FinGPT: Open-Source Financial Large Language Models

4th ACM International Conference on AI in Finance
ICAIF 2023 Tutorial

FINGPT

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AI4Finance

Agenda

Why Open-Source FinGPT?

Data Perspective:

- **Witnessing a shifting trend towards democratizing Internet-scale financial data**
- **Promoting quality of financial data in a collaborative way, crucial for accurate modelling**
- **Sharing the understandings of financial data, crucial for events**

Model Perspective:

- **Directly applying general-purpose LLMs to finance may lead to sub-optimal or even contradictory results.**
- **Example: A layoff, negative to the public, may result in market going up (positive to investors)**

Wall Street cannot open-source LLMs nor open APIs, due to FinTech institutes' internal regulations and policies.

Open-Source: Reducing Costs and Enhancing Tech Accessibility

Lowering Development Costs:

- **Resource and Knowledge Sharing:** facilitate the sharing of resources and expertise, significantly cutting down the costs of developing models from scratch.
- **Community-Driven Innovation:** Harnessing the power of community-driven development speeds up innovation and reduces the research and development expenses for individual organizations.

Minimizing Long-Term Operational Costs:

- **Strong Community Support:** backed by robust communities, ensuring efficient maintenance and updates, thereby reducing long-term operational costs.
- **Quick Issue Resolution:** Community contributions lead to rapid bug fixes and feature updates, processes that could be more time-consuming and costly in proprietary models.

Lowering the Barrier to Entry:

- **Ideal for SMEs and Startups:** Utilizing open-source financial large models can minimize initial technological investments for small and medium enterprises and startups, facilitating quicker market entry.
- **Cost-Effective Solution:** Open-source models provide a cost-effective solution, avoiding hefty initial investments and allowing businesses to allocate resources more strategically.

Estimating the Cost of Training Domain-Specific LLMs

Cost Estimation for GPT-3 Training & BloombergGPT

- **GPT-3 (175B) Estimated Cost:** According to OneFlow, training GPT-3 once costs approximately **$1.398 million**.
- **BloombergGPT (50B) Estimated Cost:** 512 GPUs for 53 days, 24 hours a day = 651,264 GPU hours. With $4.1 per hour for an A100 GPU, the total cost is approximately **$2,670,182.40**.

Scaling Down: Training a 17.5B Domain-Specific Model

- **Between $140k - $890k** based on the above estimated only for the GPU cost per training
- At least **one million dollar cost** to train a domain-specific LLM (GPU + Data + Manpower)

	GPT-3 (OpenAI)	Gopher (Google DeepMind)	MT-NLG (Microsoft/Nvidia)	PaLM (Google Research)
Model Parameters	175B	280B	530B	540B
FLOPs/Token/Model Parameter			6	
TPUs/Machine			4	
Peak FLOPS/TPU			275T	
FLOPS Utilization			46.20%	
Cost/Machine/Hour(1-year reserved)			$8.12	
Seconds/Hour			3600	
Training Cost/1000 Tokens	$0.0047	$0.0075	$0.0141	$0.0144
Train Tokens	300B	300B	270B	780B
Training Cost	$1,398,072	$2,236,915	$3,810,744	$11,216,529

Cost-Effective Strategies: Training smaller models can significantly reduce costs while maintaining efficacy.

For FinGPT: We use LoRA + open-source LLMs

- **Example**: Llama2-14B + LoRA cost about $65.6 (One A100 16 hours)
- **$1,000,000 -> $65.6**

Goals of FinGPT

Our Goals: FINGPT

- **Real-time data curation pipeline to democratize data for FinLLMs**
- **Lightweight adaptation to democratize the FinLLMs model for both individuals and institutes (frequent updates)**
- **Instruction tuning benchmark for open-source LLMs in Financial tasks**
- **Demonstrate various financial applications**

Challenges of Handling Financial Data

High Temporal Sensitivity:

- **Financial data are characterized by their time-sensitive nature**
- **Market-moving news provides a narrow window for investors to capture alpha signal**

High Dynamism:

- **Constant state of flux due to deluging of news, social media updates, etc.**
- **Retraining LLMs frequently is expensive and impractical**

Low Signal-to-Noise Ratio (SNR):

- **Financial data often contain a significant amount of irrelevant or noisy data**
- **Extracting valuable insights is labor-intensive**

