Late payment prediction of invoices through graph features

Master Thesis
By: Arthur Hovanesyan

TUDelft

Late-payment prediction of invoices through graph features

Arthur Hovanesyan

to obtain the degree of Master of Science,
Computer Science, Data Science Track
at the Delft University of Technology,
to be defended publicly on Wednesday December 18, 2019 at 12:30 PM.

Student number:	4322711	
Thesis committee:	Associate Prof. dr. Pablo Cesar,	TU Delft, (Chair)
	Assistant Prof. dr. Huijuan Wang,	TU Delft (Supervisor)
	Assistant Prof. dr. Christoph Lofi,	TU Delft
	Head Data Science. dr. Judith Redi,	Exact (Supervisor)

Preface

This report concludes the thesis project and with it the two-year journey towards receiving my master's degree in Computer Science. Thank you to Exact and especially to everyone in the Customer Intelligence/Data Science team for giving me the opportunity to work on such an awesome project. This was was not possible without the supervision of Dr. Judith Redi, Dr. Huijuan Wang, Dr. Bikash Joshi, Ir. Xiuxiu Zhan and of course everyone else from the team that chipped in and kept the morale high. Thank you for your guidance during the process. There are too many of you now to list. Thank you to my family and friends for your support throughout the journey. Without you all, this would not have been possible.

Arthur Hovanesyan
Delft, December 2019

Disclaimer

Abstract

Keeping a steady cash flow is one of the biggest if not the biggest problem that Small to Medium Enterprises (SMEs) deal with daily. Within the different types of cash flow, Accounts Receivable (AR) classifies the balance of money that needs to be paid by the company's customers. In the most typical case, after receiving goods or services, the customer receives an invoice with the amount that is owed to the supplier. However, this often does not happen before the aforementioned date, meaning that the invoice is often paid late. Intervention requires resources and over-intervention could cause unwanted customer dissatisfaction. Knowing whether an invoice is going to be paid late can be vital information. Current methods of late payment prediction focus only on the history between the seller and the buyer and are unusable when this history is not present. Intuitively, one's business depends on the relationships and transactions that it has with its neighbors. Suggesting that neighbor behavior could be useful when predicting the cash flow of a company. Unfortunately, this type of information is not always given and needs to be data mining from non-relational data. This work presents a method for building a relational network of SMEs using entity resolution and improving the current state of the art of late payment prediction using features extracted from the graph.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Keeping a steady cash flow is one of the biggest if not the biggest problem that Small to Medium Enterprises (SMEs) deal with daily. Within the different types of cash flow, Accounts Receivable (AR) classifies the balance of money that needs to be paid by the company's customers. In the most typical cases, after receiving some type of goods or services, the customer receives an invoice with the amount that is owed to the supplier. Making sure that these funds are received is not always an easy task. Many businesses with a typical Order-to-Cash process deal with a problem of customers that do not pay on time. Whether or not the customer can pay the debt, there is a clear conflict of interest between the customer and the supplier. In the analysis made by Pfohl et al [30], it is explained that for any financial transaction, the buyer will try to delay payment as long as possible, while the seller wants to be paid soon. Because of this conflicting interest, poor management of AR could lead to missed cash flow and financial instability if a significant portion of the customer base does not pay within the expected time frame. One way to combat the tardiness of the customers is to contact them before the delay becomes too big. However, intervention requires resources and over-intervention could cause unwanted customer dissatisfaction. Customers that are unlikely to be delaying payments do not need to be contacted. For a business to be able to intervene in a manner that is not too invasive, a decision needs to be made in which cases there needs to be an intervention. While this is important for all business, many small to medium enterprises (SME) don't have the resources to do comprehensive risk-assessment of all their suppliers and customers. These businesses often rely on third-party business software suites with customer relationship management (CRM) from companies such as Microsoft, Sap, and Exact.

1.1 Currently available solutions

Companies such as Oracle and SAP [3]have created software that can process invoices and automatically take actions as a result of that. In the case of Microsoft, users can install a plugin that gives them more insight into their sales invoices [2]. The tool provides a prediction on whether a specific invoice will be paid on time. The tool categorizes the invoice into two prediction classes; on-time and delayed. Attached to this prediction a confidence level is given. The confidence levels go from Low, Medium to High. The levels correspond to the 70%, 80%, and the 90% confidence thresholds respectively. Being a generic tool, the model has been trained on a range of small and medium businesses. Made to be able to serve different types of companies when it comes off the shelve. The model improves over time by using the user's data to retrain. Resulting in a model that will eventually be fitted on the data of the user. While the complete architecture of the solution is unclear, it does not seem to account for the possible transactions between the parties in the system. Rather, the predictions are made by solely looking at an individual customer and its history. Intuitively, one's business depends on the relationships and transactions that it has with its neighbors and that growth or bankruptcy does not happen in isolation. In some cases the customer becomes insolvent for a brief period, meaning it is not able to pay its debts. This will impact the outstanding sales, despite the customer being trustworthy or not. UK's association of business recovery professionals (R3) [17] explains that around 27% of insolvencies are triggered by the insolvency of another company. Adding that there is some type of "domino effect" in play. This suggests that a company's ability to pay off invoices is dependent on the insolvency of its suppliers and customers. Which in turn, also depends on further relationships. While this relational information can be beneficial, this type of data is not always available. Moreover, in cases where it is, the data is not guaranteed to be in a standardized form, rich enough that it can be used to construct a reliable network. Given this unstandardized dataset, entity resolution can be used to find the unique companies or entities in the dataset. These data mined entities can, in turn, be used to create the nodes of the desired networks. With edges in the network representing the transactions between these companies. Once the network is constructed different methods can be used to extract features from the graph. Besides features such as average degree and edge weights, in the last several years it has become more and more popular to use embedded representations of the network as features. The reason this needs to be done is that graphs cannot directly be used in machine learning algorithms, as this data needs to be Euclidean to do so. While the graph embedding concept is not new, the recent breakthroughs in deep learning and more specifically computer vision and representation learning, have inspired new methods that make graph embeddings very efficient and scalable. Making these methods usable on networks with billions of nodes and edges. While showing promising results fields of recommendation [35] and drug discovery [12].

1.2 Exact

To make this research possible, the experiments are performed using the data provided by Exact. Exact is a software company that is specialized in software for accounting, ERP, CRM and other types of software for Small to Medium Enterprises (SME). As of writing this report, the online platform has 400k users with the majority being in the Netherlands. It is estimated that approximately 20% of Dutch SMEs use Exact software. Exact strives to improve its products by incorporating features that help its customers grow. Because of the large impact that cash-flow has on these businesses, it is in Exact's best interest to help their customers manage their receivables. Chapter 4 will describe the software and how it is used in more detail.

1.3 Problem Definition and Research Questions

The described problem can essentially be split into two major parts:

1. Creating a network of Dutch SMEs from unstandardized and noisy data.
2. Improving the current methods of late payment prediction using features extracted from the network.

The thesis also provides an end-to-end solution, of how data about the business supply chains can be used to build a network of SMEs through entity resolution. Furthermore, it shows how this network can be leveraged through methods such as graph embedding, to improve the predictions of late-payments.

The focus of this thesis is to see whether the addition of features extracted from a graph of related companies can improve the accuracy of late payment predictions. To do this we define the following research question and underlying sub-questions.

- *MQ: Can graph features be used to improve the prediction of late invoice payments compared to currently popular methods?*

This is done by answering three separate sub-questions:

- SQ1: How can a network of SMEs be built from data that is unstandardized, noisy and partial?
- SQ2: How should the data and the graph be structured to be able to extract meaningful features?
- SQ3: Does the addition of graph features improve the prediction of late payments?

The defined method and experiments all try to answer one of the sub-questions. An overview of the experiments and which sub-question they try to answer can be found in chapter 6.

1.4 Contributions

Answering the predefined research questions, the contributions of this thesis can be summarized with the following:

1. A novel method for entity resolution that can be used on large scale, unstandardized, noisy and partial datasets.
2. A novel method for late payment prediction that not only combines node embeddings to improve the current standard of prediction but also makes it possible to make predictions when no historical data about the buyer is available.
3. Demonstration of both entity resolution and late payment prediction on a use case that has not been seen in the literature.

1.5 Report structure

The the complete outline of the report is as follows: In Chapter 2 we make an extensive review of the literature surrounding the topics of *entity resolution*, *late-payment prediction*, *graph embedding* and *analysis of complex networks*. We will first look at how the taxonomy is defined around these topics, their use cases, and their limitations. Chapter 3 will describe how the first problem of the thesis is tackled and more importantly how the network of Dutch SMEs is built. Chapter 4 shows how companies within the network interact during invoicing and how this is observed within Exact's system. In Chapter 5 we will describe how what the methods will be used to solve the proposed problem. Chapter 6 describes further experimentation using the created network to answer the defined research questions. Further, section Chapter 7 discusses the results gathered from the experiments and Chapter 8 gives a summary and concludes the research by answering the research questions. Finally, in section Chapter 9 we give a series of possible additions that could benefit the research in the future.

Chapter 2

Related Work

To be able to understand the problem further and see what the different solutions are currently available, we review the available literature. To scope the literature we look at the different tasks a company would have to tackle to be able to perform late-payment prediction based on a network of their customers.

2.1 Late payment prediction

The literature surrounding this topic shows different types of methodologies applied for customer scoring and determining whether there is a need for intervention.

Kim et al. [19] gives a taxonomy of categories where predictive models used in customer relationship management (CRM) can be divided into response models, churn prediction models, fraud detection models, and insolvency prediction/late payment prediction models. Both insolvency and late payment predictions are a variation of the credit scoring problem, where the goal is to define a score that corresponds to the inverse likelihood of a customer to default on some type of payment. The line between the two is drawn in the application of the model. Insolvency prediction models are used before a service is provided to a customer, predicting whether the customer will be able to raise enough money to meet its obligations. Late-payment prediction models are used on a more granular level, predicting when specific payments (i.e invoices) are going to default. While credit scoring is a well-researched topic, there has been very little research done in regards to predicting late payments.
Zeng et al. [36] show how late payment prediction could be done through machine learning. This was done by gathering invoices from four different firms including 2 fortune 500 companies, which were sent to different companies around the world. Next to basic invoice information such as entry date, due date and amount, the dataset also contained the delay of payment for every invoice. Ranging from 0 to more than 90 days. For this task, several decision tree algorithms are used such as PART and C4.5. Trained on the data to be able to predict the size of the delay in terms of five classes: no-delay, 1-30 days, 31-60, 61-90 and 90+ days. Zeng compares the difference between training a model for each separate firm and training one model on all data. The author concludes that training the model on combined data from all companies gives a significant improvement in terms of accuracy in all cases. This suggests that invoices sent by different companies (or at least those specific four companies) share similar behavioral patterns.

Similar approach was used in [15] and [16]. Hu in [15] tested the models in two separate scenarios:

- Scenario One (Binary outcome): Predicting whether an invoice is going to be paid on time (True/False)
- Scenario Two (Multiple outcomes): Predicting whether the invoice belongs to one of four delay classes: no delay, short delay (within 30 days), medium delay (30-90 days) and long delay (more than 90 days).

The author compared the results of five different models when trained on the dataset. These models are Decision Tree (DT), Random Forest (RF), AdaBoost (AB), Logistic Regression (LR) and Support Vector Machine (SVM). Overall, the Random Forest classifier seemed to give the best results. The most important features in both cases were "delay ratio" and "average days of delay" of the customer.

When looking at the multiple outcome scenarios, longer delays are the worst type of delay for the business. Additionally, classifying an invoice as "no-delay" when it is actually delayed by more than 90 days is a bigger mistake than classifying it as "delayed between 30 to 90 days". To solve this and the imbalance in

	Paper				
Feature	**Zeng [36]**	**Kim [19]**	**Cheong [8]**	**P Hu [15]**	**W Hu [16]**
amount	x	x	x	x	x
payment_term	x			x	x
number_of_paid_invoices	x		x	x	x
number_of_late_payments	x		x	x	x
ratio_paid_late	x			x	x
sum_paid	x	x		x	x
sum_paid_late	x	x		x	x
ratio_sum_paid_late	x			x	x
mean_delay	x			x	x
average_amount			x		
outstanding	x				
average_amount_outstanding	x				
outstanding_sum_amount	x				
account_manager	x			x	
billing_cylce			x		
intervention_count			x		
demographic		x			
products_used		x	x		

Table 2.1: Table showing which features have been used by different methods. Crossed cell "x" shows that the feature has been used, empty cell shows that the feature was not used.

the dataset, the authors use cost-sensitive learning. This is done by changing the weight of the cost matrix, setting higher weights for further away classes. To show that their method performs significantly better than a possible heuristic, as a point of reference both papers use the majority class as the baseline to see whether their methods improve compared to a weighted random guess.

An interesting insight between the papers [36] and [15], is that the datasets show similar class frequencies. In both cases, the majority class seemed to be invoices that are paid with a delay between 1 and 30 days. With the no-delay class being the second most frequent. In further analysis, [15] showed that there is no correlation between the amount invoiced and the delay of the payment. However [16], showed conflicting results. In this case, the amount of the invoice was the most important feature for the RF classifier.

The authors in [36][15][16] argue that to be able to predict whether a customer will pay the invoice, there have to be two levels of features. Namely features on invoice level and customer level. Invoice level features consist of information present on the invoice such as Payment Amount, Payment Term, Entry Date, Due Date, Payment Date, etc. Customer level features consist of information gathered from the history of previous invoices. With features such as Number of paid invoices, Number of delayed invoices, Ratio of delayed invoices, Average payment term, etc. In [19] the authors make use of additional features. The dataset was provided by a Korean broadcast service company where product and demographic information is available. This information consists of the type subscriptions the customer has (i.e. cable TV, Internet, etc), how long these products have been used and the demographic information: age and gender. Table 2.1 shows a complete overview of the discussed papers and the features that they use for their proposed method.

Across all papers discussed, customer level features play a major role in the prediction of the invoice. In all cases, invoices where customer information was missing (i.e. first-time customers) showed significant loss in accuracy. Moreover [16] shows that the prediction accuracy increases as the number of invoices per person increases.

The authors in [19] used a similar set of classifiers in addition to a two-layer Neural Network (ANN). The paper describes that these models are combined to, in most cases, give better results. This is done by using a simple average of the prediction probabilities of all trained models. Compared to the ensemble approach, the results show that RF gives the best results when it comes to individual models. The goal of the paper was to give a fair allocation of customers to the support agents. It shows that the supervised models outperform the general heuristic rules of allocation.

While these works predicted the likeliness of a particular invoice being delayed, [8] looked at how likely a customer was to delay payment. This subtle difference brings the method closer to the credit-scoring prob-

	Paper				
Model	**Zeng [36]**	**Kim [19]**	**Cheong [8]**	**P Hu [15]**	**W Hu [16]**
Classification	multi-class	binary/multi-class	binary	binary	binary
Logistic Regression	x	x	x	x	x
Naïve Bayes	x				
Decision Tree	x	x	x	x	
AdaBoost				x	
C4.5	x				
PART	**X**				
Random Forest		**X**		**X**	**X**
Neural Networks		x	**X**		x
SVM			x	x	
KNN					x
Ensemble		**X**	x		

Table 2.2: Table showing the classifiers used by the used by different methods. Crossed cell "x" shows that the model has been used, the larger cross shows that the model gave the best results for that problem.

lem while still using invoice data to do so. The authors show that customers from smaller companies, tend to be late more in payments. Additionally, a new measure is provided to give an idea of customer "pureness". Where if pureness=0, the customer will always delay the payments, and if pureness=1, the customer will always pay on time. The pureness metric is defined by the following formula:

$$Pureness = W_1 \cdot \frac{\text{number of invoices paid on time}}{\text{total number of invoices}} + W_2 \cdot \frac{\text{sum of value of invoices paid on time}}{\text{sum of value of all invoices}}$$

Weights 1 and 2 are set manually by the user of the model to emphasize either of the ratios. The paper concludes shows that the ANN approach outperforms the other models provided by SAS Enterprise.

Because of the similarity between the credit scoring problem and the late-payment prediction. It is also interesting to look at the methodology used for those cases. Zhou et al. [40] surveys the current state of the art of credit-scoring. Besides the general supervised learning methods that are also used in late-payment predictions such as LR, DT, and RF. There are also unsupervised and semi-supervised methods used for credit scoring. The unsupervised method that is highlighted by the paper is the K-Means algorithm. The benefits of the unsupervised methods are that there is no need for labeled data, which often is hard to come by.

To summarize, table 2.2 shows an overview of the papers on late-payment prediction and the algorithms that were used for their problem.

2.2 Financial transactions

Financial transactions can be modeled as a dynamic graph to analyze the interaction between different financial bodies. Work done by [33] explores different types of metrics in an economic system model as a complex network. The network explains monetary transactions between 105 clusters, each representing an economic activity standardized by the UN. The paper provides the following two contributions: A Network definition that is as follows:

- Node, is an economic activity cluster, with the node weight being the summed transactions within the cluster.
- An undirected Edge is present when money flows between two sectors. Its weights show the summed money flow between two clusters in either direction.

The paper applies different metrics (such as the distribution of degrees and correlations between neighbors) to find the following insights:

- Activity clusters with a large internal flow tend to cooperate with many other clusters via high volume monetary transactions.

- Activity clusters with a lower internal transaction volume prefer to transact with fewer neighboring nodes that have a higher internal flow.
- The node weights seem to follow a power-law distribution.
- Activity clusters tend to balance the monetary volume of their transactions with their neighbors, reflected by a positive link weight correlation around each node.

Graph-based approaches are also used in the domain of risk assessment and fraud detection. [22] shows an example of how graph-based semi-supervised learning can be used to improve an existing fraud detection system. The authors highlight that in networks of transactions, the presence of hubs can harm the fraud classifier. These hubs are nodes with a high degree and thus neighbors to a large number of nodes. As these nodes accumulate a large number of transactions, they tend to accumulate a large amount of risk score. To solve this issue the risk scores are normalized by the node degree.

2.3 Graph analysis and feature engineering

Graph embedding methods have seen a spike in interest and application in the last couple of years. These graph embeddings make it possible to encode graphs, making it possible to use graphs as input in various machine learning algorithms. This was previously not possible due to the non-Euclidean nature of graphs. Besides embedding, the most basic way to represent a graph is by encoding it as an adjacency matrix. However, as every row only contains information of the neighbors of a single node, adjacency matrices are a very sparse and thus inefficient representation of the graphs. Within these matrices, there is no notion of similarity if two nodes do not share any neighbors or labels. Preferably, we would like to have an embedding that lets us compare nodes (or other aspects of graph structure) that are far from one another. Representations gathered from graph embedding make this possible.

The concept of graph embedding itself has been present for decades and closely associated with dimensionality reduction. In dimensionality reduction the goal is to represent a n x m matrix as a n x a matrix, where $a << m$. While dimensionality reduction is beneficial, in representation learning it is not required. The goal of the representation is to map the graph to a latent space that makes the information used for other tasks, even if the dimensionality does not decrease. Works such as [34], [7], [39], [6] have surveyed the different graph embedding methods, describing their benefits, limitations, and taxonomies categorizing them. The surveyed works show examples of graph embedding being used in tasks such as classification, clustering, link prediction, anomaly detection, and visualization. The embedding methods can encode a complete graph or different parts of the graph to a set of vectors. Based on the output granularity, the embedded output can be divided into four different output types. Namely node embedding, edge embedding, hybrid embedding, and graph embedding. The type of output depends on the desired application and the embedding algorithm that is used.
Generally, the embedding algorithms are categorized by its method:

- Matrix Factorization: the embedding is achieved by factorization of the adjacency matrix.
- Random Walk based Deep Learning: uses the SkipGram architecture to learn effective embeddings of random walks generated from the graphs.
- Non-Random walk Deep Learning: these methods leverage network architectures such as autoencoders or graph convolution layers to embed the input.

