TISE: Bag of Metrics for Text-to-Image Synthesis Evaluation

Tan M. Dinh Rang Nguyen Binh-Son Hua

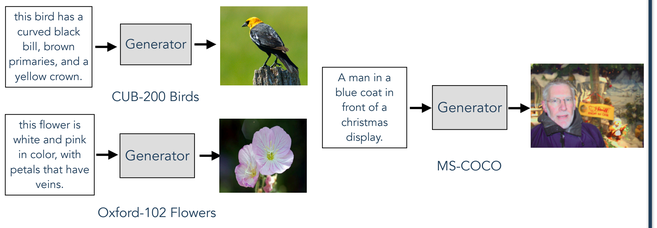
VinAI Research

SCAN ME

ECCV TEL AVIV 2022

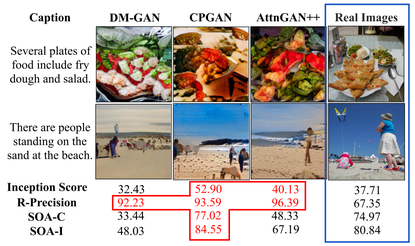
1 – Overview

Text-to-Image Synthesis (*)



Evaluation of Text-to-Image Models

Evaluating the text-to-image models is a challenging task!



But do not better quality than real images!

Better metric scores than real images

Contribution: We identify several pitfalls in the existing evaluation pipeline of text-to-image synthesis models, and propose a set of metrics combining the improved versions of existing metrics and new ones to form a unified evaluation toolbox, so-called **TISE**, for benchmarking text-to-images models fairly, robustly, and consistently.

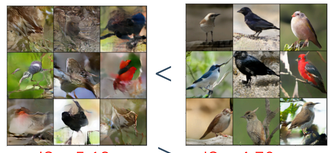
2 – Single-Object Text-to-Image Synthesis

Evaluation aspects

✦Image Realism
- Inception Score (IS) [1]
- Fréchet Inception Distance (FID) [2]

✦Text Relevance
- R-precision (RP) [3]

Inconsistent issue of IS and our IS*



IS = 5.12 > IS = 4.78

IS* = 13.05 < IS* = 15.13

Benchmark Results

Method	IS (↑)	IS* (↑)	FID (↓)	RP (↑)
GAN-INT-CLS	2.73	7.51	194.41	3.83
StackGAN++	4.10	12.69	27.40	13.57
AttnGAN	4.32	13.63	24.27	65.30
AttnGAN + CL	4.45	14.42	17.96	60.82
DM-GAN	4.68	15.00	15.52	76.25
DF-GAN	4.77	14.70	16.46	42.95
DM-GAN + CL	4.77	15.08	**14.57**	69.80
AttnGAN++ (ours)	**4.78**	**15.13**	15.01	**77.31**

Our AttnGAN++ is a strong baseline!

AttnGAN++ = AttnGAN + Spectral Normalization [5] + Tune with different hyperparameters

Inception score (IS)

Estimated by the pre-trained Inception-v3 classifier

$$\text{IS} = \exp(\mathbb{E}_x D_{KL}(p(y \mid x) \,\|\, p(y)))$$

where x is the generated image; y is the class label

Consideration:

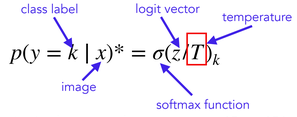
- The objects should be **distinct recognizable** (1) → $p(y \mid x)$ must have low entropy
- Having **diverse** number of object classes (2) → $p(y)$ must have high entropy

(1) + (2) → KL-divergence between $p(y)$ and $p(y \mid x)$ should be large

→ Higher value of IS is better

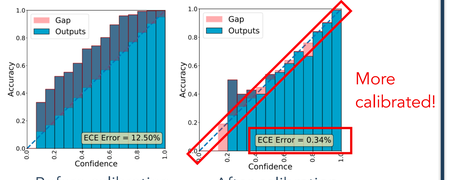
Improved IS (IS*): Calibrating Image Classifier

- Using temperature scaling [4] to calibrate the classifier



$$p(y = k \mid x)^* = \sigma(z_k / T)$$

- $p(y \mid x)^*$ is then used to compute IS → IS*



Before calibration After calibration

More calibrated!

