Rule: 6
if 'the number of masts' is two
and 'the main mast position' is 'aft the short mast'
then boat is 'Gaff-headed Schooner' {cf 0.4};
boat is 'Staysail Schooner' {cf 0.4}

$cf_{Rule:6}$ (boat is 'Gaff-headed Schooner') = *min* [cf ('the number of masts' is two),
cf ('the main mast position' is 'aft the short mast')] × 0.4
= *min* [0.9, 0.7] × 0.4 = 0.28

$cf_{Rule:6}$ (boat is 'Staysail Schooner') = *min* [0.9, 0.7] × 0.4 = 0.28

cf (boat is 'Gaff-headed Schooner') = $cf_{Rule:4}$ + $cf_{Rule:6}$ × (1 − $cf_{Rule:4}$)
= 0.09 + 0.28 × (1 − 0.09) = 0.34

cf (boat is 'Staysail Schooner') = 0.09 + 0.28 × (1 − 0.09) = 0.34

boat is	Gaff-headed Schooner	{cf 0.34}
	Staysail Schooner	{cf 0.34}
	Jib-headed Ketch	{cf 0.09}
	Gaff-headed Ketch	{cf 0.09}
	Jib-headed Yawl	{cf 0.09}
	Gaff-headed Yawl	{cf 0.09}

What is the position of the short mast?
⇒ **forward of the helm**

To what degree do you believe that the short mast position is forward of the helm? Enter a numeric certainty between 0 and 1.0 inclusive.
⇒ **0.6**

Rule: 7
if 'the number of masts' is two
and 'the short mast position' is 'forward of the helm'
then boat is 'Jib-headed Ketch' {cf 0.4};
boat is 'Gaff-headed Ketch' {cf 0.4}

$cf_{Rule:7}$ (boat is 'Jib-headed Ketch') = *min* [cf ('the number of masts' is two),
cf ('the short mast position' is 'forward of the helm')] × 0.4
= *min* [0.9, 0.6] × 0.4 = 0.24

$cf_{Rule:7}$ (boat is 'Gaff-headed Ketch') = *min* [0.9, 0.6] × 0.4 = 0.24

cf (boat is 'Jib-headed Ketch') = $cf_{Rule:6}$ + $cf_{Rule:7}$ × (1 − $cf_{Rule:6}$)
= 0.09 + 0.24 × (1 − 0.09) = 0.30

cf (boat is 'Gaff-headed Ketch') = 0.09 + 0.24 × (1 − 0.09) = 0.30

boat is	Gaff-headed Schooner	{cf 0.34}
	Staysail Schooner	{cf 0.34}
	Jib-headed Ketch	{cf 0.30}
	Gaff-headed Ketch	{cf 0.30}
	Jib-headed Yawl	{cf 0.09}
	Gaff-headed Yawl	{cf 0.09}

What is the shape of the mainsail?
⇒ **triangular**

To what degree do you believe that the shape of the mainsail is triangular? Enter a numeric certainty between 0 and 1.0 inclusive.
⇒ **0.8**

Rule: 9
if 'the number of masts' is two
and 'the shape of the mainsail' is triangular
then boat is 'Jib-headed Ketch' {cf 0.4};
boat is 'Jib-headed Yawl' {cf 0.4}

$cf_{Rule:9}$ (boat is 'Jib-headed Ketch') = *min* [c
cf ('the shape of the mainsail' is triangular)]
= *min* [0.9, 0.8] × 0.4 = 0.32

$cf_{Rule:9}$ (boat is 'Jib-headed Yawl') = *min* [0.

cf (boat is 'Jib-headed Ketch') = $cf_{Rule:7}$ + c
= 0.30 + 0.32 × (1 − 0.30) = 0.52

cf (boat is 'Jib-headed Yawl') = 0.09 + 0.32

boat is	Jib-headed Ketch	{cf
	Jib-headed Yawl	{cf
	Gaff-headed Schooner	{cf
	Staysail Schooner	{cf
	Gaff-headed Ketch	{cf
	Gaff-headed Yawl	{cf

