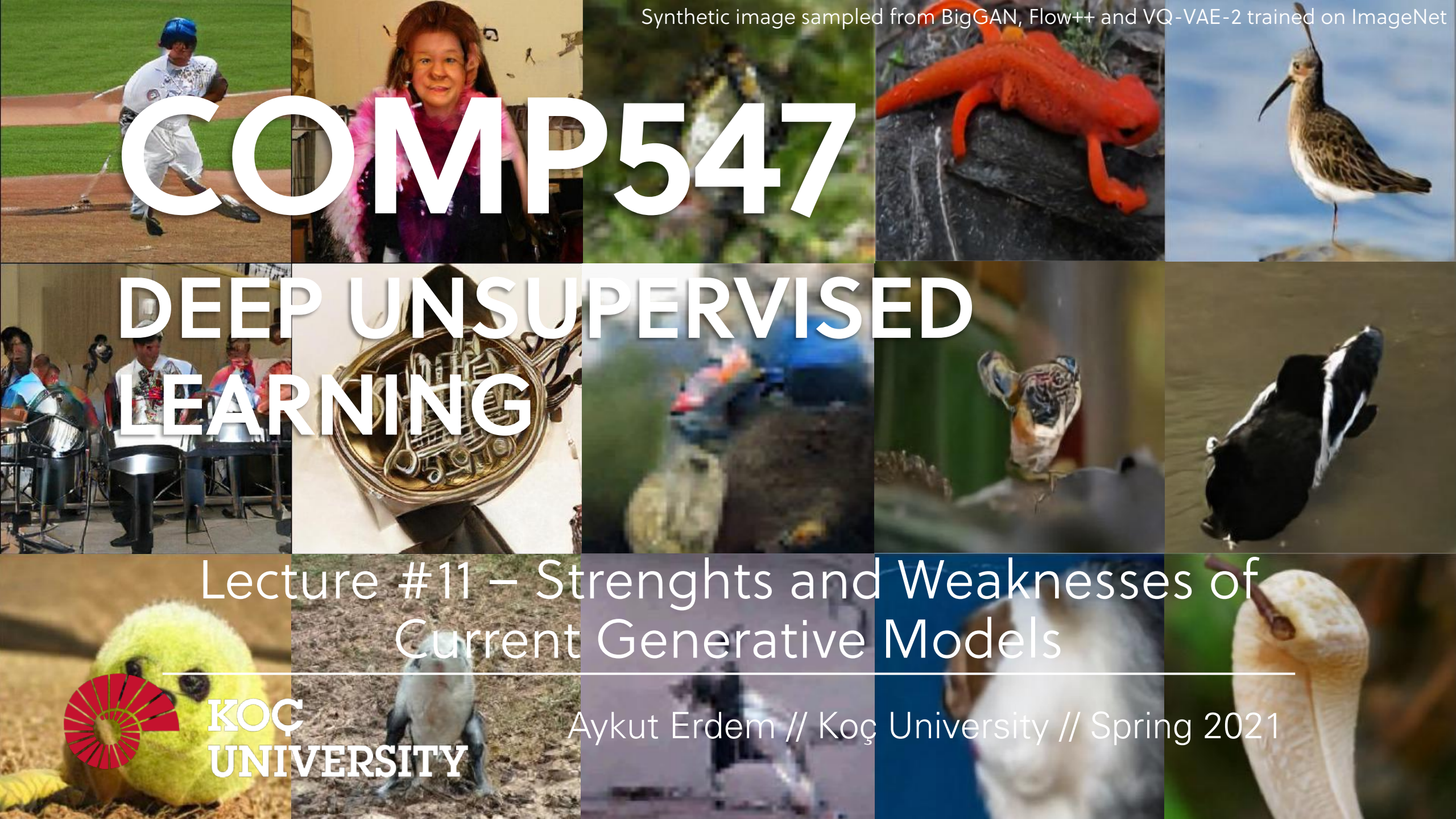


COMP547

DEEP UNSUPERVISED LEARNING

Lecture #11 – Strenghts and Weaknesses of Current Generative Models

KOÇ UNIVERSITY

Aykut Erdem // Koç University // Spring 2021

Good news, everyone!

- Assignment 3 is due April 20, 2021 (23:59)
- I will give feedback on your project proposals this week!

Previously on COMP547

- Motivation
- REINFORCE, Gumbel-Softmax, Straight-through estimator
- Sparse Coding
- Vector Quantization VAE (VQ-VAE), VQ-VAE-2, VQGAN
- Discrete Flows
- GANs for Text: SeqGAN, MaskGAN, ScratchGAN

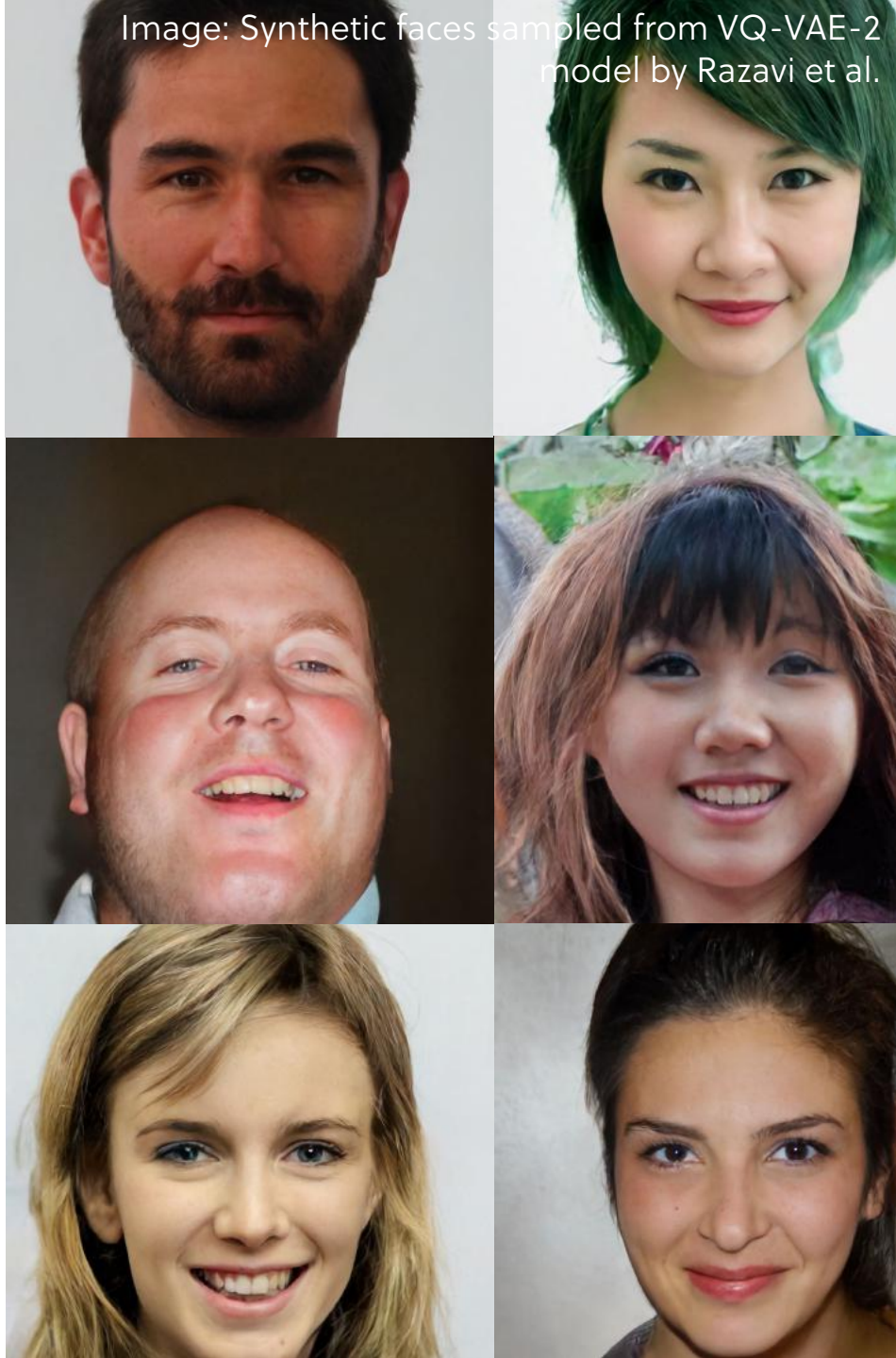


Image: Synthetic faces samoled from VQ-VAE-2 model by Razavi et al.

Lecture overview

- Autoregressive models
- Flow models
- Latent Variable models
- Implicit models

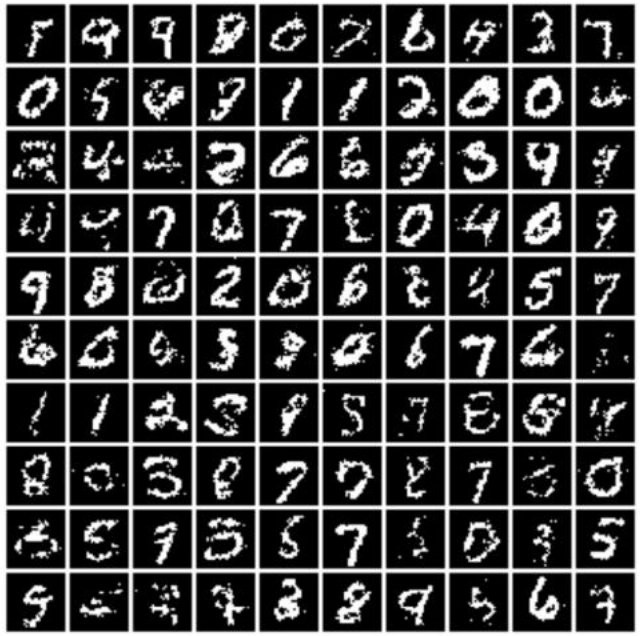
Disclaimer: Much of the material and slides for this lecture were borrowed from

—Pieter Abbeel, Peter Chen, Jonathan Ho, Aravind Srinivas' Berkeley CS294-158 class

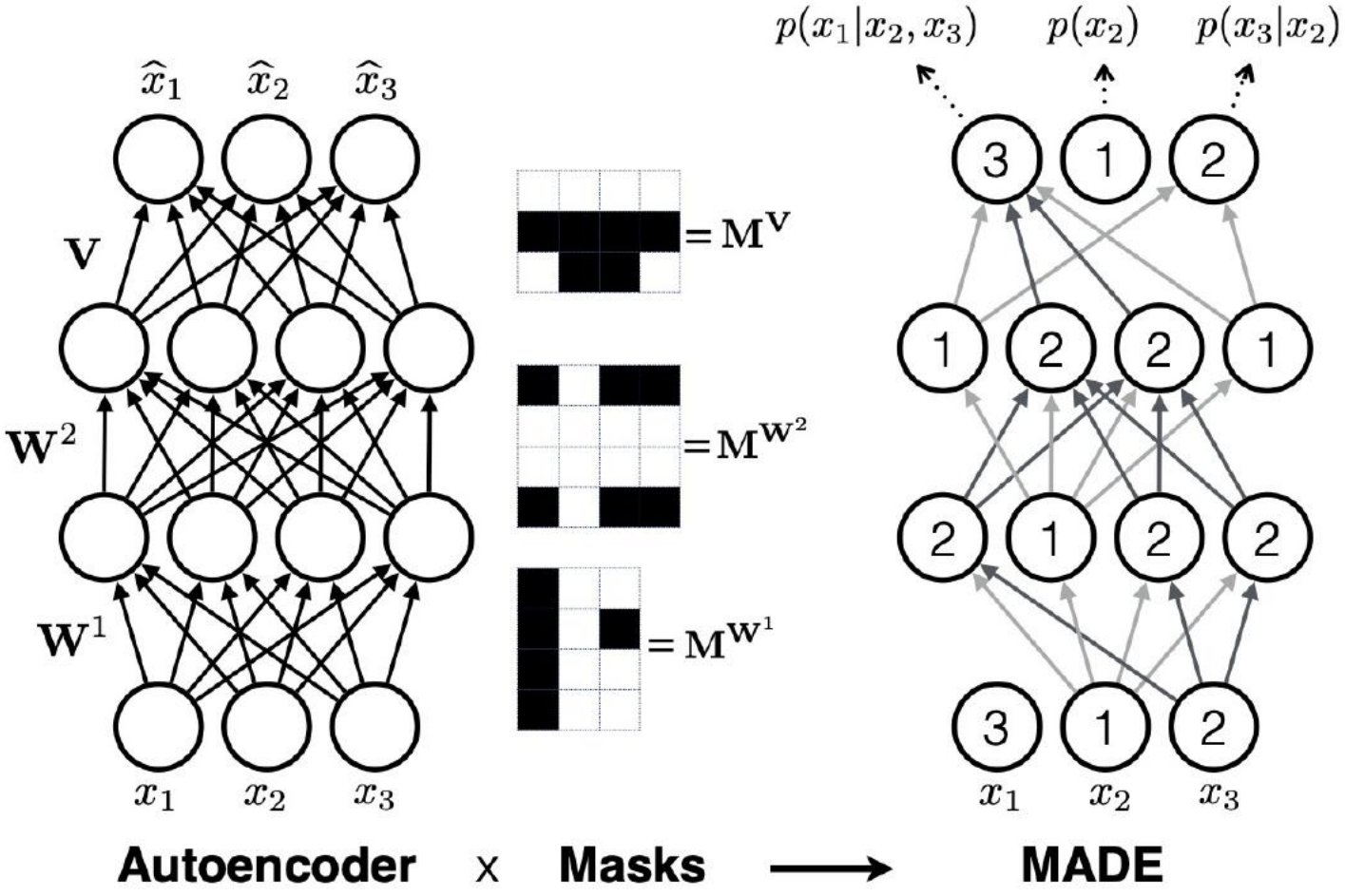
Lecture overview

- Autoregressive models
  - PixelRNN, PixelCNN, PixelCNN++, PixelSNAIL
- Flow models
- Latent Variable models
- Implicit models

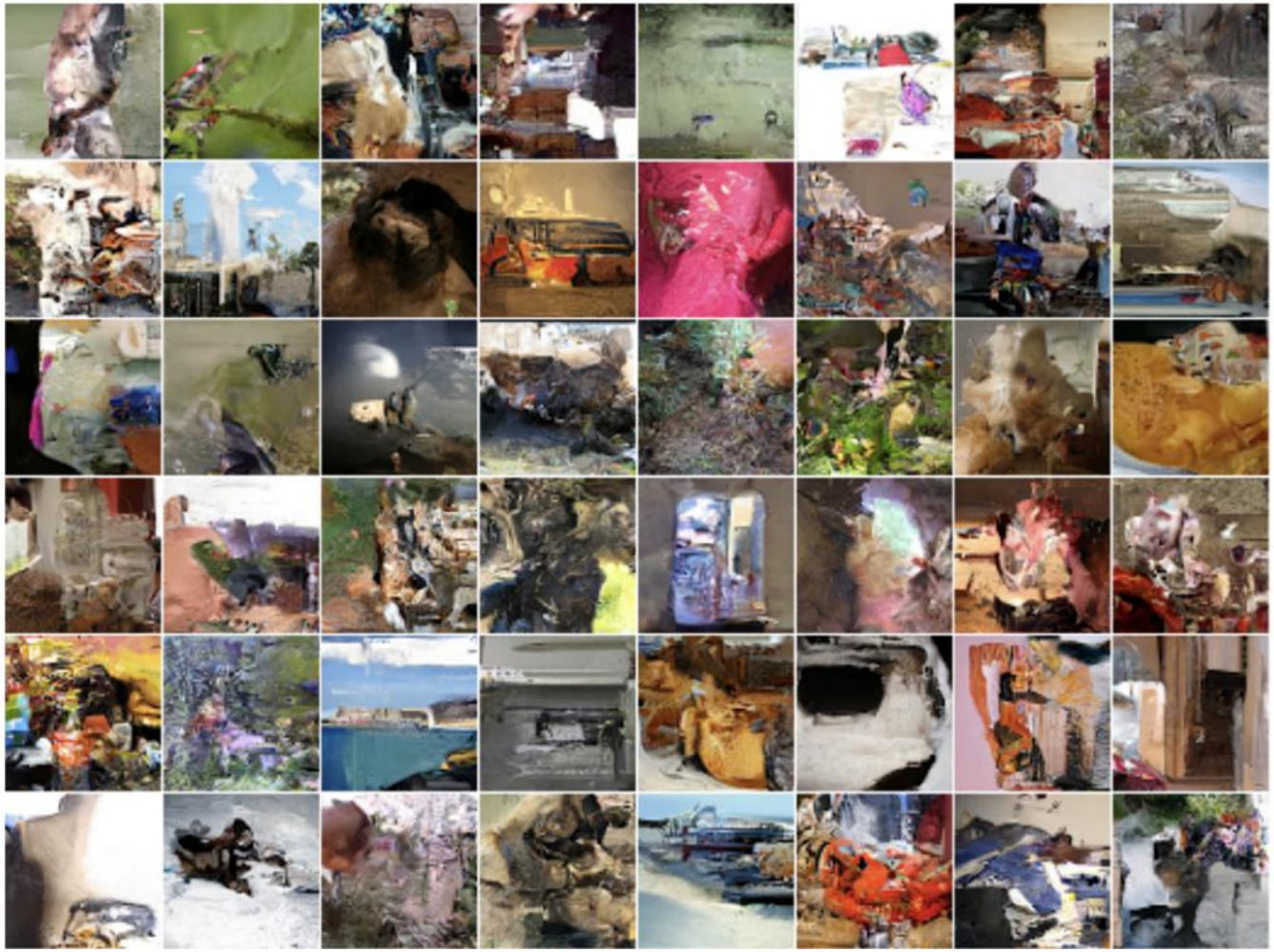
Autoregressive Models



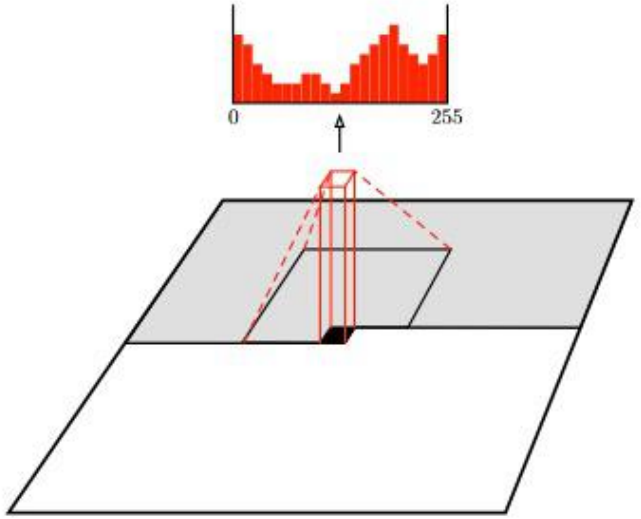
MADE (2015)



Autoregressive Models



PixelRNN/CNN (2016)



