An International Journal Volume 2 Number 1 2020

International Journal of Computer Auditing

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Published by
International Computer Auditing Education Association

Publication Office
21615 49A AVE
LANGLEY BC V3A 6C4
CANADA

eMail: journal@icaea.net
Website: https://www.icaea.net

Start-publication Date
2020

ISSN: 2562-9980 (Print)
ISSN: 2562-9999 (Online)

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International Journal of Computer Auditing

2020

Volume 2 , Number 1

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INTERNATIONAL JOURNAL OF COMPUTER AUDITING

Article

The Development of Accounting Data Analytics Curriculum

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Accounting programs are now being encouraged to incorporate data analytics into their programs. This article will provide suggestions on how to set up a data analytics program in a school of accountancy, answer why it is important to incorporate data analytics within accounting programs, and finally how to create a well-integrated curriculum.

Reference Format: Durtschi, C. and Wang, T., 2020, The Development of Accounting Data Analytics Curriculum, International Journal of Computer Auditing , Vol.2, No.1, pp.1- 4.

1 | INTRODUCTION

Accounting programs are currently encouraged or required to expand curriculum to include data analytics. The motivation comes from meeting accreditation guidelines, and the change in accreditation standards is the result of pressure from the accounting profession. The profession is rapidly moving toward more digital platforms in an effort to improve quality, efficiency and communication with clients in more easily interpreted visual formats.
The move to data analytics can feel exciting as well as intimidating as we confront a series of questions. For example:

1. What exactly do accounting firms mean by "data analytics?"
2. How does one put together a coordinated data analytics curriculum?
3. Where does data analytics belong in a curriculum?
4. What happens to curriculum when platforms change, as they do in rapidly changing technology?
5. What challenges arise when bringing a data analytics curriculum into operation?

The authors created a data analytic program and this article offers some thoughts on the answers to these five questions gleaned from the six years of experience with our program. We deliver the program to master's level students. It integrates the accounting knowledge from their undergraduate education, data analytics, forensic accounting and

internal audit (controls). We are currently integrating a data analytics program into the undergraduate curriculum. When dealing with undergraduates, many of the same approaches apply with the several caveats. First, the data analytics problems chosen must not outpace the student's accounting knowledge. Second, consider the student's overall experience to avoid overwhelming the undergraduate's already tight schedule. Third, undergraduate accounting education is focused on content and certificate preparation so data analytics, by necessity should have a dual purpose, enforcing accounting knowledge while conveying basic skills. The rest of this paper will share what we have learned.

What do accounting firms mean by data analytics?

To accounting professors, data analytics means PhD-level statistics and programming. Luckily, we came to realize this is not what accounting firms expect. Hours of talking with accounting firms made it clear that they can, and do hire data scientists for more technical tasks; the problem is that data scientists do not understand accounting or auditing. So, what firms are looking for in new accounting hires is:

1) An understanding of the limits and potential of programming
2) The ability to know what accounting questions to ask of the data
3) The ability to interpret the results of the analytics
4) The ability to use accounting knowledge to know what questions to ask next
5) Knowing how to prioritize business issues, and
6) Understanding statistics and alternative methodologies to know when results are meaningful.

In other words, firms need a link between the data scientists and accounting; someone who can link data with the operational decisions. When forming a data analytics program for accounting, that link between analytics knowledge and business operations, policies and procedures must be in the forefront. In summary, what firms' desire is accountants who can leverage analytics to facilitate the decision making process, who understand the data results in the context of accounting, and can put those results into reports which communicate (e.g., visualizations) important accounting and auditing information effectively to clients.

How does one put together a coordinated data analytics curriculum?

Data analytics, like accounting, builds from basic concepts to techniques that are more challenging. Because of this, we found it imperative to coordinate and integrate our curriculum. We have not yet found a series of textbooks that mirror an accounting curriculum at the graduate level, in that they begin with simple concepts and become more complex over a series of courses. Therefore, we built our curriculum slowly, and changed it frequently. We also found that accounting students want their data analytics problems to deal with accounting issues. They much prefer to work with accounting numbers and have the problems they solve include questions they might see on a job. That is, teaching them pure methodology without specific contexts may create some barriers.

Accordingly, we consider students accounting knowledge as we build analytical problems that move sequentially from easier concepts to relatively more advanced techniques. We start with the program's learning objectives and learning outcomes to ensure we have a consistent and coherent design. We overlay the accounting maturity level with the analytics maturity level starting from descriptive analytics to diagnostic, to predictive, then prescriptive.[1] We realized

[1] Descriptive analytics focuses on what has already happened and/or what is happening. For example, we may observe more transactions between $9,000 and $10,000 (i.e., a pattern that has already happened). Diagnostic analytics emphasizes making sense of the observed pattern. That is, based on business operations and all the imposed mechanisms (e.g., internal controls or incentive schemes), are we able to explain the observed information and provide

the importance of considering the level of taking analytics tasks in succession when we found that students could not discuss predictive tasks without an understanding of basic statistics. We rearranged our courses to require each student to complete a basic (but customized to our needs) statistics course.

We also found that the particular analytic tools and programs chosen for class was less important than we first believed. Class time spent helping students see different possibilities and how to link data with operational decisions is more important than time spent learning a tool. Students can easily access and learn different tools online for a low price or even free. A better goal for students is to learn how to approach the problem, how to start the analysis, how to interpret results and how to communicate findings.

Where does data analytics belong in a curriculum?

It is not enough to provide students with one or two data analytics courses. This is not to advocate for a longer series of courses, rather to promote the notion that repetition will increase the chance that students will retain the knowledge and skills learned in such a course and be better able to apply them in the future. In our program we consciously integrate data analytics in all courses. We encourage students in each course in the program to incorporate any skills they have learned in prior courses. For example, in our in our forensic accounting courses, students are encouraged to use their data analytics skills to solve the forensic accounting cases. The data analytics cases often have a forensic accounting or audit story embedded in the data. The internal audit classes apply to both the forensic accounting and data analytics cases as both rely students understanding of internal controls.

The purpose of this approach is that students must integrate their accounting knowledge and data analytics skills in each problem they confront. An example of a data analytics problem we have used is to give students data from accounts receivable. Students should first know what questions to ask (i.e., does the data set contain accounts long overdue?). Second, if an aging analysis shows many long-overdue accounts is that unusual? (i.e., they should know to compare across time). Finally, if it seems to be a new phenomenon, what additional questions should they ask? (i.e., was a single individual responsible for granting credit to customers that were not creditworthy? Was there a corresponding increase in the allowance for doubtful accounts? Were those delinquent accounts removed from the books in a timely manner?)

No data analytics problem is complete without a client presentation. Students must decide what information is important to convey to the client. They must anticipate client questions and prepare answers, finally, they must think about the value their analysis can create for the company.

What happens to curriculum when technology changes?

This is where coordination between data analytic faculty is important. While we meet formally as a faculty, the data analytics faculty meet informally to coordinate their courses as well. Each faculty member may have his/her own preferences but consistency across the program is still needed. However, the change in technology implies a change in all teaching materials and handouts even when tools are just for illustrative purposes (i.e., "here is one tool similar to those you may use on the job"). The coordination involves two levels: one is about the tool and the other is about the content. Choosing the tool is a challenging task as we will discuss in the next section, even though it should be

recommendations? In the previous example, it may result from the policy requiring more approvals when the transaction is more than $10,000. Predictive analytics, as the name suggests, turns our attention to predictions. For instance, are we able to predict the problematic transactions that are arranged intentionally to avoid the additional approvals? Last, prescriptive analytics attempts to answer the question "how can we go from where we are now to where we want to be." Through a series of, for example, "what-if" analysis or sensitivity analysis, we may be able to change processes or reallocate resources to reach the goal.

chosen for illustrative purposes. The content also has to be updated regularly to reflect the new practices and new possibilities. More importantly, as students grow to become more comfortable with this new skillset, we are required to make changes to push them to the next level. This means coursework requires a regular patch or even redesign of the curriculum.

What is needed to operationalize the program?

Our experience is that settling on a curriculum turns out to be a far cry from operationalizing it. The number one requirement to operationalization is **talent**. The difficulty in finding talent (those who are able and willing to take on a data analytics course) lies in the fact that as an accounting professor we are accustomed to textbooks that lay out the curriculum in an organized manner, that have problems and supplemental materials or even an online homework manager. Teaching data analytics is much more free form. Classes need to be built, but at the same time require a lot more flexibility than a typical accounting course. For example, finding or creating data analytics problems requires a different level of time and effort on the part of the professor. Adding another layer of complication is the fact that data analytic problem solutions are easily transferrable from one semester to the next so the continual creation of challenging problems is a relentless process. Another issue is that there is less lecture and more hands-on interaction with students as each student runs into unique difficulties with the problems and the technology. This requires that instructors have a level of comfort with the technology as well as the problems being set for the class.

As mentioned earlier, given our focus is on the analytics mindset and critical thinking skills, choice of software or tools becomes for illustrative purposes. However, even then, selection of an illustrative software is one of the most challenging tasks to confront the instructor when designing the curriculum. Each tool has its own benefits and limitations that are affected by multiple factors: (1) The expected learning outcome. The software has to match the learning outcome. For example, if the goal is visualization, a statistic software, though it can also do some visualization, probably does not fit. (2) Mac users. Many business applications do not run on a Mac. If a school has a limited availability of computer labs or when students are online, the tool must work easily on different platforms. (3) Level of coding and data manipulation. Our main objective is not training a computer scientist. We choose tools that reduce the level of coding and data manipulation required by students so our focus can be on higher-level skills, such as how to think through a problem, how to interpret results and how to communicate data. These skills are also transferrable to different technologies.

Finally, the **grading** rubrics are different from normal accounting questions as there are written reports, and data presentations that must be weighed and judged, usually on a comparative basis rather than an absolute solution. We have found grading rubrics that focus on critical thinking displayed by students work better for analytics type assignments.

2 | CONCLUSION

The creation and execution of a data analytics program in accounting is a challenging and rewarding task. It can do much to prepare students for the future they will face in the workplace. It also comes with challenges and hard work for instructors. While it is easy for an administrator to ask someone to create such a program, it is imperative that those who work in these programs get support in finding good faculty, accessing the technology needed, and recognition for the extra time involved in creating and maintaining these courses.

INTERNATIONAL JOURNAL OF COMPUTER AUDITING

Article

Teaching Case – Predicting the Probability of Company Bankruptcy with CAATs

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Received 30 January 2020; Received in revised form 20 July 2020; Accepted 22 July 2020

The paper provides a machine-learning experimental process for a real-world corporate financial bankruptcy case: Chunghwa Picture Tubes, Ltd., in Taiwan in 2019. The teaching case addresses major topics in financial bankruptcy analytics to enable business students to learn how to analyze leveraged finance and distressed debt and to predict bankruptcy. It is a science, technology, engineering, and mathematics (STEM) teaching case with a project-based learning method. The learning goal of the teaching case is to inspire and encourage students through planned teaching activities. Students start by thinking through problems or situations and establishing a machine-learning project using computer-assisted audit technique (CAAT) software. After students conduct a self-directed project, the student can use the new knowledge to develop a new bankruptcy-case analysis.

KEYWORDS
Machine learning, computer auditing, computer-assisted audit techniques (CAATs), bankruptcy

Reference Format: Huang, S.M. and Huang, Y.T. and Wang, L.K., 2020, Teaching Case – Predicting the Probability of Company Bankruptcy with CAATs , Vol.1, No.2, pp.5-22 .

1 | INTRODUCTION

1.1 | Teaching-Case Motivation

In September 2019, Chunghwa Picture Tubes Ltd., Taiwan (CPT) filed for bankruptcy and announced that the company would lay off approximately 2,500 employees because the company could not repay its debt (Everington, 2019). In the past, accounting education has focused on corporate bankruptcy and bankruptcy accounting issues in corporate bankruptcy processing. The level of corporate bankruptcy issues involves the loss of open-market investors, obstacles to the audit and verification business, and overall corporate image, and so on. Bankruptcy accounting issues include preparing the balance sheet on the dissolution date, accounting for liquidation costs and the profit and loss of the sale of property equipment, recovering book claims, settling debts, arranging the remaining property allocation, and so on.

However, the issues involved in the bankruptcy practice case are not limited to teaching calculation questions in advanced accounting reference books. When students learn knowledge regarding bankruptcy prediction, it not only assists an enterprise in adjusting business methods or investment goals in real time but also helps certified public accountants (CPAs) reduce the risk of auditing before issuing company confidence financial statements.

With the development of big data technology, accounting education should also advance to help students improve their ability to process and explore big data. Therefore, this teaching case attempts to use CPT's declaration of bankruptcy as a starting point, triggering students to analyze the Taiwan panel industry's operation in depth through the machine-learning model using computer-assisted audit techniques (CAATs) to predict the probability of bankruptcy. A prerequisite of the class is that students are expected to know financial accounting and business management.

