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Aspect Based Mobile Recommendation System

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***Abstract:** Now-a-days, there is a trend of changing mobile phone models in very short duration. To achieve benefit of choosing a mobile phone satisfying our requirements, mobile phone recommendation system is of great importance. As we know, there are many web sites that provide number of reviews and ratings for each and every mobile phone model available in market. From this, we can understand the consumer opinions and reviews about any mobile product. Existing systems were based on complete review of product as good or bad. But, there is need to have a way with which we can review the product with view of each aspect such as camera, battery, look etc. For this, we have developed a system which provides a recommendation of mobile phone model by considering aspects with user's choice. For this, we have used reviews, ratings provided by group of users on social website, Amazon. The data is collected with the use of "Octoparse", a web scraping software and the text data collected is analyzed using Stanford's CoreNLP for sentiment analysis. Our approach provides recommendation, considering user provided aspects (i.e. camera, battery, look etc.) with the use of apache mahout and hybrid recommendation. Our approach showed outstanding performance for mobile phone recommendation.*

***Keywords:** Recommendation system, standfords NlP, Octoparse, Apache mahout, customer reviews and ratings.*

I. INTRODUCTION

Now a day we see the rapid growth of the mobile phone users. Every user has different prospects for purchasing mobile product. In social media there is lot of information and reviews, rating are available for the other user who purchases that product. When person want to purchase mobile phone it's impossible to manually read all reviews and information about different brand and different series. In proposed work recommendation is based on the feature selected by the purchaser. Every person wish to have different features in their mobile like one person wants good camera, battery, look of phone and other person wants best gaming feature, display, waterproof mobile. We can fetch all the reviews and rating of mobiles from website using octoparse and save it in CSV format. Data obtained from the website is not processed data. Using Stanford's CoreNLP, we preprocessed the data. In preprocessing we removed stop words and extract aspect and opinions in data.

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Data is classified on the basis of sentiment in five classes viz. very positive, positive, neutral, negative, very negative. Based on this, the result is shown to the buyer. Another option is rating wise recommendation. For that, we used apache mahout. So based on ratings of mobiles phone, user decides which product to purchase.

II. RELATED WORK

Market container examination Check the gathering of things acquired in the general store or different stores to recognize the buy designs and discrete elective models. [16] Predict which items are explicit clients. The rundown ought to be browsed the arrangement of items connected. A few examinations outline forecasts of purchasing conduct in employment grouping [7, 10] that require statistic attributes of clients, for example, age, sexual orientation, instruction and occupation. In contrast to customary organizations, organizations in the web based business setting think that its hard to get data about statistic data or family foundation in light of the fact that these information are regularly viewed as close to home data. [19] It is very advantageous to get to client surveys. Positioning items and visiting tracks Therefore, strategies and calculations used to anticipate client purchasing conduct in the conventional business setting must be adjusted for internet business. In light of the test of foreseeing purchasing conduct in the online business setting, we will initially inspect the client's obtaining choice procedure.

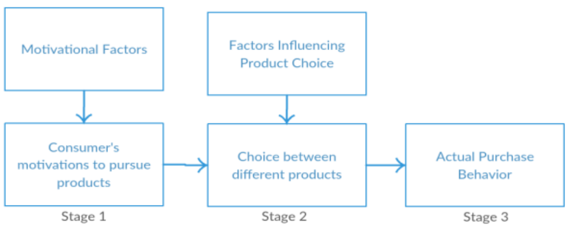

Fig. 1.Purchasing decision in the e-commerce context

Guo and Barnes [8] proposes a three-advance purchasing choice procedure in the internet business setting, as appeared in Fig 1. The initial step, consciousness of issues/inspirations. 1.Recognize purchaser discernment that items help them interface. The most effective method to interface The hole between the ideal status and the genuine status In the subsequent advance, clients must discover data about item execution or other criteria and must assess item alternatives dependent on value, brand and different highlights. Presenting framework innovation is generally acknowledged by web based business sites. This innovation isn't just But offer proper guidance to clients But likewise gives immense benefits to specialist organizations

However, we accept that customary proposal calculations can't adequately foresee purchasing conduct in the web based business setting for three reasons.: (1) Introducing framework [12, 17] Predict the things that are well on the way to hold any importance with clients, regardless of whether by exploiting the evaluations of different clients with comparative tastes. Essential counsel. Nonetheless, the anticipated positioning by the referral framework for the discretionary item shows the feeling that the client is probably going to have on that item, for instance, envisioning the sign of 'like'. This is a far route from the objective in Prediction of purchasing conduct. In light of our examinations, the utilization of CF alone to anticipate client purchasing conduct prompts terrible showing. Reference [20] Note that shoppers frequently make buys dependent on net utility, item contrasts. Objective buyers purchase items that expansion the all-out net utility.

