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FADU-EV an automated framework for pre-release emotive analysis of theatrical trailers

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Abstract
Release of a theatrical movie trailer is a major marketing practice and a considerable cost is associated with it. Evaluating the effectiveness of a theatrical movie trailer before its release could substantially contribute towards enriching its contents and economic value. The relationship between the emotional responses generated in response to a movie trailer cannot be effectively measured using traditional methods such as surveys and interviews. This paper proposes a framework to measure the effectiveness of movie trailers by measuring emotive response of viewers. A case study was conducted to study the impact of a movie trailer release on stock value of movie using virtual stock markets. Further, the case study investigated the impact of emotionally intense movie trailer over its stock price. Based on emotive content of trailers, few of the movie stocks experienced a surge of two hundred and 50 % while others experienced a marginal rise of five to 10 % only. The observed results indicated a direct relation between release of movie trailer, its emotive content and abnormal positive returns of a movie stock.

Keywords Dlib-ml · Emotive response · Social media · Machine learning · Movie trailer release · SVM

1 Introduction

As per estimates, 65% of total movie budget is for production while remaining 35% is for marketing and distribution (Annie [39]). Movie previews, or trailers are a widely used method

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for promoting movies [19, 33]. Theatrical movie trailers intend to introduce a movie to the public with the purpose of building expectations about an upcoming film. Expectations are built by showcasing actual scenes from the movie [51]. Movie trailers are expected to generate interest within the mind of a moviegoer towards the upcoming movie [13]. Release of a movie trailer is a major marketing practice and a considerable cost is associated with it. However, not all movies turn out to be profitable for production houses, yet every movie trailer release is expected to have a direct impact on the stock value of its production house [28]. Efficiency of movie advertising seem overlooked by research community, specifically how the design of movie trailers can influence investors' valuation of the movie. It is important to understand the financial impact of movie trailers on the stock value of its production house. Investors rely on movie trailers to infer the quality of the movie, and to anticipate its future success or failure at the box office [29]. Apropos to the previously mentioned discussion, theatrical movie trailers could play a decisive role in the success of any movie project; hence there is a need to evaluate them before their actual release.

Evaluating the theatrical trailer before its release could substantially contribute towards enriching its contents and sequence. A pre-release analysis is also important due to the fact that most crucial marketing decisions, such as launch of movie trailer, advertising, distribution and time of release are taken long before the actual movie release [17]. An automated framework to evaluate a movie trailer before its actual release would not only help in deciding the marketing strategy, but may also help in composing a tailored fit theatrical trailer for the audience. Effectiveness of any movie trailer corresponds to the emotive response it could generate within a viewer or respondent [27]. The relationship between the emotional responses generated in response to a movie trailer cannot be effectively measured using traditional methods such as surveys, questionnaires and interviews. According to published literature, that image component of any logical model or input is obligatory for brain to respond to, whereas verbal component is optional. People may not verbalize their actual impression regarding any marketing stimulus; hence, verbal measures are not much efficient to record consumer's perception [57]. Primitive feedback techniques like questionnaire and interviews often fail to capture the temporal emotional changes, one may experience while watching any movie trailer. Furthermore, in some cases questioning viewers about their opinions and emotional response is impractical to capture.

Emotions were primarily studied by psychologists until the role of emotions in determining actions and behavior was discovered [7]. Subsequently, it was found that emotions play a vital role in consumer decision-making [49]. Physiological changes and mental responses with respect to any marketing stimulus are not only automatic but also found to be consistent across individuals [54]. The prime challenge associated with researching consumer emotions is that, emotions often occur in a complicated context. Consumers can experience several emotions at the same time [46]. Thus, the ability to distinguish between emotions, and to see how emotions coexist, is important for marketing purposes. Facial expressions could be the best example, where emotions not only coexist but also keep changing continuously.

Research suggests that facial expressions contain 55% of the message conveyed by a person, followed by intonations and verbal expressions [38]. Hence, facial expressions were studied to correlate emotive response of a person for any given movie trailer. There are two prominent approaches namely Facial Action Coding System (FACS) [16] and facial electromyography (EMG), used for facial expression analysis in consumer research [42]. Though the said techniques can effectively be used to capture emotive response of respondents, yet very few studies provide empirical evidence of their effectiveness.

This paper attempts to develop a framework for interpreting immersive level of respondents with respect to any movie trailer. The framework intends to digitally evaluate, quantify and visualize the emotive response of a respondent towards a movie trailer. Facial expressions captured through video camera are fed into a computer program. The computer program would perform a frame by frame analysis of video input, so as to identify emotions experienced by any respondent. Intensity of identified emotions would be calculated by using Dlib-ml machine learning framework and Support Vector Machine (SVM) classifier. Subsequently, the emotion inciting capability of a movie trailer with respect to its economic value was investigated.

The rest of the paper is organized as follows, section two concludes the findings of related work, section three details the methodology for proposed framework, section four includes a case study to measure effectiveness of proposed framework, section five provides the experimental results and section six concludes the findings.

2 Related work

The approach followed for the design and deployment of the proposed framework is inspired from different research domains namely emotive analysis, business value and social media. This section consists of two parts. The first part talks about emotive analysis, the second part talks about the use of social media for decision-making and evaluating business value.

