CS3485

Deep Learning for Computer Vision

Lec 11: Adversarial Examples and Self-supervision

Announcements

- No quiz today. Next Thursday the quiz will cover 3 lectures.
- Lab 4 will be released tomorrow morning and will be due Tues Oct/22nd.

(Tentative) Lecture Roadmap

Basics of Deep Learning

- Intro to Computer Vision
- Linear Classifiers and Perceptron
- Multilayer Perceptron
- Optimization in Deep Learning
- Pytorch I – MLPs
- Pytorch II – Images and Regularization
- Convolutional Neural Networks
- Data Augmentation and Deep CNNs
- Transfer Learning and Residual Nets
- Inception Net and what CNNs learn
- Adversarial Examples and Self-supervision

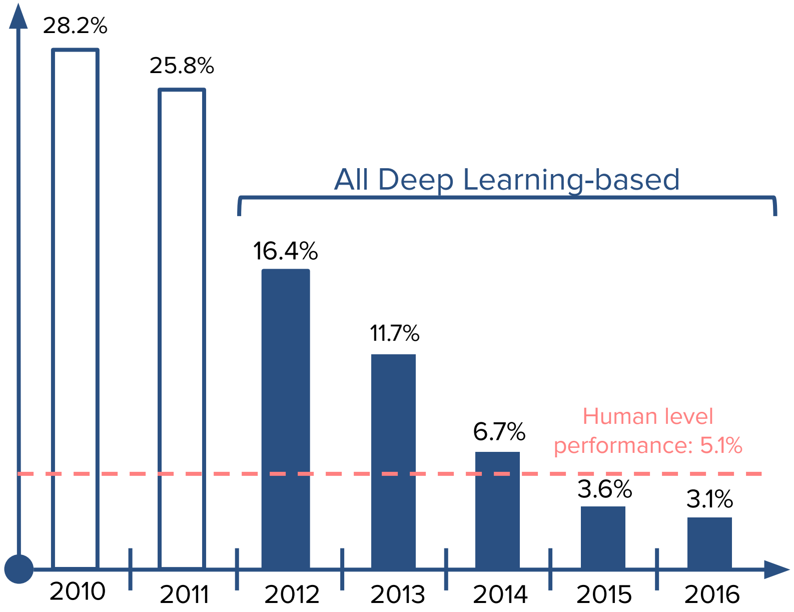
Deep Learning and Computer Vision in Practice

- Intro to MLOps
- Intro to Object Detection
- Fast Object Detection
- Intro to Image Segmentation
- Applications of Detection and Segmentation
- Autoencoders
- Image Generation with GANs
- Advanced GANs
- The Attention Mechanism
- Transformers and ChatGPT
- Image Generation by Prompt
- Misc. Topics

Deep Learning for Image Classification

- Last time, we saw how well the Inception Networks perform on ImageNet and how they can to learn interesting image features.
- But Inception V3's great result on ImageNet (5.3% Top-5 error) still pales compared to the recent **State-of-The-Art (SOTA)** for that task.
- In fact, every year (now every few months!) we see the next SOTA deep learning model **dethrone** the previous model.
- Furthermore, the Human Performance on it was long outmatched.
- But what do these results really mean?

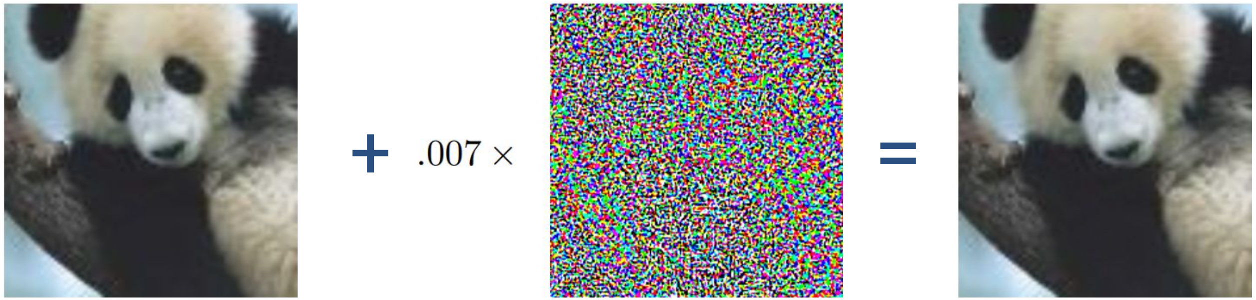
ImageNet Top 5 Classification Error Rate



2020 SOTA: 1.3% by FixEfficinetNet

Adversarial Examples

- In some ways, however it **doesn't mean** that deep learning achieved super-human recognition capacity.
- One way to see this is via **Adversarial Examples**. Consider the following classifications made by GoogLeNet trained on ImageNet:



"panda" (57.7% confidence) | "nematode" (8.2% confidence) | "gibbon" (99.3% confidence)

- Despite making the right classification for the original image, it gives a very wrong result (with certainty) on a very similar image!

