Egocentric Action Recognition by Video Attention and Temporal Context

Juan-Manuel Perez-Rua\textsuperscript{1} Antoine Toisoul\textsuperscript{1} Brais Martinez\textsuperscript{1} Victor Escorcia\textsuperscript{1}

Li Zhang\textsuperscript{1} Xiatian Zhu\textsuperscript{1} Tao Xiang\textsuperscript{1,2}

\texttt{[ j.perez-rau, a.toisoul, brais.a, v.castillo, li.zhang1, xiatian.zhu, tao.xiang ]}@samsung.com

Samsung AI Centre, Cambridge
University of Surrey

Abstract

We present the submission of Samsung AI Centre Cambridge to the CVPR2020 EPIC-Kitchens Action Recognition Challenge. In this challenge, action recognition is posed as the problem of simultaneously predicting a single ‘verb’ and ‘noun’ class label given an input trimmed video clip. That is, a ‘verb’ and a ‘noun’ together define a compositional ‘action’ class. The challenging aspects of this real-life action recognition task include small fast moving objects, complex hand-object interactions, and occlusions. At the core of our submission is a recently-proposed spatial-temporal video attention model, called ‘W3’ (‘What-Where-When’) attention [6]. We further introduce a simple yet effective contextual learning mechanism to model ‘action’ class scores directly from long-term temporal behaviour based on the ‘verb’ and ‘noun’ prediction scores. Our solution achieves strong performance on the challenge metrics without using object-specific reasoning nor extra training data. In particular, our best solution with multimodal ensemble achieves the \textit{2}nd best position for ‘verb’, and \textit{3}rd best for ‘noun’ and ‘action’ on the Seen Kitchens test set.

1. Introduction

EPIC-Kitchens is a large scale egocentric video benchmark for daily kitchen-centric activity understanding [1]. In this benchmark, the action classes are defined by combining verb and noun classes.

By combining all the 352 nouns and 125 verbs, the number of all possible action classes will reach as large as 44,000. This dataset presents a long tail distribution as often occurred in natural scenarios. Besides, human-object interaction actions might be very ambiguous. For example, in a single video clip, a person might be washing a dish whilst interacting with a sponge, faucet and/or sink concurrently, and sometimes the in-interaction active object might be completely occluded. These factors all render action recognition on this dataset extremely challenging. Whilst significant progress has been made since the inception of this challenge [1, 7], it is rather clear from the performance of all previous winner solutions that fine-grained action recognition is still far from being solved.

In this attempt, we present a novel egocentric action recognition solution based on video attention learning and temporal contextual learning jointly. By focusing on the action class related regions in highly redundant video data over space and time, the model inference is made more robust against noisy and distracting observations. To this end, we exploit a recently-proposed What-Where-When (W3) video attention model [6]. Temporal context provides additional useful information beyond individual video clips, as there are inherent interdependent relationships of human actions in performing daily life activities. For instance, it is more likely that a person is grabbing a cup if previously he/she was opening a cupboard, than for example, if the person had just opened a washing machine. A Temporal Context Network (CtxtNet) is introduced to enhance model inference by considering temporally adjacent actions happening in a time window.

To make a stronger solution, we adopt multi-modal fusion, as in [4], combining RGB (static appearance), optical flow (motion cue), and audio information together.

2. Methodology

In this section, we present the solution of our submission to the EPIC-Kitchens Action Recognition challenge. We first introduce the W3 attention model [6] in Section 2.1, and then describe our proposed temporal action context model (CtxtNet) in Section 2.2.

2.1. What-Where-When Attention

Figure 1 gives the schematic illustration of the W3 attention module. Significantly, W3 can be plugged into any existing video action recognition network, e.g. TSM [5], for end-to-end learning. Specifically, W3 accepts a single feature map $F$ as input, which can be derived from any CNN...
layer, and generates an attention map $M$ with same dimension to $F$, i.e., $F, M \in \mathbb{R}^{T\times C\times H\times W}$, where $T, C, H, W$ denote the number of video clip frame, number of feature channel, height and width of the frame-level feature map respectively. Attention mask $M$ is then used to produce a refined feature map $F'$ in a way that only action class-discriminative cues are allowed to flow forward, whilst irrelevant ones are suppressed. The attention and refined feature learning process is expressed as:

$$F' = F \otimes M, \quad M = f(F),$$

where $\otimes$ is the Hadamard product, and $f(\cdot)$ is the W3 attention function.

To facilitate effective and efficient attention learning, W3 adopts an attention factorization scheme by splitting the 4D attention tensor $M$ into a channel-temporal attention mask $M^c \in \mathbb{R}^{T\times C}$ and a spatial-temporal attention mask $M^s \in \mathbb{R}^{T\times H\times W}$. This strategy reduces the complexity of the learning problem as the size of the attention masks are reduced from $TCHW$ to $T(C + HW)$. In principle, the feature attending scheme in Eq 1 is thus reformulated into a two-step sequential process:

$$F^c = M^c \otimes F, \quad M^c = f^c(F);$$

$$F^s = M^s \otimes F^c, \quad M^s = f^s(F^c);$$

where $f^c(\cdot)$ and $f^s(\cdot)$ denote the channel-temporal and spatial-temporal attention function respectively.

