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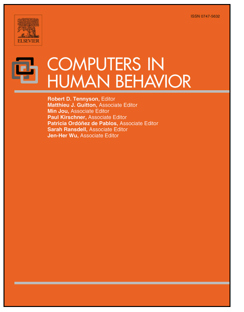

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Anticipating Movie Success through Crowdsourced Social media Videos

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Abstract:

Business houses and marketers have been relying on social media to affect consumer opinions and purchasing behaviour. In this paper a framework has been proposed to identify and quantify the emotive value of any movie trailer. The proposed framework made use of Dlib-ml (a machine learning toolkit) and a Genetic Algorithm inspired Support Vector Machine algorithm (GA*i*SVM) for parameter tuning and classification and emotive analysis of movie trailers. A case study comprising of 141 movies trailers released from Jan 1, 2017 till April 31, 2018 was done to investigate the relationship between emotive score of a movie trailer and financial returns associated with it. Results revealed a direct correlation between emotive score of a movie trailer and financial returns. Further, it was concluded that an emotionally intense movie trailer could result high financial returns in comparison to non-much emotionally intense trailers.

Keywords: Dlib-ml, Emotive response, Social media, machine learning, movie trailer release, SVM

1. Introduction

Business houses and marketers have been relying on social media to affect consumer opinions and purchasing behavior. Social media content have been frequently taken into consideration by marketing experts for deciding marketing mix. Business houses can potentially enhance profits by interacting with their customers through social media (Oh, Roumani, Nwankpa, & Hu, 2017). Researchers have found a strong correlation between consumer engagement and economic performance of business ventures. Movie trailers are advertisements, which not only capture viewer attention but also engage them to an upcoming movie. Expectations are built by showcasing actual scenes from the movie to generate interest within the mind of a moviegoer (Devlin, Chambers, & Callison, 2011). Release of a movie trailer is a major marketing practice and a considerable cost is associated with it. Efficiency of movie advertising content and execution seem overlooked by research community, specifically how the design of trailers can influence investors' valuation of the movie. For movie managers, it is very important to understand the financial impact of trailers prior to the release of the film. Evaluating the theatrical trailer before its release could substantially contribute towards enriching the contents of theatrical trailer and its sequence. A pre-release analysis is also important due to the fact that most crucial marketing decisions such as movie trailer launch, advertising, distribution and release timing are taken long before the actual movie release (Elberse, 2007). Investors rely on movie trailers to anticipate success or failure of any movie at the box office (Karray & Debernitz, 2015). Effectiveness of any movie trailer is directly proportional to the emotional appeal it could generate within a viewer (Iida, Takayuki; Goto, Akira; Fukuchi, Shoya; Amasaka, 2012).

In this paper, a framework has been proposed to identify and quantify the emotive value of any movie trailer. The proposed framework calculated the intensity of identified emotions using Dlib-ml (a machine learning toolkit) and a Genetic Algorithm inspired Support Vector Machine algorithm (GA*i*SVM) for parameter tuning and classification. Subsequently the relationship between the emotive score of a movie trailer and its performance at box office was investigated. Rest of this paper is organized as follows. Section 2 corresponds to review of literature and assumed hypothesis. Section 3 details the experiment design. Section 4 describes the case analysis followed by results and discussion in Section 5. Section 6 concludes the findings.

2. Review of Literature

The review of literature is organized in three sections. Section one is summarization of research findings relating movie trailers with financial returns. Section two includes studies investigating the correlation between emotional content of a movie trailer and its financial value. Section three briefs about available options to classify emotions.

Movie trailers are a form of advertising that are aimed to attract the viewers to theaters. The research community has studied the financial effects of trailer advertising exhaustively (Batra & Ray, 1986; Holbrook & Batra, 1987; Holbrook & Shaughnessy, 1984; Teixeira, Wedel, & Pieters, 2012). Investors invest a good deal in trailer advertising and seek greater returns on their investments. They are prepared to use newest of technologies such as Neuroscience to design custom fit trailers for enticing audiences.(Boksem & Smidts, 2015). Research has shown that forecasts of movie demand can be reasonably accurate at a very early pre-release stage, and that new information can influence anticipations about any movie's financial performance, resulting in stock price adjustments (Foutz and Jank 2010). Variation in stock returns immediately after the movie launch is the result of movie performance (Elberse & Anand, 2007; Joshi & Hanssens, 2009). Prior to a movie release in theaters, trailer advertising could provide valuable information to viewers and investors. It could also result in anticipations about the movie's future success (Karray & Debernitz, 2015). Studios need some way of measuring whether their investment will pay off months prior to release and therefore, analysis should focus on predicative factors that are available prior to release (Kaplan, 2013).

According to the popular Mehrabian Russell PAD (Pleasure, Arousal, and Dominance) model, the emotional responses to advertising mainly consist in pleasure and arousal (Mehrabian and Russell 1974; Russell, Weiss, and Mendelsohn 1989). Emotions were primarily studied by psychologists until the role of emotions in determining actions and behavior was discovered (Carlson, N.R., Heth, D.C., Miller, H., Donahoe, J.W., Buskist, W., Martin, 2009). Subsequently, it was found that emotions play a vital role in consumer decision-making (Solomon, 2008). There are two prominent approaches namely Facial Action Coding System (FACS) (Ekman & Rosenberg, 2005) and facial electromyography (EMG), used for facial expression analysis in consumer research (Poels & Dewitte, 2006). Though the said techniques can effectively be used to capture emotive response of respondents, yet very few studies provide empirical evidence of their effectiveness. All the potential factors mentioned in Table 1 are put into a trailer with the sole purpose of inciting a variety of emotions in the audience. Subsequently, recent advances in image analysis and pattern recognition open up the possibility of automatic detection and classification of emotional and conversational facial signals.

Table 1: Factors within a movie trailer that lead to a positive financial return.

Study	Potential factor for generating a positive financial return
(Stapleton & Hughes, 2005)	Graphics
(Elberse, 2007)	Star Power
(Elberse & Anand, 2007)	Production Cost
(Joshi & Hanssens, 2009)	Advertising expenditure
(Devlin et al., 2011)	Comedy and serious scenes
(Kaplan, 2013)	Social Media
(Karray & Debernitz, 2015)	Plot, violence, sex, humour, special effects and release time

