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SIMULATION OF VERDICTS IN CIVIL LIABILITY

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Abstract

Using Neural Networks we have simulated judge's sentences in the field of Civil Liability Relating to Motor Vehicles. Our Neural model has been able to pass correct sentences which respect the laws and the principle of equity. The net has learnt how to judge. In fact, it has drawn out sentences equal to court precedents which were not in the training set. The back propagation procedure has calculated sets of weight which give out new information showing and quantifying the relevance of each element of guiltiness.

Our experiment demonstrates that the net is able to better manipulate the simbols than the expert systems do because it learns from training procedure both logical rules and analogical quantifications. In our opinion it is very difficult to simulate any subjective judgement without using both rules.

1. Introduction

With this experiment, we want to demonstrate the possibility of the neural nets to simulate human judgment. We would like to point out briefly that it is possible to use the nets to a symbolic manipolation (Kosko, B. 1992).

We have simulated a typical subjective judgment to prove it. One of the most typical subjective judgments is when the judge ascribes the liability for the car accidents. That judgement originates from observing the logical rules (Rules of the Road) and from a subjective method of appraisal which is unwritten result of experience.

In our opinion the application of the neural nets in that field is very appropriate. As a matter of fact, it is not possible to judge an accident basing only on logical rules. In fact, the other experiments, which have been trying to demonstrate the liability and have been carried out using the other systems of artificial intelligence, have failed (Reisinger,L. 1981).

2. The Experimental Part

We have gathered 200 judicial precedents regarding judgement for accidents between two vehicles A and B that have occurred at intersections. They made up 70% of survey on Civil Liability Relating to Motor Vehicles (Alpa,G. & Bessone,M., 1982). Such judicial decisions have been codified through a large number of logical variables, representing the description of the accident and the following liability ascribed by the judge. The accident has been described using indexes regarding the place the accident occurs (intersection, stop signal, etc.) and the behaviour of the drivers involved (speed, overtaking, carelessness etc.). Afterwards we selected a small number of variables that could indicate all the accidents with a certain approximations.

Since one of the driver at an intersection has to give right of the way, coming from the right side, or from a minor priority road, in our simbolic representation, Driver A always has right of way and Driver B is always obliged to give right of way to vehicle A. Furthermore, another variable has been used (Stop B) to indicate whether Driver B had to stop in addition to giving right of way to vehicle A,

according to the stop sign.
The behavior of each driver (A and B) involved has been represented by three variables. The first one (speeding) indicates whether the driver was speeding close to intersection, infringing art. 102 of Italian Higway Code.
The second variable (Carelessness) represents other breaches of the Highway Code (such as overtaking, driving off the carriageway) and elements of more general blame as resklessness and negligence of the driver (dangerous driving, carelessness, etc.). The third variable indicates the lack of skill of the driver, meaning his or her technical incapacity to prevent the accident from occurring using fitting emergency manoeuvres which a good driver could have been able to execute.
In description of the accident, seven variables have been sufficient, one indicating the presence or absence of stop signal, two group of variables respectively representing A's and B's offences.
Two numerical variables have been used to represent the judgement in terms of the quantitative attribution of blame and of liability. Such variables indicate the percentage of liability of each driver involved.

3. The Architecture and the Training of the Net

The neural net has been dividend into seven inputs, six hidden cells and two output cells [Fig. 1]. The input values represent the description of the accident and the output values the evaluation of the liability given in percentage to Driver A and B. The number of necessary hidden cells has been selected empirically. Each cell has been connected with all cells of the layer above with a sigmoid transfer function.
The net has been trained trought a set of eighty typical judgements, in which we supposed that the judge applied specifically to the field of C.L.M.V. not only the information contained in the legal provisions, but also af all the knowledge that is not included in them. The net has been trained with the back propagation procedure using the Delta Rule (Rumelhart, D.E. & McClelland, J.L. 1986) function for 8000 cycles with a learning rate of 0,2.
After training, the net has learned all the sample decisions with minimum error. This means that the backpropagation method has calculated a set of weight between the connections able to present all the given judgements.

