

An aerial photograph of the ETH Zurich campus, showing a mix of historic stone buildings and modern glass-fronted structures. A prominent feature is a large, circular building with a dark dome. In the background, a river flows through the city, and a bridge is visible. The foreground shows a courtyard area with a yellow construction crane. A large blue rectangular box is overlaid on the left side of the image, containing white text.

Controlling Rate, Distortion, and Realism: Towards a Single Comprehensive Neural Image Compression Model

Zixuan Chen

Mentor: Till Aczel

Seminar in Deep Neural Networks

26.03.2024, ETH Zurich



Introduction: Image Compression

Usage: image storage and transmission



8.9M



68.34K

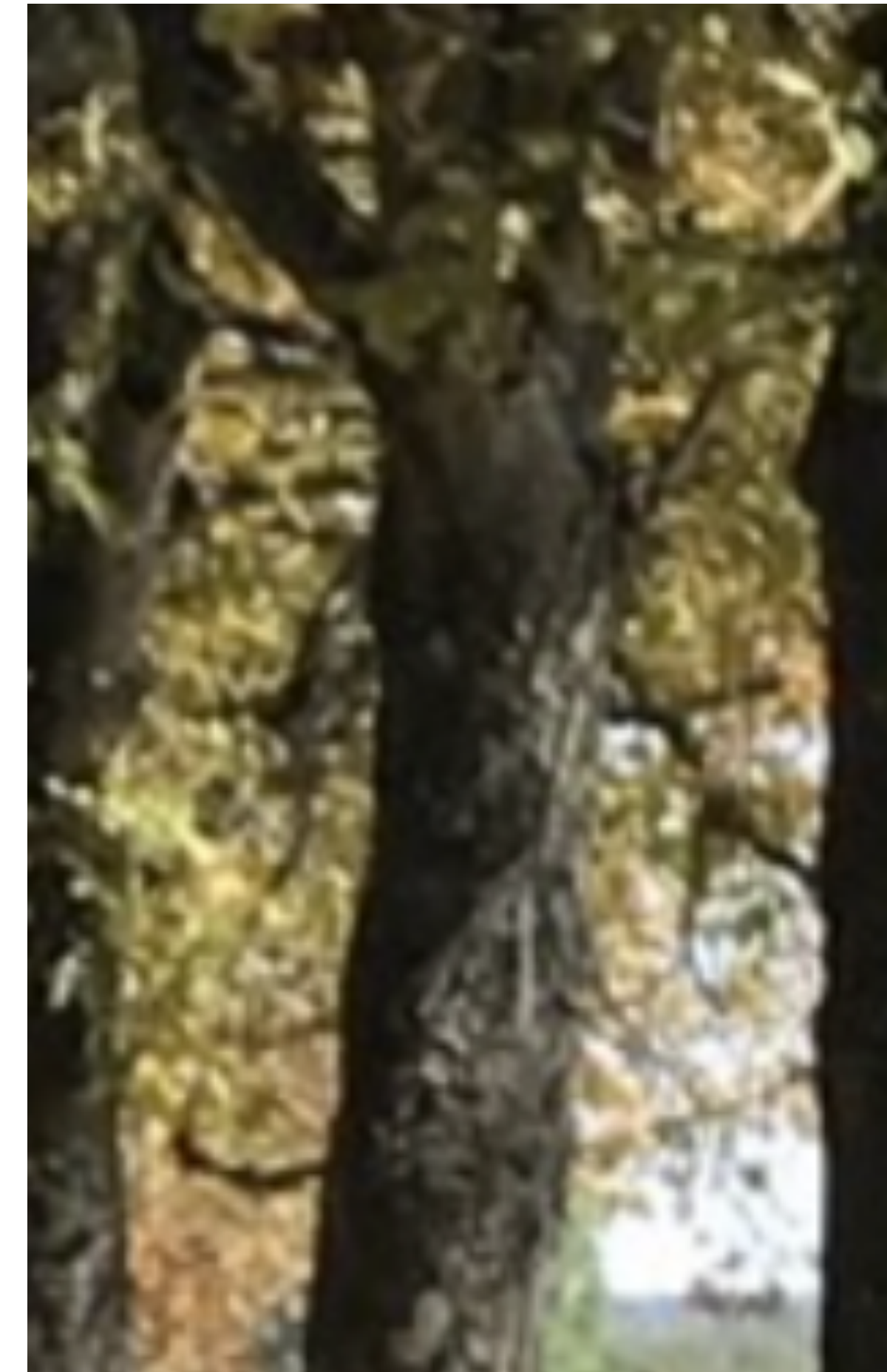


From <https://helpx.adobe.com/au/lightroom-classic/lightroom-key-concepts/compression.html>

**Three main indicators:
Rate, distortion, and realism**

Guess and discuss

Which two are of the same bit rate?
Which one maintains the most details?

