REVISITING 3D RESNETS FOR VIDEO RECOGNITION

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ABSTRACT

A recent work from Bello et al. [3] shows that training and scaling strategies may be more significant than model architectures for visual recognition. This short note studies effective training and scaling strategies for video recognition models. We propose a simple scaling strategy for 3D ResNets, in combination with improved training strategies and minor architectural changes. The resulting models, termed 3D ResNet-RS, attain competitive performance of 81.0% on Kinetics-400 and 83.8% on Kinetics-600 without pre-training. When pre-trained on a large Web Video Text dataset, our best model achieves 83.5% and 84.3% on Kinetics-400 and Kinetics-600. Code is available at: https://github.com/tensorflow/models/tree/master/official.

1 INTRODUCTION

Recent studies have shown that vision models may be significantly improved through the combination of modern training and simple scaling strategies [3, 12, 23]. For example, Bello et al. [3] remark that the canonical ResNet-200 [17] is improved from 79.0% to 83.4% (+4.4%) top-1 ImageNet accuracy through improved training methods and lightweight architectural changes. The resulting ResNet-RS model is further scaled via model depth and image resolution, reaching a competitive accuracy of 84.4% (+5.4%).

Inspired by ResNet-RS [3], our study focuses on effective training and scaling methods for video action recognition models. Using a 3D ResNet (R3D) model as the baseline, we evaluate the effect of (1) lightweight architectural changes, including the ResNet-D stem [18] and Squeeze-and-Excitation [19] and (2) improved training methods such as data augmentation and regularization. Further, we propose a simple scaling rule that simultaneously scales model depth and the temporal resolution of the input.

We evaluate the resulting models, referred to as 3D ResNet-RS (R3D-RS), on the popular Kinetics-400 and Kinetics-600 benchmarks. When trained from scratch, R3D-RS-50 model obtains a +3.8% top-1 accuracy improvement over the R3D-50 baseline. By further scaling to R3D-RS-200 with 48 input frames, our largest model achieves competitive top-1 accuracies of 81.0% and 83.8% on Kinetics-400 and Kinetics-600 respectively, on par with recent state-of-the-art models. When pre-trained on the Web Video Text dataset [29], our R3D-RS-200 model is further improved by +2.5% on Kinetics-400 and +0.5% on Kinetics-600. Lastly, we evaluate R3D-RS in a self-supervised contrastive learning setup [26] where we demonstrate +1.4% top-1 Kinetics-400 accuracy improvement over the R3D baseline.

2 RELATED WORK

Spatiotemporal networks for video recognition: A key difference between static images and videos is the additional temporal dimension. While some works model spatial and temporal features separately, it is more common to combine features through both the spatial and temporal dimensions by using 3D convolutions [30, 31, 7] or self-attention [34, 4, 27, 2, 11]

Data augmentation and regularization: When training data is insufficient or lacks diversity, regularization methods such as data augmentation [38, 10, 37, 36, 8, 9], dropout [28], stochastic
Figure 1: Kinetics-400 top-1 accuracies of the R3D baseline, SlowFast networks and the proposed R3D-RS models. The proposed training methods and architectural changes improve upon the R3D baseline by 3.8% while slightly reducing computation. The proposed simple scaling method further improves accuracy by 2.8%. R3D-RS-200\* scales up input frames and uses stronger augmentation. FLOPs are reported on a single inference view and all models use the same 30-view evaluation protocol. See Section 4 for experimental details. SlowFast accuracies are taken directly from [15] and may be improved through R3D-RS\*'s training methods.

Recent studies in image classification [3] and object detection [12] have shown that augmentation and regularization methods alone may significantly improve model accuracy without additional cost at inference.

3 METHODOLOGY

3.1 THE 3D RESNET-RS ARCHITECTURE

The full architecture specifications of our 3D ResNet-50 is presented in Table 1. We start from R3D [26] as the baseline architecture and adopt the following lightweight architectural changes to improve model performance.

