USING FUZZY AND FRACTAL METHODS FOR ANALYZING MARKET TIME SERIES

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Abstract: In this contribution, we investigate the possibilities of using fuzzy and fractal methods for analyzing time series of market data. First, we implemented and tested a fuzzy component that provides fuzzyfication by the Mamdani Larsen inference method with static rules using not only Gauss but also Cauchy and Mandelbrot distribution. Second, we implemented and tested a fractal component that provides fuzzy clustering by the Takagi Sugeno method with dynamic fuzzy rules. Looking for an optimum, we simulated many parameter combinations and compared the results. We present some interesting results of our experiments.

1 INTRODUCTION

Currently, it is not difficult to collect and store very large data representing time series. However, there is a question whether it is possible to extract any information usable for trend forecasting (meteorology, biology, seismology, finance) and how to do it.

Data about financial markets is very interesting. There are large time series available and the eventually obtained forecast can be easily tested. The question is whether a forecast exists, of course.

There are different hypotheses about processes in markets. Under Efficient market hypothesis (Fama, 1970), (Malkiel, 1996), markets were assumed to be efficient in the sense that prices reflected all current information that could anticipate future events. There is a statistical requirement that market returns were normally distributed as white noise. This traditional capital market theory has been modeled by probabilities since the first approach in (Bachelier, 1964) (originally published in 1900 as Ph.D. Thesis).

More recently, Markowitz (Markowitz, 1952), (Markowitz, 1959) used the standard deviation as a measure of the risk of investment, and the covariance of returns as a measure of diversification of investment, where uncorrelated or negative correlated stocks reduced the risk of portfolio. The next famous work based on probabilities is Black-Scholes option pricing model (Black and Scholes, 1973).

Later, some anomalies in market development have been found. They were explained by the fact that different investors have different access to information (e.g. insiders know more), different investment horizon (short-term investors, long-term investors), and different interpretation procedures. Based on these phenomenons, an Inefficient market hypothesis was formulated (Shleifer, 2000) but the anomalies cannot be modeled easily.

The probability model of markets used in (Fama, 1970), (Markowitz, 1952), (Black and Scholes, 1973) has one advantage and one disadvantage:

- The advantage is that it can be simply described by tools for Gaussian statistics.
- The disadvantage is that the measured data, i.e. the market returns, are not distributed normally. Using the current computer technology and the known time series (e.g. 103-years known daily prices of Dow Jones Industrial), the difference between the theoretically supposed distribution and the distribution found by experiments is very significant. This was documented in many works starting with Mandelbrot (Mandelbrot, 1962), (Peters, 1994) and others. Compared to normal distribution, the real distribution of market returns is characterized by asymmetry, by higher peaks at the mean and fatter tails that do not converge to zero.

The Fractal market hypothesis (Peters, 1994), (Peters, 1996) places no statistical requirements on the market development process. The goal is to include the investor behavior and to find a model that fits to observated time series. The components of investor behavior are investment horizon and crowd be-

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havior. Investors have different horizons of investment. Hence, they have different strategies for buying and selling. Further, there are panics and stampedes caused by the known crowd behavior of investors. It has been found that markets have a memory and their behavior is not characterized by white noise (no memory) as suggested in (Fama, 1970) but by black noise (Peters, 1994).

All investors are interested in the prediction of market movements. Short-term investors follow technical analysis, long-term investors follow fundamental analysis. Often a combination of both approaches will be used.

Theoretically, market movements cannot be predicted succesfully as both efficient market theory and fractal market theory say. But there is not only local noise. Also, non-regular and non-periodic global deterministic movements called “trends” are present. It is very probably not predictable when they start and how long they take. Investors try to estimate the trend begin and the trend end and use loss-limiting strategies that control buying and selling stocks.

So, the goal of such a strategy is to indicate that a trend started, resp. finished and generate a corresponding buy signal, resp. a sell signal, in such a way that the gain is greater than the loss in the investment horizon. To simplify the problem, we do not discuss problems of taxes, problems of money management, problems of hedging and other more complex strategies that are used by traders and investors.

The motivation of our project is to build controllers based on fuzzy and fractal technology and test, what can be gained with fuzzy and fractal strategies compared to the often used strategies based on technical indicators of technical analysis.

