The End-of-End-to-End: A Video Understanding Pentathlon Challenge (2020)

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Abstract

We present a new video understanding pentathlon challenge, an open competition held in conjunction with the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) 2020. The objective of the challenge was to explore and evaluate new methods for text-to-video retrieval—the task of searching for content within a corpus of videos using natural language queries. This report summarizes the results of the first edition of the challenge together with the findings of the participants. Individual reports, dataset information, rules, and released source code can be found at the competition webpage.

1. Introduction

Convolutional neural networks have yielded unprecedented progress on a wide range of image-centric benchmarks, driven through a combination of well-annotated datasets and end-to-end training. However, naively extending this approach from images to higher-level video understanding tasks quickly becomes prohibitive with respect to the computation and data annotation required to jointly train multi-modal high-capacity models.

In this challenge, we focus on an alternative experts-driven approach—features are first pre-extracted from a wide range of pretrained models (the experts) and cached as an intermediate representation (specialised for semantically relevant machine perception tasks) that can then be used to train the final system. The goal of this challenge is to build a system to retrieve videos from natural language queries across a “pentathlon” of five video retrieval benchmarks. Rather than training a retrieval system “end-to-end”, participants are provided with a diverse collection of carefully curated visual, audio and natural language pre-extracted features.

There are several benefits to the experts-driven approach: (a) Practicality—models for novel tasks can be composed together to exploit the available annotation in a data-efficient manner (by contrast, learning robust representations across all modalities from scratch would require vast levels of annotation to achieve comparable performance); (b) Effectiveness—the experts-driven approach now represents the current state-of-the-art on many video and language understanding tasks; (c) Accessibility—it enables researchers without access to industrial computing clusters to contribute towards questions of fundamental importance to video understanding.

This report summarizes the findings of the 2020 video understanding pentathlon challenge. The rest of the report is structured as follows: in Sec. 2, we describe the mechanics of the challenge together with the datasets that make up the pentathlon; in Sec. 3, we describe the challenge phases and evaluation rules. Then, in Sec. 4 we offer a brief overview of the methods used by participants in the challenge and the final competition ranking, before concluding in Sec. 5.

2. Challenge Mechanics

In this section, we describe the datasets selected to form the video pentathlon, the pre-extracted features and the baseline model provided to the participants.

2.1. Dataset Selection

The video pentathlon consisted of the five following datasets that constitute the benchmarks/challenges of the pentathlon:

- **MSVD [5]:** comprises a total of 80K descriptions (in English) for 1,970 videos sourced from YouTube (with approximately 40 sentences per video). Unlike the other datasets featured in the pentathlon, the videos contained in MSVD do not possess audio streams.

- **DiDeMo [1]:** consists of unedited, personal videos that are collected in an open-world setting and which include diverse content such as pets, music concerts and sports
Dataset | train vids | val vids | public_server_val vids | public_server_test vids | max queries per vid
---|---|---|---|---|---
MSVD [5] | 1080 | 120 | 100 | 670 | 81
DiDeMo [1] | 7552 | 840 | 1065 | 1004 | 1
ActivityNet [16] | 8007 | 1001 | 1001 | 4917 | 1
MSRVTT [31] | 5861 | 652 | 497 | 2990 | 20
YouCook2 [33] | 7745 | 968 | 969 | 3310 | 1

Table 1. Statistics of the five datasets and four partitions used in the Video Pentathlon Challenge. Paired data for the train and val splits were made available for model development. Paired data for the public_server_val and public_server_test partitions was withheld and stored on an evaluation server. The former was provided to enable participants to sanity check their models, while the latter was used to produce the final ranking of the challenge (the challenge phases corresponding to these splits are described in Sec. 3).

The dataset comprises 10,464 videos which are accompanied by approximately 3-5 pairs of descriptions and distinct moments per video.

**ActivityNet(+captions) [16]:** contains a total of 15K videos (sourced from the original ActivityNet dataset) accompanied by approximately 100K descriptive sentences. The videos, originally sourced from YouTube, exhibit a broad diversity of actions and content.

