

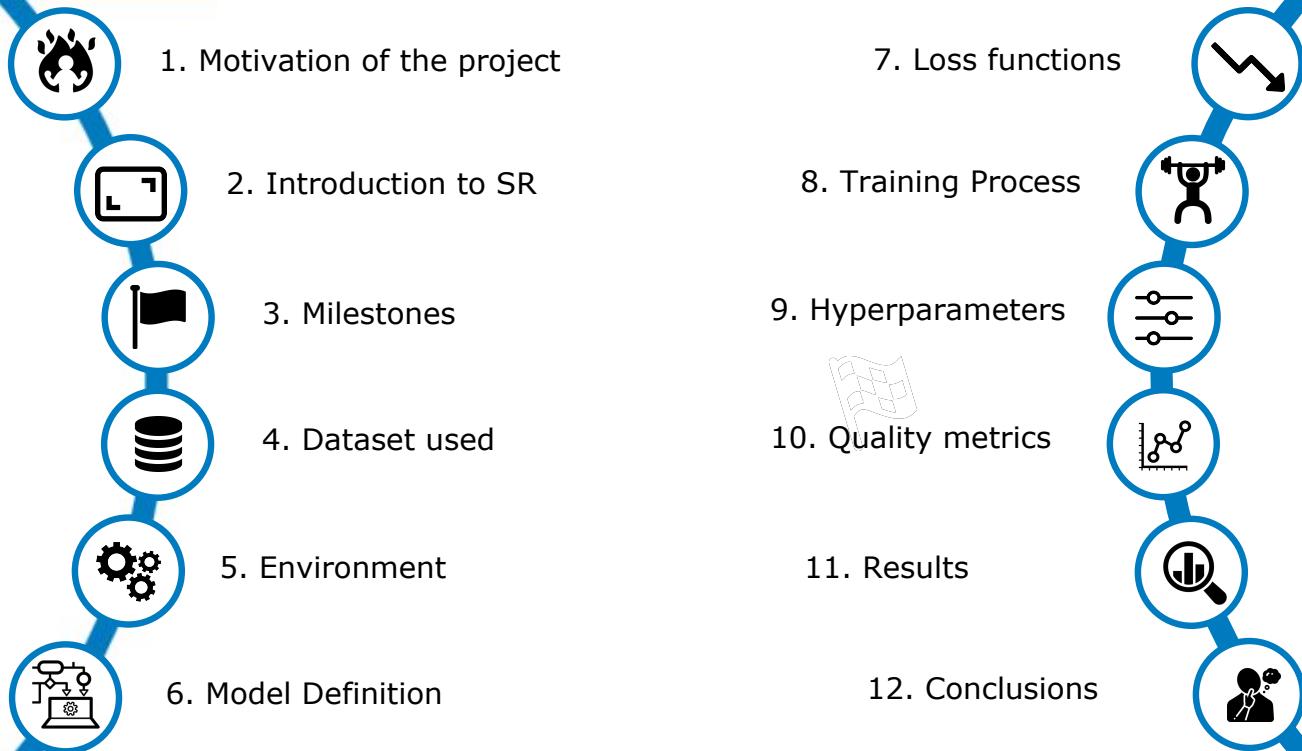
Final REVIEW

# GAN HYPER RESOLUTION

Homepage: <https://github.com/AIDL-PROJ-2022/enhanced-srgan>



# FINAL REVIEW



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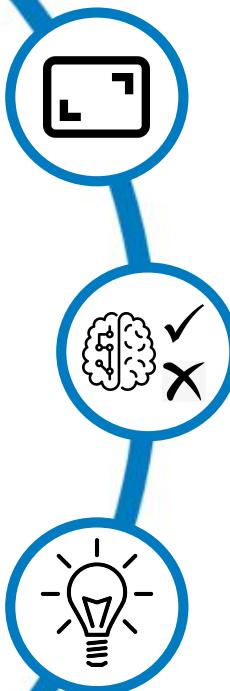
MARC BERMEJO



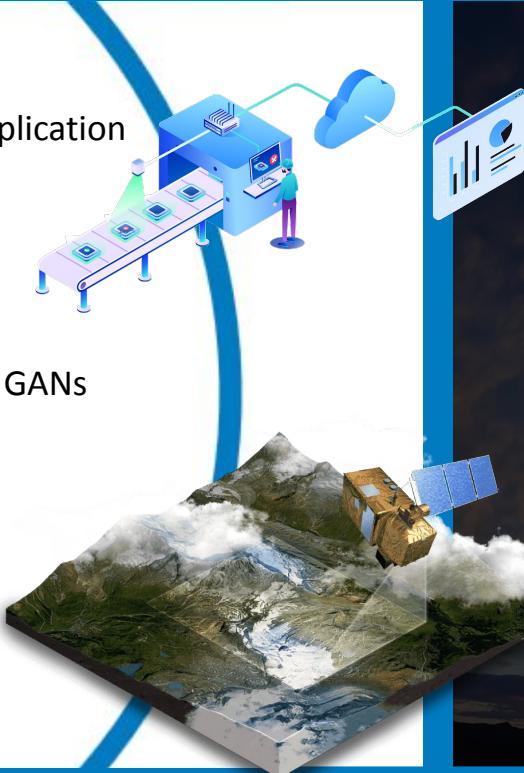
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Super Resolution and its application



Deeper understanding of GANs

Solution at business level

# MOTIVATION OF THE PROJECT



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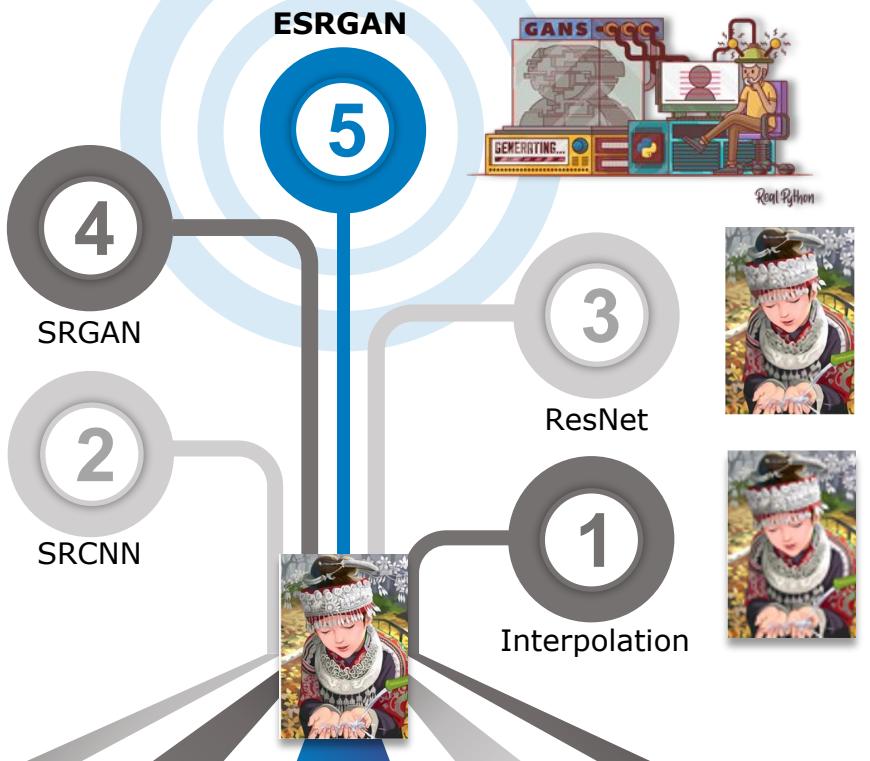
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# INTRODUCTION TO SUPER RESOLUTION