Our original approach is that we implemented and tested not only Gauss but also Cauchy and Mandelbrot distributions in our fuzzy component. The published fuzzy-controllers discussed in Section 2 (Related work) use Gaussian distribution of price deviations even though it is known that the Gaussian normal distribution does not fit to the reality very well. We compared the results and found that the Cauchy distribution is more efficient than the others.

Further, we implemented and tested a fractal component using fuzzy clustering and the Takagi Sugeno method of dynamic fuzzy rules. This method brings the best results. All methods were tested on daily prices of 100 stocks of NASDAQ100 (see Section 9 for more details).

The rest of the paper is organized as follows. In Section 2, we discuss related work. In Section 3, we introduce the developed system. In Sections 4, 5, and 6, its components are described. The synthesis of the components is discussed in Section 7. The goals of our investigation are explicitly stated in Section 8. Section 9 describes the implementation, experiments, and results. In the last section we conclude.

2 RELATED WORK

The idea that the market returns are not normally distributed is not new. It has been published in (Mandelbrot, 1962). In (Dourra and Siy, 2002), a system using the Mamdani Larsen fuzzy inference method is described but with the Gaussian distribution in background. In (Castillo and Melin, 2002), a system using the Takagi Sugeno inference method was used to calculate the fractal dimension of a time series. We extended this approach using the Hurst exponent and correlation quotient. In (Raimondi et al., 2007), a system with technical indicators and lately a fuzzy system (using triangular membership function) with static fuzzy rules is described. This system was tested with data from January, 1st, 2000 to July, 7th, 2006 and documented that the fuzzy system performed better than the system using technical indicators.

3 THE SYSTEM DEVELOPED

The main components of our system and their features:

- Technical indicator component
  (used MA, TBI, MACD, MAcut, dTD),
- fuzzy-control component
  (ROC, stochastic indicator, and support/resistence indicator are used to get input data for fuzzy component),
  - Static fuzzy rules,
  - Mamdani Larsen fuzzy inference,
  - Defuzzyfication.
- Fractal analysis component
  using additional input data (fractal dimension, Hurst exponent, correlation, trend)
  - Fuzzy clustering and dynamic fuzzy rules (Takagi Sugeno inference method),
  - Interpretation of the result.
- Decision strategies,
- Synthesis of results.

These parts will be discussed in the next sections.

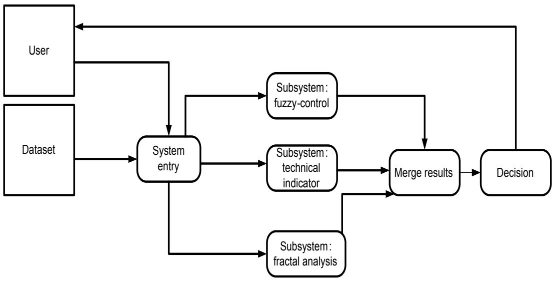

Figure 1: The system architecture and dataflow.

4 TECHNICAL INDICATORS COMPONENT

Technical analysis is based on a study of patterns on charts, as well as price trends, as well as support and resistence levels at which rising or falling trends may be halted or reversed. The main idea is that all information necessary to forecast the market is stored in the existing time series. Some technical indicators have been defined to indicate a trend's begin, its end, and its strength. Most short-term investors use technical analysis because it reflects the current investors' behavior. The effectivity of technical indicators has been investigated by (Hellstroem and Holmstroem, 1997b), (Hellstroem and Holmstroem, 1997a).

We have used it for two purposes:

- First, to get input parameters for the fuzzy control component (technical indicators (Kirkpatrick and Dahlquist, 2006) used: rate of change indicator, stochastic indicator, and Support/resistance indicator)—see Section 5.
- Second, to get input parameters for the technical indicator component (technical indicator used: MA, TBI, MACD, MAcut, dTD)—see Section 9.2. We normalized the used technical parameters into the interval [0..1].

5 FUZZY COMPONENT

Fuzzyfication provides the transformation of numeric input data (sharp data) into fuzzy data (unsharp data). Values of technical indicators such as rate of change indicator, stochastic indicator, and Support/resistance indicator have been used as input data.

