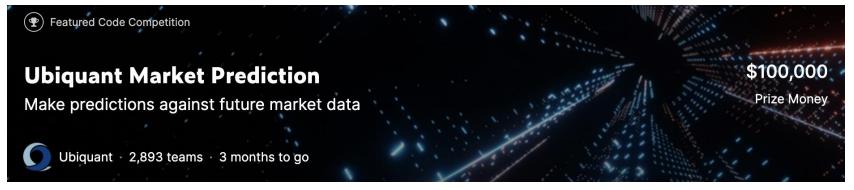
Comparison of models for Ubiquant Market Prediction

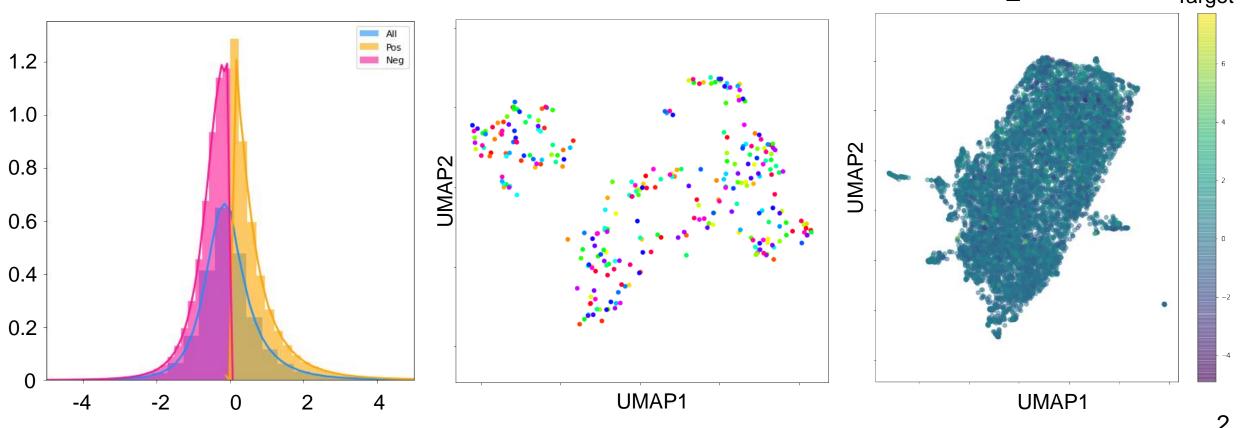
Jiabao Li, Zhihan Zhu MATH 5470 2022.4.22

https://youtu.be/Wzn00pUDEYY

Introduction



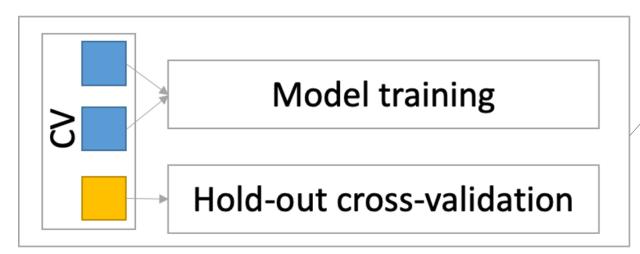
- 3,141,410 transaction data
 - Target value
 - Time_ID
 - Investment_ID
 - 300 features named f_1 to f_300 Target



Machine Learning Framework

Which model can predict the market data better?

3-fold cross-validation



Hyper-parameter tuning



Evaluation metric:

$$\rho = cor(\hat{y}, y) = \frac{\Sigma(\hat{y}_i - \bar{\hat{y}})(y_i - \bar{y})}{\sqrt{\Sigma(\hat{y}_i - \bar{\hat{y}})^2 \Sigma(y_i - \bar{y})^2}}$$

Methods - LASSO

Formula:

$$\hat{y}_i = \sum_j eta_j x_{ij}$$

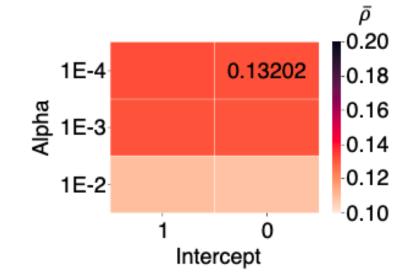
Objective function:
$$L = \sum_{i=1}^n \left(y_i - \beta_0 c - \sum_{j=1}^p \beta_j x_{ij} \right)^2 + \alpha \sum_{j=1}^p |\beta_j|$$

