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From a rule-based conception to dynamic patterns. Analyzing the self-organization of legal systems

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Abstract. The representation of knowledge in the law has basically followed a rule-based logical-symbolic paradigm. This paper aims to show how the modeling of legal knowledge can be re-examined using connectionist models, from the perspective of the theory of the dynamics of unstable systems and chaos. We begin by showing the nature of the paradigm shift from a rule-based approach to one based on dynamic structures and by discussing how this would translate into the field of theory of law. In order to show the full potential of this new approach, we start from an experiment with NEUROLEX, in which a neural network was used to model a corpus of French Council of State decisions. We examine the implications of this experiment, especially those concerning the limits of the model used, and show that other connectionist models might correspond more adequately to the nature of legal knowledge. Finally, we propose another neural model which could show not only the rules which emerge from legal qualification (NEUROLEX's goal), but also the *way* in which a legal qualification process evolves from one concept to another.

Key words: case law, dynamic systems, legal neural networks, rule based model, self-organisation

1. The Symbolic Logic-Programming Approach as Applied to the Law

This first approach is based on the symbolic processing of information, which draws on rule bases to solve problems using deductive and inductive reasoning. It has hitherto held the high ground in AI and law.

1.1. THE SYMBOLIC PROCESSING OF INFORMATION

From its origins in the 1950s, the whole philosophy of AI has been based on the symbolic processing of information. In this view, the computer operates on objects, i.e., symbols, which have no meaning in themselves but represent realities external to the machine. The representation of knowledge consists in matching the external world and a symbolic system that can be automatically processed.

In Prolog[1] for example, the *symbols* are predicates. This theoretically neutral choice turns out to be biased in practice since it in fact determines the reading of the program. A formal system consists of symbols, assembled into formulae, which are mutually generated by applying the inference rules. True formulae (logically speaking) only generate true formulae. All demonstrable *theorems* can be deduced from given *axioms*.

If it is admitted that formalization helps to consolidate rational thought, the question is how to build the tools for this reasoning process. Prolog provides a response by enabling us to explore the labyrinth of conceptual thought explicitly, i.e., by expressing the essential logical relations in a given area of knowledge.

Prolog's flexibility derives from the declarative character of knowledge. The clauses are independent of each other and there is no syntactic difference between data and rules. In declarative programming, there is no need to specify what must be done before and after a given step, or how to apply a rule. Prolog ensures the link between induction (your attempt to demonstrate a goal) and deduction (the solution strategy). Backward chaining prioritizes questioning. The goal which one tries to demonstrate by making a query is a conjecture formulated inside a problem space – i.e., the working hypothesis. Prolog III has been enriched with a new dimension, enabling constraints to be set to delimit the field within which the machine will explore all possible combinations.

Prolog is equipped with a *general algorithm* to handle non-procedural, raw knowledge. Prolog's power lies in its use of a solution strategy that can be applied to any knowledge base written in the *Horn clause* formalism (single conclusion rules). Not only is Prolog capable of saying whether a given hypothesis is true or false, but it also provides the values taken by variables (*instantiation*) for the response to be true.

Any problem that can be broken down into simple sub-goals can be solved by Prolog. This naturally presupposes that we are able to *reduce* a knowledge set into elementary modules inter-articulated into a cascade of syllogisms.

1.2. KNOWLEDGE-BASED SYSTEMS AND LEGAL APPLICATIONS: PROLOG AND ITS LIMITS

Models of this type have been developed ever since AI was first applied to law, with the aim of building knowledge-based systems or expert systems designed to emulate the knowledge of human experts. These systems use large, explicit, declarative databases of what an expert has to know in a particular domain. The statements contained in such a database are in the form of production rules denoting that, in the case of a given event, a specific action should be taken. The system sequentially chains together a set of rules until a conclusion is reached.

[1] **Prolog** (PROgrammation en LOGique) is a programming language created at the beginning of the 1970s in Alain Colmerauer's research team at the University of Marseille. We refer here to *Prolog II+* and *Prolog III* shipped by PrologIA.

Sergot (1991) has hypothesized that most legal representation systems are based on logical models that take advantage of the apparently well-structured nature of the legal domain. These systems distinguish between the representation of legal rules – usually statute law – and the inference mechanisms that produce the right conclusion for a set of facts which match the conditions on those rules.

