

SNIP: A Modern Comprehensive Social Network Investment Platform for Film Data Analysis

ABSTRACT

The return on investment (ROI) analysis about movies is a challenging but important task for movie investors in their decision making process. For investors, they are expected to get high box-office revenue with appropriate investments. Apart from movie special effects, most of investments are used to remuneration for movie actors(actress). Due to complicated factors such as audience reactions, screenplay, film types etc, it's not easy for investors to estimate upfront ROI, which makes film investment a gamble. Although most current research works aim to predict box-office revenue more specific, they can not provide investors more direct profits information about the success of the movie they would like to invest.

In this paper, we design and implement an integrated system, called Social Network Investment Platform (a.k.a SNIP), that aims to do some analysis of movies for investors. SNIP provides various modules for users to predict box-office, capture public opinion about a film, assess the value of the actor, monitor the changes of the ratio of box-office about actors, assess actor replacement and so on.

KEYWORDS

Data Analysis, Targeted Sentiment Analysis, Box-office Predicting

1 INTRODUCTION

In modern society, watching movies is becoming a central part of consumer culture which makes the great earning of investments about movies. However, how to evaluate the reasonability of investments becomes an important problem for investors. Owing to complex film markets, the success of a movie is closed related to audience reactions, screenplay, film types and starred actors(actress) or directors. Before the movie release, we cannot guarantee it can be popular or not.

In recent years, with the heat of the film market, large amounts of money pour into film industry. Investments about movies consist of actors and directors salary, film itself production. advertising fees etc. Actors and directors salary occupies a large proportion in cost of movie. However, the immaturity of the Chinese film market itself leads to a high-risk, high-reward investment environment. Recently, the group acts of "fans" do not only create a great social effect, but also produce a huge economic benefit. Without bankable stars the film script aroused no interest. In order to pursue high profit, the usual way is to use a large number of "celebrities" to promote the box office through the fan effect but only a few were success. But it has caused the soaring star worth, the consequent increase in production costs. The reason is that in spite of massive "fans", the degree of match between fans and movies is the most important factor affecting the box office. Another is that box office is decided by actors, scripts, publicity, release schedule and other aspects, actors' contribution to the movie cannot be equal to box office. The lack of an effective quantitative method to assess the

creative record of the box office contribution prevent investors from assess the investment star's rationality.

Besides the cost of production about movies, investors are concerned about box-office revenue. The research on movies maily focuses on film box-office prediction[1, 2, 17]. They use linear regression, neural networks[20] and other models to predict box office more accurately by constructing multiple features, for instance, Google [18] uses search, ad click data, and line rows to predict box office and gets 94% accuracy. Sentiment analysis in film reviews [13, 16, 19] is another aspect to do some analysis in movies and many experiments[7, 10] prove that reviews data can improve box-office predicting accuracy. However, those work are too simple to do some analysis on the components of revenue further. Generally speaking, investors are anxious to have a tool or a platform to do a more intuitive analysis of a film's return on investment. There are

In recent years, the research on film mainly focuses on the construction of user-oriented movie recommendation system[5, 26]. In general, an investor-oriented movie analysis platform is for the Chinese movie market, providing an investor-oriented integrated emotional analysis, box office prediction, actor evaluation, box office contribution analysis of the analysis of the box office analysis of the movie, focusing on the protagonist, director, audience impact on the box office.

1.1 Challenges and Solutions

Considering improvements and new methods developed moving with time, natural language process (NLP) and deep learning (DL) is sharp solution in both data mining especially text mining and machine learning area. Based on modern technique, we proposed most valuable end-to-end analyse system Film Knowledge Analyse Platform (SNIP) which cover movie data of films. The main contribution of SNIP is finding state-of-art approach to traditional movie big data mining task. We summarized the key problem that evolved system SNIP focused on.

DIFFICULTY 1.1. *Given a comment, how do you analyze the names and emotions mentioned in this comment?*

The existing sentiment analysis of movie reviews rarely seldom further analyzes the sentiment of the commentators. In social media, audiences may show different affective tendencies toward different protagonists of the movie, whereas traditional short text sentiment analysis can not capture these sentiments. To solve this problem, SNIP provides an object-oriented commentary sentiment analysis that performs named entity recognition and sentiment classification for each comment to more accurately capture the viewer's preference for a particular director (actor) of a particular movie.

DIFFICULTY 1.2. *How to quantify the director's contribution to the box office?*

Director (starring) contribution to the box office refers to the audience for the expectations of one or a few people to generate consumer spending movie tickets, analyze the contribution of a box office contribution to help get the actual business director or director value. In the analysis of the box office data, it is difficult to quantify the actual box office revenue of every star / director in a movie. There is also a lack of analysis of related modules in the existing commercial film analysis system. SNIP provides a dynamic analysis module that accounts for the share of the box office's contribution, not only to quantify the box office's contribution but also to analyze the changes in the commercial value of a master before and after the release of the movie through changes in contributions over time.

DIFFICULTY 1.3. Joint value evaluation and replacability among actors.

Since effect of an actor suffer multi uncertainties and how to make a joint-evaluation of actor impact is a big question. A lot of method focus on giving linear weight for each factor. But this weight might change and impractical when goal of analysis changing. In SNIP, we mining joint value based on relationship among actors using heterogeneous network. Qualifying similarity and measuring increase of influence by co-star of two specific actor for target film show great power on practicability of the system which enhance availability and effectiveness of SNIP a lot.

1.2 Roadmap

The rest of this paper is organized as follows, Section 2 presents an overview of SNIP. In section 3 we show integration preprocessing on heterogenous movie data and elaborate disambiguation of actors' names by construct personas. In section 4 we further study name entities recognition based on disambiguation and then describe how SNIP extract target-dependent sentiments and analyse changeable trend on sentiment. Section 5 presents dynamic impact of leader creators based on both sentiments and self attributes. In section 6 present the core value of system by phased prediction of movies which helps to maximum box-office based on reasonable investments now and future. Section 8 presents system evaluation as well as the case study. In section 9, we introduce the related work. Finally, Section 10 concludes the paper.

2 PLATFORM OVERVIEW

SNIP is a web-based integrated system for movie analysis. The screenshots of SNIP are shown in Figure 1 and the architecture overview is displayed in Figure 2. Using SNIP, users can carry out a series of analysis based on the movie centric information.

In general, SNIP consists of three layers of components, including Basic Processing Task Layer, Higher Algorithm Library Layer and Visualization Layer.

Basic Processing Task Layers provides data cleaning, data standardization and data conversion. Due to the different data sources, the data obtained can not be applied directly to the analysis. In fact, the movie data need to consider the following questions, name ambiguity elimination, used to evaluate the quality of the film at the box office, the film's reviews of object identification, actor knowledge base construction. These methods are provided in the basic processing task layer.

Higher Algorithm Library Layer contains the core technology of SNIP, including Target-Dependent Sentiment Analysis Module and Dynamic Impact of Actors and Directors Module. The layer considers the importance of film reviews to a film and combine with Machine Learning.

