

0016 Project --- Research Project: Predicting Stock Prices

Abstract

In this project, some data mining models including Orange Data Mining Tools will be trained to predict stock prices and compared to find out the features of models.

Data & Training Preparation

With Orange Data Mining Tools and packages in python, I will predict stock prices of 0016 Sun Hung Kai Properties and 0017 New World Development with their previous price data. CSV format file is easy to process. So during the data preparation step, I download the CSV datasets from Yahoo Financa. The data used for training ranges from January 3rd 2019 to June 29th 2022. For test data, it ranges from July 4th to October 28th 2022.

Fig.1 and Fig.2 show the 0016 price trends of training date and test data:

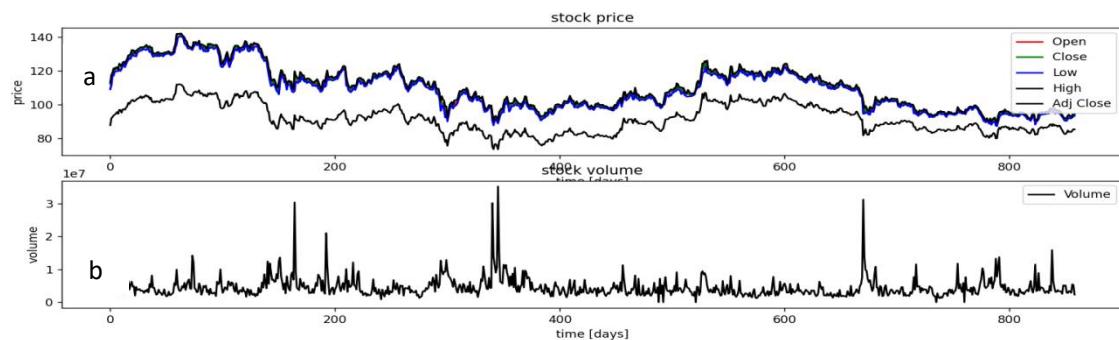


Fig.1.(a) The changes of 0016 HK Training Data. Fig.1.(b)The trading volume of 0016 HK Training Data.

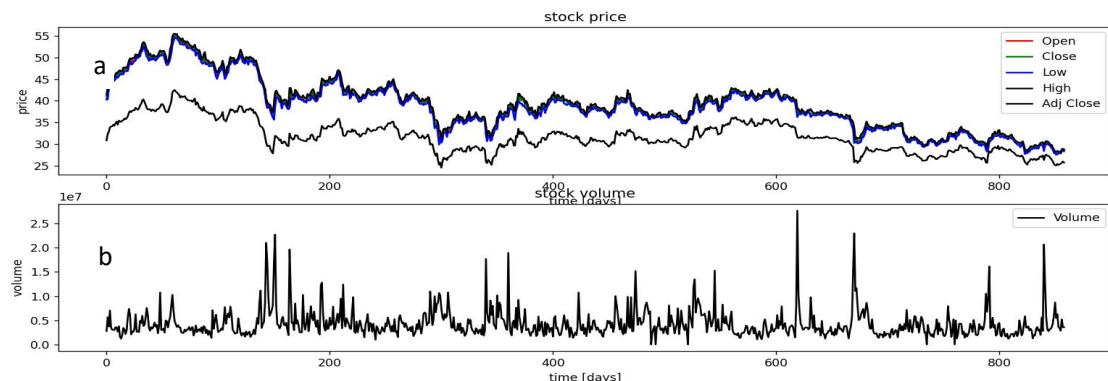


Fig.2(a).The changes of 0017 HK Training Data. Fig.2.(b)The trading volume of 0017 HK Training Data.

