Towards a Going Concern Assessment Pipeline

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***Abstract*—The assessment of the going concern analysis in the audit process is based on the professional judgment of the auditor. To support this individual and personal judgment of the auditor, a more direct source of information in the form of an automated going concern analysis could provide a solution. In this paper a method to automate the going concern analysis was set up, using a combination of 16 forecasting algorithms. To build and validate the forecasting algorithms, 225 administrations have been divided in a train and test set. The results show a confidence percentage of 97.45% for the Gradient Boosting Regressor model, 96.79% for the Decision Tree Regressor model and 77.72% for the AdaBoost Regressor model on the basis of the condition current liabilities for Administration 1.**

Keywords-Forecasting algorithms; Continuity; Going Concern; Forecasting; PyCaret.

I. Introduction

Research shows that the going concern assessment is one of the most important challenges within the decision-making process of organizations [1]. The law stipulates that management of organizations should value her assets and liabilities based on the principle of the going concern assumption, unless serious doubts concerning the continuity of the organization exists (2:284 paragraph 3 of the Dutch Civil Code). When drawing up financial statements, the going concern assumption is therefore leading, as stated in ISA 2400, ISA 4410 and Title 9, Book 2 of the Dutch Civil Code (Financial Statements and the Management Report) [2][3][4]. The auditor assesses this going concern assumption in both statutory and voluntary audit engagements, but also in review engagements and compilation engagements [5].

Audit quality and the going concern assessment is currently heavily debated worldwide. Past experience shows that, despite the fact that an unqualified audit opinion has been issued, organizations can still go bankrupt in the foreseeable future. An example of this within the Dutch context is the inadequately evaluated going concern assessment of Imtech in 2012. According to the Dutch court [6], some assumptions regarding the going concern assessment did not correspond to the actual figures. Another example are the unseen irregularities within Steinhoff, which eventually led to bankruptcy. In this case, the auditor was accused by the Dutch Authority for Financial Markets (AFM) of not obtaining sufficient and appropriate audit evidence to identify the fraud [7]. In addition, the auditor's unconscious biases, caused by among other things client relations and confidentiality, do not contribute to an independent going concern assessment [8]. With the help of data-driven control, the AFM wants to make the supervision of audit firms more efficient and effective. The Royal Netherlands Institute of Chartered Accountants (NBA) also emphasizes continuity because of the increased social interest. The NBA wants to provide auditors with more tools that the auditor can use in the assessment. In fact, for 2021, the NBA board has set continuity as a mandatory subject for continuing professional education for all auditors (except government auditors). As of the reporting periods starting on or after December 15, 2021 (2020 for public interest entities), the NBA also mandates the inclusion of a separate section "Audit Approach to Going Concern" in the audit report [9]. Regarding the United Kingdom, Brydon's report suggests that the reporting requirements of the current going concern analysis are not sufficiently fit for purpose. Brydon recommended that the current going concern assessment should be expanded in the short term in a transparent manner, which includes material uncertainties without already taking into account mitigating measures [10].

This research focuses on the approach and possible improvements to the going concern assessment. The going concern assessment is still largely dependent on the professional judgment of the auditor, who must assess whether management has made proper considerations. Research shows that technology can contribute to an improvement of audit quality [11]. By automating the going concern assessment, more time and resources can be allocated to the interpretation of the going concern analysis. This maximizes the dual aspects of audit quality: independence and expertise [11][12]. To support the individual and personal professional judgment of the auditor, an additional automated going concern assessment, a more direct source of information with possibly higher reliability, could provide a solution. Automated forecasting of figures and numbers is possible with the use of forecasting algorithms. An algorithm is “a finite, abstract, effective, compound control structure, imperatively given, accomplishing a given purpose under given provisions.”[13] An algorithm can be an instruction in the form of code that can be used, among other things, for forecasting time series [14]. This research also focuses on the question of how sufficient and appropriate audit information can be collected using these forecasting algorithms, to analyze the going concern assessment in the (statutory) audit and compilation or review engagements. This can be done with the forecasting algorithms of PyCaret [14]. The use of PyCaret leads to an automated going concern analysis that is less dependent on the individual and personal professional judgment of the auditor, thus a possible improvement of uniformity can be realized. The goal of this research is to achieve an automated going concern analysis and a uniform creation of a more reliable and valid prediction for the going concern analysis. To achieve this, this paper answers the following main question: How can machine learning be used to assess the organizational going concern assessment? Similar to previous research we apply PyCaret to test multiple algorithms in concurrence [15][16].