In the next few segments, we will take a closer look at the different types of graph embeddings and their applications.

DeepWalk [29] was the first to use random walks in combination with the SkipGrams to embed nodes into a latent space. SkipGram is a language model that maximizes the co-occurrence probability among the words that appear within a sentence. The DeepWalk method argues that random walks in a graph, starting from a seed node, can be seen as sentences of nodes. These sentences are used as context for the SkipGram model, optimizing the co-occurrence of neighbor nodes in the walk. As the number of nodes in these networks can increase to million or in some cases even billions, the softmax layer of the SkipGram is replaced by a Hierarchical Softmax layer. Instead of predicting the isolated individual nodes, the problem is turned into maximizing the probability of traversing a specific path in a binary tree. Within this binary tree, the leaves are the individual nodes of the network. This reduction of the output layer significantly reduces run-time, with a slight reduction in accuracy as a trade-off. Once the training is done, the output layer is removed, leaving the input layer and the embedding layer. The remainder of the model can be used to embed any arbitrary node from the network. Following the introduction of DeepWalk, works of LINE [32] and Node2Vec [13] showed improvements in terms of random walk strategy and alternatives for Hierarchical Softmax.

Node2Vec [13] provides an extension to the framework of DeepWalk [29] by introducing a biased method of a random walk. According to the authors, nodes within a graph can share similarities based on the following two aspects:

1. Nodes that are highly interconnected and belong to similar network clusters or communities should be embedded closely together (homophily)

2. Nodes that have similar structural roles in networks should be embedded closely together (such as hubs, bridges)

Unlike homophily, nodes with structural similarity do not have to be closely connected. real-world networks often show both of these equivalences among similar nodes. To find these similarities there needs to be a trade-off between exploring the network in the search for structurally similar nodes, but also exploring the direct neighbors that possibly belong to the same community. To be able to benefit from these aspects, the authors introduce a bias into the random walk that increases either exploration or exploitation.
Random Walk methods have been one of the first scalable methods that have been available for graph embedding of large graphs. However, more recently deep learning methods have been becoming more popular in the literature. This is due to the success achieved by the work done in deep neural network architectures such as Convolutional Neural Networks (CNNs). One of the first attempts to make the convolution kernel generic enough to be applicable for graph-structured and 3D data was done using spectral convolutions [4]. While very promising, the spectral graph convolution requires the computation of the eigendecomposition of the graph laplacian. The theoretical complexity of the decomposition is equivalent to the complexity of matrix multiplications. With a naive method, this can be done in $O(n^3)$. Methods such as the Coppersmith–Winograd algorithm [10] can reduce the time to $O(n^{2.373})$. However, even with this speedup, the method quickly becomes expensive if the size of the graph is increased. Work that was done in Kipf et al. [20] shows that the graph convolutions can be done in linear time and used for semi-supervised classification to propagate node labels. This method is similar to the Weisfeiler-Lehman algorithm where the hashing step is replaced by the convolution. One of the important contributions of this work is that the graph convolution can now be used on large graphs and even run on GPU's. This greatly reduces the run-time compared to the random walk method which cannot be run in parallel. The graph convolution method has some limitations in terms of application. For example, the embeddings do not take into account the direction of the edges, nor the weights of the edge.

The graph convolution operator has sparked a new set of neural networks and is defined by the literature as Graph Convolutional Networks (GCN) or Graph Neural Networks/Geometric Neural Networks (GNN). An example of its use is work done by Monti et al. [26]. The paper describes how cascades of twitter retweets can be used to predict whether a website contains fake news. Cascades are subsets of the social graph. Every cascade contains the propagation of the information (in this case tweets containing URLs) after several timesteps. Monti et al. propose a model that takes a cascade information as input in the form of a graph and uses two graph convolution layers in combination with pooling to predict weather the retweets contain fake news.

After training the network, the output from the second convolution layer is visualized with t-SNE. The visualization in fig. 2.1 shows that the learned features clump together samples of the same class.

The choice of embedding method depends on the task at hand. When it comes to comparing the Random Walk methods to the GNN's, the biggest difference between the two is that while Random Walk is optimized for representation, the GNN methods are end-to-end and thus are optimized for the task at hand. Arguably, the end-to-end methods should result in more accurate models since it is directly optimized for that. However, the benefits of learning a representation is that it can be done completely unsupervised. This means that there is no need for labeled data (which often is not present and costly to get) or a model to be trained to achieve the embedding.
The discussed methods are still a major topic for research. Cai et al. [6] categorize different problem settings, graph embedding methods shown in the field and, analyses the advantages and disadvantages of these methods. The author describes the four research directions for the fields of graph embedding:

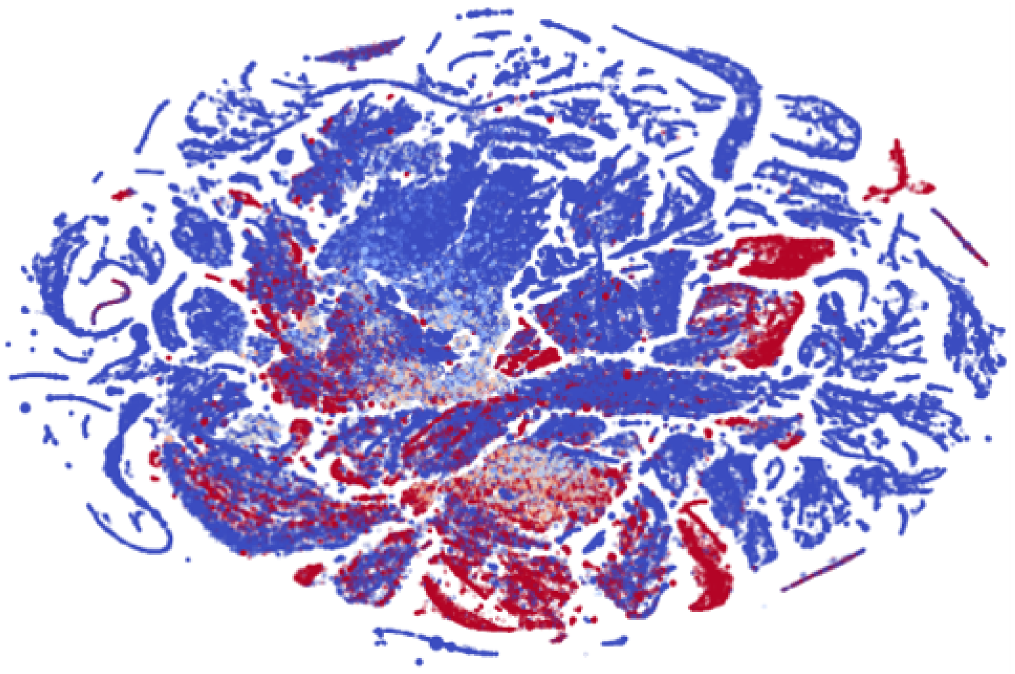


Figure 2.1: t-SNE representation of the features before the classification layer.

- Computation. The deep architecture, which takes the geometric input (e.g., graph), suffers from a low-efficiency problem. Traditional deep learning models (designed for Euclidean domains) utilize the modern GPU to optimize their efficiency by assuming that the input data are on a 1D or 2D grid. More work is needed in researching how to be able to use GPU's for graph input data.
- Problem setting. Existing graph embedding mainly focuses on embedding the static graph and the settings of dynamic graph embedding are overlooked. How to design effective graph embedding methods in dynamic domains remains an open question.
- Techniques. Current edge reconstruction based graph embedding methods are mainly based on the edges only. The global structure of a graph (e.g., paths, tree, subgraph patterns) is omitted. Intuitively, a substructure contains richer information than one single edge. An efficient structure-aware graph embedding optimization solution, together with the substructure sampling strategy, is needed.
- Applications. It is of great importance to exploring the application scenarios which benefit from graph embedding, as it provides effective solutions to the conventional problems from a different perspective.

2.3.1 Feature engineering

Since networks cannot directly be used as input in machine learning models. The problem of prediction relies primarily on the quality of engineered features. Therefore, it is important to have effective techniques that extract meaningful features from the networks. A well-known problem in this domain is the problem of link prediction, where the goal is to find missing links in a network using information about the nodes. Mutlu et al. [27] shows a taxonomy of the graph features primarily used for link-prediction (fig. 2.2). In addition to this taxonomy, works such as [23] that structural features such as graphlets can be viable depending on the problem domain.

Promising work by Zhang et al [38], shows that the combination of several techniques can be very beneficial. The authors show that the graph structure features such as Katz index, rooted PageRank and SimRank are different from the latent features learning with graph embedding methods. With this insight, a new framework is proposed named SEAL. The framework uses three types of features to predict the likelihood of a link existing between two nodes. The used features come from: a GNN method called DGCNN, embedding made

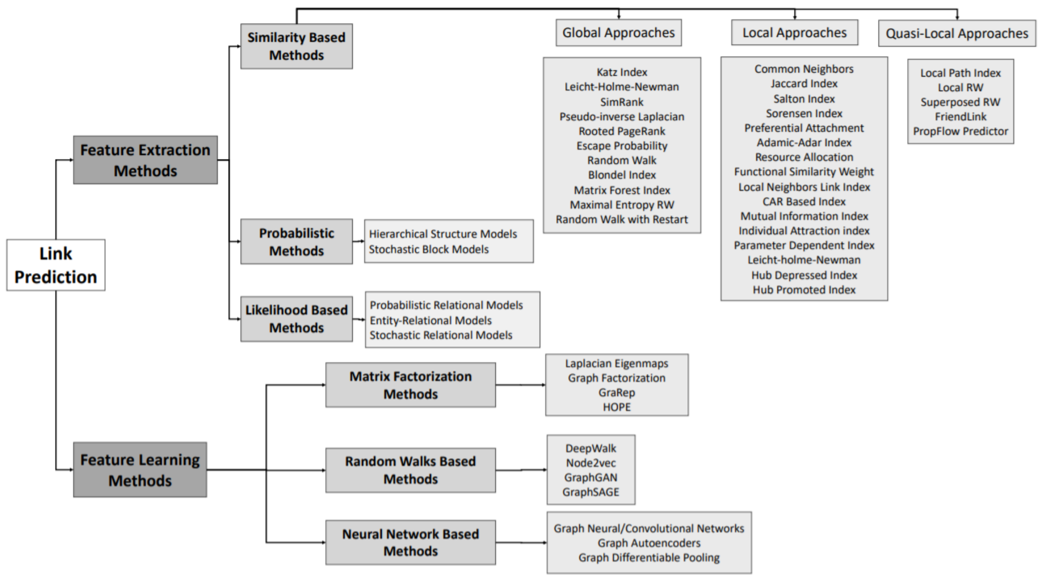


Figure 2.2: Taxonomy for the feature extraction techniques and feature learning methods for link prediction studies.

Name	Formula	Order
common neighbors	$\lvert\Gamma(x) \cap \Gamma(y)\rvert$	first
Jaccard	$\frac{\lvert\Gamma(x)\cap\Gamma(y)\rvert}{\lvert\Gamma(x)\cup\Gamma(y)\rvert}$	first
preferential attachment	$\lvert\Gamma(x)\rvert \cdot \lvert\Gamma(y)\rvert$	first
Adamic-Adar	$\sum_{z\in\Gamma(x)\cap\Gamma(y)} \frac{1}{\log \lvert\Gamma(z)\rvert}$	second
resource allocation	$\sum_{z\in\Gamma(x)\cap\Gamma(y)} \frac{1}{\lvert\Gamma(z)\rvert}$	second
Katz	$\sum_{l=1}^{\infty} \beta^{l} \lvert \text{walks}^{\langle l\rangle}(x,y) \rvert$	high
PageRank	$[\pi_x]_y + [\pi_y]_x$	high
SimRank	$\gamma \frac{\sum_{a\in\Gamma(x)}\sum_{b\in\Gamma(y)} \text{score}(a,b)}{\lvert\Gamma(x)\rvert\cdot\lvert\Gamma(y)\rvert}$	high

Figure 2.3: List of heuristic features used by the SEAL model for link prediction.

by node2vec and a list of heuristics that can be seen in fig. 2.3. The paper shows that the information from different types of features gives an increased generalized performance. With the use of heuristic features alone, in some cases, the model performed at a similar accuracy as a random guess.

2.4 Entity Resolution

Entity Resolution (ER for short, also known as Entity Matching, Entity Disambiguation, Record Linkage) describes the problem of finding unique entities from either single or multiple data sources [31]. The paper done by Konda et al. [21] describes that while there has been an effort made in understanding the problem there is very little to no published work on ER in practice, end-to-end. The general outline of the paper is to show the methodology and workflow of doing ER in a real-world scenario. It argues that every unique case needs experts to differentiate the records and heuristics. The paper contributes a description of a real-world application, the goals set by the stakeholders involved and a description of the common ER challenges in real-world applications.

The authors describe the first step to be setting up the matching rules:

1. Two records are a direct match if the unique ID is the same in both records.
2. If Titles are similar.
3. If similar individuals are involved.

The second step is blocking. In this step, candidate matches are excluded based on some rules. These rules are in this case heuristic thresholds. After the candidates were made, the data were manually labeled by a trained student (only 300 matching pairs were labeled). Train several Sci-Kit learn [28] classifiers until the best one was found. The author describes non-matching rules, to be rules that when true remove the candidate. Similar to blocking. The paper argues that the best method for ER would have a combination of ML and rule-based methods as matches.

In Chapter 3 we will further look into Entity Resolution and how it is used on the data provided by Exact.

Chapter 3

Entity Resolution

As previously mentioned one of the goals of the proposed framework is to create a network of Dutch SMEs that can be used for further network analysis and feature extraction. The way this is going to be tackled is by proposing a tailored method for recognizing unique companies in the data and building relationships between them. In the next sections, we will take a closer look into how the data of the accounts are set up, what the challenges are in building the network of companies, and how the proposed method tackles them.

3.1 Division-Accounts

With the software suite from Exact, companies and accountants can do their bookkeeping digitally. This and many other functionalities fall under the cloud solution, Exact Online (EOL). Within the EOL framework, there exist three levels of accounts. Level 1, the upper level, also called the Account, refers to a single license that an entity has purchased to be able to use the software. A single license contains administrations of several companies. For example, an accountant can purchase a license to do the bookkeeping for multiple administrations. These administrations are considered level 2. A single administration or division is a single entity that has its bookkeeping done in the system. These businesses have a collection of (Division-)Accounts which are other business entities they do business with. Depending on the business these can be either companies or any other private customer. With almost 400,000 unique divisions, the majority of these companies are situated in the Netherlands. This segment covers roughly 20% of the dutch SMEs. As this is a major segment of the Dutch market, there is a high probability that if a division sends an invoice to a company, and it happens to be an SME, that it is an administration in EOL. However, to be able to recognize that this is indeed the case, the available information needs to be cross-compared to the accounts in the dataset. To see how this can be done, we look at what type of information is available with each account.
Following this, level three will be referred to as Accounts or Division-Accounts, level two will be referred to as Divisions or Administrations and Level one will be referred to as Licenses.

In the following sections, we will look at how we can solve the deduplication problem in a dataset that contains noisy unstandardized data. The problem of deduplication is a special case of record linkage. Where instead of linking several datasets together, records that represent a single entity within a single dataset are grouped. The goal of deduplication is to transform a dataset containing duplicate records to a smaller dataset containing all unique entities. Which in this case are Dutch SMEs.

3.2 Problem of record matching

Data has been the crude oil of the twenty-first century and has been the driving force behind the changes in how companies service and do business in general. However, clean structured data is often very hard to come by. Especially when it comes to SMEs, which often do not have designated data science roles. Moreover, the needed data is often spread over different sources and needs to be integrated so that can be used to generate useful insight. Of course, these data sources often come from different parties or vendors, are unstandardized, noisy and partial. By some [1], the problems of data integration and approximate data deduplication are considered as the biggest problems in the world of data.

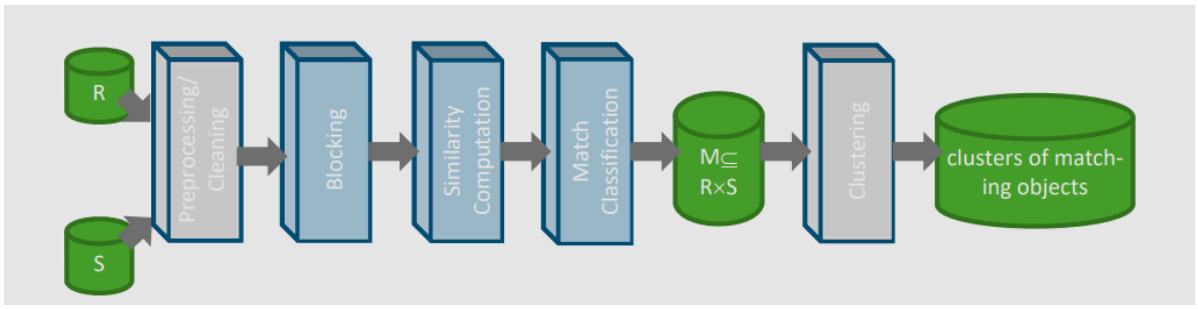


Figure 3.1: Generic pipeline of ERA

The data provided for this project was a dataset containing divisions(customers of Exact) and all of their accounts. Every account contains information of one or more companies/persons that division is doing business with. As this information can come from various sources, the data is not standardized and in most cases is incomplete. Two divisions can do business with the same supplier but have different information in almost all fields of the account. For example, the given name strings could look like one of the following: "Albert Heijn", "Albert Heijn | Allerhande Kookt", "AH" or "Alfred Heijn". Looking at the company names, if one has heard of Albert Heijn it would be easy to distinguish the four cases from each other. This is because we know what the abbreviation stands for and we are familiar with other aliases that the company has. However, it is very difficult to do this fully automatically. Besides, there are different types of information that could to be taken into account, such as address and other account details. To get a complete picture of which records are similar to each other, one would have to cross-compare all available records. While this possible for small databases, cross-comparison quickly because impossible when the sets grow to millions or billions in size. Another method would be to use a clustering algorithm that groups records together that a similar based on some metric. However, the time complexity of algorithms such as DBSCAN is quadratic in the worst case, and thus unscalable for datasets of millions. Without even considering the difficulty of defining the similarity metric for the task. To make the matching algorithm scalable and effective, there needs to be series filters and optimizations that avoid making extra comparisons. To give an overview of these steps, the next section will define the pipeline for resolving entities.

3.2.1 Generic ERA pipeline

Rahm et al. [31] give a generic overview of how an Entity Resolution Algorithm(ERA) looks like if it generalized as a pipeline of steps. This can be seen in fig. 3.1

A generic ERA method achieves final clustering of records about the same entity using the following steps:

1. Preprocessing: in the first step of the pipeline, the records are standardized and cleaned as much as possible to make the following steps easier to achieve. This can be simple sanitation or simplification of input using domain knowledge.

2. Blocking: as cross-comparison is not possible if the dataset is large enough, records are pre-grouped in blocks or clusters. Once this is done, records inside the block are then cross-compared. The benefit of this is that the comparison is only done on records that already have something in common. For example, a block could be all records that have a specific postal code.

3. Similarity comparison: In this step, different similarity metrics are calculated to create sets of features. These are used in further steps to distinguish matching from non-matching records. An example of these features is the edit distance between two names.

