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 set 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 has resulted in 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 (Yi, 1995).

The role of fuzzy theory in economics was recognized much later than in many other areas where the theory is currently being used. Tye (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. Tye 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](image)

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](image)

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](image)

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](image)

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.*

Notice that such rules consist of antecedents and consequents expressed as fuzzy word variables. Since these fuzzy values are represented as fuzzy sets, which are further represented by fuzzy unit vectors, then taking the product of two fuzzy unit vectors can derive linguistic rules. The result is a fuzzy relation. Fuzzy theory operations were not formally defined using the same classical matrix operations that we learn in Linear Algebra. Instead of the usual product-sum composition, fuzzy theory operations use max-min composition (see the Appendix for a more detailed description of this operation).

![Figure 5: Derivation and interpretation of a fuzzy relation as representative of a fuzzy rule](image)

The derivation and interpretation of such fuzzy relations can be illustrated as in Figure 5. Each fuzzy relation represents a rule associating an input to an output. A collection of rules for a given input and a given output approximates the (possibly nonlinear) relationship between them. It is important to note, though, that using only a few rules may not be enough to capture the behavior of the system. Too many rules may result in redundancy and may become computationally expensive. The optimal number of rules needed to sufficiently model any system under consideration is currently still an important research topic.

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.

6. Fuzzy Inference

In using fuzzy theory to model complex phenomena, it is the inference methodology that welcomes imprecision - therefore, it remains fuzzy. Usually, both the input and the output are nonfuzzy or crisp (although fuzzy input and/or output is also possible). Inference within fuzzy theory, also called fuzzy inference, is divided into three phases: (1) fuzzification of input, (2) rule evaluation, and (3) defuzzification of output.

**Fuzzification of input**

Given a precise or crisp input, the fuzzification process involves determining the input value's membership value in all linguistic adjectives for that particular variable (all represented as fuzzy sets). As an example, let us consider some unemployment figures. Let $\deg A(x)$ denote the degree to which $x$ is a member of the fuzzy set $A$. Referring to Figure 6, an unemployment figure of 6750 is a member of the fuzzy set Low (adjective for Unemployment) with 0.25 degrees of membership. We can also write this as $\deg Low(6750) = 0.25$. Furthermore, note that $\deg Medium (6750) = 0.75$. Similarly, given an unemployment figure of 7500, we can determine that $\deg Medium (7500) = 0.50$ and $\deg High (7500) = 0.50$.

![Figure 6: Fuzzification of crisp input via determination of fuzzy membership](image)

Recall that we have represented fuzzy sets as fuzzy unit vectors. So, the unemployment figure of 7500 is approximated by the fuzzy unit vectors $(0.0000.5000)$ and $(0.00000.5000)$, 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 $C_1 = (0.0000.2500)$ and $C_2 = (0.01100000)$, the combined output vector would be $C = C_1 \lor C_2 = (0.0111.250000)$ where the "\lor" denotes the maximum operator.

Coastal Business Review • 21
Some applications can do with fuzzy output, but most applications require nonfuzzy or crisp output. We call the process of converting a fuzzy value into a crisp value defuzzification. Again, various methods exist to accomplish this. The most common method is called Center of Gravity. This is explained further in the Appendix.

These three phases: fuzzification of input, rule evaluation, and defuzzification of output, collectively make up what we know as fuzzy inference.

7. Design of a Fuzzy Decision Support System

Most concepts introduced in Sections 4 through 6 form the foundations in designing a fuzzy decision support system for economic predictions. The author has outlined some ideas on representation of knowledge and how the inferencing scheme processes information. The author also presents the design of such a system in Figure 7. The inference mechanism (dashed box in Figure 7) contains all the rules that embody the economic prediction knowledge of one or more expert economists. All (fuzzified) input is processed using the Compositional Rule of Inference method mentioned earlier. Some rules fire and some do not. Those that fire produce fuzzy output. These are combined (denoted by $\Sigma$ in Figure 7) and finally defuzzified to produce a precise, crisp output.

![Figure 7: Design components of a fuzzy decision support system](image)

Software tools are available to speed up this design process. As indicated earlier, determining the number of rules needed to sufficiently model the behavior of a system is still a difficult problem. Other things need to be considered as well: how many adjectives to use for each variable, what kind of membership functions to use for each word adjective, and others. Software tools simplify this without losing the flexibility of allowing imprecision into the system being modeled. These are most useful for software simulations that may or may not be realized at the hardware level (e.g., electronic devices or appliances). It is important to note that most devices that sport the "Fuzzy Logic" label basically use the same design and operational features as those presented in this paper. Manufacturers simply implement and embed the fuzzy operations into a microprocessor (or a silicon chip) within the device.

