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DATA.ML.330 Media Analysis

Deep graph convolutional reinforcement learning for financial portfolio management

Final Presentation

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Contents

Introduction

Methodology

Results and Discussions

Conclusions

Introduction: Interrelations in Financial Markets

- **Economic Indicators:** Impact of GDP, unemployment, inflation, and interest rates on asset valuations.
- **Market Sentiment:** Collective trends driven by investor optimism or pessimism.
- **Geopolitical Events:** Influence of political instability, wars, and trade policies on global markets.
- **Sector Performance:** Correlated movements within industry sectors due to shared factors.
- **Monetary Policy:** Central bank policies affecting stock prices and bond yields.
- **Risk Factors:** Common risks like credit, liquidity, and operational risks linking asset movements.
- **Globalization:** Global interconnectedness leading to worldwide market effects from regional events.
- **Arbitrage Opportunities:** Price alignment across markets due to arbitrage by traders.
- **Key Takeaway:** Assets in financial markets are deeply interrelated through various economic, geopolitical, and market dynamics, influencing investment strategies and risk management.

Introduction: Interrelations in Financial Markets

Question: How to quantify the "Interrelations"

Introduction: Interrelations in Financial Markets

Traditionally, they use correlation formulas (Pearson, spearman, etc). For portfolio management. (Markowitz models)

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Introduction: Interrelations in Financial Markets

Pros:

Concrete formulas, easy to implement.

Available formula.

Mathematically proven.

Cons:

Model-based.

Assume normal distribution of returns.

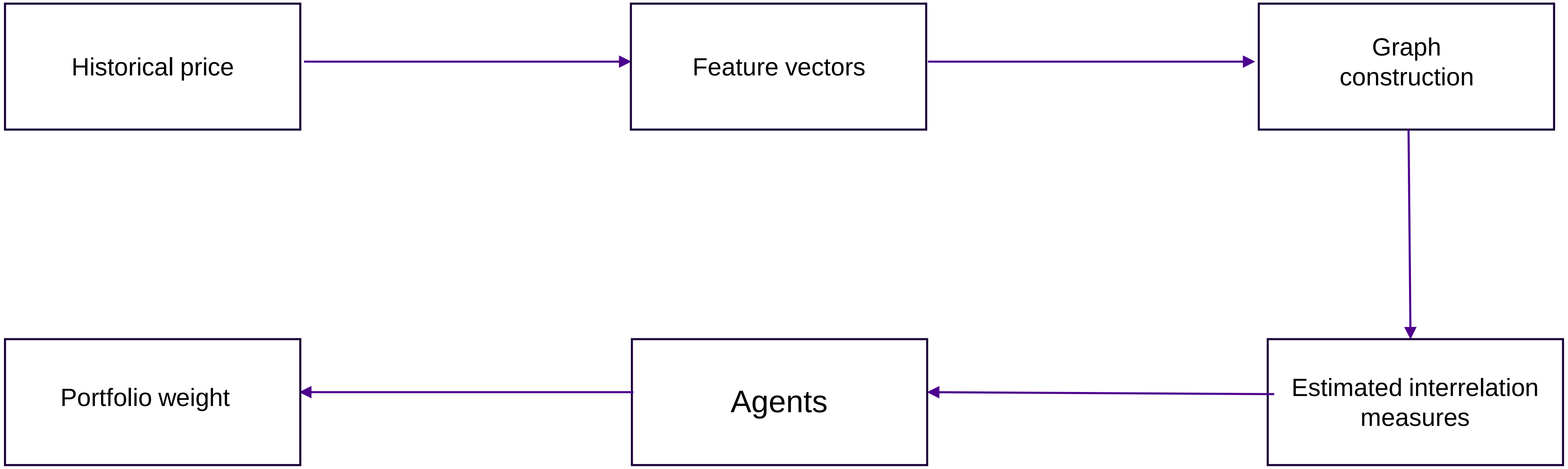
Introduction

- Field of study: Portfolio optimization, Graph convolution, Reinforcement learning.
- Problem: given historical prices of multiple assets, return the weight of the portfolio for a given period which optimize the objective function (maximize return, CVaR, sharpe ratio, etc).

$$
\begin{array}{ll}
\text{Optimize} & f(w, \tilde{\theta}) \\
\text{subject to} & w_i > 0, \quad \forall i \in \{1, 2, \dots, n\} \\
 & \sum_{i=1}^{n} w_i = 1
\end{array}
$$

- The objective is to optimize (either maximize or minimize) the function f(w, θ~) by finding w, where θ~ is a set of parameters estimated from historical data, and w is the vector of weight for each assets.

Introduction: Main idea



Introduction: Implementation

- Data processing: From raw historical data, extract financial indicators.
- Embed the time-series samples into a latent space using Auto encoder and financial features.
- Graph construction from embedding features. Graph Laplancian transformation.
- Graph convolution neural network.
- Actor-Critic reinforcement learning.
- Evaluation on test dataset (paper trade).
- Result documentation.