**MSR-VTT [31]:** contains 10K videos sourced from YouTube which are accompanied by 200K descriptive captions (thus, there are 200K unique video-caption pairs in total).

**YouCook2 [33]:** includes 2000 long untrimmed videos from 89 cooking recipes; on average, each distinct recipe has 22 videos. The videos are sourced from YouTube and contain content filmed from a third-person viewpoint with unfixed cameras.

The statistics of the five datasets are provided in Table 1, together with information about the train/test partitions.

### 2.2. Pre-extracted Experts

A diverse collection of carefully curated visual, audio and natural language pre-extracted features were provided to the participants including 8 features pre-extracted from visual perception models, 2 features from audio models and 2 features from natural language models. To produce features of a manageable size, the raw model outputs were temporally aggregated in three ways: (1) temporal average pooling (across frames); (2) temporal max pooling (across frames) and (3) “fixed_seg”, where the features were partitioned into a fixed number of uniformly spaced “chunks” (8 in total) and then average pooled within the chunk (the goal of this aggregation strategy was to preserve coarse-grained temporal information).

Since the test set of each of the datasets was already public, the features were obfuscated prior to release. Further details on the features are provided below (for each set of features, we provide the name used to describe the features on the challenge website in brackets).

#### Perception Models

We provided pre-extracted visual perception features for object, scene and action recognition, as well as for face-verification and optical character recognition (OCR). For certain categories, we provide multiple models to enable retrieval systems to benefit from with different architectures or pretraining data.

1. **Object Features (imagenet.resnext101.0):** are extracted using a ResNeXt-101 model [29] that has been pretrained on Instagram hashtags [20] and fine-tuned on ImageNet for the task of image classification. Features are extracted from frames extracted at 25 fps, where each frame is resized to $224 \times 224$ pixels. The dimension of the embeddings is 2048 and the dimension of logits is 1000.

2. **Object Features (imagenet.senet154.0):** are extracted using a SENet-154 model [13] that has been trained on ImageNet for the task of image classification. Features are extracted from frames extracted at 25 fps, where each frame is resized to $224 \times 224$ pixels. The dimension of the embeddings is 2048 and the dimension of logits is 1000.

3. **Scene Features (scene.densenet161.0):** are extracted from $224 \times 224$ pixel centre crops with a DenseNet-161 [14] model pretrained on Places365 [32]. The dimension of the embeddings is 2208 and the dimension of logits is 365.

4. **Action Features (i3d.i3d.0):** are extracted with an I3D inception model pretrained on Kinetics-400 that computes features following the procedure described by [4]. Frames are extracted at 25fps and processed in batches of 64 with a stride of 25 frames. Each frame is first resized to a height of 256 pixels (preserving aspect ratio), before a $224 \times 224$ centre crop is passed to the model. The dimension of the embeddings is 1024 and the dimension of logits is 400.
5. Instructional Video Features (s3dg.s3dg.0): are extracted with an S3D [30] model that computes features following the learning procedure described by [21] trained on the HowTo100M dataset [23]. Frames are extracted at 10fps and processed in clips of 32 frames with a stride of 16 frames. Each frame is first resized to a height of 256 pixels (preserving aspect ratio), before a $224 \times 224$ centre crop is passed to the model. The dimension of the embeddings is 1024 and the dimension of logits is 512.

6. Instagram Features (r2p1d.r2p1d-ig65m.0): are extracted with a 34-layer R(2+1)D model [28] trained on IG-65m [10] which processes clips of 8 consecutive $112 \times 112$ pixel frames, extracted at 30 fps (we use the implementation provided by [7]). The dimension of the embeddings is 512 and the dimension of logits is 359.

7. Instagram Video Features (r2p1d.r2p1d-ig65m-kinetics.0): are extracted with a 34-layer R(2+1)D model [28] trained on IG-65m [10] and then fine-tuned on Kinetics-400 [4] which processes clips of 8 consecutive $112 \times 112$ pixel frames, extracted at 30 fps (as above, we use the implementation provided by [7]). The dimension of the embeddings is 512 and the dimension of logits is 400.

