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IMPROVING DIVERSITY IN VIDEO RECOMMENDER SYSTEMS AND THE DISCOVERY OF LONG TAIL

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ABSTRACT

The sharp growth of online-systems and vast availability of high quality data lead to information overload, increasingly very difficult for the online users to find most relevant content. When looking for information about any movie, music, video, the internet users come across a bewildering number of options to fetch precise data from the recommended list. The main goal of the recommender system is to suggest high quality and top rated videos to the user. However there exist thousands of video items said to be Long Tail (videos with least rating) that stagnate idle on the web server for years that are unrevealed by users because of its least rating. The new recommender system introduced in this paper uses rating based binning technique that favors not only top rated videos to get recommended, but also recommend Long-Tail videos. This can improve diversity on recommendation and suggest best long tail videos to the user. This implies that a least popular video has a high probability to become more popular when it is placed on the related video recommendation lists of popular videos. In order to evaluate the proposed video recommender system, the datasets are crawled from YouTube©, a well-liked online video community to suggest videos with high rating along with less rated long tail videos.

Keywords: *Recommender System, Long Tail, Information Storage And Retrieval, Recommendation Diversity*

1. INTRODUCTION

YouTube established in early 2005 has been one of the successful user-generated video sharing and video recommendation website, which become a most attractive and a popular destination for all kind of users to find most videos online. In the recent decades usage of Internet is increasing exponentially [1]. E- Shopping, Digital Music systems, Video stations widely attracted the web users online now-a-days. Personalized recommendations for individual users become a key method for information retrieval and discovery of data content in today's information- rich online environment.

The main aim of developing an online recommender system is to suggest high accurate and most popular data for the online users. Combining pure search (query processing) and browsing for content, they allow users to face huge amount of information to navigate that information in an efficient and satisfying manner for the online users. Being the most-popular online video community with huge quantity user-generated content [2], YouTube exhibits unique opportunity and challenges for content discovery and recommendations. These recommendation systems acquire increase of the hint from users' interactions with the site to provide recommendation without only depending on textual descriptions or else content analysis.

Most online users prefer to look on and download the most popular, highly rated videos & digital music. There exists huge number of videos online remains idle because of less popularity with least rating. Such least popular videos are called Long-Tail Videos that are not suggested to users. The rapid growth of the number of videos available on YouTube provides enormous potential for users to find content of interest to them. In the proposed Long Tail video recommendation system, that suggests personalized set of best long tail videos to

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log in users based on their previous activity on the YouTube site. Recommending long tail videos will increase diversity and improve view count of idle videos that stagnate on the YouTube server.

1.1. Goals

Users visit video community for viewing a wide range of videos. The main goal of user is to watch a single video that they can found through direct navigation, to find specific set of videos. The users will be entertained by content they find more interesting through searching and browsing to view most relevant and precise videos. In current video recommender system, it predicts and suggests top-N highly rated video items. For entertaining the users, the recommendations are updated periodically and reflect recent activity of users on the site. The main goal is to suggest Long Tail videos that are undiscovered on online server because of its least rating and less view count. An additional important goal of the proposed system is to improve diversity through suggesting Long Tail videos for the users and maintain explicit control over personalized users recommended data.

1.2. Challenges

The most relevant video suggestion is the important watched sources of any video. The major source of views for most of the videos has highly predicted rating and view counts. In such related videos, there exists solid correlation between average view count of top N referrer video and view count value of a video been watched. Finding the most related videos can be obtained only from the logs of users clicking related videos is firmly hard to predict.

2. RELATED WORKS

Recommender systems are typically classified into three categories based on their advance to recommendation: Collaborative based, content based, and hybrid approaches. Collaborative filtering (CF) recommender system recommend video items to user by related preferences (i.e., “neighbours”) have liked in the past[3],[8]. Content based recommender systems recommend items similar to the ones the user preferred in the past [4]. Finally, hybrid approaches can combine content-based and collaborative methods in several different ways.

2.1. Rating Technique

Recommender systems usually function in a two dimensional space of users and video items. Let U be the set of users of a recommender method, and let I be the set of all possible items that can be recommended to users [3]. Then, the utility function that represents the preference of video item $i \in I$ by user $u \in U$ is often defined as $R: U \times I \rightarrow Rating$, where *Rating* in general represents hardly any numeric scale used by users to compute for each item.

