Mining Patterns from Investment Data: DSS in Support of EIA's Investment Policy Advocacy Roles

Biruk Worku Kote
birukworku13@gmail.com

Tibebe Beshah
School of Information Science, Addis Ababa University, Ethiopia
tibebe.beshah@gmail.com

Abstract

Discovering patterns which can assist policy advocacy tasks of investment promotion experts at the Ethiopian Investment Agency (EIA) is found to be vital. In this research, Class Association Rule (CAR) modeling technique was used in pattern discovery. Inspired by the concept of constraint based rule post-processing concept, this paper also discovered a mining model evaluation and rule reduction technique that is biased towards the task of investment policy advocacy. The evaluation and rule reduction technique has three rule post processing constraints called "consistency", "inclusiveness", and "diverseness".

The research result showed that in terms of "consistency", the Apriori generated mining models and in terms of "inclusiveness" and "diverseness" the Predictive Apriori models were found better. Therefore, due to their bias to the task of investment policy advocacy, the final model was chosen among the three Predictive Apriori mining models; and based on it, a Decision Support System (DSS) that assists the policy advocacy tasks undertaken by investment experts at the EIA was prepared.

Keywords: FDI; EIA; DSS; CAR; Inclusiveness; Consistency; Diverseness

1. Introduction

Investment Promotion Agencies (IPAs), like the Ethiopian Investment Agency (EIA), usually collect large volume of data from their international customers in the form of "required information". International experiences suggest four main roles for an IPA. However, IPAs are advised to take their policy advocacy role as the most valued one than the rest three. A World Bank survey in [2] discovered that the strength of an IPA's investment policy advocacy role within government has been more critical to winning investment than the rest three IPA roles.

If the investment climate is sound, investors will come and the need for promotion, servicing and targeting are reduced. However, good investment policy advocacy requires good treatment & management of Data, Information, System and Knowledge (DISK) [3]. As public sector, IPAs are in a position to identify problems in the investment environment through their working relationships with international and domestic companies. This means, they may act like the chief advocates which can influence the decisions of investment policy makers and by doing so, IPAs can save a great deal of Foreign Direct Investment (FDI) to their countries [4].

A country may invite investment into one or more of its economic sectors. An economic sector into which the country invites investors is commonly referred to as "economic sector of investment". In the case of Ethiopia, such economic sectors are classified into three as: Primary (Agriculture), Secondary (Manufacturing), and Tertiary (Service). Economic sectors of investment are encapsulation mechanisms for industries. Under each economic sector of investment, there can be a number of industries which are also referred to as "investment sectors", which in turn are further classified into sub-sectors. The choice of investment sector (specific industry of investment) by a foreign-country-experienced investor can be made only after the selection of economic sector of investment is carried out.

In [5], it states that; not only countries, but also locations within countries are selected for investment on the basis of various criteria. In [2], it is explained that the consideration of which economic sectors are attracting for investment, how many jobs are created or how much technology transferred can assist in judging whether investment incentives and tax holidays are providing appropriate value for money.

The hypothesis of this research is: "By applying data mining techniques on investment dataset, as collected form the EIA, it is possible to explore novel patterns and prepare a prototype to a predictive DSS that can assist the EIA's investment policy advocacy roles."

2. Related Work

These issues of "spillover effects of FDI and foreign-country-experience of investors to an investment hosting state" have been controversial among scholars. After literature review on the relationship between FDI & economic growth, Wan [6] found that some literatures depict a positive while others depict the existence of a negative relationship between FDI & economic growth. The author finally concluded that there are conflicting predictions concerning the growth effects of FDI in the existing literatures.

In general, three views have been reflected in the literatures as: 1) FDI & foreign country experience of investors is something beneficial for the general societal and institutional development of the hosting state through spillovers. 2) It is a "no gain" experience, and non-spillover. Rather it contradicts with environmental wellbeing and negative impacts on the domestic firms. 3) Contrary to the above two, however, other scholars refer FDI and its spillover as beneficial to a hosting state but as far as it is treated with care and supported with intensive studies and research.

