Addressing GAN limitations: resolution, lack of novelty and control on generations

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Joint works with O. Sbai, M. Aubry, A, Bordes, M. Elhoseiny, M. Riviere, Y. LeCun, M. Mathieu, P. Luc, N. Neverova, J. Verbeek.

Why do we care about generative models

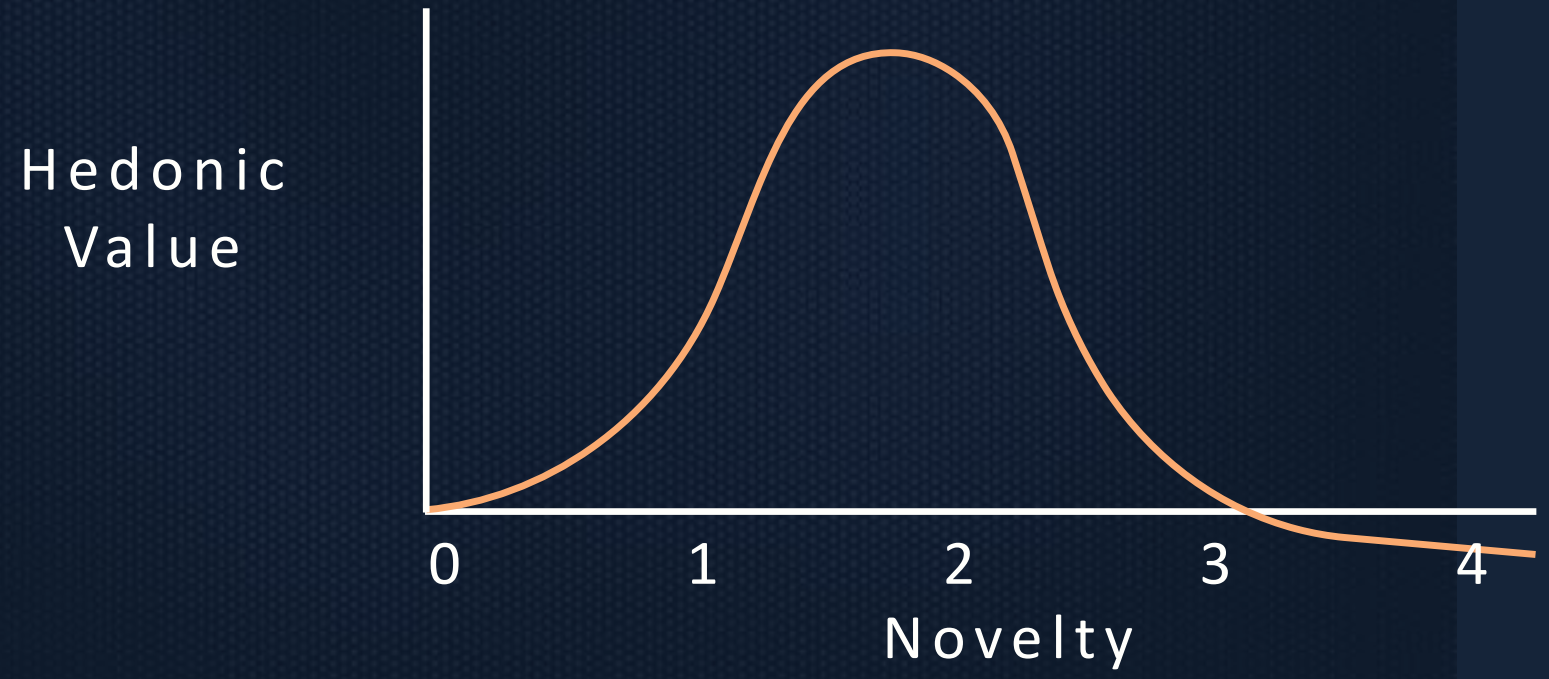
- Scene Understanding can be assessed by checking the ability to generate plausible new scenes.
- Generative models are interesting if they can be used to go beyond training data: data of higher resolution, data augmentation to help train better classifiers, use the learned representations in other tasks, or make prediction about uncertain events...

Outline

- 1/ Design inspiration from adversarial generative networks
- 2/ High resolution, decoupled generation
- 3/ Vector image generation by learning parametric layer decomposition
- 4/ Future frame prediction

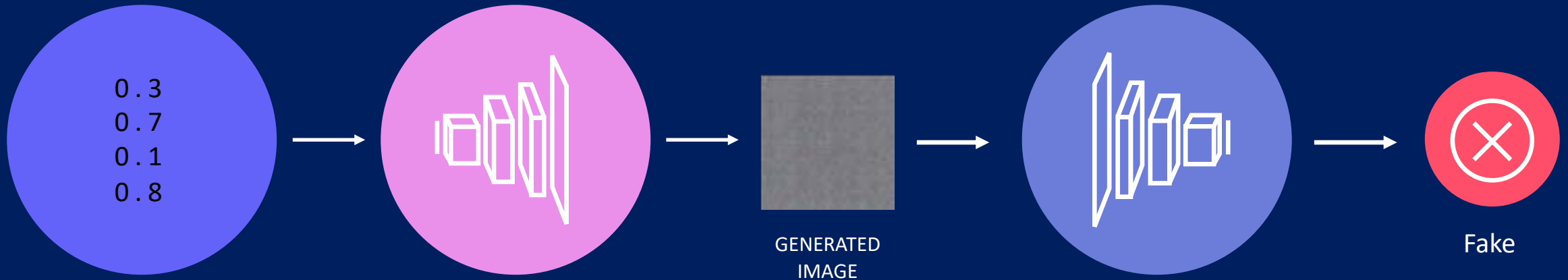
Design inspiration from generative networks

Sbai, Elhoseiny, Bordes, LeCun, Couprie, ECCV workshop 17



Generative Adversarial Networks

Goodfellow et al, 2014



Generative Adversarial Networks

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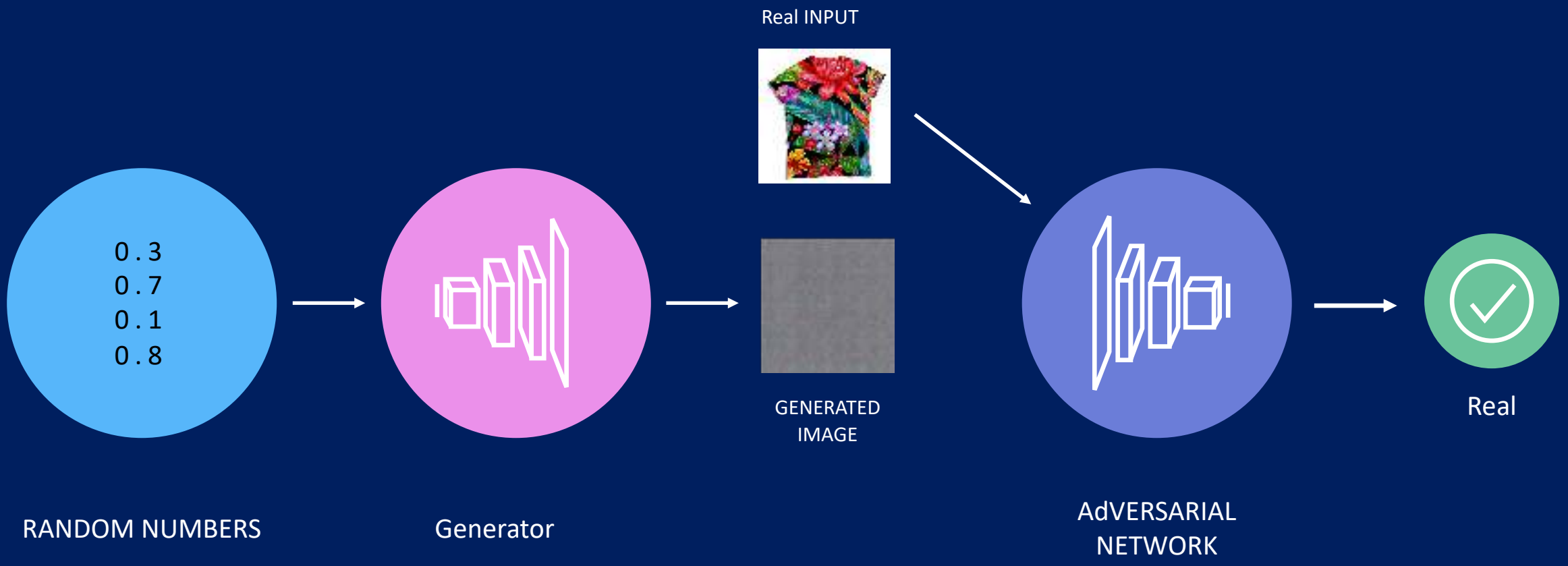
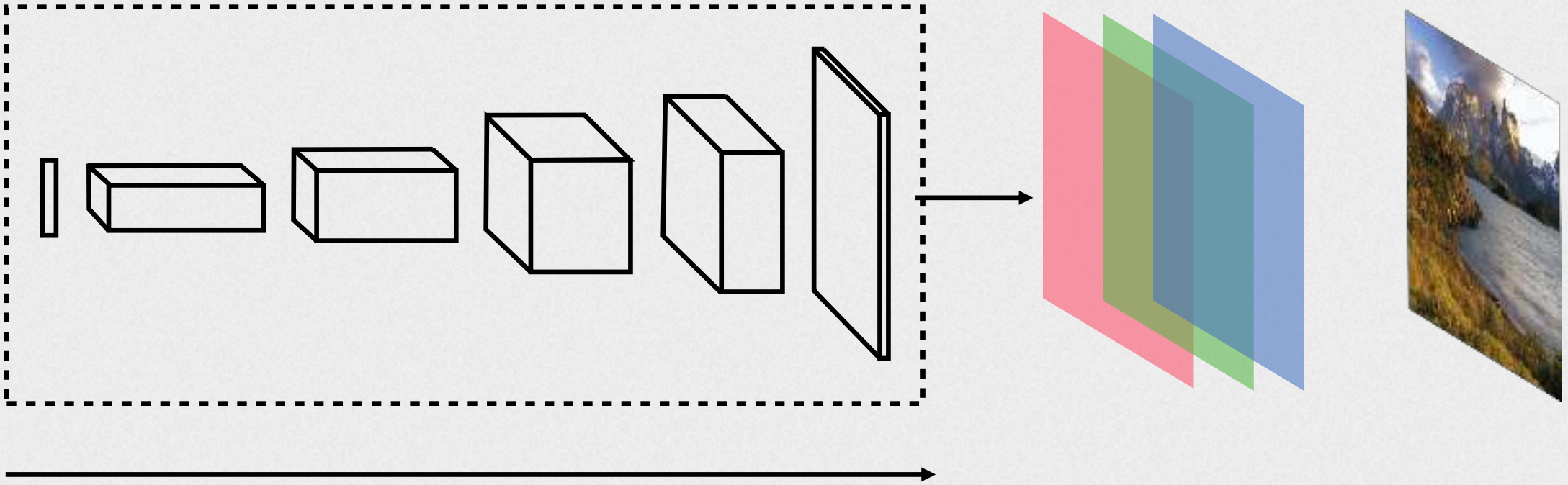
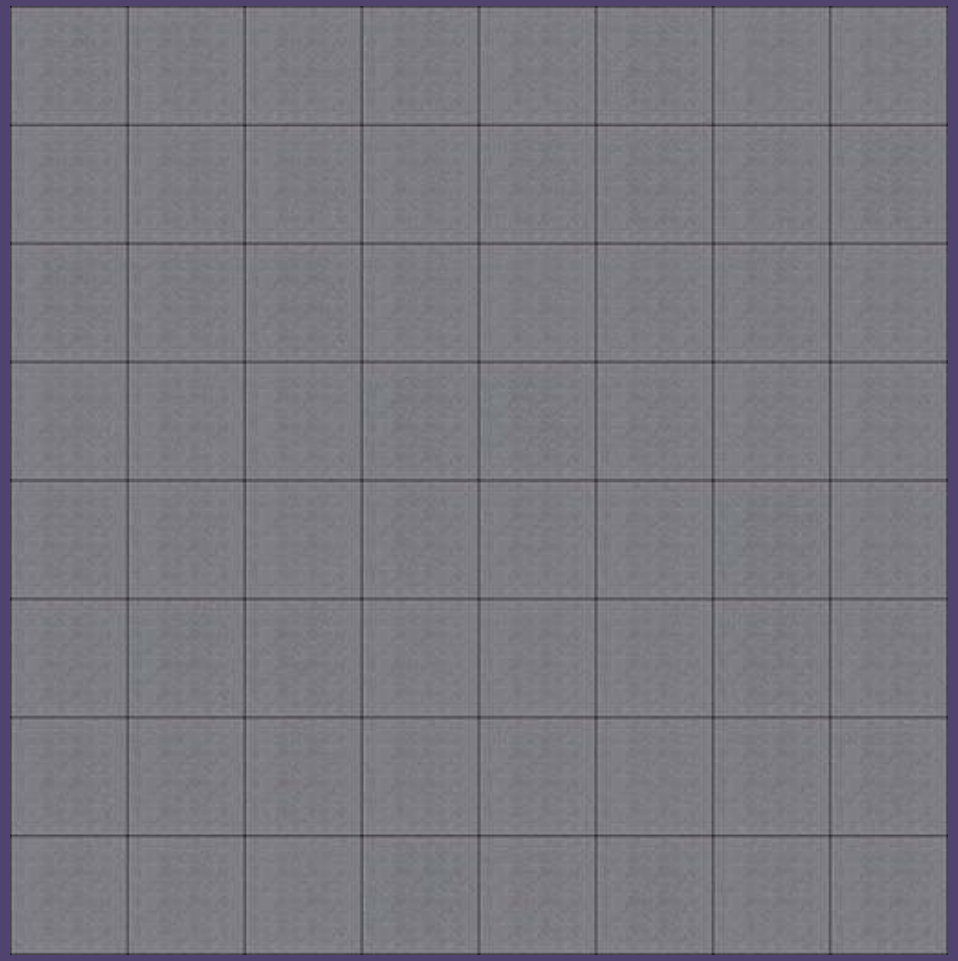


