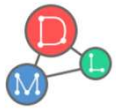


DeepTrade

STABLE: Shift-Tolerant Allocation via Black-Litterman Using Conditional Diffusion Estimates

Yejun Soun, Hosung Lee,
Suyoung Park, and U Kang
DeepTrade Technologies
Data Mining Lab
Seoul National University

Overview

- Portfolio optimization with accurate estimations from conditional generative model
  - result: best profitability and robustness

Method	S&P500 (US)			CSI300 (China)		
	ASR (↑)	RMDD (↓)	AVol (↓)	ASR (↑)	RMDD (↓)	AVol (↓)
CRP	0.82	8.89	14.44	-0.70	10.96	18.21
MVO	1.18	9.00	21.18	-0.66	13.18	25.93
MOM	0.03	11.87	17.00	-0.47	15.57	28.77
DeepTrader	-0.71	13.40	15.76	-1.18	13.40	18.76
MetaTrader	1.00	10.88	16.82	-1.09	19.40	24.15
AlphaMix	0.35	9.59	13.92	-0.80	9.59	19.11
STABLE (proposed)	**1.85**	**7.82**	**13.43**	**-0.41**	**8.85**	**17.17**
Method	**EUROSTOXX (Europe)**			**KOSPI200 (South Korea)**		
	ASR (↑)	RMDD (↓)	AVol (↓)	ASR (↑)	RMDD (↓)	AVol (↓)
CRP	1.31	5.40	12.96	0.76	8.72	26.55
MVO	0.48	8.35	16.75	0.45	11.84	29.49
MOM	1.42	5.41	12.71	0.33	13.49	23.34
DeepTrader	-2.44	15.99	12.59	0.77	9.62	23.76
MetaTrader	0.50	9.86	14.63	0.57	10.88	22.28
AlphaMix	1.31	5.75	11.77	1.47	9.96	18.76
STABLE (proposed)	**2.92**	**3.84**	**10.88**	**1.61**	**8.34**	**17.82**

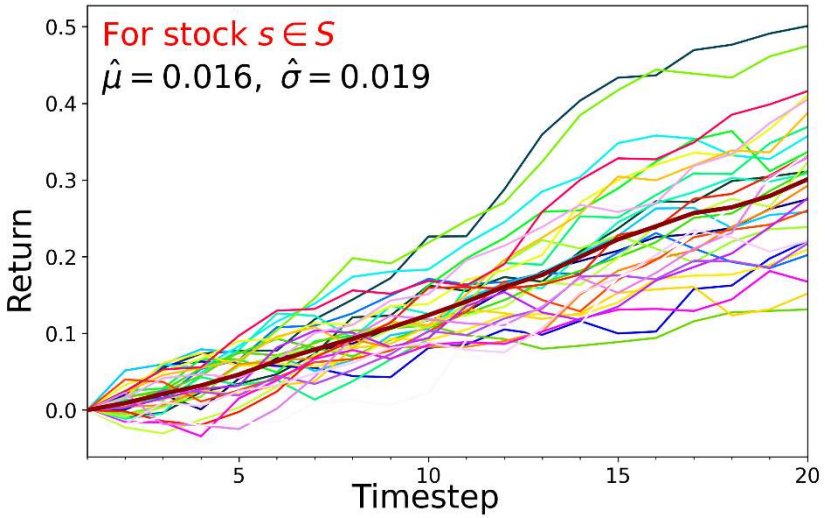
Outline

- **Problem Definition**
- Proposed Method
- Experiments
- Conclusion

Motivation

- A generative model supports iterated per-time-step, per-asset estimation
  - For every timestep, moments for every stock s

  ($s \in S$, $\hat{\mu}_\tau \in R^S$ & $\hat{\Sigma}_\tau \in R^{S \times S}$) is estimated



Problem Definition

- Given:
  - At time τ, for stock s
    - macro condition $m_\tau \in R^{d_m}$, per-stock condition $c_\tau^{(s)} \in R^{d_c}$
  - prior mean return for window size ν: $\mu_{prior,\tau}$
  - prior covariance for window size ν: $\Sigma_{prior,\tau}$
  - investment horizon: ℓ
- Allocate
  - $w_\tau^* \in \arg\max_{w_\tau} \frac{E\left[w_\tau^T R_{\tau,\tau+\ell}\right]}{\sqrt{Var\left(w_\tau^T R_{\tau,\tau+\ell}\right)}}$
- S. T.
  - the budget constraint holds: $1^T w_\tau = 1$

Challenges

- Forecasting under regime shifts.
  - How can we accurately estimate future time series in regime shifting market?
- Temporal contribution of macro vs micro impact
  - How can we decern the influence of macro factors from systematic impact and firm-specific dynamic over time?
- Certainty-aware portfolio allocation
  - How can we maintain robust performance when certainty of estimates vary over time?