8. Face features (face): are extracted in two stages: (1) Each frame (also extracted at 25 fps) is resized to $300 \times 300$ pixels and passed through an SSD face detector [17, 2] to extract bounding boxes; (2) The image region of each box is resized such that the minimum dimension is 224 pixels and a centre crop is passed through a ResNet50 [11] that has been trained for the task of face classification on the VGGFace2 dataset [3], producing an embedding for each detected face. The dimension of the embeddings is 512.

9. Optical Character Recognition Features (OCR): are extracted in two stages: (1) Each frame is resized to $800 \times 400$ pixels and passed through Pixel Link [8] text detection model to extract bounding boxes for texts; (2) The image region of each box is resized to $32 \times 256$ and then pass these through a model [19] that has been trained for scene text recognition on the Synth90K dataset [15], producing a character sequence for each detect box. They are then encoded via a pretrained word2vec embedding model [24]. The dimension of the embeddings is 300 (word2vec).

Audio Models

1. Sound Features (audio): are obtained with a VGGish model, trained for audio classification on the YouTube-8m dataset [12]. To produce the input for this model, the audio stream of each video is re-sampled to a 16kHz mono signal, converted to an STFT with a window size of 25ms and a hop of 10ms with a Hann window, then mapped to a 64 bin log mel-spectrogram. Finally, the features are parsed into non-overlapping 0.96s collections of frames (each collection comprises 96 frames, each of 10ms duration), which is mapped to a 128-dimensional feature vector. The dimension of the embeddings is 128.

2. Speech Features (speech): The audio stream of each video is re-sampled to a 16kHz mono signal. We then obtained transcripts of the spoken speech for MSRVTT, MSVD and ActivityNet using the Google Cloud Speech to Text API from the resampled signal. The language for the API is specified as English. The dimension of the embeddings is 300 (word2vec).

Natural Language Models:

1. Word2Vec Features (text-w2v): Each word of the video description is encoded using the Google News trained word2vec word embeddings [24]. The dimension of the embeddings is 300.

2. OpenAI Features (text-openai): Each word of the video description is encoded with a pretrained OpenAI-GPT model [25] to extract context-specific word embeddings (i.e., not only learned based on the current word but also the sequential context). The dimension of the embeddings is 768.

2.3. Baseline Model

In order to provide a starting point for entrants to the challenge, we provided solid baseline code for each dataset. The baseline model provided consisted of a simple joint text-video embedding which operated on pre-computed ImageNet and I3D features, supporting the method variants described in [18] and [22]. Code for the baseline model can be found at the challenge page.

3. Challenge Phases and Evaluation Rules

Submissions were made through the CodaLab website. The challenge had two phases, corresponding to the two partitions of the data which were used for the evaluation. The two phases were:

1. Development/Val Phase: The ‘public_server_val’ partition was open continuously throughout the challenge

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2. https://www.robots.ox.ac.uk/~vgg/challenges/video-pentathlon/challenge.html
3. https://competitions.codalab.org/competitions/24292
Table 2. Video Understanding Pentathlon Challenge 2020 final results. The number in parentheses indicates ranking and **bold text** highlights the top ranked result under each metric.

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2. Challenge Phase: The ‘public server test’ was used to produce the final ranking of submissions. The challenge phase took place between 9th May 2020 and 4th June 2020. This computed results on the public test partition of each dataset.

Only one submission per day per team was allowed. In total, each team could make 30 submissions to the validation set and 3 submissions to the test set. For this challenge, participants could process the text as they wished, but training on visual features from external datasets was not permitted.

Entries into the challenge were scored under a decathlon style scoring system (inspired by its usage in the visual decathlon [26]). For each of the five datasets $i \in \{1, ..., 5\}$, we first compute a measure of the quality of retrieval in each individual dataset. This “quality measure” $g_i$ comprises the geometric mean of recall @ $K$ for $K \in \{1, 5, 10\}$, computed as follows:

$$g_i = \left( \prod_{k \in \{1, 5, 10\}} r_{i,k} \right)^{\frac{1}{3}},$$  \hspace{1cm} (1)

