HALI: Hierarchical Adversarially Learned Inference

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ELEMENT AI

Hierarchical Adversarially Learned Inference

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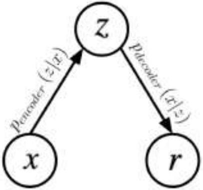
Paper is on Openreview "submitted to ICLR 2018"

Outline

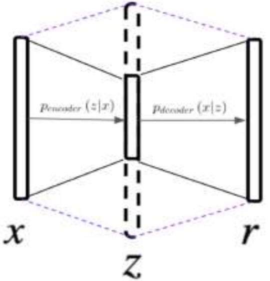
Autoencoder and Reconstruction

Autoencoder and Reconstruction

Autoencoder



Undercomplete/Overcomplete Autoencoder



$$p(z|x) = \frac{p(x|z)p(z)}{p(x)} = \frac{p(x,z)}{p(x)}$$

$$p(x) = \int p(x|z)p(z)dz$$ likely to be interactable

Variational Inference and Variational Autoencoder

Variational Inference and Variational Autoencoder

$$
\begin{aligned}
\log(p(\boldsymbol{x},\boldsymbol{z})) &= \log(p(\boldsymbol{z}\mid\boldsymbol{x})) + \log(p(\boldsymbol{x}))\\
\log(p(\boldsymbol{x})) &= \log(p(\boldsymbol{x},\boldsymbol{z})) - \log(p(\boldsymbol{z}\mid\boldsymbol{x}))\\
\log(p(\boldsymbol{x})) &= \log(\frac{p(\boldsymbol{x},\boldsymbol{z})}{q(\boldsymbol{z}\mid\boldsymbol{x})}) + \log(\frac{q(\boldsymbol{z}\mid\boldsymbol{x})}{p(\boldsymbol{z}\mid\boldsymbol{x})})\\
\log(p(\boldsymbol{x})) &= \mathbb{E}_{\boldsymbol{z}\sim q(\boldsymbol{z}|\boldsymbol{x})}[\log(\frac{p(\boldsymbol{x},\boldsymbol{z})}{q(\boldsymbol{z}\mid\boldsymbol{x})})] + KL(q(\boldsymbol{z}\mid\boldsymbol{x}) \mid\mid p(\boldsymbol{z}\mid\boldsymbol{x}))\\
\log(p(\boldsymbol{x})) &\geq \mathbb{E}_{\boldsymbol{z}\sim q(\boldsymbol{z}|\boldsymbol{x})}[\log(\frac{p(\boldsymbol{x},\boldsymbol{z})}{q(\boldsymbol{z}\mid\boldsymbol{x})})]\\
\log(p(\boldsymbol{x})) &\geq \mathbb{E}_{\boldsymbol{z}\sim q(\boldsymbol{z}|\boldsymbol{x})}[\log(\frac{p(\boldsymbol{x}\mid\boldsymbol{z})p(\boldsymbol{z})}{q(\boldsymbol{z}\mid\boldsymbol{x})})]\\
\log(p(\boldsymbol{x})) &\geq \mathbb{E}_{\boldsymbol{z}\sim q(\boldsymbol{z}|\boldsymbol{x})}[\log(p(\boldsymbol{x}\mid\boldsymbol{z}))] - KL(q(\boldsymbol{z}\mid\boldsymbol{x}) \mid\mid p(\boldsymbol{z}))
\end{aligned}
$$

GAN: Generative Adversarial Networks

GAN: Generative Adversarial Networks[2]

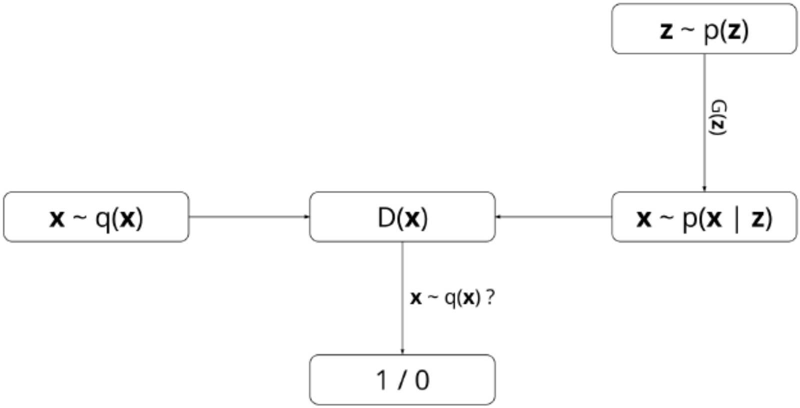


Figure: GAN[1]

[1] Graphs are taken from Ishmael Belghazi's blog post/ALI paper with his permission
[2] GAN: "Generative Adversarial Nets.", Goodfellow et al, NIPS, 2014.

