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S-ANFIS: Sentiment aware adaptive network-based fuzzy inference system for Predicting Sales Performance using Blogs/Reviews

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Abstract*:* An organization has to make the right decisions in time depending on demand information to enhance the commercial competitive advantage in a constantly fluctuating business environment. Therefore, predicting the future quantity for the next period most likely appears to be crucial. This work presents a comparative forecasting methodology regarding to uncertain customer likings in a movie domain via regressive and neuro fuzzy techniques. The main objective is to propose a new future predicting mechanism which is modeled by artificial intelligence approaches including the comparison of both auto regressive method and adaptive network-based fuzzy inference system (ANFIS) techniques to manage the fuzzy demand with incomplete information. The effectiveness of the proposed approach to the demand forecasting issue will be demonstrated using real-world data from a different movie related websites.

Here we are going to extract the information from web and utilizing it for the purpose of sales prediction for movies. There are many sales prediction methods but the use of history data will be most efficient way to predict the quality future.

Key words : ANFIS, regressive model

INTRODUCTION

"Sentiment without action is the ruin of the soul. — Edward Abbey"

With the increasing use of Web 2.0 platforms such as Web Blogs, discussion forums, Wikis, and various other types of social media, people began to share their experiences and opinions about products or services on the World Wide Web.
As an emerging communication platform, Web 2.0 has led the Internet to become increasingly user-centric. People are participating in and exchanging opinions through online community-based social media, such as discussion boards, Web forums, and blogs. Along with such trends, an increasing amount of user-generated content containing rich opinion and sentiment information has appeared on the Internet. Understanding such opinion and sentiment information has become increasingly important for both service and product providers and users because it plays an important role in influencing consumer purchasing decisions [1]. Sentiment-classification techniques can help researchers study such information on the Internet by identifying and analyzing texts containing opinions and emotions [2]. With the flourish of the Web, online review is becoming a more and more useful and important information resource for people. As a result, automatic review mining and summarizing has become a hot research topic recently. Different from traditional text summarization, review mining and

summarizing aims at extracting the features on which there-viewers express their opinions and determining whether the opinions are positive or negative[3].

Posting reviews online has become an increasingly popular way for people to express opinions and sentiments toward the products bought or services received. Analyzing the large volume of online reviews available would produce useful actionable knowledge that could be of economic values to vendors and other interested parties. The idea behind this project is based on a paper [6] where the case study is the movie domain is analyzed and which tackles the problem of mining reviews for predicting movie sales performance. The analysis shows that both the sentiments expressed in the reviews and the quality of the reviews have a significant impact on the future sales performance of products in question. For the sentiment factor for that case, author proposed Sentiment PLSA (S-PLSA), in which a review is considered as a document generated by a number of hidden sentiment factors, in order to capture the complex nature of sentiments. Training an S-PLSA model enables us to obtain a succinct summary of the sentiment information embedded in the reviews. Based on S-PLSFA, the author proposes ARSA, an Autoregressive Sentiment-Aware model for sales prediction.
In summary,

- Here first time the ratings of the review are calculated by considering the hidden sentiments in it.
- For this purpose the S-PLSA model is designed, which through the use of appraisal groups, provides a probabilistic framework to analyse sentiments in reviews.
- Then the Autoregressive model is used for product sales prediction, which reflects the effects of both sentiments and past sales performance on future sales performance and its effectiveness is shown in paper.
- But up till now for such type of prediction problem the neuro fuzzy approach with sentiment analysis has not implemented, so here the proposed model is "Adaptive Network Based Fuzzy Inference System based on sentiments" (S-ANFIS) for the future prediction.

LITERATURE SURVEY

With the upcoming recent technologies of the web, consumers have at their disposal a soapbox of unprecedented reach and power by which to share their brand experiences and opinions , positive or negative, regarding any product or service. As major companies are increasingly coming to realize, these consumer voices can wield enormous influence in shaping the opinions of other consumer and, ultimately, their brand loyalties, their purchase decisions, and their own brand advocacy. Companies can respond to the consumer insights they generate through social media monitoring and analysis by modifying their marketing messages, brand positioning, product development, and other activities accordingly [7].

A growing number of recent studies have focus on the economic values of reviews, exploring the relationship between the sales performances of products and their reviews [4] [5] [6]. Understanding the opinions and sentiments expressed in the relevant reviews plays main important role in predicting sales of future of any product or services.

Prior studies on online review mining have done in many different ways for different purposes like categorising reviews either in positive or negative i.e. called as" Thumps Up Or Thumps Down"[8].Here the reviews are recommended or not recommended .The classification is predicted by average semantic orientation of the phrase in the review that contains adjective or adverb. Here the author present the simple unsupervised learning algorithm for classifying the review as recommended or not recommended, the input for the algorithm is written review and output as classification. The PMI-IR (positive mutual Information and Information Retrieval algorithm is used ,in which the first step is to extract the phrase containing adjective or adverb ,then second stage is the semantic orientation of the extracted phrases ,using the PMI-IR algorithm. So here only categorization of reviews as positive or negative is done.

But prior studies on predictive power of reviews have used the volume of the reviews failing to consider the sentiments present in the reviews [9].

Then early work in this area was primarily focused on determining the semantic orientation of reviews. Among them, some of the studies attempt to learn a positive/negative classifier at the document level. Pang et al. [10] employ three machine learning approaches (Naive Bayes, Maximum Entropy, and Support Vector Machine) to label the polarity of IMDB movie reviews. In follow-up work, they propose to first extract the subjective portion of text with a graph min-cut algorithm, and then feed them into the sentiment classifier [11].

Instead of applying the straightforward frequency-based bag-of-words feature selection methods, Whitelaw et al. [12] defined the concept of adjectival appraisal groups" headed by an appraising adjective and optionally modified by words like "not" or "very." Each appraisal group was further assigned four types of features: attitude, orientation, graduation, and polarity. They report good classification accuracy using the appraisal groups. There are also studies that work at a finer level and use words as the classification subject. They classify words into two groups, "good" and "bad," and then use certain functions to estimate the overall "goodness" or "badness" score for the documents. Kamps and Marx [13] propose to evaluate the semantic distance from a word to good/bad with WordNet. Turney [14] measures the strength of sentiment by the difference of the Mutual Information (PMI) between the given phrase and "excellent" and the PMI between the given phrase and "poor."

