Progressive Distillation for Fast Sampling of Diffusion Models

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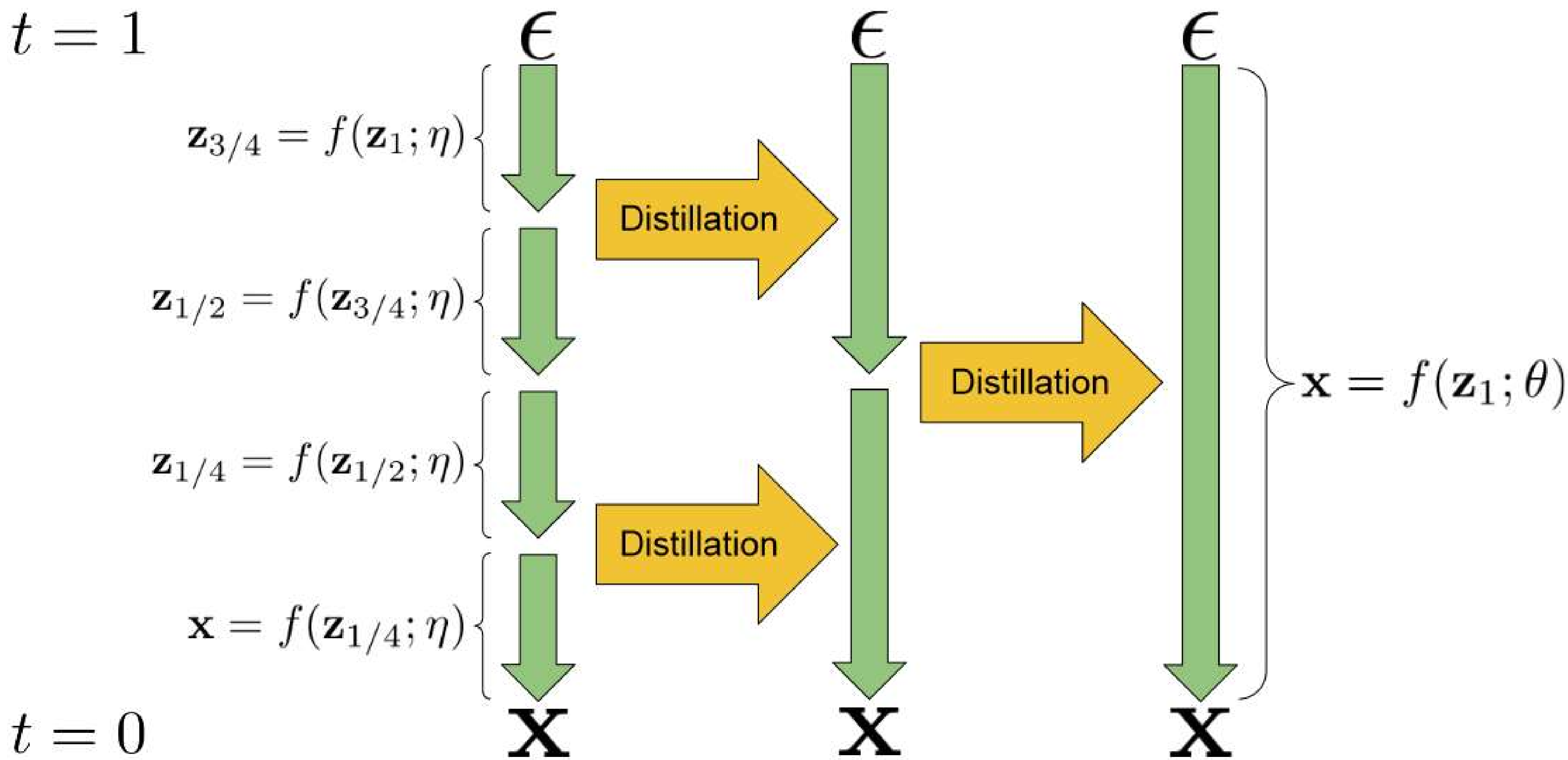
A Quick Overview



progressive_distillation.png

$\tilde{x}$ is our target

- We take two steps of DDIM
- Then $\tilde{x}$ is the image associated with taking two steps.
- The target of our distilled model is the output of our original diffusion model taking two ddim steps.
- We will cover $w()$ later

