Rule Generation for Scenario based Decision Support System on Public Finance Domain

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Abstract: This study is a part of a larger project called "Ontology Based Decision Support System". In this document, we report methodology of the Rule Generation (RG) that is planned to be taken from the knowledge queried from ontology based Knowledge Extraction System (KES). Rule generation aims producing rules for a rule based system, which will be used for future prediction of an organization or an organizational unit. The term "scenario based" implies that the system will do future prediction for possible scenarios of next movements like different budget scheduling scenarios. Future prediction will be limited to the prediction of parameters that the organization is willing to know, such as the parameters related to the objectives and the goals on their strategic plan. In literature, rule generation problems are addressed by variety of different learners; so what we plan is using a learners system with many learners possibly with different types. The system will be valuable for merging an ontology based KES and DSS with future prediction capability. In addition, this will be the first composite system (having mentioned KES+DES) for public finance domain.

1 STAGE OF THE RESEARCH

So far, we made a literature view and architectural design of the project. We build the public finance ontology to be used by the KES. In addition, we mostly decided on the methodology and required technology to build the system. As the data set, we chose EU-funded research projects on Community Research and Development Information Service (CORDIS) and the EU as the organization. Now we are working on building the DSS for the projects completed after 2010, on the evaluation of projects we are searching the relations between targets and project contents, and effects of the projects on complying with the Europe 2020 strategy. Briefly, doctoral studies are on at the stage of analysing the pilot organization and realizing the design.

2 OUTLINE OF OBJECTIVES

This study is a part of a larger project called "ontology based decision support system". We have chosen public finance as the pilot domain and the team includes domain experts as well as other colleagues working on ontology development and knowledge extraction. Overall plan of the project is developing two modules: first, for extracting knowledge from structured and unstructured data to feed a rule based decision support system and second, for the rule based decision support system making future prediction on both if-then and what-if type questions. The system is shown in Figure. 1. As to the benefits of the decision support system (DSS) the beneficiary organization will be capable of making future predictions by running simulations. Therefore, the aim of pilot project is trying different resource allocation scenarios beforehand and helping to make the best allocation option for achieving predetermined strategic goals of the organization. In general, if such systems are common enough, policy makers will have tools for Regulatory Impact Analysis (RGA).

For the what-if type questions, we expect to propose a generic predicting mechanism with the ability to make the inferences at a success rate that is significantly higher than the rate of a RBS with static rules and significantly close to the answers of the domain experts.

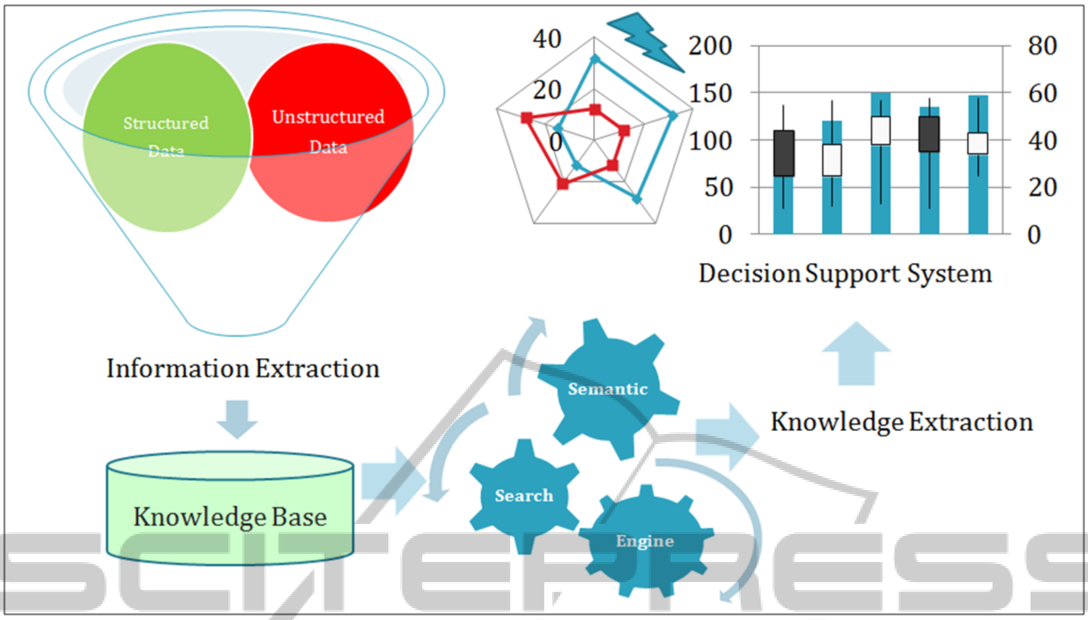

Figure 1: Ontology Based Decision Support System.

3 RESEARCH PROBLEM

Resource allocation for public agencies is a derivative of portfolio management problem (PMP) which is central in the modern financial theory. We can easily define a projection as follows; as the securities in PMP we have different projects and programmes in public resource allocation. In PMP, the target is maximizing the utility of the investor, while in public resource allocation it is maximizing the utility function related with the strategic goals and targets of the organization. Apparently, problems may be seen as belonging to the same class but for PMP many financial DSSs have been proposed and widely used, while for public resource allocation problem, the tools are limited. Another research requirement for the domain is estimating the results of the resource allocations beforehand. Today the domain experts try to analyse the outcomes by the help of specific documents and their experience.

Learning the experience is a main concept in machine learning and there are constructs like rule based system (RBS) to store and use the experience. However, in the problem, a further step that is predicting the future states of determined parameters according to the possible moves is still a challenging. This challenge may be divided into two: firstly, the possible moves may be unobserved; secondly making the simulations needs a special tool, not a standard DSS.

