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Escape Velocity backed avalanche predictor- Neural evidence from Nifty

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Abstract*: *The concept of escape velocity has been extended from physics to stochastic finance and used as an avalanche predictor. Escape velocity being an extreme event serves as a perfect proxy of this stochastic finance event. This study identifies the propensity of the capital market to explode on rare occasions, which could be termed as avalanche. The frequency of such movement (both up and down) may not be high; however, the amplitude will be significantly high. The underlying for the study is Nifty, bellwether Indian bourse. Escape velocity has been calculated for Nifty on a daily basis for 17 years and prediction modelling has been constructed applying artificial neural networks (ANN) and multiple adaptive regression splines (MARS) simultaneously. Results indicate queer coupling of US events and Nifty apart from the evident behavioural traces. This research work is aimed at providing an implicit form of avalanche predictor from a distinctly different reference point.

Keywords: *Escape Velocity, Avalanche Predictor, Behavioural Trace, Black Swan.*

I. INTRODUCTION

In an astoundingly interesting study on heliospheric economy [15], where the solar wind movement against interstellar creating the space amongst magnetic bubble layers; human heliospheric expansion was used as a space based quantitative economic model. Though escape velocity came in the said context couple of times, yet its application in the capital market was not the objective of this innovative piece of work. Another excellent piece of work depicted that complex financial system; mostly operate as a complex network with multiple junctions of overlapping tasks. Such a system, when become self-sustaining, in the absence of any stimulus whatsoever could overcomplicate itself. Due to this reason, [4] it could reach a runaway stage and ultimately run into chaos. Escape velocity made an appearance here as a velocity for an economy to attain, so that it could reach a self-sustaining network system. Similar idea has been echoed by an eminent investor, [5] who believes that demand extension and borrowing from future will prevent US economy to reach the crucial level of escape velocity. Escape velocity, referred as sustaining economic growth in several economic studies was discussed earlier without any mathematical formulation. Secular stagnation, [13] a periodic dragger of the growth wheel of economy stayed as a concern for US and Japan, thus not allowing them to reach the economic escape velocity. Bank of England Governor [3] termed escape velocity as a “momentum necessary for an economy to escape from the many headwinds following a financial crisis”. Credit giant Moody’s used escape velocity [11] as a representation of fast-track growth trajectory. While assigning rating to National Mortgage Insurance Corporation ("NMIC") and its parent, NMI Holdings, Inc. ("NMIH"), they used the keyword to indicate the pace of growth. Though, low confidence, deflationary debt spiral (as increasing deflation will be inflating the value of debt continuously) and negative multiplier effect (employment-income-demand trio would be disbalanced) have been loosely linked with escape velocity buzzword in various blogs across the globe, yet mathematical research work on implementation of the said concept was found missing. The researcher bemoaned the dearth of published studies on financial escape velocity, during the rigorous process of relevant literature scrutiny. The global financial fiasco, back in 2008 was termed as an aftermath of large scale funding of negative NPV projects [10], thus triggering the credit pendulum to go into the pit. This opened up the glaring warts of credit research, which failed to identify the probable catastrophe in due course. The fundamentals however, rest on the uneven repayment structure, where the majority of repayment happens at the later stages, forming a catastrophe bond profile by all means. Under-priced financial insurance (CDS) too added fuel to the avalanche breakdown. In a global financial scenario where, volatility was increased by leaps and bounds with the introduction of catastrophe bonds and high frequency algorithmic trading, there could be a propensity of the bourses or in certain securities to break out the barrier (circuit filter) with an escape velocity. Escape velocity, though discussed sparingly, was found to be used in economic context in most of the occasions. These obvious gaps prompted a new knowledge creation and addition to the existing body of knowledge. The current body of work is designed as a missing link between avalanche prediction (with the help of propensity of the bourses to break free from the daily circuit filters), setting up threshold for avalanche and to search for a behavioural trail. Whether avalanche can be predicted or not is a question in itself. The global quantitative finance world is in a dilemma as black-swan is fighting dragon king. The famous black-swan [14] concept also stood firm on three pillars.

