Evaluation on Predictive Portfolios using Deep Learning Models

Hypothesis

Deep learning models are good at predictions and can improve portfolios

Expected Outcome

Finance data are **sparse** and **complex**

Sparse: compared with usually how many data are needed to train deep learning models

Complex: the models will be easily overfitted or fail to be predictive

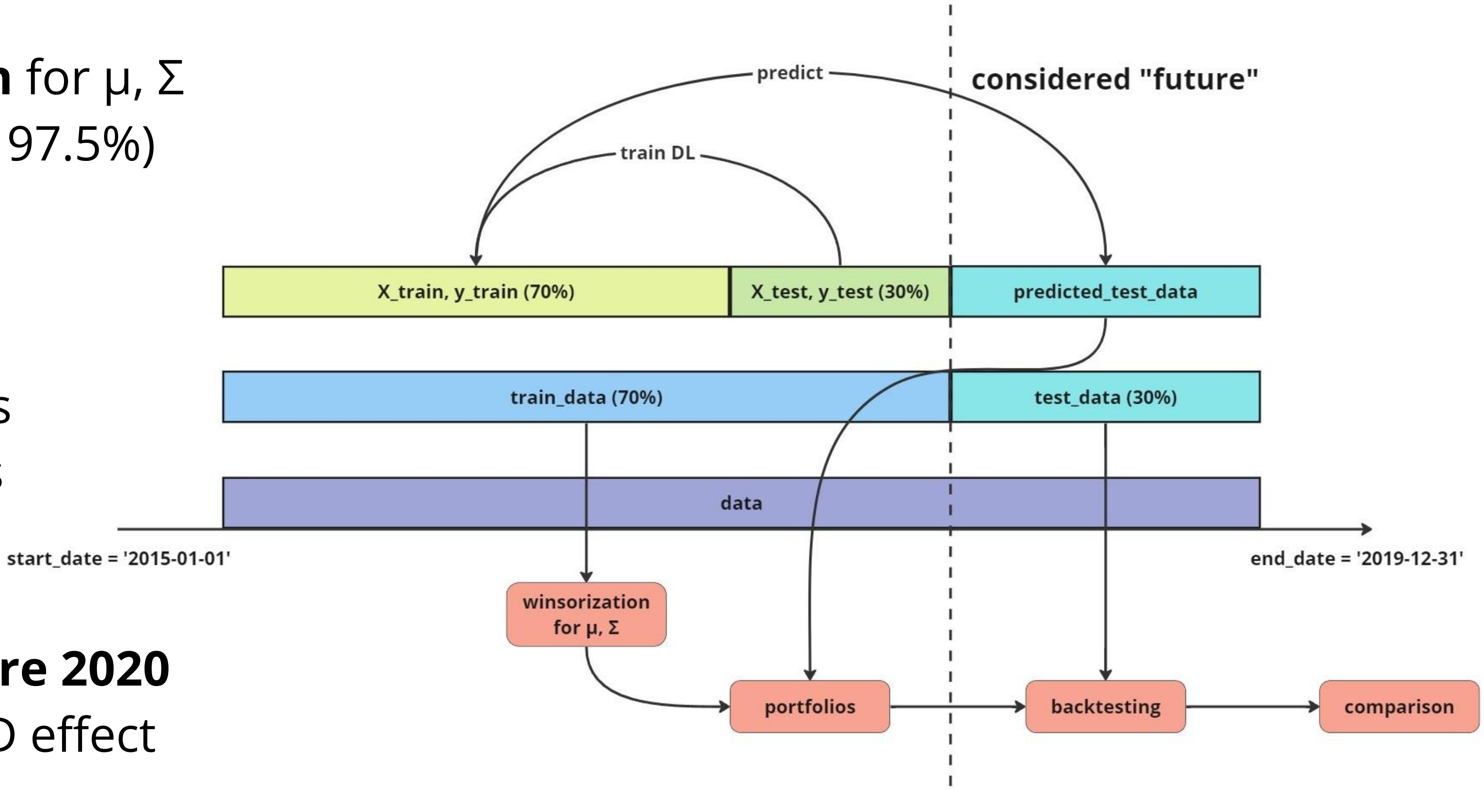
★ **Traditional models outperform deep learning models**

