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A model for the interpretation of verbal predictions

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There is a marked gap between the demands on forecasting and the results that numerical forecasting techniques usually can provide. It is suggested that this gap can be closed by the implementation of experts' qualitative predictions into numerical forecasting systems. A formal analysis of these predictions can then be integrated into quantitative forecasts.

In the framework of possibility theory, a model is developed which accounts for the verbal judgments in situations where predictions are made or knowledge is updated in the light of new information. The model translates verbal expressions into elastic constraints on a numerical scale. This numerical interpretation of qualitative judgments can then be implemented into numerical forecasting procedures.

The applicability of this model was tested experimentally. The results indicate that the numerical predictions from the model agree well with the actual judgments and the evaluation behavior of the subjects.

The applicability of this model is demonstrated in a study where bank clerks had to predict exchange rates. The analysis of qualitative judgments according to this model provided significantly more information than numerical predictions.

A general framework for an interactive forecasting systems is suggested for further developments.

Introduction

In the analysis of human predictive behavior the behavioral scientist is confronted with a puzzling situation: predicting future events correctly is undoubtedly of high survival value for any species, especially for humans living in complex interactions with their material and societal environment. This has led Friedman & Willis (1981) to assume that prediction can be regarded as the master motive in human behavior. However, a host of studies has seemingly proved that people are rather inefficient in taking into account the information necessary for a correct prediction (Meehl, 1954; Hogarth & Makridakis, 1981).

A closer analysis of the studies casting doubts on the human efficiency in forecasting reveals that the superiority of statistical predictions is especially prominent if the data are numerical and if the requested prediction is also numerical. On the other hand, if the data are non-numerical and highly configural (Lindzey, 1965), subjective judgments can be better than statistical predictions. Furthermore, experts are able to handle up to 10 variables simultaneously (Phelps & Shanteau, 1978). This result indicates that the limitations of capacity in human information processing depend on the amount of expertise or, in general, on the amount of elaboration of the applied internal model.

A tentative solution for the described contradictory situation might be that humans are comparatively efficient in qualitative forecasting but quite unsuccessful in quantitative prediction [one notable exception is the case of meteorologists, see Murphy & Winkler (1975)]. If this is the case, forecasting and planning tasks which permit verbal,

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qualitative information processing can be assumed to be less flawed by information processing biases as listed by Hogarth & Makridakis (1981, pp. 117–120).

For diagnostic tasks the necessity to implement subjective evaluation into the processing of "hard" quantitative information has led to the development of expert systems, for instance, MYCIN (Shortliffe, 1976) in which the heuristics of medical experts are represented as production rules. These production rules combined with the computers' efficiency in storing and accessing data have made MYCIN successful, and have triggered the development of other expert systems for different areas of expertise (e.g. organic chemistry, DENDRAL; geological survey, PROSPECTOR; systems programming, R1). The success of expert systems suggests to look for the heuristics and rules underlying the qualitative predictions of experts and to combine them with the results of quantitative forecasts. A necessary prerequisite for such an integrated forecasting system is the formal description of the rules underlying subjective predictions and the development of an algorithm which translates qualitative judgments into parameters or intervals in $\mathbb{R}$. If such a system turns out to work successfully, "qualitative projection techniques" and "quantitative projection techniques" (Cleary & Levenbach, 1982, p. 6) are no longer mutually exclusive alternatives but two mutually supportive facets of forecasting.

The description of the forecasting process by Butler, Kavesh & Platt (1974) captures very well the tenets of such an integrated system:

> In actual application of the scientific approaches, judgement plays, and will undoubtedly always play, an important role.... The users of econometric models have come to realize that their models can only be relied upon to provide a first approximation—a set of consistent forecasts which then must be "massaged" with intuition and good judgment to take into account those influences on economic activity for which history is a poor guide. (p. 7.)

