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InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets

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Machine Learning   Neural Networks

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TITLE	CITED BY	YEAR
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Distributed representations of words and phrases and their compositionality T Mikolov, I Sutskever, K Chen, GS Corrado, J Dean Advances in neural information processing systems, 3111-3119	7649	2013
Dropout: A simple way to prevent neural networks from overfitting N Srivastava, G Hinton, A Krizhevsky, I Sutskever, R Salakhutdinov The Journal of Machine Learning Research 15 (1), 1929-1958	6225	2014
Sequence to sequence learning with neural networks I Sutskever, O Vinyals, QV Le Advances in neural information processing systems, 3104-3112	3552	2014

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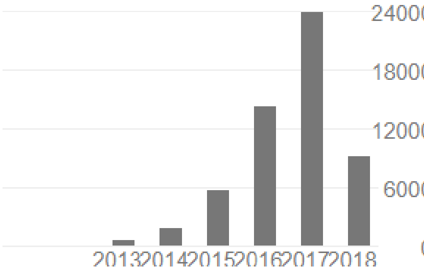


Co-founder and Research Director of OpenAI.

I spent three wonderful years as a Research Scientist at the Google Brain Team.

Before that, I was a co-founder of DNNresearch.

And before that, I was a postdoc in Stanford with Andrew Ng's group.

And in the beginning, I was a student in the Machine Learning group of Toronto, working with Geoffrey Hinton.

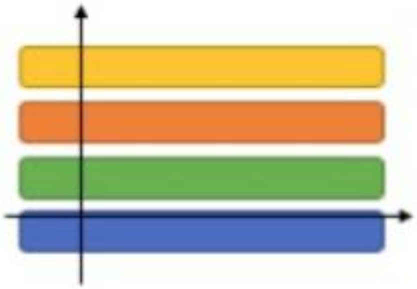
My email address is ilyasu@openai.com.

Motivation

How can we achieve
unsupervised learning of disentangled representation?

In general, learned representation is entangled,
i.e., encoded in a data space in a complicated manner

When a representation is disentangled, it would be
more interpretable and easier to apply to tasks



Related works

- Unsupervised learning of representation

  (no mechanism to force disentanglement)
  - ✓ Stacked (often denoising) auto-encoder, RBM
  - ✓ Many others, including semi-supervised approach
- Supervised learning of disentangled representation
  - ✓ Bilinear models, multi-view perceptron
  - ✓ VAEs, adversarial auto-encoders
- Weakly supervised learning of disentangled representation
  - ✓ disBM, DC-IGN
- Unsupervised learning of disentangled representation
  - ✓ hossRBM, applicable only to discrete latent factors

This work:
Unsupervised learning of disentangled representation applicable to both continuous and discrete latent factors

Generative Adversarial Nets(GANs)

Generative model trained by competition between two neural networks:

✓ Generator $x = G(z), z \sim p_z(Z)$
$p_z(Z)$: an arbitrary noise distribution

✓ Discriminator $\mathrm{D}(x) \in [0,1]$:
Probability that x is sampled from the real data $p_{data}(X)$
Rather than generated by the generator $\mathrm{G}(Z)$

Optimization problem to solve:

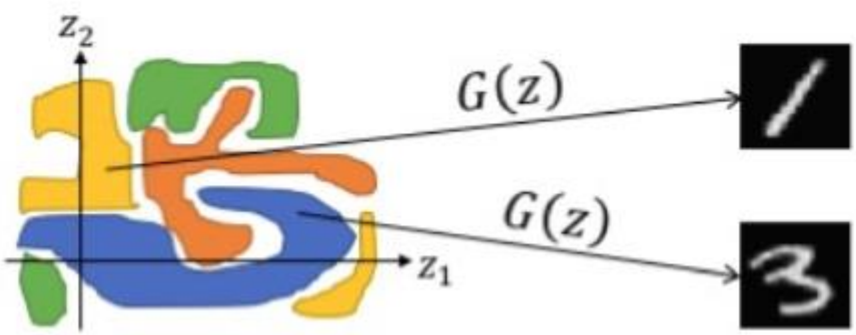
$$\min_G \max_D V(D, G) = \mathbb{E}_{x \sim P_{\text{data}}}[\log D(x)] + \mathbb{E}_{z \sim \text{noise}}[\log(1 - D(G(z)))]$$

