NYCU_Artificial_Intelligence Capstone_HW1

- This dataset is available at: here (https://github.com/hsiuyee/NYCU_Artificial_Intelligence_Capstone_Labs/tree/main/Lab1)
- This pdf is available at: here (https://hackmd.io/@Origamyee/B1pfNatqJl)
- This code is available at: here (https://github.com/hsiuyee/NYCU_Artificial_Intelligence_Capstone/tree/main/Lab1)

Part 0. Overview

In this homework, our goal is to predict the BTC/USDT cryptocurrency close price change five hours ahead and use this prediction to design our trading strategy. Below, we outline the process step by step:

1. Create Dataset
2. Clean Up Dataset
3. Algorithm and Analysis
4. Experiments
5. Discussion
6. References

Part 1. Create Dataset

To make predictions, we need OHLC (open, high, low, close) price data. Therefore, we use the Binance API to retrieve such data (details available at: Binance Public Data (https://github.com/binance/binance-public-data) and Kline/Candlestick Data (https://developers.binance.com/docs/derivatives/usds-margined-futures/market-data/rest-api/Kline-Candlestick-Data)). The implementation is handled by `preprocess.py`. We set the K-line parameters as follows:

a. `symbol = BTCUSDT`
b. `interval = '1h'`
c. `start_date = '2024-11-01'`
d. `end_date = '2025-02-01'`

If some column values are missing, we simply use `dropna` to remove them. After running `preprocess.py` , we obtain a CSV file named `klines_BTC.csv` , which follows the format below:

klines_BTC

open_time	open	high	low	close	volume	taker_buy_base_asset_volume	taker_buy_quote_asset_volume
2024-11-01 00:00:00	70321.9	70500.0	70160.9	70188.6	6293.539	3122.97	219650270.5021
2024-11-01 01:00:00	70188.7	70384.6	69312.2	69424.9	23094.976	9133.652	637407952.6586
2024-11-01 02:00:00	69424.9	69621.2	68870.4	69592.7	25645.369	12269.503	849623340.7967
2024-11-01 03:00:00	69592.7	69739.0	69357.1	69397.7	6709.285	3069.884	213563233.8988
2024-11-01 04:00:00	69397.7	69650.0	69363.9	69618.5	3543.899	1949.728	135516392.2082

Part 2. Clean Up Dataset

2.1 Feature Engineering

We add the target label **target_pct_change** to the dataset, defined by $(\text{Close}_{i+1} - \text{Close}_i)/\text{Close}_i$. Since `OHLC, Volume, Taker buy base asset volume, and Taker buy quote asset volume` alone may not fully represent the price trend, we incorporate additional common factors to enhance the model's ability to fit price changes.

Specifically, we add volatility, price_range, ma_7, and other similar features. The implementation is handled by `add_factors.py` . After running `add_factors.py` , we obtain a CSV file named `klines_BTC_with_factors.csv` , which follows the format below:

open_time	open	high	low	close	volume	taker_buy_base_asset_volume	taker_buy_quote_asset_volume	return	log_return	volatility	price_range	ma_7	ma_25	ma_99
2024-11-08 12:00:00	75952.0	76189.9	75940.0	76078.9	5211.542	2915.219	221671978.1392	0.001672110901768110	0.001670714480764680	0.004598882336064350	0.0032902359384873900	76018.25714285710	75901.02800000000	72607.94343434340
2024-11-08 13:00:00	76078.4	76300.0	75855.0	76280.3	7908.982	3965.444	301591667.8091	0.0026472517347124700	0.0026437539355157900	0.004495756127947890	0.0058492292161770000	76075.04285714290	75951.53600000000	72683.3303030303
2024-11-08 18:00:00	76390.0	77069.8	76347.1	76803.0	22926.757	12278.253	942062948.4588	0.00540646681502821	0.00539190433743863	0.0041582460364935800	0.009460662390365190	76235.8	76090.948	73066.16767676770
2024-11-08 19:00:00	76802.8	77182.9	76728.4	76894.4	15879.932	7713.071	593816108.5131	0.0011900576800385500	0.0011893501226980300	0.004157422764118060	0.005917752998588590	76352.3	76102.452	73158.66767676770
2024-11-08 20:00:00	76894.4	77080.4	76401.1	76563.5	15592.359	7334.344	562098766.1862	-0.004303304271832450	-0.00431259013516597	0.004245478524186070	0.008834193387294630	76392.75714285720	76103.66	73247.05555555560
2024-11-08 21:00:00	76563.5	76675.1	76352.7	76463.4	6415.22	3090.686	236435371.0107	-0.0013074114950336600	-0.001308266903103850	0.003962874544606640	0.004210883776212020	76493.44285714290	76105.552	73336.20505050500
2024-11-08 22:00:00	76463.4	76600.0	76278.5	76350.0	4623.227	2149.277	164366345.8872	-0.0014830624847965700	-0.0014841633104936300	0.00397988918803213	0.004204626004075150	76482.97142857140	76125.004	73422.10707070710
2024-11-08 23:00:00	76350.0	76502.0	76280.1	76482.2	3136.759	1627.846	124379920.9532	0.001731499672560590	0.0017300023551564500	0.003990098900186820	0.002906352324819830	76563.78571428570	76149.59600000000	73514.44141414140
2024-11-09 00:00:00	76482.2	76618.3	76339.1	76409.5	4076.52	1978.202	151353173.1061	-0.0009505479706388710	-0.0009510000278518610	0.003983451465706030	0.003650522605259750	76566.57142857140	76171.6	73608.50707070710
2024-11-09 01:00:00	76409.4	76529.6	76230.7	76300.0	3846.096	1832.402	139908609.45	-0.001433067877685380	-0.0014340957015346600	0.003996444810516500	0.003911822367405170	76494.71428571430	76183.348	73693.29494949500
2024-11-09 02:00:00	76300.0	76418.7	76122.4	76418.6	5312.114	2530.895	193046493.0996	0.001554390563564880	0.0015531837489651200	0.003929638227357040	0.0038833551769332000	76426.74285714290	76200.84	73780.00505050510
2024-11-09 03:00:00	76418.6	76434.1	76235.0	76330.0	2557.821	1133.323	86476310.7729	-0.0011594036006941100	-0.0011600762289974700	0.00391801284271743	0.002605386646706510	76393.3857142857	76225.216	73864.0505050505

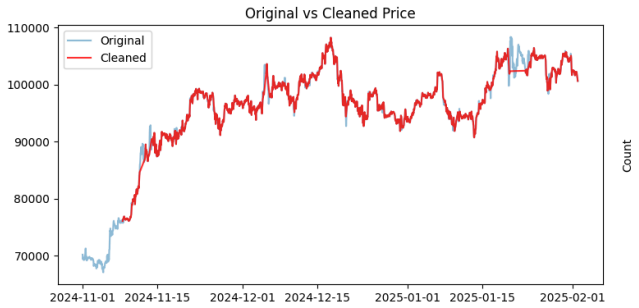
klines_BTC_with_factors

atr	ema_12	ema_26	macd	macd_signal	macd_hist	rsi	bb_middle	bb_upper	bb_lower	bb_width	bb_pct
703.7040000000000	75984.27301388220	75754.99882960540	229.2741842768160	283.91645710162300	-54.64227282480720	54.33561559591660	76048.855	76546.08809571210	75551.62190428790	0.013076675400624700	0.530212188467635
706.4319999999990	76029.81562713110	75793.91005954540	235.90556758568000	274.3142791984340	-38.4087116127543	57.994301994302200	76049.115	76546.85139302860	75551.37860697140	0.013089866805907700	0.7322363837947480
715.162666666666	76198.45815721030	75952.41402007140	246.044137138917	234.39598828793800	11.648148850979000	60.702071795777100	76049.32000000000	76583.57638079370	75515.0636192063	0.01405026056232180	1.2053542335613600
707.4039999999990	76305.52613302410	76022.19079563690	283.33533738719400	244.18385810778900	39.151479279404900	60.159710106026000	76101.07	76746.7554834799	75455.38451652010	0.016969156504104000	1.1143316059425500
708.6106666666660	76345.2144202512	76062.28779305860	282.9266271926320	251.93241192475800	30.994215267874000	57.24410957154720	76128.93000000000	76804.77766922560	75453.0823307744	0.01775534397306280	0.8214999620387290
705.8520000000000	76363.39681713560	76091.99982164380	271.3969954918720	255.82532863818100	15.571666853691400	53.24154139506000	76153.035	76840.99344205710	75465.07655794290	0.018067787897281700	0.7255695846045130
688.8973333333330	76361.33576834550	76111.11095386140	250.22481448414300	254.7052258073730	-4.48041132322993	56.15499742762260	76184.50500000000	76846.25711601500	75522.75288398500	0.017372354549392400	0.6250430455716630
680.6559999999990	76379.93026552310	76138.5990418675	241.3312236556380	252.03042537702600	-10.699201721388500	56.05325457656520	76213.595	76873.91110444330	75553.27889555670	0.017328039818703300	0.7033912229253190
677.1853333333330	76384.47945544270	76158.66578661400	225.81366882861800	246.78707406734400	-20.973405238726800	51.92060827490870	76242.425	76882.80468301530	75602.04531698480	0.0167985129805418	0.630449953700374
671.4293333333330	76371.48261614380	76169.13499103880	202.3476251049430	237.89918427486400	-35.55155916992100	54.51105409118010	76258.125	76887.3334346289	75628.9165653711	0.01650206937631640	0.5332759366335390
667.1293333333330	76378.73144442940	76187.61388620260	191.11755822680400	228.5428590652520	-37.42530083844800	54.41180290397170	76284.91500000000	76892.07746772030	75677.75253227970	0.01591828391550970	0.6100899735304370
641.0200000000000	76371.23429913250	76198.16100870850	173.07329042405800	217.44894533701300	-44.375654912955700	50.664954108800900	76292.865	76897.90727351030	75687.82272648970	0.01586104476507110	0.5306879383687930
631.7306666666660	76370.98286849680	76210.86019655450	160.1226719422270	205.983690658056	-45.8610187158294	59.385560675883300	76320.16500000000	76883.9183140038	75756.41168599620	0.01477337775681660	0.5438445316169490
603.4026666666660	76396.98550411260	76235.2409286125	161.74457550013900	197.13586762647300	-35.39129212633360	52.11359437823740	76348.88	76894.83652651080	75802.92347348920	0.01430162502739440	0.675032251396876
574.2746666666660	76411.83388809530	76254.37123446640	157.4626536288710	189.20122482695200	-31.738571198081600	62.54129716571030	76360.86000000000	76908.55350783440	75813.16649216570	0.01434487531529550	0.6210896223003050
562.5866666666660	76429.07482838830	76274.33633233560	154.73849605277100	182.30867907211600	-27.57018301934530	53.604694987347100	76389.46000000000	76906.09351725910	75872.82648274090	0.013526303687945000	0.6301115737837310

volume_change	volume_ma_7	volume_relative	obv	hour	day_of_week	is_weekend	month	target_binary	target_pct_change	target_abs_change	target_multiclass	target_log_return	target_normalized_change
-0.05847999807777180	5737.050714285720	0.9084008943868740	334093.0600000000	12	4	0	11	1	-0.26402622957697500	201.40000000000900	2	0.0026437539355157900	0.8100828433795870
0.517589611673474	6432.078	1.229615374689180	342002.0420000000	13	4	0	11	0	0.6886346896589850	-521.6999999999970	3	-0.006862744304934330	-2.0962903549067200
0.3619498300292120	16429.414714285700	1.3954701003478100	376888.4350000000	18	4	0	11	1	-0.11886431261574100	91.39999999999420	2	0.0011893501226980300	0.3421578226677970
-0.3073624848032370	17953.47042857140	0.8845048684697990	392768.3670000000	19	4	0	11	0	0.43219027343315300	-330.8999999999940	2	-0.00431259013516597	-1.0249572228729000
-0.018109208528096900	19051.095714285700	0.8184494600123110	377176.0080000000	20	4	0	11	0	0.1309123057567470	-100.10000000000600	2	-0.001308266903103850	-0.29622059691134400
-0.5885664253882300	17591.203285714300	0.36468340998650000	370760.7880000000	21	4	0	11	0	0.14852652259331700	-113.39999999999400	2	-0.0014841633104936300	-0.3296710762366190
-0.2793346136219800	14162.328	0.3264454120819680	366137.5610000000	22	4	0	11	1	-0.17285067636652100	132.1999999999970	2	0.0017300023551564500	0.3995453790023290
-0.3215217422808790	12201.147000000000	0.2570872230291140	369274.3200000000	23	4	0	11	0	0.09514523717599750	-72.69999999999710	2	-0.0009510000278518610	-0.22019756753005700
0.2995961755429730	10378.682	0.39277819669202700	365197.8000000000	0	5	1	11	0	0.14351245085189000	-109.5	2	-0.0014340957015346600	-0.3419846160136860
-0.0565246828176974	7652.873285714290	0.5025688857516500	361351.7040000000	1	5	1	11	1	-0.1551978183321980	118.60000000000600	2	0.0015531837489651200	0.3769815961521640
0.38117041280300800	6143.185000000000	0.8647165924516360	366663.8180000000	2	5	1	11	0	0.11607493777021600	-88.60000000000580	2	-0.0011600762289974700	-0.2918493968581190
-0.5184928260199240	4281.108142857140	0.5974670376565050	364105.9970000000	3	5	1	11	1	-0.051853093377474100	39.60000000000580	2	0.0005186654174306320	0.13089994446186900
-0.32316100305689900	3611.9671428571400	0.47930474767014600	365837.2300000000	4	5	1	11	1	-0.22262869088057700	170.39999999999400	2	0.0022287687697463900	0.6045197279240010
2.1630179184431000	3733.7805714285700	1.4665888622118100	371313.1510000000	5	5	1	11	0	0.06078947884460280	-46.5	2	-0.0006077100952547070	-0.17034323335913300
0.3965995857135270	4378.196285714290	1.7467624795520800	363665.4820000000	6	5	1	11	1	-0.03972615091493160	30.39999999999420	2	0.0003973404384070550	0.11101099269915600
-0.553334617384722	4283.829	0.7974055453660730	367081.4310000000	7	5	1	11	1	-0.021034753070292600	16.10000000000580	2	0.0002103696568476020	0.062326579527007900
0.22924024919575800	4334.247	0.9688008089986560	371280.4530000000	8	5	1	11	1	-0.0067933717594281800	5.19999999999709	2	6.79360251938475E-05	0.020835934367829200

2.2 Data Cleaning with Autoencoders and Z-score

Due to the high level of noise in the market, I use autoencoders and Z-score to filter out noise while preserving useful data. The refined result is shown below:



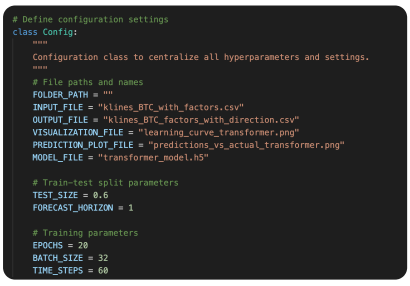
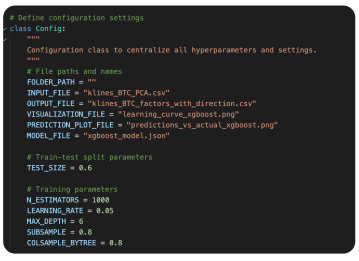
Part 3. Algorithm and Analysis

