Just in Time

Credit Risk Meets Large Language Models

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Executive Summary

The study addresses the issue of **information asymmetry** in **peer-to-peer lending**, where lenders often lack sufficient data to assess borrower credit. **By applying *BERT*** (Bidirectional Encoder Representations from Transformers)**, a *Large Language Model***, the authors **generate a credit risk score based on the borrowers' description of the credit request**. Once integrated into a XGBoost model with traditional inputs, **this score improves predictive accuracy and AUC** (Area Under Curve), demonstrating the value of combining textual insights with standard credit data.

Key takeaways:

- **Enhanced prediction:** BERT-based scores improve accuracy and AUC in credit risk assessment.
- **New insights:** Borrowers' language reveals patterns that complement traditional risk variables.
- **Model dynamics:** The inclusion of BERT scores changes how standard variables are weighted.

This approach could also be highly relevant for **traditional banking**, where **unstructured client data** (e.g., written descriptions or communications) **could complement established credit scoring systems**, strengthening both predictive power and **credit risk management practices**.

At a Glance

Keywords: Credit Risk, Large Language Models, P2P Lending, Information Asymmetry

Overview

Introduction

Data Sources and Pre-processing

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Introduction

Peer-to-Peer (P2P) lending allows borrowers and lenders to meet through online platforms, bypassing financial institutions. The main issue of this phenomenon is the **information asymmetry since lenders have few data to assess borrowers' creditworthiness.**

P2P LENDING MECHANISM

The main issue related to P2P lending is the presence of **information asymmetry**:

- ***Borrowers*** *possess* ***more and often a higher level of information*** *with respect to lenders*
- ***P2P platforms*** *ask borrowers to compile a* ***textual description*** *of the* ***loan purpose*** *and their* ***current situation***
- ***Traditional credit scoring models struggle in leveraging the information*** *contained in the* ***textual description***

The **study** tries to **estimate a credit risk score** reflecting the **likelihood of loan default based on the textual description** through a **Large Language Model (LLM)**

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Data Sources and Pre-processing Studies on LGD

The **risk score** has been **estimated** on a public dataset of the **P2P lending company *Lending Club***. The dataset is composed of 119.101 loans **including the loan description and the borrower's information about indebtedness and income**. The study has considered only the variables available at the time of the application, which are those utilized by granting models.

Data Sources

Quantitative Variables

- Borrower's annual income
- Indebtedness ratio for obligations
- Amount of credit requested by the borrower
- Credit bureau score

Categorical Variables

- Employment length of the borrower
- Credit purpose category for the loan request
- Homeownership status
- Borrower's residence state

Textual Variable

- Description of the credit request

Pre-processing

Quantitative & Categorical Variables

As for both **quantitative and categorical variables**, the **standard treatments** generally employed in traditional credit scoring models has been adopted

Textual Variable

Regarding the **textual variable** a work of **text cleaning** has been carried out, consisting in:

- Removing all descriptions that contained the default description
- Removing any temporal background on descriptions
- Replacing all HTML entities with their corresponding characters