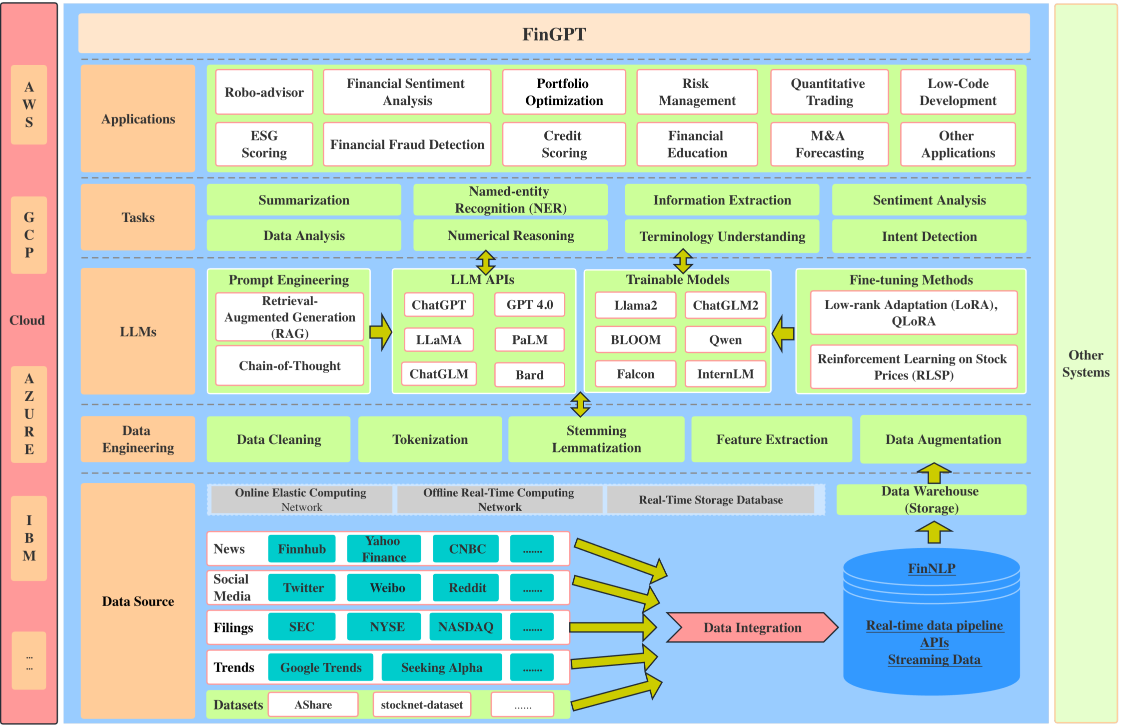
Key Features of FinGPT

Which data to train? Democratizing Internet-scale Financial Data & Data-centric design of data curation pipeline

How to train? Instruction Tuning Paradigm & Retrieval Augmented Generation (RAG)

How to train efficiently? Low-rank Adaptation (LoRA, QLoRA).

FinGPT Framework



An End-to-End Framework

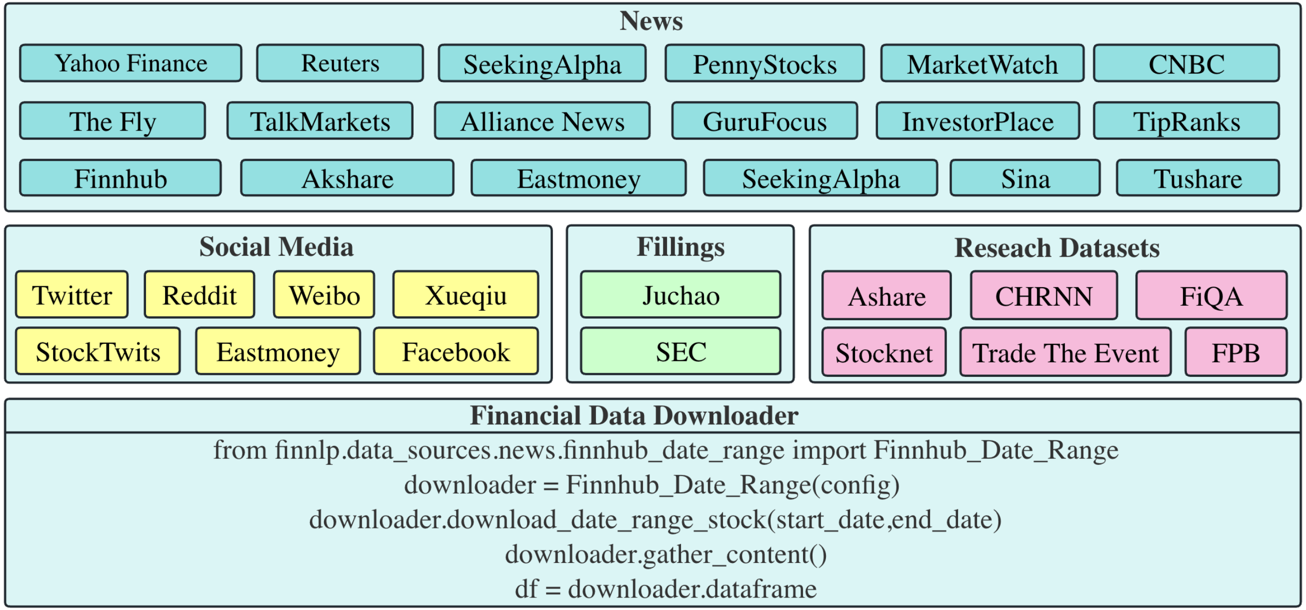
- **Applications layer**: Showcasing practical applications and demos, this layer highlights the potential capability of FinGPT in the finance sector
- **Tasks Layer**: executing fundamental tasks. These tasks serve as the benchmarks for performance evaluations and cross-comparisons in the realm of FinLLMs.
- **LLMs Layer**: takes care of the highly dynamic nature of financial data, ensuring the model’s relevance and accuracy.
- **Data Engineering Layer**: tackles the inherent challenges of high temporal sensitivity and low signal-to-noise ratio in financial data
- **Data Source Layer:** Assures comprehensive market coverage, addressing the temporal sensitivity of financial data through real-time information capture