4. Classification: Once the features are made, a classifier is used to find the matching records. This classifier is trained beforehand using a dataset that is defined for this specific task.

5. Clustering: Once the records are compared and classified, it is important to have a strategy that clusters the records into specific entity clusters. This is needed because records can match to several different records or entities. Especially when the data is noisy, this can be a major problem. The clustering makes sure that there is a split in groups of records that all belong to a specific entity. Without this final step, the entity groups implode to a small number of entities.

As previously mentioned, one of the biggest problems with entity resolution is that no one solution fits all cases. This is primarily because generic methods don't scale to larger sizes of the dataset. This often depends on the approach to be tailored for the problem at hand. While there has been work done on ER on public datasets, there has been little work done on ER in practice. Because of this, a custom ERA method has been developed to find the unique groups of records within the data of Exact.

In further sections of the chapter, the focus will be on how the data is constructed and what steps are taken to build a graph of Dutch SMEs using a tailored ERA method.

3.2.2 Data definition and preprocessing

Before we go into the further steps, we look at how the data is defined and how it is pre-processed. Every account consist of the following information:

- Name: The name of the organization or person. (Required)
- Address: The address at which the organization or person resides. It can also be a registered mailbox to receive mail. (Optional)
- Postal code: The postal code of the address. It can also be the Postal Code of the mailbox. The combination of the postal code and address number is unique. (Optional)
- Email: The email address of the organization. It can also be the email address of a contact person in the company. (Optional)
- Phone: Phone number of the organization, support line or contact person. (Optional)
- Website: Website of the organization (Optional)
- Chamber Of Commerce/Kamer van Koophandel (KvK): This is a unique identifier that every company in the Netherlands has (Optional).
- VAT Number: Identifier used for tax filing, also unique in the same manner that KvK is. (Optional)
- IBAN: Bank account number of the organization (Optional).

Importantly the user of the system does not have to fill in any of the fields except for the company name. Unfortunately, while key fields such as KvK and VAT are very useful when matching accounts together, they are only present in a small fraction of the accounts. Figure fig. 3.2 shows the number of records that contain a value in the presented fields.

As can be seen in the figure, only roughly 12% of accounts contains a KvK number, and even less has a VAT number. When we compare these two sets, we can see that while there is a lot of overlap between these accounts. Figure 3.3 shows the relationship between these sets.

However, we can see that if we group records by their respective KvK number, the majority of the groups has multiple VAT numbers among the clustered records. While having (had) different VAT or KvK numbers for one specific company is possible, because of the change in ownership, this makes it hard to group records by a single value. Even more so because the input information is not standardized by any method and is completely up to the user.

The first step of the pipeline is the preprocessing step. During this step, we try to filter out as many unusable accounts as possible and standardize as many of the values as possible to make our life easier in further steps. For example removal of characters that are not used in the alphabet and more specifically, noisy terms. As a large number of these accounts are names of organizations, they often have their legal status in their name. For example *My Company LLC*. The LLC, in this case, describes that the organization is a Limited Liability Company, similar to a BV and VoF in the Netherlands. Whether or not these terms should be removed depends on further methods of comparison. While the legal status gives useful information in terms of context, similarity metrics that look at overlap in characters will find similarities only because the companies share the same legal status. As we are using such metrics, as will be explained in further sections, the legal terms have been removed from the account name. If use case and memory permits, it is possible to extract the legal status from the name and use it in further steps or other applications. However, in our case, this information was taken out to keep the columns in the dataset as manageable as possible.

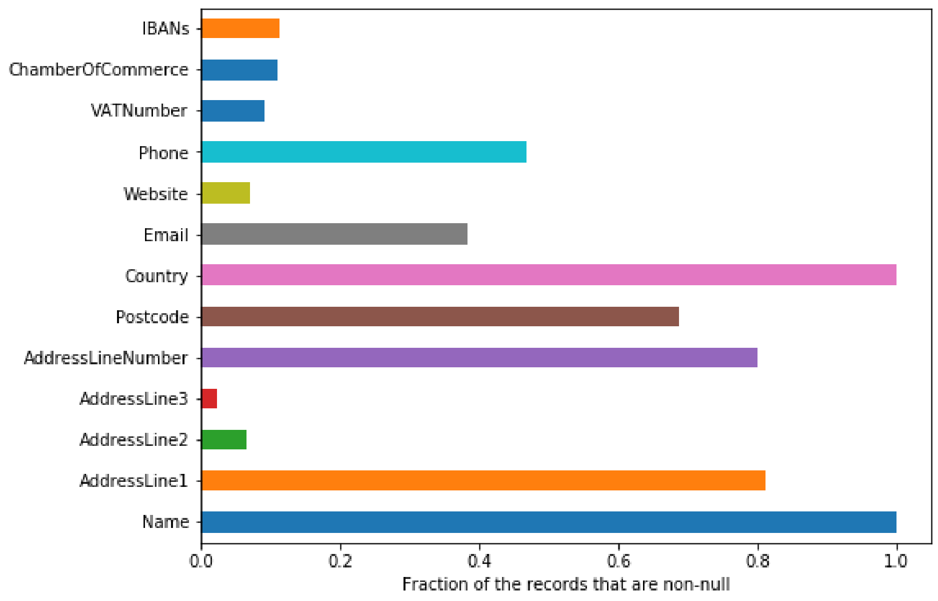


Figure 3.2: Overview of how many fields of the given accounts have been supplied with information.

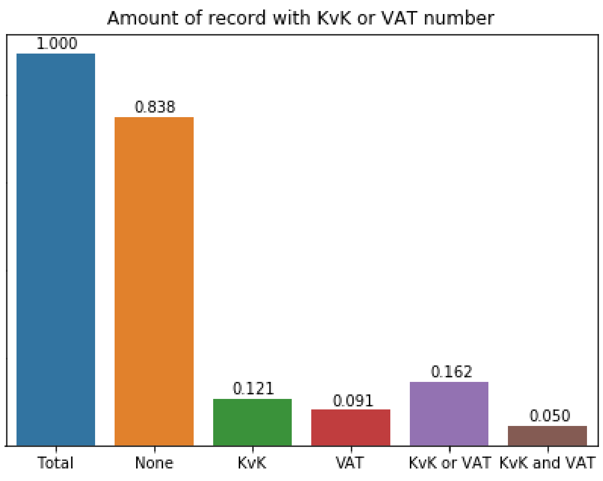


Figure 3.3: Overlap between KvK and VAT.

3.2.3 Classifier

At the heart of the Entity Resolution algorithms pipeline, we have the classifier that distinguishes between matching and non-matching records. While being a part of the pipeline, the classifier is first trained separately. Unfortunately, there is no dataset that shows ground truth of whether to accounts are about the same company. KvK and similar IDs such as VAT number are generally unique for a company, and therefore could be used to find matching records. However, there are many corner cases and legal tools that a company or person can do that complicates the situation. For example, an issue with KvK is that it is person bound. Because of this, when a person starts a new venture it often happens that this new company is put under the same KvK number. For this specific reason, the KvK system has another 2 digit code that is put after the KvK number. However, this is not always available. On the other hand, a company can also have multiple KvK's for example in the case of Exact, the company can have a second KvK for its holding.

In most situations, the KvK number is good enough to get a large chunk of the matches found. Because of this, we can use records that have been made with KvK to train a classifier.

Building the matching dataset

The dataset is built as follows: Sample 1M record pairs that have the same KvK number. These are the positive class samples. Then sample the same amount of records but make sure that the KvK does not match. These are the negative class samples. This way we have a balanced dataset that contains both matching and non-matching examples.

The next step is to create features out of the sampled records. The features are created for every pair of records. The features show the differences in values between the two records. For all fields except for the Name field, two dummy variables are created. First variable is true if field matches. The second variable is true if the two fields do not match. Both variables are false if one of the records contains a missing value. The case where both variables are true is not used.

When comparing the Name fields of the two records, the following five features are created:

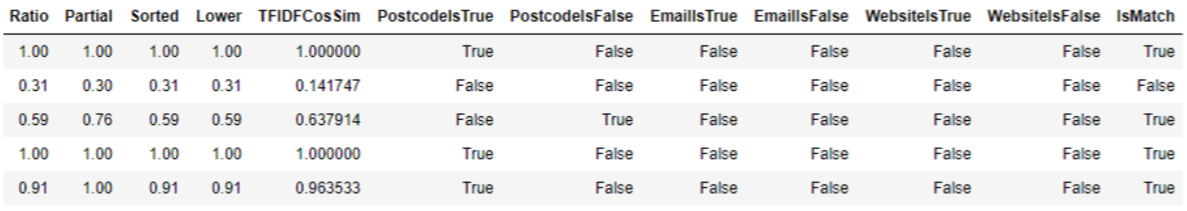
- Ratio, Levenshtein similarity calculated between the two strings. This is similar to edit-distance but all operations have a cost of 1.
- Partial, Levenshtein similarity is calculated between two strings and then normalized by the size of the smallest string. For example: "My Company BV" and "My Company" will be a perfect match in this comparison.
- Levenshtein similarity but the names are first lowercased the similarity is calculated. This is for the cases where users either use too many or forget to capitalize letters in the name.
- Levenshtein similarity between the two strings, but first these strings are tokenized and sorted. For example: "My Company" and "Company My" will be a perfect match using this metric.
- Cosine Similarity between TF-IDF vectors.

The first four features are calculated using a python library called fuzzywuzzy [9]. As for the last feature, it is calculated by first vectorizing all name strings using TF-IDF (Term Frequency - Inverse Document Frequency). The vectorization is done by counting the predefined n-grams in each string and normalizing the count by the frequency of the term in the complete collection of strings. For this problem, the size of the n-grams have been taken to 1 and 2. With 2-size words, the dimensionality is close to 1400. Any bigger n-grams and the dimensionality explodes to an unpractical size. To keep this manageable in terms of speed and memory, the size of the n-grams had been kept to a maximum of 2. Once this is done, the dataset is ready to be used to train the classifier. An example of how the features look can be seen in fig. 3.4.

Picking the classifier

An important requirement for the classifier is that we reduce the False Positive rate of the classifier. For this reason, when looking at the classifiers we optimize for precision alongside the accuracy. For our use case, it is more important that the created entities are created from a clean set of records, and not necessarily include every single record that is matched. Training on the created dataset, we get the following results:

As can be seen from the results the performance of the different models is fairly high and matching record are found with high precision. The results also show that the simple models such as the SVM model with a



Ratio	Partial	Sorted	Lower	TFIDFCosSim	PostcodeIsTrue	PostcodeIsFalse	EmailIsTrue	EmailIsFalse	WebsiteIsTrue	WebsiteIsFalse	IsMatch
1.00	1.00	1.00	1.00	1.000000	True	False	False	False	False	False	True
0.31	0.30	0.31	0.31	0.141747	False	False	False	False	False	False	False
0.59	0.76	0.59	0.59	0.637914	False	True	False	False	False	False	True
1.00	1.00	1.00	1.00	1.000000	True	False	False	False	False	False	True
0.91	1.00	0.91	0.91	0.963533	True	False	False	False	False	False	True

Figure 3.4: Example of the matching dataset used to train the matching classifier

	RandomForestClassifier	DecisionTreeClassifier	LinearSVC
AUC	0.97350	0.95693	0.97113
Accuracy	0.97350	0.95693	0.97113
Precision	0.98721	0.95341	0.99673

Table 3.1: Performance of several classifiers on the matching dataset.

linear kernel perform similar to the model complex models such as the Random Forest. A closer look at the feature importances and specifically the cosine similarity between the tf-idf vectors show that the majority of the non-matching are easily found.

Figure 3.5 shows a small sample of 250 matching and non-matching examples. By taking the cosine similarity and putting it against the partial similarity, we can see that the two classes are fairly easily separable. Because of this and precision of the model, we have taken SVM as the go-to model for match classification.

3.2.4 Custom method for Entity Resolution

As mentioned earlier a general ERA contains the following steps: preprocessing, blocking, classifying and combining. In the following section, we will describe the proposed ERA by going through the steps it takes to disambiguate the entities.

Intuition

The algorithm is specialized and optimized for the dataset at hand. The method was created with specific heuristics in mind. In our case, we know that there are several IDs or keys that can be used to group records. What about when multiple keys are available? Can we leverage the existence of these keys for a fast and scalable implementation of ER? Theoretically, with the use of multiple keys to compare with, the provided entities should be less noisy compared to the mappings made with a single key alone. In further steps, we limit the available data to a segment of the accounts that have either a KvK, VAT or IBAN number. We take specifically these accounts because we are interested in the companies within the collection. The accounts that do not have these values are often private accounts and don't belong to an organization.

Method

As Name is the only mandatory field, there is a large number of records that have a very limited amount of fields filled in. When cross-comparing these records, there is a lot of uncertainty in the comparison due to the sparsity. Because of these matches are often misclassified. For example, what is common among SMEs is change of branding or maybe even ownership. Especially since the data start in 2005 it is likely that this happens over time. So if one would take two records and try to compare them to each other, it is possible that one of the accounts holds the new brand name of the company, while the other one does not. Due to missing information, this could result in a non-match. However, it is possible that other accounts that belong to that same cluster, have the fields that can be used to match with the candidate. Generally, this is handled by cross comparing records within a block. However, if the size of the block gets bigger, it quickly becomes unscalable. In this method, the comparison is made by comparing the record the mode of the collection. The mode of a collection contains the most common value in a field in all of its fields. However, this is not always possible. For example, if one of the fields does not have a single value that is most common, but multiple that occur the same amount of time. In this case value for the field is taken at random, from one of the common values.

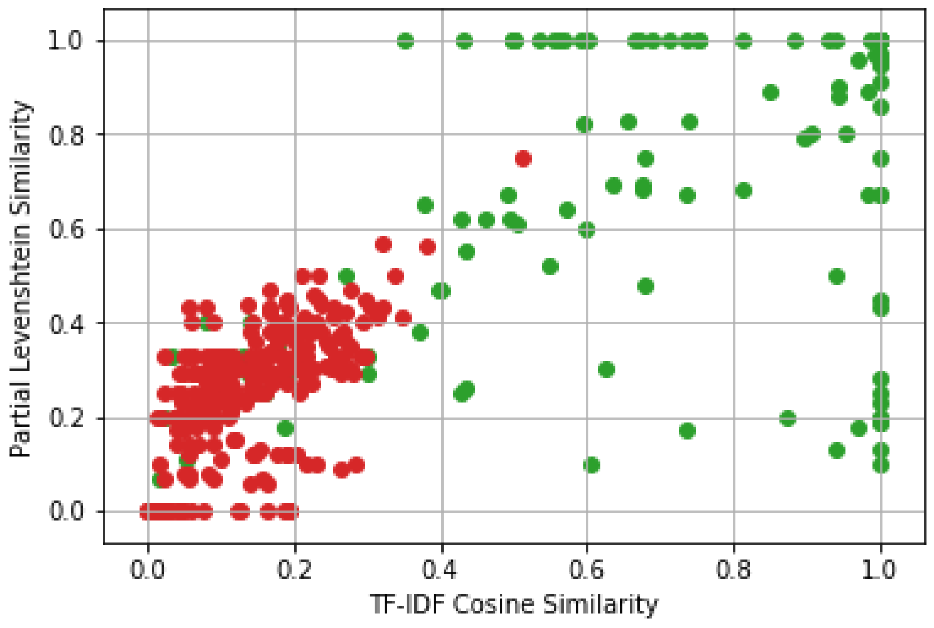


Figure 3.5: Scatter plot of matching and non-matching records, with on the x-axis the cosine similarity between the two strings and on the y-axis the partial similarity.

Step1: Initial grouping
In the first step of the algorithm, a choice is made of which fields to use for clustering. These can be any column of the dataset. Once the fields are chosen, buckets are made for each unique value or key from these columns. It is important to note that records are put in multiple buckets if more than one of the columns contains a value. In our case, we choose to use KvK, VAT, and IBAN as fields to group on. Once the initial groups are made, a single record is created from the mode of the collection that represents that group, similar to a centroid in the K-Means algorithm.

Step 2: Flagging similar clusters
Once the first set of clusters and its modes are created, the next step merges clusters that are similar to each other. This is done using the classifier that is trained beforehand and instead of cross-comparing all records, only the modes of the clusters are compared to each other. If this record pair is matched then the clusters are flagged to be merged. The goal of the merging step is to reduce the number of total clusters and to optimize the blocking step by matching groups of records together instead of doing so one by one. To further optimize the number of matches that need be made only candidate clusters are compared to each other. Candidate pairs are found by looking at whether there are any overlapping records.

Step 3: Combining matched clusters
Once the matching clusters have been flagged, a merging strategy needs to be applied to segment the matches and re-cluster them. This is done by creating a graph of the clusters and connecting clusters with one another if they have been matched in the previous step. Applying any community search algorithm on this graph will segment the clusters into communities where each community represents a collection of records of an entity. However, to avoid merging long chains of matches and other types of loosely connected communities, the algorithm combines clusters that belong to the same maximal clique. Meaning that clusters are only merged if all clusters in a segment match with one another. Once this step is done the number of clusters is generally reduced by a large amount. However, for every cluster pair that didn't match, a set of records exist that are in multiple clusters.

Step 4: Remove multi-dipping
In this step, duplicate records are removed and made sure that they only are placed in one cluster. This is done by comparing the record to the modes of the clusters it belongs to. The record is then removed from

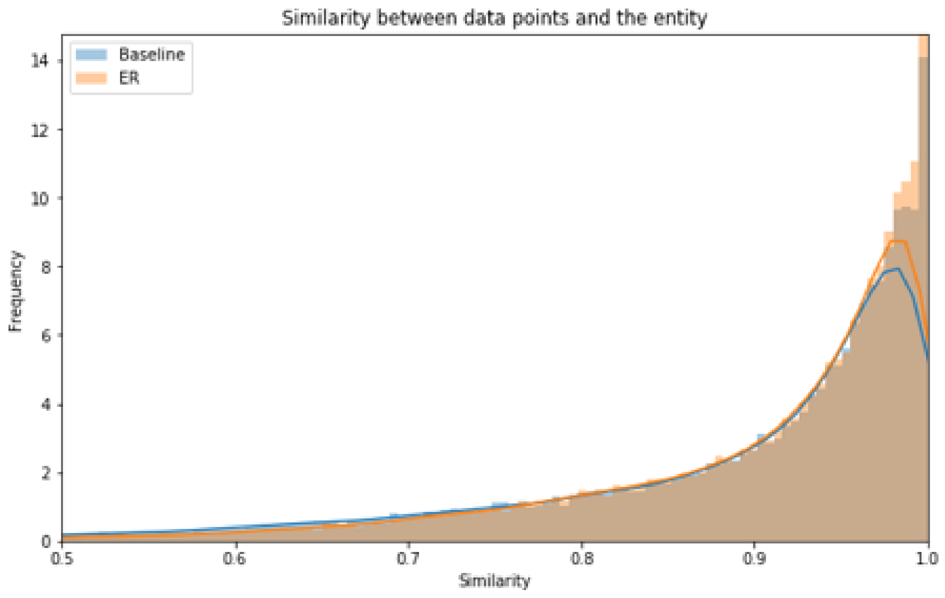


Figure 3.6: Distribution of similarity between the mode of a cluster and the inner records. Clusters smaller than 5 have been taken filtered out.

all clusters except for the one where the classifier gives the highest softmax probability. Once the final step is done, the results are clusters of records where to contents of each cluster belong to a single entity.