1	1	1	1	1
1	1	1	1	1
1	1	0	0	0
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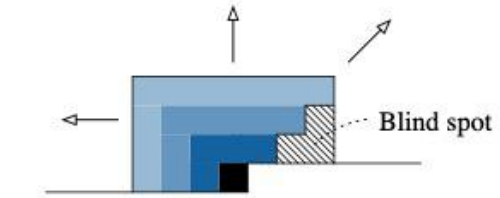
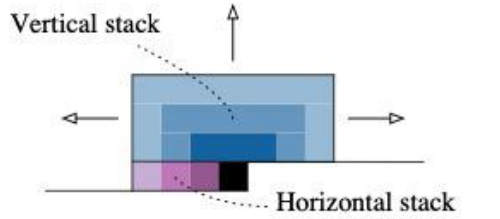
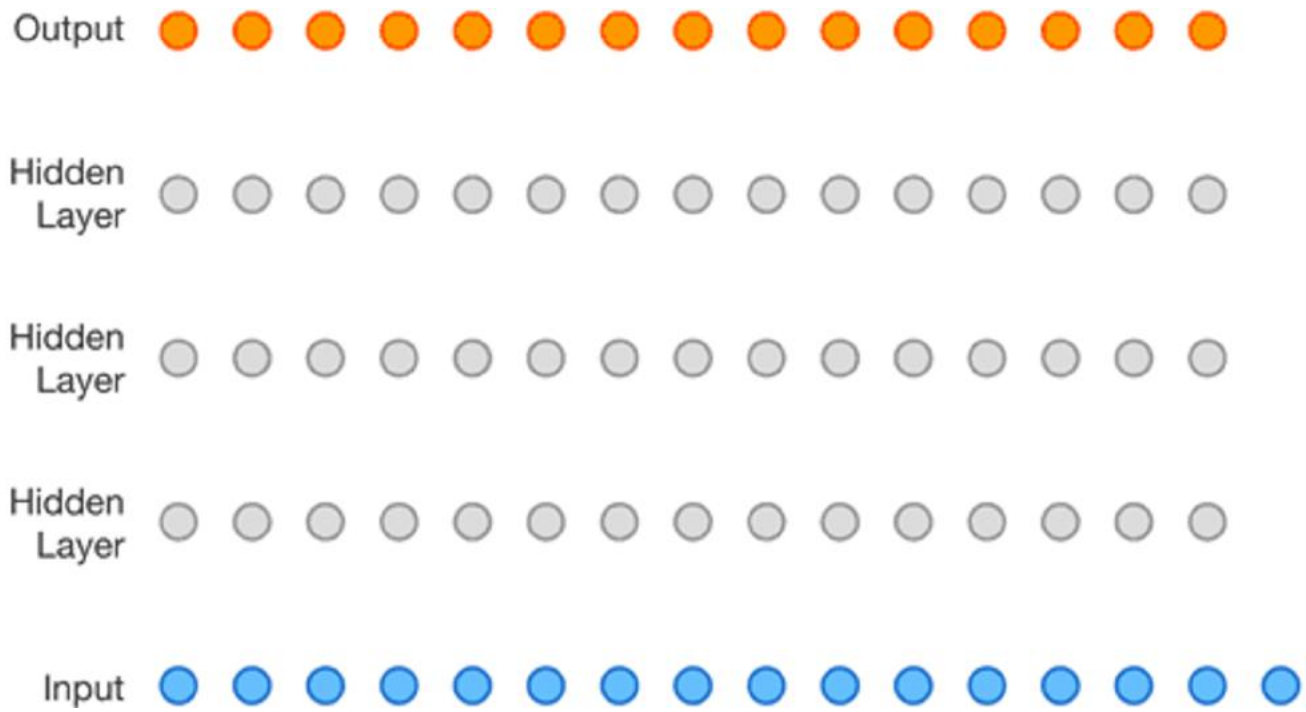
0	0	0	0	0



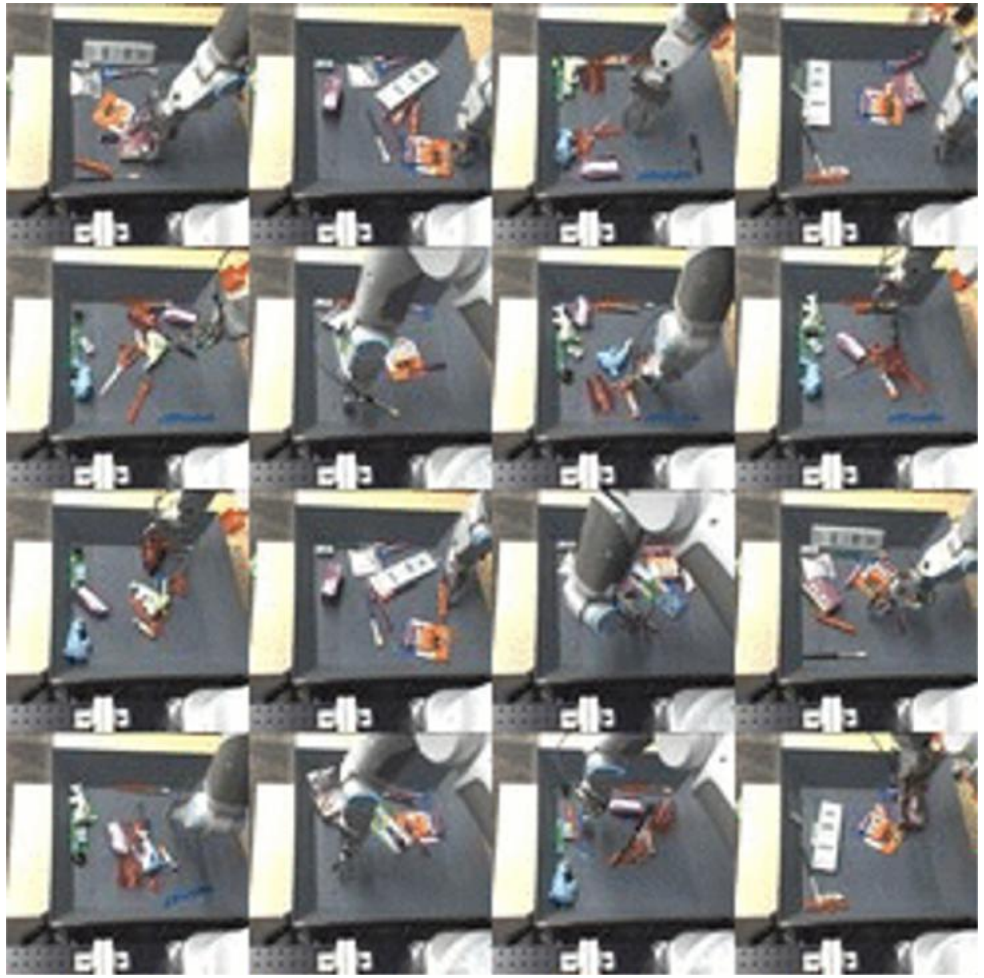


Autoregressive Models

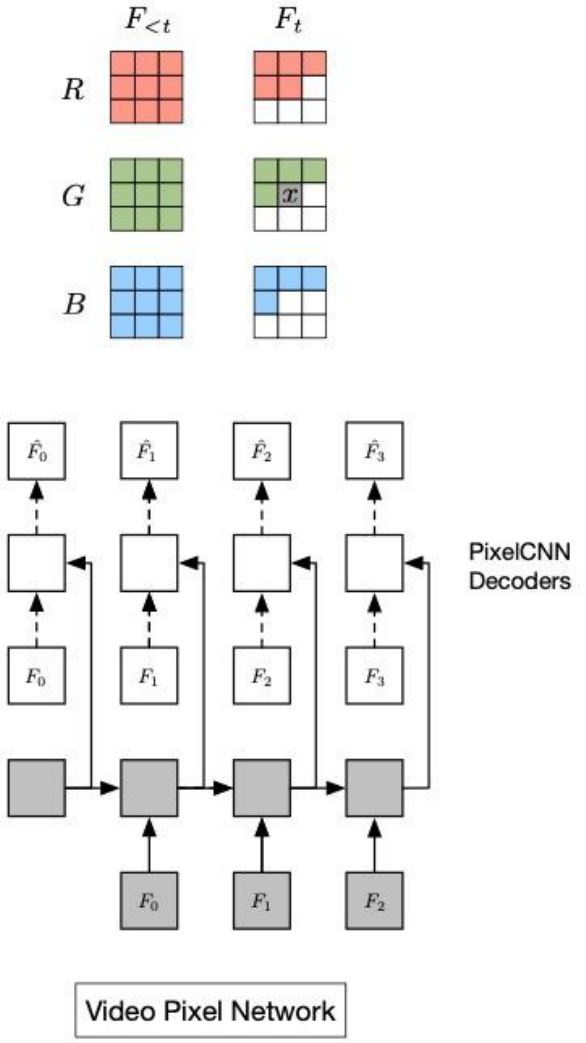


WaveNet (2016)

Autoregressive Models

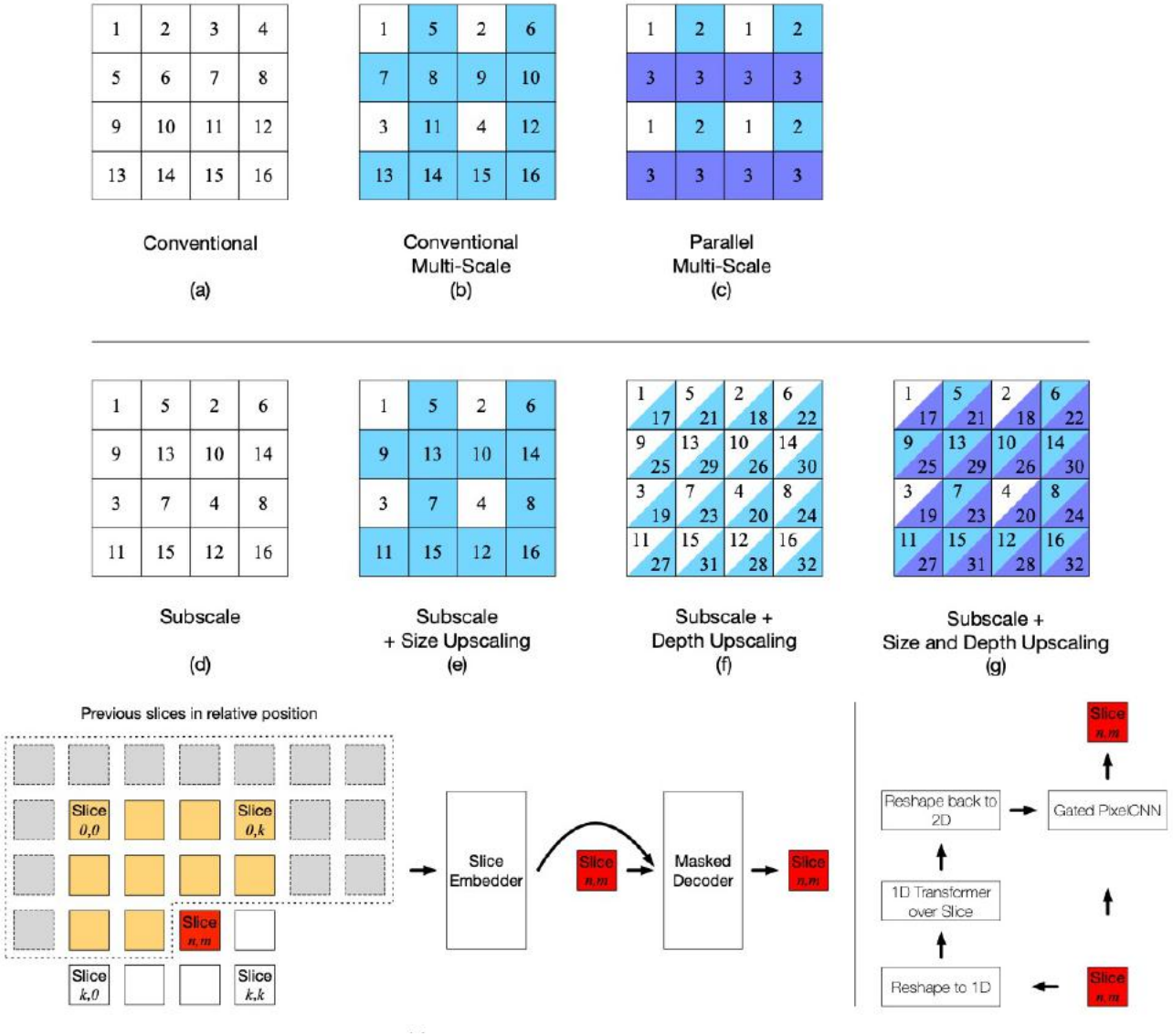


Video Pixel Networks (2017)

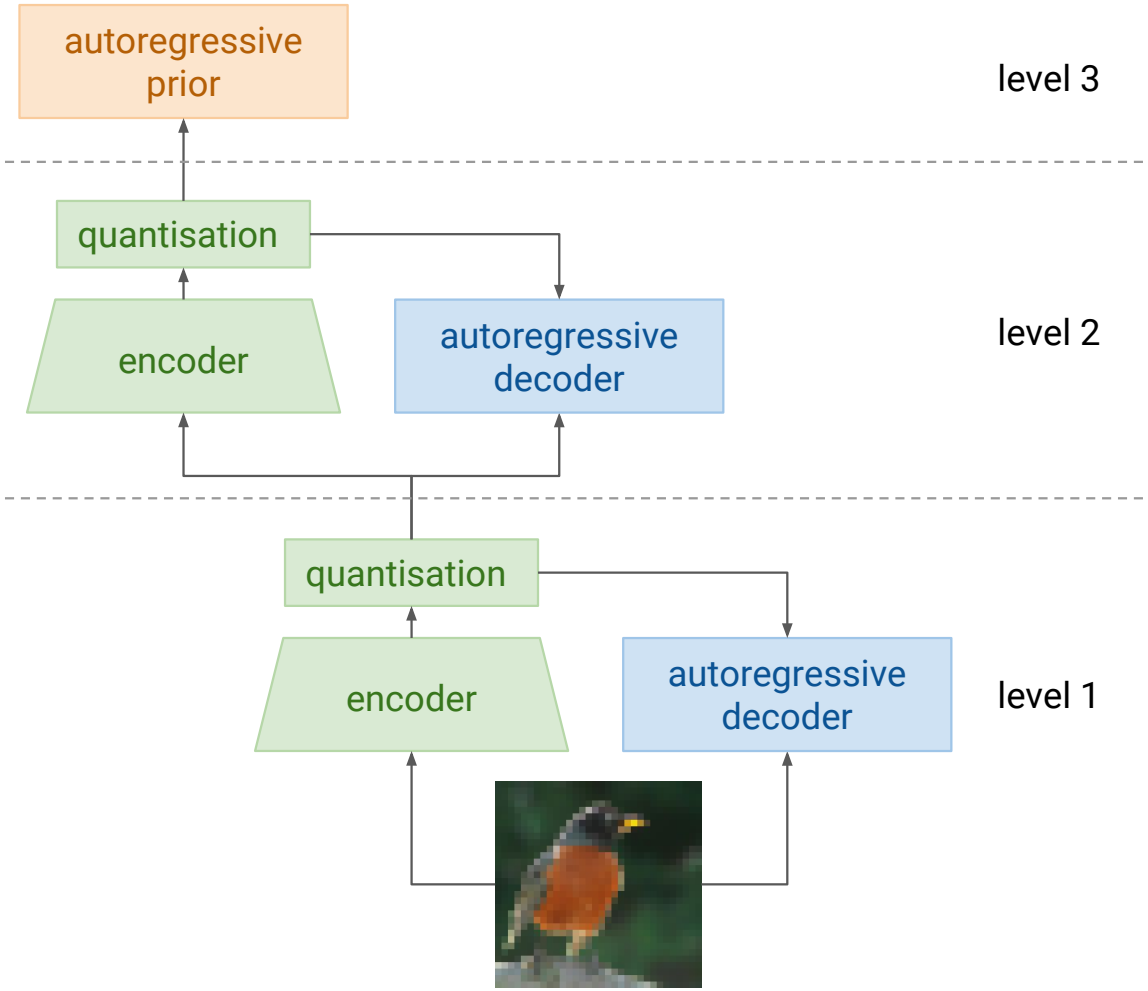


Autoregressive Models

Subscale Pixel Networks (2018)