This integrated system of qualitative and quantitative techniques in forecasting might also serve an additional function, that is, increasing the acceptability of forecasts. Among professional forecasters the following paradox of forecasting (better, perhaps, dilemma) is reported: either the result of the forecast is in line with the intuitions of the customer, then it is taken into account, or the result of the forecast and the intuitions clash, in which case the forecast is discarded. In both cases nothing is done which had not been done without the results of the forecast. By implementing the customer's intuitions (e.g. his or her "subjective econometric model") it can be expected that the additional information of the numerical forecast becomes more acceptable for the customer because it is computed in relation and addition to the analysis of the plausible reasoning of the customer or other experts.

Furthermore, under certain conditions the implementation of subjective qualitative judgments is necessary to provide an adequate database for predicting complex variables such as, for instance, productivity. The importance of productivity for economical growth is known and almost everyone has a notion about the meaning of the term productivity. If, however, numerical forecasting methods are applied to productivity only measurable variables (e.g. units fabricated during a time period in a production line) can be analyzed. Other important variables of productivity (e.g. creativity in design or planning, effectivity in administration, control of turn-over) have to be discarded, because they cannot be stated numerically.

The claim is made that the knowledge of experts in its greater part usually consists of such qualitative variables stated verbally. Since verbal statements do not fit into numerical models of forecasting they are usually neglected in the application of these models.

From a psychological point of view the investigation of predictive behavior has the following objectives (cf. Kahnemann & Tversky; 1973):

(i) How valid are human predictions?
(ii) What are the conditions for making valid or invalid predictions?
(iii) What makes predictions credible?

In the context of this paper I will confine myself mostly to point (ii) and only at the end will I touch point (i). Point (iii) is mainly dealt with in the context of research on persuasion and will not be discussed here except for the claim that by implementing the addressee's expertise into the prediction he or she will probably be more willing to take the prediction seriously.

In the context of cognitive psychology, what has been analyzed mostly are the conditions underlying the lack of validity in predictions made by human subjects (e.g. Edwards, 1968; Kahnemann & Tversky, 1973). A number of persistent biases have been shown to influence the validity of predictions negatively:

(i) conservatism, i.e. failing to take into account new information;
(ii) availability, i.e. giving too much emphasis to pieces of information easily accessible in one's own memory; and
(iii) representativeness, i.e. disregarding the statistical properties of information (e.g. sample size, correlation, base rate, randomness).

For an overview of research on these biases see Kahnemann, Slovic & Tversky (1982), Nisbett & Ross (1980), or Hogarth & Makridakis (1981). Throughout the studies cited above it is stressed that the biases found are due to the mistaken application of heuristics. Heuristics are tools for the mind that are usually helpful for tackling the complexities of the environment of humans (see, for example, Lenat, 1982). What is missing in these studies is—with few exceptions—the analysis of conditions under which these heuristics are valid and the development of means which make their application possible even in situations which are more complex than the ones under which they have emerged originally (see Sjöberg, 1982; Zimmer, submitted).

One reason for the observed lack of validity for predictions in the studies reported above might be that in many of the experiments subjects were forced to give numerical estimates of their confidence, their predictions, or their subjective probabilities for further events. As argued elsewhere (Zimmer, 1983), it seems plausible to assume that the usual way humans process information for predictions is similar to putting forward arguments and not to computing parameters. Therefore, if one forces people to give numerical estimates, one forces them to operate in a "mode" which requires "more mental effort" and is therefore more prone to interference with biasing tendencies. One main difficulty in analyzing verbal information processing is that the meaning of verbal expressions is vague and therefore cannot be translated easily into formal (e.g. numerical) terms. Fuzzy set theory provides comparatively simple methods to account for vagueness and, by putting elastic numerically stated constraints on vague concepts, fuzzy-set models of human judgment (Zimmer, 1980) permit the translation of verbal expressions into numerical expressions.