Results

To benchmark the proposed method, we compare the created entities to a baseline method of grouping accounts, which is grouping them on the provided KvK. While the proposed method works on a larger set of data and does not necessarily need KvK specifically to match records together. To make the two methods more comparable, the data is limited to the accounts that have a KvK number. The following results show the comparison of a baseline (records grouped on KvK) and the proposed method using two heuristics. The first heuristic shows the distribution of the similarity between the mode of a cluster and the records that are within it. The second heuristic shows the fraction of records that have a specific amount of modes within its cluster. A larger mode length means that there are no values that are prevalent in the cluster. If many of the records are the same, specific values of the cluster will make the majority of that cluster.

As can be seen from fig. 3.6 and fig. 3.7, for both heuristics the proposed method outperforms the baseline. However, with these heuristics, it is hard to say whether the pureness of the clusters actually improves when the proposed method is used. Because of this, further experimentation was conducted to research the pureness of the clusters as a subjective measure when evaluated by human subjects. How the experiment was conducted exactly can be read in Appendix A with the briefing that was used to explain the problem to the subject in Appendix B.

In short, the experiment was done by showing Exact fields experts samples from clusters made by the proposed algorithm the baseline. The subjects would not know what method was used to group the records. The experts would be asked to label records they think were grouped incorrectly. This is done for roughly 24 clusters. With 10 records per cluster and the clusters equally split, the subject labels 120 records for each method, resulting in 240 records per subject. The results of the questionnaires have been aggregated in fig. 3.8a and fig. 3.8b. Figure 3.8a shows the number of defects that each of the subjects has found in its questionnaire. Looking at the number of defects per category shown by fig. 3.8b it seems that in some the preferences between the methods vary between subjects. However, having asked the subjects whether they were able to predict which questions were generated by which method. None of the subjects were able to consistently predict which was which and generally saw no difference between the questions. The same could be said from looking at the statistics. Figure 3.9 shows the contingency matrix of the experiment. As can be seen from the matrix, the difference between the two methods is very small in comparison. The proposed method only has several defects less than the baseline. To see whether this difference is significant we perform a

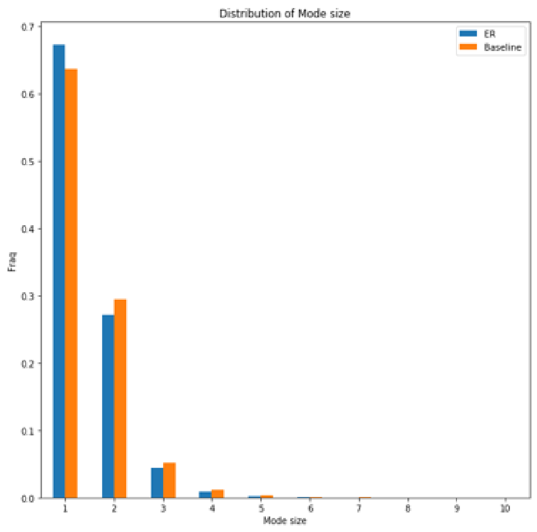
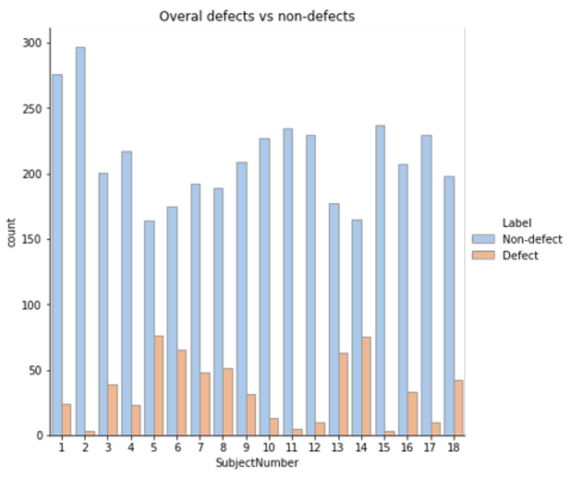
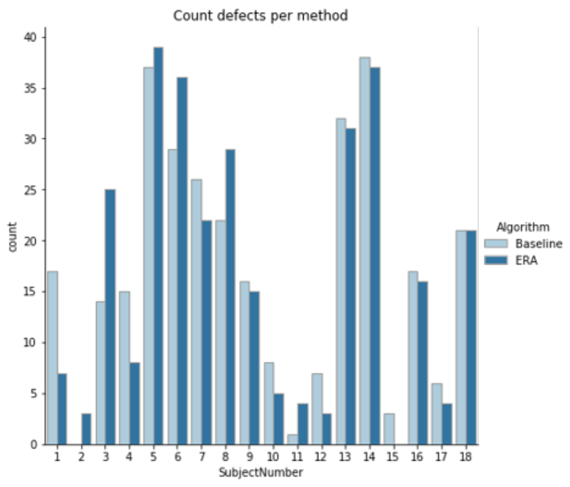


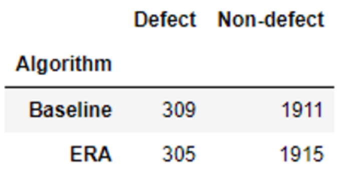
Figure 3.7: Fraction of the clusters that have a certain amount of possible modes. Clusters smaller than 5 have been taken filtered out.



(a) Defects and non-defects per subject



(b) Amount of defects per category



Algorithm	Defect	Non-defect
Baseline	309	1911
ERA	305	1915

Figure 3.9: Contingency matrix of the experiment

Chi-square test. With a p-value > 0.05, the difference between the two seems to be insignificant.

Chapter 4

Invoicing

An invoice is a document issued from the seller of goods (or services) to the buyer. This document contains information about the purchase. Such as the amount that is owed, a payment deadline and sometimes a short description of what is that is being sold. There exist two types of invoices: Sales Invoices and Purchase Invoices. This type depends on the perspective of the user. When a division is buying goods, this is registered as a purchase invoice into the system. In the case of selling goods, the invoice would be registered as a Purchase Invoice. The Invoices table contains all individual sales invoices sent from individual divisions to their customers. Every record contains several pieces of information about the invoice, such as the amount paid and the payment term. As these invoices are historical, they include information about when the actual payment has taken place. However, this information is not always available. The invoices and the corresponding payments need to be registered manually. Most common is that this information is put in by either a company administrator or accountant into the system. Figure 4.1 shows the possible interactions between the division, its customer and the bookkeeping system where the data is stored and processed.

The figure shows that there is an exchange of information between the sender and the receiver. All of the data is put into the system by the user and the user can do this whenever he/she desires to do so. These interactions don't have a specific order and are not enforced on the user in any way. Moreover, as these payments are not done automatically, there is a discrepancy between the state of the system (information available) and the actual situation. Resulting in the system to show an outstanding invoice, while in actuality it has been paid and not yet registered.
In any case, the following information about an invoice can be available:

- Amount: The amount to be paid by the customer.
- Division ID: Identifier that belongs to a single division in the system.
- Division Account ID: Identifier that belongs to a single Division Account.
- Invoice ID: Identifier that belongs to a unique Invoice.
- Entity ID: Unique Entity ID inferred from the Entity Resolution algorithm.
- Due Date: The deadline at which the payment from the buyer has to be received by the seller.
- Invoice Date: The date that describes the beginning of the payment term. Generally, this is the date when the buyer receives the invoice.
- Payment Term: The number of days that the user has to pay the invoice. Calculated by counting the number of days between the invoice date and the due date.
- Payment Date: the date at which the seller has received the payment from the buyer.
- System Invoice Date: The date at which the invoice has been entered into the system.
- System Payment Date: The date at which the invoice has been entered into the system.
- Is Late: whether an invoice was paid late. Invoice is late if the Payment Date is bigger than Due Date. The target for the machine learning models.

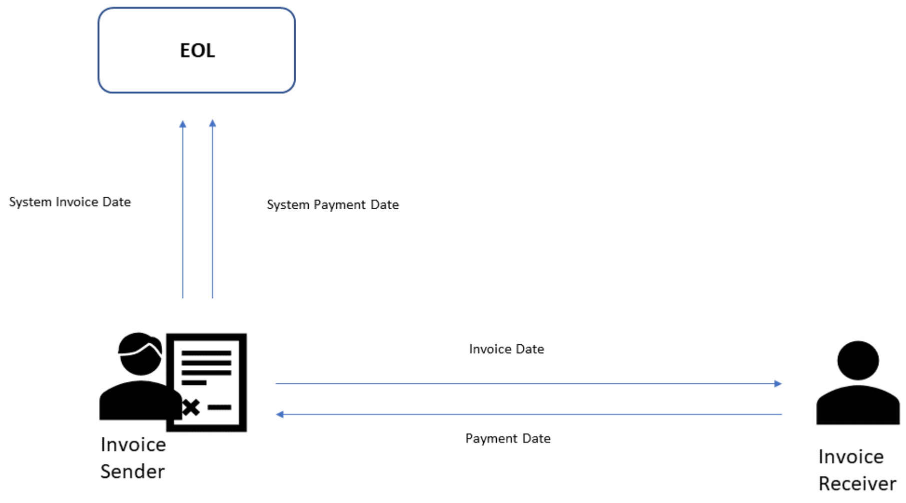


Figure 4.1: Interactions between the Division (in the illustration the Invoice Sender) and one of their accounts (Invoice Receiver in the illustration) in no specific order.

- Payment Delay: The number of days that the invoice is paid late. Step-function where the delay is the number of days from Due Date to Payment Date. Delay is 0 if payment was on time.

By looking at the most frequent date sequences, we can define a general case. This can be seen in fig. 4.2. The top 10 covers over 90% of all invoices. As can be seen, the invoice date (I) is the first date in the majority of cases. This means that most of the time the invoice is received before it is put into the system.
The most frequent sequences seem to correspond with the following chain of events:

1. The invoice is created by the seller of the goods and sent to the buyer.

2. This invoice is entered by the seller into the system as a sales invoice that has been sent to one of the accounts.

3. The buyer receives the invoice and pays this at a certain moment in time.

4. Once the payment has been received by the division, this is entered into the system either manually or some type of import method.

Further analysis over the complete dataset shows that it is the case for 97.7% of the invoices. For the remaining 2.3%, the order at which information becomes available is very different. For example, for a segment of the invoices, the payment is done before the invoice date. Resulting in a negative days-outstanding. In other cases, an invoice is registered into the system way ahead of time. An option would be when the seller has a subscription-based business model. In other cases, it is even possible that a buyer has paid for something ahead of time. The following section will focus on exploring the data through an EDA.

4.1 EDA

In this section of the chapter, we will explore the dataset to gain insight into the problem. This gained insight should help us make design decisions in further steps. During the EDA of the invoice, we look specifically for the following aspects of the dataset: The distribution, time-line, class balance and returning customers.

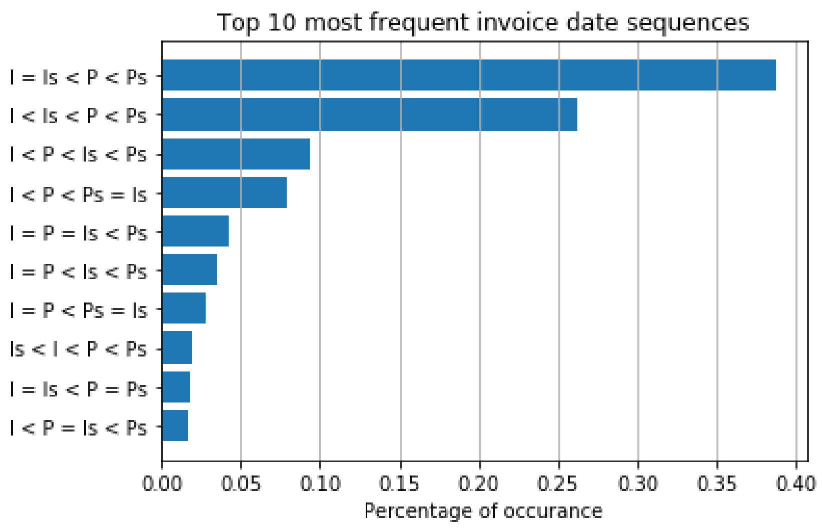
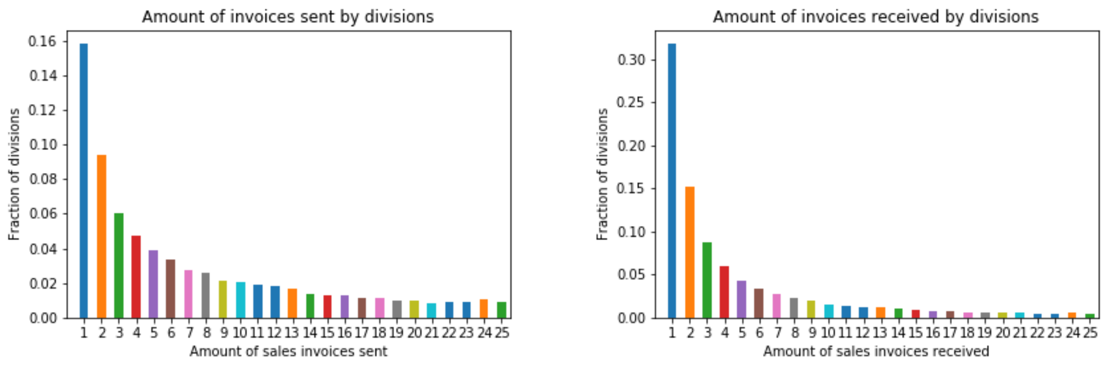


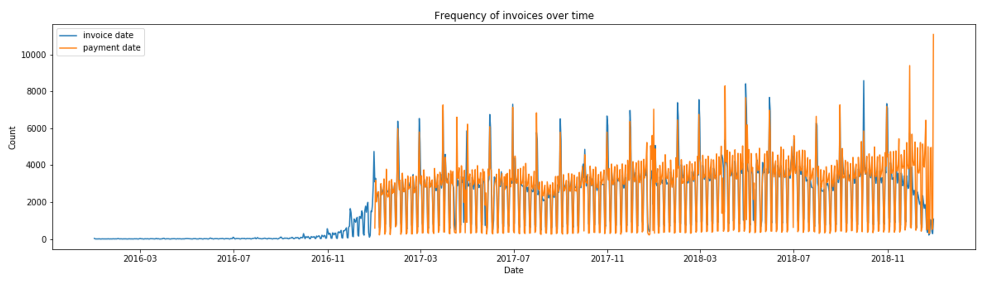
Figure 4.2: Barplot shows the most frequent sequences of dates in the system. The sequences have been coded for readability (Invoice Date = I, Payment Date = P, System Invoice Date = Is, System Payment Date = Ps,). The sequence next to a bar represents the order of the dates. Leftmost symbol is the oldest date, rightmost the most recent. Two symbols in brackets are equal, in other words these dates represent the same day.



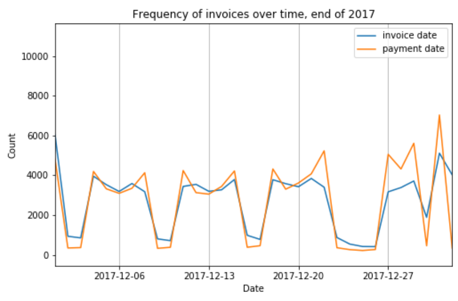
(a) Sent.

(b) Received.

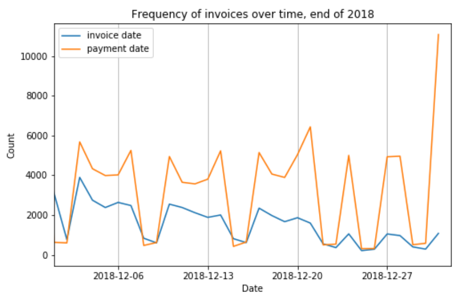
Figure 4.3: Distribution of invoices sent and received by the divisions. Only shows divisions with counts from 1 to 25 invoices.



(a) Complete timeline, Jan 2017 - Dec 2018



(b) Dec 2017



(c) Dec 2018

Figure 4.4: Overview of invoices over the duration of time. Figure (a) shows the complete view of all available data. Plots (b) and (c) show the segments during the end of the year in 2017 and 2018.

4.1.1 Distribution

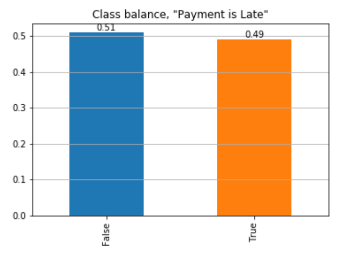
The working dataset contains all invoices sent between dutch EOL customers. Only invoices have been included that have been paid between 2017 and 2018. This collection contains more than 4,000,000 invoices sent by 41,000 divisions. The number of receiving divisions is significantly larger. This is because there is a large number of divisions that have solely received invoices and have not sent any themselves. The total amount of unique receiving divisions is roughly 120,000. While we cannot show actual divisions and their process in this report, we know that there are specific types of businesses, such as webshops that could cause this. These businesses buy from a small set of suppliers and sell to a large number of consumers. Figure 4.3 shows the distribution of sent and received invoices.

From the distributions, we can see that both sending and receiving sides follow a power law, with the majority of divisions only sending a few invoices. The received distribution shows that almost 32% of the divisions have only received in a single invoice. On the sending side, a single invoice has been sent by a smaller segment (16%). Further analysis of the data shows that on average, the divisions have sent roughly 49 invoices between 2017 and 2018. The median lies lower than the mean, with 9 invoices sent over the period. This shows that depending on the application, the data could be too sparse to model daily. As the majority of the divisions only sends several invoices per year, a granularity of weeks or months could work better during experimentation.

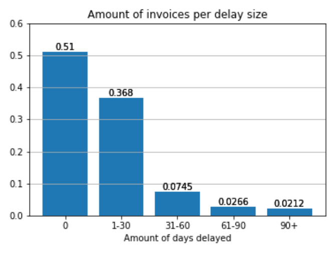
4.1.2 Timeline

To get a better idea of how the invoices are spread over the duration of time, the invoice dates and the payment dates are plotted on a timeline in fig. 4.4

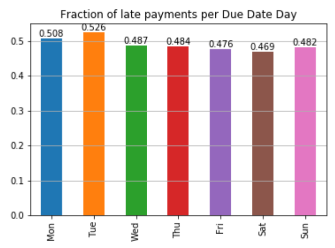
Figure 4.4a shows that there are regular peaks present every month. This is the case for both the invoices and the payments. Business days generally have a higher frequency than weekends. There are several irregularities during the holidays. A good example of this is the holiday season at the end of the year. The last week of the year has multiple official holidays. Moreover, it is also when the year-end closing is done. In some cases, payments are crammed at the end of the year to fall under the previous reporting year. Figures 4.4b and 4.4c show a decrease in activity on holidays and an increase in payments before the end of the year. Figure 4.4c shows a large peak on the last day of the year. This is most likely due to the weekend that preceded



(a) Class balance

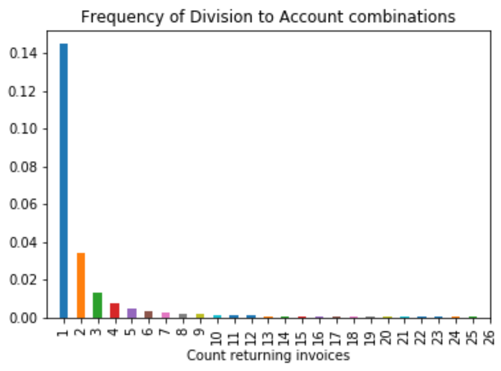


(b) Delay Magnitude

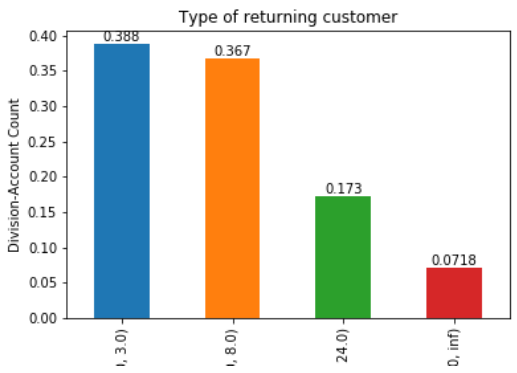


(c) Ratio late per weekday

Figure 4.5: Balances of late payment in the complete dataset, on specific weekdays and the magnitude of the delay.