GAN: Generative Adversarial Networks

$$
\begin{aligned}
\min_G \max_D V(D, G) &= \mathbb{E}_{q(\boldsymbol{x})}[\log(D(\boldsymbol{x}))] + \mathbb{E}_{p(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}))] \\
&= \int q(\boldsymbol{x}) \log(D(\boldsymbol{x})) d\boldsymbol{x} \\
&+ \iint p(\boldsymbol{z}) p(\boldsymbol{x} \mid \boldsymbol{z}) \log(1 - D(\boldsymbol{x})) d\boldsymbol{x} d\boldsymbol{z}.
\end{aligned} \tag{1}
$$

ALI: Adversarially Learned Inference

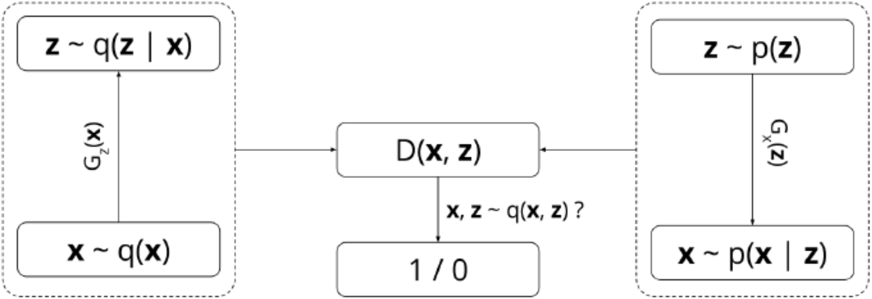
ALI: Adversarially Learned Inference[3],[4]

- It is a **Deep Directed Generative Model**
- It jointly learns a **Generative** network and an **Inference** network using an adversarial process.
- Unlike the VAE, the objective function involves **no explicit reconstruction loop**.
- ALI tends to produce **believable reconstructions with interesting variations**, instead of **pixel-perfect reconstruction**

[3] ALI: Adversarially Learned Inference, Vincent Dumoulin, Ishmael Belghazi, Ben Poole, Olivier Mastropietro, Alex Lamb, Martin Arjovsky, Aaron Courville

[4] Adversarial Feature Learning, Jeff Donahue, Philipp Krähenbühl, Trevor Darrell

ALI: Adversarially Learned Inference



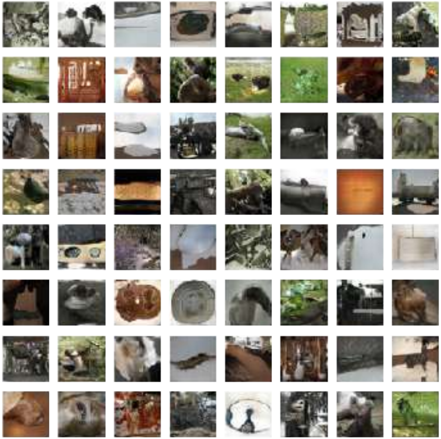
ALI: Adversarially Learned Inference

Consider the two following probability distributions over $\boldsymbol{x}$ and $\boldsymbol{z}$:

- the *encoder* joint distribution $q(\boldsymbol{x}, \boldsymbol{z}) = q(\boldsymbol{x})q(\boldsymbol{z} \mid \boldsymbol{x})$,
- the *decoder* joint distribution $p(\boldsymbol{x}, \boldsymbol{z}) = p(\boldsymbol{z})p(\boldsymbol{x} \mid \boldsymbol{z})$.

$$\begin{aligned}\min_G \max_D V(D, G) &= \mathbb{E}_{q(\boldsymbol{x})}[\log(D(\boldsymbol{x}, G_z(\boldsymbol{x})))] + \mathbb{E}_{p(\boldsymbol{z})}[\log(1 - D(G_x(\boldsymbol{z}), \boldsymbol{z}))] \\ &= \iint q(\boldsymbol{x})q(\boldsymbol{z} \mid \boldsymbol{x}) \log(D(\boldsymbol{x}, \boldsymbol{z}))d\boldsymbol{x}d\boldsymbol{z} \\ &+ \iint p(\boldsymbol{z})p(\boldsymbol{x} \mid \boldsymbol{z}) \log(1 - D(\boldsymbol{x}, \boldsymbol{z}))d\boldsymbol{x}d\boldsymbol{z}.\end{aligned} \tag{2}$$

ALI- Tiny Imagenet: Samples and Reconstruction



(a) Tiny ImageNet samples.