A formal description of knowledge underlying predictions

From the point of view of human information processing the framework for people's world knowledge can be summarized as in Table 1. The application of available procedures to information stored in the appropriate modes of representation generates new knowledge which is not due to observations. What is especially of importance in the context of prediction are the conclusions which can be drawn from propositionally represented knowledge by means of the rules of logic or the rules of an argumentative discourse. Such conclusions can be used in hindsight for explanations and in foresight for predictions. The application of the rules of logic implies that the meaning of the propositions is unambiguous, and for most systems of logic it is furthermore necessary that the propositions be either true or false. Whenever these conditions are given it can be decided for any deduction if it is valid or not. But if the meaning of the propositions and their truth-values are vague, then the rules of classical two-valued logic are not applicable. Furthermore, it is questionable if formal logic is an apt tool for modelling human reasoning. Among others, Begg (1982) has shown that people in solving syllogisms do not apply the rules of logic but "play the language

TABLE 1
Human information processing depends on

(1) Modes of representing
- (i) propositional
  - linguistic
    - on the word level
    - on the sentence level
    - on the story or script level
  - numerical
  - general symbolic
- (ii) analogue
  - imaginal (visual, kinesthetic, or auditory)
    - static
    - dynamic

These modes differ in:
- the transformations which can be applied to them (the constraints on these representations can be "strict" or "elastic");
- the mental work load they impose on the information processing capacity

(2) Available procedures

Primarily context specific are:
- (i) rules (e.g. grammars, arithmetics, "Gestalt laws" in perception, etc.) which interact with the above-mentioned applicable transformations

Less context specific are:
- (ii) heuristics, which can be regarded as tools for narrowing down the number of possible candidates among the transformation (e.g. concentrate on confirmatory evidence)

Least context specific and therefore applicable in situations of information overload are:
- (iii) rules of thumb, which can be applied almost without any constraints. They provide "quick and dirty" procedures for the reduction of information so that the processing overload is relieved (e.g. "do whatever comes to your mind first")

game", that is, they assume that conversational conventions also hold for syllogistic reasoning. On the other hand, rules for an argumentative discourse do not presuppose a precise meaning of the propositions used, but the rules for an argumentative discourse (e.g. as stated in the Gricean maxims) are not restrictive enough to analyze them formally.

For these reasons the approach taken here models the meaning of propositions as possibility functions in fuzzy set theory. The possibility functions for the meanings of concepts can be determined experimentally; that is, they are modelled according to the actual usage in normal language. According to fuzzy set theory the meaning of concept "x" in a universe of discourse "U" can be modelled by the possibility function for "x" in U, which indicates for which states in U the concept "x" fits, for which it

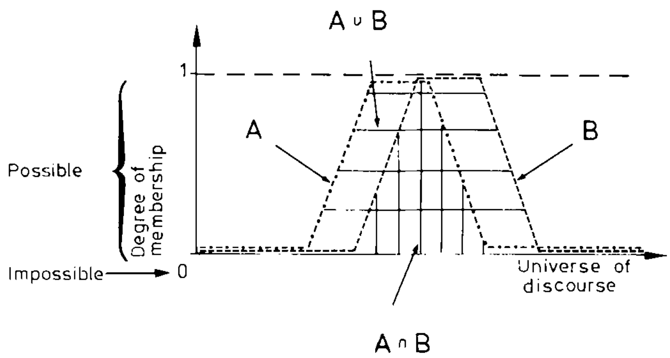

FIG. 1. Possibility distributions and binary operations upon them.

can be possibly applied, and for which it does not fit at all. Figure 1 depicts the possibility functions for two concepts as well as the basic two binary operations:

(i) the intersection: $A \cap B = \min_{U} (f_A; f_B)$

and

(ii) the disjunction: $A \cup B = \max_{U} (f_A; f_B)$.

In order to circumvent the problems in determining exact individual possibility functions [see Zimmer (1980, 1982, 1983); but Hersh & Caramazza (1976); or, for theoretical analyses, Kaufmann (1975) and Dubois & Prade (1980)] for the data reported here the possibility functions are restricted to the values: "absolutely possible" (poss $(x) = 1$); "possible" ($0 < \text{poss}(x) < 1$), and "impossible" (poss $(x) = 0$). Freksa (1981, 1982) has shown that for practical purposes this amount of specification is sufficient. Furthermore, in this approach one can avoid the debated question of how exact the information about one's own knowledge can be (cf. Nisbett & Wilson, 1977) without losing the amount of specificity necessary to apply fuzzy set theory to verbal concepts. The meaning of these concepts is then given by the elastic constraints imposed upon them by the possibility functions.

