Stock Recommendations for Individual Investors: A Temporal Graph Network Approach with Mean-Variance Efficient Sampling

Recommender Systems in Finance (Fin-RecSys)

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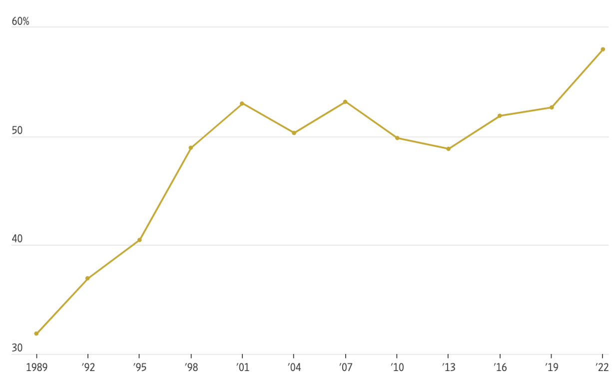
Introduction

Motivation

- **Why is stock recommendation necessary?**
  - More and more individual investors are participating in the stock market.
  - Irrational Investment Behavior of Individual Investors
    - overconfidence, disposition effect, lottery preference, and herding(Ngoc, 2014)
    - Due to these tendencies, their investment returns are generally low.
      - The average investor significantly underperformed the S&P 500 over time (Murray, 2023)



Percentage of U.S. households owning stocks (Chang, 2023)

Chang, A. C., Aladangady, A., Bricker, J., Goodman, S., Krimmel, J., Moore, K. B., ... & Windle, R. (2023). Changes in US Family Finances from 2019 to 2022.
Ngoc, L. T. B. (2014). Behavior pattern of individual investors in stock market. *International Journal of Business and Management*, *9*(1), 1-16.

Motivation

- **Why is stock recommendation necessary?**
  - Need for Assisting Individual Investors in Financial Decisions
    - There are many excellent methods for portfolio performance
      - Modern Portfolio Theory(MPT): Including stocks with low correlations to enhance returns relative to risks (Markowitz, 1952) -> portfolio diversification
      - Find optimal portfolio between minimizing the risk and maximizing the expected return

$$\min_{\{w:\ \sum w=1, w\geq 0\}} \frac{\gamma}{2} w^T \Sigma w - \mu^T w$$

    - However, individual investors do not typically follow these methods.
  - Individual investors tend to invest based on their own "**preferences**"
    - Influences include: Psychological Factors, News, Peers, Emotion, Analyst recommendations, Global events, SNS, ESG, Risk aversion, Momentum …
  - Need for a Stock Recommendation System!

What should be considered?

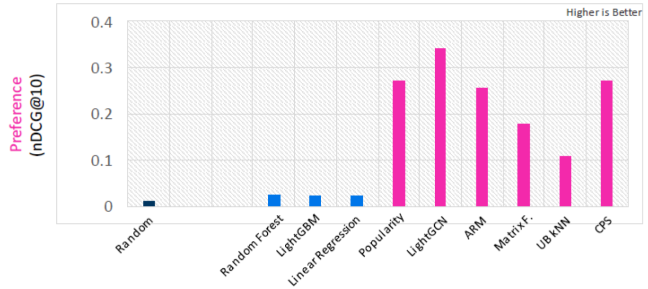
1. Individual preference

- Individual investment behaviors are highly personal and varied (Sadi et al, 2011)
- “experience holding” (Welch, 2020)

2. Portfolio performance

- Diversification effect (Markowitz, 1952)
  - Including stocks with low correlations to enhance returns relative to risks

- **Tricky Trade-off !**
  - Pricing Models vs Transaction Models
  - Customers are not always right (McCreadie et al., 2021)



Sadi, R., Asl, H. G., Rostami, M. R., Gholipour, A., & Gholipour, F. (2011). Behavioral finance: The explanation of investors' personality and perceptual biases effects on financial decisions. International journal of economics and finance, 3(5), 234-241.
Welch, I. (2020). The wisdom of the robinhood crowd (No. w27866). National Bureau of Economic Research..
Harry Markowitz. Portfolio selection*. The Journal of Finance, 7(1):77–91, 1952
McCreadie, R., Perakis, K., Srikrishna, M., Droukas, N., Pitsios, S., Prokopaki, G., ... & Ounis, I. (2021). Next-Generation Personalized Investment Recommendations. In Big Data and Artificial Intelligence in Digital Finance: Increasing Personalization and Trust in Digital Finance using Big Data and AI (pp. 171-198). Cham: Springer International Publishing.
Chung, M., Lee, Y., & Kim, W. C. (2023). Mean-Variance Efficient Collaborative Filtering for Stock Recommendation. arXiv preprint arXiv:2306.06590.

What should be considered?

- **3. Temporal aspect**
  - Stock prices and the relationship between stocks
  - User preferences continue to evolve accordingly

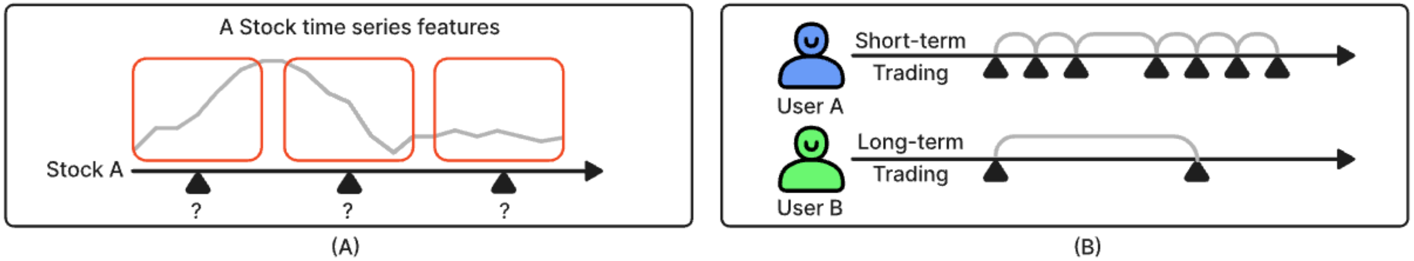


Figure 1: The importance of temproal aspects in stock recommender systems. (A) Various features of stocks would be different based on the timing of recommendations. (B) Contrasting behaviors between user A, who engages in short-term trading, and user B, who holds stocks for a long period.

Summary

- We want to lead people towards sound investments

- **1. Temporal collaborative signal**
  – Temporal Graph Network (TGN)

- **2. Portfolio diversification**
  – Mean-Variance Efficient Sampling

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Related work

Recommender Systems

- **Collaborative filtering**
  - Capturing collaborative signals and determine personalized item rankings
    - Matrix Factorization (MF), Bayesian Personalized Ranking (BPR)
- **Stock recommendation**
  - Price predictions (Feng et al, 2019; Gao et al, 2021; Wang et al., 2022)
    - Rank stocks by considering the temporal aspects of the stock market and predicting prices
    - Limitation: ignores personal preferences
  - Time-aware recommendations (Ghiye et al, 2023; Takayanagi et al, 2023)
    - Recommend considering temporal preferences and features
    - Limitation: did not consider diversification effect in portfolio management
  - The 2-step method (Swezey and Charron, 2018)
    - Rank stocks based on recommendation model, and then re-rank them using the modern portfolio theory method
    - Limitation: heuristic approach
  - Mean-variance efficient collaborative filtering (Chung et al, 2023)
    - The first study to holistically model a Matrix Factorization (MF) model by incorporating a regularization term based on portfolio theory
    - Limitation: applicable only to static models, it does not account for temporal changes in stock prices or user preferences

Gao, J., Ying, X., Xu, C., Wang, J., Zhang, S., & Li, Z. (2021). Graph-based stock recommendation by time-aware relational attention network. ACM Transactions on Knowledge Discovery from Data (TKDD), 16(1), 1-21.
Jianliang Gao, Xiaoting Ying, Cong Xu, Jianxin Wang, Shichao Zhang, and Zhao Li. Graph-based stock recommendation by time-aware relational attention network. ACM Transactions on Knowledge Discovery from Data (TKDD), 16(1):1–21, 2021.
Changhai Wang, Hui Liang, Bo Wang, Xiaoxu Cui, and Yuwei Xu. Mg-conv: A spatiotemporal multi-graph convolutional neural network for stock market index trend prediction. Computers and Electrical Engineering, 103:108285, 2022
Ghiye, A., Barreau, B., Carlier, L., & Vazirgiannis, M. (2023, September). Adaptive Collaborative Filtering with Personalized Time Decay Functions for Financial Product Recommendation. In Proceedings of the 17th ACM Conference on Recommender Systems (pp. 798-804)
Takayanagi, T., Chen, C. C., & Izumi, K. (2023). Personalized Dynamic Recommender System for Investors.
Swezey, R. M., & Charron, B. (2018, September). Large-scale recommendation for portfolio optimization. In Proceedings of the 12th ACM Conference on Recommender Systems (pp. 382-386).
Chung, M., Lee, Y., & Kim, W. C. (2023). Mean-Variance Efficient Collaborative Filtering for Stock Recommendation. arXiv preprint arXiv:2306.06590.