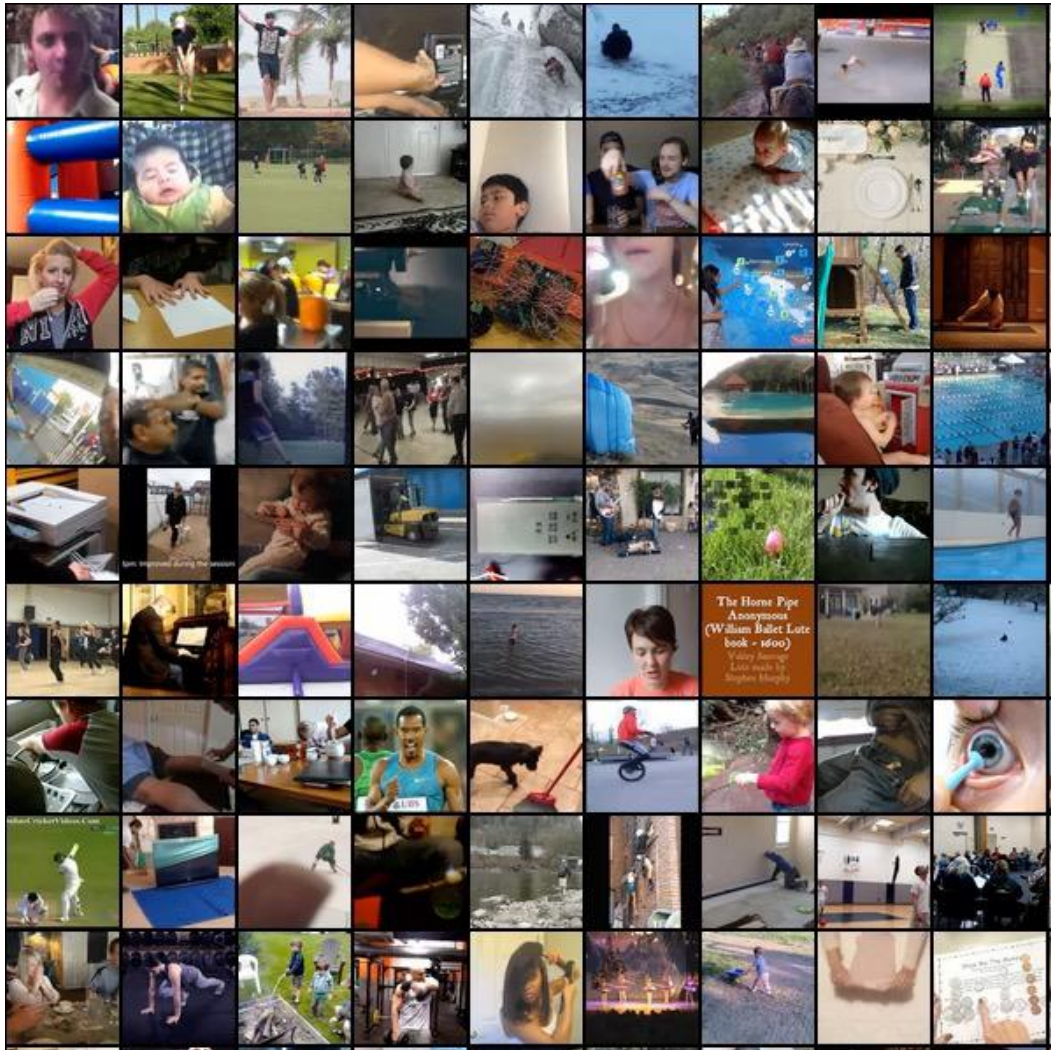


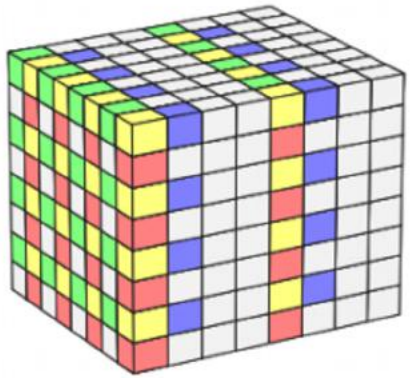
Autoregressive Models

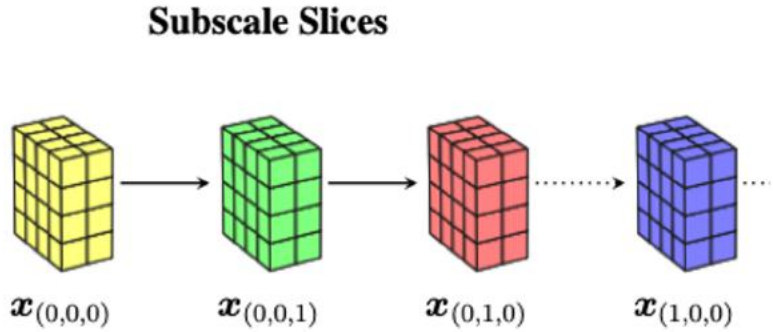


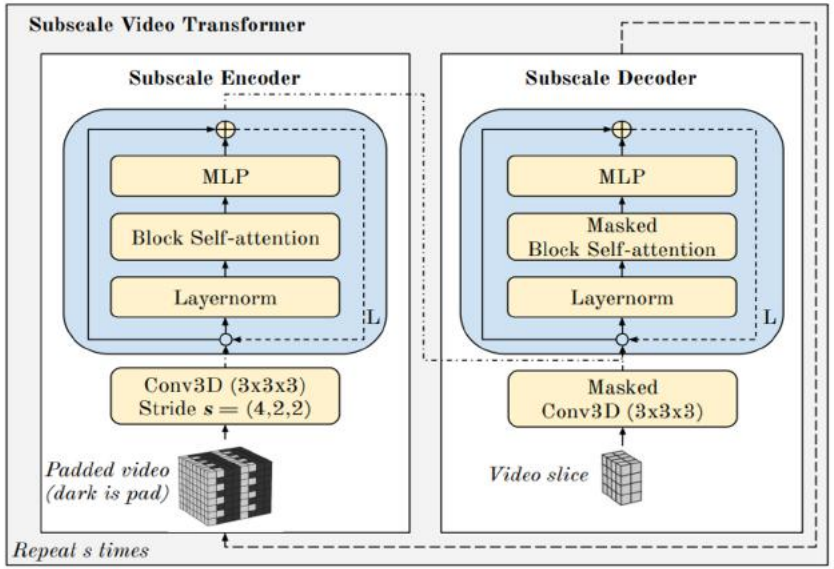
Hierarchical Autoregressive Image Models with Auxiliary Decoders (2019)

Autoregressive Models









Scaling Autoregressive Video Models (2020)

Autoregressive Models: History of LMs

SLP book, 2000 (Shannon, 1951), 3-gram

They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

Sutskever et al, 2011, RNNs

The meaning of life is the tradition of the ancient human reproduction: it is less favorable to the good boy for when to remove her bigger

Jozefowicz et al, 2016, BIG LSTMs

With even more new technologies coming onto the market quickly during the past three years , an increasing number of companies now must tackle the ever-changing and ever-changing environmental challenges online .

Liu et al, 2018, Transformer

==wings over kansas

==wings over kansas is a 2010 dhamma feature film written and directed by brian ig ariyoshi . it premiered on march 17, 2010 the film tells the story of three americans who bravely achieved a victory without expected daknfi .

==Wings Over Kansas Plot

the story begins with the faltering success of egypt 's hungry dakfunctionality when he loses his lives around the time when the embarked [...]

Radford et al, 2019, BIG Transformer

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Perez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Perez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Perez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Perez.

Perez and his friends were astonished to see the unicorn herd. [...]

Autoregressive Models: OpenAI GPT-2

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Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

While their origins are still unclear, some believe that perhaps the creatures were created when a human and a unicorn met each other in a time before human civilization. According to Pérez, "In South America, such incidents seem to be quite common."

However, Pérez also pointed out that it is likely that the only way of knowing for sure if unicorns are indeed the descendants of a lost alien race is through DNA. "But they seem to be able to communicate in English quite well, which I believe is a sign of evolution, or at least a change in social organization," said the scientist.

Autoregressive Models: OpenAI GPT-3

```
Context →                                   The City
                                            BY C. P. CAVAFY
                                            TRANSLATED BY EDMUND KEELEY
                                            [Poem text omitted]


                                            SOME TREES
                                            John Ashbery
                                            [Poem text omitted]


                                            Shadows on the Way
                                            Wallace Stevens
```

```
Nobody will come to this place.  It is a road that leads nowhere.
The solitude is deep.  The mountains are high.
But they are desolate, and they turn the traveler's face
Towards the North.  All the sounds of the world are far away.
When the wind rises above the trees,
The boughs bow to the ground.
Even the birds that inhabit the tangle of weeds
That is the roadside cover, are silent.  One listens,
But hears no roar of the forest.  One is alone.
One will be taken.
One will be taken.
There is no utterance, there is no conversation,
But one is uneasy all the same....
There is a thin blue mist,
A darkness rising like smoke,
And within that darkness
A possession of the heart.
One will be taken....  It was here, and it will be here again-
Here, under this sky empty and full of light.
```

Completion from a context suggesting the model compose a poem in the style of Wallace Stevens with the title 'Shadows on the Way'.

Autoregressive Models: OpenAI GPT-3

Context →	Helsinki is the capital and largest city of Finland. It is in the region of Uusimaa, in southern Finland, on the shore of the Gulf of Finland. Helsinki has a population of , an urban population of , and a metropolitan population of over 1.4 million, making it the most populous municipality and urban area in Finland. Helsinki is some north of Tallinn, Estonia, east of Stockholm, Sweden, and west of Saint Petersburg, Russia. Helsinki has close historical connections with these three cities. The Helsinki metropolitan area includes the urban core of Helsinki, Espoo, Vantaa, Kauniainen, and surrounding commuter towns. It is the world's northernmost metro area of over one million people, and the city is the northernmost capital of an EU member state. The Helsinki metropolitan area is the third largest metropolitan area in the Nordic countries after Stockholm and Copenhagen, and the City of Helsinki is the third largest after Stockholm and Oslo. Helsinki is Finland's major political, educational, financial, cultural, and research center as well as one of northern Europe's major cities. Approximately 75% of foreign companies that operate in Finland have settled in the Helsinki region. The nearby municipality of Vantaa is the location of Helsinki Airport, with frequent service to various destinations in Europe and Asia. Q: what is the most populous municipality in Finland? A: Helsinki Q: how many people live there? A: 1.4 million in the metropolitan area Q: what percent of the foreign companies that operate in Finland are in Helsinki? A: 75% Q: what towns are a part of the metropolitan area? A:
Target Completion →	Helsinki, Espoo, Vantaa, Kauniainen, and surrounding commuter towns

Formatted dataset example for CoQA

Autoregressive Models

Huge advances due to:

- Larger batch sizes
- More hidden units
- More layers
- Clever ways to condition on auxiliary variables
- Preprocessing
- Computer power
- Several days / weeks of training
- Fewer assumptions
  - Masked / Causal Convolutions
  - Dilated Convolutions
  - Transformers
- Architectural advances
- Loss functions
  - Relying heavily on well-behaved cross-entropy loss

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Language Models are Few-Shot Learners

Abstract

Recent work has demonstrated substantial gains on many NLP tasks and benchmarks by pre-training on a large corpus of text followed by fine-tuning on a specific task. While typically task-agnostic in architecture, this method still requires task-specific fine-tuning datasets of thousands or tens of thousands of examples. By contrast, humans can generally perform a new language task from only a few examples or from simple instructions – something which current NLP systems still largely struggle to do. Here we show that scaling up language models greatly improves task-agnostic, few-shot performance, sometimes even reaching competitiveness with prior state-of-the-art fine-tuning approaches. Specifically, we train GPT-3, an autoregressive language model with 175 billion parameters, 10x more than any previous non-sparse language model, and test its performance in the few-shot setting. For all tasks, GPT-3 is applied without any gradient updates or fine-tuning, with tasks and few-shot demonstrations specified purely via text interaction with the model. GPT-3 achieves strong performance on many NLP datasets, including translation, question-answering, and cloze tasks, as well as several tasks that require on-the-fly reasoning or domain adaptation, such as unscrambling words, using a novel word in a sentence, or performing 3-digit arithmetic. At the same time, we also identify some datasets where GPT-3's few-shot learning still struggles, as well as some datasets where GPT-3 faces methodological issues related to training on large web corpora. Finally, we find that GPT-3 can generate samples of news articles which human evaluators have difficulty distinguishing from articles written by humans. We discuss broader societal impacts of this finding and of GPT-3 in general.

GPT-3 (2020)

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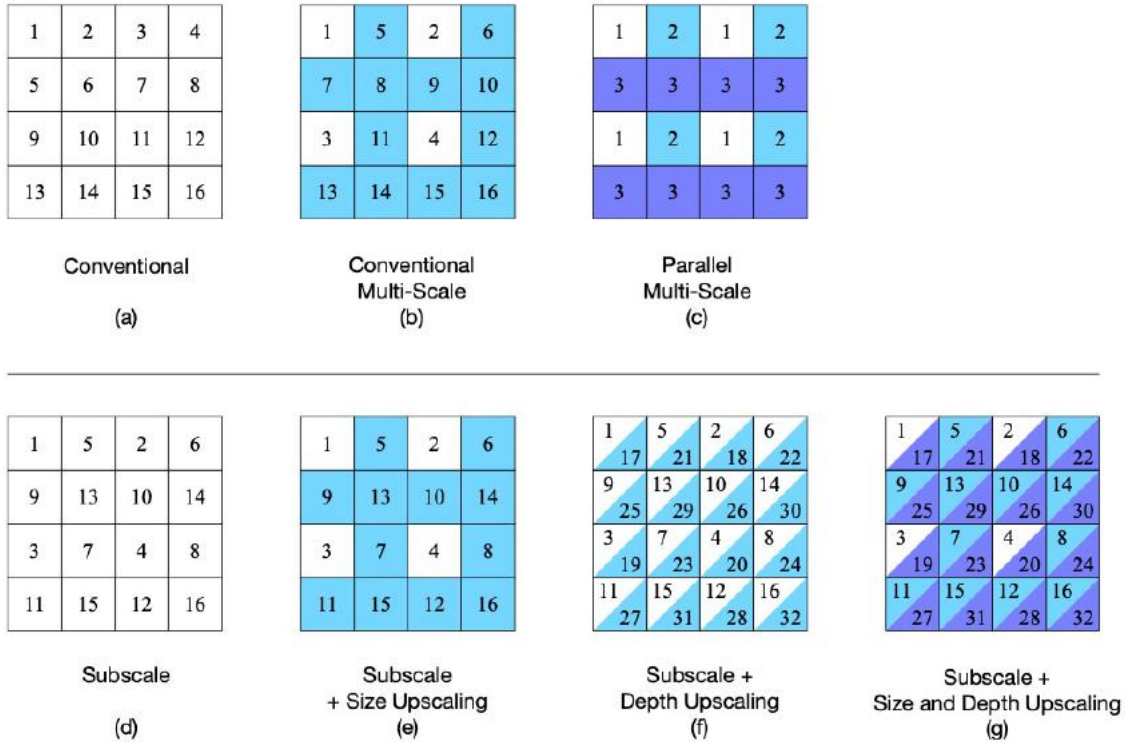

Subscale Pixel Networks (2018)

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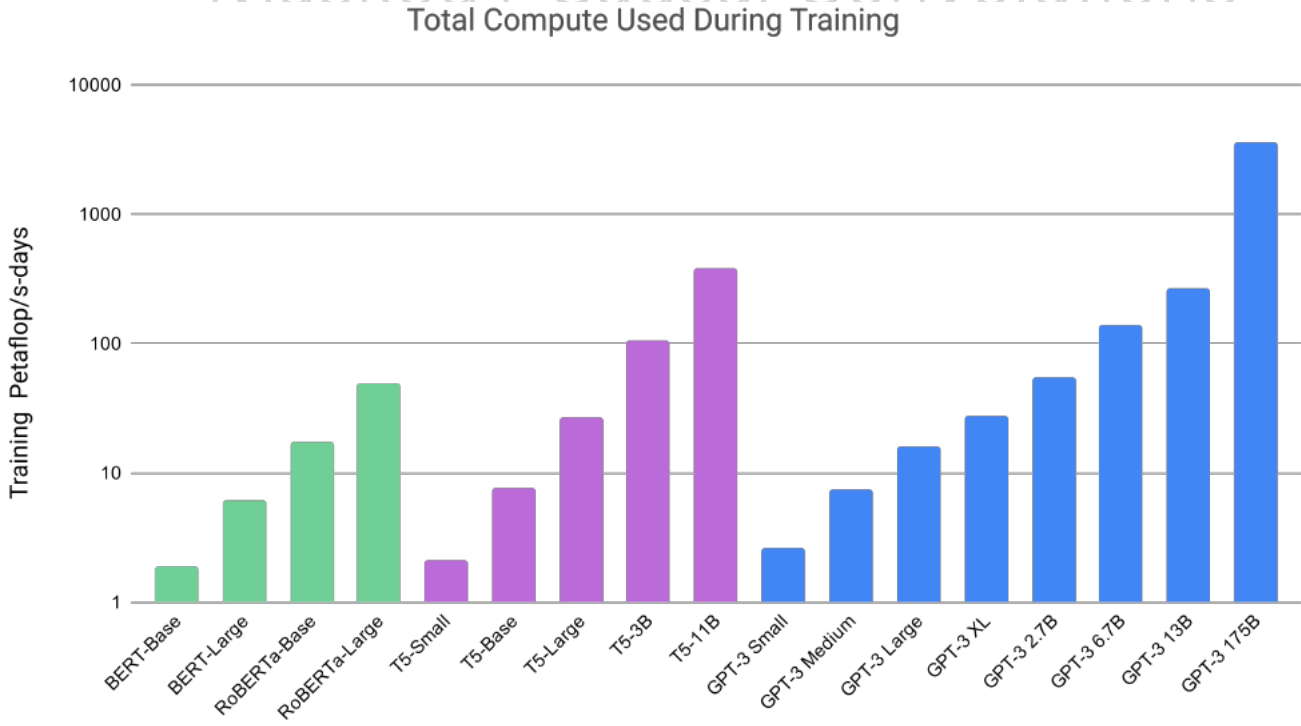

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Autoregressive Models: Future

Still only scratching the surface of what's possible.

- Advances with model-parallelism to come
- Trillion parameter language models trained on all the Internet's text (ex Google Books / Kindle / HackerNews / Reddit / Podcast transcripts, so on). Could compress the Internet's text.
- Same model for both text and pixels (image / video). Share self-attention blocks and compress both of Wikipedia and Youtube / Instagram. Only separate blocks of encoders and decoders.
- Fast sampling with better low-level core engineering - new kernels with sparsity and efficiency for the bottleneck ops. Ex: WaveRNN instead of Parallel Wavenet.
- Hybrid models with weaker autoregressive structure but trained on a larger scale (Ex: Revisiting architectures like Parallel PixelCNN that can provide a good tradeoff between autoregressive structure and sampling time with more independence assumptions.
- New architecture design choices such as self-attention which introduce inductive biases that leverage a lot of computation per parameter introduced.

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Efficient Neural Audio Synthesis

Nal Kalchbrenner [*1] Erich Elsen [*2] Karen Simonyan [1] Seb Noury [1] Norman Casagrande [1] Edward Lockhart [1]
Florian Stimberg [1] Aäron van den Oord [1] Sander Dieleman [1] Koray Kavukcuoglu [1]

Abstract

Sequential models achieve state-of-the-art results in audio, visual and textual domains with respect to both estimating the data distribution and generating high-quality samples. Efficient sampling for this class of models has however remained an elusive problem. With a focus on text-to-speech synthesis, we describe a set of general techniques for reducing sampling time while maintaining high output quality. We first describe a single-layer recurrent neural network, the WaveRNN, with a dual softmax layer that matches the quality of the state-of-the-art WaveNet model. The compact form of the network makes it possible to generate 24 kHz 16-bit audio 4× faster than real time on a GPU. Second, we apply a weight pruning technique to reduce the number of weights in the WaveRNN. We find that, for a constant number of parameters, large sparse networks perform better than small dense networks and this relationship holds for sparsity levels beyond 96%. The small number of weights in a Sparse WaveRNN makes it possible to sample high-fidelity audio on a mobile CPU in real time. Finally, we propose a new generation scheme based on subscaling that folds a long sequence into a batch of shorter sequences and allows one to generate multiple samples at once. The Subscale WaveRNN produces 16 samples per step without loss of quality and offers an orthogonal method for increasing sampling efficiency.

ages (van den Oord et al., 2016b; Reed et al., 2017) and videos (Kalchbrenner et al., 2017) and speech and music (van den Oord et al., 2016a; Mehri et al., 2016; Simon & Oore, 2017; Engel et al., 2017). The models learn the joint probability of the data by factorizing the distribution into a product of conditional probabilities over each sample. This structure lets the models allot significant capacity to estimate each conditional factor, makes them robust during training and easy to evaluate. The ordering encoded in the structure also makes the sampling process strictly serial: a sample can be generated only after samples on which it depends have been produced in accordance with the ordering. The serial aspect of the sampling process can make it slow and impractical to use these models to generate high-dimensional data like speech and video.

Our goal is to increase the efficiency of sampling from sequential models without compromising their quality. The time $T(\mathbf{u})$ that the sampling process takes is the product of the number of samples in the target $\mathbf{u}$ (e.g. the number of audio samples in a spoken utterance or the number of pixels in an image) and the time required to produce each sample. The latter can be decomposed into computation time $c(op_i)$ and overhead $d(op_i)$ for each of the N layers (operations) of the model:

$$T(\mathbf{u}) = |\mathbf{u}| \sum_{i=1}^{N} (c(op_i) + d(op_i)) \quad (1)$$

The value of $T(\mathbf{u})$ can grow prohibitively large under any of the following conditions: if $|\mathbf{u}|$ is large as in the case of high-fidelity audio composed of 24,000 16-bit samples

Autoregressive Models: Future

Still only scratching the surface of what's possible.

- Advances with model-parallelism to come
- Trillion parameter language models trained on all the Internet's text (ex Google Books / Kindle / HackerNews / Reddit / Podcast transcripts, so on). Could compress the Internet's text.
- Same model for both text and pixels (image / video). Share self-attention blocks and compress both of Wikipedia and Youtube / Instagram. Only separate blocks of encoders and decoders.
- Fast sampling with better low-level core engineering - new kernels with sparsity and efficiency for the bottleneck ops. Ex: WaveRNN instead of Parallel Wavenet.
- Hybrid models with weaker autoregressive structure but trained on a larger scale (Ex: Revisiting architectures like Parallel PixelCNN that can provide a good tradeoff between autoregressive structure and sampling time with more independence assumptions.
- New architecture design choices such as self-attention which introduce inductive biases that leverage a lot of computation per parameter introduced.

