer and can be represented by associating a trapezoid membership function to it which is obtained by the convolution of the *m* triangles associated with the boxes.

Using the dual truth model we immediately associate a truth couple (a, b) to the fuzzy representation of the judgment which is obtained as shown in Figure 6. The result is (0.55, 0.82), according to the table in Figure 6. The following formula can be used to get a nonfuzzy reading:

$$V=(1-a+b)/2= (1-0.355+0.82)/2=0.635$$

Figure 6. Judgment represented using dual truth model and uncertainty scale



a	1.00	0.82	0.73	0.64	**0.55**	0.36	0.36	0.27	0.18
b	0.18	0.27	0.36	0.45	0.55	0.73	0.73	**0.82**	1.00

It is worth remembering that (1 - *a*) expresses the *possibility* that the judgment may be "not negative" whereas b is the possibility that the judgment is positive. So V is a kind of average of the two possibilities[2].

The combined use of the dual truth model and the verbal scale gives us a powerful model for assessing verbal judgment. The main properties are the followings:

a. The problem of interpretation of labels on the part of the assessors is notably reduced as labels are replaced by two opposites which provide a more circumscribed and specific meaning for the judgment.
b. There are no arbitrary hypotheses regarding the values that the variable should assume like it happens with a predefined ordinal scale, since the fuzzy representation is a more direct representation of what the assessor actually said.
c. The assessor is free to express her/his uncertainty as s/he wishes because the scale enables them to vary the dose from *minimal uncertainty* (only one box) to *total ignorance,* by selecting the whole bar. When no answer is given, this can be interpreted as "don't know" and so represented by the closed pair (1,1) which corresponds to a maximum level of ambiguity in the judgment.
d. The fuzzy scale enables us to identify a kind of naive variance within a judgment implicit in expressions like "*usually demonstrates a high level of attention to client needs,*" "*her behavior is satisfactory in the majority of cases with some points of excellence,*" etc.

How to Aggregate Verbal Judgments

The dual truth model represents and combines in quantitative way the verbal judgments, while at the same time preserving vagueness, ambivalence and ambiguity of verbal sentences.

The following example regards multiple attribute decision making (MADM, see Chapter XII) when we have verbal or linguistic information available. Let's consider, for example, that we have to decide what evaluation to give a student essay, according the criteria *comprehensiveness, presentation, extensiveness of bibliography etc* (and let's call these criteria E_1, E_2, …, E_{10}). Let's imagine that a teacher gave the following assessment for each criterion:

E_1: Very very high (7)	E_6: Very very low (9)
E_2: More or less high (7)	E_7: Low (5)
E_3: High (3)	E_8: Low (3)

E_4: Low (7)	E_9: Medium (5)
E_5: Low (5)	E_{10}: Very very low (9)

The numbers in brackets refers to the number of elements of the term set the judgment belongs to. The first step entails transforming the verbal labels into truth couples. Table 1. thus gives us:

Fuzzy judgement	**V**	**Fuzzy judgement**	**V**
E_1: Very very High (0.22, 0.89)	0.84	E_6: Very very Low (0.91, 0.18)	0.14
E_2: More or less High (0.44, 0.67)	0.62	E_7: Low (0.71, 0.43)	0.36
E_3: High (0.4, 0.8)	0.7	E_8: Low (0.80, 0.40)	0.3
E_4: Low (0.78, 0.33)	0.28	E_9: Average (0.57, 0.57)	0.5
E_5: Low (0.71, 0.43)	0.36	E_{10}: Very very low (0.91, 0.18)	0.14

The value $\boldsymbol{V} = (1\text{-}a + b)/2$ represents the defuzzified value of the judgment, which is useful for successive combinations with fuzzy quantifiers. Let's imagine that we want to combine these evaluations in a global score that reflects that *the majority of the* E_i *criteria are met.* To do this we can use the fuzzy quantifier *most* (see Chapter XII and Box 1) which gives us a global evaluation in the form:

$(a, b) = \mathrm{F}(\mathrm{V1}, \mathrm{V2}, \ldots, \mathrm{V10}) = (0.71, 0.43).$

Still using Table 1, we can identify which verbal term is closest to the closed pair (0.71, 0.43). The pair (0.71, 0.43) corresponds to the judgment *Low* in a term set with a cardinality of 5.

Setting aside the technical details involved in the calculation, it is interesting to see that different quantifiers give us different results, as shown in Table 2. As we can see, the results are very different both for the fuzzy values as well as for the vagueness and ambiguity content.

Since the use or choice of a quantifier depends on the assessor, this kind of variability should not be seen as off-putting but, rather, as further proof of the variety of meaning and situation underlying verbal judgments.

The different ways in which judgments are combined can lead to different outputs. Examining the different scenarios, which are obtained using the different hypotheses, provide us with a multiplicity of options which can be used as the starting point for further in-depth analysis or used as a basis for comparison.

