Sentiment as a prior for movie rating prediction

by

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ABSTRACT

Movie ratings play an important role in tasks such as user movie recommendations, verifying the relationship between user-submitted reviews and ratings etc. The ability to predict the rating of a movie would be useful considering these aspects. In this work, firstly, we propose methods to predict the movie rating based on its summary. We then set out to use priors that are generally available with movie summaries in order to improve the accuracy. In order to achieve this, we consider the associated movie reviews as well while predicting the rating and provide insights on why this helps our models perform better. We use the review based sentiment along with the summary in order to predict the rating more accurately since the sentiment captures a lot of essential information that can aid rating prediction. We experiment with various deep learning architectures and the results show a significant accuracy boost of around 2% in most of the models which show the generalizability of our approach.

Keywords

Rating Prediction; Sentiment Analysis; Deep Learning

1. INTRODUCTION

The widespread usage of the internet has enabled people to share their views with the rest of the world online. This method of broadcasting opinions has gained a lot of popularity ever since. However, this led to a decrease in the quality of opinions that were shared. Due to this, people find it challenging and difficult to browse through all the opinions. This issue of bogus and random opinions is witnessed in a lot of cases where the user can provide feedback in a quick manner such as multiple choice options, checkboxes etc. Movie ratings fall in this category. Opinions requiring a text description etc such as movie reviews, however, would be much less prone to incorrect/invalid responses. Predicting the rating of a movie using the reviews along with the summary would help provide and counter these invalid ratings which cause issues in a lot of applications such as personalized movie recommendation engines etc. We propose a solution to this problem where we predict a rating for a movie considering the features embedded in the reviews along with the summaries. The sentiment of reviews is a valuable feature that we use in order to solve the task at hand better. This would lead to more accurate rating predictions and would help people make the right decisions. Traditional methods such as support vector machines (SVMs) and logistic regression do not perform well at the given task and hence we propose a deep learning based method. We verified and validated our method on Telugu movie reviews. Telugu is a Dravidian language for which very few resources and tools are available. It is morphologically very rich and an agglutinative language which makes it hard to perform natural language processing related tasks on it.

2. RELATED WORK

Movie rating prediction has been an important task for a long time and a lot of people have worked on it. Zhu et al. (Zhu, 2011) used a regression model by incorporating reviewer and product information to predict ratings of movies. Lim et al. (Lim, 2007) use a variational Bayesian approach to predict movie ratings, they solved the problem of data over-fitting by using the SVD algorithm. Armstrong et al. (Armstrong, 2008) discuss the prediction of movie ratings after learning the relationship between the rating and a movie's various attributes using a training set based on kernel regression and model trees. Ozyer et al. (Özyer, 2010) use collaborative filtering based methods to predict ratings. Fikir et al. (Fikir, 2013) also propose a method that uses simple matrix based factorization on the Netflix movie rating prediction dataset. Ganu et al. (Ganu, 2009) present two new ad-hoc and regression-based recommendation measures, both of which take into account the textual component of user reviews. Sherly et al. (Sherly, 2014) present a rule-based approach for sentiment analysis from Malayalam movie reviews. Taboada et al. (Taboada, 2011) use an approach based on lexicons to find the sentiments of sentences. Prerana Singhal and Pushpak Bhattacharyya[1] conducted a survey on the performance of various neural architectures on sentiment analysis. Kim et al. (Kim, 2014) report a series of experiments using Convolutional Neural Networks for sentence classification. Wilson et al. (Wilson, 2005) discuss phrase-level sentiment analysis, through which they identify the contextual polarity for a lexicon of sentiment expression.