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First and foremost being the lower ability to predict but with high consequences and generally could be understood with a retrospective way.

Contrary to this Sornette launched dragon king [12] concept which could be mathematically predicted with the help of probable lose measurements (termed as drawdowns) and well in advance as well. Sudden exponential growth in the capital market does send signals of a positive bubble formation, which eventually will be led to an avalanche breakdown of perpetual money machines. The interesting aspect of this endless debate hints towards a plausible explanation though. Black swan events are gigantic in proportion, rare in frequency and could change the feat of the associated underlying (capital market in this piece of work), keeping the forecasters at bay. As they are rare in nature, hence between two such events predictions are logically possible. There is an uncanny resemblance with the state change of matter. There is a sharp leap during the phase transition, where prediction of energy state with the help of temperature is not possible accurately, as the temperature in those junctions remain constant. However, once the phase changes, prediction becomes plausible and possible at the same time. Hence avalanche is quite similar to black swan and phase transition of matter. Thus, a prediction zone makes more sense, instead of one finite number. Majority of the credit studies happen along the lines of volatility testing and determination. However, this study has been clearly targeted at the rare event of avalanche. The extreme financial events could be targeted by the introduction of this unique piece of econophysical formula of escape velocity, as major crashes or avalanche are significantly similar to black swan events. Black swan [14] need not become big on day one however eventually they become gigantic in stature. Similarly, avalanche trigger will be present may be for a while but avalanche will come suddenly. Hence, instead of a point, a zone of prediction or a range of prediction could be better option. Investment banks, credit rating agencies, regulators and all layers of market participants will be able to utilise this model to predict possible catastrophe, which could lead to an avalanche breakdown.

II. METHODOLOGY

A. Econophysics Trail

Instead of choosing the path of nerd knowledge, the researcher chooses the path of econophysics. However, this comes with a caveat of travelling through the unchartered territories in an unconventional fashion. The current study has been developed on lack of mathematical modelling of escape velocity. Unlike, the blogs and articles published so far, the current piece of work focuses on the escape velocity modelling on a stock market, rather than the entire economy. In a scenario of a possible black hole, the particle should ideally escape with an escape velocity higher than the speed of light. In stock market context, if one stock wants to explode with an escape velocity, it has to break the circuit filter barriers and speed up. In such a scenario, kinetic energy equals potential energy.

Hence,

$$\vartheta=\sqrt{(2GM/r)}$$

Where, ϑ is the escape velocity, M is the mass from where the particle is moving out, r is the distance between the particle and from the place where it is moving out, G is the Newton constant (or gravitational constant) which determines the attraction-based pull. When the particle wants to break free, G will oppose the same. Now from stock market point of view, M is the volume (mass) of the Index from which the stock is going away, r is the circuit filter, as that define the feasible width within which it can move around. G could well be some kind of opposing force, as this is the attraction between the stock and the index. If we consider that G is same for all the stocks, then we find the larger the trading volume will be the escape velocity will be larger too, provided circuit filter remain constant. At the outset, it comes as an evident fact, from the premise above that large caps are more vulnerable when compared against mid-caps.

$$\vartheta=\sqrt{(2*G*\omega/\tau)}$$

Where, τ is circuit filter of the stock market under consideration; ω is the net volume on a daily basis of the same stock market; G is universal gravitational constant. Hence, if ω is on the larger side, systemic collapse or avalanche breakdown couldn't be ruled out. Since, the volume of the stock index is a cumulative volume of all the constituents (securities), hence, escape velocity is index specific and not stock specific. Again, as the large cap stocks and indices have substantially more volume over mid-caps and small caps, hence, the escape velocity for blue-chip indices would ideally be higher, when compared to the penny stocks and indices. Hence, it wouldn't be wrong to say large cap index has higher propensity to get derailed compared to small cap index. If τ or the circuit filter has been removed completely then the index theoretically can move up or down to ∞.

