







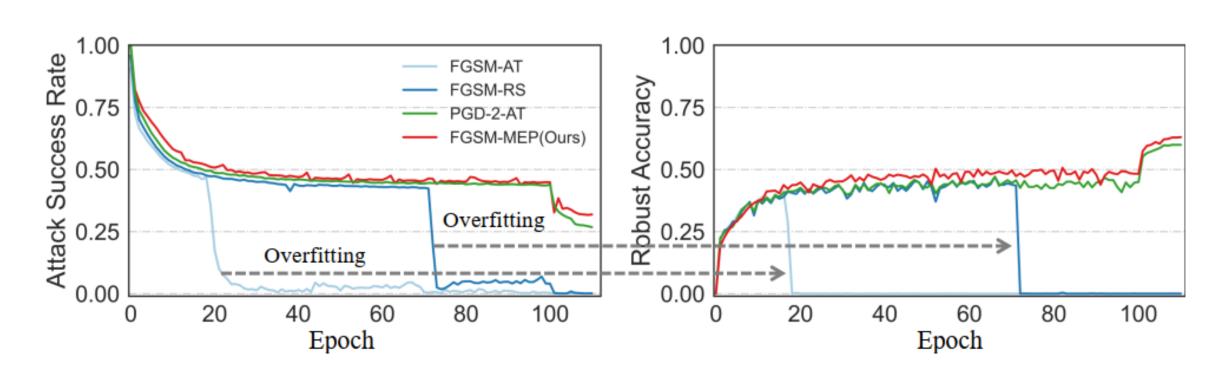
Prior-Guided Adversarial Initialization for Fast Adversarial Training

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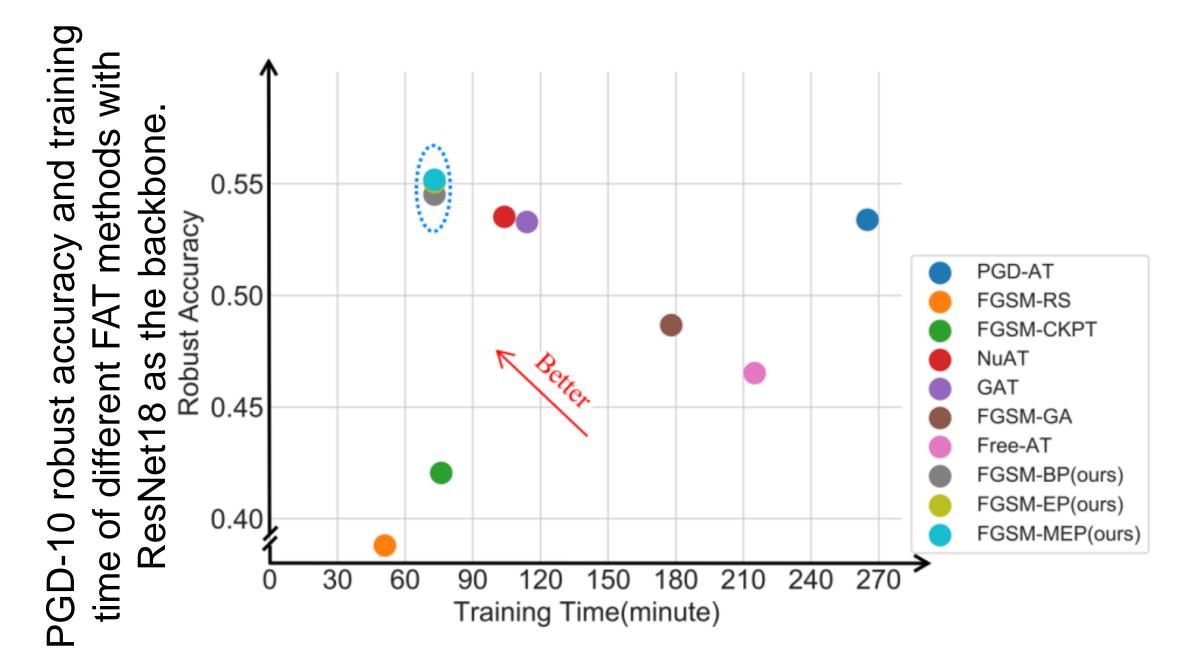
Motivation & Contribution



Motivation: We explore the difference between the training processes of standard adversarial training and fast adversarial training and observe that the attack success rate of adversarial examples (AEs) of fast adversarial training gets worse gradually in the late training stage, resulting in overfitting.