Extending previous work on explicit two-class classification, Pang and Lee [15], and Zhang and Varadarajan [16] attempt to determine the author's opinion with different rating scales (i.e., the number of stars). Liu et al. [17] build a framework to compare consumer opinions of competing products using multiple feature dimensions. After deducting supervised rules from product reviews, the strength and weakness of the product are visualized with an "Opinion Observer."

There are so many other works also done in this domain in different ways like, Li Zhuang et.al [23] A multi-knowledge based approach is proposed, which integrates WorldNet, statistical analysis and movie knowledge. The experimental results show the effectiveness of the proposed approach in movie review mining and summarizing Here he also focus on Movie review as according to him When a person writes a movie review, he probably comments not only movie elements (e.g. screen- play, vision effects, music), but also movie-related people (e.g. director, screenwriter, actor). While in product reviews, few people will care the issues like who has designed or manufactured a product. Therefore, the commented features in movie review are much richer than those in product review. As a result, movie review mining is more challenging than product review mining.

From paper by, Pimwadee Chaovalit, Lina Zhou[25],also gives the bipolar orientation of online reviews with the help of machine learning and Semantic Orientation. So such kind of classification could help consumers in making their purchasing decisions. Here the machine learning approach is applied to this problem mostly belongs to supervised classified in general and text classification techniques in particular for opinion mining. This type of technique tends to be more accurate because each of the classifiers is trained on a collection of representative data known as corpus. Thus, it is called "supervised learning". In contrast, using semantic orientation approach to opinion mining is "unsupervised learning" because it does not require prior training in order to mine the data. Instead, it measures how far a word is inclined towards positive and negative. But again some pros and cones are there in above approach, Even though supervised machine learning is likely to provide more accurate classification result than unsupervised semantic orientation, a machine learning model is tuned to the training corpus, and thus needs retraining if it is to be applied elsewhere . It is also subject to over-training and highly dependent upon the quality of training corpus.

But here the focus is on the positive and negative categorization again not considered the semantic as well as sentiment factor even if the sentiments hidden in the review, plays the main important predictive role.

Then from next paper by Arzu Baloglu, Mehmet S. Aktas [27], author focuses on classification of people opinion and sentiments (or emotions) from the contents of weblogs about movie reviews. Here also the data is crawled from the website then separated from non review data. This study is categorized under three phases. The first phase is the crawling phase, in which data is gathered from Web blogs. The second phase is the analyzing phase, in which the data is parsed, processed and analyzed to extract useful information. The third phase is the visualization phase, in which the information is visualized to better understand the results.

Here, this paper is more focused on visualization of reviews so that it can be used by the potential users for decision making, it will show web blog users what other people think about the particular movie. The blog mining process consists of following three main steps: Web crawling, sentiment analysis, and visualization.

The overall process can be given as

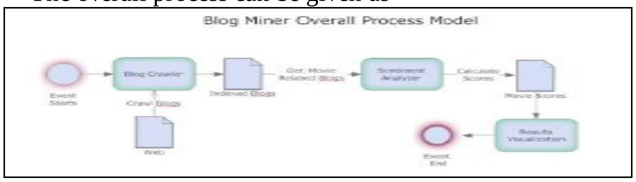


Fig 2.1: Blog Miner

Paper by P.D. Turney [8], explains simple unsupervised learning algorithm for classifying reviews as recommended or not recommended i.e. thumbs up or thumbs down. Here the first step used is use of part of speech tagger to identify phrases in the input text that contain adjective or adverb. The second step is to estimate the semantic orientation of each extracted phrase, then categorised as positive or negative i.e. Recommended or non recommended.

Paper by Jingbo Zhu, Huizhen Wang, Muhua Zhu, Benjamin K. Tsou, and Matthew Ma, Senior[28] focuses on Aspect based opinion polling. The goal of opinion polling (customer survey) is to discover customer satisfaction on a particular product, service, or business. This is traditionally done by carefully designing some questions for customers to answer. The drawbacks of such a structured survey are the expense and difficulty of question design and lack of participation because many customers do not like to participate in a question-based structured survey. To get around these difficulties, this paper focuses on opinion polling from freeform textual customer reviews, without requiring designing a set of questions in the form of a survey. Here also the author uses Supervised learning method and used at sentence level instead of document level. Here the analysis of multi aspect e.g. "the fish is great but the food is expensive", sentences is also done which was not done at earlier work.

From paper of Fabian Abel et.al.and Bing Liu,Minqing Hu,Junsheng Cheng [29][30] focuses on, analyzing blogosphere to predicate the success of music and movie products. In[29],author conduct experiments for predicting the blogging behavior within the blogosphere and apply machine learning techniques to forecast the monetary success of music and movie products.

In [30], author proposes an analysis system with a visual component to compare consumer opinions to different products, and system is called Opinion Observer. So they have taken opinions of customer for different product of the same type and then compare it with the help of some factors. This data is useful to customers as well as product manufactures in different ways, customers get detail opinion and comparison about different range of product as well as manufactures gets their strength and weaknesses of the product and so they can adopt some improvements in it if necessary.

In all the above papers, the work done till now is categorizing reviews in positive or negative review or the opinion as thumbs up or down.

Some of the papers focus the concept of Aspect based opinion analyzing, some paper uses Web crawler for getting the data for mining and then proceeding further for sentiment classification.

But this project work focusing on the main important part of the online reviews i.e. Sentiment, which are not considered by other authors and in addition, this paper focuses on the Sentiment because all the information in the review is not meaningful so the S-PLSA approach is used to get the sentiments for review. Then this output will further process with the help of Autoregressive model to predict the sales performance of the particular movie.

Here the ARSA (Autoregressive Semantic Analysis) model is used for the prediction of sale. They have graphically represented the result by taking many training samples from earlier year's movies to predict the sales of the current movies.

