ManiGAN

Woosung Choi

Text-to-Image Generation

- **[ICML 2016]** Reed, Scott, et al. "Generative Adversarial Text to Image Synthesis." International Conference on Machine Learning. 2016.
- **[StackGAN]** Zhang, Han, et al. "Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks." ICCV. 2017.
- **[AttnGAN]** Xu, Tao, et al. "Attngan: Fine-grained text to image generation with attentional generative adversarial networks." CVPR. 2018.
- **[ControlGAN]** Li, Bowen, et al. "Controllable text-to-image generation." Advances in Neural Information Processing Systems. 2019.

Text-to-Image Generation: ICML 2016

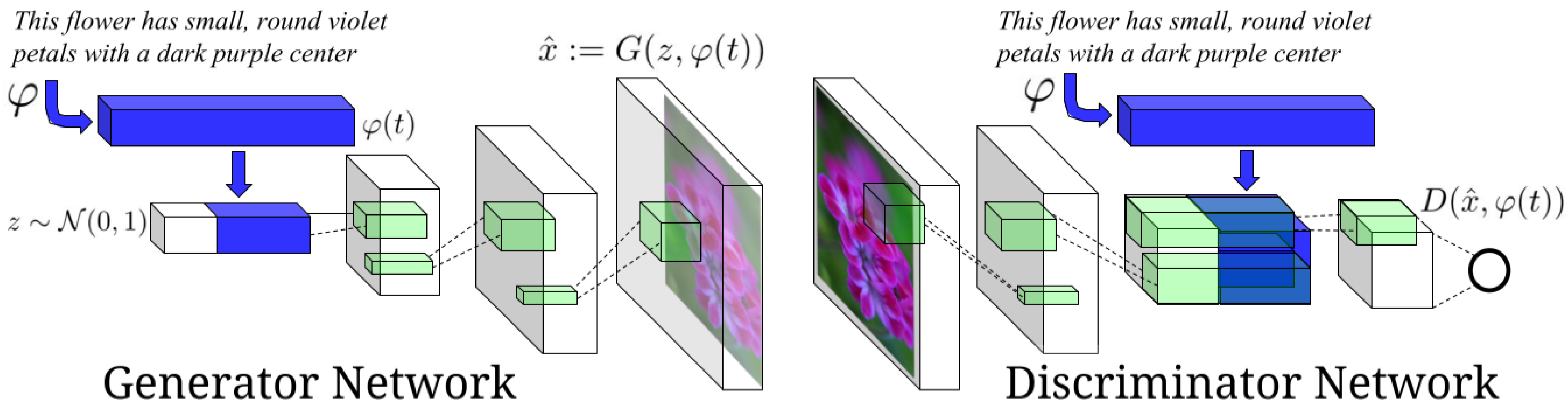


Figure 2. Our text-conditional convolutional GAN architecture. Text encoding $\varphi(t)$ is used by both generator and discriminator. It is projected to a lower-dimensions and depth concatenated with image feature maps for further stages of convolutional processing.

- conditioning by concatenatiion
    - φ: text encoder
    - $\varphi(t)$: embedding of the text description t

Text-to-Image Generation: StackGAN

- Motivation
  - [ICML 2016] can generate images that are highly related to the text, but it is very difficult to train GAN to generate ***high-resolution*** images from text
  - Simply adding more upsampling layers? : Empirically have failed
- Stacked Generative Adversarial Networks
  - State-I-GAN: sketches primitive shape and basic colors, ... (**coarse-grained**)
  - State-II-GAN: corrects defects, complete details (**fine-grained**)
- ***Conditioning Augmentation***
  - to stabilize conditional GAN training, and also improves the diversity of the generated samples

