From Game Metrics to Portfolio Optimization: An End-to-End Framework for Video Game Publisher Investment

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Abstract

The emergence of alternative data sources has created new opportunities for quantitative investment strategies, particularly in sectors with rich digital footprints. This research develops an end-to-end investment framework that leverages granular video game performance metrics to predict publisher stock returns and construct optimized portfolios. We introduce a hierarchical feature engineering pipeline that transforms game-level data into publisher-level predictive features, capturing multiple dimensions of performance including user engagement, monetization efficiency, and portfolio dynamics. Our methodology combines an enhanced triple-barrier labeling approach for return prediction with the Black-Litterman model for portfolio optimization, creating a complete pipeline from raw data to implementable trading strategies. Through comparative analysis across six major publishers, we demonstrate that neural networks consistently outperform traditional machine learning approaches. We then show how these predictions can be transformed into optimal portfolio weights using a novel integration of the triple-barrier framework with Black-Litterman portfolio optimization. This integration allows us to incorporate of our model's predictions and confidence into the final portfolio allocation decisions by balancing the Black-Litterman market prior with our model's views. Our work contributes both methodological innovations in financial machine learning and practical implementations, with source code made publicly available to support reproducibility and further research in quantitative investment strategies.

1 Introduction

The video game industry presents a unique opportunity for quantitative investment research due to its extensive generation of high-frequency, granular data about consumer behavior and product performance. While traditional financial analysis relies heavily on quarterly reports and aggregated metrics, the digital nature of gaming products enables near real-time monitoring of key performance indicators. This research investigates whether these alternative data sources can enhance both return prediction and portfolio optimization for video game publisher stocks. Recent studies have demonstrated the potential of alternative data in financial forecasting. Dessaint et al. (2024) show that such data sources can provide particularly valuable insights for short-term market predictions. Building on this foundation, we develop a comprehensive investment framework that transforms game-specific metrics into actionable portfolio strategies. Our work makes several key contributions to both the theoretical and practical aspects of quantitative investment:

1.1 Feature Engineering and Prediction

- We develop a hierarchical system that transforms granular game-level metrics into meaningful publisher-level features, incorporating both absolute performance measures and relative competitive dynamics

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- We extend Lopez de Prado's (2018) triple-barrier labeling methodology by introducing weighted labels based on price movement magnitude, providing more nuanced trading signals
- We implement and evaluate multiple machine learning architectures using purged cross-validation. Our findings show Neural Networks and LSTM's significantly outperform traditional models such as logistic regression and random forests. This demonstrates the superiority of non-linear methods in capturing complex relationships that may exist between game metrics and stock returns.
- We provide public implementations of our enhanced triple-barrier labeling system, purged cross-validation and portfolio optimization methodology on Github [1] of our purged cross-validation methodology and triple-barrier labeling system, contributing to the reproducibility and advancement of financial machine learning research.

1.2 Portfolio Optimization and Implementation

- We introduce a novel integration of the triple-barrier framework with Black-Litterman portfolio optimization, providing a method for translating binary predictions into views about publisher expected returns
- We develop a systematic approach for mapping neural network prediction probabilities to view uncertainties in the Black-Litterman framework
- We approach portfolio optimization from a Bayesian perspective, with our views on publisher returns and their associated uncertainties forming the likelihood function for expected returns. This is balanced with our prior belief of market expected returns derived using the CAPM model. We then solve for optimal portfolio weights by calculating the Black-Litterman posterior distribution of expected returns and applying mean-variance optimization.

2 Related Work

Our research contributes to the rapidly evolving field of financial machine learning while developing novel approaches for industry-specific alternative data analysis. We position our work within three key research streams: the application of machine learning to asset pricing, the use of alternative data in financial markets, and the integration of predictive signals with portfolio optimization.

2.1 Machine Learning for Asset Pricing

The emergence of machine learning in empirical asset pricing has transformed how researchers approach return prediction and portfolio construction. Kelly and Xiu (2023) provide a comprehensive framework for understanding this transformation, highlighting how machine learning methods can help address the twin challenges of large conditioning information sets and ambiguous functional forms in asset pricing. Our work extends this paradigm by introducing granular game performance metrics as a new form of conditioning information, while developing economically-motivated methods to analyze this industry-specific data.