Ideas

- Conditional Diffusion Generator (CDG)
  - Generating regime-aware return paths by conditional diffusion
- Multi-Level Guidance (MLG)
  - Modified Classifier-Free Guidance on financial domain to efficiently estimate macro and micro impact
- B-Litterman Mean Variance Optimizer (BL-MVO)
  - Certainty weighted estimation on posterior distribution for each stock s

Outline

- Problem Definition
- **Proposed Method**
- Experiments
- Conclusion

Conditional Diffusion Generator

- STABLE synsthesize regime-aware return series by conditional diffusion denoiser
- Diffusion models inject gaussian perturbations to stock returns
  - stock return is known to follow gaussian random walk
- CDG forms view mean and covariance through sampling
  - $\mu_{view,\tau} \in R^S$
  - $\Sigma_{view,\tau} \in R^{S \times S}$

Conditional Diffusion Generator

- Given
  - Macro features $m_\tau \in R^{d_m}$
  - Stock features $c_\tau^{(s)} \in R^{d_c}$
    - price feature, Kalman $\beta_\tau^{(s)} \in R^{d_m}$
- Minimize
  - $L(\theta) = E_{s,\tau,n,\epsilon}\|\epsilon - \hat{\epsilon}\|_2^2 + \beta\|\theta\|_2^2$
  - $\hat{\epsilon} = \varepsilon_\theta(m_\tau, c_\tau^{(s)}, n)$
- S.T.
  - $\epsilon \sim N(0, I)$

Multi-Level Guidance

- MLG decomposes noise as systematic impact and idiosyncratic components
- Stock returns are known to decompose into macro impact and firm-specific dynamics
- MLG estimates CDG's noise in a form aligned with the nature of the stock market

Multi-Level Guidance

- Given
  - Macro features $m_\tau \in R^{d_m}$
  - Stock features $c_\tau^{(s)} \in R^{d_c}$
- Minimize
  - $L(\theta) = E_{s,\tau,n,\epsilon} \left\| \epsilon - \epsilon_\theta(r_{n,\tau}^{(s)}, n, m_\tau, c_\tau^{(s)}) \right\|_2^2 + \beta \|\theta\|_2^2$
- Where
  - $\theta = \{\pi, \phi, W_m, W_c\}$
  - $\epsilon_\theta \left(r_{n,\tau}^{(s)}, n, m_\tau, c_\tau^{(s)} \right) = \hat{\epsilon}_{n,\tau} + z_t^{(s)} (\hat{\epsilon}_{n,\tau}^{(s)} - \hat{\epsilon}_{n,\tau})$
  - $\hat{\epsilon}_{n,\tau} = u_\phi(m_\tau^T W_m), \hat{\epsilon}_{n,\tau}^{(s)} = u_\phi \left({c_\tau^{(s)}}^T W_c \right), z_\tau^{(s)} = g_\pi \left(m_\tau^T W_m, {c_\tau^{(s)}}^T W_c \right)$

$$\underbrace{\hat{\varepsilon}_{n,\tau}}_{\text{shared (systematic)}} + \overbrace{z_\tau^{(s)}}^{\text{balancing gate}} \underbrace{\left(\hat{\varepsilon}_{n,\tau}^{(s)} - \hat{\varepsilon}_{n,\tau}\right)}_{\text{firm-specific (unsystematic)}} .$$

Black-Litterman MVO

- BL decides weight based on certainty ($\Sigma_{view,\tau}^{-1}$) of given view ($\mu_{view,\tau}, \Sigma_{view,\tau}$)
- In uncertain condition ($\Sigma_{view,\tau}^{-1} < \Sigma_{prior,\tau}^{-1}$): risk diversification (equal weight)
- In certain condition: view-based portfolio allocation

