Perceptron Benchmark Documentation

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User Guide

Perceptron is a benchmark to test safety and security properties of neural networks for perceptual tasks.

It comes with support for many frameworks to build models including

- TensorFlow
- PyTorch
- Keras
- Cloud API
- PaddlePaddle (In progress)

See currently supported evaluation metrics, models, adversarial criteria, and verification methods in *Summary*.

See current *Leaderboard*.

CHAPTER 1

Overview

perceptron benchmark improves upon the existing adversarial toolbox such as cleverhans, foolbox, IBM ART, advbox in three important aspects:

- Consistent API design that enables easy evaluation of models across different deep learning **frameworks**, computer vision **tasks**, and adversarial **criterions**.
- Standardized metric design that enables DNN models' robustness to be compared on a large collection of **security** and safety properties.
- Gives verifiable robustness bounds for security and safety properties.

More specifically, we compare perceptron with existing DNN benchmarks in the following table:

Table 1: DNN Benchmarks Comparison

Properties	Perceptron	Cleverhans	Foolbox	IBM ART
Multi-platform support	✓	✓	✓	✓
Consistent API design	✓	·	✓	·
Custom adversarial criteria	✓	·	✓	·
Multiple perceptual tasks	✓	·	·	·
Standardized metrics	✓	·	✓	·
Verifiable robustness bounds	✓	·	·	·

Explanation of compared properties:

- Multi-platform support: supports at least the three deep learning frameworks, Tensoflow, PyTorch, and Keras.
- Consistent API design: implementations of evaluation methods are platform-agnostic. More specifically, the same piece of code for an evaluation method (e.g., a C&W attack) can run against models across all platforms (e.g., Tensorflow, PyTorch, and cloud API).
- Custom adversarial criterion: a criterion defines under what circumstances an (input, label) pair is considered an adversary. Customized adversarial criteria other than misclassification should be supported.

- Multiple perceptual tasks: supports computer vision tasks other than `classification`, e.g., `object detection` and `face recognition`.
- Standardized metrics: enables DNN models' robustness to be comparable on all **security** and **safety** properties.
- Verifiable robustness bounds: supports verification of certain safety properties. Returns either a verifiable bound, indicating that the model is robust against perturbations within that bound, or return counter-examples.

CHAPTER 2

Running benchmarks

You can run evaluation against DNN models with chosen parameters using `launcher`. For example:

```
python perceptron/launcher.py \
    --framework keras \
    --model resnet50 \
    --criteria misclassification\
    --metric carlini_wagner_l2 \
    --image example.png
```

In above command line, the user lets the framework as `keras`, the model as `resnet50`, the criterion as `misclassification` (i.e., we want to generate an adversary which is similar to the original image but has different predicted label), the metric as `carlini_wagner_l2`, the input image as `example.png`.

You can try different combinations of frameworks, models, criteria, and metrics. To see more options using *-h* for help message.

```
python perceptron/launcher.py -h
```

We also provide a coding example which serves the same purpose as above command line. Please refer to *Examples* for more details.

2.1 Examples

Here you can find a collection of examples.

2.1.1 Keras Framework

Keras: ResNet50 - C&W2 Benchmarking

This example benchmarks the robustness of ResNet50 model against $C\&W_2$ attack by measuring the minimal required L_∞ perturbation for a $C\&W_2$ attack to success. You can find the example in the file *example/keras_cw_example.py*.

Run the example with command *python example/keras_cw_example.py*

```python
from __future__ import absolute_import

import numpy as np
import keras.applications as models
from perceptron.models.classification.keras import KerasModel
from perceptron.utils.image import imagenet_example
from perceptron.benchmarks.carlini_wagner import CarliniWagnerL2Metric
from perceptron.utils.criteria.classification import Misclassification

# instantiate the model from keras applications
resnet50 = models.ResNet50(weights='imagenet')

# initialize the KerasModel
preprocessing = (np.array([104, 116, 123]), 1)  # the mean and stv of the whole dataset
kmodel = KerasModel(resnet50, bounds=(0, 255), preprocessing=preprocessing)

# get source image and label
# the model expects values in [0, 255], and channles_last
image, _ = imagenet_example(data_format='channels_last')
label = np.argmax(kmodel.predictions(image))
metric = CarliniWagnerL2Metric(kmodel, criterion=Misclassification())
adversary = metric(image, label, unpack=False)
```

By running the file *examples/keras_cw_example.py*, you will get the following output:

```
Summary:
Configuration: --framework keras --model resnet50 --criterion misclassification --metric carlini_wagner_l2
The predicted label of original image is otter
The predicted label of adversary image is weasel
Minimum perturbation required: normalized MSE = 2.01e-06
```

