INTRODUCING A NEW TECHNICAL INDICATOR BASED ON OCTAV ONICESCU INFORMATIONAL ENERGY AND COMPARE IT WITH BOLLINGER BANDS FOR S&P 500 MOVEMENT PREDICTIONS

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Abstract
This research paper demonstrates the invention of the kinetic bands, based on Romanian mathematician and statistician Octav Onicescu's kinetic energy, also known as "informational energy", where we use historical data of foreign exchange currencies or indexes to predict the trend displayed by a stock or an index and whether it will go up or down in the future. Here, we explore the imperfections of the Bollinger Bands to determine a more sophisticated triplet of indicators that predict the future movement of prices in the Stock Market. An Extreme Gradient Boosting Modelling was conducted in Python using historical data set from Kaggle, the historical data set spanning all current 500 companies listed. An invariable importance feature was plotted. The results displayed that Kinetic Bands, derived from (KE) are very influential as features or technical indicators of stock market trends. Furthermore, experiments done through this invention provide tangible evidence of the empirical aspects of it. The machine learning code has low chances of error if all the proper procedures and coding are in play. The experiment samples are attached to this study for future references or scrutiny.

Keywords
Kinetic bands, Octav Onicesu's Informational Energy, Bollinger Bands, Boosting Modeling

JEL Classification
C51

Introduction

Investments are mushrooming all over the world and newer markets are increasing in the blink of an eye. However, there are several factors that play a role in ensuring an optimal environment for financial investments. The most important factor being the prediction of market trends on stock prices, as they determine the net profit and loss to the chosen business. The evolution of the market as well as the unpredictable trends, have been a major outdoing of several business investors. The ability to produce material to ease stock market predictions has been a dynamic issue within the past few years. Simple financial mistakes have led to significant crises in the world, rocking the most powerful economies. There is a current need for technical indicators that can be integrated into modelling systems in order to mimic the trends of stock market prices. The invention of the kinetic bands has a ready solution for the unpredictable market prices that could last for generations to come thus save people from financial disaster.

Methods and materials

The informational energy is a concept inspired from the kinetic expression of classical mechanics. From the informational theory point of view, the formulas informational energy is a measure of uncertainty or randomness of a probability system and was introduced and studied for the first time by Onicescu in the mid-1960s.

The informational energy and entropy are both measures of randomness, but they describe distinct features. This chapter deals with the informational energy in the framework of the statistical modelling. Here, we aim to display the main properties of the informational energy, its first and second variation, relation with entropy, and numerous worked out examples.

Definitions and Examples

For example if a random variable X=1,1,1,3,5,3 the kinetic energy is computed as following: There are 3 categories in the random vector 1,3,5 and the probabilities of each category are:

Prob(1) = 3/cardinality(X) = 3/6 = 1/2 (1)
Prob(3) = 2/6 = 1/3
Prob(5) = 1/6

KineticEnergy(X) = ″sum of squared probabilities″
= $\text{Prob}(1)^2 + \text{Prob}(3)^2 + \text{Prob}(5)^2$ (2)
= $(1/2)^2 + (1/3)^2 + (1/6)^2$
= 0.3888.

Nottice also:
If X = 1,1,1,1,1,1,....1,1,1,1 then KineticEnergy(X) = $\text{Sum}(\text{prob}(1)^2)$ = 1. (3)
In this case, there is no diversity and everything is perfect certain the kinetic energy is at maximum value 1.

Nottice in this case is something strange. Making an analogy with the atomic nuclei, this example with maximum kinetic energy is simmilar with the one in which the atomic nuclei come very close one from other, resulting in releasing large ammounts of energy as in our toy example, phenomenon called nuclear fusion.

IF X = 1,2,3,4,5,.. + infKineticEnergy(X) 0. (4)

Meaning that at maximum diversity and highest uncertainty the kinetic energy is at very low value near to zero.

Nottice in this case probably resulted from previous 1, the categories from the random vector could be interpreted as atomic nuclei resulted from expansion of the previous ones with high energy resulting in large number of atoms with low energy in the end, and we could think of that as nuclear fission.