FinGPT-FinNLP: Data-Centric Design of Data Curation Pipeline

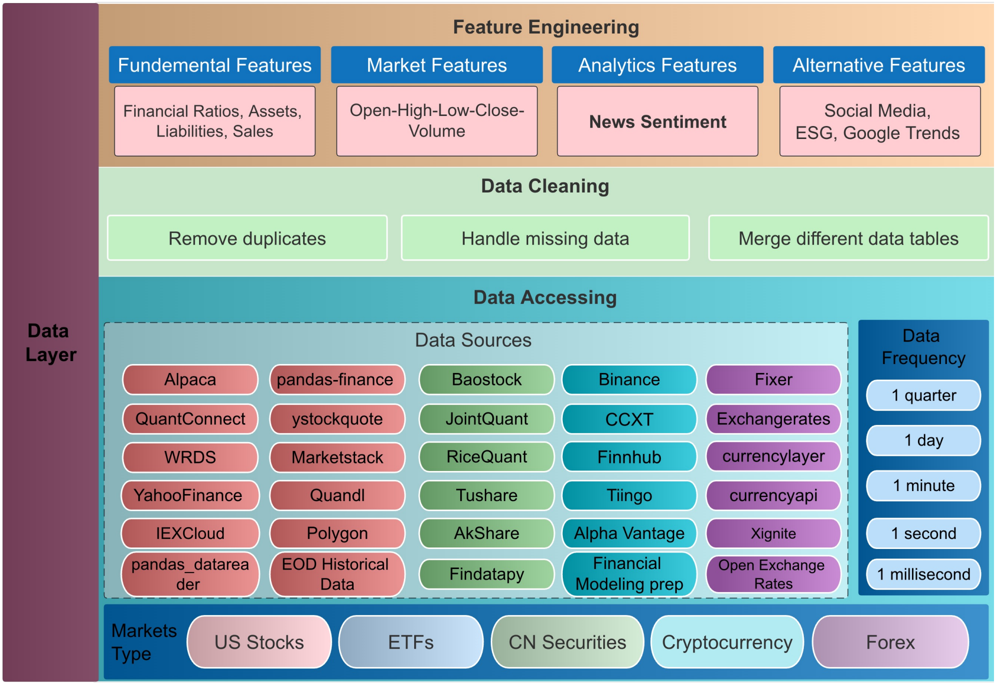
Challenges: Diverse Data Sources, Data Quality Issues, High Time-Validity

Our Solution: Data Curation Pipeline

Contributions: An open-source and data-centric framework, automating the collection and curation of real-time financial data from the Internet, with 34 financial data sources and the corresponding code.



FinGPT-FinNLP: Data-Centric Design of Data Curation Pipeline



- US

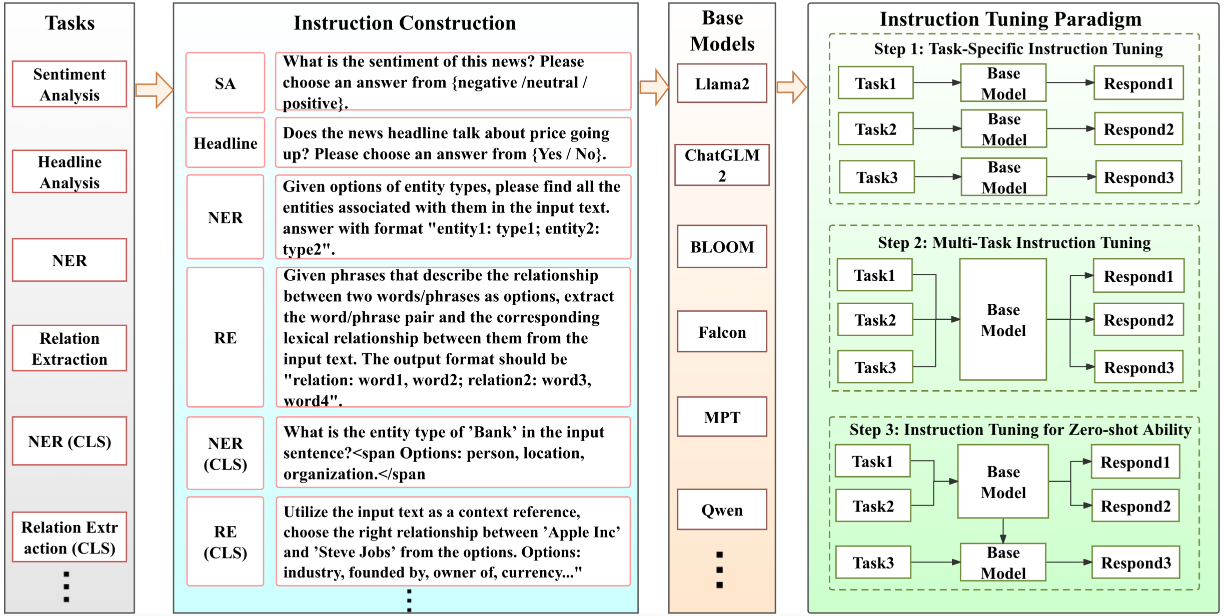
```python
# Finnhub (Yahoo Finance, Reuters, SeekingAlpha, CNBC...)
from finnlp.data_sources.news.finnhub_date_range import Finnhub_Date_Range

start_date = "2023-01-01"
end_date = "2023-01-03"
config = {
    "use_proxy": "us_free",    # use proxies to prvent ip blocking
    "max_retry": 5,
    "proxy_pages": 5,
    "token": "YOUR_FINNHUB_TOKEN"  # Available at https://finnhub.io/dashboard
}

news_downloader = Finnhub_Date_Range(config)                     # init
news_downloader.download_date_range_stock(start_date,end_date)   # Download headers
news_downloader.gather_content()                                 # Download contents
df = news_downloader.dataframe
selected_columns = ["headline", "content"]
df[selected_columns].head(10)

--------------------

#       headline                                                content
# 0     My 26-Stock $349k Portfolio Gets A Nice Petrob...        Home\nInvesting Strategy\nPortfo
# 1     Apple’s Market Cap Slides Below $2 Trillion fo...        Error
# 2     US STOCKS-Wall St starts the year with a dip; ...        (For a Reuters live blog on U.S.
# 3     Buy 4 January Dogs Of The Dow, Watch 4 More      Home\nDividends\nDividend Quick Picks\nE
# 4     Apple's stock market value falls below $2 tril...        Jan 3 (Reuters) - Apple Inc's \n
# 5     CORRECTED-UPDATE 1-Apple's stock market value ...        Jan 3 (Reuters) - Apple Inc's \n
# 6     Apple Stock Falls Amid Report Of Product Order...        Apple stock got off to a slow st
# 7     US STOCKS-Wall St starts the year with a dip; ...        Summary\nCompanies\nTesla shares
# 8     More than $1 trillion wiped off value of Apple...        apple store\nMore than $1 trilli
# 9     McLean's Iridium inks agreement to put its sat...        The company hasn't named its par
```

