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Translated from Russian.

Why popular methods of technical analysis fail to work

We assert that essentially no method, which is widely available for average traders, can work in a developed highly-liquid market. Availability of a method means either simplicity of independent realization, or the possibility to buy autotrading programs for a low price. For example, it costs almost no efforts even for a beginning trader to perform calculation of a cross point of two MA lines.

This statement can be easily proved. The market is formed by its participants: banks, trading and manufacturing companies, and, to some extent, the whole population of traders. Traders make markets effective. If one could bar speculative operations on the market, then of course the market would not be fully predictable. Though it would become possible to forecast markets quite effectively using standard methods, which are widely and successfully used in other spheres of economy - retail, banking, insurance business, etc. Total turnovers, created by traders, are not too big, in comparison to other market turnovers. But market dependencies are not very strong too. All traders strive to "squeeze dry" the market and thus they destroy market dependencies. Simultaneously there happens distribution of profit, which in extreme case can be "squeezed" from market regularities, between the whole "community" of traders. Of course, profit distribution is not equal. Obviously, the "lion's share of the pie" goes to those, who make trade using concurrence of MA lines, Elliott waves, Fibonacci levels and other methods, which are described in various literature. Some "specialists" run to other extremes, confusing complexity of a method with computational complexity – they start using "complex" methods like "Neural networks", in many cases without understanding how demanding standard algorithms of "neural networks" are to the volume and quality of processed data.

We heard an opinion that forecasts for popular indicators can self-actualize. Supposedly, the majority of traders see a forecast in their trade terminals, start to open positions in a certain direction. Owing to this, the demand grows and the price for the instrument starts changing in the direction positions that are being massively opened. But do not forget about the liquidity factor. At some point due to the skew of demand and supply there happens supply deficiency, and traders, feeling the liquidity risk, start competing in moving the prices to closest opposite positions in "Market Book", in order to close their positions earlier than others do. Usually at such moments we see sudden trend turns, which are cliff-like. Not everyone manages to close positions in time. And this is sad.

There is also an opinion, that by studying market charts carefully one can see trends, trend turns, head and shoulders, three samurais, contemplating the spring-time sakura at the hillside of Fujiyama, and other market "figures". After finding these signs, make profitable trade on their basis. The problem is that the human visual system (a trader is also a human) had been evolving for many millions of years to perform such tasks as mammoth hunting. Yes, genetically we are Cor-Magnons, pickers of mushrooms and berries, mammoth hunters. Over millions of years the human visual system adapted for forecasting of *natural* processes. But modern markets exist no more than 100 years, and are the *artificial* process. That is why the human eye easily finds in market charts some trends and figures, which are in fact absent in the market. *And that is why instead of successful pips hunting there is «loss hunting».*

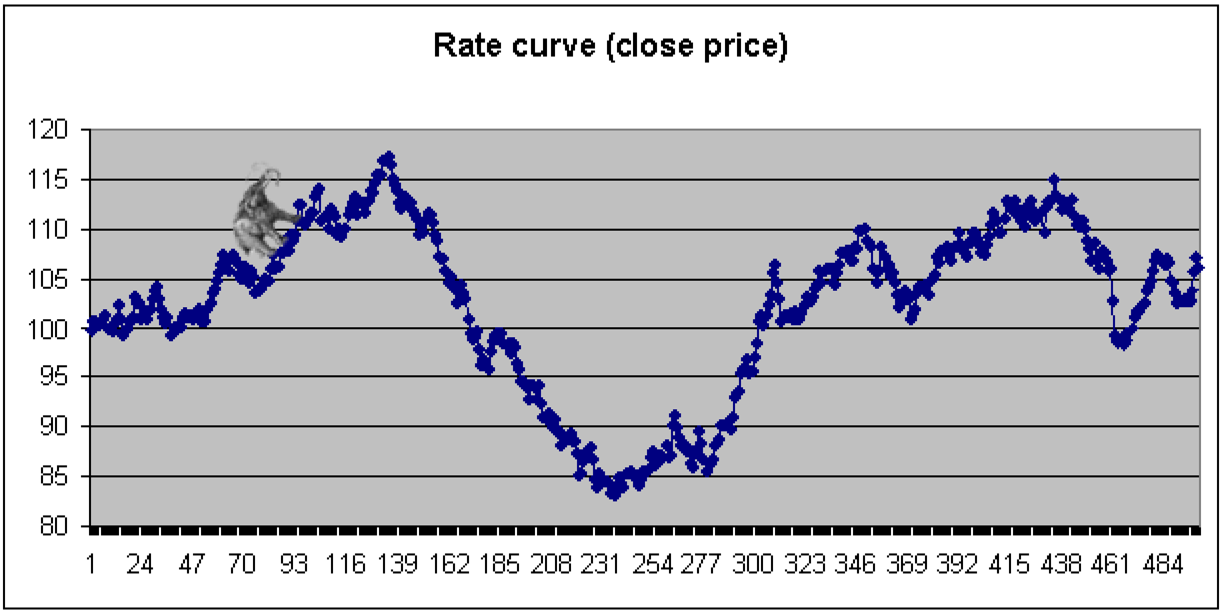
In this section we gave qualitative reasoning (Theory). Further, we will try to show the ultimate search complexity of market dependencies by the example of statistic analysis method use (Practice).

