Representative publications:

Mei Wang, Weihong Deng, Jiani Hu, Xunqiang Tao, and Yaohai Huang. "Racial faces in the wild: Reducing racial bias by information maximization adaptation network." In *Proceedings of the ieee/cvf international conference on computer vision*, pp. 692-702. 2019.

Representative citations:

1) **Iyad Rahwan**, Director of the Center for Humans and Machines at the Max-Planck Institute for Human Development and tenured professor at MIT, in his paper presented at AAAI Workshop 2020, calls our proposed RFW database a valuable resource for exploring the use of diversity to improve facial biometrics (valuable resources), and suggests that our work will be used as a guide in the future.

Algorithmic Discrimination: Formulation and Exploration in Deep Learning-based Face Biometrics

Ignacio Serna,[1] **Aythami Morales,**[1] **Julian Fierrez,**[1] **Manuel Cebrian,**[2] **Nick Obradovich,**[2] **Iyad Rahwan**[2]
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Recently, diverse and discrimination-aware databases have been proposed in (Buolamwini and Gebru 2018; Merler et al. 2019; Wang and Deng 2019). These databases are to demographic groups. Future work will go in line with this approach, as authors do in (Wang and Deng 2019).

Wang, M., and Deng, W. 2019. Mitigate Bias in Face Recognition using Skewness-Aware Reinforcement Learning. *arXiv preprint arXiv:1911.10692*.

2) **Trevor Darrell**, Director of the PATH Research Center at UC Berkeley and co-founder of the Berkeley Artificial Intelligence Laboratory, in his paper published in arXiv: 2004.06524, evaluates our proposed RFW database as being **large** and **diverse** , and that its use can address the issue of Racial bias.

Contrastive Examples for Addressing the Tyranny of the Majority

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Lisa Anne Hendricks, DeepMind*
Trevor Darrell, UC Berkeley
Novi Quadrianto, University of Sussex

training. In computer vision, bias due to gender or ethnicity has been addressed via collecting large diverse datasets [34, 2, 47] and via learning a domain invariant representation [19]. Alvi et

discrimination, i.e. indirectly conditioning the classification on protected characteristics. Wang et al [47] learn to transfer knowledge from Caucasian (source) domain to other-race (target) domains via the maximum mean discrepancy (MMD) criterion.

[47] Mei Wang, Weihong Deng, Jiani Hu, Xunqiang Tao, and Yaohai Huang. Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In *International Conference on Computer Vision (ICCV)*, pages 692–702, 2019. 3

3) **Anil K. Jain**, a member of the American Academy of Engineering, a foreign member of the Chinese Academy of Sciences, and an international authority on pattern recognition, used our proposed RFW database to test the face recognition model in his paper published in ECCV 2020 , which is cited in a total of eight places in the paper, and evaluated that our method can reduce racial bias in face recognition。

Jointly De-biasing Face Recognition and Demographic Attribute Estimation

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den biases within training data. Wang *et al.* [57] propose a domain adaptation network to reduce racial bias in face recognition. They recently extended their work using reinforcement learning to find optimal margins of additive angular margin based loss functions for different races [56]. To our knowledge, no studies

56. Wang, M., Deng, W.: Mitigating bias in face recognition using skewness-aware reinforcement learning. In: CVPR (2020)
57. Wang, M., Deng, W., Hu, J., Tao, X., Huang, Y.: Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In: ICCV (2019)

4) **Rama Chellappa**, a member of the National Academy of Engineering, an IEEE life Fellow, and a professor at Johns Hopkins University, uses our proposed RFW database to test face recognition models in his paper published in arXiv: 2112.09786, and claims to be **inspired by**, along the lines of our proposed racial bias evaluation metric.

Distill and De-bias: Mitigating Bias in Face Verification using Knowledge Distillation

Prithviraj Dhar[1], Joshua Gleason[2], Aniket Roy[1], Carlos D. Castillo[1], P. Jonathon Phillips[3], Rama Chellappa[1]
[1]Johns Hopkins University, [2]Univ. of Maryland, College Park, [3]NIST

[26, 65, 66, 69, 70] explore the issue of racial bias in face recognition, and propose strategies to mitigate the same.

