GeneGAN

Learning Object Transfiguration and Attribute Subspace from Unpaired Data

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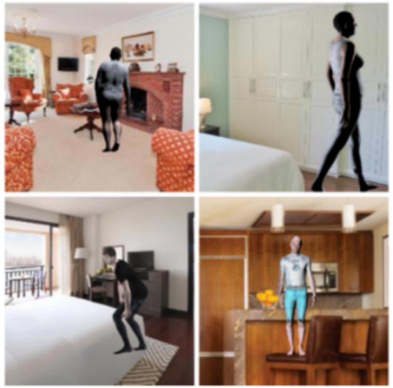
Conditional Image Generation

- Applications: Image Editing, Training Data Synthesis
- Photo-realistic modeling and rendering are difficult.

Image ⇒ Model ⇒ Transform ⇒ Render ⇒ Generated Image

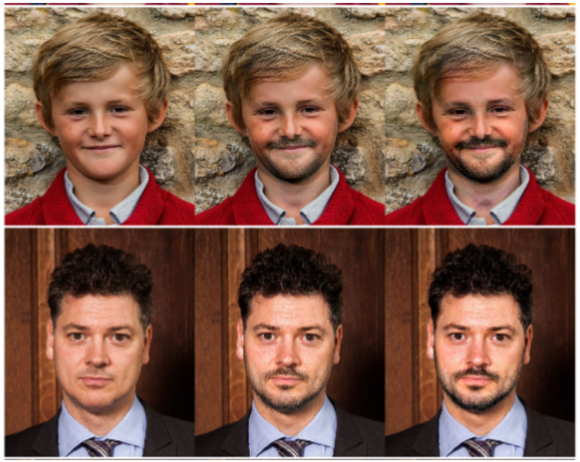
3DMM-family methods
http://cn.arxiv.org/pdf/1612.04904.pdf



SURREAL dataset (CVPR'17)

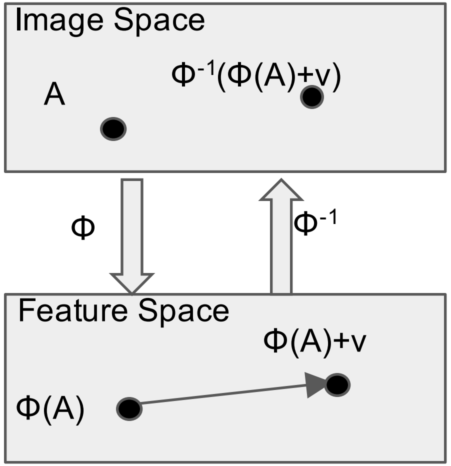
Feature Space Transformation

Image → Project → Transform → Project back → Generated Image



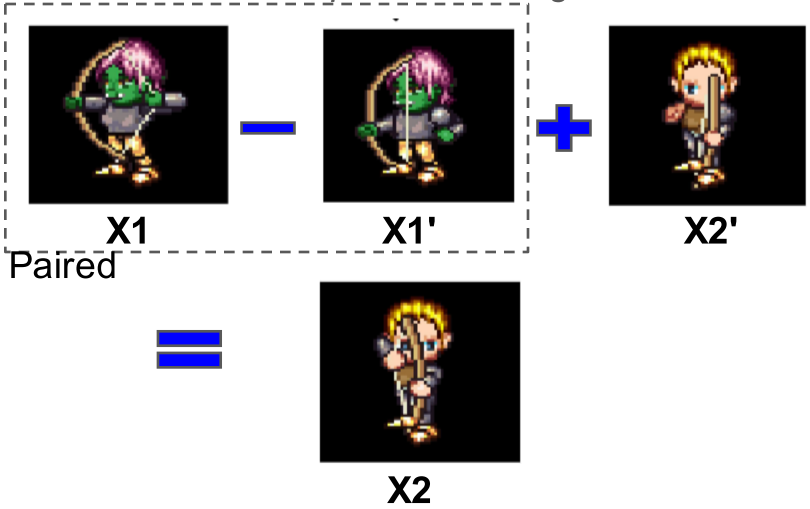
$\Phi^{-1}(\Phi(A))$ $\Phi^{-1}(\Phi(A)+½\,v)$ $\Phi^{-1}(\Phi(A)+$
$v)$ Deep Feature Interpolation (2016)

*Transformation vector **v** as difference between feature cluster centers. Diversity limited by the number of clusters.*

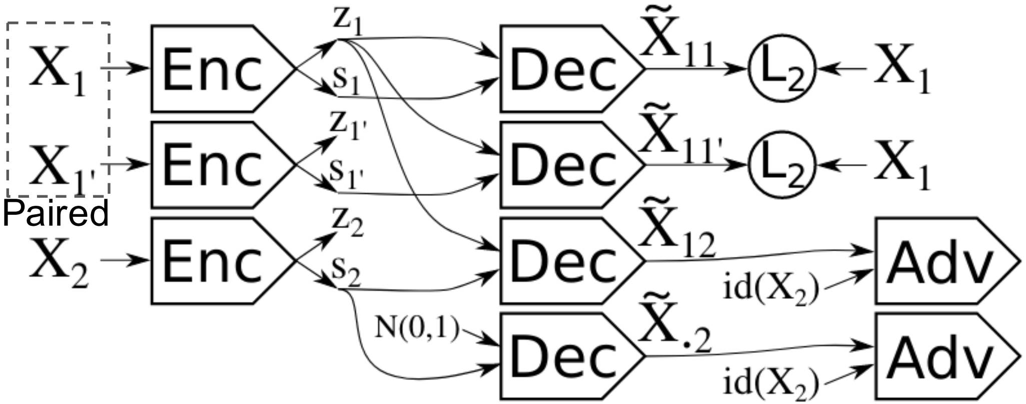


Generation by Exemplars with Paired Training Data

- Using a pair of image for specifying the transformation
  - Increase diversity.
  - *But paired training data are **hard** to collect.*



