Character-Centric Story Visualization via Visual Planning and Token Alignment

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Paper presentation for Natural Language Processing course by

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Introduction

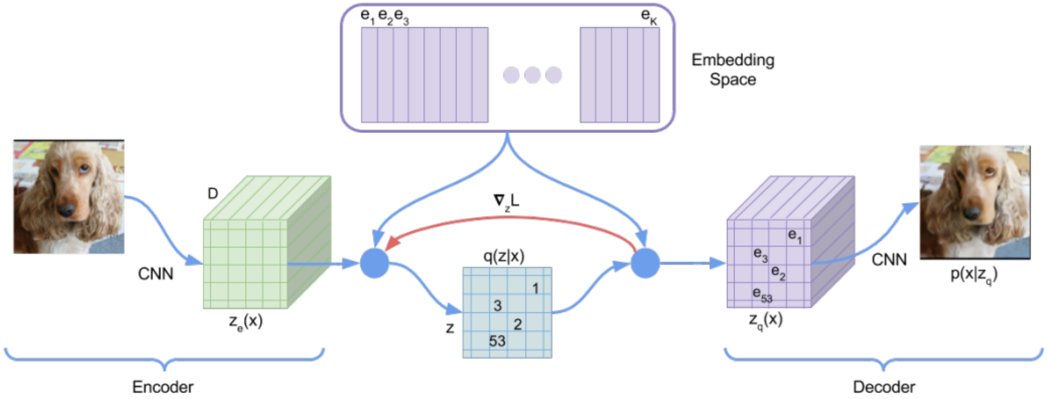
This paper proposes Character-Centric Story Visualization via Visual Planning (VP-CSV), a model that improves story visualization.

Previous works involve text-to-image generation and include:

- GAN-based (Generative Adversarial Nets) models
- DALL-E (Ramesh et al., 2021);
- VQ-VAE-LM that combines VQ-VAE (Van Den Oord et al., 2017) with a text-to-visual-token transformer (Ramesh et al., 2021; Yan et al., 2021)

Vector Quantised Variational AutoEncoder

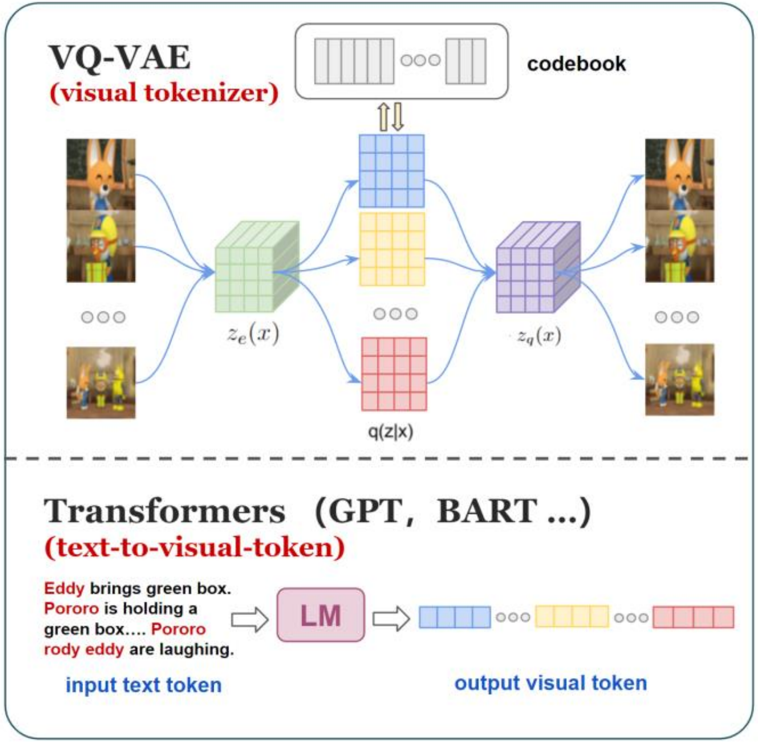
- VQ-VAE encodes images into discrete latent representations.
- Firstly, the images are encoded into continuous latent representations, then each of them is replaced with the closest embedding from the codebook.
- In this way the discrete representations are built and then fed into the decoder.