Text-to-Image Generation: StackGAN - Overview

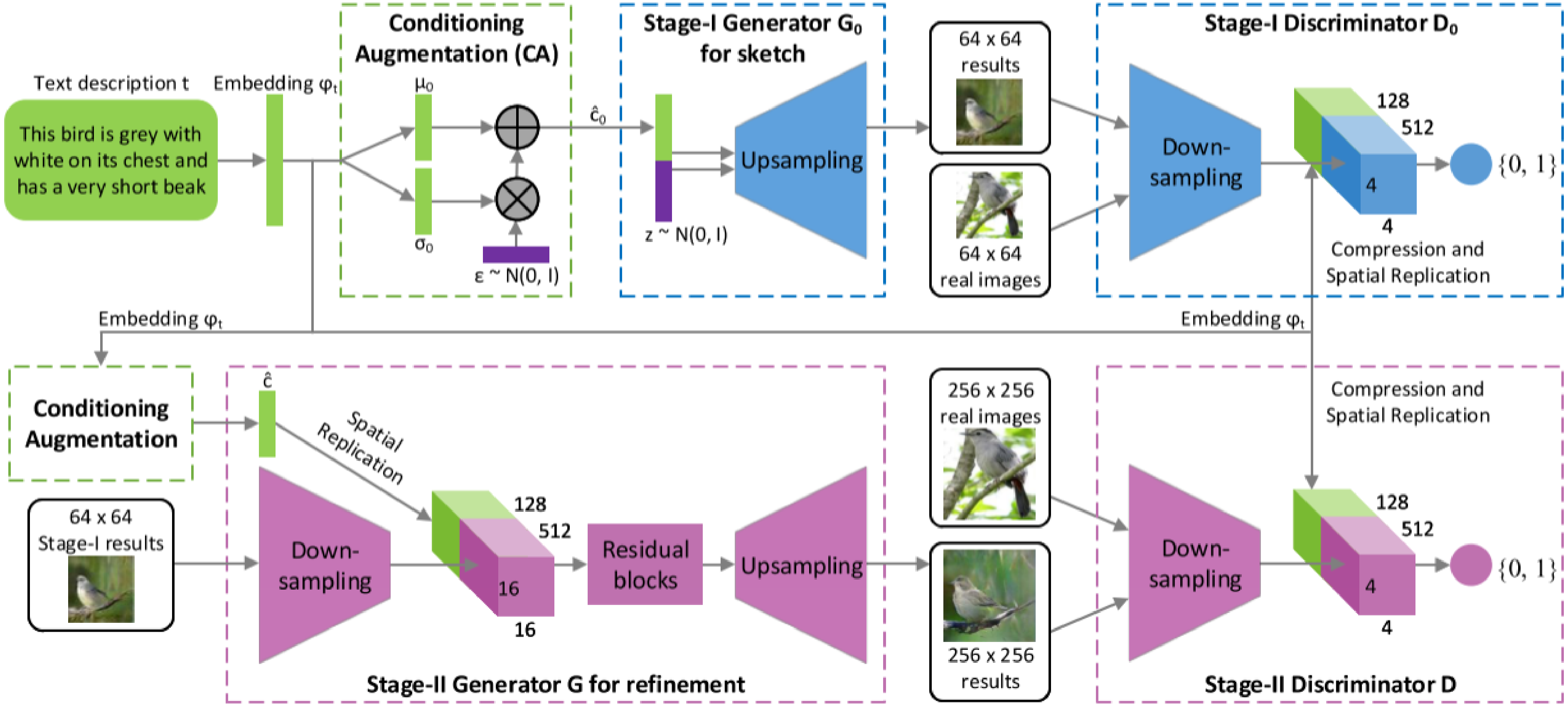


Figure 2. The architecture of the proposed StackGAN. The Stage-I generator draws a low-resolution image by sketching rough shape and basic colors of the object from the given text and painting the background from a random noise vector. Conditioned on Stage-I results, the Stage-II generator corrects defects and adds compelling details into Stage-I results, yielding a more realistic high-resolution image.

Text-to-Image Generation: StackGAN - CA

Conditioning Augmentation

- the text embedding is nonlinearly transformed to generate conditioning latent variables in [ICML 2016]
- However, latent space for the text embedding is usually high dimensional
- With limited amount of data, it usually causes discontinuity in the latent data manifold, which is not desirable
- To avoid overfitting, we add the regularization term to the objective function

$$D_{KL}(\mathcal{N}(\mu(\varphi_t), \Sigma(\varphi_t)) \,||\, \mathcal{N}(0, I))$$

Text-to-Image Generation: StackGAN - Ablation Study for CA

Figure 7. Conditioning Augmentation (CA) helps stabilize the training of conditional GAN and improves the diversity of the generated samples. (Row 1) without CA, Stage-I GAN fails to generate plausible 256×256 samples. Although different noise vector z is used for each column, the generated samples collapse to be the same for each input text description. (Row 2-3) with CA but fixing the noise vectors z, methods are still able to generate birds with different poses and viewpoints.

Text-to-Image Generation: AttnGAN

Motivation

- Conditioning GAN only on the global sentence vector lacks important fine-grained information at the word level and prevents the generation of high-quality images
- This problem becomes even more severe when generating complex scenes

AttnGAN

- To address this issue, AttnGAN allows attention-driven, multi-stage refinement for fine-grained text-to-image generation

Text-to-Image Generation: AttnGAN - Overview

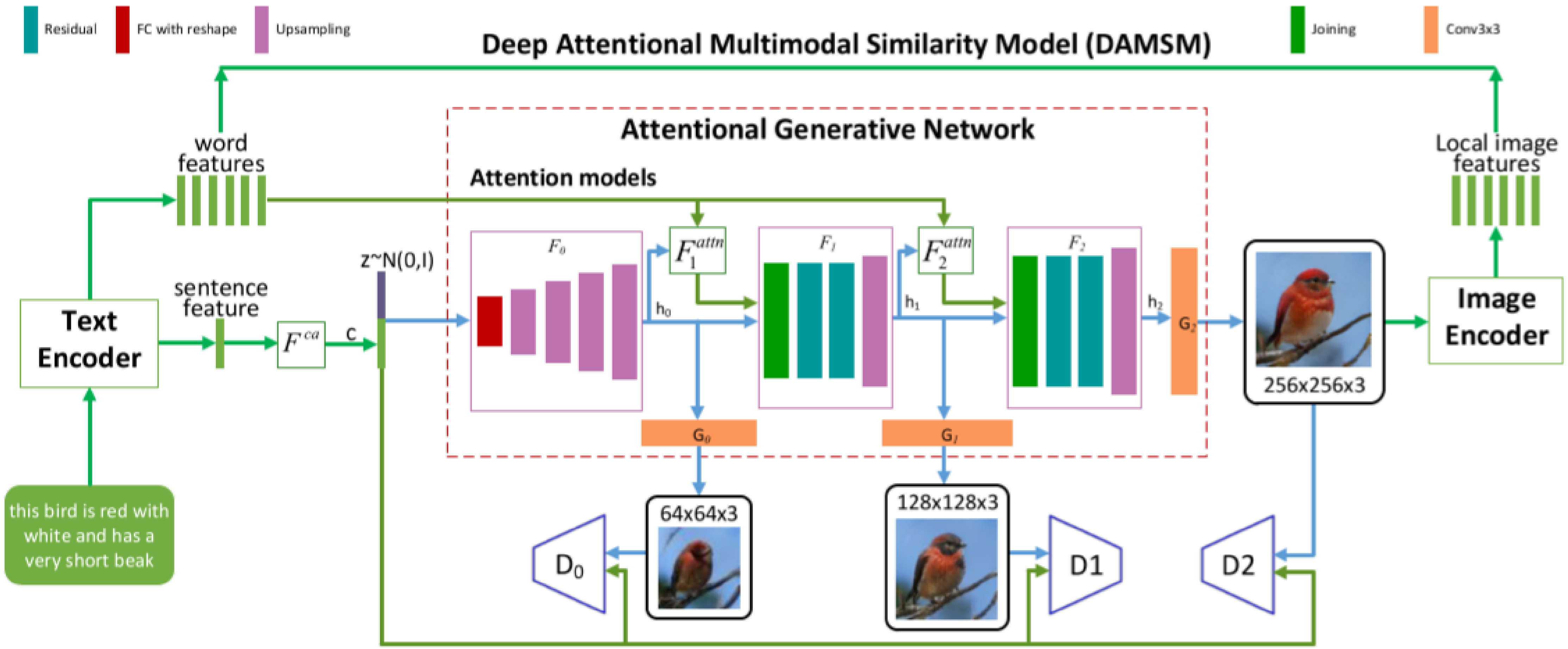


Figure 2. The architecture of the proposed AttnGAN. Each attention model automatically retrieves the conditions (*i.e.*, the most relevant word vectors) for generating different sub-regions of the image; the DAMSM provides the fine-grained image-text matching loss for the generative network.

