

# Adversarial Fisher Vectors For Unsupervised Representation Learning

Shuangfei Zhai, Walter Talbott, Carlos Guestrin, Joshua M. Susskind {szhai, wtalbott, guestrin, jsusskind}@apple.com



Question: Does a GAN learn representations of data?

Answer: Yes

Question: Do you need an encoder in order to do so?

Answer: No

## Energy Based Model view of GANs

The discriminator **D** is the negative energy function

The generator **G** approximates the density given by **D** 

The EBM can adopt the same training procedure as a GAN

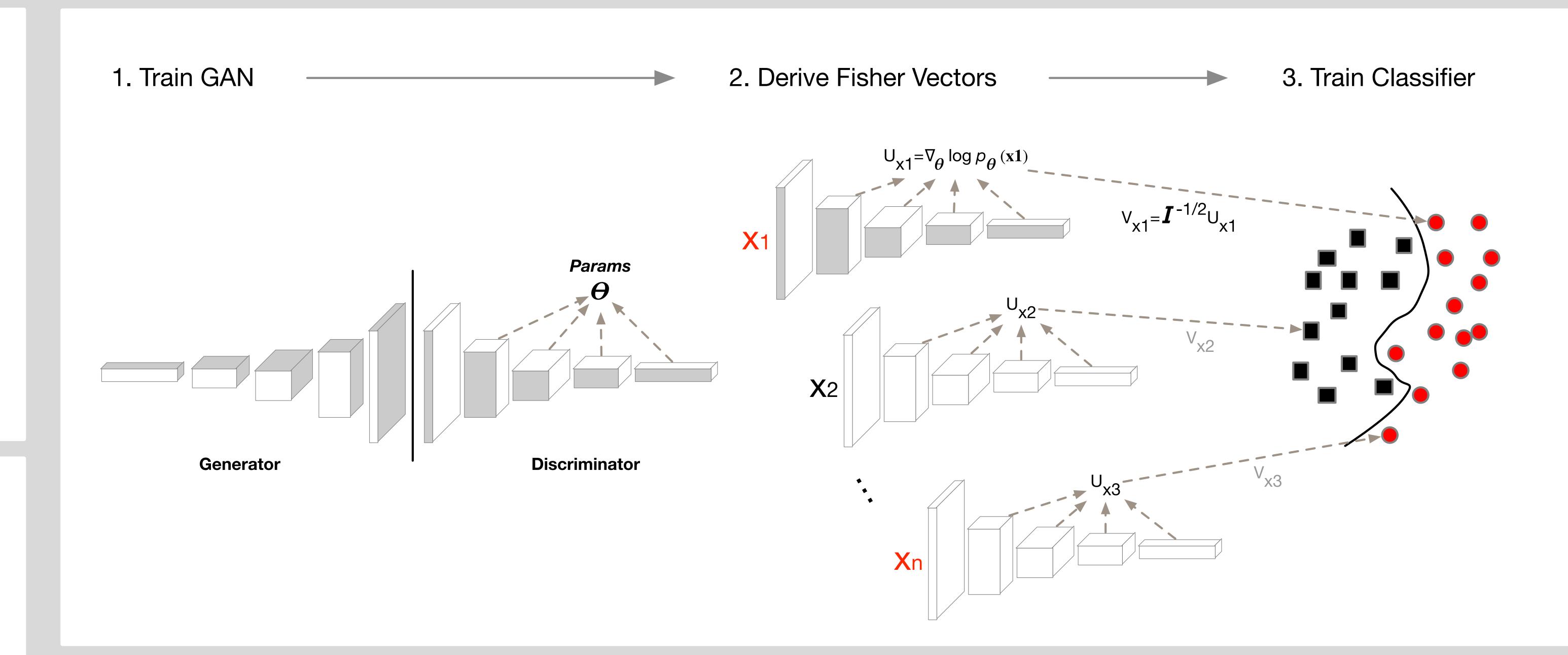
#### Adversarial Fisher Vectors

Fisher Vector represents an example x by the desired change of parameters given a density model:  $\nabla_{\theta} \log p_{\theta}(x)$ 

We let 
$$p_{\theta}(x) = \frac{e^{D_{\theta}(x)}}{\int_{x} e^{D_{\theta}(x)} dx}$$
, and assume **G** approximates  $p_{\theta}(x)$ 

$$V_{\mathbf{x}} = (diag(\mathcal{I})^{-\frac{1}{2}})U_{\mathbf{x}}$$

$$U_{\mathbf{x}} = \nabla_{\theta} D(\mathbf{x}; \theta) - \mathrm{E}_{\mathbf{z} \sim p(\mathbf{z})} \nabla_{\theta} D(G(\mathbf{z}); \theta), \ \mathcal{I} = \mathrm{E}_{\mathbf{z} \sim p(\mathbf{z})} [U_{G(\mathbf{z})} U_{G(\mathbf{z})}^T].$$



### State of The Art Linear Classification Results

Method	CIFAR10	CIFAR100	Method	#Features
Examplar CNN [29]	84.3	_	Unsupervised	_
DCGAN [38]	82.8	_	Unsupervised	_
Deep Infomax [39]	75.6	47.7	Unsupervised	1024
RotNet Linear [30]	81.8	_	Self-Supervised	~25K
AET Linear [32]	83.3	_	Self-Supervised	$\sim$ 25K
D-pool-128-50000	65.3	_	Unsupervised	512
AFV-128-50000	86.2	_	Unsupervised	1.5M
AFV-128-50000 + augment	87.1	_	Unsupervised	1.5M
AFV-256-50000 + augment	88.5	_	Unsupervised	5.9M
AFV-256-50000 + C100 + augment	89.1	67.8	Unsupervised	5.9M
D + BN supervised training	92.7	70.3	Supervised	_

#### References

- EBM vs GAN: Generative Adversarial Networks as Variational Training of Energy Based Models, Zhai et al.
- Fisher Vectors: Exploiting Generative Models in Discriminative Classifiers, Jaakkola and Haussler