$$\mathcal{L} = \underbrace{\|x - z_q(x)\|_2^2}_{\mathcal{L}_{\text{recon}}} + \underbrace{\|sg[z_e(x)] - e\|_2^2}_{\mathcal{L}_{\text{codebook}}} + \underbrace{\beta\|sg[e] - z_e(x)\|_2^2}_{\mathcal{L}_{\text{commit}}}$$

1 image from Neural Discrete Representation Learning, van den Oord et al., 2018

VQ-VAE integrated with Language Model: VQ-VAE-LM



- As the first step, VQ-VAE is trained separately
- LM takes input text sentences
- LM is trained using MLE with the visual tokens from the VQ-VAE encoder as targets.
- Visual tokens from LM are fed into the VQ-VAE decoder.
- Images are reconstructed from the decoder.
- The two models are trained from scratch by the authors.

VP-CSV: Visual Planning based Character-centric Story Visualization

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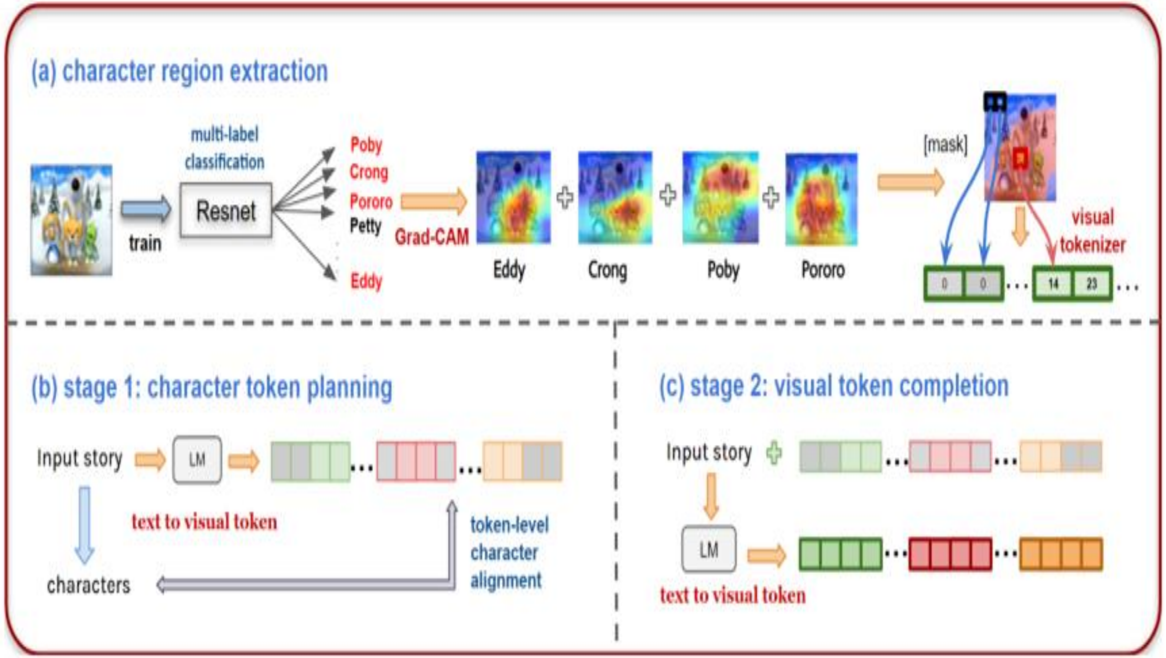
VP-CSV enhances VQ-VAE-LM with a two-stage module.



