Meta-Adaptive Stock Movement Prediction with Two-Stage Representation Learning

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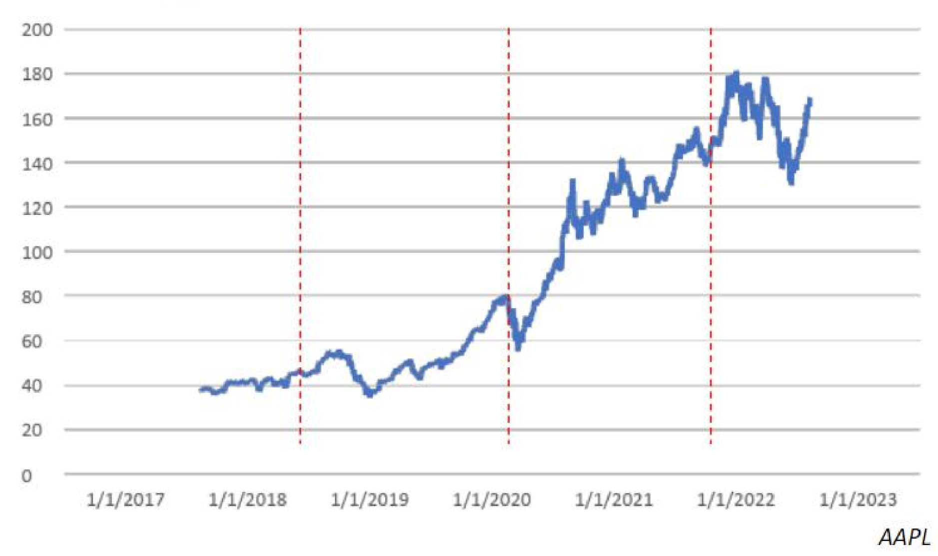
Background

Two challenges for stock prediction

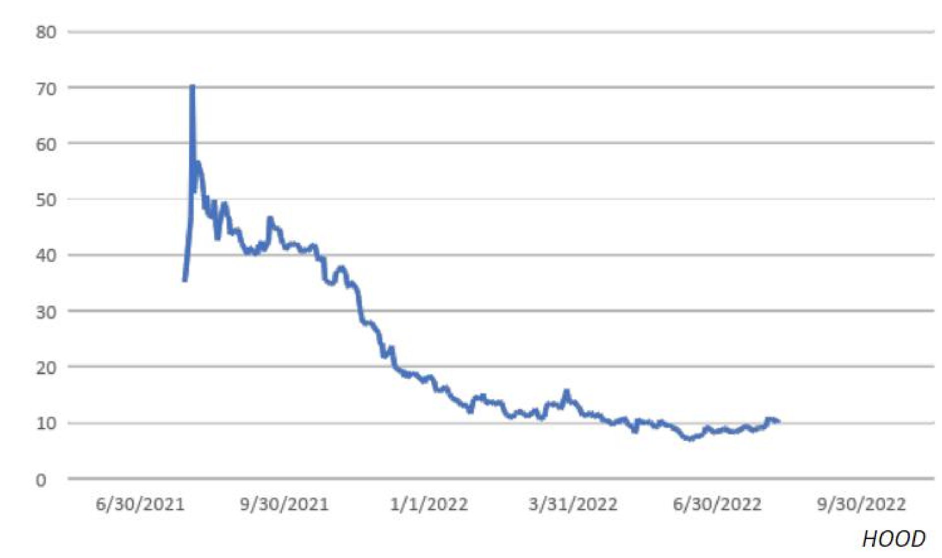
- Limited Data: Limited daily data & the models trained on small datasets may be overfitting
- Temporal Pattern Shift: Due to the fact that the environment evolves with time, the temporal distribution may shift within a large time scale.

- **Temporal Pattern Shift**



The potential shifts of temporal patterns in stock market are commonly seen, which increase the difficulty for models to learn from the historical data.

- **Limited Data**



There are always limited data and the models trained on small datasets are susceptible to overfitting. For stock price data, even daily data over decades are not big enough to make a good training set.