Visualization Layer is the interface between the system and the users. To intuitively present the analysis results, this layer is designed to be user-friendly and easy to operate. Specifically, Sentiment Tendency is to capture the changes of sentiment among audience during movie released. Box-office prediction is to predict the box office of a movie by actors, directors and audience factors. Alternative actors is to get the replaceable list of actors.

3 HETEROGENEOUS DATA INTEGRATION AND ANALYSIS

3.1 Data standardization

An obvious phenomenon is that the box office of the movie has significant difference with the year and type. In order to eliminate these effects, we define the box office score to measure the box office quality of a movie. Given the box office of a movie bo and its movie type set $T = T_1, T_2, \dots, T_k$ and release Year y , the box score is

$$bs = \frac{1}{|T|} \sum_{t \in T} \frac{\log_2 bo}{\max_{box_{y,t}}} \quad (1)$$

where \max_{box} is defined as $\max(\log_2(boset)_{year=y, type=t})$, which $boset$ is a set of boxoffice.

Similarly, due to the difference of movie types, the original movie ratings can not accurately describe the word of mouth of the movie. We evaluate the word of mouth score according to the min-max method. Given the word of mouth a movie wm and its movie type set $T = T_1, T_2, \dots, T_k$, the word of mouth score is

$$ws = \frac{1}{|T|} \sum_{t \in T} \frac{wm - \min(wms_t)}{\max(wms_t) - \min(wms_t)} \quad (2)$$

where wmt the set of the word of mouth of movies where type is t .

3.2 Persona of famous actors and directors

We provide persona analysis of famous actors and directors which is shown in Figure 1(d). The box office value of a famous director or actor is one of the most important parts of the box office. Famous Actors(directors) are the main performers(directors) over 10 movies or won the film excellent actor(director) award or have more than three million followers in social networks. Portraying the box office of famous actors or directors in historical movies can help us analyze their value and Volatility.

We use bos , bov , wms , wmv to reflect the average box office performance, the box office performance fluctuation, the average word-of-mouth performance and the volatility of word-of-mouth performance so that we can depict the performance of the historical

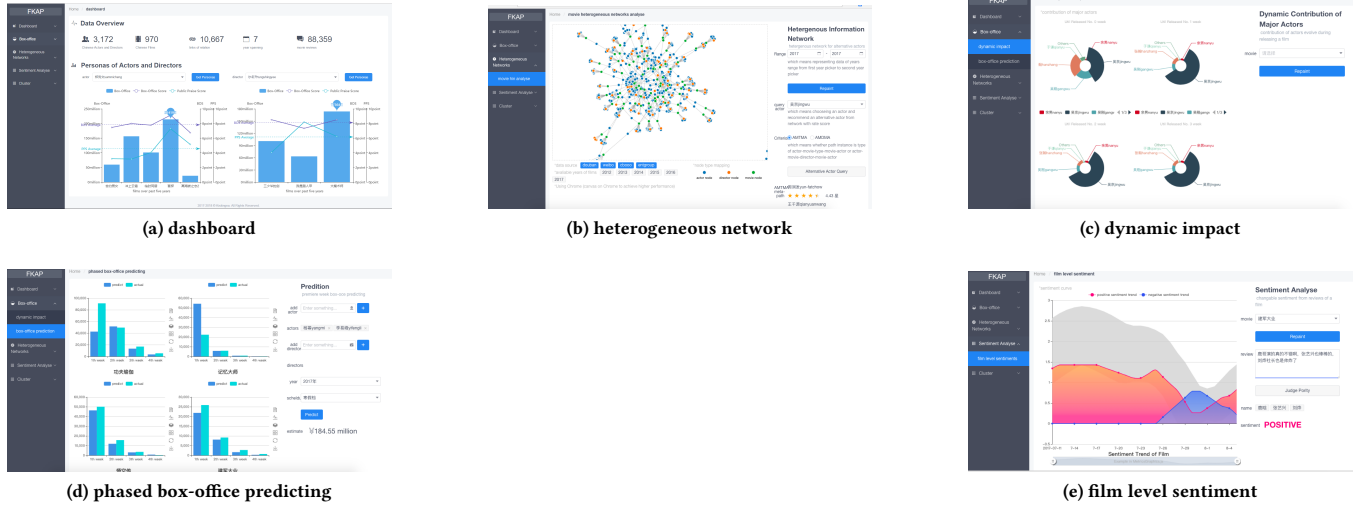


Figure 1: Screenshots of SNIP

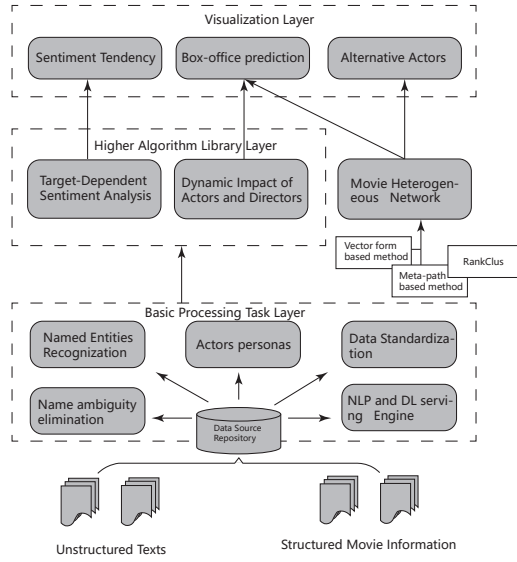


Figure 2: System architecture

movie to provide guidance for the selection of the corner.

$$bos = \frac{1}{N} \sum_{i \in N} bs_i \quad (3a)$$

$$bov = \frac{1}{N-1} \sum_{i \in N} (bs_i - bos)^2 \quad (3b)$$

$$wms = \frac{1}{N} \sum_{i \in N} ws_i \quad (3c)$$

$$wmv = \frac{1}{N-1} \sum_{i \in N} (ws_i - wms)^2 \quad (3d)$$

3.3 Named Entity Disambiguation

Named entity disambiguation is one of the most important problems in natural language processing. In named entity category, person name has strong ambiguity so that person name disambiguation is the most difficult category. However, because the project inquiry is a well-known director and famous actor, and Chinese name and English name, makes the probability of Fijian phenomenon is greatly reduced, in this collection of 2371 directors and 801 actors, one by one, through the Baidu encyclopedia content, movie actor information, can be a good solution the same problem.

4 PRACTICAL SENTIMENT ANALYSE

The main purpose of sentiment analyse is to discover views and opinions diversity [11] of different targets in films which reflect what attract audience watching the movie. The sample dataset in this area are review corpus $R = \{r_1, r_2, \dots, r_n\}$ and each r_i has film name f_i it belonging to, time point $time_i$, scores towards this film s_i and user u_i who scores. These attributes of reviews are discrete (has domain specific value) and many sentences in it contribute to the whole sentiment of this single review. Since reviews are spread in social media platform such as twitter or micro-blogs, the sentences are limited and review of movie are usually enough short. Thus, many phenomenon occurred on short texts or natural language add difficulties when analysing the sentiments of targets (e.g. Rhetoric, metaphor, proverb and nicknames)[14]. Unlike many works focus on proceed in sentence-level document-level and time-period level step by step[3], we try to figure out the sentiment to a specific actors or director(leading creator of this film)[6]. A useful prior knowledge in reviews together with reviewers' rating score or stars made by user is evaluation score of specific film. We make the best of this knowledge to enlarge our sentiment words database because user usually behave consistent sentiment to same target.

