Microsoft

Attention GAN for Fine-Grained Language-to-Image Generation

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MSR AI

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Joint work with Tao Xu, Qiuyuan Huang, Han Zhang, Zhe Gan, Xiaolei Huang, Xiaodong He

Language to Image Generation

"Generate a bird with **wings that are blue** and a **red belly**"

"Generate a bird with **wings that are black** and a **white belly**"

"Generate a bird with **wings that are red** and a **yellow belly**"

ARTIFICIAL IMAGINATION

Language-to-Image generation with GANs

this small bird has a pink breast and crown, and black primaries and secondaries.

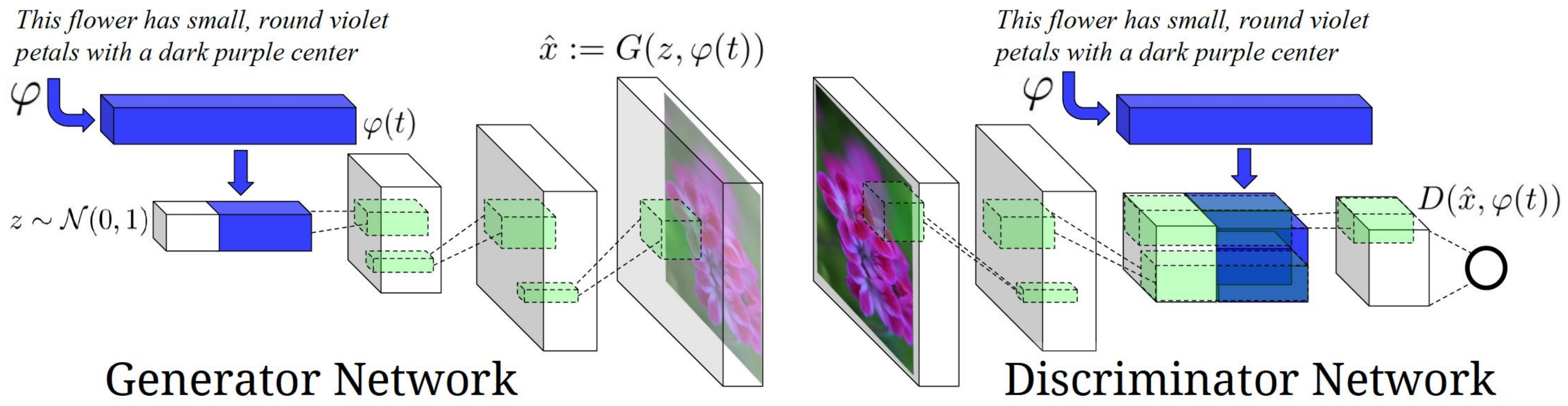


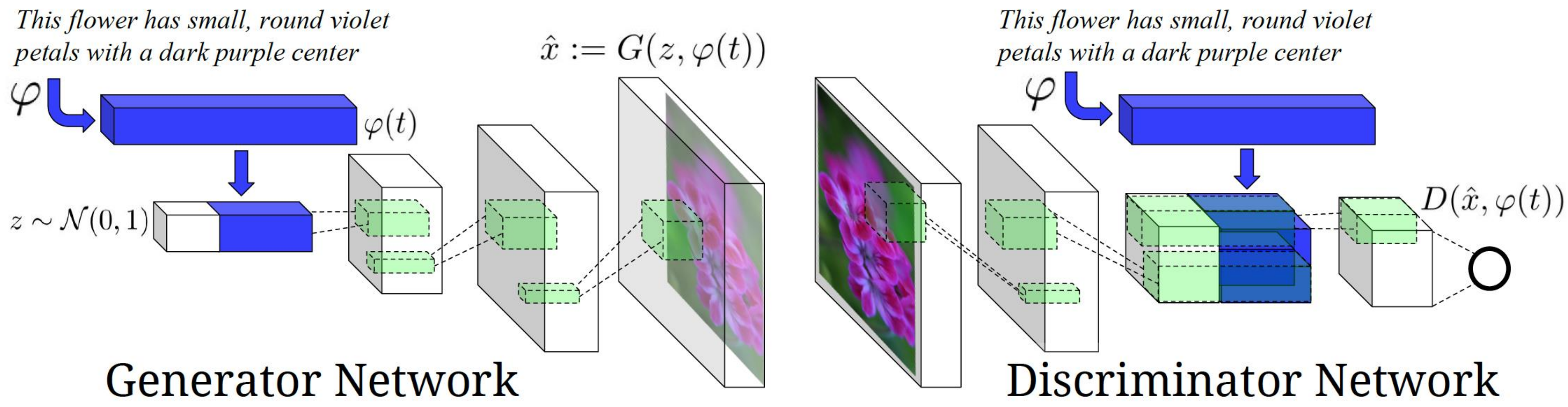
Figure 2. Our text-conditional convolutional GAN architecture. Text encoding $\varphi(t)$ is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

Objective function:

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

[Reed et al., Generative adversarial text-to-image synthesis, ICML, 2016]

Language-to-Image generation with GANs



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[Xu et al., 'AttnGAN: Fine-grained text to image generation with Attentional GANs, CVPR 2018]

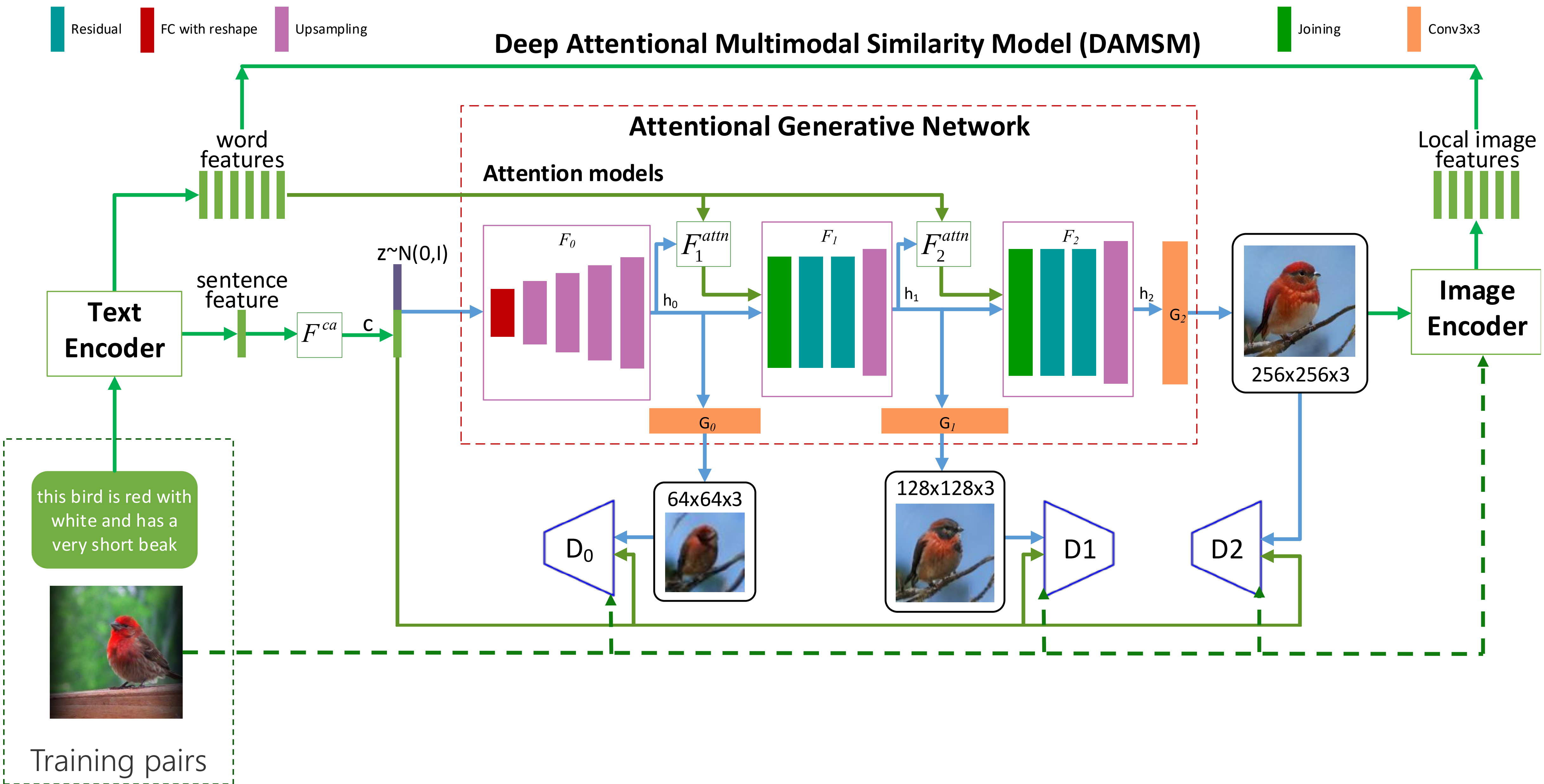
Attention Generative Adversarial Networks (AttnGANs)

