CS 291A: Deep Learning for NLP

Unsupervised Learning

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Slides adapted from V. Chen.

Final Project Presentation Schedule

- This Thursday:
- Andy Chen
- Ashwini Patil, Sai Nikhil Maram
- David Bernadett
- Ishani Gupta, Nidhi Hiremath
- Wenhu Chen, Zhiyu Chen

- Next Tuesday:
- Ismet Burak Kadron
- Jiawei Wu, Jing Qian
- XiyouZhou, JiangyueCai
- Maohua Zhu, Liu Liu
- Pushkar Shukla, Richika Sharan
- Sanjana Sahayaraj, Vivek Adarsh

- Next Thursday:
- Sharon Levy
- Conner Vercellino, Calvin Wang
- Trevor Morris, Chani Jindal
- Vivek Pradhan, Abhay Chennagiri
- Jashanvir Singh Taggar, Metehan Cekic
- Yanju Chen, Hongmin Wang

•13 mins presentation (13 slides max) + 2 mins QA
•Slides are due at 10am of the day of presentation via email (ke00@ucsb.edu).
•Final report due: 03/23 23:59PM PT. Grader: Ke Ni <ke00@ucsb.edu>

Today's Agenda

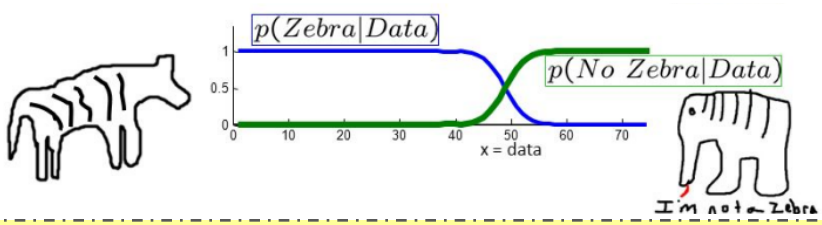
- 1. Unsupervised Learning (GAN)
- 2. Challenges in Deep Learning
- 3. Course Summary
- 4. ESCI – Course Eval
- 5. Paper Reviews (x4)

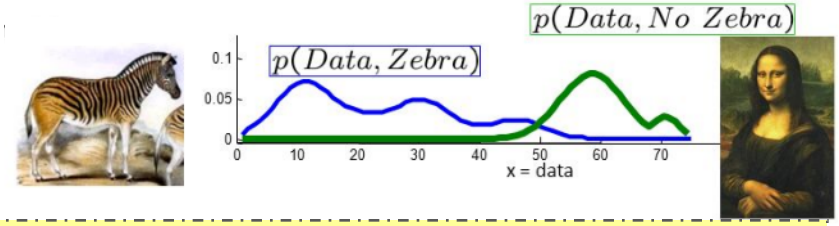
Review

Generative Model

Discriminative v.s. Generative Models

- Discriminative
  - learns a function that maps the input data (*x*) to some desired output class label (*y*)
    - directly learn the conditional distribution *P(y|x)*
- Generative
  - tries to learn the joint probability of the input data and labels simultaneously, i.e. *P(x,y)*
    - can be converted to *P(y|x)* for classification via Bayes rule

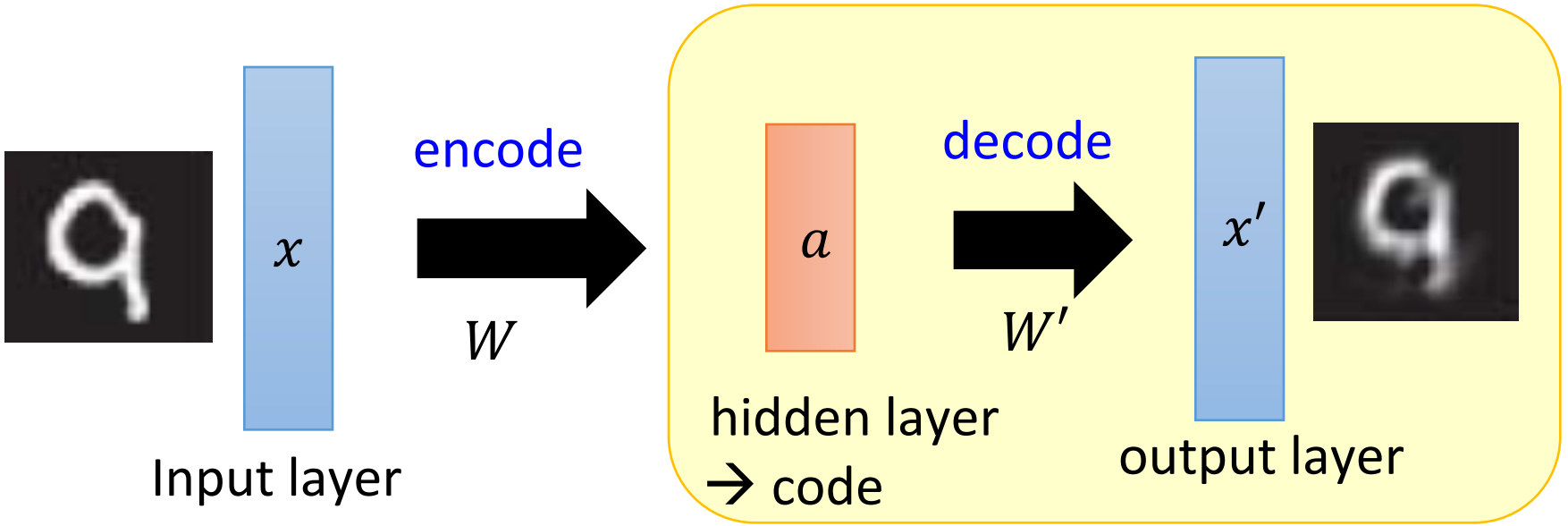




Advantage: generative models have the potential to <u>understand and explain the underlying structure</u> of the input data even when there are no labels

Generator

- Decoder from autoencoder as generator



The generator is to generate the data from the code

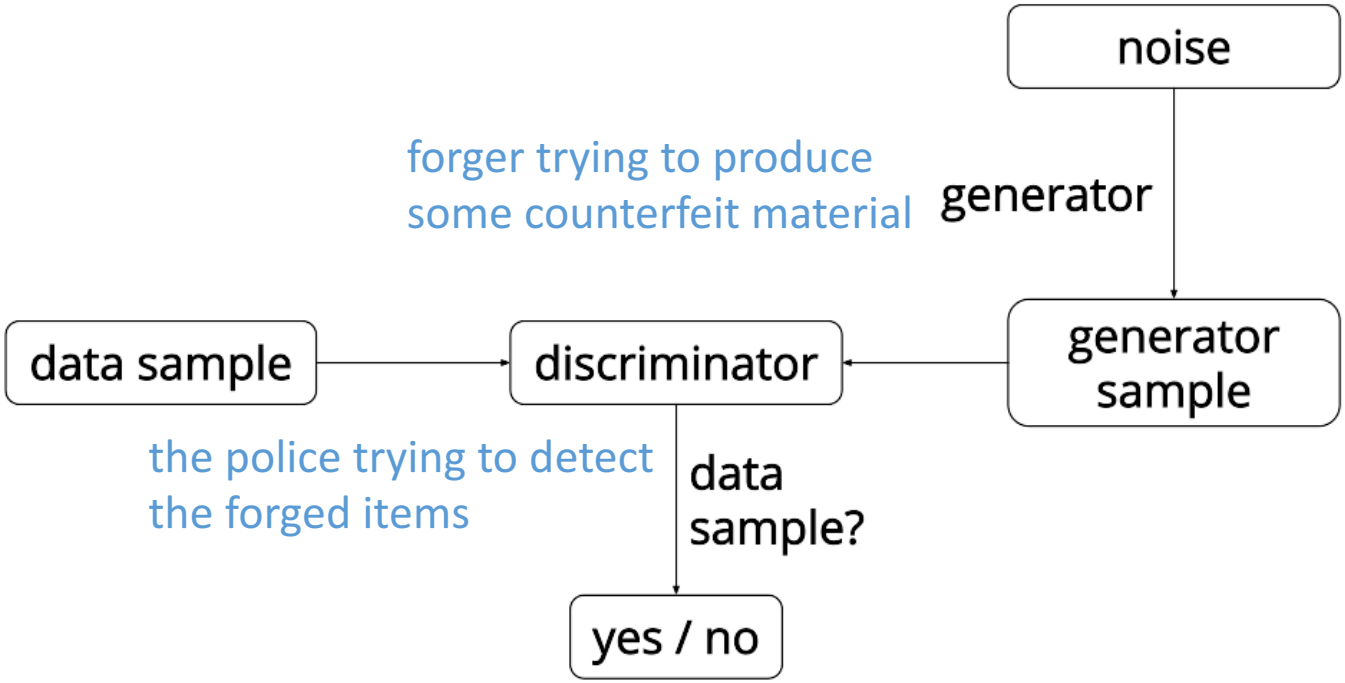
Generative Adversarial Network (GAN)

