

The FinBen: An Holistic Financial Benchmark for Large Language Models

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Abstract

LLMs have transformed NLP and shown promise in various fields, yet their potential in finance is underexplored due to a lack of thorough evaluations and the complexity of financial tasks. This along with the rapid development of LLMs, highlights the urgent need for a systematic financial evaluation benchmark for LLMs. In this paper, we introduce FinBen, the first comprehensive open-sourced evaluation benchmark, specifically designed to thoroughly assess the capabilities of LLMs in the financial domain. FinBen encompasses 35 datasets across 23 financial tasks, organized into three spectrums of difficulty inspired by the Cattell-Horn-Carroll theory, to evaluate LLMs' cognitive abilities in inductive reasoning, associative memory, quantitative reasoning, crystallized intelligence, and more. Our evaluation of 15 representative LLMs, including GPT-4, ChatGPT, and the latest Gemini, reveals insights into their strengths and limitations within the financial domain. The findings indicate that GPT-4 leads in quantification, extraction, numerical reasoning, and stock trading, while Gemini shines in generation and forecasting; however, both struggle with complex extraction and forecasting, showing a clear need for targeted enhancements. Instruction tuning boosts simple task performance but falls short in improving complex reasoning and forecasting abilities. FinBen seeks to continuously evaluate LLMs in finance, fostering AI development with regular updates of tasks and models¹.

1 Introduction

Recently, Large Language Models (LLMs) (Brown et al., 2020) such as ChatGPT² and GPT-4 (OpenAI, 2023a), have reshaped the field of natural language processing (NLP) and exhibited remarkable capabilities in specialized domains across mathematics, coding, medicine, law, and finance (Bubeck et al., 2023). With their increasing model size and extensive pre-training data, LLMs have developed the emergent capacity for in-context learning, enabling them to perform remarkably across a wide range of domain-specific tasks in zero-shot and few-shot settings (Wei et al., 2023). Within the financial domain, recent several studies (Xie et al., 2023a; Lopez-Lira and Tang, 2023; Li et al., 2023b; Xie et al., 2023b) have shown the great potential of advanced LLMs such as GPT-4 on financial text analysis and prediction tasks. While their potential is evident, a comprehensive understanding of their capabilities and limitations for finance, remains largely unexplored. This is due to a lack of extensive evaluation studies and benchmarks, and the inherent complexities associated with the professional nature of financial tasks.

Existing financial domain evaluation benchmarks including FLUE (Shah et al., 2022), BBT-CFLEB (Lu et al., 2023), and PIXIU (Xie et al., 2023b), have a limited scope and are solely focused on financial NLP tasks, primarily targeting language understanding abilities where LLMs have already been extensively evaluated. As shown in Table 1, they fail to capture other crucial facets of the financial domain, such as comprehending and extracting domain-specific financial knowledge and

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¹<https://github.com/The-FinAI/PIXIU>

²<https://openai.com/chatgpt>

resolving realistic financial tasks. As such, their efficacy in evaluating and understanding LLM performance is limited.

Furthermore, while there are newly released benchmarks in the general domain, such as MMLU (Hendrycks et al., 2020), HELM (Liang et al., 2022) and BIG-bench (Srivastava et al., 2023) compiling massive tasks across numerous institutions, they do not extend to the financial domain. The fast progression of LLMs, coupled with an incomplete understanding of their abilities and behavior, highlights the need for a systematic financial evaluation benchmark dedicated to these models.

How should an effective systematic financial evaluation benchmark be designed? We believe it should fulfill the following criteria: 1) Broad coverage: It should cover a broad spectrum of tasks to capture the financial domain’s complexity, incorporating both linguistic understanding and diverse skills like knowledge extraction, text generation, and numerical reasoning et al. 2) Real-world application orientation: The benchmark should focus on real-world scenarios, including stock market analysis and trading, highlighting LLMs’ practical application capabilities. 3) Inclusion of financial domain-specific characteristics: It also needs to address the unique aspects of finance, embedding tasks that demand specific knowledge, terminology, and concepts, demonstrating LLMs’ proficiency in the field. 4) Consideration of human-level cognition: It should gauge human-like cognitive abilities, evaluating LLMs on decision-making, problem-solving, and abstract reasoning within financial contexts.

To bridge this gap, we propose FinBen, the first open-sourced³ comprehensive evaluation benchmark designed for assessing the capabilities of LLMs in the financial domain. As shown in Figure 1, FinBen includes 35 datasets spanning 23 financial tasks organized into three Spectrums of difficulty inspired by the Cattell-Horn-Carroll (CHC) theory (Schneider and McGrew, 2012) in the fields of psychology and education, to assess LLMs across various cognitive domains, including inductive reasoning, associative memory, quantitative reasoning, crystallized intelligence, fluid intelligence, and general intelligence. Spectrum I is comprised of foundational tasks including Quantification, Extraction, and Numerical Understanding, laying the groundwork for basic cognitive skills.

³We will release all resources to the research community.

Moving up, Spectrum II delves into more complex Generation and Forecasting tasks, demanding enhanced cognitive involvement. At the apex, Spectrum III focuses on the sophisticated stock trading task, exemplifying the application of General Intelligence.

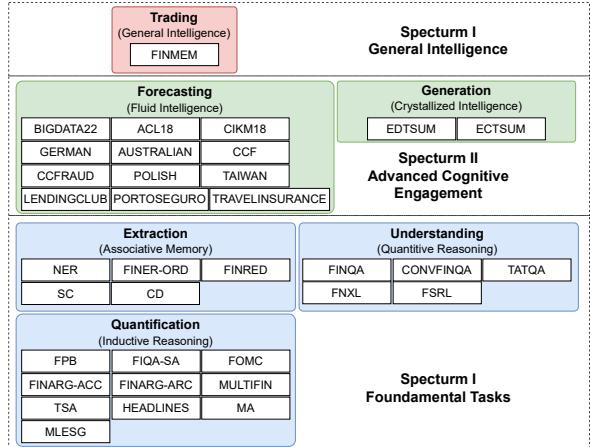


Figure 1: Evaluation framework of FinBen.

In alignment with the above criteria, FinBen distinguishes from existing benchmarks from the breadth and depth of its coverage, as well as its uniquely tailored focus on the financial domain: 1) **Wide coverage:** FinBen integrates classic NLP tasks (text analysis, knowledge extraction, question answering) with finance-specific challenges (numeric labeling) and innovates by assessing LLMs on real-world financial applications (stock prediction, credit scoring) and for the **first time** directly assess the trading performance of LLMs. This broad approach unveils LLMs’ strengths and limitations in finance comprehensively. 2) **Multi-data modality and diversity of text types:** FinBen distinguishes itself by embracing diverse data forms and text types for its tasks, including news, tweets, earnings calls, financial documents, tables, and time-series data. This variety facilitates a thorough assessment of LLMs’ comprehension and generation of financial content, highlighting their real-world utility. 3) **Diverse difficulty levels:** the FinBen incorporates tasks of varying difficulty levels, from simpler fundamental tasks like news headline classification, to advanced cognitive engagement tasks such as the stock movement prediction, and even more complex general intelligence tasks that even challenge humans, such as stock trading. This range enables a nuanced evaluation of LLMs, fully mapping their strengths and weaknesses in finance.

We test 15 representative general LLMs such as

Benchmark	Datasets	Quantification	Extraction	Understanding	Generation	Forecasting	Trading
BloombergGPT-FLUE (Wu et al., 2023)	5	3	0	2	0	0	0
PIXIU (Xie et al., 2023b)	15	4	2	2	2	5	0
FINANCEBENCH (Islam et al., 2023)	1	0	0	1	0	0	0
BizBench (Koncel-Kedziorski et al., 2023)	9	2	1	5	1	0	0
CALM-bench (Feng et al., 2023)	9	0	0	0	0	9	0
BBT-CFLEB (Lu et al., 2023)	6	2	2	1	1	0	0
CFBenchmark (Li et al., 2023a)	8	3	2	0	2	0	0
DISC-FinLLM (Chen et al., 2023c)	9	3	3	2	1	0	0
Fin-Eva (Team, 2023a)	1	1	0	0	0	0	0
FinBen	35	10	5	5	2	12	1

Table 1: Comparison of different financial benchmarks based on the number of datasets used and their distribution across various tasks including quantification, extraction, understanding, generation, forecasting, and trading.

