REDVET - Revista electrónica de Veterinaria - ISSN 1695-7504
Vol 25, No. 1 (2024)
http://www.veterinaria.org
Article Received: March 2024 Revised: April 2024Accepted: May 2024

Generative Artificial Intelligence In Trade Credit Risk Assessment

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Abstract– This paper reviews 25 articles and also demonstrates how the AI can be used to validate the credit risk of the Different Trading blocks. Generative AI and Python programs have been used to create the demonstrative output. The results are phenomenal. Credit risk assessment of a trade consignment consists of the Country Risk, Currency Risk and the consignment value risk. This can be estimated quickly using the generative AI. Frist this paper attempts to review the literature and arrive at the model for the prediction of the risks using generative AI and ranking them. The inference from this paper is that the functional context would be the backbone of a prompt engineering too.

Keywords—Generative AI, Python Programing, Trade Credit Risk, Review.

I. INTRODUCTION

Trade credit risk assessment is a large night mare for the lenders. It is estimated to have over 45% risks. The reasons are: Trade consignment is already produced with a borrowed capex, there is also an opportunity to avail working capital loans to produce the goods. During the export or import there is another credit facility availed from the seller and from a bank too. Therefore, the credit for trade is leveraged over 5 times. In most of the cases the consignment is containers. Each container does not have one consignment number so the release of a consignment is not tied to the rest of consignment numbers Hence the risk is compounded. This paper would not only review the studies in the respective field, but also provide a quick solution for corporate trade practitioners to identify a rank for the respective country credit risk.

Aim: to test if certain segment of the risks can be estimated using the generative AI
Methodology: 1. Review of 25 studies relating to the credit risk and understand the methodology 2. Use generative AI Prompts to estimate the segmental risks of the consignment with respect to the trading blocks.
Expected outcomes: 1. Reviews of 25 papers 2. Risk estimation and ranking using python code from generative AI
The output of this paper would enable industry practitioners to estimate a segmental risk (Regional Trade Block level) using generative AI

II. REVIEW OF LITERATURE

Aleksandra Lezgovko et.al (2017) find that the rationality of trade credit insurance is an effective way to manage the risks they have confirmed after analysing the output in Demental. Sanaz Pourdarab et.al (2011) a Fuzzy Expert system has been developed to assess credit risk according to specified effective financial ratios as the system inputs. Fernando A. F. et, al (2014) propose a methodological framework conceived to adjust trade-offs among evaluation criteria and provide decision-makers with a more transparent mortgage risk evaluation system. The practical implications of our framework are also discussed.

Wei Wang et. al (2020) have developed a technique that combines the ideas of WoE and Shapley values for local model-agnostic explanations with monotonic constraints in XGBoost. Jūratė Pridotkienė et.al (2006) in their research paper, "Evaluate if Exporter-provided trade credit risk evaluation is extremely important for risk-based export pricing. Striking a balance between acceptable levels of risk while also meeting customers' needs is key to maximizing revenue and customer relationships. Jaehun Sim et.al (2022) test if the order data for the other three members can be determined by each member's inventory status. Matthew Billett et.al (2022) after analysing a dataset that covers 623 unique buyers and 969 unique sellers find that the decline in trade credit leads customers to cut investment, increase leverage, and scale back trade credit provision to firms further downstream.

Jozef Zurada (2007) compares the effectiveness of three decision tree algorithms (chi-squared, entropy reduction, and Gini reduction) to predict whether a consumer defaulted upon or paid off a loan. They use an original data set containing 5960 loan applicants Such rules could be explained to business managers who would need to approve their implementation as well as loan applicants as the reason for denying a loan. Fernando A. F. et.al (2016) In Credit Risk Analysis Of Mortgage Loans Using AHP, Most of the decision makers considered AHP the "overall best" approach. Raymond Anderson (2007) traditional householding approaches are insufficient, and lenders may have to instead consider network modelling. This adds an extra level of complexity though, which may not be warranted.

Stephen Zamore et.al (2018) review draws attention to a broad range of models, to provide a more complete picture and lead to better decision-making regarding, for instance, capital structure and assessment of capital adequacy. Barbara Summers (1999)finds the value of the firm's accounts payable relative to firm size is also influenced by the firm's size, its investment in accounts receivable and marketing and customer relationship-building activity by the firms' suppliers via preferential credit offers. it is not clear whether large firms are recipients of attractive credit offers or use market position to demand such facilities.