Now further to this work I propose the Neural Network approach. Then compare ARSA and S-ANFIS[41] with alternative models that do not take into account the sentiment information, as well as a model with a different feature selection method. Experiments will confirm the effectiveness and superiority of the proposed approach.

INPUT DATA SELECTION AND PROCESSING

"You don't have to be a sales manager to appreciate the importance of sales prediction and planning."

Managing a business is a little like running a ship. As the ship's captain, you need to keep your eyes on the horizon to plan your next move. If there are storm clouds gathering, you must secure the ship's cargo and warn the deck mates to take cover below. If there are rocky waters ahead, you have to ask your crew to stand watch to help you navigate safely to the other side. If the next leg of the journey is going to be long, you need to stock up on food and supplies before leaving port.

In business, there's less chance of losing an employee to scurvy, but it's equally important to plan ahead and keep your eyes on the horizon. And the best way to plan for the future is to carefully analyze trends from the past. This is especially true when predicting future sales of a product or service.

The sales forecast is a prediction of a business's unit and money sales for some future period of time, up to several years or more. These forecasts are generally based primarily on recent sales trends, competitive developments, and economic trends in the industry, region, and/or nation in which the organization conducts business. Sales forecasting is management's primary tool for predicting the volume of attainable sales. Therefore, the whole budget process hinges on an accurate, timely sales forecast.

Here in this work of the sales prediction, we are considering the example of "Movie Domain", as it is also a biggest revenue generation industry. And here also it is necessary to get the prediction of the upcoming movie related to box office generation and category i.e. whether it'll be hit, flop or super hit etc..of the movie so that the proper steps can be taken further.

Why Movie Domain?

Predicting box-office receipts and category of a particular motion picture has intrigued many scholars and industry leaders as a difficult and challenging problem.

And from the survey regarding writing the reviews , comment , opinion online , the maximum stake is taken by entertainment industry which includes videos, songs, movies, television programs etc..

So one can get to know the clear opinion about different movies after or before it's release. Unlike electronic goods of different brands, here for movie domain we can get the exact amount of the box office revenue generation also so it will help to do the prediction with the help of earlier data.

Economic Impact of Online Reviews

Whereas marketing plays an important role in the newly released products, customer word of mouth can be a crucial factor that determines the success in the long run, and such effect is largely magnified thanks to the rapid growth of Internet. Therefore, online product reviews can be very valuable to the vendors in that they can be used to monitor consumer opinions toward their products in real time, and adjust their manufacturing, servicing, and marketing Strategies accordingly. Academics have also recognized the impact of online reviews on business intelligence, and have produced some important results in this area. Among them, some studies attempt to answer the question of whether the polarity and the volume of reviews available online have a measurable and significant effect on actual customer purchasing [18], [19], [9], [4]. To this end, most studies use some form of hedonic regression [20] to analyze the significance of different features to certain function, e.g., measuring the utility to the consumer.

This work is similar to [5] in the sense that we also exploit the textual information to capture the underlying sentiments in the reviews. However, their approach mainly focuses on quantifying the extent of which the textual content, especially the subjectivity of each review, affects product sales on a market such as Amazon, while this method aims to build a more fundamental framework for predicting sales performance using multiple factors. Foutz and Jank [21], [22] also exploit the wisdom of crowds to predict the box office performance of movies. The work presented in this paper differs from theirs in three ways. First, we use online reviews as a source of network intelligence to understand the sentiments of the public, whereas their approach uses virtual stock markets (prediction markets) as an aggregated measure of public sentiments and expectations. Second, we use a Anfis neural network model to capture the temporal relationships, whereas their approach uses nonparametric functional shape analysis to extract the important features in the shapes across various trading histories and then uses these key features to produce forecasts. Third, the prediction of this model is ongoing as time progresses and more reviews are posted, whereas their approach is limited to forecasting the box office performance in the release week.

Review Mining

With the rapid growth of online reviews, review mining has attracted a great deal of attention. Early work in this area was primarily focused on determining the semantic orientation of reviews. Among them, some of the studies attempt to learn a positive/negative classifier at the document level.Pang et al. [31] employ three machine learning approaches (Naive Bayes, Maximum Entropy, and Support Vector Machine) to label the polarity of IMDB movie reviews. In follow-up work, they propose to first extract the subjective portion of text with a graph min-cut algorithm, and then feed them into the sentiment classifier [11]. Instead of applying the straightforward frequency-based bag-of-words feature selection methods, Whitelaw et al. [12] defined the concept of adjectival appraisal groups" headed by an appraising adjective and optionally modified by words like "not" or " very." Each appraisal group was further assigned four types of features: attitude, orientation, graduation, and polarity. They report good classification accuracy using the appraisal groups. They also show that the classification accuracy can be further boosted when they are combined with standard "bag-of-words" features.

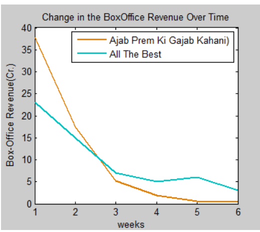
We use the same words and phrases from the appraisal groups to compute the reviews' feature vectors, as we also believe that such adjective appraisal words play a vital role in sentiment mining and need to be distinguished from other words. However, as will become evident in Section , my way of using these appraisal groups is different from that in [12]. There are also studies that work at a finer level and use words as the classification subject. They classify words into two groups, "good" and "bad," and then use certain functions to estimate the overall "goodness" or "badness" score for the documents. Kamps and Marx [13] propose to evaluate the semantic distance from a word to good/bad with WordNet. Turney[14] measures the strength of sentiment by the difference of the Mutual Information (PMI) between the given phrase and "excellent" and the PMI between the given phrase and "poor." Extending previous work on explicit two-class classification, Pang and Lee [15], and Zhang and Varadarajan [16] attempt to determine the author's opinion with different rating scales (i.e., the number of stars). Liu et al. [17] build a Frame work to compare consumer opinions of competing products using multiple feature dimensions. After deducting supervised rules from product reviews, the strength and weakness of the product are visualized with an "Opinion Observer." praposed method departs from conventional sentiment classification in that we assume that sentiment consists of multiple hidden aspects, and use a probability model to quantitatively measure the relationship between sentiment aspects and reviews as well as sentiment aspects and words.

