

Modeling Lost Information in Signal Processing

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Signal (Processing) is Everywhere

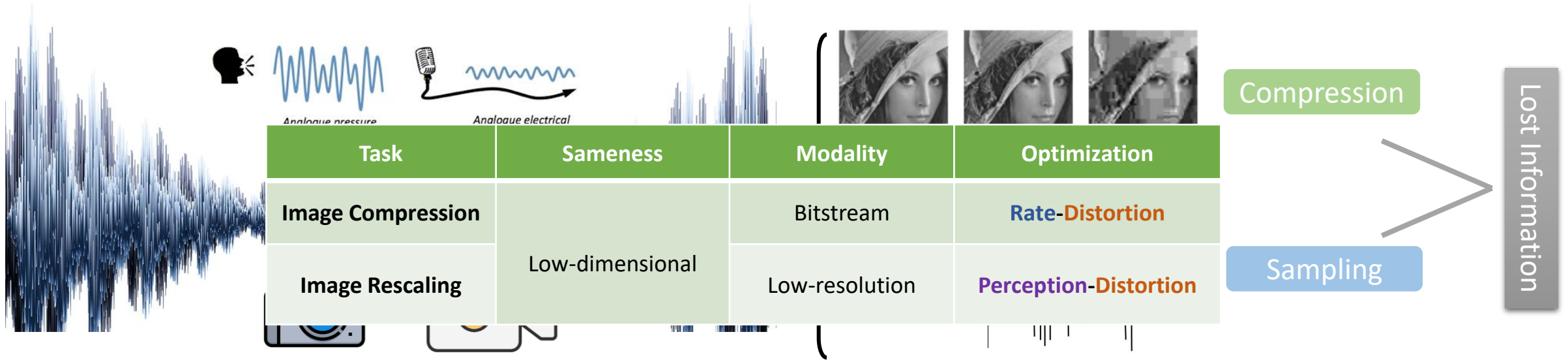


Image Compression:

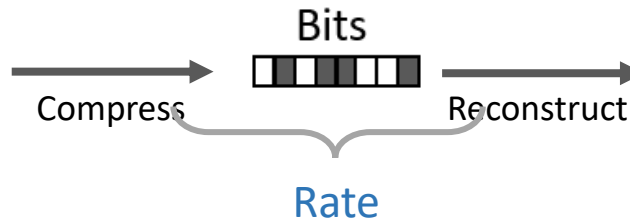
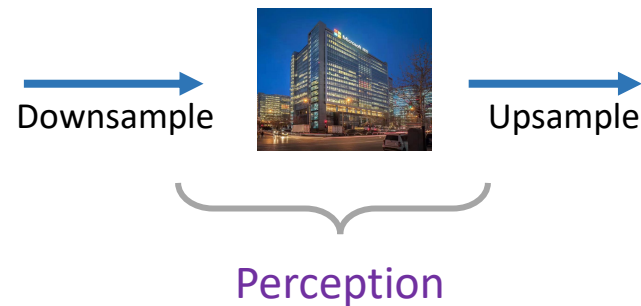
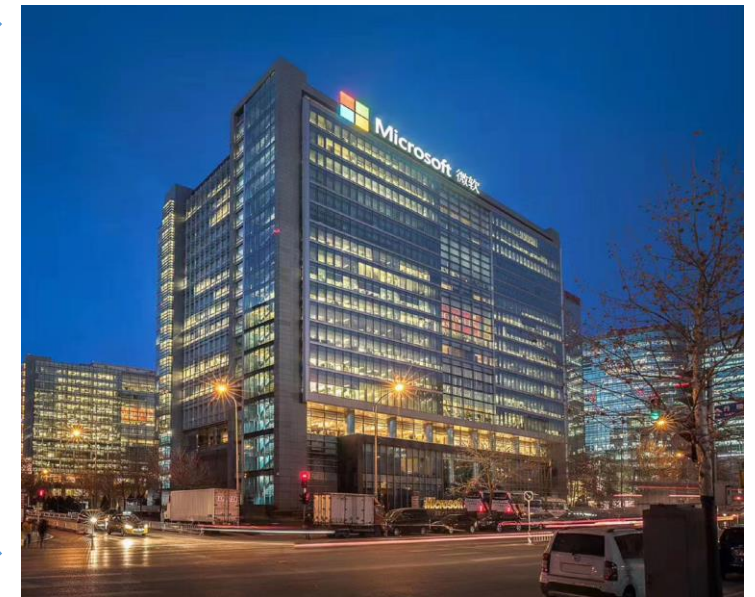
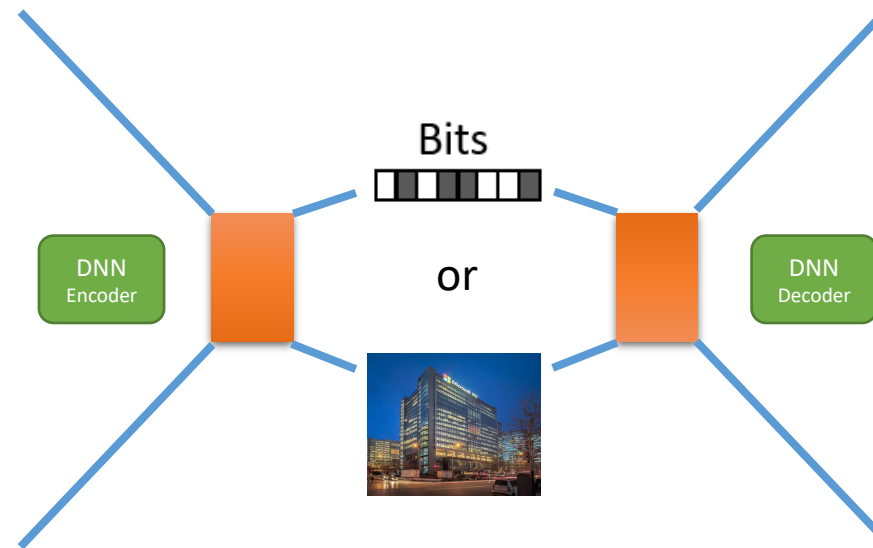


