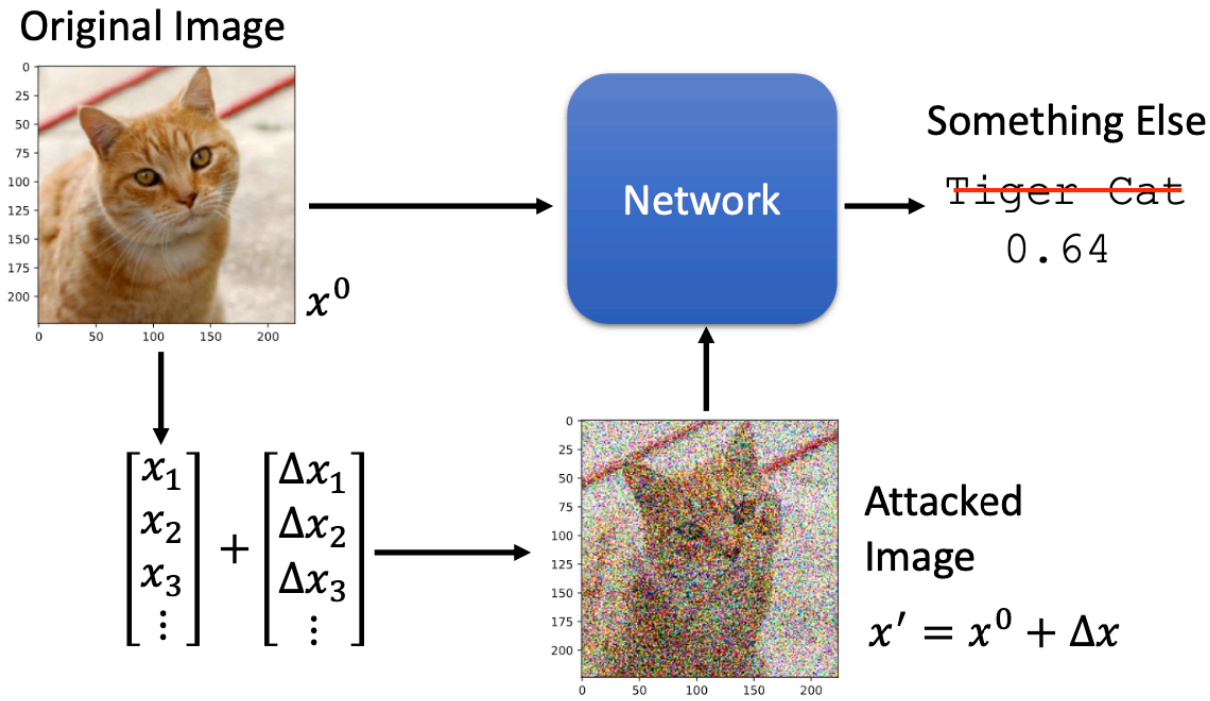
Motivation

- We seek to deploy machine learning classifiers not only in the labs, but also in real world.
- The classifiers that are robust to noises and work "most of the time" is not sufficient. 光是強還不夠
- We want the classifiers that are robust the inputs that are built to fool the classifier. 應付來自人類的惡意
- Especially useful for spam classification, malware detection, network intrusion detection, etc.

What do we want to do?

attack要做的事就是把找到原图片x^0对应的x'

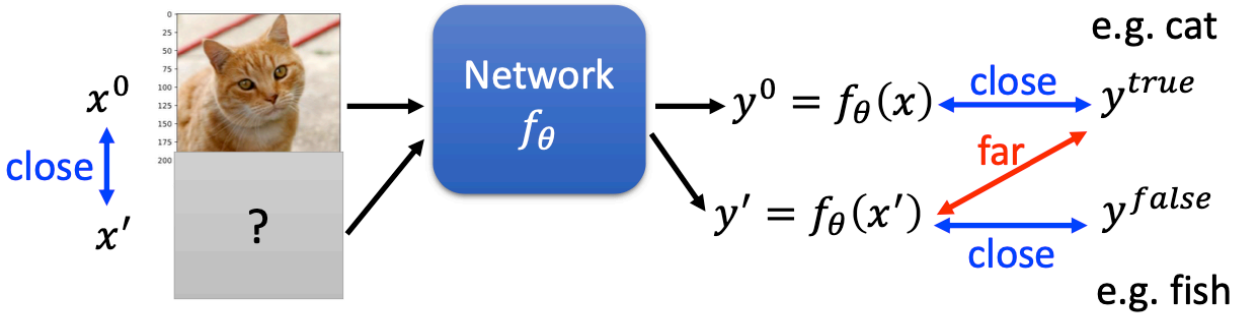


Loss Function for Attack

Training：network训练得出的结果y^0必须和y^{true}越接近越好，此时的loss function为$L_{train}(\theta) = C(y^0, y^{true})$，输入的$x$是固定的，需要不断调整$\theta$的值，使得$L_{train}(\theta)$取得最小值；

Non-targeted Attack：如果我们需要attack一个network，此时network的输出y'和y^{true}应该越大越好，此时的loss function为$L(x') = -C(y', y^{true})$，前面多了一个负号。此时的network中的参数θ是固定的，需要不断调整输入x'，使network的输出y'和y^{true}的差距尽量远；

Targeted Attack：如果我们不仅想要y', y^{true}之间的距离尽量远，还想使y', y^{false}之间的距离尽量近，就需要使用targeted attack；此时的loss function为$L(x') = -C(y', y^{true}) + C(y', y^{false})$



- ***Training:*** $L_{train}(\theta) = C(y^0, y^{true})$ x fixed
- ***Non-targeted Attack:*** $L(x') = -C(y', y^{true})$ θ fixed
- ***Targeted Attack:***

$$L(x') = -C(y', y^{true}) + C(y', y^{false})$$

- ***Constraint:*** $d(x^0, x') \leq \varepsilon$ 不要被發現

不仅需要限制输出之间的差异，还需要限制输入x^0, x'之间的差异，只有这输入之间的差异d小于ϵ，我们才可以认为x'是与x^0相似的，才达到了attack 一个network的目的，即使输入尽可能具有迷惑性，从而使网络输出错误的结果

Constraint

那么我们怎么计算d呢?