Market data analysis

Let us try to show complexity of market data analysis on a simple example. We will approach the market data analysis as the time-series analysis. We will need some knowledge about analysis of time series, autoregression, statistical hypothesis proof. *Any specialist who occupies himself with autotrading must have the basic knowledge on these topics. If there are people who disagree with this statement, they can argue against it in the article discussion.*

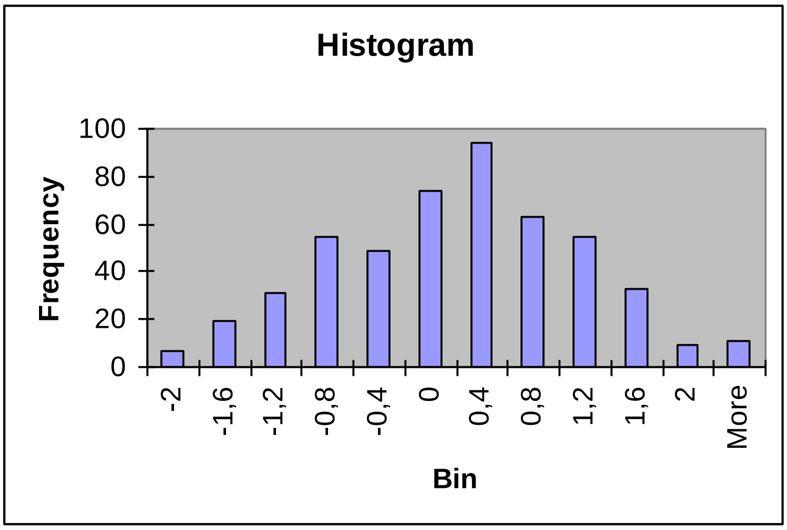
In general, analysis of dependencies in time series is understood as the search of any dependencies, that can be expressed by mathematical tools. Nevertheless, due to the framework of the article we have to limit ourselves by standard methods of analysis – analysis of autoregression and distribution.

Picture 1 shows an example of limited observation of some time series, which can be the quotation history (for example, bar closing prices) of some market instrument (currency pair, shares, market index, etc.). We can say, that the chart reminds the Forex behavior.



Picture 1 – Limited observation of some time series. Possibly quotations of some Forex currency pair. **Do you see the mammoth?**