Image Rescaling:



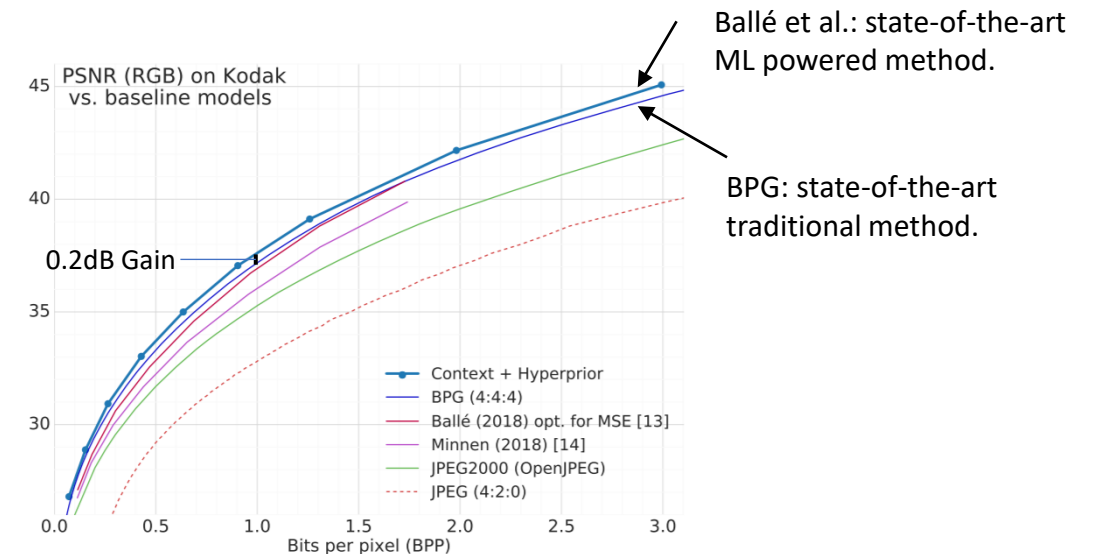
Distortion

Signal Processing with Machine Learning

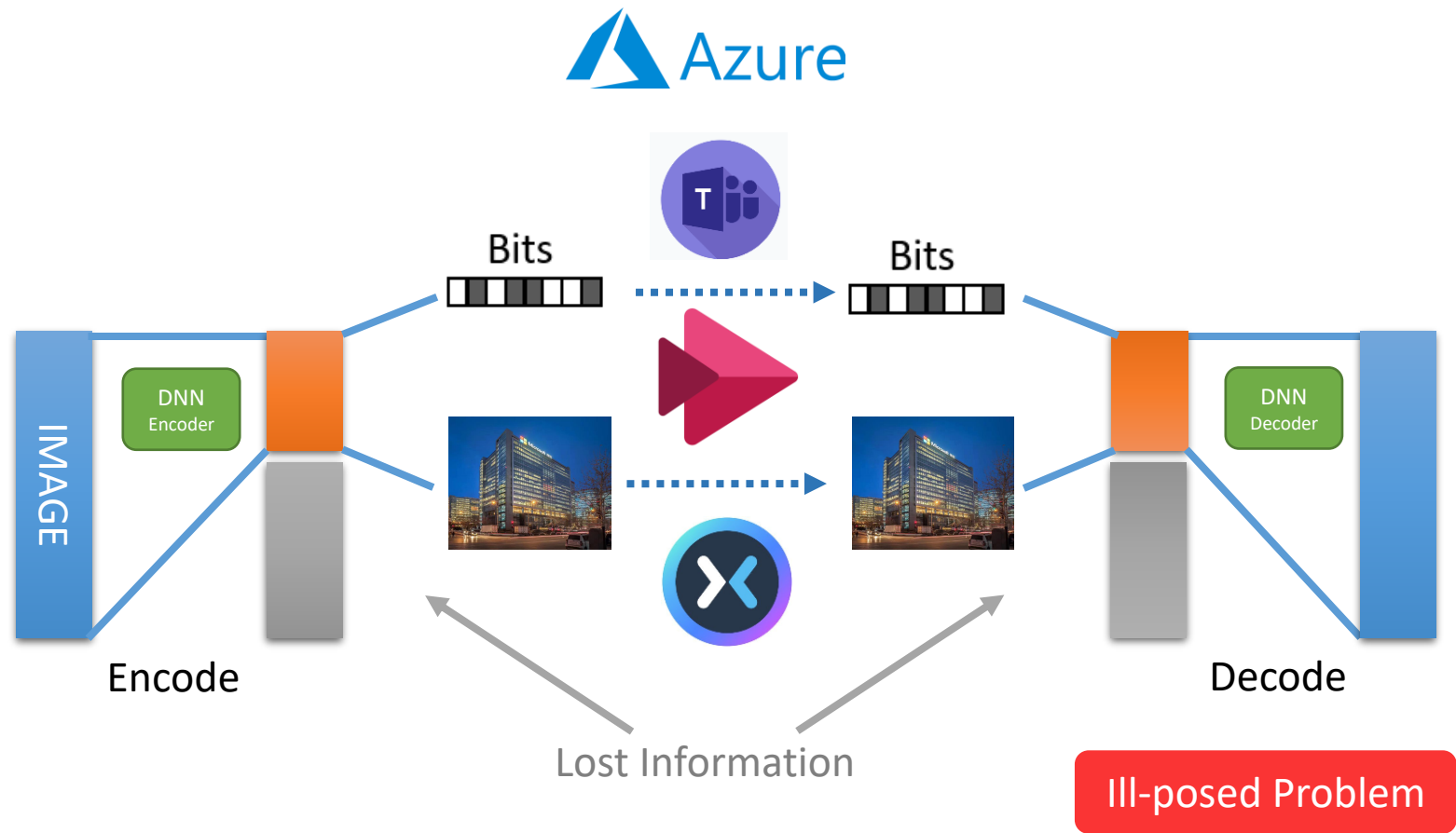


- **ML powered** signal processing becomes a hot topic and has achieved better performance than traditional method.
- **Google (Ballé et al.)**^{[1][2][3]} holds the leading position in lossy image compression for years.