4.1 Named Entities Recognition

If we want to know sentiments behind human expression, targets that people are taking about should be identified firstly. Here we concentrate on comment target about leader creators in films. The main challenging is the nicknames for actors and directors.

Sequence to sequence approach. Given a word sequence $X = \{x_1, x_2, \dots, x_n\}$ we observed and the 4-tag label set $Tags = \{O, B, E, M\}$, the objective task is to find correct corresponding labels $Y = \{y_1, y_2, \dots, y_n | y_i \in Tags\}$. By optimizing the loss function with parameter θ

$$J(\theta) = \arg \min_{\theta} \frac{1}{n} \sum_{i=1}^n \text{loss}(f(x_i; \theta), y_i) \quad (4)$$

recurrent neural networks such as *LSTM*, *BidirectionalLSTM*, *BidirectionalLSTM+CRF* [3] have been proved to be state-of-art structures. They consider both long time and short terms information and find tags with maximum possibility for sequence labeling. However, previous machine learning approaches need huge domain training data, while it is hardly to label these social media corpus accurately which are full of informality and flexibility. Especially actors get constantly evolving new roles in various films as time goes by, we hope find a simple and efficient way that recognize most of the comment targets in films reviews.

Fast and adaptive approach. In order to mining entities in linear time, we apply key word matching for leader creators in films. Online knowledge database which store film meta information can be strong support providing comprehensive and dependable analysis. Focused crawling technology based on web linkage contribute to construction of prior knowledge of **actors**, **roles** and **directors**.

Algorithm 1 Framework of nickname mining for our system

Input:

- The name set of **actors** and **directors** in each film
- The name set of **roles** for each actors used to played
- Threshold α for minim similarity of misspell and variation
- Threshold β for max tolerance of misspell and variation

Output:

- Potential comment targets mapping dictionary A, P
 - 1: Aggregating reviews group by corresponding film name along with preparing actors list A_i , directors list P_i in i th film according given **actors** and **directors**;
 - 2: Constructing actors mapping A for every actor in a_i , so dose P for every director in p_i ;
 - 3: Quality similarity between every noun morphemes w and t in **roles**, **actors** and **directors** by *Jaccard* char distance in all comments for one film;
 - 4: Recognizing potential nickname by the similarity and threshold α we set, if *Jaccard*(w, t) $> \alpha$ add it to mapping dictionary A or P ;
 - 5: Checking potential nickname in mapping dictionary, if *Levenshtein*(w, t) $> \beta$, delete it from mapping dictionary A or P ;
 - 6: **return** A, P
-

Assume average noun morphemes length is m for all n reviews and t targets for all F films. Algorithm 1 need compare $c \times nmt$

times. Since word comparing consume limited space and time and $m \ll n, t \ll n$, we extract potential comment targets in $O(n)$ time complexity which greatly less than deep learning approach. We can easily adjust designed parameter and improve efficiency with parallel framework when processing TB data.

In order to decrease the storage space of data, we replace film name and user name by mapping them using film id and user id. $f_i \in F = \{f_1, f_2, \dots, f_m\}$ and $u_i \in U = \{u_1, u_2, \dots, u_U\}$. Let score for each review be $s_i \in [0, 10]$ and $time_i$ be the timestamps. The features we finally retrieved can be summarized in table ??.

4.2 Target-Dependent Sentiment Classification

Sentences tend to be more complex when targets we want to analyse increase and sentiments detection being a hard work when analysing more objects. We take leader creator of film as major targets in this paper. Examples containing multi targets are shown as follows.

- (1) Live here now! The point of life is looking for the point.
—*A dog's purpose*
- (2) It has been a year since I were familiar with Alexander Sandro Gonzalez Inarritu whose films have a cruel irony and full bitterness.—*Bird man*
- (3) Mia had dreamed of becoming an actress known by more audience, while Sebastian want to won a place in his loving jazz. —*LaLa land*

Sentence(1) is a non-target review, while Sentence(2) shows one-target sample and Sentence(3) stands for multi-target sentences. Considering targets after NER process in section 4.1 consist of actors map list $A = \{a_1, a_2, \dots, a_A\}$ and directors map list $P = \{p_1, p_2, \dots, p_P\}$, we cluster sentences into comments set with two polarity(positive +1 and negative -1). Binary sentiment classifier play an important role in sentiment classification. Sentiment polarity $SP = \{+1, -1\}$ labeled by classifier for each sentences in corpus st_i^j of i th film with corresponding target $j, j \in A \cup P$ and targets capacity $T = |A| + |P|$. Let T_i be number of targets in film i . We try to find out following segments.

$$Neg = \bigcup_{i=1}^F ng_i \mid \text{polarity of } ng_i = -1, ng_i \in \bigcup_{j=1}^{T_i} st_i^j \quad (5)$$

$$Pos = \bigcup_{i=1}^F ps_i \mid \text{polarity of } ps_i = +1, ps_i \in \bigcup_{j=1}^{T_i} st_i^j \quad (6)$$

Since we have to retrieve *Neg* and *Pos* shown in Equation (5) and (6), we take training data R_p with scores larger than 9 for positive sentiment and R_n which scores lower than 3 for negative one. We exclude reviews R_{ambi} which scores range between 4 and 8 that might be ambiguous over sentiment in training phrase. Instead, R_p and R_n show more concentrated sentiments in words. We train a classifier on R_p and R_n , then we split R with context window according referred target in each review. Reviews segments cover target's contextual information which construct sentiment corpus *Neg* and *Pos* towards specific targets are objectives for sentiment classifier. We mainly apply it on targets segments split from R_{ambi} . Finally, we get comprehensive sentiment polarity on targets segments in R .

Review No.	Contents	Referred	Film No.	time point	Scores
1	Yang Yang's hard temperament is enough to hold up the role	Yang Yang	Ten great II of peach blossom	2016-07-25T13:36:12.000+0800	10
2	Yang Yang's acting is really embarrassing, Crystal Liu is OK	Yang Yang, Crystal Liu	Ten great II of peach blossom	2017-08-07T20:18:55.000+0800	5
3	The story of embarrassment, feeling Yehua did not love Baiqian	Yang Yang, Crystal Liu	Ten great II of peach blossom	2017-08-07T21:09:07.000+0800	2
r_i	f_i	$time_i$	s_i

Table 1: review targets after named entities recognition

Lexicon based sentiment analysis is constrained by sentence structure, latent word meaning and confused word features. We introduce bidirectional long short term memory (*Bi-LSTM*) neural network [3, 25] for end-to-end sentiment classification and automated feature learning as figure 3 shows.

