Predicting Qualified Auditor's Opinions: A Data Mining Approach

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Abstract: Data Mining tools and methods can be used to facilitate auditors to issue their opinions. Numerous of these methods have not yet been tested for the purpose of discriminating cases of qualified opinions. In this study we employ three Data Mining classification techniques to develop models capable to predict qualified auditors' reports. The input vector is composed of quantitative and qualitative variables. The three developed models are compared in terms of their performances. Additionally, variables which are associated with qualified reports and can be used as indicators are revealed. The results of this study can be useful to internal and external auditors and company decision makers.

1. Introduction

In today's modern business era auditing becomes a more demanding task. The advancements in the auditing conceptual frameworks, the massive application of information technology in business and the new knowledge extraction technologies such as data mining, constitute a field of necessities and capabilities which presents new challenges to the applied auditing methods.

The relevant research literature repeatedly recognizes the importance of the new technology and the elaborated knowledge discovery techniques in auditing. Calderon et al. [3] claim that the new auditing methodologies embrace the concept of business risk which incorporates a strategic dimension regarding the ability of a company to achieve its objectives. The new risk-based approach to auditing requires that the auditors use advanced technology that can identify factors that prevent an organization from achieving its objectives. Kirkos et al. [11] claim that the increasing number of management fraud cases amplifies the necessity of new elaborated auditing tools.

An investigation in the research literature reveals that most of the relevant studies use either sophisticated statistical methods or various versions of Neural Networks to predict the audit opinion. However numerous alternative data mining techniques remain to be tested for the tasks of predicting auditors' opinion and identifying significant predicting factors.

In this study we employ three data mining techniques to develop models capable of predicting qualified audit opinions. The techniques used are Decision Trees (DTs), Neural Networks (NNs) and Bayesian Belief Networks (BBNs). The models are compared in terms of their performances. Moreover each model reveals specific input variables which are considered significant. The sample used in the study contains data about 450 publicly listed, non-financial UK and Irish firms. The input vector consists of both quantitative and qualitative variables.

This study has implications for internal and external auditors, company decision makers, investors and financial analysts. It can also be used to predict the most probable outcome ahead of the external audit.

The paper proceeds as follows: Section 2 reviews relevant prior research. Section 3 provides an insight into the research methodology used. Section 4 describes the developed models and analyzes the results. Finally, Section 5 presents the concluding remarks.

2. Prior Research

Considerable research effort has been directed towards the development of models capable to identify cases of qualified audit opinions. Lenard et al. [15] developed two NN models and a Logit model to identify cases where firms obtained a modified audit report for going-concern uncertainty. The input vector consisted of publicly available financial ratios and account values. They concluded that a NN version model performed better achieving an accuracy rate of 95%.

Laitinen [14] used the multivariate logistic regression analysis based on 17 financial and non-financial variables. Their results showed that the likelihood of receiving a qualified audit report is larger, the lower the growth of the firm, the lower the share of equity in the balance sheet and the smaller the number of employees.

Anandarajan [2] compared three alternative methods, multiple discriminate analysis, expert systems and NNs to predict the type of going-concern report that should be issued. 14 financial ratios were used as input variables. The authors report better performance for the NN model.

Three alternative models for predicting the future going-concern status were tested from Etheridge [5]. The three models were different approaches to NNs i.e. Backpropagation NN, Categorical Learning NN and Probabilistic NN. According to the defined misclassification cost, different models have been found preferable.

Spathis [21] in a logistic regression study tested the ability of various combinations of the variables to correctly predict the audit opinion. The results of the model suggest that there is potential in detecting qualified audit reports through analysis of publicly available financial statements and firm litigation data. Spathis [22] developed a model using the multicriteria technique UTADIS. The analysis suggested that receivables to sales, net profit to total assets, sales to total assets and working capital to total assets are useful predictors of audit qualifications. The UTADIS method was found quite effective in predicting qualified/clean reports, providing an estimated classification accuracy of approximately 80%.

Hudaib [9] used Logistic Regression to explore the effects of change in managing director and financial distress together on five control variables to model audit opinion. They found that companies that are financially distressed and change their managing director are most likely to receive a qualified audit report.

Considering the disadvantages of Backpropagation NNs Gaganis [7] investigated the capability of Probabilistic Neural Networks in predicting qualified audit opinions. According to the reported results the PNN model outperforms an Artificial Neural Network model and a logistic regression model. The authors also conclude that profitability and credit rating scoring are significant factors associated with qualified reports.