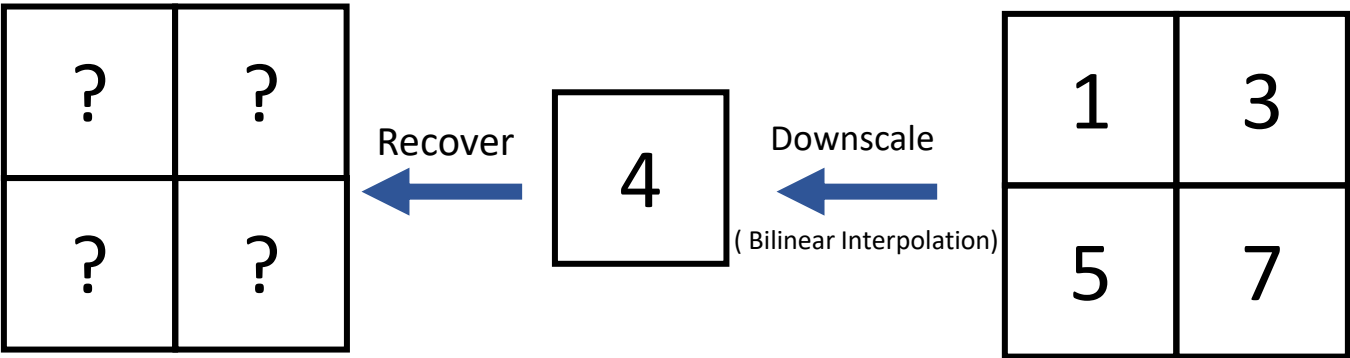
- [1] **Ballé J**, Laparra V, Simoncelli E. End-to-end optimized image compression[C]//5th International Conference on Learning Representations, ICLR 2017.
- [2] **Ballé J**, Minnen D, Singh S, et al. Variational image compression with a scale hyperprior [C]//6th International Conference on Learning Representations, ICLR 2018.
- [3] Minnen D, **Ballé J**, Toderici G D. Joint autoregressive and hierarchical priors for learned image compression[C]//Advances in Neural Information Processing Systems. 2018: 10771-10780.



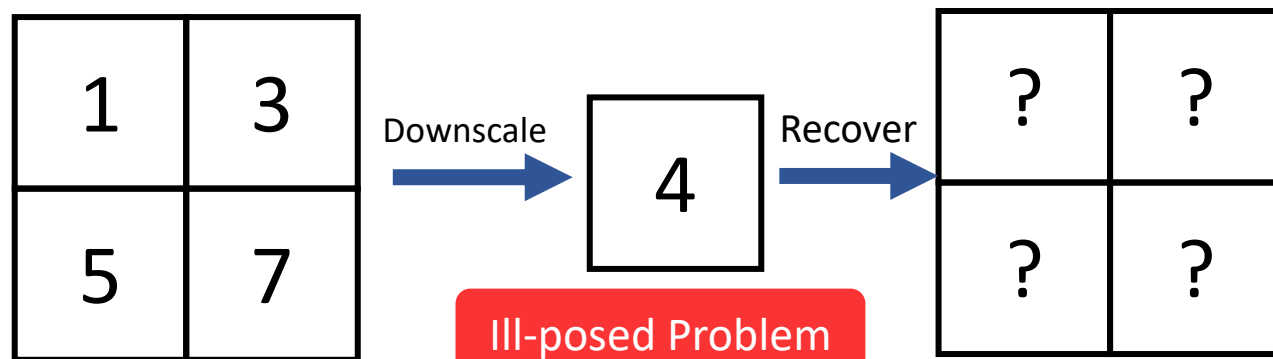
Lost Information



Lost Information
↓
Ill-posed Problem

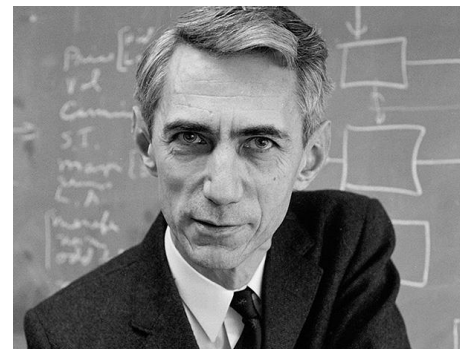
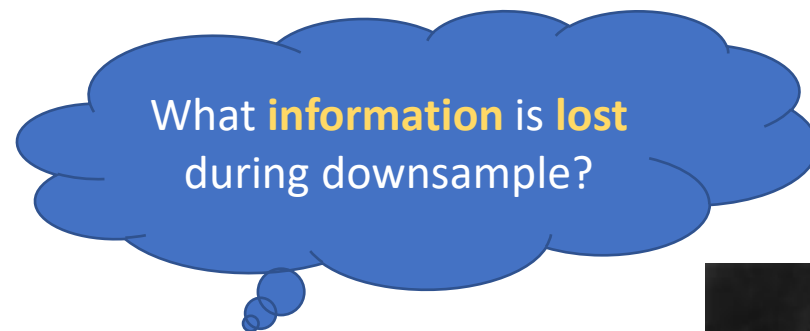