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Modelling Approach

Methodology

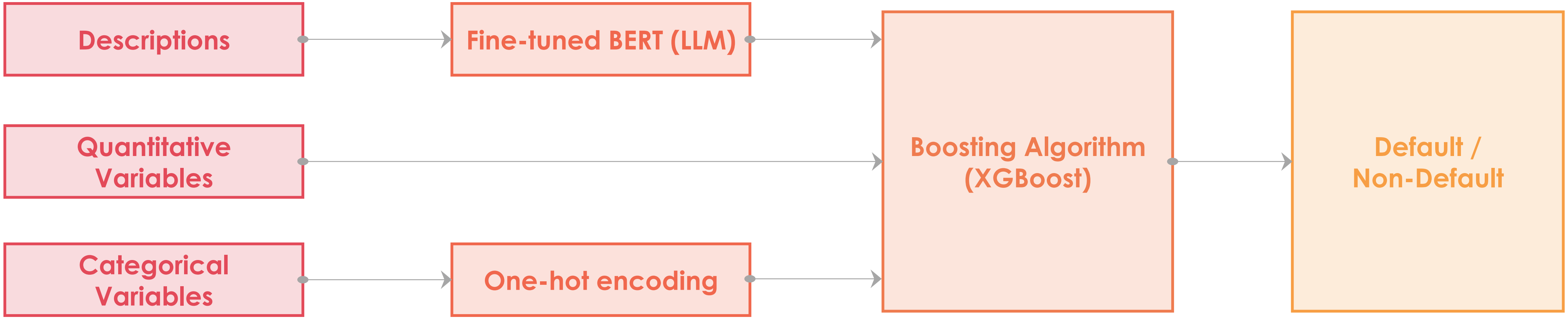
BERT’s Risk Score Generation

Examples of BERT’s Risk Score Attribution

Modelling Approach 1/3

Methodology

This study leverages **transfer learning** to enable a **fine-tuned BERT model** to generate a **score that reflects the likelihood of loan default based on textual descriptions**. The aim is to **capture nuanced signals in unstructured text data** that are **indicative of default risk**.
This BERT-generated score is then incorporated as an additional feature in a traditional loan classification model.



AS-IS	The baseline classifier, built using **XGBoost**, processes all **structured variables from the loan application**
NEW	The new approach involves the **use of unstructured variables** to which a **risk score is assigned through BERT's risk score generation**

Focus next slide

Modelling Approach 2/3

BERT's Risk Score Generation

The **risk score**, reflecting the **probability of loan default**, has been **estimated based on the loan description utilizing a LLM**. Specifically, in this study a **fine-tuned BERT** has been used. The **output** of the model is a **number within the range from 0 to 1**. The score has been subsequently integrated into the **XGBoost model** to **predict the likelihood of loan default**.

BERT model to process **loan descriptions**

Fine-tuning BERT through **transfer learning**, freezing the layers to prevent overfitting and catastrophic forgetting

Testing 126 neural network architectures, varying neurons, dropout, learning rate, to find the optimal one

Neural network training, using weighted binary cross-entropy to manage class imbalance (only ~15% defaults)

During the **training phase**, the following steps have been implemented to **prevent data-leakage**:

1. **Textual descriptions** have been **extracted from the original dataset**
2. The **data** has been **divided** into a **train set** and a **test set**
3. The **train set** has been **divided** into a **70% train subset** and a **30% test subset** to find an optimal architecture
4. The **optimal architecture** has been **trained with the training set** and **tested on the testing set** obtained in step 2

Modelling Approach 3/3

Examples of BERT's Risk Score Attribution

Below are reported the **risk scores attributed by the BERT model** on the basis of the **description of the credit request**.

BERT score	Real value	Description
0.8562	0 (Non-Default)	*getting a divorce need new apt. with new furniture because she getting everthing.*
0.8149	1 (Default)	*need help my bills. to help pay my medications and some bills.*
0.8131	0 (Non-Default)	*i can pay of some bills for my self because i been helping other people out. i could save more for my family and their need.i have a good job that i am bless with. i am from a large family seem like every one thinking i suppose to help them when i need help my self.i alway belive that the lord will.*
0.8051	0 (Non-Default)	*consolidating our debt makes our life easier live in our means with one solid low monthly payment insted of multiple payment that add up more then what ill be paying with this loan and have a little left to leave in my savings for a rainy day to be honest and thank you for your consideration good dy.*
0.8045	0 (Non-Default)	*To consolidate debt. to pay off dept*
0.0735	0 (Non-Default)	*Debt consolidation with a lower APR*
0.1146	0 (Non-Default)	*In need of funds to pay off some bills as well as minor improvements to house and yard. I have an extremely secure career, and maintaining my credit worthiness is important to me.*
0.1262	0 (Non-Default)	*Hard working individual with a stable job will use loan proceeds to consolidate outstanding credit cards balances. 1) Net monthly income - $4,432. 2) All expenses (allocated):. Rent - $1,124. Utilities- 84. Groceries 293. Auto (including fuel) 201 . Cell Phone 52. Cable/Internet 64. Personal care items 82. Entertainment/dining 93. Sales tax 65. 3) Previously answered. 4) No.*
0.1360	0 (Non-Default)	*This loan is to pay off credit ca.*
0.1871	1 (Default)	*I need money for moving expenses and for a buffer for the first month while I transition into working in my new location. I have successfully paid off two previous Lending Club loans in the past couple of years.*