A significant example of a rule-based model is the PROLOG representation of the British Nationality Act. The formalization of the text is based on trial and error (learning). Each article of the act is represented in first order predicate calculus (through *If . . . Then* rules) and is then re-arranged so that it remains coherent with the formalisation of the other articles in the text. The team of logicians also wished to show that a computer expert did not need a legal expert to formalize a legal text.

The limits of these methods have been discussed in (Leith 1986; Bourcier 1993). First of all, “legal rules” cannot be assimilated to “normative text”. The translation of a legal text into logical clauses necessarily implies an interpretative act; and the judge is always empowered to interpret “primitives”. Moreover, there is no isomorphism between “legal rules” and “logical clauses”. Nor can legal expertise be reduced to a set of “legal statements”. The insufficiencies of this model have been recognized: any legal system must be error-tolerant, which means that it must allow decisions to be reached in unpredictable and, by definition, contentious circumstances. The purely objectivist vision of a text prevents the effects of time and experience from being integrated into the machine.

This reductionist representation is appropriate for well-structured and defined domains which can be expressed in terms of necessary and sufficient conditions, but as Thomasset (1996) has said, the translation of law into logical formalism has proved disappointing, especially for reasoning in real cases.

Hofstadter in “the Boolean dream” (1985) has demonstrated the limits of this reductionist approach. The reductionist paradigm, until now coinciding with the scientific approach itself, has now been superseded by the sciences of complexity which purport to describe reality as it is (or can be reconstructed for an experiment) and not as people would like it to be.

2. Dynamic Patterns: An Alternative to Rule-Based Legal Models

The cognitive activity underlying our systems of representation, including the law, can be seen in other terms than logical inferences, as in propositional logic or predicate calculus. System dynamics shows that structured forms of organization can emerge through self-organization. These forms do not derive from a step-by-step, formal deductive process, but come about through a *shift in levels* in the global properties of the system.

The most advanced connectionist models put forward a theory where symbols arise through self-organization as meaningful macro-characteristics emerging from interactions between non-meaning-bearing micro-entities. Hence the importance of the concept of *level of organization.*

2.1. A DEFINITION OF "DYNAMIC PATTERNS"

In reaction to traditional logic, a new more dynamic vision is emerging, which considers symbols in terms of their spatio-temporal dimension (Kelso 1995).

> I envisage the brain as a constantly shifting dynamic system; more like the flow of a river in which patterns emerge and disappear, than a static landscape .... Like a river whose eddies, vortices, and turbulent structures do not exist independently of the flow itself. Mental things, symbols and the like, do not sit outside the brain as programmable entities, but are created by never ceasing dynamical activities of the brain .... Emergent properties are a significant feature of all complex systems in nature.

Due to the power of the computing *metaphor*, we have been used to think of mental structures in terms of addresses and logical operations. However, another vision is gaining ground in the cognitive sciences, which considers cognition in dynamic terms (Clergue 1997).

This approach forms part of the paradigm of complex systems and is based on simulations using networks of artificial neurons. This is the key element of interest in connectionist models, which gain further biological plausibility through Edelman's work on cognitive maps

> Although behavior and development appear structured, there are no structures. Although behavior and development appear rule-driven, there are no rules. *There is complexity*. There is a multiple, parallel, and continuously dynamic interplay of perception and action, and a system that, by its thermodynamic nature, seeks certain stable solutions. These solutions emerge from relations, not from design. When the elements of such complex systems cooperate, they give rise to behavior with a unitary character, and thus to the illusion of structure. But the order is always executory, rather than rule-driven, allowing for the enormous sensitivity and flexibility of behavior to organize and regroup around task and context .... We suggest that action and cognition are also emergent and not designed. (Thelen 1995)

Linda Thelen defines connectionist models as formalisms that produce theories which view cognition in terms of dynamic systems. Here is what she says about connectionism:

> Knowledge is assembled in real time, in context, from units that do not in and of themselves look like or contain the resultant knowledge.
>
> It views knowledge as a pattern in time as opposed to a structure, an object-like entity. We think of knowledge not as entity but as process. Processes may sometimes be in stable equilibrium and appear entity-like. But processes are dynamic; and are inherently temporal and thus changeable.
>
> It offers a potential resolution of the problem of the simultaneous global order of behavior and its local continuities and discontinuities. The explanatory power lies in the joint consideration of the micro and macro levels. *This is not traditional reductionism*. (Thelen 1995)

