Automatic Discovery of Adaptive Attacks on Adversarial Defenses

LatticeFlow

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Introduction

Adversarial defenses are proposed to address the problem of adversarial examples, but the authors of many defenses provide over-estimated robustness evaluation. These defenses are broken later with handcrafted adaptive attacks which are designed to reflect the defense mechanism, yet this approach requires strong domain expertise.

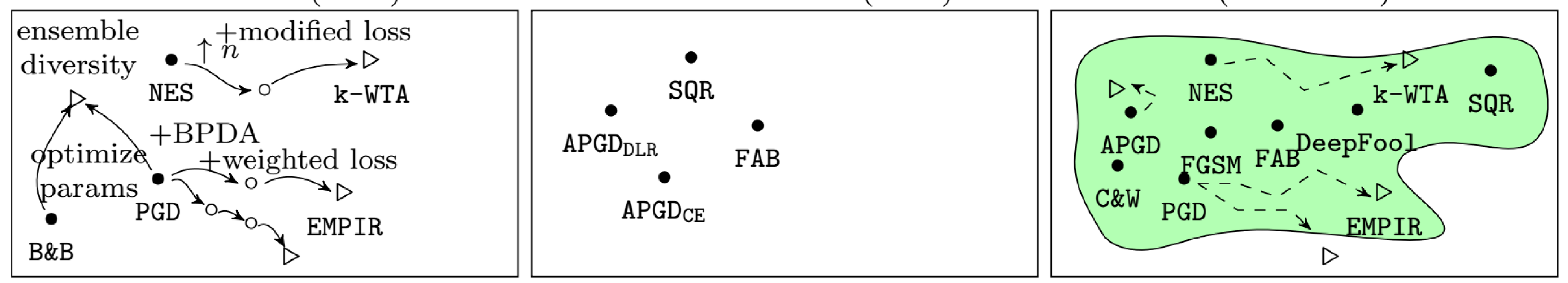
Our Work: We present an extensible tool A^3 that defines a search space over reusable blocks and automatically discovers an effective attack given the defense.

Motivation

Example Defenses	Robustness by authors		Handcrafted attacks (Tramer et al. 2020)
ME-Net (Yang et al. 2019)	53%	→	15%
Error Correcting Codes (Verma&Swami, 2019)	57%	→	5%
K-Winner Takes All (Xiao et al. 2020)	51%	→	0.2%