Models Selection

We use the following models from the `sklearn` library to predict `target_pct_change` or `target_multiclass`:

- Supervised learning: XGBoost regression and Transformer
- Unsupervised learning: K-Means (Class 1: lower than -2%, Class 2: -2% to -0.5%, Class 3: -0.5% to 0.5%, Class 4: 0.5% to 2%, Class 4: greater than 2%)

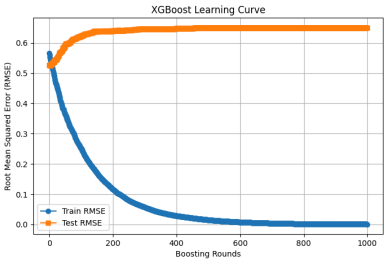
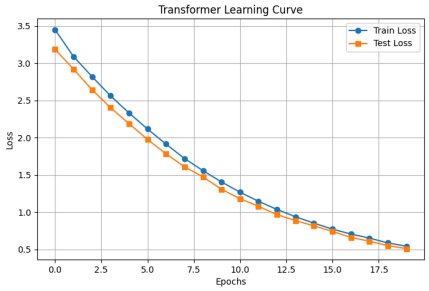
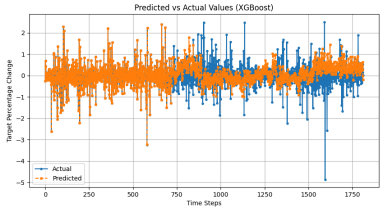
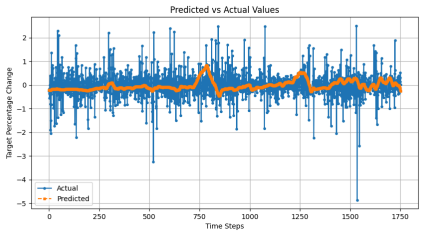
And the default hyperparameters is below:

Transformer	XGBoost	Kmeans
		

Reference Public Libraries

- scikit-learn (https://scikit-learn.org/stable/)
- hmmlearn (https://hmmlearn.readthedocs.io/en/latest/)
- XGBoost (https://xgboost.readthedocs.io/en/stable/)
- TensorFlow (https://www.tensorflow.org/?hl=zh-tw)

Evaluate the performance (supervised learning)

compare	XGBoost	Transformer
loss		
prediction		

Evaluate the performance (unsupervised learning)

Kmeans

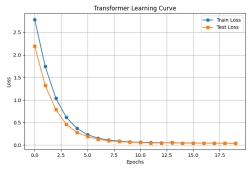
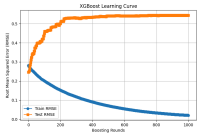
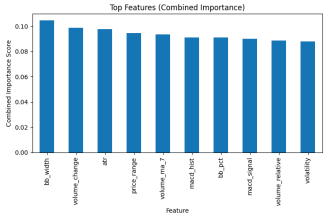
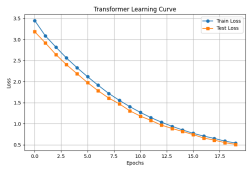
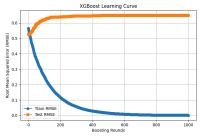
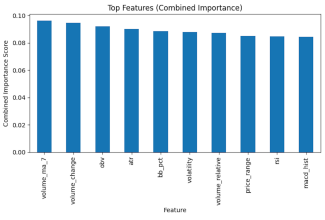
1. Silhouette Score: 0.0959 (higher is better)
2. Inertia (SSE): 2260203.5053 (lower is better)
3. Adjusted Rand Index (ARI): 0.0064 (higher is better)
4. Normalized Mutual Information (NMI): 0.0063 (higher is better)
5. Accuracy: 0.3333 (higher is better)

Part 4. Experiments

Problem 1

> What if we use a different time interval?

We modified the dataset's time interval setting from `1h` to `15m`, and the comparison results are shown below.

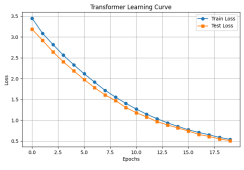
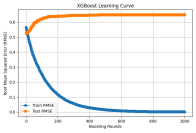
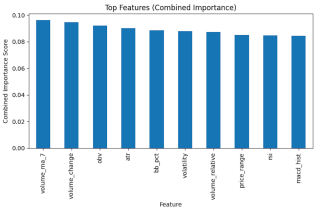
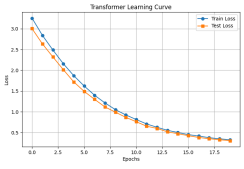
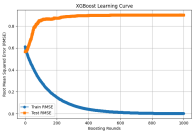
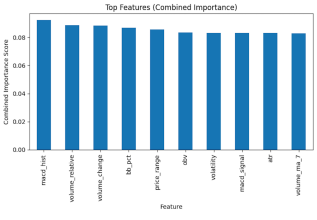
time_interval	Transformer	XGBoost	important features
15m			
1h			

As we can see, both models achieve better performance with a smaller time interval, as indicated by their lower testing loss. Intuitively, a smaller time interval functions similarly to data augmentation. Additionally, the Transformer converges more efficiently, while XGBoost overfits at a slower rate. Moreover, the important features remain unchanged.

Problem 2

> What if we do not perform data cleaning with Autoencoders and Z-score?

Intuitively, this would lead to poor training and testing results.
We compare the effect of data cleaning using Autoencoders and Z-score below:

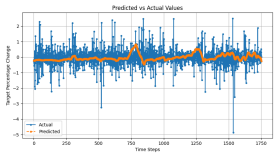
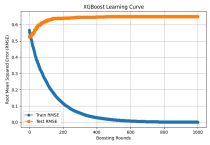
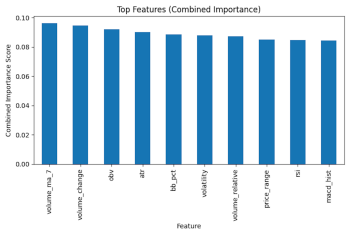
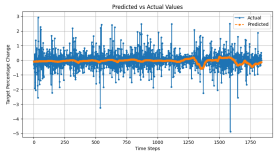
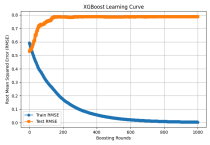
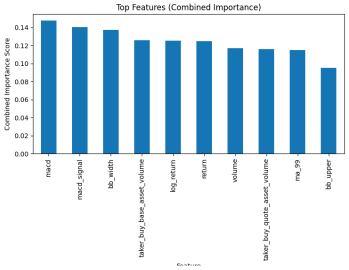
data_cleaning	Transformer	XGBoost	Important features
YES			
NO			

As we can see, if we do not perform data cleaning, the training and testing performance of XGBoost deteriorates significantly, while the Transformer model remains nearly the same. Additionally, the important features differ slightly; for example, `rsi` and `macd_signal` do not appear in the same diagram. Why do we obtain such a result? Since we did not perform data cleaning, XGBoost may learn from noise, whereas the Transformer is more resistant to noise as it can capture temporal behavior.

Problem 3

> What if we delete some important features?

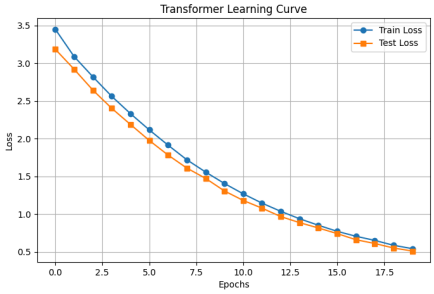
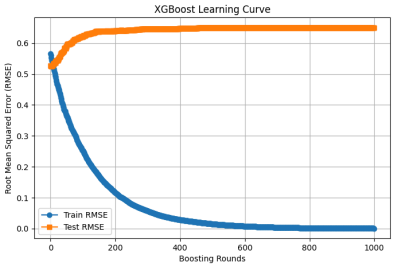
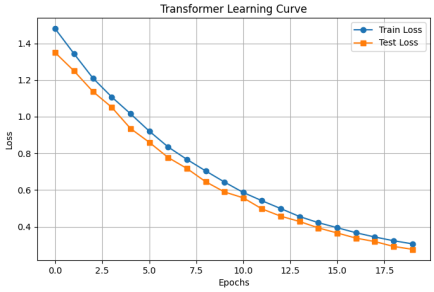
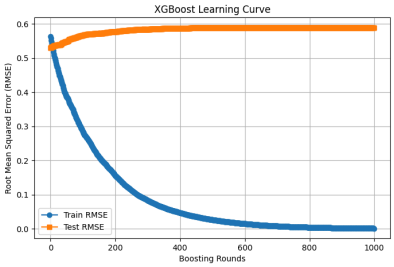
First, we define "importance" as the total decrease in impurity when a feature is used for splitting across all trees. Second, we remove the top 10 most important features and analyze their effect. The experiment results are shown below.

compare	Transformer	XGBoost	Important features
before			
after			

As we can see, when we change only the feature vectors, the Transformer model becomes more cautious after removing important features. Without key features, the model has less confidence and predicts price changes more conservatively. Additionally, this leads to an increase in XGBoost's testing loss.

Problem 4

> What if we apply the PCA method to reduce noise, remove unimportant features, and decrease training time?

compare	Transformer	XGBoost
before		
after		

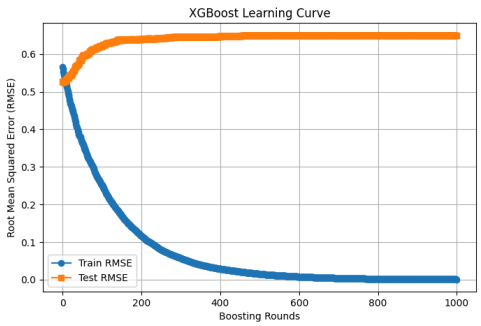
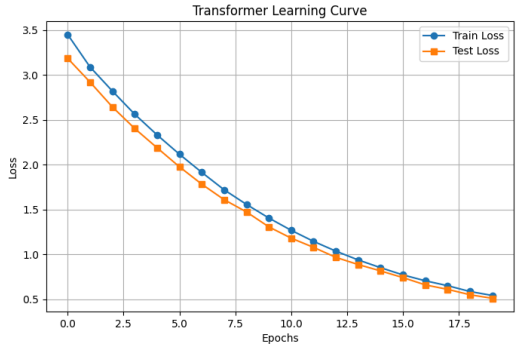
```
✅ Initial feature count (excluding targets): 34
✅ PCA reduced dimensions to 12, preserving 95.0% variance.
❌ Dropped 22 features (from 34 → 12)
✅ Retained feature names: ['open', 'high', 'low', 'close', 'volume', 'taker_buy_base_asset_volume'
, 'taker_buy_quote_asset_volume', 'return', 'log_return', 'volatility', 'price_range', 'ma_7']
✅ Explained variance plot saved to pca_explained_variance.png
✅ PCA-transformed data saved to klines_BTC_PCA.csv
origamyee@Hsiu-IdeMacBook-Pro ~/Desktop/NYCU_Artificial_Intelligence_Capstone/Lab1  main ±
python3.12 predict_transformer.py
✅ Selected 12 features for training.
```

As we can see, when we apply the PCA method to the dataset, the training and testing loss significantly decrease after a few epochs in both models. This is because the PCA model reduces correlation among feature vectors and simplifies the complexity of the problem.

Problem 5

> What if we use a non-temporal model to predict temporal behavior compared to using a temporal model?

The XGBoost model tends to overfit compared to the Transformer model. Below is an example where we use similar loss functions: Pseudo-Huber error in XGBoost and Huber loss in the Transformer model.

XGBoost	Transformer
	

As we can see, the testing loss increases as the number of training iterations increases. This is a typical sign of overfitting. Intuitively, since the data depends on time, the model may fail to capture temporal effects properly.

Part 5. Discussion

Problem 1

> Describe experiments that you would do if there were more time available.

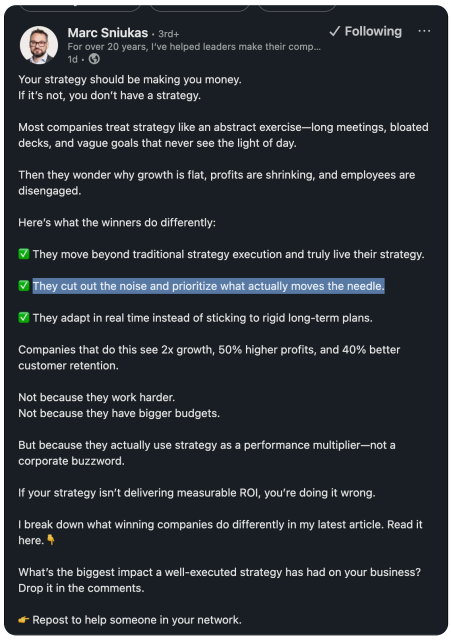
1. Add more statistical indices and analyze their effects.
2. Expand our project—since we have the next price change, we can develop a long/short strategy and evaluate its performance using PnL as a metric.
3. Predict more hyperparameters, such as the stop-loss threshold, to improve balance.
4. Try more models and analyze their effects.

Problem 2

> What I have learned from the experiments as well as your remaining questions?

Parts 1 and 2

In Parts 1 and 2, I learned how to clean up data. Initially, I thought we could simply add statistical indices to enhance our fitting power. However, after reading a LinkedIn post, I realized that the data might contain noise. This naturally led to an important question: "How can we filter out noise while keeping useful data?"



I tried to find the answer on the Internet, and the top three posts that inspired me are:

1. Towards Denoised Market Indices Pt. 1 — Static Indices (https://medium.com/@lavaroninic/towards-denoised-market-indices-pt-1-static-indices-ac9004e930b1)
2. Autoencoders Simplified: Real-World Data Cleaning Application Satejraste (https://medium.com/@satejraste/autoencoders-simplified-real-world-data-cleaning-application-5dda1b3c686d)
3. AutoEncoder (一)-認識與理解 (https://medium.com/ml-note/autoencoder-%E4%B8%80-%E8%AA%8D%E8%AD%98%E8%88%87%E7%90%86%E8%A7%A3-725854ab25e8)

Therefore, I used an autoencoder an Z-score for denoising.

Part 3

In Part 3, I learned how to use PCA for denoising. Thanks to the following tutorial, I gained an understanding of its mathematical intuition and why it works intuitively.

