FactorVAE: A Probabilistic Dynamic Factor Model Based on Variational Autoencoder for Predicting Cross-Sectional Stock Returns

Yitong Duan, Lei Wang, Qizhong Zhang, Jian Li

Boyer Sacha
Chekroun Lucie
Demeure Camille
Partensky Alexandre
Yin Jiayi

SUMMARY

1. Paper Review
2. Dataset & Model Anatomy
3. Implementation Details
4. Results

Introduction, Problem & Methodology

Goal

Build a Dynamic Factor Model (DFM) using VAE to predict cross-sectional stock returns and quantify risk through volatility modeling.

Challenges

1. Low signal-to-noise ratio in financial data
2. Relevant factors vary dynamically over time
3. Need to estimate time-varying coefficients α_s and β_s to reconstruct returns

Methodology (Core idea)

- Learn non-linear latent features from stock characteristics
- Encoder: extracts posterior factors z_{post} using in-sample returns (training only)
- Predictor: approximates z_{post} with z_{prior} using only past data + multi-head attention (avoids lookahead bias)
- Decoder: combines latent factors with α and β to reconstruct returns and risk
- Loss: reconstruction accuracy + KL divergence regularization

Model Structure & Experiments

Model Structure

- **VAE structure bounds latent space as Gaussian → models both mean and variance (risk)**
- **Posterior factors: constructed as portfolio returns weighted by latent features**
- **In-sample DFM: α modeled as distribution, β as point estimate → predicted returns follow Normal distribution**
- **Out-of-sample: use z_prior with the same α, β to predict returns**
- **Total model loss = reconstruction loss + KL divergence between posterior and prior**

Experiments

- **Cross-sectional prediction:** Rank IC metric, tested on Chinese stock market, compared with benchmarks
- **Robustness:** tested removing subsets of stocks (50, 100, 200) during training
- **Portfolio investment:** simulate long-only strategy on top 50 predicted returns; compare with risk-aware strategy incorporating volatility estimates

Dataset & Model Anatomy

Training Setup

- **Dataset:** CSI 300 equities (2010–2020) (less than original paper: ~3500 Chinese stocks)
- **Features:** Alpha158 technical indicators
- **Label**: 2-day forward return
- **Training period:** 2010-01-01 -- 2017-12-31
- **Validation period:** 2018-01-03 -- 2018-12-29
- **Testing period:** 2019-01-02 -- 2020-09-20

Model Anatomy

- **Feature Extractor:** GRU to capture time dependencies
- **Factor Encoder (training phase only):** constructs portfolios, maps into Gaussian latent variables = posterior factors
- **Factor Decoder:** reconstructs returns as $\hat{y} = \alpha + \beta z$; outputs mean & variance → expected returns + risk
- **Factor Predictor** (**inference**): multi-head attention to predict prior factors from features

Implementation Details

Hyperparameters

- **NUM_FACTORS = 32** → dimensionality of latent factors learned.
- **NUM_PORTFOLIO = 64** → number of synthetic portfolios used in the encoder.
- **EPOCHS = 10** → number of training epochs.
- **EarlyStopping(patience=6, min_delta=1e-4)** → stop if validation loss doesn't improve.

Experimental Setup

- **Library:** Torch
- **Hardware:** GPU training for large-scale experiment

Evaluation Metrics

Statistical Metrics

- Rank Information Coefficient (Rank IC)
- Rank ICIR (Information Ratio of IC)

Baselines

Paper results:

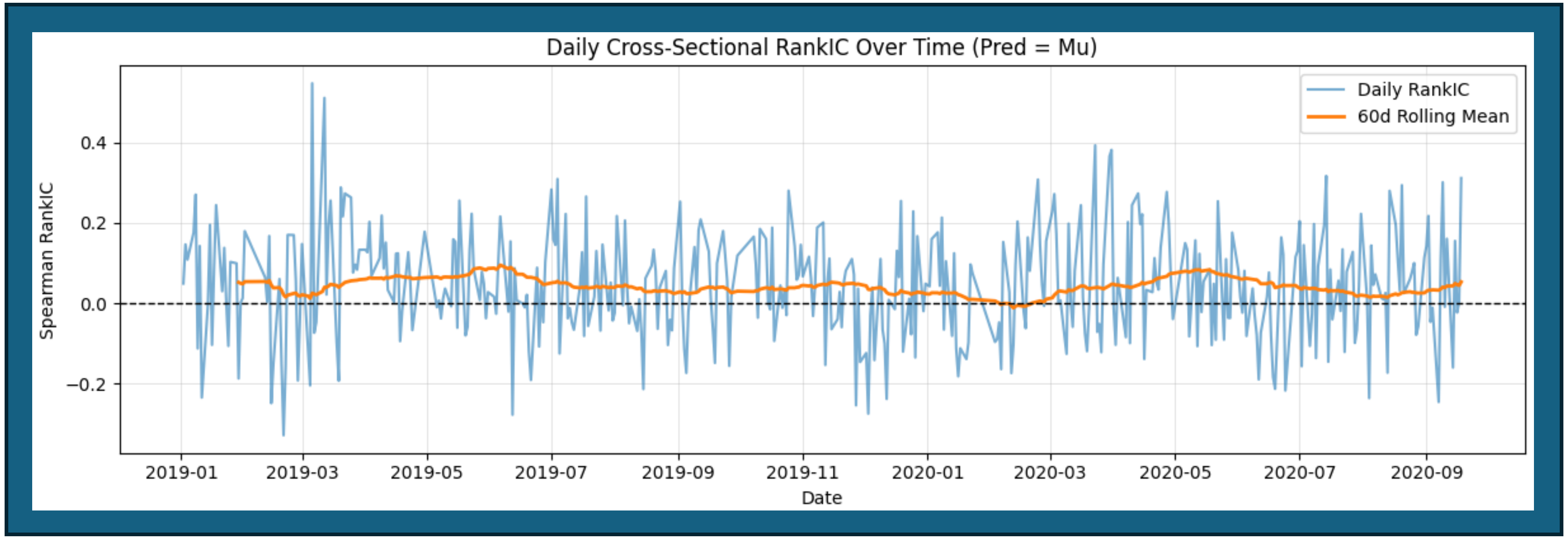
Category	Method	Rank IC	Rank ICIR
ML-based prediction model	GRU	0.032(0.002)	0.398(0.031)
	ALSTM	0.031(0.004)	0.360(0.019)
	GAT	0.034(0.002)	0.390(0.032)
	Trans	0.033(0.003)	0.417(0.032)
	SFM	0.037(0.001)	0.456(0.004)
Dynamic factor model	Linear	0.022(0.002)	0.333(0.033)
	CA	0.039(0.002)	0.442(0.036)
	FactorVAE-prior	0.042(0.003)	0.384(0.033)
	FactorVAE	**0.055(0.004)**	**0.568(0.044)**

Rank IC

Obtained Rank IC:
0.043089

RankIC:

- Rank IC (Information Coefficient): Measures correlation between model's predicted ranks and actual returns (Spearman correlation.
- *RankIC = corr(rank(r_pred), rank(r_true))*



Results analysis:

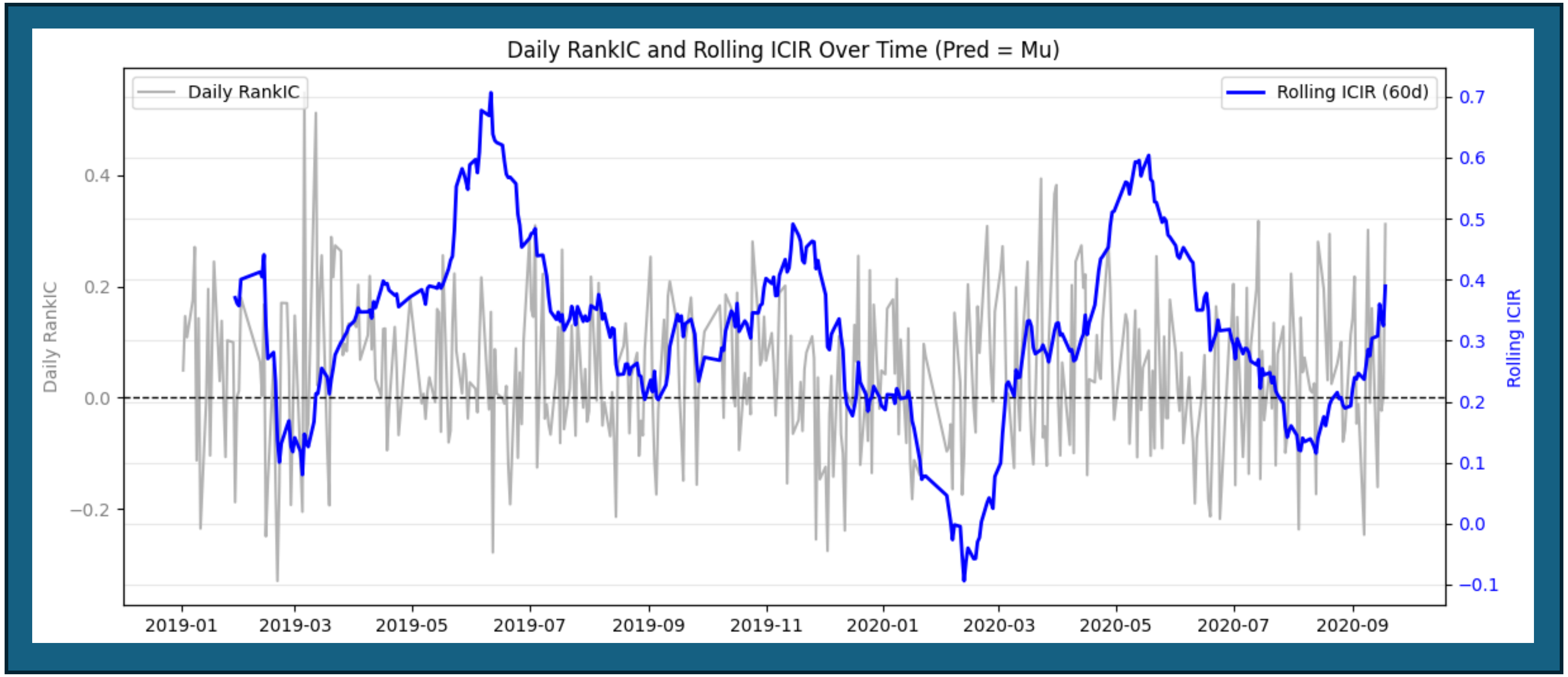
- Rank IC lower than in the original paper
- Coherent with a smaller training dataset