Methodology

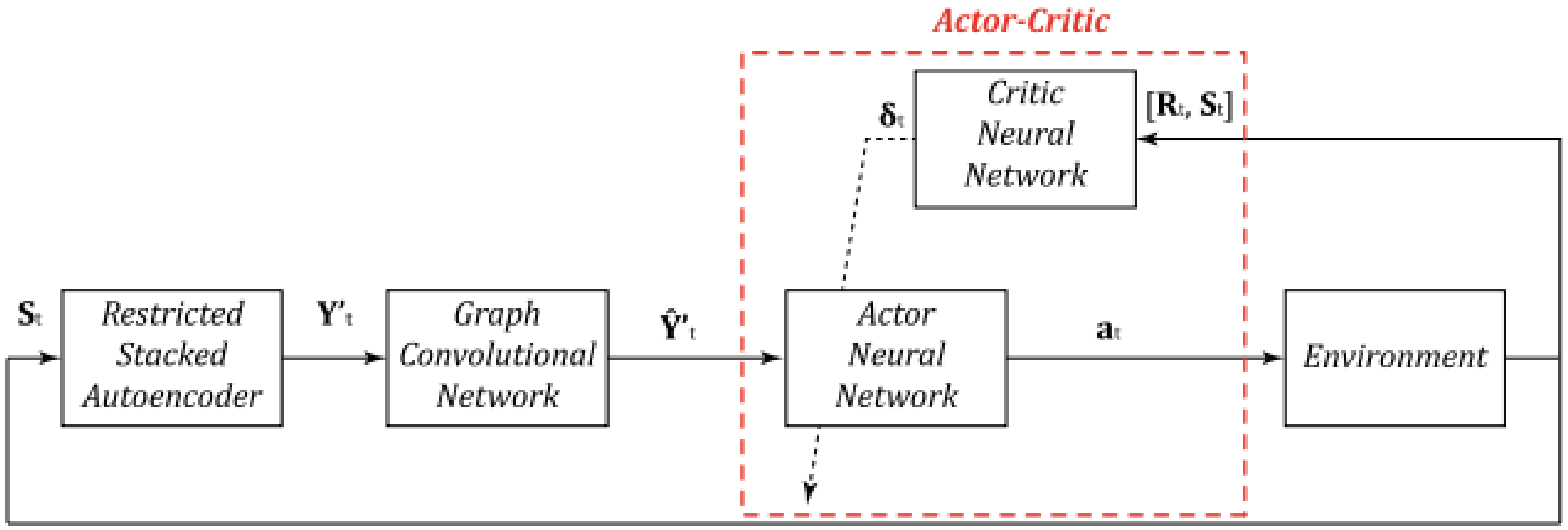


Fig. 2. Global architecture of DeepPocket.

Methodology cont.

Feature normalization from datasets based on financial mathematical models in opening, closing, low, high, and volume prices cases based on all financial indicators

Table 1
Financial Indicators Employed as Features.

Financial Indicators	Definition
Average True Range	The average true range is a technical indicator that assess the volatility of an asset in the market through a certain period.
Commodity Channel Index	The commodity channel index is a momentum-based oscillator used to help determine cyclical trend of an asset price as well as strength and direction of that trend.
Commodity Selection Index	The commodity selection index is a momentum indicator that evaluates the eligibility of an asset for short term investment.
Demand Index	The demand index is an indicator that uses price and volume to assess buying and selling pressure affecting a security.
Dynamic Momentum Index	The dynamic momentum index determines if an asset is an asset is overbought or oversold.
Exponential Moving Average	An exponential moving average is a technical indicator that follow the price of an asset while prioritizing on recent data points.
Hull Moving Average	The hull moving average is a more responsive alternative to moving average indicator that focus on the current price activity whilst maintaining curve smoothness.
Momentum	The momentum in a technical indicator that determines the speed at which the price of an asset is changing.

Methodology cont.

- Restricted stacked autoencoder for reducing the abstract features dimension complexity with time series data
  - Encoder: Mapping the input features (8 feature normalization + Low/Close/High price features) into 3 features through layers in the module for training. And use them as input for graph implementation
    - Using gym library to provide observation space
    - Applying ReLU for each module in Pytorch Sequential
  - Decoder: Reconstructing part of the original features (Low/Close/High price features).
- The architecture consists of an LSTM layer for encoding, followed by a convolutional layer, a max-pooling layer, and another LSTM layer for decoding.

Methodology cont.

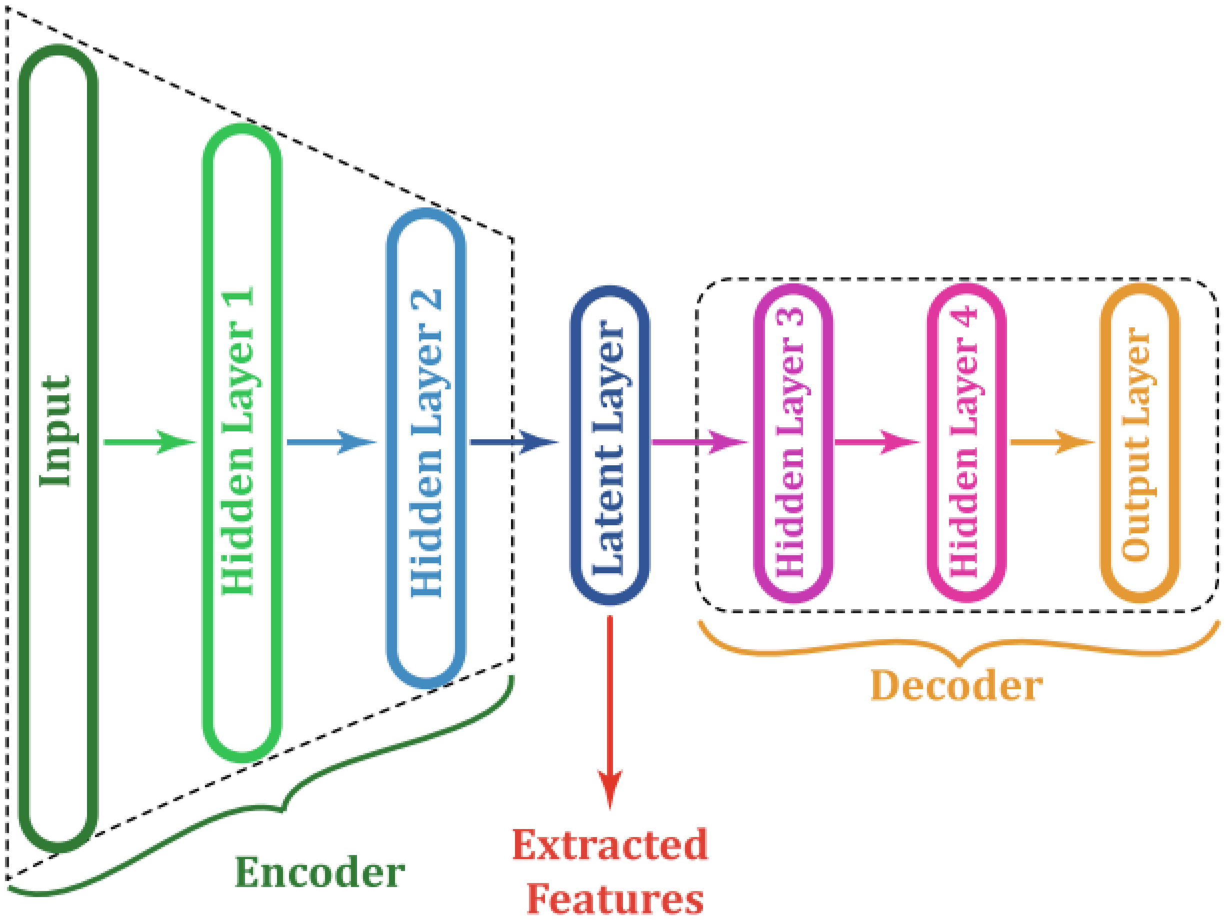


Fig. 3. Restricted stacked autoencoder.