(b) Tiny ImageNet reconstructions.

Figure: Samples and reconstructions on the Tiny ImageNet dataset. For the reconstructions, odd columns are original samples from the validation set and even columns are corresponding reconstructions.

ALI- SVHN: Samples and Reconstruction

(a) SVHN samples.

(b) SVHN reconstructions.

Figure: Samples and reconstructions on the SVHN dataset. For the reconstructions, odd columns are original samples from the validation set and even columns are corresponding reconstructions.

ALI- CIFAR10: Samples and Reconstruction

(a) CIFAR10 samples.

(b) CIFAR10 reconstructions.

Figure: Samples and reconstructions on the CIFAR10 dataset. For the reconstructions, odd columns are original samples from the validation set and even columns are corresponding reconstructions.

ALI- CelebA: Samples and Reconstruction

(a) CelebA samples.

(b) CelebA reconstructions.

Figure: Samples and reconstructions on the CelebA dataset. For the reconstructions, odd columns are original samples from the validation set and even columns are corresponding reconstructions.

ALI- Latent space interpolation

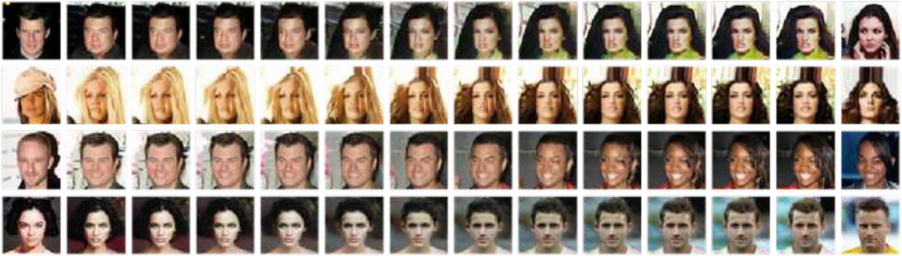


Figure: Latent space interpolations on the CelebA validation set. Left and right columns correspond to the original pairs $\mathbf{x}_1$ and $\mathbf{x}_2$, and the columns in between correspond to the decoding of latent representations interpolated linearly from $\mathbf{z}_1$ to $\mathbf{z}_2$. Unlike other adversarial approaches like DCGAN, ALI allows one to interpolate between actual data points.

ALI: Semi-Supervised Learning

Table: SVHN test set missclassification rate

Model	Misclassification rate
VAE (M1 + M2)	36.02
SWWAE with dropout	23.56
DCGAN + L2-SVM	22.18
SDGM	16.61
GAN (feature matching)	$\mathbf{8.11 \pm 1.3}$
ALI (ours, L2-SVM)	19.14 ± 0.50
ALI (ours, no feature matching)	$\mathbf{7.42 \pm 0.65}$

Table: CIFAR10 test set missclassification rate for semi-supervised learning using different numbers of trained labeled examples. For ALI, error bars correspond to 3 times the standard deviation.

Number of labeled examples	1000	2000	4000	8000
Model		Misclassification rate		
Ladder network			20.40	
CatGAN			19.58	
GAN (feature matching)	$\mathbf{21.83 \pm 2.01}$	$\mathbf{19.61 \pm 2.09}$	$\mathbf{18.63 \pm 2.32}$	$\mathbf{17.72 \pm 1.82}$
ALI (ours, no feature matching)	$\mathbf{19.98 \pm 0.89}$	$\mathbf{19.09 \pm 0.44}$	$\mathbf{17.99 \pm 1.62}$	$\mathbf{17.05 \pm 1.49}$