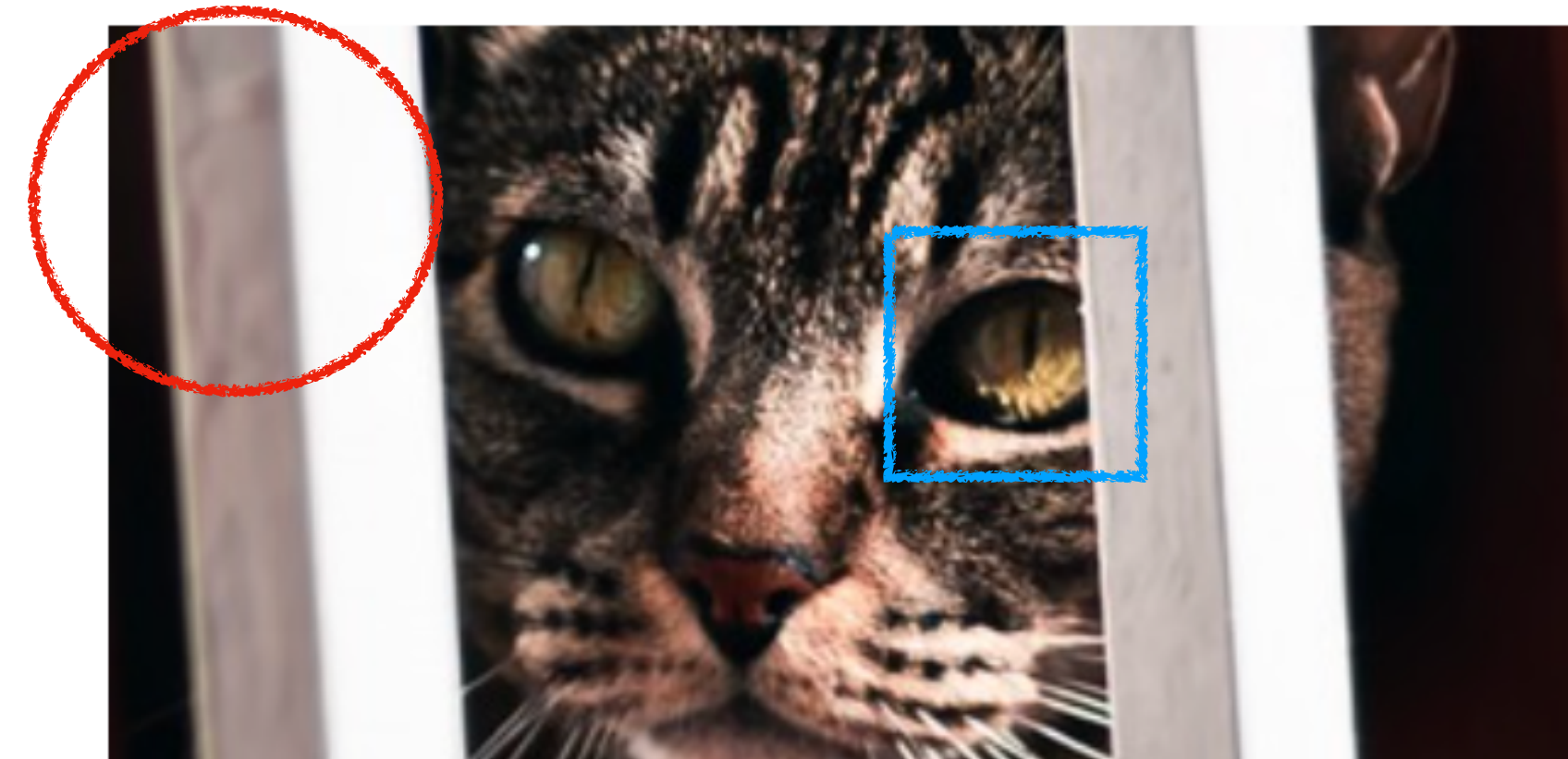
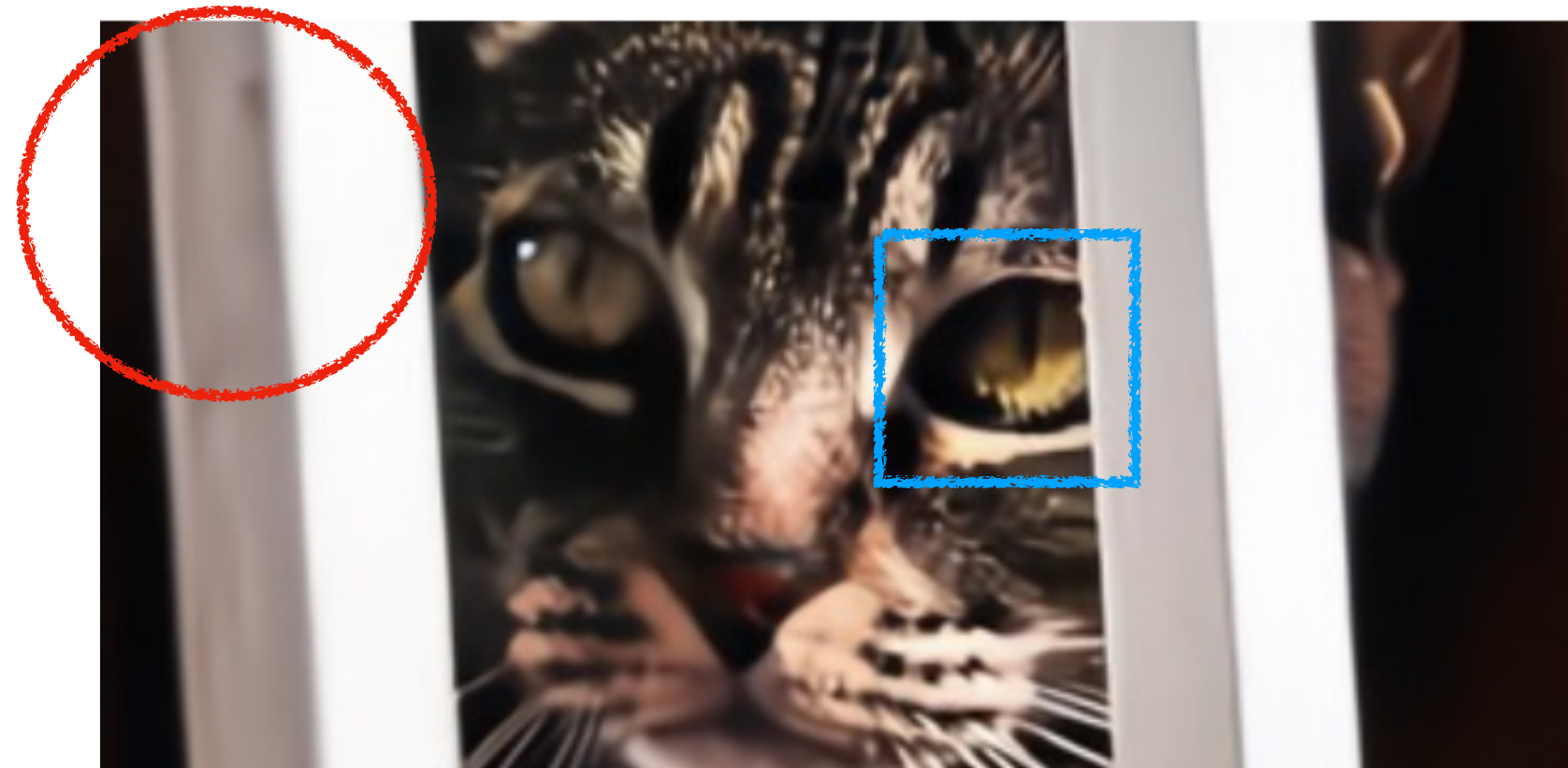
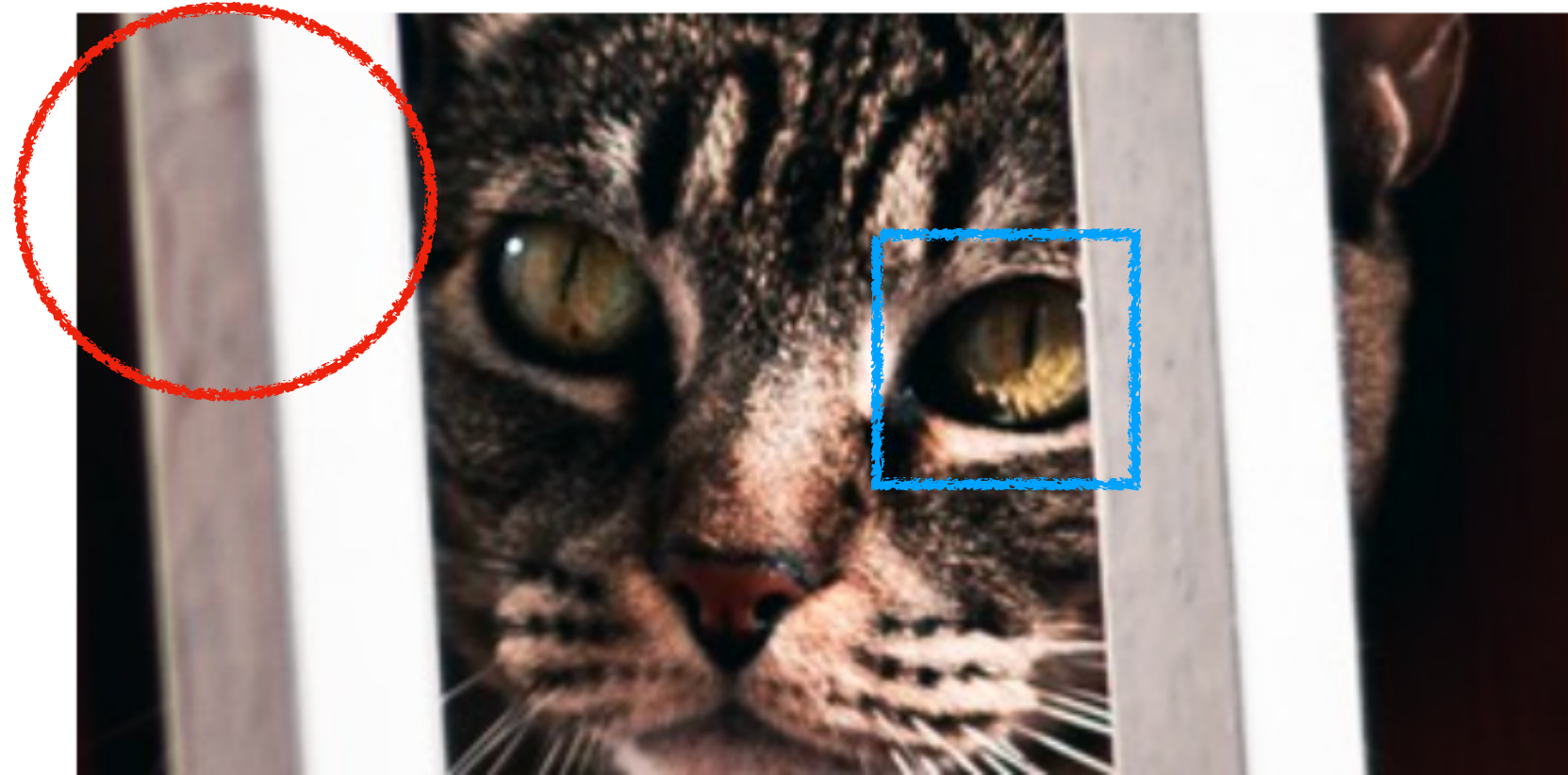


