Machine learning in finance management: Case OpusCapita

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This Bachelor's thesis presents a project commissioned by OpusCapita to create an algorithm to detect anomalies, errors or fraud in corporate payment data. The main goal of this thesis is to introduce the reader to machine learning and tell about the role and tasks of finance management students in the project.

The project was conducted with a group of IT students and two finance management students. The project took place in the spring of 2016. The purpose of the project was to create an algorithm that the client could then develop into a working tool for their international customers. The purpose of the product is to alert the user about errors and frauds in their outgoing payments so that they can then be checked manually.

This thesis is divided into three parts: a theoretical framework, project plan and project implementation. The theoretical part of this thesis concentrates on machine learning and the accounts payable process. The project plan part explains how the project was planned and how it was meant to be implemented at the beginning. It also explains the role of financial management students in the project. The project implementation part explains the phases of the project and how the financial management students' tasks in the project were carried out during the phases. At the end of this thesis the conclusion of the project is explained and the project is evaluated. The reflection part of this thesis offers ideas for future development of the algorithm from the finance management student's point of view.

The approach for this thesis is practice based. The products from finance management students were used as learning material for the IT students.

Keywords
Machine learning, finance management, payments fraud, algorithm

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1 Introduction

This thesis deals with machine learning and is made for a project conducted for OpusCapita. Machine learning is a type of artificial intelligence. It provides computers with the ability to learn without being explicitly programmed. Machine learning programs detect patterns in data and modify program actions accordingly. (Techtarget 2016.)

The purpose of the project is to create an algorithm to detect anomalies, errors or fraud in corporate payment data, specifically in out-going payments, for OpusCapita. The project will be conducted together with a class of IT (BIT) students, their teachers and two finance management students. The project takes place in spring of 2016 in three sprints. The thesis will be made from the perspective of a finance management student participating in an IT project. The thesis focuses on the tasks of the finance management student in the project and the knowledge and skills needed in helping to create the algorithm.

The history of machine learning goes back to 1952 when an IBM employee named Arthur Samuel wrote the first game-playing program for checkers. His learning programs worked surprisingly well and helped the checkers players' performance. In the 1990's machine learning became popular because of the integration of Statistics and Computer Science. A new way of thinking in Artificial Intelligence was the result of this cooperation, which is called the probabilistic approach. Because of this, the field started to shift to a more data-driven approach when the earlier approach was more knowledge-driven expert systems. The ideas developed then have lead to many current success stories. (Machine Learning in the Netherlands 2016.)

Machine learning has come quite far in today's world and many companies are thinking of using that to their advantage. According to Markets Media (2013), for example hedge funds are developing Machine Learning trading algorithms within financial markets. The algorithms are developed with a view towards finding practical applications of the large frame of theory that exists for artificial intelligence (Markets Media 2013).

OpusCapita is also a company that improves the efficiency of automated financial management processes. (OpusCapita 2016a.) Their aim is to digitalize and automate invoice handling and payments, purchasing and supplier financing as well as cash management through continuous development of software together with services. (OpusCapita 2016b.) In this project, they represented themselves as software providers.

OpusCapita believes that machine learning can be used in numerous finance management processes. They already have machine learning based fraud and anomaly detection programs installed in their cash management systems. They also have artificial intelligence for cash flow forecasting. (OpusCapita 2016b.) It was also mentioned in the project's kick-off meeting, that machine learning is important to OpusCapita in the sense that by creating an algorithm that detects anomalies, errors or fraud they can gain competitive edge if they can launch it earlier than their competitors and a working algorithm would bring them more customers and it would also broaden their selection. This project was commissioned to help them go forward with that. The theory framework of this thesis could also bring them more insight into machine learning and its uses in finance management and thus help them in developing the algorithm to a working level tool. OpusCapita will eventually use the tool internationally and that is why it is done in English.

For me professionally, machine learning means less time spent doing mechanical check ups of data at work. We use a system called SAP at my work place for finance management processes and invoicing among other things. The system already checks for double payments using the invoice number, even though I have noticed that it doesn't always work, and I think it could potentially do a lot more and free me up for more important matters that a computer is not able to do. This is where OpusCapita could potentially gain a competitive edge in the field by having something that other companies offering similar products do not have.

1.1 Project objectives and project scope

The project's objective was to create an algorithm that detects anomalies, errors or fraud in outgoing payments for Opus Capita. The tool was designed to detect any abnormal patterns in outgoing payment data, missing payments, duplicate payments and abnormal or missing salaries. It was said in the kick off meeting that in the future Opus Capita will test and develop the tool further themselves and might eventually offer it to its customers as a part of OpusCapita Payments product's Fraud & Risk management capabilities. The project is done in three sprints. Each sprint is five weeks long and has its own goals and agendas whose success is reviewed after each sprint.

My own role in the project is to help and share my knowledge about related finance management matters with the BIT students and help them go forward in the project. They need to understand the key finance management areas to be able to understand the payment data and create the algorithm.

My project tasks:

PT 1. To find finance management cases where machine learning has been used.

PT 2. To support the BIT students and help them to understand the main financial concepts needed in the project.

PT 3. To help in interpreting the payment data OpusCapita sent.

Table 1 presents the theoretical framework, project management methods and outcomes for each project task.

Table 1. Overlay matrix

Project Task	Theoretical Framework	Project Management Methods	Outcomes
PT 1. Designing a theoretical framework for the project	Chapter 2	Desktop study	Theoretical framework
PT 2. To help the BIT students to understand the main financial concepts required in making the tool	Chapter 3	Desktop study and presentations	Training material (presented in appendices 1 & 2)
PT 3. To help in interpreting OC data	Chapter 3	Discussion with OC (email), own interpretations	Training material (presented in appendix 3)

1.2 Benefits

The stakeholders in this project are OpusCapita, Haaga-Helia and students working on the project.

All parties will benefit from this project. OpusCapita will have a product that they can eventually offer to their customers who will in turn get more value for their money. All the students will benefit from this project by gaining more knowledge and experience.

Since Haaga-Helia is commissioning the project it will benefit from a successful project by getting the theses from the financial students. It might also get future commissions from OpusCapita and gain information of the development of accounting. The learning perspective in this project is no doubt important to all participants.

1.3 Key Concepts

Artificial Intelligence is a sub-field of computer science. Its goal is to enable the development of computers that are able to do intelligent things normally done by people. (Hammond 2015.)

Scrum is a framework used in project implementations, used mostly in software development projects but can be used in other kinds of projects as well. (Scrum Alliance 2016.)

Sprint means the amount of time a team has to complete its set goals. A sprint usually lasts 2-4 weeks. (Scrum Alliance 2016.)

Big Data describes the large structured and unstructured amount of data that companies deal with in their daily business. It is data from multiple sources and in many formats. It can be for example financial transactions, email, numeric data and many other things as well. (SAS 2016.)