Deep convolutional GANs

RADFORD ET AL : ICLR 2015



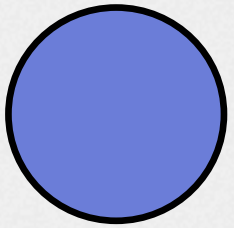


Training with pictures of about 2000 Clothing items

Texture and shape labels

Floral

Tiled

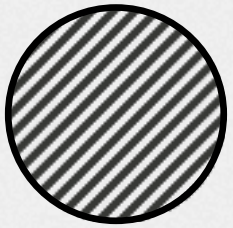


Uniform

Dotted

Animal Print

Graphical



Striped

Skirt

Pullover

T-Shirt

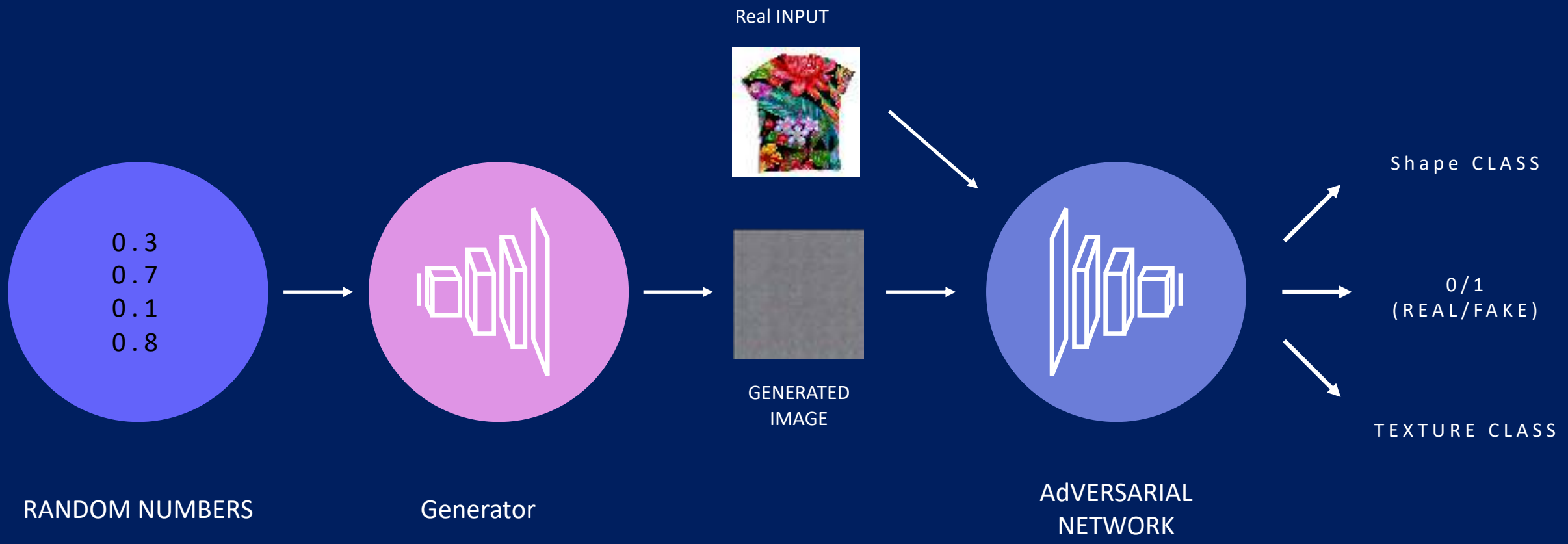
Coat

Top

Jacket

Dress

Class conditioned GAN



GAN Optimization objectives

- **Generator's loss**

$$\min_{\theta_G} \mathcal{L}_{G\ \text{real/fake}} = \min_{\theta_G} \sum_{z_i \in \mathbb{R}^n} \log(1 - D(G(z_i)))$$

- **Discriminator's loss**

$$\min_{\theta_D} \mathcal{L}_{D\ \text{real/fake}} = \min_{\theta_D} \sum_{x_i \in \mathcal{D} z_i \in \mathbb{R}^n} -\log D(x_i) - \log(1 - D(G(z_i)))$$

- **Auxiliary classifier discriminator:**

$$\mathcal{L}_D = \lambda_{D_r} \mathcal{L}_{D\ \text{real/fake}} + \lambda_{D_b} \mathcal{L}_{D\text{classif}}$$

- **Additional loss for the generator:**

$$\mathcal{L}_G = \lambda_{G_r} \mathcal{L}_{G\ \text{real/fake}} + \lambda_{G_c} \mathcal{L}_{G\ \text{creativity}}$$