Now we can conclude that the boat is p
certainly not a *Gaff-headed Ketch* or *Gaff-he*

9.3 Will a fuzzy expert system work for my problem?

We need to decide which problem is a good candidate for fuzzy technology. The basic approach here is simple: if you cannot define a set of exact rules for each possible situation, then use fuzzy logic. While certainty factors and Bayesian probabilities are concerned with the imprecision associated with the outcome of a well-defined event, fuzzy logic concentrates on the imprecision of the event itself. In other words, inherently imprecise properties of the problem make it a good candidate for fuzzy technology.

Fuzzy systems are particularly well suited for modelling human decision making. We often rely on common sense and use vague and ambiguous terms while making important decisions. Doctors, for example, do not have a precise threshold in mind when they decide whether a patient in a post-operative recovery area should be sent to a general hospital floor. Although hypothermia is a significant concern after surgery and the patient's body temperature often plays a vital role in the doctor's decision, such factors as the stability of the patient's blood pressure, and his or her perceived comfort at discharge are also taken into account. A doctor makes an accurate assessment not from the precision of a single parameter (say, a body temperature), but rather from evaluating several parameters, some of which are expressed in ambiguous terms (for instance, the patient's willingness to leave the post-operative recovery unit).

Although, most fuzzy technology applications are still reported in control and engineering, an even larger potential exists in business and finance (Von Altrock, 1997). Decisions in these areas are often based on human intuition, common sense and experience, rather than on the availability and precision of data. Decision-making in business and finance is too complex and too uncertain to lend itself to precise analytical methods. Fuzzy technology provides us with a means of coping with the 'soft criteria' and 'fuzzy data' that are often used in business and finance.

Case study 3: Decision-support fuzzy systems

I want to develop an intelligent system for assessing mortgage applications. Will a fuzzy expert system work for this problem?

Mortgage application assessment is a typical problem to which decision-support fuzzy systems can be successfully applied (Von Altrock, 1997).

To develop a decision-support fuzzy system for this problem, we first represent the basic concept of mortgage application assessment in fuzzy terms, then implement this concept in a prototype system using an appropriate fuzzy tool, and finally test and optimise the system with selected test cases.

Assessment of a mortgage application is normally based on evaluating the market value and location of the house, the applicant's assets and income, and the repayment plan, which is decided by the applicant's income and bank's interest charges.

Where do membership functions and rules for mortgage loan assessment come from?

To define membership functions and construct fuzzy rules, we usually need the help of experienced mortgage advisors and also bank managers, who develop the mortgage granting policies. Figures 9.7 to 9.14 show fuzzy sets for linguistic variables used in our problem. Triangular and trapezoidal membership functions can adequately represent the knowledge of the mortgage expert.

