Quantifying image realism via language model reasoning

Kseniia Petrushina

Moscow Institute of Physics and Technology,
Skolkovo Institute of Science and Technology

Scientific supervisor: Alexander Panchenko

2024

Introduction

As AI-generated images become more convincing, distinguishing realism from fiction is increasingly challenging.
This work proposes quantifiable realism measure to detect contextual and commonsense inconsistencies in visual content.

Problem statement

Given unknown *real* and *weird* probability distributions

$$\mathrm{P}_{\mathsf{real}}(\mathbf{x}) : \mathbb{R}^{n \times n} \to [0,1] \quad \mathrm{P}_{\mathsf{weird}}(\mathbf{x}) : \mathbb{R}^{n \times n} \to [0,1]$$

and samples from the distributions

$$\mathcal{D}_{\mathsf{r}} = \{\mathbf{x}_{\mathsf{r}}^i \mid \mathbf{x}_{\mathsf{r}}^i \sim \mathrm{P}_{\mathsf{real}}(\mathbf{x})\}_{i=1}^{N}$$

$$\mathcal{D}_{\mathsf{w}} = \{\mathbf{x}_{\mathsf{w}}^i \mid \mathbf{x}_{\mathsf{w}}^i \sim \mathrm{P}_{\mathsf{weird}}(\mathbf{x})\}_{i=1}^{N}$$

Problem statement

We need to find a *reality-check* function

$$f_{\mathsf{weird}} : \mathbb{R}^{n \times n} \to \mathbb{R}_+$$

that defines the realism score, that is for *real* image $\mathbf{x}_r$ and *weird* image $\mathbf{x}_w$, provided that they are close in a sense of similarity measure $\langle \cdot, \cdot \rangle$:

$$\langle \mathbf{x}_r, \mathbf{x}_w \rangle \leq \varepsilon,$$

the following holds true

$$f_{\mathsf{weird}}(\mathbf{x}_r) < f_{\mathsf{weird}}(\mathbf{x}_w).$$

Probability & Typicality

1. **Probability**
   Realistic objects have high probability under distribution P.

2. **Weak typicality**

$$\mathbf{x}^N = (\mathbf{x}_1, \ldots, \mathbf{x}_N) \overset{\text{iid}}{\sim} P$$

$$\mathbb{P}\Big[\lim_{N \to \infty} -\frac{1}{N} \log P(\mathbf{x}^N) = H[\mathbf{x}_n]\Big] = 1$$

Typical set is

$$A_\delta^N = \{\mathbf{x} : |-\frac{1}{N} \log P(\mathbf{x}^N) - H[\mathbf{x}_n]| < \delta\},$$

its elements are *weakly typical*.

Divergences

3. **Adversarial losses** f-divergence between densities p, q

$$D_f[q||p] \geq \mathbb{E}_q[T(\mathbf{x})] - \mathbb{E}_p[f^*(T(\mathbf{x}))]$$

Real-valued function T acts as a *critic* and produces larger values for samples from q and smaller for samples from p

4. **Maximum mean discrepancy** Given two sets of iid examples $\mathbf{x}^M$, $\hat{\mathbf{x}}^N$

$$MMD^2(\mathbf{x}^M, \hat{\mathbf{x}}^N) = \|\frac{1}{M}\sum_m \Phi(x_m) - \frac{1}{N}\sum_n \Phi(\hat{x}_n)\|^2$$

Φ is high dimensional feature space.

5. **Universal critics** Measure of randomness to decide whether $\mathbf{x}$ was drawn from P:

$$U(\mathbf{x}) = -\log \mathrm{P}(\mathbf{x}) - K(\mathbf{x})$$

$K(\mathbf{x})$ is *Kolmogorov complexity* of $\mathbf{x}$.