This means that kinetic energy is bounded between (0 and 1].

Let S=$\{p\varepsilon = p(x;\varepsilon) I \varepsilon = (\varepsilon^1,\dots,\varepsilon^n) \in E\}$ be a statistical model.
The informational energy on *S* is a function *I*:E$\rightarrow \boldsymbol{R}$ defined by

$I(\varepsilon) = \int_x^{\infty} p^2(x,\varepsilon)dx$ (5)

Observe the energy is convex and invariant under measure preserving transformations, properties similar to those of entropy.

In the finite discrete case, when $x = \{x^1, \ldots, x^n\}$, formula is replaced by:
(ε) = $I(\varepsilon) = \sum_{k=1}^{n} p^2(x^k,\varepsilon)$
(6)

While Eq. (2) is obviously finite, we need to require the integral to be finite. However, if $x = R$,we have the following result:

Let $p(x)$ be a probability destiny on Rsatisfying:

(i) $p(x)$ is continuous

(ii) $p(x) \to 0 as x \to \pm\infty$

The informational energy of p is finite, i.e... The following integral convergent:

$I(p) = \int_{-\infty}^{A} p^2(x)dx < \infty$
(7)

Proof: let $0 < a < 1$.
Then there is number $A > 0 such that p(x) < a for |x| > A$
This follows the fact that $p(x) \searrow 0 as |x| \to \infty$, Writing:

$I(p) = \int_{-\infty}^{-A} p^2(x)dx + \int_{-A}^{A} p^2(x)dx + \int_{A}^{\infty} p^2(x)dx$ (8)

We note that:

$\int_{-\infty}^{-A} p^2(x)dx < a \int_{-\infty}^{-A} p(x)dx = aF(a) < a$
(9)

$\int_{A}^{\infty} p^2(x)dx < a$ $\int_{A}^{\infty} p(x)dx = a$
(10)

Where $F(x)$ denotes the distribution function of $p(x)$ since the function $p(x)$ is continuous, it reaches its maximum on the interval $[-A, A]$, denoted by M, then we have the estimation:
$\int_{-A}^{A} p^2(x)dx < M$ $\int_{-A}^{A} p(x)dx = M(F(A) - F(-A)) < 2M$
(11)

It follows that $I(p) \leq 2a + 2M < \infty$, which ends the proof.

The Kinetic Bands
Similar to Bollinger Bands, in which the rolling mean by a fixed, past back time window usually of 20 days. The upper and lower bands are defined at +/- two standard deviations

from the rolling mean; we define the kinetic bands based on the previous kinetic energy as follows:

- Rolling kinetic: = the rolling kinetic energy of the digits from the decimal part of a stock, foreign exchange rate currency or indexes.
- Upper kinetic band: = the band consisting of points that are 2 standard deviations from the rolling kinetic.
- Lower kinetic band: = the band consisting of points that are 2 standard deviations below the mean.

Experimental Findings

For the experimental research data set (500 S&P companies), we have downloaded open-source historical data from Kaggle website ***https://www.kaggle.com/camnugent/sandp500***.
From the historical data, the Machine Learning Models optimization will take very long for some to re-run the experiment, therefore we have decided to subset by symbol 'AAL' and in this way, our historical data contains 1259 rows with closing prices starting from 08 February 2013 until 02 February 2018.
Our goals were to optimize the Machine Learning Model by tuning the parameters to find the best performance metric. We have automatically constructed the target feature called, move' with signification that the price tomorrow will be higher than price today the value of the target will be 1 and if price tomorrow will be lower than price today the cost, the goal will be 0. Since our objective is a binary variable, we have chosen accuracy as the performance metric.
As for the Machine Learning Model, we have selected the Random Forest Classifier from Python Sklearn library. The best window we found, that maximized the performance metric was of size 45. In addition, we have also selected two standard deviation distances (from the mean/ kinetic energy) in order to create the tested Bollinger Bands and Kinetic Bands.
As good practice, to ensure the data is more Gaussian-shaped, we have applied log-transformation, before feeding into the Random Forest Model, the Kinetic Bands, Kinetic Energy and Bollinger Bands. The grid of parameters for which we conducted grid search in order to find the ones that would maximize the performance metric, is the following:

- n_estimators = [1,2,3,4,5,6,7,8,9,10,20,30,40, 50, 75,100,125, 150, 175,200]
- max_depth = [2, 4, 6, 8]
- The total number of training steps was 800.