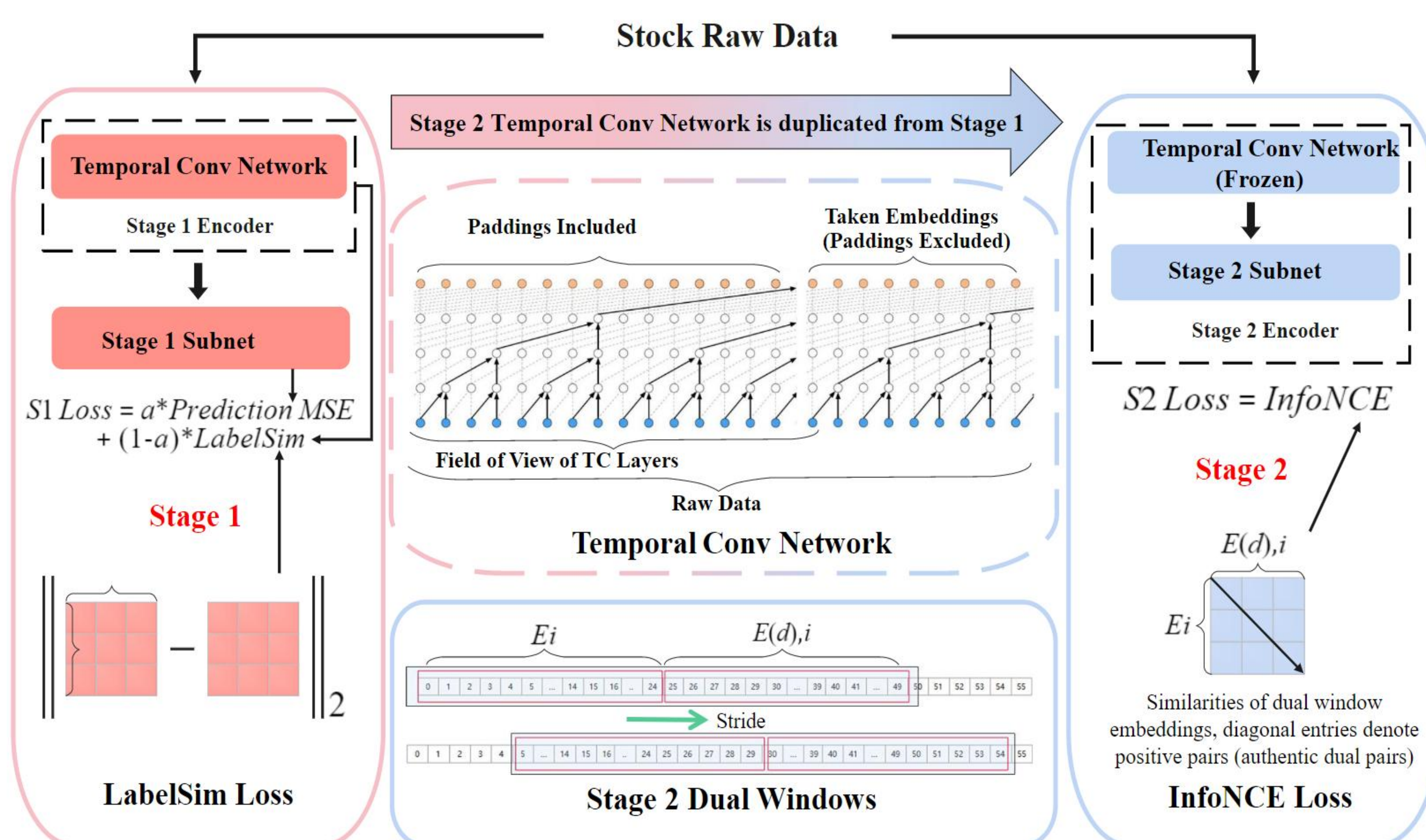
Methodology

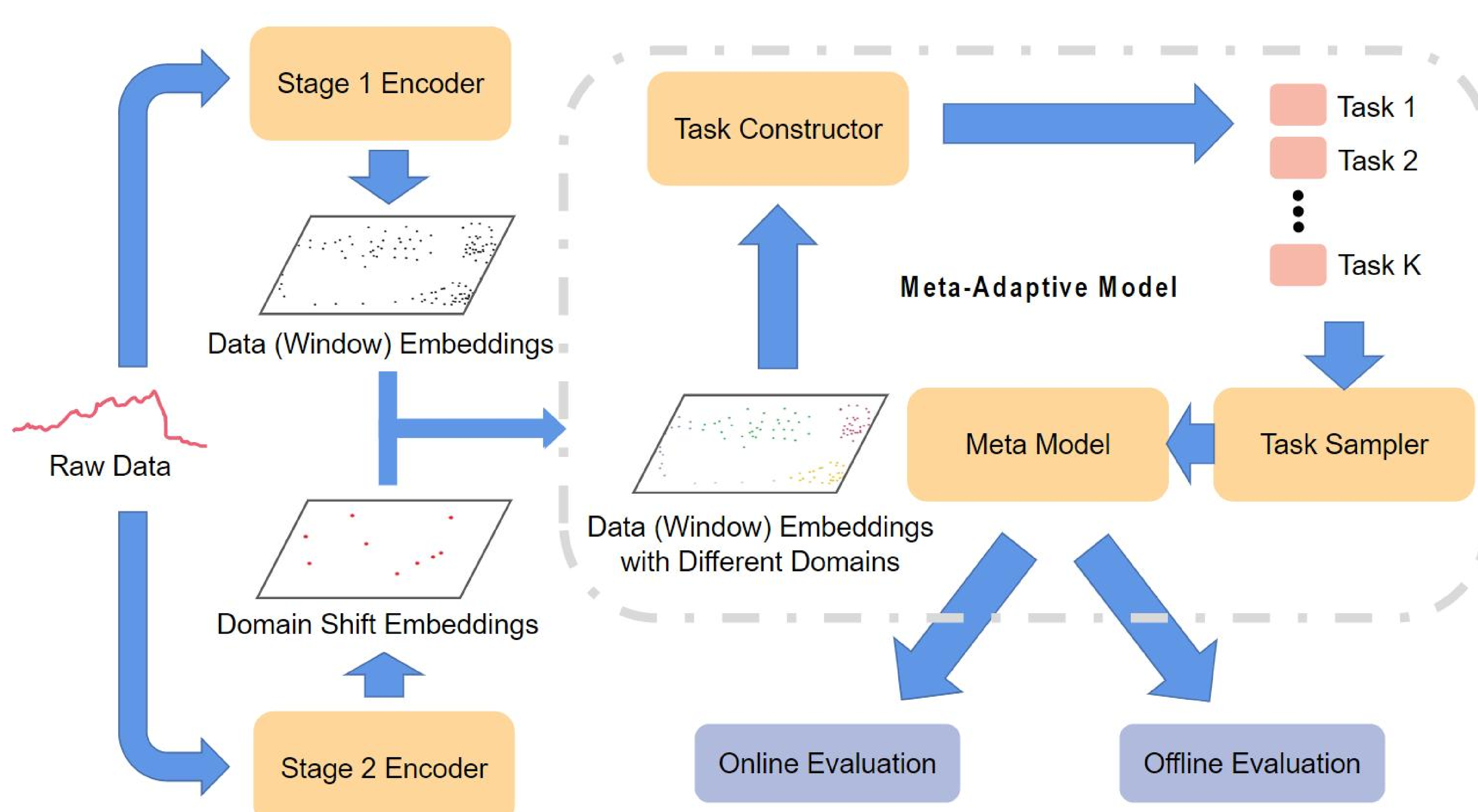
Two-Stage Representation Learning

- First Stage (Macro Representation Learning): Learn the unified representation for subsequences at the dataset level via supervised learning (details can be found in the paper).
- Second Stage (Micro Representation Learning): Detect the potential temporal domain shift via contrastive learning(details can be found in the paper).

Meta-Learning Pipeline

- Task Construction: Construct tasks for meta-learning according to the representation encoded by the first stage representation learning and the detected shifts inferred by the second stage representation learning.
- Task Evaluation: Evaluate constructed tasks' qualities via criteria from (i) the alignment of the support set and query set, (ii) temporal adjacency, and (iii) representation adjacency.
- Adaptive Meta-Training: Sample the appropriate tasks for training the model according to the result of task evaluation.





Experiments

Offline Setting

- The model has frozen after the training stage and outputs all the predictions of testing data simultaneously.