Problems with GANs

From the perspective of representation learning

✓ No restrictions on how $G(z)$ uses z

- z can be used in a highly entangled way
- Each dimension of z does not represent any salient feature of the training data



Proposed Resolution: InfoGAN
-Maximizing Mutual Information

Observation in conventional GANs:

a generated data x does not have much information
on the noise z from which x is generated
because of heavily entangled use of z

Proposed resolution = InfoGAN:

the generator $G(z, c)$ trained so that
it maximize the mutual information $\mathrm{I}(\mathrm{C}|\mathrm{X})$ between
the latent code C and the generated data X

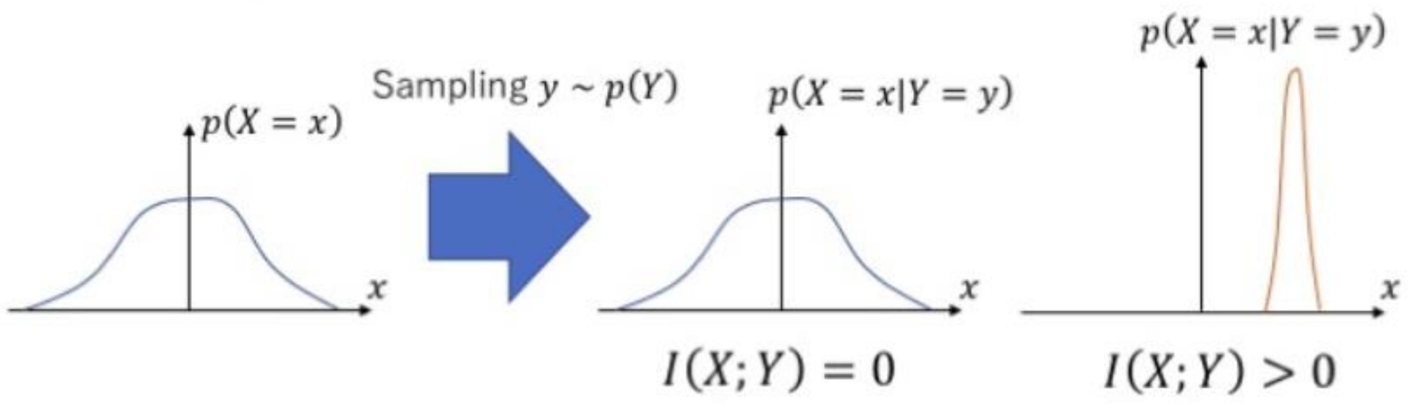
$$\min_G \max_D \{V_{\mathrm{GAN}}(G, D) - \lambda I(C|X = G(Z, C))\}$$

Mutual Information

$I(X;Y) = H(X) - H(\mathrm{X}|Y)$,where

- $H(X) = E_{x\sim p(X)}[-\ln p(X=x)]$:
  Entropy of the prior distribution

- $H(X|Y) = E_{y\sim p(Y), x\sim p(X|Y=y)}[-\ln p(X=x|Y=y)]$
  Entropy of the posterior distribution



Avoiding increase of calculation costs

Major difficulty:
Evaluation of $I(C|X)$ based on
evaluation and sampling from the posterior $p(C|X)$

Two strategies:
- ✓ Variational maximization of mutual information
  - ✓ Use an approximate function $\mathrm{Q}(C|X) = p(C = c|X = x)$
- ✓ Sharing the neural net
  between $\mathrm{Q}(C|X)$ and the discriminator $D(x)$

Variational Maximization of MI

Lower bounding mutual information

$$
\begin{aligned}
I(c; G(z, c)) &= H(c) - H(c|G(z, c)) \\
&= \mathbb{E}_{x \sim G(z,c)}[\mathbb{E}_{c' \sim P(c|x)}[\log P(c'|x)]] + H(c) \\
&= \mathbb{E}_{x \sim G(z,c)}[\underbrace{D_{\mathrm{KL}}(P(\cdot|x) \parallel Q(\cdot|x))}_{\geq 0} + \mathbb{E}_{c' \sim P(c|x)}[\log Q(c'|x)]] + H(c) \\
&\geq \mathbb{E}_{x \sim G(z,c)}[\mathbb{E}_{c' \sim P(c|x)}[\log Q(c'|x)]] + H(c)
\end{aligned}
$$