The rating $R(u, i)$ notation to symbolize a known rating (i.e., the actual rating given to item i by user u), and the $R^*(u, i)$ notation to represent the system-predicted rating for item i and user u. In particular, precision is one of the most popular decision-support metrics that measures the percentage of truly “high” ratings among those that were predicted to be “high” by the recommender system [4], [5]. The ratings in the data used in such experiments are scaling between 1 and 5(used in proposed system), wide-ranging, and therefore such items with ratings greater than 3.5 (threshold for “high” ratings, denoted by TH) as “highly-ranked”, and the ratings less than 3.5 as “non-highly-ranked.”

2.2. User-Video Co-View Graphs

The Online video community like YouTube has a billion number of users in which they will view multiple videos at a time. One of the basic set of statistics report to calculate with data can be done using video co-view numbers. The co-view data will give the number of people who viewed both videos for any pair of videos [7]. A statistical computation can be done for all sets of videos that lead to numerous ways to converge this into a graph. Figure 1 and 2 represent the view graphs generally used in recommender system to find related videos.

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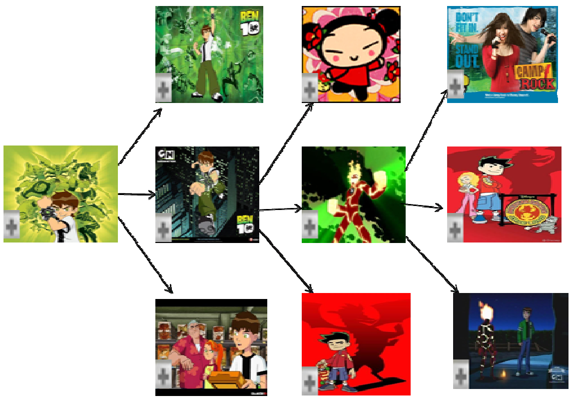

Figure 1: Video-Video co-view graph

In Figure 1, shows the co-view graph which shows the connection between the videos been watched most commonly by the same users. In Figure 2, show graph of user-view that infer co-views of multiple users. This graph is an alternative method of showing the co-view information through the user-video bipartite graph [4].

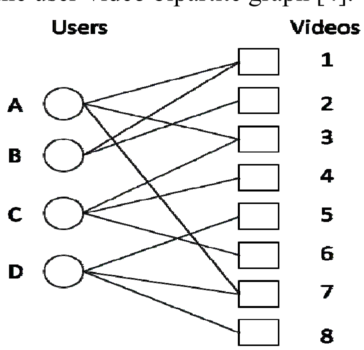

Figure 2: User- View graph

By examining the total number of paths of length 2 that exist between two videos will give total number of co-views implicitly. By computing the total number of co-views, for any particular video search the recommender system will suggest the most related videos that are viewed by users in the past.

2.3. YouTube – The Most Popular Video Recommender System

YouTube videos can be accessed in a variety of ways, such as through Google Video search, Web Link, Featured videos blog, Google search, mobile device, and features provided on YouTube itself. By 2010, Internet statistical [6] reports in that YouTube become the most popular video recommender system in which 30% of the web search videos are found in YouTube.

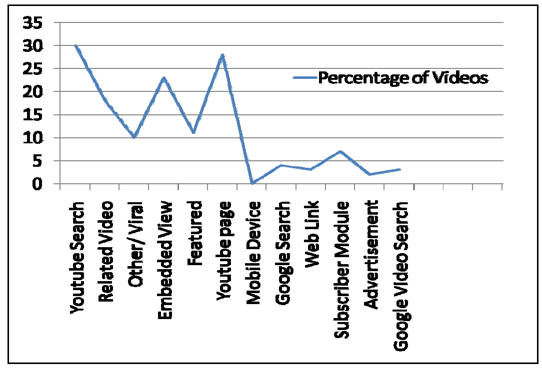

Figure 3: Statistical report on Recommender System

3. DATA DESCRIPTION

The data sets are crawled from YouTube. Section 3.1 describes how the data sets are collected from YouTube.