Propose AttnGANs to improve image generation

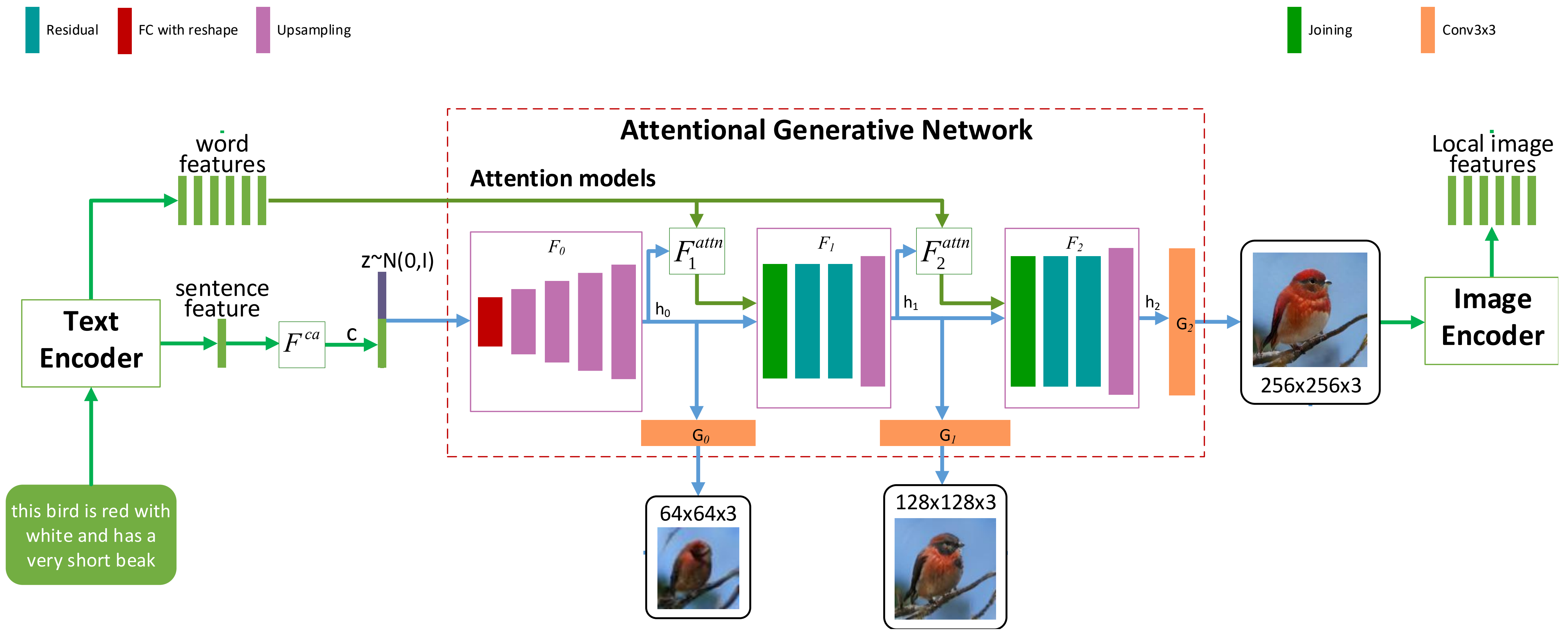
- Goals
  - Improve the quality of generated images
  - Improve the interpretability of GANs
  - Stabilize the training of GANs
- Two main contributions
  - Propose the generative networks with stacked attention to generate images from low-to-high resolutions at multiple stages.
  - Propose a deep attention multimodal similarity model to learn visually-discriminative word features in an semi-supervised manner.

[Xu, Zhang, Huang, Zhang, Gan, Huang, He, "AttnGAN: Fine-grained text to image generation with Attentional GANs", CVPR, 2018]

AttnGAN: Overview



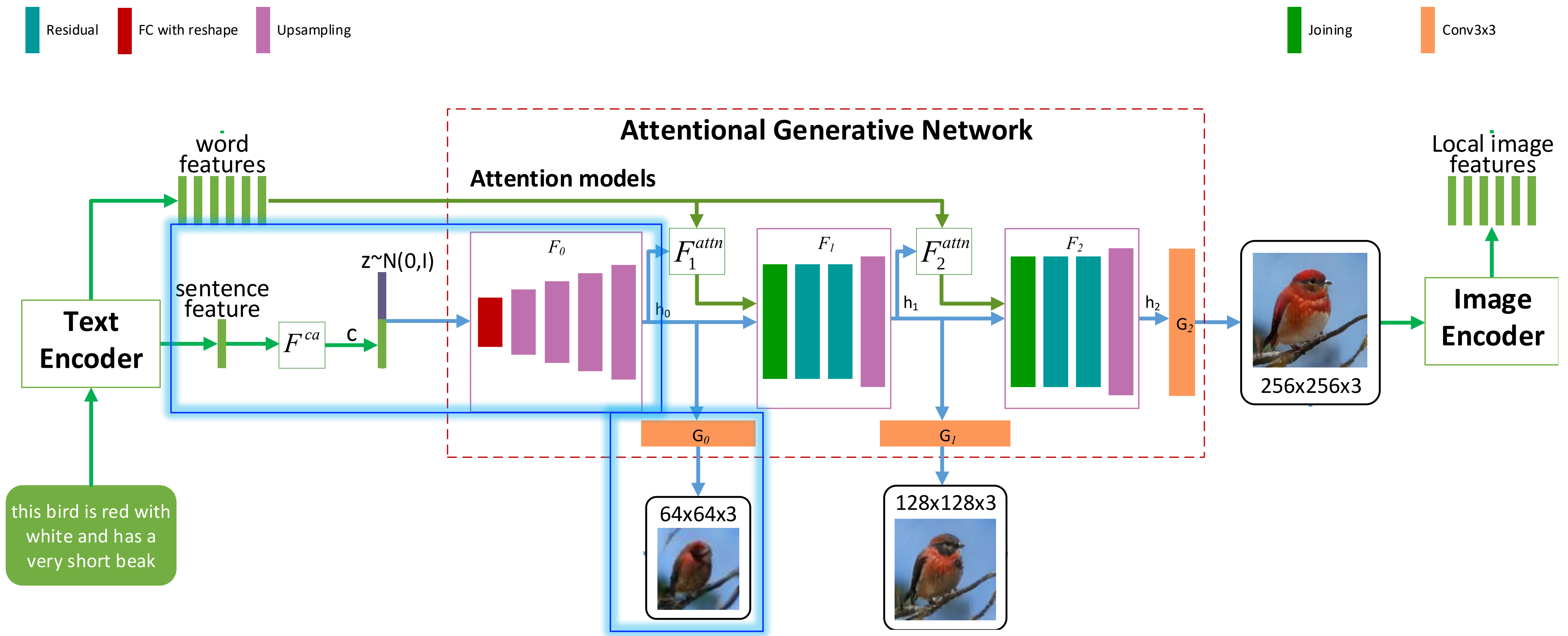
AttnGAN: Attentional Generative Network



Attentional Generative Network:

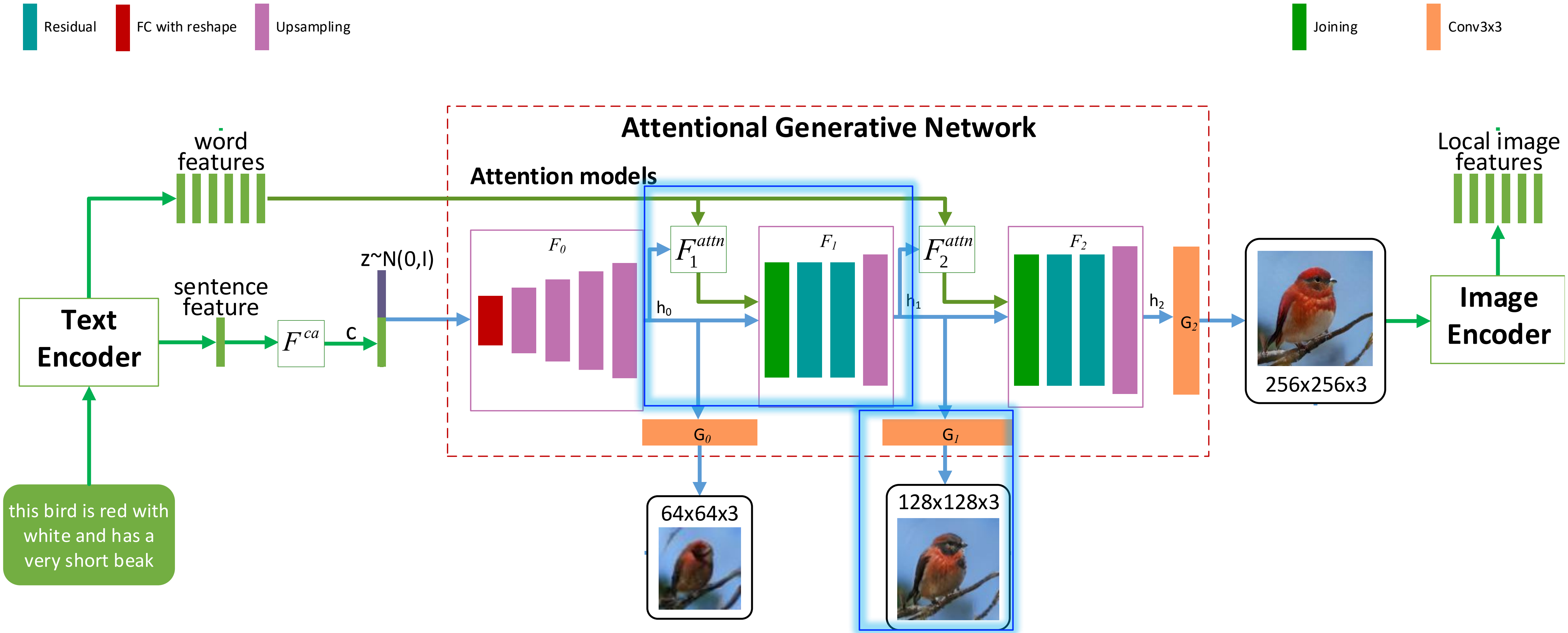
- Takes multi-level conditions (global-level sentence feature and fine-grained word features) as input.
- Generates images from low-to-high resolutions at multiple stages.

AttnGAN: Attentional Generative network



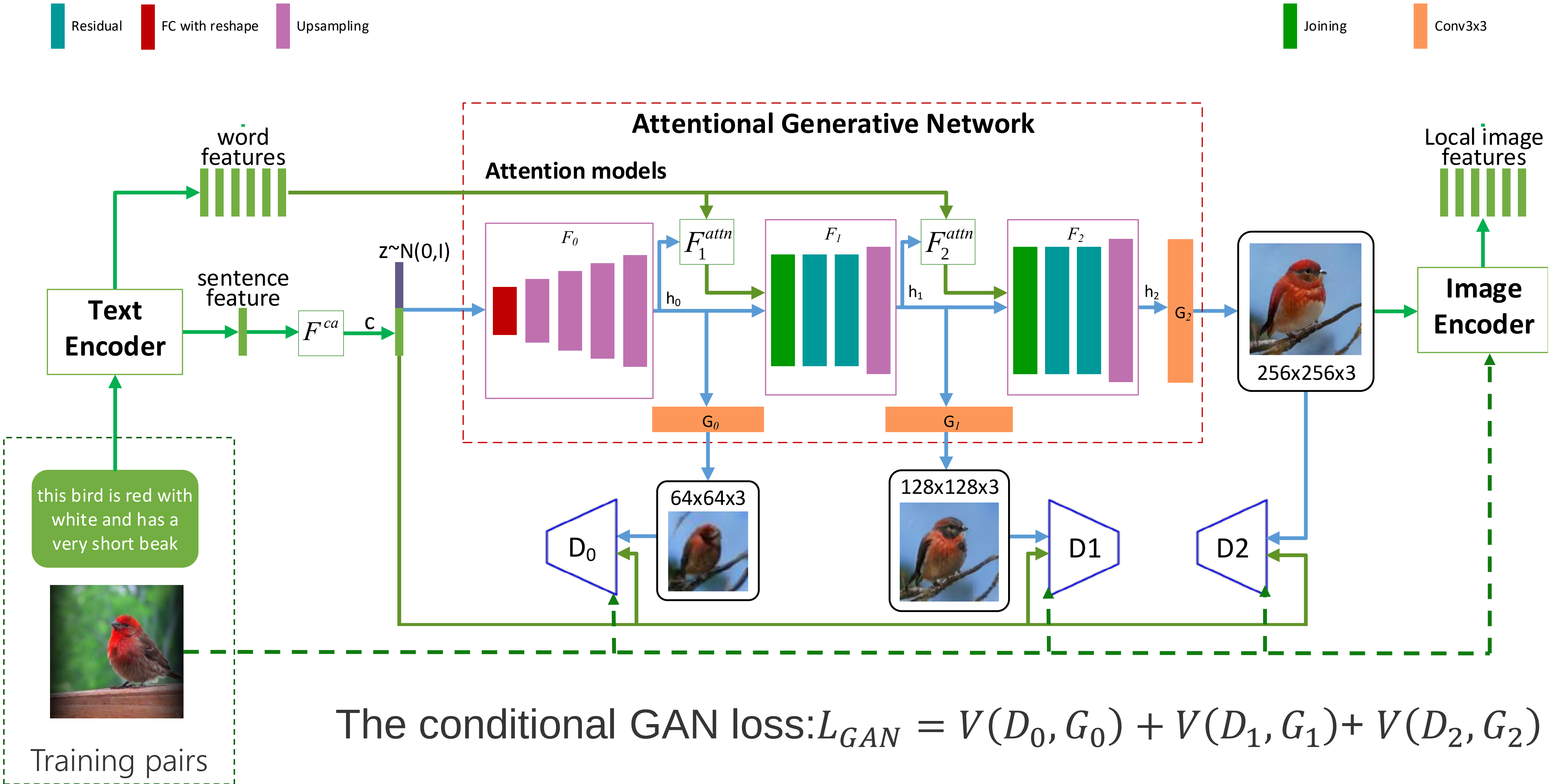
- In the first stage:
  - based on the sentence feature, the image with basic color and shape is generated by generator G_0;
  - hidden features h_0 are decoded from the sentence feature.

AttnGAN: Attentional Generative network



- In following stages, attention models are built.
  - For each region feature of previous generated image, compute its word-context vector.
  - Concatenate previous image region features (e.g., h_0) and word-context vectors to generate image with higher resolution.