1.2 | Teaching-Case Objectives

This section aims to arouse the interest of students in the topic of corporate bankruptcy prediction. Through the machine-learning model using CAATs, this section promotes the understanding of the application process of predicting corporate bankruptcy probability and checking the financial situation of an enterprise. This section provides students with three learning goals for participation in this case course:

Goal 1. Promote critical thinking regarding enterprise bankruptcy problems and situations.

Goal 2. Promote comprehension of interdisciplinary importance by integrating science, technology, engineering, and mathematics (STEM) to solve the bankruptcy analytic case problems.

Goal 3. Enable students to establish a machine-learning project using CAAT software for other bankruptcy analysis cases.

2 | NEED FOR BANKRUPTCY PREDICTION COMPETENCY FOR CERTIFIED PUBLIC ACCOUNTANTS OR AUDITORS

Before facing bankruptcy and failure, enterprises usually go through stages of a financial crisis and financial imbalance. If management deliberately hides negative information to maintain the company's business image or stock-price performance, it is usually not easy for stock market investors to immediately discover. The most famous example is Enron, which declared bankruptcy in November 2001. Through many years of careful planning, systematic financial fraud, and numerous internal transactions, management embezzled public funds and established many overseas companies to create small and chaotic subsidiaries. In a related party transaction, the Enron case caused a huge loss in the investment market due to the stock-price plunge at that time, and the follow-up also triggered the government's attention to corporate fraud (Cornford 2004).

Following the Enron accounting fraud and bankruptcy, the alleged complicity of Arthur Andersen LLP, one of the biggest CPA firms in 2001, came under intense scrutiny as an auditor. Because the U.S. Securities and Exchange Commission (SEC) does not accept audits from convicted felons, the firm agreed to surrender its CPA licenses and its right to practice before the SEC on August 31, 2002, effectively putting the firm out of business (Wikipedia, 2020). However, on May 31, 2005, in *Arthur Andersen LLP v. The United States*, the Supreme Court of the United States unanimously reversed Andersen's conviction because of serious errors in the trial judge's jury instructions (Kelly, 2006). The 2005 ruling theoretically left Andersen free to resume operations. Andersen was "nearly defunct" (Mears, 2005). Moreover, CPAs and auditors need to have the skills and knowledge to predict bankruptcy as learned from the Author Andersen case.

A software tool developed according to the needs of background audit personnel, the CAAT tool has been widely used in global audit operations. The earliest CAAT tool was the Audit Command Language (ACL) proposed by Dr. Hart Will in 1973. Using ACL software makes it easy to strengthen accounting students' data analysis skills, simulate financial statement audits, find fraud transactions, use classroom group reports to explore the risk control of emerging information technology, and guide students to identify threats or weaknesses (Hanes, Porco, and Thibodeau 2014; Caplan, Dutta, and Marcinko 2019; Chiu and Wang 2019). Therefore, the teaching case uses ACL as a machine-learning tool to predict the probability of an enterprise bankruptcy case using the supervised learning method.

3 | BACKGROUND OF THE TEACHING CASE

3.1 | Industry Outlook

Thin-film transistor liquid crystal display (TFT-LCD) manufacturing has become one of Asia-Pacific's primary industries, especially for Taiwan, Korea, China, and Japan (Lee, Chang, and Wang 2019). Worldwide, the industry is known for capital-intensive short product lifecycles, rapid technology development and migration, long production lead time, complex production networks, international divisions of labor, fluctuating demand, and price volatility (Chang 2005). The TFT-LCD has applications in various electronic goods, such as cellphones, portable videogame devices, televisions, laptops, desktops, automotive industry products, navigation and medical equipment, laser pointer astronomy, SLR cameras, and digital photo frames (IMARC Group 2019). According to IHS Markit, Figure 1 indicates that the global

TFT-LCD panel market has grown at a compound annual growth rate of 2.68% during 2018–2019, reaching a value of US$ 115 billion in 2019 (Lsi 2019). The Taiwan industry has played a key role in the global TFT-LCD panel market (Tabata 2014). The industry landscape of Taiwan is described in Table 1.

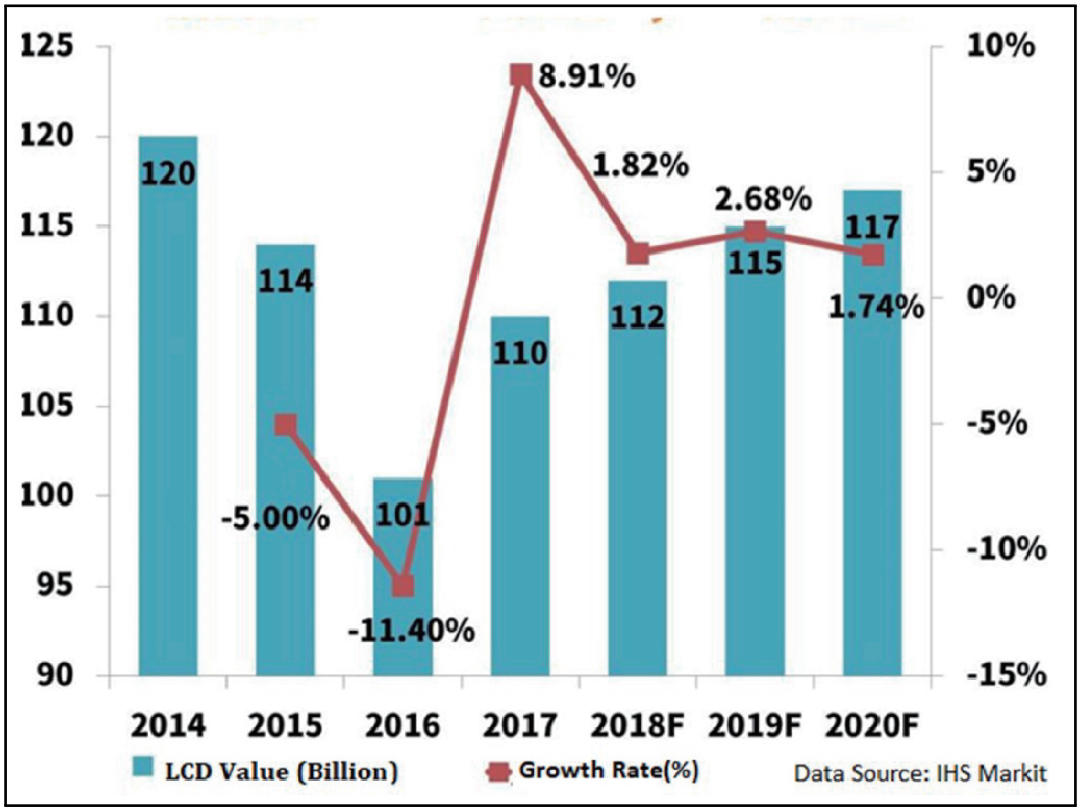


FIGURE 1 Thin-film transistor liquid crystal display; Global Market; Data Source: IHS Markit.

Table 1. Number and output value of Taiwan thin-film transistor liquid crystal display industry

	Year					
Profile	2013	2014	2015	2016	2017	2018
Company Numbers	40	41	41	42	42	42
Output Value (1000 US$)	$1,157,773	$1,146,239	$1,044,208	$876,084	$911,448	$890,698

Data Source: TEJ Database

3.2 | The Case Company

The case company, CPT, with paid-up capital of NT$ 64.7 billion, was one of the major players for the TFT-LCD global industry and was listed as a public company on the Taiwan Stock Exchange. The company headquarters was in Taiwan, and global plants were located in the UK, Malaysia, China, and so on. Its CPA firm was Ernst & Young. The company's simple financial profile between 2013 and 2018 is presented in Table 2.

On September 18, 2019, CPT was unable to pay off its reorganization due to many years of losses and debts, a substantial reduction in capital, a bounce of 1 billion in promissory notes, and several financial reports. Negative market news called for bankruptcy. This news shocked Taiwan's electronics industry, especially the TFT-LCD related industry, and caused panic in the stock market.

3.3 | Teaching Objectives and Activities

Watching CPT's bankruptcy news and videos can allow students to think critically about their ability to analyze financial ratios and make them interested in the process of bankruptcy prediction. The expected teaching-case course time is 12 hours. The key questions to answer in this case are the following:

- How can we predict the bankruptcy?
- What are the analytic parameters that we can use to analyze the bankruptcy?
- Can we create a machine-learning project to learn from the case and predict future bankruptcy cases for the TFT-LCD industry?
- What are good learning parameters that we can use for the bankruptcy machine-learning model?
- How do we know the machine-learning result model is a good knowledge model?
- How can students extend their new knowledge from the self-directed project to predict bankruptcy for other industries?

Table 2: Financial situation analysis for Chunghwa Picture Tubes 2013–2018

		Year				
Financial Analysis		2014	2015	2016	2017	2018
Human resources	Employee number	6228	5662	4779	4680	4341
Production capacity	Output value (Millions NT$)	50,910	46,565	27,000	27,827	28,449
Capital structure	Debts ratio (%)	79.48	87.68	60.30	57.6	113.59
	Long-term funding fit ratio (%)	105.19	73.83	188.09	120.06	(17.31)
Liquidity analysis	Current ratio (%)	75.85	67.44	128.34	88.10	14.40
	Quick ratio (%)	63.78	59.65	123.75	78.23	11.54
	Interest guarantee (times)	(0.37)	(1.28)	1.06	2.61	(8.09)
Operating performance	Average collection turnover (times)	8.81	8.76	10.04	17.80	15.08
	Average inventory turnover (times)	9.02	9.55	7.69	8.62	13.19
	Fixed assets turnover (times)	1.13	1.04	0.83	0.70	0.58
	Total assets turnover (times)	0.58	0.46	0.27	0.25	0.29
Return on investment	Return on total assets (%)	(1.69)	(5.58)	1.42	4.09	(27.52)
	Return on total stockholders' equity (%)	(16.17)	(49.76)	(2.62)	6.31	(96.56)
	Earnings per share	(0.61)	(1.35)	(0.27)	0.46	(3.02)
Cash flow	Cash flow ratio (%)	4.32	(2.85)	2.84	15.41	(24.46)
	Cash flow reinvestment ratio (%)	1.01	(0.90)	0.82	3.70	(6.08)
Leverage	Operating leverage	(3.66)	(0.30)	(4.72)	3.13	0.30
	Financial leverage	0.47	0.71	0.31	(30.08)	0.82

Data Source: The Financial Report of Chunghwa Picture Tubes (CPT) in 2013-2018

4 | BANKRUPTCY PREDICTION FOR THE CASE

4.1 | Financial Ratios for Bankruptcy Analytics

In addition to throwing a shock bomb on the stock market, CPT's bankruptcy also prompted investors to invest in and examine the financial statements issued by companies more closely. Many professional financial statement analysis arguments were on the stock market news, such as the following:

Argument 1: In the three years before CPT's bankruptcy declaration in 2019 (since 2016), its consolidated rev-

enue has declined significantly, and the cash flow of operating activities has been negative 1.2 billion NT$.

Argument 2: The equipment investment of CPT is only 1.1 billion. The TFT-LCD industry has intensive capital and technology expenditure. The equipment investment expenditure lags far behind that of their competitors.

Argument 3: The repayment by CPT of up to 5 billion NT$ in financing loans, compared with the 7.4 billion NT$ profit from borrowing and disposing of assets in investment activities is unclear, and it is equally confusing to dispose of assets for debt repayment.

Several methods can predict bankruptcy. The traditional method is to analyze company financial ratios and compare them with related companies in the same industry. Several financial ratios have been used in the financial analytic report, which are described as follows:

(1) Working capital (*WC*) ratio: This ratio represents the company's liquidity and solvency. If working capital is less, whether the company is in a situation of poor turnover can be determined (Sabbir 2019).

(2) Retained earnings (*RE*) ratio: The retained earnings ratio reflects the company's plans to retain part of the past profits to meet future investment strategies requiring capital expenditures in the future. Higher retained earnings and higher stability also signify that the company is more adaptable (Sabbir 2019).

(3) Turnover rate of total assets (*TOTT*): The turnover rate of total assets is an important indicator for the comprehensive evaluation of the company's operating conditions and asset utilization efficiency of all company assets. The higher the turnover rate, the better the sales ability (Sabbir 2019).

(4) Profit before tax (*PBT*) ratio: This indicator excludes the effect of tax expenses and interest expenses and measures the situation in which companies use the profitability of assets without considering the effect of tax rates and financing (Sabbir 2019).

(5) Market value (*MV*) ratio: The market value ratio is primarily used to measure the financing ability of an enterprise and reflects the stability of the basic financial structure of the enterprise through the value of the enterprise in the stock market and the capital obtained from creditors (Sabbir 2019).

(6) Z-score (Z): The Z-score model was established by a professor at New York University Stern School of Business. The financial ratios used are the working capital ratio, retained earnings ratio, total asset turnover rate, pretax profit ratio, and debt-to-market ratio. A smaller Z-score indicates a greater probability of company failure. According to the research results, companies with a Z-value of less than 1.8 are likely to be at risk of bankruptcy (Altman 1968).