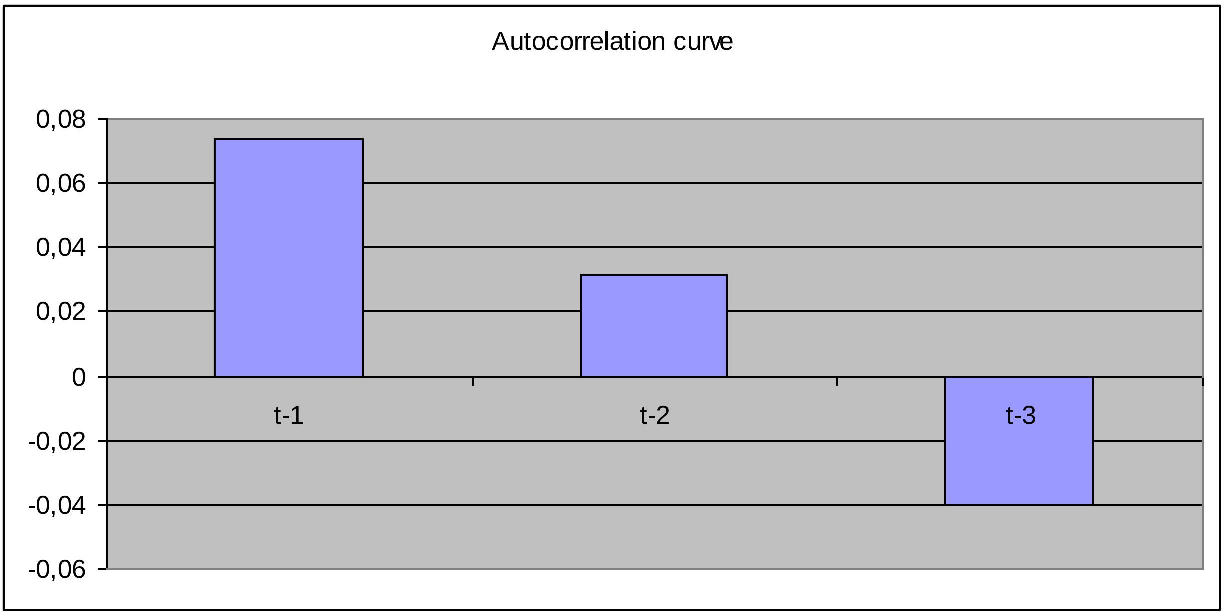
Let us remind you, that the first moment is taking of the difference from the neighboring time series counts. The operation of the initial series first moments transfer to the time series sometimes allows getting rid of nonstationarity. Let us analyze distribution of the first moments of the given time series. Picture 2 shows estimation of first moments distribution.



Picture 2 – Distribution of the first moments of time series (see Pic. 1)

This distribution can be considered normal (normal distribution) with zero mathematical expectation and single standard deviation. We do not give here calculations, which prove these conclusions, and suggest that readers should believe our bare word.

Establishment of the fact of normal distribution gives us the right to use standard methods of statistic hypotheses verification, and particularly, check the presence of autocorrelation (Pic. 3).



Picture 3 – Autocorrelation factors for moments of the 1st order of the initial time series

The autocorrelation curve in the chart descends fast. As early as at t-3 (with the lag = 3) autocorrelation changes its sign from the positive to the negative one. The maximum correlation factor was found at t-1 (with the lag 1) and is equal to 0.074. The critical correlation level in the dual-sided t-test with the significance level of 0.05 and the quantity of observations 500 is equal to approximately 0.089, which is higher than the maximum autocorrelation factor we found.
This indicates that according to statistic standards presence of autocorrelation is not proved. An alternative solution – is to use a less strict significance level (For example, 0.1 or 0.2).

Here we see the typical problem of market data analysis, all assessments of essentially important dependencies are at the boundary or beyond the limits of statistic provability. At the same time the cost of incorrect conclusions is quite definite – *losses*.

Trade strategy creation

As at the stage of preliminary analysis we observed weak, but still positive autocorrrelation, we can try to create several simple trade strategies, which use this characteristic. For simplification we will not take into account spreads and stop-levels.

It took the author of the article 20 minutes to build three simple trade strategies, which do not pretend to any optimality (advanced character), and which during decision making use only analysis of three last closed bars. Created strategies do not have settings and do not require the optimization procedure.

We will assess efficiency of strategies by the yield curve and the profit factor. The profit factor can be found as a relation of the sum of all wins to the sum of all losses

$$profit\_factor = \frac{\sum win}{\sum lose}$$

. There are also exist other criteria of trade strategies efficiency, but for purposes of the article the given criteria are enough.

