TRAINING GENERATIVE ADVERSARIAL NETWORKS WITH BINARY NEURONS BY END-TO-END BACKPROPAGATION

Hao-Wen Dong and Yi-Hsuan Yang

OUTLINES

- **♦** Backgrounds
 - ♦ Generative Adversarial Networks
 - **♦ Binary Neurons**
 - **♦ Straight-through Estimators**
- **♦ BinaryGAN**
- ♦ Experiments & Results
- Discussions & Conclusion

BACKGROUNDS

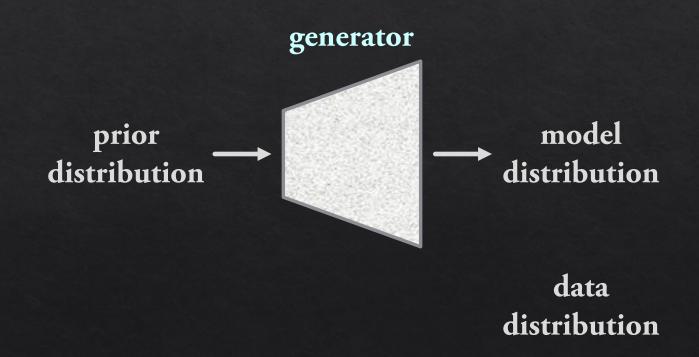
♦ Goal—learn a mapping from the prior distribution to the data distribution [2]

distribution data distribution

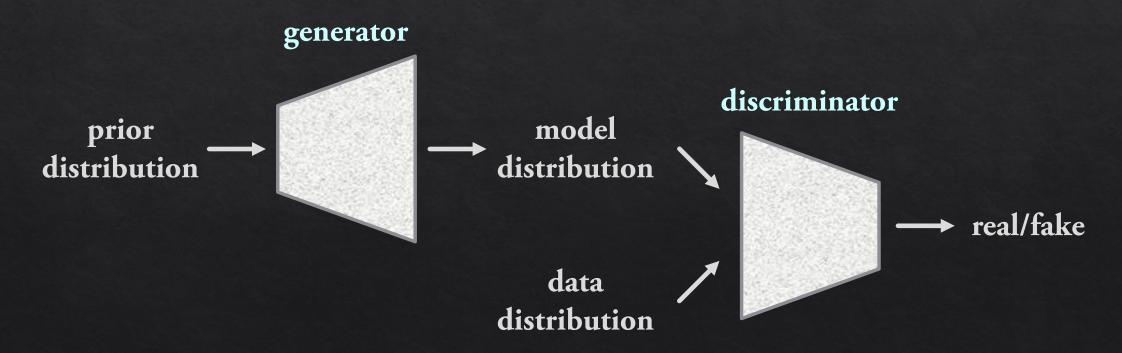
♦ Goal—learn a mapping from the prior distribution to the data distribution [2]

can be intractable
prior
distribution
distribution

Use a deep neural network to learn an implicit mapping



Use another deep neural network to provide guidance/critics



BINARY NEURONS

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 (hard thresholding)

♦ Stochastic binary neurons (SBNs):

$$SBN(x) \equiv \begin{cases} 1, & if \ z < \sigma(x) \\ 0, & otherwise \end{cases}$$
, $z \sim U[0, 1]$ (Bernoulli sampling)

BACKPROPAGATING THROUGH BINARY NEURONS

- Backpropagating through binary neurons is intractable
 - ♦ For DBNs, it involves the nondifferentiable threshold function
 - ♦ For SBNs, it requires the computation of expected gradients on all possible combinations (*exponential to the number of binary neurons*) of values taken by the binary neurons

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 - ♦ For SBNs, it requires the computation of expected gradients on all possible combinations (*exponential to the number of binary neurons*) of values taken by the binary neurons
- We can introduce gradient estimators for the binary neurons
 - ♦ Examples include Straight-through [3,4] (the one adopted in this work), REINFORCE [5], REBAR [6], RELAX [7] estimators