有以下两种主要的方法：

- L2-norm，为x^0, x'之间每个像素差异的平方和；
- L-infinity，为x^0, x'之间每个像素差异的最大值

如果我们改变图中的每个pixel，另外一幅图只改变其中一个pixel，使得这两者之间的L2-norm是一样的，但第二种方式得出的L-infinity更大

Constraint $d(x^0, x') \leq \varepsilon$

$$\begin{bmatrix} x_1' \\ x_2' \\ x_3' \\ \vdots \end{bmatrix} - \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \end{bmatrix} = \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \\ \Delta x_3 \\ \vdots \end{bmatrix}$$

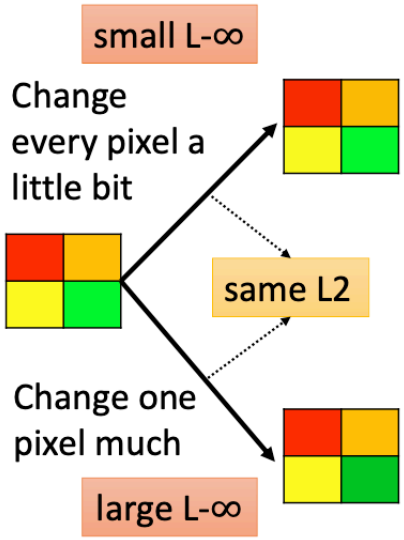
x' x^0 Δx

- L2-norm

$$d(x^0, x') = \|x^0 - x'\|_2$$
$$= (\Delta x_1)^2 + (\Delta x_2)^2 + (\Delta x_3)^2 \cdots$$

- L-infinity

$$d(x^0, x') = \|x^0 - x'\|_\infty$$
$$= max\{\Delta x_1, \Delta x_2, \Delta x_3, \cdots\}$$



How to Attack

就像我们训练一个neural network一样，但需要训练的参数是x'，此时就需要找到一个参数x^*，来最小化$L(x')$，限制条件是$d(x^0, x') \leq \epsilon$

$$x^* = arg \min_{d(x^0, x') \leq \epsilon} L(x')$$

这里我们也使用了gradient descent算法，只是此时需要调整的参数变成了x^t

- Gradient Descent

Start from original image x^0

For t = 1 to T

$x^t \leftarrow x^{t-1} - \eta \nabla L(x^{t-1})$

If $d(x^0, x^t) > \varepsilon$

$x^t \leftarrow fix(x^t)$

$$\nabla L(x) = \begin{bmatrix} \partial L(x)/\partial x_1 \\ \partial L(x)/\partial x_2 \\ \partial L(x)/\partial x_3 \\ \vdots \end{bmatrix}$$