Mullen et al. (Mullen, 2004) conducted experiments on sentiment analysis using SVMs by adding new information sources as features which previously used the limited bag of words approach. Zhang et al. (Zhang, 2015) propose a different type of character-based Convolutional Networks for text classification. Kennedy et al. (Kennedy, 2006) present two methods for determining the sentiment expressed by a movie review. Socher et al. (Socher, 2013) discuss using the parse tree of the sentence to train RTNT(Recursive Neural Tensor Network) which performs better than the basic bag-of-words approach. Maas et al. (Maas, 2011) demonstrate the generation of the word vectors capturing sentiment which enhances the accuracies of deep learning techniques. Lakkaraju et al. (Lakkaraju, 2014) have tried aspect level sentiment analysis using hierarchical Deep learning techniques. Bespalov et al. (Bespalov, 2011) propose projection of higher order sentences to low dimensional space, over which a classifier can be used to predict the sentiment of the sentence.

[1] http://www.cfilt.iitb.ac.in/resources/surveys/sentiment-deeplearning-2016-prerna.pdf

Table 1: Dataset statistics for both the sentiment classification and the rating prediction datasets created. Sentiment classification dataset consists of reviews whereas rating prediction dataset consists of reviews and summaries together. Note that PRP stands for Pronoun, CC for Conjunct, NN for Noun, VB for Verb, JJ for Adjective, and RB for Adverb.

Analysis	PRP	CC	NN	VB	JJ	RB
Reviews-All	3,900	1,174	62,618	25,803	3,558	7,603
Reviews-Unique	355	23	8,946	5,740	250	769
Summary – All	984	476	20,271	6,944	1,310	1,697
Summary - Unique	180	15	3,811	2,377	146	308
Both - All	4,884	1,650	82,889	32,747	4,868	9,300
Both - Unique	395	24	10,183	6,904	288	902

3. DATASET

Telugu, being a low resource language, we had to create two datasets for training our models. We used 123telugu.com[2] to collect the data required. The website presents data in a specific format as follows కథ (Story), ప్లస్ పాయింట్స్ (Positive points), మైనస్ పాయింట్స్ (Negative Points), సాంకేతిక విభాగం (Technical Section), ముగింపు (Conclusion), తీర్పు (Summary), రేటింగ్ (Rating). We created two separate datasets. The first is the Telugu movie rating dataset consisting of summaries, sets of reviews and ratings and the other is the Telugu sentiment classification dataset which consists of positive and negative reviews. The latter is used to train the sentiment classifier and is used as a prior for rating prediction. The anonymized dataset along with the source code can be found at https://goo.gl/WBWdT8.

3.1 ANALYSIS OF THE DATASET

Telugu movie rating dataset – This dataset consists of multiple movie summaries, their corresponding ratings, and reviews spanning across 473 movies. There are a total of 18,502 unique words in this dataset.

Table 2: Count of movies per rating class present in the dataset

Rating	1	2	3	4	5
Count	4	127	303	33	6

Telugu sentiment classification dataset - This dataset consists of annotated positive and negative reviews. It has 5,684 positive reviews and 4,553 negative reviews. There are a total of 16,001 unique words in this dataset.

3.2 DATASET STATISTICS

We analyzed the dataset and collected various statistics corresponding to the number of nouns, verbs etc in Table 1 present in the dataset. We also analyze the year-wise span of movie release dates in Table 3 and the number of movies corresponding to each of the rating classes 1-5 in Table 2. This shows the richness of the dataset and that it spans out over time which shows better diversity. This is the first dataset of its kind in Telugu. We used a parts of speech tagger developed by Siva Reddy (Reddy, 2011) to generate some of the statistics.

Table 3: Time-span of movies released per year present in the dataset

Year 20xx	12	13	14	15	16	17
Count	28	93	84	113	150	48

4. SENTIMENT PREDICTION

Sentiment prediction has been a great area of research in the recent times and is a challenging task especially in morphologically rich languages. The task requires us to classify a given sentence either as "Positive" or "Negative". In order to do this, we went ahead and tried out multiple deep learning based methods, however, we got the best results with a word-level multi-layer Convolutional Neural Network(CNN) which we used as our final model.

Table 4: Sentiment classification experiments with various models on 50-50 and 80-20 train-test data splits.

