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Logistic Retrogression Model for Evaluating the Influence of Environmental Factors on Legislative Data

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Abstract

Applicability of artificial intelligence techniques, in evaluating the influence of the environmental factors in legislative data was found amenable in an earlier study - SVM performed to satisfying results with a 21.5 percent error rate for passage of legislation as compared to the performance of ANN at 28 percent error rate and K-NN at 29 percent error rate. These techniques reported both collective influence (ANN, K-NN and SVM) and respective influence (SVM one-against-all classifier). Determining the environmental influences - individually or in combination with other factors, could only be measurably achieved using other modeling techniques, despite SVM with probabilistic output of 76 percent outperforming PNN with 71 percent out. A triangulation of both statistical and artificial intelligence modeling techniques in classification is thus proposed for decision making support in legislative drafting, given that computations involving statistical approach correctly predicted up to 98.20 percent and placed economic considerations as the most important factor for the passing of a bill with economic connotations. Other predictions involving political, social, cultural factors did not however, perform as well as the PNN and SVM with probabilistic output.

Keywords

Artificial intelligence, evaluation, classification, environmental factors, legislative drafting, statistical modelling, probabilistic neural network, probabilistic support vector machines (PSVMs).

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1. Background

The most critical stage in legislative drafting is harmonizing the government interest and the expectation of the governed (society) [1]. This must, of essence, involve the legislation meeting the expectations of the social, political, economic and cultural aspects of the governed prevailing at a given time. These interests, in an earlier study have been seemingly accommodated as much as possible as seen in the performance of the Support Vector Machines (SVM) in evaluating the environmental factors' influence [1]. SVM performed to satisfying results with a 21.5 percent error rate for passage of legislation as compared to the performance of Artificial Neural Network (ANN) at 28 percent error rate and K- nearest neighbour (K-NN) at 29 percent error rate in an earlier study [2]. These artificial intelligence modelling techniques of classification were used for purposes of supporting decision making in legislative drafting. This is because, given a set of alternatives and possible solutions, decision making can be easily narrowed to the classes classified, thus supporting decision making in the legislative drafting process.

2. Introduction

According to Crabbe [3], legislative drafting involves the attempted solution of problems faced by governments and by society as a whole. Determining the influence of the environmental factors therefore, can be argued to be subject to the problems being solved by a given legislation and by the government and the governed. Legislation is the framework by which governments achieve their purpose and is a means to attain economic, cultural, political and social policies [3]. The end product of legislative drafting should take cognizance of the cultural, economic, political and social conditions of the society within which it is intended to operate and Crabbe [3] thus contends that any of these factors or a combination thereof forms the basis of legislative drafting. These factors are presented in this study as environmental factors.

In this study, similar effort in evaluating the influence of environmental factors on legislative data was made, by embracing the artificial intelligence classification techniques with probabilistic output and the Probabilistic Neural Network (PNN) reported 71 percent test accuracy rate, while the Probabilistic Support Vector Machine (PSVM) outperformed the PNN and reported 76 percent test accuracy rate. Similar data used in earlier studies involving SVM with a 21.5 percent error rate[1]; Artificial Neural Network (ANN) at 28 percent error rate and K-nearest neighbour (K-NN) at 29 percent error rate [2], was used for this purpose. A triangulation of both statistical and artificial intelligence modeling techniques in classification is thus proposed for decision making support in legislative drafting, given that computations involving statistical approach correctly predicted up to 98.20 percent and placed economic considerations as the most important factor for the passing of a bill with economic connotations. Other predictions involving political, social and cultural factors did not however, perform as well as the PNN and SVM with probabilistic output.

2.1 Classification Problem

Classification is one of the most important tasks for different application such as text categorisation, tone recognition, image classification, micro-array gene expression, proteins structure predictions and data classification [4]. A classification task usually involves separating data into training and testing sets; and each instance in the training set contains one target value (class labels) and several attributes (features or observed variables) [5]. Classification plays a vital role in machine based learning algorithms [6] thus, a classification problem occurs when an object needs to be assigned into one of these predefined group or class based on a number of observed attributes related to that object [7].

The aim of classification is to find a classification decision model that minimizes the number of classification errors on future or test data, that is, the data that has not been used to build the model [8]. Similarly, Oladokun *et al* [9] is of the view that any classification system seeks a functional relationship in, for example, an association and attribute of the object.