The command line tool *perceptron/launcher.py* provide users a way to play different combinations of frameworks and models without writing code. For example, the following command line serves the same purpose as above example.

```
python perceptron/launcher.py \
        --framework keras \
```

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```
        --model resnet50 \
        --criteria misclassification \
        --metric carlini_wagner_l2 \
        --image example.png
```

Keras: YOLOv3 - C&W2 Benchmarking (Object detection)

This example benchmarks the robustness of YOLOv3 model (the state-of-the-art object detection model) against $C\&W_2$ attack by measuring the minimal required L_∞ perturbation for a $C\&W_2$ attack to success. The minimum Mean Squred Distance (MSE) will be logged. You can find the example in the file *example/keras_cw_yolo_example.py*. Run the example with command *python example/keras_cw_yolo_example.py*

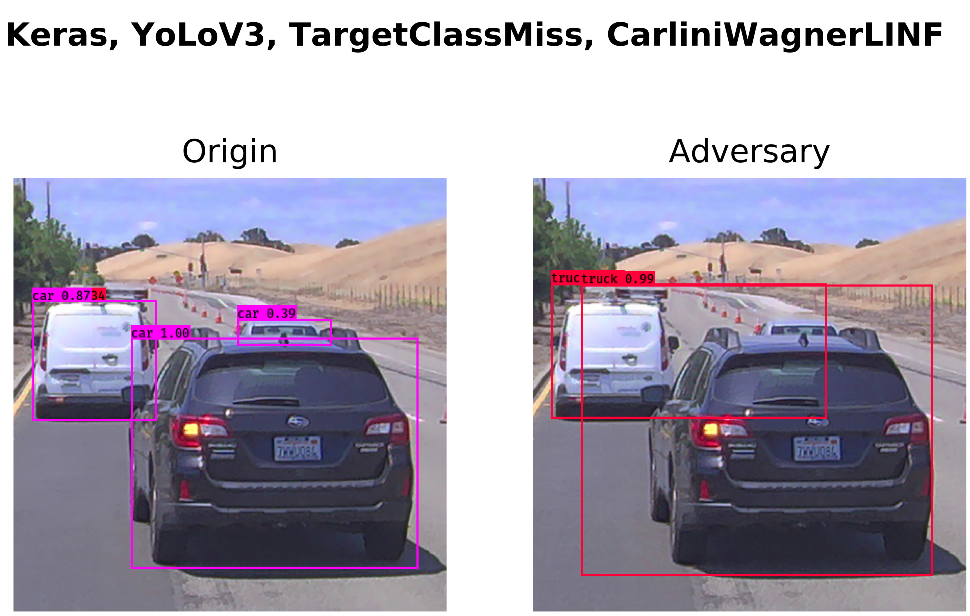
```python
from perceptron.zoo.yolov3.model import YOLOv3
from perceptron.models.detection.keras_yolov3 import KerasYOLOv3Model
from perceptron.utils.image import load_image
from perceptron.benchmarks.carlini_wagner import CarliniWagnerLinfMetric
from perceptron.utils.criteria.detection import TargetClassMiss

# instantiate the model from keras applications
yolov3 = YOLOv3()

# initialize the KerasYOLOv3Model
kmodel = KerasYOLOv3Model(yolov3, bounds=(0, 1))

# get source image and label
# the model expects values in [0, 1], and channles_last
image = load_image(shape=(416, 416), bounds=(0, 1), fname='car.png')
metric = CarliniWagnerLinfMetric(kmodel, criterion=TargetClassMiss(2))
adversary = metric(image, binary_search_steps=1, unpack=False)
```

The object detection results for the original image and the adversarial one is shown as follows.



In the following, we provide a command line which serves the same purpose as above piece of code.

```
python perceptron/launcher.py \
        --framework keras \
        --model yolo_v3 \
        --criteria target_class_miss --target_class 2 \
        --metric carlini_wagner_linf \
        --image car.png
```

The command line tool *perceptron/launcher.py* allows users to try different combinations of framework, model, criteria, metric and image without writing detailed code. In the following, we provide more API examples and their corresponding command lines.

Keras: VGG16 - Blended Uniform Noise

In this example, we try different model and metric. Besides, we choose *TopKMisclassification*. The K equals to 10 in this example. It means we want to generate an adversary whose predicted label is not among the top 10 highest possible predictions.

