Bayesian Image Reconsturuction using Deep Generative Models

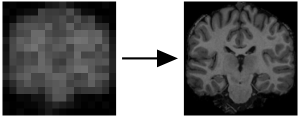
Răzvan V. Marinescu

Massachusetts Institute of Technology

Aim: image reconstruction using *pre-trained* generator models

- Adapt the state-of-the-art StyleGAN2 for medical image reconstruction

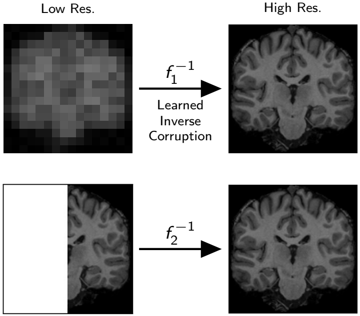
MRI reconstruction



StyleGAN2 (Karras et al, 2019)

Current image reconstruction methods have several limitations

- Require large computational resources and data
- Are specific to particular corruption tasks
- Cannot deal with distribution shifts:
  - in inputs: e.g. older populations
  - in corruption type: e.g. change in blur kernel



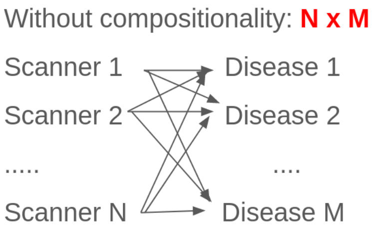
Limitation 1: State-of-the-art DL methods have large computational requirements

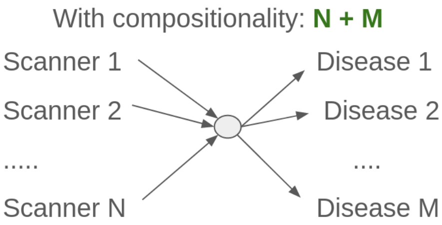
- Requirements = Computation Time + Advanced Hardware + Large Datasets
- Most computation now runs on clouds

- Currently few labs/companies have the resources to train state-of-the-art models
  - StyleGAN2: 9 days on 4 GPUs
  - GPT-3: 355 years on single GPU
- Solutions moving forward:
  - Adapting previously-trained models
  - Combine smaller models into larger ones

Limitation 2: Distribution shifts require model re-training

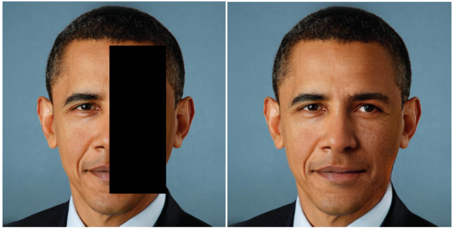
- Distribution shifts happen all the time:
  - Changes in hospital scanners, protocols, software upgrades
  - Can be continuous: population getting older due to better healthcare
- Shifts can result in combinatorial effects in number of re-training instances!
- Compositionality is one potential solution





Recent models can perform image reconstruction using **pre-trained** generative models

Image2StyleGAN++ (Abdal et al, 2020)

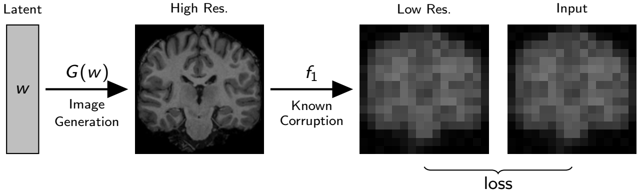


PULSE (Menon et al, 2020)

- Don't use an embedder network, so can generalise beyond the training data
- However, they are specific to a particular corruption task (either in-painting or super-resolution)
- Cannot characterize **uncertainty** and recover **multiple solutions**
- We will aim to construct a Bayesian formulation that can fully characterize the posterior over all potential solutions

