Using Compututional Linguistics to Demystify Financial Texts

যাদবপুর বিশ্ববিদ্যালয়
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Registration number: 1022204003 of 2022-2023
Roll number: 102210505006, Index number : 66/22/E
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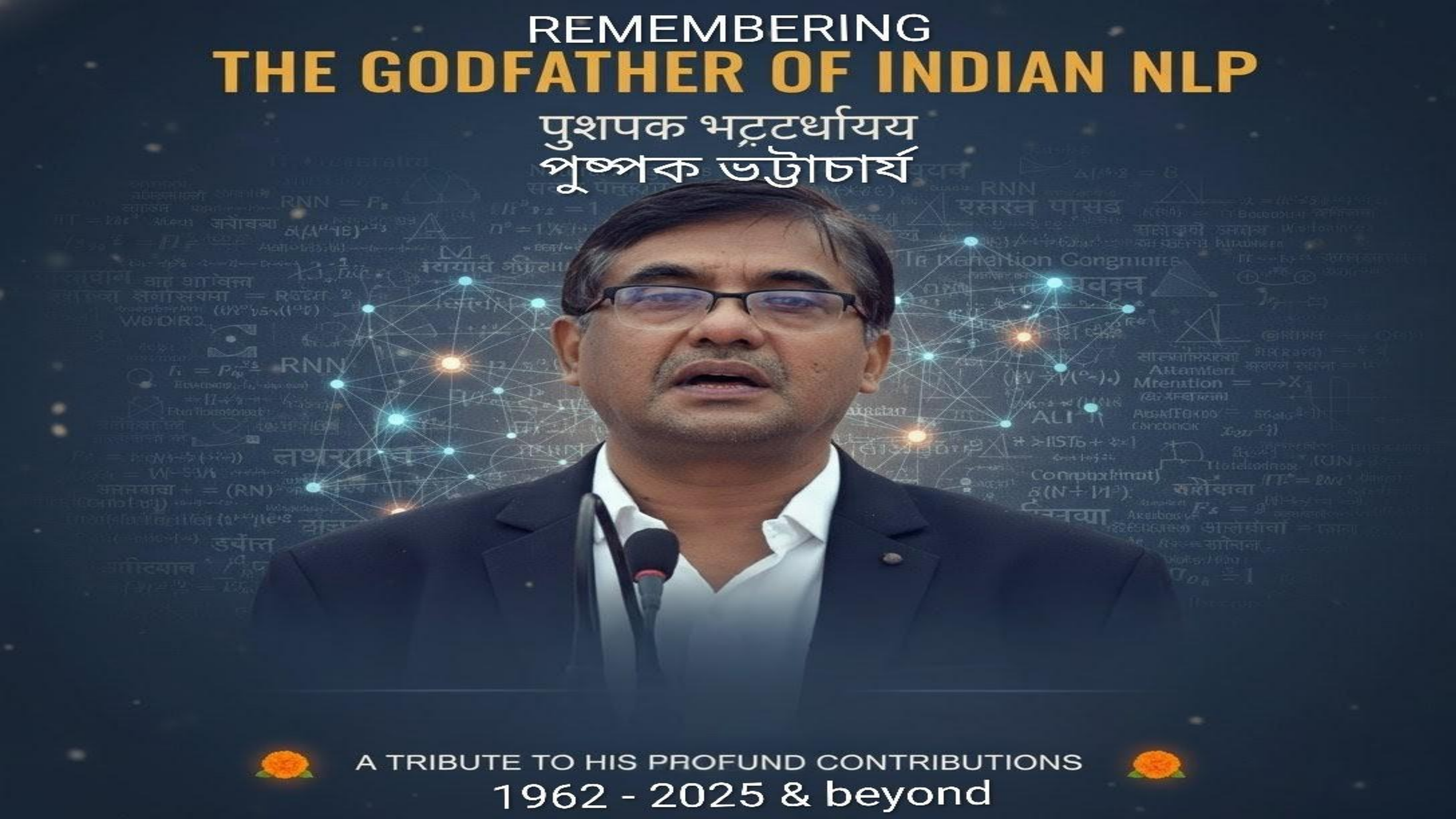
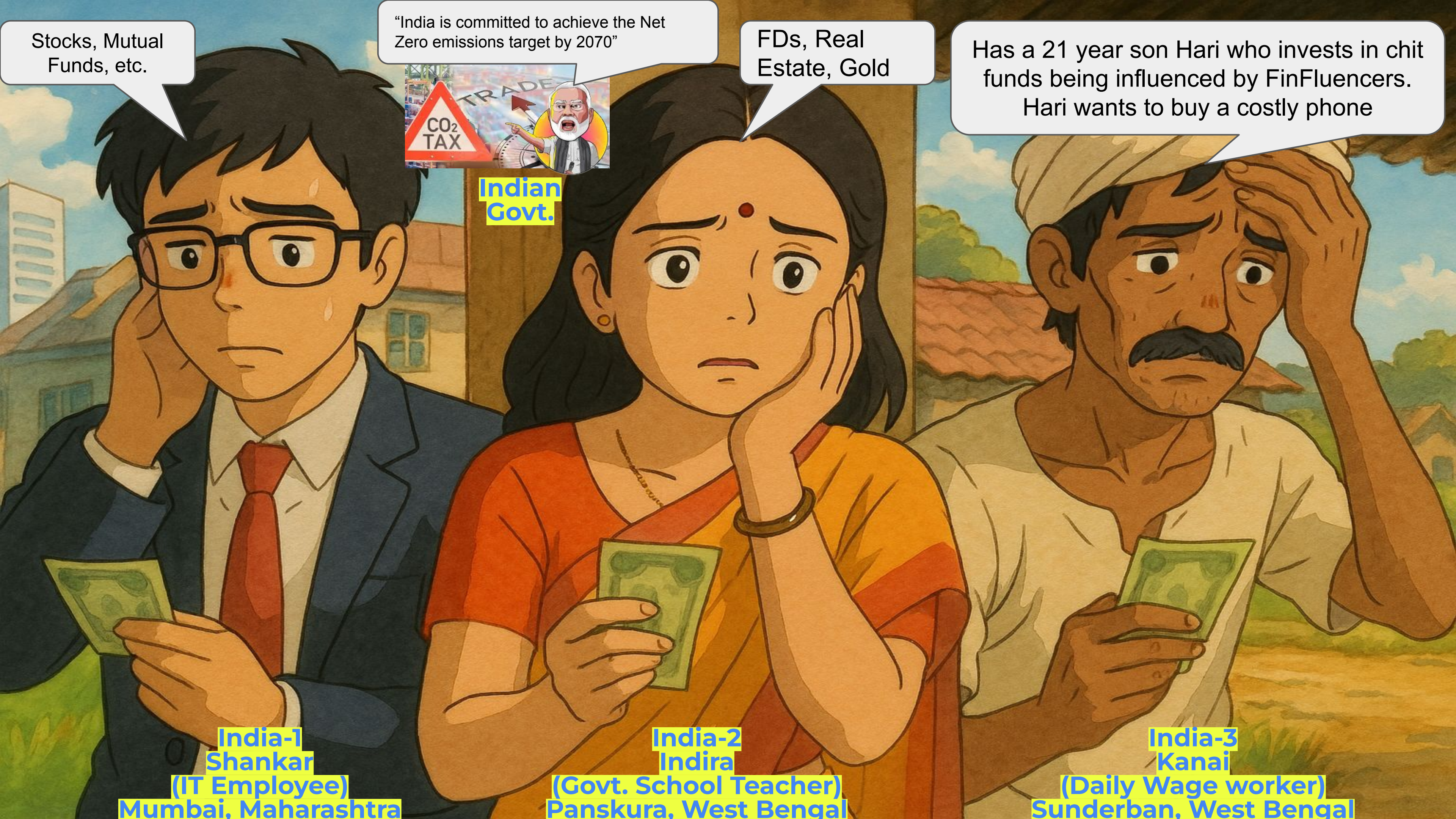


REMEMBERING
THE GODFATHER OF INDIAN NLP
पुशपक भट्ऱ्टर्धायय
পুষ্পক ভট্টাচার্য
A TRIBUTE TO HIS PROFUND CONTRIBUTIONS
1962 - 2025 & beyond

Disclaimer

- This work is a result of my PhD research only. All content reflects my doctoral studies.
- The views and opinions expressed here are solely my own and do not represent those of my current or past employers, academic institutions, or any other organizations with which I am affiliated.


Stocks, Mutual Funds, etc.
"India is committed to achieve the Net Zero emissions target by 2070"
CO_2 TAX
TRADE
Indian Govt.
FDs, Real Estate, Gold
Has a 21 year son Hari who invests in chit funds being influenced by FinFluencers. Hari wants to buy a costly phone
India-1
Shankar
(IT Employee)
Mumbai, Maharashtra
India-2
Indira
(Govt. School Teacher)
Panskura, West Bengal
India-3
Kanai
(Daily Wage worker)
Sunderban, West Bengal

Are you (financially ) literate ?

Introduction

GLOBAL CONTEXT & DEFINITION

FINANCIAL LITERACY

1 out of 3

adults worldwide are financially literate

Managing money

THE INDIAN CONTEXT (FEW FACTS)

Although Indian Sensex has grown from 800 to 50,000+ points (1990-2022), **less than 3% Indians invest in stock markets.** [As on Dec, 2023]

TRADITIONAL INVESTORS (Indira)

Invests in Gold Jewellery, Real Estate, FDs, etc. where Return on Investment (RoI) is decreasing.

STOCK MARKET INVESTORS (Shankar)

Less than 1% active traders earn more money than a bank fixed deposit over a 3-year period.

27% Indians are financially literate

Per Capita Income: **USD 2K**

Target (Developed Nation): **USD 13K**

WE DO NEED FINANCIAL EDUCATION

CHALLENGES & GLOBAL COMPARISON

News

Increasing financial literacy during the pandemic essential for India's recovery

Richest 1% Indians own more than 40% of country's wealth: Report

Only **~950 Registered Investment Advisors (RIAs)** in India. Disproportionate ratio of advisors to investors (100M+ unique investors).

FINANCIAL LITERACY AROUND THE WORLD

Introduction

The Story of Hari & Finfluencers

Hari, a 21-year-old, invests in chit funds influenced by FinFluencers to buy a costly phone.

BFSI News

Budget 2023: Analysis of green finance, and roadmap ahead

Budget 2023: Analysis of green finance, and roadmap ahead is a wnte raw dows that needs szen caudert refunse off the rorner they further to shortright invers...

Livemint

NSE to set up Social Stock Exchange (SSE) as a separate segment

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Mint Premium | MONEY

How finfluencers use fake screenshots to run scams

How finfluencers use fake screenshots to run scams normaturel of the lattest reprevenns finfluencers use fake...

Themes

Inclusive Investing

- Increasing readability of Financial Texts [ICON'2021, FNP@LREC'2022]
- Increasing reachability of Financial Content [TheWebConf (WWW'2024)]

Improved Investing

- Detecting hypernyms of Financial Terms [FinNLP@IJCAI'2021, SNCS Springer Journal 2023]
- Extracting relationship between financial entities [FIRE'2023]

Impactful (Green) Investing

- Detecting Environmental, Social, and Governance (ESG) and sustainability related concepts, issues [FinNLP@IJCAI-ECAI'2022, ICDSA'2023]
- Assessing ESG impact type, duration in English, French, Japanese, Chinese, Korean [FinNLP@IJCNLP-AACL'2023, FinNLP@LREC-COLING'2024]

Informed Investing

- Detecting in-claim numerals [FinWeb@The Web Conference'2022, NTCIR'2022, IJIT Springer Journal, Software Impacts Elsevier Journal]
- Detecting exaggerated numerals in Financial Texts
- Estimating profitability and loss from financial social media posts in Chinese [FinNLP@EMNLP'2022]
- Deciding trust worthiness of social media posts by executives [FIRE'2022]
- Financial argument analysis in English & Chinese [NTCIR'2023]

Indic Investing

- Financial argument analysis in Bengali [FIRE'2023]
- Detecting ESG theme, Sustainability, Exaggerated numerals in Hindi, Bengali & Telugu [LREC COLING'2024]
- IPO success, rating

OUTCOME

- Increase in Financial Literacy
- Reduction in wealth disparity
- Economic Prosperity of Nation

Sustainable Future

Summary

CIKM 2024 | THE WEB CONFERENCE | ACM LREC-COLING 2024 | CODS COMAD

Overview

- Recent **trends in financial Natural Language Processing (NLP) research** [Science Talks Elsevier Journal 2023]
- Using NLP to Enhance **Understandability** of Financial Text [CODS-COMAD'2023] *[HONOURABLE MENTION]*, CIKM-2024

Impactful (Green) Investing

- Detecting Environmental, Social, and Governance (**ESG**) and **sustainability** related **concepts, issues** [FinNLP@IJCAI-ECAI'2022, ICDSA'2023]
- Assessing **ESG impact type, duration** in English, French, Japanese, Chinese, Korean [FinNLP@IJCNLP-AACL'2023, FinNLP@LREC-COLING'2024]

Inclusive Investing

- Increasing **readability** of Financial Texts [ICON'2021, FNP@LREC'2022]
- Increasing **reachability** of Financial Content [TheWebConf (WWW'2024)]

Informed Investing

- Detecting **in-claim numerals** [FinWeb@The Web Conference'2022, NTCIR'2022, IJIT Springer Journal, Software Impacts Elsevier Journal]
- Detecting **exaggerated numerals** in Financial Texts
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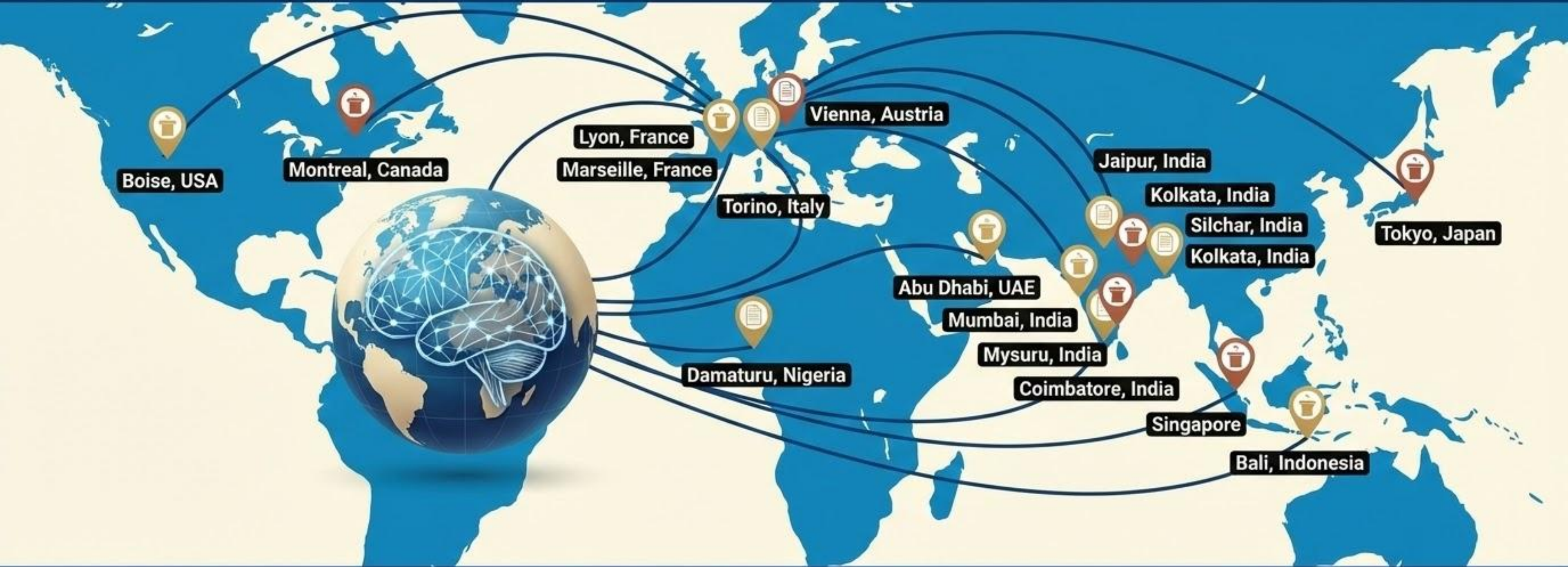
- **IPO success, rating**

Tools

- Financial Language **Understandability Enhancement Toolkit** (FLUEnT) [CODS-COMAD'2023]

GLOBAL OUTREACH:
Paper Presentations & Invited Talks



CIKM 2024
BOISE OCTOBER 21-25

THE WEB CONFERENCE
ACM LREC-COLING 2024

CODS
COMAD

Contributions & Achievements

16 tasks, **8** languages, **8** datasets, **6** tools, **24** papers

Publications & Venues

4 Journals: SNCS, IJIT, Software Impacts, Science Talks

10 Conferences, 2 Workshops, 8 Shared Tasks
ICON-2021
FinNLP@IJCAI-2021
FinWeb@The Web Conference-2022
FNP@LREC, FinNLP@IJCAI-ECAI-2022
NTCIR-16
FinNLP@EMNLP-2022
FIRE-2022
CODS-COMAD-2023
ICDSA-2023
FinNLP@ AACL-IJCNLP-2023
FIRE-2023, NTCIR-17
NTCIR-17

Key Venues:
The Web Conference WWW-2024 (Singapore)
LREC-COLING 2024 Tornio (Italy)
CIKM-2024 (Boise, USA)

Resources (Datasets & Tools)

Datasets: FinRAD, Executive/General Tweets, CReD, FAAB, IndicFinNLP

Tools: FinRead, FinCAT/FinCAT-2, FLUENT, FENCE, EID, FinLanSer, FAAB

Service & Collaborations

Mentorship: 7 students

Talks: 4 invited talks (XIM, HIT Haldia, Brainware Univ, Yobe State Univ)

Reviewing: FinNLP-ERAI@EMNLP, Manning, Springer, FinArg@NTCIR-17

Collaborations: AIRC Japan, BITS Pilani Hyderabad

Achievements

Citations & Status: 300 citations, Kaggle Datasets Expert

Awards & Grants: CODS-COMAD 2023 YRS TRACK (HONOURABLE MENTION), CODS-COMAD 2024 Travel Grant, CIKM 2024 Travel Grant, ACM PIC-2025 Travel Grant, ACM ARCS-2025 Travel Grant

Rankings: FinArg-1@NTCIR-17 (Rank-2), FinNLP@IJCNLP-AACL 2023 (Rank-1) FinNLP@LREC-COLING 2024 (Rank-3 & Rank-1)

Failures / Rejections

Rejected Papers & Proposals

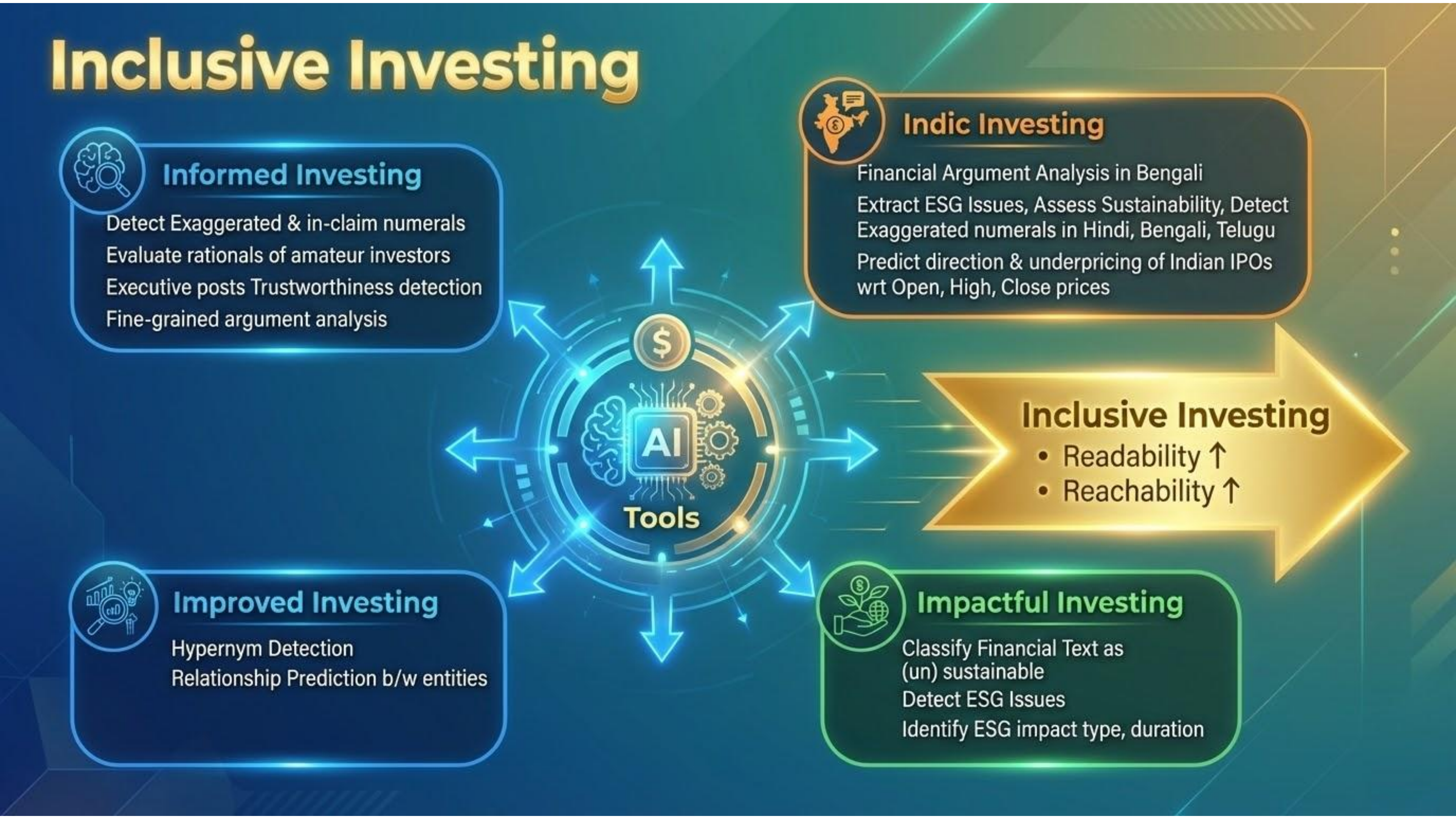
- SIGIR-2022 (resource track)
- ACM - Transaction on the Web (Special Issue)
- Financial Innovations, Springer (desk reject)
- IJDSA, Springer Journal (desk reject)
- EMNLP-2023, ARR-2035 (Main & Findings)

Denied Tools & Resources

- EMNLP-2022 demo track
- Software Impacts, Elsevier [FENCE Tool]
- FIRE-2023 [FENCE Tool]
- WWW (Doctoral Consortium) 2024
- FinNLP-KDF-EcoNLP@LREC-COLING [FENCE Tool] 2024

Desk Rejections

- Information Fusion, Elsevier (desk reject), 2024
- Expert Systems With Applications, Elsevier (desk reject), 2025
- Knowledge Based Systems, Elsevier (desk reject), 2025
- Engineering Applications of AI, Elsevier, 2025
- AACL-IJCNLP 2025


Inclusive Investing
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Detect Exaggerated & in-claim numerals
Evaluate rationals of amateur investors
Executive posts Trustworthiness detection
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Financial Argument Analysis in Bengali
Extract ESG Issues, Assess Sustainability, Detect Exaggerated numerals in Hindi, Bengali, Telugu
Predict direction & underpricing of Indian IPOs wrt Open, High, Close prices
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• Readability ↑
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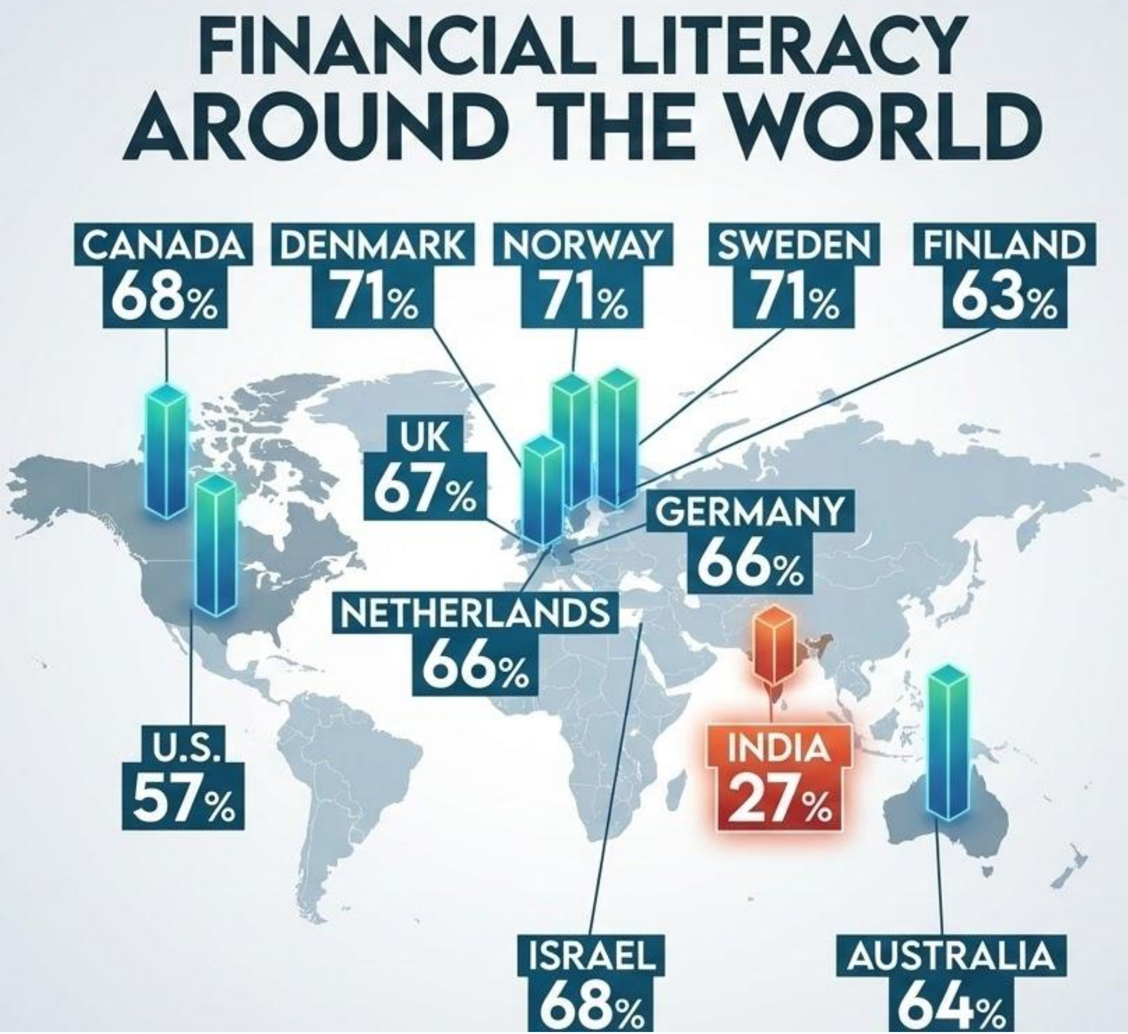
Hypernym Detection
Relationship Prediction b/w entities
Impactful Investing
Classify Financial Text as (un) sustainable
Detect ESG Issues
Identify ESG impact type, duration


FINANCIAL LITERACY AROUND THE WORLD
CANADA 68%
DENMARK 71%
NORWAY 71%
SWEDEN 71%
FINLAND 63%
UK 67%
GERMANY 66%
NETHERLANDS 66%
U.S. 57%
INDIA 27%
ISRAEL 68%
AUSTRALIA 64%

Inclusive Investing

Readability

How to quantify and improve readability of financial texts?