当$d(x^0, x^t) > \epsilon$时，就需要更新这个参数了，使用$fix(x^t)$来更新

Start from original image x^0

For t = 1 to T

$x^t \leftarrow x^{t-1} - \eta \nabla L(x^{t-1})$

If $d(x^0, x^t) > \varepsilon$

$x^t \leftarrow fix(x^t)$

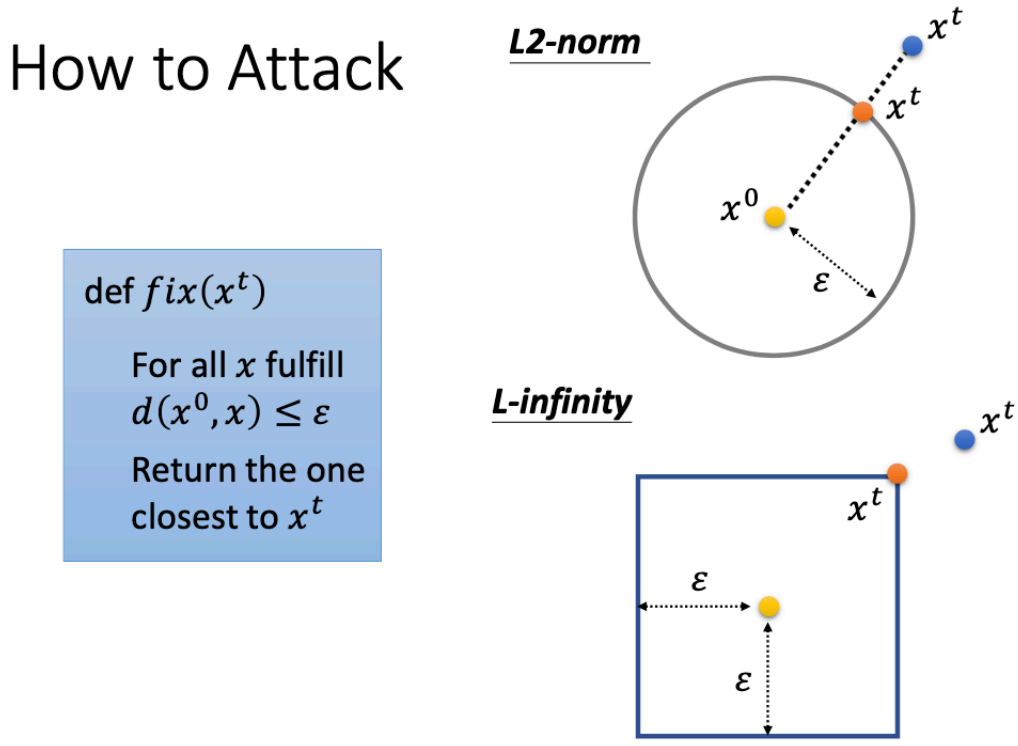
def $fix(x^t)$

For all x fulfill $d(x^0, x) \leq \varepsilon$

Return the one closest to x^t

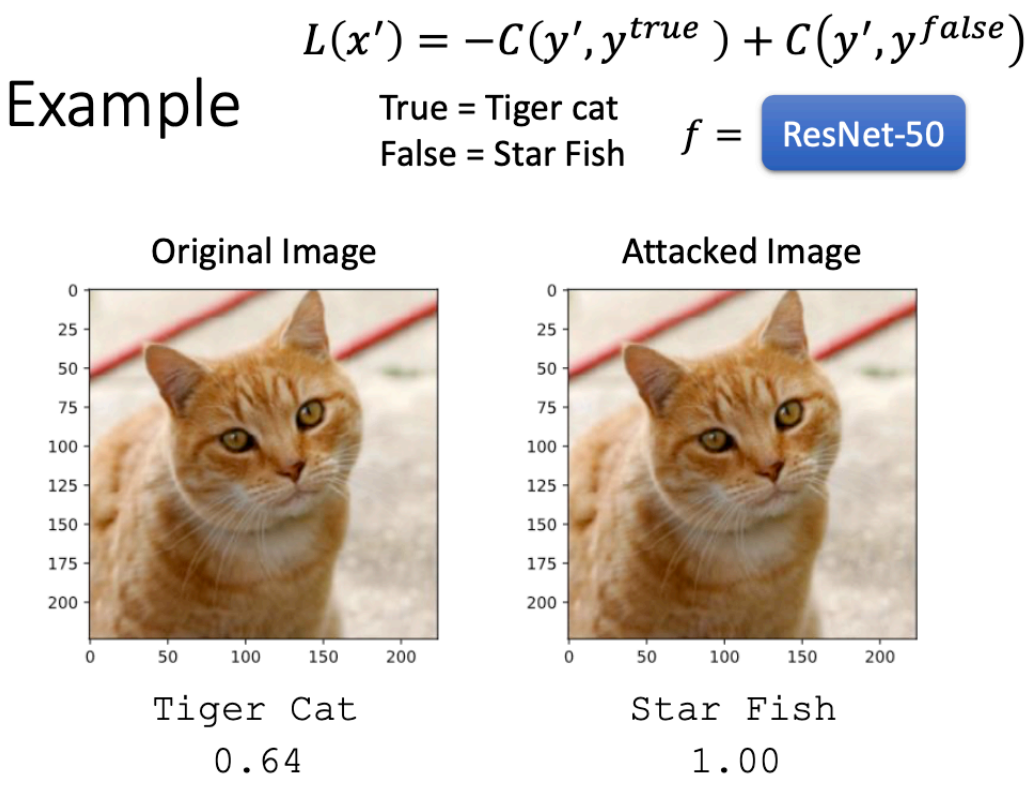
更新的参数需要满足一定的条件，

- 如果使用L2-norm，必须选择在差值在半径以内的参数，超过了这个半径，就设为ϵ；
- 如果使用L-infinity，现在超过了这个方形的区域，就必须想办法把它拉回来，在y轴方向超过了ϵ，就把值设为ϵ；在x轴方向超过了ϵ，就把值设为ϵ