B. Underlying Stochastic Time Series

The underlying stochastic time series is CNX Nifty from 2nd February 2000 to 17th August 2016. This period has been carefully chosen on the basis of presence of important global events. Dotcom bubble, Enron collapse, 9-11 in US, credit crisis (globally from 2007 to mid-2009), sharp global recovery (capital markets), rupee crackdown against USD and major political changes (locally as well as globally) feature during this eventful period.

C. Neuro Machine Learning Tool

Usually back-propagation neural network with loop of back propagating errors is a classic combination of interconnected multi-layered perceptrons. These perceptrons are cardinally processing units. They are termed as neurons. Neurons are generally structured in multiple layers. Initial signal is received in the first layer as independent variables. The ultimate layer is coined as the output layer. It is the output, which keeps on sending error information to the input, till the error is minimised and reaches a local minimum. Output usually is represented by a single neuron. Middle layers are either one or more, are often considered as a black-box.

Neurons, that are part of the definite structure, create feature vector, towards all plausible finite neurons.

$$a_j^{(l)} = \sum_{i=1}^{n} w_{ij}^{(l)} \; x^i + b_j^{(l)}$$

Where $x_1, \ldots\ldots x_n$ represent the multiple inputs of neuron j at hidden middle level *l*. The above-mentioned equation is a mathematical representation of neuron activation ($a_j^{(l)}$), at level *l*. The activation $a_j^{(l)}$ is then ably modified by non-linear differentiable function to provide output of neuron j, at level *l*. Supported by the rational application of artificial neural network structure used in natural sciences and social sciences, simple gradient descent scheme has been used [2], for continuous updation of weight and bias parameters.

$$[w^{(t+1)}, b^{(t+1)}] = [w^{(t)}, b^{(t)}] - \eta \nabla E(w^{(t)}, b^{(t)})$$

η is the learning rate of this network which is greater than zero. Apart from that $w^{(t)}$, weight vector at repetition *t* and $b^{(t)}$, the bias vectors at repetition *t complete* the equation. E (.) is the local error function, which has to be minimised by finding the local minima using gradient descent and back-propagating errors. ∇ E represents the gradient of E. Conventionally it has been observed by several researchers of repute that if the learning rate is extremely smaller, then the gradient descent mode will converge to a local minimum [2]. However, so far a value or range of possible learning rates were not found in a uniform manner, that the gradient descent converge to local minimum [1]. Mathematically it could be demonstrated that a neural network with a binary firing pattern resembles a networked computing system. The said system constitute of a directed graph with a well-defined structure [8].

Conventionally a binary alphabet A2= {0, 1} is accompanied by each perceptron or neuron which designate the neural activity. In this case 0, corresponds to non-firing neural state (no action) and 1, corresponds to a firing neural (action) state. The firing patterns (action) of Neural Network can thus be represented by the set of all binary strings of length N: $A_2^N = \{S_1 S_2 \ldots\ldots S_N : S_K \in A_2,$ k=1,2,3,…….,N}

The potency and category of each neural link is expressed with a weight S, coupled with a designated activation threshold. Transfer function indicates the state transfer (from non-firing to firing) of the neurons. The current study has been based upon [3, 6, 9, 1] Neural Network configuration in order to predict Escape Velocity (EV) of CNX Nifty. Three lags of EV have been put into use as the three inputs of the neural network.

D. Multiple Adaptive Regression Spline

Multivariate Adaptive Regression Splines or MARS (popularly known as) is a nonparametric regression mechanism without any assumption about the underlying relationship between the variables. On the contrary, MARS [7] demonstrate the relation from a newly constructed set of coefficients and basis functions generated entirely from the regression. The cardinal "mechanism" by which MARS algorithm operate as several fragmented linear regression, where each breakpoint (estimated) confirms the "region of application" for a definite regression equation.

$$Y = f(x) = \beta_0 + \sum_{m=1}^{M} \beta_m h_m(x)$$

Here the summation is across the M nonconstant terms in the model. In this equation Y is predicted as a function of the predictor x, however indirectly through a function $h_m(x)$. Intercept parameter is (β_0). This process resembles a selection mechanism of a weighted sum of basis functions from the large set of basis functions spanning all across.