Table 2. Example of multicriteria combination using fuzzy quantifiers

Quantifier	**Truth pair**	**Verbal judgement**	**Vagueness v = (b + a –1)**	**Ambivalence a = (1 - |b – a|)**	**Ambiguity** $\sqrt{(v^2 + a^2)/2}$	**Defuzzied value x 100**
Most	(0.71, 0.43)	*Low* (5)	0.14	0.72	0.52	36
Pure Average	(0.64, 0.49)	*More or less low* (7)	0.11	0.77	0.39	43
All	(0.91, 0.18)	*Very very low* (9)	0.09	0.27	0.14	14
At least one	(0.18, 0.91)	*Very very high* (9)	0.09	0.27	0.14	87
At least 70%	(0.8, 0.4)	*Low* (3)	0.2	0.6	0.32	30

Box 1. Aggregation of linguistic information through fuzzy quantifier

The aggregation of fuzzy judgments can be performed by a family of fuzzy operators called OWA (ordered weighted average). An OWA operator F of dimension n has an associated vector of weights $W = [w1, w2, \ldots, wn]^T$ such that:

1) $w_i \varepsilon [0,1]$
2) $\Sigma_i w_i = 1$

Given n fuzzy judgments $a_1, a_2, \ldots, a_n$ we can obtain an aggregated judgment in the following way:

$$F(a_1, a_2, ..., a_n) = \Sigma_i w_i b_i$$

where b_i is the i-th largest of the a_i, hence an ordering is requested to perform the calculation. OWA operators have the basic properties of an averaging operator. The pure average is the OWA operator whose weighting vector is $W = [1/n, \ldots, 1/n]$.

It is possible to demonstrate that for any OWA operator F we have:

$$\min(a_i) < F(a_1, a_2, ..., a_n) < Max(a_i)$$

i.e., OWA operators provides a gradual transition from the ‘and’ and the ‘or’ fuzzy logical connectives. Given an operator F with a weighting vector W it is possible to define the following orness measure:

$$\text{orness(W)} = \frac{1}{n-1}\sum_i ((n-i)w_i)$$

F is called an or-like (and-like) operator if orness(W) > 0.5 (< 0.5).

In our case we suppose that the value a_i represents the truth value of the proposition “The criterion E_i is satisfied” Consequently, the aggregation (max) yields the greatest available satisfaction level (i.e., the assessor is satisfied if at least one criterion is satisfied), which the *and* aggregation yields the lowest satisfaction level (i.e., the assessor is satisfied if all the criteria are satisfield). For this reason the orness measure is an optimism indi-

continued on next page

Box 1. continued

cator in the aggregation: any other operator would provide a certain degree of optimism ranging from absolute pessimism (orness(W) = 0) to absolute optimism (orness(W) = 1).

Yager (1991) shows that the calculation of the weighting vector W can be performed by means of fuzzy quantifiers: given a monotonically nondecreasing fuzzy quantifier Q(r) the weights w_i can be obtained through the following formula:

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right)$$

where *n* is the number of the criteria. Yager also demonstrates that the w_i can be interpreted as the additional satisfaction obtained if the i-th criterion is satisfied, provided the i-1 criteria are satisfied.

If the weights are calculated by means of a given fuzzy quantifier Q, it is possible to verify that the aggregated value can also be interpreted as the truth value of the proposition Q criteria are satisfied.

It is worth to note that by choosing a quantifier Q we also establish how we prefer to aggregate the judgements. For example, let's consider the quantifier most depicteed in Figure 3, Chapter XII: In this cases the aggregation performed through this quantifier is "*most* of the criteria should be satisfied." We could also find other ways to perform the aggregation by using different quantifiers, such as *all, a lot of, many, at least half,* and so on.

By calculating the weights for the fuzzy quantifier most with n=10, a=0.3, b=0.8 we have the following weight vectors:

$$W_{most} = [0 \quad 0 \quad 0 \quad 0.2 \quad 0.2 \quad 0.2 \quad 0.2 \quad 0.2 \quad 0 \quad 0]^T$$

In contrast with a pure averaging operation, the use of the OWA operators allows us to prevent from undesired compensation between positive and negative evaluation which eventually could shifts the group evaluation toward the value "average." For example, if we consider the quantifier *most*. We can observe that such a quantifier carries out an aggregation which does not keep into account the highest and the lowest available satisfaction level. The use of this quantifier entails an aggregation criteria according to which the group satisfaction we obtain is equal to zero if less than 30% of criteria are satisfied and the group incremental satisfaction gained by satisfying more than 80% of criteria is zero as well. Consequently, given a group of 100 criteria, because of the ordering, the overall evaluation will depend on the judgments belonging to the interval ranging from the 30^{th} to the 80^{th} best evaluation.

Conclusion

We have shown that with the combined use of the dual truth model, the uncertainty scale and fuzzy indicators we can hold the verbal ambiguity without too difficult computational effort. In more general terms, using fuzzy judgments has several concrete advantages:

a. Enables us to limit the problem of reduction of meaning inherent whenever we formalize knowledge because fuzzy discourse models aim to represent the characteristics of verbal information as faithfully as possible.

b. Assessor behavior in terms of attitude towards uncertainty is described more accurately. Using these uncertainty measures it is possible to ask oneself where the source of the uncertainty lies (In the assessor? In the situation? In the context? In the ambiguity with which the request was formulated? In the complexity of the task?).

It is important to remark that in fuzzy literature it is possible to find many other possible ways of representing judgments and that in general this is a very critical task when designing fuzzy systems. Rather than focusing on technical issues, through the dual truth model we wanted the readers focus their attention on some conceptual issues of judgment representation, in particular those arising from the ambiguity of verbal judgments and to which extent fuzzy logic can help to represent it. In the next chapter we turn our attention to possible approaches in modeling the second component of a verbal model, i.e., rules representation by providing several examples of verbal models.

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Endnotes

1. A previous version of this example as well as of the dual truth model has been discussed in Zollo (1998).
2. In more general terms, the formula is a defuzzification of V, that is, an operation which gives us a numerical value for V. See Klir and Yuan (1995) for a detailed study on possibility measures.