Neural Joint Source-Channel Coding

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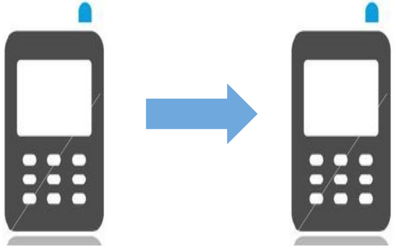
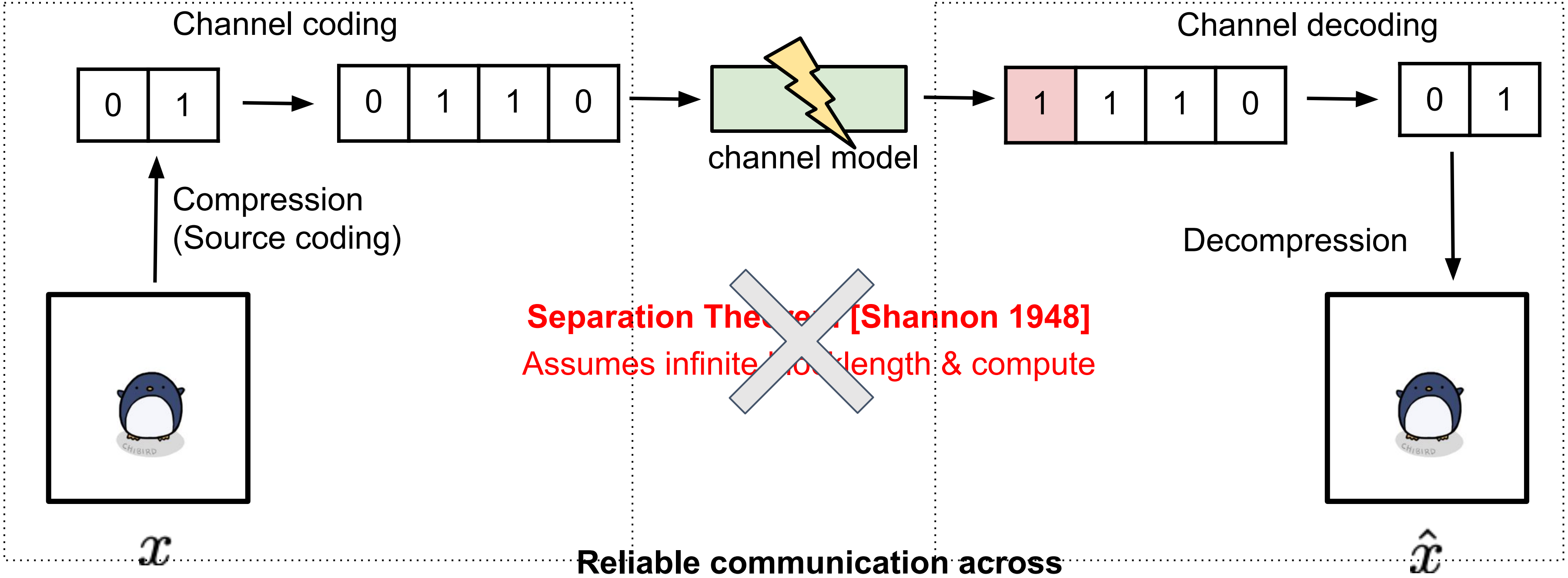
Motivation

Reliable, robust, and efficient information transmission is key for everyday communication