Without conditioning

With class conditioning

Introduction of a Style Deviation criterion

Dotted

Floral

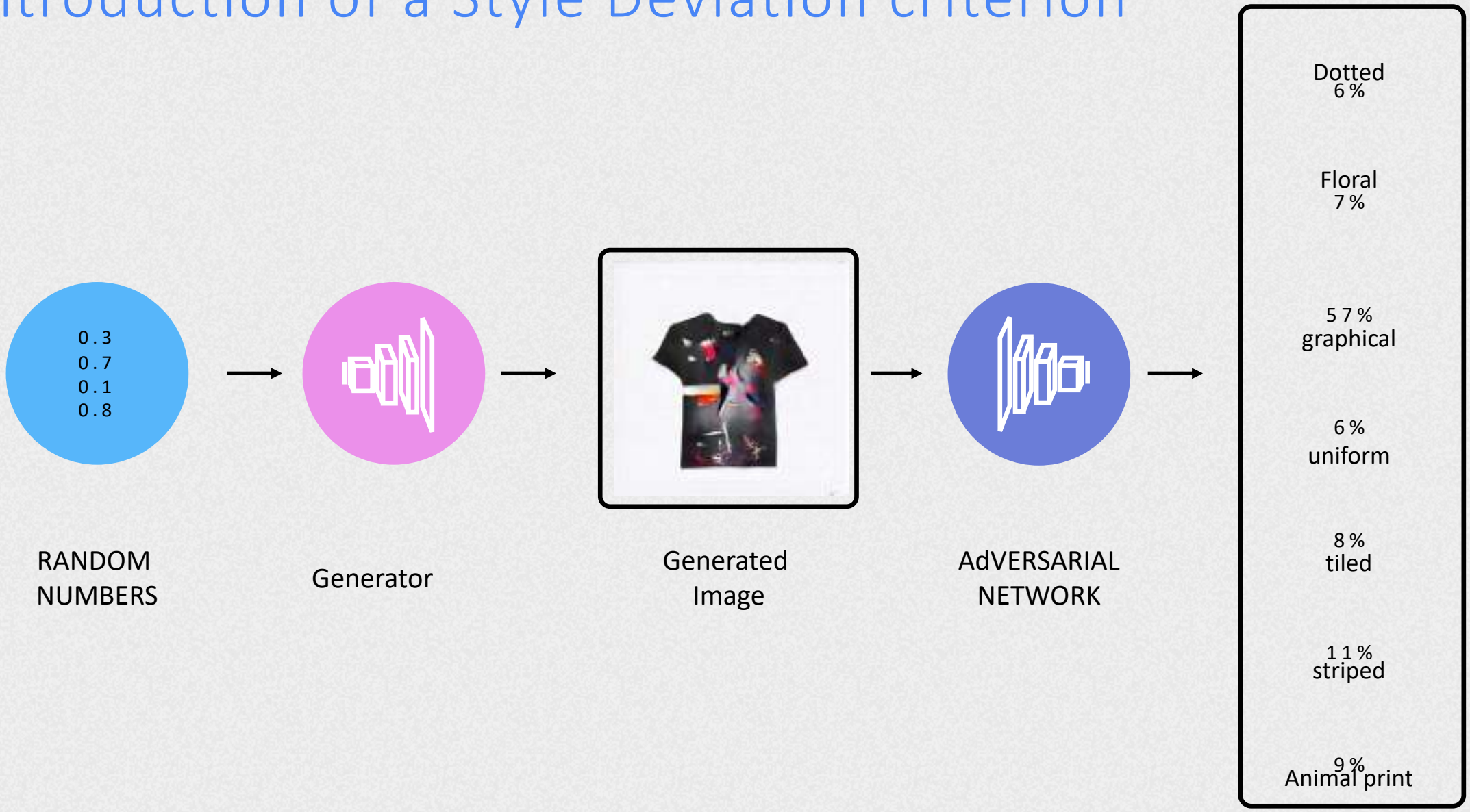
graphical

tiled

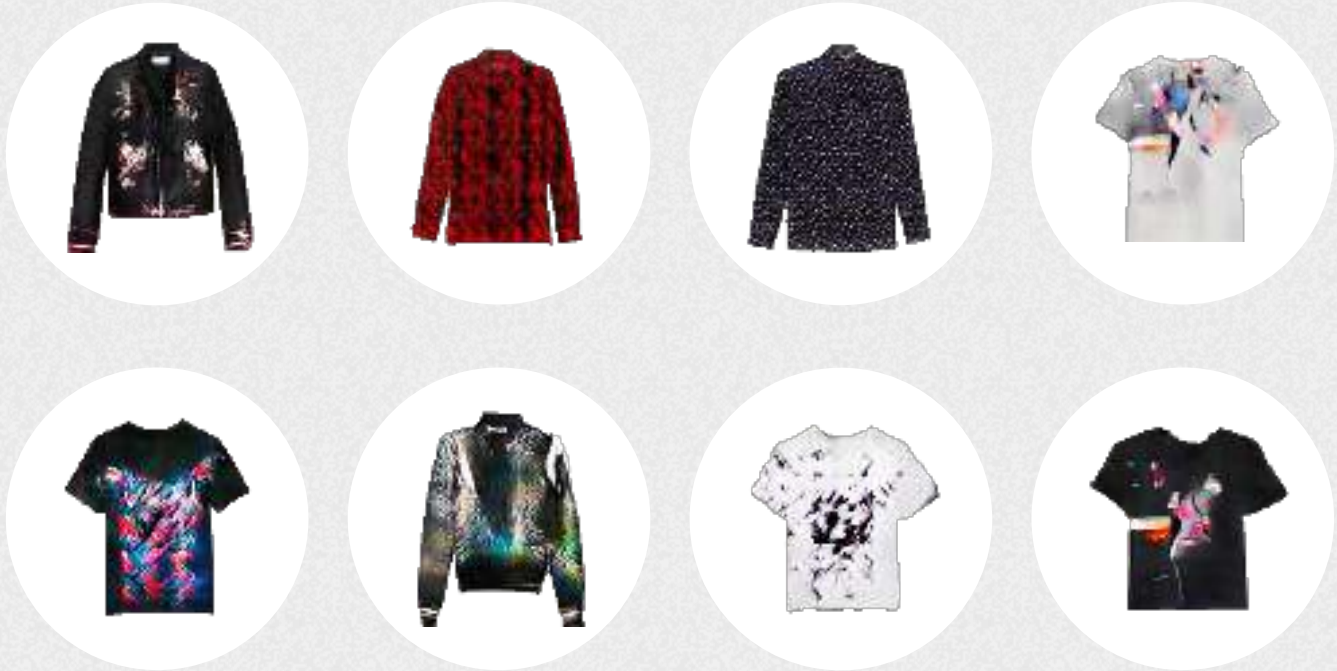
striped

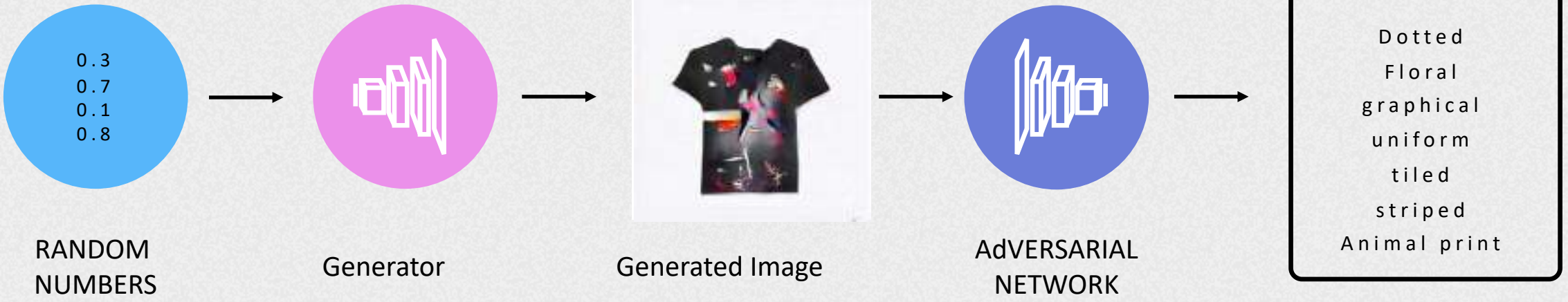
Animal print

Introduction of a Style Deviation criterion



With the Style Deviation criterion (CAN H)





Tested deviation objectives

Binary cross entropy loss :

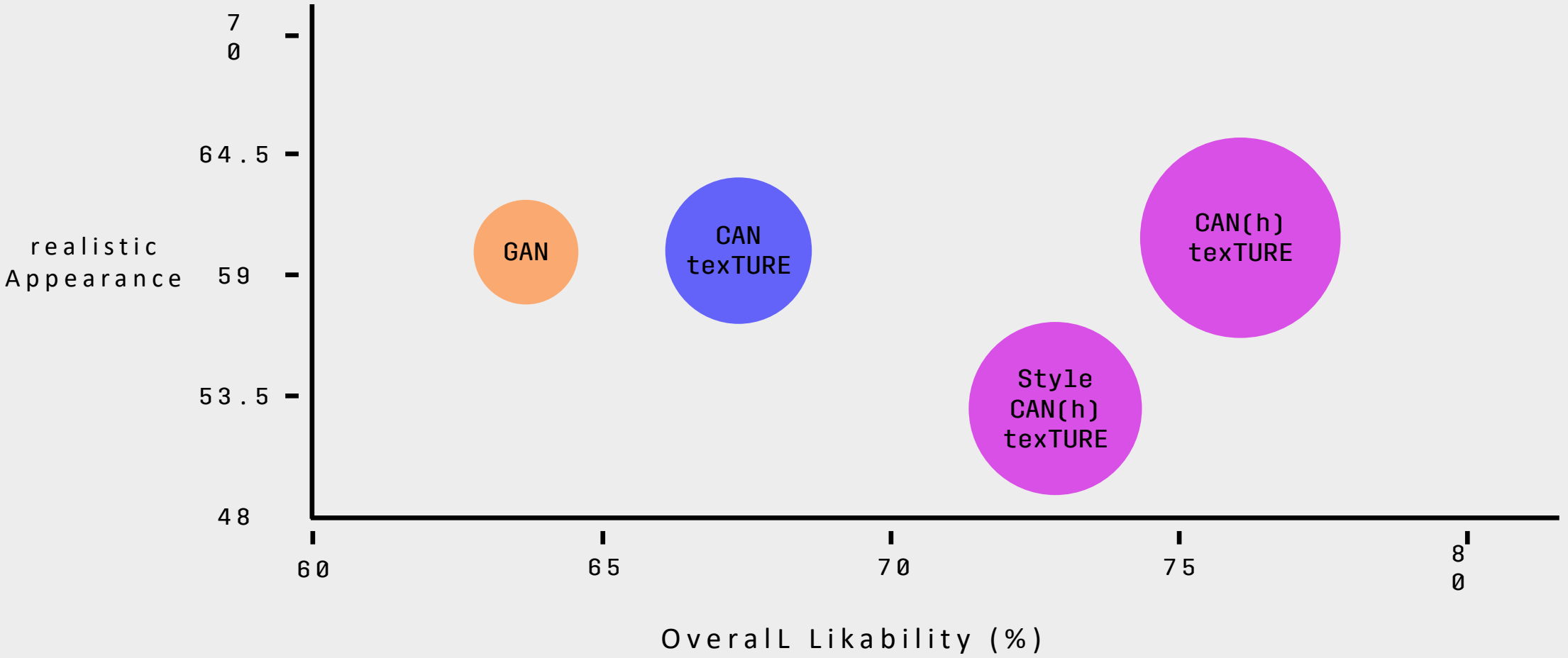
$$\mathcal{L}_{\text{CAN}} = -\sum_{k=1}^{K}\left(\frac{1}{K} log(D_c(c_k|G(z)) + (1-\frac{1}{K}) log(1 - D_c(c_k|G(z))\right)$$

Multi-class cross entropy loss:

$$\mathcal{L}_{\text{CAN(H)}} = -\sum_{x_i \in \mathcal{D}} \frac{1}{K} \log \text{softmax}(D_b(x_i))$$

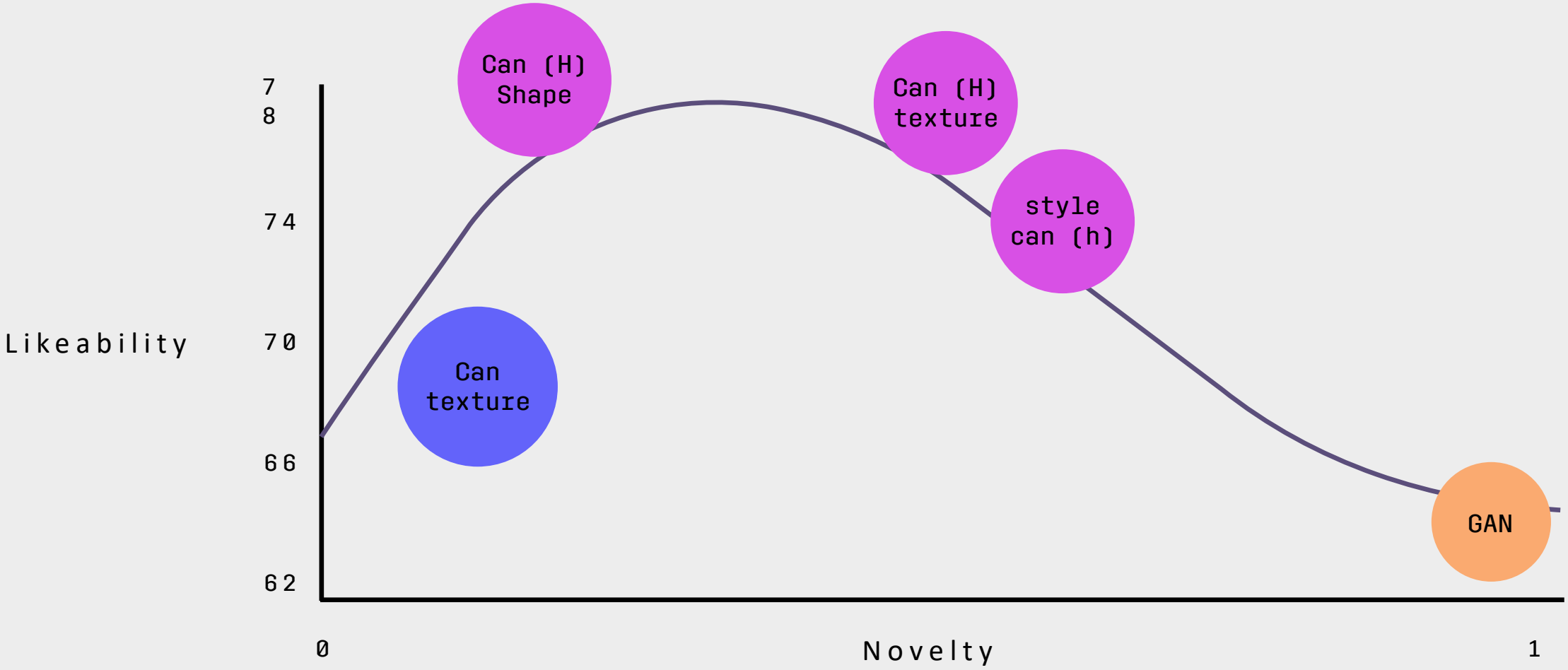
$$= -\sum_{x_i \in \mathcal{D}} \frac{1}{K} \log \left(\frac{e^{D_{b,\hat{c}_i}(x_i)}}{\sum_{k=1}^{K} e^{D_{b,k}(x_i)}} \right)$$

Human Evaluation Study



CAN: GAN with Creativity loss, (H) stands for the use of a holistic loss.

Models with texture deviation are Most Popular



judged by humans and measured as a distance to similar training images

Decoupled adversarial image generation

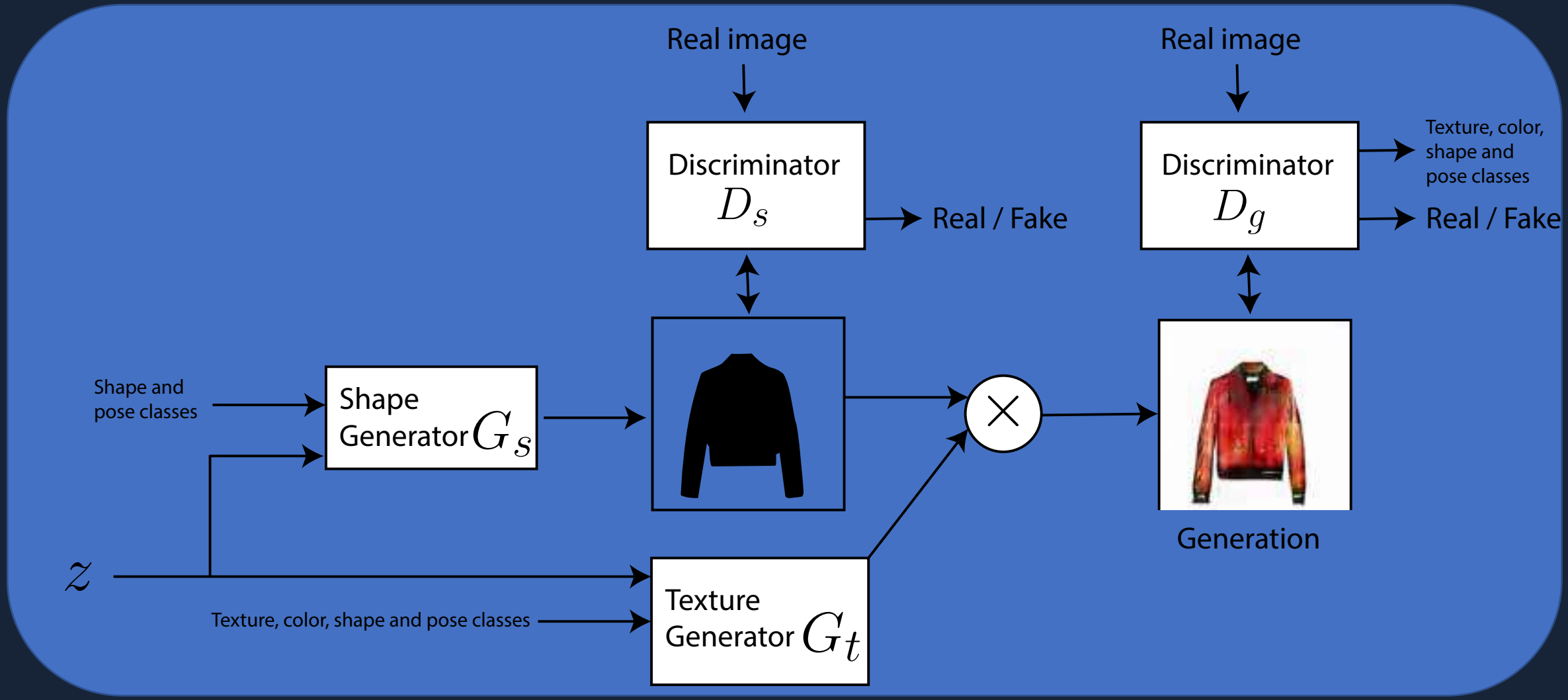
M. Riviere, C. Couprie, Y. LeCun

Motivation:
- Take advantage of white background clothing datasets
- Potentially avoid defaults in generated shapes
- Better enforce shape conditioning of generations