Rank ICIR

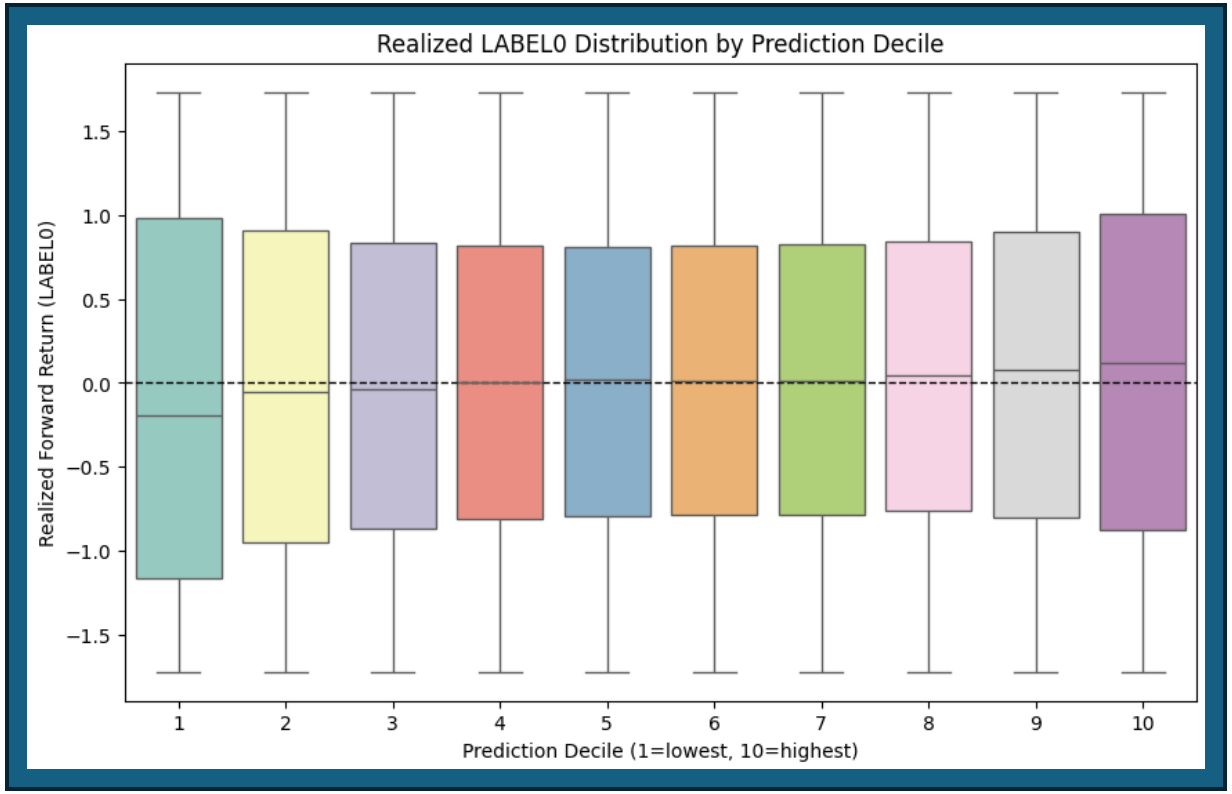
ICIR:

- ICIR (Information Coefficient Information Ratio): Stability of IC over time, computed as mean IC divided by its standard deviation.
- *ICIR = E[IC] / Std(IC)*

Obtained Rank ICIR:
0.317856
(lower than original paper / coherent with smaller training dataset)



