DGS-Net: Distillation-Guided Gradient Surgery for CLIP Fine-Tuning in AI-Generated Image Detection

Yan et al., ICML 2026 Spotlight

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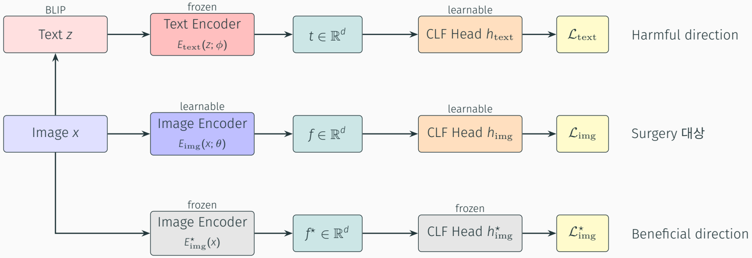
CLIP fine-tuning 시 역전파에서 gradient의 **방향을 수정**하여, 학습에 사용되지 않은 AI 이미지에 대한 **일반화 성능을 향상**시키는 방법을 제안.

- **문제 1:** Fine-tuning으로 인해 pre-trained representation이 손실되는 catastrophic forgetting.
- **문제 2:** 학습 데이터에서 label과 상관된 semantic 정보를 shortcut으로 하여 classifier가 학습되는 문제.

Method: Notation and Setup

- x: 입력 이미지
- $y \in \{0, 1\}$: 레이블 (real $= 0$, fake $= 1$)
- z: BLIP으로 생성한 x의 텍스트 설명
- $f = E_{\mathrm{img}}(x; \theta) \in \mathbb{R}^d$: 학습 중인 이미지 인코더의 feature
- $t = E_{\mathrm{text}}(z; \phi) \in \mathbb{R}^d$: 텍스트 인코더의 feature ($\phi$: frozen)
- $f^\star = E^\star_{\mathrm{img}}(x) \in \mathbb{R}^d$: frozen 이미지 인코더의 feature
- h_{img}, h_{text}, $h^\star_{\mathrm{img}}$: 각 인코더의 선형 분류 head
- $\mathcal{L}_{\mathrm{img}} = \ell(h_{\mathrm{img}}(f), y)$: 학습 중인 이미지 인코더 Loss (BCEWithLogits)
- $\mathcal{L}_{\mathrm{text}} = \ell(h_{\mathrm{text}}(t), y)$: 텍스트 인코더 Loss
- $\mathcal{L}^\star_{\mathrm{img}} = \ell(h^\star_{\mathrm{img}}(f^\star), y)$: frozen 이미지 인코더 Loss
- $g_{\mathrm{task}} = \nabla_f \mathcal{L}_{\mathrm{img}} \in \mathbb{R}^d$: 이미지 feature f에 대한 task gradient
- $g_{\mathrm{text}} = \nabla_t \mathcal{L}_{\mathrm{text}} \in \mathbb{R}^d$: 텍스트 feature t에 대한 gradient
- $g_{\mathrm{img}} = \nabla_{f^\star} \mathcal{L}^\star_{\mathrm{img}} \in \mathbb{R}^d$: frozen feature $f^\star$에 대한 gradient

Method: DGS-Net Overview

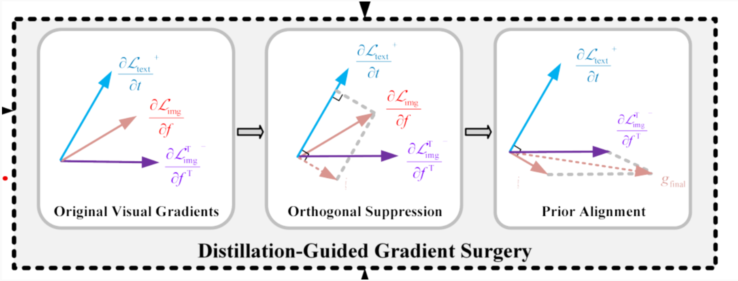


$\mathcal{L}_{\text{img}}$를 최소화하는 gradient descent 업데이트:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \frac{\partial \mathcal{L}_{\text{img}}}{\partial \theta} = \theta^{(t)} - \eta \left(\frac{\partial f}{\partial \theta}\right)^\top \frac{\partial \mathcal{L}_{\text{img}}}{\partial f}$$

$$g_{\text{final}} = \underbrace{\left(I - \hat{g}_{\text{harm}}\, \hat{g}_{\text{harm}}^\top\right) \frac{\partial \mathcal{L}_{\text{img}}}{\partial f}}_{\text{Projection}} + \underbrace{\lambda\, g_{\text{bene}}}_{\text{Add}}$$

Method: Distillation-Guided Gradient Surgery



$$g_{\text{final}} = \tilde{g} + \lambda\, g_{\text{bene}} = \left(I - \hat{g}_{\text{harm}}\, \hat{g}_{\text{harm}}^{\top}\right) \frac{\partial \mathcal{L}_{\text{img}}}{\partial f} + \lambda\, g_{\text{bene}}$$