Numerous undertakings in the referral framework center around client thing lattice and utilize tensor factorization. Be that as it may, those investigations consider just the connection between the client and the rundown and disregard the different item includes.

The referral framework for the most part does not determine the initial step of the buying choice procedure as appeared in Figure 1, however the referral framework is just a single piece of the second step of the acquiring choice procedure moreover, some referral frameworks are proposed to expand item mindfulness [4] and think about freshness and curiosity in item suggestions. [18] Such frameworks can't be utilized in determining tasks.

In this examination, we propose a two-advance expectation structure. To begin with, check the inspiration of the client. Nonetheless, all motivating forces that influence the real item buy in internet business are impractical. One model is the mental and wellbeing needs of Maslow. We exploit the connections between different items to foresee client inspiration.

The second step of the system recognizes numerous elements that influence client choices, for example, cost , brand fulfillment, financial necessities and so on. We attempt to incorporate side data about the item. To the expectation mission Settings for explicit item includes We additionally hoist these settings to choose an accumulation of items with alternatives dependent on client inspiration. At the point when clients send one acquired item into the anticipating structure, this system can restore the principal n items that most clients purchase later on.

The refreshed framework design above, directions identified with progressively coordinated client information Therefore, clients with general conduct are gathered first as indicated by snaps and added to the shopping basket conduct and assembled into gatherings. Extra suggested items rely upon the requirements of clients as indicated by framework forecasts. New clients will be positioned first in the gathering, at that point utilize the relating gathering arrangement to set the present client and recommend other comparable clients in the top gathering.

A. Cold Star Problem

Recommended tools that use general filtering, recommend each element depend on the actions of the user. The more user actions are the more interested users and more similar elements. Over time, the system will be able to give you more precise advice. However, this caused confusion and difficulty in organizing sites and recommended tools. Although newer ads are most relevant But the recommendation system tends to guide users less than the previous article But don't let the old ads overwhelm the introduction process.

B. Solution to Cold Star Problem

Content filtering is a way to answer this question. Our system uses the metadata of new products when creating suggestions while the actions of visitors are secondary in a certain period of time. In addition, we can identify visitors who are there to navigate and some visitors who know what they are looking for. For example, if someone clicks on everything from a phone envelope to a property for a short period of time, the system will assume that they are there just to navigate and will not use the click history to see instructions. When it comes to examining the phenomenon of cold start, this is just a small part. Each solution has different ways to deal with it, and after overcoming the cold start, the actual operation of the engine begins.

However, product recommendations per product will remain in all cases regardless of whether or not the user will block cookies.

C. Recommendation Strategy

The Current recommendation system declares some restriction, such as intelligence, adaptability, flexibility, limited accuracy.

This drawback can be control by implementing a hybrid architecture that combine product information with user's access log data and then create a set of recommendations for that specific user. This system manages most of the limitations and gives more effective and more correct result than existing systems.

Recommendation Systems can employ data mining policy to create suggestions using learning from the activities and quality of customers. The architecture of an online web recommendation system based on web usage mining primarily consists of three steps: Data Preprocessing, Pattern detection and generating recommendations. Data preprocessing and Pattern detection part are executing offline and the recommendations are produced online. Data preprocessing required transforming the web access logs and customers information into Suitable form for the system. Pattern observation involves using data mining techniques viz. clustering, sequential pattern mining or association rule mining. Finally the observed patterns are used to produce recommendations which give customized links or data to the user.

Recommender framework helps clients to discover and evaluate their investments. The Recommender system can utilize data mining strategies to provide guidance based on knowledge gained from the activity and quality of the customer. The Miner's Guide to online guidance systems on the web. Internet use generally consists of three steps: data processing, pre-detection, pattern generation, and hinting.