Methodology cont.

- Graph Convolutional Neural Network (GCN) for training based on the implemented module after restricted stacked autoencoder handling.
- Spectral graph convolution aspect:
  - Convolutional theory
  - Integrate GNN-based preprocessing into the Gym environment.
  - Propagation using Sigmoid function
  - Localization using the Chebysev spectral graph convolutional operator, which applies Laplacian transformation and Symmetric normalization [2]
  - Calculates correlation coefficients between the mean of observations and uses them as edge attributes for the graph.

Methodology cont.

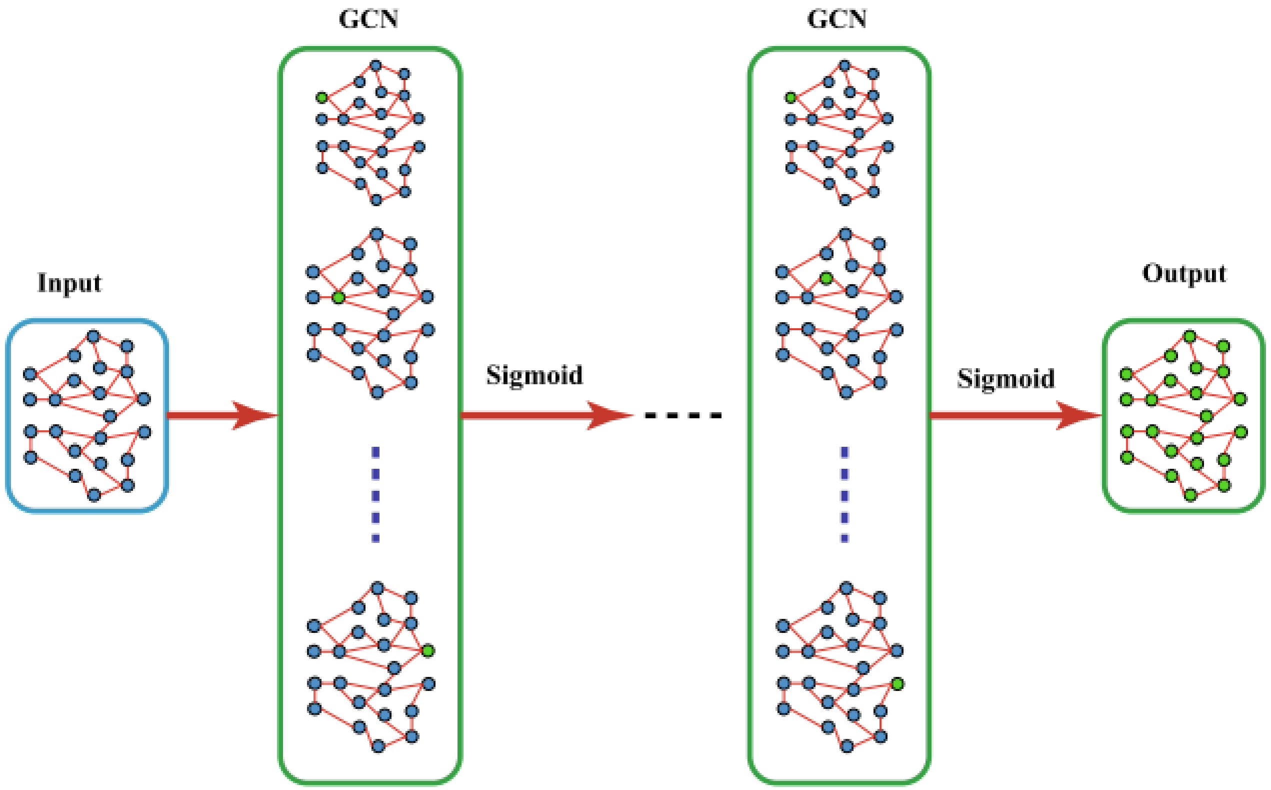


Fig. 4. Graph Convolutional Neural Network.

Methodology cont.

- Deep Reinforcement learning for studying the trend of the model

  - Categories: Critic-only, Actor-only, Actor-critic: Related to the optimal policy and the return on investment
  - Bias case
  - Feature Tensor according to the portfolio weight vector:
  - Using Softmax Layer for distributing Portfolio weight
  - Adam optimization to update the weights for both the actor and the critic

=> Minimizing the value function

Methodology cont.

