Day 8: Final Project Presentations & Going Further with ML/DL

Summer STEM: Machine Learning

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NYU Tandon School of Engineering
Brooklyn, New York

June 30, 2022

Outline

What we Have Done

- Looked at foundational steps and models
  - Regression tasks: (fish weight and housing prices)
  - Classification tasks: (cancer prediction and Iris)
  - Polynomial models
  - Deep Neural Networks
  - Convolutional Neural Networks

Building on these Topics

- The goal with engineering is to take what we know and try to build on it.
- In case of machine learning; can we use a CNN as a backbone to solve more complicated tasks with more complicated models?
- The best way to do this is to independently learn from various sources.
- What are some resources that we can use?

Resources to build on your learning

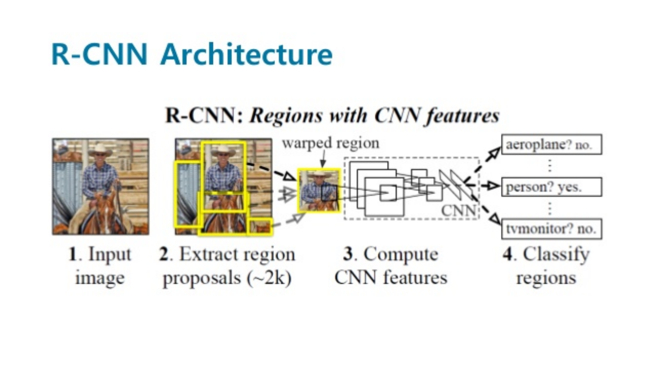
- **Finding Code:** Github and Machine Learning Mastery
- **Finding Papers:** There are many great conferences such as NeurIPS and ICML that are constantly publishing papers across topics and fields.ArXiv and SciHub
- **Theory:** StatQuest, computerphile and 3 Blue 1 Brown on Youtube.

Outline

Object Detection

- Faster-RCNN
- YoLo

Object Detection



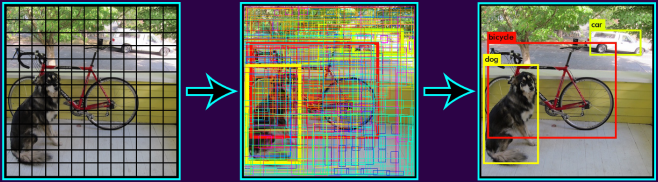
Region Proposal Based Object Detection

Object Detection

YOLO

- Divides the image into nxn grid-cells
- For each grid cell,
  - predicts B bouding boxes and it box confidence score
  - Each box will have its class probability
  - All class probability are combined to detect one object

Object Detection



YOLO (https://pjreddie.com/darknet/yolo/)

Semantic Segmentation

- Every Pixel is associated with a class
- Encoder-decoder structure
- Decode using transposed convolution or deconvolution

Image Segmentation (Source: https://www.jeremyjordan.me/semantic-segmentation/)

Instance Segmentation

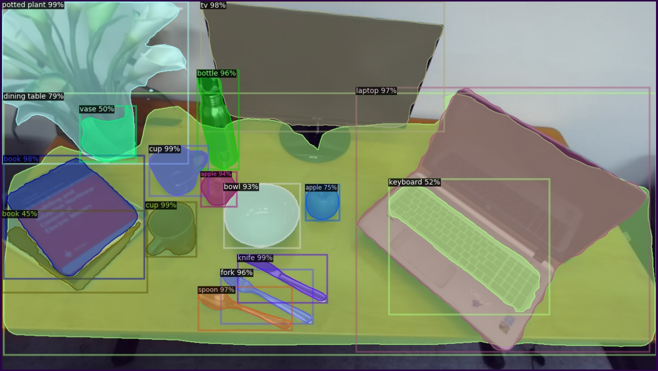
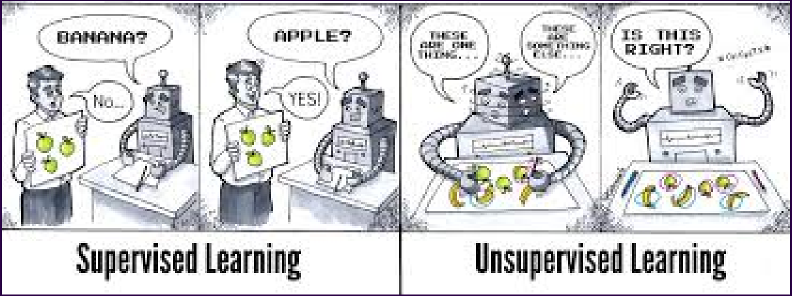