1.4 Case Company

OpusCapita is a subsidiary of Posti Group and its head office in located in Finland. OpusCapita is trying to improve the efficiency of automated financial management processes. They offer solutions like electronic invoices, electronic payments and electronic invoice workflow to payment factory and even fully-fledged financial outsourcing. Its focus is on wide-ranging Purchase-to-Pay and Order-to-Cash processes. It operates in 9 countries and has end users in over 50 countries. OpusCapita has over 11 000 customers and it employs 2 300 people. They are a leader in their sector and in 2014 their net sales were 260 million euros. (OpusCapita 2016.)

2 Machine Learning

Machine learning doesn't rely on rules-based programming as it is based on algorithms that can learn from the data that it is given. The world today has an unmanageable volume and intricacy of big data thus the need for and potential in machine learning has increased. What comes to the advantages of machine learning, no only does it go through any amount of data but it can also go through every combination of variables. (Pyle & San Jose 2016.) The advantages of machine learning compared to humans are immense.

Machine learning is essentially finding meanings in large masses of data and then making forecasts based on them. It is an important part of analysis when producing measurable business benefits thorough digitalization. Machine learning has been researched for decades but only the recent development in computer science has brought these technical and demanding methods available to the public. (Tauriainen 2015.)

2.1 Machine learning in finance

Many banks have already substituted their older statistical-modeling tools with machine-learning methods in Europe. Some have even experienced increases in sales of new products and also remarkable savings in capital expenditures. Also cash collections have increased after the machine learning technique was taken into use. These monetary gains have been reached through invention of new recommendation engines for their small and medium-sized client companies in retailing. (Pyle & San Jose 2015.) A recommendation engine reduces Big Data to small data and narrows an eventual complex decision down into a few recommendations. A well-known example of a recommendation engine is Amazon; it recommends a book based on the reading behavior of other readers. That system is based on an algorithm that learns from the past data of Amazon's users. (Finger 2014.)

In the finance and accounting industry hundred of millions of dollars have been invested in taking accounting online. The next wave of investment for accounting platform providers is driven by advanced machine learning applications. The difference compared to old technologies is that the application will also learn from the information it collects, instead of just collecting it. A New Zealand based company called Xero has invested in cloud accounting for nearly a decade and now they have an on-going project in which they are using the transactions they have gathered during one year in their advantage. The software is built to learn from the data it stores instead of just collecting it. The result of this is a system that could learn how to completely learn to do for example bank reconciliations. The accounting software will also get smarter; it will not only present the data entered in it in a clean format, it will also enable the company to use the servers to do the processing of data and automate decisions formerly done by humans. (Drury February 2016.)

Also credit card companies have fraud detection units that track financial transactions that are criminal fraudulent by nature. For consumers the fraud detections process seems instantaneous and maybe even magical. This immediate action involves many sophisticated technologies ranging from finance and economics to law and information sciences. Conventionally, detecting fraud without human involvement and data analysis techniques was impossible. There was an algorithm that would pick the suspicious transactions and a human investigator would then call the cardholder. Nowadays the companies rely on big data analytics. Machine learning and cloud computing are now the most important tools for detecting fraud. The algorithm is trained by feeding it normal data from lots of cardholders, for example filling up on a gas once a week. Over time the algorithm learns that this is a normal transaction. After this feeding data process the transactions are run through the algorithm. Then it produces a probability percentage for fraudulent transactions. The fraud system also be configured to reject any transactions above for example 95%. The more data the algorithm gets the more accurate it becomes. (Ryoo 2015.)

2.2 Machine learning in the future

Over the last decade or so, the whole financial services industry has experienced a comprehensive change. There has been different technology, regulatory, customer and competition challenges as well as market related challenges. Whilst companies are focused on the indications of this digital revolution the might miss the emerging opportunities in technological innovation. For example, for banks and capital markets robotic process automation (RPA) is already now starting to change the way they execute basic processes. (Culp 2016.)

The use of robotic process automation in finance and accounting raises a question whether or not the robots are replacing people. Some jobs might disappear. The lower paying jobs are most at risk since they are eight times more susceptible to being replaced by technology that the higher paying jobs. In contrast to humans, robots offer 100% accuracy and they will not leave the company or take sick days. (Jarvis 2015.) However, the accounts payable process needs to be divided into rule-based components that the software robots can do and those that need a human touch (Robotic Process Automation in Accounts Payable – Tomorrow is Today 2016).

As the new technologies are emerging constantly and every innovation or invention could potentially be the next big thing, one must bear in mind that not every new technology will alter the business in any way. However, some have the potential to penetrate into people's lives and into companies' daily business. A report from McKinsey Global Institute (2013) has identified 12 technologies that could potentially generate enormous economic changes and shifts. Automation of knowledge work is one of the technologies and it is an intelligent software system and it can perform knowledge-work tasks in finance management such as accounting and investments. Artificial Intelligence and machine learning are both key components used. In 2025 the economic impact is estimated to be between 5.2 and 6.7 trillion US dollars. (Manyika & al 2013.)

3 Accounts payable process

The accounts payable process includes almost all of the company's payments besides payroll. Depending on the size of the company there may be an accounts payable department or in a small business the bookkeeper or even the owner may handle it. But in all companies the most important thing of accounts payable is to only pay invoices that are correct but also most importantly authentic. The company should have some kind of safeguard in place for accounts payable process to prevent paying an inaccurate invoice, a fraudulent invoice and to prevent double payments and also to make sure that all invoices from a certain vendor are accounted for. (Accounting Coach 2016.)

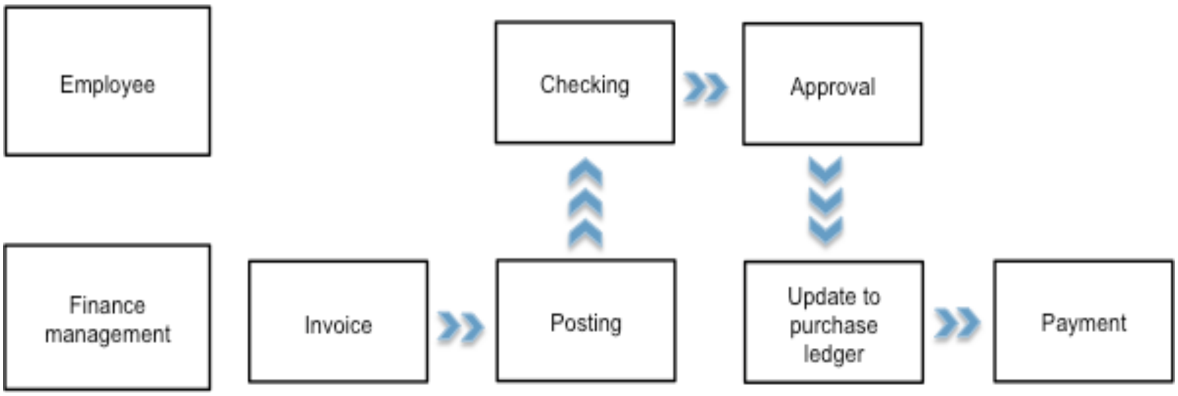

Figure 1. Invoice process. (Lahti & Salminen 2008, 51.)

