Lossy compression for lossless prediction

EECS Seminar: Advanced Topics in Machine Learning

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Motivation

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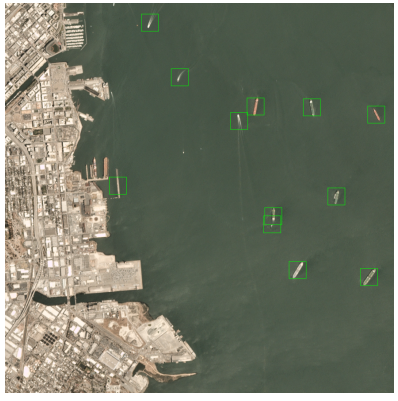

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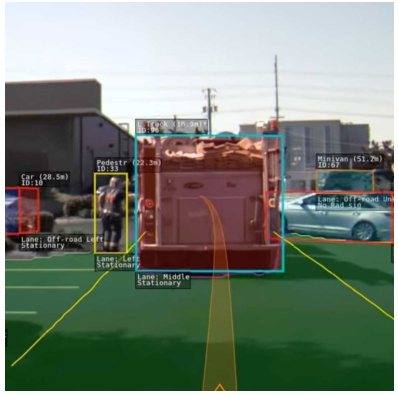

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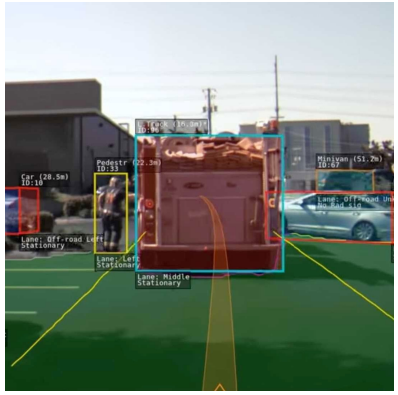

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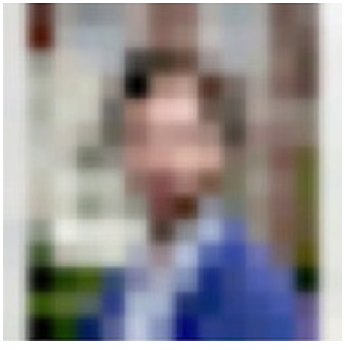

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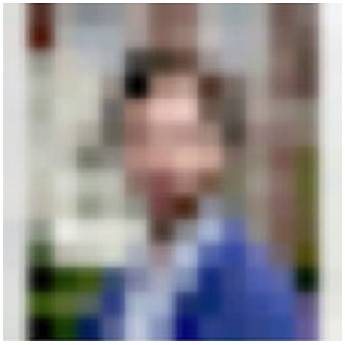

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Desired

What they designed

They designed a **task-centric** distortion that ensures good downstream performance

- Characterize minimum bit-rate to ensure high performance on desired tasks;
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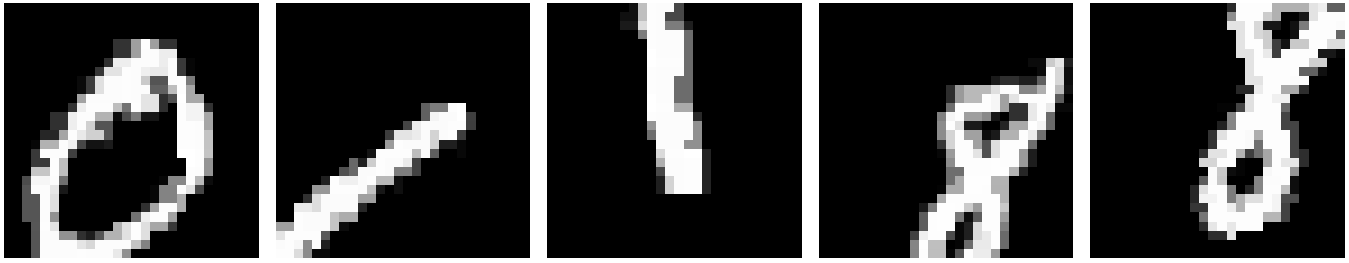