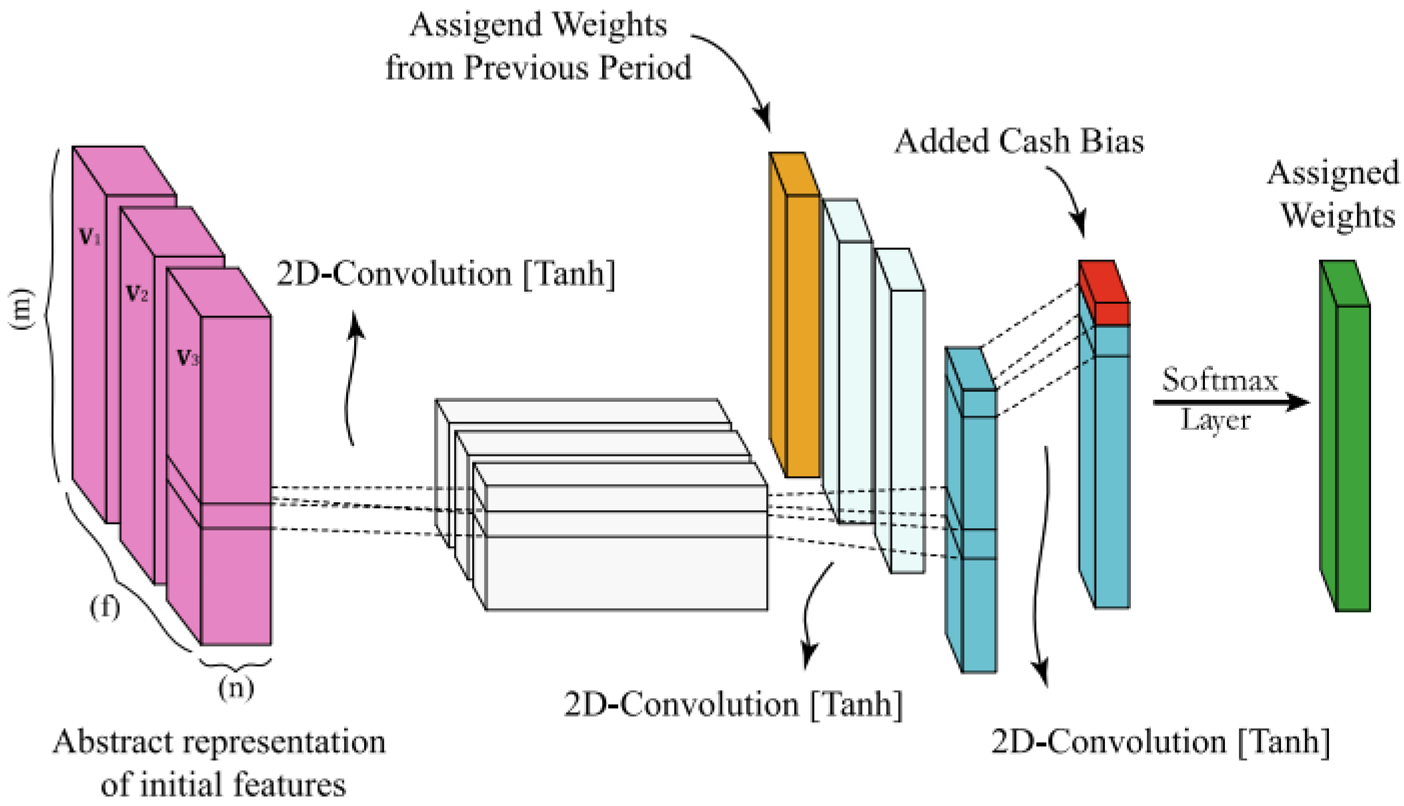


Fig. 5. Architecture of actor.

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Methodology cont.

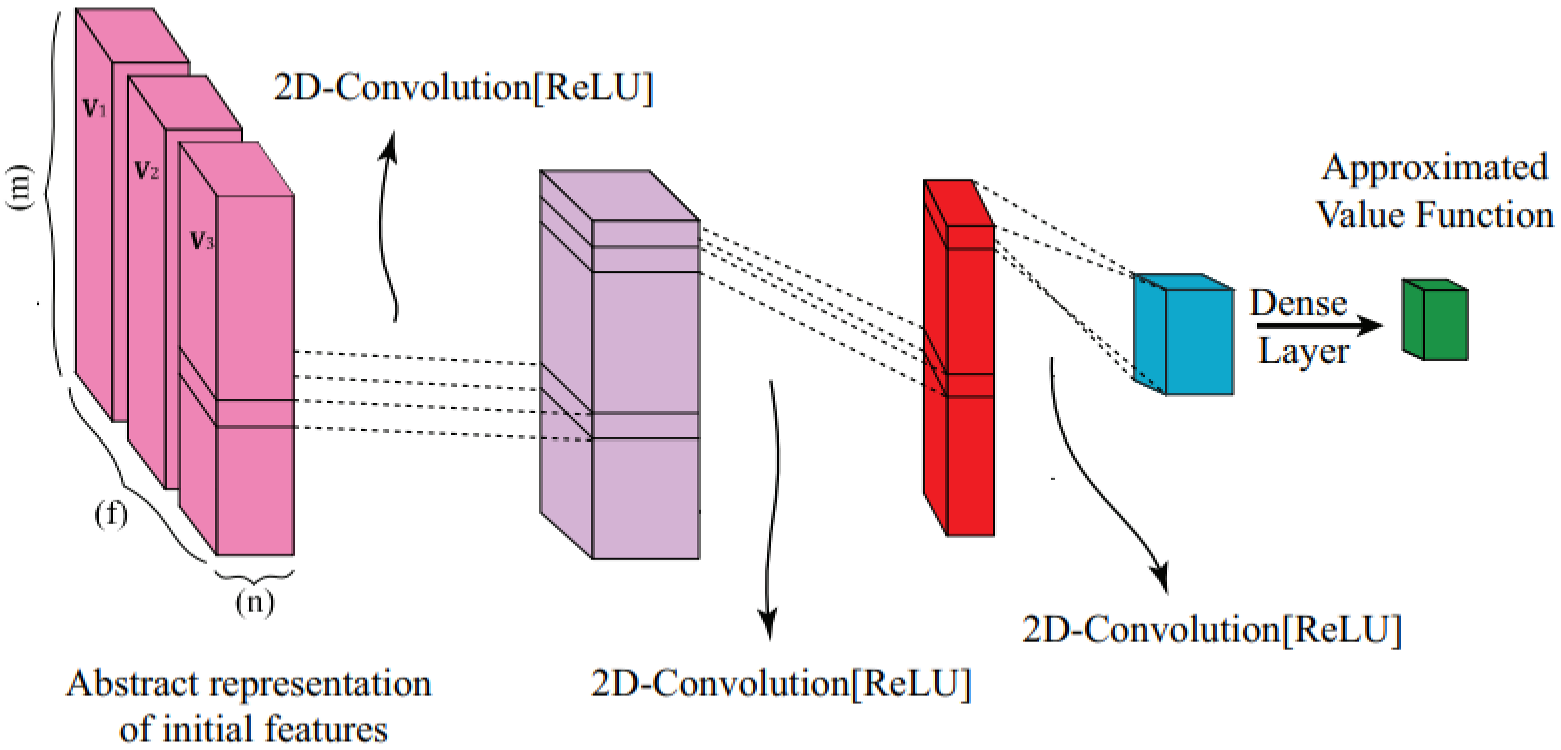

Figure 6: Critic architecture based on deep convolutional neural network

Methodology cont.