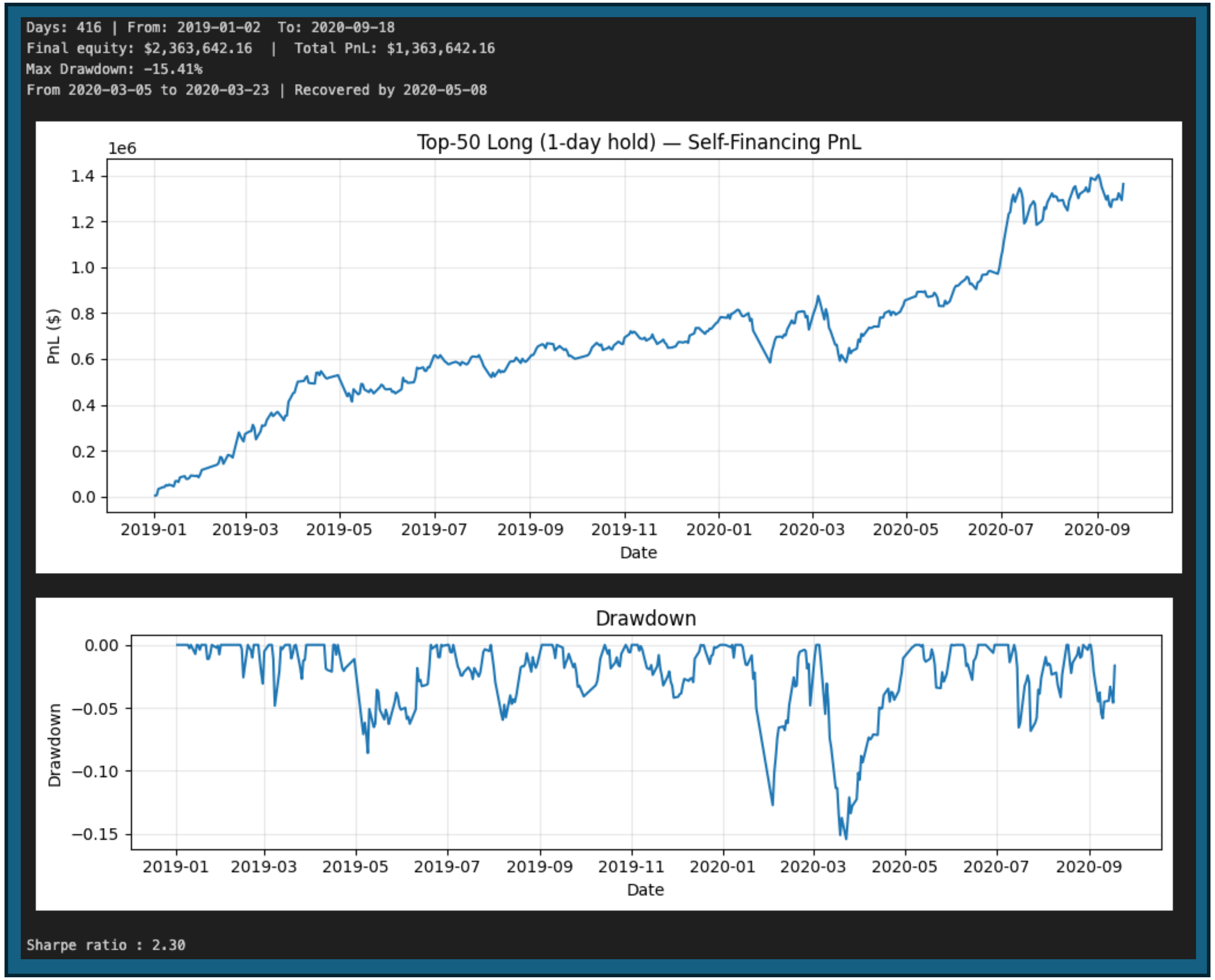
Prediction Deciles



Comments:

- The model captures a small but detectable signal across prediction deciles.
- The variance in realized returns is wider in the tails (Decile 1 and Decile 10), suggesting less stability at the extremes.
- Predictions are relatively more reliable in the middle deciles compared to the tails.