Our approach deliberately diverges from standard cross-sectional machine learning methods in finance, as exemplified by Gu et al. (2020b). While they demonstrate the power of neural networks for predicting returns across the broad market using traditional firm characteristics, we focus on developing publisher-specific models that capture unique relationships between game metrics and stock returns. This specialization reflects both the distinctive nature of the gaming industry and our novel data sources, which provide direct, high-frequency measures of publisher product performance rather than traditional financial metrics.

2.2 Portfolio Optimization

The portfolio optimization component of our work advances the literature on integrating machine learning predictions with modern portfolio theory. A fundamental challenge in quantitative investing is transforming predictive signals into implementable portfolio weights while accounting for

[1]https://github.com/Torr1n/Predicting-Video-Game-Publisher-Stock-Returns-Using-Game-Derived-Features

estimation uncertainty (Kelly and Xiu, 2023). We address this by developing a novel integration of the triple-barrier framework with Black-Litterman optimization, creating a systematic pipeline from prediction to portfolio construction. Our approach uses market equilibrium as a theoretically motivated prior that provides natural regularization by pushing our posterior towards the market-implied weights. The neural network predictions form a likelihood function through carefully calibrated views and uncertainties. This structure allows us to combine the complexity of non-linear methods with the economically anchored Black-Litterman optimization framework. By mapping prediction probabilities to view uncertainties and using triple-barrier levels to define expected returns, we provide a concrete solution to the challenge of translating alternative data insights into portfolio decisions. This creates an end-to-end framework that respects market equilibrium and estimation uncertainty while maintaining computational tractability.

2.3 Alternative Data

The use of alternative data in financial markets has grown substantially, with Dessaint et al. (2024) demonstrating its particular value in short-term market prediction. While most research focuses on broad market signals, our work represents a focused exploration of industry-specific alternative data. Kim et al. (2023) established foundational relationships between player behavior metrics and game financial performance at the individual game level. We extend this idea to create publisher-level features through the hierarchical aggregation of game metrics across the publisher's entire portfolio.

3 Methodology

Our investment framework implements a systematic approach to transforming granular game performance data into actionable portfolio decisions. At its core, the system addresses a fundamental challenge in quantitative investing: how to effectively leverage novel alternative data sources while maintaining the mathematical rigor of modern portfolio theory. The framework consists of four integrated components that form a complete pipeline from raw data to portfolio weights.

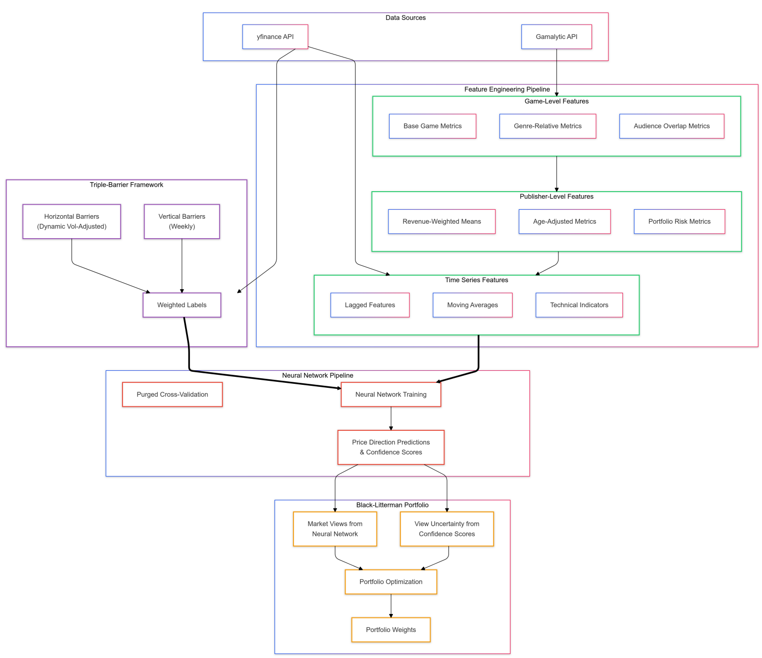

Figure 1: High-Level Framework Overview

The first component implements a hierarchical feature engineering system that transforms daily game performance metrics into predictive signals at the publisher level. This transformation occurs through carefully designed aggregation stages that preserve signal while managing dimensionality. The second component utilizes an enhanced version of the triple-barrier framework to generate probabilistic predictions about publisher stock movements, implementing sophisticated cross-validation techniques to ensure robustness. The final component translates these predictions into optimal portfolio weights through a novel integration with the Black-Litterman model, providing a mathematically rigorous way to incorporate our alternative data insights while respecting market equilibrium.