Natural Adversarial Examples

- The last image is adversarial because, despite being *seemingly easy* for a good network to classify well, that network makes a crude mistake.
- We can distinguish two types of adversarial examples: **natural** and **synthetic**.
- A natural adversarial example is a natural, organic image which is tough for the model to comprehend.
- The ImageNet-A dataset was created to be a set of natural images, **easily classified by humans**, that ResNet50 trained on ImageNet (Top-5: 7.8%) classifies very poorly.

Network Predictions Using ResNet-50 on Images from ImageNet-A

Class: Dragonfly Prediction: Manhole Cover	Class: Bullfrog Prediction: Fox Squirrel	Class: Butterfly Prediction: Washing Machine	Class: Jay Prediction: Jeep

Natural Adversarial Examples

- In-fact the ResNet-50 (the SOTA method for for some years) pre-trained model obtains an **accuracy of only 3%** on ImageNet-A!
- The same ImageNet-A's paper also show that this poor classification result is a product of the network using **wrong image cues** when classifying images:

Shape cue

Class: Candle
Prediction: Jack-o'lantern

Class: Lycaenidae
Prediction: Broom

Color cue

Class: Drangonfly
Prediction: Skunk

Class: Drangonfly
Prediction: Banana

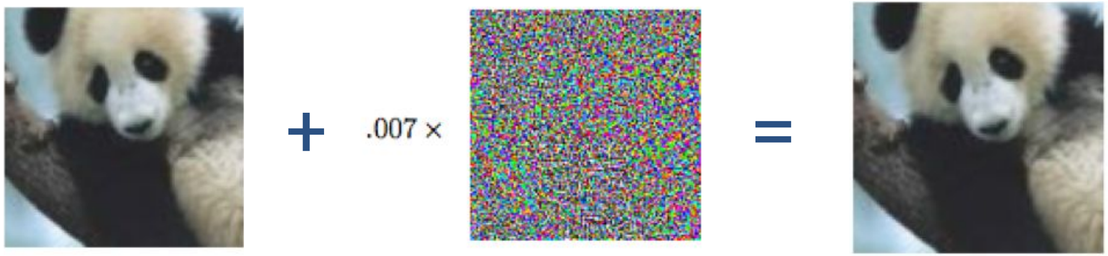
Background cue

Class: Candle
Prediction: Nail

Class: Mushroom
Prediction: Nail

Synthetic Adversarial Examples

- Besides these naturally occurring adversarial examples, one can also **synthetically** create them.
- Here we artificially **induce some noise** in an image such that it still remains very similar visually to the original, but the infused noise ends up degrading the classifier accuracy.
- This is the case of our first example, found in this paper:



$$\boldsymbol{x} \quad + \quad .007 \times \operatorname{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y)) \quad = \quad \boldsymbol{x} + \epsilon \operatorname{sign}(\nabla_{\boldsymbol{x}} J(\boldsymbol{\theta}, \boldsymbol{x}, y))$$

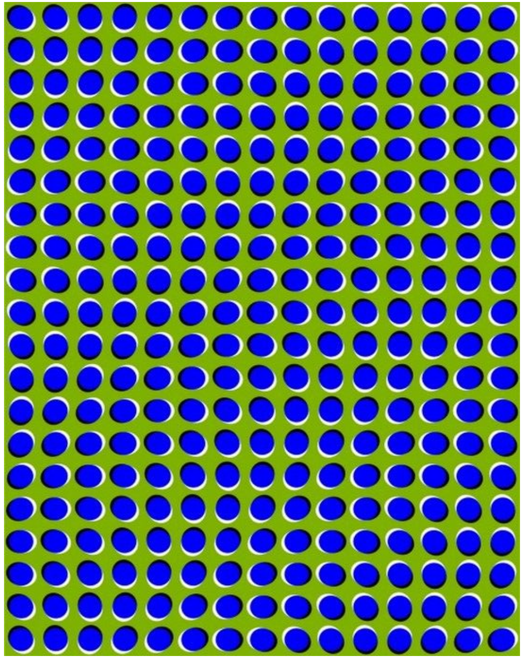
"panda"
(57.7% confidence)

