Stock Recommendations for Individual Investors

: A Temporal Graph Network Approach with Mean-Variance Efficient Sampling

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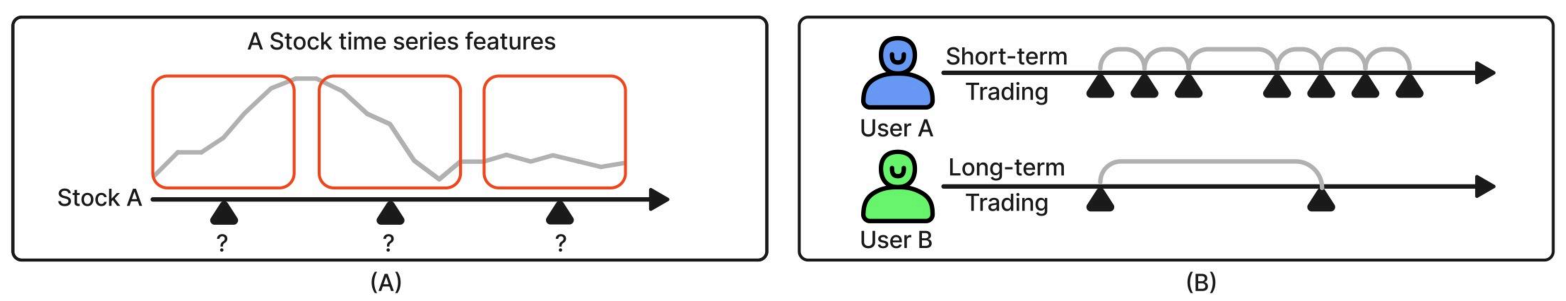
Introduction

1. Why is stock recommendation necessary?

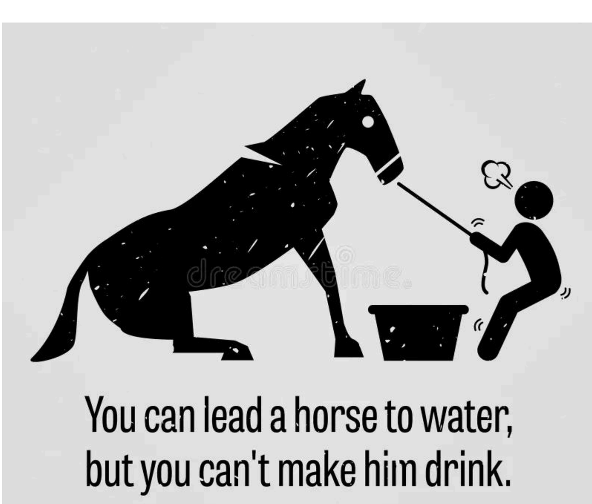
- **Irrational Investment Behavior of Individual Investors**
  - Overconfidence, disposition effect, lottery preference, and herding (Ngoc, 2014)
  - The average investor significantly underperformed the S&P 500 over time (Murray, 2023)
- **There are many excellent methods for portfolio performance**
  - Modern Portfolio Theory (MPT)
  - 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 ...



2. What should be considered in stock receommender system?

Tricky Trade-off !

