

# Towards Safe Concept Transfer of Multi-Modal Diffusion via Causal Representation Editing

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## Background

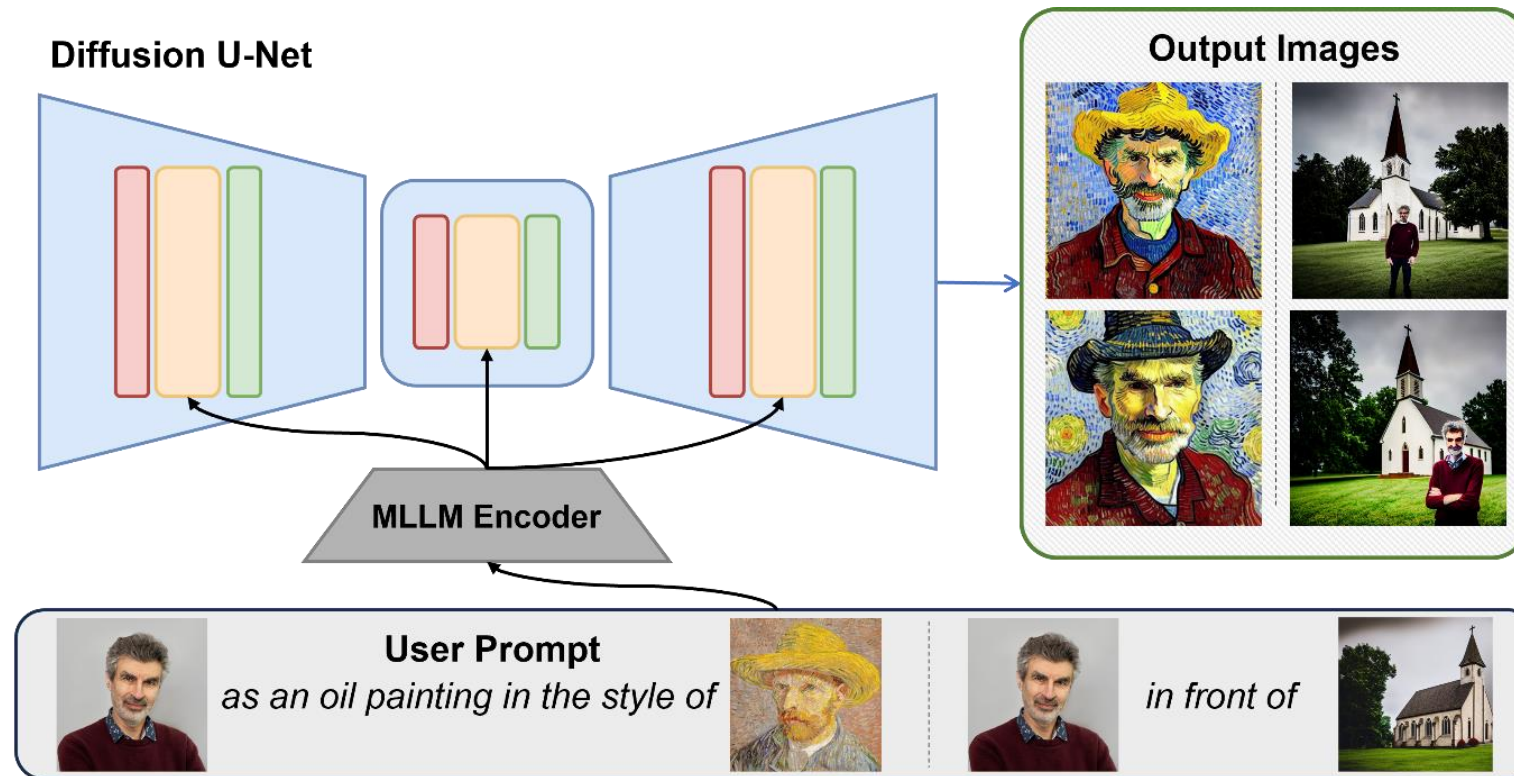


Figure 1. Multimodal Diffusion

**Misuse of Multimodal Diffusion (like Kosmos-g[1]), like copying objects/styles in other images, leads to concerns about intellectual property rights.**

[1] Pan, Xichen, et al. "Kosmos-g: Generating images in context with multimodal large language models." arXiv preprint arXiv:2310.02992 (2023).