(a) Distribution returning customers



(b) Type of returning customers

Figure 4.6: Returning customers and how often they have been seen in the dataset.

the 31st (which fell on a Monday) and Christmas falling on business days. The decrease in sent invoices at the end of 2018 is due to the exclusion of invoices paid after 2018.

Class Balance

As we consider late-payment prediction as a classification problem, it is important to know what the class balance is between late and non-late payments. Figure 4.5a shows the balance between these two classes. Fortunately, the frequency of the two is almost perfectly balanced, with only a 2% discrepancy between the two. Looking at the magnitude of the delay, we can see that for most late payments (73% of late payments), there is a short delay of payment. Mainly between 1 and 30 days. With such a large fraction of the late payment having a short delay. One could ask whether the late payments depend on the weekday at which the due date falls. A reason why this could be the case is because the businesses and more importantly the banks are closed on Sunday. A hypothesis could that the invoices of whose due dates fall on a Sunday have a higher chance to be late. However, looking at fig. 4.5c, the ratios of the weekend seems to be lower than most other business days.

Returning Accounts

Just as mentioned earlier, late payment prediction is done by looking at two levels of features; invoice level and profile level. While the information of the specific invoice to be classified is always available, there needs to be a history of invoices to be able to create a profile. Figure 4.6a shows the distribution of returning customers. We define a customer as returning if there are multiple invoices that have been sent to the same customer by the division. The figure shows that the majority of customers (more than 85%) are returning customers. Figure 4.6b shows the frequency at which the customers are returning. The first bin on the left shows that roughly 39% of the customers have only been seen twice in two years. The majority of the customers (75%) has received between 2 and 7 invoices. As profile level features only need a single historical invoice, this means that it will be possible to create a profile for the majority of the customers if these have been put into the system over several occasions.

Chapter 5

Method

In this chapter, we will look into the different experiments surrounding the problem of late payment prediction. In previous chapters we have discussed how invoicing is registered in the system and the general behaviors around the topic. In combination with the resolved entities, we now have a constructed network of Dutch SMEs that results from it. In this chapter, we will discuss the method for late payment prediction and the corresponding experiments.

5.1 Overview of late payment experiments

The goal of the experiments is to validate assumptions and to answer the defined sub-questions. The first set of experiments will show how the addition of a single group of custom-crafted features impacts the performance of the model. Following this, we will show how these features impact the payment prediction on their own, and in combination with predefined baseline features.

Experiment 1: Node scope profile features (SQ3) . Comparing the cases discussed in the literature, our dataset contains invoices between a large number of companies. To see whether global information is benefiting the prediction of late-payment, we first bring the baseline features to the node level. Meaning that we look at all invoices associated with the sender and receiver of the invoice we are trying to predict.

Experiment 2: Impact of windowing features In this experiment, we look at whether it is beneficial to only consider the most recent invoices. All previous features will be windowed to different human seasonal time frames. For example windowing on 1-month, 3-month, 6-month, and 12-month basis. The intuition behind this experiment is that companies and the people responsible for their payments change over time. Recent timely payments should outweigh the late-payment made years ago and vice-versa.

Experiment 3: Temporal features The goal of the third experiment is to see whether time-related features can improve the predictions of our models. For this experiment we specifically look at the time-frame between different payments and how this time-frame changes over the period of time. We will look specifically at the following features:

- gradient of delay at last step
- variance of delay
- time between last late payment
- mean time between late payments
- inverse temporal link weight

Experiment 4: Neighborhood scope features (SQ3) The goal of this experiment is to explore whether performance of the models can be improved by introducing information that is available from 1-hop neighbors. More specifically we look at the neighbors of the source node. The features are calculated by gathering the invoices that are sent by all 1-hop neighbors. Similar to the first experiment, node level features are calculated

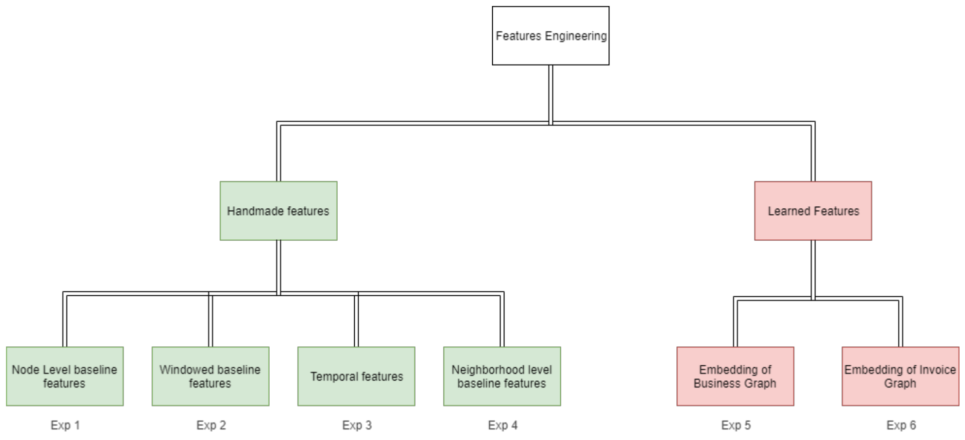

Features Engineering
Handmade features
Learned Features
Node Level baseline features
Windowed baseline features
Temporal features
Neighborhood level baseline features
Embedding of Business Graph
Embedding of Invoice Graph
Exp 1
Exp 2
Exp 3
Exp 4
Exp 5
Exp 6

Figure 5.1: Overview of experiments and type of the generated feature sets.

using the baseline features. The average of these features create the neighborhood profile feature set.

Experiment 5: Business graph embedding (SQ2, SQ3) To be able to answer SQ3, we look into different possible graph constructions. The business graph only contains the information of which companies do business with each other. In terms of the system, two companies do business with each other if one of them has added the other as an account. In this experiment the set of features will be extended with latent embeddings of the nodes. This will be done with methods such as Node2Vec. However, this method highly depends on the constructed graph. A part of this experiment (and the following ones) will show how the predictions are impacted by the constructed graph of the company invoices.

Experiment 6: Embedding of invoice graphs (SQ2, SQ3) In this experiment we will look how the graph of companies can be constructed using different available information such as accounts and invoices. With this experiment we will answer the sub-question of how the graph should be constructed to be able to benefit from extracted graph features. Some of the following graph structured will be tested:

- Static graph of companies built from accounts of the divisions. This graph does not any link weights.
- Two static graphs each for a single type of payment. One graph consists of links where a single link is a timely payment between two companies, while the other graph has a link if there is a late payment. The link weight represents the amount of

These experiments and the generated features can be split into two different groups. Namely, Handcrafted features and Learned features. Figure 5.1 shows the overview of the experiments and to which type of features they belong to.

5.2 Featuring

For the baseline the focus will be on the next features: Amount, Payment Term, # paid invoices, # late invoices, ratio between paid and late invoices, sum of the amount from paid invoices, sum of the amount from late invoices, mean delay for all invoices, # of outstanding invoices, average amount of outstanding invoice amounts, and sum of outstanding invoice amounts. The features have been chosen because this set covers the majority of the features shown in table 5.1. The baseline features can be splits into the following two groups:

- Invoice Level features: consist of information that is present on the invoice. Namely the Amount and Payment term of the invoice. This information is always present.
- Profile level features: consist of aggregate information from previous invoices. These features are not available if there have not been any invoices sent from the seller to the buyer.

	Paper				
Feature	**Zeng [36]**	**Kim [19]**	**Cheong [8]**	**P Hu [15]**	**W Hu [16]**
amount	x	x	x	x	x
payment_term	x			x	x
number_of_paid_invoices	x		x	x	x
number_of_late_payments	x		x	x	x
ratio_paid_late	x			x	x
sum_paid	x	x		x	x
sum_paid_late	x	x		x	x
ratio_sum_paid_late	x			x	x
mean_delay	x			x	x
average_amount			x		
outstanding	x				
average_amount_outstanding	x				
outstanding_sum_amount	x				
account_manager	x			x	
billing_cylce			x		
intervention_count			x		
demographic		x			
products_used		x	x		

Table 5.1: Table showing which features have been used by different methods. Crossed cell "x" shows that the feature has been used, empty cell shows that the feature was not used.

Profile level features can sometimes be tricky to calculate. As previously discussed, there is a discrepancy between the current state of invoices and what is visible in the bookkeeping system. This is because the user does not have to enter both at the same time or within any time period for that matter. What often happens is that there is a significant delay between an invoice being sent or paid and when it is put into the system. Analysis of the data shows, that the median time between the invoice date and the date at which the invoice has been put into the system is 55 days. Looking at payment, the delay is even larger. The median delay between an actual payment and when the payment is put into the system is 80 days. An explanation for this could be that as there are many invoices being sent and received, it is often more efficient for the administrator to register/import the invoices in bulk every period of time. This period can be weekly, monthly or even quarterly or yearly. With current median delay, the latter seems to be more common. Nevertheless, the method of administration is company dependent. With a large number of different companies in the system, there is a high amount variety in behavior across the invoices in the dataset. This makes it hard to predict when a division is missing a payment. It is uncertain whether the invoice is unpaid or just has not been registered yet. For this same reason, it is not possible to assume that an invoice is past due when the deadline has been past and no payment has not been seen yet. That is why the invoices that do not have a registered payment are excluded from the dataset.

But besides the missing payments, the delay that is present in most of the data causes problem in the quality of the data too. Figure 5.2 shows how featuring is done with an expanding window. This comes down to going over every invoice in the order that is was supposedly received by the customer, and creating the profile feature by looking at all previous invoices. As there is no history for the first invoice in the sequence, the features cannot be created for that specific invoice. This is also known as a cold start problem. However, because of the delay in the system, the cold start is prolonged until the invoice and the corresponding payment is put into the system. In a median case, this will be almost 3 months of no data. To be able create a generic model the training data needs to represent the actual situation at which its is going to be used. Featuring is not a problem for it is done at the latest timestep. This is because the most recent snapshot shows all available data by definition. But during modeling, when looking at historical data, only the data should be kept that is available at the point in time at which the invoice is created. And thus during training there is an extra step which filters out all unavailable invoices at each rolling iteration.

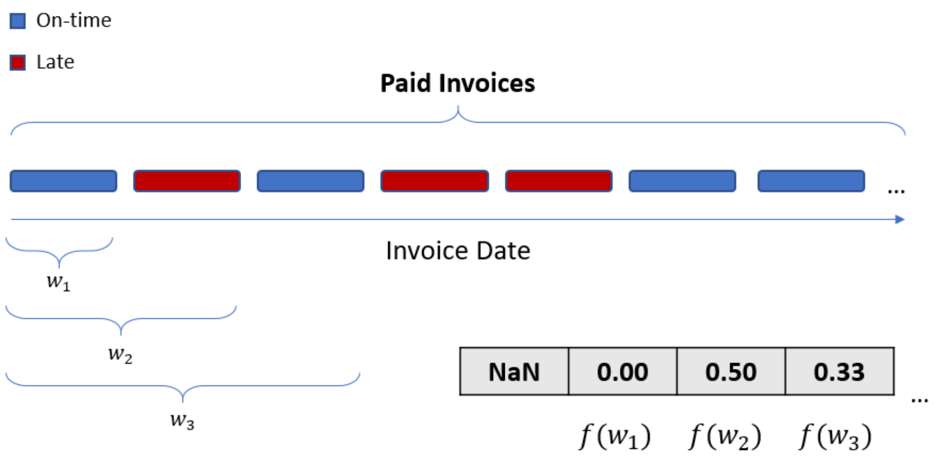


Figure 5.2: Visualization of an expanding window featuring approach. The example shows the calculation of the late-payment ratio feature. A rolling function iterates over the sequence of invoices (late in red, non-late in blue) for every invoice, every preceding available invoices are taken and passed to the feature functions.

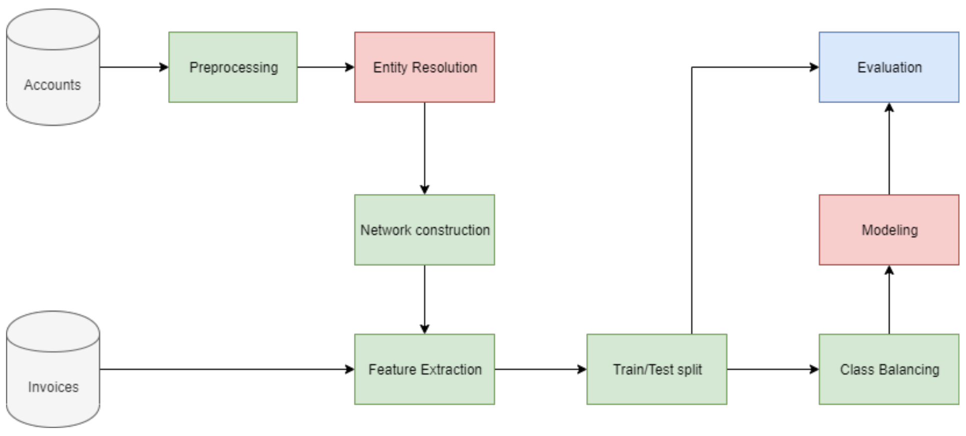


Figure 5.3: Pipeline from the data source to the prediction of late payments.

5.2.1 Modeling

Once the features are created they can be used to train a model for our problem. To do this we use models from the most popular machine learning library Sci-Kit Learn [28]. From this library, the Random Forest, Multi-Layered Perceptron and Decision Tree classifiers are used. Additionally, we use LightGBM [18], which is currently a popular and fast implementation of the Gradient Boosted Decision Tree and Random Forest. Once the models have been chosen, the next steps are taken to create a model that is as generic as possible:

- Random Seed: at the beginning of every run a random seed is set to guarantee reproducibility. Not only for the models but also for the preprocessing steps. In all cases, the random seed is set to 0.
- Dataset consistency: Every experiment has its own method of feature engineering. To make sure that the results are comparable across the experiments, the same set of invoices is used over all experiments unless specified. To keep the dataset consist in among all experiments, the invoices for which features could not be generated are padded.
- Dataset split: the complete dataset is split into a training and test set. The training data is roughly 80%, while the test set consists of the remaining 20%. The test set consists of the most recent invoices.
- Balancing: Before the training is done, the dataset is first balanced. This is done by simply oversampling the class that is less frequent in the dataset without creating any synthetic samples. This creates duplicate records in the dataset but balances the classes to the same frequency. To make sure that no

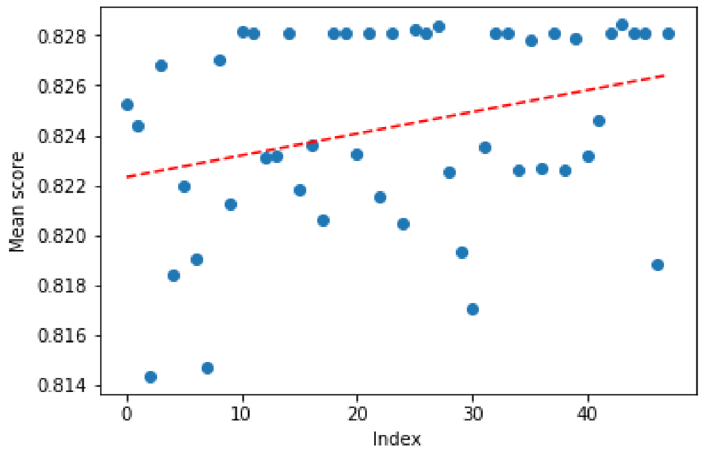


Figure 5.4: Example of bayesian optimization using the *skopt* package as described in [24] on the Random Forest Classifier. The x-axis shows the progression in time. The red line shows the trend of the performance.

samples from the test set leak into the training set and as general good practice, the balancing is only performed on the training set of the data.

- Shuffle: the training set is shuffled to make sure that the score of the model does not depend on the ordering of the data. This is done because the features are made with an expanding window, the invoices that are at the end of the dataset have features made from a larger history than the ones at the beginning. When taking a validation set from the end, the features from this segment are richer than the training set. To avoid this, the dataset is shuffled. The test set is unaltered and consists of

- Cross-validation: To reduce the chance of overfitting on the training set, during the training we apply K-Fold cross-validation. During cross-validation, the training set is first split into k folds. One by one, a single fold is chosen and used as a validation set. The remaining folds are used to train the model. At the end of all runs, the scores are gathered from measuring the performance on the test set. In all experiments, k is set to 5 unless specified otherwise.

- Parameter optimization: as is well known, most machine learning model performances depend on how well the parameters are optimized for the problem. The input features are different between runs and thus there is no single set of parameters that is optimal in all cases. To make sure that the parameters are separately optimized in combination with the input of the model, parameter optimization is part of the pipeline for every run. To do this we use *Bayesian Optimization* as described in [24]. The method searches for more optimal parameters within a predefined parameter space. An example of the process can be seen in fig. 5.4.

The complete pipeline from the data source to validation can be seen in fig. 5.3 and highlights the discussed steps on a higher level.

5.2.2 Evaluation

To be able to draw conclusions from the proposed experiments there are several methods we use to evaluate the results. The problem of late payment is defined as This is done by comparing the results of the experiments to the proposed baseline (table 2.1, table 2.2) using the Accuracy and Receiver Operating Characteristic curve (ROC curve) Area-Under-the-Curve (AUC) metrics. These two metrics are also used in the surveyed late payment prediction methods. While Accuracy is generally the most popular method of evaluation, AUC shows the quality of the model under different discrimination thresholds. More on AUC can be found in [11]. Additionally, in some cases we provide the F1-score of the model. The F1-score considers the recall and the precision of the predictions.

$$recall = \frac{TP}{TP + FN}$$

	RandomForest	MLP	DecisionTree	LGBM
Accuracy	0.81558	0.77433	0.77765	0.80442
F1	0.83108	0.78749	0.80154	0.81923
Recall	0.80734	0.74408	0.80385	0.78866
ROC AUC	0.81674	0.77861	0.77418	0.80665

Table 5.2: Performance of Random Forest, Mulit-Layered Perceptron, Decision Tree and LightGBM

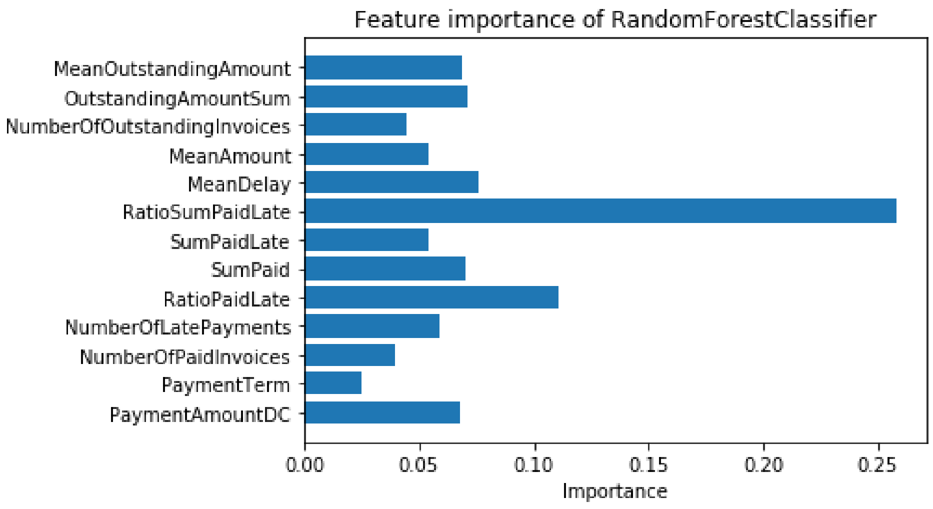


Figure 5.5: Feature importance of the Random Forest model on the baseline features

$$precision = \frac{TP}{TP+FP}$$

Recall is the fraction of positive sample (True positives or TP) that are successfully found (TP + False Negatives or FN). The precision of the predictions is similar, but calculates the fraction of the successfully found positive samples from all positively labeled predictions (TP + False Positives or FP).