Algorithm 2 Progressive distillation

Require: Trained teacher model $\hat{\mathbf{x}}_\eta(\mathbf{z}_t)$
Require: Data set $\mathcal{D}$
Require: Loss weight function $w()$
Require: Student sampling steps N
  for K iterations **do**
    $\theta \leftarrow \eta$ ▷ Init student from teacher
    while not converged **do**
      $\mathbf{x} \sim \mathcal{D}$
      $t = i/N, \;\; i \sim Cat[1, 2, \ldots, N]$
      $\epsilon \sim N(0, I)$
      $\mathbf{z}_t = \alpha_t \mathbf{x} + \sigma_t \epsilon$
      `# 2 steps of DDIM with teacher`
      $t' = t - 0.5/N, \quad t'' = t - 1/N$
      $\mathbf{z}_{t'} = \alpha_{t'} \hat{\mathbf{x}}_\eta(\mathbf{z}_t) + \frac{\sigma_{t'}}{\sigma_t}(\mathbf{z}_t - \alpha_t \hat{\mathbf{x}}_\eta(\mathbf{z}_t))$
      $\mathbf{z}_{t''} = \alpha_{t''} \hat{\mathbf{x}}_\eta(\mathbf{z}_{t'}) + \frac{\sigma_{t''}}{\sigma_{t'}}(\mathbf{z}_{t'} - \alpha_{t'} \hat{\mathbf{x}}_\eta(\mathbf{z}_{t'}))$
      $\tilde{\mathbf{x}} = \frac{\mathbf{z}_{t''} - (\sigma_{t''}/\sigma_t)\mathbf{z}_t}{\alpha_{t''} - (\sigma_{t''}/\sigma_t)\alpha_t}$ ▷ Teacher $\hat{\mathbf{x}}$ target
      $\lambda_t = \log[\alpha_t^2/\sigma_t^2]$
      $L_\theta = w(\lambda_t) \|\tilde{\mathbf{x}} - \hat{\mathbf{x}}_\theta(\mathbf{z}_t)\|_2^2$
      $\theta \leftarrow \theta - \gamma \nabla_\theta L_\theta$
    end while
    $\eta \leftarrow \theta$ ▷ Student becomes next teacher
    $N \leftarrow N/2$ ▷ Halve number of sampling steps
  end for

progressize_algorithm.png

Questions so far?

Why is $\tilde{x}$ our target, and not ϵ?

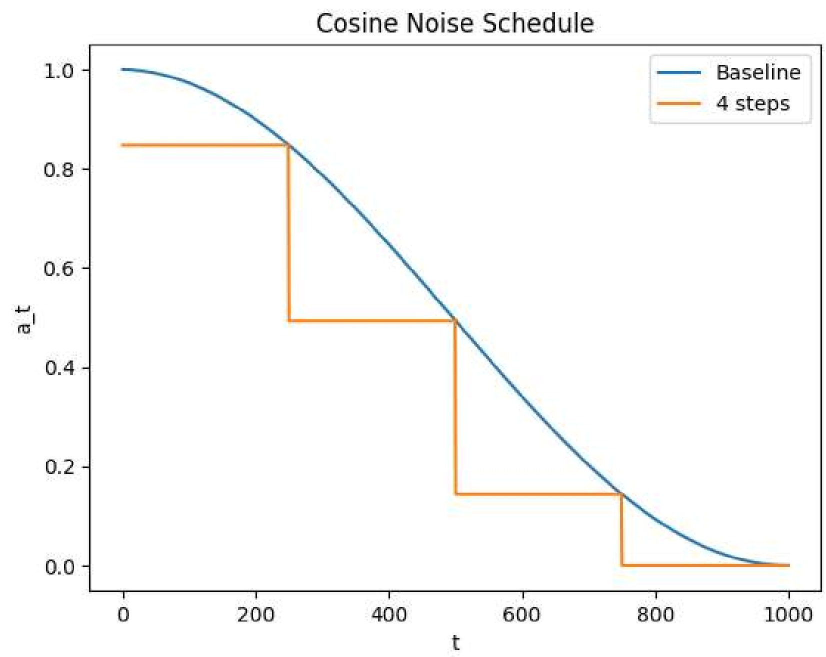
Break down of relationship between x and ϵ

