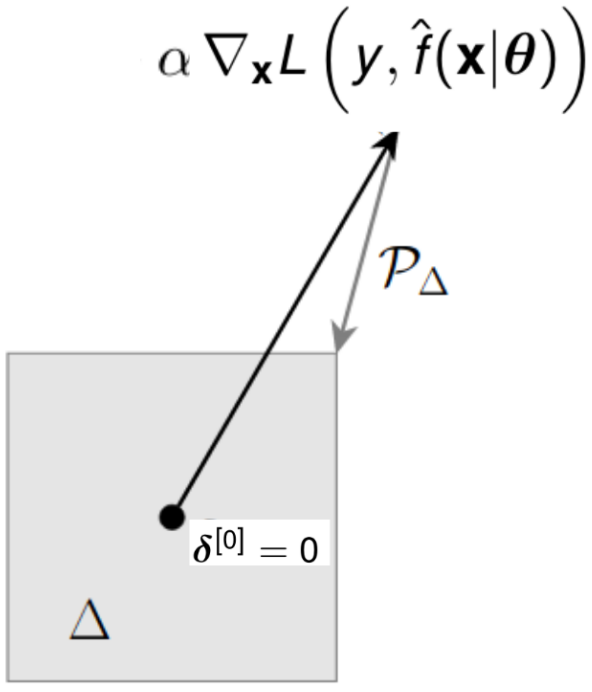
Deep Learning

Adversarial Training Advances



Learning goals

- Advanced adversarial training
- Projected gradient descent
- Fast gradient sign method

PROJECTED GRADIENT DESCENT

- In contrast to logistic regression, neural networks can have a bumpier, non-convex loss surface.
- As a consequence, Danskin's theorem does not longer hold and the inner optimization problem must be solved approximately.
- One approximation method is projected gradient descent (PGD)[1].
- Let $\hat{f}$ be the pretrained model, $\mathbf{x}$ the input to the model, y the target and $L\left(y, \hat{f}(\mathbf{x}|\boldsymbol{\theta})\right)$ the loss function used to train the network.
- In each gradient descent step, the basic PGD algorithm updates $\boldsymbol{\delta}$ as:

$$\boldsymbol{\delta}^{[t+1]} = \mathcal{P}\left(\boldsymbol{\delta}^{[t]} + \alpha \nabla_{\boldsymbol{\delta}} L\left(y, \hat{f}(\mathbf{x} + \boldsymbol{\delta}^{[t]}|\boldsymbol{\theta})\right)\right)$$

  where $\mathcal{P}$ denotes the projection onto the ball of interest.

[1] Technically speaking, it is gradient *ascent* since we are maximizing a function, but for the sake of generality, we just refer to the process here as gradient descent.

PROJECTED GRADIENT DESCENT

- In essence, $\boldsymbol{\delta}^{[t+1]}$ is obtained by moving from $\boldsymbol{\delta}^{[t]}$ (with a step size α) **in the direction** of the gradient of the loss with respect to $\boldsymbol{\delta}$ (evaluated at $\boldsymbol{\delta}^{[t]}$) and then projecting back to Δ.
- In case where the feasible set is $\mathcal{B}_{\epsilon}^{\infty}$, the projection of an arbitrary vector **z** is simply:

$$\mathcal{P}(\mathbf{z}) = \mathit{clip}(\mathbf{z}, [-\epsilon, \epsilon])$$

- Therefore, when Δ is $\mathcal{B}_{\epsilon}^{\infty}$, one gradient step is then defined as:

$$\boldsymbol{\delta}^{[t+1]} = \mathit{clip}\left(\boldsymbol{\delta}^{[t]} + \alpha \nabla_{\boldsymbol{\delta}} L\left(y, \hat{f}(\mathbf{x} + \boldsymbol{\delta}^{[t]} | \boldsymbol{\theta})\right), [-\epsilon, \epsilon]\right)$$

