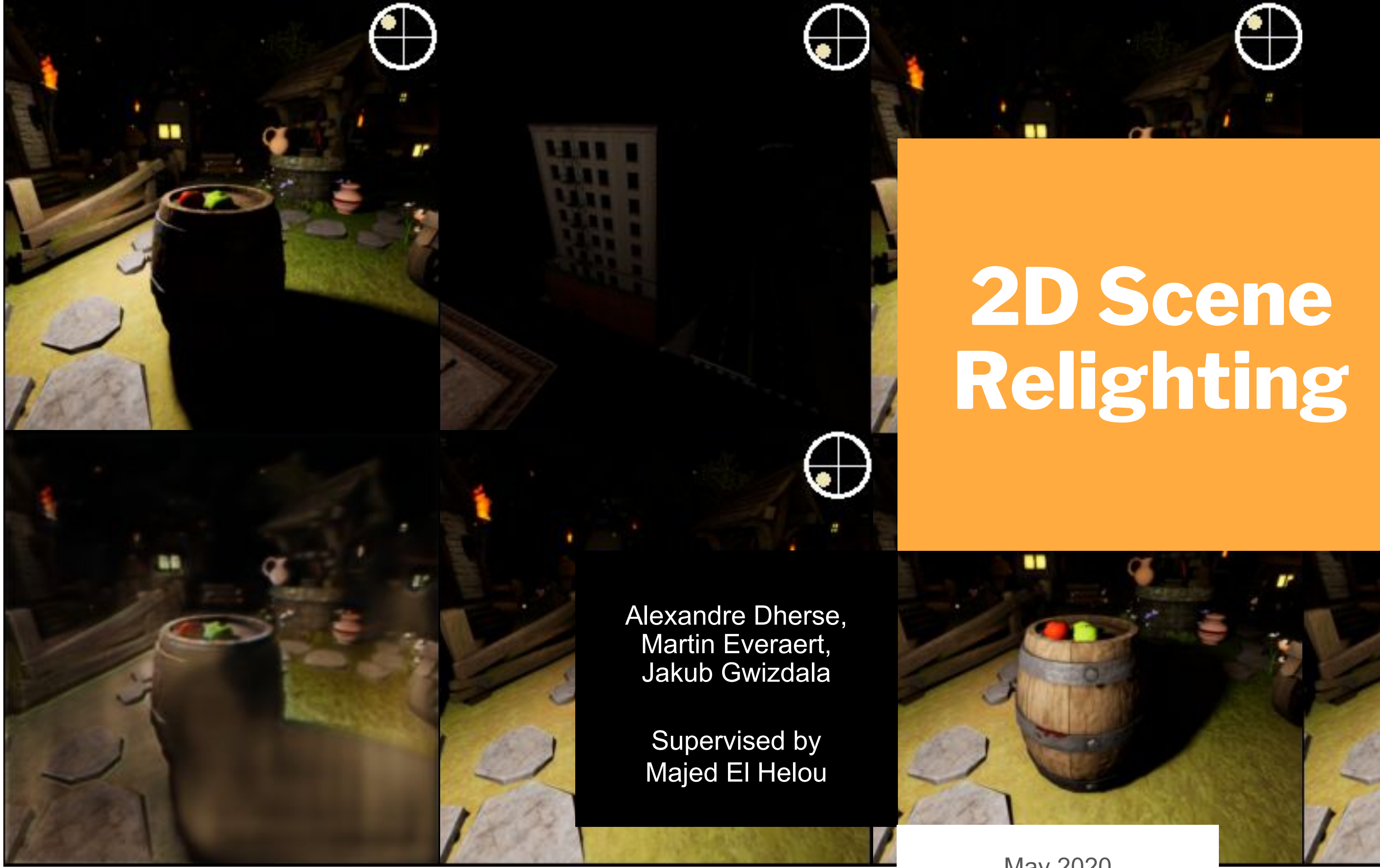

2D Scene Relighting

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Martin Everaert,
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Supervised by
Majed El Helou

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EPFL

CS-413
Computational
Photography

Introduction and motivation of the problem

Transfer the illumination from one image to another.

