SENTIMENT ANALYSIS ON HINDI REVIEWS

UNDER THE GUIDANCE OF

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INTRODUCTION

- Sentiments are hidden behind online comments on social media of all kinds.
- Sentiment analysis is the natural language processing task.
- It helps to identify and categorize opinions expressed in a piece of text, determine the reviewer’s point of view on a particular topic.

NEED FOR SENTIMENT ANALYSIS ON HINDI REVIEWS

- Little work has been done in Sentiment Analysis for Indian Languages.
- Web content in Hindi is booming .
- Sentiment Analysis of movie reviews could help in better rating of movies.

CHALLENGES & AIM

- Hindi is morphologically rich and a free order language compared to English language.
- Hindi is a resource scarce language which causes problems in collection and generation of datasets.
- Limited resources are available for this language like Hindi SentiWordNet (H-SWN).

➢ Aim is to implement the methods that can accurately predict the sentiment(polarity) of a given Hindi movie review.

METHODS IMPLEMENTED

1. Resource based classification

- ✓ using Hindi SentiWordNet (H-SWN).

2. In-language classification through various classifiers.

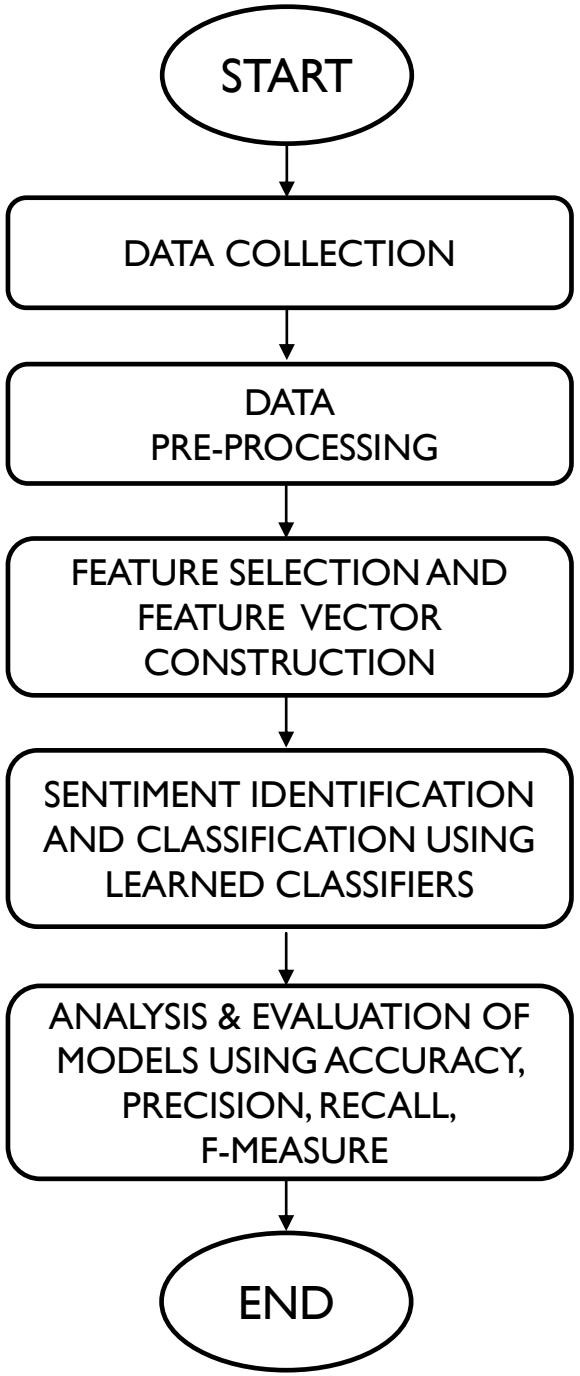
Feature extraction using 2 methods:

- ✓ Unigram Model
- ✓ TF-IDF Model

RESOURCE BASED CLASSIFICATION

- It uses Hindi SentiWordNet (H-SWN).
- Every word available in H-SWN has a corresponding positive and a negative sentiment score.
- A vote is taken for each word in a review.
- The polarity with majority is predicted as the sentiment of a review

FLOW CHART


START
DATA COLLECTION
DATA PRE-PROCESSING
FEATURE SELECTION AND FEATURE VECTOR CONSTRUCTION
SENTIMENT IDENTIFICATION AND CLASSIFICATION USING LEARNED CLASSIFIERS
ANALYSIS & EVALUATION OF MODELS USING ACCURACY, PRECISION, RECALL, F-MEASURE
END

IN-LANGUAGE CLASSIFICATION USING UNIGRAM MODEL

- A lexicon is created that contains all words in dataset except stop words and some highly frequent words that do not affect review sentiment.
- Feature matrix of size m*n

where,

m= number of reviews in our dataset

n= number of words in the lexicon

- For each element of the matrix, if that lexicon word occurs in the review, we add 1 to index of that word in lexicon set.