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Parallel Multiscale Autoregressive Density Estimation

Scott Reed [1] Aäron van den Oord [1] Nal Kalchbrenner [1] Sergio Gómez Colmenarejo [1] Ziyu Wang [1]
Dan Belov [1] Nando de Freitas [1]

Abstract

PixelCNN achieves state-of-the-art results in density estimation for natural images. Although training is fast, inference is costly, requiring one network evaluation per pixel; O(N) for N pixels. This can be sped up by caching activations, but still involves generating each pixel sequentially. In this work, we propose a parallelized PixelCNN that allows more efficient inference by modeling certain pixel groups as conditionally independent. Our new PixelCNN model achieves competitive density estimation and orders of magnitude speedup - $O(\log N)$ sampling instead of $O(N)$ - enabling the practical generation of 512×512 images. We evaluate the model on class-conditional image generation, text-to-image synthesis, and action-conditional video generation, showing that our model achieves the best results among non-pixel-autoregressive density models that allow efficient sampling.

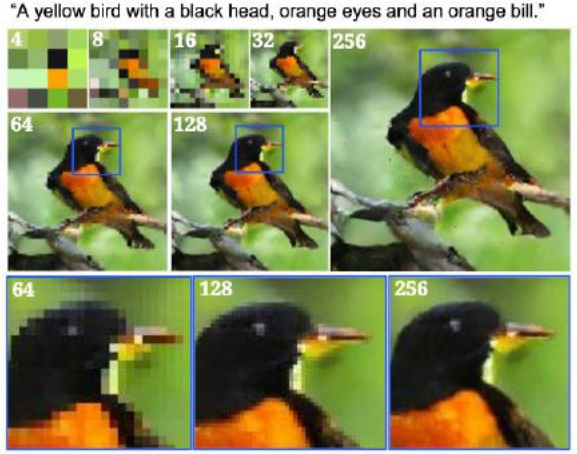
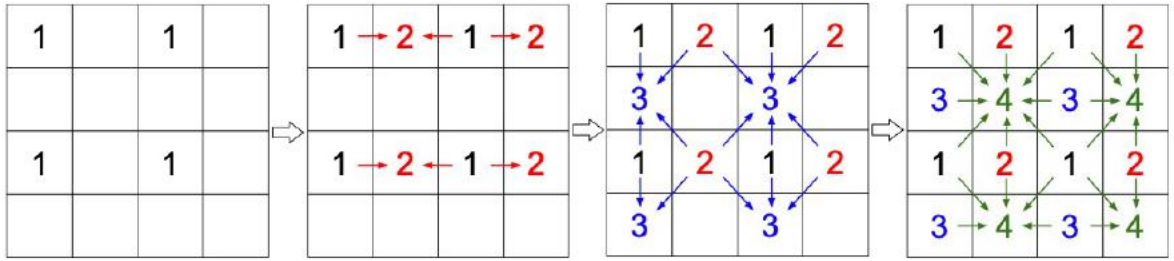


Figure 1. Samples from our model at resolutions from 4×4 to 256×256, conditioned on text and bird part locations in the CUB data set. See Fig. 4 and the supplement for more examples.

case for WaveNet (Oord et al., 2016; Ramachandran et al.,



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- Active topic with cutting edge results
- Lot of scope for more engineering and creative architecture design
- Larger models and datasets
- Successful in all of (un)conditional video, audio, text, images
- Sampling Time Engineering

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Autoregressive Models: Negatives

- No single layer of learned representation
- Currently, sampling time is slow for practical deployment.
- Not directly usable for downstream tasks.
- No interpolations.

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Lecture overview

- Autoregressive models
- Flow models
  - NICE, RealNVP, Autoregressive Flows, Inverse Autoregressive Flows, Glow, Flow++
- Latent Variable models
- Implicit models

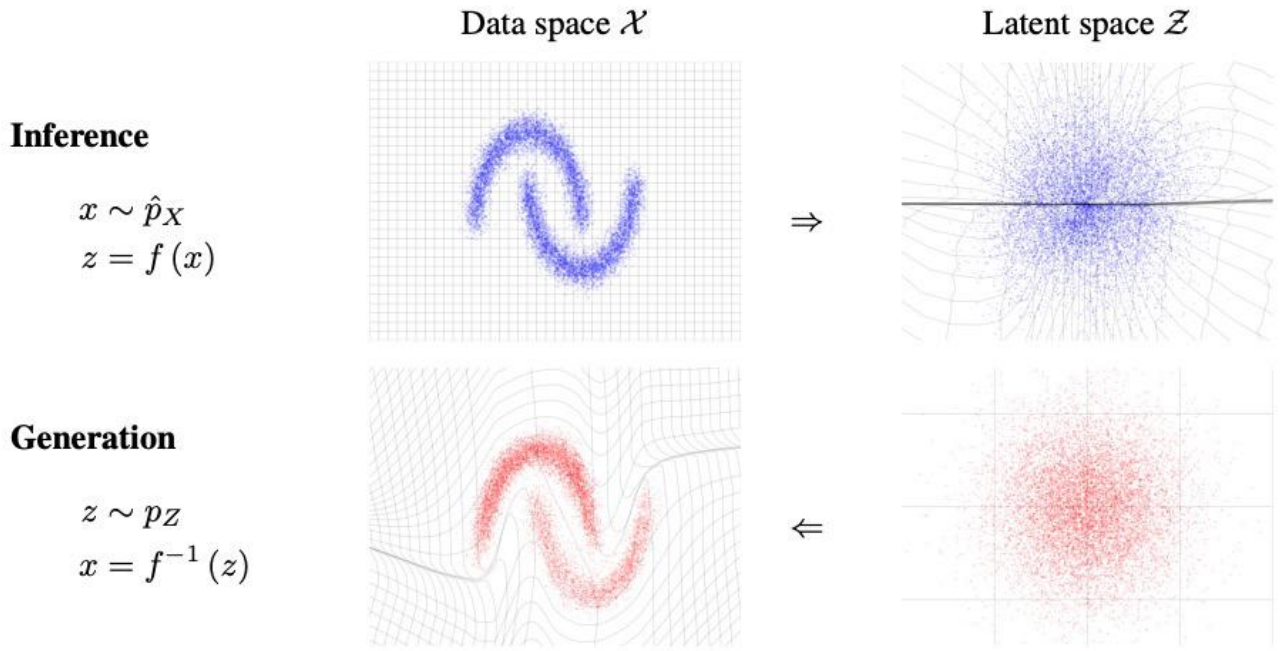
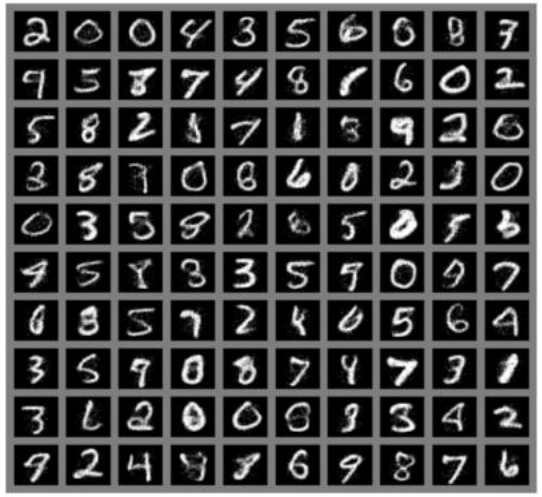


Image credit: Laurent Dinh

Flow Models



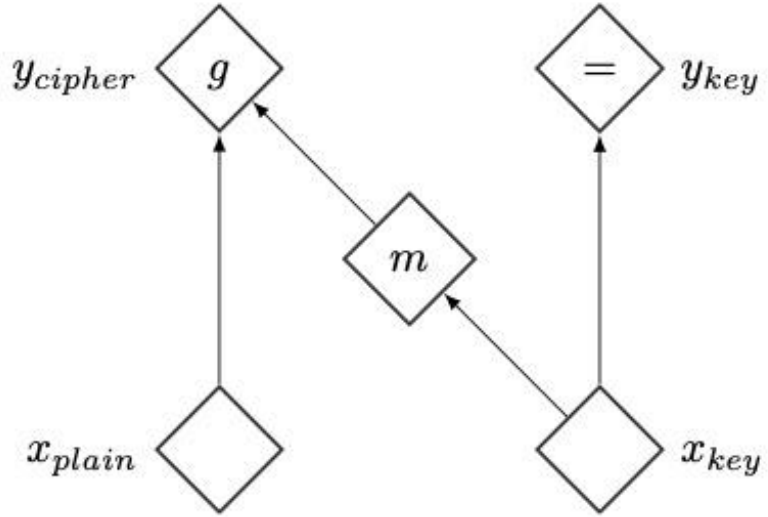
(a) Model trained on MNIST

(b) Model trained on TFD

(c) Model trained on SVHN

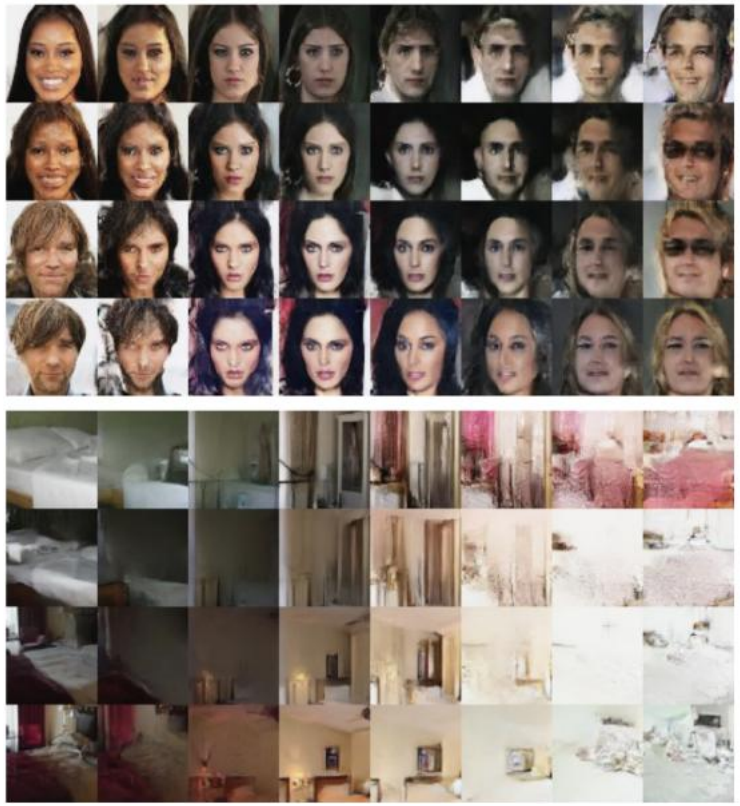
(d) Model trained on CIFAR-10

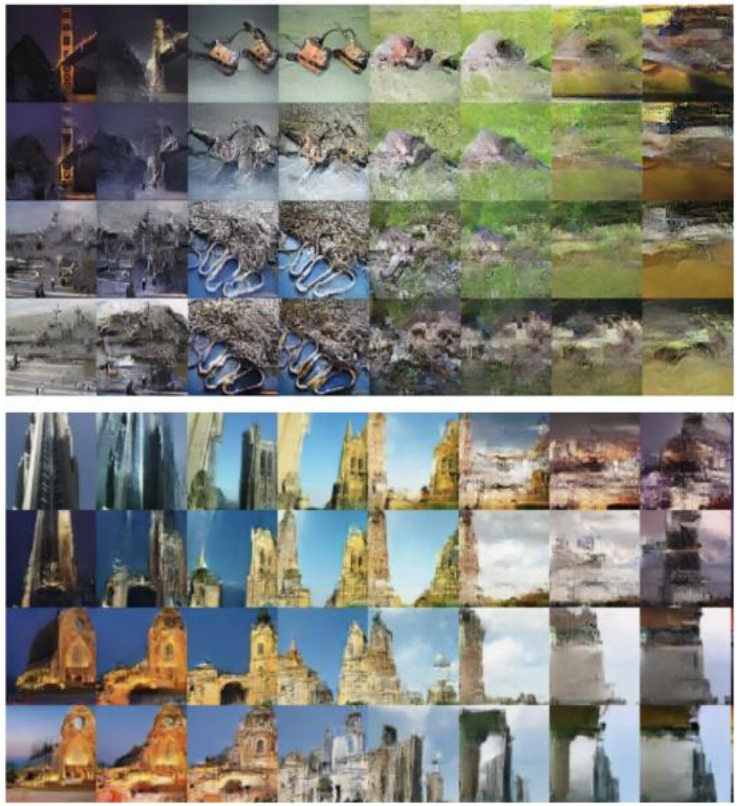
NICE (Dinh et al 2014)



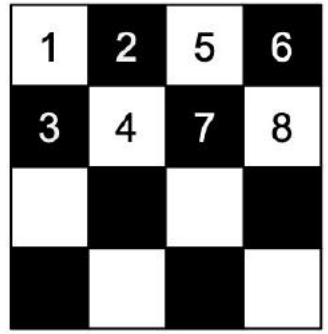
$$y_1 = x_1$$
$$y_2 = x_2 + m\left(x_1\right)$$

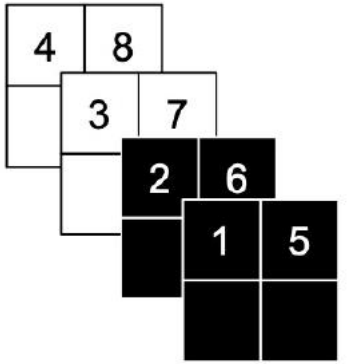
Flow Models

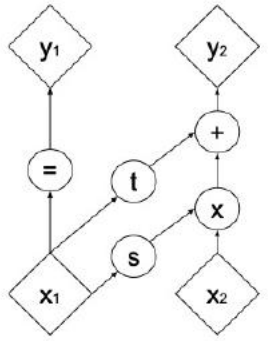




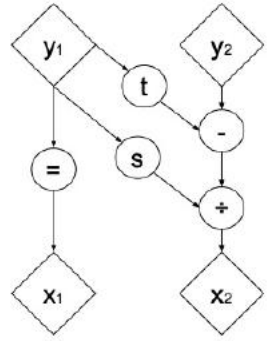
RealNVP (Dinh et al 2016)







(a) Forward propagation



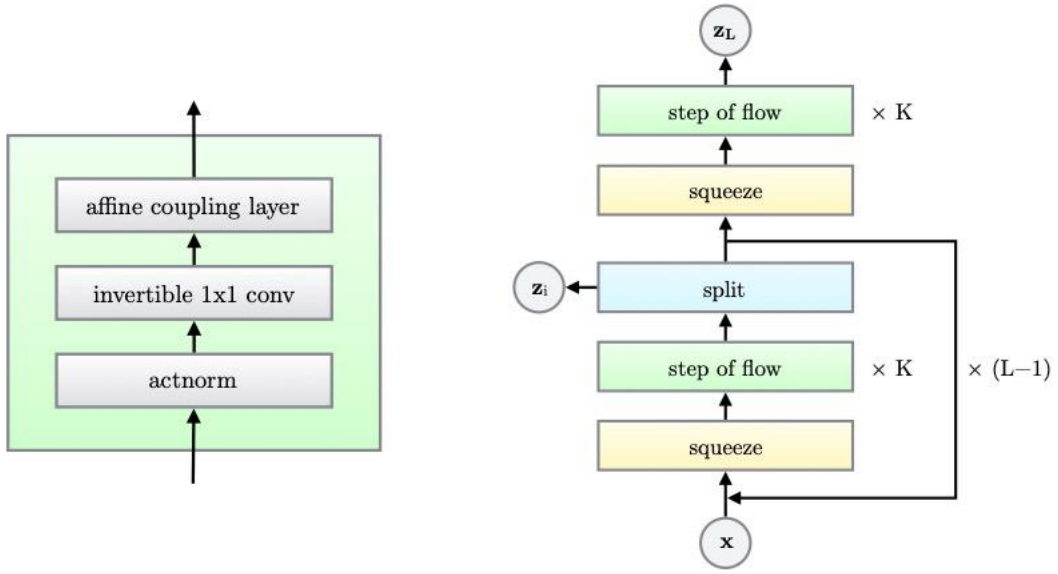
(b) Inverse propagation

$$y_{1:d} = x_{1:d}$$

$$y_{d+1:D} = x_{d+1:D} \odot \exp\left(s\left(x_{1:d}\right)\right) + t\left(x_{1:d}\right),$$

Glow: Big progress on sample quality

OpenAI Glow (2018)

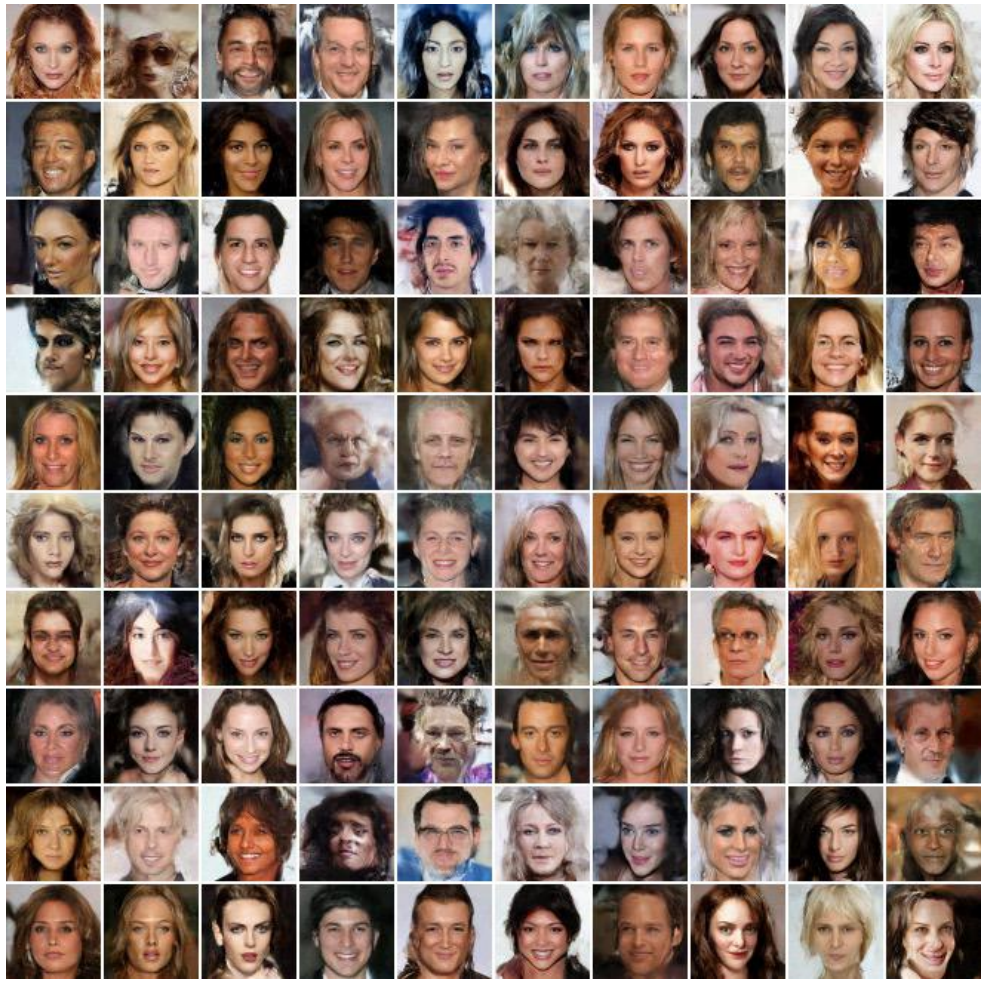


(a) One step of our flow.