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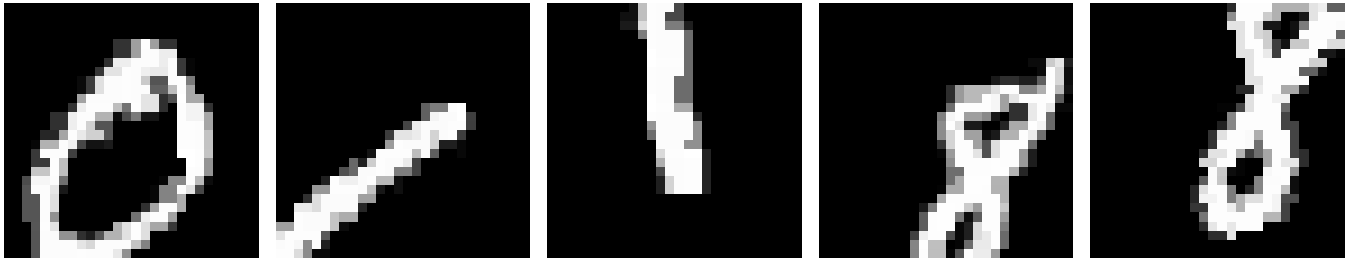

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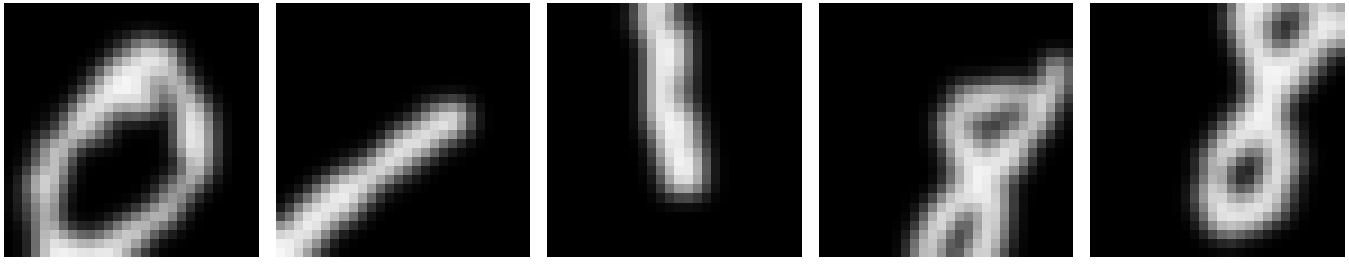

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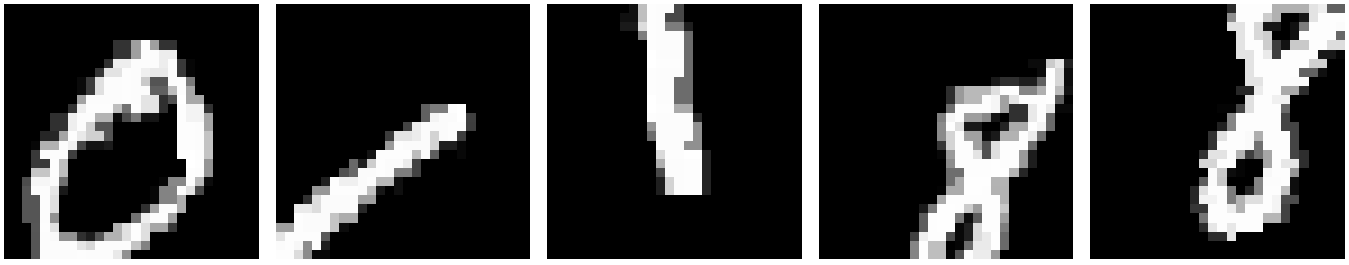

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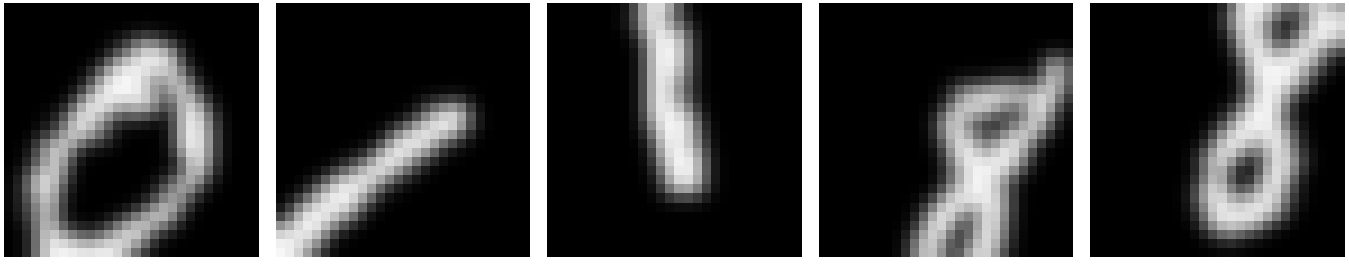