(a) Character region extraction:
Train a multi-label classifier to identify the character regions

(b) Plan module:
Train GPT-2 to generate the planned character token prepared by the previous stage with a training loss of: $L\theta = -\log p(r|s, \theta)$

(c) Completion module:
The model is trained to generate the background visual tokens z having a loss of $L\theta = -\log p(z|s, r, \theta)$

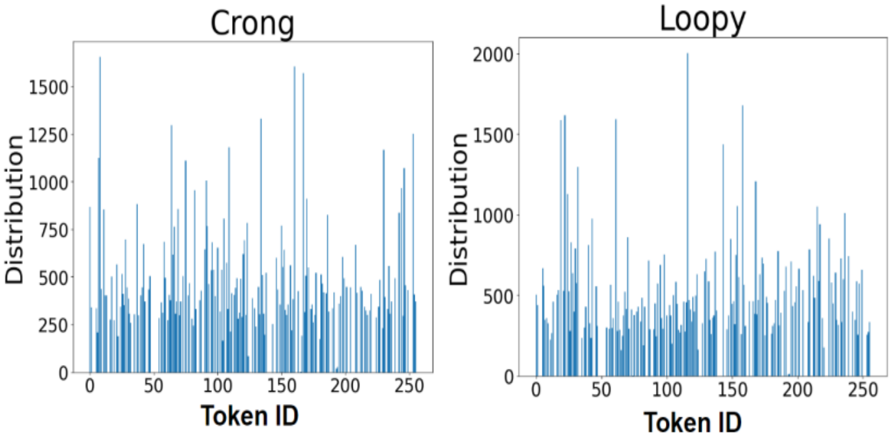
Token-level character alignment (TA)

The alignment process aims to match each character in the text with the corresponding visual token in the visual representation

- compute the visual token distribution for each character
- use a semantic loss to encourage the character-to-visual token alignment.
- calculate the semantic loss as:

$$\mathcal{L}^s(Q,\boldsymbol{p}) = -\log \sum_{\boldsymbol{z}\models Q} \prod_{\boldsymbol{z}^j\in P} p_j \prod_{\boldsymbol{z}^j\in N} (1-p_j)$$

The intuition of this objective is that if all characters' top visual tokens show up in the predicted images z (i.e. z |= Q), we increase the probability of tokens in P.



Experimental Setup

- The story-visualization dataset is Pororo-SV
- Each story is composed to 5 paragraphs
- Each paragraph is associated with an image.

Evaluation

Character preservation

- Character F1 score
- Frame Accuracy (Exact Match)

Image quality

- Frechet Inception Distance (FID)

Semantic alignment

- BLEU score
- R-precision

Human evaluation

- Visual Quality
- Character Preservation

Results (I)

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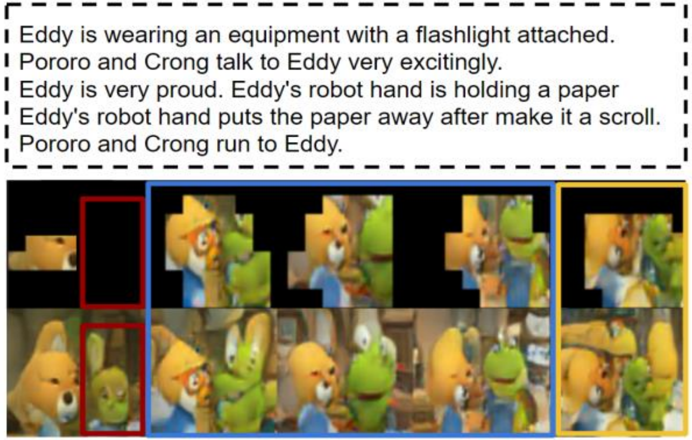
Method	Character F1	Frame Accuracy	FID↓	BLEU2/3	R-Precision
StoryGAN	18.59	9.34	158.06	3.24/1.22	1.51 ± 0.15
CP-CSV	21.78	10.03	149.29	3.25/1.22	1.76 ± 0.04
DUCO-StoryGAN	38.01	13.97	96.51	3.68/1.34	3.56 ± 0.04
VLC-StoryGAN	43.02	17.36	84.96	3.80/1.44	3.28 ± 0.00
VQ-VAE-LM	49.90	19.42	66.56	4.04/1.65	5.72± 0.02
+ Visual Planning	52.97	23.00	69.54	4.32/1.76	6.39 ± 0.00
+ Token Alignment	53.34	22.92	**63.34**	4.40/1.77	6.37 ± 0.00
VP-CSV	**56.84**	**25.87**	65.51	**4.45/1.80**	**6.95 ± 0.00**