- 역전파 시 $\frac{\partial \mathcal{L}_{\text{img}}}{\partial f}$를 g_{final}로 **교체**하여 파라미터 업데이트:

$$\theta^{(t+1)} = \theta^{(t)} - \eta \left(\frac{\partial f}{\partial \theta}\right)^{\top} g_{\text{final}}$$

Method: First-Order Approximation

임의의 feature 벡터 $u \in \mathbb{R}^d$와 loss $\mathcal{L}(u, y)$에 대해, u를 방향 e로 조금 움직였을 때의 loss를 1차(first-order) 근사하면:

$$\mathcal{L}(u + \varepsilon e,\, y) \approx \mathcal{L}(u, y) + \varepsilon \left\langle \nabla_u \mathcal{L}(u, y),\, e \right\rangle, \qquad (\varepsilon \to 0^+)$$

- 좌표 j 방향($e = e_j$)으로 보면:

$$\frac{\partial \mathcal{L}}{\partial u_j} > 0 \iff \mathcal{L}(u + \varepsilon e_j,\, y) > \mathcal{L}(u, y)$$

$\Rightarrow$ gradient가 **양수인 원소**는 그 축 방향의 perturbation이 loss를 **증가**시키고, **음수인 원소**는 loss를 **감소**시킴.

Method: Orthogonal Suppression

목적

Semantic 정보를 **전부 버리는 것이 아니라**, semantic 정보 중 detection task에 **도움이 되지 않는 성분(harmful direction)만 제거**.

- 이미지의 semantic 정보 추출: BLIP으로 이미지에 대응되는 캡션 z를 생성하고, text encoder에 넣어 text feature t를 추출.
- 텍스트 인코더 clf에서 feature gradient g_{text}를 계산한 뒤, 1차 근사에 따라 **loss를 증가시키는 양수 원소는 그대로 남기고, 음수 원소는 0**으로 매핑하여 g_{harm} 구성:

$$g_{\text{harm}} \triangleq [g_{\text{text}}]_+ \in \mathbb{R}^d, \qquad ([a]_+)_j = \max(a_j, 0)$$

- Task gradient를 g_{harm}의 **orthogonal space로 projection**:

$$\tilde{g} = \left(I - \hat{g}_{\text{harm}}\, \hat{g}_{\text{harm}}^\top\right) g_{\text{task}}, \qquad \hat{g}_{\text{harm}} = \frac{g_{\text{harm}}}{\|g_{\text{harm}}\|_2}$$

$\Rightarrow$ 업데이트 방향에서 harmful semantic 성분이 제거되어, task와 무관한 semantic 학습을 차단.

목적

Frozen 모델 기준으로 **loss를 감소시키는 방향**(beneficial direction)**을 학습에 함께 반영**하여, pre-trained feature 구조를 보존하고 catastrophic forgetting 방지.

- Frozen image encoder branch에서 feature gradient g_{img}를 계산한 뒤, **음수 원소는 그대로, 양수 원소는** 0으로 매핑하여 g_{bene} 구성:

$$g_{\text{bene}} \triangleq [g_{\text{img}}]_{-} \in \mathbb{R}^{d}, \qquad ([a]_{-})_{j} = \min(a_{j}, 0)$$

- 앞의 projection **과정을 거친 벡터** $\tilde{g}$에 g_{bene}를 λ scale**로 더함**:

$$g_{\text{final}} = \tilde{g} + \lambda\, g_{\text{bene}}$$

Experiments: AIGCDetectBench (Table 1, 2)

Table 1. Cross-model Accuracy (Acc.)