1. Principal Component Analysis(PCA) (https://www.geeksforgeeks.org/principal-component-analysis-pca/)
2. Learning Model : Unsupervised Machine Learning_主成分分析（PCA）原理詳解 (https://medium.com/ai%E5%8F%8D%E6%96%97%E5%9F%8E/preprocessing-data-%E4%B8%BB%E6%88%90%E5%88%86%E5%88%86%E6%9E%90-pca-%E5%8E%9F%E7%90%86%E8%A9%B3%E8%A7%A3-afe1fd044d4f)
3. 【机器学习】降维——PCA（非常详细） (https://zhuanlan.zhihu.com/p/77151308)

Part 6. References

1. Binance Public Data (https://github.com/binance/binance-public-data)
2. Kline/Candlestick Data (https://developers.binance.com/docs/derivatives/usds-margined-futures/market-data/rest-api/Kline-Candlestick-Data)
3. scikit-learn (https://scikit-learn.org/stable/)
4. hmmlearn (https://hmmlearn.readthedocs.io/en/latest/)
5. XGBoost (https://xgboost.readthedocs.io/en/stable/)
6. TensorFlow (https://www.tensorflow.org/?hl=zh-tw)
7. Towards Denoised Market Indices Pt. 1 — Static Indices (https://medium.com/@lavaroninic/towards-denoised-market-indices-pt-1-static-indices-ac9004e930b1)
8. Autoencoders Simplified: Real-World Data Cleaning Application Satejraste (https://medium.com/@satejraste/autoencoders-simplified-real-world-data-cleaning-application-5dda1b3c686d)
9. AutoEncoder (一)-認識與理解 (https://medium.com/ml-note/autoencoder-%E4%B8%80-%E8%AA%8D%E8%AD%98%E8%88%87%E7%90%86%E8%A7%A3-725854ab25e8)
10. Principal Component Analysis(PCA) (https://www.geeksforgeeks.org/principal-component-analysis-pca/)
11. Learning Model : Unsupervised Machine Learning_主成分分析（PCA）原理詳解 (https://medium.com/ai%E5%8F%8D%E6%96%97%E5%9F%8E/preprocessing-data-%E4%B8%BB%E6%88%90%E5%88%86%E5%88%86%E6%9E%90-pca-%E5%8E%9F%E7%90%86%E8%A9%B3%E8%A7%A3-afe1fd044d4f)
12. 【机器学习】降维——PCA（非常详细） (https://zhuanlan.zhihu.com/p/77151308)

```
# preprocess.py

import requests

import pandas as pd

from datetime import datetime, timedelta

import os



class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# API configuration

BINANCE_BASE_URL = "https://fapi.binance.com/fapi"

API_VERSION = "v1"

API_ENDPOINT = "klines"

API_LIMIT = 1500


# Pandas display options

DISPLAY_MAX_ROWS = None

DISPLAY_MAX_COLUMNS = None

DISPLAY_WIDTH = None


# Default data parameters

DEFAULT_SYMBOLS = ["BTCUSDT"]
```

```
DEFAULT_INTERVAL = "1h"

DEFAULT_START_DATE = "2024-11-01"

DEFAULT_END_DATE = "2025-02-01"

DEFAULT_FILENAME = "klines_BTC.csv"


# Date format

DATE_FORMAT = "%Y-%m-%d"




# Configure pandas display options

pd.set_option("display.max_rows", Config.DISPLAY_MAX_ROWS)

pd.set_option("display.max_columns", Config.DISPLAY_MAX_COLUMNS)

pd.set_option("display.width", Config.DISPLAY_WIDTH)




def fetch_kline_price_data(symbol: str, interval: str, start_date: str, end_date: str) -> pd.DataFrame:

"""

Fetches K-line (candlestick) data from Binance API for a given trading pair.


:param symbol: Trading pair (e.g., 'BTCUSDT')

:param interval: Time interval (e.g., '1h')

:param start_date: Start date (YYYY-MM-DD)

:param end_date: End date (YYYY-MM-DD)

:return: Processed DataFrame containing OHLC and taker buy volume data
```

```
"""
api_endpoint = f"{Config.API_VERSION}/{Config.API_ENDPOINT}"
start_time = datetime.strptime(start_date, Config.DATE_FORMAT)
end_time = datetime.strptime(end_date, Config.DATE_FORMAT)

price_data = []

while start_time < end_time:
start_time_ms = int(start_time.timestamp() * 1000)
url =
f"{Config.BINANCE_BASE_URL}/{api_endpoint}?symbol={symbol}&interval={interval}&limit={Confi
g.API_LIMIT}&startTime={start_time_ms}"

response = requests.get(url)
data = response.json()

if not data:
break

price_data.extend(data)

# Update start_time to the close time of the last retrieved data entry
last_entry = data[-1]
last_close_time = last_entry[6] # Close time (7th element in response data)
```

```
start_time = datetime.fromtimestamp(last_close_time / 1000.0)

return process_price_data(price_data, start_date, end_date)



def process_price_data(price_data: list, start_date: str, end_date: str) -> pd.DataFrame:
"""
Processes raw price data from Binance API into a structured DataFrame.

:param price_data: Raw data retrieved from API
:param start_date: Start date for filtering
:param end_date: End date for filtering
:return: Processed DataFrame with selected OHLC and taker buy volume columns
"""
df = pd.DataFrame(price_data, columns=[
"open_time", "open", "high", "low", "close", "volume", "close_time",
"quote_asset_volume", "num_trades", "taker_buy_base_asset_volume",
"taker_buy_quote_asset_volume", "ignore"
])

# Convert data types and remove invalid entries
df = df.apply(pd.to_numeric, errors="coerce").dropna()

# Convert timestamp columns to human-readable format
```

```
df["open_time"] = pd.to_datetime(df["open_time"], unit="ms")

df["close_time"] = pd.to_datetime(df["close_time"], unit="ms")


# Extract relevant columns

df = df[["open_time", "open", "high", "low", "close", "volume",

"taker_buy_base_asset_volume", "taker_buy_quote_asset_volume"]]


# Filter data within the specified date range

df = df[(df["open_time"] >= pd.to_datetime(start_date)) &

(df["open_time"] < pd.to_datetime(end_date) + timedelta(days=1))]


return df



def save_to_drive(df: pd.DataFrame, filename: str):

"""

Saves the given DataFrame to a CSV file.


:param df: DataFrame to be saved

:param filename: Name of the CSV file

"""

# Define save path

drive_path = f"{filename}"
```

```
# Save DataFrame
df.to_csv(drive_path, index=False)
print(f"File saved to {drive_path}")



if __name__ == "__main__":
# Load parameters from configuration
symbols = Config.DEFAULT_SYMBOLS
interval = Config.DEFAULT_INTERVAL
start_date = Config.DEFAULT_START_DATE
end_date = Config.DEFAULT_END_DATE
filename = Config.DEFAULT_FILENAME

# Fetch and merge data
all_data = [fetch_kline_price_data(symbol, interval, start_date, end_date)
for symbol in symbols]

# Combine all symbol data
final_df = pd.concat(all_data, ignore_index=True)

# Save to file
save_to_drive(final_df, filename)

# add_factors.py
```

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import tensorflow as tf

from tensorflow import keras

from sklearn.preprocessing import MinMaxScaler

from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier




class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

FOLDER_PATH = ""

INPUT_FILE = "klines_BTC.csv"

OUTPUT_FILE = "klines_BTC_with_factors.csv"

VISUALIZATION_FILE = "btc_targets_analysis.png"

# Technical indicator parameters

WINDOW_SIZE = 75

VOLATILITY_WINDOW = 24

MA_WINDOWS = [7, 25, 99]

EMA_SHORT = 12

EMA_LONG = 26
```

```
MACD_SIGNAL = 9

RSI_PERIOD = 14

BOLLINGER_WINDOW = 20

BOLLINGER_STD = 2

# Outlier detection parameters

ZSCORE_THRESHOLD = 3

ANOMALY_PERCENTILE = 95

# Autoencoder parameters

AUTOENCODER_LAYERS = [64, 32, 16, 32, 64]

REGULARIZATION_FACTOR = 0.001

DROPOUT_RATE = 0.2

EPOCHS = 50

BATCH_SIZE = 32

VALIDATION_SPLIT = 0.4

EARLY_STOPPING_PATIENCE = 5

# Random forest parameters

RF_ESTIMATORS = 100

RF_RANDOM_STATE = 42

# Target classification thresholds

PRICE_MOVEMENT_THRESHOLDS = [-2, -0.5, 0.5, 2]

PRICE_MOVEMENT_LABELS = ['Significant Drop', 'Small Drop', 'Sideways', 'Small Rise', 'Significant
Rise']

# Train-test split parameters

TEST_SIZE = 0.2
```

```
FORECAST_HORIZON = 1



def compute_atr(df: pd.DataFrame, window_size: int) -> pd.Series:

"""

Compute Average True Range (ATR) indicator.

Parameters:

----------

df : pandas.DataFrame

DataFrame containing OHLC price data

window_size : int

Rolling window size for ATR calculation

Returns:

--------

pandas.Series: ATR values

"""

high_low = df["high"] - df["low"]

high_prev_close = abs(df["high"] - df["close"].shift(1))

low_prev_close = abs(df["low"] - df["close"].shift(1))


true_range = pd.concat([high_low, high_prev_close, low_prev_close], axis=1).max(axis=1)

return true_range.rolling(window=window_size).mean()
```

```
def load_and_clean_data(file_path: str) -> pd.DataFrame:
"""
Load, clean, and preprocess raw price data.
Parameters:
-----------
file_path : str
Path to the CSV file containing raw price data
Returns:
--------
pandas.DataFrame: Cleaned dataframe
"""
# Load the data
df_original = pd.read_csv(file_path)

# Convert timestamp column to datetime
df_original["open_time"] = pd.to_datetime(df_original["open_time"])
df_original.sort_values(by="open_time", inplace=True)

# Make a copy before modification
df_cleaned = df_original.copy()

# Handle Missing Values
df_cleaned.dropna(inplace=True)
```

```
# Ensure Correct Data Types
numeric_cols = ["open", "high", "low", "close", "volume",
"taker_buy_base_asset_volume", "taker_buy_quote_asset_volume"]
df_cleaned[numeric_cols] = df_cleaned[numeric_cols].astype(float)

# Remove Duplicates
df_cleaned.drop_duplicates(subset=["open_time"], keep="first", inplace=True)
return df_cleaned



def add_technical_indicators(df: pd.DataFrame) -> pd.DataFrame:
"""
Add various technical indicators as features to the dataframe.
Parameters:
----------
df : pandas.DataFrame
DataFrame containing OHLC price data
Returns:
--------
pandas.DataFrame: DataFrame with added technical indicators
"""
# Price-based features
df['return'] = df['close'].pct_change() # Price returns
df['log_return'] = np.log(df['close']/df['close'].shift(1)) # Log returns
```

```
df['volatility'] = df['log_return'].rolling(window=Config.VOLATILITY_WINDOW).std() # Volatility

df['price_range'] = (df['high'] - df['low']) / df['open'] # Normalized price range


# Moving averages

for window in Config.MA_WINDOWS:

df[f'ma_{window}'] = df['close'].rolling(window=window).mean()

# ATR (Average True Range)

df["atr"] = compute_atr(df, Config.WINDOW_SIZE)


# MACD

df['ema_12'] = df['close'].ewm(span=Config.EMA_SHORT).mean()

df['ema_26'] = df['close'].ewm(span=Config.EMA_LONG).mean()

df['macd'] = df['ema_12'] - df['ema_26']

df['macd_signal'] = df['macd'].ewm(span=Config.MACD_SIGNAL).mean()

df['macd_hist'] = df['macd'] - df['macd_signal']


# RSI (Relative Strength Index)

delta = df['close'].diff()

gain = delta.where(delta > 0, 0)

loss = -delta.where(delta < 0, 0)

avg_gain = gain.rolling(window=Config.RSI_PERIOD).mean()

avg_loss = loss.rolling(window=Config.RSI_PERIOD).mean()

rs = avg_gain / avg_loss

df['rsi'] = 100 - (100 / (1 + rs))
```

```
# Bollinger Bands
bb_window = Config.BOLLINGER_WINDOW
bb_std_dev = Config.BOLLINGER_STD
df['bb_middle'] = df['close'].rolling(window=bb_window).mean()
bb_std = df['close'].rolling(window=bb_window).std()
df['bb_upper'] = df['bb_middle'] + (bb_std * bb_std_dev)
df['bb_lower'] = df['bb_middle'] - (bb_std * bb_std_dev)
df['bb_width'] = (df['bb_upper'] - df['bb_lower']) / df['bb_middle']
df['bb_pct'] = (df['close'] - df['bb_lower']) / (df['bb_upper'] - df['bb_lower'])

# Volume features
df['volume_change'] = df['volume'].pct_change()
df['volume_ma_7'] = df['volume'].rolling(window=7).mean()
df['volume_relative'] = df['volume'] / df['volume_ma_7']

# OBV (On-Balance Volume)
df['obv'] = 0
df.loc[0, 'obv'] = df.loc[0, 'volume']
for i in range(1, len(df)):
if df.loc[i, 'close'] > df.loc[i-1, 'close']:
df.loc[i, 'obv'] = df.loc[i-1, 'obv'] + df.loc[i, 'volume']
elif df.loc[i, 'close'] < df.loc[i-1, 'close']:
df.loc[i, 'obv'] = df.loc[i-1, 'obv'] - df.loc[i, 'volume']
```

```
else:
df.loc[i, 'obv'] = df.loc[i-1, 'obv']

# Time-based features
df['hour'] = df['open_time'].dt.hour
df['day_of_week'] = df['open_time'].dt.dayofweek
df['is_weekend'] = df['day_of_week'].apply(lambda x: 1 if x >= 5 else 0)
df['month'] = df['open_time'].dt.month

# Remove rows with NaN values that resulted from calculating indicators
df.dropna(inplace=True)
return df


def add_target_variables(df: pd.DataFrame) -> pd.DataFrame:
"""
Add multiple target variables for both regression and classification tasks.
Parameters:
----------
df : pandas.DataFrame
DataFrame with price data and technical indicators
Returns:
--------
pandas.DataFrame: DataFrame with added target variables
```

```
"""
# Target 1: Binary classification - will price go up in next period?
df['target_binary'] = (df['close'].shift(-1) > df['close']).astype(int)

# Target 2: Regression - percentage price change in next period
df['target_pct_change'] = df['close'].pct_change(periods=-1) * 100

# Target 3: Regression - absolute price change in next period
df['target_abs_change'] = df['close'].shift(-1) - df['close']

# Target 4: Multi-class classification - categorize price movement
thresholds = Config.PRICE_MOVEMENT_THRESHOLDS
def categorize_movement(pct_change):
for i, threshold in enumerate(thresholds):
if pct_change < threshold:
return i
return len(thresholds) # Last category

df['target_multiclass'] = df['target_pct_change'].apply(categorize_movement)

# Target 5: Regression - log return (often better for financial modeling)
df['target_log_return'] = np.log(df['close'].shift(-1) / df['close'])

# Target 6: Regression - normalized price change (compared to recent volatility)
```

```
volatility = df['close'].rolling(window=Config.BOLLINGER_WINDOW).std()

df['target_normalized_change'] = df['target_abs_change'] / volatility


# Remove NaNs from target creation

df.dropna(inplace=True)

return df




def detect_outliers(df: pd.DataFrame) -> np.ndarray:

"""

Detect outliers using statistical methods and autoencoder.

