Interactive Style Transfer

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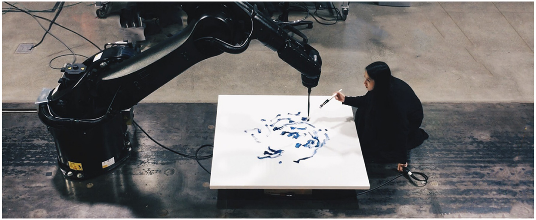
A.I. art narratives

- "Making a curatorial choice" Mario Klingelmann.

A.I. art narratives

- "Embrace the machine imperfections", Sougwen Chung



- "Give to the [algorithm's] fragments order and purpose, inhabit them until they became our own", Claire Evans

→ understand the algorithm's agency in the creative process.

A.I. artwork : a two-body problem

Goal: Develop a methodology to understand algorithm contribution in an interactive creative process.

Two components

- Algorithm : GAN generating image, RNN controlling robot, NN generating sentences...
- Artist : expresses its subjectivity from the algorithm creation.

Simple case study

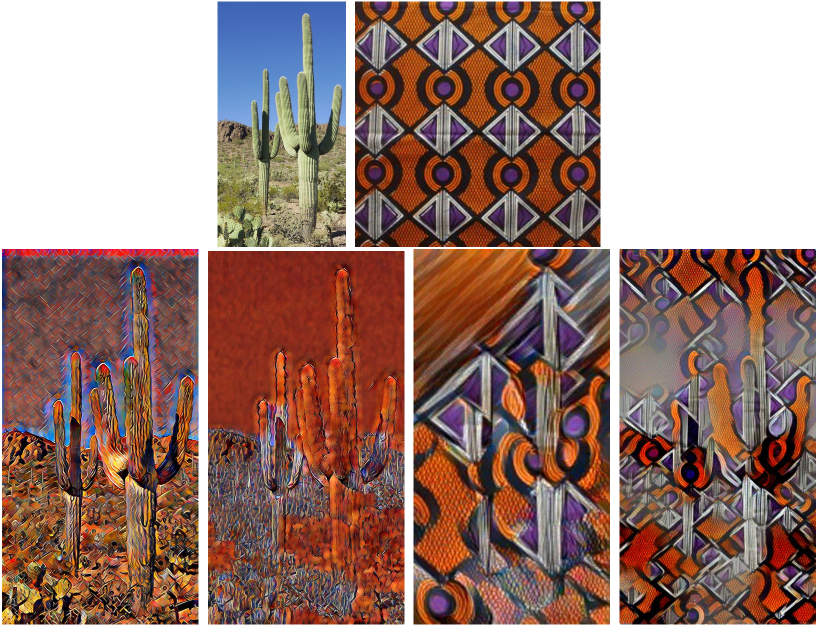
- Neural style transfer : "backtrackable" output.
- Human painter on a canvas: classical playground and feelings.

Style Transfer Algorithms

Relies on numerical quantification of 'content' and 'style' : strong intuitions, but hard define semantically, various choices in practice.

- Neural style transfer [Gatys et al., 2015]: style and content defined with CNN features, solve optimization problem.
- [Ulyanov, 2016, Johnson et al., 2016]: feedforward versions.
- STROTSS [Kolkin et al., 2019] : self-similarity for content and optimal transport for style

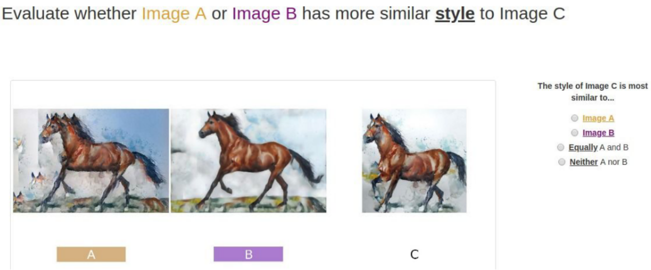
Style Transfer Algorithms



Understanding the algorithm

Style transfer evaluation [Jing et al., 2017] :

