

Improving Compositional Generation with Diffusion Models

Using Lift Scores

Chenning Yu and Sicun Gao, UC San Diego



We use diffusion model itself to reject bad images, in compositional way

Background

robot

lake

sunflower

diffusion model w/
composed text

“a robot holding a
sunflower beside a lake”

sunflower missed

diffusion models sometimes miss
components in text prompt

text prompt →

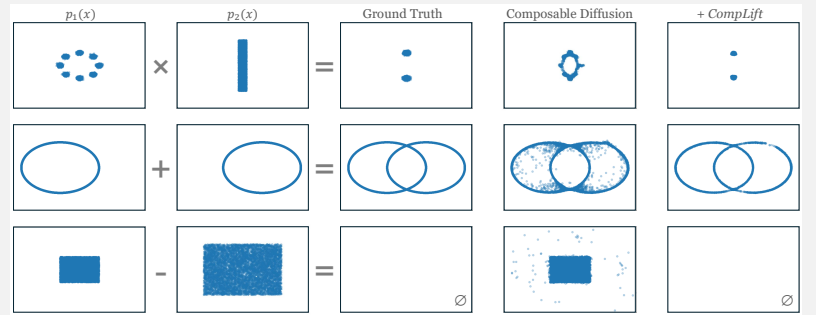
accept

reject

accepted and rejected Stable Diffusion XL images using lift scores

Key Highlights

- Training-free, use diffusion model itself
- Simple concept – compare with 0 to accept/reject
- Boosts base models by 106% (2D generation) and 16% (Image generation with SD XL)



Lift Score

An existing concept in data mining (Brin et al., 1997)

$$lift(x|c) := \log \frac{p(x|c)}{p(x)}$$

sample

constraint (e.g., a text component)

conditional distribution

unconditional distribution

Diffusion Models can Easily Estimate Lift Score

$$\log \frac{p(x|c)}{p(x)} \approx \exp(-\mathbb{E}_{t,\epsilon} ||\epsilon - \epsilon_\theta(x_t, c)||^2 + C),$$
$$\log \frac{p(x)}{p(x)} \approx \exp(-\mathbb{E}_{t,\epsilon} ||\epsilon - \epsilon_\theta(x_t, \emptyset)||^2 + C).$$