(b) Multi-scale architecture (Dinh et al., 2016).

Description	Function	Reverse Function	Log-determinant
Actnorm. See Section 3.1.	$\forall i,j : \mathbf{y}_{i,j} = \mathbf{s} \odot \mathbf{x}_{i,j} + \mathbf{b}$	$\forall i,j : \mathbf{x}_{i,j} = (\mathbf{y}_{i,j} - \mathbf{b})/\mathbf{s}$	$h \cdot w \cdot \mathtt{sum}(\log \lvert\mathbf{s}\rvert)$
Invertible 1×1 convolution. $\mathbf{W} : [c \times c]$. See Section 3.2.	$\forall i,j : \mathbf{y}_{i,j} = \mathbf{W}\mathbf{x}_{i,j}$	$\forall i,j : \mathbf{x}_{i,j} = \mathbf{W}^{-1}\mathbf{y}_{i,j}$	$h \cdot w \cdot \log \lvert\det(\mathbf{W})\rvert$ or $h \cdot w \cdot \mathtt{sum}(\log \lvert\mathbf{s}\rvert)$ (see eq. (10))
Affine coupling layer. See Section 3.3 and (Dinh et al., 2014)	$\mathbf{x}_a, \mathbf{x}_b = \mathtt{split}(\mathbf{x})$ $(\log \mathbf{s}, \mathbf{t}) = \mathtt{NN}(\mathbf{x}_b)$ $\mathbf{s} = \exp(\log \mathbf{s})$ $\mathbf{y}_a = \mathbf{s} \odot \mathbf{x}_a + \mathbf{t}$ $\mathbf{y}_b = \mathbf{x}_b$ $\mathbf{y} = \mathtt{concat}(\mathbf{y}_a, \mathbf{y}_b)$	$\mathbf{y}_a, \mathbf{y}_b = \mathtt{split}(\mathbf{y})$ $(\log \mathbf{s}, \mathbf{t}) = \mathtt{NN}(\mathbf{y}_b)$ $\mathbf{s} = \exp(\log \mathbf{s})$ $\mathbf{x}_a = (\mathbf{y}_a - \mathbf{t})/\mathbf{s}$ $\mathbf{x}_b = \mathbf{y}_b$ $\mathbf{x} = \mathtt{concat}(\mathbf{x}_a, \mathbf{x}_b)$	$\mathtt{sum}(\log(\lvert\mathbf{s}\rvert))$

Flow++: Progress on bits/dim on high entropy datasets



Flow++ (2019)

$$x \longmapsto \sigma^{-1}\left(\text{MixLogCDF}(x; \boldsymbol{\pi}, \boldsymbol{\mu}, \mathbf{s})\right) \cdot \exp(a) + b \quad (17)$$

where

$$\text{MixLogCDF}(x; \boldsymbol{\pi}, \boldsymbol{\mu}, \mathbf{s}) := \sum_{i=1}^{K} \pi_i \sigma\left((x - \mu_i) \cdot \exp(-s_i)\right)$$

mixture of logistics

Our architecture is defined as a stack of blocks. Each block consists of the following two layers connected in a residual fashion, with layer normalization (Ba et al., 2016) after each residual connection:

$$\begin{aligned}
\text{Conv} &= \text{Input} \rightarrow \text{Nonlinearity} \\
&\rightarrow \text{Conv}_{3\times3} \rightarrow \text{Nonlinearity} \rightarrow \text{Gate} \\
\text{Attn} &= \text{Input} \rightarrow \text{Conv}_{1\times1} \\
&\rightarrow \text{MultiHeadSelfAttention} \rightarrow \text{Gate}
\end{aligned}$$

Flow++: Progress on bits/dim on high entropy datasets

Model family	Model	CIFAR10 bits/dim	ImageNet 32x32 bits/dim	ImageNet 64x64 bits/dim
Non-autoregressive	RealNVP (Dinh et al., 2016)	3.49	4.28	–
	Glow (Kingma & Dhariwal, 2018)	3.35	4.09	3.81
	IAF-VAE (Kingma et al., 2016)	3.11	–	–
	Flow++ (ours)	**3.09**	**3.86**	**3.69**
Autoregressive	Multiscale PixelCNN (Reed et al., 2017)	–	3.95	3.70
	PixelCNN (van den Oord et al., 2016b)	3.14	–	–
	PixelRNN (van den Oord et al., 2016b)	3.00	3.86	3.63
	Gated PixelCNN (van den Oord et al., 2016c)	3.03	3.83	3.57
	PixelCNN++ (Salimans et al., 2017)	2.92	–	–
	Image Transformer (Parmar et al., 2018)	2.90	3.77	–
	PixelSNAIL (Chen et al., 2017)	2.85	3.80	3.52

Flow++ (2019)

Flow Models: Future

- Learning the mask for coupling
- Close the gap with autoregressive models even further - use hybrid flows?
- Fewer expressive flows vs Several shallow flows
- Usage of Multiscale Loss - bits/dim vs sample quality tradeoffs
- Representation Learning with Flows
- Initialization

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Flow Models: Future

- Glow-level samples with fewer parameters
- Glow-level samples on 1 MP (1024x1024) images.
- Dimension reduction
- Conditional Flow Models: Architecture and Execution
- **Summary:** Long way to go before GAN level samples and autoregressive model-level likelihood scores (and samples) combined with stable training and a fixed set of engineering practices.

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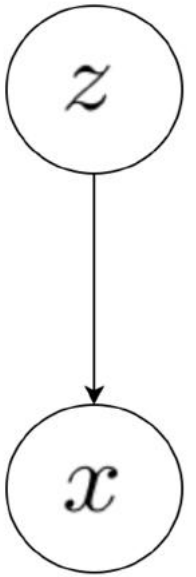
Flow Models: Negatives

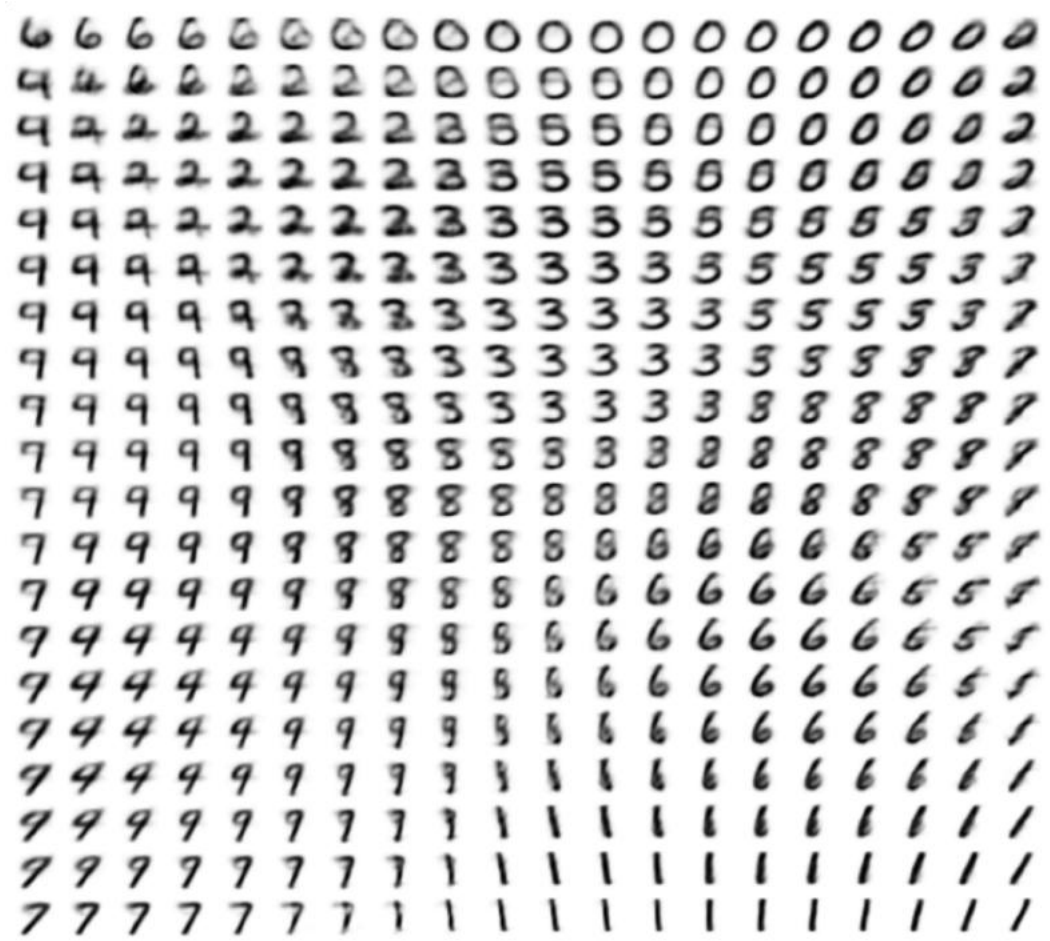
- z is as big as x. Models end up becoming big.
- As of now, no notion of lower dimensional embedding.
- Careful initialization (not really a negative)

Lecture overview

- Autoregressive models
- Flow models
- **Latent Variable models**
  - **Approximate likelihood with Variational Lower Bound**
  - **Variational Auto-Encoder, IWAE, IAF-VAE, PixelVAE (VLAE), VQ-VAE**
- Implicit models



Latent Variable Models

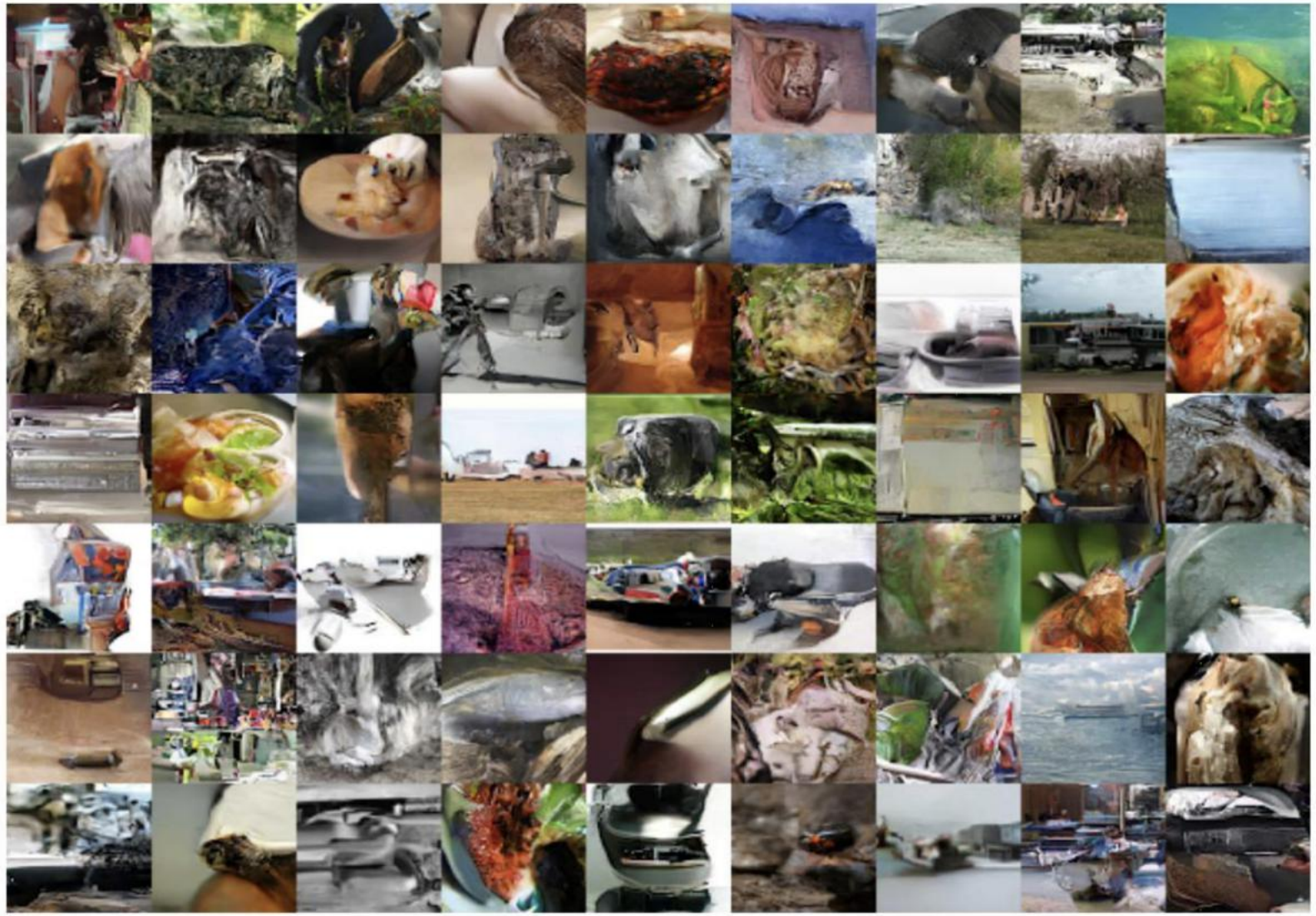


Auto-Encoding Variational Bayes
(Kingma 2013)

Latent Variable Models: PixelVAE

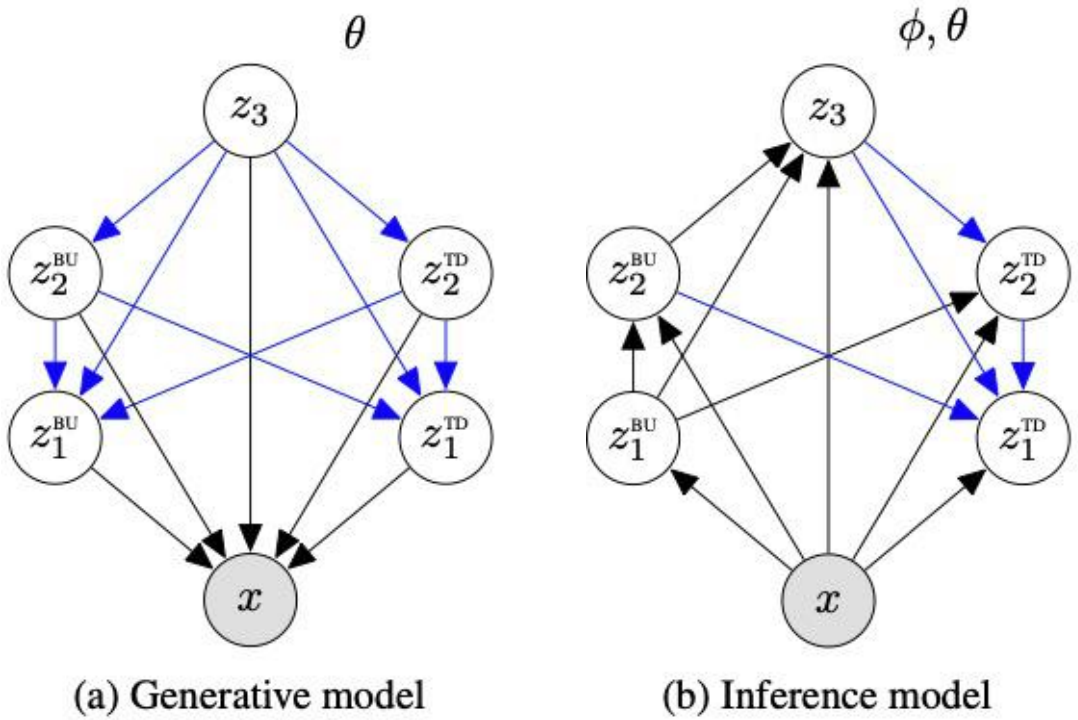
PixelVAE (2016)

Latent Variable Models: PixelVAE



PixelVAE (2016)

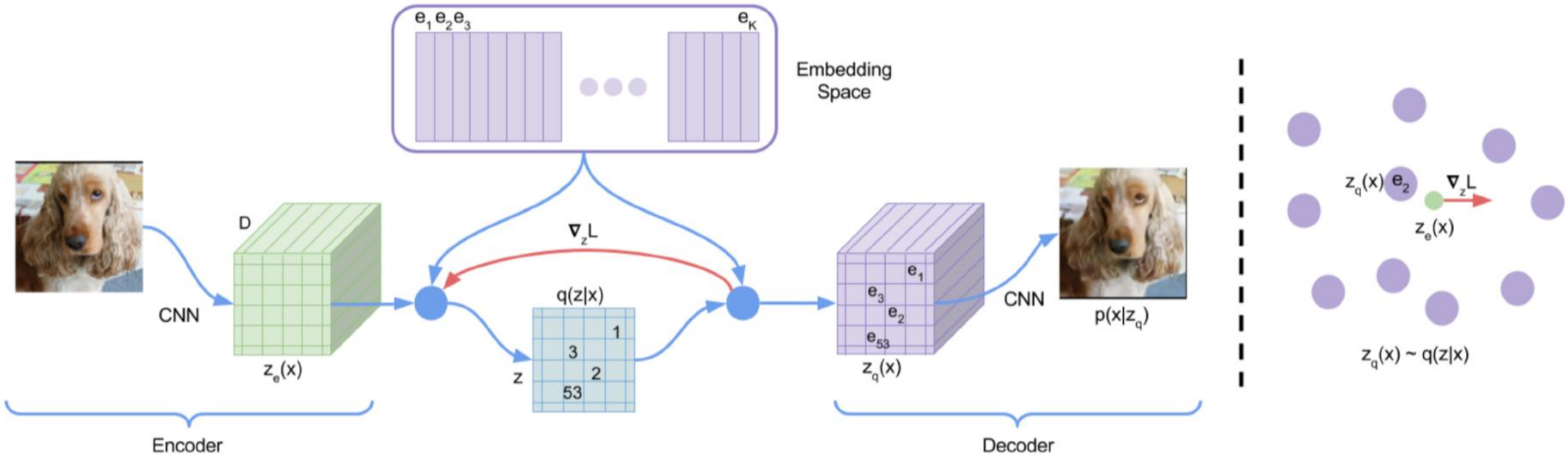
Latent Variable Models - BIVA



(a) Generative model (b) Inference model

Bidirectional-Inference Variational Autoencoder (BIVA) (Maaloe et al. 2019)

VQ-VAE



$$L = \log p(x|z_q(x)) + \|\text{sg}[z_e(x)] - e\|_2^2 + \beta\|z_e(x) - \text{sg}[e]\|_2^2$$

VQ-VAE (2017)