Having a method for general relighting of images with varied content

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Introduction and motivation of the problem

- post-production tool for images (videos) to change original lighting (aesthetic reasons or eliminating the need of light setup equipment)

- perform data augmentation before training a network, allowing a wider variety of images for training (e.g. eliminate illumination bias)

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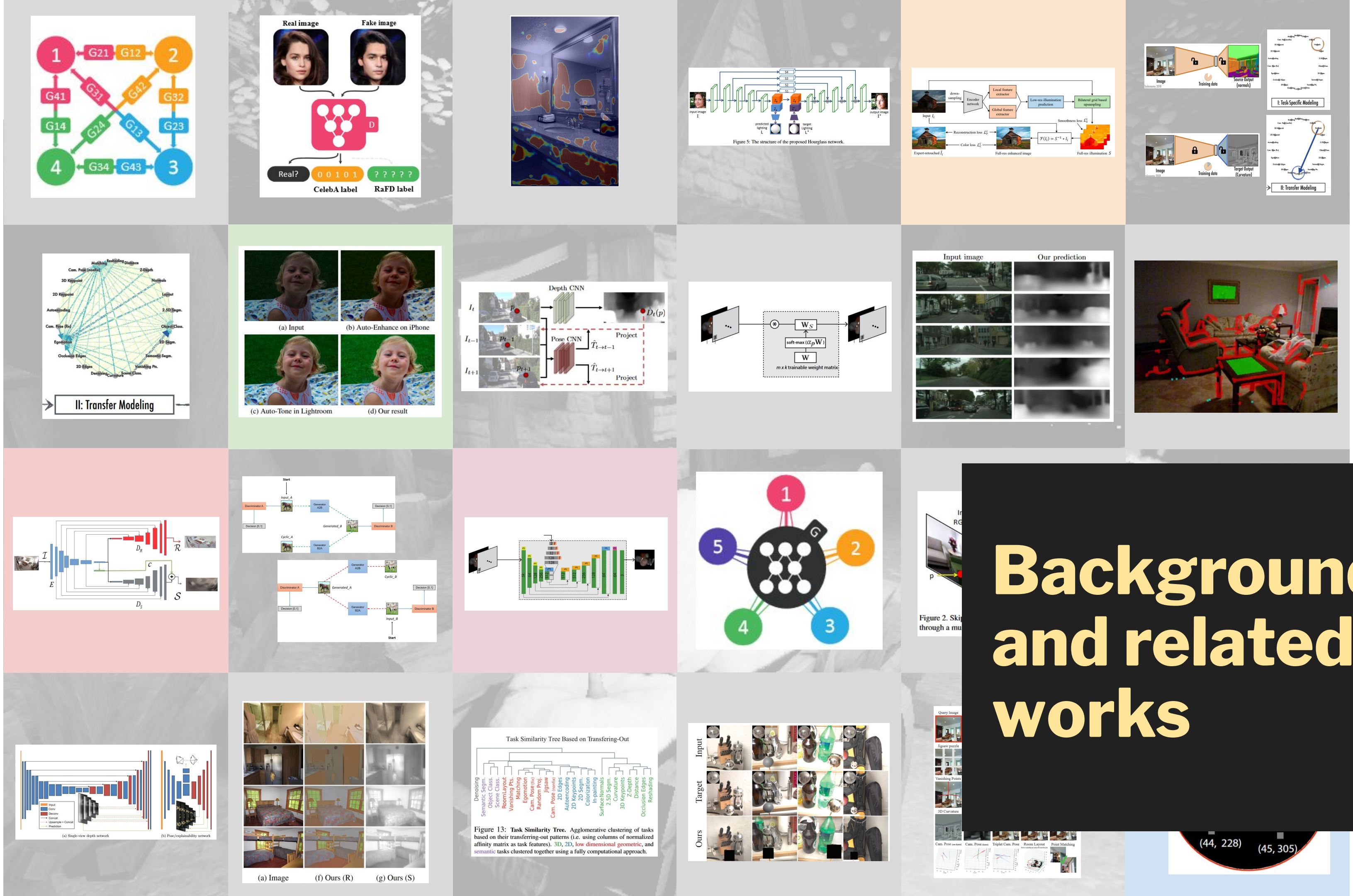
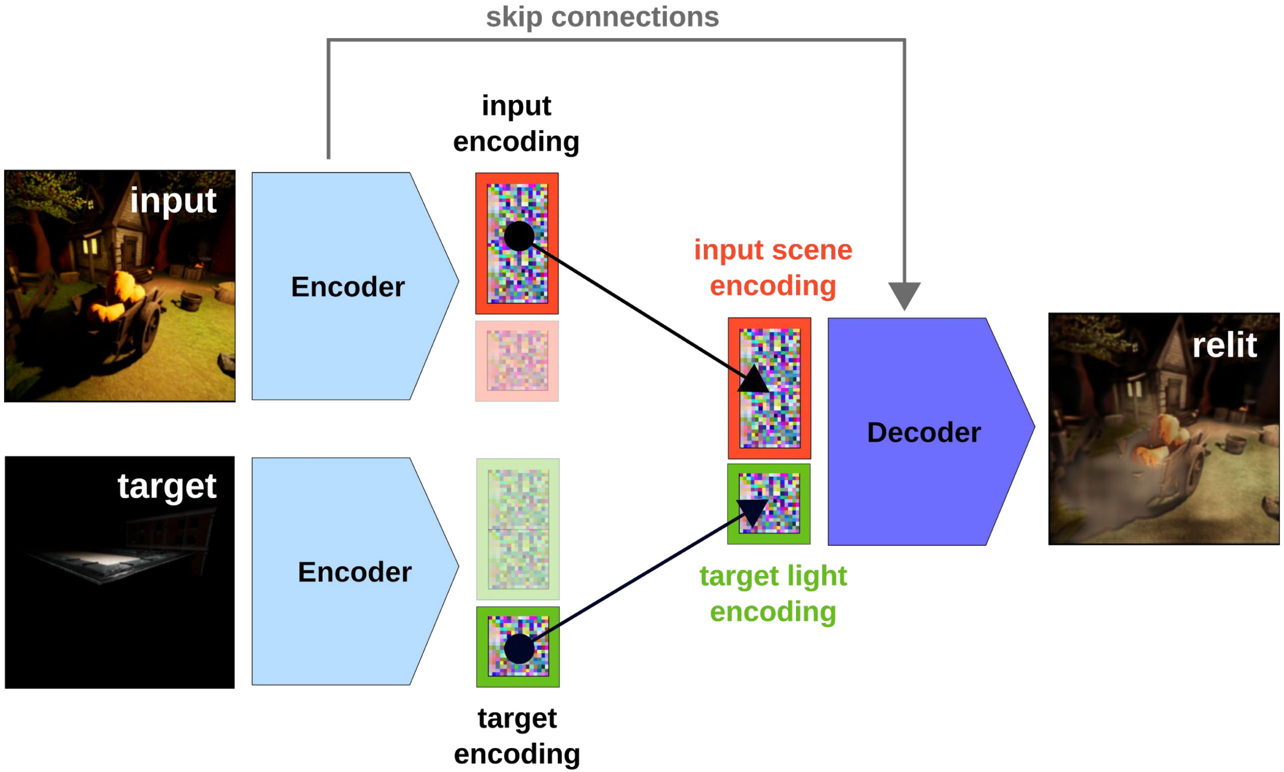