Capture Lost Information



*"High-frequency content will get **lost** during sample rate conversion."*

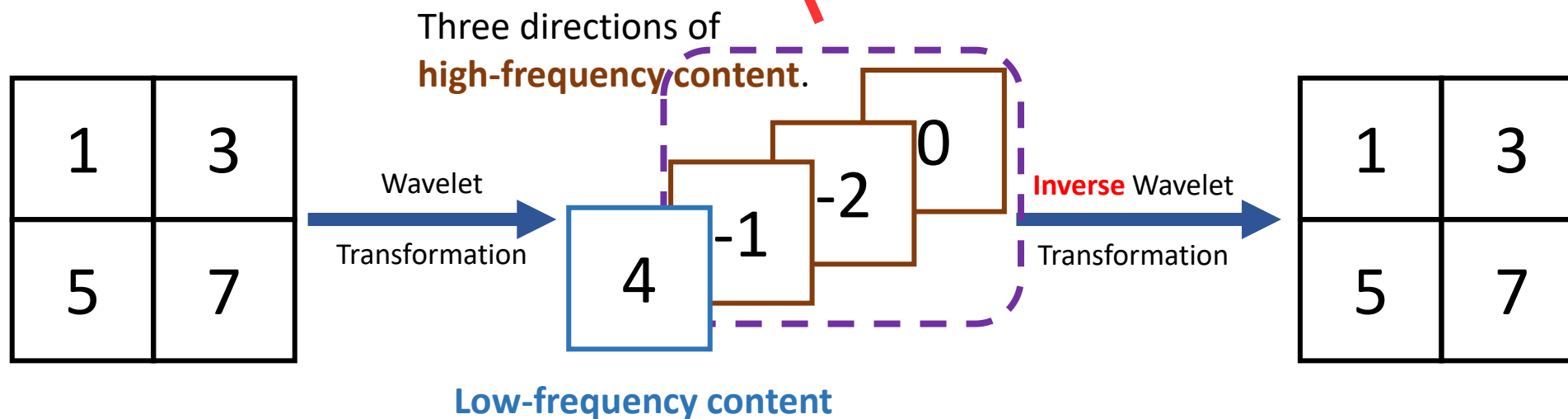
--According to Nyquist-Shannon Sampling Theorem