3.1. Data Collection

The data sets collected for particular rating threshold. Long Tail data items can be crawled. Figure 4 shows, the collected dataset include Metadata of video ID, rating of video, view count, total number of comments, Related Videos, Statistics of Referrers videos.

video ID	views	rate	ratings	comments
CRYQcIxFhf4	24490	4.62	3444	130
5hm7XxcMZFU	32043	4.19	8533	53
1fRPpRpTis4	261	3.37	4954	84
oHtRD8nkENI	23309	4.72	4689	18
cl_0uqkxoFE	20483	4.45	1061	60
2dDAySUywko	27287	4.51	8266	50
y05er2lEEXc	23143	4.86	1399	91
y19_IgmiGDI	25833	4.62	1068	72
Zk0lMR0ULO4	15	2.72	29	69
xdXEine81DE	60	3.26	466	148
wXzHZoyEA-k	558	3.08	1212	356
LdLOcyX29LA	412	3.21	393	152
CRYQcIxFhf4	244	3.62	344	133
5hm7XxcMZFU	320	3.19	851	53
gANtV_Zt0pA	20886	4.61	5464	74
uGVRuOg7p6g	18036	4.78	2791	604
RRxFjf40xbI	945	3.69	675	546
KFd4U3qP69A	657	3.87	152	1154
vjLuoM6PIUE	597	3.85	404	240
Yuh4GDx9f84	330	3.29	314	344
a8Mx_x8g7y0	92619	3.23	261	824
xdXEine81DE	60727	3.26	466	148
wXzHZoyEA-k	55880	3.08	1212	356
LdLOcyX29LA	41232	3.21	3933	152

Figure 4: Dataset crawled from YouTube

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4. LONG TAIL RECOMMENDER SYSTEM AND IMPROVING DIVERSITY

There exists large number of least popular videos named as Long Tail video items in online video server. Most common recommender will suggest the small number of popular items, well-known *hits* and the rest are located in the Long tail, which not viewed *that well*. The Long Tail video items offer the possibility to discover and explore vast amount of video items that suggest the *hidden gem (less popular videos)* from the Long Tail. Until today, the world was dominated by the *Hit or Miss* Categorization can be eliminated through the discovery of Long Tail videos. This will lead to millions of video albums could succeed in YouTube which is less popular due to least view count can be touring worldwide in future due to long tail recommendation system.

4.1. Video Popularity based Rating

Video items have to be binned based on the popularity (rating between 0-5) from the lowest to highest. Before that videos has to be ranked based on their rating. Using the number of known ratings given for each video which is obtained by YouTube data crawler, the videos are binned. Let R be the rating function, *u* be the user who rate that video *vi*. Value of ***Rate****Pop(vi)* is calculated as the average weighted sum of all the rated value of all users *U*.

RatePop(vi) = |U(vi)|, where $U(vi) = \{u \in U \mid \in R(u, vi)\}$

The Ranked Scoring or Top-N Recommendation list is expressed as a list of N videos *vi* using Rate$_{Pop(vi)}$, where N ≤n, in which the active user is expected to like the most. The usual approach consists of only videos that the active user has not already viewed or rated.

4.2. Iterative Refinement Binning

The long tail videos binning can be done using the algorithm below.

Step 1: Begin with a decision as rating limit (0 to 5) on the value of k= 5 (total number of clusters). The value can be obtained from rating value R given for each video.

Step 2: Put any initial partition that classifies the video rating into k clusters. Assign the videos randomly, or systematically as the following:

- Take the first k videos as single-element clusters
- Assign each of the remaining (N-k) training sample to the cluster with the nearest centroid.
- After each assignment, recomputed the centroid of the gaining cluster.

Step 3: Take each video in sequence and compute its distance from the centroid of each of the clusters. If a video item is not currently in the cluster with the closest centroid, switch this video item to that cluster and update the centroid of the cluster gaining the new video item and the cluster losing the video.

Step 4: Repeat step 3 until convergence is achieved, that is until a pass through the videos causes no new assignments.

At the end of iterative refinement clustering, all the videos are clustering into appropriate cluster.

4.3. PROPOSED – Long Tail Video Recommender Methodology

The collection of related videos in recommendation list and the position of a video in a related video list play a critical role in the click through rate. The list of Long Tail videos are identified and added in the recommendation list so that its popularity can be simply improved in the successive recommender list. The system will recommend the videos for the searched key. The videos are rated on 1-5 scale value. Figure 5 represents the architecture of binning based recommender system. Based on the rating value, videos are binned using Algorithm 1. The top five videos are recommended from each bin. Videos been ranked between 4 and 5 are highly predicted recommendation. The long tail videos are discovered from the bins that have less rating but considerable view count. Rating Threshold T$_R$ has been set for binning. The users can rate the videos and its new cumulative rating is computed based on view count and updated in local database. Newly computed ratings of such particular video will be binned to appropriate bins and added to recommendation list.