GPT-4, ChatGPT and the latest Gemini, and financial LLMs in FinBen, and have following findings: 1) GPT-4 outperforms all others in quantification, extraction, numerical reasoning, and the intricate stock trading task, whereas Gemini excels in generation and forecasting tasks. 2) while state-of-the-art (SOTA) LLMs such as GPT-4 demonstrate superior capabilities in quantification and simple extraction tasks, they fall short in areas requiring advanced numerical reasoning and complex information extraction. Notably, these LLMs show promise in the demanding stock trading task, yet there is a pronounced need for improvement in text generation and forecasting tasks, which rely heavily on crystallized and fluid intelligence. 3) Instruction tuning is an effective way for improve the performance on quantification and simple extraction tasks, while it is less useful on other tasks such as numerical reasoning, generation and forecasting.

2 The FinBen

Our benchmark framework evaluates financial LLMs through a hierarchy inspired by the Cattell-Horn-Carroll (CHC) theory (Schneider and McGrew, 2012), defining cognitive abilities in three Spectrums. Spectrum I includes foundational tasks like Quantification (Inductive Reasoning) using classification tasks, Extraction (Associative Memory) covering information extraction tasks, and Numerical Understanding (Quantitative Reasoning) covering numerical reasoning tasks. Spectrum II advances to Generation (Crystallized Intelligence) covering generaltion task, and Forecasting (Fluid Intelligence) with prediction tasks, requiring deeper cognitive engagement. The pinnacle, Spectrum III, encompasses strategic decision-making in trading using the current state-of-art (SOTA) financial LLM agent (Yu et al., 2023) with the stock trading task, showcasing General Intelligence (McGrew, 2009). This structured approach allows for

nuanced assessment of LLMs’ financial analytical capabilities across varied cognitive demands. Table 2 and Figure 2 shows all tasks, datasets, data statistics and evaluation metrics covered by FinBen⁴.

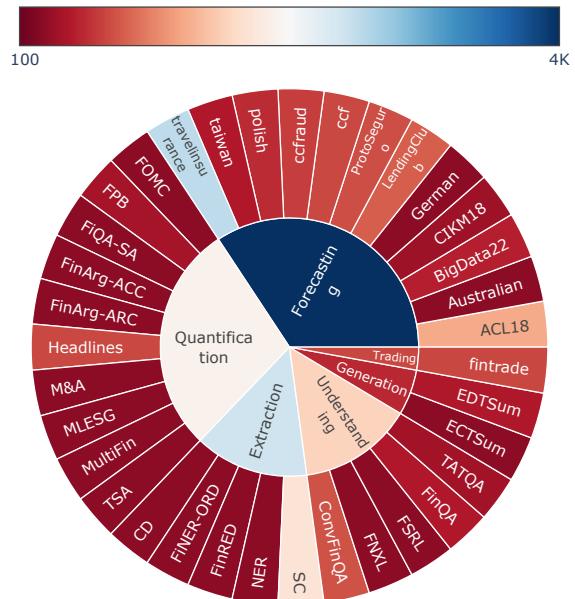


Figure 2: Evaluation datasets of FinBen.

2.1 Spectrum I: Fundamental Tasks

Spectrum I including 20 datasets from 16 tasks to evalaute financial LLMs from three perspectives including Quantification (Inductive Reasoning), Extraction (Associative Memory) and Numerical Understanding (Quantitative Reasoning).

Quantification. The auantification task include 8 classification tasks for evaluating financial LLMs, to transform financial text into categorical labels and numerical scores. As inductive reasoning (Ir), it requires LLMs to discern patterns and quantify

⁴For detail instructions of each dataset, please see Appendix C

Data	Task	Valid	Test	Evaluation	License
FPB (Malo et al., 2014)	sentiment analysis	775	970	F1, Accuracy	CC BY-SA 3.0
FiQA-SA (Maia et al., 2018a)	sentiment analysis	188	235	F1	Public
TSA (Cortis et al., 2017)	sentiment analysis	-	561	F1, Accuracy	CC BY-NC-SA 4.0
Headlines (Sinha and Khandait, 2021)	news headline classification	1,141	2,283	Avg F1	CC BY-SA 3.0
FOMC (Shah et al., 2023a)	hawkish-dovish classification	-	496	F1, Accuracy	CC BY-NC 4.0
FinArg-ACC (Sy et al., 2023)	argument unit classification	-	969	F1, Accuracy	CC BY-NC-SA 4.0
FinArg-ARC (Sy et al., 2023)	argument relation classification	-	496	F1, Accuracy	CC BY-NC-SA 4.0
MultiFin (Jørgensen et al., 2023)	multi-class classification	-	690	F1, Accuracy	Public
MA (Yang et al., 2020a)	deal completeness classification	-	500	accuracy,F1	Public
MLESG (Chen et al., 2023a)	ESG Issue Identification	-	300	accuracy,F1	CC BY-NC-ND
NER (Alvarado et al., 2015)	named entity recognition	103	980	Entity F1	CC BY-SA 3.0
FiNER-ORD (Shah et al., 2023b)	named entity recognition	-	1080	Entity F1	CC BY-NC 4.0
FinRED (Sharma et al., 2022)	relation extraction	-	1,068	F1, Entity F1	Public
SC (Mariko et al., 2020)	causal classification	-	8,630	F1,Entity F1	CC BY 4.0
CD (Mariko et al., 2020)	causal detection	-	226	F1,Entity F1	CC BY 4.0
FinQA (Chen et al., 2021)	question answering	883	1,147	EM Accuracy	MIT License
TATQA (Zhu et al., 2021)	question answering	-	1,668	F1,EM Accuracy	MIT License
ConvFinQA (Chen et al., 2022)	question answering	2,210	1,490	EM Accuracy	MIT License
FNXL (Sharma et al., 2023)	numeric labeling	-	318	F1,EM Accuracy	Public
FSRL (Lamm et al., 2018)	token classification	-	97	F1, EM Accuracy	MIT License
ECTSum (Mukherjee et al., 2022)	text summarization	-	495	ROUGE, BERTScore, BARTScore	Public
EDTSum (Zhou et al., 2021)	text summarization	-	2000	ROUGE, BERTScore, BARTScore	Public
BigData22 (Soun et al., 2022)	stock movement prediction	798	1,470	Accuracy, MCC	Public
ACL18 (Xu and Cohen, 2018)	stock movement prediction	2,560	3,720	Accuracy, MCC	MIT License
CIKM18 (Wu et al., 2018)	stock movement prediction	431	1,140	Accuracy, MCC	Public
German (Hofmann, 1994)	credit scoring	-	1000	F1, MCC	CC BY 4.0
Australian (Quinlan)	credit scoring	-	690	F1, MCC	CC BY 4.0
LendingClub (Feng et al., 2023)	credit scoring	1,344	2,690	F1, MCC	CC0 1.0
ccf (Feng et al., 2023)	fraud detection	1,138	2,278	F1, MCC	(DbCL) v1.0
ccfraud (Feng et al., 2023)	fraud detection	1,047	2,097	F1, MCC	Public
polish (Feng et al., 2023)	financial distress identification	868	1,736	F1, MCC	CC BY 4.0
taiwan (Feng et al., 2023)	financial distress odentication	681	1,364	F1, MCC	CC BY 4.0
ProtoSeguro (Feng et al., 2023)	claim analysis	1,189	2,381	F1, MCC	Public
travelinsurance (Feng et al., 2023)	claim analysis	-	3,800	F1, MCC	(ODbL) v1.0
fintrade (Yu et al., 2023)	stock trading	-	3,384	CR, SR, DV, AV, MD	MIT License

Table 2: The tasks, datasets, data statistics, and evaluation metrics included in FinBen.

sentiments within financial narratives. **1) Sentiment analysis** focuses on extracting sentiment information from financial texts. We utilize two datasets: the Financial Phrase Bank (FPB) (Malo et al., 2014), FiQA-SA (Maia et al., 2018a), and TSA (Cortis et al., 2017) dataset. **2) News headline classification** analyzes additional information, like price movements in financial texts, using the Headlines dataset (Sinha and Khandait, 2021), which includes news about "gold" from 2000 to 2019 and their 9 corresponding tags. **3) Hawkish-Dovish classification** aims to classify sentences from monetary policy texts as 'hawkish' or 'dovish,' focusing on the nuanced language and economic implications of financial texts, using the FOMC (Shah et al., 2023a) dataset. **4) Argument unit classification** categorizes sentences as claims or premises using the FinArg AUC dataset (Sy et al., 2023). **5) Argument relation detection** identifies relationships (attack, support, or irrelevant) between social media posts using the FinArg ARC dataset (Sy et al., 2023). **6) Multi-class classification** targets categorizing a variety of financial texts, including analyst reports, news articles, and investor comments, utilizing the MultiFin dataset (Jørgensen et al., 2023).

