I2AM: Interpreting Image-to-Image Latent Diffusion Models via Attribution Maps

IJCAI 2024 workshop on Explainable Artificial Intelligence (XAI)

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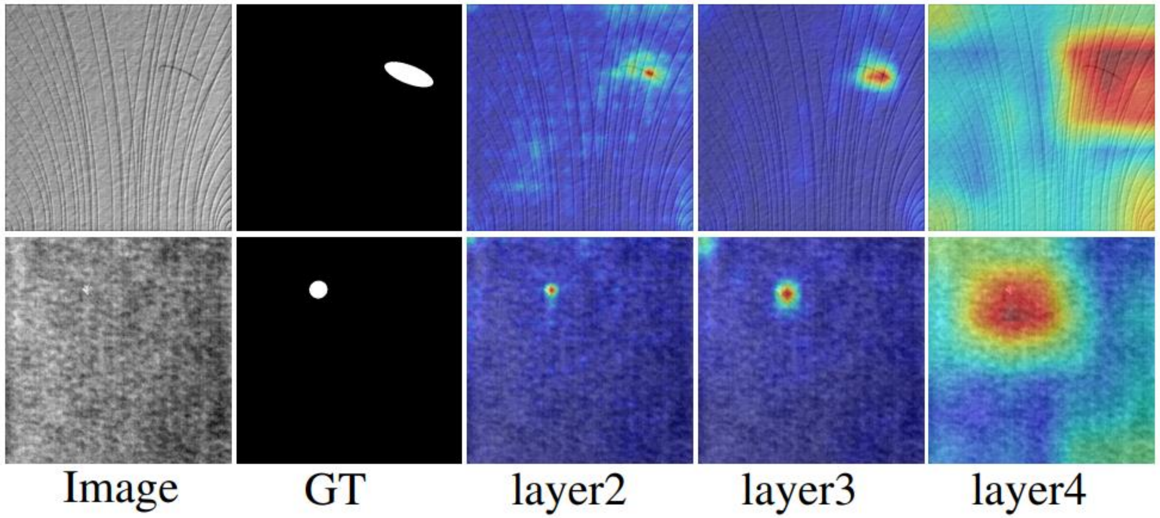
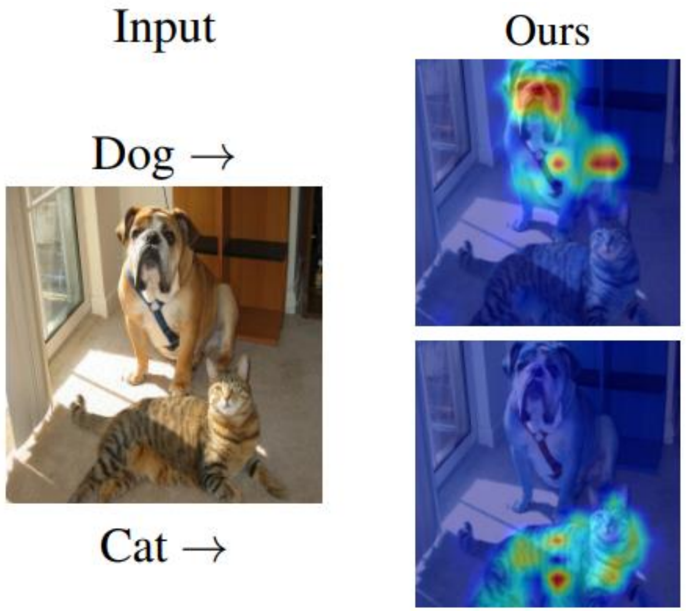
1 Motivation

- Interpreting models using attribution map
  - Explainability is essential for enhancing trust and accountability by making AI decision-making transparent
  - Earlier efforts leveraged CNN-based image classifiers to highlight areas of interest
  - Recently, the emergence of transformers has shifted the focus towards using **attention**



CNN-based: class activation map [1]



Transformer-based: attention map [2]

1 Motivation

- Interpreting latent diffusion models **(LDMs)**
  - Analysis of text-to-image LDMs using attribution maps have advanced recently
  - There is currently a shortage of studies on image-to-image **(I2I)** LDM