## Motivation

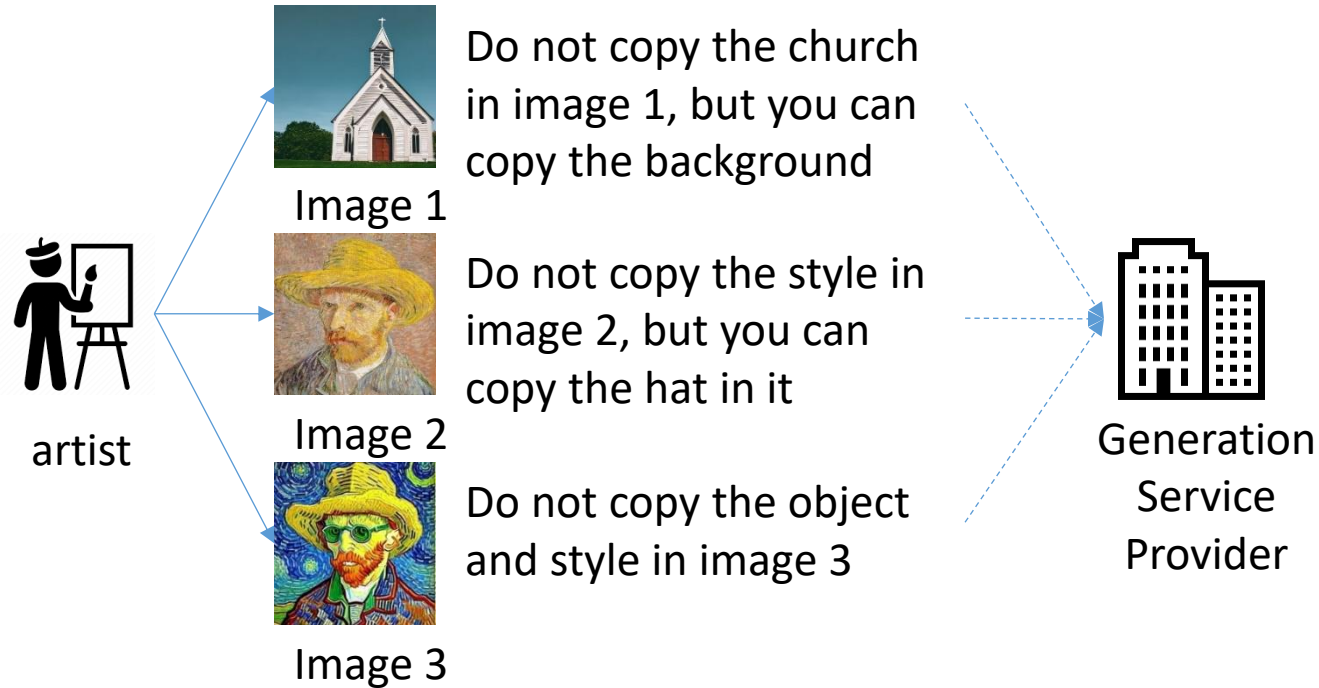


Figure 2. A possible scenario -- Artist demands

**When Generation Service meets precise demands, for example, an artist tells the service providers which part they can use and what they can not use.**