1024x1024 generations on the RTW dataset

Using Morgane's pytorch "progressive growing of GANs" available online, Karras et al., ICLR'18

Decoupled architecture



Random generations

Progressive growing

Progressive growing with decoupled architecture

Better class conditioning

Dataset	Model	Class	GAN-test
Shoes	PGAN	Pose	0.63
		Category	0.38
	Decoupled PGAN	Pose	0.63
		Category	**0.5**
Clothing	PGAN	Pose	0.42
		Gender	**0.88**
	Decoupled PGAN	Pose	**0.56**
		Gender	0.76

=
+12%

+14%
-12%

Accuracy of classifiers trained on FashionGen Clothing and FashionGen Shoes on our different models results (GAN-test metric)

Overall average improvement: 4.7%

Vector Image Generation by learning parametric layer decomposition

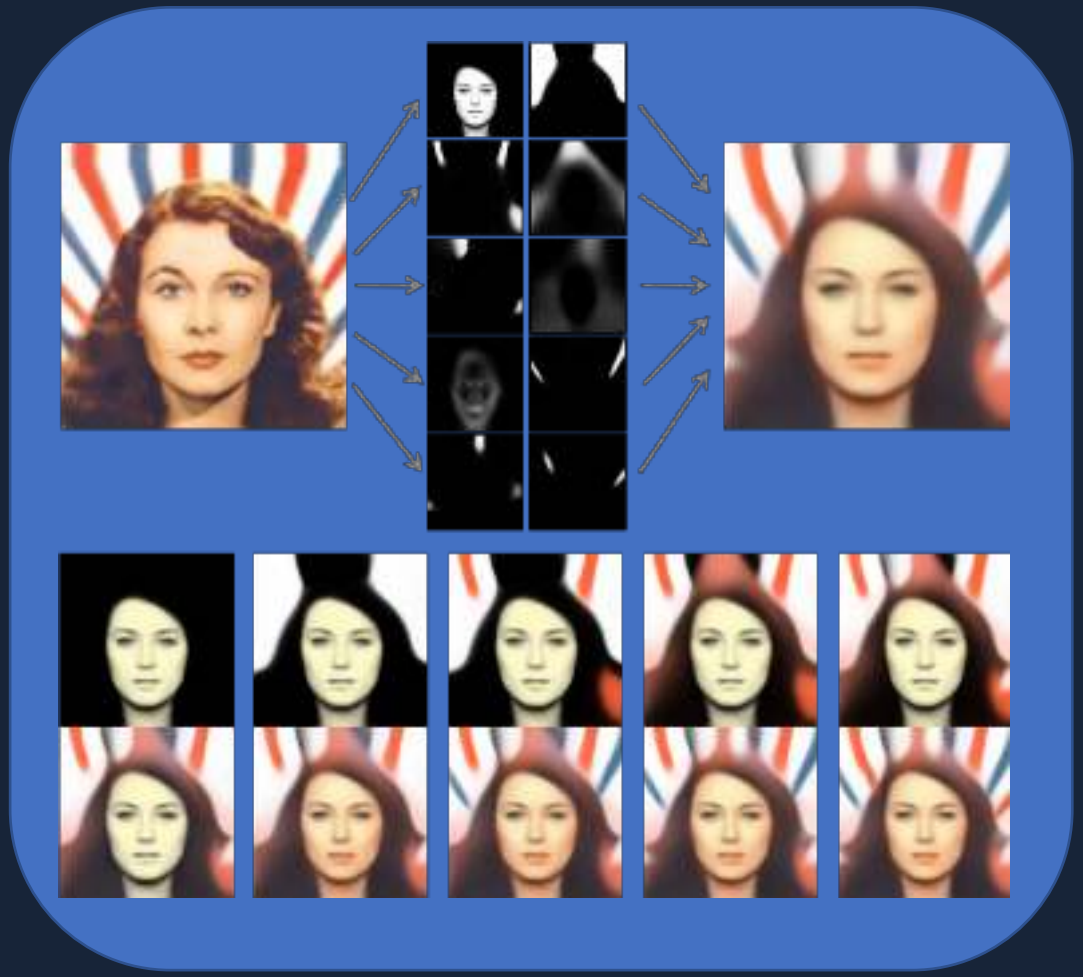
Sbai, Couprie, Aubry, arxiv dec18

Current deep generative models are great but…
… are limited in resolution, and control in generations

Related work

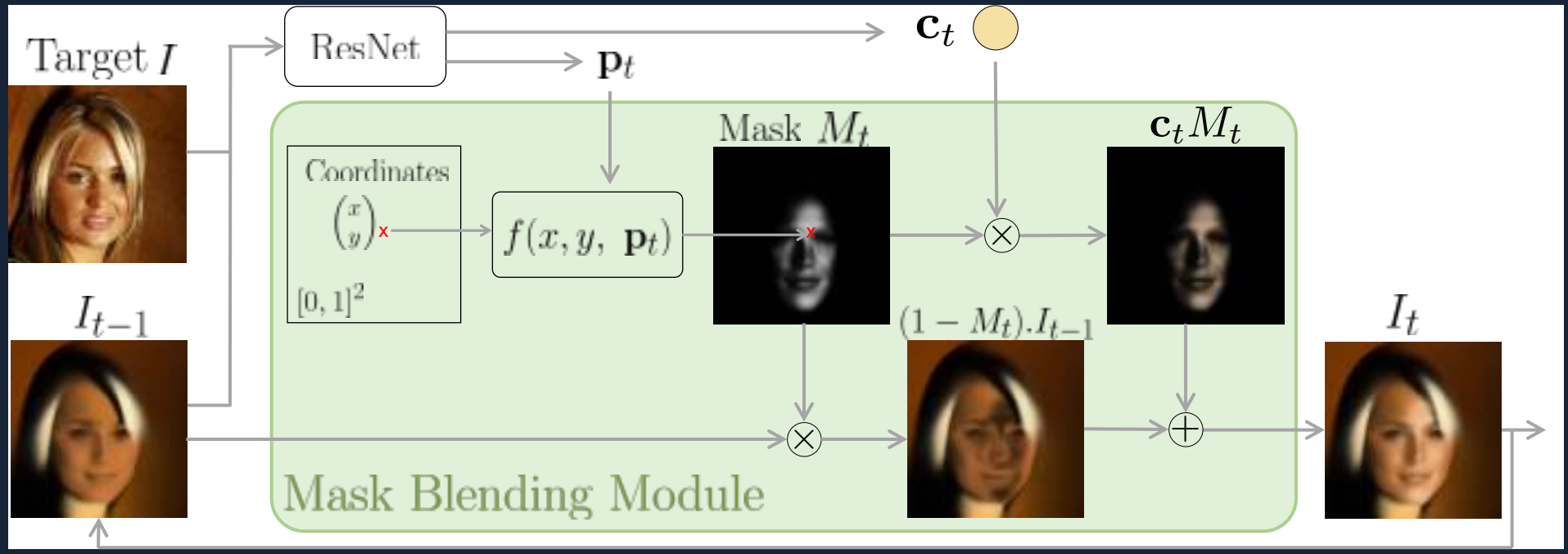
Kanan et al: Layered GANs (LR-GANs), ICLR'17
GANIN et al. SPIRAL, ICML'18

Our approach



Spoiler alert: yes, we can generate sharper images, this is just an example.

Our iterative pipeline for image reconstruction

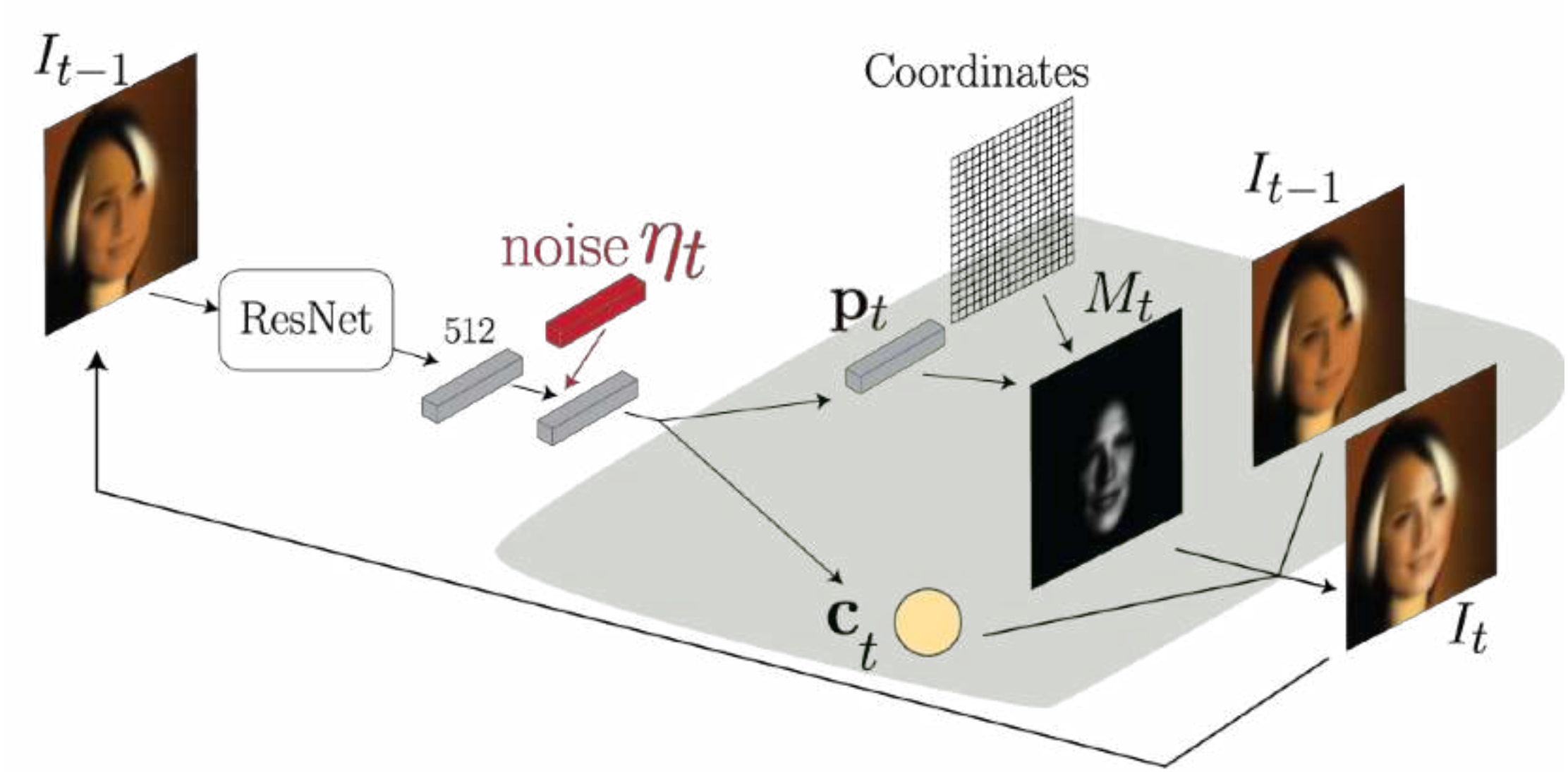


Iterative generation : $I_t = g(I, I_{t-1})$

Vectorized mask generation $M_t(x, y) = g(x, y, p_t)$

Alpha-blending $I_t(x, y) = I_{t-1}(x, y).\,(1\text{-}M_t(x, y))+ c_t M_t(x, y)$

Our iterative pipeline for image generation



Training criteria

Adversarial net criterion: Wasserstein loss with Gradient Penalty (WGAN-GP), Gulrajani et al. NIPS'17

$$\mathcal{L}_{\mathrm{D}} = -\mathbb{E}_{x\sim p_d}[D(x)] + \mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})] + \gamma\mathbb{E}_{\hat{x}\sim p_g}[(||\nabla_{\bar{x}} D(\bar{x})||_2 - 1)^2]$$