The accounts payable process can be a complex one, especially in a bigger company. Firstly, the accounts payable department deals with the accounts ledger. Accounts ledger is a part of book keeping and it is a database of the company's vendors and customers. Accounts ledger is often divided into sub ledgers like purchase and sales ledger and payments and invoices are handled there as well. A purchase ledger makes sure that purchase invoices go to acceptance rotation in time and thus also are paid in time. (E-conomic 2016.) Usually the invoice posting process is automatized according to vendors and the kind of invoices they usually send. The bookkeepers' workload is reduced and errors are also minimized. (Helanto, Kaisaniemi, Koskinen, Kuntola & Siivola 2013, 45.) Acceptance rotation means that there are usually two people in a manager position who has to check and accept the invoice for payment. The phases of purchase ledger are: ordering of goods, receiving of invoice, sending invoice to acceptance rotation, receiving invoice from acceptance rotation and finally invoice payment. (E-conomic 2016.) Even though the invoices have been checked and approved a manager needs to make sure that there is enough money in the bank account. The payment batch is approved with an electric signature. (Mäkinen & Vuorio 2002, 129.)

A sales ledger takes care of sales invoice payments and collections. The most important task is to follow up the sales receivables account. All open receivables are seen in this ledger so it is easy to see which invoice has been paid to the company. If payment is not received after one or two reminders the receivable can be moved to a collections agency for handling or try to collect it on your own. The phases of sales ledger are: booking the payments and allocating them to open invoices from the bank account, booking and sending reminders and starting collection activities. (E-conomic 2016.)

3.1 Contents of payment information

My colleague in Anttila Oy said in an interview, that initially the basic information needed for payments, such as the vendor's name, address, account number and payment terms, come from Master Data where the information is typed when a vendor is created. Anttila Oy uses an accounting program called SAP and it has separate transaction for the payment run. The transaction basically gathers all the invoices that are ready for payment and creates a payment proposition. There are many vital things that need to be correct in a payment in order it to be successful. Otherwise a whole batch of invoices sent to the bank can be rejected. (Piha 21 June 2016.)

When the payment data is sent to the bank, the bank checks the validity of the data and if there is enough money on the company's account. There are multiple accounting softwares available for companies besides SAP and if for example a program called Procountor is used, the bank will send Procountor an error log, which is then delivered to the customer. (Procountor 2016.)

All that has to be wrong is an account number or missing BIC (Bank Identifier Code). More specifically, the information needed for payments are the vendors' account number in IBAN form for payments within the EEA (European Economic Area) and EU (Piha 21 June 2016). IBAN stands for International Bank Account Number and it has been obligatory in cross-border payments since 2007. European countries not belonging to the EU or EEA have also taken the IBAN into use. It is the sending bank's responsibility to make sure that payments have the IBAN despite the currency used. Otherwise it is rejected. BIC is also essential for making payments. It is usually 8 or 11 characters long and it is used to identify the beneficiary's bank and bank's country. (Nordea 2016.)

There also needs to be the amount and currency, which the invoice is to be paid. Due date is also vital information as is the reference number and invoice number. If any of these are wrong, or even written in lower case instead of upper case the whole invoice batch is rejected and the banking system in use produces an error log. The error is then located by hand from the error log and fixed before the batch can be sent again. (Piha 21 June 2016.) If the beneficiary's address is missing altogether, the payment is also rejected (Procountor 2016).

3.2 Frauds & errors in payment data

There are many different schemes for hackers to attack companies and they are becoming increasingly complicated and difficult to detect. In addition to attacking and taking over employee accounts they are now also attacking the payment process by requesting employees to make transfers to their account or impersonating managers to withdraw money for themselves. (Green 2016.) These are scams specifically designed to trick employees into making payments to sham accounts through corporate email systems (2016 AFP Payments and Fraud and Control Survey). Hackers are usually aware of the internal controls and common policies in place to prevent fraud. This makes their actions more difficult to notice. It is a common policy to have multiple persons involved in the payment process steps. There are different people for opening vendor accounts, authorizing payments and making payments. But once hackers have the ability to manipulate IT systems, they can create new users to authorize payments and another to make payments. Since the rules of the company have been followed there are no warnings that anything deceitful has even happened. (Green 2016.)

People who commit these frauds tend to use even amounts, which means there are no pennies in the invoices they have created. They also create invoices that are just below the manager's approval limit, which can be for example $10.000. The invoice that is created can be then for example $9.998. (Warner 2016.)

According to AFP Payments Fraud and Control Survey done by Association for Financial Professionals, in 2015 wire transfers were the second most popular method for payments fraud in the US. (2016 AFP Payments and Fraud and Control Survey, 58.) A wire transfer is an electronic payment service used for transferring funds using, for example, SWIFT or BIC code. (Bank of America.) Close to 50 % of the respondents said to have been exposed to such fraud. The size of the organizations seems to have no significance but a company with fewer than 100 accounts seemed to be more exposed than a bigger one. A new challenge for companies and also for finance professionals seems to be business email compromise (BEC) scams. (2016 AFP Payments and Fraud and Control Survey, 58.)

A company may also encounter internal fraud and most companies have written policies to manage fraud risks. Internal fraud can be for example falsified hours and salary, fraudulent or unauthorized disbursements, small disbursements and unauthorized withdrawals. (The Institute of Internal Auditors.) Falsified hours and salaries schemes succeed because companies lack the sufficient control over employees' working hours. It is critical for a manger to verify hours worked and authorize timecards. Companies should also have a rule saying that no overtime will be paid unless authorized in advance. (Kranacher, Riley, & Wells 2011, 365.) Fraudulent or unauthorized disbursements occur when an employee uses his position at work to make a payment for an inappropriate and/or unauthorized purpose. Fraudulent disbursements are called on-book fraud schemes because they leave the company illegally but are recorded on the books and therefore leave an audit trail. (Association of Certified Fraud Examiners 2011, 63.)