Financial Readability Assessment Dataset (FinRAD)

A Transfer Learning Based Tool to Assess Readability of Definitions of Financial Terms (FinRead)

Financial Language Simplifier (FinLanSer)

Reachability

How to ensure financial contents reach more people?

Generator-Guided Estimation Approach for Crowd Reaction Assessment

Inclusive Investing: Readability

FinRead: A Transfer Learning Based Tool to Assess Readability of Definitions of Financial Terms

Sohom Ghosh, Shovon Sengupta, Sudip Kumar Naskar, Sunny Kumar Singh

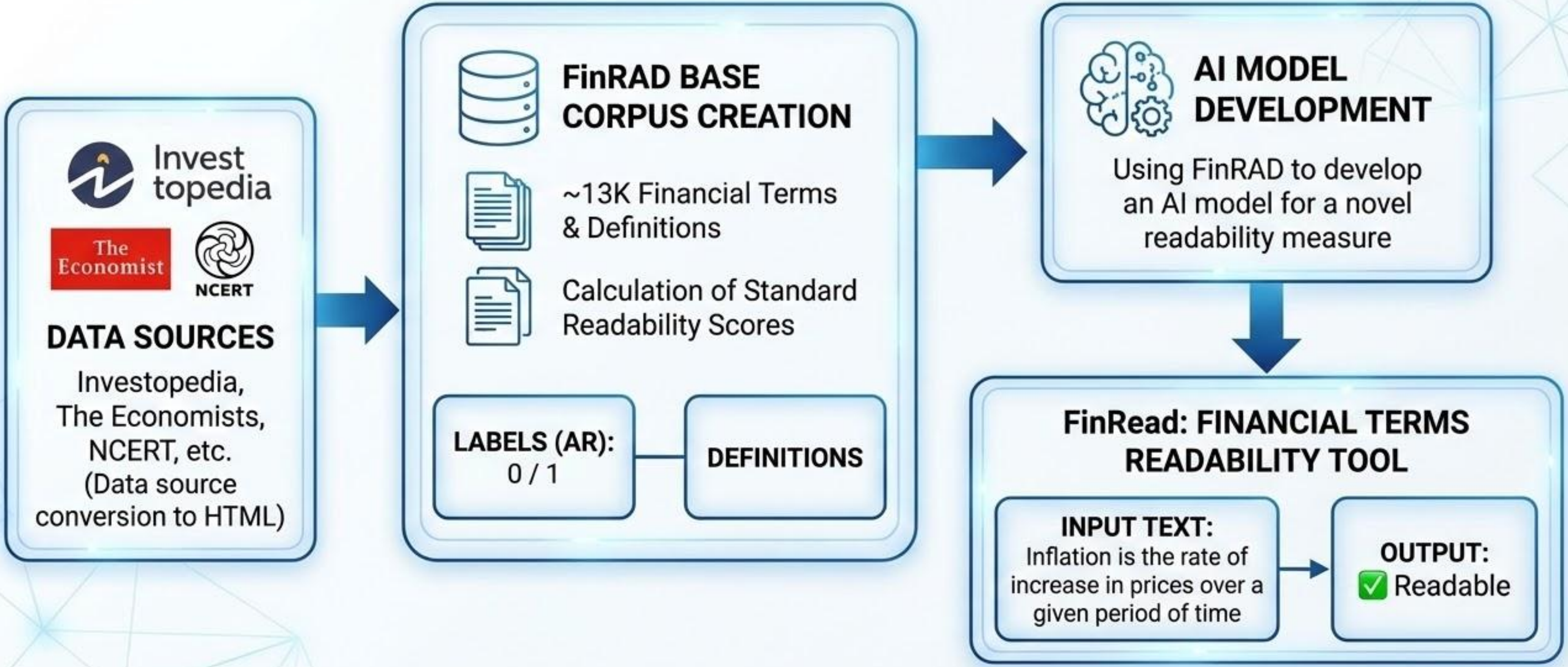
Proceedings of the 4th Financial Narrative Processing Workshop @ LREC 2022, pages 1–9
Marseille, 24 June 2022

FinRAD: Financial Readability Assessment Dataset – 13,000+ Definitions of Financial Terms for Measuring Readability

Sohom Ghosh, Shovon Sengupta, Sudip Kumar Naskar, Sunny Kumar Singh

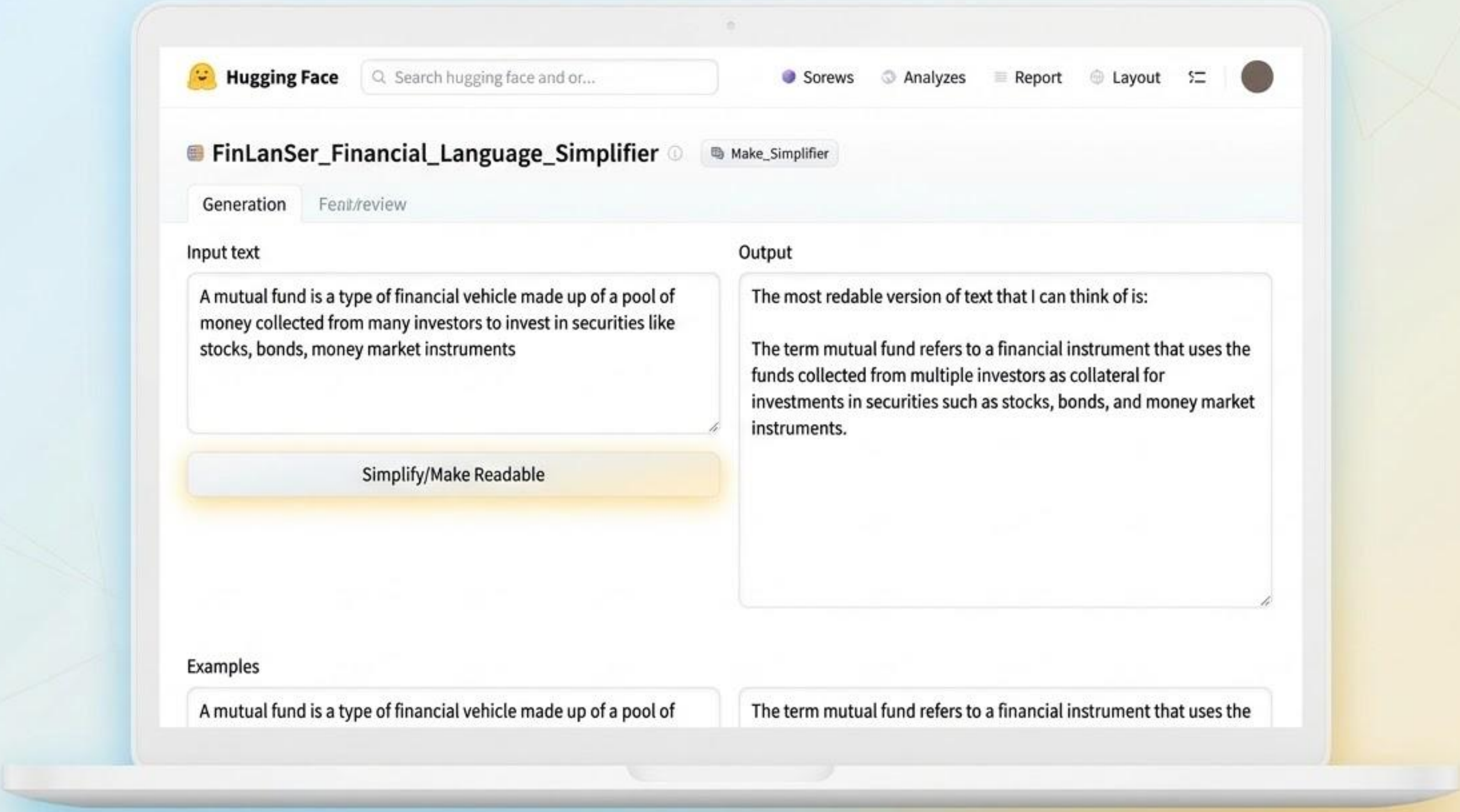
ICON, FNP@LREC-2022

Inclusive Investing: Readability



FinRead: A tool for measuring readability of definitions of financial terms

Inclusive Investing: Readability



Inclusive Investing: Readability

Contributions:

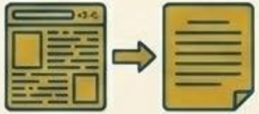
Financial Readability Assessment Dataset (FinRAD)

13,000+ Definitions of Financial Terms for Measuring Readability

FinRead: A Transfer Learning Based Tool

To Assess Readability of Definitions of Financial Terms

FinLanSer: Financial Language Simplifier



To simplify complex financial text and make it more readable

Inclusive Investing: Reachability

Problem Statement

Develop a framework to estimate if a given social media post will receive more reaction than another

THE WEB CONFERENCE 2024
IN SINGAPORE

The White House
@WhiteHouse

Happy Pride Month!

This month and every month, the Biden-Harris Administration stands proudly with the LGBTQI+ community in the enduring fight for freedom, justice, and equality.

2,081 Retweets **224** Quotes **11.6K** Likes **32** Bookmarks

The White House
@WhiteHouse

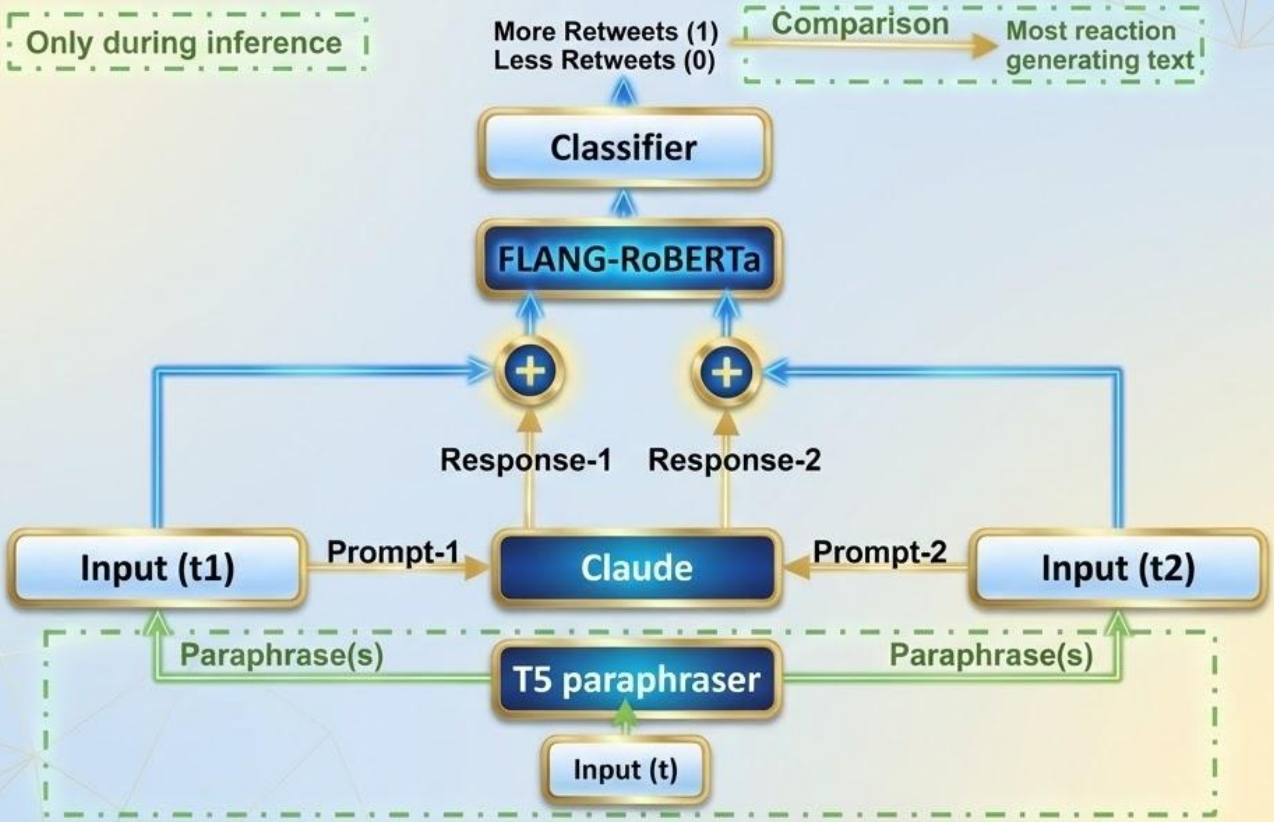
To fulfill the founding ideals of our nation, we must protect LGBTQI+ Americans from attacks on their freedom and safety.

It's time for Congress to pass the Equality Act – strengthening civil rights protections for LGBTQI+ people and families across America.

328 Retweets **36** Quotes **1,454** Likes **9** Bookmarks

TheWebConf (WWW-2024)

Inclusive Investing: Reachability



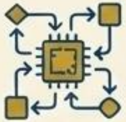
Inclusive Investing: Reachability

Contributions:

- **Task:** Crowd **R**eaction **A**ssess**M**ent (CReAM)
- **Dataset:** Crowd **R**eaction **E**stimation **D**ataset (CRED)
- **Architecture:** Generator-Guided Estimation Approach

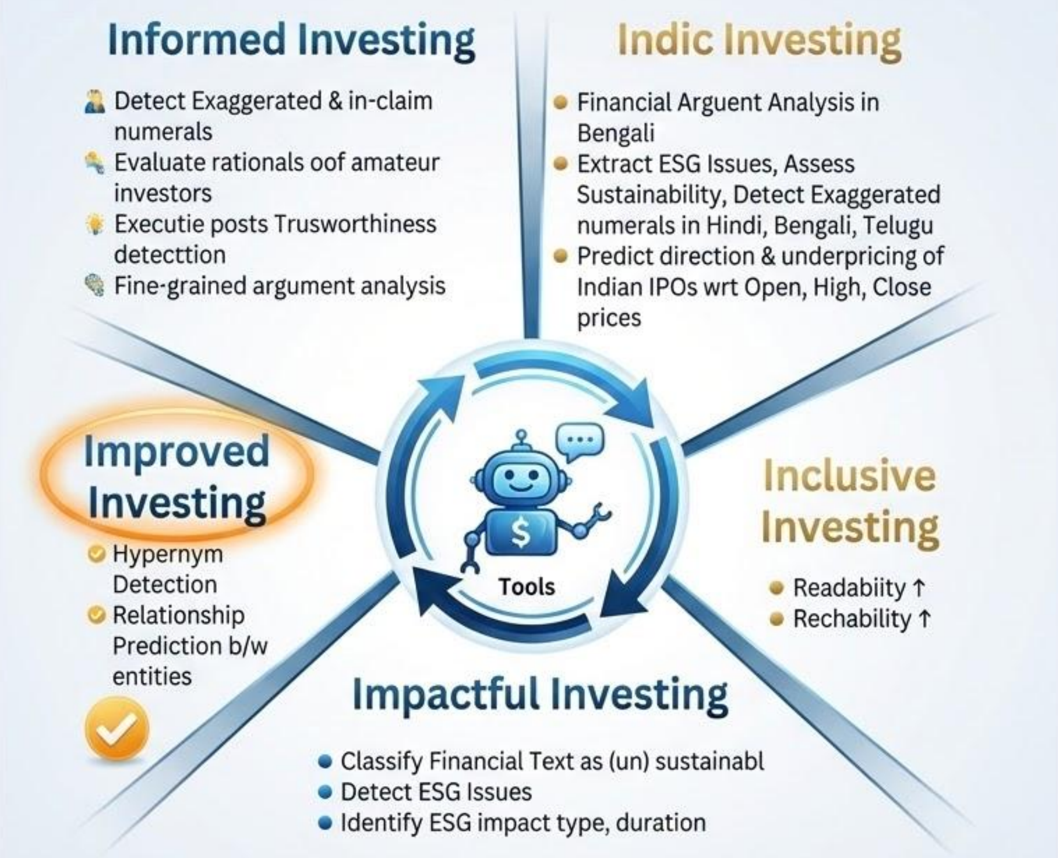
Task: Crowd Reaction AssessMent (CReAM)

Dataset: Crowd Reaction Estimation Dataset (CRED)



Architecture: Generator-Guided Estimation Approach

Improved Investing



NEWS

NEWS

Increasing financial literacy during the pandemic essential for India's recovery

Reportage. In Indian megacities millions of people have no access to banking services due to lack of knowledge or technology. Lack of universal education plays a big part.

Pia Heikkilä Photo Pia Heikkilä

30.09.2020

livemint

Business News / News / India / Richest 1% Indians own more than 40%

Richest 1% Indians own more than 40% of country's wealth: Report

2 min read • 16 Jan 2023, 06:46 AM IST

Improved Investing

- How to improve the investment process?
  - Detecting hypernyms of Financial Terms
  - Extracting relationship between financial entities

SNCS, FinNLP@IJCAI, FIRE-2023

SPRINGER LINK

Home > SN Computer Science > Article

Original Research | Published: 11 August 2023

Learning to Rank Hypernyms of Financial Terms Using Semantic Textual Similarity

Sohom Ghosh, Ankush Chopra & Sudip Kumar Naskar

SN Computer Science, 4, Article number: 610 (2023) | Cite this article

The Mask One At a Time Framework for Detecting the Relationship between Financial Entities

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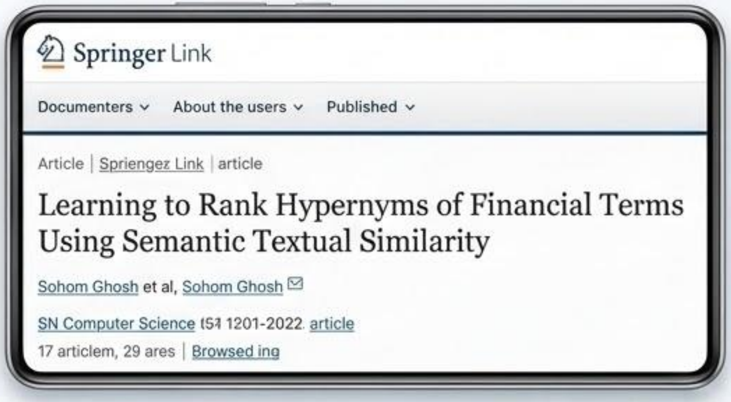
Improved Investing: Hypernym Detection


Springer Link

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Article | Spriengez Link | article

Learning to Rank Hypernyms of Financial Terms Using Semantic Textual Similarity

Sohom Ghosh et al, Sohom Ghosh

SN Computer Science (54 1201-2022. article

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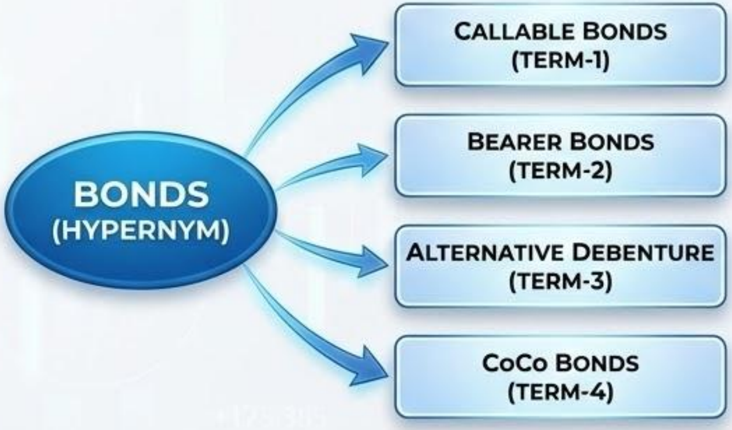
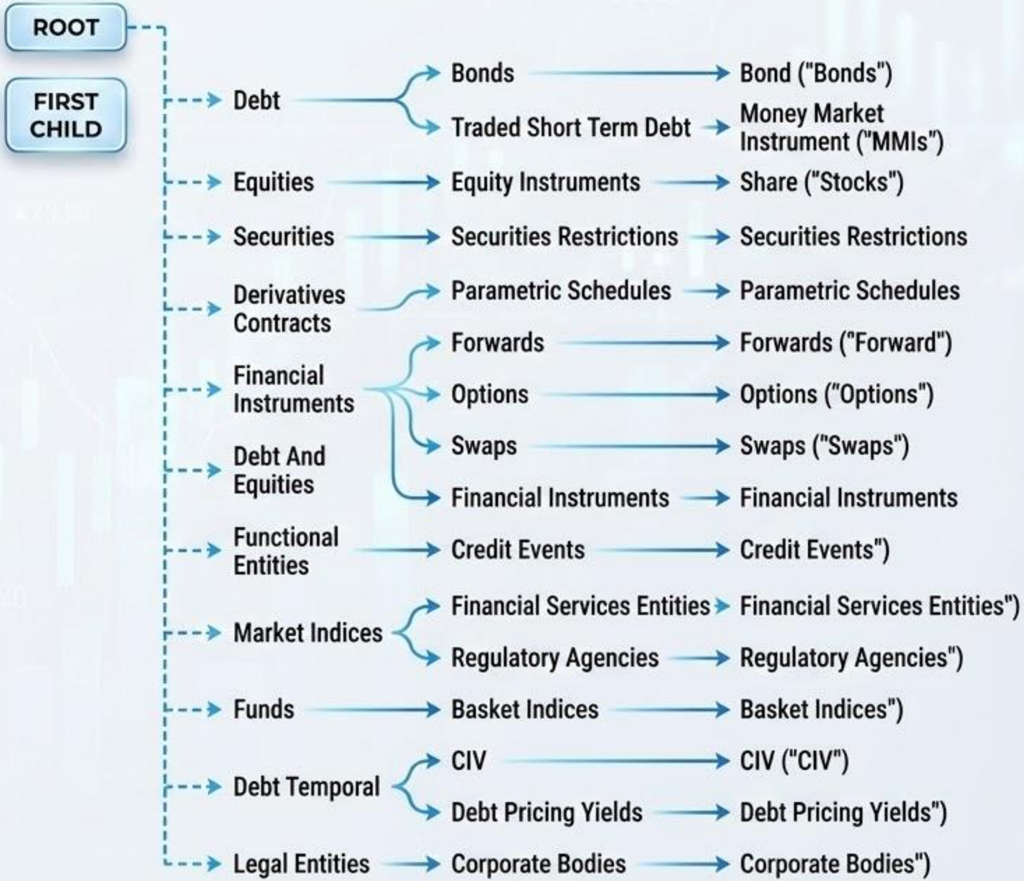
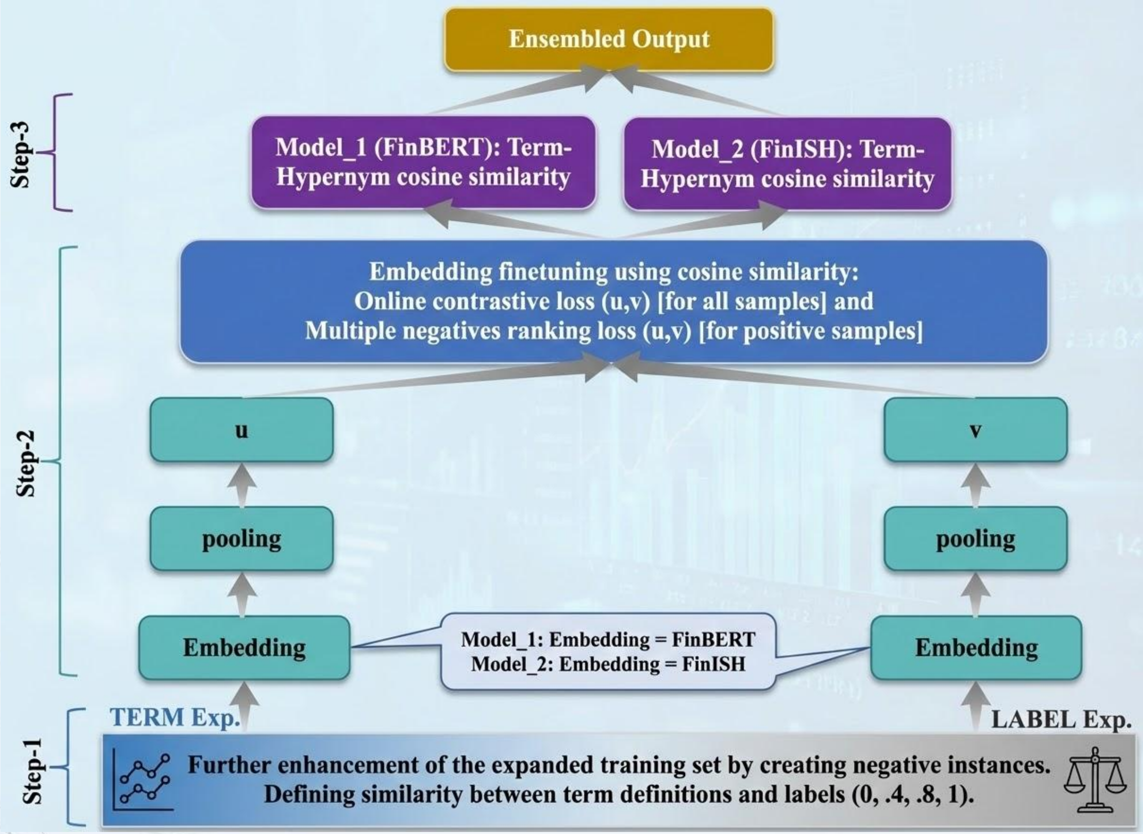




