Image Classification

Reading

- Deep Learning: chapter 12.2
  - https://www.deeplearningbook.org/contents/applications.html

- Very brief overview, will go into a bit more depth in the slides

Large-Scale Training

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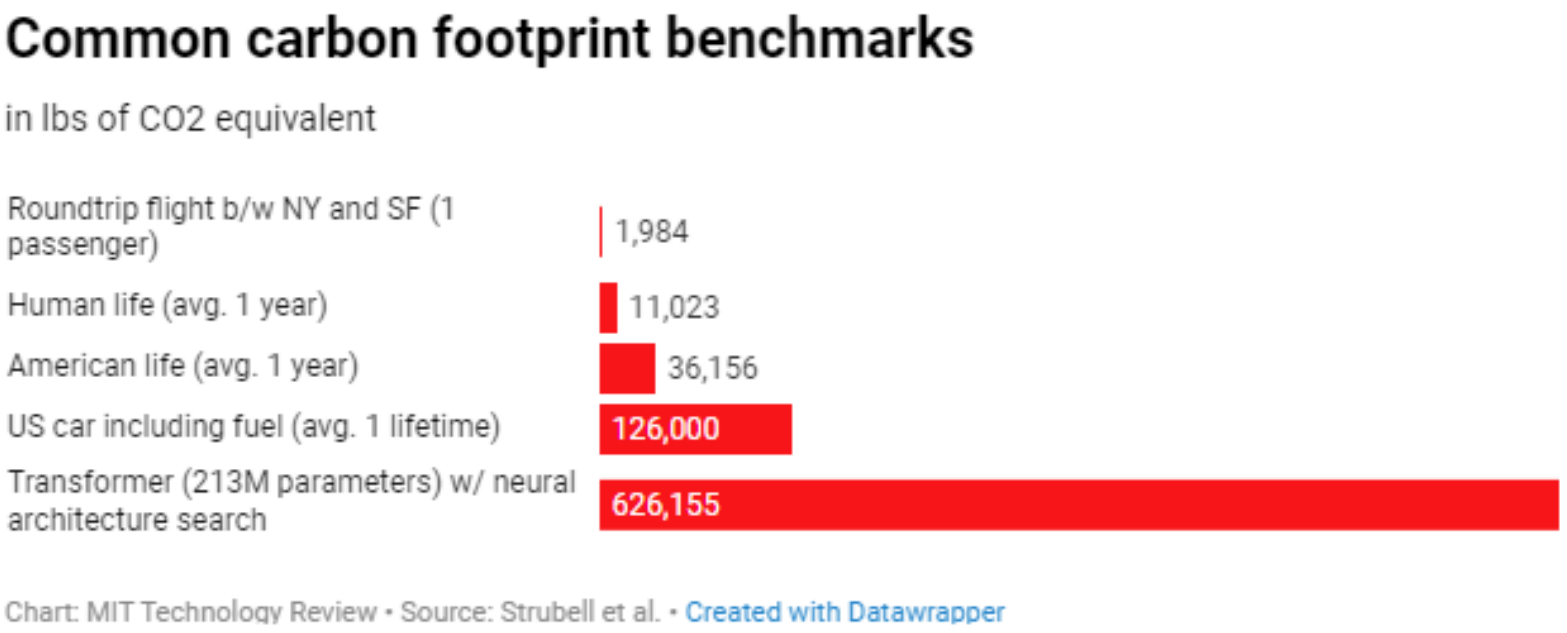
- There is a widely held belief in deep learning that bigger models are better
  - Occam's Razor (informal): you should always use the simplest model that can solve your task
  - Increasing the model complexity is rarely the solution to training issues
- Before adding more neurons, try to understand why training is not working
  - Is the data noisy, properly normalized, correctly labeled?
  - Are other hyperparameters (learning rate, loss function) reasonably chosen?
  - Are there bugs in the code (very often the case for beginners!)?



ChatGPT's electricity consumption (not including training costs) is equivalent to that of up to 175,009 Danes!

(source: https://medium.com/@chrispointon/the-carbon-footprint-of-chatgpt-e1bc14e4cc2a)

Computer Vision

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- One of the classical ML tasks
- Very easy for humans
  - One of the building blocks of intelligence
- Relatively easy to collect tons of labeled data
  - Many, many datasets and competitions
- Many applications
  - Robotics
  - Medical imaging
  - Mapping
  - Face recognition

Image Data

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- Grayscale or color images
- A grayscale image is just a matrix of integers between [0, 255]
  - where 0 is black, 255 is white, in between is (shades of) grey
- A color image is also a matrix, but each entry has three values ("channels")
  - RGB – red, green, blue
  - where [0, 0, 0] is black; [255, 255, 255] is white; [255, 0, 0] is red, etc.
- Note: each matrix is "flattened" before being sent to a fully-connected layer since those only accept vectors

Data Preprocessing

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- Normalization – normalize data to some reasonable range
  - Typically [-1, 1], [-0.5, 0.5], [0, 1]
  - Very common across all ML tasks
  - Very important for images since pixels range from 0 to 255
    - Large ranges destabilize gradient descent
  - Usually just subtract the data mean and divide by range, though normalization could be learned also
- Contrast normalization
  - Subtract the mean or reduce the contrast in some other way
  - Less common than standard normalization