Model	Acc(50-50)	Acc(80-20)
FCNN	85.54	87.30
CNN	91.05	92.47
RNN	89.02	90.19
LSTM	90.59	91.64

4.1 RECURRENT NETWORKS

We implemented single-layer and multi-layer Recurrent Neural Networks(RNNs) (Tutschku, 1995), Long Short Term Memory cells(LSTMs) (Hochreiter, 1997) and Gated Recurrent Units(GRUs) (Bengio, 2014) where the inputs were processed into character embeddings and word embeddings before passing them to the networks. Character embeddings were simple one hot encoded vectors whereas word embeddings were dynamically generated using embedding layers in our networks and also using static embeddings generated by Word2Vec (Gensim) (Rehurek, 2010). We got the best results with dynamic word based embeddings. However, convolution networks beat them, refer to Table 4.

4.2 CONVOLUTION NETWORKS

Similar to recurrent networks we processed the inputs into character and word embeddings and stacked them across as filters before passing them to the network. Dynamic word based embeddings gave us the best results and they even beat LSTM dynamic word based embeddings which were the best in recurrent networks for the task. Hence our final trained model used for sentiment prediction consisted of a convolution network with multiple convolution, dropout, relu, max-pool and fully connected layers.

5. RATING PREDICTION

We could predict the rating of a given movie just based on its summary but quite often, we have reviews for the movie along with their summary which could be utilized in order to improve the prediction capability of our networks. Using the sentiment of these reviews as a prior along with the summary aids the task at hand. In order to generate sentiment priors, we used the sentiment classification network mentioned in the previous section. The actual task of predicting the rating is a regression problem where the output would be a single floating value between 0.0 to 5.0, in order to simplify the task, we convert it into a classification problem where we round the true rating to the nearest integer which would give us a five-class classification problem.

5.1 PREDICTION WITHOUT PRIORS

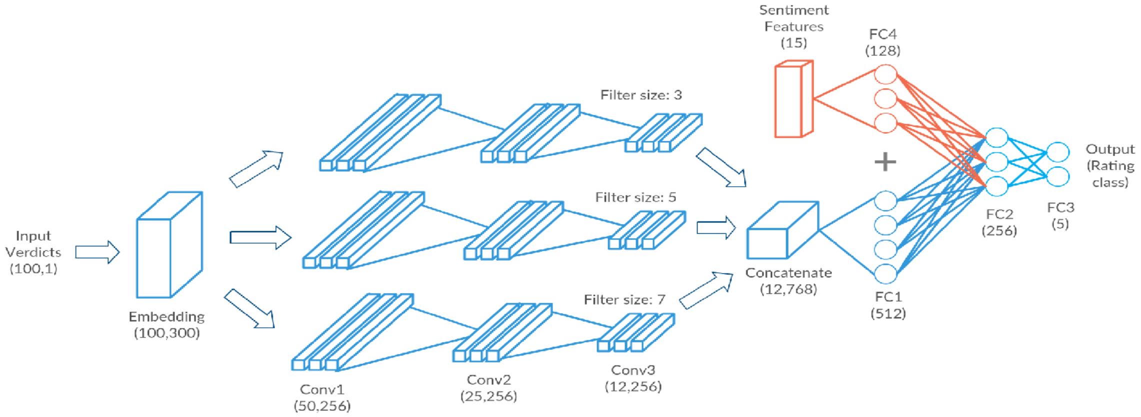
Prediction of the rating class using just the summaries alone without any other information about the movie.

5.1.1 CHARACTER EMBEDDINGS

Each character of the input summary is converted to a vector dynamically using an Embedding layer at the inputs to the

[2] http://www.123telugu.com/reviews/main/more_reviews.html

Figure 1: Branched CNN based rating prediction model architecture which considers sentiment priors along with the summaries to predict the ratings. The Conv blocks represented in the figure consist of Convolution, ReLU and Max-pool layers. We used Dropouts at various places for regularization



networks. These character vectors are then passed along to various convolution and recurrent networks. Using a one-hot encoded representation of the characters also gave similar accuracies.