PROJECTED GRADIENT DESCENT

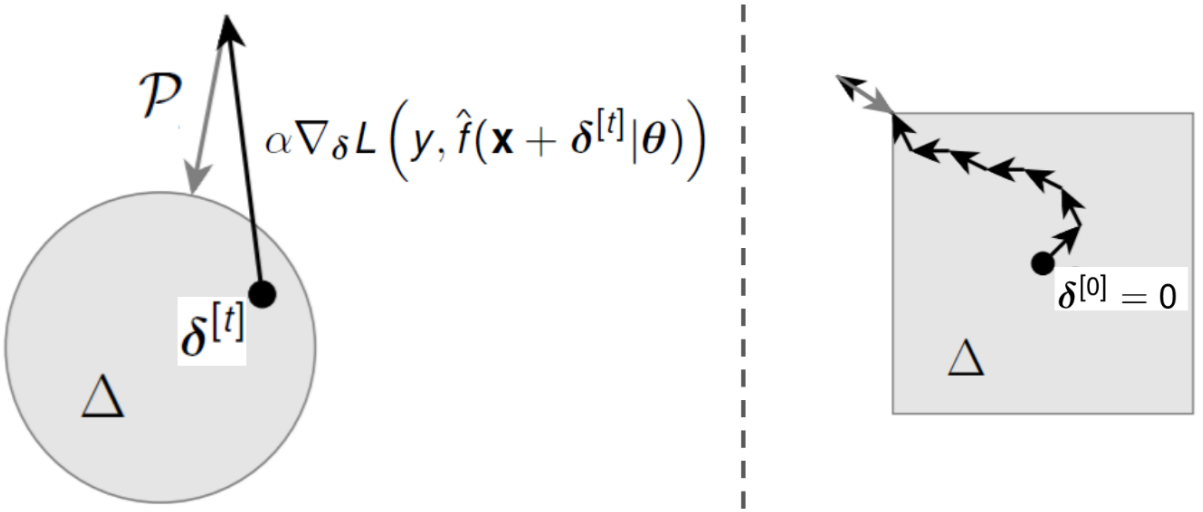


Figure: *Left*: $\delta^{[t]} + \alpha \nabla_{\delta} L(y, \hat{f}(\mathbf{x} + \delta^{[t]}|\theta))$ is projected back to the perturbation set Δ using $\mathcal{P}$. Here, Δ is $\mathcal{B}_{\epsilon}^{2}$. *Right*: Multiple steps of PGD are shown in case of $\Delta = \mathcal{B}_{\epsilon}^{\infty}$; the projection must be only executed in the last step (Kolter & Madry, 2019). (Note: A variant of PGD known as *normalized* PGD is shown here. This is why each step has the same size. See Kolter et al. (2019) for details.)

FAST GRADIENT SIGN METHOD

- Fast Gradient Sign Method (FGSM) is a special case of PGD when $\Delta = \mathcal{B}_\epsilon^\infty$ and $\alpha \to \infty$.
- As before, the projection of an arbitrary vector $\mathbf{z}$ onto $\mathcal{B}_\epsilon^\infty$ is $\mathcal{P}(\mathbf{z}) = \mathit{clip}(\mathbf{z}, [-\epsilon, \epsilon])$.
- As $\alpha \to \infty$, the elements of $\boldsymbol{\delta}$ are either set to $-\epsilon$ or ϵ depending on the sign of the corresponding component of the gradient.
- Thus, the FGSM algorithm computes $\boldsymbol{\delta}$ as

$$\boldsymbol{\delta} = \epsilon \mathit{sign}\left(\nabla_{\mathbf{x}} L\left(y, \hat{f}(\mathbf{x}|\boldsymbol{\theta})\right)\right)$$

- Note that for FGSM we only conduct one calculation and not multiple gradient descent steps.
- Furthermore, because we usually initialize $\boldsymbol{\delta}^{[0]}$ as 0

$$\nabla_{\boldsymbol{\delta}} L\left(y, \hat{f}(\mathbf{x} + \boldsymbol{\delta}|\boldsymbol{\theta})\right) = \nabla_{\mathbf{x}} L\left(y, \hat{f}(\mathbf{x}|\boldsymbol{\theta})\right)$$