3.1 Data Collection

We analyze six major video game publishers listed on different global exchanges: SEGA (6460.T), Electronic Arts (EA), Ubisoft (UBI.PA), Square Enix (9684.T), Frontier Developments (FDEV.L), and CD PROJEKT RED (CDR.WA). The study spans 88 weeks from January 2023 to September 2024, with this span chosen to ensure access to hourly stock data granularity through yfinance. We collected raw game data from the Gamalytic API, which provides daily metrics tracking multiple dimensions of game performance. These metrics include direct measures of financial performance such as revenue and sales, user engagement metrics like active player counts and playtime, and measures of a game's social awareness through wishlist additions and follower growth.

3.2 Feature Engineering Pipeline

The feature engineering pipeline, presented in Figure 2 below, begins with this granular data transforming through 5 stages. Each stage is designed to expand or aggregate our feature space and capture aspects of publisher performance.

3.2.1 Game Level Features

At the game level, the system generates both direct and derived features organized around seven key performance dimensions:

- **Engagement** features captures both quantity and quality of player interaction, combining metrics like average daily players with playtime and review scores.
- **Sentiment** factors track changes in user satisfaction by focusing on trends in review score and count.
- **Monetization** features measure revenue generation efficiency through metrics like revenue per active player-hour.
- **Stability** metrics emphasize consistency in both player base and revenue streams.
- **Social** features measure trends in the game page's follower and wishlist counts.
- **Value** focused factors evaluate engagement and review score relative to the game's price.
- **Lifecycle generation** features assess engagement and monetary performance relative to game age.

The pipeline then contextualizes individual game performance through two parallel relative analyses. The first compares each game against similar titles using Gamalytic's API to identify a game's peers based on genre and tag similarity. Then, the system generates weighted z-scores that measure performance relative to comparable games, providing insight into the base game's competitive positioning. The second analysis leverages Gamalytic's built-in audience overlap similarity scores. We again use these scores to generate weighted z-scores, which compare the base game to games competing for similar player bases. This analysis offers a complementary perspective on relative performance to our genre analysis, with our genre analysis asking, "How is the game doing relative to games with similar content?" while our audience analysis asks, "How is the game doing relative to the other games that our users play?".

3.2.2 Portfolio Level Features

Finally, these game-level features undergo publisher-level aggregation. This process is designed to prevent our publisher feature space from growing linearly with the number of games published N, which would increase the potential for over-fitting. As such, to ensure publisher features are constant in N, we use revenue-weighted aggregation to capture the economic importance of each game's features, while also using age-adjusted metrics to balance the contribution of mature titles against new releases. In addition to this direct aggregation of game features, we also include concentration

