International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 02, June 2016, pp. 31 – 36

Abnormal Web Video Detection Using IQR Method

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Abstract: *Recently, discovering outliers among large scale web videos have attracted attention of many web mining researchers. There are number of outlier videos exists in each category of web videos such as Entertainment, Sports, News and Politics, etc. The task of identifying and manipulate (to remove from the web or to share with others in the web, or to watch/download from the web etc.) such outlier web videos have gained significant important research aspect in the area of Web Mining Research. In this work, we propose a novel method to detect outliers from the web videos based on their metadata objects. Large scale web video metadata objects such as length, view counts, numbers of comments, rating information are considered for outlier detection process. The outlier detection method Inter Quartile Range (IQR) is used to find abnormal/outlier web videos of same age. The resultant outliers are analyzed and compared as a step in the process of knowledge discovery.*

Keyword: *Outliers, Inter-Quartile Range, Web Video Outliers, KDD, YouTube*

1. INTRODUCTION

The YouTube is recognized as one of the most successful user-generated video sharing sites nowadays. YouTube has over a billion users — almost one-third of all people on the Internet — and every day people watch hundreds of millions of hours on YouTube and generate billions of views [1]. In order to facilitate users to find interesting videos from a large number of videos, YouTube provides different features/metadata objects such as – view counts, rate, ratings, number of comments, favorites, key words, information regarding likes and dislikes etc.

The objective of this study is to detect outlier videos among large scale web videos using their metadata objects. To succeed in the proposed objective of the work, large scale web video metadata objects are extracted from the standard YouTube dataset website [5]. This metadata objects includes various attributes such as- ‘Category’, ‘View Counts’, ‘Rate’, ‘Number of Comments’, ‘Avg Ratings’ and ‘Length’ of each web videos.

The schematic structure of the dataset is represented in TABLE I.

The main contributions of our work are as follows:

• Web Video Metadata Object dataset extraction and effective preprocessing for the experiment.

• The analysis and knowledge discovery process from the resultant unsupervised outliers formed by the built IQR outlier model.

Many outlier models/algorithms and data mining machine learning tools are developed in recent years. Using different data mining algorithms and machine learning tools such as R programming and WEKA, it is possible to detect outliers from the web videos based on their features/metadata objects.

The rest of the paper is organized as follows: The section 2 represents related works on the clustering of web videos, section 3 represents proposed web video clustering methodology, section 4 represents performance evaluation analysis of outlier models and comparison of efficiency of outlier models, and finally section 5 represents conclusion and future enhancements.

TABLE I SCHEMATIC STRUCTURE OF WEB VIDEO METADATA OBJECT DATASET.

No.	1: Category Nominal	2: Length Numeric	3: Views Numeric	4: Rate Numeric	5: Ratings Numeric	6: **Comments** Numeric
1	People & Blogs	217.0	1157.0	3.6	5.0	3.0
2	Comedy	426.0	667.0	4.0	4.0	4.0
3	Entertainment	237.0	1063.0	0.0	0.0	1.0
4	Comedy	294.0	274.0	1.0	1.0	2.0
5	Comedy	109.0	48.0	5.0	2.0	1.0
6	People & Blogs	263.0	62.0	5.0	4.0	5.0
7	Howto & Style	34.0	3437.0	4.7	20.0	1.0
8	Comedy	50.0	385.0	2.71	7.0	9.0
9	Comedy	251.0	91.0	5.0	1.0	1.0
10	Comedy	145.0	209.0	5.0	1.0	0.0
11	Comedy	150.0	21.0	0.0	0.0	0.0
12	Comedy	19.0	189.0	5.0	1.0	0.0
13	Entertainment	14.0	91.0	0.0	0.0	0.0
14	Comedy	284.0	1146.0	4.5	2.0	1.0
15	Music	210.0	8483.0	4.85	13.0	7.0
16	Entertainment	134.0	3524.0	4.95	57.0	39.0
17	Music	181.0	498.0	5.0	2.0	0.0
18	Music	460.0	2514.0	4.55	11.0	5.0
19	Entertainment	196.0	1606.0	4.94	32.0	20.0
20	Music	136.0	11838.0	4.85	27.0	32.0
21	Music	31.0	6586.0	4.73	15.0	8.0
22	Entertainment	397.0	1893.0	4.95	22.0	6.0
23	Entertainment	50.0	6966.0	4.0	6.0	7.0
24	Entertainment	261.0	726.0	5.0	1.0	13.0

2. RELATED WORKS

This section represents some related previous works which are implemented to find abnormal web videos/ abnormal web video events using metadata objects. The related works also discussed in our previous work in which a novel attempts were made to detect abnormal web video detection using density based LOF method [1].

