



# Deep Learning for Portfolio Optimization

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The Erdős institute  
Li Zhu, Jingheng Wang, Arvind Suresh

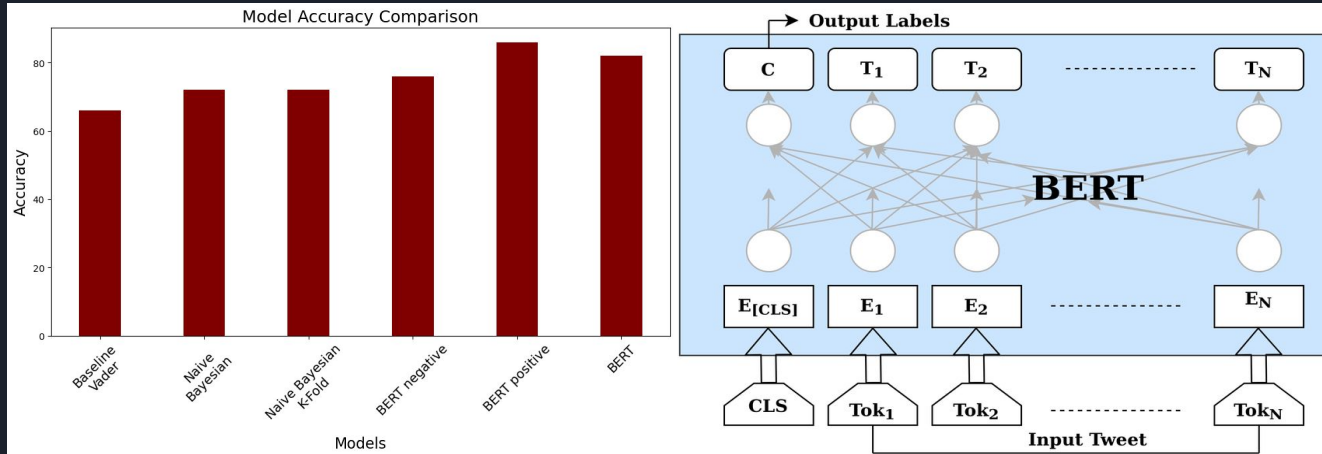


# Problem description

- Selecting the best possible mix of stocks to maximize returns while minimizing risk, based on an investor's risk tolerance, investment goals, and market conditions
- Short-term: NLP sentiment analysis combined with the Black-Litterman model
- Long-term
  - Long-Short-Term-Memories Network using stock history
  - Genetic Algorithm
  - Markowitz Mean-Variance Model
- Stakeholders: Individual Investors, Institutional Investors, Portfolio Managers and Financial Advisors, Fund Managers, Regulators and Compliance Officers, Shareholders, etc.

# Sentiment Analysis

- BERT is a transformer based encoder trained to read in a full sentence to understand context
- We preprocess the news to standardize the text
- BERT model perform better for positive messages than negative
- Overall, BERT performs better than other NLP models





# The Black-Litterman model – Short Term Prediction

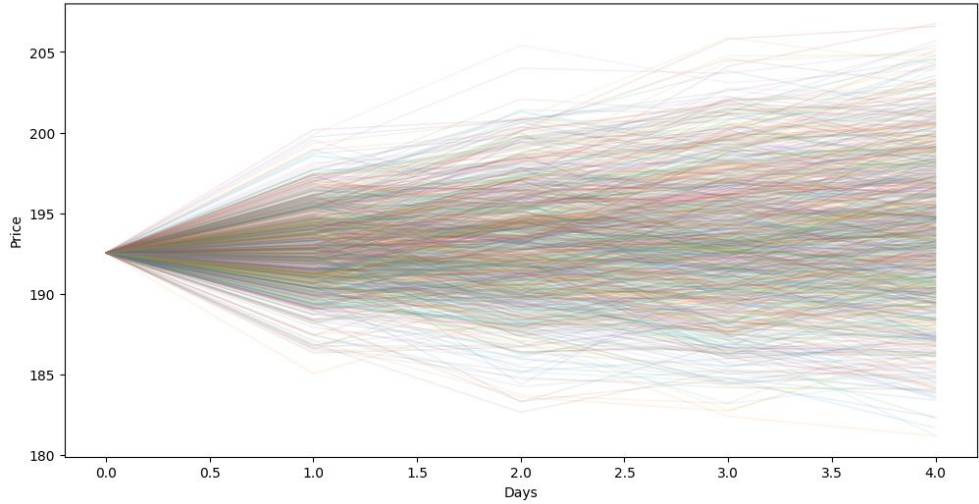
- Posterior estimate of expected returns
- $E(R) = [(\tau\Sigma)^{-1} + P^T\Omega^{-1}P]^{-1}[(\tau\Sigma)^{-1}\Pi + P^T\Omega^{-1}Q]$
- Use prior estimate of returns with investor's views and confidence
- Use sentiment score  $\gamma \in [-1,1]$  to calculate views

