StratFusion: Synthesizing Trading Strategy in Stock

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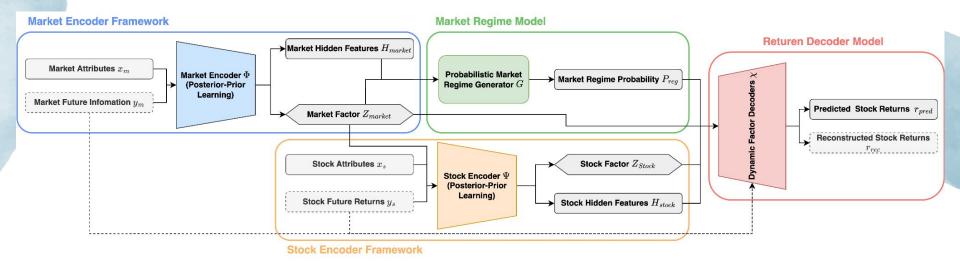
Want more diversification for strategy

- Multifaceted nature of global financial markets
- Risk-Return Balance
- External Factor Tempering

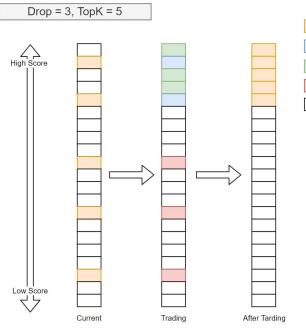


Background

- Fama & French Factor Model
- Market Regime: e.g Bull & Bear market
- Regime Switching Factor Model
- Variational Autoencoder



Topk Dropout Strategy



The stock that is held
The stock that will continue to be held
The stock that will be bought
The stock that will be sold
Other stock

	Sharpe Ratio	Max Drawdown	Compounding Annual Return
IS 2017.1.1-2021.1.1	0.789	34.20%	25.70%
OS 2016.1.1-2017.1.1	0.465	12.90%	8.94%
OS 2022.1.1-2022.11.1	-0.658	23.70%	-18.75%
OS 2023.3.10-2023.10.10	-0.448	10.30%	-3.17%

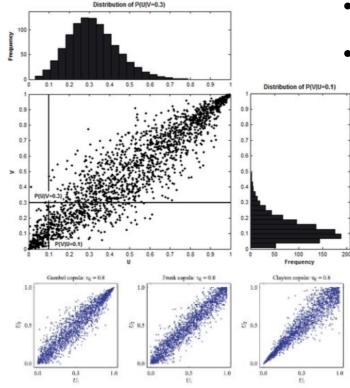
Table 1: EQUAL WEIGHTED TopkDropoutStrategy

	Sharpe Ratio	Max Drawdown	Compounding Annual Return
IS 2017.1.1-2021.1.1	0.693	34.20%	18.07%
OS 2016.1.1-2017.1.1	0.576	10.500%	10.297%
OS 2022.1.1-2022.11.1	-0.663	23.00%	-18.89%
OS 2023.3.10-2023.10.10	-0.344	10.70%	-1.44%

Table 2: Inverse-Variance Weighted TopkDropoutStrategy



Copula Mispricing Index Signal



Copula Definition:

$$P(U_1 \leq u_1, U_2 \leq u_2) = C(u_1, u_2)$$

Single Day Mispricing Index Signal:

$$\mathbb{MI}^{X|Y} = \frac{\partial C(u_1, u_2)}{\partial u_2} = \mathbb{P}(U_t^X \le u_t^X | U_t^Y = u_t^Y)
\mathbb{MI}^{Y|X} = \frac{\partial C(u_1, u_2)}{\partial u_1} = \mathbb{P}(U_t^Y \le u_t^Y | U_t^X = u_t^X)$$

• Cumulative Mispricing Index Signal:

$$ext{Flag}X^*(t) = ext{Flag}X^*(t-1) + (MI_t^{X|Y}-0.5)$$
 $ext{Flag}Y^*(t) = ext{Flag}Y^*(t-1) + (MI_t^{Y|X}-0.5)$

Open Rules:

- When FlagX reaches 0.5 or FlagY reaches -0.5, short X and buy Y.
- When FlagX reaches -0.5 or FlagY reaches 0.5, short Y and buy X.

Exit Rules:

- If trades are opened based on FlagX, then close if FlagX reaches ± 2 .
- If trades are opened based on FlagY, then close if FlagY reaches ±2.
 Once Exit, we will set all the flag to 0.