Table 1 - strategy profit factor.

Strategy	Profit factor
Strategy 1	1.17
Strategy 2	1.3
Strategy 3	1.12

As we can see in table 1, the best efficiency is demonstrated by the trade strategy No.2. But let us remember, how we assessed the certainty of autoregression. We assessed the level of confidence and performed the proof procedure of the statistic hypothesis of correlation existence. Can we also create similar procedures of significance proving for assessment of trade strategies? This is the second problem of market data analysis — imperfection of statistical tools for assessment of trade strategies, in comparison to «classic» tasks of applied statistics.

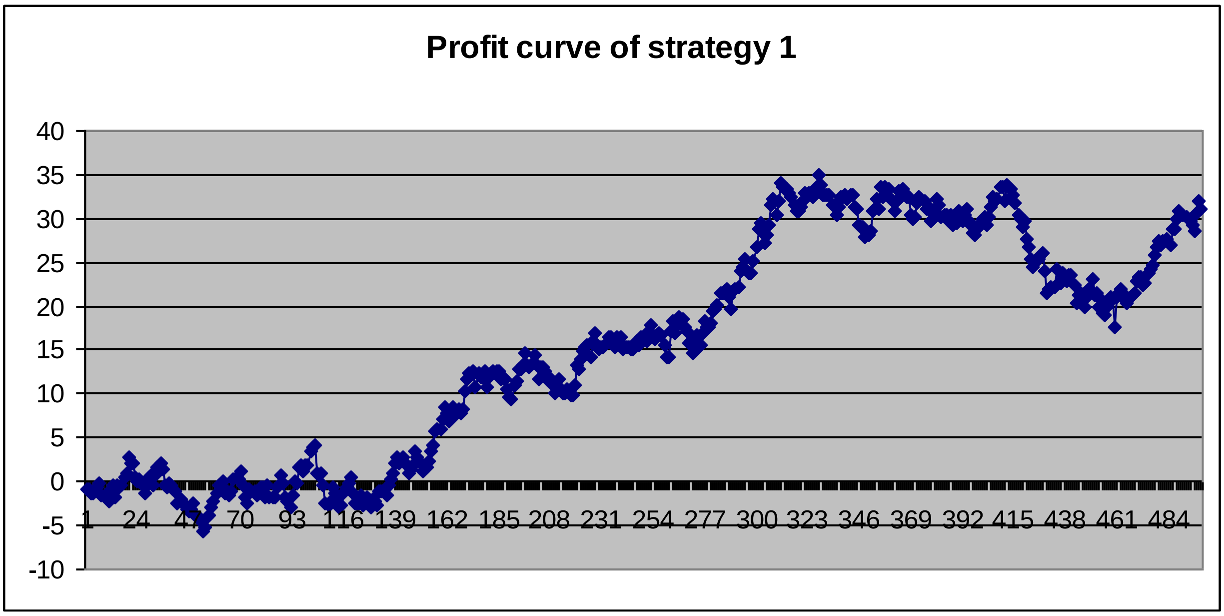
Some trade strategy specialists may say that based on their «experience» the values of profit factor found are insufficient, that it is required to reach the profit factor value of at least 2, and that it is required to decrease drawdowns. But how do they reach such values? Probably due to introduction of settings, optimization, reduction of the optimization period for «better accounting» of the latest market changes. But all such measures in «classic» applied statistics automatically tighten and complicate the proof of presence of statistic relations, effect. We do not think that the same requirements apply to the sphere of trade automation. Thus, it is impossible to avoid strict statistic analysis.