But there are also non-fraud related issues in payment data, like for example duplicate payments. A duplicate payment is a payment that is processed twice. In most cases they are not frauds, but it is an unnecessary and preventable outflow of money. Mark Van Holsbeck estimates that 2% of corporate payments are duplicates. There are many software packages that offer control over duplicate invoices but it might take some effort to find them. For example, many software packages do a duplicate payment check by invoice number but if even cent is changed or an "A" added to the number the duplicate check doesn't work anymore. Also multiple vendor numbers for the same vendor causes duplicate payments. (Warner 2016.) Human error is also a common cause of duplicate payments. These might include new or temporary staff, keying errors, IT system changes and cross-company invoicing. Honest vendors often alert the accounts payable department when they discover the mistake. (Capgemini 2012, 2.)

4 Project plan

The project plan was created by Haaga-Helia with the acceptance of the client. The project mission was to chart anomalies, risks and threats in out-going payment data and develop a software based solution that detects those and automatically alerts about them. (OpusCapita 2016.)

The project was implemented using Scrum- framework. It was originally designed to be used in software projects and it is very simple method to use. Firstly, the product owner creates a list of things it wishes to have accomplished. Secondly, the project team plans the sprint i.e. divides the list into smaller, accomplishable pieces. After each sprint the team gathers for a review and retrospective to ponder what has been achieved and how to proceed in the next sprint. (Scrum Alliance 2016.) In the review the results of the sprint were discussed and presented to OpusCapita. In those meetings, OpusCapita representatives were able to share their ideas and opinions about the progress of the product and thus also guide the BIT students in the right direction.

My role in the project is essentially to open up the relevant finance management matters to the BIT students together with one other finance management student. In practice that meant providing them with learning material and having presentations. It also meant answering questions that might arise after the presentations or during the project. My goals are to successfully explain these things to the BIT students and provide the necessary backup during their classes. Also my objective is to find cases where machine learning is applied in the field of finance management. I would evaluate my own material by the feedback I will get from the students and teachers involved. I will also help the BIT students in class by explaining the data sent by OpusCapita and I evaluated my success by the feedback I got from the students and by the questions asked after I visited the class.

5 Project implementation

This chapter describes the project more in detail and how the product was created. Firstly, it will describe the project schedule and project goals. Secondly, the project and the role of the finance students in each sprint are described thoroughly.

5.1 Sprint 1

For sprint one the finance management students' role was to help the BIT students to understand the main concepts needed for interpreting the data from OpusCapita and also to tell what is actually meant when talking about outgoing payments frauds and cyber crime. The data was sent to the project team quite late in sprint one so we had a perfect opportunity to explain these things for the BIT students. The finance team decided to give a presentation for the students on 29.2.2016 so they would then understand even a little what they were dealing with.

The finance team divided the work for the presentation based on the fact that one had access to the OpusCapita banking software and could explain that and the core of duplicate payments in detail. I then took upon myself to explain the basic finance management concepts such as accounts ledger, accounts payable, accounts receivable and payment traffic frauds (appendix 1). My finance team colleague explained the duplicate payments more in detail. OpusCapita banking software print screens were included in the presentation in order to make explaining easier. Duplicate payments were explained as well, since they are connected to payment traffic and frauds. It was important that the concepts were thoroughly explained so that the BIT students would have an understanding of what were asked of them. So I started with explanations of accounts ledger and the process of account payables. And even though this presentation had the slides about payments frauds, they were explained more thoroughly in the next session on 1.3.2016. (Appendix 2). There were not many questions asked after the presentation and I felt that maybe the students lacked the courage to ask or they didn't have anything to ask so soon after the presentation. Some kind of feedback would have been useful in any case.

The OpusCapita data sent to the project team was actual information gathered from their customers but it was made unrecognizable to us, so there were no actual names of companies or anything else that could identify any companies or customers. We saw the data as an Excel- file and the task was to help the BIT students to understand the information in different columns and in that way try to identify relevant information. Also based on our working experience the finance team advised the students that the most important matters in the Excel file and in regards to payments are the name and vendor number of the vendor, invoice number, invoice date, due date, reference number, amount of invoice and currency. The file contained 42 columns and 109 865 rows. There were two files: one had the frauds marked with colors in order for us to verify our findings and the other one had no colors or markings of any kind.

Since the whole project was about creating an algorithm for OpusCapita that would be able to detect different kinds of frauds and errors in outgoing payments data, the finance team was asked to present different types of frauds to help figure out what could be wrong in the data sent to the project team. It was told that in the data there was thirteen planted frauds and errors and everything else that would be found suspicious would be in the actual data as well.

The BIT students and their advisors realized towards the end of sprint 1, that the data file was corrupted and it converted some amounts into dates and some were not numbers at all. I contacted OpusCapita in order to get a new, uncorrupted file and it arrived on week two of sprint 2. This is why all the goals for the BIT students were not met and also why the project lagged behind a little bit during sprints 2 and 3.

The sprint end-review concluded that the sprint was used to familiarize the BIT students with machine learning and finance management basics. They also got to know different methods that could be used to detecting anomalies in payment data.

5.2 Sprint 2

The sprint was planned in the review of the previous sprint. For this sprint the finance management students' role was to explain the planted thirteen frauds and errors in the payment data (figure x) even though they needed to be found by the BIT students and their algorithm as well. A document was written where the planted frauds were explained one by one and OpusCapita then verified the findings. There were a few problematic items on which the finance team disagreed upon and for that reason I contacted OpusCapita directly and got the explanations. We disagreed on which of the rows were duplicate payments and does the time stamp have to be exactly the same in order it to be a duplicate. Also we disagreed on how often does a company have to pay to a vendor in order it to be a so-called established vendor.

Payer(	PayerA	PayeeName	Amount	Currer	DueDate	Creatio	LastUpdateUserId	SourceDescr
28	1	ZUHCGXD	2.00	LVL	2012-02-28 00:00:00.000	12	10	GPM_UI
33	9	COYYYRR	1.00	EUR	2012-02-28 00:00:00.000	12	10	GPM_UI
31	7	YDBXJRX	1.00	EUR	2012-02-28 00:00:00.000	12	12	GPM_UI
31	7	YDBXJRX	1.00	EUR	2012-03-05 00:00:00.000	11	11	GPM_UI
31	7	XSDDASX	46170.45	LTL	2012-03-13 00:00:00.000	7	7	PFC
28	1	DUQUTZL	920.30	EUR	2012-03-13 00:00:00.000	7	7	PFC
31	7	DODYVEI	2006.18	LTL	2012-03-13 00:00:00.000	7	7	PFC

Figure 2. An example of OpusCapita’s payment data.

The finance team wrote a document (appendix 3) where the frauds and errors of the data were thoroughly explained: Fraud number one is a duplicate because it has the same invoice number (column AJ) as row 2152. Also all the other information in the columns is a match.

The finance management team also planted more frauds in the payment data by hand in order to test the algorithm and if the added frauds could be found. How this was to be done was discussed in the finance team and my colleague then planted them in the file. The frauds were meant to be discussed and validated with the BIT students when they found the additional frauds in the data.