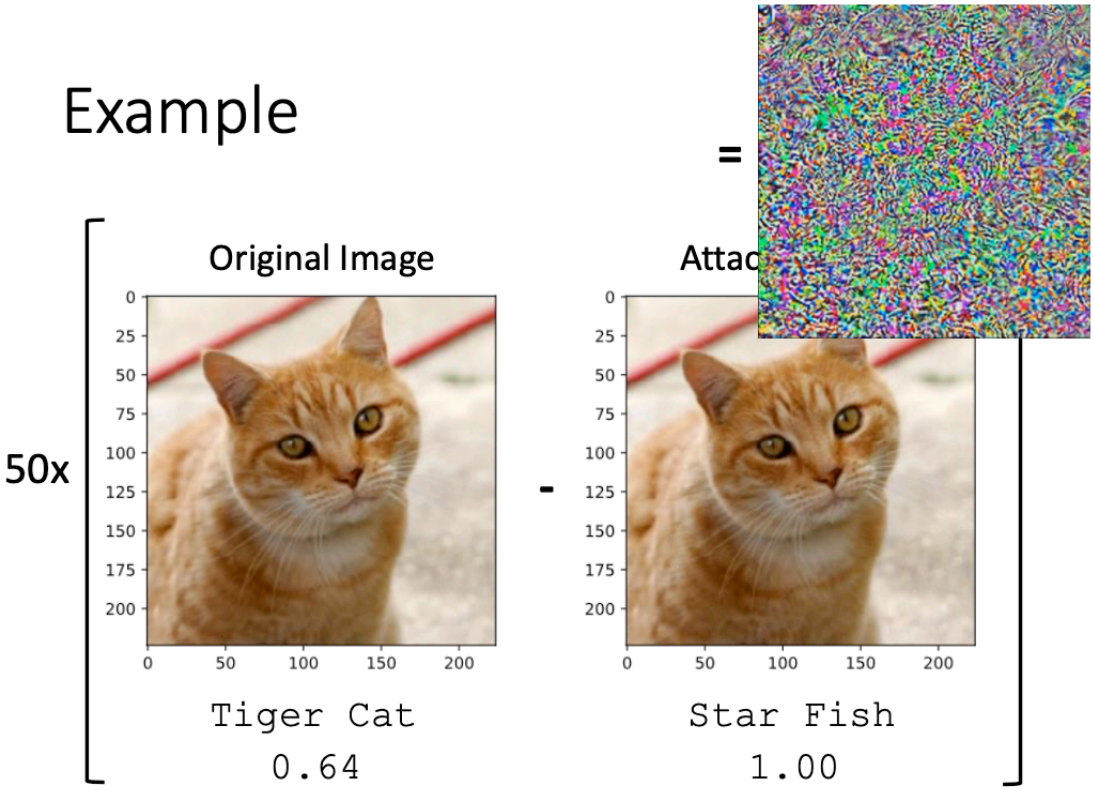


Example

如果我们现在要attack一个network，其真实类别为Tiger cat，但attack之后的network认为这是star fish



由于这两者之间的差异很小，很难识别，这里我们将差值x50来进行展示



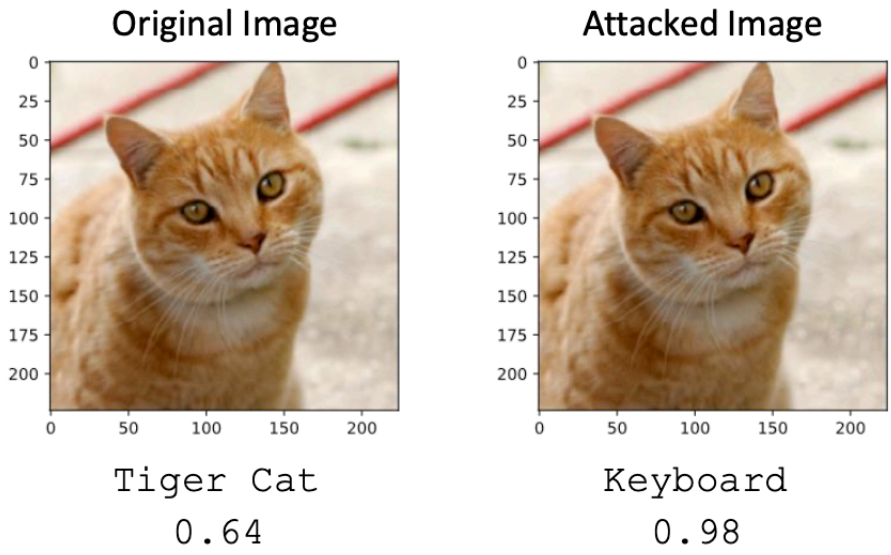
可能猫和猫之间是比较类似的，这里我们将attack的target设置为keyboard，该network认为这是keyboard的概率为0.98

Example

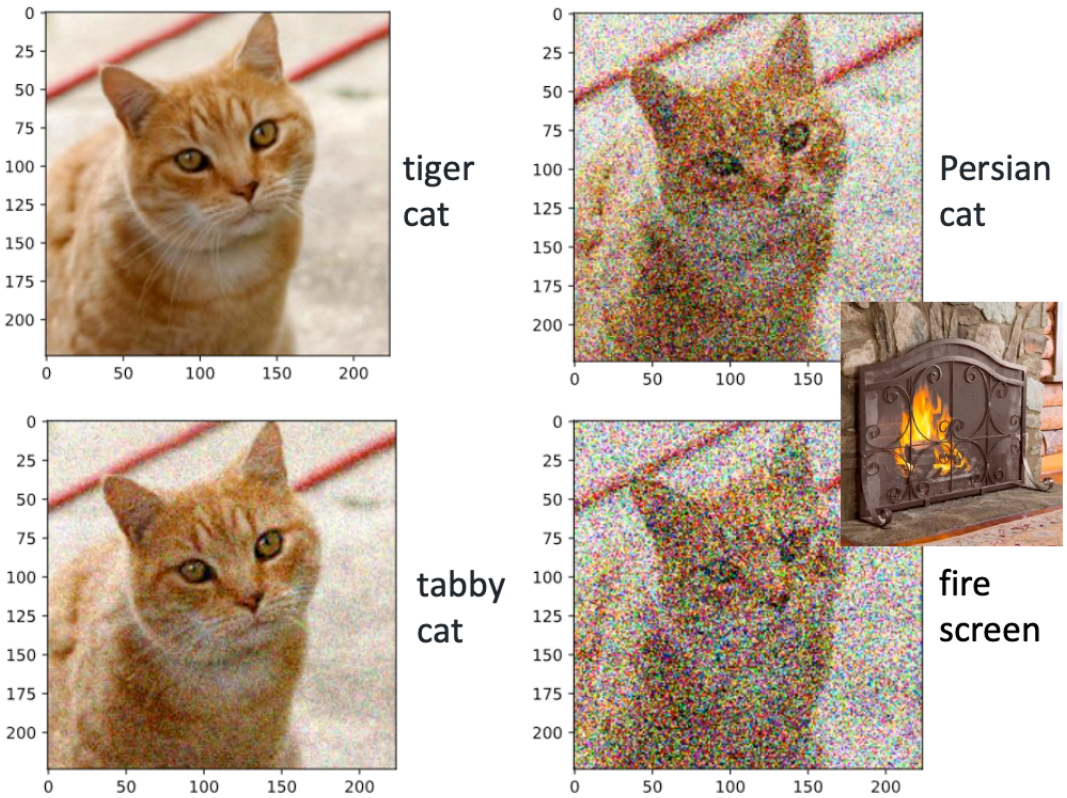
$$L(x') = -C(y', y^{true}) + C(y', y^{false})$$

