MTech(IS)

Self-Learning Systems

Project Report

**HYBRID ADAPTIVE-NETWORK-BASED FUZZY INFERENCE SYSTEM (ANFIS) WITH BOTH MAMDANI’S & SUGENO’S OUTPUTS AND ITS APPLICATION**

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Companies around the world spend billions of dollars on marketing campaigns every year. These investments typically revolve around conferences, seminars, workshops, round-tables and luncheons. Monetary outlays involve paying for the conference grounds, event management companies, agents and freelancers to do part of the executions, flights and hotels for staffs flying in, gifts, meals, handouts, and many other items that typically number in the range of tens of thousands to tens of millions of dollars per campaign. Also, many man-hours are spent in preparing the conference ground, in running the events, and in the networking between sales staffs and attendees.

1.0 EXECUTIVE SUMMARY

Notwithstanding the substantial amount of investments made, it is common to see return-on investments (ROIs) which are below par, or sometimes inflated. It is obvious that companies need solutions that can address this business pain-point and that an effective solution will lead to higher ROI on their marketing campaigns.

This project addresses the key issues impeding many of these events from achieving good ROI, and to help companies save cost, and to connect with their prospects and business opportunities. Our group drew inspiration from the issues faced at one of our workplaces which exhibits the same challenges leading to the need for such a solution. Hence this system will be used to solve a real problem in an actual company setting.

We have identified human decision-making on potential sales opportunities as one of the key issues responsible for below par ROIs on marketing campaigns. Scarce resources can force companies to rely on inexperienced freelancers or agents to make critical decisions on marketing follow-ups. But it is also challenging for companies with full-time staff doing this work, because of the difficulty in maintaining one’s performance when working with a large volume of potential sales opportunities. Poor decision-making can lead to increased costs from unsuccessful marketing efforts and/or missed sale opportunities.

Importantly, the key innovative step that we took in this project was to incorporate Mamdani’s output to the typical ANFIS model and demostrated the feasibility of this architecture. Thus, our hybrid ANFIS system is better than the typical ANFIS system because it is able to generate both Sugeno’s and Mamdani’s outputs concurrently.

We also proceeded to demonstrate the potential of our system for marketing decision-making. Our hybrid ANFIS system is designed to focus companies’ marketing efforts on the most promising sales opportunity while reducing the number of unsuccessful marketing effort. Based on our results, we believed that companies can achieve higher ROIs on their marketing campaigns by using our system.

2.0 PROBLEM DESCRIPTION

One common problem that happen for many companies is that the level of follow-ups with the event attendees may not measure up to the level of investments made. There is usually a great amount of menial work needed just having to plough through piles of survey response forms. Then there are people hired to do data entries, and to analyze the response forms. And most importantly, to decide which attendees should be followed up with.

For some companies, doing this follow-up job may not be the responsibilities of full-time staffs. This may be because the volume of work coming from the many campaigns that are run is way too much for the lean marketing and/or business development teams. As such, some companies hire freelancers or agents to do the job. These resources may be temporary data entry people who are not skilled in making good inferences on the survey responses. Sometimes, even if well trained full-time staffs are tasked with the job, the sheer volume of work may just overwhelm them.

Making good inferences and decisions can make a lot of difference in terms of cost savings and can open doors to marketing opportunities in this case. Reaching out to all attendees is not advisable even if they had indicated to be contacted for marketing purposes. The cost to do so may not be feasible, if the effort does not result in sales for the companies.

However, not reaching out to enough attendees means companies may be losing out on potential sales opportunities. So, it is important to find a balance that will maximize marketing effort on the most promising sales opportunities while minimizing the number of unsuccessful marketing effort, especially when company resources are usually quite scarce.

Often times, the optimal line to be drawn between those attendees to call and those not to call may be quite fuzzy. In this respect, humans typically lean on their own subjectivity and experiences to determine whether an attendee is a potential sales opportunity or not. A more data-driven approach that draw insights from large volumes of past marketing records is likely to be more accurate in identifying sales opportunity than a human.

