



Learning Multiple Stock Trading Patterns with Temporal Routing Adaptor and Optimal Transport

KDD 2021

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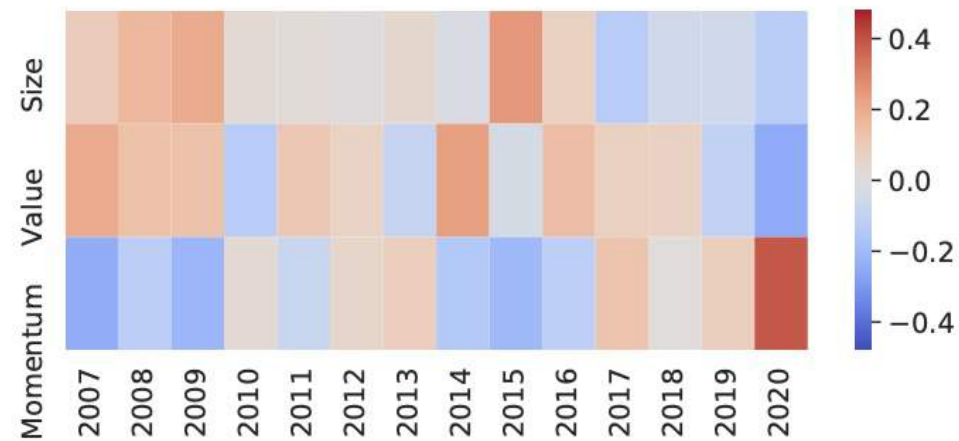
Motivation

- Investors hold various beliefs and strategies, and multiple trading patterns* in the stock market could be observed.

** A trading pattern means the causal relation between the available information at the current time (i.e., feature) and the stock price movement in the future (i.e., label).*

Motivation

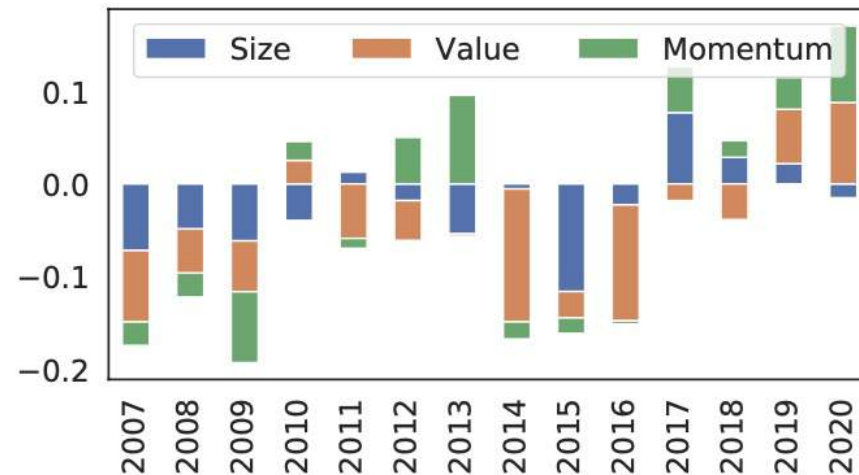
- Investors hold various beliefs and strategies, and multiple trading patterns* in the stock market could be observed.
 - e.g., excess return relative to market of three common trading strategies (size, value, momentum) changed and dominated different period



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Motivation

- But simply following the identical distribution assumption fails to capture different trading patterns.
 - e.g., linear coefficients between excess return and strategy-related feature

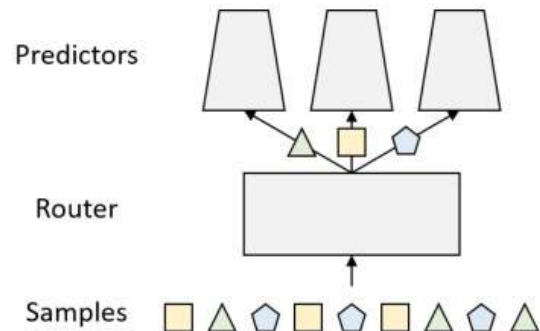


Methodology

- Temporal Routing Adaptor (TRA)
 - Empower existing NN based models with the ability to model multiple trading patterns.