True = Tiger cat
False = Keyboard

$f =$ ResNet-50

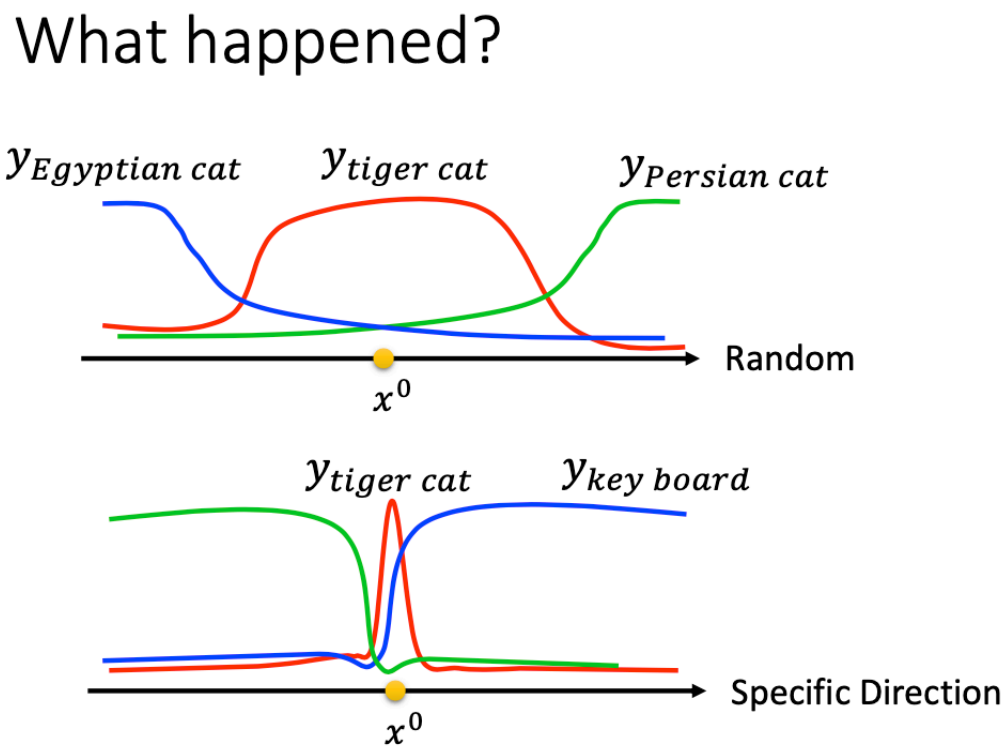


如果我们再对图片加入噪声，network认为这是Persian cat，再继续加入噪声，我们都快分辨不出这张图是一只猫了，network就认为这是fire screen



我们假设x_0是在高维平面上的一个点，沿着任意方向随机移动，我们可以看到在接近x^0 的时候，是tiger cat（正确分类）的可能性是很高的，但如果再移动多一点，是Persian cat和Egyptian cat的可能性是很高的

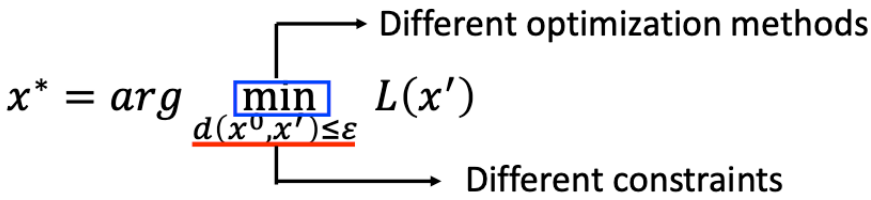
上述说的是随机方向进行移动，如果图片是225*225pixel的，那么就是5万多个高维的方向，现在我们选取其中几个特定的方向。在这几个特定的方向中，x^0可变化的范围就变得非常狭窄，x^0稍微变化一下，network输出为另一个类别（key board）的可能性就很高



Attack Approaches

- FGSM (https://arxiv.org/abs/1412.6572)
- Basic iterative method (https://arxiv.org/abs/1607.02533)
- L-BFGS (https://arxiv.org/abs/1312.6199)
- Deepfool (https://arxiv.org/abs/1511.04599)
- JSMA (https://arxiv.org/abs/1511.07528)
- C&W (https://arxiv.org/abs/1608.04644)
- Elastic net attack (https://arxiv.org/abs/1709.04114)
- Spatially Transformed (https://arxiv.org/abs/1801.02612)
- One Pixel Attack (https://arxiv.org/abs/1710.08864)
- ..... only list a few

虽然有很多方法都可以用来attack network，但这些方法的主要区别在于使用了不同的constrains，或者使用了不同的optimization methods



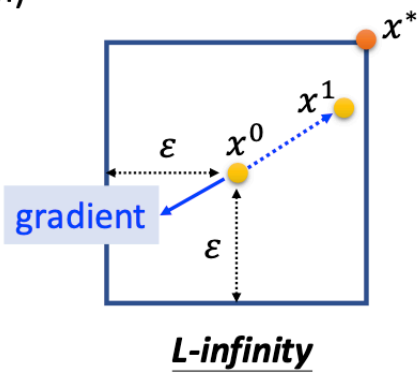
我们先介绍一下**FGSM**，对于第一维，如果$\frac{\partial L}{\partial x_1}$是大于0的值，那么$\Delta x_1 = sign(\frac{\partial L}{\partial x_1}) = +1$；如果对于第二维，如果$\frac{\partial L}{\partial x_2}$是小于0的值，不管值多大，都得出$\Delta x_2 = sign(\frac{\partial L}{\partial x_2}) = -1$；即对于$x^0$的所有维，要么$+\epsilon$，要么$-\epsilon$，即可得到最好的结果$x^*$

- Fast Gradient Sign Method (FGSM)

$$x^* \leftarrow x^0 - \varepsilon \Delta x$$

$$\Delta x = \begin{bmatrix} sign(\partial L/\partial x_1) \\ sign(\partial L/\partial x_2) \\ sign(\partial L/\partial x_3) \\ \vdots \end{bmatrix}$$

only have +1 or -1



FGSM使用L-infinity作为distance constrain，如果gradient指向左下角，那么x^*就在方框的右上角；如果gradient指向左上角，那么x^*就在方框的右下角；因此，在FGSM里面，我们只在意gradient的方向，不在意其具体的大小

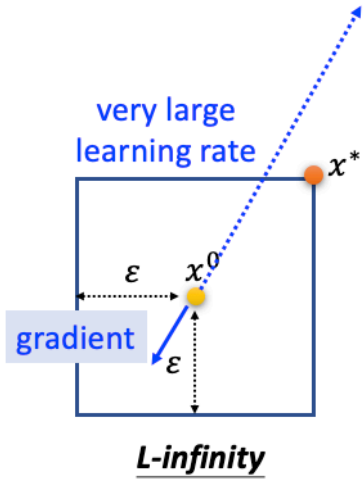
那么FGSM到底是怎么运作的呢?