Neurobiological findings from different psychological experiments have been refined with the use of technologies like, electroencephalography (EEG), magnetoencephalography (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI) [14]. Few of the research findings suggest that recognizing facial emotion draws on multiple strategies devised by a large array of varying brain structures. The study focused upon those processes and structures, whose use can correlate the data from functional imaging and lesion studies to decision making [1]. Subsequent efforts tried to predict emotions through a fusion of EEG and image data. Primary intension was to detect emotions and labelling them as a psychological response. During this experiment, recorded videos were annotated by expected emotions and efforts were made to understand user responses [48]. Researchers also tried to guess emotions and sentiments through interactive dialogue systems. Such systems can not only guess present emotional state and associated sentiments but can also decide appropriate response at every dialogue state [5]. Facial Action Coding System (FACS) are most effective in measuring emotive responses. One of the most prominent challenge in affective computing is interpersonal variability in expressing behavioral responses. Researchers collected numerous observations to decide normative distributions of base rates for these behaviors. Such base rates can identify video categories based upon recorded facial expressions [36]. A faction of researchers opine that using only speech or facial signals are not much reliable to detect emotions, especially if people don't want to conceal their feelings. Contrarily, psychological signals are much reliable to probe internal cognitive and emotional changes of respondents. Owing to the specialized equipment required to capture such psychological signals, such techniques are not much common among researchers. Further, such equipment require prior consent of the respondent which is actually not a concern in recording facial expressions [3]. In continuation to efforts promulgating the use of psychological signals for capturing emotional changes, researchers also proposed a systematic approach using Galvanic Skin Response (GSR) sensors. The proposed approach relied upon Principal Component Analysis (PCA) and on regression methods for measuring, evaluating and discriminating GSR signals of respondents [52]. In response to the growing importance of emotive analysis in contemporary society, researchers also conducted studies to understand factors associated with public attitude towards biologically inspired research practices. Studies also evaluated the impact of ethical perceptions, intentions of people to participate in such investigations on their decision making [4]. Further, the mapping from video content to emotional description can facilitate affective content analysis. Exploiting the relationship between emotion and decision making is crucial to reduce the semantic gap between low level video features and emotional response from user [55]. Semantic representations from different image and video sources were studied to enhance the exploitation of semantic representation at source level. The noisy concepts within overall semantic representation were restrained during learning phase, thereby optimizing the classification model at the concept level [10]. Subsequently, a semi-supervised multitask feature selection algorithm was proposed. This algorithm was able to mine correlations among multiple tasks, when few labeled training data are provided. Manifold learning was proposed to explore the correlations among data points [8]. Splitting the video into multiple shots and choosing a key frame with most prominent features was also recommended by researchers. The sample shots were prioritized according to their relevance towards the event of interest. An informed classifier that puts larger weights on more relevant shots was used to overcome the small sample size issue [11]. Feature interaction integrated with linear regression was also introduced to capture nonlinear property of data. The linearity guaranteed optimal speed for proposed algorithm, which was designed for a real-time Kinect entertaining system. Schatten-p norm was recommended to correlate the linear and nonlinear effect for the proposed model [9].

The popularity of social networking platforms has permanently changed the structure and working of traditional decision support systems. The use of social media is considered to have direct financial benefits for organizations [47], it offers a platform for transparent discussions leading to faster decision cycles and competition among entrepreneurs [45]. The decision-making procedure enabled by social media technology varies from traditional decision support literature. Although the role of social media in decision-making has been discussed by a lot many researchers, yet there seems a gap with regard to the appropriate choice of social media to be used [6, 43, 44]. The ability to use social media for decision-making and to manipulate social intelligence for commercial benefits, is considered to be a core expertise for any business executive [23]. Strategically aligning the information system with social media platforms can help organizations in maximizing returns on Information Technology investment. It could also result a competitive advantage over competitors. It can further offer flexibility to track, seize and react towards new business opportunities [31]. Cinema Advertising Council (CAC) consider that promotional activities through social digital media are indispensable for any movie. The estimated investment in movie advertising industry was more than \$670 m in 2013 and was expected to rise in near future ("Cinema Advertising Council | Press Releases," 2014). Reports further suggest that an average of 35 % of total movie budget is for promotions and distribution related activities only (Annie [39]). As perceived from the available literature and to the best of our understanding, there is no empirical study done so far to calculate the emotive digital response of a viewer towards movie theatrical trailers shared over social media. Quantifying emotive digital response may help evaluating the business value of a movie trailer. Hence, proposing a social media based framework to boost the business value of a movie would not only be innovative itself but would also help in escalating global efforts to promulgate digital entrepreneurship and innovation.

3 Methodology

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. 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 [29]. Social media platform like YouTube has been used and recommended by researchers for retrieving sentiment data [12]. This paper proposes a Fama-French and Dlib-ml inspired Unified framework for predicting Economic Value of movie trailers (FADU-EV). The proposed framework makes use of Dlib-ml machine learning toolkit for identifying and quantifying emotions within a reaction sequence towards a movie trailer [34]. Subsequently, the quantified emotions are used to predict its economic value using recommendations of Fama-French model (Fama [20]). Figure 1, describes the component diagram for proposed FADU-EV framework.

FADU-EV 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 [25]. Classifiers generate continuous moment-by-moment emotive outputs based upon probability as shown in Fig. 2.

