Supplementary material: SMEBA Repository

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Brief introduction

SMEBA Repository is a software toolbox for boosting adversarial attack and defense research in pixel-to-pixel vision tasks. Notice that, there is another toolbox about adversarial attack and defense, called as *CleverHans* (Papernot et al. 2016). *CleverHans* focuses on image classification task. The proposed *SMEBA* Repository serves as a good complement to *CleverHans*, especially in the pixel-to-pixel tasks.

The content of SMEBA Repository

1) "Attack_methods_library.py"

In current version, *SMEBA* Repository integrates 14 gradient descent based adversarial attack methods in this script. Please see Table.1 for more details.

2) "Pretrained_models.py"

In current version, *SMEBA* Repository integrates 16 state-of-the-art source models, as shown in the Table. 2.

3) "Loss_functions.py"

In current version, *SMEBA* Repository supports 5 loss functions for evaluating the fooling ability, *i.e.* KL, CC, NSS, BCE and MAE losses, and 5 perceptual constraints for computing the perceptibility loss, *i.e.* L_1 norm, L_2 norm, L_∞ norm, SSIM and MS-SSIM.

4) "config_global.py"

This script defines some global variables, explained below. In current version, *SMEBA* Repository supports output-space attack, feature-space attack, hybrid-space (output-space & feature-space) attack, targeted attack, nontargeted attack, clipped box-constraint, and automatic box-constraint. Users can select their desired attack version in this script.

5) "options.py"

Users can select the guide image in this script, and define the saving path of produced visualization results.

6) "Main_Ensemble_Attack.py"

This script is the main function for ensemble attack that misleads multiple threat models simultaneously. Users can select any attack to mislead any combination of threat models from library. The adversarial example produced by en-

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semble attack gains the higher transferability under *black-box* attack setting..

7) "Main_Single_Image_Space_Attack.py"

This script is the main function for attacking single threat model from *output-space*.

8) "Main_Single_Feature_Space_Attack.py"

This script is the main function for attacking single threat model from *feature-space* and *hybrid-space*. *Hybrid-space* attack produces diverse adversarial examples, which could be used to boost the adversarial training.

9) "data"

This folder provides dataset alignment and image load functions.

10) "DCN_lib"

This folder provides a library for (modulated) 2D deformable convolution with CUDA acceleration.

11) supporting flexible visualization

In current version, *SMEBA* Repository provides a flexible visualization interface for users. Users can define the desired output (the intermediate feature maps across different layers) in "**Pretrained_models.py**" ("**return**" function of each threat model), and save the visualization results at the specific path defined in the main functions.

12) adversarial training defense

In current version, *SMEBA* Repository supports 2 defensive strategies, *i.e.* adversarial training (injecting the adversarial examples produced by output-space attasks into the training set), hybrid adversarial training (injecting the adversarial examples produced by output-space, and feature-space attasks into the training set). We will add another defense in the future, *i.e.* model distillation (using a pre-trained teacher model to supervise and boost the training of a student model).

References

Papernot, N.; Goodfollow, I.; Sheatsley, R.; Feinman, R.; and McDaniel, P. 2016. cleverhans v2. 0.0: an adversarial machine learning library. In *arXiv preprint*.

Table 1: The library of Gradient back-propagation based adversarial attack methods.