Characteristics of Online Reviews

Here we will be focusing on characteristics of online reviews and their predictive power. So here we see the pattern of reviews and it's relationship to sales data by examining the real time data of Movie Domain. Here we are more interested in the reviews posted in the web sites as it gives more effectual data.

Number of Blog used in Sentiment Analysis

Lets see at the following movie performances which are released on particular date.



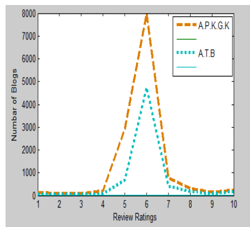


Fig 3.1: Change in the no. of Blogs and Rating
Fig 3.2: Change in box office revenue over time

In Fig.3.1, we compare the changes in the number of blog mentions of the two movies. Apparently, there exists a spike in the number of blog mentions for the movie **Ajab Prem Ki Gajab Kahani**, which indicates that a large volume of discussions on that movie appeared around its release date and good ratings has been given to that movie compared to the movie **All The Best**. In addition, the number of blog mentions are significantly larger than those for **All The Best** throughout the whole month.

Box Office Data

Besides the blogs, we also collect for each movie one month's box office data (weekly gross revenue) from the indicine.com and starboxofficeindia.com. The changes in weakly gross revenues are depicted in Figure 3.2 Apparently, the weekly gross of **Ajab Prem Ki Gajab Kahani** is much greater than **All The Best** on the release date. However, the difference in the gross revenues between the two movies becomes less and less as time goes by, with **All The Best** sometimes even scoring higher towards the end of the one-month period. To shed some light on this phenomenon, we collect the average user ratings of the two movies **Ajab Prem Ki Gajab Kahani and All The Best** from the StarBoxOfficeIndia.com website. The got the rating of 6 and 6.5 respectively.

Inference from Characteristics

Here we can note that the change in revenue is not directly proportional to number of reviews or rating and this is evident from Fig 2.1 and Fig 2.2. This implies that the number of blog mentions (and correspondingly, the number of reviews) may not be an accurate indicator of a product's sales performance. A product can attract a lot of attention (thus a large number of blog mentions) due to various reasons, such as aggressive marketing, unique features, or being controversial. This may boost the product's performance for a short period of time.

But as time goes by, it is the quality of the product and how people feel about it that dominates. This can partly explain why in the opening week,**'Ajab Prem Ki Gajab Kahani'** had a large number of blog rating mentions and staged an outstanding box office performance, but in the remaining weeks, its box office performance fell to the same level as that for **'All the Best'**. On the other hand, people's opinions (as reflected by the user ratings) seem to be a good indicator of how the box office performance evolves. Observe that, in this example, the average user rating for '**All The Best'** is higher than that for '**Ajab Prem Ki Gajab Kahani**' at the same time, it enjoys a slower rate of decline in box office revenues than the latter. This suggests that sentiments in the blogs could be a very good indicator of a product's future sales performance.

So to overcome this drawback the author suggested S-PLSA (Sentiment Probabilistic semantic analysis algorithm. That is instead of only considering the number of blogs/reviews, we have to focus on the sentiments present in that reviews.

Execution of the problem statement

The project will have a flow mentioned in the block diagram given bellow:

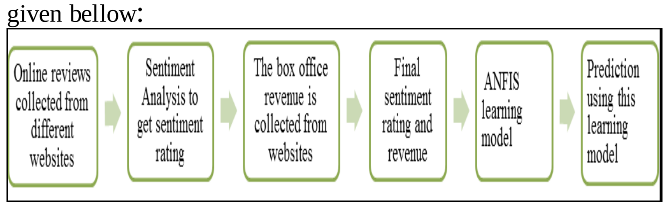


Fig 3.3: Block Diagram for Proposed System

In this the input for the process is the reviews/blogs from different web sites, for which we have to do the rating according to the sentiments present in it. Then this rating as well as the second factor i.e. box office revenue will be the next input for the proposed network.

The proposed network is Anfis, so for this the total number of inputs will be review ratings and revenue of the particular movies, and the output will be the resulting factor of this two input so it will be the categorization of the movie i.e. whether it will be flop, hit, super hit or blockbuster.

Data Processing

After collecting the reviews/blogs from different web sites [32][33][34][35],it will be analyzed by the sentiment analyzer[38] so that we will get the proper rating of that by considering the sentiment factor present in the review/blog. It is represented in the figure 3.4 and 3.5.

Here we will get the overall probabilistic sentiment rating of the blog or reviews through the analyzers then and the box-office revenue will be the inputs for the proposed system.

Then once we will get the overall sentiment rating of the blog/reviews, then with this the box-office revenue will be collected and these both act as a input to the proposed ANFIS learning model and the predicted output will be the categorization of the movie in the predefined linguistic category.

Fig 3.4 Snapshots of reviews collected

Here we will get the overall probabilistic sentiment rating of the blog or reviews through the analyzers then and the box-office revenue will be the inputs for the proposed system.

Then once we will get the overall sentiment rating of the blog/reviews, then with this the box-office revenue will be collected and these both act as a input to the proposed ANFIS learning model and the predicted output will be the categorization of the movie in the predefined linguistic category.

PROBLEM DEFINITION

As we have mentioned above, the main work of this project is, to predict the future sale of the any product/service. Here we have taken the Case study as movie because the availability of the data related to above domain is easily available with the revenue generation also. As this also plays main important factor to predict the sale of any movie .If we go for any electronic good or any other service it is not possible to get the revenue generation of that particular category in past as well as in present.

In this work we are going to predict the sale of particular movie with the help of different factor like, past box office performance, box office collection and main important factor is online reviews which are present on different movie websites.

Here we are going to extract the sentiments from the online reviews, author uses S-PLSA model for that and then with the help of categorised data form S-PLSA, they have used Autoregressive model for predicting sales performance.