Another subproblem in public resource allocation is utilizing the structured and unstructured data automatically. This data includes reports, articles and documents in any format. Previous actions, results and analyses are embedded in these documents and domain experts turn them into knowledge by manually executing them. Afterwards they contribute to the finance system by preparing new documents. The extraction of knowledge in such an environment can be addressed by ontology based KESs. For this purpose, parsing the documents to populate the ontology is another research challenge.

Our study both includes knowledge extraction from structured and unstructured data and using the extracted knowledge in the DSS. Instead of a conventional DSS, one with making simulations of possible movement combinations is targeted in the study. The question that the DSS should answer is “what is the state of the n^{th} target parameter if I allocate resources in this way? “. For the unobserved situations we plan to enrich the rule base with the generated rules.

4 STATE OF THE ART

By a broad approach, decision support systems are computer-aided systems helping in decision-making process, as the name implies (Finlay, 1989). In a more detailed definition, they have easy-to-use, interactive interfaces. They are designed especially for helping in complex management problems by using the information they store in different formats. They are expected to be flexible, extendible information systems (Turban, 1990).

There exist different taxonomies for DSS. (Power and Sharda, 2009) One choice is classifying them as model driven and data driven (Dhar and Stein, 1996). In this study, we plan to use Rule Based System (RBS), which is an example of model driven DSS. RBS is a problem solver in a situation-action manner by formally describing the situation and the action in if-then rules. RBS builds the expertise on the fields that need logical reasoning and practical experience (Buchanan and Duda, 1983)

In literature for prediction problems, time-series analysis models are commonly used. Time-series analysis is also helpful in resolving the periodical behaviours of the independent variables (Shumway and Stoffer, 2000). However, for unobserved situation a more advanced predicting mechanism is needed, such as a rule-based system (Sahoo et al., 2003). According to the research on prediction (not primarily on the 'future prediction') using RBSs; the proposed methods analyze past input and output data of the observations for gathering target output variables for given input variables. Each set of $<(i_1,v_1), (i_2,v_2)\ldots (i_n,v_n), (o_1,r_1), (o_2,r_2)\ldots (o_m,r_m)>$ defines a rule for the system.

For prediction problems where unobserved situations are expected, researchers also used Artificial Neural Networks (ANN), Support Vector Machines (SVM) and similar machine learning constructs (Min and Lee, 2005) (Khan et al., 2001) (Han et al., 2006) successfully. However, these architectures are not so comprehensible; they are packaged tools answering questions when asked, while in most cases also reasoning is necessary for analyzers. To close this gap, in literature, many methods were introduced for rule extraction by/from ANNs, SVMs and similar machine learning constructs (Kuttiyil, 2004), (Augasta and Kathirvalavakumar, 2012). In addition, rule induction methods are used for rule generation on relatively moderate problems (Triantaphyllou and Felici, 2006). In this study, a composite system that will use multiple data sets will be build. This yields that the system will use different rule extraction and induction methods to work in the most accurate and efficient way.

Before the review of the literature, let us inform that we use "rule extraction", "rule generation", "rule induction", "rule refinement" terms in the paper. We imply a broader scope for rule generation including all as in (Mitra and Hayashi, 2000). Moreover, as we plan to use a RBS with generated rules, the main research filed is rule generation and following review is on this direction. The following part of section is dedicated to review of the rule generation methods and the data sets that were used in those studies. The aim is to give the reader the ability to match best the rule generation method for his/her data set.

Andrews et al. proposed a classification scheme for rule extraction techniques by ANNs that can easily be extended to other classifiers and rule generation methods. Their scheme is based on expressive power, translucency, portability, rule quality, and algorithmic complexity (Andrews et al., 1995). Later new researches widen the definition and the scope of the concepts listed above (Jacobsson, 2005) (Browne, 1997) (Sethi et al., 2012). We can describe them shortly as below:

Expressive Power; how well the rules presented to the end user,

Translucency: the degree to which the technique considers the internal structure of classifier

Portability; the degree to which the technique is applicable to other classifier architectures

Rule Quality; according to previous studies rule quality have four aspects (Towell and Shavlik, 1993):

"Rule accuracy—the ability of the rules to generalize to unseen examples

Rule fidelity—how well the rules mimic the behavior of the classifier

Rule consistency—the extent to which equivalent rules are extracted from different networks trained on the same task (same data set)

Rule comprehensibility—the readability of rules or the size of the rule set" (Jacobsson, 2005)

Algorithmic Complexity; the total complexity of the rule extraction steps.

We find it suitable to make the taxonomy of the rule generation methods according to their translucency as it is more about the technical approach of the method and this choice is common in literature as in (Barakat and Bradley, 2010). From the translucency view of the methods, we can list pedagogical and decompositional approaches, plus the hybrid of them: eclectic approach. We will give description and examples of the approaches in the rest of this section.

4.1 Pedagogical Approach

Pedagogical rule extraction methods analyze the inputs and the outputs of the classifiers and treat them as black boxes, they do not look inside the internal structure of the classifier. As expressed before, classifiers are in types of ANNs, SVMs and similar constructs (Taha and Ghosh, 1996) (Tsukimoto, 2000).

To overcome the comprehensibility limitation (black box behavior) of the SVM, Martens et al utilized rule extraction from SVMs s (Martens et al., 2007). Actually, this is one of basic reasons for rule extraction. They compared recent rule extraction techniques for SVMs and two more techniques for trained ANNs according to the fidelity, accuracy and number of the rules. They conducted experiments on Ripley's synthetic dataset (Ripley et al., 1994), iris dataset, the breast cancer dataset, Australian credit scoring dataset from the University of California at Irvine (UCI) Machine Learning Repository (MLR) (Hettich and Bay, 1999) and the bankruptcy data of firms with middle-market capitalization (mid-cap firms) in the Benelux countries (Belgium, the Netherlands and Luxembourg) (Gestel et al., 2006). They put forward that the performance of the rules extracted from SVM is slightly less than that of the SVM. By the way, their research is valuable for the background information about the rule extraction methods up to 2006 and the SVMs.