The remainder of the paper is organized as follows: Section II describes the relevant literature regarding the auditor’s evaluation of the going concern analysis and models which give an indication of the going concern. In Section II the method and structure of the algorithms is described, followed by the results in Section IV. The conclusion and future work are presented in Section V.

II. Literature Review

The auditor's evaluation of the going concern analysis consists out of the following four main activities: 1) The auditor concludes whether there is a material uncertainty that could cast doubt on the ability of the company to continue as a going concern. 2) For the purpose of the foregoing analysis, the auditor also performs risk assessment activities and assesses whether the financial, operational, and other events and circumstances cast reasonable doubt on the ability to continue as a going concern. In doing so, the auditor looks at, among other things, the current liabilities position, negative operating cash flows or intentions to liquidate the company. 3) In addition, the auditor assesses other events and circumstances for, for example, changes in relevant laws and regulations and non-compliance with capital or other regulatory requirements. Other examples are included in ISA-570, paragraph A3 [4]. 4) Finally, the auditor should inquire about events after the balance sheet date that may have an effect on the going concern. This is included in ISA-570, paragraph 15 [4].

There are several models available that give an indication about the going concern of a company. A well-known model is the Altman Z-score, which was developed by Altman in 1968 [17]. The model was then designed and tested based on data from manufacturing companies, but further adapted for private Limited Liability Companies (LLCs) and non-manufacturing companies combined with emerging markets. Respectively, the Altman Z'-score Model and the Altman Z''-score Model. The Altman Z-score Model consists of the weighted average of five financial ratios, with each ratio consisting of two conditions. The Altman Z-score provides an indication of the probability of bankruptcy for the company in question. In this, Altman distinguishes three categories: 'Safe Zone', 'Grey Zone' and 'Red Zone'. A score of 3.0 or more leads to the category 'Safe Zone'. A score between 1.8 and 3.0 leads to the 'Grey Zone' and a score below 1.8 to the 'Red Zone'. In which the 'Safe Zone' does not indicate bankruptcy and the 'Red Zone' does indicate bankruptcy [17].

In addition to the Altman Z-score Model, there are several models available for going concern assessment. Using a structured literature review from 238 papers, Mantelaers and Zoet [18] identified 835 conditions that contribute to predicting the going concern. These elements were then analyzed based on the type of element, required information sources and organization type. From this, a top ten of the most commonly used elements for predicting the going concern was formulated. This top ten is shown in Figure 1.

Feature 01: Net income/total assets	85 (papers)
Feature 02: current ratio	74
Feature 03: EBIT/total assets (*)	65
Feature 04: retained earnings/total assets (*)	62
Feature 05: working capital/total assets (*)	60
Feature 06: sales/total assets (*)	46
Feature 07: quick ratio	41
Feature 08: current assets/total assets	39
Feature 09: total debt/total assets	39
Feature 10: cash/total assets	32

Figure 1. Top ten criteria assessing going concern

The ratios indicated with an asterisk are used in the Altman Z-score Model. The fifth element of the Altman Z-score, the market value of equity divided by total liabilities, comes in thirteenth place. This indicates that the elements of the Altman Z- score Model are frequently used. Despite its popularity, the Altman Z-score Model is only suitable for listed companies. Research shows that predicting going concern for mid-sized companies, requires models and procedures that are aimed at the mid-sized segment instead of the general Altman Z-score Model [19]. However, there are only a few going concern models available for predicting the going concern of mid-sized organizations. In this study, the adapted Altman Z-score Model by Altman and Sabato [19] is used.

In this model, the most successful financial ratios to predict the going concern were chosen for each category, namely: liquidity, profitability, leverage, coverage and activity. These financial ratios were incrementally assessed. After which, the financial ratios were logarithmically transformed to reduce the impact of the outliers resulting in an accuracy level of the model of 87% [19].

The Altman and Sabato study also compared the accuracy of the above model with a standard model, in this case a derivative of the Altman Z-score Model, the Z"-score Model was created. Comparing the Z"-score model to the Altman Z-score resulted in a higher prediction accuracy of almost 20% [19]. The conditions derived from the Altman Z-score model [17], the modified Altman Z-score models [19][20], and the top ten criteria from Mantelaers and Zoet's research [18] will be used within this research as input data for the forecasting algorithms. In which the word conditions refer to the various data points that can be used to assess the going concern of an organization. Examples include assets, liabilities, operating income before interest and tax (EBIT) and turnover.

