Lecture 27 - DL for Practitioners

DSE 512

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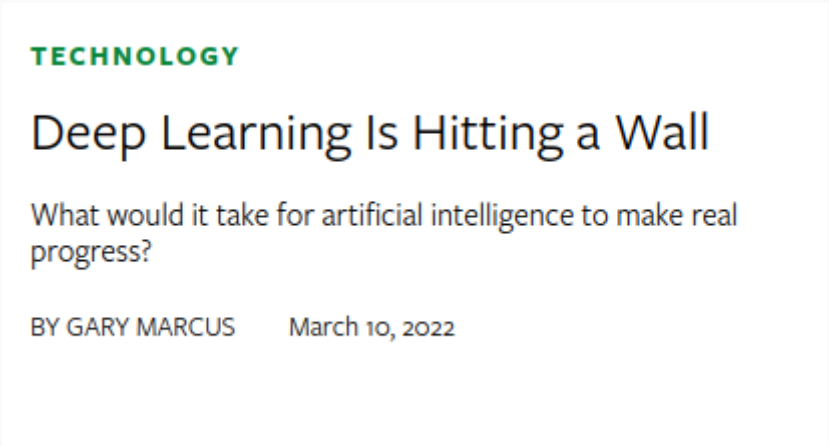
2022-05-05

From Last Time

- Homework 5 is assigned
- Questions?

More DL Background

AI Winter?



TECHNOLOGY

Deep Learning Is Hitting a Wall

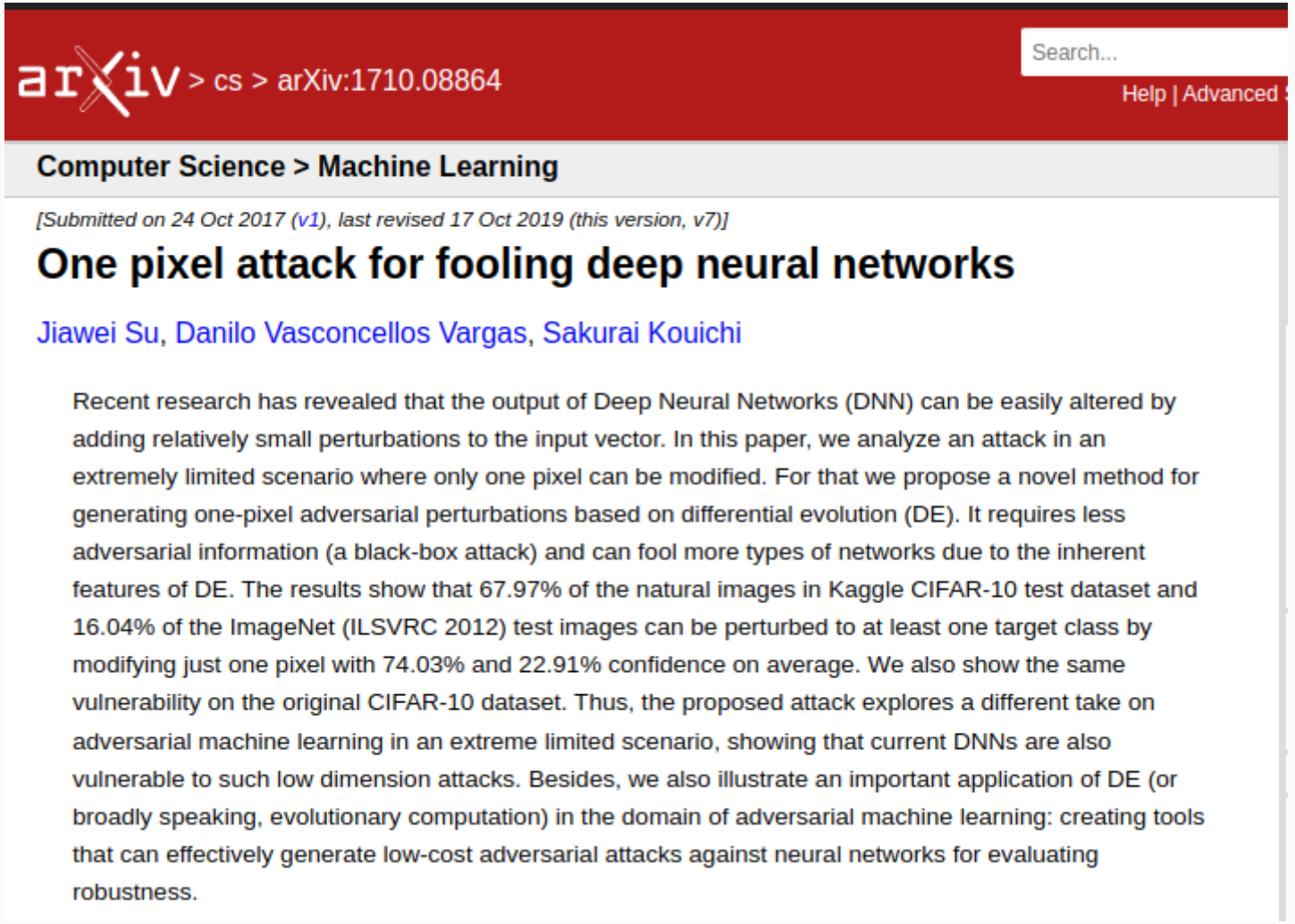
What would it take for artificial intelligence to make real progress?