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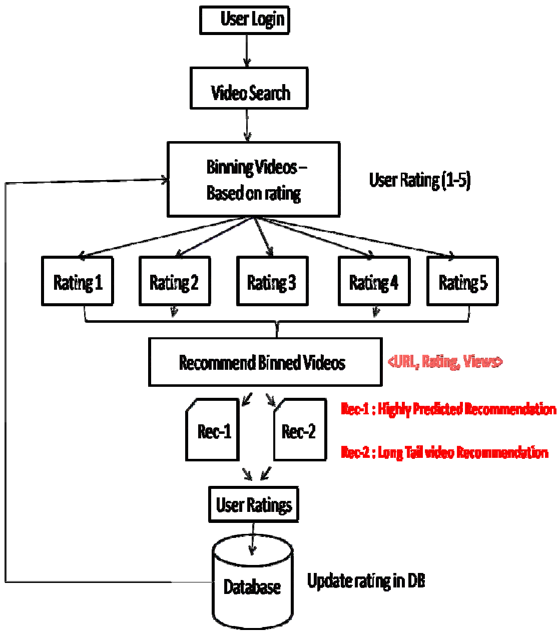

Figure 5: Binning based Recommender System Architecture

The recommender system will figure out the top videos with the highest video popularity (Rec-1) ie, rating (range 4-5). In addition to that Long Tail videos (Rec-2) ie, rating (range 1-3) with moderate view counts and least ratings are also recommended.

From the recommended videos it is assure that majority of search videos are in the range of 4-5. The count of less rated video is very less in Rec-1. The second recommender system will discover the long tail videos using Algorithm 3 that improves diversity is discussed and proved in section 4.5.

4.4. Pseudo – code: Proposed Recommendation Model

Algorithm 1: Bin Rank – BinVideo()

{**Input :** SearchKey from User U, Record User Ranking}
Function **BinVideo**(SearchKey, Url, ViewCount, Rank)
begin
Lb : Start Row of TblURL
Ub : End Row of TblURL
for i=Lb to Ub **do**
if ∃ Video Url :: € Rank equals 5
*{ Create new table **Rank5** , insert values such that rank equals 5, Select VideoPk, Url, ViewCount, Rank from TblURL where SearchKey equals SearchName and Rank=5}*
End If € Video Url
if ∃ Video Url :: € Rank equals 4
*{ Create new table **Rank4** , insert values such that rank equals 4, Select VideoPk, Url, ViewCount, Rank from TblURL where SearchKey equals SearchName and Rank>=4}*
End If € Video Url
if ∃ Video Url :: € Rank equals 3
*{ Create new table **Rank3** , insert values such that rank equals 3, Select VideoPk, Url, ViewCount, Rank from TblURL where SearchKey equals SearchName and Rank>=3}*
End If € Video Url
if ∃ Video Url :: € Rank equals 2
*{ Create new table **Rank2**, insert values such that rank equals 2, Select VideoPk, Url, ViewCount, Rank from TblURL where SearchKey equals SearchName and Rank>=2}*
End If € Video Url
if ∃ Video Url :: € Rank equals 1
*{ Create new table **Rank1**, insert values such that rank equals 1, Select VideoPk, Url, ViewCount, Rank from TblURL where SearchKey equals SearchName and Rank>=1}*
End If € Video Url
End Loop
VideoRecmd(Tbl<Rank5, Rank4, Rank3, Rank2, Rank1>)
LTRcmd(Tbl<Rank>)
End

Algorithm 2: Recommend Video - VideoRecmd()

Function **VideoRecmd**(<Rank5,Rank4,Rank3,Rank2, Rank1>)
{ Input: Tables binned using BinVideo function**}**
begin
{Create Table **Recmd** to insert rows}
Select Top five videoPk , Url, ViewCount from Tables <Rank5, Rank4, Rank3, Rank2, Rank1> whose MAX viewCount
End

Algorithm 3: Long Tail Recommendation – LTRcmd()