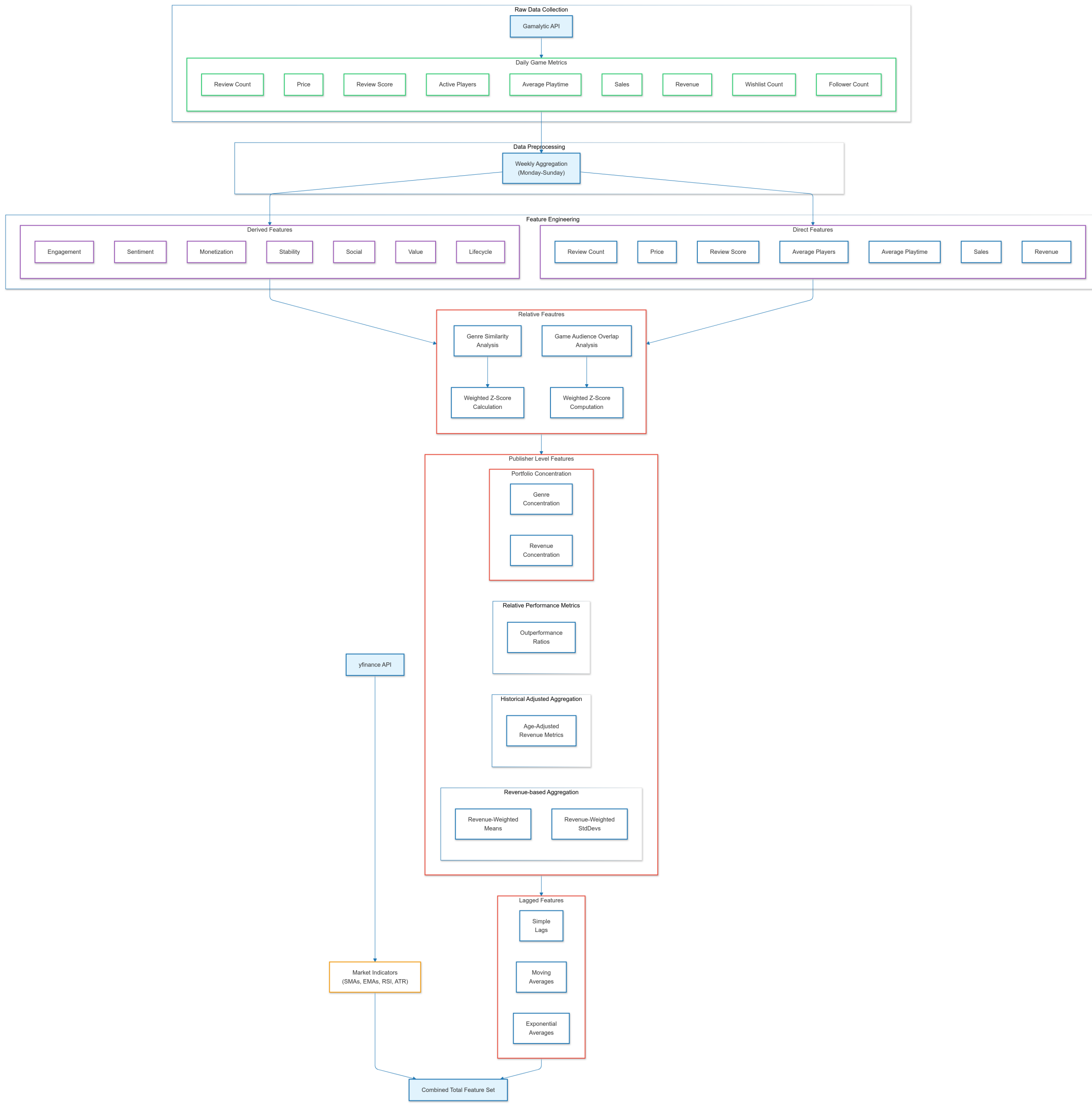

Figure 2: Feature Engineering Pipeline

metrics to assess publisher diversification across both game genres and revenue sources. Lastly, we calculate outperformance ratios to track the proportion of revenue that comes from games exceeding their peer benchmarks.

3.3 Enhanced Triple-Barrier Labeling

The prediction component of our framework implements a weighted version of the triple-barrier methodology to generate binary forecasts about publisher stock movements. This approach creates a structured way to transform continuous returns into discrete trading signals while maintaining the magnitude of market moves. Rather than using fixed return thresholds, the system adapts to changing market conditions through dynamic barrier placement.