Begg (1982) concluded from his experiments that in reasoning, people apply what they are most familiar with: the rules underlying conversation and language. Following this argument, it is necessary to model expert reasoning according to the rules of argumentation in discourse. One linguistic means for expressing these rules are quantifiers (e.g. "all", "some", "none", and "not all"). Goguen (1969) has proposed a seemingly straightforward method for modelling the meaning of vague quantifiers in this framework: starting from the meaning of crisp quantifiers in classical logic he fuzzifies them by changing the crisp constraints into elastic ones. However, one can easily see that the range of situations to which these quantifiers can be applied differs markedly: whereas "all" and "none" fit only to a very restricted range, "some" and "not all" are applicable to nearly the full range (see Fig. 2). Starting from a language-pragmatic point of view, a different approach to the modelling of vague quantifiers

FIG. 2. Scope diagrams for fuzzy quantifiers according to Goguen (1969).

for normal language seems to be more plausible: if it is assumed that the meaning of words emerges under the constraint that communicability is optimized, then the meaning of quantifiers should be modelled by possibility functions of about the same shape and the same range of applicability (see Fig. 3), as argued in Zimmer (1980). Zimmer (1982) has analyzed experimental data for this model. It turned out that, despite high intersubjective consistency, the data could not be fitted to the assumed possibility functions of Fig. 3. By analyzing the content of the items used for the empirical determination of the interpretation of the quantifiers it was found that the interpretation of the quantifiers changed with the context: for instance, in the context of science the quantifier "all" had a more restricted interpretation than in the context of everyday events. The influence of context again can be modelled by fuzzy set theory. If one determines the possibility functions for statements in the contexts (e.g. "How

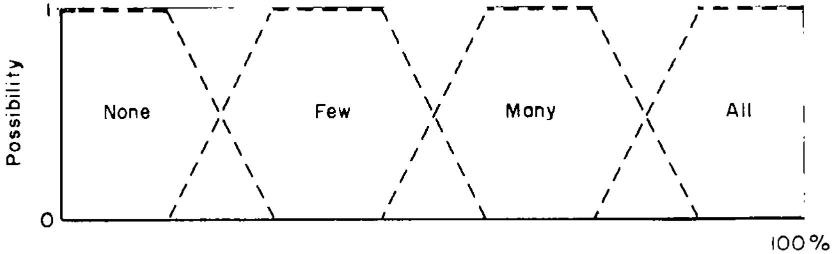

FIG. 3. Assumed scope functions for normal-language quantifiers ("all", "many", "few", and "none").