2.2 Legislative Drafting Problem

Law does not operate in the vacuum and thus, its content, in its bid to guide and regulate the conduct of affairs of those it is intended to address, must take cognisance of the cultural, economic, political and social conditions of the society within which it is to operate [3].

Nevertheless, in harmonising the foregoing interests, cognisance is taken from the contention of Hage [10] that the search for the optimal solution in the solution space involves the use of decisions based on convincing arguments. The most convincing arguments will be the arguments which rate very high in the legislative discourse in which legislative draftsmen come together with politicians, members of parliament, interested parties, lobby groups, etc. Likewise, the search for authoritative arguments and their appropriateness is a process which can be conceptualised, modelled and formalised into computer systems.

3. Related Work

3.1 Techniques in Artificial Intelligence

Wooldridge [11] contends that trends in Artificial Intelligence (AI) have gone from building intelligent entities to producing useful tools to aid problem solving in a given domain, and in the legal domain, they have been used to support decision making. The field of artificial intelligence has extended into neural networks, among other techniques, which are powerful flexible methods that have been successfully used for pattern recognition, classification and forecasting [12]. Scholarly literature make reference to classifiers as simple AI applications that form a central part of many AI systems since they are functions that use pattern matching to determine closest match. In supervised learning, classification works on the principle that each identified pattern belongs to a certain predefined class, where a class is seen here as a decision that has been made. All the observations combined with their class labels are data sets and when a new observation is received, the observation is classified based on previous experience.

3.1.1 Supervised Classification

While citing weather forecasting, bankruptcy prediction, medical diagnosis, speech recognition, stock market prediction and character recognitions as some of the classification problems, Moghadassi *et al* [7] view classification as one of the most frequently encountered decision making tasks of human activity. Scholarly articles refer to supervised classification as forming the core of data mining and outline the principles under which it works as follows-

i. The input data, also called the training set, consists of multiple records each having multiple attributes or features.
ii. Each record is tagged with a class label.
iii. The objective of classification is to analyze the input data and to develop an accurate description or model for each class using the features present in the data.
iv. This model is used to classify test data for which the class descriptions are not known [13].

Further, this technique is guided by and based on supervised classification algorithm formulated by studying a training set of data that has been manually classified and converted into a set of numerical variables, which variables are used to define rules that determine the objective of a classification task.

The most widely used classifiers include the neural networks and kernel methods that include Support vector machines, K-Nearest Neighbour algorithm, Gaussian Mixture Model, naive Bayes classifier and decision tree [14]. A review of two of these classifiers with probabilistic output is made hereunder.

3.1.2 Support Vector Machines

Hearst, *et al* [15] contend that Support vector machines (SVMs) is the *state- of- the art* learning machine based on the structural risk minimisation induction principle and has reportedly achieved superior performance in a wide range of applications [16]. Based on traditional statistics [17], scholarly literature positions SVMs as one of the supervised learning methods used for classification, wherein training examples each marked as belonging to one of two categories with its training algorithm is able to build a model that predicts whether a new example falls into one category or the other [7]. SVMs are capable of estimating probabilities more accurately than a classical multilayer perceptron (MLP), given that a standard SVM is a binary classifier and does not provide such probabilities. SVMs do not directly provide probability estimates which may be calculated using fivefold cross-validation or by directly training a kernel classifier with a logit link function and a regularized maximum likelihood score to create probabilities [18]. Platt [18] proposed the SVM+sigmoid as one other method which equally yields probabilities of comparable quality to the regularized maximum likelihood kernel method.

3.1.3 Artificial Neural Networks

Artificial neural networks are underscored as powerful and flexible methods that have been successfully used for pattern recognition, classification and forecasting, [12]. Artificial neural network is defined by Pankaj [19] as an interconnected group of artificial neurons that uses mathematical model or computational model for information processing based on a connectionist approach to computation. ANNs practically, are non-linear statistical data modelling tools, which are applicable in modelling complex relationships between inputs and outputs or finding patterns in data. As an improvement to neural networks in modeling uncertainty within the requirements of probabilistic outcomes [20], probabilistic neural networks (PNN), originally developed by Specht [21] have been used for prediction of concrete strength [22] and reliability assessment [22]. PNNs are special forms of neural networks used to implement Bayesian classification techniques incorporating Parzen univariate estimation [24] or a similar probability density function calculated for each test vector. A spherical Gaussian basis function is used although other functions equally work well. Similarly, scholarly literatures contend that PNNs are forward feed networks built with three layers and they are derived from Bayesian decision networks. They train quickly since the training is done in one pass of each training vector, rather than several and estimate the probability density function for each class based on the training samples. The PNN workings are guided by the following [24]:-