Detection Method	Real Image	Generative Adversarial Networks							Other		Diffusion Models								mAcc.
		ProGAN	CycleGAN	BigGAN	StyleGAN	StyleGAN2	GauGAN	StarGAN	WFIR	Deepfake	SDv1.4	SDv1.5	ADM	GLIDE	Midjourney	Wukong	VQDM	DALLE2	
CNN-Spot (Wang et al., 2020)	99.0	95.3	18.7	1.8	36.5	22.0	2.5	23.1	1.1	29.3	55.9	55.6	1.8	4.8	5.2	27.6	0.7	4.5	29.0
UnivFD (Ojha et al., 2023)	92.3	98.9	90.5	79.2	55.7	48.7	91.1	96.9	92.8	26.9	96.3	96.0	12.7	75.6	61.2	84.7	45.6	62.3	72.7
FreqNet (Tan et al., 2024a)	89.9	99.4	57.1	51.0	75.1	67.5	9.9	88.4	95.4	35.8	99.9	99.8	37.7	78.9	80.8	98.0	34.1	88.8	71.7
NPR (Tan et al., 2024b)	99.3	98.9	29.3	16.5	67.1	58.7	1.7	6.5	7.9	0.1	100.0	99.9	26.5	69.2	71.0	97.7	15.4	89.8	53.1
Ladeda (Cavia et al., 2024)	99.8	99.7	7.2	29.0	95.6	98.3	4.9	0.0	19.2	0.1	100.0	99.9	27.3	79.7	88.8	97.9	15.5	92.4	58.6
AIDE (Yan et al., 2024a)	93.0	95.3	88.0	96.9	89.6	97.0	90.0	97.0	42.9	9.2	99.8	99.7	92.4	98.7	63.7	98.9	90.1	98.9	85.6
C2P-CLIP* (Tan et al., 2025)	99.8	100.0	99.8	99.8	72.2	78.0	87.7	100.0	34.9	67.6	100.0	99.9	50.5	73.3	28.4	99.7	93.3	98.1	82.4
DFFreq (Yan et al., 2026)	98.0	98.0	70.9	93.6	99.0	98.9	93.8	97.4	3.5	76.0	99.9	99.8	65.9	87.8	**94.8**	99.1	76.0	95.9	85.2
SAFE (Li et al., 2025b)	99.2	99.7	85.6	83.5	88.1	96.7	89.0	99.9	8.4	17.3	99.8	99.6	36.8	90.5	86.3	98.5	84.0	92.0	80.8
Effort (Yan et al., 2024b)	**99.8**	100.0	100.0	100.0	79.6	82.1	100.0	100.0	**99.9**	76.6	100.0	99.9	53.1	81.2	44.2	99.9	96.3	75.8	88.1
NS-Net (Yan et al., 2025b)	97.7	100.0	99.9	100.0	95.7	98.6	98.5	100.0	68.9	60.6	100.0	99.9	85.3	97.2	77.4	100.0	98.9	98.8	93.2
Ours	95.3	**100.0**	**100.0**	**100.0**	**99.5**	**99.8**	**100.0**	**100.0**	84.6	**96.7**	**100.0**	**99.9**	**95.2**	**99.0**	88.0	**100.0**	**99.7**	**99.6**	**97.6**

Table 2. Cross-model Average Precision (A.P.)

Detection Method	Generative Adversarial Networks							Other		Diffusion Models								mA.P.
	ProGAN	CycleGAN	BigGAN	StyleGAN	StyleGAN2	GauGAN	StarGAN	WFIR	Deepfake	SDv1.4	SDv1.5	ADM	GLIDE	Midjourney	Wukong	VQDM	DALLE2	
CNN-Spot(Wang et al., 2020)	99.9	91.0	59.2	94.8	94.2	86.1	82.5	65.5	74.2	97.6	97.6	66.6	83.1	80.4	88.9	57.0	87.8	84.3
UnivFD (Ojha et al., 2023)	99.9	96.2	94.7	90.9	91.1	97.6	99.7	83.0	83.5	99.3	99.1	65.2	95.3	91.7	97.4	87.2	89.8	91.9
FreqNet (Tan et al., 2024a)	100.0	97.5	87.9	95.9	94.2	54.0	100.0	57.0	88.5	99.9	99.9	73.9	94.1	94.4	99.1	74.9	92.3	88.4
NPR (Tan et al., 2024b)	100.0	98.6	79.4	98.6	99.6	71.3	97.6	65.5	92.5	100.0	99.9	74.1	97.4	97.8	99.9	81.5	99.3	91.4
Ladeda (Cavia et al., 2024)	100.0	99.0	89.5	100.0	100.0	96.4	90.3	93.6	92.6	95.5	95.8	84.8	96.6	93.5	93.0	84.5	93.9	94.0
AIDE (Yan et al., 2024a)	99.6	98.2	91.6	99.4	99.9	74.1	99.7	90.8	66.5	99.9	99.9	99.4	99.9	90.3	99.9	98.9	99.9	94.5
C2P-CLIP* (Tan et al., 2025)	100.0	100.0	99.9	99.3	99.7	98.8	100.0	99.6	98.3	100.0	100.0	96.3	98.9	90.4	100.0	99.9	100.0	98.8
DFFreq (Yan et al., 2026)	100.0	98.7	98.4	100.0	100.0	98.1	99.8	89.0	87.5	100.0	99.9	98.7	99.5	99.7	100.0	99.3	99.9	98.1
SAFE (Li et al., 2025b)	100.0	99.5	97.8	99.9	100.0	96.6	100.0	73.8	91.0	100.0	100.0	98.1	99.9	**99.9**	100.0	99.9	100.0	97.4
Effort (Yan et al., 2024b)	100.0	100.0	**100.0**	99.3	99.2	**100.0**	100.0	91.1	97.9	100.0	100.0	97.5	99.8	98.9	100.0	100.0	99.9	99.0
NS-Net (Yan et al., 2025b)	100.0	100.0	99.7	99.8	99.9	97.0	100.0	99.5	95.2	100.0	100.0	**100.0**	99.8	97.0	100.0	100.0	100.0	99.2
Ours	**100.0**	**100.0**	99.9	**100.0**	**100.0**	98.8	**100.0**	**99.8**	**98.3**	**100.0**	**100.0**	99.8	**100.0**	99.6	**100.0**	**100.0**	**100.0**	**99.8**

- 학습에 사용되지 않은 생성기(unseen generator)의 데이터에 대한 detection **일반화 성능** 검증.