Text-to-Image Generation: AttnGAN vs StackGAN

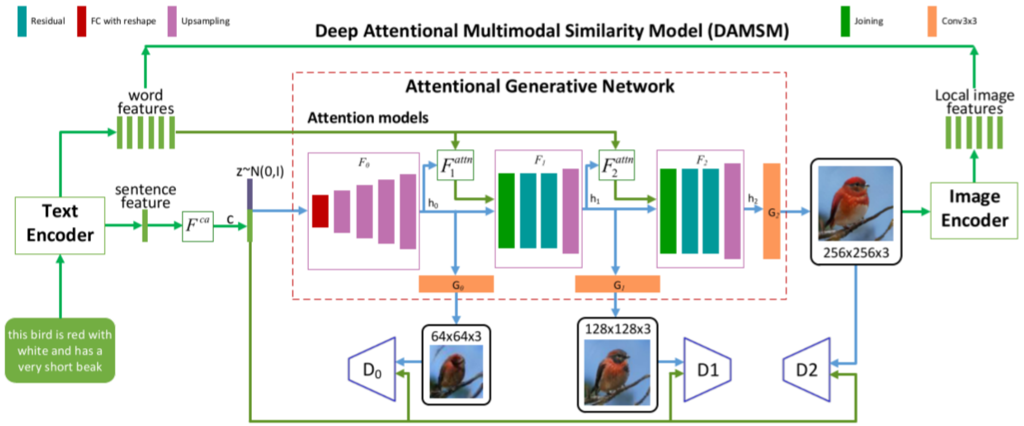


Figure 2. The architecture of the proposed AttnGAN. Each attention model automatically retrieves the conditions (*i.e.*, the most relevant word vectors) for generating different sub-regions of the image; the DAMSM provides the fine-grained image-text matching loss for the generative network.

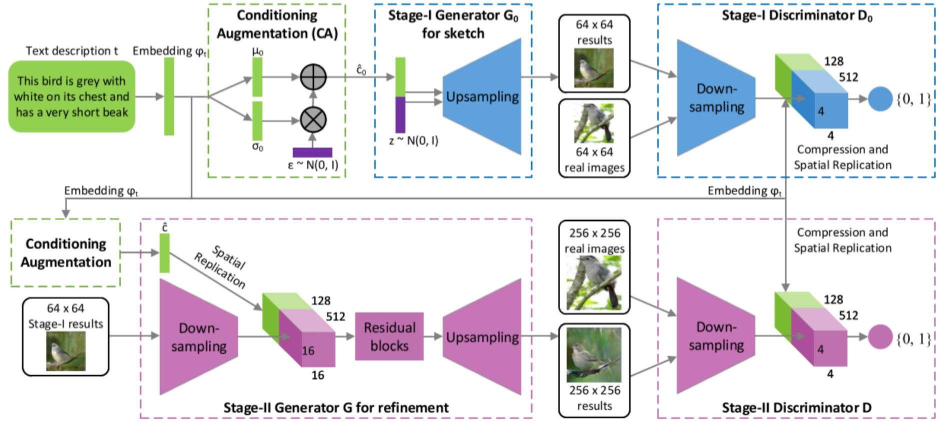


Figure 2. The architecture of the proposed StackGAN. The Stage-I generator draws a low-resolution image by sketching rough shape and basic colors of the object from the given text and painting the background from a random noise vector. Conditioned on Stage-I results, the Stage-II generator corrects defects and adds compelling details into Stage-I results, yielding a more realistic high-resolution image.

Spatial Attention (Original)

1. calculate similarity matrix for all possible pairs of words <-> sub-regions by
   - $s = e^T v$
     - $s \in \mathbb{R}^{L \times 289}$
     - $e \in \mathbb{R}^{D \times L}$, $v \in \mathbb{R}^{D \times 289}$
   - $s_{i,j}$ is the dot-product similarity: the ith word <-> the jth sub-region
2. compute normalized similarity $\bar{s}_{i,j} = \frac{exp(s_{i,j})}{\sum_{l=0}^{L-1} exp(s_{l,j})}$
3. compute region-context vector c_i, a dynamic representation of the images's sub-regions related to the i^{th} word of the sentence
   - $c_i = \sum_{j=0}^{288} \alpha_j v_j$, where $\alpha_j = \frac{exp(\gamma_1 \bar{s}_{i,j})}{\sum_{k=0}^{288} exp(\gamma_1 \bar{s}_{i,k})}$
     - set γ_1 to be 1, for the sake of simplicity

Advanced

- Controllable Text-to-Image Generation
    - **[ControlGAN]** Li, Bowen, et al. "Controllable text-to-image generation." Advances in Neural Information Processing Systems. 2019.
- Text-Guided Image Manipulation
    - **[ManiGAN]** Li, Bowen, et al. "Manigan: Text-guided image manipulation." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.

Abstract

- Goal of this paper
  - semantically edit parts of an image to match a given text that describes desired attributes (e.g., texture, colour, and background),
  - while preserving other contents that are irrelevant to the text
- ManiGAN contains two key components: ACM and DCM
- A new metric for evaluating image manipulation results
  - in terms of both the generation of new attributes
  - and the reconstruction of text-irrelevant contents.
- Experimental Results on the CUB and COCO datasets
  - demonstrate the superior performance of the proposed method.

Text-Guided Image Manipulation

- Input: an input image I and a text description S'
- Output: a realistic image I' that is semantically aligned with S'
- Constraints: preserving text-irrelevant contents existing in I