FADU-EV 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 Fig. 3. Moreover, the library is intended to facilitate both research and real world commercial projects. It identifies facial expressions through 68 key facial landmarks. These 68 facial landmarks highlight the muscles in the eyebrows, eyes, nose and mouth. Facial landmarks that contribute towards forming any significant emotion are plotted in Fig. 2 [34].

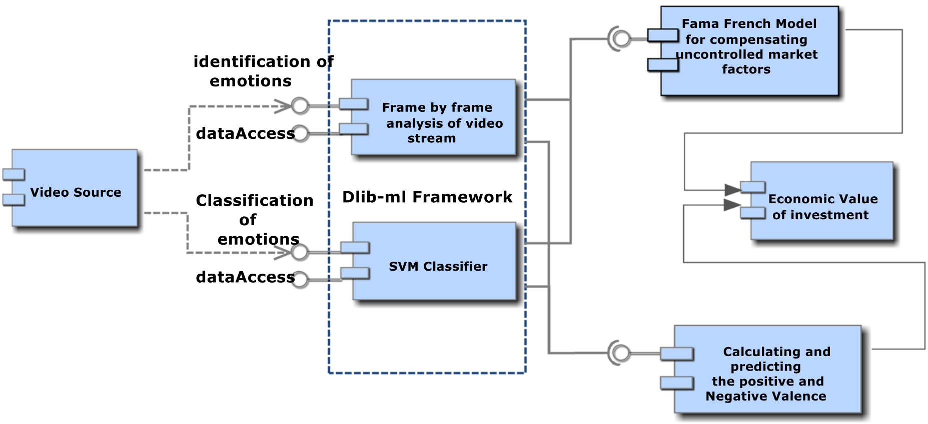

Fig. 1 Fama-French and Dlib-ml inspired Unified framework for predicting Economic Value of movie trailers (FADU-EV)

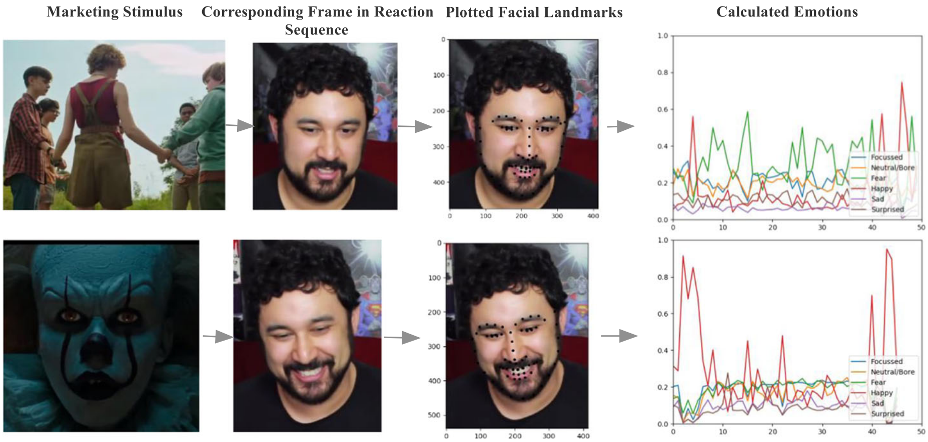

Fig. 2 Probability based outputs for identified emotions as generated by FADU-EV

FADU- EV divided training videos into a set of frames and then Dlib-ml plotted 68 facial landmarks on every face identified in each frame of the video. Subsequently, SVM classifier with Radial Basis Function (RBF) kernel was trained using the facial landmarks detected on every frame. Six discrete emotions namely happy, angry, sad, neutral, surprised and disgust were identified for every single face per frame using SVM. The classifier returns a probability corresponding to every emotion for every frame. As per available literature, emotions either have positive or negative valence [37]. Emotions are either Dimensional or Discrete. The dimensional view consists of two common dimensions namely Arousal and Valance [40]. The discrete view of emotion consists of actual emotional states like 'happy', 'sad', 'anger', 'disgust' and 'neutral' etc. [15, 24]. Effectively measuring dimensional states requires 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 [32]. 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, surprised, disgust and angry are considered to have a positive valence while neutral/bore has a negative valence for a theatrical movie trailer [41]. FADU-EV makes use of positive and negative valence of emotions within the reaction sequence of respondents to predict the economic value of a movie. Assuming the first frame "F_1" in a viewer's reaction sequence can have probabilities as [Ha_1, An_1, Sa_1, Su_1, Di_1, Ne_1] for

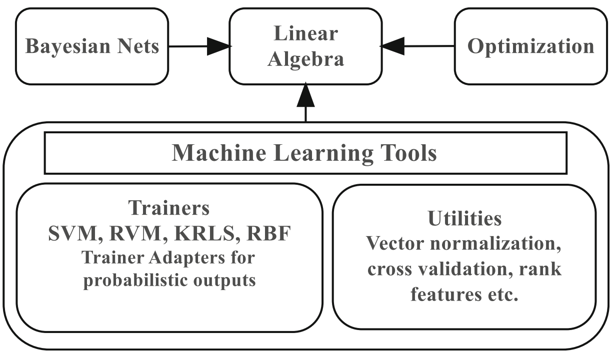

Fig. 3 Dlib-ml framework for machine learning

happy, angry, sad, surprised, 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 (PVE_s) 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 (NVE_s) is ∑Ne.

