Lossy compression for lossless prediction

EECS Seminar: Advanced Topics in Machine Learning

Romain Graux

March 17, 2022

Motivation

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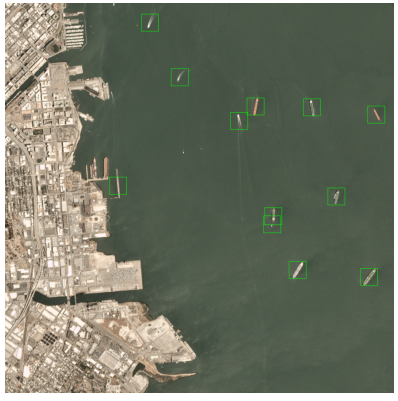

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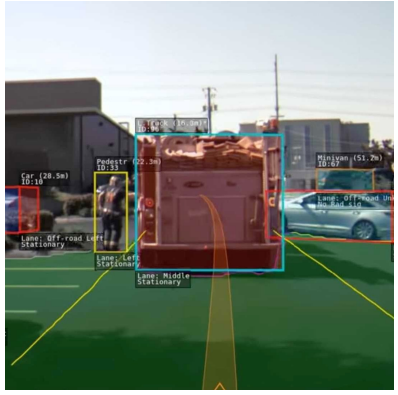

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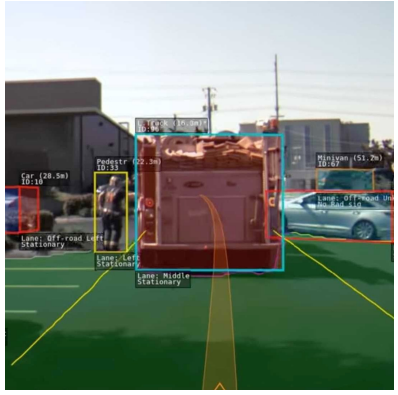

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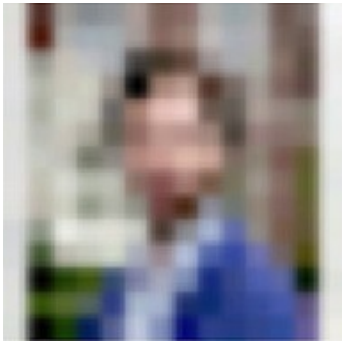

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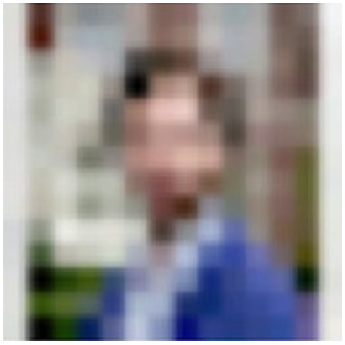

Low bitrate

Desired

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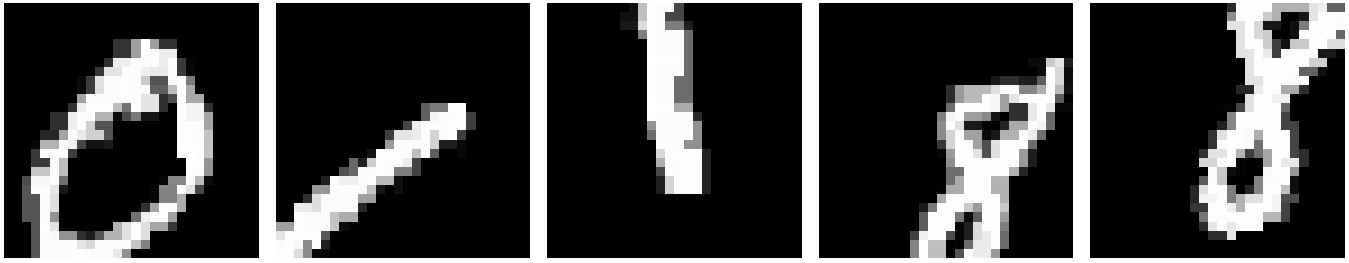
- Characterize minimum bit-rate to ensure high performance on desired tasks;
- Derive unsupervised objectives for training **task-centric** compressors;
- $> 1000x$ compression gains on Imagenet compared to JPEG (see Slide 13).

Intuition

Intuition: Augmented MNIST



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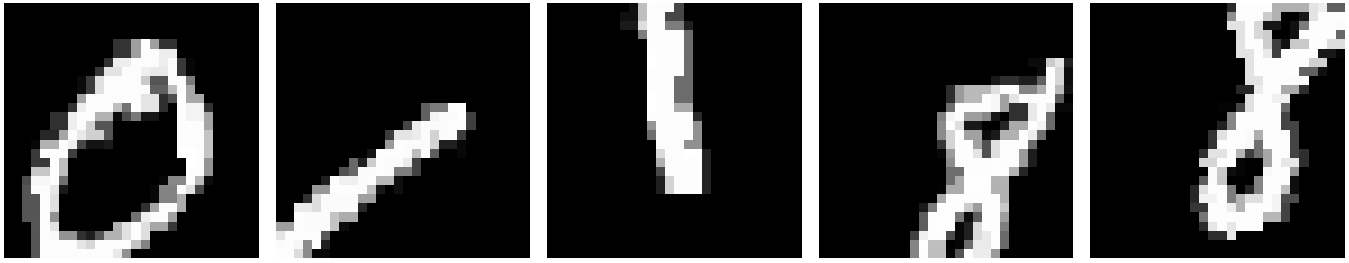

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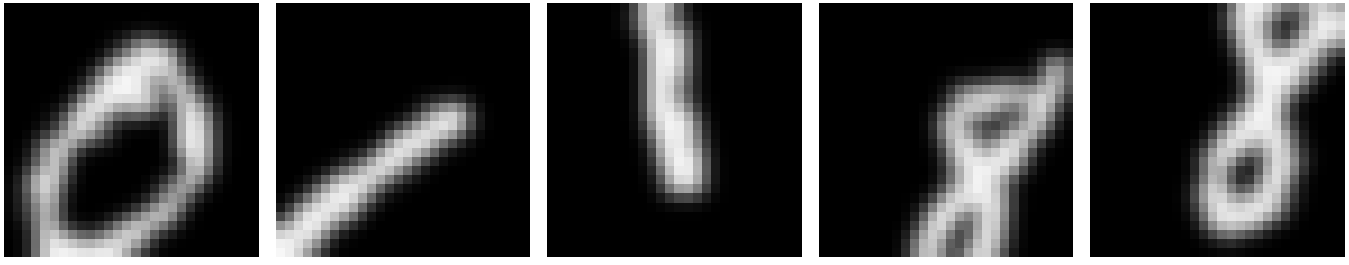

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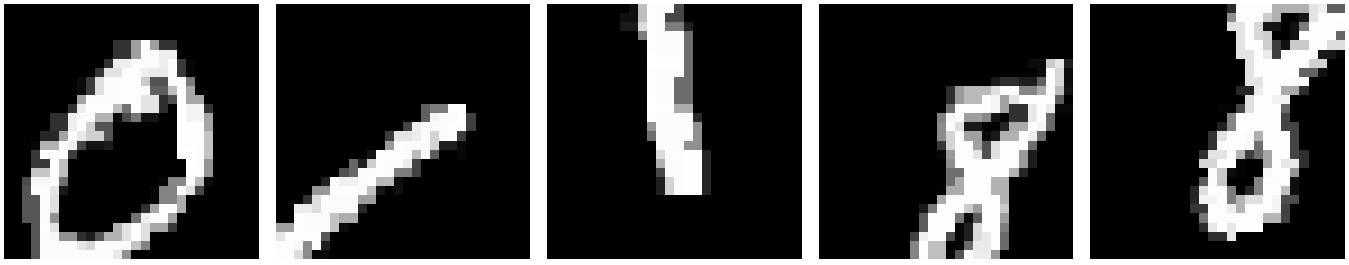