As per available literature, emotions could either have positive or negative valence (McDuff, El Kaliouby, Kodra, & Picard, 2013). Also emotions are either Dimensional or Discrete. The dimensional view consists of two common dimensions namely Arousal and Valance (Osgood, Suci, & Tannenbaum, 1975). The discrete view of emotion consists of actual emotional states like 'happy', 'sad', 'anger', 'disgust' and 'neutral' etc. (Ekman, P. and Friesen, 1976; Izard, 1977). Effectively measuring such discrete states require additional hardware such as fMRI, EEG and Galvanic Skin Response (GSR) sensors, which would defeat the purpose of a cost effective pre assessment tool for industries (Northover, 2012). In contrast, facial expression is one of the most important cue to a human's mood/emotional state. Effectively identifying the emotional state of a being via facial expression has caught the eye of many researchers (Anderson & McOwan, 2006; Katsis, Katertsidis, Ganiatsas, & Fotiadis, 2008). Various attempts have been made to do make inferences through facial expressions (Fasel & Luettin, 2003; M Pantic & Rothkrantz, 2000; Maja Pantic & Rothkrantz, 2003). Feasibility to study content based psycholinguistic features for predicting social media messages was also investigated (Hwong, Oliver, Van Kranendonk, Sammut, & Seroussi, 2017). Use of supervised machine learning to overcome the limitations of human and computer coding procedures was also proposed. It was found that if the supervised machine learning could be used to code social media content, then a vast array of online information relevant to organizational research could too be empirically evaluated (Van Zoonen & Van Der Meer, 2016). Use of Artificial Neural Networks to overcome nonlinearity within economic growth forecasting was investigated. The study applied extreme learning method for single layer feed forward neural network (Sokolov-Mladenović, Milovančević, Mladenović, & Alizamir, 2016). Analysis of metrics and machine learning techniques was done to identify users with high reputation within an online community. The proposed techniques made use of machine learning using artificial neural network and clustering to identify reliable users (Procaci, Siqueira, Braz, & Vasconcelos De Andrade, 2015). Though much progress has been made (Essa & Pentland, 1997; Maja Pantic & Patras, 2006; Shan, Gong, & McOwan, 2009; Yacoob & Davis, 1996) in recognizing facial expression with a high precision yet it remains difficult due to the subtlety, complexity and variability of facial expressions. Usually, to overcome such difficulties an effective feature extraction is done beforehand. Dlib-ml is one such feature extraction technique which has come up in the past years. Using Dlib-Ml outlines the most important features from a face such as eyes, eyebrows, nose, mouth and jawline that are also major contributors in generating an emotion. There is slew of studies (Chapelle, Haffner, & Vapnik, 1999; Doumpos, Zopounidis, & Golfinopoulou, 2007; Nowak, Jurie, & Triggs, 2006; Perronnin et al., 2010; Susskind, Littlewort, Bartlett, Movellan, & Anderson, 2007; Yang, Yu, Gong, &

Beckman, 2009) that uses Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel for classification of these extracted features. The domain of SVM, first suggested by (C.Cortes & V.Vapnik, 1995) has recently been expanded. It has now been experimented within a number of fields such as bioinformatics (e.g. gene expression), handwriting recognition, particle identification (e.g., muons), bankruptcy prediction, digital images identification (e.g., face identification) and many more. SVM classifies the data with minimum risk by drawing out the best separating hyper plane between different class labels in the feature space using an appropriate kernel function (e.g. linear, polynomial, RBF or sigmoid) (Wu, Tzeng, Goo, & Fang, 2007).

Like any other classification algorithm SVM has its own limitations. As stated by (Chou, Cheng, Wu, & Pham, 2014; Min & Lee, 2005; Wu et al., 2007; Zhao, Fu, Ji, Tang, & Zhou, 2011) to build a prediction model with high stability and prediction accuracy, there is a dire need of tuning of the various SVM parameters such as “C” and “ σ - sigma square”. The first parameter, C, determines the trade-offs between the minimization of the fitting error and model complexity. The second parameter, sigma square, is the bandwidth of the RBF kernel. Genetic algorithms (GAs) have been applied in several studies (Huang & Wang, 2006; Min & Lee, 2005) to optimize the values of parameters of SVM.

The literature concludes to the fact that there exists a correlation between movie trailer, its ability to trigger emotions and financial returns of a movie. Further, to the best of our knowledge, no work has been done to predict human emotions using facial expression (images) by using a GA optimized SVM model. The framework proposed in this paper relies on Genetic Algorithm (GA) to define a model, which can determine the appropriate RBF kernel parameters (C and sigma square) for predicting emotions through facial expression with the highest accuracy and stability. In view of the findings from literature reviewed, following hypothesis would be evaluated during case analysis:

H_1: There is no relation between the release of a movie trailer and its stock value

H_2: There is no correlation between emotional content of a movie trailer and its financial value

H_3: Parameter tuning of RBF kernel in SVM adds no significant value to perform classification of emotions

3. Experiment Design

This section details experiment design and methods adopted to validate assumed hypothesis. The emotional responses generated within a viewer while watching a movie trailer cannot be effectively measured using traditional methods such as surveys, questionnaires and interviews. Techniques like questionnaire and interviews often fail to capture the temporal emotions as they rely upon a limited set of questions and choices. Further, in some cases questioning someone about personal opinions and emotional response is not always viable. In contrast to this, facial expressions could be the best example where emotions not only coexist but also keep changing continuously. As per findings, facial expressions contain 55% of the message conveyed by a person, followed by intonations and verbal expressions (Mehrabian, 1968). Hence, facial expressions could reveal the actual emotive response of a person with respect to any movie trailer. The stock value of movie was observed through Hollywood Stock Exchange (HSX). HSX offers a near real time simulation of stock markets. HSX stock price of a movie is considered to be a strongest predictor of actual box office earnings of a movie (Elberse 2007).

Assuming the expected fluctuations within stock prices and other market variables related to the movie, a movie trailer would result in abnormal returns (AB_R) only if the stock price of the movie has experienced a change due to trailer release. Studies have proven that impact of an event is immediately reflected on the stock price of a business house. It happens due to efficient markets, perfect information and rationality of investors (Fama 1991). An event like release of a movie trailer could therefore be best suited to study the variance in stock prices of its production house.

A total of 141 movies trailers released from Jan 1, 2017 to April 31, 2018 were studied during this experiment. This sample represents a subset of all 1334 movie stocks listed on the HSX market for the said period. Selection of movies was made on the following criteria:

a) Release date of movie trailer should be within the said time frame
b) Movie should initially play on 650 screens or more (it classifies them as ‘‘wide releases’’ for the HSX)
c) At least 90 days of trading history prior to their release date should be available on HSX

Economic value of a movie trailer is measured in terms of the abnormal returns (AB_R). It is gained from the variation in the stock value of movie after trailer release. HSX, which is one of the most popular virtual movie stock market (VSM) was used to study this variation. HSX has over two million participants with most active traders tending to be heavy consumers and early adopters of movies (Elberse, 2007). Traders make use of virtual currency to increase their net worth by trading movie stocks and other financial products related to movie industry (HSX, 2017). Researchers have found that forecasts made by HSX traders are reasonably accurate in making predictions of actual box office returns (Elberse, 2007; Elberse & Anand, 2007; Gruca, 2000; Spann & Skiera, 2003). Table 2 provides descriptive statistics for the key continuous variables available at HSX with respect to the chosen sample. Figure 1 depicts an example of observed variation within stock price for a randomly selected movie from our sample.

Table 2. Mean min, max abnormal returns and standard deviation of movie stocks

Variable	Mean	Min	Max	SD
Abnormal Return = AB_R	5.81	0.19	15	3.09

Release of a movie trailer isn’t the only event happening in the stock market. There are other uncontrolled risk factors like “High minus Low (HML)”, “Small minus Big (SMB)” & “Excess Return (MktRf)”, which cannot be mapped to these returns directly. Fama- French Model identifies and handles these common risk factors associated with AB_R on any kind of stocks and bonds. Returns on stocks are expected to be highly influenced by these factors (Fama F., 1991).