Dynamic Graph Learning

- **Static Graph Learning**
  - GCN (Kipf and Welling, 2016)
  - Popular in recommendation field
    - NGCF (Wang et al., 2019), LightGCN (He et al., 2020), SGL (Wu et al., 2021)
      - Exploit collaborative signal in high-order connectivities
- **Dynamic Graph Learning**
  - TGAT (Xu et al., 2020)
    - A novel functional time encoding technique for the temporal graph attention
  - TGN (Rossi et al., 2020)
    - Based on TGAT, but nodes are initialized with memory embedding and temporal node feature
  - Few works in recommendation field
    - TGSRec (Fan et al., 2021), DGEL (Tang et al., 2023)
      - Due to the utilization of time encoding without an explicit memory updater, there exists a limitation in capturing node history effectively

Kipf, T. N., & Welling, M. (2016). Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.
Wang, X., He, X., Wang, M., Feng, F., & Chua, T. S. (2019, July). Neural graph collaborative filtering. In Proceedings of the 42nd international ACM SIGIR conference on Research and development in Information Retrieval (pp. 165-174).
He, X., Deng, K., Wang, X., Li, Y., Zhang, Y., & Wang, M. (2020, July). Lightgcn: Simplifying and powering graph convolution network for recommendation. In Proceedings of the 43rd International ACM SIGIR conference on research and development in Information Retrieval (pp. 639-648).
Wu, J., Wang, X., Feng, F., He, X., Chen, L., Lian, J., & Xie, X. (2021, July). Self-supervised graph learning for recommendation. In Proceedings of the 44th international ACM SIGIR conference on research and development in information retrieval (pp. 726-735).
Hamilton, W., Ying, Z., & Leskovec, J. (2017). Inductive representation learning on large graphs. Advances in neural information processing systems, 30.
Rossi, E., Chamberlain, B., Frasca, F., Eynard, D., Monti, F., & Bronstein, M. (2020). Temporal graph networks for deep learning on dynamic graphs. arXiv preprint arXiv:2006.10637.
Fan, Z., Liu, Z., Zhang, J., Xiong, Y., Zheng, L., & Yu, P. S. (2021, October). Continuous-time sequential recommendation with temporal graph collaborative transformer. In Proceedings of the 30th ACM international conference on information & knowledge management (pp. 433-442).
Haoran Tang, Shiqing Wu, Guandong Xu, and Qing Li. Dynamic graph evolution learning for recommendation. In Proceedings of the 46th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 1589– 1598, 2023.

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Method

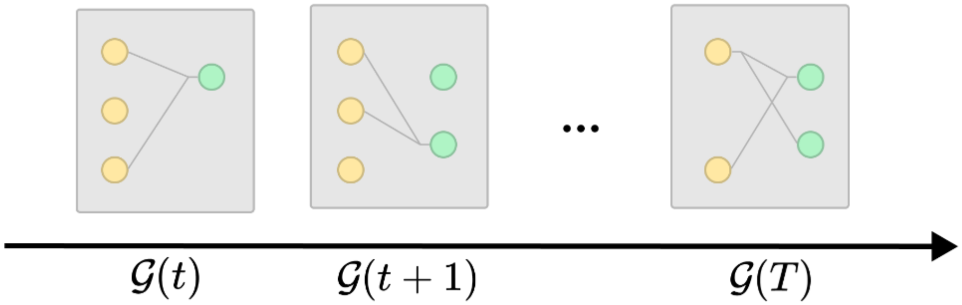
Preliminaries

- **Problem Definition**
  - Users $U = \{u_1, u_2, \dots, u_{|U|}\}$
  - Items $V = \{v_1, v_2, \dots, v_{|V|}\}$
  - Time points $T = \{t_1, t_2, \dots, t_{|T|}\}$
  - User portfolio in time t = $PO_{u,t}$
  - If user u buy the item v in time t, $y_{u,v}^{t} = 1$; Otherwise $y_{u,v}^{t} = 0$
  - The model aims to recommend the top-k items for each interaction!

User	Item	Time	Portfolio	
u_1	i_1	1		
u_2	i_1	2		
u_1	i_2	3	i_1	
u_3	i_3	4		
…	…	…		
u_9	?	10	i_2	i_3

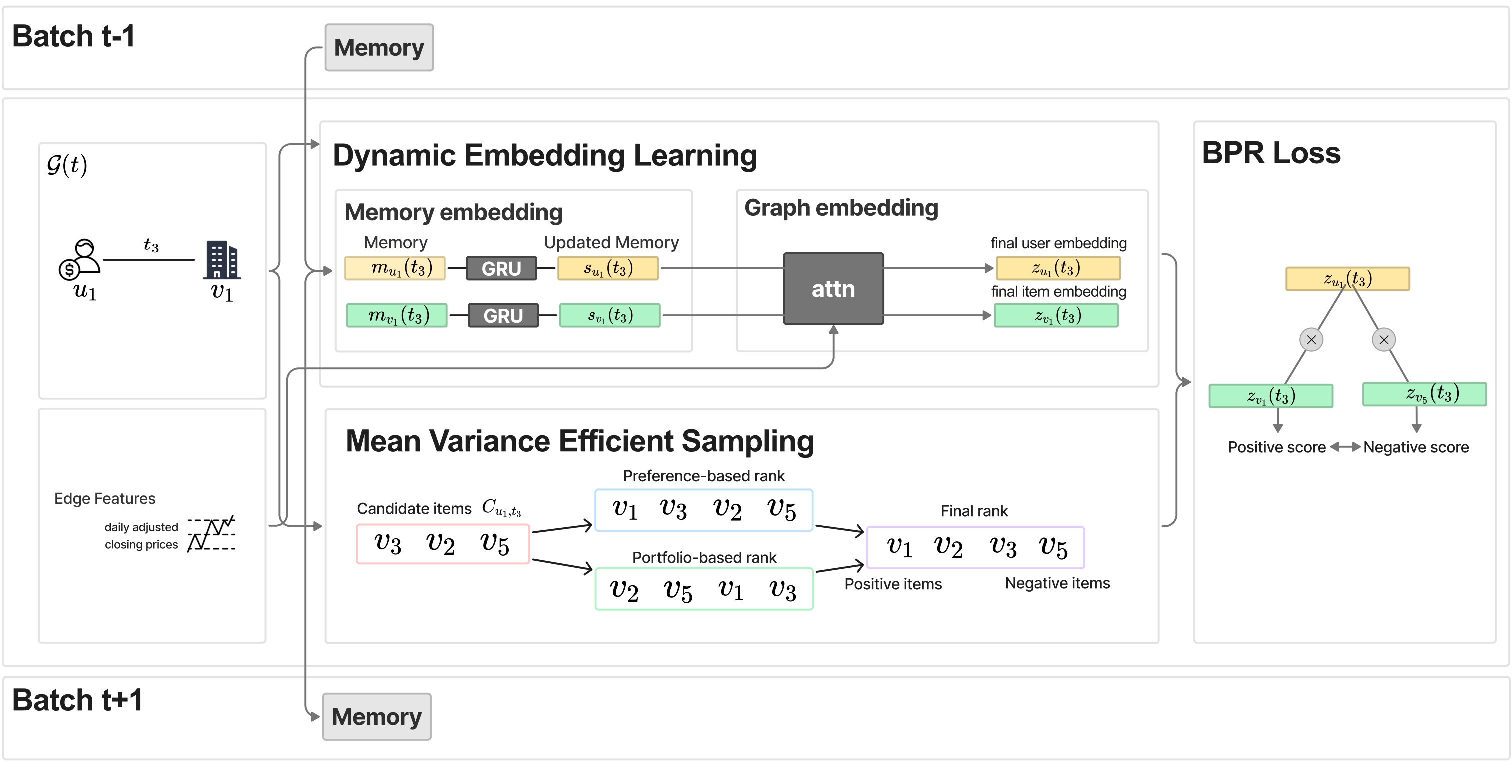
Preliminaries

- **Continuous time dynamic graph**
  - Graph $\mathcal{G}(T) = \{V, E_T\}$
  - Bipartite graph
    - V : User nodes, Item nodes
  - Edge features
    - E_T : tuple e = (u, v, t, e_{uv})
    - e_{uv} : Stock prices of an item for the past 30 days