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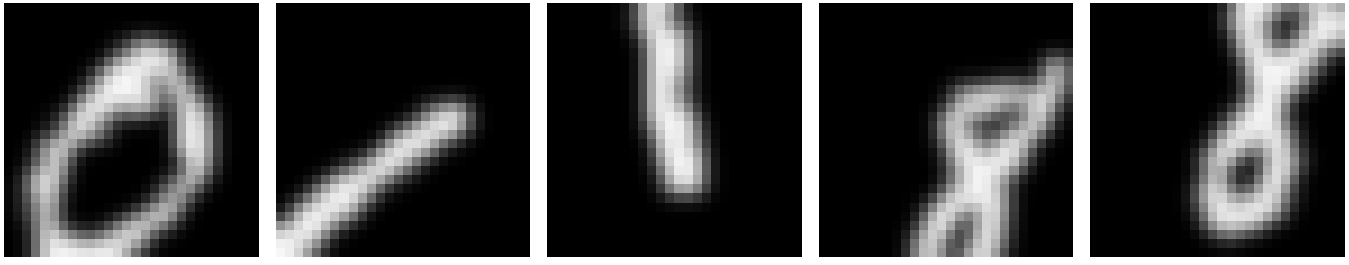

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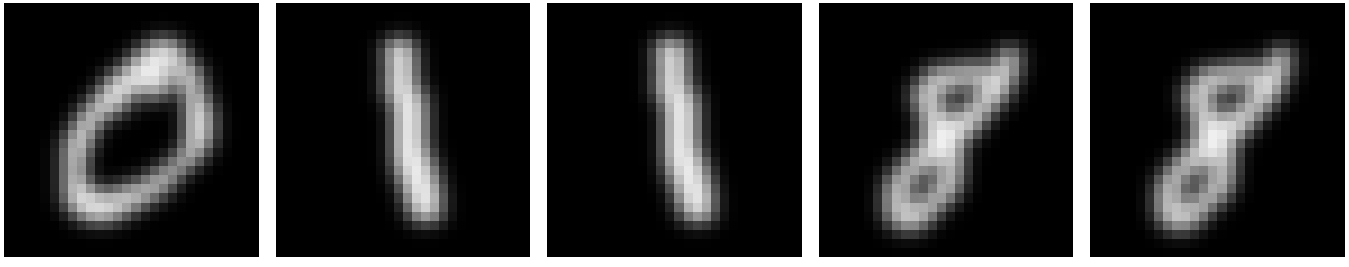

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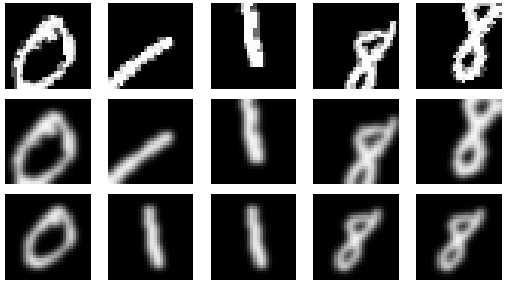

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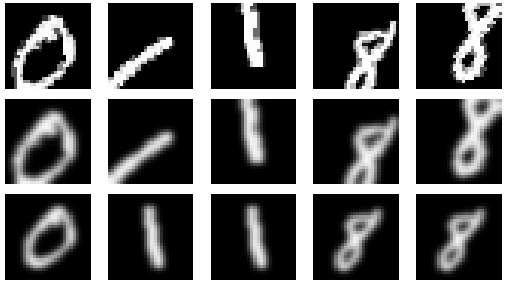

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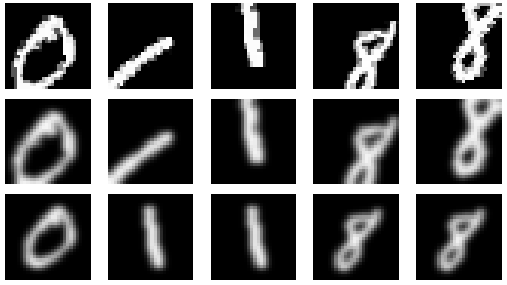

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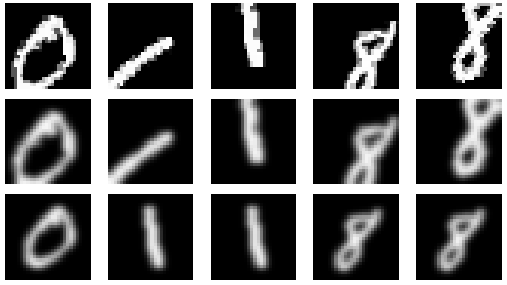

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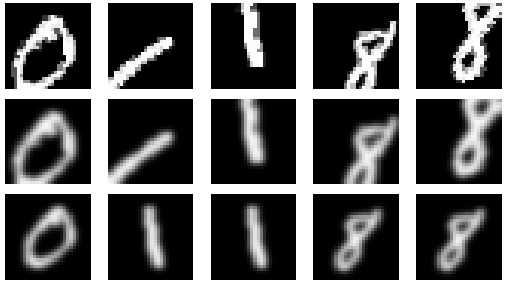

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⇒ The objective is **unsupervised**

Formalized using invariances

Formalism

Problem setup

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  - e.g. Y_1: how old is the person?
  - e.g. Y_2: does the person wear glasses?

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Problem: Would assume access $\mathcal{T}$

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Proposition

Exists a "worst task" $M(X)$ that has all information to predict any invariant task $Y \in \mathcal{T}$

$$H[M(X)|Z] = \sup_{Y \in \mathcal{T}} R[Y|Z] - R[Y|X] \leq \delta$$

What we want:

$$x \sim x^+ \iff M(x) = M(x^+) \text{ for any } x, x^+ \in X$$

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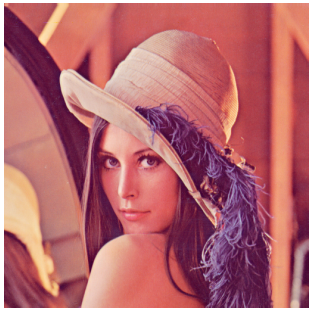

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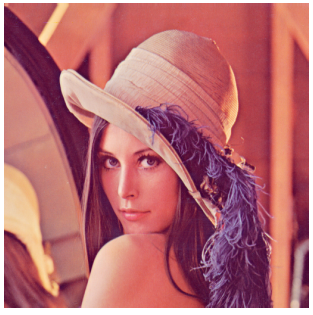

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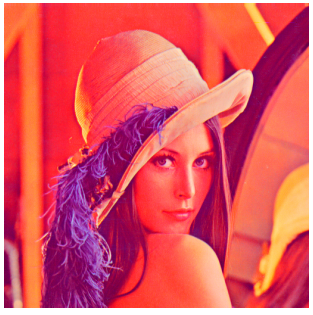

x_3: saturation

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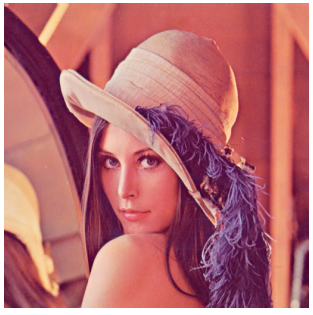

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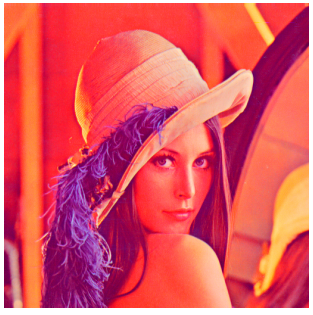

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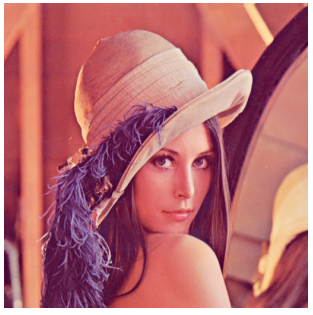

$M(x)$: unaugmented

Theorem: Rate-Invariance

Using the rate-distortion therorem [Shannon, 1959] with $R[M(X)|Z]$ as distortion:

Theorem (Rate-Invariance)

The minimum achievable bit-rate for transmitting Z s.t. for any invariant $Y \in \mathcal{T}$ we have an excess Bayes risk $R[Y|Z] - R[Y|X]$ upper bounded by δ is