*"The estimation of a **high-resolution (HR)** image from a **single low-resolution (LR) counterpart** is referred to as **super-resolution (SR)**."*



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Project  
Preparation  
(100%)



First Model  
Training  
(100%)



Final project  
Review & conclusions  
(100%)



11/05

24/05

12/06

19/06

10/07



Dataset  
Preparation & Loading  
(100%)



First metrics  
of model training  
(100%)



# PROJECT MILESTONES



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GAN HYPER RESOLUTION PROJECT

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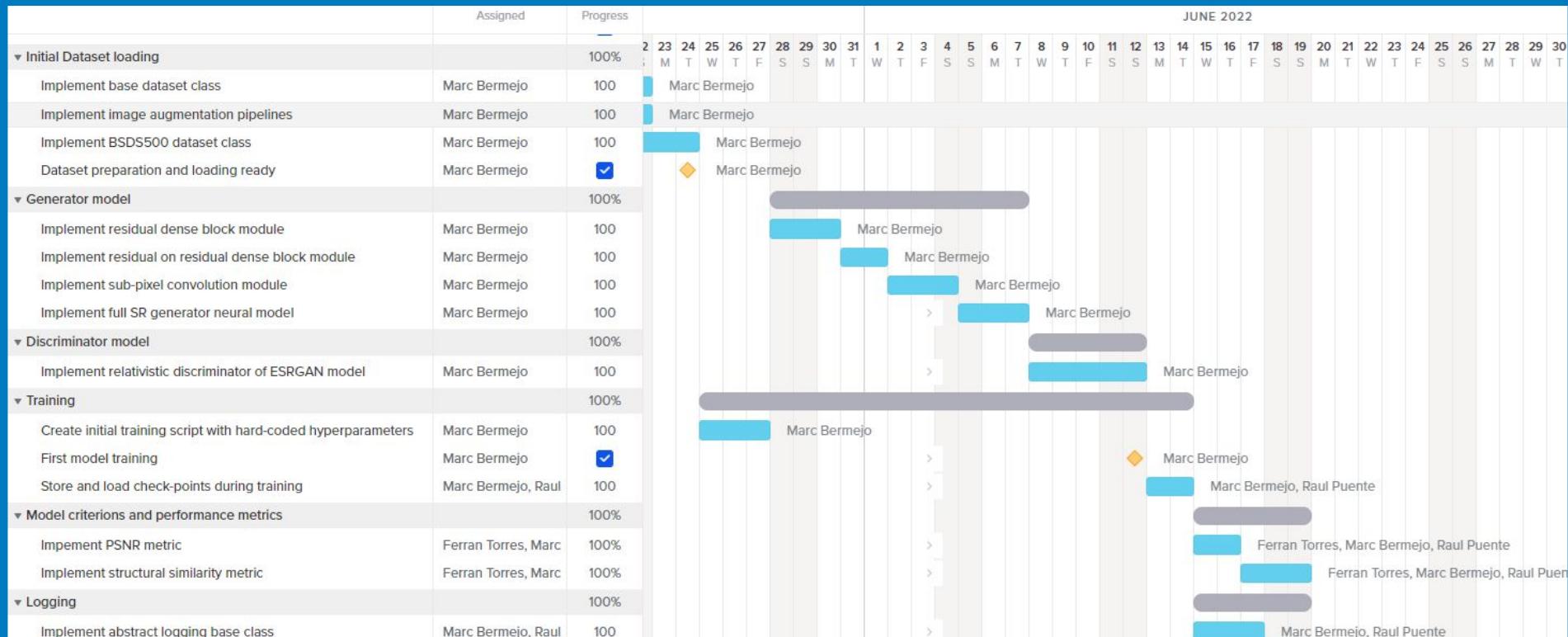
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### GAN HYPER RESOLUTION PROJECT

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GAN HYPER RESOLUTION PROJECT

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## BSDS500



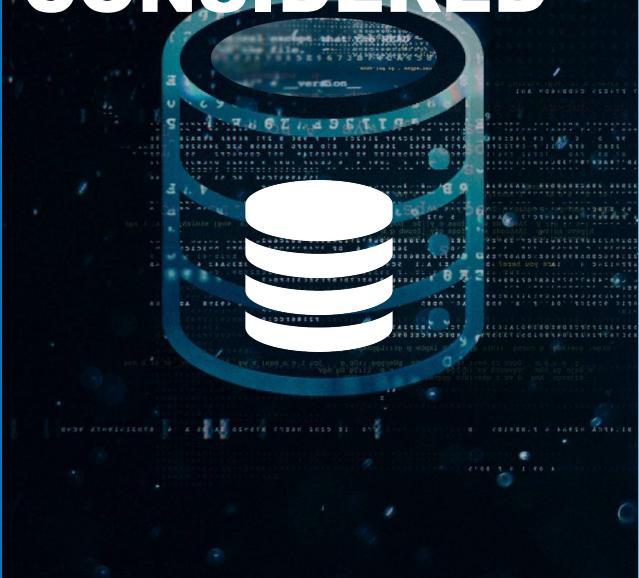
- Standard benchmark for edge and contour detection segmentation.
- Consists of 500 images, each with 5 different ground truth segmentations.
- Contains:
  - 200 images for training.
  - 100 images for validation.
  - 200 images for testing.

## DIV2K



- Recommended for SR given the different types of degradations contained in this dataset.
- Different upscaling and downscaling steps applied to obtain those degradations..
- 1000 images. All with 2K resolution.
- Contains:
  - 800 images for training.
  - 100 images for validation.
  - 100 images for testing

# DATASETS CONSIDERED



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## SET5



- Dataset that consists of 5 images ("baby", "bird", "butterfly", "head", "woman").
- Commonly used for testing performance of Image Super-Resolution models.

## SET14



- Dataset consisting of 14 images.
- Commonly used for testing performance of Image Super-Resolution models.