In the sprint review the teams presented their progress and discussed the difficulties they met during the sprint. This sprint was generally felt to be quite chaotic since the BIT students felt that they could not proceed without the corrected data and therefore a lot of time was wasted waiting. It was felt among the students that this sprint was unsuccessful in way that nothing really moved forward. The project manager also fell ill and things got a little disorganized. Luckily it was noticed and for sprint 3 the BIT students were organized into smaller and more effective group.

For my part I noticed during the meetings the finance team had with one of the BIT lecturers during sprint 2 that information sharing and communication was not quite working and the purpose of having finance management students in the project was unclear to project management. Also I found myself answering the same questions by same person many times.

5.3 Sprint 3

Sprint 3 was planned in the review of sprint 2. In this sprint the finance management students’ role was to validate the findings made by BIT students in the payment data. The assistant project manager contacted us via the communication tool Slack, which the project members used for communication in the project. So the finance team visited the class to assist the BIT students and to answer their questions on 19.4.2016. During the visit I discussed the possible look and contents for the error message with one BIT team. They had trouble identifying the relevant data, which is sent via email after the payment is done and if the algorithm recognizes any possible frauds or errors. We also discussed what should be the likely percentage, which the algorithm counts as a fraud or an error. I suggested that it should not be lower that 70-75%, otherwise the algorithm flags so many payments that they are impossible to check. So for example, the email would say that a payment made for vendor 12345, amount 2576 € is 80% likely to be a duplicate or is made to a new account, please check the payment.

I also discussed the information in the payment file with another team and helped them to understand what actually is relevant information for the algorithm. They had picked almost everything to be relevant and I helped them by narrowing down the items. That helped them and they were able to move forward in their task.

We also went through the possible errors and deviations in the payment data. The BIT students merely wanted to check they have understood everything on our presentations. They had used our material that had been shared with them after our presentations.

During sprint 3 the finance team were meant to validate the results of the newly planted errors in the payment data. However, this was never done and I suppose they didn’t find them or they didn’t have time to look at the file. This last sprint was quite busy and hectic and the BIT students felt they had not made as much progress in the project as expected.

The communication and information sharing problems from sprint 2 seemed to continue in this sprint. The finance team had explained the payment file contents in detail during sprint 1 and still the project manager didn’t know the payment data contained salary data by sprint 3.

In the project’s final review the project manager went through the project objectives, challenges and results. It was concluded, that the training data for a machine learning algorithm needs to be more precise with clear information on what is an anomaly and what is not. The payment data for this project was found to be problematic because salaries and outgoing payments were mixed in the data. The algorithm needs to be taught to detect anomalies using authentic data.

6 Reflection

This chapter summarizes the project and evaluates how the project objectives created for this thesis were met. Also ideas for future development are discussed. Finally an assessment of own learning is done.

6.1 Project summary

The project objective was to create an algorithm to detect anomalies, errors or fraud in corporate payment data, specifically in out-going payments. The project would be implemented in three sprints and between sprints the outcomes of each sprint would be presented to OpusCapita in a review. For each sprint there would be different objectives that would help the project forward and support the learning of the students.

During sprint one the finance team gave two presentations to the BIT students. One was about outgoing payments process and the other was about payment frauds. The payment data file headings were also explained so the BIT students would understand the data a little better. During sprint two the finance team's task was to explain the thirteen frauds and anomalies in the payment data Excel in detail and explain why an anomaly was an anomaly or fraud. Also more frauds and anomalies were planted in the payment data. During sprint three the finance team's initial plan was to validate the planted frauds but it was never done because the BIT students had not used the file or had not found the errors.

All projects have a project plan and ideas what needs to be accomplished during the project. Projects, however, evolve and there are delays and unexpected problems that cause changes to the initial timetable. This project was no exception. Everything did not go according to plan, which caused the sprints to be less productive than planned. The delay in getting the payment data from OpusCapita and getting the new, uncorrupted, data caused delays in sprint one and two. Also the project manager fell ill during sprint two which caused a certain level of disorder an uncertainty.

For the finance management students the most important task was to help the BIT students to understand the financial concepts needed for interpreting the payment data from OpusCapita. Understanding the concepts would give them the tools for creating the algorithm with the necessary components. In this task of supporting the BIT students the finance team gave presentations and produced learning material for the students.

The product was presented to OpusCapita in the final review where the success and the challenges were gone through. The project gave new insight to OpusCapita and in that sense it can be deemed successful. However, the project as a whole could have been better.

6.2 Project evaluation

Overall the project was a success in the way that the BIT students were able to create an algorithm and explore different methods in creating the algorithm. This gives OpusCapita some kind of direction on how to move forward with the algorithm development. I was positively surprised by how skillful the BIT students were even thought they had not studied machine learning prior to the project. However, there were some issues during the sprints that hindered the development of the project.

I think the main problem was that the project lacked leadership, which seemed to cause all the other problems. The problems were delays, communication issues and lack of direction that started to show clearly in sprint two. The delays in the beginning were, however, partly caused by waiting of the payment data. Leadership issues also caused the communication problems. I also think that there should have been reporting and meetings about the progress of the sprints and project in general. Maybe then everyone would have had the same information and the same things would not have to have been explained many times. Furthermore, the project manager was supposed to be the contact person to OpusCapita and instead I somehow ended up doing it because the project was standing still.

Also the necessity of having finance management student in the project was unclear even to some BIT students' teachers and that is why we were not included in the project early on. I would have wanted to participate in the project-planning meeting before the project started but it was done without the finance management students. I think it would have been useful to participate in the meeting and see the project as a whole and helped the finance team to figure out what the BIT students actually need. Now I felt like an outsider in the project and I had to push myself in, and even that didn't quite work.

I would have hoped for better communication and clearer task descriptions from the beginning. I also hoped for some kind of feedback on the presentations and learning material. It would have helped the finance team to understand if we were on the right track and what could have been improved. The contents of our material were based on our own discussions and evaluations. We discussed our presentations afterwards and what could have been improved and if we thought something should be improved or if something wasn't as necessary as we initially thought. The finance team pretty much handled its own feedback and improvement suggestions.

OpusCapita was present in every review after the sprints, which I found useful. We got immediate feedback concerning the sprint and suggestions and for the following sprint. I think their presence made the project also feel real for all members of the project and made it easier to commit to doing the best work possible. However, maybe a more frequent contact with them and more frequent reporting would have yielded a better result in the project. This way they could have offered more help and direction during the sprint also.

In the end it can be argued whether end result of this project was indeed a machine learning algorithm or an algorithm that recognizes for example a duplicate payment or an even sum fraud based on the fixed rules created for it. The most effective model for recognizing frauds and errors would probably a mix of fixed rules and actual machine learning. This way the algorithm would recognize for example duplicates and unusual payments to familiar vendors. This project was though a good start for creating the perfect algorithm and it revealed many issues concerning the creation of one.