Hyper-parameter:

C: fitting intercept

alpha: Controlling the strength of the L1 term

Cross-validation performance:



Methods - GBDT

Formula:

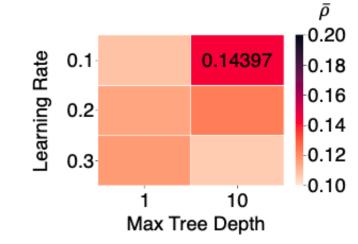
$$\hat{y}_{i} = \sum_{t=1}^{T} f_{t}\left(x_{i}\right), f_{t} \in \mathcal{F}$$

Objective function:
$$L^{(t)} = \sum_{i=1}^{n} \left(y_i - \hat{y}_i^{(t-1)} - \alpha f_t(\mathbf{x}_i) \right)^2 + \Omega(f_t)$$

Hyper-parameter:

Learning rate: weight of a new generated tree Max tree depth: how complex of a tree

Cross-validation performance:



Methods - DNN

Platform: GPU&Kaggle

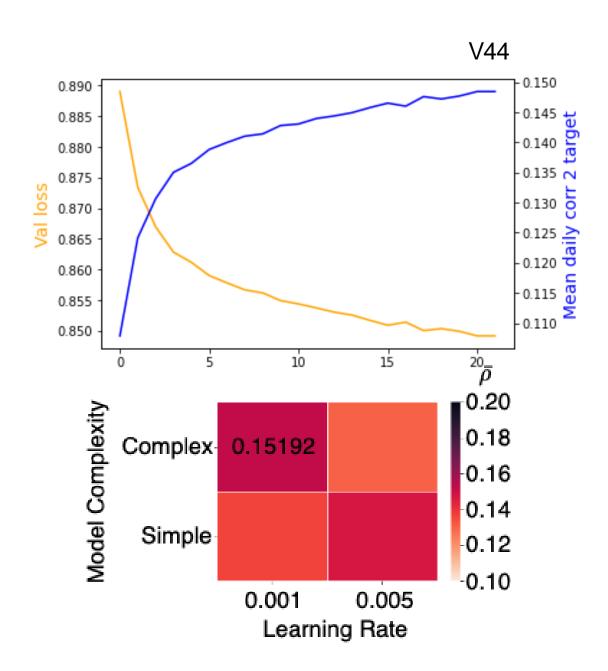
Pipeline: Kaggle::greydolphin

1	Name	1	Туре	1	Params
	id_embed layers		Embedding Sequential	1	110 K 96.4 K
206 0 206	No	n-trair	e params nable params	5	Simple
0.8		otal pai otal est		eι	params size (MB)

	Name	Type	Params
0 1	id_embedding layers	Embedding Sequential	110 K 360 K
470 0 470	Non-ti	ble params ainable params params	Complex
1.8		•	params size (MB)

Table 1: Results for DNN models

Model	Model Complex	Learning Rate	Pearson Cor	Name
DNN	complex	0.001	0.15191829	V4
DNN	complex	0.005	0.1302046	V42
DNN	simple	0.005	0.13668779	V43
DNN	simple	0.001	0.14695018	V44



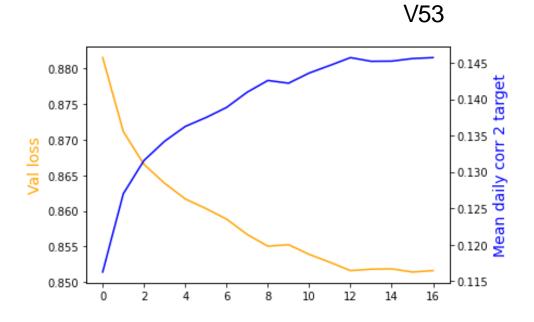
Methods - LSTM

_1	Name	Туре	Params	
0 1 2 3 4	id_embedding layers1 lstm1 lstm2 layers2	Embedding Sequential LSTM LSTM Sequential	110 K 20.1 K 99.3 K 49.7 K 545	
279 K Trainable params 0 Non-trainable params Complex 279 K Total params 1.119 Total estimated model params size (MB)				