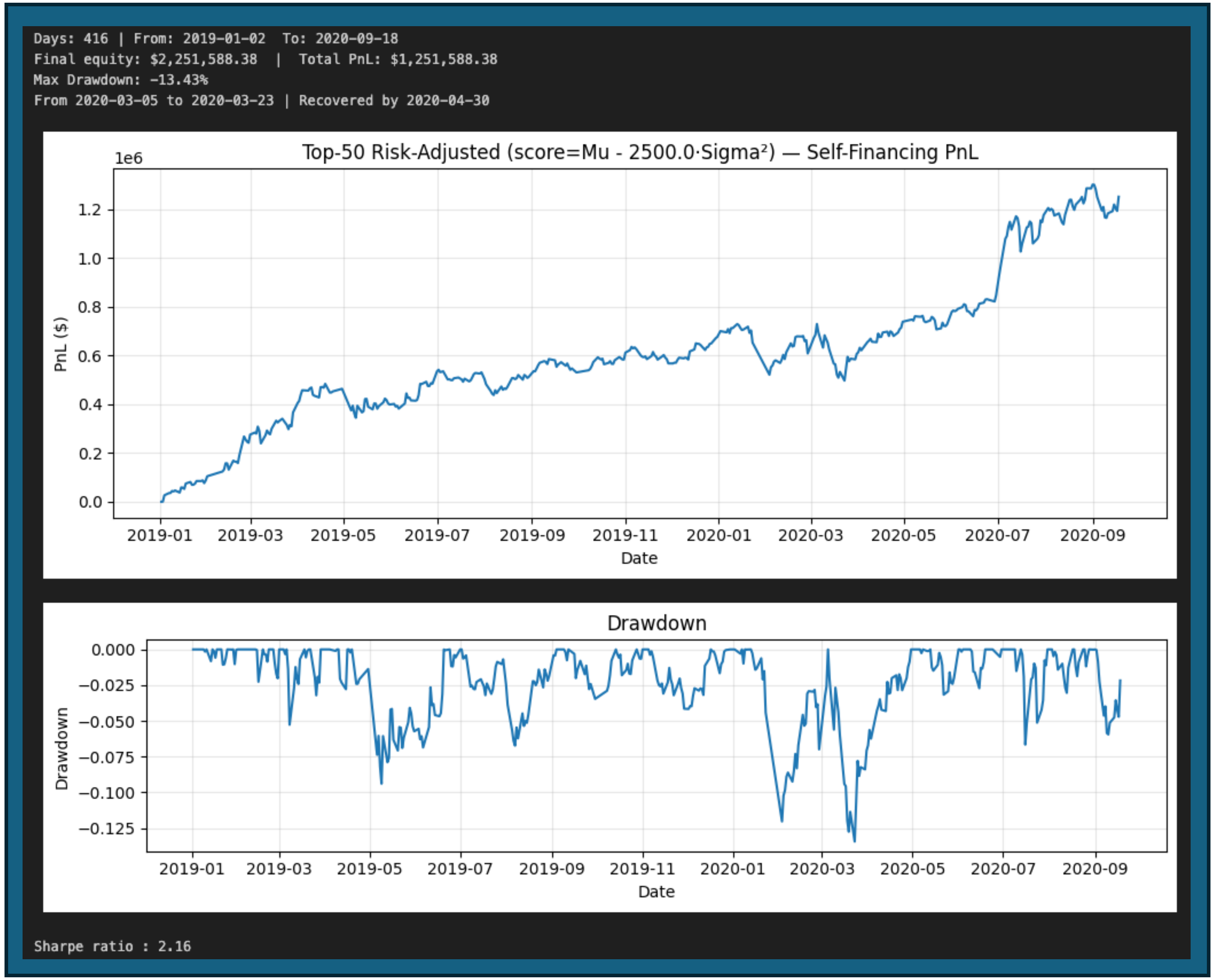
Top50-drop



<u>Top50-drop</u>:

- Each day long top-50 stocks by predicted return (Mu), 1-day hold
- Equal-weighted, self-financing, $1M start capital