Data preparation

Date	Open	High	Low	Close	AdjClose	Volume	NextPrice	NextPrice ^{10-day}	mov ^{5-day}	movi ^{10-day}	for ^{5-day}	Day_n-1	n-1%	Day_n-2	n-2%	Day_n-3	n-3%	Day_n-4		
2022/7/18	91.849998	92.449997	91.449997	92.650002	84.256012	2228297	83.619431	-0.755532	84.578851	84.110507	83.514288	82.496323	83.30114	1.1462892	83.619431	0.7612836	84.665245	-0.483354	84.48336	
2022/7/19	92.5	92.650002	91.099998	91.949997	83.619431	245332	83.758844	0.1631355	84.565209	84.065038	83.512772	83.753268	84.256012	-0.755532	83.30114	0.3820968	83.619431	0	84.665245	
2022/7/20	91.5	92.599998	91.800003	92.099998	83.755844	2015675	82.891907	-1.031495	84.415157	83.992252	83.378318	83.692725	83.619431	0.1631355	84.256012	-0.593629	83.30114	0.5458557	83.619431	
2022/7/21	91.900002	92.900003	91.150002	92.81907	8736390	82.755500	-0.164559	84.246199	83.710372	83.418315	83.936027	83.755844	-1.031495	83.619431	-0.194363	83.619431	-0.03169	84.256012		
2022/7/22	91.650002	91.650002	90.550003	91.82.755501	2155612	83.210205	0.5494547	84.04685	83.564867	83.094773	83.437979	82.891907	-0.164559	83.755844	-1.194363	83.619431	-0.03169	84.256012		
2022/7/23	90.300003	91.5	90.300003	91.5	83.210205	2295578	84.256012	1.2568254	83.783123	83.455739	82.684665	81.501466	82.755501	0.5494547	82.81907	0.3339916	83.755844	-0.651464	83.619431	
2022/7/24	91.5	92.650002	91.400002	92.256012	2377204	84.437897	0.2158718	82.655808	83.246578	82.785757	82.836149	83.210205	1.2568254	83.813185	0.82.891907	1.6456432	83.755844	0.2158718	82.81907	
2022/7/27	92.449997	92.949997	91.400002	92.849998	84.437897	2045527	84.619774	0.2158718	82.633073	83.373894	83.301245	83.805725	84.256012	0.2158718	83.210205	1.4754104	82.755501	0.2329718	82.81907	
2022/7/28	92.800003	93.050003	92.93	93.050003	84.619774	2668249	85.256355	0.752284	83.610338	83.510304	83.833593	84.550894	84.437897	0.2158718	84.256012	0.4317342	83.210205	1.6939857	82.755501	
2022/7/29	92.849998	93.849998	92.699997	93.75	85.256355	4711859	84.256012	-1.173335	83.710372	83.855875	84.189837	85.003697	84.619774	0.752284	84.437897	0.9693017	84.256012	1.187266	83.210205	
2022/8/1	93.849998	93.849998	91.599998	92.650002	84.256012	2311091	82.846443	0.164658	84.505594	84.356049	84.889056	86.584085	85.256355	-1.173335	84.619774	-0.429878	84.437897	-0.215407	84.256012	
2022/8/2	92.349998	92.349998	90.5	91.099998	82.846443	3256325	82.71003	-0.164658	83.905594	84.56521	84.956319	84.60862	84.256012	-1.67296	85.256355	-2.82666	84.619774	-0.095646	84.437897	
2022/8/3	91.099998	91.5	90.349998	91.949997	82.71003	2180924	83.525590	0.9895692	83.828595	84.233296	84.361827	83.268566	82.846443	-0.164658	84.256012	-1.83486	85.256355	0.986669	84.619774	
2022/8/4	90.949997	91.949997	90.949997	91.849998	83.525503	204829	84.892595	1.6330833	83.724014	83.937723	83.914207	82.487092	82.71003	0.9895692	82.846443	0.8232822	84.256012	-0.863451	85.256355	
