Towards Creativity Characterization of Generative Models via Group-based Subset Scanning

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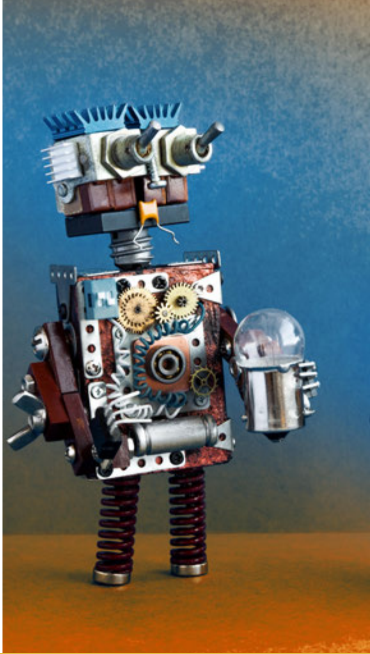
Why is important to characterize creativity in generative models?

Deep generative models, have been employed widely in sample generation, hypothesis generation research. However, such models **discourage** out-of-distribution generation to avoid spurious sample generation, thereby **limiting** their creativity.

Computational Creativity Definition

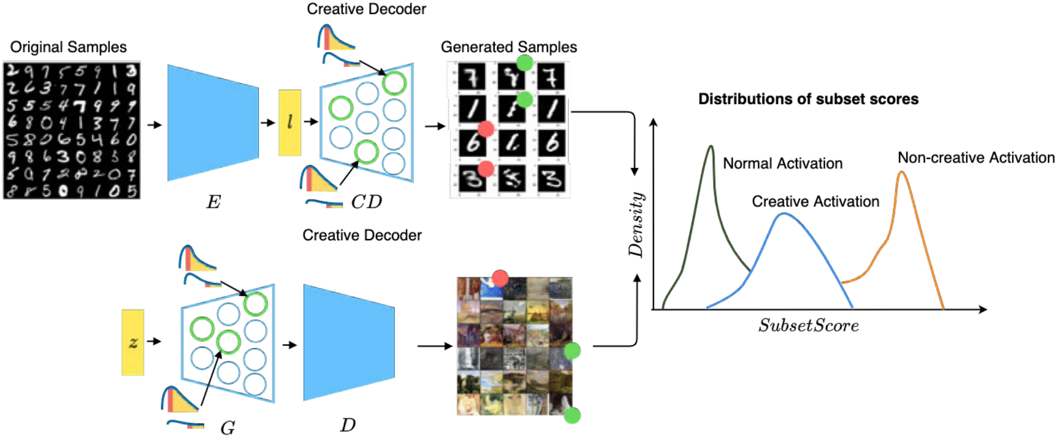
While there is strong agreement that **evaluating the creativity** of an artifact is an **integral** part of computational creativity, there is significant **disagreement as to how** this evaluation can be modeled [Said-Metwaly et al., 2017].

One of the accepted characterisations of a creative artefact is that it is simultaneously **novel** and **valuable** [Csikszentmihalyi and Wolfe, 2014, Grace and Maher, 2016, Franceschelli and Musolesi, 2021].

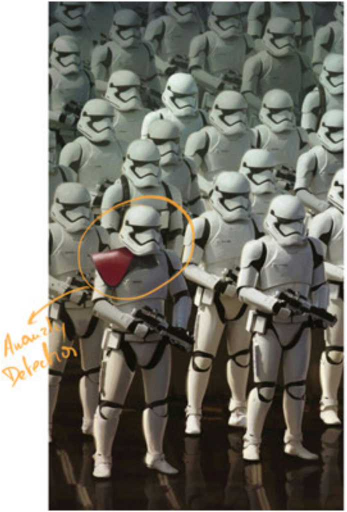


Creativity Characterization of Generative Models

We propose an approach to detect and characterize the novelty of creative processes and artifacts, within the framework of off-the-shelf generative models.

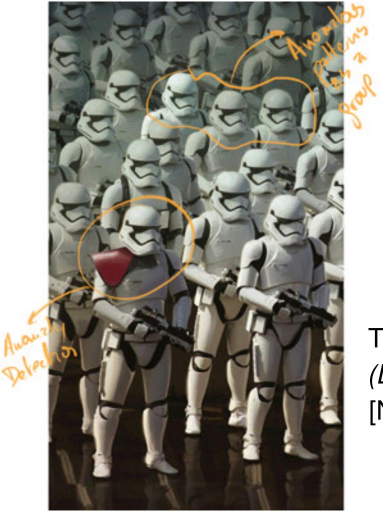


Group-based Subset Scanning: Why?



- Novelty detection identifies individual samples as anomalous.
  - Looking for **single** anomalous sample.
  - The sample is obvious once identified.
  - **Apriori knowledge** of what to look for.

Group-based Subset Scanning: Why?