In view of this, we have devised a hybrid ANFIS system that can replace humans who are making such a decision. As far as we know, this is the first such ANFIS system deployed for such a job.

**Hybrid ANFIS Architecture**

3.0 SOLUTION

This project deploys the typical ANFIS architecture based on the Sugeno model, with an additional sixth layer. This sixth layer produces a Mamdani-type fuzzy output. In other words, our hybrid ANFIS architecture is able to generate both Sugeno’s and Mamdani’s outputs.

**3.1 Reasons for Why ANFIS is Suitable to Solve this Problem**

A neural fuzzy system, such as ANFIS, is very suited to the task of automating marketing decision-making because marketing decisions are typically represented linguistically, rather than numerically. For example, the seniority of attendees is often used to guide marketing decision. It is fairly common for seniority to be described using linguistic labels such as “junior”, “mid”, and “senior” instead of numerical values. A typical marketing decision can be of the form “If seniority is senior, then contact the attendee”.

The use of linguistic labels can lead to the uncertainty of membership of elements, such that it is not easy to tell whether an attendee’s seniority is “junior”, “mid”, or “senior”. This issue of the uncertainty of membership can be effectively addressed by fuzzy logic. However, fuzzy logic has some challenges of its own that need to be addressed when implementing it. The core challenges are: (1) devising the parameters of the membership function objectively, and (2) updating the rule base in a systematic way.

ANFIS brings together the combined benefits of the two major techniques (Fuzzy Logic and Neural Network) to address these challenges. It works by applying Neural Network Pattern Recognition to tune the parameters of the ANFIS architecture objectively and systematically. Some of the highlights of the ANFIS system are:

* Using fuzzy IF-THEN rules to mimic human thinking pattern;
* Quick deployment;
* Fast learning;
* Enables the incorporation of both linguistic and quantitative knowledge for problem solving.

**3.2 System Design/Model – Components of the System**

This hybrid ANFIS model comprises six layers. We have included a sixth layer that transforms the output of the typical ANFIS fifth layer into a Mamdani-type linguistic label output (Fig 1). Details of the dataset used to train and test this ANFIS model are in Appendix B.

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Fig 1. Basic Structure of the Hybrid ANFIS Architecture

Layer 1 – Fuzzification of input variables

This layer comprises 12 adaptive nodes for each of the four inputs’ three linguistic labels:

1. Seniority
   1. Junior
   2. Mid
   3. Senior
2. Purchase propensity
   1. No plan
   2. Within the next 3 years
   3. Within the next 12 months
3. Company size
   1. Small
   2. Medium
   3. Big
4. Contactable
   1. Don’t contact me
   2. Send only content to me
   3. Email or call me

We used Gaussian Membership Function (MF) to model the membership grade for each of the 12 linguistic labels. The Gaussian MF comprises two parameters, mu (i.e., m) and sigma (i.e., k), and is shown in Figure 2. The ANFIS system was used to estimate the values of the two antecedent parameters, m and k, for each node. Therefore, there are 24 trainable variables from this layer.

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Fig 2. Gaussian Membership Function

Layer 2 – Obtaining the firing strength of rules

This layer has 81 fixed nodes that corresponded to the number of rules that can be derived from four inputs that each has three linguistic labels i.e., 34 = 81. Each node takes the product of its own set of four inputs from layer 1 to generate its output, which is the firing strength of its rule.

Layer 3 – Normalizing the firing strength of rules

Layer 3 has 81 fixed nodes that normalizes the firing strength of all the rules by dividing each firing strength by the summation of all firing strengths.

Layer 4 – Multiplying normed firing strengths by First-Order Sugeno Fuzzy model

This layer consisted of 81 adaptive nodes that take normed firing strengths, input variables and their coefficients to calculate the output for each rule. Each rule in the first-order Sugeno fuzzy model has five parameters that were estimated from the ANFIS model. That is, four coefficients for each of the inputs and one coefficient for the bias term. Therefore, there are 405 trainable variables from this layer.