- What are the reference's main conclusions?

DeepPocket, a portfolio management framework, aims to increase expected return while hedging risk by exploiting time-varying correlations between financial instruments.

DeepPocket successfully managed risks during the Covid-19 crisis, demonstrating its effectiveness in portfolio risk management.

Future work includes addressing situations with limited buyers and sellers, directly selecting stocks, and developing deep learning models for long-term investment strategies.

Methodology cont.

- What did you learn from the reference?
- DeepPocket is a portfolio management framework that uses deep learning techniques.
- It employs restricted, stacked autoencoders and actor-critic reinforcement learning.
- The framework optimizes investment strategies by leveraging time-varying correlations between financial instruments.
- DeepPocket's goals include increasing expected returns and reducing risks.
- It has been effective in risk management during the Covid-19 crisis.
- Future improvement directions for DeepPocket:
  - Addressing market liquidity issues.
  - Developing models for long-term investment strategies.

Methodology cont.

- What are your own conclusions about the use of AI in the reference?

Complexity: Implementing and fine-tuning AI models like DeepPocket requires specialized knowledge and expertise, potentially limiting accessibility to smaller investors.

Data dependency: AI models heavily rely on data, and their performance may suffer if the data is incomplete, biased, or not representative of future market conditions.

Interpretability: Some AI models, particularly deep learning algorithms, are considered black boxes, making it challenging for users to understand and trust the decision-making process.

Results and Discussions

Experimental setting:

- Public trading data from New York Stock Exchange
  - Portfolio includes: 28 stocks
  - Daily trading data
  - Training Set: 7 years

    2002-04-01 to 2009-04-16
  - Test Set : 90 days

    2010-03-15 to 2010-07-21

    (Data set 1 in [1])
  - Data provider: Yahoo finance

- Our implementation has its basis on open-source code project [3]

Sector	Stock
Technology	Apple.Inc (AAPL)
	Cisco Systems Inc. (CSCO)
	Intel Corporation (INTC)
	Oracle Corporation (ORCL)
	IBM (IBM)
	Honeywell (HON)
	Verizon Communications Inc. (VZ)
Financial Services	Manulife Financial Corporation (MFC)
	JPMorgan Chase & Co. (JPM)
	Bank of America Corporation (BAC)
	The Toronto-Dominion Bank (TD)
Industries	3 M Company (MMM)
	Caterpillar Inc. (CAT)
	The Boeing Company (BA)
	General Electric Company (GE)
Consumer Defensive	Walmart Inc. (WMT)
	The Coca-Cola Company (KO)
Consumer Cyclical	The Home Depot, Inc. (HD)
	Amazon.com, Inc. (AMZN)
Healthcare	Johnson & Johnson (JNJ)
	Merck & Co., Inc. (MRK
	Pfizer Inc. (PFE)
	Gilead Sciences, Inc. (GILD)
Energy	Enbringe Inc. (ENB)
	Chevron Corporation (CVX)
	BP p.l.c. (BP)
	Equinor (EQNR)