- GAN-based models are outperformed by VQ-VAE-LM-based models

Metrics	VLC. vs VQ-VAE-LM		
	VLC.	VQ-VAE-LM	Tie
Visual	27.45	**62.75***	9.80
Character	37.25	**41.18**	21.57
	VQ-VAE-LM vs + TA		
	VQ-VAE-LM	+ TA	Tie
Visual	33.33	**42.10**	24.56
Character	38.59	**40.35**	21.06
	VQ-VAE-LM vs VP-CSV		
	VQ-VAE-LM	VP-CSV	Tie
Visual	34.51	**44.25**	21.24
Character	33.17	**52.21***	14.62

- Adding Token Alignment to VQ-VAE-LM produces better Visual Quality than VQ-VAE-LM alone according both automatic metric and human evaluation
- Overall VP-CSV model produces the best scores

Results (II)

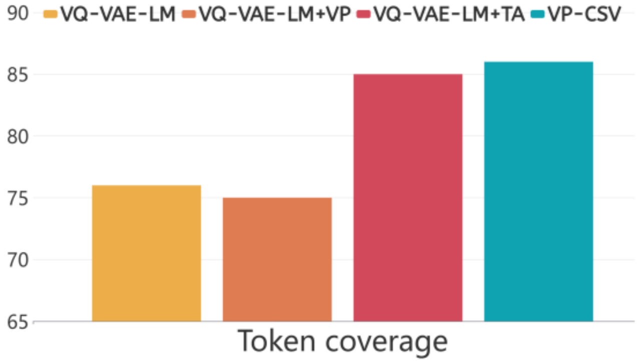


Analysis on character alignment

- Models with TA outperform the others

Analysis on visual planning

- Blue square represents correct character identification with background masked
- Red squares highlight errors of the completion module in generating non-existing characters
- Orange square underlines poor image quality



Conclusion

- In this paper, visual planning and character token alignment was proposed to improve character preservation and visual quality.
- Results show that the VP-CSV model outperforms all other models.
- Future research can aim at integrating actions and relationships among characters.

LIMITATIONS

- It is hard to generate every individual in the image.
- The image quality is still low.
- It is still hard to see the clear action performed by each character.

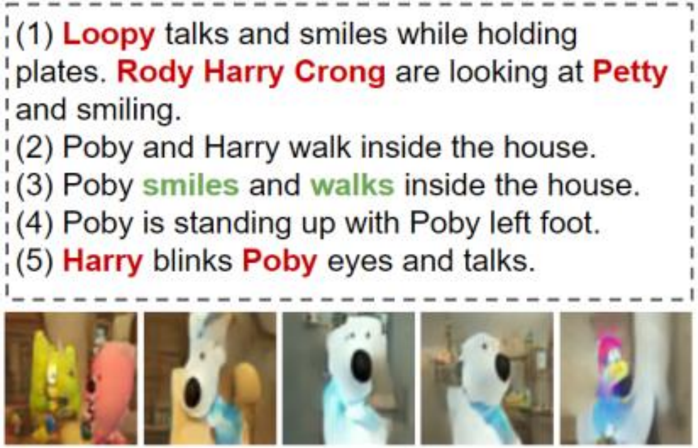


Figure 8: Limitation of generation image sequence.