LLM-Based Quantitative Intelligence

Project Proposal

TEAM

Team Leader: ZhaoCheng Li

Team Members:
Chengyan Guo
Yaohua Feng
Junlang Liang
Longsheng Huang
Jianjun Lu

Presenter: Chengyan Guo

November 19, 2025

Outline

Background: Signals, Models and Intelligence

Quantitative Investment
—Signals

Modern quantitative research relies on **Alpha factors** built from multi-source structured and unstructured data.

Yet **factor innovation is slowing down** while data volume and complexity grow exponentially.

LLM-Driven Intelligence
—Models

LLMs combine broad, domain-spanning knowledge with a strong ability to **interpret heterogeneous information**.

LLMs' general reasoning capabilities suffice as **quantitative intelligence engines**.

Our Direction
—Intelligence

Traditional factor engineering is **experience-heavy** and **hard to scale**.

We build an **LLM-based, multi-source quantitative intelligence pipeline** to automate Alpha generation, screening, and execution.

Related Work: Evolution of Quantitative Techniques

Towards Agent Era

Technique	Data	Representative Works		
Statistics	Expert knowledge	Carhart (1997), ***Four-Factor Model***	Hou (2015), ***Anomaly Digestion***	Harvey (2016), ***Factor Proliferation***
Classical ML	Structured data	Ou (1989), ***LR***	Huang (2005), ***Random Forest***	Tay (2001), ***SVM***
Deep Models	Time-series data	Tsantekidis (2017), ***CNN***	Fischer (2018), ***LSTM***	Zhang (2019), ***Transformer***
LLMs	Semantic textual data	Araci (2019), ***FinBERT***	Lopez (2023), ***ChatGPT Forecasting***	Yang (2023), ***FinGPT***
Multi-Agent LLM	Multi-source data	Yu (2024), ***Multi-Role LLMs***	Li (2025), ***Reflective Trading Agents***	Tang (2025), ***Agent Alpha Mining***

...

Problem Definition and Objectives

Problem Definition: We address a **daily-frequency and multi-source** quantitative forecasting task in the Chinese A-share market.

Input. For stock i and day t:

$$X_{i,t} = \{M_{i,t},\ T_{i,t}\}.$$

$M_{i,t}$: structured features; $T_{i,t}$: texts aligned to (i, t).

Data Scope

- **Time Horizon:** 2014–2024
- **Universe:** CSI 300 + SSE 50
- **Frequency:** Daily features & labels

Target. Predict next-day log return:

$$f(i,t) \to \hat{r}_{i,t+1}, \quad r_{i,t+1} = \ln\left(\frac{P^{\text{close}}_{i,t+1}}{P^{\text{close}}_{i,t}}\right).$$

$\hat{r}_{i,t+1}$: model-predicted next-day log return.

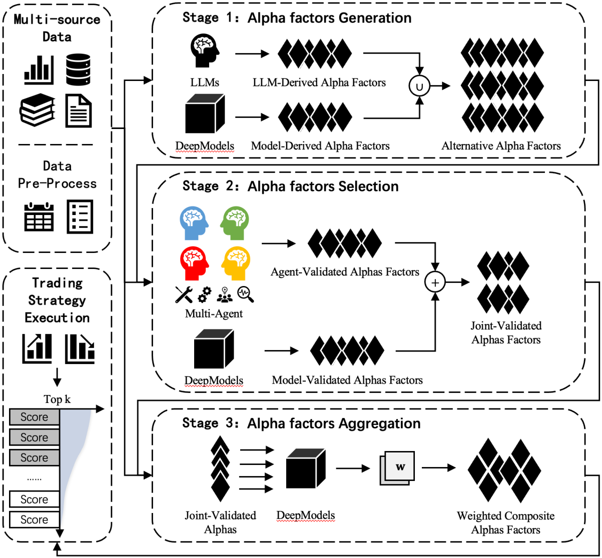
$P^{\text{close}}_{i,t}$: closing price of stock i on day t.

Objectives

What can an **LLM-based quantitative intelligence** actually do?