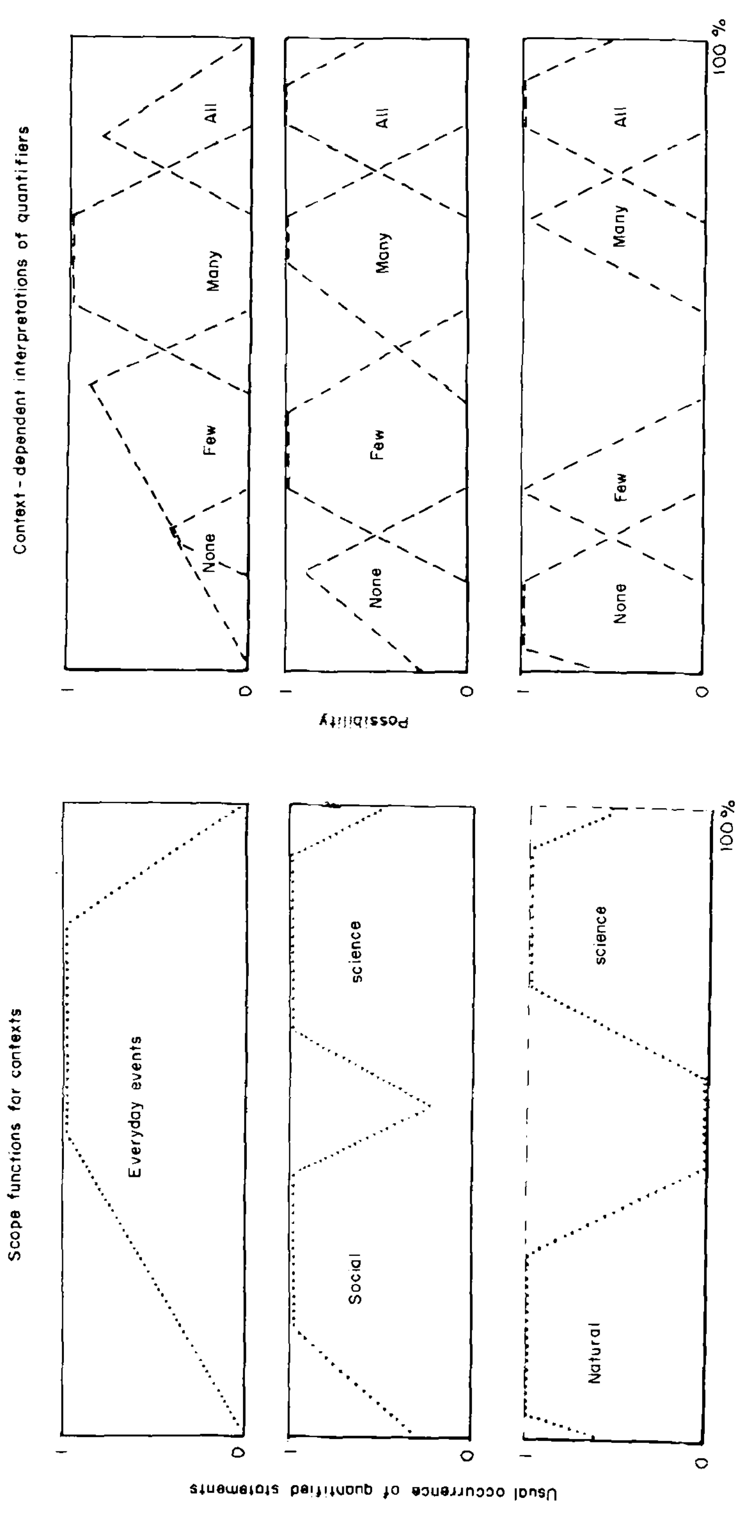

FIG. 4. The context-specific meanings of quantifiers in the contexts "science", "humanities", and "everyday events".

often does it happen in context 'A' that a statement is made, which is true in approximately $x\%$ of all cases?") then the context—specific interpretation of a quantifier is given by its context-independent possibility function modified by the given context. The modification is done by the MIN-rule for the "and" operator. The data fit quite well to this simple model for the context-specific interpretation of quantifiers (see Fig. 4 for illustration).

In the model developed so far, the representation of propositional knowledge can be interpreted numerically by means of the elastic constraints imposed on the interpretations. In order to give a formal description of human predictive behavior it is necessary to define additionally how new information is integrated into the existing knowledge.

A model for integrating new information into knowledge

Various experiments on the capacity of humans to update their existing knowledge in the light of new information have revealed that people tend to stick to their initial opinion very tenaciously (see Phillips & Edwards, 1966). This bias towards suboptimal information processing has been termed conservatism; yet in one experiment Zimmer (1983) was able to show that it is not information in general which is processed conservatively, but predominantly the numerically expressed information. For this reason, a more general approach to the modification of knowledge in the light of new information is taken here. It starts from the assumption that the existing knowledge is represented in verbally stated propositions consisting of vague concepts and vague quantifiers. It is furthermore assumed that the resistance of propositions against modification depends on the time this knowledge has remained the same and/or on the amount of supporting information amassed for the proposition in question. The impact of the new information then depends on the salience this information has, compared with the resistance of the existing knowledge against change. These assumptions can be modelled as operations on fuzzy sets, which modify the possibility functions accordingly.