"nematode"
(8.2% confidence)

"gibbon"
(99.3% confidence)

Synthetic Adversarial Examples

- When generating adversarial examples synthetically, we are creating something that is **analogous to an optical illusion** to humans.
- We explicitly search for the noise pattern that will **break the system**.
- This is done in a strategy similar to what we saw in gradient descent: “How can I change this noise pattern to **maximize the classification error** of the original image?”
- Research also suggests that we **can always** find adversarial examples to any deep learning system due to:
  - NNs are too linear for some regions of the input space (source),
  - The high dimensionality of its search space (source),
  - Etc. (source, source).



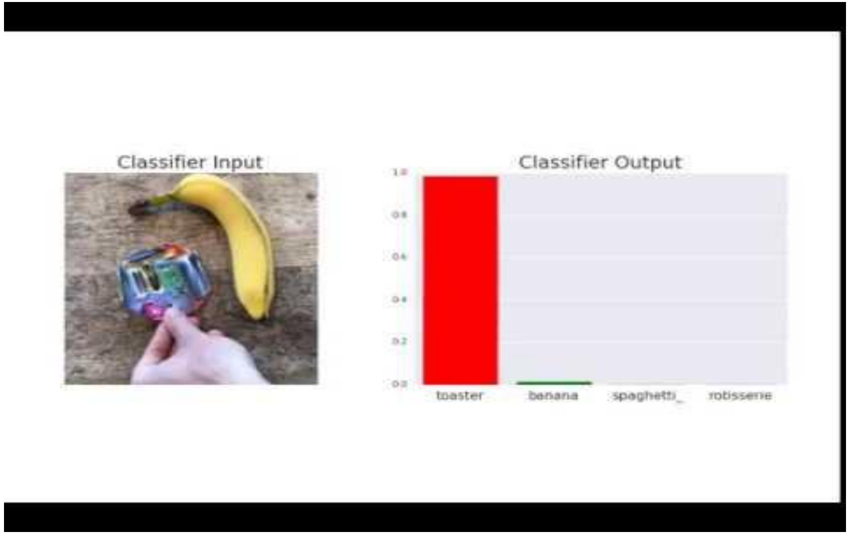
OBS.: The **image** above is not a gif or a video

DL Predictions Are (Mostly) Accurate but Brittle

- The main takeaway is this: deep learning is **very performant**, but also **very brittle**.
- The one simplest solution to improve the performance of one model against adversarial examples is **data augmentation**.
- But research shows that adding the adversarial data to the training set won't be enough for general tasks (like ImageNet).
- However, **augmentation can work for specific tasks.**

Placing a (weird) sticker on the image can totally change its classification

Source

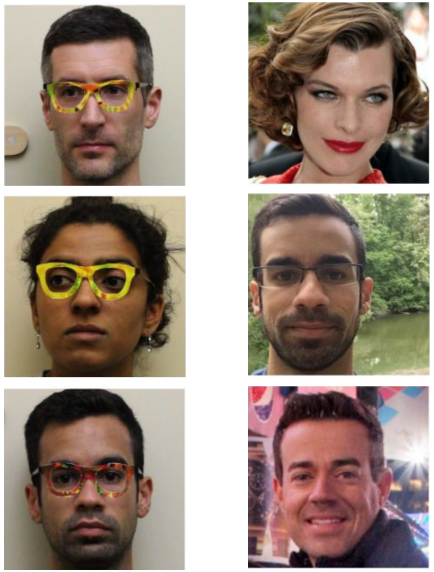


DL Predictions Are (Mostly) Accurate but Brittle

- Brittleness of ML is a thing and **adversarial examples can basically always be found**. Should we be worried?
- The quick answer: in some applications, **yes**.