Function **LTRcmd**(Tbl <Rcmd>)
{ **Input :** Table **Recmd** , contains top five videos from each bin <Rank5,Rank4,Rank3,Rank2,Rank1>)}
Begin
{Create Table LTRecmd to insert rows}
*Select Top five videoPk, Url, ViewCount from Tables **Recmd** where Rank between 1 and 3*
End

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Algorithm 4: Update User Rating – UpdateRank()

Function UpdateRank()
Begin
OldCount : viewCount
OldRank : rank
newCount:= OldCount+1;
newRank:= (OldRank+newRank)/newCount;

<Update newCount, newRank in table TblURL >
BinVideo(SearchKey,Url,newCount,newRank)

End

4.5. Improving Diversity

Among the video items in YouTube, it is known that the videos rated by most users (i.e, the video with the highest number of known rating) as a Most popular video, and the video with least number of users view (i.e, the video with smallest number of known rating) as a Long Tail video. From the developed recommender system the empirical evaluation results shown in Figure 6 proves that 12 distinct videos are found for search name "Image Processing" with rating threshold TR between 4 and 5. If the threshold TR is minimized (ie, rating less than 3) 34 distinct videos are obtained. If the recommender system suggest each one user the most well-liked video with highest rating (with sufficiently uppermost predicted rating), it is more to be expected for masses of users to get hold of the equivalent recommendation (e.g., the best viewed video). As discussed in section 4.2, videos are clustered based on their ratings and those clusters are used for recommending long tail videos. The proportion of truly "high" ratings predicted to be "high" by the recommender system.

Top 1 – Recommendation of : Image Processing	Rating Accuracy	Diversity
"Popular Video" [Video with largest known rating]	4.0 – 5.0	12 distinct videos
"Long Tail Video" [Video with smallest known rating]	1.0 – 3.0	34 distinct videos

Figure 6 Emprical Evaluation : Rating Accuracy vs Diversity Tradeoff

Note: Recommendations (top videos for each user) are generated for 17 users among the videos predicted above the acceptable threshold 4.0 (out of 5) and Long Tail as threshold below 3.0 (out of 5) using a standard video popularity based Rating

The result shows by fixing Rating Threshold TR as 4.0 to 5.0 recommend only 12 distinct videos with high accuracy is found out of just about 60 available distinct videos that are recommended transversely to all users is shown in figure 6. This recommender system can improve the diversity of recommendations from 12 to up to 34 distinct videos (a 3-fold increase) by recommending the long-tail videos to each one user (i.e., the least popular video among extremely predicted video for each user) instead of the popular video. However, high diversity can be obtained at the considerable expense of accuracy, i.e., drop from 4.0 rating threshold to 3.0 and below with a small loss in accuracy of rating value.

5. IMPLEMENTATION MODEL

5.1. User Reviews & Rating

The two basic entities which appear in this long tail recommender system are the user (sometimes also referred to as viewers) and the video (also referred to as viewing item in the bibliography). A user is a person who utilizes the recommender system given that view about various video items and receives recommendations about new items from the system. In the proposed recommendation model, the input is User Rating R(U,Vi) where U is the User who rated the Video , Vi is the Video been rated by User U, R is the rating value given for that particular video by user.

Figure 7 shows the recommendation list for the search on 'Image processing'. The video url, rank, rating, view count is displayed. Ratings (also said to be votes), that express the opinion of users on items. Ratings are normally provided by the user and follow a specified numerical scale (example: 1-not fair to 5-excellent). The user rating is stored in local database. An activity log is stored about the recent activity of the user who viewed and rated a particular video.

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Figure 7: Searching a video 'Image Processing'

5.2. Update Video view count & ratings

Using Algorithm 4 discussed in section 4.4. , the user rating is consumed and stored as log. The new ranking is computed using Standard ranking method and view count is updated.

5.3. Binning Videos based on Rating

Recommendation is a list of N videos that the active users U<1, 2, 3,...., N>, will like the most using activity logs stored in section 5.3. Videos been included in the suggestion list should not appear in the list of items already rated by the active user. In order to avoid repeated recommendation, the Video list is been binned based on their rating values. Using Algorithm 1 discussed in Section 4.4., the function BinVideo() start binning videos based on rating given by users in past. In the end of this approach there exists five distinct tables that can hold videos with rating <rank 5, rank 4, rank 3, rank 2, rank 1> shown in Figure 10.