```
import numpy as np
import keras.applications as models
from perceptron.models.classification.keras import KerasModel
from perceptron.utils.image import imagenet_example
from perceptron.benchmarks.blended_noise import BlendedUniformNoiseMetric
from perceptron.utils.criteria.classification import TopKMisclassification

# instantiate the model from keras applications
vgg16 = models.VGG16(weights='imagenet')

# initialize the KerasModel
# keras vgg16 has input bound (0, 255)
preprocessing = (np.array([104, 116, 123]), 1)  # the mean and stv of the whole
↪dataset
kmodel = KerasModel(vgg16, bounds=(0, 255), preprocessing=preprocessing)

# get source image and label
# the model expects values in [0, 255], and channles_last
image, _ = imagenet_example(data_format='channels_last')
label = np.argmax(kmodel.predictions(image))
metric = BlendedUniformNoiseMetric(kmodel, criterion=TopKMisclassification(10))
adversary = metric(image, label, unpack=False, epsilons=100)  # choose 100 different
↪epsilon values in [0, 1]
```

The corresponding command line is

```
python perceptron/launcher.py \
        --framework keras \
        --model vgg16 \
        --criteria topk_misclassification \
        --metric blend_uniform_noise \
        --image example.png
```

By running the example file *examples/keras_bu_example.py*, you will get the output as follows.

```
Summary:
Configuration: --framework Keras --model VGG16 --criterion Top10Misclassification --metric BlendedUniform
The predicted label of original image is otter
The predicted label of adversary image is guinea pig, Cavia cobaya
Minimum perturbation required: normalized MSE = 3.43e-02
```

Keras: Xception - Additive Gaussion Noise

In this example, we show the performance of model *Xception* under the metric *Additive Gaussian Noise*.

```
import numpy as np
import keras.applications as models
from perceptron.models.classification.keras import KerasModel
from perceptron.utils.image import imagenet_example
from perceptron.benchmarks.additive_noise import AdditiveGaussianNoiseMetric
from perceptron.utils.criteria.classification import TopKMisclassification

# instantiate the model from keras applications
xception = models.Xception(weights='imagenet')

# initialize the KerasModel
# keras xception has input bound (0, 1)
mean = np.array([0.485, 0.456, 0.406]).reshape((1, 1, 3))
std = np.array([0.229, 0.224, 0.225]).reshape((1, 1, 3))
kmodel = KerasModel(xception, bounds=(0, 1), preprocessing=(mean, std))

# get source image and label
# the model Xception expects values in [0, 1] with shape (299, 299), and channles_last
image, _ = imagenet_example(shape=(299, 299), data_format='channels_last')
image /= 255.0
label = np.argmax(kmodel.predictions(image))
metric = AdditiveGaussianNoiseMetric(kmodel, criterion=TopKMisclassification(10))
adversary = metric(image, label, unpack=False, epsilons=1000)  # choose 1000 different epsilon values in [0, 1]
```

The corresponding command line is:

```
python perceptron/launcher.py \
        --framework keras \
```

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```
        --model xception \
        --criteria topk_misclassification \
        --metric additive_gaussian_noise \
        --image example.png
```

By runnig the corresponding example file *examples/keras_ag_example.py*, you will get the following output.

```
Summary:
Configuration: --framework Keras --model Xception --criterion Top10Misclassification --metric AdditiveGaussian
The predicted label of original image is otter
The predicted label of adversary image is meerkat, mierkat
Minimum perturbation required: normalized MSE = 4.33e-02
```

2.1.2 PyTorch Framework

Note: for the pytorch model, the range of the input image is always in $[0, 1]$.

PyTorch: ResNet18 - C&W Benchmarking

This example verifies the robustness of ResNet18 model against $C\&W_2$ by measuring the required L_2 pertubutation for a $C\&W_2$ attack to success. The example with more details can be found in the file *example/torch_cw_example.py*.

```python
import torch
import torchvision.models as models
import numpy as np
from perceptron.models.classification.pytorch import PyTorchModel
from perceptron.utils.image import imagenet_example
from perceptron.benchmarks.carlini_wagner import CarliniWagnerL2Metric
from perceptron.utils.criteria.classification import Misclassification

# instantiate the model
resnet18 = models.resnet18(pretrained=True).eval()
if torch.cuda.is_available():
    resnet18 = resnet18.cuda()
```

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```
# initialize the PyTorchModel
mean = np.array([0.485, 0.456, 0.406]).reshape((3, 1, 1))
std = np.array([0.229, 0.224, 0.225]).reshape((3, 1, 1))
fmodel = PyTorchModel(
    resnet18, bounds=(0, 1), num_classes=1000, preprocessing=(mean, std))

# get source image and label
image, label = imagenet_example(data_format='channels_first')
image = image / 255.  # because our model expects values in [0, 1]
metric = CarliniWagnerL2Metric(fmodel, criterion=Misclassification())
adversary = metric(image, label, unpack=False)
```

The corresponding command line is

```
python perceptron/launcher.py \
        --framework pytorch \
        --model resnet18 \
        --criteria misclassification \
        --metric carlini_wagner_l2 \
        --image example.png
```

By running the example file *example/torch_cw_example.py*, you will get the following output.