Layer 5 – Summed output of the Sugeno model

Layer 5 has a single fixed node that computes the overall output from the summation of all 81 outputs calculated from Layer 4.

Layer 6 – Mamdani output

The sixth layer is akin to the first layer of the typical ANFIS because it also fuzzify the inputs given to it. However, the sixth layer differed from the first layer of the ANFIS by treating the outputs of the first-order Sugeno model in the ANFIS’s fifth layer as its inputs. This layer comprises three adaptive nodes for each of its three linguistic labels:

1. Discard the contact of this attendee
2. Send brochure to this attendee
3. Email and/or call this attendee

Gaussian MF was used to model the membership grade for each of the three linguistic labels, and the ANFIS system estimated the values of the two consequent parameters for each node. Therefore, there are 6 trainable variables from this layer and a total of 435 trainable variables for the entire system.

**3.3 Specifications of the Hybrid ANFIS System**

The hybrid ANFIS system was coded using the TensorFlow machine learning library. The loss term and optimizer specified for the system were Huber loss and Adam optimizer. There are two Python files that form the hybrid ANFIS system, anfis.py and actions.py. The codes in the anfis.py file do the following tasks:

1. Defines the anfis class
2. Sets all the 30 trainable parameters of the Gaussian MF for both inputs’ and output’s fuzzy linguistic labels
3. Set all the 405 trainable coefficients of the First-Order Sugeno Fuzzy Model
4. Creates the six layers of the hybrid ANFIS system
5. Defines the functions for training and testing the system, and for plotting the results.

The actions.py file is an application of anfis.py to marketing decision-making. It takes input data on Seniority, Purchase Propensity, Company Size, and Contactable to generate 81 if-then rules that have both Sugeno’s and Mamdani’s outputs. This file gives the following outputs:

1. A display of the 30 Gaussian MF parameters for both inputs’ and output’s fuzzy linguistic labels
2. A display of the 405 coefficients of the First-Order Sugeno Fuzzy Model
3. Plots of the

a) Training losses,

b) Validation losses,

c) Training – Mean deviation between predicted & actual values,

d) Validation – Mean deviation between predicted & actual values,

e) Seniority MF,

f) Purchase Propensity MF,

g) Company Size MF,

h) Contactable MF, &

i) Actions MF

4.0 RESULTS

Our hybrid ANFIS system has demonstrated its potential for improving marketing decision-making in companies and this will lead to higher ROIs on marketing campaigns. The system:

1. Is capable of automating marketing decision-making
2. Has an intuitive graphical representation for marketing decision-making
3. Makes linguistic labels of input variables highly interpretable

**4.1 Findings**

We trained the hybrid ANFIS system for 1,000 epochs with the dataset split by a 80 to 20 ratio for training and testing. We used these approaches to optimize the training of the system:

1. Sugeno’s predicted values – We used the Sugeno’s predicted values to calculate training losses, instead of Mamdani’s predicted values
2. Rectified Linear Unit (ReLU) activation – The outputs of Layer 1, 4 and 6 were passed to ReLu activations
3. L2 Regularization – We applied L2 regularization to all 435 trainable parameters
4. Initialization – We restricted the values of mu to fall roughtly around 0.1, 0.5, and 0.9 for the first, second, and third linguistic labels respectively. Values of mu were further constrained to between the range of 0.0 to 1.0. Similarly, the values of sigma was also constrained between the range of 0.0 to 0.33.

We obtained models with losses of around 0.1 (Fig 3 & 4) and predicted values that were very close to the actual values (Fig 5 & 6). We agreed that this was an acceptable level of training performance, given the time constraint that we are facing and proceeded to examine the results of the trained hybrid ANFIS system.