i. Vectors are first normalised prior to input into the network;
ii. There is an input unit for each dimension in the vector;
iii. Input layer is connected to the hidden layer;
iv. Hidden layer has a node for classification;
v. Each hidden node calculates the dot product of the input vector and a test vector subtracts 1 from it and divides the result by the standard deviation squared;
vi. Output layer has a node for each pattern classification; and
vii. The sum for each hidden node is sent to the output layer and the highest value wins.

It is noted in scholarly literature that PNN trains immediately but execution time is slow; requires a large amount of space memory; only works for classifying data; and the training set must be a thorough representation of the data. However, PNNs

handle data that has spikes and points outside the norms better than other neural nets. Further, one of the disadvantages of PNN models compared to multilayer perceptron networks is that PNN models are large due to the fact that there is one neuron for each training row. This causes the model to run slower than multilayer perceptron networks when using scoring to predict values for new rows.

Tran *et al* [24] developed and validated a PNN model and the predictive performance of the model was compared with a traditional parametric model using discriminant analysis on the same data set. The PNN Tool of the MATLAB software package was used as a PNN classifier; while computations and statistical tests were performed by the SPSS software package on the Discriminant model. Comparison of results were in goodness-of-fit test and in the performance rate, where the PNN model outperformed the Discriminant model in prediction and significantly outperformed the Discriminant model, save in the significant factors where the Discriminant model moves closer to the performance of the PNN model. The PNN model, reported performance rate of 71.5 percent and 66.9 percent in calibration and validation data sets. However, the Discriminant model although reported performance rate of 42.8 percent and 36. 4 percent in calibration and validation data sets, the results covered all input data and reported 55.6 percent and 51.0 percent in calibration and validation data sets, using hydraulic factor [24].

In other related studies, PNN models were used in predicting concrete strength [22] and reliability assessment [23] and had fast calibration without any optimizing process. This was reported as one advantage of PNN over Neural network models however, PNN models based on statistical techniques, with assumptions of probability distributions on their model structures, are bound to affect the predictive performance of PNN models [20].

3.2 Techniques used in Modeling

Models have been frequently used in problem formation and solution [20]. Examples of models include deterministic and statistical models (model driven types) whose structures are decided by experts; and artificial intelligence based models (data driven) whose structures are decided by the sample data [25].

3.2.1 Data-driven models

(a) Deterministic Models

Deterministic models are used where relationships between components are certain and for describing direct relationships between the input factors and the output and examples here include linear and exponential models. Deterministic models have the ability to translate mathematical expressions into analytical form and the relationship between input factors and output is straight forward [20].

(b) Statistical Models

Statistical models, based on statistical theory for modeling phenomenon where random noise in components exists assumes parametric density functions for measurement errors and certain probabilistic relationships between input data and output data [25]. Examples of statistical models include the Markov models, based on the Markov chain theory; the Ordinal regression models, popular for dealing with relationship(s) between an integer valued output and one or more explanatory variables; and the Linear discriminant models used for classifying or predicting individuals or objects into mutually exclusive and exhaustive classes of a set on independent variables or predictors [20].

Tran [20] contends that statistical models seem robust in handling outputs or ordinal data type, taking into account probabilistic relationships.

3.2.2 Artificial-intelligence based models

These are models whose structures are data driven and no assumptions are made regarding the model structures [20], since they are designed to mimic the operations of the human brain and natural life involving learning and generalizing from lessons and predicting future targets [26]. These models are categorized as ’blackbox models’ since they are mainly concerned with input and output data without specifying the underlying mechanism. Examples include artificial neural network models and probability neural network models [20]. These models have the ability to detect non-linear underlying processes [25] and can handle both scale and ordinal data types [20].