Image generated using Mask-RCNN
(https://github.com/facebookresearch/detectron2)

Outline

Unsupervised Learning



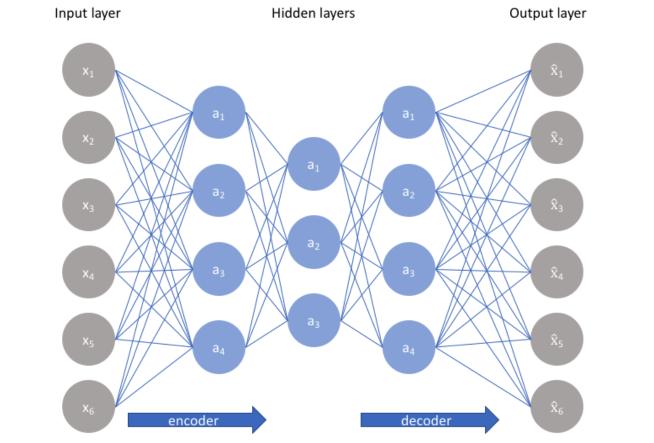
Generative models

- Generate images, art, speech. Generation architectures can be modified based on the task at hand.

Benefits and Use Cases

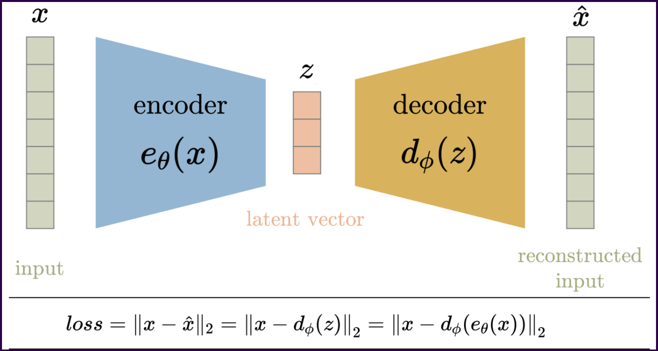
- When dataset collection is difficult or expensive. (For example MRI scans).
- When there is a limit on available data. (With rare cancers, there may not be many positive cases.) (Start of COVID with few recorded cases.)
- Various novel applications. (Generation or Art)

Autoencoders



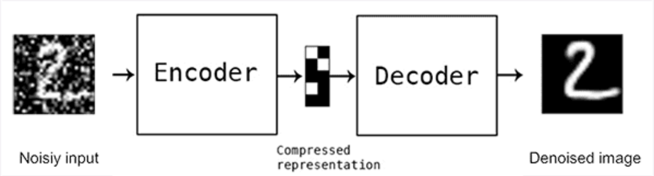
From Jeremy Jordan's Post on Autoencoders