Deep Visual Analogy-Making, NIPS'15



Disentangling Factors of Variation, NIPS'16

X1 and X1' are required to have the same label, i.e., s1 == s1'.

Feature Space Interpolation Methods

	Generation by Exemplar	Unpaired Training data	Exploits Cyclic Loss
Deep Feature Interpolation	✗	✓	✗
InfoGAN	✗	✓	✗
Visual Analogy-Making	✓	✗	✗
Disentangling Factors of Variation	✓	✗	✓
CycleGAN	✗	✓	✓
GeneGAN	✓	✓	✓

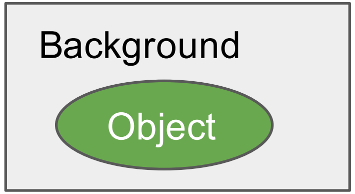
GeneGAN Training Data

- A positive set and a negative set
  - need not be paired

	Glasses	Hair	Lighting	Smiling
Positive	Eyeglass/sun glasses	Bangs	Side/Up/Down	Smiling
Negative	No glasses	Bald/Receding Hairline	Frontal lighting	Not smiling

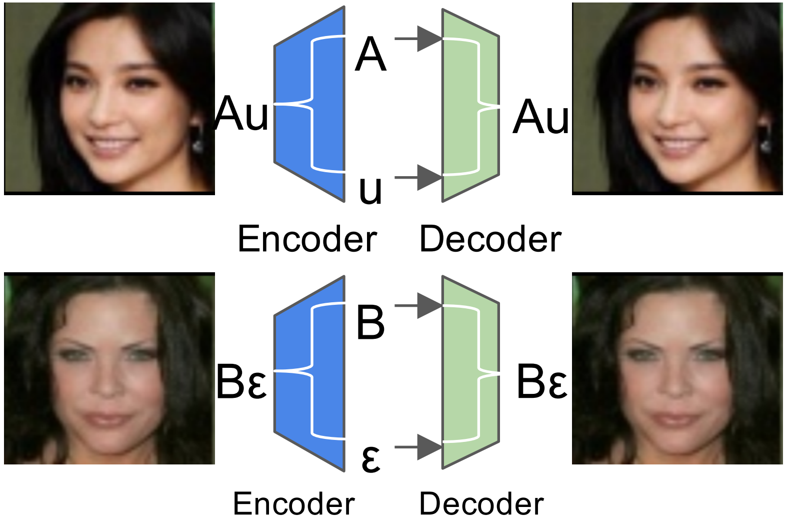
GeneGAN components: Encoder and Decoder

- Encoder: disentangle the object (smiling) from the background (face). Object can be abstract.
- Decoder: inverse of Encoder

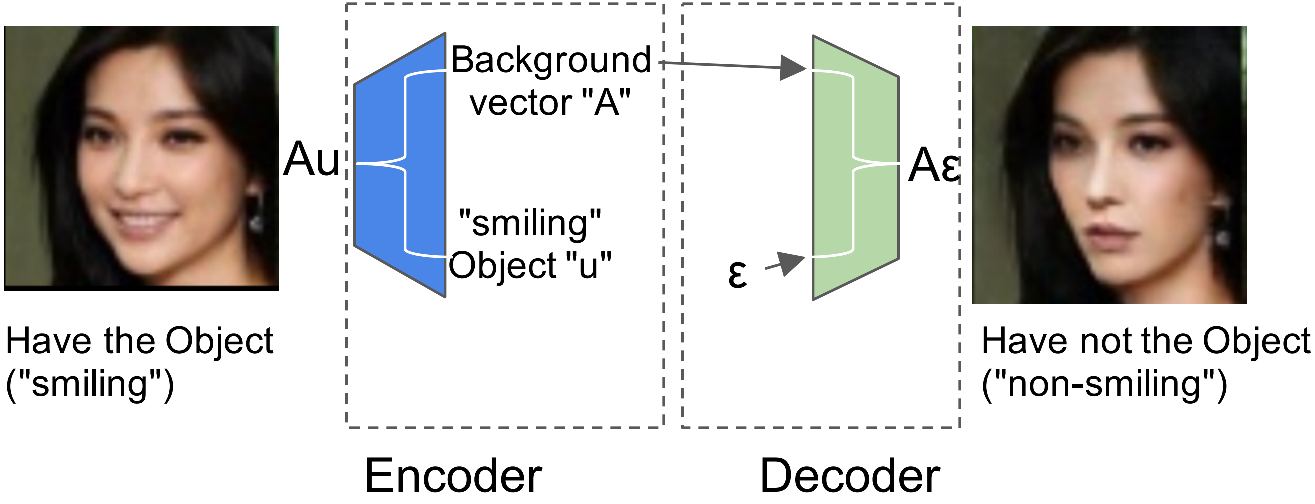


Have the Object (positive)