FinGPT-Benchmark: Instruction Tuning Paradigm for Financial Data

Current limitation: Focused on Single-Task Instruction Tuning

Our Solution: Expanding Instruction Tuning Paradigm on **Task-Specific, Multi-Task, and Zero-Shot Tuning**

Contributions: An Instruction Tuning paradigm, specifically **tailored for open-source Large Language Models (LLMs) in the financial sector**. Promotion of openness and reproducibility.



FinGPT-Benchmark: Single-Task Tuning

Data: https://huggingface.co/datasets/FinGPT/fingpt-sentiment-train

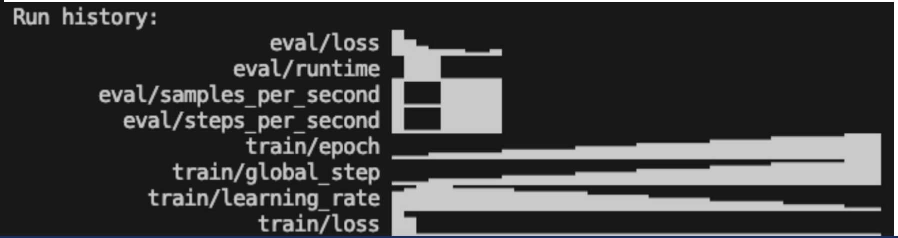
Model: https://huggingface.co/FinGPT/fingpt-sentiment_internlm-20b_lora

Code: https://github.com/AI4Finance-Foundation/FinGPT/blob/master/fingpt/FinGPT_Benchmark/train_lora.py

Model Name	Base-Model	FPB	FiQA	TFNS	NWGI
InternLM-20b-1gpu_8epochs_lr2e4_bs8_fp16	internlm-20b	0.878	**0.892**	**0.904**	**0.646**
FinGPT v3.3	llama2-13b	**0.882**	0.874	0.903	0.643
FinGPT v3.2	llama2-7b	0.850	0.860	0.894	0.636
FinGPT v3.1	chatglm2-6b	0.855	0.850	0.875	0.642

```
Run summary:
                eval/loss 0.00395
             eval/runtime 428.8234
  eval/samples_per_second 35.807
    eval/steps_per_second 4.477
              train/epoch 7.99
        train/global_step 7672
      train/learning_rate 0.0
               train/loss 0.0021
        train/total_flos 5.522384844073468e+18
        train/train_loss 0.05217
     train/train_runtime 49268.0316
```

We used a newly release model **InternLM-20B to fine-tune the sentiment analysis task** and achieved SOTA



FinGPT-Benchmark: Multi-Task Tuning

==== **Financial Sentiment Analysis** ====

Instruction: What is the sentiment of this news? Please choose an answer from {negative/neutral/positive}.
Input: Glaxo's ViiV Healthcare Signs China Manufacturing Deal With Desano
Answer: positive