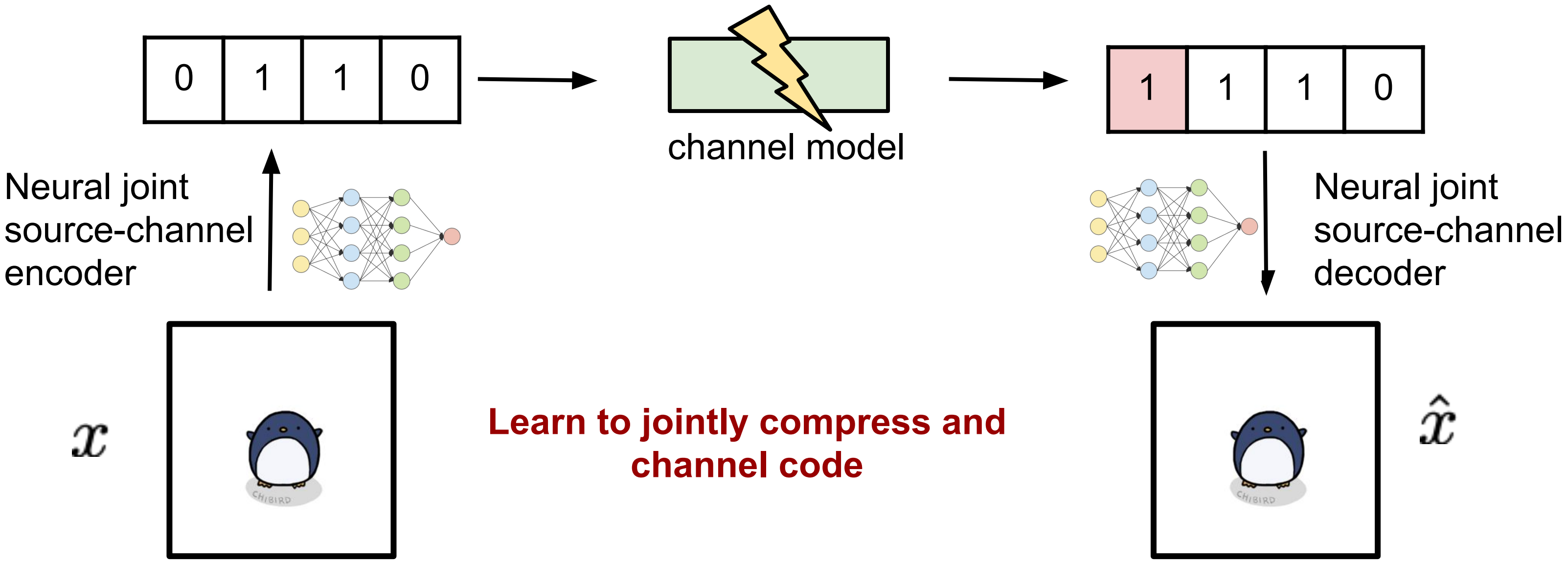


Problem Statement

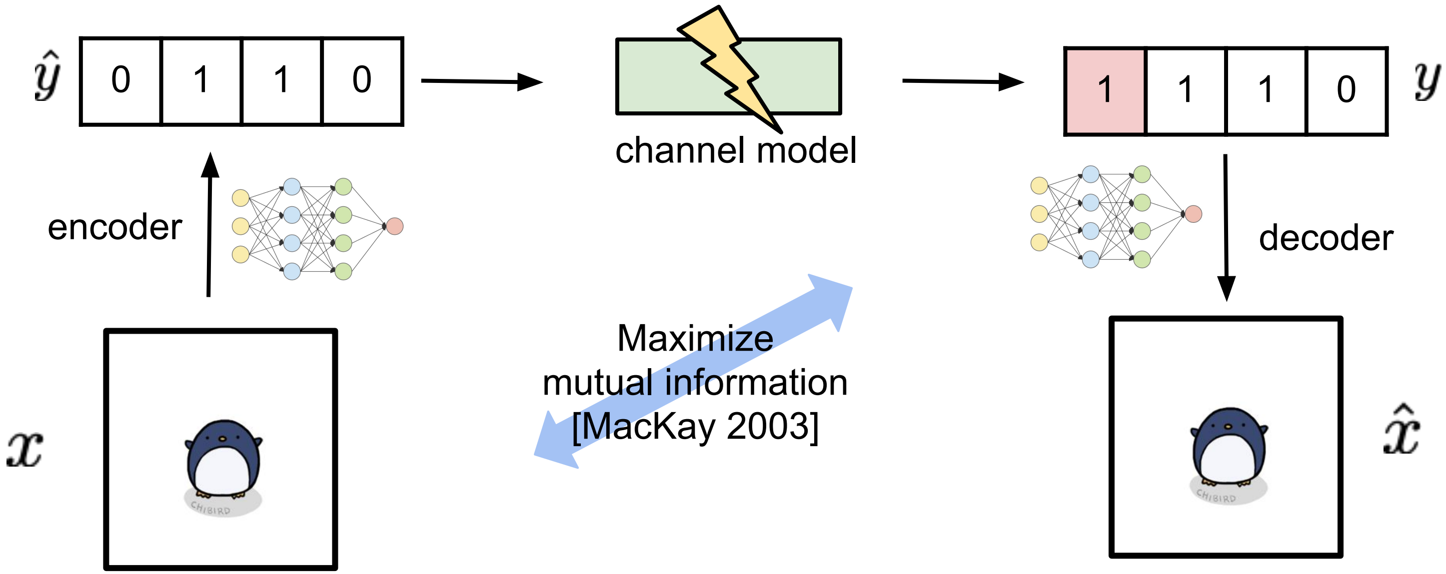


Reliable communication across noisy channel

Neural Joint Source-Channel Coding

