BigFace: A New Paradigm Toward High-Performance (Masked) Face Recognition

Technical Details of our submissions at MFR-ICCV2021, WebFace260M track

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Acknowledgement

Acknowledgement and Our Members

- We appreciate the organizers of this challenge for a chance to deep dive into the Masked Face Recognition Research.
- Our Members:
 - Jong-Ju Shin for the preparation of the (masked) dataset, and insightful discussion.
 - Pyeong-Gang Lim and Deepflow team for their devoted efforts to developing and maintaining our internal Distributed Machine Learning Infrastructure.
 - **Yong-Hyeon Kim** for the initial research of the Masked Face Recognition as our formal colleague.



This challenge was a great chance to verify the effectiveness (usefulness) of our "BigFace" paradigm.

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"BigFace" paradigm



"BigFace" Paradigm

Linear Scaling Raw in the Face Recognition

- Inspired by a lighting surge of Big Models in the Language Modeling Field [1], we believe **Big** *Face* Recognition (FR) Models also give a great impact on performance, if there is no dataset bottleneck.
- We verified FR with mask also is governed by the Linear Scaling Raw (Power Raw) on the WebFace42M [2].





[1] J Kaplan et. al, Scaling Laws for Neural Language Models, arXiv:2001.08361v1, 2020 [2] Z. Zhu et. al, WebFace260M: A Benchmark Unveiling the Power of Million-scale Deep Face Recognition, CVPR, 2020





"BigFace" Paradigm

"BigFace-Distill", a promising algorithm exploiting such BigFace Models

- Many FR applications do not allow the use of such **BigFace** Models due to a huge amount of their memory consumption and latency.
- To tackle the aforementioned limitations, we can employ the *Knowledge Distillation (KD)* algorithms for extracting informative knowledge from the **BigFace** Models into smaller models applicationspecific.
- This challenge was a great chance to verify the effectiveness (usefulness) of our "BigFace" paradigm.
- After finishing a training of *BigFace* model once, it can alleviate a cost of labeled train-dataset building via the *Semi-Supervised KD*.



our BigFace model (i.e. ResNet600) improved the Masked Face Recognition (MFR) score over our student models.



Mask-Augmentation, Models, and BigFace-Distill

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Our Approach





Mask Augmentation

Combination of two off-the-shelf masked face synthesis tools

We use two off-the-shelf masked face generation tools [1,2]



Figure 1. Examples of synthesized masked-face images from the . Samples in the first and second row are gener-WebFace42M ated via [1], and [2] respectively. From [1] we can augment synthesized images with various shapes and textures of face masks, but resulting images are slightly unnatural. In contrast, [2] generates relatively natural masked-face images, however, limited to synthesis with various commodity face masks.

- Recognition).

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We sampled mask-augmented face images from the WebFace42M ratio of 0.35 rather than 0.5. By the sampling ratio, we could roughly steer our interest between MFR and SFR (Standard Face





Plain ResNet is Enough

In the first round, we adopted a simple Mixture-Of-Expert (MoE) [1] structure



• However, we observed the plain ResNet shows a better performance than that of our MoE variant.

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Model



Plain ResNet is Enough

Block Diagram of the model we used in this challenge [1]:



- Plain ResNet shows much faster inference than that of our MoE.
- Since we did not know the largest model acceptable under the FRUITS-1000 protocol [2], we gradually increased the trainable parameters of our model.
- Finally, ResNet240 was employed in our feature-extraction network.
- In this model, most BN weights and running statistics are absorbed into the previous convolution weights manually after finishing a training process.

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Model

	Number of Blocks			
Architecture	Stage1	Stage2	Stage3	
ResNet120	3	13	40	
ResNet140	3	15	48	
ResNet200	6	26	60	
ResNet240	3	25	88	
ResNet600	3	70	220	
ResNet1.2K	3	80	512	

Table 1. ResNet variants we used in this challenge. The ResNet240 is adapted for the final submission. We utilized the ResNet600 and ResNet1.2K as a teacher model for the knowledge distillation



BigFace-Distill

Loss Function and the Final Results

 $\mathcal{L} := \mathcal{L}_{\text{CosFace}} + \lambda \mathcal{L}_{\text{distill}}$

,where



Our last two submission results:

Submission

ResNet240 ResNet240-Dis Table 2. The last two submi as our teacher network in th

1] H. Wang et. al, CosFace: Large Margin Cosine Loss for Deep Face Recognition, arXiv:1801.09414v2, 2018

[2] M. Yan et. al, VarGFaceNet: An Efficient Variable Group Convolutional Neural Network for Lightweight Face Recognition, arXiv:1910.04985v4, 2019 [3] C. Nhan et. al, ShrinkTeaNet: Million-scale Lightweight Face Recognition via Shrinking Teacher-Student Networks, arXiv:1905.10620v1, 2019

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We adopted a convex combination of the CosFace [1] and Angular-Distillation [2,3] loss.

$$\frac{e^{s(\cos(\theta_{y_i})-m)}}{s(\cos(\theta_{y_i})-m) + \sum_{j=1, j \neq y_i} e^{s\cos(\theta_j)}},$$

$$\left\| \frac{\mathbf{x}_{i}^{s}}{\|\mathbf{x}_{i}^{s}\|_{2}} \right\|_{2}^{2}$$
, $m = 0.4, s = 64$, and $\lambda = 9$.

1	Sco					
	MFR	SFR				
)	0.0803	0.0235				
still	0.0769	0.0241				
ission results. We used the ResNet600						
e ResNet240-Distill submission.						

BigFace-Distill

Training Details

- The data-parallelism for the feature-extraction network, and model-parallelism for the faceclassification weights.
- In the model-parallelism, we adopted an idea from the PartialFC [1] (excluding sampling of classes).
- Micro-batching [2], Gradient-Checkpoint [3], ZeRO-Redundancy Optimizer [4], Mixed-Precision [5] on activation and gradient (including communication of the grad.) etc. were employed as need.
- Batch-size of 256 per each rank, LARS [6] optimizer, initial Learning Rate (LR) of 0.01 (Linear LR Scaling [7].), warm-up LR [7], weight-decay of 0.0005, multi-step LR scheduling, and maximum epochs of 30 were set for all training sessions.
- All models were trained on the PyTorch1.8 framework. Training sessions were conducted on 32~64 NVIDIA's Tesla V100 GPU cards.

[1] X. An et. al, Partial FC: Training 10 Million Identities on a Single Machine, arXiv:2010.05222v2, 2021

[2] E. Hoffer et. al, Train longer, generalize better: closing the generalization gap in large batch training of neural networks, arXiv:1705.08741v2, 2018

[3] T. Chen et. al, Training Deep Nets with Sublinear Memory Cost, arXiv:1604.06174v2, 2016

[4] S. Rajbhandari et. al, ZeRO: Memory Optimizations Toward Training Trillion Parameter Models, arXiv:1910.02054v3, 2020

[5] S. Narang et. al, Mixed Precision Training, ICLR, 2018

^[6] Y. You et. al, Large Batch Training of Convolutional Networks, arXiv:1708.03888v3, 2017 [7] P. Goyal et. al, Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour, arXiv:1706.02677v2, 2018



The "BigFace" paradigm is still ongoing research and we plan to be published shortly.

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