where $r_{i,k}$ represents the recall @k on the $i^{th}$ dataset, i.e., the rate at which the correct video is retrieved amongst the top $k$ ranked results. The overall pentathlon score used for the final ranking of the submissions is then computed as follows:

$$S = \sum_{i=1}^{5} \alpha_i \max\{0, g_i - g_i^{\text{offset}}\}^{\gamma},$$ \hspace{1cm} (2)

where $\gamma$ is an exponential scaling factor that rewards gains in performance more heavily as they grow greater, the value is set to 2; $g_i^{\text{offset}}$ is a value that ensures that the baseline models achieve a score of 250 points on each dataset. The baselines, therefore, act to calibrate the difficulty of each dataset; $\alpha_i$ is assigned the value $1000(1 - g_i^{\text{offset}})^{-\gamma}$, which ensures that a perfect score $g_i$ achieves a results of 1000.
4. Challenge methods and teams

The video understanding pentathlon challenge received 56 submissions from 10 teams in total. The evolution of the leaderboard on the val partition is shown in Fig. 1. Table 2 reports the scores using all metrics on the final test partition for each team. Of these, the 4 top teams have declared their affiliation and submitted technical reports. In this document, we provide a brief introduction to the technical reports in order of their overall rank on the public leaderboard. Please refer to the technical reports for more details.

Table 3 details the winners of the video understanding pentathlon challenge 2020, announced as part of The End-of-End-to-End: A Video Understanding Pentathlon workshop at CVPR 2020.

**Rank 1: MMT** is the top-ranking entry by INRIA and Google. The overall framework of their proposed approach is shown in Fig. 2. The team used a multi-modal transformer to jointly encode different video modalities which allowed each of them to attend to the others. The features were then augmented with an expert type encoding and a temporal position encoding. To encode text, they investigated how to jointly optimize the language embedding together with the multi-modal transformer. Team MMT ensembled 16 models for each dataset for their final submission. A more detailed study of the method is given in the conference paper version of the method [9].

**Rank 2: cszhe** is the second ranking entry by Renmin University of China. Firstly, the team proposed a hierarchical graph reasoning model [6] which decomposed video-text matching into hierarchical levels for fine-grained retrieval. The overall framework of the proposed hierarchical graph reasoning model is shown in Fig. 3. Secondly, they explored query expansion and hubness mitigation methods (by using an Inverted Softmax [27]) during the inference to improve a naive nearest neighbor search. Thirdly, they demonstrated that it is beneficial to use additional datasets in a simple multi-task training approach. For the final submission, 3 - 5 models were ensembled for each dataset.

**Rank 3: LEgG0dt** is the third ranking entry by Xinhua Zhiyun Technology Co. Ltd. The team proposed a hybrid sequence encoder in combination with collaborative experts.
Figure 4. The overall framework of the third place proposed approach – a hybrid sequence encoder.

| Team                  | Members                        | Loss                               | LM                | Ensemble # | Cross-dataset | Temporal agg. | Expert agg. | QE  | HM  |
|-----------------------|--------------------------------|------------------------------------|-------------------|------------|---------------|---------------|-------------|-----|-----|
| 1. MMT                | Valentin Gabeur, Chen Sun, Karteeq Alahari, Cordelia Schmid | Max-Margin Ranking Loss            | Pretrained BERT   | 16         | Yes           | Transformer +Max pool | Transformer +MEE | Yes | No  |
| Inria                 |                                 |                                    |                   |            |               |               |             |     |     |
| Google AI             |                                 |                                    |                   |            |               |               |             |     |     |
| 2. cszhe              | Shizhe Chen, Yida Zhao, Qin Jin | Inverted Softmax +Max-Margin Ranking loss | Glove +BiLSTM +HGR | 5          | Yes           | HGR           | HGR         | Yes | Yes |
| Renmin, Uni. of China.|                                 |                                    |                   |            |               |               |             |     |     |
| 3. LEgG0drt           | Kaixu Cui, Hui Liu, Chen Wang, Yudong Jiang | Max-Margin Ranking loss                  | OpenATGPT + BiGRU +GhostVLAD +1D-Conv | 1          | Yes           | N.A.          | Concat      | Yes | No  |
| Xinhua Zhiyun Tech. Co. Ltd. |                                 |                                    |                   |            |               |               |             |     |     |
|                      |                                 |                                    |                   |            |               |               |             |     |     |

