StoryGAN:
A Sequenital Conditional GAN for Story Visualization

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Reviewer: Byeong Jo Kim

Introduction

Story Visualization task

- to **generate a sequence of images** to **describe a story** written in a **multi-sentence paragraph**

Two Challenge

- the sequence of images must **consistently** and **coherently** depict the whole story
  - compared with image generation
    - coherent image sequence
- **display the logic** of the storyline
  - compared with video generation
    - smooth motion transitions is not important
    - sharp change of scenes

StoryGAN

D. Cer, Y. Yang, S.-y. Kong, N. Hua, N. Limtiaco, R. S. John, N. Constant, M. Guajardo-Cespedes, S. Yuan, C. Tar, et al. **Universal sentence encoder**. arXiv preprint arXiv:1803.11175, 2018. 3, 7

128-d

$$S = [\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_T]$$

one generated image per sentence
with **locally** and **globally consistent**
sentence – image story – images

$$\hat{\boldsymbol{X}} = [\hat{\boldsymbol{x}}_1, \hat{\boldsymbol{x}}_2, \cdots, \hat{\boldsymbol{x}}_T]$$

StoryGAN

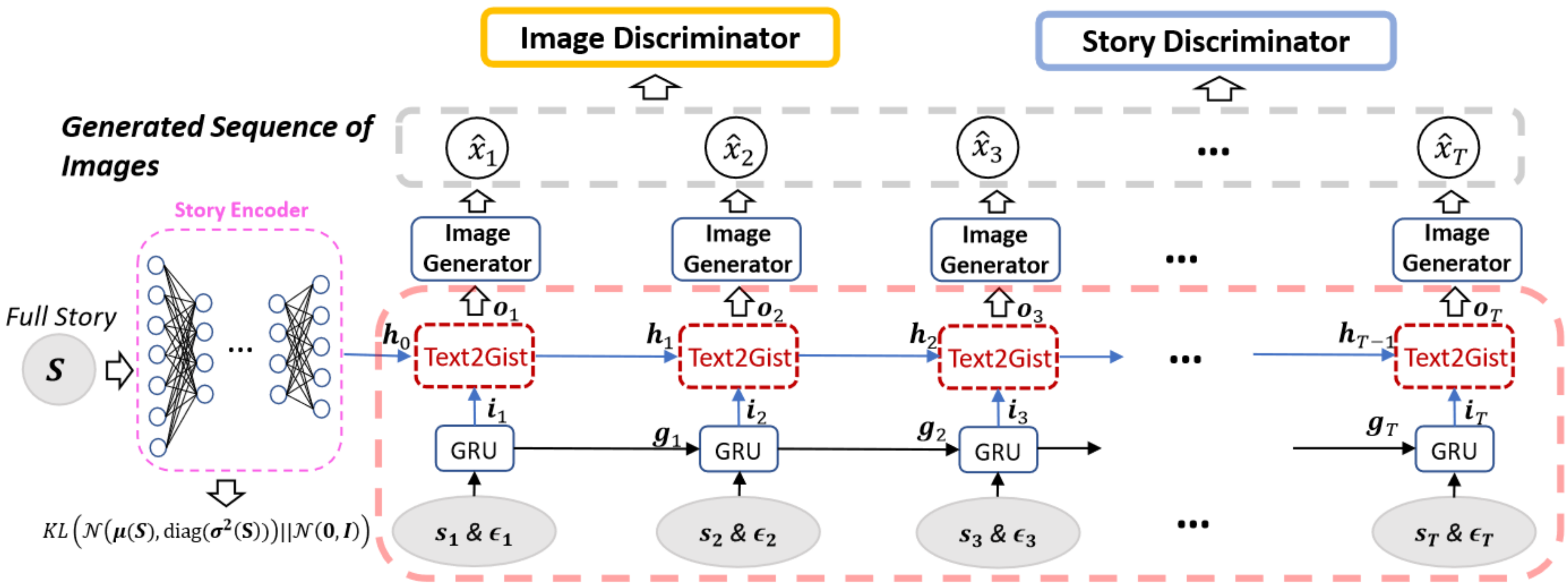
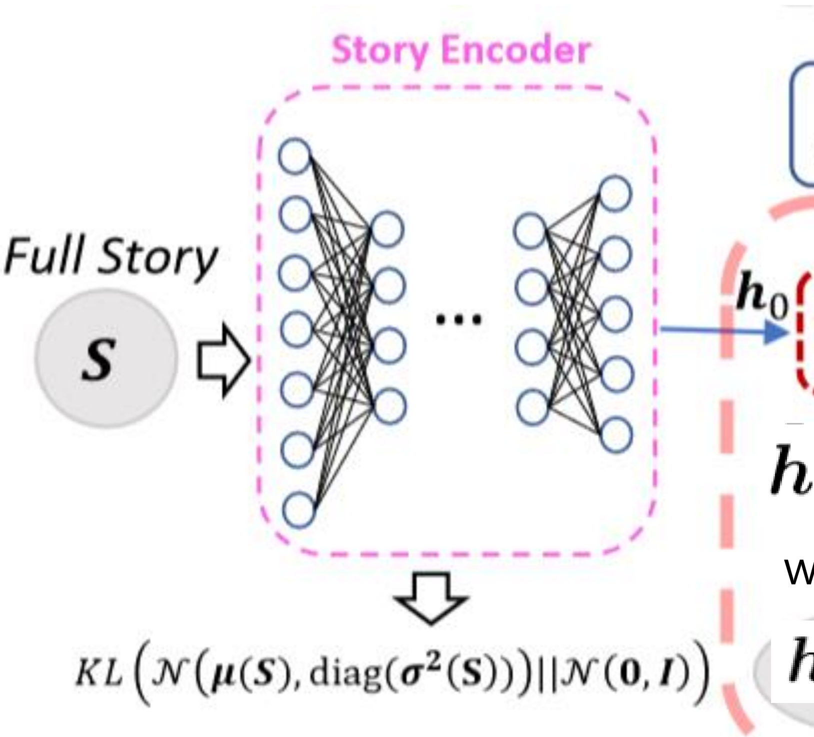