AttnGAN: the conditional GAN loss



The conditional GAN loss: $L_{GAN} = V(D_0, G_0) + V(D_1, G_1) + V(D_2, G_2)$

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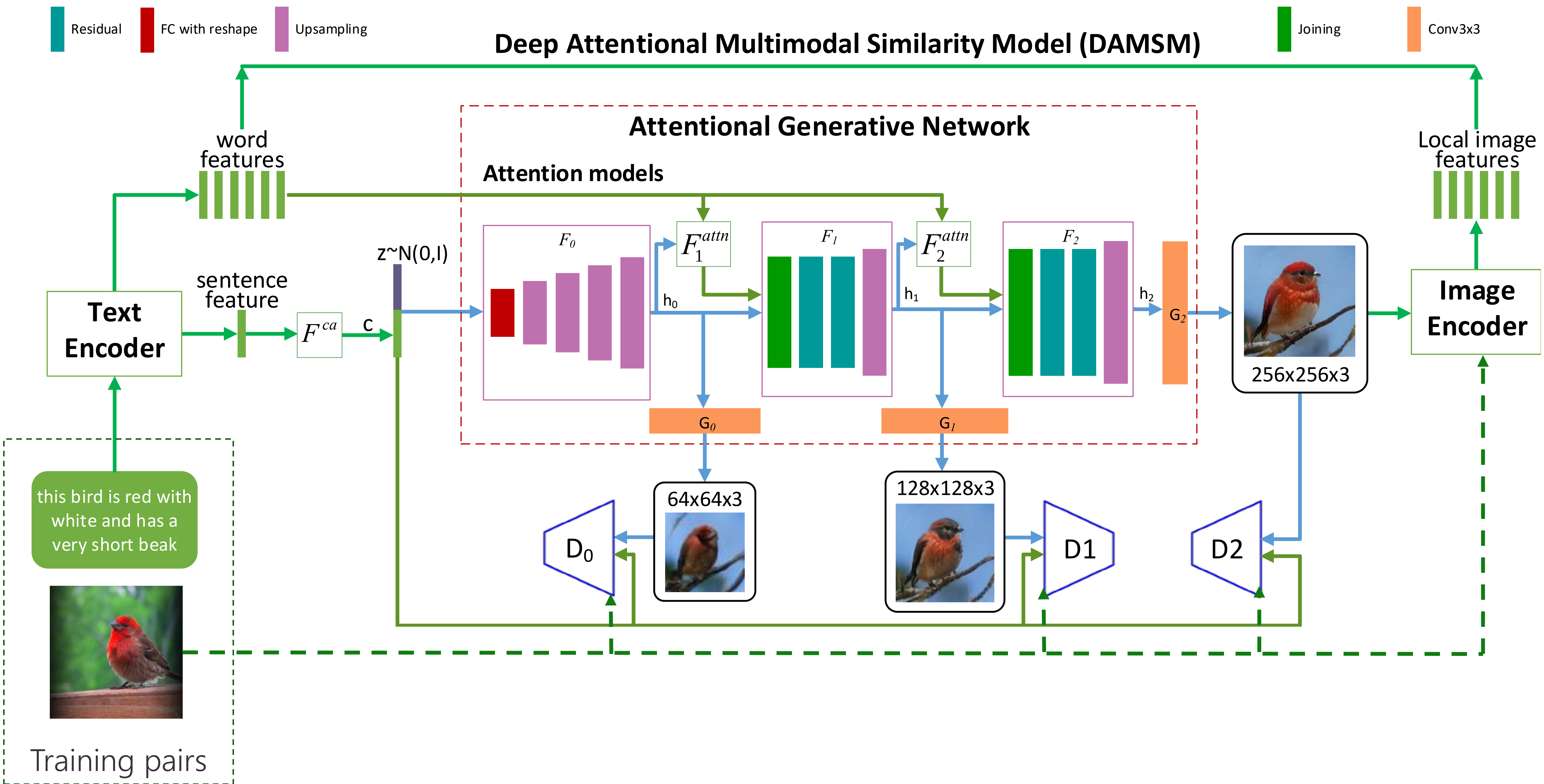

AttnGAN: DAMSM sub-network

Deep Attentional Multimodal Similarity Model (DAMSM)

word features

Local image features

Text Encoder

Image Encoder

- Text encoder (LSTM) extracts word features $e_1, e_2, \ldots, e_T$
- Image encoder (CNN) extracts image region features $v_1, v_2, \ldots, v_N$, where N = 288
- Attention mechanism: for the *i-th* word, compute its region-context vector c_i,

$$c_i = \sum_{j=0}^{288} \alpha_j v_j, \quad \text{where } \alpha_j = \frac{\exp(\gamma_1 \bar{s}_{i,j})}{\sum_{k=0}^{288} \exp(\gamma_1 \bar{s}_{i,k})}$$

  - $\bar{s}_{i,j}$ is the dot product between features of the i-th word and the j-th image region;
- Compute the similarity score $R(c_i, e_i)$ between word and image from cosine similarity between e_i and c_i;
- Compute the similarity score between the sentence (D) and the image (Q) from the fine-grained word-region pair information.

$$R(Q, D) = \log\left(\sum_{i=1}^{T-1} \exp(\gamma_2 R(c_i, e_i))\right)^{\frac{1}{\gamma_2}}$$

this bird is red with white and has a very short beak

Training pairs

AttnGAN: DAMSM sub-network

Deep Attentional Multimodal Similarity Model (DAMSM)

word features

Local image features

Text Encoder

Image Encoder

- The DAMSM loss: maximize the similarity score between the images and their corresponding text descriptions (ground truth), i.e.,

$$L_{DAMSM} = -\sum_{i=1}^{M} \log P(D_i|Q_i)$$

  - M is the number of training pairs.

- The DAMSM loss provides a fine-grained word-region matching loss for training the generator.

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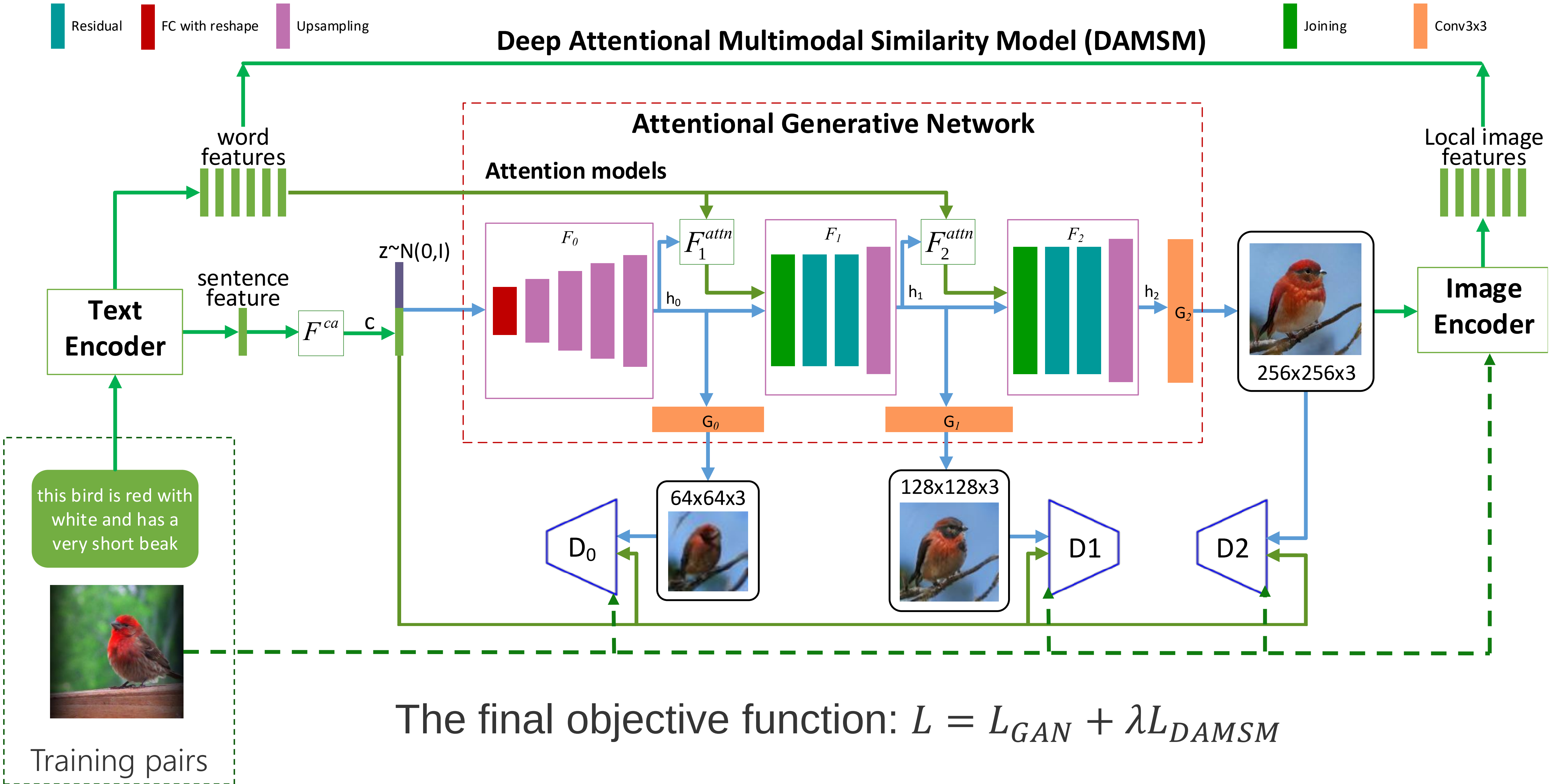
Training pairs