Economic value of a movie trailer is measured in terms of the abnormal returns (ABR). It is gained from the variation in the stock value of movie after the trailer release. 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. Returns on stocks are expected to be highly influenced by these factors [20]. Fama- French Model identifies and handles these common risk factors associated with ABR on any kind of stocks and bonds. Data about movie stock pricing is taken from Hollywood Stock Exchange (HSX), which is one of the most popular virtual movie stock market. HSX has over two million participants with most active traders tending to be heavy consumers and early adopters of movies [17]. Traders make use of virtual currency to increase their net worth by trading movie stocks and other financial products related to movie industry [26]. Researchers have found that forecasts made by HSX traders are reasonably accurate in making predictions of actual box office returns [17, 18, 22, 50]. Further, investors use virtual stock markets to forecast movie demand, even before the release of movie [21]. Fama- French inspired 3-factor equations are implemented within FADU-EV to predict the impact of PVE and NVE on stock pricing. Procedure to calculate PVE, NVE and ABR is detailed in Algorithm 1. To validate the performance of proposed FADU-EV, a case study was undertaken. The case study was executed in two phases. First phase corresponds to identification and measuring of emotive response of respondents. During this phase, crowd sourced videos of theatrical trailer review, which were voluntarily shared on YouTube, were used to train a computer program [53]. The computer program performed a frame-by-frame analysis of theatrical trailer. Further, it also identified and measured the intensity of emotions (PVE & NVE) stimulated by movie theatrical trailer.

Second phase of case study calculates the returns on stock value using the emotive score of a movie trailer. For this, abnormal return (ABR) on a movie stock value is calculated. ABR is equal to difference between the actual and expected stock value of movie, as shown in Eq. 3. Later in this phase a relationship is established between ABR and emotive score (PVE & NVE) within the trailer. The model uses linear regression to establish a relation between ABR & (PVE & NVE), while taking into consideration the coefficients of the Fama-French 3 factor model (HML,MktRF & SMB) as shown in Eq. 4 [30].

Algorithm 1: predicting the abnormal return for any movie trailers using FADU-EV

Input:

V [] = Reaction sequences of viewers from YouTube corresponding to movie trailers. (Data set used for training)

R [] = Stock data (closing value in HSX dollars) for all the movies in V []

T = Recorded reaction sequence for movie trailer to estimate its economic value

HML, MktRf and **SMB** = Coefficients from Fama-French 3 factor model

Step 1: Input reaction sequence videos V [].

Step 2: Segregate each video within V [] into frames and for each frame go to step 3.

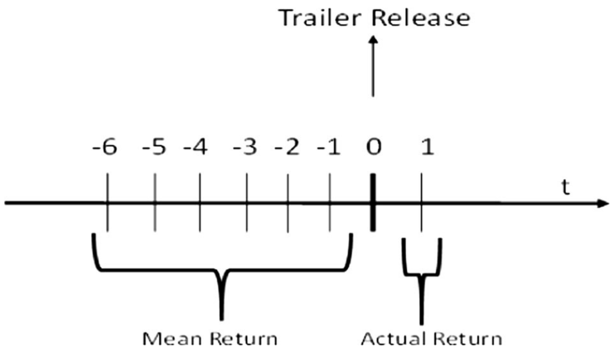

Fig. 4 Estimating the impact of movie theatrical trailer release on its stock value

Step 3: Use Dlib-ml to plot 68 key landmarks on faces identified within frames of reaction sequences.
Step 4: Train SVM classifier with RBF kernel to classify six emotions namely happy, sad, neutral, anger, surprised and disgust.
Step 5: For every sequence in V, calculate Positive Valence Emotive score "PVE" as

$$PVE_s = \left(\sum_{k=0}^{n} Ha_k + An_k + Su_k + Sa_k + Di_k\right)/n\Big) \tag{1}$$

and Negative Valence Emotive score "NVE" as.

$$NVE_s = -\left(\sum_{k=0}^{n} Ne_k\right)/n \tag{2}$$

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

Step 6: Calculate abnormal returns ABR for every movie in R [] resulted from movie trailer release as Actual Return (A_m) and Mean Return (E_m), here

$$E_m = \left(\sum_{i=-1}^{-6} Ri\right)/6 \tag{3}$$

Let R_i be the closing value of the movie stock on day "i" and E_m be the mean return of the movie stock, calculated over an event window of [−1,-6] from the theatrical trailer release [0]. A_m presents actual return of the movie stock "m" on [+1], as shown in Fig. 4. The difference between A_m and E_m gives us the abnormal return value i.e. $ABR_m = A_m - E_m$.

