CMPT 983

Grounded Natural Language Understanding

April 08, 2021

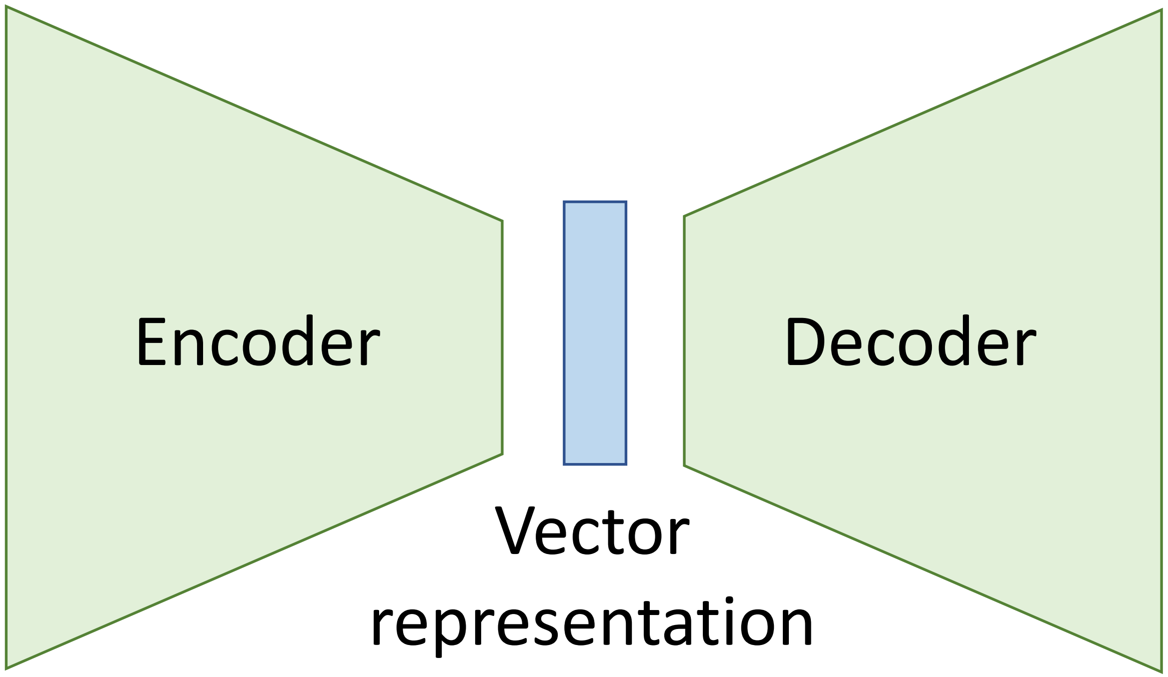
Content generation from language

Content generation from language

Translating across modalities

Text

A white bird with
a black crown
and yellow beak



Image

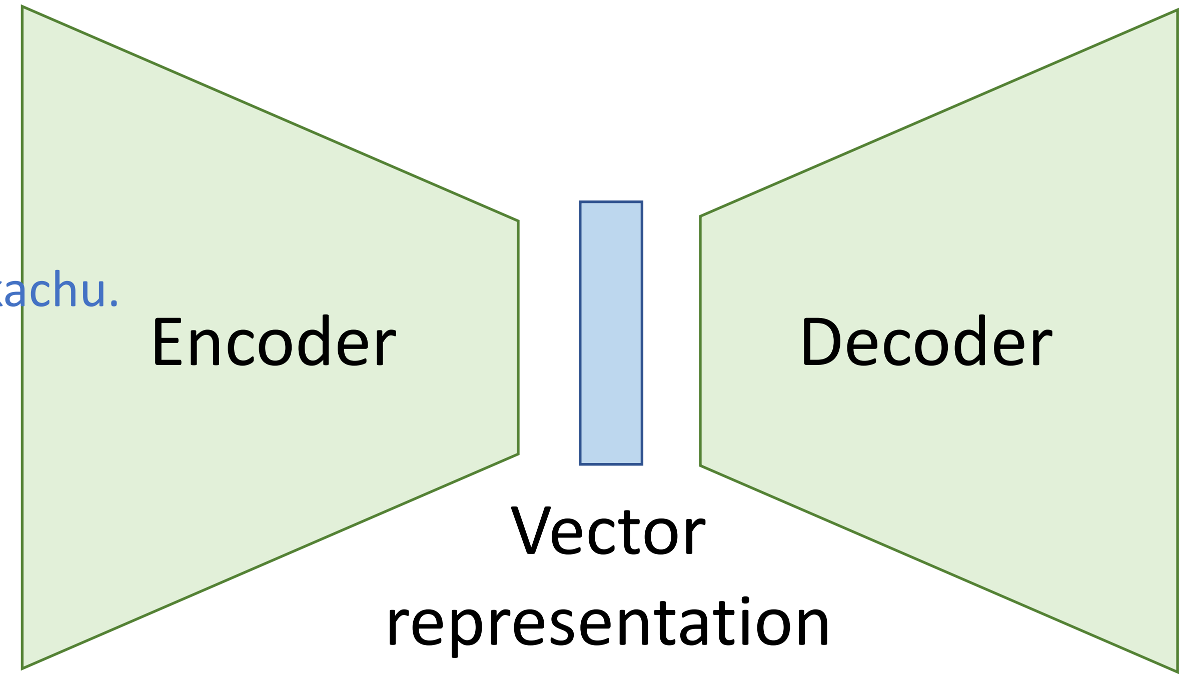
“StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks”
[Zhang et al, ICCV 2017]

Translating across modalities

Text

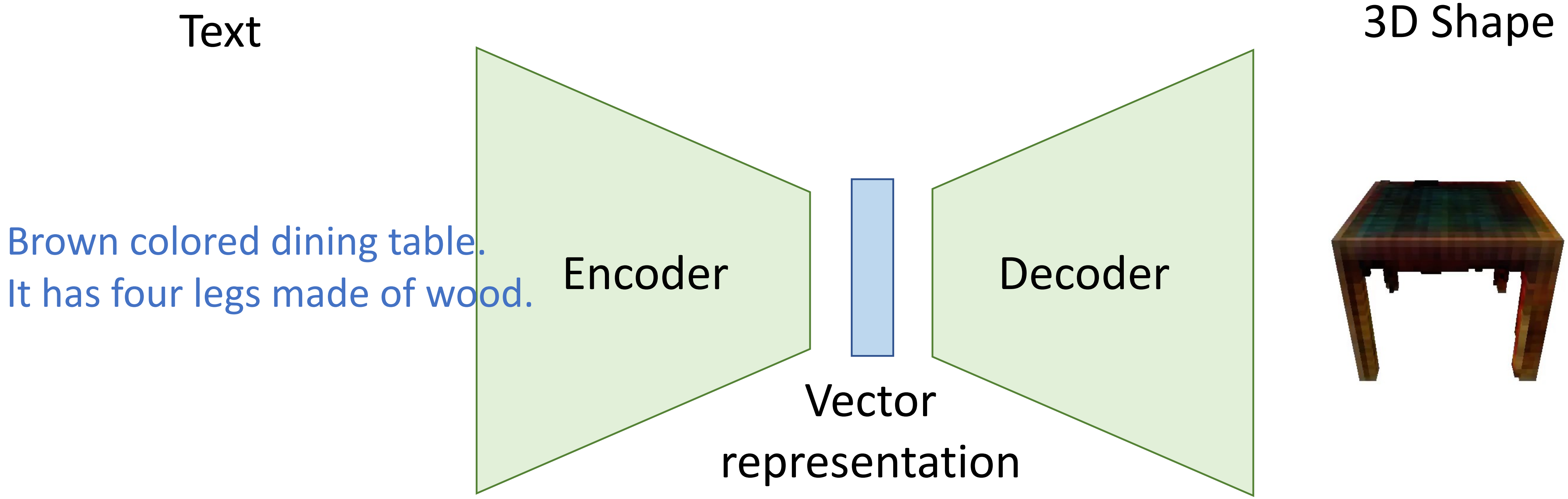
Image

a teapot in the shape of a pikachu.
a teapot imitating a pikachu



“Dall-e”
[Ramesh et al, https://openai.com/blog/dall-e/]

Translating across modalities

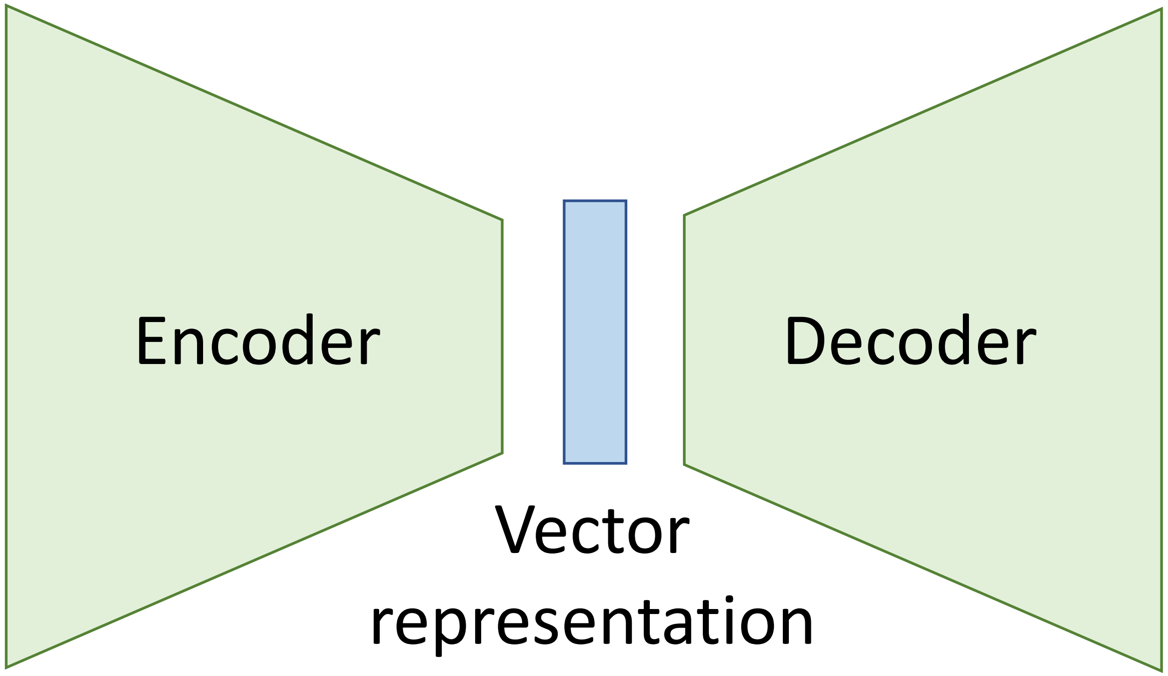


"Text2Shape: Generating Shapes from Natural Language by Learning Joint Embeddings"
[Chen et al, ACCV 2018]

How is generating images and shapes different from generating text?

