# adversarial_crafts说明文档

161250098 彭俊杰

### 1.分类模型训练（Classifier）

为了考虑攻击算法在不同模型间的迁移性，我针对FashionMNIST数据集训练了两个层次结构存在差异的分类模型，其中fashionMNIST模型识别准确率差不多92%（训练数据未增强），cnn5模型识别准确率大约93%（对训练数据进行数据增强），其结构分别如下：

fashionMNIST:

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
Flatten_1 (Flatten)          (None, 784)               0
_________________________________________________________________
Reshape (Reshape)            (None, 28, 28, 1)         0
_________________________________________________________________
BatchNorm_1 (BatchNormalizat (None, 28, 28, 1)         4
_________________________________________________________________
Conv2D_1 (Conv2D)            (None, 28, 28, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 14, 14, 32)        0
_________________________________________________________________
Conv2D_2 (Conv2D)            (None, 12, 12, 64)        18496
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
dropout_2 (Dropout)          (None, 6, 6, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2304)              0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               590080
_________________________________________________________________
dropout_3 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                16448
_________________________________________________________________
BatchNorm_2 (BatchNormalizat (None, 64)                256
_________________________________________________________________
dense_last (Dense)           (None, 10)                650
=================================================================
Total params: 626,254
Trainable params: 626,124
Non-trainable params: 130
```

cnn5:

```
=================================================================
conv2d_11 (Conv2D)           (None, 28, 28, 32)        320
_________________________________________________________________
batch_normalization_17 (Batc (None, 28, 28, 32)        128
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 28, 28, 32)        9248
_________________________________________________________________
batch_normalization_18 (Batc (None, 28, 28, 32)        128
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 14, 14, 32)        0
_________________________________________________________________
dropout_18 (Dropout)         (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 12, 12, 64)        18496
_________________________________________________________________
batch_normalization_19 (Batc (None, 12, 12, 64)        256
_________________________________________________________________
dropout_19 (Dropout)         (None, 12, 12, 64)        0
_________________________________________________________________
conv2d_14 (Conv2D)           (None, 10, 10, 128)       73856
_________________________________________________________________
batch_normalization_20 (Batc (None, 10, 10, 128)       512
_________________________________________________________________
dropout_20 (Dropout)         (None, 10, 10, 128)       0
_________________________________________________________________
conv2d_15 (Conv2D)           (None, 8, 8, 256)         295168
_________________________________________________________________
batch_normalization_21 (Batc (None, 8, 8, 256)         1024
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 4, 4, 256)         0
_________________________________________________________________
dropout_21 (Dropout)         (None, 4, 4, 256)         0
_________________________________________________________________
flatten_4 (Flatten)          (None, 4096)              0
_________________________________________________________________
dense_9 (Dense)              (None, 512)               2097664
_________________________________________________________________
batch_normalization_22 (Batc (None, 512)               2048
_________________________________________________________________
dropout_22 (Dropout)         (None, 512)               0
_________________________________________________________________
dense_10 (Dense)             (None, 128)               65664
_________________________________________________________________
batch_normalization_23 (Batc (None, 128)               512
_________________________________________________________________
dropout_23 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_11 (Dense)             (None, 64)                8256
_________________________________________________________________
batch_normalization_24 (Batc (None, 64)                256
_________________________________________________________________
dropout_24 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_12 (Dense)             (None, 10)                650
=================================================================
```

### 2.失败探索（attack(failed).py）

在学习了GAN相关知识之后，准备借鉴其原理，尝试通过深度神经网络构建图片生成器，Generator直接向原始图片添加扰动生成对抗样本。大体设想如下：首先将之前训练好的分类模型作为Discriminator，冻结其各个层的权重（不在训练过程中变化），然后在输入之前添加若干个全连接层，用于调整原图片像素（添加扰动）；然后关键在于保持对抗样本与原始图片的相近性，最初我的做法是在作为generator的若干个全连接层中间均添加Lambda层（用clip对各个像素点的变化进行限制），不过由于keras模型构建的僵硬性，Lambda层在训练过程中被直接忽视了......于是我决定采取另一种做法，在自定义loss函数中添加ssim相关的项，不过又苦于无法取得ssim相关项与错误分类项的平衡，又只能放弃......