5.1 Technical Indicators as Input for the Fuzzy Component

In this component, technical indicators will be computed to be used as basics of input data for the fuzzy component.

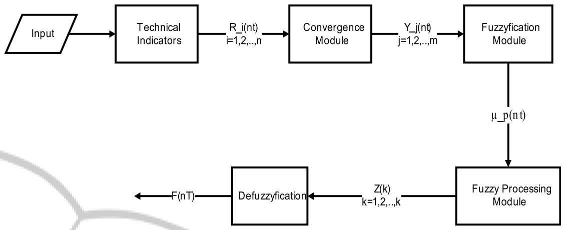

Figure 2: Fuzzy component.

Rate of Change (ROC). This indicator describes the absolute difference between the the current stock price and the price n days ago:

$$
\begin{aligned}
sp &= \text{last closing stock price} \\
ROC &= sp(today) - sp(today - ndays)
\end{aligned}
$$

Stochastic Indicator. The main idea behind stochastic indicator is that rising price tends to close near its previous highs, and falling price tends to close near its previous lows (definitions are given below). K - D stochastic indicatr was introduced by Lane (Lane, 1984). Usually, indicator $K(nT)$ (denoted often as %K - fast line) und $D(nT)$) (denoted often as %D - slow line) are used. We computed two values for time interval n, where

$$
\begin{aligned}
sp &= \text{last closing stock price} \\
lp &= \text{the lowest price} \\
hp &= \text{the highest price} \\
ap &= \text{average price of m days} \\
K(nT) &= \frac{sp(today) - lp}{hp - lp} * 100 \\
D(nT) &= \sum_{i=n-3}^{n} \frac{K(iT)}{3}; n \geq 3
\end{aligned}
$$

Low resp. high price means here the lowest resp. the highest stock price in the given time interval. The lag of 3 days used in D(nT) is a value recommended by traders. Very probably, it represents an experience that price changes older that 3 days have a very small influence.

Support/Resistance Indicator.

$$\begin{aligned} sl &= \text{Support level} \\ rl &= \text{Resistance level} \\ \text{sl} &= Avg(nT) - 2 * \sigma(nT), \\ \text{rl} &= Avg(nT) + 2 * \sigma(nT), \\ \text{where} & \\ \sigma(nT) &= \sqrt{\frac{\sum_{i=n-m}^{n}(sp(day_i) - Avg(day_i))^2}{m}}, \\ Avg(nT) &= \text{ap} \\ &= \frac{\sum_{i=n-m}^{n} sp(day_i)}{m} \end{aligned}$$

5.2 Convergence Module: More Input Parameters

In this component, the indicators mentioned above are used to generate more parameters. We used the following equations from (Dourra and Siy, 2002):

$$\begin{aligned} Y_{ROC}(nT) &= \frac{R(nT) - R((n-30)T))}{R((n-30)T)}, \\ n \geq 30, & \\ Y_{d(ROC)}(nT) &= Y_{ROC}((n-2)T) - Y_{ROC}(nT), \\ n \geq 2, & \\ Y_D(nT) &= D(nT), \\ Y_K(nT) &= K(nT), \\ Y_{D-K}(nT) &= Y_D(nT) - Y_K(nT), \\ Y_{Res}(nT) &= Avg(nT) + 2 * \sigma(nT) - R(nT), \\ n \geq 30, & \\ Y_{Sup}(nT) &= R(nT) - (Avg(nT) + 2 * \sigma(nT)), \\ n \geq 30, & \\ Y_{Avg}(nT) &= R(nT) - Avg(nT), n \geq 30, \end{aligned}$$

$R(nT)$ is the stock price on the n-th day, $D(nT)$ und $K(nT)$ are indicators defined above and $Avg(nT)$ is the average stock price during the observation time interval.

5.3 Fuzzyfication, Fuzzy Processing, and Defuzzyfication

This part of our system generates forecast using the Mamdani Larsen inference method. The membership functions and rules are implemented as being static. The indicators described above have been used as input parameters in a similar way as in (Dourra and Siy, 2002). We used 11 fuzzy rules for fuzzyfication and the Gaussian bell function (in the first approach - the imp rovement is given in Section 9.1) as the membership function ($SUP = 100$ und $INF = 0$). The output membership function is shown in Fig. 3.

