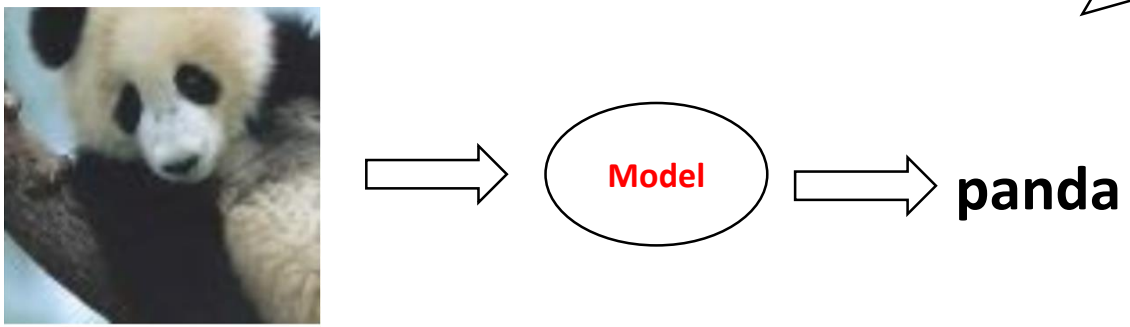
欺骗AI，从定向到实际

介绍人：汪嘉来

Part I：基于黑盒的定向攻击

背景

- DNNs正在被广泛引用，如图片分类、语音识别、恶意代码检测…



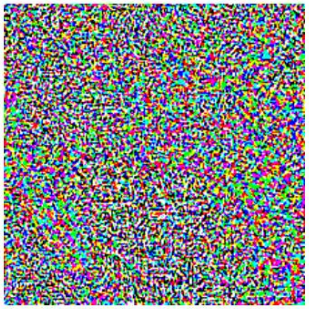
背景

- 神经网络很容易受到对抗样本的攻击：

$\boldsymbol{x}$

"panda"
57.7% confidence

$+ .007 \times$



$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"nematode"
8.2% confidence

$=$

$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"gibbon"
99.3 % confidence

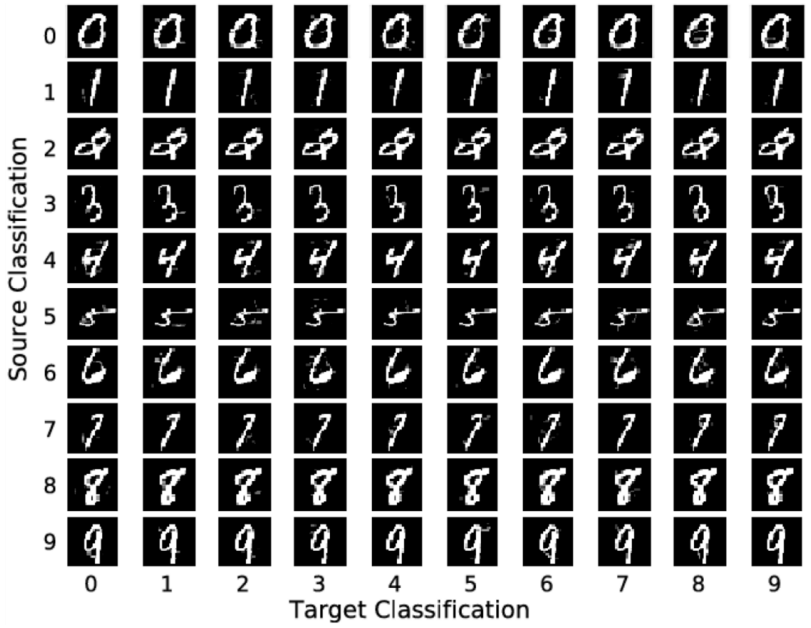
相关工作

- 白盒攻击：模型内部信息完全透明
  - Fast Gradient Sign(FGS)
  - Basic Iterative Method(BIM)
  - Jacobian-based Saliency Map Attack (JSMA)
  - Carlini & Wagner Attack (CW)
  - DeepFool

- 黑盒攻击：无法获取模型信息
  - Particle Swarm Optimization（PSO）
  - DE(Differential Evolution（DE）
  - ZOO
  - AutoZOO
  - Decision-based attack

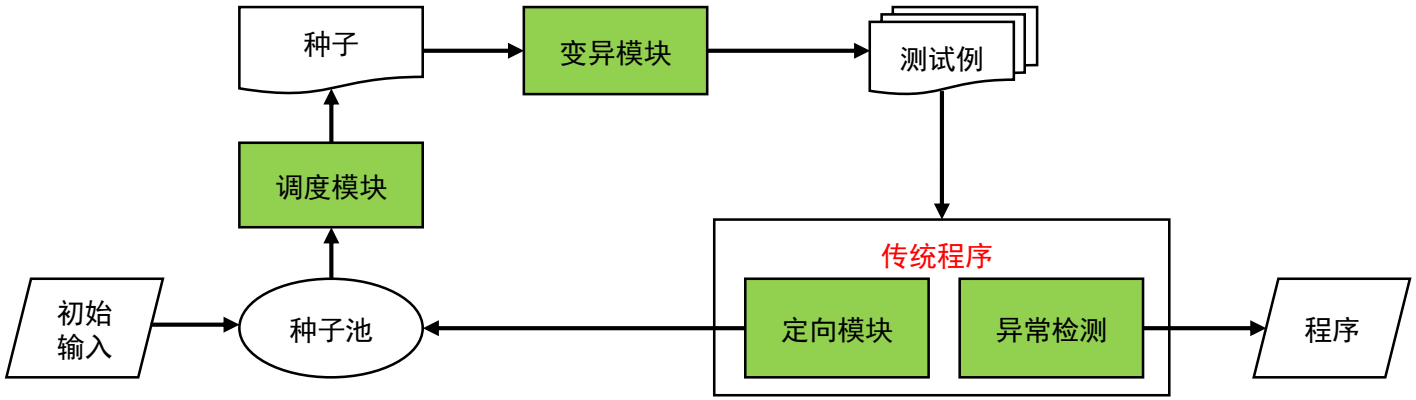
定向攻击

- 生成能够定向攻击神经网络的对抗样本:



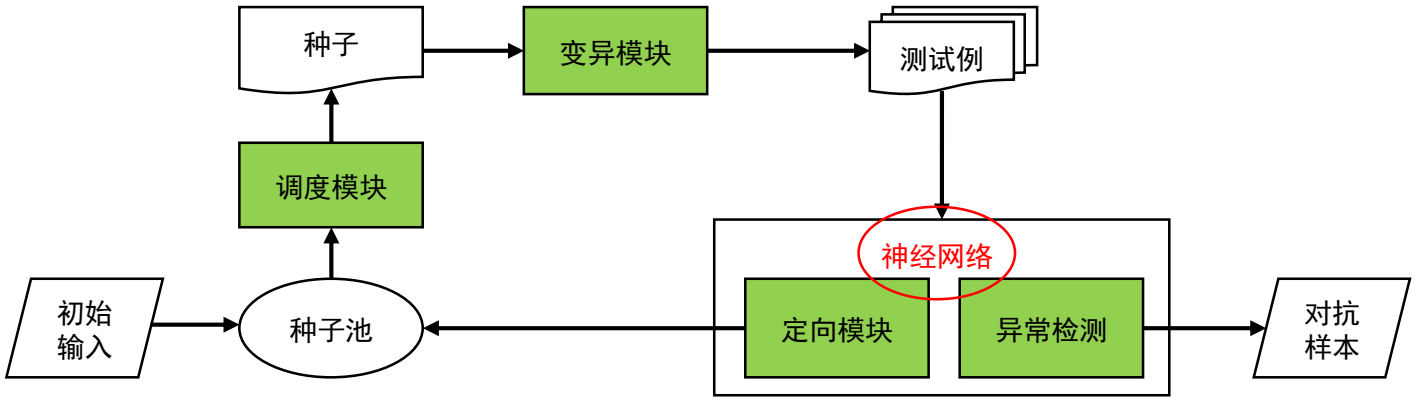
发掘传统程序中的漏洞

- 基于定向的模糊测试:

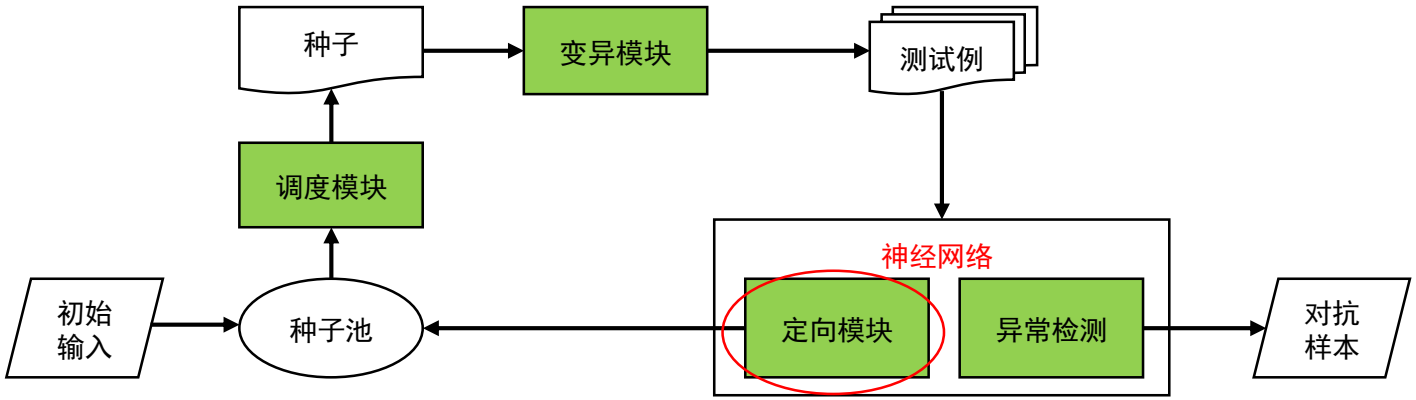


- 将能够缩短与定向目标距离的样例送入种子池

发掘神经网络中的漏洞

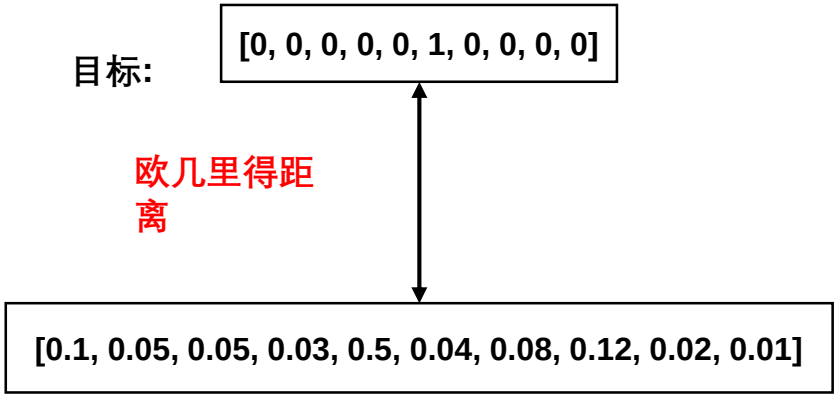


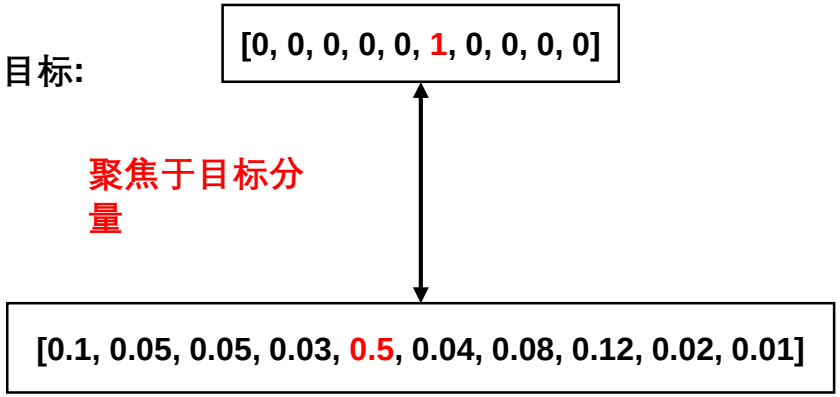
定向模块



定向模块

- 定向目标: [0,0,0,0,1,0,0,0,0,0]

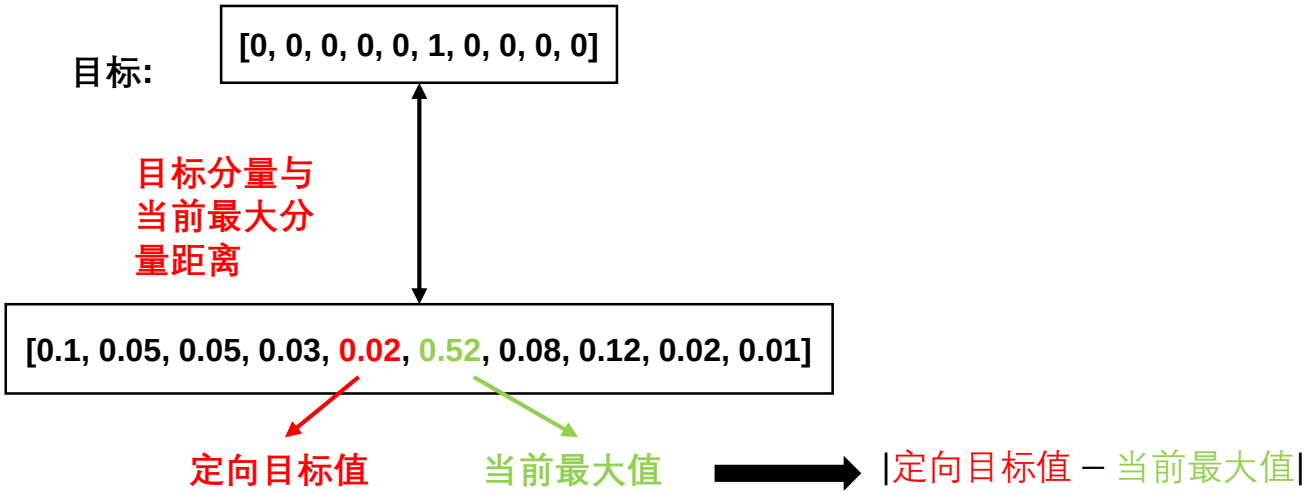




定向模块

- 定向目标: [0,0,0,0,1,0,0,0,0,0]