7) Deal completeness classification predicts if mergers and acquisitions events are "completed" or remain "rumors" based on news and tweets, employing the MA dataset (Yang et al., 2020a). **8) ESG issue identification** focuses on detecting Environmental, Social, and Governance (ESG) concerns in financial documents using the MLESG dataset (Chen et al., 2023a). For all datasets, evaluation utilizes the accuracy and F1 Score.

Extraction. The extraction task including 5 datasets from 4 information extraction tasks, evaluating LLMs' ability to accurately retrieve specific financial information from large datasets, a process tied closely to Associative Memory (Ma). **1) Named entity recognition** extracts entities like LOCATION, ORGANIZATION, and PERSON from financial agreements and SEC filings, using the NER (Alvarado et al., 2015) and FiNER-ORD (Shah et al., 2023b) datasets. **2) Relation extraction** identifies relationships such as "product/material produced" and "manufacturer" in financial news and earnings transcripts with the FINRED dataset (Sharma et al., 2022). **3) Causal classification** discerns whether sentences from financial news and SEC filings convey causality us-

ing the SC dataset (Mariko et al., 2020). **4) Causal detection** identifies cause and effect spans in financial texts with the CD dataset (Mariko et al., 2020). The evaluation of these tasks is focused on the F1 score (Goutte and Gaussier, 2005) and Entity F1 score (Derczynski, 2016).

Understanding. The understanding task includes 5 datasets from 4 numerical reasoning tasks, challenging LLMs to interpret and analyze complex numerical data and intricate financial statistics, associated with the Quantitative Reasoning (Gq) ability. **1) Question answering** focuses on solving questions through multi-step numerical reasoning with financial reports and tables, utilizing the FinQA (Chen et al., 2021) and TATQA (Zhu et al., 2021) dataset. **2) Multi-turn question answering** is an extension on QA with multi-turn questions and answers based on financial earnings reports and tables, using the ConvFinQA dataset (Chen et al., 2022). **3) Numeric labeling** aims at tagging numeric spans in financial documents using 2,794 labels with the FNXL dataset (Sharma et al., 2023). **4) Token classification** aims at identifying common attributes and comparative elements in textual analogies by extracting analogy frames, utilizing the FSRL dataset (Lamm et al., 2018). Entity F1 score (Derczynski, 2016) and the Exact Match Accuracy (EMAcc) metric (Kim et al., 2023) are used to evaluate these tasks.

2.2 Spectrum II: Advanced Cognitive Engagement

Spectrum II has 14 datasets across 6 tasks designed to assess the Generation (Crystallized Intelligence) and Forecasting (Fluid Intelligence) capabilities of LLMs, requiring deeper cognitive engagement.

Generation. The generation task gauges the models' proficiency in producing coherent, informative, and relevant text outputs, involving the Crystallized Intelligence (Gc). We focus on the *text summarization* task utilizing the ECT-SUM (Mukherjee et al., 2022) dataset for summarizing earnings call transcripts and the EDT-SUM (Zhou et al., 2021) dataset for abstracting financial news articles into concise summaries. It's evaluated using ROUGE scores (Lin, 2004), BERTScore (Zhang et al., 2019), and BART Score (Yuan et al., 2021), metrics that quantify to measure the alignment, factual consistency, and information retention between machine-generated and expert summaries.

Forecasting. The forecasting task leverages

Fluid Intelligence (Gf), challenging models to adaptively predict future market and investor behaviors from emerging patterns. It includes 12 datasets from 5 forecasting tasks. **1) Stock movement prediction** focuses on forecasting stock directions as either positive or negative, based on historical prices and tweets, utilizing three datasets: Big-Data22 (Soun et al., 2022), ACL18 (Xu and Cohen, 2018) and CIKM18 (Wu et al., 2018). **2) Credit scoring** classifies individuals as "good" or "bad" credit risks using historical customer data, employing datasets including: German (Hofmann, 1994), Australia (Quinlan) and LendingClub (Feng et al., 2023). **3) Fraud detection** involve categorizes transactions as "fraudulent" or "non-fraudulent", using two datasets: ccf (Feng et al., 2023) and ccFraud (Feng et al., 2023). **4) Financial distress identification** aims to predict a company's bankruptcy risk, using the polish (Feng et al., 2023) and taiwan dataset (Feng et al., 2023). **5) Claim analysis** anonymizes client data for privacy, labeling a "target" to indicate claim status, using two datasets: PortoSeguro (Feng et al., 2023) and travelinsurance (Feng et al., 2023). F1 score and Matthews correlation coefficient (MCC) (Chicco and Jurman, 2020) are used for evaluating these tasks.

2.3 Spectrum III: General Intelligence

Trading. Strategic decision-making in Trading (Punt, 2017), categorized under Spectrum III, is the pinnacle task for financial LLMs, emphasizing their use of General Intelligence (g). This task evaluates the model's proficiency in synthesizing diverse information to formulate and implement trading strategies, a challenge even for experts, representing the highest level of cognitive capability in financial analysis. The SOTA financial LLM agent *FinMem* (Yu et al., 2023) are used to evaluate LLMs on sophisticated stock decisions, based on the FinTrade dataset we curated of seven major stocks, simulating real-world trading through historical prices, news, and sentiment analysis. Performance is measured by Cumulative Return (CR) (Ariel, 1987), Sharpe Ratio (SR) (Sharpe, 1998), Daily (DV) and Annualized volatility (AV) (Zhou et al., 2023), and Maximum Drawdown (MD) (Magdon-Ismail and Atiya, 2004), offering a comprehensive assessment of profitability, risk management, and decision-making prowess.

3 Evaluation

We evaluate the zero-shot and few-shot performance of 15 representative general LLMs and financial LLMs on the FinBen benchmark, including: 1) ChatGPT: An instruction-following LLM with 175B parameters developed by OpenAI. 2) GPT-4 (OpenAI, 2023b): A powerful instruction-following LLM with approximately 1T parameters, proposed by OpenAI. 3) Gemini Pro (Team et al., 2023): A multimodal AI LLM with 50T parameters, released by Google. 4) LLaMA2-70B (Touvron et al., 2023): An instruction-following LLM with 70B parameters developed by MetaAI. 5) ChatGLM3-6B (Du et al., 2022): A conversational LLM with 6B parameters, jointly released by Zhipu AI and Tsinghua KEG. 6) Baichuan2-6B (Baichuan, 2023): An open-source LLM with 6B parameters, launched by Baichuan Intelligent Technology. 7) InternLM-7B (Team, 2023b): An open-sourced 7B parameter base model tailored for practical scenarios, proposed by SenseTime. 9) Falcon-7B (Almazrouei et al., 2023): A 7B parameter causal decoder-only LLM model trained on 1500B tokens of RefinedWeb enhanced with curated corpora. 10) Mixtral 8×7B (Jiang et al., 2024): A LLM with the Sparse Mixture of Experts (SMoE) architecture. 11) Code Llama-7B (Roziere et al., 2023): An open-source LLM model for generating programming code, launched by Meta AI with 7B parameters. 12) FinGPT (Yang et al., 2023a): An 7B instruction finetuned financial LLM with sentiment analysis tasks. 13) FinMA-7B (Xie et al., 2023b): An 7B instruction finetuned financial LLM with multiple NLP and forecasting tasks. 14) DISC-FinLLM (Chen et al., 2023c): An open-sourced financial LLM, fine-tuned from Baichuan-13B-Chat (Baichuan, 2023). 15) CFGPT (Li et al., 2023a): An open-source LLM, specifically designed for the financial sector and trained on Chinese financial datasets, which comprises 7 billion parameters. All experiments are conducted exclusively using 5 NVIDIA TITAN RTX graphics GPUs and 2 NVIDIA GeForce RTX 3090 GPUs, taking approximately 20 hours to complete. On average, 2 GPUs are allocated per experiment, amounting to a total of approximately 20400 GPU hours.