3D ResNet-D stem: We adapt the ResNet-D [18] stem to 3D inputs by using three consecutive 3D convolutional layers. The first convolutional layer employs a temporal kernel size of 5 while the remaining two convolutional layers employ a temporal kernel size of 1. Detailed layer specifications are shown in Table 1 right.

3D Squeeze-and-Excitation: We adapt Squeeze-and-Excite [19] to spatio-temporal inputs by simply using a 3D global average pooling operation for the squeeze operation. A SE ratio of 0.25 is applied in each 3D bottleneck block for all experiments.

Self-gating: We further plug in a self-gating module [35] in each 3D bottleneck block after the SE module.

3.2 IMPROVED TRAINING STRATEGIES

Data augmentation: We apply scaling jittering, random cropping and RandAugment [9] as our data augmentation methods. We apply the same augmentation strategy to all frames in a video clip, which we experimentally find to achieve good performance.
Table 1: (Left) Blocks used in the R3D-RS architecture. Kernel sizes are denoted as \{Temporal \times Spatial^2, Filters\} and the kernel is underlined when the spatial stride is 2 (1 otherwise). SE: squeeze-and-excitation. SG: self-gating. SD: stochastic depth. (Right) R3D-RS-50 architecture.

| Model         | LS | SD | WD | 350-EP | SJ | SE | D-stem | RA | FLOPs (B) | Top-1 |
|---------------|----|----|----|--------|----|----|--------|----|-----------|-------|
| R3D-50        | ✅ |✅  |✅  |        |    |✅  |        |    | 60        | 74.4  |
| -             | ✅ |✅  |✅  | 350-EP |    |    |        |    | 60        | 74.9 (+0.5) |
| -             | ✅ |✅  |✅  | SJ     |    |    |        |    | 60        | 76.1 (+1.2)  |
| -             | ✅ |✅  |✅  | SE     |    |    |        |    | 60        | 76.3 (+0.2)  |
| -             | ✅ |✅  |✅  | D-stem |    |    |        |    | 60        | 76.4 (+0.1)  |
| -             | ✅ |✅  |✅  | RA     |    |    |        |    | 60        | 77.4 (+1.0)  |
| -             | ✅ |✅  |✅  |        |    |    |        |    | 60        | 77.9 (+0.5)  |
| -             | ✅ |✅  |✅  |        |    |    |        |    | 58        | 78.2 (+0.3)  |
| R3D-RS-200    | ✅ |✅  |✅  |        |    |    |        |    | 307       | 80.7  |
| R3D-RS-200    | ✅ |✅  |✅  |        |    |    |        |    | 307       | 81.0 (+0.3)  |

Table 2: Additive study of the training methods and architectural changes used in this paper. LS: label smoothing. SD: stochastic depth. WD: reduced weight decay. 350-EP: increase training epochs to 350. SJ: scale jittering. SE: squeeze-and-excitation. D-stem: 3D ResNet-D stem. RA: 3D RandAugment. All models are trained from scratch on Kinetics-400 and evaluated using the 30-view protocol.

3.3 Scaling Strategies for Video Recognition

Similar to [3], we scale R3D-RS models by increasing model depth and input resolution. Fig 2 presents our scaling analysis. We found scaling the temporal dimension of the input to be more effective than scaling the spatial dimensions. We scale the number of frames of model input from 32 to 48 and keep the spatial resolution to 224 \times 224 for training.

4 Experiments

4.1 Experimental settings

We experiment on the Kinetics-400 [22] and Kinetics-600 [6] benchmarks and report top-1 and top-5 accuracy as evaluation metrics.
Figure 2: Scaling 3D-ResNet-RS models via depth, spatial resolution or input frames. Models are denoted as “RS-depth”. Unless specified otherwise, models are trained from scratch on Kinetics-400 with input size $32 \times 224^2$. “@f48” and “@f64” denote scaling input temporal frames to 48 and 64. “@i256” and “@i288” denote scaling training input spatial resolution to 256 and 288. FLOPs are calculated on single view inference at $32 \times 256^2$. Details can be found in Sec. 4.3 and 4.4.