Contribution:

- We propose a prior-guided adversarial initialization to prevent overfitting after investigating several initialization strategies.
- ➤ We also propose a regularizer to guide the model learning for better robustness by considering both the currently generated perturbation and the prior-guided initialization.
- Extensive experiments on four datasets demonstrate that the proposed method can outperform state-of-the-art FAT methods in terms of both efficiency and robustness.



Comparisons of clean and robust accuracy (%) and training time (minute) on the CIFAR-10 dataset.

Method		Clean	PGD-10	PGD-20	PGD-50	C&W	AA	$\overline{\left \mathrm{Time}(\mathrm{min}) \right }$
FGSM-BP	Best	83.15	54.59	53.55	53.2	50.24	47.47	73
	Last	83.09	54.52	53.5	53.33	50.12	47.17	
FGSM-EP	Best	82.75	54.8	53.62	53.27	49.86	47.94	73
I GOWI-LI	Last	81.27	55.07	54.04	53.63	50.12	46.83	
FGSM-MEP	Best	81.72	55.18	54.36	54.17	50.75	49.00	73
	. —	81.72	55.18	54.36	54.17	50.75	49.00	

Methods

Prior From the Previous Batch (FGSM-BP): The adversarial perturbation can be defined as:

$$\boldsymbol{\delta}_{B_{t+1}} = \Pi_{[-\epsilon,\epsilon]} \left[\boldsymbol{\delta}_{B_t} + \alpha \cdot \operatorname{sign} \left(\nabla_{\mathbf{x}} \mathcal{L} (f(\mathbf{x} + \boldsymbol{\delta}_{B_t}; \mathbf{w}), \mathbf{y}) \right) \right],$$

Prior From the Previous Epoch (FGSM-EP): The adversarial perturbation can be defined as:

$$\boldsymbol{\delta}_{E_{t+1}} = \Pi_{[-\epsilon,\epsilon]} \left[\boldsymbol{\delta}_{E_t} + \alpha \cdot \operatorname{sign} \left(\nabla_{\mathbf{x}} \mathcal{L}(f(\mathbf{x} + \boldsymbol{\delta}_{E_t}; \mathbf{w}), \mathbf{y}) \right) \right],$$

Prior From the Momentum of All Previous Epochs (FGSM-MEP): The adversarial perturbation can be defined as:

$$\mathbf{g}_{c} = \operatorname{sign} \left(\nabla_{\mathbf{x}} \mathcal{L}(f(\mathbf{x} + \boldsymbol{\eta}_{E_{t}}; \mathbf{w}), \mathbf{y}) \right),$$

$$\mathbf{g}_{E_{t+1}} = \mu \cdot \mathbf{g}_{E_{t}} + \mathbf{g}_{c},$$

$$\boldsymbol{\delta}_{E_{t+1}} = \Pi_{[-\epsilon, \epsilon]} \left[\boldsymbol{\eta}_{E_{t}} + \alpha \cdot \mathbf{g}_{c} \right],$$

$$\boldsymbol{\eta}_{E_{t+1}} = \Pi_{[-\epsilon, \epsilon]} \left[\boldsymbol{\eta}_{E_{t}} + \alpha \cdot \operatorname{sign}(\mathbf{g}_{E_{t+1}}) \right].$$

The proposed regularization term can be added into the training loss to update the model parameters:

$$\mathbf{w}_{t+1} = \arg\min_{\mathbf{w}} \left[\mathcal{L}(f(\mathbf{x} + \boldsymbol{\delta}_{adv}; \mathbf{w}), \mathbf{y}) + \lambda \cdot \| f(\mathbf{x} + \boldsymbol{\delta}_{adv}; \mathbf{w}) - f(\mathbf{x} + \boldsymbol{\delta}_{pgi}; \mathbf{w}) \|_{2}^{2} \right],$$