4 Results

Table 3 and Table 4 shows the performance of 12 representative LLMs on all datasets in the FinBen.

4.1 Foundamental Tasks Analysis

From Table 3, for fundamental tasks, we can see that GPT-4 stands out with the highest average performance, closely followed by ChatGPT, and Gemini. Among all open-sourced LLMs, the financial LLM FinMA-7B showcases superior performance on several classification tasks, such as FPB, even exceeding larger models like GPT-4. This is attributed to its tailored instruction tuning on the training datasets. For general-purpose LLMs, LLaMA2 70B leads in average performance, due to the large model size. Among models tailored for the Chinese language, ChatGLM2-6B outperforms InternLM 7B in average performance, indicating its effectiveness in handling financial tasks. However, CFGPT sft-7B-Full, fine-tuned on Chinese financial data, exhibits limited improvement on a few datasets and even declining performance on others like MultiFin compared to its base model InternLM 7B. This trend suggests a language-based discrepancy, highlighting that fine-tuning with Chinese data may adversely affect performance on English tasks, underscoring the complexities of cross-lingual adaptation in model training.

Notably, in **quantification** datasets such as Headlines, models like Gemini and other financially tuned LLMs, including FinMA-7B, perform on par with or even better than GPT-4. However, when tackling **understanding** tasks in datasets like FinQA and ConvFinQA, GPT-4 and ChatGPT significantly outperform others, highlighting the limited numerical reasoning capabilities of models like Gemini and LLaMA2-70B. Challenges persist in **extraction** datasets requiring complex information extraction and numeric labeling, such as FinRED, CD, FNXL, and FSRL, where all models, including GPT-4, fall short, indicating a need for further enhancement in these areas.

In conclusion, SOTA LLMs like GPT-4 exhibit strong performance across quantification tasks. However, there's a clear gap in numerical reasoning and complex information extraction tasks, pinpointing the necessity for further development. Instruction tuning has shown to enhance performance significantly, suggesting a valuable approach for improving model capabilities in specialized financial tasks. The results highlight the complexity of cross-lingual model tuning and the importance of careful language consideration in enhancing LLMs' effectiveness across diverse financial tasks.

Dataset	Metrics	Chat GPT	GPT 4	Gemini	LLaMA2 7B-chat	LLaMA2 70B	ChatGLM3 6B	FinMA 7B	FinGPT 7b-lora	InternLM 7B	Falcon 7B	Mixtral 7B	CFGPT sft-7B-Full
FPB	F1	0.78*	0.78*	0.77	0.35	0.73	0.37	0.88	0.00	0.27	0.07	0.29	0.35*
	Acc	0.78*	0.76*	0.77	0.29	0.72	0.38	0.88	0.00	0.20	0.05	0.37	0.26*
FiQA-SA	F1	0.60	0.80	0.81	0.00	0.83	0.60	0.79	0.00	0.00	0.77	0.16	0.42*
	RMSE↓	0.53	0.50	0.37	0.36	0.57	0.34	0.80	-	0.33	0.50	0.50	1.05
Headlines	AvgF1	0.77*	0.86*	0.78	0.60	0.63	0.60	0.97	0.60	0.60	0.45	0.60	0.61*
	F1	0.64	0.71	0.53	0.53	0.49	0.47	0.49	0.00	0.00	0.30	0.37	0.16*
FOMC	Acc	0.6	0.69	0.60	0.00	0.47	0.55	0.46	0.00	0.00	0.30	0.35	0.21*
	MicroF1	0.50	0.60	0.31	0.51	0.58	0.50	0.27	0.00	0.47	0.23	0.39	0.05
FinArg-ACC	MicroF1	0.39	0.40	0.60	0.28	0.36	0.30	0.08	0.00	0.37	0.32	0.57	0.05
	MicroF1	0.59	0.65	0.62	0.56	0.63	0.22	0.14	0.00	0.33	0.09	0.37	0.05
MA	MicroF1	0.85	0.79	0.84	0.81	0.86	0.50	0.45	0.00	0.74	0.39	0.34	0.25
	MLESG	0.25	0.35	0.34	0.18	0.31	0.14	0.00	0.00	0.24	0.06	0.17	0.01
NER	EntityF1	0.77*	0.83*	0.61	0.00	0.04	0.01	0.69	0.00	0.00	0.00	0.24	0.00
FINER-ORD	EntityF1	0.28	0.77	0.14	0.00	0.07	0.00	0.00	0.00	0.00	0.00	0.05	0.00
FinRED	F1	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SC	F1	0.80	0.81	0.74	0.20	0.61	0.40	0.19	0.00	0.58	0.67	0.83	0.15
CD	F1	0.00	0.01	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FinQA	EmAcc	0.58*	0.63*	0.00	0.00	0.06	0.00	0.04	0.00	0.00	0.00	0.00	0.00
TATQA	EmAcc	0.00*	0.13*	0.18	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00
ConvFinQA	EmAcc	0.60*	0.76*	0.43	0.00	0.25	0.00	0.20	0.00	0.00	0.00	0.31	0.01
FNXL	EntityF1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FSRL	EntityF1	0.00	0.01	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EDTSM	Rouge-1	0.17	0.20	0.39	0.11	0.25	0.14	0.13	0.00	0.12	0.15	0.12	0.01
	BertScore	0.66	0.67	0.72	0.59	0.68	0.46	0.38	0.50	0.51	0.57	0.61	0.51
	BartScore	-3.64	-3.62	-3.87	-4.26	-3.81	-4.94	-5.71	-7.25	-4.51	-6.1	-4.47	-7.08
ECTSUM	Rouge-1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BertScore	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	BartScore	-5.18	-5.18	-4.93	-5.18	-4.86	-5.18	-5.18	-5.18	-5.18	--5.18	-5.18	-5.18
BigData22	Acc	0.53	0.54	0.55	0.55	0.47	0.47	0.51	0.45	0.52	0.55	0.46	0.45
	MCC	-0.025	0.03	0.04	0.03	0.00	0.03	0.02	0.00	0.02	0.00	0.02	0.03
ACL18	Acc	0.50	0.52	0.52	0.51	0.51	0.49	0.51	0.49	0.52	0.51	0.49	0.48
	MCC	0.005	0.02	0.04	0.01	0.01	0.00	0.03	0.00	0.02	0.00	0.00	-0.03
CIKM18	Acc	0.55	0.57	0.54	0.54	0.49	0.42	0.50	0.49	0.57	0.47	0.42	0.41
	MCC	0.01	0.02	0.02	-0.01	-0.07	0.04	0.08	0.00	0.01	-0.06	-0.05	-0.07
German	F1	0.20	0.55	0.52	0.52	0.17	0.52	0.17	0.52	0.44	0.23	0.53	0.53
	MCC	-0.10	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.07	0.00	0.00
Australian	F1	0.41	0.74	0.26	0.26	0.41	0.26	0.41	0.41	0.27	0.26	0.26	0.29
	MCC	0.00	0.47	0.00	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	-0.10
LendingClub	F1	0.20	0.55	0.65	0.73	0.17	0.65	0.61	0.00	0.71	0.02	0.61	0.05
	MCC	-0.10	-0.02	0.19	0.04	0.00	0.19	0.00	0.00	0.18	-0.01	0.08	0.01
ccf	F1	0.20	0.55	0.96	0.00	0.17	0.96	0.00	0.00	1.00	0.10	0.00	0.00
	MCC	-0.10	-0.02	-0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
ccfraud	F1	0.20	0.55	0.90	0.88	0.17	0.90	0.01	0.00	0.77	0.62	0.48	0.03
	MCC	-0.10	-0.02	0.00	-0.05	0.00	-0.00	-0.06	0.00	-0.05	-0.02	0.16	0.01
polish	F1	0.20	0.55	0.86	0.82	0.17	0.01	0.92	0.07	0.90	0.76	0.92	0.40
	MCC	-0.10	-0.02	0.14	0.08	0.00	0.01	-0.01	0.02	-0.01	0.05	0.00	-0.02
taiwan	F1	0.20	0.55	0.95	0.75	0.17	0.95	0.95	0.82	0.48	0.00	0.95	0.70
	MCC	-0.10	-0.02	0.00	-0.07	0.00	0.00	0.00	0.01	0.04	0.00	0.00	0.00
portoseguro	F1	0.20	0.55	0.95	0.01	0.17	0.97	0.04	0.00	0.95	0.95	0.72	0.00
	MCC	-0.10	-0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00
travelinsurance	F1	0.20	0.55	0.00	0.00	0.17	0.00	0.00	0.00	0.98	0.79	0.77	0.00
	MCC	-0.10	-0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.03	0.00	0.01

Table 3: The zero-shot and few-shot performance of different LLMs on the FinBen. All results via our evaluations are the average of three runs. “-” represents the result that is currently unable to yield due to model size or availability, and “*” represents the result from the previous paper.