original

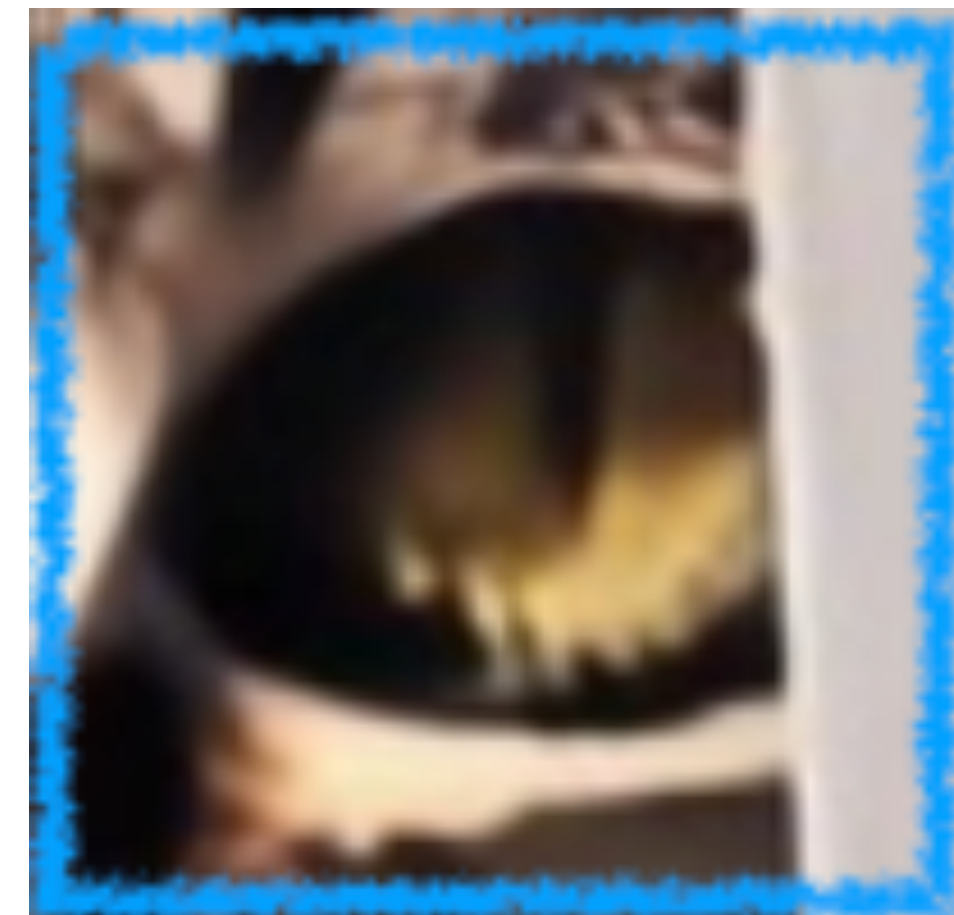
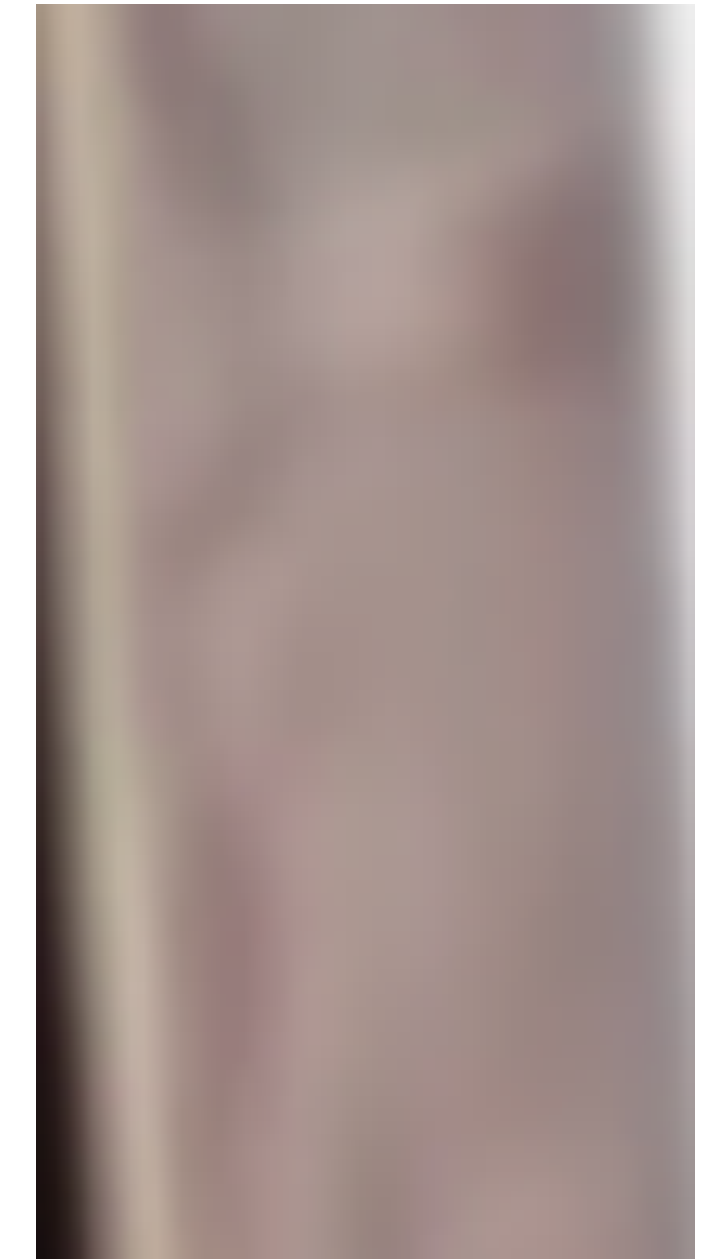
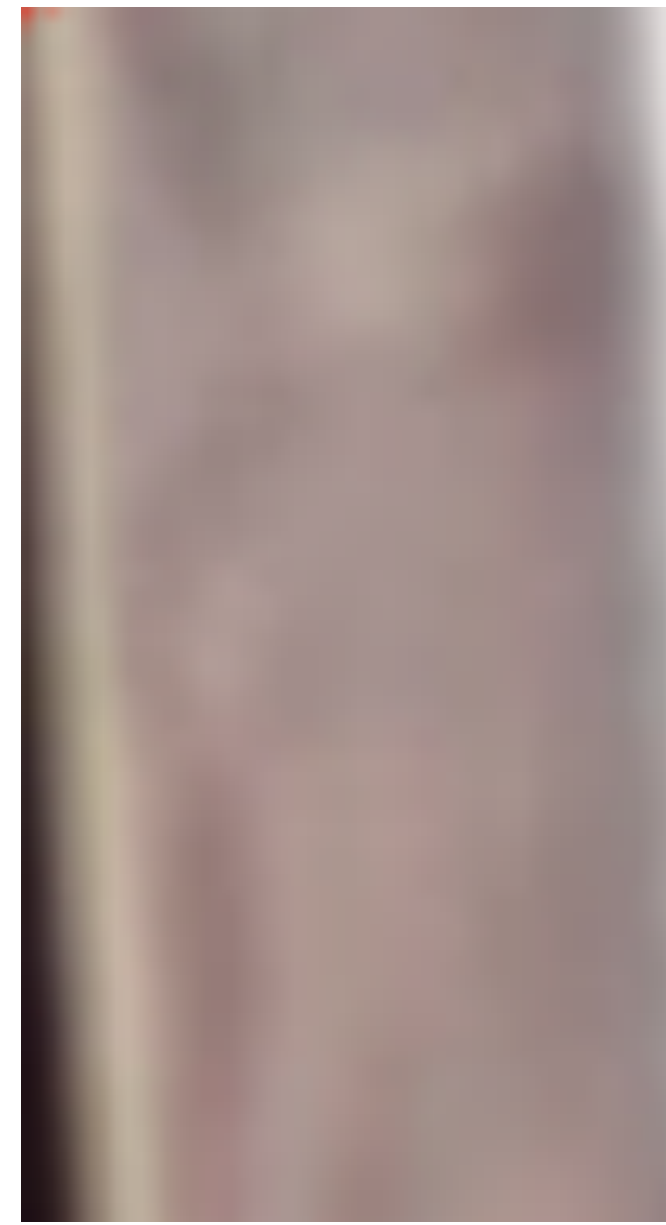
From Iwai et al. [*thisp]

Bit-rate: BPP(bits per pixel)

original



Bit-rate



origin

low rate

high rate

Measurements of Distortion

$$MSE(f, g) := \frac{1}{|V|} \int_V |f(x) - g(x)|^2 dx \quad (\text{Mean Squared Error}),$$

$$PSNR(f, g) := 10 \log_{10} \left(\frac{m^2}{MSE(f, g)} \right) \quad (\text{Peak Signal to Noise Ratio})$$

V: a rectangular region of the image

f, g: images

m: the maximum possible pixel value of the image

Distortion

lower distortion = **closer** to the original image



PSNR = 40 dB



PSNR = 30 dB



PSNR = 20 dB

Realism \neq distortion



GT



Contrast-stretched



Mean-shifted



JPEG-compressed



Blurred



Salt-pepper noise

From Wang, et al. [*sameMSE]

Measurements of Realism

1. FID

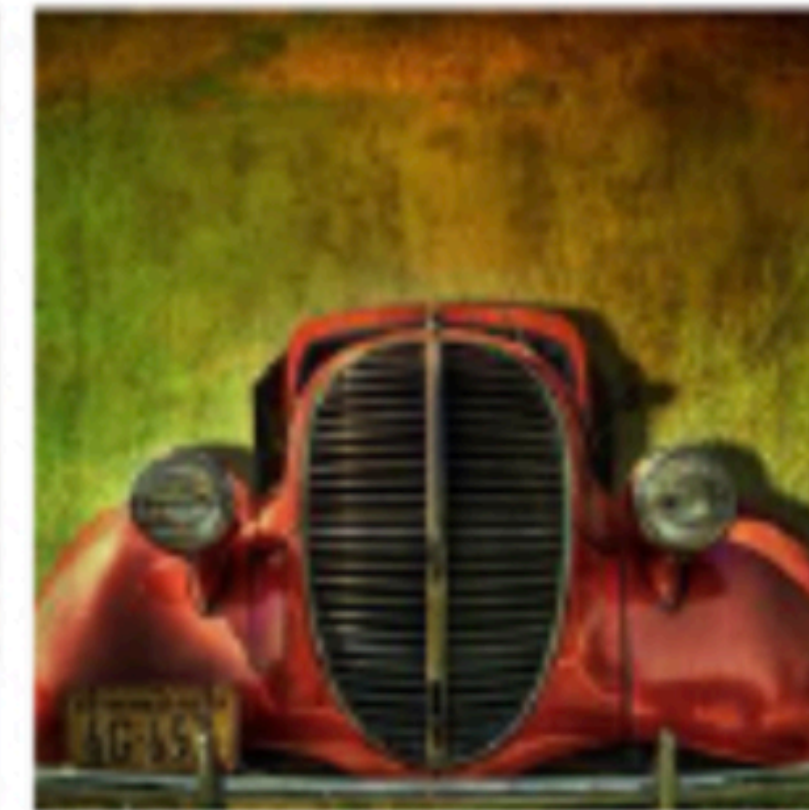
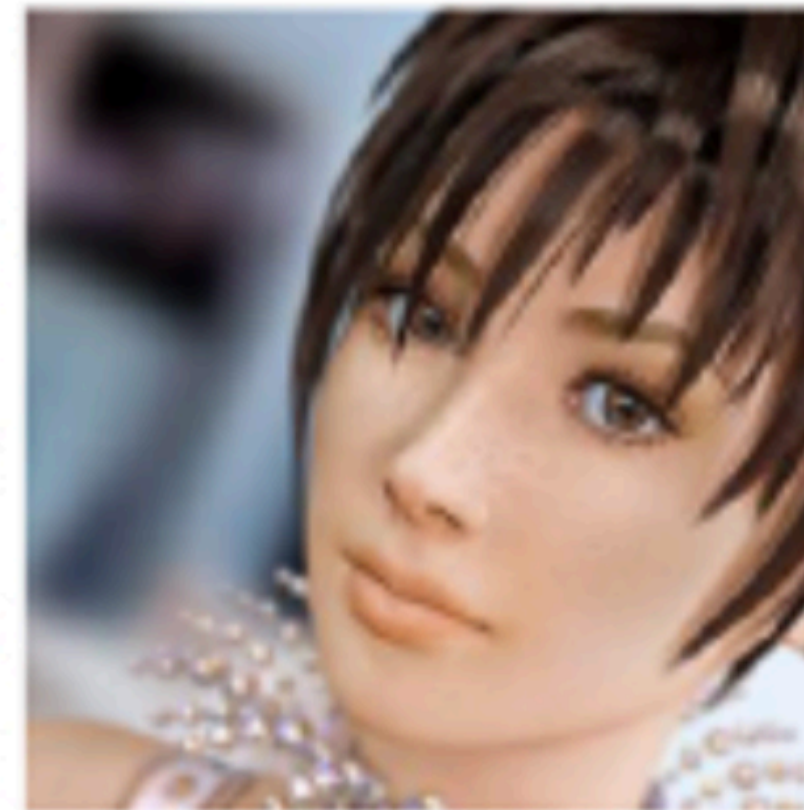
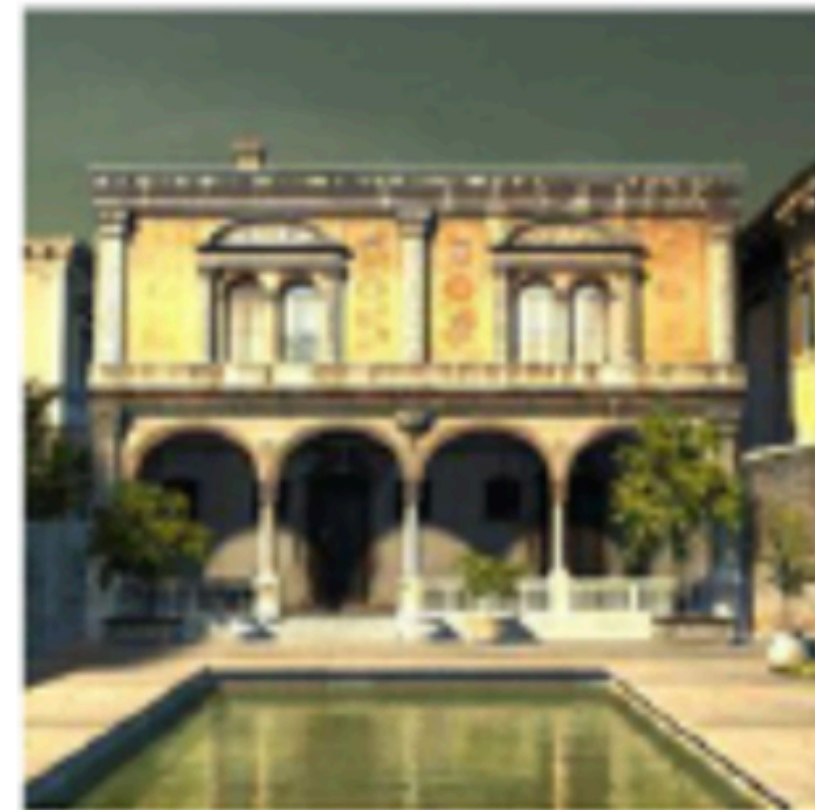
2. LPIPS