Individual preference



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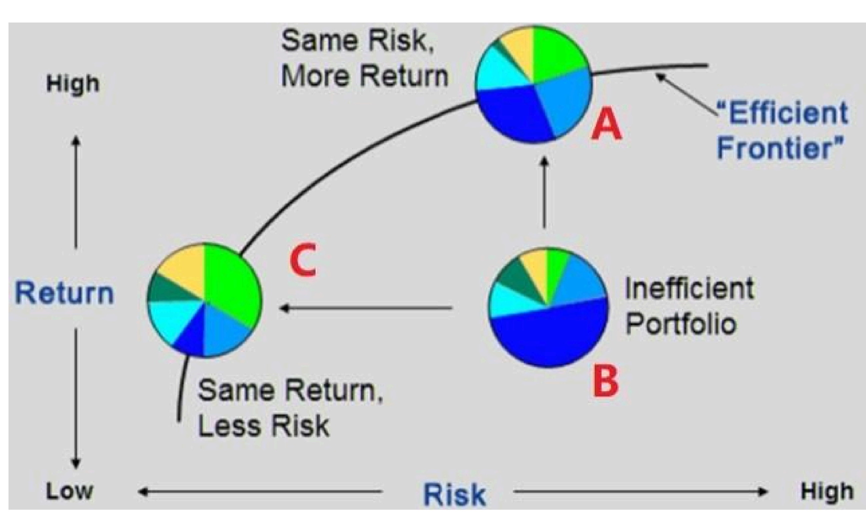
Investment performance



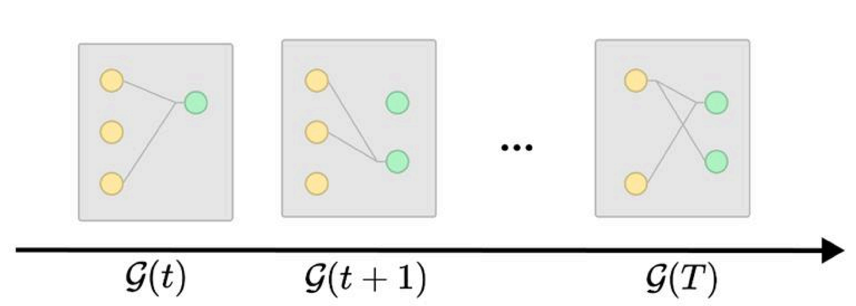
Preliminaries

Problem Definition

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

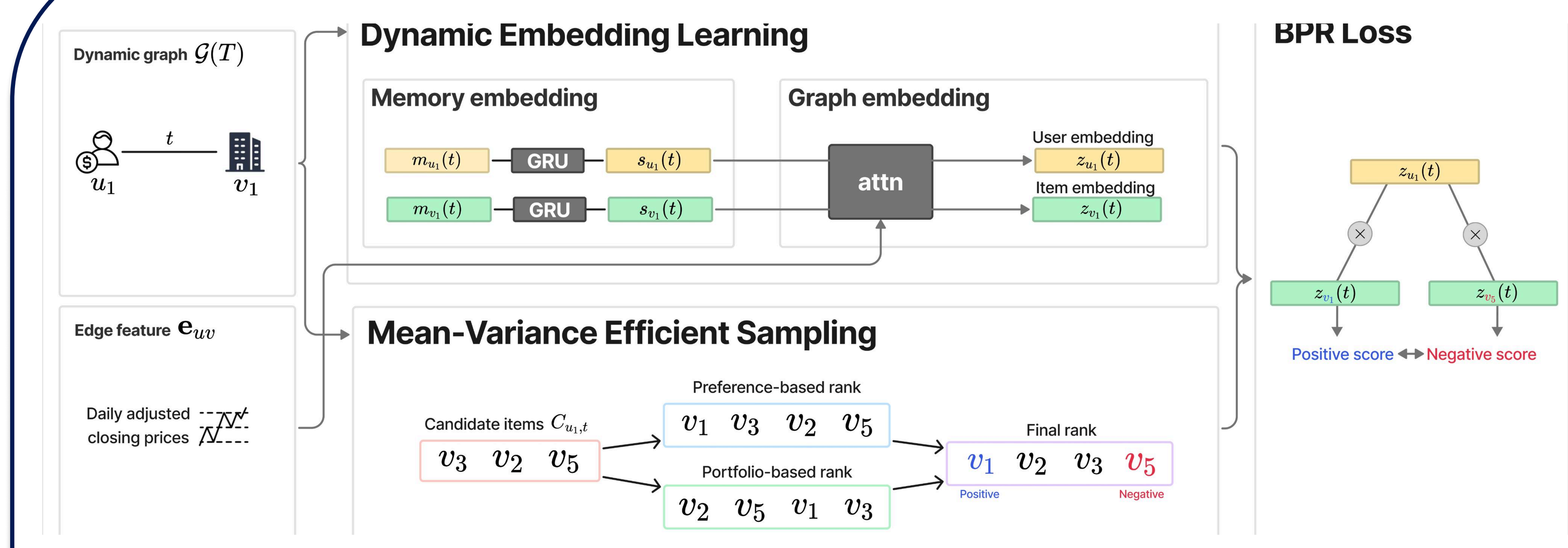
For each user and time, the model aims to recommend the top-k items.

