Supplementary Material for
Turbo Training with Token Dropout

Tengda Han¹
htd@robots.ox.ac.uk
Weidi Xie¹,²
weidi@robots.ox.ac.uk
Andrew Zisserman¹
az@robots.ox.ac.uk

¹ Visual Geometry Group
Department of Engineering Science
University of Oxford
² Coop. Medianet Innovation Center
Shanghai Jiao Tong University
Shanghai, China

We provide the implementation details in Sect. 1. For the code and models of this paper, please refer to our project page: https://www.robots.ox.ac.uk/~vgg/research/turbo/.

1 Implementation Details

Architectural Details. In our implementation, we adopt the standard ViT-B architectures as [8, 14]. Specifically, the encoder is a 12-layer transformer with 768 feature dimension and the light-weight decoder is a 8-layer transformer with 512 feature dimension. The input spatial-temporal patch has a size of $t \times h \times w = 2 \times 16 \times 16$. We use sinusoidal positional embeddings [14]. For both the action classification and long-video activity classification tasks, we pass the encoder’s final-layer ‘CLS’ token into a linear layer for classification. For learning video-language representation, we project both the video feature and language feature with a 2-layer MLP, then compute the InfoNCE loss $\mathcal{L}_{NCE}$ as introduced in the main paper Page 5.

| Config                      | Act. Classification | V-L Training | Long-video Activity Classification |
|-----------------------------|---------------------|--------------|-----------------------------------|
| ViT-B encoder depth         | 12 layers           | 12 layers    | 12 layers                          |
| ViT-B encoder dimension     | 768                 | 768          | 768                                |
| decoder depth               | 8 layers            | 8 layers     | 8 layers                           |
| decoder dimension           | 512                 | 512          | 512                                |
| optimizer                   | AdamW [8]           | AdamW        | AdamW                              |
| base learning rate          | 1e-3                | 1e-4         | 3e-4                               |
| weight decay                | 0.05                | 0.05         | 0.05                               |
| learning rate schedule      | cosine-decay [8]    | cosine-decay | cosine-decay                       |
| warm-up epochs              | 10                  | 0.5          | 10(BF), 5(COIN)                    |
| training epochs             | 100                 | 5            | 100(BF), 50(COIN)                  |
| repeated sampling [8, 14]   | 1                   | 4            | 4                                  |
| augmentation                | RandAug(9, 0.5) [8] | MultiScaleCrop | RandAug(9, 0.5)                   |
| label smoothing [8]         | 0.1                 | -            | 0.1                                |
| mixup [8]                   | 0.8                 | -            | 0.8                                |
| cutmix [8]                  | 1.0                 | -            | 1.0                                |
| drop path [8]               | 0.1                 | 0.0          | 0.1                                |

Table 1. Implementation details of action classification, video-language training and long-video activity classification tasks.

Training Details. The details of training action classification, video-language training and long-video activity classification tasks are listed in Table 1. Note that, for action classification and long-video activity classification tasks, we use the same data augmentation as

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in [8, 10]; for video-language training, we only use basic cropping augmentation due to the adequate amount of training data from the HTM-AA [3] dataset (3.3M clip-sentence pairs).

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