Figure 8: Binning videos based on rating

5.4. Recommending Top – 5 Bin Videos

In the recommendation list, using Algorithm 2 discussed in section 4.4., the top five distinct videos been suggested to users that is fetched from each bin. These will leads to a high diverse recommendation, that is, the videos that have high accuracy are suggested along with other less rated videos. Figure 10 represents output as, with equal number of ranking recommendation leads to the least popular video to get rated by upcoming users to rate considerably and improve its rating accuracy further.

Figure 9: Recommended videos on 'Image Processing'

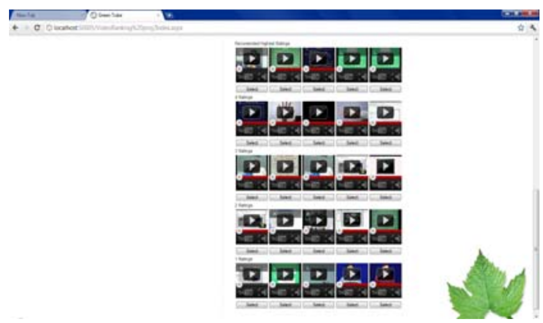

Figure 10: Rating based binned video recommendation

5.5. Highly Predicted, Long Tail Video Recommendation

The Top N videos (N=5) are recommended to the users is discussed in section 5.4. Using Algorithm 2, the highly predicted videos are recommended the users. In order to focus on Long Tail videos (ie, videos with less rating value) the rating Threshold of recommendation is minimized. In this model, the rating threshold from 1 to 3 is focused and the best videos out of less rated video are recommended shown in Figure 11. This will improve diversity and the discovery of long tail is achieved.

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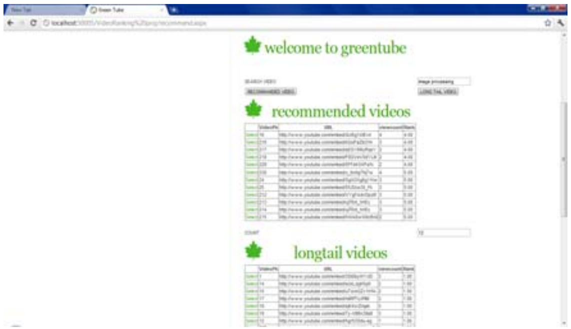

Figure 11: Normal Recommendation & Long Tail Recommendation

5.6. Re-Bin Videos based on recent update

New user rating and views are stored in activity log table. User activity is recorded and new updated view count and new cumulative rating average is computed using algorithm 4, UpdateRank(). This will provide new rating value of each video been updated. If the video is a Long Tail (rating 1-3) and if its new rating is 5 , then using algorithm 4 its rating average is computed is shown in screen 5.The experimental result conclude that if a long tail video is recommended to users, the new rating will improve the rating accuracy of that particular video. In the next updated round (after re-binning videos) of recommendation it will be binned to highly predicted rating bins.

For example if the old rating is 2 and new rating is 5 (given by user U), cumulative rating average is computed as 3. Now that particular video will be binned to Rank3 bin. Further if its rating is increased by user views and rating will bin that video to highest rating threshold bin. Hence the unveiled less popular Long Tail video been recommended in the proposed system will improve the rating of the video and improve diversity with a minimal loss in accuracy.

6. EXPERIMENTAL RESULTS

Taken YouTube videos as data set in the proposed recommender model, out of 60 videos in each search domain the videos are binned using algorithm 1.Videos with rank5 and rank4 videos are binned in individual tables. Figure 12 shows the experimental result on the ranking been binned. Figure 13 shows the chart that suggests the counting value on rank1, rank2, rank3.

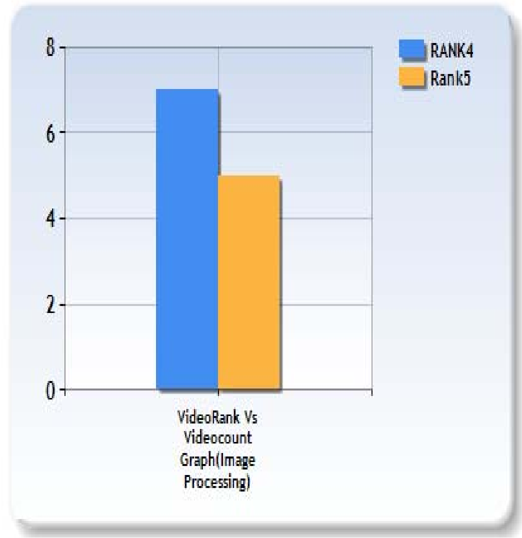

Figure 12: Recommended- High Predicted videos (Ratings 4 to 5)