Overview / Data Processing

Winsorization for μ, Σ
(2.5% ≤ data ≤ 97.5%)

5 years of
20 stock prices
from 8 sectors

Use data **before 2020**
to avoid COVID effect



Traditional Portfolios

According to the lecture notes,

Heuristic Portfolios:

- Equally Weighted Portfolio (**EWP**) (**noob portfolio**)
- Quintile Portfolio (**QP**)
- Maximum Sharpe Ratio Portfolio (**MSRP**)

Risk-Based Portfolios:

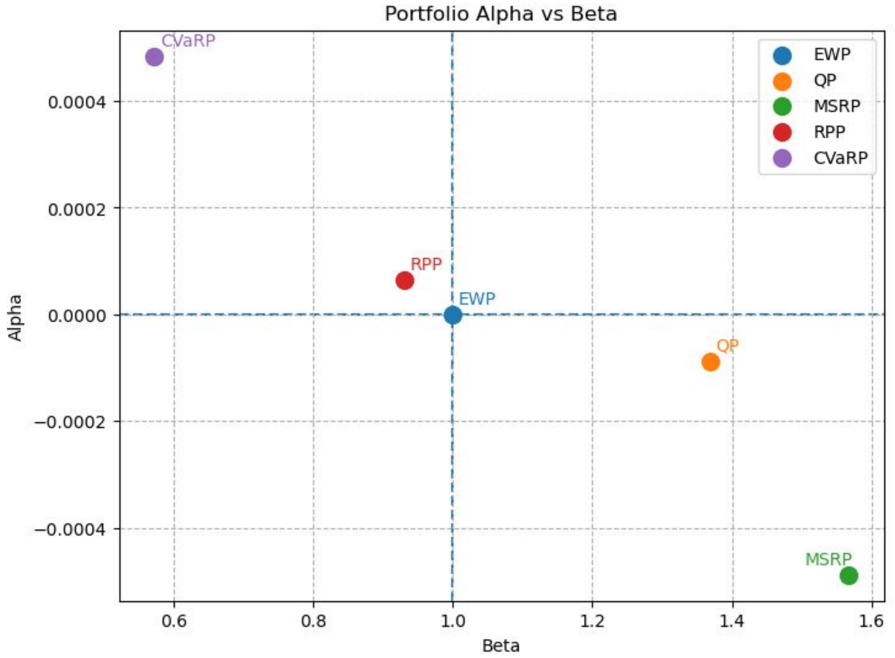
- Risk Parity Portfolio (**RPP**) with Convex Formulation
- Conditional Value-at-Risk Portfolio (**CVaRP**)

Backtesting Metrics:

- Cumulative returns
- Drawdown
- Alpha, Beta

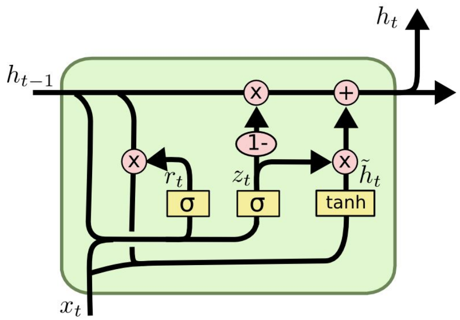
Goal: High Alpha, Low Beta

Benchmark: Alpha = 0, Beta = 1 (Noob portfolio)