Image Discriminator
Story Discriminator
Generated Sequence of Images
$\hat{x}_1$
$\hat{x}_2$
$\hat{x}_3$
$\hat{x}_T$
Story Encoder
Image Generator
Image Generator
Image Generator
Image Generator
Full Story
S
h_0
h_1
h_2
h_{T-1}
o_1
o_2
o_3
o_T
Text2Gist
Text2Gist
Text2Gist
Text2Gist
i_1
i_2
i_3
i_T
g_1
g_2
g_T
GRU
GRU
GRU
GRU
$KL\left(\mathcal{N}(\boldsymbol{\mu}(\boldsymbol{S}), \mathrm{diag}(\boldsymbol{\sigma}^2(\boldsymbol{S})))||\mathcal{N}(\mathbf{0}, \boldsymbol{I})\right)$
s_1 & ϵ_1
s_2 & ϵ_2
s_3 & ϵ_3
s_T & ϵ_T

StoryGAN – Story Encoder



$$S = [\boldsymbol{s}_1, \boldsymbol{s}_2, \cdots, \boldsymbol{s}_T]$$

E( )

$$\boldsymbol{h}_0$$

$$\boldsymbol{h}_0 \sim E(\boldsymbol{S}) = \mathcal{N}(\boldsymbol{\mu}(\boldsymbol{S}), \boldsymbol{\Sigma}(\boldsymbol{S}))$$

with reparameterization trick

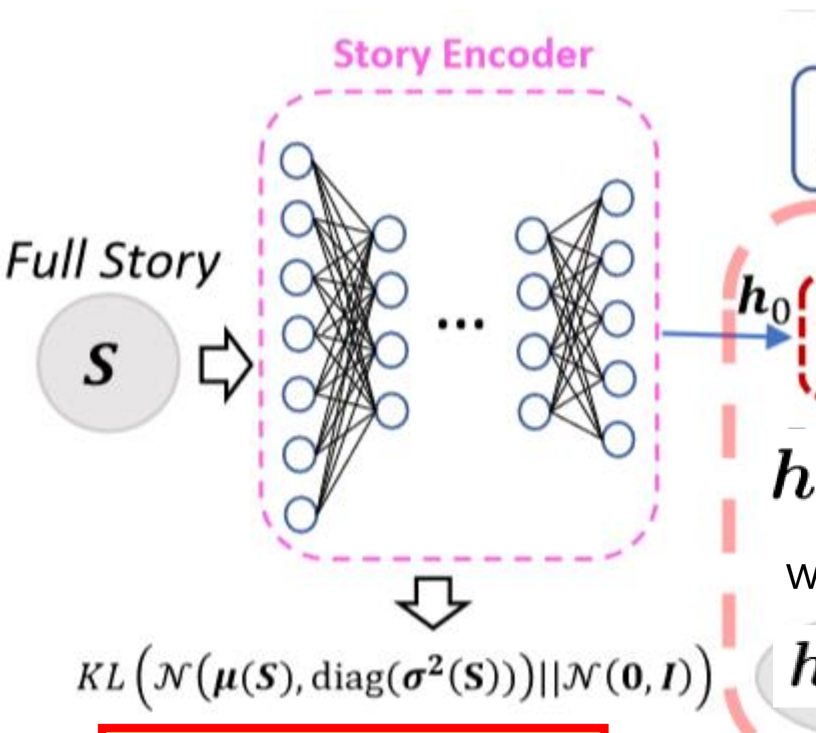
$$\boldsymbol{h}_0 = \boldsymbol{\mu}(\boldsymbol{S}) + \boldsymbol{\sigma}^2(\boldsymbol{S})^{\frac{1}{2}} \odot \boldsymbol{\epsilon}_S$$

$$\boldsymbol{\epsilon}_S \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})$$

leading to a compact, semantic **representation** of S
adding **randomness** to the generation process

$$\mathcal{L}_{KL} = KL\left(\mathcal{N}\left(\boldsymbol{\mu}(\boldsymbol{S}), \mathrm{diag}(\boldsymbol{\sigma}^2(\boldsymbol{S}))\right) \| \mathcal{N}(\boldsymbol{0}, \boldsymbol{I})\right)$$