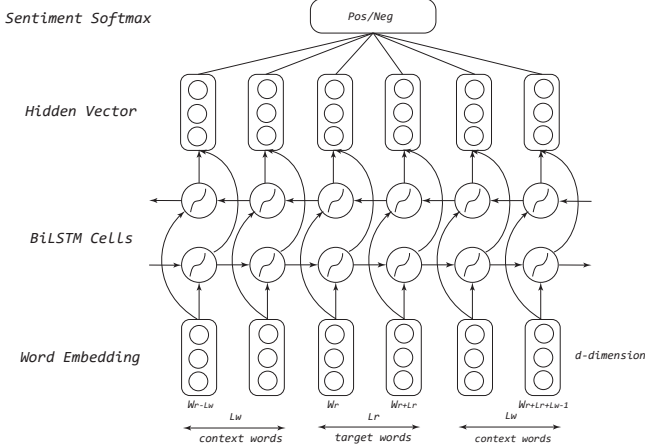


Figure 3: Structure of Bi-LSTM Sentiment Classifier, where L_r for target words length and L_w for context length we extract from original sentence. First layer in Bi-LSTM stands for forward hidden layer and the second layer are the backward one.

Specially, word sequence are represented as a low dimensional, continuous and valued vector. It is called word embedding and we use pre-trained vectors so as to make better use of semantic and grammatical associations. Assume each d -dimension vector $W_i = \mathbb{R}^{d \times |V|}$ for i th word in whole vocabulary V . Targets words with L_r length cover $tw = \{W_r, W_{r+1}, \dots, W_{r+L_r-1}\}$ and context words $cw = \{W_{r-L_w}, \dots, W_{r-1}, W_{r+L_r}, \dots, W_{r+L_r+L_w-1}\}$ with window length L_w surround corresponding targets words tw . *BiLSTM* maps word vectors to fix-length sentence vector by recursively transformation above vectors of previous time step h_{t-1} . Cells for *BiLSTM* in Figure 3 contains neural gates: input gates, forget gates, and output gates which adaptively remember input vector, forget history, and generate output vector. We add softmax layer to output sentiment of sentence vector which cover

hidden representation of vectors for specific target segment as Figure 1 shows. Core calculation in LSTM cells are listed in bellow equations. \odot is element-wise multiplication and σ is sigmoid activation, $W_i, W_f, W_o, b_i, b_f, b_o$ are parameters for input, forget and output gates.

$$i_t = \sigma(W_i \odot [h_{t-1}; w_t] + b_i) \quad (7a)$$

$$f_t = \sigma(W_f \odot [h_{t-1}; w_t] + b_f) \quad (7b)$$

$$o_t = \sigma(W_o \odot [h_{t-1}; w_t] + b_o) \quad (7c)$$

$$g_t = \tanh(W_r \odot [h_{t-1}; w_t] + b_r) \quad (7d)$$

$$c_t = i_t \odot g_t + f_t \odot c_{t-1} \quad (7e)$$

$$h_t = o_t \odot \tanh(c_t) \quad (7f)$$

4.3 Film-level Sentiment Trend

In this section, we mainly care about how to predict latent sentiment transform. Obviously, we quantify explicit sentiment towards special actors or directors. Although all information came from overall corpus, we can not deny that different sentiment exist in different time period during movie life. Audience's sentiments have trends and always behave dynamically. Previous work concentrate on sentiment polarity and we extend it by capture dynamic time-period sentiment. Denote a time period range from $time_r = [time_i, time_j]$, we capture review statistical sum R_{f_i} of each movie f_i at time period $time_r$ from *Pos* and *Neg*. Then we get different target j 's positive or negative sentiment transformation at different $time_r$.

$$SentimentPos_i^j(time_r) = 10 \cdot \frac{|pos_i^j \text{ in } time_r|}{R_{f_i}} \quad (8)$$

$$SentimentNeg_i^j(time_r) = 10 \cdot \frac{|neg_i^j \text{ in } time_r|}{R_{f_i}} \quad (9)$$

Dynamic sentiment on leader creator shows how people transform their attention from different targets in movies. We pick out most interesting part (actor) from them and label it the main factor which mainly contribute to the box-office of specific film. The trend analyse is shown in Figure 4.

To measure the smoothness of the sentiment time series, we use slice window to capture the changes in the emotional inclination of the reviews. We Denote upper bound and lower bound of a day $r, UBP_i^j(r), LBP_i^j(r), UBL_i^j(r)$ and $LBN_i^j(r)$.

$$UBP_i^j(r) = \text{mean}_i^j(\text{time}_r) + \lambda \cdot \text{std}_i^j(\text{time}_r) \quad (10)$$

$$LBP_i^j(r) = \text{mean}_i^j(\text{time}_r) - \lambda \cdot \text{std}_i^j(\text{time}_r) \quad (11)$$

where

$$\text{mean}_i^j(r) = \frac{1}{2d} \sum_{k=r-d}^{r+d} \text{SentimentPos}_i^j(\text{time}_k) \quad (12)$$

$$\text{std}_i^j(r) = \frac{1}{2d} \sum_{k=r-d}^{r+d} (\text{SentimentPos}_i^j(\text{time}_k) - \text{mean}_i^j(\text{time}_r))^2 \quad (13)$$

Because the time series follows Gaussian Distribution, and we set $\lambda = 2$, means that confidence intervals is 0.0456,

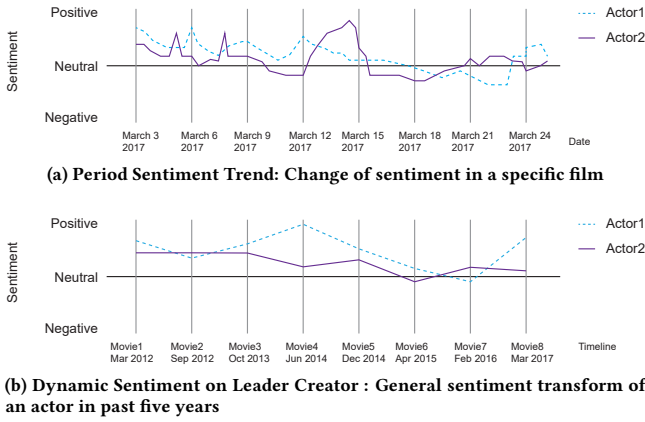


Figure 4: Film-level sentiment trend analyse of different time period. a) shows the change of sentiment in one film life period which indicates what attract people. b) shows the average sentiment of a specific actor which indicates highest moments and lowest moment of an actor career

5 THE ESTIMATE ABOUT BOX OFFICE INFLUENCES OF ACTORS AND DIRECTORS

The goal of this module is to find who is the most bankable person in a movie and to capture the dynamic trends about actors and directors during the period of a movie released. As figure 5 shows, the box office influences can be made up of three parts: the actor's/direct's own box office appeal, media exposure and feedback from audience. For simplify, we regard actors and directors as creators.

