From Creditworthiness to Trustworthiness with alternative NLP/NLU approaches

Charles Crouspeyre – Eléonore Alesi – Karine Lespinasse
Dnalytiks - Live with AI - MITSIC University Paris 8
charles@dnalytiks.com - eleonore.alesi@livewithai.org - karine.lespinasse-sabourault@univ-paris8.fr

Abstract

The word "Credit" comes from the Latin 'credere' which means "to give trust". The way this trust is being given today by financial institutions is mainly based on statistical methods, using financial information - such as the revenues of an individual, the money he/she spends monthly, etc. - to quantify the chances of a successful loan repayment. By definition, this method of quantifying risk limits the access to financial services to individuals who have banking information history. In emerging markets, as described here, a huge part of the population doesn't meet these criteria and is accordingly left outside of the equation. This paper discusses alternative approaches to allow these unbanked people to access financial services in reviewing current and innovative Natural Language Processing and Natural Language Understanding methods. The latter support excellent risk quantification results without affecting the privacy of the borrower and result in moving from biased creditworthiness to broader trustworthiness.

1 Introduction

About 90% of today's global data were created over the last two years alone[1]. The most recent estimations indicate that 80% of the total existing data is unstructured[2]. This vast expanse of data contains valuable information that can be used to augment a wide range of processes in the financial sector including fraud detection, market prediction, customer relationship management but also credit scoring.

Contemporarily, the way credit risk is being assessed by financial institutions relies heavily on financial information, or creditworthiness, such as the FICO scores. In the USA, for example, over 90% of top lenders use FICO Scores as their credit scores[3]. The makers of the FICO scores have not publicized how the scores are calculated[4]. But they disseminated the weights of the criteria that they look at as: 35% payment history, 30% amount owed, 15% length of history, 10% new credit, 10% types of credit used. Consequently, as they can only provide little of this type of information, "two billion of adults - more than half of the world's working adults - are still excluded from formal financial services" according to the UNCDF Annual report[5].

Such scoring models are even less applicable to emerging markets, since the majority of the population doesn't possess any type of financial information. For example, in the Philippines, 77% of the population is considered unbanked -i.e. doesn't have a bank account, according to the BSP, the Central Bank of the Philippines[6].

Aligned with the United Nations' Financial Inclusion pillar, one of the key pillars required to reach its 17 Sustainable Development Goals, this article aims at exploring NLU-based viable alternative forms of risk analysis to enable greater access to credit.

2 Creditworthiness evaluated via Machine Learning approaches

Recent advances in Machine Learning, and more broadly in Artificial Intelligence [Bach et al., 2019], have enabled the emergence, in the last few years, of alternative methods for qualifying and quantifying the creditworthiness of an individual, using non-financial information innovative

1 - https://www.ibm.com/products/software

2 - https://www.techrepublic.com/article/unstructured-data-the-smart-persons-guide

3 - https://www.fico.com/en/products/fico-score

4 - http://money.com/money/3770477/new-fico-score-factors

5 - https://www.uncdf.org/financial-inclusion

6 - http://nine.cnnphilippines.com/business/2018/07/11/2017-financial-inclusion-survey-bsp.html

Proceedings of the First Workshop on Financial Technology and Natural Language Processing (FinNLP@IJCAI 2019), pages 96-98, Macao, China, August 12, 2019.

approaches such as phone log analysis [Shema, 2019] or [Agarwal et al., 2018] or social network analysis[7]. A few startups have emerged from those efforts, and have displayed encouraging results in helping solving the problem of financial inclusion for emerging markets including Lenddo in Singapore, previously mentioned, or Sesame Credit in China.

Nevertheless, these approaches tend to be invasive, with little care over the users' privacy, e.g. requiring the sharing of personal contacts with the system, etc. For this reason, another approach, based on Natural Language Processing (NLP) & Natural Language Understanding (NLU) tools, could enable a new baseline to quantifying risk with regards to predicting borrower repayment behavior and exclusively accessing information directly related to the user. This approach would also allow a change of paradigm, from scoring the Creditworthiness of an individual to scoring his Trustworthiness.

Creating NLP tools that preserve privacy has been addressed in the healthcare industry. The US National Library of Medicine's Lister Hill National Center for Biomedical Communications[8] uses NLP to "de-identify" clinical information in narrative medical reports, protecting patient privacy while preserving clinical knowledge.

In this specific case, NLP has be used to ensure that all the information related to individual private information can be identified and then "de-identified."

3 Trustworthiness evaluated via NLU approaches

In the last few years, NLP and NLU have gained a lot of traction across industries, thanks to the progress made in Deep Learning and the capability it has brought along to analyze text at a semantic level - with discoveries such as word embeddings [Mikolov et al., 2013], when previous approaches were mostly limited to statistical analysis.

This new capacity enabled a deeper level of analysis, allowing different levels of understanding of a text document, for example combining the content itself with the non-explicit information such as emotions. Such capacity is being used by call centers for example to detect sentiment such as anger and stress through analysis of sentences' structures and the choice of words [Kumar et al., 2012] or [Seyeditabari et al., 2018] in order to adapt answers provided by the representative to a request, in real time.

This NLP-based approach, generalized to credit scoring, allows to bridge the gap and understand hidden patterns that cannot be humanly detected. It relies on many more data points than usual decision-making processes, providing better estimates and enabling to identify patterns requiring further attention from the decision maker, while getting a more nuanced view of trustworthiness with an improved rating accuracy of loans.

It could, among other criteria, help to:

- Detect & score business knowledge of the borrower by understanding the person's entrepreneurial ability and attitude toward financial planning. This approach has been successfully implemented by platforms such as Capital Float and Microbnk;
- Detect fraud attempt by automatically detecting incoherencies in the information provided by the borrower [Iter et al., 2018];
- Detect attempts to convey alternative messages: as discovered by [Netzer et al., 2018] where data from Peer-to-Peer lending platforms such as Lending Club and Prosper is analyzed, showing that the inclusion of alternative messages - such as religious references, in loan application would lead to poorer repayment rate. A potential explanation of this phenomenon could be an attempt from the borrower to call to the lender's emotions, as a way to falsely convince him of a favorable outcome.

Additionally, as showcased by the company Microbnk in their related patent US20170018030A1, this type of model could even be more powerful if combined with other alternatives forms of data such as psychometric data. For example:

- Counting the number of times, a borrower presses a key Vs. the number of characters in his description;
- Combining NLP with voice tone analysis -among other external parameters.

4 Discussion

In this article, it has been explored how Natural Language Processing/Natural Language Understanding could bring financial solutions to the unbanked populations through innovative approaches. NLP being fundamentally less invasive than requiring direct access to a person's full contact list or social media account, it represents a fairer way to assess risk with a capability to reach a broader audience.

However, monitoring criteria that would indicate, for example, the education level of a person, through grammatical analysis, as a proxy for potentially quantifying the income level of a person would re-inject the initial biases, likewise deteriorating the score of an individual because this person lives in a low-income neighborhood. Particular attention will be required to maximize an ethical methodology in implementing NLP/NLU solutions.

7 - https://patents.justia.com/patent/8694401

8 - https://lhncbc.nlm.nih.gov/project/de-identification-tools

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