StoryGAN – Story Encoder



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$$\boldsymbol{\epsilon}_S \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$$

add the regularization term in

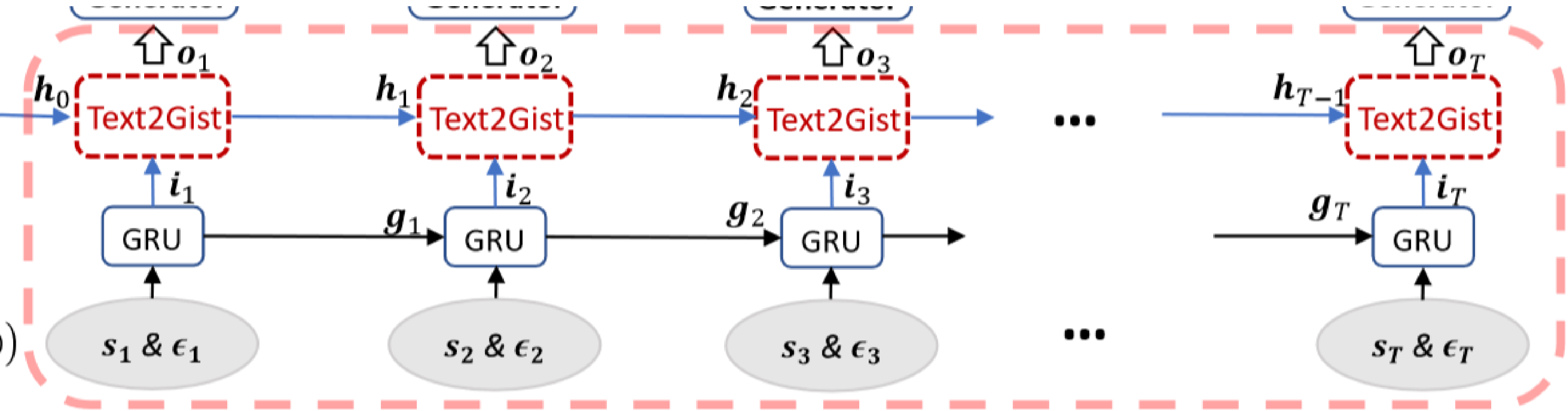
H. Zhang, T. Xu, H. Li, S. Zhang, X. Huang, X. Wang, and D. Metaxas. Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In ICCV, 2017. 1, 2, 3, 4, 6

le semantic **representation** of S

ac the generation process

$$\mathcal{L}_{KL} = KL\left(\mathcal{N}\left(\boldsymbol{\mu}(\boldsymbol{S}), \mathrm{diag}(\boldsymbol{\sigma}^2(\boldsymbol{S}))\right) || \mathcal{N}(\mathbf{0}, \boldsymbol{I})\right)$$

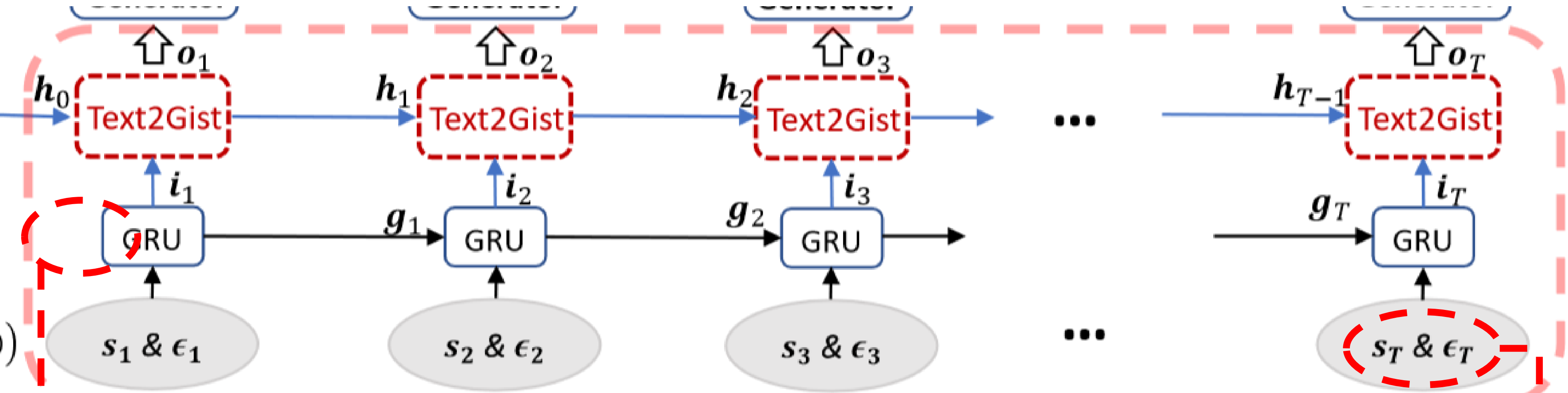
StoryGAN – Context Encoder



- how to update the **contextual information** to effectively capture background changes
- how to combine **new inputs** and **random noise** when generating each image, to visualize the change of characters, which may shift dramatically