Model

- **P**ort**fo**lio **T**emporal **G**raph **N**etwork **Rec**ommender(PfoTGNRec)



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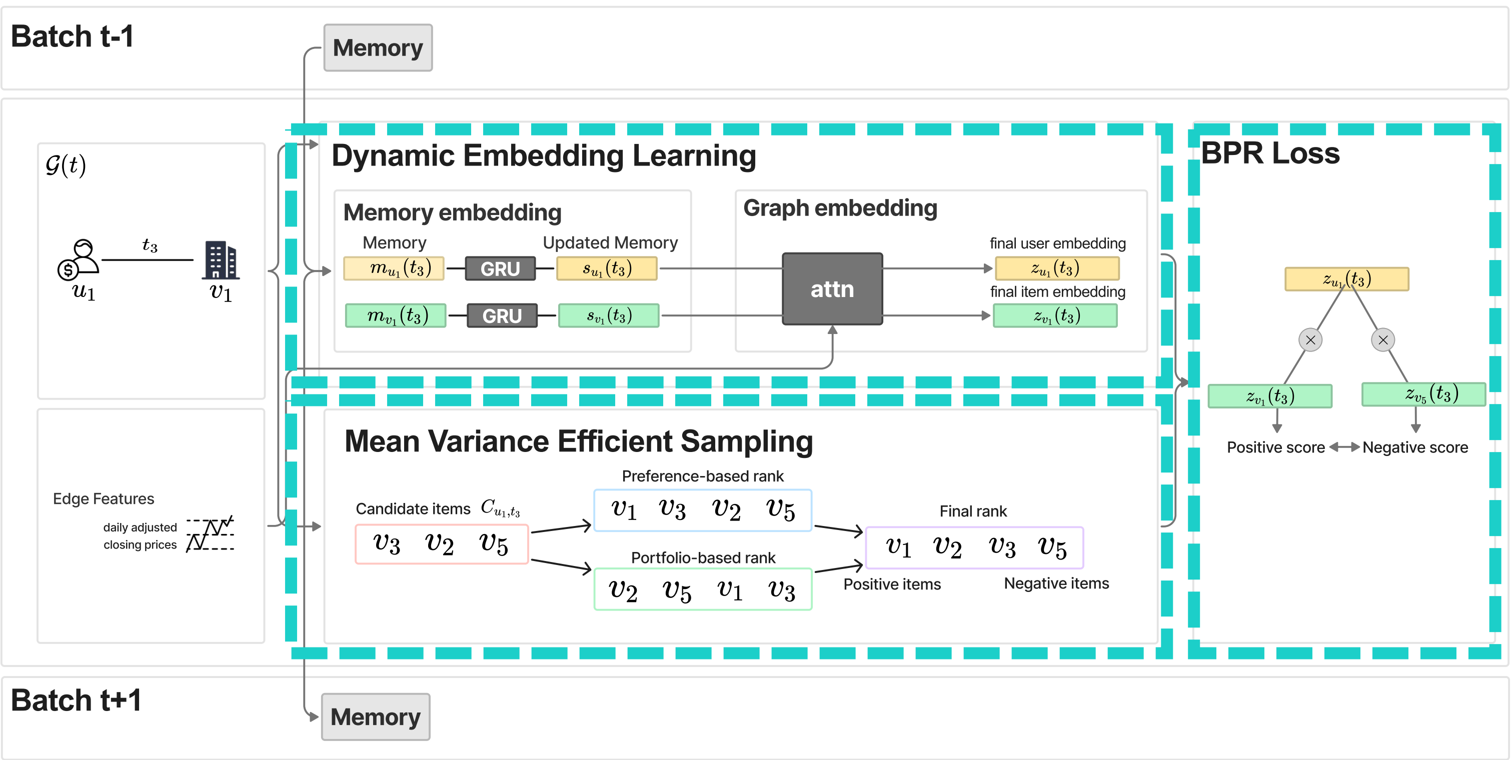
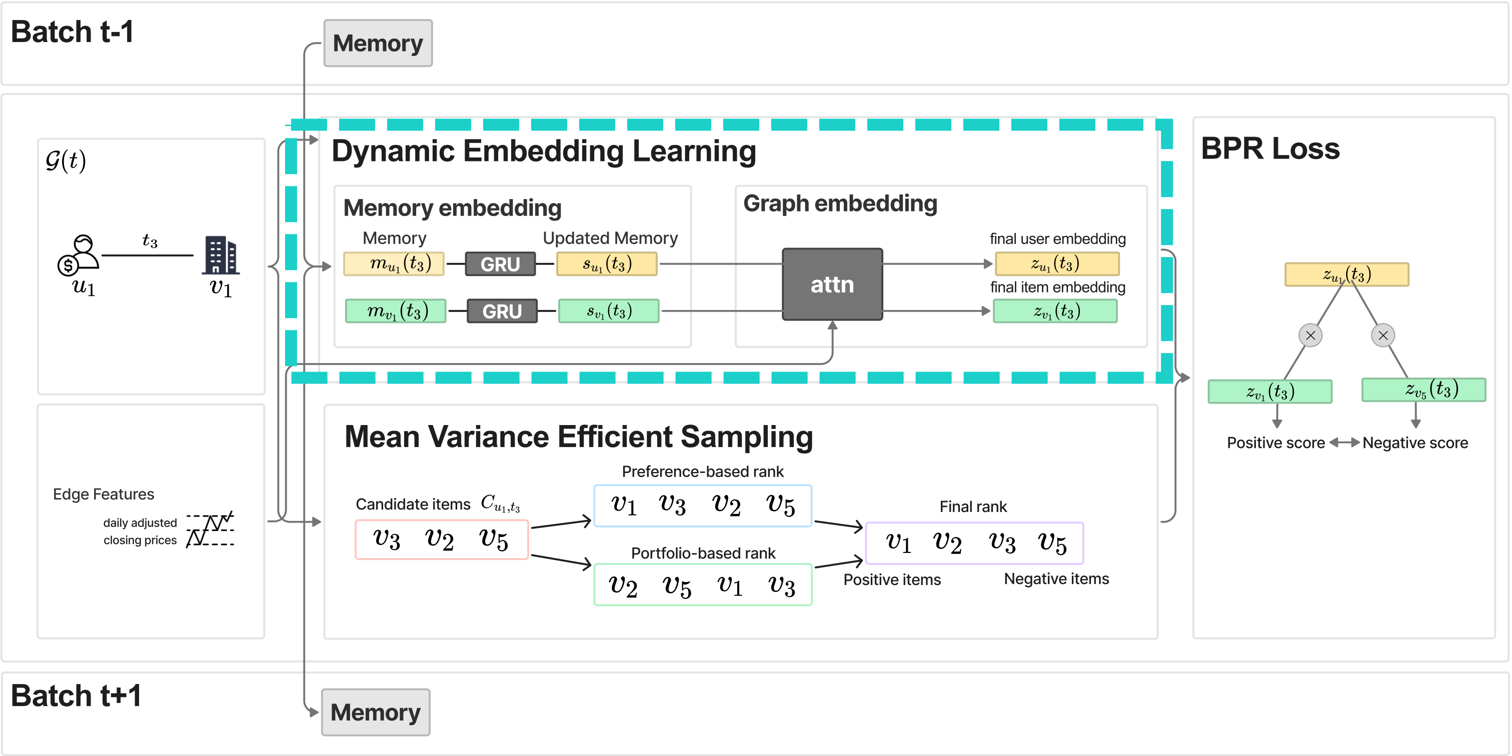
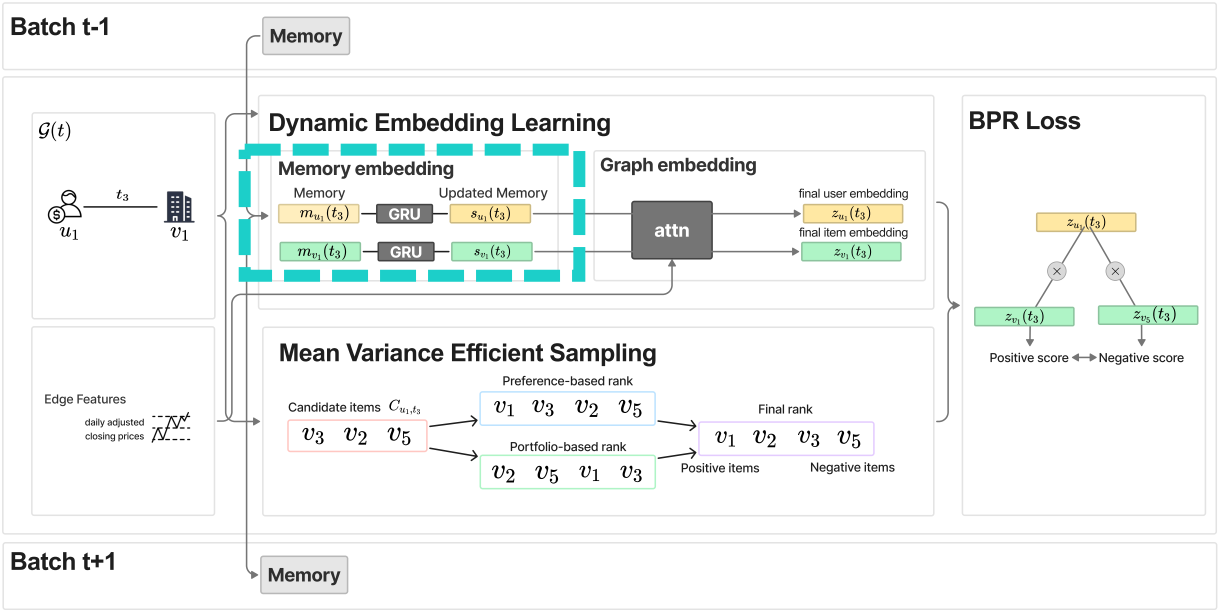