AttnGAN: Overview

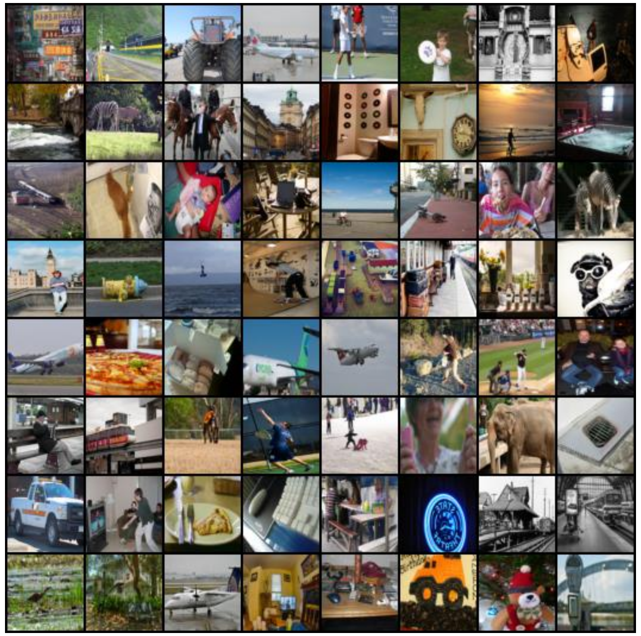


The final objective function: $L = L_{GAN} + \lambda L_{DAMSM}$

Experiments

- Datasets

<table>
<tr><th rowspan="2">Datasets</th><th colspan="2">CUB-2011</th><th colspan="2">MS-COCO</th></tr>
<tr><th>train</th><th>test</th><th>train</th><th>test</th></tr>
<tr><td># samples</td><td>8,855</td><td>2,933</td><td>80,000</td><td>40,000</td></tr>
<tr><td>caption/ image</td><td>10</td><td>10</td><td>5</td><td>5</td></tr>
</table>



- Evaluation metrics:
  - **Inception score** reflects the quality and diversity of the generated images.
  - **R-precision** reflects whether the generated images are well conditioned.

Comparison with previous methods

- On CUB dataset, our AttnGAN achieves 4.36 inception score, which significantly outperforms the previous best inception score of 3.82.
- On the COCO dataset, our AttnGAN boosts the best reported inception score from 9.58 to 25.89, a 170.25% improvement relatively.

Dataset	GAN-INT-CLS [1]	GAWWN [2]	StackGAN [3]	StackGAN-v2 [4]	PPGN [5]	Our AttnGAN
CUB	$2.88 \pm .04$	$3.62 \pm .07$	$3.70 \pm .04$	$3.82 \pm .06$	\	**$4.36 \pm .03$**
COCO	$7.88 \pm .07$	\	$8.45 \pm .03$	\	$9.58 \pm .21$	**$25.89 \pm .47$**

[1] S. Reed, Z. Akata, X. Yan, L. Logeswaran, B. Schiele, and H. Lee. Generative adversarial text-to-image synthesis. In ICML, 2016.
[2] S. Reed, Z. Akata, S. Mohan, S. Tenka, B. Schiele, and H. Lee. Learning what and where to draw. In NIPS, 2016.
[3] H. Zhang, T. Xu, H. Li, S. Zhang, X. Wang, X. Huang, and D. Metaxas. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In ICCV, 2017.
[4] H. Zhang, T. Xu, H. Li, S. Zhang, X. Wang, X. Huang, and D. N. Metaxas. Stackgan++: Realistic image synthesis with stacked generative adversarial networks. arXiv: 1710.10916, 2017.
[5] A. Nguyen, J. Yosinski, Y. Bengio, A. Dosovitskiy, and J. Clune. Plug & play generative networks: Conditional iterative generation of images in latent space. In CVPR, 2017.

Quantitative analysis

- The DAMSM loss is important

Method	inception score	R-precision(%)
AttnGAN1, no DAMSM	$3.98 \pm .04$	10.37 ± 5.88
AttnGAN1, $\lambda = 0.1$	$4.19 \pm .06$	16.55 ± 4.83
AttnGAN1, $\lambda = 1$	$4.35 \pm .05$	34.96 ± 4.02
AttnGAN1, $\lambda = 5$	$4.35 \pm .04$	58.65 ± 5.41
AttnGAN1, $\lambda = 10$	$4.29 \pm .05$	63.87 ± 4.85
AttnGAN2, $\lambda = 5$	$\mathbf{4.36 \pm .03}$	$\mathbf{67.82 \pm 4.43}$

Higher inception score means better image quality and diversity.

Higher R-precision rate means better conditioned.

The inception score and the corresponding R-precision rate of AttnGAN models on CUB.
- "AttnGAN1" architecture has one attention model and generates images of 128x128 resolution;
- "AttnGAN2" architecture has two attention models and generates images of 256x256 resolution.

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Quantitative analysis

- Stacking more attention models helps

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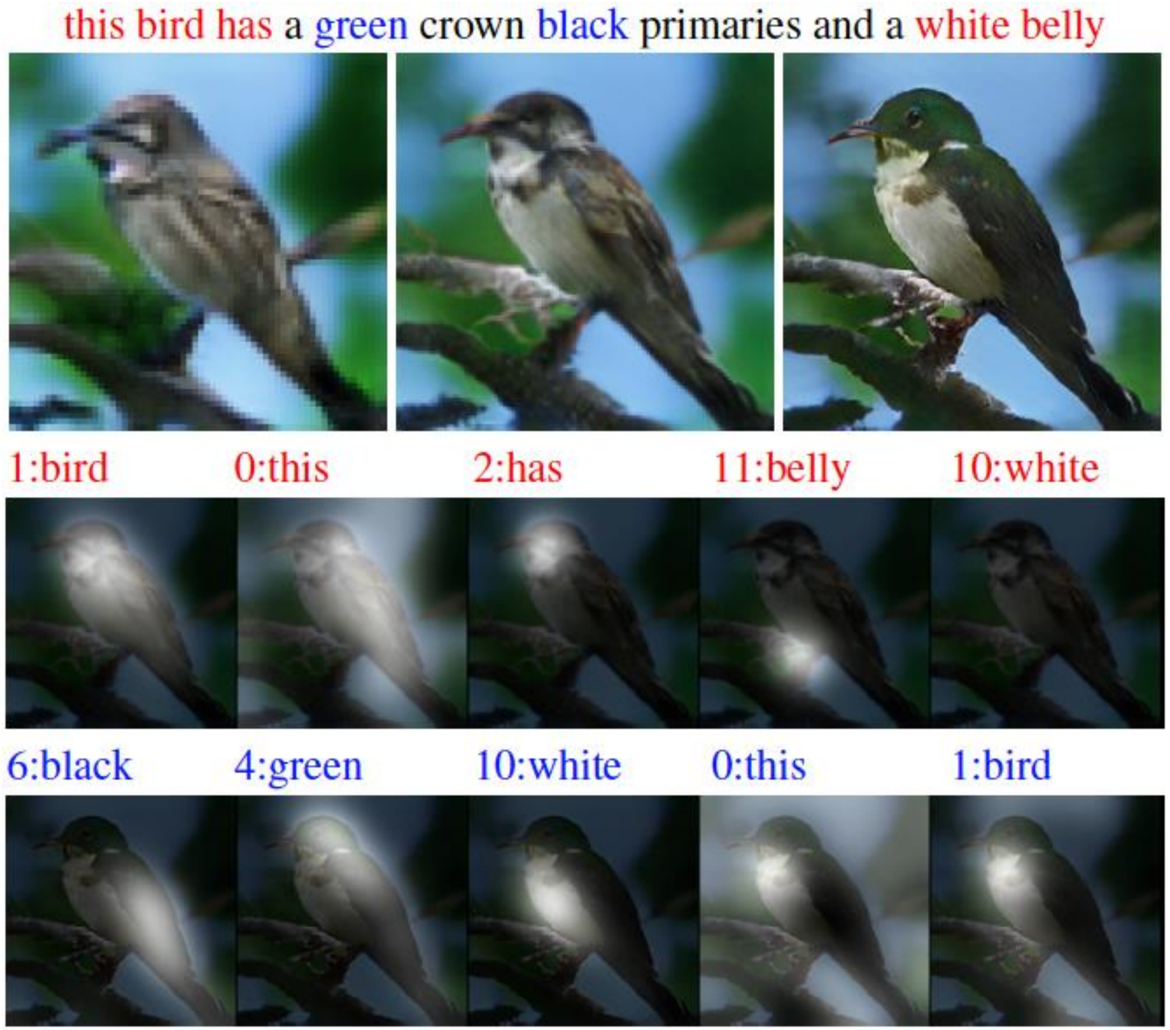
Examples – CUB attention maps