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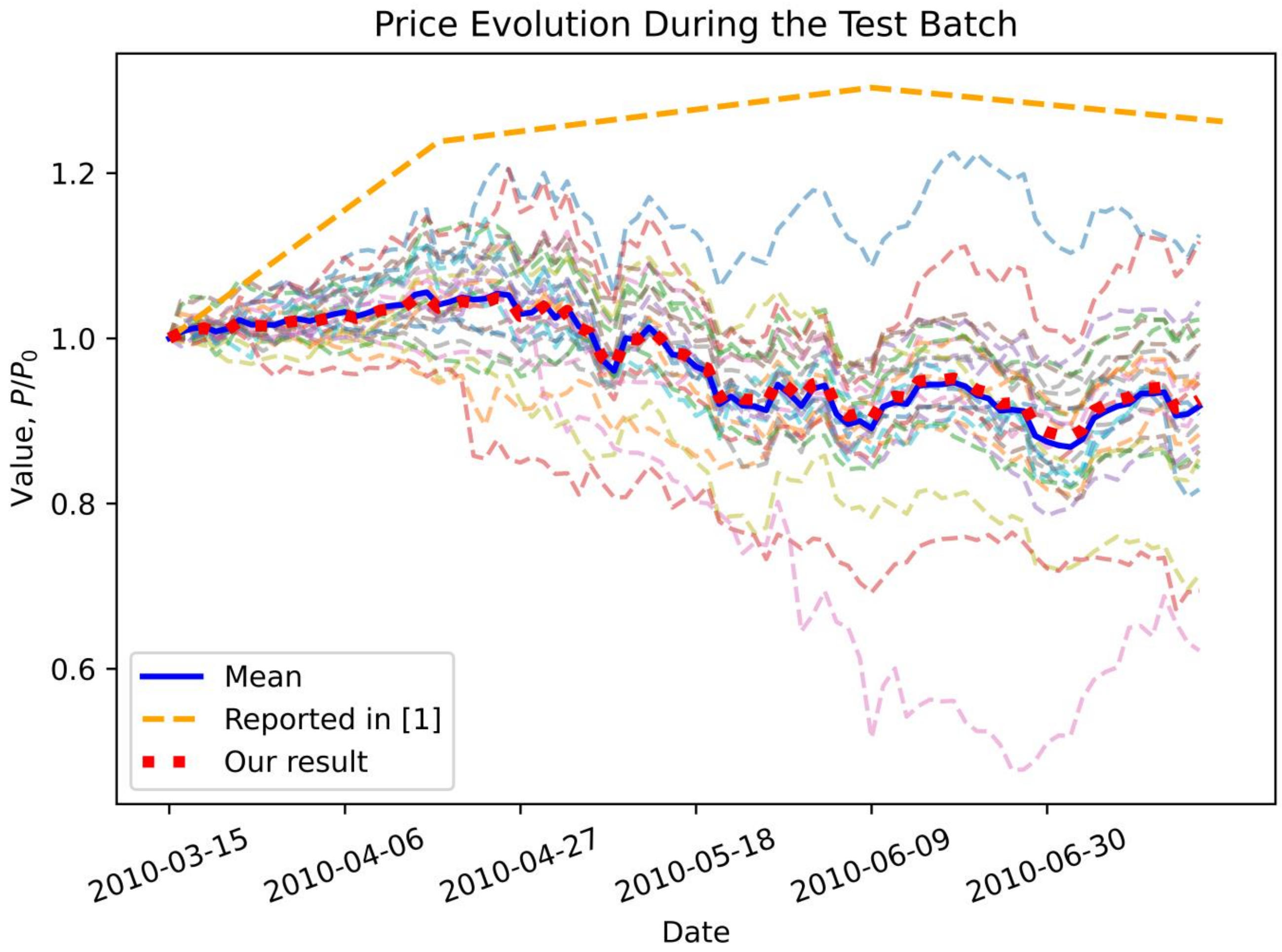
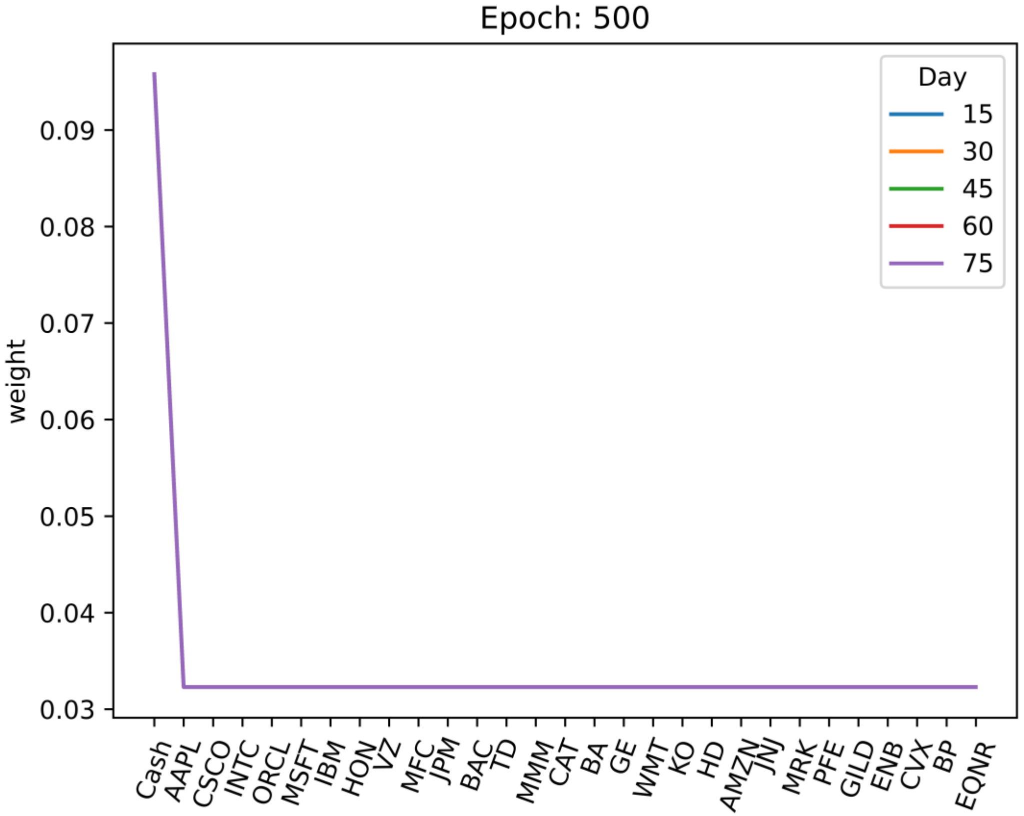
Results and Discussions cont.

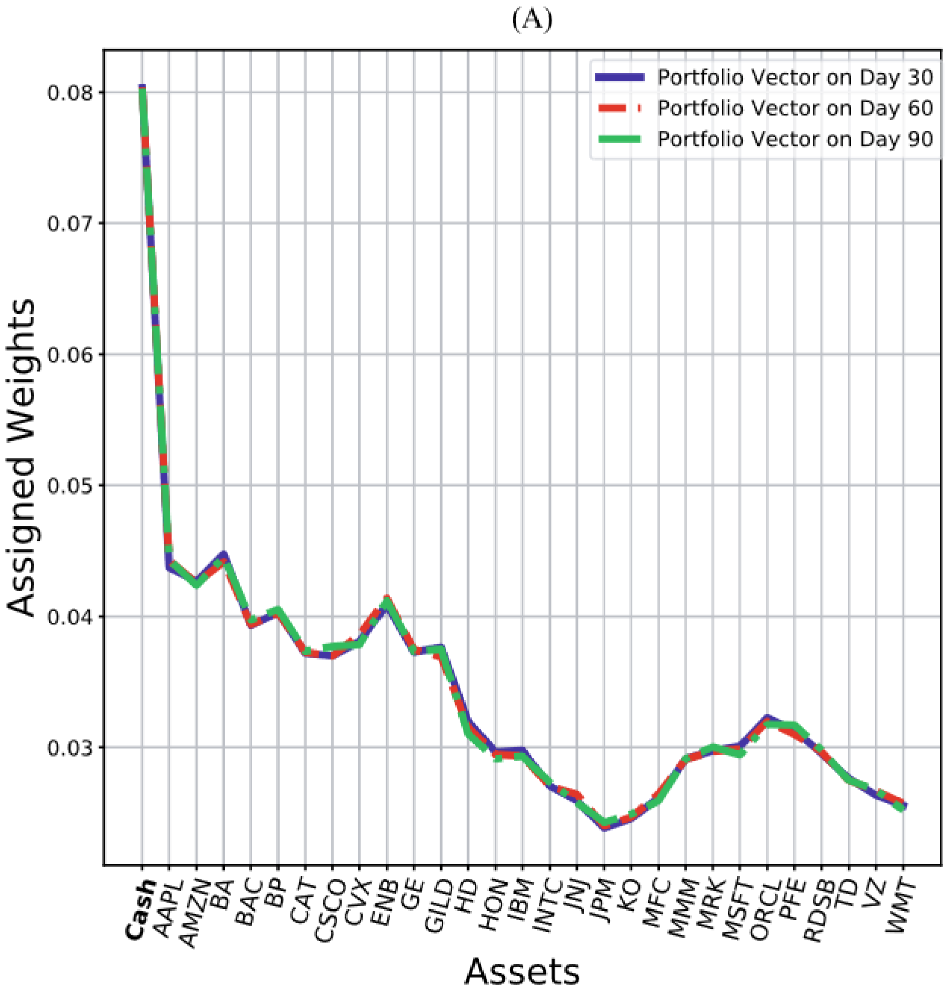
- The reference paper clearly outperforms the market index
- Now, the model basically converges to a static policy weighting all assets equally
- Our current result fails to take advantage of price fluctuations
- Equally weighting the assets is not the worst policy
    - It reduces volatility compared to any individual asset
    - Commissions are minimized when trades are not done