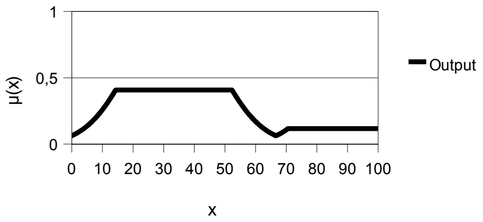

Figure 3: Output membership function.

The output membership function is sent to the defuzzyfication module. We used the center-of-area method producing a value in the interval [0..100].

6 FRACTAL ANALYSIS COMPONENT

This component uses stock prices as input data. In the part Fractal data calculation (see Fig. 4), the following data will be computed:

- Box dimension and fractal dimension,
- Hurst exponent,
- Correlation,
- Trend in interval.

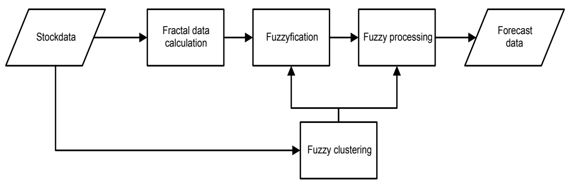

Figure 4: Fractal architecture.

The fractal dimension of the time series is a real number of the interval [1;2] which can be seen as a metric measuring how much the time series is jagged. A value near 1 means that there is a trend similar to a line, a value near 2 means that there are very many positive or negative changes in the interval. To measure the fractal dimension, a box covering method is used. The graph of the time series has to be covered by a set of smallest quadratic nonoverlapping boxes of the same size. The fractal dimension (exact: the fractal capacity dimension) is the number of such boxes that contain at least one point of the object (Castillo and Melin, 2002). Then, we can calculate the fractal dimension using the following formula:

$$Dim = \frac{\log_{10}(number-of-boxes)}{\log_{10}(\frac{1}{size-of-boxes})} \quad (1)$$

The box size is normalized in relation to the size of the interval.

To obtain the Hurst exponent, we first have to eliminate all linear trends from the data. Then, we define a time interval N and find the range R and the standard deviation S in this interval. We can derive the Hurst quotient as $\frac{R}{S}$ or calculate the Hurst exponent (values in interval [0;1]) as:

$$H = \frac{\log(\frac{R}{S})}{\log(\frac{N}{2})} \quad (2)$$

Time series with H near to 1 have trends, time series with H near to 0 are near to a white noise and no trend can be found and forecasted. The Hurst exponent has a close relation to the fractal dimension:

$$Dim = 2 - H \quad (3)$$

The correlation quotient (value of interval [-1;1]) specifies the linear correlation between elements of the time series. A value near to 1 indicates a positive trend, values near to -1 indicate a negative trend. The following formula (Bravais-Pearson) will be used ($\bar{x}$ is a mean value):

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (4)$$

The trend in an interval is calculated as the difference between the stock value at the begin and at the end of the interval.

The fuzzy-component used for the fractal analysis subsystem (Fig. 1) uses fractal data (fractal dimension, Hurst exponent, correlation coefficient, and trend) as input parameters. They are processed by a fuzzy control system using the Takagi Sugeno inference method. The membership function and the rules are not defined as being static. They will be found dynamically using fuzzy clustering of time series in a similar way as in (Castillo and Melin, 2002).

We assigned the cluster number to 4, being inspired by (low, medium, big, large). The clustering is analysed by the c-mean clustering method. It gives us the weights a_{ij} we need for the output function calculation. In our system, this process will be repeated any 150 days with the last 364 data sets.

Having the membership functions given by clustering the fuzzyfication can start to calculate the output function directly according to:

$$y_{res} = \frac{\sum_{i=1}^{n} E_i * (a_{i0} + a_{i1} * x_1 + ... + a_{im} * x_m)}{\sum_{i=1}^{n} E_i} \quad (5)$$

There are more methods available how to calculate variables E_i which denote how much the rule R_i matches. We have used c-mean clustering that calculates E_i using

$$E_i = \frac{1}{(\frac{||\vec{x}-\vec{c_i}||}{\sum_{k=1}^{c}||\vec{x}-\vec{c_k}||})^{\frac{2}{m-1}}} \quad (6)$$

The value of the output function has to be qualified in some way, i.e. we have to specify the threshold for buy and sell signals. To find some empirical values we analysed 100 stocks in the time interval $2003-2009$. We found using simulation that is was most effective (at least in the analysed time interval) to have $+6\%$ as a threshold that should be crossed to generate a buy signal and -6% as a threshold for sell signal.