III. RESULTS & DISCUSSIONS

Table 1.0 depicting the goodness of fit of the neural model

Neural Model	Model Fit	Predictions
Observations	3277	819
MAE Absolute	0.03339	0.03339
RMSE Absolute	0.04856	0.04802
Adj R Square	82.8%	82.8%

The table above depicts steady but substantially low values of both the error measures (namely, MAE and RMSE). Further assistance is evident from the adjusted R square values (82.8%, in both occasions).

Neural Model

$$\varepsilon\vartheta_{neural} = -0.0151318 + 0.771135\varepsilon\vartheta_1 - 0.634446\,\varepsilon\vartheta_1\varepsilon\vartheta_2 - 1.3883\,\varepsilon\vartheta_1\varepsilon\vartheta_3 + 0.763359\,\varepsilon\vartheta_1^2 + 1.005\,\varepsilon\vartheta_2\varepsilon\vartheta_3 + 0.374173\,\varepsilon\vartheta_3$$

Diagram 1.0. Depicting the rang-bound nature of the residuals of the following neural model

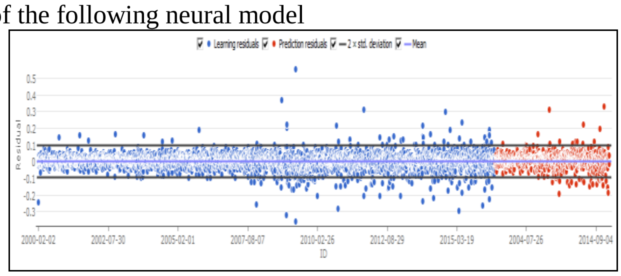
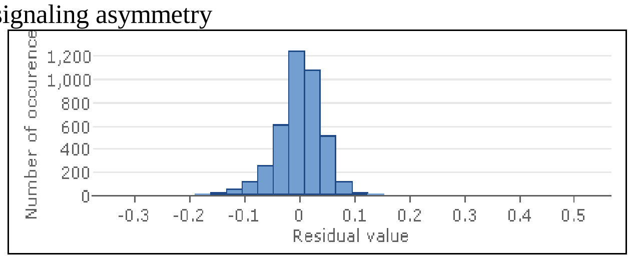


Diagram 1.1. Depicting the histogram of the residuals signaling asymmetry



Residuals are mostly range bound from 0.2 to -0.2. Residuals are found to be asymmetric, rules out probabilistic man-made symmetry. During the neural network analysis, it has been observed that about 3.6% (148 observations) residual data points are outliers.

Multiple Adaptive Regression Splines

Table 1.1

Model Specifications	Value
Independents	3
Dependents	1
Basis functions	9
Order of interactions	1
Penalty	2
Threshold	0.0005
GCV Error	11.73558
Prune	Yes

The output classifies the presence of Prune, to reduce complexity, improve accuracy by reduction of decision trees in a calculative measure. GCV or generalized cross validation too minimizes prediction error; hence a lower GCV is an indicator of a robust predictive model. Basis functions are various combinations of the independent variables on which the accuracy rests. Basis functions are represented by "Hinge Functions", hence they are range-bound and having a max value. Value of hinge function is referred to as "Knots". The value of knots proves that the study has impact since most of the knots are well above 1000. Also, knot EV2 being the most repetitive indicate towards the importance of EV2 as a predictor of avalanche.

