

TTIC 31230, Fundamentals of Deep Learning

David McAllester, Autumn 2023

Adjusting Generation

Temperature and Guidance

Temperature-Adjusted Generation

$$\text{Training: } \Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{(x,y) \sim \text{Pop}}[-\ln P_\Phi(y|x)]$$

$$P_\Phi(y|x) = \underset{y}{\operatorname{softmax}} s_\Phi(y|x)$$

$$\text{Desired Generation: } P_\Phi^\beta(y|x) = \underset{y}{\operatorname{softmax}} \beta s_\Phi(y|x) \propto P_\Phi(y)^\beta$$

Temperature Adjusted Generation for Language

In practice we use

$$\begin{aligned} P_{\Phi}^{\beta}(y_{i+1} \mid y_1, \dots, y_i) &= \underset{y_{i+1}}{\text{softmax}} \beta s_{\Phi}(y_{i+1} \mid y_1, \dots, y_i) \\ &\propto P_{\Phi}(y_{i+1} \mid y_1, \dots, y_i)^{\beta} \end{aligned}$$

This is different from

$$P_{\Phi}^{\beta}(y_1, \dots, y_N) \propto P_{\Phi}(y_1, \dots, y_N)^{\beta}$$

Temperature-Adjusted Generation for Language

In language translation we take $\beta = \infty$ ($\text{softmax} \Rightarrow \text{argmax}$).

For language generation $\beta = 1$ tends to yield rambling and incoherent text.

On the other hand $\beta = \infty$ generates repetition.

We look for a Goldilocks β .

An alternative to temperature-adjusted generation is top-P sampling, also called nucleus sampling, which is similar in structure and performance.

There is a literature on generation adjustment for language.

Temperature-Adjusted Reverse-Diffusion

$$z(t - \Delta t) = z(t) + \left(\frac{\hat{E}_\Phi[y|t, z(t)] - z(t)}{t} \right) \Delta t + \frac{1}{\sqrt{\beta}} \epsilon \sqrt{\Delta t}$$

As with language generation, this is not the same as $P_\Phi^\beta(y) \propto P_\Phi(y)^\beta$

Classifier Guidance

Diffusion Models Beat GANs on Image Synthesis

Dharwali and Nichol, May 2021

For **class-conditional** generation of imangenet images $P(y|x)$ they train an **unconditional** diffusion image model $P_\Phi(y)$ and utilize a pretrained imangenet classification model $P_\Psi(x|y)$.



Classifier Guidance

They note that

$$P(y|x) = \frac{P(y)P(x|y)}{P(x)} \propto P(y)P(x|y)$$

For generation they modify the reverse-diffusion process so as to intuitively approximate

$$P_{\Phi,\Psi}^{\beta,\gamma}(y|x) = \text{softmax}_y \beta(s_{\Phi}(y) + \gamma s_{\Psi}(x|y)) \propto P_{\Phi}(y)^{\beta} P_{\Psi}(x|y)^{\beta+\gamma}$$

Classifier Guidance

$$z(t - \Delta t) = z(t) + \left(\frac{\hat{E}_\Phi[y|t, z(t)] - z(t)}{t} + \gamma s_\Psi(x|z(t)) \right) \Delta t + \frac{1}{\sqrt{\beta}} \epsilon \sqrt{\Delta t}$$

This is different from, but motivated by,

$$P_{\Phi, \Psi}^{\beta, \gamma}(y|x) \propto P_\Phi(y)^\beta P_\Psi(x|y)^{\beta+\gamma}$$

Conditional Diffusion Models

$P_\Phi(y \mid \text{panda bear chemist})$



panda mad scientist mixing sparkling chemicals, artstation

Train $\hat{E}_\Phi[y|t, z(t), \textcolor{red}{x}]$

Classifier Free Guidance (Self-Guidance)

Classifier Free Diffusion Guidance

Ho and Salimans, December 2021 (NeurIPS workshop)

Training: $\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{(x,y) \sim \text{Pop}}[-\ln P_{\Phi}(y|x)]$

$$P_{\Phi}(y|x) = \underset{y}{\operatorname{softmax}} s_{\Phi}(y|x)$$

We introduce a special x -value \emptyset and arrange that

$$\text{Pop}(y|\emptyset) = \text{Pop}(y).$$

Guidance

For $\beta > 0$ they modify the reverse-diffusion process to intuitively approximate

$$P_\Phi^\beta(y|\textcolor{red}{x}) = \underset{y}{\operatorname{softmax}} \beta s_\Phi(y|\textcolor{red}{x}) - (\beta-1)s_\Phi(y|\emptyset) \propto \frac{P_\Phi(y|\textcolor{red}{x})^\beta}{P_\Phi(y|\emptyset)^{\beta-1}}$$

For $\beta = 1$ we have no adjustment.

$$P_\Phi^1(y|x) = P_\Phi(y|x)$$

For $\beta \gg 1$ (used in practice) we have.