**Channel-temporal attention** The channel-temporal attention focuses on the ‘what-when’ facets of video attention. Specifically it measures the importance of a particular object-motion pattern evolving temporally across a video sequence in a specific way. For this, we squeeze the spatial dimensions ($H \times W$) of each frame-level 3D feature map to yield a compact channel descriptor $d_{\text{chnl}} \in \mathbb{R}^{T\times C}$ as in [3]. Moreover, we use both max and mean pooling operations as in [9], and denote the two channel descriptors as $d_{\text{avg-c}}$ and $d_{\text{max-c}} \in \mathbb{R}^{C\times 1\times 1}$ (indicated by the purple boxes in the top of Fig. 1).

To extract the inter-channel relationships for a given frame, we then forward $d_{\text{avg-c}}$ and $d_{\text{max-c}}$ into a MLP $\theta_{c-frm}$. The above $f_{\text{Whatrame-level channel-temporal attention}}$ can be expressed as:

$$M^c_{\text{frm}} = \sigma(f_{\theta_{c-frm}}(d_{\text{avg-c}}) \oplus f_{\theta_{c-frm}}(d_{\text{max-c}})) \in \mathbb{R}^{C\times 1\times 1},$$

where $f_{\theta_{c-frm}}(\cdot)$ outputs channel frame attention and $\sigma(\cdot)$ is the sigmoid function.

In EPIC-Kitchens, it is critical to model the temporal dynamics of active objects in interaction with the human subject. To capture this information, a small channel temporal attention network $\theta_{c-vid}$ is introduced, composed of a CNN network with two layers of 1D convolutions, to reason about the temporally evolving characteristics of each channel dimension (Fig. 1 top-right). This results in our channel-temporal attention mask $M^c$, computed as:

$$M^c = \sigma(f_{\theta_{c-vid}}(\{M^c_{\text{frm}}\}_{i=1}^{T})).$$

Concretely, this models the per-channel temporal relationships of successive frames in a local window specified by the kernel size $K_{c-vid}$, and composed by two layers.

**Spatial-temporal attention** In contrast to the channel-temporal attention that attends to dynamic object feature patterns evolving temporally in certain ways, this submodule attempts to localize them over time. Similarly to the previous module, we apply average-pooling and max-pooling along the channel axis to obtain two compact 2D spatial feature maps for each video frame, denoted as $d_{\text{avg-s}}$.
context information by designing a Temporal Context Network (CtxtNet). An overview of CtxtNet is shown in Fig. 2.

In particular, CtxtNet is made of two parallel 3-layer MLP streams, one for noun and one for verb. Each stream generates a low rank matrix (of size $125 \times R$ for verbs and $R \times 352$ for noun) whose multiplication yields the probability of each action, i.e., the action matrix of size $125 \times 352$. The hyperparameter $R$ controls the rank of the factorisation so as allowing to choose the trade-off between complexity of the reconstruction (the number of parameters) and the model capacity. To encode the spatio-temporal context, the two streams act on a temporal context of $T$ frames. In practice, we found that rank $R = 16$ and a time window $T = 5$ leads to the best results on a held-out validation set.

### Table 1. TSM with different attention modules

| Model | Verb Top-5 | Noun Top-5 | Action Top-5 |
|-------|------------|------------|--------------|
| TSM   | 57.9       | 43.5       | 40.8         |
| TSM+NL [8] | 60.1       | 49.0       | 42.8         |
| TSM+W2 | 63.4       | 50.0       | 43.3         |
| TSM-W2 | 54.6       | 32.7       | 30.8         |

### Table 2. TSM using different ResNet backbones on the validation set

| Model | Verb Top-5 | Noun Top-5 | Action Top-5 |
|-------|------------|------------|--------------|
| TSM ResNet-50 | 58.88      | 42.74      | 40.40        |
| TSM ResNet-101 | 62.14      | 45.16      | 34.28        |
| TSM ResNet-152 | 63.39      | 45.70      | 34.78        |

### Table 3. Effect of CtxtNet

| Model   | Verb Top-5 | Noun Top-5 | Action Top-5 |
|---------|------------|------------|--------------|
| Action Prior [7] | 69.18      | 57.76      | 49.58        |
| CtxtNet (Ours) | 69.18      | 57.76      | 49.58        |

### 3. Experiments

#### Setup

In the video classification track of EPIC-Kitchens, there are three classification tasks involved: noun classification, verb classification, and their combination. Two different held-out testing sets are considered:

- Seen Kitchens Testing Set (S1), and Unseen Kitchens Testing Set (S2).

