Conference - Business Informatics Research

Deep Learning for Information Extraction in Finance Documents – Corporate Loan Operations

Abstract

This paper describes a knowledge -based artificial intelligence (AI) system called MARBLE that evaluates the riskiness of business loan applicants. MARBLE is an acronym for a decision support system (DSS) for managing and Recommending business loan evaluation. A unique feature of MARBLE is that it has the capacity to learn; this is achieved by equipping MARBLE with an inductive inference engine that complements its deductive problem solver. The paper explains the AI system that uses inference rules to simulate the thought process of a lending officer when evaluating a loan request. The inductive learning approach and the learning logic of MARBLE are described and, additionally, there is an illustration of the system's operation in the loan evaluation process. The paper concludes with an empirical study of a MARBLE application.

# Introduction

Corporate lending is a complex business process. Regulations, global connectivity, heterogeneous participants and disparate operational environment of products and services delivery aggravate the complexity of this business process. Front office operations include sales pipeline, credit pipeline, regulations management and relationship management. The back office operations include loan document processing, anti money laundering checks, loan approvals and funding. In this project, our focus is to improve the back office operations.

Back office operations high level business process I depicted in the figure 1. Document processing is the stage where the business users receive a set of documents from the corporate lender. The key data points from the documents is extracted and sent to the next stage. Anti money laundering process involves laws, regulations and procedures to  prevent criminal behaviours in financial transactions. Once the checks are successful, the funding team processes the loan and funds the lender.

The key challenge in the document process is the voluminous and variety of document set. Each loan request involves more than 100 pages on an average and 10 customers on an average per day. Some customers may submit 500 page documents as well. The variety challenge includes the type of the documents; invoices, bill of lading, courier services, air way and additional supporting documents. The task of the document processing is to extract data points from such humongous datasets.

Currently, data processing is done manually by makers and checkers. A checklist of bank rules, conventional methods and personal judgment are used to extract the data points from documents. The first challenges is that this painstaking and tedious process results in loan process delay and introduces risk of human errors. The second challenge is the accuracy of the data points. For example, the customers submit documents with spelling errors, non-standard currency formats and date formats. Despite the increase in inefficiency in the process most of the banks are reluctant to use web applications to simplify document processing stage. For example, the web application is a platform for the corporate loan applications and when customers submit the applications, the data points can be easily extracted automatically with simple rules. However, the customers are reluctant to use the web applications as the customers are reluctant to move away from the traditional methods. For example, they prefer to generate the invoices from their organization systems and submit as pdf files as it is convenient for them rather than changing their systems or manually entering the data in the bank web applications.

To overcome these issues, in this paper we propose deep learning and NLP based system for document processing in loan operations. Deep learning have been fruitfully used in a variety of business fields including marketing [Chui, 2018], accounting{T sun}, healthcare [Leung] and finance (ding, Yue, hseih, Chen). Most of the studies have used neural networks for predicting stock market predictions[ding X, Yue, hsieh], ,Trading and investment applications[Chen] and credit and loan applications [Zhu]. Natural language processing (NLP) provides algorithms and techniques to analyse human language computationally. It has been used successfully for spell checks [Neha], text extraction [] and data formats [kibble].

This study aims to develop a loan operations data extraction system (LODES) using deep learning and NLP techniques. The purpose of using the deep learning algorithm in document processing stage is to simplify a makers’ and checkers’ job, to reduce human errors and to achieve more efficiency and productivity. Secondly, the study uses natural language processing techniques to address the challenge of spelling errors and non-standard formats. This study explores the power of using deep learning and NLP models in banks and the key general objectives of this study are:

1. To apply deep learning techniques to improve the efficiency in data point extraction from the voluminous document sets
2. To apply the natural language processing techniques to improve the accuracy in data point extraction from the voluminous document sets.