- Both use deep convolutional networks.

Realism

low FID

~ high realism



high realism



low realism

High Realism itself makes no sense



original



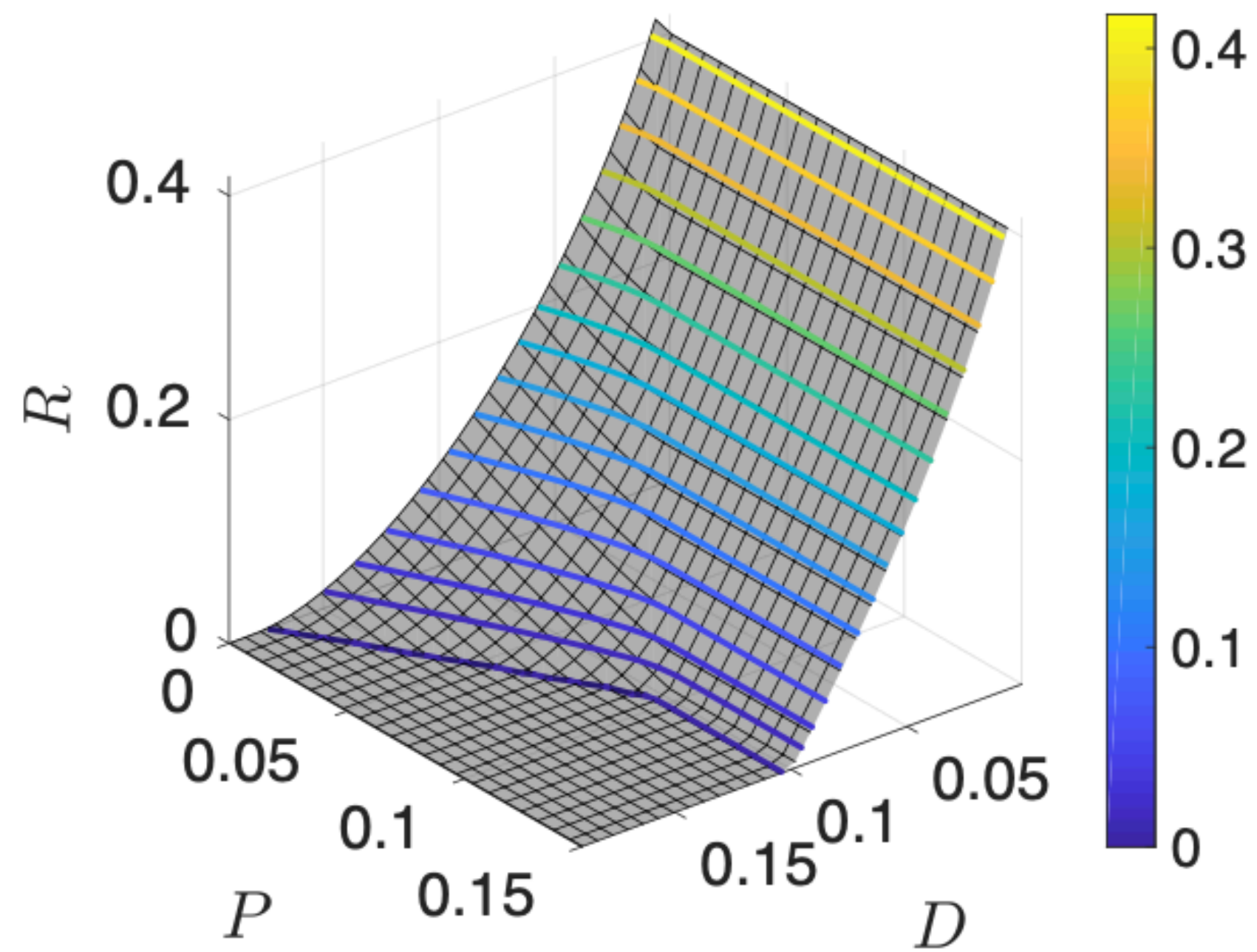
reconstructed

We want **low bit rate, **low** distortion, and **high** realism!**

However, these three indicators **cannot be achieved simultaneously!**

Rate-distortion-realism Tradeoff

(Curves on the blackboard)



- Fix rate R
- Fix distortion D
- Fix FID's upper bound P

Tradeoff: takeaway messages

- At low bit rates, the tradeoff becomes stronger.
- To optimize one metric, the other two need to be sacrificed.

A Classic Compression Pipeline:

Single-rate, no realism control

Single-rate v.s. Variable-rate

Loss function

Previous Work

- Learning based:
 - Generative:
 - GAN-based: **Multi-realism**, HiFiC, PQMIM
 - Diffusion-based: HFD, **DIRAC**
 - Non-Generative: ELIC, Charm, IVR, Hyperprior
- Non-Learning based: VTM, JPEG

“Green”: able to adjust Distortion-realism tradeoff in one model

GAN Based Training

Motivation: how to adjust the balance between rate, distortion, and realism within a single model?

This Paper: Pipeline

(See Blackboard)

beta: realism weight (higher beta means higher realism and higher distortion, vice versa)

This Paper: Loss function

$$\mathcal{L}_{1st} = \lambda_R^{(q)} R(\hat{\mathbf{y}}_q) + \lambda_d d(\mathbf{x}, \hat{\mathbf{x}}_q) + \mathcal{L}_P(\mathbf{x}, \hat{\mathbf{x}}_q)$$

bit rate,

MSE,

LPIPS

$$\mathcal{L}_{2nd} = \lambda_R^{(q)} R(\hat{\mathbf{y}}_q) + \lambda_d d(\mathbf{x}, \hat{\mathbf{x}}_q) + \beta(\lambda_P \mathcal{L}_P(\mathbf{x}, \hat{\mathbf{x}}_q) + \lambda_{adv} \mathcal{L}_{HRRGAN}^G)$$