(7) Long-term fund fit (*LF*) ratio: The long-term fund fit ratio reflects the solvency of the enterprise, analyzing the problems of blind investments, long-term assets squeezing liquidity, or excessive debt, which is conducive to strengthening the company's internal management and external supervision (Sabbir 2019).

(8) Loan dependency (*LD*): The lower the ratio of the indicator of loan dependency, the more protected the creditors are, which also means that the company has better financing ability (Sabbir 2019).

4.2 | Machine-Learning Method

The applied machine-learning function is also epoch-making in the field of auditing. There are usually no clear judgment rules in a large amount of enterprise data. There are two main categories of machine learning:

- Supervised learning: During the training process, the answer is given to the machine, that is, the data are "labeled." For example, after showing the machine 1000 photos of apples and oranges, we can ask machine whether the new photo is apple or orange. (Rouse 2020; Lang 2020). Figure 2 illustrates the four main phases in the process flow for supervised learning.
- Unsupervised learning: There is no standard answer given to the training data and no need to input tags manually in advance; thus, the machine does not know whether the classification results are correct when learning. During training, the user must provide input examples to the machine, which automatically determines potential rules from these examples (Rouse 2020; Lang 2020).

Phase 1: Data Preparation

Because the machine determines the laws from the massive amount of data, it must deal with inconsistent data formats, missing or invalid values, and so on to keep the data clean. The other process of this phase is feature extraction, which extracts useful features from the data, such as each member's gender, age, consumption amount, and so on and then quantifies these features (e.g., gender can be set to 0 or 1).

Phase 2: Training

Data scientists choose machine-learning models with appropriate performance. Many machine-learning algorithms exist, such as neural networks, random forests, support vector machines, decision trees, and so on. These algorithms are too difficult to learn for most business school students, especially accounting students. To avoid the difficulty, CAAT tools, such as ACL, integrate the above artificial intelligence (AI) algorithms as a backhand learning model. Students can simply use the frontend TRAIN command interface to submit the training data with several parameters into the backend AI algorithms to implement the machine-learning process, which runs suitable AI algorithms. The system generates a prediction model.

Phase 3: Model Evaluation

Students need to evaluate the prediction model. Several methods exist to evaluate the performance of the prediction model. Students need to learn these methods and make a professional judgment to select a good prediction model.

Phase 4: Prediction

If students accept the prediction model, they can put the model into the prediction dataset using the PREDICT command. The result of the dataset includes two new fields, the prediction value and prediction probability.

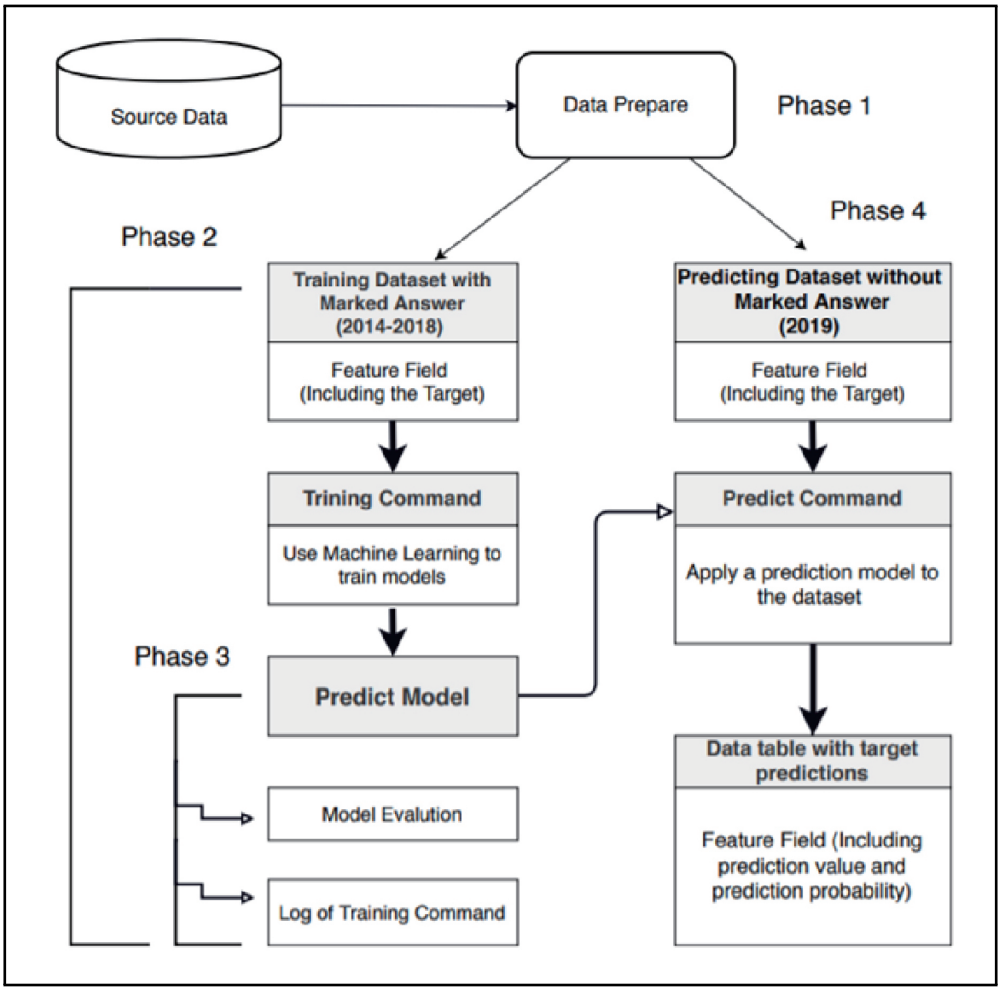


FIGURE 2 *Structure diagram of the machine-learning process.*

4.3 | Phase 1: Data Preparation

The operating conditions of other companies in the Taiwan panel industry in the same year are therefore relevant to this teaching case. Because CPT went bankrupt in 2019, the training data period for this case is 2014–2018, comprising the quarterly financial data of Taiwan public panel industry listed companies (called Panel_Training_Data.xlsx). The prediction data file contains the 2019 quarterly financial data for the Taiwan public panel industry listed companies (called Panel_Predict_Data.xlsx). Table 3 presents the fields of training and prediction data.

Table 3. Data structure of the teaching case.

Field Name	Data Type	Description
Co. No	Text	The ID of the company
Financial Date	Numeric	Date of financial data
Current Assets	Numeric	Current assets include cash or bank deposits, short-term investments, accounts and notes receivable, inventory, prepaid expenses, etc.
Current Liabilities	Numeric	Current liabilities refer to the balance sheet, such as short-term bank loans, commercial promissory notes payable, bills payable, accounts payable, fees payable, the portion of long-term loans due within one year, and payments to creditors.
Retained Earnings	Numeric	Retained income refers to the internal accumulation accumulated in the enterprise formed by the enterprise from the profits realized over the years, including the accumulative surplus reserve and undistributed profit.
Sales Revenues	Numeric	Sales revenue is the income received by a company from its sales of goods or the provision of services.
Long-term funding fit ratio	Numeric	(Shareholders* equity + long-term liabilities)/(fixed assets + long-term investments)
Loan dependency	Numeric	Long-term and short-term loans + contingent liabilities guaranteed by the loan)/shareholders' equity.
NCA Ratio	Numeric	(Current assets-current liabilities)/ total assets
RE Ratio	Numeric	Retained earnings/total assets
Pretax Ratio	Numeric	Income before tax and interest expense/total assets
MV Ratio	Numeric	Market values/total liabilities
Z-score	Numeric	According to the Z-score model proposed by Altman (1968)
Banky	Text	Labeled "YES" or "NO"

Students must import the Panel_Training_Data.xlsx file with training data into ACL for further machine-learning processing using the command "Import" on the ACL software menu. Students can select the import command by following the wizard to import the data with the table name "Panel_Training_Data." Figure 3 depicts the import process flow.

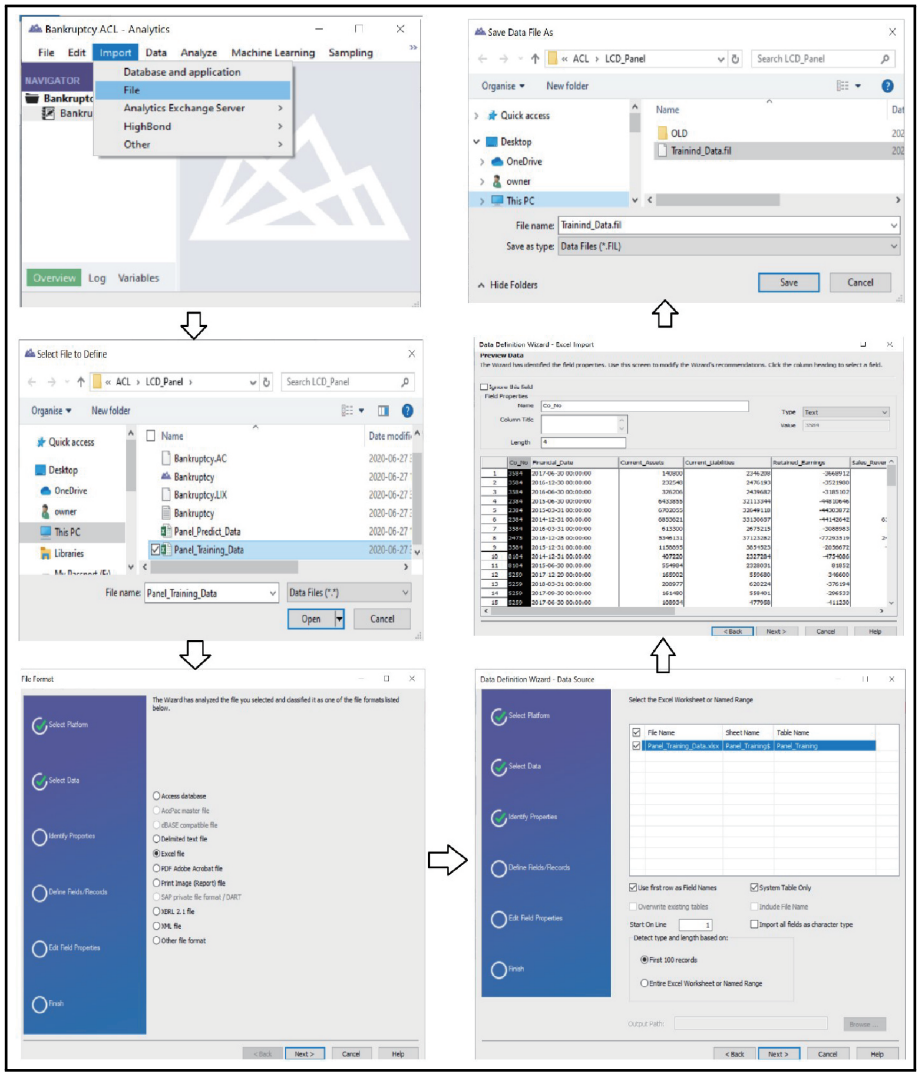


FIGURE 3 Import process flow.

4.4 | Phase 2: Training

The ACL software has added the "Machine Learning" command. It is divided into datasets using tagging classification features: the "Training" machine recognition rules and "prediction." The two parts of the results of the new dataset and the detailed operation process are as follows:

(1) Machine-learning time: The function provides users with the time to set the machine-learning analysis data

to determine the best model and maximum analysis time for each data point to determine the analysis measurement mode, marker classification features, and training factors.

(2) Select prediction variables: Many factors can cause corporate bankruptcy, such as wrong investment decisions, an unstable investment environment, too-low cash flow, or deliberate fraud by management. Many possible factors have been summarized through research in the industry and academia. The Z-score model proposed by Altman (1968) is based on credit-risk characteristics of companies and individuals. The model then weights each score and calculates the total score to determine the probability of default. Students can select the prediction target as Banky, and the selected forecast variables are the Z-score and RE ratio for their first practice.

(3) Training model selection: the training model is divided into two categories; classification and regression. The result of the prediction required in this teaching case is "Bankrupt," which is divided into two types of results: "Yes," which indicates a high probability of bankruptcy, and "No," which indicates a less likely bankruptcy, so in this case, the classification type is suitable . In this teaching case, the prediction model formed by machine-learning training is named the "Banky_Model," and the result of the model evaluation data file is stored as "Banky_Evaluation." The ACL forms prediction models and model evaluation results as shown in Figure 4.