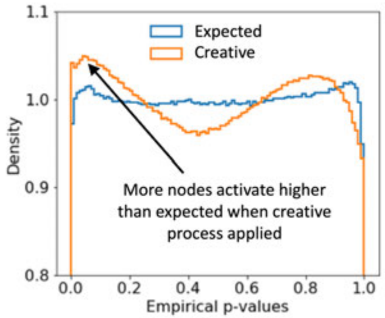


- Novelty detection identifies individual samples as anomalous.
  - Looking for **single** anomalous sample.
  - The sample is obvious once identified.
  - **Apriori knowledge** of what to look for.
- We expand those ideas to identify groups of samples as anomalous.
  - **Multiple samples** are affected.
  - Individual samples only **slightly anomalous**.
  - **Little knowledge** of what pattern may be like.

This work has its foundations on *Linear-Time Subset Scanning (LTSS)*

[Neill, 2012, McFowland III et al., 2013, Speakman et al., 2016]

Group-based Subset Scanning: How?

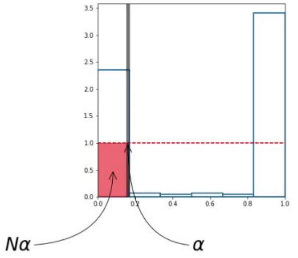


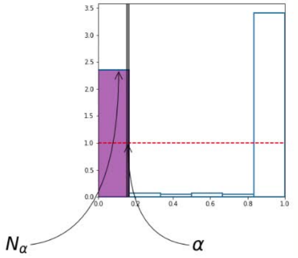
Assumption

Activations from creative samples have a different distribution of p-values than expected samples.

p-value is the proportion of background activations (H_0), drawn from the same node for several “expected” samples, greater than the activation from a test sample.

Group-based Subset Scanning: How? (Cont.)





$$\max_{\alpha} \varphi(\alpha, N_\alpha, N) = \frac{N_\alpha - N\alpha}{\sqrt{N}} \tag{1}$$

Where N_α is the number of p-values less than α

N is the number of p-values

α is the level of significance

φ is a scoring function

How we score a test sample?

Scoring functions operate on a test sample in order to measure how much the p-values deviate from uniform.

Group-based Subset Scanning: How? (Cont.)

NPSS maximization

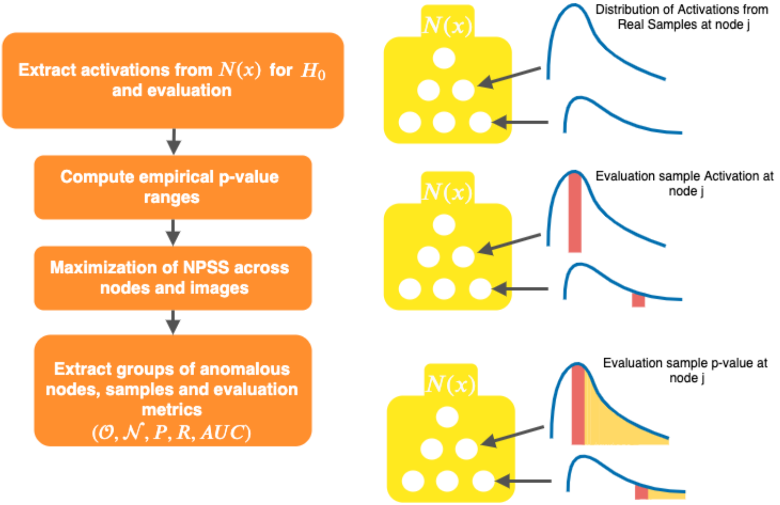
Scoring functions may be viewed as set functions that operate on subsets of nodes. We search for the highest scoring subset of nodes that maximize the deviance from uniform.

$$F(S) = \max_{\alpha} F_{\alpha}(S) = \max_{\alpha} \varphi(\alpha, N_{\alpha}(S), N(S)) \tag{2}$$

Group vs. Individual Scanning

For group-based scanning our search space is: $S = X_{\hat{S}} \times O_{\hat{S}}$, where $X_{\hat{S}}$ is a subset of test samples and $O_{\hat{S}}$ is a subset of nodes' activations.
For individual scanning we work with only one X_i.

Group-based Subset Scanning: How? (Cont.)



Experimental Setup

Nine evaluators did the human annotation over generated from either the creative generative process or regular decoding.

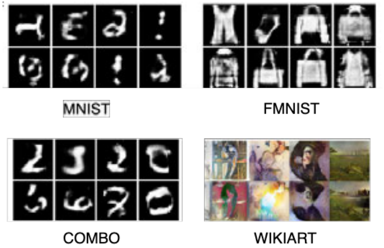
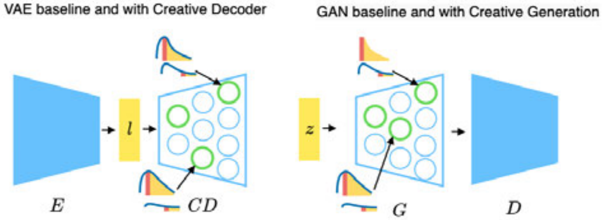


Image adapted from [Das et al., 2020]

