Day 9+10: Final Project Presentations & Going Further with ML/DL

Summer STEM: Machine Learning

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Outline

Schedule

1. Finishing Up Projects (9:00-11:00am)
2. Make Presentations (11:00-12:00am)
3. Lunch (12:00pm-1:00pm)
4. Presentations (1:10-3:00pm)
5. Final Material: Going Further with ML/DL (3:00-4:00pm)
6. Goodbye! (4:00pm - ∞?)

Outline

Presentation Guidelines

- 8-10 minutes per group
- Talk about your project:
  - **Goal**: features and targets. What are you predicting?
  - **Dataset**: Where is it from, what does it consist of. Features, targets.
  - **Model**: What is your model? MLP? CNN? What is the architecture? Why?
  - **Training**: How did your model train? Challenges?
  - **Inference**: How was your models predictions on new data?
  - **Going Forward**: "We'd like to continue by..."
  - **Learning**: what did you learn/take away from this project? From this course?
- Put your slides on the master Google-Slides slide-deck (check email)

Outline

1. Schedule
2. Presentation Guidelines
3. Akshaj's Talk
4. Generative Adversarial Networks
5. Course Takeaway

Outline

GANs: Generative Adversarial Networks

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- **Goal of Generator**: generate fake samples indistinguishable from real samples

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- 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

Implementation

- Generator Model: (on board)

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  - Draw sample from multi-dim noise vector

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  - Game-theory: converge to maximin of the cost function

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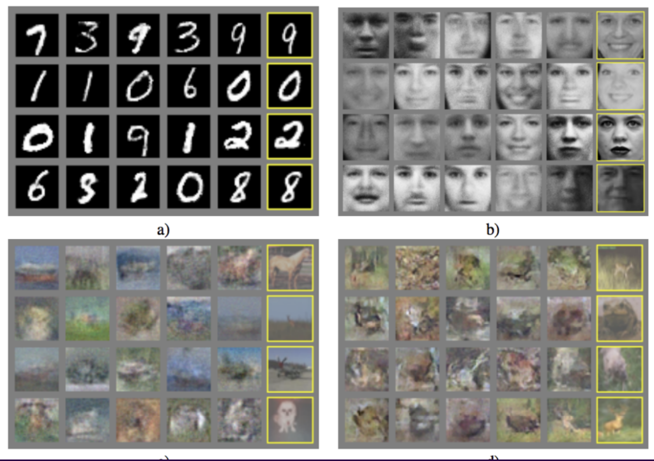
  - Balancing act: train D, train G, train D, train G, ...
  - Cost function for each network?
    - Binary Cross Entropy for each
    - Freeze D: Update weights of G to **maximize** BCE
    - Freeze G: Update weights of D to **minimize** BCE
  - Game-theory: converge to maximin of the cost function
- Multi-dim noise vector allows interpolation between samples and can be trained to determine output class of image

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

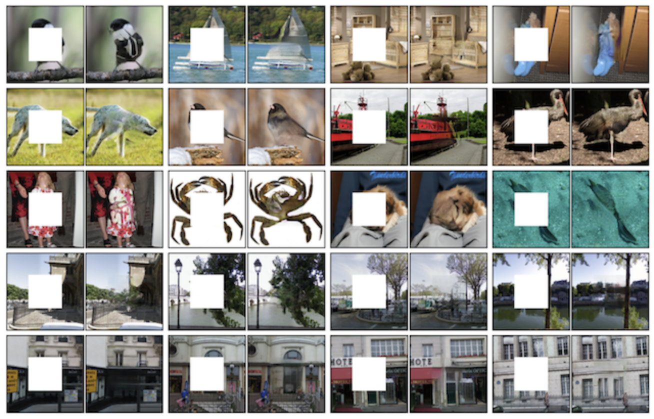
Progress

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

Celebrity Faces

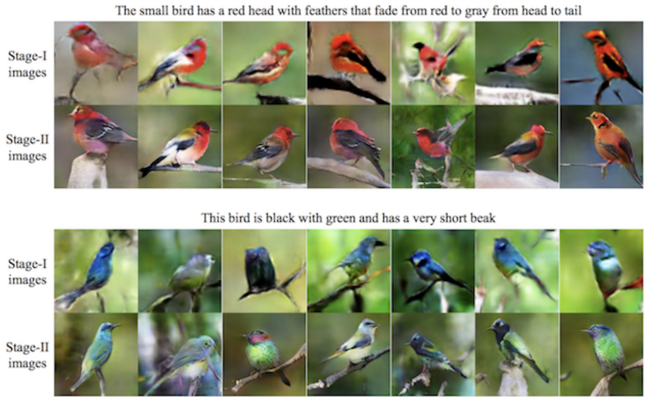
Human face generation one of the most difficult tasks

Occlusion



Recreate missing parts of an image

Text to Image



produce image based on a description

Videos

- Progressive Growing of GANs, 2017
- Few-Shot Adversarial Learning of Realistic Neural Talking Head Models, 2019

Applications of GANs?

- Applications often obscure/tough to think of
- Entering realm of computers outperforming humans on creative tasks

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  - Supervised Learning: Linear/Logistic Regression and Neural Networks
- If you're interested in pursuing further, you know where to look!
- If not, that's valuable information for deciding what to do with your future!

Thank You!

- Thank You, Thank You, Thank You!