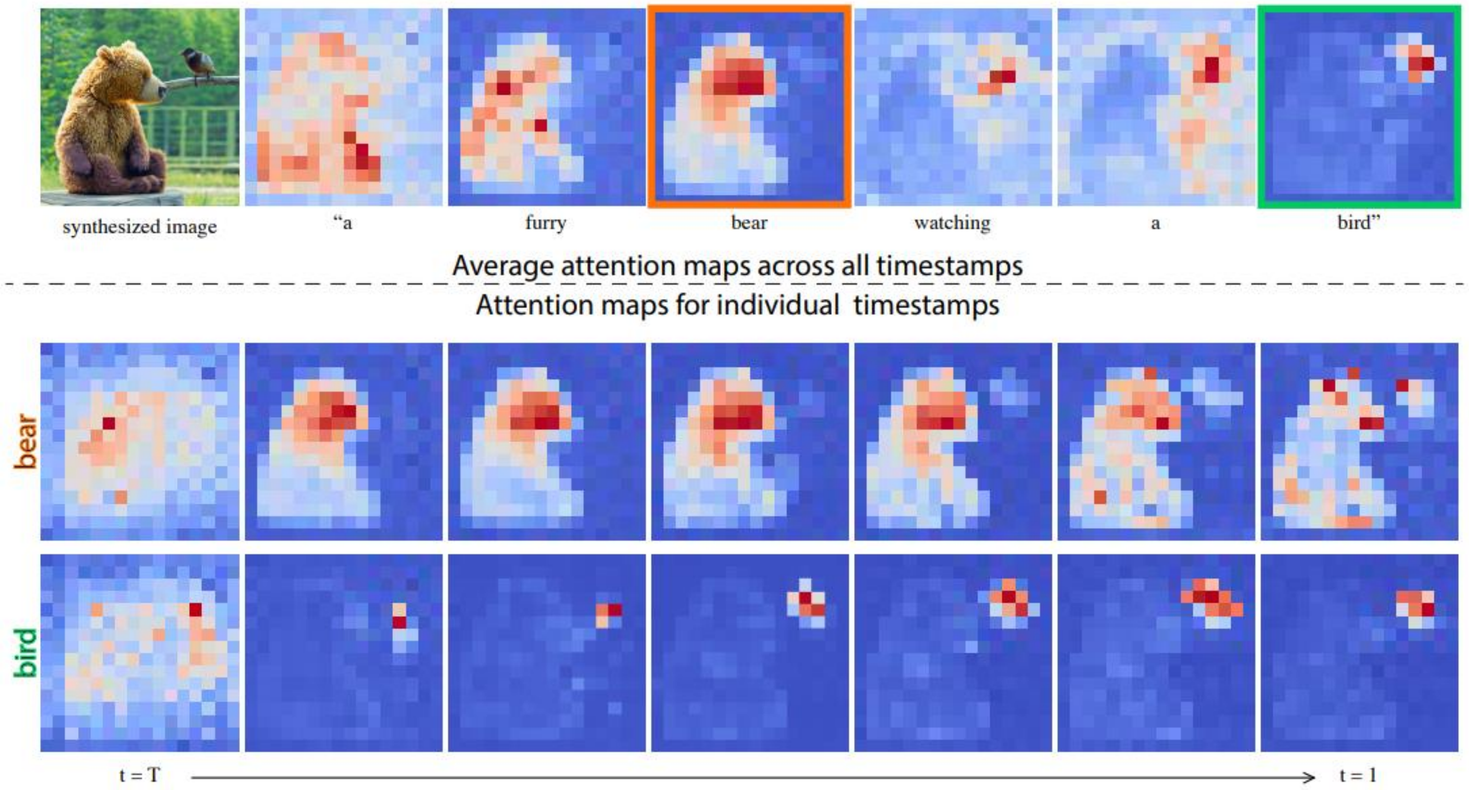


Image source [3]

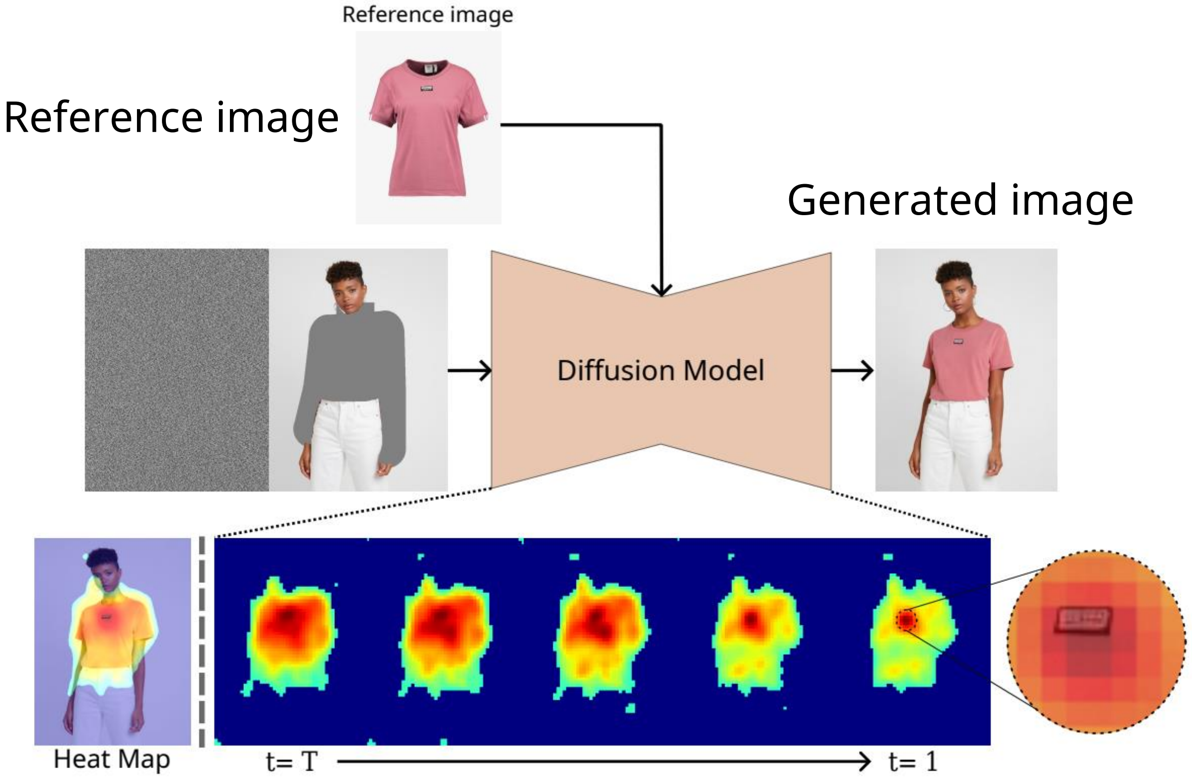
Image source [4]