Background and related works

Overall architecture scheme



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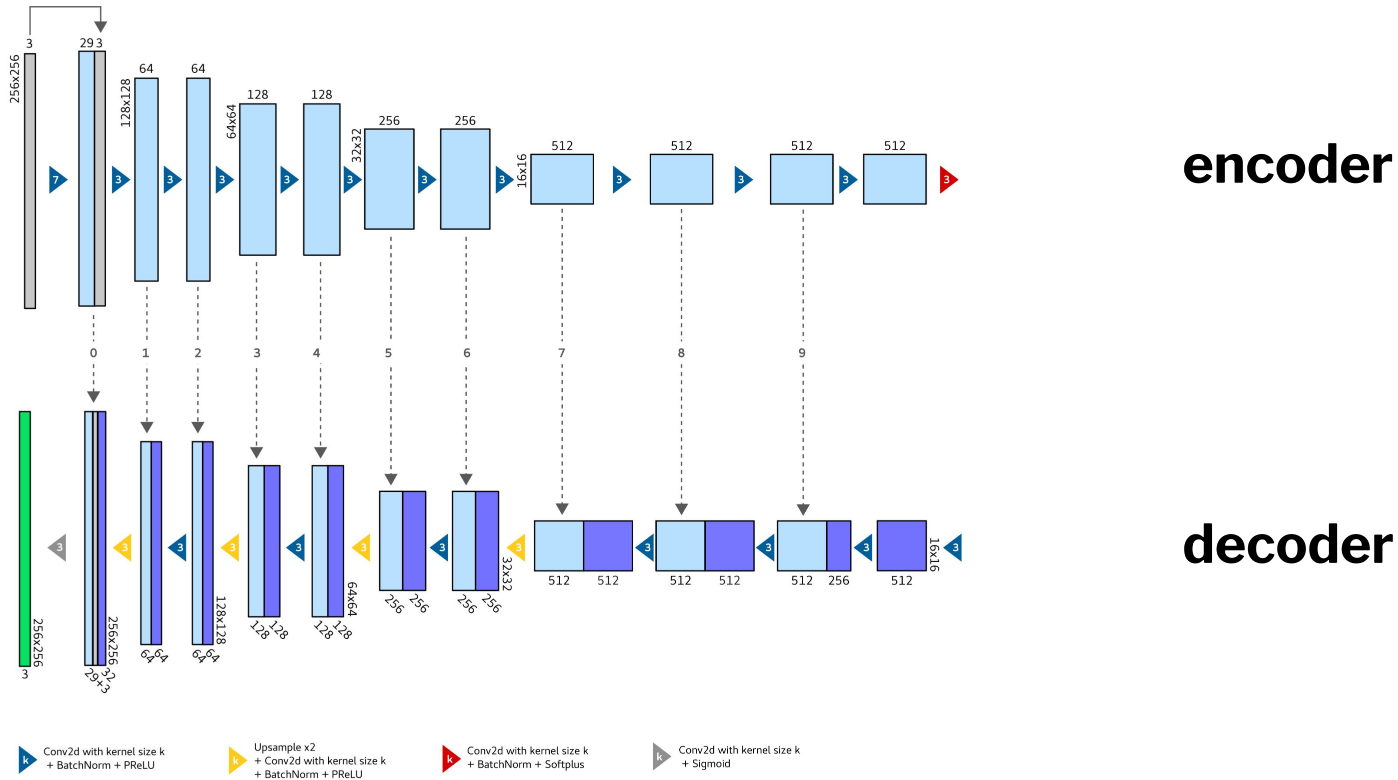
Details of the solution @all