VQ-VAE

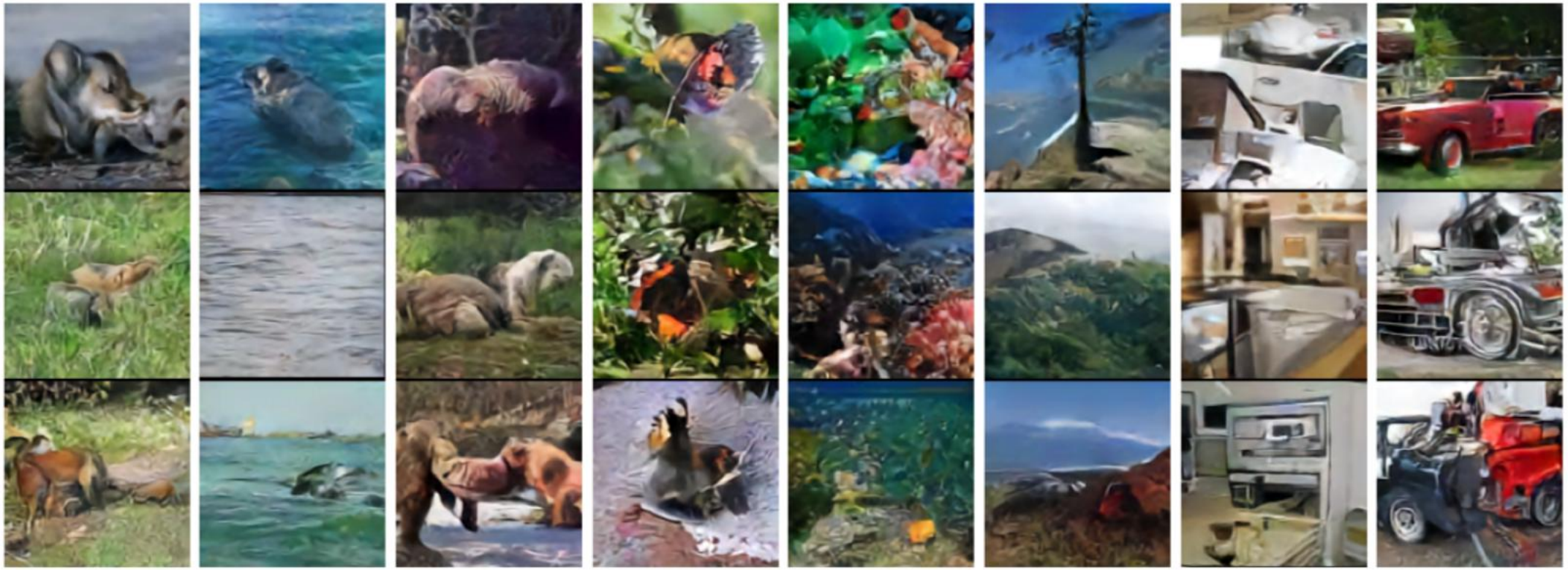
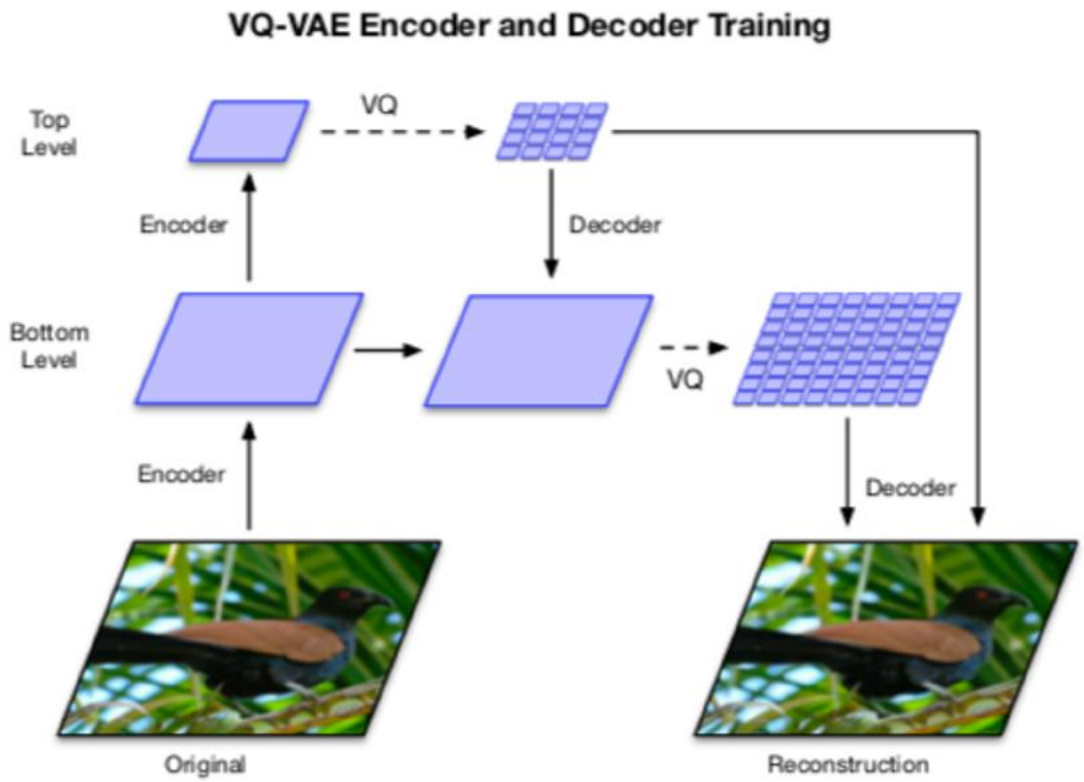
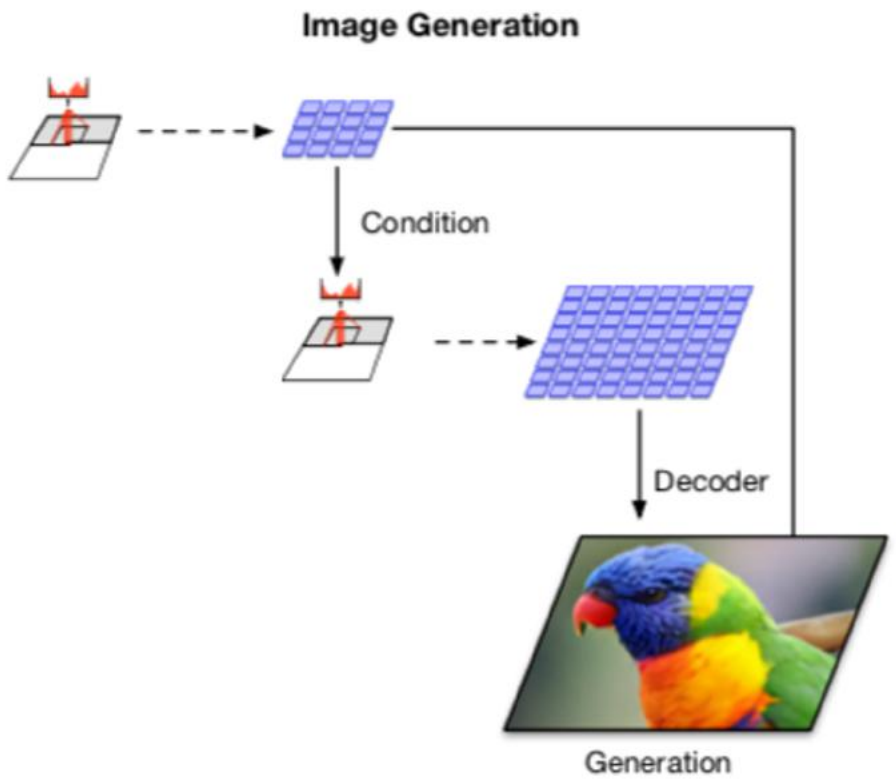


Figure 3: Samples (128x128) from a VQ-VAE with a PixelCNN prior trained on ImageNet images. From left to right: kit fox, gray whale, brown bear, admiral (butterfly), coral reef, alp, microwave, pickup.

VQ-VAE (2017)

VQ-VAE 2.0





VQ-VAE 2.0 (2019)

VQ-VAE 2.0

VQ-VAE 2.0

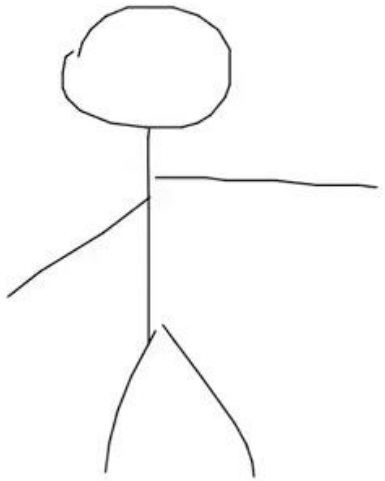
BigGAN Deep

Well known VAE Applications

- Sketch-RNN
- World Models
- Visual concepts for RL (beta-VAE)
- Generative Query Networks

Well known VAE Applications: Sketch-RNN

yoga poses generated by moving through the learned representation (latent space) of the model trained on yoga drawings



https://magenta.tensorflow.org/assets/sketch_rnn_demo/index.html

Well known VAE Applications: World Models

At each time step, our agent receives an **observation** from the environment.

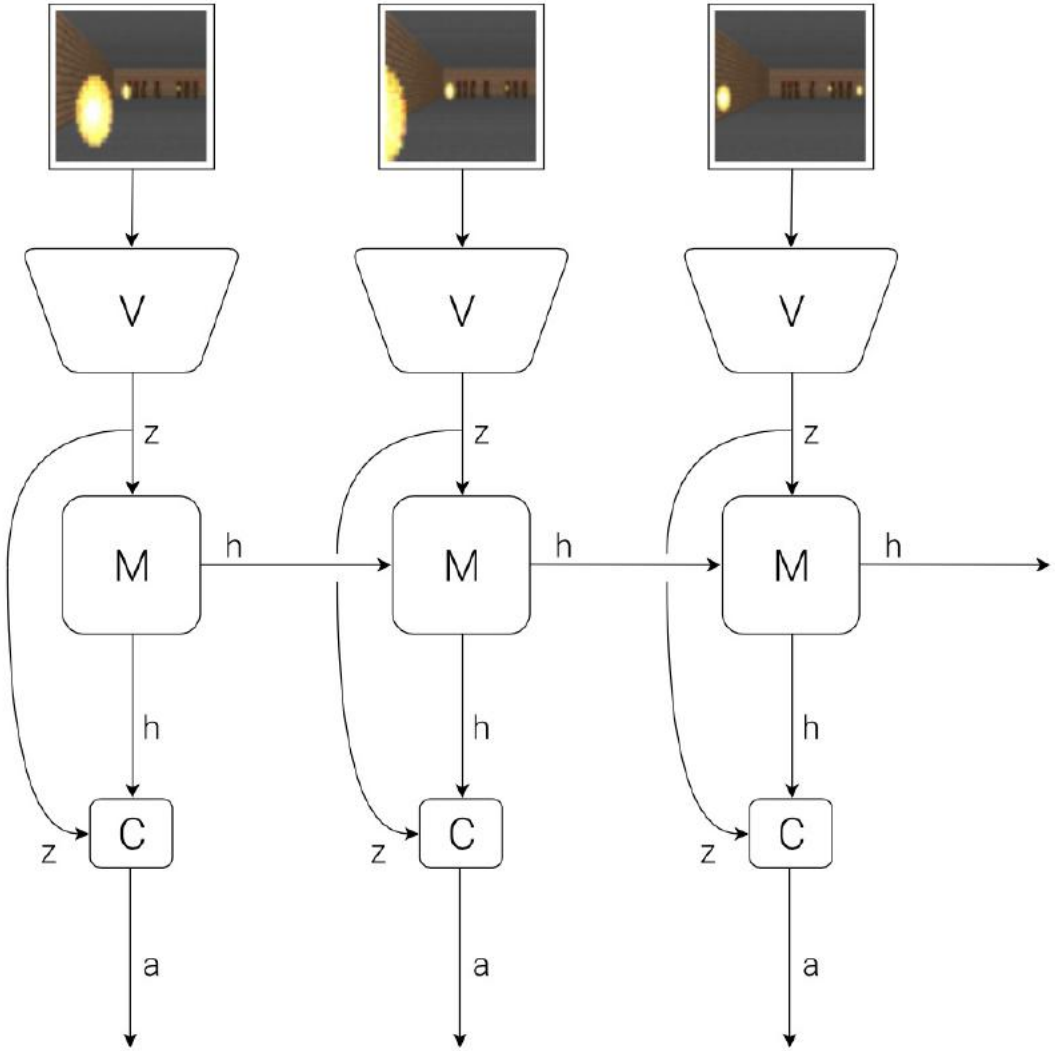
World Model

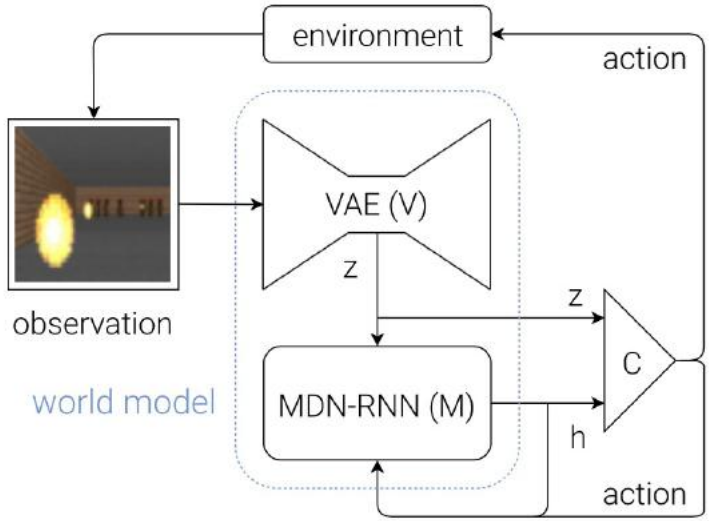
The **Vision Model (V)** encodes the high-dimensional observation into a low-dimensional latent vector.

The **Memory RNN (M)** integrates the historical codes to create a representation that can predict future states.

A small **Controller (C)** uses the representations from both **V** and **M** to select good actions.

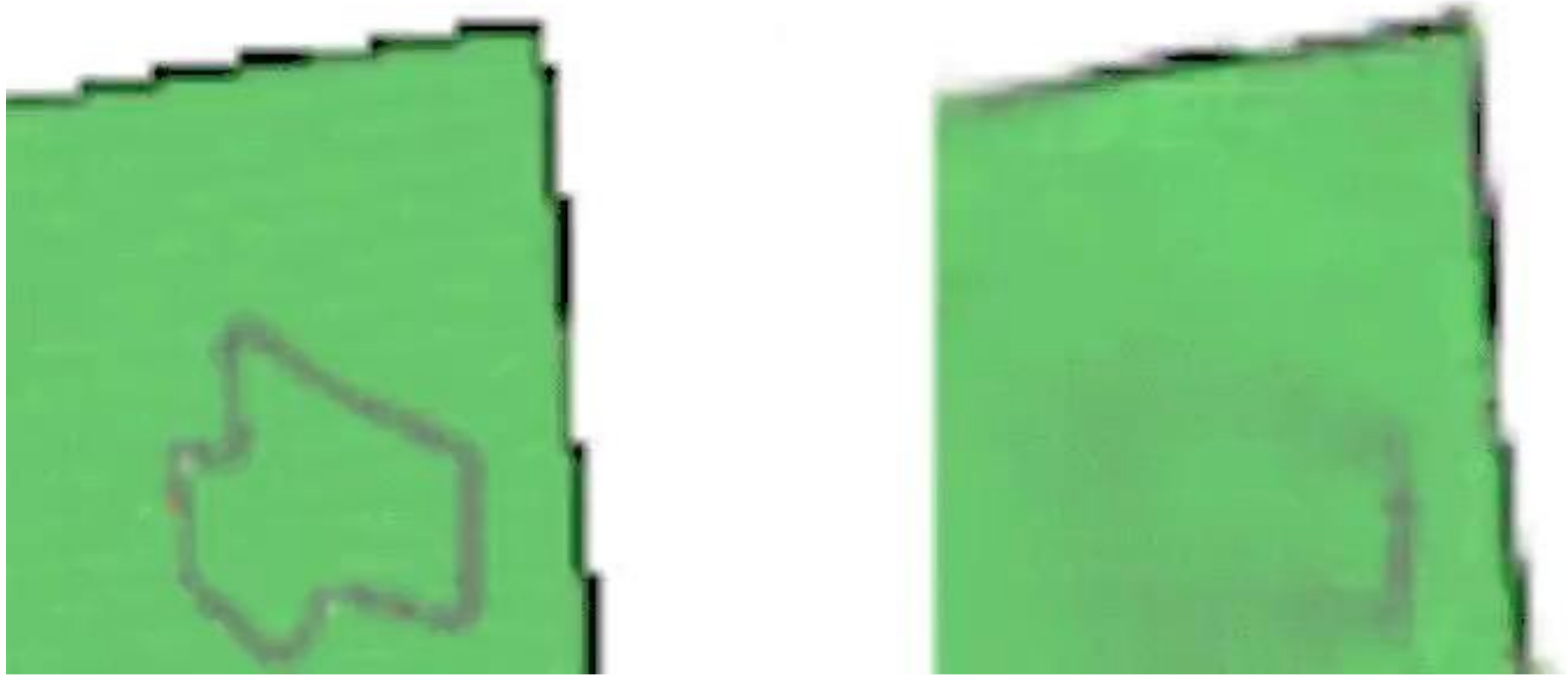
The agent performs **actions** that go back and affect the environment.





https://worldmodels.github.io

Well known VAE Applications: World Models



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Well known VAE Applications: beta-VAE

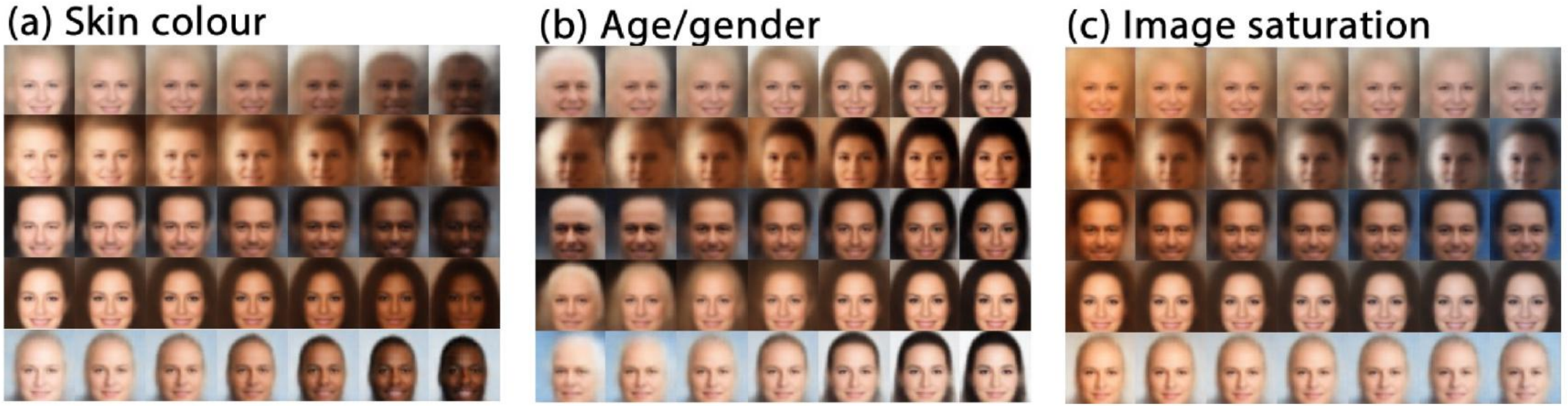

Figure 4: **Latent factors learnt by β-VAE on celebA:** traversal of individual latents demonstrates that β-VAE discovered in an unsupervised manner factors that encode skin colour, transition from an elderly male to younger female, and image saturation.