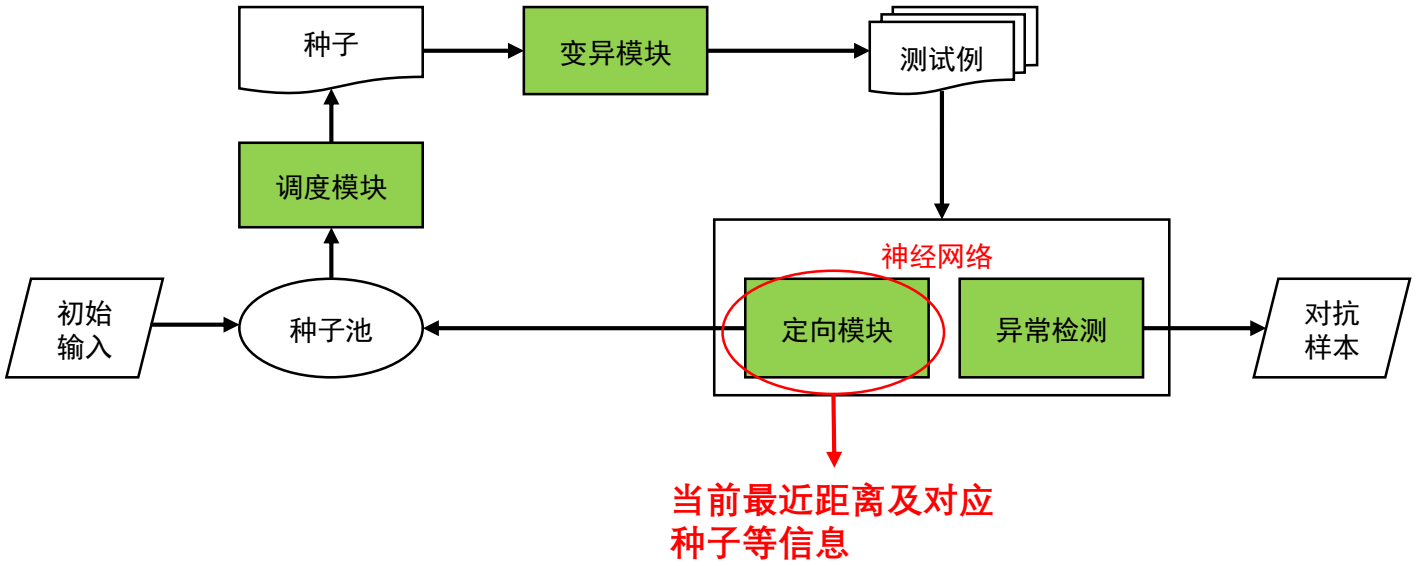
我们希望离目标更近



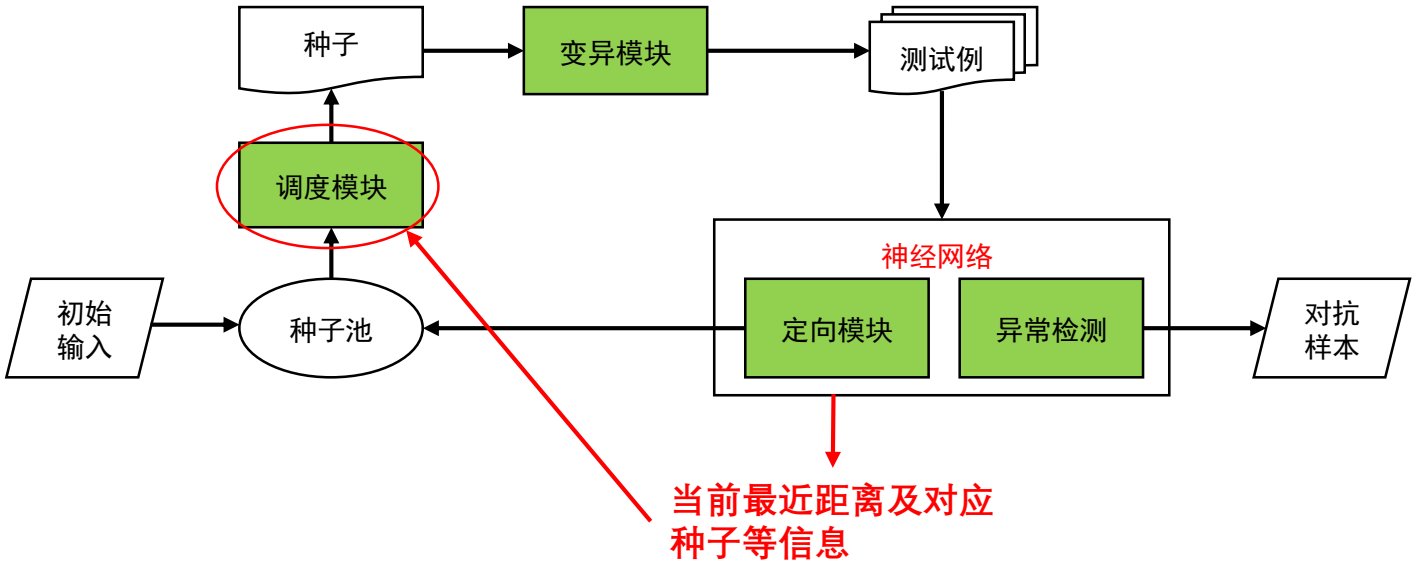
定向模块

- 确定定向标准后，我们就可以衡量与定向目标之间的距离
- 随着迭代的进行，会不断地更新最短距离

定向模块


种子
变异模块
测试例
调度模块
神经网络
初始
输入
种子池
定向模块
异常检测
对抗
样本
当前最近距离及对应
种子等信息

调度模块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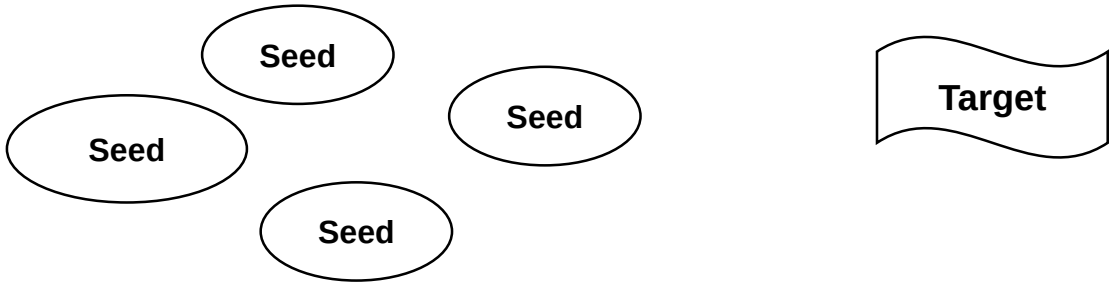
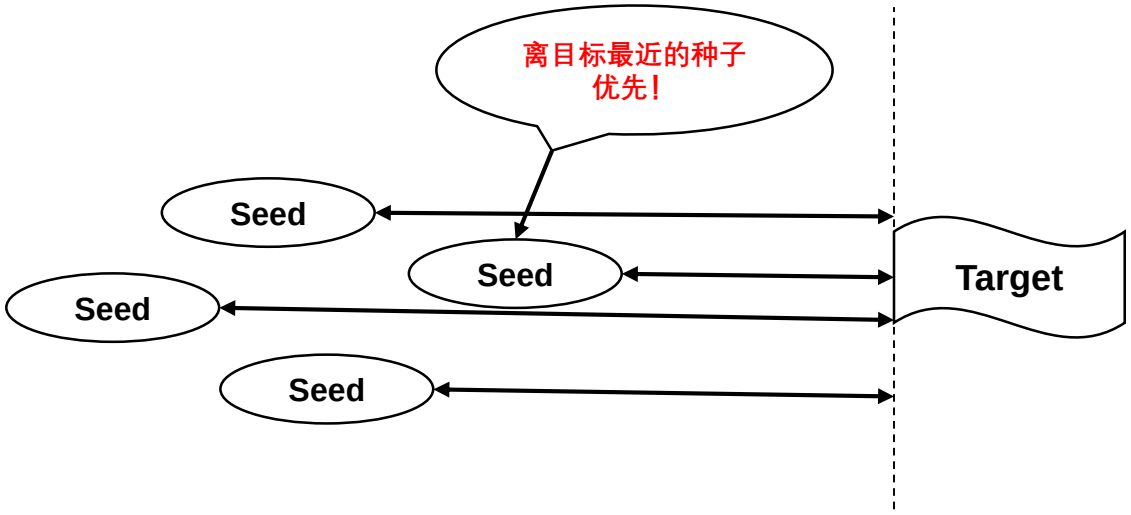
调度策略

采取策略优先变异某些种子:



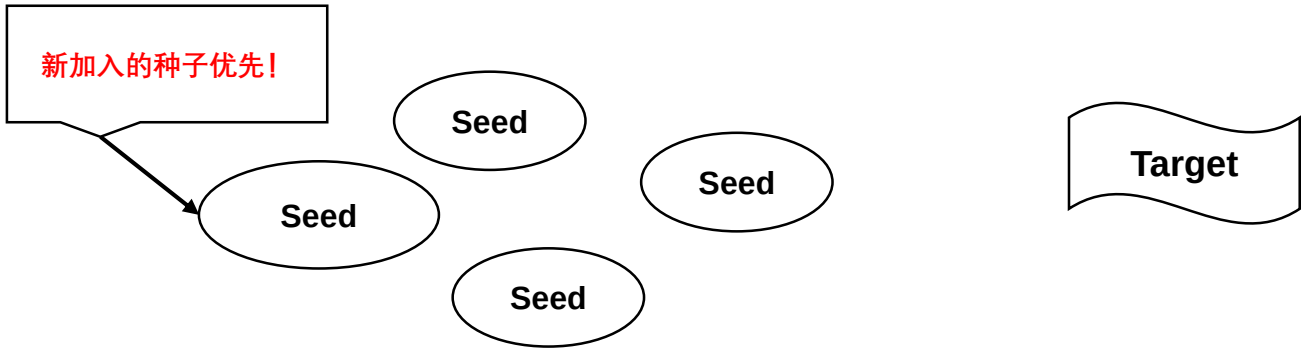
调度策略

首选策略：越接近于定向目标的种子，被选取的概率越高



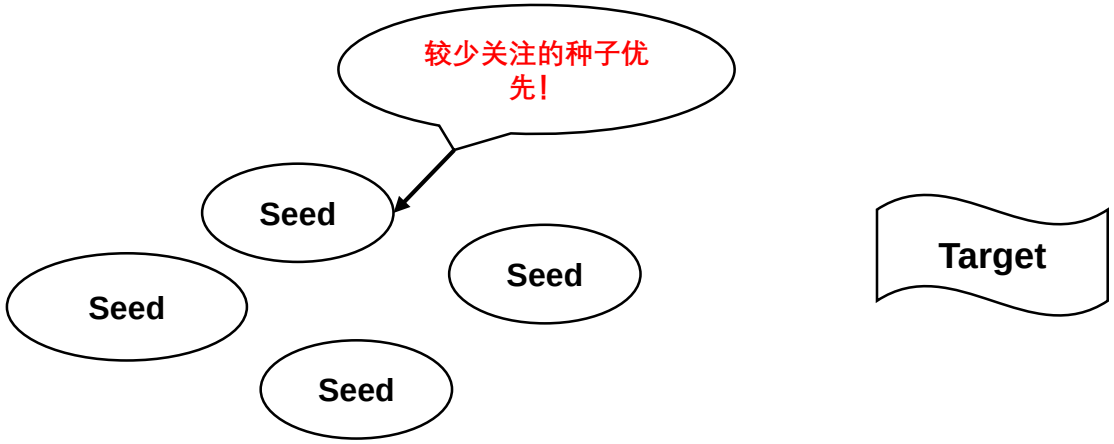
调度策略

候选策略：新加入的种子，被选取的概率更高



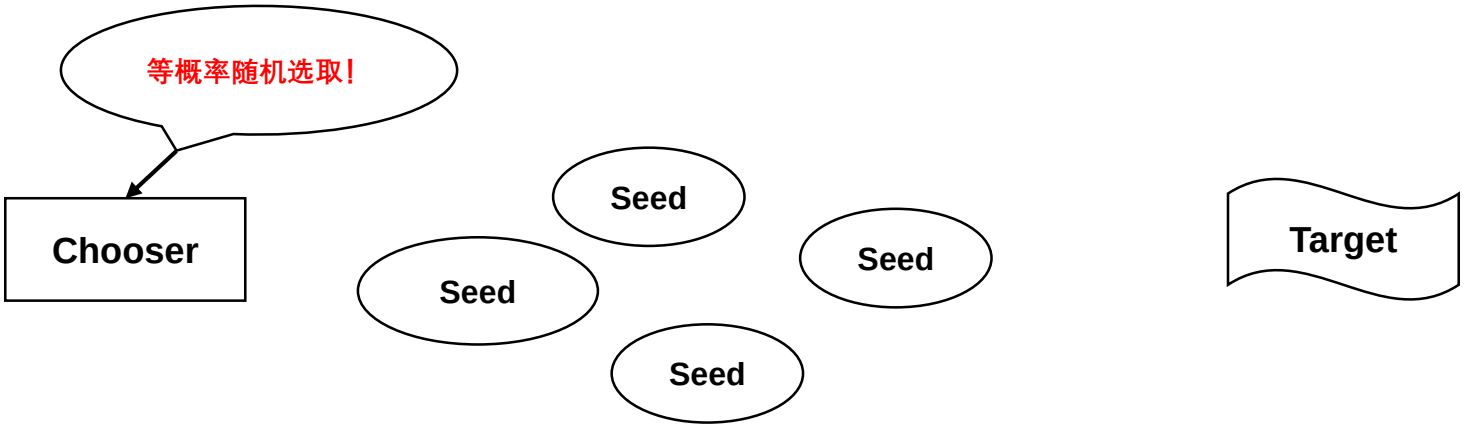
调度策略

候选策略：较少被挑选的种子，被选取的概率更高

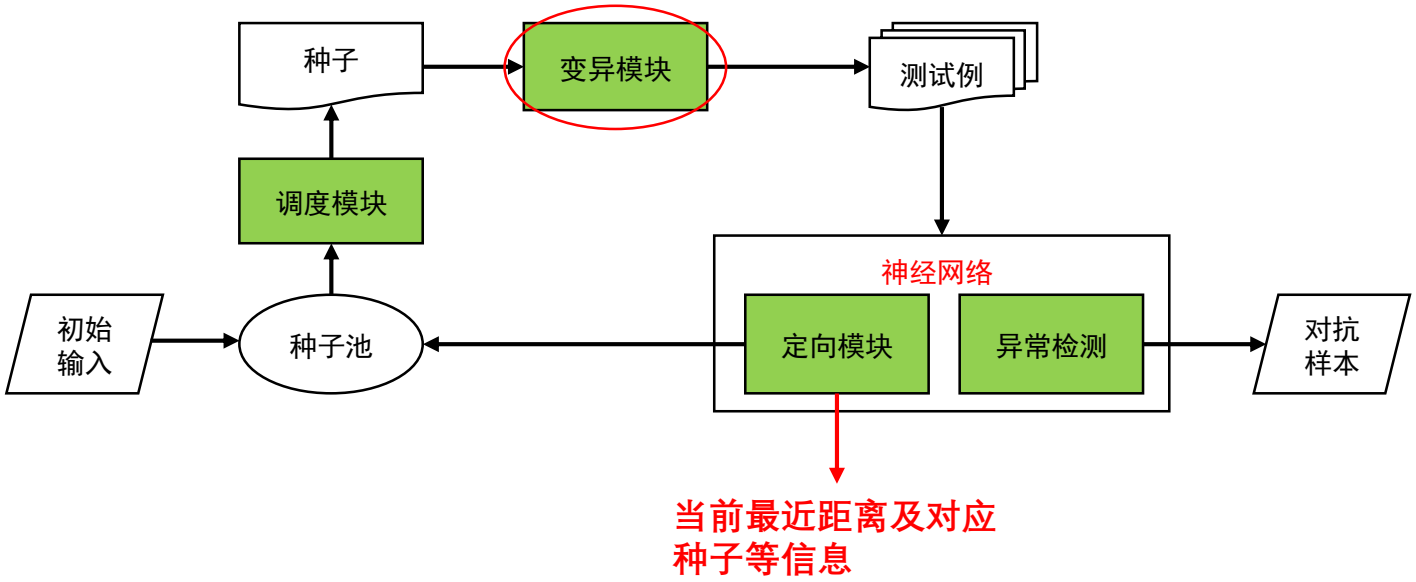


调度策略

候选策略：随机选取



变异模块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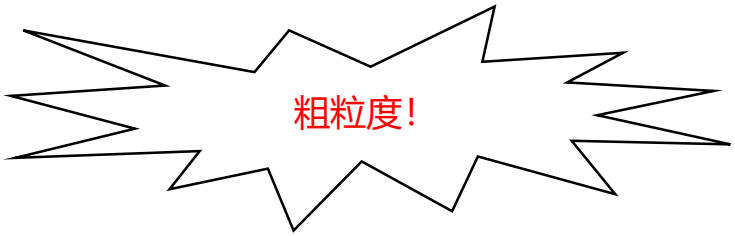
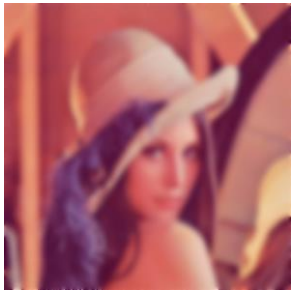
变异模块

- 常见的变异操作:



原始图

加噪声



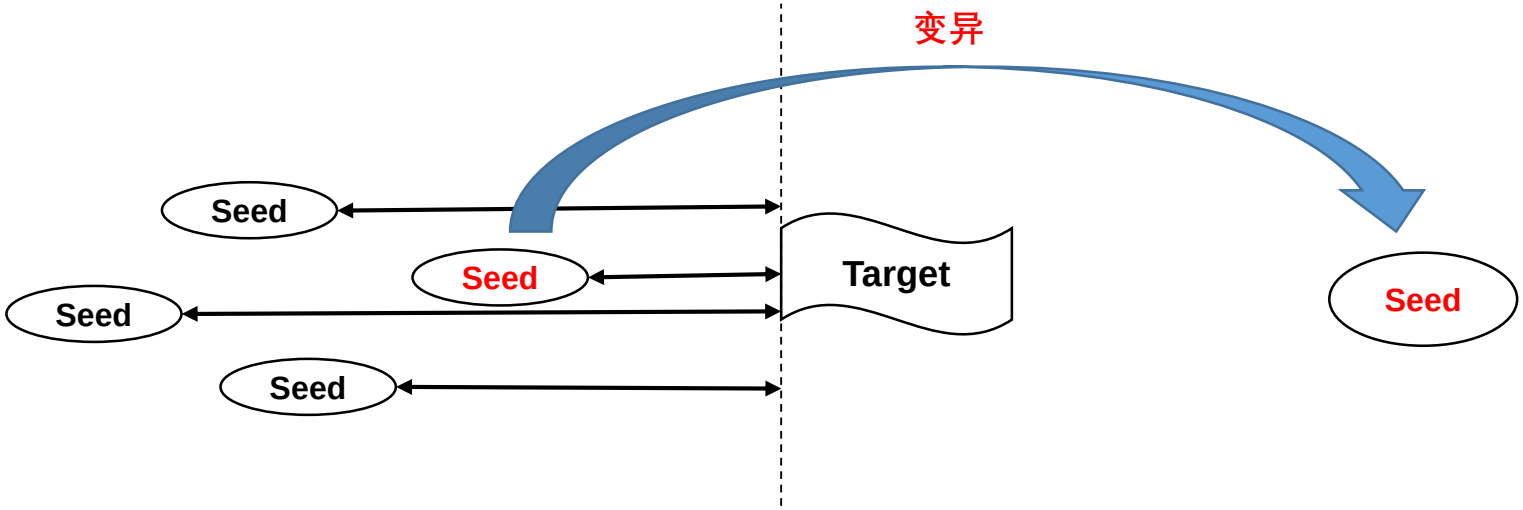
模糊化

平移化

粗粒度变异的后果

- 破坏原本最近种子的优势
- 毫无规律的变异类似于暴力破解

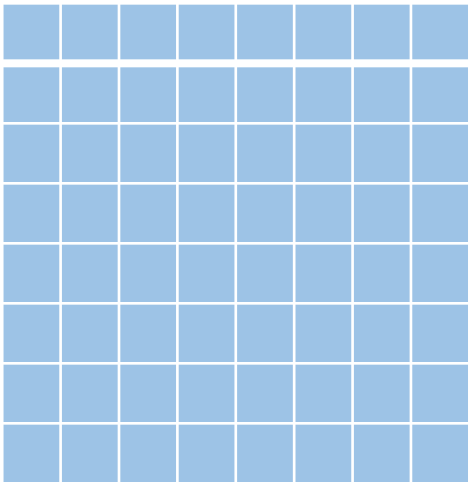
由于变化太大，距离更远了。。。



变异模块

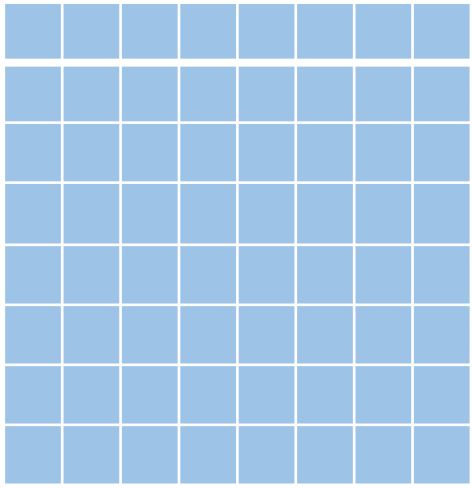
=

矩阵

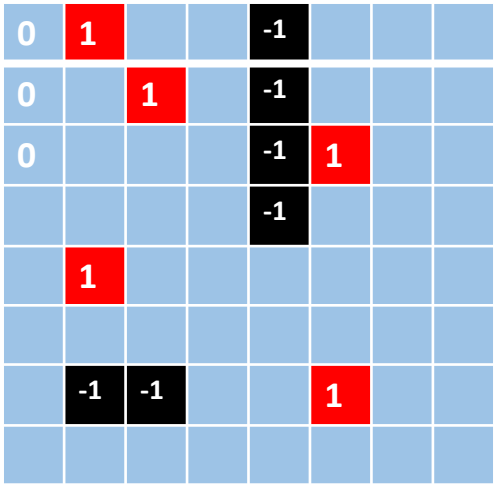


变异模块

矩阵



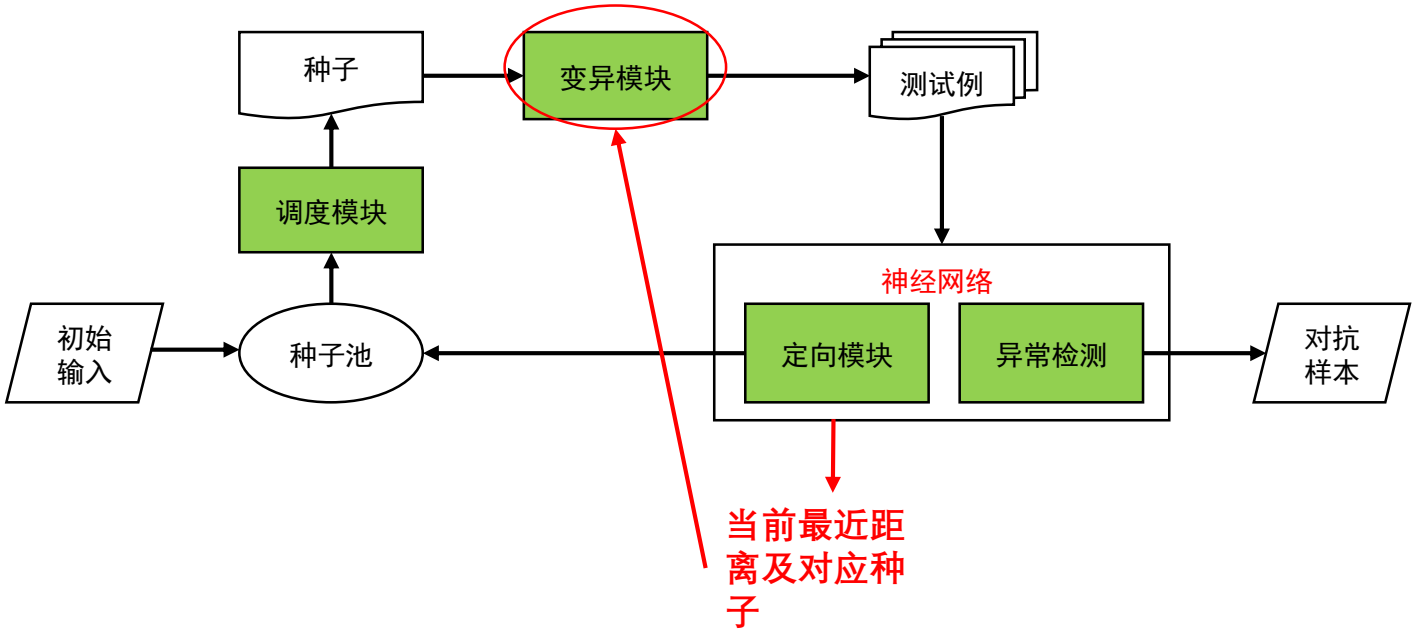
变异方向矩阵



红：1，增加　黑：-1，减少
蓝：0，不变

怎么调控三种值的比例？

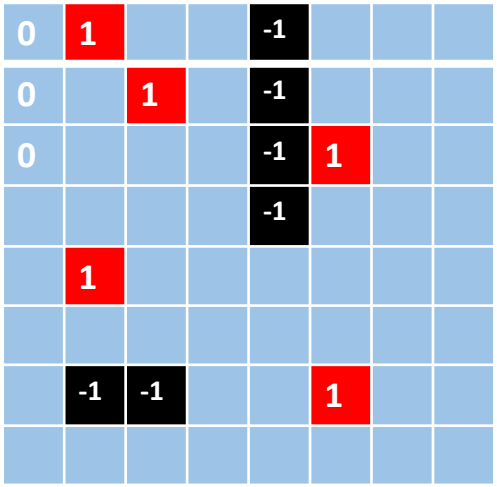
变异模块



变异模块

- 常见的变异操作:

变异方向矩阵



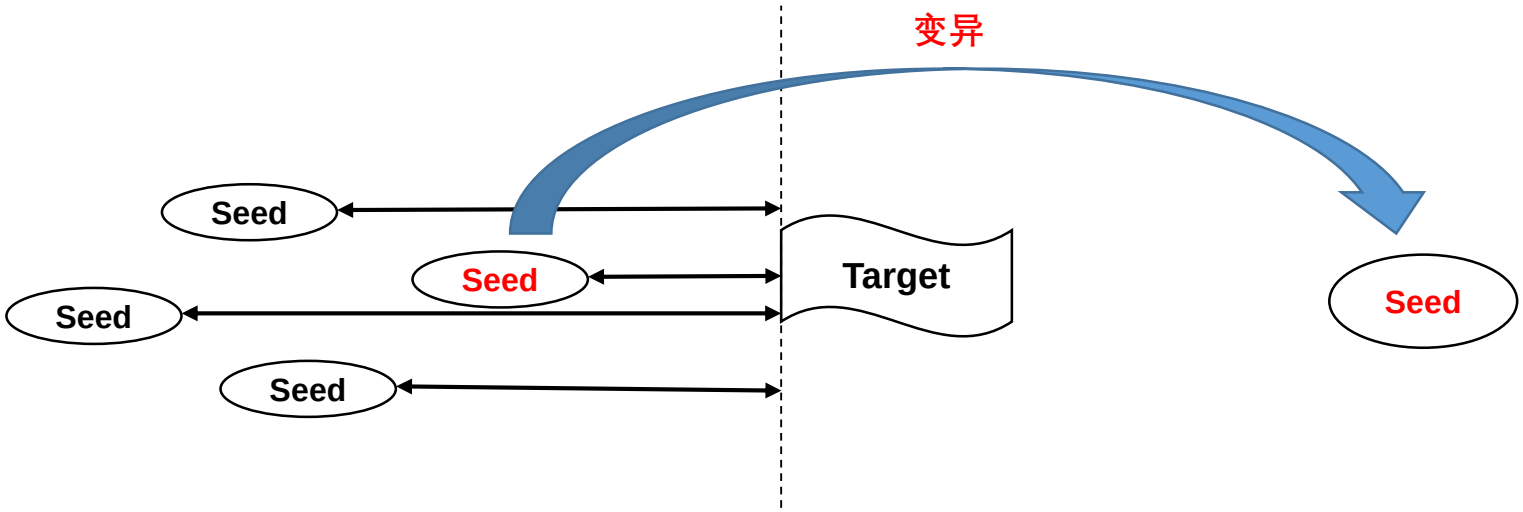
红：1，增加　黑：-1，减少
蓝：0，不变

由距离值调控：

- 与定向目标距离值较大时：1和-1的占比要大
- 与定向目标距离值较小时：1和-1的占比要调小

陷入局部最优

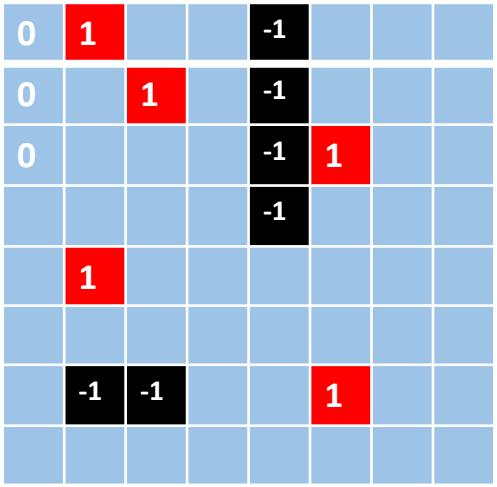
由于变化太大，距离更远了。。。



变异模块

- 常见的变异操作:

变异方向矩阵



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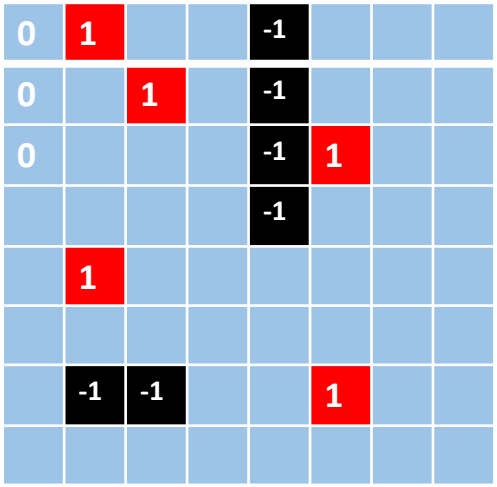
自动检测：

- 当发现陷入停滞时，强行动态调整

变异模块

- 常见的变异操作:

变异方向矩阵



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自动检测：

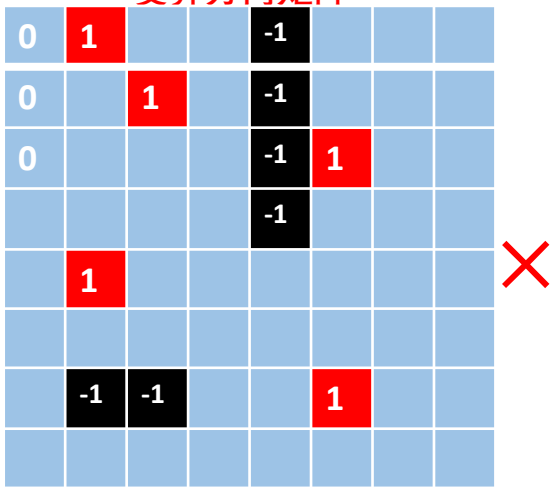
- 当发现陷入停滞时，强行动态调整

污点分析：

- 保留那些表现好的位置

变异模块

变异方向矩阵



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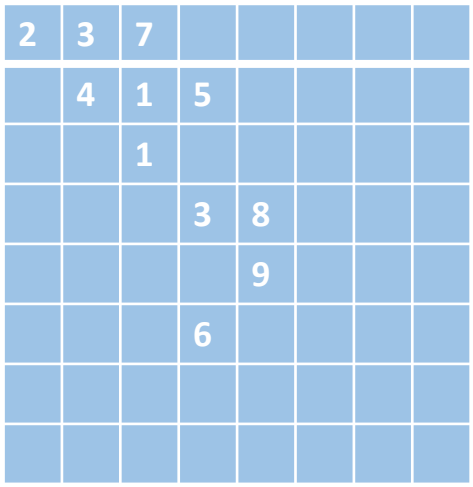
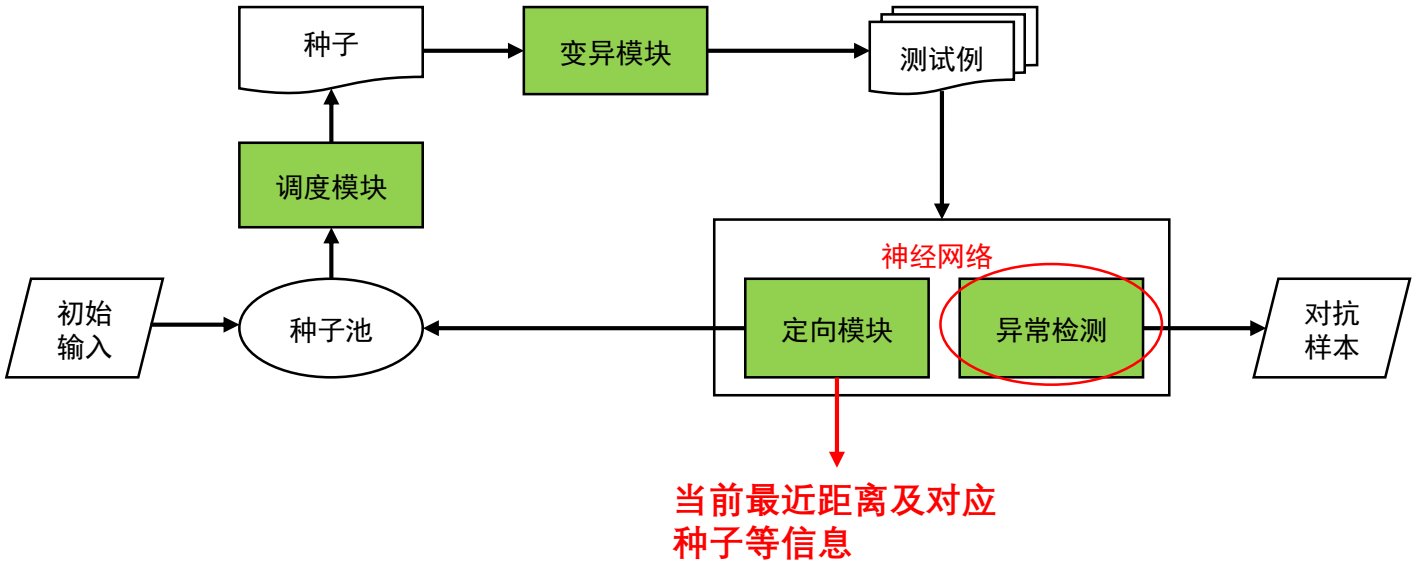
变异大小矩阵



红：1，增加　黑：-1，减少

蓝：0，不变

整体流程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实验结果

原图

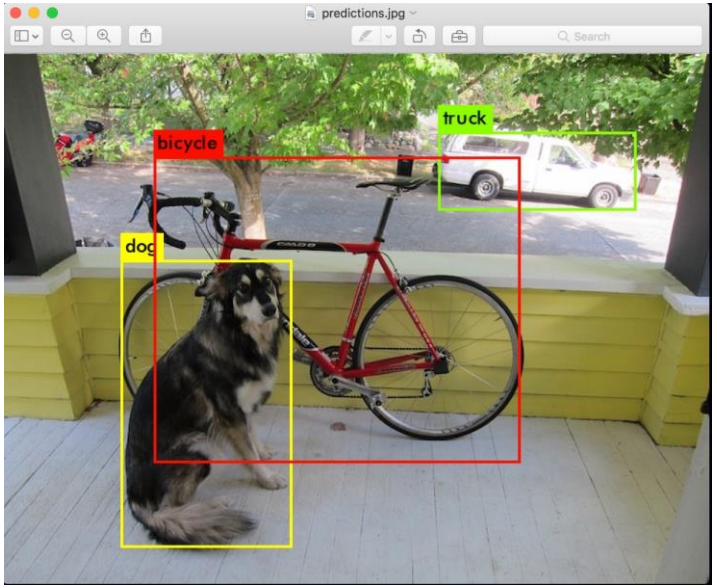
不同的定向目标

Part I：over

Part II：欺骗YOLOv3

背景

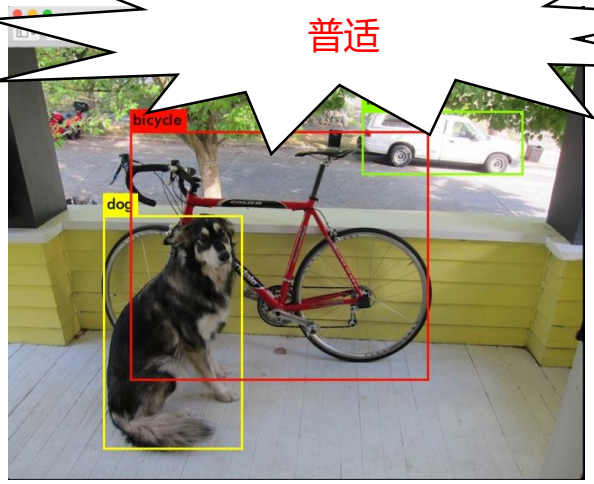
- 什么是目标检测系统？（YOLOv3）



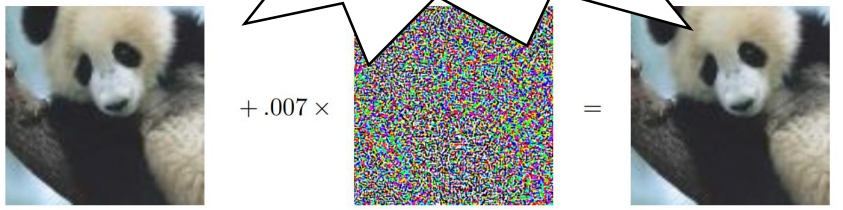
背景

- 欺骗目标检测系统和传统对抗样本工作区别?

普适



特定



$\boldsymbol{x}$

"panda"
57.7% confidence

$\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"nematode"
8.2% confidence

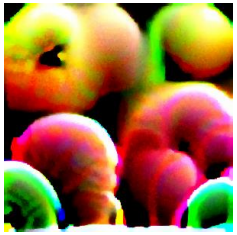
$\boldsymbol{x} + \epsilon\text{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$