-> **RNN based Context Encoder**

StoryGAN – Context Encoder



randomly sampled isometric Gaussian distribution

- GRU + Text2Gist

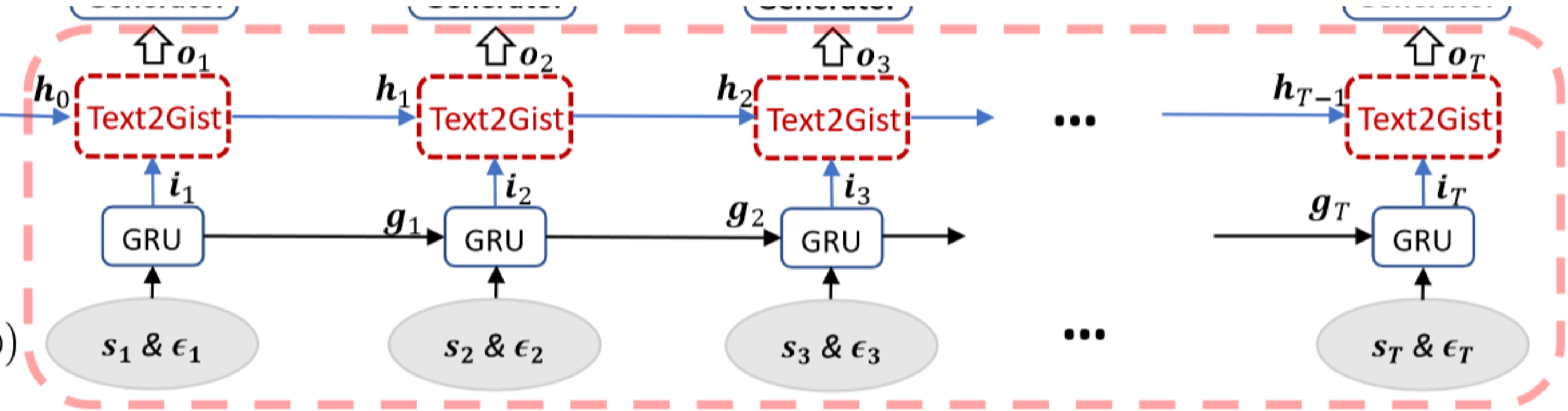
concatenation of sentence and isometric Gaussian noise

$$i_t, g_t = \mathrm{GRU}(s_t, \epsilon_t, g_{t-1}),$$

$$o_t, h_t = \mathrm{Text2Gist}(i_t, h_{t-1}).$$

"Gist" vector: combines all the global and local context information

StoryGAN – Context Encoder



update gate

decide how much information from the previous step should be kept

reset gate

determine what to forget from h

$$z_t = \sigma_z \left(\boldsymbol{W}_z \boldsymbol{i}_t + \boldsymbol{U}_t \boldsymbol{h}_{t-1} + \boldsymbol{b}_z \right),$$

$$r_t = \sigma_r \left(\boldsymbol{W}_r \boldsymbol{i}_t + \boldsymbol{U}_r \boldsymbol{h}_{t-1} + \boldsymbol{b}_r \right),$$

$$\boldsymbol{h}_t = (\boldsymbol{1} - \boldsymbol{z}_t) \odot \boldsymbol{h}_{t-1} + \boldsymbol{z}_t \odot \sigma_h \left(\boldsymbol{W}_h \boldsymbol{i}_t + \boldsymbol{U}_h (\boldsymbol{r}_t \odot \boldsymbol{h}_{t-1}) + \boldsymbol{b}_h \right),$$

$$\boldsymbol{o}_t = \text{Filter}(\boldsymbol{i}_t) * \boldsymbol{h}_t,$$

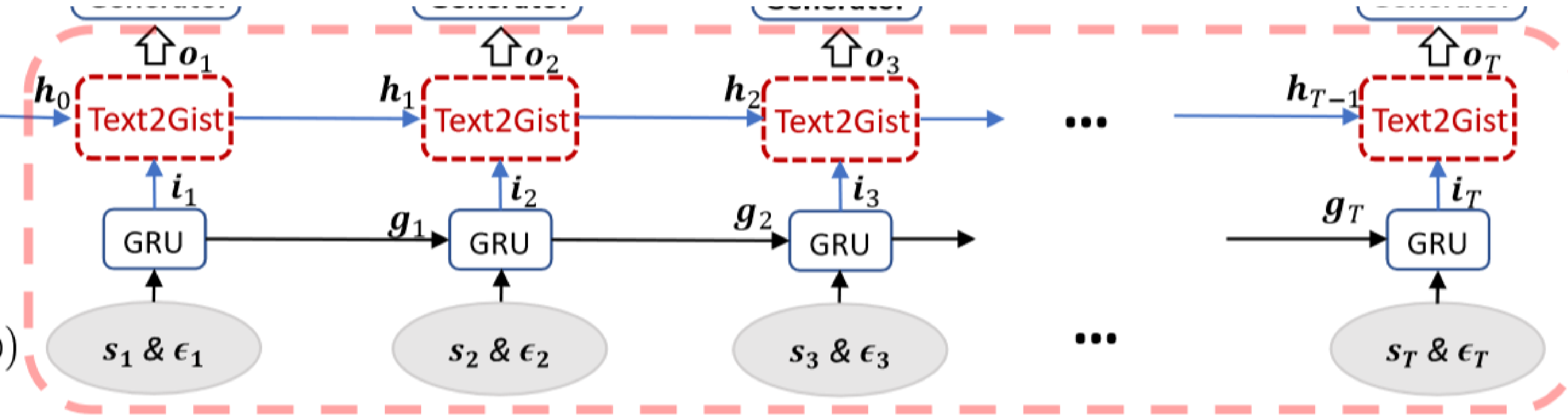
Convolution

Filter(): transforms vector i to a multi-channel filter

1D filter

$\boxed{C_{out} \times 1 \times 1 \times \text{len}(\boldsymbol{h}_t)}$

StoryGAN – Context Encoder



update gate

decide how much information from the previous step should be kept

Convolution

Filter(): transforms vector i_t to a multi-channel filter $\boxed{C_{out} \times 1 \times 1 \times \text{len}(\boldsymbol{h}_t)}$
1D filter

i_t: from sentence
h_t: from story

infuse the global contextual information from h_t and local formation from i_t
help s_t to pick out the important part from the story