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Fig 3

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Fig 4

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Fig 5

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Fig 6

4.1.1 Premise Parameters of Input Variables

We first examined the 24 premise parameters of the 12 linguistic labels of the input variables (Fig 7). All of the parameters complied to its range of allowed values. That is, values of mu were between 0.0 to 1.0 and values of sigma were between 0.0 to 0.33.

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Fig 7

These parameters in combination with the Gaussian MF generate the values needed to graphically plot the learned Gaussian MF for each of the four input variables’ linguistic labels (Fig 8, 9, 10, & 11).

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Fig 8

A close up of a map

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Fig 9

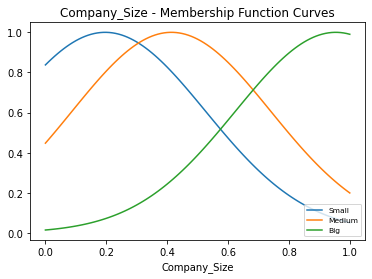


Fig 10

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Fig 11

The interpretation of these plots is straightforward. Suppose that we have an input value of 0.2 for Seniority, then the membership grades for this input are the values of the vertical axis where a vertical line from 0.2 on the horizontal axis intercepts each of the three curves (Fig 12). Therefore, the input is most likely to be “Junior” because this was the highest membership grade for the value 0.2.

A close up of a device

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Fig 12. An Example of How to Interprete the Seniority MF

4.1.2 Consequent Parameters of Target Output

We next inspected the six consequent parameters of the three linguistic labels of the target output (Fig 13). All of the parameters also complied to the range of allowed values. Figure 14 shows the plot of the Actions MF. The same technique of interpreting the input variables’ MF plots also apply to the Actions MF. Sugeno’s outputs from the fifth layer serve as the input to calculate the Mamdani’s output of the sixth layer. We will discuss how to compute Sugeno’s output in the section below.

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Fig 13

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Fig 14

4.1.3 Fuzzy If-Then Rules & Coefficients Matrix of First-Order Sugeno Model

Finally, we shifted our attention to the learned fuzzy if-then rules and the coefficients matrix of first-order Sugeno fuzzy model. We have listed the basic structure of the learned fuzzy if-then rules, so that our readers would have a more concrete understanding of how marketing decision-making can be implemented by our hybrid ANFIS system (Fig 15). Sugeno’s outputs are referred to as Actions in these rules. All 81 if-then rules can be constructed from the basic structure by substituting the linguistic labels accordingly.

Fig 15. Basic Structure of the Learned Fuzzy If-Then Rules



For example, the if-then rule for an attendee who is a junior employee with no plan for purchase, is working in a small company, and has indicated that he/she does not want to be contacted is shown in Fig 16.

Fig 16. An Example of the Learned Fuzzy If-Then Rules



The next step of using this rule is to apply the first-order Sugeno fuzzy model to calculate the Sugeno’s output of the rule. Continuing with the rule shown in Figure 16, this calculation requires the set of coefficients for this particular rule. These coefficients are displayed in the first row of the coefficients matrix (Fig 17).

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Fig 17. Samples of the Coefficients Matrix for First-Order Sugeno Fuzzy Model

With these coefficients, the value of the Sugeno’s output for the example rule can be computed by substituting the values of input variables accordingly in the equation below:

ACTIONS = 0.240384(SENIORITY) + 0.985717(PURCHASE PROPENSITY) + 0.248951(COMPANY SIZE) + 0.378607(CONTACTABLE) + 0.869713

5.0 CONCLUSION

**5.1 Observations & Insights**

It has been a fruitful experience working on this system, and there were numerous learning observations and insights that we took from this project. However in the interest of brevity, we would like to just talk about the most impactful learning point of this project.

5.1.1 ANFIS Architecture can be Extended to Generate Mamdani-Type Outputs

Without a doubt, the most significant achievement of this project was to extend the functionalities of the ANFIS system such that it is now capable of generating both Sugeno’s and Mamdani’s output. The road to getting the hybrid system to work has not been easy.