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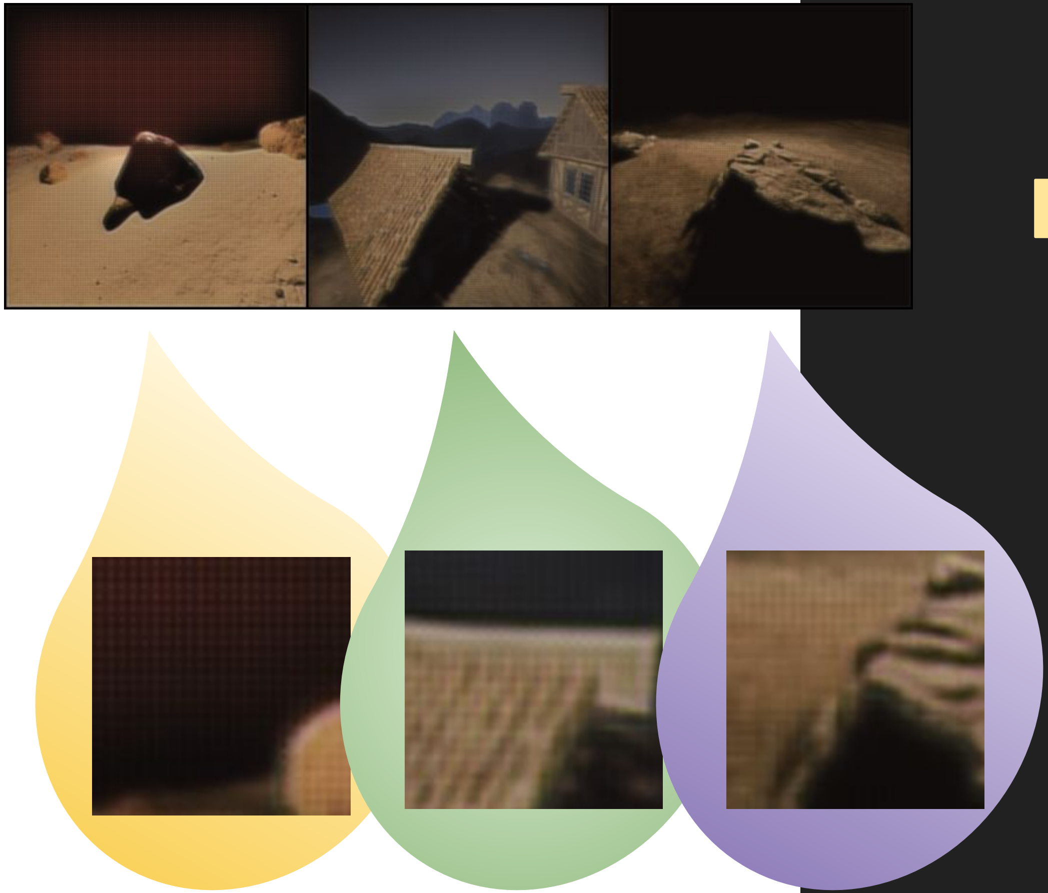
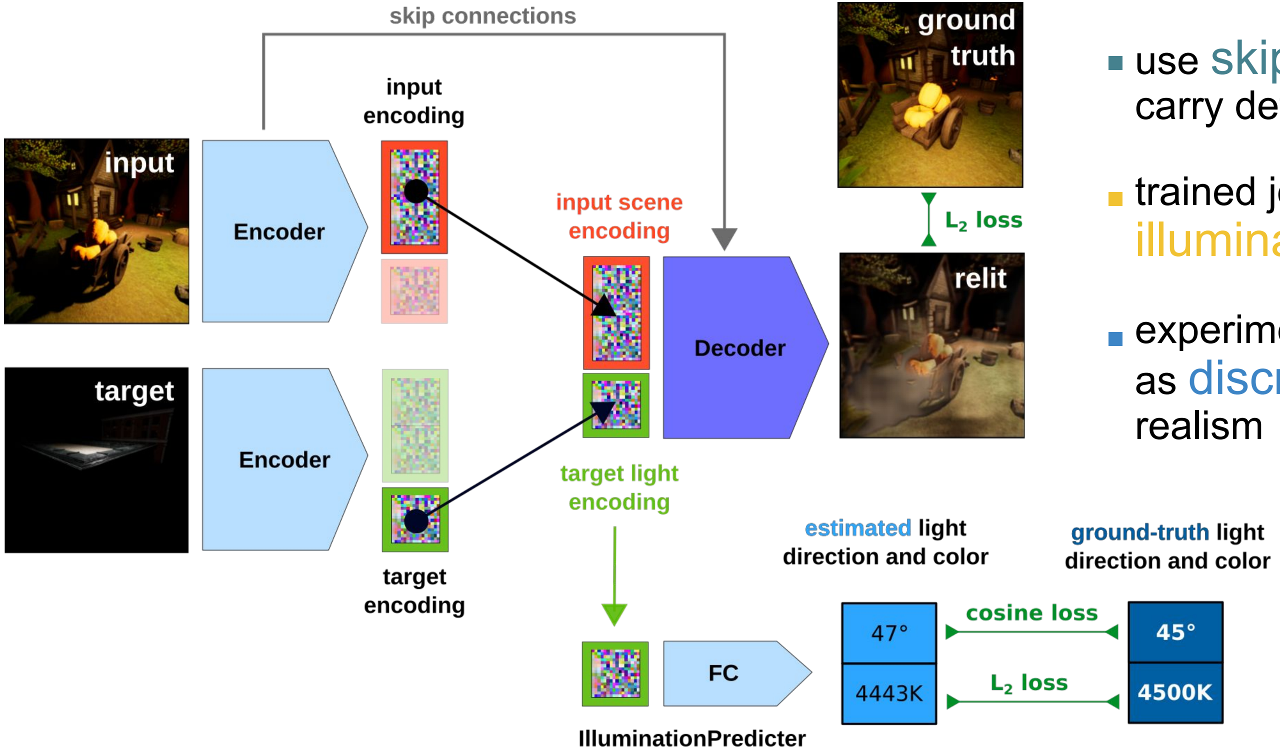


Implementation detail: checkerboard artifacts

Details of the solution @1



- split the latent variable into light and scene
- use skip-links from input to carry details
- trained jointly with an illumination predicter
- experiments with a PatchGAN as discriminator for more realism

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Experimental results @1 (eval w/o discriminator)