# DATASETS CONSIDERED



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## Data Visualization / Logging



Local Resources



Development



Google Cloud

# ENVIRONMENT USED



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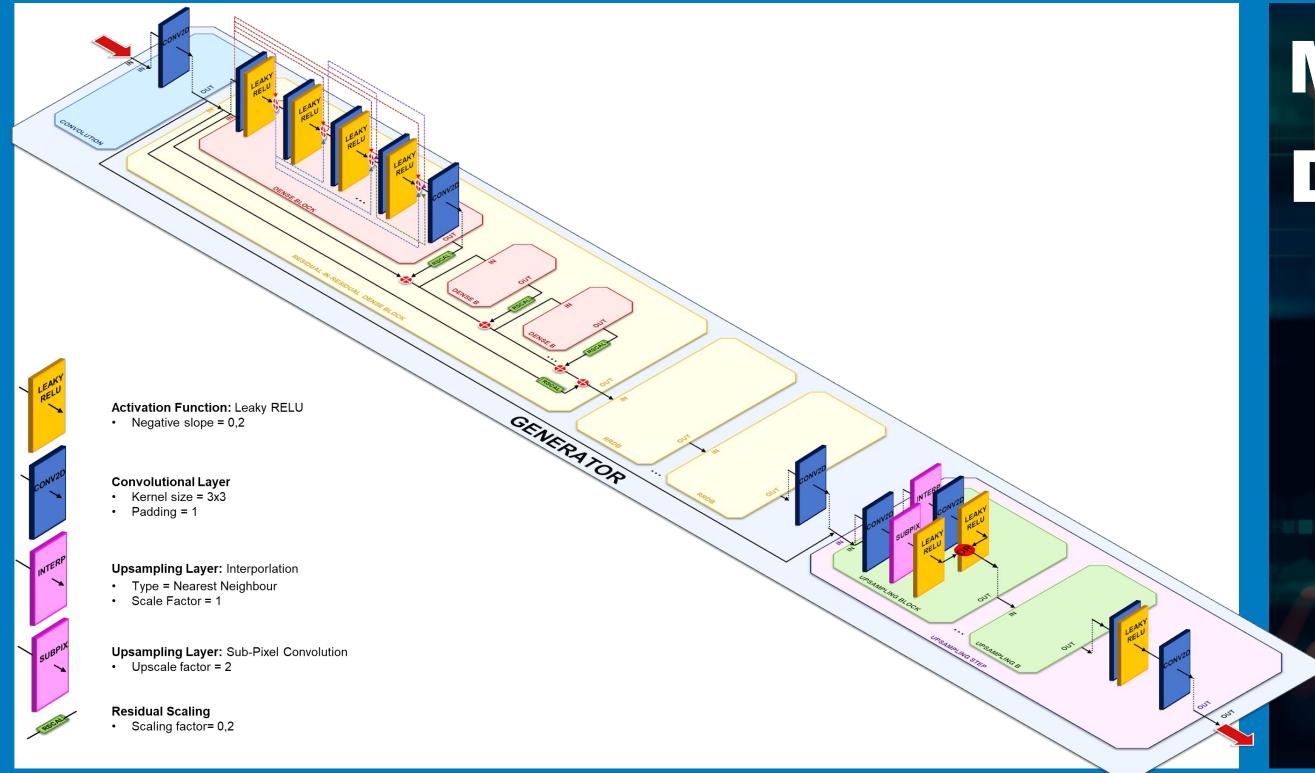
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# MODEL DEFINITION

```
#selection = The entire object, the deselected mirror modifier object
mirror_ob.select
modifier_ob.select
bpy.context.scene.objects.active = modifier_ob
print("Selected", modifier_ob.name) # modifier ob is the active ob
```



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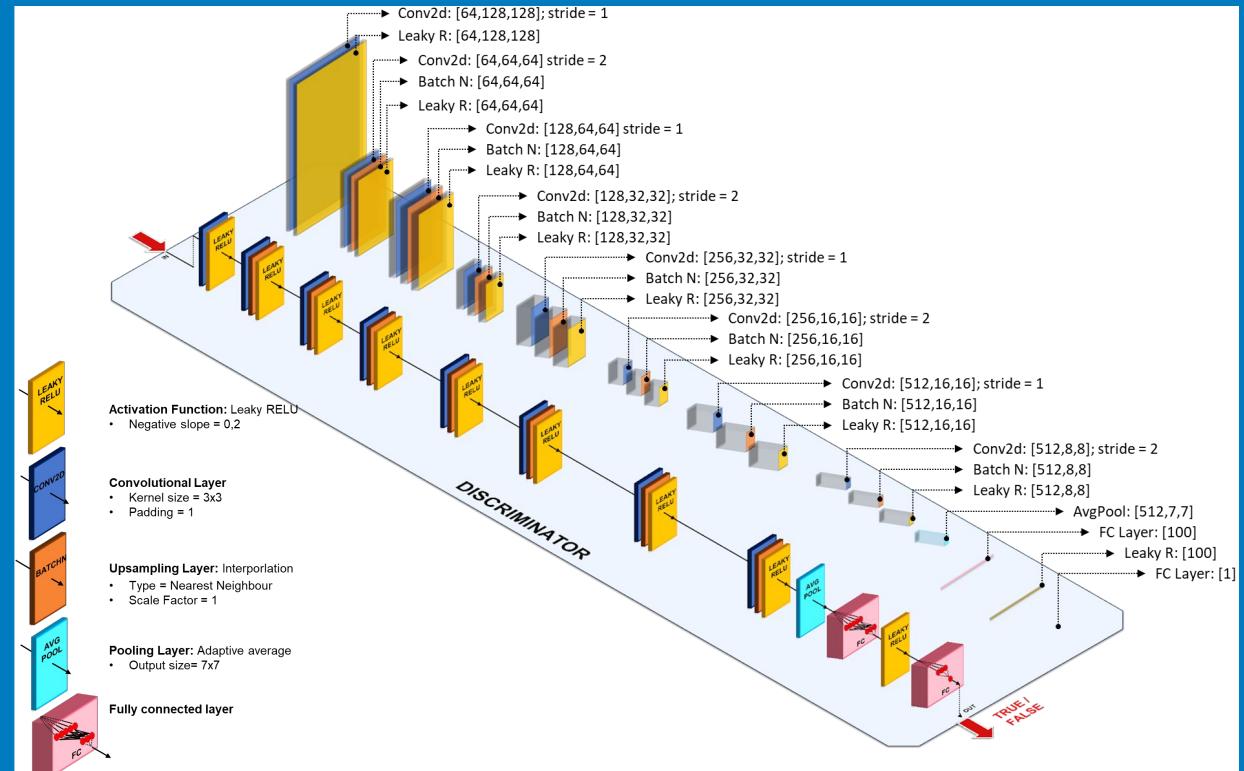
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# MODEL DEFINITION



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## Network Interpolation:

- Used to remove unpleasant noise generated by the GAN maintaining a Good perceptual quality.
- Process followed:
  - Train a PSNR-oriented Generator ( $G_{PSNR}$ ).
  - Fine tune to obtain the GAN-based network  $G_{GAN}$ .
  - Apply interpolation to all the corresponding parameters of the 2 networks to reach a final interpolated model.