Crowd sourced trailer review videos, which were voluntarily shared on YouTube, were used for training our framework. 153 reaction sequences/videos corresponding to trailers of 141 movies from YouTube were used to gather facial expressions as shown in Figure 2. Most of the videos shared on YouTube channels have more than one respondent watching a movie trailer, hence the total number of viewers within these 153 reaction sequences comes out to be more than 350 as shown in Figure 2.

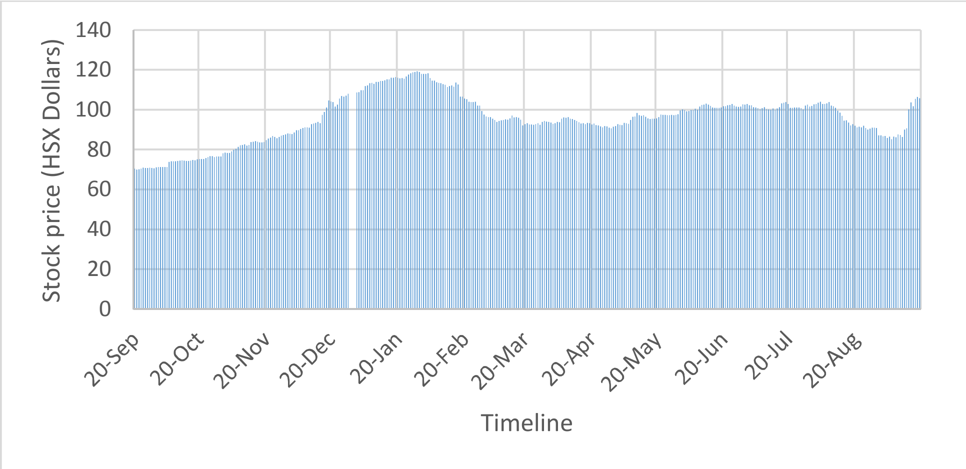

Figure 1. Sample stock price variation of Blade Runner 2049 movie

Each of these reaction sequences were uploaded under a dedicated YouTube channel and the authenticity of these YouTube channels is measured in terms of its subscriber base and total number of views on the videos. These two parameters formed the basis of selection criteria for gathering these sequences. Using the chosen parameters, following minimum requirements were adopted for selecting a particular reaction sequence.

a) YouTube channel of the reaction sequence must have at least 5,000 subscribers.
b) YouTube channel of the reaction sequence must have at least 10, 00,000 views in total.

Table 3 presents a list of prominent YouTube channels considered to obtain reaction sequence. A high count of subscriber base and views supports the facts that the reaction sequences on these channels are genuine.

Table 3. Sample list of YouTube channels satisfying the minimum criteria for selection

Channel Name	Total Views	Subscribers
ScreenJunkies News	1,68,81,02,656	15,37,211
Beyond The Trailer	58,20,96,154	7,22,658
Dwayne N Jazz	50,86,48,911	13,47,560
Tyrone Magnus	49,20,50,726	12,63,444
The Reel Rejects	19,66,79,583	5,44,717
Blind Wave	16,74,97,637	2,95,543
Carnatavr T	9,50,31,090	1,09,438
Ecomog Media Group	8,61,32,803	2,97,088
AdikTheOne	6,66,35,033	3,55,459

Figure 2. Sample emotions identified during different reaction sequences

Most of the research findings are focused to study post release analysis of movie receipts from box office. This experiment intends to focus on pre-release period of a movie to study the impact of trailer release on financial returns. Chosen measure for financial return is the movie's "stock price" as traded at HSX.

The dawn of social media has offered a platform, where millions of people can share their opinion, sentiments and reviews in real time. Social media is considered to be a good substitute of surveys, news stories and other primitive methods for recording and analyzing sentiments. Crowd sourced data sources have provided a reliable platform to quantitative investors, which can be used to construct portfolios and risk management (Karray & Debernitz, 2015). Social media platform like YouTube has been used and recommended by researchers for retrieving sentiment data (Chen, Chang, & Yeh, 2017). This paper proposes an Emotion Analysis Framework (EAF) based on Dlib-ml, SVM and GA for predicting the impact of emotional appeal of trailer on the financial returns generated by it. The proposed methodology makes use of Dlib-ml machine learning toolkit (King, 2009), SVM and Genetic Algorithms for identifying and quantifying emotions within a reaction sequence towards a movie trailer. Component diagram of the proposed framework is shown in Figure 3. Subsequently, cross sectional analysis to map the emotional appeal of a trailer with the movie's box financial returns was performed.

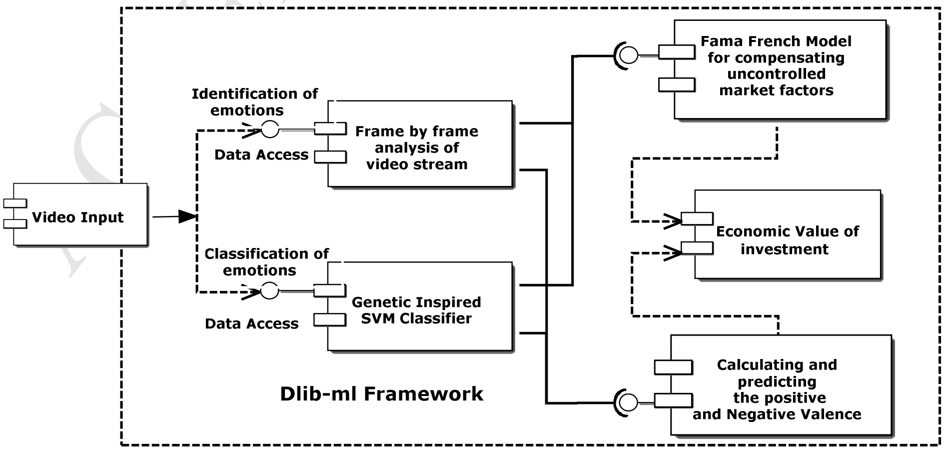

Figure 3. Overall research method

4. Case Study

Event studies are based on the observation that, effect of an event is immediately reflected in stock price (Fama 1991). To validate the assumed hypothesis, event of interest in this study is the release of a new movie trailer. Another crucial element is the "event window" which is termed as the time frame in which the effect of event under observation is measured on stock prices. As suggested by literature, the pre event window should be a 'five –six' day event window and the post event window should be a 'one-day' event window i.e. day after the release of theatrical trailer. These event windows are conventionally acceptable length in context of movie industry (Mackinlay, 1997; Wiles & Danielova, 2009). Further, a short window is appropriate as one can pinpoint it on HSX website and would limit the impact of high frequency confounding factors. A short event window can widen the scope to investigate that, variation in stock price is because of theatrical release only rather than because of confounding factors about movie or its competitors.

