Uncertainty in Economic Predictions

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Abstract:
Experienced economists often express imprecise but highly relevant economic predictions in vague terms. A brief overview of the applicability of fuzzy sets theory in economics is presented in this paper. The discussion focuses on how this theory can simplify the process of expressing knowledge from expert economists. This can be used in the design of a decision support system for economic predictions.

1. Introduction

As small businesses grow, making the correct decisions to ensure continued growth and success in the competitive arena becomes increasingly more important. A decision-making tool commonly used is forecasting. Methods range from simple linear regression, multiple linear regression, nonlinear regression, trend analysis, decomposition, moving averages, adaptive filtering, exponential smoothing, simulation, and others. The choice of forecasting method depends on, among other things, whether the time horizon of interest is for short, intermediate, or long term range. The primary objectives of this paper are (1) to present some fundamentals of fuzzy sets theory (Zadeh, 1965), also known as fuzzy theory, and how these apply to model-less approximations in economics; and (2) to develop a rough design of a decision support system for economic forecasting. The expressive power of fuzzy theory simplifies the approximation process and even results in richer models that consider inherent imprecision and uncertainty. The author designed this paper to introduce the reader to several concepts without getting too bogged down with the theories concerned.

2. Uncertainty in Economics

Economics is a social science that studies how societies deal with problems of relative scarcity. The theories of the field have grown increasingly more precise and more mathematically sophisticated. However, this also has resulted into a persistent gap between economic reality and predictions from these ever more sophisticated theories.

One reason for this is that experts have formulated these theories through classical mathematics, based on classical set theory, Boolean logic, and classical theory of additive measures. This is not realistic in economics because (1) human reasoning and decision making in natural language is based on genuine uncertainty embedded in natural language; and (2) when the required complexity for obtaining realistic models becomes unmanageable, we must simplify. To preserve relevance of predictions to the real world, one can allow some uncertainty in the models (Klir and Yuan, 1995).

The role of fuzzy theory in economics was recognized much later than in many other areas where the theory is currently being used. Shackle (1961) was perhaps the first to argue that probability theory, which is accepted in economics as the only mathematical tool for expressing uncertainty, is not meaningful for capturing the nature of uncertainty in economics. Shackle argued that uncertainty associated with imagined actions whose outcomes are to some extent unknown should be expressed as degrees of possibility rather than probabilities. One of the most fascinating approaches was a reformulation of economic theory by Claude Ponsard (1981, 1988). Ponsard took advantage of fuzzy theory and its capability to represent uncertainty and imprecision. He initially proposed three fuzzy mathematical models that deal with economic choice, economic calculation, and general economic equilibrium (Ponsard, 1988). A more comprehensive look at the applicability of fuzzy theory in economics is given in a book by Billot (1992).

3. Generating Economic Predictions

Experienced economists often express imprecise but highly relevant economic predictions in vague terms, such as

"The price of oil is not likely to increase substantially in the near future."

Common sense determines such predictions, employing the economist's knowledge (distinct from accepted economic theories) and relevant information. These are all often expressed in linguistic terms as well — most of which are inherently imprecise in nature. Fuzzy theory can approximate and deal with propositions expressed in natural language.

Consider, for example, the following scenario. We are interested in designing a decision support system that takes as input values of key economic indicators (and other pertinent information) to generate reliable economic predictions. As often happens with the design of any expert system, acquiring and representing expert knowledge is the main issue in this endeavor. To tackle this, we will request the expert economist to express his or her knowledge in fuzzy "IF ... THEN ..." rules. The decision support system will then use these rules in making its predictions. Of course, economists may have quite a variety of rules that they employ in making their predictions, but this is not of concern in the current paper.

4. Fuzzy Word Variables

The inherent uncertainty in natural language is captured in fuzzy sets theory by fuzzy linguistic variables (Zadeh, 1975), also known as fuzzy word variables. To explain this concept, consider a leading economic indicator: unemployment. Normally, one would say that unemployment is low, average, or high (other categories such as very low and very high may be available). Classical set theory dictates that these adjectives are represented as disjoint sets. We can envision this as given in Figure 1 below.

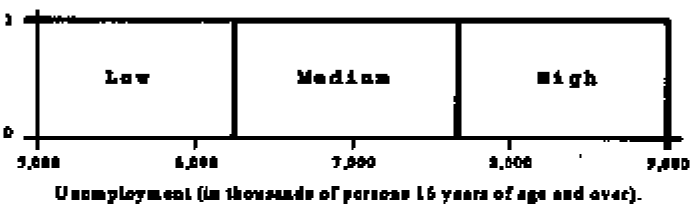


Figure 1: Classical set theory interpretation of word adjectives for *unemployment*.

Set membership in fuzzy theory is a matter of degree: membership is expressed as shades of grey, not black or white. This degree of membership is a value between 0 and 1. Therefore, adjectives are represented as (not necessarily) overlapping sets in which actual unemployment values can be members to some degree. This is illustrated in Figure 2 where triangular functions are used for the membership functions to characterize the fuzzy terms.