8. Conclusions

Traditional forecasting methods tend to be relatively complicated. Furthermore, experts usually allow some imprecision into their predictions. It also is difficult to express one's knowledge of a particular process, specially if beliefs, uncertainty, and other factors influence it. More complex systems cannot be modeled sufficiently using precise mathematical methods simply because most of these systems are inherently imprecise. In this paper, the author has illustrated how fuzzy logic concepts may play an important role in a large field of study such as economics (in particular, economic prediction). Although much of the discussion was relatively introductory, the author has presented the applicability of this often misunderstood so-called "Fuzzy Logic" in the art of forecasting.

Note

The author does not claim to be an expert economist. The ideas expressed by the author in this paper merely reflect preliminary research on a project that he is currently setting up. The author's expertise and primary area of research is on various aspects of fuzzy sets theory and its applicability in artificial intelligence and the cognitive sciences.

References


Appendix

1. Alternate representation of a fuzzy set
Consider the adjective Low for the word variable Unemployment in the text. Let the set of nine values \( y_1 = 5000, y_2 = 5500, y_3 = 6000, y_4 = 6500, \ldots, y_9 = 9000 \) be representative of Unemployment rates (in thousands of persons). Also, let the membership function, \( \mu \), for this adjective be characterized as illustrated in Figure 3. Hence, the adjective Low can also be expressed as the linear combination

\[
\text{Low} = \mu / y_1 + \mu / y_2 + \mu / y_3 + \ldots + \mu / y_9
\]

\[
= 1.0/5000 + 1.0/5500 + 1.3/6000 + 0.5/6500 + 0/7000 + 0/7500 + 0/8000 + 0/8500 + 0/9000
\]

where the \( \mu \)'s indicate membership degrees and the "/" symbol is used as a separator. Equation (1) may also be written as

\[
\text{Low} = f_{\mu} \mu(y)/y
\]

where \( U = \{5000, 5500, 6000, \ldots, 9000\} \)

and where the membership function \( \mu \) is defined accordingly.

2. Interpretation of linguistic hedges
Consider the fuzzy set representation of the adjective Low as illustrated in Figure 3. Given the term

\[
x^* = \text{very } x = \text{very Low}
\]

then the meaning of \( \text{very } x \) can be denoted by (from Zadeh, 1972)

\[
\text{very } x = x^*
\]

and, more generally, if

\[
x = f_{\mu} \mu(y)/y
\]

then

\[
\text{very } x = f_{\mu} \mu(2y)/y
\]

As an example, consider the adjective Low as expressed in Equation (1). The term "very Low" can be written as

\[
\text{very Low} = \mu_1 / y_1 + \mu_2 / y_2 + \mu_3 / y_3 + \ldots + \mu_9 / y_9
\]

which can be viewed schematically as in Figure 4 in the text.

3. Representing knowledge as fuzzy IF ... THEN rules

Given the following rule:

\[
R2: \ "\text{If unemployment rates are very low, then the labor force is doing very good.}\"
\]

We can represent the phrases "unemployment rates are very low" and "labor force is doing very good" with the fuzzy unit vectors

\[
A = (1, 1, 1, 0.25, 0, 0, 0, 0)
\]

and

\[
B = (0, 0, 0, 0, 0.25, 1, 0.25, 0, 0)
\]

respectively. The fuzzy relation, \( R \), that approximates prediction rule R2 above can be derived by using max-min composition as illustrated in the following equation:

\[
R = A^+ \ast B \text{ where } r_{ij} = \max (\min (a_{ij}, b_{ij}))
\]

which gives us

\[
\begin{array}{ccccccc}
0 & 0 & 0 & 1/4 & 1 & 1/4 & 0 & 0 & 0 \\
0 & 0 & 0 & 1/4 & 1 & 1/4 & 0 & 0 & 0 \\
0 & 0 & 0 & 1/4 & 1 & 1/4 & 0 & 0 & 0 \\
0 & 0 & 0 & 1/16 & 1/16 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{array}
\]

The fuzzy relation \( R \) above depicts a relationship between the input (or antecedent) "unemployment rates are very low" and the output (or consequent) "labor force is doing very good." The derivation and interpretation of this fuzzy relation is given in Figure 5 in the text.

4. Fuzzy rule evaluation via the Compositional Rule of Inference

Consider an Unemployment figure of 6000 such that \( \mu \). Low (6000) = 1.0 which can be represented as the fuzzy unit vector \( A' = (0, 0, 0, 0, 0, 0, 0, 0) \), and rule R2 given above which is represented by the fuzzy relation \( R \) in Equation (vii). Notice that the result of multiplying a fuzzy unit vector to a fuzzy relation is a fuzzy unit vector. In other words, the result of

\[
C' = A' \ast R = (0, 0, 0, 0, 0, 0, 0, 0) \]

is a fuzzy set. This process is also known as the Compositional Rule of Inference in fuzzy theory (Zadeh, 1965).

