YieldFlow API

Financial Models & Mathematical Formulas

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Company: YieldFlow Analytics

Key Mathematical Innovations:

- Enhanced Portfolio Optimization (EPO) with Correlation Shrinkage
- News-Enhanced Portfolio Optimization (NEPO) Integration
- FinBERT-LSTM-VAR Enhanced Dividend Forecasting
- Monte Carlo Simulation with Dynamic Confidence Intervals

1. Enhanced Portfolio Optimization (EPO)

1.1 Core Objective Function

The Enhanced Portfolio Optimization maximizes the Sharpe ratio:

$$\boxed{\text{maxSharpe} = \frac{\boldsymbol{\mu}^T \mathbf{w} - r_f}{\sqrt{\mathbf{w}^T \Sigma \mathbf{w}}}}$$

Where:

- $\boldsymbol{\mu}$ = Expected returns vector for all assets
- $\mathbf{w}$ = Portfolio weight vector
- r_f = Risk-free rate (typically 3-month Treasury rate)
- Σ = Shrunk covariance matrix
- T = Transpose operator

1.2 Correlation Shrinkage Algorithm

Step 1: Sample Correlation Matrix

$$\boxed{\mathbf{R}_{\text{sample}} = \text{corr}(\mathbf{X})}$$

- $\mathbf{X}$ = Historical returns matrix $(n_{\text{periods}} \times n_{\text{assets}})$

Step 2: Target Correlation Matrix

$$\boxed{\mathbf{R}_{\text{target}} = \mathbf{I}}$$

- $\mathbf{I}$ = Identity matrix (assumes zero correlation between assets)

Step 3: Optimal Shrinkage Parameter

$$\boxed{\lambda^* = \frac{1}{T} \cdot \frac{\sum_i \sum_{j \neq i} \text{var}(r_{ij})}{\sum_i \sum_{j \neq i} (r_{ij} - \delta_{ij})^2}}$$

- T = Number of time periods
- r_{ij} = Sample correlation between assets i and j
- δ_{ij} = Target correlation (0 for $i \neq j$, 1 for $i = j$)

Step 4: Shrunk Correlation Matrix

$$\mathbf{R}_{\text{shrunk}} = \lambda^* \mathbf{R}_{\text{target}} + (1 - \lambda^*)\mathbf{R}_{\text{sample}}$$

2. News-Enhanced Portfolio Optimization (NEPO)

2.1 Hybrid Optimization Formula

$$\mathbf{w}_{\text{NEPO}} = \alpha \mathbf{w}_{\text{EPO}} + (1 - \alpha)\mathbf{w}_{\text{news}}$$

$\mathbf{w}_{\text{NEPO}}$ = Final NEPO portfolio weights

$\mathbf{w}_{\text{EPO}}$ = Enhanced Portfolio Optimization weights

$\mathbf{w}_{\text{news}}$ = News sentiment-adjusted weights

α = Blending parameter (typically 0.7)

2.2 News Sentiment Integration

$$S_i = \frac{\sum_j (s_{ji} \cdot c_j \cdot r_j)}{\sum_j (c_j \cdot r_j)}$$

S_i = Aggregated sentiment score for asset i

s_{ji} = Sentiment score of article j about asset i $(-1$ to $+1)$

c_j = Source credibility weight $(0.7$ to $1.0)$

r_j = Recency weight based on article age

Recency Weight Formula:

$$r_j = e^{-\lambda_{\text{decay}} \cdot \text{days}_j}$$

λ_{decay} = Decay parameter (typically 0.1)
days_j = Age of article j in days

3. Enhanced Dividend Forecasting (FinBERT-LSTM-VAR)

3.1 Enhanced Gordon Growth Model

$$D_{\text{forecast}} = D_{\text{current}} \times (1 + g_{\text{enhanced}})^t$$

3.2 Enhanced Growth Rate Calculation

$$g_{\text{enhanced}} = g_{\text{base}} + g_{\text{news}} + g_{\text{momentum}} + g_{\text{quality}}$$

Component Formulas:

$$g_{\text{base}} = \frac{\text{ROE} \times (1 - \text{payout ratio}) + \text{payout growth}_{3yr}}{2}$$

$$g_{\text{news}} = \beta_{\text{news}} \times S_{\text{sentiment}} \times \text{volatility adjustment}$$

$$g_{\text{momentum}} = \alpha_{\text{momentum}} \times (g_{\text{recent}} - g_{\text{long-term}})$$

3.3 FinBERT Sentiment Processing

$$S_{\text{processed}} = \tanh(S_{\text{raw}} \times \text{amplification factor})$$

S_{raw} = Raw FinBERT output $(-1$ to $+1)$
Amplification factor = 1.5 for dividend analysis
$\tanh()$ = Hyperbolic tangent function (bounds output)

4. Dynamic Confidence Calculation

$$C_{\text{total}} = \sum_{i=1}^{5} w_i \times C_i$$

Where confidence components are:

C_1 = Data quality confidence ($w_1 = 0.25$)
C_2 = Financial strength confidence ($w_2 = 0.30$)
C_3 = News consistency confidence ($w_3 = 0.20$)
C_4 = Model fit confidence ($w_4 = 0.15$)
C_5 = Company stability confidence ($w_5 = 0.10$)

5. Monte Carlo Confidence Intervals

$$\text{dividend}_{\text{sim}} = \text{dividend}_{\text{base}} \times \exp(\mu\Delta t + \sigma\sqrt{\Delta t}\,Z)$$

$Z \sim \mathcal{N}(0,1)$ = Standard normal random variable
μ = Expected growth rate, σ = Volatility, Δt = Time step

6. Advanced Risk Metrics

6.1 Value at Risk (VaR)

$$\boxed{\text{VaR}_\alpha = \mu_{\text{portfolio}} + \sigma_{\text{portfolio}} \times \Phi^{-1}(\alpha)}$$

$\mu_{\text{portfolio}}$ = Expected portfolio return
$\sigma_{\text{portfolio}}$ = Portfolio standard deviation
$\Phi^{-1}(\alpha)$ = Inverse normal CDF at confidence level α

6.2 Conditional Value at Risk (CVaR)

$$\boxed{\text{CVaR}_\alpha = \mathbb{E}[R | R \leq \text{VaR}_\alpha]}$$

$\mathbb{E}[R|\text{condition}]$ = Conditional expectation of returns

6.3 Performance Metrics

$$\boxed{\text{Sharpe} = \frac{R_{\text{portfolio}} - R_f}{\sigma_{\text{portfolio}}}}$$

$$\boxed{\text{Sortino} = \frac{R_{\text{portfolio}} - R_f}{\sigma_{\text{downside}}}}$$

7. Key Implementation Parameters

- Risk-free rate: 4.5% (3-month Treasury)
- Lookback period: 252 trading days
- Rebalancing: Monthly
- News decay factor: 0.1 (10-day half-life)
- FinBERT model: ProsusAI/finbert
- Monte Carlo iterations: 10,000

Conclusion

The YieldFlow API implements state-of-the-art quantitative finance methodologies combining traditional portfolio theory with modern AI and machine learning techniques. Our mathematical models provide superior risk-adjusted returns through sophisticated correlation modeling, real-time news sentiment integration, and dynamic risk assessment.