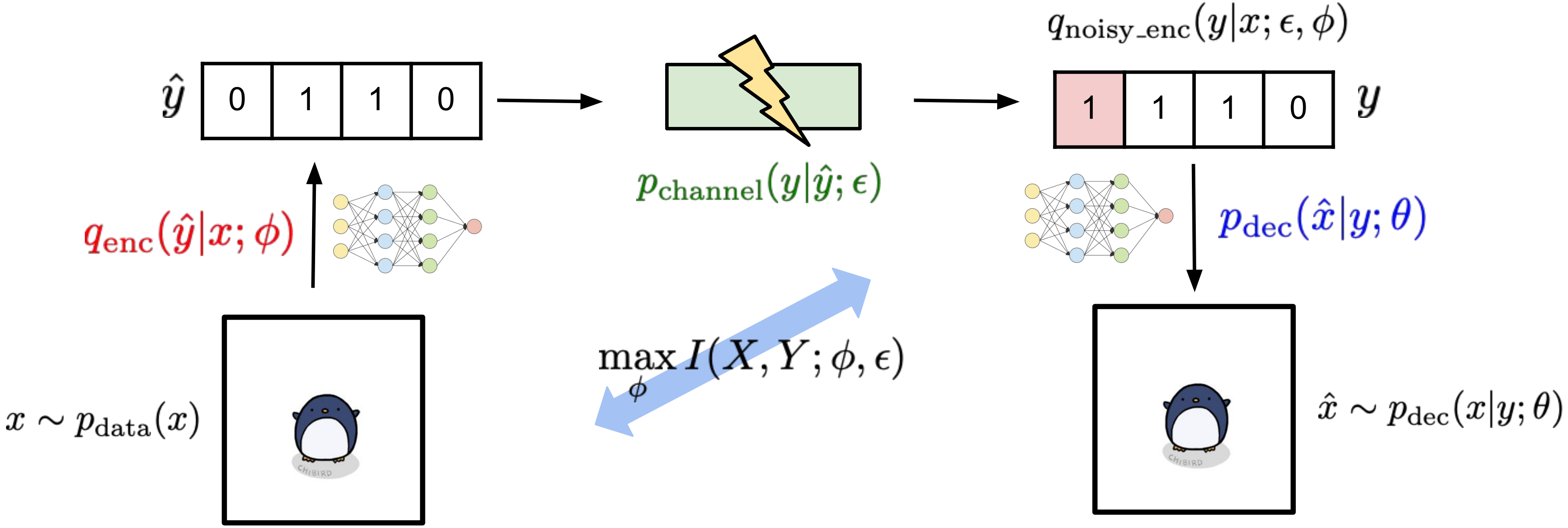


NECST Model



$\hat{y}$
0
1
1
0
channel model
1
1
1
0
y
encoder
decoder
Maximize
mutual information
[MacKay 2003]
x
CHIBIRD
CHIBIRD
$\hat{x}$