	ACL18		KDD17	
Model	Acc	MCC	Acc	MCC
MOM	0.470	−0.064	0.498	−0.013
LSTM	0.532	0.067	0.516	0.018
ALSTM	0.549	0.104	0.519	0.026
StockNet	0.550	0.017	0.499	0.499
Adv-ALSTM	0.572	0.148	0.531	0.052
MAN-SF	0.608	0.195	−−	−−
MASSER-ResNet	0.552	0.099	0.535	0.074
MASSER-GRU	0.579	0.141	**0.543**	0.073
MASSER-ResNet*	**0.624**	**0.244**	0.542	**0.078**
MASSER-GRU*	0.581	0.162	**0.543**	**0.047**

Table 1: Offline Setting Acc and MCC on **ACL18** and **KDD17** (* means adaptation)

Online Setting

- The model is allowed to update its parameters for the next input after each sequential temporal prediction.

	ACL18	
Model	Acc	MCC
LSTM	0.516	0.045
GRU	0.509	0.041
ALSTM	0.487	0.012
MASSER-ResNet	0.612	0.216
MASSER-ResNet-BOCPD	**0.625**	**0.251**

Table 2: Online Setting Acc and MCC on **ACL18**

Online Backtesting

- We report the return rate of a portfolio constructed by the prediction of the online setting.

Models	Achieved return rate
Stock	5.59%
LSTM	8.81%
GRU	8.55%
ALSTM	13.14%
MASSER-ResNet	**29.52 %**

Table 3: Average Online Return Rate on **ACL18**

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