Table 3: Comparisons of models trained from scratch on Kinetics-400. Inference “Views” is presented in $\text{view}_{\text{temporal}} \times \text{view}_{\text{space}}$. “48↑”: scaling up input #frames from 32 to 48. RA: RandAugment for 3D video clip.

**Table 3:** Comparisons of models trained from scratch on Kinetics-400. Inference “Views” is presented in $\text{view}_{\text{temporal}} \times \text{view}_{\text{space}}$. “48↑”: scaling up input #frames from 32 to 48. RA: RandAugment for 3D video clip.

Training from scratch: Our main results are reported under the settings of training from scratch on Kinetics-400 and Kinetics-600. We use SGD with a 0.9 momentum rate and a batch size of 1024 for 350 epochs on TPUv3 devices [21]. We apply a cosine decay learning rate schedule with an initial learning rate 0.8 and a linear learning rate warm-up that is applied over the first 5 epochs. 0.5 dropout [28] is applied for regularization.

Inference: We adopt the 30 views protocol [15] to report inference results. 10 temporal clips are uniformly sampled along the temporal axis. For each clip, we use 3 $256 \times 256$ spatial crops.

4.2 Training from scratch results on Kinetics

Table 3 presents our results of training from scratch on the Kinetics-400 benchmark. Comparing to the R3D-50 baseline [3], the modern training methods and architectural changes introduced in R3D-RS-50 significantly improve the top-1 and top-5 accuracy by 3.8% and 2.7%, respectively. After scaling the model depth from R3D-RS-50 to R3D-RS-200, the top-1 and top-5 accuracy are
improved by 2.2% and 0.7%, respectively. The top-1 accuracy is further improved by 0.3% by scaling input frames from 32 to 48. Lastly, adopting the 3D RandAugment strategy improves the top-1 accuracy by another 0.3%.

We further evaluate our best R3D-RS-200 models on Kinetics-600 and report the results in Table 4.

4.3 ABLATION OF THE TRAINING METHODS AND ARCHITECTURAL CHANGES

We present detailed ablation studies of our training methods and architectural changes in Table 2 on Kinetics-400 and report top-1 accuracy. Starting from the R3D-50 baseline, we gradually apply 0.1 label smoothing (+0.5%), stochastic depth with an initial drop rate of 0.2 (+1.2%), 4e-5 weight decay (+0.2%), prolonging training epochs to 350 (+0.1%), scale jittering augmentation (+1.0%), squeeze-and-excitation module with 0.25 rate (+0.5%), 3D ResNet-D stem (+0.3%) and RandAugment (+0.3%). The 3D ResNet-D stem also slightly reduces model FLOPs from 60B to 58B.

4.4 EFFECTIVENESS OF THE SIMPLE SCALING RULE

The effectiveness of our simple scaling method is studied in Fig. 2. Scaling from R3D-RS-50 to R3D-RS-200 improves accuracy by +2.2%. However, further depth scaling from R3D-RS-200 to R3D-RS-270 (-0.5%) or R3D-RS-300 (-0.7%) hurt performance. Scaling input frames from 32 to 48 improves another +0.3%. We further studied scaling training (inference) spatial resolution from 224 (256) to 256 (288) or larger but the model accuracy drops. All models are trained from scratch on Kinetics-400 and top-1 accuracy are reported.

4.5 IMPROVEMENTS FROM PRETRAINING

Table 5 shows the results of using large scale pre-train dataset Web Videos and Text (WVT) [29]. The WVT dataset contains 70 million video clips collected by using labels of the Kinetics-700 data set as query string in YouTube. For more details of the data set please refer to [29]. We pretrain our R3D-RS-200 under the video classification task (i.e. input video clips to predict the action labels). We used the same input size (48×224×224) as previous experiments. We pretrain the model on WVT for 4 epochs using learning rate 1.6, SGD with momentum 0.9 on TPUv3 128 cores. The pretrained model is finetuned on Kinetics-400 for 10000 steps with learning rate 0.05. We have observed various level of improvements of the final model quality on Kinetics-400 (+2.5%) and Kinetics-600 (+0.5%).