Table 3. A summary of the methods from the Top-3 winning teams in the Video Understanding Pentathlon challenge 2020 with the participants’ names and affiliations. LM: Language Model, agg.: Aggregation, QE: Query Expansion. HM: Hubness mitigation. Ensemble #: Ensemble Size

[18] to construct a common space for the video retrieval task via multi-modal common space learning. The overall framework of the hybrid sequence encoder is shown in Fig. 4. During training, they trained jointly on all datasets and selected the best performance model for each dataset, and then fine-tuned on each datasets for the final submission.

Rank 4: haoxiaoshuai is the fourth ranking entry by Chinese Academy of Sciences. The team designed a new bi-directional hard-negative ranking loss (Bi-HNRL) that emphasizes on the hardest negatives in the training stage. Specially, they focused on the hardest negative video and query sentence (closest to a positive pair) instead of summing over all negatives.

5. Conclusion

We introduced a new Video Understanding Pentathlon challenge at CVPR 2020. The results of the challenge were announced at a Video Understanding Workshop at CVPR, which was also accompanied by invited keynote and spotlight talks.

6. Affiliations

Visual Geometry Group, Univ. of Oxford: Samuel Albanie, Yang Liu, Arsha Nagrani, Ernesto Coto, Andrew Zisserman. Inria: Antoine Miech, Ivan Laptev, Karteeq Alahari, Valentin Gabeur, Cordelia Schmid. Google: Rahul Sukthankar, Valentin Gabeur, Cordelia Schmid, Chen Sun. IVUL, KAUST: Bernard Ghanem, Renmin Univ. of China: Shizhe Chen, Yida Zhao, Qin Jin, Xinhua Zhiyun Tech Co. Ltd. Kaixu Cui, Hui Liu, Chen Wang, Yudong Jiang. Chinese Academy of Sciences. Xiaoshuai Hao.

7. Acknowledgements

The organisers would like to express their gratitude to the creators of the original datasets used in this challenge. They would like to thank in particular Juan Carlos Niebles, Ranjay Krishna, Luowei Zhou, Lisa Ann Hendricks, Jun Xu, Tao Mei, Ting Yao, Yong Rui, David L. Chen, Bryan Russell and Anna Rohrbach for their assistance. We gratefully acknowledge the support of the Programme Grant See-bibyte EP/M013774/1.
References

[1] Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. Localizing moments in video with natural language. In Proceedings of the IEEE International Conference on Computer Vision, pages 5803–5812, 2017. 1, 2

[2] G. Bradski. The OpenCV Library. Dr. Dobb’s Journal of Software Tools, 2000. 3

[3] Qiong Cao, Li Shen, Weidi Xie, Omkar M Parkhi, and Andrew Zisserman. Vggface2: A dataset for recognising faces across pose and age. In 2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018), pages 67–74. IEEE, 2018. 3

[4] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6299–6308, 2017. 2, 3

[5] David L Chen and William B Dolan. Collecting highly parallel data for paraphrase evaluation. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 190–200. Association for Computational Linguistics, 2011. 1, 2

[6] Shizhe Chen, Yida Zhao, Qin Jin, and Qi Wu. Fine-grained video-text retrieval with hierarchical graph reasoning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10638–10647, 2020. 5

[7] J. H. Daniel. ig65m-pytorch. https://github.com/moabitcoin/ig65m-pytorch, 2019. 3

[8] Dan Deng, Haifeng Liu, Xuelong Li, and Deng Cai. PixelLink: Detecting scene text via instance segmentation. In Thirty-Second AAAI Conference on Artificial Intelligence, 2018. 3

[9] Valentin Gabeur, Chen Sun, Karteek Alahari, and Cordelia Schmid. Multi-modal Transformer for Video Retrieval. In European Conference on Computer Vision (ECCV), 2020. 5

[10] Deepi Ghadiyaram, Du Tran, and Dhruv Mahajan. Large-scale weakly-supervised pre-training for video action recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 12046–12055, 2019. 3