Model	CR (%)↑	SR↑	DV (%)↓	AV (%)↓	MD (%)↓
Buy and Hold	-4.83±18.9	0.0541±0.647	3.68±1.18	58.3±18.8	35.3±13
GPT-4	28.3±12.5	1.42±0.575	2.78±0.949	44.1±15	18.5 ± 6.92
ChatGPT	5.46±15.5	0.139±0.755	3.14±1.16	49.9±18.5	32.1±10.3
LLaMA2-70B	4.07± 20.2	0.486±1.12	2.41±0.873	38.2±13.9	23.1±11.9
Gemini	21±21.6	0.861±0.832	2.5± 1.23	39.7±19.6	22.5±7.9

Table 4: The average trading performance (95% Confidence Interval) comparison for different LLMs across 8 stocks. The results include large LLMs only ($\geq 70B$), as models with smaller contexts have difficulty understanding the instructions and producing a static strategy of holding.

4.2 Advanced Cognitive Engagement Tasks Analysis

In the **text generation** task, Gemini emerges as the frontrunner on the EDTSM abstractive text

summarization dataset, illustrating its prowess in generating coherent summaries. Nevertheless, all models face challenges with extractive summarization, which demands the generation of precise label sequences for sentences. In the **forecasting** task, Gemini distinguishes itself across most datasets, except in the Australian credit scoring dataset, where GPT-4 demonstrates superior performance.

Among open-source LLMs, LLaMA2 70B stands out in text summarization, whereas LLaMA2-7B-chat excels in forecasting tasks. Despite instruction tuning with datasets like BigData22 and ACL18, FinMA 7B lags behind peers such as Falcon 7B in forecasting performance, underscoring the need for more effective improvement strategies. CFGPT sft-7B-Full consistently shows a decrease in performance compared to its foundational model, InternLM 7B. For forecasting, it is crucial to acknowledge that all LLMs do not meet expected outcomes and fall behind traditional methodologies. This consistent observation with existing studies (Feng et al., 2023; Xie et al., 2023b) underlines a notable deficiency in LLMs' capacity to tackle advanced cognitive tasks as effectively as conventional methods.

This analysis reveals significant potential for enhancement in LLMs, including industry leaders like GPT-4 and Gemini, particularly in text generation and forecasting tasks that demand higher cognitive skills.

4.3 General Intelligence Tasks Analysis

The comparative analysis of various Large Language Models (LLMs) on the complex task of stock trading, which demands a high degree of general intelligence, is presented in Table 4⁵. The results indicate a superior performance of all LLMs over the traditional Buy & Hold strategy, highlighting their efficacy in formulating more advantageous trading decisions. Among the evaluated LLMs, GPT-4 distinguishes itself by attaining the highest Sharpe Ratio (SR), exceeding 1. This achievement underscores GPT-4's proficiency in optimizing profit against the risk, a capability that appears somewhat diminished in other LLMs, which tend to expose investors to higher risk for lesser returns. Additionally, GPT-4 demonstrates the minimal Max Drawdown (MDD), suggesting that it limits potential losses more effectively than its counterparts, thereby offering a more secure investment avenue.

⁵For detail trading performance, please see Appendix E

In contrast, ChatGPT exhibits significantly lower performance metrics, indicating limitations in its financial decision-making capabilities. Gemini, on the other hand, secures the position of second-best performer, showcasing lower risk and volatility in comparison to GPT-4, yet maintaining commendable returns. When considering open-source models, it is observed that LLaMA-70B, despite its lower volatility, yields the least profit among the LLMs, highlighting a trade-off between risk management and profitability.

For smaller models with parameters less than 70 billion, a marked inability to adhere to trading instructions consistently across transactions is noted, attributed to their limited comprehension, extraction capabilities, and constrained context windows. This limitation underscores the critical challenges smaller LLMs face in tasks requiring intricate financial reasoning and decision-making, thereby spotlighting the necessity for more advanced models to tackle such high-level cognitive tasks effectively.

In essence, the exceptional performance of LLMs in the stock trading task illuminates their capacity to embody general intelligence within the financial domain. This capacity, rooted in the integration of diverse cognitive skills and the application of these skills to real-world financial challenges, heralds a new era of financial analysis and decision-making. Our findings, thereby, not only affirm the significant potential of LLMs in navigating the complexities of financial markets but also suggest a promising trajectory for their further development and application in tasks demanding a high level of general intelligence.

5 Conclusion

In this work, we introduce a comprehensive financial benchmark the FinBen specifically designed for evaluating LLMs in the financial domain. This benchmark encompasses 35 diverse datasets from 23 tasks, organized into three spectrums of difficulty. Unlike previous benchmarks in the financial domain, the FinBen extends its evaluation to encompass a broad spectrum of tasks, including quantification, extraction, understanding, generation, forecasting. Notably, for the first time, it incorporates a direct trading task through an agent-based evaluation framework. Our comprehensive evaluation of 15 representative LLMs yields several key insights: 1) GPT-4 emerges as the top performer in tasks related to quantification, extraction, un-

derstanding, and trading, whereas Gemini leads in generation and forecasting tasks. 2) While existing LLMs demonstrate commendable performance on foundational tasks, their effectiveness on more cognitively demanding tasks and those requiring general intelligence appears constrained. 3) The findings highlight the capacity of LLMs to directly inform trading decisions, suggesting a promising avenue for future research. Moving forward, we aim to expand FinBen to encompass additional languages and a wider array of financial trading tasks, further broadening the benchmark’s applicability and utility in advancing the field of financial LLMs.

Limitations

Despite the groundbreaking efforts to benchmark LLMs in the financial domain through the FinBen, we acknowledge several inherent limitations that could impact the benchmark’s effectiveness and applicability:

Dataset Size Limitations: A primary challenge faced in the development of the FinBen is the restricted size of available datasets, a common issue in the niche field of open-source financial data. This limitation may affect the depth of the models’ financial understanding and their ability to generalize across the full spectrum of financial contexts.

Model Size Limitations: Due to computational resource constraints, our evaluation was limited to the LLaMA 70B model. This restriction potentially overlooks the capabilities and performance nuances that larger or differently architected models might demonstrate on FinBen’s comprehensive task suite. **Generalizability:** The tasks, particularly those involving trading and forecasting, are predominantly based on data from American markets and English-language texts. This focus may limit the benchmark’s applicability to global financial markets, where linguistic diversity and unique market dynamics play a crucial role. **Potential Negative Impacts:** While the FinBen aims to propel the field of financial language understanding forward, it is crucial to consider the potential for misuse, such as the propagation of financial misinformation or the exertion of unethical influence on markets. These risks underscore the importance of responsible usage and further safeguards in the deployment of LLMs trained or evaluated with the FinBen⁶.

⁶For a detailed ethical and legal statement concerning this work, please see Appendix.

Ethical Statement

The development and dissemination of the FinBen by the authors carry full responsibility for any potential violation of rights or arising legal issues. Diligent efforts have been undertaken to ensure the construction of the FinBen respects privacy and conforms to established ethical guidelines. The datasets compiled within FinBen are shared under the MIT license, with the expectation that users agree to adhere to its conditions.

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A Contributions

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B Other LLMs Performance

Table 5 presents other LLMs’ performance in the FinBen.

C Instructions

For detail instruction of each dataset, please see Table 6 and Table 7.

