An Agent-Based Black-Litterman Framework

Thesis Proposal & Literature Review

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Introduction

- **Motivation:** Asset managers often face the challenge of constructing and combing multiple asset views—drawn from diverse data sources and forecast methodologies.
- **Opportunity:** Advances in large language models (LLMs) enable more nuanced, domain-specific, objective perspectives for multi-source data, complementing traditional factor-based, optimization-based approaches.
- **Challenge:** Existing Black-Litterman framework implementations typically rely on single or homogeneous views, which may not reflect evolving market regimes, multi-asset correlations, or differences in model confidence.

Black Litterman Foundation

- Black-Litterman model (Black & Litterman, 1992) employed Bayesian framework to incorporate subjective forecast to update on the prior and CAPM implied portfolio weights.
  - Starts with the market-implied prior: $\Pi = \lambda \Sigma w_{\text{mkt}}$
  - $E[R] = \left[(\tau\Sigma)^{-1} + P^\top \Omega^{-1} P\right]^{-1} \left[(\tau\Sigma)^{-1}\Pi + P^\top \Omega^{-1} Q\right]$
  - Subjective views are introduced via a pick matrix P and a view vector Q
  - Confidence in each view is captured by the diagonal covariance matrix Ω (often modeled as proportional to $\tau\Sigma$).
- Traditional implementations assume a single forecasting source, limiting adaptability.

Main Idea

- Develop an **Agent-Based Black-Litterman (ABBL)** framework for *multi-asset allocation*.
- Extend the traditional Black-Litterman model by introducing domain-trained expert LLM as forecasting agents for equities, fixed income, FX, and commodities.
- Agents use specialized data and context window: market structure, factors, fundamentals, macro indicators, yield curves, option chains, rate differentials, etc.
- To tackle the challenge with judging view quality, train & Test on both the views accuracy & constructed portfolios performance
- **Original Contribution**:an flexible, multi-modal Black-Litterman architecture that systematically reconciles heterogeneous data and forecast from specialized agents with the equilibrium prior.

Multi-Asset Allocation and Factor Models

- Factor models (Fama & French, 1993; Ang, 2014) decompose returns into systematic risk factors.
- Traditional models do not integrate multiple specialized predictive models dynamically.
- Need for a framework that incorporates **heterogeneous** multi-asset views.

Combining Multi-source Views

- (Luo et al, 2022)Extends Black-Litterman to combine diverse views with varying source, horizons, data availability and structures.
- Introduces a practical framework to aggregate multi-source views aggregation for fundamental & quant managers
  - Fundamental Managers: The paper demonstrates how the BL model can incorporate diverse views such as analyst recommendations, alpha capture programs, and data science insights.
  - Quant Manager: It explores how systematic investors can optimally mix signals from different models, even when they have limited history or breadth.
- Assigns **dynamic confidence levels** to views, refining risk-adjusted allocations and real-world constraints.

Macro Activities Simulation

- **EconAgent** (Li, Gao, and Li, 2024) introduces an LLM-powered agent-based framework for macroeconomic simulation.
- Unlike traditional agent-based models (ABMs), it enhances agent heterogeneity, memory, and adaptive decision-making.
- Simulates labor, consumption, financial markets, and taxation, producing realistic macroeconomic trends.
- Demonstrates Phillips Curve and Okun's Law correlations while responding to external shocks like COVID-19 downturns.

LLM-Based Portfolio Construction

- **FolioLLM** (Popov and Roshka, 2024) applies LLMs to ETF portfolio construction.
- Integrates Retrieval-Augmented Generation (RAG), LoRA, and Kolmogorov-Arnold Networks (KAN) for structured financial data processing.
- Trained on 12,224 ETFs, incorporating Markowitz’ s mean-variance optimization.
- Outperforms GPT-3.5 in generating higher-return, lower-volatility portfolios based on Sharpe ratios and Harmonic Portfolio Symmetry (HPS).
- Addresses data quality, ethical risks, and regulatory challenges for AI-driven investment tools.

Data Source

- **WRDS**: Historical equity, bond, option data (FRED, CRSP, Compustat, CRB, TAQ).
- **Bloomberg**: Treasury yields, FX rates, commodity prices, inflation forecasts.
- **Auxiliary Sources**: Global macro data, Central bank announcements, news sentiment indicators
- Data cleaning, rolling window structure, backtesting for validation.

Why Is It Important?

- **Bridging Theory & Practice:** Merges agent-based forecasting with Black-Litterman for a richer, more adaptive portfolio approach.
- **Enhanced Risk Management:** Diverse "views" can improve out-of-sample performance versus single-forecast or factor-only methods.
- **Stakeholder Benefits:** *Asset Managers, Institutions, Researchers* can all leverage a unified, multi-asset framework.
- **Market Dynamics Insight:** Heterogeneous agents capture real-world complexities, aiding better decision-making across regimes.

Future Plans

- **LLM Integration**: Use *EconAgent* (Li et al., 2024) for macroeconomic simulation.
- **Sentiment Data**: Event-driven news sentiment analysis to refine investment views.
- **Sector-Based data**: Sector-based heterogeneous agent for equity & bond.
- **Regime Shifts**: Machine learning for detecting market volatility and economic regimes.
- **ESG Investing**: Extend framework to incorporate sustainability and thematic strategies.