BY GARY MARCUS March 10, 2022

When the stakes are higher, though, as in radiology or driverless cars, we need to be *much* more cautious about adopting deep learning. When a single error can cost a life, it's just not good enough. Deep-learning systems are particularly problematic when it comes to "outliers" that differ substantially from the things on which they are trained. Not long ago, for example, a Tesla in so-called "Full Self Driving Mode" encountered a person holding up a stop sign in the middle of a road. The car failed to recognize the person (partly obscured by the stop sign) and the stop sign (out of its usual context on the side of a road); the human driver had to take over. The scene was far enough outside of the training database that the system had no idea what to do.

https://nautil.us/deep-learning-is-hitting-a-wall-14467/

DL Model Fragility



arXiv > cs > arXiv:1710.08864

Search...

Help | Advanced

Computer Science > Machine Learning

[Submitted on 24 Oct 2017 (v1), last revised 17 Oct 2019 (this version, v7)]

One pixel attack for fooling deep neural networks

Jiawei Su, Danilo Vasconcellos Vargas, Sakurai Kouichi

Recent research has revealed that the output of Deep Neural Networks (DNN) can be easily altered by adding relatively small perturbations to the input vector. In this paper, we analyze an attack in an extremely limited scenario where only one pixel can be modified. For that we propose a novel method for generating one-pixel adversarial perturbations based on differential evolution (DE). It requires less adversarial information (a black-box attack) and can fool more types of networks due to the inherent features of DE. The results show that 67.97% of the natural images in Kaggle CIFAR-10 test dataset and 16.04% of the ImageNet (ILSVRC 2012) test images can be perturbed to at least one target class by modifying just one pixel with 74.03% and 22.91% confidence on average. We also show the same vulnerability on the original CIFAR-10 dataset. Thus, the proposed attack explores a different take on adversarial machine learning in an extreme limited scenario, showing that current DNNs are also vulnerable to such low dimension attacks. Besides, we also illustrate an important application of DE (or broadly speaking, evolutionary computation) in the domain of adversarial machine learning: creating tools that can effectively generate low-cost adversarial attacks against neural networks for evaluating robustness.

https://arxiv.org/abs/1710.08864

Some Famous Image Datasets

- MNIST
  - handwritten digits
- CIFAR
  - 10 and 100 class "common item" dataset
  - 60k hand-labeled images
- Imagenet
  - 1000 class "common item" dataset
  - Nearly 15 million hand-annotated images