# Motivation

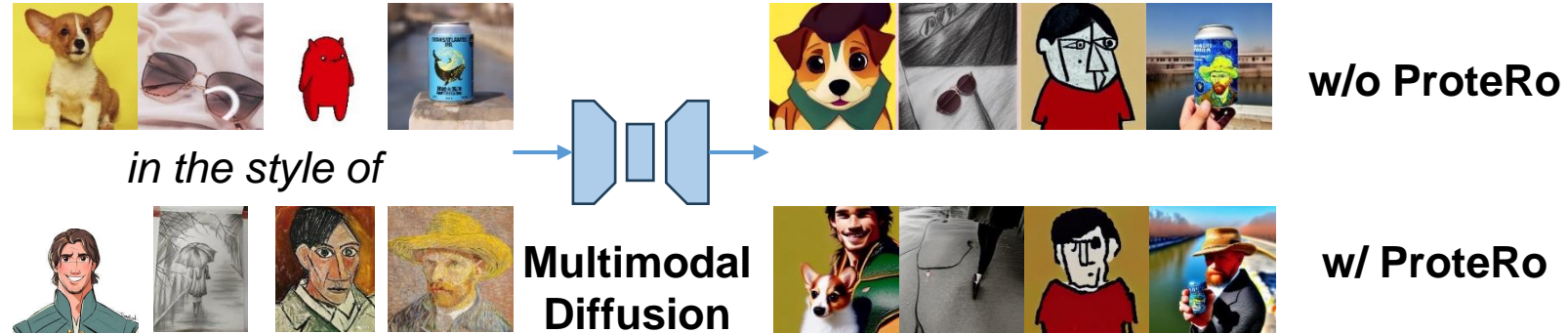


Figure 3. ProteRo [2] under multimodal setting

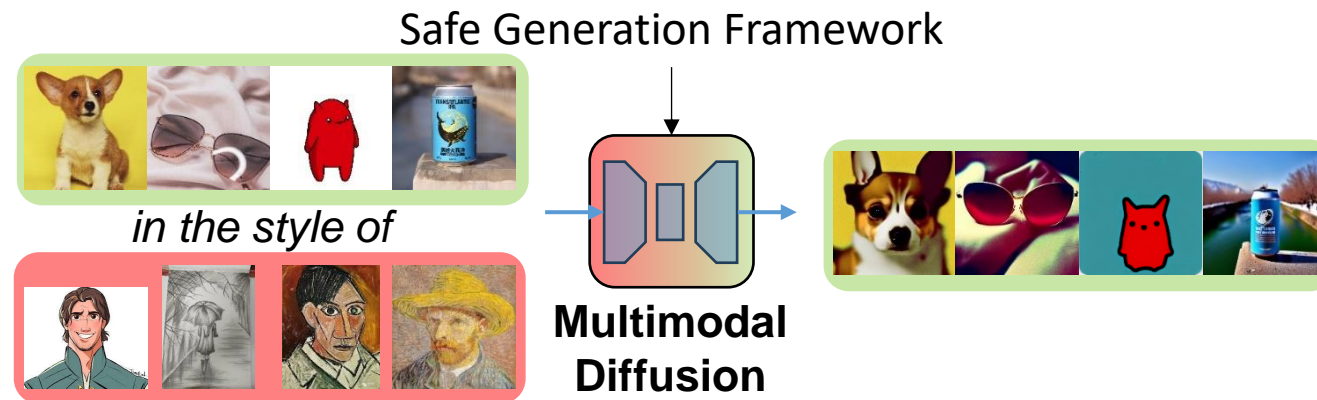


Figure 4. Wanted results with unsafe style



# Method

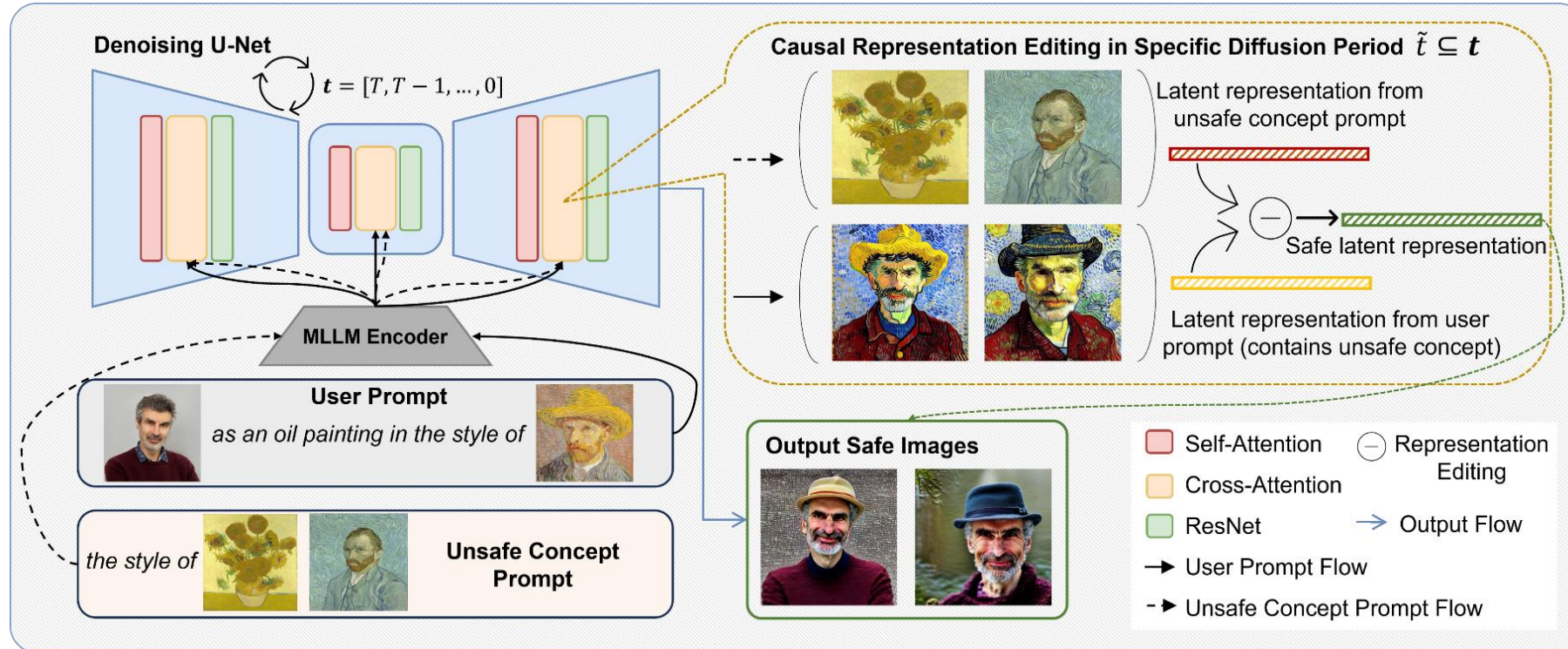


Figure 5. Pipeline for Safe Concept Transfer

## Three Phases:

1. **Search:** Searching for the unsafe input;
2. **Prototype:** Utilizing the MLLM encoder to get the unsafe embedding;
3. **Refine:** Remain safe parts of the embedding.