Translating across modalities

Image



Text

man in black shirt
is playing guitar

Image captioning

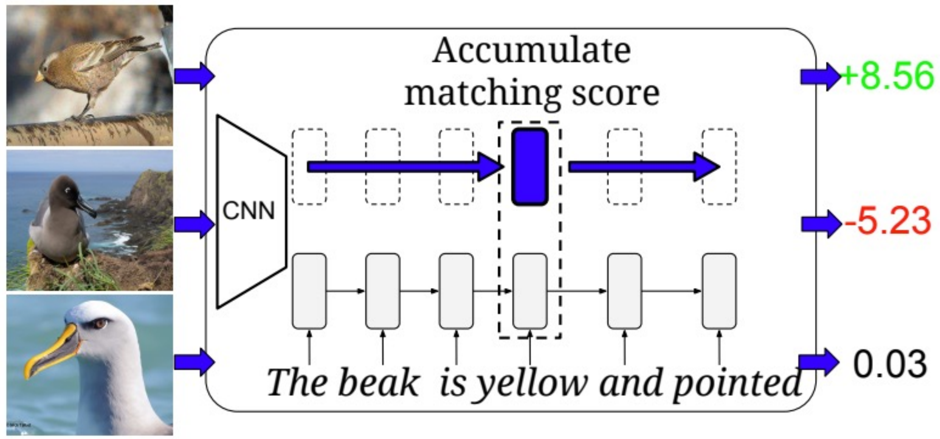
"Deep Visual-Semantic Alignments for Generating Image Descriptions"
[Karpathy and Fei-Fei CVPR 2015]

Generating Content

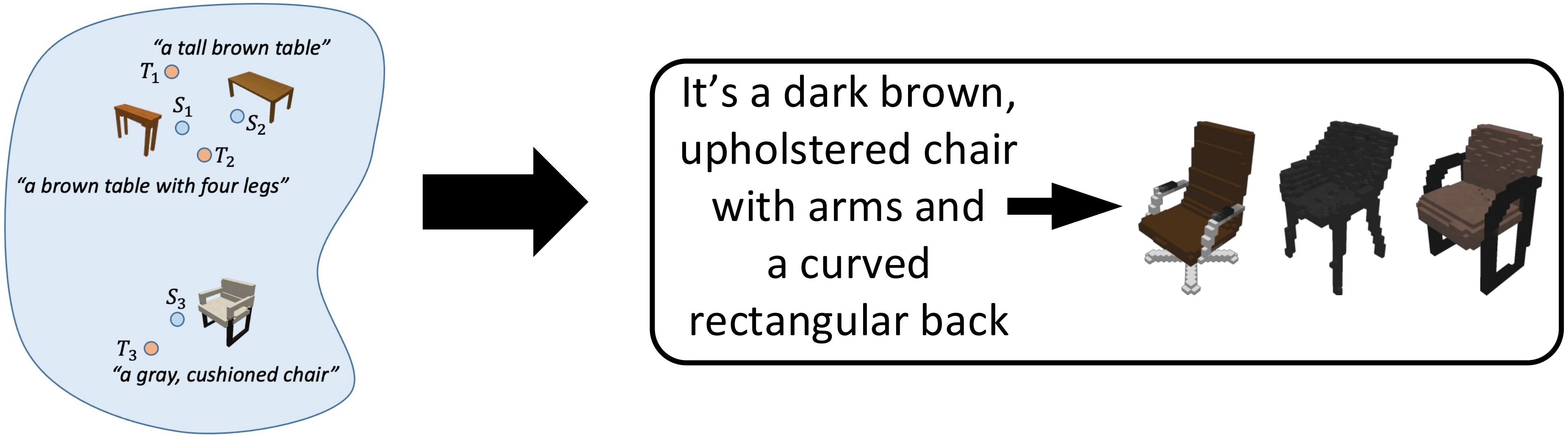
- Recall: retrieval as most basic form of generation

Generation as retrieval

Learn joint embedding → Embed and retrieve



"Learning Deep Representations of Fine-Grained Visual Descriptions" (Reed et al, CVPR 2016)

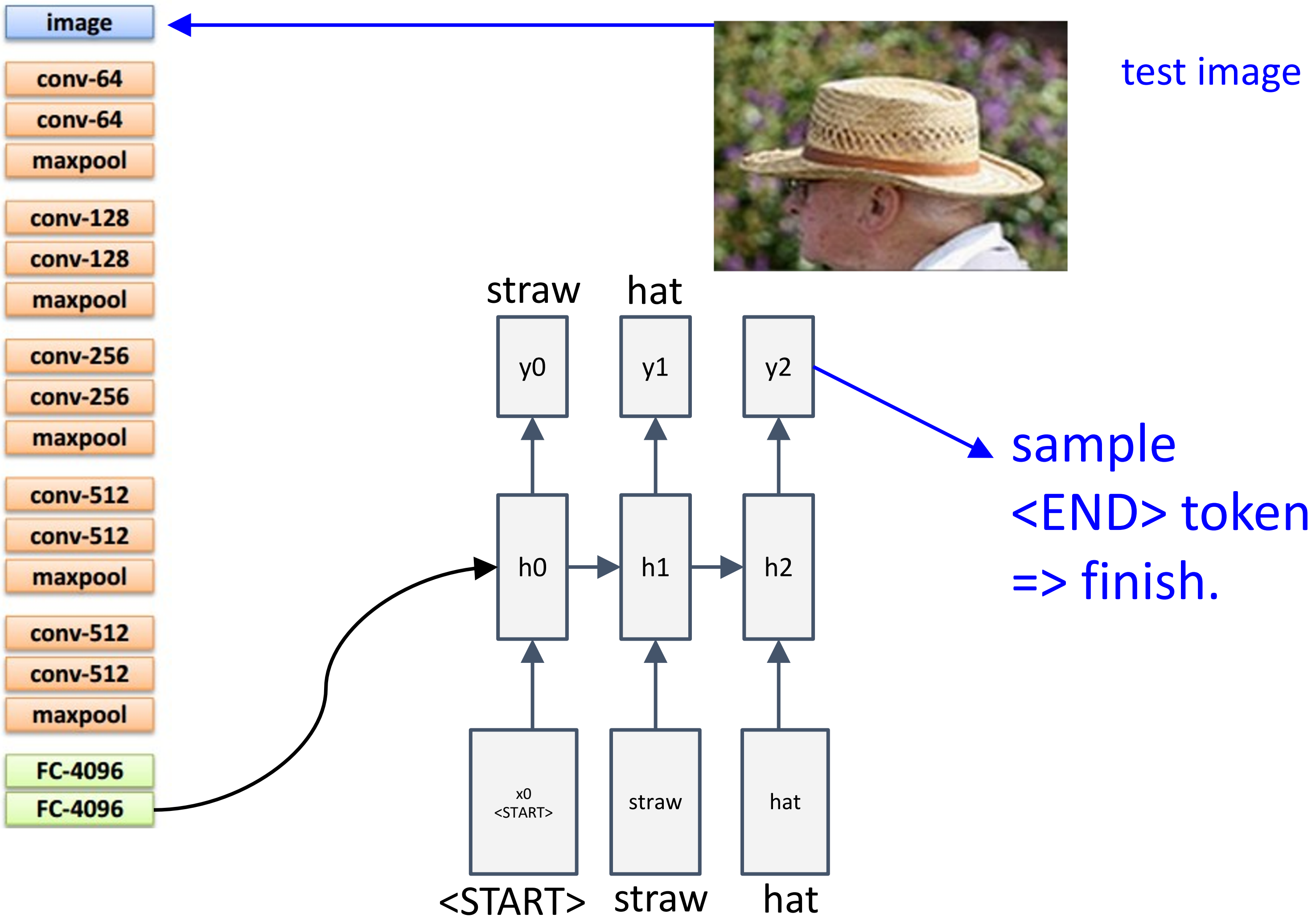


"Text2Shape: Generating Shapes from Natural Language by Learning Joint Embeddings" (Chen et al, ACCV 2018)

Generating Content

- Recall: retrieval as most basic form of generation
- Recall: can model as output as a sequence and generate autoregressively

Autoregressive captioning

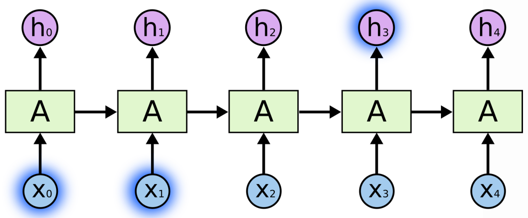


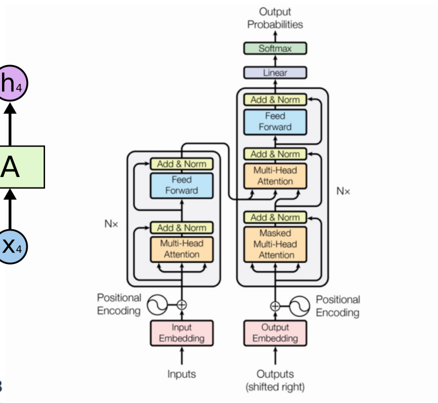
Output from previous step is fed as input into next

Generating Content

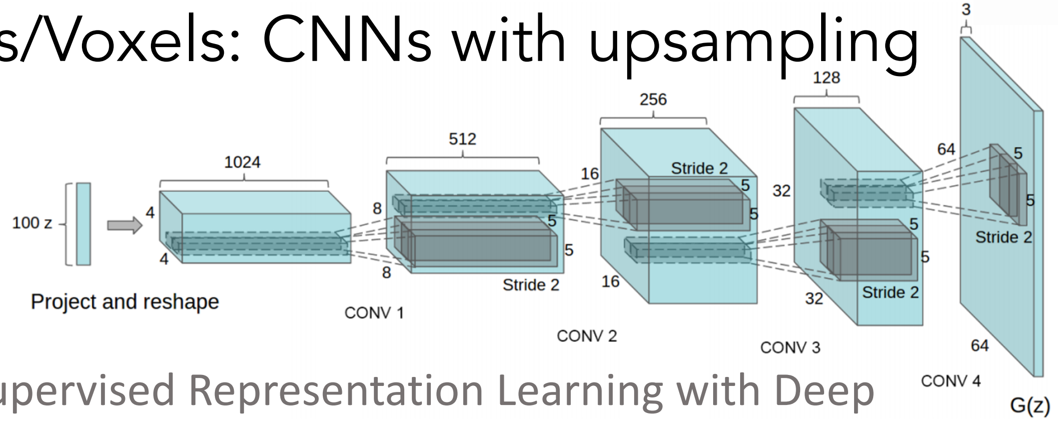
- Recall: retrieval as most basic form of generation

- Recall: can model as output as a sequence and generate autoregressively





- Decoders:
  - Language: RNNs/Transformers
  - Images/Voxels: CNNs with upsampling



"wrongly called deconvolutions"

Radford et al, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", ICLR 2016

Taxonomy of machine learning models

Models different probability distributions

Discriminative models:
Learn p(y|x) → Assign labels to data; Feature learning (with labels)

Generative Model:
Learn p(x) → Detect outliers; Feature learning (without labels); Sample to generate new data