STRAIGHT-THROUGH ESTIMATORS

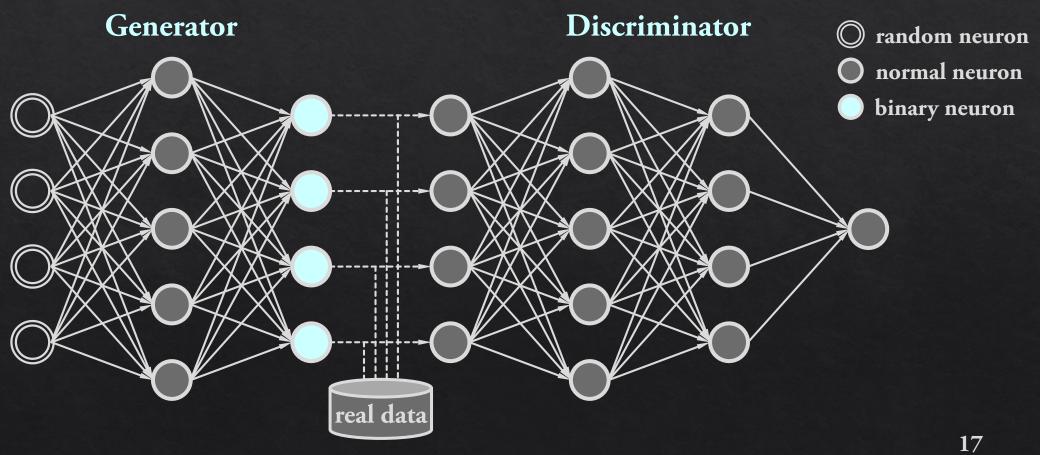
- ♦ Straight-through estimators: [3,4]
 - ♦ Forward pass—use hard thresholding (DBNs) or Bernoulli sampling (SBNs)
 - ♦ Backward pass—pretend it as an identity function

STRAIGHT-THROUGH ESTIMATORS

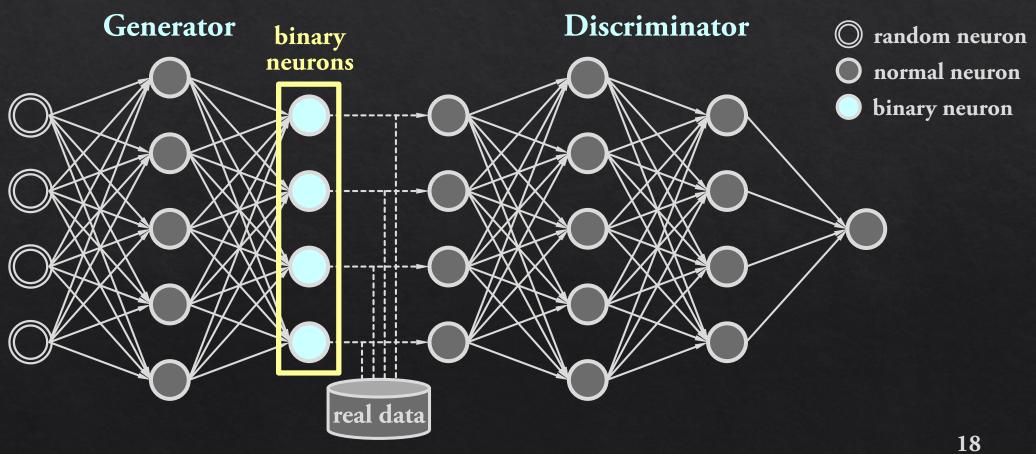
- ♦ Straight-through estimators: [3,4]
 - ♦ Forward pass—use hard thresholding (DBNs) or Bernoulli sampling (SBNs)
 - Backward pass—pretend it as an identity function
- ♦ Sigmoid-adjusted straight-through estimators
 - Use the derivative of the sigmoid function in the backward pass
 - ♦ Found to achieve better performance in a classification task presented in [4]
 - **♦ Adopted in this work**