#### Validation set

To allow for apples-to-apples comparison to other methods, we used the same validation set as [4].
Table 4. Final scores on the testing server. Setting: 8 frames per video. Modalities: RGB-W3, RGB, Flow, Audio. Backbone: ResNet-50 [2]. S1: Seen Kitchens; S2: Unseen Kitchens. Results obtained in the EPIC-Kitchens test server with 1 crop and 2 clips per-video. (X): Position in the 2020 ranking.

|        | Verb |        | Noun |        | Action |
|--------|------|--------|------|--------|--------|
|        | Top-1 | Top-5  | Top-1 | Top-5  | Top-1  | Top-5  |
| S1     | 69.43 (2) | 57.60 (4) | 91.23 (2) | 81.84 (4) | 49.71 (3) | 34.69 (4) |
| S2     | 73.18 (3) | 61.25 (3) | 40.00 (3) | 24.62 (6) | 60.53 (3) | 41.38 (6) |

Experimental details  We used the recent Temporal Shift Module (TSM) [5] as the baseline video recognition model in all the experiments. We trained our models for 50 epochs with SGD, at a learning rate of 0.02. The models were initialized by ImageNet pre-training. Unless otherwise mentioned, our default backbone network is a ResNet-152. W3 models were trained with mature feature regularisation (MFR) as described in [6]. The CtxtNet was trained with Adam in a second stage. Firstly, we employed our multi-modal ensemble to compute the verb and noun logits of each video segment. The CtxtNet then maps those verb and noun logits to an action probability matrix. For both branches of CtxtNet, the MLP is a stack of three linear layers. Each of them was formed by a linear projection, batch norm, PReLU and Dropout. For all the experiments, unless otherwise mentioned, we sampled two clips and a single central crop per video. Finally, for our last submission, we assembled two models per modality, except for audio, for which we only used a single model.

3.1. Attention Model Comparison

We compared our W3 attention with existing competitive alternatives. For fair comparison experiments, all attention methods use the same ResNet-50 based TSM [5] as the underlying video model.

Table 1 shows that our W3 attention module is the strongest amongst several competitors.

3.2. Backbone Network Evaluation

We tested our method with different backbone networks. Table 2 shows that ResNet-152 [2] is slightly better than ResNet-101, and almost five points better than ResNet-50. Importantly, it is shown that W3 further brings extra model performance improvement on top of the strongest backbone on noun and action classification. However, we observed that the performance of verb is not benefited from W3. This can be exploited by using both type of models for the RGB modality.

3.3. Temporal Context Network

Table 3 shows that our CtxtNet module produces better scores than the action prior method introduced by [7]. CtxtNet brings a large gain on the seen kitchen setting at a small cost on the unseen kitchen setting. Note, noun and verb accuracy scores are unaffected since this does not change their predictions.

3.4. Multi-Modalities

Table 4 reports the final results of our method using three modalities: RGB, optical flow, and audio. This was made by a logit-level ensemble of regular RGB model (ResNet-152), W3-attended RGB model (ResNet-152), optical flow model (ResNet-152), and audio model (ResNet-34). For audio, we used spectrograms with the same format of [4].

4. Conclusion

In this report, we summarised the model designs and implementation details of our solution for video action classification. With the help of the proposed W3 video attention and temporal context learning, we achieved top-3 video action classification performance on the leaderboard.

References

[1] Dima Damen, Hazel Doughty, Giovanni Maria Farinella, Sanja Fidler, Antonino Furnari, Evangelos Kazakos, Davide Moltisanti, Jonathan Munro, Toby Perrett, Will Price, et al. Scaling egocentric vision: The epic-kitchens dataset. In ECCV, 2018.
[2] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016.
[3] Jie Hu, Li Shen, and Gang Sun. Squeeze-and-excitation networks. In ICCV, 2018.
[4] Evangelos Kazakos, Arsha Nagrani, Andrew Zisserman, and Dima Damen. Epic-fusion: Audio-visual temporal binding for egocentric action recognition. In CVPR, 2019.
[5] Ji Lin, Chuang Gan, and Song Han. TSM: Temporal shift module for efficient video understanding. In ICCV, 2019.
[6] Juan-Manuel Perez-Rua, Brais Martinez, Xiatian Zhu, Antoine Toisoul, Victor Escorcia, and Tao Xiang. Knowing what, where and when to look: Efficient video action modeling with attention. arXiv preprint arXiv:2004.01278, 2020.
[7] Will Price and Dima Damen. An evaluation of action recognition models on epic-kitchens. arXiv preprint arXiv:1908.00867, 2019.
[8] Xiaolong Wang, Ross Girshick, Abhinav Gupta, and Kaiming He. Non-local neural networks. In CVPR, 2018.
[9] Sanghyun Woo, Jongchan Park, Joon-Young Lee, and In So Kweon. Cham: Convolutional block attention module. In ECCV, 2018.