Coding Process



$$p(x,\hat{y},y,\hat{x}) = p_{\text{data}}(x)q_{\text{enc}}(\hat{y}|x;\phi)p_{\text{channel}}(y|\hat{y};\epsilon)p_{\text{dec}}(\hat{x}|y;\theta)$$

Learning Objective

- Mutual information maximization
  - *Y* should capture as much information about *X* as possible, *even after corruption!*
  - Estimation is hard ☹️ [Barber & Agakov 2004]
- Variational lower bound is nicer:

$$\max_{\phi} I(X,Y;\phi,\epsilon) = \max_{\phi} H(X) - H(X|Y;\phi,\epsilon)$$

$$\geq \max_{\theta,\phi} \boxed{\mathbb{E}_{x\sim p_{\mathrm{data}}(x)}\mathbb{E}_{y\sim q_{\mathrm{noisy\_enc}}(y|x;\epsilon,\phi)}[\log p_{\mathrm{dec}}(x|y;\theta)]}$$

[Kingma & Welling 2014]
[Vincent 2008]

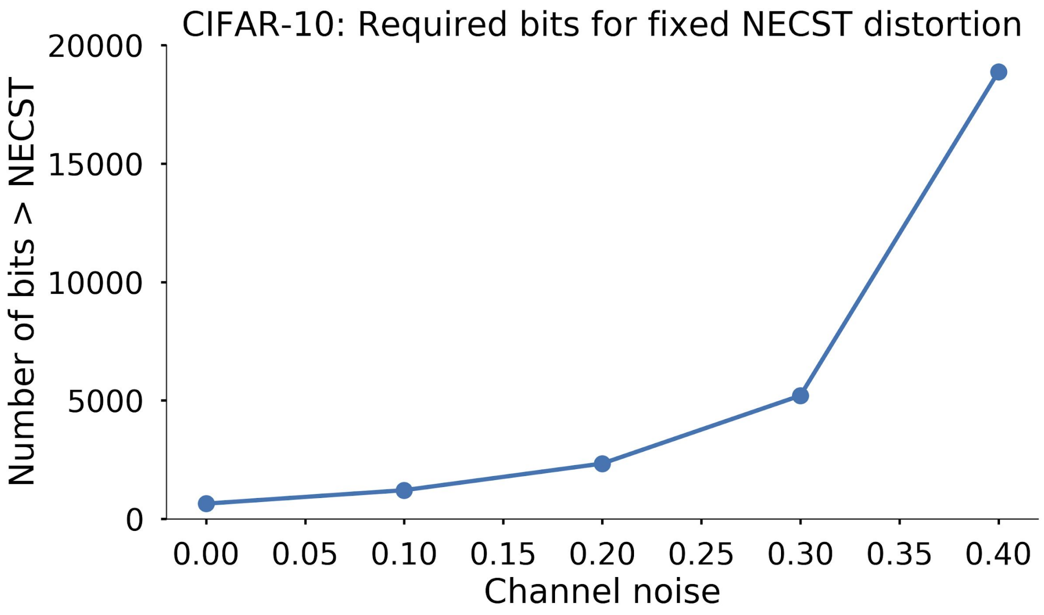
Reconstruction loss!

Optimization Procedure

- Our latent variables *y* are discrete ☹️
- Use VIMCO: [Mnih and Rezende 2016]
  - Draw multiple (*K*) samples from inference network, get tighter lower bound