reset gate

determine what to forget from h

$$\boldsymbol{o}_t = \text{Filter}(\boldsymbol{i}_t) * \boldsymbol{h}_t,$$

StoryGAN – Discriminators

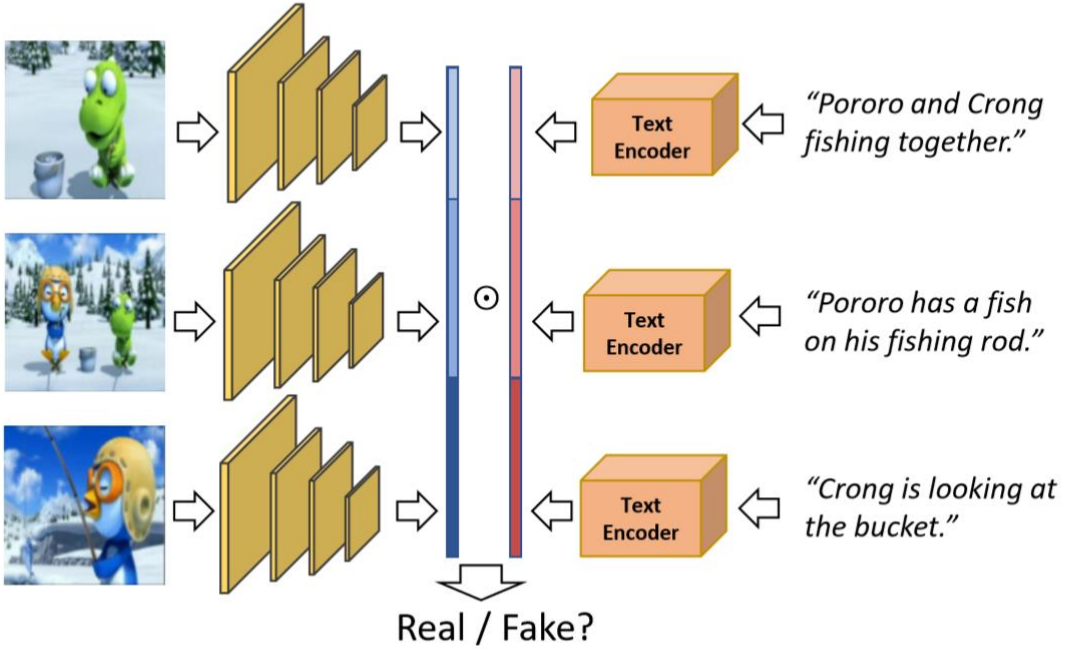
Image Discriminator

$$\{\boldsymbol{s}_t, \boldsymbol{h}_0, \hat{\boldsymbol{x}}_t\} \Longleftrightarrow \{\boldsymbol{s}_t, \boldsymbol{h}_0, \boldsymbol{x}_t\}$$

- the **same sentence** can have a significantly **different generated image** depending on the **context**,
- so it is important to give the **encoded context information** to the **discriminator**

Story Discriminator

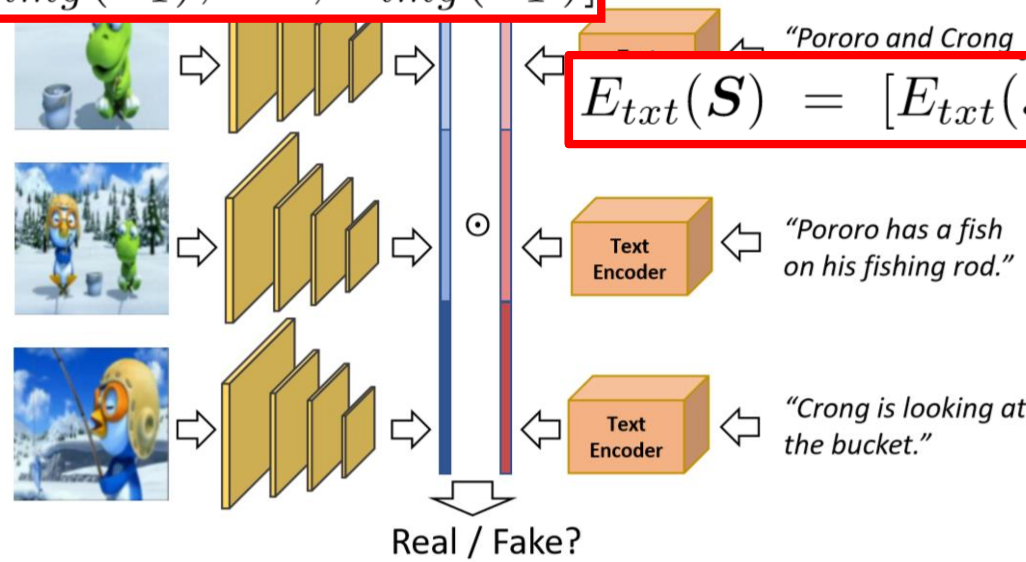
- enforce the global consistency of the generated image sequence given story S



StoryGAN – Discriminators

$$E_{img}(\boldsymbol{X}) \ = [E_{img}(\boldsymbol{x}_1), \cdots, E_{img}(\boldsymbol{x}_T)]$$

$$E_{txt}(\boldsymbol{S}) \ = \ [E_{txt}(\boldsymbol{s}_1), \cdots, E_{txt}(\boldsymbol{s}_T)]$$



$$D_S = \sigma\left(\boldsymbol{w}^\intercal\left(E_{img}(\boldsymbol{X}) \odot E_{txt}(\boldsymbol{S})\right) + b\right)$$