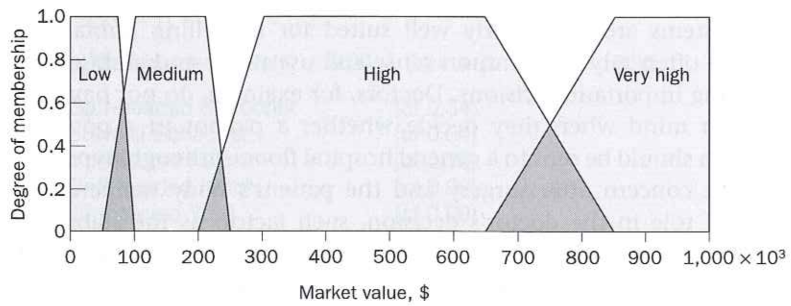

Figure 9.7 Fuzzy sets of the linguistic variable *Market value*

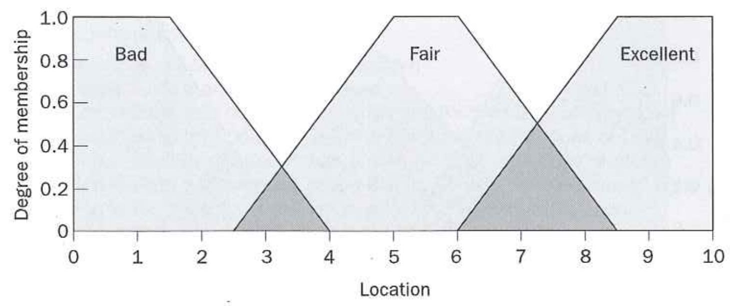

Figure 9.8 Fuzzy sets of the linguistic variable *Location*

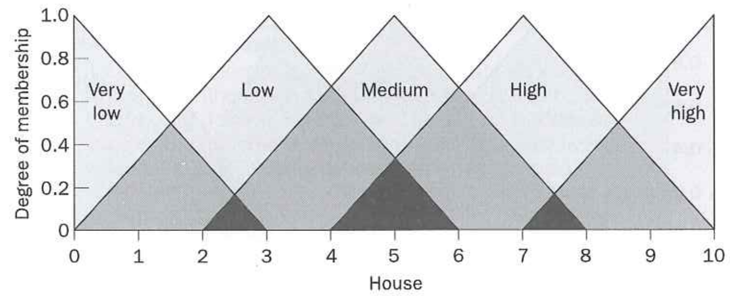

Figure 9.9 Fuzzy sets of the linguistic variable *House*

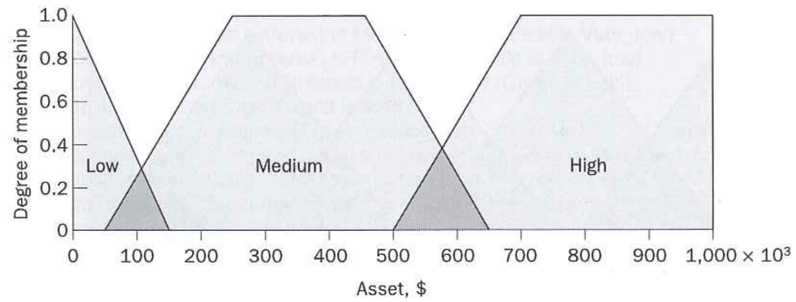

Figure 9.10 Fuzzy sets of the linguistic variable *Asset*

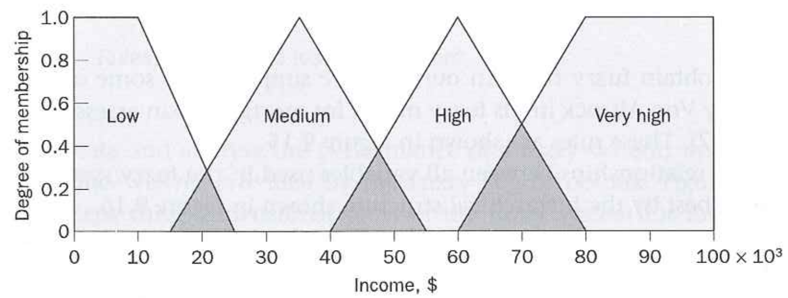

Figure 9.11 Fuzzy sets of the linguistic variable *Income*

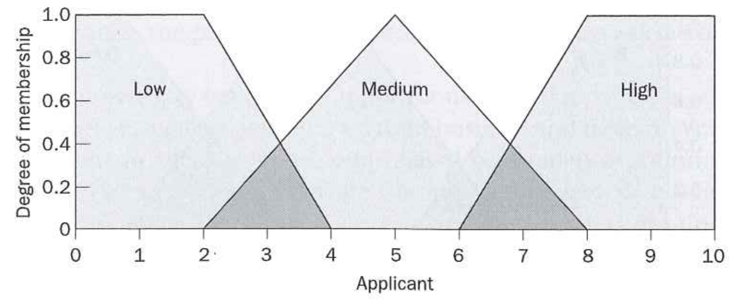

Figure 9.12 Fuzzy sets of the linguistic variable *Applicant*

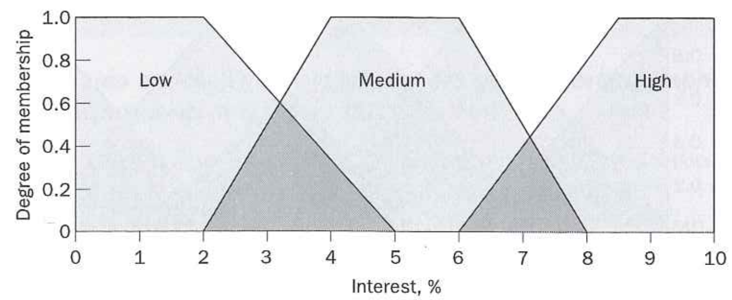

Figure 9.13 Fuzzy sets of the linguistic variable *Interest*

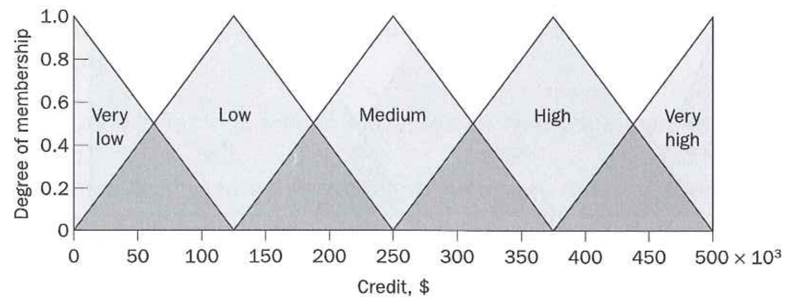

Figure 9.14 Fuzzy sets of the linguistic variable *Credit*

Next we obtain fuzzy rules. In our case, we simply adapt some of the basic rules used by Von Altrock in his fuzzy model for mortgage loan assessment (Von Altrock, 1997). These rules are shown in Figure 9.15.

Complex relationships between all variables used in the fuzzy system can be represented best by the hierarchical structure shown in Figure 9.16.

To build our system we use the MATLAB Fuzzy Logic Toolbox, one of the most popular fuzzy tools currently on the market.

The last phase in the development of a prototype system is its evaluation and testing.

Rule Base 1: Home Evaluation

1. If (Market_value is Low) then (House is Low)
2. If (Location is Bad) then (House is Low)
3. If (Location is Bad) and (Market_value is Low) then (House is Very_low)
4. If (Location is Bad) and (Market_value is Medium) then (House is Low)
5. If (Location is Bad) and (Market_value is High) then (House is Medium)
6. If (Location is Bad) and (Market_value is Very_ high) then (House is High)
7. If (Location is Fair) and (Market_value is Low) then (House is Low)
8. If (Location is Fair) and (Market_value is Medium) then (House is Medium)
9. If (Location is Fair) and (Market_value is High) then (House is High)
10. If (Location is Fair) and (Market_value is Very_high) then (House is Very_high)
11. If (Location is Excellent) and (Market_value is Low) then (House is Medium)
12. If (Location is Excellent) and (Market_value is Medium) then (House is High)
13. If (Location is Excellent) and (Market_value is High) then (House is Very_high)
14. If (Location is Excellent) and (Market_value is Very_high) then (House is Very_high)

