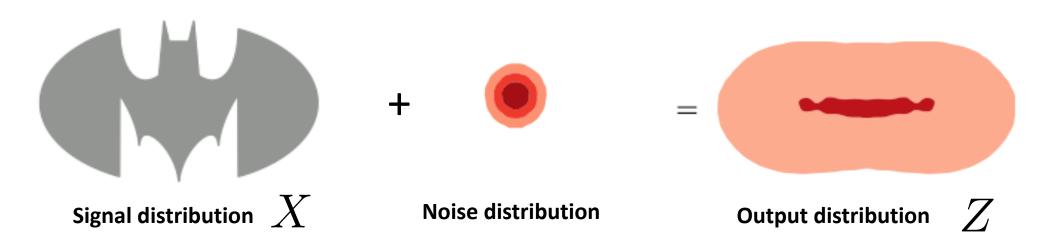




Exact Rate-Distortion in Autoencoders via Echo Noise

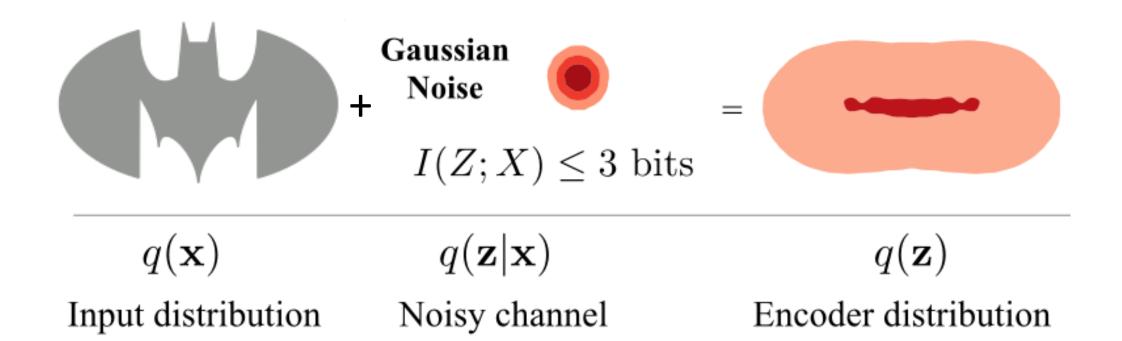
Rob Brekelmans, Daniel Moyer, Aram Galstyan, Greg Ver Steeg arXiv:1904.07199, NeurIPS 2019





$$I(Z;X) = h(Z) - h(Z|X)$$

Entropy of Entropy output of noise

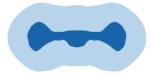


Typical assumptions for mutual information bounds for noisy channel:

- Noise is Gaussian
- Noise is conditionally independent
- Tight only if encoded distribution is Gaussian

Information in Echo Channel

$$I(Z;X) = h(Z) - h(Z|X) \label{eq:interpolation}$$
 Entropy of output noise





Shape is the same – differ only by a scale function S(x)

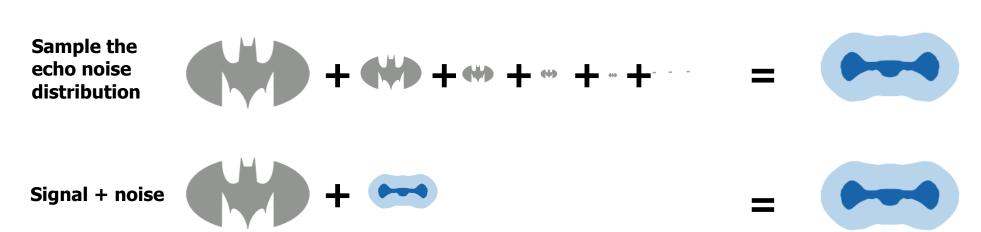
$$I(Z;X) = -\mathbb{E}\log|\det S(\mathbf{x})|$$

- Exact analytic expression for rate
- S(x) parametrized by any neural network
- No assumptions of Gaussianity or independence in Z

How to sample echo noise to get self similarity

Self-similarity between noise distribution and output distribution is the key

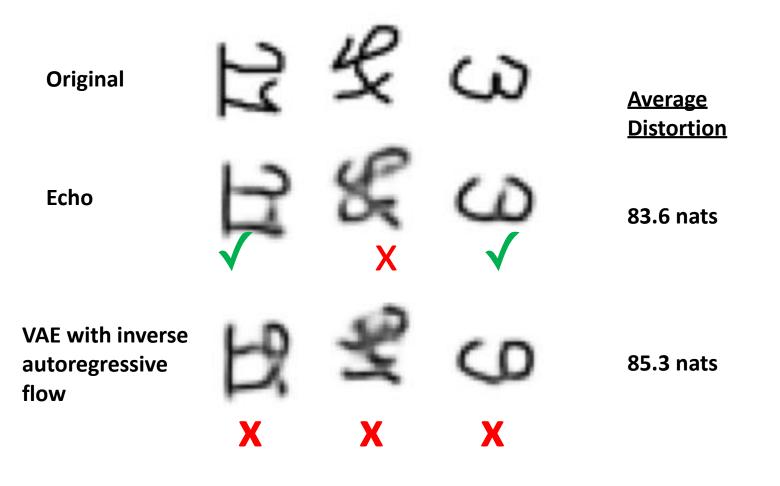




$$I(Z;X) = -\mathbb{E}\log|\det S(\mathbf{x})|$$

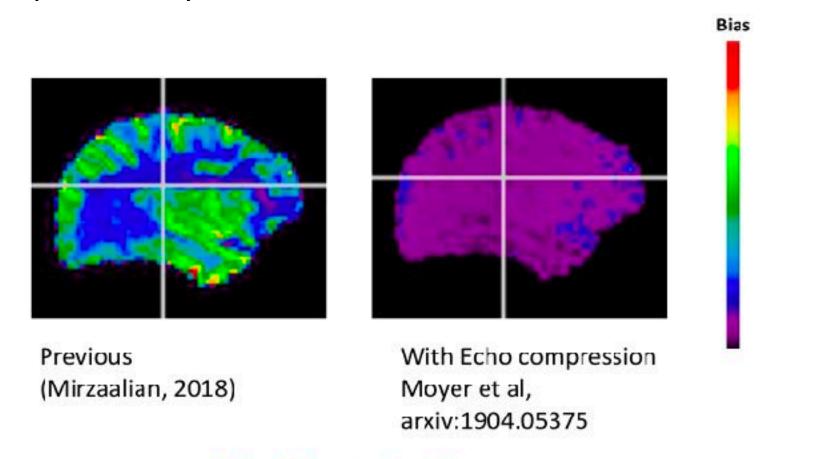
Better compression reduces distortion at low rates

Lossy reconstruction a rate of 30 nats



Invariance = compression (NeurIPS 2018, <u>arXiv:1805.09458</u>), so we can use echo for invariant representation learning

Example: compress away fMRI scanner "site bias": arXiv:1904.05375



More bias → Less bias

Conclusion

- Echo is a more powerful noise model, with an exact, analytic formula for the mutual information (instead of loose bounds)
- Useful wherever lossy compression / rate-distortion appear:
 - (supervised) information bottleneck
 - VAE
 - invariant representation learning
 - Disentangling

Paper: <u>arXiv:1904.07199</u>, NeurIPS 2019

Contact: brekelma@usc.edu, gregv@isi.edu

Code: https://github.com/brekelma/echo