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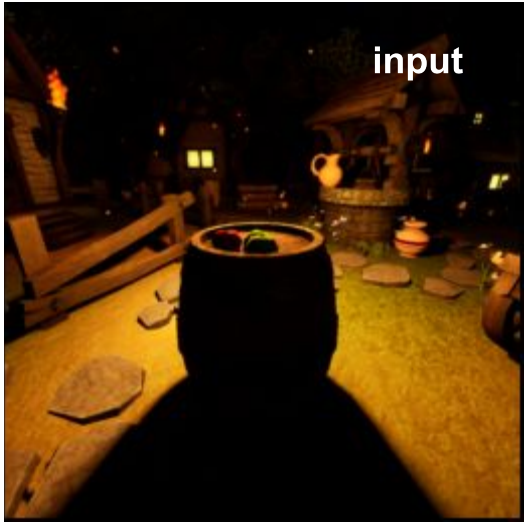

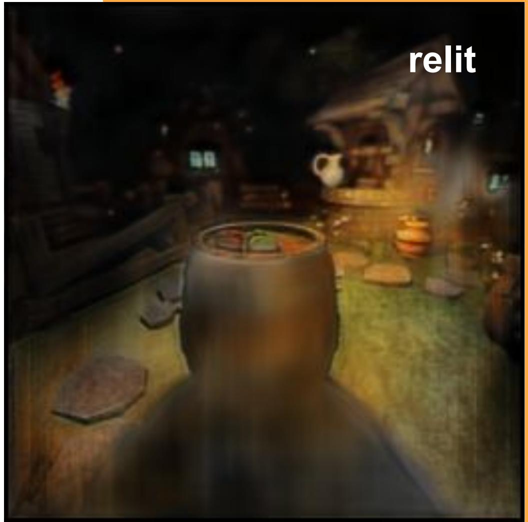

L_2 loss

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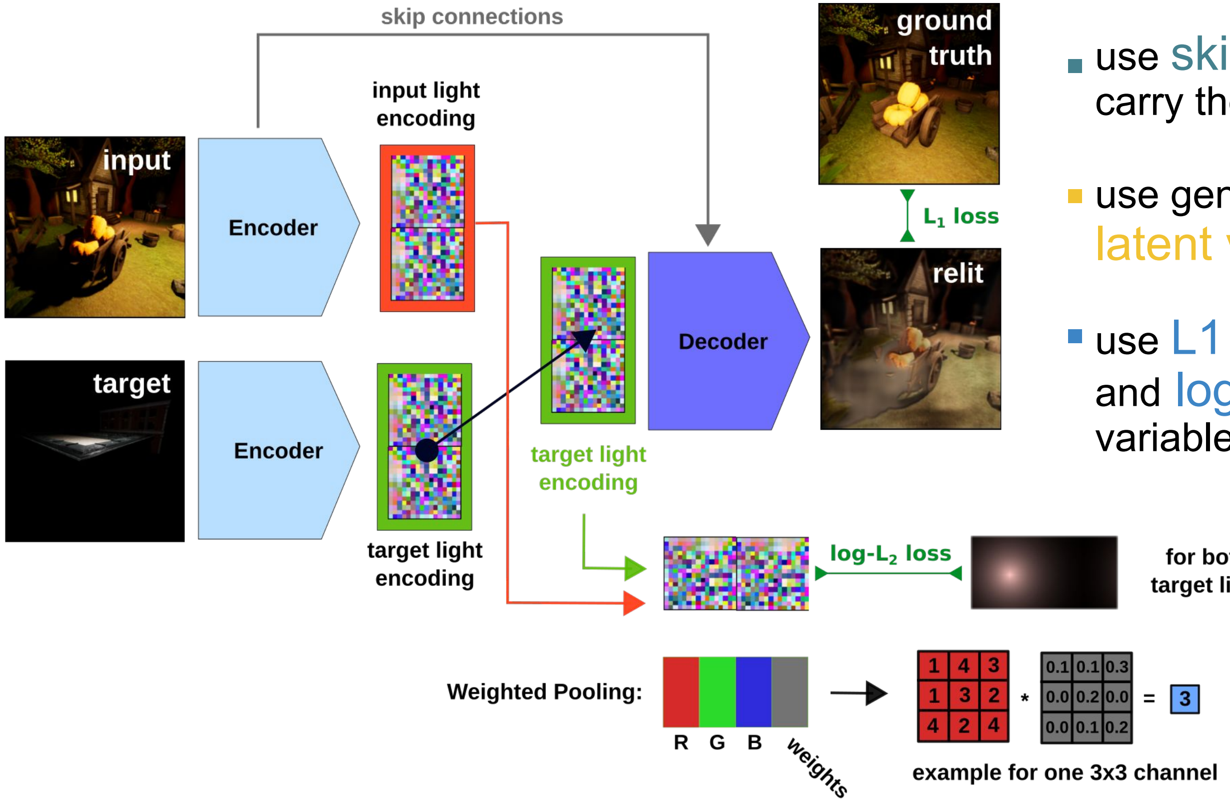
Experimental results @1 (eval w/ discriminator)