我们可以看作FGSM是使用了非常大的一个learning rate，使x飞出了方形区域，由于L-infinity的限制，输出会被限制到方形区域内部，即x^*在方形区域的右上角

$$x^* \leftarrow x^0 - \varepsilon \Delta x$$

$$\Delta x = \begin{bmatrix} sign(\partial L/\partial x_1) \\ sign(\partial L/\partial x_2) \\ sign(\partial L/\partial x_3) \\ \vdots \end{bmatrix}$$

only have +1 or -1



White Box v.s. Black Box

在之前的attack中，我们假设已经知道了network的参数θ，目标是找到最优化的x'，这种attack就称为**White Box**

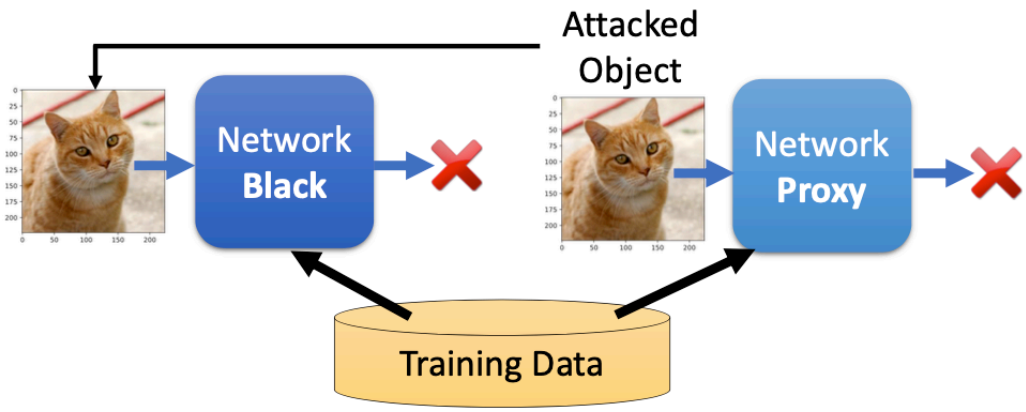
但在大多数的情况中，我们都不知道network的参数，但也需要去attack这个network，这就是**Black Box**

Black Box Attack

如果我们现在已经知道了black network的training data，那么我们就可以用同样的training data来训练一个proxy network，再生成attacked object，如果能过成功attack新的proxy network，那么我们就可以把这个object也作为black network的输入，也可以attack成功

如果不能得到相应的training data，network如果是一个在线版本，我们可以输入大量的图片，得出相对应的分类结果，从而可以组合成相对应的训练资料，来得出proxy network

If you have the training data of the target network
Train a proxy network yourself
Using the proxy network to generate attacked objects
Otherwise, obtaining input-output pairs from target network



也有一些实验数据证明黑箱攻击是有可能成功的，现在假设Black Box有五种，现在我们来训练proxy network，我们用ResNet-152生成的图片，如果black box的network也是ResNet-152，那么attack成功的几率就会非常高，表格中的4%表示系统辨识的准确率

Black

Proxy	ResNet-152	ResNet-101	ResNet-50	VGG-16	GoogLeNet
ResNet-152	4%	13%	13%	20%	12%
ResNet-101	19%	4%	11%	23%	13%
ResNet-50	25%	19%	5%	25%	14%
VGG-16	20%	16%	15%	1%	7%
GoogLeNet	25%	25%	17%	19%	1%

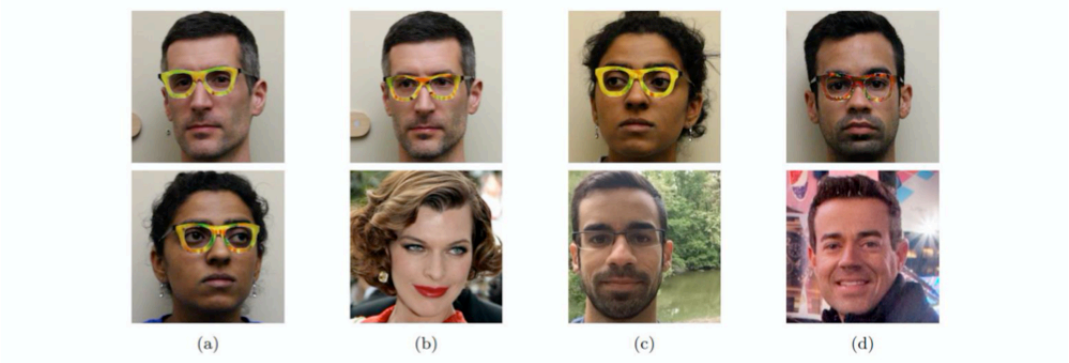
https://arxiv.org/pdf/1611.02770.pdf

Attack in the Real World

1. An attacker would need to find perturbations that generalize beyond a single image.

2. Extreme differences between adjacent pixels in the perturbation are unlikely to be accurately captured by cameras.

3. It is desirable to craft perturbations that are comprised mostly of colors reproducible by the printer.



- You can attack audio
  - https://nicholas.carlini.com/code/audio_adversarial_examples/
  - https://adversarial-attacks.net
- You can attack text