Improved Investing: Hypernym Detection



Improved Investing: Hypernym Detection

Contributions:

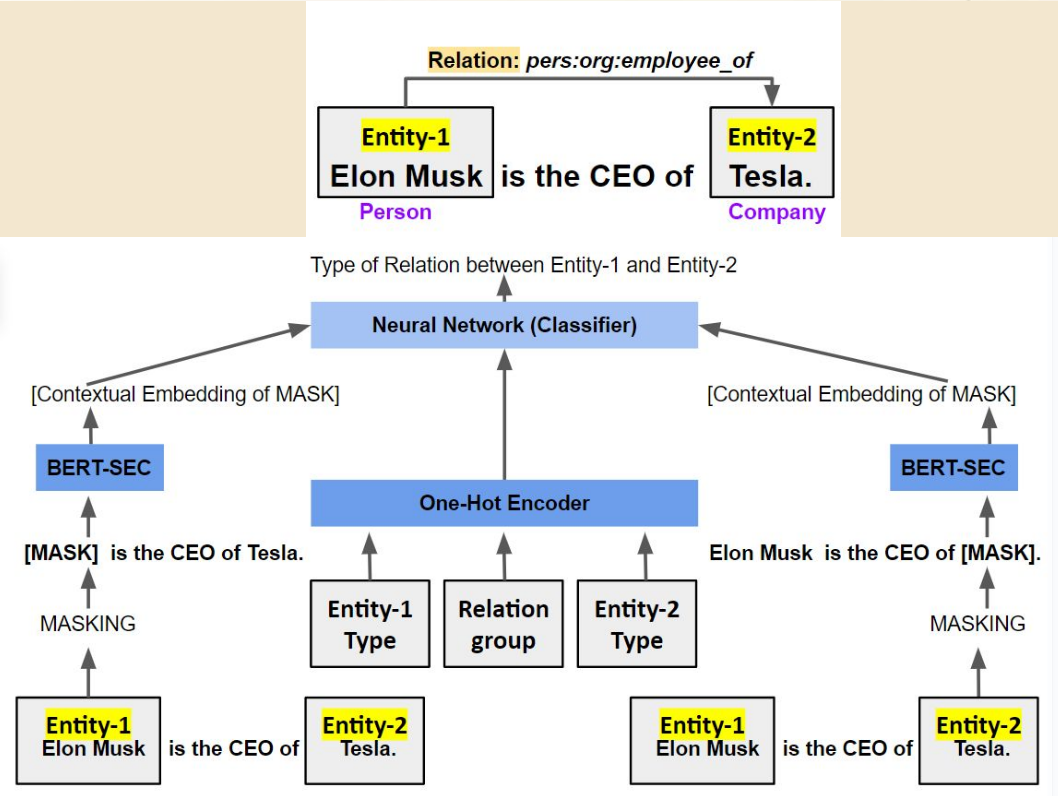
Method:
Negative Sampling

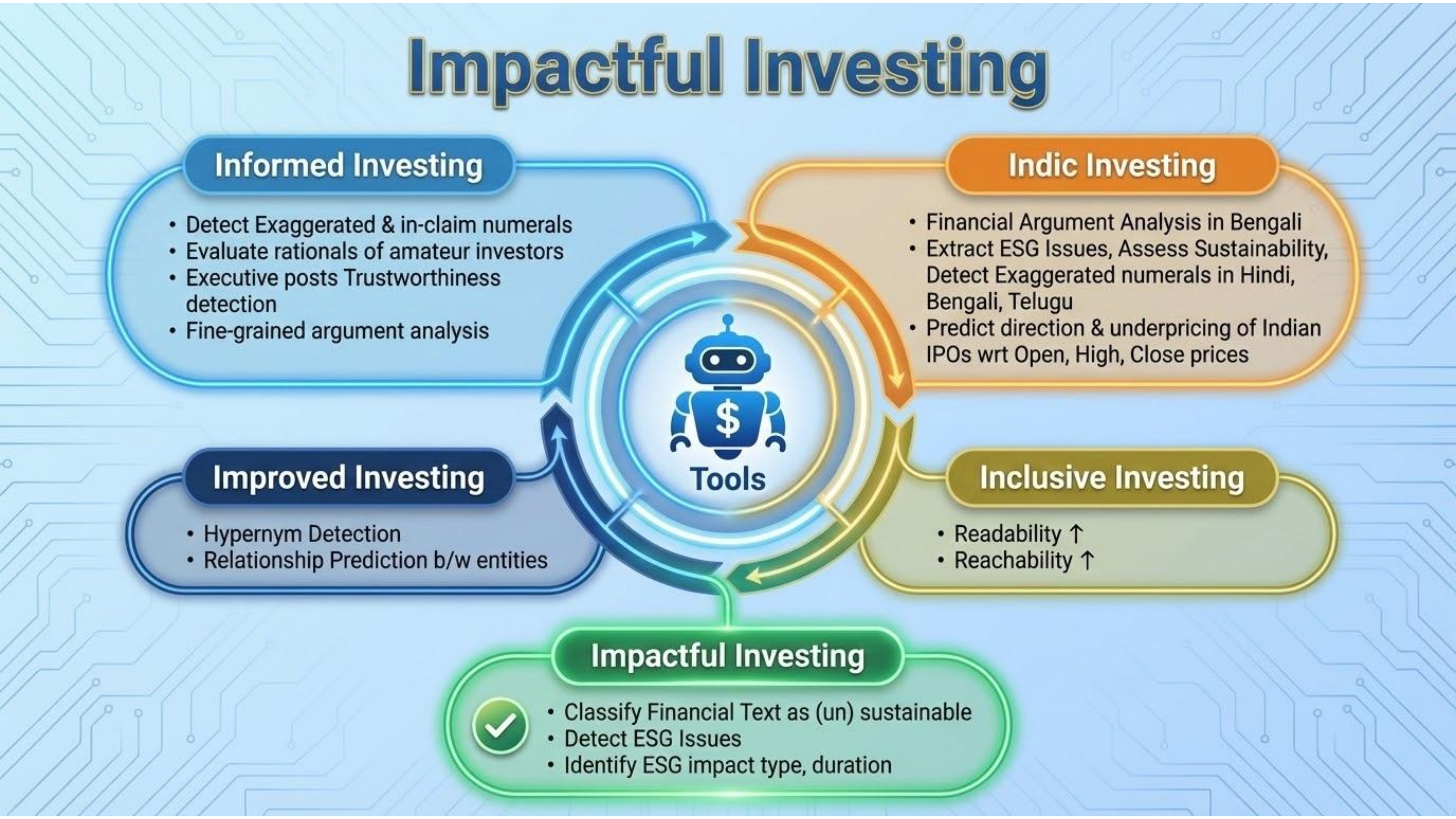
System:
State of the Art system capable of ranking a set of hypernyms for a given financial term

Improved Investing: Relation Extraction

Contributions:

- Framework: **Mask One At a Time (MOAT)**
- Benchmarked with existing open source generative Large Language Models (LLMs)




Impactful Investing
Informed Investing
• Detect Exaggerated & in-claim numerals
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• Readability ↑
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Impactful Investing
• Classify Financial Text as (un) sustainable
• Detect ESG Issues
• Identify ESG impact type, duration

Budget 2023: Analysis of Green Finance, and Roadmap Ahead

NEWS

The government will have to spend another 11lakh crore every year till 2030 to reach its Panchamrit target which it committed to at COP26 in Glasgow. So, will the Finance Minister push the accelerator on Green Finance, or will other sectors continue to be a priority?

ETBFSI News

Budget 2023: Analysis of green finance, and roadmap ahead

Updated: January 31, 2023, 17:16 IST

mint

NSE to set up Social Stock Exchange (SSE) as a separate segment

1 min read • 23 Dec 2022, 10:10 AM IST **Livemint**

Finance Minister Nirmala Sitharaman, in her Union Budget speech of 2019-20, had proposed creation of a Social Stock Exchange

Impactful (Green) Investing

Contributions:

How to ensure that the investments are towards betterment of the Earth and have positive impact towards the environment?

Detecting ESG and sustainability related concepts, issues, and impact

Assessing ESG Impact Type

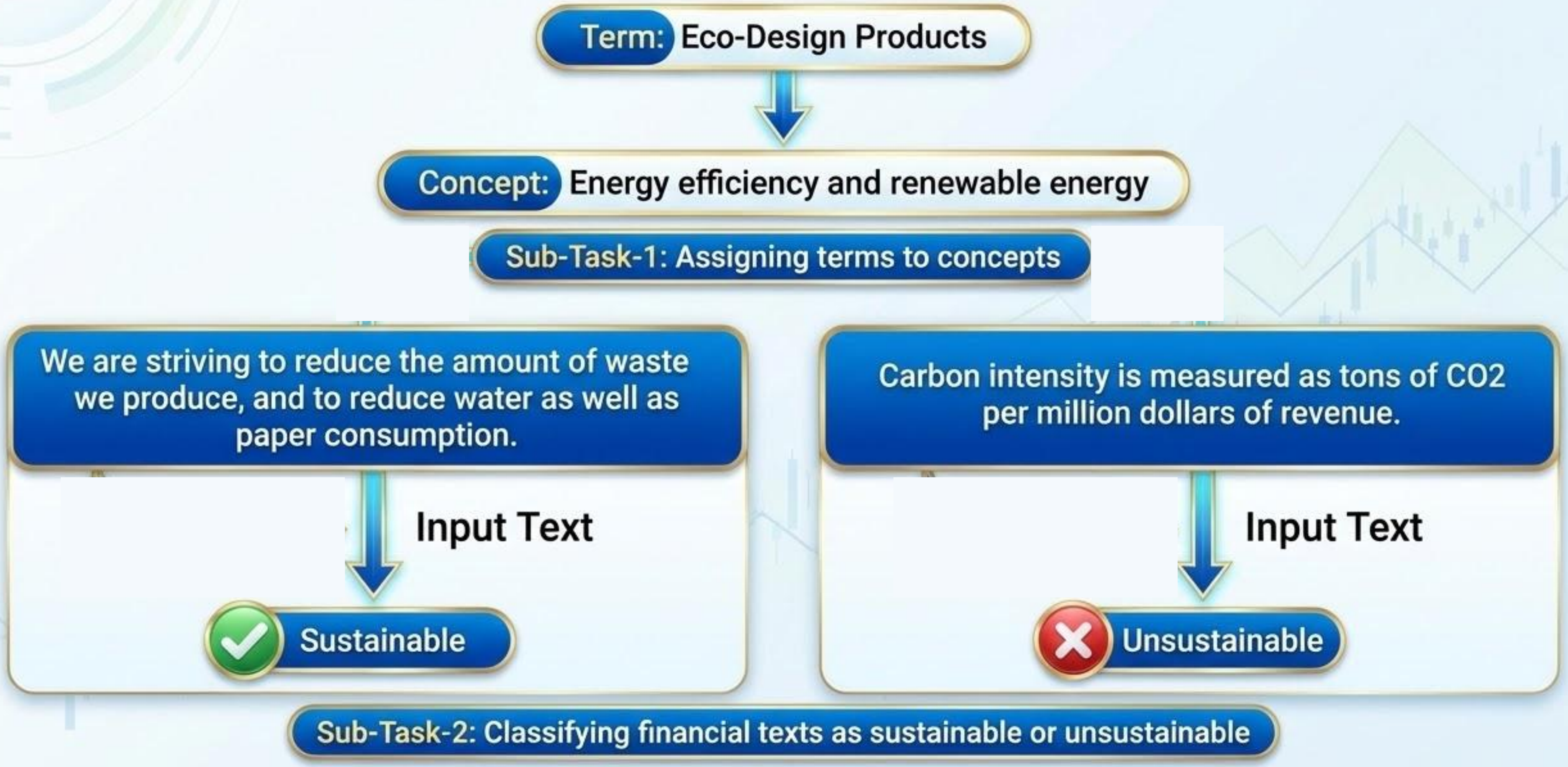
Assessing ESG Impact Duration

- Ranking Environment, Social And Governance Related Concepts And Assessing Sustainability Aspect Of Financial Texts
- Detecting Issues Related to Environmental, Social, and Corporate Governance using SEC-BERT
- A low resource framework for Multi-lingual ESG Impact Type Identification
- Fine-tuning Language Models for predicting the impact of events associated to financial news articles

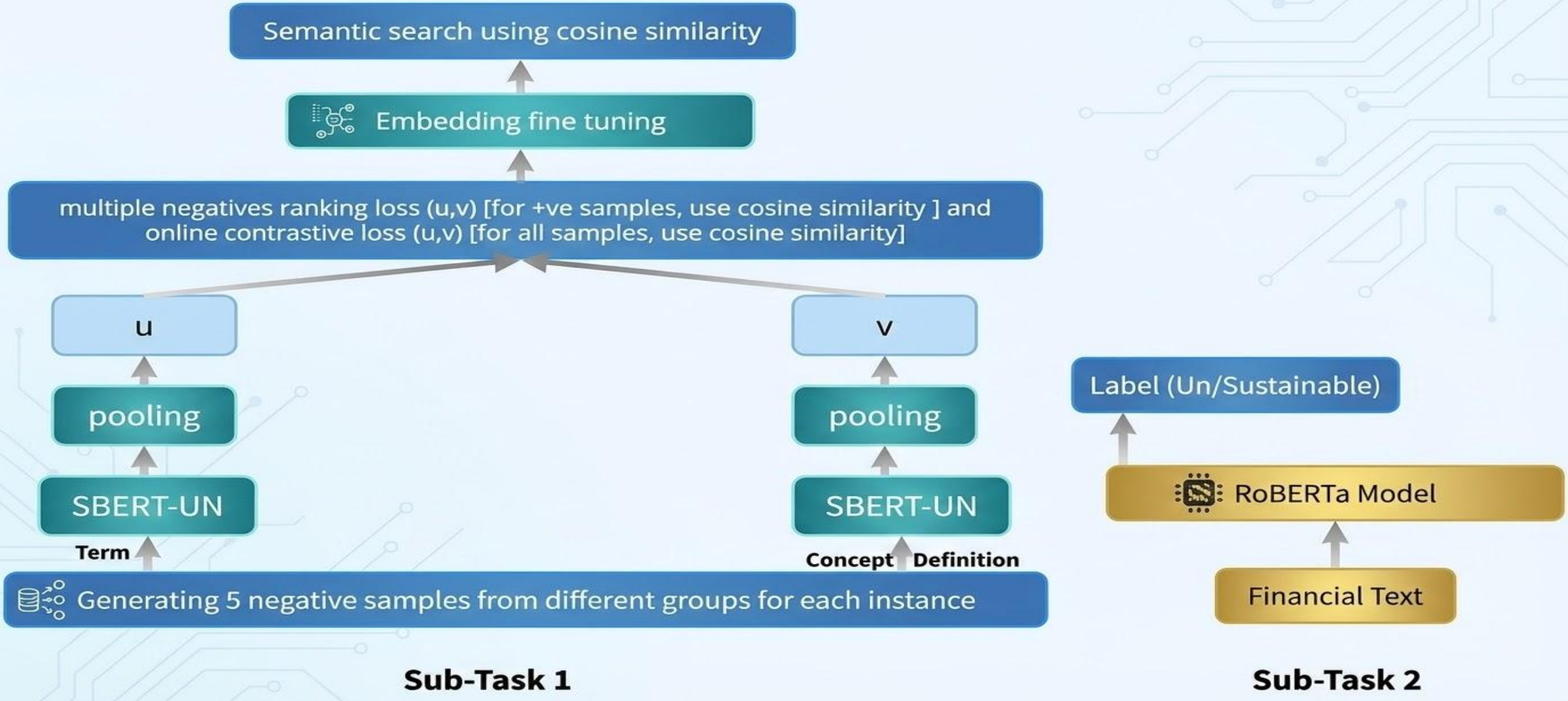
Venues: FinNLP @ (IJCAI, AACL, LREC_COLING), ICDSA-2023

SCAN ME SCAN ME SCAN ME SCAN ME

Impactful (Green) Investing: ESG concept & Sustainability detection



Impactful (Green) Investing: ESG concept & Sustainability detection



Impactful (Green) Investing: ESG Issue Detection

Output (ESG Issue)

Opportunities in Nutrition & Health

Classification

SEC-BERT pre fine-tuned Model

Input (Title + Content of NEWS article)

United Natural Food Unveils Sustainability Goals Covering Climate, Waste Reduction and Food Access

Impactful (Green) Investing: ESG Impact Type Assessment

Input Text:
Chinese: “氣候異常，歐洲就是不下雨！看農業大國荷蘭如何抗旱...”

Output:
Opportunity/Risk/Cannot Distinguish/Related to ESG/Not related to ESG topic

Input Text:
English: “”Verizon Innovative Learning celebrates 10 years and $1 billion in contributions to education... ””

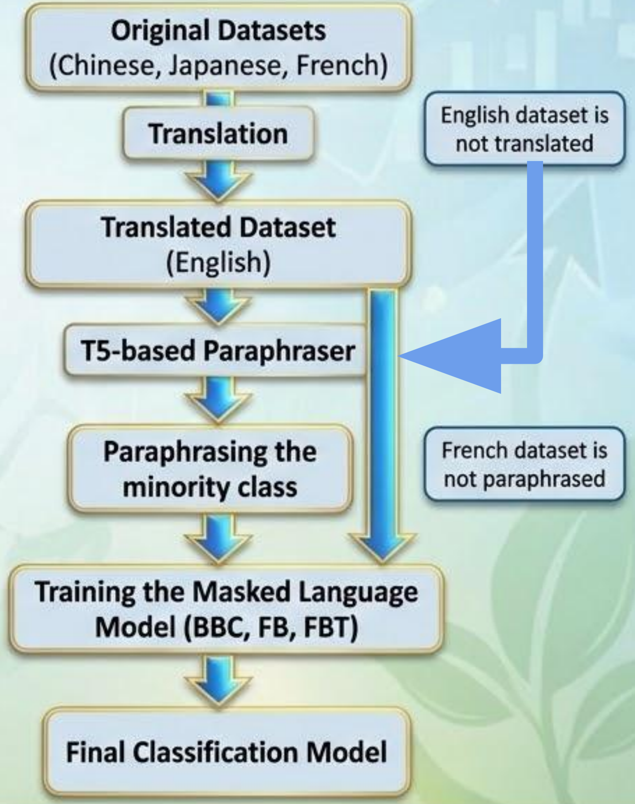
Output:
Opportunity/Risk

Input Text:
French: “”Démocratie, Pouvoir, loi Avia... Cinq questions ouvertes après la fermeture du compte Twitter de Donald Trump... ””

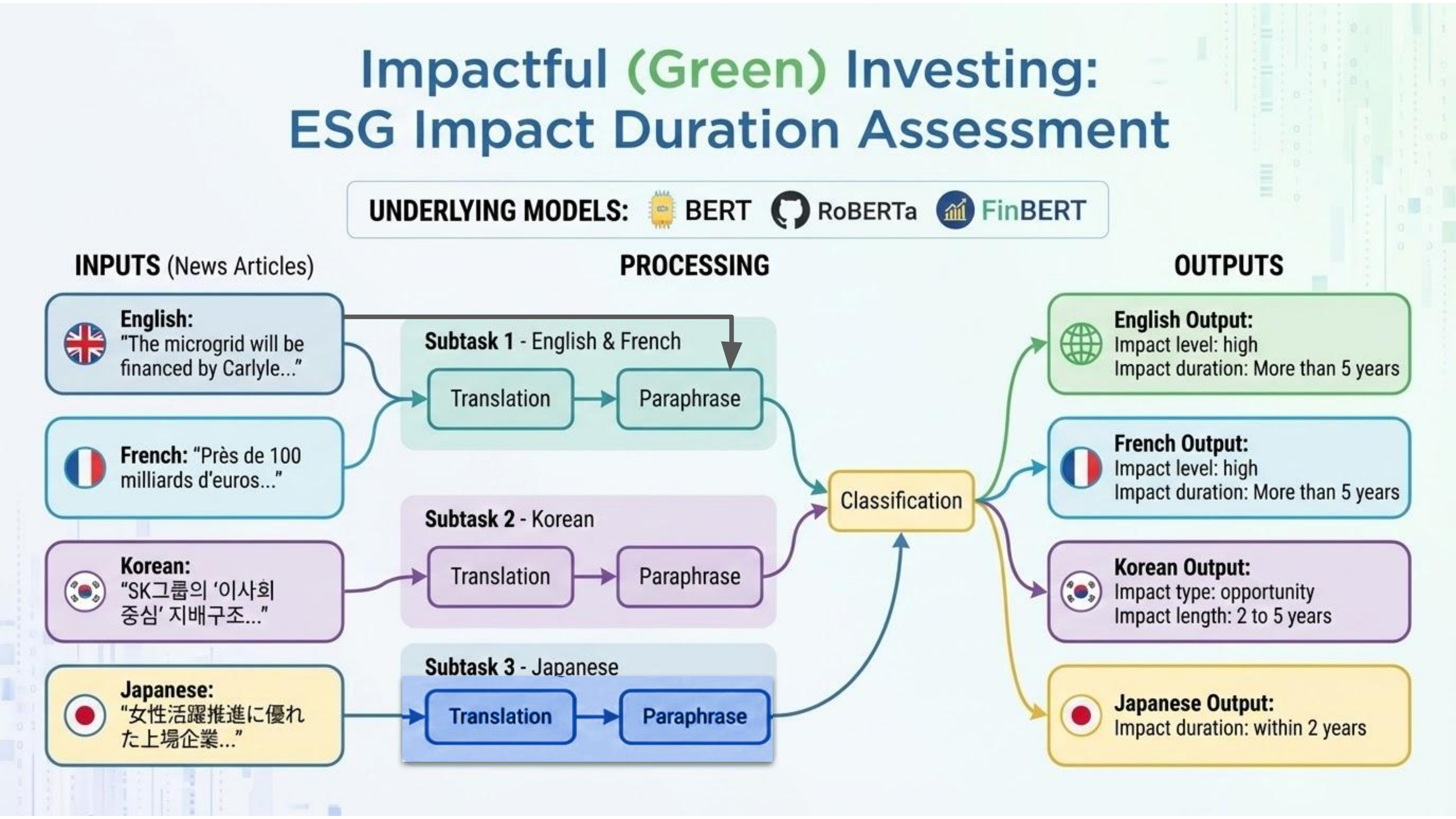
Output:
Opportunity/Risk

Input Text:
Japanese: “エプソンは、事業戦略の選択肢の一つとして、他社と業務提携などを行うことがあります。...”