2022/8/5	92.099998	93.5	91.550003	93.349998	84.829593	268966	85.210884	0.3749338	83.787673	83.719469	83.640358	82.424348	83.528503	1.6330833	82.71003	2.638813	82.846443	0.4698103	84.256012	
2022/8/6	92.400002	93.800003	93.699997	93.300003	84.710774	2172305	87.029686	2.1344715	84.001382	83.646716	83.643368	84.624327	84.892593	2.01414	82.71003	3.0236405	82.846443	0.210414	82.71003	
2022/8/9	93.699997	97.949997	92.699997	97.699997	87.029686	13050021	85.529182	-1.724129	84.20145	83.837691	84.060292	85.8210884	2.1344718	84.892593	2.5174081	83.528503	4.1916027	82.71003	0.210414	
2022/8/10	95.699997	95.699997	93.599998	94.050003	85.529182	4204563	87.166092	1.9138614	84.478518	84.674339	85.199136	87.198332	87.029686	-1.724129	85.210884	0.3735415	84.892593	0.7498758	83.528503	
2022/8/11	95.75	96	94.949997	95.849998	87.166092	2767283	87.075157	-0.104324	84.587946	85.23817	85.532096	86.691377	85.529182	1.9138614	87.029686	0.156735	82.210884	2.2945319	84.892593	
2022/8/12	96	96.199997	95.25	95.75	87.075157	1665391	86.711395	-0.417756	84.842378	85.965687	86.442278	87.090171	87.166092	-0.104324	85.529182	1.807541	87.029686	0.0522477	83.210884	
2022/8/15	95.75	96.050003	95.050003	95.349998	86.711395	1266155	87.075157	0.4195089	85.024458	86.4022	88.247965	88.334676	87.075157	-0.417756	87.166092	-0.521644	85.529182	1.3822335	87.029686	
2022/8/16	95.599998	96	95.75	94.949997	95.75	87.075157	1743692	87.75721	0.7832923	85.269997	86.702302	86.252413	86.903569	86.711395	0.4195089	87.075157	0	87.166092	-0.104324	85.529182
2022/8/17	96.949997	96.949997	96	96.5	87.75721	2202886	87.166092	-0.673583	85.692868	86.711397	88.102944	87.238711	87.075157	0.7832923	86.711395	1.2060872	87.075157	0.7832923	87.166092	0.210414
2022/8/18	96.650002	96.699997	95.599998	95.849998	87.166092	2174564	87.257042	0.104341	86.197586	87.157002	88.069481	87.345265	87.75721	-0.673583	87.075157	0.104432	86.711395	0.5243798	87.075157	
2022/8/19	95.349998	96.199997	95.099998	95.949997	87.257042	1850181	87.075157	-0.208447	86.561345	87.157002	87.785303	87.380147	87.166092	0.104341	87.75721	-0.569945	87.075157	0.2088828	86.711395	
2022/8/22	95.949997	96.5	95.449997	95.75	87.075157	1543597	86.165756	-1.044386	86.79779	87.193379	87.924279	87.784494	87.257042	-0.208447	87.166092	-0.104324	87.75721	-0.777205	87.075157	
2022/8/23	95.75	95.75	94.150002	94.75	86.165756	2362650	84.847122	-1.530346	86.984217	87.266132	87.471124	87.074729	87.075157	-1.044386	87.257042	-1.250657	87.166092	-1.147621	87.75721	
2022/8/24	94.75	94.75	92.650002	93.300003	84.847122	2319583	84.938072	0.1071928	86.897824	87.094251	87.105987	86.280449	86.165756	-1.530346	87.075157	-2.558749	87.257042	-2.761863	87.166092	