Proposed method

Extracting atomic facts

Using multi-modal model $f_{cap} : \mathbb{R}^{n \times n} \to T^{m \times L}$ we obtain m sequences of language tokens of length L, which describe the details about the image:

$$f_{cap}(\mathbf{x}) = F_A = \{[t_1^i, \ldots, t_L^i] \mid i \in \overline{1, m}\}$$

Pairwise natural language inference

For each ordered pair of facts $(f_i, f_j) \in F_A \times F_A$ we calculate entailment score via $f_{nli} : T^L \times T^L \to [-1, 1]$. The results are presented in the form of a matrix

$$S_{ij} = f_{nli}(f_i, f_j).$$

Aggregating pairwise scores

We take the sum of matrix elements, if both pairs (f_i, f_j) and (f_j, f_i) are contradictory and average it by the number of pairs:

$$f_{agg}(S) = -\frac{1}{m^2} \sum_{i<j} (S_{ij} + S_{ji}) \mathbb{I}[S_{ij}, S_{ji} < 0]$$

Proposed method

Resulting metric

The final formula for *reality-check* function is

$$f_{weird} = f_{agg} \circ f_{nli} \circ f_{cap}$$

Hypothesis

Resulting reality scores $R = \{f_{weird}(\mathbf{x})\}$ will correlate with probability densities $P = \{P_{real}(\mathbf{x})\}$:

$$r_s = \rho_{R(f_{weird}(\mathbf{x})), R(P_{real}(\mathbf{x}))} \leq -0.5$$

Computational experiments

Data

Figure: Examples of *real* and *weird* images.

Metrics

1.

$$\text{Accuracy} = \frac{1}{N} \sum_{i=1}^{N} \mathbb{I}[\mathsf{f}_{\text{weird}}(\mathbf{x}_r^i) < \mathsf{f}_{\text{weird}}(\mathbf{x}_w^i)]$$

2. Spearman's rank correlation coefficient

Results

f_{cap} \ f_{nli}	sileod	MoritzLaurer	t5-true
LLaVa	**0.68**	0.42	0.63
BLIP	0.53	**0.68**	0.53
GPT-2	0.37	0.32	0.37
GPT-4o	0.63	**0.68**	0.37

Table: Accuracy of realistic images detection using various functions for f_{cap} and f_{nli}.
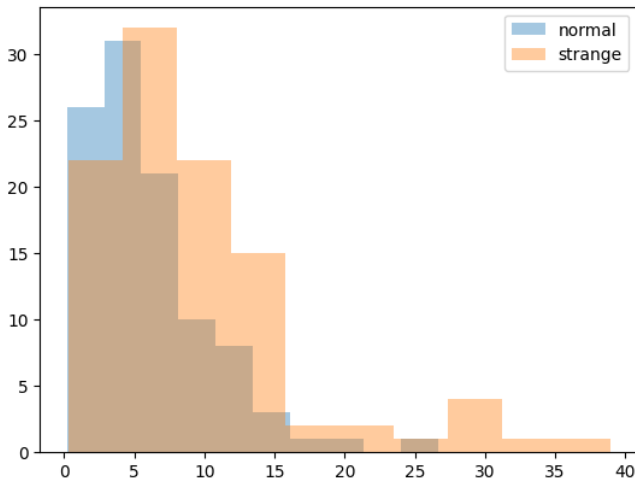
Results

Figure: Reality scores for the whole dataset obtained using *LLaVa* model for captioning and *sileod* model for contradiction detection.
$p - value = 4e - 5$ for Kolmogorov–Smirnov test.

Conclusion

- ▶ New interpretable method of quantifying image realism.
- ▶ Hypotheses about properties of the *reality-check* function.
- ▶ Computational experiments with different configurations.

Future work:

- ▶ Conduct experiments with measuring correlation with other methods.
- ▶ Carry on comprehensive study of ablation.

Literature

1. Lucas Theis. 2024. What makes an image realistic?. Proceedings of the 41st International Conference on Machine Learning.
   URL: `https://arxiv.org/abs/2403.04493`

2. Sewon Min et al. 2023. FActScore: Fine-grained Atomic Evaluation of Factual Precision in Long Form Text Generation. Association for Computational Linguistics.
   URL: `https://aclanthology.org/2023.emnlp-main.741`

3. Nitzan Bitton-Guetta et al. 2023. Breaking Common Sense: WHOOPS! A Vision-and-Language Benchmark of Synthetic and Compositional Images
   URL: `https://arxiv.org/abs/2303.07274`