1. Dynamic embedding learning

- **Create node embeddings from dynamic graph**
  - TGN encoder



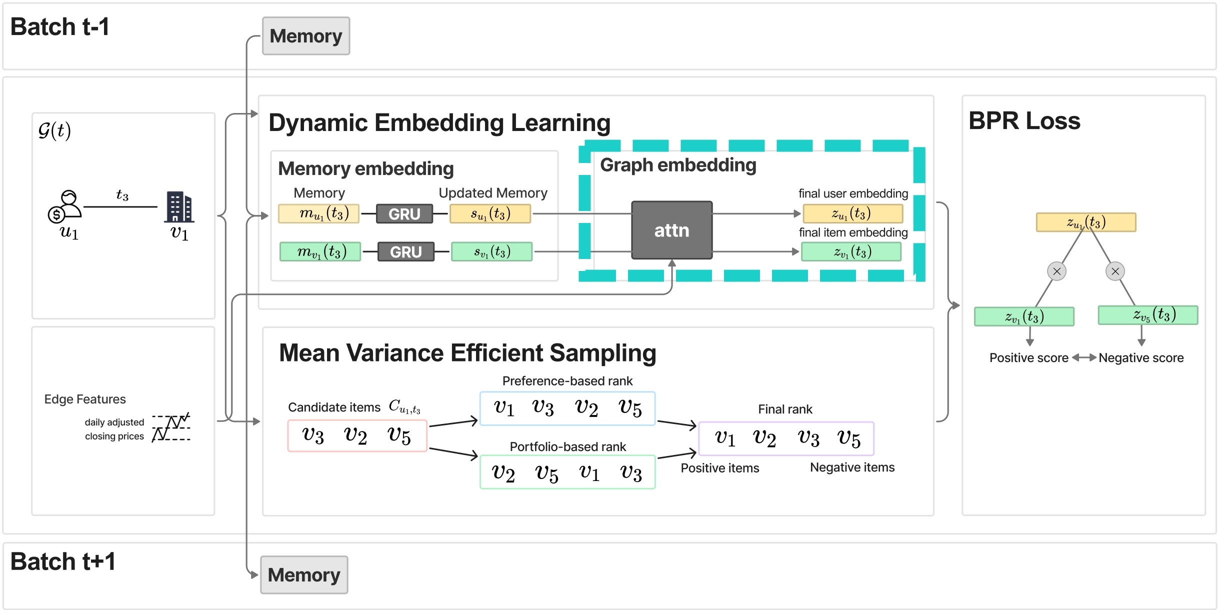
1. Dynamic embedding learning



- **Memory embedding** $s_i(t)$
  - $s_i(t) = GRU\big(m_i(t), s_i(t^-)\big)$
    - $m_i(t) = s_i(t^-) \| s_j(t^-) \| \Delta t \parallel \mathbf{e}_{ij}$
      - Δt: time embedding
      - $\mathbf{e}_{ij}$: edge feature

"Stores node history"