Detailed algorithms of FGSM-MEP:

Algorithm 3 FGSM-MEP

Require: The epoch N, the maximal perturbation ϵ , the maximal label perturbation $\epsilon_{\mathbf{y}}$, the step size α , the dataset \mathcal{D} including the benign sample \mathbf{x} and the label \mathbf{y} , the dataset size M, the network $f(\cdot, \mathbf{w})$ with parameters \mathbf{w} , the decay factor μ , the hyper-parameter λ , the adversarial initialization set \mathcal{D}^{δ} and the historical model gradient \mathcal{D}^{m} .

```
1: for n = 1, ..., N do
                for i = 1, ..., M do
                          if n == 1 then
                                \delta_{pgi} = \mathbf{U}(-\epsilon, \epsilon)
                                 \mathbf{g}_c = \operatorname{sign}\left(\nabla_{\mathbf{x}_i} \mathcal{L}(f(\mathbf{x}_i + \boldsymbol{\delta}_{pgi}; \mathbf{w}), \mathbf{y}_i)\right)
                                 \mathcal{D}_i^m = \mathbf{g}_c
                                \delta_{adv} = \Pi_{[-\epsilon,\epsilon]}[\delta_{pgi} + \alpha \cdot \mathbf{g}_c]
                                 \mathcal{D}_i^{\delta} = \delta_{adv}
                                 \mathbf{w} \leftarrow \mathbf{w} - \nabla_{\mathbf{w}} [\mathcal{L}(f(\mathbf{x}_i + \boldsymbol{\delta}_{adv}; \mathbf{w}), \mathbf{y}_i) + \lambda \cdot ||f(\mathbf{x} + \boldsymbol{\delta}_{adv}; \mathbf{w}) - f(\mathbf{x} + \boldsymbol{\delta}_{pgi}; \mathbf{w})||_2^2]
                               \delta_{pgi} = \mathcal{D}_i^{\delta}
                                 \mathbf{g}_c = \operatorname{sign}\left(\nabla_{\mathbf{x}_i} \mathcal{L}(f(\mathbf{x}_i + \boldsymbol{\delta}_{pgi}; \mathbf{w}), \mathbf{y}_i)\right)
                                \mathcal{D}_i^m = \mu \cdot \mathcal{D}_i^m + \mathbf{g}_c
                                \boldsymbol{\delta}_{adv} = \Pi_{[-\epsilon,\epsilon]}[\boldsymbol{\delta}_{pgi} + \alpha \cdot \mathbf{g}_c]
                                \mathcal{D}_i^{\delta} = \Pi_{[-\epsilon,\epsilon]}[\delta_{pgi} + \alpha \cdot \operatorname{sign}(\mathcal{D}_i^m)]
                                  \mathbf{w} \leftarrow \mathbf{w} - \nabla_{\mathbf{w}} [\mathcal{L}(f(\mathbf{x}_i + \boldsymbol{\delta}_{adv}; \mathbf{w}), \mathbf{y}_i) + \lambda \cdot ||f(\mathbf{x} + \boldsymbol{\delta}_{adv}; \mathbf{w}) - f(\mathbf{x} + \boldsymbol{\delta}_{pgi}; \mathbf{w})||_2^2]
                         end if
                 end for
19: end for
```