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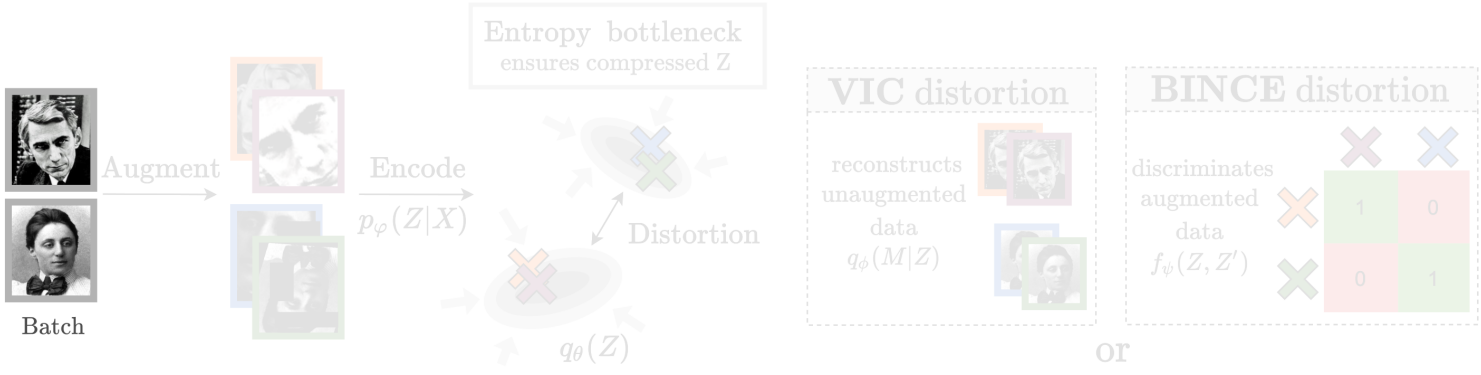
$\Rightarrow$ a δ decrease in *log-loss* save exactly δ bits

In practice

Training architecture



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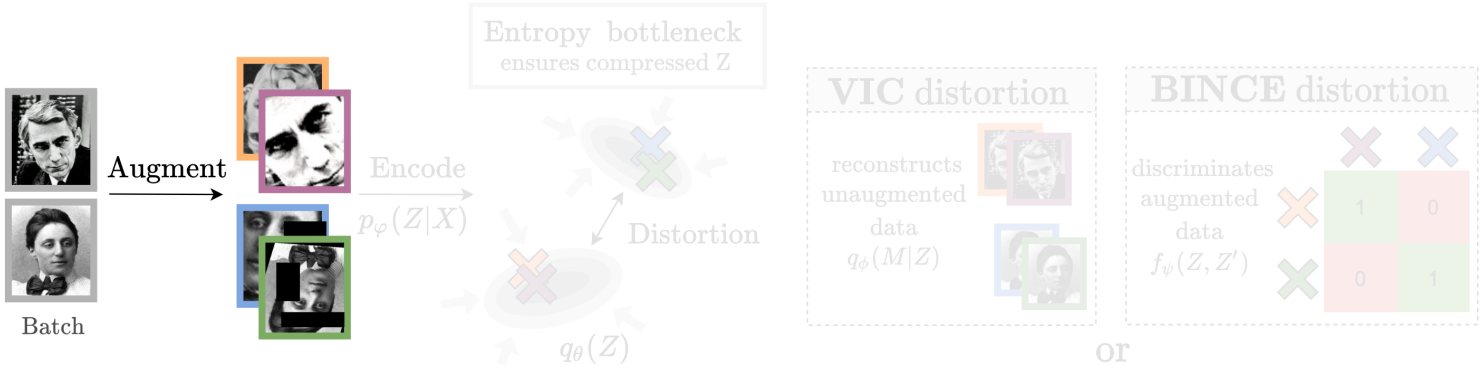

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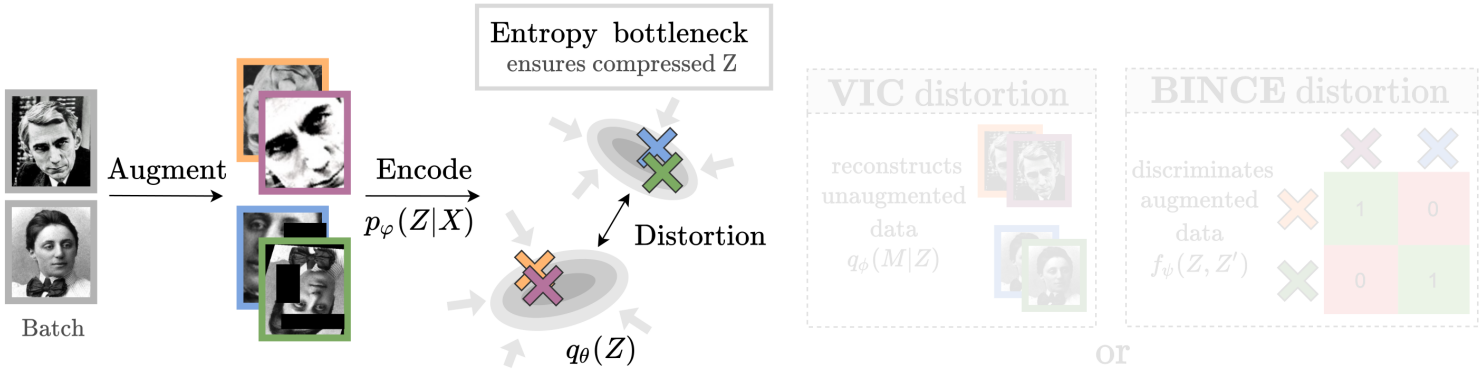

Entropy bottleneck: compressed Z

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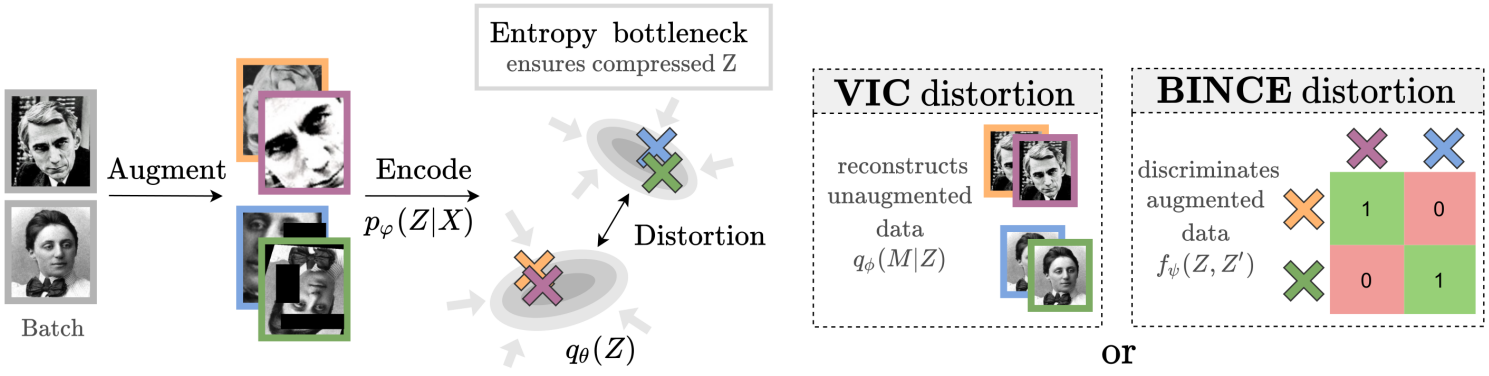

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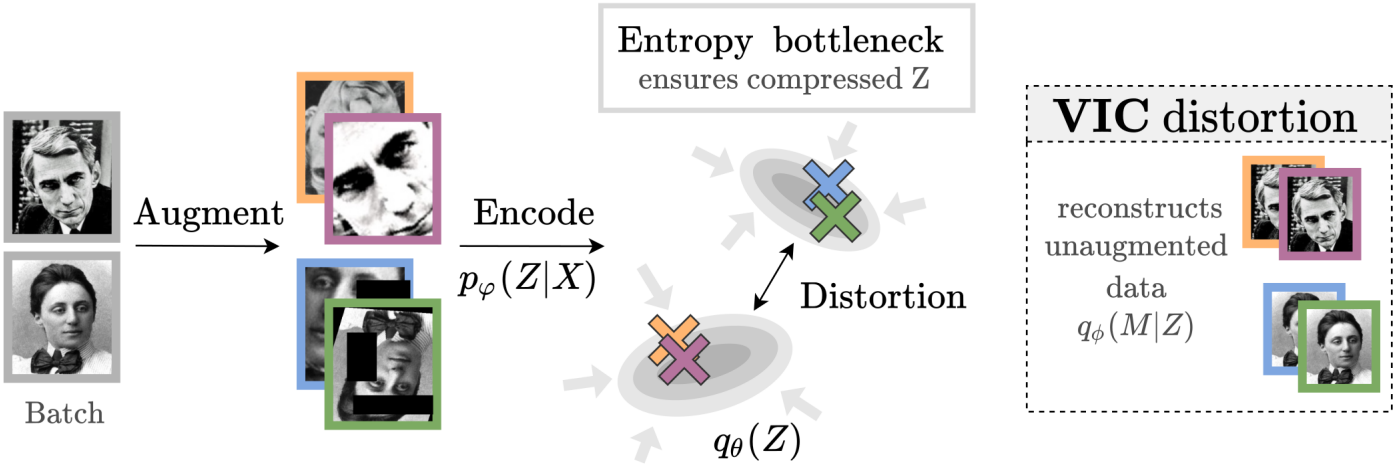
Variational Invariant Compressor



