

Stock Return Prediction under the Common Task Framework (CTF)

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This report summarizes the model design and results of a Common Task Framework (CTF) experiment for cross-sectional stock return prediction using linear, nonlinear, and ensemble models.

1. R

This study applies the CTF framework to predict monthly stock excess returns using firm-level characteristics. The main objectives are to evaluate the predictive performance of different models, construct long-short portfolios, and compare linear versus nonlinear machine learning approaches.

2. D

Data were split into training (pre-2000) and testing (2000-2023) periods. Features with missing rates below 50% were retained, missing values were filled with median values from training data, and all predictors were standardized. This ensured consistent feature scales and prevented forward-looking bias.

3. M

The experiment implements three models:

- Model 1 - Simple Factor Model (linear benchmark)
- Model 2 - Random Forest (nonlinear ML model)
- Model 3 - MVO Ensemble (Mean-Variance Optimization)

These represent linear, nonlinear, and ensemble approaches, respectively.

4. M

This baseline model uses ranked cross-sectional factors such as size, value, and profitability. For each month, features are ranked and averaged to form a composite signal. A long-short portfolio is constructed by longing the top 20% and shorting the bottom 20%. This serves as a benchmark for evaluating machine learning improvements.

5. M

The Random Forest model captures nonlinear interactions between firm-level features.

It uses 50 trees ($n_estimators=50$, $max_depth=5$, $min_samples_leaf=50$) and standardized features. The model is robust to noise and avoids overfitting through ensemble averaging. Monthly predictions are used to rank stocks and form long-short portfolios similar to Model 1.

6. M

The ensemble combines Model 1 and Model 2 through Mean-Variance Optimization (MVO). By computing the expected return vector (μ) and covariance matrix (Σ) from training data, optimal weights are derived as $w = \text{inv}(\Sigma) * \mu$ normalized by its absolute sum. The resulting combination maximizes the portfolio Sharpe ratio and reduces volatility.

7. P

Model comparison results:

- Model 1 (Factor): 2.43% annual return, Sharpe 0.10, max drawdown -66.33%.
- Model 2 (Random Forest): 8.19% annual return, Sharpe 0.50, max drawdown -38.06%.
- Model 3 (MVO Ensemble): 7.88% annual return, Sharpe 0.51, max drawdown -35.95%.

Machine learning and ensemble models substantially outperform the linear baseline in both return and risk-adjusted metrics.

8. V

Cumulative return plots show smoother performance for ML and ensemble models. Sharpe ratio and drawdown comparisons confirm that the ensemble achieves superior risk-adjusted outcomes. The MVO model occupies the efficient frontier region with higher returns and lower volatility.

9. C

The results validate that nonlinear ML methods capture richer structures in cross-sectional data. Random Forest improves predictive accuracy, while the MVO ensemble enhances stability and risk control. Future extensions include integrating LightGBM/XGBoost, rolling cross-validation, and dynamic ensemble weighting.

10.

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