Continuous-Time Dynamic Graph



User-item interactions that change over time.

Method



Portfolio Temporal Graph Network Recommender (PfoTGNRec)

(1) Dynamic Embedding Learning

- **Memory embedding (GRU)**
  - We generate memory embeddings for each node to capture the dynamic nature, storing nodes' history.
- **Graph embedding (GAT)**
  - Temporal embeddings for a dynamic graph are generated, learning collaborative signals.

(2) Mean-Variance Efficient Sampling

- Diversification score, motivated by **MVECF** (Chung et al., 2023)

$$y_{ui}^{MV} = \frac{\frac{\mu_i}{\gamma} - \frac{1}{2}\sum_{j:j\neq i}\frac{1}{|y_u|}\sigma_{ij}}{\sigma_i^2}$$

Stocks with **high returns** and **low risks** will have high diversification scores!

- Preference based rank + Portfolio based rank → Final rank

$P_{u,t} = \text{top-ranked items from the final rank}$

$N_{u,t} = \text{bottom-ranked items from the final rank}$

(3) Optimization: BPR Loss

- Bayesian Personalized Ranking (BPR) loss is applied to the pairs of positive and negative items

$$\mathcal{L}_{BPR} = \sum_{(u,p,n,t)\in D} -\log\sigma\left(\mathbf{z}_u(t)^T\mathbf{z}_p(t) - \mathbf{z}_u(t)^T\mathbf{z}_n(t)\right)$$

Data & Evaluation

Dataset

- **Greek market** Individual investor transactions
- **Period** Jan 2018 ~ Nov 2022
- **Chronological split** (8:1:1)
- **Preprocessing**: Buy orders, Item filtering, Daily portfolio
- **Description** 152,084 interactions, 8,337 users, 92 items
- Avg num of stocks in user portfolio: 6.26 (median 5)

Baselines

- **Recommender models**
  - BPR, WMF, LightGCN, SGL
  - DyRep, Jodie, TGAT, TGN
- **Price-based models**
  - Return, Sharpe ratio
- **Stock recommendation models**
  - two-step method
  - MVECF