Experiments & Results

Comparisons on CIFAR-10

Method		Clean	PGD-10	PGD-20	PGD-50	C&W	AA	Time(min)
PGD-AT 37	Best	82.32	53.76	52.83	52.6	51.08	48.68	265
	Last	82.65	53.39	52.52	52.27	51.28	48.93	
FGSM-RS 49	Best	73.81	42.31	41.55	41.26	39.84	37.07	51
1 0531-165 [12]	Last	83.82	00.09	00.04	00.02	0.00	0.00	
FGSM-CKPT 25	Best	90.29	41.96	39.84	39.15	41.13	37.15	76
	Last	90.29	41.96	39.84	39.15	41.13	37.15	
NuAT 42	Best	81.58	53.96	52.9	52.61	51.3	49.09	104
	Last	81.38	53.52	52.65	52.48	50.63	48.70	
GAT 41	Best	79.79	54.18	53.55	53.42	49.04	47.53	114
	Last	80.41	53.29	52.06	51.76	49.07	46.56	
FGSM-GA 2	Best	83.96	49.23	47.57	46.89	47.46	43.45	178
	Last	84.43	48.67	46.66	46.08	46.75	42.63	
Free-AT(m=8) 39	Best	80.38	47.1	45.85	45.62	44.42	42.17	215
		80.75	45.82	44.82	44.48	43.73	41.17	
FGSM-BP (ours)	Best	83.15	54.59	53.55	53.2	50.24	47.47	73
(0415)	Last	83.09	54.52	53.5	53.33	50.12	47.17	
FGSM-EP (ours)	Best	82.75	54.8	53.62	53.27	49.86	47.94	73
T GOM ET (Guis)	Last	81.27	55.07	54.04	53.63	50.12	46.83	
FGSM-MEP (ours)	Best	81.72	55.18	54.36	54.17	50.75	49.00	73
- Com man (ours)	Last	81.72	55.18	54.36	54.17	50.75	49.00	

Comparisons on Tiny ImageNet

Method		Clean	PGD-10	PGD-20	PGD-50	C&W	AA	Time(min)
PGD-AT 37	Best	43.6	20.2	19.9	19.86	17.5	16.00	1833
1 02 111 [22]	Last	45.28	16.12	15.6	15.4	14.28	12.84	
FGSM-RS 49	Best	44.98	17.72	17.46	17.36	15.84	14.08	339
1 0511-165 [10]	Last	45.18	0.00	0.00	0.00	0.00	0.00	
FGSM-CKPT 25	Best	49.98	9.20	9.20	8.68	9.24	8.10	464
	Last	49.98	9.20	9.20	8.68	9.24	8.10	
NuAT 42	Best	42.9	15.12	14.6	14.44	12.02	10.28	660
114111 [12]	Last	42.42	13.78	13.34	13.2	11.32	9.56	
GAT 41	Best	42.16	15.02	14.5	14.44	11.78	10.26	663
G.11 [11]	Last	41.84	14.44	13.98	13.8	11.48	9.74	
FGSM-GA 2	Best	43.44	18.86	18.44	18.36	16.2	14.28	1054
1 0011 011 [2]	Last	43.44	18.86	18.44	18.36	16.2	14.28	
Free-AT(m=8) 39	Best	38.9	11.62	11.24	11.02	11.00	9.28	1375
1100-111 (m=0) [<u>02</u>]		40.06	8.84	8.32	8.2	8.08	7.34	
FGSM-BP (ours)	Best	45.01	21.67	21.47	21.43	17.89	15.36	458
TOSHI DI (ouis)	Last	47.16	20.62	20.16	20.07	15.68	14.15	
FGSM-EP (ours)	Best	45.01	21.67	21.47	21.43	17.89	15.36	458
(1.11.12)	Last	46.00	20.77	20.39	20.28	16.65	14.93	<u> </u>
FGSM-MEP (ours)	Best	43.32	23.8	23.4	23.38	19.28	17.56	458
(" ")		45.88	22.02	21.7	21.6	17.44	15.50	

Comparisons on ImageNet

ImageNet	Epsilon	Clean	PGD-10	PGD-50	Time (hour
Free-AT(m=4)[39]		68.37 63.42 52.09	48.31 33.22 19.46	48.28 33.08 12.92	127.7
FGSM-RS 49	$\begin{array}{c c} \epsilon = 2 \\ \epsilon = 4 \\ \epsilon = 8 \end{array}$	67.65 63.65 53.89	48.78 35.01 0.00	48.67 32.66 0.00	44.5
FGSM-BP (ours)		68.41 64.32 53.96	36.24	49.10 34.93 14.33	63.7