Output:
N/A/Neutral/Positive/Negative



BBC = bert-base-cased, FB = FinBERT, FBT = FinBERT Tone



Impactful (Green) Investing:
ESG Impact Duration Assessment
UNDERLYING MODELS: BERT RoBERTa FinBERT
INPUTS (News Articles)
PROCESSING
OUTPUTS
English: "The microgrid will be financed by Carlyle..."
French: "Près de 100 milliards d'euros..."
Korean: "SK그룹의 '이사회 중심' 지배구조..."
Japanese: "女性活躍推進に優れた上場企業..."
Subtask 1 - English & French
Translation
Paraphrase
Subtask 2 - Korean
Translation
Paraphrase
Subtask 3 - Japanese
Translation
Paraphrase
Classification
English Output: Impact level: high Impact duration: More than 5 years
French Output: Impact level: high Impact duration: More than 5 years
Korean Output: Impact type: opportunity Impact length: 2 to 5 years
Japanese Output: Impact duration: within 2 years

Impactful (Green) Investing

Contributions:

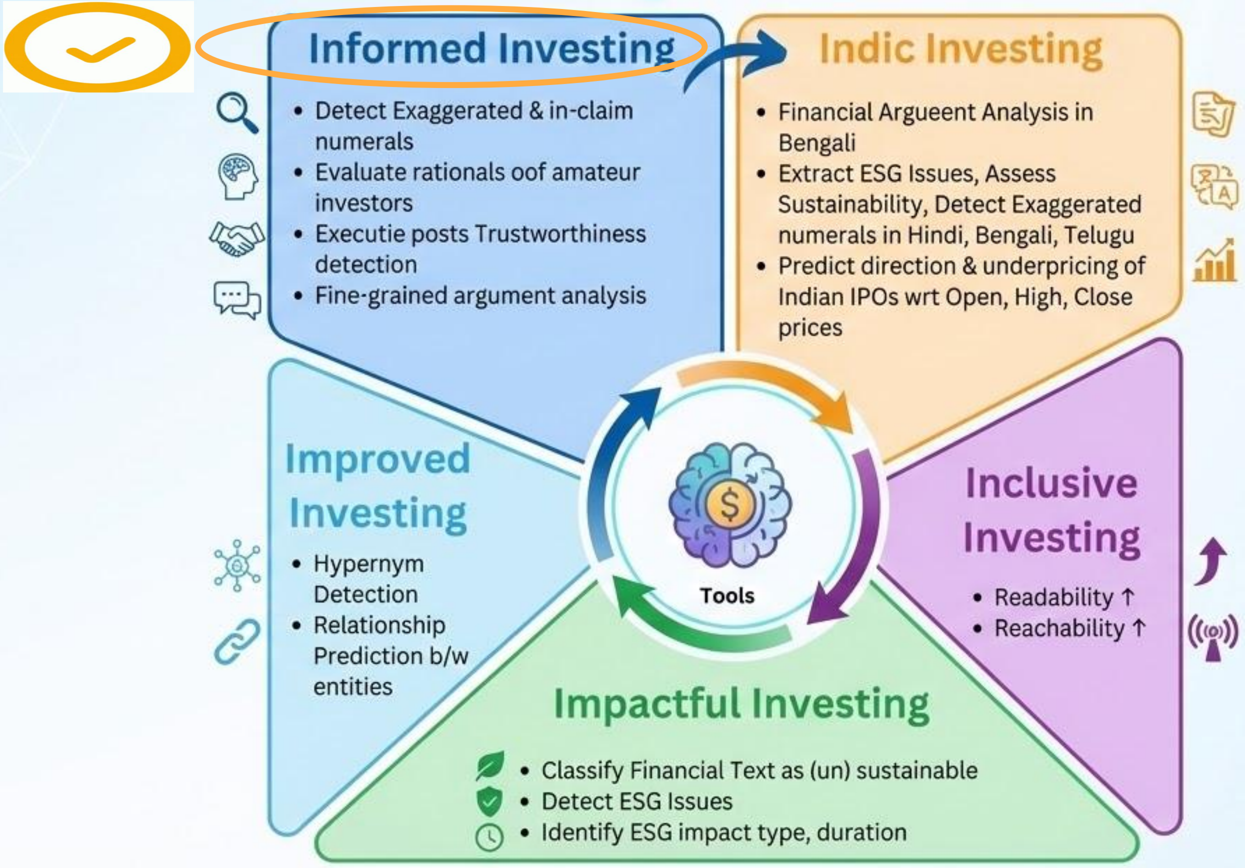
Trained Sentence Transformers
Automatically ranks ESG-related concepts for unknown terms.

Fine Tuned RoBERTa
Classifies financial texts as ‘sustainable’ or ‘not sustainable’.

Tool: ESG Issue Detector (EID)
A tool developed for detecting ESG issues.

Low Resource Framework
Proposed a framework for assessing ESG Impact Type.

Informed Investing



NEWS: Financial Manipulation & Scams

BS News

Manipulation via Youtube: Sebi penalises Arshad Warsi, wife, 29 others

Sebi noted that Arshad Warsi has made a profit of Rs 29.43 lakh and his wife has earned a profit of Rs 37.56 lakh

mint Premium | **MONEY**

How finfluencers use fake screenshots to run scams

Neil Borate, Sashind Ningthoukhongjam | 8 min read | 31 Aug 2023, 12:00 AM IST

Informed Investing

How to safeguard investors from misinformation?

- Detecting in-claim numerals
- Detecting Exaggerated Numerals in Financial Texts
- Estimating profitability and loss from financial social media
- Deciding trust worthiness of social media posts by executives
- Financial Argument Analysis

Informed Investing

Estimating profitability and loss from financial social media posts in Chinese

- Analyzes sentiment and trends in Chinese financial social media posts.
- Develops models to predict potential profitability and loss.
- Provides insights for informed investment decisions in the Chinese market.

Venue: FinNLP@EMNLP'2022

Informed Investing - Claim Detection

NTCIR 16 Conference: Proceedings of the 16th NTCIR Conference on Evaluation of Information Access Technologies, June 14-17, 2022 Tokyo Japan

NTCIR

LIPI at the NTCIR-16 FinNum-3 Task: Ensembling transformer based models to detect in-claim numerals in Financial Conversations

Sohom Ghosh   Sudip Kumar Naskar

FiNCAT: Financial Numeral Claim Analysis Tool

Authors: Sohom Ghosh, Sudip Kumar Naskar Authors Info & Claims

WWW '22: Companion Proceedings of the Web Conference 2022 • April 2022 • Pages 583–585

• https://doi.org/10.1145/3487553.3524635

Home › International Journal of Information Technology › Article

Detecting context-based in-claim numerals in Financial Earnings Conference Calls

Original Research | Published: 15 May 2022

Volume 14, pages 2539–2568, (2022) Cite this article

Information Technology

International Journal of Information Technology

Aims and scope ›

Submit manuscript ›

Springer, May 2022

FiNCAT-2: An enhanced Financial Numera Claim Analysis Tool

Sohom Ghosh [a] [b], Sudip Kumar Naskar [b]

Software Impacts, Elsevier, 2022

Informed Investing - Claim Detection

Input Text	Output
For the full year we continue to expect an adjusted effective tax rate in the range of 23% to 24%.	Claim ✓
Free cash flow a really good start to the year at $1.1 billion.	Not Claim ✗

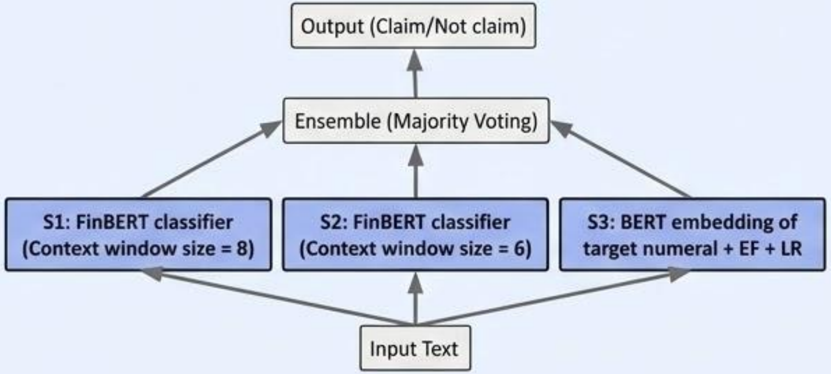
FinCAT-2

OUTPUT 1

Last year our profit was $2.2M [Out-of-Claim]. This year it will increase to $3M [In-claim].

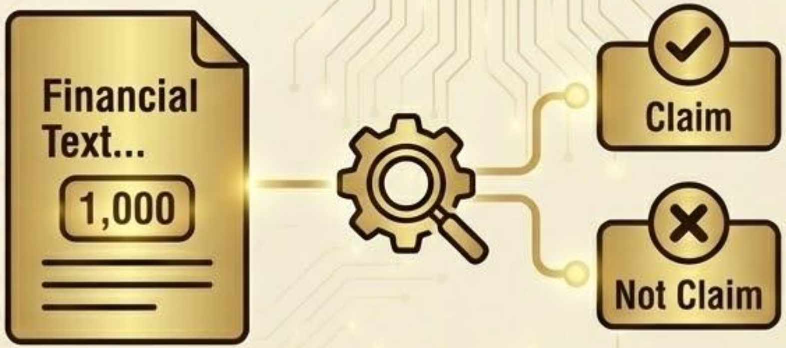
OUTPUT 2

numeral	prediction	probability
$2.2M	Out-of-Claim	0.0409
$3M	In-claim	0.8873



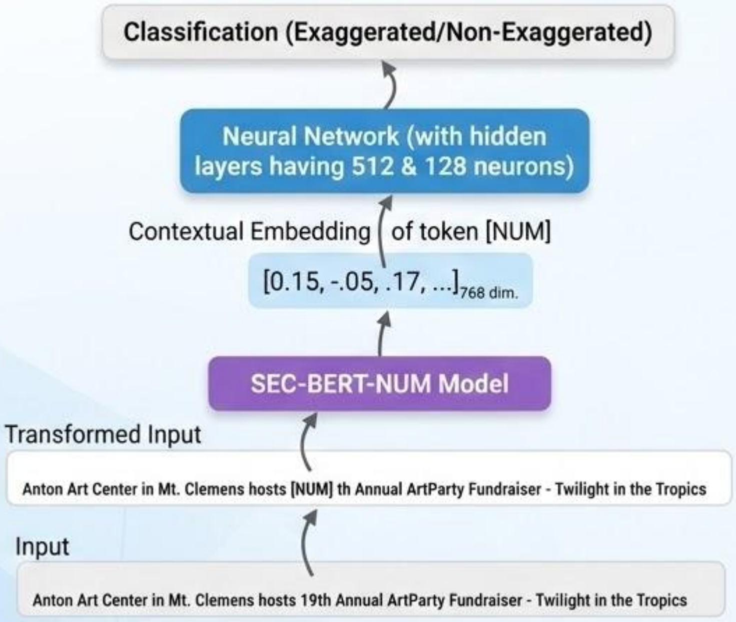
Informed Investing - Claim Detection

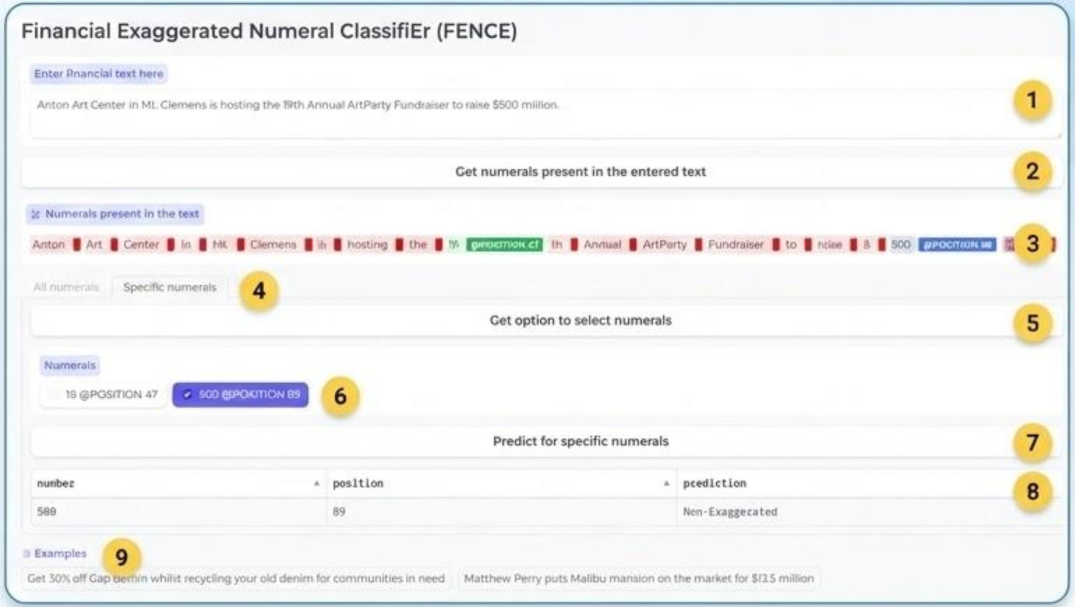
Contributions:



System to detect number present in a given financial text is a claim or not

Informed Investing - Exaggerated Numeral Detection





Informed Investing - Exaggerated Numeral Detection

Contributions:

- Framework: To detect Exaggerated Numerals
- Tool : Financial Exaggerated Numeral ClassifiEr (FENCE)

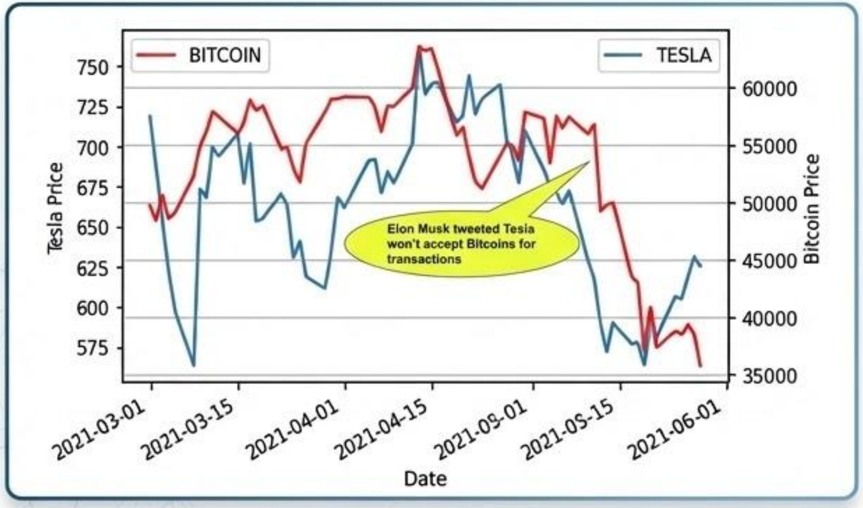
Informed Investing: Deciding trust worthiness of social media posts by executives

Evaluating Impact of Social Media Posts by Executives on Stock Prices

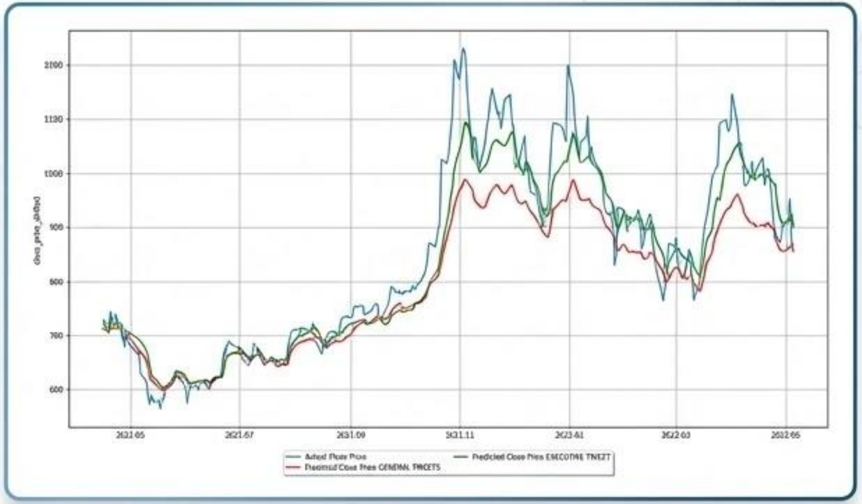
FIRE-2022

Authors: Anubhav Sarkar, Swagata Chakraborty, Sohom Ghosh, Sudip Kumar Naskar

Informed Investing: Deciding trust worthiness of social media posts by executives



Case Study: Impact of Executive Tweets on Crypto Prices



Model Performance: Predicting Stock Price Movements

Informed Investing: Deciding trust worthiness of social media posts by executives

Contributions:

Executive Influence on Price

Established social media posts by executives have deeper influence on close price movements.

Sentiment-Based Prediction

Proposed how to use sentiments from social media to accurately predict the close prices.

Platform Comparison (Reddit vs. Twitter)

Proved Reddit shows a similar trend like Twitter, however, Twitter is more effective in this task than Reddit.

Informed Investing : Financial Argument Analysis

NTCIR-17 (2023)

NTCIR 17 Conference: Proceedings of the 17th NTCIR Conference on Evaluation of Information Access Technologies, December 12-15, 2023, Tokyo, Japan

DOI: https://doi.org/10.20736/0002001281

LIPI at the NTCIR-17 FinArg-1 Task: Using Pre-trained Language Models for Comprehending Financial Arguments

Swagata Chakraborty, Anubhav Sarkar, Dhairya Suman (dhairyasuman@gmail.com), Sohom Ghosh, Sudip Kumar Naskar

NTCIR-17 (2023)

Informed Investing: Financial Argument Analysis

Input Text

English: "Japan as a geography for us is a high transactional market."

Output

Premise/ Claim

Task-2 (Sub-Task 1): Argument Unit Identification (Earnings Conference Call)

Input Text-1

English: "Japan as a geography for us is a high transactional market."

Input Text-2

English: "The improvement in that in Q3 is obviously very high margin and also the bottom."

Output

Support/ Attack/ None

Task-2 (Sub-Task 2): Argument Relation Identification (Earnings Conference Call)

Input Text-1

Chinese: "我設定看到 7.99雖然不一定會來 買進 預計用今年領到的股到最金64萬多 和現金30萬 總共94萬多 全部跟他賭一把 先用用貸借出64萬 一拿到股利現金 馬上還掉"

Input Text-2

Chinise: "[illegible]多[illegible]有必要一直跟這些拼嗎 ??? 買這些的自貼就是價低 殖利率高 未來要考慮的是 向會已經面重要損???生意越來越少??? 未來它的獲利????"

Output

Support/ Attack/ None

Task 2: Identifying Attack and Support Argumentative Relations (Social Media)

MODEL	MACRO-F1 (VALIDATION SET)	MICRO-F1 (VALIDATION SET)
RNN + Specy Tokenizer	0.3571	0.5270
FastTest + NN	0.7155	0.7173
Glove Embeddings + CNN	0.6952	0.6957
BART-BASE-CASED + BERT TOKENIZER	0.7336	0.7337
BERT-SEC	**0.7476**	**0.7430**
FinBERT	0.7398	0.7401

Table 2: Results of Task 1, Sub-Task 1: Argument Unit Identification

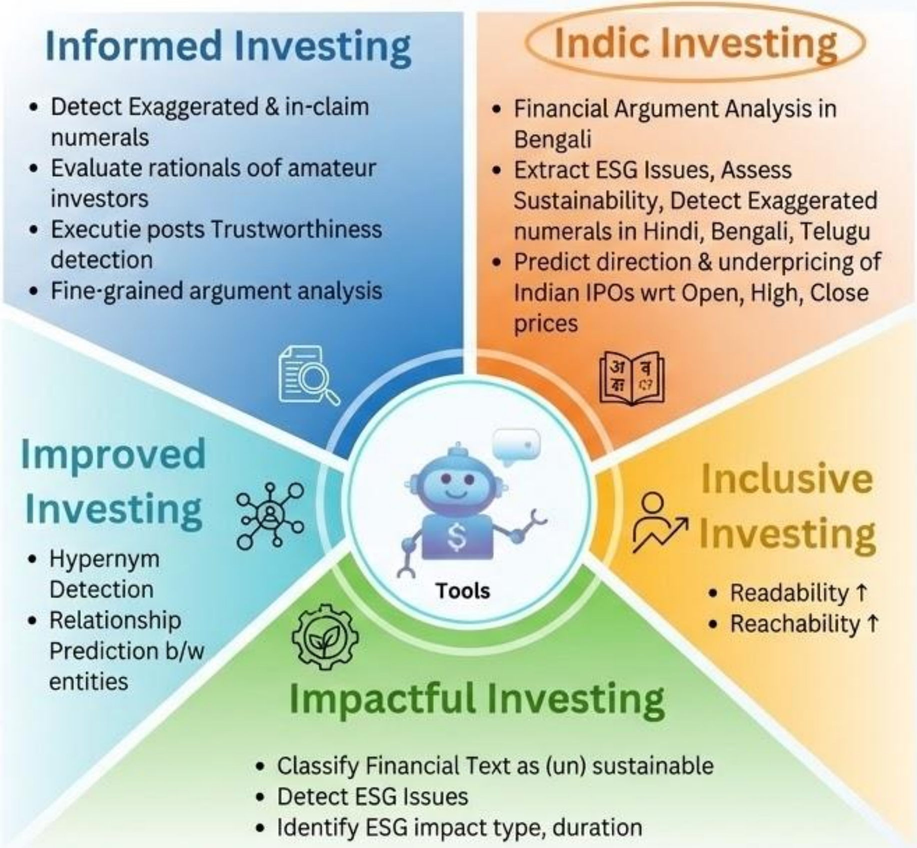
MODEL	DATA	VALIDATION	
		MICRO F1	MICRO F1
DiztilBERT	Original	0.3313	0.5721
DistilBERT	Paraphaased	0.7942	0.4811
Flang-Roberta	Original	0.7971	0.3633
Flang-Roberta	Paraphssed	0.7971	0.3633
BERT-SEC	Original	0.474	0.5647
RERT-SEC	Paraphassed	0.7998	0.4900
Cross Encoder (BERT)	Original	0.7998	0.3353
Cross Encoder (BERT)	Paraphaased	0.7913	0.4956
Cross-Encoder (BERT-SEC)	Original	0.7607	0.476
Crose-Encoder (RERT-SEC)	Paraphessed	0.7651	0.4807
Cross Encoder (FinBERT Finetuned)	**Original**	**0.8275**	**0.5398**
Cross Encoder (MLM-FinBERT)	Original	0.8000	0.3298
Cross-Encoder (MLM-FinBERT)	Paraphassed	0.7913	0.3452

Table 3: Results of Task 2, Sub-Task 2: Argument Relation Identification

LANGUAGE	MODEL	DATA	VALIDATION	
			MICRO-F1	MUICRO-F1
English	BERT-base	Original	0.6453	0.6793
English	BERT-bass	Paraphrased	0.6219	0.6753
Englioh	FLANG-RaBERTs	Paraphrased	0.6219	0.6754
Eoglish	Cross Encoder (SBERT)	Original	0.6293	0.6796
Eoglieh	Cross Encoder (SBERT)	Paraphrased	0.6500	0.6850
English	Cross Eucoder (OistdROBERTA)	Original	0.7933	0.7372
Englieh	Cross Encoder (DiotdROBERTA)	Paraphrased	0.6920	0.7374
Eoglish	Cross Encoder (Flang-Rebette)	Original	0.6932	0.7342
Eoglieh	Cross Eucoder (Flang-Rebette)	Paraphrased	0.6846	0.7141
English	**Cross Eucoder (BENT-SEC)**	**Originual**	**0.6893**	**0.7442**
Englieh	Cross Eocoder (BER7-3EC)	Paraphrased	0.6090	0.7960
Eoglish	Cross Eucoder (MLM on BERT SEC)	Original	0.6946	0.7160
Eoglish	Cross Encoder (MLM on BERT-SEC)	Paraphrased	0.6871	0.7180
Chinese	SBERT-Chmeee	Crigmal	0.6221	0.6430
CTiinere	Cross Sneader (SBBDT-Chinese)	Original	0.6333	0.4432

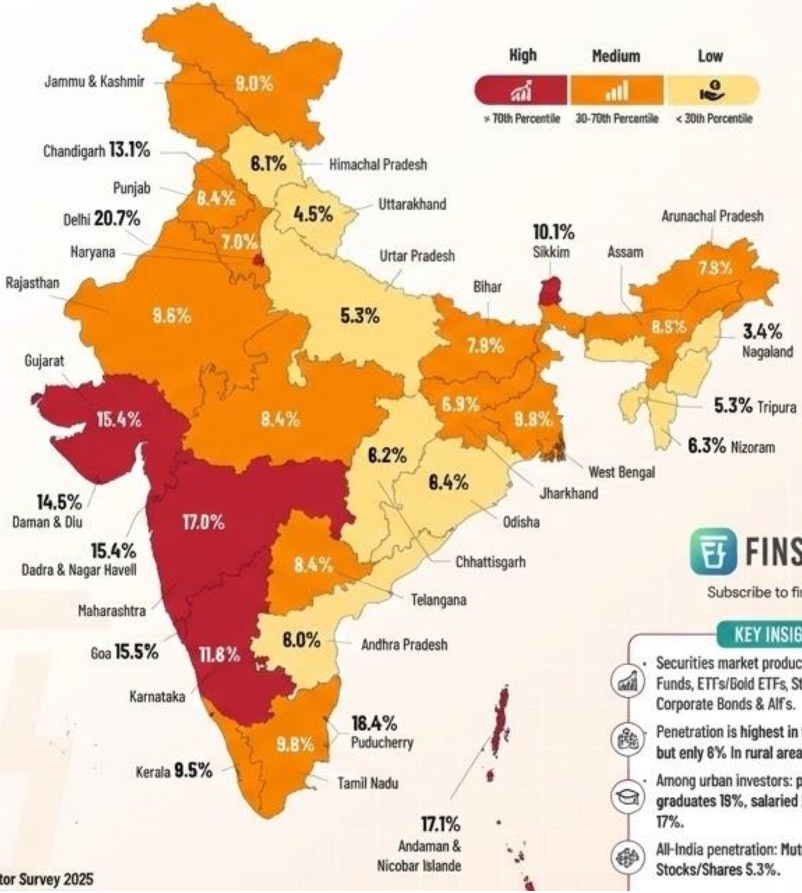
Table 4: Result of Tack 3: Meutifsine Acenorentiative Relation in Secial Media Discnstion

Indic Investing



ONLY 9.5% OF INDIA INVESTS!