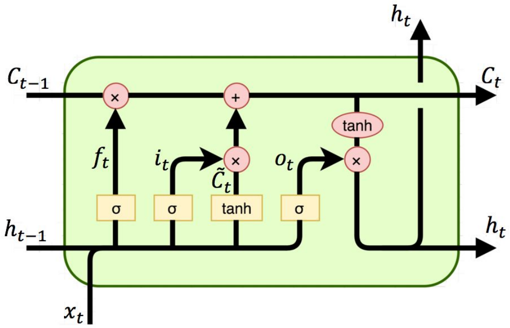


Deep Learning Models

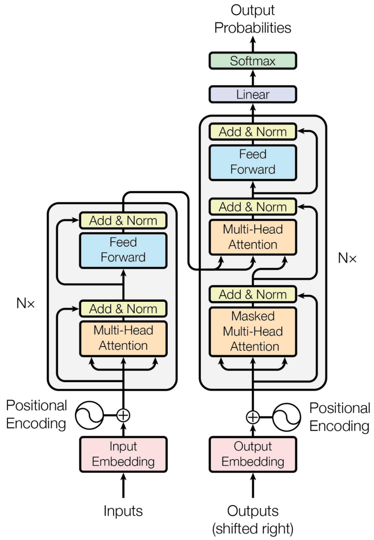
Gated Recurrent Unit (GRU)



Long Short-Term Memory (LSTM)



Transformer



Designed for **sequential data** (such as NLP for ChatGPT)

Complexity: GRU < LSTM < Transformer

★ Use predictions to construct portfolios (valid **ONLY IF** predictions are good)

Training 😎

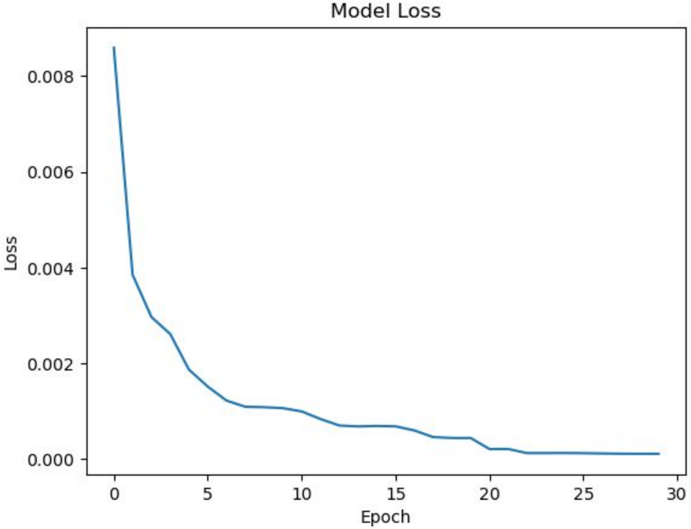
Time series cross-validation

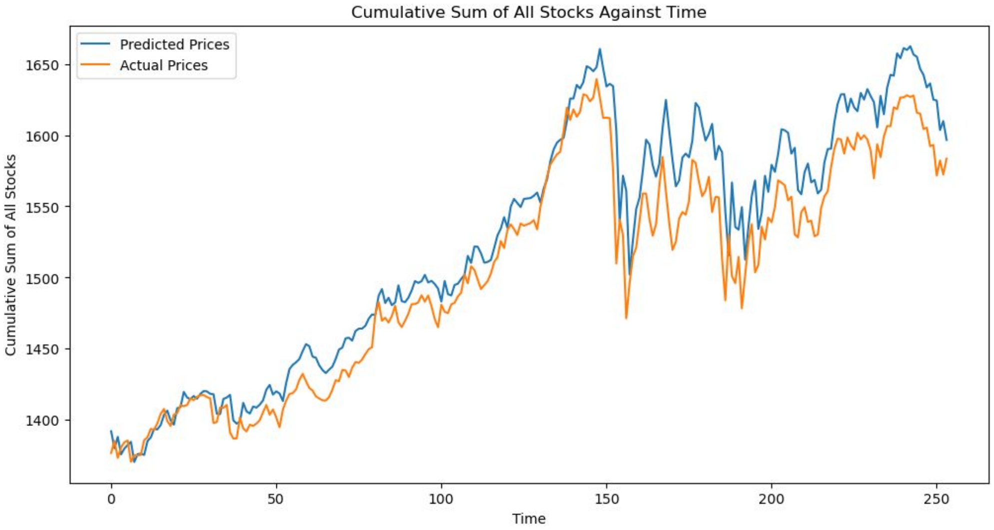
Hyperparameters: Adam / ~~SGD~~, window_size, split, learning_rate, epochs, num_heads, dff, ...