Data Augmentation

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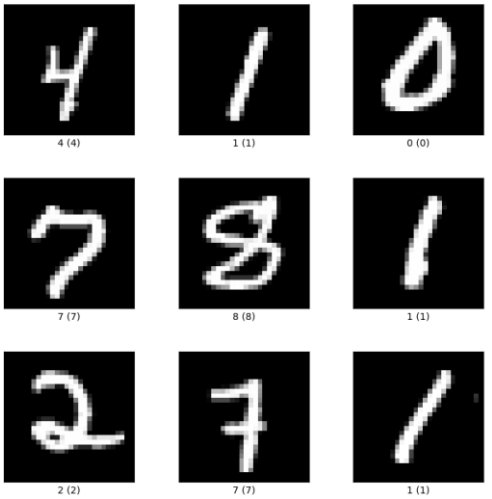
- One of the most important tricks in image classification
- Increase dataset size by adding small perturbations to images
  - Small rotations, translations, stretching, noise
- Statistically, this is not justified
  - Data no longer IID, it is essentially made up
  - It is very effective, however
  - Notion of distribution in images is quite blurry
  - Keep in mind deep learning is as much about optimization as it is about statistical learning

Standard Datasets

- Many datasets out there
- General datasets with many classes (cats, dogs, cars)
  - CIFAR, ImageNet
- Specialized datasets
  - Handwritten digits – MNIST
  - Office
  - Street signs
  - Birds
  - Video datasets

MNIST

- The “Hello, world” dataset of ML
- Relatively easy dataset that is still quite useful as a toy-but-not-so-toy dataset
- Grayscale 28×28 images
  - 10 classes of handwritten images
  - 60,000 training images (6K per class)
  - 10,000 test images (1K per class)



- An easy dataset because most pixels are either black or white
  - You can solve it with SVMs also
  - Even small NNs achieve 95+% accuracy

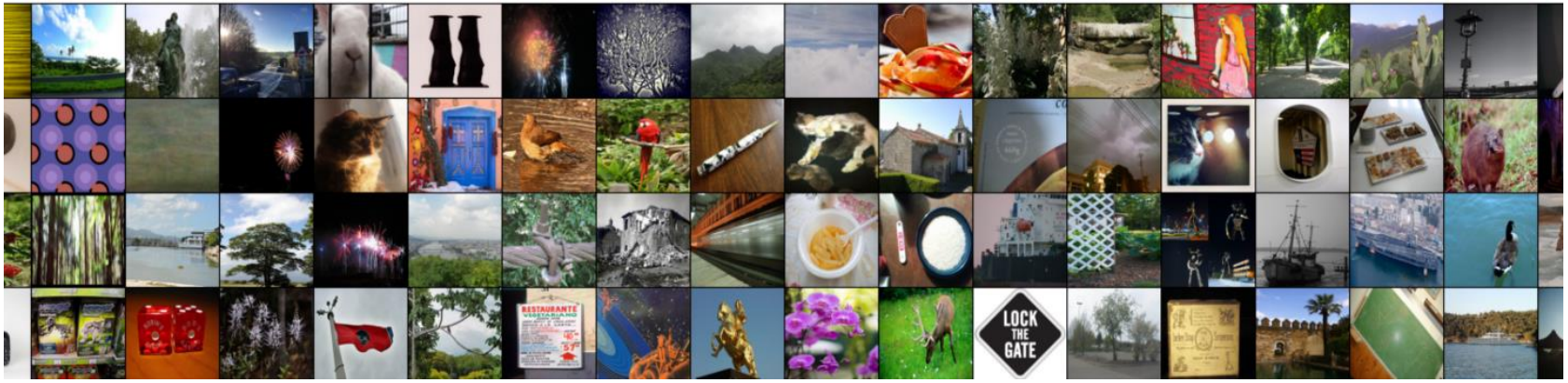
CIFAR

- Deceptively hard dataset
- $32 \times 32 \times 3$ color images of everyday objects
  - Birds, cars, planes, etc.
    - 10-class and 100-class versions

- Basic architectures achieve ~80% accuracy on CIFAR-10
  - Need larger architectures to get to the 90s
  - CIFAR-100 is even harder
- Challenge is that images are too rich but have too few pixels

ImageNet

- One of the most popular and challenging datasets
  - More than 14m images and 21 thousand classes
- $224 \times 224 \times 3$ color images of everyday objects
  - Classes very specific, sometimes it's hard to distinguish
- Very hard dataset
  - Sometimes multiple objects, occlusion, etc.
  - Need very large models/a lot of computation to get to ~90% accuracy
  - Even humans achieve only ~95% accuracy



RPI Buildings

- Charles Yu ‘23 and I collected images of buildings on campus
  - One building per image
  - Different time of day, weather conditions, distance
- 11 buildings: Lally, Sage, Troy, 87gym, library, Ricketts, Voorhees, Greene, JEC, Amos Eaton, Empac
  - about 500 images per building
- Each image is $4000 \times 3000 \times 3$
  - Probably needs to be shrunk for easier learning