7 SYNTHESIS OF COMPONENT RESULTS

In the previous parts, all three components have been described. The obtained results, i.e. the buy and sell signals, have to be merged together as shown in Fig. 1.

First, we used the following merging formula, which we denote as absolute merging:

$$result = rFC + \frac{(rTI - 0.5) * 100}{2} + \frac{rFR - 50}{2} \quad (7)$$

where rFC is the result of fuzzy-control, rTI is the result of the technical indicators, rFR is the result of the fractal component. The variable $result$ is in the interval $[-50...150]$.

Second, we used the following formula, which can be denoted as mean merging:

$$FC = doFC * rFC \quad (8)$$

$$FI = doTI * (rTI * 100) \quad (9)$$

$$FR = doFR * rFR \quad (10)$$

$$result = \frac{FC + TI + FR}{doFC + doTI + doFR} \quad (11)$$

where variables doFC, doTI, and doFR have values 0 or 1 and indicate whether the results of the fuzzy control (FC), the technical indicators (TI), and/or the fractal control (FR) are present.

7.1 Decision Strategies

The resulting value of the whole system is a numeric one, but we need a qualitative value for the decision. This means, we need thresholds for the definition of signals for buy and sell. We defined two thresholds UTL (upper limit) and LTL (lower limit) and implemented the following strategies:

- Low risk strategy - $LTL = 49$ and $UTL = 51$ - very careful but the frequency of buy and sell can be very high.
- High risk strategy - $LTL = 40$ and $UTL = 60$ - more risk but the frequency of buying and selling is not as high.
- Variable border - the last values (0 means all past data, 256 means the last 256 days) have been analysed and the best combination of LTL and UTL will be used.

In Section 9, we show which decision strategy brings the best results.

8 GOALS OF OUR INVESTIGATION

As we stated in Section 1, market returns (exactly, increments of market returns) are not distributed normally in real markets, even though normal distribution will be used in routine business. We stated the following questions as objectives of our investigation:

- which parameter combination used in the technical indicator component will bring the highest gain,
- which distribution function will bring the highest gain when used in the fuzzy-controller,
- which tuple of fractal analysis parameters will bring the highest gain,
- which component of our system will generate the highest gain,
- which combination of components can generate more gain than each of them separately.

9 IMPLEMENTATION, EXPERIMENTS, AND RESULTS

The presented system has been implemented in Java as a multi-threaded component of our information system (Kroha and Gemeinhardt, 2001), (Kroha and Baeza-Yates, 2005), (Kroha et al., 2006), (Kroha and Reichel, 2007), (Kroha et al., 2007), (Kroha and Nienhold, 2010). A detailed description of the design and implementation of the presented system is out of the scope of this paper and is given completely in (Lauschke, 2010).

For our experiments with the implemented system we used time series of all stocks from NASDAQ100 (daily prices) in the time interval from January, 1st, 2003 to October, 1st, 2009. When looking for the parameters' value by simulation, we used an investment of \$ 10.000 and transaction costs of \$ 10. The implemented system runs on Apple MacPro with 8 cores, 8 GB of memory, and 2.26 GHz.

9.1 Non-Gaussian Distribution used in the Fuzzy Component Contribution

In the following Table 1, we can see the results, i.e., the value (in thousands) of the invested \$ 10,000) when changing the distribution in the fuzzy-controller and the strategy. The elapsed time was about 15 minutes.

Table 1: Results of Fuzzy-Control component.

Strategy	Gauss	Cauchy	Mandelbrot
Low Risk	\$ 15.3	\$ 16.8	\$ 14.5
High Risk	\$ 17.8	\$ 19.9	\$ 19.3
Var. Border 0	\$ 17.7	\$ 19.7	\$ 18.3
Var. Border 256	\$ 15.2	\$ 14.7	\$ 15.1

We found that in most cases (Table 1) the Cauchy distribution used in the fuzzy-controller gives the best results (about 99 %) and the Gauss distribution the worst results (about 78 %). Considering strategies, the high risk strategy results were the best.