A good work by Gorge and Greenway [7] provides a comprehensive evaluation of the empirical evidence on productivity, wages and exports spillovers in developing, developed, and transitional economies. Mello [8] also investigated that; while the motivation and strategy of the investing Multi National Enterprise (MNE) is of importance, so is the scope for efficiency spillovers to domestic firms which depend also on the capabilities of the local firms to absorb the new knowledge. Blonigen [9] made empirical examination of literatures mostly about list of exogenous factors which determine FDI decision making by Multi-National Enterprises (MNEs). In [10], the application of data mining by the research endeavors in the investment domain is generally advised. However, empirical data mining research work which specifically raises the issue of investment policy advocacy from pattern discovery point of view could not be found. Looking for a pattern discovery and data mining solution to investment policy advocacy problems, this research can, therefore, be considered a ground work for future researches of its kind.

3. The Proposed Solution

3.1 Preprocessing

The EIA dataset contains 20+ years (Jan. 1992-Present date) of investment data; having 61, 059 individual investment records. For recency and data reduction purposes, this research is based on the last five years (Jan. 2008- Dec. 2012), which contains 35, 366 individual investment records only. All records contain equal number of data explaining attributes, that is 13; and all except one, are categorical. Each record represents an individual investment project. However, not all the 13 attributes were found important in explaining the investment business. Therefore, only the useful ones, which are 4, are considered in this study and the rest 9 are dropped out through the data cleaning process. The 4 business explaining attributes are: Type_of _Investor (Domestic, Wholly_Foreign, Joint_with_Domestic, Public, Ethiopian_by_Birth, Foreign_but_Domestic); Investment_Type (Domestic, Foreign, Public);

Form_ of_Company (Sole, PLC, Share, Public); Economic_Sector (Primary, Secondary, Tertiary).

Each record in the EIA dataset is an investor's record who registered to invest either in local or in foreign currency (FDI) in Ethiopia. However, as this research addresses the investment policy advocacy problem, only from the FDI and foreign-country-experienced investors' side, all records with values of "Domestic" and "Public" were wiped out as they are not FDI. Finally, the count of all investment records which explain the investment business with the foreign-country-experienced investors in Ethiopia reduced to 5,635.

Another pre-processing task was the task of additional attribute derivation. A study of this kind, which is related to foreign-country-experiences of investors investing in a host country, can be studied better if it considers the international investment agreements between the countries where the investors came from (i.e., the investors' countries of experiences) and the host state (in the case of this research, it is Ethiopia). Such agreements include international trade relationships, international economic agreements, and investment agreements concluded between the investor's countries of experience and the host state.

Ethiopia has entered into three international investment agreements and treaties; the Bilateral Investment Treaties (BITs), the Double Taxation Treaties (DTTs), and the Economic Partnership Agreements (EPAs), with a number of countries of the world. Based on this fact, and in order to reflect the effects of international agreements into the research; three new attributes; "Is_BIT", "Is_DTT", and "Is_EPA", were derived. The attributes were derived in order to check whether or not an investor is from a country with which Ethiopia has entered into one ore more of the three international agreements. The three newly created attributes are: Is_BIT (BIT, Non_BIT); Is_DTT (DTT, Non_DTT), and Is_EPA (EPA, Non_EPA).

3.2 Experimental Settings

The purpose of the data mining phase, in this research, is developing mining models through application of various experimentations. The final cleaned investment dataset with 5,635 investment records was divided into two as: training-set (75% * 5,635 = 4,226 records) and test-set (25% * 5,635 = 1,408 records). Despite the difference in data size, all experimentation setups applied on both sets were exactly the same. Three separate CAR experimentation setups were applied to both sets.

Due to lack of data mining experience and absence of a data mining research in the domain area, the domain experts at the EIA could not be able to provide minimum support (Min_sup), minimum confidence (Min_conf), and predictive accuracy (n) values for the research. This problem has called for statistical derivation of rule interestingness measures, from the dataset itself. Therefore, in this research, three combinations of rule interestingness measures were derived from the dataset, using statistical techniques and by avoiding statistical biases to the extent possible (see Table 1).