CLASSIFIERS USED:

We have used various classifiers for our in-language classification model:

- Logistic Regression
- Stochastic Gradient Descent
- Naive Bayes
- Support Vector Machine
- Decision Tree
- Neural Network
- Voting Classifier

IN-LANGUAGE CLASSIFICATION USING TF-IDF MODEL

- TfidfVectorizer() function is available in scikit-learn library.
- It is used to convert a collection of raw documents to a matrix of TF-IDF features.
- TF-IDF score of a word in a review= term frequency* inverse document frequency (idf)

where,

idf= 1/(1+log(no. of reviews in which the word occurs))

EXPERIMENTAL SETUP

Actual Value

Predicted Value	positives	negatives
positives	True Positive(t_p)	False Positive(f_p)
negatives	False Negative(f_n)	True Negative(t_n)

Table 1: Confusion Matrix

$$Accuracy = \frac{t_p + t_n}{t_p + t_n + f_p + f_n}$$

$$Recall = \frac{t_p}{t_p + f_n}$$

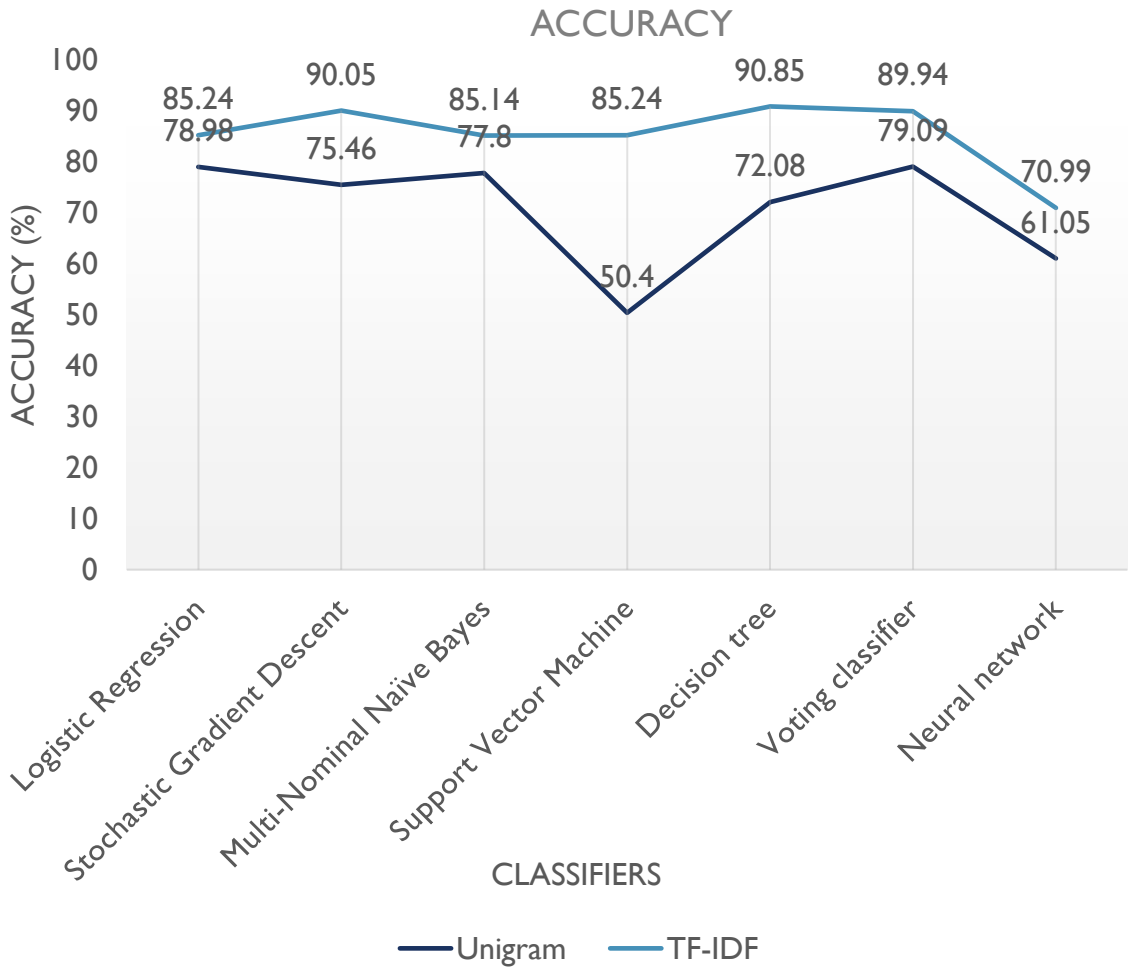
$$F - measure = \frac{2 * Precision * Recall}{Recall + Precision}$$