Black-Litterman MVO

- Given
  - View from CDG+MLG
    - $\mu_{view,\tau} \in R^S, \Sigma_{view,\tau} \in R^{S \times S}$
  - Prior distribution
    - $\mu_{prior,\tau} \in R^S, \Sigma_{prior,\tau} \in R^{S \times S}$
- Maximize
  - $w_\tau^* \in arg \max_{w_\tau} \frac{w_\tau^T \mu_{BL,\tau}}{\sqrt{w_\tau^T \Sigma_{BL,\tau} w\_\tau}}$
  - $\mu_{BL,\tau}$ & $\Sigma_{BL,\tau}$ → preliminaries
- S.T.
  - $\mathbf{1}^T w_\tau = 1$

Outline

- Problem Definition
- Proposed Method
- **Experiments**
- Conclusion

Research Questions

- Q1) Investment performance and robustness
  - BL-MVO
- Q2) Time series estimation accuracy
  - CDG+MLG
- Q3) Stock embedding quality
  - Kalman β

Datasets

- 4 major datasets with sector-diversified universe
  - Period
    - train: 2013-01-01 ~ 2024-09-30
    - test: 2024-10-01 ~ 2025-03-31
  - Regions
    - USA (55 stocks)
    - CHINA (55 stocks)
    - EURO (37 stocks)
    - KOREA (44 stocks)

Experiments

- State-of-the-art performance and robustness

Method	S&P500 (US)			CSI300 (China)		
	ASR (↑)	RMDD (↓)	AVol (↓)	ASR (↑)	RMDD (↓)	AVol (↓)
CRP	0.82	8.89	14.44	-0.70	10.96	18.21
MVO	1.18	9.00	21.18	-0.66	13.18	25.93
MOM	0.03	11.87	17.00	-0.47	15.57	28.77
DeepTrader	-0.71	13.40	15.76	-1.18	13.40	18.76
MetaTrader	1.00	10.88	16.82	-1.09	19.40	24.15
AlphaMix	0.35	9.59	13.92	-0.80	9.59	19.11
STABLE (proposed)	**1.85**	**7.82**	**13.43**	**-0.41**	**8.85**	**17.17**
Method	**EUROSTOXX (Europe)**			**KOSPI200 (South Korea)**		
	ASR (↑)	RMDD (↓)	AVol (↓)	ASR (↑)	RMDD (↓)	AVol (↓)
CRP	1.31	5.40	12.96	0.76	8.72	26.55
MVO	0.48	8.35	16.75	0.45	11.84	29.49
MOM	1.42	5.41	12.71	0.33	13.49	23.34
DeepTrader	-2.44	15.99	12.59	0.77	9.62	23.76
MetaTrader	0.50	9.86	14.63	0.57	10.88	22.28
AlphaMix	1.31	5.75	11.77	1.47	9.96	18.76
STABLE (proposed)	**2.92**	**3.84**	**10.88**	**1.61**	**8.34**	**17.82**

Experiments

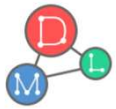
- State-of-the-art on conditional timeseries estimation

	S&P500		CSI300		EUROSTOXX		KOSPI200	
Method	MSE (↓)	DTW (↓)	MSE (↓)	DTW (↓)	MSE (↓)	DTW (↓)	MSE (↓)	DTW (↓)
Diffusion-TS	3.90	5.73	5.71	6.78	3.05	5.80	9.41	8.70
AEC-GAN	4.27	6.58	4.57	6.13	3.70	7.40	10.18	9.28
KoVAE	4.58	5.93	5.46	7.28	2.61	5.43	9.83	8.73
STABLE (proposed)	**3.51**	**5.62**	**3.89**	**6.09**	**2.49**	**4.78**	**8.15**	**8.67**

Experiments

- The nearest neighbor analysis on U.S stocks shows the embedding faithfully encodes stock identity

Query	Top 1	Top 2	Top 3	Top 4	Top 5
TSLA @ 2021-06-28	AAPL	AVGO	MA	META	ECL
TSLA @ 2024-12-31	NVDA	AVGO	AAPL	MSFT	GOOGL
BAC @ 2021-06-28	JPM	WELL	WFC	DUK	MCD
BAC @ 2024-12-31	WFC	JPM	ECL	LIN	APD



DeepTrade

Outline

- Problem Definition
- Proposed Method
- Experiments
- **Conclusion**

Conclusion

- The Conditional Diffusion Generator (CDG) for accurate per-stock estimation
- The Multi-Level Guidance (MLG) for separating macro and micro impacts via a learnable gate
- The Black-Litterman Mean-Variance Optimizer (BL-MVO) for robust allocations
- STABLE increases ASR by up to 122.9% and reduces MSE by up to 15.7%