Florida International University - University of Miami TRECVID 2017

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Abstract

This paper demonstrates the framework and results from the team "Florida International University - University of Miami (FIU-UM)" in the TRECVID 2017 [1] Ad-hoc Video Search (AVS) task [2]. The following four runs were submitted:

- M_D_FIU_UM.17_1*: CNN features + Linear SVM*
- M_D_FIU_UM.17_2*: CNN features + Linear SVM + Scores from other groups*
- M_D_FIU_UM.17_3*: CNN features + Linear SVM + Rectified Linear Score Normalization*
- M_D_FIU_UM.17_4*: CNN features + Linear SVM + Scores from other groups + Rectified Linear Score Normalization*

In the first step, the features are extracted by the convolutional neural network (CNN) structure of GoogLeNet [3] for all runs. Then, the scores of each concept for the key frames are generated using the linear support vector machine (SVM) classifiers. For Run 2 *and Run* 4*, the scores generated by the ITI-CERTH team last year are integrated for score fusion and enhancement. Meanwhile, for Run* 3 *and Run* 4*, a new rectified linear score normalization algorithm is used. As a result, from the submission results, Run* 2 *outperforms the other three runs. The submission details are listed as follows.*

- Class*: M (Manually-assisted runs)*

- Training type*: D (IACC & non-IACC non-TRECVID data)*
- Team ID*: FIU-UM (Florida International University - University of Miami)*
- Year*: 2017*

1 Introduction

In year 2015 and the prior years, the TRECVID project [4] includes a semantic indexing (SIN) task which aims to recognize the semantic concept contained within a video shot. It has been well-acknowledged that there are several challenges in the SIN task, such as data imbalance, scalability, and semantic gap [5, 6, 7, 8, 9, 10, 11, 12]. In year 2016, the task was changed to the Ad-hoc video search (AVS) task which is to model the end user search use-cases. Comparing to the SIN task, the AVS task looks for not only the video segments that contain persons, objects, activities, locations, etc., but also the video segments of their combinations. The AVS task remains the same for this year.

The automatic annotation of semantic concepts in video shots can be essential for retrieval, categorization, and other video exploitations [13, 14, 15, 16, 17, 18, 19, 20]. The semantic concept retrieval research directions include (1) developing robust learning approaches that adjust to the increasing size and the diversity of the videos; (2) fusing the information from other sources such as audio and text; and (3) detecting the low-level and mid-level features that have a high discriminating capability [21, 22, 23, 24, 25, 26, 27, 28].

The size of the high-level semantic concepts provided by IACC remains the same as the AVS task of the previous year, which has 346 concepts in total. For each of the 346 semantic concepts, a list of ground truth labels is provided for training. Given the same test collection (IACC.3) and master shot reference, 30 Ad-hoc queries were released by NIST for testing. Each query can be a combination of some of the 346 concepts and/or some other concepts not included in the training set. Each participated group is allowed to submit a maximum of $1,000$ possible shots from the test collection for each query, which are ranked according to their likelihood of containing the target query. The submission result is rated by using the mean inferred average precision (mean xinfAP) [29] based on the assessment of a 2-tiered random sampling (1-200@100% and 201-1000@11.1%).

This paper is organized as follows. Section 2 describes our proposed framework and the specific approaches utilized for each run. Section 3 shows the submission results in details. Section 4 summarizes the whole paper and proposes some future directions to pursue and plan for next year.

2 The Proposed Framework

Our framework of the TRECVID 2017 AVS task is shown in Figure 1. In this year, key frames are already extracted from the videos in the IACC.3 collection and are provided to the participants. Thus, the key frame extraction step is skipped; while the key frames extracted in the previous years are used for training.

2.1 CNN Feature Extraction

A pre-trained deep learning model called AlexNet [30] was utilized in our framework last year. AlexNet is a CNN structure trained on the ImageNet database for object feature extraction and contains five convolutional layers and three fully-connected layers. In this year, the GoogLeNet [3] which is a 22 layers deep network as shown in Figure 1 is used. The CNN features are extracted for all the training and testing key frames from the pool5 layer, i.e., the last layer before the softmax layer with $1,000$ dimensions. The GoogLeNet structure is well trained and proven to achieve great performance.