- Computational cost : not relevant here.
- Quantitative evaluations : measure how well the quantitative objective has been achieved.
- Crowd-sourcing approaches (AMT):



Limits of quantitative evaluation

STROTSS method [Kolkin et al., 2019]

- style similarity defined with earth movers distance (EMD)
- uses relaxed earth movers distance (REMD) :

$$\mathrm{REMD} \approx 0.6\ \mathrm{EMD}$$

- Sinkhorn earth movers distance [Cuturi, 2013] (SEMD) :

$$\mathrm{SEMD} \approx 1.05\ \mathrm{EMD}$$

Limits of quantitative evaluation

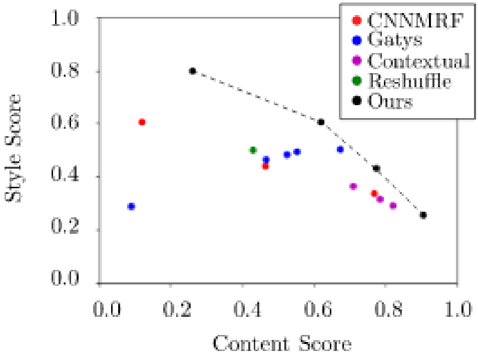
(left) content, (right) style

Limits of quantitative evaluation

STROTSS outputs with REMD (left) and SEMD (right)

Limits of crowd-sourcing based evaluation.

- novice people opinions
- limited to a style/content preservation trade-off
- capture an average taste/trend



Qualitative Predictive Evaluation

Pair dataset from *Cathédrale de Rouen series*, Monet.

Qualitative Predictive Evaluation

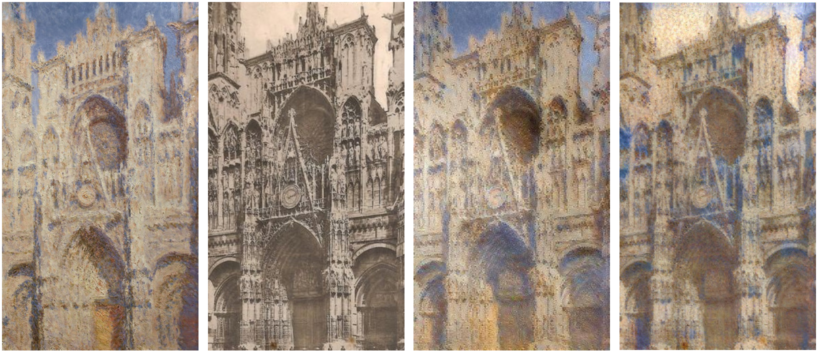


Figure: Detail of *Le Portail de la cathédrale de Rouen au soleil*, Monet, corresponding photograph and style transfer outputs (using STROTSS and GATYS).

Style Transfer in Painting Experiments

Method: Use style transfer outputs in interactive games with a painter.

Goal: Observe the agency intertwining between painter and algorithms.

Motivate painters to the experiment:

- Algorithms could be a medium to interact with their own past productions.
- Algorithm generated outputs as *computational landscapes*.

Set-up

Set-up: Project style transfer outputs on the canvas and update it along the painting.

We focus here on painting portraits with a few important rules

- All the painters can see are stylized versions of an initial portrait.
- Algorithms outputs are projected directly on the canvas.
- The algorithms outputs are suggestions.

Some Feed-back of the interaction

Some artists feedback

- Tracing the agency by the colors.
- Loosing track of the original real material along the paintings.
- Human and machine spaces are different. The interface itself plays a role in characterizing the computational creativity.
- Algorithms are **computational catalysts**.

Conclusion

- Expert resources are under-exploited (*e.g.* evaluation of style transfer method).
- Computational creativity fields address the word choice in the creative agency of the algorithms in creative processes.
- "Simple" A.I. algorithms are enough to have rich agency structures between algorithms' outputs and painters.

Questions

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References I

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