==== **Financial Relation Extraction** ====

Instruction: Given phrases that describe the relationship between two words/phrases as options, extract the word/ph
rase pair and the corresponding lexical relationship between them from the input text. The output format should be "
relation1: word1, word2; relation2: word3, word4". Options: product/material produced, manufacturer, distributed b
y, industry, position held, original broadcaster, owned by, founded by, distribution format, headquarters location, sto
ck exchange, currency, parent organization, chief executive officer, director/manager, owner of, operator, member o
f, employer, chairperson, platform, subsidiary, legal form, publisher, developer, brand, business division, location of
formation, creator.
Input: Wednesday, July 8, 2015 10:30AM IST (5:00AM GMT) Rimini Street Comment on Oracle Litigation Las V
egas, United States Rimini Street, Inc., the leading independent provider of enterprise software support for SAP AG'
s (NYSE:SAP) Business Suite and BusinessObjects software and Oracle Corporation's (NYSE:ORCL) Siebel , Peop
leSoft , JD Edwards , E-Business Suite , Oracle Database , Hyperion and Oracle Retail software, today issued a state
ment on the Oracle litigation.
**Answer: product_or_material_produced: PeopleSoft, software; parent_organization: Siebel, Oracle Corpora
tion; industry: Oracle Corporation, software; product_or_material_produced: Oracle Corporation, software;
product_or_material_produced: Oracle Corporation, software**

==== **Financial Headline Classification** ====

Instruction: Does the news headline talk about price in the past? Please choose an answer from {Yes/No}.
Input: april gold down 20 cents to settle at $1,116.10/oz
Answer: Yes

==== **Financial Named Entity Recognition** ====

Instruction: Please extract entities and their types from the input sentence, entity types should be chosen from {pers
on/organization/location}.
Input: Subject to the terms and conditions of this Agreement , Bank agrees to lend to Borrower , from time to time p
rior to the Commitment Termination Date , equipment advances (each an " Equipment Advance " and collectively t
he " Equipment Advances ").
Answer: Bank is an organization, Borrower is a person.

Challenges: Task Interference & Hallucination

Task reformulation: We implement a strategy of task reformulation, we reform the instructions of all tasks into classification format

Instruction: [prompt] Input: [input] Answer: [output]

Instruction: [prompt] Options: [options] Input: [input] Answer: [output]

FinGPT-Benchmark: Multi-Task Tuning

Phase	Dataset	Llama2	Falcon	MPT	BLOOM	ChatGLM2	Qwen
Task-Specific	FPB	0.863	0.846	**0.872**	0.810	0.850	0.854
	FiQA	**0.871**	0.840	0.863	0.771	0.864	0.867
	TFNS	0.896	0.893	**0.907**	0.840	0.859	0.883
	NWGI	**0.649**	0.636	0.640	0.573	0.619	0.638
	Avg	0.820	0.804	**0.821**	0.748	0.798	0.811
Multi-Task	FPB	0.861↓	0.845↓	0.870↓	0.766↓	0.836↓	**0.873↑**
	FiQA	0.825↓	**0.881↑**	0.863-	0.737↓	0.822↓	0.870↑
	TFNS	0.890↓	0.880↓	**0.892↓**	0.789↓	0.858↓	0.890↑
	NWGI	0.652↑	0.647↑	0.651↑	0.530↓	0.618↓	**0.653↑**
	Avg	0.807	0.813	0.819	0.701	0.784	**0.822**
Performance Gain		-1.3%	+0.7%	-0.2%	-4.7%	-1.4%	**+1.1%**

Table 3: Sentiment Analysis Instruction Tuning Results: The table reports detailed F1-scores for base models tuned during task-specific and multi-task phases on each sentiment analysis dataset. Arrows (↑↓) denote the influence of multi-task settings on Instruction Tuning results, with performance gains calculated between phases based on average F1 scores across all datasets.

Task	Phase	Llama2	Falcon	MPT	BLOOM	ChatGLM2	Qwen
NER	Task-Specific	0.637	0.619	0.615	**0.729**	0.645	0.679
	Multi-Task	0.678↑	0.600↓	0.682↑	**0.709↓**	0.629↓	0.666↓
	Performance Gain	+4.1%	-1.9%	**+6.7%**	-2.0%	-1.6%	-1.3%
HC	Task-Specific	**0.942**	0.940	0.938	0.930	**0.942**	0.936
	Multi-Task	**0.938↓**	0.932↓	0.928↓	0.898↓	0.932↓	0.922↓
	Performance Gain	**-0.4%**	-0.8%	-1.0%	-3.2%	-1.0%	-1.4%
RE	Task-Specific	0.395	**0.428**	0.309	0.425	0.340	0.371
	Multi-Task	0.674↑	0.576↑	0.667↑	**0.697↑**	0.557↑	0.640↑
	Performance Gain	+27.2%	+14.8%	**+35.8%**	+27.2%	+21.7%	26.9%

Table 4: Multi-Task Instruction Tuning Summary: The table reports entity-level F1 scores for NER, relation-only F1 for RE, and standard classification F1 for HC. It includes both task-specific and multi-task models for comparison. Arrows (↑↓) signify performance gains from multi-task settings, calculated in each task's last row.

For Single-Task job:

- No single model dominates across all tasks.
- The effectiveness of models varies depending on the specific task.