The authors Chueh-Wei Chang, et al. [2], proposed a framework for spatial relationship construction, abnormal event detection and video content searching with respect to visual surveillance applications. The proposed system [2] can automatically detect the abnormal events from monitoring areas, and select the representative key frame(s) from the video clips as an index, then store the color features of the suspect objects into the surveillance database.

In the work of [3], the authors Fan Jiang, Ying Wu, and Aggelos K. Katsaggelos have proposed a multi-sample-based similarity measure, where HMM training and distance measuring were based on multiple samples. The proposed experimental results on real surveillance video showed an enhancement of the presented method over a baseline method that uses single sample- based similarity measure and spectral clustering approach.

The authors [4] Tushar Sandhan et al. have proposed the unsupervised learning algorithm - Proximity (Prx) clustering for abnormality detection in the video sequence. The proposed Prx clustering method tried to select only the dominant class sample points from the dataset. For each data sample, the algorithm assigned the degree of belongingness to the dominant cluster. Experimental results for clustering performance evaluation on artificial dataset show that the Prx clustering outperforms the other clustering methods, for clustering the single dominant class from the dataset.

In the work of [5], the authors Thi-Lan Le and Thanh-Hai Tran proposed a technique which, we can apply only HOG-SVM detector on extended regions detected by background subtraction. This method takes advantages of the background subtraction method (fast computation) and the HOG-SVM detector (reliable detection). Also the paper [5] discussed a hybrid method for abnormal event detection which allows removing several false detection cases.

The authors Yang Cong et al [6] proposed the Sparse Reconstruction Cost (SRC) over the normal dictionary to measure the normalness of the testing sample. Then the proposed technique of [6] used the column wise coordinate descent to solve the matrix decomposition represented formulation, which empirically leads to a similar solution to the group sparsity formulation.

Based on inherent redundancy of video structures, Cewu Lu et al [7] proposed an efficient sparse combination learning framework. It was accomplished decent performance in the uncovering phase without compromising result value. The short running time was guaranteed because the new method effectively turns the original complicated problem to one in which only a few costless small-scale least square optimization steps are involved.

The authors Yang Cong et al [8] have made experimental attempt to identify abnormal events via a sparse reconstruction over the normal bases. The method of [8] provides a unified solution to detect both local abnormal events (LAE) and global abnormal events (GAE). The experiment of [8] further extended to maintain online abnormal event recognition by updating the dictionary incrementally. Also researches on three benchmark datasets and the comparison to the state-of-the-art methods authenticated the compensation of proposed algorithm.

The experimental results of Bin Zhao et al [9] revealed a fully unsupervised dynamic sparse coding method for discovering abnormal events in videos based on online sparse re-constructability of query signals from an atomically learned event dictionary, which generates sparse coding bases. Using an intuition that normal events in a video are more likely to be re-constructible from an event dictionary, whereas abnormal events are not.

The authors Du Tran et al [10] depicted a method to discover abnormal motion in videos. The interior of the approach was to detect portion of video that corresponds to sudden changes of motion variations of a set of defined points of curiosity. The proposed optical flow technique tracked those points of curiosity. There were plenty variations in the optical flow patterns in a mob scene when there are cases those showing abnormalities.

The authors Du Tran et al [11] proposed to discover spatiotemporal paths for video event detection. This new formulation was accurately found and locate video events in cluttered and crowded scenes, and was vigorous to camera motions. The proposed method [11] was compatible with different types of video features or object detectors and robust to false and missed local recognitions.

3. PROPOSED METHOD

The guidelines to format figures and tables are given below. Each table and figure must be cited in the body text. All figures need to be numbered with Arabic numerals as shown in Figure 1. Figures must be center aligned and placed nearer to the first reference in the text.

In this section, we present novel methodology of the proposed abnormal web video detection approach. The web video metadata objects are extracted from standard web video database website [12], preprocessed and stored in a database [14]. Then the refined data will be given to proposed outlier detection models as inputs and resultant abnormal web videos will be extracted and analyzed for knowledge discovery. The system model of the proposed technique is represented in Fig. 1, and it consists of the following components:

A) Web Video Metadata Objects Collection Process
B) Data Refinement Process

C) Abnormal Web Video Detection Process
D) Result Analysis and KDD Process

3.1 Web Video Metadata Objects Collection Process

The different kind of web video metadata objects are extracted using InfoExtractor tool [15] and web video metadata objects are then preprocessed stored in a disk [14] with CSV or ARFF file format for experimental purpose. The summary of the dataset is represented in TABLE II.

