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STATISTICAL AND NEURAL APPROACHES TO SMART-MONEY DETERMINATION

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Abstract

This paper deals with methods to estimate smart-money, a domain which is both open textured and vague. Here, smart-money estimation is studied in three ways: first, cases are statistically analyzed, second, some computerized methods used in DOLOR are studied, and finally, neural networks are introduced as a means to make reliable smart-money estimates. In terms of modelling, both the statistical formula as well as the neural networks can account highly for the variance found in smart-money granted. Therefore, neural networks should be added to the DOLOR system as an additional method to make smart-money estimates.
Keywords: smart-money, vagueness, open texture, statistics, multiple regression, neural networks, backpropagation.

1 Introduction

Until 1943 it was unclear whether the term 'damages' in the then-current Civil Code also applied to immaterial damages, such as suffering and the loss of pleasures of life. However, in that year, the High Court ruled that a lower court's particular adjudication of smart-money was reasonable and fair (Van Kreuningen/Bessem, 21 May 1943, NJ 1943, 455). The concept of smart-money was now established, but the way it should be applied, that is, how the precise amount of smart-money should be determined for specific cases, had to be developed in case law.

Smart-money is an open textured and vague concept. It is open textured because, although a great deal is known about the factors that should be taken into account, there is no doubt that in extraordinary cases new factors may arise which prove to be relevant. Smart-money is also a vague concept because, even if all relevant factors are known, it is unclear how the factors should be weighted and combined to produce a precise sum of smart-money.

This paper provides an overview of research results with regard to smart-money. A particular advantage of using this domain is that cases have been exceptionally well documented since 1959 (cf. The smart-money book, 1991). This has inspired many persons, including researchers of the Computer/Law Institute, to analyze the available data on smart-money by means of statistical analysis. Results of statistical analyses are discussed in section 2. Section 3 discusses various computerized tools which support the process of making smart-money determinations for specific cases. These methods have actually been implemented in DOLOR, a system which supports judges, lawyers, insurers, and other parties who may be concerned with smart-money. Section 4 presents the results of applying neural networks to the problem of smart-money determination.

2 Statistical analyses

For years, the Computer/Law Institute has carried out statistical research on smart-money. Ferwerda (1987) started this line of research. Vollbehr (1989, 1990) analyzed a large number of cases and developed a method for estimating smart-money, a method which has been implemented in the DOLOR data base. In 1992, Groendijk carried out a new statistical analysis for the purpose of updating this method. With statistical analysis, insight can be gained into the question which factors are important for smart-money determination. Table 1 presents various factors and their correlation with smart-money granted. It is based on the statistical analysis of 398 cases taken from the DOLOR data base (Groendijk, 1992).

Factor	*Correlation*	*Variance explained*	*N*	*sig. p <*
Injury severity	.859	.737	398	.0001
Functional disablement	.854	.729	336	.0001
Duration of hospitalization	.568	.322	302	.0001
Duration unfitness for work	.447	.199	343	.0001
Scar scale (scars only)	.359	.129	133	.0001
Scar scale (full)	.218	.047	323	.0001
Age of claimant	-.208	.043	307	.0002
Life expectancy	.185	.034	305	.0011
male/female	.132	.017	395	.0085
decision date	-.009	.0	398	.8627

Table 1: Correlations between various factors and smart-money granted

For each case, the injury severity was scored by an authorized physician on a seven-point scale ranging from (1) slight injuries (e.g., bruises and grazes) to (7) phenomenal injuries (e.g., spinal court cut) (cf. The smart-money book, 1991). This score correlates very highly with smart-money granted. A positive correlation is not a surprise but it is remarkable that the correlation is actually this strong (.859). All the more so because on this two dimensional scale a large diversity of injuries is laid down. Functional disablement, expressed as a percentage, is quite a complex concept. Nevertheless, it is often used by insurers and others dealing with smart-money determination, because the determination of functional disablement is very well defined in the Guide to the Evaluation of Permanent Impairment.

With respect to duration of hospitalization, it appears that the more time the victim has spent in hospital or the more time the victim was unable to work due to the inflicted injuries, the more smart-money will be granted.

Scars are classified on a four-point scale. Again, scoring is performed by an authorized physician. There are four categories. Category 0 indicates that the injuries have not led to scars, category 1 denotes a single not very significant scar, category 2 denotes a single prominent scar of multiple scars and category 3 denotes severe scars or disfigurements of body or face. Two correlations are given. The first reference to scars in Table 1 applies to the correlation between scar scale and smart-money if indeed scars were present (only scores in categories 1, 2 and 3 included). The second reference to scars gives the correlation between smart-money granted and the full scar scale (category 0 included).