D Related Work

D.1 Financial Large Language Models

Recent years have seen a significant surge in research on finance-specific LLMs, expanding on the groundwork laid by general-purpose language models (Lee et al., 2024; Liu et al., 2023b;

Dataset	Metrics	Baichuan 7B	CodeLLaMA 7B	DISC- FinLLM
FPB	F1	0.36	0.34	0.29
	Acc	0.32	0.39	0.26
FiQA-SA	F1	0.17	0.66	0.32
TSA	RMSE \downarrow	1.07	0.43	0.32
Headlines	AvgF1	0.60	0.60	0.60
	F1	0.16	0.14	0.19
FOMC	Acc	0.25	0.27	0.28
FinArg-ACC	MicroF1	0.34	0.28	0.29
FinArg-ARC	MicroF1	0.17	0.25	0.29
MultiFin	MicroF1	0.06	0.21	0.29
M&A	MicroF1	0.02	0.54	0.29
MLESG	MicroF1	0.00	0.10	0.29
NER	EntityF1	0.00	0.07	0.12
FINER-ORD	EntityF1	0.00	0.00	0.00
FinRED	F1	0.00	0.00	0.00
SC	F1	0.57	0.85	0.00
CD	F1	0.00	0.00	0.00
FinQA	EmAcc	0.00	0.00	0.00
TATQA	EmAcc	0.00	0.00	0.00
ConvFinQA	EmAcc	0.00	0.00	0.00
FNXL	EntityF1	0.00	0.00	0.00
FSRL	EntityF1	0.00	0.00	0.00
EDTSUM	Rouge-1	0.22	0.10	0.22
	BertScore	0.54	0.67	0.61
	BartScore	-4.57	-3.62	-4.13
	Rouge-1	0.00	0.00	0.00
ECTSUM	BertScore	0.00	0.00	0.00
	BartScore	-5.18	-5.18	-5.18
BigData22	Acc	0.53	0.52	0.44
	MCC	-0.01	-0.01	-0.05
ACL18	Acc	0.50	0.51	0.50
	MCC	0.00	0.00	0.02
CIKM18	Acc	0.53	0.51	0.44
	MCC	-0.05	0.02	-0.03
German	F1	0.52	0.66	0.52
	MCC	0.00	0.00	0.00
Australian	F1	0.26	0.43	0.26
	MCC	0.00	0.00	0.00
LendingClub	F1	0.72	0.81	0.72
	MCC	-0.01	0.00	0.00
ccf	F1	0.97	0.00	0.66
	MCC	0.00	0.00	-0.04
ccfraud	F1	0.00	0.06	0.46
	MCC	0.00	0.00	0.02
polish	F1	0.91	0.47	0.92
	MCC	0.02	0.04	0.00
taiwan	F1	0.70	0.36	0.95
	MCC	-0.02	-0.03	0.00
portoseguro	F1	0.01	0.88	0.63
	MCC	0.01	-0.01	-0.02
travelinsurance	F1	0.03	0.02	0.00
	MCC	-0.09	0.00	0.00

Table 5: The zero-shot and few-shot performance of other LLMs on the FinBen.

Xie et al., 2023a; Zhang et al., 2024; Dai et al., 2024). Financial pre-trained language models (Fin-PLMs) like FinBERT (Araci, 2019; Yang et al., 2020b; Liu et al., 2020), derived from BERT, and FLANG (Shah et al., 2022), based on ELECTRA, have been developed using domain-specific data for enhanced performance in tasks like sentiment analysis and stock prediction. The open-source release of Meta AI’s LLaMA (Touvron et al., 2023) has fueled further innovation in Financial LLMs (FinLLMs), with models like FinMA (Xie et al., 2023b), InvestLM (Yang et al., 2023b), and Fin-GPT (Wang et al., 2023; Liu et al., 2023a) leveraging advanced tuning strategies (Zhang et al., 2023a)

for financial applications. BloombergGPT (Wu et al., 2023) stands out as a BLOOM-based, closed-source models tailored for the financial industry. Additionally, the Chinese financial sector has seen the emergence of models like XuanYuan 2.0 (Zhang et al., 2023c), integrating broad and specialized knowledge, FinBART (Hongyuan et al., 2023) for financial communication, and CFGPT (Li et al., 2023a), which includes a comprehensive dataset for targeted pre-training and fine-tuning.

D.2 Financial Evaluation Benchmarks

Financial evaluation benchmarks, such as the pioneering FLUE (Shah et al., 2022), have been in-

troduced to measure model performance in the financial sector, covering five key NLP tasks: financial sentiment analysis (Shah et al., 2022), news headline classification (Sinha and Khandait, 2020), named entity recognition (NER) (Salinas Alvarado et al., 2015), structure boundary detection and question answering (QA) (Maia et al., 2018b). Building upon FLUE, FLARE (Xie et al., 2023b) added the evaluation of time-series processing capabilities, i.e., forecasting stock price movements. In addition, in Chinese financial benchmarks, there are more recently released chinese datasets like CFBenchmark (Lei et al., 2023), DISC-FINSFT (Chen et al., 2023b), and CGCE (Zhang et al., 2023b). However, these benchmarks have a limited scope and have not yet to address more complex financial NLP tasks such as event detection (Zhou et al., 2021), and realistic financial tasks, despite the fact that there were previous efforts on stock trading (Liu et al., 2022; Han et al., 2023a,b).