Autoencoders

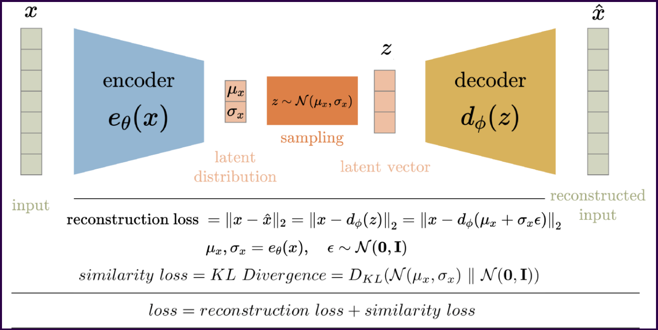


From Aqeel Anwar's Post on Autoencoders

Autoencoder for denoising



Variational Autoencoders



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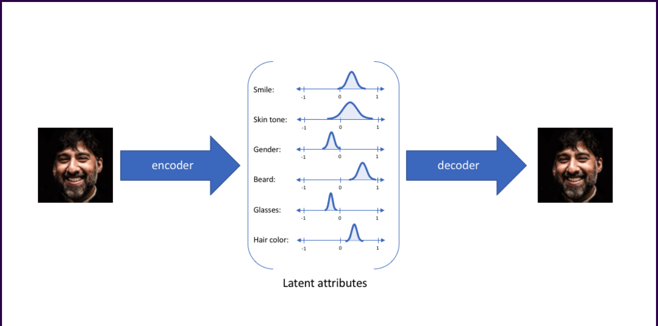
Variational Autoencoders



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Variational Autoencoders

VAE face generation implemented by Wojciech Mormul

GANs: Generative Adversarial Networks

- Invented in 2014 by Ian Goodfellow
- Goal: generate samples never seen before
- How: game between two networks
  - Generator Network
  - Discriminator Network
- **Goal of Generator**: generate fake samples indistinguishable from real samples
- **Goal of Discriminator**: be able to tell apart real and fake samples

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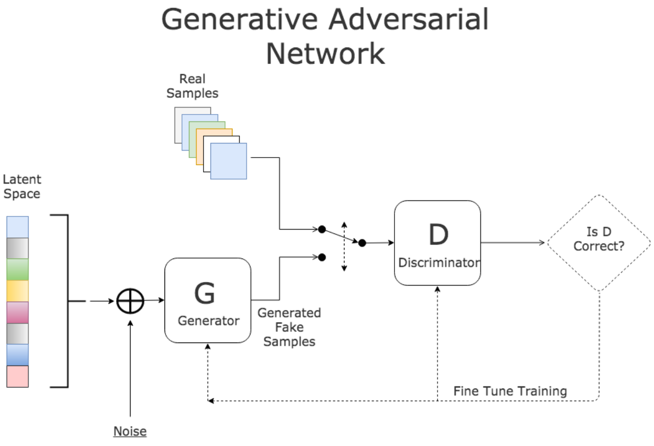
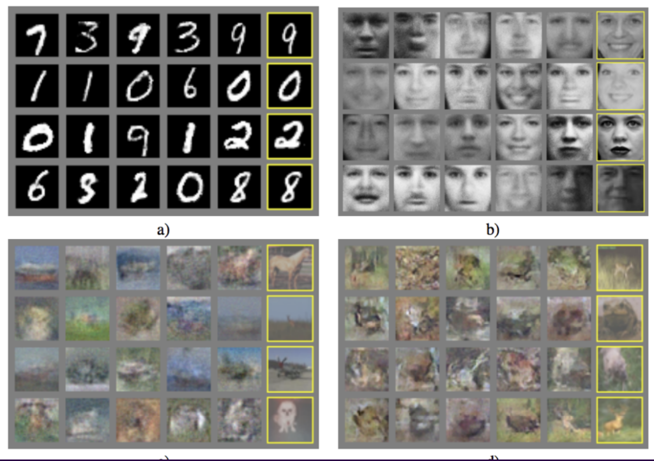
GANs: Generative Adversarial Networks



Beginning



Generated images (yellow) on a) MNIST b) TFD c) CIFAR-10 (MLP model) d) CIFAR-10 (Conv model)
"Generative Adversarial Networks", Goodfellow et. al. 2014

Progress

Improvement of GANs in producing photo-realistic faces over the years

Applications of GANs: Cats that Don't Exist

This cat does not exist

Applications of GANs: Celebrity Faces

Human face generation one of the most difficult tasks

Applications of GANs: Image Colouring

Image Colorization (Source: https://github.com/jantic/DeOldify)