SCAN: Learning Hierarchical Compositional Visual Concepts

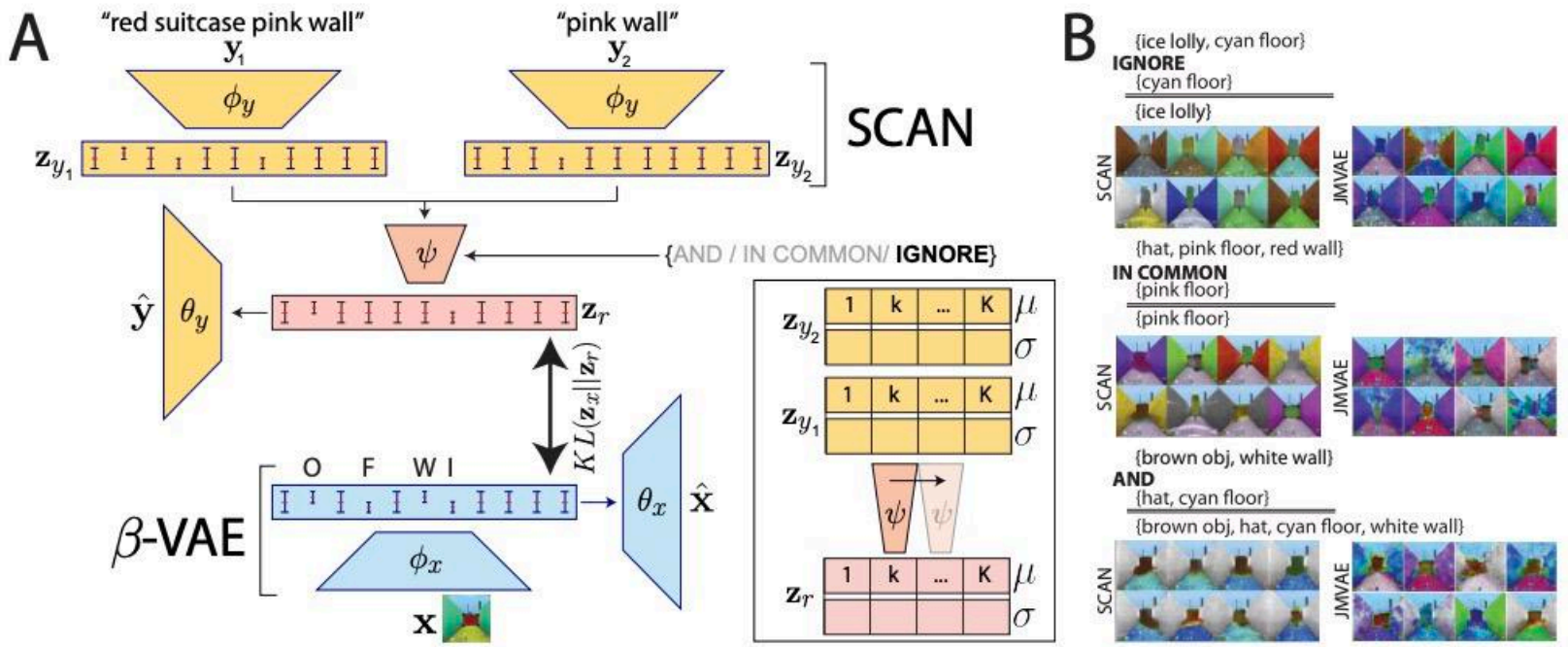

Figure 3: **A**: Learning AND, IN COMMON or IGNORE recombination operators with a SCAN model architecture. Inset demonstrates the convolutional recombination operator that takes in $\{\mu^k_{y_1}, \sigma^k_{y_1}; \mu^k_{y_2}, \sigma^k_{y_2}\}$ and outputs $\{\mu^k_r, \sigma^k_r\}$. The capital letters correspond to four disentangled visual primitives: object identity (I), object colour (O), floor colour (F) and wall colour (W). **B**: Visual samples produced by SCAN and JMVAE when instructed with a novel concept recombination. SCAN samples consistently match the expected ground truth recombined concept, while maintaining high variability in the irrelevant visual primitives. JMVAE samples lack accuracy. Recombination instructions are used to imagine concepts that have never been seen during model training. **Top**: samples for IGNORE; **Middle**: samples for IN COMMON; **Bottom**: samples for AND.

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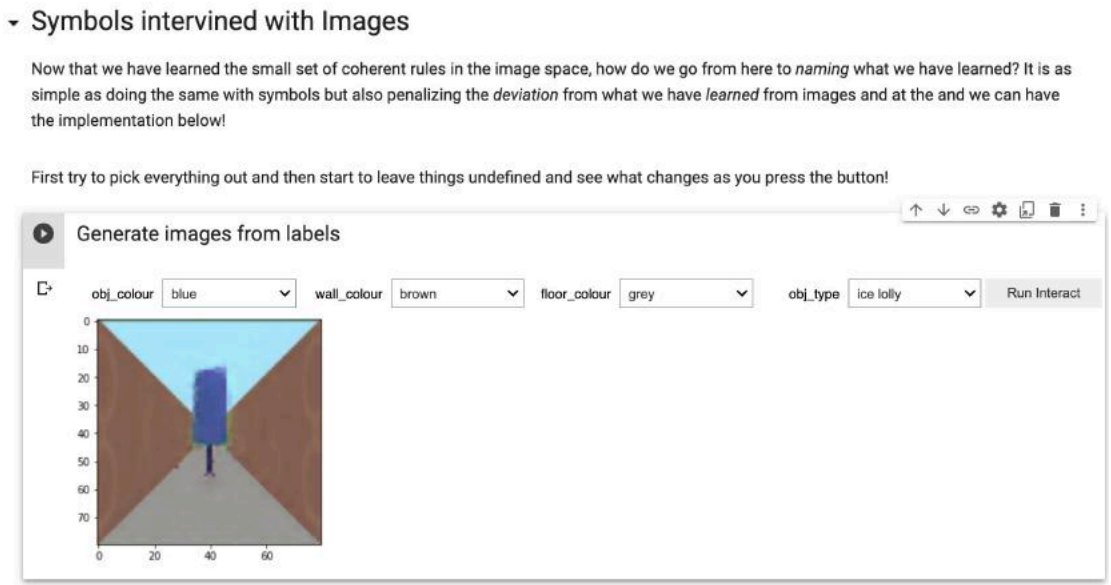
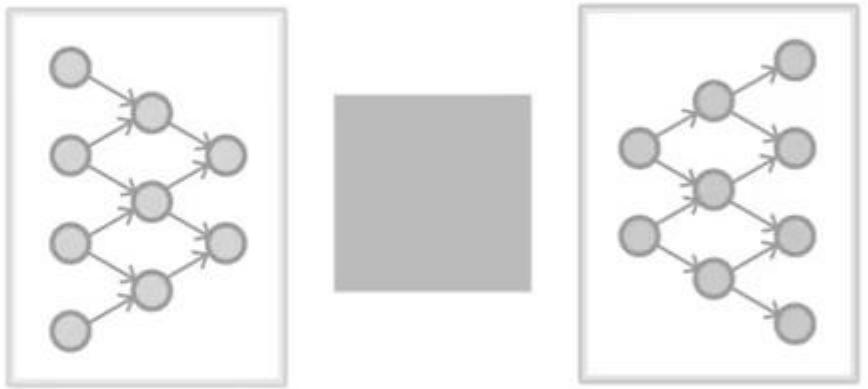


Colab Notebook (by Ahmet Sahin): https://colab.research.google.com/drive/1GD_Rdj-oPaWm_Y8DaUFdBfJWwMXl8B9R?usp=sharing#scrollTo=0xd_Qnq954ZI

Well known VAE Applications: Generative Query Networks



VAE: Advantages

- Notion of “compressed” representation learning
- Also gives you approximate log-likelihood
- Interpolations, retrospective analysis of what the model learns
- Disentangled representations
- Generative Model + Density Model + Latent Variables + Dimensionality Reduction

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VAE: Disadvantages

- Blurry samples
- Factorized gaussian posterior or decoder assumptions maybe too limiting
- Success on large scale is still on-going work
- Encouraging disentanglement with the KL term still only shown on relatively toy domains
- There maybe other ways to learn better representations or to get better samples or get better density estimates (basically, not the best at any one thing but gives you all together)

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- Modern decoders [cross-entropy based, weakly autoregressive]
- More powerful posteriors
- Hierarchical latent variable models to learn coarse and fine features and interpolations
- Discrete latent variable models to prevent posterior collapse and still be able to use PixelCNN-like decoders
- Scale at the level of Flow Models training

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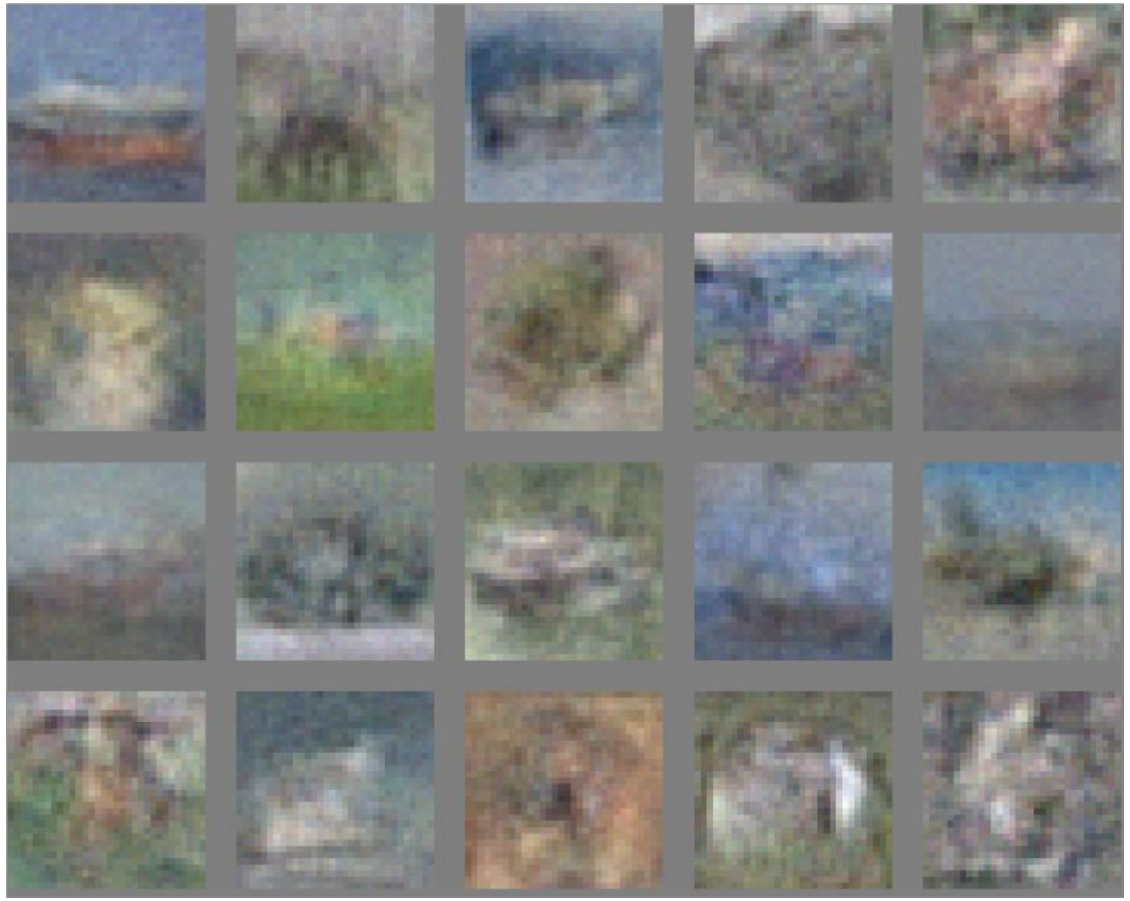
Lecture overview

- Autoregressive models
- Flow models
- Latent Variable models
- **Implicit models**
  - **Generative Adversarial Networks (GAN)**

Generative Adversarial Networks

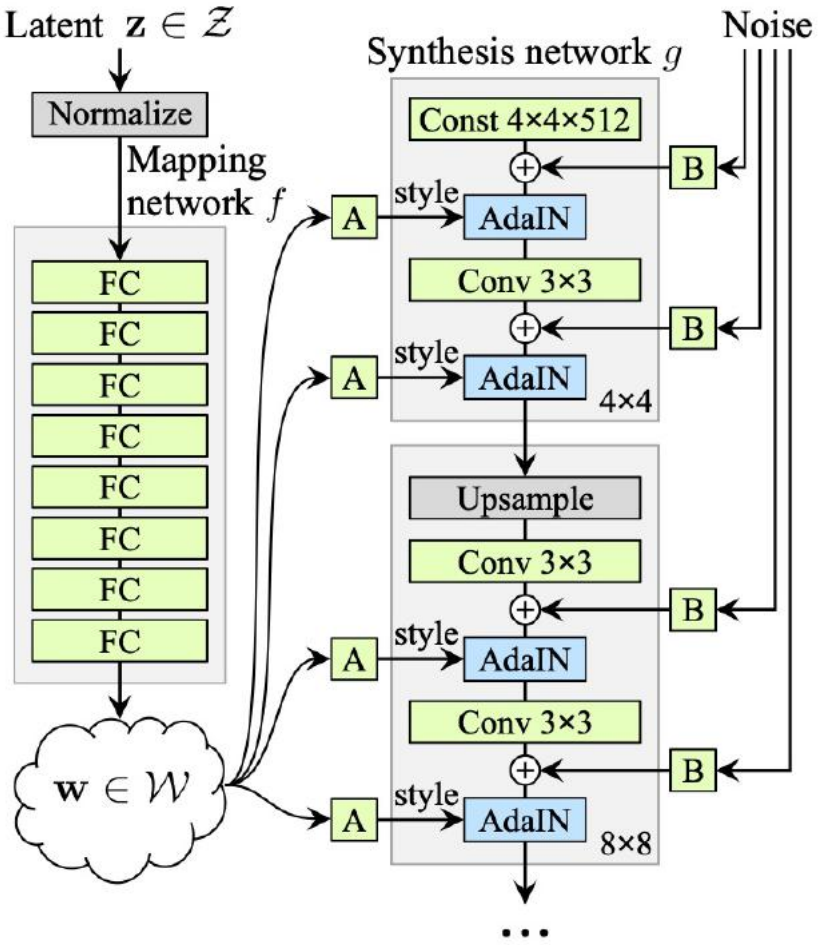


Original GAN (2014) - Goodfellow et al

Generative Adversarial Networks

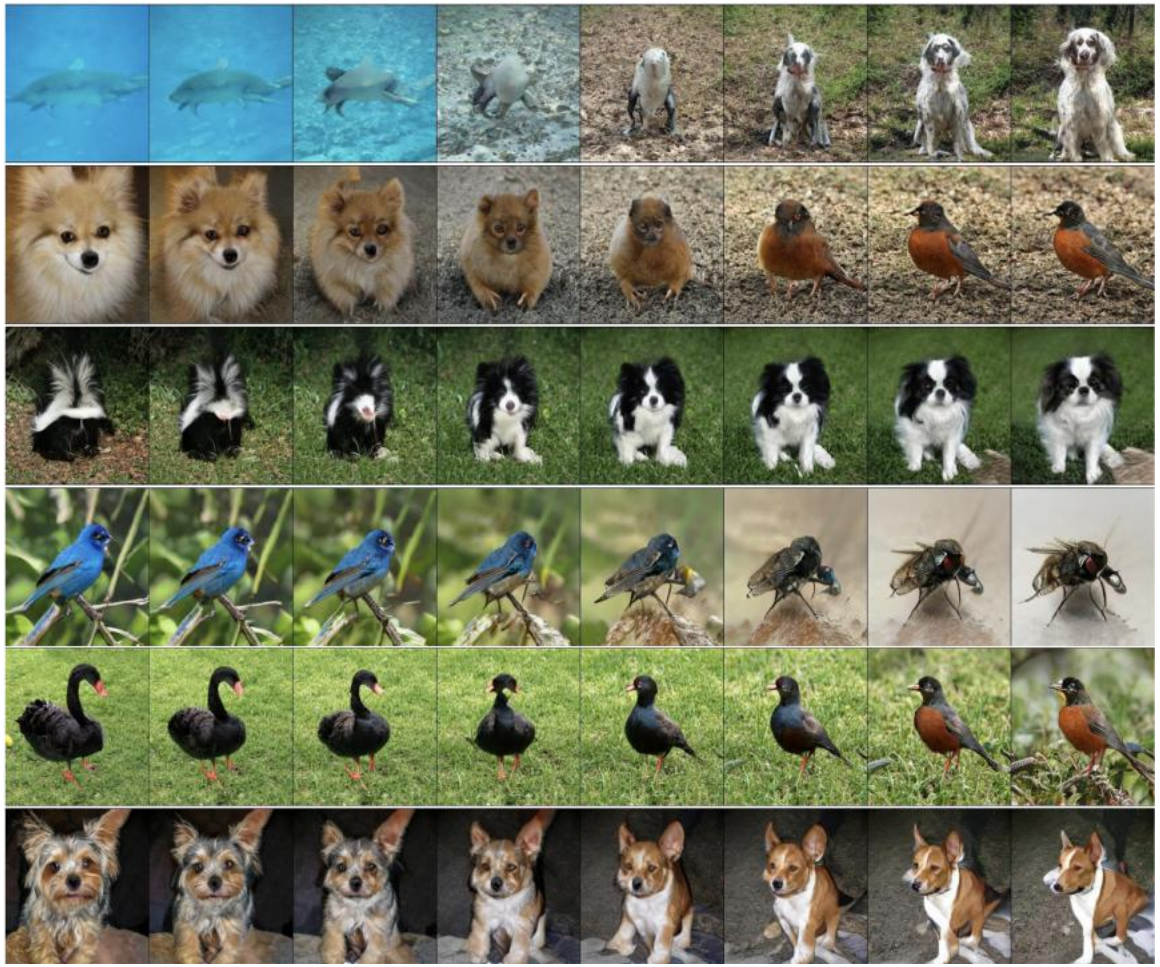
DCGAN - Radford, Metz, Chintala 2015

Generative Adversarial Networks

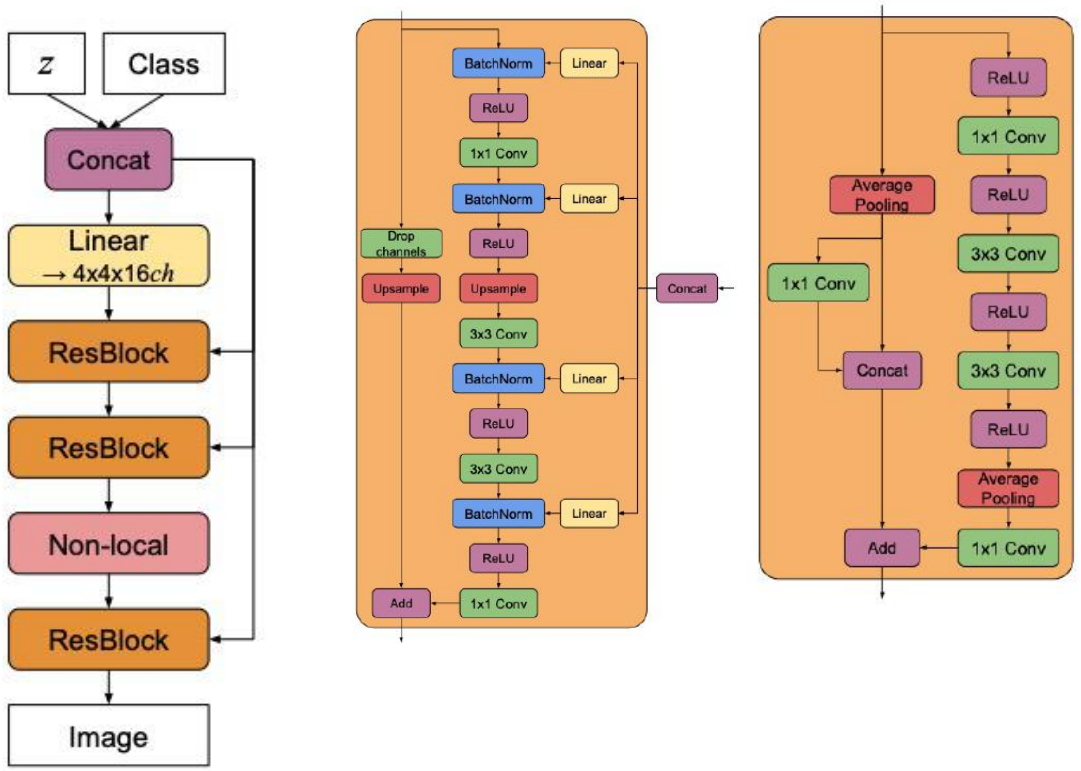


StyleGAN (2019)