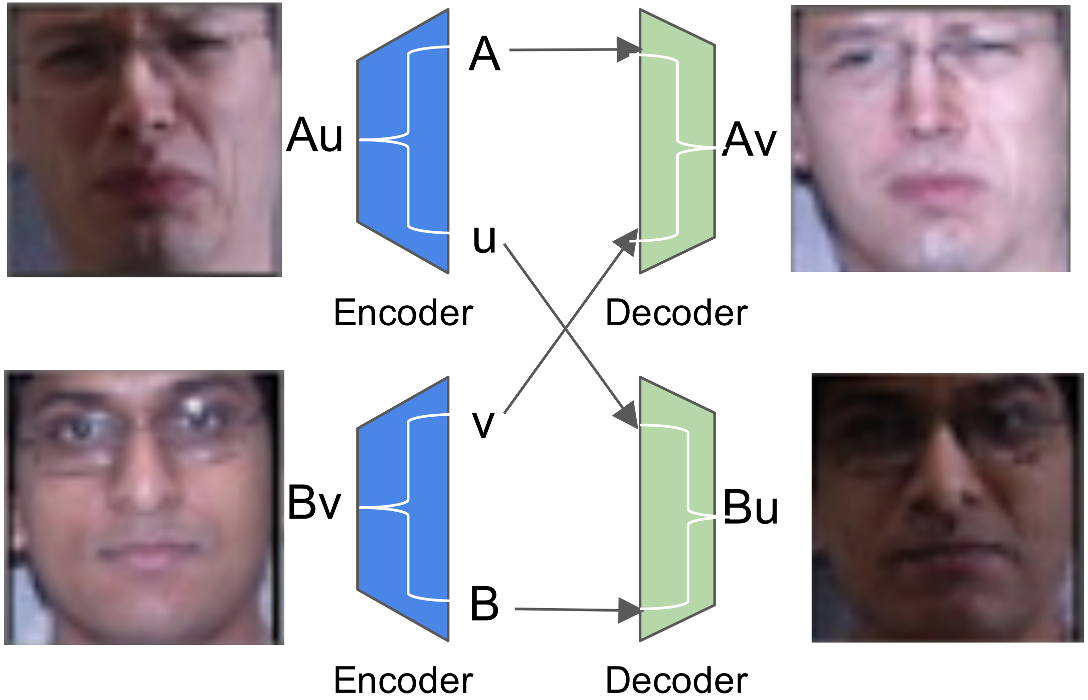
Have not the Object (negative)