random sample timestep/noise

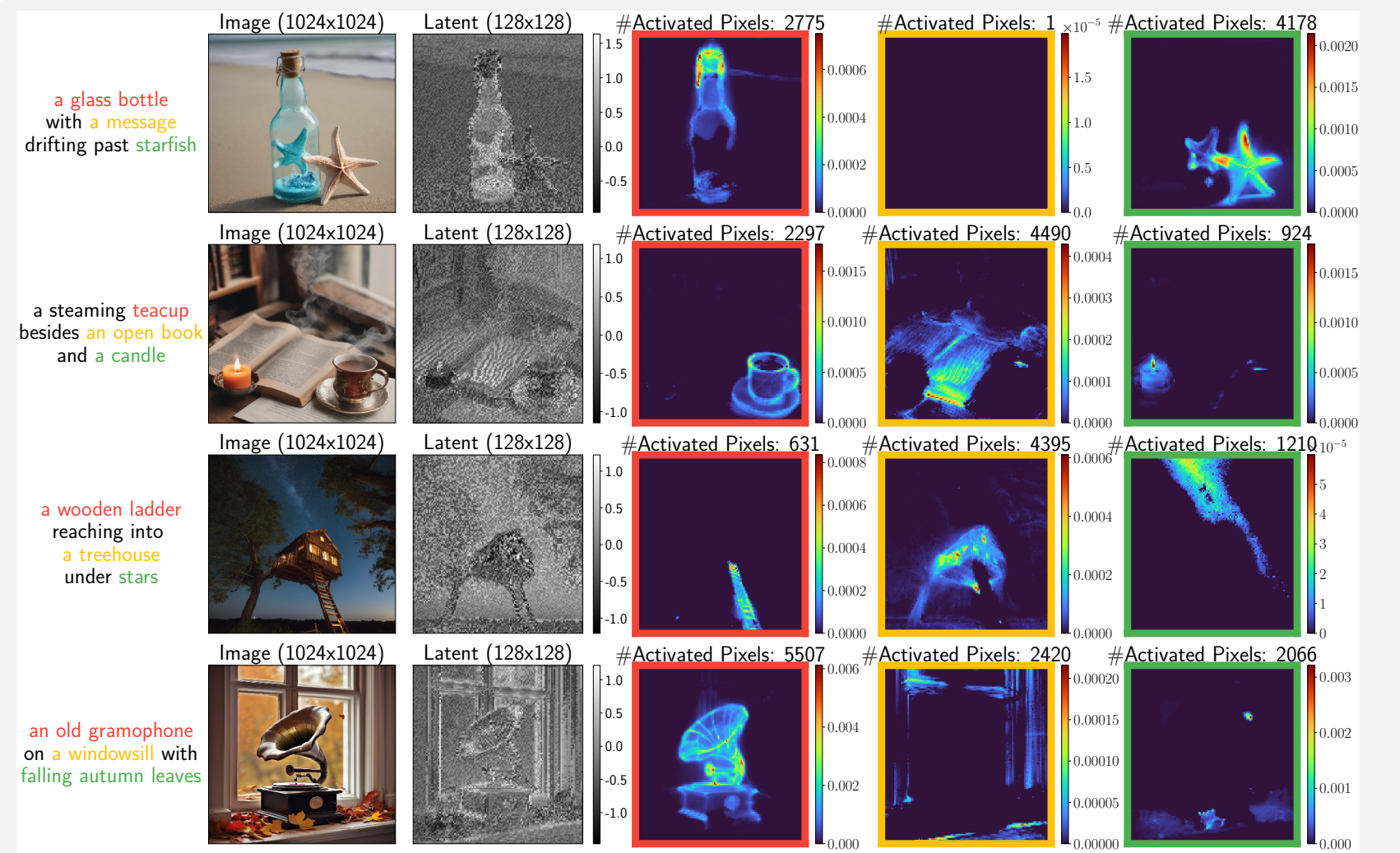
diffusion model

We use lift score as rejection criterion to check alignment of each individual component; then compose the criterion to accept/reject

Type	Algebra	Acceptance Criterion
Product	$c_1 \wedge c_2$	$\min_{i \in [1,2]} lift(x c_i) > 0$
Mixture	$c_1 \vee c_2$	$\max_{i \in [1,2]} lift(x c_i) > 0$
Negation	$\neg c_1$	$lift(x c_1) \leq 0$

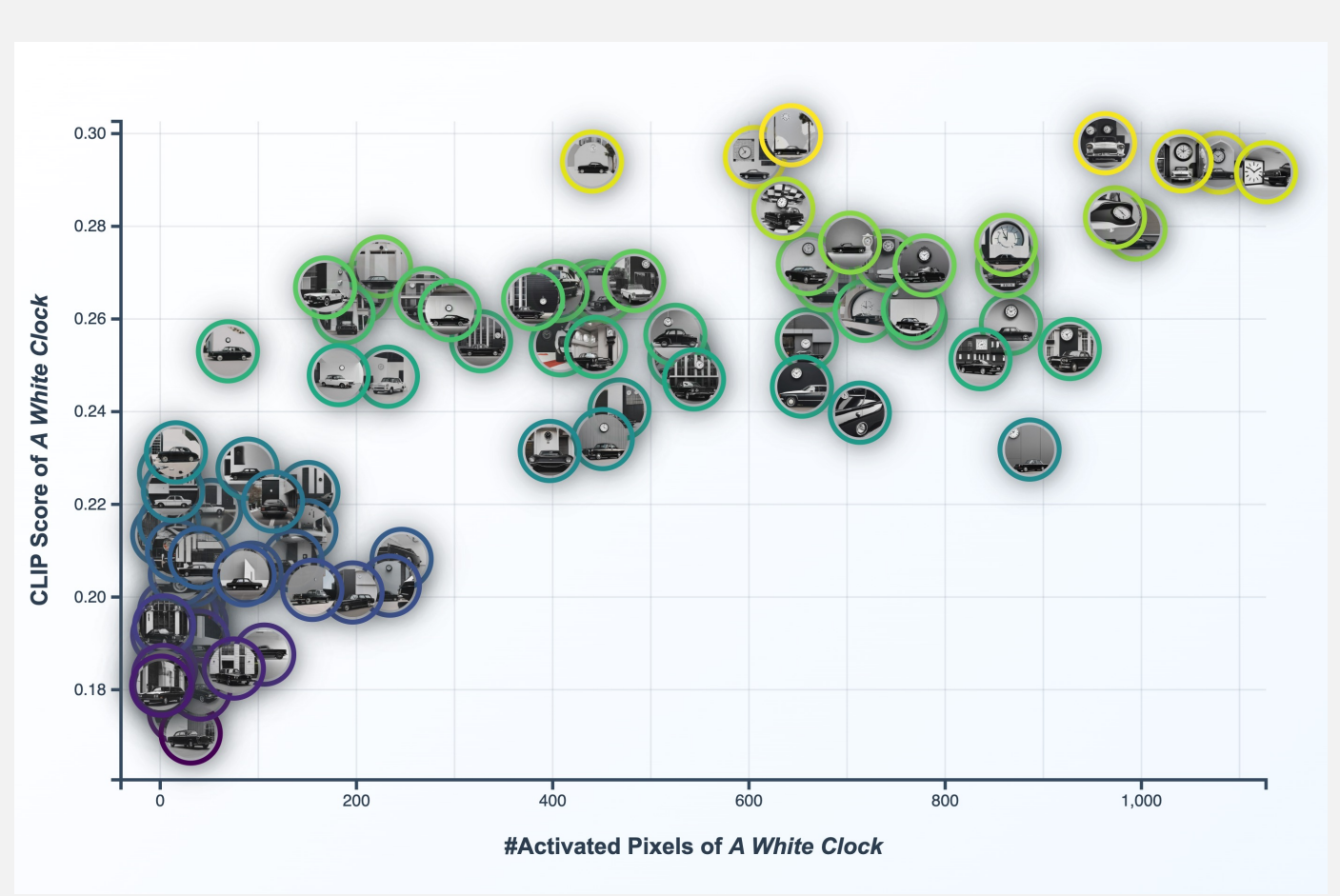
Table 1. Examples of Compose for multiple conditions.

Visualization in Latent Space



lift score shows strong correspondence to each text component;
activated pixels are pixels with positive lift scores

Correlation with CLIP Score



images with missing components
tend to have (1) lower CLIP score
and (2) fewer activated pixels with positive lift scores
prompt: a black car and a white clock