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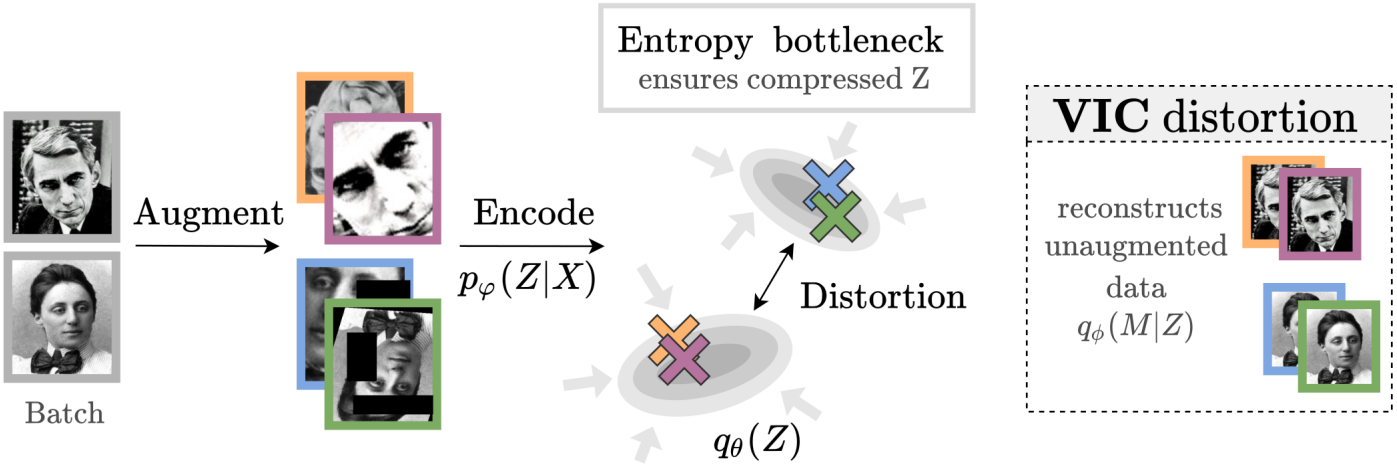
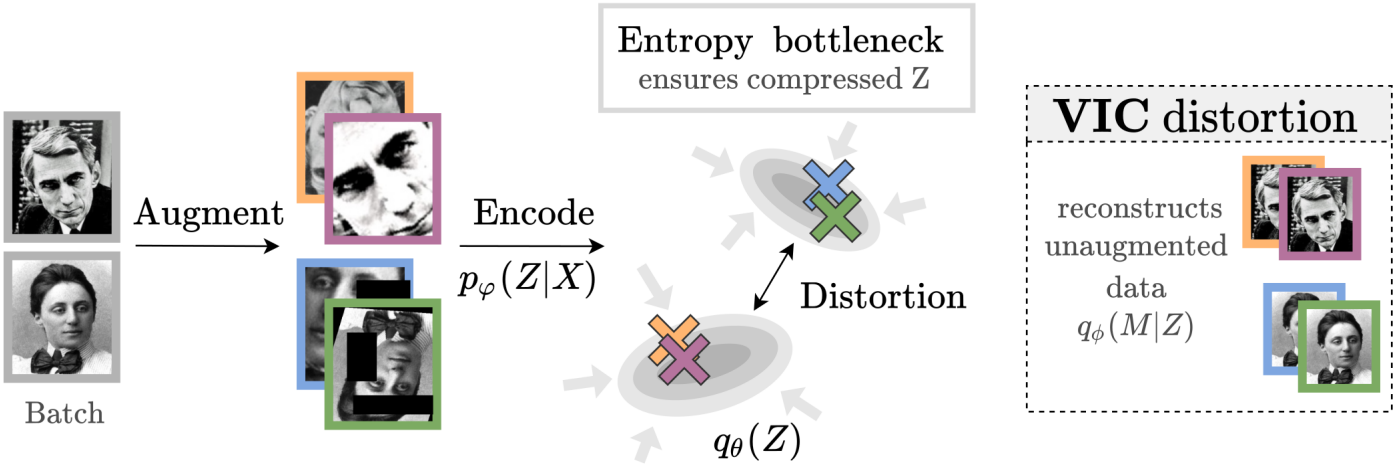


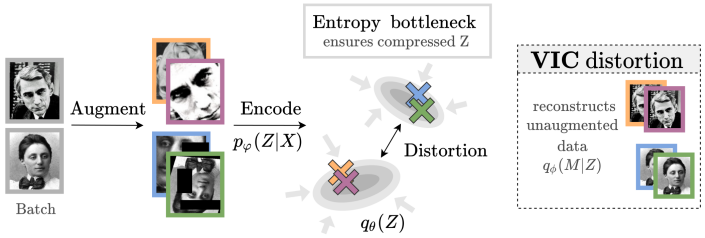
- Reconstruct the prototypicals

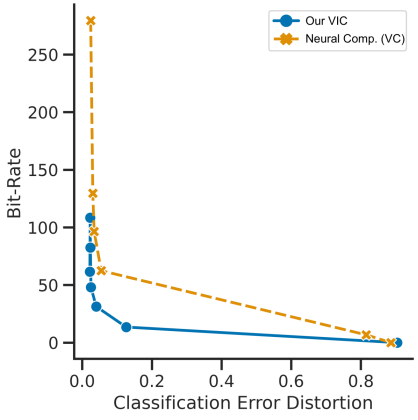
Variational Invariant Compressor



- Reconstruct the prototypicals
- Unaugmented images

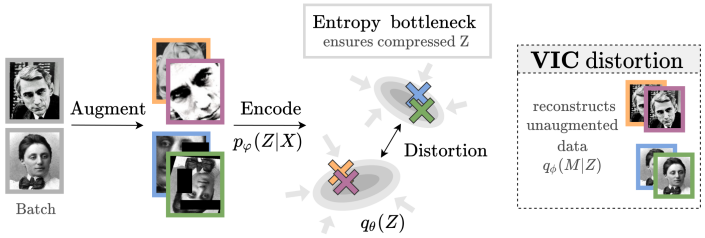
Variational Invariant Compressor

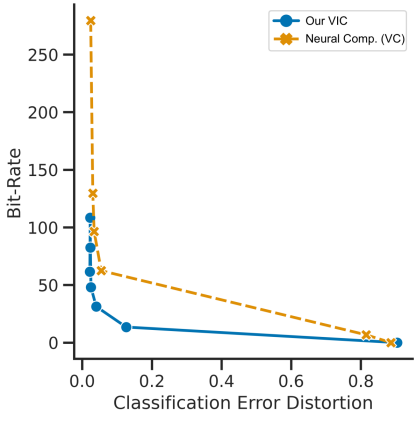




Rate-Error curve

Variational Invariant Compressor





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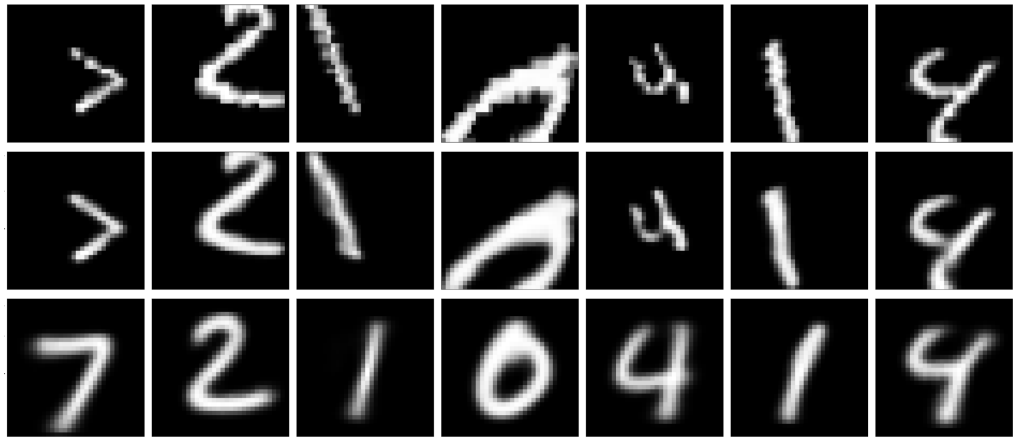