Highest BERT score

Lowest BERT score

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Conclusions

Model Results

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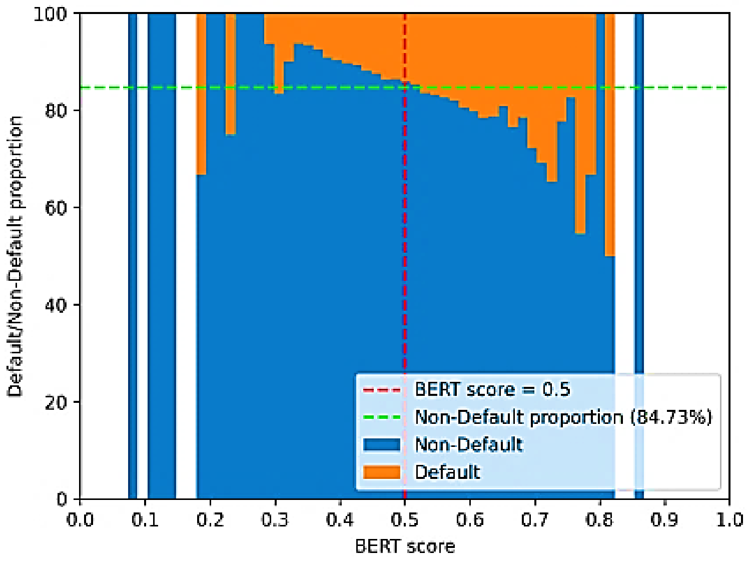
Model Results

BERT Score as a Credit Risk Score

Analysis

The **effectiveness** of the **BERT score** in **utilizing loan descriptions** to **predict default risk** is evaluated.



Overall, the trend suggests that **higher BERT scores are indicative of a greater likelihood of default**, highlighting the BERT score's usefulness as a **risk assessment tool**.

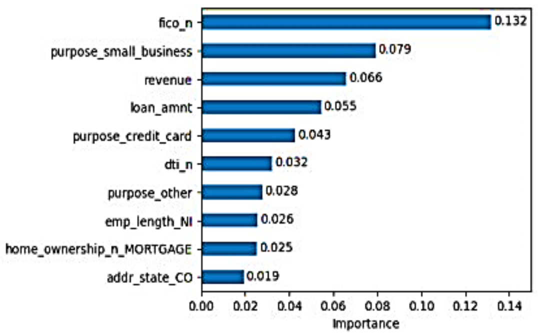
Overall Evaluation

Model Perfomance

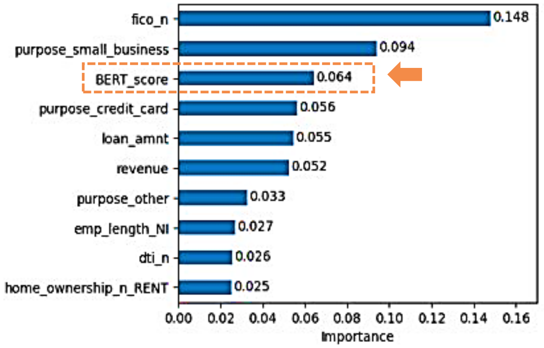
Metric	AS-IS	NEW
Precision	↑ 21.68 %	22.49 %
Recall	↓ 66.14 %	63.60 %
Accuracy	↑ 58.35 %	60.66 %

Feature Importance

AS-IS



NEW



Incorporating the BERT score results in:

- **improved the Accuracy and Precision** but **diminished recall** with respect to traditional credit scoring models
- *the **BERT risk score** being **among the most relevant variables**, reshaping the role played by other variables*

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