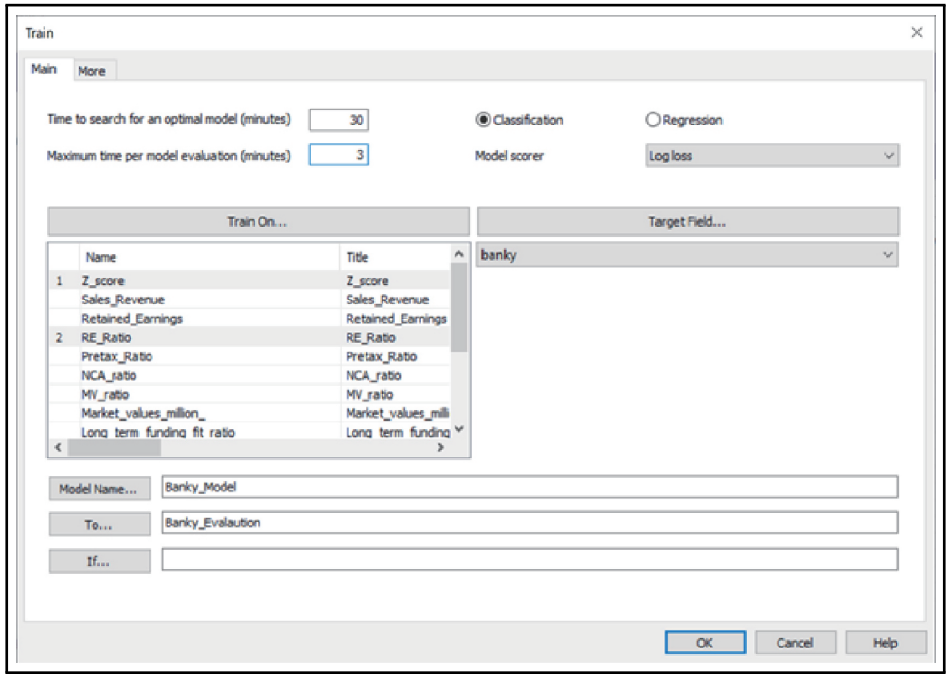


FIGURE 4 Set the machine-learning training method and time.

After the training, ACL selects the best machine-learning algorithm from the selected scorer to build the prediction model. In this case, ACL selects "ExtraTreesClassifier" as the machine-learning algorithm (Figure 5). For the details of the algorithm, students can read relative machine-learning textbooks (Geurts, Ernst, and Wehenkel 2006). For data analytics, it is more important to evaluate the model than to go into detail regarding the algorithm.

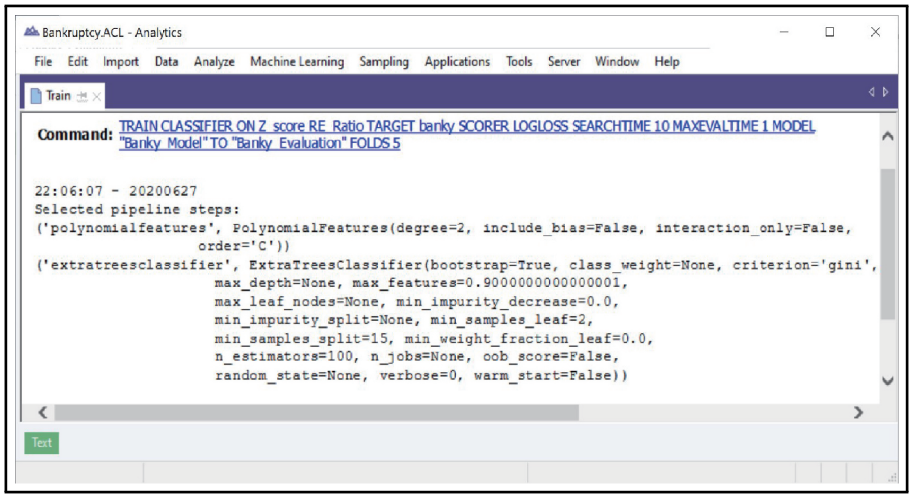


FIGURE 5 Machine-learning training result.

4.5 | Phase 3: Model Evaluation

To learn how to evaluate the classification models, students need to know the confusion matrix (Figure 6). The true positive (TP), true negative (TN), false positive (FP), and false negative (FN) are extracted from the confusion matrix after the classification operation (Narkhede, 2018).

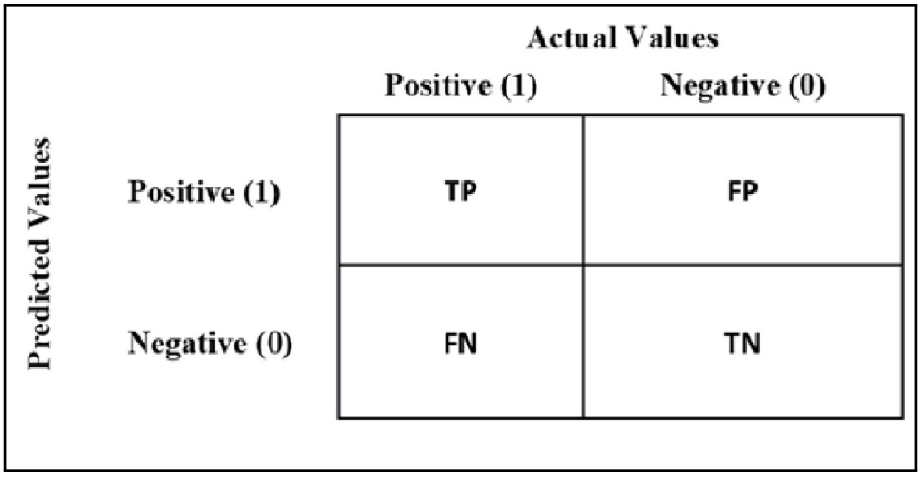


FIGURE 6 Confusion Matrix; Data Sources: Narkhede (2018).

When the "training" machine-learning analysis data rules are completed, ACL provides the model correlation coefficients found according to the learning process and the weight standard of the relevant indicators and evaluates the reliability of the model formed after machine learning. Figure 6 presents the machine-learning training prediction

model evaluation results and the definition of the metrics.

To determine the detection efficiency of the proposed algorithms, metrics, such as accuracy, precision, recall, and F1, can be used. The definitions of these metrics are listed in Figure 7. Because the scorer is defined in Figure 3 as LOGLOSS, a lower value is better for the model evaluation.

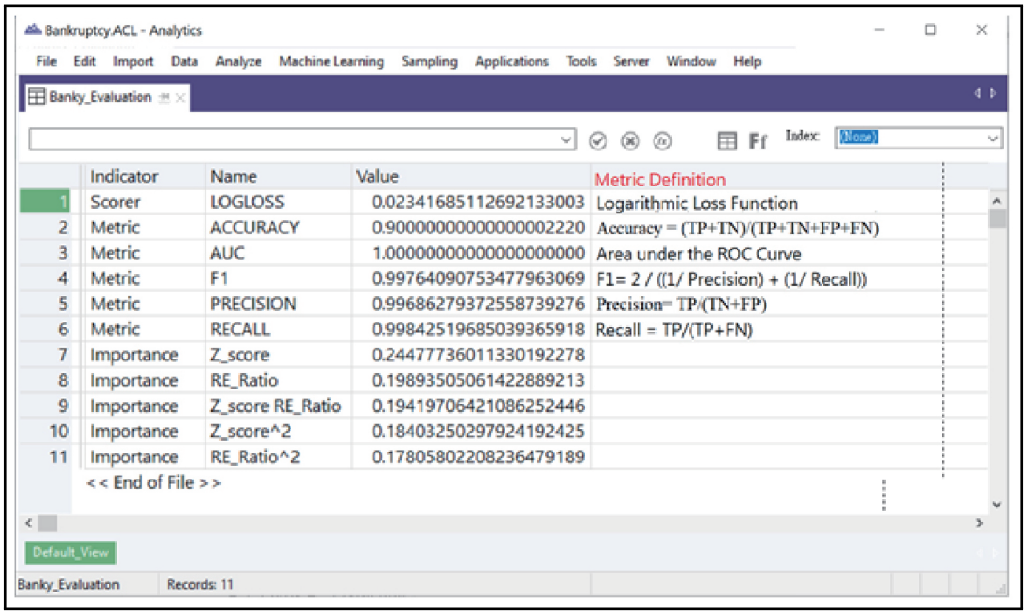


FIGURE 7 Evaluation results.

4.6 | Phase 4: Prediction

When the training model has been established, the teacher can perform a "prediction" function on the new dataset (no classification features) according to the learning process model to determine whether the judgment results of the new data are accurate. First, the prediction data file (i.e., Panel_Predict_Data.xlsx) is imported. Then, the machine learning in the function menu and the Predict command are clicked. Figure 8 illustrates the Predict command interface. Students input the model name "Banky_Model.model," which is trained in the training process phase. After the prediction instruction is executed, the system automatically saves the prediction results to the "Banky_Predict_2019" table (Figure 8). There is a predicted "YES" for company number (Co_No) 2475, that is, CPT. Thus, the machine-learning case successfully predicts the CPT bankruptcy before the company declared bankruptcy.

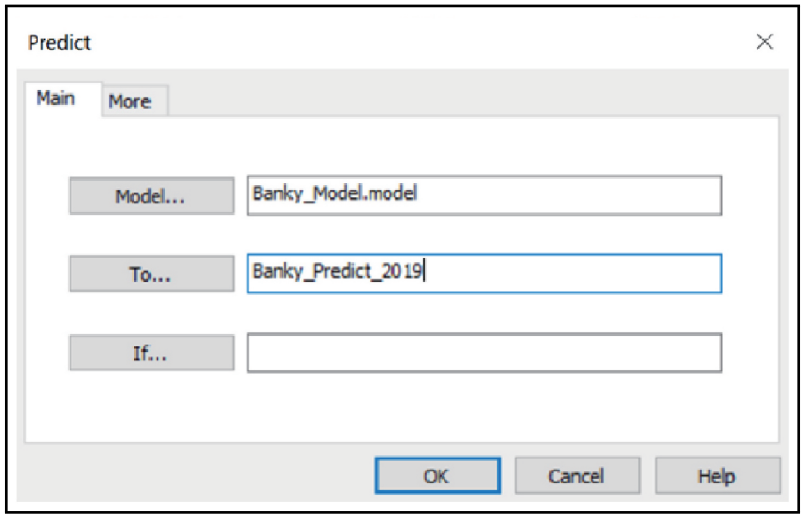


FIGURE 8 Predict command interface.

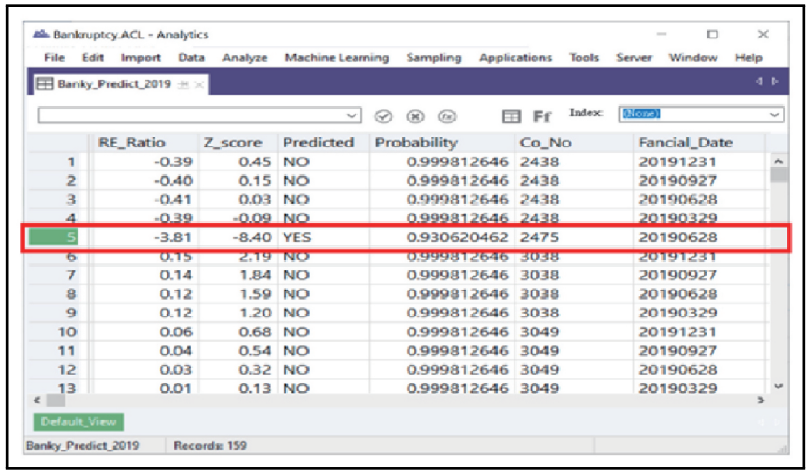


FIGURE 9 Predicted result interface.

5 | CONCLUSION AND SELF-LEARNING ASSIGNMENT

Students can learn from the above process by performing a self-directed project for bankruptcy prediction. Some assignments that can be used in class are as follows:

Practice 1: Using different fields and scorers to train the Panel_Training_Data and predict the Panel_Predict_Data.

Practice 2: Discussing why most training models predict the "NO" result.

Practice 3: Reviewing how to deal with imbalanced labeled data for the bankruptcy prediction project.

This teaching case aims to increase student interest in the prediction of corporate bankruptcy. This teaching case uses the catering industry as an example to design the self-learning experiment to assess student learning effectiveness standards and design examples of a related implementation in the catering industry.

The design of teaching cases must include teaching objectives, activity content, implementation methods and procedures, and requirements. Successfully implementing teaching cases relies not only on the teachers' professional experience but also on detailed advanced planning and stimulating student interest in learning. The design of this teaching case, by combining the real case of corporate bankruptcy with machine learning, aims to provide students with forward-looking and innovative teaching, which can trigger their willingness to understand and continue to discuss in-depth issues related to business management.

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INTERNATIONAL JOURNAL OF COMPUTER AUDITING

Article

Application of Machine Learning in Auditing Teaching: A Case Study of Predicting the Audit Report Type of China ST Listed Companies

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Received 2 February 2020; Received in revised form 25 July 2020; Accepted 27 July 2020

Artificial intelligence is an important emerging technology in the accounting industry. Fear and hype associated with artificial intelligence and its impact on accounting and auditing jobs have pervaded the professional fields of accounting and auditing. It is important to develop AI competency in accountants and auditors. This paper presents a teaching case for a professor or lecturer to use for teaching machine learning to accounting students. The case is based on openly available data from the China Stock Market & Accounting Research database and aims to teach students how to predict the future audit report type of a China ST listed company. Through case teaching, students can learn skills related to computer-assisted auditing tools and machine learning (such as ACL) develop the confidence to apply artificial intelligence in their education and future work.