Fig.3 shows the data I use during later process, n-day moving average is calculated by the embedded function AVERAGE of Excel and n-day forecast is calculated by the FORECAST function.

For the Orange data mining part, I choose five data mining models which include Random

Forest, Neural Network, Linear Regression, kNN and SVM to analyze the characters of the stock prices.

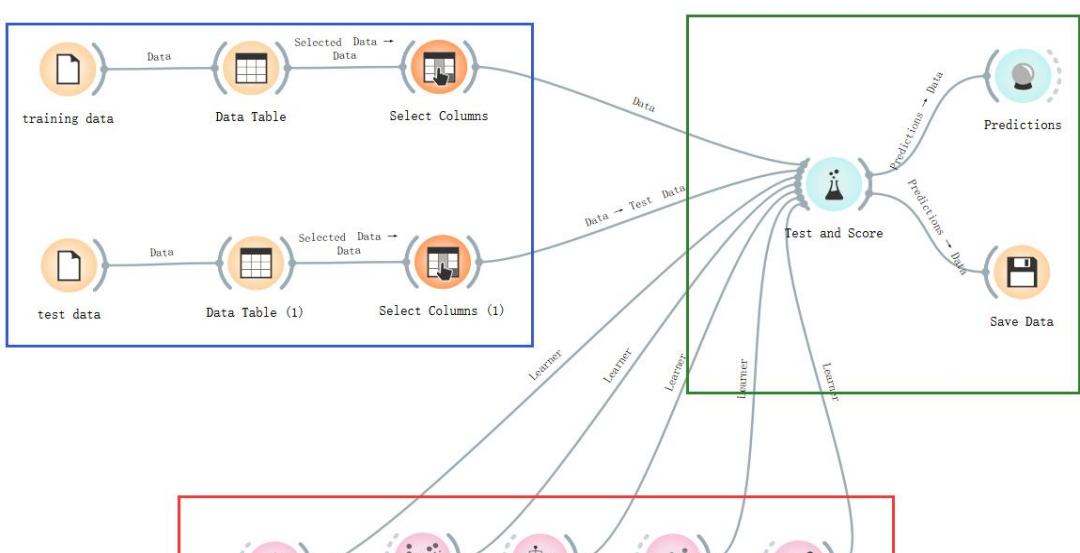


Fig.4 shows the whole training process(Blue: Data preparation and Data choosing, Red: Training models & Testing, Green: Predict & Saving Data)

Choosing columns to train

Features 1

I use three ways to divide the data to train the models provided by Orange Data Mining platform. For the first group, I use High, Open, Low, Volume, Close and AdjClose to train the models. The results are as Fig.4.

0016	Model	Train	Test	MSE	RMSE	MAE	R2
	kNN	0.009	0.000	197.713	14.061	9.669	-1.202
	SVM	0.020	0.002	88.051	9.384	2.680	0.019
	Random Forest	0.027	0.001	74.653	8.640	1.745	0.169
	Linear Regression	0.003	0.001	73.577	8.578	1.673	0.181
	Neural Network	0.495	0.001	665.939	25.806	19.355	-6.416

0017	Model	Train	Test	MSE	RMSE	MAE	R2
	kNN	0.007	0.003	96.960	9.847	9.482	-12.568
	SVM	0.019	0.003	61.942	7.870	6.810	-7.668
	Random Forest	0.030	0.002	18.039	4.247	3.346	-1.524
	Linear Regression	0.004	0.000	0.168	0.410	0.287	0.976
	Neural Network	0.501	0.002	69.872	8.359	7.513	-8.778

Fig.5 The Train Time, Test Time, MSE, RMSE, MAE and R2 of Models with High, Open, Low, Volume, Close and AdjClose.

Features 2

For the second group, I use the data Day_n-1, Day_n-2, Day_n-3, Day_n-4, Day_n-5 and their change rate as well to train the models and the data NextPrice to be the Target, with Date as the meta. All the data I use above which is not provided by Yahoo Finance is calculated by myself with the assistance of Excel. The results are as Fig.5.

0016	Model	Train	Test	MSE	RMSE	MAE	R2
	kNN	0.007	0.001	75.228	8.673	1.828	0.162
	SVM	0.014	0.002	102.665	10.132	2.209	-0.143
	Random Forest	0.034	0.002	71.791	8.473	1.434	0.200
	Linear Regression	0.007	0.001	2.284	1.511	0.328	0.975
	Neural Network	0.575	0.002	12118.508	110.084	27.132	-133.958

0017	Model	Train	Test	MSE	RMSE	MAE	R2
	kNN	0.008	0.002	20.781	4.559	3.924	-1.908
	SVM	0.014	0.003	51.265	7.160	5.667	-6.174
	Random Forest	0.033	0.002	8.355	2.891	2.136	-0.169
	Linear Regression	0.006	0.001	1.692	1.301	0.609	0.763
	Neural Network	0.558	0.002	32.374	5.690	4.939	-3.530

Fig.6 The Train Time, Test Time, MSE, RMSE, MAE and R2 of Models with Day_n-1, n-1%, Day_n-2, n-2%, Day_n-3, n-3%, Day_n-4, n-4%, Day_n-5, n-5%.

Features 3

The third group of data I choose to use as feature is the 5-day moving average, 10-day moving average, 5-day forecast and 10-day forecast. All these datas are calculated with Excel as well. Nextprice is set to be the Target with Date as the meta. With these data, the training results are as Fig.6 shows.

