Scalable Variational Inference

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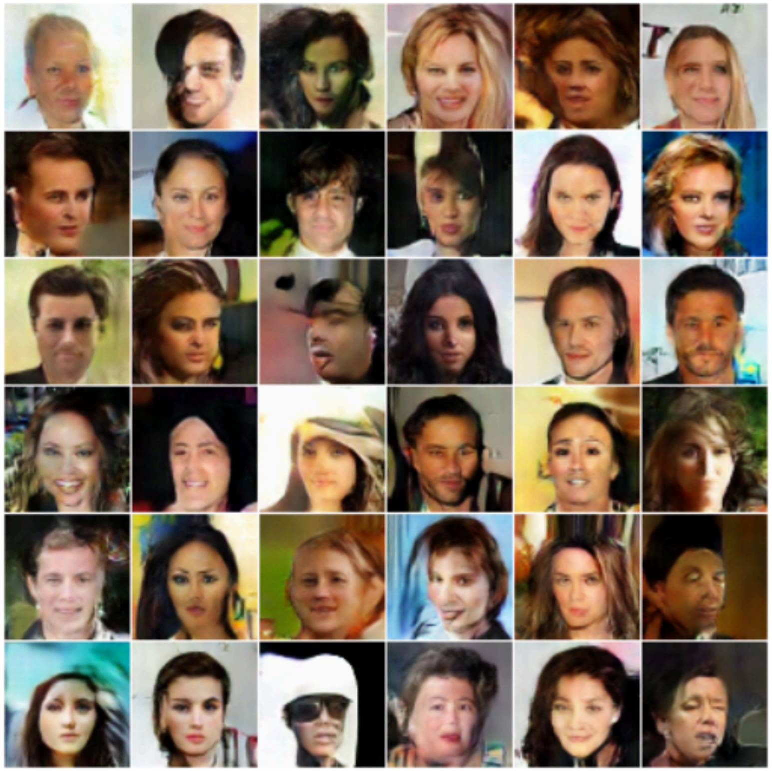
But why do we need it?

Why model $p(x)$

- Generate new data



[Zhao et. al. Energy-based generative adversarial network]

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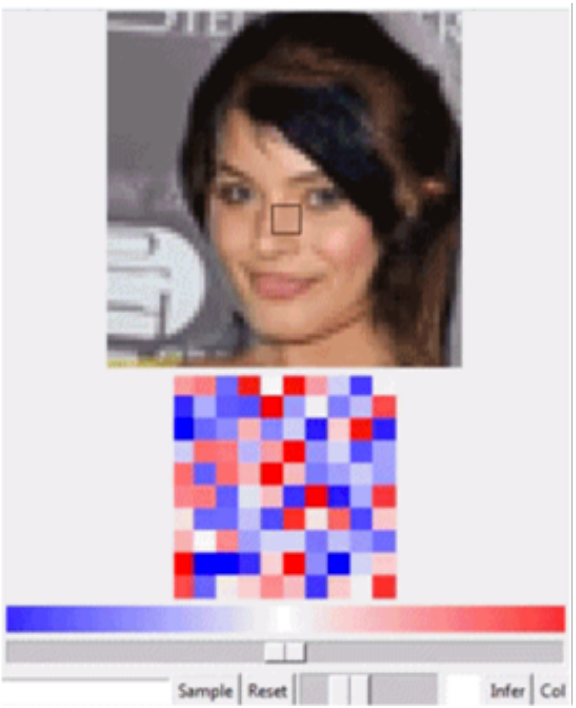

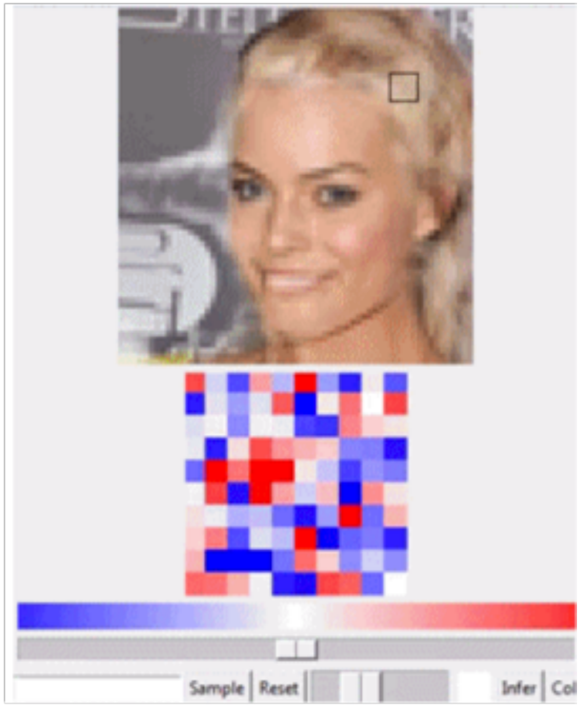

[**DL Cade**, https://petapixel.com/2016/09/27/neural-photo-editor-like-fully-automatic-photoshop/]