Table 1: Statistically derived and selected rule interestingness measures

No.	*Min_sup*	*Min_conf*	*Predictive accuracy(n)*	
			For training set experiment	*For test set experiment*
1	4.42%	12.88%	488	483
2	7.45%	21.87%	265	272
3	3.69%	26.6%	405	468

As it can be seen in Table 1, the values of Predictive accuracy (n) used for training set have variations with that of the test set. The reason is, as it is explained in [11], in Apriori, Min-sup and Min-conf values are required percentage values on an unseen data whereas in Predictive Apriori, support & confidence are combined and merged in to a single measure called "predictive accuracy". This measure is expressed in the form of the number of rules required (n).

In this research, Predictive accuracy values were set to be equal to the count of rules as a result of a corresponding experiment using the Apriori algorithm. For example, in the first Apriori experiment, Min_sup=4.42% and Min_conf=12.88% were applied on the training dataset. The resulting count of all CARs generated was 488. Here, the number 488 is a Predictive accuracy value and used in the corresponding Predictive Apriori experiment on the same training dataset (the arrows in Table 2 & 3 represent this). This was done from the intention of generating any possible number of best Predictive Apriori rules up to the number of rules actually found as a result of a previous, corresponding, Apriori experiment on the same dataset. Therefore, while the Min_sup & Min_conf percentage values can be same for both the training and test sets, the values of predictive accuracy can vary between the two sets.

3.3 Experimentation and discussion of results

Once the rule interestingness measures were prepared, as discussed above, six sets of experiments (three experiments using the Apriori and another three experiments using the Predictive Apriori algorithm) were prepared from each of the training and the test sets. This resulted in the creation of a total of twelve CAR mining models (six training and six test models). Prepared by applying either of the Apriori and the Predictive Apriori algorithm on the two datasets, each training model was set to have a corresponding test model which was later used as an evaluation control model. The CARs were generated from the three experiments on the training dataset, using Apriori and Predictive Apriori algorithms. Experiments made on the training dataset are named as training experiments (or training models) whereas those made on the test dataset are called test experiments (or test models). The result of the six training model creation experiments is presented in Table 2 whereas that of the six test models is presented in Table 3.

Table 2: Results from the mining experiments on the training dataset

No.	*Experimentation setup*		*CARs*	*Rules distribution among class values*			*Range of support & confidences in the rules (%)*		
	Algorithm	*Min_sup & Min_conf*		*Primary*	*Secondary*	*Tertiary*	*Primary*	*Secondary*	*Tertiary*
1	Apriori	4.42% & 12.88%	488	101 (21%)	152 (31%)	235 (48%)	15-34	21-41	38-80
2	Predictive Apriori	n = 488	346	107 (31%)	136 (39%)	103 (30%)	35-72	13-82	27-94
3	Apriori	7.45% & 21.87%	265	33 (13%)	72 (27%)	160 (60%)	22-29	22-39	38-80
4	Predictive Apriori	n = 265	264	59 (22%)	102 (39%)	103 (39%)	25-72	25-82	27-94
5	Apriori	3.69% & 26.60%	405	20 (5%)	128 (32%)	257 (63%)	27-38	27-41	35-80
6	Predictive Apriori	n = 405	346	107 (31%)	136 (39%)	103 (30%)	35-72	13-82	27-94

Table 3: Summary of results from the mining experiments on the test dataset

No.	*Experiment setup*		*CARs*	*Rules distribution among class values*			*Range of support & confidences in the rules (%)*		
	Algorithm	*Min_sup & Min_conf*		*Primary*	*Secondary*	*Tertiary*	*Primary*	*Secondary*	*Tertiary*
1	Apriori	4.42% & 12.88%	483	88 (18%)	150 (31%)	245 (51%)	38-14	56-21	91-36
2	Predictive Apriori	n = 483	329	98 (30%)	119 (36%)	112(34%)	86-2	91-7	99-28
3	Apriori	7.45% & 21.87%	272	34 (13%)	72 (26%)	166(61%)	33-22	46-22	91-36
4	Predictive Apriori	n = 272	271	55 (20%)	104 (39%)	112(41%)	86-25	91-25	99-28
5	Apriori	3.69% & 26.60%	468	57 (12%)	149 (32%)	262(56%)	38-27	56-27	91-30
6	Predictive Apriori	n = 468	329	98 (30%)	119 (36%)	112(34%)	86-2	91-7	99-28