(Spoiler alert: Easily overfit or underfit)

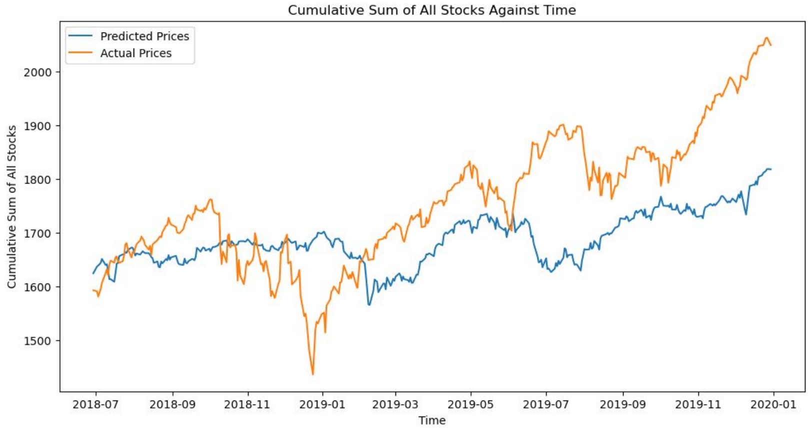
★ **Intuition: Manual tuning to match as much as to X_test in training**

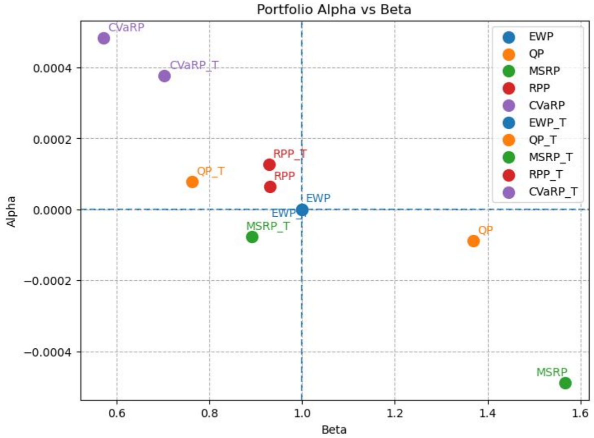
Then use the model to predict test_data (future)