1. What is corporate loan operations

2. What is the challenge

3. Current approaches to challenge

4. How deep learning is useful for business?

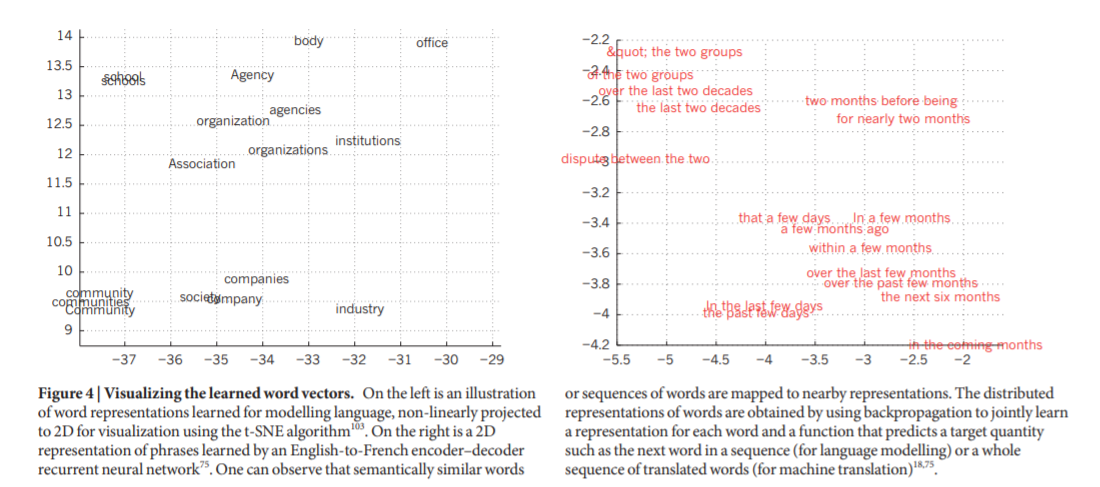
5. In this paper, we present

# Background:

## Loan operations background (Business process)

## Deep Learning (Technical)

Conventional machine-learning techniques are limited in their ability to process natural data in their raw form. Constructing a pattern-recognition or machine-learning system required careful feature engineering to extract the information from documents. Representation learning is a set of techniques that allows a machine to be fed with raw data and to automatically discover the representations needed for information detection and extraction. Deep-learning methods are representation-learning methods with multiple levels of representation-learning methods with multiple layers or levels of representations or features. The key aspect of deep learning is that these layers of features are not designed by human engineers: they are learned from data using a general-purpose learning procedure. Figure 2 shows the vector representation of the learned models in the n-dimensional space.

 BERT is a pre-trained deep learning natural language framework that has given state-of-the-art results on a wide variety of natural language processing tasks. This is a generic fleixible framework where the tool can be trained on new datasets. In our case, we use the labelled human datasets to further train bert framework for data point extraction.

There are two steps in BERT framework: pre-training and fine-tuning. During pre-training, the model is trained on unlabeled data over different pre-training tasks. For fine tuning, the BERT model is first initialized with the pre-trained parameters, and all of the parameters are fine-tuned using labeled data from the downstream tasks.

Iterations….

Any other details…

## Natural language processing (Technical)

Spellcheck

Document tokenization

Sliding window algorithm

The training phase is limited with the number of maiximum words or tokens. Loan application documents usally consists of more than 100 pages on average. Theerfore to train the mode, sliding window approach is used. As illustrated in the figure below, a sliding window is used to scan through the pages in the document and create a n-vector (only n words in the whole vocabulary) for each page and overlap of m words.

# Problem Definition:

## Problem Statement

Input – The input to our task is the pdf file which consists of multiple pages with information related to invoices, la… The Figure X shows the sample pdf file

Output – The output of the task is the extraction of values of specific list of data points form the document. Some example data points include; buyer name, seller name, invoice number, invoice date, currency etc. Figure Y shows the sample data points and the values.

## Challenges

What challenges are expected?

0. Various types of documents

eg:

1. The data is embedded in the text.

eg:

2. Data format varies from customer to customer

eg:

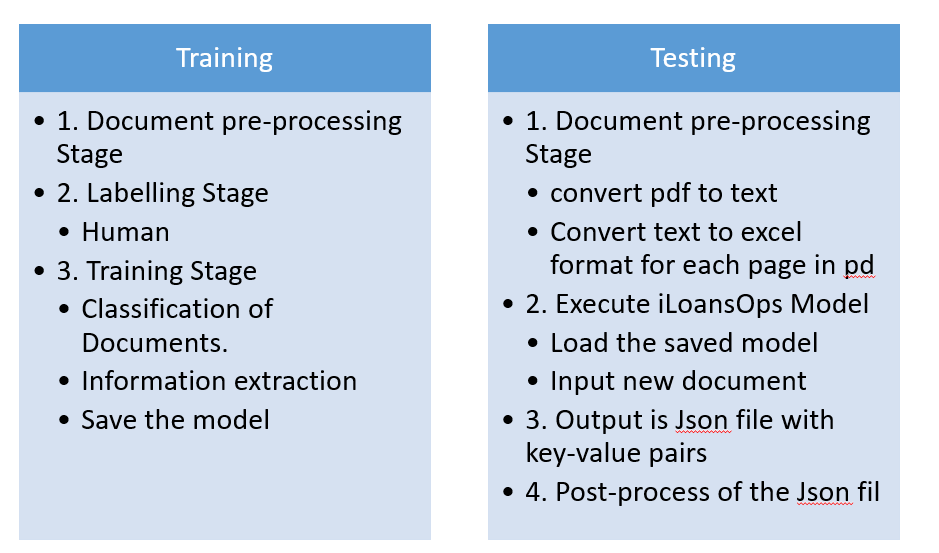
3. Date Formats challenges

eg:

4. currency format

# LODES Design:

Figure 4 shows the solution design for LODES system. There are two basic phases of mode; NN learning, and testing. The system is trained on historical examples of input and output variables. During this learning process, the system learns to recognize patterns by constructing the relationship between inputs and outputs coming up with the final output. Then, a comparison between the actual and desired output occurs and errors are calculated



## Training Stage

1. Document pre-processing Stage

convert pdf to text [OCR]

Convert text to excel format for each page in pdf[Python]

2. Labelling Stage

Human labeling [For each format, 10 samples]

3. Training Stage

Classification of Documents. Adresses C0 [Spacy...Classifier]

Information extraction [Deep learning APIs] Adresses C1,C2

4. Save the model [Reg\_DL\_Model, Unstructured DB]

## Testing Stage

1. Document pre-processing Stage

convert pdf to text [OCR]

Convert text to excel format for each page in pdf[Python]

2. Execute iLoansOps Model

Load the respective saved model with new document as an input

Json output with key-value pairs

3. Post-process of the Json file

Standardise Date formats [Regular expressions in Python] Adresses C4

Standartise currency formats [CurrencyConverter in Python] Adresses C5

## Visuals of Bert Training

<https://arxiv.org/pdf/1906.04341.pdf>

# Experiments

## 1. Data

The banking data set had 140 personal loan applications. Of these, 94 cases were used in the training and 46 were used in the testing. Both training and testing data sets contained half-good applications and half-bad application

Defining the network parameters: Deciding on the optimal parameters for the MLFN model is a critical issue. The best model is one that has the combination of parameters that minimizes the mean squared error.

Number of hidden neurons: The objective of the first successive trials was to hit upon the optimal number of hidden neurons that would enable the network to evaluate loan applications with the best performance.

Learning rate: This research carried out different trials to decide on a learning rate that successfully directed the degree of weight modification during the training epochs. For each trial, there were different runs of the network. The error threshold was set at 0.05 levels and the number of epochs was set at 10000. Then, the average epochs needed to reach 0.05 were calculated.

The training would stop whenever the performance of the network reached below 0.05 or when the training epochs reached 10000 even if the goal was not met.

## 2. Classification evaluations

Accuracy, F1scores

What failed? Analysis where the model will not perform correctly

## 3. Information Extraction evaluation

Validation score

What failed? Analysis where the model will not perform correctly

## 4. Discussions

# Literature Review

## 1. Deep learning in finance applications

## 2. Loan operations research

# Conclusion

# References

1. Leung MK, Xiong HY, Lee LJ, Frey BJ. Deep learning of the tissue-regulated splicing code. Bioinformat-ics. 2014; 30(12):121–9
2. Ding X, Zhang Y, Liu T, Duan J, editors. Deep learning for event-driven stock prediction. International Conference on Artificial Intelligence; 2015
3. Conference on Artificial Intelligence; 2015
4. Chen AS, Leung MT, Daouk H. Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index. Computers & Operations Research. 2003; 30(6):901–23.
5. casting and trading the Taiwan Stock Index. Computers & Operations Research. 2003; 30(6):901–23
6. Yue, Jun & Rao, Yulei. (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory. PLoS ONE. 12. 10.1371/journal.pone.0180944.
7. Hsieh TJ, Hsiao HF, Yeh WC. Forecasting stock markets using wavelet transforms and recurrent neural networks: An integrated system based on artificial bee colony algorithm. Applied Soft Computing. 2011; 11(2):2510–25
8. Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018). Notes from the AI frontier: Applications and value of deep learning. McKinsey global institute discussion paper, April 2018. Retrieved June 12, 2019 from <https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-ai-frontier-applications-and-value-of-deep-learning>.
9. Ting (Sophia) Sun (*2019*) Applying Deep Learning to Audit Procedures: An Illustrative Framework. Accounting Horizons: September 2019, Vol. 33, No. 3, pp. 89-109.
10. B. Zhu, W. Yang, H. Wang, Y. Yuan, A hybrid deep learning model for consumer credit scoring, in: International Conference on Artificial Intelligence and Big Data (ICAIBD), 2018, pp. 205–208. doi:10.1109/ICAIBD. 2018.8396195.
11. Neha Gupta, Pratistha Mathur (2012) “Spell Checking Techniques in NLP: A Survey”, International Journal of Advanced Research in Computer Science and Software Engineering, Volume 2, Issue 12, December 2012, pp. 217-221
12. Kibble, R.: Introduction to Natural Language Processing. University of London (2013)
13. J. Jiang Information extraction from text. C.C. Aggarwal, C. Zhai (Eds.), Mining text data, Springer, United States (2012), pp. 11-41

ics. 2014; 30(12):121–9