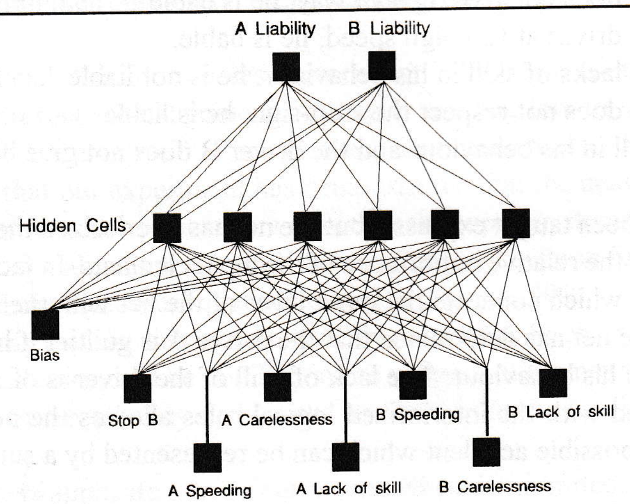

Figure 1: Structure of the neural network judging car accidents.

4. Experimental Results

The judgement meter calculated by the net allows us to judge all the possible accidents, that can be represented through the provisions with repetition of seven variables of class two (true-false).

The judgements given for the cases that have been foreseen in training appeared to be similar to case precedents and, anyway, were always reasonable acceptable.

Two phenomena can be underlined from the analysis of the judgements of the nets:

1) the net judges a case having one or more similar precedents, not by repeating or making an average of the judgements gathered (in training), but considers as more biased those precedents (even if a little different) in which the judge's evaluations appeared to be more suitable to the general evaluation principles of court precedents.

2) the net also draws out judgements in cases differing from the ones that have been gathered.

It is interesting the net verdict drawn out from the set of data representing accidents in which the driver of the vehicle with right of way is responsible only for lack of skill in his or her behaviour, basically meaning that he or she did not make the proper emergency manoeuvres an ''average driver'' would have performed. In this case whatever the offence Driver B committed (he or she had to give the way), the neural nets decides that Driver A has no liability whatsover.

The lack of skill alone of the driver is of no influence in determining liability, the same as court precedents unknown to the net (Court of Cassation, Rome, 6.3.1991).

This outcome shows that the net has learned ''legal knowledge'' that is unwritten and unforeseen in programming, and the actual relationship of importance that connect the rules one to the other depending on the described facts which are also unknown.

5. Analysis of the results

From the juridical point of view the net deducts extremely correct sentences. In fact, these nets respect every rule of the road and the net's solution does not seem to be unreasonable or incompatible with legislation or equity.

But how can the net reproduct all the judge's sentences without introducing all the logical rules (laws), used when a judge ascribes the liability to somebody ?

In our opinion, after the training, a set of weights is able to represent also a logical rules:

1)If the driver of the vehicle does not give right of way, he is liable.

2)If the driver of the vehicle drives at too high speed, he is liable.

3)If the driver of the vehicle lacks of skill in his behaviour, he is not liable.

4)If the driver of the vehicle does not respect the stop-sign, he is liable.

5)If the driver A lacks of skill in his behaviour and the driver B does not give him right of way, the driver B is liable. Etc.

These logical rules have not been taught expressly but the net has interiorized them through training.

The model is able to quantify the relative importance of the input elements. In fact, we can see in Fig. 2 the average of the weights which connects the input layer of the net with the hidden cells.

The picture shows us that the net has determined that the driver A is guiltier if he drives at too high speed than if he is careless in his behaviour. The lack of skill of the driver is of no importance.

This quantification associated with the interiorized logical rules allowes the net to infer the right quantity of liability in every possible accident which can be represented by a simple model.