$$P_\Phi^\beta(y|\textcolor{red}{x}) \approx \underset{y}{\operatorname{softmax}} \beta(s_\Phi(y|\textcolor{red}{x}) - s_\Phi(y|\emptyset)) \propto \left(\frac{P_\Phi(y|\textcolor{red}{x})}{P_\Phi(y|\emptyset)} \right)^\beta$$

Guidance

$$P_{\Phi}^{\beta}(y|\textcolor{red}{x}) = \underset{y}{\operatorname{softmax}} \beta(s_{\Phi}(y|\textcolor{red}{x}) - s_{\Phi}(y|\emptyset)) \propto \left(\frac{P_{\Phi}(y|\textcolor{red}{x})}{P_{\Phi}(y|\emptyset)} \right)^{\beta}$$

$$z(t-\Delta t) = z(t) + \left(\frac{(\hat{E}_{\Phi}[y|t, z(t), \textcolor{red}{x}] - \hat{E}_{\Phi}[y|t, z(t), \emptyset]) - z_t}{t} \right) \Delta t + \frac{1}{\sqrt{\beta}} \epsilon \sqrt{\Delta t}$$

Guidance

$$P_{\Phi}^{\beta}(y|\textcolor{red}{x}) \propto \left(\frac{P_{\Phi}(y|\textcolor{red}{x})}{P_{\Phi}(y|\emptyset)} \right)^{\beta}$$

Ho and Salimans motivate this from Classifier Guidance and

$$P(x|y) \propto \frac{P(y|x)}{P(y)}$$

But this is false.

$$P(x|y) = \frac{P(x)P(y|x)}{P(y)} \not\propto \frac{P(y|x)}{P(y)}$$

Guidance

$$z(t-\Delta t) = z(t) + \left(\frac{(\hat{E}_\Phi[y|t, z(t), \textcolor{red}{x}] - \hat{E}_\Phi[y|t, z(t), \textcolor{red}{blurry}]) - z_t}{t} \right) \Delta t + \frac{1}{\sqrt{\beta}} \epsilon \sqrt{\Delta t}$$

This will make the generated image sharper.

A More General Formulation

Consider a Markovian VAE with deterministic encoder $z_1(y)$ and $z_{i+1}(z_i)$ and where $z_N(z_{N-1})$ is a constant \emptyset .

This holds for language models but also seems reasonable for image VAEs provided that a stochastic generator is trained in conjunction with the encoder (I claim).

Deterministic encoding yields an enormous simplification (a good thing).

$$\text{enc}^*, \text{gen}^* = \underset{\text{enc}, \text{gen}}{\operatorname{argmin}} E_y[-\ln(P_{\text{gen}}(y|z_1)P_{\text{gen}}(z_1|z_2)\cdots P_{\text{gen}}(z_{N-1}|\emptyset))]$$

A More General Formulation

$$\text{enc}^*, \text{gen}^* = \underset{\text{enc}, \text{gen}}{\operatorname{argmin}} E_y[-\ln(P_{\text{gen}}(y|z_1)P_{\text{gen}}(z_1|z_2)\cdots P_{\text{gen}}(z_{N-1}|\emptyset))]$$

In a language model we generate one word at a time.

But we can also consider the case where z_i is a vector whose dimension is (slightly) decreasing as i increases.

Instead of adding one word at a time we add a small number of numbers (dimensions) at a time.

In this case we can use

$$P_{\text{gen}}(z_{i-1}|z_i) = \hat{z}_{i-1}(z_i) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, I)$$

A More General Formulation

$$\text{enc}^*, \text{gen}^* = \underset{\text{enc}, \text{gen}}{\operatorname{argmin}} E_y[-\ln(P_{\text{gen}}(y|z_1)P_{\text{gen}}(z_1|z_2)\cdots P_{\text{gen}}(z_{N-1}|\emptyset))]$$

$$P_{\text{gen}}(z_{i-1}|z_i) = \hat{z}_{i-1}(z_i) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, I)$$

$$\text{enc}^*, \text{gen}^* = \underset{\text{enc}, \text{gen}}{\operatorname{argmin}} E_y \|y - z_1\|^2 + \sum_{i=1}^{N-1} \|z_i - \hat{z}_i(z_{i+1})\|^2$$

Conditional Generation

Training the encoder and the decoder conditioned on x (as in a language translation model). This trains $\hat{z}_{i-1}(z_i, x)$.

For generation we then have

$$\text{Unadjusted: } z_{i-1} = \hat{z}_{i-1}(z_i, x) + \epsilon$$

$$\text{Temperature Adjusted: } z_{i-1} = \hat{z}_{i-1}(z_i, x) + \frac{1}{\sqrt{\beta}} \epsilon$$

$$\text{Guidance Adjusted: } z_{i-1} = \hat{z}_{i-1}(z_i, x_{\text{good}}) - \hat{z}_{i-1}(z_i, x_{\text{bad}}) + \frac{1}{\sqrt{\beta}} \epsilon$$

Output z_1

END