5 EXPERIMENTS OF UNSUPERVISED LEARNING

We further test the model scaling strategy in self-supervised manner. For simplicity, we use the algorithm of CVRL [26] which learns spatiotemporal invariance features from short video clips. We pretrain the models for 800 epochs to ensure convergence. Pretraining batchsize is set to 2048 and we adopt lars optimizer with an initial learning rate of 0.64 to stablize training. For linear evaluation, we simply adopt SGD with initial learning rate of 64 and train for 100 epochs with batchsize of 1024.

| Model            | FLOPs×Views | Params | Top-1 |
|------------------|-------------|--------|-------|
| SlowFast [15]    | 213×10×3    | -      | 81.1  |
| SlowFast, +NL [15] | 234×10×3    | 59.9   | 81.8  |
| X3D-XL [14]      | 48×10×3     | 20.3   | 81.9  |
| MViT-B, 32×3 [13] | 170×5×1     | 36.8   | 83.4  |
| MViT-B-24, 32×3 [13] | 236×5×1     | 52.9   | 83.8  |
| R3D-RS-200       | 205×10×3    | 122.0  | 83.1  |
| R3D-RS-200 (48↑) | 307×10×3    | 122.0  | 83.8  |

Table 4: Comparisons of models trained from scratch on Kinetics-600. Inference “Views” is presented in viewtemporal × viewspace. “48↑”: scaling up input #frames from 32 to 48. SlowFast networks adopt the 16×8 setting with a R101 backbone.
We report the top-1 accuracy on Kinetics-400 in Table 6. Aligning with observation in Fig. 2, we find the performance saturating phenomenon as the model depth increase in self-supervised learning as well.

| Model                          | Pretrain | Dataset | FLOPs (B) × Views | Top-1 |
|--------------------------------|----------|---------|------------------|-------|
| VTN [25]                       | ImageNet-21K | Kinetics-400 | 4218×1×1 | 78.6  |
| TimeSformer-L [5]              | ImageNet-21K | Kinetics-400 | 2380×1×3 | 80.7  |
| ViViT-L/16×2 FE [1]            | ImageNet-21K | Kinetics-400 | 3980×1×3 | 81.7  |
| Swin-L [24]                    | ImageNet-21K | Kinetics-400 | 604×4×3 | 83.1  |
| Swin-L, 384 [24]               | ImageNet-21K | Kinetics-400 | 2107×10×5 | 84.9  |
| ViViT-H/16×2 [1]               | JFT       | Kinetics-400 | 3981×4×3 | 84.9  |
| R3D-RS-200 (48↑)               | WVT       | Kinetics-400 | 307×10×3 | 83.5  |

Table 5: Kinetics-400/600 result comparisons of our R3D-RS models and other models when pretrained on large-scale datasets.

| Model                          | R3D-RS-50 | R3D-RS-101 | R3D-RS-152 | R3D-RS-200 | R3D-RS-270 |
|--------------------------------|-----------|------------|------------|------------|------------|
| Top-1                          | 66.1      | 67.1 (+1.0) | 67.1 (+0.0) | 67.3 (+0.2) | 67.5 (+0.2) |

Table 6: Linear evaluation results of R3D-RS models based on self-supervised pretraining on Kinetics-400.

6 CONCLUSION

In this work, we revisit 3D ResNets in the light of the modern techniques that commonly applied in image classification. The proposed training and scaling strategies, along with lightweight architectural changes, significantly improve 3D ResNet models when trained from scratch on the popular Kinetics-400 and Kinetics-600 benchmarks. We believe our methods can benefit more models for action recognition and boarder video applications.
REFERENCES