In the case of a single timestep $||\epsilon_\theta(x_T) - \epsilon||_2^2$, could be optimized by an identity, and is not particularly useful. As our number of steps decreases to 4, this step becomes 1/4 of our total steps. ($a_T \simeq 0$)

$$\hat{x}_\theta(z_t) = \frac{1}{\alpha_t}(z_t - \sigma_t \hat{\epsilon}_\theta(z_t))$$

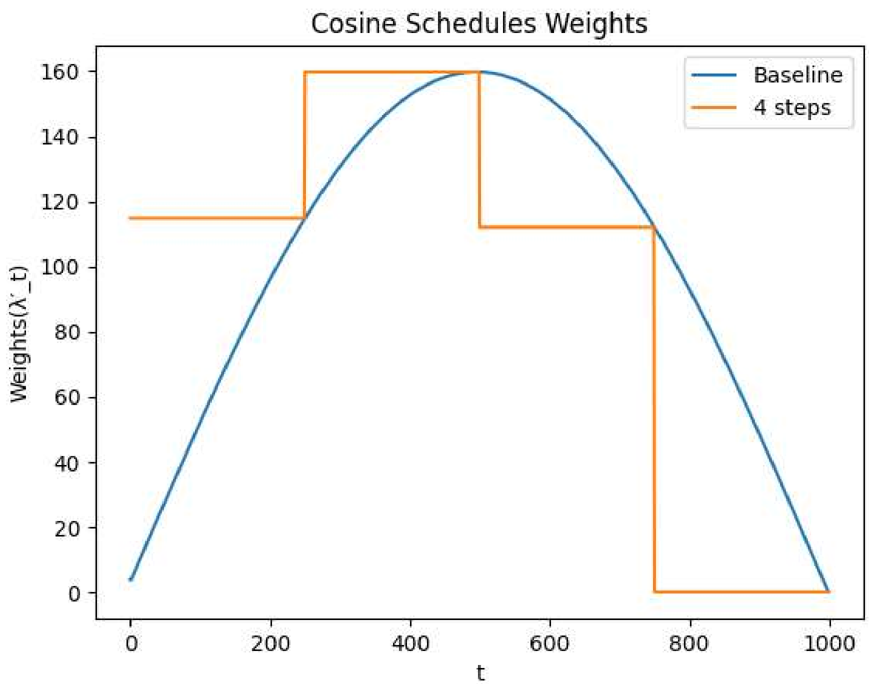
Our Options:

- Just predict x directly.
- Predict x and ϵ
- Predict $v = \alpha_t \epsilon + \sigma x$



$w()$ is 0!

$w()$ is 0, or very close to 0 near 0 and T. This problem becomes more aparent when we decrease the number of steps to 4. Our weights w becomes almost 0 for one of our 4 steps!



Alternative Weights

$L_\theta = max(\frac{\alpha_t^2}{\sigma_t^2}, 1)||\hat{x} - x_t||_2^2$ ‘truncated SNR weighting’

$L_\theta = (1 + \frac{\alpha_t^2}{\sigma_t^2})||\hat{x} - x_t||_2^2$ ‘SNR+1 weighting’

I just clipped the weights.

```
continuous_weights(CosineNoiseSchedule().alpha_bar).clip(min=1)
```

Results

Notice the evaluations at powers of 2.