A critical observation of the research literature reveals that the researchers employ either some version of Neural Networks or regression analysis. Remarkably there is a number of Data Mining techniques which, although have been extensively applied to similar research fields like bankruptcy prediction, have not be tested for their applicability to predict qualified reports. Just to mention some of them, Data mining techniques suitable for classification problems are Decision Trees, Naïve Bayesian Classifiers, Bayesian Belief Networks, Rough Sets and Support Vector Machines.

3. Research Methodology

3.1 Data

The data used in this study come from the FAME (Financial Analysis Made Easy) Data Base. FAME contains data about 3,000,000 UK and Irish firms..

After excluding the financial companies (i.e. banks and insurance companies) by considering the companies' two digits SIC code, we selected the publicly listed firms which obtained at least one qualified report over the last ten years. Some of the firms obtained qualified reports for more than one year. In a considerable number of cases the qualified reports were of successive years. This could reflect problems related to structural characteristics of specific companies which are permanent for a time period. Thus the multiple participation in the sample of a firm for each year it obtained a qualified report could create observations containing repetitive information. Since such observations could bias the sample we preferred to introduce only once each qualified firm. In total the sample contained 225 qualified firms. The qualified firms were matched with equal number of unqualified firms. The match has been performed in terms of activity (4 digits SIC code) and fiscal year to eliminate macroeconomic influences. The final sample contained 450 firms.

A number of companies participating in the sample contained missing values. A method for handling missing values is to eliminate the relevant observations. Another approach is to substitute the missing values with the mean per class value. In order to avoid information loss which is caused by the elimination of observations we preferred to substitute the missing values.

3.2 Variables

The selection of variables to be used as candidates for participation in the input vector was based upon prior research work, linked to the topic of qualified opinion detection.

Much of the research literature examined the relationship between the level of audit fees and the possibility to obtain a qualified report. Firth [6] claims that larger auditees with higher fee levels are less likely to obtain a qualified audit opinion. Firth also found a positive but insignificant association between audit fees and qualified opinion. Hudaib et al. [9] classify high audit fees as the ratio of Audit Fees to auditee's Total Assets and claim that since the auditee executes dismissal the focus should be on the auditee. We also test this variable as a candidate to participate in the input vector. Fees paid for non auditing services such as bookkeeping, consultancy, investigation work etc. could also impair the auditor's objectivity. Non-Audit Fees is another variable checked in this study.

A number of studies [12], [18] indicate that firms with high probability of default are more likely to receive qualifications. FAME contains the credit rating score Quiscore as a measure of the likelihood of default. Quiscore is included in our tested variables. Several studies associate the size of the auditee with the possibility to obtain qualification [8], [13]. Ireland [10] claims that large companies are more likely to have good accounting systems and internal controls, thus reducing disagreements and limitations on scope. We check the auditee's size by using Total Assets and Turnover.

In the relevant research literature there are contradicting arguments concerning the association of the auditor's size and the possibility to issue a qualified opinion. Shank [19] found no association between the two variables. Warren [24] contradicts these results. We use the binary variable IfBig to indicate if the auditor is a big 5 auditing firm (KPMG, PricewaterhouseCoopers, Deloitte & Touch, Ernst & Young, Arthur Andersen).

Clients with a high probability of bankruptcy are more likely to receive qualified opinions because their ability to continue as a going concern is in greater doubt [18]. A surrogate for probability of bankruptcy is the Altman Z-Score [1] as a control variable to investigate the association of audit opinion and financial distress.

Auditors give 'subject to' qualifications when there are uncertainties about material events. Liquidity is a direct measure of the financial health of a company. The possibility of a qualified audit report is higher when the financial health of a company deteriorates. We check liquidity by using the ratio Current Assets to Current Liabilities (Current ratio), the Liquidity Ratio and the ratio Working Capital to total Assets.

Sundgren [23] associates qualified opinions with current year loss. We use the variable Profit (Loss) before Taxation. The analysis of Laitinen [14] showed that the qualification of an audit report is associated with the growth of the firm (percentage change in net sales). We check the variable Turnover Trend as a possible predictor.

Numerous studies associate qualified opinions with profitability ([16], [20], [21], [22]). We selected the profitability related ratios Profit before Taxation Margin, Return on Shareholders Funds, and Return to Total Assets.

In the present study we would like to test if trends in a company's performance can be associated with qualified opinions. Trend analysis assesses whether there is a functional dependency between the variables over time. The measures Current Assets trend, Current Liabilities trend, Total Assets trend and the measure Increase (decrease) Cash and Equiv. are tested for their applicability to act as possible predictors. Some additional typical financial ratios and measures are also tested in relation to their ability to predict qualified opinions. These are the ratios Solvency Ratio%, Gearing% and the measures Current Liabilities, Long term Liabilities, Shareholders funds, Working Capital.