Representation Learning

"There are many interesting recent development in deep learning…The most important one, in my opinion, is adversarial training (also called GAN for Generative Adversarial Networks). This, and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion." – **Yann LeCun**

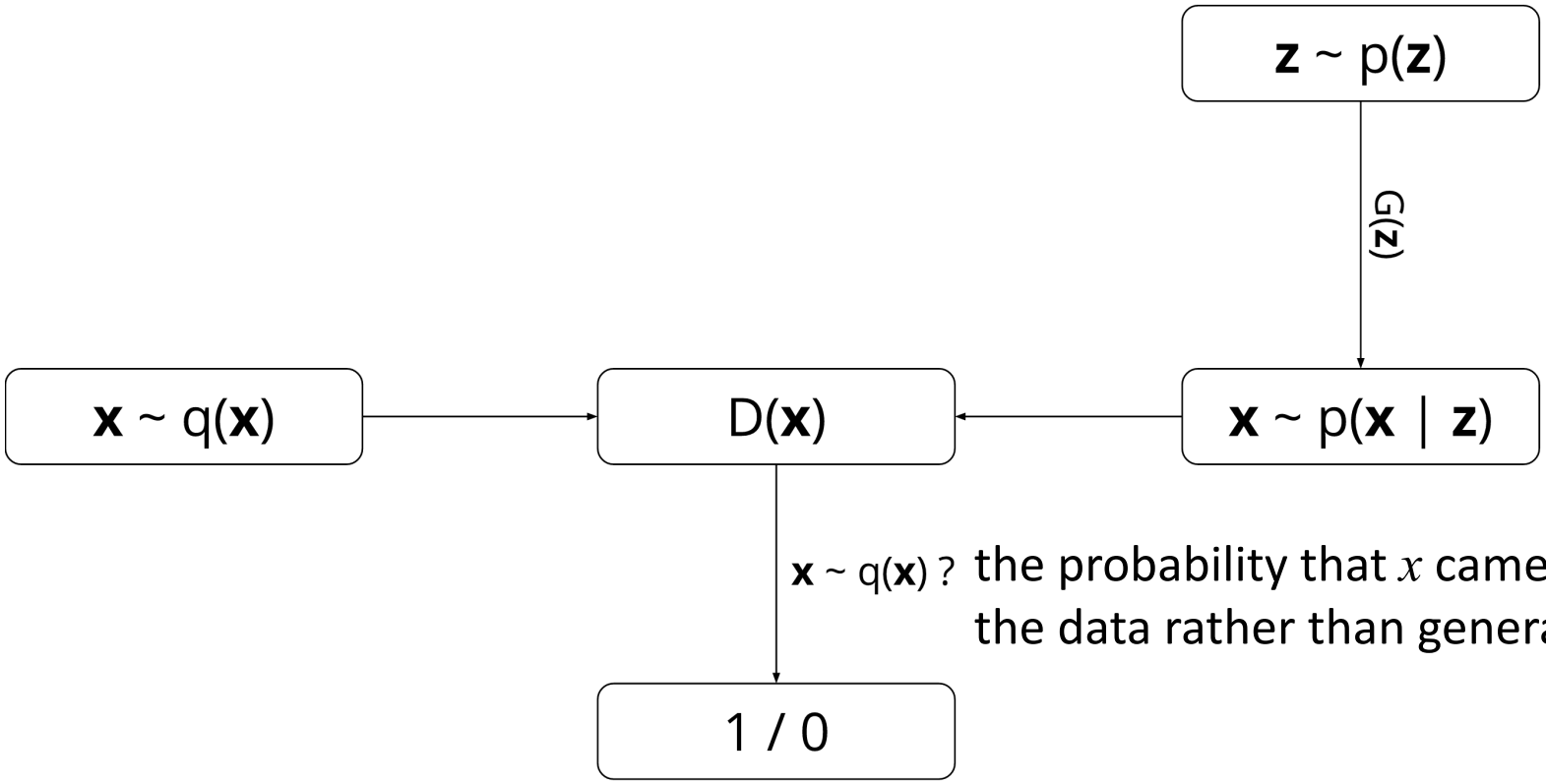
Generative Adversarial Networks (GAN)

- Two competing neural networks: generator & discriminator



Training two networks jointly → the generator knows how to adapt its parameters in order to produce output data that can fool the discriminator

Generative Adversarial Networks (GAN)



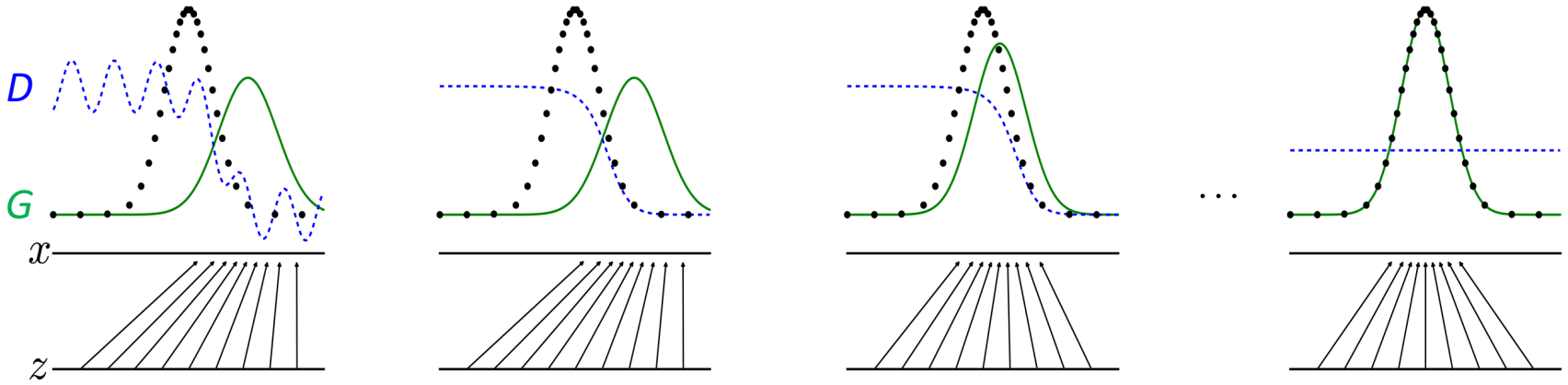
GAN Objective

$D(x)$: the probability that x came from the data rather than generator

$$\min_G \max_D V(D,G)$$

$$= \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x}))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))]$$

$$= \int q(\mathbf{x}) \log(D(\mathbf{x}))d\mathbf{x} + \iint p(\mathbf{z})p(\mathbf{x} \mid \mathbf{z}) \log(1 - D(\mathbf{x}))d\mathbf{x}d\mathbf{z}$$



GAN Training Algorithm

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

Discriminator

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right) \right].$$

end for

Generator

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Piazza Poll: What will likely happen if GAN's training objective converges?