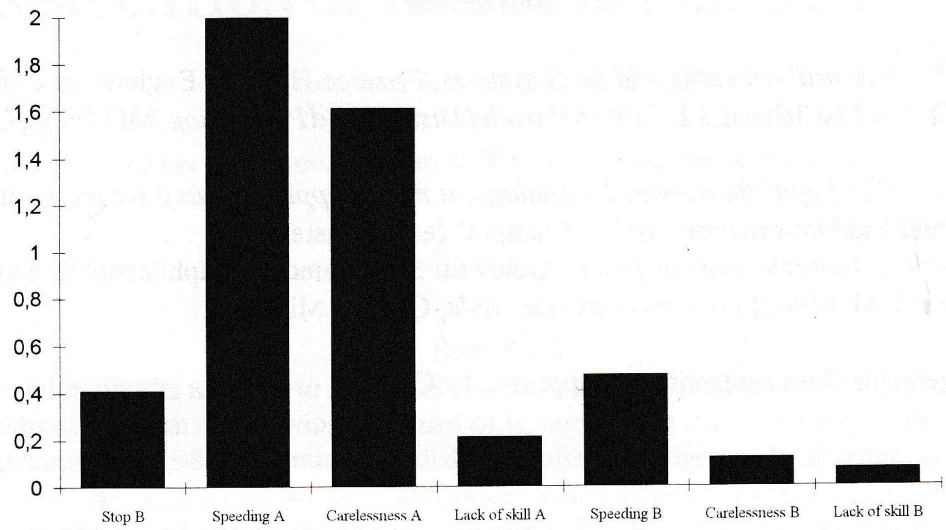

Fig.2: Average of the weights which connects the input layer of the net with the hidden cells.

6. Conclusion

We suppose to have reached two goals with our experiment:

Firstly, we have demonstrated the possibility that the judge can be replaced by a well-trained neural net. This net must respect laws, rules and a unit of value applicated by judges.

Such a neural judgement would be useful at least in the judgement of first instance and would guarantee the same judgement for every case. In fact, it is not very unusual that two different judges give two different evaluations for the same accident.

The computerization of the judgement proposed herein does not totally replace the judge's work, some points being difficoult to computerize and representing the limit of this research. These are:

1. Cases that have particular and complex aspects, involving several branches of law, the automation of which can be programmed only after the automation of all the field that are involved with the specific case.

2. Sometimes a judicial decision creates a precedent. This innovation is very important for legal regulations as it represents the alignment of already existing law to social reality. The neural net proposed herein is ''conservative'': it brings every new case back to the logic of his precedents.

Secondly, we think that our experiment has demonstrated that the neural nets constitute a model of a symbolic manipulation which is more powerful than the expert systems. Whereas the expert systems applicate a series of logical rules, the neural nets are able to calculate a function which represents both the logical rules and the analogical quantification (Phillips,L.1991).

First of all, we may say that the nets induce a rule from training. Such a rule, which is able to represent logical and analogical rules, will be codified in the weights of the neural net connections.

Afterwards, during the recall, they deduce the answers from the application of the rule induced by experience.

In our opinion the nets applicate a two degree process (induction-deduction) which can be used not only for a direct interpretation of the reality (video images, sounds and so on) but also for a manipulation and for a symbolic reasoning.

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SIMULATION OF HUMAN HEDONIC CHOICES

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Abstract

Neural networks are able to learn structures by using typical examples of this structure as input, without necessarily knowing the rules of it, even if the data are fuzzy (Rumelhart, D.E. & McClelland, J.L.1986). Human like/dislike choices are the result of complex perceptions whose components are not known or quantifiable in their importance in decision making: this is the case for example when tasting foodstuffs (Frijters, J.E.R., 1988). Using neural networks we have simulated a human subjective choice of taste employing as input chemical data and as output the taster's choice of a Panel test about the quality of wines and oils. The nets, after training cycles with a few examples, were able to give responses to the quality of all samples with little percentage judgement difference compared to each taster and related to the average Panel's judgement. The nets worked out sets of weights that give out new information showing and quantifying the relevance of each set of input data for the individual taster's choice.