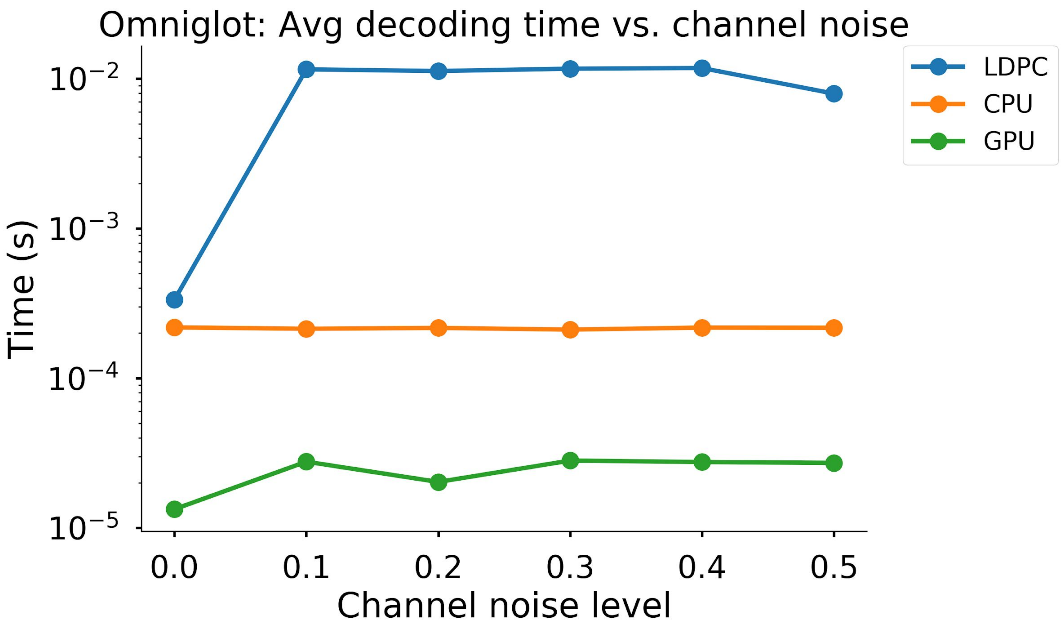
$$\mathcal{L}^K(\phi, \theta; x, \epsilon) = \sum_{x \in \mathcal{D}} \underbrace{\boxed{\mathbb{E}_{y^{1:K} \sim q_{\text{noisy\_enc}}(y|x;\epsilon,\phi)}}}_{\text{Multiple samples of } y} \underbrace{\boxed{\left[\frac{1}{K} \sum_{i=1}^{K} p_{\text{dec}}(x|y^i;\theta) \right]}}_{\text{Multiple reconstruction loss terms}}$$

Fixed Rate: Comparison vs. Ideal Codes



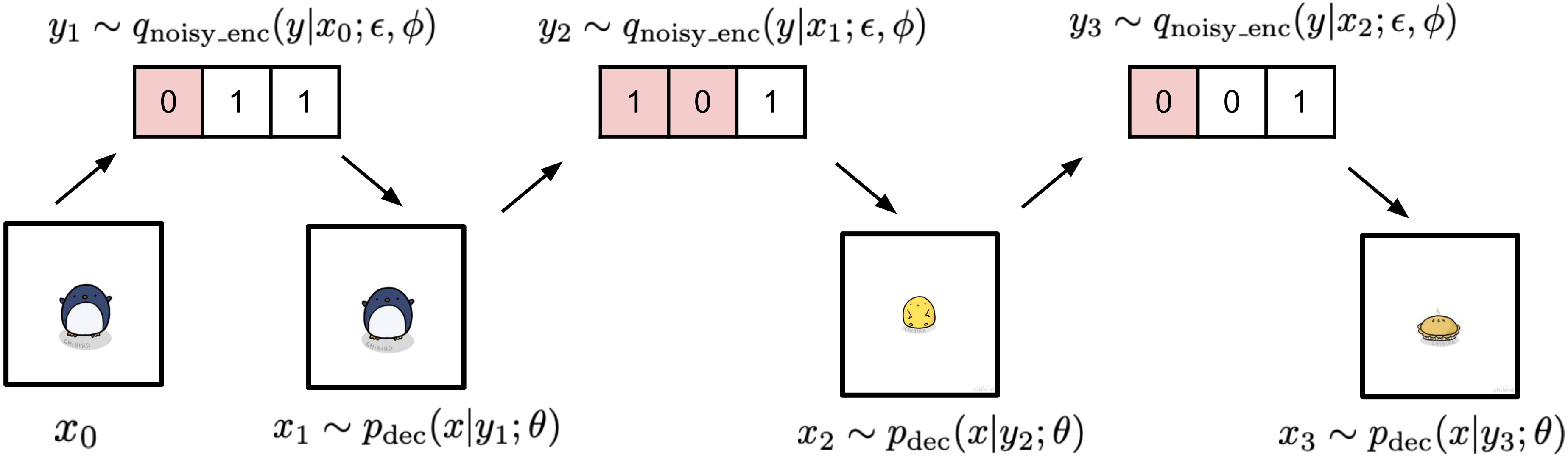
We need *a much smaller number of bits* to get the same level of distortion, even vs. WebP [Google 2010] + ideal channel code