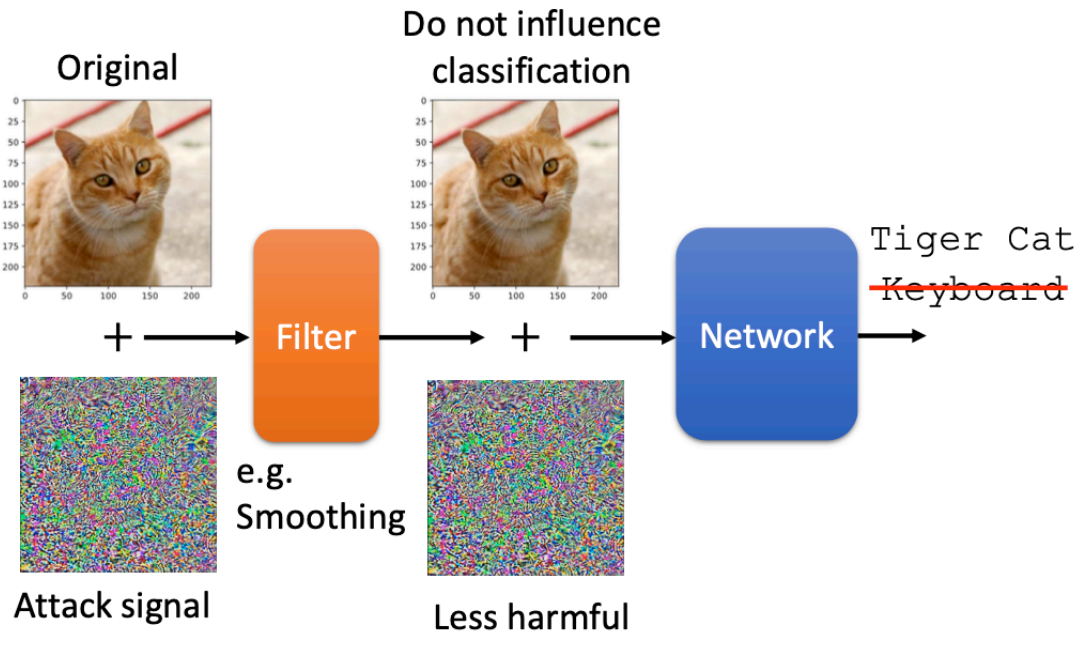
Article: Super Bowl 50
Paragraph: "*Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver's Executive Vice President of Football Operations and General Manager. Quarterback Jeff Dean had jersey number 37 in Champ Bowl XXXIV.*"
Question: "*What is the name of the quarterback who was 38 in Super Bowl XXXIII?*"
Original Prediction: John Elway
Prediction under adversary: Jeff Dean

https://arxiv.org/pdf/1707.07328.pdf

Defense

- Adversarial Attack cannot be defended by weight regularization, dropout and model ensemble.
- Two types of defense:
  - ***Passive defense***: Finding the attached image without modifying the model
    - Special case of Anomaly Detection
  - ***Proactive defense***: Training a model that is robust to adversarial attack

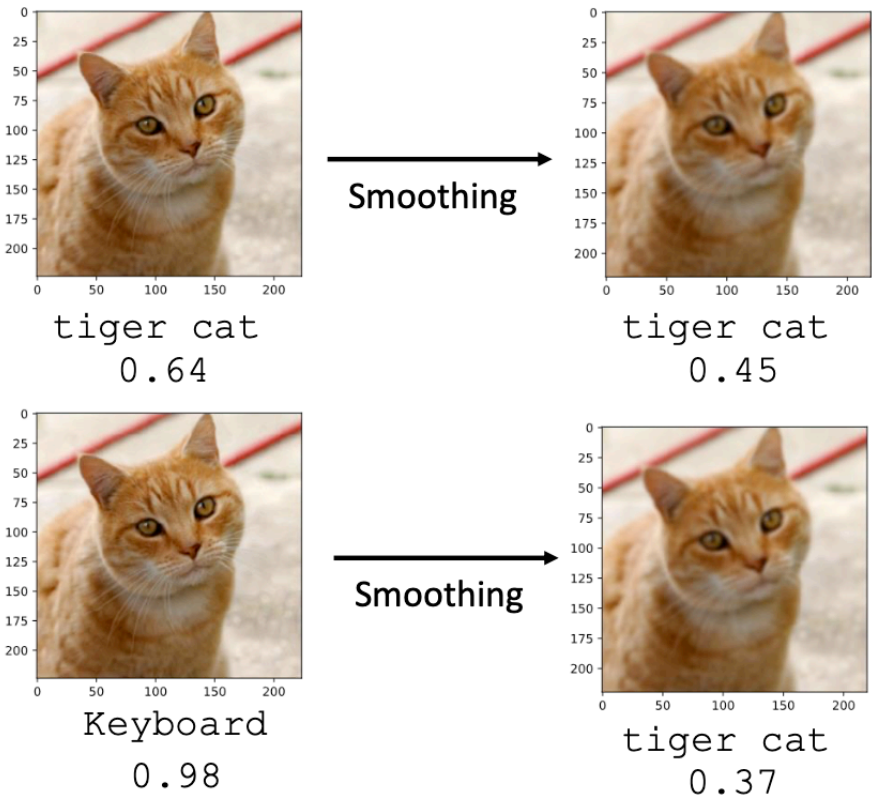
Passive defense



这个filter可以是smoothing，对于原来输入的attack图片network认为其是keyboard，经过smoothing之后，network就认为是tiger cat了，是正确的分类结果