1 Introduction

Several tests have shown the particular ability of the nets, in comparison with normal algorithms, in simulating human perception (Churchland, P.S. & Sejnowski, T.J., 1992). The most researched field is that of visual cognition, where the computer should be able to recognize an object when there is a lack of information about its definition or if the bounds of it are not geometrically described (Lisberger, S.G. & Sejnowski, T.J.,1992). In a hedonic choice the computer can make a further perception step: on the basis of an already known perception, that is, of a classification already having occurred, the net should be able to work out a judgement of taste for each specific similar perception, at least saying whether the object is a good or a bad one.

The chemical analysis of foodstuffs alone generally doesn't allow inductive judgements about the individual taster's choice. The analysis performed by the sense evaluates those qualities that are not provided by the chemical analysis, even the most advanced, probably because the compound of sense information produced by the nervous system allows us to perceive those relations between sensations that are insignificant if considered separately (Wold,S. et al., 1983). Furthermore, the simulation of individual taste choices has not been sufficiently researched in AI, whereas the importance of such individual preferences is well known in decision making (Slovic, P., 1990).

The advantages of such applications are to be seen in an improvement of evaluation criteria of goods based on an increased objectivity of judgement. The computer in fact is not affected by those influences (i.e. tiredness, prejudice etc.) that can create errors in evaluation. Another advantage comes from the possibility of a standardization of judgement evaluation, because computers allow a better control of the experimental conditions and therefore a higher repeatability. This is especially true if we consider that the Panel test is now a fundamental criterion, at least in the European Community, for the trademark attribution of certain goods, as for example in the case of oil when attributing the "extra virgin olive oil". trade mark (Regulation EC, 1987).

2 Model Description

Representative samples of wines (n°150) and olive oils (n°67) were submitted to net judgement using analytical data produced by official analysis methods. The analytical parameters we chose were for wines: Density, Alcoholic degree, Total alcoholic degree, Total reductor sugar, Dry extract, Total acidity, Volatile acidity, Ph, Ash, Total sulphur dioxide, Free sulphur dioxide, Methyl alcohol; for oils: Acidity, Polyphenols, Peroxides, $UV = K_{270}$ and $\Delta K = K_{268} - \left[\frac{(K_{262} + K_{274})}{2}\right]$