Martens et al. also provided a new approach in order to increase both the accuracy and the comprehensibility of the extracted rules. Normally, the classifiers' accuracy on classification is better than the rule sets' accuracy on the same data set as seen in (Martens et al., 2007). They ascribed the loss to the data inconsistency. Naming the process as active learning, they relabelled the samples after the training with the labels of the trained SVM. The wine, balance, sonar, German credit, contraceptive method of choice datasets from the UCI data repository (Hettich and Bay, 1999), binary synthetic dataset of Ripley (Ripley et al., 1994), Belgian and Dutch credit risk datasets were used to test the new approach and results show that active learning increases the accuracy and fidelity. In the study, the researchers also express that RE methods are better than rule induction methods for high-dimensional data having nonlinear relations while rule induction techniques can perform better on data sets where data can actually be described in simple rules (Martens et al., 2009).

Kahramanli and Allahverdi, proposed a new method for RE from trained adaptive neural networks, which uses artificial immune systems. Electrocardiogram (ECG) and Breast Cancer datasets from UCI MLR were used in tests (Kahramanli and Allahverdi, 2009). They showed ANNs with adaptive activation functions provide better fitting than classical architectures with fixed activation functions.

Setiono et al. proposed another ANN based, recursive RE mechanism that firstly considers some part of the discrete attributes (the necessary to generate discrete valued rules) in the rule generation. If the rule set is not efficient enough, all the discrete attributes are considered in the second step, finally continuous attributes are also considered to achieve the desired accuracy. They have used the German credit dataset from UCI MLR ((Hettich and Bay, 1999) and the Bene1, Bene2 datasets that were obtained from major financial institutions in Benelux countries (Setiono et al., 2008).

4.2 Decompositional Approach

Decompositional rule extraction algorithms utilize internal structures of the learners, such as the hidden layers of the ANN, U-matrix of the Self Organizing Map (SOM), the hyperplane of the SVM or the weights of internal vectors (Setiono and Liu, 1997). It is observable that some methods assign linguistic meanings to the nodes. As the algorithms deal with the internal nodes, computational complexities for them get exponential.

As an instance, Li and Chen proposed a SVM based RE mechanism. Their process includes the following activities in order; feature selection by Genetic Algorithm (GA), constructing hyper-rectangle rules by Support Vector Clustering (SVC), rule simplification by hyper rectangle combination, interval extension and dimensionality reduction ((Li and Chen, 2014). They used six datasets from the UCI MLR (Hettich and Bay, 1999) to test their method on extracting classification rules.

In another SVM based method, Wang et al. used rule extraction for clustering problem on strip hot-dip galvanizing by defining convex hulls on the hyper-plane of the SVM. Later, the convex hull defined for each cluster, formed a rule. Process also includes k-means clustering preprocess. They applied the algorithm to real strip hot-dip galvanizing process (Box and Jenkins, 1976).

Not only supervised learning methods are used for RE, also methods with unsupervised classifiers such as SOMs are used. Leng et al. proposed a hybrid neural network, called the self-organizing fuzzy neural network (SOFNN), to extract fuzzy rules from the training data (Leng et al., 2005). The SOFNN consists of five layers and the first hidden layer consists of ellipsoidal basis function (EBF) neurons. The learning method includes adding and pruning neurons. For realizing RE, when some neurons have similar membership functions, they were gathered in the same group and combined into a new membership function. They tested their method on generated data sets regarding to three-input nonlinear function and pH neutralization process, in addition to the well-known Box–Jenkins furnace data set (Box and Jenkins, 1976).

In order to find a new method for RE, Etchellls et al. proposed an algorithm from the neural network trained for binary classification using 1-from-N binary coded ordinal explanatory variables. Their algorithm, called Orthogonal Search-based RE (OSRE), reduces the number of the orthogonal rules for each data point by eliminating those orthogonal rules for which there is no change in activation, i.e. redundant conditional clauses in the antecedent part of the rule are omitted. They have used Monks' data (Thrun et al., 1991) and Wisconsin's breast cancer data (Bache and Lichman, 2013) to test their method and compare it with the some other methods (Etchells and Lisboa, 2006).

A typical decompositional RE method was proposed by Malone et al. for the automatic extraction of rules from trained SOMs. Their technique performs an analysis of the U-matrix of the network for extracting the components on the map. Then component boundaries were used to form basis of the rules. They used Iris, Monks and Lung Cancer data sets (Bache and Lichman, 2013) in order to compare their method's accuracy (Malone et al., 2006).

4.3 Eclectic Approach

The hybrid of the two approaches; decompositional and pedagogical is specifically called as "eclectic" approach. Barakat and Diederich proposed an example eclectic approach by using SVMs. Their study is one of the methods showing that methods applied on ANNs are applicable to SVMs as well. They used four datasets from UCI MLR: Pima Indians Diabetes, Heart Diseases, Breast Cancer and Hepatitis datasets (Bache and Lichman, 2013). They contributed on evaluating the quality of the extracted rules by analyzing the number of training patterns, the leave-one-out accuracy of SVM , the number of support support models, the number of rules/ antecedents, the classification accuracy of SVM on test dataset, the accuracy and fidelity of the rules (Barakat and Diederich, 2006).

4.4 Other Methods

The methods that are classified in the previous categories mostly use ANN and SVM types and they are called as RE methods. However, there are many methods producing rules using different techniques and not in the previous categories, as we will mention below.