1 Motivation

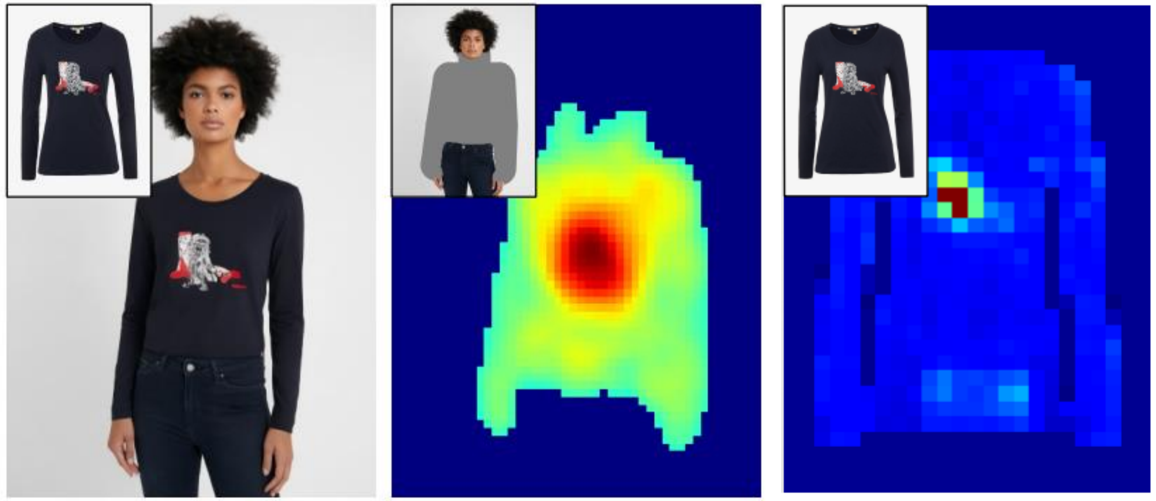
- Differences between text-to-image and image-to-image
  - Text-conditioned models
    - ✓ generate images that visually interpret provided text descriptions
    - ✓ Token-wise interpretation is practical
    - ✓ Etc.
  - Image-conditioned models
    - ✓ transform a reference image into a different visual form of the image
    - ✓ Patch-wise interpretation is less practical due to the spatial and contextual continuity
    - ✓ Etc.

Research Topic

- Interpreting image-to-image latent diffusion models focusing on inpainting
- Basic image-to-image LDMs performing inpainting task (VITON)
  - Input clothing **(reference image)** condition utilizing cross-attention
  - Concatenate various conditions to noisy input
  - Model (U-Net) generates more clear image by predicting the noise