Table 1.2

Name	Coeff EV	Knots EV_1	Knots EV_2	Knots EV_3
Intercept	2784.64			
Term 1	0.136919	3246.9		
Term 2	0.301461			1710.4
Term 3	-0.252437		5143.2	
Term 4	0.460506	1858.9		
Term 5	-0.116493			2427.5
Term 6	0.387753	5143.2		
Term 7	0.463579		3998.9	
Term 8	-0.651587		4580.6	
Term 9	-0.142526		2914.8	

Table 1.3

Regression Statistics in MARS

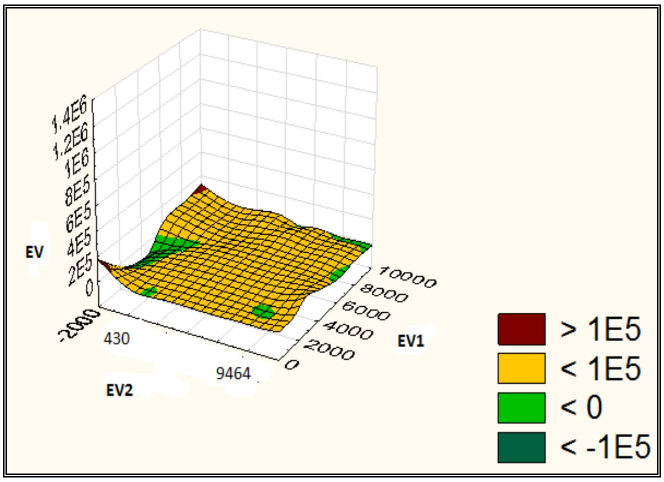
Mean (Observed)	2805.23258
Standard Deviation (Observed)	827.690171
Mean (Predicted)	2805.23258
Standard Deviation (Predicted)	754.170412
Mean (Residual)	0.0000000
Standard Deviation (Residual)	341.024939
Adjusted R Square	0.82982392

Mean of residual is zero; means that sum of the error term is zero. This in turn satisfies the condition of robustness of the MARS model. It could be observed that R^2 statistics in this calculation is equal to neural model R^2 value (82.8%).

MARS Model

$\varepsilon\vartheta_{mars}$ = 2.78464318732542e+003 - 1.36919801692453e-001*max(0, 3.24696965760131e+003-$\varepsilon\vartheta_1$) + 3.01461348514046e-001*max(0, $\varepsilon\vartheta_3$-1.71036524503335e+003) - 2.52437186026319e-001*max(0, 5.14315108947567e+003-$\varepsilon\vartheta_2$) + 4.60506356417637e-001*max(0, $\varepsilon\vartheta_1$-1.85890213993357e+003) - 1.16493321550952e-001*max(0, $\varepsilon\vartheta_3$-2.42751233149832e+003) + 3.87753320789109e-001*max(0, $\varepsilon\vartheta_1$-5.14315108947567e+003) + 4.63579395219228e-001*max(0, $\varepsilon\vartheta_2$-3.99894672132550e+003) - 6.51587403368507e-001*max(0, $\varepsilon\vartheta_2$-4.58057567038345e+003) - 1.42526170026109e-001*max(0, $\varepsilon\vartheta_2$-2.91481844279365e+003)

Diagram 1.2. Depicting the relative movement of $\varepsilon\vartheta_1, \varepsilon\vartheta_2$ and $\varepsilon\vartheta$ as a surface, hence predicting zone of avalanche



This model has to be used in the following way:

Post prediction of EV ($\varepsilon\vartheta$) by either MARS or Neural Networks (since both enjoy similar accuracy levels), we would be able to identify EV2 ($\varepsilon\vartheta_2$). Suppose, EV is predicted for a definite Monday, automatically that EV becomes the EV2 for the following Wednesday. Now, whether EV2 is in the zone of Avalanche or not will be easily identifiable by the zone definition (covered in detail in "Concluding Remarks"). This could well be used as a possible avalanche trigger.