Applications of GANs: Image Synthesis

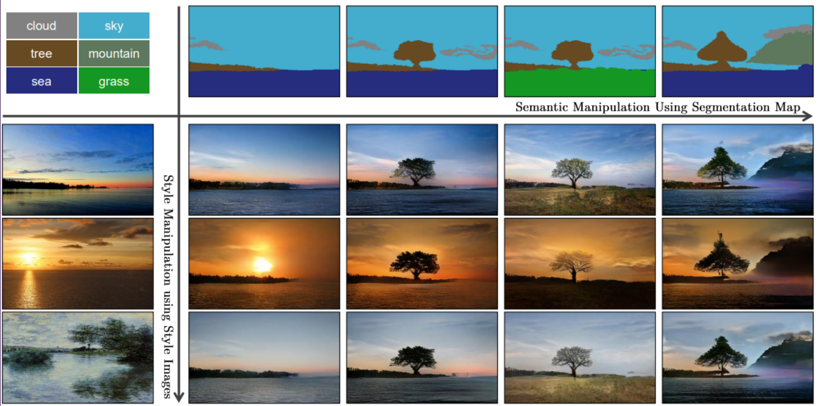


Image Synthesis (Source: https://github.com/NVlabs/SPADEn)

Applications of GANs: Image Super Resolution

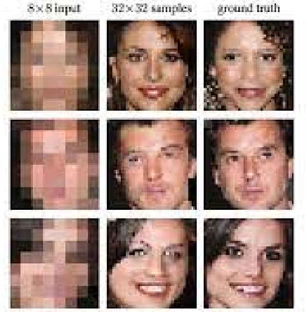


Figure 1: Illustration of our probabilistic pixel recursive super resolution model trained end-to-end on a dataset of celebrity faces. The left column shows 8 × 8 low resolution inputs from the test set. The middle and last columns show 32 × 32 images as predicted by our model vs. the ground truth. Our model incorporates strong face priors to synthesize realistic hair and skin details.

Image Super-Resolution (Source: Dahl et al., "Pixel recursive super resolution")

Outline

How Would You Use ML/DL?

- Think about potential applications with deep learning.
- Discuss its social implications.

Can AI/ML be Biased?

- At the start, a Neural Network just has randomly initialized weights.
- It then trains and backprogates on a given dataset.
- Do our nodes harbor any racism, sexism, homophobia or transphobia?

Can AI/ML be Biased?

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- It then trains and backprogates on a given dataset.
- Do our nodes harbor any racism, sexism, homophobia or transphobia?
- No!
- Neural Networks aren't sentient.
- Neural Networks have no understanding of human emotions, biases or anything else.

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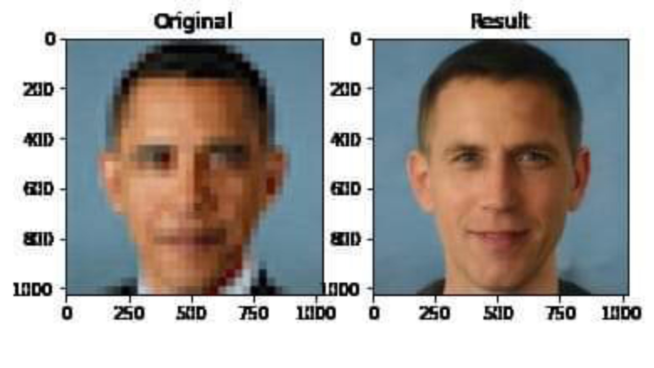
Biased model outputs

PULSE is a face depixelizing algorithm, but...



So where does the Bias come from?

Biases Inherent in Data: CheXpert

CheXpert is a dataset of medical images in the form of Chest X-Rays. The dataset is inherently biased as when looking for rare diseases, most patients would test negative.
More than 90% of sames are negative cases. As a result, a model can assume every patient is disease free and still have an accuracy of 90%
As a result, models aren't incentivized to learn about underrepresented classes in a dataset.

Biases not Inherent in Data: Celeb A

Biases not Inherent in Data: Celeb A

- In case of CheXpert, when studying rare diseases, it is more likely to not have the disease than having it.
- But sometimes, data in the real world isn't biased but our dataset might be.
- Celeb-A is a great case for such a problem.
- **Celeb-A:** "traditionally attractive". predomintally white and cis. Heavy make-up. Potential Photoshop. 4K cameras.
- **In the real world:** Most people not models. People of Colour. Trans and Non-binary. Images aren't taken on professional cameras with professional makeup.