ALI- Conditional Generation

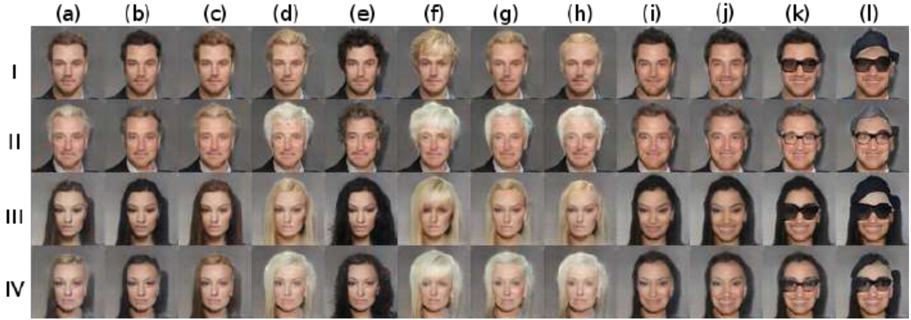


Figure: The attributes are male, attractive, young for row I; male, attractive, older for row II; female, attractive, young for row III; female, attractive, older for Row IV. Attributes are then varied uniformly over rows across all columns in the following sequence: (b) black hair; (c) brown hair; (d) blond hair; (e) black hair, wavy hair; (f) blond hair, bangs; (g) blond hair, receding hairline; (h) blond hair, balding; (i) black hair, smiling; (j) black hair, smiling, mouth slightly open; (k) black hair, smiling, mouth slightly open, eyeglasses; (l) black hair, smiling, mouth slightly open, eyeglasses, wearing hat.

HALI: Hierarchical Adversarially Learned Inference

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What is HALI?

- HALI is a hierarchical Generative model with a Markovian structure.
- It jointly trains generative and inference model.

HALI provides ...

- semantically meaningful reconstructions with different levels of fidelity.
- progressively more abstract latent representations.
- useful representation for downstream tasks.

HALI: Hierarchical Adversarially Learned Inference

The encoder and decoder distributions:

$$\begin{tikzcd} \boldsymbol{x} \arrow[r, bend left, "T_{\boldsymbol{z}_1|\boldsymbol{x}}"] & \boldsymbol{z}_1 \arrow[l, bend left, "T_{\boldsymbol{x}|\boldsymbol{z}_1}"] \arrow[r, bend left, "T_{\boldsymbol{z}_2|\boldsymbol{z}_1}"] & \boldsymbol{z}_2 \arrow[l, bend left, "T_{\boldsymbol{z}_1|\boldsymbol{z}_2}"] \arrow[r, bend left, "T_{\boldsymbol{z}_3|\boldsymbol{z}_2}"] & \cdots \arrow[l, bend left, "T_{\boldsymbol{z}_2|\boldsymbol{z}_3}"] \arrow[r, bend left, "T_{\boldsymbol{z}_L|\boldsymbol{z}_{L-1}}"] & \boldsymbol{z}_L \arrow[l, bend left, "T_{\boldsymbol{z}_{L-1}|\boldsymbol{z}_L}"] \end{tikzcd}$$

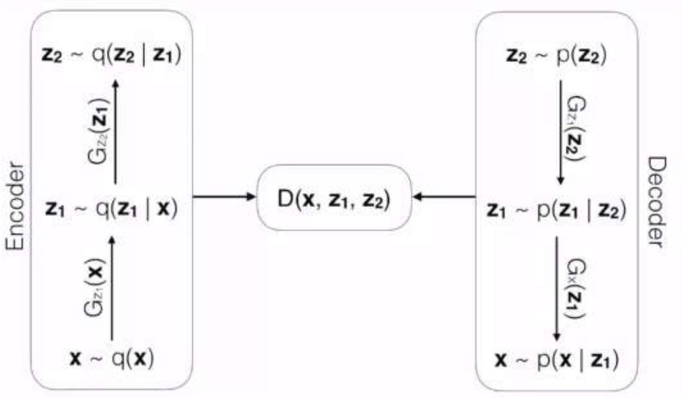
Joint distribution of the encoder:

$$q(\boldsymbol{x}, \ldots, \boldsymbol{z}_L) = \prod_{l=2}^{L} q(\boldsymbol{z}_l \mid \boldsymbol{z}_{l-1})\, q(\boldsymbol{z}_1 \mid \boldsymbol{x})\, q(\boldsymbol{x}), \tag{3}$$

Joint distribution of the decoder:

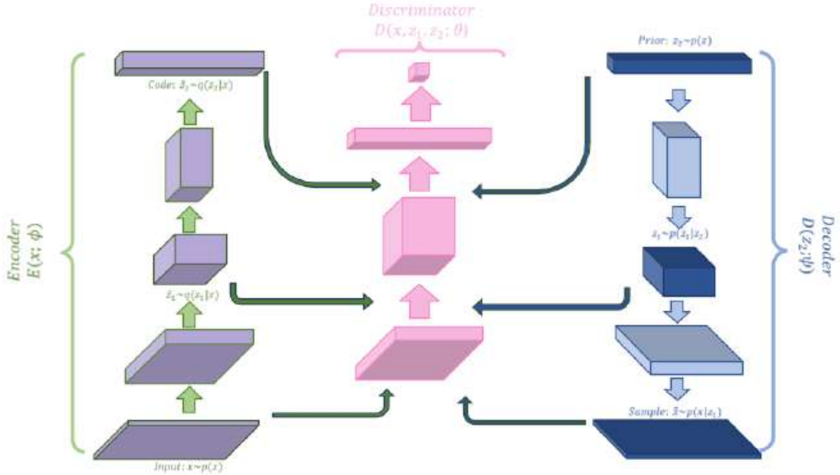
$$p(\boldsymbol{x}, \ldots, \boldsymbol{z}_L) = p(\boldsymbol{x} \mid \boldsymbol{z}_1) \prod_{l=2}^{L} p(\boldsymbol{z}_{l-1} \mid \boldsymbol{z}_l)\, p(\boldsymbol{z}_L). \tag{4}$$

HALI: Hierarchical Adversarially Learned Inference



$$\mathcal{L}^l(\boldsymbol{x}) = \mathbb{E}_{\boldsymbol{z}_l \sim T_{\boldsymbol{z}_l \mid \boldsymbol{x}}}[-\log(p(\boldsymbol{x} \mid \boldsymbol{z}_l))]$$

HALI: Hierarchical Adversarially Learned Inference



HALI *vs* ALI

- Both relies on joint training of the generative and inference models.
- HALI leverages the hierarchical architecture to:
  - Offer reconstruction of the same datasample with increasing levels of fidelity.
  - Abstraction of learned representation increases as we go up the hierarchy.
  - Flexible inference model that provides useful representations for downstream tasks.

Results

Qualitative Results - SVHN - Reconstruction

(a) SVHN from $\boldsymbol{z}_1$

(b) SVHN from $\boldsymbol{z}_2$

Figure: Reconstructions for SVHN from $\boldsymbol{z}_1$ and reconstructions from $\boldsymbol{z}_2$. Odd columns corresponds to examples from the validation set while even columns are the model's reconstructions

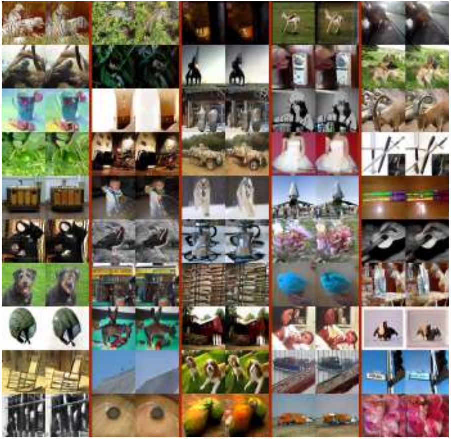
Qualitative Results - CIFAR10 - Reconstruction

(a) CIFAR10 from $\boldsymbol{z}_1$

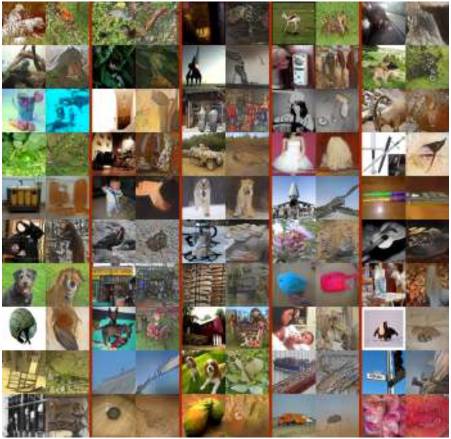
(b) CIFAR10 from $\boldsymbol{z}_2$

Figure: Reconstructions for CIFAR10 from $\boldsymbol{z}_1$ and reconstructions from $\boldsymbol{z}_2$. Odd columns corresponds to examples from the validation set while even columns are the model's reconstructions