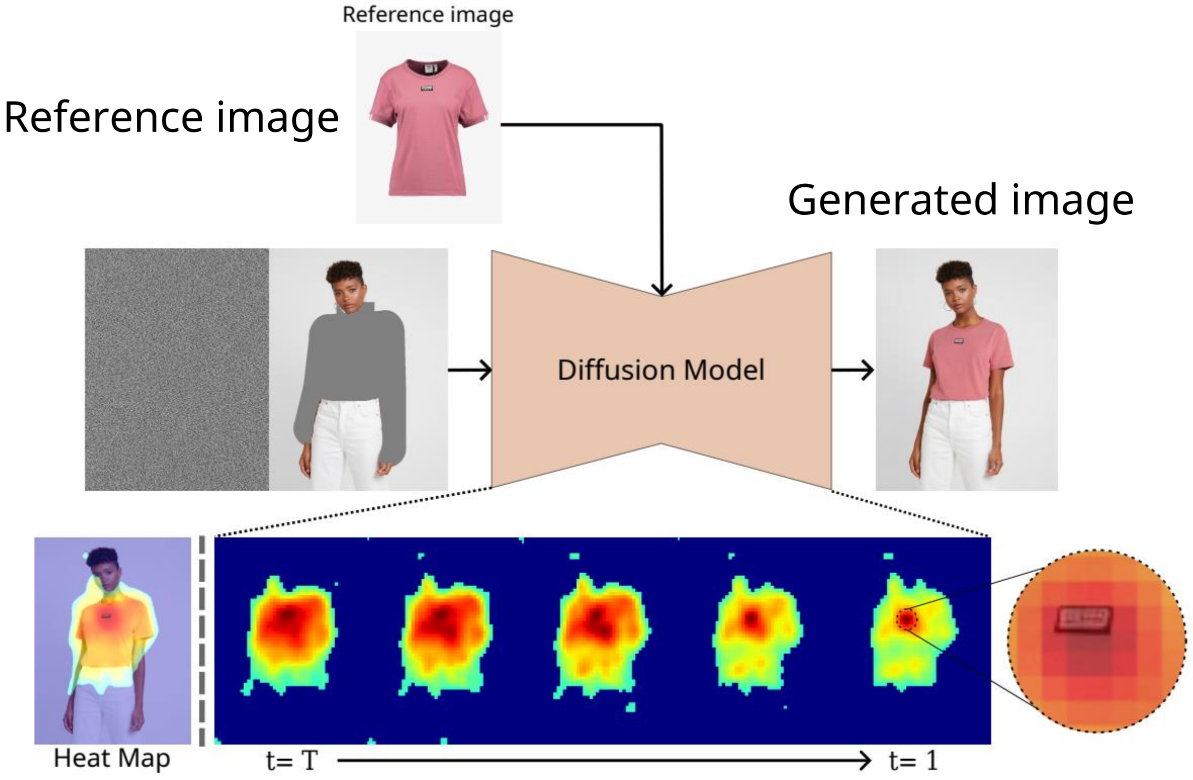
Attribution maps for generated/reference images



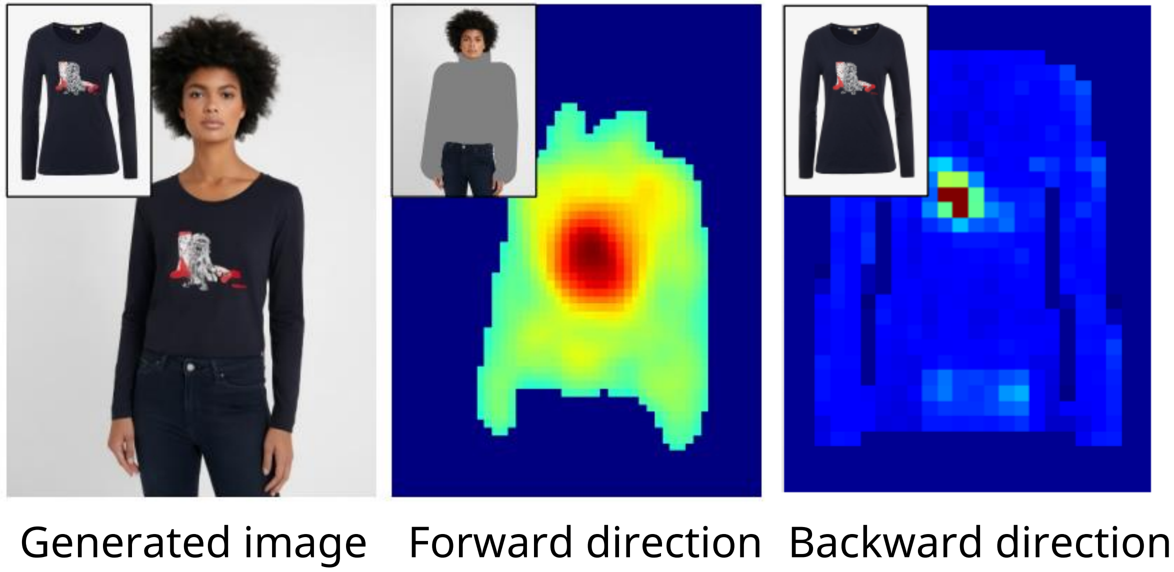
Generated image Forward direction Backward direction

3 Methodology

- I^2AM: **I**mage-to-**I**mage **A**ttribution **M**aps method
  - Use cross-attention map **(attribution map)** to visualize generation process
  - Analyze generation process across time steps, attention heads
  - While text is abstract, image (e.g., clothes) maintains spatial information in latent space
  - So, we can facilitate clear visualization of the condition