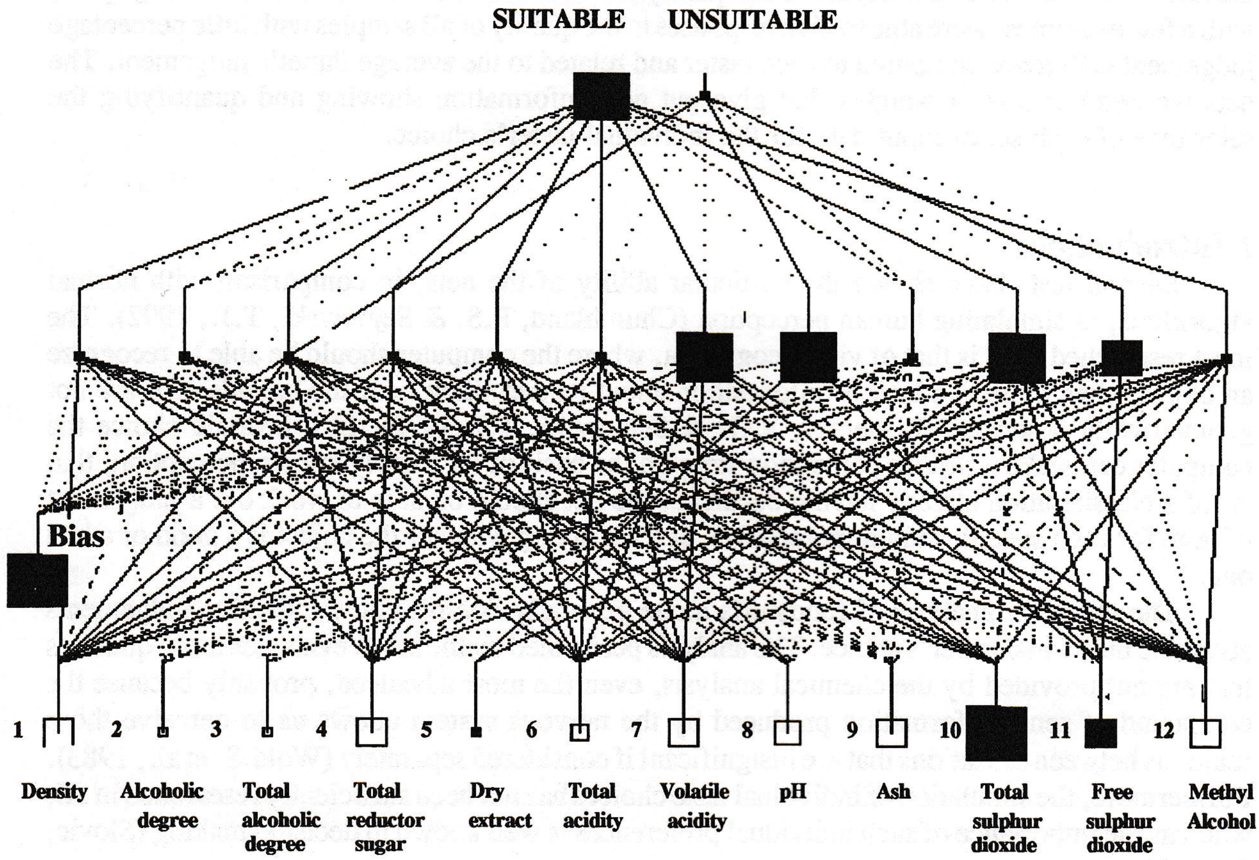

FIGURE 1: Structure of the neural network judging the suitability of a wine for the quality trademark. The 12 input units represent the chemical analisys of the wine, the two output units give out the suitability for the quality trade mark. The net is able to judge with a difference of 20% compared with the average judgements of a Panel, but with a percentage slightly over the one given by each Panel member.

The same samples were submitted to a Panel test. The wine net was made up of 12 nodes in input, 12 hidden and 2 nodes in output; and the net for oil of 5 nodes in input, 5 hidden and 1 node in output. The input data were given by the analytical values that have previously been indicated. The output data show a comparison with the judgements of the Panel of tasters and indicate whether that sample of wine or oil is suitable for the quality trademark.