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D.Apache Mahout

Apache Mahout is an open source project that is fundamentally used for making scalable machine learning algorithms. It use popular machine learning techniques like:

- Recommendation
- Classification
- Clustering

At the heart of Collaborative filtering applications lie user-item interactions. Mahout models those as a (user, item, value) triple in a Preference object. For memory efficiency, only numeric identifiers are allowed. The Preference Array encapsulates a set of interactions belonging to either a user or an item. The dataset holding all known interactions is represented by a Data Model. This class provides a variety of convenient access or methods like getNumUsers() to find the number of users in the data or getPreferencesForItem(itemID) to get all interactions for a particular item. Mahout offers several implementations that are able to manage interaction data in memory, on disk, in relational databases and key-value stores

Our basic inspiration for this problem statement comes from [4]. We discovered a mix of other concepts in [1] and [2] in their documents and used the same framework as they were, even if there were change. In addition, we have taken into account considerations [3] because they present a new method of analyzing sentences at the phrase level, which determines whether the expressions is neutral or polarize and then differentiate the polarity of polar expression.

Challenges

- Efficiently storing and retrieving large archives
- In addition, the reviews are sometimes loud and full of grammatical errors. These problems are difficult to manage. Clear the data set and delete duplicate data to handle this.
- Problems with identifying perspectives that are being discussed in a given examination and the corresponding feelings. Example - "The new iPhone has a bad camera. But with a long battery life. "This is a negative camera confidence while the battery is positive.
- If the opinion is a natural comparison, refer to many products in one review. For example - "I just bought an iPhone but my Samsung Grand has a better processor." Here, iPhone is the original product. But the opinion is not directly mentioned
- Problems with anaphora correction Example - "The new iPhone has a lithium battery. It's really bad." This is difficult for the system to answer the question "What does it mean?"

III. PROPOSED ARCHITECTURE

Because The instinct behind our model is that the aspects drawn from the product's feedback set may be similar or related. Therefore, considering the most common aspects for confidence analysis may not be the correct representation of comments. Users may talk the same features of the product in various words; Grouping aspects before determining the most frequently discussed issues will prevent neglect of important issues. It also helps to ensure that there will be no duplication. . When gathering, the extremity of each gathering is determined as the normal estimation of the terminals of all sides in the gathering

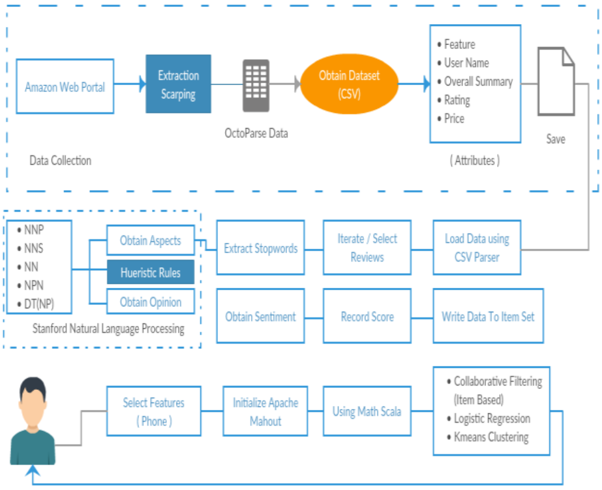

Fig. 2.Proposed Architecture

A.Initializing

The project can be divided into three major tasks, namely extraction and processing, aspect data and type checking and terminal determination.

Data extraction is data collection. (User reviews and other metadata) from popular e-commerce websites

The check messages we extracted from the data set contain a lot of unclean information, so we created a cleaning script for the data set. It removes unnecessary characters, hyperlinks, symbols, excess space and other text formats that our algorithms cannot process. From the cleaned data set, we extract the description of the validation text for our analysis.

The purpose of this step is to separate the instances of the product and the modifiers that express their views about certain aspects. The output of this step is list of nouns, adjectives that act as a statement. Enter into the next step of grouping. We define rules based on POS tagging of words in a review sentence. For example, a word that has a relation to rely on "nsubj" with a verb, a token will be a noun of a phrase, and a word that has a reliance on "acomp" will be an adjective of this noun. Therefore, we will separate this pair into pairs of related modifiers. The processing process converts unstructured data (raw html) into a structured format. (Relative table type structure) which our tools can be used to define various aspects and corresponding feelings for each product.. Aspect Category (Entity and Attribute (Opinion)). Indicate all the E elements and A attributes that are commented on in the given message. Should choose E and A from the pre-defined Entity inventory. And attribute labels (Eg design efficiency, price, quality) per domain E belongs to A. Each pair determines the image category of the given message.