0016	Model	Train	Test	MSE	RMSE	MAE	R2
	kNN	0.003	0.002	77.225	8.788	2.723	0.140
	SVM	0.011	0.002	84.794	9.208	2.605	0.056
	Random Forest	0.021	0.001	80.329	8.963	2.826	0.105
	Linear Regression	0.004	0.001	79.909	8.939	2.622	0.110
	Neural Network	0.504	0.001	505.602	22.486	16.913	-4.631

0017	Model	Train	Test	MSE	RMSE	MAE	R2
	kNN	0.004	0.001	24.801	4.980	4.075	-2.471
	SVM	0.013	0.002	85.615	9.253	8.390	-10.981
	Random Forest	0.024	0.001	181.846	13.485	12.919	-24.447
	Linear Regression	0.006	0.000	3.444	1.856	0.911	0.518
	Neural Network	0.505	0.001	145.227	12.051	10.218	-19.323

Fig.7 The Train Time, Test Time, MSE, RMSE, MAE and R2 of Models with 5-day moving average, 10-day moving average, 5-day forecast and 10-day forecast.

Models and datasets analyze

Models Datasets \	kNN	SVM	Random Forest	Linear Regression	Neural Network	Average
0016Feature1	-1.202	0.019	0.169	0.181	-6.416	-1.4498
0017Feature1	-12.568	-7.668	-1.524	0.976	-8.778	-5.9124
0016Feature2	0.162	-0.143	0.200	0.975	-133.958	-26.5528
0017Feature2	-1.908	-6.174	-0.169	0.763	-3.530	-2.2036
0016Feature3	0.140	0.056	0.105	0.110	-4.631	-0.844
0017Feature3	-2.471	-10.981	-24.447	0.518	-19.323	-11.3408
Average	-2.9745	-4.1485	-4.277666	0.5871666	-29.4393	

Fig.8 shows the R2 scores of different models and features

From Fig.8 we can know that Linear Regression has the highest R2 scores and Neural Network has the poorest R2 scores. From this we learn that models has no priority. Which model will I choose depends on that whether the model is suitable.

For the time cost, kNN and Linear Regression have the least time cost, SVM and Random Forest rank second, Neural Network has the most expensive time cost.

In summary, Linear Regression is the most suitable model for these datasets. As for kNN, SVM and Random Forest, they are better than Neural Network, but they are still not suitable. Neural Network in Orange is completely unsuitable for thses datasets for the reason that it has the longest training time and the poorest R2 scores.

Stocks	10-day moving average	5-day moving average	10-day forecast	5-day forecast	Machine learning based on previous prices	Machine learning based on previous price change %
0016	1. 946031108	1. 474533752	1. 46184226	1. 271818095	1. 673	0. 609
0017	0. 829025001	0. 61777859	0. 610074765	0. 512898511	0. 281	0. 911

Fig.9 shows the MAE of the stocks

New Methods(TCN)

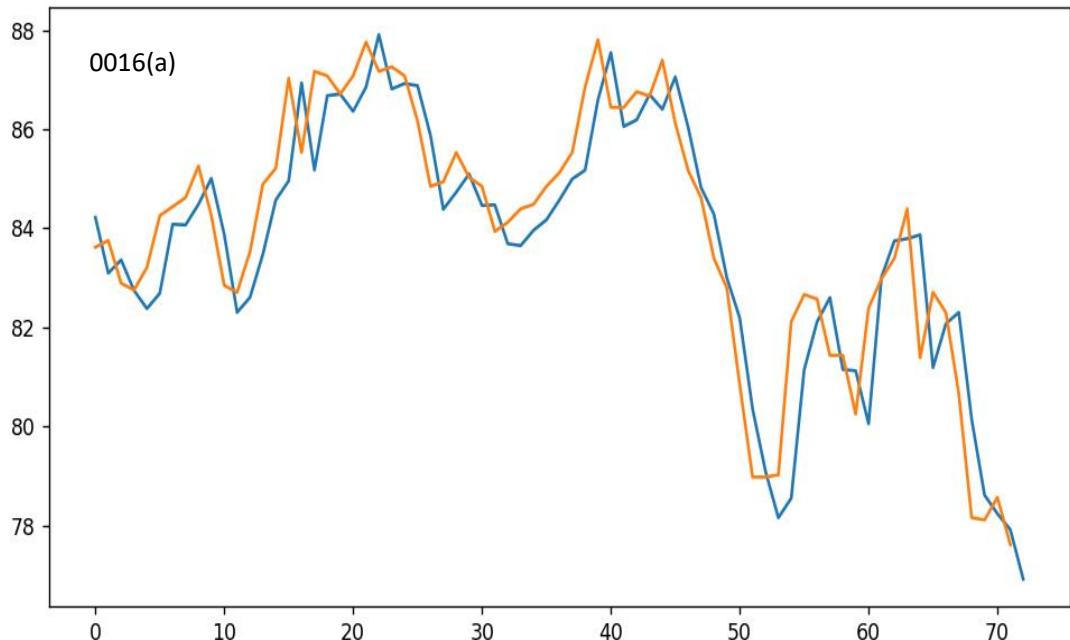
I choose TCN model (Temporal Convolutional Network) as the new method I use to predict stock prices. I choose this model for the simple reason that time plays an important role in the process of predicting prices. This model combines two different models CNN and RNN which enable TCN has brilliant performance when predicting stock prices.