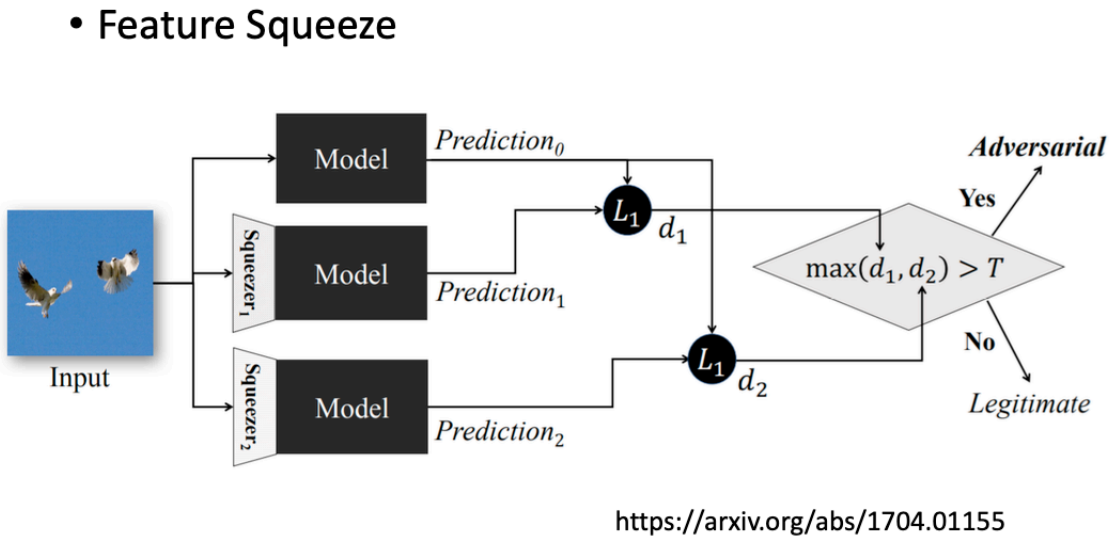
Q：那么为什么smoothing可以达到这种效果呢?

A：只有某几种方向上的的信号可以使attack成功。如果使用了smoothing这种filter，就把这几种信号改变了，那么attack就失效了；加上smoothing并不会伤害原来的图片，所以network仍然可以得出正确的结果

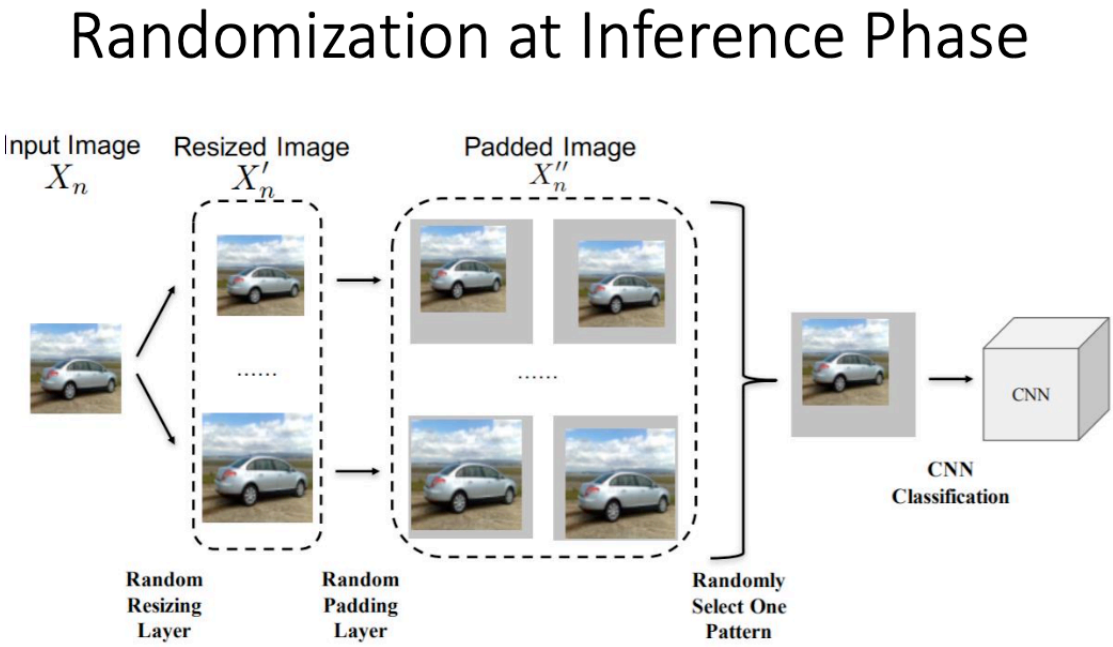


根据这种思想，有学者就提出了feature squeeze

对于同一个input，我们先得出model的输出结果$Prediction_0$，再根据$Squeeze_1$，$Squeeze_2$得出结果$Prediction_1, Prediction_2$，如果$Prediction_0$和$Prediction_1, Prediction_2$之间的差值d很大，那么我们就可以认为input是来attack的



还有另外一种方法



https://arxiv.org/abs/1711.01991

Proactive defense

首先我们通过某种算法找出漏洞，找到相应的adversarial input，再把这些input和之前的training data一起作为新的input data，输入network，相当于进行了data augmentation，这个过程进行T次，每次的input data都是不一样的

Given training data $X = \{(x^1, \hat{y}^1), (x^2, \hat{y}^2), \cdots, (x^N, \hat{y}^y)\}$

Using X to train your model

For t = 1 to T

This method would stop algorithm A, but is still vulnerable for algorithm B.

For n = 1 to N 找出漏洞

Find adversarial input $\tilde{x}^n$ given x^n by an attack algorithm Using algorithm A

We have new training data different in each iteration

$X' = \{(\tilde{x}^1, \hat{y}^1), (\tilde{x}^2, \hat{y}^2), \cdots, (\tilde{x}^N, \hat{y}^y)\}$ Data Augmentation

Using both X' to update your model 把洞補起來

如果attacker知道了我们是使用算法A来进行模拟，那么attacker可以使用算法B来进行attack，那么我们的network并不能抵御这种attack