An Agent-Based Black-Litterman Framework

Literature Review & Data Explanation

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Feb 17$^{\text{th}}$, 2025

Motivation and Overview

- **Motivation:**
  - Real-world asset allocation involves integrating multiple data sources, asset classes, and forecasting approaches.
  - Traditional portfolio frameworks often rely on a single, homogeneous set of views that may not capture market complexities or regime shifts.
- **Opportunity:**
  - Advances in agent-based models and large language models (LLMs) enable *domain-specific* forecasting for equities, fixed income, FX, commodities, and more.
  - Combining these heterogeneous signals under one consistent optimization framework can enhance both *performance* and *risk management*.

Agent-Based Black-Litterman (ABBL) Framework

- **Concept:**
  - Build on a *market equilibrium prior*, then incorporate multiple specialized agent forecasts (e.g., Equity Agent, FX Agent, Commodity Agent).
  - Each agent brings unique data and modeling techniques, reflecting distinct market dynamics.
- **Key Mechanism:**
  - Assign *confidence weights* to each agent's forecast, informed by historical accuracy or market conditions.
  - Produce a final, posterior view for each asset class that blends the market equilibrium prior with the aggregated agent forecasts.
- **Outcome:**
  - A multi-asset allocation that dynamically adjusts as agents update their views.
  - Enhanced robustness to market regime changes, since multiple perspectives feed into the allocation process.

Key Advantages

- **Heterogeneous Insights:**
  - Incorporates specialized, *domain-trained* forecasts rather than relying on a single outlook.
- **Adaptability:**
  - Views evolve with changing data, letting the final allocation respond to market events and shifting fundamentals.
- **Risk Management:**
  - Cross-asset correlations and volatility are continuously updated, helping maintain balanced exposures.
- **Practical Utility:**
  - Asset managers of various sizes can scale this approach without building large in-house teams for each asset class.

Multi-Asset Allocation and Factor Models

- Black-Litterman model (Black & Litterman, 1992) employed Bayesian framework to incorporate subjective forecast to update on the prior and CAPM implied portfolio weights.
- (Luo et al, 2022) extends Black-Litterman to combine diverse views with varying sources, horizons, data availability, and structures.
- Introduces a practical framework to aggregate multi-source views for fundamental & quant managers.
- Assigns **dynamic confidence levels** to views, refining risk-adjusted allocations and real-world constraints.

Incorporating Dynamic Confidence in Allocation

- We extend the idea of dynamic confidence levels to asset allocation, inspired by Kim et al. (2024).
- Their work shows that LLMs generate predictive confidence scores, which can inform decision-making.
- Similar to earnings forecasts, portfolio allocation can leverage confidence-adjusted probabilities:
  - **Direct LLM output:** Using model-assigned confidence levels as a weighting factor.
  - **Probability-weighted approach:** Averaging multiple views based on estimated certainty.
- This enhances risk-adjusted allocation, improving robustness to model uncertainty.

LLM-Driven ETF Day Trading Strategy

- We adopt an **ETF-based approach** for day trading, inspired by Popov et al. (2024).
- ETFs ensure **data quality** and provide a straightforward way to estimate trading costs ($\sim 0.5\%$).
- Unlike Abe et al. (2024), who use a simple 40/60 stock-bond portfolio, we aim for a **more diversified strategy**, including non-US investments.
- Key daily macroeconomic variables Abe et al. considered:
  - US stock futures (returns)
  - US 5-year and 30-year interest rates
  - US yield curve spread (30Y–10Y)
  - Volatility Index (VIX)
  - US Dollar Index
- Our approach relies on a similar but more comprehensive set of daily variables.

Enhancing Portfolio Construction with LLMs

- Instead of directly adjusting asset weights, we generate **individual asset views** and integrate them into a Black-Litterman (BL) model.
- The BL framework allows for:
  - Aggregation of multi-source views (LLM, quant models, and macro signals).
  - **Dynamic confidence weighting** based on LLM-assigned certainty.
  - Risk-adjusted allocation that adapts to real-world constraints.
- This approach enhances **robustness** in decision-making while ensuring consistency across diversified assets.
- Future extensions include expanding beyond ETFs into global macro products such as **FX forwards, swaps, and structured options**.