The theory of TCN is from “An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling”. And thanks to code on CSDN platform(<https://blog.csdn.net/FrankieHello/article/details/113409856>) and python package from philipperemy on Github (<https://github.com/philipperemy/keras-tcn>).

The dilated convolution operation F on element s of the sequence is defined as below, x is the input of a 1-D sequence and the filter f .

$$F(s) = (\mathbf{x} *_d f)(s) = \sum_{i=0}^{k-1} f(i) \cdot \mathbf{x}_{s-d \cdot i}$$

The Figures below show the results.



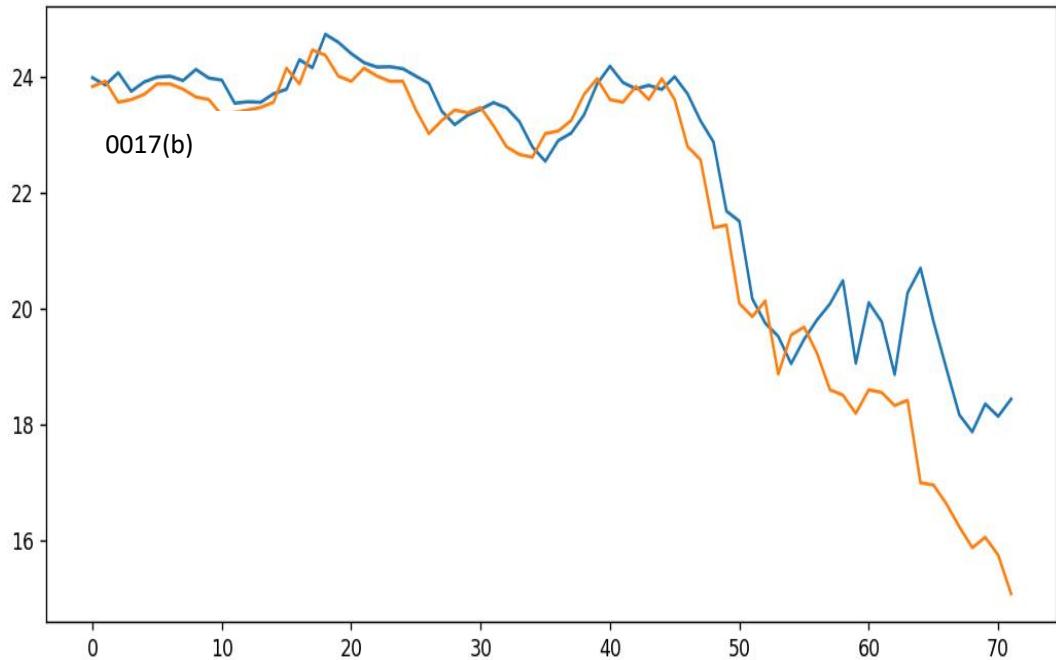


Fig.10(a). shows the prediction curve(orange) and the real curve(blue) of 0016 stock

Fig.10(b). shows the prediction curve(orange) and the real curve(blue) of 0017 stock