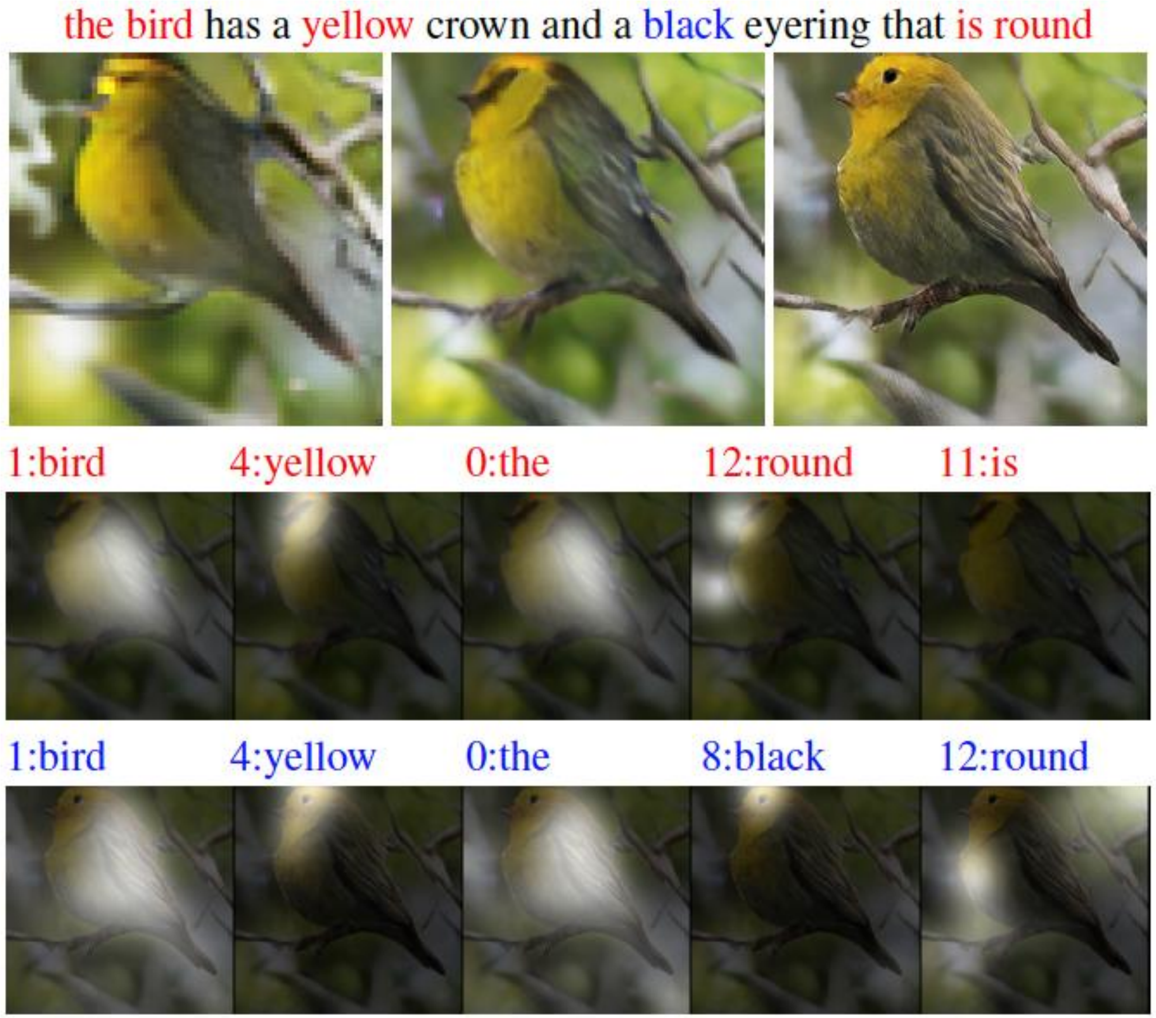
this bird is red with white and has a very short beak.

Challenges – COCO attention maps

A fruit stand display with bananas and kiwi.

Examples – CUB attention maps





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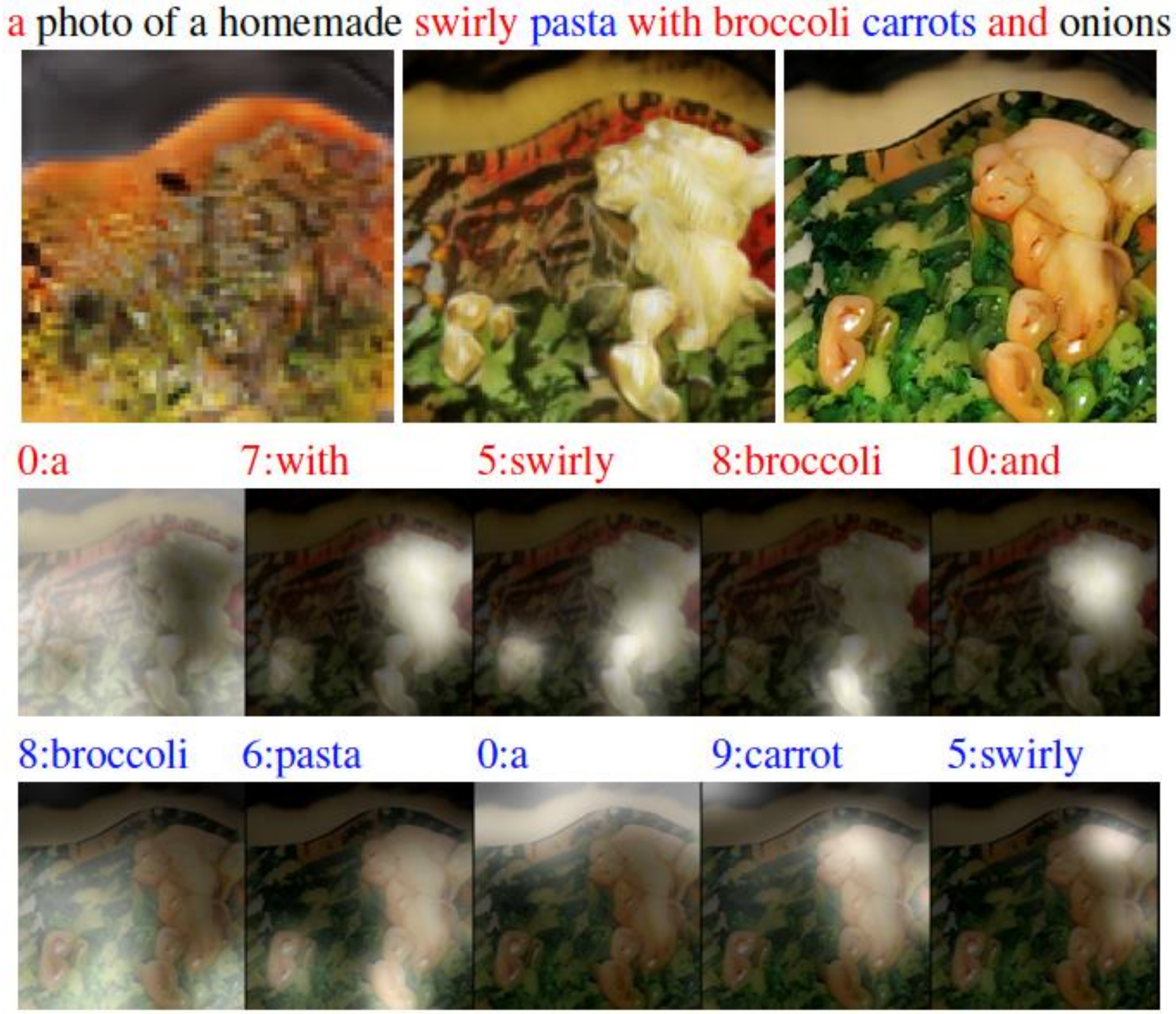
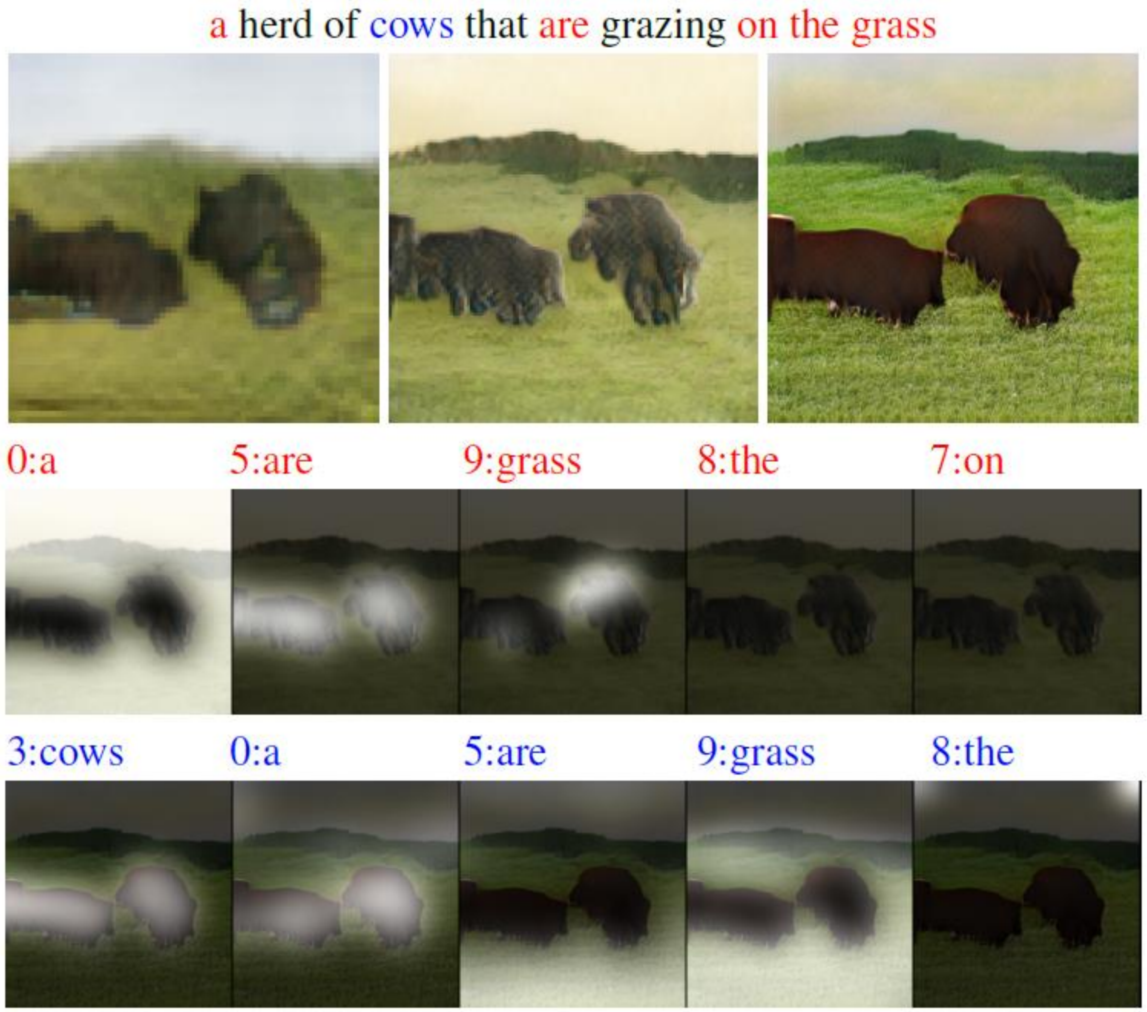