- Use binary neurons at the output layer of the generator
- Use sigmoid-adjusted straight-through estimators to provide the gradients for the binary neurons
- ♦ Train the whole network by end-to-end backpropagation

(implemented by multilayer perceptrons)



(implemented by multilayer perceptrons)



EXPERIMENTS & RESULTS

TRAINING DATA

- ♦ Binarized MNIST handwritten digit database [8]
 - \diamond Digits with nonzero intensities $\rightarrow 1$
 - \diamond Digits with zero intensities \rightarrow 0

Sample binarized MNIST digits

5	0	Ч	1	9	2	1	3	6	9	0	5	6	ø	7	6
1	4	3	5	3	6		7	ı	8	1	9	3	9	8	5
2	8	6	9	ч	Ø	9	1	5	3	3	0	7	#	9	8
7	2	4	3	2	7	ъ	8	0	9	4	1	4	#	6	0

IMPLEMENTATION DETAILS

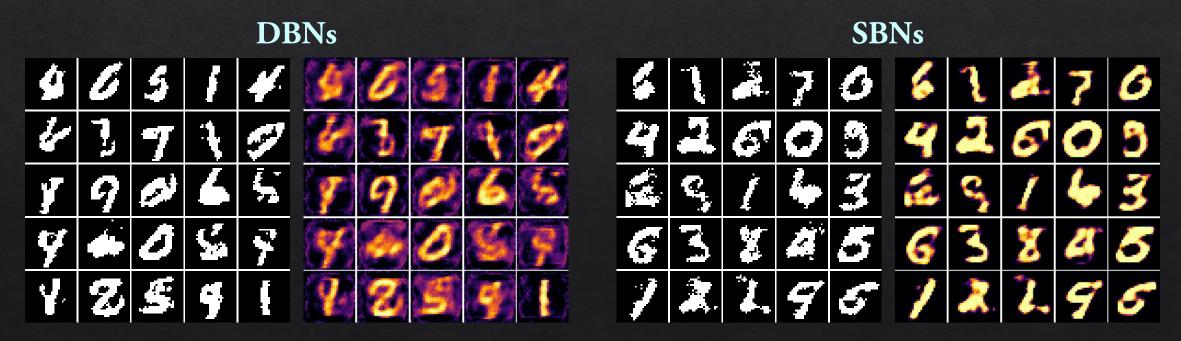
- ♦ Batch size is 64
- ♦ Use WGAN-GP [9] objectives
- **♦ Use Adam optimizer [10]**
- ♦ Apply batch normalization [11] to the generator (but not to the discriminator)
- ♦ Binary neurons are implemented with the code kindly provided in a blog post on the R2RT blog [12]

IMPLEMENTATION DETAILS

- **♦** Apply slope annealing trick [13]
 - ♦ Gradually increase the slopes of the sigmoid functions used in the sigmoidadjusted straight-through estimators as the training proceeds
 - ♦ We multiply the slopes by 1.1 after each epoch
 - ♦ The slopes start from 1.0 and reach 6.1 at the end of 20 epochs

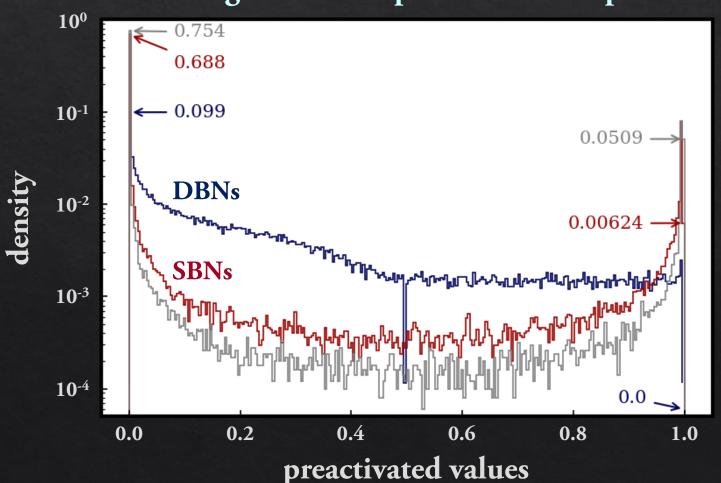
EXPERIMENT I—DBNs vs SBNs

- **DBNs and SBNs can achieve similar qualities**
- They show distinct characteristics on the preactivated outputs