5 Fuzzy unit vector \( A \) comes directly from Figure 3 in the text and Equation (viii). Fuzzy unit vector \( B \) may be derived as follows: assume that the adjective "good" may be approximated by a fuzzy set whose membership function is the same as Medium in Figure 2 of the text, using the appropriate range of values.
5. Defuzzification via Centroid of Gravity

The most common defuzzification method is called Centroid of Gravity. To compute the crisp value $x$ given a fuzzy unit vector $C = (0 0 1 1 1 .25 0 0 0)$ defined over the set $U = \{0, 5, 10, 15, 20, 25, 30, 35, 40\}$, the following formula is used:

$$x = \frac{\sum_{y \in U} y \cdot \mu(y)}{\sum_{y \in U} \mu(y)}$$

The defuzzified value of $C$ may be computed as

$$x = \frac{10 \cdot 1 + 15 \cdot 1 + 20 \cdot 1 + 25 \cdot .25}{1 + 1 + 1 + .25} = \frac{51.25}{3.25} = 15.7692$$
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From the Editor

This is the fifth annual issue of the Coastal Business Review as published by Coastal Carolina University's E. Craig Wall Sr. School of Business Administration and Computer Science. We have made every effort in the hope that this issue will be as well received as the previous issues have been.

This year we have provided an outlet for meaningful, interesting research with a varied range of articles from authors located in South Carolina and the Southeast.

We have articles of interest to a broad range of South Carolina and Grand Strand businesses. The articles are organized according to four broad interest areas: tourism, small business, medium to large business and business education.

We would like to invite readers of this journal to submit a paper for possible inclusion in the 1997 edition.

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The deadline for submissions for the 1997 edition is December 15, 1996.
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# Table of Contents

**Tourism Interest Articles**

Marketing the Myrtle Beach Area:
Methodology and Preliminary Results of Its Success  
*Donna Smaldone • Tom Russo*

Horry County—Emergence of Its Thriving
Tourism/Retirement-Based Economy  
*Robert L. Pugh • Robert T. Barrett*

Predicting the Number of Tourists That Visit
A Vacation Destination  
*Thomas Secret*

Uncertainty in Economic Predictions  
*Benjoe A. Juliano*

**Small Business Articles**

The Adoption of Document Imaging Processing Systems in the Small Business Community  
*Gregory B. Turner • Mark Hartley*

The Benefits of Object-Based Authoring Systems for Small Businesses  
*Cari E. Keller, Jr. • Benjoe A. Juliano*

The Home Office Deduction Post-Solomon  
*James R. Hasselback • Sherri Kraftsbick*

**Medium to Large Business Interest Articles**

Relative Efficiency of Electric Cooperatives in South Carolina: An Application and Test of Data Envelopment Analysis  
*William B. Tankersley • Julita E. Tankersley*

South Carolina's Governor's Quality Award and Its First Recipient  
*Lilly M. Lancaster*

**Educational Interest Articles**

A Research Note On An Ongoing Examination of Literacy Expectations  
*Robert D. Nale • Dennis A. Rauch*

The Effectiveness of Undergraduate Education in Business Administration Based on the Perceptions of Internal and External Constituencies  
*Virginia B. Lessen • Wilbur L. Garland*
The Center for Economic and Community Development

The Center for Economic and Community Development was established in April 1989 as a separate unit of the E. Craig Wall Sr. School of Business Administration and Computer Science. The center's mission is consistent with the expressed goals of the university, to conduct programs of basic and applied research and programs of public service, to provide leadership, to act as a resource, and to improve the quality of life throughout the service area. To accomplish these goals, the center functions as a bridge between the university and the community, drawing upon the unique talents and expertise of faculty and students to serve economic and community needs. It provides five types of assistance: planning and decision support; technical assistance/applied research; educational programs; information, counseling, and referral services; and student involvement. Funds are provided by the Horry County Higher Education Commission and external sources ranging from private companies to nonprofit and government entities. These funds have enabled the center to undertake research and programs which provide major economic and social benefits to all of the citizens of the Waccamaw region.

Since its inception, the center has initiated or participated in more than 100 projects and investigations. Among the most significant are:

- Development of computer software and a computerized decision support system to assist planning efforts of the former Horry County Economic Development Board (now PARTNERS Economic Development Corporation) and management information systems for the Waccamaw Regional Planning and Development Council
- Assessing the economic effects of the closure of the Myrtle Beach Air Force Base
- Applied research efforts for Grand Strand Water & Sewer Authority, Burroughs and Chapin Company, Inc., WCI Investments, the cities of Conway, Myrtle Beach, and many others
- Perceptual studies for nonprofit entities such as the United Way and Horry Cultural Arts Council
- Humanitarian efforts such as an assessment of living conditions in the Buckspur and Burgess communities and economic impacts of Hurricane Hugo
- Assessment and analysis of Horry county government operations for the Horry County Council and development of computerized data bases that contain regional economic data and statistics which are made available to the public upon request.

The Center continues to be an informed advocate of economic growth of Horry County as well as a participant in improving the overall quality of life in the Waccamaw region. The results of these activities continue to be valuable resources to all of the citizens of our service area.

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