Convolution networks - The input to the CNN consists of all the character embeddings stacked as filters which are then passed along the network to predict an output rating class. The network has a branched structure where filters of various sizes are used in the convolution layers in each of the branches and the outputs are concatenated before being passed onto fully connected layers to predict the output rating class.

Recurrent networks - For LSTM, GRU, and RNN based networks we feed in character vectors one at a time as input and the predicted output is passed forward to multiple fully connected dense layers which predict the rating class.

5.1.2 WORD EMBEDDINGS

Each word in the input is mapped to its corresponding dictionary index. Each index is then converted into a vector. These vectors are generated either dynamically using an Embedding layer or statically using Gensim.

Convolution networks - Similar to character level based convolution networks, we stack all the word vectors as filters and pass them as inputs to the convolution network.

Recurrent networks - The word vectors are fed as inputs one at a time and the final output of the recurrent network is then passed on to a fully connected layer which predicts the rating class.

5.1.3 SENTENCE EMBEDDINGS

Sentence vectors were generated using Doc2Vec. Doc2Vec takes all the sentences at once and generates sentence vectors using an unsupervised algorithm. However, the generation of sentence vectors requires all the data to be fed into Doc2Vec i.e both train and test sentences and hence this cannot be performed on unseen data since it's not feasible to generate vectors on the fly without having the entire dataset. Hence the test data used while classification would not be considered as truly unseen data.

Fully connected networks - Since the entire summary is encoded using a single vector, there is no advantage in using convolution or recurrent based networks here. Hence, we just pass the sentence vector through a few fully connected networks which finally predict the rating class.

5.2 PREDICTION WITH PRIORS

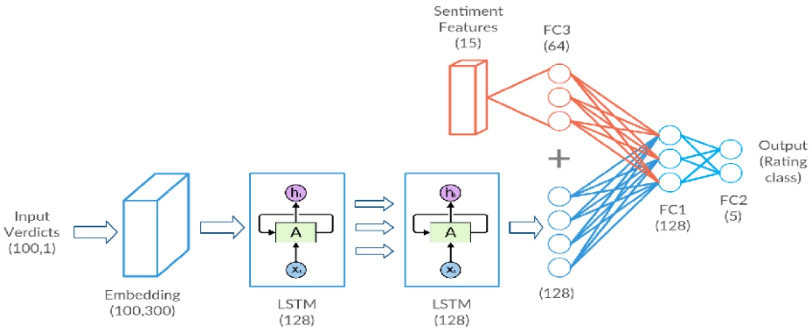
Each summary is also associated with a set of comments or one line reviews that complement the summary and hence can help us predict the rating better. For each of these reviews, we compute the sentiment using our sentiment prediction network that we have described in section 4. The network gives us a probability of the reviews being a positive review. We create a vector of these probabilities for all the reviews present. This vector acts as our sentiment prior which we use to predict the rating. We have also tried getting an average of the sentiment for all the reviews and using that as a prior instead but that did not give us the best results since we lose a lot of information in this process about the individual reviews themselves. Since all the movie summaries don't have the same number of reviews associated with them, we pad the priors to a certain length with a neutral sentiment while creating the sentiment priors.

5.2.1 INCLUSION OF PRIORS

Now that we have the priors defined, we need to decide where to include them in the networks. Considering the convolution networks, inserting the priors before the convolution layers doesn't work well since it's not essentially a filter associated with the input summary. In recurrent networks, passing on the priors (after a re-projection into the required shape using a dense layer) and appending them to the input did not give them enough weight and they were not able to influence the classification much. Finally, we decided to append the sentiment priors before the fully connected layers of both convolution (refer to Figure 1) and recurrent networks (refer to Figure 2).

Concatenating the sentiment features gave us the best results, however, we also tried other approaches such as Multiplying and Adding the projected sentiment features with the fully connected layer outputs of various networks after passing the summary along etc, but concatenation ensured that none of the features are lost and they gave us the best results.