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Generator

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- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

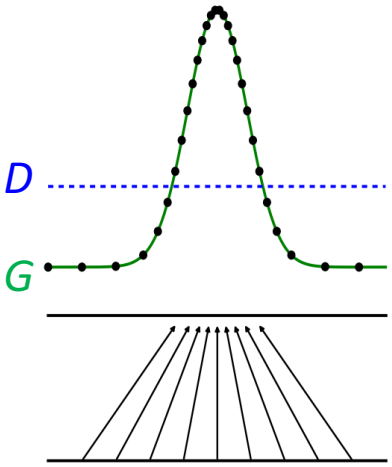
end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

GAN Nash Equilibrium

- Global optimality
  - Discriminator

$$D^*(\mathbf{x}) = \frac{q(\mathbf{x})}{q(\mathbf{x}) + p(\mathbf{x})}$$



  - Generator

$$G^*(\mathbf{z}) \text{ s.t. } p(\mathbf{z}) = q(\mathbf{x})$$

Two competing networks are trained towards global optimality

GAN-Generated Bedrooms

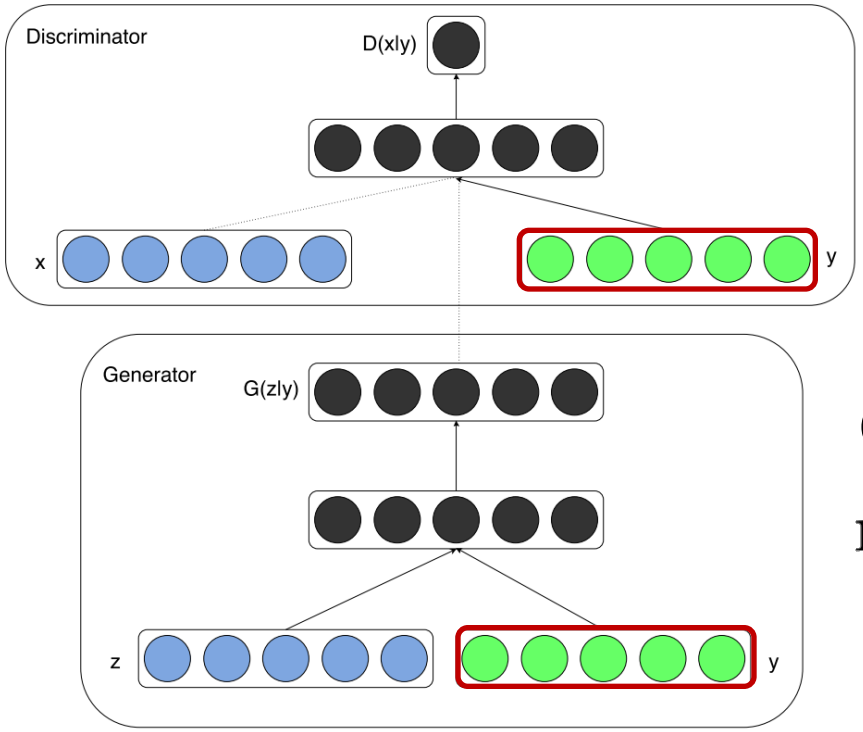
Applications of Generative Models

- Semi-supervised learning
  - few training samples with annotations
  - generate more training data using GAN

Conditional GAN

Generator Conditioned on Labels

Conditional GAN



GAN

$$\min_G \max_D V(D,G)$$

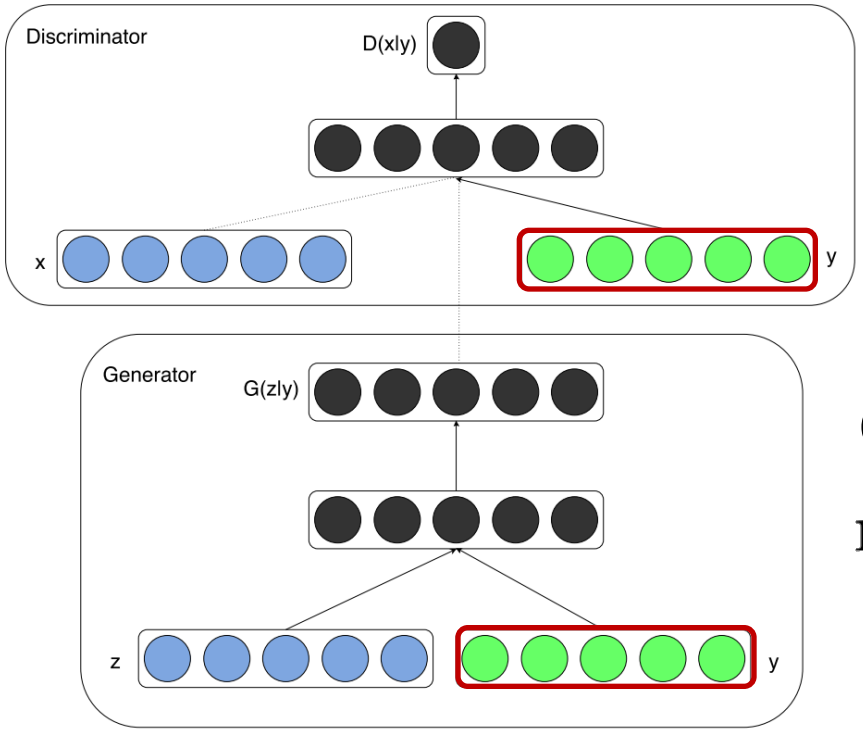
$$= \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x}))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))]$$

Conditional GAN

$$\min_G \max_D V(D,G)$$

$$= \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x} \mid \mathbf{y}))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z} \mid \mathbf{y})))]$$

Quick Question: When would Conditional GAN be useful for NLP and CV tasks?