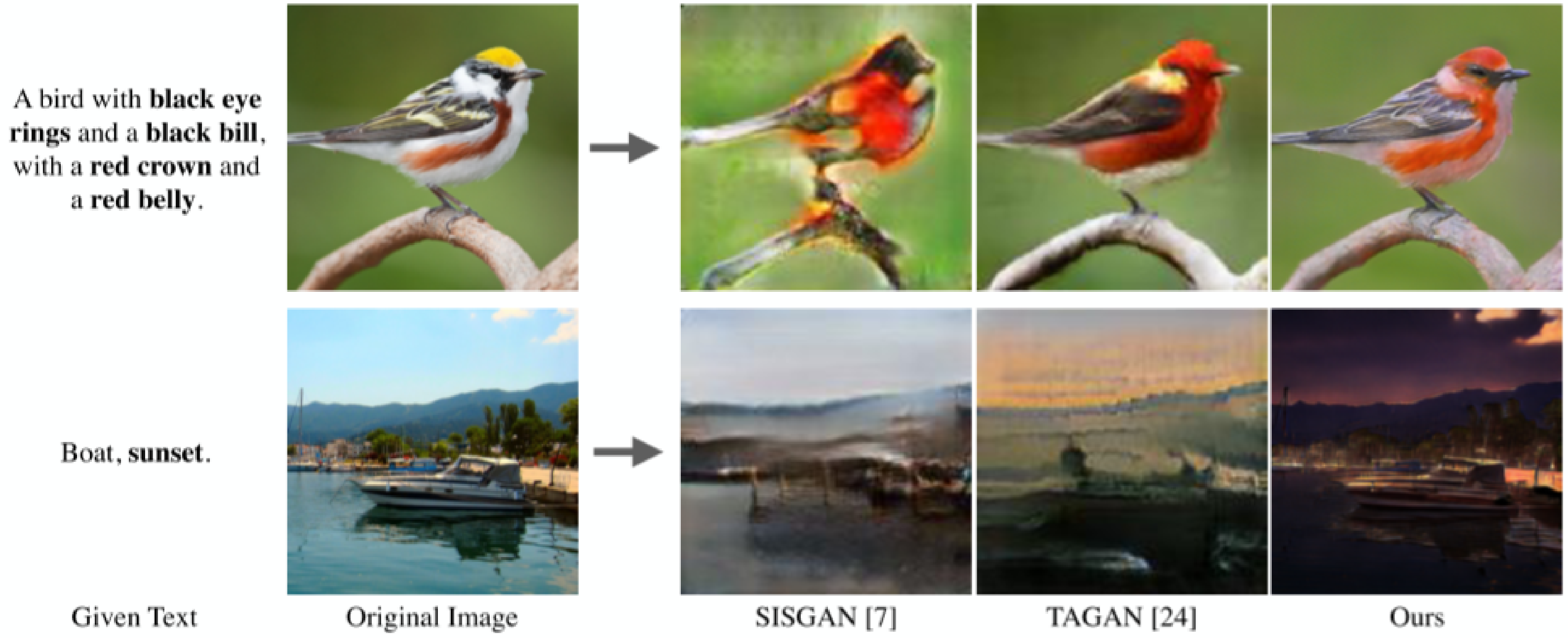


Figure 1: Given an original image that needs to be edited and a text provided by a user describing desired attributes, the goal is to edit parts of the image according to the given text while preserving text-irrelevant contents. Current state-of-the-art methods only generate low-quality images, and fail to do manipulation on COCO. In contrast, our method allows the original image to be manipulated accurately to match the given description, and also reconstructs text-irrelevant contents.

Key Components

- ACM
  - selects image regions relevant to the given text
  - and then correlates the regions with corresponding semantic words for effective manipulation
  - Meanwhile, it encodes original image features to help reconstruct text-irrelevant contents.
- DCM
  - rectifies mismatched attributes
  - and completes missing contents of the synthetic image
- Channel-wise Attention
- Spatial Attention

Overall Architecture (simple)

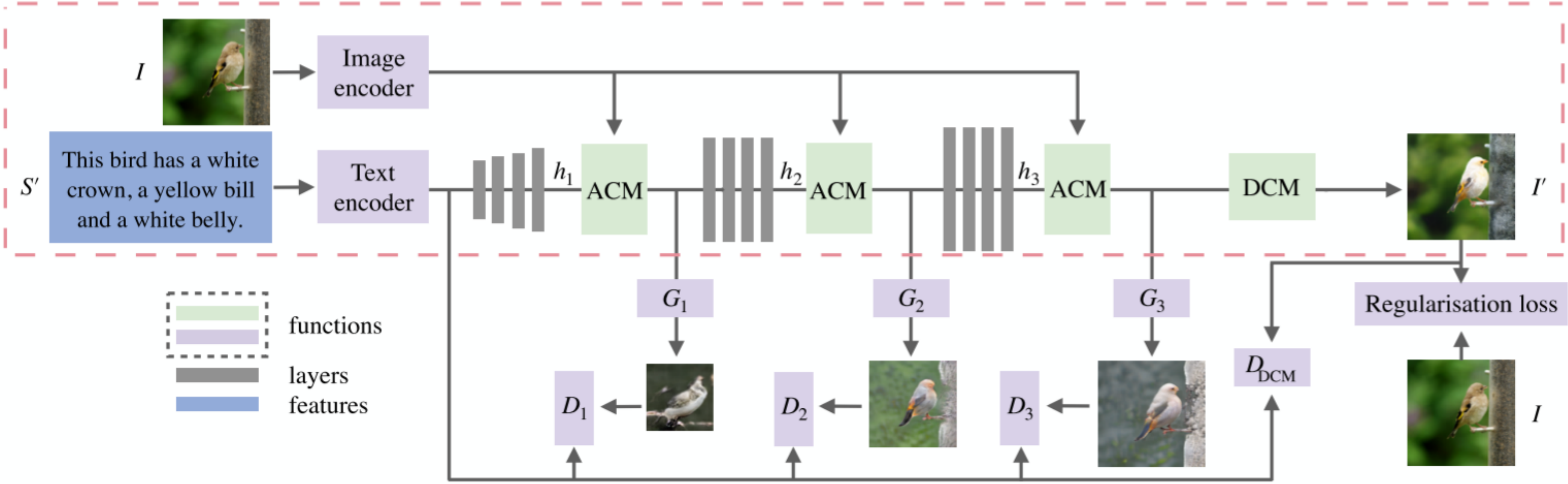


Figure 2: The architecture of ManiGAN. The red dashed box indicates the inference pipeline that a text description S' is given by a user, while in training, the text S' is replaced by S that correctly describes I. ACM denotes the text-image affine combination module. DCM denotes the detail correction module. The attention is omitted for simplicity. Please see supplementary material for full architecture.