Method: We perform image reconstruction by combining two models

1. a pre-trained generator G (StyleGAN2)
2. a known forward corruption model f_1



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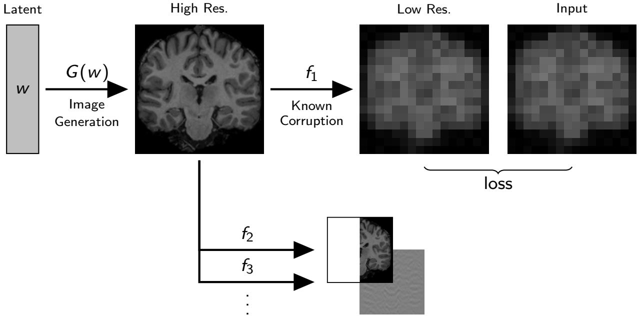

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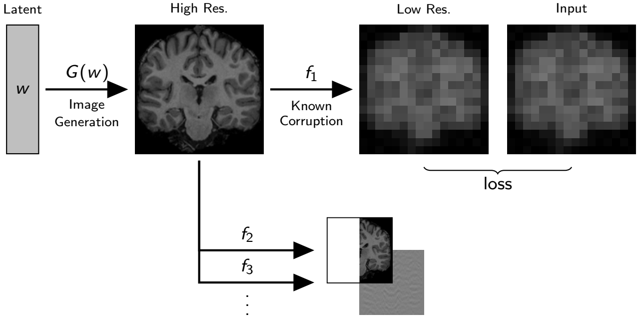
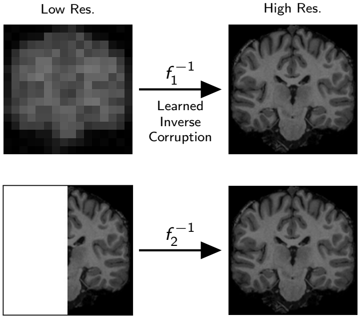


Ours (Marinescu et al, arXiv, 2020)



Previous

Reconstructed image is given by computing the Bayesian maximum a-posteriori (MAP) estimate

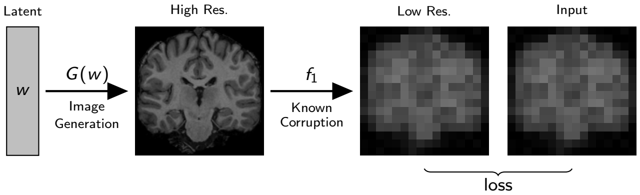
- We optimise:

$$w^* = \arg\max_w p(w)p(I|w)$$

- For uninformative prior $p(w)$ and Gaussian noise model (pixelwise independent), we get:

$$w^* = \arg\min_w ||I - f \circ G(w)||_2^2$$

- This can be optimised with SGD
- Once we get w^*, the the reconstructed image is $G(w^*)$



- We started from the original StyleGAN2 inversion

- We started from the original StyleGAN2 inversion
- Yet the reconstruction was not good $\rightarrow$ required several changes

$$w^*, \eta^* = \arg\min_{w,\eta} ||\phi(I) - \phi \circ f \circ G(w, \eta)||_2^2$$

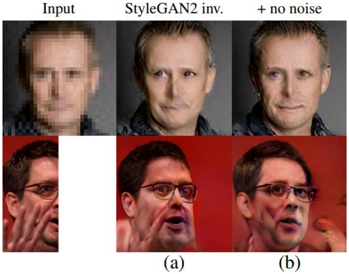
(a)

Good reconstructions require further modifications

- We started from the original StyleGAN2 inversion

$$w^* = \arg\min_w ||\phi(I) - \phi \circ f \circ G(w)||_2^2$$

- Yet the reconstruction was not good $\rightarrow$ required several changes
    - remove noise layers



- We started from the original StyleGAN2 inversion
- Yet the reconstruction was not good $\rightarrow$ required several changes
  - optimize latents at all resolutions

$$\mathbf{w} = w_1, .., w_L$$

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} ||\phi(I) - \phi \circ f \circ G(\mathbf{w})||_2^2$$

Input StyleGAN2 inv. + no noise + $\mathcal{W}^+$ optim.