- Tokenization: Humans can read and understand the language because we can easily identify words, sentences, paragraphs, etc. in a given document. Most NLP frameworks allow computers to understand which parts of the text are words, sentences or paragraphs.

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- Parts of Speech Tagging: Another characteristic of language comprehension is human ability to identify grammatical elements in the language. For example, we can easily search in sentences that define words that act as verbs, nouns or pronouns, etc. The NLP framework allows the computer to specify the syntax functions of each word in the text.
- Dependency Parsing: When we look at any sentence, we can identify not only But grammatical elements But also the relevance of each other in the form of things that are "subject" and what is "object" in the given sentence We also understand what the noun phrases in the sentence are and how they relate to other phrases, including words in the given sentence. The NLP toolkit also helps in this work.
- Co-reference Resolution: Humans can easily decipher how pronouns relate to various grammatical elements in a sentence.

B. Extracting Keywords (Aspects)

To reproduce what Amazon does, I'll show you how to separate keywords. I will use the rules-based approach to take advantage of the grammatical structure of comments. The assumption for this method of work is to write general opinions in a manner that respects the rules of grammar. The grammar rules we will use are:

"The most common nouns in messages that delete commonly used words will reveal key words (aspects) in the text."

1. In applying this rule to the opinion warehouse, product inspection requires advance processing.
2. Separate the token from the data warehouse.
3. Delete common words
4. Separate all nouns
5. Find the top 5 most common nouns. These words will be key words / characteristics.

Sentiment Polarity Each E # that specifies a pair of specified messages must be defined from the set P = {positive, negative and neutral}

For the purposes of this project, user reviews were collected from e-commerce website: amazon.com

Tools used:

- Octoparse: contains mechanisms for collecting data. The data collection process is divided into 2 steps:
- Collect a complete list of products under mobile phones category.
- Collect all the user reviews for each product.

The data was stored in a relational database to allow for easy access in the future. The crawling process was divided into 2 steps:

- Collect a complete list of products under mobile categories (Mobile Phone)
- Collect all the user reviews for each product.

The data was stored in a CSV file for easy reference.

The following section explains the process of crawling in detail using the example of amazon.

- http://www.amazon.com/robots.txt was used to obtain the sitemap. The various urls provided in the sitemap were used to create the seed set to start the crawl.
- Each of the seed urls provide a list of all products for a particular category.
- The urls for each product were then followed to obtain the complete list of user reviews.
- The crawled data was stored in a relational database. We decided to use CSV file format to store our data.
- It is an industry standard capable of storing large volumes of data while still maintaining the speed of retrieval.
- The Stanford NLP Tool will use the reviews (along with meta data such as user rating of the product, reliability of the user, rating of the review itself etc) to provide sentiment to the various aspects of the product being discussed.

C. Aspect Detection

- Identify each Aspect or (Entity E) towards which a sentiment is communicated in the given content. To take care of this issue, a blend of both Machine Learning and standard based methodologies was utilized.
- An Named Entity Recognition (NER) model was executed utilizing Conditional Random Fields (CRFs) utilizing various kinds of logical data alongside an assortment of highlights, for example, word prefixes and shapes that are useful in anticipating the distinctive named substance (NE) classes.
- When multiple aspects are present in a sentence, general purpose sentiment analysers are not quite useful as various aspects may portray conflicting polarities. Example: “The service was splendid but the food was inedible”. Here, the extracted entities give out opposite polarities and hence a decentralized approach has to be taken for this task.
- When there exists only 1 aspect in the review, a general purpose and normally more accurate sentiment analysis model can be used

D. Obtaining Recommendation

The basic interface for all of Mahout‘s recommenders is modeled in the Recommender class, which offers the functionality of recommending items for a particular user (top-N recommendation) as well as estimating the preference of a user towards an unknown item (rating prediction). In real-world use cases, one might not want to include all existing items when computing recommendations. This could be either due to latency constraints or requirements of a business use case (e.g. some items might be temporarily out of stock).

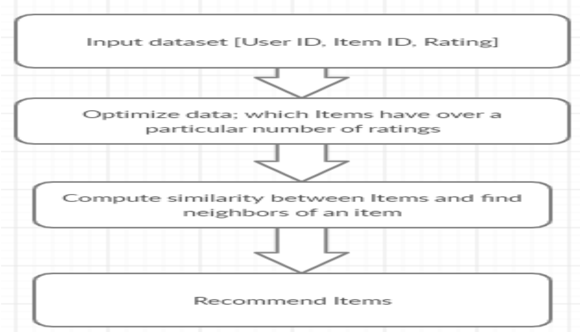

Fig. 3. Recommendation process in Mahout

For such a scenario, Mahout provides a customizable CandidateItemsStrategy class, which is responsible for fetching all items that might be recommended for a particular user.