In the domain of law, neural networks appeared at the end of the 1980s (Warner 1989, 1993) (Van Opdorp et al. 1991) (Philipps 1989, 1991). The first motivation to seek out this modeling method stemmed from the understanding that the structure of the law does not correspond to a finite number of determinate concepts. Laws are made up both of computable parts and of open-structured parts, whose contents depend on interpretative discretion and application. This discretion by definition cannot be expressed as rules since it is a power to exercise judgment without the constraint of the law. For Warner, legal reasoning proceeds in a manner that takes into account the dynamic and fluid nature of the problem domain. In order, therefore, to represent the knowledge and processes involved, sequential processors or von Neuman machines cannot be used. It requires a model suited to handling parallel problem solving processes.

2.2. CONNECTIONISM AND LEGAL KNOWLEDGE

Up to now, AI research in the field of law has fastened on rule-based and case-based knowledge. Rule-based knowledge is ineffective for fields containing a large number of open-structured concepts which have to be filled in according to the circumstances of each case. The case-based approach used for solving conflicting and undetermined rules requires cases to be indexed on the basis of predefined features.

Both of these models require an *a priori* model.

An increasing number of legal researchers involved in cognitive modelling are attempting to build models which should generate their own heuristic techniques to improve the sensitivity of the network to various changes in the features; incremental changes between cases should be made automatically, following the judges' decisions. This model is linked to the auto-poiesis paradigm.

Indeed knowledge sources are not homogeneous in the legal field. In addition to statute law (written in the form of *static* rules), case law consists of a set of cases identifying features which are characteristic of the legal problem, and these cases are subsumed under concepts or *dynamically* compared with precedents. For Luhmann (1985), the legal system is circular: the decisions create norms, and norms create decisions. Certain interactions derive from legislative rules, while others operate through successive equilibrations and the self-construction of patterns. This means that rules stemming from statute texts and rules derived from practice and practical needs operate all at the same time. The mind does not simply *create* rules but also *compose* rules for action if these actions seem more effective. The judge or the administrative decision-maker interprets the facts and the rules in such a way as to render the activity of judging sensitive to the environment. This dynamic process of adaptation is also called case-law or *jurisprudence* (in French). There is a radical opposition between the positivist conception of the law and the idea of law which emerges from a set of individual decisions and interactions with several systems of constraints. This opposition is the subject of an ongoing discussion in the theory of law.

For these reasons, Artificial Neural Networks have become a privileged tool for the study of case law. They have been applied for the functions of classification, approximation or grouping together of facts and cases (Isik 1996). In the administrative domain, the function of classification serves to check the accuracy of decisions which have already been taken: for example, choosing the residence of a person requesting a foreign vehicle registration, classifying the criteria for deducting VAT, distinguishing between tax schemes for wage-earners and non wage-earners. They form an "aid for interpreting the conditions fixed by the ruling" (Karpf 1991).

2.3. THE NEUROLEX EXPERIMENT

We have conducted an experiment which applies neural networks to the judicial review of administrative decisions (local by-laws). We summarize the underlying assumptions of the model .

NEUROLEX is designed to extract legal decision rules from a multilayer neural network. We examined a corpus of municipal law decisions consisting of 378 judgments of the Council of State concerning the validity of by-laws made by mayors in the field of public order. NEUROLEX is a supervised network. The output layer of the network consisted of two units: the decision to declare void or valid the initial by-law. The input vector consisted of variables that are distributed across four subsets: regulations, types of by-laws, factual circumstances and normative standards.

The NEUROLEX model draws on an "equivalence principle" stating that connectionist classifiers are functionally equivalent to a set of logical rules. We hypothesized that the most efficient method for extracting the logical rules would be implicit enumeration using constraints propagation methods.

But the extraction of relevant knowledge presupposes at the outset the delimitation of a validity domain. A validity domain is related to the idea that there exists an area of the training base on which the generalization works well. In NEUROLEX, the validity domain is thus determined on the basis of the statistical regularities observed from the training rule. In other models, it can be determined from *a priori* knowledge, either related to the data coding or formulated by a human expert. In NEUROLEX, we have derived constraints on the input hypercube of the neural network. This enables the initial cardinality (complexity) of the domain to be reduced.