1	Name	Type	Params		
0 1 2 3 4	id_embedding layers1 lstm1 lstm2 layers2	Embedding Sequential LSTM LSTM Sequential	110 K 28.7 K 395 K 197 K 1.1 K		
732 K Trainable params 0 Non-trainable params Simple 732 K Total params 2.930 Total estimated model params size (MB)					

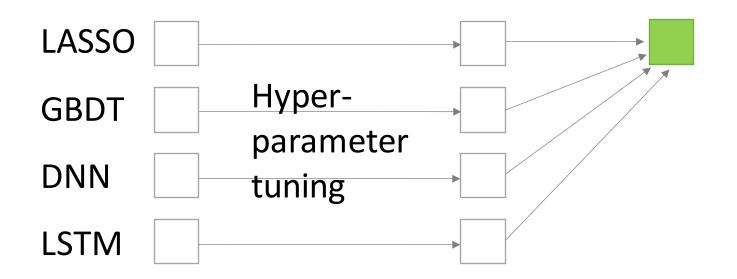
Table 2: Results for LSTM models

Model	Model Complex	Learning Rate	Pearson Cor	Name
LSTM	complex	0.001	0.14113208	V5
LSTM	complex	0.005	0.11254942	V52
LSTM	simple	0.001	0.14182154	V53
LSTM	simple	0.005	0.12764723	V54





Results & conclusion



Independent test dataset (25% data)

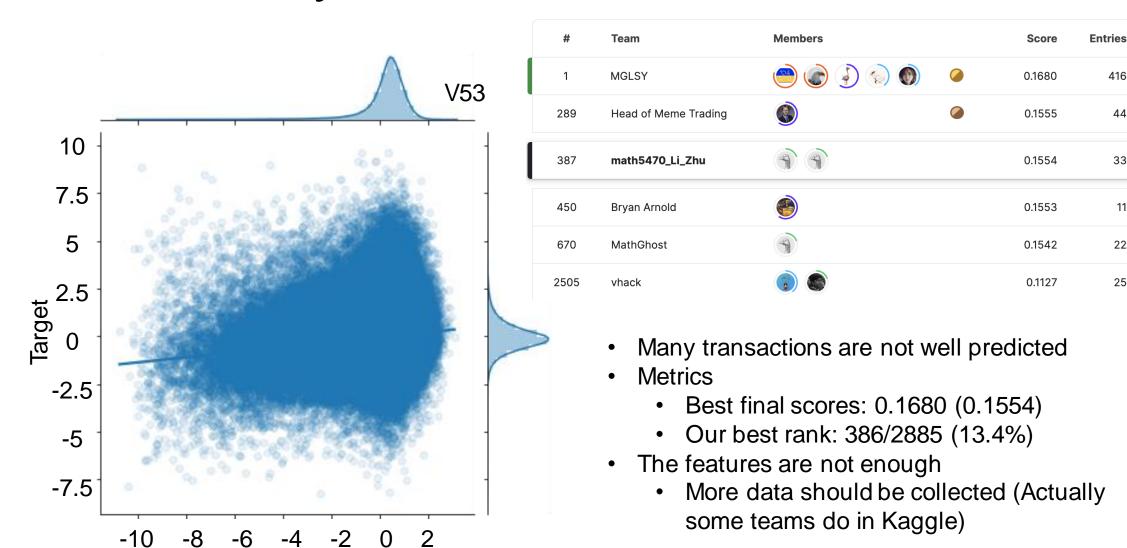
Performance:

Model	ρ in validation dataset	ρ in Kaggle	
LASSO	0.13063	0.1076	Sum
GBDT	0.15513	0.1193	fina
DNN	0.15191	0.1348	
LSTM	0.14182	NA	com

Summited for the final round competition

Case study & Discussion

Predicted



Last

11h

20h

20h

20d

2d

8h

416

44

33

11

22

25

Code

Thank you