9.2 Technical Indicators Component and its Contribution

We used the technical indicators with the following parameters: Moving Average (17), TBI (9,17), TBI-line = 100, MACD(12,26) - always calculated any 3 days. The highest gain (about 60%) was achieved for the most simple merging (for variable border 0), but it was rather small compared to fuzzy-control. Hence, we do not describe the details about the used methods of technical indicators merging here.

9.3 Fractal Component and its Contribution

In this experiment, we used the 6 % threshold as explained above and used the rules recomputation, i.e.

the new clustering, every 150 days. The highest gain (about 100 %) was achieved when using the tuple [box-dimension;correlation] for fuzzy clustering. The gain was higher than that of the other components. To get the results, we needed about 32 minutes.

Table 2: Results of fractal component.

Input	Result
Box-corr	$ 20,024.19
Hurst-corr	$ 17,797.11
Box-Hurst-corr	$ 16,038.22
Box-Hurst-corr-Trend	$ 16,951.81

9.4 Synthesis of Components and their Contributions

We just described the individual behavior of components. The next question was whether we can get more profit when using some specific combination of the components' results. Because of the very large number of possible combinations, the simulation alltogether took about 71 hours. The best gain of 88.4 % was obtained with the following parameters of our system:

- Synthesis of the components' results = mean,
- Distribution used in fuzzy-controller fuzzyfication = Cauchy,
- Clustering in fractal analysis according to [Hurst exponent; correlation],
- Decision strategy = high risk.

We do not discuss the details of the synthesis because we can see that the best solution is to use only the fractal component (higher gain than the combination with other components).

9.5 Comparison with the Strategy Buy & Hold

One of the often used strategies is Buy & Hold. A stock will be bought at the begin of the interval and sold at the end of interval. In the next experiment, we choose an interval (21.11.2000 - 26.9.2008) in which the value of the German market index DAX was more or less equal at the begin and at the end.

Then, we simulated how much an investor would have earned when using our fuzzy or fractal controller for his/her transactions. The Tables 3, 4 contains quotients that denote how many times the investement would have been increased. We can see that the fractal method brings slightly better results than the Buy & Hold strategy but in this case technical indicators bring good results.

The number of transactions is important, too. The Buy & Hold used only 2 transactions, fuzzy approach used 7 transactions, technical indicators 70 transactions, and fractal approach 117 transactions.

Table 3: Comparison with Buy & Hold - Fuzzy and Fractal methods.

Index	Buy & Hold	Fuzzy	Fractal
DAX	0.9365	1.2236	1.0326
Nasdaq100	0.6636	0.5206	0.8755

Table 4: Comparison with Buy & Hold - Technical Indicators.

Index	Techn. Ind.	The best combination
DAX	1.5593	0.6884
Nasdaq100	0.6306	0.7256

10 CONCLUSIONS

As we have discussed, market returns are not distributed normally and the Gauss distribution used in our fuzzy-controller delivered the worst results. According to the Fractal market hypothesis, non-periodical trends exist that correspond to the global determinism component of the process and black noise that corresponds to the local randomness component.

The result is that it is not possible to forecast market changes but it seems to be possible to achieve some gain in the long-term investment when usig fuzzy or fractal technology. Of course, we did not consider taxes but they are different in various countries and changes in time. Further, the data processing, especially in the case of fractal analysis, is very time consuming as given above.

In the light of the recent financial crisis we have to mention that we can only use public data for our processing and forecasting. May be that there is a currently hidden accounting fraud by a company like by Enron in 2001 which was named by the magazine Fortune as the America's Most Innovative Company for six consecutive years or by Lehman & Brothers in 2008. May be that there is a currently hidden accounting fraud by a state caused by years of unrestrained spending like in Argentina in 1999 or in Greece in 2008. We cannot expect too much from public data processing.

In further work, we will try to combine the fuzzy and fractal methods with our text classification of market news (Kroha et al., 2006), (Kroha and Reichel, 2007), (Kroha et al., 2007), (Kroha and Nienhold, 2010). The goal would be to investigate whether the result could be improved.

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