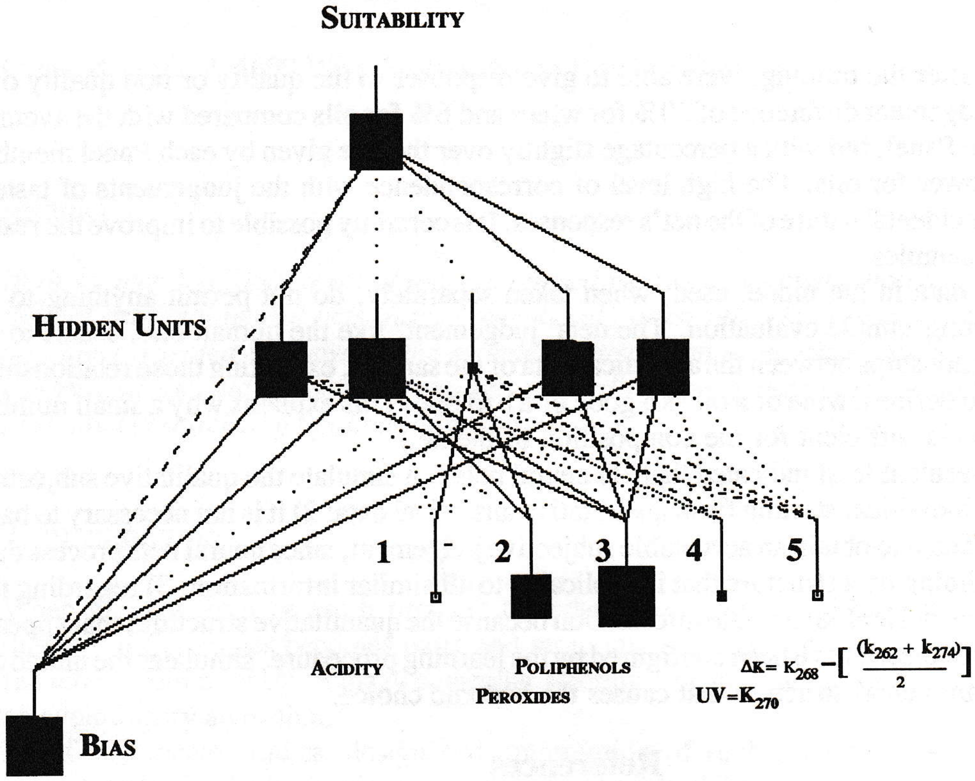

FIGURE 2: Structure of the network judging the suitability of a oil for the "extra virgin olive oil" trade mark. The net is able to judge with a difference of 6% compared with the average judgements of a Panel, but with a lower percentage compared to the one given by each Panel member.

The nets were trained through a set of 10 prototypical samples for the wines and 20 for the oils, with the back- propagation procedure using the 'delta rule' and sigmoid functions for 1,000,000 cycles.

Regarding wines, for the hedonic choice the net considers the following data important: Free sulphur dioxide, Total sulphur dioxide, Ash, pH. It is interesting to note that in commodity science a number of studies have attempted to show the existence of these correlations without however reaching an acceptable conclusion. Because this induction by the net of the principal components of the subjective judgement of a wine is interesting, we therefore tried to reproduce it in the field of olive oils where such correlations were in part already known.

The data that the net considers important for the subjective evaluation of oils are the polyphenols content and the value of peroxides. It is known that the polyphenols, natural anti-oxidants, preserve the aroma of the oils (Maga, J.A. 1978), while the peroxides are an index of the oxidation of the oils. It is interesting to note that this relationship is so reinforced in the net, that the cases in which the net was further from the taster's judgements are cases of oils in which the polyphenols and the peroxides gave a judgement that was opposite to the actual Panel one.

3 Discussion

The nets, after the training, were able to give responses to the quality or non quality of a sample with a judgement difference of 20% for wines and 6% for oils compared with the average judgement of the Panel, but with a percentage slightly over the one given by each Panel member for wines and lower for oils. The high level of correspondence with the judgements of tasters shows the non-accidental nature of the net's responses. It is certainly possible to improve the result by using larger samples.

The input data in the model used, when taken separately, do not permit anything to be inferred concerning sample evaluation. The nets' judgement, like the human one, seems to be based on the relationships between the analytical data of the sample, extracting those relationships that allow man to define a wine or a oil as a good or a bad one. This explains why a small number of analytical data is sufficient for the composition of the net.

This first result at least indicated that: 1) neural nets can simulate the qualitative subjective judgement of an individual starting from quantitative analytical data; 2) it is not necessary to have a large amount of data to obtain an acceptable subjective judgement, since neural nets process data analogically, building up a structure that is applicable to all similar information; 3) regarding the first point, a neural net is able to create information because the quantitative structure, that appears after the weights of the net have been configured by the learning procedure, simulates the unknown part of the human mental structure that causes the hedonic choice.

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