Variational Maximization of MI

With $Q(c,x)$ approximating $p(C=c|X=x)$,we obtain an variational Estimate of the mutual information:

$$
\begin{aligned}
L_I(G,Q) &= E_{c\sim P(c),x\sim G(z,c)}[\log Q(c|x)] + H(c) \\
&= E_{x\sim G(z,c)}[\mathbb{E}_{c'\sim P(c|x)}[\log Q(c'|x)]] + H(c) \\
&\leq I(c;G(z,c))
\end{aligned}
$$

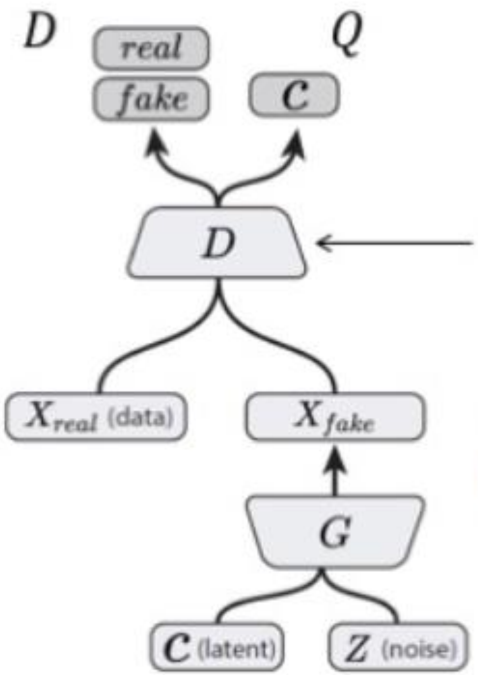
Optimization problem to solve in InfoGAN:

$$
\min_{G,Q}\max_{D} V_{\mathrm{InfoGAN}}(D,G,Q) = V(D,G) - \lambda L_I(G,Q)
$$

Sharing layers between D and Q

- ✓ Model $Q(c, x)$ using neural network
- ✓ Reduce the calculation costs by

Sharing all the convolution layers with D



Convolution layers of the discriminator

Given DCGANs,
InfoGAN comes for negligible additional costs!

Image from Odena, *et al.*, arXiv:1610.09585.

Experiment – MI Maximization

- InfoGAN on MNIST dataset
- Latent code $c \sim Cat(K = 10, p = 0.1)$
  =10-class categorical code

The lower bound $L_I(G, Q)$ is quickly
Maximized to $H(c) = 2.3$

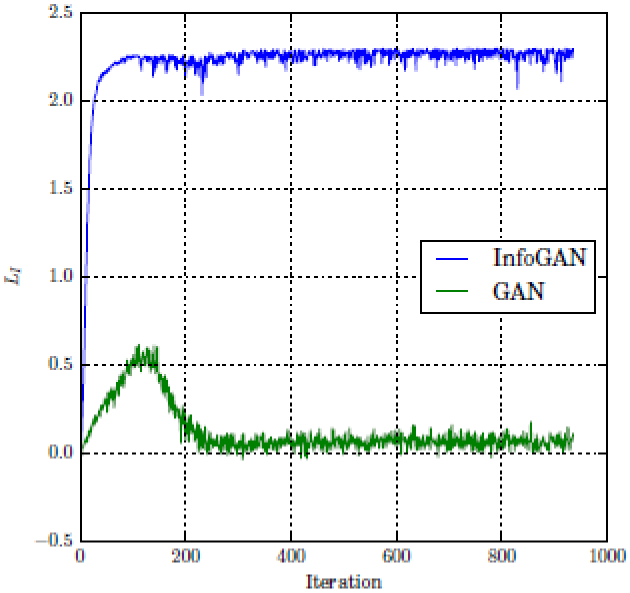
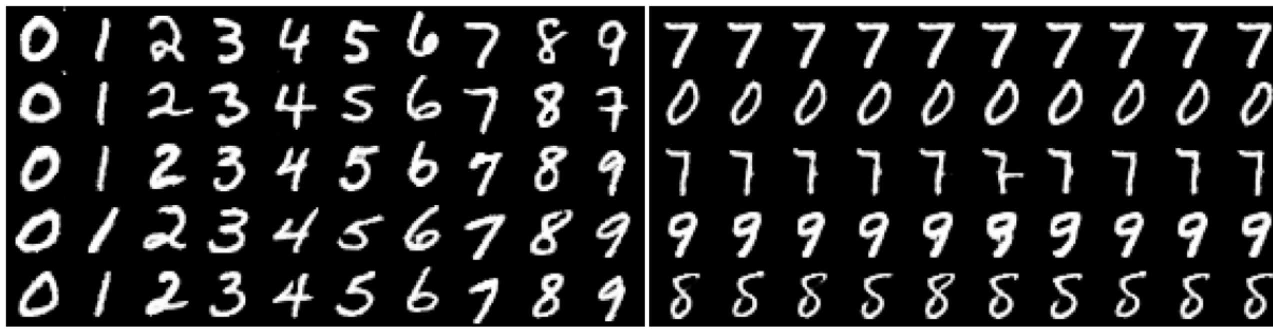