5.1 Contribution of Creators

The creator's own box office appeal. Actor's own box office appeal includes historical box office results and historical word of mouth performance, in which the film's historical movie box office performance can objectively reflect the creative ability of gold absorption, while the historical reputation score can objectively reflect the creative performance by Audience recognition, so this article at the

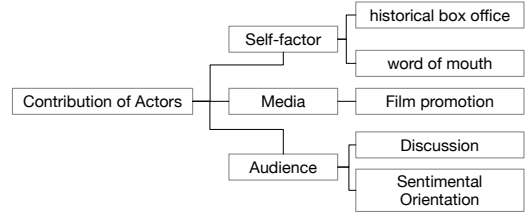


Figure 5: Composition of creative influence

same time using the history of the box office and the history of reputation to measure the creative box office call ability.

We define the box office quality *boq* to measure the box office generated by the creator itself based on the historical film data. As for directors, we define $boq(c) = wms(c) \cdot bos(c)$. Considering different role importance, as for actors, we define $boq(c) = f(c) \cdot wms(c) \cdot bos(c)$, where $f(c)$ is the influence factor and it depends on the position k that the actor c is. The larger k is, the smaller $f(c)$ gets.

Media exposure. The movie's promotional period is always accompanied by a wide range of media coverage, the media's title content reflects the current public focus, if an actor or director appear in the title a lot, you can explain the public familiarity and attention more. We define $mej_j(c)$ as the number of times the creator c referred to by the media in the j th week.

Feedback from the audience. Liu [15] mentioned the impact of word-of-mouth on the box office is very large and Craig [4] added to the equation online buzz variables expressing awareness and purchase intention and examined factors that contributed to higher levels of e-WOM. With the rapid development of the Internet, people can express their emotions on social media at any time. Thanks to the development of social media networks, the promotion of the movie has also gradually increased the proportion of online publicity. At the same time, the content of the discussion of the movie has also formed a considerable amount of data. The movie review often includes the concept of "If you can get the audience's idea of fitfittan actor or master from the commentary, you can see whether the source of the audience's emotional inclination toward the movie comes from the influence of the movie's main actor (including the protagonist). We define $aco_j(c)$ as the number of times the creator c referred to by the active comments in the j th week.

5.2 Dynamic Impact of Creators

In the short life of the movie, the contribution of the genre to the box office is obviously not constant. With the development of the Internet media, real-time feedback of the movie users on the movie will affect the watching desire of the non-movie users, and the positive contribution Refers to the potential box office or the desire to watch the increase; the negative is the box office to bring the negative image, to dispel the wishes of watching. Therefore, in the film's life, the star effect on the box office's contribution is dynamic,

the project will be divided into the life of the movie before the release, the first week of release, the second week of release, the third week of release, released the fourth Friday A period, respectively, to explore the five periods of major box office contributions.

We define the DIR (Dynamic Impact Ratio) as $DIR_j(c) = \frac{DIP_j(c)}{\sum_{k \in C} DIP_j(k)}$ to measure the ratio of the box office contribute from creator c to all box box office contribute in j th week, where

$$DIP_j(c) = w_1 \frac{boq(c)}{\sum_c boq(c)} + w_2 \frac{\sum_{i=0}^j mep_j(c)}{\sum_{i=0}^j \sum_c mep_j(c)} + w_3 \frac{\sum_{i=0}^j aco_i(c)}{\sum_{i=0}^j \sum_c aco_i(c)} \quad (14)$$

where w_1, w_2, w_3 is three coefficients to embody the importance of creator's own box-office appeal, media exposure and feedback from the audience. In practice, we set $w_1 = 0.1, w_2 = 0.2, w_3 = 0.7$.

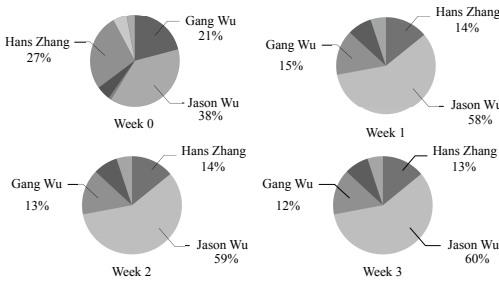


Figure 6: Changes of Wolf Warriors II

Figure 6 shows dynamic impact of creators in "Wolf Warriors II". Before the movie released (week 0), the attentions people payed to Hans Zhang, Gang Wu and Jason Wu were equal while with the movie's release and the increase in the heat of the film, more and more people went to the movies for the sake of Jason Wu. Meanwhile, the dynamic influence process can reflect a major change in the importance of the movie. We can see that Jason Wu has greatly improved his value through the movie himself.

6 BOX-OFFICE PREDICTING

Movie box office is influenced by many factors, such as investment budget, script, director, actor, post production, producer and producer, media publicity and movie reputation. On the whole, we quantify the factors that affect movie box office from the film itself, the director, the actor and the audience. The opening week due to the lack of effective comments, so just for the release of the film at the box office during the period of life prediction problem, we consider the factors associated with the film at the box office and did not join the historic influence of sentiment analysis, in the opening week after we join in the model of the value of emotional factors.

6.1 Premiere week box-office predicting

Table 2 shows the features we used in the task of predicting premiere week box office. As is mentioned above, the box office of a movie depends on not only movie factors itself including actors, directors, type, movie propaganda and so on but also influenced by audience reactions. In addition, the time the movie released also

Symbol	Description
<i>sc</i>	The mean <i>bos</i> of famous creators
<i>gsc</i>	The mean <i>wms</i> of famous creators
<i>std</i>	The variance <i>bos</i> of famous creators
<i>gstd</i>	The variance <i>wms</i> of famous creators
<i>starcounts</i>	The number of famous creators
<i>schedule</i>	The schedule that the movie came out
<i>year</i>	The year that the movie came out

Table 2: Features

has a certain impact on the movie box office. In general, predicting premiere week box-office can capture the influences of famous creators(actors and directors) to the movie. We provide Premiere week box-office predicting by using traditional box-office predicting model Support Vector Regression. This Module can help people to assess the influence of stars in the movie.