### Formula:

$$\theta_G^{\text{INTERP}} = (1 - \alpha) \theta_G^{\text{PSNR}} + \alpha \theta_G^{\text{GAN}}$$

- $\alpha$ = Interpolation parameter

# MODEL DEFINITION



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## Network Interpolation:



# MODEL DEFINITION



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## Content Loss ( $L_{content}$ ):

- Mean error calculated between each pixel from the real image from the generated one.
- Ensures that the activations of higher layers are similar between the Ground Truth and the generated images.
- The project is prepared to work either with L1 (Mean Absolute Error) or L2 (Mean Squared Error) functions. Set to L1 by default.

### Formula:

$$L1LossFunction = \sum_{i=1}^n |y_{true} - y_{predicted}|$$

$$L2LossFunction = \sum_{i=1}^n (y_{true} - y_{predicted})^2$$



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# LOSS FUNCTION



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## Relativistic Adversarial Loss ( $L_D^{Ra}$ , $L_G^{Ra}$ ):

- Error that tries to predict if the real image ( $x_r$ ) is relatively more realistic than the generated one ( $x_f$ ):

$$D_{Ra}(x_r, x_f) = \sigma(C(\text{Real}) - \mathbb{E}[C(\text{Fake})]) \rightarrow 1$$

More realistic  
than fake data?

$$D_{Ra}(x_f, x_r) = \sigma(C(\text{Fake}) - \mathbb{E}[C(\text{Real})]) \rightarrow 0$$

Less realistic  
than real data?

- $\sigma$  = Sigmoid
- $C(x)$  = Non-Transformed discriminator output
- $E_{x_f}[\cdot]$  = Average for all fake data in a minibatch

### Formula:

$$L_D^{Ra} = -E_{x_r}[\log(D_{Ra}(x_r, x_f))] - E_{x_f}[\log(1 - D_{Ra}(x_f, x_r))]$$

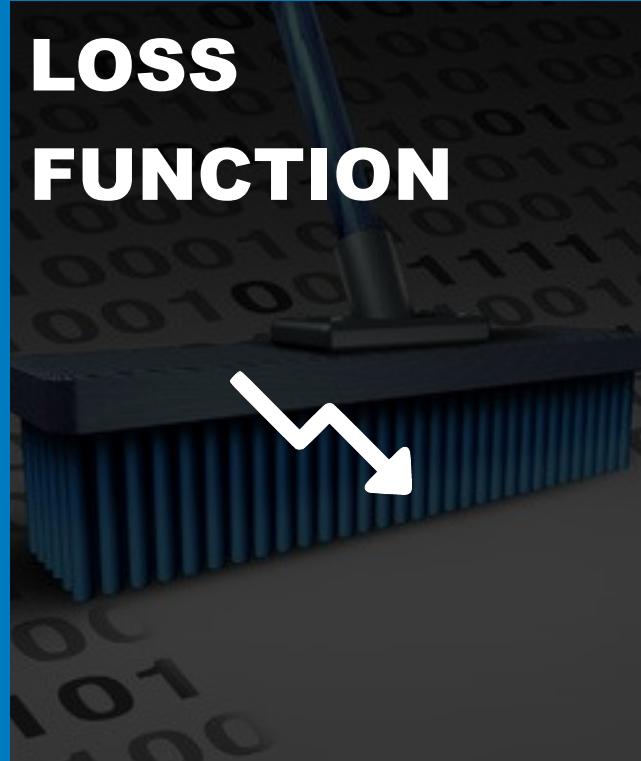
$$L_G^{Ra} = -E_{x_r}[\log(1 - D_{Ra}(x_r, x_f))] - E_{x_f}[\log(D_{Ra}(x_f, x_r))]$$

- $x_f = G(x_r)$
- $x_f$  = LR image



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# LOSS FUNCTION



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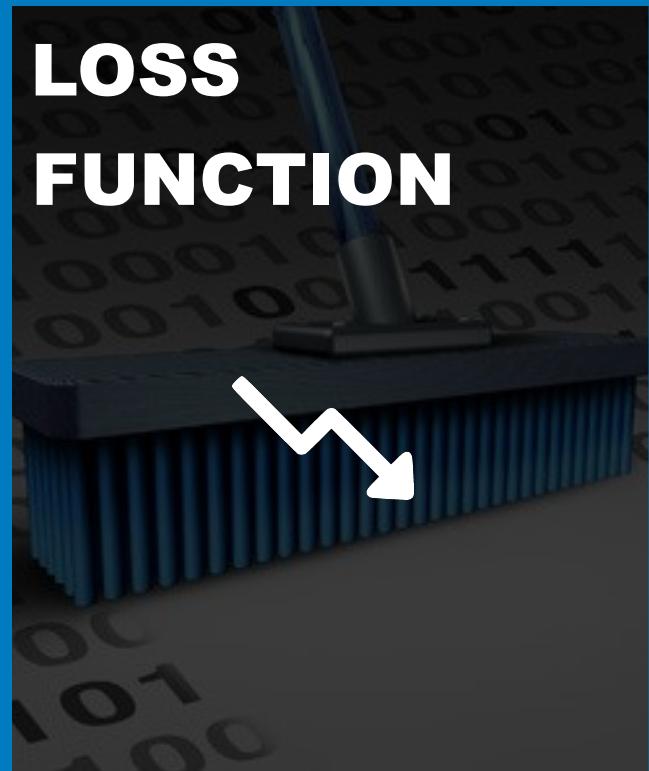


## Perceptual Loss ( $L_{percept}$ ):

- Also known as VGG Loss because this error estimation between both generated and real images is done from a pretrained network (VGG19 in this case).
- Evaluated before last VGG activation layer → Improvement compared to SRGAN.

### Formula:

$$l_{VGG/i,j} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} \left( \phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y} \right)^2$$



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## Total Loss ( $L_G$ ):

- Loss function considered during the training of the complete GAN model (Generator + Discriminator)