Our work: automate this adaptive process

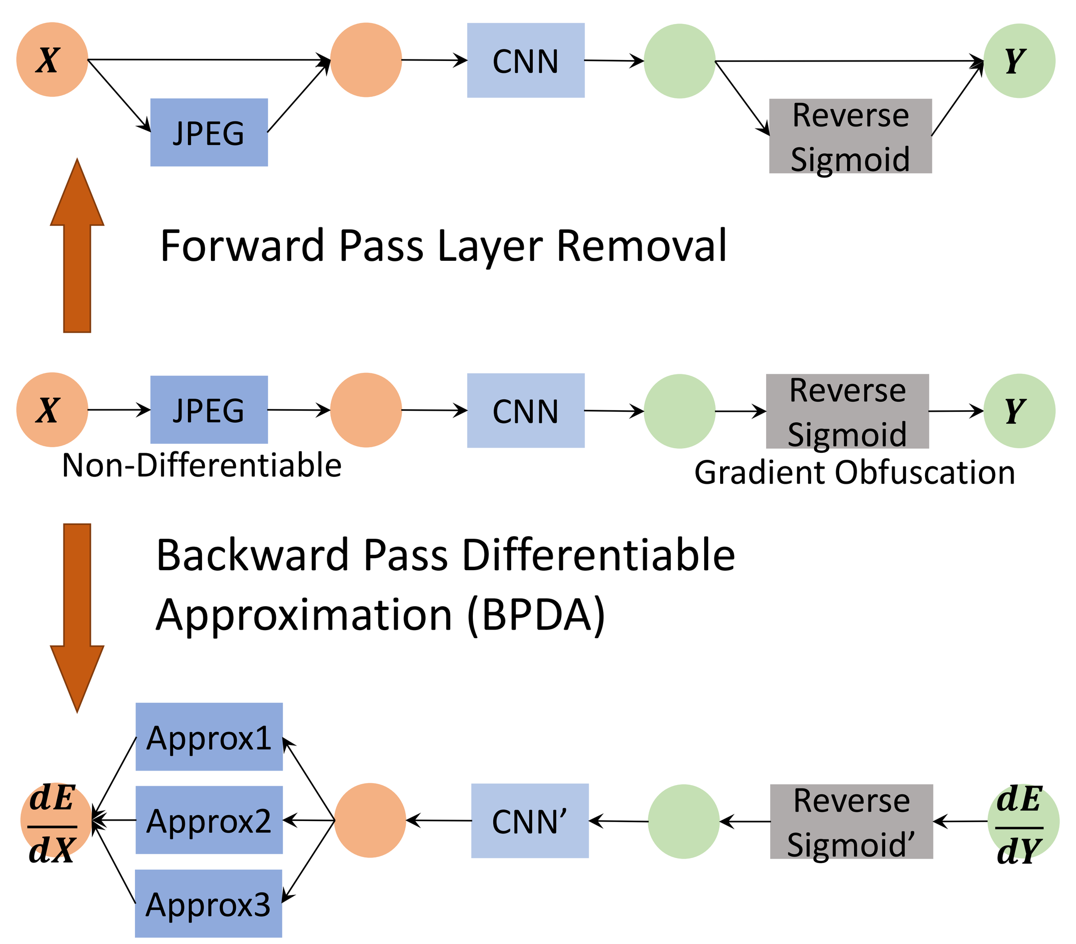
Robustness Evaluation Paradigms



Requires Manual Effort | Covers a Small Space | Automate the Manual Process

Network Transformation

X: Input, Y: Logits, E: Loss. Candidates: $4 \times 3 = 12$.



Attack Algorithms & Parameters

Space Formulation:

```
(Attack Search Space)
  𝕊 ::=  𝕊; 𝕊 | randomize 𝕊 | EOT 𝕊, n | repeat 𝕊, n |
         try 𝕊 for n | Attack with params with loss ∈ 𝕃
```

- 8 attacks in the search space - *FGSM, PGD, C&W, DeepFool, NES, APGD, FAB, SQR.*
- Generic Parameters - *Randomize, Repeat, EOT.*
- Attacks Specific Parameters.
- Sequence of Attacks - *Evaluate attacks sequentially and return the first adversarial examples found.*
- Try S for n - *set the runtime constraint for the attack to be n seconds.*

Loss Functions

Space Formulation:

```
(Loss Function Search Space)
  𝕃 ::=  targeted Loss, n with Z | untargeted Loss with Z |
         targeted Loss, n - untargeted Loss with Z
  Z ::=  logits | probs
Loss ::= CrossEntropy | HingeLoss | L1 | DLR | LogitMatching
```

- Difference between targeted and untargeted loss is the sign of the loss function.
- Logits/Probs means whether to add a softmax to logits.

Loss Functions

$$\ell_{\texttt{CrossEntropy}} = -\sum_{i=1}^{K} y_i \log(Z(x)_i)$$

$$\ell_{\texttt{HingeLoss}} = \max(-Z(x)_y + \max_{i \neq y} Z(x)_i, -\kappa)$$

(Carlini & Wagner, 2017)

$$\ell_{\text{L1}} = -Z(x)_y$$

$$\ell_{\text{DLR}} = -\frac{Z(x)_y - \max_{i \neq y} Z(x)_i}{Z(x)_{\pi_1} - Z(x)_{\pi_3}}$$

(Croce & Hein, 2020b)

$$\ell_{\texttt{LogitMatching}} = \|Z(x') - Z(x)\|_2^2$$

Results

- A^3 is evaluated on *23* diverse defenses.
- Compared with AutoAttack (AA), the state of art ensemble of fixed attacks (Croce and Hein 2020).
- *10* cases: **3.0%-50.8%** additional adversarial examples.
- *13* cases: ~**2x** faster attack time. AutoAttack contains expensive but ineffective attacks.

		Robust Accuracy (1 - Rerr)			Runtime (minutes)			Search
CIFAR-10, l_∞, $\epsilon = 4/255$		AA	A^3	Δ	AA	A^3	Speed-up	A^3
A1*	Stutz et al. (2020)	77.64	**26.87**	-50.77	101	205	0.49×	659
A2	Madry et al. (2018)	44.78	**44.69**	-0.09	25	20	1.25×	88
A3†	Buckman et al. (2018)	2.29	**1.96**	-0.33	9	7	1.29×	116
A4†	Das et al. (2017) + Lee et al. (2018)	0.59	**0.11**	-0.48	6	2	3.00×	40
A5	Metzen et al. (2017)	6.17	**3.04**	-3.13	21	13	1.62×	80
A6	Guo et al. (2018)	22.30	**12.14**	-10.16	19	17	1.12×	99
A7†	Ensemble of A3, A4, A6	4.14	**3.94**	-0.20	28	24	1.17×	237
A8	Papernot et al. (2015)	2.85	**2.71**	-0.14	4	4	1.00×	84
A9	Xiao et al. (2020)	19.82	**11.11**	-8.71	49	22	2.23×	189
A10	Xiao et al. (2020)$_{\text{ADV}}$	64.91	**17.70**	-47.21	157	2,280	0.07×	1,548
CIFAR-10, l_∞, $\epsilon = 8/255$								
B11*	Wu et al. (2020)$_{\text{RTS}}$	60.05	**60.01**	-0.04	706	255	2.77×	690
B12*	Wu et al. (2020)$_{\text{TRADES}}$	**56.16**	56.18	0.02	801	145	5.52×	677
B13*	Zhang and Wang (2019)	**36.74**	37.11	0.37	381	302	1.26×	726
B14	Grathwohl et al. (2020)	**5.15**	5.16	0.01	107	114	0.94×	749
B15	Xiao et al. (2020)$_{\text{ADV}}$	5.40	**2.31**	-3.09	95	146	0.65×	828
B16	Wang et al. (2019)	50.84	**50.81**	-0.03	734	372	1.97×	755
B17*	Wang et al. (2020)	50.94	**50.89**	-0.05	742	486	1.53×	807
B18*	Sehwag et al. (2020)	57.19	**57.16**	-0.03	671	429	1.56×	691
B19†	B11 + Defense in A4	60.72	**60.04**	-0.68	621	210	2.96×	585
B20†	B14 + Defense in A4	15.27	**5.24**	-10.03	261	79	3.30×	746
B21	B11 + Rand Rotation	49.53	**41.99**	-7.54	255	462	0.55×	900
B22	B14 + Rand Rotation	22.29	**13.45**	-8.84	114	374	0.30×	1,023
B23	Hu et al. (2019)	6.25	**3.07**	-3.18	110	56	1.96×	502