(1)

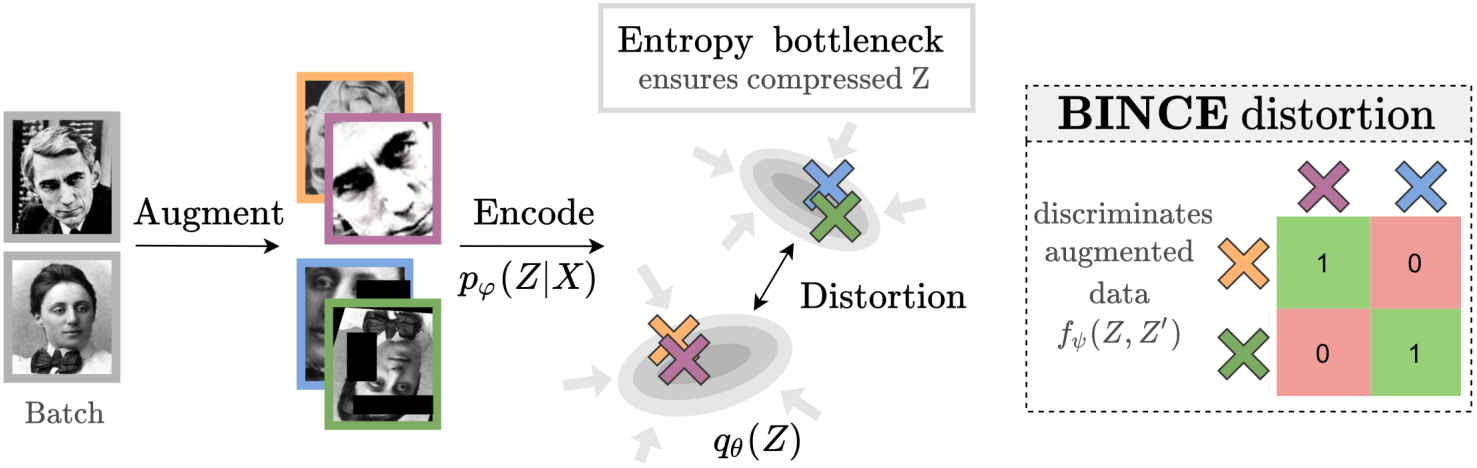
(2)

(3)

Reconstructions that allow 99% downstream accuracy

(1) Source (2) Standard compression [130 bits] (3) Invariant compression [48 bits]

Bottleneck InfoNCE: Intuition



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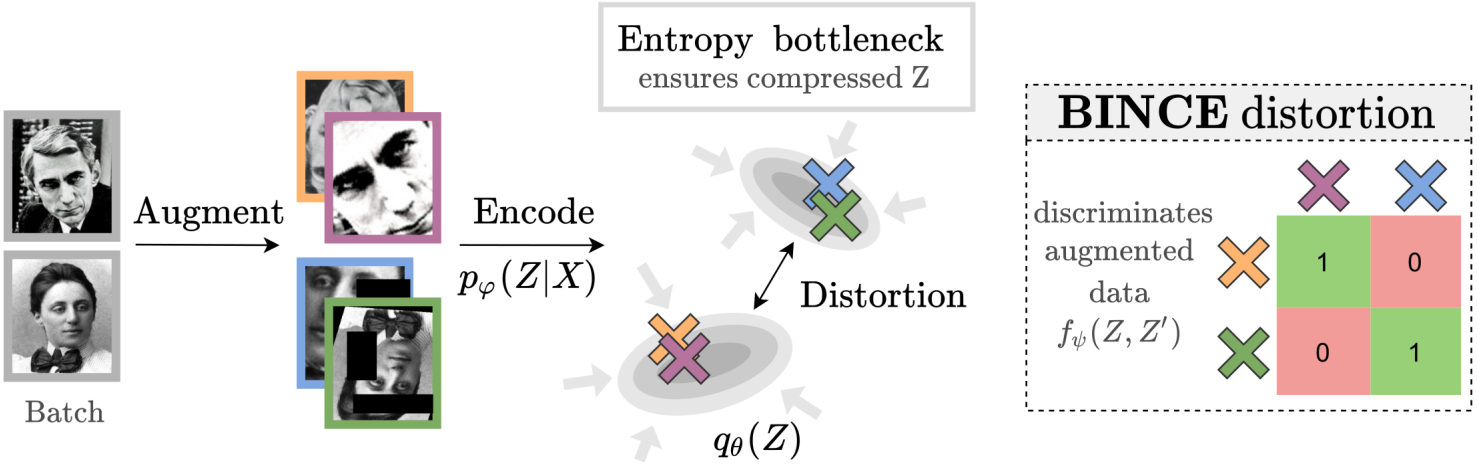
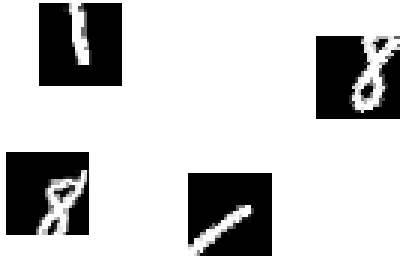


Contrastive learning



Latent representation

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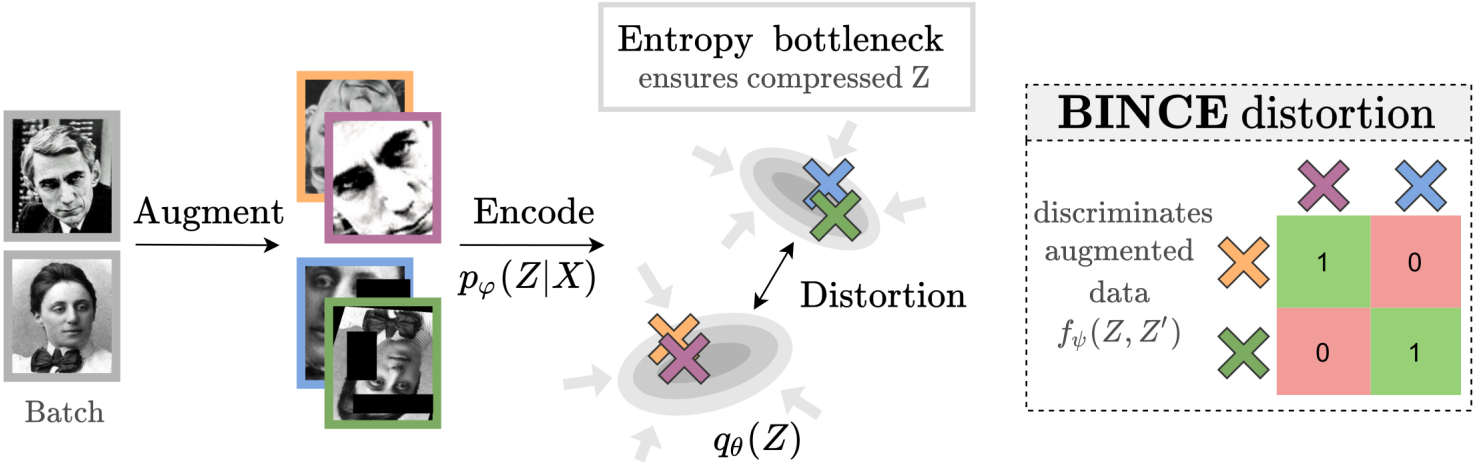

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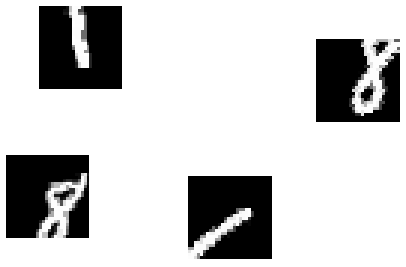

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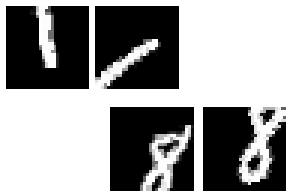