In total, we selected 26 financial ratios. In an attempt to reduce dimensionality, we ran one way ANOVA to test whether the differences between the two classes were significant for each variable. If the difference was not significant (high *p*-value), the variable was considered non-informative. Results of ANOVA are depicted in Table 1.

As can be seen in Table 1, 16 variables presented low *p*-values ($p < = 0.05$). These variables were chosen to participate in the input vector, while the remaining variables were discarded. The selected variables were Turnover, Profit before Taxation, Working Capital, Solvency Ratio, Gearing %, Return on Shareholders Funds, Return on Total Assets, QuiScore, IfBig, Total Assets, Current Liabilities, Long Term Liabilities, Shareholders Funds, Audit Fee, Zscore and the ratio Audit Fees to Total Assets.

	Qualified		**Unqualified**			
Variables	**Mean**	**StDev**	**Mean**	**StDev**	**F**	**P**
Turnover	**109981**	**624955**	**490298**	**1665774**	**8.56**	**0.004**
Profit (Loss) before Taxation	**-44020**	**412009**	**58349**	**367942**	**7.70**	**0.006**
Profit before Taxation Margin	0.0294	1.2603	0.0705	0.4356	0.20	0.654
Working Capital	**10059**	**93915**	**54668**	**194939**	**8.94**	**0.003**
Increase (Decrease) Cash & Equiv.	-302	9166	3310	27512	3.39	0.066
Current Ratio	2.408	5.046	2.955	5.331	1.24	0.266
Liquidity Ratio	2.163	4.998	2.690	5.344	1.16	0.282
Solvency Ratio %	**38.97**	**42.90**	**54.30**	**24.81**	**21.00**	**0.000**
Gearing%	**271.4**	**859.3**	**79.5**	**199.0**	**9.59**	**0.002**
Current Assets (Trend)	26.5	149.4	22.8	65.0	0.11	0.735
Total Assets (Trend)	11.34	106.55	24.12	79.95	1.95	0.163
Current Liabilities (Trend)	27.40	91.39	26.69	83.57	0.01	0.933
Return on Shareholders Funds	**-112.7**	**189.6**	**-5.1**	**101.1**	**51.64**	**0.000**
Return on Total Assets %	**-67.49**	**116.15**	**-2.40**	**26.74**	**66.92**	**0.000**
Turnover % Trend	20.9	129.2	36.2	97.4	1.72	0.191
QuiScore	**32.06**	**29.08**	**61.06**	**26.44**	**121.92**	**0.000**
If Big	**0.4170**	**0.4942**	**0.6116**	**0.4885**	**17.52**	**0.000**
Total Assets	**120227**	**702949**	**687713**	**2776016**	**8.76**	**0.003**
Current Liabilities	**57664**	**425605**	**156541**	**569321**	**4.34**	**0.038**
Long Term Liabilities	**66946**	**366974**	**259546**	**1101855**	**4.39**	**0.037**

Shareholders funds	**15334**	**199740**	**288748**	**1259448**	**10.34**	**0.001**
Audit Fees	**98.1**	**317.4**	**301.7**	**798.7**	**12.33**	**0.000**
Non Audit Fees	171.2	749.0	354.2	1042.9	3.66	0.057
Zscore	**-4.22**	**21.23**	**1.26**	**1.66**	**14.23**	**0.000**
WC/TA	-0.396	4.843	0.137	0.146	2.67	0.103
Audit Fees/TA	**0.02776**	**0.12978**	**0.00280**	**0.00302**	**8.25**	**0.004**

Table 1
Descriptive statistics, F and P values by one way ANOVA
Bold characters indicate the significant input variables

Descriptive statistics provide some initial indicators concerning the characteristics of firms which obtain qualified opinions. Unqualified firms tend to be considerably bigger in terms of Total Assets, Turnover and Shareholders Funds. The audit fees paid by the unqualified firms are higher than those paid by the qualified firms but this can be attributed to their bigger size. The ratio Audit Fees to Total Assets reveals that qualified firms pay much higher Audit Fees relatively to their size. Non Audit fees seem not to be significant. All variables related to profitability present lower mean values for the qualified firms. Trends seem not to be significant since all trend variables present high p-values. Z-score mean value is much lower for the qualified firms indicating that financial distress may be associated with qualified reports. Finally liquidity seems to be irrelevant since all relevant ratios have high p-values and were rejected from the input vector.

