Abstract

Current state-of-the-art human activity recognition is focused on the classification of temporally trimmed videos in which only one action occurs per frame. We propose a simple, yet effective, method for the temporal detection of activities in temporally untrimmed videos with the help of untrimmed classification. Firstly, our model predicts the top k labels for each untrimmed video by analysing global video-level features. Secondly, frame-level binary classification is combined with dynamic programming to generate the temporally trimmed activity proposals. Finally, each proposal is assigned a label based on the global label, and scored with the score of the temporal activity proposal and the global score. Ultimately, we show that untrimmed video classification models can be used as stepping stone for temporal detection. Our method wins runner-up prize in ActivityNet Detection challenge 2016.

1. Introduction

Emerging real-world applications require an all-round approach to the machine understanding of human behaviour, which goes beyond the recognition of simple, isolated activities from video.

As a step towards this ambitious goal, in this work we address the problem of detecting the temporal bounds of activities in temporally untrimmed videos.

2. Methodology

Whereas (i) video-level features are used for untrimmed video classification task, (ii) frame-level features are used for activity proposal generation and scoring. Finally, (iii) a video’s classification score is augmented with the scores of the activity proposals for proposal classification.

2.1. Features

We make use of the features provided on ActivityNet’s [2] web page1.

2.1.1 Video-level features

ImageNetShuffle features are video-level features generated by [4] using a Google inception net (GoogLeNet [5]). CNN features are extracted from the pool5 layer of GoogLeNet [5] at a two frames per second rate. Frame-level CNN features are mean pooled to construct a representation for the whole video. Mean pooling is followed by L1-normalisation.

We train a one-versus-rest linear SVM for each class, and use the resulting SVM scores $S = \{s_1^i, ..., s_c^i, ... s_C^i\}$, where $C$ is number of classes, as INS features.

Motion Boundary Histogram (MBH) features are generated with the aid of the improved trajectories [7] executable2. We train another battery of one-versus-rest SVMs using a linear kernel on the MBH features, and use the resulting SVM scores $S_m = \{s_1^m, ..., s_c^m, ... s_C^m\}$ as global video features.

2.1.2 Frame level features

C3D Features features are generated at 2 frames per second using a C3D network [6] with temporal resolution of 16 frames. Once again we train a frame level one-versus-rest SVM classifier for each activity class using a linear kernel. The scoring of frame $t$ is defined by the resulting SVM scores: $S_t = \{s_1^t, ..., s_c^t, ... s_C^t\}$. Finally, we perform mean pooling along the frames for each class to get another score vector $S^3$, which is used for video classification.

1http://activity-net.org/challenges/2016/download.html
2http://lear.inrialpes.fr/people/wang/improved_trajectories
2.2. Untrimmed video classification

Untrimmed video classification is achieved by fusing all video level scores using a linear SVM as a meta classifier. Video level scores \( S^v \), \( S^{m} \) and \( S^{3} \) are stacked up to make a single score vector. A linear SVM is trained on the training set of stacked scores, and evaluated on the validation and testing sets. The output scores \( S^v \) outputted by the meta SVM are normalised by dividing them by the sum of the top \( k \) scores. The parameter \( k \) was cross-validated on the validation set and set to 3 – it contributes to improve the mean average precision metric.

We believe that, since SVM scores are not probabilities, normalisation by top \( k \) scores is required to be able to compare them across all videos.

2.3. Activity detection in untrimmed videos

Activity proposals are detected by (i) training a binary random forest (RF) classifier [1] for each class on the frame-level C3D features, and (ii) casting activity proposal generation as an optimisation problem [3], which makes use of these binary decisions.

2.3.1 Binary random forest classification

The binary RF classifies each frame into a negative (i.e. no activity taking place) or a positive bin (i.e. something is happening). The positive score of a frame \( t \) is denoted by \( s^r_t \). Temporal trimming is then achieved by dynamic programming as follows.