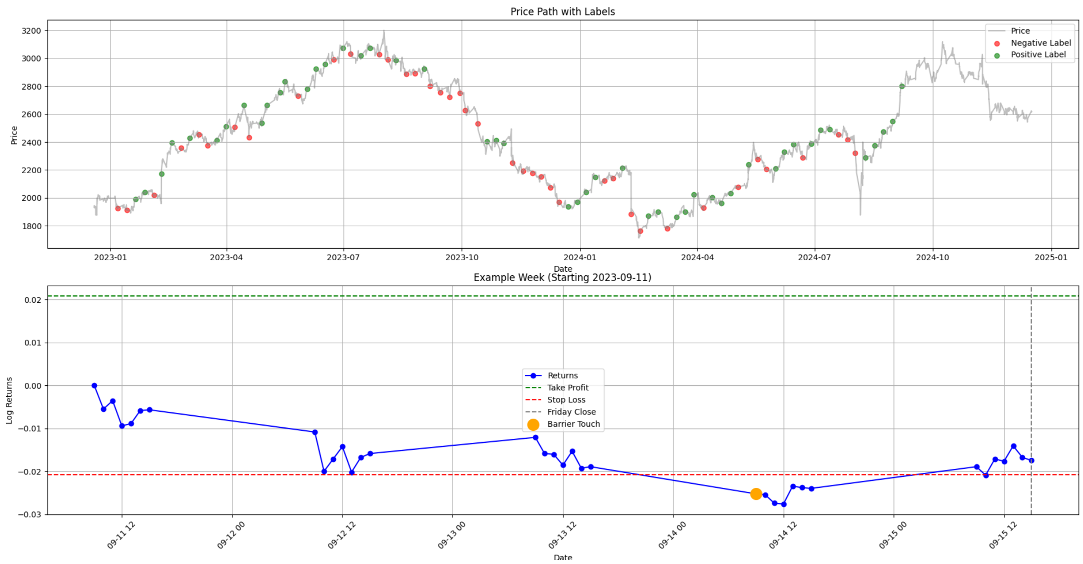

Figure 3: Triple-barrier labeling, where the bottom barrier is hit and we label the example -1.

3.3.1 Barriers

The framework establishes three types of barriers for each weekly prediction window.

Vertical barriers define a weekly horizon that aligns with our feature engineering frequency, providing a consistent timeframe for evaluating price movements.

Horizontal barriers, consisting of **Upper** (take-profit) and **Lower** (stop-loss) thresholds, are dynamically calculated:

- Upper Take-Profit barrier: $\mu + 1.5 \cdot \sigma$
- Lower Stop-Loss barrier: $\mu - 1.5 \cdot \sigma$

where μ and σ are weekly estimates of expected returns and volatility estimated using a rolling window over hourly price data. This adaptive approach ensures our classification boundaries reflect current market conditions rather than arbitrary fixed levels.

3.3.2 Weight Calculation

A key innovation in our implementation lies in the treatment of vertical barrier touches. Traditional implementations assign binary labels based solely on the direction of price movement when the vertical barrier is reached. Our enhanced approach introduces a weighting scheme based on the price path's proximity to horizontal barriers. For example, in cases where the vertical barrier is reached first, we compute weights based on the proximity of the terminal price to the nearest horizontal barrier. The weight is calculated as the ratio of the observed return r_t to the return that would have been required to hit the nearest barrier $r_{barrier}$, capped at 1: $w_t = \min(1, \frac{|r_t|}{r_{barrier}})$ This weighting scheme ensures that price movements that come close to breaching a horizontal barrier are given more importance during model training than those that remain near the starting price, offering 0 returns.

3.3.3 Problem Formulation

Given a set of publisher features $X_t \in \mathbb{R}^d$ at time t, we aim to predict the direction of stock returns $y_t \in \{-1, 1\}$, where:

$$y_t = \begin{cases} 1 & \text{if take-profit barrier is reached} \\ -1 & \text{if stop-loss barrier is breached} \\ \text{sign}(r_t) & \text{if vertical barrier is hit} \end{cases}$$

Here, r_t denotes the log return of the stock at time t.

3.4 Prediction Framework

To reduce the effect of optimization bias, we performed model selection and hyperparameter tuning using SEGA, then used the same model architecture across all publishers. For SEGA, the neural network consistently demonstrated superior performance, achieving a weighted validation error of 0.2388 and an F1 score of 0.7843 on temporal validation splits. This performance significantly surpasses traditional machine learning approaches, with Random Forest and Logistic Classification models achieving validation errors of 0.4578 and 0.4708 respectively. These models were merely used as baselines for model selection and to confirm our hypothesis that non-linear methods are superior in this case.

Our neural network architecture uses three hidden layers of 64 neurons, a learning rate of 0.0001, ReLU activation functions and dropout regularization of 0.3. This configuration emerged from coordinate descent, using grid-search to choose hyperparameters that minimized validation set performance.