$$S_T = \begin{cases} S_0 + [(S_{MC}^+ - S_0) \cdot \gamma] & \text{if } \gamma \text{ in } (0, 1] \\ S_0 - [(S_0 - S_{MC}^-) \cdot \gamma] & \text{if } \gamma \text{ in } [-1, 0) \end{cases}$$

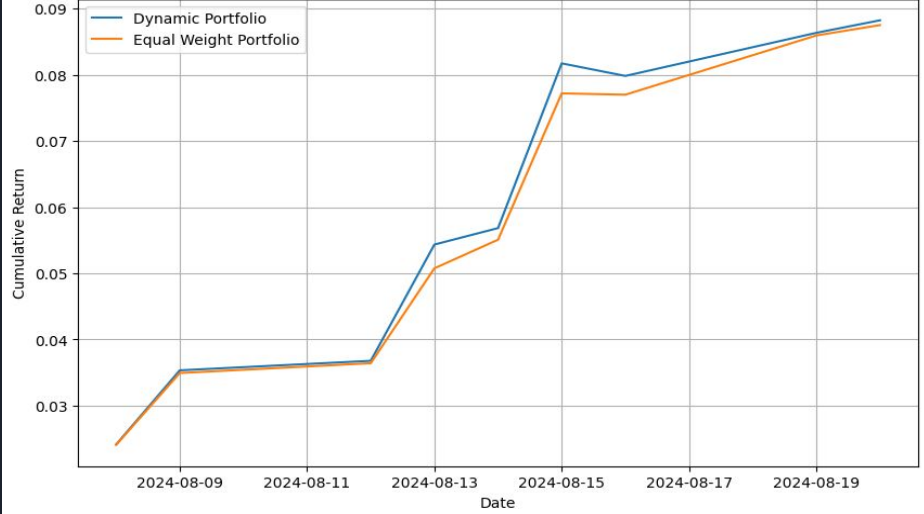
$$Views = \ln\left(\frac{S_T}{S_0}\right)$$



AAPL Monte Carlo Simulation



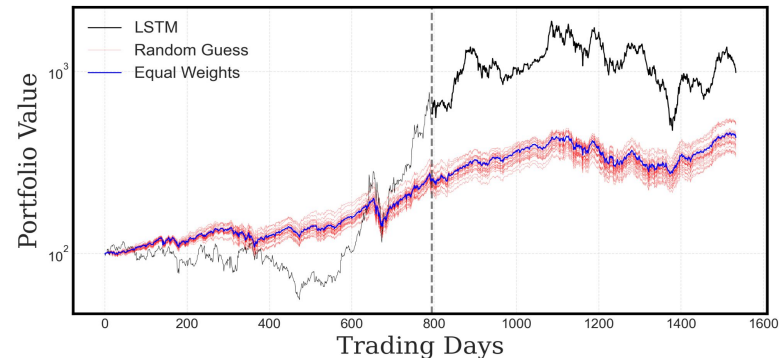
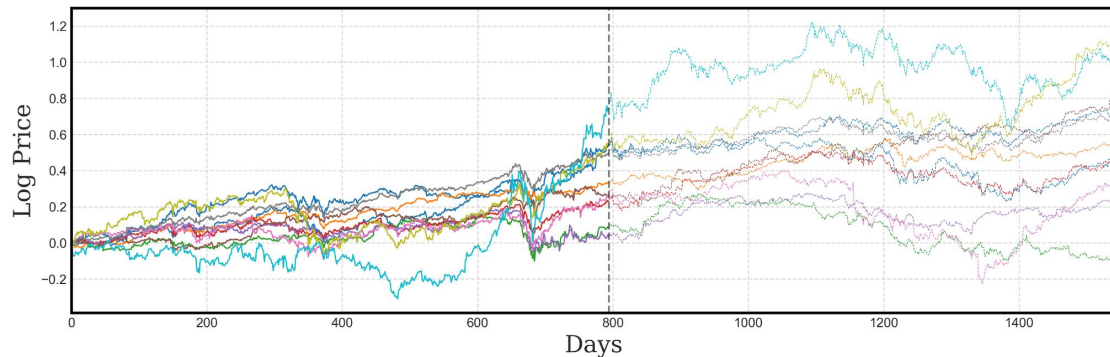
Cumulative Returns Comparison: Dynamic vs. Equal Weight Portfolios