Some Common CNN's

- AlexNet (Alex Krizhevsky, Hinton)
- VGG (Oxford)
- ResNet (Microsoft Research)

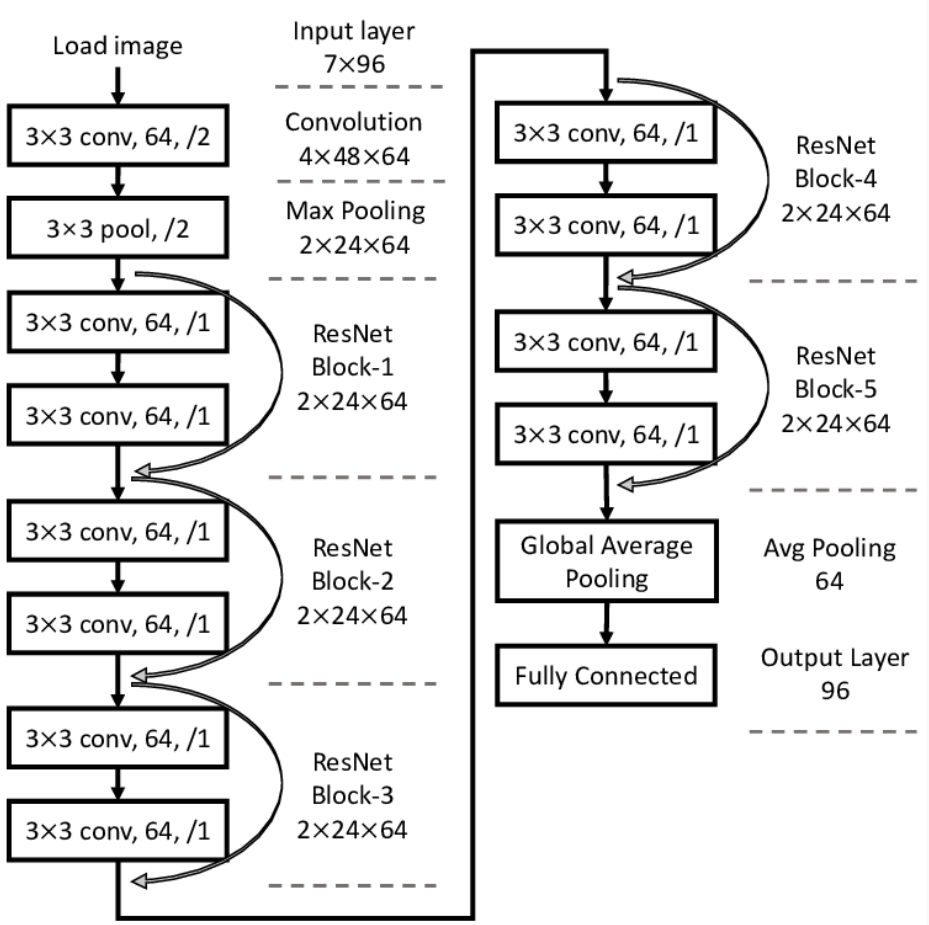


Image from https://www.researchgate.net/figure/The-structure-of-ResNet-12_fig1_329954455

Some History

- AlexNet was the first big splash for DL
- Imagenet competition:
  - Best before 2012: 25% top-5 error rate
  - 2012: (AlexNet) 15.3% top-5 error rate (Winner)
  - 2014: (VGG-16) 7.3% top-5 error rate (Runner up)
  - 2015: (ResNet) 3.57% top-5 error rate (Winner)

ResNet

- Residual Neural Network
- Major insight: utilizes "skip connections"
- Different architectures with differing numbers of hidden layers
- 18, 34, 50, 101, 152, ...