### 3.Github开源项目foolbox（依赖Python3,NumPy和SciPy库）

在研究对抗样本生成相关的论文及github开源项目时，偶然发现foolbox——IBM's Python toolbox to create adversarial examples（https://github.com/bethgelab/foolbox），通过查阅其使用手册，发现其提供了我之前看到的各种图像攻击算法的实现，截图如下：

## Gradient-based attacks

| | |
|---|---|
| `GradientAttack` | Perturbs the input with the gradient of the loss w.r.t. |
| `GradientSignAttack` | Adds the sign of the gradient to the input, gradually increasing |
| `FGSM` | alias of `foolbox.attacks.gradient.GradientSignAttack` |
| `LinfinityBasicIterativeAttack` | The Basic Iterative Method introduced in [R37dbc8f24aee-1]. |
| `BasicIterativeMethod` | alias of `foolbox.attacks.iterative_projected_gradient.LinfinityBas` |
| `BIM` | alias of `foolbox.attacks.iterative_projected_gradient.LinfinityBas` |
| `L1BasicIterativeAttack` | Modified version of the Basic Iterative Method that minimizes |
| `L2BasicIterativeAttack` | Modified version of the Basic Iterative Method that minimizes |
| `ProjectedGradientDescentAttack` | The Projected Gradient Descent Attack introduced in [R367e8 |
| `ProjectedGradientDescent` | alias of `foolbox.attacks.iterative_projected_gradient.ProjectedGra` |
| `PGD` | alias of `foolbox.attacks.iterative_projected_gradient.ProjectedGra` |
| `RandomStartProjectedGradientDescentAttack` | The Projected Gradient Descent Attack introduced in [Re6066 |
| `RandomProjectedGradientDescent` | alias of `foolbox.attacks.iterative_projected_gradient.RandomStartP` |
| `RandomPGD` | alias of `foolbox.attacks.iterative_projected_gradient.RandomStartP` |
| `MomentumIterativeAttack` | The Momentum Iterative Method attack introduced in [R86d3 |
| `MomentumIterativeMethod` | alias of `foolbox.attacks.iterative_projected_gradient.MomentumIter` |
| `LBFGSAttack` | Uses L-BFGS-B to minimize the distance between the input an |
| `DeepFoolAttack` | Simple and close to optimal gradient-based adversarial attack. |
| `NewtonFoolAttack` | Implements the NewtonFool Attack. |
| `DeepFoolL2Attack` | |
| `DeepFoolLinfinityAttack` | |
| `ADefAttack` | Adversarial attack that distorts the image, i.e. |
| `SLSQPAttack` | Uses SLSQP to minimize the distance between the input and t |
| `SaliencyMapAttack` | Implements the Saliency Map Attack. |
| `IterativeGradientAttack` | Like GradientAttack but with several steps for each epsilon. |