Name of copula	Bivariate copula $C_{ heta}(u,v)$	Tail Dependence
Clayton	$\left[\max\{u^{-\theta} + v^{-\theta} - 1; 0\}\right]^{-1/\theta}$	Lower Tail Dependence
Frank	$-\frac{1}{\theta}\log\left[1+\frac{(\exp(-\theta u)-1)(\exp(-\theta v)-1)}{\exp(-\theta)-1}\right]$	No tail dependence but stronger in the center
Gumbel	$= \exp \left[-\left((-\log(u))^{ heta} + (-\log(v))^{ heta} ight)^{1/ heta} \right]$	Upper Tail Dependence

Stock Selection

Selection Range: ETF and Stocks from MorningStar Sectors

Fundamental Analysis: Select Top 10 Market Cap Stocks from each sectors and construct trading pairs with similar business scope

Statistical Tests:

• Augmented Dickey-Fuller Test

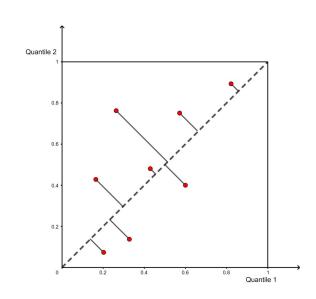
$$H_0: \rho = 1$$
: Non-Stationarity $H_1: \rho < 1$: Stationarity

Mangold's Test

$$H_0: \theta = 0$$
: No Tail Dependency $H_1: \theta \neq 0$: Tail Dependency

• Quantile-Quantile Distance Verification

Stock Selected: AAPL META, USB WFC, ABBV BMY, PPG CHRCY

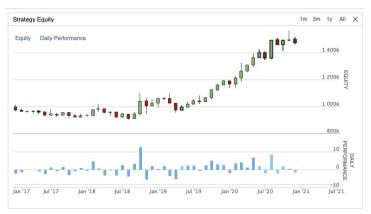


Strategy Execution & BackTest Results

• Fitting the copula - Happens at the first day of each month

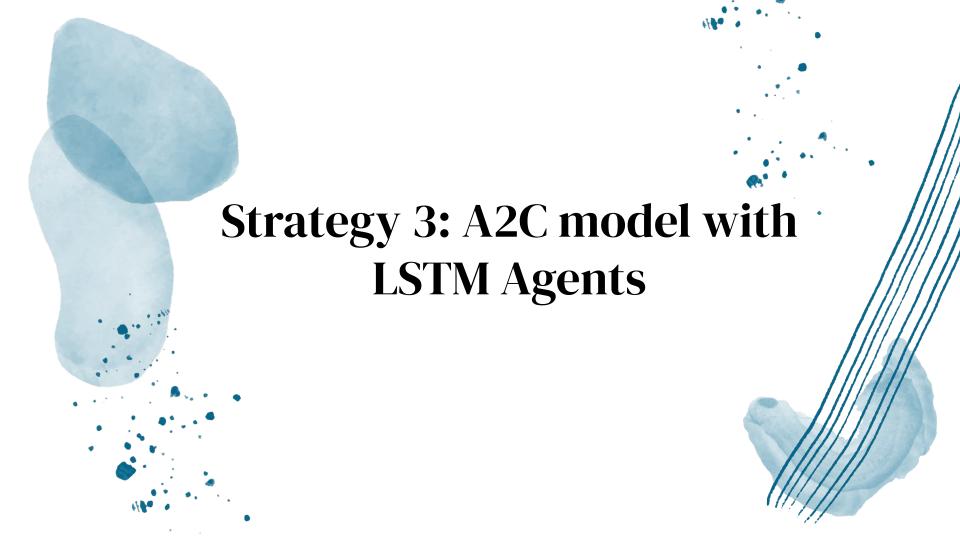
We use the historical 125 days returns data fit an empirical marginal density distribution. Meanwhile, we will use the same historical datasets to select an optimal copula for each trading pairs.

- Calculating Mispricing Index Happens on everyday market open
- Order Execution Happens on everyday market open



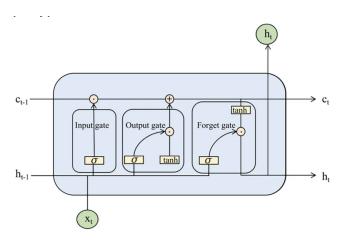


	Sharpe Ratio	Max Drawdown	Compounding Annual Return
IS 2017.1.1-2021.1.1	0.532	13.800%	10.220%
OS 2016.1.1-2017.1.1	0.323	12.200%	5.098%
OS 2022.1.1-2022.11.1	2.166	13.200%	59.643%
OS 2023.3.10-2023.10.10	0.831	4.5%	16.894%
ST 2020.3	1.567	7.800%	55.267%



Long Short Term Memory (LSTM)

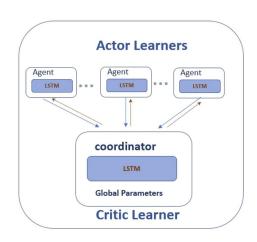
- Avoid vanishing gradient problem
- Make decisions based on both long-term and short-term information
- Filter out irrelevant information
- Suitable for financial data analysis!



Restrictions of LSTM

- Overfitting Stock Market Volatility
- Stationarity Input Data
- Sensitive to Influence of External Factors
- Results: Unstable and high volatility of trading performance

Advantage Actor Critic (A2C) Trading



- **State s:** information about the current environment;
- Action a: the action based on the current state(buy/sell/hold several shares of each stocks);
- **Actor learner:** producing the probability distribution for action *a* given the current state *s*;
- **Critic Learner:** estimates the expected value(rewards) for the given state s;
- **Rewards r:** maximization target of the problem. Defined as **PnL** (profit and loss)of the portfolio between time t and t-1.