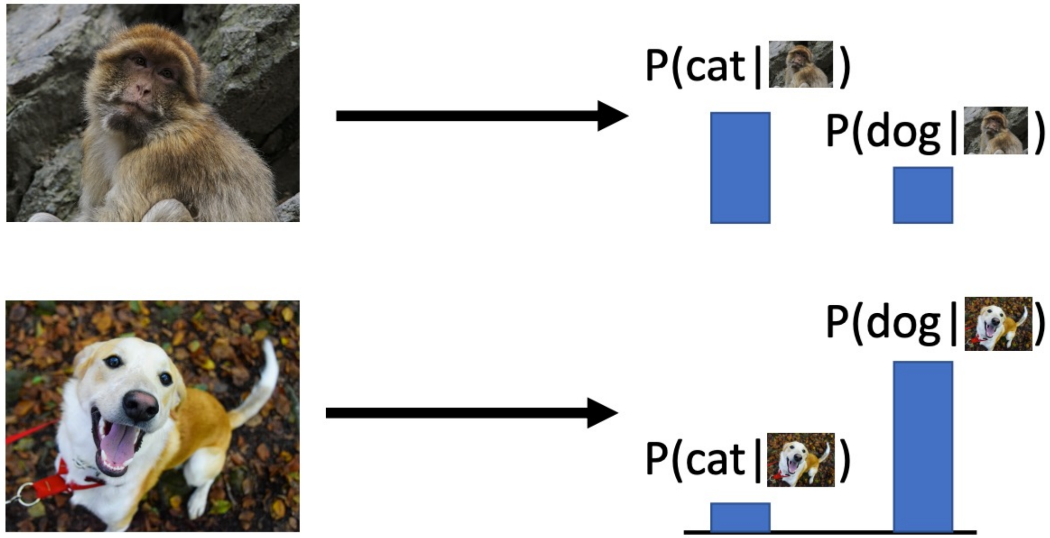
Conditional Generative Model:
Learn p(x|y) → Assign labels, while rejecting outliers!; Generate new data conditioned on input labels

Slide credit: Justin Johnson (https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/schedule.html, L19,20)

Taxonomy of machine learning models

Models different probability distributions

Discriminative models:
Learn p(y|x)

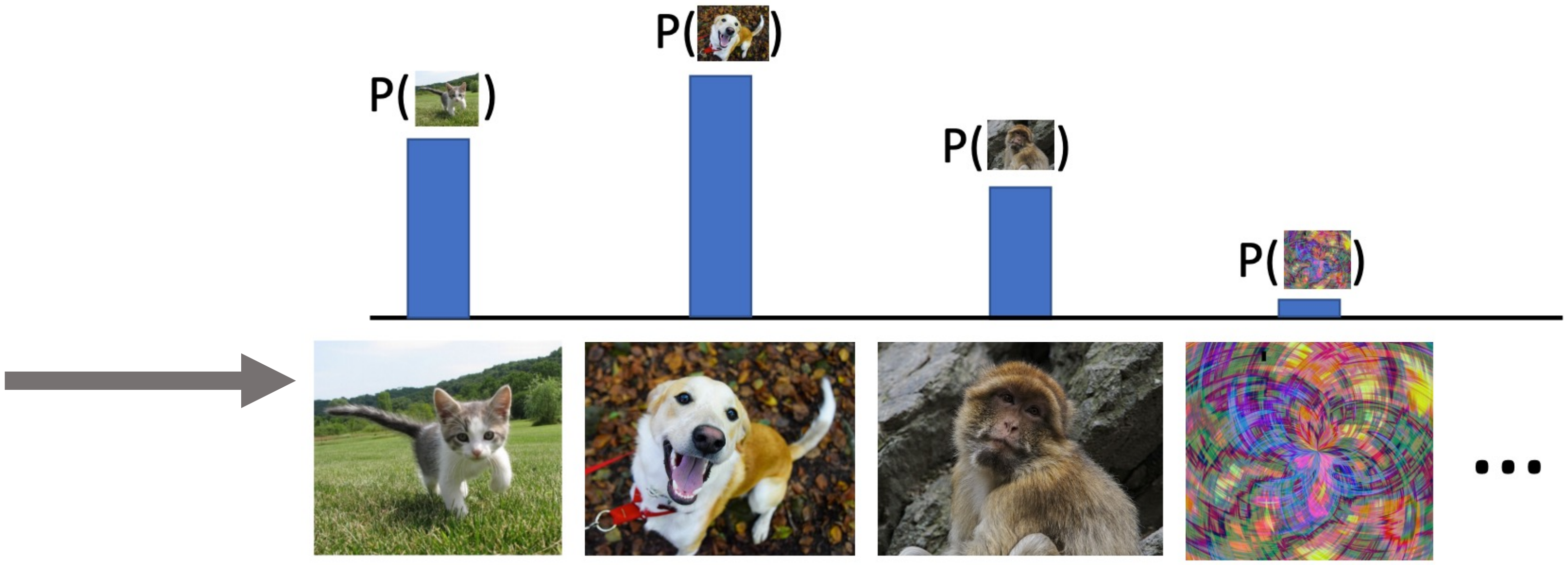


Discriminative model: No way for the model to handle unreasonable inputs; it must give label distributions for all images

Taxonomy of machine learning models

Models different probability distributions

Generative Model:
Learn p(x)



Generative model: All possible images compete with each other for probability mass

Model can "reject" unreasonable inputs by assigning them small values

Taxonomy of machine learning models

Models different probability distributions

Recall **Bayes' Rule:**

Discriminative Model

(Unconditional) Generative Model

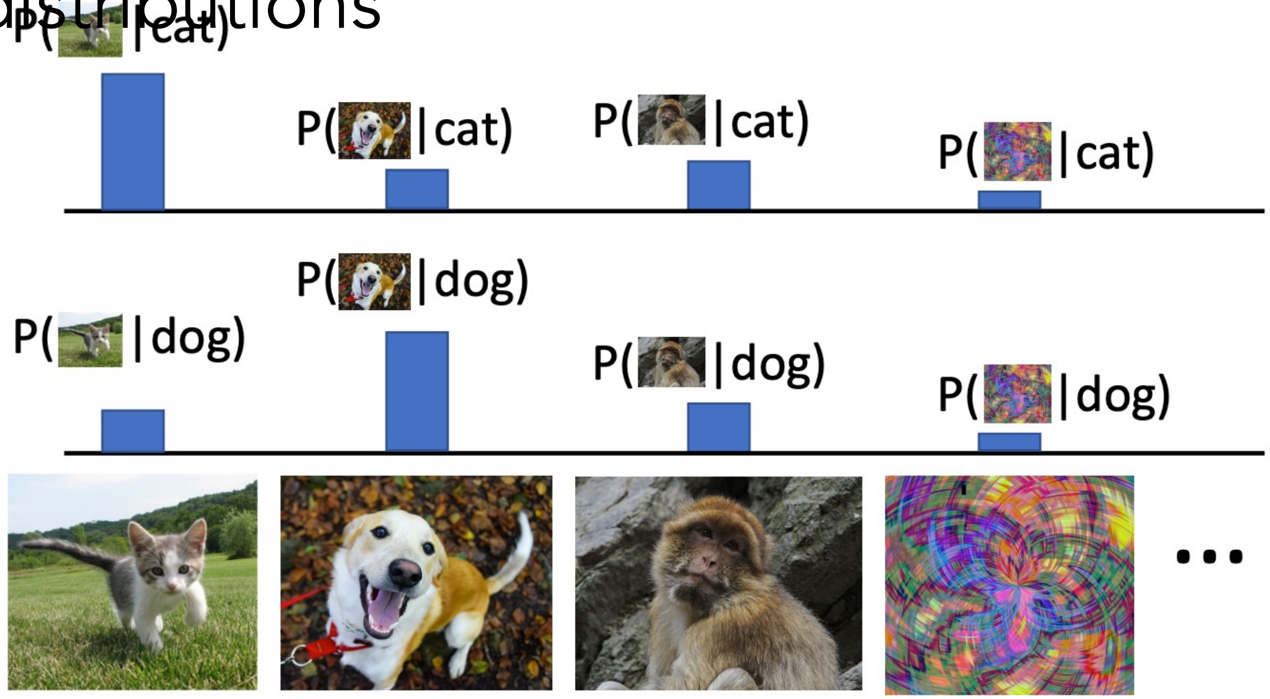
$$\boxed{P(x \mid y)} = \frac{\boxed{P(y \mid x)}}{\boxed{P(y)}}\boxed{P(x)}$$

Conditional Generative Model

Prior over labels

We can build a conditional generative model from other components!

Conditional Generative Model:
Learn p(xly)



Conditional Generative Model: Each possible label induces a competition among all images

Taxonomy of machine learning models

Models different probability distributions

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Taxonomy of generative models

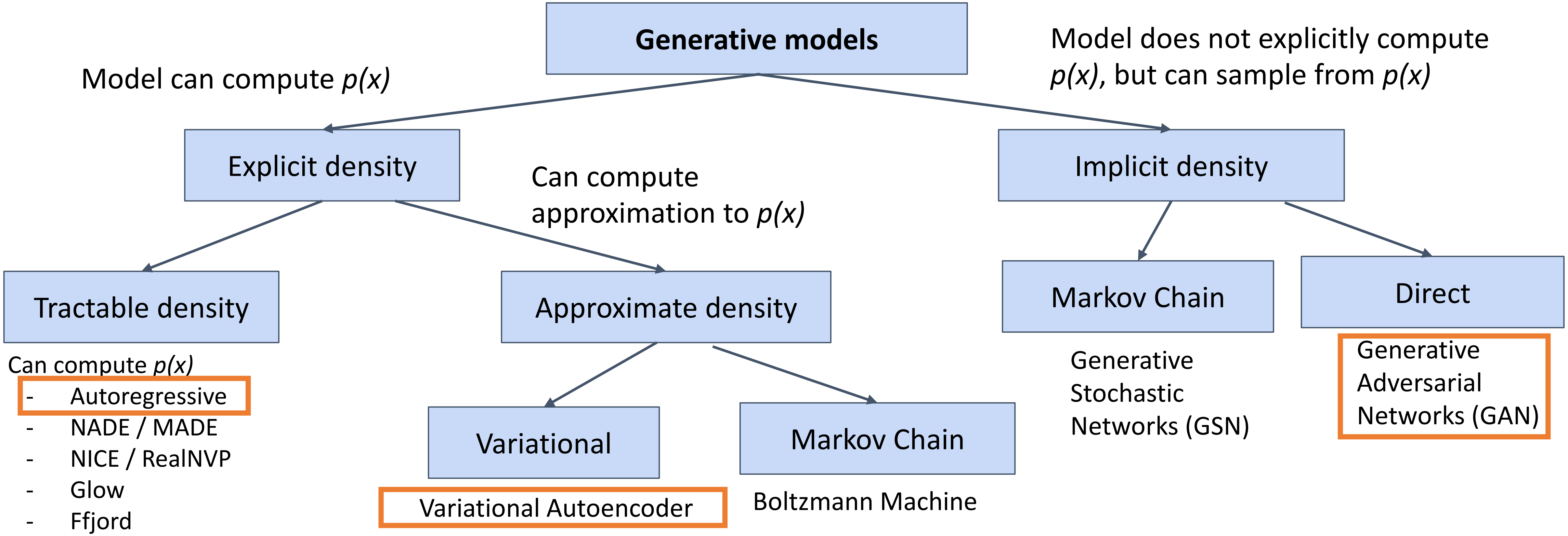


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Taxonomy of generative models