Qualitative analysis - generalization ability

- Change some most attended words in the text descriptions

this bird has wings that are black and has a white belly

this bird has wings that are red and has a yellow belly

this bird has wings that are blue and has a red belly

Qualitative analysis - generalization ability

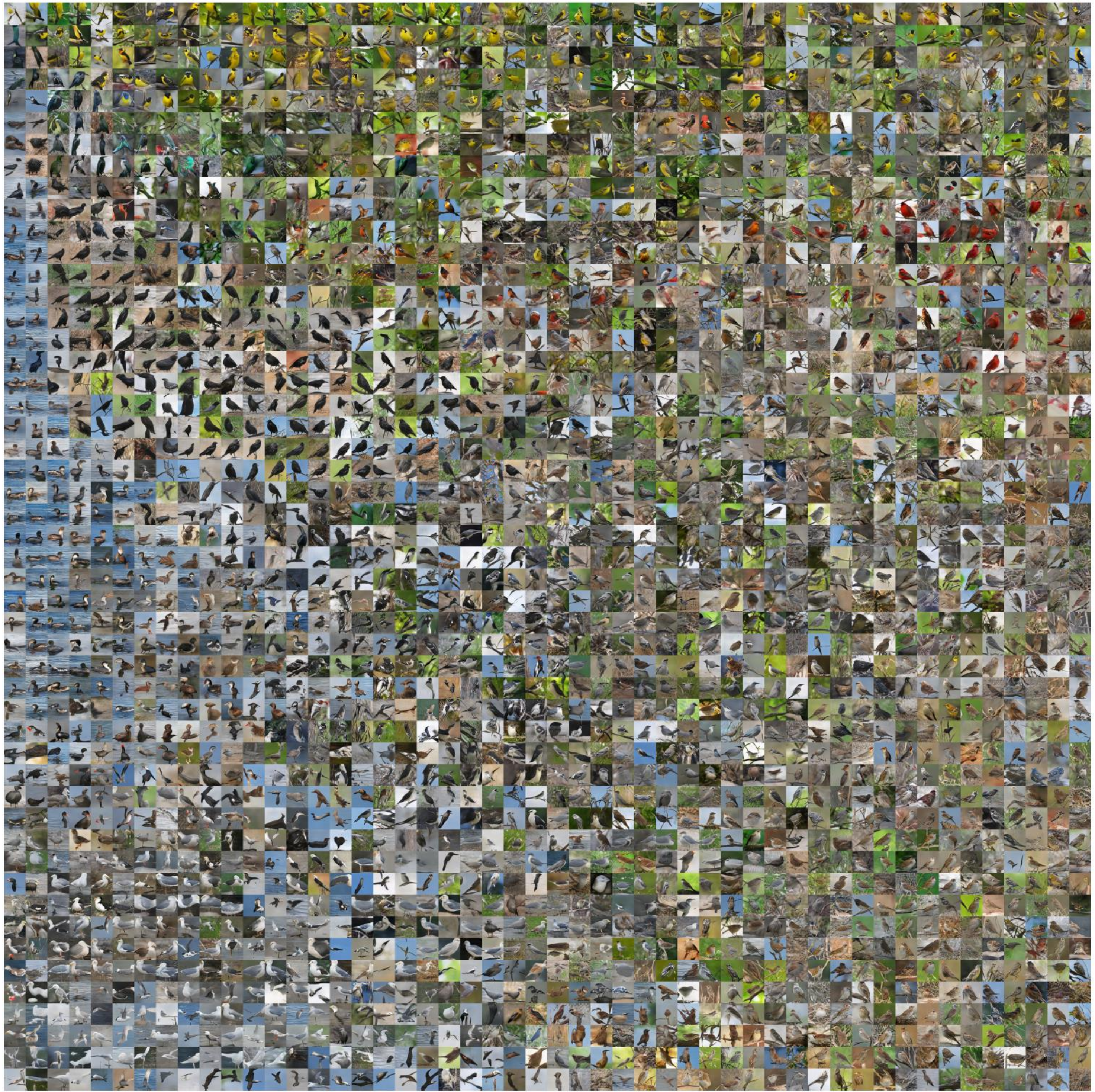
- Images generated from descriptions of novel scenarios