6.2 Phased Box-office Predicting

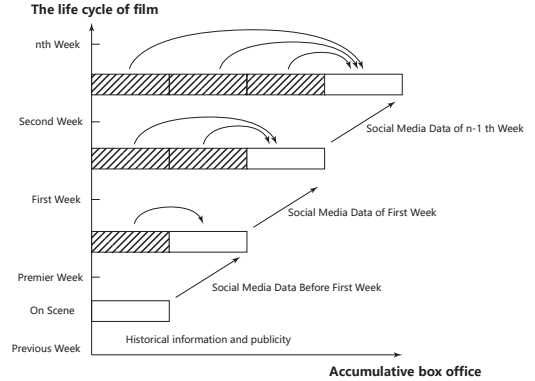


Figure 7: Multi-stage box office prediction model

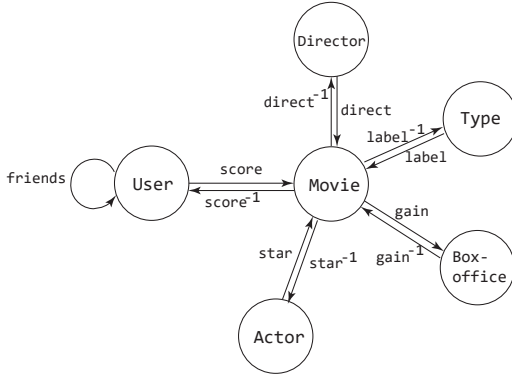
In the past prediction of box office, we usually only forecast the overall box office, but often ignored the movie's influence on movie box office due to the audience's attitude. Such as "wolf 2", the movie box office to be among the world's top 100, because in the release process, because the audience warmly, attracted the audience is not the original film (film series the fans, fans, like the kind of audience) to watch a movie, which leads to the box office continued to rise however, the traditional model is unable to capture this phenomenon. Therefore, as shown in Figure 7, from the pre launch to the 1 months after the release, we set up the box office prediction model with the weekly variation of the weekly release to predict the box office for the first week, the box office for second weeks, the third week box office and the box office at the fourth week.

In this section, we add two type features: $weibo_i$, The ratio of creative comments and all comments until the i th week and $week_i$ The box office in the i th week. With these additional messages

obtained from audience and current box office, the results we predict are more similar to real box office, shown in Table 3.

7 MINING MOVIE HETEROGENEOUS NETWORK

In order to discover important relation and promotion between two actors, we focus on mining movie heterogeneous information network[22]. Discovering interesting topology of network provide great insight about the system innate character. A movie heterogeneous information network (MHIN) is a domain information network with multiple types of entities and relations [23]. We construct our MHIN with multiple objects such as movies (M), directors (D), users (U), Actors (A), Types (T) and box-offices (B). Figure 8 shows typical MHIN schema defined by us. Links exist between users and movies denoting score and score-by relations, between movies and actors(directors) denoting star(direct) and star-by(direct-by) relations, between movies and types denoting label and (labeled) relations, between movies and box-offices denoting gain and gain by relations. Also, we can add other attributes into the movie heterogeneous network (e.g years (Y), producers (P)). Meta-path is a connect relation between two types of objects in MHIN. Denote network schema for our MHIN is $\mathcal{S} = (\mathcal{A}, \mathcal{R})$, where \mathcal{A} represent object types and \mathcal{R} indicate different types of relationships. A meta-path \mathcal{P} is defined in the form of $A_1 \xrightarrow{R_1} A_2 \xrightarrow{R_2} \dots \xrightarrow{R_k} A_{k+1}$. Length of \mathcal{P} is defined by number of relations it contains. Semantic composite relations are implied in meta-paths[21]. For example, we can evaluate the similarity of movies or actors by length-2 meta-path MDM (movie-director-movie), MAM (movie-actor-movie) or AMA (actor-movie-actor), AMTMA(actor-movie-type-movie-actor).



(a) Structure of movie heterogeneous network

Figure 8: Social network schema of MHIN.

7.1 Rank Based Cluster For Actors

In this section, we introduce a way [24] to make distinguish between A-list and B-list actors. We prefer applying cluster based classifier on actors popularity recognition. Strong available mutually reinforcing relations between cluster and rank are helpful to deal with different levels of actors. We defined recursion formula by following empirical rules.

RULE 7.1. *high rank actors star more high rank movies*

RULE 7.2. *high rank movies attract more high rank actors*

RULE 7.3. *actors get high rank with high rank co-stars*

Suppose we want K clusters of actors. According the star relationship between actors and movies, we define matrix $M_{MA}(i, j) = c_{ij}$ representing actor j 's contribution of movie i (see Section 3.1) and similarly, $M_{AA}(i, j) = m_{ij}$ stands for number of movies that actor i and actor j co-starred. Note that $W_{AM} = W_{MA}^T$, and $i = \{1, 2, \dots, m\}, j = \{1, 2, \dots, n\}$. According the 3 rules we proposed, we have

$$r_A(i) = \alpha \sum_{j=1}^m W_{AM}(j, i) r_M(i) + (1 - \alpha) \sum_{j=1}^n W_{AA}(i, j) r_A(j) \quad (15a)$$

$$r_A(j) \leftarrow \frac{r_A(j)}{\sum_{j'=1}^n r_A(j')} \quad (15b)$$

$$r_M(i) = \sum_{j=1}^n W_{MA}(i, j) r_A(j) \quad (15c)$$

$$r_M(i) \leftarrow \frac{r_M(i)}{\sum_{i'=1}^m r_M(i')} \quad (15d)$$

Note that $\alpha \in [0, 1]$ is a believe factor of weighed component of rule 3, $r_A(j)$ and $r_M(i)$ are normalized rank score vector. We finally get r_A which should be primary eigenvector of $\alpha W_{AM} W_{MA} + (1 - \alpha) W_{AA}$. Further, we capture posterior probability $\pi_{i,k}$ that a_i from cluster k , Once an actor acts a movie, he is more likely to star high ranked film and for movie, its success are more likely contributed by high rank actor. Thus we have K dimensional vector $s_{a_i} = \{\pi_{i,1}, \pi_{i,2}, \dots, \pi_{i,K}\}$ where $\pi_{i,k}$ denotes a_i 's coefficient for component k .

The cluster center and the distance between each actor and each cluster can be defined as

$$S_{A_k} = \frac{\sum_{a \in A_k} s(a)}{|A_k|} \quad (16a)$$

$$\text{Distance}(a, A_k) = 1 - \cos(s_{a_i}, S_{A_k}) \quad (16b)$$

Algorithm 2 RankClus for Actors

Input:

Our movie information network $MHIN = (M, A; W)$

Cluster Number K

Output:

K clusters of actors A_i and rank of actor in each cluster

- 1: iter = 0;
 - 2: Init partitions for A , get $PA^{iter} = \{A_i^{iter}\}_1^K$;
 - 3: Repeat following until $PA^{iter} - PA^{iter-1} < \epsilon$ or iterations reach limitation
 - 4: For all cluster calculate r_A followed by rank function
 - 5: Evaluate Θ for mixture model and get component efficient estimations s_{a_i} for each actor a_i
 - 6: Update centers $S_{A_k}^{iter}$ of each cluster A_k
 - 7: Reassign each actor a_i according distance between a_i and each cluster center A_k^{iter}
-

	Metric	Model				
Week	Metric	SVR	RF	GBDT	LR	LASSO
First	MSE	0.09393658	0.2683265	0.6354384	1.09512416	0.74275155
	R2score	0.63495534	-1.8019927	-2.1466284	-3.5673886	-2.0977628
	EVC	0.6082226	0.4194317	0.20241852	-3.0608791	-0.9281806
Second	MSE	0.2716661	0.3192046	0.51210881	0.51052539	0.05284060
	R2score	0.0693802	-1.0037243	-0.78307969	-0.74885631	0.81898915
	EVC	0.1977912	-0.1190541	-0.08409798	-0.69472796	0.91647358
Third	MSE	0.3949564	1.0082170	0.764787	0.73353798	0.0896601506
	R2score	0.6605046	0.0296122	0.297479	0.369467937	0.9229302356
	EVC	0.713641	0.0253357	0.611827	0.37283487	0.9758343006
Forth	MSE	0.745514	0.6839145	2.03964614	1.373235192	0.5025655348
	R2score	0.573410	0.1461468	0.16642220	0.214224192	0.7124281104
	EVC	0.63220	0.4586132	0.05054086	0.325419958	0.7183931246

Table 3: Evaluation of Predicting Model

7.2 Alternative Actors

In this section, we discuss method choosing alternative actors for casting agents. The basic idea is measure similarity between actors. Since movie information network has been built, we then introduce meta path-based similarity framework [23] for alternative actors. The example is show in table 4.