Where:
n_estimators: integer, optional (default = 100)

The number of trees in the forest:
max_depth: integer or None, optional (default = None)

The maximum depth of the tree:
If None, then nodes are expanded until all leaves are pure or until all leaves contain less than min_samples_split samples.

Results

The optimal number of estimators was found to be 175, and the max_depth parameter was established to be six this resulting in the best accuracy score of **0.537**.

After training the model on complete data with these parameters, a plot was created to describe the feature importance, displaying that the lower kinetic band and the upper kinetic band both more influential power then Bollinger bands in predicting trends.

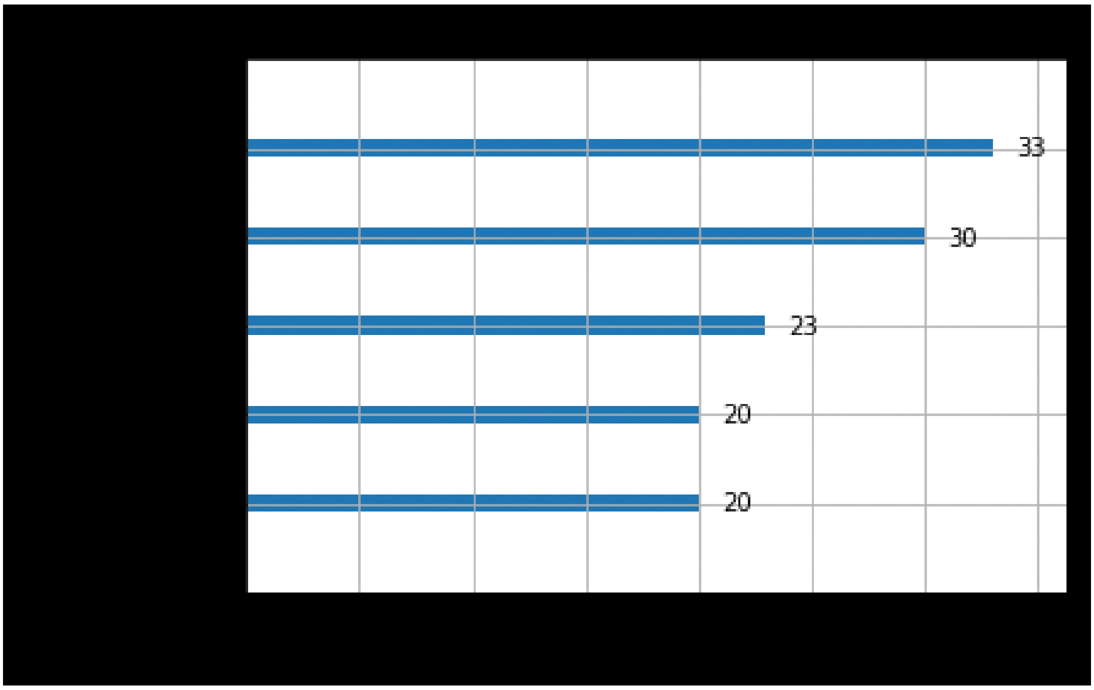

Fig. no 1. Feature importance of Kinetic Bands in comparison to Bollinger Bands

Source: Project Kinetic Bands, Alexandru Daia, 2018

Conclusions

The result of the experimentation of the kinetic bands proves that they can be quite reliable in predicting the prices of commodities through the analysis of previous data. The kinetic band indicator is the best technical indicator that can survive to the next generation producing highly accurate results that predict the future prices. The machine has the potential of knocking off the competition from the already existing devices that complete the projection task as well as price predictions as technical indicators. Research continues to improve on some of the parts that can make the machine work even better.

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