Liukai Wang et. Al, (2019) with an enhanced hybrid ensemble machine learning approach. empirical results show that financial-based information, such as TOC, and NIR, is most useful in predicting SMEs' credit risk in SCF, and multi-source information fusion is meaningful in better predicting the credit risk. Hunt, et.al (2022) the impact of a poorly conceived risk-return gambit in the pursuit of high revenue growth may yield far more perilous consequences, including placing the survival of a firm in jeopardy Xiaofeng et.al (2023) The research results show that the TCRC-based method for assessing the associated credit risk in the supply chain is closer to the actual operating environment of the supply chain

Rasa Kanapickiene et.al (2019) the inclusion of non-financial variables in the model does not substantially improve the characteristics of the model. The designed models can be used by suppliers when making decisions of granting a trade credit for small or micro-enterprises. Ali AghaeiRad et.al (2016) in their research paper, Improve credit scoring using transfer of learned knowledge from the self-organizing map The hybridization technique contributes to boosting the performance of FNN for credit scoring; Linda Allen et. al 2003 Survey the most recent BIS proposals for the credit risk measurement of retail credits in capital regulations. They also describe the recent trend away from relationship lending toward transactional lending, These trends create the opportunity to adopt more analytical, data-based approaches to credit risk measurement.

Terrádez Gurrea (2015). Finds that decision trees replace the equation in parametric regression models with a set of rules. This feature is an important aid for the decision process of risk experts, as it allows them to reduce time and then the economic cost of their decisions AM Costello (2019) Analyse the collaborative theory offers the view that the suppliers place a higher liquation value on the collateral although the trade creditors have the legal right to the underlying credit Kayla Freeman (2022) finds that Credit concentration avoidance is more pronounced when the lender has experienced more recent portfolio defaults and when the firm's customers are riskier in terms of either default risk or long payable periods. Kanapickiene, R., & Spicas, R (2019) designed models that can be used by suppliers when making decisions of granting a trade credit for small or micro-enterprises.

FIGURE I GENERATIVE AI PROMPT FOR COUNTRY RISK RANKING

Give me a python code to run on collab to collect export and import data of different countries from opensource like world bank or comtrade and estimate the variance (risk) and display the rank of variances in descending order in a bar graph by country and by product in another. The chart needs to display the top 10 countries and top 10 products please.

II FLOW OF THE PROGRAM

The Python Code has been Segmented into the following sections for obtaining the risk ranking:

Fig. 1 Flow of the Programs

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II. PYTHON CODE SEGMENTS

```
import requests
import pandas as pd
import gspread
from oauth2client.service_account import ServiceAccountCredentials
import matplotlib.pyplot as plt
```

Fig. 2 Importing Python Libraries for the Task

```
def fetch_world_bank_data(indicator, start_year=2010, end_year=2023):
    url                                                                =
f"http://api.worldbank.org/v2/country/all/indicator/{indicator}?date={start_year
}:{end_year}&format=json&per_page=10000"
response = requests.get(url)
    data = response.json()[1]
    return pd.DataFrame(data)
world_bank_exports = fetch_world_bank_data('NE.EXP.GNFS.CD')
world_bank_imports = fetch_world_bank_data('NE.IMP.GNFS.CD')
```

Fig. 3 Python Code for Fetching the world bank data for a specified period and for imports & exports

```
def clean_world_bank_data(df):
    df = df[['countryiso3code', 'date', 'value']].dropna()
    df['date'] = df['date'].astype(int)
    df = df.groupby(['countryiso3code', 'date']).agg({'value': 'sum'}).reset_index()
    df = df.pivot(index='countryiso3code', columns='date', values='value')
    return df
exports_df = clean_world_bank_data(world_bank_exports)
imports_df = clean_world_bank_data(world_bank_imports)
```

Fig. 4 Python Code to clean imports & exports data

```
def calculate_change(df):
    df['change'] = df.iloc[:, -1] - df.iloc[:, -2]
    return df

exports_change = calculate_change(exports_df)
imports_change = calculate_change(imports_df)

# Rank countries based on the change
exports_change['rank'] = exports_change['change'].rank(ascending=False)
imports_change['rank'] = imports_change['change'].rank(ascending=False)

# Display top 10 countries by export and import change
top_exports = exports_change.sort_values('rank').head(10)
top_imports = imports_change.sort_values('rank').head(10)

print("Top 10 countries by export change:")
print(top_exports)

print("\nTop 10 countries by import change:")
print(top_imports)

def upload_to_google_sheets(df, sheet_name, worksheet_name):
    scope = ["https://spreadsheets.google.com/feeds",
"https://www.googleapis.com/auth/drive"]
    creds =
ServiceAccountCredentials.from_json_keyfile_name('cred
entials.json', scope)
    client = gspread.authorize(creds)
        try:
        sheet = client.open(sheet_name)
    except gspread.SpreadsheetNotFound:
        sheet = client.create(sheet_name)
        try:
        worksheet = sheet.worksheet(worksheet_name)
    except gspread.WorksheetNotFound:
        worksheet =
sheet.add_worksheet(title=worksheet_name, rows="100",
cols="20")
        worksheet.clear()
   orksheet.update([df.reset_index().columns.values.tolist()]
+ df.reset_index().values.tolist())
```