This is despite 63% Indian households having some form of awareness about securities and market products in India.



KEY INSIGHTS

- Securities market products include Mutual Funds, ETTs/Bold ETFs, Stocks, REITa/InelTs, Corporate Bonds & Alf's.
- **Penetration is highest in top 9 metros (23%) but only 8% in rural areas.**
- Among urban investors: **pestgraduates 27%, graduates 19%, salaried 23%, self-employed 17%.**
- All-India penetration: **Mutual Funds/ETFs 8.7%, Stocks/Shares 5.3%.**

Source: SEBI Investor Survey 2025

Indic Investing

- How to keep investors informed in Indian Languages?

Financial Argument Analysis in Bengali

Rima Roy Sohom Ghosh Sudip Kumar Naskar

IndicFinNLP: Financial Natural Language Processing for Indian Languages

Sohom Ghosh[1], Arnab Maji[2], Aswartha Narayana[3], Sudip Kumar Naskar[4]

Predicting Success & Ratings of Indian IPOs

FIRE-2023

LREC COLING-2024

Indic Investing: Financial Argument Analysis in Bengali

CONTRIBUTION

- Created two datasets in Bengali: Financial argument unit classification, Argument relation Identification
- Created a user friendly tool Financial Argument Analysis in Bengali (FAAB)

PROBLEM STATEMENT

Given: Financial argumentative text in Bengali

Task-1: Classify as ‘Premise’ or ‘Claim’

Task-2: Classify relation: “support’, ‘attack’, or ‘none”

GIVEN DATASETS

- Two English datasets for argument unit classification & relation identification.
- **Source:** Chen et al. (Earnings Conference Call), **License:** Share-alike

PROCESS OF CREATING OUR OWN DATASETS

Translation
(IndicTrans@AI4Bharat)

Evaluation (Two-step):
1. Manual 100 instances
100 instances (BertScore, CometScore)
2. Automated 8000 samples
(BertScore, Labse-based cosine similarity, Threshold-based retention)

TASK EXAMPLES

Task-1

Text: এবং এই প্রেক্ষাপটে, অবশ্যই, তারা পুরোনো কিছু কাজের বোঝা তুলে নিচ্ছে এবং স্থানান্তর করছে, কিন্তু তারা পুরো ব্যবসায়িক প্রক্রিয়ার আধুনিকীকরণ করছে।

Label: 0 (Premise)

Task-2

Text-1: তাই প্রথমবার আমরা ঘোষণা করেছিলাম যে আমাদের ২০ লক্ষেরও বেশি বিজ্ঞাপনদাতা আছেন যারা ফেসবুকে বিজ্ঞাপন কিনছেন।

Text-2: ৮২% মানুষ যারা আমাদের সাথে বিজ্ঞাপন শুরু করেন তারা আমাদের খুব সাধারণ বিজ্ঞাপন পণ্য দিয়ে শুরু করেন।

Label: 0 (No relation)

Indic Investing: Financial Argument Analysis in Bengali

Results of Task-1

Model Name	Accuracy	Precision	Recall	F1 Score
SSB	0.700	0.690	0.694	0.692
MNB	0.714	0.691	0.745	0.717
AIB	0.711	0.700	0.712	0.706
DBMC	0.681	0.656	0.721	0.681
BBMC ★	**0.719**	**0.697**	**0.745**	**0.721**
Llama-2 (Type zero shot)	0.55	0.484	0.287	0.354
Llama-2 (Type few shot)	0.522	0.500	0.186	0.271
Llama-2 (Finetune)	0.528	0.531	0.254	0.344

SSB = sagorsarker bangla bert base
MNB = monsoon nlp bangla electra
AIB = aibharat indic bert
BBMC = bert base multilingual cased
DBMC = distilbert base multilingual cased

Indic Investing: Financial Argument Analysis in Bengali

Results of Task-2

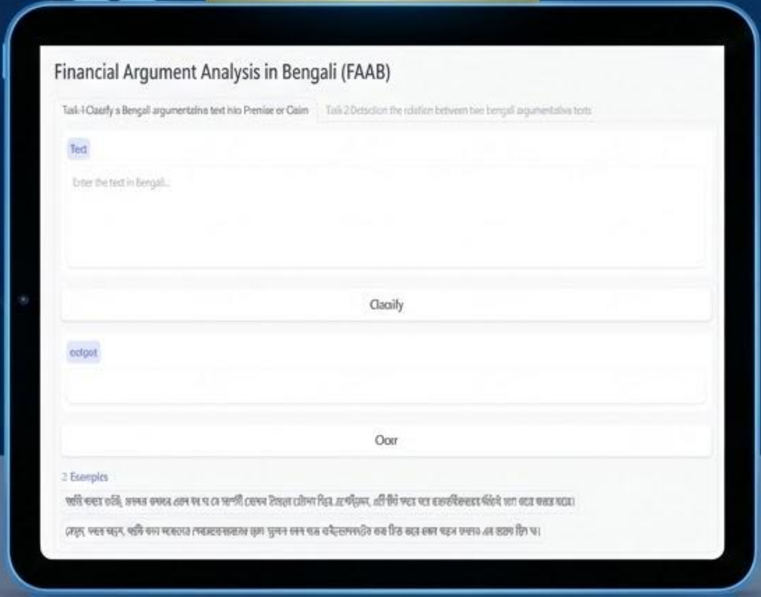
Model Name	Accuracy	Precision Macro	Precision Macro	Recall Micro	Recall Macro	F1 Score Micro	F1 Score Macro
SSB	0.708	0.708	0.442	0.708	0.417	0.708	0.419
MNB	0.705	0.705	0.235	0.705	0.333	0.705	0.275
AIB	0.682	0.682	0.476	0.682	0.348	0.682	0.303
DBMC	0.699	0.699	0.442	0.699	0.392	0.699	0.386
BBMC ☆	**0.755**	**0.755**	**0.488**	**0.755**	**0.460**	**0.755**	**0.460**

SSB = sagorsarker bangla bert base, MNB = monsoon nlp bangla electra, AIB = aibharat indic bert,
DBMC = distilbert base multilingual cased, BBMC = bert base multilingual cased

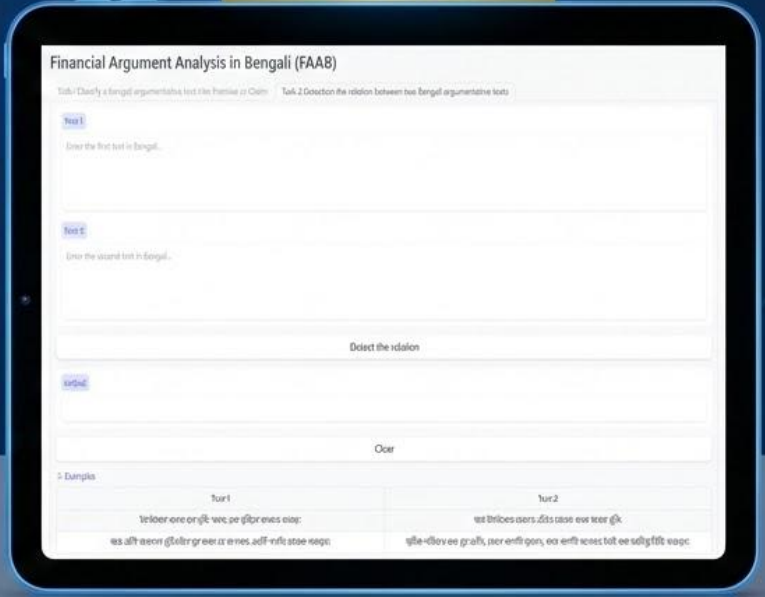
Indic Investing: Financial Argument Analysis in Bengali

User Interface Financial Argument Analysis In Bengali (FAAB)

Task-1



Task-2



Indic Investing: IndicFinNLP

PROBLEM STATEMENT

Input Text & Number

Hindi: हम 58 गवस्याओं के जरिए ओयक आपार वाती आपसी साझेदारी को आगे बढ़ा रहे हैं
Bengali: আমাদের মতে, 16 শতাংশেরও বেশি সুদ হার দিয়ে লাভজনকভাবে ব্যবসা সম্ভব নয়।
Telugu: 500 చెప్పన అందజేయమంది.

Output [magnitude]

0/1/2/3/4

Task-1: Exaggerated Numeral Detection in Indic Financial Texts

Input Text

Hindi: हम नवीकरणीय बिजली का प्रतिशत बढ़ाना जारी रखे हुए हैं (19 टीसीओ। ई से अधिक से बचने के लिए)।
Bengali: আমরা নবায়নযোগ্য বিদ্যুতের পরিমাণ বৃদ্ধি করে চলেছি (১৯ টিসিও২ই-র বেশি বিদ্যুৎ ব্যবহার না করে)।
Telugu: మేము పునరుత్పాదక విద్యుత్తు వాటాన్ని పెంచడం కొనసాగిస్తాము (19 టీసీఓఇ ని నివారించడం):

Output

Unsustainable /Sustainable

Task-2: Sustainability Assessment in Indic Financial Texts

Input Text

Hindi: एबीएन एमरो मे लेंडिंग, इन्वेस्टमेंट पोर्टफोलियो को नेट जीरो के साथ संरेखित किया
Bengali: ঋণ, বিনিয়োগ পোর্টফোলিওগুলিকে নেট জিরোর সঙ্গে সামঞ্জস্য করতে এবিএন আমরো
Telugu: రుణాలను సమలేఖనం చేయడానికి, నికర సున్నాతో పెట్టుబడి దస్త్రాలను సమలేఖనం చేయడానికి ABN AMRO

Output

One of 10 ESG theme

Task-3: ESG Theme Determination in Indic Financial Texts

Languages: **Hindi, Bengali, Telugu**

Tasks: **Exaggerated Numeral Detection, Sustainability Assessment, ESG Theme Determination**

Indic Investing: IndicFinNLP

EXAGGERATED NUMERAL DETECTION DATASET

Source:

- Budget speeches of Hindi, Bengali, and Telugu-speaking states (Punjab, Uttarakhand, Haryana, West Bengal, Telangana, and Andhra Pradesh) starting from the year 2011 till 2023
- Financial texts filtered from the Samanantar corpus (Rameshet al., TACL 2022)

Language	0	1	2	3	4
Hindi	2435	3624	1444	2485	652
Bengali	1574	1886	931	1416	323
Telugu	1737	1800	983	1182	314

Table 1: Task-1 label wise distribution. 0/1/2/3/4 are the magnitudes

indic	number_english	number_indic	start_posn	end_posn	language	magnitude
মাটিল ম্যানুকান (১৯৯৪-২০০১), রিয়েল এস্টেট বিনিয়োগকারী।	2001	২০০১	22	26	bengali	3

Indic Investing: IndicFinNLP

RESULTS: EXAGGERATED NUMERAL DETECTION

हा HINDI (H)

Model	Pr	Re	F1	Acc
IB+LGB	0.44	0.49	0.45	0.49
MB+XGB	0.63	0.64	0.63	0.64
IB+XGB	0.46	0.49	0.46	0.49
MB+SVM	0.69	0.68	0.68	**0.68**

বা BENGALI (B)

Model	Pr	Re	F1	Acc
IB+LGB	0.51	0.51	0.50	0.51
MB+XGB	0.62	0.62	0.61	0.62
IB+XGB	0.51	0.50	0.48	0.50
MB+SVM	0.66	0.65	0.65	**0.65**

అ TELUGU (T)

Model	Pr	Re	F1	Acc
IB+LGB	0.44	0.46	0.44	0.46
MB+XGB	0.59	0.60	0.59	0.60
IB+XGB	0.41	0.43	0.41	0.43
IB+XGB	0.69	0.68	0.68	**0.68**

Table 4: Tasks (Ts) 1, 2, 3 results for Languages (L) Hindi (H), Bengali (B), Telugu (T). E=English, -P= -Paraphrased, IB=IndicBERT, MB=MBERT, XGB=XGBoost, LGB=LightGBM, Pr=Precision, Re=Recall, Acc=Accuracy. **Bold** means the best. MBERT is Multi-ligual BERT

Indic Investing: IndicFinNLP

SUSTAINABILITY ASSESSMENT DATASET

SOURCE & PROCESS

- Translated existing dataset proposed by Kangand El Maarouf (FinSim4-ESG FinNLP-2022)
- from English to Indian languages (Hindi, Bengali, and Telugu).
- Retained only the high quality ones.
- Quality Metric: BERTScore (BS(F1)) & Cosine Similarity (Sim.)

य HINDI (H)

METRICS

BS(F1): >= 0.90
Sim.: >= 0.75

CLASS DISTRIBUTION

S (Sustainable): 1212
US (Unsustainable): 1026

অ BENGALI (B)

METRICS

BS(F1): >= 0.88
Sim.: >= 0.68

CLASS DISTRIBUTION

S (Sustainable): 1203
US (Unsustainable): 1025

త TELUGU (T)

METRICS

BS(F1): >= 0.88
Sim.: >= 0.80

CLASS DISTRIBUTION

S (Sustainable): 1119
US (Unsustainable): 953

EXAMPLE (HINDI)

sentence_indic	label	language
आपके संगठन का सकल वैश्विक स्कोप 1 उत्सर्जन मीट्रिक टन में कितना था?	unsustainable	hindi

Table 2: Task-2 data distribution & thresholds. S=Sustainable, US=Unsustainable. BS=BERTScore, Sim.=Cosine Similarity

Indic Investing: IndicFinNLP

RESULTS: SUSTAINABILITY ASSESSMENT

HINDI (H)

IB

Pr: 0.86 Re: 0.86
F1: 0.86 Acc: 0.86

MB

Pr: Re: F1: 0.77
0.77 0.77 0.77 0.77

MLM-IB

Pr: Re: F1: Acc
0.29 0.54 0.38 0.54

E-Ro

Pr: Re: F1: Acc
0.95 0.95 0.95 0.95

BENGALI (B)

IB

Pr: 0.80 Re: 0.80
F1: 0.80 Acc: 0.80

MB

Pr: Re: F1: 0.76
0.76 0.76 0.76 0.76

MLM-IB

Pr: Re: F1: Acc
0.81 0.81 0.81 0.81

E-Ro

Pr: Re: F1: Acc
0.92 0.92 0.92 0.92

TELUGU (T)

IB

Pr: 0.79 Re: 0.79
F1: 0.79 Acc: 0.78

MB

Pr: Re: F1: 0.89
0.90 0.89 0.89 0.89

MLM-IB

Pr: Re: F1: Acc
0.90 0.90 0.90 0.90

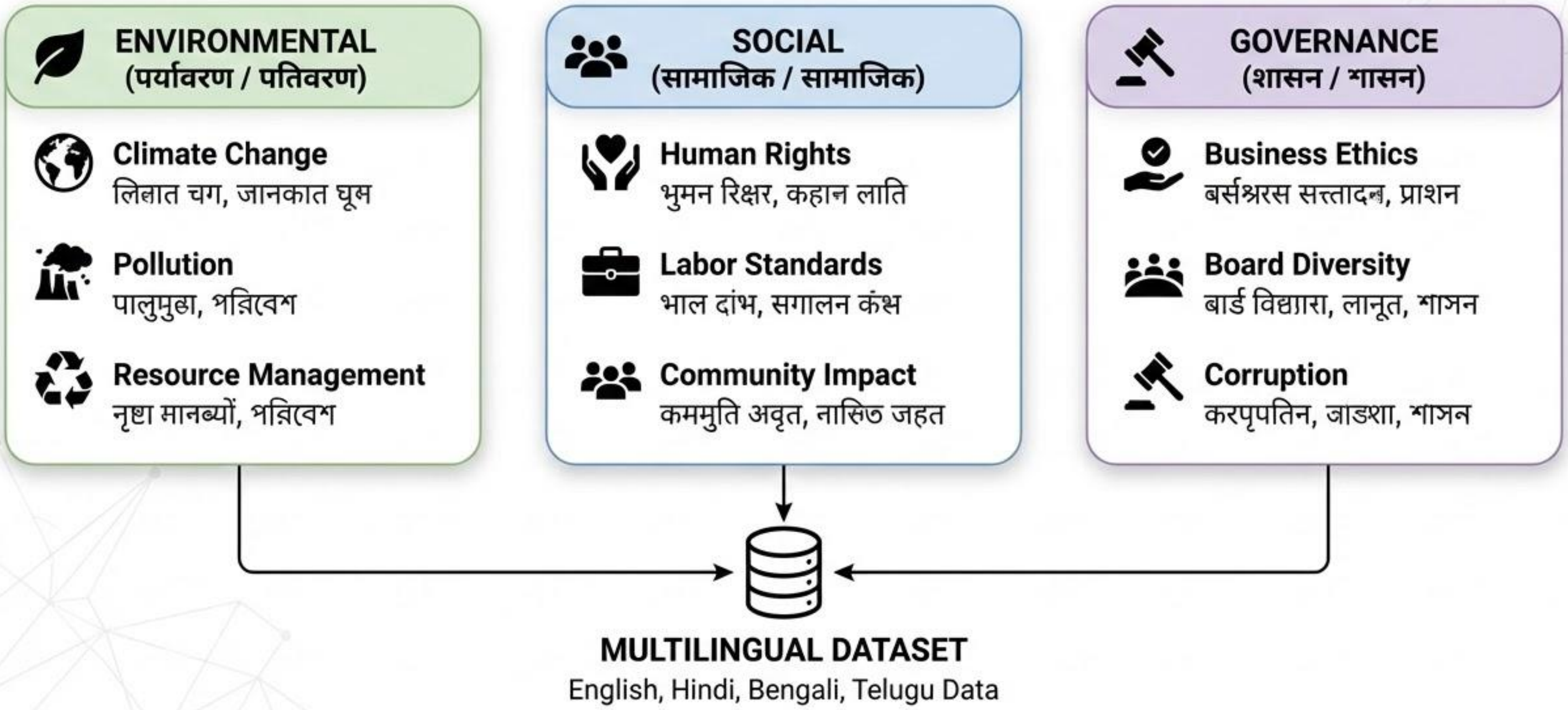
E-Ro

Pr: Re: F1: Acc
0.92 0.92 0.92 0.92

Table 4: Tasks (Ts) 1, 2, 3 results for Languages (L) Hindi (H), Bengali (B), Telugu (T). Model Abbreviations: E=English, -P= -Paraphrased, IB=IndicBERT, MB=MBERT, XGB=XGBoost, LGB=LightGBM, Ro=RoBERTa. Metric Abbreviations: Pr=Precision, Re=Recall, Acc=Accuracy. Note: **Bold** means the best.

Indic Investing: IndicFinNLP

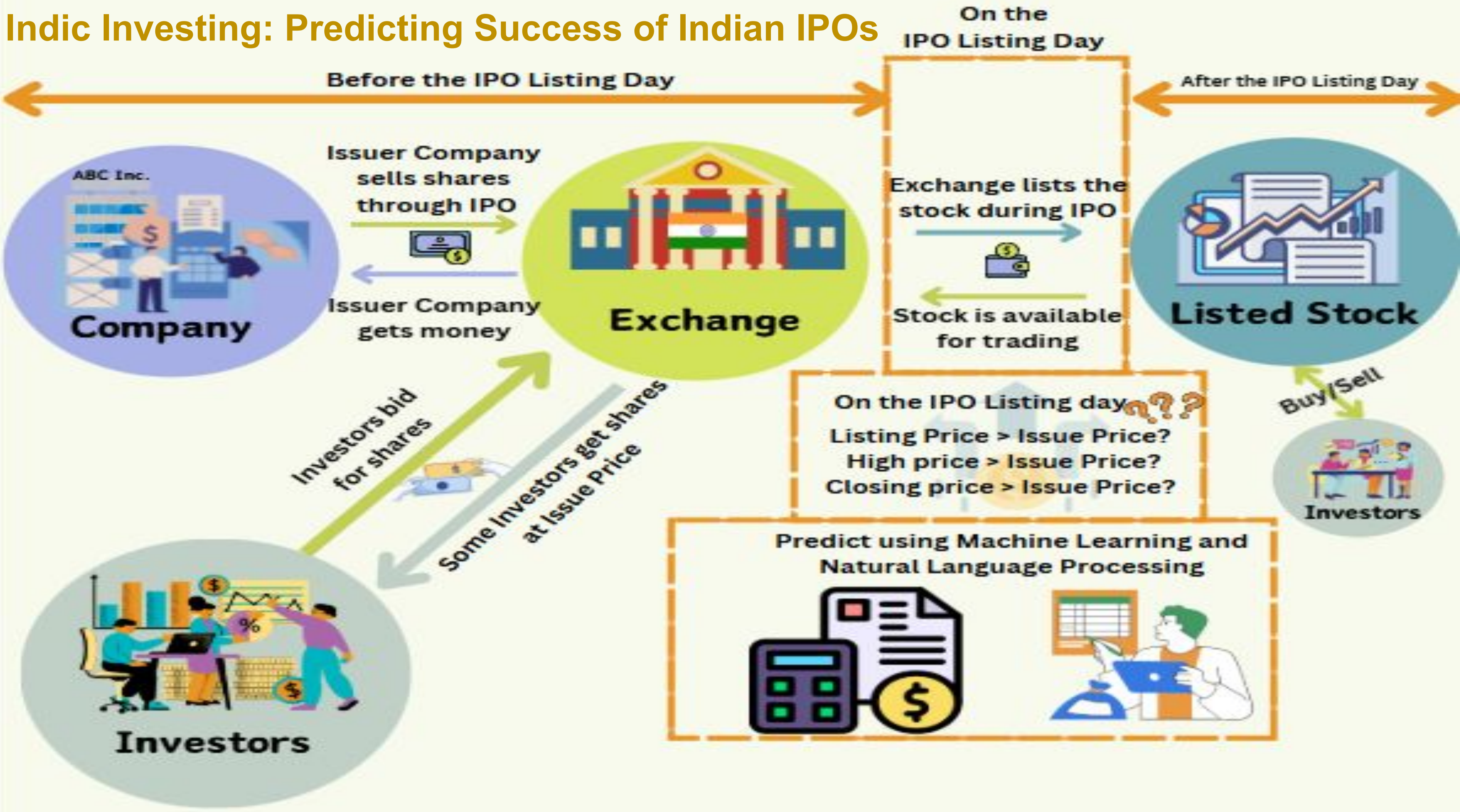
ESG THEME DETERMINATION DATASET



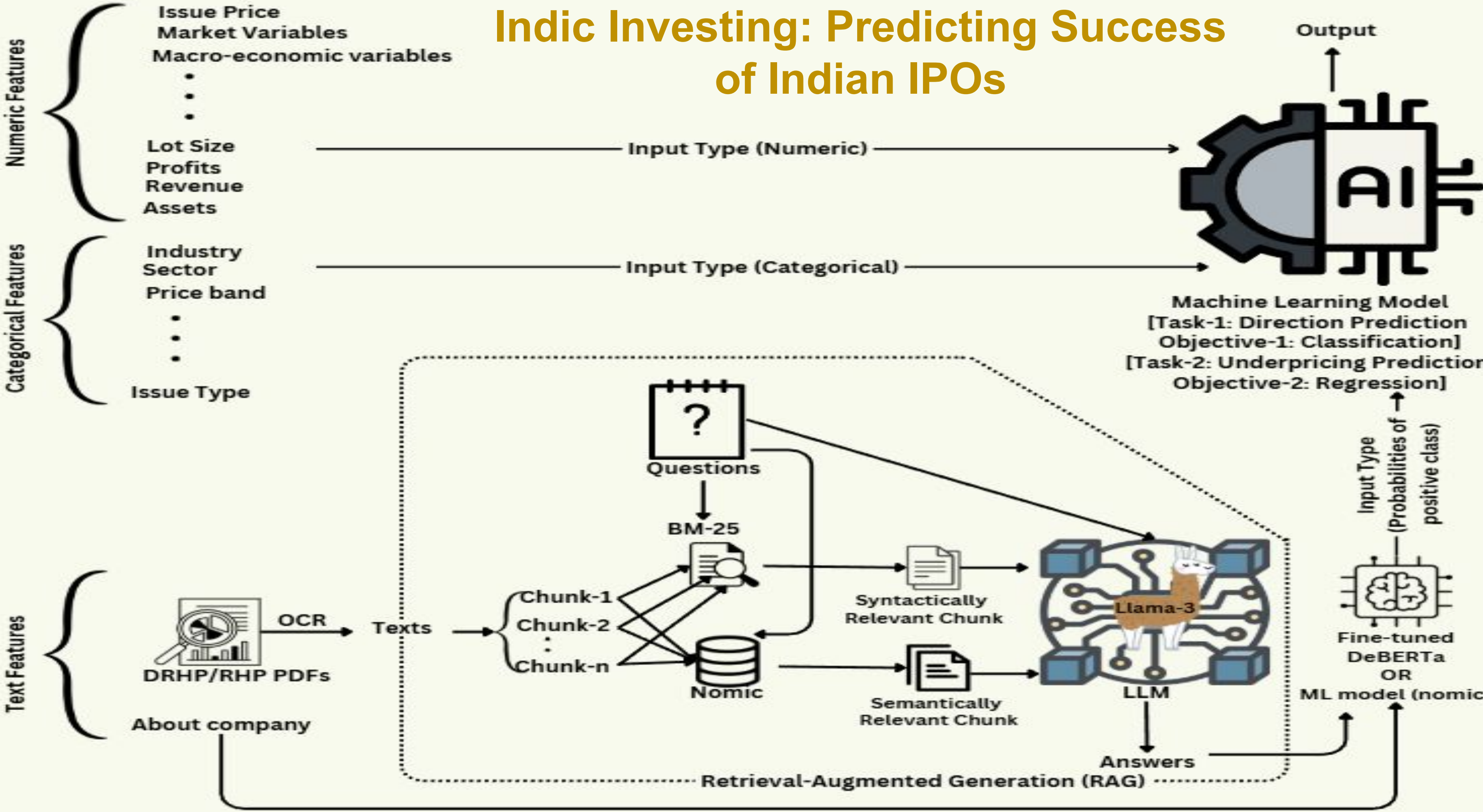
Indic Investing: IndicFinNLP

RESULTS: ESG THEME DETERMINATION

Indic Investing: Predicting Success of Indian IPOs



Indic Investing: Predicting Success of Indian IPOs



Indic Investing: Predicting Success of Indian IPOs

Datasets

Two multi-modal datasets (Main Board IPOs & SME IPOs).