The purpose of this research is to generate an automated going concern analysis. In order to do so the forecasting algorithms of PyCaret are used within this research. PyCaret uses different mathematical models translated into eponymous forecasting algorithms, namely: 1) Extreme Gradient Boosting, 2) CatBoost Classifier, 3) Light Gradient Boosting Machine, 4) K Neighbors Classifier, 5) Random Forest Classifier, 6) Extra Trees Classifier, 7) Gradient Boosting Classifier, 8) Logistic Regression, 9) Linear Discriminant Analysis, 10) AdaBoost Classifier, 11) Ridge Classifier, 12) Decision Tree Classifier, 13) Quadratic Discriminant Analysis, 14) SVM - Linear Kernel, 15) Naive Bayes and 16) Dummy Classifier. Each forecasting algorithm is tailored to specific situations, such as seasonality. In addition, each forecasting algorithm works with its own assumptions and interpretations, resulting in different forecasts [14]. For a detailed explanation we refer to the PyCaret website. By comparing the predictions of each model with each other and the actual realized figures, a ranking can be made with regards to the best performing algorithm. In this way, the most suitable forecasting algorithm can be chosen for each type of input data.

III. METHOD

This paper uses the predictive models of PyCaret, combined with the predefined conditions as input data. In this section, the process from input data to results is explained step by step using the short-term debt condition of Administration 1. The overall process of the system is visually shown in Figure 2. For illustration purposes, the structure of the system is explained for only one administration and condition. However, this process will be repeated for all conditions separately to achieve a complete picture of the organizations' performance regarding the going concern analysis.

To obtain the source data, the existing period balances were exported from Exact Online for eight to thirteen years, depending on the administration and availability. The exported cumulative monthly balance sheets were checked for empty cells. An empty cell can occur if there are, for example, no current liabilities in a period. To avoid errors, the empty cells have been replaced by the amount €0.00. Moreover, the cumulative monthly balance sheets were transposed to obtain the correct input for the algorithm. The beginning and ending balances correspond to months one and twelve of the respective year. To avoid double counting in the dataset, the beginning and ending balances were removed in the transposed file. After cleaning the individual cumulative monthly balance sheets per year, the years were merged into one file. Then, based on the merged cumulative monthly balance sheets per administration, the individual conditions (e.g., current liabilities, equity, sales, etc.) were filtered. This led to a dataset per administration per condition per month.

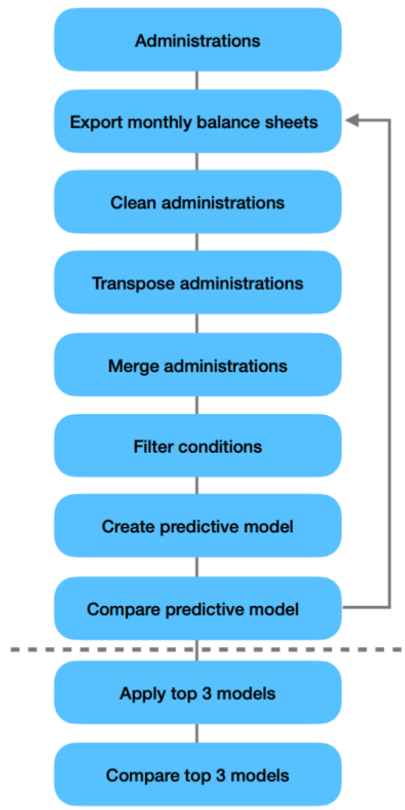

Figure 2. Structure system

The dataset per administration per condition per month for the years present is then presented to PyCaret's regression module (v 2.3.2). The regression module is a supervised machine learning module used for estimating the relationship between a dependent variable and independent variables. PyCaret uses different mathematical models translated into similarly named forecasting algorithms to see which model makes the best predictions.

In doing so, each forecasting algorithm works with its own assumptions and interpretations, resulting in different forecasts. The model that best fits the administration is shown at the top and the model with the least fit is shown at the bottom. The predictions and the true value of each are then stored in one file and compared. To assess the accuracy of the predictions, the (percentage) deviations per month and at the total level were calculated from these real figures.

IV. Results

For the current liabilities condition from Administration 1, the results are explained below. Using PyCaret's regression module, the Gradient Boosting Regressor, Decision Tree Regressor and the AdaBoost Regressor models emerge as the most accurate. The actual current liabilities figures from Administration 1 are visually represented in Figure 3.