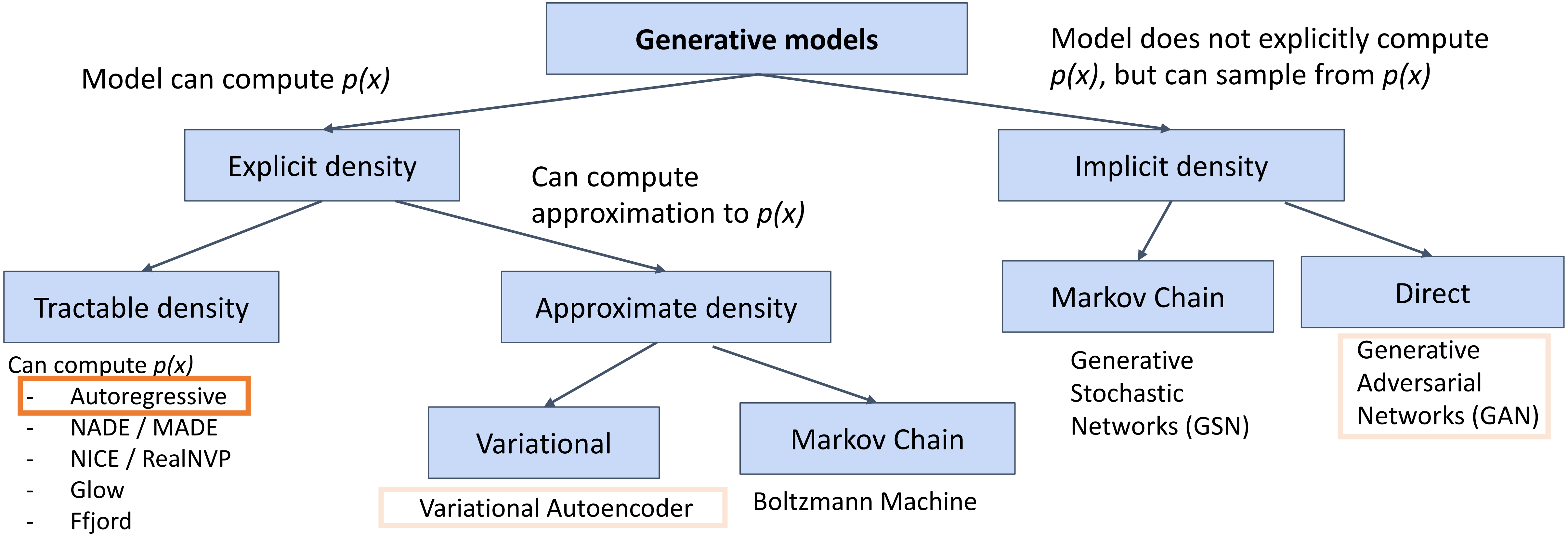


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Explicit Density Estimation

Goal: Write down an explicit function for $p(x) = f(x, W)$

Given dataset $x^{(1)}, x^{(2)}, \dots x^{(N)}$, train the model by solving:

$$W^* = \arg\max_{W} \prod_i p(x^{(i)})$$

Maximize probability of training data
(Maximum likelihood estimation)

$$= \arg\max_{W} \sum_i \log p(x^{(i)})$$

Log trick to exchange product for sum

$$= \arg\max_{W} \sum_i \log f(x^{(i)}, W)$$

This will be our loss function!
Train with gradient descent

Slide credit: Justin Johnson (https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/schedule.html, L19,20)

Explicit Density: Autoregressive models

Goal: Write down an explicit function for $p(x) = f(x, W)$

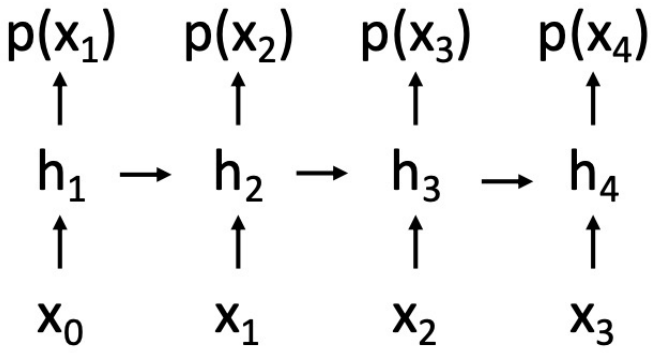
Assume x consists of multiple subparts:

$$x = (x_1, x_2, x_3, \ldots, x_T\ )$$

Break down probability using the chain rule:

$$\begin{aligned} p(x) &= p(x_1, x_2, x_3, \ldots, x_T\ ) \\ &= p(x_1)p(x_2 \mid x_1)p(x_3 \mid x_1, x_2) \ldots \\ &= \textstyle\prod_{t=1}^{T} p(x_t \mid x_1, \ldots, x_{t-1}) \end{aligned}$$

Probability of the next subpart given all the previous subparts



This is exactly what we had with the language modeling with RNNs and Transformers for captioning

Slide credit: Justin Johnson (https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/schedule.html, L19,20)

PixelRNN

Generate image pixels one at a time, starting at the upper left corner

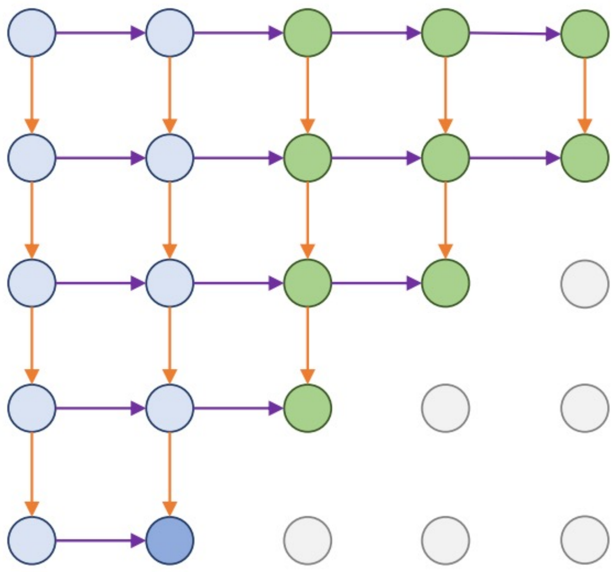
Compute a hidden state for each pixel that depends on hidden states and RGB values from the left and from above (LSTM recurrence)

$$h_{x,y} = f(h_{x-1,y}, h_{x,y-1}, W)$$

At each pixel, predict red, then blue, then green: softmax over [0, 1, …, 255]

Each pixel depends **implicity** on all pixels above and to the left:

Problem: Very slow during both training and testing; N x N image requires 2N-1 sequential steps



Van den Oord et al, "Pixel Recurrent Neural Networks", ICML 2016

Slide credit: Justin Johnson (https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/schedule.html, L19,20)

PixelCNN

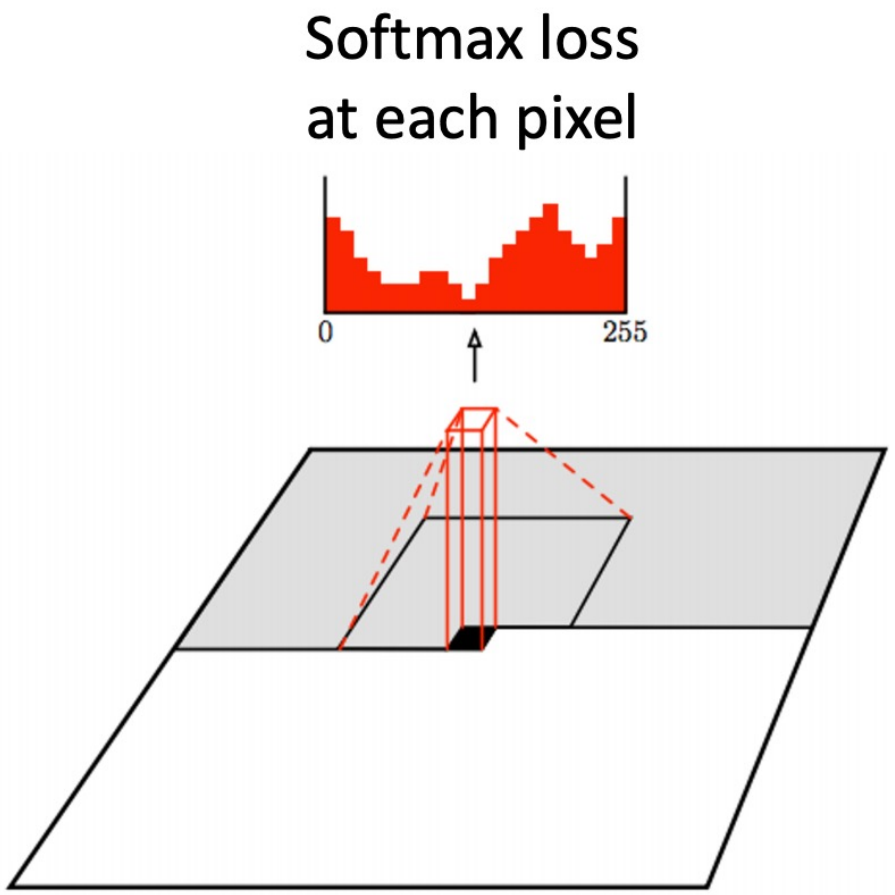
Still generate image pixels starting from corner

Dependency on previous pixels now modeled using a CNN over context region

Training: maximize likelihood of training images

Training is faster than PixelRNN (can parallelize convolutions since context region values known from training images)

Generation must still proceed sequentially => still slow



Van den Oord et al, “Conditional Image Generation with PixelCNN Decoders”, NeurIPS 2016

Slide credit: Justin Johnson (https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/schedule.html, L19,20)

Autoregressive models: PixelRNN and PixelCNN

Pros:

- Can explicitly compute likelihood p(x)
- Explicit likelihood of training data gives good evaluation metric
- Good samples

Con:

- Sequential generation => slow

Improving PixelCNN performance

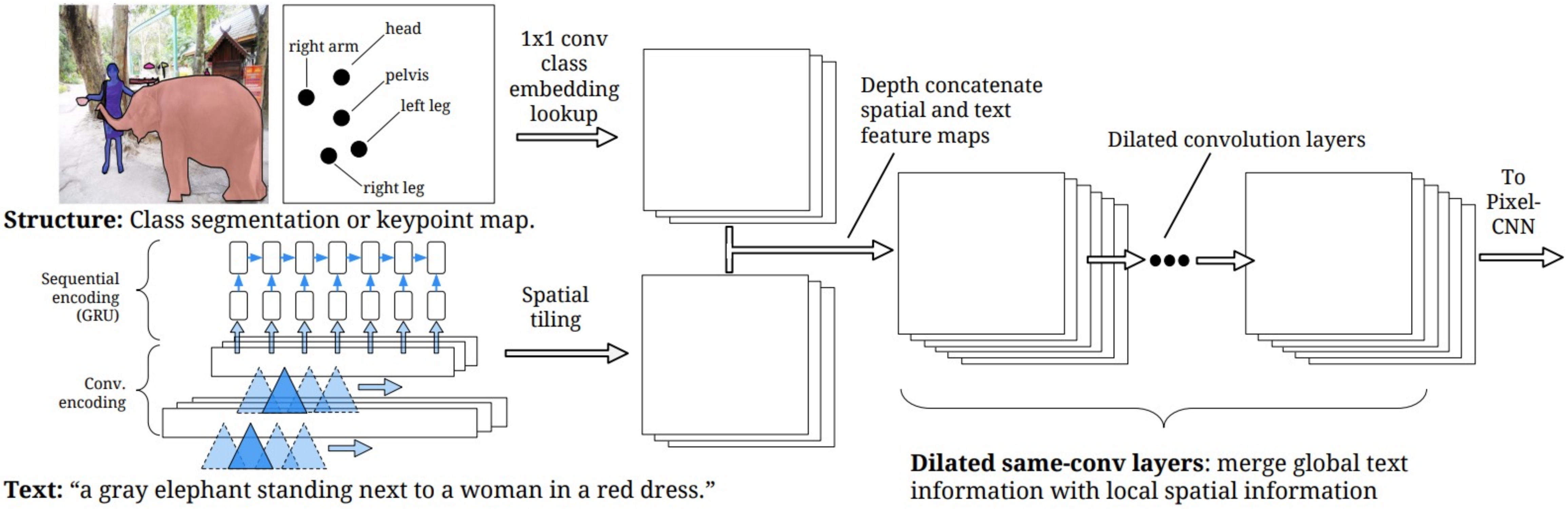
- Gated convolutional layers
- Short-cut connections
- Discretized logistic loss
- Multi-scale
- Training tricks
- Etc…

See

- Van der Oord et al. NIPS 2016
- Salimans et al. 2017 (PixelCNN++)

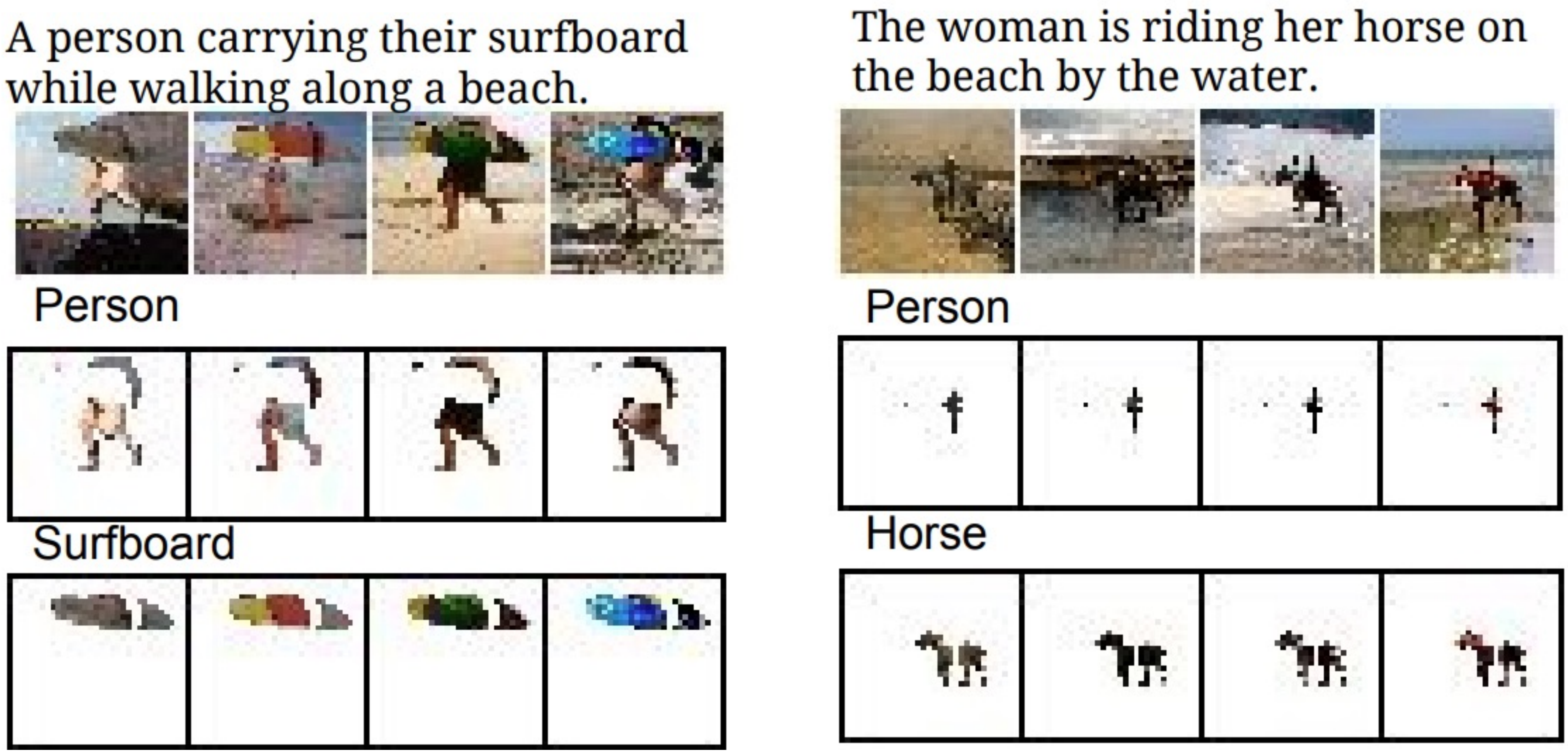
Slide credit: Justin Johnson (https://web.eecs.umich.edu/~justincj/teaching/eecs498/FA2020/schedule.html, L19,20)

Text-based image generation with PixelCNN



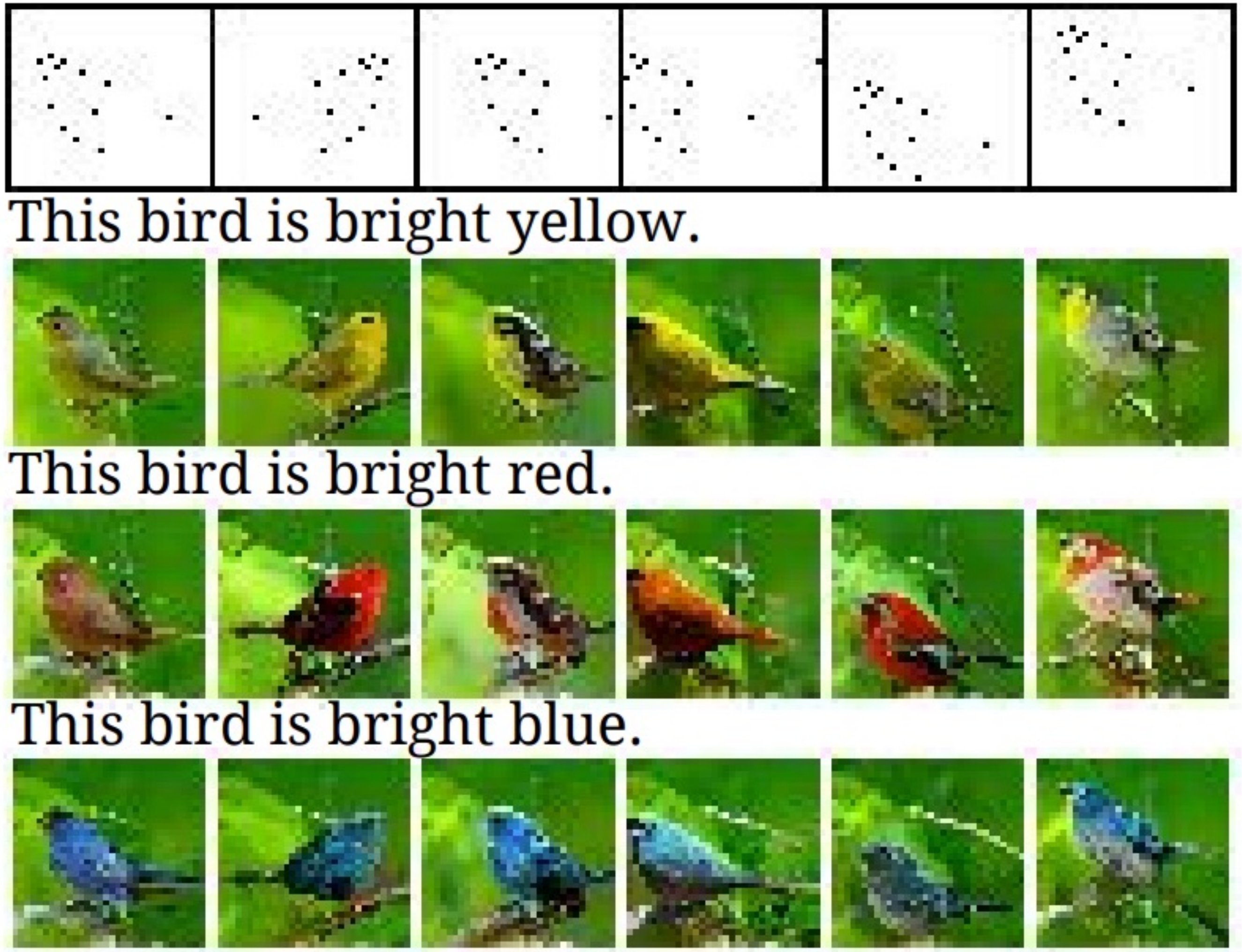
Text- and Structure-conditional PixelCNN, http://www.scottreed.info/files/txtstruct2pixel.pdf, Reed et al, 2016

Text + segmentations



Text- and Structure-conditional PixelCNN, http://www.scottreed.info/files/txtstruct2pixel.pdf, Reed et al, 2016

Text + keypoints



Text- and Structure-conditional PixelCNN, http://www.scottreed.info/files/txtstruct2pixel.pdf, Reed et al, 2016