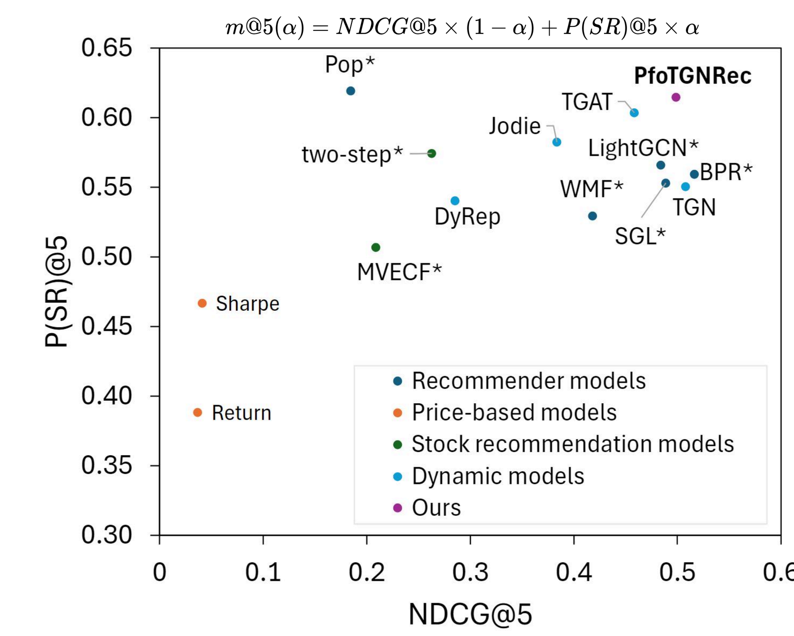
Evaluation

- **Interaction-based ranking strategy**
- **Recommendation** Hit Ratio@k, NDCG@k (Normalized Discounted Cumulative Gain)
- **Investment** Return(R) and Sharpe ratio(SR) of equal-weighted portfolio
  - Difference, Percentage improvement

Experiment

RQ1. Combined Metric of User Preferences and Portfolio Performance

Our model offers the most balanced approach,
enhancing investment performance while reflecting individual preferences.



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**

Note: The best and the second best performing models are highlighted in bold and underline, respectively.

RQ2. Recommendation Performance

RQ3. Portfolio Performance

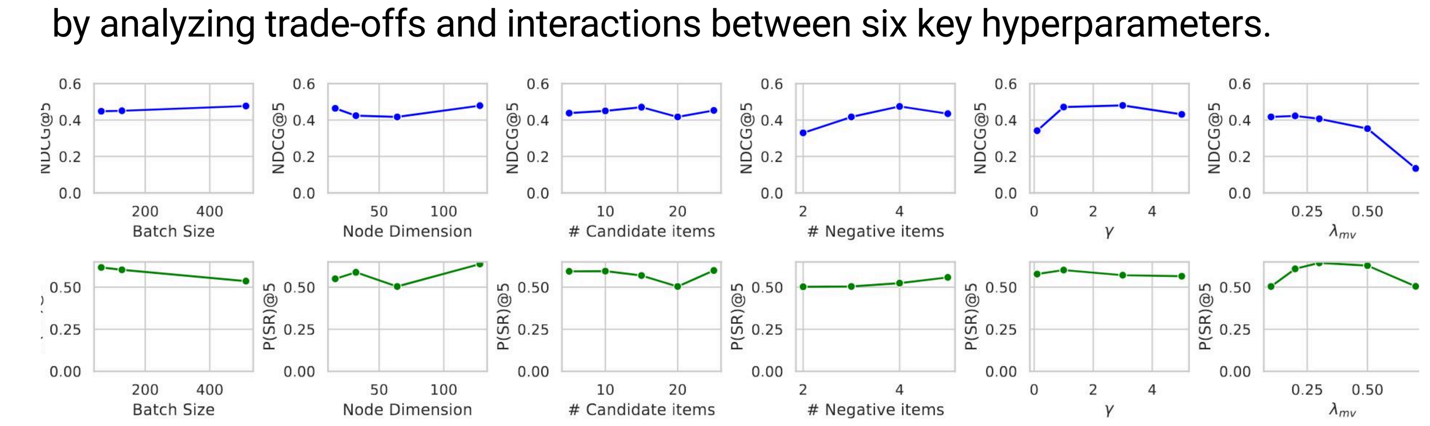
Our model falls slightly short of TGN, sacrificing a certain level of recommendation performance.
Our model records superior performance across most metrics, despite a few exceptions.

	Recommendation effectiveness				Portfolio performance							
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
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
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
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
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
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
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**

Note: Models with * exclude cold start user results. The best and second best performing models are highlighted in bold and underline, respectively.

RQ4. Hyperparameter Study

We guide the optimization of our model for both recommendation and investment tasks,
by analyzing trade-offs and interactions between six key hyperparameters.



- γ : hyperparameter for risk-aversion level
- λ_{MV}: balance between preference and portfolio performance