Step 7: Use linear regression calculate the value of coefficients as given below

$$ABR_m = \alpha_1 PVE_m + \alpha_2 NVE_m + \beta_1 HML + \beta_2 MktRf + \beta_3 SMB + \varepsilon \tag{4}$$

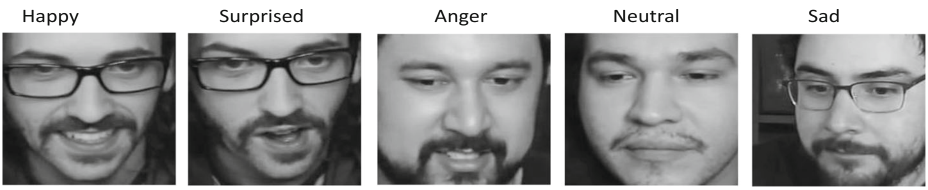

Fig. 5 Sample emotions identified during different reaction sequences

S. No.	Movie
1	Wonder Woman
2	War for the Planet of Apes
3	Dunkirk
4	Blade Runner 2049
5	Leap
6	The Lego Ninjago Movie
7	Justice League
8	Ferdinand
9	IT
10	Annabelle: Creation (2017)
11	Thor: Ragnarok
12	The Hitman's Bodyguard
13	Star Wars: The Last Jedi aka Epiode VIII
14	Kingsman: The Golden Circle
15	Home Again
16	The dark tower
17	Battle Of Sexes
18	Wonder
19	Logan Lucky
20	The Mountain between us
21	American Made

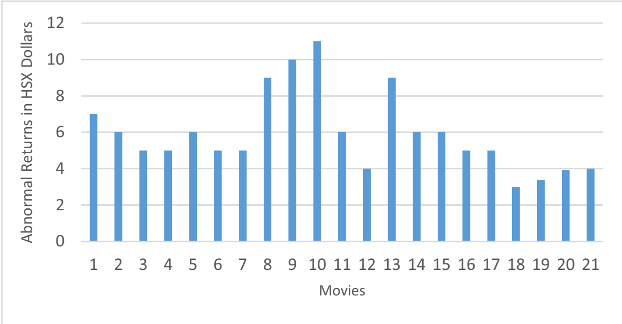

Fig. 6 Sample showing impact of theatrical trailer release on HSX stock value of movie

Step 8: Record and input reaction sequence for movie trailer as T.

Step 9: Run the trained SVM classifier on T and for each frame {1...k}, record the probabilities of identified emotion as $\{Ha_k, An_k, Sa_k, Su_k, Di_k, Ne_k\}$.

Step 10: Use steps 2, 3, 5 and 9 to calculate PVE and NVE for T.

Step 11: Use the values of coefficients from Step 7 and PVE, NVE from **Step 10** to calculate the estimated value of ABR for T.

One-day event window i.e. day after the release of theatrical trailer announcement is in reference to conventionally acceptable length in context of movie industry [35, 56]. 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.

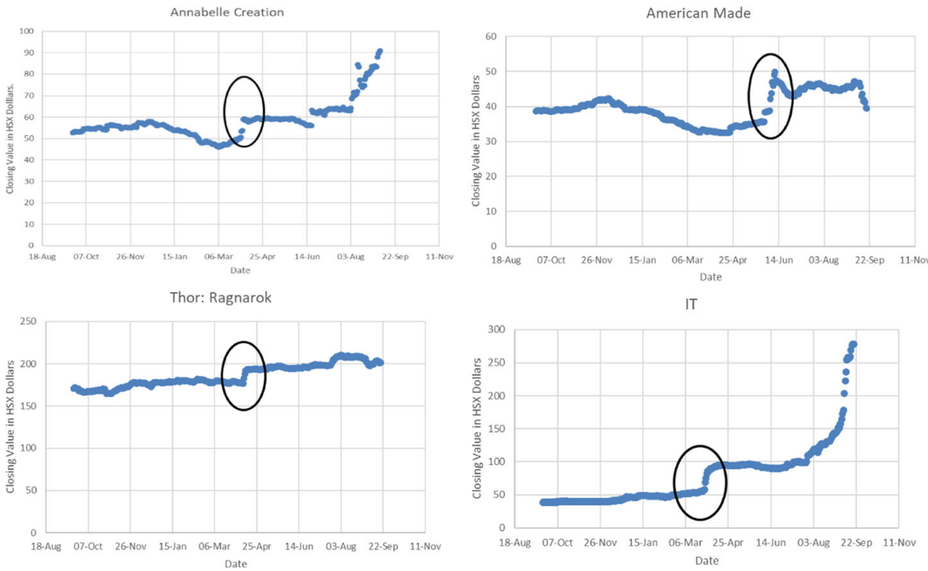

Fig. 7 Annabelle Creation, American Made, Thor: Ragnarok and IT witnessed a rise in their stock values after trailer release

Table 1 Ten best performing movie trailers

Movie	ABR (in HSX Dollars)	Theatrical Trailer Release Date
Despicable Me 3	14	14-Dec-16
Annabelle: Creation (2017)	11	01-Apr-17
IT	10	29-Mar-17
Star Wars: The Last Jedi aka Episode VIII	9	14-Apr-17
Ferdinand	9	28-Mar-17
The Greatest Showman	7	28-Jun-17
American Assassin	7	18-Jun-17
Wonder Woman	6	03-Nov-16
Jumanji: Welcome to the Jungle	6	29-Jun-17
Pitch Perfect 3	6	25-Jun-17

YouTube videos of people watching movie trailers, called reaction sequence were fed into an actualization of proposed framework, so as to recognize their emotional state. Two hundred and seventy eight such videos were used to train Support Vector Machine (SVM) classifier. The classifier attained an average precision of 0.87. The above algorithm took approximately 1.8 s to analyze an average 90 s long reaction sequence on Intel i5 2.7 GHz processor with 12 GB of RAM.