[1] A. Arnab, M. Dehghani, G. Heigold, Chen Sun, Mario Lucic, and C. Schmid. Vivit: A video vision transformer. ArXiv, abs/2103.15691, 2021. 6
[2] Irwan Bello. Lambdanetworks: Modeling long-range interactions without attention. 2021. 1
[3] Irwan Bello, William Fedus, Xianzhi Du, Ekin D Cubuk, Aravind Srinivas, Tsung-Yi Lin, Jonathon Shlens, and Barret Zoph. Revisiting resnets: Improved training and scaling strategies. arXiv preprint arXiv:2103.07579, 2021. 1, 2, 4, 4
[4] Irwan Bello, Barret Zoph, Ashish Vaswani, Jonathon Shlens, and Quoc V. Le. Attention augmented convolutional networks. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), October 2019. 1
[5] Gedas Bertasius, Heng Wang, and L. Torresani. Is space-time attention all you need for video understanding? ArXiv, abs/2102.05095, 2021. 6
[6] Joao Carreira, Eric Noland, Andras Banki-Horvath, Chloe Hillier, and Andrew Zisserman. A short note about kinetics-600, 2018. 3
[7] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In CVPR, 2017. 1
[8] E. D. Cubuk, Barret Zoph, Dandelion Mané, Vijay Vasudevan, and Quoc V. Le. Autoaugment: Learning augmentation strategies from data. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 113–123, 2019. 1
[9] E. D. Cubuk, Barret Zoph, Jonathon Shlens, and Quoc V. Le. Randaugment: Practical data augmentation with no separate search. ArXiv, abs/1909.13719, 2019. 1, 2
[10] Terrance Devries and Graham W. Taylor. Improved regularization of convolutional neural networks with cutout. ArXiv, abs/1708.04552, 2017. 1
[11] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. 2021. 1
[12] Xianzhi Du, Barret Zoph, W. Hung, and Tsung-Yi Lin. Simple training strategies and model scaling for object detection. ArXiv, abs/2107.00057, 2021. 1, 2
[13] Haoqi Fan, Bo Xiong, Karttikeya Mangalam, Yanghao Li, Zhicheng Yan, J. Malik, and Christoph Feichtenhofer. Multiscale vision transformers. ArXiv, abs/2104.11227, 2021. 4, 5
[14] Christoph Feichtenhofer. X3d: Expanding architectures for efficient video recognition. In CVPR, 2020. 4, 5
[15] Christoph Feichtenhofer, Haoqi Fan, Jitendra Malik, and Kaiming He. Slowfast networks for video recognition. ICCV, pages 6201–6210, 2019. 2, 4, 5
[16] Golnaz Ghiasi, Tsung-Yi Lin, and Quoc V. Le. Dropblock: A regularization method for convolutional networks. In NeurIPS, 2018. 2
[17] Kaiming He, X. Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 770–778, 2016. 1
[18] Tong He, Zhi Zhang, Hang Zhang, Zhongyue Zhang, Junyuan Xie, and Mu Li. Bag of tricks for image classification with convolutional neural networks. 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pages 558–567, 2019. 1, 2
[19] Jie Hu, L. Shen, and Gang Sun. Squeeze-and-excitation networks. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 7132–7141, 2018. 1, 2
[20] Gao Huang, Yu Sun, Zhuang Liu, Daniel Sedra, and Kilian Q Weinberger. Deep networks with stochastic depth. In ECCV, 2016. 2, 3