3.3 Evaluation Methods for Model Performance

Evaluating or testing the model performance involves quantifying the model error calculated as the difference between the predicted values and corresponding true values. Model performance is

high when the model error is low [27]. The root mean square error (RMSE) and the correlation coefficient (R) are used in continuous value outputs [28] while in categorical and ordinal output, the confusion matrix is used to assess the performance of classifiers in classifying an object into one of the categorical targets [29]. The goodness-of-fit test is another form of testing model performance to establish whether the proposed model is consistent with the set of observations [30]. Testing the model performance involves presenting a data set to the model and computing the model error [20]. The testing process is done using data that was not used in the construction of the model [31]and this is achieved by randomly dividing the dataset into two - the construction dataset (training or calibration data set) and the testing dataset [32].

4. Presentation of results

Copy All the legislative data collected and used in the two studies [2] [1] and consequently used in this study were subjected to a rating/scaling technique given each of the environmental factors influence on it on a scale of 5, 4, 3, 2, and 1, respectively, with an additional attribute (Others) introduced in the study to take care of emerging trends and developments in the legislative drafting practices.

4.1 Probabilistic Neural Networks results

A total of the 300 legislative data collected and used in the artificial neural network classification task [1] and implemented using the MATLAB classifier tool, was subjected to the classification process using probabilistic neural network and the performance reported an error rate of 29 percent. The image below shows the error rate at 29 per cent.

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Test Accuracy Rate: 71.0%
Test Error Rate: 29.0%
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4.2 Probabilistic Support Vector Machines results

A total of the 300 legislative data collected used in the artificial neural network classification tasks [2] and implemented using the MATLAB classifier tool, was subjected to the classification process for a probabilistic output using support vector machine technique and the performance reported an error rate of 24 percent, outperforming the probabilistic neural network which had an error rate of 29 percent.

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Test Accuracy Rate: 76.0%
Test Error Rate: 24.0%
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4.3 Output from Statistical Approach to Classification

Earlier study reported performance results and confirmed that AI related techniques were amenable to supporting decision making in legislative drafting tasks; and reported 71 percent for the K-nearest neighbour technique [2], 72 percent for the artificial neural network technique [2] and 78.5 percent collective influence [1] by the environmental factors using support vector machines (SVM); and using the One-Against-All SVM technique of classification significantly measured the influence of each of the environmental factors on the legislative data analyzed [1]. Notable performance was reported in the One-Against-All classifier technique with the Economical category at 90 percent accuracy rate; Political, Cultural, Others and Social category at 100 percent accuracy rate. However, sensitivity rate and F-measure could not be measured under the Social, Cultural and Others category [1]. One explanation, subject to the scaling technique adopted in the study, is that there were fewer legislative in these categories.

During the data analysis using SVM classification techniques, overlaps were reported, wherein some data had a combination of two or more competing influence on a given data; and in terms of rating, the two or more of these factors scored the highest score - five (5). Political factor, in combination with the other factors, influenced 41 of the analyzed data with competing influence (in terms of rating); Economic factor, in combination with the other factors, influenced 30 of the analyzed data with competing influence (in terms of rating); Social factor, in combination with the factors, influenced 6 of the analyzed data with competing influence (in terms of rating); Cultural factor, in combination with the other factors, influenced 9 of the analyzed data with competing influence (in terms of rating); and the Other factor, in combination with the other factors, influenced 22 of the analyzed data with competing influence (in terms of rating). Similarly, out of the 500 legislative data collected, the political factor influenced 165 of the analyzed data with highest score; economic factor influenced 206 of the analyzed data with highest score; social factor influenced 79 of the analyzed data with highest score; cultural factor influenced 4 of the analyzed data with

highest score; and the Other factors influenced 14 of the analyzed data with highest score.

During the classification, these influences could not be reflected using the AI techniques used in these studies. Other classification approaches were therefore, proposed in dissecting these influences in a bid to inform the drafting process as follows-

(a) Establishing which of the environmental factors in competing influence can stand on its own and does not require combination with other factors for purposes of passage of a bill (on a probability basis); and
(b) Establishing which of the environmental factors in competing influence cannot stand on its own and requires a combination with other factors for purposes of passage of a bill (on a probability basis).