The first challenge that we had to conquer was figuring how to modify the existing codes from the ANFIS workshop to fit the architecture of the hybrid system. The materials from the course and the workshop gave us plenty of guidance on how to proceed with the modification. On top of these materials, we also read the original ANFIS paper by Jang (1993) and that helped us greatly.

The real challenge came next when we tried to train the system. In the dozens of initial attempts in training the system, we faced the difficulty of getting the losses to drop beyond 0.85. After a steady decline in the first few hundred epochs, the training losses would plateau around 0.85 regardless of the number of epochs assigned for training.

This problem halted our progress for several days, but we eventually began to lower the training losses. The first breakthrough was changing our focus from minimizing the losses of the Mamdani’s predicted values to that of the Sugeno’s predicted values. Not only did we start to see further reduction in training loss, we also observed that the Mamdani’s output continued to be generated accurately.

Based on this observation, we hypothesised that lower training losses, and consequently lower validation losses, can be achieved by controlling the losses from the fifth layer of a hybrid ANFIS system, instead of its sixth layer. Furthermore, this change would not affect the training of the sixth layer.

We then proceed to further reduce the training losses by incorporating (1) ReLu activation functions, (2)L2 regularization, and (3) the initialization of values for parameters of the Gaussian MF. These changes swiftly brought the training losses down.

Examining the Mamdani’s output and its application to marketing decision-making made us realised that our system has the potential of solving problems beside marketing. As illustrated clearly in this application, we believed that there are many more instances where human judgement is represented as linguistical if-then rules. Whereas the typical ANFIS system provide the users with a numerical value to inform their decision, we are able to generate a much more human interpretable linguistic output that users can easily understand.

**5.2 Future Actions – Improvements to the System & Further Research**

The tight time constraint of this project limited some of the ideas that we had planned to implement. Therefore, these ideas will be presented here as possible actions that can be considered for future development of the system.

5.2.1 Further Reducing Training Losses and Increasing Accuracy of the System

We believed that there is still room to further improve the training results of our system. If time permits in the future, it is worth considering tuning the system further to achieve better results. A potential approach to doing so is to use Genetic Programme (GP) to evolve the Hybrid ANFIS system, because this technique has the potential to accelerate the manual process in optimizing this system.

5.2.2 Incorporate More Membership Functions Into the System

We had planned to make the option of selecting other membership functions, beside Gaussian MF, available for anfis.py. These other options would include the (1) Triangular MF, (2) Trapezoidal MF, and (3) Bell MF. Having these alternative MFs would increase the range of problems that our system can effectively address, and thus increasing the usefulness of the system.

5.2.3 Train the System to Select the Optimal Number of Fuzzy Labels

Although ANFIS has resolved many of the challenges posed by Fuzzy Logic, it is still reliant on external experts to help it define the number of fuzzy labels for the system. While this might not be an issue for cases where there are knowledgeable experts able to do this task competently, the performance of the system suffers when there is incomplete knowledge to guide the number of fuzzy labels to select.

We thinks that it might be possible to get the system to learn how to select the optimal number of fuzzy labels. We again think that GP might be a promising first step to take in our experiments, because of its strength in optimization of system.

APPENDIX A. USER MANUAL

The Hybrid ANFIS System requires the list of packages detailed in the requirements.txt file. Users are advised to create a new environment before running the codes in anfis.py and actions.py. Anaconda users can install all the required packages using either this command “***pip install -r requirements.txt***” or “*conda install -r requirements.txt*”.

The following files are needed to run the system: (1) anfis.py, (2) actions.py, and (3) Data\_combined.csv. We recommend that users save these files together in the same folder, and run the Python scripts using Spyder.

APPENDIX B. DATASETS

**Dataset – Input Variables & Target Output**

Issues of data privacy prevented us from training our system on actual marketing survey data. However, we have created a python script that generates synthetic data that mimics the statistical properties of the actual data. The dataset comprises four input variables and one target output. These input variables are:

(1) Seniority,

(2) Purchase Propensity,

(3) Company Size, and

(4) Contactable.