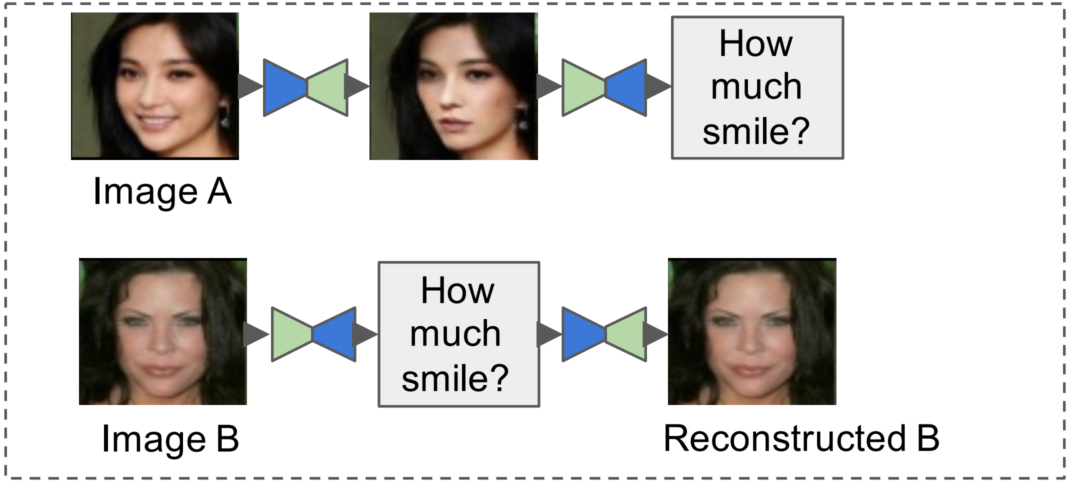
GeneGAN Usage: Object Removal



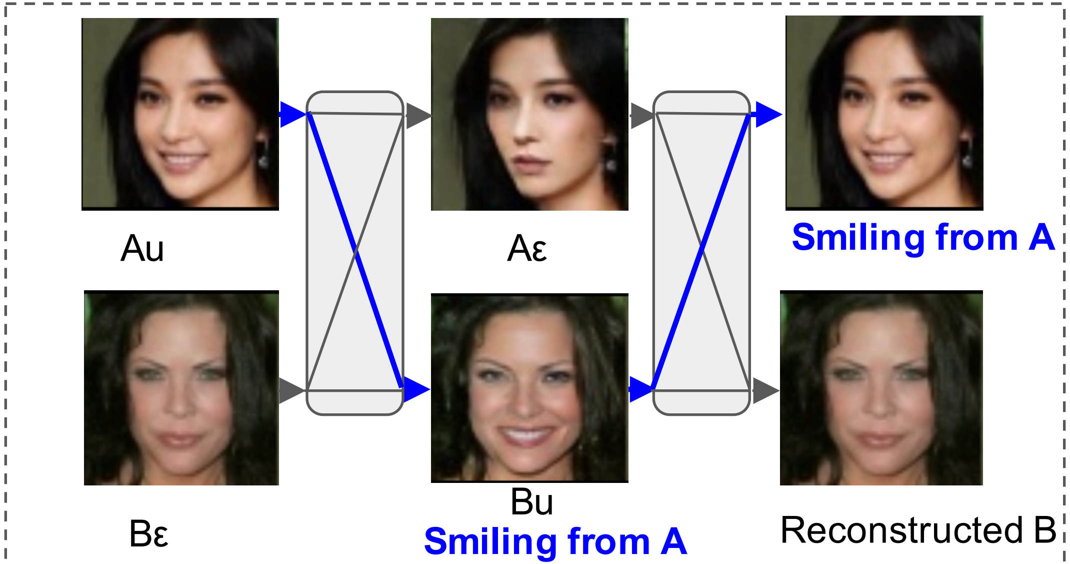
GeneGAN Usage: Swapping Objects



Underdetermined
CycleGAN pattern

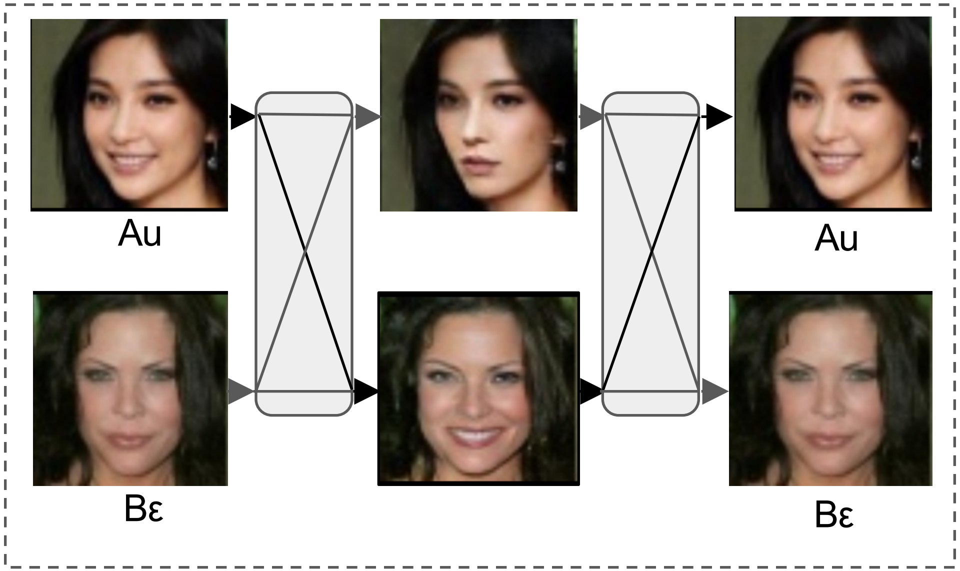


Information Preserving