Mistakes in Face Recog. because of a glass

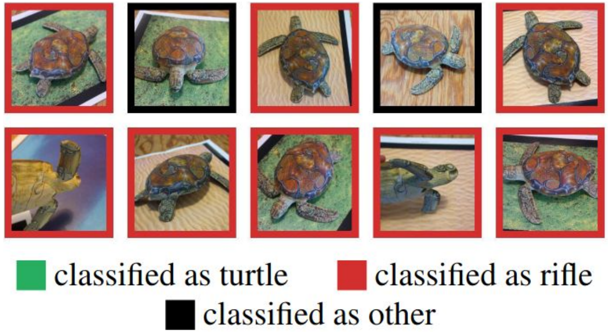
Source



Input Image Retrieved ID

Different perspectives of a Turtle lead to classifying it as a Rifle

Source



Covering parts of a stop sign lead to wrong classifications

Source

The issue of Robustness in Deep Learning

- As the world evolve to a more Deep Learning centered world, we find issues to resolve in fields like:
  - **Security/Certainty**: How can we make software that produces the desired outputs when given the right inputs?
  - **Safety**: How can we ensure that the software is safe for usage, i.e., it does not harm its users (specially in certain applications)?
  - **Alignment**: Need to understand the "failure modes" of Deep Learning, i.e., in which situations/environments the software won't produce the desired outputs with certainty.
- This only elucidate the importance of the study of **robustness** in neural networks, i.e., their ability of **tolerating perturbations** that might affect the system's functions.
- As this issue is critical when applying Deep Learning in many safety-critical and socially-impactful applications, which makes many practitioners **skeptical of DL's future**.
- Research, however, has greatly advance in this field of DL robustness.

Exercises (*In pairs*)

- Which computer vision applications are crucially dependent on robustness? In which ways could you augment their datasets to improve robustness?

What we've seen so far

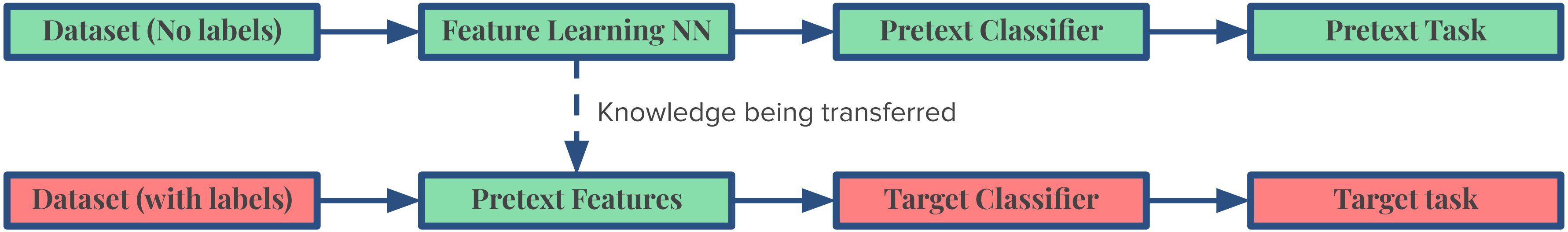
- So far we noticed a few interesting things about Deep Learning for the task of Image Classification:
  - Deep learning performs very well in classification,
  - The deeper the network, the better the results, but the harder the training,
  - Once the network is trained in some general dataset (like ImageNet), we can use it to solve classification problems is other domains (like cat/dog classification),
  - This process works well because of the good feature learning step deep learning provides.
- Despite the amazing performance of this process, there are two issues it doesn't tackle:
  - Labeled datasets are expensive and time-consuming (ImageNet took 3 years to get labeled). The dataset in itself can be small, with very **few labeled data points**,
  - It may be **very specific** (like in medical imaging) that using features learned from a general dataset may not suffice.
- For these reasons, we cover the task of **Self-supervised learning** today.

Self-supervision

- The learning in deep learning is based on **Supervised Learning** (SL), where data and labels are available.
- Another way to to do learning is via **Unsupervised Learning** (UL), when we only have datapoints (tasks like data clustering and dimensionality reduction).
- One possible middle way between SL and UL is called **Self-Supervised Learning** (SSL), where **the data provides the labels for supervision**.
- SSL is also linked to how infants learn about the world, hence another reason to do research on it.
- The general strategy for SSL is pre-train the network with a task, called **pretext task**, created with only the datapoints.

Pretext and downstream task

- The aim of the pretext task is to guide the model to learn **intermediate representations** of data, i.e., to do feature learning.
- This is useful in understanding the underlying structural meaning of the data, which will be beneficial for the practical **downstream (**or **target) tasks**.
- The downstream task uses the transfer process of the pretext model to a specific task.



- Many ideas have been proposed by researchers for different image-based tasks to train using the SSL method.