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- Generate new data
- Detect anomalies and outliers (e.g. fraud detection)
- Work with missing data
- Represent your data in a nice way (e.g. model p(molecule) to search for drugs)

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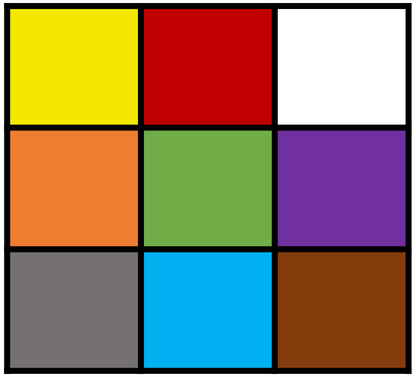

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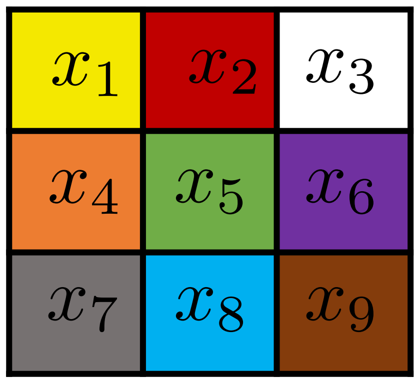

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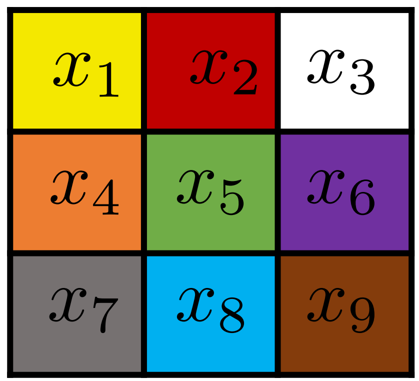

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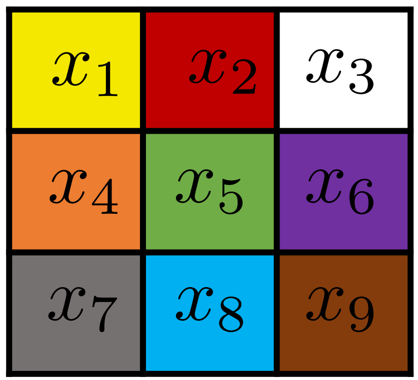

[Oord, Aaron van den, Nal Kalchbrenner, and Koray Kavukcuoglu.

"Pixel recurrent neural networks." (2016)]

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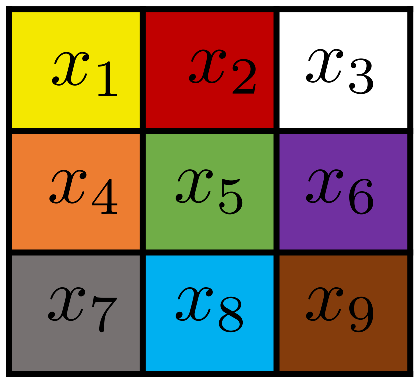
- $\log \widehat{p}(x) = \mathrm{CNN}(x)$ — Infeasible

- Use the chain rule — Cool, but slow to generate



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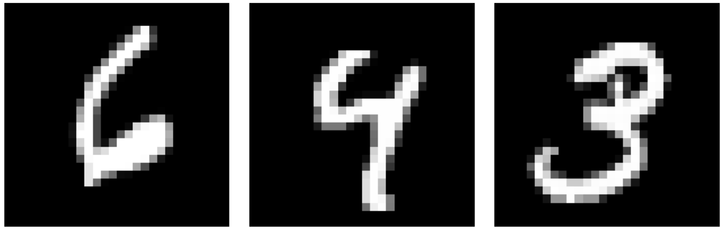

. . .

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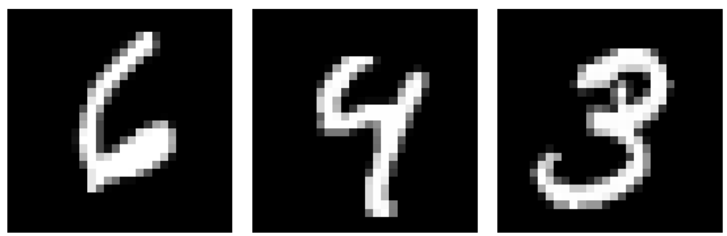

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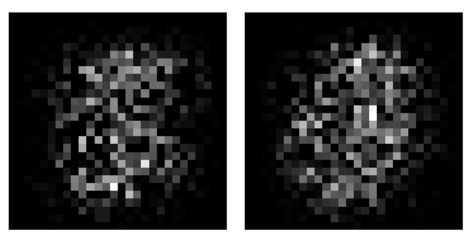
Samples:



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$$p(x) = \int p(x \mid t)\, p(t) dt$$