| `IterativeGradientSignAttack` | Like GradientSignAttack but with several steps for each epsilo |
| `CarliniWagnerL2Attack` | The L2 version of the Carlini & Wagner attack. |
| `DecoupledDirectionNormL2Attack` | The Decoupled Direction and Norm L2 adversarial attack from |
| `SparseFoolAttack` | A geometry-inspired and fast attack for computing sparse adv |

### Score-based attacks

| | |
|---|---|
| `SinglePixelAttack` | Perturbs just a single pixel and sets it to the min or max. |
| `LocalSearchAttack` | A black-box attack based on the idea of greedy local search. |
| `ApproximateLBFGSAttack` | Same as `LBFGSAttack` with approximate_gradient set to True. |

### Decision-based attacks

| | |
|---|---|
| `BoundaryAttack` | A powerful adversarial attack that requires neither gradients nor probabiliti |
| `SpatialAttack` | Adversarially chosen rotations and translations [1]. |
| `PointwiseAttack` | Starts with an adversarial and performs a binary search between the advers |
| `GaussianBlurAttack` | Blurs the input until it is misclassified. |
| `ContrastReductionAttack` | Reduces the contrast of the input until it is misclassified. |
| `AdditiveUniformNoiseAttack` | Adds uniform noise to the input, gradually increasing the standard deviatior |
| `AdditiveGaussianNoiseAttack` | Adds Gaussian noise to the input, gradually increasing the standard deviatic |
| `SaltAndPepperNoiseAttack` | Increases the amount of salt and pepper noise until the input is misclassifiec |
| `BlendedUniformNoiseAttack` | Blends the input with a uniform noise input until it is misclassified. |
| `BoundaryAttackPlusPlus` | A powerful adversarial attack that requires neither gradients nor probabiliti |

### Other attacks

| | |
|---|---|
| `BinarizationRefinementAttack` | For models that preprocess their inputs by binarizing the inputs, this attac |
| `PrecomputedAdversarialsAttack` | Attacks a model using precomputed adversarial candidates. |

通过对以上各种攻击算法的尝试，发现：

1.尽管Gradient-based类算法（FGSM,DeepFool...）具有极高的ssim(80~90)，但是对抗样本的迁移性极差，基于模型fashionMNIST生成的对抗样本就算能让fashionMNIST的正确预测类别概率降到0.1以下，却无法对模型cnn5的预测产生影响，依旧高达0.9......

2.Score-based类算法由于基于预测的梯度，在我梯度差异悬殊的两个分类模型fashionMNIST和cnn5上同样表现差强人意，对抗样本迁移性依旧不太行......

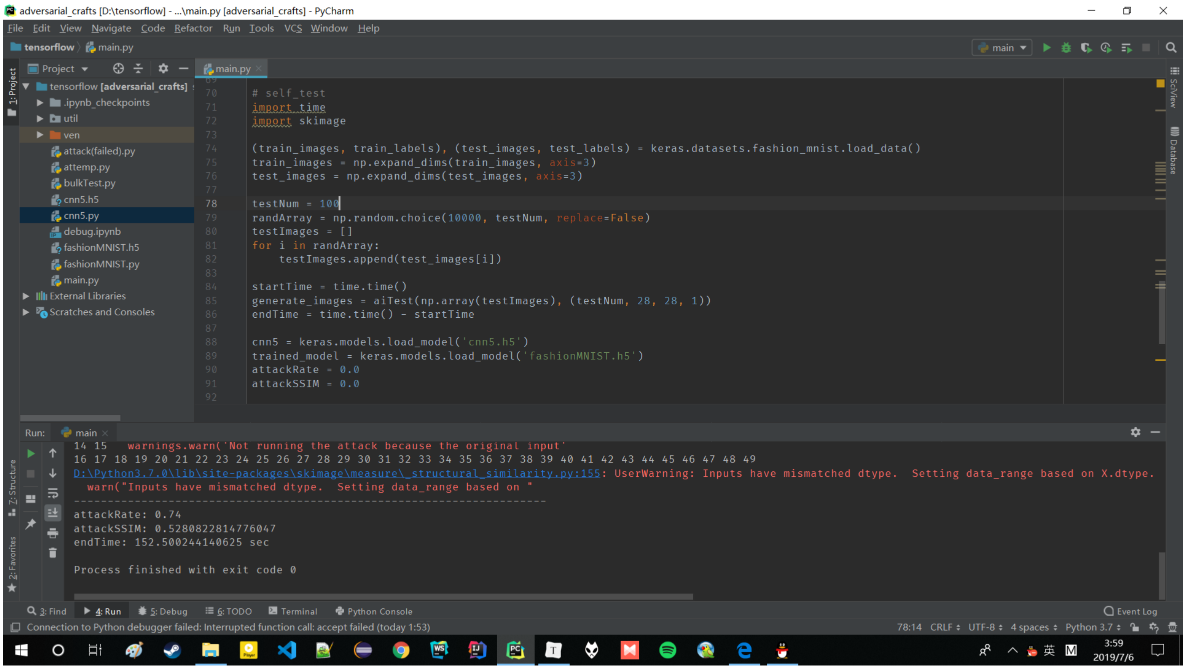
3.Other attacks是一些特殊情况下的攻击算法，同样不符合我的预期目标......