Overall Architecture

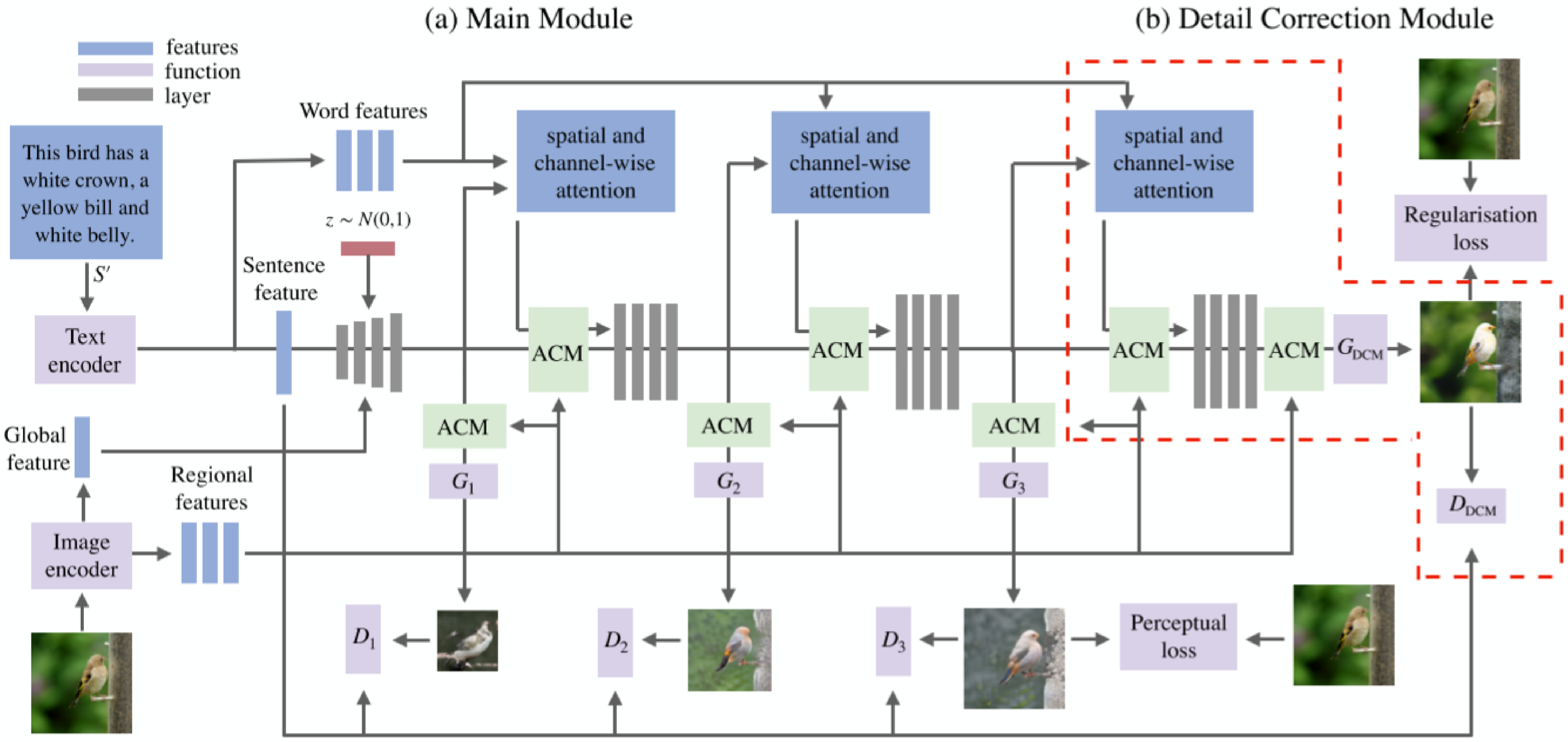


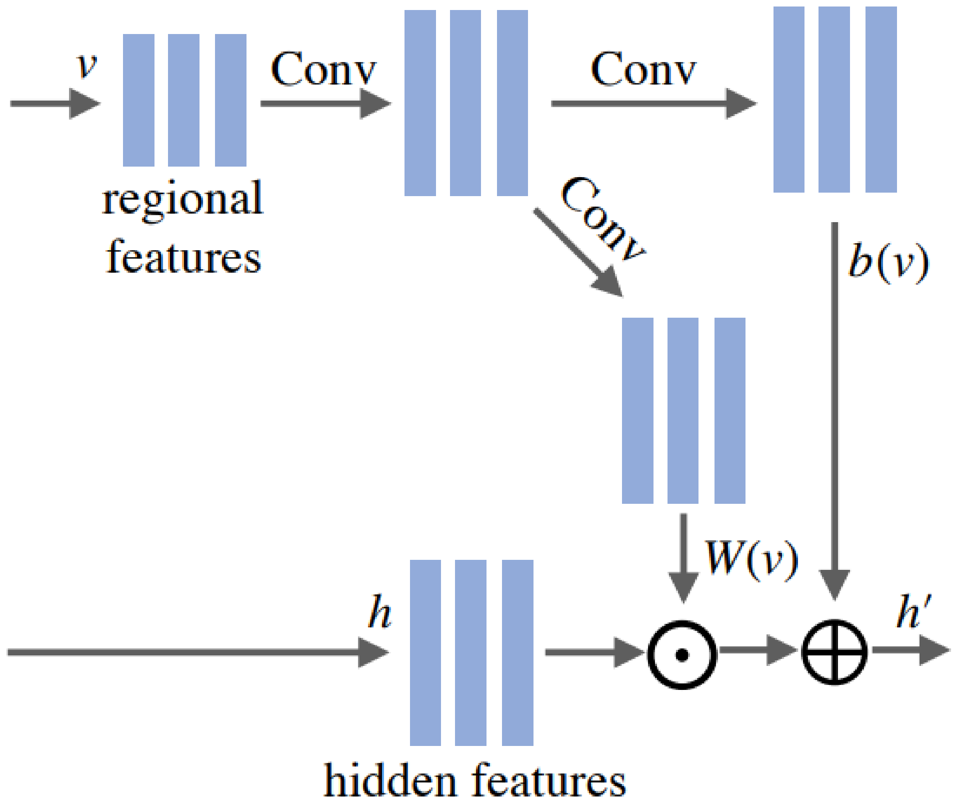
Figure 9: The architecture of ManiGAN. ACM denotes the text-image affine combination module. Red dashed box indicates the architecture of the detail correction module.