TABLE II: SUMMARY OF THE DATASET

Summary	Length	Views	Avg Rate	Ratings	Comments
Min.	0.0	1	0.0	0.0	0.0
1st Qu.	83.0	579	3.67	2.0	1
Median	194.0	2220	4.69	6.0	4
Mean	223.5	11342	3.87	20.93	18.23
3rd Qu.	296.0	8176	5.0	17.0	13
Max.	5412.0	3281256	5.0	4629	5772

3.2 Data Refinement Process

The raw web video metadata objects are preprocessed to get stable result in the experiment. Missing values are replaced by median value of each attribute. The noise and redundancy in the database are removed for the better accuracy in the results. A typical structure of refined web video metadata object dataset is presented in TABLE I. In the TABLE I, the attribute 'Category' is nominal and contains 16 different classes (ex- 'Comedy', 'Music', 'UNA', 'Sports' etc) of web videos [12]. The remaining attributes are numeric and represents meta-objects of each web videos.

3.3 Abnormal Web Video Detection Process

The proposed work uses IQR method to identify abnormal videos in the web video metadata object dataset. The procedure to detect abnormal videos using metadata objects based on IQR method is discussed as follows:

The entry at (value at) Q1 can be calculated by: ¼(total number of entries +1)

Upper Quartile (Q3):

The meta-object values such that 75% of all metadata object entries are less than this value.

The entry at Q3 is calculated by:

¾ (total number of entries +1) Median (Q2)

It is defined as middle point of web video meta-object data value that divides the middle two quartiles. It is the value such that 50% of all entries are less than this value.

The IQR is a measure of distribution. It is the difference between the lower quartile and upper quartile. i.e.

IQR=Q3-Q1.

The Inter-Quartile Range is frequently used to find outliers in datasets. Outliers are observations that fall below

Q1 - 1.5(IQR) or above

Q3 + 1.5(IQR)

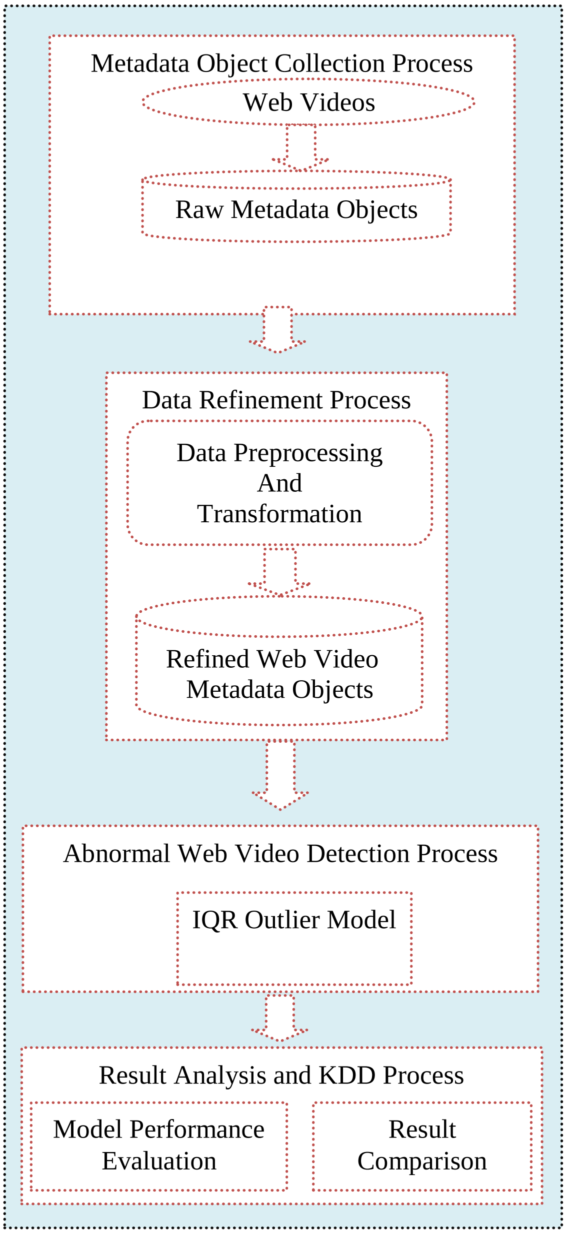

Figure 1 System model of the proposed methodology

3.4 Result Analysis and KDD Process

In Data Mining strategy, the performance evaluation and result analysis are significant steps to discover the knowledge. In this component of the proposed model, we are discovering abnormal web videos, using IQR outlier model. At this stage, the resultant outliers will be analyzed in depth to find abnormal web videos using their meta-objects.