4.4 A Case for Triangulation of AI and Statistical Approaches to Modeling

Attalla and Hegazy [33] used two techniques to develop models for predicting cost deviation - statistical analysis and artificial neural networks (ANNs). While both models had similar accuracy, the ANN model was more sensitive to a larger number of variables; yet both contribute to a better understanding of the reasons for cost deviation in reconstruction projects and provide a decision support tool to quantify that deviation. The need to establish which of the environmental factors in competing influence can stand on its own and does not require combination with other factors for purposes of passage of a bill; and which of the environmental factors in competing influence cannot stand on its own and requires a combination with other factors for purposes of passage of a bill, can be done using statistical approach. This reasoning is premised on the fact that some of the artificial intelligence based models like PNN are based on statistical techniques. Similarly, statistical models seem robust in handling outputs or ordinal data type, taking into account probabilistic relationships [20]. These interests have been incorporated in the design of a logistical regression model.

4.5 Logistic Regression Model for Legislative Drafting

The relationship between the event of a bill meeting the threshold and external factors that affect the bill's passing is given by the model -

$$L^* = \ln\left(\frac{p_i}{1-p_i}\right) = \mu + \alpha C_i + \beta E_i + \delta P_i + \gamma S_i + \xi_i$$

Where the cultural factors C_i include a series of external variables of a cultural nature, E_i representing economic factors (a,b,c), P_i representing political factors (a,b,c) and S_i representing social factors (a,b,c). α, β *and* γ are weighted vectors while ξ represents the residual components that include the unobserved social, cultural, political and economic factors and α is a constant term for the ideal scenario.

Data sets used during the SVM classification, with a combination of influences by respective factors in both competing influence and overall influence, in terms of rating in a given legislative, were used; while computations and statistical tests were performed by the E-VIEWS software package on the Logistical regression model. Statistical results evaluating the respective environmental factor's influence on the 500 legislative data collected for the SVM classifier [1], as dependable variables and tabulated results from which the respective models were derived, are presented in the subsections hereunder.

4.5.1 Cultural Factor

A logistic regression analysis was conducted to predict passing of a bill for 500 legislative data using social, cultural, political, economic and *Other* underpinnings as predictors. The political and economic followed by cultural considerations were dropped in the first and second iterations, respectively, at the preliminary assessment. A test of the full model against a constant only model was statistically significant, indicating that the predictors as a set reliably distinguished between passing and rejection of the bill (chi square was equal to 8.599, **p** should be less than 0.05 with df equals to 2). The findings were that for every unit increase of the *likert scale measure* for the cultural factor with social and other underpinnings, the odds in favour of a bill being passed were decreased by multiplicative factors of 0.29, and 0.13 (with reported standard errors being 0.109346 and 0.073240) respectively. Surprisingly, from the results, a bill would seem less likely to be passed if drafted with purely cultural considerations alone, and whereas the social and *other* factors were more significant; the former being more important at conventional levels (the empirical two-tailed **p**-value

is reported, which should be less than 0.05). This supports the conclusion that Social and Economic factors are useful predictors of passing of a bill with cultural connotations.

The validity of the predicted probabilities from the classification table was 55.15 percent and accounting for 8.64 percent gain. The Logistical regression model showing the cultural factor is represented below.

$$L^* = ln\left(\frac{P_i}{1-P_i}\right) = 1.29\text{-}0.29S_i + \xi$$

4.5.2 Economic factor

For every unit increase of the *likert scale measure* for the economic factor with social, economic, political, cultural and *Other* underpinnings, the odds in favour of a bill being passed were increased by significant multiplicative factor of 5.55 for the economic undertone, decreased by a multiplicative factor of 0.52 for a weak political factor and decreased by a multiplicative factor of 0.54 for an unimportant social factor with reported standard errors being 0.538447, 0.352340 and 0.305519, respectively. Political and cultural considerations were dropped after preliminary assessments as unimportant influences. This finding supports the conclusion that economic considerations are largely the most important factor for the passing of a bill with economic connotations; with the validity of the predicted probabilities correctly predicting at 98.20 percent. The Logistical regression model with economic factor is represented below.