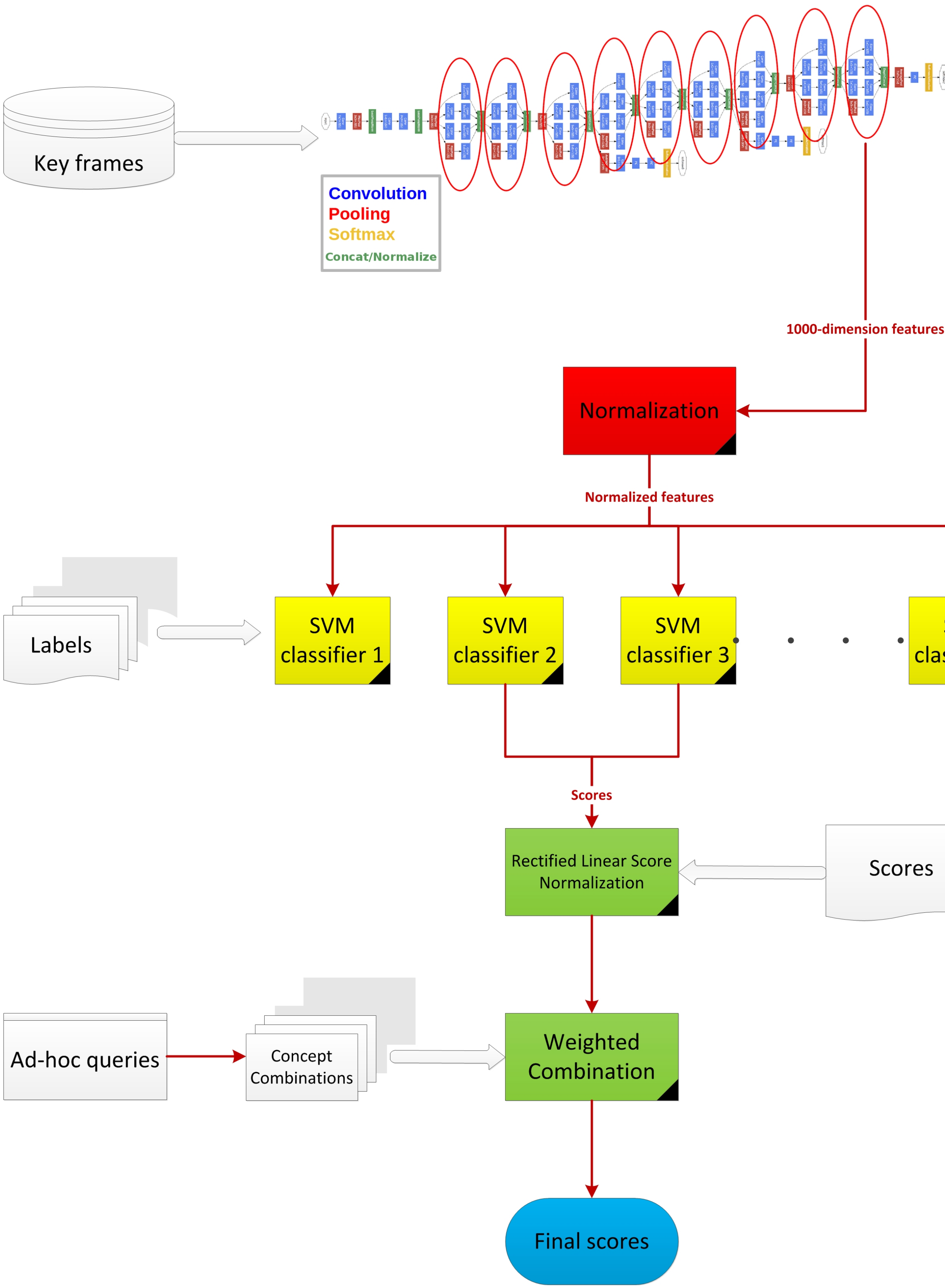


Figure 1: The designed framework for the TRECVID 2017 AVS task

2.2 Classification

After feature extraction, the feature vectors are normalized for each key frame. Support Vector Machine (SVM), one of the state-of-the-art algorithms in the data mining area [31, 32, 33, 34, 35, 36, 37, 38] including multimedia classification, is used for classification and concept score generation. The general idea of SVM is to build a separating hyperplane to classify the data instances so that the geometric margin is maximized. For efficiency, linear kernels are adopted in our proposed framework.