Parameters:

----------

df : pandas.DataFrame

DataFrame with features

Returns:

--------

numpy.ndarray: Boolean mask where True indicates an outlier

"""

# Get feature columns (exclude timestamps and targets)

feature_cols = [col for col in df.columns if col not in [

'open_time', 'hour', 'day_of_week', 'is_weekend', 'month',

'target_binary', 'target_pct_change', 'target_abs_change',

'target_multiclass', 'target_log_return', 'target_normalized_change'
```

```
]]

# Statistical outlier detection (Z-score method)
def detect_outliers_zscore(df, columns, threshold=Config.ZSCORE_THRESHOLD):
outliers_mask = np.zeros(len(df), dtype=bool)
for col in columns:
z_scores = np.abs((df[col] - df[col].mean()) / df[col].std())
col_outliers = z_scores > threshold
outliers_mask = outliers_mask | col_outliers
return outliers_mask

outliers_mask_zscore = detect_outliers_zscore(df, feature_cols)
print(f"Z-score method identified {outliers_mask_zscore.sum()} outliers")

# Autoencoder-based outlier detection
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df[feature_cols])

# Define autoencoder model with regularization
input_dim = scaled_data.shape[1]
layers = Config.AUTOENCODER_LAYERS
# Build the autoencoder model
autoencoder = keras.Sequential()
# Encoder
```

```
autoencoder.add(keras.layers.Dense(
layers[0], activation='relu', input_shape=(input_dim,),
kernel_regularizer=keras.regularizers.l2(Config.REGULARIZATION_FACTOR)))
autoencoder.add(keras.layers.Dropout(Config.DROPOUT_RATE))
for units in layers[1:len(layers)//2 + 1]:
autoencoder.add(keras.layers.Dense(units, activation='relu'))
# Decoder
for units in layers[len(layers)//2 + 1:]:
autoencoder.add(keras.layers.Dense(units, activation='relu'))
autoencoder.add(keras.layers.Dense(input_dim, activation='linear'))

# Compile model
autoencoder.compile(optimizer='adam', loss='mse')

# Train the autoencoder with early stopping
early_stopping = keras.callbacks.EarlyStopping(
monitor='val_loss',
patience=Config.EARLY_STOPPING_PATIENCE,
restore_best_weights=True
)

autoencoder.fit(
scaled_data, scaled_data,
epochs=Config.EPOCHS,
```

```
batch_size=Config.BATCH_SIZE,

shuffle=True,

validation_split=Config.VALIDATION_SPLIT,

callbacks=[early_stopping],

verbose=1

)


# Compute reconstruction error

reconstructed = autoencoder.predict(scaled_data)

reconstruction_error = np.mean(np.abs(scaled_data - reconstructed), axis=1)


# Define anomaly threshold

threshold = np.percentile(reconstruction_error, Config.ANOMALY_PERCENTILE)

# Combine outlier detection methods

outliers_mask_combined = (reconstruction_error > threshold) | outliers_mask_zscore

print(f"Combined methods identified {outliers_mask_combined.sum()} outliers")

return outliers_mask_combined



def analyze_feature_importance(df: pd.DataFrame, feature_cols: list) -> tuple:

"""

Analyze feature importance for different target variables.

Parameters:

----------
```

```
df : pandas.DataFrame

DataFrame with features and targets

feature_cols : list

List of feature column names

Returns:

--------

tuple: Dataframes with feature importance for binary and regression targets

"""

X = df[feature_cols]

# For binary classification

y_binary = df['target_binary']

clf = RandomForestClassifier(

n_estimators=Config.RF_ESTIMATORS,

random_state=Config.RF_RANDOM_STATE

)

clf.fit(X, y_binary)

binary_importances = pd.DataFrame({

'feature': feature_cols,

'importance': clf.feature_importances_

}).sort_values('importance', ascending=False)


print("\nTop 10 important features for binary classification:")

print(binary_importances.head(10))
```

```
# For regression (percentage change)
y_pct = df['target_pct_change']
reg = RandomForestRegressor(
n_estimators=Config.RF_ESTIMATORS,
random_state=Config.RF_RANDOM_STATE
)
reg.fit(X, y_pct)
reg_importances = pd.DataFrame({
'feature': feature_cols,
'importance': reg.feature_importances_
}).sort_values('importance', ascending=False)

print("\nTop 10 important features for price change regression:")
print(reg_importances.head(10))
return binary_importances, reg_importances



def visualize_data_and_targets(df_original: pd.DataFrame, df_cleaned: pd.DataFrame,
binary_importances: pd.DataFrame, reg_importances: pd.DataFrame):
"""
Visualize various aspects of the dataset and targets.
Parameters:
----------
df_original : pandas.DataFrame
```

```
Original unprocessed DataFrame

df_cleaned : pandas.DataFrame

Processed DataFrame with features and targets

binary_importances : pandas.DataFrame

Feature importances for binary classification

reg_importances : pandas.DataFrame

Feature importances for regression

"""

plt.figure(figsize=(15, 15))


# Plot 1: Original vs Cleaned Price

plt.subplot(3, 2, 1)

plt.plot(df_original["open_time"], df_original["close"], label="Original", alpha=0.5)

plt.plot(df_cleaned["open_time"], df_cleaned["close"], label="Cleaned", alpha=0.8, color='red')

plt.title("Original vs Cleaned Price")

plt.legend()


# Plot 2: Binary Target Distribution

plt.subplot(3, 2, 2)

df_cleaned['target_binary'].value_counts().plot(kind='bar')

plt.title("Binary Target Distribution (Up/Down)")

plt.xlabel("Price Direction (1=Up, 0=Down)")

plt.ylabel("Count")
```

```
# Plot 3: Percentage Change Distribution
plt.subplot(3, 2, 3)
plt.hist(df_cleaned['target_pct_change'], bins=50)
plt.title("Price Percentage Change Distribution")
plt.xlabel("Percentage Change (%)")
plt.ylabel("Frequency")

# Plot 4: Multi-class Target Distribution
plt.subplot(3, 2, 4)
df_cleaned['target_multiclass'].value_counts().sort_index().plot(kind='bar')
plt.title("Multi-class Target Distribution")
plt.xlabel("Price Movement Category")
plt.ylabel("Count")
plt.xticks(range(len(Config.PRICE_MOVEMENT_LABELS)), Config.PRICE_MOVEMENT_LABELS,
rotation=45)

# Plot 5: Correlation Between Different Target Variables
plt.subplot(3, 2, 5)
target_corr = df_cleaned[['target_binary', 'target_pct_change', 'target_abs_change',
'target_multiclass', 'target_log_return', 'target_normalized_change']].corr()
plt.imshow(target_corr, cmap='coolwarm')
plt.colorbar()
plt.title("Correlation Between Target Variables")
plt.xticks(range(6), target_corr.columns, rotation=90)
```

```
plt.yticks(range(6), target_corr.columns)


# Plot 6: Top features importance (combined importance)
plt.subplot(3, 2, 6)
combined_importance = binary_importances.set_index('feature')['importance'] +
reg_importances.set_index('feature')['importance']
combined_importance.sort_values(ascending=False).head(10).plot(kind='bar')
plt.title("Top Features (Combined Importance)")
plt.tight_layout()
plt.xlabel("Feature")
plt.ylabel("Combined Importance Score")

plt.tight_layout()
plt.savefig(Config.VISUALIZATION_FILE)
plt.show()



def prepare_train_test_splits(df: pd.DataFrame, test_size=None, forecast_horizon=None):
"""
Prepare chronological train/test splits for time series data.
Parameters:
----------
df : pandas.DataFrame
The cleaned dataframe with features and targets
```

```
test_size : float, optional

Proportion of data to use for testing

forecast_horizon : int, optional

How many periods ahead to forecast

Returns:

--------

dict containing train/test splits for different target variables

"""

if test_size is None:

test_size = Config.TEST_SIZE

if forecast_horizon is None:

forecast_horizon = Config.FORECAST_HORIZON

# Feature columns (everything except targets and datetime)

feature_cols = [col for col in df.columns if col not in [

'open_time', 'target_binary', 'target_pct_change', 'target_abs_change',

'target_multiclass', 'target_log_return', 'target_normalized_change'

]]

# Split chronologically

split_idx = int(len(df) * (1 - test_size))

train_df = df.iloc[:split_idx].copy()

test_df = df.iloc[split_idx:].copy()

print(f"Training data from {train_df['open_time'].min()} to {train_df['open_time'].max()}")

print(f"Testing data from {test_df['open_time'].min()} to {test_df['open_time'].max()}")

# Prepare scalers
```

```
feature_scaler = MinMaxScaler()

X_train = feature_scaler.fit_transform(train_df[feature_cols])

X_test = feature_scaler.transform(test_df[feature_cols])

# Prepare regression target scalers

regression_scalers = {}

regression_targets = ['target_pct_change', 'target_abs_change',

'target_log_return', 'target_normalized_change']

y_train_dict = {}

y_test_dict = {}

# Classification targets

y_train_dict['binary'] = train_df['target_binary'].values

y_test_dict['binary'] = test_df['target_binary'].values

y_train_dict['multiclass'] = train_df['target_multiclass'].values

y_test_dict['multiclass'] = test_df['target_multiclass'].values

# Regression targets (scaled)

for target in regression_targets:

scaler = MinMaxScaler()

y_train_dict[target] = scaler.fit_transform(train_df[[target]])

y_test_dict[target] = scaler.transform(test_df[[target]])

regression_scalers[target] = scaler

return {

'X_train': X_train,

'X_test': X_test,

'y_train': y_train_dict,
```

```
'y_test': y_test_dict,
'feature_scaler': feature_scaler,
'regression_scalers': regression_scalers,
'feature_columns': feature_cols,
'train_dates': train_df['open_time'],
'test_dates': test_df['open_time']
}


def main():
"""
Main function to execute the entire data processing pipeline.
"""
# Step 1: Load and clean data
df_cleaned = load_and_clean_data(Config.INPUT_FILE)
df_original = df_cleaned.copy() # Save original for visualization comparison
# Step 2: Add technical indicators
df_cleaned = add_technical_indicators(df_cleaned)
# Step 3: Add target variables
df_cleaned = add_target_variables(df_cleaned)
# Step 4: Detect and remove outliers
outliers_mask = detect_outliers(df_cleaned)
df_cleaned = df_cleaned[~outliers_mask]
# Get feature columns for analysis
```

```
feature_cols = [col for col in df_cleaned.columns if col not in [
'open_time', 'hour', 'day_of_week', 'is_weekend', 'month',
'target_binary', 'target_pct_change', 'target_abs_change',
'target_multiclass', 'target_log_return', 'target_normalized_change'
]]
# Step 5: Analyze feature importance
binary_importances, reg_importances = analyze_feature_importance(df_cleaned, feature_cols)
# Step 6: Visualize data and targets
visualize_data_and_targets(df_original, df_cleaned, binary_importances, reg_importances)
# Step 7: Save cleaned data with multiple targets
df_cleaned.to_csv(Config.OUTPUT_FILE, index=False)
# Step 8: Prepare train/test splits
splits = prepare_train_test_splits(df_cleaned)
print("\nSplits created for all target types.")
# Print summary statistics
print("\nDataset Summary:")
print(f"Original dataset shape: {df_original.shape}")
print(f"Cleaned dataset shape with multiple targets: {df_cleaned.shape}")
print(f"Number of features: {len(feature_cols)}")
print(f"Number of target variables: 6")



if __name__ == "__main__":
main()
```

```
# add_factors_without_data_cleaning.py

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import tensorflow as tf

from tensorflow import keras

from sklearn.preprocessing import MinMaxScaler

from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier




class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

FOLDER_PATH = ""

INPUT_FILE = "klines_BTC.csv"

OUTPUT_FILE = "klines_BTC_with_factors.csv"

VISUALIZATION_FILE = "btc_targets_analysis.png"

# Technical indicator parameters

WINDOW_SIZE = 75

VOLATILITY_WINDOW = 24

MA_WINDOWS = [7, 25, 99]

EMA_SHORT = 12
```

```
EMA_LONG = 26

MACD_SIGNAL = 9

RSI_PERIOD = 14

BOLLINGER_WINDOW = 20

BOLLINGER_STD = 2

# Outlier detection parameters

ZSCORE_THRESHOLD = 3

ANOMALY_PERCENTILE = 95

# Autoencoder parameters

AUTOENCODER_LAYERS = [64, 32, 16, 32, 64]

REGULARIZATION_FACTOR = 0.001

DROPOUT_RATE = 0.2

EPOCHS = 50

BATCH_SIZE = 32

VALIDATION_SPLIT = 0.4

EARLY_STOPPING_PATIENCE = 5

# Random forest parameters

RF_ESTIMATORS = 100

RF_RANDOM_STATE = 42

# Target classification thresholds

PRICE_MOVEMENT_THRESHOLDS = [-2, -0.5, 0.5, 2]

PRICE_MOVEMENT_LABELS = ['Significant Drop', 'Small Drop', 'Sideways', 'Small Rise', 'Significant
Rise']

# Train-test split parameters
```

```
TEST_SIZE = 0.2

FORECAST_HORIZON = 1



def compute_atr(df: pd.DataFrame, window_size: int) -> pd.Series:

"""

Compute Average True Range (ATR) indicator.

Parameters:

----------

df : pandas.DataFrame

DataFrame containing OHLC price data

window_size : int

Rolling window size for ATR calculation

Returns:

--------

pandas.Series: ATR values

"""

high_low = df["high"] - df["low"]

high_prev_close = abs(df["high"] - df["close"].shift(1))

low_prev_close = abs(df["low"] - df["close"].shift(1))


true_range = pd.concat([high_low, high_prev_close, low_prev_close], axis=1).max(axis=1)

return true_range.rolling(window=window_size).mean()
```

```
def load_and_clean_data(file_path: str) -> pd.DataFrame:
"""
Load, clean, and preprocess raw price data.
Parameters:
-----------
file_path : str
Path to the CSV file containing raw price data
Returns:
--------
pandas.DataFrame: Cleaned dataframe
"""
# Load the data
df_original = pd.read_csv(file_path)

# Convert timestamp column to datetime
df_original["open_time"] = pd.to_datetime(df_original["open_time"])
df_original.sort_values(by="open_time", inplace=True)

# Make a copy before modification
df_cleaned = df_original.copy()

# Handle Missing Values
df_cleaned.dropna(inplace=True)
```

```
# Ensure Correct Data Types
numeric_cols = ["open", "high", "low", "close", "volume",
"taker_buy_base_asset_volume", "taker_buy_quote_asset_volume"]
df_cleaned[numeric_cols] = df_cleaned[numeric_cols].astype(float)

# Remove Duplicates
df_cleaned.drop_duplicates(subset=["open_time"], keep="first", inplace=True)
return df_cleaned



def add_technical_indicators(df: pd.DataFrame) -> pd.DataFrame:
"""
Add various technical indicators as features to the dataframe.
Parameters:
-----------
df : pandas.DataFrame
DataFrame containing OHLC price data
Returns:
--------
pandas.DataFrame: DataFrame with added technical indicators
"""
# Price-based features
df['return'] = df['close'].pct_change() # Price returns
```

```
df['log_return'] = np.log(df['close']/df['close'].shift(1)) # Log returns
df['volatility'] = df['log_return'].rolling(window=Config.VOLATILITY_WINDOW).std() # Volatility
df['price_range'] = (df['high'] - df['low']) / df['open'] # Normalized price range

# Moving averages
for window in Config.MA_WINDOWS:
df[f'ma_{window}'] = df['close'].rolling(window=window).mean()
# ATR (Average True Range)
df["atr"] = compute_atr(df, Config.WINDOW_SIZE)

# MACD
df['ema_12'] = df['close'].ewm(span=Config.EMA_SHORT).mean()
df['ema_26'] = df['close'].ewm(span=Config.EMA_LONG).mean()
df['macd'] = df['ema_12'] - df['ema_26']
df['macd_signal'] = df['macd'].ewm(span=Config.MACD_SIGNAL).mean()
df['macd_hist'] = df['macd'] - df['macd_signal']