Type	Path instance	Meta-path
I(AMA)	Andy-M ₁ -Sara	Actor-Movie-Actor
II(AMTMA)	John-M ₂ -Comedy-M ₃ -Sara	Actor-Movie-Type-Movie-Actor
	Ben-M ₄ -War-M ₃ -Sara	
	Drew-M ₅ -Dracula-M ₂ -John	
III(AMDMA)	Diana-M ₆ -Spielberg-M ₁ -Andy	Actor-Movie-Director-Movie-Actor
	John-M ₂ -Luc Besson-M ₅ -Drew	
	Sara-M ₃ -Tom Tykwer-M ₅ -Drew	

Table 4: Different Types of meta-path in MHIN

Denote actors a_1 and a_2 then $p_{a_1 \rightsquigarrow a_2}$ is a path instance between a_1 and a_2 , $p_{a_1 \rightsquigarrow a_1}$ is a path instance between a_1 and a_1 , $p_{a_2 \rightsquigarrow a_2}$ is a path instance between a_2 and a_2 . We then get similarity between a_1 and a_2 by calculate

$$s(a_1, a_2) = \frac{2 \times |\{p_{a_1 \rightsquigarrow a_2} : p_{a_1 \rightsquigarrow a_2} \in \mathcal{P}\}|}{|\{p_{a_1 \rightsquigarrow a_1} : p_{a_1 \rightsquigarrow a_1} \in \mathcal{P}\}| + |\{p_{a_2 \rightsquigarrow a_2} : p_{a_2 \rightsquigarrow a_2} \in \mathcal{P}\}|} \quad (17)$$

Base on this measure of actors, we can not only know similarities but also get multi metrics that reflect how actors link with others. Query a specific actor a_i and then return a recommend actor list r_{a_i} that ordered by similarities. Investors can determine the scope of

film plan or prepare backup candidate for chief actor. In SNIP we also analyse different types of meta path instances for providing comprehensive alternative information for other actors.

8 SYSTEM EVALUATION AND CASE STUDY

In the case study, we use two concrete tasks to demonstrate how investors can apply SNIP to the analysis of movie box office.

Task 1: Movie Inclusion. It's important for investors to analyze the performance of a movie. Movie performance not only refers to box office income, word of mouth, but also includes the changes in the audience and the change of the influence of the director during the screening process.



Figure 9: Dynamic Impact of Wolf Warriors II

Fig.4 shows dynamic impact of creators in "Wolf Warriors II". Before the movie released (week 0), the attentions people payed to

Hans Zhang, Gang Wu and Jason Wu were equal while with the movie's release and the increase in the heat of the film, more and more people went to the movies for the sake of Jason Wu. Meanwhile, the dynamic influence process can reflect a major change in the importance of the movie. We can see that Jason Wu has greatly improved his value through the movie himself. To some extent, Jason Jing has more box office attractiveness, and investing in the actor's next movie is very likely to get high box office gains.

Task 2: Evaluation of investment quality. Investors usually need to assess the movie's expected box office and measure the actor's return on investment. Because there is a strong correlation between movie box office and audience feedback, the box office of the first week is less affected by audience feedback, so the first week box office can be regarded as the baseline of box office. The first week box office prediction can measure the expected revenue of the movie, and the actor replacement module can help investors to screen the appropriate actors at the right price at the appropriate box office in the first week.

In SNIP, we give a interface to query expected box-office when combine many factors into an investment. Such as Chinese actor *YangMi* and *YifengLi* and year selector into 2017 winter, the expected outcome is 184.55 million. We confirm the result as table 5 shows. The data indicated that two star co-star relation really play an important role in box-office improvement compared with single star.

Actors	year	schedule	Outcome
YangMi + YifengLi	2017	Winter	184.55 m
YangMi + YifengLi	2016	May Day	143.83 m
YifengLi	2016	May Day	123.60 m

Table 5: Estimate first week box-office for future investment

Task 3: Quantify sentiment and choose suitable actor. The following part will show the film sentiment analysis. Taking a pretty hot film Kung Fu Yoga in 2017 into consideration, at the first ten days, positive sentiment control the major opinion. While as time goes on, negative sentiment burst much higher than normal positive sentiment. We can see from figure 10 that people begin to criticize Jack Chen about this film. Even though at last, the public sentiment turn steady, we still believe Kung Fu Yoga has a tough time.

At last, we want to give a rank list of alternative actors when investors choose major actor. We give rank order from both AMTMA and AMDMA meta-path based method. If we query *JingWu* (Chinese major actor of Wolf Warriors II), we get highest score of 4.43 for Chow Yun Fat (Famous Chinese actor) based on his performers' experience especially film types that has been played in. Table 6 give details.

9 RELATED WORK

Box-office forecasting is a challenging but import task for movie contributors in their decision making process. Empirical studies of the determinants of box office revenues have mostly focused on post-production factors - that is, ones known after the film has

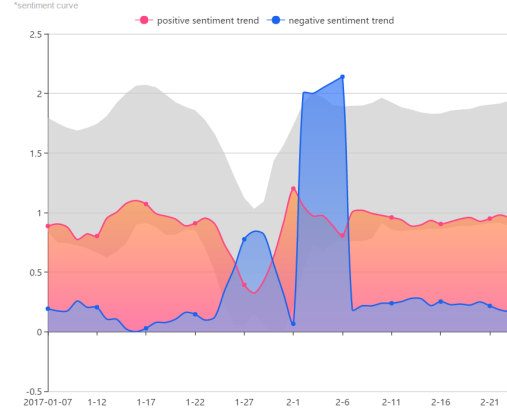


Figure 10: Film trend of Kung Fu Yoga

Alternative Actor Name	rank score
yun-fatchow	4.43
qianyuanWang	4.38
qingYe	4.38
tomeroz	4.36
hakonFung	4.35

Table 6: Highest 5 recommend alternative actors for JingWu

been completed and/or released with audience reactions. Early in [15] shows that word of mouth (WOM) can help explain box office revenue. The results of experiments from [12] show that the utilization of SNS data can improve the forecasting accuracies of machine learning-based algorithms and their combination. [8] regard the textual and content analysis of the screenplays of films as chief among the pre-production factors. [9] presents new box-office forecasting models to enhance the forecasting accuracy by utilizing review sentiments and employing non-linear machine learning algorithms.