Rule Base 2: Applicant Evaluation

1. If (Asset is Low) and (Income is Low) then (Applicant is Low)
2. If (Asset is Low) and (Income is Medium) then (Applicant is Low)
3. If (Asset is Low) and (Income is High) then (Applicant is Medium)
4. If (Asset is Low) and (Income is Very_high) then (Applicant is High)
5. If (Asset is Medium) and (Income is Low) then (Applicant is Low)
6. If (Asset is Medium) and (Income is Medium) then (Applicant is Medium)
7. If (Asset is Medium) and (Income is High) then (Applicant is High)
8. If (Asset is Medium) and (Income is Very_high) then (Applicant is High)
9. If (Asset is High) and (Income is Low) then (Applicant is Medium)
10. If (Asset is High) and (Income is Medium) then (Applicant is Medium)
11. If (Asset is High) and (Income is High) then (Applicant is High)
12. If (Asset is High) and (Income is Very_high) then (Applicant is High)

Rule Base 3: Credit Evaluation

1. If (Income is Low) and (Interest is Medium) then (Credit is Very_low)
2. If (Income is Low) and (Interest is High) then (Credit is Very_low)
3. If (Income is Medium) and (Interest is High) then (Credit is Low)
4. If (Applicant is Low) then (Credit is Very_low)
5. If (House is Very_low) then (Credit is Very_low)
6. If (Applicant is Medium) and (House is Very_low) then (Credit is Low)
7. If (Applicant is Medium) and (House is Low) then (Credit is Low)
8. If (Applicant is Medium) and (House is Medium) then (Credit is Medium)
9. If (Applicant is Medium) and (House is High) then (Credit is High)
10. If (Applicant is Medium) and (House is Very_high) then (Credit is High)
11. If (Applicant is High) and (House is Very_low) then (Credit is Low)
12. If (Applicant is High) and (House is Low) then (Credit is Medium)
13. If (Applicant is High) and (House is Medium) then (Credit is High)
14. If (Applicant is High) and (House is High) then (Credit is High)
15. If (Applicant is High) and (House is Very_high) then (Credit is Very_high)

Figure 9.15 Rules for mortgage loan assessment

To evaluate and analyse the performance of a fuzzy system, we can use the output surface viewer provided by the Fuzzy Logic Toolbox. Figures 9.17 and 9.18 represent three-dimensional plots of the fuzzy system for mortgage loan assessment. Finally, the mortgage experts would try the system with several test cases.

Decision-support fuzzy systems may include dozens, and even hundreds, of rules. For example, a fuzzy system for credit-risk evaluation developed by BMW

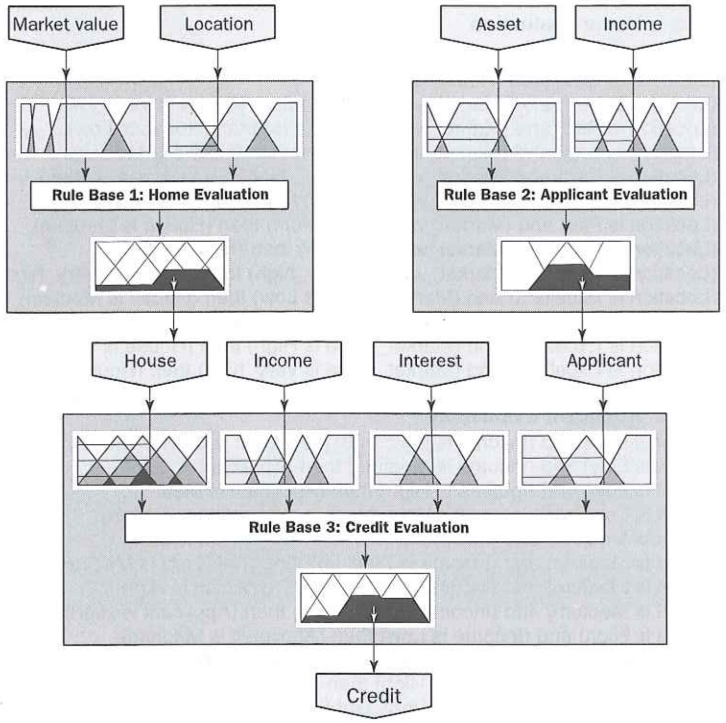

Figure 9.16 Hierarchical fuzzy model for mortgage loan assessment

Bank and Inform Software used 413 fuzzy rules (Güllich, 1996). Large knowledge bases are usually divided into several modules in a manner similar to that shown in Figure 9.16.

