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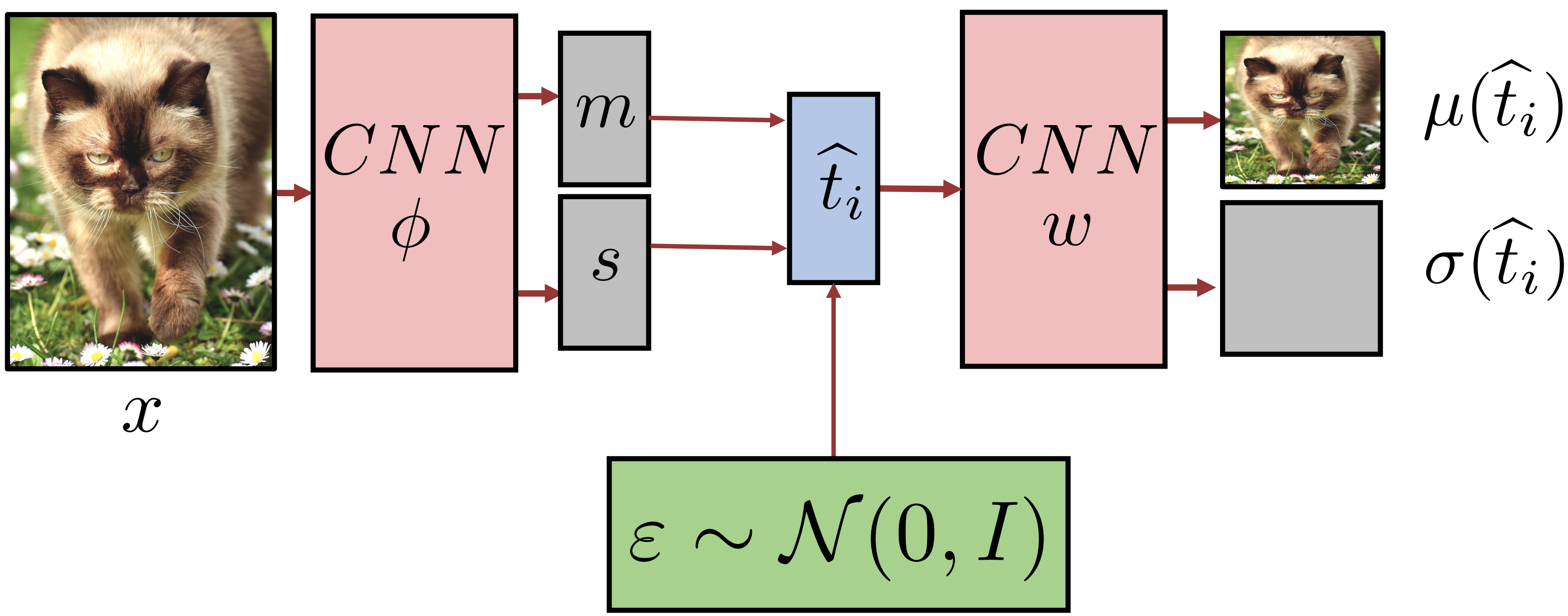

Variational Autoencoder summary

- Infinite mixture of Gaussians
- To learn: EM + approximate q with Gaussians + stochastic variational inference
- Like plain autoencoder, but with noise and KL regularization
- Generates nice images