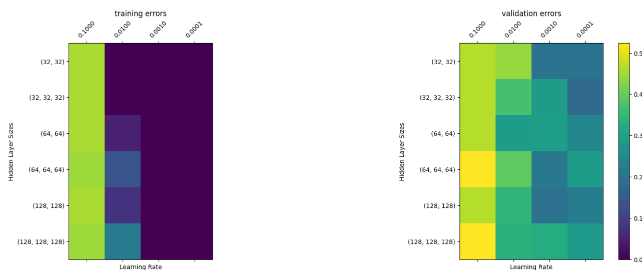

Figure 4: Hidden Dimension Size vs Learning Rate

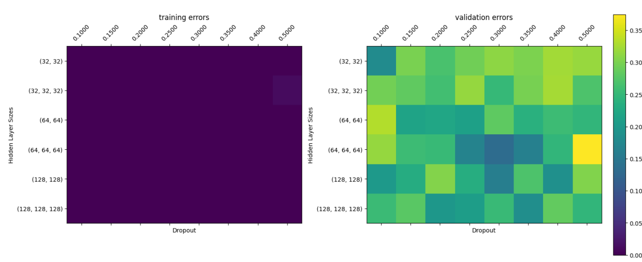

Figure 5: Hidden Dimension Size vs Dropout

We implement purged cross-validation with an eight-week embargo window to prevent forward-looking bias, ensuring validation samples with lagged features could not overlap our training data and contaminate our testing process. The training incorporates sample weights from our enhanced triple-barrier labeling, focusing the model's attention on economically significant price movements.

3.5 Portfolio Optimization

The final component of our framework provides a systematic method for translating neural network predictions into optimal portfolio weights through the Black-Litterman model. This integration creates a mathematical bridge between modern machine learning techniques and classical portfolio theory, allowing us to combine the flexibility of neural networks with the economic foundations of equilibrium asset pricing.

Our implementation maps the neural network's outputs to Black-Litterman views through a carefully designed transformation process. For positive predictions, we use the take-profit barrier level as the expected return view, with confidence derived directly from the model's sigmoid prediction probability. Negative predictions are handled symmetrically, using the stop-loss barrier with confidence calculated as one minus the sigmoid prediction probability. This approach creates a natural connection between our prediction framework and portfolio optimization, ensuring consistency between our predicted barrier and our views on expected returns.

The system handles the Black-Litterman uncertainty matrix, Ω through a simple approach that transforms model confidence scores into uncertainties that form its diagonal elements. We implement a quadratic relationship where uncertainty equals one minus confidence squared, ensuring that less confident predictions receive appropriately higher uncertainty weights in the portfolio optimization process. This uncertainty mapping provides a systematic way to reduce position sizes when our model expresses lower confidence in its predictions.

Market equilibrium serves as our prior, calculated using market capitalization weights and historical covariance estimates. This provides a theoretically motivated starting point that helps regularize our portfolio weights, pushing them toward market-implied values when our predictive signals are weak or uncertain. The final optimization maximizes the Sharpe ratio while respecting these equilibrium constraints and our model-derived views, creating portfolios that balance return potential against risk. The implementation maintains computational efficiency through careful system design and parallel processing where appropriate. We implement weekly rebalancing to evaluate the strategy in a research setting, with portfolio updates directly driven by new predictions. This creates a practical framework that can adapt to evolving market dynamics while maintaining consistent exposure to our game-derived signals.

4 Results

We evaluate our framework's performance through extensive backtesting across both training and test periods. The initial model development and hyperparameter optimization used data from January 2023 through September 2024, while the final portfolio strategy evaluation covered September 2024 through January 2025. We evaluate the entire strategy end-to-end on our test set only once. This separation ensures a clean assessment of our framework's out-of-sample performance by minimizing the impact of optimization bias from the use of validation sets for hyperparameter tuning.

