

## Intelligent time series forecasting

*Introduction of system of data oscillators, improving the predictions and analysis quality of the system based on neural networks time series processing models is the subject of this paper. The system is processing the data to predict quotes of the financial instruments listed on exchanges: stocks, cryptocurrencies.*

### Time series predictive system

Forecasting and prediction based on historical data is a common for all industries, including semi-automated analytical systems based on statistics analysis tools and fully automated systems based on data processing algorithms and artificial intelligence approaches. Such systems had proved efficiency in normalized or less volatile environments. As for the systems with high level of volatility, straightforward solutions cannot be applied with the same level of efficiency.

During creation of the system, based on historical data processing and predictions of stock and other types of financial instruments listed on stock exchanges, I have faced with multiple challenges, addressing the spikes of volatility and market shifts. Initial approach for the predictive analysis system was to aggregate historical data, structure, normalize if required and process it with neural networks based on regression and long short-term memory (LSTM) models. Such approach is bringing descent results level, but further optimization is required.

To the moment, the system is processing following inputs of data:

1. Market prices for financial instruments (quotes), per day: highest, lowest, median, open and close prices.
2. Market volumes for financial instruments (volume): volume at the end of trading day.
3. Fundamental companies data, updated on half-year basis: revenue, costs, credit limits, profitability. This data is not available for cryptocurrencies and not added.
4. News with positive and negative marking.
5. Processed or calculated data based on listed above.

Forecasting stock prices is characterized by data intensity, noise, non-stationary, unstructured nature, a high degree of uncertainty and hidden dependencies, due to this reasons prediction of the system can be false for each particular financial instrument, that is why assessment for portfolio is used, with a focus to maximize the profit of portfolio during certain period.

Mechanism to assess the quality of predictions for each financial instrument: prediction considered successful if quote predicted (QP) is actually higher comparing to actual price on the market, so if trader actually places trade with amount of N financial instruments (N) actual price (QA) can make profit (P), higher than transaction costs (C), during next 3 days if sold with the highest price (QH) during this period:

$$QP_{t1} > QA_{t1} \quad (1)$$

$$P = N * QH_{t2} - N * QA_{t1} > C \quad (2)$$

$$QH_{t2} > QA_{t1} + C \quad (3)$$

For portfolio A, formed with financial instruments  $A_k$ :  $A = \{A_1 \dots A_k\}$ , the profitability is evaluated every day, so till end of evaluated period the profit for N days:

$$P(A) = \sum_{i=1}^N P(A_i) > 0 \quad (4)$$

During execution of the time series prediction system if become clear that data itself comes with high level of noise and had to be enriched with new entry attributes. Two oscillators were selected for use, calculated based on the available historical data: Chande Momentum Oscillator and Aroon Indicator. Both oscillators are producing the indication of market trends for periods for each financial instrument, to take investors sentiments at the moment into focus for making predictions.

The Aroon Indicator is actually comprised of two separate indicators: Aroon up and the Aroon down. Aroon up is calculated based on the length of time since a particular security or index has reached a recent high. Conversely, Aroon down is a measurement of time since a recent low. Number of periods taken: 10 days, 25 days, 50 days.

$$Aroon\ Oscillator = Aroon\ Up - Aroon\ Down \quad (5)$$

$$Aroon\ Up = \frac{Number\ of\ Periods - Number\ of\ Periods\ Since\ Highest\ High}{Number\ of\ Periods} * 100 \quad (6)$$

$$Aroon\ Down = \frac{Number\ of\ Periods - Number\ of\ Periods\ Since\ Lowest\ Low}{Number\ of\ Periods} * 100 \quad (7)$$

Chande Momentum Oscillator calculates the difference between the sum of recent gains and the sum of recent losses and then divides the result by the sum of all price movement over the same period.

$$Chande\ Momentum\ Oscillator = \frac{Number\ of\ High\ Close\ per - Number\ of\ Low\ Close}{Number\ of\ High\ Close\ pe + Number\ of\ Low\ Close} \quad (8)$$

Illustrations of oscillators can be found below:



Figure 1: Aroon Oscillator



Figure 2: Chande Momentum Oscillator

Test runs were executed for 2500 stocks listed on NYSE exchange for neural networks based on regression and LSTM models. 4 runs executed for each period and neural network type and medians of results used for predictions and following qualitative analysis execution.

Table 1.

Comparison of predictions with and without oscillators – stocks

Period	Profit, %			
	No oscillators, Regression	No oscillators, LSTM	With Oscillators, Regression	With Oscillators, LSTM
2018-11-15 – 2019-11-15	64.8%	68.2%	84.0%	72.8%
2019-11-15 – 2020-11-15	38.1%	36.2%	43.8%	39.6%

Acquired results show that application of oscillators can significantly improve results of selected predictive models. The difference in profitability between periods is mainly due to nature of markets: growing overall 2018-2019 and highly volatile 2019-2020. The results were stable during 82% of test runs. The efficiency significantly improves for regression neural network with flash of network after every run, and less effective in LSTM.

Test results are showing that application of Aroon Indicator is bringing at least 40% of false prices change signals as this indicator does not involve volumes of trades, can't be fully mitigated by Chande Momentum Oscillator. Further system will be improved with few more attributes to mitigate discovered issues: on-balance volume, stochastic oscillator and other calculated parameters.

### References

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