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DataModel dataModel = new FileDataModel(new File("datarec.csv"));
PreferenceArray prefsOfUser = dataModel. getPreferencesFromUser(userID);
Furthermore, a user can provide a Rescores to postprocess recommendations, e.g. to emphasize special offers.
List topItems = recommender.recommend(userID,10); float preference = recommender. estimatePreference(userID,itemID);
Neighborhood methods form the most traditional and frequently used approach to collaborative filtering. They are also known as k-methods. Neighbors are as close as they calculate suggestions by searching for users with tastes or items that have been ranked in the same way. Mahout provides implementations for both, the user based and the item-based approach. In a UserBasedRecommender [9], a User Neighborhood selects users that act as a jury for finding items to recommend. Due to its simplicity and scalability, the item-based approach [8, 10] represents the most widely deployed recommendation algorithm. It can present the items most similar to a given item (a popular non-personalized way of recommending) and can provide preferences for items as justification for recommendations. In Mahout, the item-based approach is realized by an ItemBasedRecommender together with a measure to compute similarities between items, represented by an Item Similarity. Implementations for lots of popular measure such Pearson correlation, cosine similarity, Jacquard coefficient or loglikelihood ratio [3] are available. Similar to interaction data, precompted item similarities can be loaded from disk or a relational database.

E. Sentiment Polarity

To obtain metric for features of the products we need to identify the opinion of that feature from various reviews available. We see the objective of perusing various audits as finding generally held conclusions and gauging the positive against the negative, and we wish to mechanize this kind of errand utilizing NLP and AI systems machine learning techniques.
Each distinguished Aspect and Category pair of the given content must be doled out an extremity, from a set P = {positive, negative, neutral}. The nonpartisan mark applies to somewhat positive or somewhat negative assessment. When the polarities of the aspects are found, the corresponding polarity of the categories is tuned accordingly and the final polarity of a category is maintained and updated with each review.

IV. EXPERIMENTAL SETUP

In information recapture with binary classification, precision (also called Positive forecast) is the tiny part of recaptured case that are relevant, while recall (also called sensitivity) is the tiny part of the relevant case that are recapture. Precision and recall are based on understanding and measuring significant. In simple word High recall means algorithm has more relevant result. High accuracy means relevant return algorithm is significantly more relevant than irrelevant results
The most important category measurements for binary categories are:

ItemBasedRecommender recommender = new GenericItemBasedRecommender(dataModel, new PearsonCorrelationSimilarity(dataModel)); List similarItems = recommender.mostSimilarItems(itemID,3);
Obtaining Recommendation in 3 categories