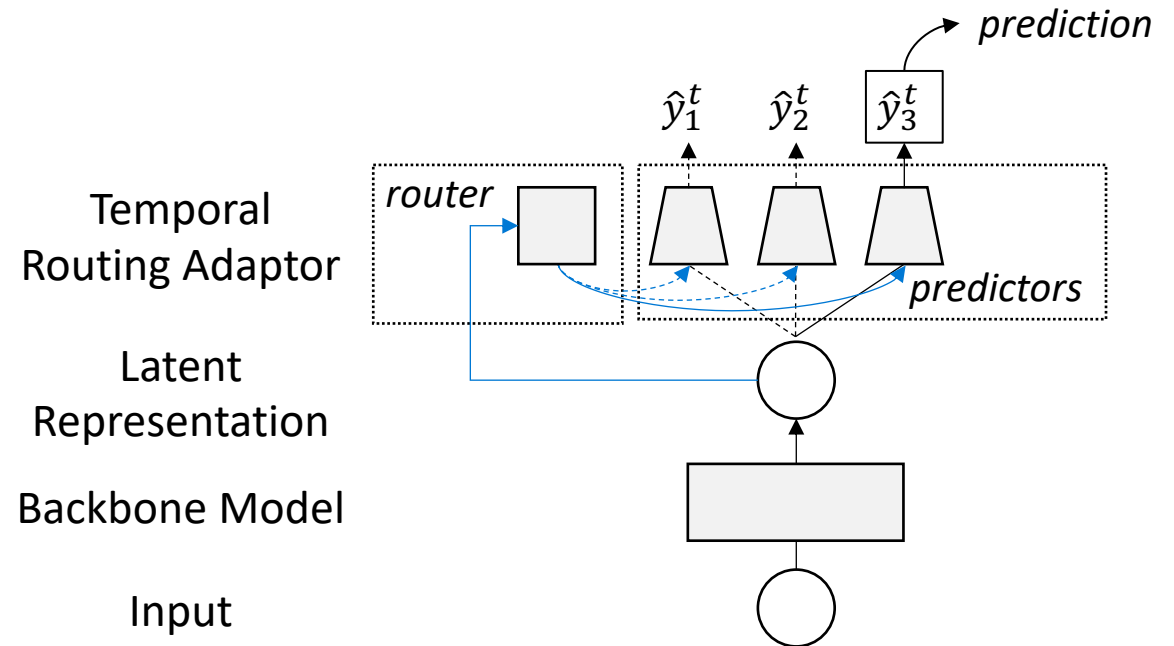
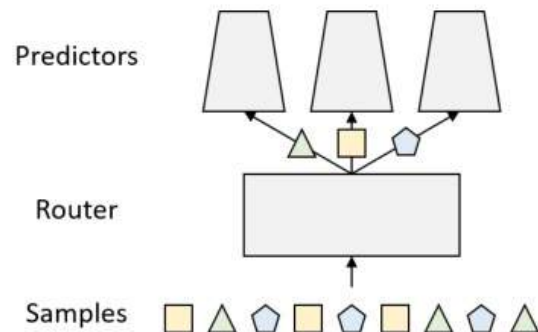
Methodology

- Temporal Routing Adaptor (TRA) = predictors + router
 - Empower existing NN based models with the ability to model multiple trading patterns.
 - Predictors: Responsible for representing multiple patterns
 - Router: Responsible for detecting a sample's underlying pattern and its assignment