GAN

$$\min_G \max_D V(D,G)$$

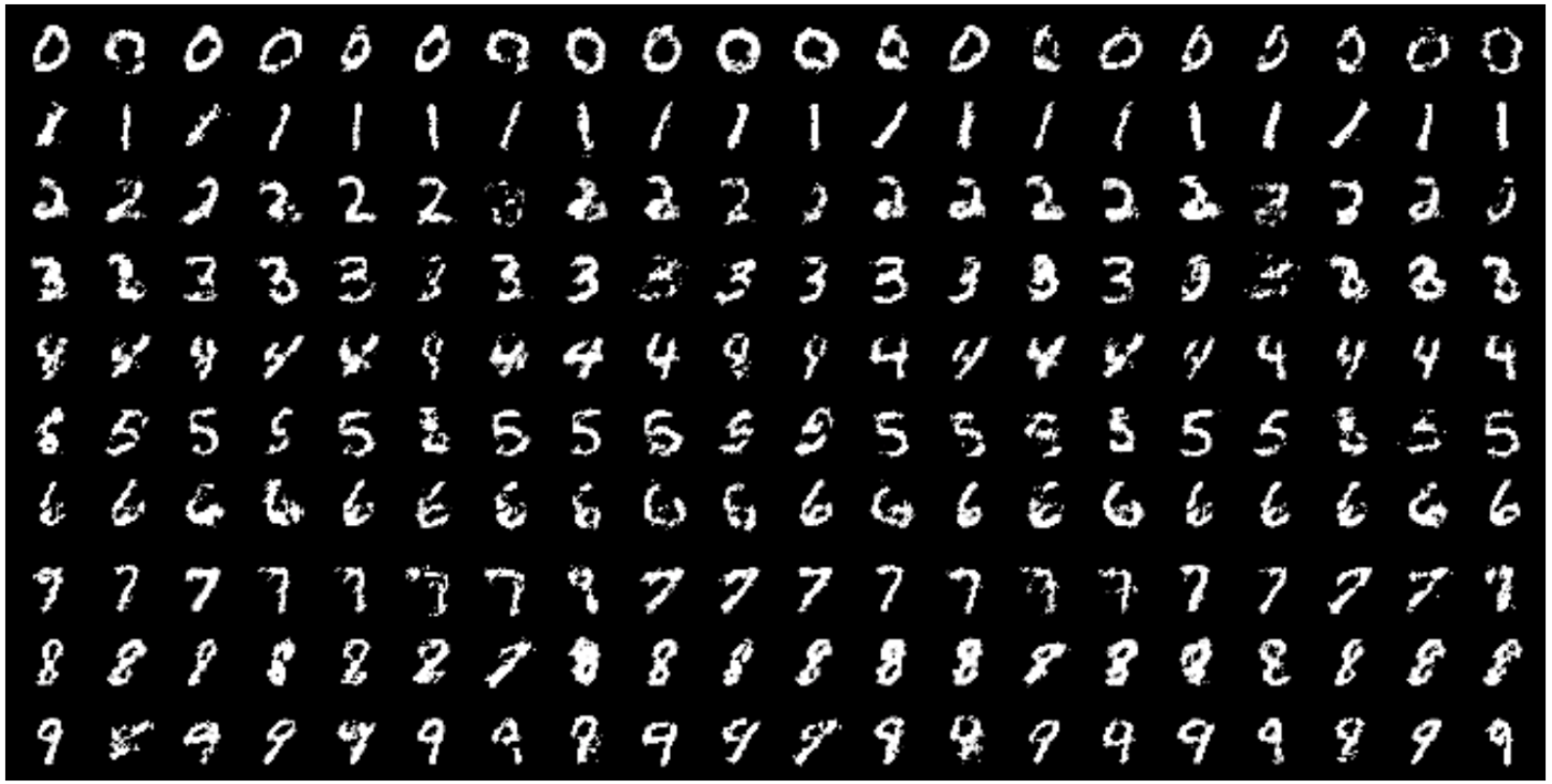
$$= \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x}))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))]$$

Conditional GAN

$$\min_G \max_D V(D,G)$$

$$= \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x} \mid \mathbf{y}))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z} \mid \mathbf{y})))]$$

Generated Images Conditioned on Label



Each row is conditioned on one label and each column is a different generated sample.

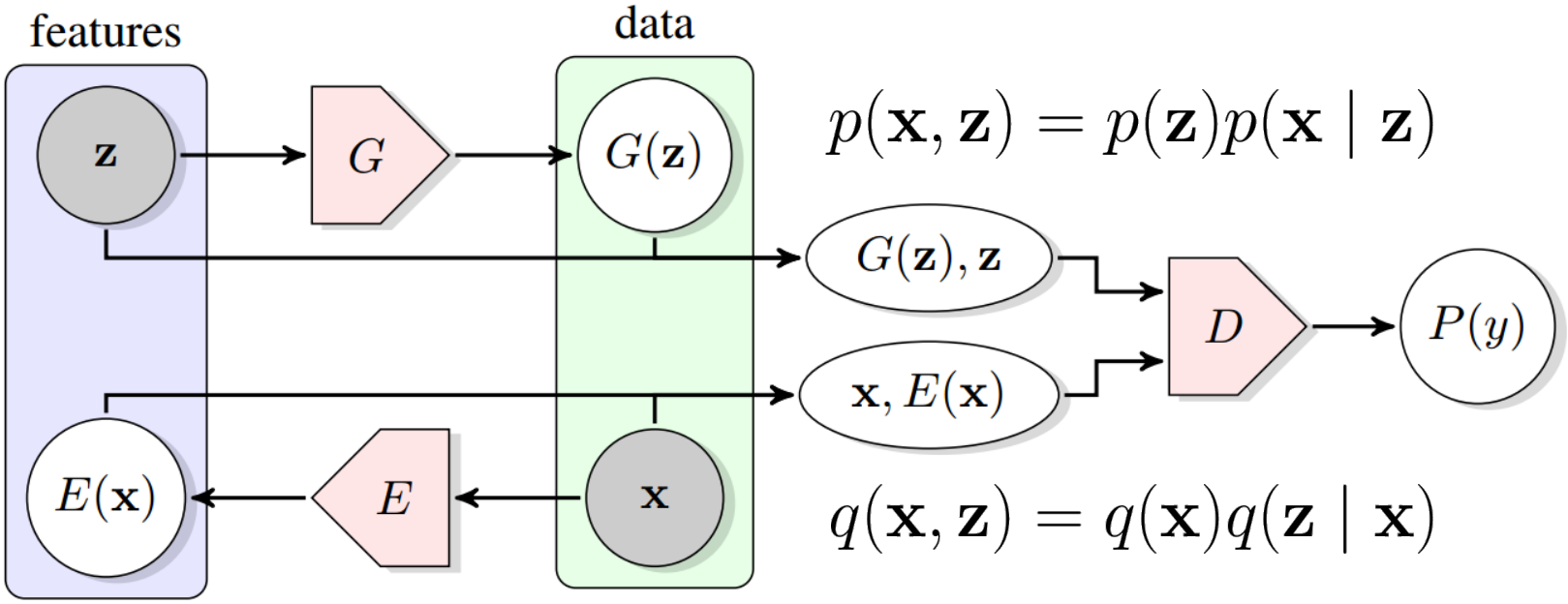
Adversarially Learned Inference (ALI)

Inference with Latent Variables

Adversarially Learned Inference (ALI) / Bidirectional GAN (BiGAN)

Inference is important but ignored by GAN

- Idea: incorporate latent variables for inference
- Inference: given x, what z is likely to have produced it



ALI / BiGAN

$$\min_{E,G} \max_{D} V(D, G, E)$$

$$= \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x}, E(\mathbf{x})))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z}), \mathbf{z}))]$$

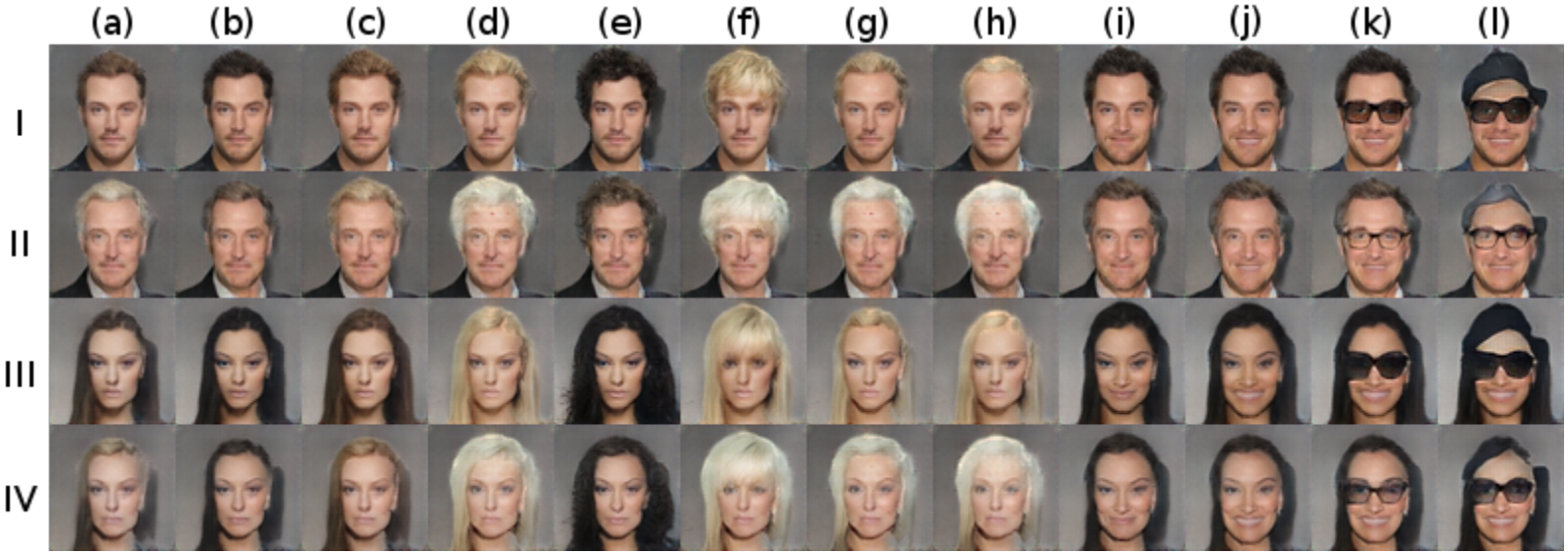
$$q(\mathbf{x}, \mathbf{z}) = q(\mathbf{x})q(\mathbf{z} \mid \mathbf{x}) \qquad p(\mathbf{x}, \mathbf{z}) = p(\mathbf{z})p(\mathbf{x} \mid \mathbf{z})$$