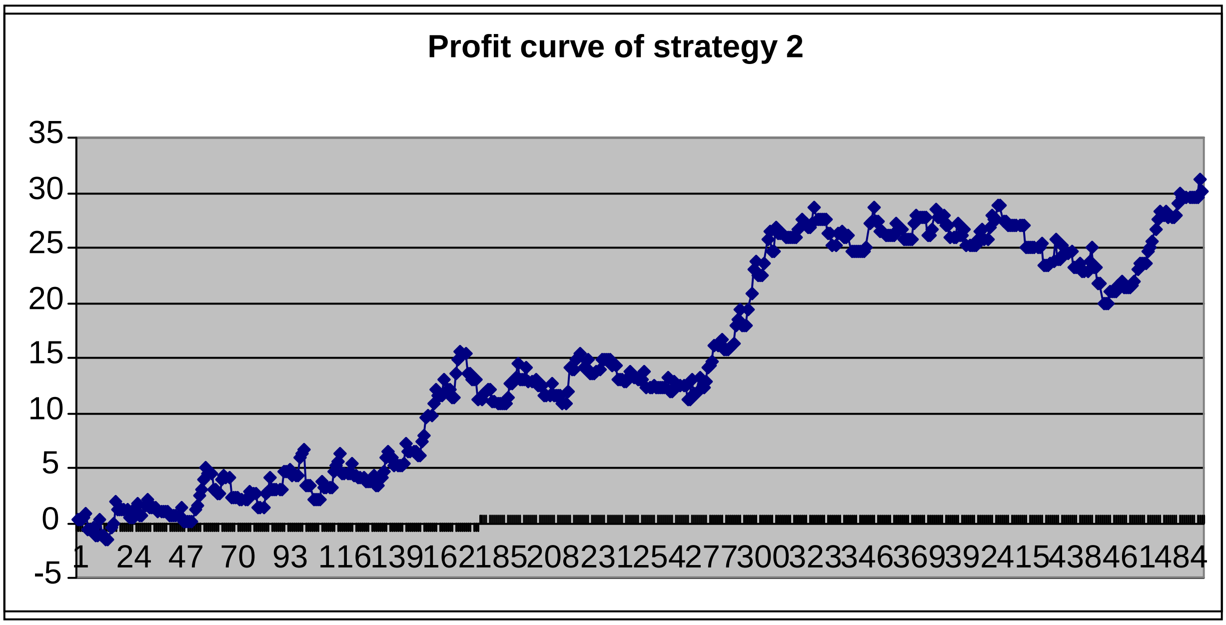
Below are yield curves for the given trade strategies, which were created using the available limited data samples (Pic. 1). Do you feel sure about profitability of these trade strategies? Have you decided to use them in trade? Take the risk.

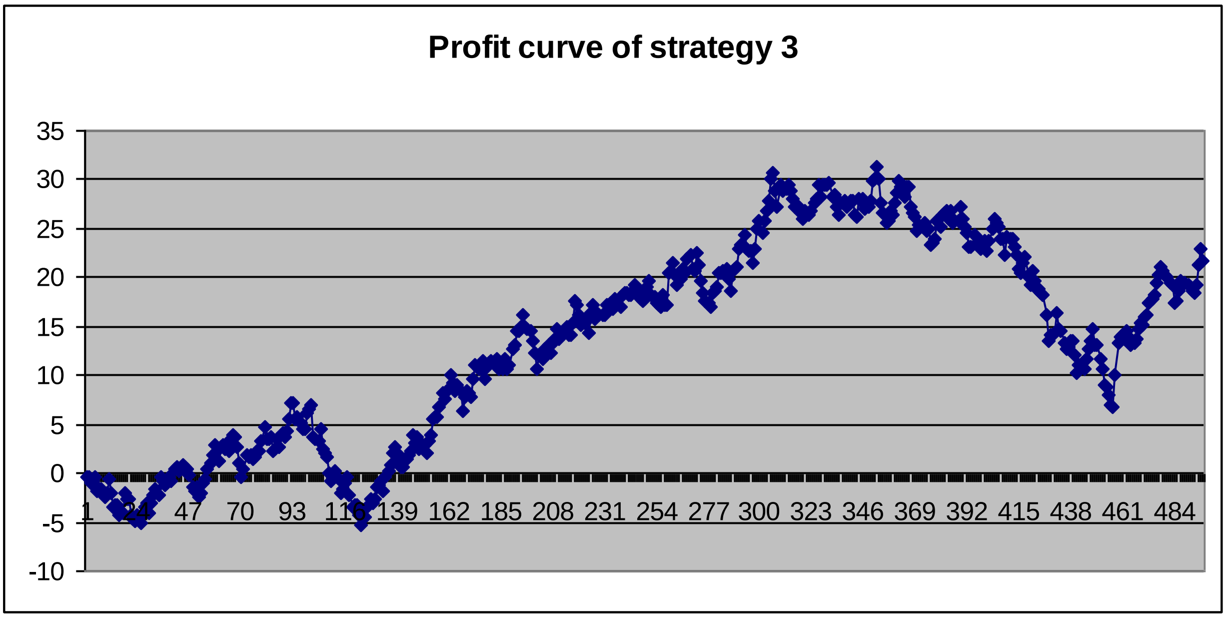
Let us show our hands, the time series, shown on picture 1, is fully described by the Brownian motion model and created using a good random number generator from the package MS Excel