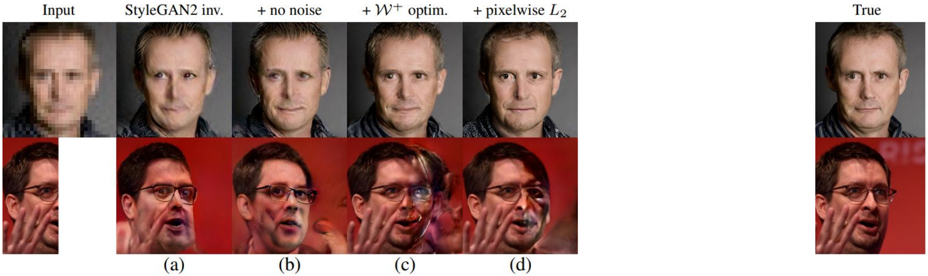
(a) (b) (c)

True

Good reconstructions require further modifications

- We started from the original StyleGAN2 inversion
- Yet the reconstruction was not good → required several changes
  - add pixelwise loss

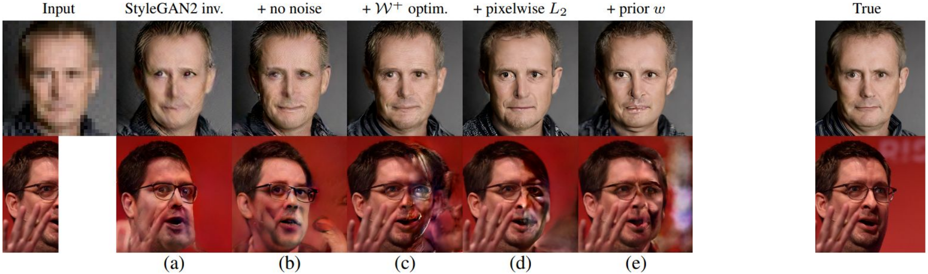
$$\mathbf{w}^* = \arg\min_{\mathbf{w}} ||\phi(I) - \phi \circ f \circ G(\mathbf{w})||_2^2 + ||I - f \circ G(\mathbf{w})||_2^2$$



Good reconstructions require further modifications

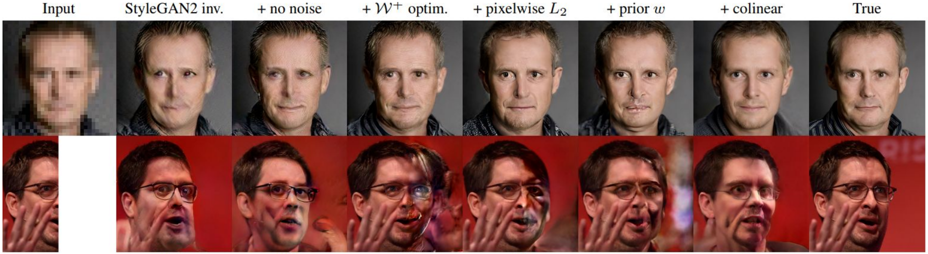
- We started from the original StyleGAN2 inversion
- Yet the reconstruction was not good → required several changes
  - gaussian prior on latents

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} ||\phi(I) - \phi \circ f \circ G(\mathbf{w})||_2^2 + ||I - f \circ G(\mathbf{w})||_2^2 + \sum_i \left(\frac{w_i - \mu}{\sigma_i} \right)^2$$



- We started from the original StyleGAN2 inversion
- Yet the reconstruction was not good $\rightarrow$ required several changes
  - force latents to be colinear

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} ||\phi(I) - \phi \circ f \circ G(\mathbf{w})||_2^2 + ||I - f \circ G(\mathbf{w})||_2^2 + $$
$$+ \sum_i \left(\frac{w_i - \mu}{\sigma_i} \right)^2 - \sum_{i,j} \frac{w_i w_j^T}{|w_i||w_j|}$$

