Credit risk early warning system using fuzzy expert systems
Recent financial crisis revealed major issues with the ability of financial institutions to recognize increases in credit risk early enough.

Main causes were identified:

- Too much focus on underwriting and compliance
- Lack of a dedicated organizational unit and personnel
- Lack of interdepartmental and intragroup communication
- Poor data quality
- Inadequate IT systems
Goal of the Early Warning System

❖ Differentiate between clients who can be saved from default by taking appropriate actions and clients whom the bank would like to divorce
❖ Minimize losses by taking appropriate actions early on
❖ Proactively manage the client’s financials
❖ First lender to identify a high risk client will collect more than others
❖ First lender to identify a troubled client which can be saved can win him over
A Classification Problem

<table>
<thead>
<tr>
<th>Classification</th>
<th>Real status</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>No action required</td>
<td>Performing</td>
<td>Default</td>
</tr>
<tr>
<td>Monitor</td>
<td>Type 1 error</td>
<td>Well done</td>
</tr>
<tr>
<td>Monitor</td>
<td>Type 1 error</td>
<td>Well done</td>
</tr>
</tbody>
</table>

- Type 1 error reduces efficiency
- Type 2 error reduces effectiveness
- Resources are modeled as a constraint, goal is to minimize errors
Monitoring Process

- Acquisition
- Underwriting
- Monitoring
- Classification proposal
- Individual Assessment
- Final classification
- Collections
- Restructuring
- Workout
- Strategy design & enforcement
Signal Data Sources

- Internal data (CRM, collateral database, ...)
- Group data (leasing, insurance, factoring, ...)
- Financial statements
- Macroeconomic and industry analyses
- Credit bureau
- Capital markets
- Government databases (land registry, subsidies, official papers, ...)
- Media
- Payment transactions
- Network analysis
Signal Evaluation

- **Precision** = number of defaulted clients with signal / total clients with signal
- **Coverage** = number of defaulted clients with signal / total defaulted clients
- **Workload** = number of clients with signal
- **Time to default** = average time between first occurrence of the signal and actual default
Fuzzy Logic

- Traditional logic

- Fuzzy logic
Fuzzy Expert System

- Rules are defined using linguistic variables
- Signals can be combined with auxiliary variables (segment, industry, exposure, ...)
- All rules for which at least one signal is triggered are fired simultaneously
- Rules can have weights making them more or less important
- System is easily tuned for available capacity by adjusting the minimal membership degree threshold of output variables
An Example

- Rule 1: If connected client’s rating downgrade is large and rating is weak than monitoring class is W2
- Rule 2: If connected client’s rating downgrade is large and rating is medium than monitoring class is W1
- Connected client’s rating downgrade = 6 notches, client rating = 5
Handling Model Complexity

- Rule blocks
  - Connected party rating downgrade
  - Owner’s rating downgrade
  - Key customers rating downgrade
  - Connected party default
  - Owner default
  - Key customers default

- Adjusting membership degrees
  - High quality collaterals
  - Clients previously in monitoring, restructuring or workout
Auto tuning

- Each rule can have a weight corresponding to its importance / predictive power
- Rules can be fuzzy as well
- Rule weights can be adjusted automatically using new data
- Weights for rules which are declining in predictive power can be automatically decreased and vice versa
System Architecture

For example, a certain signal may only be valid or accurate enough to be used only within a certain segment of clients or within a particular industry. Signals (linguistic variables) and auxiliary variables are combined into rules. For example:

IF rating downgrade is large AND rating is bad THEN choose strategy 2.

All rules for which at least one signal is triggered are fired simultaneously. Rules can have weights making them more or less important in the overall model. Rule weights also serve as a basis for simple auto tuning of the model.

After rules have been defined the univariate analysis described for signals takes place only on individual rule level. The process of signal and rule definition, fuzzification and univariate analysis is iterative until a satisfactory solution has been found and accepted by model developers, domain experts and end users.

5.1 Model architecture

Model architecture is depicted in Figure 4. System collects necessary data and feeds it into the model scoring engine. Signal values are calculated and fuzzified. Next, support for each rule is calculated using standard fuzzy logic operators (AND, OR, NOT). Defuzzification can be done using standard methods, but if we want our system to react to even a single signal alert we need an alternative approach. One simple and effective way to accomplish this is that for each class we calculate membership degree as the maximum support of rules which result in this particular class. This way system will be very sensitive because only rules with maximum support for each class are taken into account.

After defuzzification every class has a corresponding membership degree. In order to reduce complexity we can directly manipulate the membership degrees. More details are given in the following sub chapter.

Each class now has a membership degree assigned and the model can propose a classification. We do this by assigning a threshold (Figure 5). One of the classes should be designated as default in case a particular client does not reach any of the thresholds. If a client exceeds the threshold of two or more classes, a resolution logic must be defined. One simple logic is that most conservative class wins. For example, if the client exceeds thresholds in "no action required" and "close monitoring required" classes, the latter will be the class proposed by the model.

Thresholds must be easily changeable in order to tune the system and align it to available resources. An optional step, usually done for large clients, typically corporates, institutions and sovereigns, is that EWS only proposes a classification where clients in classes other than "no action required" are individually and manually assessed. Final classification is then made by expert judgement.

5.2 Handling complexity

A common error in fuzzy expert systems development is having too many indicators and rules. Such a system is hard to interpret, implement and very hard to maintain. One approach to handling complexity of the model is rule blocks (Figure 6). Several signals about rating downgrade and default of parties connected to a particular client (owners, key customers, etc.) are merged into a general one describing all connected customers. One rule can then be defined using "connected customers" rather than having six different rules.

Signals → Fuzzification → Rules

Defuzzification → Membership degree adjustment → Classification proposal

Individual assessment (optional) → Final classification
### Validation

<table>
<thead>
<tr>
<th>Test case</th>
<th>Model outcome at N-th month prior to default</th>
<th>Domain experts’ remarks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3m</td>
<td>6m</td>
</tr>
<tr>
<td>Case 1</td>
<td>R</td>
<td>R</td>
</tr>
<tr>
<td>Case 2</td>
<td>S1</td>
<td>NA</td>
</tr>
<tr>
<td>Etc.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table 2**
Conclusion

- Fuzzy expert system proved to be a better option compared to traditional statistical techniques in terms of predictive power, robustness, interpretability, etc.

- Validation continues to be an issue

- Future research:
  - Model auto-tuning
  - Social Network Analysis