Training dataset: We use the BUPT-BalancedFace [65] dataset for training. For gender bias reduction, we cre-

light pairs, medium-medium pairs and dark-dark pairs. This measure is inspired by previous works such as [65, 69]. In

[65] M Wang and W Deng. Mitigating bias in face recognition using skewness-aware reinforcement learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9322–9331, 2020. 2, 4, 5, 7, 8, 9, 14, 15, 16, 17
[66] M Wang, W Deng, J Hu, X Tao, and Y Huang. Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 692–702, 2019. 1, 2

5) **Rama Chellappa**, a member of the American Academy of Engineering, an IEEE life Fellow, and a professor at Johns Hopkins University, in his paper published in ICCV 2021, states that our work discovers and **highlights** the problem of racial bias in face recognition and proposes algorithms to eliminate that bias。

PASS: Protected Attribute Suppression System for Mitigating Bias in Face Recognition

Prithviraj Dhar*[1], Joshua Gleason*[2], Aniket Roy[1], Carlos D. Castillo[1], Rama Chellappa[1]
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is gender-balanced. [38, 46] presents an evaluation datasets that is balanced in terms of race and provide the verification protocols for the same.

as race and gender. [46, 45, 21] highlight the issue of racial bias in face recognition, and propose strategies to mitigate the same. In the context of gender bias [5, 29], most ex-

[46] M Wang, W Deng, J Hu, X Tao, and Y Huang. Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 692–702, 2019. 2

6) **Maja Pantic**, Fellow of the Royal Academy of Engineering and Professor of Emotion and Computation at Imperial College, in her paper published in IJCV 2021, states that our work demonstrates that all existing state-of-the-art face recognition models are biased against skin colour。

Mitigating Demographic Bias in Facial Datasets with Style-Based Multi-attribute Transfer

Markos Georgopoulos[1] · James Oldfield[2] · Mihalis A. Nicolaou[2] · Yannis Panagakis[3] · Maja Pantic[1]

worse on darker-skinned females. Moreover, state-of-the-art face recognition models have been reported to demonstrate bias with regards to the age, gender, and skin tone of the input face (Serna et al. 2019; Wang et al. 2019; Nagpal et al. 2019). In most cases, these demographic disparities in model

Wang, M., Deng, W., Hu, J., Tao, X., & Huang, Y. (2019). Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In *Proceedings of the IEEE international conference on computer vision*, pp. 692–702.

7) **Jie Zhou**, IAPR Fellow and professor at Tsinghua University, cited our work continuously in his papers published in TPAMI 2022, ICCV 2021, CVPR 2021, etc., saying that our proposed database is popular (popular) measurement data, and pointing out that our work builds **better face recognition models by reducing the racial bias. face recognition models**.

Gait Recognition in the Wild: A Benchmark

Zheng Zhu[1*] Xianda Guo[2*] Tian Yang[2] Junjie Huang[2]
Jiankang Deng[3] Guan Huang[2] Dalong Du[2] Jiwen Lu[1†] Jie Zhou[1]
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models with less bias. Besides, recent de-bias researches in the biometrics community [59, 11, 58] may also alleviate this problem.

[58] Mei Wang and Weihong Deng. Mitigate bias in face recognition using skewness-aware reinforcement learning. *arXiv preprint arXiv:1911.10692*, 2019. 8

[59] Mei Wang, Weihong Deng, Jiani Hu, Xunqiang Tao, and Yaohai Huang. Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In *CVPR*, 2019. 8

WebFace260M: A Benchmark for Million-Scale Deep Face Recognition

Zheng Zhu, *Member, IEEE*, Guan Huang, Jiankang Deng, *Student Member, IEEE*, Yun Ye, Junjie Huang, *Member, IEEE*, Xinze Chen, Jiagang Zhu, Tian Yang, Dalong Du, Jiwen Lu, *Senior Member, IEEE*, and Jie Zhou, *Senior Member, IEEE*

enable FRUITS. Considering the COVID-19 coronavirus epidemic [28], [48] and reported biased face recognition deployments [31], [90], [91], three evaluation tasks are performed: Standard Face Recognition (SFR), Masked Face Recognition (MFR), and Unbiased Face Recognition (UFR). For MFR, we

[90] M. Wang and W. Deng, "Mitigate bias in face recognition using skewness-aware reinforcement learning," 2019, *arXiv:1911.10692*.