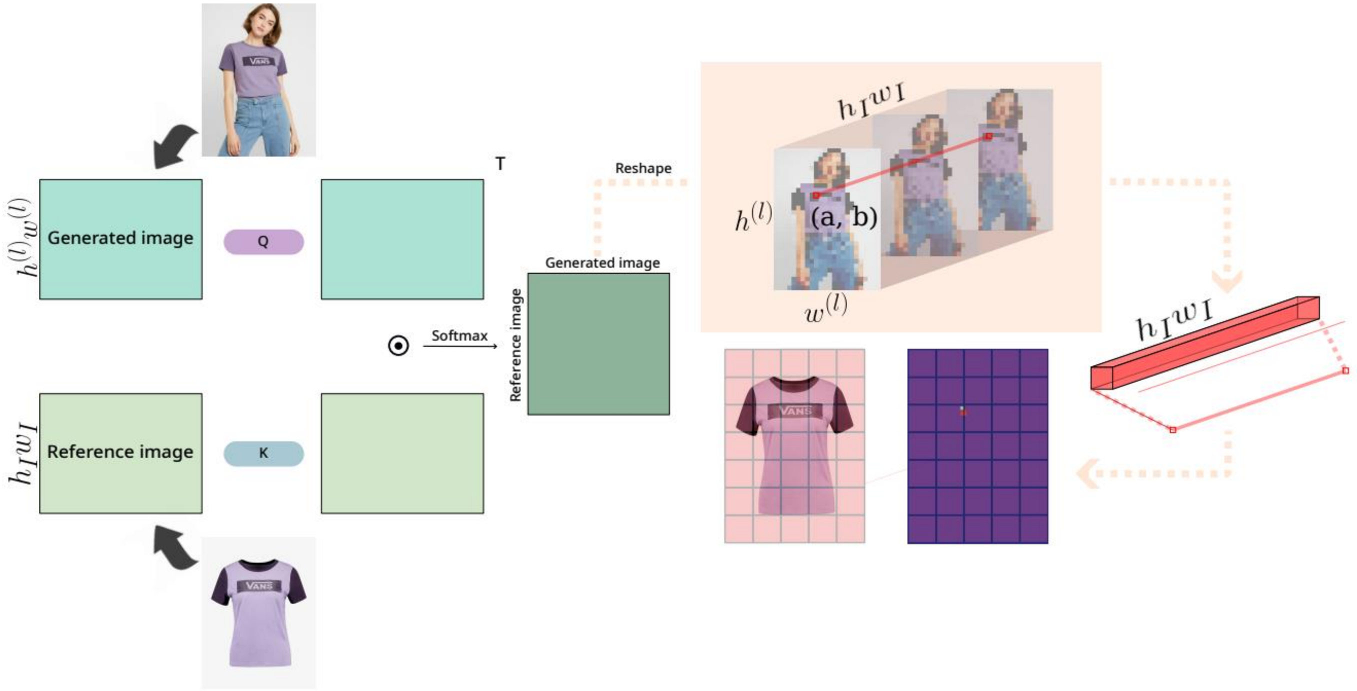
Attribution maps for generated/reference images



3 Methodology

- I^2AM: **I**mage-to-**I**mage **A**ttribution **M**aps method
  - Attribution maps for generated/reference images
    - ✓ Time-and-head integrated attribution maps
    - ✓ Head/Time integrated attribution maps
    - ✓ Specific-reference attribution maps

$\mathbf{t}: [\mathbf{1}, \mathbf{T}]$, **attention head: 8**



$$\text{Softmax}\left(\frac{(\mathbf{W}_q^{(l)}\mathbf{f}_t^{(l)})(\mathbf{W}_k^{(l)}\mathbf{c}_I)^\top}{\sqrt{d}}\right)$$

soft-max in forward direction

$$\text{Softmax}\left(\frac{(\mathbf{W}_k^{(l)}\mathbf{c}_I)(\mathbf{W}_q^{(l)}\mathbf{f}_t^{(l)})^\top}{\sqrt{d}}\right)$$