E Trading Accumulative Returns

Table 8 and below Figures show detail trading performance,

Figure 3: Accumulative Returns of LLM Trading Strategies on AAPL

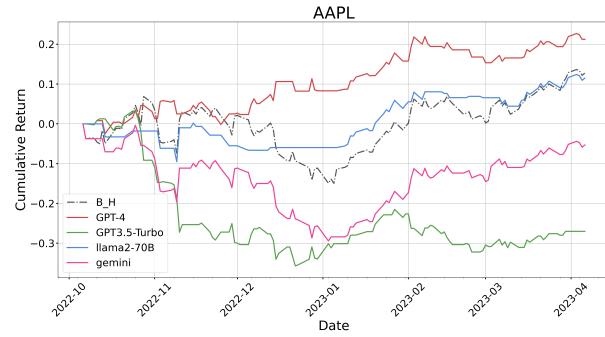


Figure 4: Accumulative Returns of LLM Trading Strategies on AMZN

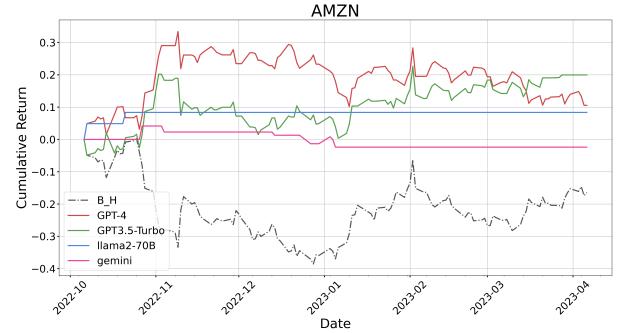


Figure 5: Accumulative Returns of LLM Trading Strategies on COIN

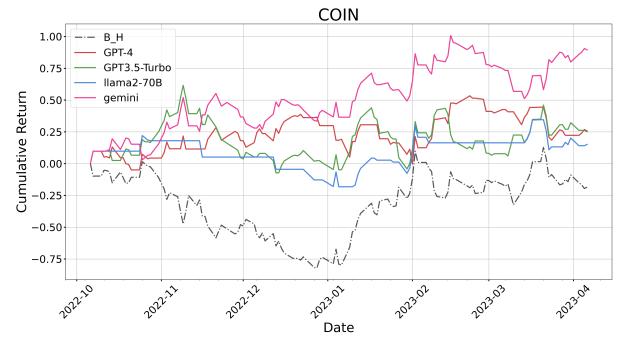


Figure 6: Accumulative Returns of LLM Trading Strategies on GOOG

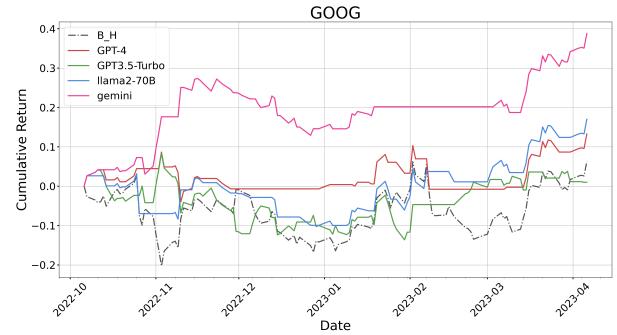


Figure 7: Accumulative Returns of LLM Trading Strategies on MSFT

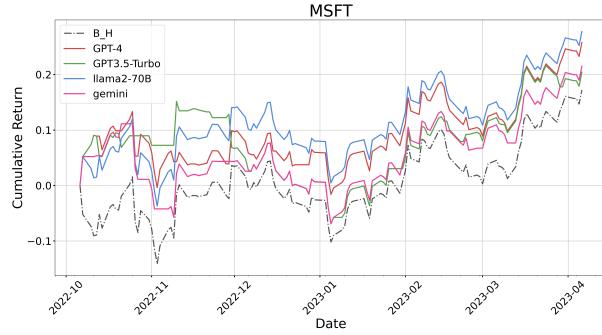


Figure 8: Accumulative Returns of LLM Trading Strategies on NFLX

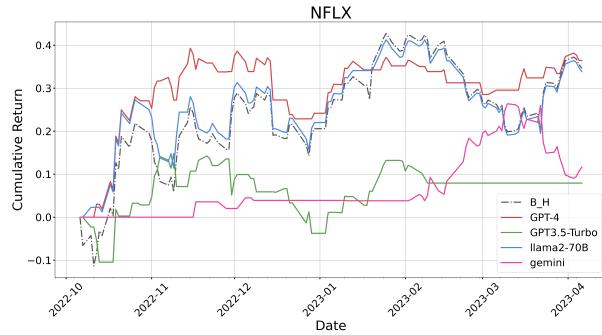


Figure 10: Accumulative Returns of LLM Trading Strategies on TSLA

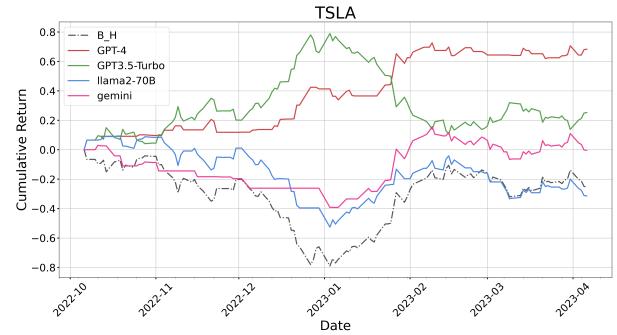
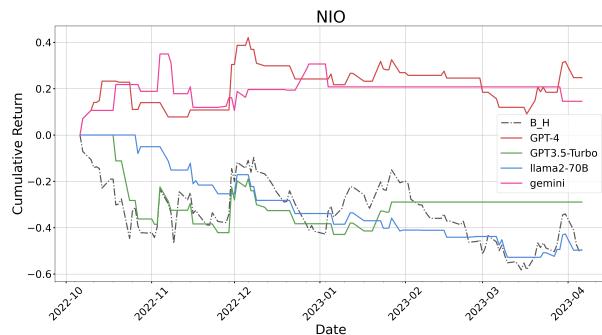


Figure 9: Accumulative Returns of LLM Trading Strategies on NIO



Data	Prompt
FPB	<p>"Analyze the sentiment of this statement extracted from a financial news article. Provide your answer as either negative, positive or neutral. For instance, 'The company's stocks plummeted following the scandal.' would be classified as negative."</p>
FiQA-SA	<p>"What is the sentiment of the following financial {category}: Positive, Negative, or Neutral?"</p>
Headlines	<p>"Consider whether the headline mentions the price of gold. Is there a Price or Not in the gold commodity market indicated in the news headline? Please answer Yes or No."</p>
NER	<p>"In the sentences extracted from financial agreements in U.S. SEC filings, identify the named entities that represent person ('PER'), an organization ('ORG'), or a location ('LOC'). The required answer format is: 'entity name, entity type'. For instance, in 'Elon Musk, CEO of SpaceX, announced the launch from Cape Canaveral.', the entities would be: 'Elon Musk, PER; SpaceX, ORG; Cape Canaveral, LOC'"</p>
FiNER-ORD	<p>"In the list of tokens, identify {tid} each accordingly. If the entity spans multiple tokens, use the prefix B-PER, B-LOC, or B-ORG for the first token, and I-PER, I-LOC, or I-ORG for the subsequent tokens of that entity. The beginning of each separate entity should always be labeled with a B-PER, B-LOC, or B-ORG prefix. If the token does not fit into any of the three named categories, or is not a named entity, label it as 'O'."</p>
FinQA	<p>"Given the financial data and expert analysis, please answer this question:"</p>
ConvFinQA	<p>"In the context of this series of interconnected finance-related queries and the additional information provided by the pretext, table data, and post text from a company's financial filings, please provide a response to the final question. This may require extracting information from the context and performing mathematical calculations. Please take into account the information provided in the preceding questions and their answers when formulating your response:"</p>
BigData22	<p>"Contemplate the data and tweets to guess whether the closing price of {tid} will surge or decline at {point}. Please declare with either Rise or Fall."</p>
ACL18	<p>"Scrutinize the data and tweets to envisage if the closing price of {tid} will swell or contract at {point}. Respond with either Rise or Fall."</p>
CIKM18	<p>"Reflect on the provided data and tweets to anticipate if the closing price of {tid} is going to increase or decrease at {point}. Respond with either Rise or Fall."</p>
ECTSum	<p>"Given the following article, please produce a list of 0 and 1, each separated by ' ' to indicate which sentences should be included in the final summary. The article's sentences have been split by ' '. Please mark each sentence with 1 if it should be included in the summary and 0 if it should not."</p>
EDTSum	<p>"You are given a text that consists of multiple sentences. Your task is to perform abstractive summarization on this text. Use your understanding of the content to express the main ideas and crucial details in a shorter, coherent, and natural sounding text."</p>
German	<p>"Assess the creditworthiness of a customer using the following table attributes for financial status. Respond with either 'good' or 'bad'. And the table attributes including 13 categorical attributes and 7 numerical attributes are as follows:"</p>
Australian	<p>"Assess the creditworthiness of a customer using the following table attributes for financial status. Respond with either 'good' or 'bad'. And the table attributes including 13 categorical attributes and 7 numerical attributes and values have been changed to meaningless symbols to protect confidentiality of the data. :"</p>
FOMC	<p>"Examine the excerpt from a central bank's release below. Classify it as HAWKISH if it advocates for a tightening of monetary policy, DOVISH if it suggests an easing of monetary policy, or NEUTRAL if the stance is unbiased. Your response should return only HAWKISH, DOVISH, or NEUTRAL."</p>
TSA	<p>"Given the following financial text, return a sentiment score for Ashead as a floating-point number ranging from -1 (indicating a very negative or bearish sentiment) to 1 (indicating a very positive or bullish sentiment), with 0 designating neutral sentiment. Return only the numerical score first, follow it with a brief reasoning behind your score."</p>
FinArg - ACC	<p>"Analyze sentences from earnings conference calls and identify their argumentative function. Each sentence is either a premise, offering evidence or reasoning, or a claim, asserting a conclusion or viewpoint. Return only premise or claim."</p>
FinArg - ARC	<p>"In this task, you are given a pair of sentences. Your objective is to ascertain the type of argumentative relation between these two sentences. The relation could either be 'NoRelation', indicating no discernible relation between the sentences, 'Support', indicating that the first sentence supports the second, or 'Attack', indicating that the first sentence disputes or contradicts the second. Return only one of the three classifications: 'norelation', 'support', or 'attack'."</p>
MultiFin	<p>"In this task, you're working with English headlines from the MULTIFIN dataset. This dataset is made up of real-world article headlines from a large accounting firm's websites. Your objective is to categorize each headline according to its primary topic. The potential categories are {category}. Your response should only include the category that best fits the headline."</p>
MA	<p>"In this task, you will be given Mergers and Acquisitions news articles or tweets. Your task is to classify each article or tweet based on whether the mentioned deal was completed or remained a rumour. Your response should be a single word - either 'complete' or 'rumour' - representing the outcome of the deal mentioned in the provided text."</p>
MLESQ	<p>"You're given English news articles related to Environmental, Social, and Corporate Governance (ESG) issues. Your task is to classify each article based on the ESG issue it pertains to, according to the MSCI ESG rating guidelines. The ESG issues include {category}. Your output should be the most relevant ESG issue label, followed by a brief rationale based on the article content."</p>

Table 6: The prompt of each dataset.