The resistance of a given quantified proposition, Q at time $t(i)$, is

$$b_i = f[d(\mathbf{Q}_i; \mathbf{Q}_{i-1})], \qquad 0 \le b_i \le 1, \tag{1}$$

where f is a monotonically decreasing function and d is the fuzzy distance (see Kaufmann, 1975). The saliency of new information is given by α $(0 \le \alpha \le 1)$. The integration of new information, $I(i+1)$, into the existing knowledge, $Q(i)$, is then modelled by

$$\mathbf{Q}_{i+1}^{(x)} = \max_x \left[b\mathbf{Q}_i^{(x)} + (1-b)\mathbf{I}_{i+1}^{(x)}; \frac{\min_x [\alpha \mathbf{I}_{i+1}^{(x)}; \mathbf{Q}_i^{(x)}]}{\max_x [\mathbf{I}_{i+1}^{(x)}; \mathbf{Q}_i^{(x)}]} \right]. \tag{2}$$

This model for the revision of world knowledge cannot be tested directly. One possible way would be to ask subjects for their subjective estimates of the impact of old and new information. For the reasons stated above, this does not seem to be a viable approach because it would force subjects to assign numbers to ingredients of their knowledge which are most probably represented in a verbal propositional mode. The approach chosen instead consists of the following steps.

A. Determination of independent or initial (uncontrolled) variables:

(i) *calibration of fuzzy quantifiers.* The conversational interpretation of the following quantifiers has been determined empirically: practically all (always), many (often), few (seldom), practically none (never).

(ii) *calibration of adequacy of assessments.* How adequate the initial knowledge remains after new information has been given (e.g. "on the contrary", "definitely not", "perhaps", "indeed").

(iii) *calibration of the belief strength for the existing knowledge* (strong, intermediate, weak).

(iv) *calibration of the saliency of new information* (high, intermediate, low).

B. Determination of the dependent variable:

Observation of verbal statements about the belief strength after quantified statements have been confronted with quantified new information, which is either confirmatory, neutral, or conflicting.

The experiment was done with 15 German undergraduate students in psychology. They were asked to give examples for quantified statements (see (i)) from their own knowledge and to indicate how strong they believed that these statements were true (see (iii)). A typical example for such a statement is: "If I attend all the classes of a course, I will always succeed in the final exam" (belief strength low). Afterwards they were given new information (see (v)) which varied in saliency (see (iv)). Their verbal reactions to this new information fit well into the verbal expressions calibrated in step (ii). Every subject received 144 items of new information, that is, one item for every combination of conditions (i), (iii), and (iv). The results of the verbal reactions of a single subject to new information is given in Table 2; the belief strength in the existing knowledge and the saliency of the new information were both intermediate.

The regularity of the entries in Table 2 indicates that this subject processed the information in a systematic fashion and that she took the new information into account.

TABLE 2

	Quantified new information ($\mathbf{I}_{i+1}$)			
Old knowledge $\mathbf{Q}_i$	Practically all (always)	Many (often)	Few (seldom)	Practically none (never)
Practically none (never)	on the contrary	definitely	perhaps	indeed
Few (seldom)	definitely not	perhaps	indeed	perhaps
Many (often)	perhaps	indeed	perhaps	definitely not
Practically all (always)	indeed	perhaps	definitely not	on the contrary

Since all the possibility functions for the quantifiers and the assessments in the table are known, it can be determined whether equation (2) models the revision of world knowledge adequately. The fit of a model is about equally high for the conditions where the belief in the existing knowledge is either intermediate or low. In the case of strong belief in the existing information the model predicts a stronger change than the one actually occurring.

With the model developed so far, it is possible to predict the impact new information will have on an existing body of knowledge. It can also be used to analyze the initial belief strength after the impact of the new information has been observed. Qualitative arguments can therefore be described by numerically stated elastic constraints, which in turn can be implemented into a numerical forecasting system.