Figure 2: LSTM based rating prediction model architecture which considers sentiment priors along with the summaries to predict movie ratings



5.3 EMPIRICAL VALIDATION AND EXPLANATION

To validate our claim that sentiment priors act as one of the most important features in the prediction of a movie rating, we train simple fully connected networks to predict the rating of a movie using just the sentiments from reviews corresponding to the movie. These results confirm our claim and hence we proceed to use the sentiment of reviews as priors along with the summaries to predict the ratings of movies.

6. EXPERIMENTS

We performed various experiments on the datasets created and reported the accuracies achieved in Table 5. We also tried to pass sub-word level embeddings as inputs to an LSTM which were generated using a CNN but did not achieve any significant improvements in the results mainly because Telugu, unlike English, is an agglutinative language.

We use Keras (Chollet, 2015) on top of the Tensorflow backend in order to implement all the models mentioned. We use a categorical cross-entropy loss and the Adam optimizer with a learning rate of 0.001 for all our models. We use a batch size of 512 for all models. RNN based models and character embedding based models are trained for 1000 epochs whereas the rest of the models are trained for 200 epochs.

Table 5: Accuracies on rating prediction for movies

Model	**No Prior**	**With Prior**
Naive Bayes	65.64	-
Random Forests	**67.90**	-
Polynomial SVM	63.15	-
Word-CNN	89.47	90.74
Word-LSTM	**90.32**	**92.40**
Word-GRU	89.68	91.32
Char-CNN	84.21	85.89
Char-LSTM	85.62	85.68
Char-GRU	85.68	85.99
Sent-FCNN	90.48	92.38

6.1 EXAMPLES

We have provided a few qualitative examples of our method predicting the ratings of movies (refer to Figure 3)

6.2 RESULTS

We notice that traditional methods are outperformed significantly by deep learning based methods. We also see a significant improvement in accuracies considering the priors as well while predicting the ratings in most models and nominal accuracy improvements in the remaining models.

6.2.1 ANALYSIS

From the obtained results, we see that word-level models gave better accuracies than character-level models in general. Character-level models consider one character at a time, hence having a large input size compared to word level models. Recurrent networks face issues with sequences that are too long and hence don't perform too well with character-level encodings. Convolution networks don't ensure temporal relations since there is no concept of memory involved there and hence having character level input would imply that features generated by the embedding layer (or one hot vectors) are not the best possible representations of the input data and hence perform poorly. Word-embeddings however, prove to work much better in both convolution and recurrent networks.

Sentence embeddings proved to be a great advantage when used with fully connected neural networks but as the size of the dataset increases, these vectors become less and less useful since the entire sentence (of varying size) is forced to be described in terms of a fixed sized embedding which is a limitation of these embeddings.