```
Summary:
Configuration: --framework PyTorch --model Resent18 --criterion Misclassification --metric CarliniWagnerL2
The predicted label of original image is otter
The predicted label of adversary image is weasel
Minimum perturbation required: normalized MSE = 8.92e-08
```

Above example shows that it is easy to fool a well-tuned classifier by adding small pertubation to the target.

PyTorch: VGG11 - SaltAndPepper Noise

In this example, we choose a different model and metric from above example. The detailed example file is at *examples/torch_sp_example.py*

```python
from __future__ import absolute_import
import torch
import torchvision.models as models
import numpy as np
from perceptron.models.classification.pytorch import PyTorchModel
from perceptron.utils.image import imagenet_example
from perceptron.benchmarks.salt_pepper import SaltAndPepperNoiseMetric
from perceptron.utils.criteria.classification import Misclassification

# instantiate the model
vgg11 = models.vgg11(pretrained=True).eval()
if torch.cuda.is_available():
    vgg11 = vgg11.cuda()

# initialize the PyTorchModel
mean = np.array([0.485, 0.456, 0.406]).reshape((3, 1, 1))
std = np.array([0.229, 0.224, 0.225]).reshape((3, 1, 1))
fmodel = PyTorchModel(
    vgg11, bounds=(0, 1), num_classes=1000, preprocessing=(mean, std))

# get source image
image, _ = imagenet_example(data_format='channels_first')
image = image / 255.  # because our model expects values in [0, 1]

# set the label as the predicted one
true_label = np.argmax(fmodel.predictions(image))
# set the type of noise which will used to generate the adversarial examples
metric = SaltAndPepperNoiseMetric(fmodel, criterion=Misclassification())
adversary = metric(image, true_label, unpack=False) # set 'unpack' as false so we can␣
↪access the detailed info of adversary
```

The corresponding command line is

```
python perceptron/launcher.py \
        --framework pytorch \
        --model vgg11 \
        --criteria misclassification \
        --metric salt_and_pepper_noise \
        --image example.png
```

By running the example file *example/torch_sp_example.py*, you will get the following output:

```
Summary:
Configuration: --framework PyTorch --model Vgg11 --criterion Misclassification --metric SaltAndPepper
The predicted label of original image is weasel
The predicted label of adversary image is black-footed ferret, ferret, Mustela nigripes
Minimum perturbation required: normalized MSE = 3.35e-05
```

The model *VGG11* does not produce the correct prediction at the beginning. By revising only two pixels, we are able to fool the classifier to make another wrong prediction.

PyTorch: ResNet18 - Brightness Verification

This example verifies the robustness of ResNet18 model against brightness variations, and it will give a verifiable bound. The detailed example file is at *examples/torch_br_example.py*


```
from __future__ import absolute_import

import torch
import torchvision.models as models
import numpy as np
from perceptron.models.classification.pytorch import PyTorchModel
from perceptron.utils.image import imagenet_example
from perceptron.benchmarks.brightness import BrightnessMetric
from perceptron.utils.criteria.classification import Misclassification

# instantiate the model
resnet18 = models.resnet18(pretrained=True).eval()
if torch.cuda.is_available():
    resnet18 = resnet18.cuda()

# initialize the PyTorchModel
mean = np.array([0.485, 0.456, 0.406]).reshape((3, 1, 1))
std = np.array([0.229, 0.224, 0.225]).reshape((3, 1, 1))
fmodel = PyTorchModel(
    resnet18, bounds=(0, 1), num_classes=1000, preprocessing=(mean, std))

# get source image and print the predicted label
image, _ = imagenet_example(data_format='channels_first')
image = image / 255.  # because our model expects values in [0, 1]

# set the type of noise which will used to generate the adversarial examples
metric = BrightnessMetric(fmodel, criterion=Misclassification())

# set the label as the predicted one
label = np.argmax(fmodel.predictions(image))

adversary = metric(image, label, unpack=False, verify=True)  # set 'unpack' as false so we can access the detailed info of adversary
```

The corresponding command line is

```
python perceptron/launcher.py \
        --framework pytorch \
```

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```
        --model resnet18 \
        --criteria misclassification \
        --metric brightness --verify\
        --image example.png
```