$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

5.3 Baseline

As previously mentioned in chapter 5, to be able to show that the proposed method improves the currently available methods of late-payment prediction, the results need to be compared to a baseline. This baseline model is constructed from the papers available on the topic of late-payments prediction. Table 2.1 and Table 2.2 show an overview of the used features and models from the literature. In the next section, these resources are used to construct a baseline.

5.3.1 Results

Table 5.2 shows the performance of several classifiers that have been gathered from the overview of most used modelstable 2.2. The Random Forest classifier gives the best results in terms of accuracy, F1 and AUC. Interestingly, The LightGBM model is underperforming compared to the RF model. To get a better understanding of the impact of the features, we can look at the feature importance from the trained models. Figure 5.5 show the feature importance of the RF model. The two most important features seem to be 'Ratio Paid Late' and 'Ratio Sum Paid Late'. These represent the ratio of invoices paid late, and the ratio of the summed amount that was late, respectively. In cases where there is a low variance in payment amounts between the invoices, these two numbers should be almost equal. Other features seem to have similar importance to each other, except for the Payment Term feature. To further analyze this, a heatmap is created showing the Pearson correlation between the features. This can be seen in Figure 5.6. Similar finding can be seen in the correlation between

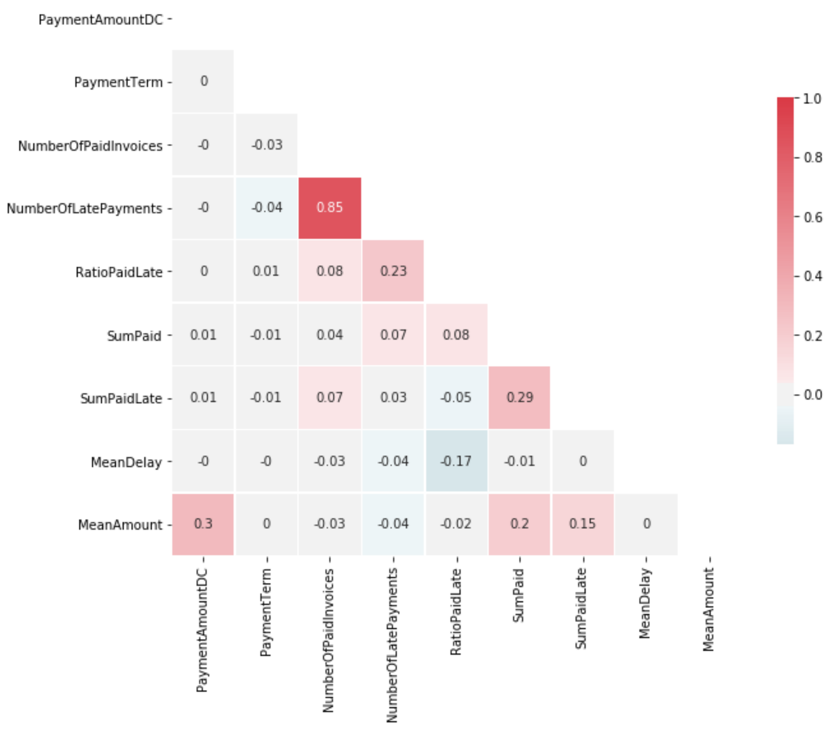


Figure 5.6: Heatmap showing the correlations between all baseline features.

Payment Term and the target variable, "IsLate". A more interesting find is that almost no feature correlates with strongly one another. The exception here is "Number of late payments" and "Number of paid invoices". Because of this strong correlation, it can be beneficial to remove this feature from the set as there is a little amount of information added by leaving the feature in at the cost of run-time.

Chapter 6

Experiments

In this chapter we will discuss the experiments and the methods that have been introduced in chapter 5. The chapter is split into two segments. The first segment will look into the experimentation of custom features. These are features that have been handcrafted by looking into different scopes for the baseline features or are introduced as new features altogether. The second segment of the chapter looks into learned features using graph embedding.

6.1 Custom features

In this section we will look how the custom handmade features perform to the baseline shown above. With these experiments the goal is primarily to test the quality of other custom features other than the ones that were shown in the literature. Additionally, these experiments should help us in answering SQ3, namely whether any additional information from the network improves the performance of our predictions. This is done step by step by iteratively increasing the scope of features. To be able to build a graph of that encodes invoices, a segment of the dataset

6.1.1 Experiment 1: Node level profiling

In this experiment we investigate the effects of raising the baseline features to the scale of the node, to see whether it improves the accuracy of the model. In the baseline model all features were based on the history between the sender of the invoices and its receiver. However, over the duration the two parties are also involved with invoices from and to other companies. These transactions could possibly give insight about the behavior of the two parties by leveraging data of other administrations.
For the featuring we introduce two new sets of features. Baseline features calculated on all outgoing invoices from the source entity, and all incoming invoices coming into the target entity. The choice was made to include these two sets, and not for example all outgoing invoices of the target entity, is because divisions are missing this type of data. Purely because the majority of the divisions in the dataset, has not sent any invoices to another division. However, to avoid any overlap in information between this global information and the baseline, the pairwise invoices between the source and target have been removed.

Results

The results of the experiment can be summarized by the following tables. The first table shows the results of the Random Forest model, which performed best on the baseline, on different segments of the new features. As can be seen in the table, the addition of the incoming and outgoing features next to the existing baseline features increase all measures across the board. The table below shows the other models performed on this combination of features.

Similar to the baseline, Random Forest outperforms all models by a margin. Almost for all models the addition of the incoming and outgoing features has increased the performance. However, the MLP model seems to have trouble with the addition of the dimensionality. With Accuracy slightly higher than 50%, it performs almost as bad as random guessing.

	Baseline	Incoming	Outgoing	In + Out	Baseline + In + Out
Accuracy	0.81558	0.80721	0.75055	0.82508	0.83086
F1	0.83108	0.82346	0.77216	0.84048	0.84579
Recall	0.80734	0.80011	0.75219	0.82006	0.82541
ROC AUC	0.81674	0.80822	0.75032	0.82579	0.83163

Table 6.1: Performance of node level features on a Random Forest model.

	RandomForest	MLP	DecisionTree	LGBM
Accuracy	0.83086	0.56358	0.79528	0.79104
F1	0.84579	0.71995	0.81789	0.80627
Recall	0.82541	0.56291	0.81746	0.84138
ROC AUC	0.83163	0.66062	0.79211	0.78929

Table 6.2: Performance of multiple classifiers on the combination of incoming invoices of the target node

6.1.2 Experiment 2: Time sensitive customer profiling

In this experiment we look whether it is beneficial to only consider most recent invoices. The features will be windowed to different human seasonal time frames. For example: windowing on 3-month, 6-month and 12-month basis. The intuition behind this experiment is that companies and the people responsible for their payments change over time. Recent timely payments should outweigh the late-payment made years ago and vice-versa. The difference between these features and the baseline is that for the baseline complete aggregates are taken for all available data. Because of this, features such as the *Sum of Invoice Amounts* will have larger values the more invoices and time are available.

So for this experiment the featuring is done using time windows, instead of all preceding data points. Primarily windows of 3-months, 6-months and 1-year. Because of the way the windowed methods calculate the features there are often more sparse. For example, when no invoices are sent within the period of the window. In order to keep the datasets the same between the experiments and the baseline, the features are padded with zeroes in cases where the feature cannot be calculated. The following table shows the result of the experiment.

As can be seen in table 6.3 limiting invoices to a recent time window does not directly improve the accuracy of the model. This could be due to how different divisions are amongst each other. The dataset contains roughly 150000 with each their own types of behaviors. Moreover, there is a high variance between the amount of invoices that every division sends. Among these divisions majority only sends several invoices a year, while others send hundreds. In future steps the static n-day window of time could be replace by a more dynamic method that considers the amount of invoices that are sent by the divisions.

6.1.3 Experiment 3: Alternatives to profile features

In this experiment we look whether new features can be introduced that consider the late payments and the delay of the payments as a signal. Specifically in this experiment we will look at the following features:

- gradient/slope of delay at last steps
- variance of delay
- time since last late payment
- mean time between late payments

	Baseline	90-day window	180-day window	365-day window
Accuracy	0.81558	0.78573	0.80992	0.81541
F1	0.83108	0.80335	0.82555	0.83085
Recall	0.80734	0.77883	0.80039	0.80674
ROC AUC	0.81674	0.78670	0.81126	0.81663

Table 6.3: Results based on several metrics using the Random Forest model

	Baseline	Temporal	Baseline + Temporal
Accuracy	0.81558	0.77002	0.81489
ROC AUC	0.81674	0.76335	0.81575

Table 6.4: Performance of hand crafted temporal features compared to the baseline.

	Baseline	Neighborhood	Baseline + Neighborhood	Baseline + In + Out + Neighborhood
Accuracy	0.81558	0.73463	0.82790	0.83265
ROC AUC	0.81674	0.73193	0.82533	0.82998

Table 6.5: Performance of neighborhood features on Random Forest model compared to the baseline and previous node level feature experiment.

- inverse temporal link weight

Compared to the existing features, with these features we look at the delay and the late payments as a signal. With the gradient and variance we try to get more information on the volatility of the target's payments. For example, if the customer is becoming more lax over time this would be visible in the the gradient of the delay. The mean time between late payments and the time since the last late payment can could be useful if the late payments are done periodically. The inverse temporal link weight is inspired by the *Temporal Link Weight* introduced in [37]. The goal of the feature as described in the paper is to assign more weight to events that happened early in the process to account for the possible spreading and snowball-effect. For our use case we would like to do the opposite, and rather have the weight to be high if the payment were made late recently and decay the weight over time. This is done using the following formula of *Inverse Temporal Link Weight*:

$$\phi(\alpha) = \sum_{m=1}^{n} (\frac{t_{jk}^{(m)}}{t_{max}})^{\alpha}$$

The event at which there is a late payment is defined by $t_{jk}^{(m)}$, from node j to node k at timestep m. t_{max} is the normalizing factor and is set to the latest possible timestep m. Since we have two years of data, t_{max} is set to 730. The factor α is set with $\alpha > 1$ to increase the weight exponentially the more recent it is. The parameter can be used to create similar features but with different settings for alpha. Looking at the other features the calculations more are straightforward. With the gradient, the delay is first smoothed out using a moving average. The slope is then taken at the last step. The calculation of the other features is straightforward. The following table shows these features perform compared to our baseline:

As can be seen from table 6.4, these features do not perform as well as the baseline features. However, these features perform only 5% worse than the baseline, with a very small feature set. The benefits of this is that the training is quicker and easier to tune as a result. The combination of the baseline and the temporal features does not seem to show any improvements.

6.1.4 Experiment 4: Neighborhood level profiling

The goal of this experiment is to explore whether performance of the models can be improved by introducing information that is available from 1-hop neighbors. More specifically we look at the neighbors of the source node. This is similar to the node level features in experiment 1. However, now instead of looking at the invoices neighborhood pays, we look into the invoices that are sent by the neighborhood. The baseline features aggregate the invoices from the neighborhood and generate a single set of features. This should give information about how much money the neighborhood has and how much they are still owed by others.

Table 6.5 shows the performance of these generated features. As can be seen from the table the neighborhood features perform well when combined with the baseline feature set. The results from experiment 1 showed that node level profiles can improve the performance of the predictions, even when the features are made from a similar set of invoices. The neighborhood features on the other hand do not use any of the invoices that have been used by the other features sets. However, the results from table 6.5 do not show a large increase in performance when combined with the incoming and outgoing features. Moreover, comparing to the results from experiment 1, the increase is marginal. Nonetheless, with the use of the same defined features as in the literature but raising the scope at which they are calculated, we have increased the performance. The next section will show how this can be done with learned features.

	All	Returning Customers (has profile)	First-Time Customers (no profile)
2017	1919709	645995	1271114
2018	2403094	919900	1483194
Total	4322803	1565895	2754308

Table 6.6: The number of invoices per year and customer type

	All Invoices	Returning	Non-Returning
I	0.62990	0.60300	0.65469
$I+E$	0.77733	0.77807	0.77632
$I+P$	0.76316	0.81678	-
$I+P+E$	0.80209	0.82541	-
$I+P+E_s$	0.79344	0.82385	-
$I+P+E_t$	0.79853	0.82463	-

Table 6.7: Table shows the AUC of a Random Forest model on different combinations of features and invoice situations. The left-hand size contains sets that are identified as follows: I - invoice, P - Profile (from history), E - embedding of G_b both source and target, E_s - embedding of source in G_b, E_t - embedding of target in G_b. The features are concatenated.

6.2 Learned features

In the previous experiments we have tested custom made features for the task of late-payment that have been proposed by the literature. We have introduced other features and tested how they perform compared to current methods. Furthermore we tested how the predictions improve, when the features are calculated on the neighborhood level. In the following section we will look into the a method that can provide learned method based on a generic framework. To be able to build a graph that encodes invoices, a segment of the dataset is put aside for the network construction. The previous experiment were run using data between 2017 and 2018 of *returning* customers. Meaning that only samples were evaluated where a profile could be built. In the following experiments the data is split in half. The exact amount of invoices can be seen in table 6.6. The data from 2017 is used to create a static network of invoices (experiment 6). While the network constructed in experiment 5 does not use any invoice information, any data after 31-12-2017 is excluded from the construction of the graph. This is done to keep consistency between the two experiments. Once the graphs have been constructed the training and test data between them is the same.

6.2.1 Experiment 5: Business Graph Embedding

In this experiment we test the effects of Graph Embedding and whether the learned features can be leveraged for the predictions of late-payments. During this experiment we look specifically into node2vec [13]. As described previously in chapter 2, node2vec is a special case of DeepWalk [29] where the random walk can be biased by making it more likely to explore further nodes or stay in the direct neighborhood of the seed node. Additionally, node2vec replaces hierarchical sampling used by DeepWalk to approximate the softmax probabilities with negative sampling.

The input for this experiment is a graph of divisions that is constructed using the accounts provided and matched using the explained entity resolution method. For simplicity we will also refer to this graph as the business graph or G_b. The graph contains the companies that have added one-another as an account somewhere over the last 15 years. Being connected however does not mean that invoices will be sent between the connected companies. But, in order to be able to send an invoice to a company the sender needs to have that company as an account. In other words, the business graph shows where invoices can possibly go to and more generally shows which of the companies do business with one another. The graph is undirected, unweighted and is constructed from Accounts data until 01-01-2018.

In the first experiment we explore the effects of these learned features on the performance of our model. For the simplicity of this experiment we keep the default hyper-parameters used by node2vec. These settings include the walk-length and number of walks, p and q. Without any changes to the p and q parameters, the algorithm acts similar to DeepWalk with negative sampling and a more efficient walk generation. The following table shows the performance of the node embeddings. Performance of other models were worse on all counts and have been omitted from the results for the sake of readability.

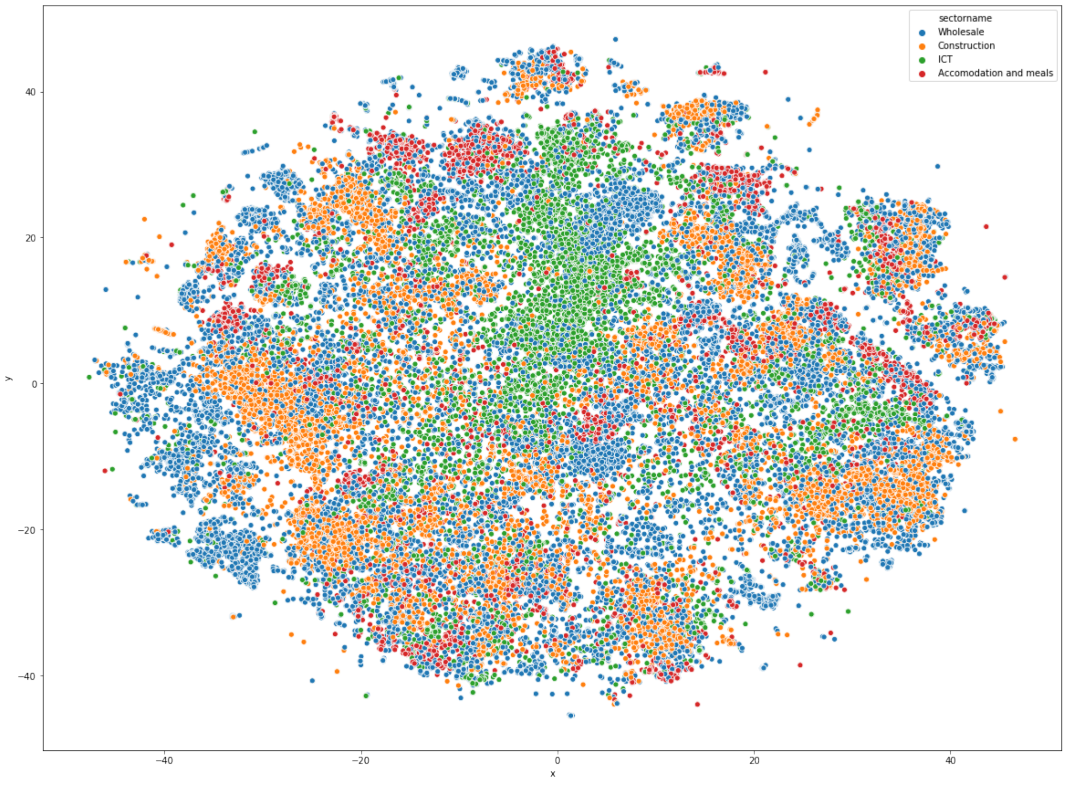


Figure 6.1: t-SNE clustering of the embeddings made with node2vec

The table shows results for the follow feature sets, the baseline, baseline with the embedded features of the source node concatenated, same as the previous but the embeddings of the target node are also concatenated. For the final setup the node embedding features have been reduce in dimensionality using PCA. Using PCA the dimensionality of the embedding is reduced from 128 to 10. As can be seen from the table, in all cases where the node features have been added to the existing baseline feature set, the prediction improved. The biggest improvement is when the embedding of both nodes is added. Although, individually it seems that information about the target is slightly more important than source embedding. The most interesting results are regarding the performance of the embeddings when the profile of a companies is not available. There is a major increase in performance compared to predicting the late payment based on only invoice information. The invoice information only consists of the Amount that needs to be paid and the corresponding payment term. This is a major benefit to a late payment framework. From the surveyed literature, none were able to make predictions when there was no historical data. The use of these features opens the possibility to classify invoices where no other invoices are present in the history. In other words these types of features can help solve the cold start problem by providing context features of the companies involved. With such a large fraction of the dataset suffering from the cold start problem, this method provides a large improvement compared to the methods gathered from the literature.