3 – Multiple-Object Text-to-Image Synthesis

Demanding evaluation aspects

- Image Realism
- Text Relevance
- Object Accuracy
- Object Fidelity
- Positional Alignment
- Counting Alignment
- Paraphrase Robustness
- Explainable

Improved version of existing metrics

New metrics

Positional Alignment

- **Constructing evaluation data**
  - Define a set of positional words, called W
  - $D_w = \{(P_{wi}, Q_{wi})\}_{i=1}^{N_w}$ for each $w \in W$

matched caption mismatched caption

P_{wi} → (i) replace w with its antonym; (ii) keeping other words → Q_{wi}

P_{wi}: A man is **in front of** the blue car

Q_{wi}: A man is **behind** the blue car

- **Positional Alignment (PA) metric**
  - Use T2I model to generate image R_{wi} from P_{wi}
  - Use R_{wi} to query input caption from $\{P_{wi}, Q_{wi}\}$
  - If P_{wi} is returned → success case

$$\text{PA} = \frac{1}{|W|} \sum_{w \in W} \frac{k_w}{N_w}$$

positional alignment quality with word w

k_w: the number of success cases

N_w: the number of captions having word w

$|W|$: the total number of positional words

Ranking Score

$$\text{RS} = \frac{1}{2}(\#\text{IS}^* + \#\text{FID}) + \frac{1}{2}(\#\text{O-IS} + \#\text{O-FID}) + \frac{1}{2}(\#\text{SOA-I} + \#\text{SOA-C}) + \#\text{PA} + \#\text{CA} + \#\text{RP}$$

$\#(metric) \in \{1..N\}$: ranking of the method with the $metric$

N: the number of considered methods

Existing metrics: Improved Version

Current problems: overfitting

- **RP** [3]: Training T2I models and computing RP used the same encoder module (DAMSM)
- **SOA** [6]: CPGAN and SOA used the same pre-trained YOLO-v3

Solution: Replace them by other independent, better models

- **RP** [3]: DAMSM → CLIP
- **SOA** [6]: YOLO-v3 → Mask-RCNN

Object Fidelity

- Crop the object set from generated images
  - Use off-the-shelf object detector
- Compute IS* on the cropped objects → **O-IS**
- Compute FID on the cropped objects → **O-FID**

Counting Alignment

- **Constructing evaluation data**

$D = \{(t_i, c_i)\}_{i=1}^{1000}$

caption ground truth (GT) counting

- **Counting Alignment (CA) metric**
  - Use T2I model to generate the image from caption
  - Count the number of objects in generated image
    - ➡ Use an off-the-shelf object counter
  - Measure error(GT count, predicted count)

$$\text{CA} = \frac{1}{|D|} \sum_{i=1}^{|D|} \sqrt{\frac{1}{N_{ic}} \sum_{j=1}^{N_{ic}} (\hat{c}_{ij} - c_{ij})^2}$$

c_{ij}, $\hat{c}_{ij}$: GT and predicted count in image i for object class j

N_{ic}: number of GT object types in image i

Benchmark Results

Method	Image Realism	Text Relevance	Object Accuracy	Object Fidelity	Counting Alignment	Positional Alignment
GAN-CLS	1.0	2.0	1.0	1.0	1.0	1.0
StackGAN	2.5	1.0	2.0	2.0	2.0	2.0
AttnGAN	5.0	5.0	5.5	4.5	6.0	3.0
DM-GAN	6.5	7.0	7.0	7.5	8.0	5.0
CPGAN	7.5	8.0	**10.0**	7.5	4.0	6.0
DF-GAN	7.0	3.0	4.0	8.5	5.0	4.0
AttnGAN + CL	6.5	6.0	5.5	5.0	7.0	7.0
DM-GAN + CL	8.5	9.0	8.0	7.0	9.0	**10.0**
DALLE-mini (zero-shot)	2.5	4.0	3.0	3.0	3.0	8.0
AttnGAN++ (Ours)	**9.0**	**10.0**	9.0	**9.0**	**10.0**	9.0
Real Images	*10.0*	*11.0*	*11.0*	*11.0*	*11.0*	*11.0*

Ranking scores for each evaluation aspect

4 – Conclusion

✓ We provide the comprehensive benchmarks for T2I synthesis models for both single- and multi- object case.

✓ We propose the improved version of existing metrics + new ones to evaluate many vital evaluation aspects.

✓ We release a Python assessment toolbox called **TISE** to advocate fair comparisons and reproducible results for future T2I synthesis research.

Our TISE toobox is **available!**

https://github.com/VinAIResearch/tise-toolbox

References

[1] Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., Chen, X.: Improved techniques for training gans. In: NeurIPS (2016)

[2] Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B., Hochreiter, S.: Gans trained by a two time-scale update rule converge to a local nash equilibrium. In: NeurIPS (2017)

[3] Xu, T., Zhang, P., Huang, Q., Zhang, H., Gan, Z., Huang, X., He, X.: Attngan: Fine-grained text to image generation with attentional generative adversarial net- works. In: CVPR (2018)

[4] Guo, C., Pleiss, G., Sun, Y., Weinberger, K.Q.: On calibration of modern neural networks. In: ICML (2017)

[5] Miyato, T., Kataoka, T., Koyama, M., Yoshida, Y.: Spectral normalization for generative adversarial networks. In: ICLR (2018)

[6] Hinz, T., Heinrich, S., Wermter, S.: Semantic object accuracy for generative text- to-image synthesis. In: TPAMI 2020

[*] Source: Example captions and images are randomly taken from each dataset.