Up to this point only the modification of one proposition at a time has been modelled. Usually predictions rely not only on one statement or proposition, but on a number of them usually organized by means of causal relationships. Nisbett & Ross (1980) report a couple of studies which indicate that humans usually organize their world knowledge by causal relations, even if the information given is not causal, but merely diagnostic. This preferred mode of knowledge organization in the form of causal schemata has to be taken into account in models of human prediction. I am working on the generalization of the approach developed above to more than one related or unrelated proposition. The idea behind this generalization is to model the subjects' assumptions about causal relationships, that is causal schemata underlying the individual knowledge base. These schemata are used to interpret qualitative arguments (Zimmer, submitted). The experiment which motivated this generalization makes clear why I assume that this approach might probably be fruitful for forecasting.

Verbal vs numerical forecasting: an application to exchange rates

A typical example for an economic prediction task of high complexity is the forecasting of exchange rates. This is a very common task for bank clerks, especially in European countries, because the commerce depends heavily on the correct timing of buying and selling (that is, whenever the exchange rates are favorable). The influences on the exchange rate stem from quantitative variables (GNP percentage increase, amount of budget deficit, interest rates, etc.) as well as from qualitative variables (stability of governments, general climate in economy, etc.).

In order to find out how experts reason in such a situation, I have performed an experiment† in which subjects (24 German bank clerks responsible for foreign exchange) were asked to predict what the exchange rate between the U.S. dollar and the Deutschmark would be after four weeks. Twelve subjects had to give the predictions "in their own words as if they were talking to a client", whereas the other 12 were asked to give numerical estimates (percentage of change). These two experimental conditions were chosen because the verbal predictions are what clients usually ask for, whereas the numerical predictions resemble the predictions made by the economic forecasting institutes in Germany twice a year. Both groups were asked to verbalize the steps of reasoning leading to their prediction. In order to make possible a comparison of the predictions, it was necessary to calibrate the judgments of the first group. This

† In a different context I have reported other aspects of the results of this experiment (Zimmer, 1983).

was done in an interactive procedure where subjects had to give verbal labels for differences in exchange rates presented to them on a CRT-monitor by a computer (TRS 80). The comparison of the verbal predictions with the estimates of the numerical forecasting group revealed that the first group was more correct and more internally consistent. While this is interesting in itself, another point might be more important: the slight difference in the instructions given caused marked differences in the way the subjects performed their task, as revealed by the verbal reports. The verbal prediction group used quantitative variables (e.g. the percentage GNP increase) as well as qualitative variables (e.g. the stability of the German government) for deriving their predictions, whereas the numerical forecasting group merely took into account variables which are usually expressed numerically. Furthermore, the verbal reports of the subjects' reasoning revealed that the verbal prediction group applied highly elaborated causal schemata, into which they fitted their assessments of the quantitative and qualitative variables. On the other hand, the protocols of the numerical prediction group consisted mostly of unconnected lists of singular assessments. From this result it seems plausible to assume that the superiority in the verbal forecasting condition is caused by the fact that the knowledge base on which these subjects relied was broader and allowed for more elaboration. However, it has to be kept in mind that the heuristic of causal schemata can be also misleading; Nisbett & Ross (1980) report ample evidence for the deleterious effects of misinterpreting diagnostic information as causal. The major difference between the studies reported in Nisbett & Ross (1980) and this experiment lies in the fact that the bank clerks were actively searching for information and only implemented their own knowledge into their reasoning.

Conclusions

The implications of the suggested model can be captured in the following way:

(i) the knowledge base for intuitive forecasts is internally represented in a propositional verbal mode; and
(ii) the reasoning underlying these forecasts is governed by communicative constraints and follows elaborated causal schemata.

The first implication can be tested by comparing the model with a numerical alternative in which numbers are assumed to be fuzzy, that is, characterized by elastic constraints in $\mathbb{R}$ (see Yager, 1983), and in which they are individually calibrated. If this alternative model describes the predictive behavior as well, one can conclude that it is not the underlying mode of knowledge representation that is decisive, but the means of handling vagueness in subjective judgments.

The studies of Begg (1982), Zimmer (1982, submitted), as well as the theoretical analysis of "rational belief" by Kyburg (1983) indicate that describing human reasoning in the framework of classical logic might be a mistaken approach. However, the suggested alternative has to become more strictly formalized in order to allow for decisive tests [see, for instance, Smith (1982) for the controversies about the "Gricean maxims" in conversation]. On the other hand, the assumption of causal schemata necessitates the investigation under which situational conditions this heuristic is applicable and under which it leads to biases.