GeneGAN pattern

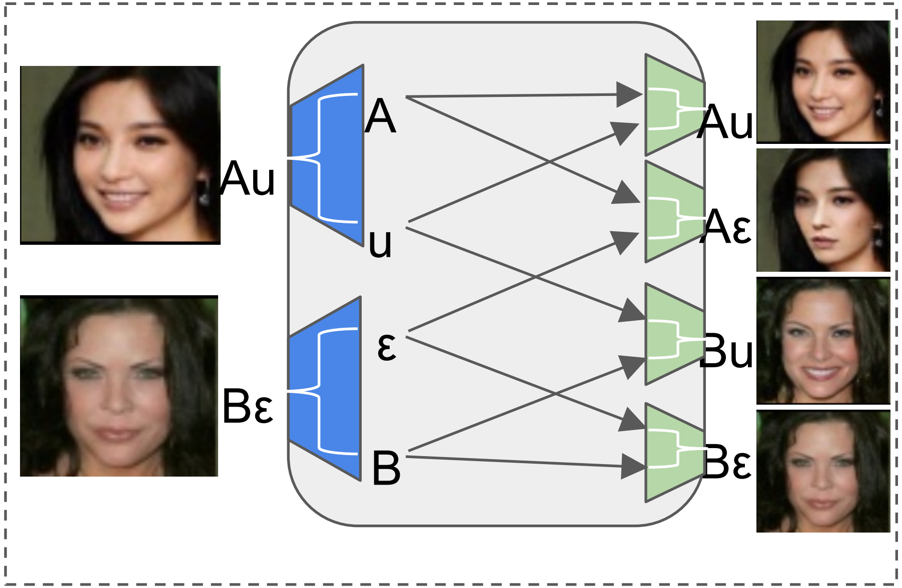


Shorten the Cycle to help Training

- Lift the grandchildren to be children

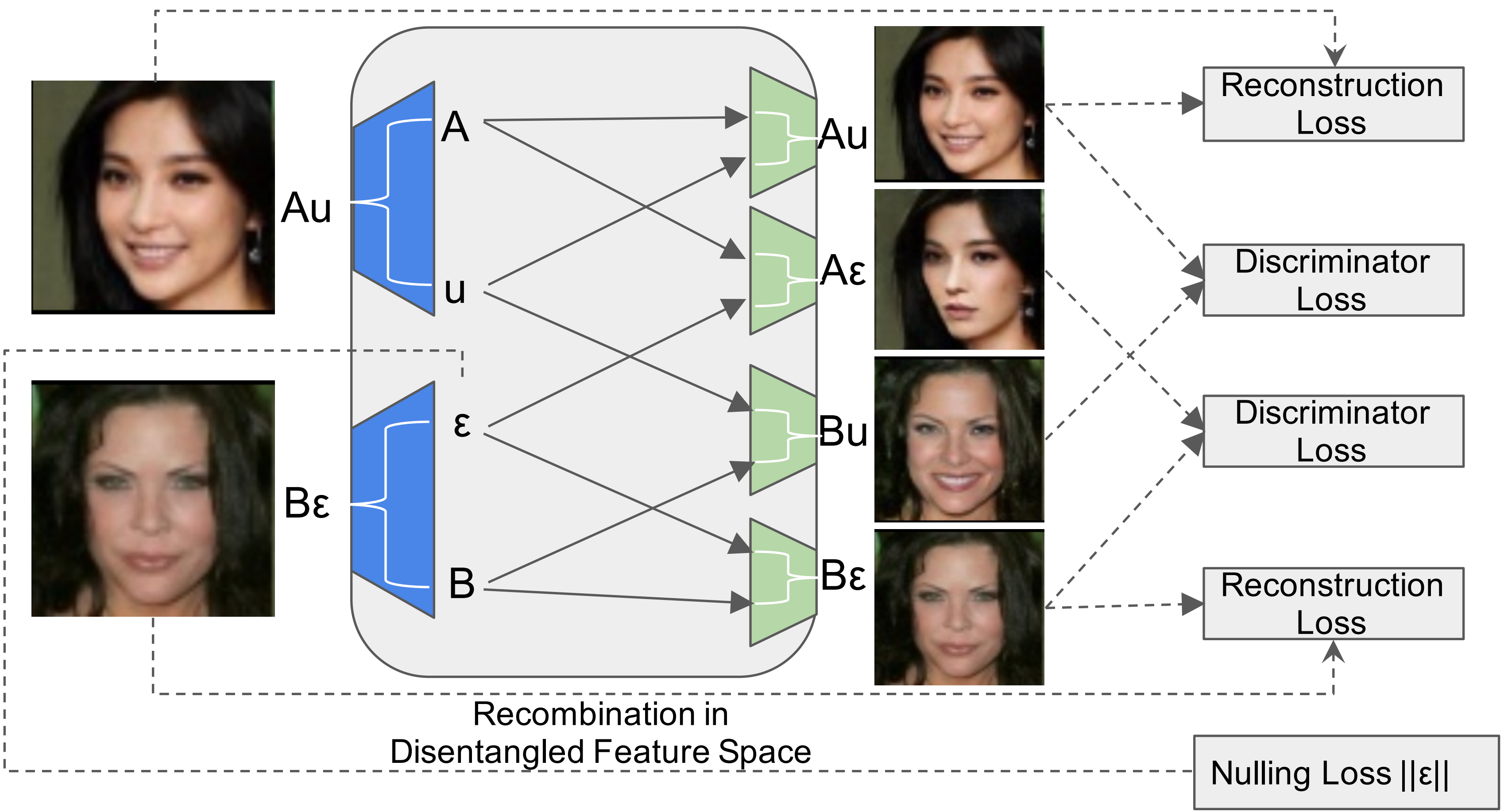


Two generations



Only one "generation", less distortions.