# RSI (Relative Strength Index)
delta = df['close'].diff()
gain = delta.where(delta > 0, 0)
loss = -delta.where(delta < 0, 0)
avg_gain = gain.rolling(window=Config.RSI_PERIOD).mean()
avg_loss = loss.rolling(window=Config.RSI_PERIOD).mean()
rs = avg_gain / avg_loss
```

```
df['rsi'] = 100 - (100 / (1 + rs))

# Bollinger Bands
bb_window = Config.BOLLINGER_WINDOW
bb_std_dev = Config.BOLLINGER_STD
df['bb_middle'] = df['close'].rolling(window=bb_window).mean()
bb_std = df['close'].rolling(window=bb_window).std()
df['bb_upper'] = df['bb_middle'] + (bb_std * bb_std_dev)
df['bb_lower'] = df['bb_middle'] - (bb_std * bb_std_dev)
df['bb_width'] = (df['bb_upper'] - df['bb_lower']) / df['bb_middle']
df['bb_pct'] = (df['close'] - df['bb_lower']) / (df['bb_upper'] - df['bb_lower'])

# Volume features
df['volume_change'] = df['volume'].pct_change()
df['volume_ma_7'] = df['volume'].rolling(window=7).mean()
df['volume_relative'] = df['volume'] / df['volume_ma_7']

# OBV (On-Balance Volume)
df['obv'] = 0
df.loc[0, 'obv'] = df.loc[0, 'volume']
for i in range(1, len(df)):
if df.loc[i, 'close'] > df.loc[i-1, 'close']:
df.loc[i, 'obv'] = df.loc[i-1, 'obv'] + df.loc[i, 'volume']
elif df.loc[i, 'close'] < df.loc[i-1, 'close']:
```

```
df.loc[i, 'obv'] = df.loc[i-1, 'obv'] - df.loc[i, 'volume']

else:

df.loc[i, 'obv'] = df.loc[i-1, 'obv']


# Time-based features

df['hour'] = df['open_time'].dt.hour

df['day_of_week'] = df['open_time'].dt.dayofweek

df['is_weekend'] = df['day_of_week'].apply(lambda x: 1 if x >= 5 else 0)

df['month'] = df['open_time'].dt.month


# Remove rows with NaN values that resulted from calculating indicators

df.dropna(inplace=True)

return df



def add_target_variables(df: pd.DataFrame) -> pd.DataFrame:

"""

Add multiple target variables for both regression and classification tasks.

Parameters:

-----------

df : pandas.DataFrame

DataFrame with price data and technical indicators

Returns:

--------
```

```
pandas.DataFrame: DataFrame with added target variables
"""
# Target 1: Binary classification - will price go up in next period?
df['target_binary'] = (df['close'].shift(-1) > df['close']).astype(int)

# Target 2: Regression - percentage price change in next period
df['target_pct_change'] = df['close'].pct_change(periods=-1) * 100

# Target 3: Regression - absolute price change in next period
df['target_abs_change'] = df['close'].shift(-1) - df['close']

# Target 4: Multi-class classification - categorize price movement
thresholds = Config.PRICE_MOVEMENT_THRESHOLDS
def categorize_movement(pct_change):
for i, threshold in enumerate(thresholds):
if pct_change < threshold:
return i
return len(thresholds) # Last category

df['target_multiclass'] = df['target_pct_change'].apply(categorize_movement)

# Target 5: Regression - log return (often better for financial modeling)
df['target_log_return'] = np.log(df['close'].shift(-1) / df['close'])
```

```
# Target 6: Regression - normalized price change (compared to recent volatility)
volatility = df['close'].rolling(window=Config.BOLLINGER_WINDOW).std()
df['target_normalized_change'] = df['target_abs_change'] / volatility

# Remove NaNs from target creation
df.dropna(inplace=True)
return df



def detect_outliers(df: pd.DataFrame) -> np.ndarray:
"""
Detect outliers using statistical methods and autoencoder.
Parameters:
-----------
df : pandas.DataFrame
DataFrame with features
Returns:
--------
numpy.ndarray: Boolean mask where True indicates an outlier
"""
# Get feature columns (exclude timestamps and targets)
feature_cols = [col for col in df.columns if col not in [
'open_time', 'hour', 'day_of_week', 'is_weekend', 'month',
'target_binary', 'target_pct_change', 'target_abs_change',
```

```
'target_multiclass', 'target_log_return', 'target_normalized_change'

]]


# Statistical outlier detection (Z-score method)

def detect_outliers_zscore(df, columns, threshold=Config.ZSCORE_THRESHOLD):

outliers_mask = np.zeros(len(df), dtype=bool)

for col in columns:

z_scores = np.abs((df[col] - df[col].mean()) / df[col].std())

col_outliers = z_scores > threshold

outliers_mask = outliers_mask | col_outliers

return outliers_mask


outliers_mask_zscore = detect_outliers_zscore(df, feature_cols)

print(f"Z-score method identified {outliers_mask_zscore.sum()} outliers")


# Autoencoder-based outlier detection

scaler = MinMaxScaler()

scaled_data = scaler.fit_transform(df[feature_cols])


# Define autoencoder model with regularization

input_dim = scaled_data.shape[1]

layers = Config.AUTOENCODER_LAYERS

# Build the autoencoder model

autoencoder = keras.Sequential()
```

```
# Encoder
autoencoder.add(keras.layers.Dense(
layers[0], activation='relu', input_shape=(input_dim,),
kernel_regularizer=keras.regularizers.l2(Config.REGULARIZATION_FACTOR)))
autoencoder.add(keras.layers.Dropout(Config.DROPOUT_RATE))
for units in layers[1:len(layers)//2 + 1]:
autoencoder.add(keras.layers.Dense(units, activation='relu'))
# Decoder
for units in layers[len(layers)//2 + 1:]:
autoencoder.add(keras.layers.Dense(units, activation='relu'))
autoencoder.add(keras.layers.Dense(input_dim, activation='linear'))

# Compile model
autoencoder.compile(optimizer='adam', loss='mse')

# Train the autoencoder with early stopping
early_stopping = keras.callbacks.EarlyStopping(
monitor='val_loss',
patience=Config.EARLY_STOPPING_PATIENCE,
restore_best_weights=True
)

autoencoder.fit(
scaled_data, scaled_data,
```

```
epochs=Config.EPOCHS,

batch_size=Config.BATCH_SIZE,

shuffle=True,

validation_split=Config.VALIDATION_SPLIT,

callbacks=[early_stopping],

verbose=1

)


# Compute reconstruction error

reconstructed = autoencoder.predict(scaled_data)

reconstruction_error = np.mean(np.abs(scaled_data - reconstructed), axis=1)


# Define anomaly threshold

threshold = np.percentile(reconstruction_error, Config.ANOMALY_PERCENTILE)

# Combine outlier detection methods

outliers_mask_combined = (reconstruction_error > threshold) | outliers_mask_zscore

print(f"Combined methods identified {outliers_mask_combined.sum()} outliers")

return outliers_mask_combined



def analyze_feature_importance(df: pd.DataFrame, feature_cols: list) -> tuple:

"""

Analyze feature importance for different target variables.

Parameters:
```

```
-----------

df : pandas.DataFrame

DataFrame with features and targets

feature_cols : list

List of feature column names

Returns:

--------

tuple: Dataframes with feature importance for binary and regression targets

"""

X = df[feature_cols]

# For binary classification

y_binary = df['target_binary']

clf = RandomForestClassifier(

n_estimators=Config.RF_ESTIMATORS,

random_state=Config.RF_RANDOM_STATE

)

clf.fit(X, y_binary)

binary_importances = pd.DataFrame({

'feature': feature_cols,

'importance': clf.feature_importances_

}).sort_values('importance', ascending=False)


print("\nTop 10 important features for binary classification:")

print(binary_importances.head(10))
```

```
# For regression (percentage change)
y_pct = df['target_pct_change']
reg = RandomForestRegressor(
n_estimators=Config.RF_ESTIMATORS,
random_state=Config.RF_RANDOM_STATE
)
reg.fit(X, y_pct)
reg_importances = pd.DataFrame({
'feature': feature_cols,
'importance': reg.feature_importances_
}).sort_values('importance', ascending=False)

print("\nTop 10 important features for price change regression:")
print(reg_importances.head(10))
return binary_importances, reg_importances



def visualize_data_and_targets(df_original: pd.DataFrame, df_cleaned: pd.DataFrame,
binary_importances: pd.DataFrame, reg_importances: pd.DataFrame):
"""
Visualize various aspects of the dataset and targets.
Parameters:
----------
```

```
df_original : pandas.DataFrame

Original unprocessed DataFrame

df_cleaned : pandas.DataFrame

Processed DataFrame with features and targets

binary_importances : pandas.DataFrame

Feature importances for binary classification

reg_importances : pandas.DataFrame

Feature importances for regression

"""

plt.figure(figsize=(15, 15))


# Plot 1: Original vs Cleaned Price

plt.subplot(3, 2, 1)

plt.plot(df_original["open_time"], df_original["close"], label="Original", alpha=0.5)

plt.plot(df_cleaned["open_time"], df_cleaned["close"], label="Cleaned", alpha=0.8, color='red')

plt.title("Original vs Cleaned Price")

plt.legend()


# Plot 2: Binary Target Distribution

plt.subplot(3, 2, 2)

df_cleaned['target_binary'].value_counts().plot(kind='bar')

plt.title("Binary Target Distribution (Up/Down)")

plt.xlabel("Price Direction (1=Up, 0=Down)")

plt.ylabel("Count")
```

```
# Plot 3: Percentage Change Distribution
plt.subplot(3, 2, 3)
plt.hist(df_cleaned['target_pct_change'], bins=50)
plt.title("Price Percentage Change Distribution")
plt.xlabel("Percentage Change (%)")
plt.ylabel("Frequency")

# Plot 4: Multi-class Target Distribution
plt.subplot(3, 2, 4)
df_cleaned['target_multiclass'].value_counts().sort_index().plot(kind='bar')
plt.title("Multi-class Target Distribution")
plt.xlabel("Price Movement Category")
plt.ylabel("Count")
plt.xticks(range(len(Config.PRICE_MOVEMENT_LABELS)), Config.PRICE_MOVEMENT_LABELS,
rotation=45)

# Plot 5: Correlation Between Different Target Variables
plt.subplot(3, 2, 5)
target_corr = df_cleaned[['target_binary', 'target_pct_change', 'target_abs_change',
'target_multiclass', 'target_log_return', 'target_normalized_change']].corr()
plt.imshow(target_corr, cmap='coolwarm')
plt.colorbar()
plt.title("Correlation Between Target Variables")
```

```
plt.xticks(range(6), target_corr.columns, rotation=90)

plt.yticks(range(6), target_corr.columns)


# Plot 6: Top features importance (combined importance)

plt.subplot(3, 2, 6)

combined_importance = binary_importances.set_index('feature')['importance'] +
reg_importances.set_index('feature')['importance']

combined_importance.sort_values(ascending=False).head(10).plot(kind='bar')

plt.title("Top Features (Combined Importance)")

plt.tight_layout()

plt.xlabel("Feature")

plt.ylabel("Combined Importance Score")


plt.tight_layout()

plt.savefig(Config.VISUALIZATION_FILE)

plt.show()



def prepare_train_test_splits(df: pd.DataFrame, test_size=None, forecast_horizon=None):

"""

Prepare chronological train/test splits for time series data.

Parameters:

----------

df : pandas.DataFrame
```

```
The cleaned dataframe with features and targets

test_size : float, optional

Proportion of data to use for testing

forecast_horizon : int, optional

How many periods ahead to forecast

Returns:

--------

dict containing train/test splits for different target variables

"""

if test_size is None:

test_size = Config.TEST_SIZE

if forecast_horizon is None:

forecast_horizon = Config.FORECAST_HORIZON

# Feature columns (everything except targets and datetime)

feature_cols = [col for col in df.columns if col not in [

'open_time', 'target_binary', 'target_pct_change', 'target_abs_change',

'target_multiclass', 'target_log_return', 'target_normalized_change'

]]

# Split chronologically

split_idx = int(len(df) * (1 - test_size))

train_df = df.iloc[:split_idx].copy()

test_df = df.iloc[split_idx:].copy()

print(f"Training data from {train_df['open_time'].min()} to {train_df['open_time'].max()}")

print(f"Testing data from {test_df['open_time'].min()} to {test_df['open_time'].max()}")
```

```
# Prepare scalers

feature_scaler = MinMaxScaler()

X_train = feature_scaler.fit_transform(train_df[feature_cols])

X_test = feature_scaler.transform(test_df[feature_cols])

# Prepare regression target scalers

regression_scalers = {}

regression_targets = ['target_pct_change', 'target_abs_change',

'target_log_return', 'target_normalized_change']

y_train_dict = {}

y_test_dict = {}

# Classification targets

y_train_dict['binary'] = train_df['target_binary'].values

y_test_dict['binary'] = test_df['target_binary'].values

y_train_dict['multiclass'] = train_df['target_multiclass'].values

y_test_dict['multiclass'] = test_df['target_multiclass'].values

# Regression targets (scaled)

for target in regression_targets:

scaler = MinMaxScaler()

y_train_dict[target] = scaler.fit_transform(train_df[[target]])

y_test_dict[target] = scaler.transform(test_df[[target]])

regression_scalers[target] = scaler

return {

'X_train': X_train,

'X_test': X_test,
```

```
'y_train': y_train_dict,

'y_test': y_test_dict,

'feature_scaler': feature_scaler,

'regression_scalers': regression_scalers,

'feature_columns': feature_cols,

'train_dates': train_df['open_time'],

'test_dates': test_df['open_time']

}



def main():

"""

Main function to execute the entire data processing pipeline.