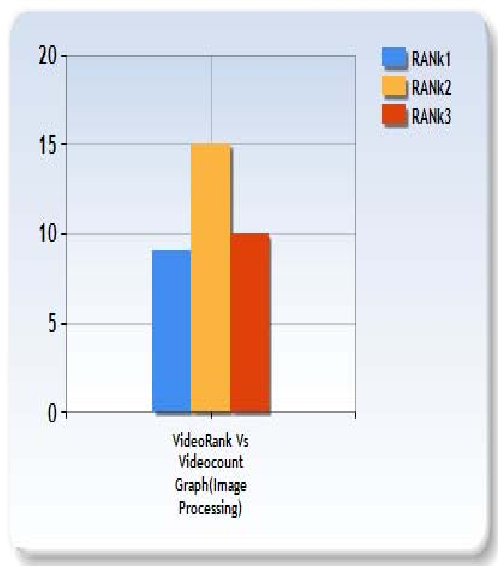

Figure 13: Recommended- Long Tail Videos (Rating 1 to 3)

After binning the videos, the total count on normal recommendation with highest rating threshold is evaluated. The total count on long tail recommended videos with less rating threshold is computed and compared with normal recommendation.

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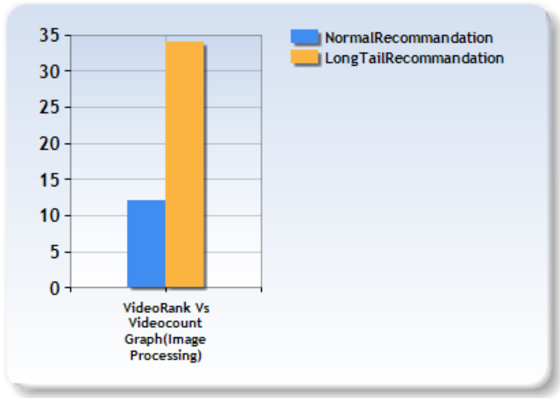

Figure 14: Normal Recommendation vs Long Tail Recommendation

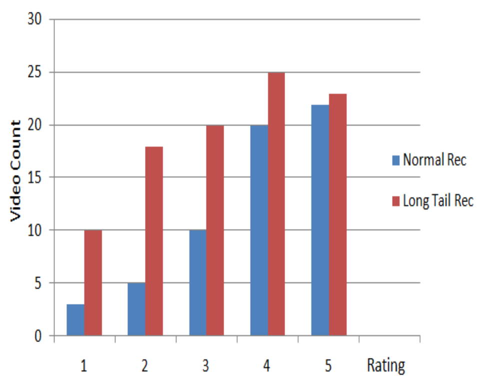

Figure 15: Rating vs View Count Graph

The chart in Figure 14, Figure 15 shows the normal recommendation will have less count on videos, whereas long tail recommendation will give high count on video recommendations. The experimental result shows that the diversity can be improved if the long tail recommendation provide improved diversity and discovery of long tail will be achieved.

7. CONCLUSIONS AND FUTURE WORK

Recommender systems lead to major progress over the last decade, which improve the expected efficiency of suggestions in video recommender systems. The consistent empirical estimation of the proposed technique provides robust diversity improvement across numerous real-world datasets and using diverse rating prediction techniques. The diversity of the proposed technique improve through minimizing the rating threshold to obtain more long tail videos that are not viewed by users from video server for that lasts idle for long time. The proposed item popularity based Long Tail video ranking technique provides significant improvements in recommendation diversity with only a small amount of accuracy loss. Finally, the evaluation of the long tail video recommendation system on the diversity of video views shows that the existence of online recommendation helps to increase the diversity of video views in further binning levels, which means that recommendation helps viewers discover more long tail videos of their interest rather than the popular videos only.

Our future plans consist of a series of experiments whose intention will be further extended and followed by understanding the usability of new binning and other clustering algorithms such as Y-means, K-means techniques to improve more diversity and discovering long tail videos. Through these experiments we will be able to compare the performance of binning and grasp the conditions under which each technique generates better results. The final stage will be to increase and extend existing rating based binning algorithms by employing various intelligent techniques.

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