Predicting the price gains in the first day of Initial Public Offering (IPO) has been a popular subject and Quintana et al. proposed a rule-based system utilizing genetic algorithms for the predictions about the gains (Quintana et al., 2005). They have constructed the rule-base using 840 past IPOs as training set. They have parameterized an IPO by filling some predefined variables for the IPO and the price gain. The rules, i.e. if $lb_1 < v_1 < ub_1$, $lb_2 < v_2 < ub_2$ … $lb_7 < v_7 < ub_7$ then gain is r_1, are produced from these existing IPOs. For the outlier cases, they have utilized genetic algorithm with Michigan approach.

For Complex Event Processing (CEP), Margara et al. achieved rule generation by analyzing the historical traces with their ad-hoc learning algorithms. They produced partial rules, combined them into one rule that gives necessary conditions to alert a critical phenomena. They used the dataset including time stamped information about the positions and the status of buses in the city of Dublin (Margara et al., 2014). Their solution on producing rules in order to detect a composite event from timely logs is quite inspiring, but on most problems answering a question like "is there a fire or not?" is not enough, the RE mechanism should give a more detailed output set. For a similar problem, Sannino et al. proposed a mobile system for Obstructive Sleep Apnea (OSA) event detection and they tested their approach on an apnea-ECG database ((Penzel et al., 2000). They used a new RE mechanism called DEREx based on Differential Evolution. DEREx generates and selects desired individuals in a population, and then rules are encoded from the selected individuals (Sannino et al., n.d.) (De Falco, 2013)

Rule generation was also utilized on the problem of prediction of promoters in the DNA sequences by Karli. He proposed a new method called Inductive Rule Extraction Method (IREM), which takes attribute-value pairs as classes and selects the best pairs to use in extraction of the rules. Cost function that was used in selection, mainly depends on class-based entropies. Method was tested on the E. Cole promoter gene arrays of DNA, which were collected from the UCI MLR (Bache and Lichman, 2013) ((Karl, 2014). In a close topic, for gene expression profiling Chen et al. tried RE from trained SVM with multiple kernels (Chen et al., 2007). They used

ALL-AML leukemia dataset (Golub et al., 1999) and colon tumor dataset (Alon et al., 1999)

As an example of rule induction, Y. Qian et al. introduced a method from decision tables based on converse approximation (CA). In their study basically, CA is used to give the definition of the upper and lower approximations of a target concept under a granulation order. They explained and gave the usage of their algorithm on two simple custom data sets (Qian et al., 2008).

5 METHODOLOGY

As expressed below, the final output of this work is an ontology based DSS with scenario-based future predicting capability. In the general view of the planned tasks, the list isas follows: analyzing the resources that belong to the pilot organization, determining the parameters related with the fields of prediction and determining the resources, which will be used to assign values of those parameters. The mentioned determinations are being made together with the domain experts in the research team. As the data set, we chose EU-funded research projects completed after 2010 on CORDIS and the EU as the organization. Now, we are working on the policy documents of the EU such as EUROPE 2020 strategy, definitions of the programmes, scope of the subjects and other project related data published in The EU Open Data Portal and CORDIS project database. Later on, a conventional RBS will be created. However, since we do not have a method that will automatically feed the RBS with rules and facts yet, we will manually produce rules and facts from the resources and make the RBS capable of giving reasonably accurate answers for the past data on manually generated test cases. On the next phase, we will develop the dynamic rule extraction mechanism for making predictions on the inexperienced scenarios. As mentioned before, we will develop a learners system for dynamic rule generation. According to determined decision parameters and deductions on obtaining these parameters, necessary learner types and their working principles (such as ordering, weights, and necessary computations) will be specified. When all the system specifications are ready, creation of the learners, the derivation of feature vectors, training, testing and optimization phases will be conducted. After the learners system is established, the complete DSS (with whole knowledge base) will be tested on the scenarios that were prepared at the beginning of the study and then necessary optimizations will take place.

To make the whole “ontology based decision support system” work, finally, we will combine the ontology based knowledge extraction system and the scenario based DSS to constitute the system that can enrich its knowledge base from both structured and unstructured data. The key point on the combining method is the query results should be data sets, which can be easily processed by training algorithms. As mentioned before, this will make other researches possible on the extracted knowledge.

Remaining of this part gives the phases of the study in detail.

5.1 Building the Ontology

This part of the study is mostly completed; the others are in progress or waiting status. In this phase, firstly to gain domain expertise we have discussed key terms in budgeting, accounting and necessary related topics in public finance with domain experts on regular meetings. After defining relations, making simplifications and grouping were done and finally sub ontologies and relations between sub ontologies were determined. (Since this study is not about ontology development, details will not be given.)

5.2 Determining the Properties of the Knowledge Base

In this phase high-level policy papers, budgets of past years, reports as programme budget realizations are being inspected. By the inspection, necessary decision parameters, intermediate parameters, key performance indicators (KPI), key goal indicators (KGI) and similar important information for defining the facts and the rules will be specified. A sample analysis on the relations of the pilot domain can be seen in Figure 3. The process includes

revealing the relations and effects between these concepts and defining the resources containing that information. For this purpose, together with the domain experts, we are making analysis on the query and report needs of decision makers. The domain experts will evaluate the success rate of the studies in this phase. In addition, all the tests in next phases will check and update these outputs.

By the way, domain experts in our team have public finance experience; however, it would be better if we could work with EU officers during the project.