"""

# Step 1: Load and clean data

df_cleaned = load_and_clean_data(Config.INPUT_FILE)

df_original = df_cleaned.copy() # Save original for visualization comparison

# Step 2: Add technical indicators

df_cleaned = add_technical_indicators(df_cleaned)

# Step 3: Add target variables

df_cleaned = add_target_variables(df_cleaned)

# Step 4: Detect and remove outliers

# outliers_mask = detect_outliers(df_cleaned)

# df_cleaned = df_cleaned[~outliers_mask]
```

```
# Get feature columns for analysis
feature_cols = [col for col in df_cleaned.columns if col not in [
'open_time', 'hour', 'day_of_week', 'is_weekend', 'month',
'target_binary', 'target_pct_change', 'target_abs_change',
'target_multiclass', 'target_log_return', 'target_normalized_change'
]]
# Step 5: Analyze feature importance
binary_importances, reg_importances = analyze_feature_importance(df_cleaned, feature_cols)
# Step 6: Visualize data and targets
visualize_data_and_targets(df_original, df_cleaned, binary_importances, reg_importances)
# Step 7: Save cleaned data with multiple targets
df_cleaned.to_csv(Config.OUTPUT_FILE, index=False)
# Step 8: Prepare train/test splits
splits = prepare_train_test_splits(df_cleaned)
print("\nSplits created for all target types.")
# Print summary statistics
print("\nDataset Summary:")
print(f"Original dataset shape: {df_original.shape}")
print(f"Cleaned dataset shape with multiple targets: {df_cleaned.shape}")
print(f"Number of features: {len(feature_cols)}")
print(f"Number of target variables: 6")



if __name__ == "__main__":
```

```
main()


# add_factors_drop.py

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import tensorflow as tf

from tensorflow import keras

from sklearn.preprocessing import MinMaxScaler

from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier




class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

FOLDER_PATH = ""

INPUT_FILE = "klines_BTC.csv"

OUTPUT_FILE = "klines_BTC_with_factors.csv"

VISUALIZATION_FILE = "btc_targets_analysis.png"

# Technical indicator parameters

WINDOW_SIZE = 75

VOLATILITY_WINDOW = 24
```

```
MA_WINDOWS = [7, 25, 99]

EMA_SHORT = 12

EMA_LONG = 26

MACD_SIGNAL = 9

RSI_PERIOD = 14

BOLLINGER_WINDOW = 20

BOLLINGER_STD = 2

# Outlier detection parameters

ZSCORE_THRESHOLD = 3

ANOMALY_PERCENTILE = 95

# Autoencoder parameters

AUTOENCODER_LAYERS = [64, 32, 16, 32, 64]

REGULARIZATION_FACTOR = 0.001

DROPOUT_RATE = 0.2

EPOCHS = 50

BATCH_SIZE = 32

VALIDATION_SPLIT = 0.4

EARLY_STOPPING_PATIENCE = 5

# Random forest parameters

RF_ESTIMATORS = 100

RF_RANDOM_STATE = 42

# Target classification thresholds

PRICE_MOVEMENT_THRESHOLDS = [-2, -0.5, 0.5, 2]

PRICE_MOVEMENT_LABELS = ['Significant Drop', 'Small Drop', 'Sideways', 'Small Rise', 'Significant
```

```
Rise']

# Train-test split parameters

TEST_SIZE = 0.2

FORECAST_HORIZON = 1



def compute_atr(df: pd.DataFrame, window_size: int) -> pd.Series:

"""

Compute Average True Range (ATR) indicator.

Parameters:

----------

df : pandas.DataFrame

DataFrame containing OHLC price data

window_size : int

Rolling window size for ATR calculation

Returns:

--------

pandas.Series: ATR values

"""

high_low = df["high"] - df["low"]

high_prev_close = abs(df["high"] - df["close"].shift(1))

low_prev_close = abs(df["low"] - df["close"].shift(1))


true_range = pd.concat([high_low, high_prev_close, low_prev_close], axis=1).max(axis=1)
```

```
return true_range.rolling(window=window_size).mean()



def load_and_clean_data(file_path: str) -> pd.DataFrame:

"""

Load, clean, and preprocess raw price data.

Parameters:

-----------

file_path : str

Path to the CSV file containing raw price data

Returns:

--------

pandas.DataFrame: Cleaned dataframe

"""

# Load the data

df_original = pd.read_csv(file_path)



# Convert timestamp column to datetime

df_original["open_time"] = pd.to_datetime(df_original["open_time"])

df_original.sort_values(by="open_time", inplace=True)



# Make a copy before modification

df_cleaned = df_original.copy()
```

```
# Handle Missing Values
df_cleaned.dropna(inplace=True)

# Ensure Correct Data Types
numeric_cols = ["open", "high", "low", "close", "volume",
"taker_buy_base_asset_volume", "taker_buy_quote_asset_volume"]
df_cleaned[numeric_cols] = df_cleaned[numeric_cols].astype(float)

# Remove Duplicates
df_cleaned.drop_duplicates(subset=["open_time"], keep="first", inplace=True)
return df_cleaned



def add_technical_indicators(df: pd.DataFrame) -> pd.DataFrame:
"""
Add various technical indicators as features to the dataframe.
Parameters:
----------
df : pandas.DataFrame
DataFrame containing OHLC price data
Returns:
--------
pandas.DataFrame: DataFrame with added technical indicators
"""
```

```
# Price-based features
df['return'] = df['close'].pct_change() # Price returns
df['log_return'] = np.log(df['close']/df['close'].shift(1)) # Log returns
# df['volatility'] = df['log_return'].rolling(window=Config.VOLATILITY_WINDOW).std() # Volatility
# df['price_range'] = (df['high'] - df['low']) / df['open'] # Normalized price range

# Moving averages
for window in Config.MA_WINDOWS:
df[f'ma_{window}'] = df['close'].rolling(window=window).mean()
# ATR (Average True Range)
# df["atr"] = compute_atr(df, Config.WINDOW_SIZE)

# MACD
df['ema_12'] = df['close'].ewm(span=Config.EMA_SHORT).mean()
df['ema_26'] = df['close'].ewm(span=Config.EMA_LONG).mean()
df['macd'] = df['ema_12'] - df['ema_26']
df['macd_signal'] = df['macd'].ewm(span=Config.MACD_SIGNAL).mean()
# df['macd_hist'] = df['macd'] - df['macd_signal']

# RSI (Relative Strength Index)
delta = df['close'].diff()
gain = delta.where(delta > 0, 0)
loss = -delta.where(delta < 0, 0)
avg_gain = gain.rolling(window=Config.RSI_PERIOD).mean()
```

```
avg_loss = loss.rolling(window=Config.RSI_PERIOD).mean()

rs = avg_gain / avg_loss

# df['rsi'] = 100 - (100 / (1 + rs))


# Bollinger Bands

bb_window = Config.BOLLINGER_WINDOW

bb_std_dev = Config.BOLLINGER_STD

df['bb_middle'] = df['close'].rolling(window=bb_window).mean()

bb_std = df['close'].rolling(window=bb_window).std()

df['bb_upper'] = df['bb_middle'] + (bb_std * bb_std_dev)

df['bb_lower'] = df['bb_middle'] - (bb_std * bb_std_dev)

df['bb_width'] = (df['bb_upper'] - df['bb_lower']) / df['bb_middle']

# df['bb_pct'] = (df['close'] - df['bb_lower']) / (df['bb_upper'] - df['bb_lower'])


# Volume features

# df['volume_change'] = df['volume'].pct_change()

# df['volume_ma_7'] = df['volume'].rolling(window=7).mean()

# df['volume_relative'] = df['volume'] / df['volume_ma_7']


# OBV (On-Balance Volume)

# df['obv'] = 0

# df.loc[0, 'obv'] = df.loc[0, 'volume']

# for i in range(1, len(df)):

# if df.loc[i, 'close'] > df.loc[i-1, 'close']:
```

```
# df.loc[i, 'obv'] = df.loc[i-1, 'obv'] + df.loc[i, 'volume']
# elif df.loc[i, 'close'] < df.loc[i-1, 'close']:
# df.loc[i, 'obv'] = df.loc[i-1, 'obv'] - df.loc[i, 'volume']
# else:
# df.loc[i, 'obv'] = df.loc[i-1, 'obv']

# Time-based features
df['hour'] = df['open_time'].dt.hour
df['day_of_week'] = df['open_time'].dt.dayofweek
df['is_weekend'] = df['day_of_week'].apply(lambda x: 1 if x >= 5 else 0)
df['month'] = df['open_time'].dt.month

# Remove rows with NaN values that resulted from calculating indicators
df.dropna(inplace=True)
return df



def add_target_variables(df: pd.DataFrame) -> pd.DataFrame:
"""
Add multiple target variables for both regression and classification tasks.
Parameters:
----------
df : pandas.DataFrame
DataFrame with price data and technical indicators
```

```
Returns:
--------
pandas.DataFrame: DataFrame with added target variables
"""
# Target 1: Binary classification - will price go up in next period?
df['target_binary'] = (df['close'].shift(-1) > df['close']).astype(int)

# Target 2: Regression - percentage price change in next period
df['target_pct_change'] = df['close'].pct_change(periods=-1) * 100

# Target 3: Regression - absolute price change in next period
df['target_abs_change'] = df['close'].shift(-1) - df['close']

# Target 4: Multi-class classification - categorize price movement
thresholds = Config.PRICE_MOVEMENT_THRESHOLDS
def categorize_movement(pct_change):
for i, threshold in enumerate(thresholds):
if pct_change < threshold:
return i
return len(thresholds) # Last category

df['target_multiclass'] = df['target_pct_change'].apply(categorize_movement)

# Target 5: Regression - log return (often better for financial modeling)
```

```
df['target_log_return'] = np.log(df['close'].shift(-1) / df['close'])


# Target 6: Regression - normalized price change (compared to recent volatility)
volatility = df['close'].rolling(window=Config.BOLLINGER_WINDOW).std()
df['target_normalized_change'] = df['target_abs_change'] / volatility


# Remove NaNs from target creation
df.dropna(inplace=True)
return df




def detect_outliers(df: pd.DataFrame) -> np.ndarray:
"""
Detect outliers using statistical methods and autoencoder.
Parameters:
-----------
df : pandas.DataFrame
DataFrame with features
Returns:
--------
numpy.ndarray: Boolean mask where True indicates an outlier
"""
# Get feature columns (exclude timestamps and targets)
feature_cols = [col for col in df.columns if col not in [
```

```
'open_time', 'hour', 'day_of_week', 'is_weekend', 'month',
'target_binary', 'target_pct_change', 'target_abs_change',
'target_multiclass', 'target_log_return', 'target_normalized_change'
]]

# Statistical outlier detection (Z-score method)
def detect_outliers_zscore(df, columns, threshold=Config.ZSCORE_THRESHOLD):
outliers_mask = np.zeros(len(df), dtype=bool)
for col in columns:
z_scores = np.abs((df[col] - df[col].mean()) / df[col].std())
col_outliers = z_scores > threshold
outliers_mask = outliers_mask | col_outliers
return outliers_mask

outliers_mask_zscore = detect_outliers_zscore(df, feature_cols)
print(f"Z-score method identified {outliers_mask_zscore.sum()} outliers")

# Autoencoder-based outlier detection
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df[feature_cols])

# Define autoencoder model with regularization
input_dim = scaled_data.shape[1]
layers = Config.AUTOENCODER_LAYERS
```

```
# Build the autoencoder model
autoencoder = keras.Sequential()
# Encoder
autoencoder.add(keras.layers.Dense(
layers[0], activation='relu', input_shape=(input_dim,),
kernel_regularizer=keras.regularizers.l2(Config.REGULARIZATION_FACTOR)))
autoencoder.add(keras.layers.Dropout(Config.DROPOUT_RATE))
for units in layers[1:len(layers)//2 + 1]:
autoencoder.add(keras.layers.Dense(units, activation='relu'))
# Decoder
for units in layers[len(layers)//2 + 1:]:
autoencoder.add(keras.layers.Dense(units, activation='relu'))
autoencoder.add(keras.layers.Dense(input_dim, activation='linear'))

# Compile model
autoencoder.compile(optimizer='adam', loss='mse')

# Train the autoencoder with early stopping
early_stopping = keras.callbacks.EarlyStopping(
monitor='val_loss',
patience=Config.EARLY_STOPPING_PATIENCE,
restore_best_weights=True
)
```

```
autoencoder.fit(
scaled_data, scaled_data,
epochs=Config.EPOCHS,
batch_size=Config.BATCH_SIZE,
shuffle=True,
validation_split=Config.VALIDATION_SPLIT,
callbacks=[early_stopping],
verbose=1
)

# Compute reconstruction error
reconstructed = autoencoder.predict(scaled_data)
reconstruction_error = np.mean(np.abs(scaled_data - reconstructed), axis=1)

# Define anomaly threshold
threshold = np.percentile(reconstruction_error, Config.ANOMALY_PERCENTILE)
# Combine outlier detection methods
outliers_mask_combined = (reconstruction_error > threshold) | outliers_mask_zscore
print(f"Combined methods identified {outliers_mask_combined.sum()} outliers")
return outliers_mask_combined


def analyze_feature_importance(df: pd.DataFrame, feature_cols: list) -> tuple:
"""
```

```
Analyze feature importance for different target variables.

Parameters:

----------

df : pandas.DataFrame

DataFrame with features and targets

feature_cols : list

List of feature column names

Returns:

--------

tuple: Dataframes with feature importance for binary and regression targets

"""

X = df[feature_cols]

# For binary classification

y_binary = df['target_binary']

clf = RandomForestClassifier(

n_estimators=Config.RF_ESTIMATORS,

random_state=Config.RF_RANDOM_STATE

)

clf.fit(X, y_binary)

binary_importances = pd.DataFrame({

'feature': feature_cols,

'importance': clf.feature_importances_

}).sort_values('importance', ascending=False)
```

```
print("\nTop 10 important features for binary classification:")
print(binary_importances.head(10))

# For regression (percentage change)
y_pct = df['target_pct_change']
reg = RandomForestRegressor(
n_estimators=Config.RF_ESTIMATORS,
random_state=Config.RF_RANDOM_STATE
)
reg.fit(X, y_pct)
reg_importances = pd.DataFrame({
'feature': feature_cols,
'importance': reg.feature_importances_
}).sort_values('importance', ascending=False)

print("\nTop 10 important features for price change regression:")
print(reg_importances.head(10))
return binary_importances, reg_importances



def visualize_data_and_targets(df_original: pd.DataFrame, df_cleaned: pd.DataFrame,
binary_importances: pd.DataFrame, reg_importances: pd.DataFrame):
"""
Visualize various aspects of the dataset and targets.
```

```
Parameters:
----------
df_original : pandas.DataFrame
Original unprocessed DataFrame
df_cleaned : pandas.DataFrame
Processed DataFrame with features and targets
binary_importances : pandas.DataFrame
Feature importances for binary classification
reg_importances : pandas.DataFrame
Feature importances for regression
"""
plt.figure(figsize=(15, 15))

# Plot 1: Original vs Cleaned Price
plt.subplot(3, 2, 1)
plt.plot(df_original["open_time"], df_original["close"], label="Original", alpha=0.5)
plt.plot(df_cleaned["open_time"], df_cleaned["close"], label="Cleaned", alpha=0.8, color='red')
plt.title("Original vs Cleaned Price")
plt.legend()

# Plot 2: Binary Target Distribution
plt.subplot(3, 2, 2)
df_cleaned['target_binary'].value_counts().plot(kind='bar')
plt.title("Binary Target Distribution (Up/Down)")
```

```
plt.xlabel("Price Direction (1=Up, 0=Down)")
plt.ylabel("Count")

# Plot 3: Percentage Change Distribution
plt.subplot(3, 2, 3)
plt.hist(df_cleaned['target_pct_change'], bins=50)
plt.title("Price Percentage Change Distribution")
plt.xlabel("Percentage Change (%)")
plt.ylabel("Frequency")

# Plot 4: Multi-class Target Distribution
plt.subplot(3, 2, 4)
df_cleaned['target_multiclass'].value_counts().sort_index().plot(kind='bar')
plt.title("Multi-class Target Distribution")
plt.xlabel("Price Movement Category")
plt.ylabel("Count")
plt.xticks(range(len(Config.PRICE_MOVEMENT_LABELS)), Config.PRICE_MOVEMENT_LABELS,
rotation=45)

# Plot 5: Correlation Between Different Target Variables
plt.subplot(3, 2, 5)
target_corr = df_cleaned[['target_binary', 'target_pct_change', 'target_abs_change',
'target_multiclass', 'target_log_return', 'target_normalized_change']].corr()
plt.imshow(target_corr, cmap='coolwarm')
```

```
plt.colorbar()
plt.title("Correlation Between Target Variables")
plt.xticks(range(6), target_corr.columns, rotation=90)
plt.yticks(range(6), target_corr.columns)

