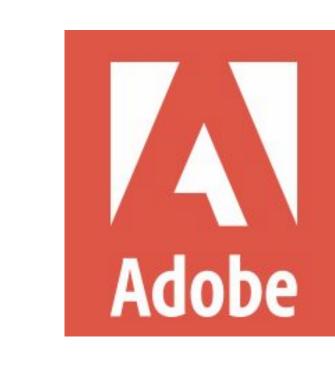


## Towards Fair Knowledge Distillation using Student Feedback

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**BIRD** learns bias-aware representations

from the teacher  $f_{\tau}$  by training the

a. In Stage I, BIRD updates a copy of

**b.** in Stage II, the updated model  $f_{C}$  is

**c.** in Stage III, the student model  $f_s$  is

distills unbiased representations using

used to train  $\phi$  with bias-feedback

meta-gradients from  $L_{outer}$ , and

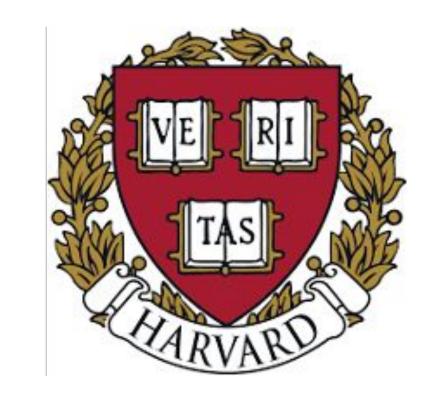
FAIRDISTILL (from Stage II).

FAIRDISTILL operator using a

the student model with  $L_{inner}$ ,

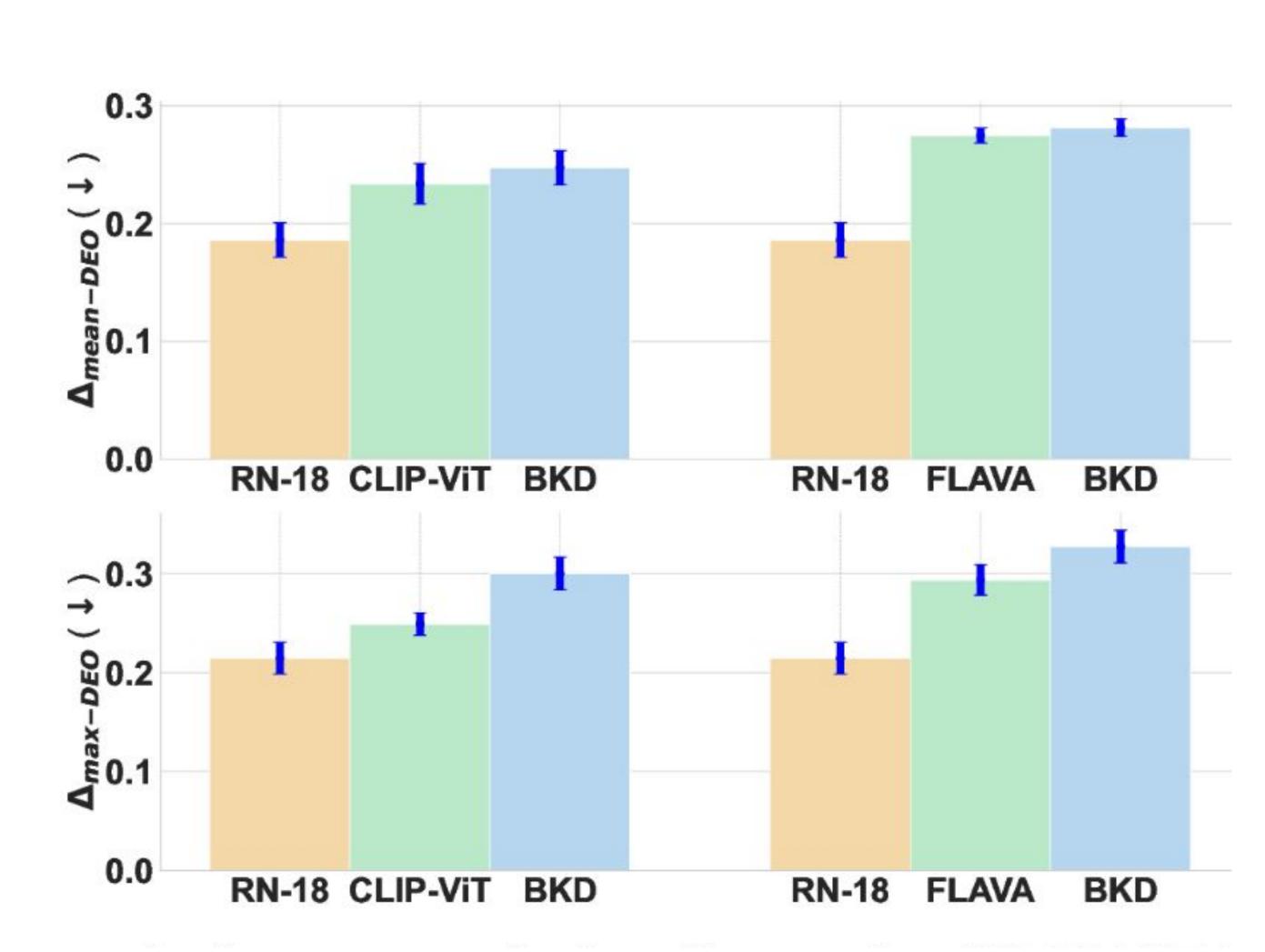
meta-learning framework:

information in the form of



## Fairness & Knowledge Distillation: How can we incorporate student feedback to perform Bias Aware Distillation?

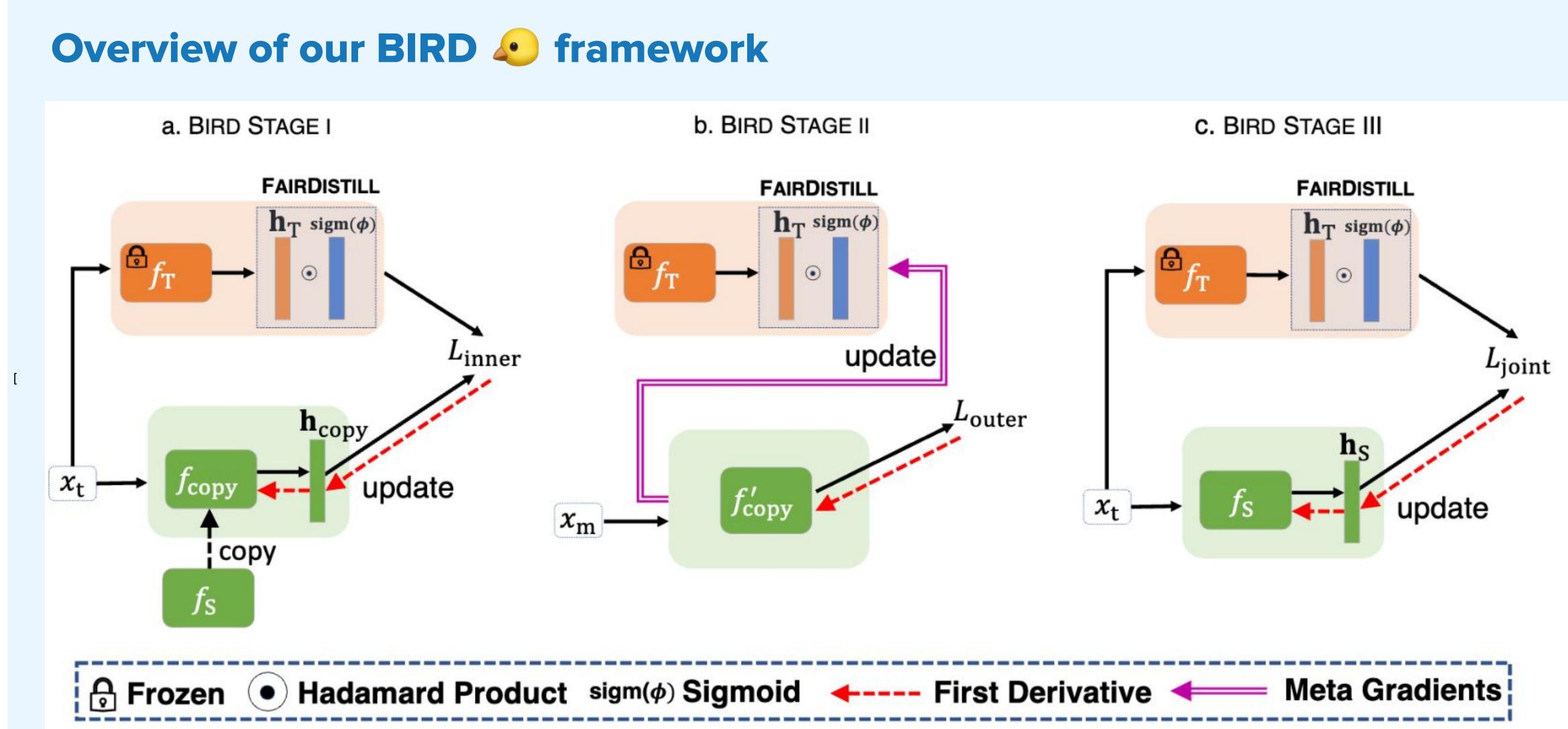
## Student mimics the fairness properties of the teacher



Fairness baseline teacher (CLIP-ViT/B32, FLAVA), baseline (ResNet-18), and distilled student models using base KD (BKD)