Qualitative Results - Imagenet128 - Reconstruction



(a) ImageNet128 from $\boldsymbol{z}_1$



(b) ImageNet128 from $\boldsymbol{z}_2$

Figure: ImageNet128 reconstructions from $\boldsymbol{z}_1$ and $\boldsymbol{z}_2$. Odd columns corresponds to examples from the validation set while even columns are the model's reconstructions

Qualitative Results - Imagenet128 - Samples

(a) ImageNet128

Figure: Samples from 128 × 128 ImageNet128 dataset

Qualitative Results - CelebA - Samples

(a) CelebA

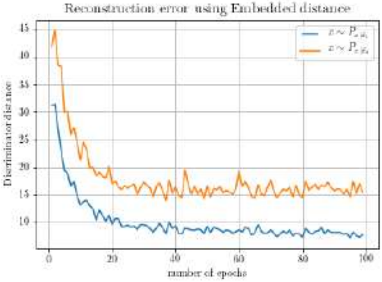
Figure: Samples from 128 $\times$ 128 CelebA dataset

Quality of the reconstruction: HALI *vs* ALI

	Mean	Std	# Best
Data	77.13	12.48	
VAE	81.28	10.50	5
ALI	84.60	5.73	3
HALI $\boldsymbol{z}_1$	91.35	5.62	27
HALI $\boldsymbol{z}_2$	86.28	5.64	3

Table: Summary of CelebA attributes classification from reconstructions for VAE, ALI and the two levels of HALI.

Perceptual Reconstructions[5]



(a) (b)

Figure: Comparison of average reconstruction error over the validation set for each level of reconstructions using the Euclidean (a) and discriminator embedded (b) distances.

[5] Autoencoding beyond pixels using a learned similarity metric. A Larsen, S Sønderby, Hugo Larochelle, and Ole Winther. arXiv preprint arXiv:1512.09300, 2015

Figure: Inpainting on center cropped images on CelebA

	MNIST (# errors)
VAE (M1+M2) [kingma et al, 2014]	233 ± 14
VAT [Miyato et al, 2017]	136
CatGAN	191 ± 10
Adversarial Autoencoder [makhzani et al, 2015]	190 ± 10
PixelGAN [makhzani et al, 2017]	108 ± 15
ADGM [Maaloe et al, 2016]	96 ± 2
Feature-Matching GAN [Salimans et al, 2016]	93 ± 6.5
Triple GAN [li et al, 2017]	91 ± 58
GSSLTRABG [dai et al, 2017]	79.5 ± 9.8
HALI (ours)	**73**

Table: Comparison on semi-supervised learning with state-of-the-art methods on MNIST with 100 labels instance per class. Only methods without data augmentation are included.

Figure: Inpainting on center cropped images on SVHN

Figure: Inpainting on center cropped images on MS-COCO dataset

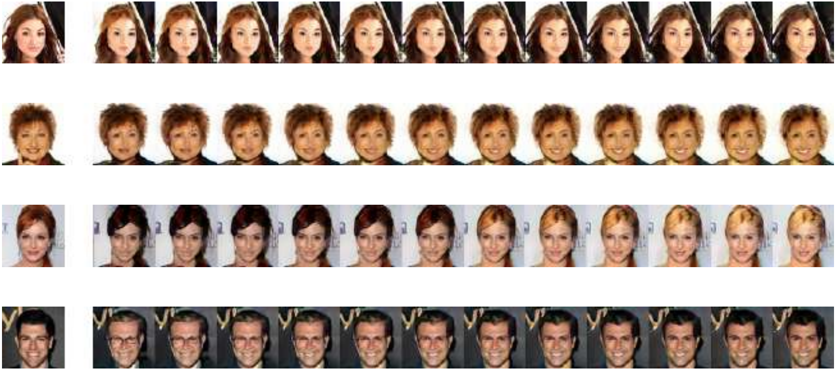


Figure: Real CelebA faces (right) and their corresponding innovation tensor (IT) updates (left). For instance, the third row in the figure features Christina Hendricks followed by hair-color IT updates. Similarly, the first two rows depicts usage of smile-IT and the 4th row glasses-plus-hair-color-IT.

Questions/Answers?!

Thanks!