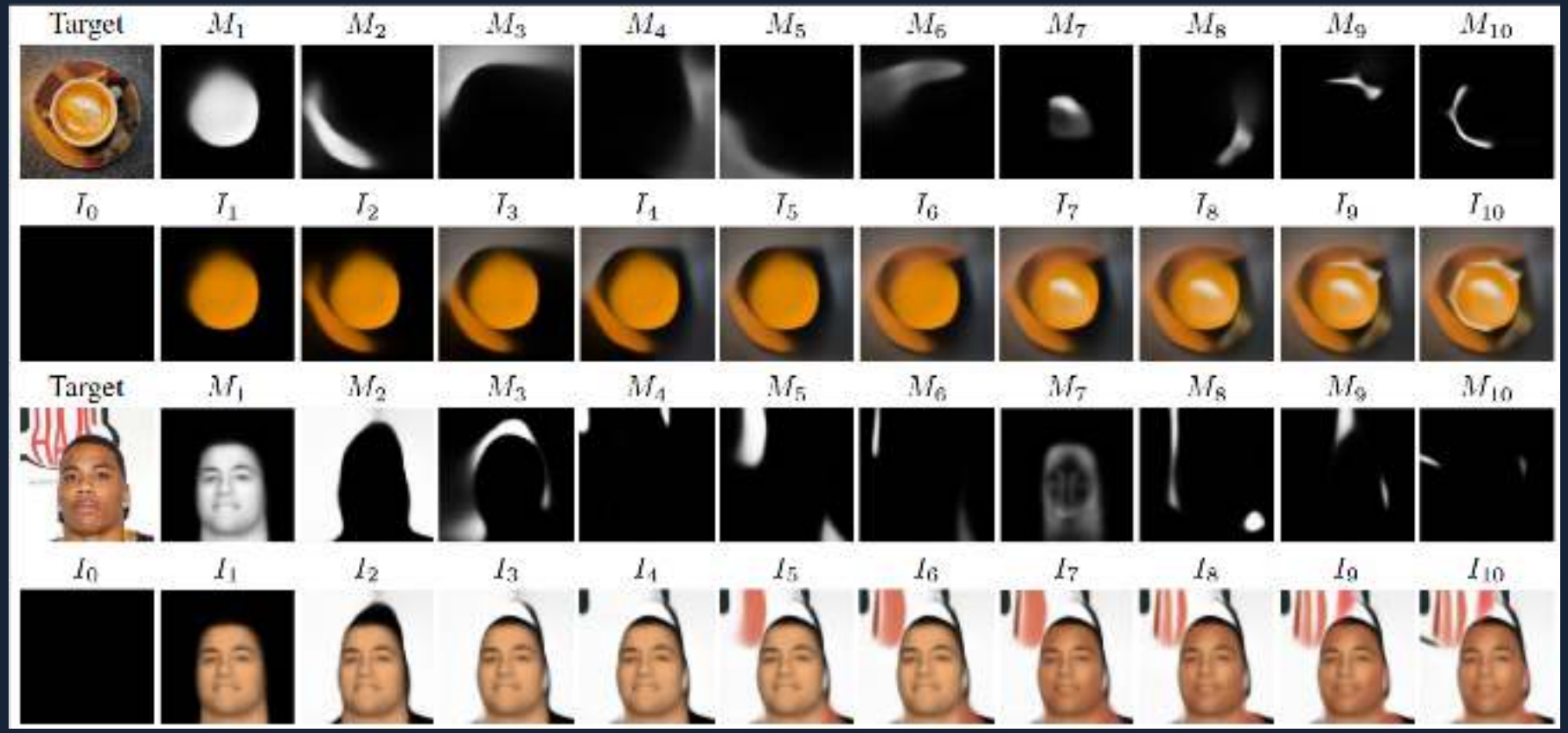
Our generator loss in the GAN setting:

$$\mathcal{L}_{\mathrm{G}}^{\mathrm{ADV}} = -\mathbb{E}_{\hat{x}\sim p_g}[D(\hat{x})].$$

Our generator loss in the image reconstruction setting:

$$\mathcal{L}_{G}^{\mathrm{REC}} = \mathcal{L}_1 + \lambda\mathcal{L}_{\mathrm{G}}^{\mathrm{ADV}}$$

Results using a l1 reconstruction loss



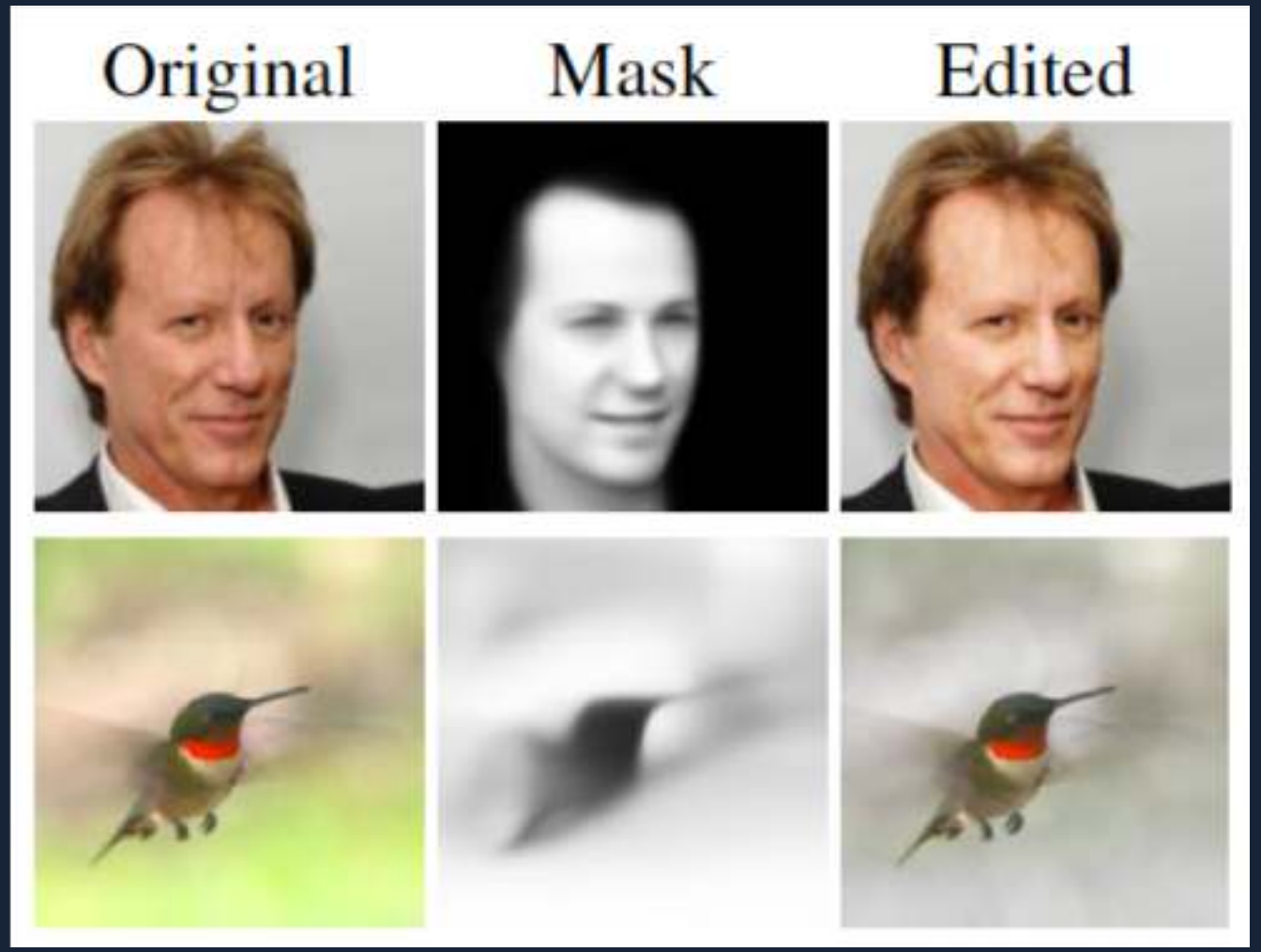
Results using a l1 reconstruction loss

Target

Our iterative reconstruction

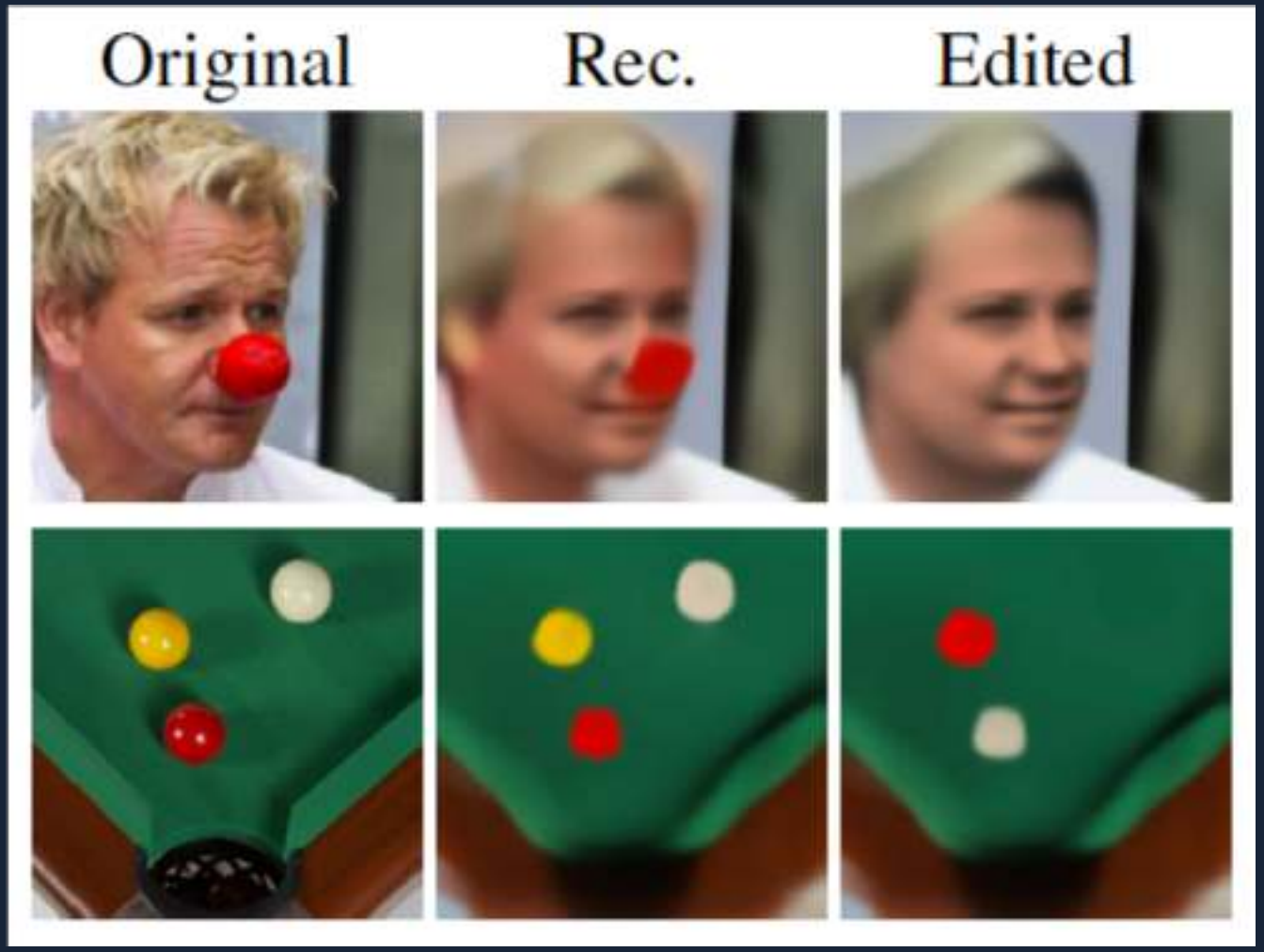
Applications

Editing the original image using extracted masks, by performing local modifications of luminosity (top), or color modification using a blending of masks (bottom).