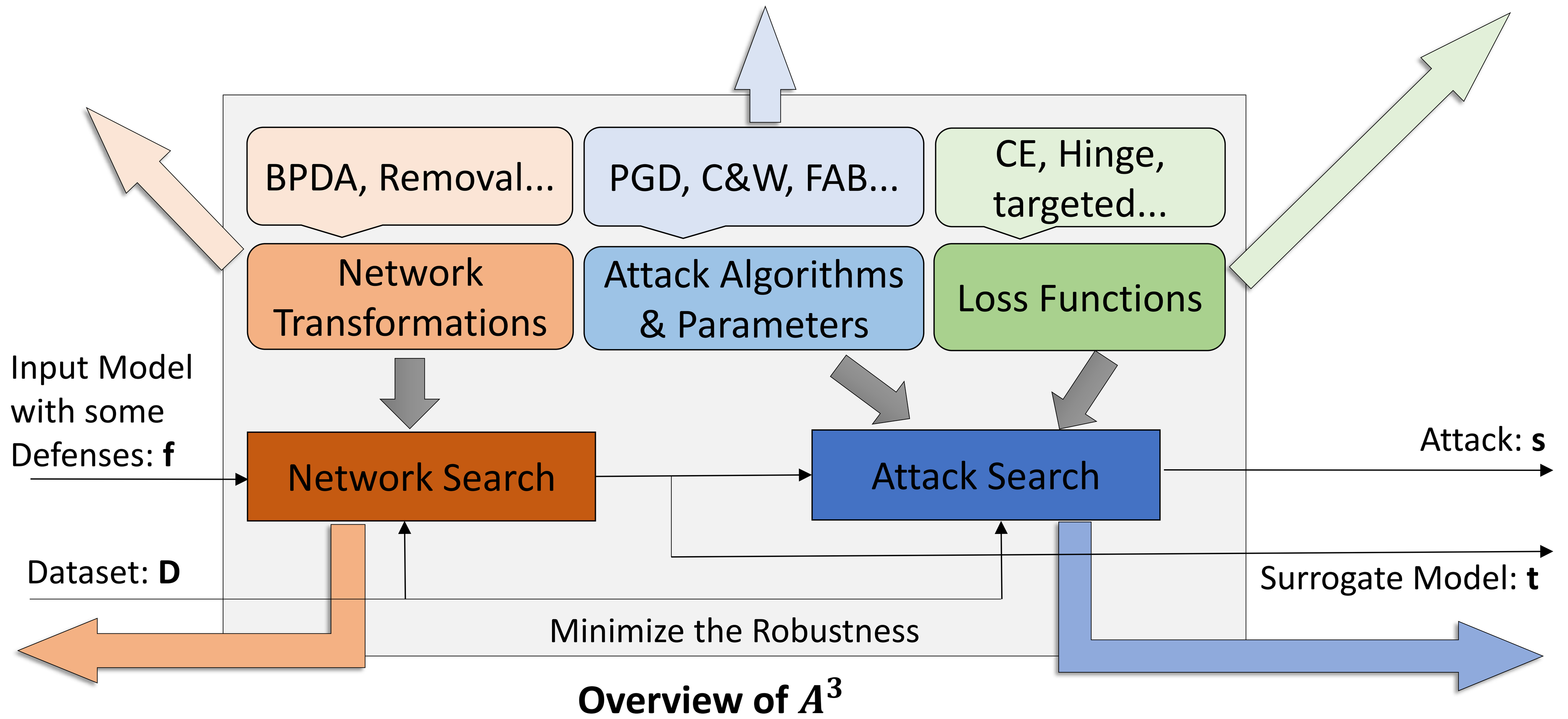
*model available from the authors, †model with non-differentiable components.

Network Search

Goal: Find the best surrogate model **t** to apply attack with. We use **t** to generate adversarial images but use **f** to evaluate.

Search: Exhaustive search. Use PGD as the test attack to evaluate each candidate.

Complexity: Cheap to perform



Overview of A^3

Attack Search

Goal: Find the best sequence of attacks **s**

Search: For number of attacks in the **s**, repeat 1-3 (Greedy):
1. Get a set of samples from **D** for attack evaluation
2. Use Tree Parzen Estimation to select attacks
3. Use Successive Halving to select the best attack

Complexity: We constrained the per sample attack runtime. The search time bound is 4/3 of the attack runtime bound.