4. Experiments and Results Analysis

Three models, each based on a different method, were built. The first model was the C4.5 Decision Tree. The software used was the TANAGRA [17] data mining research software. The tree was built with 0.25% confidence level. The whole sample was used as the training set. The constructed decision tree included 55 nodes and 28 leaves.

C4.5 Variables
Z-Score
Gearing
ROSF
Turnover
CurLiab

Table 2

The Decision Tree uses as first level splitter the variable Z-Score. In the first splitting node the tree differentiates 210 out of 225 unqualified firms and 132 out of 225 qualified firms according to their Z-Score value. It seems that companies in rather good financial position manage to obtain clean reports where financially distressed companies tend to obtain qualified reports. As second level splitters one variable associated with leverage (Gearing) and one variable associated with profitability (Return on Shareholders funds) are used. Table 2 exhibits the high level splitter variables.

In terms of performance, against the training sample the tree managed to classify correctly 408 cases achieving a general performance of 90.67%. Accuracy per class rate is 92.00% for the qualified (207 cases) and 89.33% for the unqualified (201 cases) firms.

The second model was the multilayer perceptron. The model was built with Tanagra Software [17]. After testing a number of alternative designs we choose a topology with one hidden layer containing 10 hidden nodes. The defined learning rate for training was 0.15 and the error rate threshold was 0.01. The network was trained by using the whole sample and was tested against the training sample. The general achieved performance was 81.56%. In particular the model classified correctly 175 qualified firms (77.78%) and 192 unqualified firms (85.33%).

MLP Variables
ROSF
AUDITFEETA
ZSCORE

Table 3

In order to estimate the attributes' contribution for the multilayer perceptron classifier, Tanagra performs an iterative test by excluding each time an attribute and recalculating the error rate for each case. Although the differences are rather small, it is worth to mention that the variables ROSF (Return on Shareholders Funds) and Z-score which are used as high level splitters in the C4.5 tree, present higher statistical value in the error rate change test. The variable Audit Fee to Total Assets appears also to have considerable contribution.

The third model was the Bayesian Belief Network. In order to develop the network we used the BN Power Predictor software. It is common in Bayesian Belief Network software packages that the user has to define the structure of the network. The algorithm of BN Power Predictor is capable to extract the network from the data by learning from the training set [4]. One limitation of the software used is that it does not accept continuous input values and it requires discretised data. We performed supervised entropy based discretisation because this method uses the class information to define the intervals. Thus the discretised data are more suitable for the classification task.

The model was built by using the whole sample as training set. The network achieved a general classification accuracy of 86.44% against the training set managing to classify correctly 184 out of 225 qualified firms (accuracy rate 81.78%) and 205 out of 225 unqualified firms (accuracy rate 91.11%).

BBN Variables
Z-Score
ROSF
Turnover
Gearing
PLBT
ROTA
QuiScore
Long Term Liabilities

Table 4

The Bayesian Belief Network associates directly specific input variables with the class attribute by recording dependencies between them. Remarkably the network depicts dependencies between the class attribute and the variables Z-Score and ROSF. These variables have also been found significant both by the C4.5 Decision Tree and the Multilayer Perceptron classifier. Additionally the network records dependencies between qualification and the variables Turnover and Gearing which also have been found significant by the C4.5 tree. The variables which are associated with qualification according to the Bayesian Belief Network are shown in Table 4.

4.1 The models' validation

Using the training set in order to estimate a model's performance might introduce a bias. To eliminate such a bias the performance of the models is estimated against previously unseen patterns. The two software packages used adopted different validation methods. BNP allowed the user to test a BBN classifier against a separated previously unseen data set were TANAGRA embodied a 10-fold validation module. In order to obtain comparative results we had to follow common validation procedures for all the models. Thus for the BNP case we performed manually 10-fold cross validation. In 10-fold cross validation, the sample is divided in ten folds. For each fold the model is trained by using the remaining nine folds and tested by using the hold out fold. Finally the average performance is calculated. Table 5 summarizes the 10-fold cross validation performances of the three models.

Model	Qualified	Unqualified	Total
BBN	76.44 %	88.00 %	82.22 %
MLP	78.44 %	83.78 %	81.11 %
C4.5	76.62 %	78.76 %	77.69 %

Table 5 10-fold cross validation performance

As expected the accuracy rates are lower for the validation set than the accuracy rates for the training set. However each model presents a different behaviour. The Decision Tree which succeeds the best performance against the training sample reduces its classification accuracy by a magnitude of 13% and manages to classify correctly 77.69% of the total cases. The performance of C4.5 is the lowest compared with the other two models. The MLP model classified correctly 81.11% of the total cases. Remarkably this performance is almost equal with its accuracy rate against the training sample. Finally the BBN model although presents a considerable decrement of its performance, achieves the best accuracy rate (82.22% of the total cases).