ACM: Text-Image Affine Combination Module

```python
# The implementation of ACM (affine combination module)
class ACM(nn.Module):
    def __init__(self, channel_num):
        super(ACM, self).__init__()
        self.conv = conv3x3(cfg.GAN.GF_DIM, 128)
        self.conv_weight = conv3x3(128, channel_num)    # weight
        self.conv_bias = conv3x3(128, channel_num)      # bias

    def forward(self, h, v):
        out_code = self.conv(v)
        out_code_weight = self.conv_weight(out_code)
        out_code_bias = self.conv_bias(out_code)
        return h * out_code_weight + out_code_bias
```

- $h' = h \odot W(v) + b(v)$
  - $h \in \mathbb{R}^{C \times H \times D}$, $v \in \mathbb{R}^{256 \times 17 \times 17}$
- ACM $\approx$ PoCM

ACM: Figure



(a) Text-Image Affine Combination Module

Chnnel-wise Attention

- $ChannelAttention(w, v_k) = f_k^{\alpha} \in \mathbb{R}^{C \times (H_k \cdot W_k)}$
  - input: word features $w \in \mathbb{R}^{D \times L}$ and hidden visual features $v_k \in \mathbb{R}^{C \times (H_k \cdot W_k)}$
  - where H_k and W_k denote the height and width at stage k.

Channel-wise Attention

- The channel-wise attention module at the k^{th} stage
  i. input: word features $w \in \mathbb{R}^{D\times L}$ and hidden visual features $v_k \in \mathbb{R}^{C\times(H_k\cdot W_k)}$
    - , where H_k and W_k denote the height and width at stage k.

  ii. compute $\tilde{w_k} = F_k w$, where F_k is an embedding layer ($D \to (H_k \cdot W_k)$)
    - w are first mapped into the same semantic space as the visual features v_k
    - producing $\tilde{w_k} = F_k w$, where $F_k \in \mathbb{R}^{(H_k\cdot W_k)\times D}$

  iii. compute channel-word correlation matrix $m^k \in \mathbb{R}^{C\times L}$
    - $m^k = v_k \tilde{w_k}$
      - $[C, L] = [C, (H_k \cdot W_k)] \times [(H_k \cdot W_k), L]$
    - m^k$ aggregates correlation values between channels and words across all spatial locations.

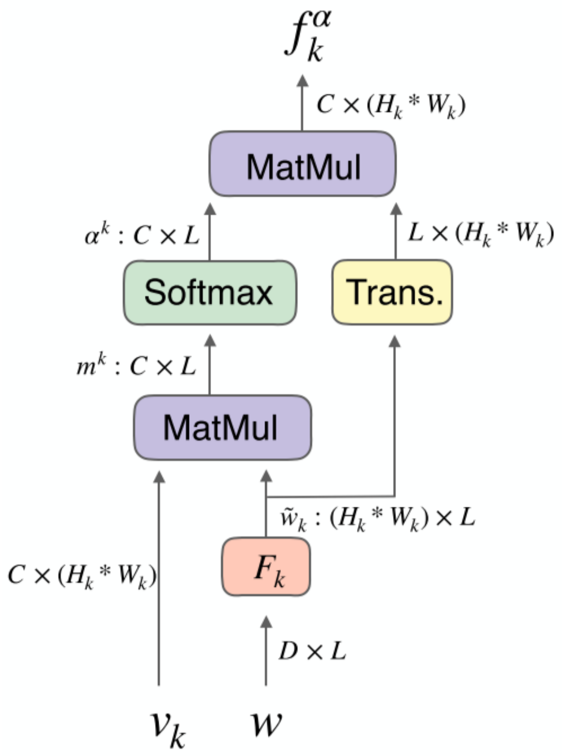
Channel-wise Attention (2)

- The channel-wise attention module at the k^{th} stage
  i. input: word features $w \in \mathbb{R}^{D \times L}$ and hidden visual
  ii. compute $\tilde{w_k} = F_k w$, where F_k is a word perception layer
  iii. compute channel-word correlation matrix $m^k \in \mathbb{R}^{C \times L}$
  iv. compute attention weight $\alpha^k_{i,j} = \frac{exp(m^k_{i,j})}{\sum_{l=0}^{L-1} exp(m^k_{i,l})}$
    - $\alpha^k_{i,j}$ is the correlation between i^{th} channel in v_k and the j^{th} word in S
    - higher value, larger correlation
  v. obtain final channel-wise attention feature $f^\alpha_k \in \mathbb{R}^{C \times (H_k \cdot W_k)}$
    - $f^\alpha_k = \alpha^k (\tilde{w_k})^T$
      - $[C, (H_k \cdot W_k)] = [C, L] \times [L, (H_k \cdot W_k)]$

Channel-wise Attention: Code

```
class ChannelAttention(nn.Module):
    def __init__(self, idf, cdf):
        super(ChannelAttention, self).__init__()
        self.conv_context2 = conv1x1(cdf, 64*64)
        self.conv_context3 = conv1x1(cdf, 128*128)
        self.sm = nn.Softmax()
        self.idf = idf

    def forward(self, v_k, w, ih, iw):

        batch_size, L = w.size(0), w.size(2)
        w_tilde = w.unsqueeze(3)

        if (ih == 64):
            w_tilde = self.conv_context2(w_tilde).squeeze(3)
        else:
            w_tilde = self.conv_context3(w_tilde).squeeze(3)

        attn_c = torch.bmm(v_k, w_tilde)
        attn_c = attn_c.view(batch_size * self.idf, L)
        attn_c = self.sm(attn_c)
        attn_c = attn_c.view(batch_size, self.idf, L)

        attn_c = torch.transpose(attn_c, 1, 2).contiguous()

        fk = torch.bmm(w_tilde, attn_c)
        fk = torch.transpose(fk, 1, 2).contiguous()
        fk = fk.view(batch_size, -1, ih, iw)

        return fk, attn_c
```