2.3 Rectified Linear Score Normalization

A new rectified linear score normalization algorithm is proposed this year. Different from traditional score normalization algorithms, a rectified function is applied as shown in Algorithm 1. The idea here is to eliminate the effect of "bad" scores of a concept in an Ad-hoc query before the next step. If the score of a concept in a frame is greater than a certain threshold, the concept is considered definitely to appear in that frame and thus its score is set to 1. Meanwhile, if the score of a concept in a frame is lower than a certain threshold, it is very unlikely to appear in that frame. Thus, the score would be set to 0 in this case to eliminate its effect in the fusion stage as the scores of those selected concepts will be multiplied in the next stage.

The thresholds $threshold_{high}$ and $threshold_{low}$ are generated based on our empirical studies. Generally speaking, they are calculated based on the positive to negative ratio (PN_{ratio}) in the train data set. If the scores are good enough, strict thresholds will be used, i.e., setting more high scores to 1 and setting more low scores to 0. In this study, $threshold_{high}$ is set to the score ranked half PN_{ratio} on average, while $threshold_{low}$ is set to the score ranked 5 times PN_{ratio} on average. The sample score distribution before rectified linear normalization is depicted in Figure 2(a) and the distribution after applying rectified linear normalization is presented in Figure 2(b).

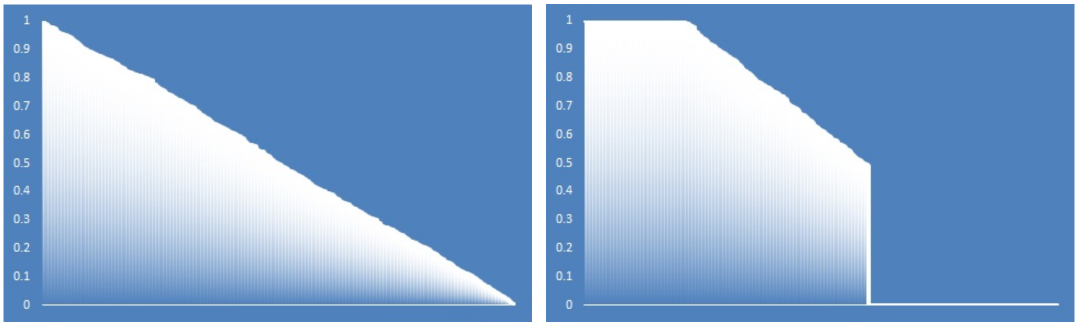
Algorithm 1 The proposed rectified linear score normalization algorithm.

for all scores **do**
  if $score \geq threshold_{high}$ **then**
    $score_{normed} = 1$;
  else if $score \leq threshold_{low}$ **then**
    $score_{normed} = 0$;
  else
    $score_{normed} = \frac{score}{threshold_{high}}$.
  end if
end for

2.4 Query Formulation and Score Combination

All the four runs are manually-assisted runs. For an initial ad-hoc query, a group member formulates it into a combination of concepts based on its topic and query interface without the knowledge of the collection or the search results. For queries containing the concepts not included in the 346 concepts from the training set (e.g., the concept "couch" in "Find shots of a man sitting down on a couch in a room"), a similar concept like "sofa" is selected.

Meanwhile, in order to increase the number of object categories and have more options in score fusion, the pre-trained ImageNet models are also applied to generate the scores for ImageNet concepts. The GoogLeNet model for ImageNet1000, provided by the Caffe development team, is applied to the frames in the test data set. Take the same query as an example. The scores of the concept "studio couch, day bed" in ImageNet are utilized for score combination in the next step. The scores are generated from the pool5 layers as well.



(a) (b)

Figure 2: Sample score distribution (a) before & (b) after rectified linear normalization.