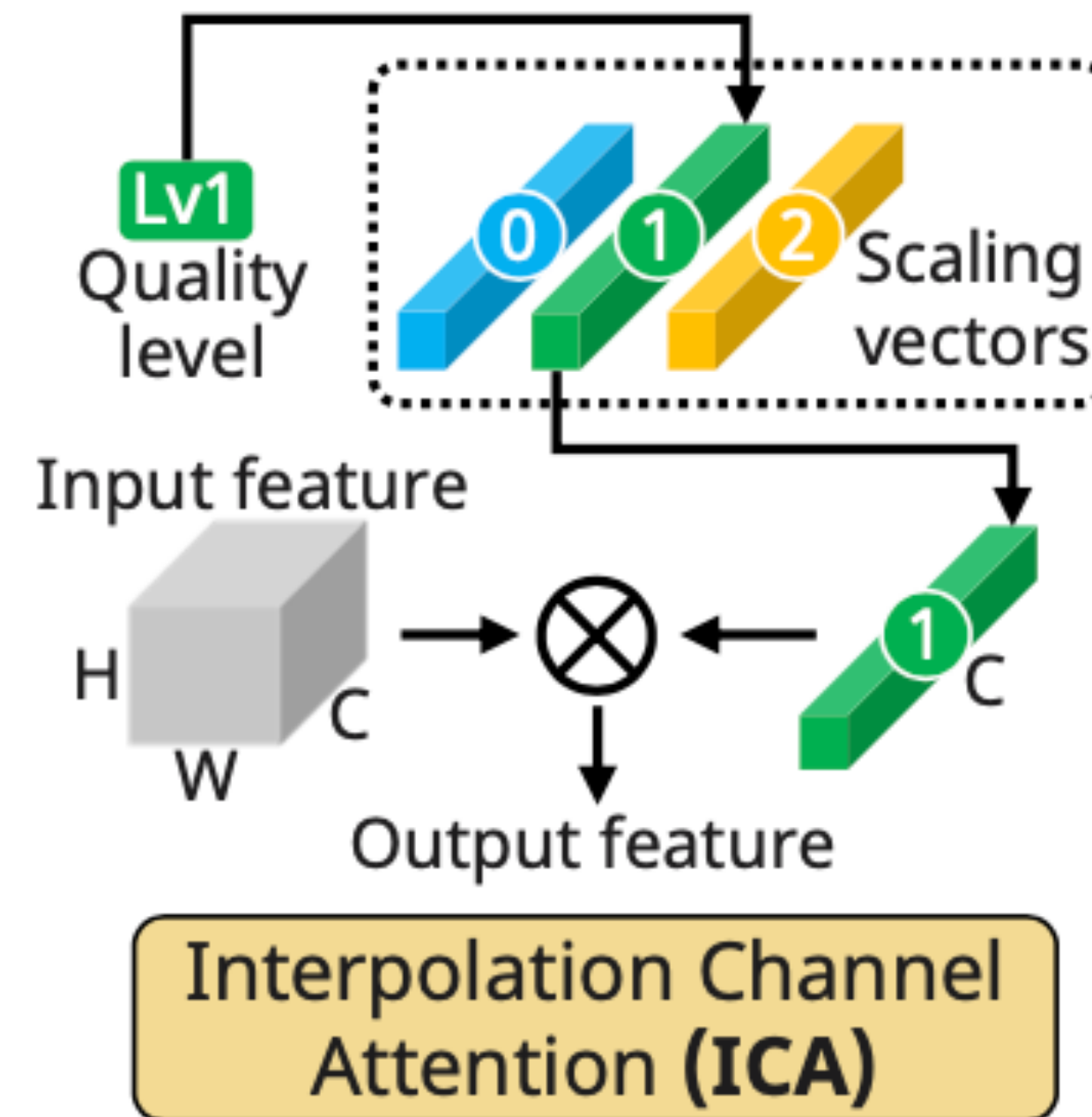
bit rate,

MSE,

LPIPS,

adversarial loss

To control the rate: Insert Interpolation Channel Attention Layers



Discriminator - RaGAN

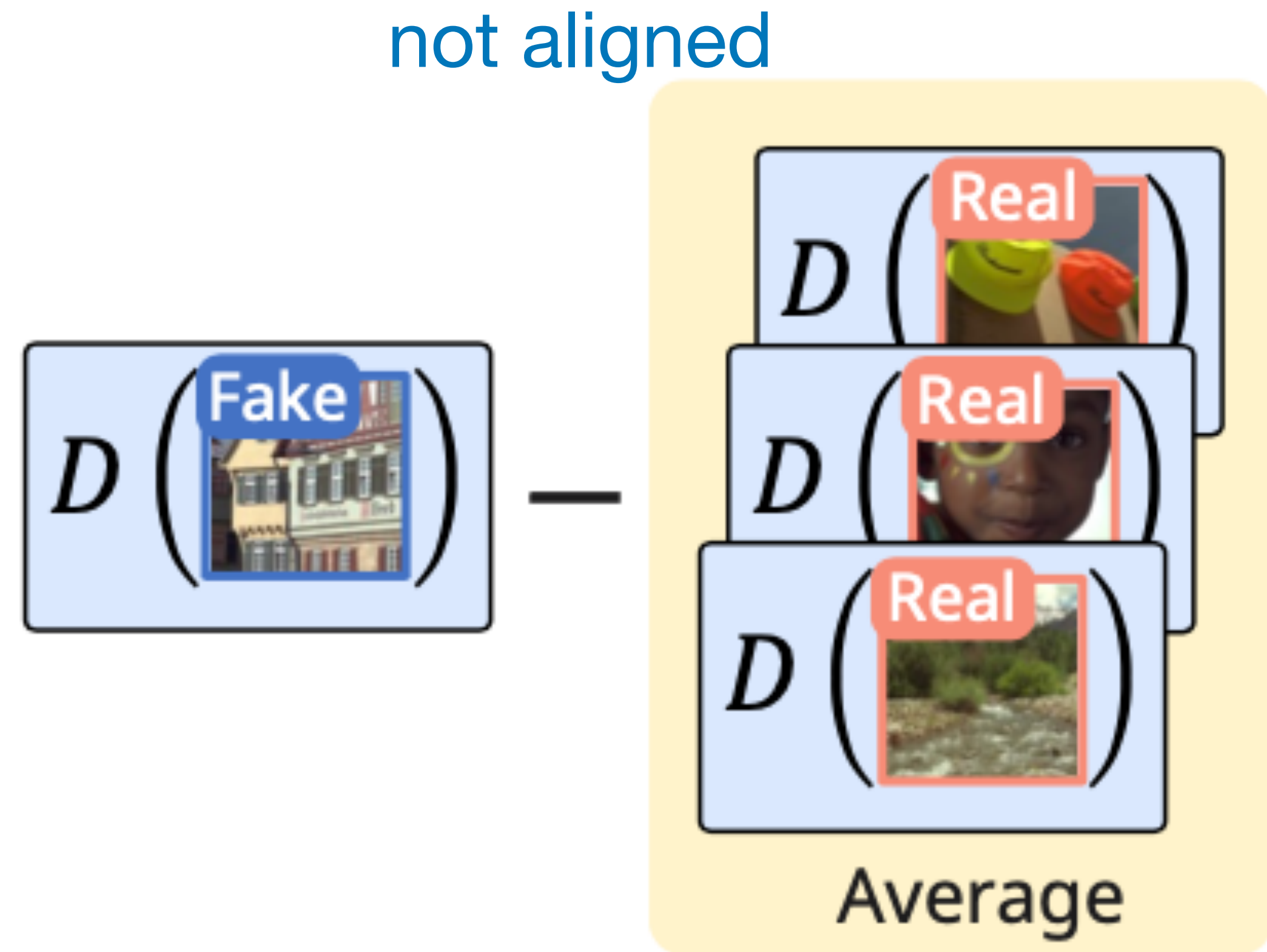
Relativistic Average GAN

$$p_r(x_r, x_f) = \sigma(D(x_r) - \mathbb{E}_{x_f}[D(x_f)])$$

$$p_f(x_r, x_f) = \sigma(D(x_f) - \mathbb{E}_{x_r}[D(x_r)])$$

$$\mathcal{L}_{\text{RaGAN}}^G = -\log p_f(x_r, x_f) - \log(1 - p_r(x_r, x_f))$$

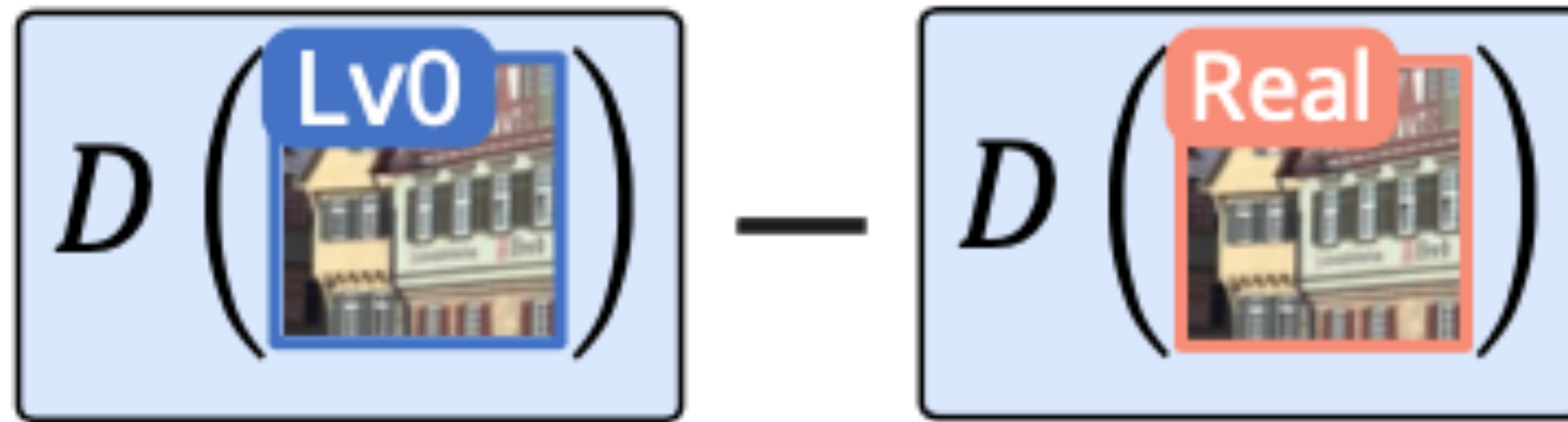
$$\mathcal{L}_{\text{RaGAN}}^D = -\log p_r(x_r, x_f) - \log(1 - p_f(x_r, x_f)),$$