As it is presented in Table 2, in all the three Apriori generated training models, there is a trend that the largest number of CARs are generated for the "Tertiary" sector whereas the smallest are for the "Primary" ones. Contrary to this, in two out of the three training experiments with Predictive Apriori, the largest number of rules are generated to the "Secondary" sector whereas the smallest are to the "Primary" ones.

The largest number of most dependable CARs (in terms of confidence level), for all the three Apriori generated training models, are associated with the "Tertiary" sector whereas the least dependable ones belong to the "Primary" one. The same is true with the rules from the Predictive Apriori generated training models (in terms of predictive accuracy).

Whenever predictive accuracy (n) increases, in the case of the three Predictive Apriori generated training models, the number of CARs are found either increasing or remained unchanged. When "n" increases from 265 to 405, the number of CARs also increases from 264 to 346. However, when "n" is raised from 405 to 488, the number of CARs remained unchanged (=346). This means all Predictive Apriori generated CARs from training experiment #4 (with n = 265) are subsets of the rules from training experiments #2 & 6 (each with n = 346). However, a kind of trend is not noticed with the Apriori generated CARs. Since the Apriori generated models are determined by a combination of two factors, that is Min_sup & Min_conf; rising the Min_sup level form 3.69% to 4.42% and then to 7.45% or the Min_conf level from 12.88% to 21.87% and then to 26.60% individually, doesn't merely make one model to be a subset of the other. Rather, the three Apriori models could only have some rules in common.

The number of Predictive Apriori generated CARs, under all the three training experiments are less than that of the Apriori ones. In one of the training experiments, however, this difference becomes very insignificant. In training experiment #3, the Apriori generates 265 rules whereas in the training experiment #4, Predictive Apriori produces 264 CARs after generating with predictive accuracy of 265 CARs. Even if the number of rules generated using the two algorithms under training experiments #3 & 4 is almost equal, the two have only 9 CARs in common.

All the three training experiments which were made using the Apriori algorithm have their 9 best rules in common. On the other hand, all the three Predictive Apriori training experiments have their 264 rules in common. Furthermore, the 9 rules which are intersections to the three Apriori generated training models are also members of the 264 Predictive Apriori generated rules.

3.4 Model evaluation and selection

The six predictive models, which were built on training data set, were evaluated for predictive strength. Ultimately and based on a chosen model, a prototype to a DSS that can assist policy advocacy tasks of investment promotion experts at the EIA was developed. The goal of this evaluation step was to select one dependable CAR mining model which is a concise representative of the EIA dataset, a complete and lossless one as much as possible, and quality in terms of its rule strength.

The methodology followed for evaluation is by using the test experiments as controls which can help in testing and evaluating their corresponding training models (experiments) through comparison of the results between the two.

Throughout this evaluation, the research uses the terms "best rules", "best CARs" & "best replicas" and they all represent one same thing, that is, a set of N CARs, where $\{N| N > 0\}$, form a training or a test model, the measure of rule strength of which (i.e., confidence level/Predictive Accuracy) is greater than or equal to 70%. The 70% accuracy level is chosen intentionally based on the concept of constraint based association rule filtering explained in [1].

One constraint driven pattern discovery technique discussed in [1] is rule post-processing after the actual data mining task is completed. That is, the filtering out of any unwanted patterns by placing some constraint conditions suitable for the course of the business so that coming up with the required type of rules.

In this research, the final model to be selected was required to be a set of CARs which are considerably enough to be taken as supportive for the task of investment policy advocacy. For that, the rules must have good quality, both in terms of the numeric rule strength measures (i.e., confidence level/predictive accuracy) and other qualitative measures like being non-confusing in its prediction. In most literatures, association rule experiments are carried out for rule strength higher or equal to 50%. Therefore, in this final model selection process, 70% is a reasonably good constraint to be considered as a minimum numeric rule strength measure which helps for rule post-processing.