The factor age of the claimant correlates negatively with smart-money, that is, the older the claimant, the less smart-money will be granted. This effect is most prominent if combined with severe injuries, that is injuries for life. This is probably the case because the younger the claimant, the longer the injuries have to be dealt with. Age and gender can be combined to calculate a new factor: life expectancy. (Gender is important because females generally live longer than males.) In theory, ‘life expectancy’ offers a better measurement of time for suffering than age does, but apparently, since age correlates higher, judges prefer the somewhat more worldly age scale.

In terms of smart-money received, being male offers a very slight advantage over being female. There is no significant correlation between ‘decision date’ and smart-money. The statistical analysis uses indexed smart-money figures. Apparently, the increase of smart-money keeps pace with inflation.

In the research presented here, only a limited number of factors has been investigated. Moreover, most of these factors are objective. In the literature, the factors cited are more various and of a more personal, subjective nature (e.g., Knol, 1985). It would be interesting to investigate these factors as well. However, they are not provided by DOLOR. In this respect, the research by Pieters and Busschbach (1988) is worth mentioning here. On the promise not to disclose any details or the names of the providers, they managed to obtain a quite large number of files on amicable settlements with regard to smart-money by a number of insurance companies. From these files they were able to deduce a number of factors of a more personal and subjective nature. Their results are presented in Table 2.

	correlation	*variance explained*	*significant*
Career limitations	.3550	.126	yes
Cognitive neurological disturbances	.2075	.043	yes
Neurological disturbances of character	.1622	.026	yes
Recreational limitations	.2055	.042	yes
Psychological trauma	.1798	.032	yes
Occupation	.0444	.002	no
Loss of holiday	.0398	.002	no
Victim guilty	.0283	.001	no
Marrying opportunities decreased	-	-	-

Table 2: Correlations, proportion of variance explained and significance of various subjective factors and smart-money granted in amicable decisions[1]

Table 2 shows that the influence of most of these factors cannot be shown statistically significant, or that the proportion of variance explained by the factor is small. Obviously, in a single case, such a factor may be the crucial determinant of the smart-money granted. Of many factors, it is simply not clear whether they are important because they do not occur so often. For instance, ‘marrying opportunities decreased’ is a factor often cited in the literature, but the researchers could not investigate this factor because it was named in one case only.

[1] Adapted from Pieters and Busschbach (1989).

3 Computer-supported smart-money determination

The computer program DOLOR is basically an electronic version of the smart-money book. It offers three methods to determine smart-money: searching for similar cases, a formula created by the joint insurance companies, and using a prediction based on statistical analysis.

3.1 Searching for similar cases

One way to gain insight into appropriate amounts of smart-money is to search for similar cases in the DOLOR data base. DOLOR allows to make queries in which the factors can be combined in several ways. Factors may be placed in conjunctive or disjunctive fashion, and factors taking continuous values may be selected with a cut-off value. For instance, one can request all cases in which a male victim older than 21 was injured in class six. No research data are available on how valid smart-money estimates based on using the DOLOR data-base turn out. However, the impression is that data base searches only provide a general insight in the relevant factors and an approximate height.

3.2 The smart-money formula

In 1984, the Dutch Alliance of Insurers issued a guideline to help determine the amount of smart-money. The goals were to diminish the uncertainty around smart-money, to control increased costs and to standardize the amount payed (The smart-money report, 1984). This guideline provides the so-called 'smart-money formula'. The formula grants Dfl 15.- for every day the injured person has been in hospital, and Dfl 10.- for every day until consolidation (i.e., fully cured or a permanent but stable disablement). In case of permanent functional disablement, the formula grants another Dfl 400.- for every percent functional disablement and the product of Dfl 10.- for every percent functional disablement and the remaining statistically expected life span. The Dutch Alliance of Insurers limits the applicability of the formula to cases in which the victim has no permanent disablement or the disablement is between 3% and 30%. Furthermore, the formula is not applicable in case of damages of extraordinary nature, for instance, aesthetic damages (visual scars). Testing the smart-money formula to real data provides a correlation of .64 ($N=141$, $p<.0001$).

3.3 The statistical formula

Vollbehr (1989, 1990) statistically analyzed the DOLOR data base. The results led to a formula estimating the amount of smart-money, known in the DOLOR terminology as 'the statistical formula'. The statistical formula bases its prediction on other factors than the smart-money formula. Groendijk (1992) performed a new analysis in order to update the statistical formula. The data presented here stem from this investigation.

