

Applying the PC Integrator to **Fully** Unconditional CIFAR-10 Image Generation

Remark. Although this section concerns image generation (not robotics), we keep the notation from the main paper (e.g., τ).

Our vector field is written as $v_t(\tau_t^c; \theta)$. In practical robotics tasks, at least one condition (e.g., current/past observations) is provided; the conditional form is

$$v_t(\tau_t^c; \theta \mid \mathbf{c}) \quad (\text{equivalently } v_\theta(\tau_t^c, \mathbf{c}, t)).$$

Here, the superscript c denotes the *correction* phase; to avoid confusion, the condition is boldface \mathbf{c} . Thus, the PC integrator has not been separately validated on the **fully** unconditional base vector field $v_t(\tau_t^c; \theta)$.

Experiment. We run a simple CIFAR-10 experiment to check whether the PC integrator can generate images from Gaussian noise in a **fully** unconditional setting. As mentioned in the main paper, the PC integrator does not require any additional training and only modifies the inference formulation; therefore, all results in this sheet are derived from the same single weight.

Reference implementation: <https://github.com/atong01/conditional-flow-matching>.

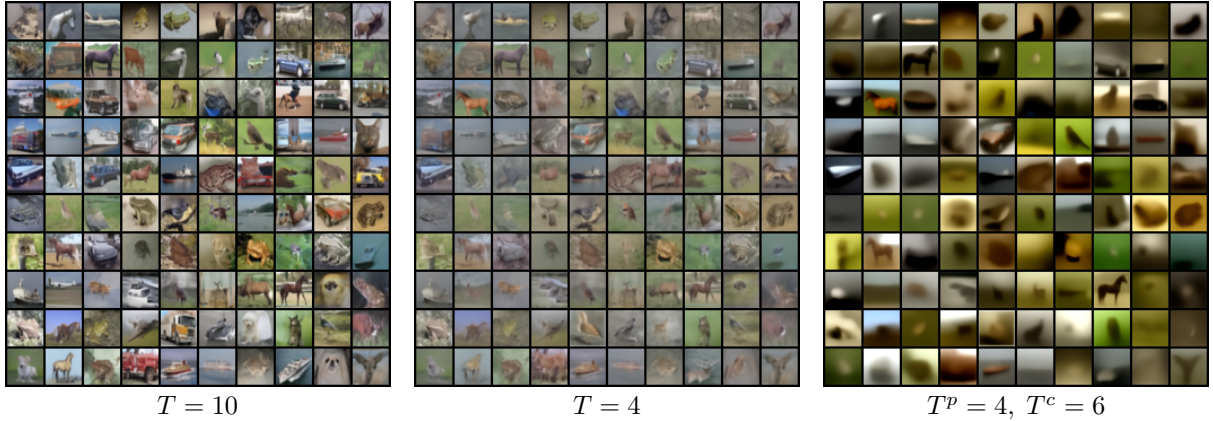


Figure 1: Left: images from 10 sampling steps. Middle: images from 4 steps. Right: P-C result by taking the 4-step prediction ($T^p = 4$) and adding 6 correction steps ($T^c = 6$), so $T^p + T^c = 10$.

Observation. Despite of meaningful predictions, the correction phase introduces blurring and mode corruption. This suggests that the PC integrator does not guarantee generalization to **fully** unconditional generation.

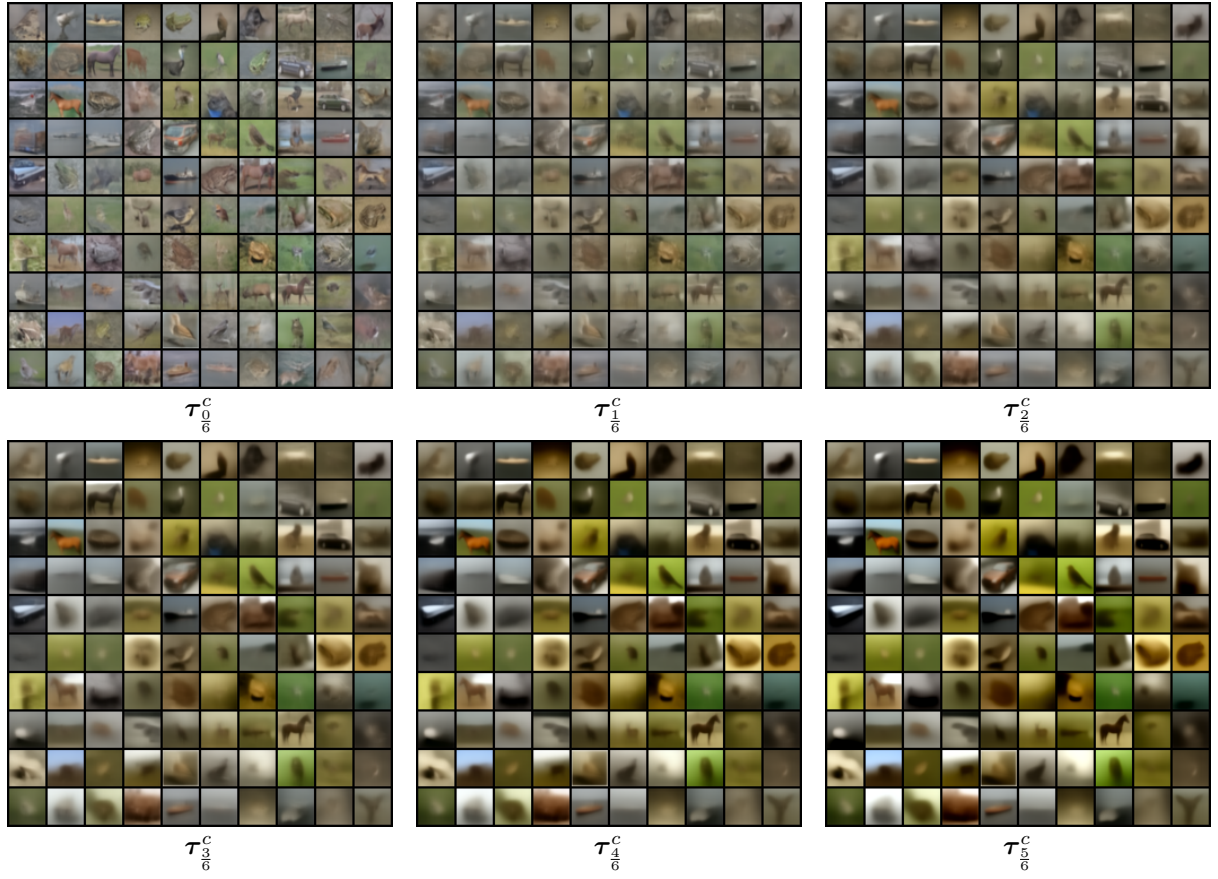


Figure 2: Intermediate results during the correction stage for Fig. 1 (right).