### Formula:

$$L_G = L_{percep} + \lambda L_G^{Ra} + \eta L_{content}$$

- $\lambda, \eta$ = weights assigned to each Loss function to balance terms

# LOSS FUNCTION



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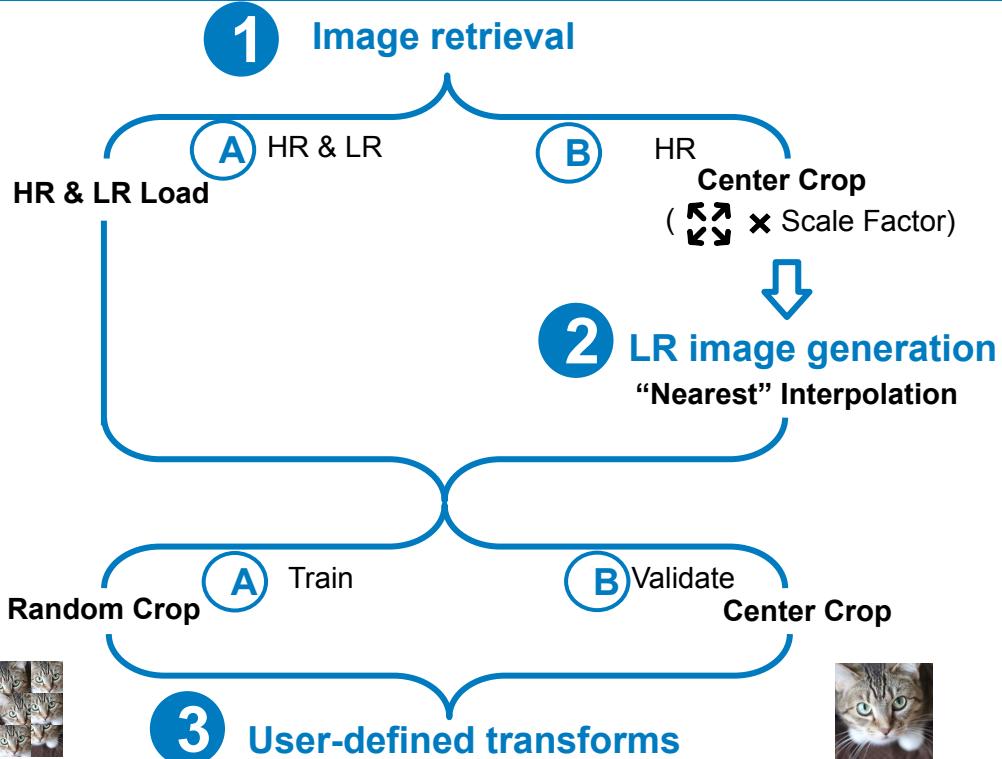
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# TRAINING PROCESS



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### 3 User-defined transforms

#### 4 Warm-Up (Pre-training)

#### 5 Training (Complete GAN)

Hard

Compression

$P=0,25$



Coarse Dropout

$P=0,25$



Spatial

Flip  
 $P=0,25$

OR  
 $P=0,75$

Transpose  
 $P=0,25$



Spatial

Flip  
 $P=0,25$

OR  
 $P=0,75$

Transpose  
 $P=0,75$



# TRAINING PROCESS

1



## DATA AUGMENTATION

A **Albumentations**



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1

2

3

4

5

6

## Image data Augmentation

Training: Paired Random Crop  
 Validation: Paired Center Crop

## Loss Function

Content Loss

## Training process

Generator

## Optimization

Adam Optimizer with Learning rate =  $2e-4$

## Scheduler

Steps applied = 175000 &  $\gamma=0,5$

## Metrics Logging

Pre-training: Content Loss  
 Validation: Content Loss / Perceptual Loss / SSIM / PSNR

# TRAINING STEPS

②



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1

2

3

4

5

6

## Image data Augmentation

Random Crop for Training / Random Center Crop for Validation  
Spatial Transformation

## Loss Function

Content Loss, Perceptual Loss / Generator Adversarial Loss

## Training process

- 1- Generator training for every mini-batch freezing the Discriminator.
- 2- Discriminator training for same mini-batch freezing the Generator.

## Optimization

Adam Optimizer with Learning rate = 1e-4

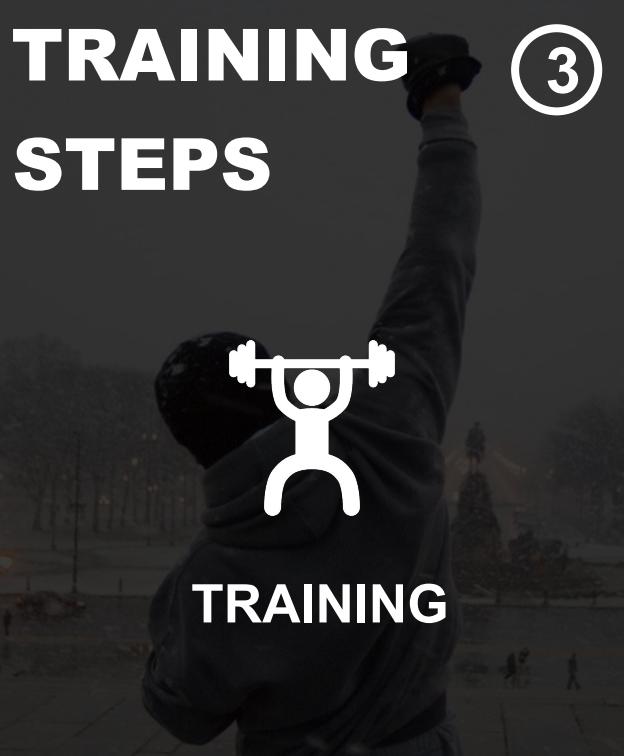
## Scheduler

Steps applied = [50000, 100000, 200000, 300000] &  $\gamma=0,5$

## Metrics Logging

Content Loss, Perceptual Loss / Generator Adversarial Loss / Total Loss/  
Discriminator Adversarial Loss / Perceptual Loss/ PSNR / SSIM

# TRAINING STEPS



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## Hyperparameters

### Description

scale_factor	Scale factor relation between the low resolution and the high resolution images.
batch_size	Data loader configured mini-batch size.
pretraining/num_epoch	Number of epoch needed to complete the pre-training (PSNR-driven) step.
pretraining/cr_patch_size	High-resolution image crop size. Needs to be a tuple of (H, W). If set to None, any crop transform will be applied.
pretraining/lr	Configured learning rate for the pre-training step optimizer. Adam optimizer will be used for this step.
pretraining/sched_step	Learning rate scheduler decay rate for the pre-training step.
pretraining/sched_gamma	Multiplicative factor of the learning rate scheduler decay for the pre-training step.
pretraining/train_datasets	Dataset(s) used during training of the pre-training step. Must be one of 'div2k', 'bsds500'.
pretraining/val_datasets	Dataset(s) used during validation of the pre-training step. Must be one of 'div2k', 'bsds500'.
training/num_epoch	Number of epoch needed to complete the training step.
training/cr_patch_size	Number of epoch needed to complete the pre-training (GAN-driven) step.
training/g_lr	Configured generator's learning rate for the training step optimizer. Adam optimizer will be used for this step.
training/d_lr	Configured discriminator's learning rate for the training step optimizer. Adam optimizer will be used for this step.
training/g_sched_steps	List of mini-batch indices learning rate decay of the generator's training scheduler.
training/g_sched_gamma	Multiplicative factor of the generator's learning rate scheduler decay for the training step.
training/d_sched_steps	List of mini-batch indices learning rate decay of the discriminator's training scheduler.
training/train_datasets	Dataset(s) used during training of the training step. Must be one of 'div2k', 'bsds500'.
training/val_datasets	Dataset(s) used during validation of the training step. Must be one of 'div2k', 'bsds500'.
generator/num_basic_blocks	Number of basic (a.k.a residual-on-residual dense blocks) of the generator network.
training/d_sched_gamma	Multiplicative factor of the discriminator's learning rate scheduler decay for the training step.