In this project we used sentiment analyser to extract the online sentiments from different websites and then portion of data is segmented for ANFIS i.e. “Adaptive Neural Fuzzy Inference Systems” and ARSA. So here we can compare the output through two approaches.

Representation of the Problem Statement

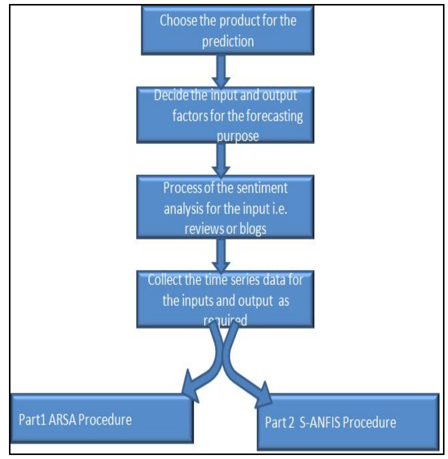
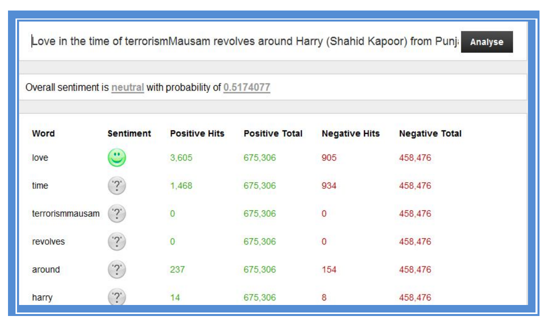


Fig 4.1: Representation of problem statement

Here in this project the processing is shown as the figure above,i.e.

- Firstly we are choosing the product for prediction; here we have to select any newly released movie or the upcoming movie.
- Here for the prediction purpose we have decided the input as well as output criteria.
- The input will be rating of movie after sentiment analysis [37] and revenue of the movie in different weeks after release and output will be overall categorization of the movie i.e. whether the movie is flop, hit , super hit
- So the first input will be the sentiment rating of the movie



Sentiment rating using S-PLSA

The next input will be the box office revenue of the movie in rupees. It is again foundout from the websites, we have taken it according to the week wise collection after the elease of the movie.

- The output for the pair of above input will be the final category of the movie, here we have define different 8 categories of the movie starting from Disaster to Blockbuster.

Categories of movie are as shown in fig 4.2bellow,

Ratings(according to sentiment analysis)	Box Office Revenue		Category	
0	(0-20 Cr)	0	Disaster	0
1	(10-30 Cr)	1	(Flop)	1
2	(20-40 Cr)	2	(Bellow Avarage)	2
3	(30-50 Cr)	3	Avarage	3
4	(40-60 Cr)	4	(Above Avarage)	4
5	(50-70 Cr)	5	(Hit)	5
6	(60-80 Cr)	6	(Super Hit)	6
7	(70-90 Cr)	7	(SuperDuper Hit)	7
8	(80-100 Cr)	8	(BolckBuster)	8
9	(90-100 Cr)	9		
10	(>100 Cr)	10		

The linguistic labels used for this input output as Disaster, Flop, Bellow Average, Average, Above Average, Super Hit, Super Duper Hit and Blockbuster.

For above learning model we can take as many as possible training samples, here we have taken the movies from 2009-2012.

For data analysis we have considered some movies and represented it in graphical format in respect to weekly revenue and rating before and after release.

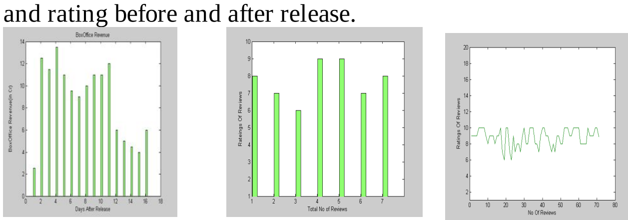


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Fig 4.3: Graphical Representation of Rating and Revenue

So here we can predict the sales of the movie if

- We have the review rating before release which we can easily get from the reviews present on different websites.
- We have ratings of the release day.
- We have the rating and revenue of the first week, we can predict for the further weeks.
- And if we have only revenue of the release day and even not Rating present online.(This can be happen if very few or no reviews are present for the movie)

The system can be used in decision support for the movie domain. The decision support system helps in improving the overall movie promotion before the release of the movie itself.

The Existing Model (ARSA)

Here the author studied the problem of mining sentiment information from blogs; website reviews and investigates ways to use such information for predicting product sales performance. Based on an analysis of the complex nature of sentiments, they propose Sentiment PLSA (S-PLSA), in which a blog entry is viewed as a document generated by a number of hidden sentiment factors. Training an S-PLSA model on the blog data enables us to obtain a succinct summary of the sentiment information embedded in the blogs. Then present ARSA, an autoregressive sentiment-aware model, to utilize the sentiment in-formation captured by S-PLSA for predicting product sales performance. Extensive experiments were conducted on a movie data set. Then they have compared ARSA with alternative models that do not take into account the sentiment information.

As a case study, the authors have considered the movie domain. The choice of using movies rather than other products in their study is mainly due to data availability, in that the daily box office revenue data are all published on the Web and readily available, unlike other product sales data which are often private to their respective companies due to obvious reasons.

Aside from the S-PLSA model which extracts the sentiments from blogs for predicting future product sales, they also consider the past sale performance of the same product as another important factor in predicting the product's future sales performance. They capture this effect through the use of an autoregressive model, which has been widely used in many time series analysis problems, including stock price prediction. Combining this AR model with sentiment in- formation mined from the blogs, they proposed a new model for product sales prediction called the Autoregressive Sentiment Aware (ARSA) model.