Taxonomy of generative models

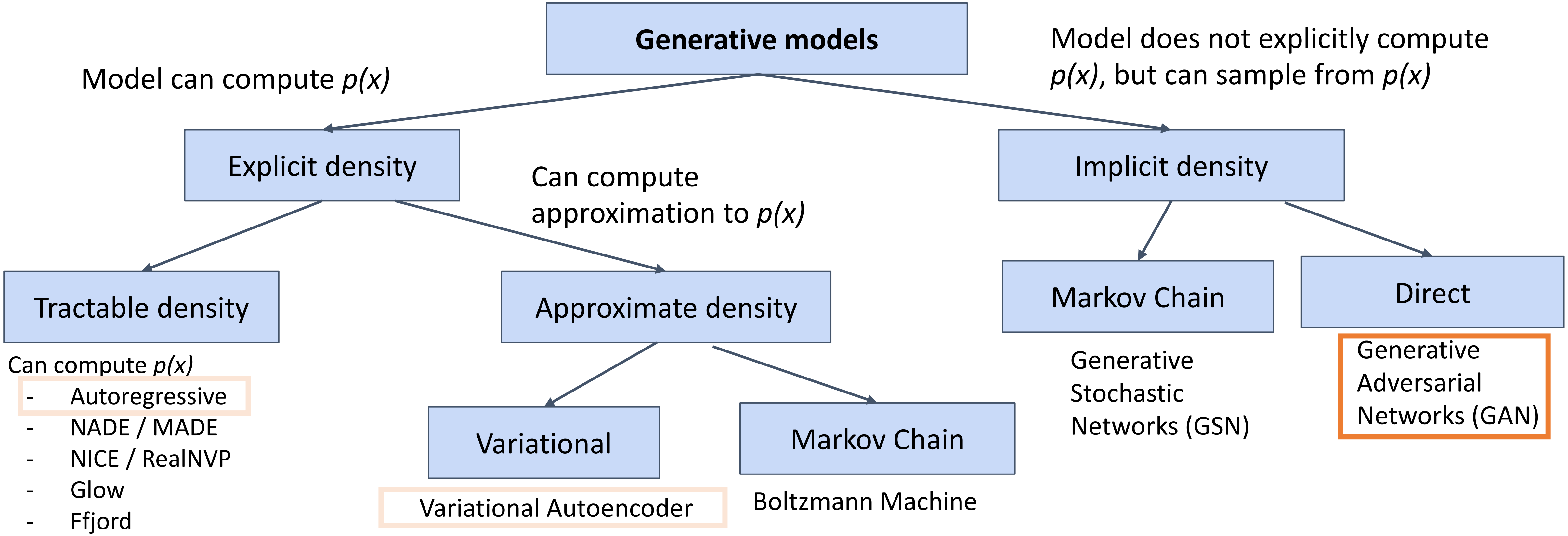
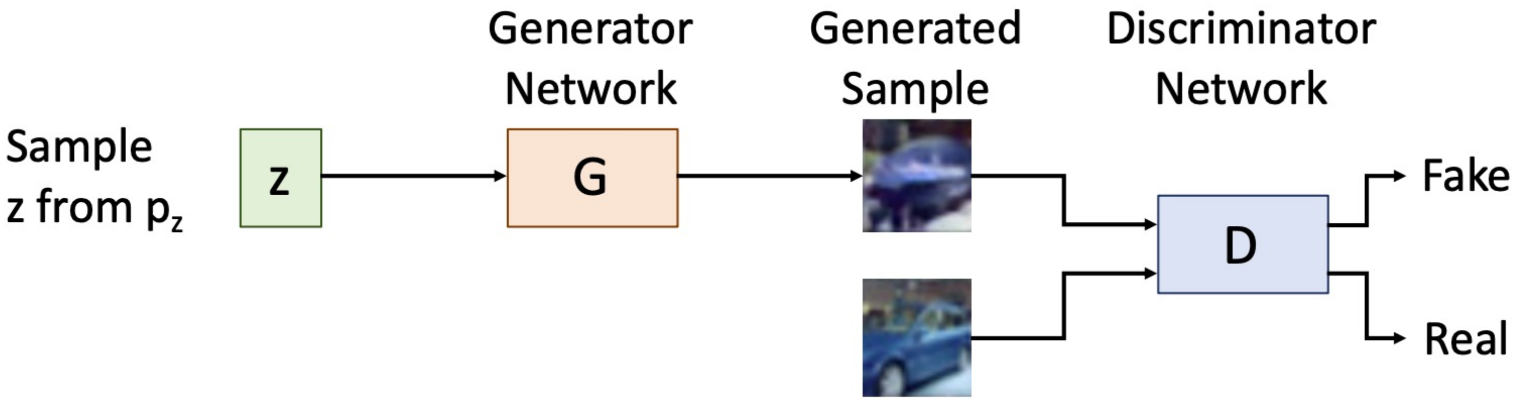


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Generative Adversarial Networks (GAN)

Jointly train generator G and discriminator D with a **minimax game**

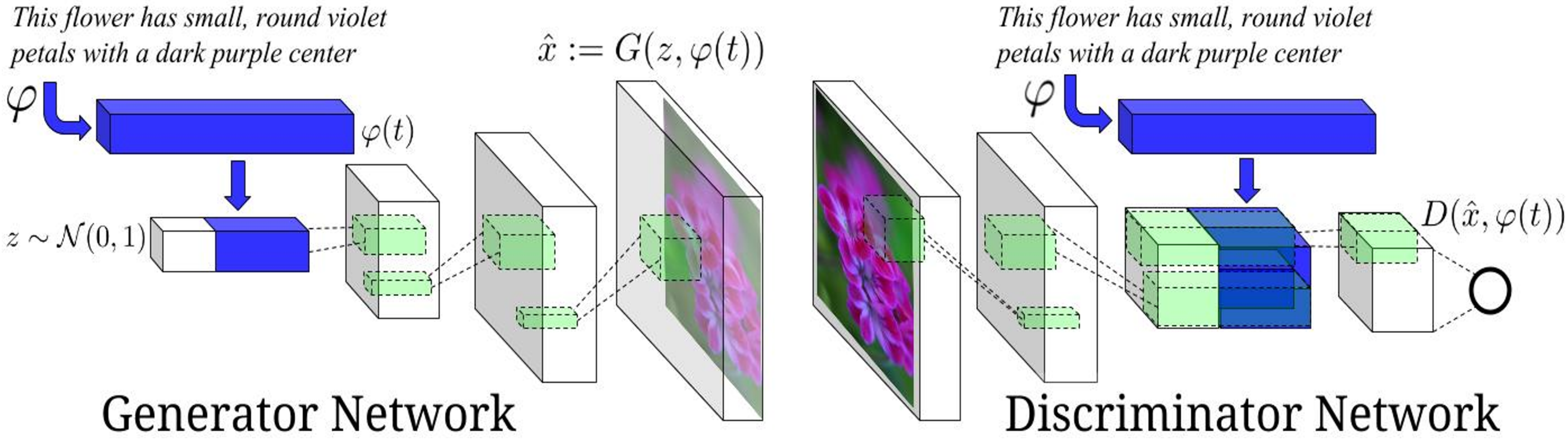
$$\min_{G}\max_{D}\left(\overbrace{E_{x\sim p_{data}}[\log D(x)]}^{\substack{\textbf{Discriminator wants}\\ \textbf{D(x) = 1 for real data}}} + E_{z\sim p(z)}\left[\overbrace{\underbrace{\log\left(1-D(G(z))\right)}_{\substack{\textbf{Generator wants}\\ \textbf{D(x) = 1 for fake data}}}}^{\substack{\textbf{Discriminator wants}\\ \textbf{D(x) = 0 for fake data}}}\right]\right)$$



Goodfellow et al, “Generative Adversarial Nets”, NeurIPS 2014

Text to image with GANs

- Generator and Discriminator are alternately trained



Generative Adversarial Text to Image Synthesis, https://arxiv.org/pdf/1605.05396v2.pdf, Reed et al, ICML 2016

Text to image with GANs

- Image encoder (CNN ϕ) and text encoder (char-CNN-RNN φ) are pre-trained to produce a joint embedding where the embedded representations can be used to predict the class label of the image

$$\frac{1}{N}\sum_{n=1}^{N}\Delta(y_n, f_v(v_n)) + \Delta(y_n, f_t(t_n))$$

$$f_v(v) = \arg\max_{y\in\mathcal{Y}} \mathbb{E}_{t\sim\mathcal{T}(y)}[\phi(v)^T\varphi(t))]$$

$$f_t(t) = \arg\max_{y\in\mathcal{Y}} \mathbb{E}_{v\sim\mathcal{V}(y)}[\phi(v)^T\varphi(t))]$$

Generative Adversarial Text to Image Synthesis, https://arxiv.org/pdf/1605.05396v2.pdf, Reed et al, ICML 2016

Datasets

- CUB-200 (Birds)
  - 11,788 images of birds from 200 categories
- Oxford-102 (Flowers)
  - 8,189 images of flowers from 102 categories
- MSCOCO
  - 330K images
- 5 captions per image

Caltech-UCSD-Birds (CUB) 200

an all black bird with a distinct thick, rounded bill.

this small bird has a yellow breast, brown crown, and black superciliary

this flower is white and pink in color, with petals that have veins.

bright droopy yellow petals with burgundy streaks, and a yellow stigma.

The man at bat readies to swing at the pitch while the umpire looks on.

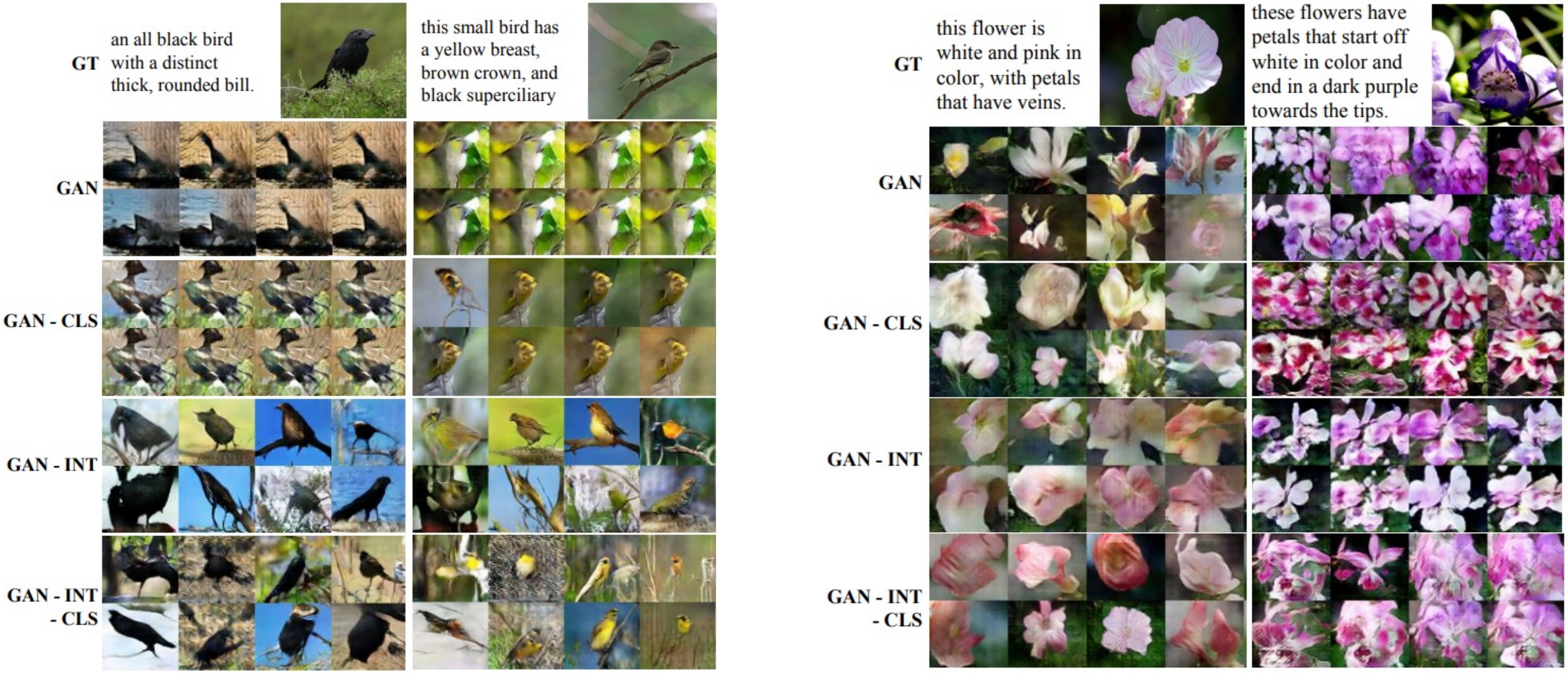
Bunk bed with a narrow shelf sitting underneath it.