1. Dynamic embedding learning

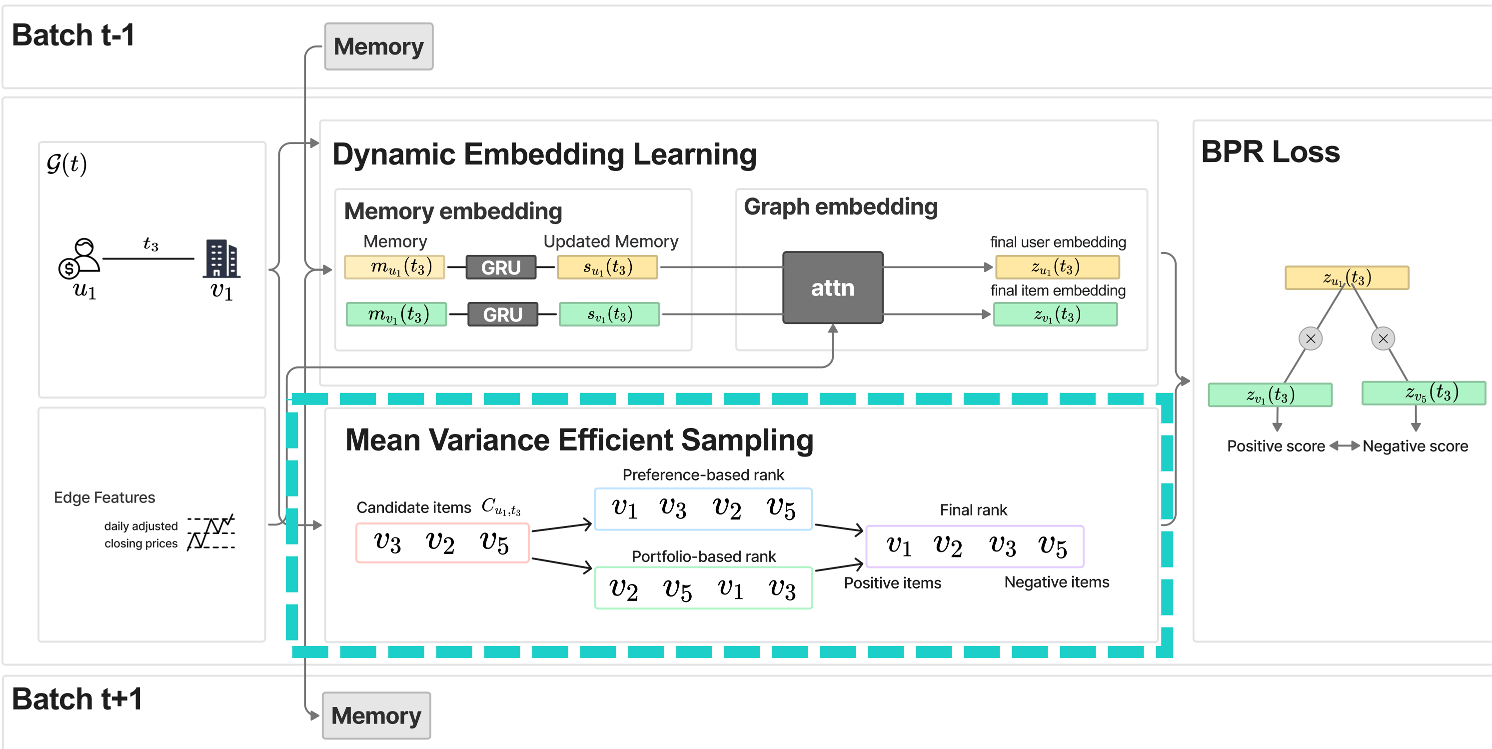


- **Graph embedding $z_i(t)$**
  - $z_i(t) = \sum_j \mathrm{attn}\big(s_i(t), s_j(t)\big)$
    - attn: Graph Attention Networks (GAT)

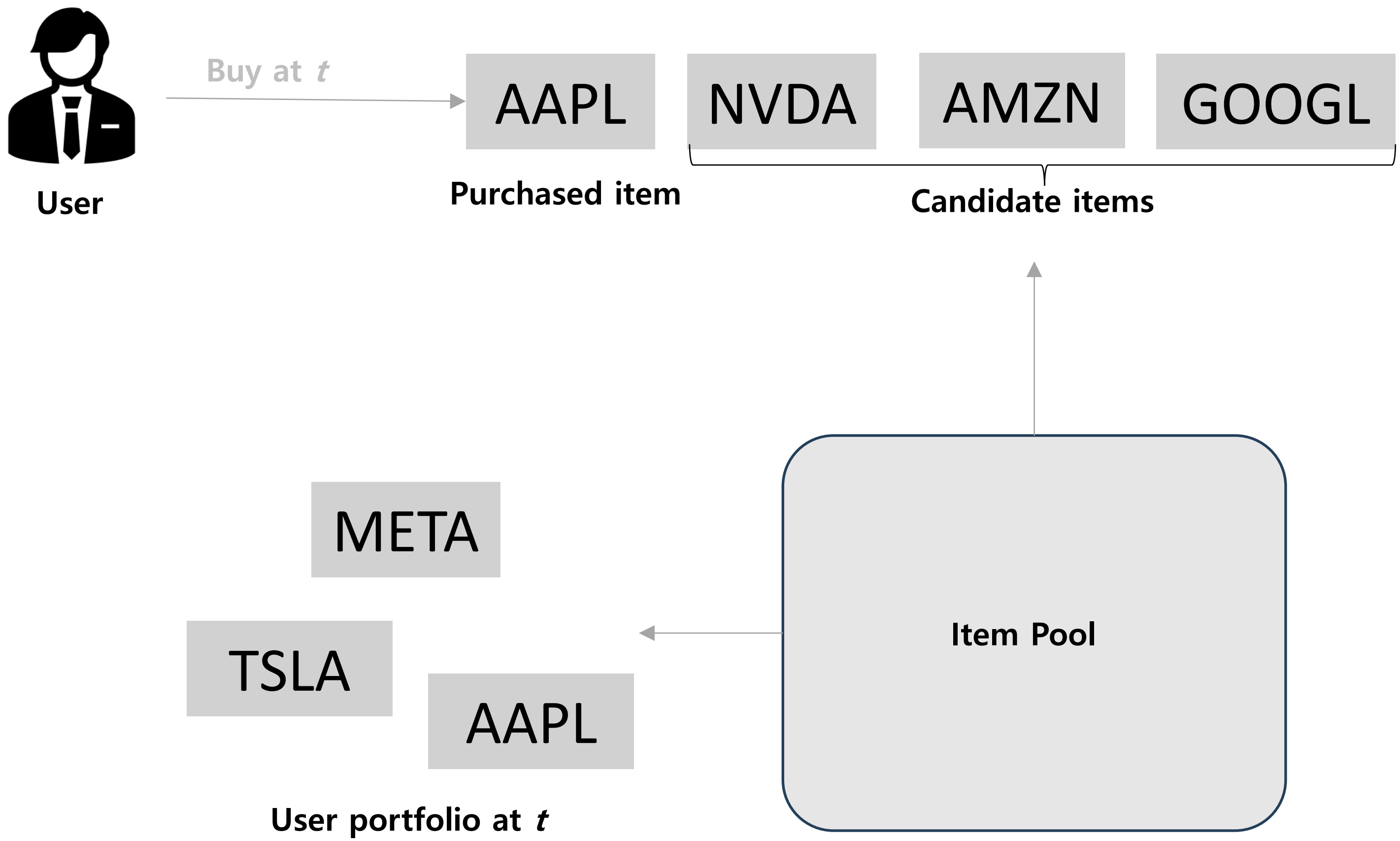
"Learns collaborative signal"

2. Mean Variance Efficient Sampling

- **Use MVECF(Chung et al., 2023) for diversification-enhancing sampling.**
  - Positive & Negative sampling based on MVECF



2. Mean Variance Efficient Sampling



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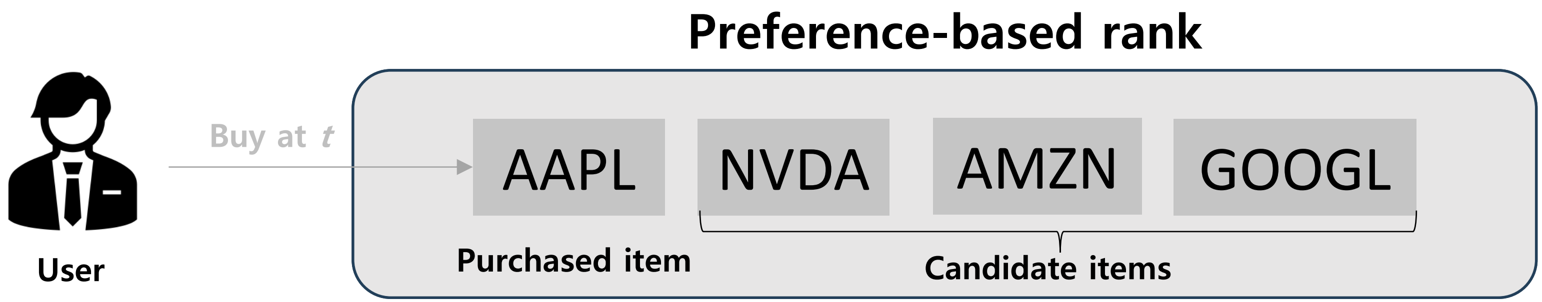