In order to compare our scores with others, we integrate the scores from the ITI-CERTH team which performed very well last year. Since the performance of the weighted geometric mean of the scores is often better than the weighted arithmetic mean, which has been reported by several groups, we fuse the scores of the selected concepts by calculating their weighted geometric mean. The same weights are used for score combination based on our empirical studies in all runs as follows, where N is the total number of concepts integrated.

$$score_{query} = \prod_{i}^{N} (score_{concept_i})^{weight_i} \tag{1}$$

3 Experimental Results

3.1 Data

Given the information (including the IACC.3 test collection, master shot reference, and 30 Ad-hoc queries) released by NIST and the concept definitions, a list of at most 1,000 shot IDs from the test collection for each ad-hoc query was returned and ranked according to their likelihood of containing the target query. TRECVID 2017 test data set (IACC.3) contains $4,593$ Internet Archive videos with the durations between 6.5 and 9.5 minutes (144GB, 600 hours in total). The training data set combines the development and testing data sets from the 2010 to 2015 issues of the SIN task, namely the IACC.1.tv10.training, IACC.1.A-C, and IACC.2.A-C data sets. Each contains about 200 hours of videos drawn from the IACC.1 and IACC.2 collections using videos with durations ranging from 10 seconds to (3.5 to 6.4) minutes, respectively. The TRECVID data set has been widely used in research [39, 40, 41, 42].

The overall framework of the TRECVID 2017 AVS task contains three stages:

1. Model training: using TRECVID 2010-2012 training videos as the training data.
2. Model evaluation: using TRECVID 2013-2015 training videos as the testing data to evaluate the framework and tune the parameters of the models.
3. Model testing: using TRECVID 2010-2015 training videos as the TRECVID 2017 training data, and TRECVID 2017 testing videos as the testing data to generate the ranking results for the submission.

3.2 Evaluation

All (30) queries are evaluated by assessors at NIST after pooling and sampling. Measures (indexing) are shown as follows [43].

1. Mean extended inferred average precision (mean xinfAP) [29] which allows the sampling density to vary so that it can be 100% in the top strata. This is the most important one for average precision.

2. As in the past years, other detailed measures based on recall and precision are generated and given by the sample_eval software provided by the TRECVID team.

3.3 Performance

All of the measures below were based on the assessment of a 2-tiered random sampling (1-200@100% and 201-1000@11.1%) of the full submission pools and the sample_eval software was used to infer the measures. Figures 3, 4, 5, and 6 present the performance of our ad-hoc query video search results. The x-axis are the concept numbers; while the y-axis present the inferred average precision values. More clearly, Table 1 shows the inferred mean average precision (MAP) values of the first 5, 10, 15, 20, 30, 100, 200, 500 and 1000 shots. The numbers of the returned inferred true shots and the mean xinfAP values are shown in Table 2.

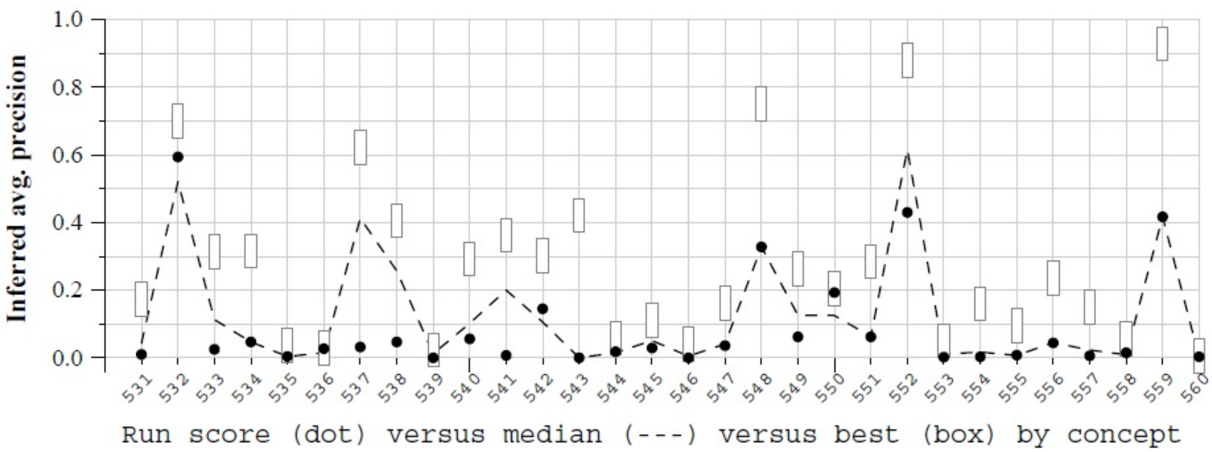


Figure 3: Run scores (dot) versus median (—) versus best (box) for *M_D_FIU_UM.17_1*