KEYWORDS
accounting, computer auditing, machine learning, CAATs, education, teaching case

Reference Format: Huang, S.M. and Chen, C.P. and Wong, T.C., 2020, Application of Machine Learning in Auditing Teaching: A Case Study of Predicting the Audit Report Type of China ST Listed Companies, Vol.2, No.1, pp.23- 40.

1 | INTRODUCTION

The emergence and development of higher education in a country is the product of its specific economic and social history and culture, and its development direction must be closely connected with the needs of the country and society. As the representatives of the global education community jointly discussed at the International Conference on Artificial Intelligence and Education held in Beijing in May 2019, the era of artificial intelligence has arrived, and the direction of education reform and development must grasp the pulse of the times and cultivate the knowledge and skills of artificial intelligence (China Education and Research Network, 2019).

Producing high-end talent is an important mission of current education. In the education on the subject of auditing provided by modern colleges and universities, it is necessary to incorporate an awareness of the trend of social development in order to train and prepare students in the talents relating to new audit skills and knowledge for the society and its development. Machine learning has penetrated various areas of society, and modern auditing has also experienced unprecedented changes from its influence. Machine learning can substantially improve audit efficiency, reduce audit errors, reduce audit risks, and save audit costs. The use of machine learning in auditing has emerged as a trend in audit development. College and professional education on auditing must actively explore the applications of machine learning in auditing and its education and cultivate socially aware, talented individuals who possess knowledge and skills in the latest auditing techniques.

2 | IMPLICATIONS OF MACHINE LEARNING FOR AUDITORS

Nowadays, machine learning is receiving increasing attention from accounting firms owing to its potential impact on auditing. Several major accounting firms are actively investing in machine learning research and application development (Dickey et al., 2019). Dalal (1999) reported that the results of using artificial intelligence (AI) technology in auditing showed that AI technology could not only save audit costs but also markedly improve audit efficiency. However, the machine learning algorithms and program design presented in the paper were too complicated to learn for an accounting student.

Machine learning has high potential to provide augmented analyses to auditors, but it is not likely to replace auditors. For most computer auditing professionals, machine learning is just another tool in the auditor's toolkit of computer-assisted auditing tools (CAATs). This is a capability that already exists in CAATs such as IDEA and ACL (Dai, Vasarhelyi 2016). ACL is the world's first general-purpose computer audit software. It was invented by Dr. Hart Will in 1987. It uses the logic and interface required by auditors to execute complex auditing operations with a few simple instructions (Coderre, 2009). This was a disruptive and innovative invention that changed the methods of global auditing. ACL has both machine learning and prediction commands (Galvanize, 2019a). Through the software, auditors can simply perform machine learning processes by following a stepwise procedure without knowing the underlying complicated algorithms. This enables auditors to focus on their audit object and evaluate the effectiveness of the machine learning model.

3 | THE TEACHING CASE

3.1 | Motivation of the Teaching Case Design

Audit reports for an enterprise's accounting statements can take the form of a non-going concern (clean) report or going concern (financial distress) report. The types of audit reports issued by certified public accountants (CPA) have a significant impact on a listed company and its stakeholders. If a CPA issues a going concern audit report, it will not only affect investors' judgment of the company but also result in a financing and government regulation impact to the company and the CPAs. The issuance of a wrong type of report can have consequences for the accountant and the auditor. A prediction model is important for a CPA to assess the risk and audit quality. Prior studies have developed many mathematical and machine learning models to predict the type of audit report that should be issued to clients (Anandarajan & Anandarajan, 1999; Hooda et al., 2020; Jia, 2012). These complicated models require expert data scientists to run them, and the result can be difficult to understand for a CPA.

China is one of the fastest growing economies in the world. Along with the economic boom, it has also witnessed a tremendous growth in financial fraud cases (Abikoff & Perkins, 2019). The case in this study is intended to teach accounting students to download an openly available dataset, namely the China Stock Market & Accounting Research (CSMAR) database, to analyze the types of audit reports associated with the annual reports of listed companies in China. The case uses the CAATs tool ACL and machine learning commands to simplify the full machine learning prediction process.

Machine learning will play a big part in improving the quality of audit field work in the future. The learning objectives of the case are to enable accounting students to use AI technology and related theoretical frameworks to perform machine learning on historical data and big data collected from economic databases, to examine the regularity of data, and to generate judgment models to predict specific economic activities. The case presents a learning platform to develop students' critical-thinking and problem-solving skills. It can help students to experience the power of using machine learning to derive insights into listed companies' financial data. The learning evaluation aims to ensure that students have gained an understanding of machine learning skills and knowledge by performing the machine learning process by themselves.

3.2 | CSMAR Database Overview

CSMAR is a comprehensive research-oriented database focusing on China's financial sector and economy. It was developed by Shenzhen CSMAR Data Technology Co., Ltd. The CSMAR database contains 18 time and data series, including factor research, character characteristics, green economy, stocks, companies overseas, information, funds, bonds, industries, economy, and commodity futures, among others. It includes more than 150 databases and more than 4,000 tables, which together total to more than 40,000 data fields. It meets international professional standards and is adapted to China's features. The data of the listed companies used in the case was collected from the Guo Tai'an Economic and Financial Database in CSMAR, and the other data were collected from the annual reports of 2014–2018 ST listed companies (Shanghai Stock Exchange and Shenzhen Stock Exchange) of China (http://www.gtarsc.com/#/index).

According to the current Chinese Auditing Standards, the audit opinions issued by the certified public accountant in

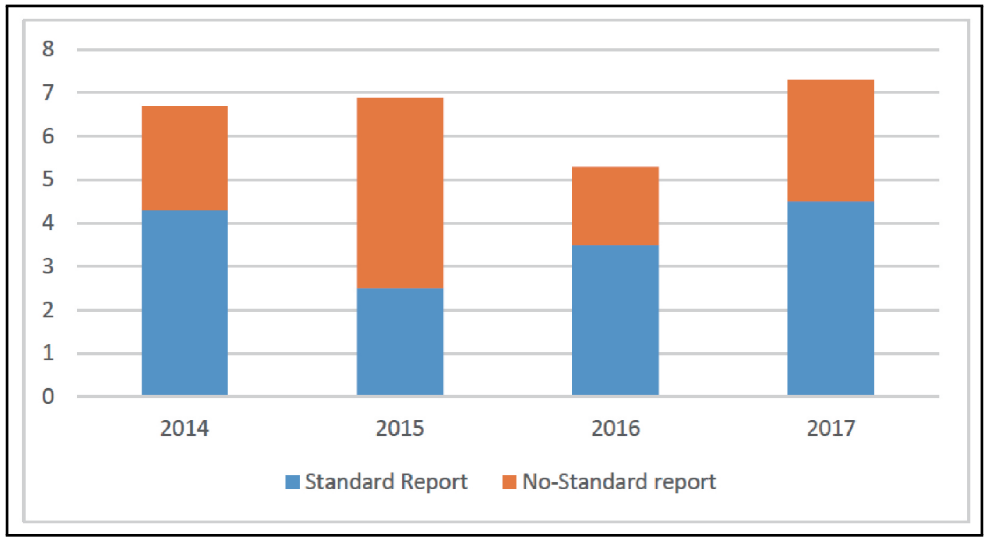


FIGURE 1 Number of listed ST companies in China between 2014 and 2018.

the audit report are divided into five categories after the audit procedure: the first category is the standard unqualified opinion; the second category is the unqualified opinion with emphasized matters; the third category is reserved opinions; the fourth category is negative opinions; and the fifth category is unable to express opinions. Audit reports that issue the first type of audit opinion are classified as standard audit reports, and audit reports that issue the other four types of audit opinions are classified as non-standard audit reports (see Table 1).

Table 1. Audit report types in China and the United States (USA).

China Audit Report Category	USA Audit Report Type	CSMAR Audit Report Type
Standard Unqualified Opinion	Unqualified Opinion	Standard Audit Report
Unqualified Opinion with Emphasized Matters	Qualified Opinion	Non-Standard Audit Report
Reserved Opinions		
Negative Opinions	Adverse Opinion	
Unable to Express Opinions	Disclaimer of Opinion	

3.3 | The Experiment Process

Figure 2 shows an overview of the experiment process for this case study. The experiment includes three major machine learning processes, namely data preparation, model training, and prediction. Students need to follow these steps to finish the case experiment.

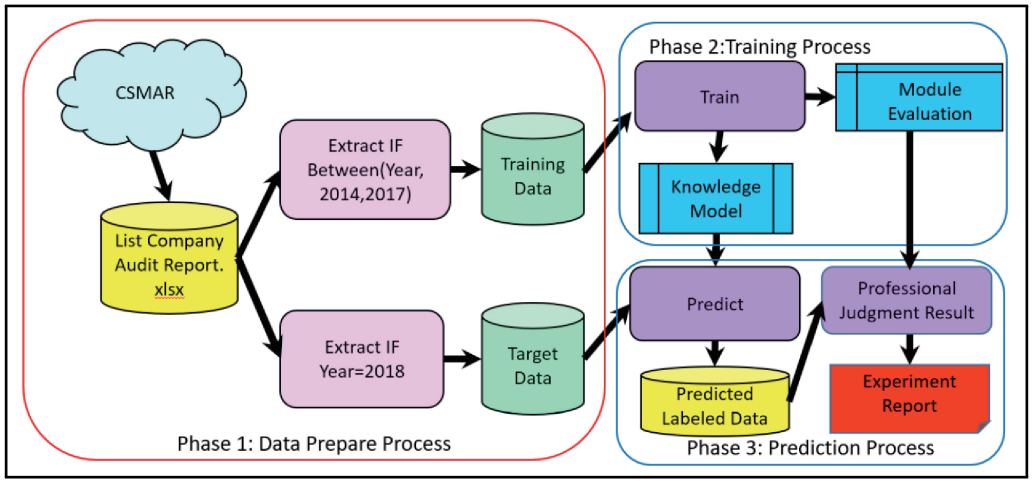


FIGURE 2 Case experiment process diagram

4 | PHASE 1: DATA PREPARATION PROCESS

4.1 | Understanding the Data Structure

The data of the listed companies used in the case was collected from the Guo Tai'an Economic and Financial Database in CSMAR, and the other data was collected from the annual reports of 2014–2018 ST listed companies in China (Shanghai Stock Exchange and Shenzhen Stock Exchange). Excluding invalid sample data, a total of 561 instances of data from 192 ST listed companies were selected as valid data for the subsequent machine learning process.

This case mainly predicted the type of annual audit report of ST listed companies. Therefore, the type of audit report was the target field. The type of audit report issued by a certified public accountant is affected by a variety of factors. This case selected the "Type of Previous Audit Opinion," "CPA Change," "Accounting Firm Change," "Change Rate of Total Assets," "Change Rate of Operating Revenue," "Change Rate of Non-operating Revenue," "Change Rate of Total Profit," "Non-operating Profit Ratio," "Current Ratio Change," and "Asset-liability Ratio Change" as the main variables. They are important factors that affect the type of audit report, and these factors were the characteristic columns of this case (see Table 2).

Table 2. Variables of the target and feature fields.

Field	Serial Number	Variable	Full Name of Variable	Type	Description
Target Field	1	ART	Audit Report Type	Text	0 Standard Audit Report
					1 Non-standard Audit Report
Feature Field	1	TPAO	Type of Previous Audit Opinion	Text	1 Standard Unqualified Opinion
					2 Unqualified Opinion with Emphasis
					3 Reservations
					4 Negative Opinion
					5 Cannot Express Opinion
	2	CPAC	CPA Change	Text	0 None Changed
					1 One CPA Changed
					2 Changes for All CPAs
	3	AFC	Accounting Firm Change	Text	0 Unchanged
					1 Changed
	4	CRTA	Change Rate of Total Assets	Numeric	Change Rate of Total Assets = (Total Assets at The End of The Period - Total Assets at The Beginning of The Period)/Total Assets at The Beginning of The Period
	5	CROR	Change Rate of Operating Revenue	Numeric	Change Rate of Operating Revenue = (Operating Revenue for The Current Period - Operating Revenue for The Previous Period) / Operating Revenue for The Previous Period
	6	CRNOR	Change Rate of Non-operating Revenue	Numeric	Change Rate of Non-operating Revenue = (Non-operating Revenue in The Current Period - Non-operating Revenue in The Previous Period) / Non-operating Revenue in The Previous Period
	7	CRTP	Change Rate of Total Profit	Numeric	Change Rate of Total Profit = (Total Profit for The Current Period - Total Profit for The Previous Period) / Total Profit for The Previous Period
	8	NOPR	Non-operating Profit Ratio	Numeric	Non-operating Profit Ratio = Net Non-operating Revenue and Expenses / Total Profit
	9	CRC	Current Ratio Change	Numeric	Current Ratio Change = (Current Ratio of Current Period - Current Ratio of Previous Period) / Current Ratio of Previous Period
	10	ALRC	Asset-liability Ratio Change	Numeric	Asset-liability Ratio Change = (Asset-liability Ratio for The Current Period - Asset-liability Ratio for The Previous Period) / Asset-liability Ratio for The Previous Period

4.2 | Downloading the Open Data and Importing it to ACL

The experiment uses a project-based approach. A student needs to create a new folder, namely Audit_Machine_Learning, to save the source data and other related files. To download the experiment data, the student has to register with CSMAR at http://us.gtadata.com/. After signing into CSMAR, the student has to go to "Data Query" to download the "Au-

dit Opinion" data for the period January 01, 2014 to 31 December 2018 and save the file as ST_Listed_Company.xlsx (see Figure 3).