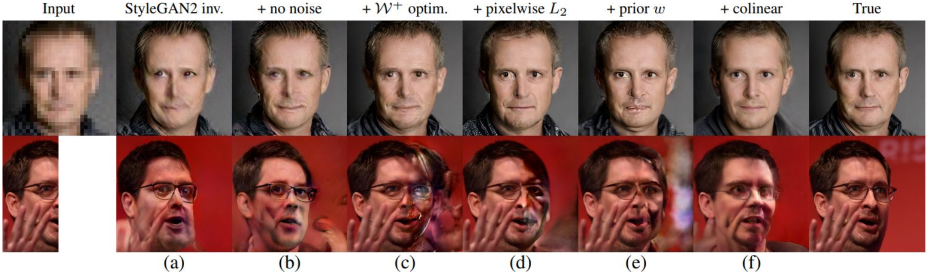


(a) (b) (c) (d) (e) (f)

Good reconstructions require further modifications

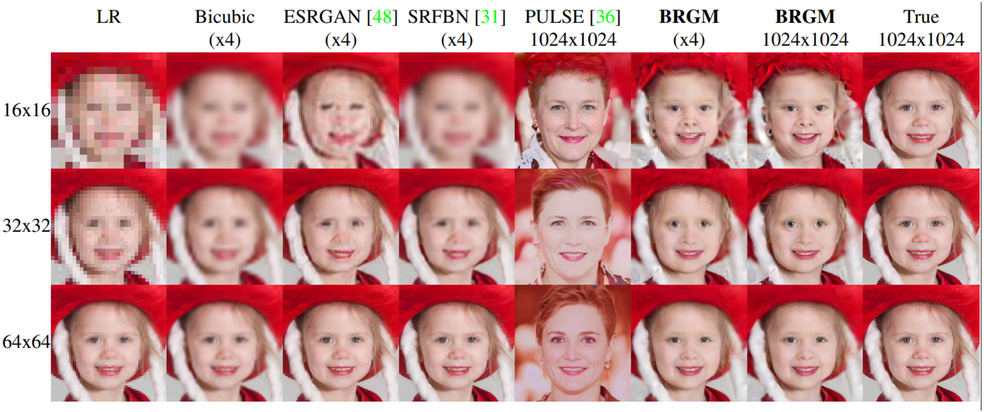
- We started from the original StyleGAN2 inversion
- Yet the reconstruction was not good $\rightarrow$ required several changes
  - Analytically expressed the full likelihood (Marinescu et al, 2021)

$$\mathbf{w}^* = \arg\min_{\mathbf{w}} ||\phi(I) - \phi \circ f \circ G(\mathbf{w})||_2^2 + ||I - f \circ G(\mathbf{w})||_2^2 + \\ + \sum_i \left(\frac{w_i - \mu}{\sigma_i} \right)^2 - \sum_{i,j} \frac{w_i w_j^T}{|w_i||w_j|}$$



Results on super-resolution using the FFHQ dataset

- We achieve state-of-the-art (SOTA) results on small inputs resolutions 16x16
- On larger resolutions (>32x32), we achieve very good results, albeit not SOTA



Marinescu et al, arXiv, 2020

Similar results on super-resolution for medical datasets

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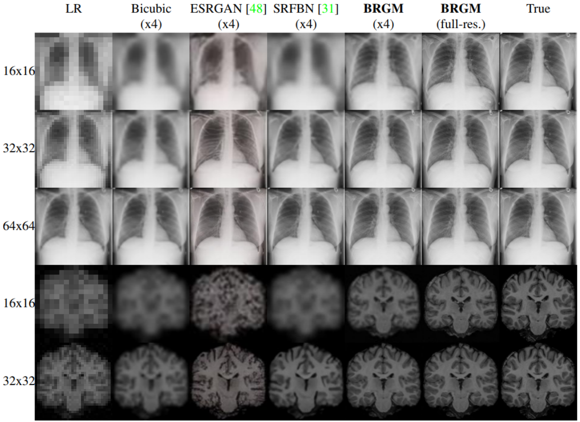

Marinescu et al, arXiv, 2020

Inpainting also achieves state-of-the-art results

- Best previous method (SN-PatchGAN, CVPR 2019) does not work for large masks
- Our method can "hypothesize" missing structure