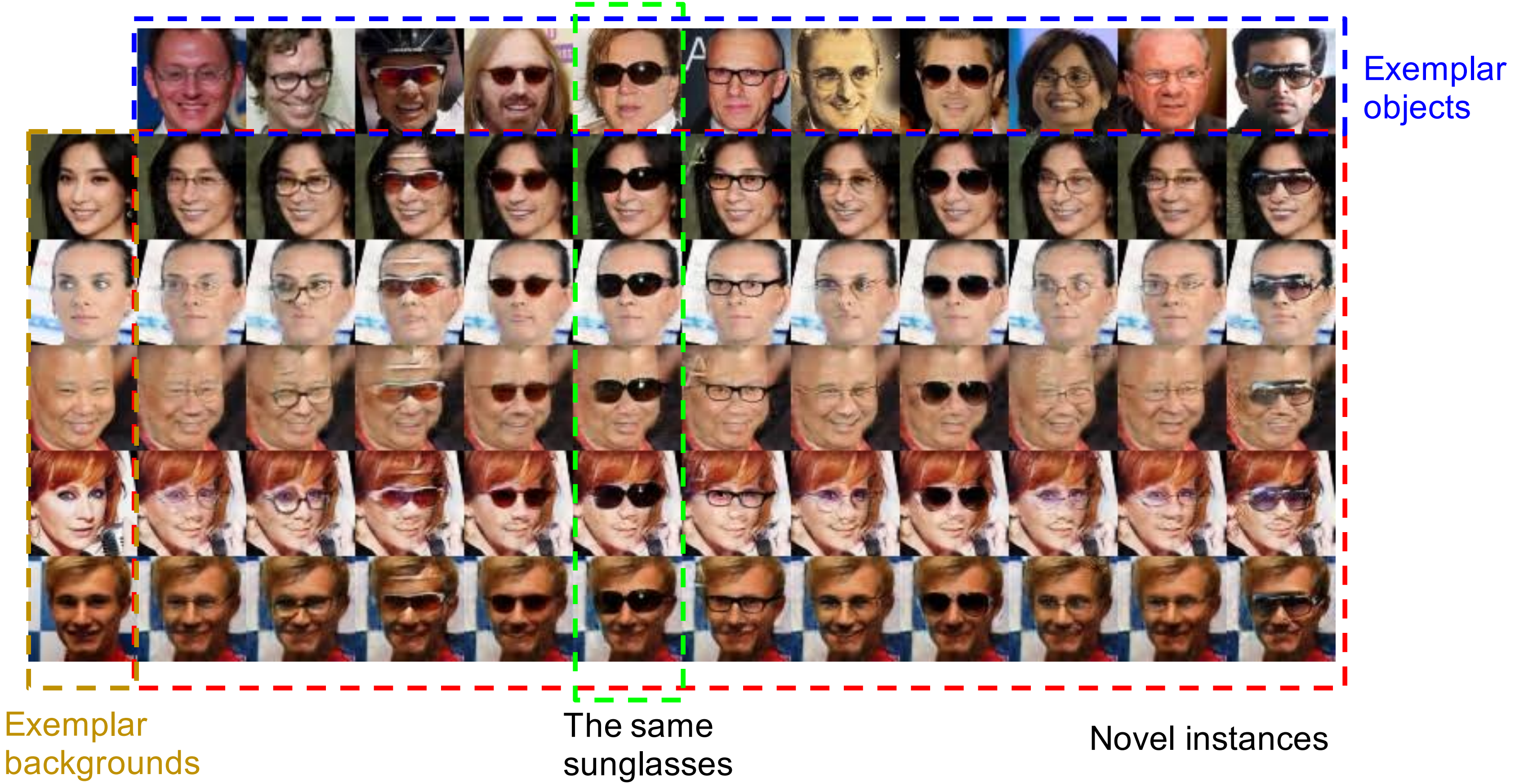
GeneGAN Training Diagram



Mechanism

- Constraints
  - Discriminator loss used in Adversarial Training
    - The background output of encoder will not contain smiling information, as "Bε" is not smiling
    - "u" contains the smiling information. As "Bu" is smiling.
  - Nulling loss
    - the object output of encoder will not contain background information, as "ε" can replace it without problem.
  - Reconstruction loss
    - Decoder and Encoder are inverse to each other
    - "A" contains background information, as Decoder can recreate "Au" from "A" and "u"

Experiments: Diversity from Exemplars



Swapping Attributes: Diversity of Smiles

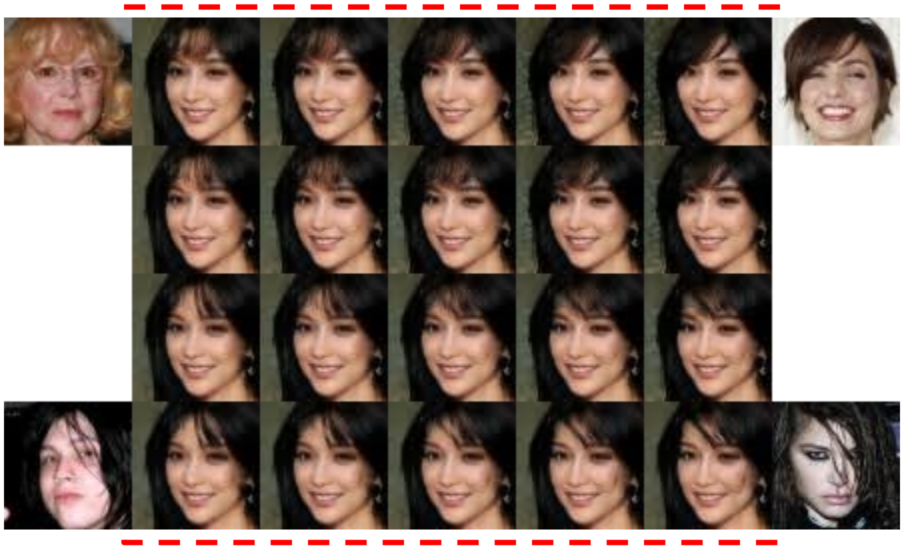
Can tell a smile by the mouth, and sometimes by eyes.

Object Subspace

- Multidimensional representation of hair

Interpolation in Object Subspace

Check the directions of the hairs.