Framework	5	10	15	20	30	100	200	500	1000
M_D_FIU_UM.17_1	0.340	0.333	0.329	0.320	0.310	0.230	0.196	0.144	0.120
M_D_FIU_UM.17_2	0.447	0.420	0.404	0.398	0.383	0.334	0.287	0.202	0.158
M_D_FIU_UM.17_3	0.353	0.353	0.340	0.322	0.311	0.252	0.235	0.160	0.138
M_D_FIU_UM.17_4	0.420	0.387	0.384	0.383	0.384	0.309	0.270	0.191	0.154

Table 1: The MAP values at first *n* shots for all 4 runs

The evaluation results demonstrate that the performance of our framework is above the average of all the groups, while we perform the best for queries 537, 538, 539, and 544. By applying the rectified linear score normalization algorithm before the score fusion, the better performance in Run 3 than Run 1 is achieved. For most queries, the proposed normalization algorithm improves the xinfAP values, especially for queries 537, 538, and 552. While the result of Run 4 is similar to that of Run 2, the rectified linear score normalization step helps improve the xinfAP value for queries 538 and 552 as well, and makes our team performs the best for query 538.

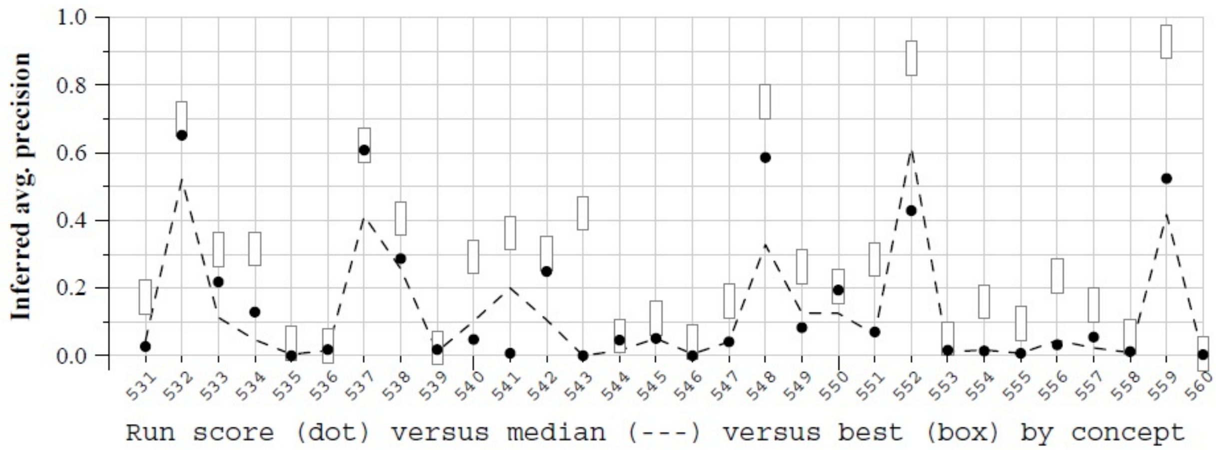


Figure 4: Run scores (dot) versus median (—) versus best (box) for *M_D_FIU_UM.17_2*