Movie producers have a tendency to release a series of movie trailers at different time for attracting audience. Previously mentioned techniques can jointly evaluate emotive score of different trailers of a movie released at different intervals of time, before actual movie release. The release of the theatrical trailer in itself can provide an insight to viewer's expectation from the movie. Thus, this case study would be experimenting with two hypothesis as given below:

H_1: There is no impact of a theatrical movie trailer release on its stock value
H_2: There is no relation between emotive score and theatrical movie trailer performance

Section below details about the case study conducted with respect to previously stated methodology.

4 Case study

To evaluate given hypothesis, a case study according to previously stated methodology was undertaken. This case study is based on the observation that, the effect of an event is

Table 2 Ten worst performing movie trailers

Movie	ABR (in HSX Dollars)	Theatrical Trailer Release Date
American Made	4	05-Jun-17
The Hitman's Bodyguard	4	13-Apr-17
The Mountain between us	3.93	31-May-17
Logan Lucky	3.37	29-May-17
The Disaster Artist	3	18-Jul-17
Flatliners	3	13-Jun-17
Wonder	3	24-May-17
Polaroid	2	29-Jun-17
Columbus	0.61	23-Jun-17
Menashe	0.19	20-Apr-17

Table 3 Mean min, max abnormal returns and standard deviation of movie stocks

Variable	Mean	Min	Max	SD
Abnormal Return = ABR_m	5.36	0.19	14	2.71

immediately reflected in its stock price due to efficient markets, perfect information and rationality of investors [20]. Initially this case study evaluates the effect of theatrical trailers on their respective HSX stock value. Hollywood theatrical trailers released from December 2016 until July 2017 constitutes the input set for this case study. Actualization of FADU-EV analyzed crowdsourced videos of theatrical trailer reviews, shared on YouTube channels. Frame by frame analysis of videos provided Ha, An, Sa, Su, Di and Ne values to calculate PVE_s and NVE_s of a viewer's reaction sequence. Figure 5 below presents the sample emotions identified during different reaction sequences.

We studied the stock prices of One Hundred and Thirty Nine Movies released during the said period. Figure 6 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. Figure 7 presents few of the prominent movies from the case study, which experienced high stock values after trailer release. It can be clearly noticed in Fig. 7 that the stock value of movies 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. Tables 1 and 2 presents ten best performing and worst performing movie trailers and their stock returns. Table 3 briefs the mean, min, max abnormal return and standard deviation of movie stocks investigated during the case study. There was a maximum \$14 and minimum \$0.19 rise in the stock value of the movie while there was an average \$5.36 rise in the stock value of 139 movies studied.

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 50 % while others experienced a marginal rise of five to 10 % only. Ideally, this variance in appreciation of stock values could result from the contents of trailer itself. Following section investigates the impact of emotionally intense theatrical trailer on stock value of its movie in comparison to a trailer, which cannot trigger much of emotions. 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 Eq. 5 given below [2]. Regression analysis resulted in a coefficient of determination equal to 0.9477 (R^2). Table 4 presents the calculated values for regression coefficients like ε, α1, α2, α3, β1, β2 [2].

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,

Table 4 Calculated values of ε, α1, α2, α3, β1, β2

ε	3.238705157
α1	10.45228338
α2	14.19635983
α3	−108.598059
β1	98.06145267
β2	−15.19620395

Table 5 Calculated values of PVEs and NVEs for best performing theatrical trailers

Movie	Change in Stock Value	PVEs	NVEs
Despicable Me 3	14.0	0.51	0.0012
Annabelle: Creation (2017)	11.0	0.47	0
IT	10.0	0.32	0.018
Star Wars: The Last Jedi aka Episode VIII	9.0	0.494	0.011
Ferdinand	9.0	0.31	0.02
Wonder Woman	7.0	0.313	0.065
The Greatest Showman	7.0	0.45	0.001
American Assassin	7.0	0.35	0.07
Thor: Ragnarok	6.0	0.524	0.065
War for the Planet of Apes	6.0	0.451	0.01

represented by ε in Eq. 4. Such unobserved factors too can affect the accuracy of anticipated abnormal returns. 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 5 estimates the effect of emotionally intense trailer on stock performance by calculating PVE and NVE, termed as $Predicted_{PVE_k}$ *and* $Predicted_{NVE_k}$):

$$\alpha_1 PVE_m + \alpha_2 NVE_m = ABR_m - \beta_1 HML - \beta_2 MktRf - \beta_3 SMB - \varepsilon \tag{5}$$

Coefficient values within Eq. 5 are taken from Table 4 and confounding factors like HML, Mkt-Rf and SMB are with reference to Fama-French model for second theatrical trailer. Robustness of Eq. 5 was further be evaluated through an accuracy parameter as given in Eqs. 6 and 7. Calculated accuracy parameter ϵ [0, 1]. Higher the accuracy achieved, higher will be the robustness of the Eq. 5.

Accuracy Equations:

$$Accuracy\_PVE = 1 - \sum_{k=0}^{n} \frac{\left|Predicted_{PVE_k} - Actual_{PVE_k}\right| / Actual_{PVE_k}}{n} \tag{6}$$

$$Accuracy\_NVE = 1 - \sum_{k=0}^{n} \frac{\left|Predicted_{NVE_k} - Actual_{NVE_k}\right| / Actual_{NVE_k}}{n} \tag{7}$$

Here "n" is the number of movies in the sample.