For Multi-Task job:

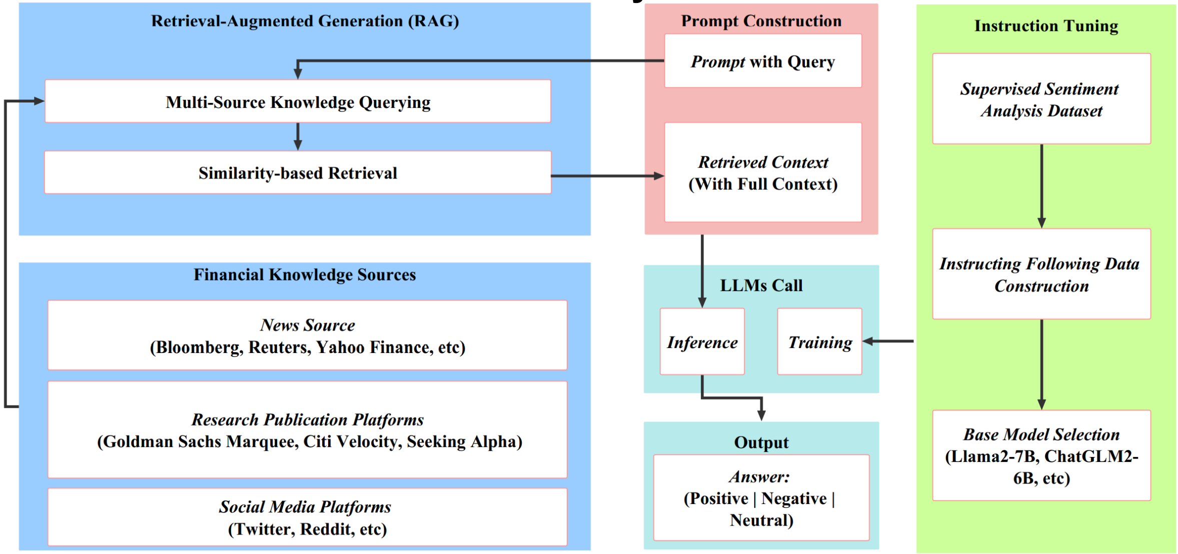
- Some models that perform exceptionally well in single-task jobs may not excel in multi-task job scenarios.
- The performance of models can be different in multi-task settings compared to single-task settings.

FinGPT-RAG: Retrieval Augmented Generation Framework

Current limitation: most financial news lack of adequate context information

Our Solution: use **instruction tuning + retrieval augmented generation (RAG)** to fill up contexts

Contributions: Integrate external knowledge retrieval to **enhances information depth and context**. Utilizing speci instruction tuning processes, **the LLMs respond more accurately** to financial sentiment analysis tasks, achieving performance improvements of **15% to 48% in accuracy and F1 scores**



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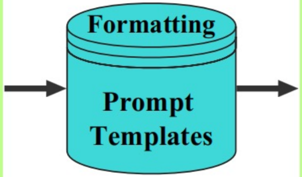
FinGPT-RAG: Retrieval Augmented Generation Framework

Format Instruction-following Dataset

Sentence	Label
Consumer credit $18.9BN, Exp. $16BN, Last $9.6BN.	2
Estee Lauder Q2 adj. EPS $2.11; FactSet consensus $1.90.	1
The situation of coated magazine printing paper will continue to be weak.	0



Prompt	Response
Human: Determine the sentiment of the financial news as negative, neutral or positive: Consumer credit $18.9BN, Exp. $16BN, Last $9.6BN. Assistant:	Positive
Human: Classify the tone of the financial news as positive, neutral, or negative: Estee Lauder Q2 adj. EPS $2.11; FactSet consensus $1.90. Assistant:	Neutral
Human: Analyze the sentiment of the financial news as neutral, positive, or negative: The situation of coated magazine printing paper will continue to be weak. Assistant:	Negative

Training Objective

$$\mathcal{L}_{\text{CausalLM}} = -\sum_{t=1}^{T} \log P(w_t | w_1, w_2, \ldots, w_{t-1}; \theta)$$

$$\nabla_\theta \mathcal{L}_{\text{CausalLM}} = -\sum_{t=1}^{T} \frac{\partial \log P(w_t | w_1, w_2, \ldots, w_{t-1}; \theta)}{\partial \theta}$$

FinGPT-RAG: Experiment Settings

Dataset

Training Datasets		
Twitter Financial News - training[1]	9540	This dataset 2 is a corpus of news tweets that pertain to the financial sector.
FiQA[2]	961	
Testing Datasets		
Twitter Financial News - val[1]	2388	This dataset is the validation split of the Twitter Financial News.
Financial PhraseBank[3]	4840	This dataset consists of financial news articles from LexisNexis, annotated for quality by 16 finance and business experts.