Determining the normal return of a particular stock is necessary to assess the effect of a particular event. Normal return "Em" (in(1)) is termed as the performance of a stock over an event window when no event is taking place. The trading stock value of a movie "m" at a time "t" is termed as Mt. The estimated normal return for a movie "m" is Em and is obtained by calculating the mean of the returns for movie "m" within the five-day time period preceding the trailer release (at time t = 0) and ranging from t = -6 to t = -1 as shown in Figure 4.

$$Em= (\sum_{t=-1}^{-6} M_t)/6 \qquad (1)$$

The stock's abnormal return (AB_R) is then obtained by subtracting its expected return Em from the real return "Am" occurring over the event window (Srinivasan and Bharadwaj 2004). AB_R (in (2)) represents the stock price change that takes place after the event has occurred and is calculated for each day in the event window:

$$AB_R= Am – Em \qquad (2)$$

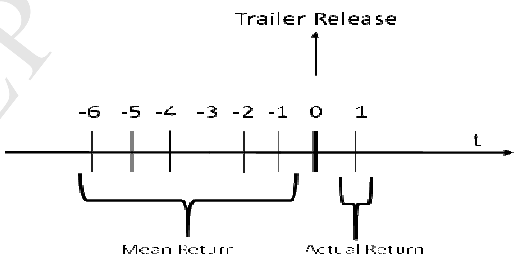

Figure 4. Estimating the impact of movie theatrical trailer release on its stock value

4.1 Emotion Analysis Framework (EAF)

Traditionally, sentiments are analyzed with the help of analysts, survey data, news stories and other technical indicators as suggested by domain experts. These techniques may not only get affected by the opinion bias of domain expert but are also not suitable to process data in real time. EAF relies upon visual biological reactions measured through facial expressions. It identifies and measure the intensity of expressions based upon classifiers used to recognize smiles, eyebrow rises, and expressions of anger, disgust, positive and negative valence. Such facial expressions are highly relevant to understand viewer's response and are validated by research community (Hazlett & Hazlett, 1999). Classifiers generate continuous moment-by-moment emotive outputs based upon probability as shown in Figure 6.

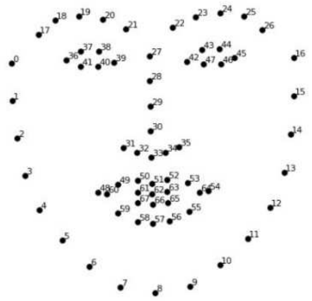

Figure 5. Facial landmarks considered by Dlib-ml for identifying emotion

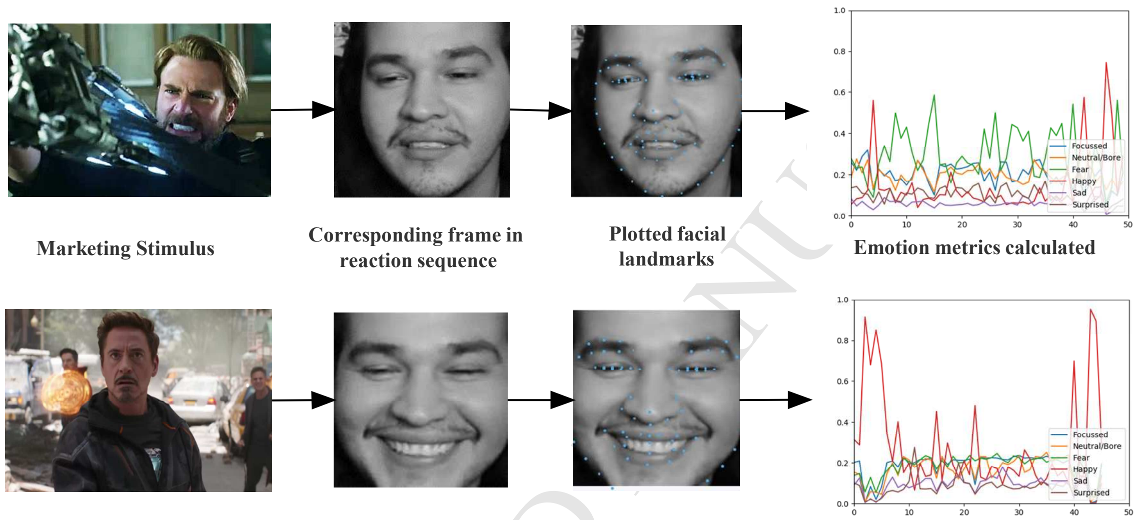

Figure 6. Probability based outputs for identified emotions as generated by GA*i*SVM

EAF performs sentiment analysis by using Dlib-Ml for feature extraction and GA*i*SVM for classification of different emotions from facial expressions.

4.1.1 Feature Extraction

For feature extraction, EAF uses Dlib-ml which is a cross platform open source software library that is inspired by ideas from component-based software engineering and design by contract. It is a collection of independent software components, each accompanied by extensive documentation and thorough debugging modes to facilitate software development and research as shown in Figure 7. Moreover, the library is intended to facilitate both research and real world commercial projects. It identifies facial expressions through 68 key facial landmarks which are treated as features by EAF to perform classification. These 68 facial landmarks highlight the muscles in the eyebrows, eyes, nose and mouth. Facial landmarks that contribute towards forming any significant emotion are shown in Figure 5 (OpenFace API Docs,2018)and are plotted in Figure 6 (King, 2009).

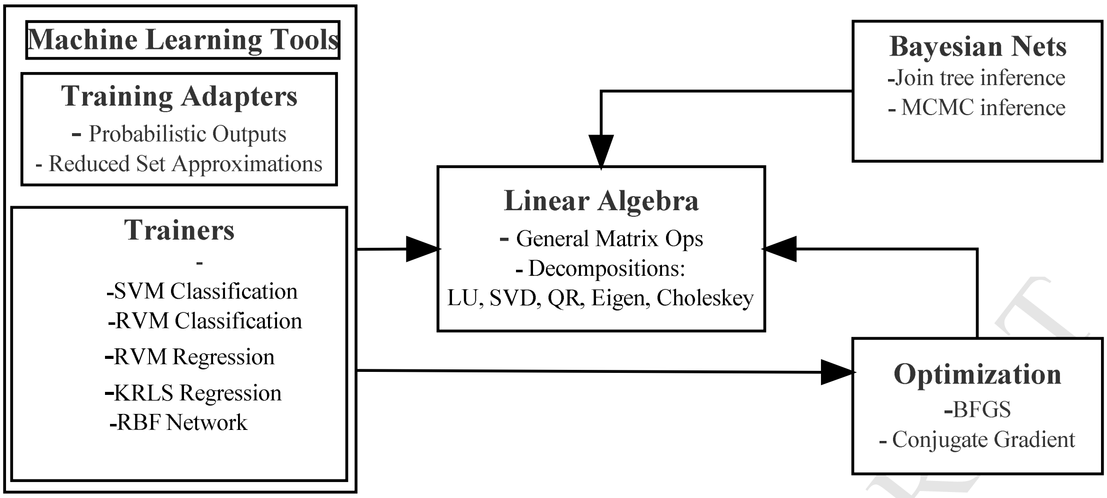

Figure 7. Dlib-ml framework for machine learning

4.1.2 Classification of emotions

Before performing classification we tune the parameters of SVM using a GA as shown in Figure 8 to achieve a higher degree of precision.