Fig. 5 Python Code to clean imports & exports data

```
def upload_to_google_sheets(df, sheet_name, worksheet_name):
    scope = ["https://spreadsheets.google.com/feeds",
"https://www.googleapis.com/auth/drive"]
    creds =
ServiceAccountCredentials.from_json_keyfile_name('cre
dentials.json', scope)
    client = gspread.authorize(creds)

    try:
        sheet = client.open(sheet_name)
    except gspread.SpreadsheetNotFound:
        sheet = client.create(sheet_name)

    try:
        worksheet = sheet.worksheet(worksheet_name)
    except gspread.WorksheetNotFound:
        worksheet =
sheet.add_worksheet(title=worksheet_name, rows="100",
cols="20")

    worksheet.clear()

worksheet.update([df.reset_index().columns.values.tolist(
)] + df.reset_index().values.tolist())
```

Fig. 6 Python code to upload the output data into a google sheet

```
plot_bar_chart(top_exports, 'Top 10 Countries by Export Change',
'Change in Export Value')
plot_bar_chart(top_imports, 'Top 10 Countries by Import Change',
'Change in Import Value')
except Exception as e:
print(f"An error occurred while plotting the chart: {e}")
```

Fig. 7 Python code for Error Handling

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```
    upload_to_google_sheets(top_exports, 'Trade Data Analysis', 'Top Exports')
    upload_to_google_sheets(top_imports, 'Trade Data Analysis', 'Top Imports')
except FileNotFoundError:
    print("The credentials file was not found. Please check the path and try again.")

# Plotting bar charts
def plot_bar_chart(df, title, ylabel):
    df = df.sort_values('change', ascending=False)
    plt.figure(figsize=(10, 6))
    plt.bar(df.index, df['change'], color='skyblue')
    plt.xlabel('Countries')
    plt.ylabel(ylabel)
    plt.title(title)
    plt.xticks(rotation=45, ha='right')
    plt.show()
```

Fig. 8 Python code for plotting the bar charts

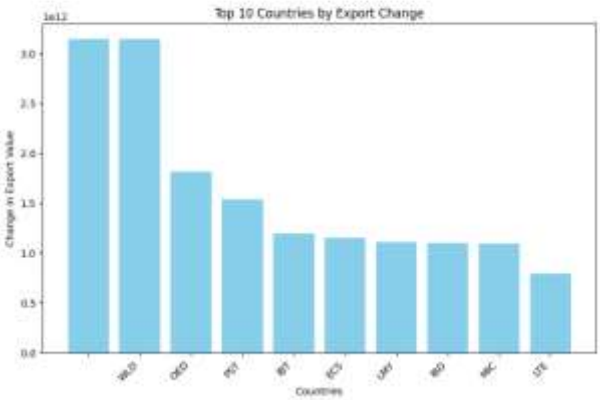

Fig. 9 Top 10 countries by Exports change (Variance or Risks)

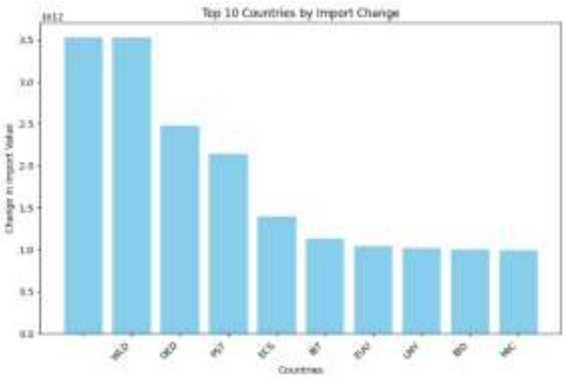

Fig. 10 Top 10 countries by Imports change (Variance or Risks)

B. CONCLUSION

Though care has been taken not to edit the prompt or the response, there was a significant difference in what was sought from the Generative AI to what it provided. We asked for top 10 countries and products. It provided top ten trade blocks. Though charts were provided as commodities the data was not relevant. There were a few revisions in the prompts to get to this point. Though the AI was able to deliver a result to a lower level than requested, The commodity ranking request could not be comprehended by the AI. It was not sure how to handle blanks in the database. We will find a bar chart without a column. If an user is asked did the Open source AI deliver something relevant? The answer is Yes was it accurate? The answer is no. Despite these comments the solution was cost effective. Can a python programmer fix the issues of the generative AI? The answer is dissenting. One may conclude that the Solution can be elaboration of the functional requirement. This means, the AI while reducing the technical load is migrating the load to the functional specialists.

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