By **pairing each sentence and image**, the story discriminator can consider both **local matching** and **global consistency jointly**

StoryGAN – Objective function

$$\min_{\boldsymbol{\theta}} \max_{\boldsymbol{\psi}_I, \boldsymbol{\psi}_S} \alpha \mathcal{L}_{Image} + \beta \mathcal{L}_{Story} + \mathcal{L}_{KL}$$

$$\begin{aligned} \mathcal{L}_{Image} = \textstyle\sum_{t=1}^{T} \big(& \mathbb{E}_{(\boldsymbol{x}_t, \boldsymbol{s}_t)} \left[\log D_I(\boldsymbol{x}_t, \boldsymbol{s}_t, \boldsymbol{h}_0; \boldsymbol{\psi}_I) \right] \\ & + \mathbb{E}_{(\boldsymbol{\epsilon}_t, \boldsymbol{s}_t)} \left[\log(1 - D_I(G(\boldsymbol{\epsilon}_t, \boldsymbol{s}_t; \boldsymbol{\theta}), \boldsymbol{s}_t, \boldsymbol{h}_0; \boldsymbol{\psi}_I)) \right] \big) \end{aligned}$$

$$\begin{aligned} \mathcal{L}_{Story} = \; & \mathbb{E}_{(\boldsymbol{X}, \boldsymbol{S})} \left[\log D_S(\boldsymbol{X}, \boldsymbol{S}; \boldsymbol{\psi}_S) \right] \\ & + \mathbb{E}_{(\boldsymbol{\epsilon}, \boldsymbol{S})} \left[\log(1 - D_S([G(\boldsymbol{\epsilon}_t, \boldsymbol{s}_t; \boldsymbol{\theta})]_{t=1}^{T}), \boldsymbol{S}; \boldsymbol{\psi}_S)) \right] \end{aligned}$$

StoryGAN – Algorithm

Algorithm 1 Training Procedure of StoryGAN

Input: Encoded sentence vectors $\boldsymbol{S}_n = [\boldsymbol{s}_{n1}, \boldsymbol{s}_{n2}, \cdots, \boldsymbol{s}_{nT}]$ and corresponding images $\boldsymbol{X}_n = [\boldsymbol{x}_{n1}, \cdots, \boldsymbol{x}_{nT}]$ for $n = 1, \cdots, N$.
Output: Generator parameters $\boldsymbol{\theta}$ and discriminator parameters $\boldsymbol{\psi}_I$ and $\boldsymbol{\psi}_S$.

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for $iter = 1$ to max_iter **do**
  for $iter_I$ = 1 to k_I **do**
    Sample a mini-batch of story-sentence pairs $\{(\boldsymbol{s}_t, \boldsymbol{S}, \boldsymbol{x}_t)\}$ from the training set.
    Compute $\boldsymbol{h}_0$ as the initialization of the Text2Gist layer and the KL regularization term as Eq. (1).
    Generate a single output image $\hat{x}$.
    Update $\boldsymbol{\psi}_I$ and $\boldsymbol{\theta}$.
  end for
  for $iter_S$ = 1 to k_S **do**
    Sample a mini-batch of story-image pair $\{(\boldsymbol{S}, \boldsymbol{X})\}$ from training set.
    Compute $\boldsymbol{h}_0$ and update $\boldsymbol{h}_t$ at each time step t
    Generate image sequence $\hat{\boldsymbol{X}}$.
    Update $\boldsymbol{\psi}_S$ and $\boldsymbol{\theta}$.
  end for
end for

image

story

- using **Adam** optimizer
- **different mini-batch sizes** for image and story discriminators

StoryGAN – Experiments

Video generation result is too blurry and not comparable to StoryGAN

- our comparisons are mainly to ablated versions of our proposed model
- for a fair comparison, use same image generator, context encoder and discriminators

ImageGAN: ImageGAN follows the work in [28, 36] and does not use the story discriminator, story encoder and Context Encoder. Each image is generated independently. However, for a reasonable comparison, we concatenate s_t, encoded story S and a noise term as input. Otherwise, the model fails on the task. This is the simplest version of StoryGAN.

SVFN: In "Story Visualization by Filter Network" (SVFN), the concatenation in SVC is replaced by a filter network. Sentence s_t is transformed into a filter and convolved with the encoded story. Specifically, the image generator input is $o_t = \text{Filter}(i_t) * h_0$ instead of Eq. 7.

SVC: In "Story Visualization by Concatenation" (SVC), the Text2Gist cell in StoryGAN is replaced by simple concatenation of the encoded story and description feature vectors [31]. Compared to ImageGAN, SVC includes the additional story discriminator, and is visualized in Figure 4.

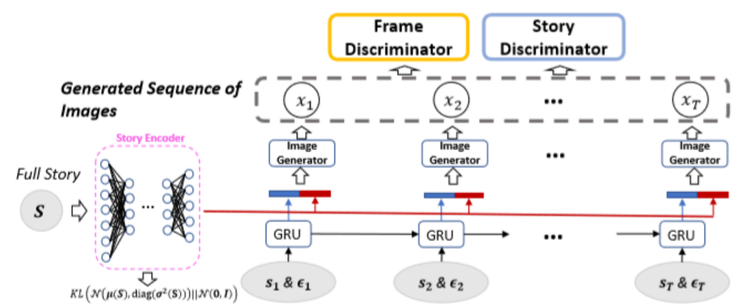


Figure 4: The framework of the baseline model SVC, where the story and individual sentence are concatenated to form the input.