IV. OUTCOME AND ANALYSIS

Since, both neural and mars have similar robustness, hence considering neural equation below:

$\varepsilon\vartheta_{neural} = -0.0151318 + 0.771135\varepsilon\vartheta_1$ -0.634446 $\varepsilon\vartheta_1\varepsilon\vartheta_2$ -1.3883 $\varepsilon\vartheta_1\varepsilon\vartheta_3$ + 0.763359 $\varepsilon\vartheta_1^2$ + 1.005 $\varepsilon\vartheta_2\varepsilon\vartheta_3$ + 0.374173 $\varepsilon\vartheta_3$

$\varepsilon\vartheta_{neural} = y$

Moreover, $if\ we\ consider\ \varepsilon\vartheta_1 = \varepsilon\vartheta_2 = \varepsilon\vartheta_3 = x$, for special case,

Change of escape velocity for unit change in lag of escape velocity is,

$$\frac{dy}{dx} = 1.14 - 0.5x$$

Integrating back the tiny changes, we get

$$y = -0.25\, x^2$$

Hence, under certain special conditions, escape velocity prediction too follows power law. Though, $\varepsilon\vartheta_1 = \varepsilon\vartheta_2 = \varepsilon\vartheta_3$ condition sounds theoretical, yet if the values are different in a narrow band ($\Delta\ \varepsilon\vartheta$ <0.005%) power law condition satisfies. Which confirms that escape velocity of the bourses is found to have a square power law relationship with its lags. This result is similar to another research that proves 'inverse cubic power law in volatility proxy' for the same underlying i.e. CNX Nifty; moreover another important research that pre-dates as well proves that even the returns of the same underlying asset class follow 'inverse cubic power law' [6], [9].

Interesting to note here that standard deviation of escape velocity (Nifty)from 2000 till 2016 is 8.2%, which tapers down to 6.2% (2009 till 2016) and further comes down to 4.9% (2013 till 2016). Even from 2000 till 2016-time frame, the per day standard deviation comes to 0.002% i.e. $\Delta\ \varepsilon\vartheta$. Since, the actual $\Delta\ \varepsilon\vartheta$ is lower than the narrow band threshold for power law condition to be satisfied, thus CNX Nifty avalanche pattern could well be predicted with escape velocity.

Escape velocity is nothing but the measurement of propensity to break free. The current study could point out certain crucial threshold for the Indian bourses. Interesting outcome has been spotted in the diagram above. Though largely escape velocity (EV), looked range-bound, yet in a queer zone it deep-dives below the zero mark (where, EV1 is hovering from 4000 to 6000 and EV2 is below 400). Explosion in escape velocity (EV) has been spotted twice (both times, EV tending to 2*10^5). Interestingly, both times, EV2 equals -2000, and, EV1 is zero and 10,000. Hence, volatility from EV1 is near nothing in two defined zones (50 to 4000 and 6000 to 10000), however, EV2 below 400 (upto -2000) resembled an avalanche trigger as both upside and downside explosion occurred post this. EV2 below 400 conditions was found to be satisfied on two specific dates. The first date is 25th July 2001 and the second being 20th May 2009.

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Ex-Investment Banker turned Researcher (Post-Doctoral) in the domain of Economics & Finance. Having thirty-seven noted Publications to credit in the Journals of repute till date. Specialty rests in Behavioural Finance, Econophysics, Investment Modelling, Index Construction & Machine Learning. His goal is to establish worldwide Research credentials in the domain of Finance & Economics. He covers, subjects like financial analytics, financial econometrics and financial engineering in reputed Universities in India and Europe. Currently taking care of 'Laboratory in Risk Management with Econophysics' in IMCU, Christ University, Bangalore. Successfully completed a three-year post-doc 'Major Research Project' as well.

Recipient of the Tuzla University Gold Medal, with 17 years of academic career. Currently in the Full Professor role, with the main focus on research in the area of finance and teaching at all three study levels at the Faculty of Economics (esp. heading the Doctoral Studies). Authored and co-authored six books and over 100 scientific and research papers published nationally and internationally. Mentored and supervised over 30 master and three doctoral dissertations, with other regular engagements.