$$= \iint q(\mathbf{x})q(\mathbf{z} \mid \mathbf{x}) \log(D(\mathbf{x}, \mathbf{z}))d\mathbf{x}d\mathbf{z}$$

$$+ \iint p(\mathbf{z})p(\mathbf{x} \mid \mathbf{z}) \log(1 - D(\mathbf{x}, \mathbf{z}))d\mathbf{x}d\mathbf{z}$$

Conditional ALI

- Conditional generation: providing a conditioning variable y for generator, encoder, discriminator



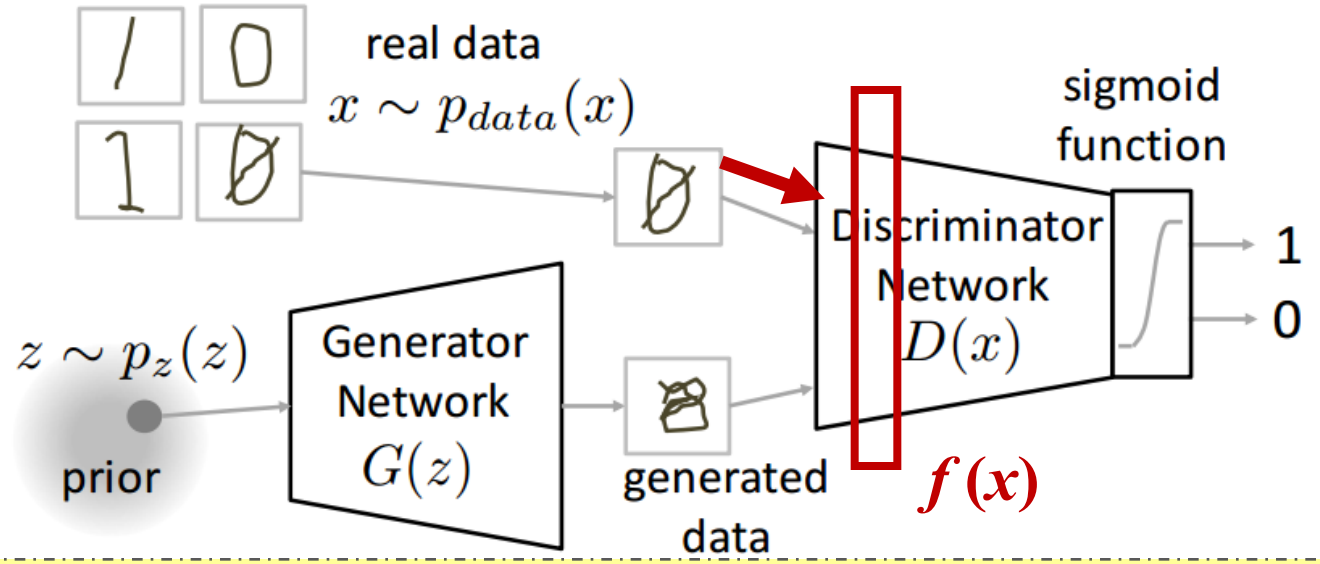
Latent variables can represent attributes

Improvement of Training GAN

Stableness and Robustness

Feature Matching (Generator Objective)

- Idea: match the expected values of the features in an intermediate layer of discriminator
- Generator's objective: $\left\| \mathbb{E}_{q(\mathbf{x})} f(\mathbf{x}) - \mathbb{E}_{p(\mathbf{z})} f(G(\mathbf{z})) \right\|_2^2$



Generators utilize the features used by discriminators as objective

Unrolled GAN (Generator Objective)

- Idea: allow generator to consider discriminator's capability
- Iterative optimization procedure

$$\theta_D^0 = \theta_D$$
$$\theta_D^{k+1} = \theta_D^k + \eta^k \frac{\partial f(\theta_G, \theta_D^k)}{\partial \theta_D^k}$$
$$\theta_D^* = \lim_{k \to \infty} \theta_D^k$$

$$f(\theta_G, \theta_D) = \mathbb{E}_{q(\mathbf{x})}[\log(D(\mathbf{x}; \theta_D))] + \mathbb{E}_{p(\mathbf{z})}[\log(1 - D(G(\mathbf{z}; \theta_G); \theta_D))]$$

- **Surrogate objective** for generator

$$f_K(\theta_G, \theta_D) = f(\theta_G, \theta_D^K(\theta_G, \theta_D))$$

$$\theta_G \leftarrow \theta_G - \eta \frac{\partial f_K(\theta_G, \theta_D)}{\partial \theta_G}$$

$$\theta_D \leftarrow \theta_D - \eta \frac{\partial f(\theta_G, \theta_D)}{\partial \theta_D}$$

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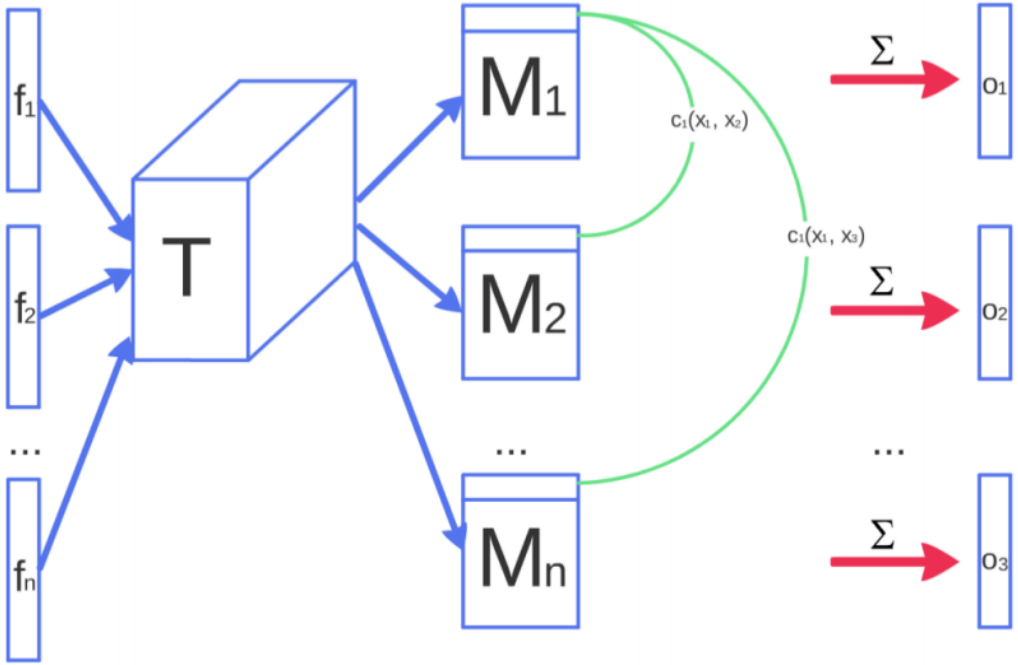
$$\theta_D \leftarrow \theta_D - \eta \frac{\partial f(\theta_G, \theta_D)}{\partial \theta_D}$$

$$\frac{\partial f_K(\theta_G, \theta_D)}{\partial \theta_G} = \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_G} + \frac{\partial f(\theta_G, \theta_D^K(\theta_G, \theta_D))}{\partial \theta_D^K(\theta_G, \theta_D)} \frac{\partial \theta_D^K(\theta_G, \theta_D)}{\partial \theta_G}$$