Rotation Classification task

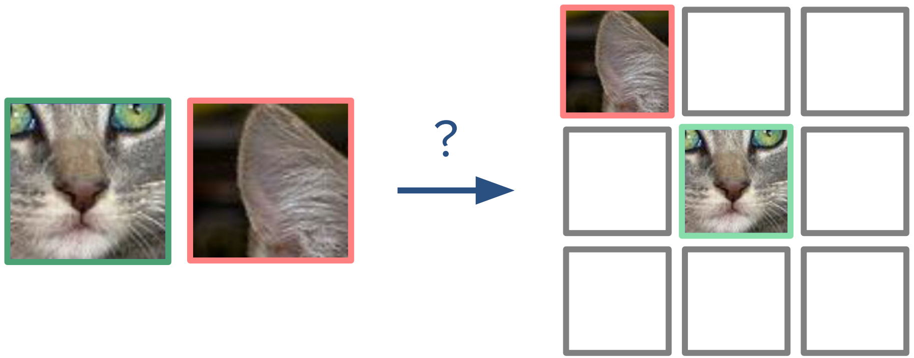
- A simple pretext task for vision problems is **rotation classification**, proposed in 2018.
- Here, the dataset images are rotated by random multiples of 90 degrees (e.g., 0°, 90°, 180°, or 270°) and the network is tasked at detecting the rotation (out of 4 possible).

90° 270° 180° 0° 270° 270° 90°

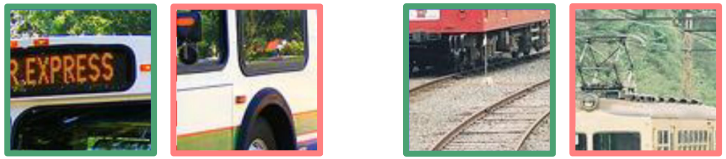
- The authors showed that adding this pretrain step **improved their target classification** step and **also took account for the rotation data augmentation**.
- Furthermore, the pretext task itself is useful in some settings (like detecting if a cell phone is upside down)

Patch Localization Task

- In the Patch Localization task, proposed in 2015, the goal is to **localize an image patch based on another patch**.
- This involves randomly sampling a patch (green border) and then one of eight possible neighbors (red border) and have the network predict its relative position (1 out of 8).



***Try it yourself*: where are the red ones placed according to the green ones?**



- According to the authors, this pretext task would help the network learn **spatial context information** more efficiently.

SimCLR Task

- Another example of pretext task is called SimCLR (**Sim**ple Framework for **C**ontrastive **L**earning of Visual **R**epresentations), published in 2020.
- It uses the concept of **Contrastive Learning**, that relies on comparing pairs of dataset images.
- The idea is simple: for each image from the dataset, create a set of augmentations for it.
- Then, train a CNN (ResNet in their case), followed by an MLP, that **maximizes the similarity** between pairs of augmentations from the same image and minimizes it for different images.
- After training, use only the CNN as your feature representer for transfer learning.

SimCLR Task

- The augmentations used in the were cropping, resizing, rotation, noise addition, etc.

Original | Crop + Resize | Crop + Resize + Flip | Distort | Rotate | Cutout | Noise

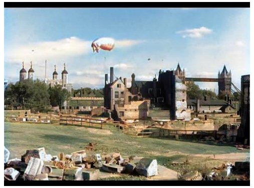
- The rationale behind these simple transformations of individual images is
  - They wanted to encourage "consistent" representation of the same image under various transformations,
  - Since the pre-training data lacks labels, we can't know a priori which image contains which object class,
  - The authors found that these simple transformations suffice for the neural net to learn good representations.

Self-supervised learning beyond Classification

- Summary:
  - Pretext tasks focus on “visual common sense”, e.g., predict rotations, spatial context, etc.
  - The models are forced to learn good visual features in order to solve the pretext tasks.
  - We (usually) don’t care about the performance of these pretext tasks, but rather how useful the learned features are for downstream tasks
- Self-supervised learning has being applied to many other computer vision tasks besides classifications, for example:
  - **Image Inpainting**: fill in missing parts of an image.
  - **Image Semantic Clustering**: group images that are similar in content together in different clusters.
  - **Image Coloring**: turning a grayscale image into an RGB one,
  - **Video Coloring**: same as image coloring but for videos.
- Starting from next class, we’ll study other Computer Vision tasks beyond Image Classification.

Video: *Video Automatic Colorization*

AI Colorized footages of old cities



London

Beijing

Tokyo

Paris

New York

Video: Go AlphaGo!