soft-max in backward direction

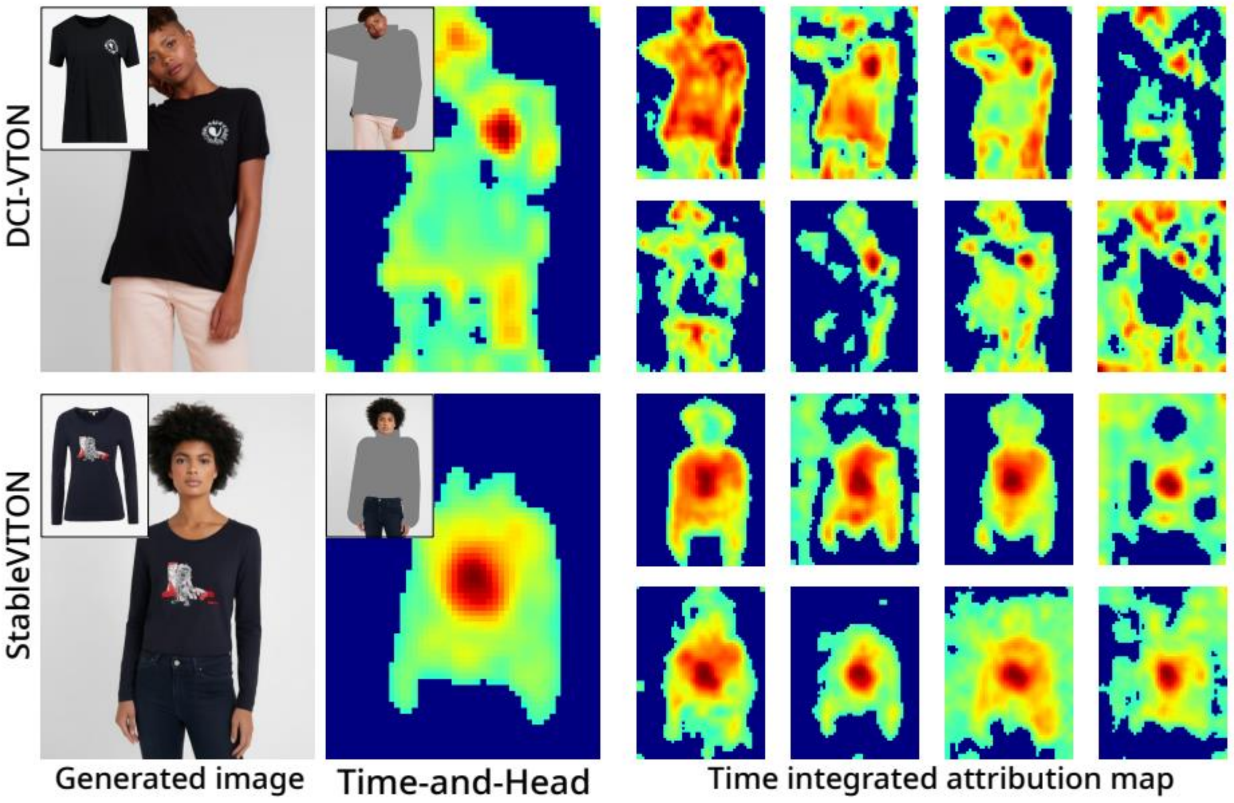
4 Experimental results

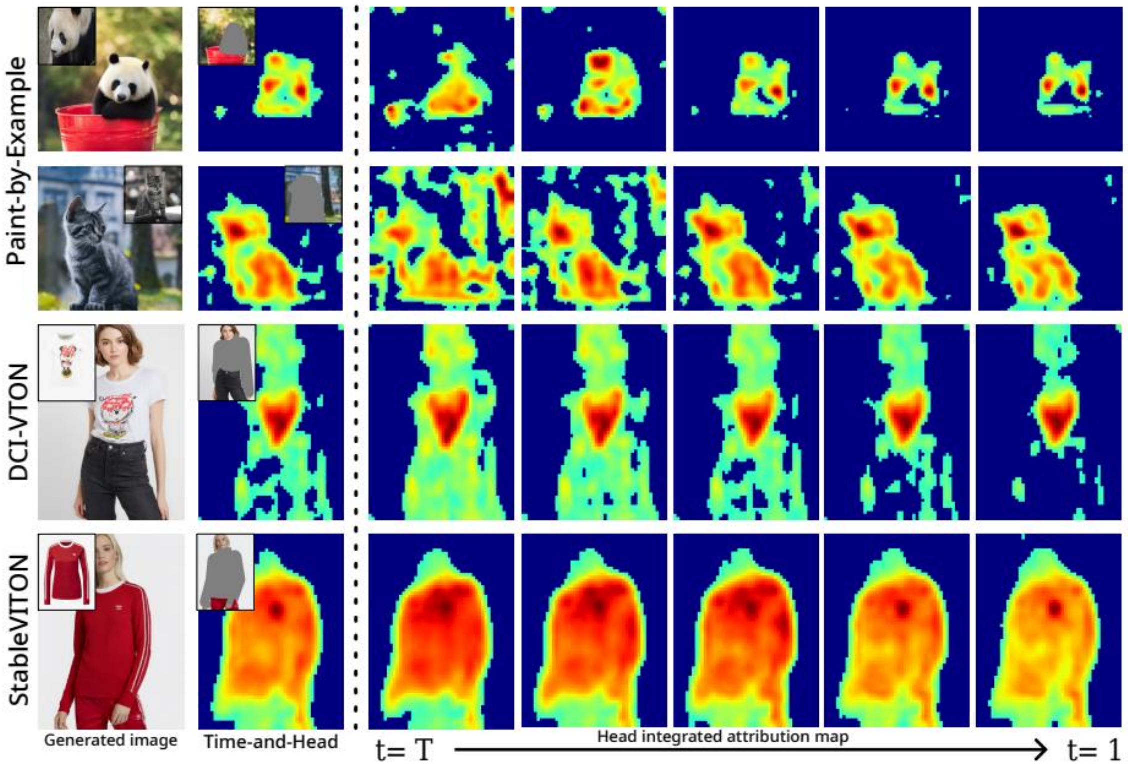
- I^2AM: **I**mage-to-**I**mage **A**ttribution **M**aps method
  - Attribution maps for generated/reference images
    - ✓ Time-and-head integrated attribution maps
    - ✓ Head/Time integrated attribution maps
    - ✓ Specific-reference attribution maps
- Models
  - Paint-by-example [5]
  - DCI-VTON [6]
  - StableVITON [7]
- Sampler
  - DDIM