"gibbon"
99.3 % confidence

动机

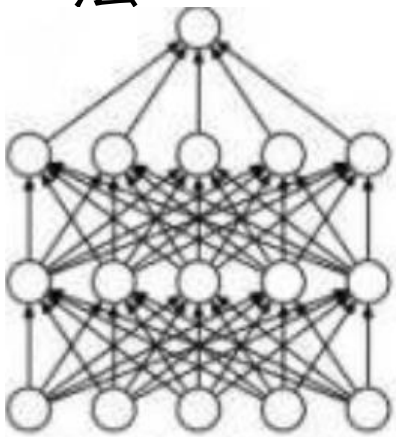
- 欺骗YOLOv3，让目标（人）消失

恶意的patch，如何产生？

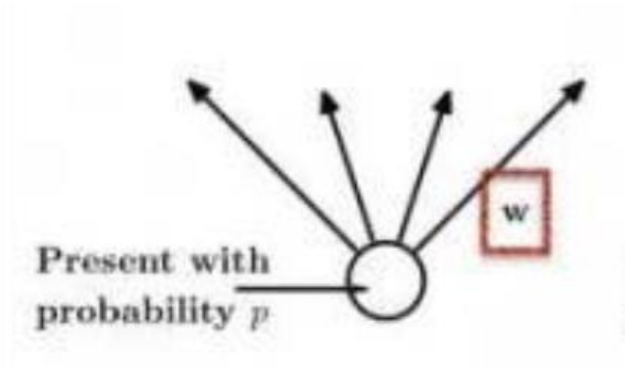


先验知识

- YOLOv3开源，白盒场景，考虑用针对白盒的算法②模仿类似模型训练过程：



神经网络

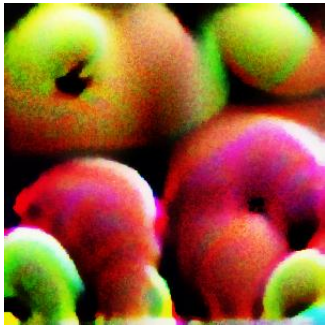


内部参数

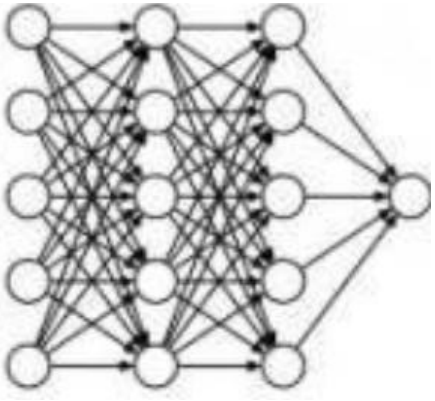
损失函数：
loss

先验知识

- YOLOv3开源，白盒场景，考虑用针对白盒的算法优化过程：



图片



训练好的神经网络

优化目标

损失函数：loss

如何制定优化目标

物体所处的位置

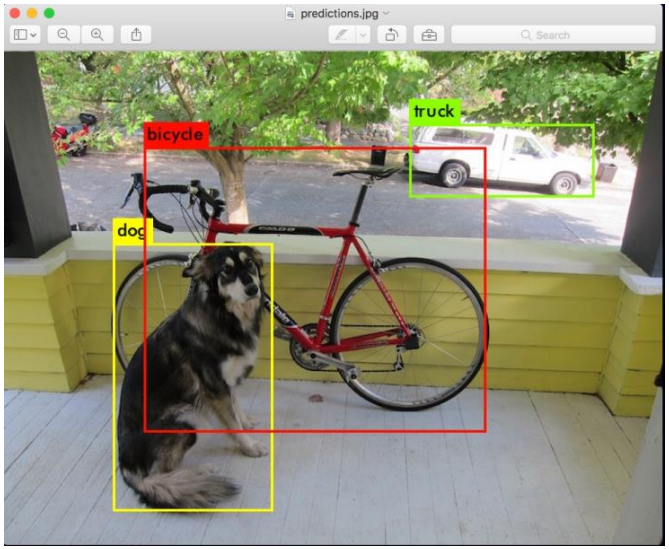
- YOLOv3的输出=置信度+预测类别概率分布+位置信息

这里是否存在物体?

这里什么物体?

置信度 > 阈值 ?

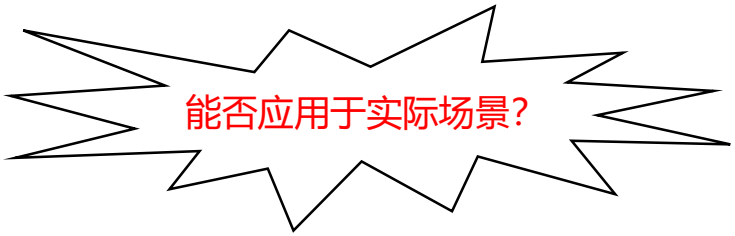
Loss=置信度



如何制定优化目标

- 损失函数:

Loss=置信度



如何制定优化目标

- 损失函数:

Loss=置信度+颜色损失

颜色损失项：$$L_{nps} = \sum_{p_{\text{patch}} \in p} \min_{c_{\text{print}} \in C} |p_{\text{patch}} - c_{\text{print}}|$$

如何制定优化目标

- 损失函数:

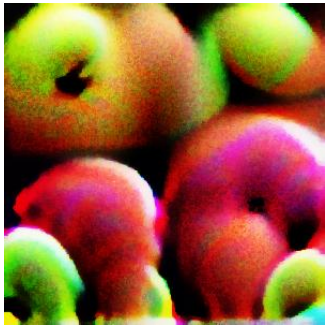
Loss=置信度+颜色损失项+平滑项

颜色损失项： $L_{nps} = \sum_{p_{\text{patch}} \in p} \min_{c_{\text{print}} \in C} |p_{\text{patch}} - c_{\text{print}}|$ $\boldsymbol{C_{\text{print}}}$：可打印像素值

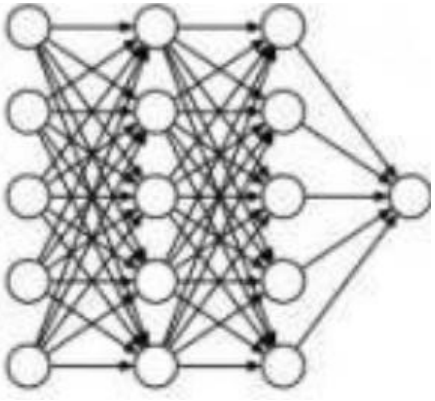
平滑项： $L_{tv} = \sum_{i,j} \sqrt{((p_{i,j} - p_{i+1,j})^2 + (p_{i,j} - p_{i,j+1})^2}$

开始训练

- 在loss的指引下，开始针对打底图片进行训练



打底图片



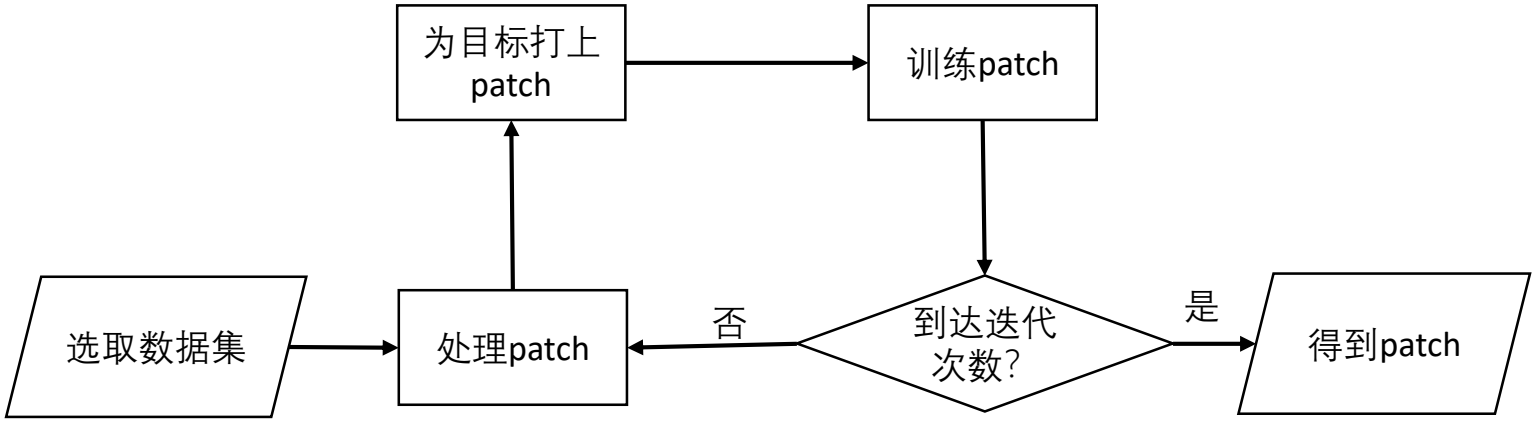
训练好的神经网络

优化目标

损失函数：loss

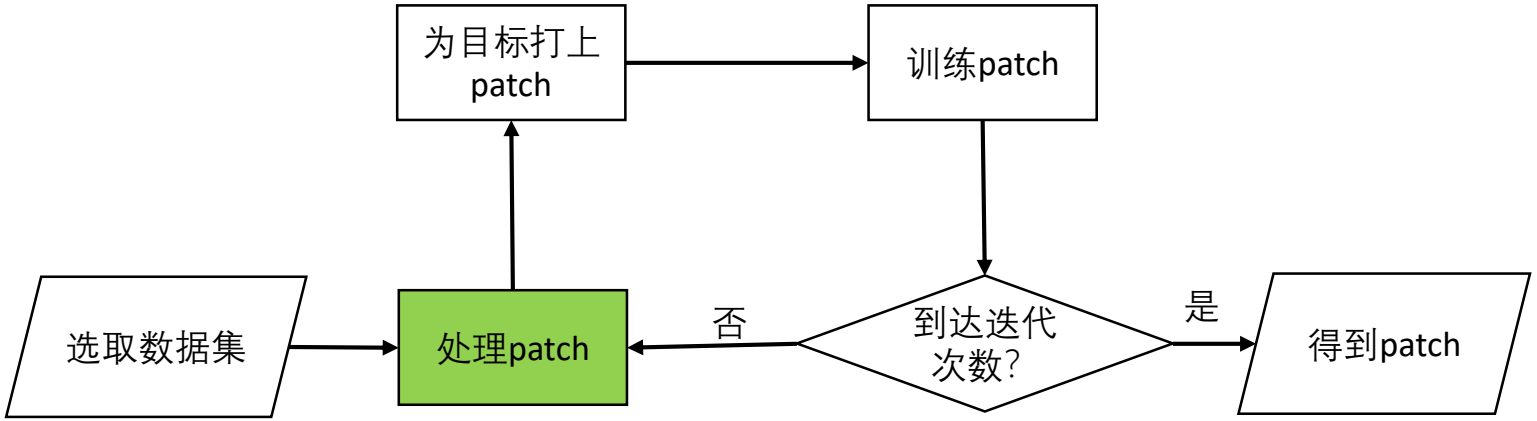
如何训练？

- 训练过程:



处理patch

- 训练过程:

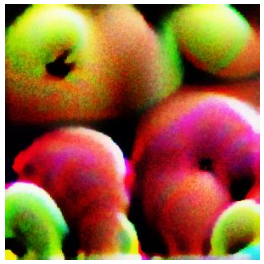


处理patch

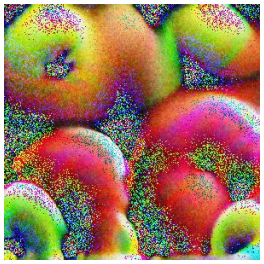
- Patch需要增强鲁棒性:

加噪声、旋转、改变亮度、对比度

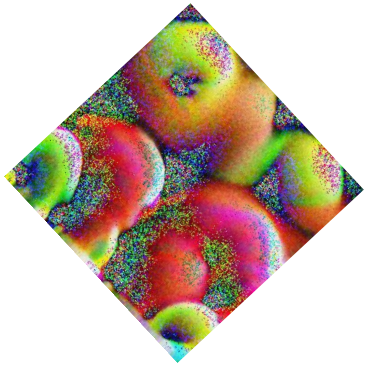
底图应该很重要!



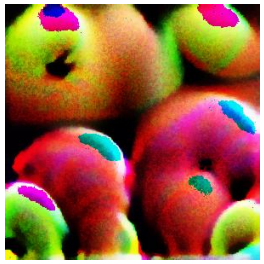
原始底图



加噪声



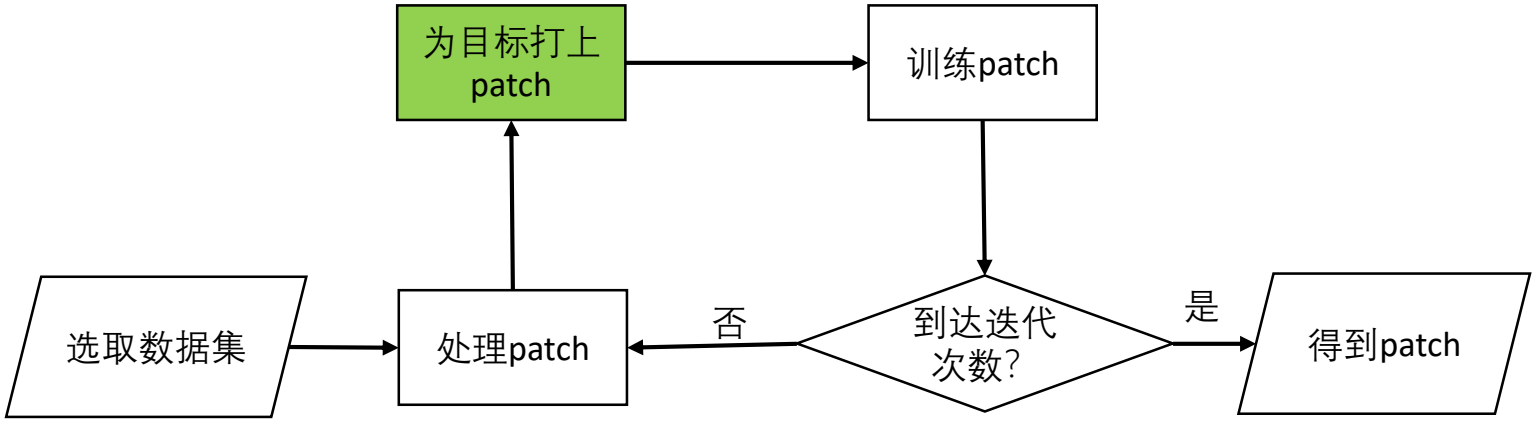
旋转



调整亮度

打patch

- 训练过程:

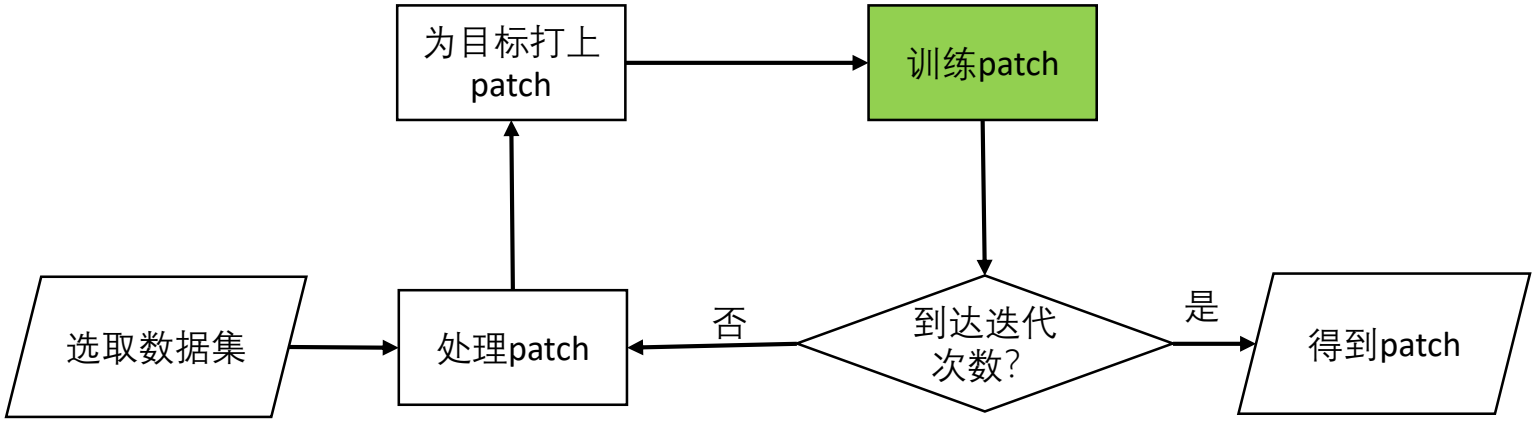


为目标打patch

- 需要把patch添加到图片中的人

训练patch

- 训练过程:



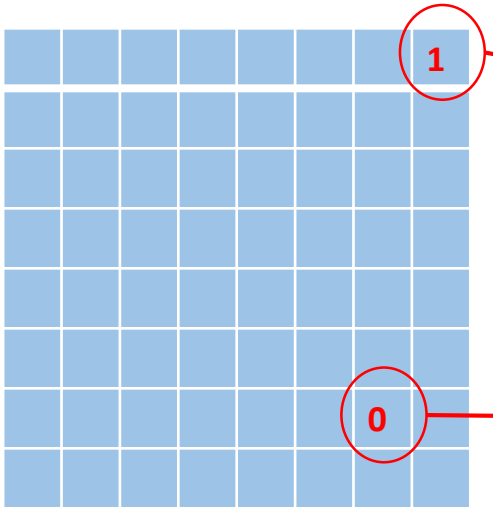
训练patch

- 基于损失函数，使用合适的优化器，进行训练；

训练能够持续进行吗？

训练patch

- 基于损失函数，使用合适的优化器，进行训练；
- 图片像素经预处理后，像素值的值域为[0,1]：



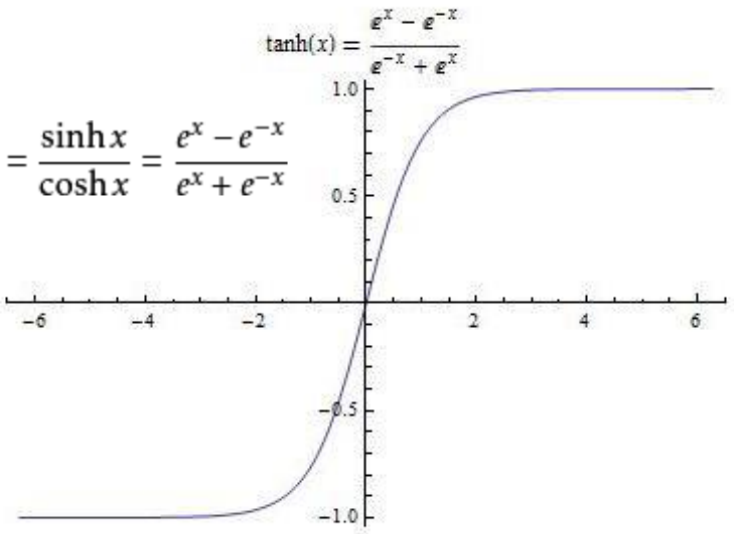
当前像素值1，梯度指引“我”继续增加，但我还能增加吗？

当前像素值0，梯度指引“我”继续减少，但我还能减少吗？

训练patch

- 转换优化对象到另一值域:

$$\tanh x = \frac{\sinh x}{\cosh x} = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



$$\frac{1}{2}(\tanh(x_{\text{orig}} + \text{扰动}) + 1)$$

新的优化对象

将原图转换到tanhx域即可得到：x_{orig}

结果

谢谢

Q&A