## Method

### Phase 1 – Search: Searching for the unsafe input

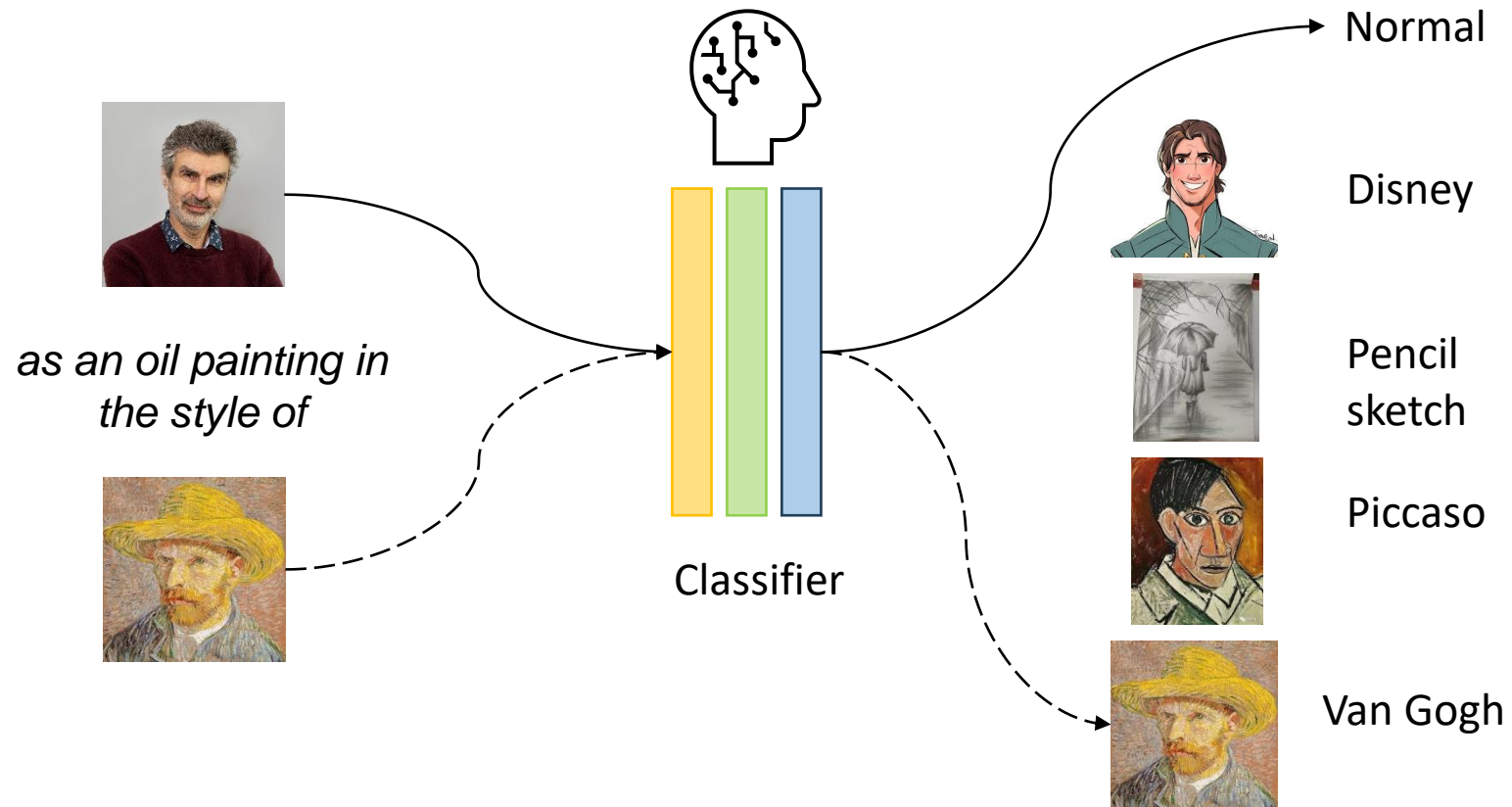


Figure 6. Searching for the unsafe input

# Method

## Phase 2 - Prototype: Utilizing the MLLM encoder to get the unsafe embedding

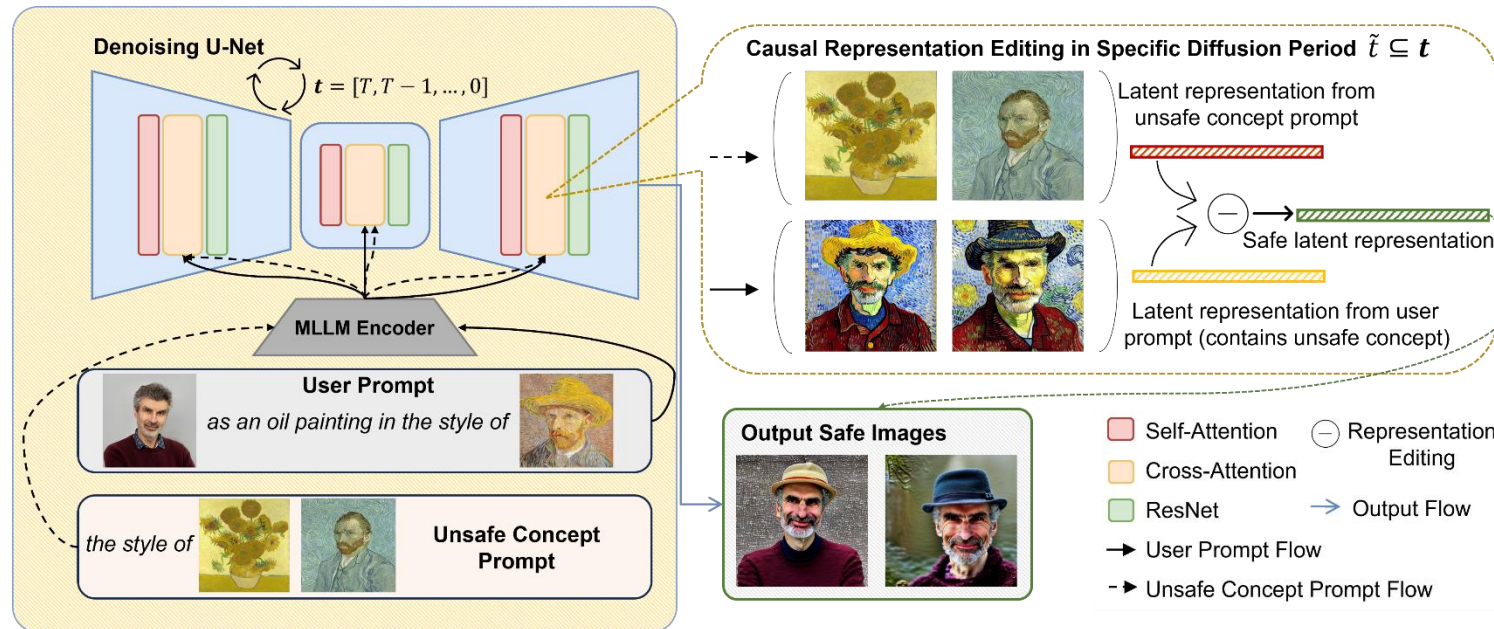


Figure 7. Utilizing the MLLM encoder to get the unsafe embedding