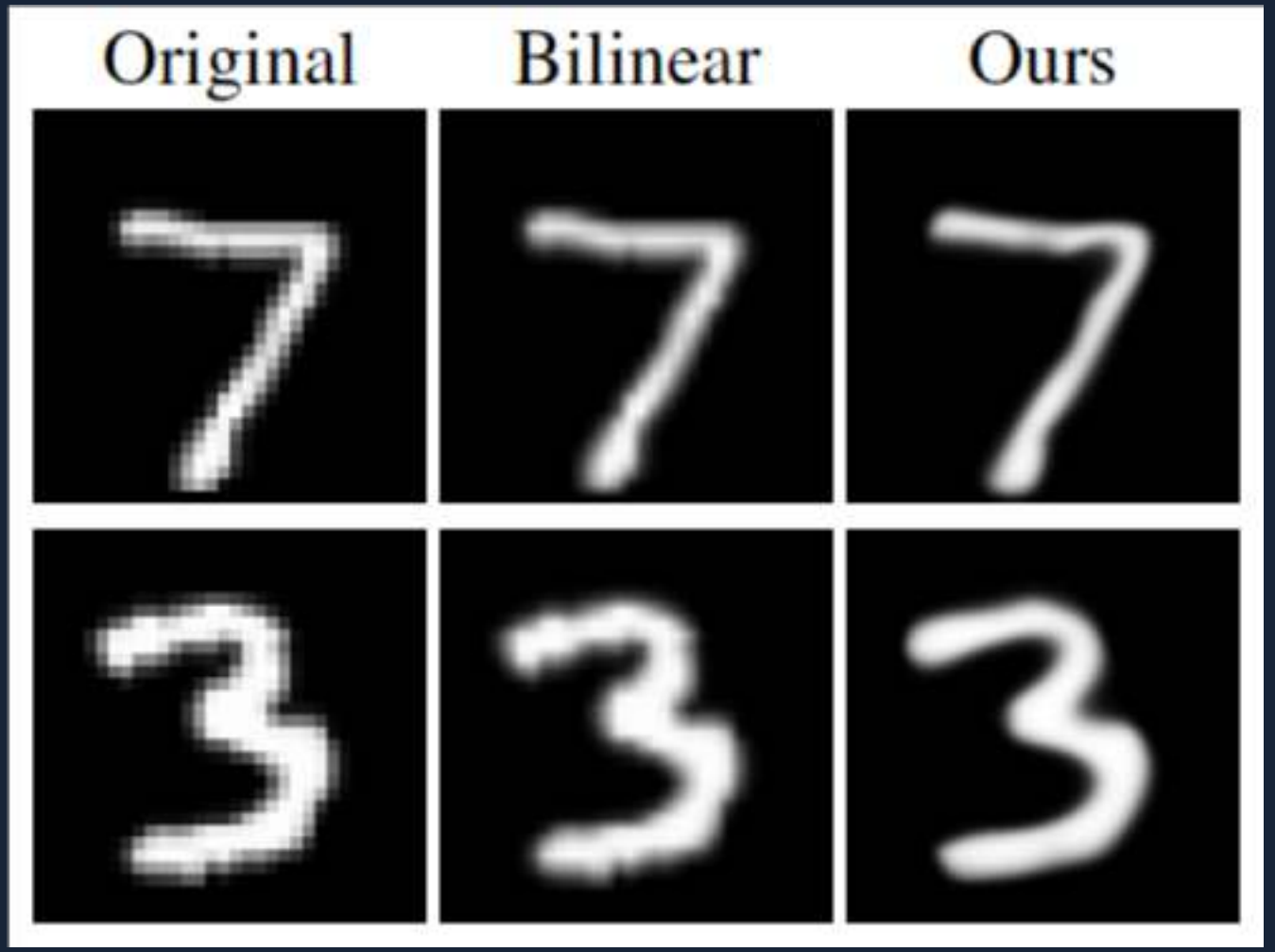
Applications

Image editing using masks:
Using chosen extracted mask(s) from image reconstruction, we apply object removal (top) and color modifications with object removal (bottom).

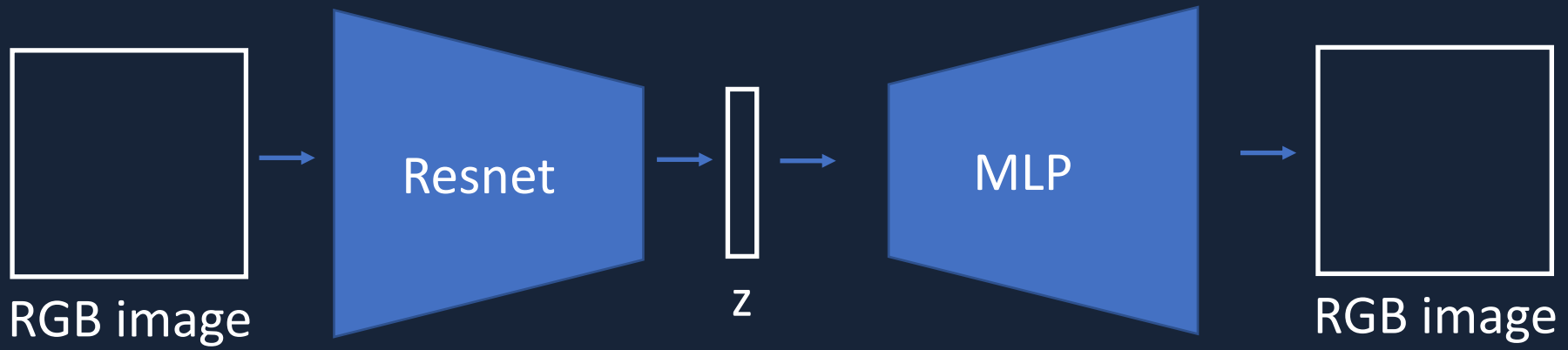


Applications

Image vectorization: Reconstruction results on MNIST images. Our model learns a vectorized mask representation of digits that can be generated at any resolution without interpolation artifacts.