Data	Prompt
FinRED	<p>"Given the following sentence, identify the head, tail, and relation of each triplet present in the sentence. The relations you should be looking for are {category}. If a relation exists between two entities, provide your answer in the format {category}. If there are multiple triplets in a sentence, provide each one on a new line."</p>
SC	<p>"In this task, you are provided with sentences extracted from financial news and SEC data. Your goal is to classify each sentence into either 'causal' or 'noise' based on whether or not it indicates a causal relationship between financial events. Please return only the category 'causal' or 'noise'."</p>
CD	<p>"Your job in this task is to perform sequence labeling on a provided text section, marking the chunks that represent the cause of an event and the effects that result from it. For each token in the text, assign a label to indicate its role in representing cause or effect. The labels you should use are 'B-CAUSE', 'I-CAUSE', 'B-EFFECT', 'I-EFFECT', and 'O'. A 'B-' prefix is used to denote the beginning of a cause or effect sequence, while an 'I-' prefix is used for continuation of a cause or effect sequence. If a token is not part of either a cause or effect sequence, label it as 'O'. Provide your answer as a sequence of 'token:label' pairs, with each pair on a new line."</p>
TATQA	<p>"Please answer the given financial question based on the context. Context: {context} Question: What is the amount of total sales in 2019?"</p>
FNXL	<p>"In the task of Financial Numeric Extreme Labelling (FNXL), your job is to identify and label the semantic role of each token in a sentence. The labels can include {category}"</p>
FSRL	<p>"In the task of Textual Analogy Parsing (TAP), your job is to identify and label the semantic role of each token in a sentence. The labels can include {category}."</p>
LendingClub	<p>"Assess the client's loan status based on the following loan records from Lending Club. Respond with only 'good' or 'bad', and do not provide any additional information. For instance, 'The client has a stable income, no previous debts, and owns a property.' should be classified as 'good'."</p>
ccf	<p>"Detect the credit card fraud using the following financial table attributes. Respond with only 'yes' or 'no', and do not provide any additional information. Therein, the data contains 28 numerical input variables V1, V2, ..., and V28 which are the result of a PCA transformation and 1 input variable Amount which has not been transformed with PCA. The feature 'Amount' is the transaction Amount, this feature can be used for example-dependant cost-sensitive learning. For instance, 'The client has attributes:{category}'"</p>
ccfraud	<p>"Detect the credit card fraud with the following financial profile. Respond with only 'good' or 'bad', and do not provide any additional information. For instance, 'The client is a female, the state number is 25, the number of cards is 1, the credit balance is 7000, the number of transactions is 16, the number of international transactions is 0, the credit limit is 6.' should be classified as 'good'."</p>
polish	<p>"Predict whether the company will face bankruptcy based on the financial profile attributes provided in the following text. Respond with only 'no' or 'yes', and do not provide any additional information."</p>
taiwan	<p>"Predict whether the company will face bankruptcy based on the financial profile attributes provided in the following text. Respond with only 'no' or 'yes', and do not provide any additional information."</p>
Porto-Seguro	<p>"Identify whether or not to files a claim for the auto insurance policy holder using the following table attributes about individual financial profile. Respond with only 'yes' or 'no', and do not provide any additional information. And the table attributes that belong to similar groupings are tagged as such in the feature names (e.g., ind, reg, car, calc). In addition, feature names include the postfix bin to indicate binary features and cat to indicate categorical features. Features without these designations are either continuous or ordinal. Values of -1 indicate that the feature was missing from the observation."</p>
travelinsurance	<p>"Identify the claim status of insurance companies using the following table attributes for travel insurance status. Respond with only 'yes' or 'no', and do not provide any additional information. And the table attributes including 5 categorical attributes and 4 numerical attributes are as follows:{category}"</p>
fintrade	<p>"Given the information, can you make an investment decision? Just summarize the reason of the decision. please consider only the available short-term information, the mid-term information, the long-term information, the reflection-term information. please consider the momentum of the historical stock price. When cumulative return is positive or zero, you are a risk-seeking investor. But when cumulative return is negative, you are a risk-averse investor. please consider how much share of the stock the investor holds now. You should provide exactly one of the following investment decisions: buy or sell. When it is really hard to make a 'buy'-or-'sell' decision, you could go with 'hold' option. You also need to provide the id of the information to support your decision. {investment_info} {grcomplete_json_suffix_v2} Your output should strictly conforms the following json format without any additional contents: {"investment_decision": string, "summary_reason": string, "short_memory_index": number, "middle_memory_index": number, "long_memory_index": number, "reflection_memory_index": number}"</p>

Table 7: The example prompt for each dataset. FiQA-SA has two types of text, including news headlines and tweets. We will fill the detailed text type into **{category}** for each data sample. For stock movement prediction data such as BigData22, we will fill **{tid}** and **{point}** with the detailed stock name and time from each data sample.

Ticker	Model	CR (%)	SR	DV (%)	AV (%)	MD (%)
TSLA	Buy and Hold	-25.2137	-0.7203	4.4099	70.0043	57.6765
	GPT-4	68.3089	2.8899	2.9780	47.2739	10.7996
	GPT3.5-Turbo	25.2137	0.7203	4.4099	70.0043	51.3186
	llama2-70B	-31.4144	-1.0412	3.8014	60.3450	48.6173
	gemini	-0.3790	-0.0148	3.2271	51.2280	35.6707
NFLX	Buy and Hold	34.6251	1.3696	3.1852	50.5634	20.9263
	GPT-4	36.4485	2.0088	2.2860	36.2894	15.8495
	GPT3.5-Turbo	7.9337	0.4610	2.1680	34.4160	17.9578
	llama2-70B	33.8460	1.4741	2.8928	45.9216	20.3910
	gemini	11.6298	1.0073	1.4546	23.0906	16.5106
AMZN	Buy and Hold	-16.4428	-0.7448	2.7812	44.1508	33.8847
	GPT-4	10.5539	0.4923	2.7012	42.8802	22.9294
	GPT3.5-Turbo	19.9636	0.9611	2.6171	41.5454	19.2191
	llama2-70B	8.3595	1.9715	0.5342	8.4804	0.0000
	gemini	-2.3838	-0.5321	0.5645	8.9605	6.4291
MSFT	Buy and Hold	17.2161	0.9709	2.2339	35.4623	15.0097
	GPT-4	25.7826	1.5818	2.0535	32.5989	14.9889
	GPT3.5-Turbo	20.4179	1.3600	1.8915	30.0259	20.3211
	llama2-70B	27.7664	1.5708	2.2270	35.3524	15.0097
	gemini	21.5082	1.3701	1.9777	31.3957	17.5051
COIN	Buy and Hold	-18.4787	-0.3369	6.9098	109.6904	60.5084
	GPT-4	25.7631	0.5619	5.7761	91.6934	35.7526
	GPT3.5-Turbo	25.1141	0.4772	6.6312	105.2669	53.9628
	llama2-70B	15.1836	0.4395	4.3528	69.0979	35.3249
	gemini	89.4782	1.7648	6.3879	101.4048	40.3246
AAPL	Buy and Hold	12.7371	0.7759	2.0682	32.8323	20.6591
	GPT-4	21.2334	1.9274	1.3879	22.0328	6.4237
	GPT3.5-Turbo	-27.0152	-1.9193	1.7734	28.1517	33.1619
	llama2-70B	11.4855	1.1550	1.2529	19.8885	9.2776
	gemini	-5.3097	-0.3637	1.8392	29.1971	26.6450
GOOG	Buy and Hold	6.3107	0.3081	2.5806	40.9660	21.1907
	GPT-4	13.2811	0.9667	1.7308	27.4762	12.2209
	GPT3.5-Turbo	0.9990	0.0614	2.0490	32.5265	20.9316
	llama2-70B	17.0030	1.1057	1.9374	30.7546	13.2088
	gemini	38.7956	3.0341	1.6110	25.5732	13.7311
NIO	Buy and Hold	-49.4263	-1.1895	5.2351	83.1048	52.2083
	GPT-4	24.7684	0.9438	3.3063	52.4861	29.3384
	GPT3.5-Turbo	-28.9321	-1.0096	3.6105	57.3149	39.5907
	llama2-70B	-49.6947	-2.7868	2.2466	35.6639	42.6221
	gemini	14.5673	0.6212	2.9543	46.8977	23.0110

Table 8: The overall trading performance comparison for different LLMs across various stocks. The results include large LLMs only ($\geq 70B$), as models with smaller contexts have difficulty understanding the instructions and producing a static strategy of holding.