$$L^* = ln\left(\frac{P_i}{1-P_i}\right) = -20.49 - 0.54S_i + 5.55E_i + \delta$$

4.5.3 Political Factor

For every unit increase of the *likert scale measure* for the political factor with social, economic, cultural and *other* underpinnings, the odds in favour of a bill being passed were decreased by multiplicative factors of 0.14 for the social consideration but increased by a multiplicative factor of 0.17 for the economic consideration with reported standard errors 0.119102 and 0.086702, respectively. It would appear that an economic consideration is important in the passing of a political bill while the social consideration undermines the chances of passing of a political bill. The validity of the predicted probabilities is reported at 57.83 percent and the Logistical regression model for the political factor is represented as -

$$L^* = ln\left(\frac{P_i}{1-P_i}\right) = -0.29 - 0.14S_i + 0.17E_i + \alpha$$

4.5.4 Social factor

For every unit increase of the *likert scale measure* for the social factor with political, economic, cultural and *other* underpinnings, the odds in favour of a bill being passed decreased by multiplicative factor of 0. 13 for the social consideration but was increased by a multiplicative factor of 0.20 for the economic undertone with reported standard errors being 0.119565 and 0.086741, respectively. Given that at the second iteration, the parameter co-efficient were negative for all except for the economic factor, the criteria for selecting the variable for the next iteration ignored the rule for **p** less than 0.05. Instead the economical variable was selected discretionally on account of its positive parameter co-effecient.

The probability for the economical variable renders the variable very important in the passing of a bill belonging to the social category. The validity of the predicted probabilities correctly predicted 55.44 percent in this regard.

The Logistical Regression Model for the Social Factor is represented below-

$$L^* = \ln\left(\frac{P_i}{1-P_i}\right) = 1.17 - 0.13S_i + 0.20E_i + \gamma$$

5. Discussions and conclusion

Copy The use of artificial intelligence classification techniques, though with marked improvement, does not explain how results are arrived at although performance as a general concept is emphasized. Needless to mention, they do not evaluate instances where there are, for example, conflicting opposing forces influencing the passage/non passage of a legislation, although the output is in one direction - a passage with a given measure.

We note that the performances of all these classification techniques report collective influence of the environmental factors on the legislative data. These experiments follow the principle that bills are drafted to be passed into law and that the environment factors' influence has to be factored in the legislative drafting process. The same principle can apply to underscore reasons for considering why bills fail and are not passed. Similarly, the functionality of this approach does not peg any

formula to achieve a given performance. Needless to mention, the results do inform decision making in the drafting process.

The application of statistical approach however, was able to further explain instances where conflicting opposing forces influence a given legislative data and which of the environmental factor(s) are likely to influence the passage/non passage of legislation. Further analysis of the environmental factors' influence involving statistical methods; give insight to areas for prioritization and concentration in the consultation process while drafting a given bill. This approach apart from, knowing the effect of inclusion and non-inclusion of these factors in certain drafting tasks, similarly informs and support decision making in the drafting tasks. This, for example, has been achieved through considerations for the negative or positive co-efficient in regression analysis. However, it should be noted that although, the negative co-efficient influence the positive outcome of passing a bill, yet, it could actually be this negative pointer that should not be overlooked, since it has the propensity to reduce the chances of a bill being passed.

It follows, therefore, that support to a drafting task, in addition to adopting techniques or approaches that narrow the gap for the decision making process and pointers to factors that minimize chances of passage or improve the probability of passage, however, minor need not be ignored. Further, computations involving statistical approach places economic considerations as the most important factor for the passing of a bill with economic connotations yet it would appear that an economic consideration is equally important in the passing of a political bill, while the social consideration undermines the chances of passing of a political bill. The validity of the predicted probabilities are reported in this regard.

Both artificial intelligence based models and statistical models' approach to problem solving is amenable to legislative drafting practices in aiding the decision making process, pertinent in the legislative process.

The influence of environmental factors cannot be underestimated, yet the law making actors need to check the absurdities that characterize some of the demands of the environmental factors. The need to however, strike a balance, at the earliest opportunity, between the legislative drafting process and the environmental factors for an effective legislative process can be achieved since their influence is known to have an impact at all the stages of the said legislative drafting process.

The changing face of the environmental factors (past, present and future) also plays a big role in the legislative process and should be considered in the design of future models for regulating legislative drafting practices. The need for a harmonizing model to take into account the societal changes that impact on the life of legislation and the constitutional implications could form an extension of this study.

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(ii) "Evaluating the influence of environmental factors on legislative data using Support Vector Machines techniques" (ICCIR, 12); Available at www.cit.mak.ac.ug/iccir/downloads/ICCIR-12; and

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