Results and Discussions cont.



Weight allocation during the test batch using our code (best result so far)

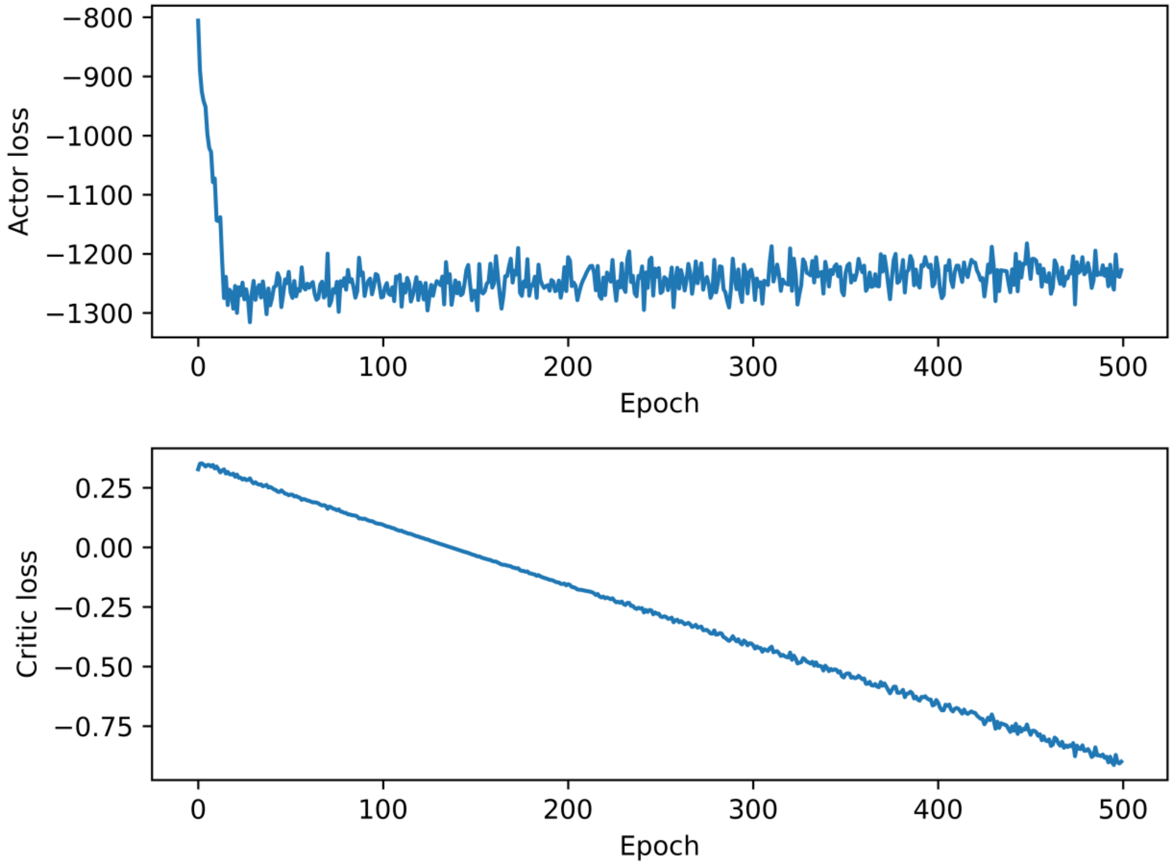


Weight allocation during the test batch of the reference paper [1]

Results and Discussions cont.

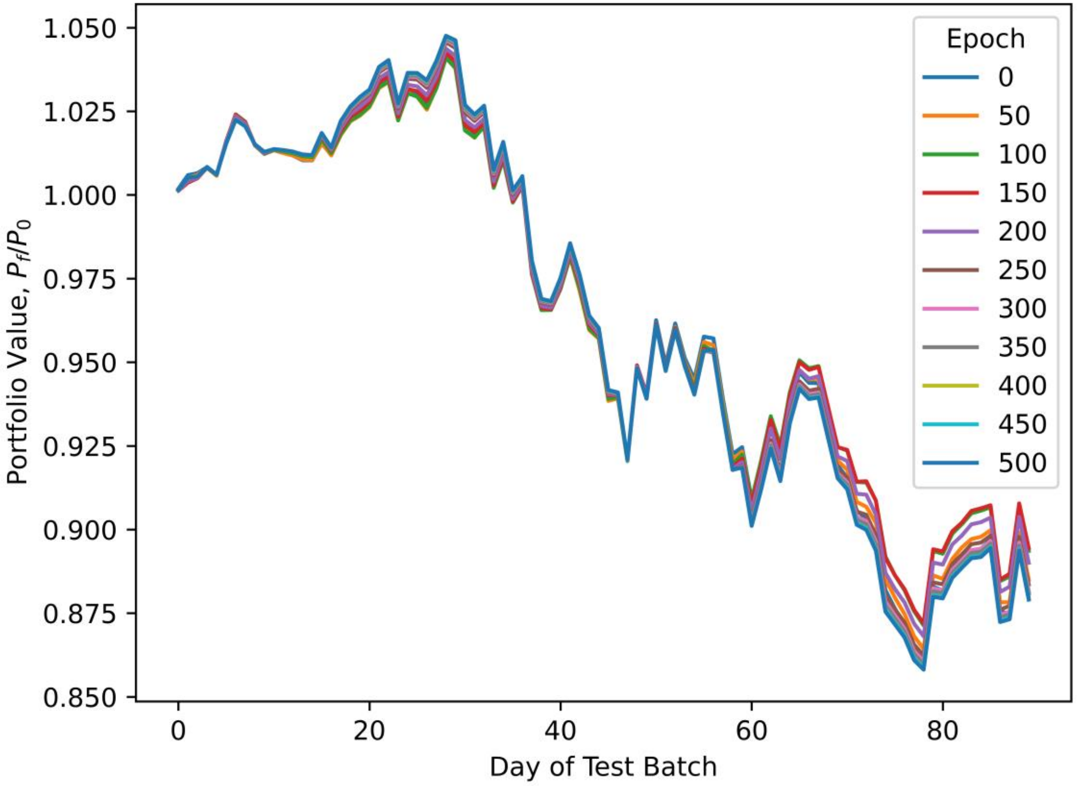
Loss function evolution during training process corresponding portfolio weighting seen in last slide