PyTorch

Installation

```
pip install torch torchvision
```

Resnet Example

Throughout, our example is modified from the pytorch example https://pytorch.org/hub/pytorch_vision_resnet/

```
import torch
model = torch.hub.load('pytorch/vision:v0.10.0', 'resnet18', pretrained=True)
```

```
Downloading: "https://github.com/pytorch/vision/archive/v0.10.0.zip" to /home/mschmid3/.cache/torch/
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /home/mschmid3/.cache/to
100.0%
```

Is This a Dog?

Getting the Image

```
import urllib
url, filename = ("https://github.com/pytorch/hub/raw/master/images/dog.jpg", "dog.jpg")
urllib.request.urlretrieve(url, filename)

from PIL import Image
input_image = Image.open(filename)
```

Preprocessing

All pre-trained models require the same image normailization

- 3-channel RGB (3 x H x W)
- H and W are at least 224
- values in `[0, 1]`
- normalized to mean `[0.485, 0.456, 0.406]` and sd `[0.229, 0.224, 0.225]`
- minibatches

Preprocessing

```
from torchvision import transforms
dim = 224
mean = [0.485, 0.456, 0.406]
sd = [0.229, 0.224, 0.225]
preprocess = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(dim),
    transforms.ToTensor(),
    transforms.Normalize(mean=mean, std=sd),
])
input_tensor = preprocess(input_image)

input_batch = input_tensor.unsqueeze(0)
```

Apply the Model

```
with torch.no_grad():
    output = model(input_batch)

output.shape
```

```
torch.Size([1, 1000])
```

```
output[0, range(8)]
```

```
tensor([-1.2817, -1.3418, -0.7523, -0.1647, -0.8529,  1.3985])
```

```
probabilities = torch.nn.functional.softmax(output[0], dim=0)
probabilities[range(8)]
```

```
tensor([4.4294e-07, 4.1711e-07, 7.5207e-07, 1.3535e-06, 6.8011e-07, 6.4618e-06])
```

Imagenet Labels

```
import wget
imagenet_labels = 'https://raw.githubusercontent.com/pytorch/hub/master/imagenet_classes.
wget.download(imagenet_labels)

with open("imagenet_classes.txt", "r") as f:
    categories = [s.strip() for s in f.readlines()]

# Show top categories per image
top5_prob, top5_catid = torch.topk(probabilities, 5)
for i in range(top5_prob.size(0)):
    print(categories[top5_catid[i]], top5_prob[i].item())
```

```
bucket 0.008743884973227978
plunger 0.006772770546376705
hook 0.005883164703845978
paper towel 0.005243285093456507
ashcan 0.005110110156238079
```

NO! This is a Bucket

Why Did This Happen?

- We aren't training, we're evaluating
- Need to call `model.eval()`
- For training we use `model.train()`

Making a Prediction Function

```
def predict_with_resnet(input_batch, nlayers):
    model = torch.hub.load('pytorch/vision:v0.10.0', 'resnet' + str(nlayers), pretrained=
    model.eval()

    with torch.no_grad():
        output = model(input_batch)

    probabilities = torch.nn.functional.softmax(output[0], dim=0)
    top5_prob, top5_catid = torch.topk(probabilities, 5)
    for i in range(top5_prob.size(0)):
        print(categories[top5_catid[i]], top5_prob[i].item())
```

Predictions

```
predict_with_resnet(input_batch, 18)
```

```
Samoyed 0.8846226930618286
Arctic fox 0.045805230736732 48
white wolf 0.044276077300310135
Pomeranian 0.005621373653411865
Great Pyrenees 0.004652000498026609
```

```
predict_with_resnet(input_batch, 50)
```

```
Samoyed 0.8732959032058716
Pomeranian 0.030270766466856003
white wolf 0.019671263173222542
keeshond 0.01107351016253233
Eskimo dog 0.009204256348311901
```

```
predict_with_resnet(input_batch, 34)
```

```
Samoyed 0.8840289115905762
Pomeranian 0.039363887161016464
Arctic fox 0.025501668453216553
keeshond 0.023505182936787605
white wolf 0.004716045688837767
```

```
predict_with_resnet(input_batch, 101)
```

```
Samoyed 0.951001763343811
Pomeranian 0.019060354679822922
white wolf 0.0076106698252260685
Eskimo dog 0.005612253211438656
keeshond 0.0036319640930742025
```