Qualitative analysis - generalization ability

- Novel images (failure cases) generated by AttnGAN on the CUB test set

Utilizing t-SNE to embed a large number of images generated by the AttnGAN

CUB-2011



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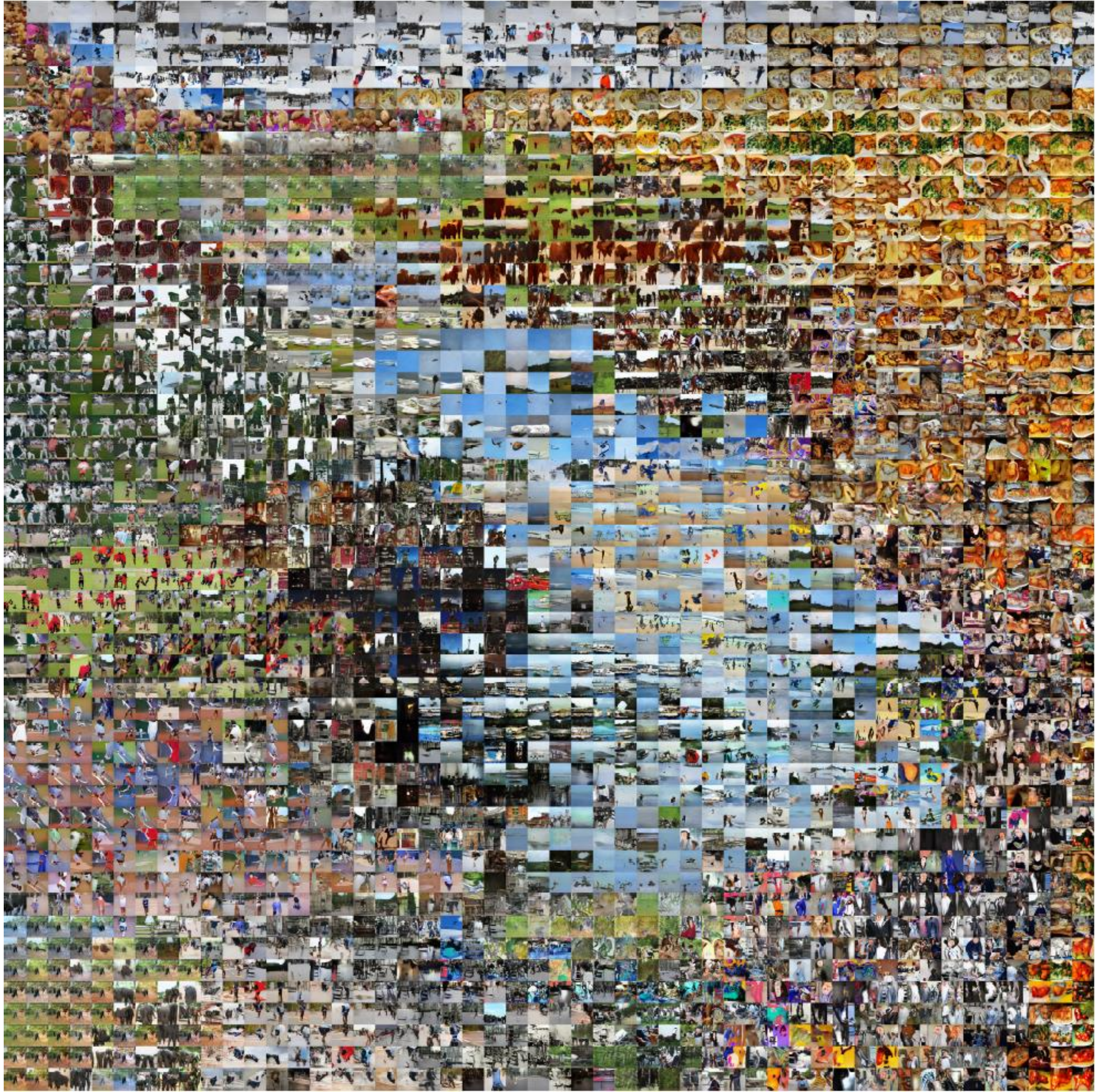
MS-COCO



DrawingBot vs CaptionBot

A herd of cows that are grazing on the grass.

An old clock next to a light post in front of a steeple.

The girl is surfing a small wave in the water.

A stop sign flying in the sky.

A red bus is floating on a lake.

What Microsoft CaptionBot sees... https://www.captionbot.ai/

I think it's a herd of cattle grazing on a lush green field.

I think it's a clock tower in the middle of the street.

I think it's a young girl riding a wave on a surfboard in the water.

I think it's a red and white sign.

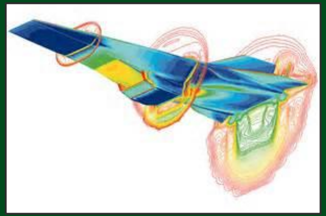
I think it's a boat that is sitting on a bus.

Summary

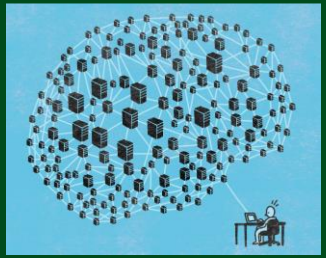
- An Attentional Generative Adversarial Network (AttnGAN) is proposed for fine-grained language-to-image generation.
- Our AttnGAN significantly outperforms previous state-of-the-art GAN models.
- AttnGAN is more stable to train, and has better interpretability.
- AttnGAN code: https://github.com/taoxugit/AttnGAN
- DrawingBot demo: under construction
- CaptionBot demo: https://www.captionbot.ai/

Widest selection of GPUs in the cloud

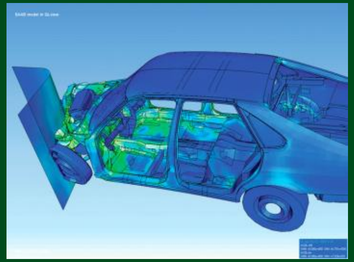
High Performance Computing



AI & Machine Learning



Remote Visualization



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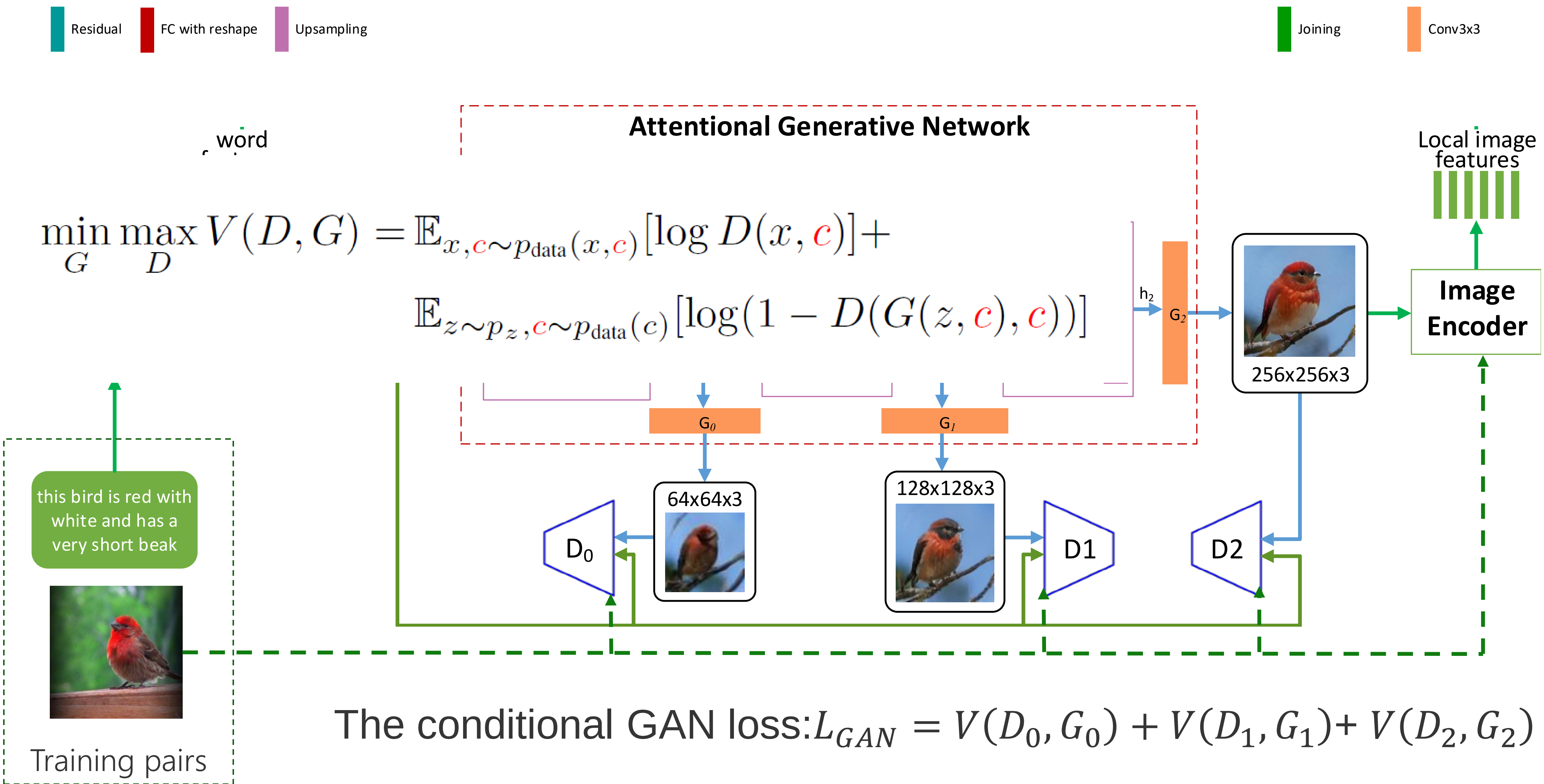
AttnGAN: the conditional GAN loss



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