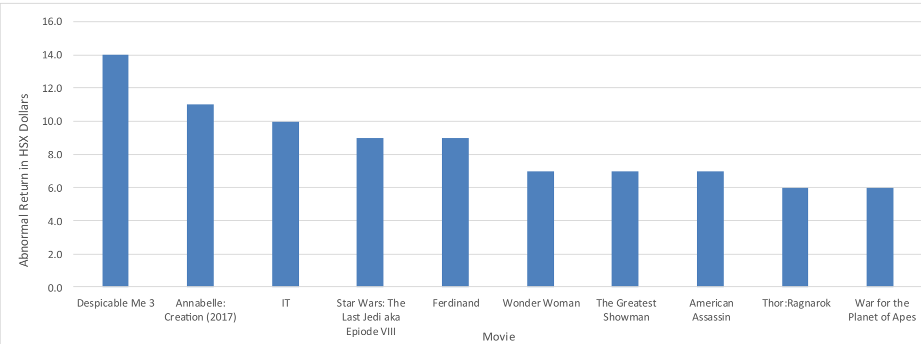

Fig. 8 Abnormal returns associated with ten best performing movie trailers

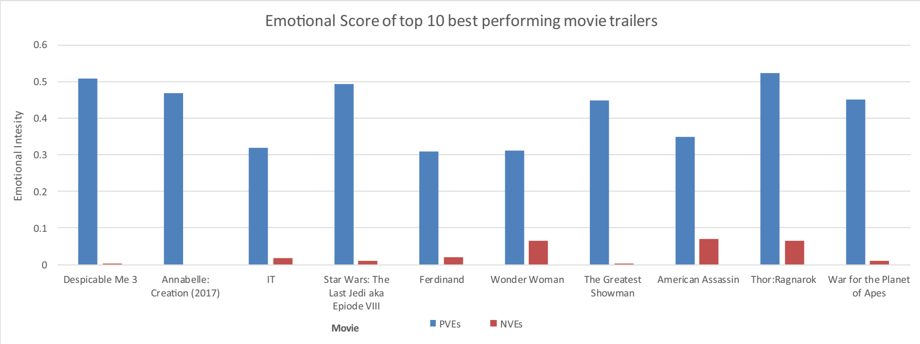

Fig. 9 Measured PVEs and NVEs of best performing movie trailers

5 Results and discussion

ABR, 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. Table 5 corresponds to ten best performing movie trailers and Fig. 8 presents abnormal returns associated with them. Figure 9 briefs the measured PVEs and NVEs of best performing movie trailers. Subsequently, Table 6 corresponds to ten worst performing movie trailers and Fig. 10 presents abnormal returns associated with them. Figure 11 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.

We used the Shapiro-Wilk W test to verify that ABR follows a normal distribution ($W = .91$, $p = 0.01$).Thus, it is proven that a trailer release significantly affects the movie's stock returns. The case study concludes an average increase of $ 5.36 in stock price for each movie, after the release of movie trailer. The average positive effect on abnormal returns disapproves H_1, surprisingly all the trailers resulted in positive abnormal returns after the release of theatrical movie trailer.

Relational mapping between abnormal returns (ABR) and the emotional score (PVE & NVE) for the top performing movie trailer sequences of a movie, released at different time is given in Table 7. From the recorded observations, it could be clearly inferred that ABR is directly proportional to PVE where as it is inversely proportional to recorded NVE for any

Table 6 Calculated values of PVEs and NVEs for worst performing theatrical trailers

Movie	Change in Stock Value	PVEs	NVEs
American Made	4	0.17	0.099
The Hitman's Bodyguard	4	0.21	0.13
The Mountain between us	3.93	0.31	0.14
Logan Lucky	3.37	0.33	0.01
The Disaster Artist	3	0.17	0.21
Flatliners	3	0.21	0.1
Wonder	3	0.1	0.099
Polaroid	2	0.11	0.13
Columbus	0.61	0.2	0.23
Menashe	0.19	0.14	0.2

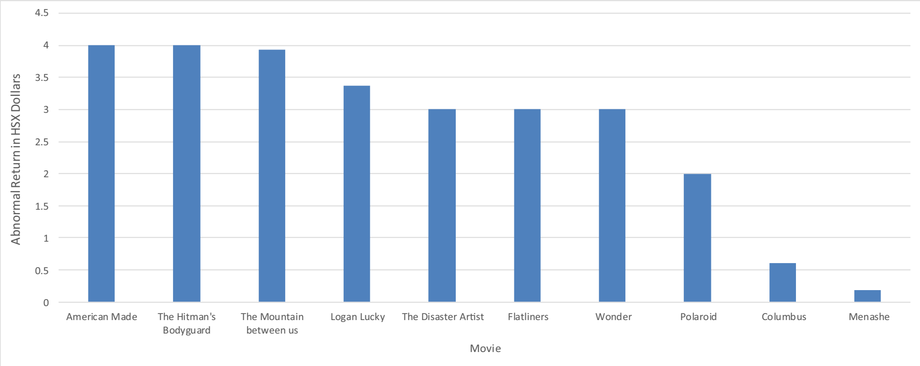

Fig. 10 Abnormal returns associated with ten worst performing movie trailers

movie trailer. Subsequently, it can also be inferred that PVE for trailer 1 > PVE for trailer 2, 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 Despicable me 3, which was released on Dec 14, 2016 (Trailer 1) and resulted in ABR of 14.0. Whereas the second trailer of the same movie, which was released on Mar 14, 2017 (Trailer 2), resulted in an ABR of 6.0 only. The same trend was observed for Trailer 1 and Trailer 2 of best performing movie trailers.