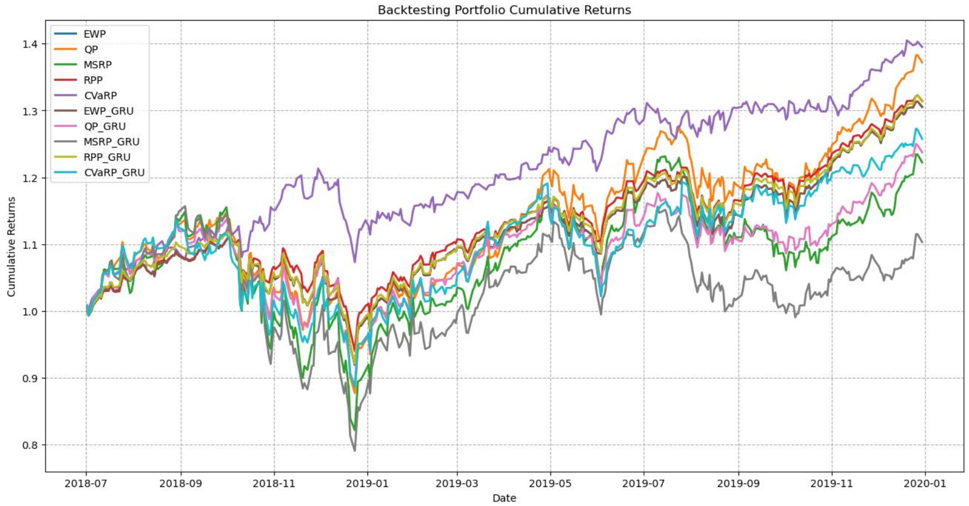


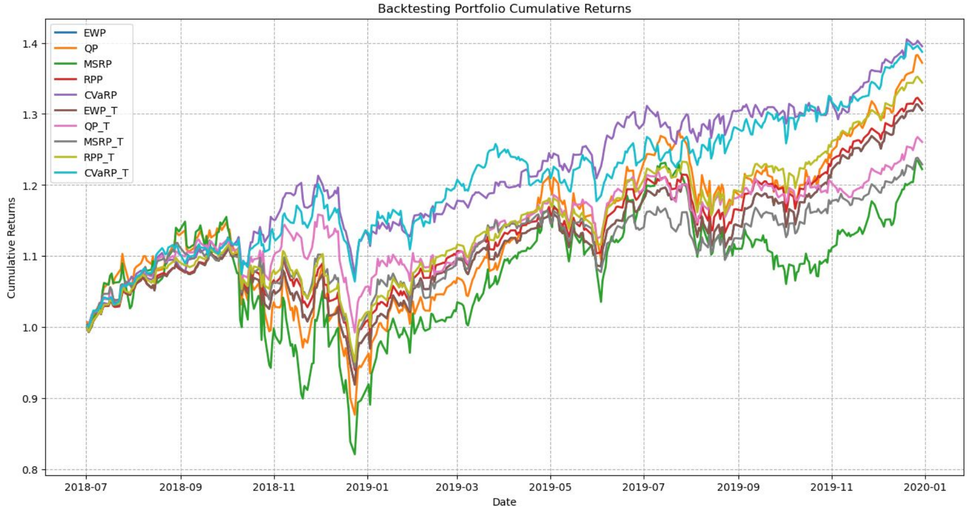


Backtesting 🥶

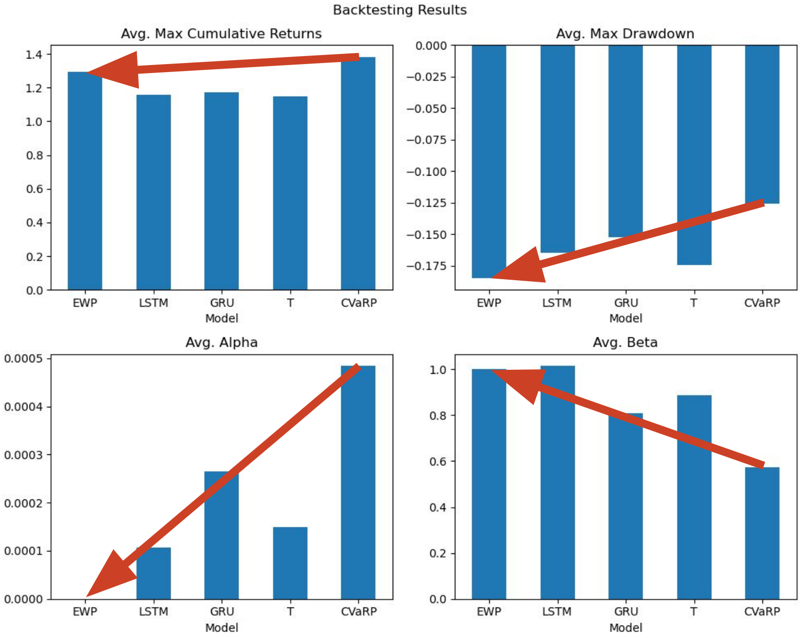








Verdict



Conclusion

- Portfolios closer to EWP (noob portfolio)
- Predictive data not recommended
- Worse than randomness (fake information)
- Expected, otherwise I am rich

Bias

- Economy during the period was generally increasing so no significant losses
- Tried from 2018 to 2023 (COVID) and cumulative returns from CVaRP only up to 1.05

Potential Improvements

- Enhanced data cleaning to reduce noises (de-trending, seasonality decomposition, PCA, ...)
- Advanced feature engineering (rolling averages, time-based aggregations, ...)
- Advanced deep learning model designs (ensemble learning, different architectures, ...)
- Macroeconomic indicators (inflation, GDP, sentiment, ...)