EXPERIMENT I—DBNs vs SBNs

Histograms of the preactivated outputs



DBNs

- more values in the middle
- a notch at 0.5 (the threshold)

SBNs

- more values close to 0 and 1

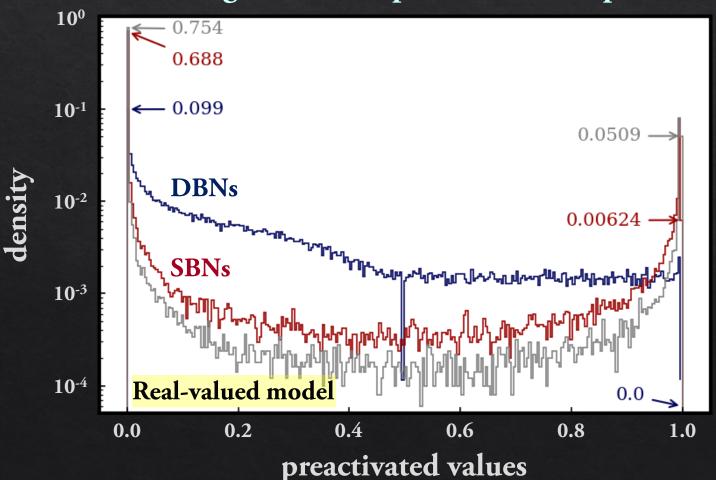
EXPERIMENT II—REAL-VALUED MODEL

- Use no binary neurons
- ♦ Train the discriminator by the real-valued outputs of the generator



EXPERIMENT II—REAL-VALUED MODEL

Histograms of the preactivated outputs



DBNs

- more values in the middle
- a notch at 0.5 (the threshold)

SBNs

- more values close to 0 and 1

Real-valued model

- even more U-shaped

EXPERIMENT III—GAN OBJECTIVES

- * WGAN [14] model can achieve similar qualities to the WGAN-GP
- ♦ GAN [2] model suffers from mode collapse issue



EXPERIMENT IV—MLPs vs CNNs

♦ CNN model produces less artifacts even with a small number of trainable parameters (MLP—0.53M; CNN—1.4M)

MLP model										CNN model											
DBNs					SBNs					DBNs						SBNs					
4	6	5	I	4	6	1	T.	7	0	4	9	3	9	D	9	9	9	E	Ţ		
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DISCUSSIONS & CONCLUSION

DISCUSSIONS

- ♦ Why is binary neurons important?
 - ♦ Open the possibility of conditional computation graph [4,13]
 - ♦ Move toward a stronger AI that can make reliable decisions

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- Why is binary neurons important?
 - ♦ Open the possibility of conditional computation graph [4,13]
 - Move toward a stronger AI that can make reliable decisions
- Other approaches to model discrete distributions with GANs
 - ♦ Replace the target discrete outputs with continuous relaxations
 - ♦ View the generator as agent in reinforcement learning (RL) and introduce RL-based training strategies

CONCLUSION

♦ A new GAN model that

- can generate binary-valued predictions without further post-processing
- can be trained by end-to-end backpropagation

♦ Experimentally compare

- deterministic and stochastic binary neurons
- the proposed model and the real-valued model
- ♦ GAN, WGAN, WGAN-GP objectives
- **⋄** MLPs and CNNs

FUTURE WORK

♦ Examine the use of gradient estimators for training a GAN that has a conditional computation graph

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Thank you for your attention