[11] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Identity mappings in deep residual networks. In European conference on computer vision, pages 630–645. Springer, 2016. 3

[12] Shawn Hershey, Sourish Chaudhuri, Daniel P. W. Ellis, Jort F. Gemmeke, Aren Jansen, Channing Moore, Manoj Plakal, Devin Platt, Rf A. Saurous, Bryan Seybold, Malcolm Slaney, Ron Weiss, and Kevin Wilson. Cnn architectures for large-scale audio classification. In International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017. 3

[13] Jie Hu, Li Shen, Samuel Albanie, Gang Sun, and Enhua Wu. Squeeze-and-excitation networks. IEEE transactions on pattern analysis and machine intelligence, 2019. 2

[14] Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 4700–4708, 2017. 2

[15] Max Jaderberg, Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Synthetic data and artificial neural networks for natural scene text recognition. arXiv preprint arXiv:1406.2227, 2014. 3

[16] Ranjay Krishna, Kenji Hata, Frederic Ren, Li Fei-Fei, and Juan Carlos Niebles. Dense-captioning events in videos. In Proceedings of the IEEE international conference on computer vision, pages 706–715, 2017. 2

[17] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In European conference on computer vision, pages 21–37. Springer, 2016. 3

[18] Yang Liu, Samuel Albanie, Arsha Nagrani, and Andrew Zisserman. Use what you have: Video retrieval using representations from collaborative experts. In British Machine Vision Conference, 2019. 1, 3, 6

[19] Yang Liu, Zhaowen Wang, Hailin Jin, and Ian Wassell. Synchronously supervised feature learning for scene text recognition. In Proceedings of the European Conference on Computer Vision (ECCV), pages 435–451, 2018. 3

[20] Dhruv Mahajan, Ross Girshick, Vignesh Ramanathan, Kaiming He, Manohar Paluri, Yixuan Li, Ashwin Bharame, and Laurens van der Maaten. Exploring the limits of weakly supervised pretraining. In Proceedings of the European Conference on Computer Vision (ECCV), pages 181–196, 2018. 2

[21] Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. End-to-end learning of visual representations from uncurated instructional videos. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 9879–9889, 2020. 3

[22] Antoine Miech, Ivan Laptev, and Josef Sivic. Learning a text-video embedding from incomplete and heterogeneous data. arXiv preprint arXiv:1804.02516, 2018. 1, 3

[23] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In Proceedings of the IEEE international conference on computer vision, pages 2630–2640, 2019. 3

[24] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781, 2013. 3

[25] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. Improving language understanding by generative pre-training. URL https://s3-us-west-2, 2018. 3

[26] Sylvestre-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. Learning multiple visual domains with residual adapters. In Advances in Neural Information Processing Systems, pages 506–516, 2017. 4
[27] Samuel L Smith, David HP Turban, Steven Hamblin, and Nils Y Hammerla. Offline bilingual word vectors, orthogonal transformations and the inverted softmax. arXiv preprint arXiv:1702.03859, 2017. 5

[28] Du Tran, Heng Wang, Lorenzo Torresani, Jamie Ray, Yann LeCun, and Manohar Paluri. A closer look at spatiotemporal convolutions for action recognition. In Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, pages 6450–6459, 2018. 3

[29] Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, and Kaiming He. Aggregated residual transformations for deep neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1492–1500, 2017. 2

[30] Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy. Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification. In Proceedings of the European Conference on Computer Vision (ECCV), pages 305–321, 2018. 3

[31] Jun Xu, Tao Mei, Ting Yao, and Yong Rui. Msr-vtt: A large video description dataset for bridging video and language. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 5288–5296, 2016. 2

[32] Bolei Zhou, Agata Lapedriza, Aditya Khosla, Aude Oliva, and Antonio Torralba. Places: A 10 million image database for scene recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017. 2

[33] Luowei Zhou, Chenliang Xu, and Jason J Corso. Towards automatic learning of procedures from web instructional videos. In AAAI Conference on Artificial Intelligence, pages 7590–7598, 2018. 2