This research uses a new mechanism for rule evaluation and best model selection by defining three evaluation constraints: "consistency property", "inclusiveness property", and "diverseness property".

Consistency property of a model refers to a mining training model's ability to replicate its own best CARs on its counter test model.

Assume set T is a predictive training model built on the training dataset and S is its counter test model built on the test dataset. Also assume that all the experimentation setup applied on both S & T are the same. If C, represented as {C| C C L and C ≠ Ø }, is a non-empty subset of L where L is the set of all "best class association rules" of T, and L' is the set of all "best class association rules" of S, then the relation R from T to S is said to be consistent iff C is the subset of L' and is represented as R = { T→S| C C L and C C L'}. The consistency property represents stability so that dependability of the rule regardless of a change in dataset.

Inclusiveness property of a model refers to a mining training model's ability to include best CARs of other models which are developed on the same training set as its own members.

Assume Q & J are two predictive training models. If C, represented as {C| C C L and C ≠ Ø}, is a non-empty subset of L where L is the set of all "best class association rules" of Q and L' is the set of all "best class association rules" of J, then the relation Z from Q to J is said to be inclusive iff C is the subset of L' and is represented as Z = {Q→J| C C L and C C L'}. The inclusiveness property represents the lossless behavior of a model. If a model can make other model as its subsets, the model losses nothing. Furthermore, it represents the other models as well as it may include better rules than what is included in its subset models.

Diverseness property of a model refers to the property of a model to incorporate best CARs which have rare items at their consequent side, where a 'rare item' refers to either of the two rare values, "Primary" and "Secondary", of the class attribute "Economic_Sector".

Assume N is a predictive training model and M is its counter test model. If A is the set of rare items, represented as A = {"Primary", "Secondary"} and Y is an element of A, represented as {Y| Y E A}, and if C, which is represented as {C| C C L and C ≠ Ø}, is a non-empty subset of L where L is the set of all "best class association rules" of N having Y at their consequent side and L' is the set of all "best class association rules" of M having Y at their consequent side, then a relation V from N to M is said to be diverse iff C is the subset of L' and is represented as V = {N→M| C C L and C C L'}.The diverseness property represents the completeness and usability of a model. In some situations, a best model may not be the one that is strong in predicting only one common thing and ignores other predictable aspects of the problem at hand. For that matter, a common thing does not require a prediction. Rather, a complete model which can predict every predictable aspect of the problem to some reasonably acceptable degree of accuracy can be considered a better model. In this regard, the diverseness property can be a key property in addressing "the rare item problem" as it has the capability to select models which support CARs that point to rare consequents.

The result of the comparative evaluation of the consistency and diverseness of the six predictive training models, in comparison to their counter test models, is depicted in Tables 4 and 5.

Table 4: Apriori models for rule consistency & diverseness

Model No.	*Apriori generated training & test models*					*Rule consistency and diverseness property*
	No. of CARs generated from the training dataset (A)	*No. of all best CARs replicated on the counter test model (B)*	*Proportion all "best replicas" (B / A)*100*	*No. of rare CARs replicated(C)*	*Proportion of rare CARs replicated (C /B)*100*	
1	488	55	11%	0	0%	A consistent, non diverse model.
3	265	46	17%	0	0%	A consistent, non diverse model.
5	405	64	16%	0	0%	A consistent, non diverse model.

Table 5: Predictive Apriori models for rule consistency & diverseness

Model No.	*Predictive Apriori generated models*					*Rule consistency and diverseness property*
	No. of CARs generated from the training dataset (A)	*No. of all best CARs replicated on the counter test model (B)*	*Proportion all "best replicas" (B / A)*100*	*No. of rare CARs replicated(C)*	*Proportion of rare CARs replicated (C /B)*100*	
2	329	2	0.6%	0	0%	A consistent, non diverse model.
4	271	16	6%	5	31%	A consistent and diverse model. 5 out of 16 rules (i.e., 31% of replicated CARs) are belong to sectors other than the default.
6	329	2	0.6%	0	0%	A consistent, non diverse model.