Discriminator - RGAN

Relativistic GAN

aligned



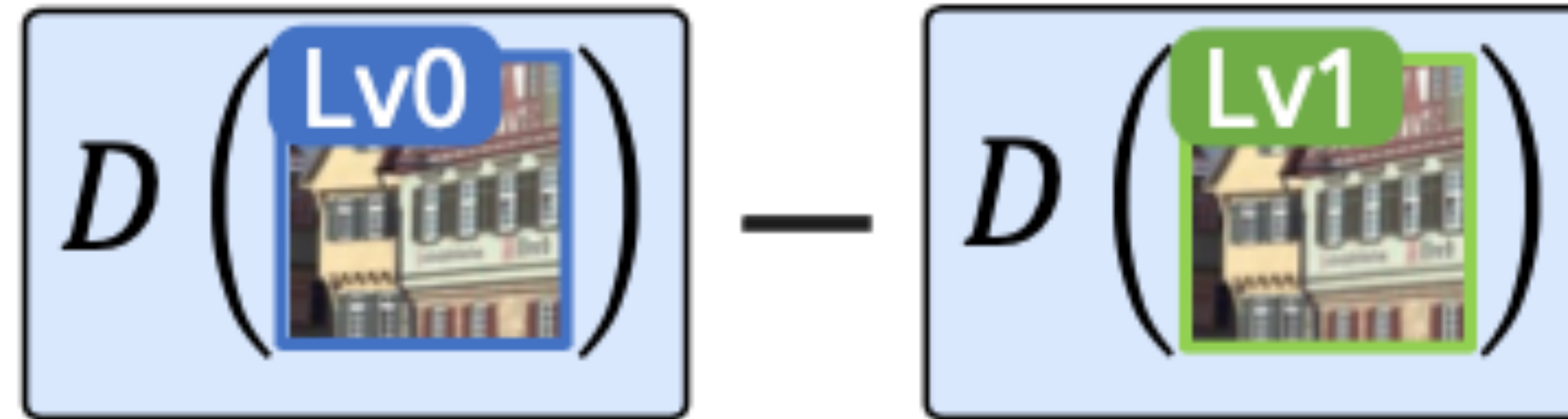
$$\mathcal{L}_{\text{RGAN}}^G = -\log \sigma(D(x_f) - D(x_r))$$

$$\mathcal{L}_{\text{RGAN}}^D = -\log \sigma(D(x_r) - D(x_f)).$$

Discriminator - HRRGAN

Higher Rate Relativistic GAN

To avoid over-penalty on realism

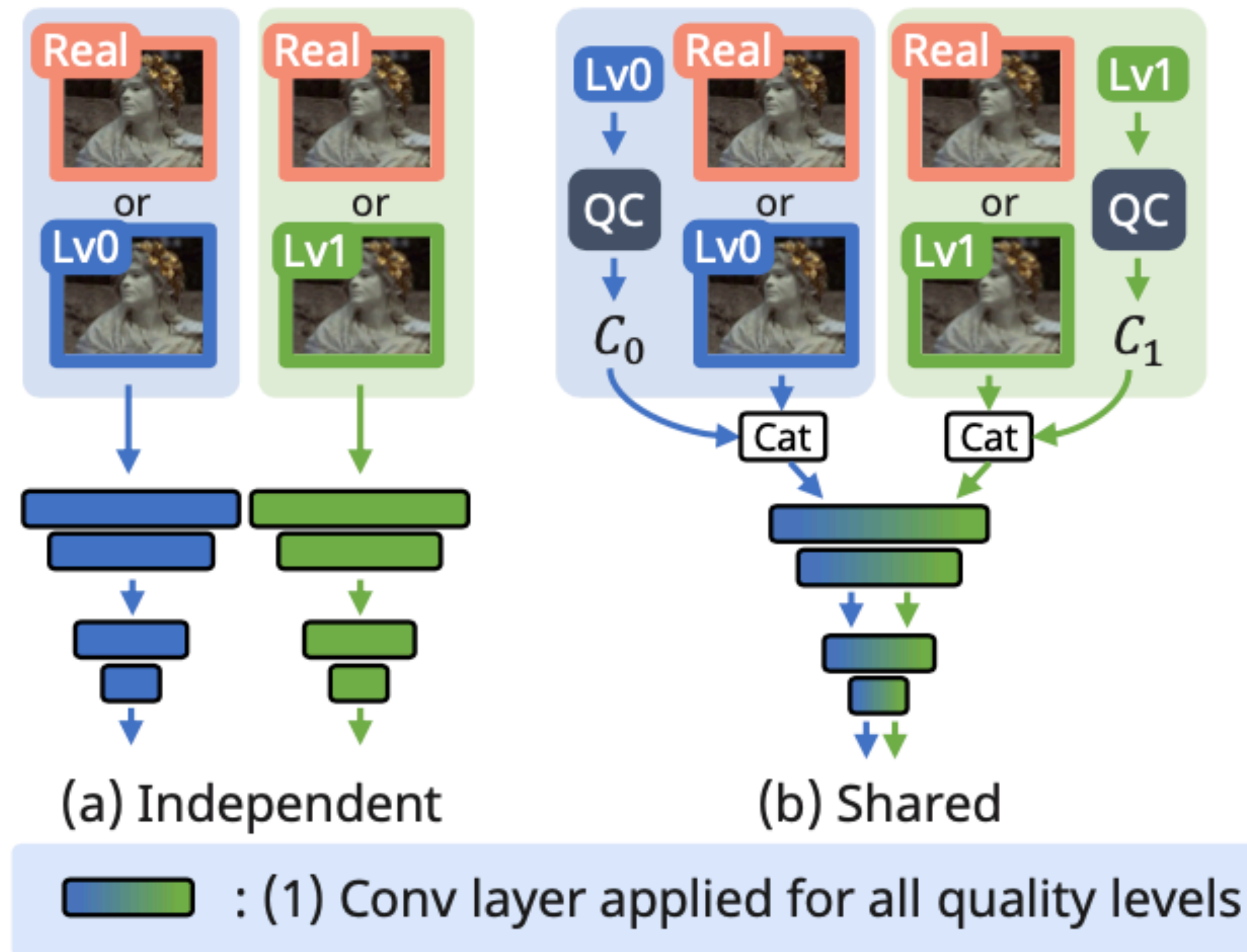


$$\mathcal{L}_{\text{HRRGAN}}^G = -\log \sigma(D(\hat{\mathbf{x}}_q) - \text{sg}(D(\hat{\mathbf{x}}_{q+1})))$$

$$\mathcal{L}_{\text{HRRGAN}}^D = -\log \sigma(D(\mathbf{x}) - D(\hat{\mathbf{x}}_q)),$$