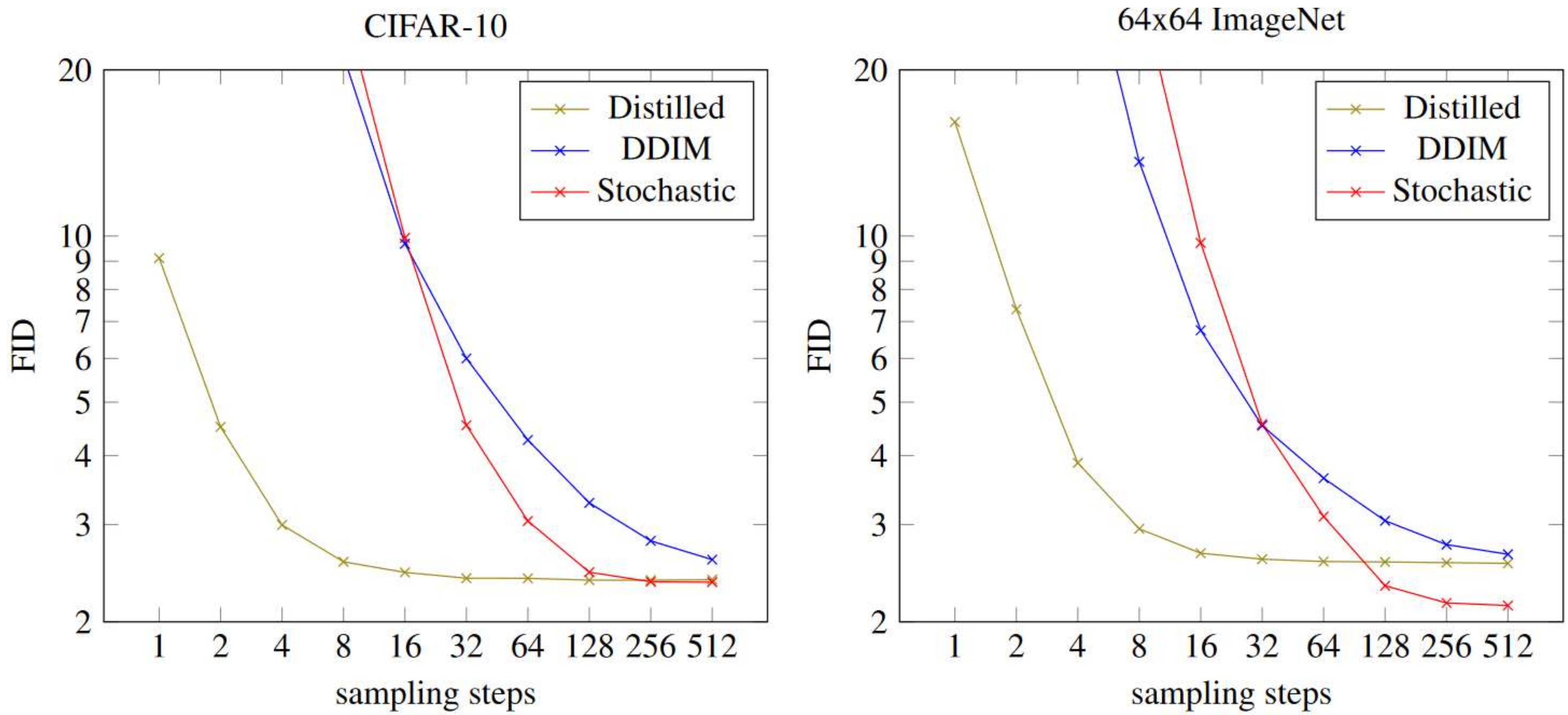


image.png

Derivation of the distillation target

from Appendix G

N : student sampling steps

$t' = t - \frac{0.5}{N}$: 1 teacher step, 1/2 student step

$t'' = t - \frac{1}{N}$: 2 teacher steps, 1 student step

We want to have 1 student step have input z_t and output $\tilde{z}_{t''}$ equal to $z_{t''}$

$$\tilde{z}_{t''} = \alpha_{t''}\tilde{x} + \frac{\sigma_{t''}}{\sigma_t}(z_t - \alpha_t\tilde{x}) =$$

$$(\alpha_{t''} - \frac{\sigma_{t''}}{\sigma_t}\alpha_t)\tilde{x} + \frac{\sigma_{t''}}{\sigma_t}z_t = z_{t''}$$

$$(\alpha_{t''} - \frac{\sigma_{t''}}{\sigma_t}\alpha_t)\tilde{x} = z_{t''} - \frac{\sigma_{t''}}{\sigma_t}z_t$$

$$\tilde{x} = \frac{z_{t''} - \frac{\sigma_{t''}}{\sigma_t}z_t}{(\alpha_{t''} - \frac{\sigma_{t''}}{\sigma_t}\alpha_t)}$$

Implmentation Notes

"We sample this discrete time such that the highest time index corresponds to a signal-to- noise ratio of zero, i.e. α1 = 0, which exactly matches the distribution of input noise z1 ∼ N (0, I) that is used at test time"

This is critical, I lost a lot of time on this one. I didn't notice the problem until late in the process, so this might have actually been the cause for many other issues.

Cosine schedule seemed important for training model that predicts x instead of ϵ. Otherwise training unstable.

I did not succeed in using this technique on a parent model that predicts the noise. This may have been a bug, but training was a lot smoother with a parent that predicted x instead of ϵ.