Methodology

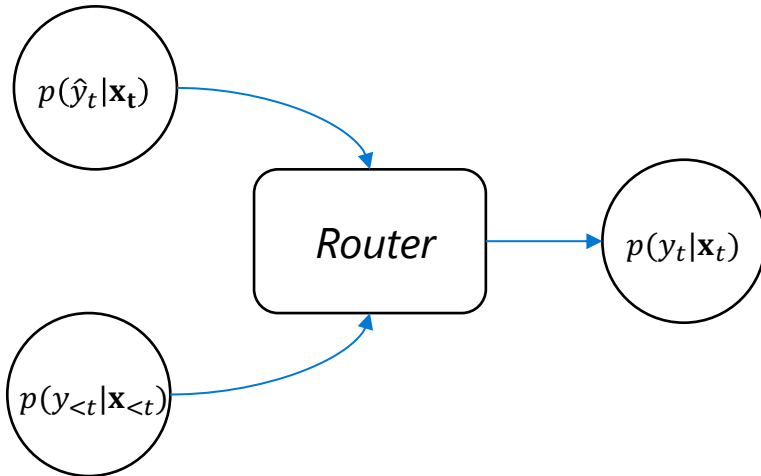
- Temporal Routing Adaptor (TRA) = **predictors** + router
 - Predictors: Responsible for representing multiple patterns
 - Extending our TRA on a backbone model avoid heavy parameters and provide fair comparison with backbone model.