Stock Selection

- JPM
- BRK.B
- AAPL
- AMZN
- MSFT

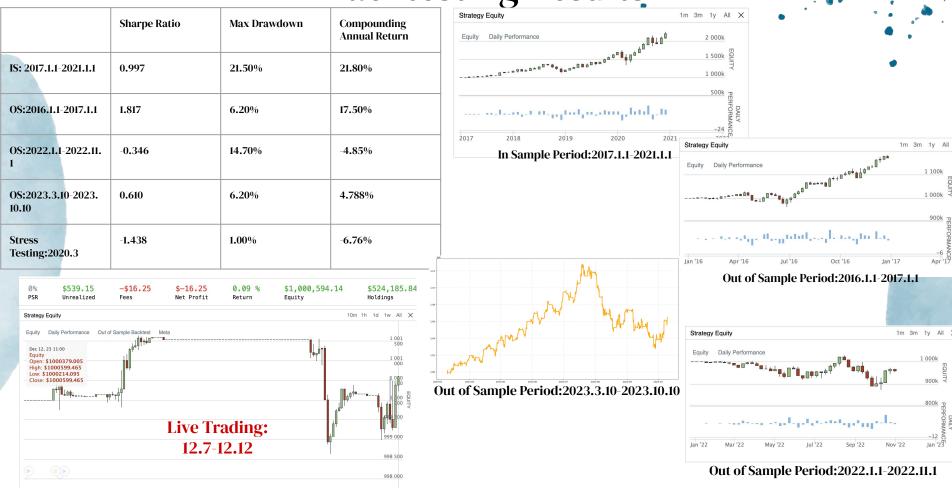
Top 5 stocks sorted by Maket Cap selected from Financial Service, Consumer Service and Technology Sectors.

Indicator Selection

- Relative Strength Index (RSI)
- Autoregressive Integrated Moving Average (ARIMA)
- Volatility
- Relative Daily Volume (RDV)
- Bandwidth
- Percent B (%B)
- Momentum (MOM)

Model Training Period: 2017.1.1 - 2021.1.1 Trading Frequency: Every 10 trade days

Backtesting Results





Advantages of GPT

• Advantages of GPT in sentiment analysis

- Training Free
- High Accuracy
- Customization
- Intepretability

• Prompt Engineering

You will work as a Sentiment Analysis Expert for Financial News for Apple, focusing on financial indicators such as earnings, market trends, and investor opinions. Your answer will include 2 lines. In the first line, you will answer 1 sentence to analyze why the news is good or bad for Apple. Then, in the second line, you will answer with an integer between 1 and 10, with 1 being most BEARISH, 10 being most BULLISH.

Role Assignment

Focus on Relevant Factors

Structured Response Format

Analytical Reasoning

Clear Sentiment Ratings

Key Findings and Trading Strategy

• EDA Key Findings:

- Correlation between news sentiment and stock returns in next 60 minutes.
- Label 2 indicates strong return decrease
- Label 6 indicates strong return increase

Addressing LookAhead Bias:

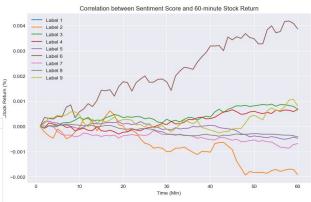
- **GPT-3.5-turbo: Up to Sep 2021**
- O Backtesting: From Jan 2022

• Out-Of-Sample Result (2023.1.1 - 2023.12.1):

- O Annual Return: 11.467%
- O Sharpe Ratio: 0.728
- O Max Drawdown: 4.200%









Optimize Portfolio Risk Using Risk Parity

- **1.** Calculate Volatility: historical volatility for each asset.
- 2. Generate Covariance Matrix;
- **3.** Calculate Risk Contribution: $RC_i = w_i \cdot \sigma_i \cdot \sum_{j=1}^N w_j \cdot c_{ij}$ where w_i is the weight of asset i
- **4.** Optimization Algorithm: $\min_{\mathbf{w}} \left\{ \sum_{i=1}^{N} \left(RC_i \frac{1}{N} \right)^2 \right\}$
- **5. Measure Leverage:** Adjust the portfolio weights to achieve the targeted risk parity condition by applying leverage to the assets accordingly.

Portfolio Performance

EQUAL WEIGHTS ASSET ALLOCATION

	Sharpe Ratio	Max Drawdown
IS 2017.1.1-2021.1.1	1.34	17.14%
OS 2016.1.1-2017.1.1	1.27	4.97%
OS 2022.1.1-2022.11.1	0.84	10.08%
OS 2023.3.10-2023.10.10	1.37	5.5%

Table 7: Portfolio Statistics

RISK PARITY ASSET ALLOCATION

	Sharpe Ratio	Max Drawdown
IS 2017.1.1-2021.1.1	1.34	14.76%
OS 2016.1.1-2017.1.1	1.13	4.97%
OS 2022.1.1-2022.11.1	1.12	4.97%
OS 2023.3.10-2023.10.10	1.41	4.64%

Table 8: Portfolio Statistics



Thank You!