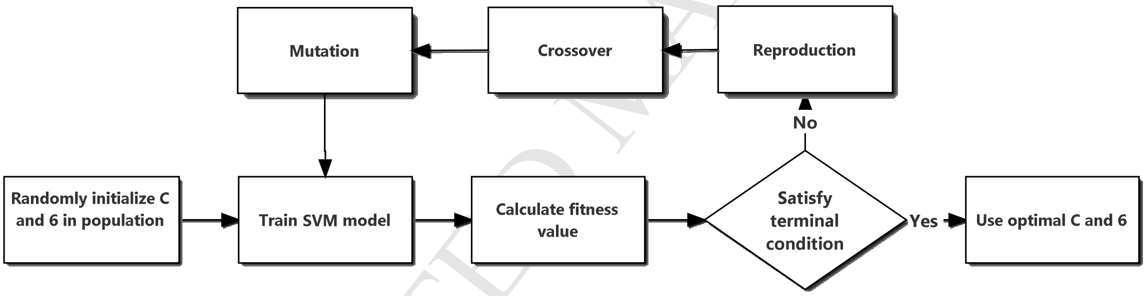

Figure 8. Parameter tuning process of SVM

To accomplish this, we encoded the SVM parameters C and σ to form a chromosome for the GA optimization process as shown in Figure 9. Consequently, chromosome X was represented as X = {C, σ} and was initialized with random values to start the tuning process with training parameters as mentioned in Table 4. Starting off with these random values, the SVM was trained on a set of pre annotated images. The SVM was then tested to classify a new set of images and its precision over the new set was taken as the fitness function for the tuning process.

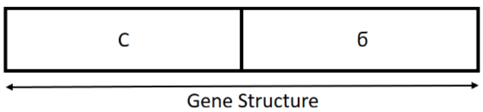

Figure 9. Chromosome representation in GA

Table 4. GA optimization process training parameters

Parameter	Value
Population Size	300
Generations	100

Selection Method	Tournament
Mutation Method	Uniform
Crossover Method	Two point
Mutation Probability	0.3
Crossover Probability	0.6

Once tuned, the new Genetic Algorithm inspired Support Vector Machine (GA*i*SVM) classifier with RBF kernel was used to detect six discrete emotions namely happy, angry, sad, neutral, surprise and disgust for every single face per video frame in the reaction sequences taken from YouTube. The classifier returns a probability corresponding to every emotion for every face identified in each frame. An emotion with positive valence would have a positive effect on the overall emotional score of the video and vice versa. Emotions such as happy, sad, surprise, disgust and angry are considered to have a positive valence while neutral/bore has a negative valence for a theatrical movie trailer (Pham & Wang, 2017). For e.g. the first frame "F1" in a viewer's reaction sequence can have probabilities as [Ha1, An1, Sa1, Su1, Di1, Ne1] for happy, angry, sad, surprise, disgust and neutral emotional state respectively. Each of these probability values represent the likelihood of the viewer to be experiencing a particular emotion at any given time. Based on observed probabilities, the Positive Valence Emotive score (PVEs) of the entire reaction sequence with "n" frames towards a theatrical movie trailer is calculated as ∑Ha, An, Sa, Su, Di while the Negative Valence Emotive score (NVEs) is ∑Ne.

Algorithm 1: Classifying emotions from a YouTube reaction sequence

Input:
V [] = Reaction sequences of viewers from YouTube corresponding to movie trailers. (Data set used for training)
T = Recorded reaction sequence for movie trailer to estimate its economic value

Step 1: Input reaction sequence videos V []
Step 2: Segregate each video within V [] into frames and for each frame go to step 3
Step 3: Use Dlib-ml to plot 68 key landmarks on faces identified within frames of reaction sequences
Step 4: Train GA*i*SVM classifier with RBF kernel to classify six emotions namely happy, sad, neutral, anger, surprise and disgust
Step 5: For every sequence in V with "n" frames, calculate Positive Valence Emotive score "PVE" as

$$PVE_s = (\sum_{k=0}^{n} Ha_k + An_k + Su_k + Sa_k + Di_k)/\text{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

and Negative Valence Emotive score "NVE" as

$$NVE_s = -(\sum_{k=0}^{n} Ne_k)/\text{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where n represents total number of frames in V[k]

4.2 Cross sectional analysis

To understand the correlation of a trailer's emotional appeal and abnormal returns, we performed a cross-sectional analysis using regression. The regression equation has AB_R as the dependent variable and the trailer variables and Fama-french factors as predictors. α and β denote the vectors of regression coefficients for the trailer variables and Fama-french factors respectively, and ϵ is the regression error term:

$$AB_R = \alpha(trailer\ variables) + \beta(Fama\ french\ factors) + \epsilon \quad \ldots\ldots (5)$$

The trailer variables consists of the emotional valence scores (PVE and NVE) and the Fama-french factors are used in accordance with 3 factor model. Hence the final equation for calculating AB_R for a movie "m" is

$$AB_R = \alpha_1 PVE_m + \alpha_2 NVE_m + \beta_1 HML + \beta_2 MktRf + \beta_3 SMB + \varepsilon \quad \ldots\ldots (6)$$

The proposed method to relate abnormal returns to emotional content of theatrical trailer has explicitly taken into account some movie specific and time-invariant unobserved factors, represented by ε in above equation. Such unobserved factors too can affect the accuracy of anticipated abnormal returns.

5. Results and discussion

AB_R, PVE and NVE for entire of the movie set was calculated. Owing to the required brevity of manuscript and limitations related to graphical representation of dataset, we have detailed only the ten best and ten worst performing movie trailers within result section.

5.1 Results of the event study

We used the Shapiro-Wilk W test to verify that AB_R follows a normal distribution (W = .92, p=0.01).Thus, it is proven that a trailer release significantly affects the movie's stock returns. The case study concludes that every movie within the sample has experienced an average increase of $ 5.81 in its stock value after the trailer release. The average positive effect on abnormal returns disapproves H_1, surprisingly all the trailers resulted in positive abnormal returns after the release of movie trailer. Table 5 corresponds to observed AB_R values for ten best performing movie trailers and Table 6 details AB_R for ten worst performing movie trailers.

Table 5. Ten best performing movie trailers

Movie	AB_R (in HSX Dollars)	Theatrical Trailer Release Date
Black Panther	15	Oct 16, 2017
Avengers Infinity War	15	Nov 29, 2017
Incredibles 2	12	Nov 18, 2017
Annabelle: Creation (2017)	11	Apr 01, 2017
IT	10	Mar 29, 2017
Star Wars: The Last Jedi aka Epiode VIII	9	Apr 14, 2017
Ferdinand	9	Mar 28, 2017
Tag	8	Mar 20, 2018
Rampage	8	Nov 16, 2017
Skyscraper	7	Feb 4, 2018

Table 6. Ten worst performing movie trailers

Movie	AB_R (in HSX Dollars)	Theatrical Trailer Release Date
Ocean's 8	6	Dec 19, 2017
Ready Player One	6	Dec 10, 2017
Ant-Man and the Wasp	5	Jan 30, 2018
Mission Impossible - Rouge Nation	5	Feb 4, 2018
Solo: A Star Wars Story	4	Apr 8, 2018
Game Night	4	Nov 9, 2017
American Made	4	Jun 5, 2017
The Hitman's Bodyguard	4	Apr 13, 2017
Sicario	3	Mar 19, 2018
Pandas	3	Jan 11, 2018

We studied the stock prices of One Hundred and Forty One Movies released during the said period. Figure 10 presents a sample showing the change in stock value of movies after the release of their theatrical trailer. Results show that release of a theatrical trailer results in appreciation of stock value of movies.