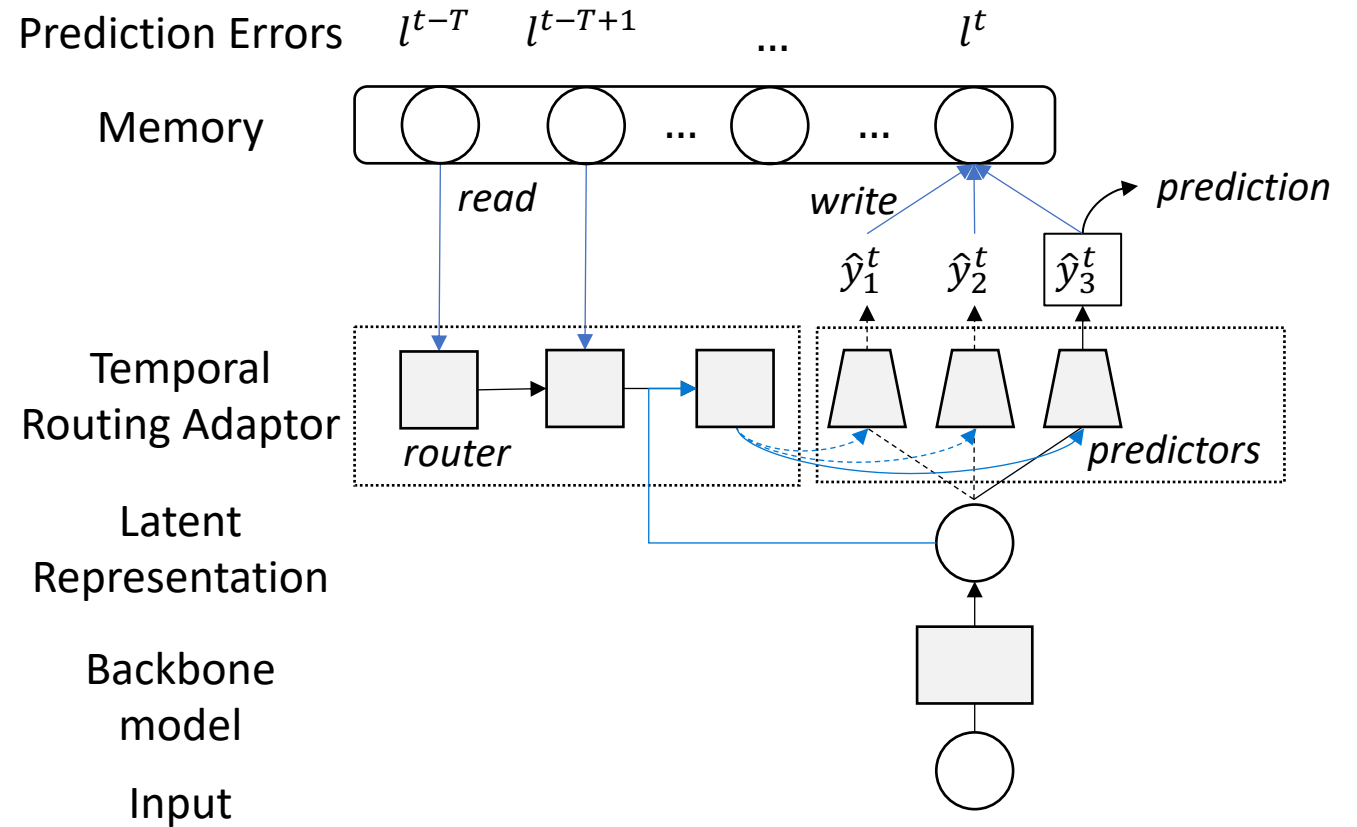
Methodology

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latent representation



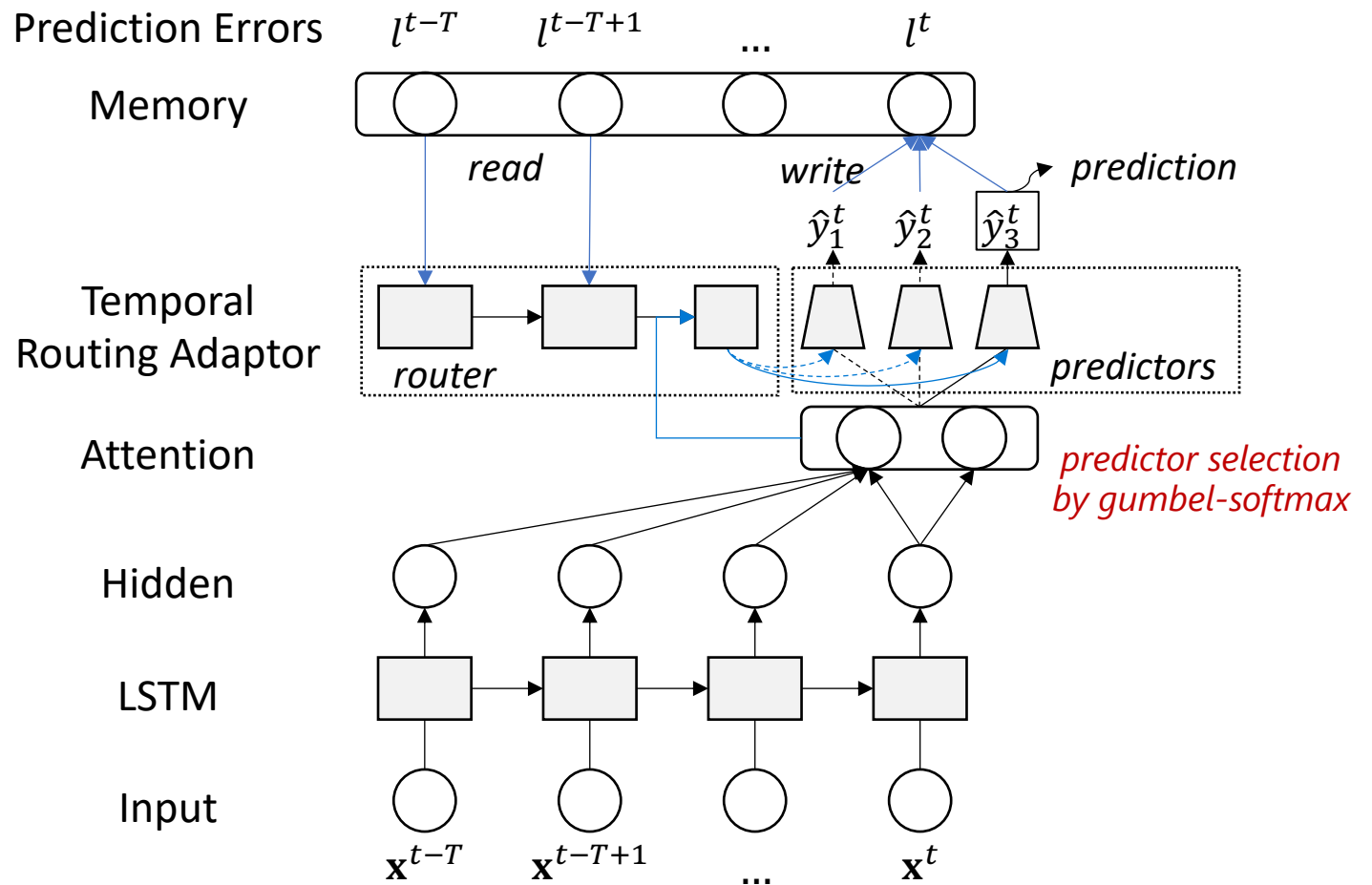
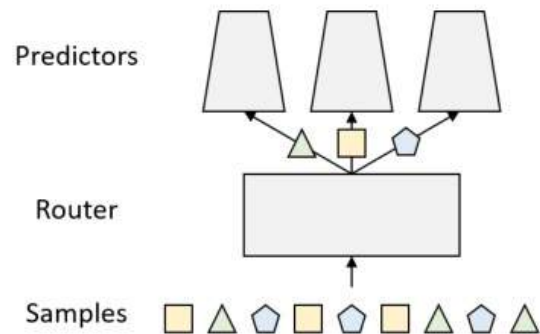
temporal prediction errors