# LSTM – Long Term Prediction

- Recurrent neural network (RNN)
- Capture both short-term fluctuations and long-term trends in financial data
- Memory Cells, Forget Gates -> Adaptive learning



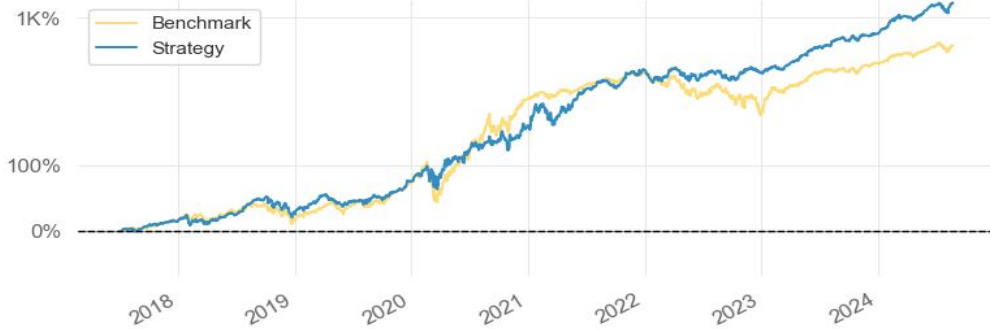


# The Markowitz Model v.s GA

Performance Metrics			Performance Metrics		
	Benchmark	Strategy		Benchmark	Strategy
Start Period	2017-07-03	2017-07-03	Start Period	2017-07-03	2017-07-03
End Period	2024-08-22	2024-08-22	End Period	2024-08-22	2024-08-22
Risk-Free Rate	0.0%	0.0%	Risk-Free Rate	0.0%	0.0%
Time in Market	100.0%	100.0%	Time in Market	100.0%	100.0%
Cumulative Return	572.26%	1,327.74%	Cumulative Return	572.26%	836.52%
CAGR%	20.22%	29.3%	CAGR%	20.22%	24.14%
Sharpe	1.21	1.67	Sharpe	1.21	1.17
Prob. Sharpe Ratio	99.92%	100.0%	Prob. Sharpe Ratio	99.92%	99.9%
Smart Sharpe	1.08	1.5	Smart Sharpe	1.12	1.09
Sortino	1.73	2.62	Sortino	1.73	1.72
Smart Sortino	1.55	2.35	Smart Sortino	1.6	1.59
Sortino/√2	1.22	1.85	Sortino/√2	1.22	1.22
Smart Sortino/√2	1.1	1.66	Smart Sortino/√2	1.13	1.13
Omega	1.36	1.36	Omega	1.23	1.23

### Cumulative Returns vs Benchmark (Log Scaled)

3 Jul '17 - 22 Aug '24



### Cumulative Returns vs Benchmark (Log Scaled)

3 Jul '17 - 22 Aug '24





# Conclusion and Future work

- LSTM model behaves the best
- Genetic Algorithms need more tuning of parameters to get better results
- Use sentiment analysis doesn't have significant improvement
- Each optimization method has its strengths and weaknesses, and the choice of method often depends on the specific objectives, constraints, and preferences of the investor or portfolio manager