The training process is as following:

```

Model: "sequential"
-----
Layer (type)          Output Shape       Param #
-----
tcn (TCN)            (None, 10)        2940
dense (Dense)         (None, 1)         11
-----
Total params: 2,951
Trainable params: 2,951
Non-trainable params: 0
-----
Epoch 1/200
22/22 [=====] - 1s 13ms/step - loss: 0.3600 - mae: 0.3600 - val_loss: 0.0414 - val_mae: 0.0414
Epoch 2/200
22/22 [=====] - 0s 4ms/step - loss: 0.0728 - mae: 0.0728 - val_loss: 0.0290 - val_mae: 0.0290
Epoch 3/200
22/22 [=====] - 0s 4ms/step - loss: 0.0483 - mae: 0.0483 - val_loss: 0.0292 - val_mae: 0.0292
Epoch 4/200
22/22 [=====] - 0s 5ms/step - loss: 0.0417 - mae: 0.0417 - val_loss: 0.0255 - val_mae: 0.0255
Epoch 5/200
22/22 [=====] - 0s 4ms/step - loss: 0.0423 - mae: 0.0423 - val_loss: 0.0297 - val_mae: 0.0297
-----
Epoch 200/200
22/22 [=====] - 0s 4ms/step - loss: 0.0242 - mae: 0.0242 - val_loss: 0.0182 - val_mae: 0.0182

```

Fig.11 shows the training process of 0016.

```

Model: "sequential"
-----
Layer (type)          Output Shape       Param #
=====
tcn (TCN)            (None, 10)        2940
dense (Dense)        (None, 1)         11
=====
Total params: 2,951
Trainable params: 2,951
Non-trainable params: 0
-----
Epoch 1/200
22/22 [=====] - 2s 14ms/step - loss: 1.9853 - mae: 1.9853 - val_loss: 0.4689 - val_mae: 0.4689
Epoch 2/200
22/22 [=====] - 0s 4ms/step - loss: 0.3095 - mae: 0.3095 - val_loss: 0.0929 - val_mae: 0.0929
Epoch 3/200
22/22 [=====] - 0s 4ms/step - loss: 0.0637 - mae: 0.0637 - val_loss: 0.0156 - val_mae: 0.0156
Epoch 4/200
22/22 [=====] - 0s 4ms/step - loss: 0.0272 - mae: 0.0272 - val_loss: 0.0174 - val_mae: 0.0174
Epoch 5/200
22/22 [=====] - 0s 4ms/step - loss: 0.0217 - mae: 0.0217 - val_loss: 0.0204 - val_mae: 0.0204
-----
Epoch 200/200
22/22 [=====] - 0s 4ms/step - loss: 0.0155 - mae: 0.0155 - val_loss: 0.0105 - val_mae: 0.0105

```

Fig.11 shows the training process of 0017.

From the training process above we can find that the MAE is much lower than any kind of predictions in Orange and Excel. After 200 epoches the MAE finally reach 0.0242 and 0.0155 which is 30 times smaller than the models I use in Orange and Excel.

To summarize, TCN model is much more suitable for this application because it is connected with time and stock price vary with time. In other models time is considered as a feature more. Other models won't memorize the data in previous time. However, TCN could remember that for a long time to make proper predictions.

Discussion

Through this project, the most important finding I have is not the TCN model but the experience of choosing the most suitable model for different applications. I used to consider neural network as an advanced model and linear regression as a inferior method.

But the training results are much different from what I thought. Neural network has the longest training time and the poorest performance. However, linear regression is the quickest model and has the highest R2 scores.

I can conclude that there is no priority between models. In different situations, we should choose different models to adapt to the situations. A best model for everything is impossible. Different models has different characters and are suitable for different features. Models vary with features.

The second finding I have is that choosing features is important for a good training process. After data preparation, I have lots of features to choose to train the model. But some features are beneficial some are harmful. If you add some useless feature into the model, it will increase the training time without higher R2 scores or lower MAE. This is why we need correlation coefficient to analyze the relationship between datas. I used to have a vague imperssion about this but now the reason is clear.

By and large, to dig out the information hidden in the raw data or to analyze the relationships between data, we must use various features and different models to get suitable results. To achieve this, the characters of models should be taken into account and the theory of it should be clear.

Reference

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