As it can be seen from Tables 4 and 5, all the six rules are consistent, but to different degrees. However, the only diverse model found is the second Predictive Apriori generated model. The other five models were found to be non-diverse. Concerning the five none diverse models, all of their replicated rules belong to the default "Tertiary" sector. On the other hand, out of the 16 "best replicas" of the only diverse model, the 5 (i.e., 31%) are found to be rare rules.

In general, the Predictive Apriori generated models were found to be best in terms of "diversity" and "inclusiveness" whereas in terms of "consistency", the Apriori generated models were found best. The interpretation of this is that the Apriori generated models are stable. However, their prediction stability is up to predicting about the default "Tertiary" sector. Generally, they can dependably predict which combination of an investor's attributes can bring to know the investor's tendency to choose the default "Tertiary" sector. However, these models are dull about prediction towards the rare sectors.

The Predictive Apriori models on the other hand are better predictors of investors' choice about rare sectors. Furthermore, they are good representatives of other models generated by a lesser volume of dataset, that means they are lossless. However, especially towards the default sector, the Predictive Apriori models are not as stable predictors as the Apriori models.

The first thing that requires a decision here is therefore; a choice between "diversity +

inclusiveness" versus "consistency", that means, choosing between a Predictive Apriori or an Apriori model. However, this decision by itself is up to answering the question "which kind of model is considered best for the task of investment policy advocacy?" and answering the question in return needs referring a good definition of knowledge discovery data mining in [12] as a non trivial extraction of implicit, previously unknown, and potentially useful information from data.

A predictive model for policy advocacy shall be consistent, all round, as well as strong. Even if a compromise is required in any of these, the model shall be complete. This is because, advocators must feel confident that what they are lobbying about the country's investment climate brings at least something better, and by no means worse, than how they are currently doing it. Furthermore, they must feel that the model can tell them something novel, which they cannot address intuitively and through their day-to-day observations. Finally, they need a complete model which has the ability to predict "everything", where "everything" means all predictable trend given the combination of facts. Otherwise, the usability of the model falls in doubt. Therefore, the final model is generally better to be more diverse and more inclusive about the novel trends, and less accurate towards "predicting" a trivial information which can be reached upon by default. This can generally be achieved when the model is selected among the Predictive Apriori generated ones.

The second decision is easier. Once which type of model to select is known, which model to select is a matter of comparing among the models in that selected class. Therefore, among the three Predictive Apriori generated predictive models, the forth model (which is the one generated with n = 272) is best in terms of "consistency" and "diverseness" whereas the other two are equally best in terms of "inclusiveness". However, even if the two are best in terms of inclusiveness, their inclusiveness is a complete one. This means they include all the 271 rules of model #4 as their subsets. As these models are Predictive Apriori generated models and inclusiveness is tested on the bed of the same dataset, all the best rules of model #4 are also among the best rules of the other two models. Even if the two include additional rules over what model #4 (which is their subset and intersection) does include, the difference is a set of weakest rules.

Having these logical grounds, Predictive Apriori mode #4 (with n = 272) was found better and selected as the final model of this research. Finally, selecting all the "best rules", the predictive accuracies of which are >= 70%, out of the chosen model, a prototype to a DSS which is capable of predicting foreign-country-experienced investors' choice of economic sector of investment was developed.

```
1. Invr.Txt="Foreign but domestic" &&
   DttTxt="NON_DTT IS_EPA=EPA" ==>
   Economic_Sector=Tertiary 62
   acc:(0.94766)
2. Invr.Txt=Foreign but domestic
   IS_EPA=EPA 68 ==>
   Economic_Sector=Tertiary 64
   acc:(0.93632)
3. Form_of_Company=Sole Invr.Txt=Foreign
   but domestic IS_BIT=BIT IS_DTT=NON_DTT
   68 ==> Economic_Sector=Tertiary 62
   acc:(0.8941)
4. Form_of_Company=Sole Invr.Txt=Foreign
   but domestic IS_DTT=NON_DTT 100 ==>
   Economic_Sector=Tertiary 90
   acc:(0.87941)
5.  Form_of_Company=Sole Invr.Txt=Foreign
   but domestic 112 ==>
   Economic_Sector=Tertiary 98
   acc:(0.85223)
```