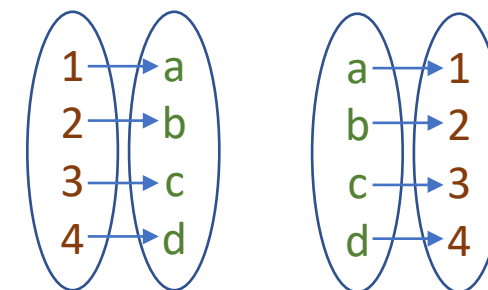
Claude Shannon



Harry Nyquist

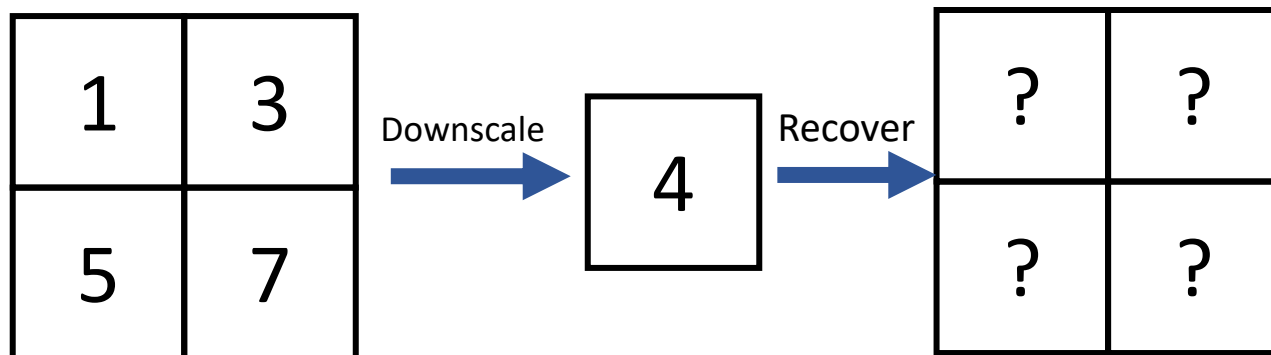


$$f(x) = y \quad f^{-1}(y) = x$$



Inverse Function

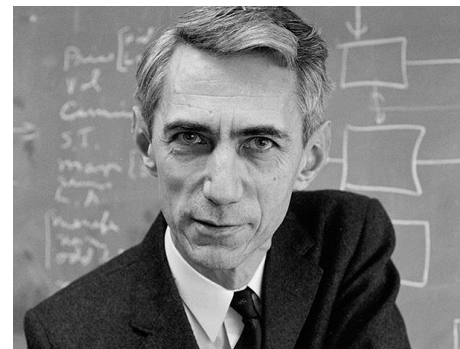
Capture Lost Information



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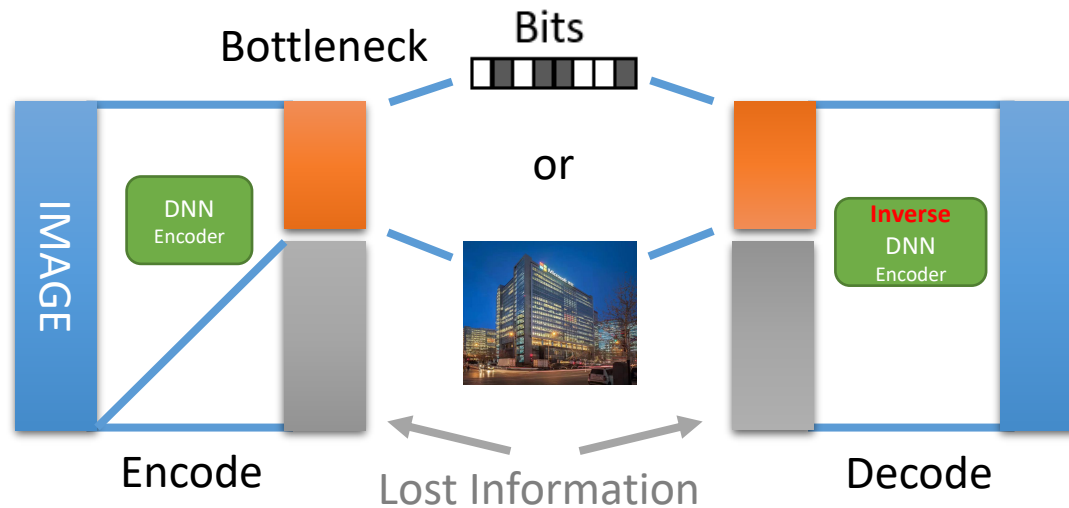
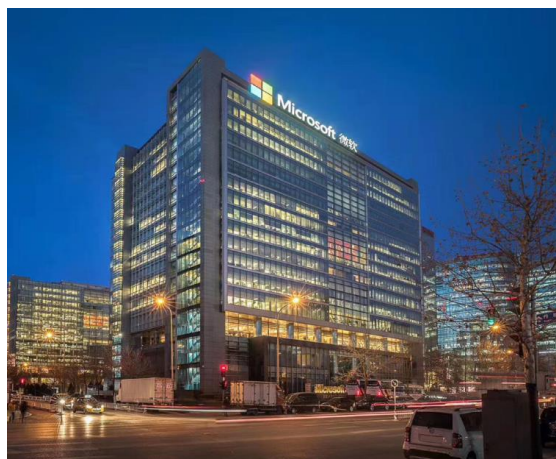
What **information** is **lost** during downsample?



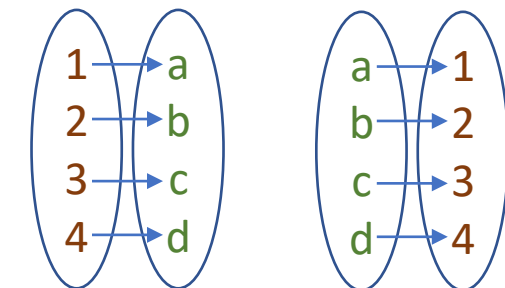
Claude Shannon



Harry Nyquist



What is the **inverse function** of a **DNN** model?