After downloading the source data, the student has to create a project in the ACL software, called Audit_Report_Opinion, and import ST_Listed_Company.xlsx into the project according to the steps shown in Figure 4. The operation steps are as follows. After logging into the ACL main interface, create "Audit_Report_Opinion.acl" in the "Create Analysis" field; click to enter the page; select the "Table" column in the "+" drop-down menu of "NAVIGATOR"; select the "Local" item in turn. Next, after selecting the "File" item on the page, select the Excel library document (or other type of library document) to be converted; then, click the document to enter the variable setting adjustment page of the database. In this page, the student has to set or adjust the field type of each variable as in Table 2.



FIGURE 3 The CSMAR audit opinion data download process.

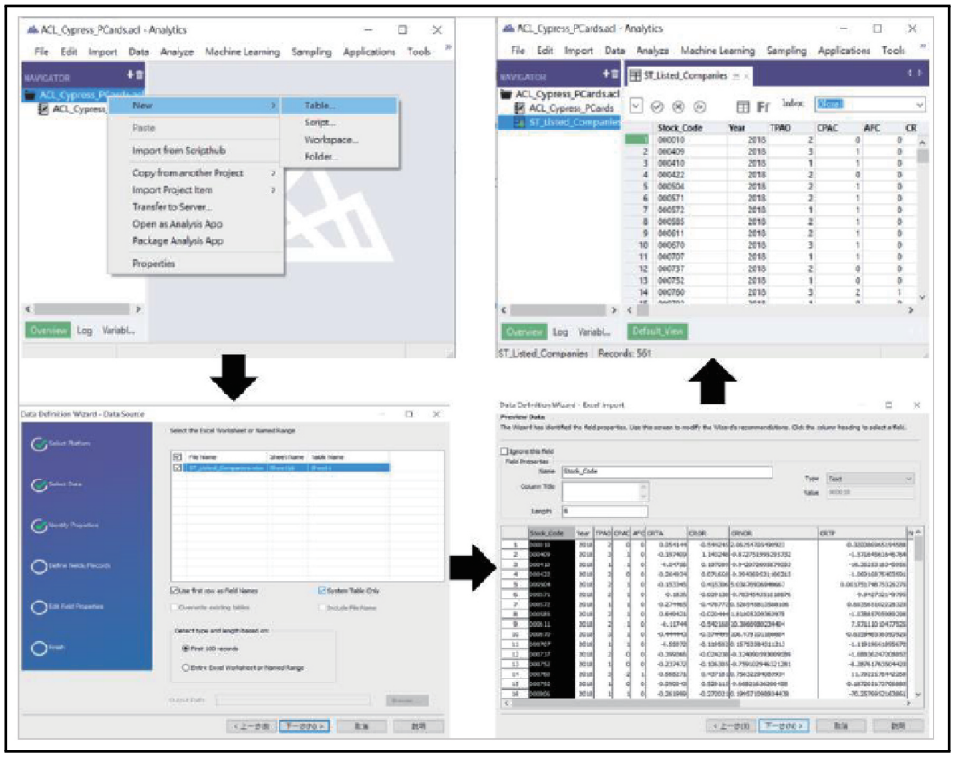


FIGURE 4 The process of importing data into an ACL project.

4.3 | Preparing Training Data and Target Data

In this step, the student separates the data into two groups, namely training data and target data. ACL has an "Extract" command that makes it easy to extract the data according to a user-specified condition. To prepare the training data, the student applies the Extract command by setting IF between(Year, 2014,2017) (see Figure 5). The ST_Listed_Company_Training table then appears in the project. The Student has to apply the same command with IF Year=2018 to generate the target data as table name ST_Listed_Company_Target.

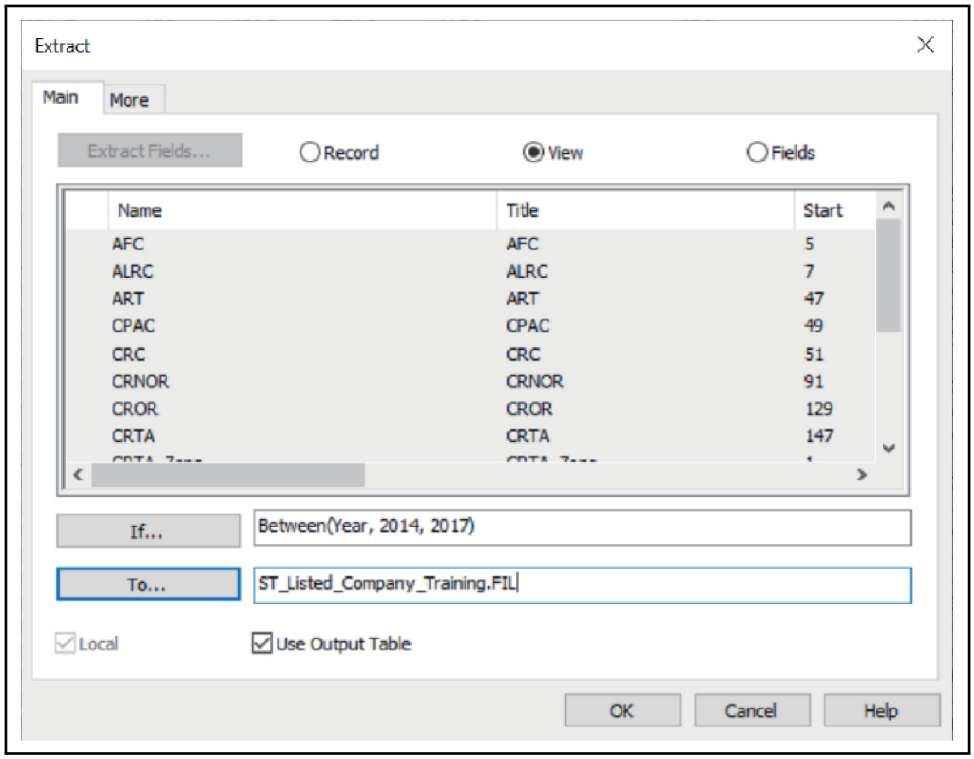


FIGURE 5 The process of separating the training data.

5 | HASE 2: TRAINING PROCESS

5.1 | Training Model Selection

After preparing the training data table and the target data table, the student has to select "Machine Learning" from the menu bar and then select the "Train" command to enter the parameter settings.

(1) Processing Time Setting
In general, ACL advises 45 minutes per 100 MB of data as the specified time for the "Maximum time per model evaluation (minutes)." The student specifies a search time that is at least 10x the maximum evaluation time per model (Galvanize, 2019b). Our training table was 115 KB in size.

Per model evaluation time = 115 KB/(100 x 1000) KB x 45 minutes = 1 minute
Time to search for an optimal model = Per model evaluation time x 10 = 10 minutes

(2) Training Model Setting

There are two types of training models: classification and regression.

- Classification models use classification machine learning algorithms, such as logistic regression, linear support vector machine, random forest, extremely randomized trees, and gradient boosting machine, to train a model.
- Regression models use regression machine learning algorithms, such as elastic net, lasso, ridge, linear support vector machine, random forest, extremely randomized trees, and gradient boosting machine, to train a model.

The learning objective of the case is to predict the audit opinion type. The prediction result that is required in this teaching case is the type of annual audit report of ST listed companies, represented as "0" for standard audit report and "1" for non-standard audit report. The model we used was a classification machine learning model, and the target field was ART ("Audit Report Type").

(3) Model Scorer Setting

The model scorer is a metric for scoring the models generated during the training process. The generated model with the best value for this metric is kept, and the rest of the models are discarded. ACL will show the metric scores for the discarded models for reference after training. To evaluate the prediction performance of the machine learning model, Model Scorer can be used as a guideline. There are several different Model Scorers that are used in different evaluation models. The choice depends on the audit object and the data features. Table 3 shows the evaluation metrics that can be used in ACL. Students are encouraged to review more literature references for further understanding.

Table 3. Machine learning evaluation metrics (Galvanize, 2019b).

Training Model	Model Scorer	Description
Classification	Log loss	Log loss and log likelihood loss, also known as logistic loss or cross-entropy loss, were designed with the idea of maximum likelihood estimation. Minimizing the log loss is desirable.
	Area under the Curve (AUC)	AUC refers to the probability with which the classifier outputs a positive sample is greater than the probability with which it outputs a positive negative sample. Maximizing the AUC is desirable.
	Accuracy	Accuracy refers to the ratio of the number of correctly predicted samples to the total number of predicted samples. Maximizing the accuracy is desirable.
	F1	F1 is an index used to measure the accuracy of two classification models. Maximizing the F1 is desirable.
	Precision	Precision is the ratio of the number of positive samples correctly predicted to the number of positive samples predicted. Maximizing the precision is desirable.
	Recall	Recall refers to the ratio of the number of correctly predicted positive samples to the total number of true positive samples. Maximizing the recall is desirable.
Regression	Mean squared error	Mean squared error is a measure of the degree of difference between the estimated and the estimated. Minimizing the mean squared error is desirable.
	Mean absolute error	Mean absolute deviation is the average of the absolute value of the deviation between all individual observations and the arithmetic mean. Minimizing the mean squared error is desirable.
	R^2	R^2 is the coefficient of determination; it measures the degree of fit of a regression line to the sample data. Maximizing the R2 is desirable.

(4) Training on Key Fields Selection

A key field is a measurable property of the object that is being analyzed by machine learning. The quality of the key fields that are selected has a major impact on the quality of the model that is produced after the training process. The ideal key field selection will contain all the essential features that might have a bearing on the specific learning object, which will lead to the best possible model outcomes.

In this case, students can use their knowledge to select the key fields or just select all fields as key fields to practice the machine learning process. We suggest students start form a simple choice that selects all text features without the company name, namely AFC, CPAC, and TPAO, as the three fields for their first experiment. Figure 6 shows the experiment process interface.

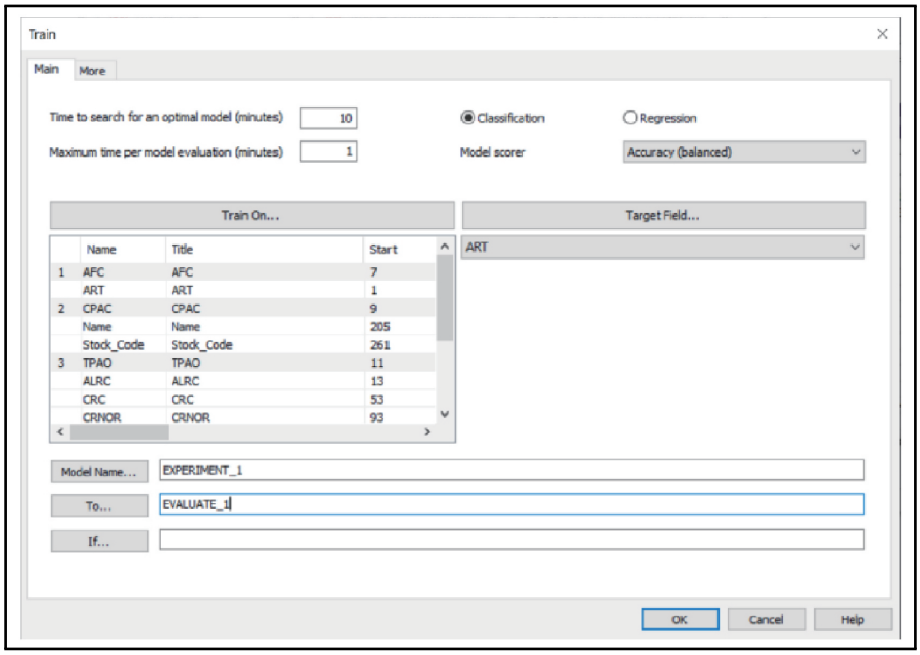


FIGURE 6 Experiment 1 Interface.

5.2 | Results and Analysis

After the training process, the student needs to analyze the training result and discuss the performance of the obtained model. The student first needs to discuss which machine learning algorithm was selected to obtain the best value for the log loss metric. Figure 7 displays the result one linear support vector machine algorithm (denoted as "linearsvc") that was selected as a model for this experiment. It was the best algorithm for the accuracy metric.