6.3 Project objectives and how they were met

The project objectives for this thesis were:
1. To find finance management cases where machine learning has been used.
2. To support the BIT students and help them to understand the main financial concepts needed in the project.
3. To help in interpreting the payment data OpusCapita sent.

Project objective one has been a challenge throughout the project. There simply is not much research done on the specific matter of machine learning in finance management cases. There is a lot written about machine learning in general and how it is used in predicting stock markets for example. So this project objective was not entirely met due to lack of information.

Project objective two was met by giving presentation to the BIT students were the finance management concepts and payment processes and frauds were explained. The presentations were given to the students as learning material to be used whenever needed.

Project objective was met buy providing detailed explanations of the payment data content and headings and contacting OpusCapita for unclear items.

6.4 Ideas for future development

There is still work to be done with the algorithm even though the basis has been created and the different methods creating it were explored at least to some extent. The payment data needs to be authentic and also more data is required for the algorithm to be able to recognize the frauds and errors in the payment data at a high certainty rate. Also the algorithm would then be able to recognize the vendor patterns, i.e. how much should be paid a month to a certain vendor.

As mentioned in chapter 3.1 if the banking program notices an error in a batch of invoices the whole batch is rejected. This should be developed so that only the ones that are suspicious are blocked and the rest go through. When the payments with errors are checked by hand they could be then sent separately.

When thinking even further ahead, it would be useful if the algorithm could recognize the payment terms used when payment is done after the invoice’s due date. For example if there is a cash discount for payments made in 14 days and the invoice is paid after that, it could flag the payment and it would be checked.

But when thinking ahead one must also think about the resources it requires to develop a machine learning algorithm. It requires professionals from many fields; this project for example had coders, machine learning expert and finance management process experts. And I learned from this project that it is difficult to find a common language with everyone. One moment I thought everyone understood one another only to realize that we were not even talking about the same thing. This might be one of the reasons why machine learning has not yet fully been utilized in finance management; it is difficult to find people who understand a little from all the required fields.

6.5 Self assessment

During this project I learned a lot about machine learning, artificial intelligence and automation. I also gained valuable knowledge about how they could be used in my profession. I also got to understand what it is like to work for a client in a project that is time-pressed and even the smallest hesitation or lack of instructions causes delays that are hard to catch up.

I did not have prior knowledge about machine learning and it was interesting to read about it and try to understand how it can be used in finance and finance management. I also did not know anything about algorithms or coding. This project helped me to understand it a little.

Working in an IT project was new for me and it had its challenges. I realized that that BIT students thought of things a little bit differently than I did, so getting my point across was difficult sometimes and also it was challenging to understand their way of thinking. Sometimes pictures seemed to help when trying to explain the account payable process. They also used pictures when explaining some of the methods they used for creating the algorithm.

Overall, this project was a great learning experience and I am glad I got to participate in it. I have gained a lot of insight into how machine learning works and how it could make my job easier and also more reliable. It helped me also to understand how much work goes into creating an algorithm that works in this kind of situations. I have come to understand that machine learning will change the financial world and the way companies work.

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Appendices

Appendix 1. Outgoing payments

HAAGA-HELIA
ammattikorkeakoulu

Lähtevät maksut

Annu Hellström & Elena Turapina
29.2.2016

HAAGA-HELIA
ammattikorkeakoulu

Sisällysluettelo

- Mikä on reskontra?
- Ostolaskut
- OpusCapita print screenit
- Duplikaatit
- Maksuliikennepetokset
- Mistä voi huomata maksuliikennepetoksen?
- Lähdeluettelo

1

HAAGA-HELIA
ammattikorkeakoulu

Mikä on reskontra?

- Reskontra on asiakkaiden ja toimittajien rekisteri yrityksen kirjanpidossa
- Reskontrassa käsitellään kirjanpidon maksu- ja laskutapahtumia
- Usein osto- ja myyntireskontran tehtävät on eroteltu osto- ja myyntireskontraan

3

HAAGA-HELIA
ammattikorkeakoulu

Ostoreskontra

- Huolehtii, että toimittajalaskut menevät ajoissa hyväksyntäkiertoon ja maksuun
- Voidaan seurata velkasaldoja eri toimittajille
- Ostoreskontran työvaiheet:
  - Tavaran tilaaminen
  - Laskun vastaanottaminen
  - Laskun siirtäminen hyväksyntäkierrokselle
  - Laskun vastaanottaminen
  - Laskun maksu

Myyntireskonta

- Huolehtii asiakaslaskujen maksusta ja perinnästä
- Tärkein tehtävä seurata asiakassaatavien saldoa
- Asiakasluettelosta löytyy kaikki avoimet laskut
- Saatavien perintä
- Mikäli maksua ei saada 1-2 maksumuistutuksen jälkeen, asia voidaan siirtää perintätoimiston hoidettavaksi tai jatkaa itse perintätoimia
- Myyntireskontran työvaiheet:
  - Suoritusten kirjaaminen ja kohdistaminen avoimiin asiakaslaskuihin pankkitililtä
  - Maksumuistutusten kirjaaminen ja lähettäminen
  - Perintätoimenpiteiden aloittaminen.

4

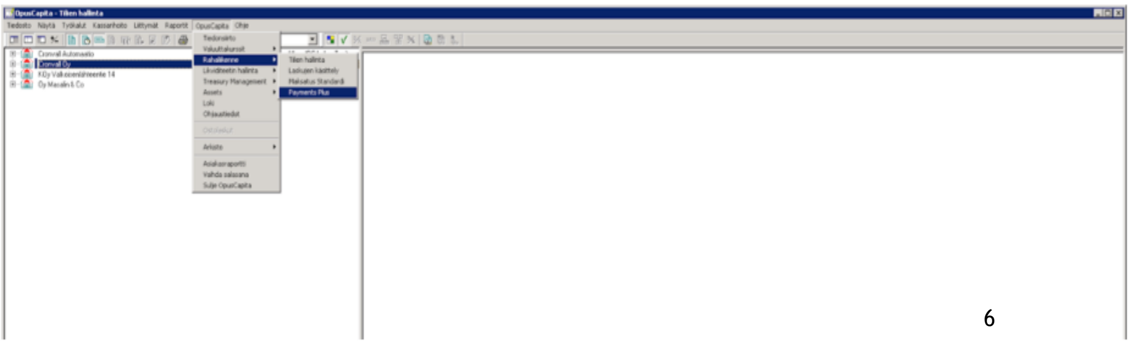
Ostolaskut

- Kirjataan ostoreskontraan (ERPn osa)
- Maksamisen osalta tärkeät tiedot:
  - Toimittajan nimi / numero järjestelmässä
  - Laskun numero
  - Laskun antamispäivämäärä
  - Eräpäivä
  - Viitenumero
  - Bruttosumma, valuutta
- Maksuaineiston muodostaminen ERPssa -> siirto OpusCapitaan