Methodology

Proposed Machine Learning and NLP based decision system for predicting if an IPO will be successful.

Framework

To extract important portions from documents like DHRP, RHP and used them as features.

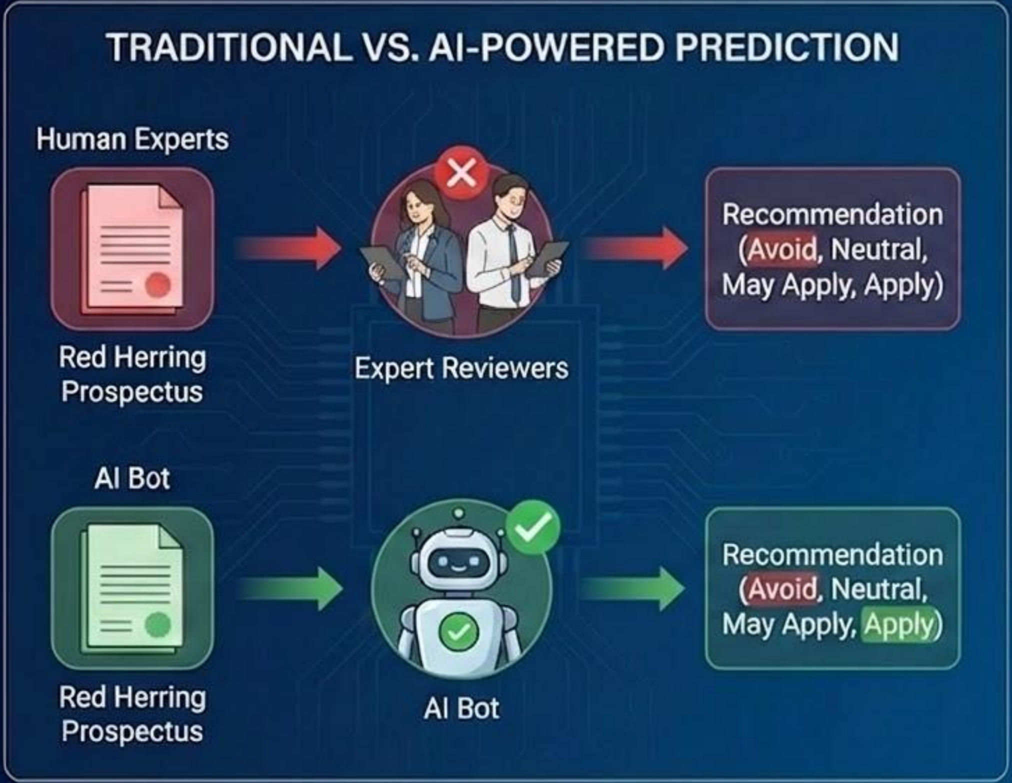
Relevance

Investigate the relation between of GMP and success of an IPO.

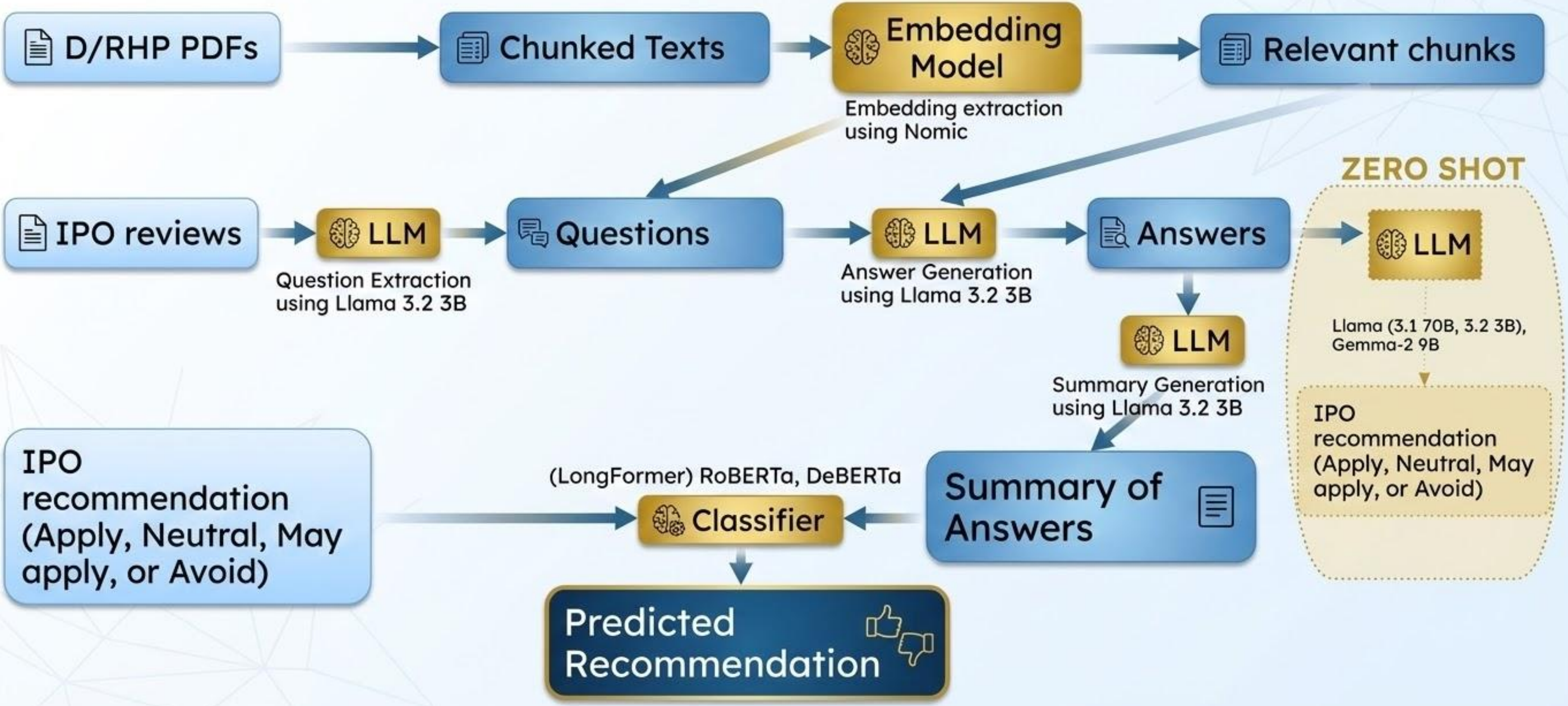
Benchmark

Evaluate the performance of Large Language Models (LLMs) like Gemini and Gemini and Llama in predicting success.

Indic Investing: Predicting Ratings of Indian IPOs



Indic Investing: Predicting Ratings of Indian IPOs



Indic Investing: Predicting Ratings of Indian IPOs

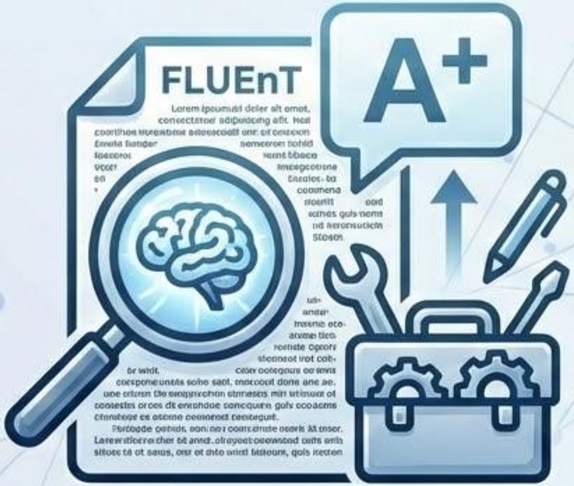
New Datasets

- Two new India-specific datasets (Main Board IPOs & SME IPOs) for rating prediction task.

Methodology & Performance

- Novel method mining prospectus using Retrieval Augmented Generation & fine-tuned small encoder.
- Outperforms state-of-the-art Large Language Models (LLMs) like Llama-3 under zero shot settings.

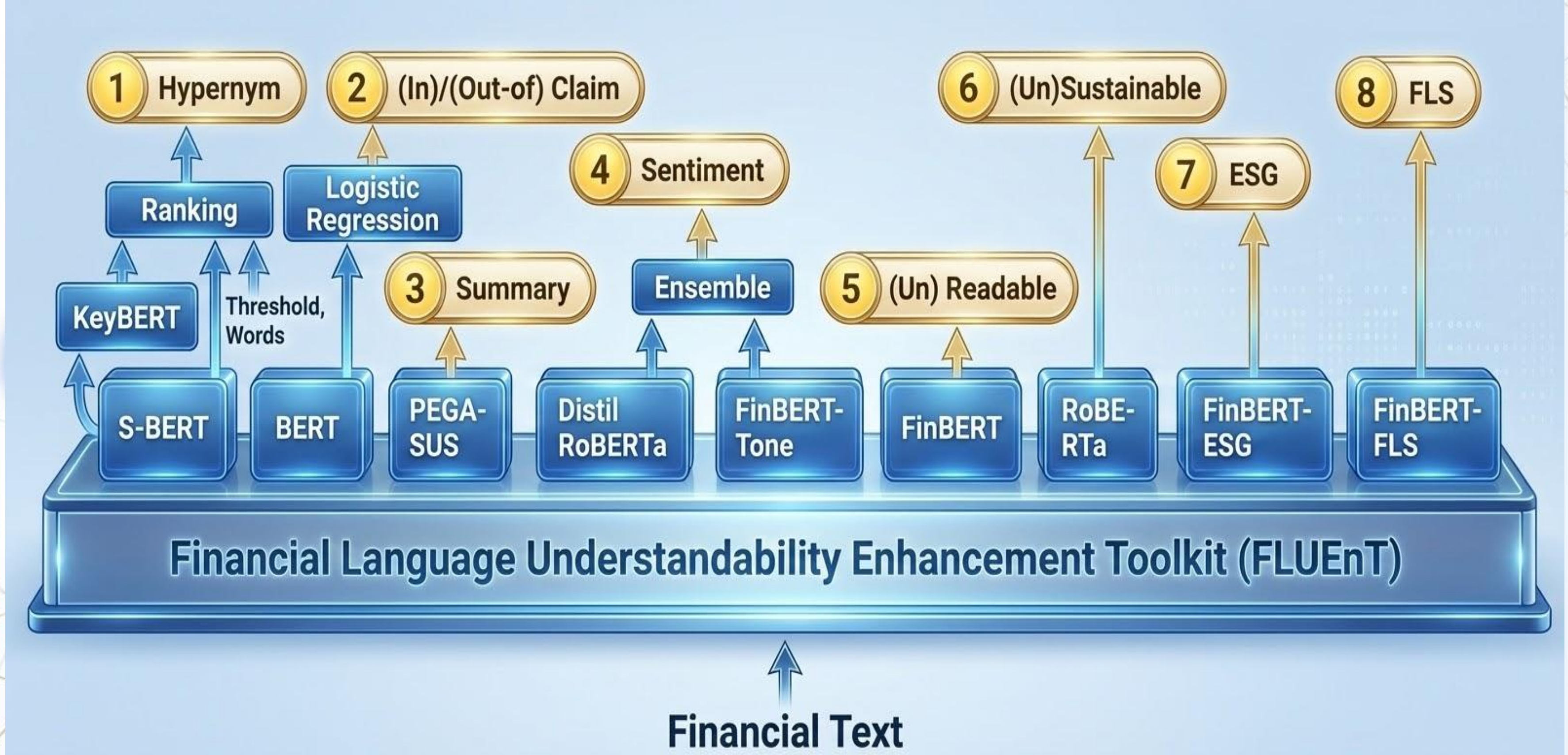
Tools for FinNLP



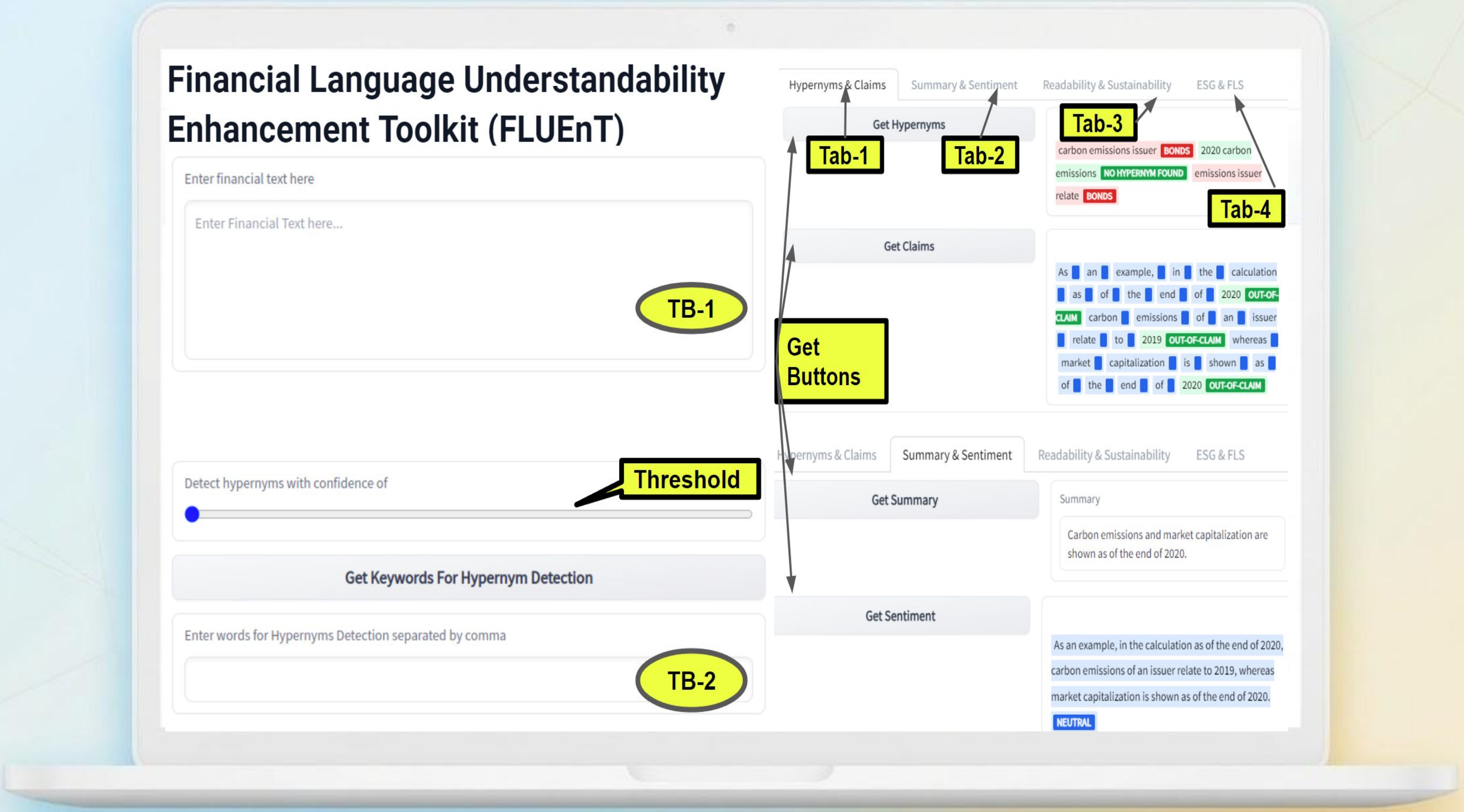
FLUEnT: Financial Language Understandability Enhancement Toolkit

CODS COMAD-2023

Tools for FinNLP



Tools for FinNLP



Conclusions & Future Works

Key Research Tasks

1. Assess Readability & Simplify FTs
2. Assess Reachability of FTs
3. Retrieve Hypernyms for Financial Jargon
4. Determine Relationship between Financial Entities
5. Classify FTs as Sustainable/Unsustainable
6. Detect ESG Issues from English FTs
7. Identify ESG Impact Type & Duration
8. Detect Exaggerated & In-claim Numerals
9. Evaluate Rationals of Amateur Investors
10. Evaluate Trustworthiness of Executive Posts
11. Fine-grained Argument Understanding in FTs
12. Financial Argument Analysis in Bengali
13. Extract ESG Issues & Detect Numerals (Hindi, Bengali, Telugu)
14. Predict Success of Indian IPOs
15. Predict Ratings of Indian IPOs
16. Develop Tools for Processing FTs

Summary of Contributions

CIKM-2024

- 16 Tasks
- 8 Datasets
- 6 Tools
- 24 Papers
- 8 Languages
- 2 Workshops
- 4 Journals
- 8 Shared Tasks
- 10 Conferences

Conclusions & Future Works

Focussed on improving financial well-being for social good

Key Themes

- Inclusive
- Improved
- Impactful (Green)
- Informed
- Indic

Developed Tools for FinNLP

- FinRAD, FinRead, FinLanSer, CReAM, EID, FAAB, etc.

Challenges

- Lack of annotation expertise in vernacular languages & finance

Next Steps

- Embracing multi-modality (images, speeches, video)
- Financial Reasoning through Reinforcement Learning
- Measuring Real World Impact
- AI agents for FinNLP

THE NEW INDIAN EXPRESS

NATION WORLD STATES OPINIONS CITIES

Hyderabad

Hyderabad school introduces financial literacy classes

A dedicated textbook on financial literacy has been introduced for these classes and is taught once a week as part of the curriculum.

Representative image Photo | Express

Express News Service

Updated on: 15 Oct 2025, 10:09 am · 1 min read

Good News

perplexity.ai/finance

Enter Symbol

India Markets Crypto

NIFTY 50 ^NSEI	↘ 0.4% -97.65	24,487.4	
S&P BSE Sen... ^BSESN	↘ 0.46% -368.49	80,235.59	
Nifty Bank In... ^NSEBANK	↘ 0.84% -467.05	55,043.7	
Bitcoin BTCUSD	↗ 1.04% +$1,236.16	$119,944.10	

Market Summary Updated 16 minutes ago

Banking & Financials Lead Market Decline
Heavyweight stocks like HDFC Bank (-1.30%), ICICI Bank (-1.06%), and Bajaj Finance (-2.83%) dragged the Sensex, Nifty 50, and Nifty Bank indices lower. Persistent foreign investor (FII) outflows and sector-wide weakness contributed to the negative sentiment.

Auto & IT Stocks Provide Support
Among the major gainers, Maruti Suzuki (+1.98%), Tech Mahindra (+2.03%), and Mahindra & Mahindra

Ask any question about finance

THE ECONOMIC TIMES

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Home ETPrime Markets Market Data Masterclass ▾ News Industry SME Politics Wealth MF

Best of Wealth Tax ▾ New Income Tax Bill Save Invest Insure ▾ Borrow ▾ Earn Legal / Will Plan

Business News › Wealth › Save

10 must-try AI finance tools in 2025 that help you save, invest, and grow faster

Curated by *Lavanya Mallidi*, ET Online | Oct 20, 2025, 11:14:39 AM IST

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Lab-mates
Atanu Mondal, Madhusudan Ghosh, etc.

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Pramit Bhattacharya, Nildari Prosad Lahiri, Angan Mitra, etc.

(Ex-)/Colleagues:
Sachin Umrao, Shovon Sengupta, Ankush Chopra, Shruti Agrawal, Aswartha Narayana, Souvik Meta, Bibhash Chakraborty, Debaisis Bal, etc

Parents:
Baba & Ma

ACM India:
CODS COMAD-2024, PIC-2025, ARCS-2025 Travel Grant, SIGIR Travel Grant for CIKM-2024

Employer:
Fidelity Investments

Upcoming Presentation

InFiNITE (∞): Indian Financial Narrative Inference Tasks & Evaluations

Sohom Ghosh, Arnab Maji, Sudip Kumar Naskar

📜 The 5th Workshop on 'Evaluation & Comparison of NLP Systems' | 📅 23rd December 2025

📌 co-located at IJCNLP-AACL 2025, IIT Mumbai, India

The way ahead!

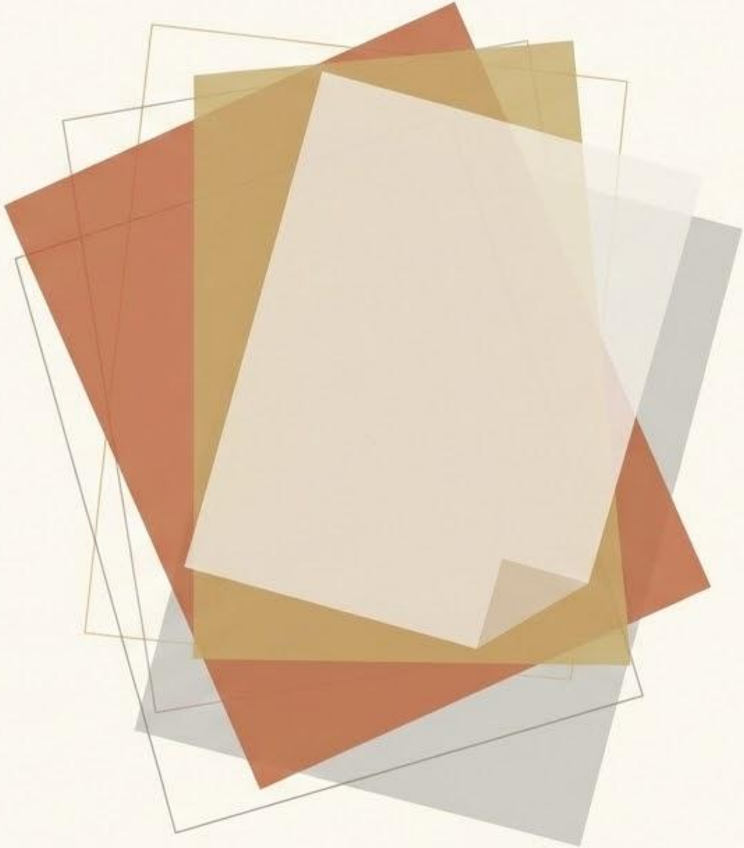
“বিদ্যার বোঝা নহে,
বিদ্যার বাহান হওয়াই জীবনের লক্ষ্য”

- রবি ঠাকুর

from financial literacy to financial intelligence

APPENDIX

Supporting Materials, Data, and References



Published Research Papers

- **Sohom Ghosh**, “Demystifying Financial Texts Using Natural Language Processing”, In CIKM-2024, DOI: https://doi.org/10.1145/3627673.3680258
- Neelabha Banerjee, Anubhav Sarkar, Swagata Chakraborty, **Sohom Ghosh**, Sudip Kumar Naskar, “Fine-tuning Language Models for predicting the impact of events associated to financial news articles", In FinNLPKDF-EcoNLP@ LREC-COLING, May 2024, DOI:https://aclanthology.org/2024.finnlp-1.25.pdf
- **Sohom Ghosh,** Arnab Majhi, Aswartha Narayana, “IndicFinNLP: Financial Natural Language Processing for Indian Languages”, In LREC-COLING 2024, May 2024. DOI: https://aclanthology.org/2024.lrec-main.789.pdf
- **Sohom Ghosh,** Chung-Chi Chen, Sudip Kumar Naskar, “Generator-Guided Crowd Reaction Assessment”, In TheWebConf (WWW-2024) https://doi.org/10.1145/3589335.3651512
- **Sohom Ghosh**, Sachin Umrao, Chung-Chi Chen, Sudip Kumar Naskar, “The Mask One At a Time Framework for Detecting the Relationship between Financial Entities", In FIRE 2023, Dec 2023.https://doi.org/10.1145/3632754.3632756
- Rima Roy, **Sohom Ghosh**, Sudip Kumar Naskar, “Financial Argument Analysis in Bengali", In FIRE 2023, Dec 2023: https://doi.org/10.1145/3632754.3632763
- Swagata Chakraborty, Anubhav Sarkar, Dhairya Suman, **Sohom Ghosh**, Sudip Kumar Naskar, "LIPI at the NTCIR-17 FinArg-1 Task: Using Pre-trained Language Models for Comprehending Financial Arguments", In NTCIR-17, Dec 2023. :https://doi.org/10.20736/0002001281
- N Harsha Vardhan, **Sohom Ghosh**, Ponnurangam Kumaraguru, Sudip Kumar Naskar, "A low resource framework for Multi-lingual ESG Impact Type Identification", In FinNLP@IJCNLP-AACL, Nov 2023.https://aclanthology.org/2023.finnlp-2.8/
- **Sohom Ghosh**, Ankush Chopra, Sudip Kumar Naskar, “Learning to Rank Hypernyms of Financial Terms Using Semantic Textual Similarity”, in SN Computer Science, Springer, 4, 610 (2023), https://doi.org/10.1007/s42979-023-02134-z
- **Sohom Ghosh**, Sudip Kumar Naskar, “Recent trends in financial natural language processing research”, in Science Talks, Elsevier, Volume 8, 100270, (2023) https://doi.org/10.1016/j.sctalk.2023.100270