4. RESULTS AND DISCUSSIONS

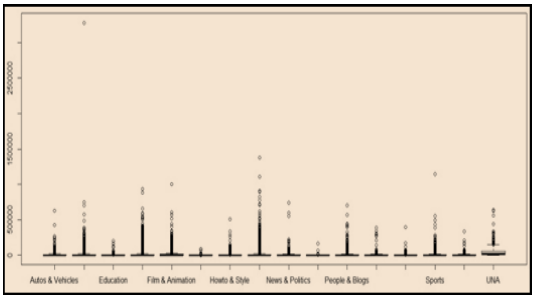

Figure. 2 (a) Box plot representation of 'Views'

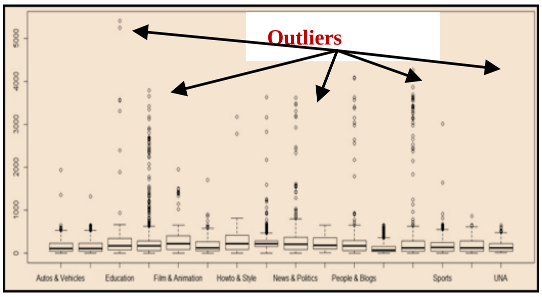

Figure 2 (b) Box plot representation of 'Length'

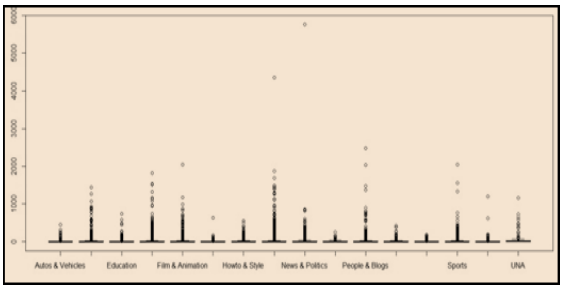

Figure 2 (c) Box plot representation of 'Comments'

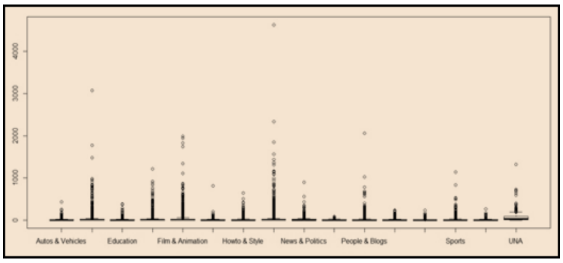

Figure 2 (d) Box plot representation of 'Ratings'

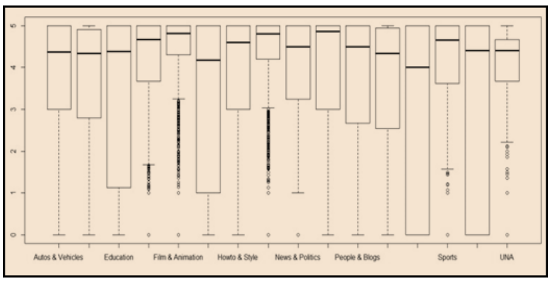

Figure 2 (e) Box plot representation of 'Rate'

The meta-objects of different categories of 47660 web videos of same age (1400 days) are extracted, preprocessed and stored in database [12] [13] for abnormal video detection.

It is observed from the box plot graphical representation, the web video dataset contains several outliers in each of the numeric metadata attribute with respect to different categories of web videos. Sample outliers are addressed in Figure 2(b). In view of this an attempt is made to find the outlier density factor and is represented in Figure 3. The Figure 3 reveals that, the dataset contains outliers (abnormal videos) and the density of the outlier factor is positively skewed with bandwidth 0.016.