After studying a satisfying validity domain, we derived a set of equivalent clauses such as:

directing-traffic AND public-order AND NOT closingup-road $\Rightarrow$ abuse-power

This rule would be translated as follows:

"In the domain of directing traffic and in a factual situation relative to the standard of public order, the Council of State judge comes to the conclusion that the only local decision which does not represent an abuse of power (i.e., an illegal by-law) would be the closure of the road".

More than one thousand "equivalent logical rules" could be extracted and analyzed by experts. More importantly, the interpretation of the extracted rules led us to classify *five types of clauses* concerning our previous example of traffic regulation:

- Confirming explicit legal rules of the statutes (the judge applies statutes)
- Adding conditions to explicit legal rules (the judge details statutes)
- Confirming general, explicit principles (the judge confirms his own general principles)
- Extracting new rules (the judge creates regularities by recurrent reasoning on facts)
- Extracting meta-knowledge (the judge creates new general principles).

This experiment – technical details may be found in Bochereau, Bourcier, and Bourgine (1991) – has shown that a neural network is able to learn the weightings from a set of legal decisions. Equivalent logical rules can be extracted and processed. The extracted rules enable one to check how the case was analysed in instances where discretionary power was involved in the decision-making process. The network can thus extract implicit decision-making rules that *even an expert* could not have formulated because he has no means of access to them. More importantly, the system can evaluate whether the probability of a judge's voiding a by-law is greater than the probability of his reaching the opposite decision.

2.4. LIMITS OF NEUROLEX

The first objective in our experiment was to test the efficiency of methods for extracting expertise. But experts in fact found it difficult to read these rules. We submitted the results to judges, but apart from *formula* in the manner of series of many terms and boolean separators such as IF a AND NOT b AND c AND d IF NOT e THEN f, they were unable to "understand" and validate the rules. So, because the model did not claim to find *universal* applicable rules, there is little point in using neural networks for translating weights into rules for a rule-based system. Moreover, due to the reduction of decision-making process into logical formulae, the network paradoxically lost its capacity to "represent" the fluidity and continuity of the learning process. The system *reproduces* the learning rules but does not *learn* from the exercise of judgment: it cannot therefore be considered as *dynamic* because the time dimension is not taken into account.

Let us look at the "lessons" formulated by Hunter (1996) on neural networks in law. For him, the limits include: the lack of explanations provided by the system, the number of cases needed to "train" the learning base, the choice of cases, and the choice of attributes. We shall look at these various criticisms in relation to NEUROLEX.

Neural networks cannot explain their own reasoning; they operate like a black box. In our experiment, we did not use the network to classify rulings but in order to discover *regularities in decisions* (Bourcier 1995). This is what Warner has to say on neural networks, which could be used specifically:

> . . . to explore those areas of legal reasoning that are in truth the most fluid and dynamic . . . . Once then, the norms have been discovered, they can be applied in a far more formal fashion. The new norms can be added in a knowledge base of the intelligent knowledge-based system and applied to determine the result to be arrived at in light of the facts presented.

It is possible to explain the conclusions by building a dependence network between formal neurons, which generates *If* . . . . *Then* rules. But these rules are unable to be used as planned for a knowledge-based system since they were more like the "quick and dirty rules" used to trim the work of an expert (system).

In response to the objection that the network can only "learn" from a large number of cases, we would reply that it is possible to reduce the generalization of the results by *constructing a validity domain* limited to the rules obtained. One can also calculate the number of cases needed to train the network properly. Ideally, the network does not need thousands of cases but only *a certain number*, corresponding to the number of facts introduced in the input layer. This number can be calculated.

The argument on the bias in the learning base is valid, since the choice of a reference corpus is always arbitrary. We chose published cases, which were already pre-selected by the Council of State. These cases are therefore not *hypotheticals*. However, since the Council of State is a high court which directs the policy of lower courts, these cases can also be considered as prototypical, representing the key successive steps of jurisdictional policy making "right at the top".

Lastly, the argument pertaining to the "the descriptive power of the paradigm" is relevant. The rulings from a higher court (in France) have fairly poor descriptions of the facts. The Council only describes the facts in so far as they relate to concepts or principles and not as raw facts. The decisions are therefore highly standardized. This also means that identifying new features (which appear at certain stages in the development of case law) can be the only method for extracting new rules.