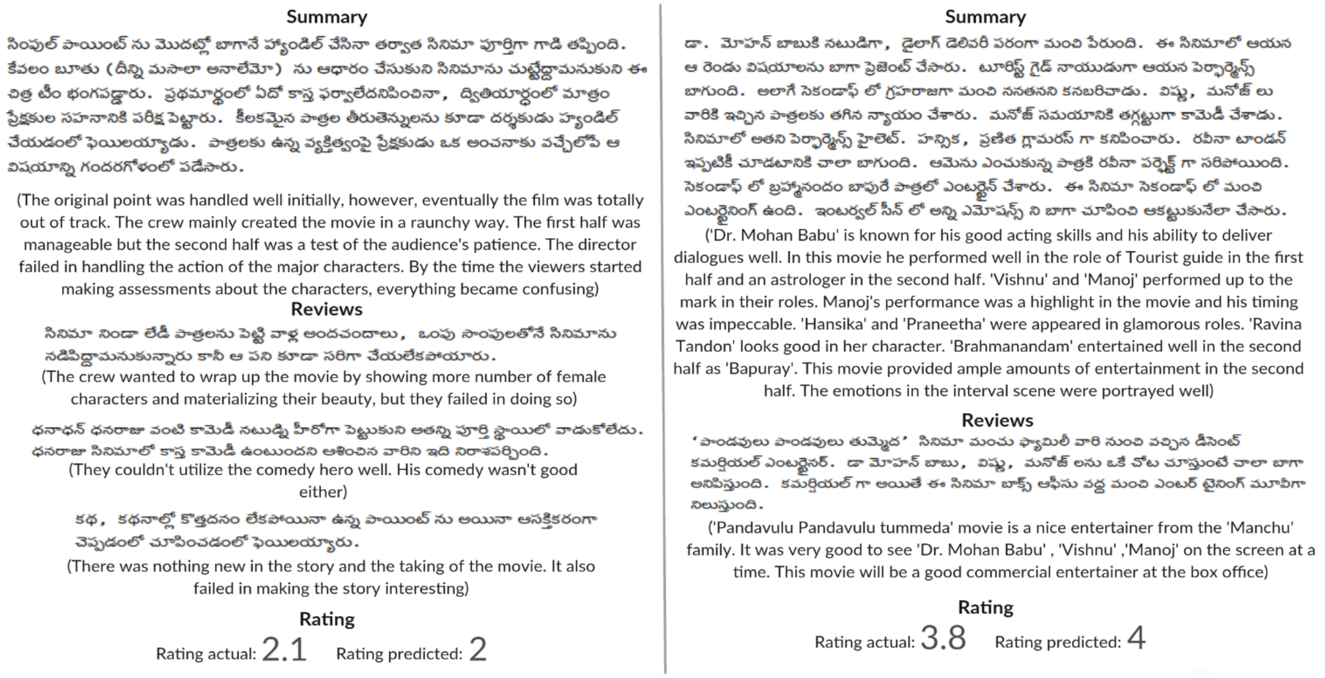
We observe that LSTMs and GRUs outperform RNNs due to various limitations such as vanishing or exploding gradients etc that have been discussed in various papers such as (Hochreiter, 1997) in the past.

On the whole, we see that considering priors always improve the accuracies in all the models as stated in Table 5. This confirms our claim that review sentiment is an important prior for rating prediction of movies.

7. CONCLUSION AND FUTURE WORK

Considering the sentiment of the reviews as a prior increased the accuracy by around 2% in various models. We managed to achieve good results even though Telugu is an agglutinative language which makes the task a challenging one. We plan to increase the priors by taking into consideration the actors, genre, directors, plot of the movie etc. which would help us boost the accuracy further. We also plan to extend this to other languages similar to Telugu such as Turkish, Korean, Japanese and Mandarin.

Figure 3: Qualitative examples of ratings predicted for movies



Summary

సింపుల్ పాయింట్ ను మొదట్లో బాగానే హ్యాండిల్ చేసినా తర్వాత సినిమా పూర్తిగా గాడి తప్పింది. కేవలం బూతు (దీన్ని మసాలా అనాలేమో) ను ఆధారం చేసుకుని సినిమాను చుట్టేద్దామనుకుని ఈ చిత్ర టీం భంగపడ్డారు. ప్రథమార్థంలో ఏదో కాస్త ఫర్వాలేదనిపించినా, ద్వితియార్థంలో మాత్రం ప్రేక్షకుల సహనానికి పరీక్ష పెట్టారు. కీలకమైన పాత్రల తీరుతెన్నులను కూడా దర్శకుడు హ్యాండిల్ చేయడంలో ఫెయిలయ్యాడు. పాత్రలకు ఉన్న వ్యక్తిత్వంపై ప్రేక్షకుడు ఒక అంచనాకు వచ్చేలోపే ఆ విషయాన్ని గందరగోళంలో పడేసారు.

(The original point was handled well initially, however, eventually the film was totally out of track. The crew mainly created the movie in a raunchy way. The first half was manageable but the second half was a test of the audience's patience. The director failed in handling the action of the major characters. By the time the viewers started making assessments about the characters, everything became confusing)

Reviews

సినిమా నిండా లేడీ పాత్రలను పెట్టి వాళ్ల అందచందాలు, ఒంపు సొంపులతోనే సినిమాను నడిపిద్దామనుకున్నారు కానీ ఆ పని కూడా సరిగా చేయలేకపోయారు.