2.3.2 Activity proposal generation

Given the frame-level scores \( \{s^r_t, t = 1, \ldots, T\} \) for a video of length \( T \), we want to assign to each frame a binary label \( l_t \in \{1, 0\} \) (where zero represents the ‘background’ or ‘no-activity’ class), which maximises:

\[
E(L) = \sum_{t=1}^{T} s^r_t - \lambda \sum_{t=2}^{T} \psi(t, l_{t-1}),
\]

where \( \lambda \) is a scalar parameter, and the pairwise potential \( \psi(t) \) is defined as:

\[
\psi(t, l_{t-1}) = 0 \text{ if } l_t = l_{t-1}, \psi(t, l_{t-1}) = \alpha \text{ otherwise},
\]

where \( \alpha \) is a parameter which we set by cross validation. This penalises labellings \( L = \{l_1, \ldots, l_T\} \) which are not smooth, thus enforcing a piecewise constant solution. All contiguous sub-sequences form the desired activity proposal (which can be as many as there are instances of activities). Each activity proposal is assigned a global score \( S_a \) equal to the mean of the scores of its constituting frames.

This optimisation problem can be efficiently solved by dynamic programming [3]. It can easily be extended for simultaneous detection and classification [3].

2.3.3 Activity detection

The top (in this case 2) activity proposals in each video are assigned the label of top untrimmed classification class (\( \alpha \)). For example, if \( c = 10 \) is the top class for the video with score \( S^v_{10} \) and \( \alpha \) is the top activity proposal with score \( S_a \) (\( \alpha \)), then a detection of class 10 is flagged with the temporal bounds determined by activity proposal \( \alpha \) and score \( S^v_{10} = S^v_{10} \times S_a \). Similarly, we can generate more detections for each of the top classes by using top activity proposals.

3. Implementation

We used the precomputed features provided by the competition organisers. We used SciKit-learn for linear SVM and random forest Implementation. Our code available at https://github.com/gurkirt/actNet-inAct.

4. Results

We report results for untrimmed classification and activity detection on ActivityNet [2]. We use the same evaluation setting as described in challenge [2].

4.1. Untrimmed classification

| Method          | Validation Set | Testing Set |
|-----------------|----------------|-------------|
|                | TOP-1 (%)      | mAP (%)     | TOP-1 (%)   | mAP (%)     |
| Caba et al. [2] | -              | 42.50%      | -           | 42.20%      |
| Proposed        | 76.89%         | 89.38%      | 77.08%      | 89.38%      | 82.49%      |

Table 1: Untrimmed classification performance on validation and testing set in percentage.

4.2. Activity detection

| TIoU threshold \( \delta \) | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|-----------------------------|-----|-----|-----|-----|-----|
| Validation-Set proposed    | 12.50% | 11.90% | 11.11% | 10.40% | 10.70% |
| Validation-Set Caba et al. [2] | 52.12% | 47.94% | 43.50% | 39.22% | 34.47% |
| Testing-Set proposed       | -   | -   | -   | -   | -   |

Table 2: Activity detection performance on validation and testing set. Quantity \( \delta \) is the Temporal Intersection over Union (TIoU) threshold.
Figure 1: Plot shows ground truth in blue, binary classifier score in red and piece-wise constant proposal produce by DP optimisation. Binary classifier scores are high where activity is happening, which produces well aligned segment proposal with ground truth.

Figure 2: Plot shows ground truth in blue, binary classifier score in red and piece-wise constant proposal produce by DP optimisation. We can see two proposal are mostly aligned with ground truth.

Figure 3: Plot shows ground truth in blue, binary classifier score in red and piece-wise constant proposal produce by DP optimisation. Our method completely fails to trim two instance but only produce one segment for whole video as binary classifier score are high throughout the video duration.

5. Conclusion and Future Work

We show that activity detection can be achieved via untrimmed video classification. Our dynamic programming-based approach is efficient, and has shown a clear potential for generating good quality activity proposal.

The approach can be easily extended for simultaneous detection and classification without requiring classification scores at video level, which open ups the opportunity for online activity classification, detection and prediction.

References

[1] L. Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[2] F. Caba Heilbron, V. Escorcia, B. Ghanem, and J. Carlos Niebles. Activitynet: A large-scale video benchmark for human activity understanding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 961–970, 2015.

[3] G. Evangelidis, G. Singh, and R. Horaud. Continuous gesture recognition from articulated poses. In *ECCV Workshops*,
[4] P. Mettes, D. Koelma, and C. G. M. Snoek. The imagenet shuffle: Reorganized pre-training for video event detection. In *Proceedings of the ACM International Conference on Multimedia Retrieval*, New York, USA, 2016.

[5] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–9, 2015.

[6] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri. Learning spatiotemporal features with 3d convolutional networks. *arXiv preprint arXiv:1412.0767*, 2014.

[7] H. Wang and C. Schmid. Action Recognition with Improved Trajectories. In *Proc. Int. Conf. Computer Vision*, pages 3551–3558, 2013.