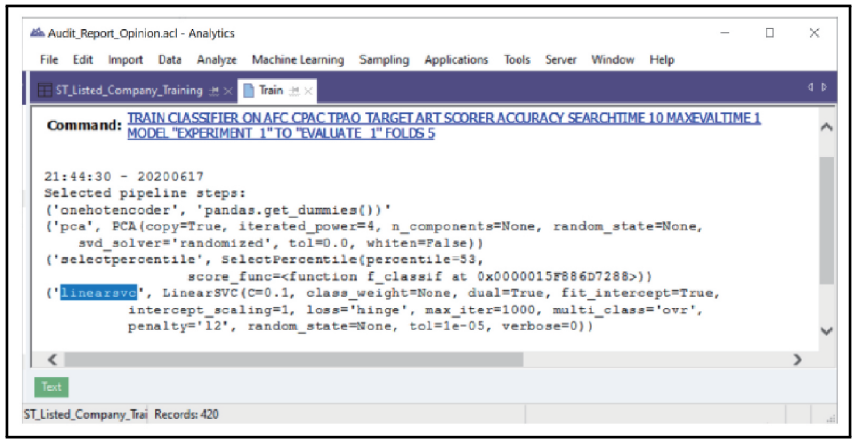


FIGURE 7 Training result interface.

Another result was the evaluation result of the model generated by machine learning (see Figure 8). The accuracy for this model was 0.74. The system also shows other metrics such as the F1, precision, and recall values. Students can discuss these metrics and make a judgment for each metric.

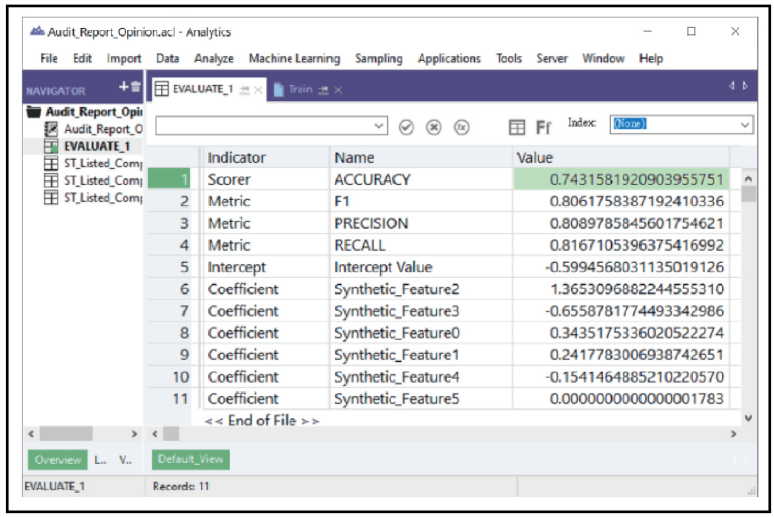


FIGURE 8 Evaluation result of the model.

Precision is the proportion of positive identifications that were actually correct. For example, if 80 predictions were correct out of 100 predictions, the precision score would be 0.8. Recall is the probability of a certain result being predicted. If a certain result actually occurs 100 times but only 80 of them were predicted, the recall is is 0.8. F1 is a comprehensive evaluation index that combines recall and precision and takes into account the accuracy of the prediction and the probability with which the actual result was predicted. Finally, accuracy is the ratio of all accurately predicted samples to all predictions. In this case, the accuracy was only 0.74315, which was the lowest among all metrics.

6 | PHASE 3: PREDICTION PROCESS

After ACL constructs a machine learning model, the student can perform a prediction test on the target database. The steps are as follows. First, open the table "ST Listed Companies_Target .fil"; click "Machine Learning" in the menu bar; and select the "Predict" instruction. Then, select the generated prediction model "Experiment_1" on the model selection interface, and name the result of the prediction test "Prediction_1". Finally, run the prediction operation (See Figure 9).

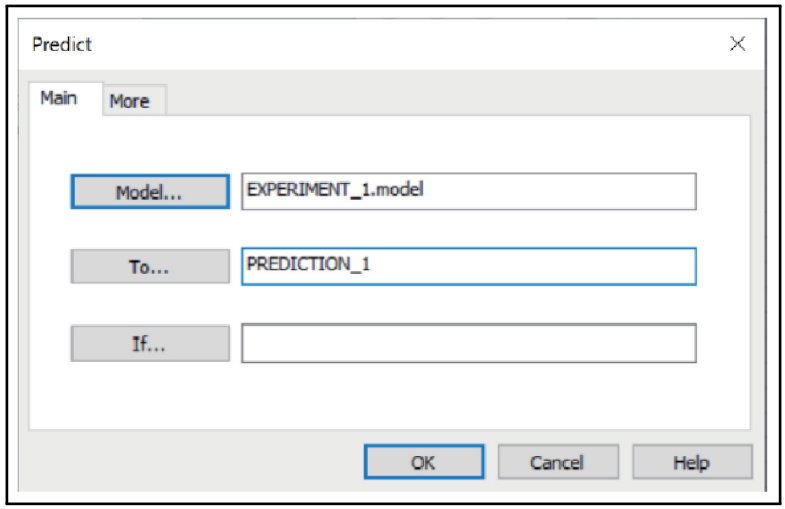


FIGURE 9 Running the prediction operation.

After the execution of the prediction instruction, students can open the "PREDICTION_1" file and compare the prediction results with the actual results to analyze the accuracy of the prediction result (Figure 10).

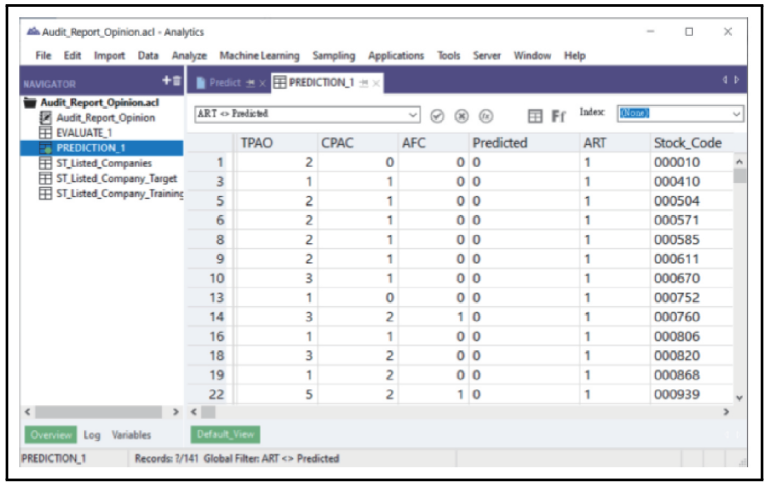


FIGURE 10 Prediction_1 interface.

According to the prediction result, there were 95 of 141 records incorrectly predicted by the training model. Students should conduct another training to obtain a better model.

7 | FURTHER STUDY AND SELF-LEARNING EXPERIMENT

7.1 | Assignment and Evaluation

Students can learn from the above process to execute a self-directed project focused on predicting audit report types. The following example assignments can be considered.

Practice 1: Select all numeric fields as training features to perform the classification learning with a different metric scorer.

Practice 2: Select a part of text and the numeric fields as training features to perform the classification learning with a different metric scorer.

Practice 3: Discuss which model provides a better prediction result.

After finishing the experiment and assignment, it is important to evaluate the students' feedback. In the evaluation program, teachers should pay attention to the assessment of the whole process of the students' experiment, including significance of the topic, variable selection, data evaluation, experimental results, report content, and presentation performance, among others, and design a simple scoring table (see Table 4). The scoring items are as follows:

(1) Significance of the topic: This item evaluates whether the topic selection of the student was innovative, creative, and practical.

(2) Variable selection: This item evaluates whether the prediction variables selected by the student were scientific and reasonable for the prediction objectives.

(3) Data evaluation: This item evaluates whether the student assessed the integrity and scientific rationality of the data.

(4) Experimental results: This item evaluates the accuracy and impact of the final prediction results.

(5) Report content: This item evaluates the effectiveness of the writing and content structure of the students' report.

(6) Presentation performance: This item evaluates the quality of the student's presentation.

Table 4. Experiment scoring table.

Items	Significance of Topic 10%	Variable Selection 10%	Data Evaluation 20%	Experimental Results 20%	Report Content 20%	Presentation Performance 20%	Comprehensive Score 100%
Scores							
Teacher's Comments:							

7.2 | Self-Learning Experiment Design

This part aims to improve students' mastery of the knowledge and skills involved in case teaching. Through practice and experimentation, the students can develop the practical ability to collect data from a database and use ACL for predicting audit-related business issues. The main requirements include the following:

(1) Please select a research topic in the audit field under the guidance of the instructor. The research topic must have certain practical significance in the current audit practices.
(2) Determine the prediction objectives and variables of the topic, and use open data to obtain the sample data required for the topic.
(3) Import the data into ACL software, and perform the prediction process according to the prediction methods and steps taught in this paper.
(4) Properly evaluate the prediction results, submit a written experimental report, and deliver a presentation.

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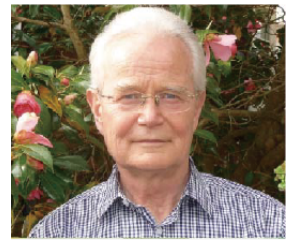
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INTERNATIONAL JOURNAL OF COMPUTER AUDITING

Comments after listening to the 2020 Massey Lectures: "Reset: Reclaiming the Internet for Civil Society" by Ronald J. Deibert

Hart will PhD, CPA, CMA

University of Victoria, Professor Emeritus of
Information Systems and Computer Auditing, Canada
Inventor of ACL and Founder of ACL Services Ltd., Canada



The Massey Lectures of the Canadian Broadcasting Corporation (CBC) were established in honour of the founder of Massey College at the University of Toronto, the former Governor General of Canada Vincent Massey [1]. Since 1961 CBC Radio has been broadcasting the CBC Massey Lectures, bringing Canadians and other listeners around the world some of the greatest minds of our times, exploring the ideas that make us who we are and asking the questions that make us better human beings [2]. In the 2020 Massey Lectures renowned tech expert Ronald J. Deibert explores the disturbing impact of social media. The lecture series titled "Reset: Reclaiming the Internet for Civil Society". Drawing from his work as the director of Citizen Lab, which has made headlines for its cyber espionage research, Deibert talked about the personal, social, political, economic and ecological implications of social media [3].

After listening to Dr. Deibert's lectures I wrote the following letter to Nahlah Ayed who is the host of the nightly CBC Radio program Ideas and the Massey Lectures. - Dr. Jack Huang felt that it amplified my earlier comments on big data and information systems in the previous issue of the JCA and wanted me to relate them also to our readers in this issue.

Dear Nahlah Ayed:

Congratulations on your creative and critical involvement in the CBC IDEAS programs and the Massey Lectures!

The enlightened and enlightening lectures by Prof. Deibert prompt me to send you my by now somewhat antiquated "Academic Swan Song" based on a lecture that I gave at Chung Cheng National University in Taiwan in March 2007. It was published as a commentary in the inaugural Journal of Computer Auditing in the Spring of 2019 as "Big Data: Ideology vs. Enlightenment."

(Some JCA readers may have wondered about the "philosophical content" of my earlier comment and paper in our

technical journal, but the editor thought that my remarks then and now below could help us further in our efforts to remain relevant in today's world as "agents of enlightenment" - if that is what we would want to be. As computer auditors we are certainly at the forefront of the digital wave that is crushing us increasingly as individuals and members of families, organizations, societies, states and our world. We are constantly developing new tools and techniques; however, do we also dare to address the real threats and dangers? Can we contribute to reclaiming the internet for civil society?)

Enlightenment implies "daring to know" (Kant) as the courage to ask critical questions courageously also in response to information systems issues. The concepts and questions applied to the "Big Data Ideology" suggested "Data Governance" as a framework for enlightened control of data technology and its abuse, misuse or proper use. They can and should also be applied to computer algorithms and models in terms of "Model Governance" or to the use and waste of natural resources for information technology as "IT Resource Governance." As accountants, auditors and computer auditors we certainly know about governance in various contexts – but do we really dare to know what that means or should mean today? Are we "hiding" behind antiquated accountability and auditability concepts and constructs?

Professor Deibert's lectures contain enough "food for thought" to ask the critical questions and to debate the issues - even in the context of decolonization.

The "We have always done it that way!" mantra is no longer tenable in resource-rich or resource-poor, capitalistic, still colonially administered and by now multicultural democracies. Colonial and capitalistic ideology has influenced too many uncritical generations of citizens and created intolerable inequalities here and around the world. Already in 1776 Adam Smith made important distinctions between wealth and welfare (in terms of "productive and unproductive labour") both privately and nationally. Why should "smart entrepreneurs" and their monopolistic corporations be permitted today to reap the whole wealth derived from claiming and (ab)using private resources such as our personal data or public resources such as water and land containing valuable and increasingly rare materials? Seducing whole populations to interface constantly with personalized "tempting offers to buy, listen, read or view" on the internet causes numerous private and common welfare costs. These are eventually payable by the rest of us and even by future generations. – Would Adam Smith consider these practices today as "productive labour" deserving monopolistic wealth?