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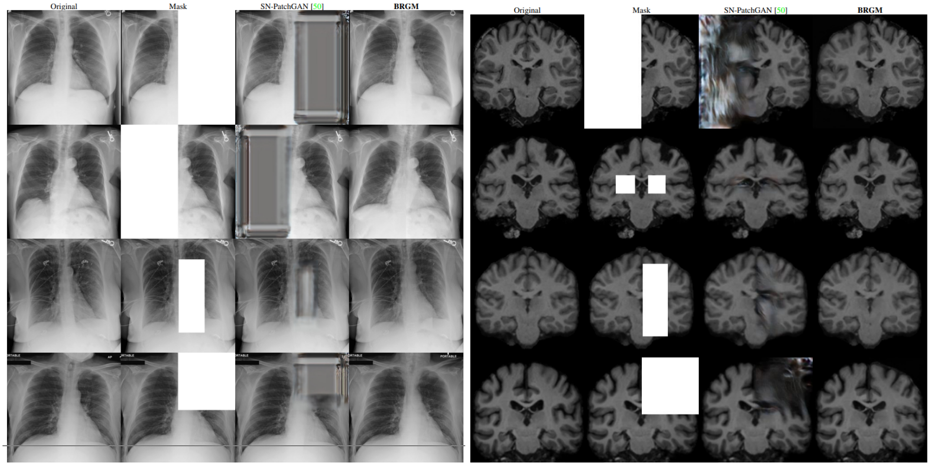


Results confirmed through quantitative evaluation

- Three different datasets, at different resolutions
- Human study with 20 raters

Super-resolution

Dataset	**BRGM**	PULSE [36]	ESRGAN [48]	SRFBN [31]
FFHQ 16^2	**0.24**/25.66	0.29/27.14	0.35/29.32	0.33/**22.07**
FFHQ 32^2	0.30/18.93	0.48/42.97	0.29/23.02	**0.23/12.73**
FFHQ 64^2	0.36/16.07	0.53/41.31	0.26/18.37	**0.23/9.40**
FFHQ 128^2	0.34/15.84	0.57/34.89	0.15/15.84	**0.09/7.55**
X-ray 16^2	**0.18/11.61**	-	0.32/14.67	0.37/12.28
X-ray 32^2	0.23/10.47	-	0.32/12.56	**0.21/6.84**
X-ray 64^2	0.31/10.58	-	0.30/8.67	**0.22/5.32**
X-ray 128^2	0.27/10.53	-	0.20/7.19	**0.07/4.33**
Brains 16^2	**0.12/12.42**	-	0.34/22.81	0.33/12.57
Brains 32^2	**0.17**/11.08	-	0.31/14.16	0.18/**6.80**

Inpainting

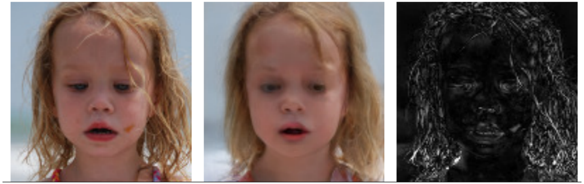
	BRGM				SN-PatchGAN [50]			
Dataset	LPIPS	RMSE	PSNR	SSIM	LPIPS	RMSE	PSNR	SSIM
FFHQ	**0.19**	**24.28**	**21.33**	**0.84**	0.24	30.75	19.67	0.82
X-ray	**0.13**	**13.55**	**27.47**	**0.91**	0.20	27.80	22.02	0.86
Brains	**0.09**	**8.65**	**30.94**	**0.88**	0.22	24.74	21.47	0.75

Human evaluation

Dataset	**BRGM**	PULSE [36]	ESRGAN [48]	SRFBN [31]
FFHQ 16^2	**0.42**	0.32	0.11	0.15
FFHQ 32^2	0.39	0.02	0.12	**0.47**
FFHQ 64^2	0.14	0.08	0.32	**0.45**
FFHQ 128^2	0.14	0.10	**0.39**	0.38

- It can fail for images that are too dissimilar to the training ones
  - Because generator cannot extrapolate easily

- Can be inconsistent with the input image



Bayesian Image Reconstruction – Summary

- Proposed a method for image reconstruction using pre-trained deep generative models
- Solution is given by the Bayesian MAP estimate
- State-of-the-art results on super-resolution and inpainting