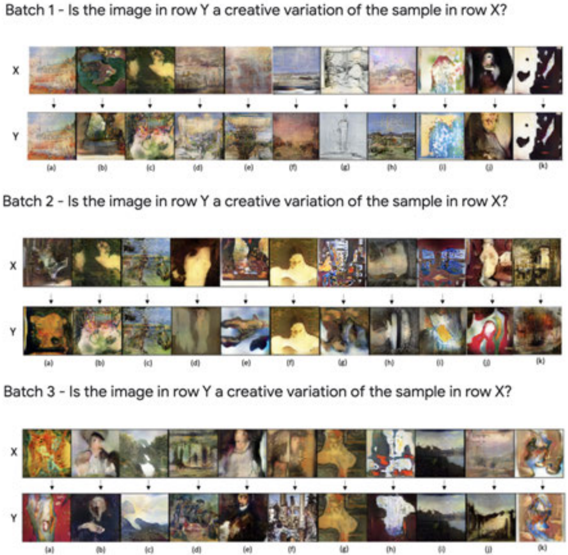


We test it under a creative VAE Decoder and a Creative Generator variant of ArtGAN architectures [Das et al., 2020, Tan et al., 2019].

Experimental Setup (Cont.)

In our preliminary study, ten voluntaries evaluated the artifacts following [Amabile, 1982].

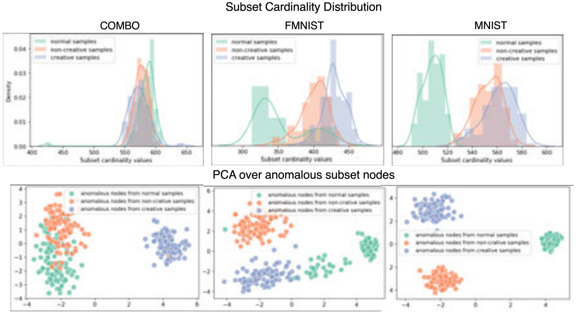
- We show the **baseline generated** by standard ArtGAN and the **sampled subset** of artifacts selected.
- We ask if the sample **is creative compared to** the initial image.
- Each evaluator provides **short description** of what makes a sample creative and non-creative.



Results for Creative Decoder

Group of activations for

Different types of samples are distinctive. We start noticing some overlap for normal and creative samples in more complex datasets.



Space	Dataset	Subset Scanning		
		50%	10%	Indv.
Pixel Space	MNIST	0.971	0.791	0.255
Activation Space	MNIST	**0.991**	**0.972**	0.531
Pixel Space	FMNIST	0.952	0.743	0.381
Activation Space	FMNIST	**0.990**	**0.962**	0.596
Pixel Space	Combo	0.921	0.713	0.490
Activation Space	Combo	**0.998**	**0.949**	0.626

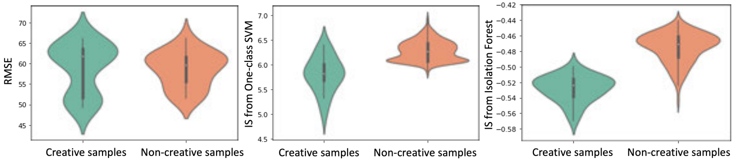
Detection power

The characterization improves when detecting the creative samples in the activation space, than when we scan over the pixel space.

Results for Creative ArtGAN

We used the generated subset score distribution for **anomalous activations as a guide for generating "creative" samples.**

Space	# nodes	Subset Scanning	
		50%	Indv.
Pixel Space	16384	0.762	0.504
Layer 1	8192	**0.905**	0.571
Layer 2	32768	**0.913**	0.528



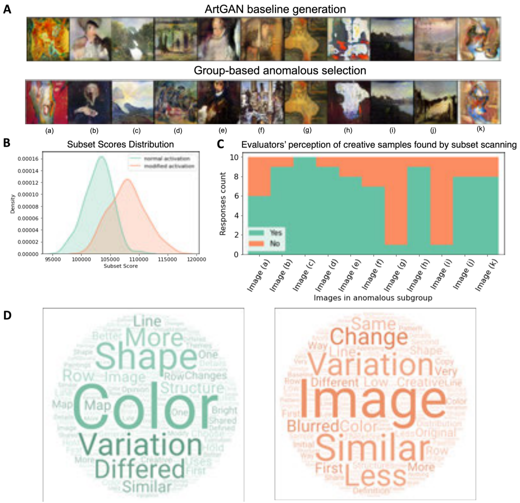
We observe that

IS scores have higher values for non-creative samples, and lower scores for the samples selected by our guided "creative" sampling method.

Results for Creative ArtGAN (Cont.)

The **anomaly-guided generations** were evaluated with respect to creativity by a group of observers. Across the three example batches, on average **78% of the images** were consistently found as creative by evaluators' perception.

Creative samples were described with changing one property (*different color palette* or *variation on the structure*).



Conclusions & Future Work

- We provide both the **subset of the generated artifacts** identified as creative and the **corresponding nodes** in the network that identified those samples as creative.
- Future research will consider questions to evaluators to provide a **disentanglement of creativity properties** such as novelty, surprise, and value.
- We plan to leverage the proposed creativity quantification as a control for generation of artifacts that are **consistent with human perception** of the novelty component of creativity.

Adversarial Robustness Toolbox

Code

Paper

Asante, Thanks, Gracias!



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