Obviously it is very hard to break ideological fixations anywhere and everywhere, but I hope that Prof. Deivert's eloquent and profound Massey Lectures will be convincing to more people here at home and around the world to remember the lessons of the (European) Enlightenment and to practice critical thinking in tackling the following questions:

1. How can we encourage critical thinking in all societal contexts?
2. How can we encourage the development of governance methods and models for all facets of information technology: data, algorithms, networks and machinery?
3. How can or could we select and empower "Infotech Governors"?

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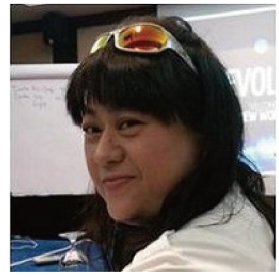
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FCPA Watch: 2016 - 2020 Enforcement Trends

Sherry Huang CFAP, CEAP, CIA

Chair, ICAEA Taiwan Chapter
Chair, Professional Development Committee, IIA Taiwan
CEO, Jacksoft Commerce Automation Ltd., Taiwan

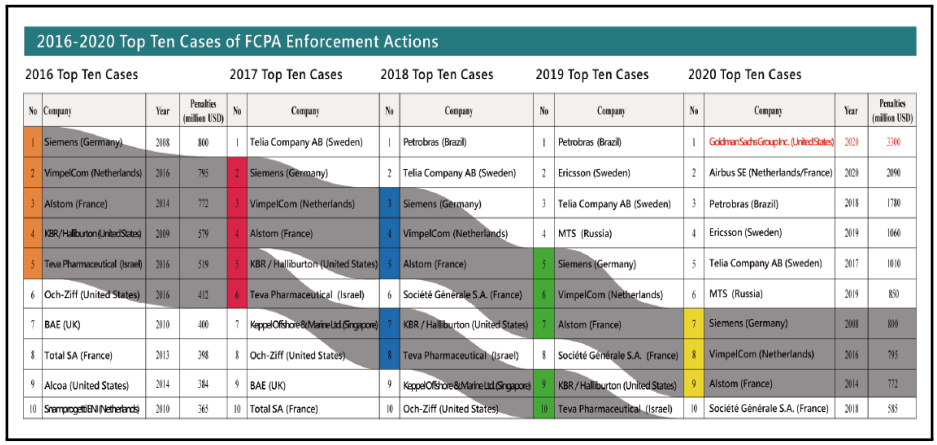


In current situation, companies who accept bribes would receive huge panalties and economic losses. Corporate governance should come up with the solution to prevent enterprise bribery and correction. Enterprises need to build their compliance strategies of anti-corruption and anti-bribery to prevent risks [1]. With the increased globalization business environment and complex business models, an enterprise is going to face corruption risk inland or aboard. Current situation of global anti-bribery enforcement enforced strictly, especially Foreign Corrupt Practices Act (FCPA) enforcement. FCPA was legislated in 1977 and amended three times in 1988, 1994 and 1998. The purpose is to forbid American citizens to bribe enterprises and foreign government officials. It could create fair and honest business environment to develop and maintain specific business action. FCPA mainly includes anti-bribery and accounting clause. The anti-bribery clause banned enterprises or personals to provide bribing promises and gifts to foreign government officials, even to maintain improper business advantages for themselves. Accounting clause requires the securities issuer to maintain the correct bookkeeping records and the establishment of an effective internal control. Therefore, it could truly reflect the correct transaction records and properly authorized, and prohibit any behavior that may directly or indirectly lead to false or misinformation.

With the increasingly strict environmental supervision, FCPA's maximum penalty records over the years has been continuously refreshed, showing that its enforcement has continued to strengthen. Since 2016, SIEMENS AG in Germany has received FCPA's maximum penalty records, which paid US$800M. Fine has increased in the following years. In 2017, Telia Company AB, the Swedish telecom giant was fined about US$1B, and in 2018, Petroleo Brasileiro (PBR) was fined US$1.78B as the highest record. In 2019, Ericsson telecom of Sweden was fined US$1.06 B and ranked second. By 2020, Goldman Sachs of the United States paid US$3.3B in fines, breaking the fine record for violating the FCPA (See Figure 1).

About 70% to 90% Non-U.S. companies have dominated the Top Ten list in Figure 1. Harry Cassin's commentary "The FCPA unfairly punishes foreign companies. Or does it? " argued that 53% to 67% FCPA corporate enforcement actions have been against U.S. companies. One reason of non-U.S. companies always dominate Top Ten is the "culture"

gap. Outside the United States, many executives and lawyers are still reluctant to cooperate with DOJ investigations, at least initially. And their lack of initial cooperation has contributed to so many foreign companies ending up on the Top Ten list [2].



2016-2020 Top Ten Cases of FCPA Enforcement Actions

2016 Top Ten Cases

No	Company	Year	Penalties (million USD)
1	Siemens (Germany)	2008	800
2	VimpelCom (Netherlands)	2016	795
3	Alstom (France)	2014	772
4	KBR/Halliburton (United States)	2009	579
5	Teva Pharmaceutical (Israel)	2016	519
6	Och-Ziff (United States)	2016	412
7	BAE (UK)	2010	400
8	Total SA (France)	2013	398
9	Alcoa (United States)	2014	384
10	Snamprogetti/ENI (Netherlands)	2010	365

2017 Top Ten Cases

No	Company
1	Telia Company AB (Sweden)
2	Siemens (Germany)
3	VimpelCom (Netherlands)
4	Alstom (France)
5	KBR / Halliburton (United States)
6	Teva Pharmaceutical (Israel)
7	Keppel Offshore & Marine Ltd (Singapore)
8	Och-Ziff (United States)
9	BAE (UK)
10	Total SA (France)

2018 Top Ten Cases

No	Company
1	Petrobras (Brazil)
2	Telia Company AB (Sweden)
3	Siemens (Germany)
4	VimpelCom (Netherlands)
5	Alstom (France)
6	Société Générale S.A. (France)
7	KBR / Halliburton (United States)
8	Teva Pharmaceutical (Israel)
9	Keppel Offshore & Marine Ltd (Singapore)
10	Och-Ziff (United States)

2019 Top Ten Cases

No	Company
1	Petrobras (Brazil)
2	Ericsson (Sweden)
3	Telia Company AB (Sweden)
4	MTS (Russia)
5	Siemens (Germany)
6	VimpelCom (Netherlands)
7	Alstom (France)
8	Société Générale S.A. (France)
9	KBR / Halliburton (United States)
10	Teva Pharmaceutical (Israel)

2020 Top Ten Cases

No	Company	Year	Penalties (million USD)
1	Goldman Sachs Group Inc. (United States)	2020	2300
2	Airbus SE (Netherlands/France)	2020	2090
3	Petrobras (Brazil)	2018	1700
4	Ericsson (Sweden)	2019	1060
5	Telia Company AB (Sweden)	2017	1010
6	MTS (Russia)	2019	850
7	Siemens (Germany)	2008	800
8	VimpelCom (Netherlands)	2016	795
9	Alstom (France)	2014	772
10	Société Générale S.A. (France)	2018	585

FIGURE 1 2016-2020 FCPA Top 10 Cases Trend

The court comprehensively considers various factors, consider and calculate the fines for the offender's actions, including the severity of the crime, crime involved amount, the scale of the personnel involved, and status of the person involved in the company. The attitude of accepting government investigation is another consideration factor. Sometimes, the involved enterprise could have great degree of fine reduction even not to prosecute. In the case of Goldman Sachs, the company fails to be proactive in disclosing bribery to the Ministry of Justice and delay in providing relevant evidence, thus breaking the fine record. In 2016, Siemens' record has ranked the seventh highest-paid fine in history. The enforcement of the FCPA has been increased year by year. Additionally, in recent years, U.S. Department of Justice and other countries cooperate in investigations has become normal.

There are more than 200 cases with 50 countries which involve within FCPA enforcement actions in 2015 - 2019 [3]. Therefore, modern companies urgently need to adopt cost-effective regulatory strategies to reduce related risks and prove the authenticity of their law commitments and whether they meet government standards. Continuously monitor on violation actions effectively prevents and reduce the risk of violations.

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Highlights of the annual achievements

As I reflect upon this year, I am immensely proud of the progress of our chapter in the Middle East. I would like to extend my sincerest gratitude to the local chapter chairs, our members and industry partners for all their contributions to the chapter's growth over the past year.

Throughout 2019, ICAEA ME Chapter continued to spread the culture of data analytics among the professional as well as students' communities. The chapter provided access to valuable CAATS tools i.e., Galvanize/ACL and training services to the audit community. In addition, ICAEA ME Chapter continues to offer diverse training through seminars, workshops, contests and online webinars. More than 300 students and professionals have participated in our live webinars and workshops. About 35 professionals have got the ICCP certificates and became certificated members. In addition to Jordan, ICAEA ME Chapter launched new local chapters in UAE, Qatar, Bahrain, Egypt, Iraq, Palestine, Lebanon and Oman. This year ICAEA ME Chapter has conducted the regional CAATs Contest for universities. The contest has been successfully conducted in Jordan, Egypt, Palestine, Bahrain, Algeria, Saudi Arabia, Morocco and Iraq. About 228 students in 76 teams have participated in the contest.



Workshops in Data Analytics & GRC

During 2019, ICAEA ME Chapter held 10 trainings and 12 webinars. About 50 professionals attended the training and 31 passed the ICCP exams to be certificated members at ICAEA. ICCP trainings were focused on CAATs tools to help auditors to make search from the irregularities from the given data to provide more analytical results. The main topics that have been covered in the training were Computer Auditing Overview, Understanding CAATs, Data Importing, Data Importation & Verification Skill and Knowledge, Working with Expression & Filters, Computed Fields, Functions, Data Analysis Skill and knowledge, and Audit Finding Report & Remediation Skill and Knowledge. Moreover, ICAEA ME Chapter held 5 workshops on GRC. About 25 professionals attended the workshops to earn ICAEA CPEs. The workshops introduced the GRC standards, which defined an international framework model related to GRC i.e., known as GRC Capability Model. During the workshops, participants have examined various functional segments. The course uses the Highbond from Galvanize as a platform for GRC implementation. The main covered topics were Strategic alignment, Identifying strategic objectives and risks, Assessing strategic risk, Responding to risk, Tracking assurance, Compliance maps and Governance activities.



University of Jordan

MOU to promote Data Analytics Culture among University of Jordan students

Amman - Jordan, this Memorandum of Understanding (MOU) made between the UJ and Jordan ICAEA Chapter to establish a mutual co-operation between them. Recognizing the value of ICAEA services in the computer auditing education and training, UJ and ICAEA agree to give UJ students an overview of the main activities of computer audit to become successful computer auditors in the future. ICAEA will review the courses that are related to auditing and support it with the practical hands-on using one of the CAATs tool such as ACL. ICAEA will assess the required competency for the students to become a computer auditor by defining learning map as per recent standards and accreditation bodies. ICAEA agreed to advise JU to adopt the recommendation of AACSB i.e., Standard A7 to support accounting degree programs to include skills and knowledge related to data creation, data sharing, data analytics, data mining, data reporting, and storage within and across organizations. It is agreed to promote the culture of data analytics among the students and promote ICCP certificates with favorable exam fees. The MoU encourages the students to become certificated members at ICAEA Association to motivate them having computer auditing responsibilities and maintain their professional competency via CPE (e.g., 12 per year).



CAATS Contest to promote Data Analytics Culture among students

During 2019-2020, ICAEA ME Chapter held 8 CAATs contests. The contest has been successfully conducted in Jordan, Egypt, Palestine, Bahrain, Algeria, Saudi Arabia, Morocco and Iraq. About 228 students in 76 teams have participated in the contests. The contest was 4 hours-long with ten cases. In order to let the students compete and win the contest, they must solve at least four cases and solve the highest number of problems among the other teams. They used CAATs tools e.g., ACL to solve the cases of the contest. The contest was open book (only hardcopy) without internet connection. After completion, students have submitted the solutions to the judges, who are experts in CAATs tools and data analytics. Students have exported the result tables as excel sheets, saved and compressed the project and all related files and logs as ZIP format.

The winning team in each country has been honored with the Trophy that certifies that they have been ranked at the first place in the local contest.

All other participants were awarded certificates of participation and have been given further training on ACL to enhance their knowledge and skills in data analytics.



Results from our recent students survey with 50 respondents in ICAEA course



International Journal of Computer Auditing

Published by

International Computer Auditing Education Association

Publication Office

21615 49A AVE

LANGLEY BC V3A 6C4

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Website

https://www.icaea.net

Start-publication Date

2020

About ICAEA

International Computer Auditing Education Association (ICAEA) is registered as a non-profit organization in BC, Canada with Society Incorporation Number S-0060477.

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