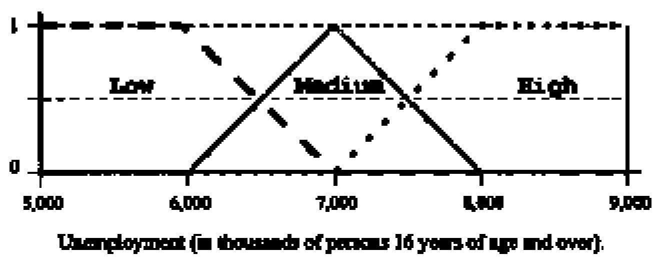


Figure 2: Fuzzy theory representation of word adjectives for unemployment

In actual implementations of fuzzy word variables, fuzzy sets are represented as fuzzy unit vectors over the range of values under consideration. For example, let us again consider the word variable for unemployment. Assume that it has been decided that there will be nine values over the range 5,000 to 9,000 (in thousands of persons). Then the fuzzy set representation of the adjective Low would be as illustrated in Figure 3. Here, representing this fuzzy set as a linear combination of the nine values chosen and their corresponding membership is convenient (see the Appendix for an explanation of this alternate representation).

Another important feature of fuzzy theory is the use of linguistic hedges (also called word hedges in this context) in improving the expressiveness of vague concepts (Zadeh, 1972). Hedges such as very, more or less, much, essentially, slightly, etc., may be viewed as operators that act on the fuzzy set representing the meaning of its operand. Zadeh's (1972) formalism is rather complex for this discussion and so we limit this to the simplest form: hedges of Type I. These are hedges that can be approximated by an operator acting on a single fuzzy set.

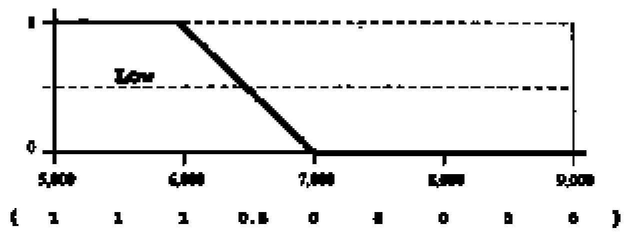


Figure 3: Using a fuzzy unit vector to represent a fuzzy set.

Recall the fuzzy set representation of the word adjective Low as illustrated in Figure 3. Now consider the term
[Equation 1 goes in here]
then the meaning of very x can be denoted by
[Equation 2 goes in here]
which can be viewed schematically as in Figure 4.

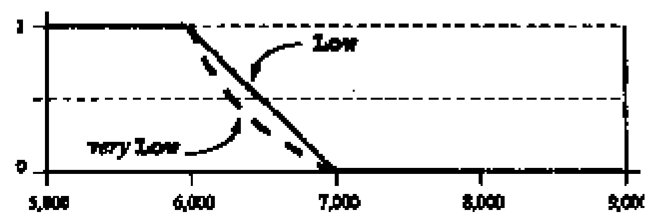


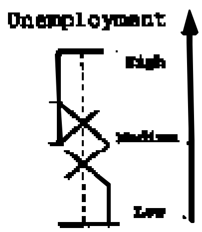
Figure 4: The effect of the hedge very to the fuzzy set Low.

Zadeh (1972) has various interpretations for other word hedges such as much, more or less, slightly, and others. Any further detail on these is beyond the scope of the current paper.

5. Fuzzy Rules for Prediction

One of the expressive powers of fuzzy theory is that knowledge may be represented as a set of rules. For example, an expert economist may tell us that his or her predictions were based on the following rule:

R7: "IF unemployment rates are relatively low and average personal income is high,
THEN the labor force is doing slightly good."



More complex rules similar to rule R7 given above are common. Such rules may have multiple inputs (or antecedents), multiple outputs (or consequents), or both. A more detailed discussion of these issues is beyond the scope of the current paper.

Recall that we have represented fuzzy sets as fuzzy unit vectors. So, the unemployment figure of 7500 is approximated by the fuzzy unit vectors (0 0 0 0 .5 0 0 0) and (0 0 0 0 0 .5 0 0 0), respectively. Fuzzy input is evidently possible simply by using the fuzzy unit vector representation of the fuzzy value.

Rule evaluation

How are rules evaluated in this scenario? It is important to note that for any one input, all rules are evaluated (in parallel) to generate some output. Not all rules will apply to the given input. Those that are significant are said to "fire." In fuzzy theory, rule evaluation is merely a matter of matrix multiplication. Recall that such an operation in fuzzy theory uses max-min composition. The result of multiplying a fuzzy unit vector to a fuzzy relation is a fuzzy unit vector. In other words, the result is a fuzzy set (see the Appendix for an example). This process is known as the Compositional Rule of Inference in fuzzy theory (Zadeh, 1965).

Defuzzification of output

There may be more than one fuzzy output (fuzzy unit vectors) resulting from the previous step of rule evaluation, depending on how many rules fired. Various methods of combining these outputs into a single output vector are available. The most common method is to compute the piecewise maximum of the vectors. For example, given C1 = (0 0 0 .25 1 .25 0 0 0) and C2 = (0 0 1 1 0 0 0 0 0), the combined output vector would be C = C1 V C2 = (0 0 1 1 1 .25 0 0 0) where the "V" denotes the maximum operator.