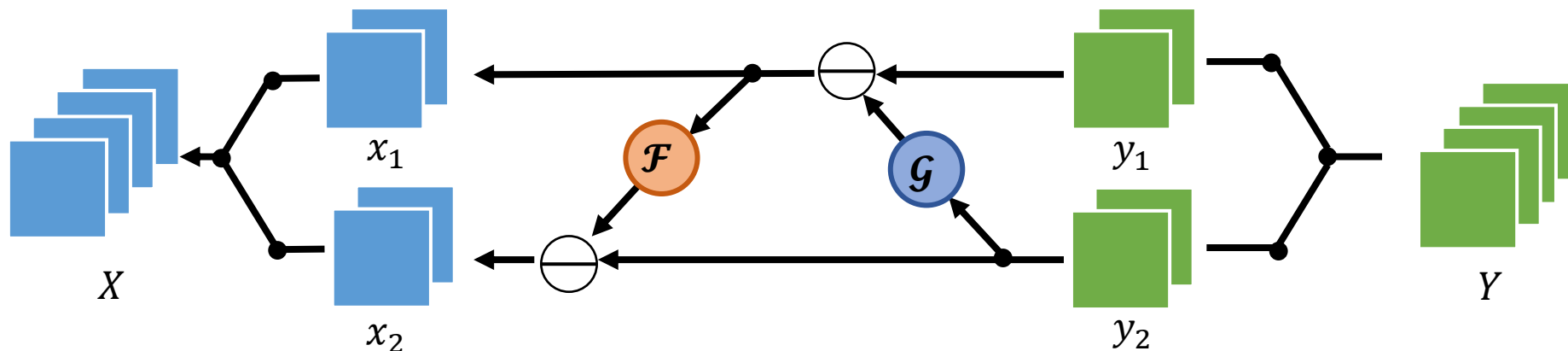
$$f(x) = y \qquad f^{-1}(y) = x$$


Forward Pass

$$y_2 = x_2 + \mathbf{g}(y_1)$$

Inverse Pass

$$x_1 = y_1 - \mathcal{F}(x_2)$$



Face the “Lost Information” Challenge

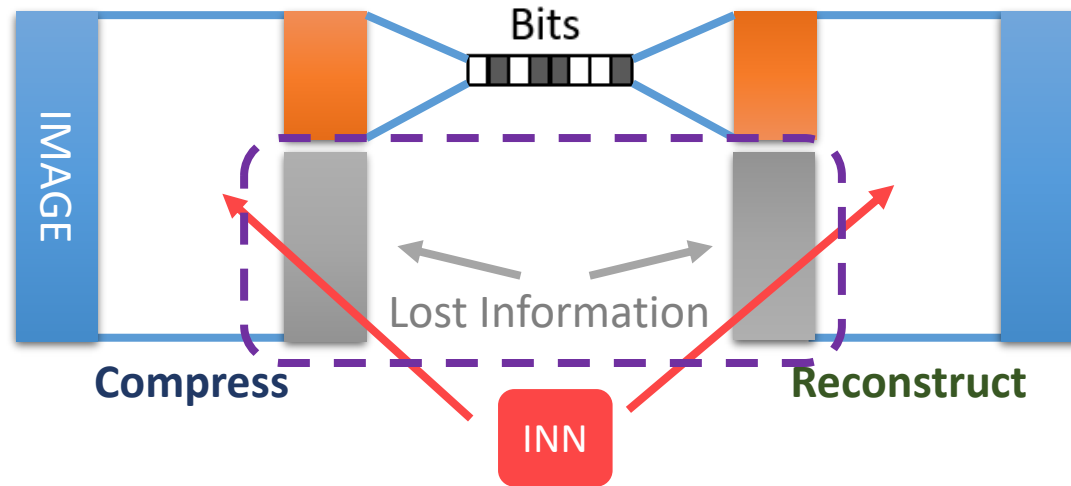


Question:

If we (____) the lost information...

(A). Preserve

(B). Abandon

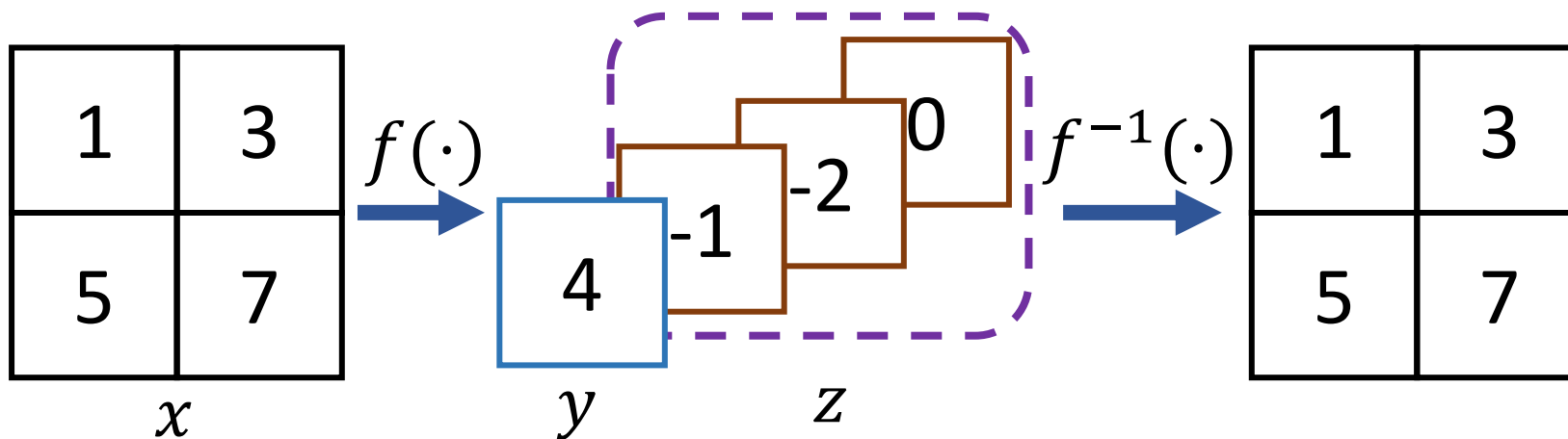


How to **compress**?



How to **reconstruct**?

Do we have a better choice?

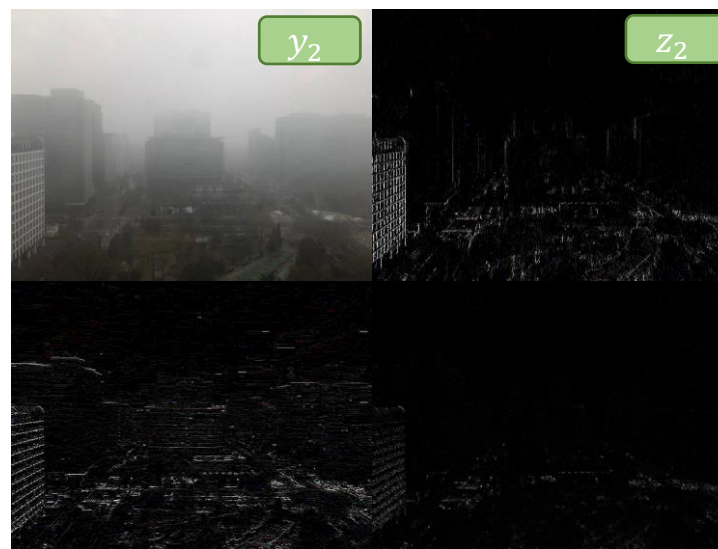
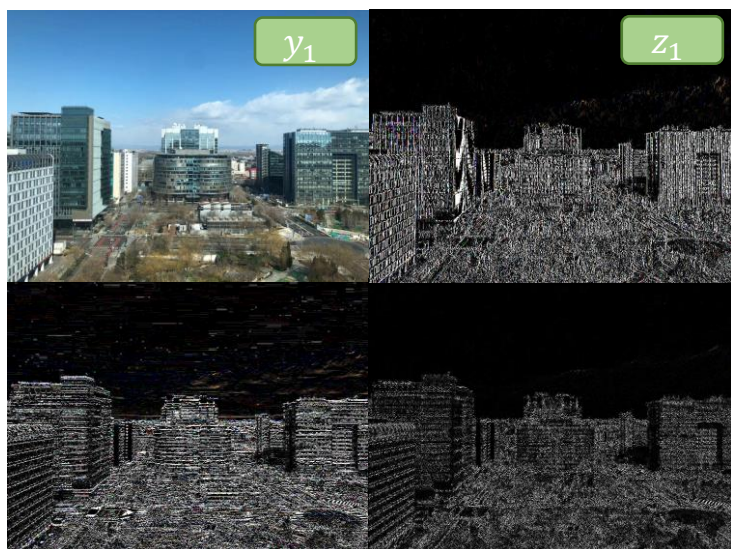


Why z can't be abandoned?

$$f(p(x)) = p(y)p(z|y)$$

Answer: z is case-specific!