sg: stop gradient operation

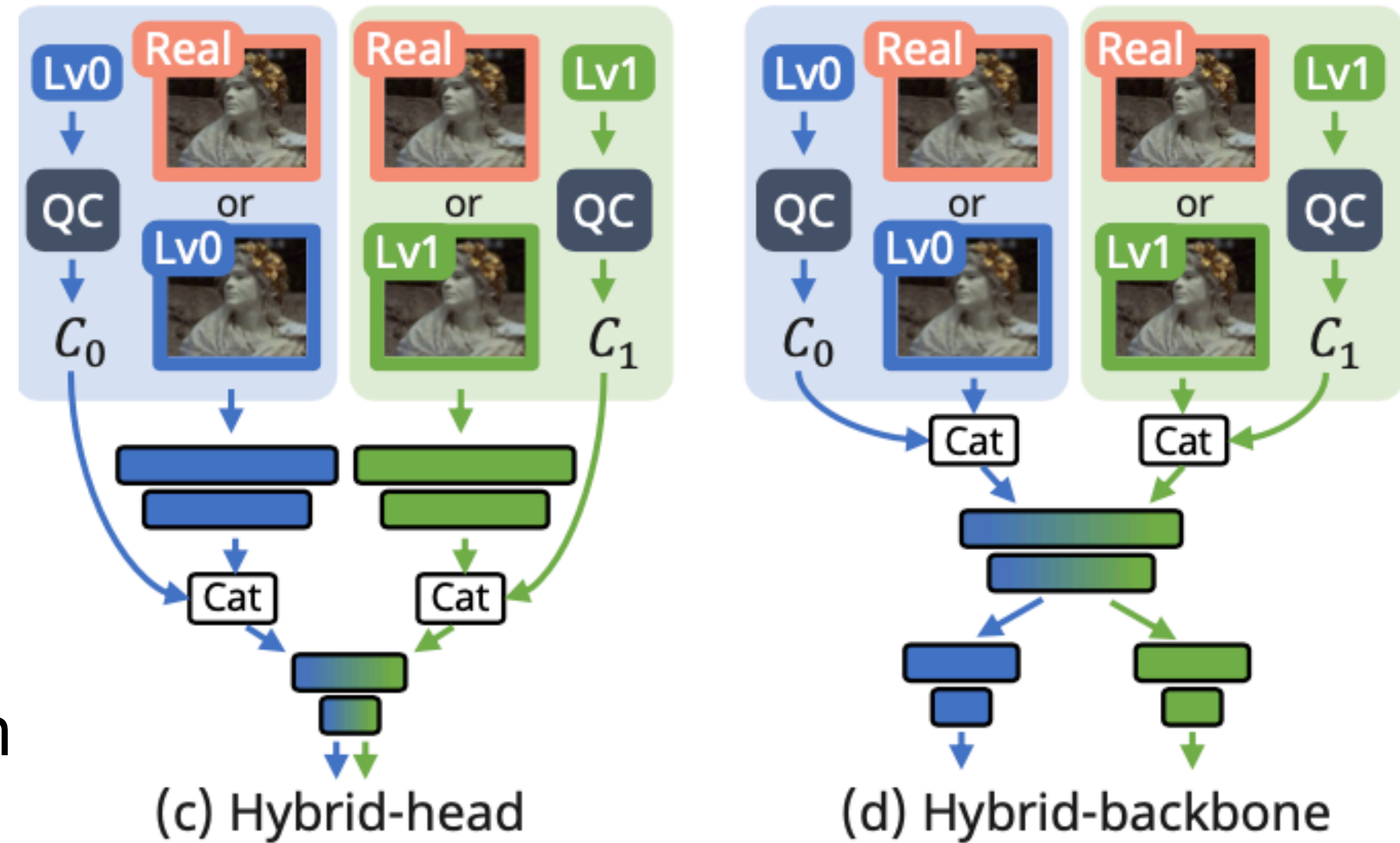
Independent vs Shared Discriminator



Hybrid Discriminator

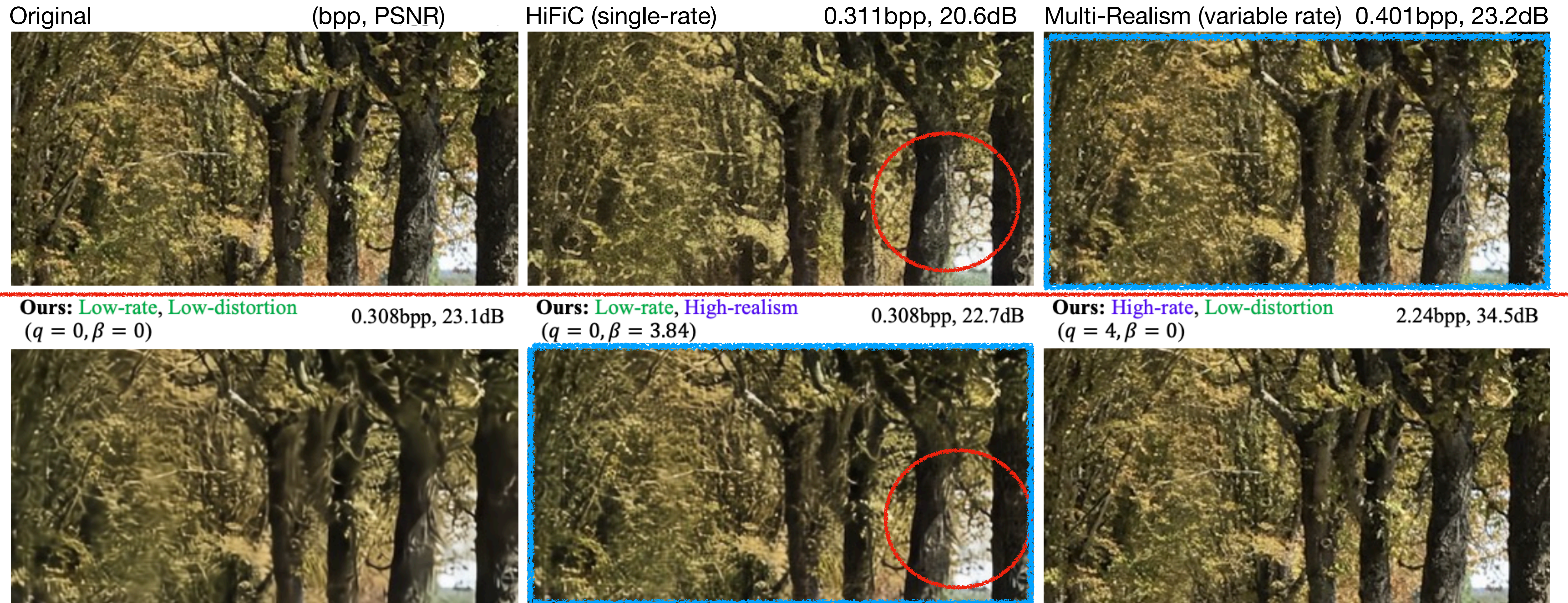
backbone: extract and encode features

head: produce prediction



  : (2) Conv layer applied for a specific quality level

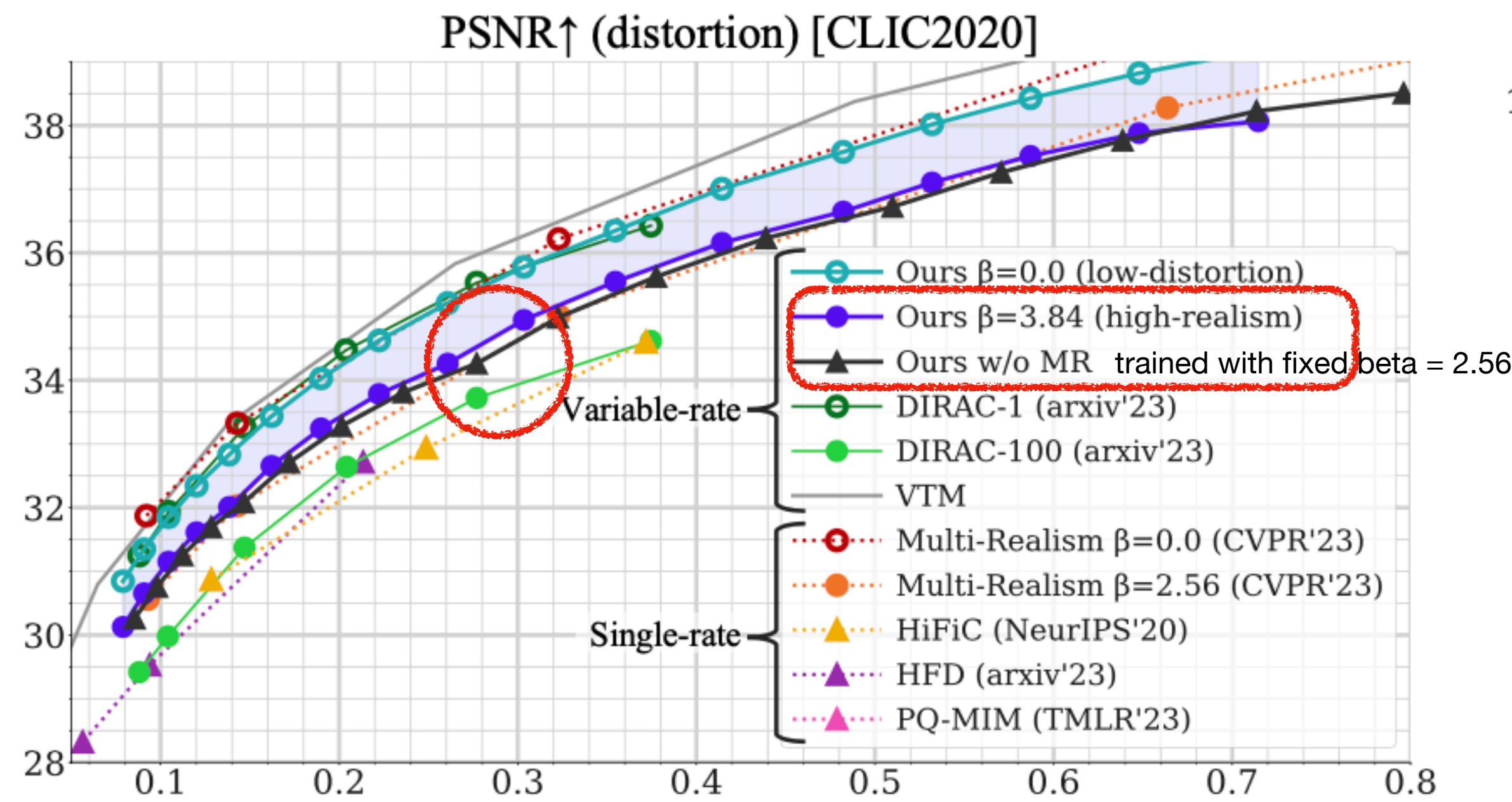
Experimental Results: Compare with Generative Models



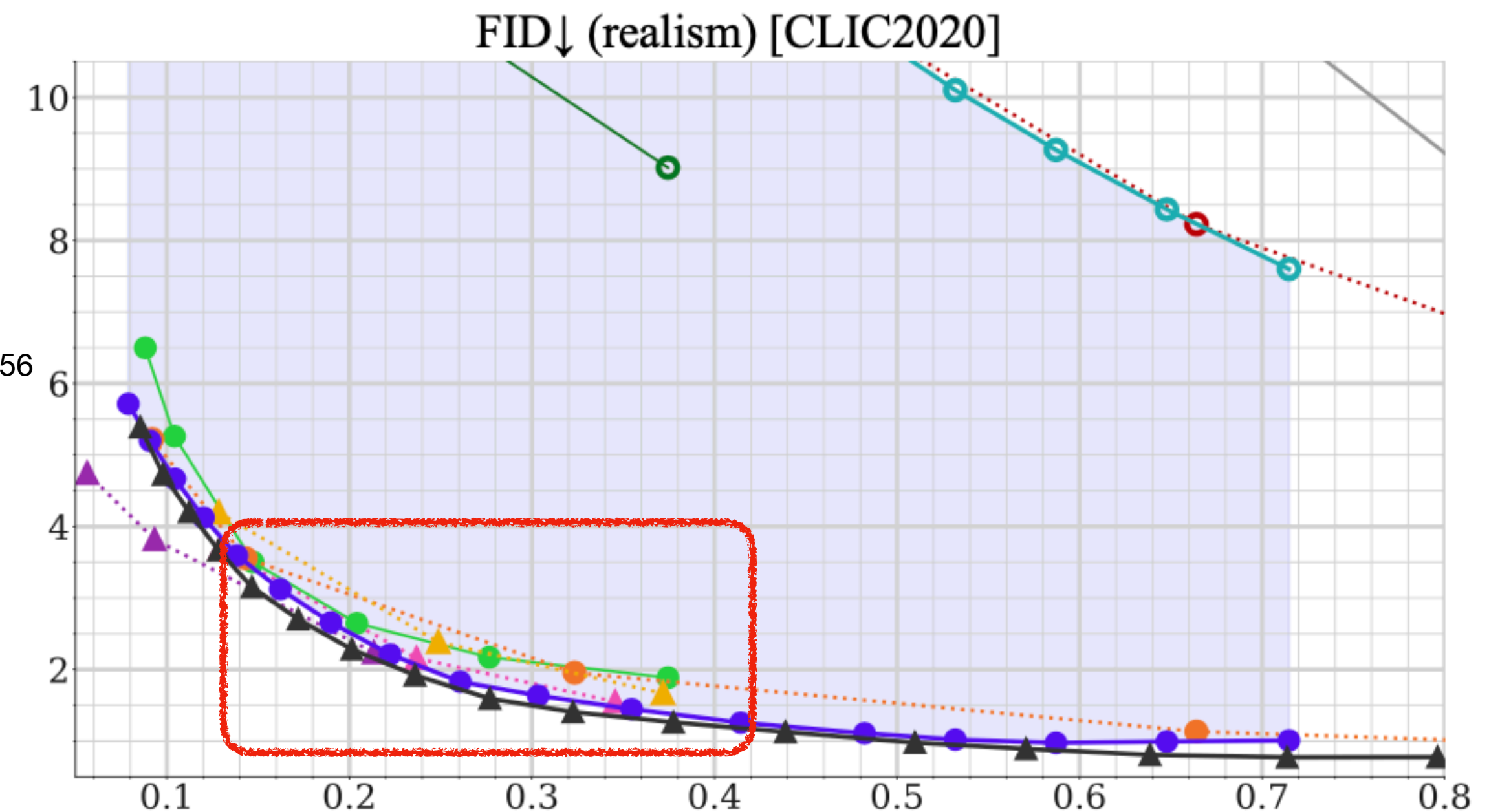
better texture!