Figure 12 is the graphical representation of Table 7 comparing the ABR, PVE & NVE of top performing trailers released at different time. X & Y axis depict the ABR 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 a movie Despicable Me 3, is 0.51 while the maximum PVE for second trailer of the same movie is 0.39. Similarly for ABR, maximum return was for the first trailer of Despicable Me 3 i.e. $14. 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

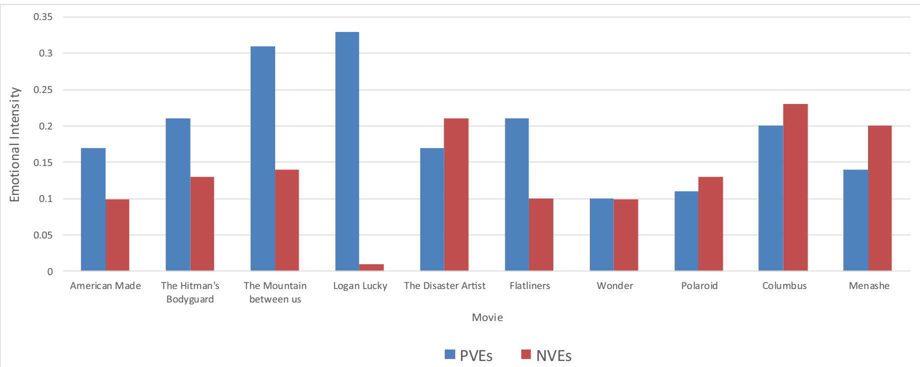

Fig. 11 Measured PVEs and NVEs of worst performing movie trailers

Table 7 Calculated values of PVEs and NVEs for ten best performing theatrical trailers released on different dates

Movie	Trailer 1			Trailer 2		
	ABR	PVE	NVE	ABR	PVE	NVE
Despicable Me 3	14.0	0.51	0.0012	6.0	0.37	0.11
Annabelle: Creation (2017)	11.0	0.47	0	5.0	0.39	0.13
IT	10.0	0.32	0.018	4.7	0.35	0.2
Star Wars: The Last Jedi aka Episode VIII	9.0	0.494	0.011	5.0	0.39	0.21
Ferdinand	9.0	0.31	0.02	3.0	0.11	0.1
Wonder Woman	7.0	0.313	0.065	3.0	0.21	0.16
The Greatest Showman	7.0	0.45	0.001	3.0	0.2	0.11
American Assassin	7.0	0.35	0.07	2.0	0.29	0.14
Thor: Ragnarok	6.0	0.524	0.065	3.0	0.41	0.18
War for the Planet of Apes	6.0	0.451	0.01	1.0	0.2	0.1

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, crowdsourced platforms like YouTube can prove to be reliable input source for training emotion driven platforms. The values of *Accuracy_PVE* and *Accuracy_NVE* were 0.73 and 0.79 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.

6 Conclusion

The case study also 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

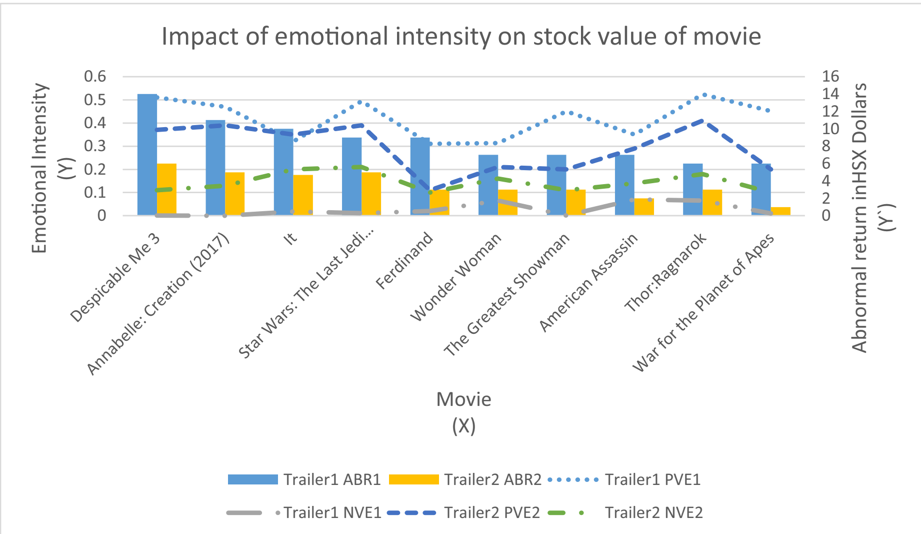

Fig. 12 Measured PVEs and NVEs of two theatrical movie trailers released on different dates

facilitate the composers in compiling a theatrical trailer which may trigger highly emotive reaction sequence within prospective viewers. The technique proposed would be of great help to production houses, promoters, marketers and other stakeholders to predict stock value of a movie with respect to emotional content of its trailer. In future, we intend to extend this case study with actual respondents instead of using YouTube videos. The framework proposed in this paper can also be used for evaluating product design, fine-tuning advertisement efforts and deciding other marketing mix for business houses.

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