Extending to a Multi-Agent Framework

- Inspired by **TradingAgents** (Xiao et al., 2025) and **FINCON** (Yu et al., 2024), we aim to expand from a **single-agent** to a **multi-agent** system in the second step.
- This transition enhances modularity, improving the integration of alternative data and feedback mechanisms.
- The framework introduces:
  - **News Agent**: Incorporates real-time alternative data sources (news, social media) for macro sentiment tracking.
  - **Macro Agent**: Simulates macroeconomic trends rather than relying solely on market data.
  - **Manager Agent**: Oversees agent interactions, refining decision-making through feedback loops.
- Multi-agent structures improve **collaborative reasoning**, risk awareness, and systematic investment belief updates.
- Enhances **dynamic adaptability** to market conditions, optimizing both short-term trading and long-term strategies.

Innovation & Our Contribution (1/2)

- **Multi-Agent Integration:**
  - We propose a *single framework* that integrates multiple, specialized forecasting agents into a standard market allocation process.
  - Each agent focuses on a specific asset domain (e.g., equity fundamentals, FX macro signals).
- **Formalizing Heterogeneity:**
  - Agents utilize diverse data frequencies (daily, monthly, quarterly), unique factor models, and even text-based sentiment analysis.
  - We provide a *structured method* for weighting these diverse views, ensuring that the final portfolio reflects real-world complexities.

Innovation & Our Contribution (2/2)

- **Confidence Weighting Mechanism:**
  - Incorporate adjustable *confidence scores* for each agent, potentially linked to backtested performance or data reliability.
  - Allows for a refined blend of "expert opinions" while mitigating noise from less reliable sources.
- **Enhanced Out-of-Sample Robustness:**
  - By uniting multiple forecasting signals under a Bayesian-style update, the portfolio can better adapt to volatile or shifting market conditions.
  - Minimizes over-reliance on any single predictive method, *increasing resilience* to model-specific errors.
- **Scalable Design:**
  - The ABBL framework can be extended to additional asset classes or specialized themes (ESG, emerging markets) with minimal structural changes.

Overview of Required Data

- **Equities:**
  - Daily price, returns of ETF, equity constituent for our investment universe, fama french factors data
  - Fundamentals, analyst revisions, news coverage and market sentiment
- **Fixed Income:**
  - Yield curve, key economic data release, corporate bond spreads, federal fund futures
  - Central bank interest rate announcements.
- **FX:**
  - Exchange rates, interest rate differentials, economic indicators from major currency blocks.
- **Commodities:**
  - Spot and futures prices, inventory levels, demand-supply dynamics.

Data Sourcing

- **Databases:** We are building and finalizing a data pipeline for the agent to download, clean and align data from:
  - *WRDS (CRSP, Compustat)* equity and bond prices, returns, fundamental,
  - *Bloomberg* for real-time/historical bond yields, FX rates, commodity quotes.
  - *FRED* for various economic activities and indicators
  - *Ken.French Library* daily factor data to help add interpretability to agent views.
  - *Central Bank Communications* (Fed, ECB) for text-based signals on monetary policy.
  - *RavenPack* for daily event-driven signals.

Data Preprocessing

Additional steps for training and validating our agent frameworks include:

- Align daily or monthly data across all assets, filling or discarding missing entries where appropriate.
- Mask data to prevent data leakage for the validation and OOS period.
- Performs some numerical transformation such as zscoring and exponential weighting to ensure desired statistical properties and predictabilities for our agent.
- Create rolling windows for agent calibration and out-of-sample backtesting.

Workflow and Construction

- **Rolling Forecast Updates:**
  - Each agent periodically refreshes forecasts depending on the horizon and updating frequency of the underlying. Agent will be scheduled to only obtain the data as it released (e.g. Daily for equity price, monthly for PCE).
  - Updated forecasts feed into the *ABBL* module for posterior return/covariance generation.
- **Portfolio Construction:**
  - Start from our multi-asset portfolio of ETF
  - Optimize final weights under a mean-variance scheme with historical returns and asset covariances
  - Aggregate the multi-agent views to the view vectors and separately use agent provided confidence level, or assign an estimated confidence level to the agent view
  - Update the final portfolio using Black Litterman model.

Backtesting

- Compare *ABBL* allocations to benchmarks:
  - Single-view Black-Litterman based on sell-side report and single LLM source.
  - Factor-based portfolio
  - Equal weighted portfolio.
- Evaluate performance on rolling window view accuracy as well as portfolio metrics **Sharpe ratio**, **drawdown**, and **volatility**.