# Method

## Phase 3 - Refine: Using projection to get unsafe parts

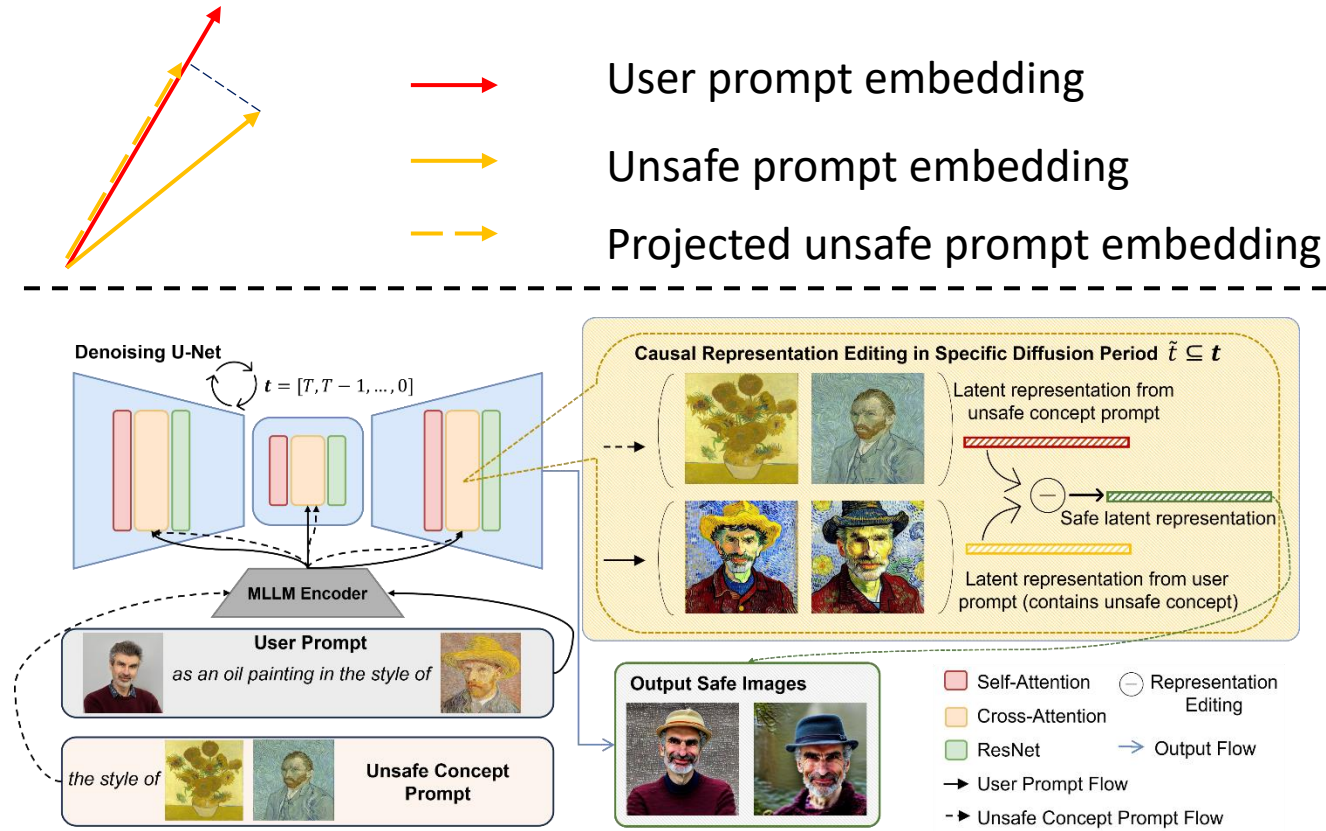


Figure 8. Using projection to get unsafe parts



# Experiment - object

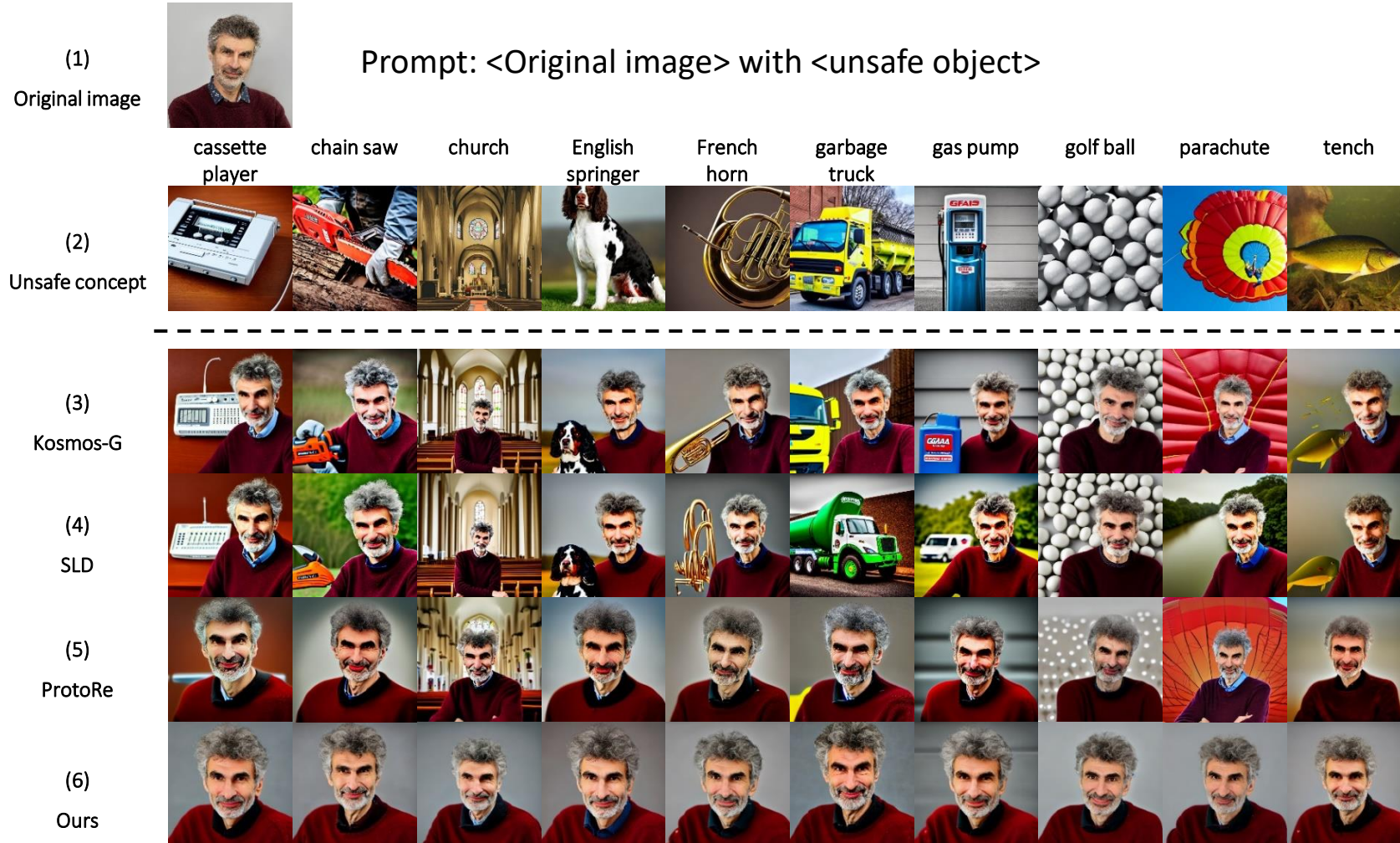


Figure 9. Qualitative results of safe object generation

# Experiment - style

Prompt: <Original image> in the style of <unsafe style>