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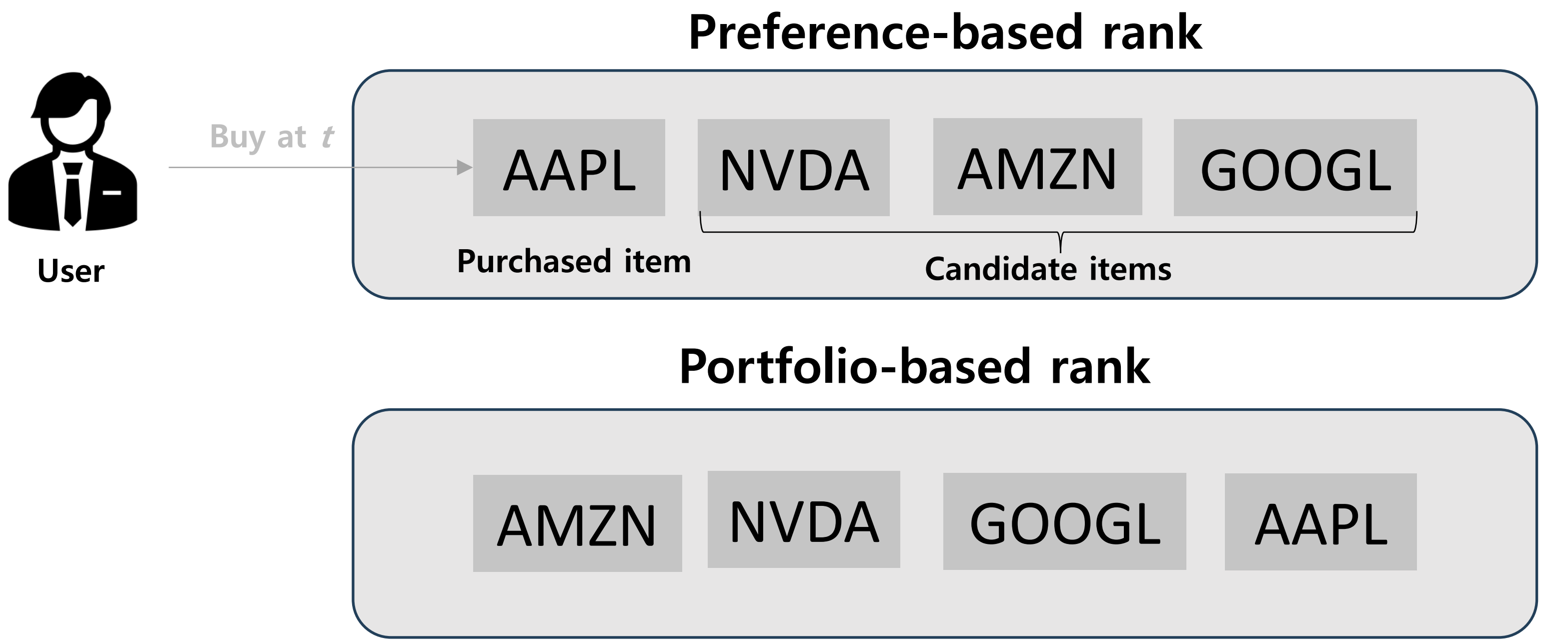


- **Diversification score**
  - $y_{ui}^{MV} = \left(\frac{\mu_i}{\gamma} - \frac{1}{2}\sum_{j:j\neq i} \frac{1}{|y_u|}\sigma_{ij}\right) / \sigma_i^2$
    - μ_i=mean return of item i
    - σ_i^2=risk of item i
  - Stocks with high returns and low risks will have high diversification scores.

2. Mean Variance Efficient Sampling

User

Buy at t

Preference-based rank $\times (1 - \lambda_{MV})$

AAPL	NVDA	AMZN	GOOGL
Purchased item	Candidate items		

Portfolio-based rank $\times \lambda_{MV}$

AMZN	NVDA	GOOGL	AAPL

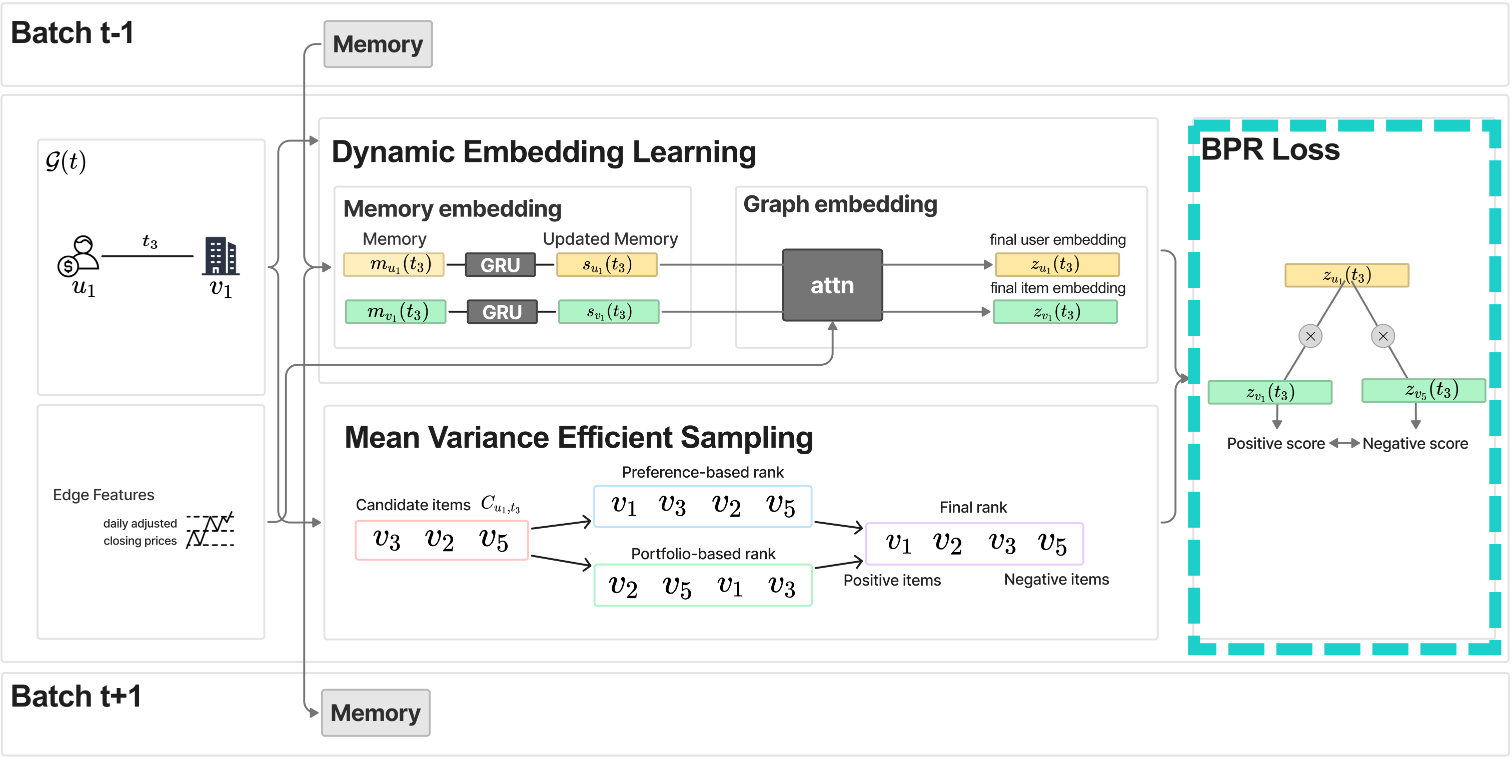
Final Rank

NVDA	AMZN	AAPL	GOOGL
Positive		Negative	Negative

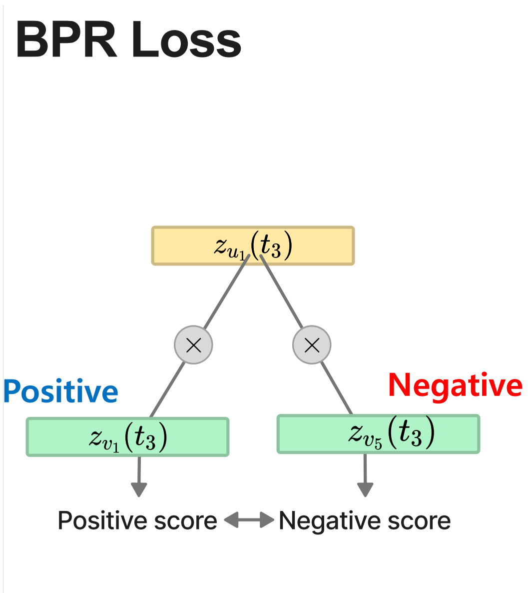
- λ_{MV} : trade-off hyperparamter
- **In experiment,**
  20 candidate items
  1 positive items
  3 negative items

3. BPR loss

- **BPR loss**
  - Positive and Negative



3. BPR loss



- **BPR (Bayesian Personalized Ranking) loss**
  - $\mathcal{L}_{BPR} = \frac{1}{N}\sum_{(u,p,n,t)\in D} -\log\sigma\left(z_u(t)^T z_p(t) - z_u(t)^T z_n(t)\right)$