Ofcourse the increase in utility and performance does not come entirely free. A Problem with node embeddings in general is that it cannot be updated when new data becomes available. This can be a problem with using graph embedding for classification. The runtime of the embedding algorithm scales primarily with the amount of edges in the graph. While the featuring of the profile features can be done in about 20 minutes, the embedding of the accounts graph takes almost 12 hours to run. While this is not a problem in the grand scheme of things, it is not possible to recalculate the embedding every time a new connection is made. This is a known problem that many graph embedding methods struggle with. A compromise could be that the embedding is calculated once a day for the next day or even once a week or once a month depending on the availability of the resources and the size of the graph. A more dynamic method of using the embedded features is tested in further experiments.

As can be seen from the table, the learned features gives a better prediction in a situation where only invoice information is present. The combination of the invoice features and the learned features further in-

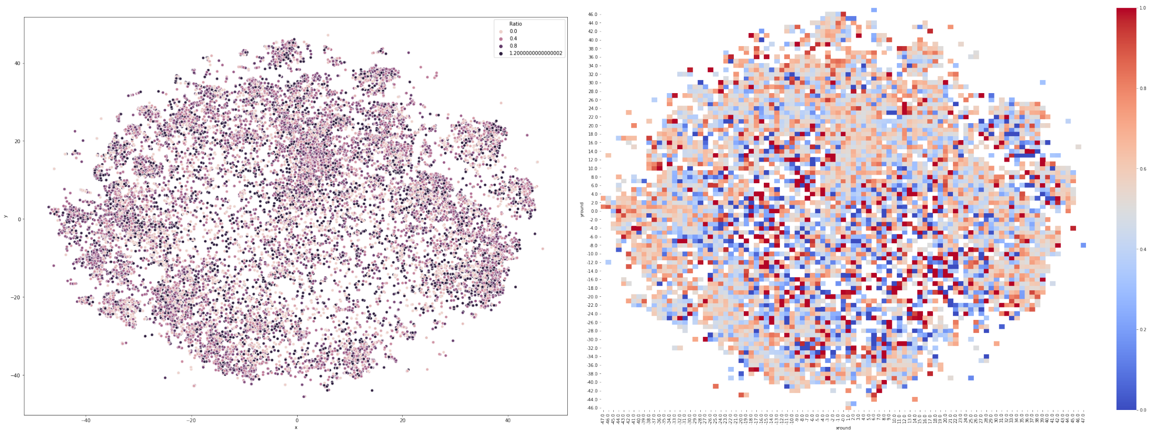


Figure 6.2: Scatter plot (left) and heatmap (right) of the t-SNE embedding showing the relation to the position of a node and its percentage of received late payments.

creases the accuracy. Interestingly, the learned features are not dependent on time or the previous invoices between the companies. Moreover, none of the invoice information is embedded in them. But rather the features are supposed to represent the nodes in a latent space. Whether these latent features could be interpreted and correlated to an aspects of the company is still an open research problem.

Work from Bruss et al. [5] shows different ways of how these features are incorporated into their prediction. The paper discusses two different methods, namely directly concatenating the feature set or training a separate classifier that and passing the predictions as a feature to the existing classifier. The first method has been described above. However, while being the superior method in the paper discussed by Bruss, similar improvements were not seen during experimentation. Moreover the general results of this method show a reduction in performance across the board from 3% to 4%. Due to its performance and overall readability of the chapter, the results of the stacking have been omitted.

To understand why there is such an increase in performance we explore the embedding by visualising it using t-SNE. The main benefit of t-SNE is that it is a great method for visualizing high dimensional data into readable 2-dimensional clusters. More on t-SNE can be found in [25]. Figure 6.1 shows the created representation embedded to a 2-dimensional space using t-SNE. The sector information of a few largest sectors is labeled after the dimensional reduction is applied, to show possible similarity between companies. The plot clearly shows clustering and segmentation of nodes that share the same sector. It is important to note that the sector information has not been used during any of the preprocessing or embedding of the networks. Additionally, this shows that the graph generated using entity resolution is well structured and carries valuable information about the supply chain between the SMEs in the graph.

fig. 6.2 shows the relation between the position of a node and its percentage of received late payments. The scatterplot shows the exact location and ratio of late payment of a node, but it is prone to overlapping. The heatmap on the other hand, divides the plane into a grid and calculates it per cell. However, this causes extreme values in cells where there are not enough nodes. Disregarding this, both visualizations do not show that the position of the node corresponds to its likeliness to pay late. Finally, we can look whether the combination of certain sector pairs is more likely to have late payments. This can be seen in fig. 6.3. The hue of the cells shows the ratio of late payment while the annotated number shows the actual amount of invoices in that cell. While there are no clear heavy hitters, sectors such as the Industrial sector receive a fairly high amount of late payments from the Distribution of water and waste sector.

6.2.2 Experiment 6: Invoice Graph Embedding

In the previous experiment we have shown learned features which were gathered using node embeddings on the business graph. This graph only contained information about which companies do business with each other. This graph did not contain any further information about the invoices sent between nodes. However, creating a network that models the invoices between companies is not a trivial task, especially as node embedding methods are only limited to (un)directed and (un)weighted graphs. With invoice being able to be either late or on-time, we cannot model the events with a single network unless the edges are typed. Unfortunately, this is not supported by the node2vec architecture unless some workaround is applied. To still

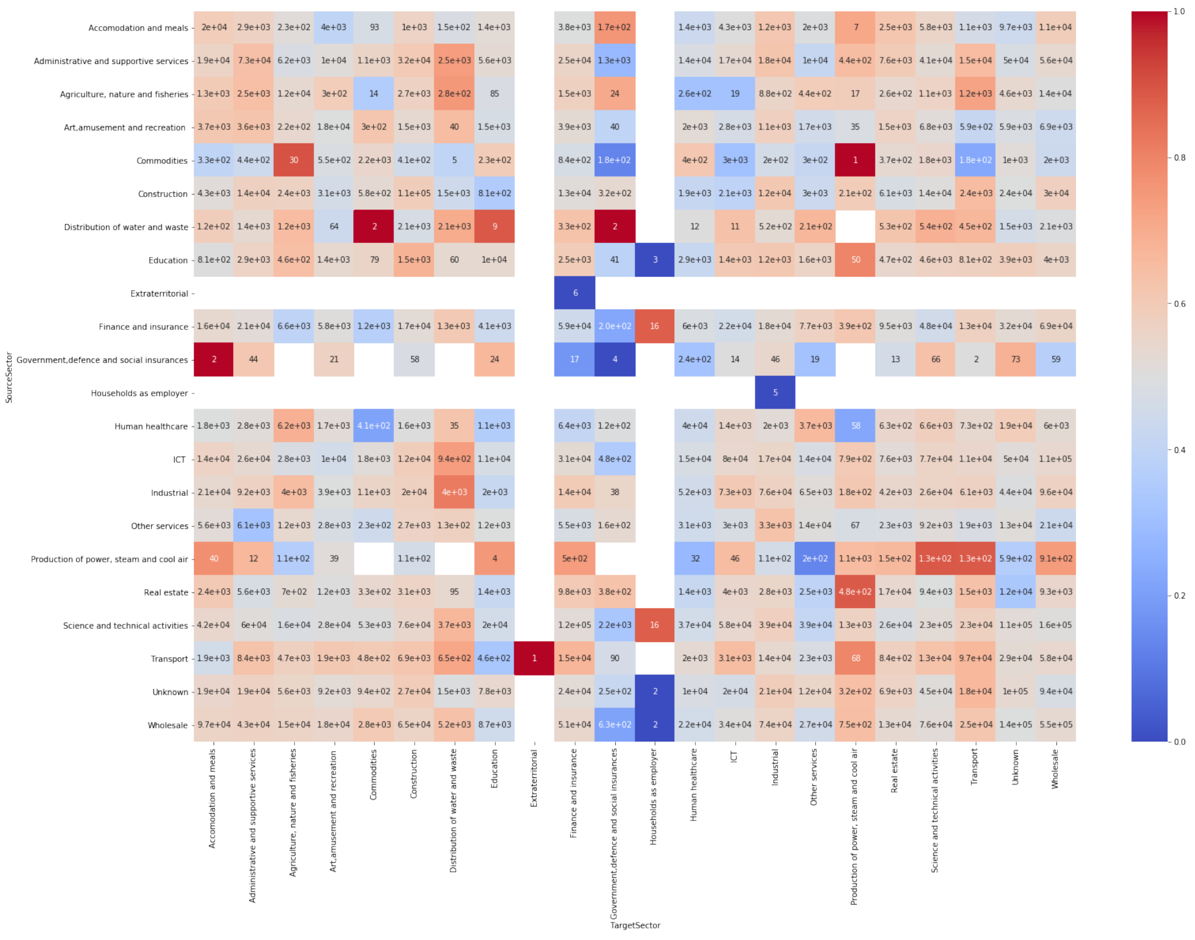
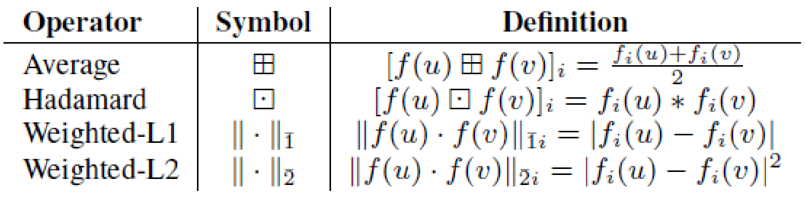


Figure 6.3: Heatmap shows the interaction between the sector of the source node and the target node. Annotated values show the count of invoices with this sector combination, where as the hue describes the ratio of invoices that have been paid late.

	All Invoices (Business Graph)	All Invoices (Invoice Graphs)
I	0.62990	0.62990
$I+E$	0.77732	0.77919
$I+P$	0.76316	0.76316
$I+P+E$	0.80209	0.80020
$I+P+E_{neg}$	-	0.79701
$I+P+E_{pos}$	-	0.79800
$I+P+E_s$	0.79344	0.78830
$I+P+E_t$	0.79853	0.79676

Table 6.8: Comparison of business graph embedding versus embedding of the invoice graph measuring AUC. The left-hand size contains sets that are identified as follows: I - invoice, P - Profile (from history), E - embedding of both source and target, E_s - embedding of source, E_t - embedding of target, E_{pos} - embedding of source and target from the late invoice graph., E_{neg} - embedding of source and target from the non-late invoice graph. The features are concatenated.



Operator	**Symbol**	**Definition**
Average	$\boxplus$	$[f(u) \boxplus f(v)]_i = \frac{f_i(u)+f_i(v)}{2}$
Hadamard	$\boxdot$	$[f(u) \boxdot f(v)]_i = f_i(u) * f_i(v)$
Weighted-L1	$\Vert \cdot \Vert_{\bar{1}}$	$\Vert f(u) \cdot f(v) \Vert_{\bar{1}i} = \vert f_i(u) - f_i(v) \vert$
Weighted-L2	$\Vert \cdot \Vert_{\bar{2}}$	$\Vert f(u) \cdot f(v) \Vert_{\bar{2}i} = \vert f_i(u) - f_i(v) \vert^2$

Figure 6.4: Choice of binary operators for learning edge features. The definitions correspond to the ith component of $g(u; v)$.

be able to use node2vec for the node embedding the invoices are split over two separate graphs. One of the graphs contains all late invoices while the other contains all invoices that were paid on time. Unlike the business graph, these graphs are directed in the direct of the node that receives the invoice. These edges are also weighted. This weight represents the count of invoices that have been paid by the receiver(target) to the sender(source). Further exploration shows the quality of the generated features and performance when the node2vec framework is tuned.

The most simple way of using the generated features is to direct use the latent features as the input to the classifier. With two graphs, this results into a total of 4 sets of features. The embedding of the source node from both graph, and the same for the target node. However, due to the embedding not always being available, for example because a node has never sent or received late invoice payments, the feature set is padded to match the input size. Table 6.8 shows the performance of the embedded features compared to the embedding of the business graph. This set of features performs very similar to the performance of the business graph but at the benefit of faster runtime.

This method decreases the runtime of the algorithm in two different ways:

1. Since invoices can only be sent to existing accounts, the invoice graph is a subset of the business graph. With only a fraction of the accounts receiving invoices, the invoices graph count significantly less edges than the business graph.

2. Additionally the two graphs are directional. This reduces the amount of possible paths and reduces the time needed to calculate the transition probabilities.

Alongside the node2vec frame work, Groover et al. provide several operators that can be used to do classification on edge level. These operators are shown in fig. 6.4. According to the paper, the Hadamard operator outperformed raw features and any other operators that were tested. Testing out this operator, we combine the raw features of the embedded target and source nodes using the Hadamard operator. This is done for each graph separately. However, the performance of the operator is lower than using raw features as input by roughly 3% across the board and has therefore been omitted from the report.

6.2.3 Split graph tuning

Looking at the previous experiments, we saw that the introduction of dimensionality reduction improved the performance of the model. This suggests that the default embedding dimensionality of 128, is possibly too

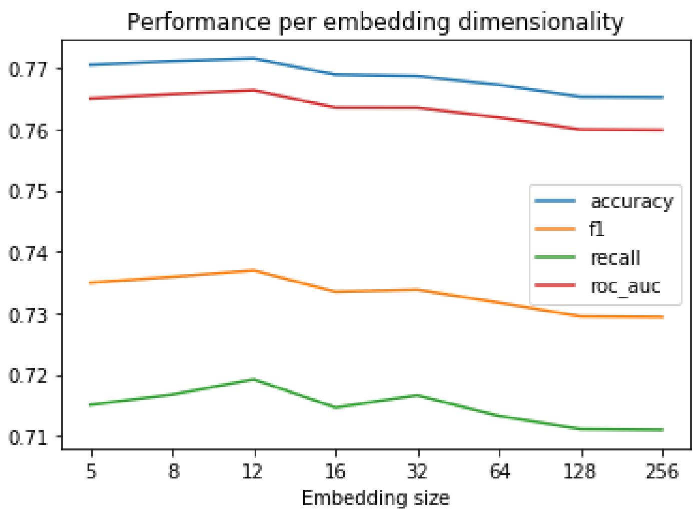


Figure 6.5: Figure showing the performance of the model per different embedding sizes.

large for the graph and could possible be reduced. Looking at work done by Bruss et al. [5], the embedding size of the their network was the most optimal around size 10. To investigate the effect of the dimensionality size, we create several embedding at different embedding sizes. This can be seen in fig. 6.5.

The different embeddings show that the more optimal embedding sizes are much lower than the default embedding size of 128 set by node2vec. The embedding size is set for both graphs at the same time. The performance is measured The embedding size that gives the best performance seems to be 12 from the set of parameters that has been tried out. This is consistent with all performed metrics.

The general performance from the node embedding experiments have been very promising. However node2vec and graph embedding methods can really give different results depending on the tuning of the hyper-parameters. So in the following steps we will look into the performance differences when the embedding method is tuned. Specifically, we will look into the walk length, number of walks, p and q. Where the latter two bias the random walk probability.

The tuning of these parameters is done using Grid Search. This comes down to exhaustively trying out all parameter given combinations. With 4 hyperparameters and 5 settings for each parameter, totals to 625 trials. The chosen search space is similar to the one discussed in [13] with p and q values between 0.25 and 2.0. Figure 6.6 shows the mean results of the tuned parameters. As can be seen from the figures the mean difference in AUC varies only slightly between the trials. This can be seen throughout the measurement of the trials.

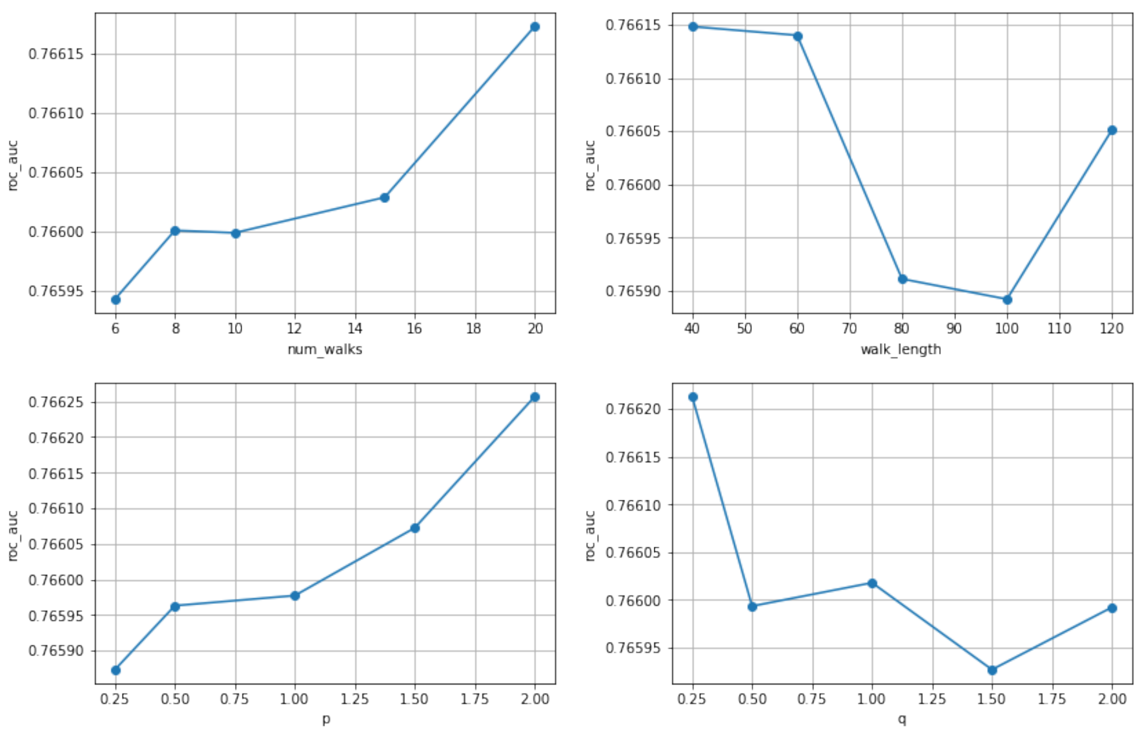


Figure 6.6: Mean results of tuned node2vec parameters.

Chapter 7

Discussion

Previous chapters of the report have shown different methods for entity resolution and late payment prediction. While some of the experiments and results speak for themselves, others have shown interesting aspects worth exploring further. In this section of the report, we discuss the results of the experiments and aspects of the method used in them.

7.1 Entity Resolution

The tailored method for Entity Resolution has been critical in creating the dataset and network needed for this research. The performed experiment with field experts has shown that it is at least as good a known baseline for matching. However, with some further work, some aspects could be improved to make the algorithm usable in more general cases. While the method was specifically designed to be able to compare different fields such as Company Name, Address, Phone number, etc. this did not seem to work as expected with the available data. Moreover, the classifier that was trained to match based on only the Name features was not only very similar in performance on the training data but also worked much better in the pipeline of the resolution algorithm. The reason why this could be the case is that most of the records only have a select view of their fields filled in. When combined with other records in a cluster, the entity is generated from the most common values in each column. Problematic is that the mode of a set of records can make value combinations that are not present in the input data. This is partly by design because this increases the chance of having a representing entity that is more information-rich. In a worse case, it causes an incorrect combination of fields. Generally, this is not too big of a problem if the solution has a classifier that can deal with these examples. However, in combination with the lack of a proper training set where these types of patterns can be found, the model that only looked at the Name records was much more stable in the algorithm.

Besides the quality of the classifier, there has been little exploration done into the scalability of the algorithm. While the proposed method should be more scalable. Whether it would be usable in practice depends on the purity of the found clusters compared to a baseline. For this reason, the benchmarking was set primarily to test the algorithm on its quality of produced clusters. To further explore how the algorithm compares in terms of speed and scalability, it would need experimentation with other ER methods. Due to the time constraint of the project and its scope, we have not looked further into this besides some initial exploration.