# Plot 6: Top features importance (combined importance)
plt.subplot(3, 2, 6)
combined_importance = binary_importances.set_index('feature')['importance'] +
reg_importances.set_index('feature')['importance']
combined_importance.sort_values(ascending=False).head(10).plot(kind='bar')
plt.title("Top Features (Combined Importance)")
plt.tight_layout()
plt.xlabel("Feature")
plt.ylabel("Combined Importance Score")

plt.tight_layout()
plt.savefig(Config.VISUALIZATION_FILE)
plt.show()



def prepare_train_test_splits(df: pd.DataFrame, test_size=None, forecast_horizon=None):
"""
Prepare chronological train/test splits for time series data.
Parameters:
```

```
    ----------
    df : pandas.DataFrame
        The cleaned dataframe with features and targets
    test_size : float, optional
        Proportion of data to use for testing
    forecast_horizon : int, optional
        How many periods ahead to forecast
    Returns:
    --------
    dict containing train/test splits for different target variables
    """
    if test_size is None:
        test_size = Config.TEST_SIZE
    if forecast_horizon is None:
        forecast_horizon = Config.FORECAST_HORIZON
    # Feature columns (everything except targets and datetime)
    feature_cols = [col for col in df.columns if col not in [
        'open_time', 'target_binary', 'target_pct_change', 'target_abs_change',
        'target_multiclass', 'target_log_return', 'target_normalized_change'
    ]]
    # Split chronologically
    split_idx = int(len(df) * (1 - test_size))
    train_df = df.iloc[:split_idx].copy()
    test_df = df.iloc[split_idx:].copy()
```

```
print(f"Training data from {train_df['open_time'].min()} to {train_df['open_time'].max()}")

print(f"Testing data from {test_df['open_time'].min()} to {test_df['open_time'].max()}")

# Prepare scalers

feature_scaler = MinMaxScaler()

X_train = feature_scaler.fit_transform(train_df[feature_cols])

X_test = feature_scaler.transform(test_df[feature_cols])

# Prepare regression target scalers

regression_scalers = {}

regression_targets = ['target_pct_change', 'target_abs_change',

'target_log_return', 'target_normalized_change']

y_train_dict = {}

y_test_dict = {}

# Classification targets

y_train_dict['binary'] = train_df['target_binary'].values

y_test_dict['binary'] = test_df['target_binary'].values

y_train_dict['multiclass'] = train_df['target_multiclass'].values

y_test_dict['multiclass'] = test_df['target_multiclass'].values

# Regression targets (scaled)

for target in regression_targets:

scaler = MinMaxScaler()

y_train_dict[target] = scaler.fit_transform(train_df[[target]])

y_test_dict[target] = scaler.transform(test_df[[target]])

regression_scalers[target] = scaler

return {
```

```
'X_train': X_train,

'X_test': X_test,

'y_train': y_train_dict,

'y_test': y_test_dict,

'feature_scaler': feature_scaler,

'regression_scalers': regression_scalers,

'feature_columns': feature_cols,

'train_dates': train_df['open_time'],

'test_dates': test_df['open_time']

}



def main():

"""

Main function to execute the entire data processing pipeline.

"""

# Step 1: Load and clean data

df_cleaned = load_and_clean_data(Config.INPUT_FILE)

df_original = df_cleaned.copy() # Save original for visualization comparison

# Step 2: Add technical indicators

df_cleaned = add_technical_indicators(df_cleaned)

# Step 3: Add target variables

df_cleaned = add_target_variables(df_cleaned)

# Step 4: Detect and remove outliers
```

```
outliers_mask = detect_outliers(df_cleaned)

df_cleaned = df_cleaned[~outliers_mask]

# Get feature columns for analysis

feature_cols = [col for col in df_cleaned.columns if col not in [

'open_time', 'hour', 'day_of_week', 'is_weekend', 'month',

'target_binary', 'target_pct_change', 'target_abs_change',

'target_multiclass', 'target_log_return', 'target_normalized_change'

]]

# Step 5: Analyze feature importance

binary_importances, reg_importances = analyze_feature_importance(df_cleaned, feature_cols)

# Step 6: Visualize data and targets

visualize_data_and_targets(df_original, df_cleaned, binary_importances, reg_importances)

# Step 7: Save cleaned data with multiple targets

df_cleaned.to_csv(Config.OUTPUT_FILE, index=False)

# Step 8: Prepare train/test splits

splits = prepare_train_test_splits(df_cleaned)

print("\nSplits created for all target types.")

# Print summary statistics

print("\nDataset Summary:")

print(f"Original dataset shape: {df_original.shape}")

print(f"Cleaned dataset shape with multiple targets: {df_cleaned.shape}")

print(f"Number of features: {len(feature_cols)}")

print(f"Number of target variables: 6")
```

```
if __name__ == "__main__":

main()


# predict_XGBoost.py

import pandas as pd

import numpy as np

import os

import matplotlib.pyplot as plt

import xgboost as xgb

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import mean_squared_error


# Define configuration settings

class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

FOLDER_PATH = ""

INPUT_FILE = "klines_BTC_PCA.csv"

OUTPUT_FILE = "klines_BTC_factors_with_direction.csv"

VISUALIZATION_FILE = "learning_curve_xgboost.png"
```

```
PREDICTION_PLOT_FILE = "predictions_vs_actual_xgboost.png"

MODEL_FILE = "xgboost_model.json"

# Train-test split parameters

TEST_SIZE = 0.6

# Training parameters

N_ESTIMATORS = 1000

LEARNING_RATE = 0.05

MAX_DEPTH = 6

SUBSAMPLE = 0.8

COLSAMPLE_BYTREE = 0.8


def load_data(file_path: str) -> pd.DataFrame:

"""Load the CSV file and return a DataFrame."""

return pd.read_csv(file_path).dropna()


def prepare_features(df: pd.DataFrame):

"""Prepare features for XGBoost, excluding attributes containing 'target'."""

if 'target_pct_change' not in df.columns:

raise ValueError("❌ 'target_pct_change' column is missing from the dataset.")


# Select numerical features except those containing "target" and timestamp

feature_cols = [col for col in df.columns if "target" not in col and col != "open_time"]


if not feature_cols:
```

```
raise ValueError("❌ No valid features selected! Check the dataset structure.")

print(f"☑ Selected {len(feature_cols)} features for training.")

X = df[feature_cols].values
y = df['target_pct_change'].values

# Standardize features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

return X_scaled, y, scaler, df

def train_xgboost(X, y, test_size=0.3):
"""Train an XGBoost model with Huber loss and return the trained model and evaluation results."""
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, shuffle=False)

model = xgb.XGBRegressor(
objective="reg:pseudohubererror", # ☑ Correct objective for Huber-like loss
n_estimators=Config.N_ESTIMATORS,
learning_rate=Config.LEARNING_RATE,
max_depth=Config.MAX_DEPTH,
subsample=Config.SUBSAMPLE,
colsample_bytree=Config.COLSAMPLE_BYTREE,
```

```
eval_metric="rmse" # Keep RMSE for evaluation tracking

)



model.fit(

X_train, y_train,

eval_set=[(X_train, y_train), (X_test, y_test)],

verbose=True

)



evals_result = model.evals_result()



y_pred = model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

print(f"☑ XGBoost Model MSE (Huber Loss): {mse:.4f}")



return model, evals_result







def save_model(model, output_path: str):

"""Save the trained XGBoost model to a file."""

model.save_model(output_path)

print(f"☑ Model saved to {output_path}")
```

```
def save_predictions(df: pd.DataFrame, y_pred, output_path: str):
"""Save the predicted values to CSV file."""
df['predicted_return'] = y_pred.flatten()
df.to_csv(output_path, index=False)
print(f"☑ Predictions saved to {output_path}")

def plot_predictions(y_true, y_pred, output_path: str):
"""Plot actual vs. predicted values and save the figure."""
plt.figure(figsize=(10, 5))
plt.plot(y_true, label="Actual", linestyle="solid", marker="o", markersize=3)
plt.plot(y_pred, label="Predicted", linestyle="dashed", marker="s", markersize=3)
plt.xlabel("Time Steps")
plt.ylabel("Target Percentage Change")
plt.title("Predicted vs Actual Values (XGBoost)")
plt.legend()
plt.grid()
plt.savefig(output_path)
print(f"☑ Prediction plot saved to {output_path}")

def plot_learning_curve(evals_result, output_path: str):
"""Plot the learning curve for XGBoost and save the image."""
train_rmse = evals_result["validation_0"]["rmse"]
test_rmse = evals_result["validation_1"]["rmse"]
```

```
plt.figure(figsize=(8, 5))

plt.plot(train_rmse, label="Train RMSE", marker="o")

plt.plot(test_rmse, label="Test RMSE", marker="s")

plt.xlabel("Boosting Rounds")

plt.ylabel("Root Mean Squared Error (RMSE)")

plt.title("XGBoost Learning Curve")

plt.legend()

plt.grid()

plt.savefig(output_path)

print(f"☑ Learning curve saved to {output_path}")


def main():

"""Main execution function."""

file_path = Config.INPUT_FILE

output_path = Config.OUTPUT_FILE

learning_curve_path = Config.VISUALIZATION_FILE

prediction_plot_path = Config.PREDICTION_PLOT_FILE

model_path = Config.MODEL_FILE


df = load_data(file_path)

X, y, scaler, df_filtered = prepare_features(df)


model, evals_result = train_xgboost(X, y, test_size=Config.TEST_SIZE)
```

```
save_model(model, model_path)


y_pred = model.predict(X)

save_predictions(df_filtered, y_pred, output_path)


plot_predictions(y, y_pred, prediction_plot_path)

plot_learning_curve(evals_result, learning_curve_path)


if __name__ == "__main__":

main()


# predict_transformer.py

import pandas as pd

import numpy as np

import os

import matplotlib.pyplot as plt

import tensorflow as tf

from tensorflow.keras.models import Model, load_model

from tensorflow.keras.layers import Input, Dense, Dropout, LayerNormalization,
MultiHeadAttention, GlobalAveragePooling1D, Add

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler
```

```
# Define configuration settings

class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

FOLDER_PATH = ""

INPUT_FILE = "klines_BTC_with_factors.csv"

OUTPUT_FILE = "klines_BTC_factors_with_direction.csv"

VISUALIZATION_FILE = "learning_curve_transformer.png"

PREDICTION_PLOT_FILE = "predictions_vs_actual_transformer.png"

MODEL_FILE = "transformer_model.h5"

# Train-test split parameters

TEST_SIZE = 0.6

FORECAST_HORIZON = 1

# Training parameters

EPOCHS = 20

BATCH_SIZE = 32

TIME_STEPS = 60


def load_data(file_path: str) -> pd.DataFrame:

"""Load the CSV file and return a DataFrame."""

return pd.read_csv(file_path).dropna()
```

```
def prepare_features(df: pd.DataFrame):

"""Prepare all available features for Transformer model, excluding attributes containing 'target'."""

# Ensure target column exists

if 'target_pct_change' not in df.columns:

raise ValueError("❌ 'target_pct_change' column is missing from the dataset.")


# Select all numerical features except those containing "target" and timestamp

feature_cols = [col for col in df.columns if "target" not in col and col != "open_time"]


# Validate feature selection (ensure we have at least one feature)

if not feature_cols:

raise ValueError("❌ No valid features selected! Check the dataset structure.")


print(f"☑ Selected {len(feature_cols)} features for training.")


# Extract feature matrix (X) and target variable (y)

X = df[feature_cols].values

y = df['target_pct_change'].values # Prediction target


# Standardize features

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)


# Define time step length for Transformer input
```

```
time_steps = Config.TIME_STEPS

# Create sequences for Transformer input
X_transformer = np.array([X_scaled[i-time_steps:i] for i in range(time_steps, len(X_scaled))])
y_transformer = y[time_steps:]

# Retain proper indexing from the original DataFrame
df_filtered = df.iloc[time_steps:].copy()

return X_transformer, y_transformer, scaler, df_filtered

def transformer_encoder(inputs, head_size=64, num_heads=4, ff_dim=128, dropout=0.2):
"""Transformer encoder block with dropout and L2 regularization."""
x = MultiHeadAttention(num_heads=num_heads, key_dim=head_size)(inputs, inputs)
x = Dropout(dropout)(x)
x = Add()([x, inputs])
x = LayerNormalization(epsilon=1e-6)(x)

x_ff = Dense(ff_dim, activation="relu", kernel_regularizer=tf.keras.regularizers.l2(0.01))(x)
x_ff = Dropout(dropout)(x_ff)
x_ff = Dense(inputs.shape[-1])(x_ff)
x = Add()([x, x_ff])
x = LayerNormalization(epsilon=1e-6)(x)
```

```
return x

def build_transformer_model(input_shape, num_layers=6):
"""Build Transformer model with multiple encoder layers."""
inputs = Input(shape=input_shape)
x = inputs
for _ in range(num_layers):
x = transformer_encoder(x)
x = GlobalAveragePooling1D()(x)
x = Dropout(0.02)(x)
outputs = Dense(1)(x)

model = Model(inputs, outputs)
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0005), loss='huber')
return model

def train_transformer(X, y, test_size=0.3, epochs=20, batch_size=32):
"""Train a Transformer model and return the trained model and loss history."""
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_size, shuffle=False)

model = build_transformer_model(input_shape=(X_train.shape[1], X_train.shape[2]))

history = model.fit(
X_train, y_train,
```

```
epochs=epochs,
batch_size=batch_size,
validation_data=(X_test, y_test),
verbose=1
)
return model, history

def plot_predictions(y_true, y_pred, output_path: str):
"""Plot actual vs. predicted values and save the figure."""
plt.figure(figsize=(10, 5))
plt.plot(y_true, label="Actual", linestyle="solid", marker="o", markersize=3)
plt.plot(y_pred, label="Predicted", linestyle="dashed", marker="s", markersize=3)
plt.xlabel("Time Steps")
plt.ylabel("Target Percentage Change")
plt.title("Predicted vs Actual Values")
plt.legend()
plt.grid()
plt.savefig(output_path)
print(f"☑ Prediction plot saved to {output_path}")

def plot_learning_curve(history, output_path: str):
"""Plot the learning curve for Transformer and save the image."""
plt.figure(figsize=(8, 5))
plt.plot(history.history['loss'], label='Train Loss', marker='o')
```

```
plt.plot(history.history['val_loss'], label='Test Loss', marker='s')
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.title("Transformer Learning Curve")
plt.legend()
plt.grid()
plt.savefig(output_path)
print(f"☑ Learning curve saved to {output_path}")

def save_model(model, output_path: str):
"""Save the trained model to a file."""
model.save(output_path)
print(f"☑ Model saved to {output_path}")

def save_predictions(df: pd.DataFrame, y_pred, output_path: str):
"""Save the predicted values to CSV file."""
df['predicted_return'] = y_pred.flatten()
df.to_csv(output_path, index=False)
print(f"☑ Predictions saved to {output_path}")

def main():
"""Main execution function."""
file_path = Config.INPUT_FILE
output_path = Config.OUTPUT_FILE
```

```
learning_curve_path = Config.VISUALIZATION_FILE

prediction_plot_path = Config.PREDICTION_PLOT_FILE

model_path = Config.MODEL_FILE


df = load_data(file_path)

X, y, scaler, df_filtered = prepare_features(df)


model, history = train_transformer(X, y, test_size=Config.TEST_SIZE, epochs=Config.EPOCHS,
batch_size=Config.BATCH_SIZE)


save_model(model, model_path)


y_pred = model.predict(X)

save_predictions(df_filtered, y_pred, output_path)


plot_predictions(y, y_pred, prediction_plot_path)

plot_learning_curve(history, learning_curve_path)


if __name__ == "__main__":

main()

# predict_kmeans.py

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt
```

```
from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans

from sklearn.metrics import silhouette_score, adjusted_rand_score, normalized_mutual_info_score,
accuracy_score

from scipy.optimize import linear_sum_assignment

from sklearn.metrics import accuracy_score


# Define configuration settings

class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

INPUT_FILE = "klines_BTC_with_factors.csv"

OUTPUT_FILE = "klines_BTC_clusters.csv"

CLUSTER_PLOT_FILE = "kmeans_clusters.png"

# Clustering parameters

TIME_STEPS = 60

N_CLUSTERS = 5 #  分成  4  群

RANDOM_STATE = 42 #  保證每次結果一樣


def load_data(file_path: str) -> pd.DataFrame:

"""Load the CSV file and return a DataFrame."""

df = pd.read_csv(file_path).dropna()
```

```
return df


def prepare_features(df: pd.DataFrame):
"""Prepare time-series features for unsupervised learning."""
# 過濾掉 target 和時間欄位，避免影響特徵選擇
feature_cols = [col for col in df.columns if "target" not in col and col != "open_time"]

if not feature_cols:
raise ValueError("❌ No valid features selected! Check the dataset structure.")

print(f"☑ Selected {len(feature_cols)} features for clustering.")