Generators can move towards better directions based on what discriminators tell

Minibatch Discrimination (Discriminator Objective)

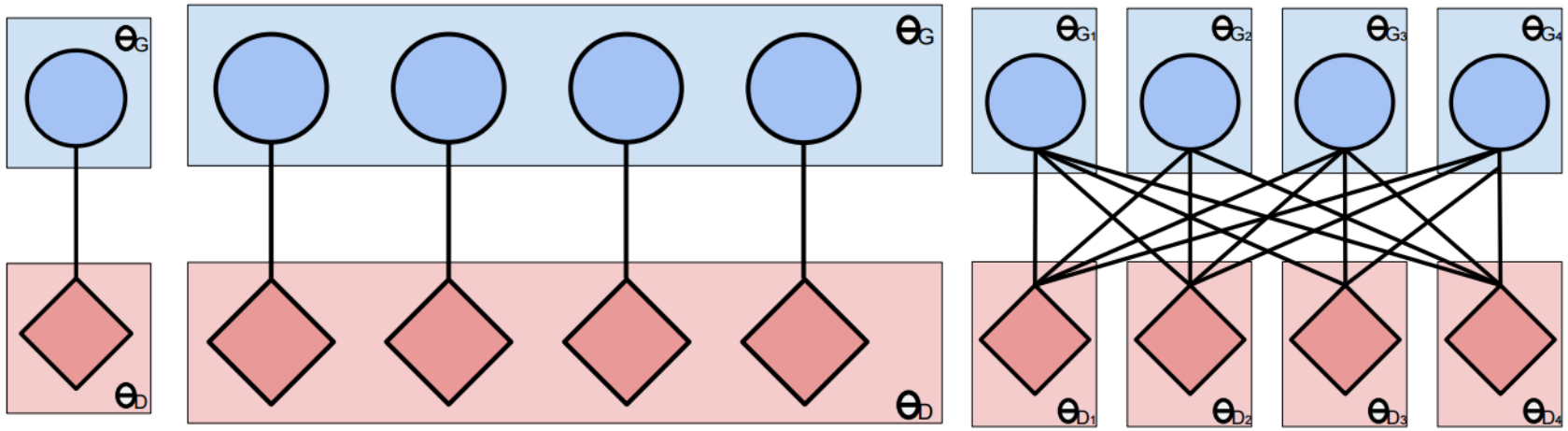
- Idea: allow the discriminator to see multiple data examples in combination to avoid collapsing to a single mode



Considering a batch in combination results in better robustness and diversity

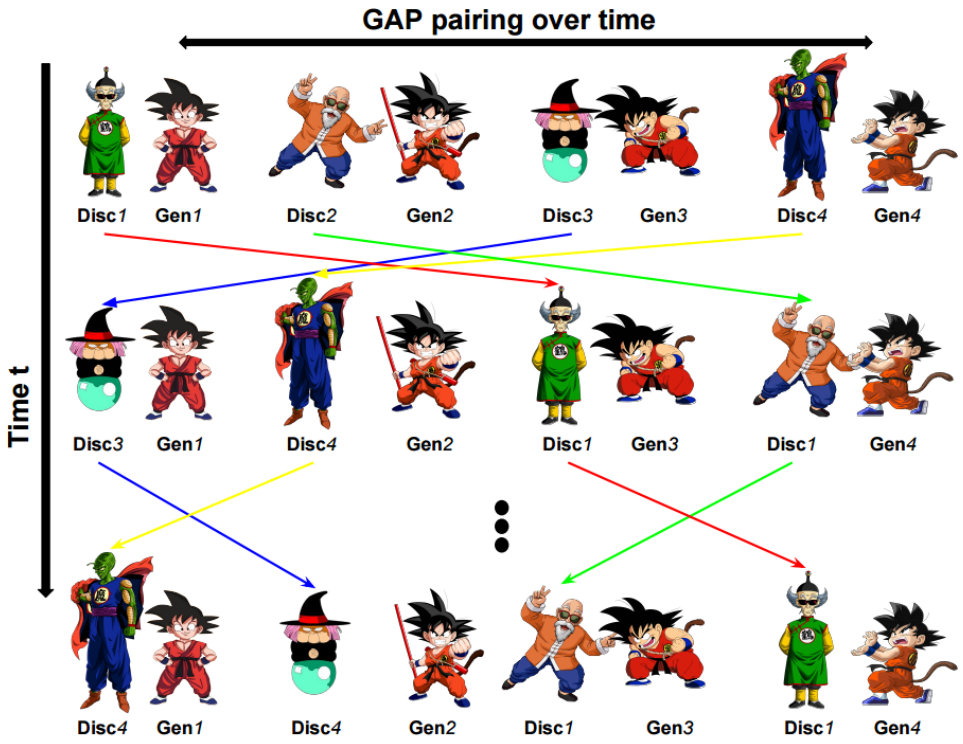
Generative Adversarial Parallelization (GAP)
(Discriminator Objective)

- Idea: train multiple GANs and allow different discriminators to discriminate difference generators



(a) GAN (b) GANs trained by data-parallelism (c) GAP

Generative Adversarial Parallelization (GAP)
(Discriminator Objective)



Algorithm 1 Training procedure of GAP.

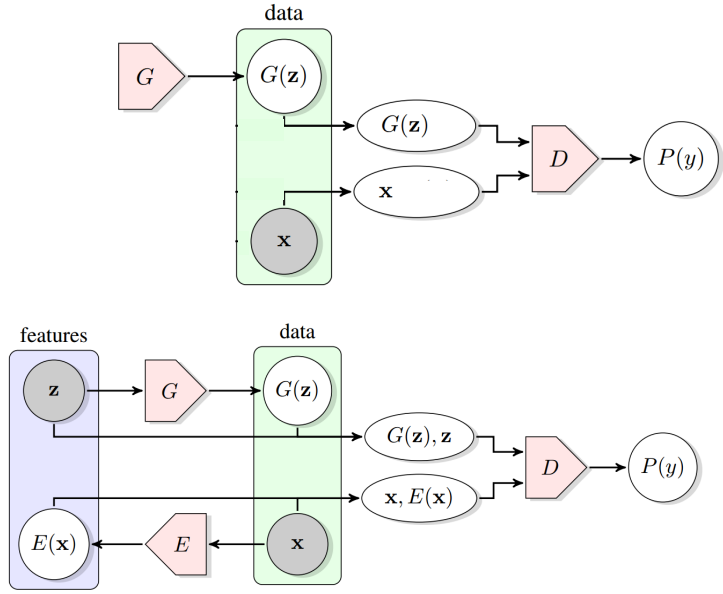
Let T be total number of weight updates.
Let N be the total number of GANs.
Let K be the swapping frequency.
Let $\mathcal{M} = \{(G_1, D_1), (G_2, D_2), \cdots, (G_N, D_N)\}$.
while $t < T$ **do**
  Update $\mathcal{M}_{i_t} = (G_{i_t}, D_{i_t})\ \forall i = 1 \cdots N$.

  if $t\ \%\ K == 0$ **then**
    Randomly select $\frac{N}{2}$ pairs with indices (i, j) w/o replacement.
    Swap D_i and D_j (G_i and G_j) $\forall i \neq j$.
  end if
end while
Select the best GAN based on GAM evaluation.