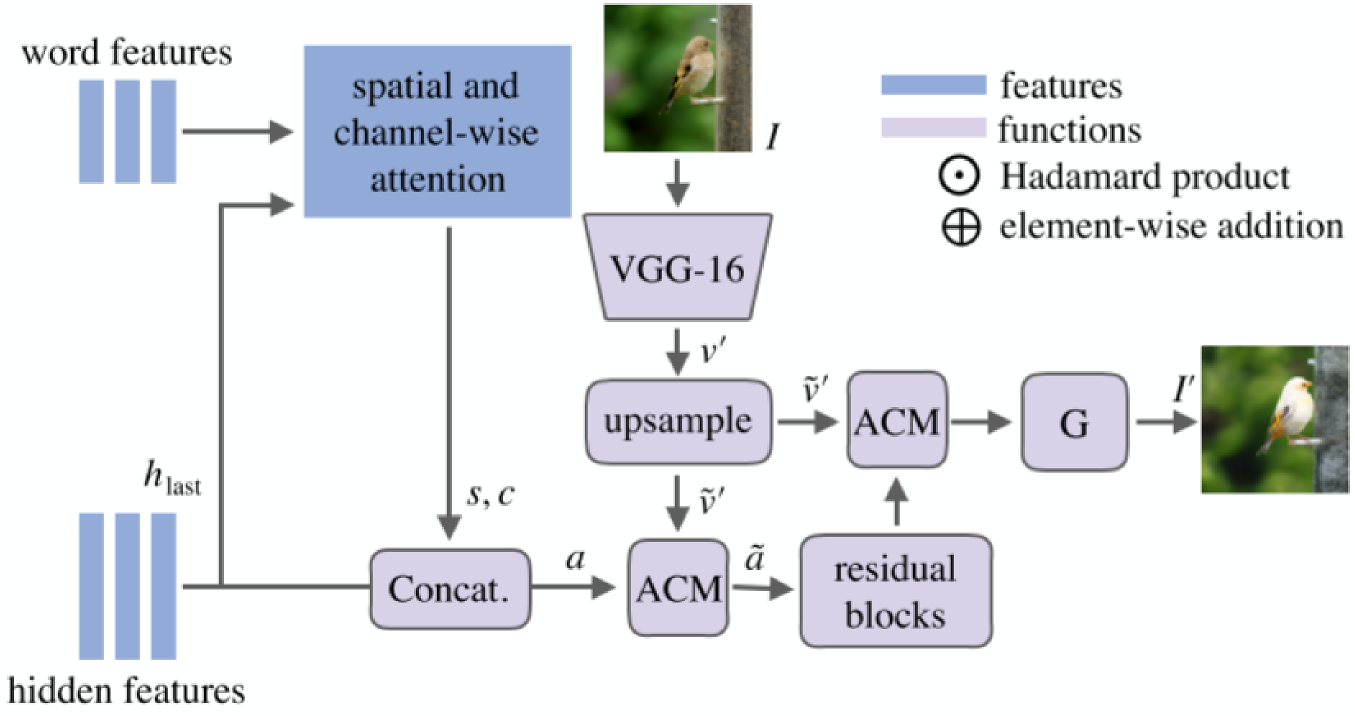
Channel-wise Attention: Figure



(a) channel-wise attention

Detail Correction Module (DCM)

- enhance the details and complete missing contents in the synthetic image
  - $\approx$ skip connections in U-Nets
- input: last hidden features h_{last} from last ACM, word features $w \in \mathbb{R}^{D \times L}$, and VGG-feature of the original image I