Figure 4: Time-and-Head integrated attribution map visualization, both with and without CFG. The dispersion of attention scores exceeded the inpainting mask's range when CFG was not used.

4 Experimental results

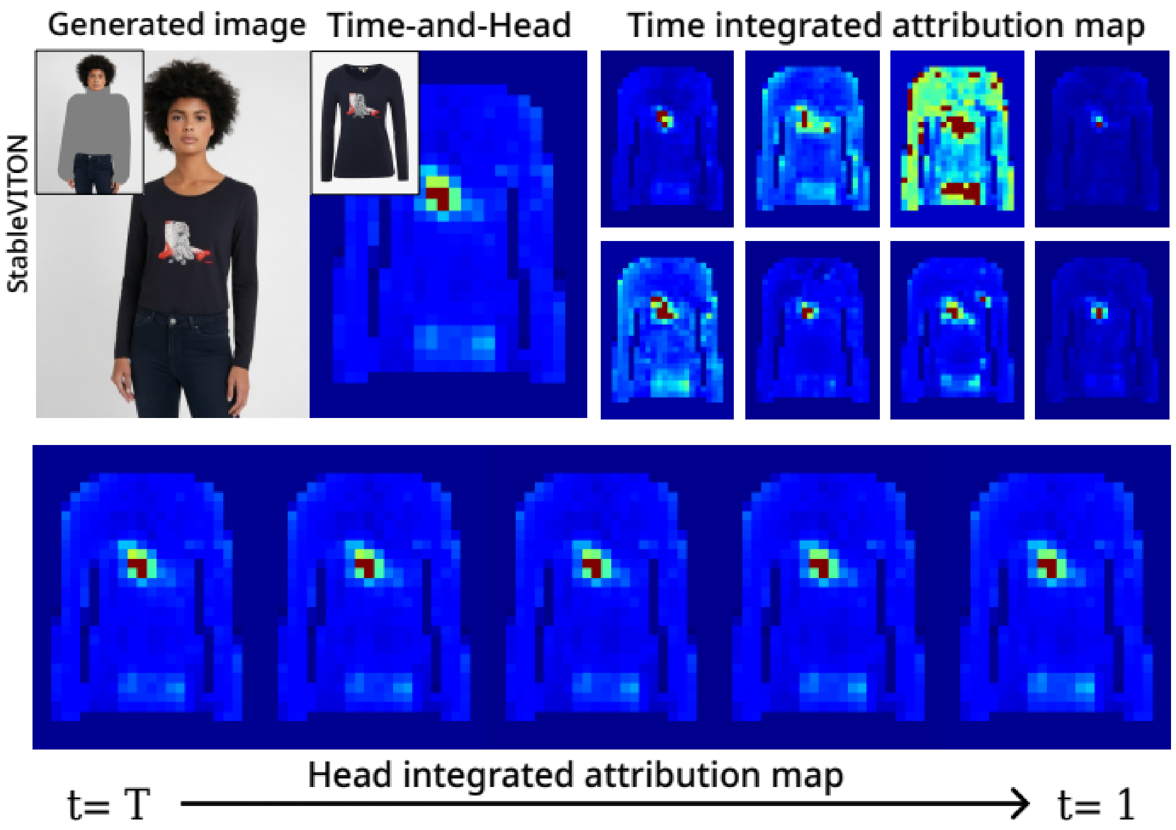
- Results of attribution maps for the generated image
  - The model gradually forms the object’s structure, consistently assigning high attention scores to important features such as facial details or clothing logos.