Real World Biases leaking into Machine Learning

Keep in mind, the bias comes from Biased Data!! Not the model having any bigotry.
Bigotry and under-represented data in the real world can leak into machine learning.

- Biases and Racism in Law Enforcement can leak into model predictions. This only furthers existing inequity. AI in law enforcement
- Dataset Generation might often be predominantly white and cishet masculine with the sources of data and the engineers building these datasets not realizing the importance of diversity in datasets.

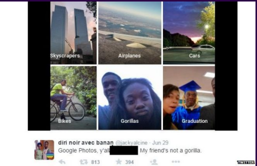
Insidious Effects on Machine Learning performance

(From the article Design AI so that it's fair)

- When Google Translate converts news articles written in Spanish into English, phrases referring to women often become 'he said' or 'he wrote'.
- Software designed to warn people using Nikon cameras when the person they are photographing seems to be blinking tends to interpret Asians as always blinking.

Insidious Effects on Machine Learning performance

- Google misclassifying people as gorillas,



- Chat bot trained on data from tweets "Tay" learns to be racist and sexist as a result of the sheer number bigoted twitter users.

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How do we solve these issues?

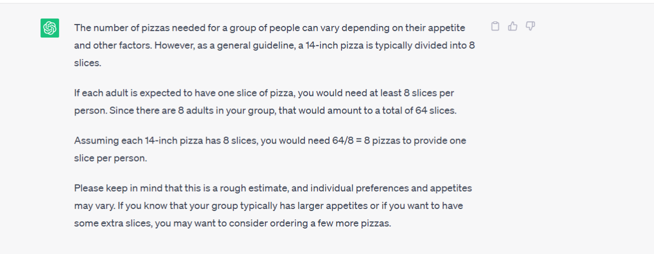
Safety of AI

Boston Dynamics Parkour Atlas: What machine learning algorithms might have been used here?

Safety of AI

- The same model can have drastically different performance for different hyper-parameters.
- 100% accuracy is rarely achieved on unseen data.
- Should we let a medical robot with CNN-based vision system perform surgery autonomously?
- If a self-driving car crashes and hurts people, who should be responsible for it?

Safety of AI

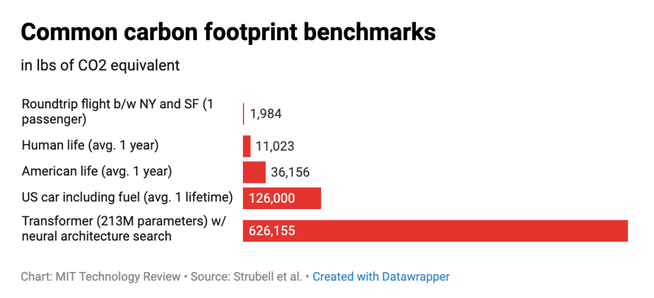

The number of pizzas needed for a group of people can vary depending on their appetite and other factors. However, as a general guideline, a 14-inch pizza is typically divided into 8 slices.

If each adult is expected to have one slice of pizza, you would need at least 8 slices per person. Since there are 8 adults in your group, that would amount to a total of 64 slices.

Assuming each 14-inch pizza has 8 slices, you would need 64/8 = 8 pizzas to provide one slice per person.

Please keep in mind that this is a rough estimate, and individual preferences and appetites may vary. If you know that your group typically has larger appetites or if you want to have some extra slices, you may want to consider ordering a few more pizzas.

Carbon Footprint of Deep Learning



Source: MIT Tech Review

Outline

Course Takeaway

- ML is the combination of math and computer science.
- We've only shown you a subsection
  - Supervised Learning: Linear/Logistic Regression and Neural Networks
- Deep learning has wide applications, but we are also responsible for its consequences. —The greater the power, the greater the responsibility!

Thank You!

- Thank You!