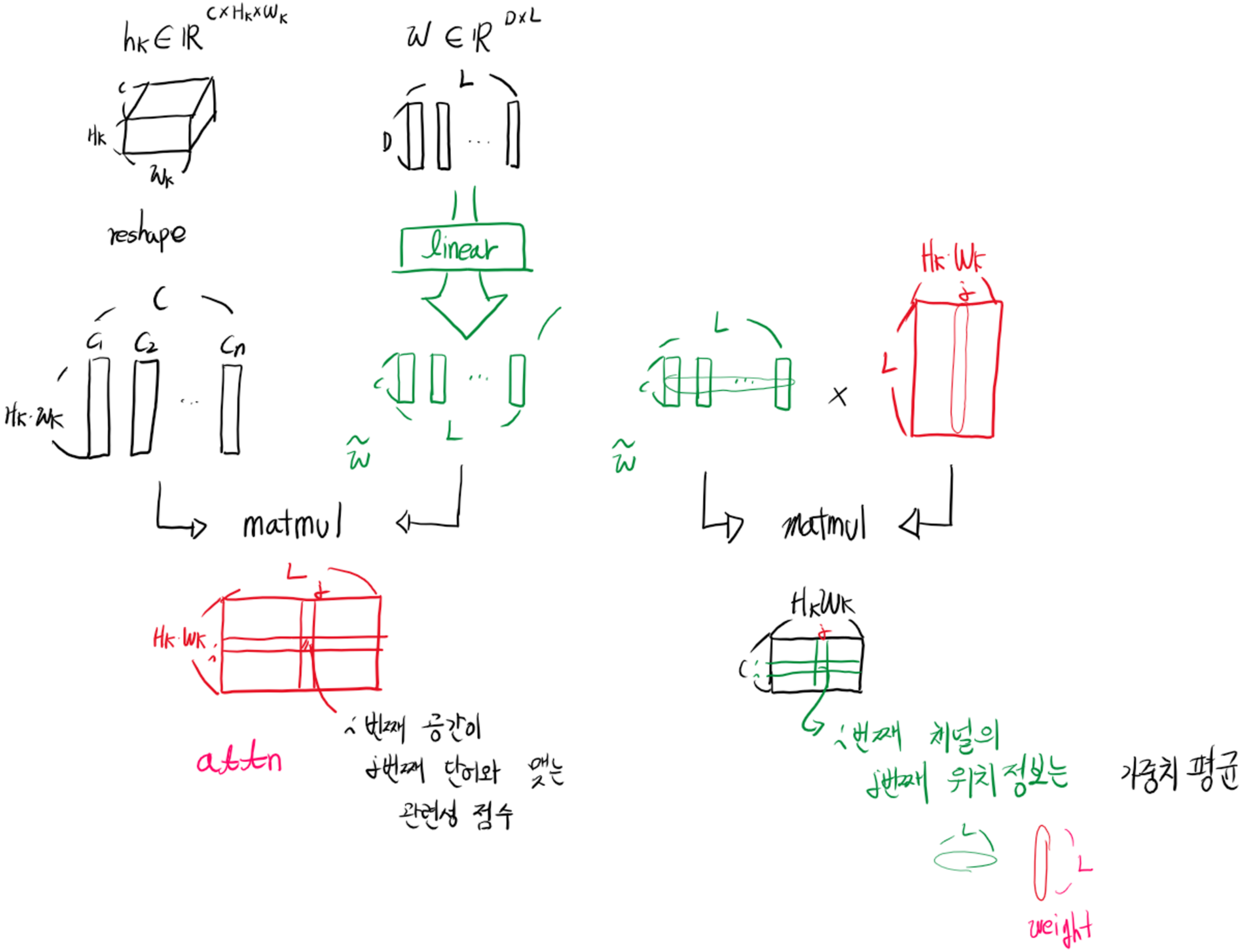


(b) Detail Correction Module

Spatial Attention in MagiGAN

1. input: word features $w \in \mathbb{R}^{D \times L}$ and hidden visual features $h_k \in \mathbb{R}^{C \times (H_k \cdot W_k)}$
   - , where H_k and W_k denote the height and width at stage k.
2. compute $\tilde{w_k} = E_k w$, where E_k is an embedding layer ($D \rightarrow C$)
   - w are first mapped into the same semantic space as the visual features v_k
   - producing $\tilde{w_k} = E_k w$, where $E_k \in \mathbb{R}^{C \times D}$
3. $attn = softmax(h_k \tilde{w})$
4. compute $v_k = \tilde{w}(attn)^T$

Spatial Attention: Figure



Spatial Attention: code

```
class SpatialAttentionGeneral(nn.Module):
    def __init__(self, idf, cdf):
        super(SpatialAttentionGeneral, self).__init__()
        self.conv_context = conv1x1(cdf, idf)
        self.idf = idf

    def forward(self, h_k, w):

        batch_size, idf, ih, iw = h_k.shape
        batch_size, D, L = w.shape

        h_k = h_k.view(batch_size, -1, ih * iw).transpose(-1, -2).contiguous()
        w_tilde = self.conv_context(w.unsqueeze(3)).squeeze(3)
        # => h_k = [batch_size, ih * iw, idf], w_tilde = [batch_size, idf, L]

        # Get attention
        attn = torch.bmm(h_k, w_tilde).softmax(-1) # [batch_size, id * iw, L]
        attn = torch.transpose(attn, -1, -2).contiguous()
        # => attn = [batch_size, L,  id * iw]

        v_k = torch.bmm(w_tilde, attn) # [batch_size, idf, id*iw]
        attn = attn.view(batch_size, -1, ih, iw)

        return v_k, attn
```

Overall Architecture: review

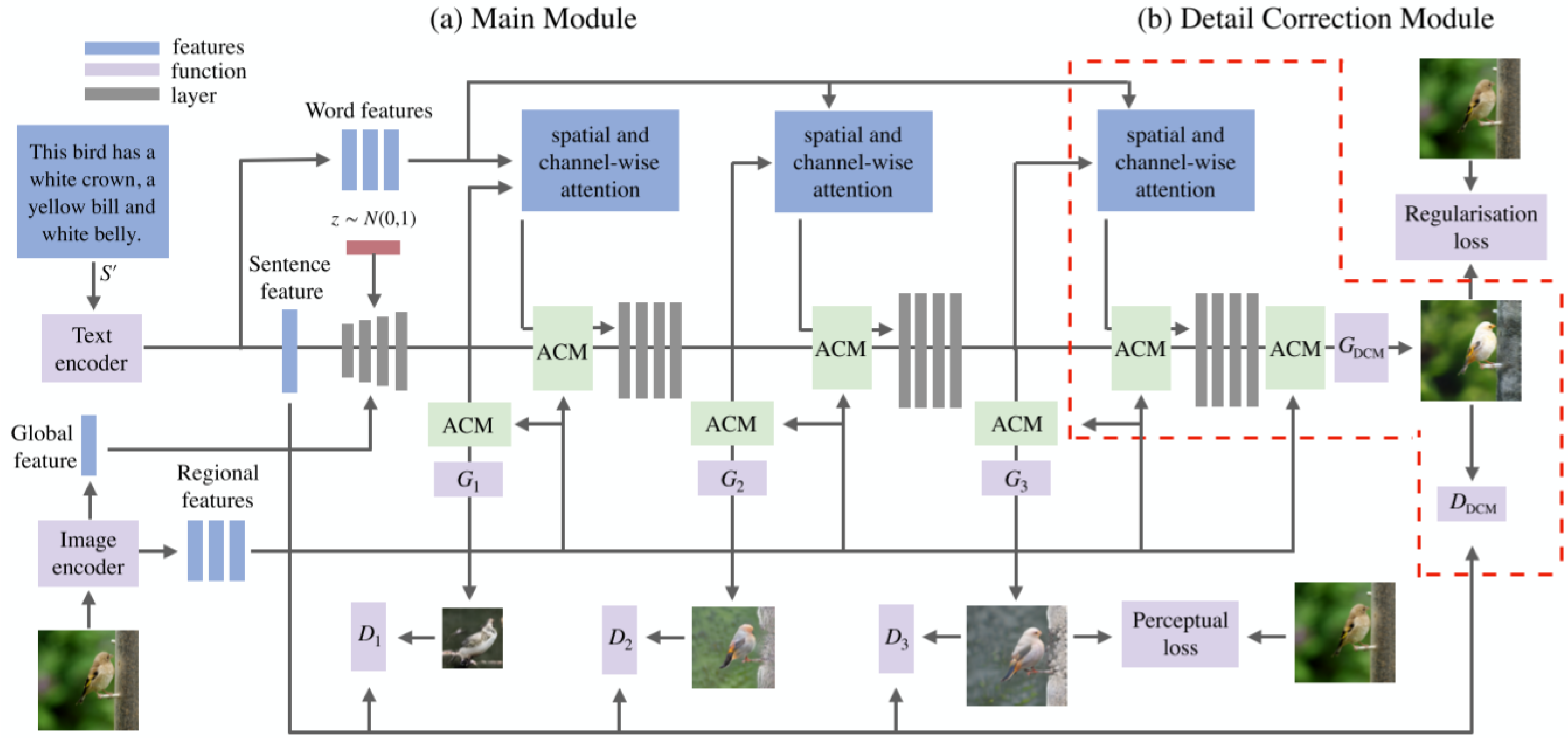


Figure 9: The architecture of ManiGAN. ACM denotes the text-image affine combination module. Red dashed box indicates the architecture of the detail correction module.