The statistical formula is based on the multiple regression method. A number of factors are combined to obtain a smart-money estimate. Because the injury category correlates the highest with smart-money ($N=398$; $r=.86$, $p<.001$), this factor is chosen as the main determinant. As explained before, many of the factors contain overlapping information. For instance, duration of hospitalization correlates with smart-money granted ($r=.57$, $N=302$, $p<.0001$) but also correlates with injury severity ($r=.46$, $N=302$, $p<.0001$). The inclusion of other factors in the formula is only meaningful for multiple regression if the information adds something new. To establish this, a so-called partial correlation coefficient can be calculated. In casu, the correlation between duration of hospitalization and smart-money with the influence of injury severity taken out (corr.= .26, $N=302$, $p<.0001$) is significant and can therefore be included in the formula. Age also proved to add a significant partial correlation (corr.=-.16, $N=307$, $p<.004$) and is therefore included in the formula. The inclusion of duration of hospitalization and age is limited to those injury categories in which these factors show a significant influence. For duration of hospitalization, these injury categories are the categories 2, 3, 5 and 6. Age is only included in categories 6 and 7 (injuries for life). The details of implementation of these results are specified in Groendijk (1992). The statistical formula requires the user to specify at least the applicable injury category. If duration of hospitalization is specified, the smart-money estimate is modified in the injury categories 2, 3, 5 and 6. The specification of age leads to an modification of the estimate in category 6 and 7. Testing the statistical formula to all cases in the data base, using the applicable factors, shows a correlation of .89 (N=398, p<.0001).

4 Neural networks applied

Applying the technique of neural networks to open texture has been done before (e.g., Opdorp *et al.*, 1991; Bench-Capon, 1993). The approach presented here is very similar to the approach taken by Bench-Capon. The main difference, however, is that he worked with hypothetical cases, whereas in this study the cases are real.

In setting up a neural network, it must be decided how the input factors and the output should be represented on the input and output layer. The input of the network is based on nine factors which are mapped on 28 nodes. These factors are: injury severity, functional disablement, duration of hospitalization, duration of unfitness for work, scars, gender, age, life expectancy and decision date. That is, all factors provided by DOLOR are used as input. A problem is that sometimes the values of particular factors are missing. Allowing only the cases which provide the values of all nine factors would lead to an unacceptable loss of cases. Neural networks can also learn from incomplete cases but then a method has to be designed to deal with incomplete data. The general approach taken here is to add for each factor a node which indicates whether the value of that factor is missing. The seven point scale of injury severity is mapped to seven nodes. Representation of a particular injury score is simply a matter of turning the right node on and the rest off. The four-point scar scale is represented similarly. Gender is represented by two nodes, that is one for male and one for female. The other factors, functional disability, duration of hospitalization, duration of unfitness for work, age, life expectancy and decision date, are continuous values and are simply represented using one node. Also associated with each factor is one node representing whether the quality expressed by the factor is indeed applicable. For instance, for the factor 'duration of hospitalization' this 'quality' node is fully activated if indeed the claimant has spent time in hospital. The output of the network is the smart-money granted. This value is mapped on one node of which an activation of 0.0 indicates no smart-money granted and an activation of 1.0 the highest amount of smart-money found in the data base.

Another decision relates to the number of hidden layers and hidden nodes in each of these layers. Experimentation quickly revealed that very good results could be obtained by using one hidden layer only with 14 hidden nodes in it.

Before discussing the experiments, we have to discuss what the network has to achieve. With regard to the statistical formula, the design process can be summarized as follows: first analyse all the data, then derive a model from the analysis results, and, finally, evaluate the model by using the data again. Approximately the same can be done by using neural networks. First, the network is trained, that is all cases are presented to the network sequentially, the output of the network is compared to the actual amount of smart-money granted, the weights of the network are modified according to the backpropagation algorithm and this procedure is repeated until the output of all cases is sufficiently close to the actual amounts of smart-money granted. Second, in doing so, the neural network develops an internal model of smart-money determination. Finally, the neural network is evaluated. Here, a difference arises with statistical methods. If the neural network is tested to all data again, it will almost inevitably lead, and indeed does as will be seen later, to high results. This is because in general backpropagation is not very constrained in finding a solution, whereas in statistics there are often inherent limitations, such as the linear relation assumed with respect to correlation. The more interesting question with neural networks is therefore how well the networks capabilities can be generalized, that is, how good the network's smart-money estimates are with regard to cases it has not been trained on.