S. No.	Movie
1	Flatliners
2	American Assassin
3	Pitch Perfect 3
4	The Greatest Showman
5	A Bad Moms Christmas
6	Jumanji : Welcome to the Jungle
7	Polaroid
8	Darkest Hour
9	The Disaster Artist
10	The Shape Of Water
11	Call me by your Name
12	Mother
13	Molly's Game
14	Jeepers Creepers 3
15	The Man Who Invented Christmas
16	A Current War
17	All the Money in the World

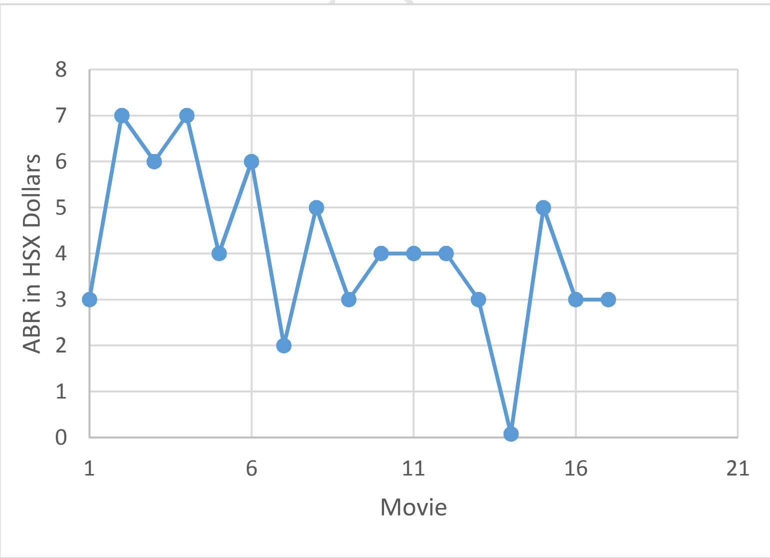

Figure 10. Sample showing impact of theatrical trailer release on HSX stock value of movie

Figure 11 presents the case of Ocean's 8, which experienced high stock values after trailer release. It can be clearly noticed in Figure 11 that the stock value of Ocean's 8 followed almost a flat graph before the trailer release but had a sharp rise on the day of trailer release. Further, the study revealed the fact that theatrical trailer release has resulted in a rise in movie's stock value. However, the study witnessed a rise in movie's stock value after release of theatrical trailer, yet the recorded rise was not uniform. Few of the movie stocks experienced a surge of two hundred and sixty percent while others experienced a marginal rise of five to ten percent only. Ideally, this variance in appreciation of stock values could result from the contents of trailer itself.

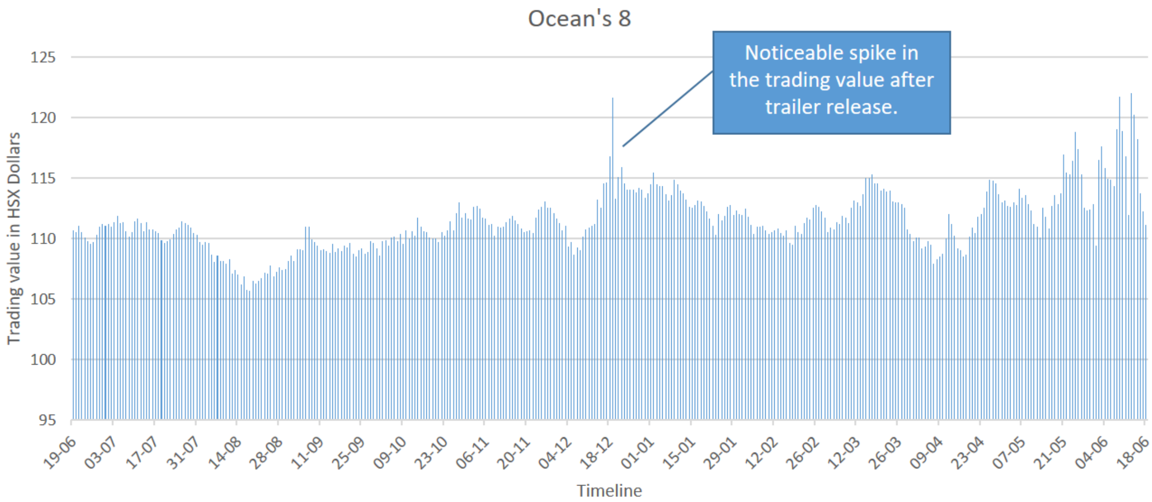

Figure 11. Ocean's 8 witnessed a rise in their stock values after trailer release

5.2 Results of EAF

We have used a dataset of 2841 images to validate the precision of proposed GA*i*SVM in contrast to generic SVM. The images in this dataset are cropped facial images from YouTube reaction sequences and are pre classified in to one of six categories (0=Angry, 1=Disgust, 2=Happy, 3=Sad, 4=Surprise, 5=Neutral). We used the 80:20 split ratio for training and testing respectively. Hence the training and testing proposed method consisted of 2273 and 568 images respectively. The precision attained by GA*i*SVM against generic SVM after testing is given in Table 7:

$$Precision = \frac{True\ Positive}{True\ Postive+False\ Negative} \tag{7}$$

Table 7. Precision attained through GA*i*SVM against generic SVM

Emotion classified	Precision	
	GA*i*SVM	SVM
Happy	0.92	0.89
Sad	0.90	0.71
Surprise	0.91	0.82
Angry	0.89	0.84
Disgust	0.89	0.81
Neutral	0.90	0.85

The average precision achieved for GA*i*SVM was 0.901 whereas for SVM it was 0.82. This clearly proves that GA*i*SVM outperformed generic SVM. Hence H_3 can be rejected because a SVM with parameter tuning done is found to be more effective than generic SVM without parameter tuning. Table 8 corresponds to the emotive scores of ten best performing movie trailers. Figure 12 briefs the measured PVEs and NVEs of best performing movie trailers. Subsequently, Table 9 corresponds to the emotive scores of ten worst performing movie trailers. Figure 13 briefs the measured PVEs and NVEs of worst performing movie trailers. It can be inferred that the trailers which were able to generate a high PVE and low NVE gave better returns on stock value.