In a comparative assessment of the models' performance we can conclude that the Bayesian Belief Network outperforms the other two models. MLP achieves a marginally lower performance. Finally, the Decision Tree's performance is considered satisfactory.

In assessing the performance of a model, another important consideration is the Type I and Type II error rates. A Type I error is committed when a qualified company is classified as unqualified. A Type II error is committed when an unqualified company is classified as qualified. Although in most cases Type I and Type II errors have different costs, in this research topic both types of errors have significant costs. The misclassification of a qualified firm may lead to a clean report which does not disclose the true picture of the company, where the misclassification of an unqualified firm may lead to an unfairly qualified report which may cause to the company economic injuries. In our study the three developed models have a comparable classification accuracy rate for the qualified cases. For the unqualified cases the BBN model has a significantly lower error rate followed by the MLP and the C4.5 models.

4.2 Analysis of variables' significance

Another aim of this study is to locate the variables which are of significant importance in discriminating the qualified cases from the unqualified ones. All of the three models agree that financial distress, which is measured by the input variable Z-Score, is associated with audit qualifications. Profitability matters are also strongly related to qualifications since the three models associate the variable ROSF (Return on

Shareholders Funds) with qualifications. These variables are proposed as possible indicators. Both C4.5 and BBN models reveal dependencies between audit qualification and the variables Gearing and Turnover thus providing clue that leverage and sales performance can be related to qualified opinions. Liquidity seems to be irrelevant since all of the three variables associated with liquidity were discarded according to the results of ANOVA.

In terms of the possible relation between auditor's characteristics and qualified opinions, our results seem to grant credits to auditors. Only the MLP model associates the level of audit fees with qualified reports by ranking the variable Audit Fees to Total Assets in the second place of the attributes' contribution table. Moreover the similar input variable Audit Fees is rejected by all of the three models. None of the three models associates the qualitative variable IfBig (which indicates if the auditor is a big auditing firm) with qualified reports. Finally the variable Non Audit Fees were discarded according to ANOVA.

5. Conclusions

In this study we employed three Data Mining classification techniques to develop models capable to identify cases of qualified audit opinions. The techniques used are C4.5 Decision Tree, Multilayer Perceptron Neural Network and Bayesian Belief Network. The sample contained 450 publicly listed, non-financial UK and Irish firms. Half of the firms contained in the sample obtained qualified audit reports. The input vector contained both qualitative and quantitative variables. Preliminary feature selection has been performed by running one way ANOVA.

The three developed models have been proven capable to discriminate the qualified cases. In a 10 fold cross validation procedure the Bayesian Belief Network achieves the highest classification accuracy managing to classify correctly 82.22% of the total observations, 88.00% of the unqualified firms and 76.44% of the qualified firms. The Multilayer Perceptron model achieves a marginally lower performance. The MLP classified correctly 81.11% of the total, 83.78% of the unqualified and 78.44% of the qualified observations. Finally the Decision Tree Model achieved the lowest performance having an accuracy rate of 77.69% of the total, 78.76% of the unqualified and 76.62% of the qualified cases. The three models have almost similar Type I error rates. The differences in their overall performance arise mainly from their different Type II error rates. In terms of Type II errors the BBN model outperformed the MLP model by a magnitude of 4% and the C4.5 model by a magnitude of 9%. The C4.5 model has been proven the most balanced having comparable Type I and Type II error rates.

According to our results financial distress and profitability are strongly related to qualified opinions since the corresponding variables Z-Score and Return on Shareholders Funds have been selected by all of the three models. The variables Gearing and Turnover have been found significant by the C4.5 and BBN models. All the liquidity related variables were rejected. Finally three out of four variables concerning the auditor's characteristics i.e. the variables Audit Fees, Non Audit Fees and the qualitative variable indicating that the auditor is a big auditing firm have been found irrelevant. Only the MLP model associated the variable Audit Fees to Total Assets with qualified opinions.

As usually happens, this study can be used as a stepping stone for further research. Other Data Mining methods like Support Vector Machines and Rough Sets which enjoy good reputation for their classification capabilities remain to be tested in terms of performance and explanatory power. We believe that financial matters measured with financial ratios and account values have been well covered in this study. However there are numerous qualitative variables which remain for further study. These variables include the change of managing director, the composition of the board of directors, the frequency the auditors are changed and bad news characteristics as firm litigation. Standing within industry studies could reveal industry specific indicators. We hope that the research presented in this paper will therefore stimulate additional work regarding these important topics.

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