## **Problem Formulation**

Given a dataset **D**<sup>train</sup> and a biased teacher model  $f_{\tau}$  optimized for predictive performance on  $\mathbf{D}^{\mathrm{train}}$ , we aim to learn a student model  $f_{\varsigma}$ whose representations do not reflect any undesirable discriminatory biases (i.e., they are fair) and achieve high predictive performance (i.e., they are accurate).



a. BIRD STAGE I	b. BIRD STAGE II	c. BIRD STAGE III
FAIRDISTILL $h_{T} \operatorname{sigm}(\phi)$ $L_{inner}$ $x_{t}$ $f_{copy}$ $f_{s}$	FAIRDISTILL $h_T \operatorname{sigm}(\phi)$ update $f'_{copy}$	FAIRDISTILL $h_{T} \operatorname{sigm}(\phi)$ $L_{joint}$ $x_{t}$ $f_{S}$ $update$

<b>BIRD</b> improves	fairness	of knowledg	e distillation

Shown is the comparative performance of **BIRD** on CelebA Dataset (Left) for three foundation models and on CIFAR10-S dataset (Bottom) for ResNet18→ResNet18. Note that all results indicate avg. performance across five independent runs. Arrows (↑↓) indicate the direction of desired

performance. BIRD retains the predictive power (AUROC) of the baseline while improving fairness criterion (shaded).

Method	AUROC (†)	F1-score (†)	$\Delta_{ ext{mean-DEO}}(\downarrow)$	$\Delta_{ ext{max-DEO}}(\downarrow)$
Baseline	$98.91 \pm 0.02$	$88.34 \pm 0.17$	$26.26 \pm 0.70$	47.94±1.94
BKD	$98.95 \pm 0.02$	$88.90 \pm 0.13$	$25.30 \pm 0.63$	$46.92 \pm 2.16$
<b>FitNet</b>	$98.89 \pm 0.01$	$88.15 \pm 0.08$	$26.55 \pm 0.66$	$48.86 \pm 1.85$
AT	$98.99 \pm 0.02$	$88.95 \pm 0.12$	$25.16 \pm 0.33$	$46.08 \pm 2.27$
AD	$98.44 \pm 0.11$	$85.98 \pm 0.43$	$16.20 \pm 1.18$	<b>31.94</b> ±3.89
MFD	$98.93 \pm 0.03$	$88.32 \pm 0.10$	$27.27 \pm 0.34$	$49.16 \pm 1.62$
BIRD	$99.12 \pm 0.02$	$89.45 \pm 0.14$	$19.77 \pm 0.37$	$38.26 \pm 1.73$

Model	Method	AUROC (†)	$\Delta_{\text{mean-DEO}}(\downarrow)$	$\Delta_{\text{max-DEO}}(\downarrow)$
Flava	Baseline	$84.43 \pm 0.12$	$27.48 \pm 0.64$	29.37±1.53
	BKD	$84.42 \pm 0.11$	$27.39 \pm 0.58$	$29.36 \pm 1.41$
	<b>FitNet</b>	$84.47 \pm 0.10$	$26.59 \pm 0.62$	$28.56 \pm 0.68$
	AD	$84.35 \pm 0.05$	$10.54 \pm 0.80$	$12.93 \pm 0.79$
	MFD	$84.45 \pm 0.11$	$26.64 \pm 0.62$	$28.63 \pm 0.68$
	BIRD	$85.48 \pm 0.02$	$2.53 \pm 0.17$	$4.12 \pm 0.59$
CLIP- ViT/32	Baseline	87.01±0.26	23.38±1.72	24.91±1.15
	BKD	$87.07 \pm 0.26$	$23.26 \pm 1.67$	$24.62 \pm 1.14$
	FitNet	$87.17 \pm 0.13$	$22.84 \pm 1.03$	$24.17 \pm 1.22$
	AD	$88.20 \pm 0.17$	$17.02 \pm 1.03$	$17.82 \pm 0.97$
	MFD	$87.22 \pm 0.11$	$21.99 \pm 0.70$	$23.70 \pm 1.58$
	BIRD	$88.55 \pm 0.03$	$3.44 \pm 0.92$	<b>5.19</b> $\pm$ 1.06
CLIP- R50	Baseline	87.72±0.06	21.11±0.30	$21.97 \pm 0.41$
	BKD	$87.72 \pm 0.06$	$21.10 \pm 0.40$	$22.07 \pm 0.41$
	FitNet	$87.54 \pm 0.14$	$22.01 \pm 1.05$	$23.30 \pm 1.15$
	AD	$88.51 \pm 0.02$	$5.33 \pm 0.19$	$7.93 \pm 0.22$
	MFD	$87.49 \pm 0.12$	$22.56 \pm 0.56$	$23.52 \pm 0.33$
	BIRD	$87.93 \pm 0.01$	$2.65 \pm 0.29$	$4.49 \pm 0.48$