[91] M. Wang, W. Deng, J. Hu, X. Tao, and Y. Huang, "Racial faces in the wild: Reducing racial bias by information maximization adaptation network," in *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, 2019, pp. 692–702.

does gender. Following common practices [90] in the community, we adopt skewed error ratio (SER) and standard deviation (STD)

WebFace260M: A Benchmark Unveiling the Power of Million-Scale Deep Face Recognition

Zheng Zhu[1,2*] Guan Huang[2*] Jiankang Deng[3] Yun Ye[2] Junjie Huang[2]
Xinze Chen[2] Jiagang Zhu[2] Tian Yang[2] Jiwen Lu[1†] Dalong Du[2] Jie Zhou[1]
[1]Tsinghua University [2]XForwardAI [3]Imperial College London
{zhengzhu,lujiwen}@tsinghua.edu.cn {guan.huang,dalong.du}@xforwardai.com
j.deng16@imperial.ac.uk

8) In his paper published in Science Robotics 2020, Stanford assistant professor **Monroe Kennedy** states that our work demonstrates racial bias in the application programming interface for face recognition。

Robots are not immune to bias and injustice

Monroe Kennedy III is an Assistant Professor, Department of Mechanical Engineering, Stanford University, Stanford, CA, USA. Email: monroek@stanford.edu

trians with darker skin tones (*1*). Researchers have also shown that racial bias exists in commercial facial recognition application programming interfaces or APIs (*2*).

2. M. Wang, W. Deng, J. Hu, X. Tao, Y. Huang, Racial faces in the wild: Reducing racial bias by information maximization adaptation network, in *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, Seoul, Korea, 27 October to 2 November 2019.

Popular evaluations for face recognition including LFW families [26, 88, 63], CFP [49], AgeDB [37], RFW [70], MegaFace [29], IJB families [30, 74, 36] mainly target the pursuit of the accuracy, which have been almost saturated recently. In real-world application scenarconstruction, metrics and baselines results. Sampling balanced data and recent de-bias researches [70, 69, 18, 17] may alleviate this problem to some extent. For the ethics of

[69] Mei Wang and Weihong Deng. Mitigate bias in face recognition using skewness-aware reinforcement learning. *arXiv preprint arXiv:1911.10692*, 2019. 8

[70] Mei Wang, Weihong Deng, Jiani Hu, Xunqiang Tao, and Yaohai Huang. Racial faces in the wild: Reducing racial bias by information maximization adaptation network. In *CVPR*, 2019. 2, 6, 7, 8

9) **Li Fei-Fei**, a member of the National Academy of Engineering, a member of the National Academy of Medicine, and a member of the American Academy of Arts and Sciences, in his paper published in CVPR 2021, follows our proposed depth domain adaptive classification framework。

Scalable Differential Privacy with Sparse Network Finetuning

Zelun Luo Daniel J. Wu Ehsan Adeli Li Fei-Fei
Stanford University

dataset is small or specialized. To tackle this, we turn to the sizable corpus of work in domain adaptation. There are three main tracks of research in this area [50]: methods incentivizing the learning of domain-agnostic features via direct optimization [17], adversarial approaches [47, 25], and data-reconstruction approaches [6]. Most of these methods

[50] Mei Wang and Weihong Deng. Deep visual domain adaptation: A survey. *Neurocomputing*, 312:135–153, 2018.