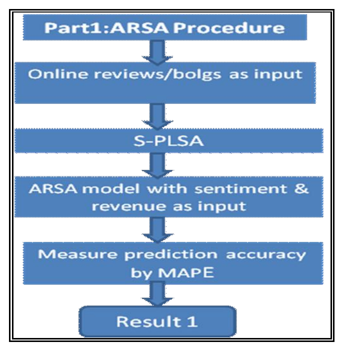


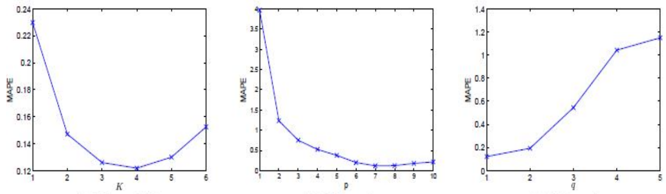
Fig 4.4: The structural design of ARSA

In this model authors have implemented the autoregressive models with sentiments incorporated with it. So first the sentiments has been calculated with the probabilistic latent sentiment analysis model, i.e. SPLSA , then this probabilistic rating and the box office revenue both act as the input to the ARSA i.e. autoregressive sentiment analysis model which is a time series model.

For training purpose different combinations has been considered. Like, rating before release, after release, box office revenue of weekends as well as week days etc.

So here the author chosen different parameters for optimal performance like k,p and q i.e. how many preceding days we will be considering for taking reviews/blogs and how many reviews/blogs we will be considering so we can change the values of the above factors. So we can very any of the factor by keeping others constant.

So the author got optimum result using the optimal values of K and p, we vary q from 1 to 5 to study its effect on the prediction accuracy. As shown in Figure 4.5 ,the best prediction accuracy is achieved at q = 1, which implies that the prediction is most strongly related to the sentiment information captured from blog entries posted on the immediately preceding day. This can be represented as,



(a) Effect of K (b) Effect of p (c) Effect of q

Fig 4.5 : The effect of parameters on the prediction accuracy

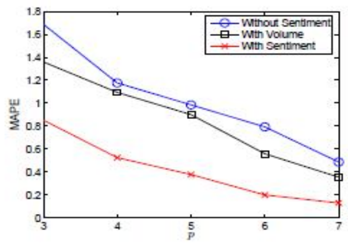


Fig 4.6 :ARSA vs alternative methods

Proposed Model

Artificial intelligence prediction techniques have been receiving much attention lately in order to solve problems that are hardly solved by the use of traditional methods. They have been cited to have the ability to learn like humans, by accumulating knowledge through repetitive learning activities. Therefore the objective here is to propose new forecasting techniques via the artificial approaches to manage demand in a fluctuating environment. In this study, a comparative analysis based on neural techniques i.e. ARSA and ANFIS is presented for prediction of the movie performance in future. The artificial techniques used in this study are explained as follows.

Adaptive network-based fuzzy inference system

Adaptive network-based fuzzy inference system (ANFIS) [ ]can construct an input–output mapping based on both human knowledge in the form of fuzzy if-then rules with appropriate membership functions and stipulated input–output data pairs. It applies a neural network in determination of the shape of membership functions and rule extraction. ANFIS architecture uses a hybrid learning procedure in the framework of adaptive networks. This method plays a particularly important role in the induction of rules from observations within fuzzy logic.

Here in this work the Anfis system will have two input membership function and one output membership function as Sentiment Rating, Box-Office Revenue and output is overall category of the movie depending on the rule based system.
The working of the ANFIS system can be described as,

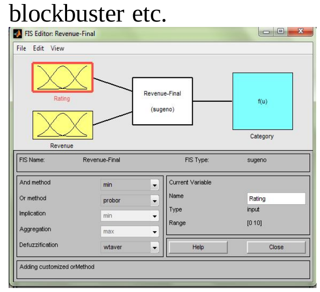
Fig 4.7: The Structural Design of proposed analysis-ANFIS

Fuzzification

The neuro-fuzzy model will be run with types input–output membership functions (MFs) considering the over fitting of the model with constructed about 50 rules. Triangular-shaped-built-in MF (triMF) trapezoidal-shaped-built-in MF (trapMF), generalized bell-shaped built-in MF (gbellMF) and gaussian curve built-in MF (gaussMF)will be utilized as the MF types with the numbers of 2 MFs for input functions. Output functions will be evaluated according to the characteristics of being constant or linear. We can show the tentative results of the prediction study to find the best definition of the constructed ANFIS structure in tabular format.

The proposed ANFIS structure can be represented below:

Here the inputs will be in the range of 0-10 and the output is again scaled to 0-8 for the linguistic terms like flop. hit, blockbuster etc.



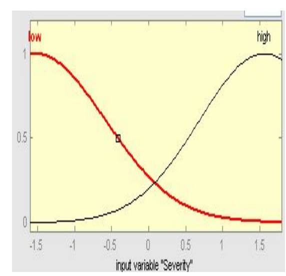


Fig 4.8(a) : Two input, one output MF Sugeno Model
Fig 4.8(b): Input Gaussian MF

Rule antecedent and Rule consequent

The rule based Anfis model structure can be represent as shown bellow.

Rule :1 if rating is 1 and box-office revenue is 10-20Cr then movie is flop

Rule :2 if rating is 5 and box-office revenue is 40-50Cr then movie is Hit

Rule :3 if rating is 9 and box-office revenue is >100Cr then movie is Block Buster

So in Anfis the rule model structure will be like given bellow,

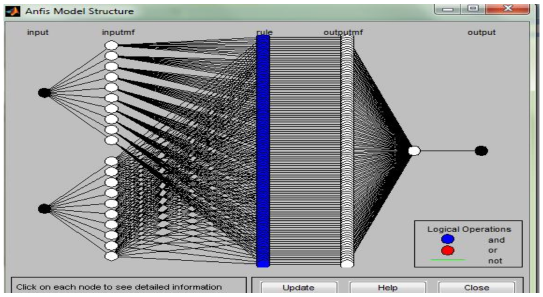


Fig 4.9: Anfis model structure

Here in this work the testing result can be obtained after the training, checking and testing process. The desired output can be shown as,

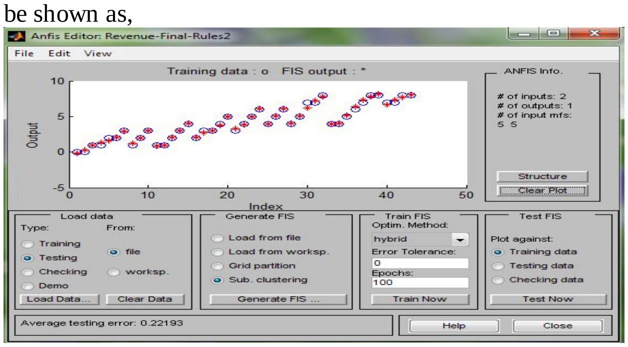


Fig 4.10: The proposed learning model

Purpose for using Adaptive Neuro Fuzzy Inference System

The usage of artificial intelligence has been applied widely in most of the fields of computation studies. Main feature of this concept is the ability of self learning and self-predicting some desired outputs. The learning may be done with a supervised or an unsupervised way. Neural Network study and Fuzzy Logic are the basic areas of artificial intelligence concept. Adaptive Neuro-Fuzzy study combines these two methods and uses the advantages of both methods.