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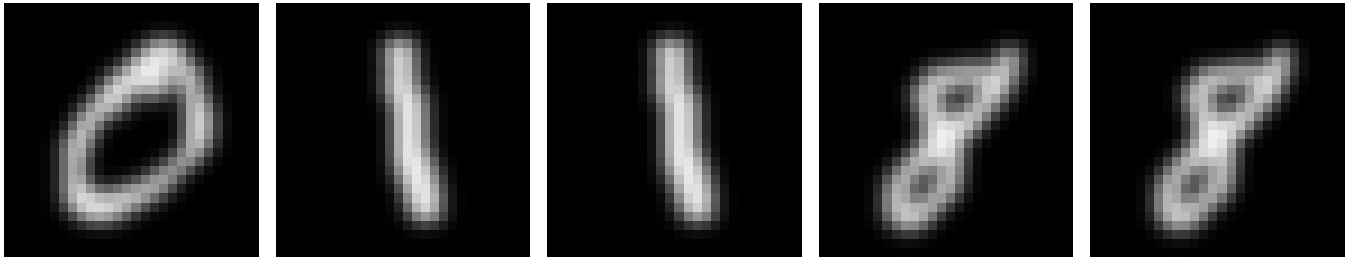

Their neural compressor: 48 bit-rate

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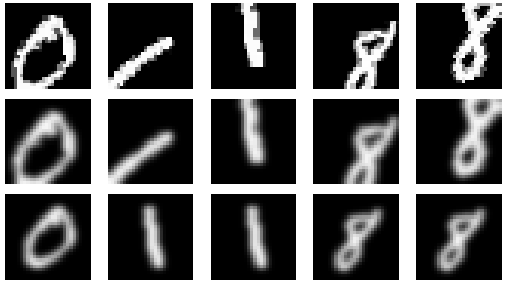

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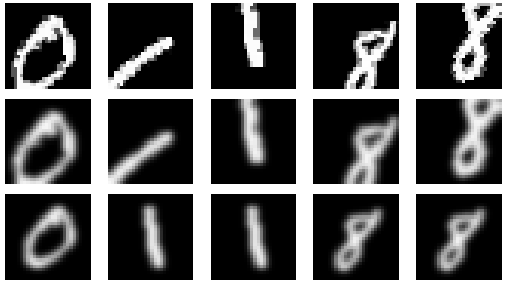

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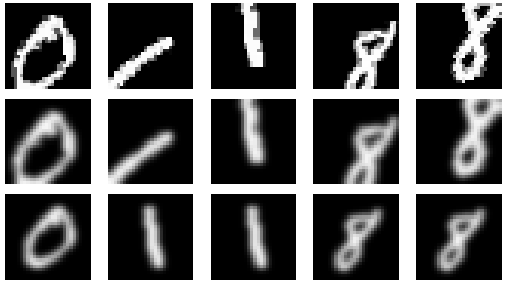

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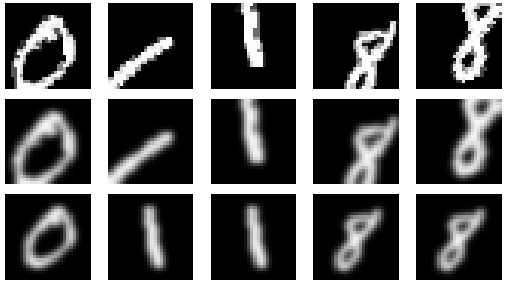

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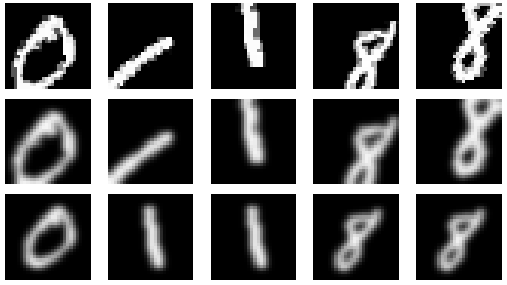

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⇒ The objective is **unsupervised**

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- Minimum achievable bit-rate to store X
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Performance