A. Feature Based Recommendation

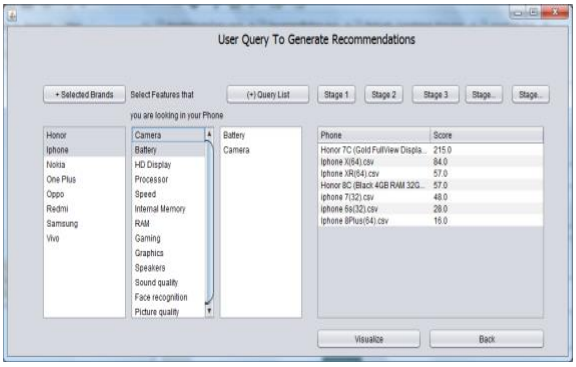

Fig. 4. Feature Based Recommendation

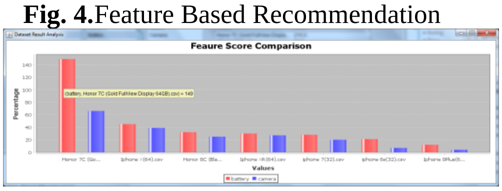

Fig. 5. Visualization and comparison of various recommended models

B. Price Based Recommendation

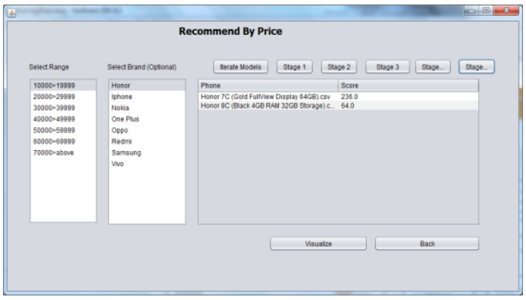

Fig. 6.Recommend by Price and Brand

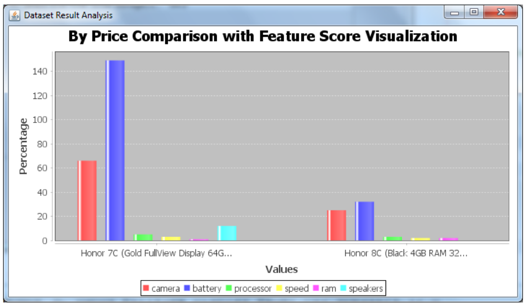

Fig. 7. Visualization and comparison of various recommended models price wise and model wise

C. Using Overall Ratings

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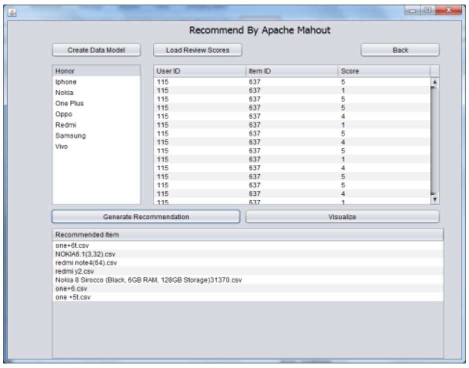

Fig. 8.Recommend by Overall rating

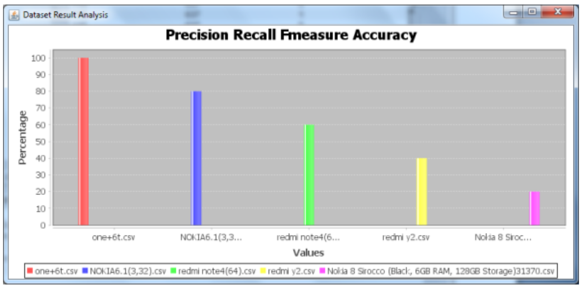

Fig. 9.Visualization and comparison of various recommended models by overall ratings

D.Calculating Precision Recall F-measure:

In retrieving data with binary number precision (Also called positive predictive value) is the part of the retrieved instance that is relevant while the recall (Also known as sensitivity) is the part of the corresponding instance

Accuracy and recall depend on understanding and measuring relevance. In simple terms, high accuracy means that the relevant return algorithm is significantly more relevant than irrelevant results, while high recall means that the algorithm delivers the most relevant results.

- Precision:
  $$P = TP/(TP + FP)$$
- Recall
  $$R = TP/(TP + FN)$$
- F Measure
  $$tp + tn/tp + tn + fp + fn$$

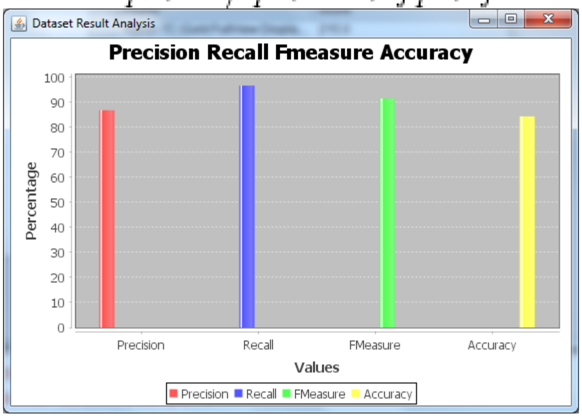

Fig. 10. Key Index Parameters

Table- I: Name of the Table that justify the values

PRECISION	86.90292758089369
RECALL	96.7409948542024
FMEASURE	91.55844155844156
ACCURACY	84.4311377245509

V.CONCLUSION

In this paper, we have presented a framework for recommending the mobile phones to user. We have proposed a modeling method that models the rating and review data from Amazon. In addition, we have proposed a method for creating a probability topic model to separate latent phone instructions using the Octoparse data extraction tool set. We have applied the proposed framework to a real world large scale dataset from Amazon, using Octoparse , with more than 10000 data records, and the output shows outstanding mobile phone recommendation accuracy.

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