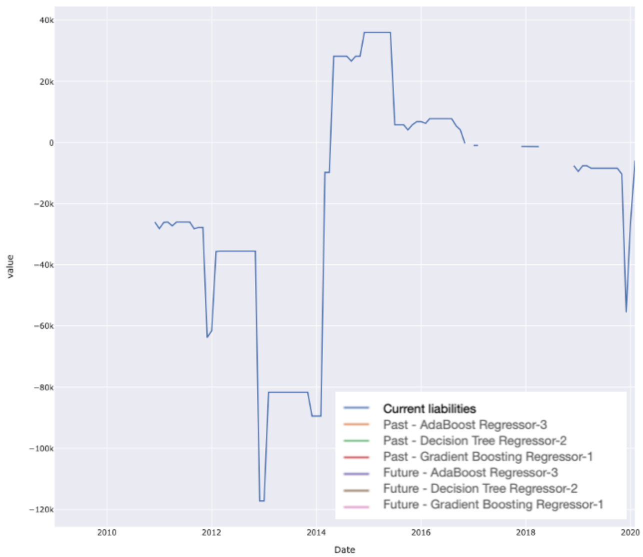

Figure 3. Actual figures current liabilities, Administration 1

The results of the top three models are then added in Figure 4, where the blue line represents the actual short-term debt figures, and the other colored lines represent the predictions. The forecasts within PyCaret consist of two parts per model: Past and Future. Past predicts back into the past based on an adaptive training set consisting out of several years after the predicted year. Future predicts a predetermined time period (in this case six months) based on actual historical figures.

Figure 4. Forecasted figures current liabilities, Administration 1

In addition, the results of the different forecasting algorithms for the current liabilities of Administration 1 were then merged into one CSV file. In addition, the (percentage) deviations were calculated based on the actual figures. In this way, the forecasts are compared with the actual figures. For example, for the period 2010-12-11, the deviation between the AdaBoost Regressor model and the actual value of the current liabilities is €911.00, which represents a deviation of 3.5%. The results for the current liabilities of Administration 1 are visually shown in Table 1.

Table 1. Results top 3 models current liabilities, Administration 1

Model	Deviation percentage	Confidence percentage
Gradient Boosting Regressor	02.55%	97.45%
Decision Tree Regressor	03.21%	96.79%
AdaBoost Regressor	22.28%	77.72%

On average, a deviation percentage of 2.55% for Gradient Boosting Regressor, 3.21% for Decision Tree Regressor and 22.28% for AdaBoost Regressor was achieved for short-term debt. This leads to a confidence percentage of 97.45%, 96.79% and 77.72%, respectively.

V. Conclusion and Future Work

Going concern assessment is currently heavily debated all over the world. This within the larger context of the current societal debate on audit quality. With cases such as Imtech and Steinhoff [1][5] proving that going concern assessments needs to be a viable part of the audit. In this article we aim to answer the main question: "*How can machine learning be used to assess the organizational going concern assessment?*" This research presents a first step towards an automated process of going concern assessment. The goal of this research was to predict the different individual variables that affect the going concern assessment of the auditor. A confidence percentage of 97.45% for the Gradient Boosting Regressor model, 96.79% for the Decision Tree Regressor model and 77.72% for the AdaBoost Regressor model was measured on the basis of the current liabilities for Administration 1. This means that the predictions of the algorithms are reliable with 97.45% for the Gradient Boosting Regressor model. The results therefore show that individual variables can be predicted with the various algorithms of the PyCaret Library. This means that the machine learning used in this paper, particularly PyCaret, can be used to assess the organizational going concern assessment.

The insights derived from our study provide a better understanding of the ability to predict numbers based on the general ledger of organizations. This means that the Altman Z-score as a whole can be predicted, resulting in a predictive continuity. Future research should focus on creating an indicator of the going concern assessment. In our study, we draw our conclusions based upon data collected solely from the Dutch context, which limits, in terms of sampling, a broader generalization towards non-Dutch organizations. Future research should focus on further generalization towards other countries. In addition, the sample only consisted of small and medium sized organizations, future research should focus on further generalization towards other industries (non-governmental). Related to the previous limitation is the sample size, which is limited to 221 organizations. Although this is a rather large sample size, the total number of organizations in the Netherlands is much larger. In addition, the predictions are now based on a single variable. For future research, multivariable predictions can be applied to see if this will increase the predictive value. Future research should also focus on comparing the forecast with the going concern paragraphs (used or not) in the financial statements concerned. In this way, it can be determined whether or not there is uncertainty about continuity, or in the accounting policies or events after the balance sheet date, and whether this matches the results of the algorithms.

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