Model the Case-Specific Lost Information



$$f(p(x)) = p(y)p(z|y)$$

Reparameterization

Let $z' = h_y(z)$,
when $z \sim p(z|y)$,
 $\rightarrow z' \sim N(0, I_k)$.

Safely abandon z , before sending y
Easily find back z , after receiving y

Case-specific $z \sim p(z|y)$

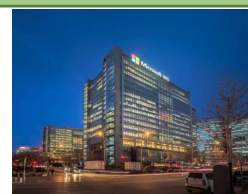
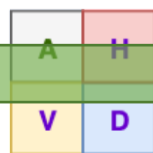
Case-agnostic:
Follow a Gaussian!
Independent from y !

Case-agnostic $z' \sim N(0, I_k)$

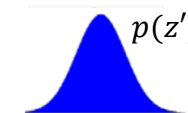
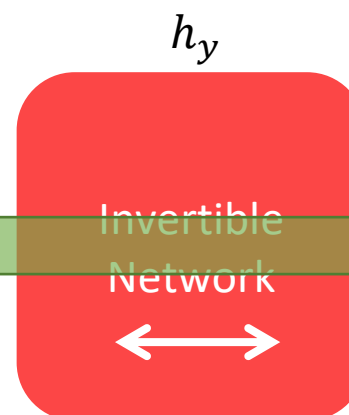


$p(x)$

Wavelet
Transformation

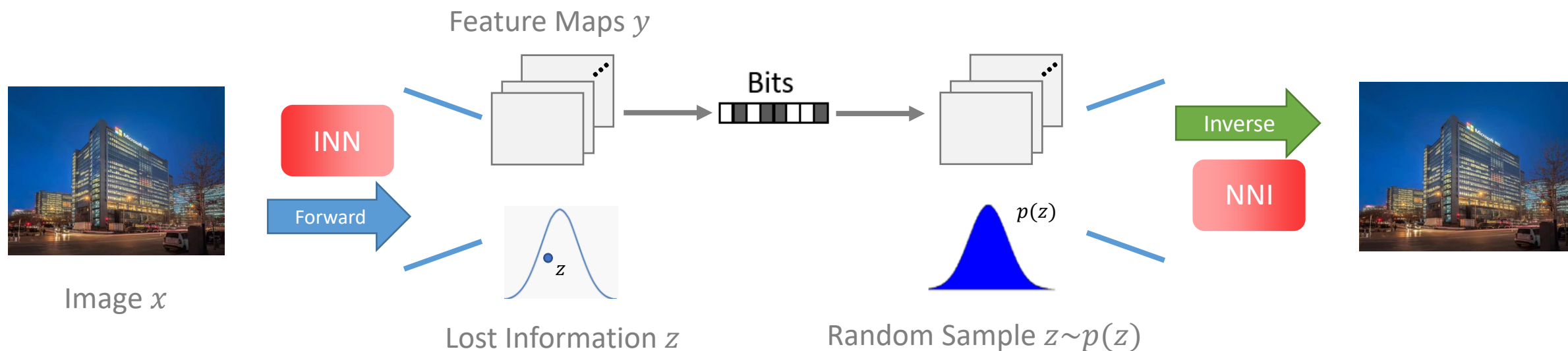


$p(y)$



$p(y')$

Modeling Lost Information

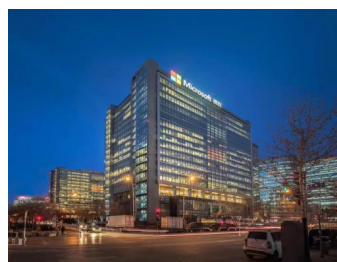


Training Objective	Rescaling	Compression
Distortion	L_1 or L_2 Reconstruction Loss	
Perception	LR Guidance	
Rate	Bitrate (likelihood(y))	
Distribution Matching	Backward JS Divergence Loss	

Rescaling Performance (PSNR)

PSNR (dB)	Scale	Param↓	Set5↑	Set14↑	BSD100↑	Urban100↑	DIV2K val↑
Bicubic & RCAN ECCV 2018	2x	15.4M	38.27	34.12	32.41	33.34	-
Bicubic & SAN CVPR 2019	2x	15.7M	38.31	34.07	32.42	33.10	-
TAD & TAU ECCV 2018	2x	-	37.69	33.90	32.62	31.96	36.13
CAR & EDSR (SOTA) TIP 20	2x	51.1M	38.94	35.61	33.83	35.24	38.26
Ours MSRA, ECCV20	2x	1.66M	43.99 (+5.05dB)	40.79 (+5.18dB)	41.32 (+7.49dB)	39.92 (+4.68dB)	44.32 (+6.06dB)
Bicubic & RCAN ECCV 2018	4x	15.6M	32.63	29.0	27.84	27.03	30.92
Bicubic & SAN CVPR 2019	4x	15.7M	32.64	28.92	27.78	26.79	-
TAD & TAU ECCV 2018	4x	-	31.59	28.36	27.57	25.56	30.25
CAR & EDSR (SOTA) TIP 20	4x	52.8M	33.88	30.31	29.15	29.28	32.82
Ours MSRA, ECCV20	4x	4.35M	36.19 (+2.31dB)	32.67 (+2.36dB)	31.64 (+2.49dB)	31.41 (+2.13dB)	35.07 (+2.25dB)