Hyperparameters

Parameters	Value
Learning rate	1e-5
Weight decay	0.1
Batch size	32
Training epochs	10
LR scheduler	CosineAnnealing
Num warmup steps	0
Max token length	512
GPUs	8*A100 (40G)

1: https://huggingface.co/datasets/zeroshot/twitter-financial-news- sentiment
2: https://huggingface.co/datasets/pauri32/fiqa-2018
3: https://huggingface.co/datasets/financial_phrasebank

FinGPT-RAG: Baseline Methods

Baseline Methods

Model Name	Introduction
BloombergGPT	BloombergGPT is a 50 billion parameter language model that is trained on a wide range of financial data. As it's a closed-source model, we directly use their reported performance on the FPB dataset.
ChatGPT	ChatGPT, a closed-source LLM by OpenAI, employs a four-step process for sentiment analysis: API setup, data preparation, making requests with GPT-4.0 API, and interpreting the direct sentiment output.
Llama-7B	Llama-7B, an open-source LLM by Meta primarily trained in English, was acquired and maintained in its original inference configuration as our base model.
ChatGLM2-6B	ChatGLM2-6B is an open-source LLM crafted by Tsinghua University, supporting both Eng- lish and Chinese.
FinBERT	FinBERT is a financial sentiment analysis model which is fine-tuned on the pretrained BERT language model.

FinGPT-RAG: Case Study and Experiment Results

Instruction Tuning

Dataset	FPB		Twitter Val	
Metrics	Acc	F1	Acc	F1
FinBERT [1]	-	-	0.725	0.668
BloombergGPT [29]	-	0.510	-	-
ChatGLM2-6B [32]	0.474	0.402	0.482	0.381
Llama-7B [24]	0.601	0.397	0.544	0.363
ChatGPT 4.0 [15]	0.643	0.511	0.788	0.652
Ours	**0.758**	**0.739**	**0.863**	**0.811**

Table 1. Comparison between our model and the baselines on the datasets of financial phaseBank (FPB) and Twitter Val.

With and w/o RAG

Metrics	Acc	F1
ChatGPT 4.0 w/o RAG	0.788	0.652
ChatGPT 4.0 w/ RAG	**0.813**	**0.708**
Ours w/o RAG	0.863	0.811
Ours w/ RAG	**0.881**	**0.842**

Table 2. Experimental results on the Twitter Val dataset.

A Case Study of RAG

	Text	Result
w/o RAG	$ENR - Energizer shakes off JPMorgan's bear call.	Neutral
w/ RAG	*"Energizer shakes off JPMorgan's bear call. JPMorgan* ***hikes Energizer Holdings (NYSE:ENR) to a Neutral rating from Underweight****... We came away* ***encouraged*** *by some of the company's initiatives and believe their focus on innovation and brand investment can lead to relative outperformance going forward... Shares of Energizer are* ***0.46% premarket to $50.44****."*	**Positive**

Table 3. Case study: before and after using RAG.

FinGPT-Forecaster: The Future of Robo-Advisory Services

FinGPT-Forecaster

FinGPT-Forecaster takes random market news and optional basic financials related to the specified company from the past few weeks as input and responds with the company's **positive developments** and **potential concerns**. Then it gives out a **prediction** of stock price movement for the coming week and its **analysis** summary.

This model is finetuned on Llama2-7b-chat-hf with LoRA on the past year's DOW30 market data. Inference in this demo uses fp16 and **welcomes any ticker symbol**. Company profile & Market news & Basic financials & Stock prices are retrieved using **yfinance & finnhub**. This is just a demo showing what this model is capable of. Results inferred from randomly chosen news can be strongly biased. For more detailed and customized implementation, refer to our FinGPT project: https://github.com/AI4Finance-Foundation/FinGPT

Disclaimer: Nothing herein is financial advice, and NOT a recommendation to trade real money. Please use common sense and always first consult a professional before trading or investing.

Ticker

Companys from Dow-30 are recommended

AAPL

Date

Date from which the prediction is made, use format yyyy-mm-dd

2023-11-08

n_weeks

3

Information of the past n weeks will be utilized, choose between 1 and 4

If checked, the latest quarterly reported basic financials of the company is taken into account.

☐ Use Latest Basic Financials

Clear

Submit

Information

Response

FinGPT-Forecaster: The Future of Robo-Advisory Services

FinGPT-Forecaster is an LLMs model that synthesizes **recent market news** and **relevant financial ratios** of a given company to provide a dual output — a rundown of the **company's latest positive strides and potential concerns**, as well as **a forecast of the stock price movements** for the upcoming week, complete with an analytic summary.

Developed with **a fine-tuned Llama-2–7b-chat-hf with LoRA**, leveraging the latest year's market data from the **DOW 30**, **FinGPT-Forecaster** not only brings **precision** to predictions for **these blue chips** but also demonstrates **remarkable generalization capabilities** across various stock symbols.

FinGPT-Forecaster stands as a testament to the promise and potential of AI in finance, **a junior robo-advisor** that combines ease of deployment with strategic foresight, **marking a significant milestone on our path to the future of automated financial advisory.**

FinGPT-Forecaster: How to Use?

FinGPT-Forecaster is hosted on Hugging Face Spaces, allowing anyone with internet access to use it without any cost. It's the embodiment of open-source philosophy — shared, improved, and used by a community of developers and financial analysts alike.