Published Research Papers

- **Sohom Ghosh**, Sudip Kumar Naskar, “Fincat-2: An enhanced Financial Numeral Claim Analysis Tool”, in Software Impacts, VOLUME 12, 100288, Elsevier, May 2022. https://doi.org/10.1016/j.simpa.2022.100288
- **Sohom Ghosh**, Sudip Kumar Naskar, “Detecting context-based in-claim numerals in Financial Earnings Conference Calls”, in International Journal of Information Technology, Springer, May 2022 https://doi.org/10.1007/s41870-022-00952-7
- Priyank Soni, **Sohom Ghosh**, Sudip Kumar Naskar, “Detecting Issues Related to Environmental, Social, and Corporate Governance using SEC-BERT ”, in proceedings of 4th International Conference on Data Science and Applications (ICDSA 2023), Jaipur, India https://doi.org/10.1007/978-981-99-7820-5_27
- **Sohom Ghosh**, Sudip Kumar Naskar, “Using Natural Language Processing to Enhance Understandability of Financial Texts”, in proceedings of 6th Joint International Conference on Data Science & Management of Data (10th ACM IKDD CODS and 28th COMAD), Mumbai, India https://doi.org/10.1145/3570991.3571051 [Honourable Mention (YRS Track)]
- **Sohom Ghosh**, Sudip Kumar Naskar, “FLUEnT: Financial Language Understandability Enhancement Toolkit”, in proceedings of 6th Joint International Conference on Data Science & Management of Data (10th ACM IKDD CODS and 28th COMAD), Mumbai, India https://doi.org/10.1145/3570991.3571067
- Anubhav Sarkar, Swagata Chakraborty, **Sohom Ghosh** and Sudip Kumar Naskar, “Evaluating Impact of Social Media Posts by Executives on Stock Prices”, in proceedings of the 14th meeting of Forum for Information Retrieval Evaluation (FIRE-2022), Kolkata, India. https://doi.org/10.1145/3574318.3574339
- **Sohom Ghosh**, Sudip Kumar Naskar, “LIPI at the FinNLP-2022 ERAI Task: Ensembling Transformers for assessing Maximum Possible Profit and Loss from online financial posts”, in Proceedings of the fourth workshop on Financial Technology and Natural Language Processing (collocated with EMNLP 2022), pp 111-115, Abu Dhabi, UAE (2022) https://aclanthology.org/2022.finnlp-1.13.pdf

Published Research Papers

- **Sohom Ghosh**, Sudip Kumar Naskar, “Ranking Environment, Social And Governance Related Concepts And Assessing Sustainability Aspect Of Financial Texts”, in Proceedings of the fourth workshop on Financial Technology and Natural Language Processing (collocated with IJCAI-ECAI 2022), pp 243-249, Vienna, Austria (2022) https://aclanthology.org/2022.finnlp-1.33.pdf
- **Sohom Ghosh**, Shovon Sengupta, Sudip Kumar Naskar, Sunny Kumar Singh, “FinRAD: Financial Readability Assessment Dataset - 13,000+ Definitions of Financial Terms for Measuring Readability”, in Proceedings of the FNP workshop of the 13th Language Resources and Evaluation Conference (LREC-2022), pp 1-9 , Marseille, France http://www.lrec-conf.org/proceedings/lrec2022/workshops/FNP/pdf/2022.fnp-1.1.pdf
- **Sohom Ghosh**, Sudip Kumar Naskar, “LIPI at FinCausal 2022: Mining Causes and Effects from Financial Texts”, in Proceedings of the FNP workshop of the 13th Language Resources and Evaluation Conference (LREC2022), pp 130–132, Marseille, France http://www.lrec-conf.org/proceedings/lrec2022/workshops/FNP/pdf/2022.fnp-1.20.pdf
- **Sohom Ghosh**, Sudip Kumar Naskar, “LIPI at the NTCIR-16 FinNum3 task: Ensembling transformer based models to detect in-claim numerals in financial conversations”, in Proceedings of the 16th NTCIR Conference on Evaluation of Information Access Technologies, pp 92-94, Tokyo, Japan. http://research.nii.ac.jp/ntcir/workshop/OnlineProceedings16/pdf/ntcir/02-NTCIR16-FINNUM-GhoshS.pdf

Published Research Papers

- **Sohom Ghosh**, Sudip Kumar Naskar,“FiNCAT: Financial Numeral Claim Analysis Tool”, in proceedings of FinWeb@TheWebConf (formerly ACMWWW) (2022), pp 583-585, Lyon, France https://doi.org/10.1145/3487553.3524635
- **Sohom Ghosh**, Shovon Sengupta, Sudip Kumar Naskar, Sunny Kumar Singh, “FinRead: A Transfer Learning Based Tool to Assess Readability of Definitions of Financial Terms”, in proceedings of 18th International Conference on Natural Language Processing (ICON-2021), pp 658-659 https://aclanthology.org/2021.icon-main.81.pdf
- Ankush Chopra, **Sohom Ghosh**, Term Expansion and FinBERT fine-tuning for Hypernym and Synonym Ranking of Financial Terms, In proceedings of FinNLP’21 (FinSim-3) (collocated with IJCAI-2021), pp 46-51, Montreal, Canada https://aclanthology.org/2021.finnlp-1.8.pdf

Contributions & Achievements

16 tasks, 8 languages, 8 datasets, 6 tools, 24 papers

2 workshops | **4 journals** | **8 shared tasks** | **10 conferences**

- 4 Journals
  - **SNCS** (Springer), **IJIT** (Springer), **Software Impacts** (Elsevier), **Science Talks** (Elsevier)
- 10 Conferences, 2 Workshops, 8 Shared Tasks
  - Venues: **ICON-2021** Silchar (India), FinNLP@**IJCAI-2021** Montreal (Canada), FinWeb@**The Web Conference-2022** Lyon (France), FNP@**LREC** Marseille (France), FinNLP@**IJCAI-ECAI-2022** Vienna (Austria), NTCIR-16 Tokyo (Japan), FinNLP@**EMNLP-2022** Abu Dhabi (UAE), **FIRE-2022** Kolkata (India), **CODS-COMAD-2023** Mumbai (India), **ICDSA-2023** Jaipur (India), FinNLP@ **AACL-IJCNLP-2023** Bali (Indonesia), **FIRE-2023** Goa (India), **NTCIR-17** Tokyo (Japan) , **The Web Conference WWW-2024 (Singapore) , LREC-COLING 2024 Tornio (Italy), CIKM-2024 (Boise, USA)**
- Resources (8 datasets, 6 tools)
  - **FinRAD** (dataset), **FinRead** (tool), **Financial Claim Analysis Tool (FinCAT, FinCAT-2) (tool)**, Financial Language Understandability Enhancement Toolkit (**FLUEnT**) (tool), **Executive / General Tweets** (dataset), **FENCE - Financial Exaggerated Numeral ClassifiEr** (tool), **EID - ESG Issue Detector** (tool), **FinLanSer** (tool), **CReD** (dataset), **FAAB** (dataset + tool), **IndicFinNLP** (dataset)
- Service
  - **Mentored 7 students** (undergraduates & post graduates), **Delivered 4 invited talks** (XIM, Bhubaneshwar; HIT Haldia; Brainware University, Yobe State University Nigeria), **Reviewed** several research papers & book proposals (FinNLP-ERAI@EMNLP, Manning publishers book proposals, Social Network Analysis and Mining [Springer], FinArg@NTCIR-17)
- Achievements
  - **300 citations in Google Scholar, Kaggle Datasets Expert, CODS-COMAD 2023 YRS TRACK** (HONOURABLE MENTION), **CODS-COMAD 2024 Travel Grant, CIKM 2024 Travel Grant, ACM PIC-2025 Travel Grant, ACM ARCS-2025 Travel Grant**
  - **FinArg-1@NTCIR-17** TASK-1 SUB-TASK-2 (**Rank-2**), FinNLP@IJCNLP-AACL 2023 ESG Impact type shared task (**Rank-1** for Chinese & Japanese), FinNLP@LREC-COLING 2024 ESG Impact Duration (**Rank-3** in English impact length & impact type and **Rank-1** in French Impact Length)
- Collaborations
  - Artificial Intelligence Research Center, National Institute of Advanced Industrial Science and Technology, Japan (**Dr. Chung-Chi Chen**)
  - BITS, Pilani, Hyderabad, India (**Dr. Sunny Kumar Singh, Mr. Shovon Sengupta**)

Summary

- Overview
  - Recent **trends in financial Natural Language Processing (NLP)** research {Science Talks Elsevier Journal 2023}
  - Using NLP to Enhance **Understandability** of Financial Text {CODS-COMAD'2023} ***[HONOURABLE MENTION]***, **CIKM-2024**
- Inclusive Investing
  - Increasing **readability** of Financial Texts {ICON'2021, FNP@LREC'2022}
  - Increasing **reachability** of Financial Content {**TheWebConf** (WWW'2024)}
- Improved Investing
  - Detecting **hypernyms** of Financial Terms {FinNLP@IJCAI'2021, SNCS Springer Journal 2023}
  - Extracting **relationship** between financial entities {FIRE'2023}
- Impactful (Green) Investing
  - Detecting Environmental, Social, and Governance (**ESG)** and **sustainability** related **concepts, issues** {FinNLP@IJCAI-ECAI'2022, ICDSA'2023}
  - Assessing **ESG impact type, duration** in English, French, Japanese, Chinese, Korean {FinNLP@IJCNLP-AACL'2023, FinNLP@LREC-COLING'2024}
- Informed Investing
  - Detecting **in-claim** numerals {FinWeb@The Web Conference'2022, NTCIR'2022, IJIT Springer Journal, Software Impacts Elsevier Journal}
  - Detecting **exaggerated numerals** in Financial Texts
  - Estimating **profitability and loss** from financial social media posts in Chinese {FinNLP@EMNLP'2022}
  - Deciding **trust worthiness** of social media posts by executives {FIRE'2022}
  - Financial **argument analysis** in English & Chinese {NTCIR'2023}
- Indic Investing
  - Financial **argument analysis** in Bengali {FIRE'2023}
  - Detecting **ESG theme, Sustainability, Exaggerated numerals** in Hindi, Bengali & Telugu [**LREC COLING**'2024]
  - **IPO success, rating**
- Tools
  - Financial Language **Understandability Enhancement Toolkit** (FLUEnT) {CODS-COMAD'2023}

Outro

CIKM-2024

Task-1: Given a financial text (FT), we want to assess its readability and simplify it
Task-2: Given two FTs, we want to assess which one would to reach more people
Task-3: Given a financial jargon in a FT, we would like to retrieve its hypernym
Task-4: Given two entities in a FT, we would like to determine the relationship between them
Task-5: Classify a FT as Sustainable or Unsustainable
Task-6: Detect ESG Issues from FTs in English
Task-7: Identify ESG impact type & duration from FTs.
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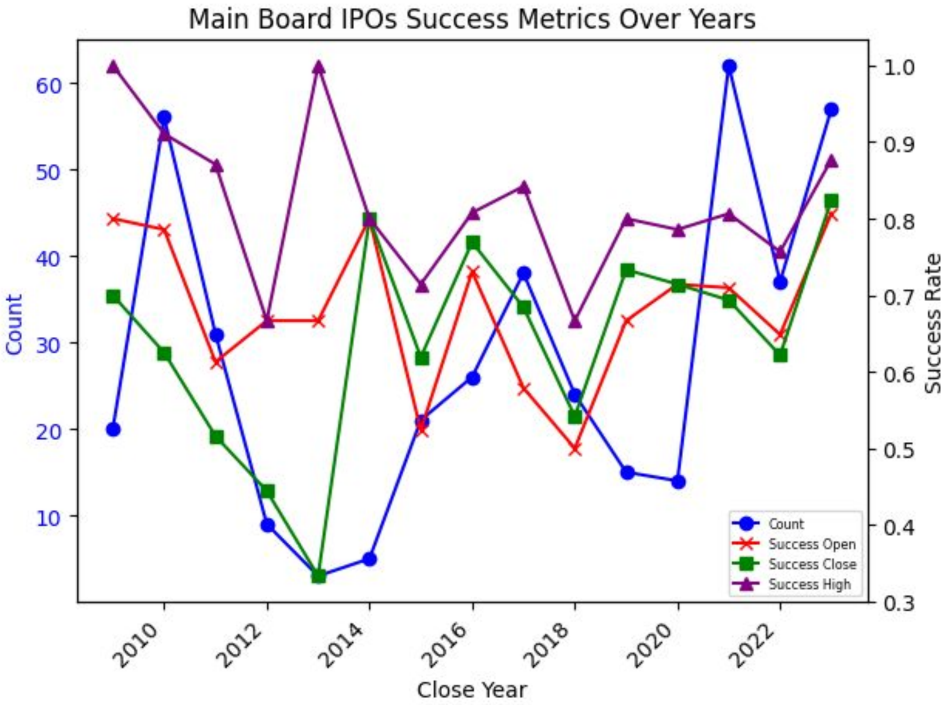
Task-13: Extract ESG Issues, Assess Sustainability, and Detect exaggerated numerals from FTs in Hindi, Bengali, & Telugu
Task-14: Predict success of Indian IPOs
Task-15: Predict ratings of Indian IPOs
Task-16: Develop tools for processing FTs

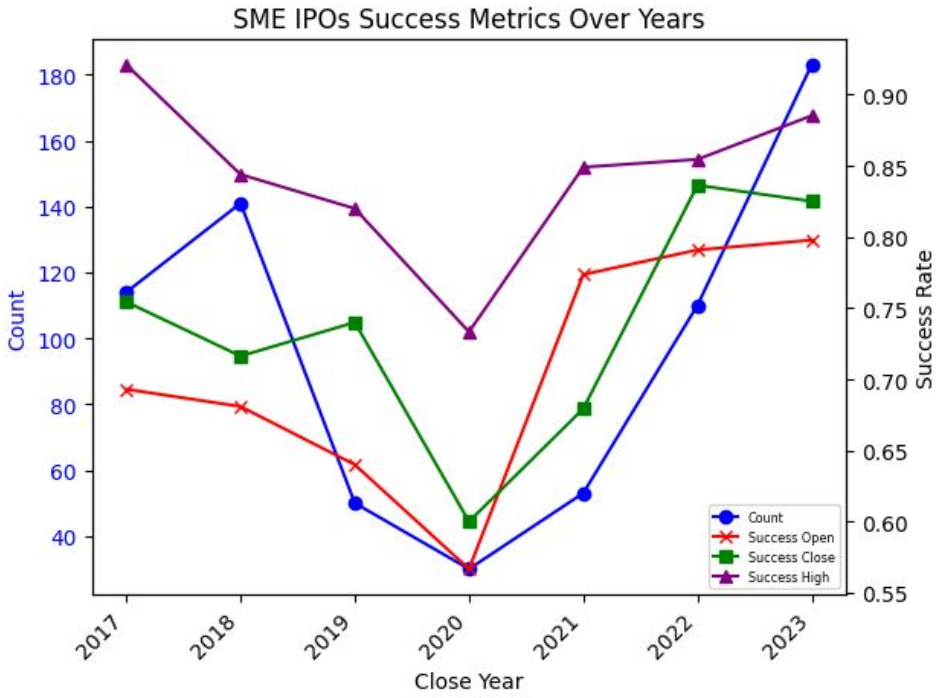
16 tasks, 8 datasets, 6 tools, 24 papers, 8 languages

2 workshops, 4 journals, 8 shared tasks, 10 conferences

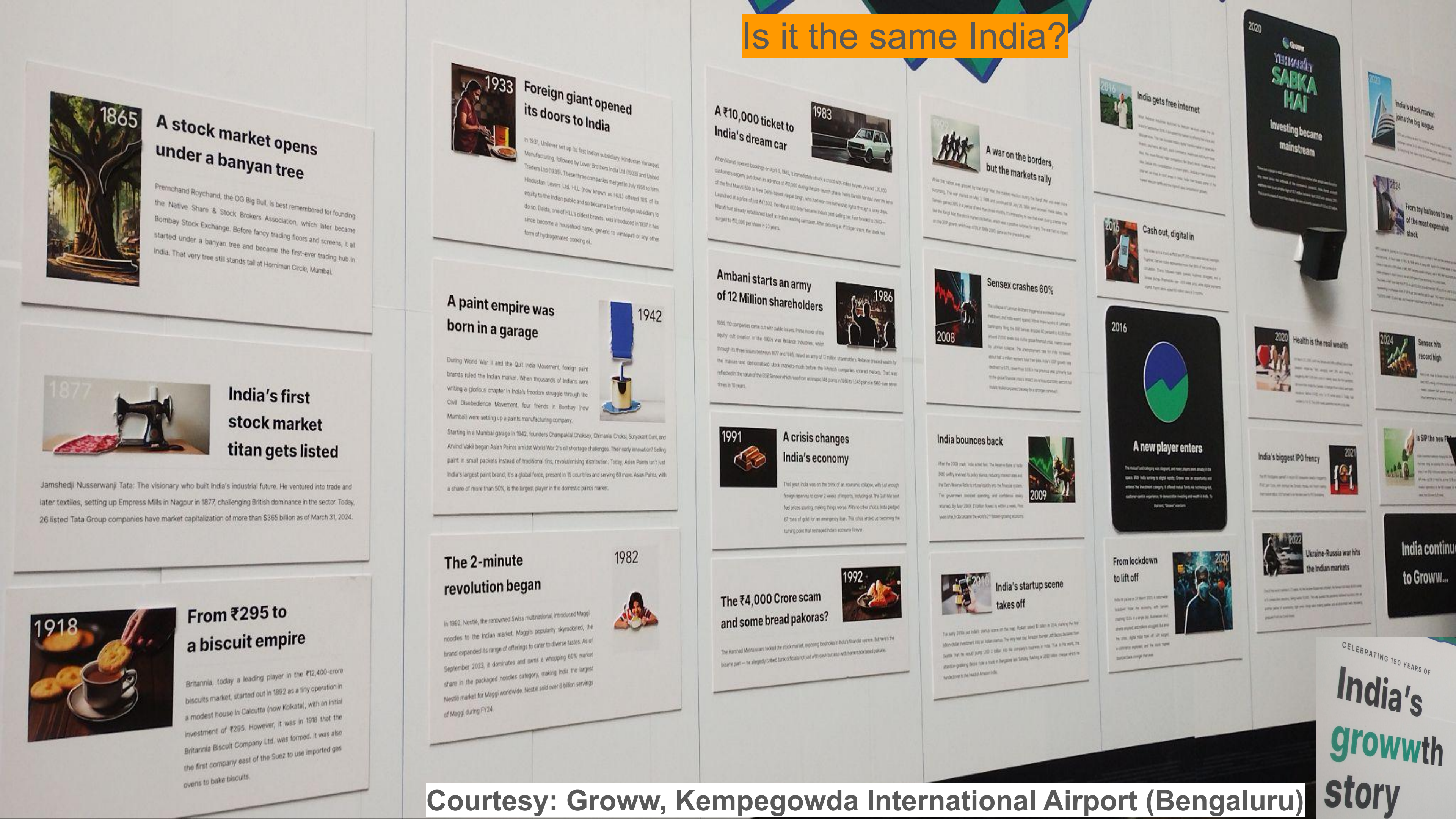
Task #	Metric	Approach Summary	SOTA	Performance	New Data	Language	New Tool
1	AU-ROC	FinBERT finetune	Yes	0.993	Yes	English	Yes
2	F1	RoBERTa + Claude (LLM)	Yes	0.731	Yes	English	No
3	Acc.	SBERT finetune	Yes	0.967	No	English	No
4	F1	SEC-BERT + Neural Network	No	0.736	No	English	No
5	Acc.	RoBERTa finetune	No	0.932	No	English	No
6	F1	SEC-BERT finetune	No	0.715	No	English	Yes
7	F1	FinBERT finetune	No	0.929 (IT)	No	English	No
7	F1	Trans-Prp + FinBERT finetune	No	0.756 (IT)	No	French	No
7	F1	Trans-Prp + FinBERT finetune	Yes	0.679 (IT)	No	Japanese	No
7	F1	Trans-Prp + FinBERT finetune	Yes	0.677 (IT)	No	Chinese	No
7	F1	Trans-Prp + PLM finetune	No	0.5882 (ID)	No	English	No
7	F1	Trans-Prp + PLM finetune	Yes	0.5616 (ID)	No	French	No
8	F1	Ensemble (FinBERT, BERT + Logistic Regression)	No	0.948	No	English	Yes
9	MPP, ML	SBERT Chinese + Classifier, FinBERT	No	0.575 (MPP), 0.598 (ML)	No	Chinese	No
10	MAPE	Gated Recurrent Unit	Yes	0.382	Yes	English	Yes
11	F1	Cross Encoder (FinBERT Finetuned)	No	0.789	No	English	No
11	F1	Translate + Cross Encoder (SEC-BERT)	No	0.641	No	Chinese	No
12	F1	MBERT, Cross Encoder (MBERT)	No	0.721 (1st task), 0.755 (2nd Task)	Yes	Bengali	Yes
13	F1	MBERT+Classifier, Translate + RoBERTa, Translate+MBERT	Yes	0.680 (1st task), 0.950 (2nd task), 0.590 (3rd task)	Yes	Hindi	No
13	F1	MBERT+Classifier, Translate + RoBERTa, Translate+MBERT	Yes	0.650 (1st task), 0.920 (2nd task), 0.550 (3rd task)	Yes	Bengali	No
13	F1	MBERT+Classifier, Translate + RoBERTa, Translate+MBERT	Yes	0.680 (1st task), 0.920 (2nd task), 0.580 (3rd task)	Yes	Telugu	No
14	F1	McL (Num, Cat, Txt) (Classification)	Yes	0.947 (Open-MB), 0.935 (High-MB), 0.931 (Close-MB)	Yes	English	No
14	MAE	McL (Num, Cat, Txt) (Regression)	Yes	0.167 (Open-MB), 0.193 (High-MB), 0.194 (Close-MB)	Yes	English	No
14	F1	McL (Num, Cat, Txt) (Classification)	Yes	0.893 (Open-SME), 0.942 (High-SME), 0.911 (Close-SME)	Yes	English	No
14	MAE	McL (Num, Cat, Txt) (Regression)	Yes	0.239 (Open-SME), 0.263 (High-SME), 0.256 (Close-SME)	Yes	English	No
15	F1	LongFormer RoBERTa Llama 3.1 70B	Yes	0.952 (MB) 0.423 (SME)	Yes	English	No
16	NA	Gradio (frontend)	NA	NA	NA	Various	Yes

Indic Investing: Predicting Success of Indian IPOs



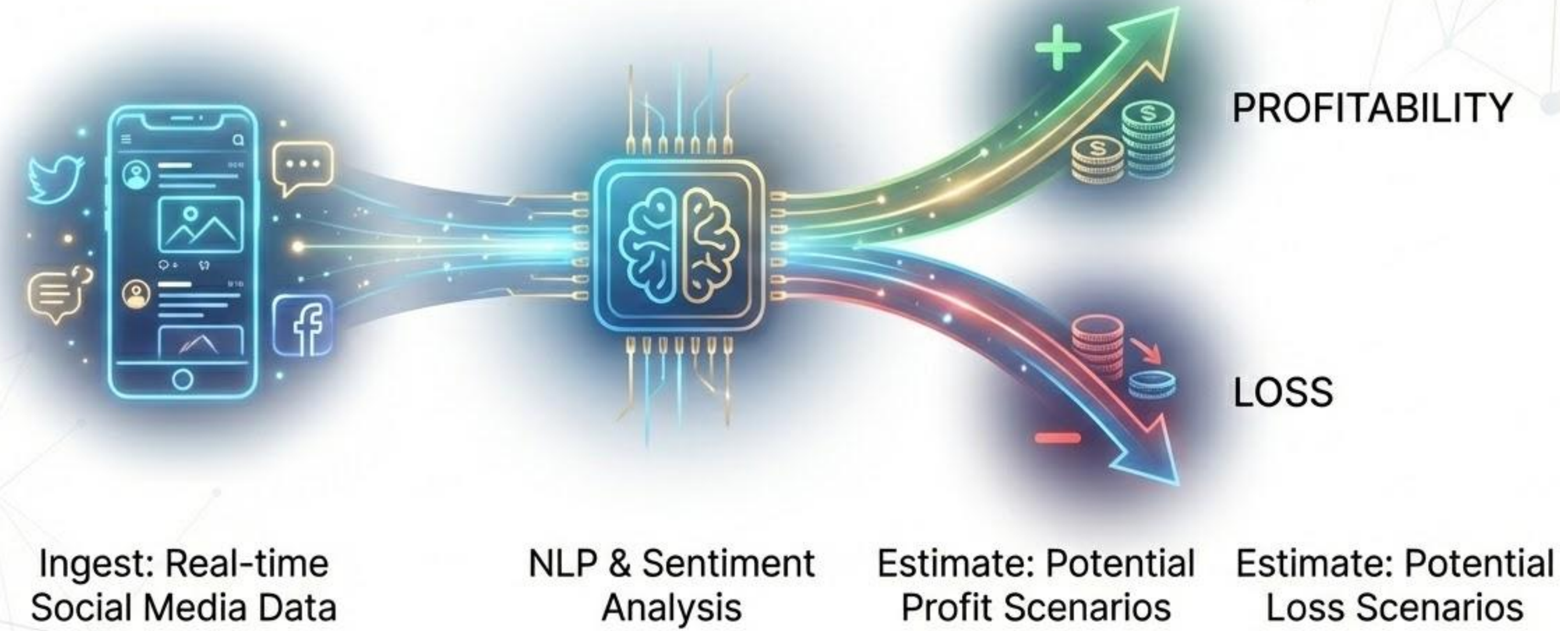


Is it the same India?