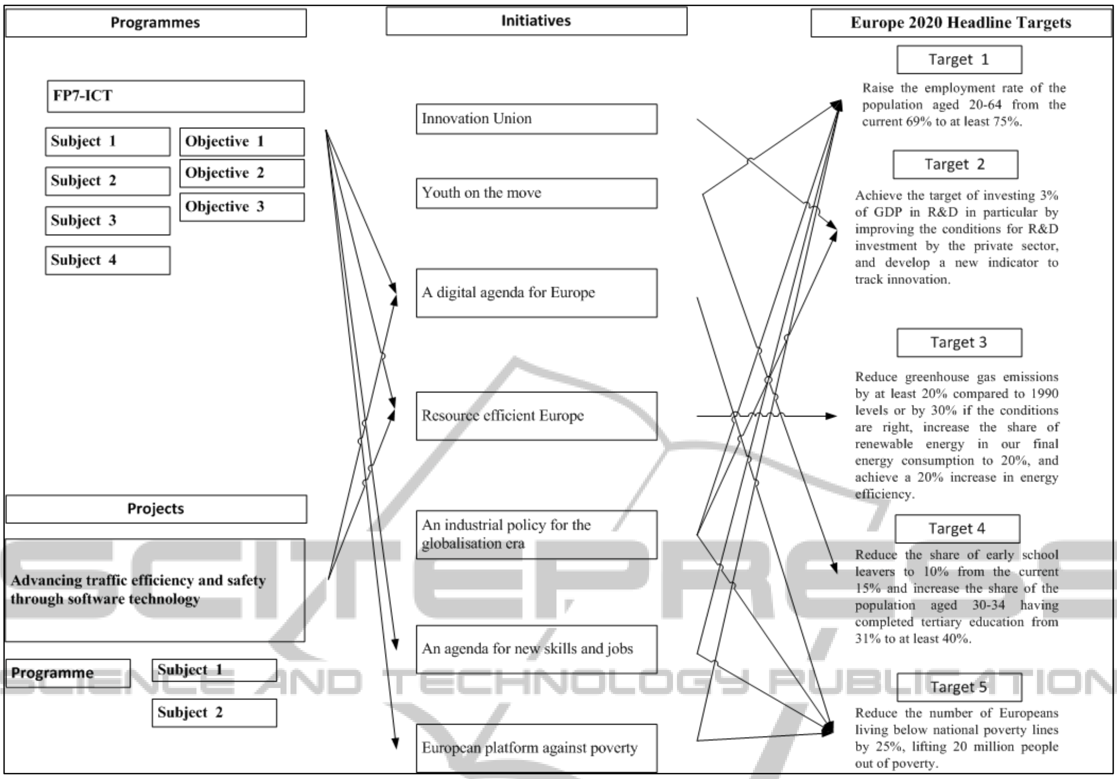

Figure 3: A sample analysis on relations between projects and organizational targets.

5.3 Developing Static Rules Base

In this phase, a custom system development life cycle for RBS development will be defined and it will be repeated in the next phases. According to properties defined in the previous phase, we will manually formulate facts and rules, and we will introduce them to the RBS. Then we will make verification and validation tests on the RBS with an enriched knowledge base. We aim the following gains by the tests:

- resolving the issues as ambiguities in the information resource
- resolving the knowledge base errors and anomalies in the definitions of the facts and the rules
- resolving the errors in the inference engine
- determining the situations that may result in misconception when using the system, and resolving these by the activities like providing ease-of-use, making input validation, checking the system messages

To measure the success rate of these outputs we will apply methods in following two categories.

5.3.1 Static Methods

- Inspection of rules and facts by the domain experts manually
- Automatic syntax checks
- Automatic logical anomaly checks like integrity and rule pair checks

5.3.2 Dynamic Methods

- Running the test cases obtained from past data
- Running the test cases designed by domain experts, organization personnel (if possible) and researchers
- Running the randomly generated test cases obeying some semantic constraints, if the above test cases are not found sufficient

5.4 Developing Dynamic Rule Extraction Mechanism

The dynamic rule generation mechanism is the part of the system that will make rule simulation, answer the questions that cannot be answered by static rules and predict the future states of the decision parameters. To develop this mechanism according to determined decision parameters and deductions on obtaining these parameters, necessary learner types and their working principles will be determined. By the analysis on the data sets, features for different learner types will be chosen and then the training, testing, optimization activities will follow. In addition, we will develop an external application for domain experts for training the system by asking what-if type questions and saving the answers to the system. We plan to run all the test cases that we run on the static rules base.

6 EXPECTED OUTCOME

The expected outcome of the project is an ontology based DSS which has two big modules: ontology based KES and scenario based DSS. Second one is the expected outcome of this thesis. As given in Figure 1, the system starts with processing structured/unstructured data and transforming them to knowledge, which is suitable for feeding knowledge base of the DSS. It is planned to send queries to the KES and get a data set about a topic. This approach is chosen because the result as a data set is standard and can be used for other researches as well. KES also has a knowledge base that should not be confused with the knowledge base of the DSS.

We plan to implement the DSS by a RBS with both static and dynamic rules. By a *dynamic rules base*, we mean a rule generation system (RGS). Two basic innovations are aimed by the proposed Rule Generation System (RGS). Firstly, it is a novel approach on generating rules for many related but different topics, so the architecture is able to give comprehensible reasoning about composite events and it gives a design template for similar research. Second innovation is producing rules for answering the what-if type questions like if-then type ones.

In this paragraph, let us tell why we need the dynamic rules. To make the system initialization for the chosen topic, firstly previous experiences and answers of domain experts for some (present or produced) cases should be stored to the system knowledge base. After this process, the RBS should be able to use its power on making inferences about the present situation and make reasoning. However, gathered as described below, a static knowledge base will not be sufficient to explain the results of scenarios that have not been observed before, we mean here static knowledge base will not be sufficient on "explaining answers of what-if type questions". To overcome this, we propose a RBS with both static and dynamic rules. The basic view of the system is in Figure. 4. The system has basic features of a RBS (Hayes-Roth, 1985) plus dynamic rule base.

What is expected from this RGS is giving the rule that defines the result, suggestion or the action related to a particular if case. The difference of the dynamic rule base's answer from a conventional RBS's answer is that it may be the result of a computation, generalization or another process by the system module, which is responsible for a particular topic. We plan to realize this system by different the constructs as ANNs, SVMs and other rule generation methods, as seen in Figure 6. A necessary amount of learners will be deployed and they will be in suitable type for the related dataset. After training the whole system with data set from the KES, it will be possible to generate rules and resolve inexperienced situations by the help of its internal learner capabilities such as generalization.