Discriminators can have better robustness because seeing different generated modes

Concluding Remarks

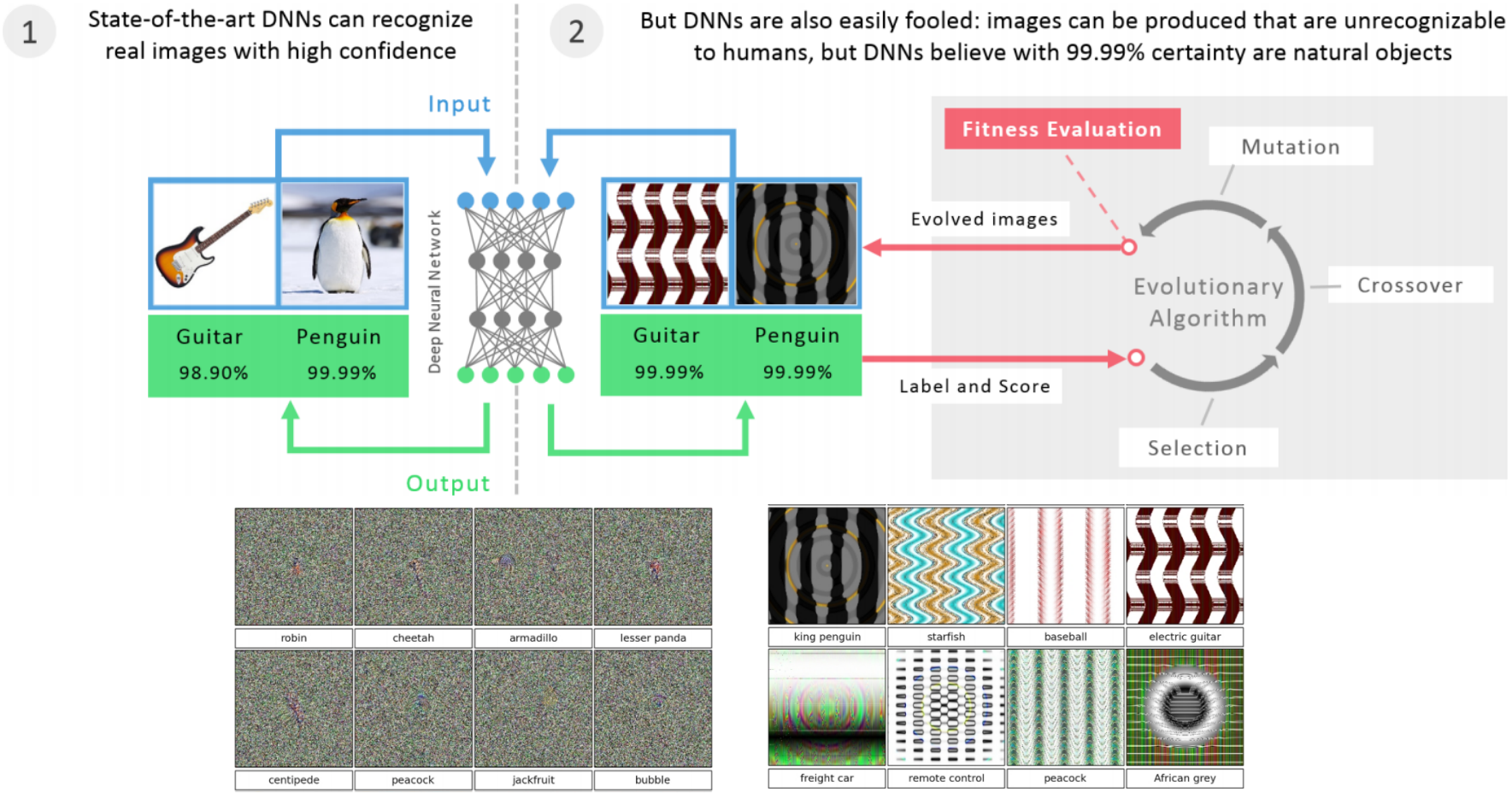
- Generative adversarial networks (GAN)
  - jointly train two competing networks, **generator** and **discriminator**
- Adversarially learned inference (ALI) / bidirectional GAN (BiGAN)
  - jointly train three networks, **generator**, **encoder**, and **discriminator**
  - latent variables can be encoded
- Training tricks
  - Generator objective: feature matching, unrolled GAN
  - Discriminator objective: minibatch discrimination, generative adversarial parallelization (GAP)
- Applications
  - semi-supervised learning