Bi-linearly interpolated

ε instance

Conclusion & Future Work

- Disentangle the factors in feature space
  - Feature space = object space + background space
- Only require unpaired training data
  - Two unpaired image: positive and negative
- Usage cases
  - For single input, can output disentangled object code and background code.
  - For two inputs that both contain objects, can swap the objects in them. The objects can be null.
  - Can interpolate the objects in feature space.
- Futre work
  - Investigate whether more complex crossbreeding patterns between more parents would allow further improvements

References

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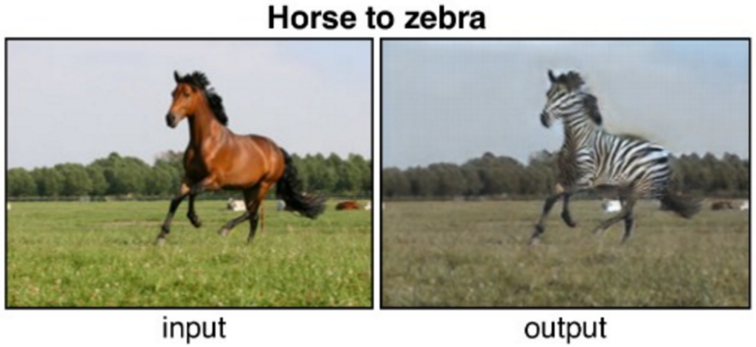
More in the paper.

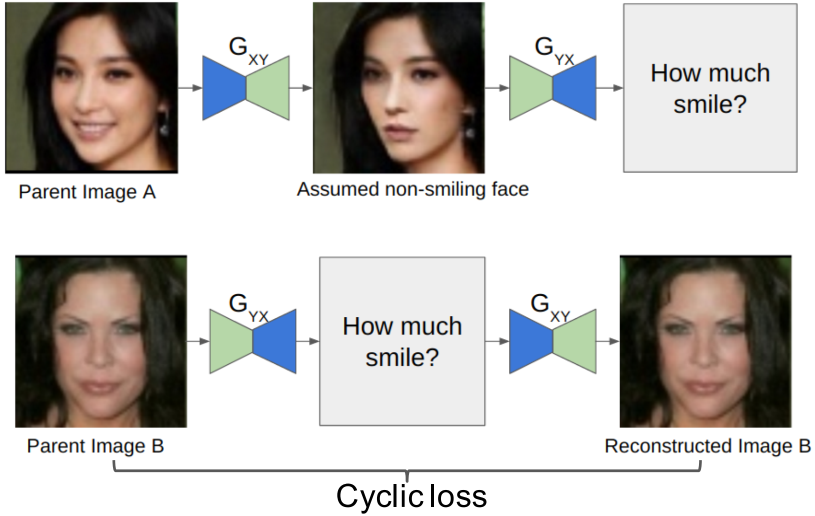
Backup after this slide

Github: https://github.com/Prinsphield/GeneGAN

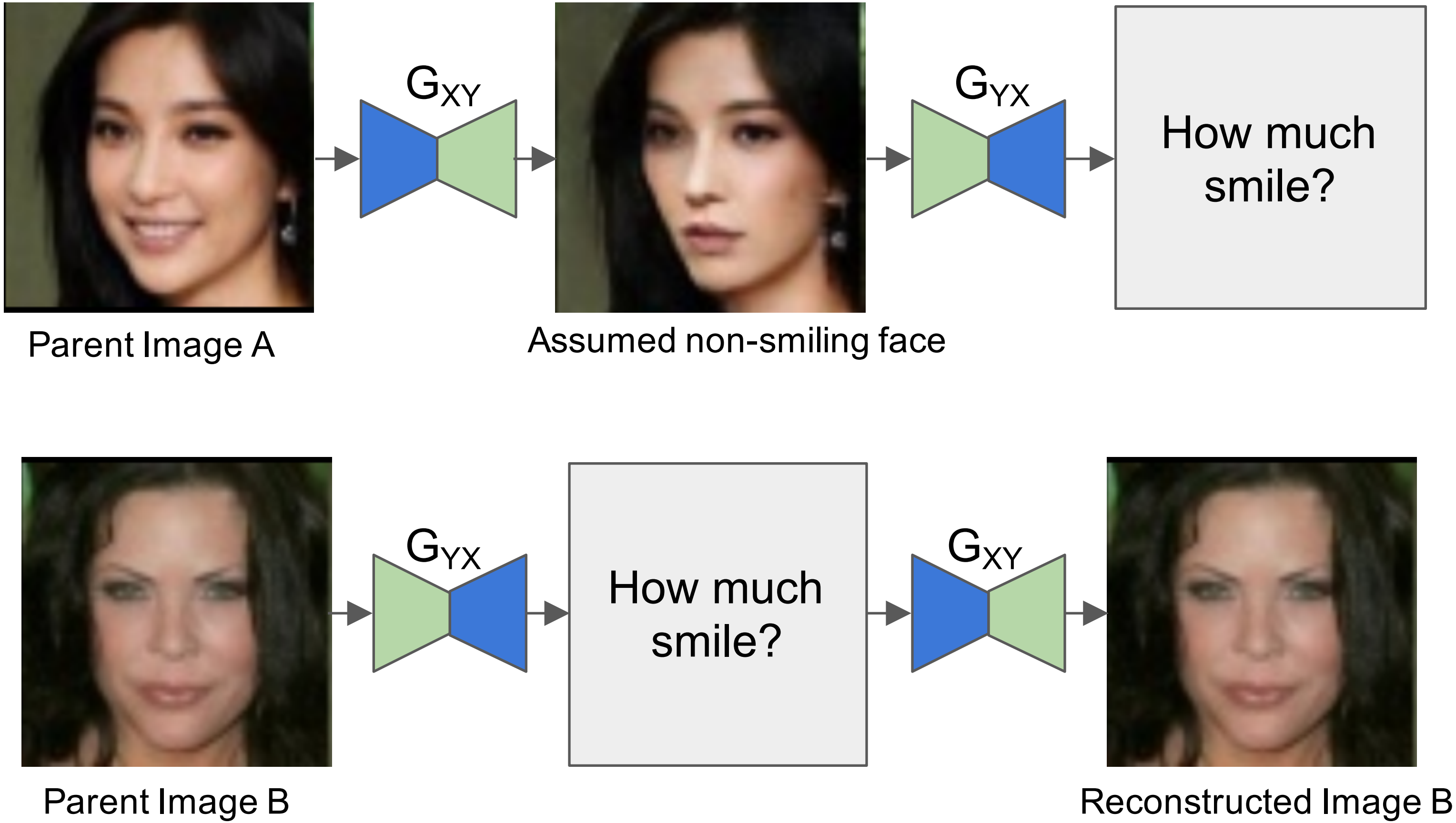
CycleGAN/DiscoGAN and Object Transfiguration