Methodology

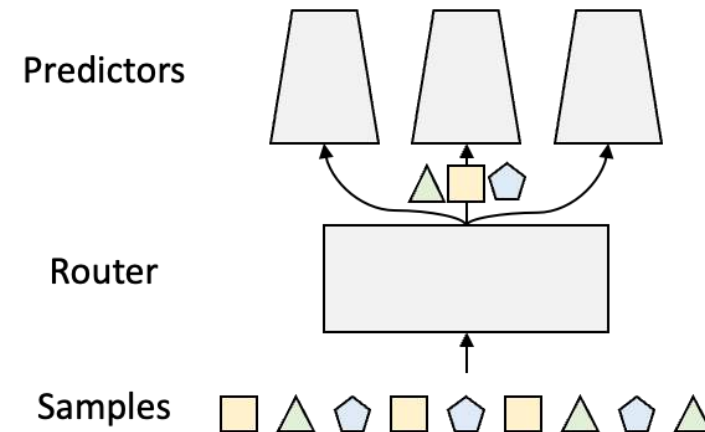
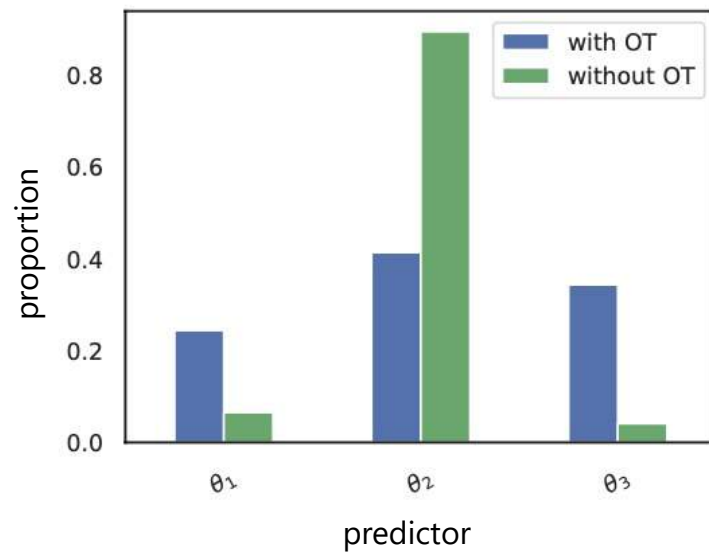
- Temporal Routing Adaptor (TRA) = predictors + router

- An implementation of TRA on RNN:



Methodology

- Optimal Transport (OT):
 - While TRA has the capacity to model multiple patterns, it can easily fall to some trivial solutions like selecting only one:



Methodology

- Optimal Transport (OT):
 - While TRA has the capacity to model multiple patterns, it can easily fall to some trivial solutions like selecting only one.
 - Introducing constraint to make assigned samples more balanced?

Methodology

- Optimal Transport (OT):
 - *+Objective*: assign samples to predictors to minimize the overall loss
 - *Constraint*: keep the assigned samples proportional to the relative share of the pattern

$$\min_{\mathbf{P}} \langle \mathbf{P}, \mathbf{L} \rangle,$$

$$s.t. \sum_{i=1}^N \mathbf{P}_{ik} = v_k * N, \forall k = 1 \dots K$$

$$\sum_{k=1}^K \mathbf{P}_{ik} = 1, \forall i = 1 \dots N$$

$$\mathbf{P}_{ik} \in \{0, 1\}, \forall i = 1 \dots N, k = 1 \dots K,$$

where \mathbf{P}_{ik} is the router assignment matrix, \mathbf{L} is the cost matrix.