Hunter's final objection focuses on the choice of input attributes. In the case of NEUROLEX, we would have liked to take the factual data before it reached the court – i.e., directly from the trial record. But we were denied access. Moreover, by choosing facts unknown to the judge, we would have biased our analysis of the decision-making rules that he used. An alternative would have been to take the whole vocabulary of the case (or the summary) as full text in the input layer. But we did not have a large enough corpus from the Council of State, since in the field of municipal law, there were unfortunately not enough decided cases since 1920.

3. In Search of Other Connectionist Models

Because of the objections to neural networks based upon the multi-layer perceptron approach, we decided to look for other models, better adapted to the problems raised by the theory of legal knowledge. Given the focus of our research, we realized that dynamic models might shed new light on questions that lawyers are asking about how their methods of reasoning evolve. In fact, a law case always seeks to solve the conflict between two arguments. Usually the court uses an argument which corresponds either to the application of the law or to its own case law (known in French law as "jurisprudence constante"). But at certain moments, under pressure from events or due to developments in the problem, the court is forced to change its own argumentation. This shift can either occur abruptly through the radical adoption of a new approach, or on the contrary, there may be a more gradual move between the "states" of case law, with visible symptoms in the arguments of the parties that the judge has to examine. It can therefore be hypothesized that using fine-tuned dynamic models, it should be possible to *observe* case law as *"forms in progress"* by tracing the dynamic evolution of the linguistic symbols and structures (words or syntagms). A *turnaround* in case law then becomes a "moment" which is particularly interesting to study from the point of view of how argumentative disorder is reorganized into a new conceptual order.

The theories of complexity help us in understanding this dynamic in cognitive systems through the phase transitions typical of self-organized systems. The various aspects of cognition are not due to the juxtaposition of different systems of organization, but result from the *emergence* of different levels of organization within a single system. The cognitive system, which represents a stream of mental images and concepts varying over time, can be compared to a surface of energy contoured with hills and valleys. The categories are fractal-dimension attractors towards which these images converge and stabilize. This cognitive landscape is a phase space which transforms over time, and the attraction basins are remodeled each time an individual's experience is either enriched or changes (Kelso 1991, 1995). These attraction basins can be thought of as "concepts" about which the judge will eventually have to make decisions.

Take, for example, the Hopfield network. This is a connectionist model which includes the time dimension. In this perspective, categorization (which helps recognize a pattern as either belonging or not to a category) is no longer a *yes or no* question, but a process of convergence towards a stable state, once the system has emerged from the indecision area between two categories, known as the "saddle point" in a landscape of states. In this case, categorization is like a pathway through a phase space in which the fundamental concept of *Content Addressable Memory* applied to the Hopfield network gives a perfect account of the stationary dynamics (Hopfield 1988).

The attractor is a symbol reached by the system during the relaxation stage when it converges on a fixed point. And the length of time taken to converge reflects the difficulties of reaching this symbol from the initial state. Unintended symbols also sometimes emerge. But isn't this exactly how the judge reasons when he has to choose between several decisions about concepts?

> By dynamical systems theory, I mean the study of sets of numerical variables (e.g. activation levels) that evolve in time in parallel and interact through differential equations .... Mathematical characterizations of dynamical systems that formalize the insights of the subsymbolic paradigm would be most helpful in developing the paradigm. Smolensky (McClelland, 1986)

This sort of theory can give a new stimulus to the analysis of how case law develops by studying the modalities which cause cognitive systems to self-organize. In addition to knowledge that is structured in rigid propositional symbols, and to which legal theory gives an almost exclusive place, there are also forms of reasoning processes which use other more subtle and more *dynamic* types of representations.

Let us now take another model, Kohonen's maps. Kohonen published a first article on this subject, entitled "*Self-organized Formation of Topologically Correct Feature Maps*" (Kohonen, 1982). It was followed two years later by "*Self-Organization and Associative Memory*". The expression used to describe this model (*Self-Organizing Maps* or SOM) underscores the active nature of the process that occurs in these maps. And they are indeed maps, since the topological organization of the units plays a key role.

A Self-Organizing Map is a two-dimensional topographic representation of input data of N dimensional vectors. The data belonging to the same category find themselves next to each other in the topographic space. The way the data are organized is preserved in their representation and they are known as "*topology-preserving maps*" or "*topographic feature maps*". Kohonen networks therefore help to visualize the classification of patterns (Herault and Jutten, 1994).

