

School of Computer Science and Engineering **College of Engineering**

Evolving Neuro-Fuzzy System

For Portfolio Management

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Motivation

Recently, Explainable Artificial Intelligence (XAI) has been on the rise. More companies are opting for models which are both highly accurate and highly interpretable. Although, traditional Neural Networks produce great results, they are black-box models which lack in interpretability. Thus, in this project, a partially online evolving density-based fuzzy convolutional neural network (EDFCNN) was developed to predict stock prices.



Results



Key Features

Evolving: Data-Driven model that learns and forgets rules as time passes. Interpretable: Produces rules based on input data which determines the predicted output.

We tested EDFCNN in predicting up to 14 days in the future. EDFCNN displayed superb performance (R2 > 0.99) consistently on various types of financial securities and market conditions.



Applications

Interpretable Results

Rules in the knowledge base in EDFCNN will be continuously updated as new data flows into the model. This construction of linguistic variables will provide interpretability to the deep learning structure, which on its own, is a highly accurate system. Each rule created by EDFCNN takes the following form:

Improved Financial Indicators

Security	Percentage Improvement	
	R2	RMSE
SPY	1406%	-53%
DJI	285%	-64%
AAPL	940%	-53%

Portfolio Rebalancing

Trading Strategy:

Improved Financial Indicators were used to determine if a trade signal was generated for the stock on the rebalancing day. Next, we compared the price of the stock on the next rebalancing day. If the Predicted MACD generated a buy signal and the price of the stock was expected to go down, then we would purchase the stock. The converse applies to sell orders. If there are multiple securities with buy signals, then the proportion that would be bought would be determined using the Markowitz Efficient Frontier Technique.

IF X_1 *is* arg max_{*j*1}($A_{1,1}, ..., A_{1,j_1}$) *AND* X_2 *is* ... *AND* ..., **THEN** Y_m is arg max_l($C_{m,1}, \ldots, C_{m,l}$).

Which can then be converted into:

IF the velocity of the closing price on t-8 is low, **AND** the momentum of the closing price on t-6 is normal, AND the velocity of the closing price on t-5 is very high, AND the velocity of the closing price on t-6 is normal, AND the momentum of the closing price on t-3 is high, **THEN** the velocity of the closing price on t+1 is <u>high</u>.

-30% TSLA 474% The predicted-MACD was better than vanilla-MACD for all securities tested. Both the showed MACD and R2 substantial improvements. This means that with EDFCNN we can generate MACD-based trade signals closer to the peaks and troughs of the stock prices to maximise the profits.

Security	Vanilla MACD	Predicted MACD
SPY	-\$22.44	\$259.13
DJI	\$3,475.20	\$29,966.40
AAPL	\$9.41	\$156.73
TSLA	-\$62.01	\$528.37
Total	\$3,400.16	\$30,910.63



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