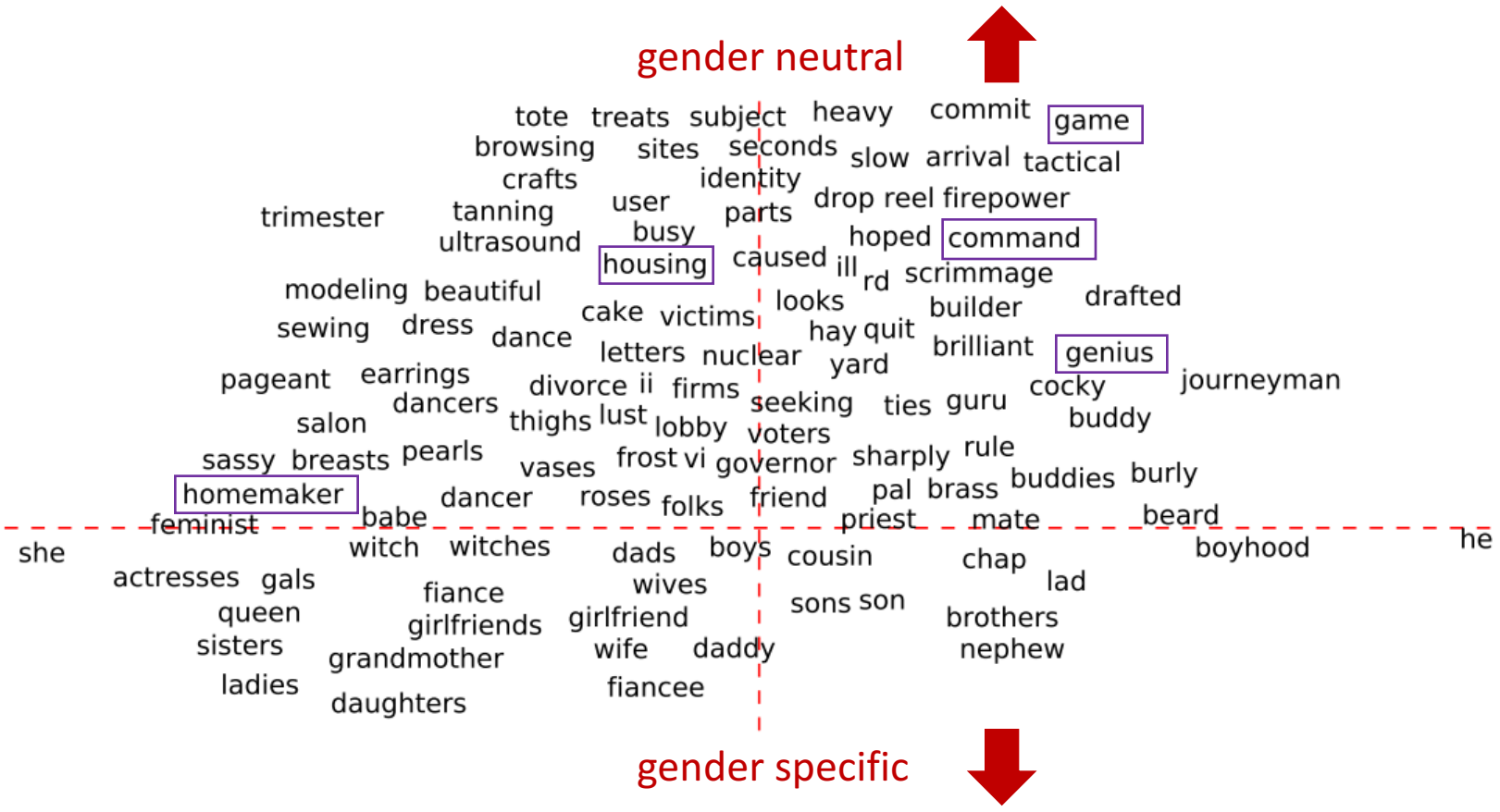
Challenges in Deep Learning

- **Deep Learning Issues**
- From “Going Deeper” to “Compressing more lightly”
- CNN v.s. RNN
- Deep Learning in Robotics
- Generative Models

DNN are easily fooled



Bias Issue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governor
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burly
feminist
babe
priest
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dads
boys
cousin
chap
boyhood
he
actresses
gals
wives
lad
fiance
sons
son
queen
girlfriends
girlfriend
brothers
sisters
wife
daddy
nephew
grandmother
ladies
fiancee
daughters
gender specific

Outline

- Deep Learning Issues
- **From “Going Deeper” to “Compressing more lightly”**
- CNN v.s. RNN
- Deep Learning in Robotics
- Generative Models

Model Compression

- Deeper models achieve better accuracy: GoogLeNet, ResNet
- SqueezeNet aims at AlexNet-level accuracy with smaller model, motivated by
  i. Smaller CNNs require less communication across servers during distributed training
  ii. less bandwidth to export a new model from the cloud to an autonomous car
  iii. more feasible to deploy on FPGAs and other hardware with limited memory

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CNN v.s. RNN

- CNN is also able to capture knowledge from windowed data for sequential input
- RNN mainly benefits from learning the sequential information → order matters

- Efficiency? Effectiveness? Combination?

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- Deep Learning Issues
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- CNN v.s. RNN
- **Deep Learning in Robotics**
- Generative Models

Deep Learning in Robotics

- Traditional: humanoids or manipulators
- Trend: policy search framework / reinforcement learning
  - Failure cost is expensive
    - Cloud robotics
    - Learning from demonstration
  - Decisions should be made in real time
    - Model size reduction
    - Transferring learned knowledge for a new task

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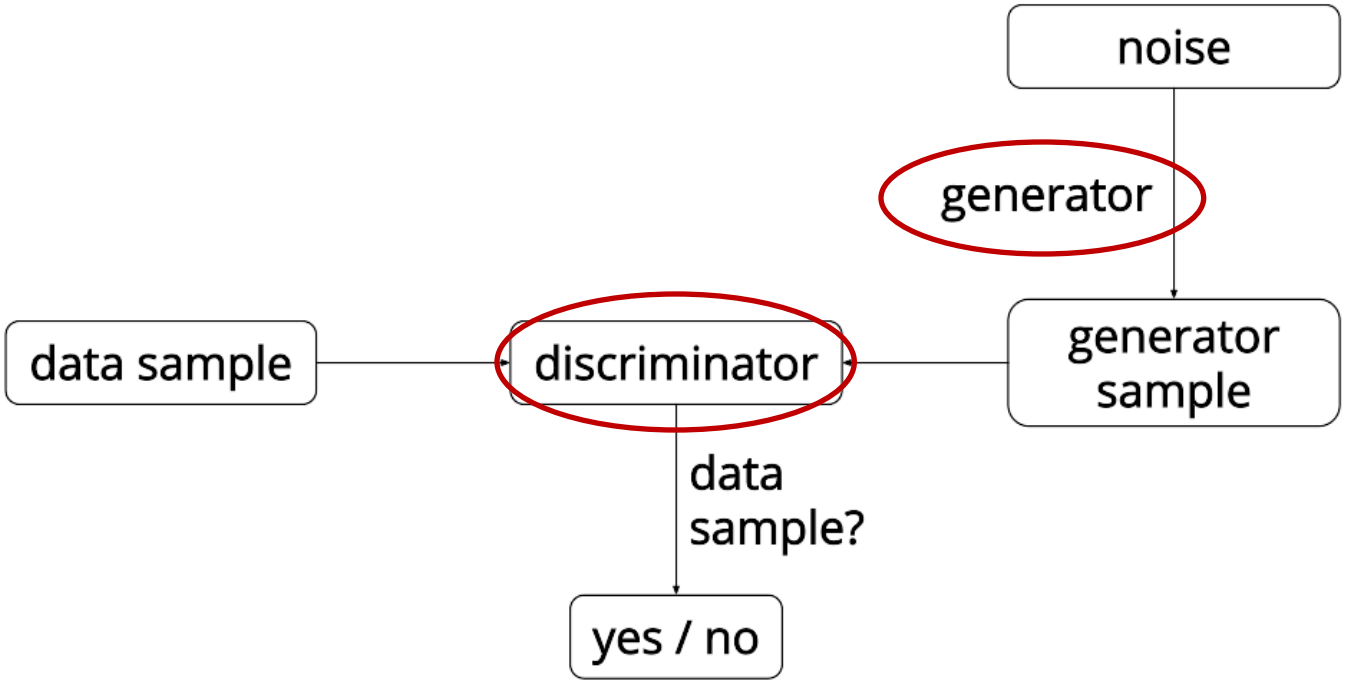
- CNN v.s. RNN
- Deep Learning in Robotics
- **Generative Models**

Generative Adversarial Networks (GAN)



Two players reach a Nash equilibrium to produce an optimal generator

Group Discussion:

Other challenges in deep learning, and DL4NLP?

Concluding Remarks

- Deep Learning Issues
  - DNNs are easily fooled
  - Bias issue
- From “Going Deeper” to “Compressing more lightly”
  - less communication
  - less bandwidth to export
  - feasible to deploy
- CNN v.s. RNN
- Deep Learning in Robotics: policy search/reinforcement learning
  - Expensive cost: cloud robot, learning from demonstration
  - Real-time decision: model compression, knowledge transfer
- Generative Models: GAN
  - Adversarial framework: generator & discriminator

Course Summary

- So far we've covered word embeddings, NN basics, Recur. NNs, RNNs, LSTMs/GRUs, Seq2Seq, Attention & Memory, ConvNets, Lang & Vision, Deep Reinforcement Learning, GANs…
- Each topic could be a course of its own (e.g., CS231N, DRL), but we have to balance depth and breadth.
- You've also given chances to work on ML competition assignments in real-world settings.
- Hopefully through paper reviews and in-class presentations it help you improve your understanding of DL papers, polish presentation skills, and prepare you for conf. presentations.
- Through course projects, we hope that you get to explore and conduct cutting-edge research in deep learning for NLP.
- **Final Message: ML is the fastest growing area of CS, and hopefully you learned something from this course that could benefit your own research.**

ESCI – Course Evaluation

- Very important for future iterations of the course.

Paper Review:

- Hongmin : Generative Adversarial Nets, Goodfellow et al., NIPS 2014
- Burak : Auto-encoding variational Bayes, Kingma and Welling, ICLR 2014
- Pushkar : Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, Redford et al., 2015
- Liu : Semi-supervised Sequence Learning, Dai et al., NIPS 2015