- Automatic **ALPHA GENERATION** from multi-source data
- Automatic **FACTOR EVALUATION & FILTERING** to ensure robustness
- Daily **EXECUTION DECISIONS** driven by validated factors
- **CONTINUAL UPDATING** as new market and textual data arrive

Methodology: Overall Pipeline



Stage 1. Deep models and LLMs generate candidate alpha factors (set union).

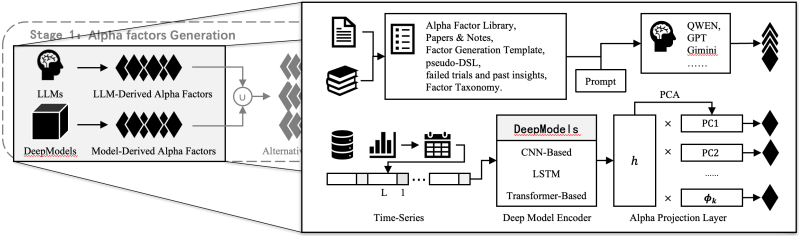
Stage 2. Deep models and multi-agent LLMs jointly select alphas (set intersection).

Stage 3. A deep model learns weights w for a composite trading alpha.

Methodology: Zooming into Alpha Factor Generation

Alpha factors are analogous to **feature channels** in CV.

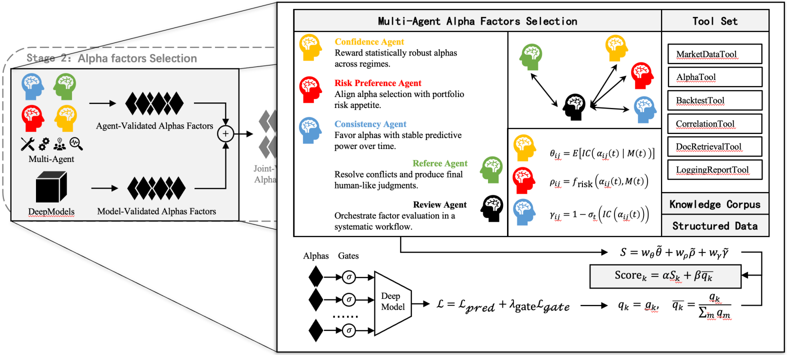
CV models extract edge/texture/shape patterns, while our system extracts momentum, sentiment, and structural signals from multi-source financial data.



Document-driven factor synthesis
LLMs read domain documents via structured prompts and propose both classical and novel alpha-factor candidates.

Time-series–driven factor extraction
DeepModels encode time series into latent representations h, which are projected by PCA to obtain orthogonal factors.

Methodology: Zooming into Alpha Factors Selection



How do multiple agents negotiate and reach consensus?

In the *first round*, Agents **independently score factors**; in the *review round*, disputed factors enter a ***refinement round***, after which the Referee Agent finalizes consensus.

How do DeepModels autonomously filter uninformative alphas?

Each candidate factor passes through a **gated Net** with Sigmoid gating and L1 sparsity. Training on historical returns drives uninformative gates toward zero.

Experimental Design

Hyperparameters to Tune

Category	**Key Hyperparameters**
Data	Lookback window length L; rebalancing frequency
Stage 1	Number of produced alphas
Stage 2	Model–based quality weights $(w_\theta, w_\rho, w_\gamma)$; aggregation weights (α, β)
Stage 3	Training hyperparameters of the aggregation model
Execution	Position cap; turnover cap; allocation threshold

Baselines: traditional statistical models; classical ML models; attention/Transformer-based models; LLM- or agent-based variants.

Evaluate with:

Category	**Metrics**
Predictive	IC; RankIC
Portfolio performance	Annualized return; volatility; max drawdown
Cost & turnover	Turnover; cost-adjusted return
Stability	Regime-wise stability
Simulation	Simulated-trading PnL

Project Timeline

Time	Task
Week 1–2	Parallel Development of Three Stages
Week 3	System Integration & Hyperparameter Search
Week 4	Comprehensive Evaluation & Full Paper
Week 5	Presentation Materials & Demo

Goal: Build an end-to-end, continuously updating multi-agent LLM system for quantitative intelligence.

Conclusion & Q&A

Thank you for your attention!

Questions & Discussion

LLM-Based Quantitative Intelligence