L_2 loss

Details of the solution @2



- latent space represents only light conditions
- use skip-links from input to carry the scene information
- use generated ground-truth latent variables
- use L1 reconstruction loss and log-L2 loss for latent variable

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Experimental results @2 (train)

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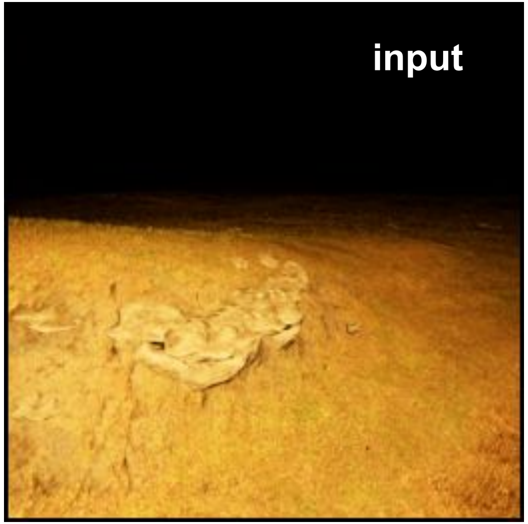

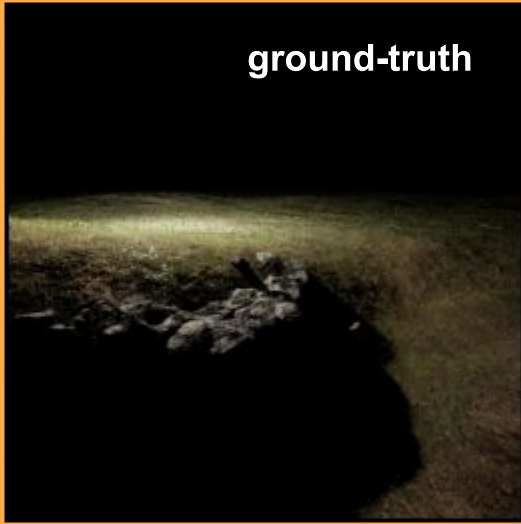

L_1 loss

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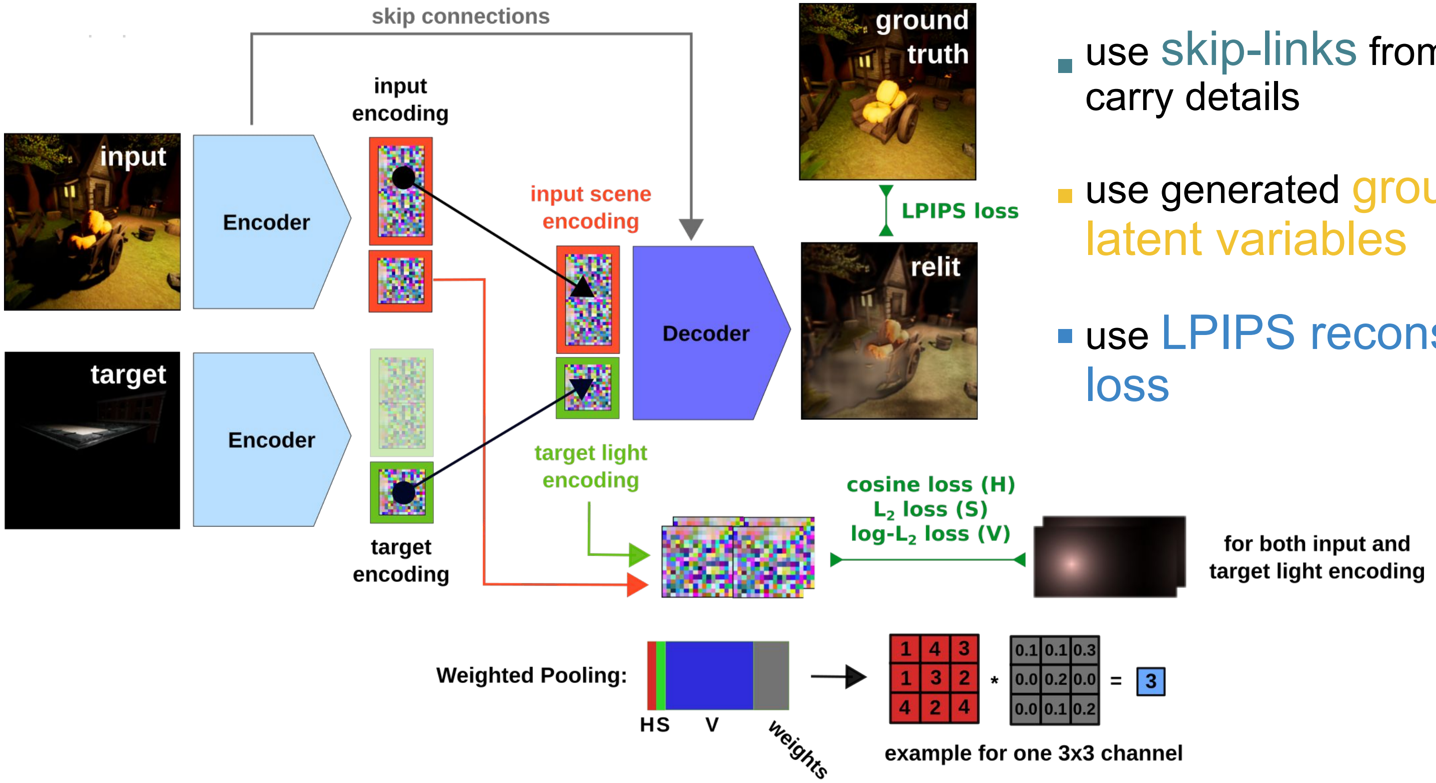
Experimental results @2 (eval)

