**Digitalizing beauty: On NFT art and its price**

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**Motivation**

- **NFT art market**
  - Market cap US$ 41 billion in 2021: 30 %
  - Sales of contemporary art market: 22%
  - Some stylized facts of contemporary art trading
    - Inherent trading
    - Price inequality
    - Centralized patrons
  - Less transparency in pricing

**Statistical Regularities**

- **Color quantification (K means)**

**Figure 1. Log price box plot for top 10 collections**

**Figure 2. ArtBlocks sales and prices**

**Figure 3. Color palette for ArtBlocks #17225316**

**Figure 4. Dominant colors from 3,964 artworks**

- **Luminance**: Perceived brightness to RGB colour  
  i.e. saturation-brightness
  - HSB = 0.2939^2 + 0.587G^2 + 0.114R^2
- **Composition-level statistics**
- **Pairwise spatial statistics**
  - For a set of images \(\{x_i\}\)  
  - \(\text{Skew} = \left( \frac{\theta_3}{\theta_2} \right)^{\frac{1}{2}}\)  
  - \(\text{Kurt} = \left( \frac{\theta_4}{\theta_2} \right)^{\frac{1}{2}}\)
  - \(\text{Energy Spectral Density (ESD)}\)

**Figure 5. Image statistics vs. Prices**

**Figure 6. Process pipeline**

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**Preliminary Result**

- **Spatial Energy Spectrum**

**Figure 7. Some stylized facts of contemporary art trading in 2021:**

- 30 %
- Sparseness (Kurtosis)
- Asymmetry (Skewness)
- Composition-level statistics
- Energy of signal
  - Perceived brightness to RGB colour
- Illiquidity
- Price inequality

**NEURAL NETWORK**

- **Interpretability**
  - Learned Features: What features has the NN learned?
  - Concepts: Which abstract concepts has the NN learned?
  - Adversarial Learning
  - Influential Instances
- **Integrated gradient**
  - Sundararajan, Taly & Yan (2017)
  - Input-output pairs \(\{x_i, f(x_i)\}_{i=1}^n \in \mathbb{R}^d \times [0,1]\)
  - Network classifier \(f: \mathbb{R}^d \to [0,1]\)
  - Basis functions \(\{\phi_i(x)\}_{i=1}^m \in \mathbb{R}^m\)

**Figure 8. Attribution \(a_i(x, x')\) is contributions of \(x_i\) to \(f(x)\) relatively to baseline input \(x'\)**

**IG Axioms - I**

1. Sensitivity \(\forall x_i \neq x'_i \exists \delta \phi_i(x) \neq \delta \phi_i(x') : f(x_i) \neq f(x'_i) \land a_i(x_i, x'_i) = a_i(x'_i, x'_i)\)
   - Relu \(f(x) = 1 - \max(0,1-x)\)
   - Suppose \(x' = 0, x = 2, a_i(x, x') = \delta \phi_i\)

2. Implementation Invariance \(\forall f, g \in \mathcal{F} : f(x) = g(x) \land a_i(x, x') = a_j(x, x')\)
   - \(\mathcal{G}(x) = \frac{\partial}{\partial x} g(x - x')\)
   - satisfies 1. and 2. where \(a \in [0,1]\) allows the linear interpolation between baseline and original image

**IG Axioms - II**

Proposition \(f: \mathbb{R}^d \to [0,1]\) is differentiable almost everywhere \>
\(\sum_i \mathcal{G}(x) = f(x) - f(x')\)

Generalization - Path Methods (PM)

Let \(\gamma = (\gamma_1, \ldots, \gamma_n) \to \mathbb{R}^d\) be a smooth function specifying a path in \(\mathbb{R}^d\) from \(x'\) to \(x\) and \(\alpha \in [0,1]\), then \(PM(f(x) = \frac{\partial}{\partial \alpha} g(x)\frac{\partial g(x)}{\partial \alpha})dx\)

**Future work**

- Process pipeline

**Reference**