Bottleneck

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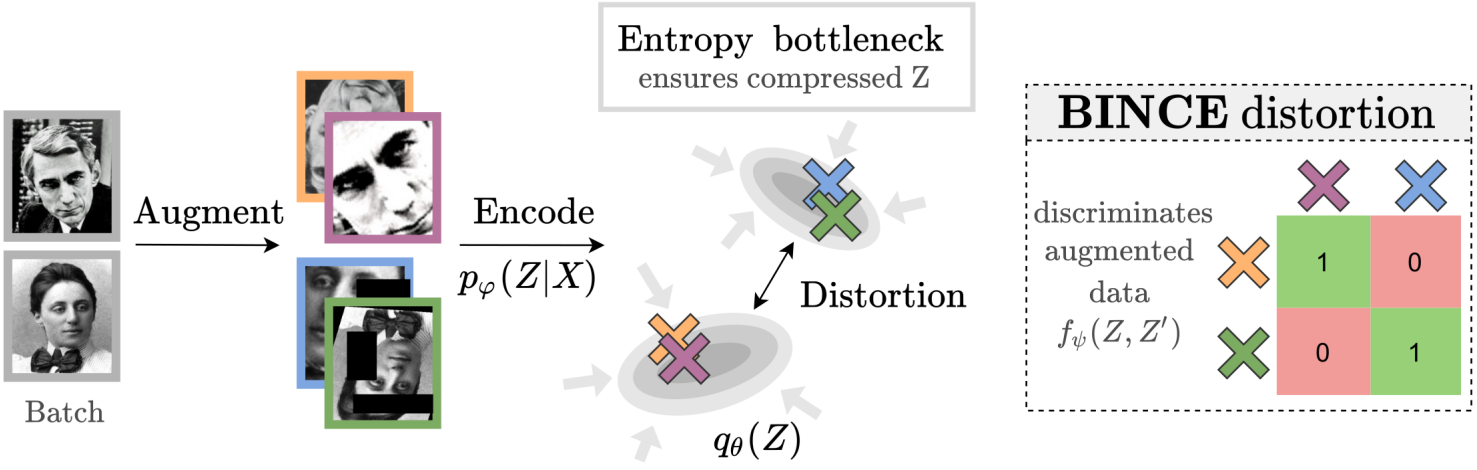

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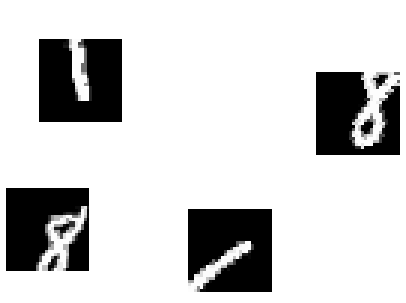

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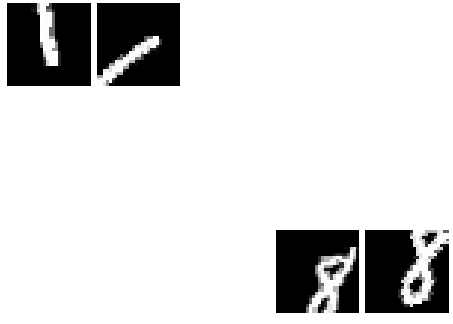

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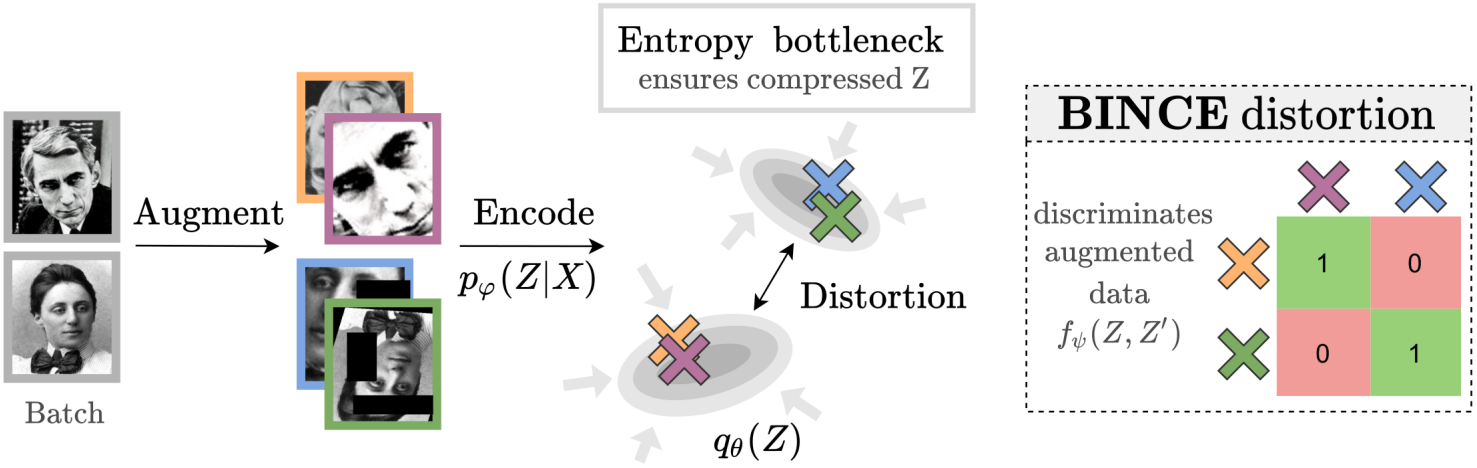

Pros:

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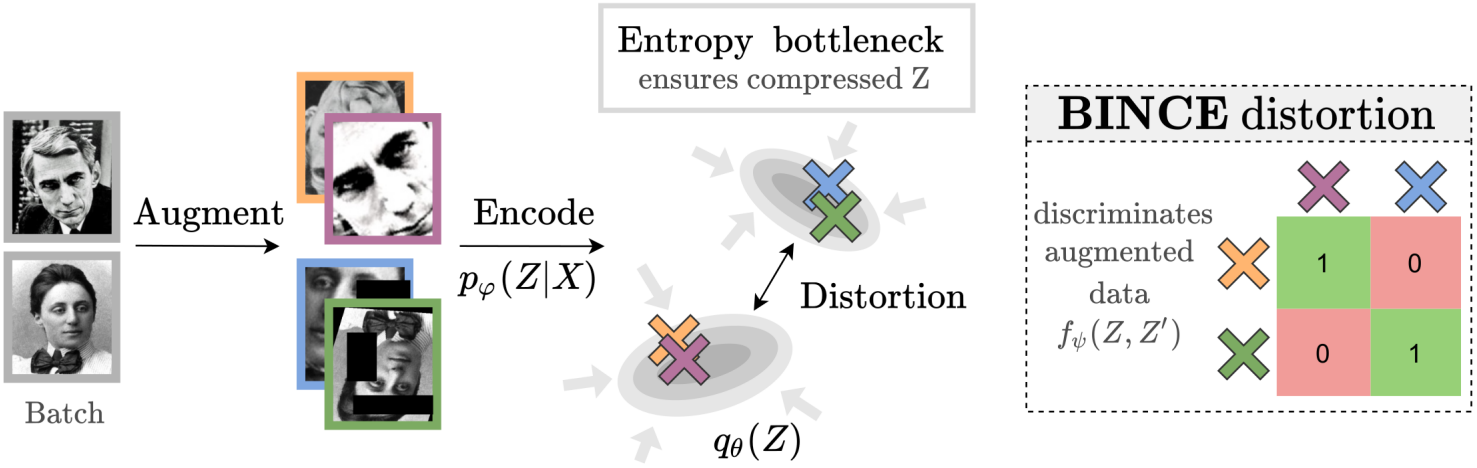

Pros:

- does not have to reconstruct high dimensional data

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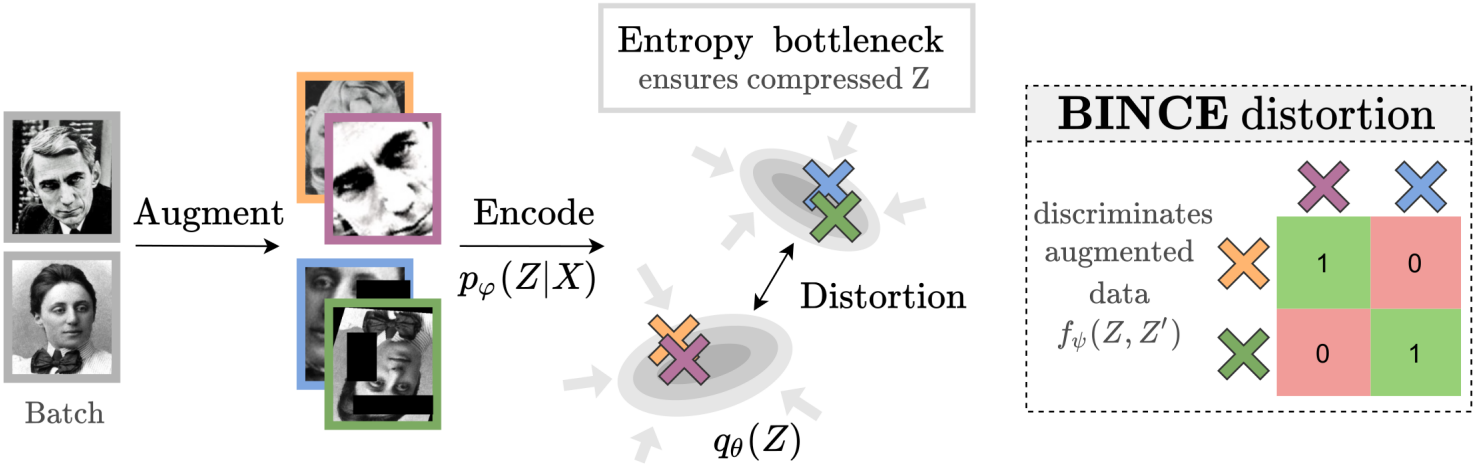

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- gives representations that are approx. linearly separable

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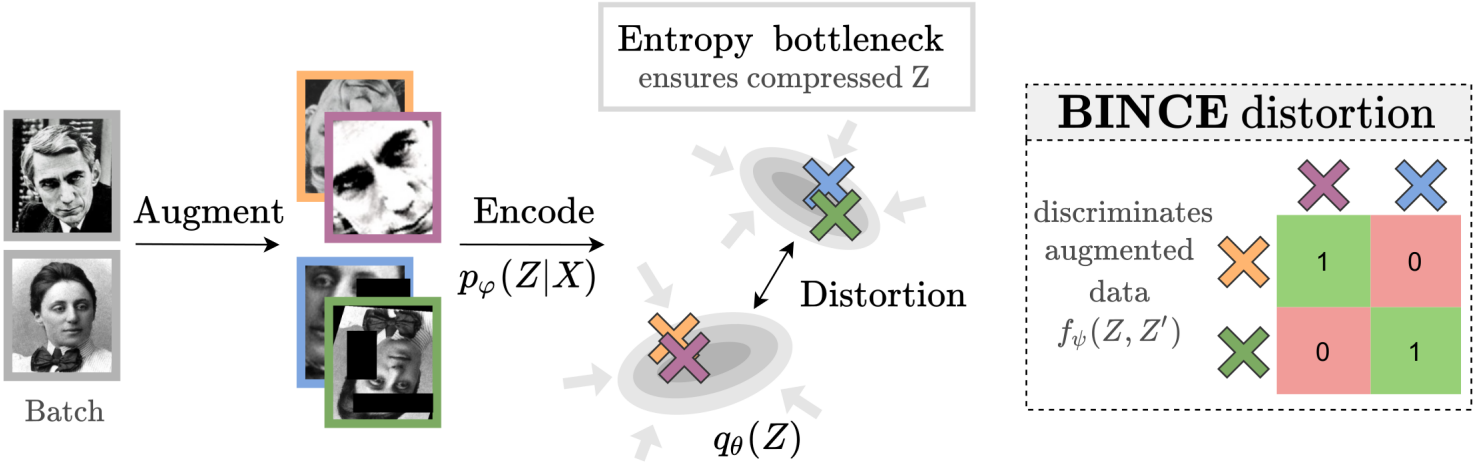

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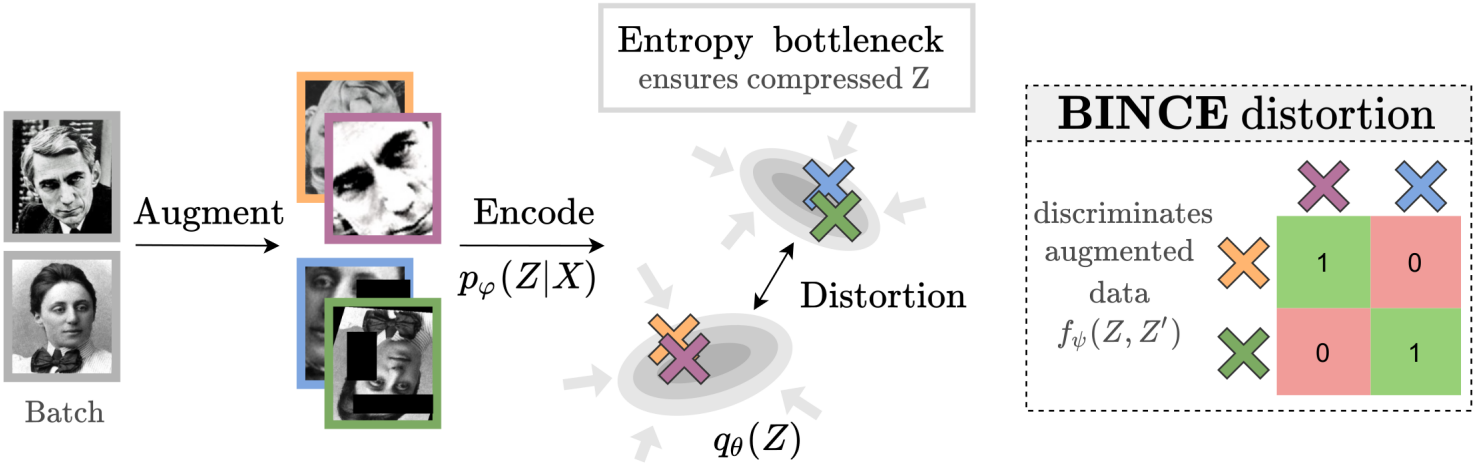

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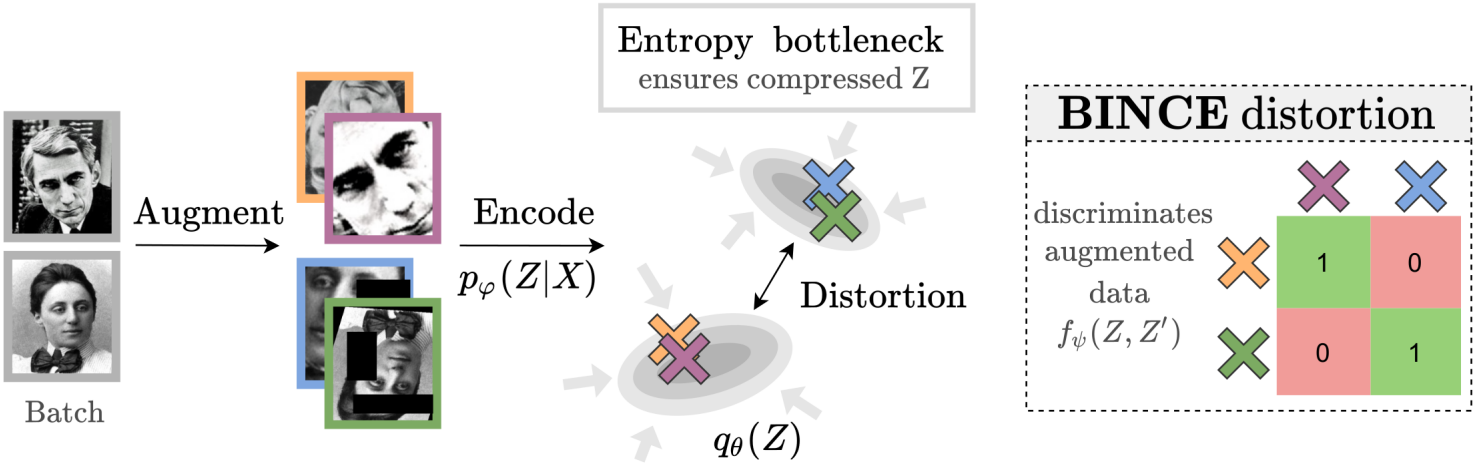

Pros:

- does not have to reconstruct high dimensional data
- gives representations that are approx. linearly separable

Cons:

- diminishes interpretability
- has a high bias, needs lot of negative examples

Trained encoder : CLIP

Idea: Can simply add an entropy bottleneck to a SOTA SSL

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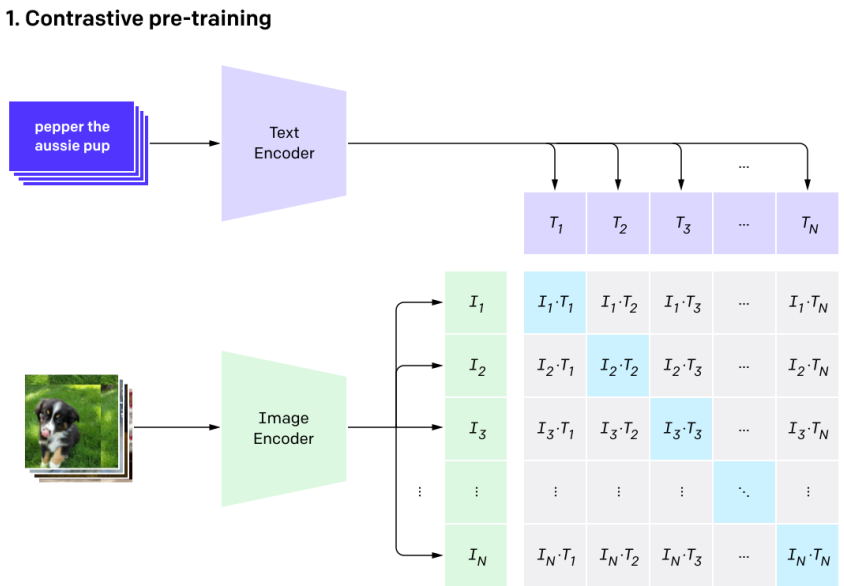
CLIP: trained on +400M of image/text pairs



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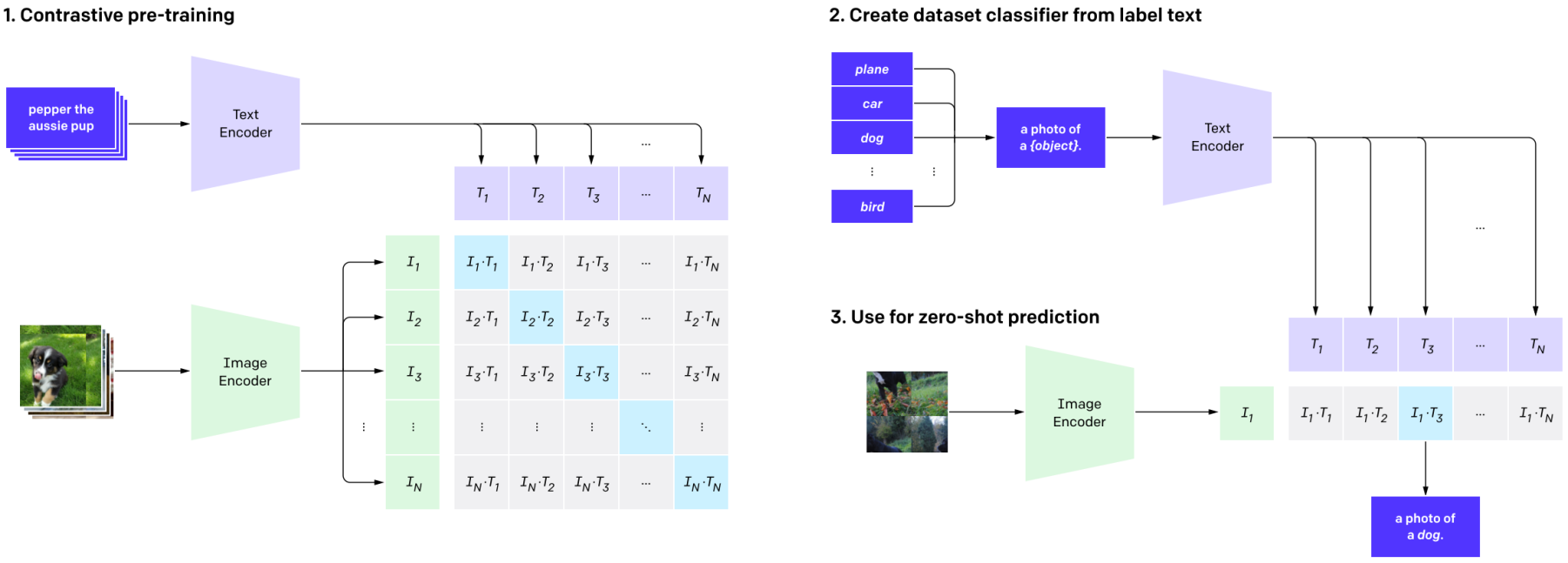

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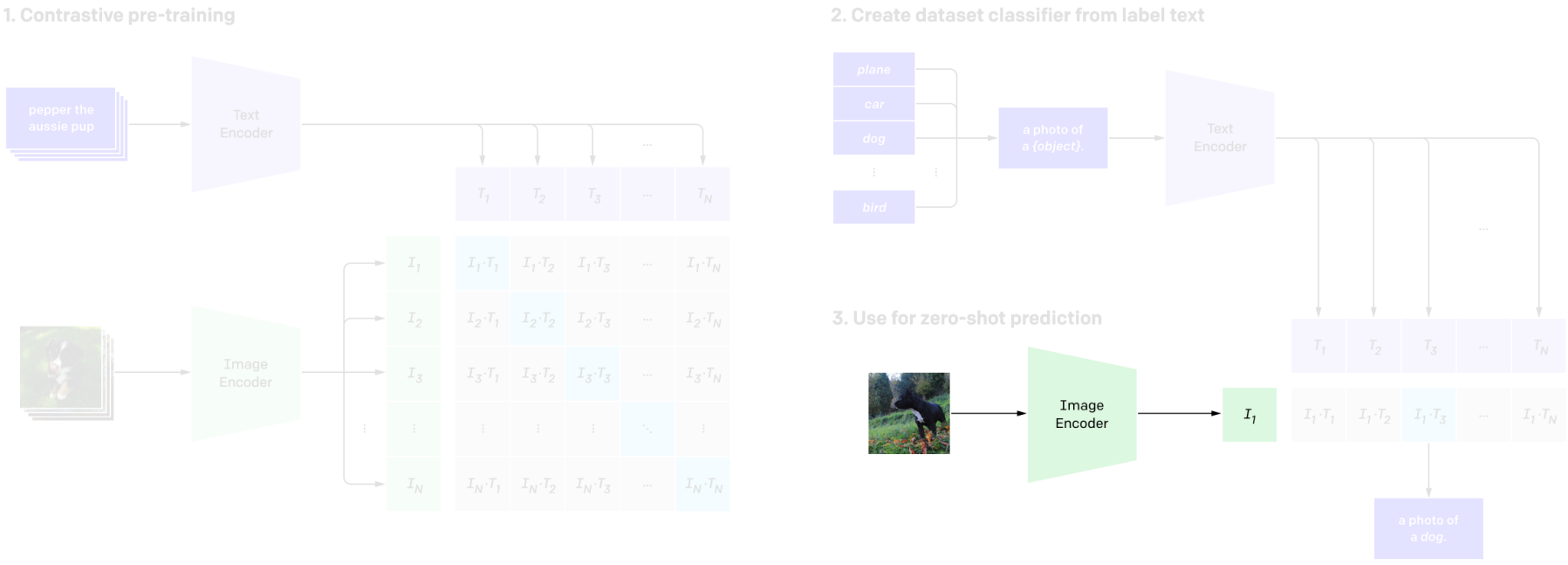

Bottleneck InfoNCE: Experiment

1. Download SOTA SLL (CLIP) and freeze it

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	ImageNet	STL	PCam	Cars	CIFAR10	Food	Pets	Caltech
Rate gains vs JPEG	1104×	35×	64×	131×	7×	109×	150×	126×
Our Acc. [%]	76.3	98.7	80.9	79.6	95.2	88.3	89.5	93.4
Supervised Acc. [%]	76.1	99.0	82.6	49.1	96.7	81.8	90.4	94.5

Discussion

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Strengths

- Rates

Weaknesses

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Discussion

Strengths

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Weaknesses

- Irrecoverable loss
- Interpretability of compressed data
- Set of transformations hard to find

$\Rightarrow$ Achieved orders of magnitude improvements in compression for predicitons. It's one of the first paper on lossy compression in a multi-tasks setting.

Thank you!