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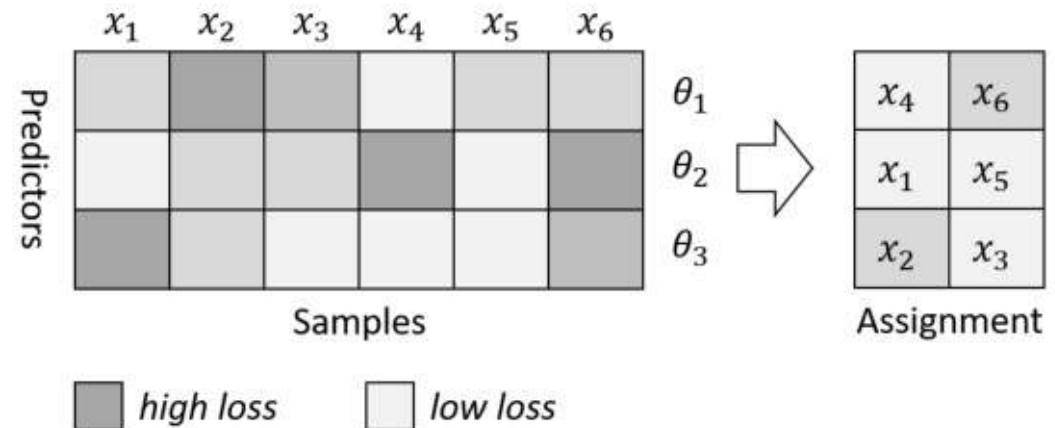
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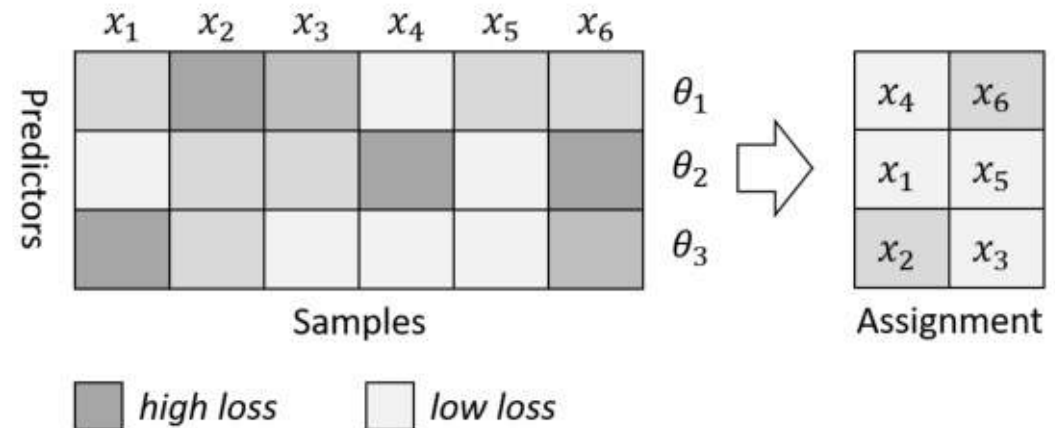
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- To emulate OT assignment during testing, we guide the learning of the router through adding an auxiliary regularization term into the objective:

$$\min_{\Theta, \pi, \psi} \mathbb{E}_{(\mathbf{x}_i, y_i) \in \mathcal{D}^{\text{train}}} [\ell(\mathbf{x}_i, y_i; \Theta, \pi, \psi) - \lambda \sum_{k=1}^K \mathbf{P}_{ik} \log(q_{ik})].$$

Experiments

- Task: Stock Ranking Prediction
- Dataset: CSI800 Stocks on China A-share Market
- Metrics:
 - Regression metrics: MSE, MAE
 - Finance ranking metrics: Information Coefficients (IC), Information Ratio of IC (ICIR).
 - Portfolio metrics: Annual Return (AR), Annual Volatility (AV), Sharpe Ratio (SR), Max Drawdown
- Baselines:
 - Linear, LightGBM, MLP, SFM (KDD 17), ALSTM (IJCAI 17, IJCAI 19), Transformer (IJCAI 20)
 - Heuristic methods for learning multiple patterns: ALSTM+TS, Transformer+TS