Text to image with GANS: Results

- CLS: Add discriminator to distinguish if (image,text) match or not

  (real image, right text), (real image, wrong text), (fake image, right text)

- INT: Add interpolated text embeddings (fake additional text embeddings)



Generative Adversarial Text to Image Synthesis, https://arxiv.org/pdf/1605.05396v2.pdf, Reed et al, ICML 2016

Text to image with GANS: Results

Very low res!
64 x 64

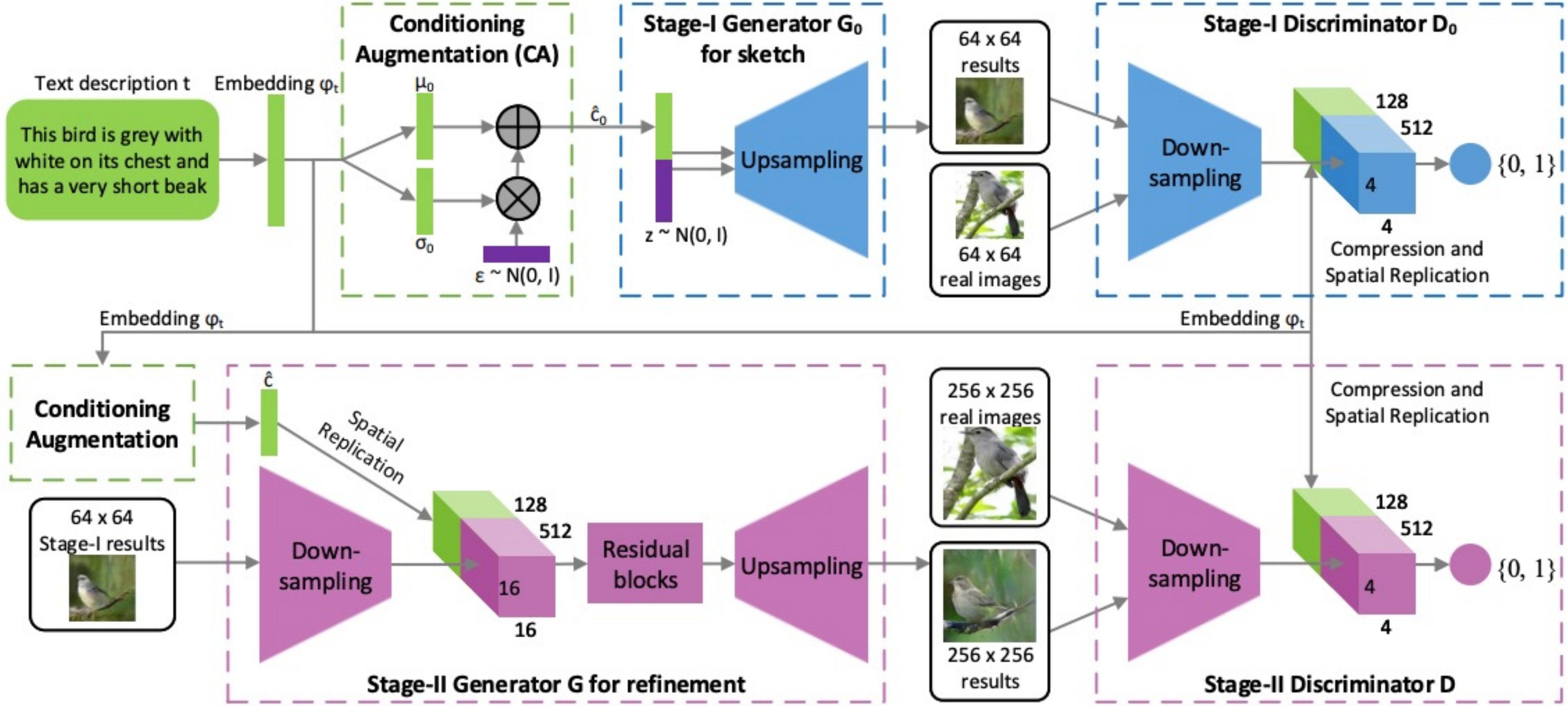
Follow up work:
128 x 128

Still low res!

Generative Adversarial Text to Image Synthesis, https://arxiv.org/pdf/1605.05396v2.pdf, Reed et al, ICML 2016

StackGAN

Generate low resolution, and then pass through another GAN for improved resolution



StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
https://arxiv.org/pdf/1612.03242.pdf, Zhang et al, ICCV 2017

StackGAN: Results

StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
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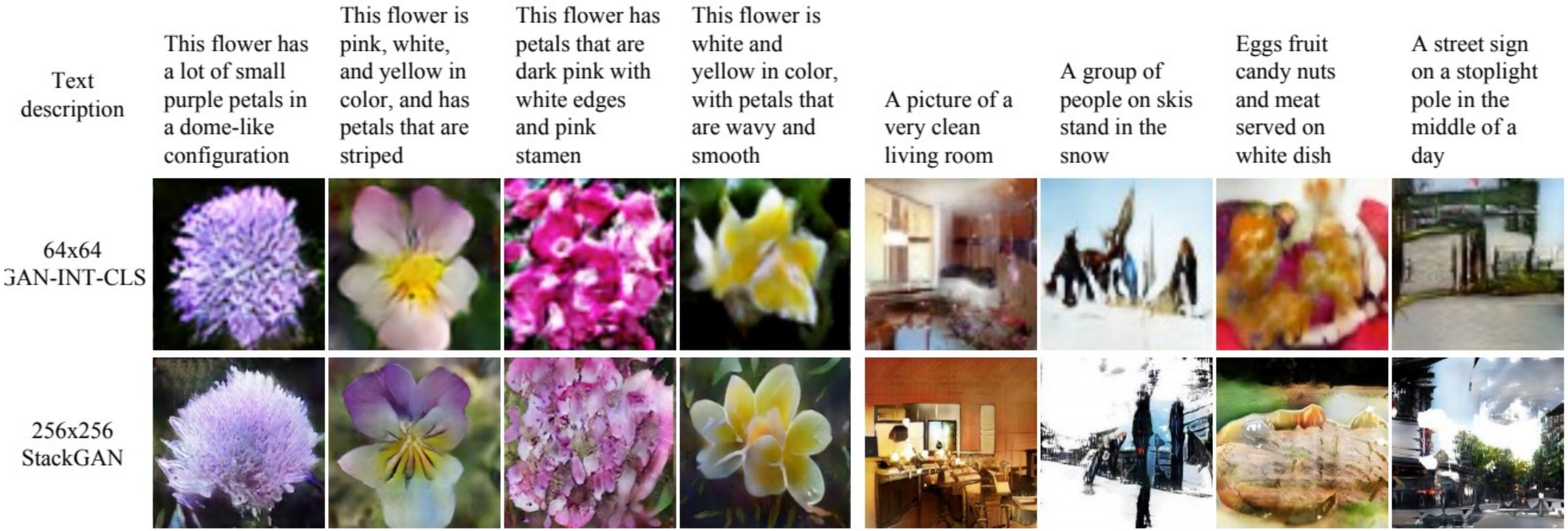
StackGAN: Results



StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
https://arxiv.org/pdf/1612.03242.pdf, Zhang et al, ICCV 2017

StackGAN: Evaluation

- Inception Score: $I = \exp(\mathbb{E}_{\boldsymbol{x}} D_{KL}(p(y|\boldsymbol{x}) \,||\, p(y)))$
    - Use inception model to predict class y
    - Want good models to generate diverse but meaningful images
    - Large distance between marginal prior (of labels) and conditional prior
- Human rank images generated by models

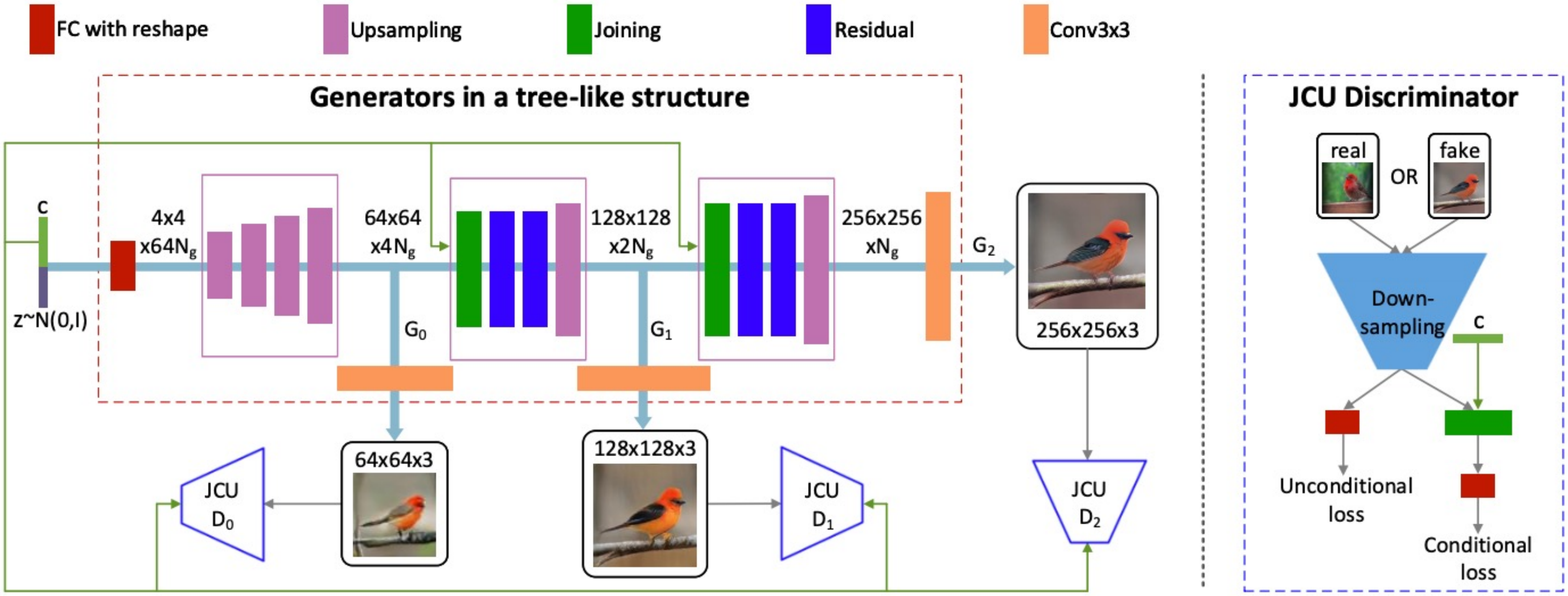
Metric	Dataset	GAN-INT-CLS	GAWWN	Our StackGAN
Inception score	CUB	$2.88 \pm .04$	$3.62 \pm .07$	$\mathbf{3.70 \pm .04}$
	Oxford	$2.66 \pm .03$	/	$\mathbf{3.20 \pm .01}$
	COCO	$7.88 \pm .07$	/	$\mathbf{8.45 \pm .03}$
Human rank	CUB	$2.81 \pm .03$	$1.99 \pm .04$	$\mathbf{1.37 \pm .02}$
	Oxford	$1.87 \pm .03$	/	$\mathbf{1.13 \pm .03}$
	COCO	$1.89 \pm .04$	/	$\mathbf{1.11 \pm .03}$

StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks
https://arxiv.org/pdf/1612.03242.pdf, Zhang et al, ICCV 2017

StackGAN++

Generalization of StackGAN (Multiscale)

Joint Discriminator
- if image is real/fake (unconditional loss)
- if text+image match (conditional loss)



Color constancy regularization

StackGAN++: Realistic Image Synthesis with Stacked Generative Adversarial Networks
https://arxiv.org/pdf/1710.10916.pdf, Zhang et al, TPAMI 2018

StackGAN++

- Generalization of StackGAN (arbitrary number of Generators/Discriminators)
- Color constancy regularization
- Joint Discriminator (similar to +CLS from Reed et al)
  - if image is real/fake (unconditional loss)
  - if text+image match (conditional loss)
- Alternately train generator and discriminator

$$\mathcal{L}_{G_i} = \underbrace{-\frac{1}{2}\mathbb{E}_{\hat{x}_i \sim p_{G_i}}[\log(D_i(\hat{x}_i)]}_{\text{unconditional loss}} \underbrace{-\frac{1}{2}\mathbb{E}_{\hat{x}_i \sim p_{G_i}}[\log(D_i(\hat{x}_i, \overline{e})]}_{\text{conditional loss}},$$

$$\mathcal{L}_{D_i} = \underbrace{-\frac{1}{2}\mathbb{E}_{x_i \sim p_{data_i}}[\log D_i(x_i)] - \frac{1}{2}\mathbb{E}_{\hat{x}_i \sim p_{G_i}}[\log(1 - D_i(\hat{x}_i)]}_{\text{unconditional loss}} + \underbrace{-\frac{1}{2}\mathbb{E}_{x_i \sim p_{data_i}}[\log D_i(x_i, \overline{e})] - \frac{1}{2}\mathbb{E}_{\hat{x}_i \sim p_{G_i}}[\log(1 - D_i(\hat{x}_i, \overline{e})]}_{\text{conditional loss}},$$

StackGAN++: Realistic Image Synthesis with Stacked Generative Adversarial Networks
https://arxiv.org/pdf/1710.10916.pdf, Zhang et al, TPAMI 2018

StackGAN++: Results

- FID (Frechet Inception distance): measures distance between generated and real distribution

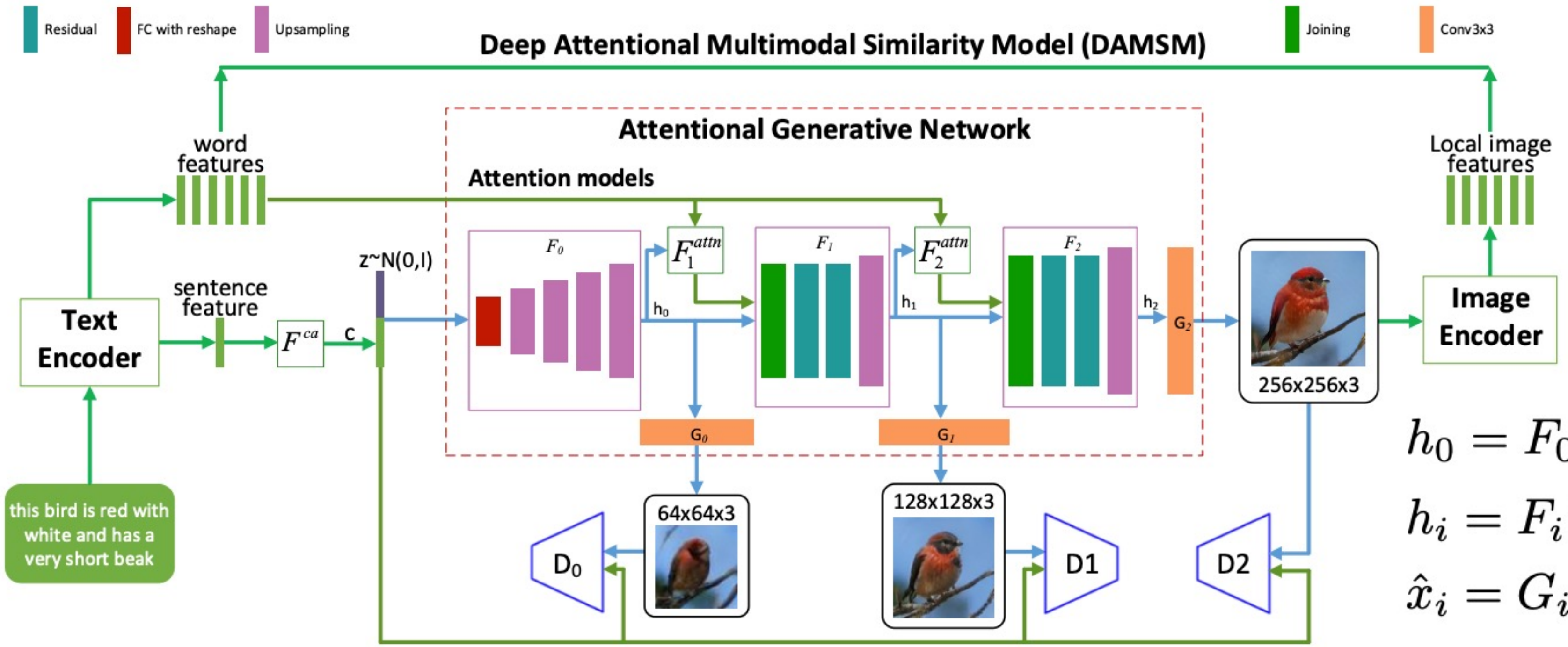
Metric	CUB			Oxford		COCO	
	GAN-INT-CLS	GAWWN	Our StackGAN-v1	GAN-INT-CLS	Our StackGAN-v1	GAN-INT-CLS	Our StackGAN-v1
FID ↓	68.79	67.22	**51.89**	79.55	**55.28**	**60.62**	74.05
FID* ↓	68.79	53.51	**35.11**	79.55	**43.02**	60.62	**33.88**
IS ↑	2.88 ± .04	3.62 ± .07	**3.70 ± .04**	2.66 ± .03	**3.20 ± .01**	7.88 ± .07	**8.45 ± .03**
IS* ↑	2.88 ± .04	**3.10 ± .03**	3.02 ± .03	2.66 ± .03	**2.73 ± .03**	7.88 ± .07	**8.35 ± .11**
HR ↓	2.76 ± .01	1.95 ± .02	**1.29 ± .02**	1.84 ± .02	**1.16 ± .02**	1.82 ± .03	**1.18 ± .03**

Dataset		CUB	Oxford-102	COCO	LSUN-bedroom	LSUN-church	ImageNet-dog	ImageNet-cat
FID ↓	StackGAN-v1	51.89	55.28	**74.05**	91.94	57.20	89.21	58.73
	StackGAN-v2	**15.30**	**48.68**	81.59	**35.61**	**25.36**	**44.54**	**28.59**
IS ↑	StackGAN-v1	3.70 ± .04	3.20 ± .01	**8.45 ± .03**	**3.59 ± .05**	**2.87 ± .05**	8.84 ± .08	**4.77 ± .06**
	StackGAN-v2	**4.04 ± .05**	**3.26 ± .01**	8.30 ± .10	3.02 ± .04	2.38 ± .03	**9.55 ± .11**	4.23 ± .05
HR ↓	StackGAN-v1	1.81 ± .02	1.70 ± .03	**1.45 ± .04**	1.95 ± .01	1.86 ± .02	1.90 ± .01	1.88 ± .02
	StackGAN-v2	**1.19 ± .02**	**1.30 ± .03**	1.55 ± .05	**1.05 ± .01**	**1.14 ± .02**	**1.10 ± .01**	**1.12 ± .02**

StackGAN++: Realistic Image Synthesis with Stacked Generative Adversarial Networks
https://arxiv.org/pdf/1710.10916.pdf, Zhang et al, TPAMI 2018

AttnGAN

- Attention based similarity matching of image and text that tries to align regions of the image to words in the text
- m generators (G_i), each taking hidden state h_i to produce image $\hat{x}_i$



$$h_0 = F_0(z, F^{ca}(\overline{e}));$$
$$h_i = F_i(h_{i-1}, F_i^{attn}(e, h_{i-1}))$$
$$\hat{x}_i = G_i(h_i).$$

AttnGAN: Fine-Grained Text to Image Generation with Attentional Generative Adversarial Networks
https://arxiv.org/pdf/1711.10485.pdf, Xu et al, CVPR 2018

AttnGAN:

- Attention based similarity matching of image and text that tries to align regions of the image to words in the text
- m generators (G_i), each taking hidden state h_i to produce image $\hat{x}_i$
- Total Loss:

$$\mathcal{L} = \mathcal{L}_G + \lambda \mathcal{L}_{DAMSM}, \quad \text{where } \mathcal{L}_G = \sum_{i=0}^{m-1} \mathcal{L}_{G_i}$$

- Main contribution:
  - Semi-supervised training to match image regions to text
  - Attention-based match score $R(Q, D)$of image (Q) to text (D) based on attention-based match of words to regions in the image
  - Train to optimize match based on words (w) and sentences (s)
  - Estimate probability of text given image and vice versa

$$\mathcal{L}_{DAMSM} = \mathcal{L}_1^w + \mathcal{L}_2^w + \mathcal{L}_1^s + \mathcal{L}_2^s.$$

$$P(D_i|Q_i) = \frac{\exp(\gamma_3 R(Q_i, D_i))}{\sum_{j=1}^{M} \exp(\gamma_3 R(Q_i, D_j))}$$

$$\mathcal{L}_1^w = -\sum_{i=1}^{M} \log P(D_i|Q_i), \quad \mathcal{L}_2^w = -\sum_{i=1}^{M} \log P(Q_i|D_i),$$

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AttnGAN: Results

Inception Scores

Dataset	GAN-INT-CLS [20]	GAWWN [18]	StackGAN [31]	StackGAN-v2 [32]	PPGN [16]	Our AttnGAN
CUB	$2.88 \pm .04$	$3.62 \pm .07$	$3.70 \pm .04$	$3.82 \pm .06$	/	$\mathbf{4.36 \pm .03}$
COCO	$7.88 \pm .07$	/	$8.45 \pm .03$	/	$9.58 \pm .21$	$\mathbf{25.89 \pm .47}$

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Next time

- Monday (4/12): More on content generation from language
- Thursday (4/15): Last day – project discussion and conclusion
  - Watch other group's project video before class
  - Project video due by 11:59pm 4/14
  - Project report due by 11:59pm 4/15