AI for the Preservation of Cultural Heritage

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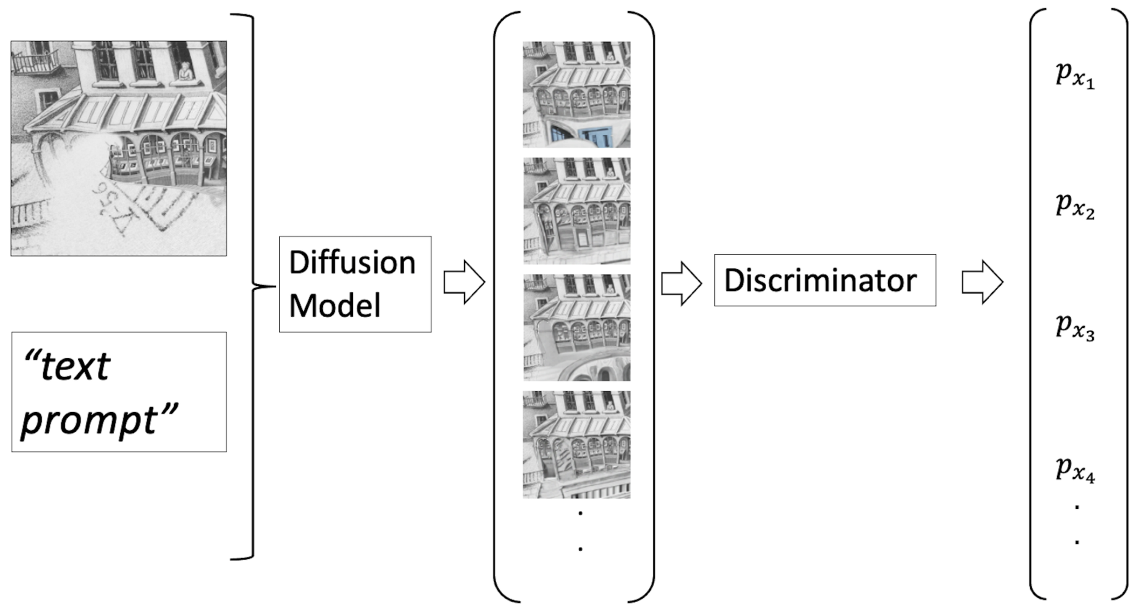
Contributions

- Ensemble of different techniques
- End-to-end methodology
- Quantitative metrics to analyze results
- Qualitative analysis through human evaluators

The Discriminator Module

What's the probability that the restored painting is an original?



- With **black-box** models the discriminator is placed at the end to select the best restoration alternative.
- With **white-box** access to the model, the discriminator's gradients are used to guide the diffusion.

Using AI to assist in the restoration of artwork by generating content that is **coherent**, with the **author**, the **painting** and its time **period**.

García Martínez - Ecce Homo

T.Garcia- Composicion constructiva

M.C. Escher - Print Gallery

Cezanne - Turning Road

Inpainting Model selection

The model selection depends on the context

Model	Type	Input size	Output Size
CoModGANs	StyleGan	512x512	512x512
LaMa	Fourier Conv	2048x2048	2048x2048
GLIDE	Text guided diff	6000x6000	256x256

Quantitative metrics

Method	Koniq ↑	Brisque ↓	Dom ↑
CoModGANs	36.12	43.37	1.05
LaMa	38.76	42.38	1.10
GLIDE	41.61	7.94	1.04

Average values for each metric. Koniq compares against diverse and real dataset of image quality, Brisque compares against dataset with known distortions, DOM compares edge sharpness.

Human evaluators

Presented with inpainted options, asked to provide a probability of an inpainted image to be fake/real and to disclose their art knowledge

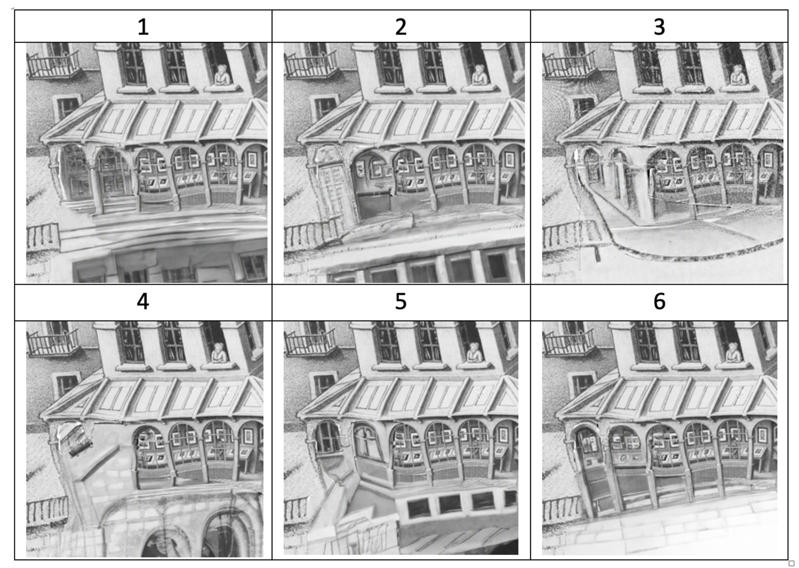


Image Idx	Human	Model
1	0.33	0.0
2	0.34	0.0
3	0.56	0.88
4	0.35	0.0
5	0.33	0.0
6	0.37	0.98