Extremely Fast Decoding



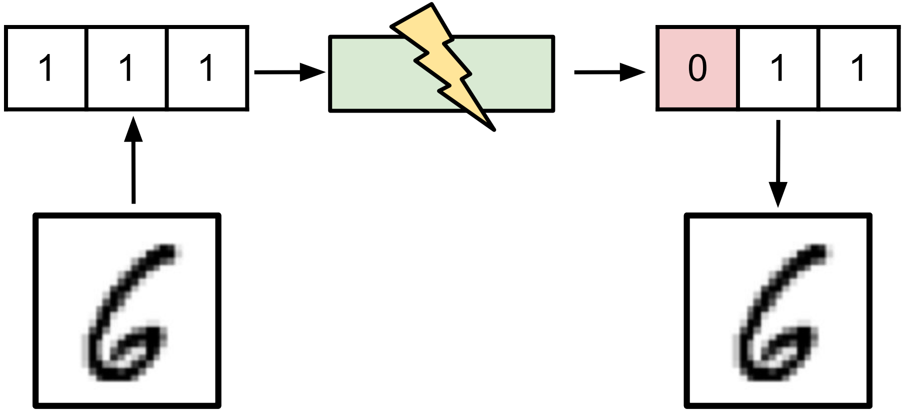
Up to 2x orders of magnitude in speedup on GPU vs. LDPC decoder [Gallager 1963]

Learning the Data Distribution

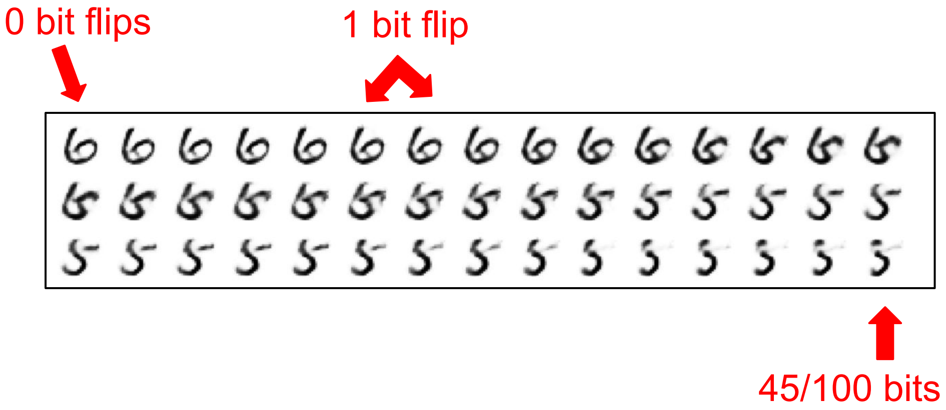


<u>Theorem (informal):</u> NECST learns an implicit model of $p_{\text{data}}(x)$

Robust Representation Learning



1) Encoded redundancies:
interpolation in latent space by bit-flip



2) Improved downstream classification: improves accuracy by as much as 29% across variety of classifiers when inputs are corrupted by noise!

Summary

- End-to-end deep generative modeling framework for the JSCC problem
- Better bitlength efficiency than separation scheme on CIFAR10, CelebA, SVHN
- Another way to learn robust latent representations
- Get an extremely fast decoder for free

Thanks!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Code: https://github.com/ermongroup/necst

Poster #165: Tuesday, June 11th @ **Pacific Ballroom**