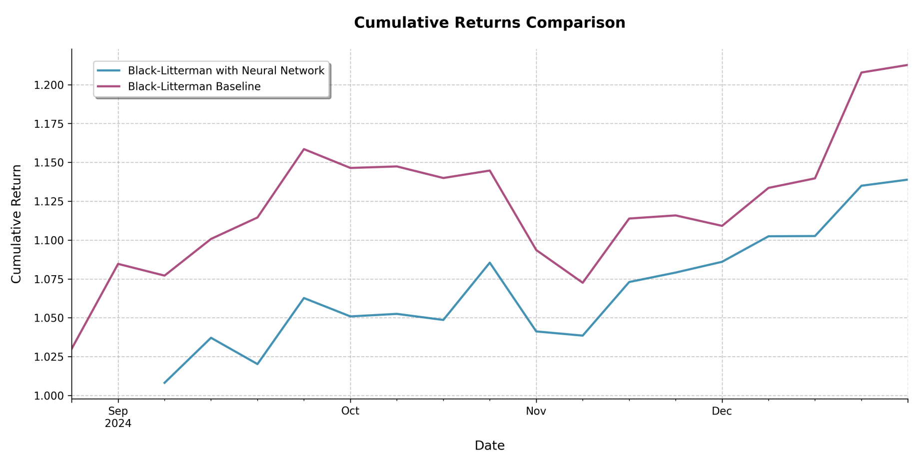

Figure 6: Cumulative Strategy Returns

To evaluate the complete investment framework, we implement two portfolio strategies: our neural network-guided approach and a baseline that relies primarily on market equilibrium. The baseline provides a challenging comparison by implementing the Black-Litterman model with minimal views, effectively capturing the market's implicit expectations about publisher returns. Our neural network-guided strategy achieved a cumulative return of 1.1389 with a Sharpe ratio of 2.4012 and maximum drawdown of -0.0432. The market equilibrium baseline showed stronger absolute performance with a cumulative return of 1.2127 and Sharpe ratio of 2.6981, though it experienced a larger maximum drawdown of -0.0742.

5 Discussion

The results present several interesting insights about the value of game performance metrics in portfolio management. While our framework did not outperform the market equilibrium baseline in absolute returns, it demonstrated potential advantages in risk management. The lower maximum drawdown and similar Sharpe ratio suggest that game-derived signals may offer particular value in identifying and managing potential market volatility.

This risk management capability could stem from the unique nature of our alternative data. Game performance metrics provide direct, high-frequency measures of consumer engagement with publishers' core products. Changes in these engagement patterns might serve as early indicators of market volatility, even if they don't consistently predict directional movements. This aligns with recent research suggesting that alternative data sources often excel at capturing specific aspects of market behavior rather than providing comprehensive predictive signals (Dessaint et al. 2024).

5.1 Limitations

Several limitations of our current approach warrant discussion. Our 88-week study period does not provide a promising relationship with our space of over 1000 publisher aggregate features. In addition to this data range's limitations for highly parameterized model training, it also may not capture the full range of market conditions affecting publisher stocks.

The framework's performance should also be considered in the context of implementation costs. While the similar Sharpe ratios suggest some efficiency in risk-adjusted returns, the weekly rebalancing frequency would likely impact real-world performance through transaction costs. This suggests that the strategy might be most valuable as a component of a broader multi-factor approach rather than as a standalone investment strategy. Additionally, our feature engineering pipeline's computational complexity could present challenges for real-time deployment, even with its current use of parallel processing.

6 Conclusion and Future Work

This research demonstrates both the opportunities and challenges in leveraging industry-specific alternative data for quantitative investment. We develop a complete pipeline from granular game metrics to portfolio decisions, introducing several methodological innovations in feature engineering, prediction, and portfolio optimization. While the standalone strategy shows mixed results compared to market equilibrium, our framework provides valuable insights about the potential role of game performance metrics in investment management.

The work makes several contributions to the practical implementation of alternative data strategies. Our hierarchical feature engineering system provides a template for handling industry-specific metrics while maintaining computational tractability. The enhanced triple-barrier framework offers a systematic approach to generating trading signals from high-frequency alternative data. Perhaps most importantly, our Black-Litterman integration demonstrates how machine learning predictions can be incorporated into classical portfolio theory while respecting market equilibrium and uncertainty.

Future research could explore several promising directions. The framework's apparent strength in risk prediction suggests potential value in developing specialized volatility forecasting models using game metrics. Integration with other alternative data sources or traditional factors could enhance the strategy's effectiveness. Additionally, exploring different rebalancing frequencies or portfolio constraints might improve practical implementability.

The source code and implementation details are publicly available, providing a foundation for further research in quantitative investment strategies using alternative data. This contribution to the open-source community aims to accelerate innovation in applying machine learning to investment management while maintaining rigorous mathematical foundations.

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