7.2 Invoice prediction

While custom feature experiments have shown significant improvement to the basic late payment prediction, the learned features using the business graph have shown a possible way to tackle the cold start problem. The cold start problem is a well-known problem in machine learning and other information systems where no inference can be done due to the lack of initial information. In our case, this is due to the fact that there are no previous invoices sent between a pair of companies. Generally, as a user uses the software, more and more data becomes available that can be used by the system's features. Nonetheless, having to make a prediction for an invoice without history is very common as roughly 40% of the company pairs have only been seen once in the dataset. Moreover, the average amount of time between a user sending an invoice and putting it in the system easily racks up to several months. Because of this, a large segment of the invoices does not have a history during inference. In this case, it is possible that only information is available about the invoice itself and nothing more.

At the same time, there are different features that could potentially help the performance of the predictions. For example, when no history is available for transactions between two companies, it is sometimes possible to use the information from the other transactions of the nodes. This information is of course only available if the nodes have exchanged invoices with other nodes in the network. While we have not extensively experimented with extended versions of the baseline. From experience, these methods underperform compared to the learned node embeddings. Nevertheless, no exhaustive research has been done in exploring new types of baselines for invoices dealing with the cold start problem. Newfound features could be used in combination with learned node embeddings to improve the performance further.

Interestingly, the results of the business graph experiment show that the embedding of the target node does not provide any improvements to the performance of the model. A reason for why this could be the case is because the profile is already strictly information about the target. However, this would suggest that the addition of the context to the profile does not give any additional information that can be of use to the model. More generally, the performance of the node embedding on the business graph could possibly be due to it being the superset of the invoice graph. Additionally, the business graph contains more connections compared to the graph of invoices. This due to the fact that not every division sends invoices or has registered everything within the period that has been explored during this research.

Thanks to the entity resolution done by the proposed method, we are not only able to solve the cold start problem but do much more. Since the business connection only has to be done by one side of the relation, we in some cases can make predictions for companies that have not even become a part of the platform yet. Of course, it is important to understand what is allowed with the data and when you are crossing any moral or ethical boundaries. Nonetheless, these examples show the added utility of the proposed methods.

Chapter 8

Conclusion

In this report, we have presented how late-payment prediction can be done through graph features when relational data is not available. In the first steps of the project, we have introduced a method that can generate the needed relational data through recognition of shared connections and matching of entities. In further steps, this network of companies has been used to not only improve the existing methods of late payment prediction but also provide utility in cases where very little information is available.

At the start of the research, a set of questions were defined to guide research and to clarify a general goal of the project. The main research question was as follows: ***Can graph features be used to improve the prediction of late invoice payments compared to currently popular methods?*** With the research completed, we have sufficiently gathered enough information to answer the defined sub-questions.

SQ1: How can a network of SMEs be built from data that is unstandardized, noisy and partial?
To create the needed relational dataset a tailored entity resolution algorithm was created. The algorithm showed that similar records can be found by leveraging the most frequent values in a cluster and move separate records between clusters using a matching classifier. It was shown that the pureness of the created clusters is similar to the currently best case scenario baseline. Additionally, the algorithm can create clusters from incomplete data that is beyond the capabilities of the baseline.

SQ2: How should the data and the graph be structured to be able to extract meaningful features?
With one of the following two methods, *(1)* graph that shows business between companies and, *(2)* a setup where late and non-late payments are constructed separately. The business graph represents the most simple network construction possible and does not contain any invoice information. The embedding of a large graph can be slow and thus difficult to tune. With the construction of the split invoice graph, the embedding time is reduced from 12 hours to 20 minutes. This makes the method much more usable when training time is an issue. The two methods showed similar results and both improved over the performance of the baseline.

SQ3: Does the addition of graph features improve the prediction of late payments?
As can be seen from the results, the addition of the extracted features has improved the performance in several of the experiments. Besides improving on the baseline, the learned node embeddings give a large amount of utility by unlocking the possibility to predict invoices where invoice history is not available. Meaning it is the case for both new and returning customers. The visualization of the latent features has shown that entity resolution has been successful in constructing a network that holds vital contextual information.

Chapter 9

Future Work

In this section, we will discuss the possible future steps for the described method and implemented framework. Some of these features are aspects where we think the research done and the proposed framework could benefit from if looked into. Many of these aspects are direct follow-ups for the research done. However, due to the limited time and scope of this thesis, these aspects were not further investigated.

9.1 Entity Resolution

Throughout the project, a method was developed that successfully was able to apply entity resolution on a large dataset. Having done this, and having used this method to build a relational graph of Dutch SMEs, has created many opportunities. The future work in this segment is not only focused on improving the resolution algorithm but also into possible avenues for the created network.

9.1.1 Matching based on context information:

The proposed algorithm provides a method for entity resolution based on the information that is provided in the accounts of the divisions. From further experimentation and testing with field experts, it became apparent that sometimes there was not enough information provided by the records to decide whether they match. However, as these accounts are used for functionalities such as invoicing and other types of transactions, it is possible to leverage the information that is provided in these transactions as context to improve the resolution. This can be done for example, by recognizing similar templates across invoices or data mining context from descriptions of transactions.

9.1.2 Recognition of private entities:

A major challenge in this data is the separation between private entities and natural persons. This problem arises due to the similarity in naming between the two types of entities. For example, taking the following two names: Albert Heijn and Alfred Heijn. While the two names are very similar in terms of character-level similarity, they represent different types of entities. While Albert Heijn is a large franchise of supermarkets, Albert Heijn is probably a person. This type of ambiguity increases the noise in the data and poses a major problem for the quality of the resolved entities. Since the goal of the algorithm is to match the record together that belongs to an entity (private and public) and give a single clean representation of that entity, it is in the best interest to filter out the natural persons out as part of the algorithm pipeline.

9.1.3 Testing on public datasets:

While the method was specifically made for the problem for Exact's dataset, it is not completely limited in terms of the dataset. Due to how the algorithm works, it should be usable on other datasets once a set of columns has been chosen for grouping.

9.2 Late-Payment prediction

While there have been many different features that have been tried and experimented with, we have only scratched the surface of what is possible. There are still many types of features and methods that could be used to improve the performance of the models and give more insight into how these businesses interact with each other.

9.2.1 Modeling of cashflow and node interactions

While the goal of this research was to see whether existing late payment prediction methods could be improved using network information. The overarching reason for modeling invoices is due to it being used to estimate a companies cashflow. With this project serving as a proof of concept for the usefulness of the network, it would be interesting to see whether it could be used to model the flow of cash from one business to another. With a large sample of the Dutch SMEs, such research could be used to model the Dutch economy to some extent. Besides cash flow, it would be interesting to see whether other interactions between companies could be modeled. For example, the flow of goods, change in KPI's or bankruptcy status.

9.2.2 GNN models

One method that could perform very well on the data is the set of models that fall under Graph Neural Networks. The majority of these methods make use of the Graph Convolutional layer that learns features from the proximity of each node. A major problem with this approach is that it is much slower and scales much worse than the methods that have been applied in this research. Nonetheless, GNNs also knows as Geometric Deep Learning is currently a very active field that has many different fields it is applied in. However, as writing this report, I have not seen any GNN applications in the scope of financial networks or payment predictions. Due to the scalability, the complexity of the GNN architectures and the scope of the project, GNNs were left for future steps.

Appendix A

Experiment protocol: Investigating the subjective quality of generated entities.

A.1 Motivation

Entity Resolution (ER) describes the problem of finding unique entities in a single or among multiple sources of records. The later is more commonly known as record linkage if the goal of the method is to enrich a database with external information. Record linkage methods are generally measured by the precision and recall of the classification if ground truth is available. However these methods of validation can be problematic [14]. Moreover, whether the mapping of entities is good enough for the task at hand, is task dependent and somewhat subjective. The baseline method that will be compared against are clusters made by grouping the records on the Chamber Of Commerce number, also known as Kamer van Koophandel (KvK) number. To understand whether the method provides a better representation compared to the current standard or other type of baseline, the methods should be compared in a subjective test. Within this test records from a single cluster will be evaluated by a domain expert. This will show the quality of the generated cluster, and whether it brings an improvement compared to the current baseline.

A.2 Research Questions

The goal of the experiment is to find out how the proposed clustering methods perform in when evaluated by domain experts. Moreover, we are trying to find whether the proposed method outperforms the baseline during the evaluation.

- How pure are the clusters made with KvK and the proposed method?
- Does the proposed method provide better clusters compared than the current baseline method?

A.3 Independent Variables / Setup

The independent variable in this experiment is the source algorithm which has grouped the records shown to the expert. To make a sure that the clusters are comparable to each other, we will include records of the same entity. Additionally, for both methods, the same data will be used to create the clusters. The questionnaires consists of 18 multiple choice questions, one question for each of the following: 2 algorithms and per (baseline, proposed) algorithm, 4 large, 4 medium and 4 small clusters. The cluster sizes are classified as follows:

- large: cluster size between 10000 and 5000
- medium: cluster size between 1000 and 500
- small: cluster size between 100 and 50

Every question will show 10 different records, which gives a sample size of 120 per algorithm/version/person combination. Each records has a checkbox next to it. The user is able to check any of the records that he/she finds to be clustered incorrectly. We expect that a single question will take roughly 30 seconds to complete. With 24 questions, it will take a user about 12 minutes to complete the task. For the experiment we perform a within group comparison, giving us evaluations of several clusters. To cover a larger set of clusters, the questionnaire will be generated using random companies every single time. Every version will have a different set of companies. This is to cover as much clusters from the methods as possible while keeping the questionnaire short and with some variation in terms of entities. We hope to have at least 3 people per version, that is at least 9 human subjects in total.

For every subject, we will create an excel sheet that contains the questionnaire in one of the three versions. The subjects will not have any overlapping clusters. The human subjects will be asked to evaluate the questions without using any external resources. To make sure that there is no learning or recency effects, the order of the questions will be randomized. To have as least noise as possible in the produced labels, the human subject should be a field expert.

A.4 Brand level vs Franchise level

Entities exist on different levels of branding. To be able to distinguish companies from the brands, the focus will be on comparing records on individual company level. For example, different McDonald's restaurants could be grouped on a brand level, encapsulating all franchised restaurants. However, for further use cases of the algorithm it is important to distinguish between different real-world entities. The problem with trying to make a distinction between a brand level and franchise level entity, is that there often was not enough information to make that choice. The majority of accounts have missing values, which makes the sample a lot more uncertain. Because of this, the experts will specifically be asked to distinguish the companies on franchise level and not on brand level if possible.

A.5 Validation

For the validation we will look at the following aspects of the produced labels:

- Number of defects per human subject.
- Number of defects per algorithm.

To show the significance of these measurements, a Chi-square test will be performed on the results. The conclusion of the experiment will conclude whether or not the proposed ER algorithm outperforms the baseline, and will show how pure both methods are when evaluated by field experts.

Appendix B

Experiment Briefing

Thank you for helping us test the quality of the account matching algorithm. The goal of the matching algorithm is to group accounts together that belong to a single entity. We define an entity as a brand-level company, organization or person. The match is made by cross-referencing the given information to other "similar" accounts.

To validate the quality of the algorithm, we would like to ask you help us find mismatched accounts. To do this, we have created a list of questions. Every question will contain a set of accounts sampled from a single cluster. These clusters are either made by matching accounts on KvK or by the proposed method. As part of the questions we ask you to checkmark the records you think do not belong with the rest of the accounts. If none of the accounts belong together, you can mark all of the records.

The questions are set up as follows:

- Every question will contain a sample of 10 accounts.
- Every account will show you basic information such as Name, Address, Postalcode, Emailaddress of the correspondent, Website and Phonenumber. However, not all information is always provided.
- The questions are generated randomly and were not handpicked.
- For every entity, there will be a question made by each of the methods. Naturally, you will not know by which algorithm the records were grouped.
- This also means that there will be multiple questions about the same company.
- The comparison can seem difficult, but you can go back to previous questions.
- The questions don't necessarily have defect records. There are no wrong or right answers.

Further notes:

- Please read through all the information in a single question before checkmarking any of the records.
- If you are unsure about your choice, it is possible to use external sources to help you (e.g. Google).
- Some clusters contain accounts that are almost 15 years old.
- In case the company changed its name, both new and old names will be present in the cluster.

Bibliography

[1] 3 top data challenges and how firms solved them. URL `https://www.ibmbigdatahub.com/blog/3-top-data-challenges-and-how-firms-solved-them`.

[2] Microsoft dynamics 365 late payment prediction. `https://appsource.microsoft.com/en-us/product/dynamics-365-business-central/PUBID.microsoftdynsmb%7CAID.late-payment-prediction%7CPAPPID.3d5b2137-efeb-4014-8489-41d37f8fd4c3?tab=Overview`. Accessed: 2019-06-02.

[3] Business content: Payment predictions: Sap analytics cloud, Feb 2019. URL `https://www.sapanalytics.cloud/resources-business-content-payment-predictions/`.

[4] Joan Bruna, Wojciech Zaremba, Arthur Szlam, and Yann LeCun. Spectral networks and locally connected networks on graphs. *arXiv preprint arXiv:1312.6203*, 2013.

[5] C Bayan Bruss, Anish Khazane, Jonathan Rider, Richard Serpe, Antonia Gogoglou, and Keegan E Hines. Deeptrax: Embedding graphs of financial transactions. *arXiv preprint arXiv:1907.07225*, 2019.

[6] Hongyun Cai, Vincent W Zheng, and Kevin Chen-Chuan Chang. A comprehensive survey of graph embedding: Problems, techniques, and applications. *IEEE Transactions on Knowledge and Data Engineering*, 30(9):1616–1637, 2018.

[7] Haochen Chen, Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. A tutorial on network embeddings. *arXiv preprint arXiv:1808.02590*, 2018.

[8] Michelle LF Cheong and Wen SHI. Customer level predictive modeling for accounts receivable to reduce intervention actions. -, 2018.

[9] Adam Cohen. Fuzzywuzzy. URL `https://chairnerd.seatgeek.com/fuzzywuzzy-fuzzy-string-matching-in-python/`.

[10] Don Coppersmith and Shmuel Winograd. Matrix multiplication via arithmetic progressions. *Journal of symbolic computation*, 9(3):251–280, 1990.

[11] Tom Fawcett. An introduction to roc analysis. *Pattern recognition letters*, 27(8):861–874, 2006.

[12] Justin Gilmer, Samuel S Schoenholz, Patrick F Riley, Oriol Vinyals, and George E Dahl. Neural message passing for quantum chemistry. In *Proceedings of the 34th International Conference on Machine Learning-Volume 70*, pages 1263–1272. JMLR. org, 2017.

[13] Aditya Grover and Jure Leskovec. node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 855–864. ACM, 2016.

[14] David Hand and Peter Christen. A note on using the f-measure for evaluating record linkage algorithms. *Statistics and Computing*, 28(3):539–547, 2018.

[15] Peiguang Hu. *Predicting and improving invoice-to-cash collection through machine learning*. PhD thesis, Massachusetts Institute of Technology, 2015.

[16] Weikun Hu. *Overdue invoice forecasting and data mining*. PhD thesis, Massachusetts Institute of Technology, 2016.

[17] Richard HG Jackson and Anthony Wood. The performance of insolvency prediction and credit risk models in the uk: A comparative study. *The British Accounting Review*, 45(3):183–202, 2013.

[18] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. In *Advances in Neural Information Processing Systems*, pages 3146–3154, 2017.

[19] Jongmyoung Kim and Pilsung Kang. Late payment prediction models for fair allocation of customer contact lists to call center agents. *Decision Support Systems*, 85:84–101, 2016.

[20] Thomas N Kipf and Max Welling. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907*, 2016.

[21] Pradap Konda, Sanjay Subramanian Seshadri, Elan Segarra, Brent Hueth, and AnHai Doan. Executing entity matching end to end: A case study. Technical report, Technical report pages. cs. wisc. edu/˜ anhai/papers/umetrics-tr. pdf, 2019.

[22] Bertrand Lebichot, Fabian Braun, Olivier Caelen, and Marco Saerens. A graph-based, semi-supervised, credit card fraud detection system. In *International Workshop on Complex Networks and their Applications*, pages 721–733. Springer, 2016.

[23] Daoyuan Li, Jessica Lin, Tegawendé François D Assise Bissyande, Jacques Klein, and Yves Le Traon. Extracting statistical graph features for accurate and efficient time series classification. In *21st International Conference on Extending Database Technology*, 2018.

[24] Gilles Louppe. Bayesian optimisation with scikit-optimize. 2017.

[25] Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(Nov):2579–2605, 2008.

[26] Federico Monti, Fabrizio Frasca, Davide Eynard, Damon Mannion, and Michael M Bronstein. Fake news detection on social media using geometric deep learning. *arXiv preprint arXiv:1902.06673*, 2019.

[27] Ece C Mutlu and Toktam A Oghaz. Review on graph feature learning and feature extraction techniques for link prediction. *arXiv preprint arXiv:1901.03425*, 2019.

[28] Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in python. *Journal of machine learning research*, 12(Oct):2825–2830, 2011.

[29] Bryan Perozzi, Rami Al-Rfou, and Steven Skiena. Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 701–710. ACM, 2014.

[30] Hans-Christian Pfohl and Moritz Gomm. Supply chain finance: optimizing financial flows in supply chains. *Logistics research*, 1(3-4):149–161, 2009.

[31] Erhard Rahm and Eric Peukert. Large scale entity resolution., 2019.

[32] Jian Tang, Meng Qu, Mingzhe Wang, Ming Zhang, Jun Yan, and Qiaozhu Mei. Line: Large-scale information network embedding. In *Proceedings of the 24th international conference on world wide web*, pages 1067–1077. International World Wide Web Conferences Steering Committee, 2015.

[33] Huijuan Wang, E Van Boven, A Krishnakumar, M Hosseini, H Van Hooff, T Takema, N Baken, and Piet Van Mieghem. Multi-weighted monetary transaction network. *Advances in Complex Systems*, 14(05): 691–710, 2011.

[34] Zonghan Wu, Shirui Pan, Fengwen Chen, Guodong Long, Chengqi Zhang, and Philip S Yu. A comprehensive survey on graph neural networks. *arXiv preprint arXiv:1901.00596*, 2019.

[35] Rex Ying, Ruining He, Kaifeng Chen, Pong Eksombatchai, William L Hamilton, and Jure Leskovec. Graph convolutional neural networks for web-scale recommender systems. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 974–983. ACM, 2018.

[36] Sai Zeng, Prem Melville, Christian A Lang, Ioana Boier-Martin, and Conrad Murphy. Using predictive analysis to improve invoice-to-cash collection. In *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1043–1050. ACM, 2008.

[37] Xiu-Xiu Zhan, Alan Hanjalic, and Huijuan Wang. Information diffusion backbones in temporal networks. *Scientific reports*, 9(1):6798, 2019.

[38] Muhan Zhang and Yixin Chen. Link prediction based on graph neural networks. In *Advances in Neural Information Processing Systems*, pages 5165–5175, 2018.

[39] Ziwei Zhang, Peng Cui, and Wenwu Zhu. Deep learning on graphs: A survey. *arXiv preprint arXiv:1812.04202*, 2018.

[40] Xun Zhou, Sicong Cheng, Meng Zhu, Chengkun Guo, Sida Zhou, Peng Xu, Zhenghua Xue, and Weishi Zhang. A state of the art survey of data mining-based fraud detection and credit scoring. In *MATEC Web of Conferences*, volume 189, page 03002. EDP Sciences, 2018.