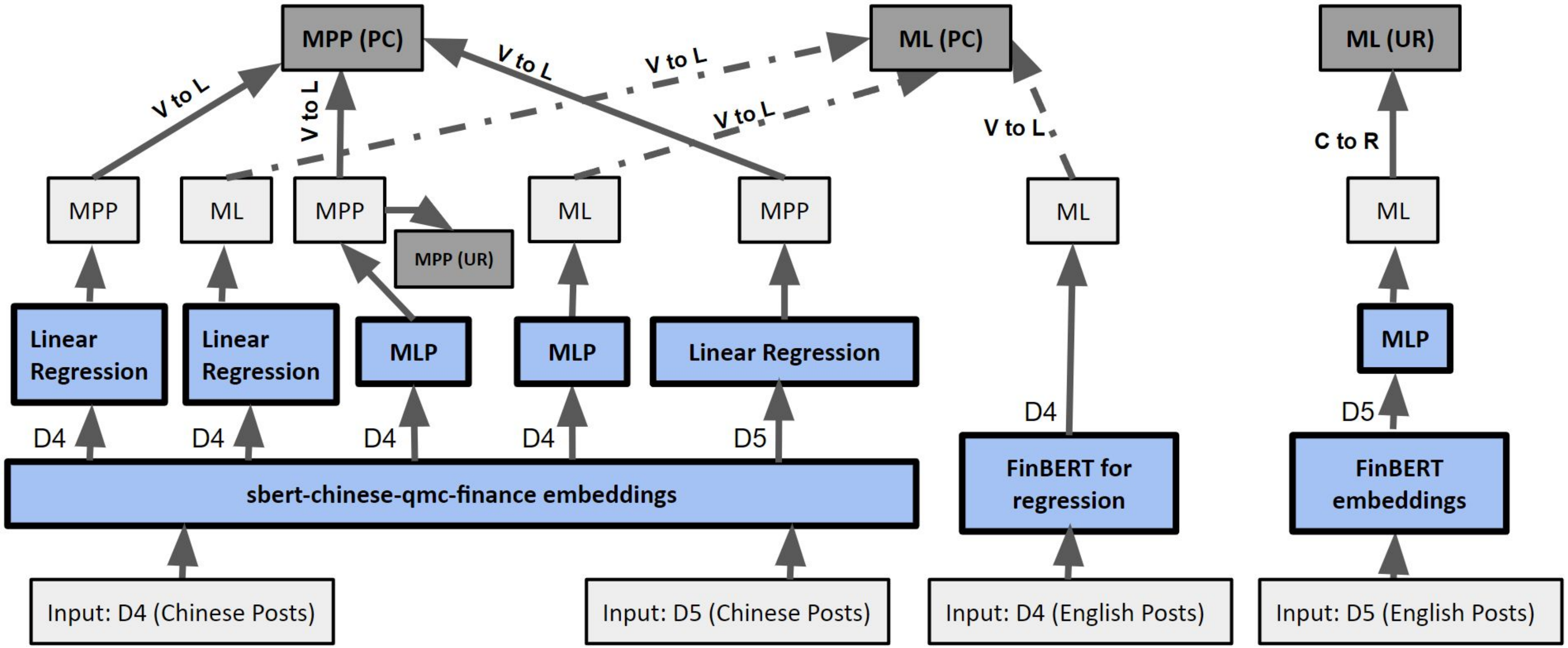


Courtesy: Groww, Kempegowda International Airport (Bengaluru)

Informed Investing: Estimating profitability and loss from financial social media



Informed Investing: Estimating profitability and loss from financial social media



Improved Investing: Relation Extraction

Model	P	R	F1
SEC-BERT	0.206	0.454	0.284
$EMB_{E1,\ E2}$+NN	0.731	0.701	0.709
MOAT	**0.748**	**0.743**	**0.736**

TABLE 3.11: Performance of discriminative LLMs.

Model	P	R	F1
MOAT	0.748	**0.743**	**0.736**
-relation group, entity types	0.736	0.725	0.720
+$SBERT_{SDP}$	0.694	0.687	0.679
+POS tags	0.747	0.738	0.737
MOAT (per relation group)	**0.839**	0.672	0.715
MOAT (LUKE)	0.467	0.545	0.497

TABLE 3.12: Ablation Study.

Type	LLM	P	R	F1
Zero Shot	Falcon	0.538	0.434	0.362
	Dolly	0.400	0.316	0.253
	MPT	0.295	0.380	0.255
	LLaMA-2	0.192	0.260	0.202
Few Shot	Falcon	0.246	0.258	0.242
	Dolly	0.348	0.234	0.245
	MPT	0.296	0.156	0.128
	LLaMA-2	**0.786**	0.352	0.314
Classifier	MOAT	0.726	**0.724**	**0.717**

TABLE 3.13: MOAT versus generative LLMs.

Inclusive Investing: Reachability

Results

Setup	Model	Accuracy	F1
Classifier	FLANG-RoBERTa	50.0%	66.7%
Zero-Shot	FLAN-UL2	50.2%	2.6%
	Claude	51.0%	9.2%
	React T5	52.3%	30.0%
GGEA	GGEA (ChatGPT)	67.2%	68.1%
	GGEA (FLAN-UL2)	69.6%	70.1%
	GGEA (Claude)	**71.9%**	**73.1%**

Improved Investing: Hypernym Detection

Algorithm 1 Algorithm to generate negative samples from existing training set

Require: $T > 0$ and $L > 0$ ▷ T is the augmented set of financial terms and L consists of corresponding labels i.e., hypernyms. $TT > 0$ and $LL > 0$ are the set of definitions of terms and labels respectively obtained after performing data augmentation

Require: Function FR(n) and Function FC(n) ▷ Function FR and FC returns the root node and first child node corresponding to node n respectively where n is one of the 17 labels i.e., leaf nodes/hypernyms

Ensure: $length(T) = length(TT) = length(L) = length(LL)$

$NT \leftarrow \{\}$ ▷ NT is the new set of definitions of financial terms to be created by appending negative samples

$NL \leftarrow \{\}$ ▷ NL is the new set of definitions of labels corresponding to terms in NT

$NS \leftarrow \{\}$ ▷ NS is the set of assigned similarity scores between the newly selected definitions of terms and labels in NT & NL respectively

$k \leftarrow 0.0$ ▷ 'k' is a hyper-parameter. Keeping k = 0.0 gives the best result

for each term t ∈ T, term definition td ∈ TT, corresponding label l ∈ L and label definition ld ∈ LL **do**

  $NT \leftarrow NT \cup \{td\}$

  $NL \leftarrow NL \cup \{ld\}$

  $NS \leftarrow NS \cup \{1.0\}$ ▷ Assign a similarity score of 1.0 as the term and the label definition belong to the original set

  $ln \leftarrow FR(l)$ ▷ Extract root node of label 'l'

  $lc \leftarrow FC(l)$ ▷ Extract first child node of label 'l'

  R, RR ε_r L, LL where length(R)=10, length(RR)=10 ▷ Randomly select 10 labels from 'L 'and corresponding label definitions from 'LL' ensuring none of the labels are 'l' and none of their corresponding terms is 't'. This is done for creating the negative set

  for each label la ∈ R and corresponding definition lnd ∈ RR **do**

    $NT \leftarrow NT \cup \{td\}$

    $NL \leftarrow NL \cup \{lnd\}$

    $lan \leftarrow FR(la)$ ▷ Extract root node of label 'la'

    $lac \leftarrow FC(la)$ ▷ Extract first child node of label 'la'

    if $lac = lc$ **then** ▷ Check if first child nodes are the same. This implies root nodes are also the same.

      $NS \leftarrow NS \cup \{2 * k\}$

    else if $lan = ln$ **then** ▷ Check if root child nodes are same when first child nodes are different

      $NS \leftarrow NS \cup \{1 * k\}$

    else ▷ When first child nodes and root nodes are different

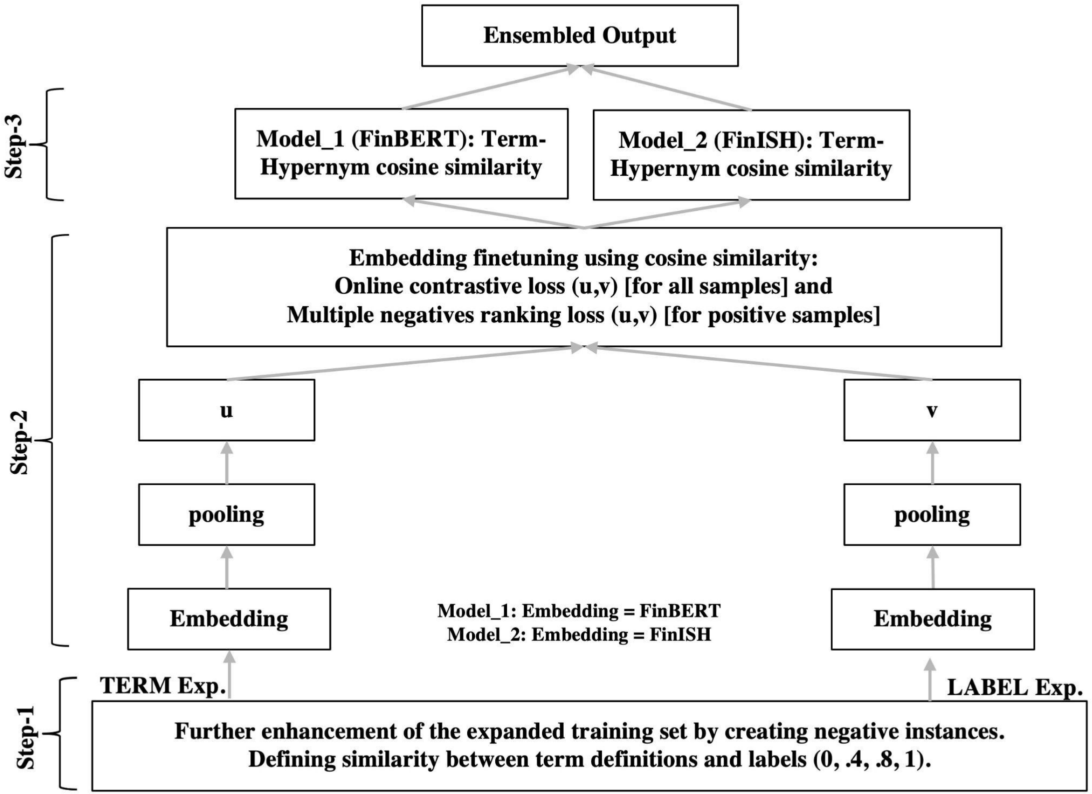
      $NS \leftarrow NS \cup \{0 * k\}$

    end if

  end for

end for

return NT, NL, NS



Improved Investing: Hypernym Detection

			Validation Set		Test Set	
SLN.	**Model**	**Data Aug.**	**MR**	**Acc.**	**MR**	**Acc.**
1	Base-1	No	2.158	0.498	1.941	0.564
2	Base-2	No	1.201	0.876	1.750	0.669
3	BERT	No	1.177	0.899	-	-
4	BERT	Yes	1.153	0.928	-	-
5	FinBERT	No	1.117	0.928	1.257	0.886
6	FinBERT	Yes	1.110	0.942	1.220	0.895
7	SFinBERT_neg (Our old model) [5]	Yes	1.086	0.947	1.156	0.917
8	dicoe_1 [107]	No	-	-	1.180	0.889
9	dicoe_2 [107]	Yes	-	-	1.162	0.904
10	MiniTrue_2 [95]	No	-	-	1.315	0.865
11	MiniTrue_1 [95]	No	-	-	1.346	0.855
12	MiniTrue_3 [95]	No	-	-	1.337	0.825
13	mxx [90]	Yes	*1.06*	*0.96*	**1.113**	**0.941**
14	yseop_1 [108]	Yes	-	-	1.236	0.883
15	yseop_2 [108]	Yes	-	-	1.141	0.917
16	SFinBERT_neg_th	Yes	1.110	0.938	-	-
17	SFinBERT_neg_ss	Yes	1.105	0.933	-	-
18	SFinHyp_neg	Yes	1.072	0.952	-	-
19	SFinHyp_more_data	Yes	1.306	0.813	-	-
20	**Ensemble_7_18 (Our new Model)**	Yes	**1.053**	**0.967**	-	-

TABLE 3.7: Results on validation and test set. Org. represents original and Ext. represents extended. Base refers to baseline. MR is Mean Rank.

Impactful (Green) Investing: ESG concept & Sustainability detection

Sl. No.	Base Model	Data Augmentation	Mean Rank	Accuracy
1	all-mpnet-base-v2	No (only positives)	1.4692	0.6923
2	all-mpnet-base-v2	Yes (1 negative per positive)	1.5769	0.7000
3	sbert_un	No (only positives)	1.5308	0.6769
4	sbert_un	Yes (1 negative per positive)	1.4769	0.7308
5	sbert_un	Yes (1 negative per positive) + concepts	1.4615	0.7154
6	sbert_un	Yes (1 negative per positive) - concept definitions + concepts	1.4846	0.7462
7	sbert_un	Yes (1 negative per positive) [out of group sampling]	1.4385	0.7462
8	sbert_un	Yes (5 negative per positive) [out of group sampling]	**1.4308**	**0.7615**
9	sbert_un	Yes (15 negative per positive) [out of group sampling]	1.5308	0.7000
10	sbert_un	Yes (5 negative per positive) [out of group sampling] {batch size = 40, epoch = 30}	1.4154	0.7462
11	sbert_un	Yes (5 negative per positive) [out of group sampling] {batch size = 40, epoch = 20}	1.4615	0.7462
12	roberta classifier	-	1.4846	0.7538
13	sbert_un	Yes (1 negative per positive) [same group & out of group sampling]	1.4615	0.7462
14	sbert_un	Yes (5 negative per positive) [same group & out of group sampling]	1.5000	0.7385
15	baseline-1	-	2.5308	0.3769
16	baseline-2	-	1.6846	0.7154

TABLE 4.3: Results of Sub-Task 1 on the validation set.
NOTE: Where not mentioned, definitions of concepts were used with batch size of 20 for 15 epochs.

Sl. No.	Model	Accuracy
1	roberta-base	0.9338
2	finbert	**0.9426**
3	sbert_un	0.8653
4	sub-task1 finetune	0.8543

TABLE 4.4: Results of Sub-Task 2 on the validation set.

ST	Sub.	Accuracy	Mean Rank
1	1	**0.7103**	**1.5172**
1	2	0.7034	1.6689
2	1	0.9219	-
2	2	**0.9317**	-

TABLE 4.5: Test set results for sub-tasks (ST) 1 and 2. Sub.: Submission

Impactful (Green) Investing: ESG Issue Detection

Sl. No.	Model	Dataset	Accuracy	F1	Precision	Recall
1	distilbert	Eng (T)	0.637	0.624	0.662	0.637
2	sec-bert	Eng (T)	0.650	0.653	0.639	0.65
3	finbert-esg	Eng (T)	0.667	0.655	0.684	0.667
4	sec-bert	Eng (T+C)	0.717	0.708	0.732	0.717
5	finbert-esg	Eng (T+C)	0.688	0.678	0.697	0.688
6	sec-bert pre-ft	Eng (T+C)	**0.725**	**0.715**	**0.726**	**0.725**
7	finbert-esg pre-ft	Eng (T+C)	0.692	0.682	0.700	0.692
8	sec-bert pre-ft	Eng + Fr2Eng (T)	0.646	0.640	0.684	0.646
9	finbert-esg pre-ft	Eng + Fr2Eng (T)	0.629	0.621	0.645	0.629
10	sec-bert pre-ft	Eng + Fr2Eng (T+C)	0.692	0.687	0.703	0.692
11	finbert-esg pre-ft	Eng + Fr2Eng (T+C)	0.687	0.683	0.702	0.687
12	Ensemble 6 & 7	Eng (T + C)	0.696	0.688	0.722	0.696
13	FLAN-UL2	Eng (T)	0.367	0.339	0.627	0.367
14	FLAN-UL2	Eng (T + C)	0.417	0.417	0.596	0.696

TABLE 4.7: Results (Eng = English, Fr2Eng = French translated to English, C = content, T = Title, ft = fine tuned)

Informed Investing - Claim Detection

Sl. No.	Model	F1-Macro
1	TF-IDF + LR	0.6345
2	TF-IDF + RF	0.6603
3	TF-IDF + XG-Boost	0.6646
4	FB + LR	0.7990
5	FB + RF	0.7763
6	FB + XG-Boost	0.7994
7	FB classifier (depenent text)	0.7250
8	FB classifier (CW=6) + EF	0.8244
9	FB classifier (CW=6) + category	0.8315
10	CapsNet (baseline) [172]	0.5736
11	S1	0.8585
12	S2	0.8439
13	S3	0.8318
14	**Ensemble S1, S2, S3**	**0.8671**

TABLE 5.2: Overall Results. LR = Logistic Regression, RF = Random Forest, FB = FinBERT, CW = Context Window Size and EF = Engineered Features

Model	Macro-F1	Micro-F1
S1 (CW=8, only)	0.8585	0.6345
S2 (CW=6, only)	0.8439	0.6603
S3 (only)	0.8318	0.6646
S3 (-EF)	0.8238	0.7990
S3 (-EF, only largest token)	0.7934	0.7763
FinBERT classifier (CW=4)	0.8408	0.7994
FinBERT classifier (CW=5)	0.8318	0.7250
FinBERT classifier (CW=7)	0.8381	0.8244
FinBERT classifier (CW=9)	0.8247	0.8262
FinBERT classifier (CW=10)	0.8407	0.8585
Ensemble S1, S2, S3	**0.8671**	**0.9479**

TABLE 5.4: Ablation Study. CW = Context Window, EF = Engineered Features

Informed Investing: Estimating profitability and loss from financial social media

		Train/Valid.		MPP (Pairwise Comparison)			MPP (Unsupervised Ranking)		
Sl.#	Model	Data	Language	Train	Valid.	Test (D3)	Train	Valid.	Test (D2)
1.1	SB-1	D4	Chinese	100.00%	70.00%	54.02%	8.04%	2.98%	11.83%
1.2	SB-2	D4	Chinese	62.18%	67.50%	48.28%	3.89%	2.45%	**18.27%**
1.3	SB-3	D5	Chinese	99.63%	60.00%	41.38%	-	-	17.46%
1.4	SB-4	D4	English	51.92%	47.50%	50.57%	2.11%	3.94%	4.17%
1.5	SB-5	D5	English	99.59%	45.00%	55.17%	-	-	16.63%
1.6	Ensemble (§5.6.4.1)	-	-	-	72.50%	**57.47%**	-	-	-

TABLE 5.8: MPP Results

		Train/Valid.		ML (Pairwise Comparison)			ML (Unsupervised Ranking)		
Sl.#	Model	Data	Language	Train	Valid.	Test (D3)	Train	Valid.	Test (D2)
2.1	SB-1	D4	Chinese	97.44%	52.50%	50.57%	-10.26%	-2.16%	-7.81%
2.2	SB-2	D4	Chinese	57.69%	55.00%	50.57%	-5.55%	-8.01%	-5.56%
2.3	SB-3	D5	Chinese	99.65%	52.50%	47.12%	-	-	**-3.90%**
2.4	SB-4	D4	English	58.00%	50.00%	**59.77%**	-1.87%	-1.35%	-6.29%
2.5	SB-5	D5	English	91.24%	55.00%	44.83%	-	-	-4.11%
2.6	Ensemble (§5.6.4.2)	-	-	82.05%	57.50%	50.57%	-	-	-

TABLE 5.9: ML Results

Informed Investing: Deciding trust worthiness of social media posts by executives

Evaluating Impact of Social Media Posts by Executives on Stock Prices

Anubhav Sarkar*
Swagata Chakraborty*

Sohom Ghosh
Sudip Kumar Naskar

Exp	Stock	Data	MAE	RMSE	R_a^2	MAPE (%)
Exp 3.1	TSLA (T)	Y+G	56.365	79.701	0.790	5.852
		Y+E	**34.362**	**48.261**	**0.923**	**3.817**
Exp 3.2	AAPL (T)	Y+G	4.700	5.922	0.859	2.932
		Y+E	**3.075**	**3.860**	**0.940**	**1.990**
Exp 3.3	BTC (T)	Y+G	4681.737	5584.437	0.572	9.675
		Y+E	**2842.190**	**3679.708**	**0.814**	**5.830**
Exp 3.4	ETH (T)	Y+G	315.075	407.849	0.641	8.663
		Y+E	**278.507**	**356.633**	**0.725**	**7.724**
Exp 3.5	TSLA (R)	Y+G_r	44.625	61.403	0.811	4.481
		Y+E_r	**42.283**	**58.994**	**0.826**	**4.247**

TABLE 5.15: Result of Experiments 3

Stock	Data	MAE	RMSE	R_a^2	MAPE (%)
TSLA (T)	Y+G	59.621	83.765	0.768	6.174
	Y+E	**34.362**	**48.261**	**0.923**	**3.817**
AAPL (T)	Y+G	3.899	5.004	0.899	2.459
	Y+E	**3.071**	**3.849**	**0.940**	**1.988**
BTC (T)	Y+G	3676.006	4631.177	0.706	7.492
	Y+E	**2842.190**	**3679.708**	**0.814**	**5.830**
ETH (T)	Y+G	309.507	392.286	0.668	8.557
	Y+E	**278.507**	**356.633**	**0.725**	**7.724**
TSLA (R)	Y+G_r	**46.953**	**68.659**	**0.844**	**4.954**
	Y+E_r	57.674	82.634	0.774	6.043

TABLE 5.16: Result of Experiment 4

Informed Investing: Financial Argument Analysis

MODEL	DATA	VALIDATION MICRO F1	VALIDATION MACRO F1
DistilBERT	Original	0.7913	0.5321
DistilBERT	Paraphrased	0.7942	0.4811
Flang-Roberta	Original	0.7971	0.5653
Flang-Roberta	Paraphrased	0.7971	0.5456
BERT-SEC	Original	0.813	0.5647
BERT-SEC	Paraphrased	0.7880	0.4900
Cross Encoder (BERT)	Original	0.7898	0.5383
Cross Encoder (BERT)	Paraphrased	0.7913	0.4956
Cross-Encoder (BERT-SEC)	Original	0.7695	0.476
Cross-Encoder (BERT-SEC)	Paraphrased	0.7681	0.4807
Cross Encoder (FinBERT Finetuned)	**Original**	**0.8275**	**0.5298**
Cross-Encoder (MLM-FinBERT)	Original	0.8000	0.5054
Cross-Encoder (MLM-FinBERT)	Paraphrased	0.7913	0.5482

Table 3: Results of Task 2, Sub-Task 2: Argument Relation Identification

LANGUAGE	MODEL	DATA	VALIDATION MICRO F1	VALIDATION MACRO F1
English	BERT-base	Original	0.6453	0.6783
English	BERT-base	Paraphrased	0.6319	0.6568
English	FLANG-RoBERTa	Paraphrased	0.6392	0.6754
English	Cross Encoder (SBERT)	Original	0.6404	0.6796
English	Cross Encoder (SBERT)	Paraphrased	0.6500	0.6880
English	Cross Encoder (DistilROBERTA)	Original	0.7055	0.7472
English	Cross Encoder (DistilROBERTA)	Paraphrased	0.6920	0.7374
English	Cross Encoder (Flang-Roberta)	Original	0.6932	0.7342
English	Cross Encoder (Flang-Roberta)	Paraphrased	0.6858	0.7314
English	**Cross Encoder (BERT-SEC)**	**Original**	**0.6932**	**0.7342**
English	Cross Encoder (BERT-SEC)	Paraphrased	0.6800	0.7000
English	Cross Encoder (MLM on BERT-SEC)	Original	0.6846	0.7160
English	Cross Encoder (MLM on BERT-SEC)	Paraphrased	0.6871	0.7180
Chinese	SBERT-Chinese	Original	0.6321	0.6450
Chinese	Cross Encoder (SBERT-Chinese)	Original	0.6503	0.6432

Table 4: Result of Task 3: Identifying Argumentative Relation in Social Media Discussion