Developments in the neurosciences, the psychology of learning and in the observation of *cognitive and social* systems suggest that the symbolic paradigm and its underlying computational model of knowledge should be re-assessed in some AI approach using natural language as "mirroring the decision making process". The key issue therefore is now to find a new solution specifying how knowledge is structured on the basis of what our language capacities reveal.

This solution should exist provided we base this structuring process in dynamic systems and in spatio-temporal representations. The idea of symbols being processed as continually variable signals is based on the connectionist model. In Kohonen's self-organizing layers, space is structured symbolically. Each hill represents the emergence of a concept whose flanks define the scope of the semantic field. In the models put forward by Hopfield (1988) and Freeman (1987), it can be seen that structure can emerge from temporality in the *succession of the system behaviors*, i.e., through more or less stable dynamics.

4. Observing the Process of a Reversal in Case-Law: The Emergence of a New Concept through Lexical Self-Organization

We propose to use a dynamic model which is able to represent not only the rules which emerge from the process of legally analysing a case (NEUROLEX's goal), but also the *way* in which such a process evolves from one concept to another. NEUROLEX had aimed to represent the state of a corpus of decisions (statics). We propose to make "visual" the formation of case-law (dynamics). Data have been extracted of a full-text legal data bank and will be formalized and processed by a Self-Organizing Map in the following way.

We have chosen a domain of private law, to wit surety or guarantee, that is the undertaking of a third party to pay a debt, should the principal debtor fail to pay the creditor. This involves a three-party relationship, in which the guarantor's undertaking is supplemental to the main debt relationship between debtor and creditor.

In 1982, after several years of hesitation, the French Cour de cassation (civil Supreme Court) recognised a new variant of this institution called the *garantie à première demande* (first request guarantee). By this arrangement, the third party guarantor undertakes to pay the guaranteed sum of money *unconditionally upon request*. The guarantee takes the form of a simple letter and stands entirely apart from the main contract between debtor and creditor. This turnabout entails an entirely new reading of a whole line of earlier precedents on guarantees.

We used a very large set of texts (full text) taken from the LEXIS database on French law to trace the development of the *forms* as they could be observed through the text (words and phrases) the Court uses. What we observe can be cast in the form of a lexical map of the different concepts involved – security, delegation, and guarantee, as these terms are used in the Court's decisions.

The notion of *first request guarantee* did not emerge "out of the blue" from the judge's mind. It gradually made its way into usage, first from the outside (most other legal systems had already adopted it), then from the inside, through the retro-fitting of lexical sets around concepts.

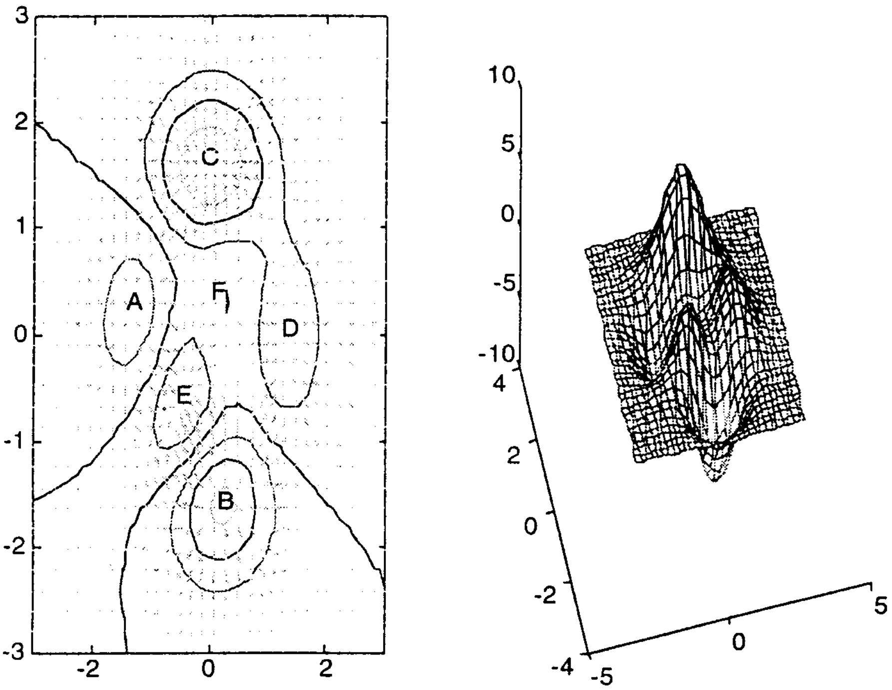
During the first stage (from 1970 to 1975), the words "GUARANTEE", "FIRST", "REQUEST" are found scattered without apparent order throughout the judgments. On the one hand, if one queries the database about all three terms together, using a co-occurrence operator, no document is returned in reply. On the other hand, the rival concepts of "DELEGATION" and "SECURITY" were numerous in the documents in reply.