(The crew wanted to wrap up the movie by showing more number of female characters and materializing their beauty, but they failed in doing so)

ధనాధన్ ధనరాజు వంటి కామెడీ నటుడ్ని హీరోగా పెట్టుకుని అతన్ని పూర్తి స్థాయిలో వాడుకోలేదు. ధనరాజు సినిమాలో కాస్త కామెడీ ఉంటుందని ఆశించిన వారిని ఇది నిరాశపర్చింది.

(They couldn't utilize the comedy hero well. His comedy wasn't good either)

కథ, కథనాల్లో కొత్తదనం లేకపోయినా ఉన్న పాయింట్ ను అయినా ఆసక్తికరంగా చెప్పడంలో చూపించడంలో ఫెయిలయ్యారు.

(There was nothing new in the story and the taking of the movie. It also failed in making the story interesting)

Rating

Rating actual: 2.1 Rating predicted: 2

Summary

డా. మోహన్ బాబుకి నటుడిగా, డైలాగ్ డెలివరీ పరంగా మంచి పేరుంది. ఈ సినిమాలో ఆయన ఆ రెండు విషయాలను బాగా ప్రెజెంట్ చేసారు. టూరిస్ట్ గైడ్ నాయుడుగా ఆయన పెర్ఫార్మెన్స్ బాగుంది. అలాగే సెకండాఫ్ లో గ్రహరాజగా మంచి నటనని కనబరిచాడు. విష్ణు, మనోజ్ లు వారికి ఇచ్చిన పాత్రలకు తగిన న్యాయం చేశారు. మనోజ్ సమయానికి తగ్గట్టుగా కామెడీ చేశాడు. సినిమాలో అతని పెర్ఫార్మెన్స్ హైలెట్. హన్సిక, ప్రణీత గ్లామరస్ గా కనిపించారు. రవీనా టాండన్ ఇప్పటికీ చూడటానికి చాలా బాగుంది. ఆమెను ఎంచుకున్న పాత్రకి రవీనా పర్ఫెక్ట్ గా సరిపోయింది. సెకండాఫ్ లో బ్రహ్మానందం బాపురే పాత్రలో ఎంటర్టైన్ చేశారు. ఈ సినిమా సెకండాఫ్ లో మంచి ఎంటర్టైనింగ్ ఉంది. ఇంటర్వెల్ సీన్ లో అన్ని ఎమోషన్స్ ని బాగా చూపించి ఆకట్టుకునేలా చేసారు.

('Dr. Mohan Babu' is known for his good acting skills and his ability to deliver dialogues well. In this movie he performed well in the role of Tourist guide in the first half and an astrologer in the second half. 'Vishnu' and 'Manoj' performed up to the mark in their roles. Manoj's performance was a highlight in the movie and his timing was impeccable. 'Hansika' and 'Praneetha' were appeared in glamorous roles. 'Ravina Tandon' looks good in her character. 'Brahmanandam' entertained well in the second half as 'Bapuray'. This movie provided ample amounts of entertainment in the second half. The emotions in the interval scene were portrayed well)

Reviews

‘పాండవులు పాండవులు తుమ్మెద’ సినిమా మంచు ఫ్యామిలీ వారి నుంచి వచ్చిన డీసెంట్ కమర్షియల్ ఎంటర్టైనర్. డా మోహన్ బాబు, విష్ణు, మనోజ్ లను ఒకే చోట చూస్తుంటే చాలా బాగా అనిపిస్తుంది. కమర్షియల్ గా అయితే ఈ సినిమా బాక్స్ ఆఫీసు వద్ద మంచి ఎంటర్ టైనింగ్ మూవీగా నిలుస్తుంది.

('Pandavulu Pandavulu tummeda' movie is a nice entertainer from the 'Manchu' family. It was very good to see 'Dr. Mohan Babu' , 'Vishnu' ,'Manoj' on the screen at a time. This movie will be a good commercial entertainer at the box office)

Rating

Rating actual: 3.8 Rating predicted: 4

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