# 轉換為矩陣
X = df[feature_cols].values

# 標準化
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# 創建時間序列窗口
time_steps = Config.TIME_STEPS
if len(X_scaled) <= time_steps:
raise ValueError("❌ Not enough data to generate sequences. Increase dataset size.")
```

```
X_sequences = np.array([X_scaled[i-time_steps:i] for i in range(time_steps, len(X_scaled))])

X_flat = X_sequences.reshape(X_sequences.shape[0], -1)


print(f"☑ Prepared sequences for clustering: {X_flat.shape}")


df_filtered = df.iloc[time_steps:].copy()


return X_flat, scaler, df_filtered


def run_kmeans(X):

"""Run K-Means clustering on time-series sequences."""

print(f" ◇  Running K-Means on shape: {X.shape}")


# Apply K-Means clustering

kmeans = KMeans(n_clusters=Config.N_CLUSTERS, random_state=Config.RANDOM_STATE,
n_init=10)

clusters = kmeans.fit_predict(X)


unique, counts = np.unique(clusters, return_counts=True)

print(" ◇  Cluster distribution:", dict(zip(unique, counts)))


return clusters, kmeans


from scipy.optimize import linear_sum_assignment
```

```
from sklearn.metrics import accuracy_score


def compute_accuracy(true_labels, predicted_clusters):
"""Compute accuracy by mapping predicted clusters to true labels using the Hungarian algorithm."""
if len(true_labels) != len(predicted_clusters):
print("⚠ Warning: Length mismatch between `target_multiclass` and predicted clusters. Adjusting.")
min_len = min(len(true_labels), len(predicted_clusters))
true_labels, predicted_clusters = true_labels[:min_len], predicted_clusters[:min_len]

# Create a contingency matrix
contingency_matrix = np.zeros((Config.N_CLUSTERS, Config.N_CLUSTERS), dtype=int)
for i in range(len(true_labels)):
contingency_matrix[true_labels[i], predicted_clusters[i]] += 1

# Hungarian Algorithm for optimal label assignment
row_ind, col_ind = linear_sum_assignment(contingency_matrix.max() - contingency_matrix)
mapping = {col: row for row, col in zip(row_ind, col_ind)}

# Map predicted clusters to the best-matching true labels
predicted_mapped = np.array([mapping[c] for c in predicted_clusters])
accuracy = accuracy_score(true_labels, predicted_mapped)

return accuracy
```

```
def evaluate_clustering(X, clusters, kmeans, true_labels=None):
"""Evaluate clustering performance using internal and external metrics."""
print("\n ◇  Clustering Evaluation Metrics:")
# Internal metrics
silhouette_avg = silhouette_score(X, clusters)
inertia = kmeans.inertia_
print(f"☑ Silhouette Score: {silhouette_avg:.4f} (higher is better)")
print(f"☑ Inertia (SSE): {inertia:.4f} (lower is better)")

if true_labels is not None:
if len(true_labels) != len(clusters):
print("⚠ Warning: `target_multiclass` and `clusters` have different lengths!")
true_labels = true_labels[:len(clusters)]

ari = adjusted_rand_score(true_labels, clusters)
nmi = normalized_mutual_info_score(true_labels, clusters)
accuracy = compute_accuracy(true_labels, clusters)

print(f"☑ Adjusted Rand Index (ARI): {ari:.4f} (higher is better)")
print(f"☑ Normalized Mutual Information (NMI): {nmi:.4f} (higher is better)")
print(f"☑ Accuracy: {accuracy:.4f} (higher is better)")
```

```
return silhouette_avg, inertia


def plot_clusters(clusters, output_path: str):
"""Visualize the distribution of clusters."""
unique_clusters, counts = np.unique(clusters, return_counts=True)

plt.figure(figsize=(10, 5))
plt.bar(unique_clusters, counts, alpha=0.7, color='blue', edgecolor='black')
plt.xlabel("Cluster Label")
plt.ylabel("Number of Samples")
plt.title("K-Means Cluster Distribution")
plt.grid()
plt.savefig(output_path)
print(f"☑ Cluster plot saved to {output_path}")

def save_clusters(df: pd.DataFrame, clusters, output_path: str):
"""Save the clustering results to a CSV file."""
df = df.iloc[:len(clusters)].copy() #  確保長度匹配
df['cluster'] = clusters
df.to_csv(output_path, index=False)
print(f"☑ Cluster labels saved to {output_path}")

def main():
"""Main execution function."""
```

```
file_path = Config.INPUT_FILE

output_path = Config.OUTPUT_FILE

cluster_plot_path = Config.CLUSTER_PLOT_FILE


df = load_data(file_path)

X, scaler, df_filtered = prepare_features(df)


clusters, kmeans = run_kmeans(X)


# 確保 `target_multiclass` 存在

if 'target_multiclass' in df_filtered.columns:

true_labels = df_filtered['target_multiclass'].values

else:

true_labels = None

print("⚠ Warning: `target_multiclass` column not found, external evaluation skipped.")


# Evaluate clustering

evaluate_clustering(X, clusters, kmeans, true_labels)


save_clusters(df_filtered, clusters, output_path)

plot_clusters(clusters, cluster_plot_path)


if __name__ == "__main__":

main()
```

```
# predict_GMM.py

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.preprocessing import StandardScaler

from sklearn.decomposition import PCA

from sklearn.metrics import silhouette_score, adjusted_rand_score, normalized_mutual_info_score, accuracy_score

from hmmlearn.hmm import GaussianHMM


# Define configuration settings

class Config:

"""

Configuration class to centralize all hyperparameters and settings.

"""

# File paths and names

INPUT_FILE = "klines_BTC_with_factors.csv"

OUTPUT_FILE = "klines_BTC_clusters_hmm.csv"

CLUSTER_PLOT_FILE = "hmm_clusters.png"

# HMM-GMM clustering parameters

N_HIDDEN_STATES = 5 # Hidden states (市場狀態數量)

MAX_ITER = 500 # HMM  訓練迭代次數

RANDOM_STATE = 42 #  保證每次結果相同
```

```
PCA_COMPONENTS = 0.87 #  保留  95%  資訊量


def load_data(file_path: str) -> pd.DataFrame:

"""Load the CSV file and return a DataFrame."""

df = pd.read_csv(file_path).dropna()

return df


def prepare_features(df: pd.DataFrame):

"""Prepare time-series features for HMM-GMM clustering."""

#  過濾掉  target  和時間欄位，避免影響特徵選擇

feature_cols = [col for col in df.columns if "target" not in col and col != "open_time"]


if not feature_cols:

raise ValueError("❌ No valid features selected! Check the dataset structure.")


print(f"☑ Selected {len(feature_cols)} features for clustering.")


#  轉換為矩陣

X = df[feature_cols].values


#  標準化

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)
```

```
# 降維 (保留 95% 變異數)
pca = PCA(n_components=Config.PCA_COMPONENTS)
X_pca = pca.fit_transform(X_scaled)

print(f"☑ 原始維度: {X_scaled.shape[1]}, PCA 降維後: {X_pca.shape[1]}")

return X_pca, scaler, df

def run_hmm_gmm(X_pca):
"""Run HMM-GMM clustering on time-series data."""
print(f" ◇ Running HMM-GMM on shape: {X_pca.shape}")

# 訓練 HMM-GMM
hmm = GaussianHMM(n_components=Config.N_HIDDEN_STATES, covariance_type="full",
random_state=Config.RANDOM_STATE, n_iter=Config.MAX_ITER)
hmm.fit(X_pca)
hidden_states = hmm.predict(X_pca)

# 印出隱藏狀態分佈
unique, counts = np.unique(hidden_states, return_counts=True)
print(" ◇ Hidden State Distribution:", dict(zip(unique, counts)))

return hidden_states, hmm
```

```
def evaluate_clustering(X_pca, hidden_states, true_labels=None):
"""Evaluate the clustering performance with internal and external metrics."""
print("\n ◇ Clustering Evaluation Metrics:")
# Internal metrics
silhouette_avg = silhouette_score(X_pca, hidden_states)
print(f"☑ Silhouette Score: {silhouette_avg:.4f} (higher is better)")

if true_labels is not None:
# 確保 `true_labels` 和 `hidden_states` 具有相同長度
if len(true_labels) != len(hidden_states):
print("⚠ Warning: `target_multiclass` and `hidden_states` have different lengths!")
true_labels = true_labels[:len(hidden_states)]

# External metrics
ari = adjusted_rand_score(true_labels, hidden_states)
nmi = normalized_mutual_info_score(true_labels, hidden_states)
accuracy = accuracy_score(true_labels, hidden_states)

print(f"☑ Adjusted Rand Index (ARI): {ari:.4f} (higher is better)")
print(f"☑ Normalized Mutual Information (NMI): {nmi:.4f} (higher is better)")
print(f"☑ Accuracy: {accuracy:.4f} (higher is better)")

return silhouette_avg
```

```
def plot_clusters(hidden_states, output_path: str):
"""Visualize the distribution of hidden states."""
unique_states, counts = np.unique(hidden_states, return_counts=True)

plt.figure(figsize=(10, 5))
plt.bar(unique_states, counts, alpha=0.7, color='blue', edgecolor='black')
plt.xlabel("Hidden State")
plt.ylabel("Number of Samples")
plt.title("HMM-GMM Hidden State Distribution")
plt.grid()
plt.savefig(output_path)
print(f"☑ Cluster plot saved to {output_path}")

def save_clusters(df: pd.DataFrame, hidden_states, output_path: str):
"""Save the clustering results to a CSV file."""
df = df.iloc[:len(hidden_states)].copy() #  確保長度匹配
df['hidden_state'] = hidden_states
df.to_csv(output_path, index=False)
print(f"☑ Hidden states saved to {output_path}")

def main():
"""Main execution function."""
file_path = Config.INPUT_FILE
output_path = Config.OUTPUT_FILE
```

```
cluster_plot_path = Config.CLUSTER_PLOT_FILE

df = load_data(file_path)
X_pca, scaler, df_filtered = prepare_features(df)

hidden_states, hmm = run_hmm_gmm(X_pca)

# 確保 `target_multiclass` 存在
if 'target_multiclass' in df_filtered.columns:
true_labels = df_filtered['target_multiclass'].values
else:
true_labels = None
print("⚠ Warning: `target_multiclass` column not found, external evaluation skipped.")

# Evaluate clustering
evaluate_clustering(X_pca, hidden_states, true_labels)

save_clusters(df_filtered, hidden_states, output_path)
plot_clusters(hidden_states, cluster_plot_path)

if __name__ == "__main__":
main()

# PCA.py
```

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.decomposition import PCA

from sklearn.preprocessing import StandardScaler


# Configuration

class Config:

INPUT_FILE = "klines_BTC_with_factors.csv"

OUTPUT_FILE = "klines_BTC_PCA.csv"

EXPLAINED_VARIANCE_PLOT = "pca_explained_variance.png"

N_COMPONENTS = 0.95 # Keep 95% variance


def load_data(file_path: str):

"""Load the dataset and remove non-numeric and target columns."""

df = pd.read_csv(file_path)

# Exclude columns that contain "target" (since they are labels)

feature_cols = [col for col in df.columns if "target" not in col and df[col].dtype in [np.float64,
np.int64]]

print(f"☑ Initial feature count (excluding targets): {len(feature_cols)}")

return df, df[feature_cols], feature_cols


def apply_pca(df_features, feature_names):

"""Apply PCA to reduce dimensionality while preserving variance."""
```

```
scaler = StandardScaler()

X_scaled = scaler.fit_transform(df_features)


# Apply PCA

pca = PCA(n_components=Config.N_COMPONENTS)

X_pca = pca.fit_transform(X_scaled)


# Number of selected components

n_selected = pca.n_components_

n_dropped = len(feature_names) - n_selected


# Get retained feature names (sorted by explained variance)

retained_features = np.array(feature_names)[np.argsort(-
pca.explained_variance_ratio_)[:n_selected]]

print(f"☑ PCA reduced dimensions to {n_selected}, preserving {Config.N_COMPONENTS * 100}%
variance.")

print(f"❌ Dropped {n_dropped} features (from {len(feature_names)} → {n_selected})")

print(f"☑ Retained feature names: {list(retained_features)}")


return X_pca, pca, n_selected, n_dropped, retained_features


def plot_explained_variance(pca):

"""Plot the cumulative explained variance ratio."""

plt.figure(figsize=(8, 5))

plt.plot(np.cumsum(pca.explained_variance_ratio_), marker="o", linestyle="--")
```

```
plt.xlabel("Number of Components")

plt.ylabel("Cumulative Explained Variance")

plt.title("PCA Explained Variance Ratio")

plt.grid()

plt.savefig(Config.EXPLAINED_VARIANCE_PLOT)

print(f"☑ Explained variance plot saved to {Config.EXPLAINED_VARIANCE_PLOT}")


def save_pca_data(df, X_pca, retained_features, output_path):

"""Save the PCA-transformed data along with original target labels."""

df_pca = pd.DataFrame(X_pca, columns=[f"PC{i+1}" for i in range(X_pca.shape[1])])


# Add back the target columns (which were excluded from PCA)

target_cols = [col for col in df.columns if "target" in col]

df_pca[target_cols] = df[target_cols].iloc[len(df) - len(df_pca):].reset_index(drop=True)

df_pca.to_csv(output_path, index=False)

print(f"☑ PCA-transformed data saved to {output_path}")


def main():

"""Main function to execute PCA processing."""

df, df_features, feature_names = load_data(Config.INPUT_FILE)

X_pca, pca, n_selected, n_dropped, retained_features = apply_pca(df_features, feature_names)

plot_explained_variance(pca)

save_pca_data(df, X_pca, retained_features, Config.OUTPUT_FILE)
```

```
if __name__ == "__main__":

main()
```