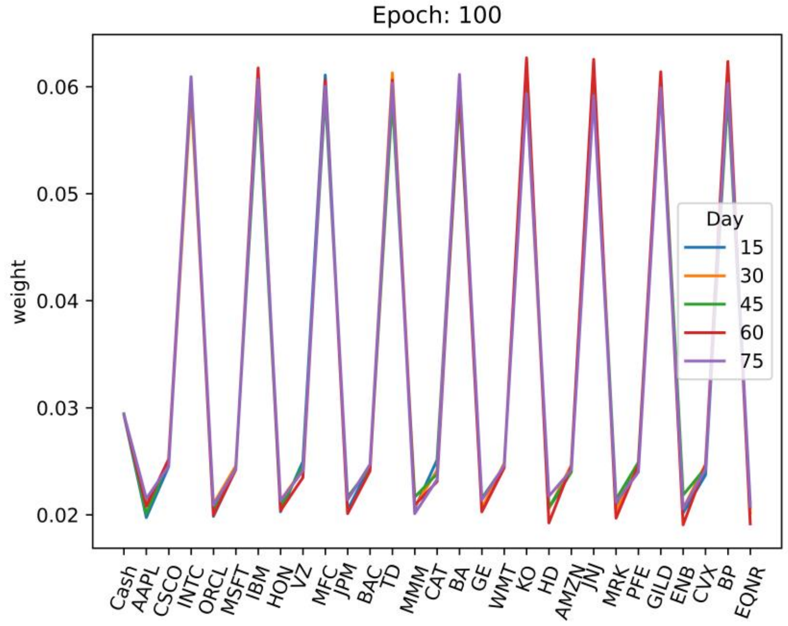
- Actor loss converges quickly while critic network steadily decreases

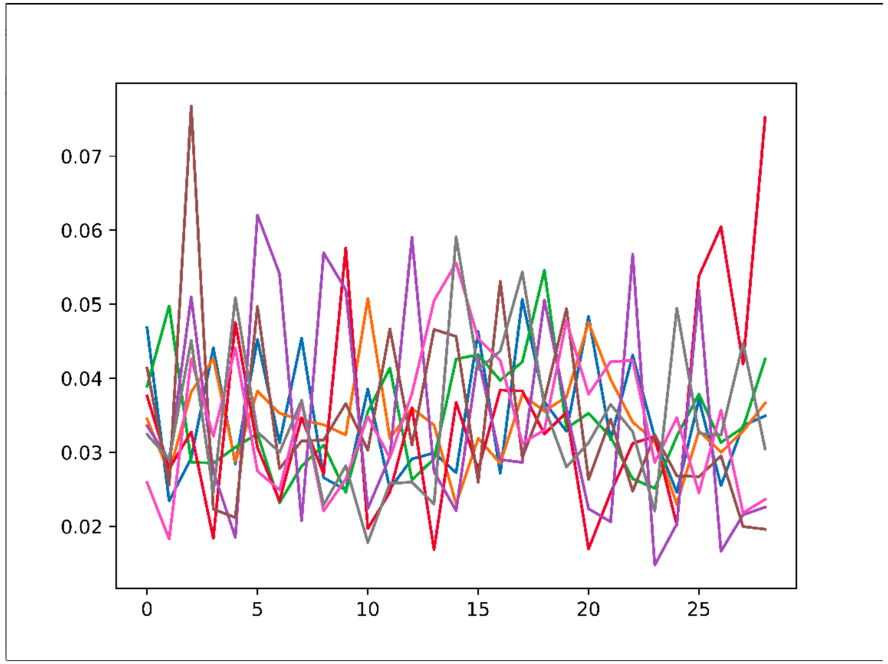


Results and Discussions cont.

Trials and Errors







Conclusions

- We have not succeeded to get the model working as in the reference

- What did you learn from this project briefly?
  - Reinforcement learning method and implementation in gym.
  - The need to design a quantitatively good evaluation metrics for our research results.
  - Confirmation that beating the market with statistical methods is challenging
- Future paths:
  - Design base line model (Markowitz models)
  - Testing working DeepPocket model with
    - newer market data or
    - different portfolio composition e.g. Helsinki Stock Exchange

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References

[1] Soleymani, Farzan, and Eric Paquet. “Deep Graph Convolutional Reinforcement Learning for Financial Portfolio Management – DeepPocket.” Expert systems with applications 182 (2021): 115127-. Web.

[2] torch_geometric.nn.conv.ChebConv — pytorch_geometric documentation. (n.d.). https://pytorch-geometric.readthedocs.io/en/latest/generated/torch_geometric.nn.conv.ChebConv.html

[3] MCCCSunny. (n.d.). GitHub - MCCCSunny/DeepPocket: Deep Graph Convolutional Reinforcement Learning for Financial Portfolio Management - DeepPocket. GitHub. https://github.com/MCCCSunny/DeepPocket/tree/master