# HYPER-PARAMETERS



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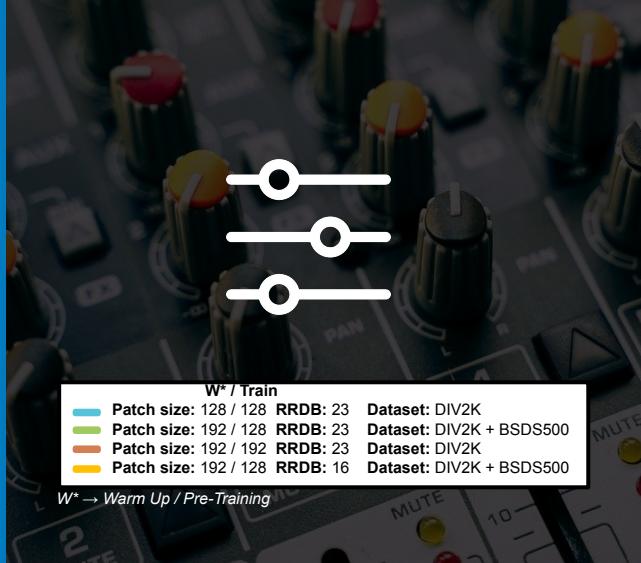
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## Hyperparameters

scale_factor	4	4	4	4
batch_size	16	16	16	16
pretraining/num_epoch	8000	8000	8000	8000
pretraining/cr_patch_size	[192,192]	[128, 128]	[192,192]	[192,192]
pretraining/lr	0,0002	0,0002	0,0002	0,0002
pretraining/sched_step	175000	175000	175000	175000
pretraining/sched_gamma	0.5	0.5	0.5	0.5
pretraining/train_datasets	["div2k"]	["div2k"]	["bsds500", "div2k"]	["bsds500", "div2k"]
pretraining/val_datasets	["div2k"]	["div2k"]	["div2k"]	["div2k"]
training/num_epoch	6000	6000	6000	6000
training/cr_patch_size	[192,192]	[128, 128]	[128, 128]	[128, 128]
training/g_lr	0,0001	0,0001	0,0001	0,0001
training/d_lr	0,0001	0,0001	0,0001	0,0001
training/g_sched_steps	[50000, 100000, 175000, 250000]	[50000, 100000, 175000, 250000]	[50000, 100000, 175000, 250000]	[50000, 100000, 175000, 250000]
training/g_sched_gamma	0.5	0.5	0.5	0.5
training/d_sched_steps	[50000, 100000, 175000, 250000]	[50000, 100000, 175000, 250000]	[50000, 100000, 175000, 250000]	[50000, 100000, 175000, 250000]
training/train_datasets	["div2k"]	["div2k"]	["bsds500", "div2k"]	["bsds500", "div2k"]
training/val_datasets	["div2k"]	["div2k"]	["div2k"]	["div2k"]
generator/num_basic_blocks	23	23	16	23
training/d_sched_gamma	0.5	0.5	0.5	0.5

# HYPER-PARAMETERS



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## Structural Similarity Index(SSIM):

- Given 2 images, SSIM is an index with values in the range (-1,1), which estimates the level of similarity between those two images.
  - +1 = very similar or the same.
  - 1 = very different
- It combines different comparison functions:
  - Luminance  $l(x,y)$ .
  - Contrast  $c(x,y)$
  - Structure  $s(x,y)$

### Formula:

$$\text{SSIM}(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma$$

- $\alpha, \beta, \gamma$ = weights assigned to each feature

# QUALITY METRICS



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## Peak Signal-to-Noise (PSNR):

- Ratio between maximum possible value (power) of a signal and power of distorting noise that affects the quality of its representation.
- Metric used to compare different image enhancement algorithms systematically to evaluate which produces better results using the same dataset.

### Formula:

$$PSNR = 20 \log_{10} \left( \frac{MAX_f}{\sqrt{MSE}} \right)$$

- MSE** = L2 loss
- MAX<sub>f</sub>** = Maximum existing signal value in our original “known to be good” image.

# QUALITY METRICS



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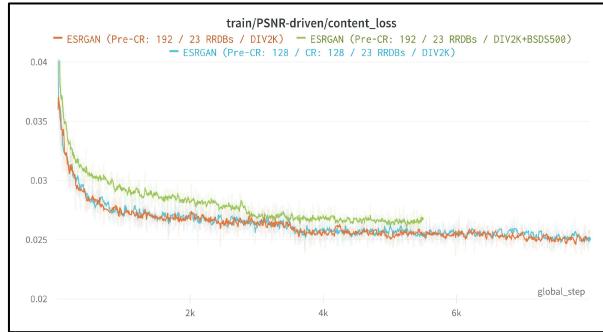
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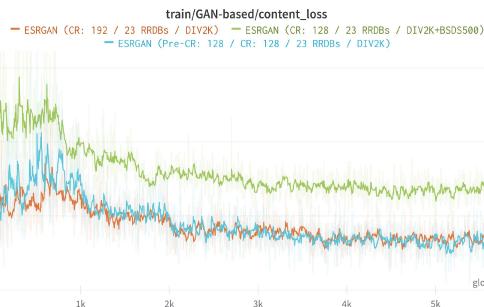
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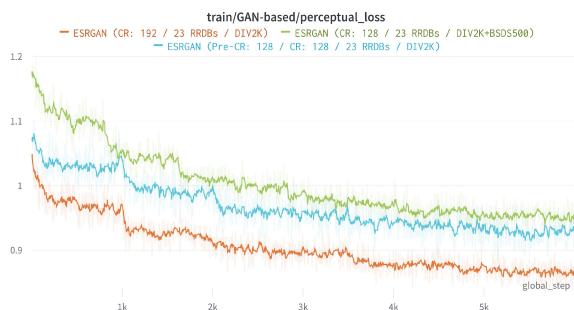
## CONTENT LOSS WARM-UP



## CONTENT LOSS TRAINING



## PERCEPTUAL LOSS TRAINING



# RESULTS FOR DISCUSSION



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## GAN HYPER RESOLUTION PROJECT