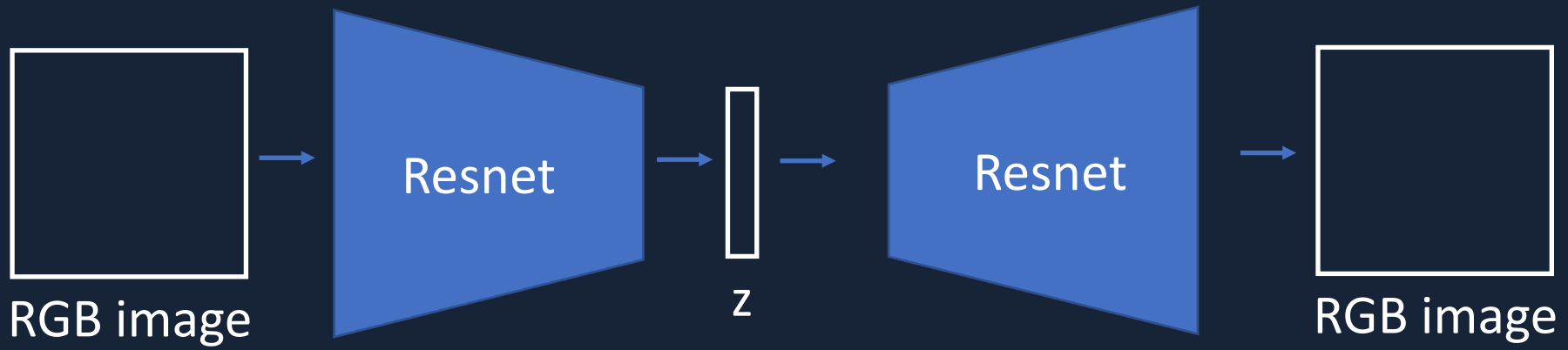


Baselines



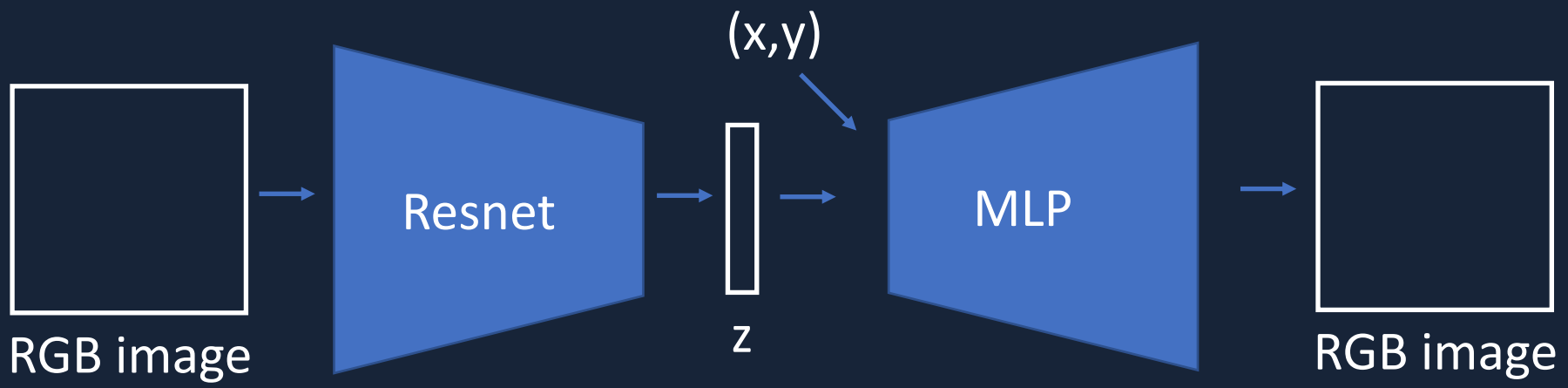
1/ MLP-baseline

Baselines



1/ MLP-baseline
2/ ResNet baseline

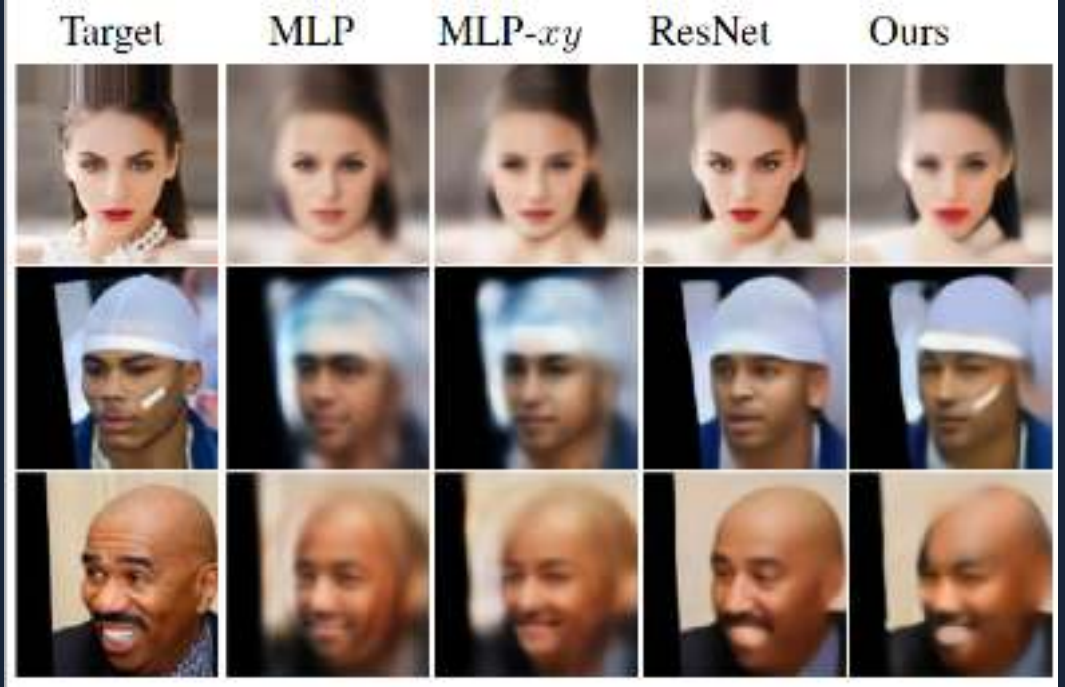
Baselines



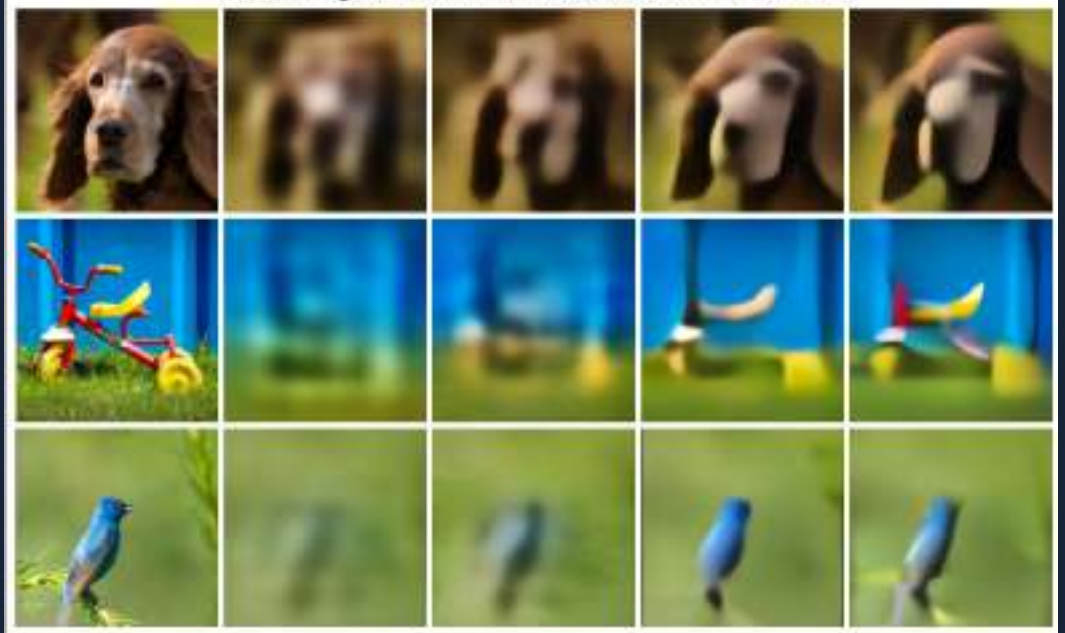
1/ MLP-baseline
2/ ResNet baseline
3/ MLP-xy baseline

Comparative results

- Using a l1 reconstruction loss
- Parameters for our approach:
20 masks, p of size 10, c of size 3:
260 parameters
- Baselines: size of the latent
code z = 20x13=260



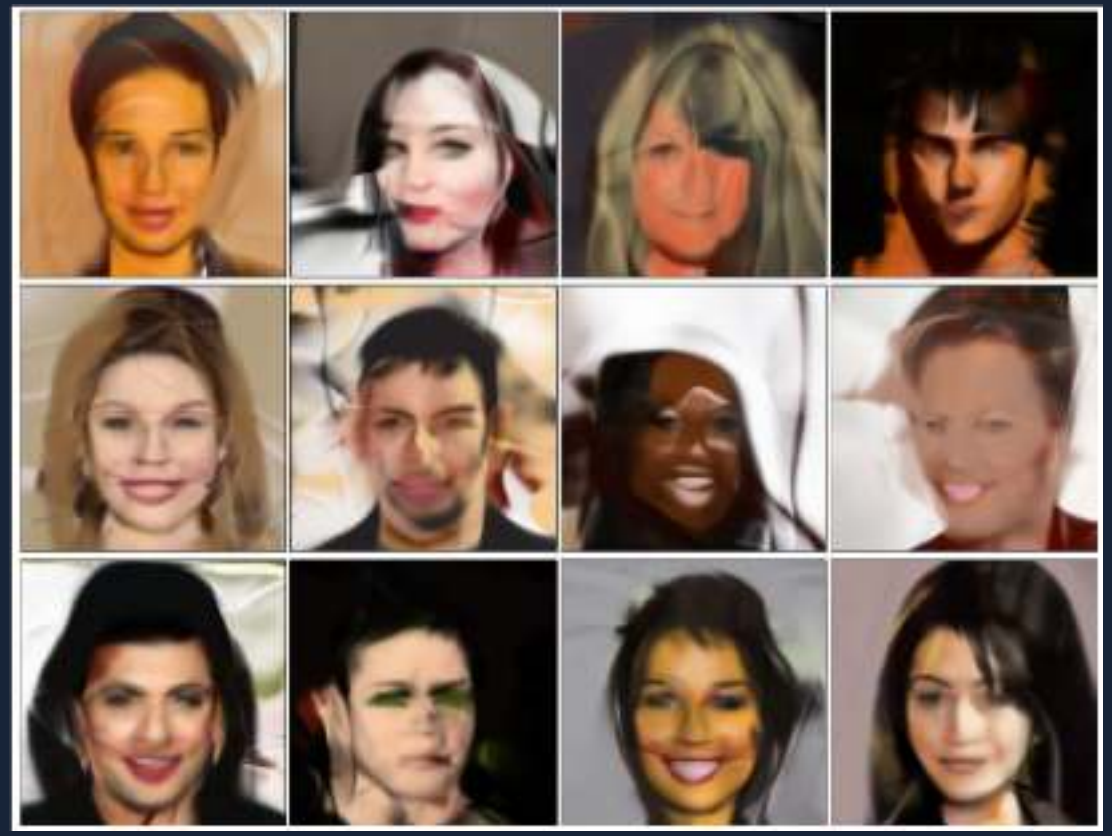
(a) Comparison with baselines on CelebA.



(b) Comparison with baselines on ImageNet.

GAN results

CelebA generations trained on 64x64 images, sampled at 256x256

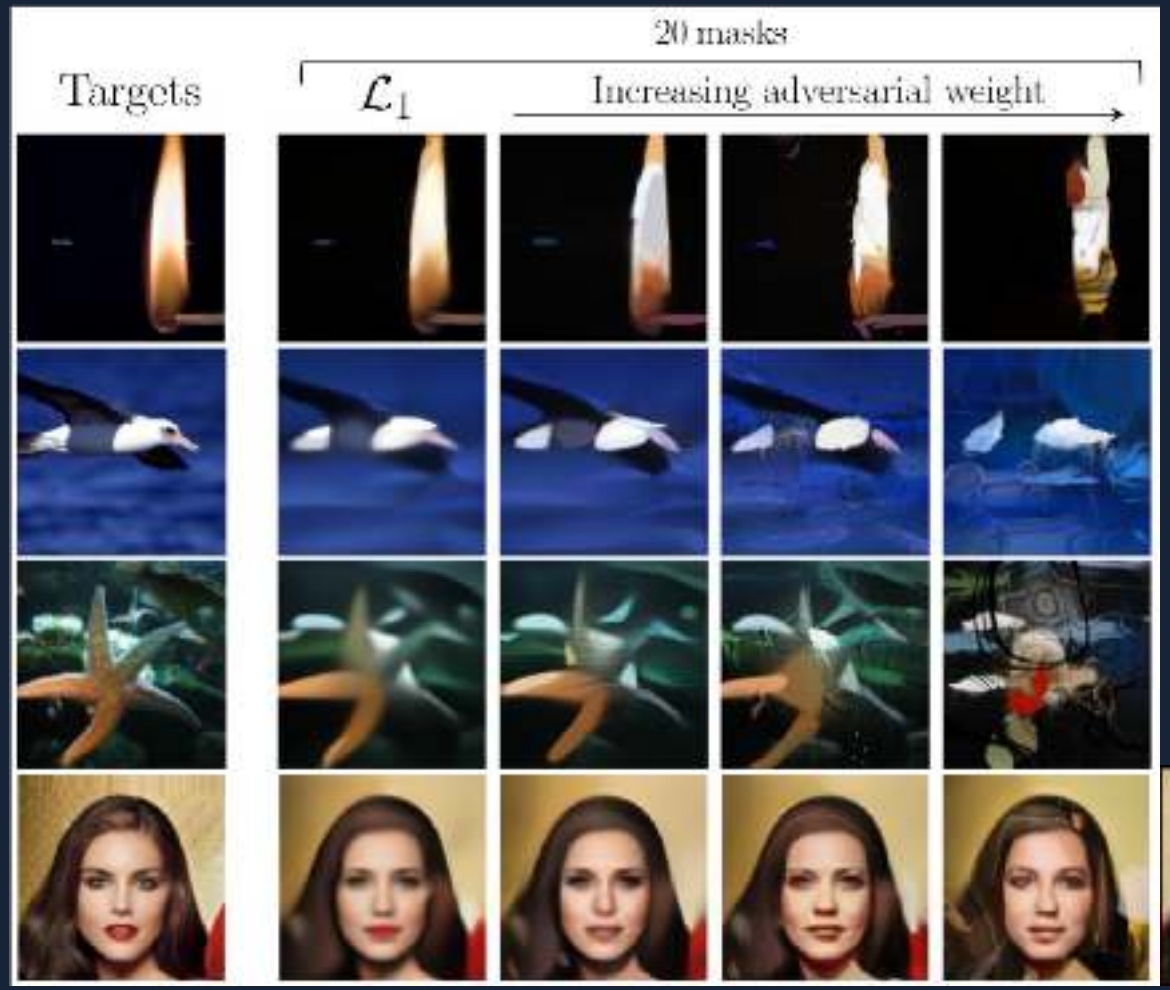


CIFAR10 generations trained on 32x32 images, sampled at 256x256

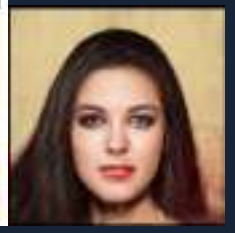
GAN Results on ImageNet

trained on 64x64 images, sampled at 1024x1024

Results



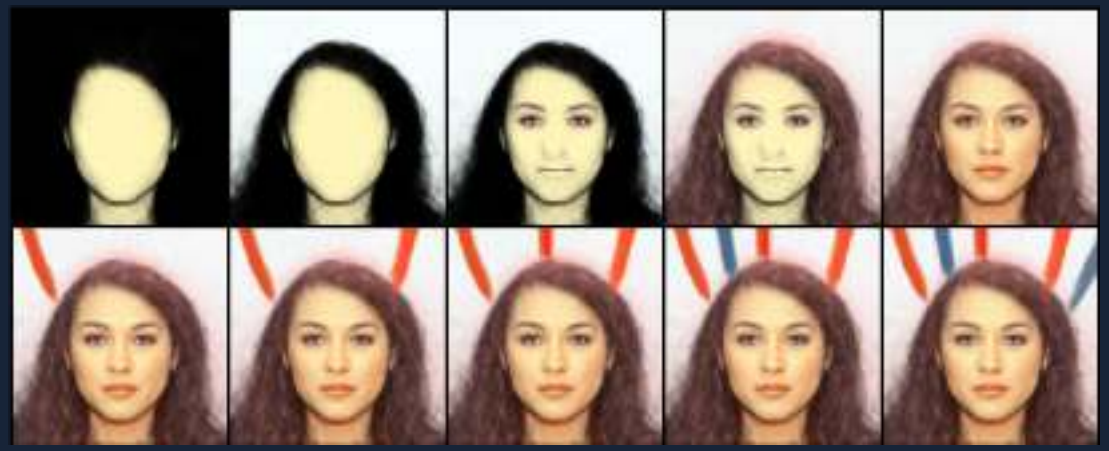
Result with perceptual loss



Target

Perceptual loss

Conclusion and Future work



Faster training
Use class conditioning
Texture image generation

Predicting next frames in videos

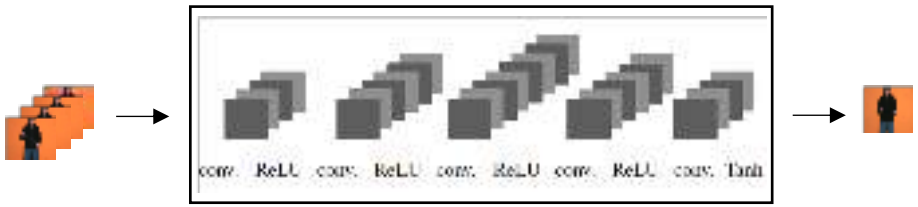
Michael Mathieu, Camille Couprie, Yann LeCun, ICLR16