Table 8. Calculated values of PVEs and NVEs by GA*i*SVM for best performing theatrical trailers

Movie	Change in Stock Value	PVEs	NVEs
Black Panther	15	0.61	0.001
Avengers Infinity War	15	0.6	0.002
Incredibles 2	12	0.51	0.0012
Annabelle: Creation (2017)	11.0	0.313	0.001
IT	10.0	0.35	0.07
Star Wars: The Last Jedi aka Episode VIII	9.0	0.494	0.011
Ferdinand	9.0	0.31	0.02
Tag	8	0.47	0
Rampage	8	0.47	0.018
Skyscraper	7	0.32	0.065

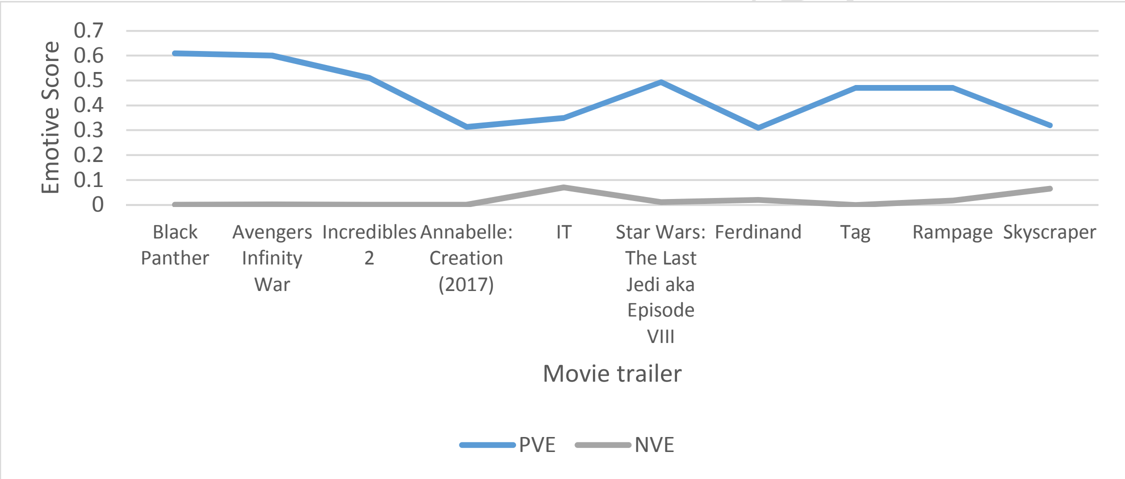

Figure 12. Measured PVEs and NVEs of best performing movie trailers

Table 9. Calculated values of PVEs and NVEs by GA*i*SVM for worst performing theatrical trailers

Movie	Change in Stock Value	PVEs	NVEs
Ocean's 8	6	0.31	0.14
Ready Player One	6	0.33	0.01
Ant-Man and the Wasp	5	0.17	0.21
Mission Impossible - Rouge Nation	5	0.21	0.1
Solo: A Star Wars Story	4	0.1	0.099
Game Night	4	0.11	0.13
American Made	4	0.17	0.099
The Hitman's Bodyguard	4	0.21	0.13
Sicario	3	0.1	0.21
Pandas	3	0.14	0.2

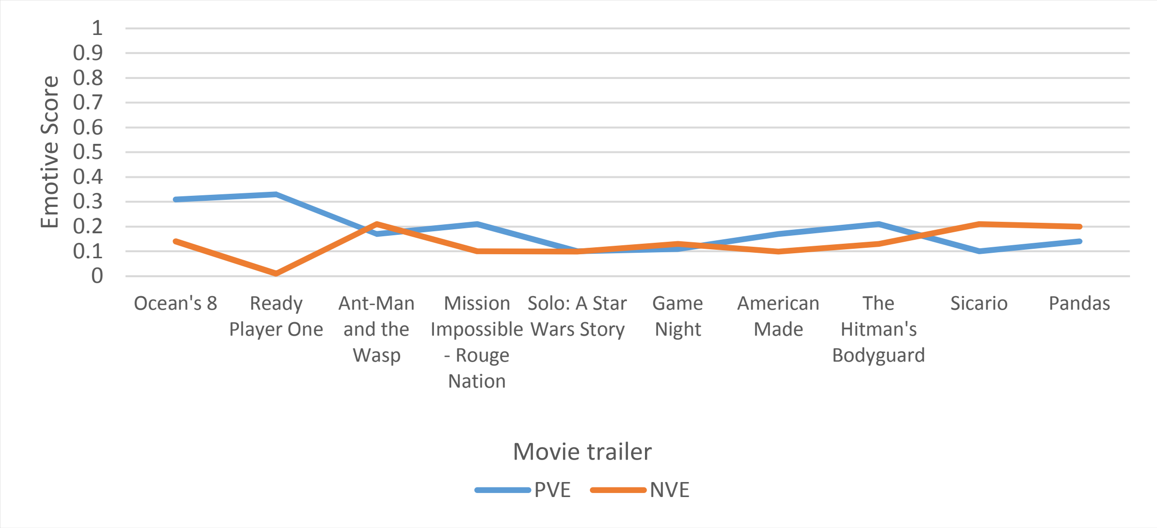

Figure 13. Measured PVEs and NVEs of worst performing movie trailers

5.3 Results of the cross sectional analysis

Presuming the emotional content of trailer as a motivation to buy movie stock, we performed regression analysis to explore the relation between abnormal returns of movie stock and emotional potency of the theatrical trailer with reference to equation 8 given below (Agrawal, Kishore, & Rao, 2006). Regression analysis resulted in a coefficient of determination equal to 0.9375 (R^2). Table 10 presents the calculated values for regression coefficients like ε, α1, α2, α3, β1, β2 (Agrawal et al., 2006).

Table 10. Calculated values of ε, α1, α2, α3, β1, β2

ε	2.9781516
α1	14.8198115
α2	11.86158165
α3	-87.651695
β1	113.894895
β2	-17.5159189

To evaluate H_2, we took into consideration two theatrical trailers of same movie, released on different dates. The computer program subsequently evaluated the emotive response of viewers for those two movie trailers, Termed as $Actual_{PVE_k}$ *and* $Actual_{NVE_k}$. We repeated the procedure for entire of the movies studied. Equation 8 estimates the effect of emotionally intense trailer on stock performance by calculating PVE and NVE, termed as $Predicted_{PVE_k}$ *and* $Predicted_{NVE_k}$):

$$\alpha_1 PVE_m + \alpha_2 NVE_m = AB_R - \beta_1 HML - \beta_2 MktRf - \beta_3 SMB - \varepsilon \ldots\ldots\ldots\ldots (8)$$

Coefficient values within equation 8 are taken from Table 10 and confounding factors like HML, Mkt-Rf and SMB are with reference to Fama-French model for second theatrical trailer. Robustness of equation 6 was further be evaluated through an accuracy parameter as given in equation 9 and 10. Calculated accuracy parameter ϵ [0, 1]. Higher the accuracy achieved, higher will be the robustness of the equation 6.
Accuracy Equations:

$$Accuracy\_PVE = 1 - \sum_{k=0}^{n} \frac{\left|Predicted_{PVE_k} - Actual_{PVE_k}\right| / Actual_{PVE_k}}{n} \quad \ldots\ldots\ldots \quad (9)$$

$$Accuracy\_NVE = 1 - \sum_{k=0}^{n} \frac{\left|Predicted_{NVE_k} - Actual_{NVE_k}\right| / Actual_{NVE_k}}{n} \quad \ldots\ldots\ldots \quad (10)$$

Here “n” is the number of movies in the sample.