10) **Andrew Zisserman**, Member of the Royal Academy of Sciences, **Alberto L. Sangiovanni-Vincentelli**, Member of the American Academy of Engineering, **Wenwu Zhu**, Member of the European Academy of Sciences, **Shuicheng Yan**, Member of the Academy of Engineering, Singapore, **Matti Pietikäinen**, Fuking-Sun Prize winner, **Luc Van Gool**, Mal Prize winner, and **Song-Chun Zhu**, Mal Prize winner, have all included our work as a representative article in their papers in the field of deep domain adaptation. Laureate **Luc Van Gool**, and Marr Laureate **Song-Chun Zhu** have all included our works as representative articles in the field of deep domain adaptation in their papers。

Learning to Discover Novel Visual Categories via Deep Transfer Clustering

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Our work is also related to metric learning [29, 30, 31] and domain adaptation [36]. Actually, we *build* on metric

[36] Mei Wang and Weihong Deng. Deep visual domain adaptation: A survey. *Neurocomputing*, 2018. 3

A Review of Single-Source Deep Unsupervised Visual Domain Adaptation

Sicheng Zhao, *Senior Member, IEEE*, Xiangyu Yue, *Graduate Student Member, IEEE*, Shanghang Zhang, Bo Li, Han Zhao, Bichen Wu, Ravi Krishna, Joseph E. Gonzalez, Alberto L. Sangiovanni-Vincentelli, *Fellow, IEEE*, Sanjit A. Seshia, *Fellow, IEEE*, and Kurt Keutzer, *Life Fellow, IEEE*

ods. Similar to [41]–[43], we focus on deep DA, but use a different taxonomy that provides different insights. There

[41] M. Wang and W. Deng, "Deep visual domain adaptation: A survey," *Neurocomputing*, vol. 312, pp. 135–153, Oct. 2018.

Auxiliary Learning with Joint Task and Data Scheduling

Hong Chen [1] **Xin Wang** [1 2] **Chaoyu Guan** [1] **Yue Liu** [1] **Wenwu Zhu** [1]

pendent dataset. The joint task-data consideration can make it handle some domain adaptation (Wang & Deng, 2018) or multimodal scenarios (Zhu et al., 2015; Wang et al., 2021a) with both task and data level adaptation.

Wang, M. and Deng, W. Deep visual domain adaptation: A survey. *Neurocomputing*, 312:135–153, 2018.

Learning Target-Domain-Specific Classifier for Partial Domain Adaptation

Chuan-Xian Ren, *Member, IEEE*, Pengfei Ge, Peiyi Yang, and Shuicheng Yan, *Fellow, IEEE*

of many practical cross-domain applications. To solve it, unsupervised domain adaptation (UDA) methods [8]–[12] try to transfer knowledge from a label-rich source domain to an unlabeled target domain. However, these methods need to

[11] M. Wang and W. Deng, "Deep visual domain adaptation: A survey," *Neurocomputing*, vol. 312, pp. 135–153, Oct. 2018.

Deep ladder reconstruction-classification network for unsupervised domain adaptation

Wanxia Deng[a], Zhuo Su[b], Qiang Qiu[c], Lingjun Zhao[a], Gangyao Kuang[a], Matti Pietikäinen[b], Huaxin Xiao[d], Li Liu[b,d,*]

main with a related but different distribution. Recently, the combination of DNNs and UDA has achieved remarkable improvements [6,7].

[7] M. Wang, W. Deng, Deep visual domain adaptation: a survey, Neurocomputing 312 (2018) 135–153.

Advances in deep concealed scene understanding

Deng-Ping Fan[1*], Ge-Peng Ji[2], Peng Xu[3], Ming-Ming Cheng[4], Christos Sakaridis[1] and Luc Van Gool[1]

ios is challenging. Recent practice demonstrates that various techniques can be used to alleviate this problem, e.g., domain adaptation [185, 186], transfer learning [187], few-shot learning [188], and meta-learning [189].

185. Wang, M., & Deng, W. (2018). Deep visual domain adaptation: a survey. *Neurocomputing, 312*, 135–153.

Graph-based Hierarchical Knowledge Representation for Robot Task Transfer from Virtual to Physical World

Zhenliang Zhang[1] Yixin Zhu[2] Song-Chun Zhu[2]

models to the physical world. In general, Sim2Real can be categorized into three different strategies: domain adaptation [13], [14], [15], system identification [16], and domain randomization [17]. This paper's focus is perpendicular to the

[15] M. Wang and W. Deng, "Deep visual domain adaptation: A survey," *Neurocomputing*, vol. 312, pp. 135–153, 2018.