4.所幸Decision-based类算法对模型的依赖性并不强，对抗样本能较好地在模型间迁移。通过对比各个Decision-based算法生成的对抗样本的攻击成功率以及ssim指标，发现**AdditiveUniformNoiseAttack**及**AdditiveGaussianNoiseAttack**表现较好，最后通过反复对比，选择通过**AdditiveUniformNoiseAttack**实现我的adversarial_crafts，**AdditiveUniformNoiseAttack**通过向输入添加高斯噪声，逐渐增加标准偏差，直到输入被错误分类。在参考foolbox源码后，即将**AdditiveUniformNoiseAttack**代码实现整合为util包供项目使用。

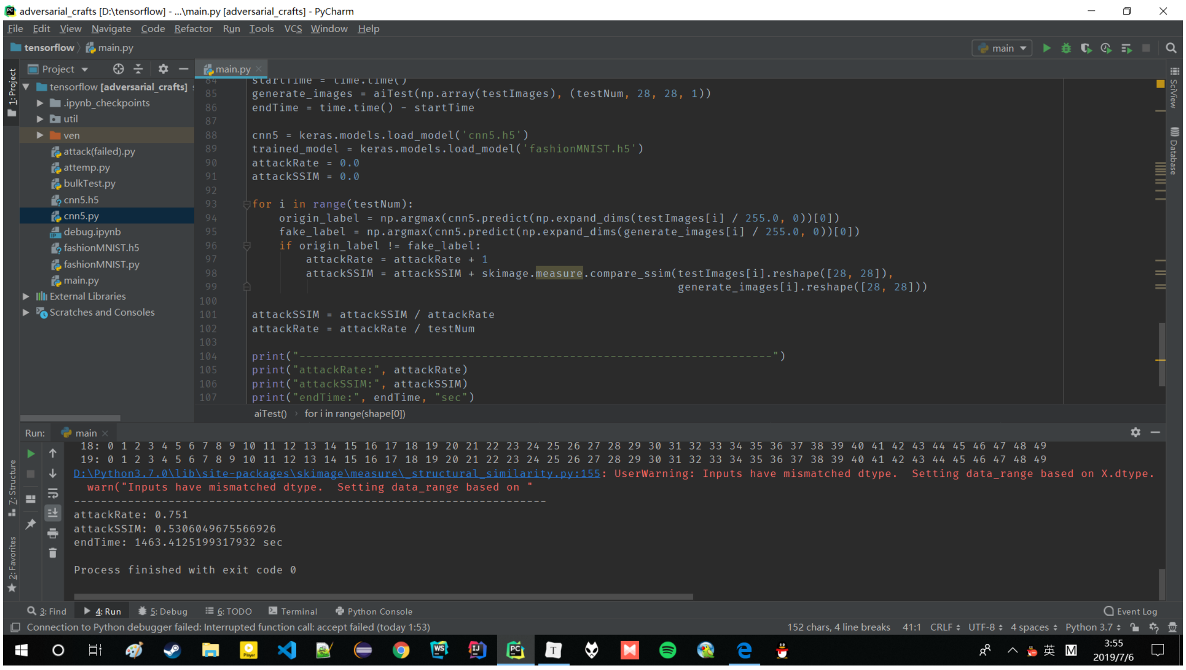
## 4.项目本地运行情况

**基于fashionMNIST模型利用AdditiveUniformNoiseAttack生成对抗样本，并在cnn5模型上进行迁移攻击：**

生成100张对抗样本结果：




测试1000张对抗图片结果：




ps：对抗样本生成时间约为 1.5s / 张