In spite of the often large number of rules, decision-support fuzzy systems can be developed, tested and implemented relatively quickly. For instance, it took just two person-years to develop and implement the fuzzy system for credit-risk evaluation. Compare this effort with the 40 person-years it took to develop MYCIN.

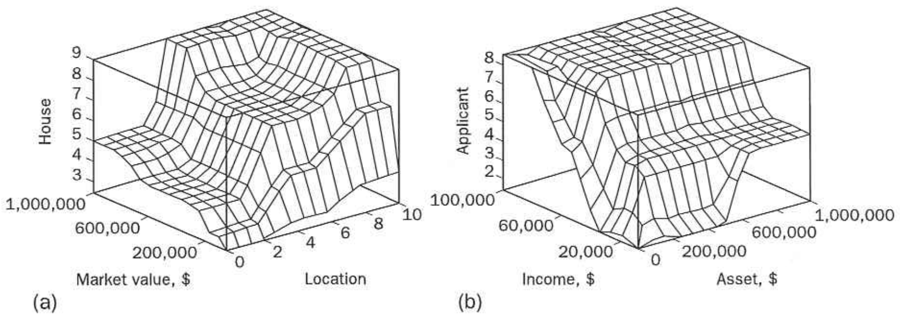

Figure 9.17 Three-dimensional plots for Rule Base 1 and Rule Base 2

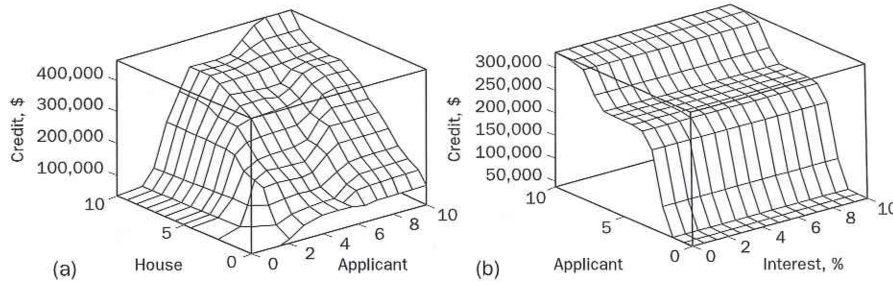

Figure 9.18 Three-dimensional plots for Rule Base 3

9.4 Will a neural network work for my problem?

Neural networks represent a class of very powerful, general-purpose tools that have been successfully applied to prediction, classification and clustering problems. They are used in a variety of areas, from speech and character recognition to detecting fraudulent transactions, from medical diagnosis of heart attacks to process control and robotics, from predicting foreign exchange rates to detecting and identifying radar targets. And the areas of neural network applications continue to expand rapidly.

The popularity of neural networks is based on their remarkable versatility, abilities to handle both binary and continuous data, and to produce good results in complex domains. When the output is continuous, the network can address prediction problems, but when the output is binary, the network works as a classifier.

Case study 4: Character recognition neural networks

I want to develop a character recognition system. Will a neural network work for this problem?

Recognition of both printed and handwritten characters is a typical domain where neural networks have been successfully applied. In fact, **optical character recognition** systems were among the first commercial applications of neural networks.

What is optical character recognition?
It is the ability of a computer to translate character images into a text file, using special software. It allows us to take a printed document and put it into a computer in editable form without the need of retyping the document.

To capture the character images we can use a desktop scanner. It either passes light-sensitive sensors over the illuminated surface of a page or moves a page through the sensors. The scanner processes the image by dividing it into hundreds of pixel-sized boxes per inch and representing each box by either 1