Data Analysis (it is also possible to use the RAND function in Excel). *In other words, as a matter of principle, it is impossible to build a profitable trade strategy at this time series.* But it so strongly reminds the Forex quotation series! Very strongly…

In this case we already know the time series model and we know its characteristics for sure. But in fact we fail to fully identify the model of market time series. Moreover, we can only detect some «weak» statistic dependencies.







Summing up the results

By a simple example we demonstrated some complex problems, which arise during creation of trade strategies:

1. A simple visual analysis of trade strategy efficiency does not give good results for the same reason, for which the visual recognition of trends and figures does not give any results. A human eye is genetically adapted to mammoth hunting and gathering, but not to analysis of complex artificial processes.
2. Simple technical analysis tools, including popular indicators and instruments for trade robots creation, prevent traders from making money. Popular tools do not allow a trader to stand out from the «crowd» to get a bigger piece of the trader's pie. He only gets «crumb» that is «spread» in a thin layer among the whole family of traders. And even this crumb is effectively swallowed by spreads and commission fees of intermediary-brokers.
3. Practically important statistic relations that are found in market data fail to pass standard procedures of hypothesis proving.
4. For widely spread metrics of trade strategy efficiency there are no sound estimates of confidence intervals, procedures of critical values identification (authors of the article had to develop such procedures themselves). It is hard to express numerically our chances to get profit when following some trade strategy.
5. We can only roughly identify statistic conditions for markets, such as, for example, distributions. Stationary state of market time series or their transformations cannot be proved.

In our opinion, solution of the above mentioned problems may consists in usage of the market history, which covers significant period of observations (5 and more years). We also suggest to widely use cross-testing of trade strategies and simulation modeling, nonparametric assessment methods. However, all these suggestions require complex software, extended programming and significant computational resources.

We invite all interested readers to participate in the discussion of the listed problems, offer your solutions, and share your experience.

Mathematics. Model of market time series.

In this article we tried to present our ideas, using mathematics in the minimum required volume. In order to understand the section it is enough to have the basic knowledge of applied statistics and time series mathematics. This offer is intended for readers-mathematicians, who are exacting to accuracy of definitions.

Let us describe mathematically the limitation of the task sphere. We have a task to find dependencies in limited observations of the time series x which has the following structure $x_t = f(x_{t-1},\dots,x_{t-n}) + \varepsilon(t)$, where $n \geq 0, M(f) = 0, M(\varepsilon) = 0, \frac{D(f)}{D(\varepsilon)} \to 0$. In this case f - is a deterministic component, $\varepsilon(t)$ - is a random component, M – is the mathematical expectation, D - dispersion. In other words we consider the time series with zero mathematical expectation (average) of series terms, with an additive random term (additive error), in which the interference level is significantly higher than the deterministic component. An example of the extreme degenerate case of such series is random deviations $x_t = \varepsilon(t)$, which can be achieved by taking the first moment ($\Delta = x_t - x_{t-1}$) from the Brownian motion model $x_t = x_{t-1} + \varepsilon(t)$.

In the article we hypothesize that market time periods can be described with almost sufficient accuracy using the given model.