Making a Preprocessing Function

```
from PIL import Image
from torchvision import transforms
def preprocess(filename):
    input_image = Image.open(filename).convert('RGB')
    dim = 224
    mean = [0.485, 0.456, 0.406]
    sd = [0.229, 0.224, 0.225]
    preprocess = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(dim),
        transforms.ToTensor(),
        transforms.Normalize(mean=mean, std=sd),
    ])
    input_tensor = preprocess(input_image)
    input_batch = input_tensor.unsqueeze(0)
    return input_batch
```

What Is This?

Identifying Known Objects

What happens when we show it images it has seen?

```
def string_vec_contains(vec, value):
    for v in vec:
        if value == v:
            return True
    return False
```

```
string_vec_contains(categories, 'stove')
```

```
True
```

```
string_vec_contains(categories, 'pot')
```

```
True
```

What Is This?

Stove Predictions

```
input_batch = preprocess('stove.jpg')
predict_with_resnet(input_batch, 34)
```

```
hard disc 0.28327348828315735
dishwasher 0.147591695189476
can opener 0.06293792277574539
water bottle 0.062163639813661575
oil filter 0.056593675166368484
```

```
input_batch = preprocess('stove.jpg')
predict_with_resnet(input_batch, 101)
```

```
hard disc 0.2116469293832779
tape player 0.11292723566293716
china cabinet 0.07321552187204361
barometer 0.053209833800792694
loudspeaker 0.04002181068062782
```

```
input_batch = preprocess('stove.jpg')
predict_with_resnet(input_batch, 50)
```

```
hard disc 0.9527970552444458
oil filter 0.009614785201847553
tape player 0.005083377007395029
barometer 0.00492066191509366
stove 0.0043748836033046246
```

```
input_batch = preprocess('stove.jpg')
predict_with_resnet(input_batch, 152)
```

```
hard disc 0.3098987936973572
spotlight 0.05348089337348938
tape player 0.04961665719747543
stove 0.038500864058732986
car wheel 0.03589474409818649
```

What Is This?

Stove Predictions

```
input_batch = preprocess('stove_eye_covers
predict_with_resnet(input_batch, 34)
```

```
typewriter keyboard 0.2084062248468399
dial telephone 0.18769077956676483
beaker 0.0371890626847744
barrel 0.03656706586480141
ladle 0.033604662865400314
```

```
input_batch = preprocess('stove_eye_covers
predict_with_resnet(input_batch, 101)
```

```
ladle 0.12029356509447098
rotisserie 0.06697414815425873
radio 0.06427623331546783
beaker 0.06244540214538574
dishwasher 0.052622828632593155
```

```
input_batch = preprocess('stove_eye_covers
predict_with_resnet(input_batch, 50)
```

```
ladle 0.11306107044219971
beaker 0.08212278038263321
tray 0.05218195170164108
barometer 0.04987306147813797
Petri dish 0.04542011767625809
```

```
input_batch = preprocess('stove_eye_covers
predict_with_resnet(input_batch, 152)
```

```
vending machine 0.24071547389030457
rotisserie 0.14042000472545624
espresso maker 0.056181155145168304
radio 0.04111208766698837
typewriter keyboard 0.027740538120269775
```

What Is This?