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Experiment

Experiment

- **Dataset**
  - Individual investor transaction dataset
    - *Greece market (provided by Glasgow univ.)*
  - Period
    - 1/2018 ~ 11/2022
  - Preprocessing
    - Buy orders
    - Item filtering
      - Stocks with missing value
      - Stocks with unchanged prices for 30 consecutive days
    - Portfolio
      - Based on the transaction history up until the day before
  - Description
    - 152,084 interactions
    - 8,337 users
    - 92 items

Baselines

- **Static Recommender models**
  - Pop, BPR, LightGCN, SGL
- **Price-based models**
  - Return, Sharpe (non-personalized)
- **Stock recommendation models**
  - Two-step, MVECF
- **Dynamic Recommender models**
  - DyRep, Jodie, TGAT, TGN

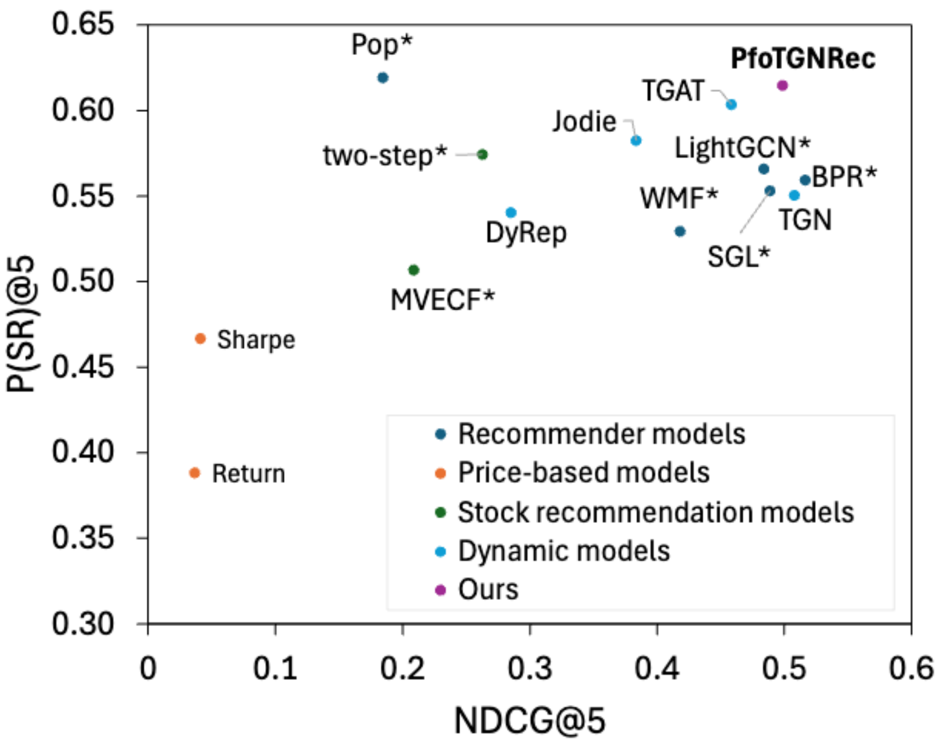
Evaluation

- **Chronological split**
  - According to interaction timestamps
  - train-validation-test with 8:1:1

- **Interaction-based ranking strategy**
  - Final metric is averaged over test interactions
  - For static baselines, recommendations are made consistently with the same item set ranked within train period throughout all test periods
- **Evaluation (Recommendation)**
  - Recommend the top *k* stocks with the highest scores
  - Hit Ratio@*k*, NDCG (Normalized Discounted Cumulative Gain)@*k*
- **Evaluation (Investment)**
  - Recommend the top k stocks with the highest scores
  - Return (R) and Sharpe ratio (SR) of equal-weighted portfolio
    - Difference: $\triangle R = R - R_{\text{init}}$, $\triangle SR = SR - SR_{\text{init}}$
    - Percentage improvement: $P(R) = P(R > R_{\text{init}})$, $P(SR) = P(SR > SR_{\text{init}})$
  - Out-of-sample: We use the stock prices for the 30 days following the interaction, thus incorporating uncertainty about the future

Experiment

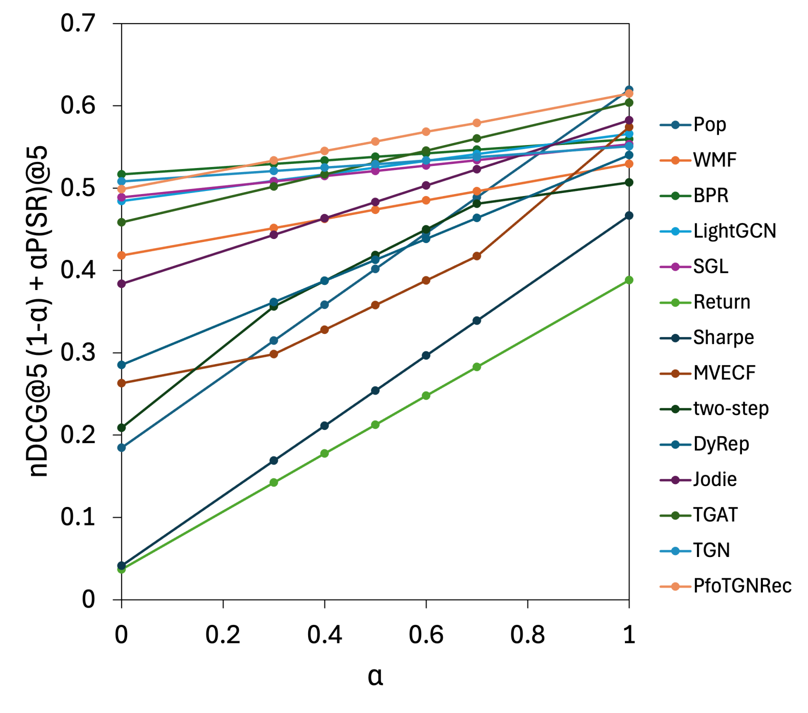
- **Comparison of Performance Considering Both User Preferences and Portfolio Performance(RQ1)**
  - To comprehensively evaluate the two metric, we selected two representative metrics
  - NDCG@5, P(SR)@5



Experiment

- **Comparison of Performance Considering Both Recommendation and Portfolio Performance(RQ1)**
  - To provide a precise numerical comparison, we used a combined metric
  - $Combined\ Metric = \alpha \times P(SR)@5 + (1-\alpha) \times NDCG@5$

Model	$\alpha = 0.3$	$\alpha = 0.4$	$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$
Pop	0.3149	0.3584	0.4019	0.4454	0.4889
WMF	0.4516	0.4627	0.4738	0.4850	0.4961
BPR	0.5294	0.5337	0.5380	0.5423	0.5466
LightGCN	0.5087	0.5169	0.5250	0.5332	0.5414
SGL	0.5081	0.5145	0.5210	0.5274	0.5338
Return	0.1422	0.1774	0.2126	0.2477	0.2828
Sharpe	0.1688	0.2113	0.2539	0.2965	0.3390
MVECF	0.2981	0.3279	0.3578	0.3876	0.4174
two-step	0.3563	0.3875	0.4186	0.4497	0.4809
DyRep	0.3617	0.3872	0.4128	0.4383	0.4638
Jodie	0.4434	0.4632	0.4831	0.5030	0.5228
TGAT	0.5021	0.5166	0.5311	0.5456	0.5601
TGN	0.5207	0.5250	0.5292	0.5335	0.5378
PfoTGNRec	**0.5334**	**0.5450**	**0.5566**	**0.5683**	**0.5799**