Comparisons on CIFAR-100

Method		Clean	PGD-10	PGD-20	PGD-50	C&W	AA	Time(min)
PGD-AT 37	Best	57.52	29.6	28.99	28.87	28.85	25.48	284
	Last	57.5	29.54	29.00	28.90	27.6	25.48	
FGSM-RS 49	Best	49.85	22.47	22.01	21.82	20.55	18.29	70
1 00.11 100 [12]	Last	60.55	00.45	00.25	00.19	00.25	0.00	
FGSM-CKPT 25	Best	60.93	16.58	15.47	15.19	16.4	14.17	96
	Last	60.93	16.69	15.61	15.24	16.6	14.34	
NuAT 41	Best	59.71	27.54	23.02	20.18	22.07	11.32	115
	Last	59.62	27.07	22.72	20.09	21.59	11.55	
GAT 42	Best	57.01	24.55	23.8	23.55	22.02	19.60	119
	Last	56.07	23.92	23.18	23.0	21.93	19.51	
FGSM-GA 2	Best	54.35	22.93	22.36	22.2	21.2	18.88	187
	Last	55.1	20.04	19.13	18.84	18.96	16.45	
Free-AT(m=8) 39	Best	52.49	24.07	23.52	23.36	21.66	19.47	229
1100 111 (III - 0) [III]	Last	52.63	22.86	22.32	22.16	20.68	18.57	
FGSM-BP (ours)	Best	57.58	30.78	30.01	28.99	26.40	23.63	83
room Dr (ours)	Last	83.82	30.56	29.96	28.82	26.32	23.43	
FGSM-EP (ours)	Best	57.74	31.01	30.17	29.93	27.37	24.39	83
	<u>. </u>	57.74	31.01	30.17	29.93	27.37	24.39	
FGSM-MEP (ours)	Best	58.78	31.88	31.26	31.14	28.06	25.67	83
, ,	Last	58.81	31.6	31.03	30.88	27.72	25.42	

Comparisons with WideResNet34-10

CIFAR-10	Clean	PGD-10	PGD-20	PGD-50	AA	Time(h
PGD-AT 🔼	85.17	56.1	55.07	54.87	51.67	31.9h
FGSM-RS [12]	74.3	42.3	41.2	40.9	38.4	5.8h
FGSM-CKPT 5	91.8	44.7	42.6	42.2	40.4	8.7h
NuAT [11]	85.30	55.8	54.68	53.75	50.06	11.8h
GAT [10]	85.17	56.3	55.23	54.97	50.01	12.9h
FGSM-GA 🗓	82.1	48.9	47.1	46.9	45.7	20.3h
Free-AT 8	80.1	47.9	46.7	46.3	43.9	23.7h
FGSM-MEP(ours)	85.09	57.72	56.86	56.4	50.11	8.3h

Ablation study

CIFAR-10	Clean F	PGD-50	C&W	AA	Time(min)
FGSM-RS	Best 73.81	41.26	39.84	37.07	51
	Last 83.82	00.02	0.00	0.00	
GSM-BP w/o regularizer	Best 86.51	45.77	44.8	43.30	51
oon Di wyo regularizer	Last 86.57	44.39	43.82	42.08	
GSM-EP w/o regularizer	Best 85.97	45.97	44.6	43.39	51
,	Last 86.3	44.97	43.8	42.84	
GSM-MEP w/o regularize	Best 86.33	46.71	45.5	43.99	51
,	Last 86.61	45.69	44.8	43.26	
GSM-RS with regularizer	Best 84.41	50.63	48.76	46.80	73
	Last 84.41	50.63	48.76	46.80	
GSM-BP with regularizer	Best 83.15	53.2	50.24	47.47	73
	Last 83.09	53.33	50.12	47.17	
GSM-EP with regularizer	Best 82.75	53.27	49.86	47.94	73
	Last 81.27	53.63	50.12	46.83	
GSM-MEP with regularizer	Best 81.72	54.17	50.75	49.00	73
	Last 81.72	54.17	50.75	49.00	

Conclusion

- Prior-guided adversarial initialization: we propose to adopt historically generated adversarial perturbations to initialize adversarial examples.
- A simple yet effective regularizer: we also propose a simple yet effective regularizer to further improve model robustness, which prevents the current perturbation deviating too much from the prior-guided initialization.
- > Superiority: extensive experimental evaluations are performed on three benchmark databases to demonstrate the superiority of the proposed method.
- The code is released at https://github.com/jiaxiaojunQAQ/FGSM-PGI.