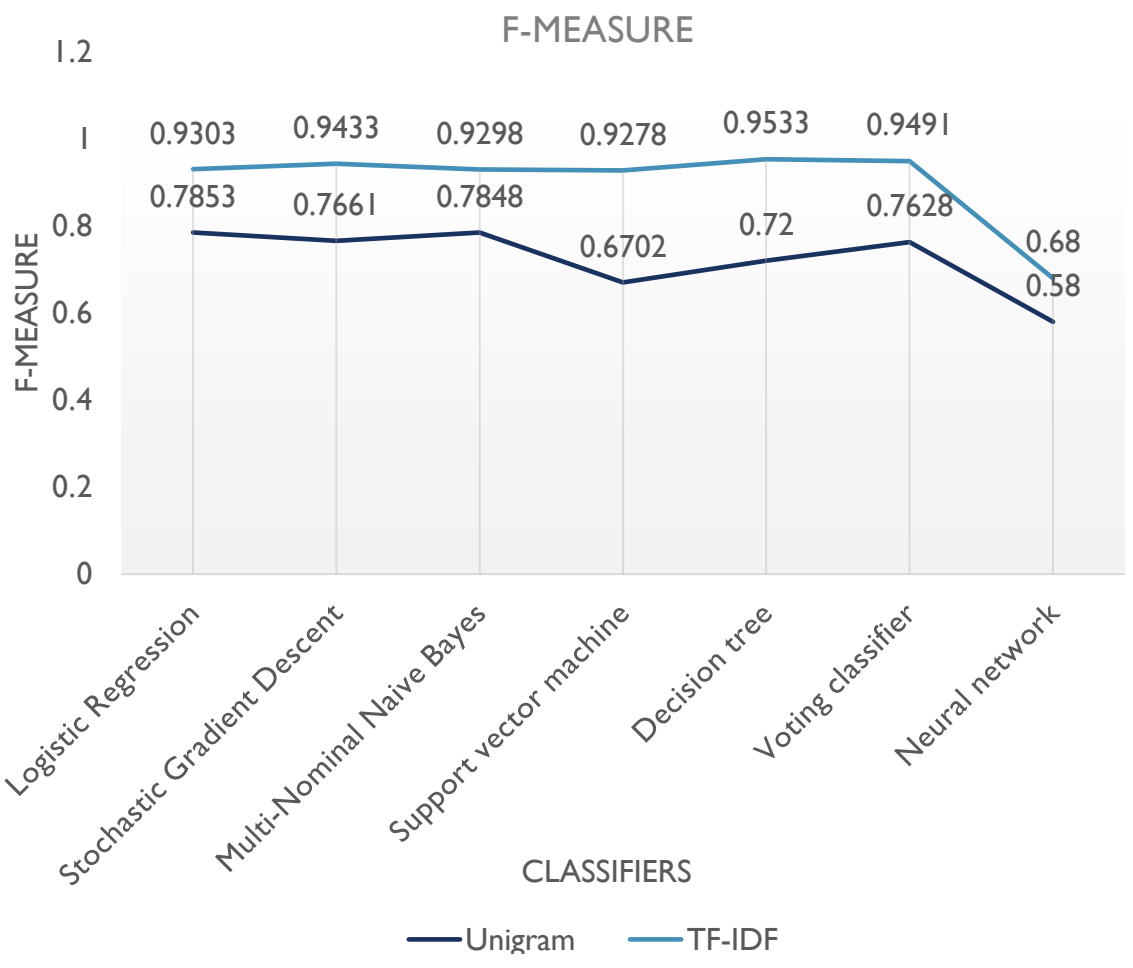
$$Precision = \frac{t_p}{t_p + f_p}$$

RESULTS

S.No	Classifiers Used	Accuracy (%)		F-measure	
		Unigram	TF-IDF	Unigram	TF-IDF
1.	Logistic Regression	78.98	85.24	**0.7853**	0.9303
2.	Stochastic Gradient Descent	75.46	90.05	0.7661	0.9433
3.	Multi-Nominal Naive Bayes	77.8	85.14	0.7848	0.9298
4.	Support Vector Machine	50.4	85.24	0.6702	0.9278
5.	Decision Tree	72.08	**90.85**	0.72	**0.9533**
6.	Voting Classifier	**79.08**	89.94	0.7628	0.9491
7.	Neural Network	61.05	70.99	0.58	0.68

GRAPHICAL ANALYSIS





CONCLUSION & FUTURE SCOPE

- ✓ In-language classification approach performs best than Resource based classification.
- ✓ The TF-IDF method of Feature Matrix Generation gives better results than Unigram Model.
- Resource-based Sentiment Analysis Approach could be extended to include Word Sense Disambiguation and lexical chaining approach to get better results.
- Hindi SentiWordNet (H-SWN) currently contains limited words. Improving dictionary can give much better predictions.
- Present models implemented do not support negation rules.

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THANK YOU