Experiment

- **Recommendation performance (RQ2)**

	Model	HR@3	HR@5	NDCG@3	NDCG@5	P(R)@3	P(R)@5	P(SR)@3	P(SR)@5	ΔR@3	ΔR@5	ΔSR@3	ΔSR@5
Static Recommender	Pop	0.1586	0.2787	0.1355	0.1845	0.5174	**0.5479**	0.5670	**0.6193**	-0.003	0.0106	0.1860	0.3533
	WMF	0.4654	0.5588	0.3797	0.4183	0.4561	0.4417	0.5228	0.5294	-0.0212	-0.0379	0.0374	0.0408
	BPR	0.5635	0.6538	**0.4794**	**0.5166**	0.5234	0.4970	0.5595	0.5594	0.0064	-0.0079	0.1499	0.1555
	LightGCN	0.5378	0.6399	0.4419	0.4841	0.5333	0.5041	0.5712	0.5660	0.0083	-0.0055	0.1664	0.1663
	SGL	0.5297	0.6054	0.4578	0.4888	0.5071	0.4912	0.5558	0.5531	-0.0003	-0.0223	0.1325	0.0908
Price-based model	Return	0.0389	0.0621	0.0274	0.0368	0.3065	0.3438	0.3403	0.3883	-0.1747	-0.1819	-0.5236	-0.4699
	Sharpe	0.0453	0.0665	0.0324	0.0411	0.4137	0.4174	0.4743	0.4667	-0.0832	-0.1011	-0.1269	-0.1362
Stock Recommender	MVECF	0.2170	0.2321	0.2025	0.2087	0.4286	0.4149	0.5081	0.5068	-0.0426	-0.0644	-0.0281	-0.0482
	two-step	0.2767	0.3834	0.2193	0.2629	0.4479	0.4425	0.5526	0.5743	-0.0227	-0.0335	0.1457	0.1849
Dynamic Recommender	DyRep	0.3047	0.4533	0.2243	0.2852	0.4581	0.4499	0.5383	0.5403	-0.0235	-0.034	0.0769	0.0919
	Jodie	0.4324	0.5757	0.3247	0.3838	0.5156	0.4924	0.5757	0.5824	0.0074	-0.0022	0.2186	0.2617
	TGAT	0.5138	0.6318	0.4100	0.4585	**0.5826**	0.5423	**0.6129**	0.6037	**0.0460**	0.0343	**0.3178**	0.3452
	TGN	**0.5673**	**0.6809**	0.4611	0.5079	0.5405	0.5107	0.5612	0.5506	0.0260	0.0075	0.1959	0.1899
Our Model	PfoTGNRec	0.5572	0.6674	0.4532	0.4986	0.5652	0.5434	0.6125	0.6147	0.0407	**0.0349**	0.3053	**0.3649**

- **Static and Dynamic Recommender Models:** These models consistently outperform others in recommendation performance.
- **Price-based and Existing Stock Recommender Models:** These models exhibit lower recommendation performance.
- **Our Model vs. TGN:** While our model slightly trails TGN, we intentionally traded off some recommendation performance for enhanced diversification through MVECF sampling.

Experiment

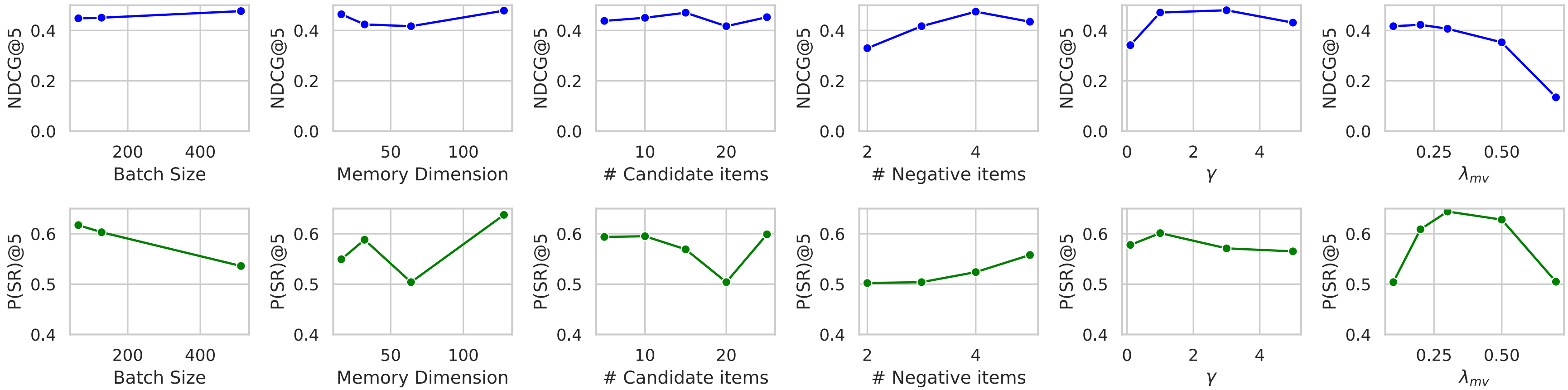
- **Portfolio performance (RQ3)**

	Model	HR@3	HR@5	NDCG@3	NDCG@5	P(R)@3	P(R)@5	P(SR)@3	P(SR)@5	ΔR@3	ΔR@5	ΔSR@3	ΔSR@5
Static Recommender	Pop	0.1586	0.2787	0.1355	0.1845	0.5174	**0.5479**	0.5670	**0.6193**	-0.003	0.0106	0.1860	0.3533
	WMF	0.4654	0.5588	0.3797	0.4183	0.4561	0.4417	0.5228	0.5294	-0.0212	-0.0379	0.0374	0.0408
	BPR	0.5635	0.6538	**0.4794**	**0.5166**	0.5234	0.4970	0.5595	0.5594	0.0064	-0.0079	0.1499	0.1555
	LightGCN	0.5378	0.6399	0.4419	0.4841	0.5333	0.5041	0.5712	0.5660	0.0083	-0.0055	0.1664	0.1663
	SGL	0.5297	0.6054	0.4578	0.4888	0.5071	0.4912	0.5558	0.5531	-0.0003	-0.0223	0.1325	0.0908
Price-based model	Return	0.0389	0.0621	0.0274	0.0368	0.3065	0.3438	0.3403	0.3883	-0.1747	-0.1819	-0.5236	-0.4699
	Sharpe	0.0453	0.0665	0.0324	0.0411	0.4137	0.4174	0.4743	0.4667	-0.0832	-0.1011	-0.1269	-0.1362
Stock Recommender	MVECF	0.2170	0.2321	0.2025	0.2087	0.4286	0.4149	0.5081	0.5068	-0.0426	-0.0644	-0.0281	-0.0482
	two-step	0.2767	0.3834	0.2193	0.2629	0.4479	0.4425	0.5526	0.5743	-0.0227	-0.0335	0.1457	0.1849
Dynamic Recommender	DyRep	0.3047	0.4533	0.2243	0.2852	0.4581	0.4499	0.5383	0.5403	-0.0235	-0.034	0.0769	0.0919
	Jodie	0.4324	0.5757	0.3247	0.3838	0.5156	0.4924	0.5757	0.5824	0.0074	-0.0022	0.2186	0.2617
	TGAT	0.5138	0.6318	0.4100	0.4585	**0.5826**	0.5423	**0.6129**	0.6037	**0.0460**	0.0343	**0.3178**	0.3452
	TGN	**0.5673**	**0.6809**	0.4611	0.5079	0.5405	0.5107	0.5612	0.5506	0.0260	0.0075	0.1959	0.1899
Our Model	PfoTGNRec	0.5572	0.6674	0.4532	0.4986	0.5652	0.5434	0.6125	0.6147	0.0407	**0.0349**	0.3053	**0.3649**

- **Our Model :** Consistently shows superior performance across all metrics.
- **Price-based Models:** Show the lowest performance, highlighting the difficulty in predicting future prices.
- **Stock Recommendation Models**: Did not perform well in investment performance. This may be due to their inability to effectively handle the dynamic nature

Experiment

- **Hyperparameter study (RQ4)**
  - **Six key hyperparameter:** batch size, memory dimension, number of candidate items, number of negative items, γ, λ_{MV}



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Conclusion

Conclusion

- **A framework for stock recommender system**
  - 1. Captures the temporal dynamics of user behavior and stock market
  - 2. Integrates portfolio diversification into recommendations
- **Experiments**
  - Our model demonstrated the best performance in weighted metrics that consider both recommendation and investment performance.
  - Conducted an hyperparameter study.
- **Future works**
  - Incorporating static features of users and items as node features
  - Accounting for various user behaviors in recommender system

Thank you for listening!