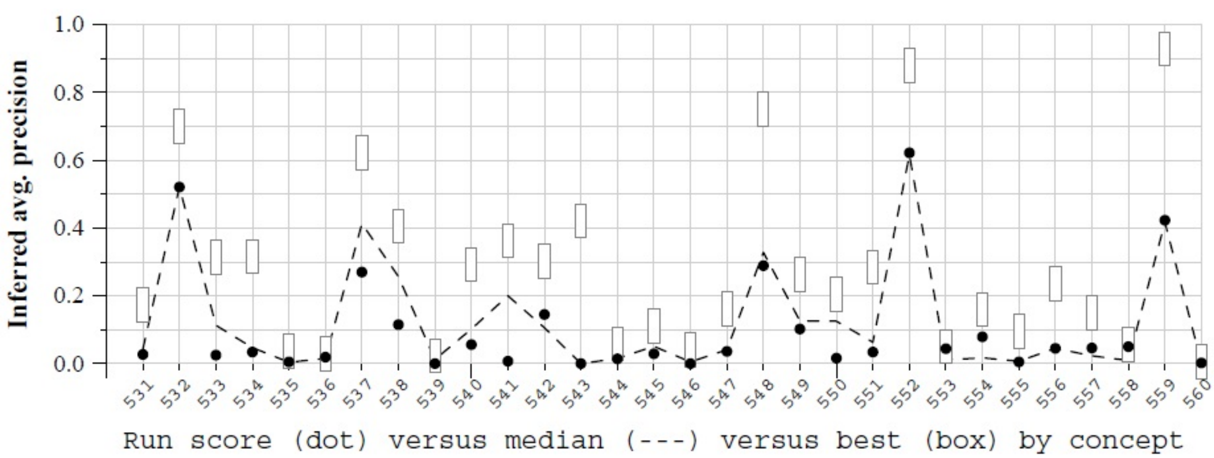


Figure 5: Run scores (dot) versus median (—) versus best (box) for *M_D_FIU_UM.17_3*

Framework	# of inferred true shots returned	Mean xinfAP values
M_D_FIU_UM.17_1	3608	0.088
M_D_FIU_UM.17_2	4731	0.147
M_D_FIU_UM.17_3	4125	0.102
M_D_FIU_UM.17_4	4623	0.145

Table 2: The numbers of inferred true shots returned and the mean xinfAP values

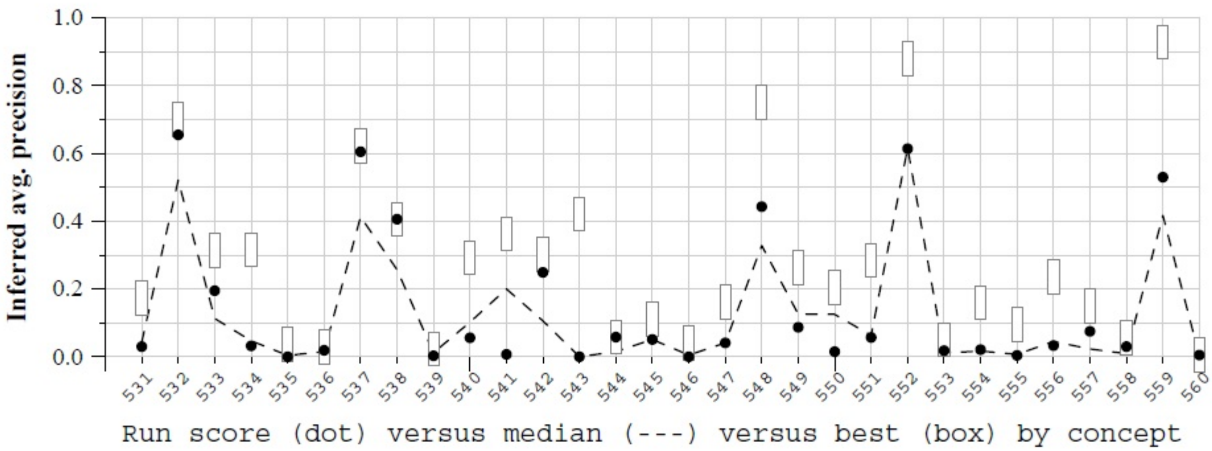


Figure 6: Run scores (dot) versus median (—) versus best (box) for *M_D_FIU_UM.17_4*

4 Conclusion and Future Work

In this notebook paper, the framework and results of team FIU-UM in the TRECVID 2017 AVS task are summarized. It can be seen that a lot of improvements still need to be done based on the results. The following directions will be investigated.

- In our framework, only global features are utilized. The object-level features can also be explored by R-CNN (Regional CNN).
- Non-linear SVM classifiers need to be adopted to address the data imbalance issue.
- More advanced CNN structures can be integrated and scores from them can be fused.
- Temporal correlations can be considered to reach a better performance.
- More training data should be collected by a general purpose search engine like Google using the query definition to further improve the retrieval accuracy.

In this year, there are still several very "hard" queries which challenged all groups. For instance, the query "Find shots of children playing in a playground" was not easy to interpret since the concept "playground" varies a lot. Furthermore, it is considered hard to find images related to the query "Find shots of a person holding opening closing or handing over a box" by Google. Therefore, it will be helpful to exchange ideas and thoughts with other groups so that novel approaches can be developed for further performance improvements.

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