It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely-used case. Operation of ANFIS looks like feed-forward back propagation network. Consequent parameters are calculated forward while premise parameters are calculated backward. There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order. Since ANFIS combines both neural network and fuzzy logic, it is capable of handling complex and nonlinear problems. Even if the targets are not given, ANFIS may reach the optimum result rapidly. The architecture of ANFIS consists of five Sugeno inference systems or Tsukamoto inference system can be used. Layers and the number of neurons in each layer equals to the number of rules. In addition, there is no vagueness in ANFIS as opposed to neural networks.

ANFIS structure herein described is based on the Takagi-Sugeno model which, as shown in [12], can be represented as 5-layer fuzzy neuronal networks. This example of a 5-layer fuzzy neuronal network is shown in Figure. The first layer is used for the input fuzzification. In the second layer the fuzzy rule performance weight is calculated. The third layer is the normalization layer. In the fourth layer, the consequent rule values are calculated and multiplied by the respective rule performance weight and the fifth layer does the defuzzification. Another reason for using Anfis is The hybrid algorithm used in ANFIS structure consists of the least squares method and the back propagation gradient descent method for training FIS membership function parameters to emulate a given training data. The hybrid algorithm is composed of a forward pass and a backward pass. In the forward pass of the hybrid learning algorithm, the least squares method is used to optimize the consequent parameters with the premise parameters fixed. After the optimal consequent parameters are found, the backward pass starts immediately. In the backward pass of the algorithm, the gradient descent method is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm.

Here the employed training errors are the mean squared error (MSE) of the training data set at each epoch and the mean absolute percentage error (MAPE) of the checking data set at each time. If Yt is the actual observation for time period t and Ft is the forecast for the same period, then MSE and MAPE are defined as in Eqs a and b

$$MSE = \frac{1}{N}\sum (Y_t - F_t)^2 \qquad \text{(a)}$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} ((Y_t - F_t)/Y_t) * 100 \qquad \text{(b)}$$

CONCLUSION

The wide spread use of online reviews as a way of conveying views and comments has provided a unique opportunity to understand the general public's sentiments and derive business intelligence. In this paper, we have explored the predictive power of reviews using the movie domain as a case study, and studied the problem of predicting sales performance using sentiment information mined from reviews. I can approached this problem as a domain-driven task, and managed to synthesize human intelligence (e.g., identifying important characteristics of movie reviews), domain intelligence (e.g., the knowledge of the "seasonality" of box office revenues), and network intelligence (e.g., online reviews posted by moviegoers). The outcome of the proposed models leads to actionable knowledge that can be can readily employed by decision makers. A center piece of the work is the of S-PLSA and Anfis model for sentiment analysis that helps us move from simple "negative or positive" classification toward a deeper comprehension of the sentiments in blogs. Using SPLSA as a means of "summarizing" sentiment information from reviews, I have developed S-ANFIS, model for predicting sales performance based on the sentiment information and the product's past sales performance. The accuracy and effectiveness of the proposed models can been confirmed by the experiments on movie data sets. Equipped with the proposed models, companies will be able to better harness the predictive power of reviews and conduct businesses in a more effective way. So the proposed S-ANFIS(input processed with sentiment analysis) model is general frameworks for sales performance prediction as it is a self learning model and would certainly benefit from the development of more sophisticated models for sentiment analysis and future quality prediction.