Number	Method	Gradient Descent Method	Frequency	Perceptual Constraint	Transferability	Goal	Dataset	Box-constraint	
$attack_1$	AdaEq2M	1_{st} -randn momentum &	Iterative	$L_1, L_2, L_{\infty},$	white-box &	Targeted &	SALICON, MIT1003	clipped	
		2_{nd} -plus momentum		SSIM, MS-SSIM	black-box	Non-targeted	CAT2000, DHF1K		
$attack_2$	Adam-decay-IM	Adam: vanilla 1_{st} momentum &	Iterative	$L_1, L_2, L_\infty,$	white-box &	Targeted &	SALICON, MIT1003	clipped	
		2_{nd} -decay momentum		SSIM, MS-SSIM	black-box	Non-targeted	CAT2000, DHF1K		
$attack_3$	Adam-vanilla-IM	Adam: vanilla 1_{st} momentum &	Iterative	$L_1, L_2, L_\infty,$	white-box &	Targeted &	SALICON, MIT1003	clipped	
		vanilla 2_{nd} momentum		SSIM, MS-SSIM	black-box	Non-targeted	CAT2000, DHF1K		
$attack_4$	MSGD-MIM		Iterative	$L_1, L_2, L_\infty,$	white-box &	Targeted &	SALICON, MIT1003	clipped	
		MSGD: vanilla 1_{st} momentum		SSIM, MS-SSIM	black-box	Non-targeted	CAT2000, DHF1K		
$attack_5$	SGD-IFGSM	SGD: no momentum	Iterative	$L_1, L_2, L_\infty,$	white-box	Targeted &	SALICON, MIT1003	clipped	
				SSIM, MS-SSIM		Non-targeted	CAT2000, DHF1K		
$attack_6$	SGD-IFGV	SGD: no momentum	Iterative	$L_1, L_2, L_\infty,$	white-box	Targeted &	SALICON, MIT1003	clipped	
				SSIM, MS-SSIM		Non-targeted	CAT2000, DHF1K		
	AdaGrad-plus-IM	AdaGrad: 2_{nd} -plus momentum	Iterative	$L_1, L_2, L_\infty,$	white-box	Targeted &	SALICON, MIT1003	-1:4	
$attack_7$				SSIM, MS-SSIM		Non-targeted	CAT2000, DHF1K	clipped	
1.	AdaGrad-decay-IM	AdaGrad: 2_{nd} -decay momentum	Iterative	$L_1, L_2, L_\infty,$	white-box	Targeted &	SALICON, MIT1003		
$attack_8$				SSIM, MS-SSIM		Non-targeted	CAT2000, DHF1K	clipped	
	AdaEq2M-V2	vanilla 1_{st} momentum &	Iterative	$L_1, L_2, L_\infty,$	white-box &	Targeted & SALICON, MIT1003	olin d		
$attack_9$		2_{nd} -plus momentum		SSIM, MS-SSIM	black-box	Non-targeted	CAT2000, DHF1K	clipped	
	Hot&Cold	SGD: no momentum	Iterative	SSIM	white-box		SALICON, MIT1003	clipped	
$attack_{10}$						Targeted	CAT2000, DHF1K		
$attack_{11}$	PGD	SGD: no momentum	Iterative	L_1, L_2, L_∞	white-box	Targeted &	SALICON, MIT1003	clipped	
		Start from a random state				Non-targeted	CAT2000, DHF1K		
$attack_{12}$	Adam-decay-C&W	Adam: only using short-term	Iterative	L_0, L_2, L_∞	white-box	Targeted &	SALICON, MIT1003	automatic	
		momentums				Non-targeted	CAT2000, DHF1K		
$attack_{13}$	AdaEq2M-C&W	1_{st} -randn momentum &	Iterative	L_0, L_2, L_∞	white-box	Targeted &	SALICON, MIT1003	automatic	
		2_{nd} -plus momentum				Non-targeted	CAT2000, DHF1K		
$attack_{14}$	proposed SMBEA	short-term momentums	Iterative	L_1, L_2, L_∞	white-box &	Targeted &	SALICON, MIT1003	clipped	
		long-term momentums			black-box	Non-targeted	CAT2000, DHF1K		

Table 2: The library of source models: state-of-the-art deep saliency models.

Number	Model	Backbone Network	bone Network Multi-scale Convolution Form Attention		Attention Module	Refinement	Adversarial Training
$model_1$	${ m GazeGAN_1}$	U-Net	Single-stream	Standard Convolution	Ø	Ø	Ø
$model_2$	$SALICON_2$	VGG16	Single-stream	Standard Convolution	Ø	Ø	Ø
$model_3$	Global-pix2pix	ResNet	Single-stream	Standard Convolution	Ø	Ø	Ø
$model_4$	${\rm GazeGAN_2}$	U-Net	Multi-stream	Standard Convolution	Ø	Ø	YES
$model_5$	DCN_LSTM_1	VGG16 & Inception-ResNet	Multi-stream	Standard Convolution &	Squeeze-and-Excitation &	ConvLSTM	Ø
				Modulated Deformable Convolution	Pyramid Spatial Attention		
$model_6$	DCN_2	VGG16 & Inception-ResNet	Multi-stream	Standard Convolution &	Squeeze-and-Excitation &	Ø	Ø
				Modulated Deformable Convolution	Pyramid Spatial Attention		
$model_7$	SAM_VGG_1	VGG16	Single-stream	Standard Convolution &	~	ConvLSTM	Ø
				Dilated Convolution	Ø		
$model_8$	SAM_VGG_2	VGG16	Single-stream	Standard Convolution &	0.0. 0.0144	ConvLSTM	Ø
				Dilated Convolution	Softmax Spatial Attention		
$model_9$	SAM_ResNet	ResNet	Single-stream	Standard Convolution &		ConvLSTM	YES
				Dilated Convolution	Softmax Spatial Attention		
$model_{10}$	CSC_Net	U-Net	Multi-stream	Standard Convolution	Softmax Spatial Attention	Ø	Ø
$model_{11}$	SalGAN_BCE	VGG16	Single-stream	Standard Convolution	Ø	Ø	Ø
$model_{12}$	DCN_Inception	Inception-ResNet	Single-stream	Standard Convolution	Ø	Ø	Ø
$model_{13}$	DeepGaze_only_VGG	VGG19	Single-stream	Standard Convolution	Ø	Ø	Ø
$model_{14}$	DCN_SAM_VGG	VGG19	Single-stream	Standard Convolution &		ConvLSTM	
				Modulated Deformable Convolution	Softmax Spatial Attention		Ø
$model_{15}$	Local-pix2pix	ResNet	Multi-stream	Modulated Deformable Convolution	Squeeze-and-Excitation &	Ø	Ø
					Pyramid Spatial Attention		
$model_{16}$	DenseSal	DenseNet	Single-stream	Standard Convolution	Ø	Ø	Ø