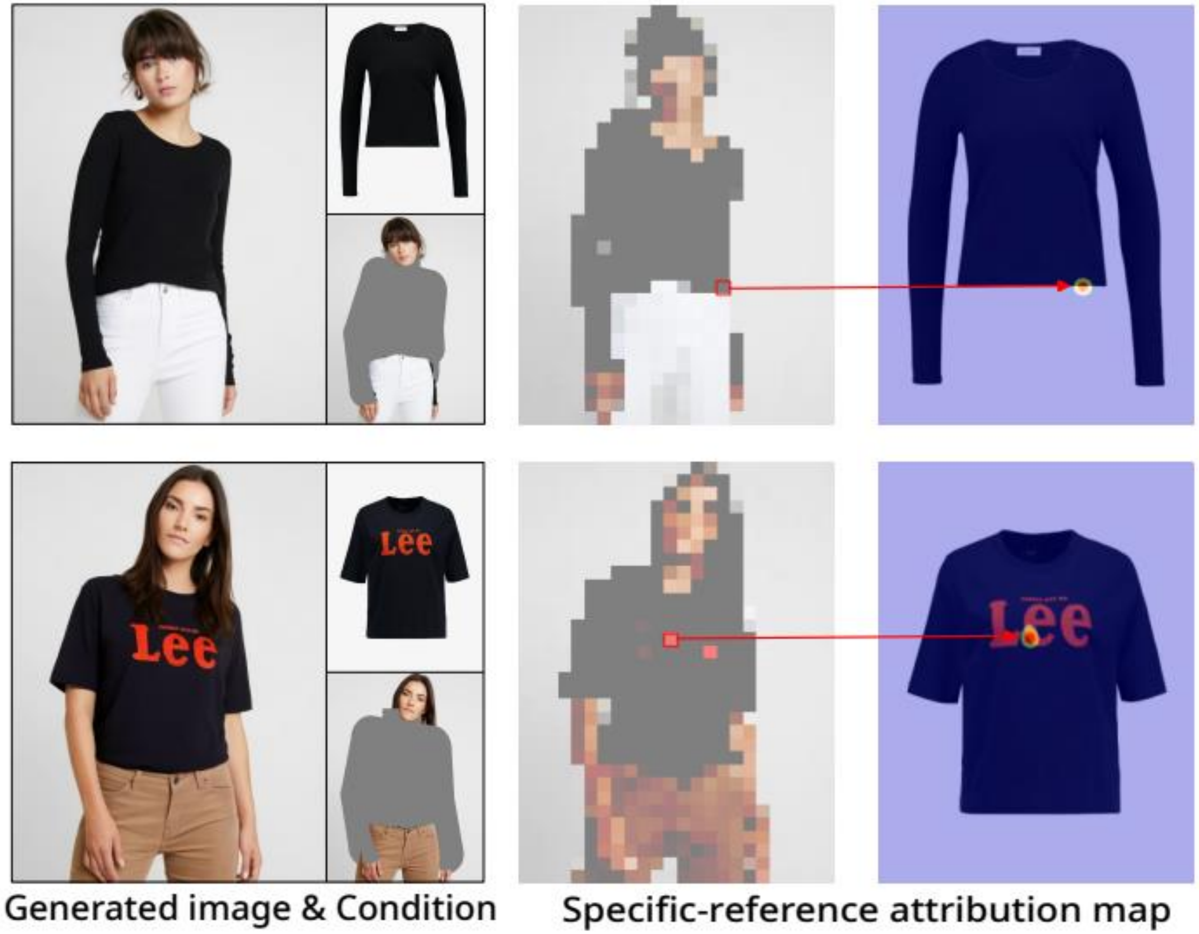




Experimental results

- Results of attribution maps for the reference image
  - To confirm whether meaningful information is extracted from the reference image for image synthesis, one needs to examine the reference attribution map





5 Conclusion

- Our contributions
  - Propose analysis and visualization methods for I2I LDMs
  - Provide insights into generation process of I2I LDMs by analyzing attribution maps at each time and attention head
  - Present attribution maps for the generated and reference images using characteristics of I2I LDMs

6 Reference papers

[1] Jiang, Peng-Tao, et al. “Layercam: Exploring hierarchical class activation maps for localization.” IEEE Transactions on Image Processing (2021)

[2] Chefer, Hila, Shir Gur, and Lior Wolf. "Transformer interpretability beyond attention visualization." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2021.

[3] Hertz, Amir, et al. "Prompt-to-prompt image editing with cross attention control." *arXiv preprint arXiv:2208.01626* (2022).

[4] Tang, Raphael, et al. "What the daam: Interpreting stable diffusion using cross attention." *arXiv preprint arXiv:2210.04885* (2022).

[5] Yang, Binxin, et al. "Paint by example: Exemplar-based image editing with diffusion models." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2023.

[6] Gou, Junhong, et al. "Taming the power of diffusion models for high-quality virtual try-on with appearance flow." *Proceedings of the 31st ACM International Conference on Multimedia*. 2023.

[7] Kim, Jeongho, et al. "Stableviton: Learning semantic correspondence with latent diffusion model for virtual try-on." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2024.

Thank you.

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