Figure 1: Lower bound L_I over training iterations

Experiment – Disentangled Representation

- InfoGAN on MNIST dataset
- Latent codes
  - c_1:10-class categorical code $c_1 \sim \mathrm{Cat}(\mathrm{K}=10, \mathrm{p}=0.1)$
  - c_2, c_3:continuous code,

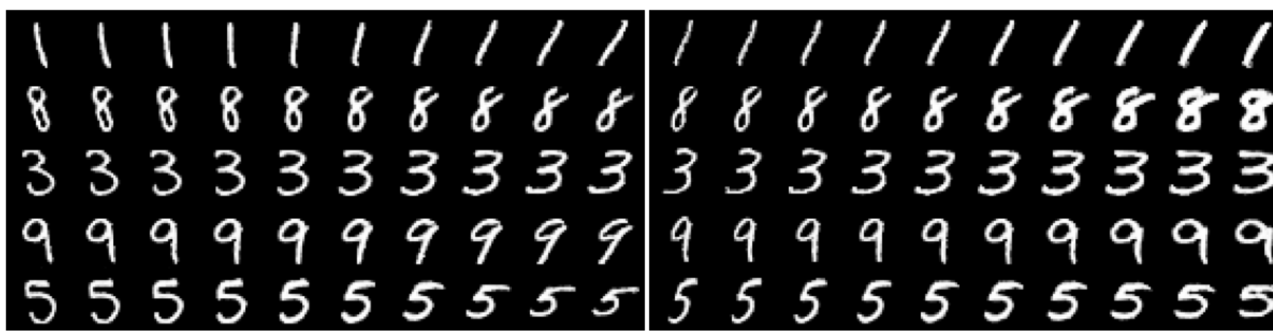
  $c_2, c_3 \sim Unif(-2,2)$



(a) Varying c_1 on InfoGAN (Digit type) (b) Varying c_1 on regular GAN (No clear meaning)

✓ c_1 can be used as a classifier with 5% error rate.