Relational mapping between AB_R and the emotional score (PVE & NVE) for the top performing movie trailer sequences of a movie, released at different time is given in Table 11. From the recorded observations, it could be clearly inferred that AB_R is directly proportional to PVE where as it is inversely proportional to recorded NVE for any movie trailer. Subsequently, it can also be inferred that PVE for first trailer is greater than PVE for second trailer, it means that the first trailer of a movie was able to incite a higher range of emotions within viewers in comparison to the second trailer. For instance, the first trailer of Black Panther, which was released on Oct 16, 2017 and resulted in AB_R of 15.0. Whereas the second trailer of the same movie, which was released on Jan 8, 2018, resulted in an AB_R of 7.0 only. The same trend was observed for first and second trailer of best performing movie trailers.

Table 11. Calculated values of PVEs and NVEs for ten best performing theatrical trailers released on different dates

Movie	Trailer 1			Trailer 2		
	AB_R	PVE	NVE	AB_R	PVE	NVE
Black Panther	15	0.61	0.001	7	0.37	0.11
Avengers Infinity War	15	0.6	0.002	7	0.39	0.13
Incredibles 2	12	0.51	0.0012	5	0.35	0.2
Annabelle: Creation (2017)	11.0	0.313	0.001	5	0.39	0.21
IT	10.0	0.35	0.07	3	0.11	0.1
Star Wars: The Last Jedi aka Epiode VIII	9.0	0.494	0.011	3	0.21	0.16
Ferdinand	9.0	0.31	0.02	3	0.2	0.11
Tag	8	0.47	0	2	0.29	0.14
Rampage	8	0.47	0.018	3	0.41	0.18
Skyscraper	7	0.32	0.065	1	0.2	0.1

Figure 14 is the graphical representation of Table 11 comparing the AB_R, PVE & NVE of top performing trailers released at different time. X & Y axis depict the AB_R of two trailers of a movie, released at different time in the form of bar graph. Production houses generally release 3-4 trailers before the actual movie release. Each of these trailers are different from the previous one. The maximum PVE value received for the first trailer of movie Black Panther, is 0.61 while the maximum PVE for second trailer of the same movie is 0.37. Similarly for AB_R, maximum return was for the first trailer of Black Panther i.e. $15. Based on this interpretation the first trailer of the movie has proved to be the most effective amongst all, because it was able to generate highest PVE and lowest NVE as shown by line graph in X & Y` axis. Hence, evaluating movie trailers prior to their launch may not only help then in anticipating its financial success but may also help to customize movie trailers for triggering emotions with higher positive valence. The observed results also show a direct relation between a theatrical trailer and its stock value. Further, the case study concluded that an emotionally intense movie trailer might result in much higher abnormal returns than a moderately intense movie trailer. Furthermore, crowd sourced platforms like YouTube can prove to be reliable input source for training emotion driven platforms. The values of *Accuracy_PVE* and *Accuracy_NVE* were 0.79 and 0.77 respectively, which clearly disproves H_2 and support the statement that there is a direct relation between emotional content in a movie trailer and the movie's abnormal stock returns.

The results clearly put forward a need of pre-release emotive analysis of movie trailers as they can contribute towards the box office returns of a movie. Such analysis will not only make movie trailer more affective but also will enable the production houses to predict the box office returns of a movie. Further this study could be expanded to pin point the exact elements within a trailer which resulted in generation of a particular emotion either positive or negative valence. Results also emphasize on the fact that release date of trailers is a crucial factor for production houses. Scheduling the release dates of multiple trailers of the same movie could also impact the returns on stock value. The proposed framework could help in designing tailored advertising campaigns for production houses, so as to incite highest values of emotions with positive valence. The primary limitation of this case study is its dependency on HSX to measure financial returns pertaining to movie stock trading. Although literature studied provided evidence in supports of the authenticity of HSX, yet there is no other virtual stock market like HSX, to validate observed stock prices.

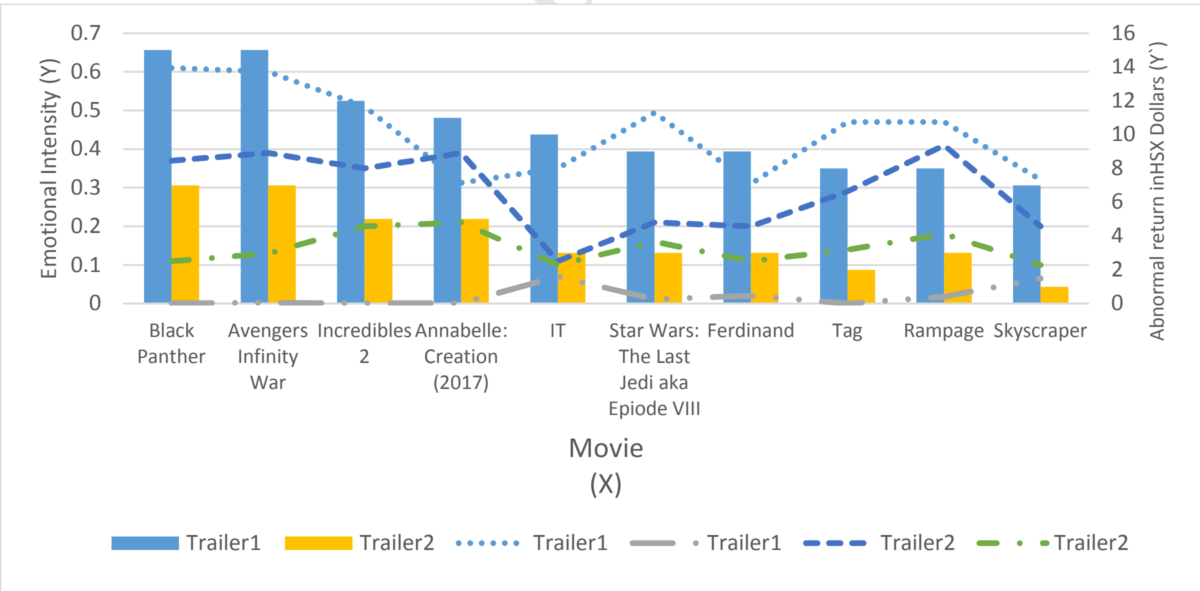

Figure 14. Measured PVEs and NVEs of two theatrical movie trailers released on different dates

Conclusion

The case study promulgates the fact that pre-release evaluation of emotional intensity of theatrical trailers would not only help in predicting the movie's stock value, but may also facilitate the composers in compiling a theatrical trailer which may trigger high emotional response within prospective viewers. The proposed GA*i*SVM model outperforms the generic SVM model for predicting emotions from facial images hence could be a reliable option to evaluate consumer engagement. The case study was limited to only those production houses which were listed on HSX, hence we did not take into account production houses not listed on HSX and are keen towards making regional and low budget movies. GA*i*SVM model has been fine tuned to identify primitive emotional responses and do not take into account emotive state like contempt and anticipation. The future scope of this study lies with the actual use of this framework to compile emotionally intense movie trailers and predicting financial returns associated with it. The proposed framework has direct implications for movie production houses to optimally allocate advertising budgets and maximize their profits. Further, it could be used for evaluating product design, fine-tuning advertisement efforts and deciding other marketing mix for business houses.

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- Release of movie trailer has a positive effect on the stock value of the movie.
- Higher the emotional appeal of trailer, higher is the impact on stock value.
- SVM performs better if its parameter tuning is done.