Given that the conditions can be identified under which the suggested model captures the information in intuitive forecasts, an integrated framework for prediction becomes possible. The interaction of qualitative and quantitative aspects in forecasting can be examplified in a generalized version of "a product's lifecycle" by Chambers, Mullick & Smith (1974).

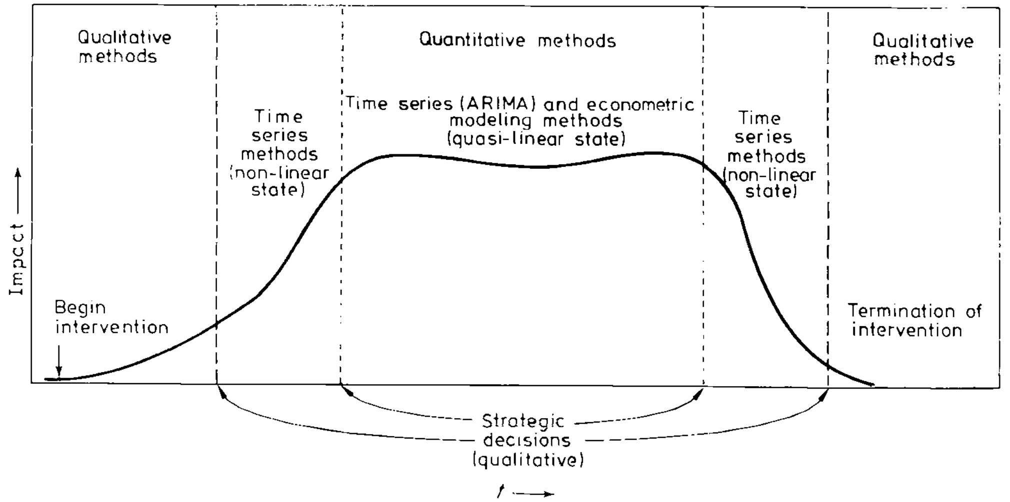

FIG. 5. The "life cycle" of an impact in its relation to forecasting techniques [modified from Chambers *et al.* (1974)].

TABLE 3

Decision maker (user)	Forecasting device
(START) ⟶ Verbal description or world knowledge ⟶	Interpretation (determination of the elastic constraints of the applied concepts, evaluation of the explicity or implicity given causal relationships)
↑	↓
Decision (END) ⟵ Evaluation ⟵	Check for internal consistency
↑	↓
	Integration into data-base
	↓
	Detection of systematic fluctuations, time lags, trends, which are not expressed in the verbal description
	↓
	Forecast (numerical)
	↓
⟵	Translation into verbal descriptions

Figure 5 indicates not only the different qualitative and quantitative phases in an impact analysis but, furthermore, the qualitative strategic reasoning underlying the decisions about the applicability of different forecasting techniques.

Viewing forecasting as a means to improve decision making forces one to look for efficient ways of making the forecasting information usable for the decision maker. The approach reported here suggests an interactive forecasting process as depicted in Table 3.

In this interactive forecasting process the right-hand side consists of the forecasting expert system which determines interactively the individual knowledge base and the derived predictions. Furthermore, it simultaneously analyzes quantitative external data as well as numerical interpretations of qualitative judgments by means of traditional time-series analyses and forecasting techniques. In order to get it working it will be necessary to develop further the interpretation and translation algorithms and the evaluation of underlying causal schemata. Nevertheless, this sketch for a forecasting expert system might provide a framework for future developments, which bridge the gap between the expertise and the prediction skills on the side of the decision maker and the analytical tools of numerical forecasting.

This is an expanded version of a paper read at the Second International Symposium on Forecasting, Istanbul, 1981. I want to thank the other contributors for many valuable suggestions made in the discussion. The final form of this manuscript has gained much clarity in style as well as in arguments from discussions with Jennifer J. Freyd and Gisela Redeker.

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