REFERENCES

[1] Rubicon Consulting, “Online Communities and Their Impact on Business: Ignore at Your Peril,” 25 Mar. 2009; http://rubiconconsulting.com/ downloads/whitepapers/Rubicon webcommunity
[2] Yan Dang,Yulei Zhang, and Hsinchun Chen “A Lexicon-Enhanced Method for Sentiment Classification: An Experiment on OnlineProduct Reviews”, University of Arizona.
[3] Li Zhuang “Movie Review Mining and Summarization”, Microsoft Research Asia Department of Computer Science and Technology, Tsinghua University Beijing
[4] D. Gruhl, R. Guha, R. Kumar, J. Novak, and A. Tomkins, “The Predictive Power of Online Chatter,” Proc. 11th ACM SIGKDD Int’l Conf. Knowledge Discovery in Data Mining (KDD), pp. 78-87, 2005.
[5] A. Ghose and P.G. Ipeirotis, “Designing Novel Review Ranking Systems: Predicting the Usefulness and Impact of Reviews,” Proc. Ninth Int’l Conf. Electronic Commerce (ICEC), pp. 303-310, 2007.
[6] Y. Liu, X. Huang, A. An, and X. Yu, “ARSA: A Sentiment-Aware Model for Predicting Sales Performance Using Blogs,” Proc. 30th Ann. Int’l ACM SIGIR Conf. Research and Development in Information Retrieval (SIGIR), pp. 607-614, 2007
[7] Bo Pang1 and Lillian Lee,” Opinion mining and sentiment analysis”.
[8] P.D. Turney, “Thumbs Up or Thumbs Down?: Semantic Orientation Applied to Unsupervised Classification of Reviews,” Proc. 40th Ann. Meeting on Assoc. for Computational Linguistics (ACL), pp. 417-424, 2001.
[9] D. Gruhl, R. Guha, D. Liben-Nowell, and A. Tomkins, “Information Diffusion through Blogspace,” Proc. 13th Int’l Conf. World Wide Web (WWW), pp. 491-501, 2004.
[10] L. Cao, Y. Zhao, H. Zhang, D. Luo, C. Zhang, and E.K. Park, “Flexible Frameworks for Actionable Knowledge Discovery,” IEEE Trans. Knowledge and Data Eng., vol. 22, no. 9, pp. 1299- 1312, Sept. 2009
[11] B. Pang and L. Lee, “A Sentimental Education: Sentiment Analysis Using Subjectivity Summarization Based on Minimum Cuts,” Proc. 42nd Ann. Meeting on Assoc. for Computational Linguistics (ACL), pp. 271-278, 2004.
[12] C. Whitelaw, N. Garg, and S. Argamon, “Using Appraisal Groups for Sentiment Analysis,” Proc. 14th ACM Int’l Conf. Information and Knowledge Management (CIKM), pp. 625-631, 2005.
[13] J. Kamps and M. Marx, “Words with Attitude,” Proc. First Int’l Conf. Global WordNet, pp. 332-341, 2002.
[14] P.D. Turney, “Thumbs Up or Thumbs Down?:Semantic Orientation Applied to Unsupervised Classification of Reviews,” Proc. 40th Ann. Meeting on Assoc. for Computational Linguistics (ACL), pp. 417-424, 2001.
[15] B. Pang and L. Lee, “Seeing Stars: Exploiting Class Relationships for Sentiment Categorization with Respect to Rating Scales,” Proc. 43rd Ann. Meeting on Assoc. for Computational Linguistics (ACL),pp. 115-124, 2005.
[16] Z. and B. Varadarajan, “Utility Scoring of Product Reviews,” Proc. 15th ACM Int’l Conf. Zhang Information and Knowledge Management (CIKM), pp. 51-57, 2006.
[17] B. Liu, M. Hu, and J. Cheng, “Opinion Observer: Analyzing and Comparing Opinions on the Web,” Proc. 14th Int’l Conf. World Wide Web (WWW), pp. 342-351, 2005.
[18] Chevalier and D. Mayzlin, “The Effect of Word of Mouth on Sales: Online Book Reviews,” J. Marketing Research, vol. 43, no. 3, pp. 345-354, Aug. 2006.
[19] C. Dellarocas, X.M. Zhang, and N.F. Awad, “Exploring the Value of Online Product Ratings in Revenue Forecasting: The Case of Motion Pictures,” J. Interactive Marketing, vol. 21, no. 4, pp. 23-45,
[20] S. Rosen, “Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition,” J. Political Competition,” J. Political Economy, vol. 82,no. 1, pp. 34-55, 1974
[21] N.Z. Foutz and W. Jank, “The Wisdom of Crowds: Pre-Release Forecasting via Functional Shape Analysis of the Online Virtual Stock Market,” Technical Report Marketing Science Inst. Of Reports, 07-114 2007.
[22] N.Z. Foutz and W. Jank, “Pre-Release Demand Forecasting for Motion Pictures Using Functional Shape Analysis of Virtual Stock Markets,” Marketing Science, to be published, 2010.
[23] Li Zhuang,Feng Jing,Xiaoyan Zhu,” Movie Review Mining and Summarization”
[24] Minqing Hu and Bing Liu. 2004. Mining and summarizing customer reviews.In Proceedings of ACM-KDD , pp.168-177,2004
[25] Pimwadee Chaovalit, Lina Zhou ,”Movie Review Mining: a Comparison between Supervised and Unsupervised Classification Approaches “,Proceedings of the 38th Hawaii International Conference on System Sciences – 2005
[26] Janyce M. Wiebe, "Learning Subjective Adjectives from Corpora," presented at the 17th National Conference on Artificial Intelligence, Menlo Park, California, 2000.
[27] Arzu Baloglu,Mehmet S. Aktas,”BlogMiner: Web Blog Mining Application for Classification of Movie Reviews”, Fifth International Conference on Internet and Web Applications and Services. 2010
[28] Jingbo Zhu, Huizhen Wang, Muhua Zhu, Benjamin K. Tsou, and Matthew Ma, Senior,” Aspect-Based Opinion Polling from Customer Reviews”, ieee transactions on affective computing, vol. 2, no. 1, January-march ,pp 37-50,2011
[29] Fabian Abel, Ernesto Diaz-Aviles, Nicola Henze, Daniel Krause and Patrick Siehndel,” Analyzing the Blogosphere for Predicting the Success of Music and Movie Products”,

International Conference on Advances in Social Networks Analysis and Mining,pp 276-280,2011
[30] Bing Liu,Minqing Hu,Junsheng Cheng," Opinion Observer: Analyzing and comparing Opinions on the web",
[31] B. Pang, L. Lee, and S. Vaithyanathan, "Thumbs Up? Sentiment Classification Using Machine Learning Techniques," Proc. ACL-02 Conf. Empirical Methods in Natural Language Processing (EMNLP), 2002.
[32]http://www.starboxoffice.com/movie/default.aspx?bid=2011%2fJanuary%2freviews_201 10105 _3&m=3-Idiots,
[33] http://www.rottentomatoes.com/m/3_idiots/
[34]http://www.mouthshut.com/Hindi-Movies/3-Idiots-reviews-925106887
[35] http://www.imdb.com/title/tt1187043/reviews
[36] http://www.cs.bham.ac.uk/~axk/Assign1.doc
[37]http://people.kyb.tuebingen.mpg.de/pgehler/code/index.html
[38] http://sentiment.brandlisten.com/analyse
[39] Jyh-Shing Roger Jang, Chuen-Tsai Sun, Neuro Fuzzy Modelling and Control
[40] Ajith Abraham & Baikunth Nath, Hybrid intelligent systems design- A review of a decade of research, School of computing & information technology, Monash University,Australia, Ajith.Abraham,Baikunth.Nath@infotech.monash.edu.au
[41] Adaptation of Fuzzy Inference System Using Neural Learning A. Abraham Computer Science Department, Oklahoma State University, USA ajith.abraham@ieee.org, http://ajith.softcomputing.net