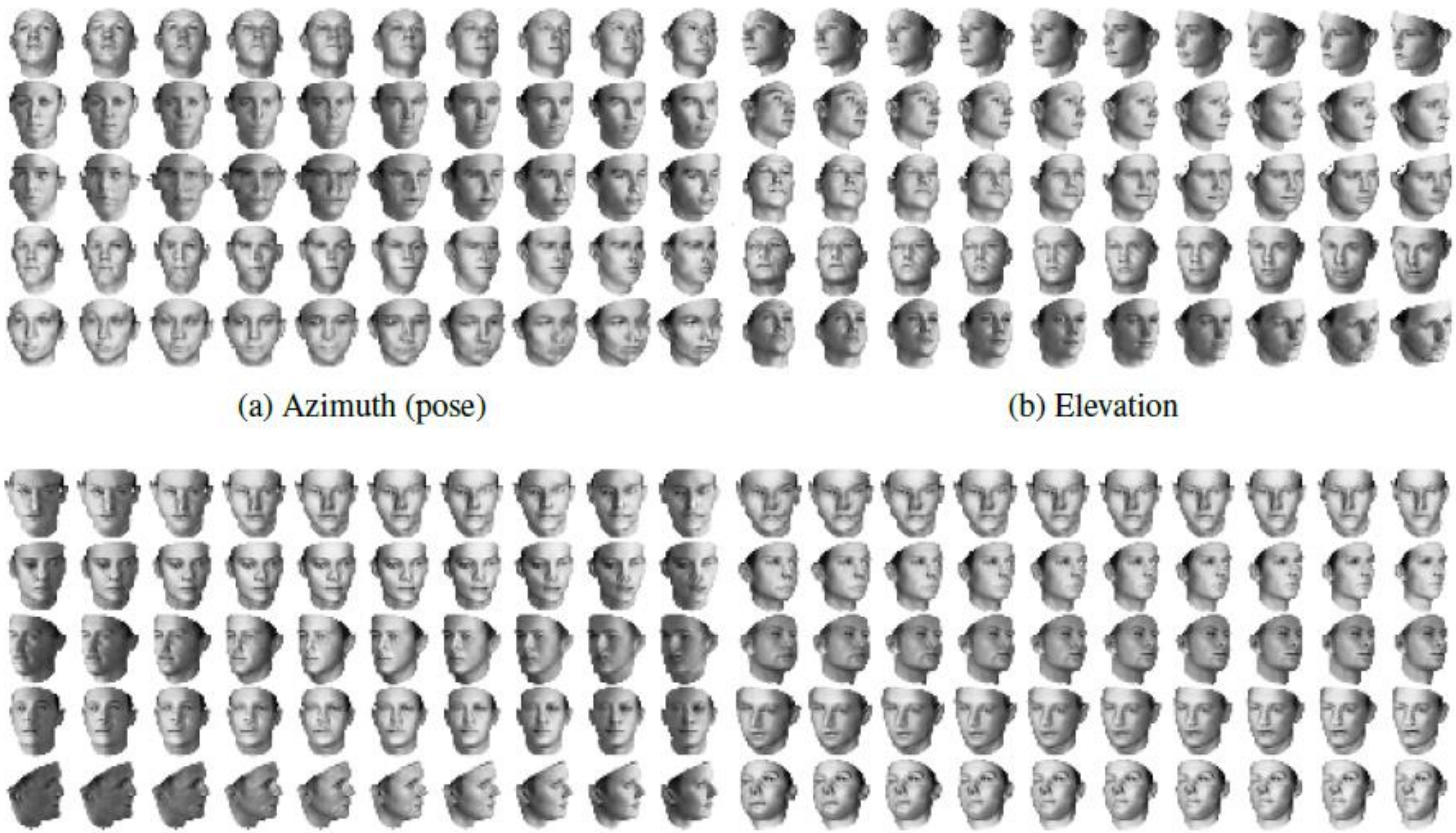
✓ c_2 and c_3 captured the rotation and width respectively



(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation) (d) Varying c_3 from -2 to 2 on InfoGAN (Width)

Experiment – Disentangled Representation

Dataset: P. Paysan, et al., AVSS, 2009, pp. 296-301.



(a) Azimuth (pose) (b) Elevation

(c) Lighting (d) Wide or Narrow

Experiment – Disentangled Representation

Dataset: M. Aubry, et al., CVPR, 2014, pp. 3762-3769.

(a) Rotation (b) Width

InfoGAN learned salient features without supervision

Experiment – Disentangled Representation

Dataset: Street View House Number

(a) Continuous variation: Lighting (b) Discrete variation: Plate Context

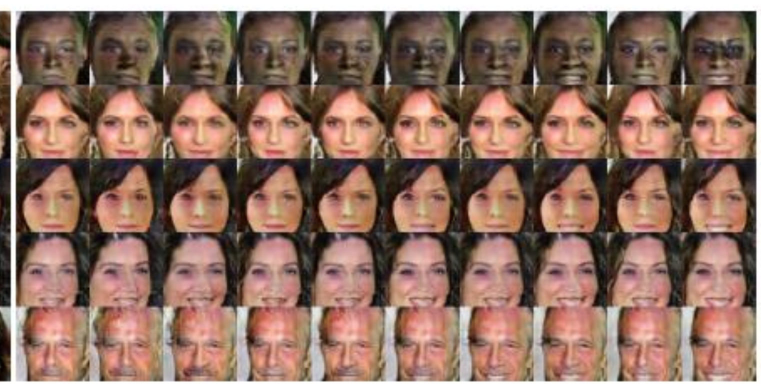
Experiment – Disentangled Representation

Dataset: CelebA

(a) Azimuth (pose)

(b) Presence or absence of glasses

(c) Hair style



(d) Emotion

Conclusion

- **Goal**
  - ✓ Unsupervised learning of disentangled representations
- **Approach**
  - ✓ GANs + Maximizing Mutual Information between generated images and input codes
- **Benefit**
  - ✓ Interpretable representation obtained without supervision and substantial additional costs

Future Prospect

- Mutual information maximization can be applied to other methods, e.g. VAE
- Learning hierarchical latent representation
- Improving semi-supervised learning
- High-dimensional data discovery