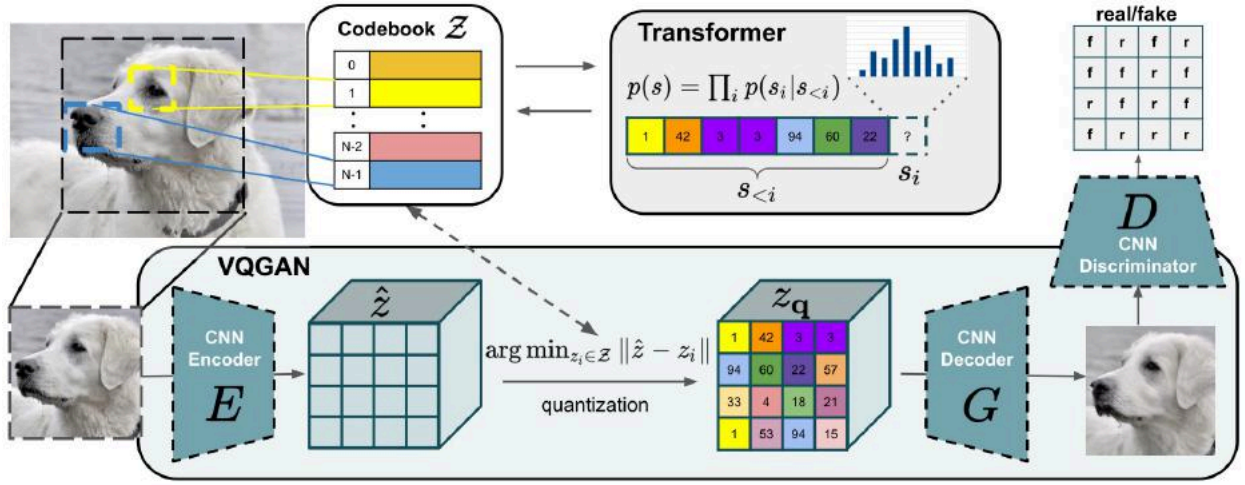
Generative Adversarial Networks



BigGAN (2019)



VQGAN



VQGAN (2020)

Generative Adversarial Networks: Future

- Hard to predict against them given an array of the most powerful generation results for images.
- Progress in unconditional GANs.
- Handling more fine-grained details
- More complex scenes (multiple people with objects)
- Video generation

Generative Adversarial Networks: Future

- Lipschitzness constraints (New approaches)
- Conditioning tricks (Feeding in noise at different levels, batch / instance normalization)
- Architecture design (Upsampling, downsampling, deep vs wide tradeoff)
- Objective functions (Hinge Loss …)
- Stability and scalability (Deeper models with fewer parameters + larger batch sizes)
- Perturbations at different levels (StyleGAN) + Coarse / Fine interpolations

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Generative Adversarial Networks: Negatives

- Plenty of varying engineering tricks and details
- Hard to know which piece is significantly helping push the cutting edge results
- Ablations for large scale datasets are time-consuming
- Unconditional GANs - sample diversity (or mode dropping behavior)
- Evaluation metrics to account for generalization
- Ablations / Key pieces / engineering details isn't a negative specific to GANs

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GANs or Density Models?

- Not true that density models do not need comparable level of engineering details and hacks to work as GANs (e.g.: FiLM conditioning, gating, LayerNorm, ActNorm).
- Not true that there is absolutely no theoretical understanding of GANs: Lag behind empirical practice and difficulty doesn't mean non-existence
- Blurry / improbable samples (vs) Mode collapse :: Compression at the cost of sample quality : Sample quality at the cost of missing modes
- Apart from amazing samples, GANs are more popular because:
  - Works well with less compute (Ex: Good 1024 x 1024 (megapixel) Celeb A samples with few couple hours of training on a single V100 GPU)
  - Density models are huge, require distributed training - not doable by too many people. Takes a lot more time to output reasonably sharp samples.
  - Interpolations and conditional generation [some success on Glow but not possible with autoregressive models] - adoption by artists.

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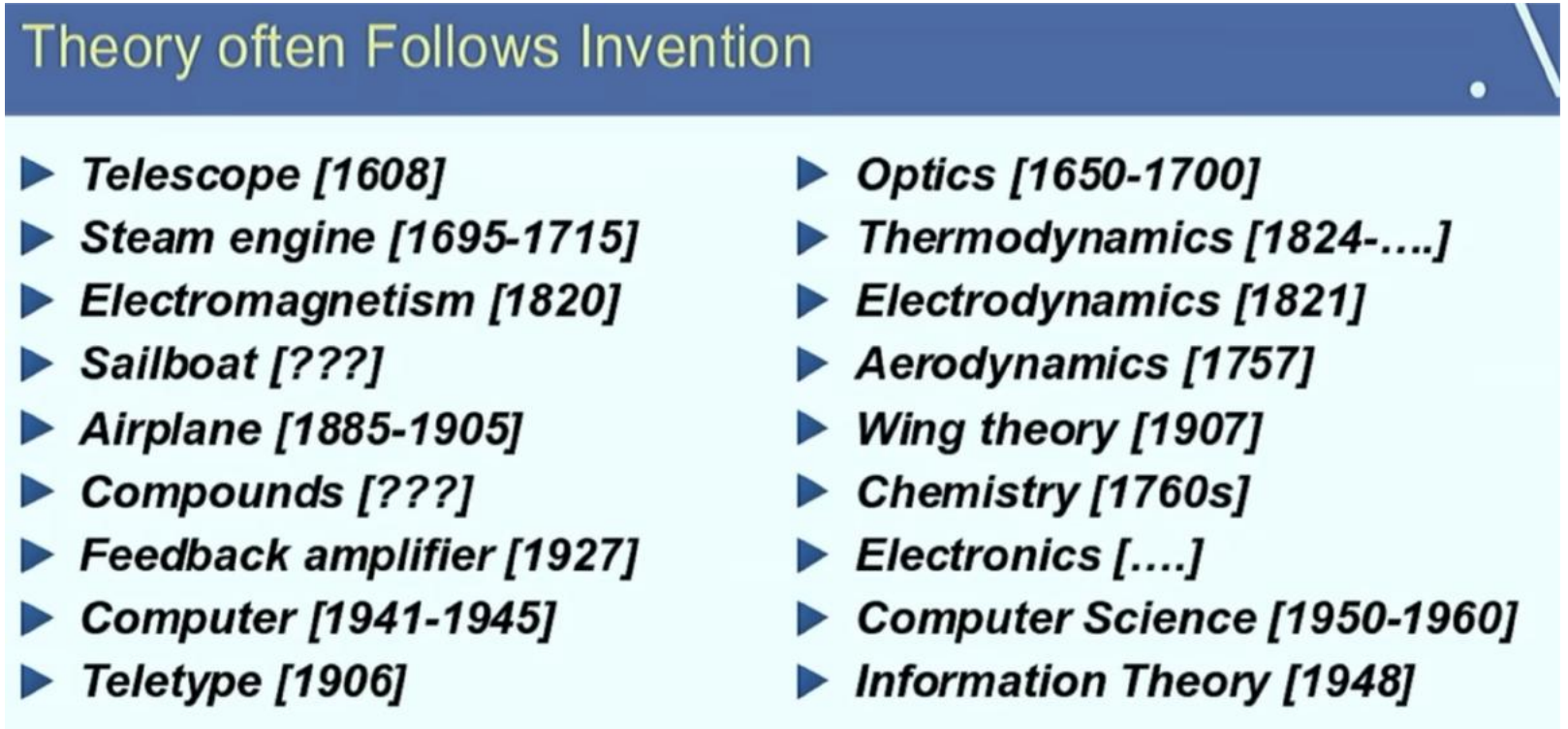
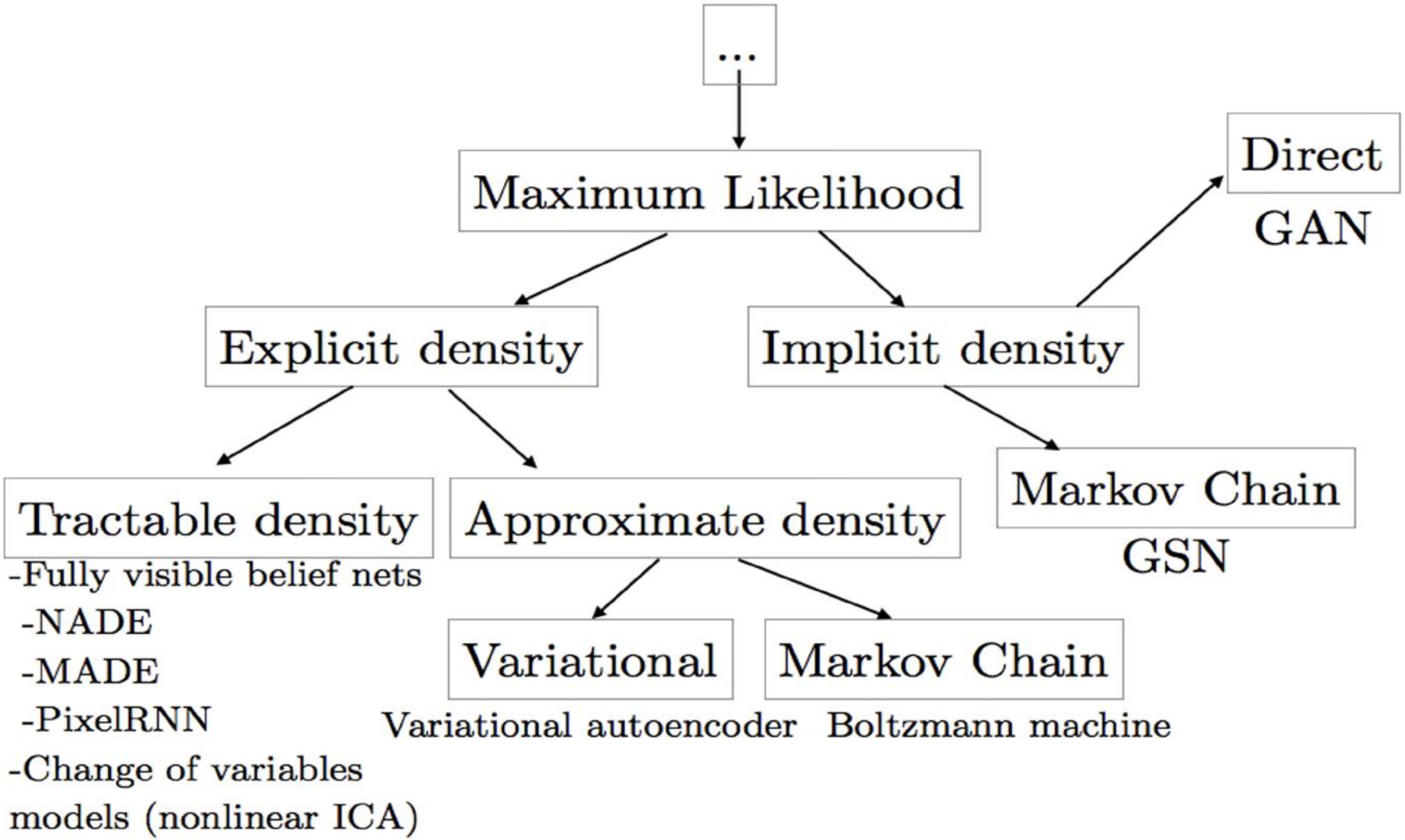
  - Density models are huge, require distributed training - not doable by too many people. Takes a lot more time to output reasonably sharp samples.
  - Interpolations and conditional generation [some success on Glow but not possible with autoregressive models] - adoption by artists.

GANs or Density Models?

- **Bright side**: Upto to aesthetics / taste in terms of betting on one (density models vs GAN)
- Many technological advances in the past have been possible without rigorous science built for them (science followed later) [Le Cun: Epistemology of DL]



Taxonomy


...
Maximum Likelihood
Direct
GAN
Explicit density
Implicit density
Tractable density
Approximate density
Markov Chain
GSN
-Fully visible belief nets
-NADE
-MADE
-PixelRNN
-Change of variables
models (nonlinear ICA)
Variational
Markov Chain
Variational autoencoder
Boltzmann machine

If training density models...

- If you only care about density and not sampling, go for autoregressive models
- If you care about sampling time but not too much, autoregressive is still fine. Just use smaller models and preferably RNNs [or write efficient convolution / self-attention]

- If you really can't afford linear (in number of dimensions) sampling, weaker autoregressive models (log time) such as Parallel PixelCNN are worth considering.
- Notion that autoregressive models are meant for "discrete" is unfounded.
  Ex: Alex Graves' Handwriting Recognition, Sketch-RNN, World Models, CPC.

- Flow Models are good for modeling densities of continuous valued data and are getting better for discrete (pixels). Larger models needed for complex datasets.
- If you want both representations and sampling or just want to try the simplest thing first, variational auto-encoders with factorized decoders are a natural first choice.

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When GANs?

- Cool samples
- Really large images and HQ datasets like faces, buildings, etc.
- Class-conditional models
- Image to Image translation problems (edges / seg-map to real image, adding texture, adding color, etc.)
- If you care only about perceptual quality and want controllable generation and don’t have lot of compute, GAN is the best choice.

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Summary

TABLE 1: Comparison between deep generative models in terms of training and test speed, parameter efficiency, sample quality, sample diversity, and ability to scale to high resolution data. Quantitative evaluation is reported on the CIFAR-10 dataset [114] in terms of Fréchet Inception Distance (FID) and negative log-likelihood (NLL) in bits-per-dimension (BPD).

Method	Train Speed	Sample Speed	Param. Effic.	Sample Quality	Relative Divers.	Resolution Scaling	FID	NLL (in BPD)
Generative Adversarial Networks								
DCGAN [169]	★★★★★	★★★★★	★★★★☆	★★★☆☆	★☆☆☆☆	★★☆☆☆	17.70	-
ProGAN [102]	★★☆☆☆	★★★★★	★★★★☆	★★★☆☆	★★☆☆☆	★★★★★	15.52	-
BigGAN [17]	★★★★☆	★★★★★	★★★★☆	★★★★☆	★☆☆☆☆	★★★★☆	14.73	-
StyleGAN2 + ADA [103]	★★★☆☆	★★★★★	★★★★☆	★★★★☆	★★☆☆☆	★★★★★	2.42	-
Energy Based Models								
IGEBM [42]	★★★☆☆	★★☆☆☆	★★★★★	★★★☆☆	★★★☆☆	★★★☆☆	37.9	-
Denoising Diffusion [80]	★★☆☆☆	★★☆☆☆	★★★☆☆	★★★★☆	★★★★☆	★★★★☆	3.17	$\leq$ 3.75
DDPM++ Continuous [191]	★★☆☆☆	★★★☆☆	★★★☆☆	★★★★☆	★★★★☆	★★★★☆	2.92	2.99
Flow Contrastive [51]	★☆☆☆☆	★★★☆☆	★☆☆☆☆	★★☆☆☆	★★★☆☆	★★☆☆☆	37.30	$\approx$ 3.27
VAEBM [226]	★★☆☆☆	★★★☆☆	★★★☆☆	★★★☆☆	★★★☆☆	★★★★☆	12.19	-
Variational Autoencoders								
Convolutional VAE [110]	★★★★★	★★★★★	★★★★☆	★★☆☆☆	★★★★☆	★★☆☆☆	106.37	$\leq$ 4.54
Variational Lossy AE [27]	★☆☆☆☆	★☆☆☆☆	★☆☆☆☆	★★☆☆☆	★★★★☆	★☆☆☆☆	-	$\leq$ 2.95
VQ-VAE [171], [215]	★★☆☆☆	★★★☆☆	★★☆☆☆	★★★☆☆	★★★★☆	★★★★★	-	$\leq$ 4.67
VD-VAE [29]	★★★☆☆	★★★★☆	★★★☆☆	★★★☆☆	★★★★☆	★★★★★	-	$\leq$ 2.87
Autoregressive Models								
PixelRNN [214]	★☆☆☆☆	★☆☆☆☆	★☆☆☆☆	★☆☆☆☆	★★★★★	★★★☆☆	-	3.00
Gated PixelCNN [213]	★☆☆☆☆	★☆☆☆☆	★☆☆☆☆	★★☆☆☆	★★★★★	★★★☆☆	65.93	3.03
PixelIQN [161]	★☆☆☆☆	★☆☆☆☆	★☆☆☆☆	★★☆☆☆	★★★★★	★★★☆☆	49.46	-
Sparse Trans. + DistAug [30], [99]	★★☆☆☆	★☆☆☆☆	★★☆☆☆	★★★★☆	★★★★★	★★★☆☆	14.74	2.66
Normalizing Flows								
RealNVP [39]	★☆☆☆☆	★★★★☆	★☆☆☆☆	★☆☆☆☆	★★★★★	★★★☆☆	-	3.49
Masked Autoregressive Flow [165]	★★☆☆☆	★☆☆☆☆	★★☆☆☆	★☆☆☆☆	★★★☆☆	★★☆☆☆	-	4.30
GLOW [111]	★☆☆☆☆	★★★★☆	★☆☆☆☆	★★☆☆☆	★★★★★	★★★★☆	45.99	3.35
FFJORD [56]	★☆☆☆☆	★★★☆☆	★★★★★	★★☆☆☆	★★★★★	★★☆☆☆	-	3.40
Residual Flow [24]	★★☆☆☆	★★★★☆	★★★★☆	★★☆☆☆	★★★★★	★★★★☆	46.37	3.28

[Bond-Taylor et al. 2021]

Next lecture:
Self-Supervised Learning