- Pros
  - Learn from Unpaired Data
  - Exploits Cyclic loss to stabilize training
- Cons
  - Backgrounds change when transforming objects
  - Under-determination problem
    - non-smiling is well defined. But smiling's have different levels and styles.

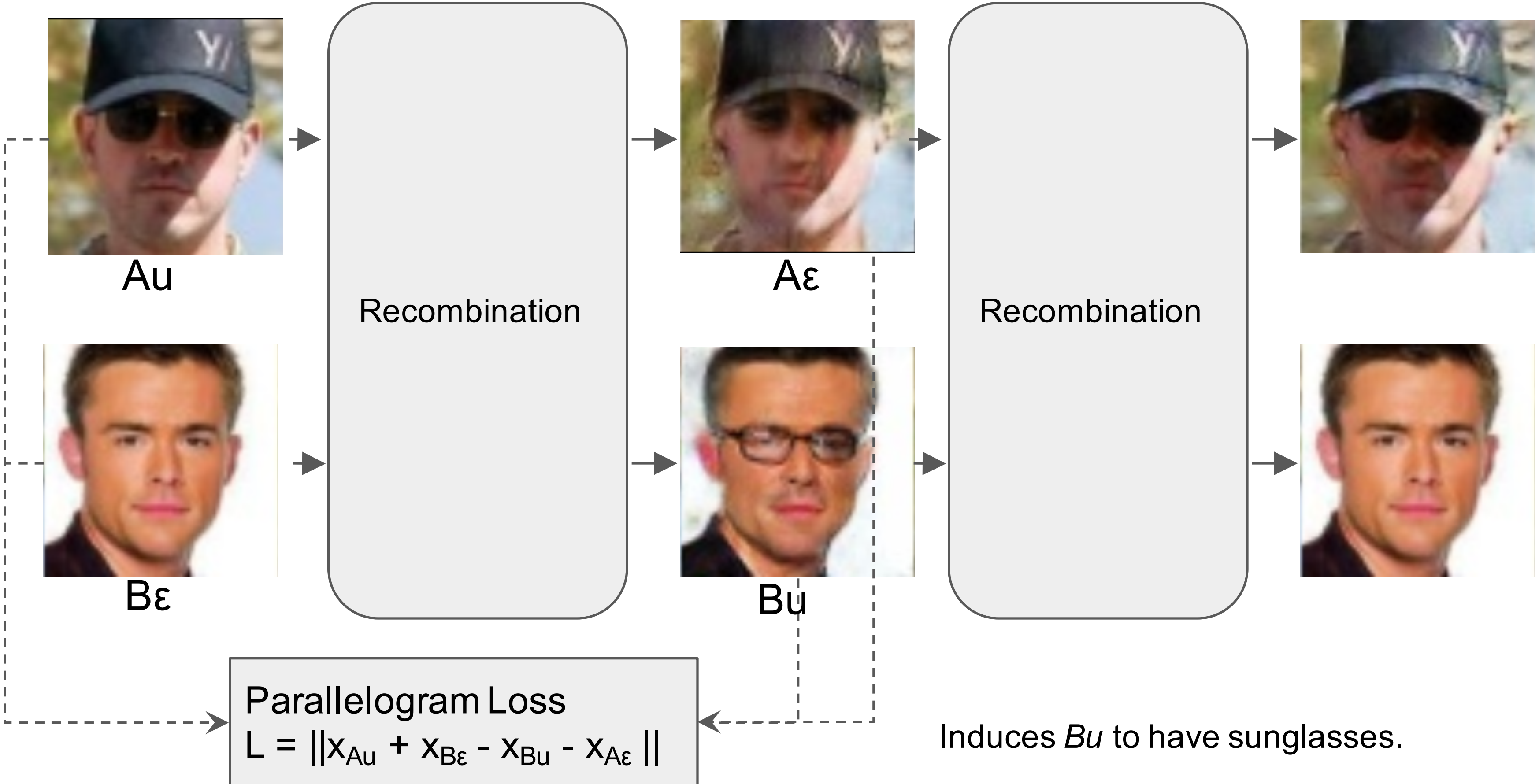




Underdetermination Problem



Parallelogram loss



Induces *Bu* to have sunglasses.