The proposed system seen in Figure 6 has a modular structure where modules can produce independent results. It must be noted that any module has its own data set and they do not feed each other. The data sets are gathered by different query results from the KES. The arrows on the figure mean; on execution, the rule selector will go in the direction or in the opposite direction of the arrows. Non-technically saying when an answer is waiting to be given, the system will consider the related topics; it may be for the results or for the causes. When all the rules about different topics are generated, they will be collected in the RBS's knowledge base. The mentioned search for related topics of an event will be achieved by the RBS, here we figure them separately in order to show that they will be generated separately.

Another notification that should be given is about the purpose of the learners as ANNs and SVMs on what-if type questions. They have the strength to give an output vector when you provide the input vector, where these vectors are meaningful representations in our problem domain. From this, we may conclude that they can answer what-if type questions. Right, they can answer desired question but they cannot always explain their answer. Surely, we do not admit this on various real world problems. Instead, they will be used for RE, and what-if questions will be answered by the rules that learners generated. When using the rule sets but not the learners themselves, one should feel disturbed about losing learners' capabilities such as learning and generalization, since the rules are extracted from learner not from the data set. Researches as (Martens

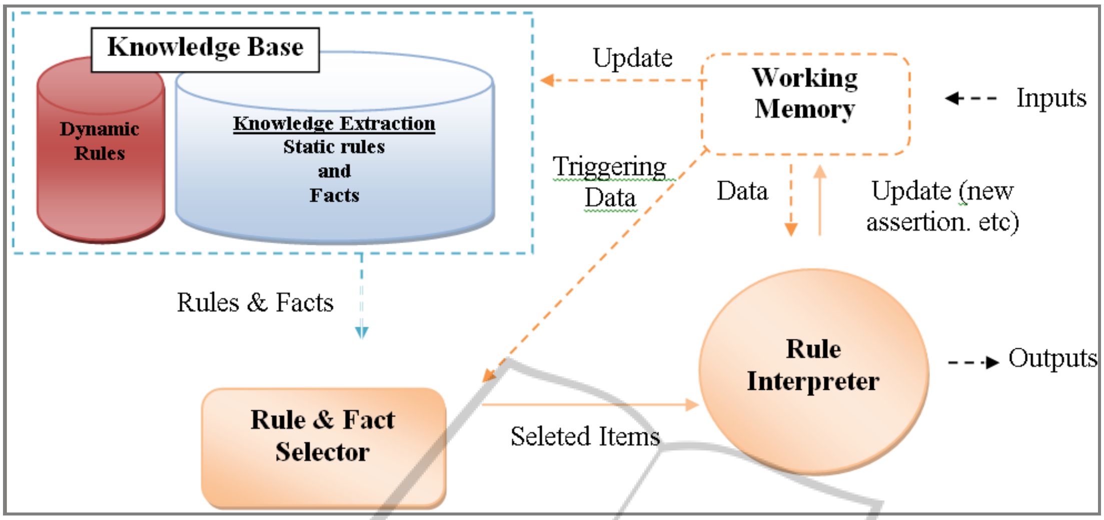

Figure 4: DSS with Dynamic Rule Set.

(Martens et al., 2009) show that the learners have better accuracy than the accuracy of the rule set they generated. Even so, in this study, we sacrifice accuracy in a small rate not to lose comprehensibility. We pictured the mentioned scenario in Figure 5.

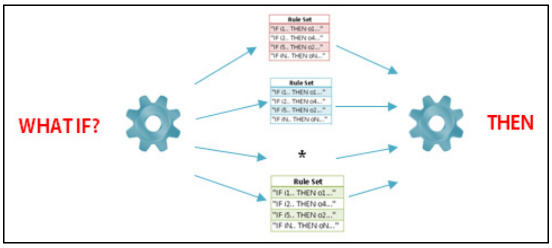

Figure 5: System answering what-if type questions.

REFERENCES

Alon, Uri, Barkai, Naama, Notterman, Daniel A, Gish, Kurt, Ybarra, Suzanne, Mack, Daniel, and Levine, Arnold J. 1999. Broad patterns of gene expression revealed by clustering analysis of tumor and normal colon tissues probed by oligonucleotide arrays. *Proceedings of the National Academy of Sciences*, 96(12), 6745–6750.

Andrews, Robert, Diederich, Joachim, and Tickle, Alan B. 1995. Survey and critique of techniques for extracting rules from trained artificial neural networks. *Knowledge-based systems*, 8(6), 373–389.

Augasta, M Gethsiyal, and Kathirvalavakumar, T. 2012. Rule extraction from neural networks—A comparative study. *Pages 404–408 of: Pattern Recognition, Informatics and Medical Engineering (PRIME), 2012 International Conference on*. IEEE.

Bache, K., and Lichman, M. 2013. *UCI Machine Learning Repository*.

Barakat, Nahla, and Bradley, Andrew P. 2010. Rule extraction from support vector machines: a review. *Neurocomputing*, 74(1), 178–190.

Barakat, Nahla, and Diederich, Joachim. 2006. Eclectic Rule-Extraction from Support Vector Machines. *International Journal of Computational Intelligence*, 2(1).

Box, George EP, and Jenkins, Gwilym M. 1976. *Time series analysis, control, and forecasting*.

Browne, Antony. 1997. *Neural network analysis, architectures and applications*. CRC Press.

Buchanan, B.G., and Duda, R.O. 1983. Principles of rule-based expert systems. *Advances in Computers*, 22, 163–216.

Chen, Zhenyu, Li, Jianping, and Wei, Liwei. 2007. A multiple kernel support vector machine scheme for feature selection and rule extraction from gene expression data of cancer tissue. *Artificial Intelligence in Medicine*, 41(2), 161–175.