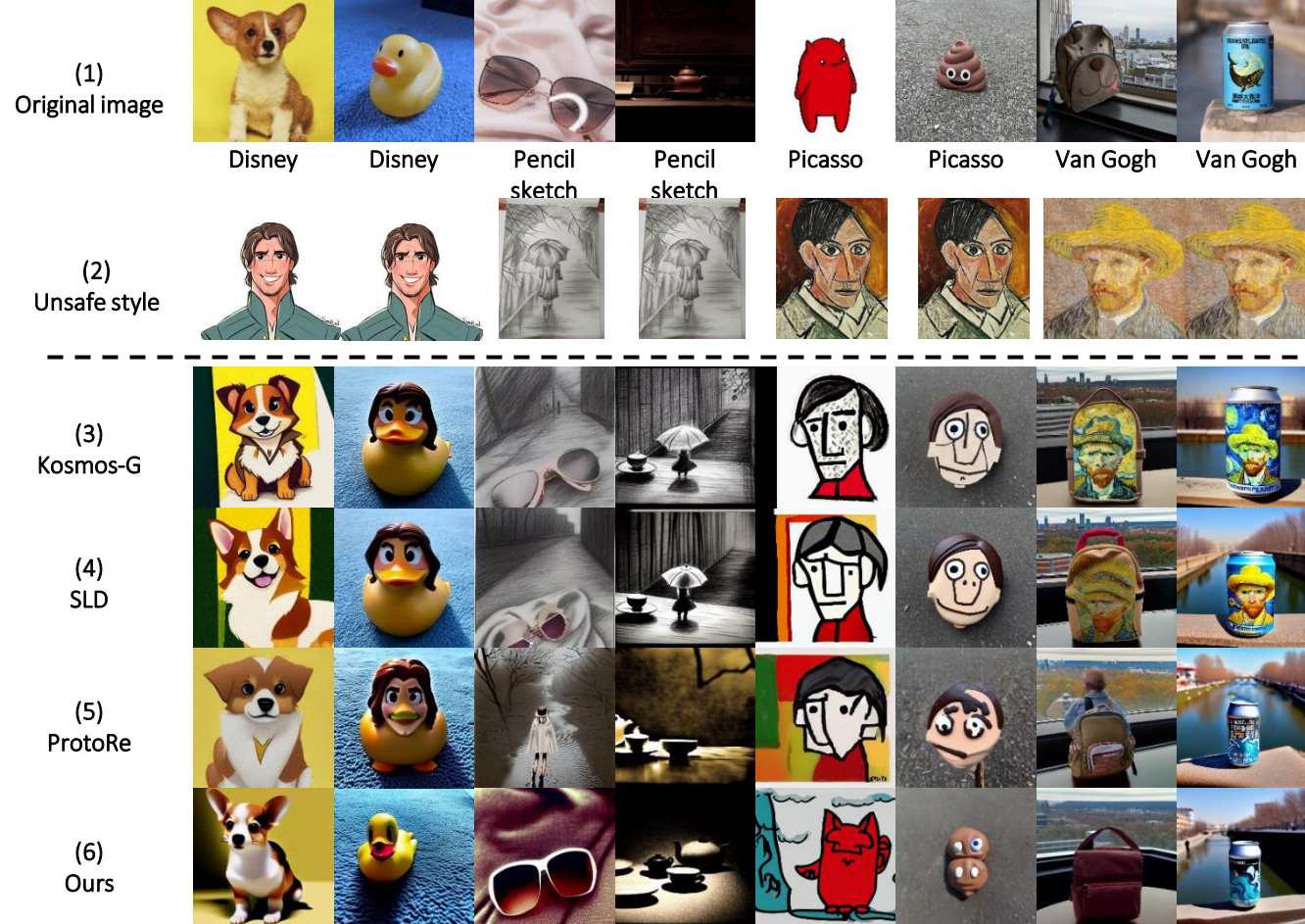


Figure 10. Qualitative results of safe object generation



# Experiment – Quantitative Results

Object	Top-1 Accuracy of Object Transfer (%) ↓										
	cassette player	chain saw	church	English springer	French horn	garbage truck	gas pump	golf ball	parachute	tench	Average
Kosmos-G	5.2	50.6	96.6	27.2	12.0	52.6	34.4	24.2	43.2	16.6	36.26
Kosmos-G-Neg	9.4	51.6	95.6	31.8	6.6	59.6	32.4	28.6	39.4	11.4	36.76
SLD	0.8	18.4	95.6	15.4	11.4	30.6	16.2	7.0	27.6	1.8	22.48
ProtoRe	<b>0</b>	<b>0</b>	15.6	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	0.2	0.8	<b>0</b>	1.66
CRE	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>	<b>0</b>