Inputting Data
To start your forecasting journey, you simply need to:

1. **Select Your Ticker Symbol**: Enter the ticker symbol for the company you are interested in, such as '**AAPL**' for Apple Inc. or '**MSFT**' for Microsoft.
2. **Set Your Date**: Choose the specific day (formatted as **yyyy-mm-dd**) from which you want the prediction to commence.
3. **Determine the News Timeframe**: Decide on the number of **past weeks** for which you'd like to gather market news. This helps the model to understand recent trends and sentiments.
4. **Incorporate Financials**: Opt-in to add the **latest basic financials** for a more informed prediction, if desired.

https://huggingface.co/spaces/FinGPT/FinGPT-Forecaster

https://huggingface.co/FinGPT/fingpt-forecaster_dow30_llama2-7b_lora

Potential Applications of FinGPT

Robo-advisor	Financial Sentiment Analysis	Quantitative Trading	Portfolio Optimization	Equity Research Report Analysis and Generation
Credit Scoring	Mergers and acquisitions (M&A) forecasting	ESG (Environmental, Social, Governance) Scoring	Retrieval Augmented Generation (RAG) and Financial Information	Risk Management
Fraud Detection	Know Your Customer (KYC) Processes Automation	Anti-Money Laundering (AML) Measures Enhancement	Insolvency Prediction	Regulatory Compliance
Low-code Development	Financial Education	Business Plan (BP) Analysis	Insurance Underwriting	Intelligent Customer Service

FinGPT Project 2023 Academic Achievements

October 2023

- ***FinGPT: Instruction Tuning Benchmark for Open-Source Large Language Models in Financial Datasets***; Instruction Workshop @ NeurIPS 2023; https://arxiv.org/abs/2310.04793

- ***FinGPT: Democratizing Internet-scale Data for Financial Large Language Models***; Instruction Workshop @ NeurIPS 2023; https://arxiv.org/abs/2307.10485

September 2023

- ***Enhancing Financial Sentiment Analysis via Retrieval Augmented Large Language Models***; ICAIF 2023; https://arxiv.org/abs/2310.04027

July 2023

- ***Instruct-FinGPT: Financial Sentiment Analysis by Instruction Tuning of General-Purpose Large Language Models***; FinLLM 2023@IJCAI 2023; https://arxiv.org/abs/2306.12659

- ***FinGPT: Open-Source Financial Large Language Models***; FinLLM 2023@IJCAI 2023; https://arxiv.org/abs/2306.06031

FinGPT Project 2024 Recruitment (Academic)

1. Retrieval-Augmented Generation (RAG): Enhancing LLMs with external knowledge retrieval.
2. LLMs Hallucination: Addressing and mitigating false information generation in LLMs.
3. FinGPT-Forecaster as a Robo-Advisor: Developing automated financial advisory systems.
4. Bias Detection and Mitigation in LLMs: Focusing on fairness and ethical aspects.
5. Language Model Personalization: Customizing LLMs for individual user preferences.
6. Cross-Lingual Transfer Learning: Utilizing LLMs across different languages.
7. LLMs in Risk Assessment and Management: Applying LLMs for financial risk predictions.
8. Sentiment Analysis in Financial Markets: Leveraging LLMs for market sentiment interpretation.
9. Real-time Market Trend Prediction: Utilizing LLMs for dynamic market analysis.
10. Regulatory Compliance Monitoring with LLMs: Automating legal compliance in finance.
11. LLMs in Fraud Detection: Enhancing fraud detection capabilities using LLMs.
12. Automated Financial Reporting: Utilizing LLMs for generating financial reports.
13. Natural Language Understanding in Trading Bots: Incorporating LLMs in Algorithmic Trading.
14. Customer Service Bots in Finance: Enhancing customer interaction using LLMs.
15. AI Ethics in Finance: Studying the ethical implications of LLMs in finance.
16. Data Privacy and Security in LLMs: Ensuring data protection in financial models.
17. Algorithmic Trading Strategy Optimization: Using LLMs for refining trading algorithms.
18. Predictive Analytics for Investment Decisions: Leveraging LLMs for investment insights.
19. Portfolio Management with AI: Automating portfolio selection and management.
20. LLMs for Financial Education and Literacy: Using LLMs to educate users about finance.

Conclusion

The models and data pipeline are open-sourced on huggingface :
Model: https://huggingface.co/FinGPT
Data Pipeline: https://github.com/AI4Finance-Foundation/FinNLP

FinGPT Github Repo: https://github.com/AI4Finance-Foundation/FinGPT
Tutorials for Beginners: [Training] Beginner's Guide to FinGPT: Training with LoRA and ChatGLM2–6B One Notebook, $10 GPU

Education Channel: https://byfintech.medium.com/
- https://medium.datadriveninvestor.com/introducing-fingpt-forecaster-the-future-of-robo-advisory-services-50add34e3d3c
- https://medium.datadriveninvestor.com/fingpt-powering-the-future-of-finance-with-20-cutting-edge-applications-7c4d082ad3d8
- https://medium.datadriveninvestor.com/fingpt-ii-cracking-the-financial-sentiment-analysis-task-using-instruction-tuning-of-3333bce428c4

Discord Group: https://discord.gg/trsr8SXpW5
LinkedIn Group: https://www.linkedin.com/groups/14297568/

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