L_1 loss

Details of the solution @3



- split the latent variable into light and scene
- use skip-links from input to carry details
- use generated ground-truth latent variables
- use LPIPS reconstruction loss

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Experimental results @3 (train)

LPIPS loss

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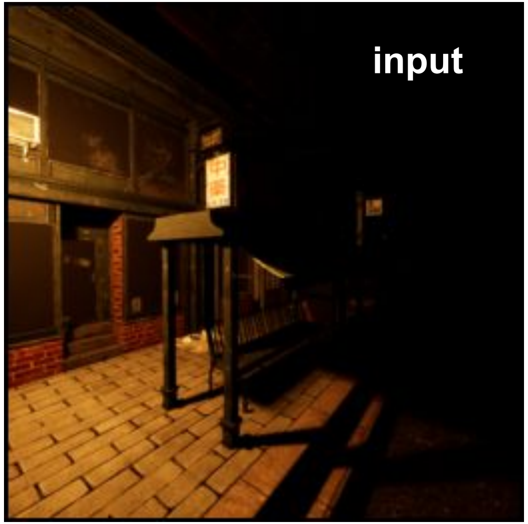
Experimental results @3 (eval)



LPIPS loss

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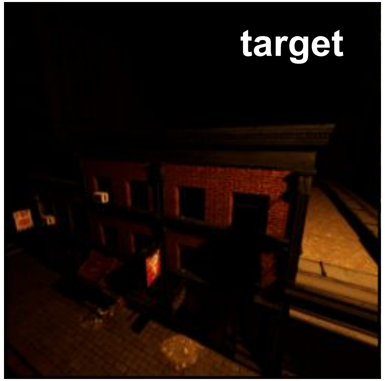
Experimental results @3 (eval)



LPIPS loss

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Experimental results

	@1	@2	@3
Metric name	IlluminationPredicter	Envmap	Envmap + scene
MSE	0.0238	**0.0219**	0.0254
SSIM	**0.3365**	0.1832	0.2988
PSNR	18.11 dB	**18.66** dB	18.10 dB
LPIPS	0.3268	0.2738	**0.2564**

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Pros and cons of the proposed method

- good results compared to identity mapping (relit = input) as well as for estimating light conditions (illumination predicter)
- color temperature much easier to estimate and transfer than light direction
- tendency to remove shadows instead of really change light direction (L_2 loss)
- poor realism

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Conclusion

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- experimenting with more variations: tune the network depth, latent variable size, regularization (as L_2-regularization), loss factors and functions (L_1,L_2, LPIPS, ...)

- for realism, conduct GAN experiments – e.g. use conditional GAN

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Thanks!

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Thanks!

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