5

OpusCapita pankkiyhteysohjelmisto

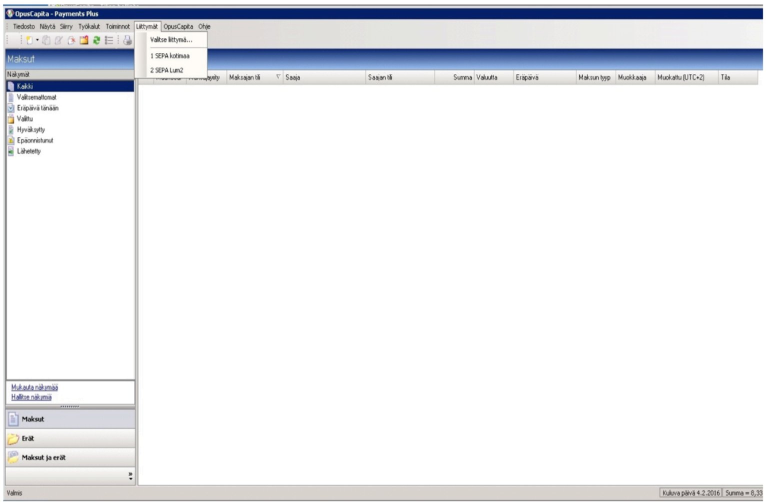
- OpusCapita Tilien hallinta – noudetaan pankeista tiliotteet, viitesuoritukset ja valuuttakurssit
- OpusCapita Payments Plus – lähetetään maksut ja palkat



6

HAAGA-HELIA
ammattikorkeakoulu

1. Maksuaineiston siirto reskontrasta

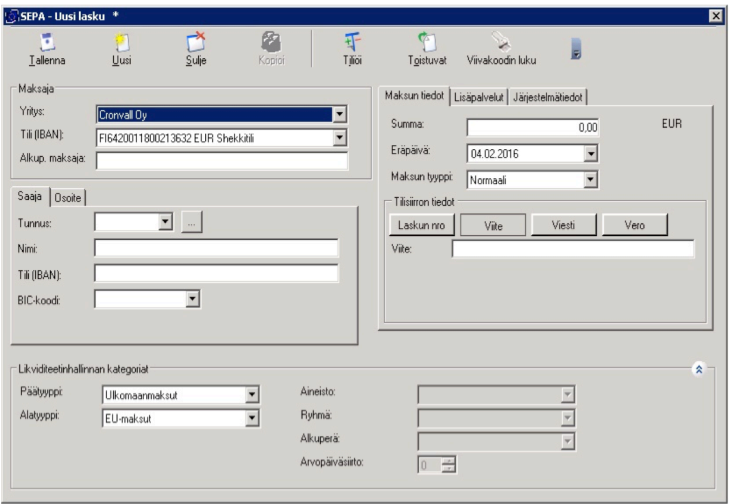


- Maksuaineisto siirretään OpusCapitaan liittymällä
- Jos maksu todettu virheelliseksi, se voidaan hylätä -> on muodostettava uudelleen reskontrassa

7

HAAGA-HELIA
ammattikorkeakoulu

2. Maksun syöttäminen käsin



- Pakolliset kentät:
  - Maksaja
  - Maksajan tilinumero
  - Saaja
  - Saajan tilinumero
  - BIC määräytyy automaattisesti
  - Summa
  - Eräpäivä
  - Viite/viesti

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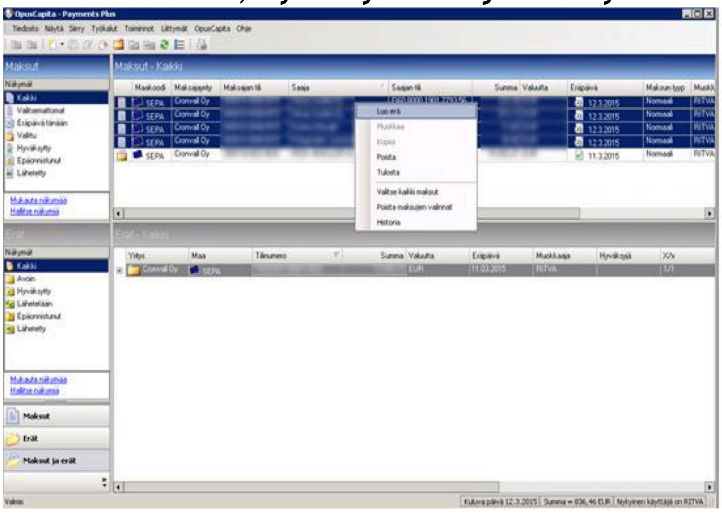
3. Maksuerät, hyväksyminen ja lähetys



- Syötetyt/tuodut laskut poimitaan eriksi
- Voidaan muuttaa vielä tiliä ja maksupvm
- Erä on hyväksyttävä
- Hyväksytty erä lähetetään pankkiin

9

HAAGA-HELIA
ammattikorkeakoulu

Duplikaatit

Lasku kirjattu reskontraan kahteen kertaan → Molemmat laskut maksetaan → Tuplamaksuista ilmoittaa useimmiten toimittaja

Lasku maksettu ohi reskontran → Suoritus on jätetty kirjaamatta reskontraan → Lasku maksetaan uudestaan reskontran kautta

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HAAGA-HELIA
ammattikorkeakoulu

Duplikaatit

Lasku maksettu väärälle tilille
Toimittajalta/ rahoitus-yhtiöltä saapuu perintäkirje
Lasku maksetaan perintä-toimistolle
Toimittaja palauttaa virheellisen suorituksen

11

HAAGA-HELIA
ammattikorkeakoulu

Maksuliikennepetokset

- Kasvava ilmiö
- Tietojen kalasteluja yrityksiltä puhelimitse ja sähköpostitse
- Huijaukset tapahtuvat sekä suomeksi että englanniksi
- Soittavat esim. ulkoistuskumppanin nimissä
- Ns. toimitusjohtajahuijaukset, jossa rikolliset lähestyvät maksuliikenteestä vastaavaa sähköpostitse ja pyytävät tekemään tilisiirron
- Tekaistut laskutustietojen muutokset

12

Mistä voi huomata maksuliikennepetoksen?