StoryGAN – Experiments with CLEVR-SV

CLEVR -> CLEVR-SV

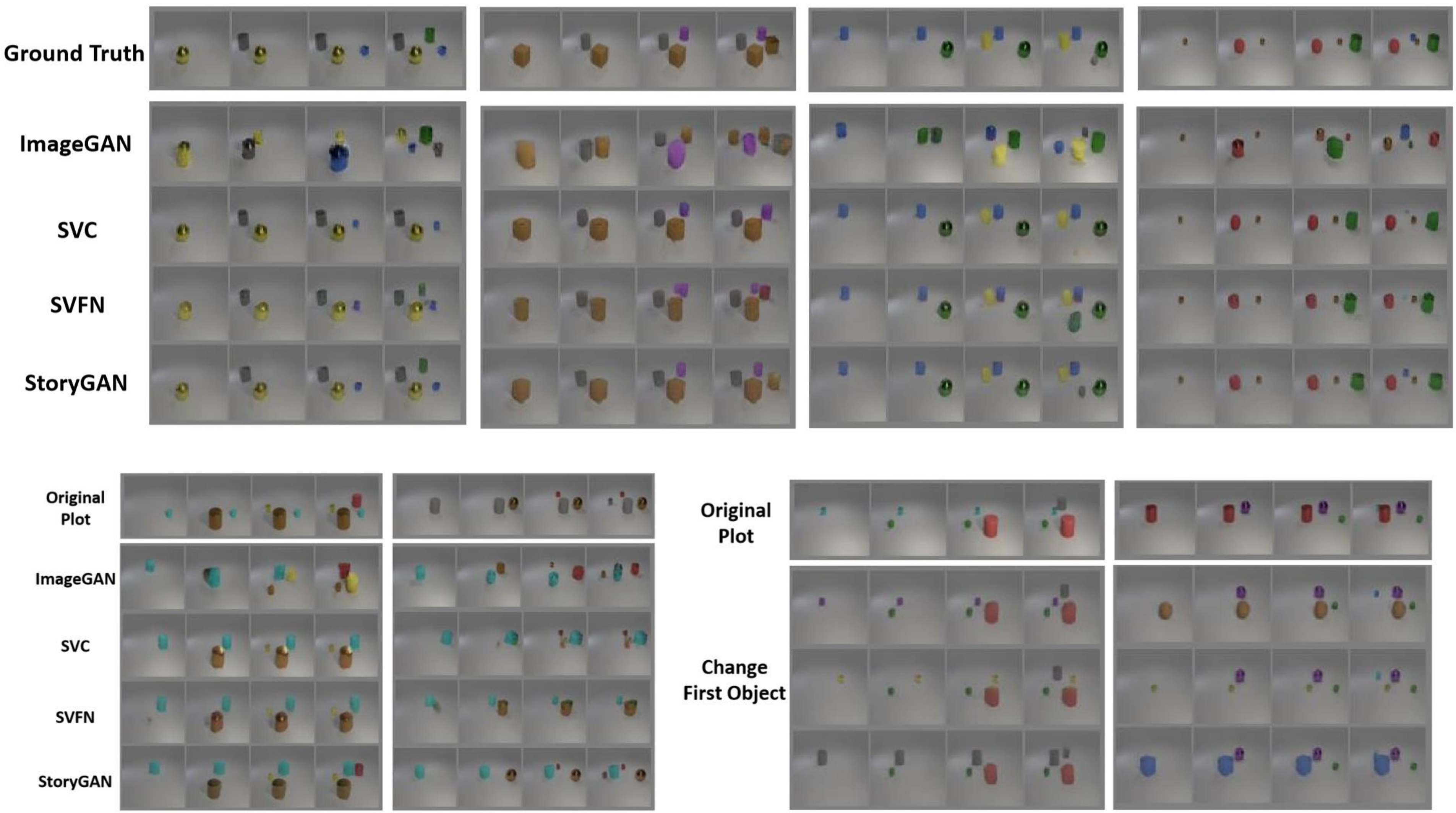
- the **maximum number of objects** in one story is limited to four.
- objects are made of **metallic/rubber** with **eight different colors** and **two different sizes**.
- the **object shape** can be cylinder, cube or sphere.
- the object is **added one at a time**, resulting in a **four-image** sequence per story.

StoryGAN generates more feasible images than others

- **Text2Gist** cell tracks the progress of story
- **story and image discriminators** keep the consistency of objects in the generation process
- using the **Story Encoder** to initialize the Text2Gist cell gives better result on first generated image