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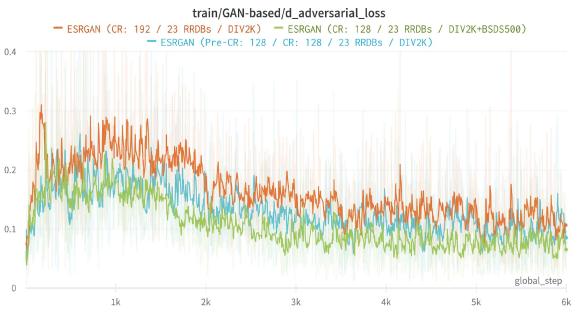
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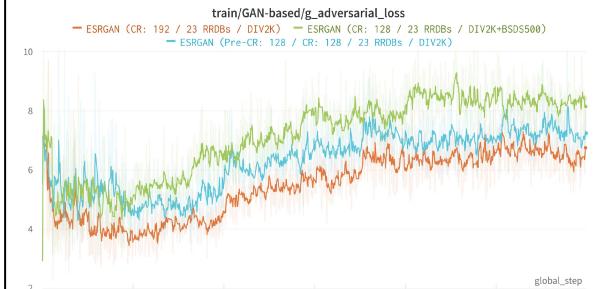
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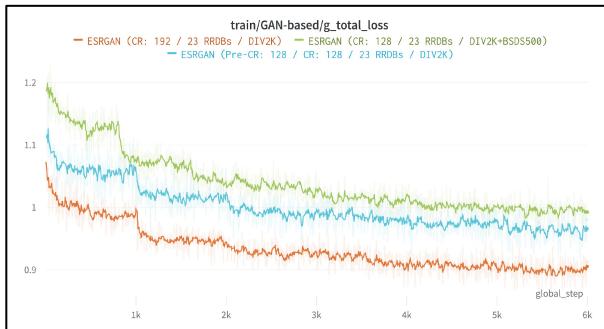
### DISCRIMINATOR ADVERSARIAL LOSS TRAINING



### GENERATOR ADVERSARIAL LOSS TRAINING



### TOTAL LOSS GAN TRAINING



# RESULTS FOR DISCUSSION



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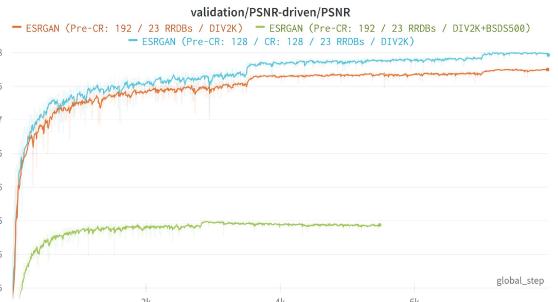
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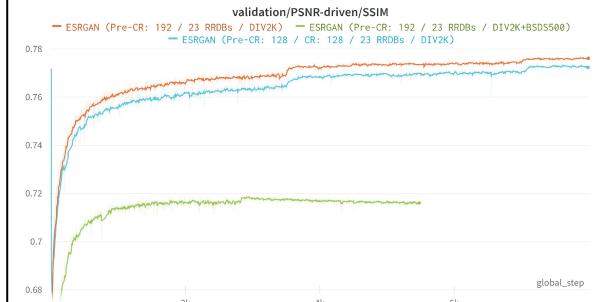
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### PSNR WARM-UP VALIDATION



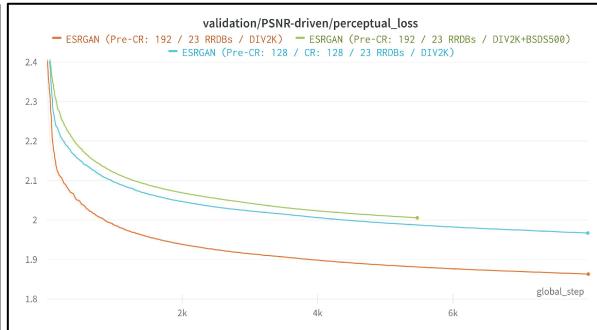
### SSIM WARM-UP VALIDATION



### CONTENT LOSS WARM-UP VALIDATION



### PERCEPTUAL LOSS WARM-UP VALIDATION



# RESULTS FOR DISCUSSION



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### GAN HYPER RESOLUTION PROJECT

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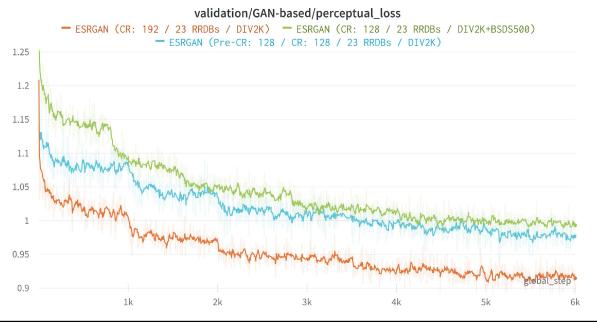
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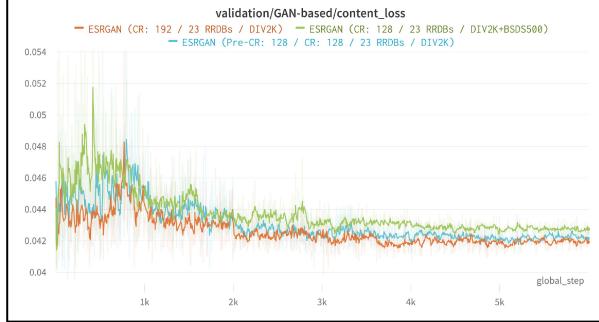
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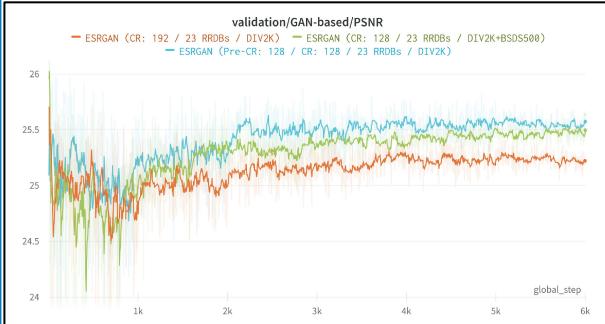
### PERCEPTUAL LOSS GAN VALIDATION



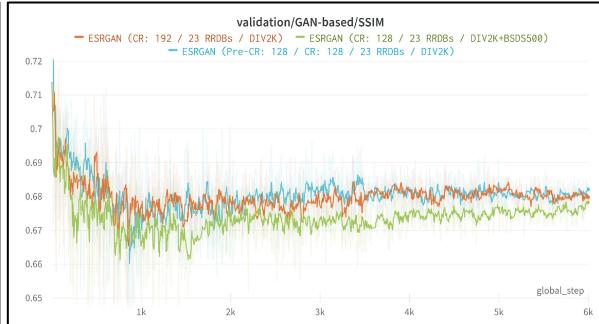
### CONTENT LOSS GAN VALIDATION



### PSNR GAN VALIDATION



### SSIM GAN VALIDATION



# RESULTS FOR DISCUSSION



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### GAN HYPER RESOLUTION PROJECT