* Our dataset is publicly available at <https://github.com/microsoft/glib>

Experiments

- Heuristic methods for learning multiple patterns harm the model performance:

Method	Ranking Metrics				Portfolio Metrics			
	MSE (↓)	MAE (↓)	IC (↑)	ICIR (↑)	AR (↑)	AV (↓)	SR (↑)	MDD (↓)
Linear	0.163	0.327	0.020	0.132	-3.2%	16.8%	-0.191	32.1%
LightGBM	0.160(0.000)	0.323(0.000)	0.041	0.292	7.8%	15.5%	0.503	25.7%
MLP	0.160 (0.002)	0.323 (0.003)	0.037	0.273	3.7%	15.3%	0.264	26.2%
SFM	0.159 (0.001)	0.321 (0.001)	0.047	0.381	7.1%	14.3%	0.497	22.9%
ALSTM	0.158 (0.001)	0.320 (0.001)	0.053	0.419	12.3%	13.7%	0.897	20.2%
Trans.	0.158 (0.001)	0.322 (0.001)	0.051	0.400	14.5%	14.2%	1.028	22.5%
ALSTM+TS	0.160 (0.002)	0.321 (0.002)	0.039	0.291	6.7%	14.6%	0.480	22.3%
Trans.+TS	0.160 (0.004)	0.324 (0.005)	0.037	0.278	10.4%	14.7%	0.722	23.7%
ALSTM+TRA (Ours)	0.157 (0.000)	0.318 (0.000)	0.059	0.460	12.4%	14.0%	0.885	20.4%
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Experiments

- With both TRA and OT, our method can give consistent gains:

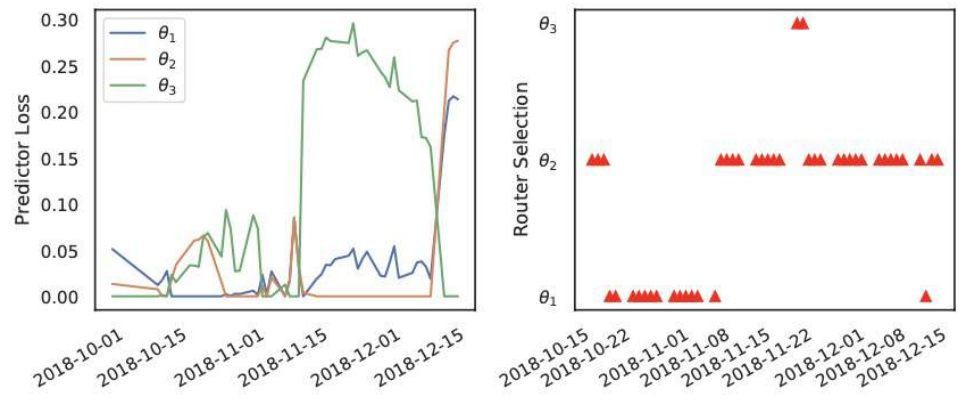
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Incremental Analysis

- During test, TRA selects predictor with smaller loss:

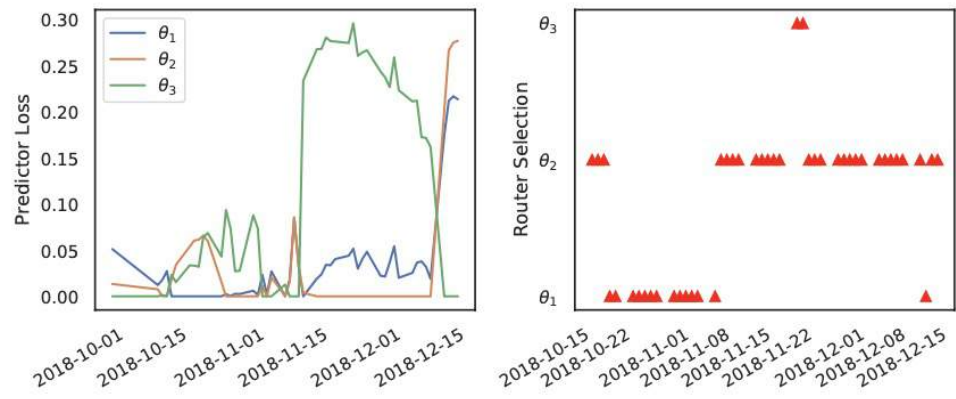
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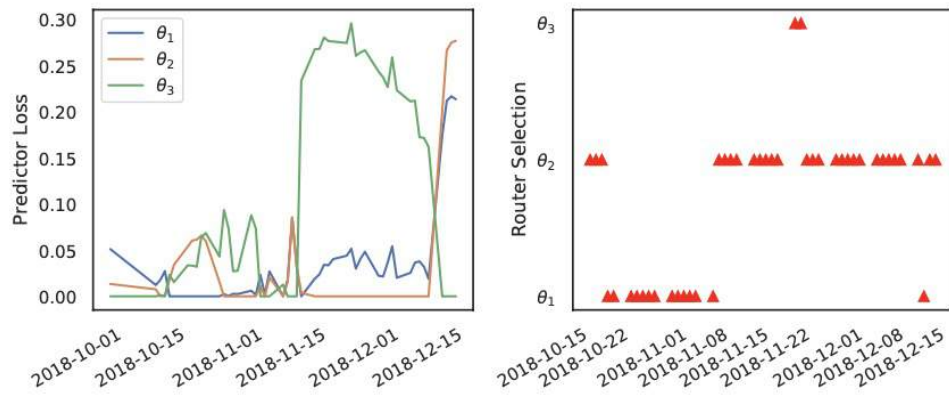
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- TRA benefits most from using both latent representation and temporal prediction error as input:



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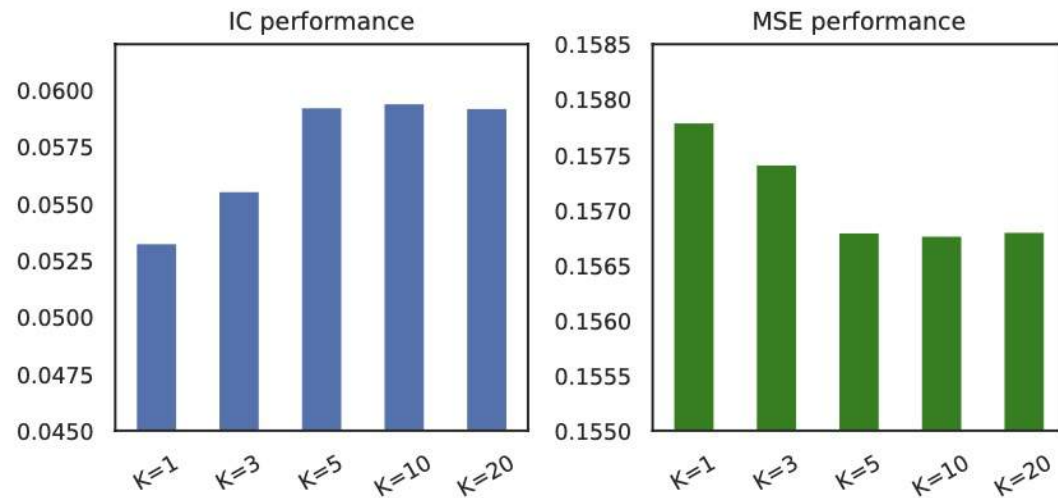
Information	MSE (\downarrow)	MAE (\downarrow)	IC (\uparrow)	ICIR (\uparrow)
Random	0.159 (0.001)	0.321 (0.002)	0.048	0.362
LR	0.158 (0.001)	0.320 (0.001)	0.053	0.409
TPE	0.158 (0.001)	0.321 (0.001)	0.049	0.381
LR+TPE	0.157 (0.000)	0.318 (0.000)	0.059	0.460

Incremental Analysis

- A moderate selection of # predictors (i.e., trading patterns) could give desirable performance gains:

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Thank you!

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