Stove Predictions

```
input_batch = preprocess('stove_pot.jpg')
predict_with_resnet(input_batch, 34)
```

```
dial telephone 0.12105247378349304
reflex camera 0.12073760479688644
measuring cup 0.08727884292602539
can opener 0.05370359495282173
projector 0.03471950814127922
```

```
input_batch = preprocess('stove_pot.jpg')
predict_with_resnet(input_batch, 101)
```

```
ladle 0.2898538410663605
measuring cup 0.15415646135807037
barometer 0.12850868701934814
espresso maker 0.06878988444805145
dishwasher 0.05793755128979683
```

```
input_batch = preprocess('stove_pot.jpg')
predict_with_resnet(input_batch, 50)
```

```
hard disc 0.18501941859722137
frying pan 0.09731835126876831
tape player 0.08419615030288696
stethoscope 0.07998504489660263
strainer 0.07762958109378815
```

```
input_batch = preprocess('stove_pot.jpg')
predict_with_resnet(input_batch, 152)
```

```
strainer 0.22474919259548187
espresso maker 0.10625191777944565
stove 0.0950375497341156
frying pan 0.09055980294942856
measuring cup 0.06810993701219559
```

What Is This?

Stove Predictions

```
input_batch = preprocess('pot.jpg')
predict_with_resnet(input_batch, 34)
```

```
measuring cup 0.4072619080543518
gasmask 0.09784889966249466
spotlight 0.05999481678009033
strainer 0.0467490591108799
water jug 0.0331653542816638 95
```

```
input_batch = preprocess('pot.jpg')
predict_with_resnet(input_batch, 101)
```

```
coffeepot 0.28866541385650635
measuring cup 0.18772068619728088
ladle 0.129950612783432
dishwasher 0.09591767191886902
frying pan 0.08545246720314026
```

```
input_batch = preprocess('pot.jpg')
predict_with_resnet(input_batch, 50)
```

```
measuring cup 0.29147830605506897
strainer 0.14410176873207092
coffeepot 0.05094141140580177
water jug 0.047999233007431 03
frying pan 0.04500320926308632
```

```
input_batch = preprocess('pot.jpg')
predict_with_resnet(input_batch, 152)
```

```
coffeepot 0.2809428572654724
measuring cup 0.19728830456733704
espresso maker 0.16359879076480865
dishwasher 0.05741313472390175
water jug 0.05394719913601875
```

Identifying Unknown Objects

What happens when we show it images it *has not* seen?

```
string_vec_contains(categories, 'thinking
```

```
False
```

```
string_vec_contains(categories, 'big thin
```

```
False
```

What Is This?

Thinking Face Predictions

```
input_batch = preprocess('big_think.png')
predict_with_resnet(input_batch, 34)
```

```
piggy bank 0.5996401309967041
jack-o'-lantern 0.12286479771137238
mouse 0.05163700133562088
ocarina 0.03909693658351898
mask 0.03525783121585846
```

```
input_batch = preprocess('big_think.png')
predict_with_resnet(input_batch, 101)
```

```
crash helmet 0.40559521317481995
jack-o'-lantern 0.1542121022939682
piggy bank 0.10804979503154755
mouse 0.06449303030967712
football helmet 0.028007907792925835
```

```
input_batch = preprocess('big_think.png')
predict_with_resnet(input_batch, 50)
```

```
piggy bank 0.41932418942451477
mouse 0.18913999199867249
ping-pong ball 0.061573710292577744
soap dispenser 0.04287487640976906
jack-o'-lantern 0.029319854453206062
```

```
input_batch = preprocess('big_think.png')
predict_with_resnet(input_batch, 152)
```

```
jack-o'-lantern 0.37505489587783813
piggy bank 0.31303077936172485
mask 0.05067762732505798
wall clock 0.04246150702238083
toilet seat 0.041972700506448746
```

Wrapup

Wrapup

- What exactly have we learned?
- Deep Learning is not infallible; trust it blindly at your peril
- It can often correctly classify things it knows about
- Things the model has not seen at all are unlikely to be identified remotely correctly
- What about rare events?

Questions?