As a tool in evaluating the outcome of the network, correlation is used again, that is the correlation between the outcomes of the network and the actually granted smart-money in the cases put forward to the network. Here, two correlations are of interest. First, the correlation for training cases: this number gives insight into how well the network has managed to learn the cases in the training set. Second, the correlation found with regard to the test set, a set of cases especially kept apart for evaluation. The latter number indicates how well the knowledge of the network can be generalized. In general, the correlation for unseen cases will be lower than the correlation for cases the network has been trained with. Obviously, the most interesting correlation is the correlation between actually granted smart-money and neural network estimates on cases the network has never seen before. In each of the experiments, 10% of the cases (i.e., 40 cases) were randomly drawn, excluded from the training session, and used for the evaluation.

A problem in evaluating the results of the network's design is that correlations between the networks output and the actually granted smart-money in the test cases vary with the content of the randomly chosen test set. Therefore, a special procedure was designed in which all cases take their turn in functioning as test case. The procedure is as follows. Initially, the cases are in a random order. Then the first 40 cases (i.e., case 1 to 40) are selected as test cases while the neural network is being trained on the remaining set of 358. This is repeated taking the second set of cases (i.e., case 41 to 80) and so on. By the tenth time, only 38 cases

	# runs	corr. training set	Var. expl. training set	# of cases training/test	corr. test set	Var. expl. test set
1	390	.947	.896	358/40	.935	.875
2	330	.952	.906	358/40	.828	.685
3	410	.95	.901	358/40	.823	.676
4	350	.955	.912	358/40	.844	.693
5	330	.947	.896	358/40	.971	.931
6	420	.947	.896	358/40	.887	.762
7	480	.943	.889	358/40	.892	.664
8	400	.952	.906	358/40	.824	.622
9	160	.943	.89	358/40	.860	.447
10	260	.950	.903	358/38	.804	.647

Table 3: Experiments to establish the generalization capability of the network for smart-money

are present in the test set because there are 398 cases in the data base. The results of the experiments are shown in Table 3. The columns on the left, on correlation and proportion variance explained, apply to the training set, the columns on the right to the test set consisting of unseen cases. Obviously, a final model which is actually to be used to support making estimations, should use all cases in the training set.

As can be seen in the third column of the table, the correlation between the network's output and the actually granted smart-money in the training cases varies only slightly (on average .948). This is understandable because apart from the fact that on each experiment a different set of 40 cases was taken out, the training sets are very much the same. In all experiments the correlation found is very close to .95. With respect to unseen cases, these networks perform also quite well. The lowest value found for correlation is .804, the highest .971, the average of all values being .867.

5 Conclusion

Table 4 provides an overall picture of the results on all the methods provided by DOLOR and the results of applying backpropagation to the problem of estimating smart-money.

Method used	*Correlation*	*Variance explained*	*N*	*sig. p <*
Searching for similar cases	n.a.	n.a.	n.a.	n.a.
Smart-money formula	.69	.47	102	.0001
Statistical formula	.89	.79	398	.0001
Backpropagation (training set)	.95	.90	10 x 358	.0001
Backpropagation (test set)	.87	.75	10 x 40	.0001

Table 4: Correlations between smart-money granted and the estimates of various methods

For various reasons, the test results cannot be compared directly. 'Searching for similar cases' cannot be compared to the other methods because no hard data on the performance of this method are available. A comparison of the smart-money formula on the one hand and the statistical formula and the backpropagation model on the other hand, is unfair because the smart-money formula is a normative formula, whereas the statistical formula and the backpropagation model are descriptive in nature. However, from the fact that highly descriptive models are possible and the fact that the smart-money formula scores less than these models, it can be concluded that the Dutch Alliance of Insurers has not really succeeded in making the smart-money formula the standard.

Also, the statistical formula and the backpropagation model cannot be compared directly. On the concrete level, a direct comparison is impossible because the statistical formula is evaluated on the same data set on which it was developed, whereas for neural networks, the evaluation includes an evaluation of test results with regard to unseen cases. Furthermore, the statistical formula uses only three factors whereas the neural network uses all factors available. On a more general level, a direct comparison of neural networks and statistics is hard because these paradigms are so different. For instance, in statistics, it is customary to ignore factors which are not statistically significant whereas with neural networks it is stressed that these factors taken together may provide additional information.

Nevertheless, within the context of DOLOR, the main objective is to support smart-money estimates by supplying a variety of methods. This way, the user is able to study smart-money from different perspectives. The performance of backpropagation is very comparable to the score of the statistical formula and can therefore be recommended as an additional method for smart-money estimation and therefore should be implemented in the DOLOR system.

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