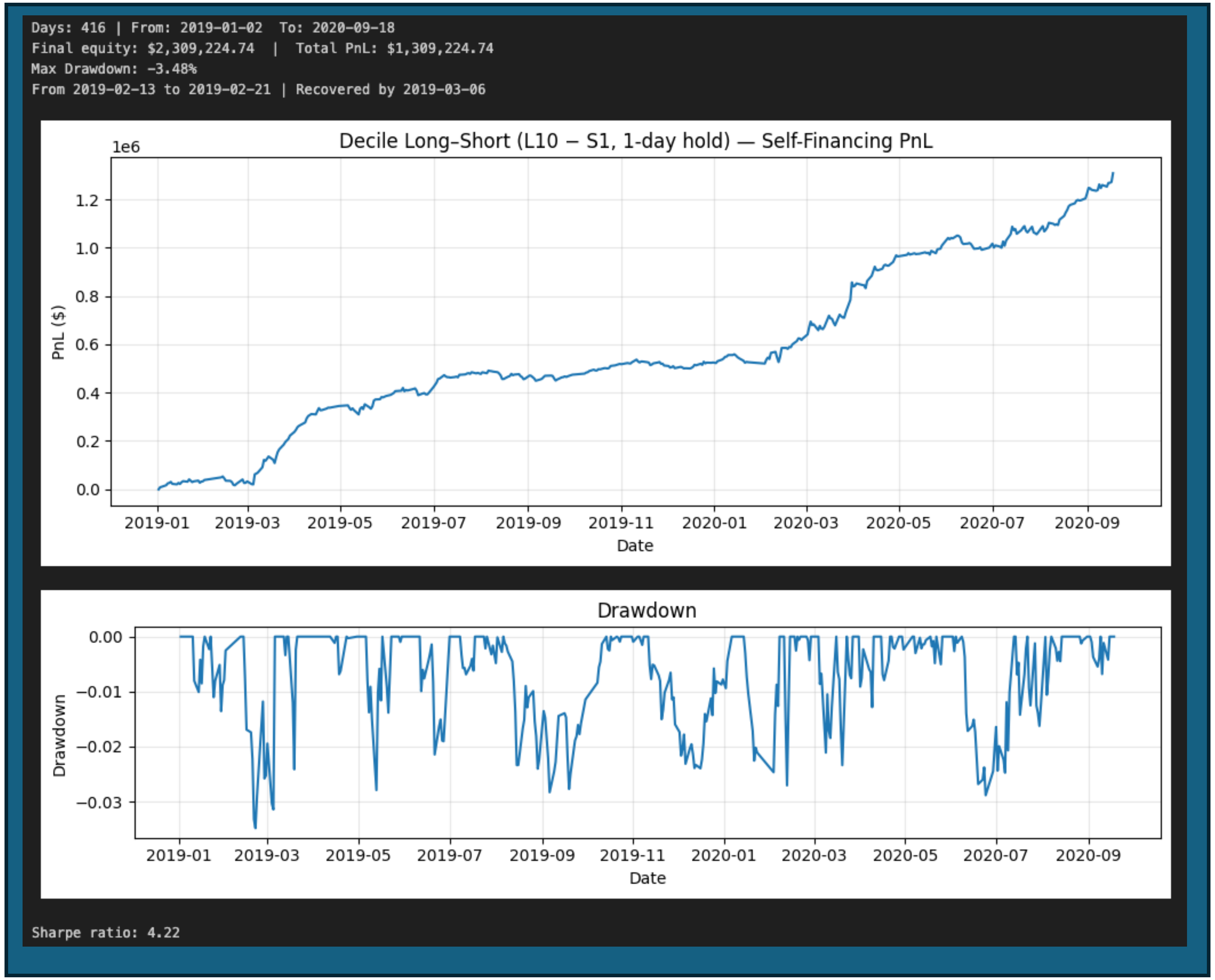
Top50-drop penalized



Top50-drop penalized:

- Ranks by risk-adjusted score = Mu − $\lambda \cdot \sigma^2$
- Penalizes stocks with higher predicted risk (σ^2), favors more stable names
- Leads to lower max drawdown