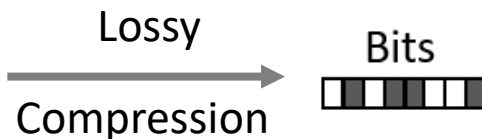
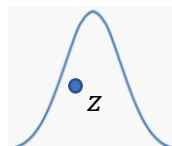
Compression Performance (PSNR/bpp)



HR Image x

INN

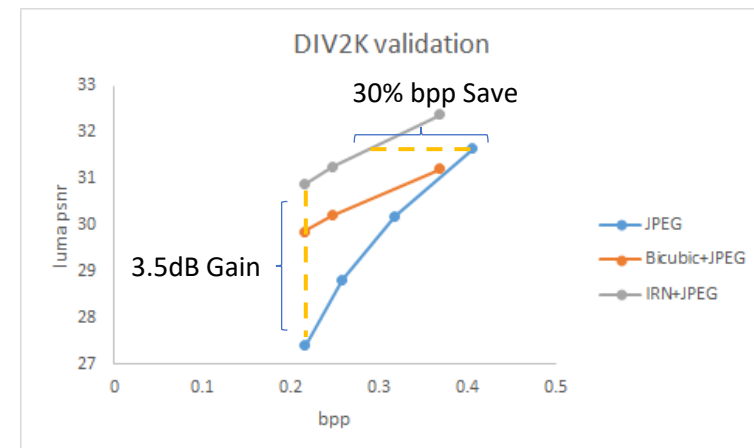
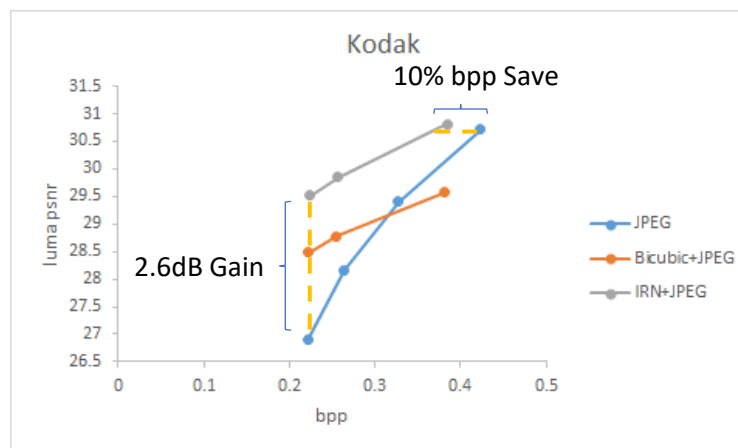
Forward



When Compress a **High**-Resolution Image into **Low** Bitrate:
downscale + compress > compress

IRN: Invertible Rescaling Net

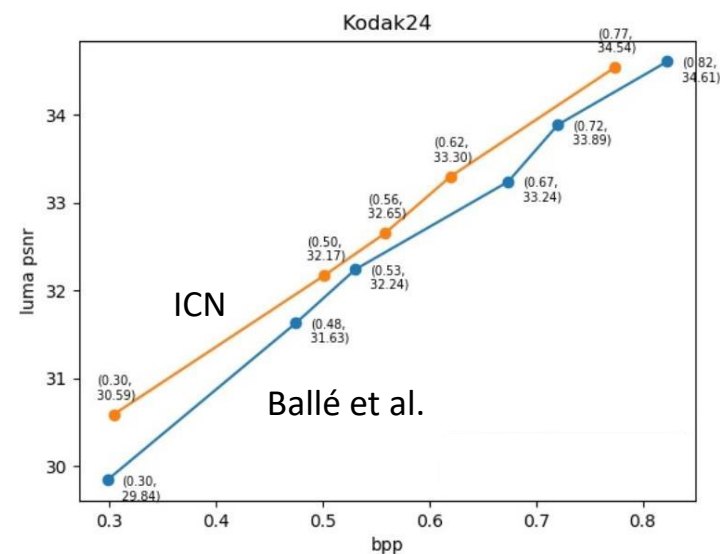
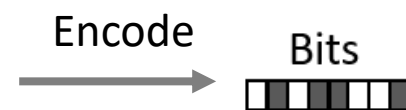
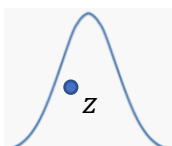
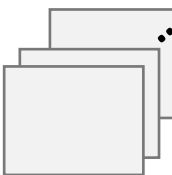
ICN: Invertible Compression Net



HR Image x

INN

Forward



Thanks!

The code is available: <https://github.com/pkuxmq/Invertible-Image-Rescaling>
For any further question, contact: shuz@microsoft.com

Machine Learning Group



Lead by Prof. Tie-Yan Liu, focus on fundamental and innovative machine learning research, including machine learning theory, algorithms and applications. Actively contribute to academic community. Conduct many impactful techniques into Microsoft products, including Bing, Advertising, Xbox, Azure etc.



Super-human Mahjong AI

		output language									
input language	Czech	Nedved NICT									
	German	Microsoft MSRA.MADL	Microsoft MSRA.MADL								
	English	Microsoft MSRA.MADL	Microsoft MSRA.MADL	peterzong GTCOM-Prim	NiuTrans NEU	Microsoft MSRA.MASS	edunov Facebook	pa-translation AI-Transla			
	Finnish	DL-61 USYD									
	French	Microsoft MSRA.MADL									
	Gujarati	NiuTrans NEU									
	Kazakh	NiuTrans NEU									
	Lithuanian	peterzong GTCOM-Prim									
	Russian	Microsoft MSRA.SCA									
	Chinese	Microsoft MSRA.MASS									

First place in WMT 2019