Starting in 1980, these concepts (DELEGATION and SECURITY) gradually disappeared from the decision.

At the same time, the semantic network around the emerging concept of "first request guarantee" was enriched with facts and arguments used by litigants. The arguments cite items from the facts of the cases by extracting such expressions as "guarantee" "first letter", "on my first request", etc.). And the terms "GUARAN-

TEE", "FIRST" and "REQUEST" are gradually joined. The new concept finally stabilized in two leading cases in 1982. The case law dealing with the now firmly established concept of "FIRST REQUEST GUARANTEE" doubled in the five years following 1984.

The test was carried out using existing argumentative "forms", which produce a network around each concept. The emergence of a new concept becomes visible through a dynamic process of self-organization around the gradually-forming attraction basins. Scattered forms upset the equilibrium, fall into a attraction basin and become "fixed" at a given moment. The items are no longer under discussion, and they disappear from the argumentation. But they are discussed until the concept is firmly established. In fact, the text self-organizes to allow a concept to appear. This, in turn, will then enable the network to relax.



The above diagram[2] illustrates how the above described processes of emergence might be simulated. There are two relatively deep attraction basins: A and B. These basins are isolated from each other by the peaks C, D, and E, and by the slopes which indicate the areas of indecision between them. In terms of system dynamics, these are the saddle-points of the phase space.

[2] Graphics from MATLAB using an aleatory number matrix (Gaussian distribution) with the QUIVER (X, Y, U, V) function which automatically draws the "velocity vectors" with the (u, v) components to points (x, y).

Let us imagine that basin A represents the concept of “DELEGATION” and basin B the concept of “CAUTION” (security in English). Basin F is hardly visible in the landscape and could model the emergence of the concept in the process of being created of “FIRST REQUEST GUARANTEE”. In this conception, the dynamical system embedded in the corpus of Court decisions would find its course by taking into account the competing attraction zones and the unstable areas between these zones. In other words, these represent the successive arguments and parallels which will eventually contribute to the turnabout in the line of cases.

In this last generation of neural networks (implementing Self-Organizing Maps), it is therefore possible to show how structure can emerge from a succession of the system behaviors, through more or less stable dynamics. These models can explain how a system can change qualitatively without external control. The system chooses the best adaptive response as the environment changes.

In this approach, insights into the nature of legal reasoning should focus more on the representation of *transition* between determinate concepts than on the relationship between determinate and open-structured concepts. We hope to show during the next stage of this research that this approach provides an alternative to the logical representation of legal knowledge and a means to display the dynamics of time in judicial creativity.

5. Conclusion

In this article we have attempted to analyze how different cognitive learning models can be utilized in the representation of legal knowledge. We have examined the reductionist approach to representation, as adopted in a logical formalisms. We have also shown the limitations of the first experiments in using connectionist models in law. Models derived from these but based on non-linear dynamic models seem to offer new perspectives for representing such unstable legal phenomena as the evolution of case law. The question is whether the processing of complexity using self-organizing models can be applied to legal systems.

It is one of the interesting paradoxes of knowledge that humans are capable at once of recognizing in the real world what has already been learnt and of inventing new conceptual frameworks to adapt to that reality (Grossberg 1987). In other words, humans know when to assimilate a set of data to a learnt form, as well as when to adapt existing frameworks to integrate new data (Piaget 1975). We define complexity as the emergent property of non-linear systems at the interface between stability and instability. It forms the new frontier for scientific thought, massively under strain from reductionist determinism. The theory of determinist chaos (Bergé 1994) shows than order and disorder can co-exist, and that a minute change in one of the parameters can make systems which are extremely sensitive to initial states suddenly diverge.

This theory opens new research areas for analyzing legal systems in terms of dynamic evolution rather than sudden radical shifts.

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