	ImageGAN [28]	SVC	SVFN	StoryGAN
SSIM	0.596	0.641	0.654	0.672

StoryGAN – Experiments with CLEVR-SV

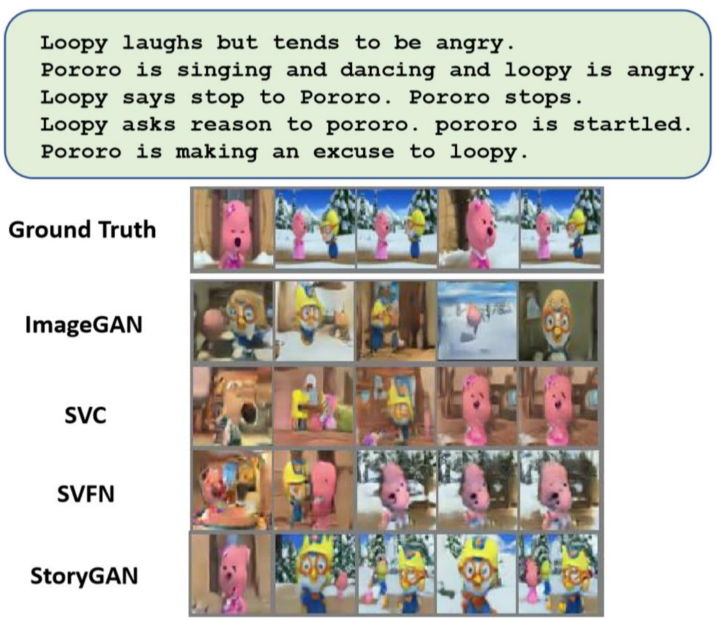


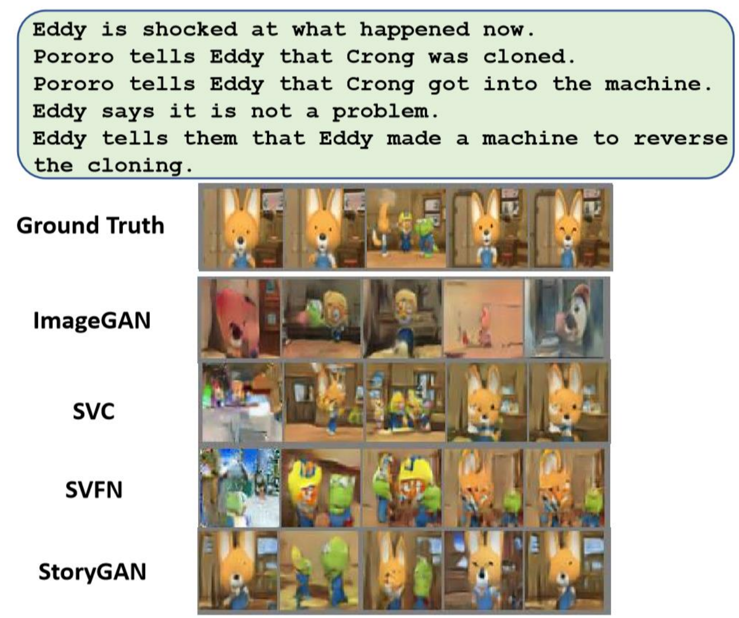
StoryGAN – Experiments with Pororo-SV

Pororo -> Pororo-SV

- randomly pick out one frame during training as the real image sample
- five continuous images form a single story

StoryGAN's **first image** has a much **higher quality** than other baselines -> **Story Encoder**





StoryGAN – Experiments

`Input Story:` *c1 and c2 are standing in the snow. c1 tells a story to c3. c3 wants to joint c1 and c2. c1 continuous to talk. c1 looks down. They suddenly noticed that there is something lying on the snow.*

Method	ImageGAN	SVC	SVFN	StoryGAN
Rank	$2.91_{\pm 0.05}$	$2.42_{\pm 0.04}$	$2.77_{\pm 0.04}$	$1.94_{\pm 0.05}$

	StoryGAN vs ImageGAN		
Choice (%)	StoryGAN	ImageGAN	Tie
Visual Quality	74.17 ± 1.38	18.60 ± 1.38	7.23
Consistence	79.15 ± 1.27	15.28 ± 1.27	5.57
Relevance	78.08 ± 1.34	17.65 ± 1.34	4.27

Network Structure

Layer	Story Encoder
1	LINEAR-($128 \times T$, 128), BN, RELU
Layer	Context Encoder
1	LINEAR-(NOISEDIM + TEXTDIM, 128), BN, RELU
2	GRU-(128, 128)
3	Text2Gist-(128, 128)
Layer	Filter Network
1	LINEAR-(128, 1024), BN, TANH
2	RESHAPE(16, 1, 1, 64)
Layer	Image Generator
1	CONV-(C512, K3, S1, P1), BN, RELU
2	UPSAMPLE-(2,2)
3	CONV-(C256, K3, S1, P1), BN, RELU
4	UPSAMPLE-(2,2)
5	CONV-(C128, K3, S1, P1), BN, RELU
6	UPSAMPLE-(2,2)
7	CONV-(C64, K3, S1, P1), BN, RELU
8	UPSAMPLE-(2,2)
9	CONV-(C3, K3, S1, P1), BN, TANH
Layer	Image Discriminator
1	CONV-(C64, K4, S2, P1), BN, LEAKY RELU
2	CONV-(C128, K4, S2, P1), BN, LEAKY RELU
3	CONV-(C256, K4, S2, P1), BN, LEAKY RELU
4	CONV-(C512, K4, S2, P1),BN, LEAKY RELU
5*	CONV-(C512, K3, S1, P1), BN, LEAKY RELU
6	CONV-(C1, K4, S4, P0), SIGMOID
Layer	Story Discriminator (Image Encoder)
1	CONV-(C64, K4, S2, P1), BN, LEAKY RELU
2	CONV-(C128, K4, S2, P1), BN, LEAKY RELU
3	CONV-(C256, K4, S2, P1), BN, LEAKY RELU
4	CONV-(C512, K4, S2, P1),BN, LEAKY RELU
5	CONV-(C32, K4, S2, P1),BN, CONCAT
6	RESHAPE-(1, $32 \times 4 \times T$)
Layer	Story Discriminator (Text Encoder)
1	LINEAR-($128 \times T$, $32 \times 4 \times T$), BN