By running the example file *example/torch_sp_example.py*, you will get the following output:

```
Summary:
Configuration: --framework PyTorch --model ResNet18 --criterion Misclassification --metric Brightness
The predicted label of original image is otter
The predicted label of adversary image is giant panda, panda, panda bear, coon bear, Ailuropoda melanoleuca
Minimum perturbation required: normalized MSE = 1.01e-01
Verifiable bound: (2.0642983467839073, 0.08535178777230501)
```

user/../images/pytorch_resnet18_misclassification_brightn

In above figure, we only show the adversarial exampe when we increase the brightness. Let (L, U) denotes the verifiable bound. The value (L) (resp. U) means if we want to increase (resp. decrease) the brightness to generate adversary example, the minimal brightness pertubation we need is (L) (resp. U). (Note: brightness pertubation L means multiplying each pixel in the image with value L)

Caution: when using the verifiable metric, if the parameter *verify* is not set to *True*, the program will just slice the search space according to the epsilon value, not the minimal step the verifiable metric requires. Hence, the output verifiable bound has a wider range than the actual verifiable bound.

2.1.3 Cloud Framework

Cloud API: Google SafeSearch - Spatial Benchmarking

This example benchmarks the robustness of the SafeSearch API provided by Google cloud AI platform against spatial transformation attacks by attack by measuring the minimal required pixel-wise shift for a spatial attack to success.

```
from __future__ import absolute_import
from perceptron.utils.image import imagenet_example, load_image
from perceptron.models.classification.cloud import GoogleSafeSearchModel
from perceptron.benchmarks.contrast_reduction import ContrastReductionMetric
from perceptron.utils.criteria.classification import MisclassificationSafeSearch
import numpy as np
from perceptron.utils.tools import plot_image
from perceptron.utils.tools import bcolors


# before running the example, please set the variable GOOGLE_APPLICATION_CREDENTIALS␣
↪as follows
# export GOOGLE_APPLICATION_CREDENTIALS="[PATH]"
# replace [PATH] with the file path of the JSON file that contains your service␣
↪account key
# For more details, please refer to https://cloud.google.com/docs/authentication/
↪getting-started#auth-cloud-implicit-python
```

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```
model = GoogleSafeSearchModel()

# get source image and label
image = load_image(dtype=np.uint8, fname='porn.jpeg')
metric = ContrastReductionMetric(model, criterion=MisclassificationSafeSearch())
adversary = metric(image, epsilons=10, unpack=False)
```

The corresponding command line is

```
python perceptron/launcher.py \
        --framework cloud \
        --model google_safesearch \
        --criteria misclassification_safesearch \
        --metric contrast_reduction \
        --image porn.jpeg
```

Run the corresponding example file *examples/safesearch_noise_example.py* The information printed on the screen is:

```
Summary:
Configuration: --framework Cloud --model GoogleSafeSearch --criterion Misclassification --metric ContrastReduction
The predicted label of original image is {'adult': 5, 'spoof': 1, 'medical': 1, 'violence': 1, 'racy': 5}
The predicted label of adversary image is {'adult': 2, 'spoof': 1, 'medical': 1, 'violence': 1, 'racy': 3}
Minimum perturbation required: normalized MSE = 9.13e-02
```

Note: For each cloud model, we have a specific criterion. Here the criterion for *Google Safesearch* is *misclassification_safesearcha*.

2.2 Leaderboard

2.2.1 Salt & Pepper noise benchmarking

Robustness measured by the minimum perturbation required to successfully fool the model. Perturbation size measured by the Mean Squared Error (MSE) between adversarial and original image.

2.2.2 Rotation angle with verifiable Robustness

The prediction on test image is verifiable robust in the range of rotation angles indicated in the plot.

2.2.3 More being visualized and added

Coming Soon. . .

2.3 Summary

2.3.1 Supported attacks

2.3.2 Supported models

2.3.3 Supported adversarial criterions

2.3.4 Supported distance metrics

2.4 `perceptron.benchmarks`

2.4.1 Safety Metrics

2.4.2 Security Metrics

2.5 `perceptron.models`

2.5.1 Wrapper for Classification Models

2.5.2 Wrapper for Object Detection Models

2.5.3 Wrapper for Cloud API Models

2.6 `perceptron.utils.adversarial`

2.6.1 Adversarial for Classification Models

2.6.2 Adversarial for Object Detection Models

2.7 `perceptron.utils.criteria`

2.7.1 Detailed description

Criterial for Classification Models

Criterial for Object Detection Models

2.8 `perceptron.utils.distances`

CHAPTER 3

Indices and tables

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