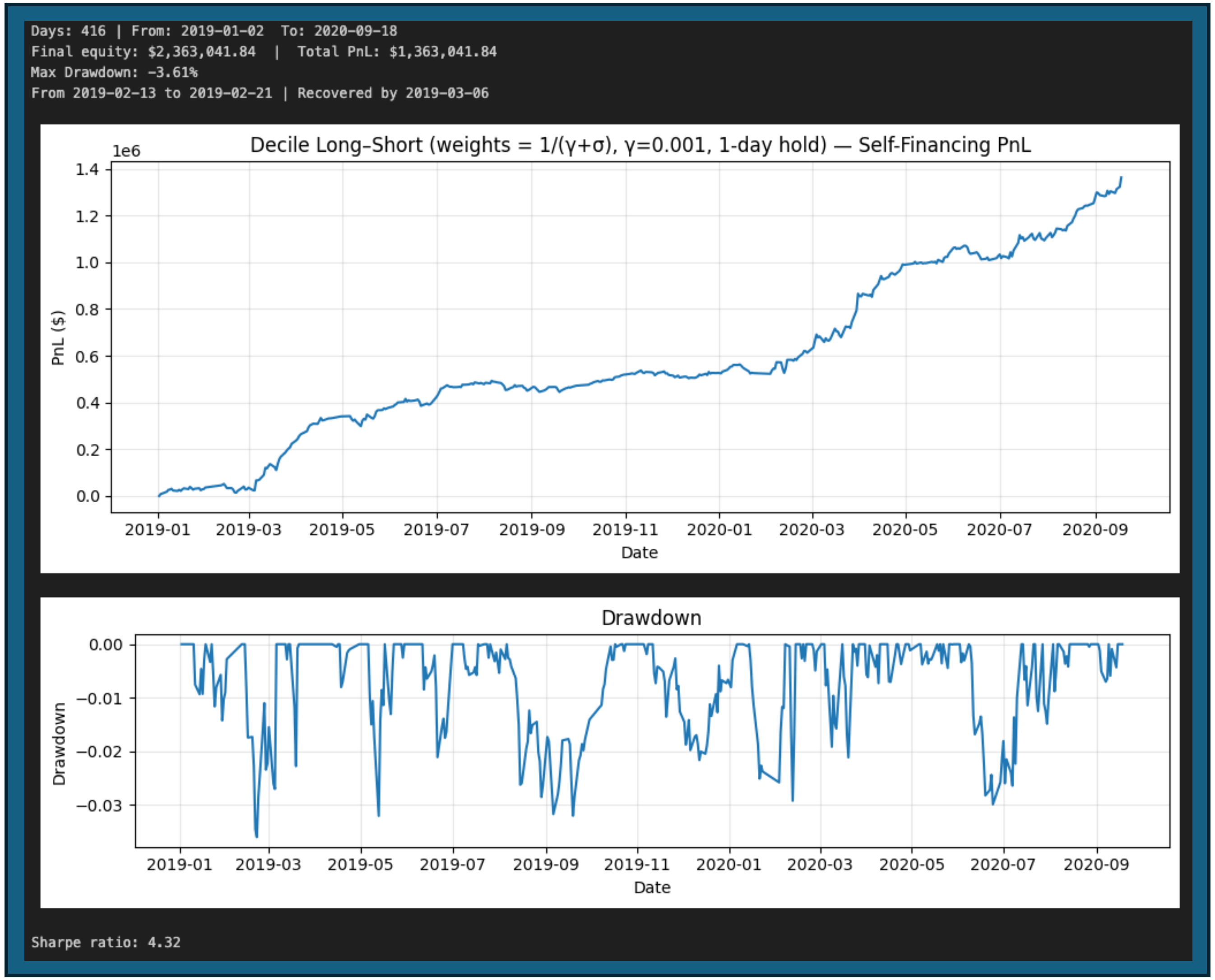
Long-short decile



<u>Long–Short Decile:</u>

- Each day long top 10% (Mu) and short bottom 10%
- Market-neutral, equal-weighted
- Avoids the covid drawdown : max drawdown (−3.5%)

Long-short decile penalized



Long–Short Decile penalized:

- Similar to previous long-short but reweights the portfolio according to 1/(gamma + sigma)

Limitations and possible improvments

Limitations:

- **High computation time** (40 min by epoch) -> couldn't optimize hyperparameters
- **Very low interpretability** (black-box model)
- **Bad performance during exceptionnal market regimes** (COVID crisis)

Possible Improvements

- **Better computational power**
- Include **more stocks** in the training dataset
- Try the model on **different markets** (US market, European Market)
- Modify the model to adapt for **different market regimes**
- Compare with **stronger baseline**
- Test for **robustness**

Thank you!

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