[21] Norman P. Jouppi, Cliff Young, Nishant Patil, David A. Patterson, Gaurav Agrawal, Raminder Bajwa, Sarah Bates, Suresh Bhatia, Nan Boden, Al Borchers, Rick Boyle, Pierre-luc Cantin, Clifford Chao, Chris Clark, Jeremy Coriell, Mike Daley, Matt Dau, Jeffrey Dean, Ben Gelb, Tara Vazir Ghaemmaghami, Rajendra Gottipati, William Gulland, Robert Hagmann, Richard C. Ho, Doug Hogberg, John Hu, Robert Hundt, Dan Hurt, Julian Ibarz, Aaron Jaffey, Alek Jaworski, Alexander Kaplan, Harshit Khaitan, Andy Koch, Naveen Kumar, Steve Lacy, James Laudon, James Law, Diemthu Le, Chris Leary, Zhuyuan Liu, Kyle Lucke, Alan Lundin, Gordon MacKean, Adriana Maggiore, Mairé Mahony, Kieran Miller, Rahul Nagarajan, Ravi Narayanaswami, Ray Ni, Kathy Nix, Thomas Norrie, Mark Omernick, Narayana Penukonda, Andy Phelps, Jonathan Ross, Amir Salek, Emad Samadiani, Chris Severn, Gregory Sizikov, Matthew Snellham, Jed Souter, Dan Steinberg, Andy Swing, Mercedes Tan, Gregory Thorson, Bo Tian, Horia Toma, Erick Tuttle, Vijay Vasudevan, Richard Walter, Walter Wang, Eric Wilcox, and Doe Hyun Yoon. In-dataset performance analysis of a tensor processing unit. CoRR, abs/1704.04760, 2017. 4
[22] Will Kay, Joao Carreira, K. Simonyan, B. Zhang, Chloe Hillier, Sudheendra Vijayanarasimhan, Fabio Viola, Tim Green, T. Back, A. Natsev, Mustafa Suleyman, and Andrew Zisserman. The kinetics human action video dataset. ArXiv, abs/1705.06950, 2017. 3
[23] Alexander Kolesnikov, L. Beyer, Xiaohua Zhai, J. Puigcerver, Jessica Yung, S. Gelly, and N. Houlsby. Big transfer (bit): General visual representation learning. In ECCV, 2020. 1
[24] Ze Liu, Jia Ning, Yue Cao, Yixuan Wei, Zheng Zhang, Stephen Lin, and Han Hu. Video swin transformer, 2021. 6
[25] Daniel Neimark, O. Bar, Maya Zohar, and Dotan Asselmann. Video transformer network. ArXiv, abs/2102.00719, 2021. 6
[26] Rui Qian, Tianjian Meng, Boqing Gong, Ming-Hsuan Yang, Huisheng Wang, Serge Belongie, and Yin Cui. Spatiotemporal contrastive video representation learning. In CVPR, 2021. 1, 2, 5
[27] Prajit Ramachandran, Niki Parmar, Ashish Vaswani, Irwan Bello, Anselm Levskaya, and Jonathon Shlens. Stand-alone self-attention in vision models. 2019. 1
[28] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(56):1929–1958, 2014. 1, 4
[29] Jonathan C Stroud, David A Ross, Chen Sun, Jia Deng, Rahul Sukthankar, and Cordelia Schmid. Learning video representations from textual web supervision. arXiv preprint arXiv:2007.14937, 2020. 1, 5
[30] Graham W Taylor, Rob Fergus, Yann LeCun, and Christoph Bregler. Convolutional learning of spatiotemporal features. In ECCV, 2010. 1
[31] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. Learning spatiotemporal features with 3d convolutional networks. In ICCV, 2015. 1
[32] Du Tran, Heng Wang, L. Torresani, and Matt Feiszli. Video classification with channel-separated convolutional networks. 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pages 5551–5560, 2019. 4
[33] Du Tran, Heng Wang, L. Torresani, Jamie Ray, Y. LeCun, and Manohar Paluri. A closer look at spatiotemporal convolutions for action recognition. 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6450–6459, 2018. 4
[34] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. 2017. 1
[35] Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy. Rethinking spatiotemporal feature learning: Speed-accuracy trade-offs in video classification. In ECCV, 2018. 2
[36] Sangdoo Yun, Dongyoon Han, Seong Joon Oh, Sanghyuk Chun, Junsuk Choe, and Y. Yoo. Cutmix: Regularization strategy to train strong classifiers with localizable features. 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pages 6022–6031, 2019. 1
[37] Hongyi Zhang, Moustapha Cissé, Yann Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. ArXiv, abs/1710.09412, 2018. 1
[38] Zhun Zhong, L. Zheng, Guoliang Kang, Shaotai Li, and Y. Yang. Random erasing data augmentation. In AAAI, 2020. 1