Comparing with previous work, SNIP succeed in integrating unstructured reviews with structured information to enhance and extend application of system. We first extract and qualify sentiment which is core part of audience react information. Specially, we choose more state-of-art techniques (e.g LSTM[11], Heterogenous Network[22]). It is hard to overemphasize the value of NLP in system. Many study [9, 12, 25] focus on single point of film industry taking the IMDB data as the foundation. Instead, we make hard to integrate many aspects which is the distinctive features of the Chinese film market, as well as give interpretable visualized result for follow-up decision. In addition, dynamic analyse of tendency and impact also employ time series model and statistical analysis. To the best of knowledge, SNIP is a comprehensive solution to overcome tradition difficulty on film data analysis currently.

10 CONCLUSION

The return on investment (ROI) analysis about movies is a challenging but important task for movie investors in their decision making process. For investors, they are expected to get high box-office revenue with appropriate investments. Apart from movie special effects, most of investments are used to remuneration for movie actors(actress). Due to complicated factors such as audience reactions, screenplay, film types etc, it's not easy for investors to estimate upfront ROI, which makes film investment a gamble. Although most current research works aim to predict box-office revenue more specific, they can not provide investors more direct profits information about the success of the movie they would like to invest.

In this paper, we design and implement an integrated system, called Film Social Network Investment Platform (a.k.a SNIP), that aims to do some analysis of movies for investors. SNIP provides various modules for users to predict box-office, capture public opinion about a film, assess the value of the actor, monitor the changes of the ratio of box-office about actors, assess actor replacement and so on.

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REFERENCES

- [1] Sitaram Asur and Bernardo A Huberman. 2010. Predicting the future with social media. In *Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology-Volume 01*. IEEE Computer Society, 492–499.
- [2] Suman Basuroy, Subimal Chatterjee, and S Abraham Ravid. 2003. How critical are critical reviews? The box office effects of film critics, star power, and budgets. *Journal of marketing* 67, 4 (2003), 103–117.
- [3] Tao Chen, Ruifeng Xu, Yulan He, and Xuan Wang. 2017. Improving sentiment analysis via sentence type classification using BiLSTM-CRF and CNN. *Expert Systems With Applications* 72 (2017), 221–230.
- [4] C Samuel Craig, William H Greene, and Anthony Versaci. 2015. E-word of mouth: early predictor of audience engagement: how pre-release fiE-WOMfi drives box-office outcomes of movies. *Journal of Advertising Research* 55, 1 (2015), 62–72.
- [5] Qiming Diao, Minghui Qiu, Chao-Yuan Wu, Alexander J Smola, Jing Jiang, and Chong Wang. 2014. Jointly modeling aspects, ratings and sentiments for movie recommendation (JMARS). In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 193–202.
- [6] Li Dong, Furu Wei, Chuanqi Tan, Duyu Tang, Ming Zhou, and Ke Xu. 2014. Adaptive Recursive Neural Network for Target-dependent Twitter Sentiment Classification. (2014), 49–54.
- [7] Gerda Gemser, Martine Van Oostrum, and Mark AAM Leenders. 2007. The impact of film reviews on the box office performance of art house versus mainstream motion pictures. *Journal of Cultural Economics* 31, 1 (2007), 43–63.
- [8] III Hunter, Starling David, Susan Smith, and Saba Singh. 2016. Predicting box office from the screenplay: A text analytical approach. *Journal of Screenwriting* 7, 2 (2016), 135–154.
- [9] Minhoe Hur, Pilsung Kang, and Sungzoon Cho. 2016. Box-office forecasting based on sentiments of movie reviews and Independent subspace method. *Information Sciences* 372 (2016), 608–624.
- [10] Mahesh Joshi, Dipanjan Das, Kevin Gimpel, and Noah A Smith. 2010. Movie reviews and revenues: An experiment in text regression. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, 293–296.
- [11] Arzoo Katiyar and Claire Cardie. 2016. Investigating LSTMs for Joint Extraction of Opinion Entities and Relations. (2016), 919–929.
- [12] Taegu Kim, Jungsik Hong, and Pilsung Kang. 2015. Box office forecasting using machine learning algorithms based on SNS data. *International Journal of Forecasting* 31, 2 (2015), 364–390.
- [13] Svetlana Kiritchenko, Xiaodan Zhu, and Saif M Mohammad. 2014. Sentiment analysis of short informal texts. *Journal of Artificial Intelligence Research* 50 (2014), 723–762.
- [14] Jiwei Li and Eduard H Hovy. 2014. Sentiment Analysis on the People's Daily. (2014), 467–476.
- [15] Yong Liu. 2006. Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of marketing* 70, 3 (2006), 74–89.
- [16] Asha S Manek, P Deepa Shenoy, M Chandra Mohan, and KR Venugopal. 2017. Aspect term extraction for sentiment analysis in large movie reviews using Gini Index feature selection method and SVM classifier. *World wide web* 20, 2 (2017), 135–154.
- [17] Pablo Marshall, Monika Dockendorff, and Soledad Ibáñez. 2013. A forecasting system for movie attendance. *Journal of Business Research* 66, 10 (2013), 1800–1806.
- [18] Reggie Panaligan and Andrea Chen. 2013. Quantifying movie magic with google search. *Google Whitepaper/Industry Perspectives+ User Insights* (2013).
- [19] Bo Pang, Lillian Lee, et al. 2008. Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval* 2, 1–2 (2008), 1–135.
- [20] Ramesh Sharda and Dursun Delen. 2006. Predicting box-office success of motion pictures with neural networks. *Expert Systems with Applications* 30, 2 (2006), 243–254.
- [21] Yizhou Sun and Jiawei Han. 2013. Meta-Path-Based Search and Mining in Heterogeneous Information Networks. *Tsinghua Science & Technology* 18, 4 (2013), 329–338.
- [22] Yizhou Sun, Jiawei Han, Charu C Aggarwal, and Nitesh V Chawla. 2012. When will it happen?: relationship prediction in heterogeneous information networks. (2012), 663–672.
- [23] Yizhou Sun, Jiawei Han, Xifeng Yan, Philip S Yu, and Tianyi Wu. 2011. PathsIm: Meta path-based top-k similarity search in heterogeneous information networks. *Proceedings of The Vldb Endowment* 4 (2011), 992–1003.
- [24] Yizhou Sun, Jiawei Han, Peixiang Zhao, Zhijun Yin, Hong Cheng, and Tianyi Wu. 2009. RankClus: integrating clustering with ranking for heterogeneous information network analysis. (2009), 565–576.
- [25] Duyu Tang, Bing Qin, Xiaocheng Feng, and Ting Liu. 2015. Target-Dependent Sentiment Classification with Long Short Term Memory. *arXiv: Computation and Language* (2015).
- [26] Duyu Tang, Bing Qin, Ting Liu, and Yuekui Yang. 2015. User Modeling with Neural Network for Review Rating Prediction.. In *IJCAI*. 1340–1346.