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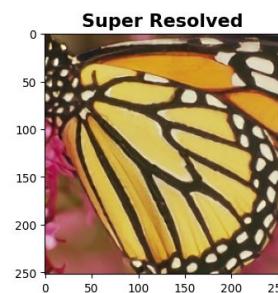
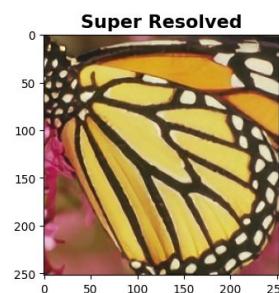
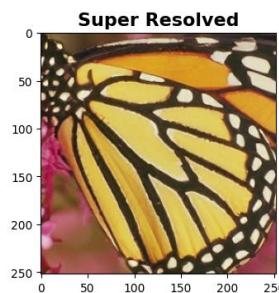
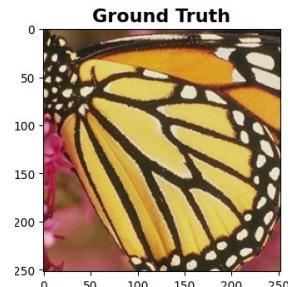
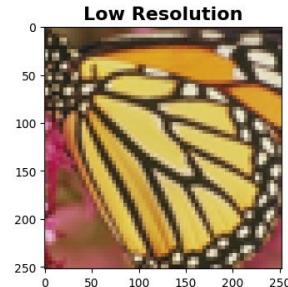
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**PSNR: 25.97db / SSIM: 0.87**

**PSNR: 26.41db / SSIM: 0.88**

**PSNR: 26.11db / SSIM: 0.88**

**PSNR: 25.96db / SSIM: 0.88**

# RESULTS FOR DISCUSSION

**W\* / Train**

Patch size: 128 / 128 RRDB: 23	Dataset: DIV2K
Patch size: 192 / 128 RRDB: 23	Dataset: DIV2K + BSDS500
Patch size: 192 / 192 RRDB: 23	Dataset: DIV2K
Patch size: 192 / 128 RRDB: 16	Dataset: DIV2K + BSDS500

*W\* → Warm Up / Pre-Training*



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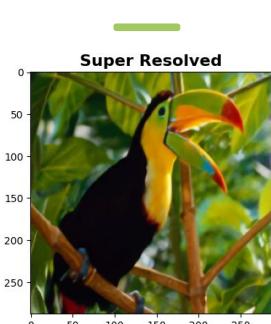
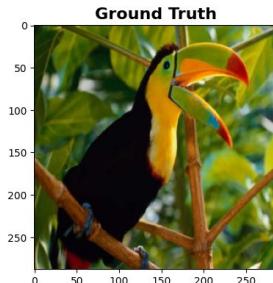
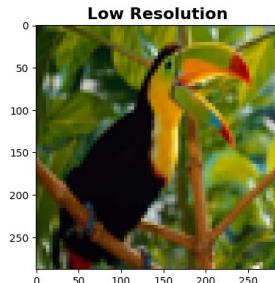
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PSNR: 32.47db / SSIM: 0.9

PSNR: 32.3db / SSIM: 0.9

PSNR: 31.93db / SSIM: 0.9

PSNR: 32.02db / SSIM: 0.9

# RESULTS FOR DISCUSSION

 **W\* / Train**

Patch size: 128 / 128	RRDB: 23	Dataset: DIV2K
Patch size: 192 / 128	RRDB: 23	Dataset: DIV2K + BSDS500
Patch size: 192 / 192	RRDB: 23	Dataset: DIV2K
Patch size: 192 / 128	RRDB: 16	Dataset: DIV2K + BSDS500

*W\* → Warm Up / Pre-Training*

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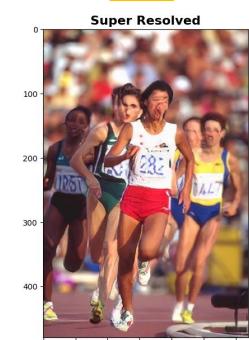
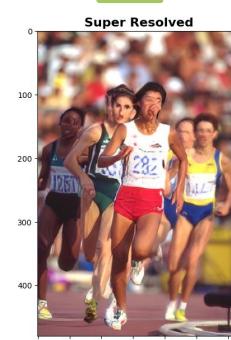
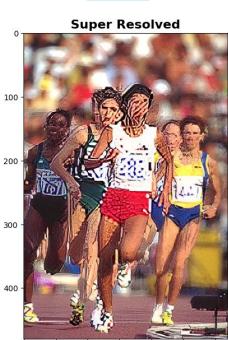
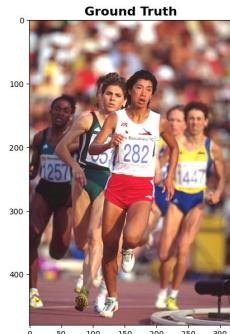
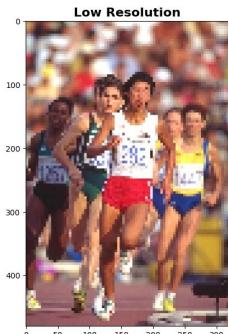
MARC BERMEJO



RAÚL PUENTE



FERRAN TORRES



PROJECT ADVISOR:  
DANI FOJO

#### GAN HYPER RESOLUTION PROJECT

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# RESULTS FOR DISCUSSION

**W\* / Train**

Patch size: 128 / 128 RRDB: 23	Dataset: DIV2K
Patch size: 192 / 128 RRDB: 23	Dataset: DIV2K + BSDS500
Patch size: 192 / 192 RRDB: 23	Dataset: DIV2K
Patch size: 192 / 128 RRDB: 16	Dataset: DIV2K + BSDS500

W\* → Warm Up / Pre-Training



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Model	Datasets	SET5		SET14	
		PSNR	SSIM	PSNR	SSIM
Pre-CR: 128 / CR: 128 / 23 RRDBs	DIV2K	32,47dB	0,9335	31,01dB	0,9749
Pre-CR: 192 / CR: 192 / 23 RRDBs	DIV2K	32,30dB	0,9329	31,20dB	0,9746
Pre-CR: 192 / CR: 128 / 23 RRDBs	DIV2K+BSDS500	31,93dB	0,9266	30,57dB	0,9717
Pre-CR: 192 / CR: 128 / 16 RRDBs	DIV2K+BSDS500	32,01dB	0,9274	30,75dB	0,9730
ESRGAN (Original) - Benchmark	DIV2K	32,73dB	0,9011	28,99dB	0,7917

# RESULTS FOR DISCUSSION



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Training balance between Generator & Discriminator is key.



Network Interpolation reduces noise generated during GAN training. Good perceptual performance is kept.



Deeper models improve recovered textures and reduce unpleasant noise.

# CONCLUSIONS DRAWN



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Broader data helps the generator to generalize but reduces overall performance.



To achieve Good performance for a specific scene type, model needs training with similar scenes firstly.



Datasets with sharper edges (BSDS500) help improving performance with less information and reducing artifacts.



Datasets with sharper edges (BSDS500) have lower overall performance for easier images.

# CONCLUSIONS DRAWN



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# THANK YOU!