Comparable realism with lower bit rate!

Quantitative Evaluation



bpp(bit rate)

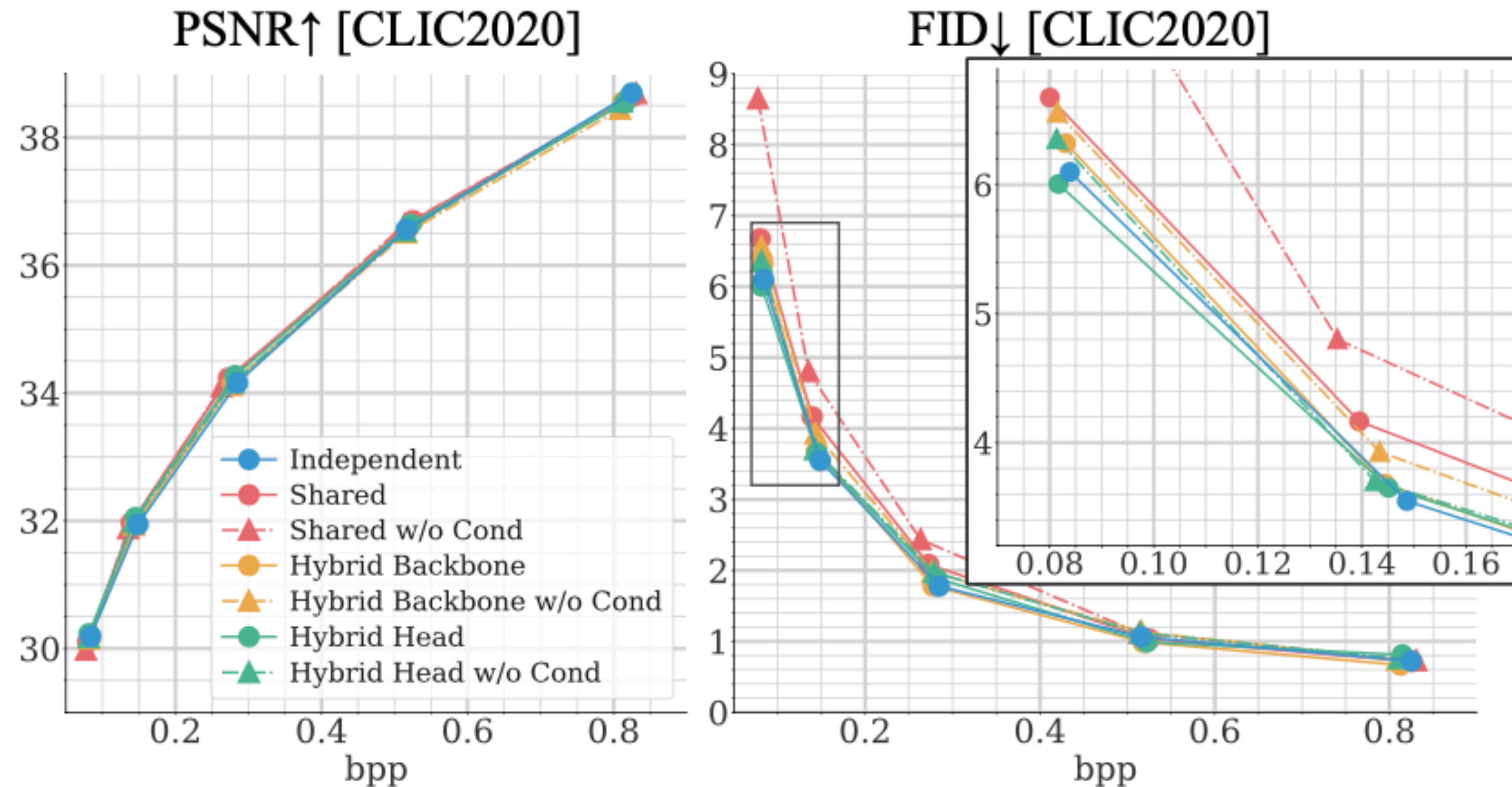


bpp(bit rate)

Quantitative Evaluation

- Perform fine rate-tuning
- high realism model: surpassed DIRAC on both indicators

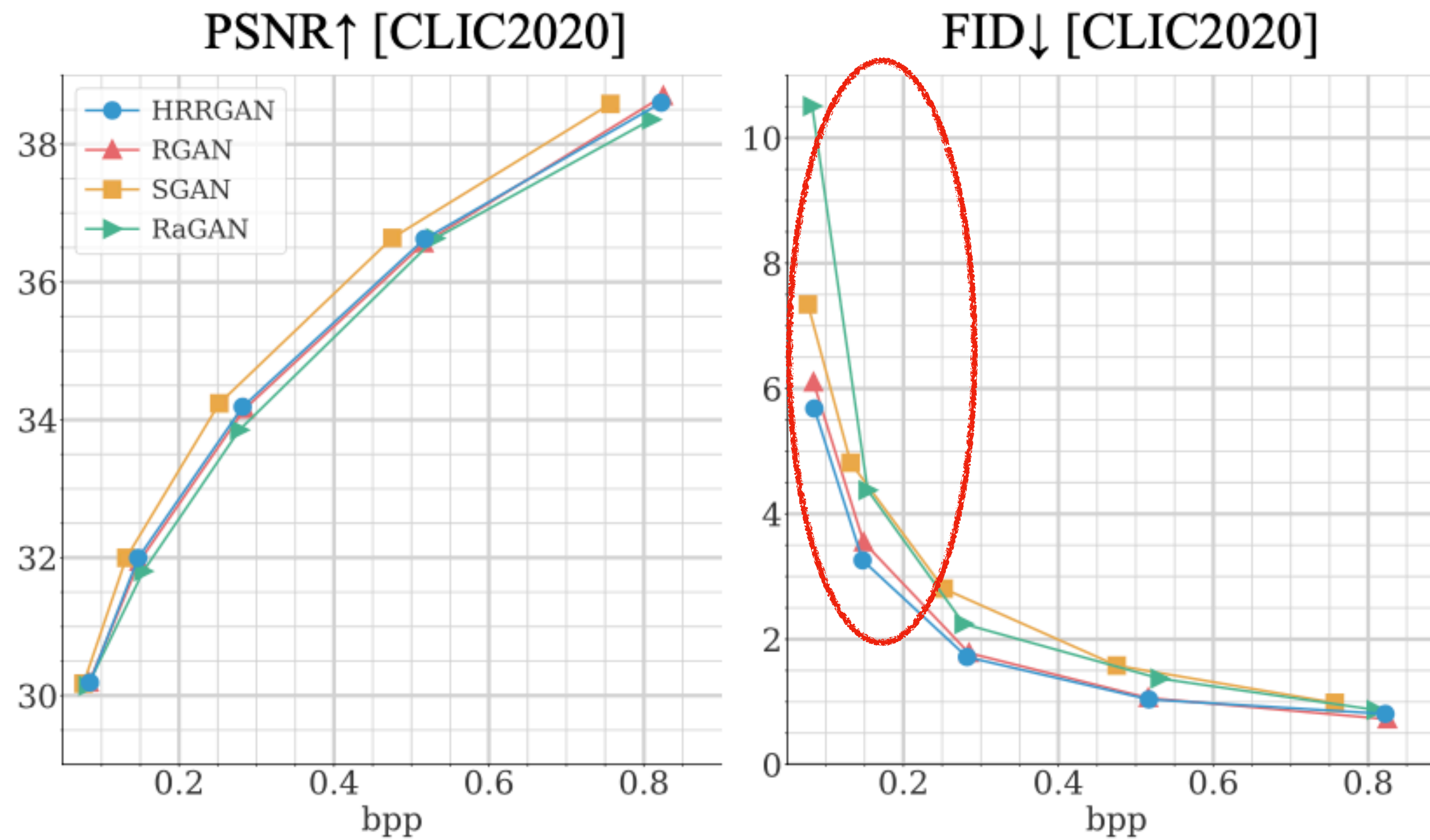
Results of Different Discriminator designs



(a) Results on $Q = 5$

- Hybrid discriminators outperformed shared discriminators in FID
- Quality-level specific layers are beneficial

Effect of HRRGAN



- Average calculation harms performance

Trained with fixed beta = 2.56

RGAN: Relativistic GAN

SGAN: Standard GAN

RaGAN: Relativistic Average GAN

HRRGAN: Higher Rate Relativistic GAN

Limitation

- Control the rate and realism uniformly
cannot perform precise (e.g. pixel-level) control

References

- [*multi-real] Agustsson, Eirikur, et al. "Multi-realism image compression with a conditional generator." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023.
- [*hyperprior] Ballé, Johannes, et al. "Variational image compression with a scale hyperprior." *arXiv preprint arXiv:1802.01436* (2018).
- [*measure] Becker Axel. "A review on image distortion measures." (2000).
- [*realism] Fan, Shaojing, et al. "Image visual realism: From human perception to machine computation." *IEEE transactions on pattern analysis and machine intelligence* 40.9 (2017): 2180-2193.
- [*thisp] Iwai Shoma, Tomo Miyazaki, and Shinichiro Omachi. "Controlling Rate, Distortion, and Realism: Towards a Single Comprehensive Neural Image Compression Model." *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. 2024.
- [*diffPSNR] Loukil Habiba, Moez Hadj Kacem, and Mohamed Salim Bouhlel. "A new image quality metric using system visual human characteristics." *International Journal of Computer Applications* 60.6 (2012).
- [*sameMSE] Wang, Zhou, et al. "Image quality assessment: from error visibility to structural similarity." *IEEE transactions on image processing* 13.4 (2004): 600-612.
- [*tradeoff] Yochai Blau and Tomer Michaeli. Rethinking lossy compression: The rate-distortion-perception tradeoff. In *Proceedings of the 36th International Conference on Machine Learning(ICML)*, 2019.