De Falco, Ivanoe. 2013. Differential Evolution for automatic rule extraction from medical databases. *Applied Soft Computing*, 13(2), 1265–1283.

Dhar, Vasant, and Stein, Roger. 1996. Intelligent decision support methods: the science of knowledge work.

Etchells, Terence A, and Lisboa, Paulo JG. 2006. Orthogonal search-based rule extraction (OSRE) for trained neural networks: a practical and efficient approach. *Neural Networks, IEEE Transactions on*, 17(2), 374–384.

Finlay, Paul N. 1989. *Introducing decision support systems*. NCC Blackwell.

Gestel, Tony Van, Baesens, Bart, Suykens, Johan AK, Van den Poel, Dirk, Baestaens, Dirk-Emma, and Willekens, Marleen. 2006. Bayesian kernel based classification for financial distress detection. *European journal of operational research*, 172(3), 979–1003.

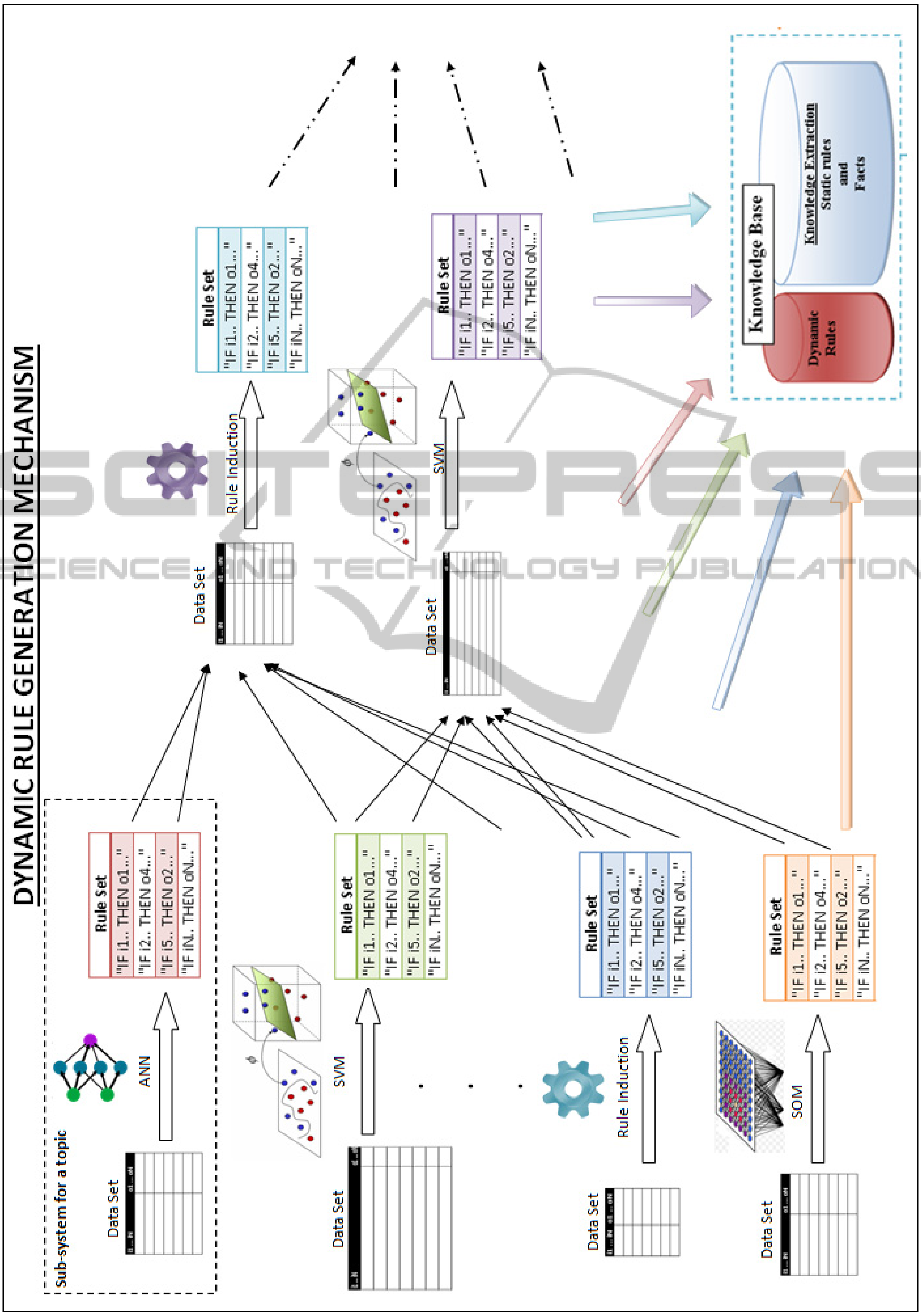

Figure 6: Rule Generation System.

Golub, Todd R, Slonim, Donna K, Tamayo, Pablo, Huard, Christine, Gaasenbeek, Michelle, Mesirov, Jill P, Coller, Hilary, Loh, Mignon L, Downing, James R, Caligiuri, Mark A, *et al.* 1999. Molecular classification of cancer: class discovery and class prediction by gene expression monitoring. *science*, 286(5439), 531–537.

Han, Jiawei, Kamber, Micheline, and Pei, Jian. 2006. *Data mining: concepts and techniques*. Morgan kaufmann.

Hayes-Roth, F. 1985. Rule-based systems. *Communications of the ACM*, 28(9), 921–932.

Hettich, S., and Bay, S. D. 1999. *The UCI KDD Archive (http://kdd.ics.uci.edu)*.

Jacobsson, Henrik. 2005. Rule Extraction from Recurrent Neural Networks: ATaxonomy and Review. *Neural Computation*, 17(6), 1223–1263.