Table 1. Quantitative Results of safe object transfer

Discriminator	Style	Top-1 Accuracy of Style Transfer (%) ↓				
		Kosmos-G	Kosmos-G-Neg	SLD	ProtoRe	CRE
ResNet-50	Disney	53.9241	61.4557	56.7089	47.5949	<b>11.3924</b>
	Pencil Sketch	19.2405	44.3671	14.8101	12.9747	<b>0.6962</b>
	Picasso	21.8354	36.519	11.2658	3.6709	<b>0.3165</b>
	Van Gogh	44.4304	60.443	26.2658	2.7848	<b>0.5696</b>
ViT-base	Disney	39.557	44.2405	36.6456	29.557	<b>1.3291</b>
	Pencil Sketch	15.5063	35.8861	10.5063	6.7722	<b>0.6329</b>
	Picasso	22.1519	35.1266	15.3165	5.1899	<b>1.6456</b>
	Van Gogh	44.1139	60.443	27.9114	3.2278	<b>0.3797</b>
Average		32.5949	47.3101	24.9288	13.9715	<b>2.1202</b>

Table 2. Quantitative Results of safe style transfer



# Experiment – Complex Scenarios

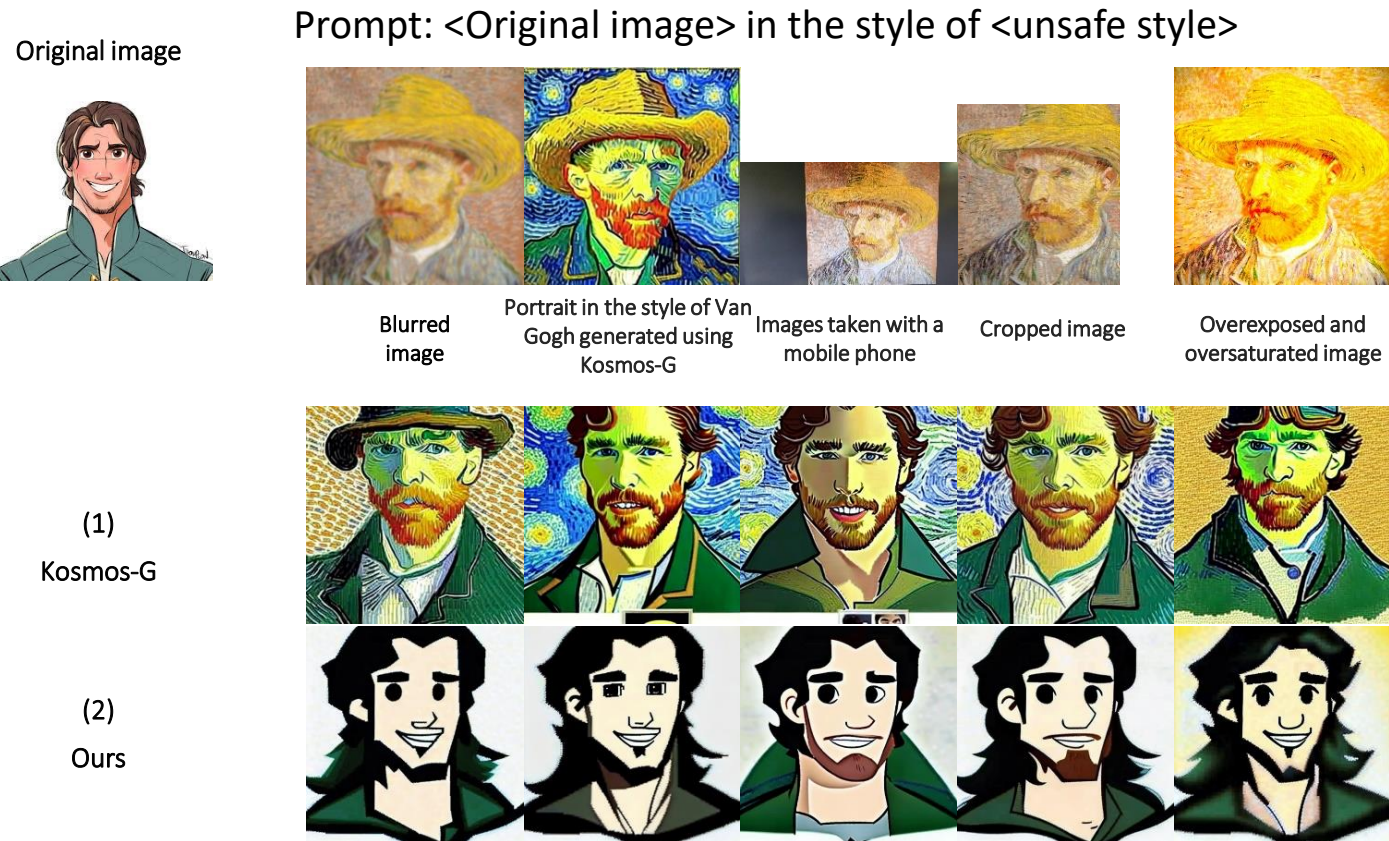


Figure 11. Qualitative results of complex Scenarios

# Conclusion