3.5 Model Deployment

Once the models were developed, evaluated, and a final working model is selected, the best 25 CARs were taken out of the selected final model and a prototype to a predictive DSS was prepared. As the system requirements are identified as a result of the research output, the object oriented software analysis, design, and development approach was followed to analyze the requirements, to design them and finally to develop it. Figure 1 shows the GUI for the EIA sector predictor DSS.

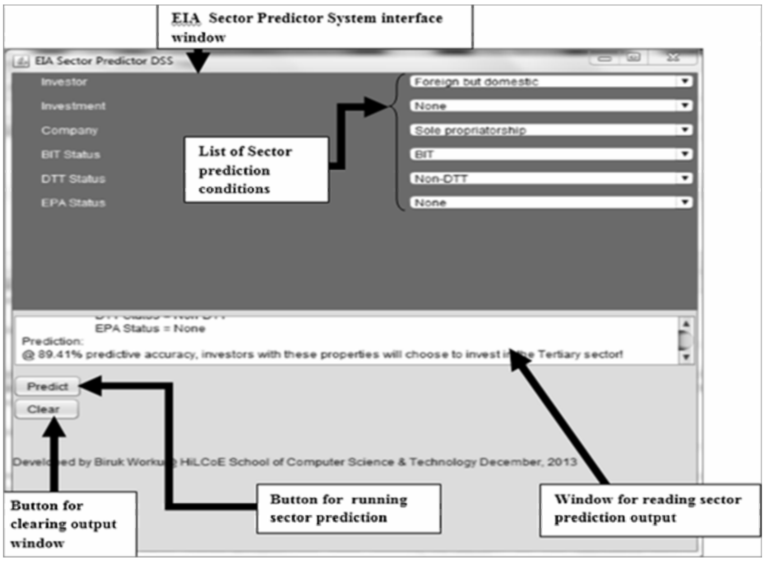

Figure 1: Graphical User Interface of the EIA Sector Predictor prototype system

4. Conclusion and Recommendations

In this research, the investment dataset, as collected from EIA, was explored from data mining point of view. Investment data have diverse features. They have a number of data explaining attributes that can be utilized for various useful investment business goals. If mined, patterns from investment datasets have a lot to provide for a better investment climate. Mining rules that assist the task of policy advocacy at the EIA, which is addressed in this research work, can be considered a good evidence to show such possibility.

Applying the Apriori and Predictive Apriori algorithms on the EIA's investment dataset, six data mining experiments were made and six CAR models were generated. Furthermore, this research explored new model evaluation techniques which are biased to the task of investment policy advocacy. The context aware model evaluation techniques, explored and applied in this research, can be used whenever the domain experts are unable to evaluate the created mining models. Moreover, the same concept and technique can be applied in other business areas which have similar problem.

Finally, as a solution to the decision making problem in the business domain, and based on the results from the mining models, a prototype of a decision support system was developed. The developed DSS can assist the EIA's investment policy advocators in their policy advocacy decisions.

Through data mining researches and application of data mining tools and techniques, good investment policies can be devised. Furthermore, current computer science and data mining technologies can be integrated with the tasks of investment in general and investment policy advocacy roles undertaken by IPAs in particular.

As an IPA, the EIA should strive for the better of its policy advocacy roles. This in turn can be achieved only when more research and exploration to the huge accumulation of data at the agency's custody is undertaken. To this regard, any number of data mining researches and decision support tools cannot be said enough.

As discussed earlier, the most important one among the tasks of an IPAs is the task of policy advocacy. This task is most important because it is a powerful arm for the generation of FDI and favorable spillovers through policy implementations. As it can be noted from the output of this research, the knowledge about the various attributes and combination of attributes of foreign-country-experienced investors provides for technology supports to the advocacy roles.

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