- Pyöristetyt laskusummat
- Laskun summa on juuri alle hyväksymisrajan
- Tietyltä toimittajalta alkaa tulla epätavallisen monta tai suurta laskua
- Laskuissa on outo osoite
- Palkat, vakuutusmaksut tms. maksetaan epätavallisen useasti

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Appendix 2. Frauds in outgoing payments

HAAGA-HELIA
ammattikorkeakoulu

Maksuliikennepetokset

Annu Hellström & Elena Turapina
1.3.2016

HAAGA-HELIA
ammattikorkeakoulu

Maksuliikennepetokset

- Kasvava ilmiö
- Tietojen kalasteluja yrityksiltä puhelimitse ja sähköpostitse
- Huijaukset tapahtuvat sekä suomeksi että englanniksi
- Soittavat esim. ulkoistuskumppanin nimissä
- Ns. toimitusjohtajahuijaukset, jossa rikolliset lähestyvät maksuliikenteestä vastaavaa sähköpostitse ja pyytävät tekemään tilisiirron
- Tekaistut laskutustietojen muutokset

2
01/03/16

HAAGA-HELIA
ammattikorkeakoulu

Mistä voi huomata maksuliikennepetoksen?

- Pyöristetyt laskusummat
- Laskun summa on juuri alle hyväksymisrajan
- Tietyltä toimittajalta alkaa tulla epätavallisen monta tai epätavallisen suuria laskuja
- Laskuissa on outo osoite
- Palkat, vakuutusmaksut tms. maksetaan epätavallisen useasti

3
01/03/16

HAAGA-HELIA
ammattikorkeakoulu

E-Crime/Cyber Crime

- Tarkoittaa datan vakoilua ja kaappausta, tekijänoikeus-rikkomuksia, tietokone sabotaasia, tili- ja taloustietojen manipulaatiota

- KPMG:n tutkimuksen mukaan jopa 40% saksalaisista yrityksistä on joutunut e-rikoksien uhriksi viimeisen 2 vuoden aikana

- 24.3.2016 KPMG.n webinaari "Payment transactions as a risk factor - Examples from current practice and preventive actions on fraud and e crime"

4
01/03/16

Lähdeluettelo

- KPMG 2016: E-crime in payment transactions: A call to action. URL:https://home.kpmg.com/de/en/home/insights/2016/02/e-crime-in-payment-transactions.html. Luettu: 29.2.2016.
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  Luettu: 25.2.2016.

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01/03/16

Appendix 3. Frauds and scenarios

Petokset ja skenaariot

Fraud nro 1 on duplikaatti. Täsmälleen sama laskunro (sarake AJ), summa ja muut tapahtumat kuin rivillä 2152. Rivi 2153 on myös lähellä duplikaattia, mutta laskunumero on eri.

Fraud nro 2 on duplikaatti. Täsmälleen samat tiedot, kuin rivillä 2701. Sarake AJ on sama, ja myös kellonaika (Sarake W).

Fraud nro 3 on duplikaatti rivin 2973 kanssa. Aikaleimat ovat täsmälleen samat kummassakin. (P, Q, R, V, W..) Mutta myös kaikki muut tiedot paitsi sarake D ovat samat (Payee name). Duplikaatit löytyy useimmiten niin, että vertaa onko laskunumero sama (sarake AJ), summaa, ja maksun saajaa. Lisäksi voi sitten verrata esim. Payment datea.

Fraud 4 5 ja 6 ovat tasasummahuijauksia, niin kuin arvelinkin aikaisemmin. Tämä on sisäinen väärinkäytös. Mielestäni tämä vaatii sitten jo enemmän kuin OC:n datan, esimerkiksi työntekjöiden tilinumerot. Datasta löytyy kuitenkin kaikki tiedot, kuten viitenumero. Tässä kohtaa petosta lähdetään tutkimaan summan perusteella sarakkeesta E, ja koska huomataan sen olevan tasasumma, tutkitaan myös pankkitili, sarake M, ja jos se ei ole minkään toimittajan (sarake D) on asia hälyttävä. Sen lisäksi ajattelin, että jossain tapauksissa myös viitenumero (sarake AJ) voi olla outo, mutta datassa on montaa erilaista tehdäkseni sen enempää johtopäätöksiä.

Fraud 7 on iso maksu eksoottiseen maahan. Sarakkeessa T ei ole muita HongKongiin meneviä maksuja. (Tässä kohtaa algoritmi voisi hälyttää, jos johonkin maahan on menossa maksu ensimmäisen kerran.) Kyseessä ns. CEO/CFO huijaus tai muu ulkoinen petos. Sarake X:ssä lukee myös Standard Chartered, eli kyseessä myös epätavallinen pankki, koska sitä ei löydy muualta tiedostosta.

Fraud 8 on myös iso maksu eksoottiseen maahan. Kyseessä on myös palkka-ajo (näkyy sarakkeesta K), joten se tekee myös asiasta epäilyttävän. Epäilyttävän isoa palkkaa haetaan aineistosta vertaamalla paljonko henkilölle (sarake D) on maksettu aikaisemmin palkkaa (sarake E) ja katsotaan onko joku maksu tästä poikkeava.

Fraud 9 on duplikaattimaksu toimittajalle. Sarakkeesta AJ näkee, että laskun numero on sama kuin rivillä 79893. Sarakkeesta D näkee, että kyseessä myös sama toimittaja. Näitä jos voisi jotenkin seurata, että kuinka useasti maksetaan jollekin toimittajalla, esim 1-2 kertaa kuukaudessa, niin sitten se 3. kerta on poikkeavaa ja menisi siihen virheviestiin. Näitä toimittajalle meneviä tuplia haetaan seuraamalla paljonko toimittajalle (sarake D) tyypillisesti maksetaan, esim. Onko aina sama summa vai liikkuuko se jossain välillä (esim. 20 000-30 000). Samoin voisi verrata meneekö maksu aina samalle tilille (sarake M).

Fraud 10 on käytetty samaa laskunumeroa (sarake AJ) kuin samalle toimittajalle maksettu lasku rivillä 79808. Kyseessä mahdollisesti inhimillinen erehdys tms. Summa on kuitenkin yleinen kyseiselle toimittajalle maksettu maksu.

Fraud 11 on tupla palkka-ajo rivin 82577 kanssa. Mm. sarakkeessa D sama saaja, sarakkeessa M sama saajan tilinumero. Muutenkin tiedot ovat identtiset. Koska kyseessä on palkka-ajo, tiedon voi suodattaa sarakkeella K ja/tai D, palkan saaja. Tällöin näkyy sarakkeesta G (due date) että palkka on mennyt samassa kuussa kahdesti.

Fraud 12 on tupla rivin 82920 kanssa. Invoice nr sarakkeessa AJ on sama, samoin muut tiedot summaa myöten. Samoin sarake AH:ssa on sama viitenumero.

Fraud 13 on OC:n mukaan erään kuukauden palkka-aineistosta poistettu palkkarivi. Tätä oli mahdoton löytää päättelemällä.