Kahramanli, Humar, and Allahverdi, Novruz. 2009. Rule extraction from trained adaptive neural networks using artificial immune systems. *Expert Systems with Applications*, 36(2), 1513–1522.

Karl, G. 2014. Promoter prediction using IREM (inductive rule extraction method).

Khan, Javed, Wei, Jun S, Ringner, Markus, Saal, Lao H, Ladanyi, Marc, Westermann, Frank, Berthold, Frank, Schwab, Manfred, Antonescu, Cristina R, Peterson, Carsten, *et al.* 2001. Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks. *Nature medicine*, 7(6), 673–679.

Kuttiyil, A.S. 2004. Survey of rule extraction methods.

Leng, Gang, McGinnity, Thomas Martin, and Prasad, Girijesh. 2005. An approach for on-line extraction of fuzzy rules using a self-organising fuzzy neural network. *Fuzzy sets and systems*, 150(2), 211–243.

Li, Ai, and Chen, Guo. 2014. A new approach for rule extraction of expert system based on SVM. *Measurement*, 47, 715–723.

Malone, James, McGarry, Kenneth, Wermter, Stefan, and Bowerman, Chris. 2006. Data mining using rule extraction from Kohonen self-organising maps. *Neural Computing and Applications*, 15(1), 9–17.

Margara, Alessandro, Cugola, Gianpaolo, and Tamburrelli, Giordano. 2014. Learning From the Past: Automated Rule Generation for Complex Event Processing.

Martens, David, Baesens, Bart, Van Gestel, Tony, and Vanthienen, Jan. 2007. Comprehensible credit scoring models using rule extraction from support vector machines. *European journal of operational research*, 183(3), 1466–1476.

Martens, David, Baesens, BB, and Van Gestel, Tony. 2009. Decompositional rule extraction from support vector machines by active learning. *Knowledge and Data Engineering, IEEE Transactions on*, 21(2), 178–191.

Min, Jae H, and Lee, Young-Chan. 2005. Bankruptcy prediction using support vector machine with optimal choice of kernel function parameters. *Expert systems with applications*, 28(4), 603–614.

Mitra, Sushmita, and Hayashi, Yoichi. 2000. Neuro-fuzzy rule generation: survey in soft computing framework. *Neural Networks, IEEE Transactions on*, 11(3), 748–768.

Penzel, T, Moody, GB, Mark, RG, Goldberger, AL, and Peter, JH. 2000. The apnea-ECG database. *Pages 255–258 of: Computers in Cardiology 2000*. IEEE.

Power, Daniel J, and Sharda, Ramesh. 2009. Decision support systems. *Springer handbook of automation*, 1539–1548.

Qian, Yuhua, Liang, Jiye, and Dang, Chuangyin. 2008. Converse approximation and rule extraction from decision tables in rough set theory. *Computers and Mathematics with Applications*, 55(8), 1754–1765.

Quintana, D., Luque, C., and Isasi, P. 2005. Evolutionary rule-based system for IPO underpricing prediction. *Pages 983–989 of: Proceedings of the 2005 conference on Genetic and evolutionary computation*. ACM.

Ripley, Brian D, Whittle, P, Kay, J, Hand, DJ, Tarassenko, L, Brown, PJ, Titterington, DM, Taylor, C, Gilks, WR, Critchey, F, e*t al.,* 1994. Neural Networks And Related Methods For Classification. Discussion. Reply. *Journal of the Royal Statistical Society. Series B. Methodological*, 56(3), 409–456.

Sahoo, R.K., Oliner, A.J., Rish, I., Gupta, M., Moreira, J.E., Ma, S., Vilalta, R., and Sivasubramaniam, A. 2003. Critical event prediction for proactive management in large-scale computer clusters. *Pages 426–435 of: Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM.

Sannino, Giovanna, De Falco, Ivanoe, and De Pietro, Giuseppe. An automatic rule extraction-based approach to support OSA events detection in an mHealth system.

Sethi, Kamal Kumar, Mishra, Durgesh Kumar, and Mishra, Bharat. 2012. Extended Taxonomy of Rule Extraction Techniques and Assessment of KDRuleEx. *International Journal of Computer Applications*, 50.

Setiono, Rudy, and Liu, Huan. 1997. NeuroLinear: From neural networks to oblique decision rules. *Neurocomputing*, 17(1), 1–24.

Setiono, Rudy, Baesens, Bart, and Mues, Christophe. 2008. Recursive neural network rule extraction for data with mixed attributes. *Neural Networks, IEEE Transactions on*, 19(2), 299–307.

Shumway, R.H., and Stoffer, D.S. 2000. *Time series analysis and its applications*. Springer Verlag.

Taha, Ismail, and Ghosh, Joydeep. 1996. Three techniques for extracting rules from feedforward networks. *Intelligent Engineering Systems Through Artificial Neural Networks*, 6, 23–28.

Thrun, Sebastian B, Bala, Jerzy W, Bloedorn, Eric, Bratko, Ivan, Cestnik, Bojan, Cheng, John, De Jong, Kenneth A, Dzeroski, Saso, Fisher, Douglas H, Fahlman, Scott E, *et al.* 1991. The monk's problems: A performance comparison of different learning algorithms.

Towell, Geoffrey G, and Shavlik, Jude W. 1993. Extracting refined rules from knowledge-based neural networks. *Machine learning*, 13(1), 71–101.
Triantaphyllou, Evangelos, and Felici, Giovanni. 2006. *Data mining and knowledge discovery approaches based on rule induction techniques*. Vol. 6. Springer.
Tsukimoto, Hiroshi. 2000. Extracting rules from trained neural networks. *Neural Networks, IEEE Transactions on*, 11(2), 377–389.
Turban, Efraim. 1990. *Decision support and expert systems: management support systems*. Prentice Hall PTR.