4 input images

Our 2 predictions

Deep multiscale video prediction beyond Mean square error

- Result with a simple convolutional network trained minimizing an l2 loss



- Our result using
  - A multiscale architecture
  - an image gradient different loss
  - Use adversarial training

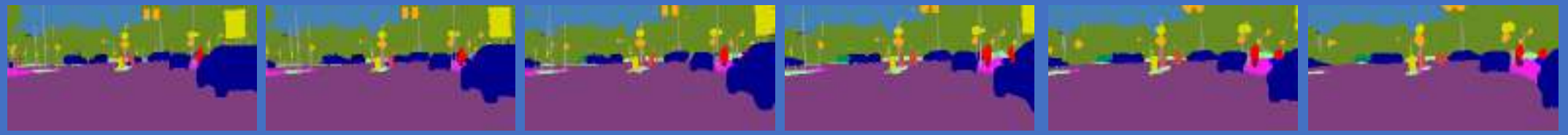
Predicting deeper into the future of semantic segmentations

P. Luc, N. Neverova, C. Couprie, J. Verbeek, Y. LeCun ECCV18

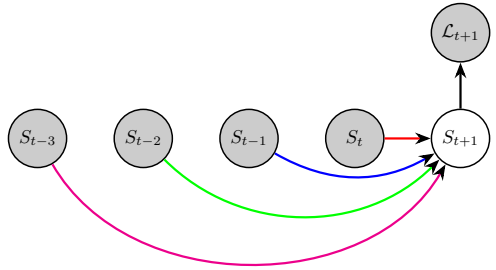
- Predictions in the RGB space quickly become blurry despites previous attempts
- Idea: predict in the space of semantic segmentation

4 input images

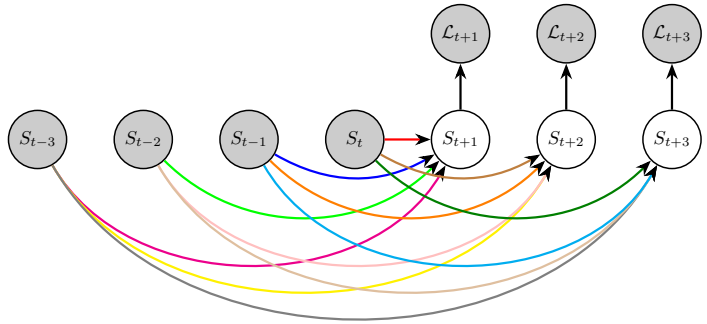
Our 2 predictions



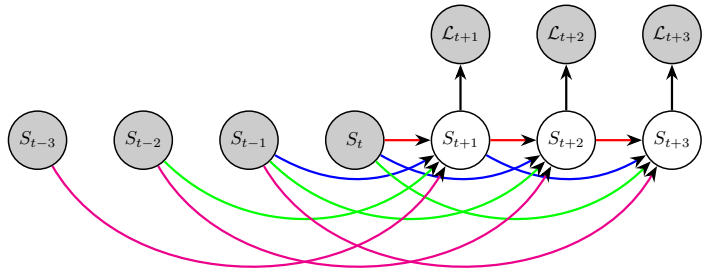
Approach – predicting deeper into the future



Single time-step



Batch model



Autoregressive model

Same color = shared weights

Autoregressive mode is only possible for X2X, S2S, XS2XS

Autoregressive model is either :

- used for inference without additional training (w.r.t. to single time step model) AR
- Fine-tuned using BPTT
  AR fine-tune

Some results

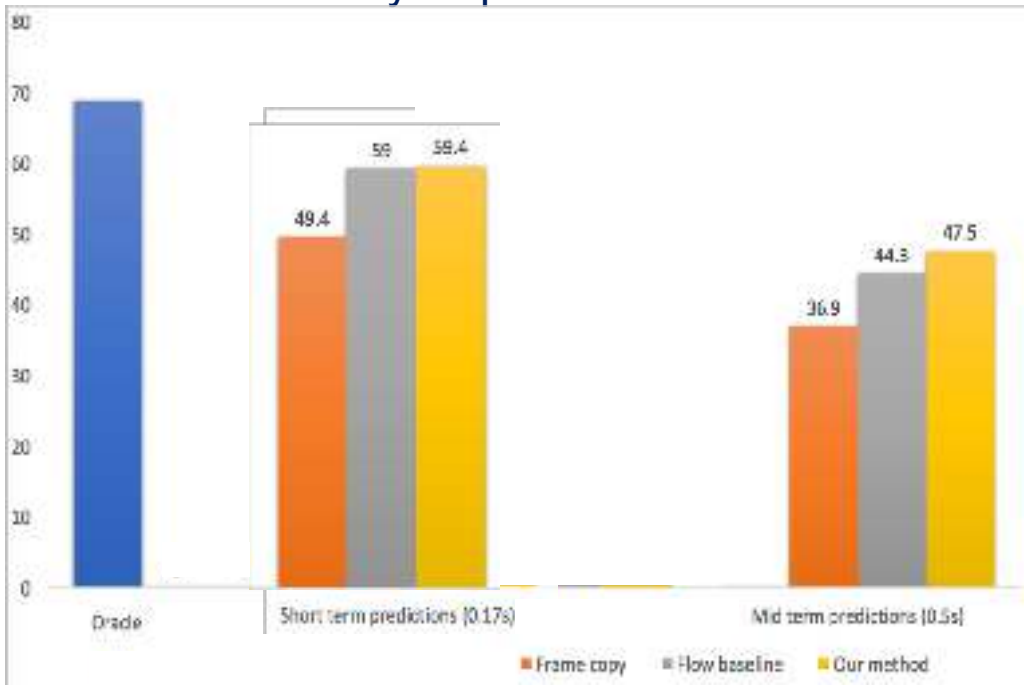
Baselines :

- Copy the last input frame to the output
- Estimate flow between the two last inputs, and project the last input forward using the flow

Flow baseline

Our AutoRegressive fine-tune result

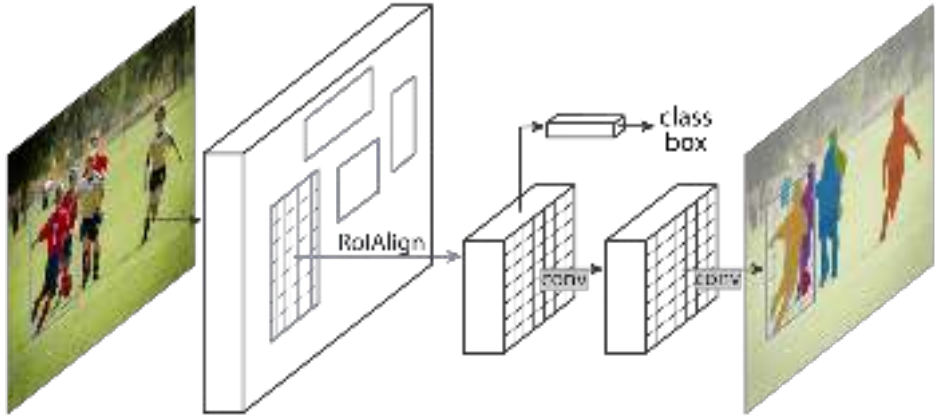
Performance measure (mean IoU) of our approach and baselines on the Cityscapes dataset

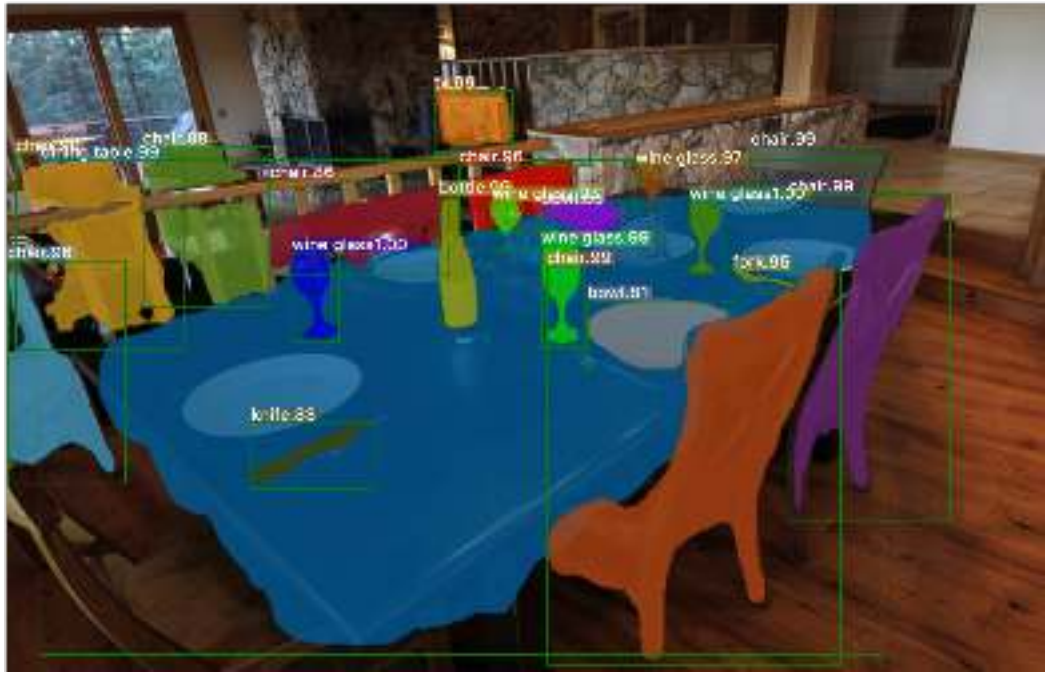


Instance level segmentation: Mask RCNN

K. He G. Gkioxari P. Dollar R. Girshick'17

- Extends Faster RCNN [Ren et al.'15] by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition



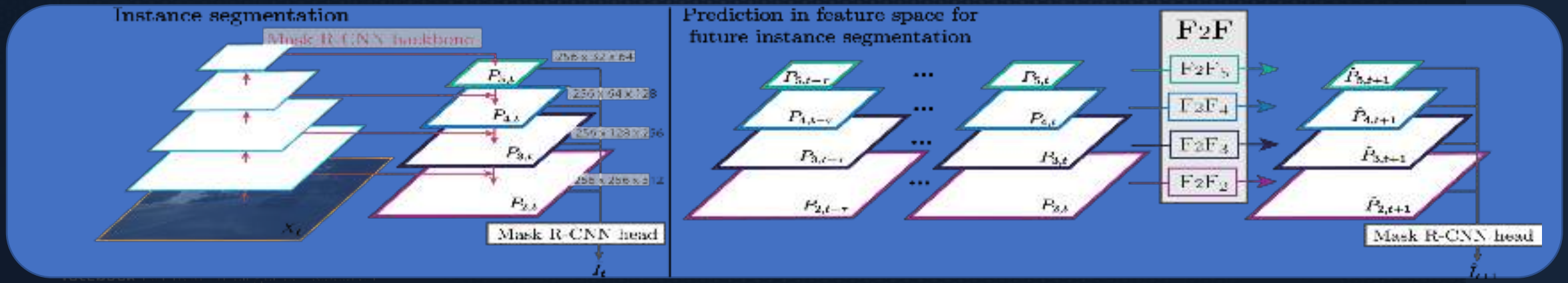


Predicting future segmentation instances by forecasting convolutional features

P. Luc, C. Couprie, Y. LeCun, J. Verbeek, ECCV18

Luc, Neverova et al. ICCV17

F2F predictions



Conclusions

Some open problems:
- Automatic metrics to evaluate generative models performances
- Non deterministic training losses for future prediction

Torch code online :
- For future video prediction:
- Vector image generation: available soon on Othman Sbai's github
  - of RGBs : on Michael Mathieu's github
  - of semantic segmentations : on Pauline's Luc github
  - of instance segmentation : on Pauline's Luc github