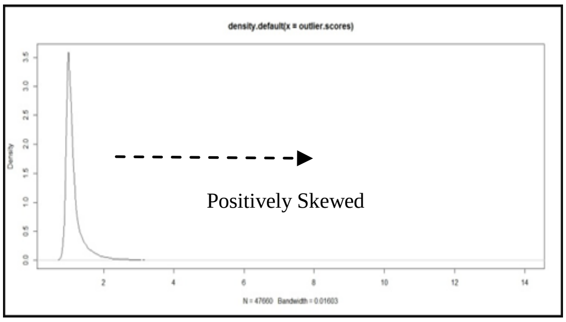

Figure 3 *Outlier Density Factor*

The TABLE III represents results obtained by the IQR method using WEKA. Out of 67697 web videos 3115 were labeled as outliers and remaining web videos labeled as non-outliers. It is observed from the experimental result that, the web video category 'Films and Animation' contains more abnormal web videos as compared to remaining categories. The categories 'Auto and Vehicle', 'Comedy', 'Entertainment', 'People and Blogs', 'Music', 'Sports', and 'News and Politics' are contains more that 5% abnormal videos respectively. Also, the categories 'Non Profit and Activism', 'Gaming', and 'Science and Technology' contains less number of abnormal web videos.

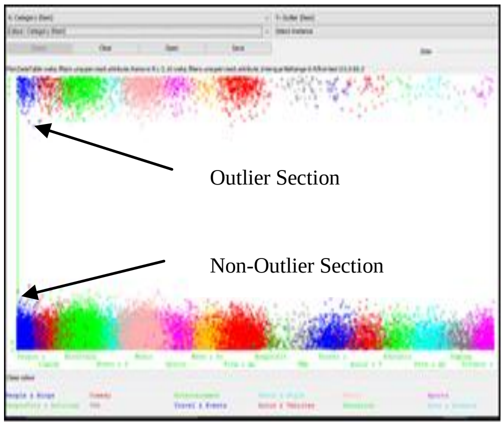

Figure 4 Graphical representation of Outliers/Non-Outliers

TABLE III CATEGORY WISE ABNORMALITY RESULT

Category	Total	Normal	Abno-rmal	Abno-rmality percentage
Auto and Vehicle	686	645	41	5.98
Comedy	2885	2687	198	6.86
Education	532	514	18	3.38
Entertain ment	11474	10706	768	6.69
People and Blogs	3637	3428	209	5.75
How to and Style	2017	1945	72	3.57
Music	13974	12999	975	6.98
Sports	2821	2665	156	5.53
News and politics	1559	1475	84	5.39
Films and Animation	4631	4188	443	9.57
Non Profit and Activism	130	128	2	1.54
UNA	238	227	11	4.06
Travel and Events	878	849	29	3.3
Pets and Animals	878	846	32	3.64
Gaming	429	422	7	1.63
Science and Technolog y	891	872	19	2.13

In Figure.4, the X-axis represents 16 different categories of web videos; each color represents unique web video category and Y-axis represents Outliers and non-outliers sections. The 'Entertainment', 'Comedy', 'Music' categories contains more number of abnormal web videos as compared to remaining categories. The Figure 5 represents percentage of abnormality in each web video categories.

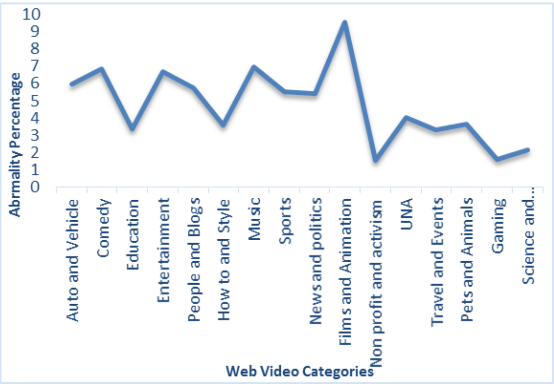

Figure 5 Category wise abnormality percentage

5. CONCLUSION AND FUTURE WORK

In this work, novel attempts are made to detect abnormal videos from large web video meta-object database. The Inter Quartaile Range (IQR) outlier detection technique was employed with large scale data, so that abnormal web videos based on their meta-objects are found effectively. The proposed IQR method identified and extracted top 3115 abnormal web videos and labeled the output dataset with 'Outliers' and 'Non-Outlier'. The future work is to predict abnormal web video based on web video meta-objects.

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International Journal of Advances in Computer and Electronics Engineering
Volume: 01 Issue: 02, June 2016, pp. 31 – 36

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