FAST GRADIENT SIGN METHOD

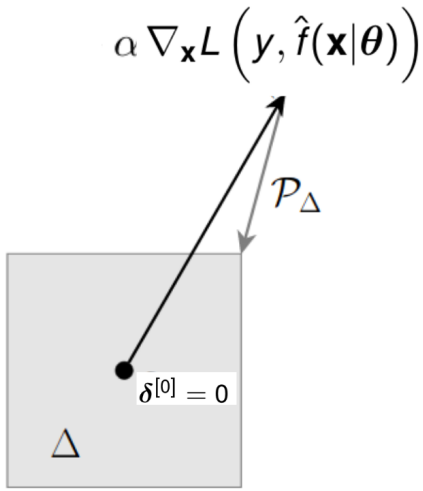


Figure: δ is obtained by setting each element of $\nabla_{\mathbf{x}} L\left(y, \hat{f}(\mathbf{x}|\theta)\right)$ to $-\epsilon$ or ϵ depending on its sign. Note that this slightly changes the direction of the step that is taken (Kolter & Madry, 2019).

- Implicitly, the (element-wise) *sign* function is simply a way to constrain the size of the "step" that we take in the direction of the gradient. It is basically equal to a projection of the step back on Δ (which is $\mathcal{B}_{\epsilon}^{\infty}$).

FAST GRADIENT SIGN METHOD

- Note: The optimal attack against the linear binary classifier we saw in the last section was also FGSM!

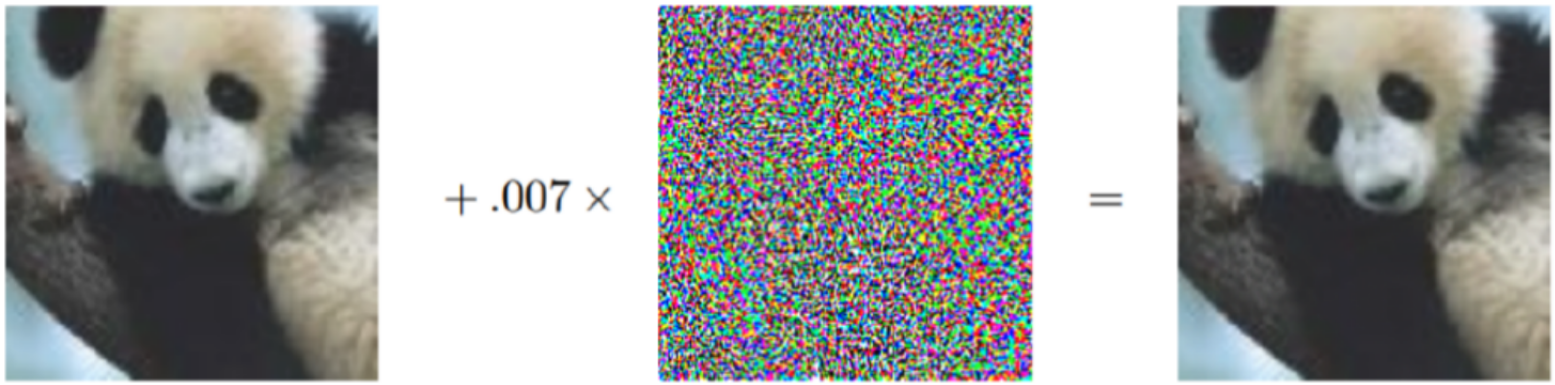


Figure: By adding an imperceptibly small vector whose elements are equal to the sign of the elements of the gradient of the cost function with respect to the input, GoogLeNet's classification of the image was changed from 'panda' to 'gibbon'. In this example, the ϵ is 0.007 (Goodfellow, 2017).

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