TTIC 31230, Fundamentals of Deep Learning

David McAllester, Autumn 2023

Adjusting Generation

Temperature, Guidance, and Majority Voting

Temperature-Adjusted Generation

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

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

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

Temperature Adjusted Generation for Language

In practice we use

$$\begin{aligned} P_\Phi^\beta(y_{i+1} \mid y_1, \ldots, y_i) &= \operatorname*{softmax}_{y_{i+1}} \beta s_\Phi(y_{i+1} \mid y_1, \ldots, y_i) \\ &\propto P_\Phi(y_{i+1} \mid y_1, \ldots, y_i)^\beta \end{aligned}$$

This is different from

$$P_\Phi^\beta(y_1, \ldots, y_N) \propto P_\Phi(y_1, \ldots, y_N)^\beta$$

Temperature-Adjusted Generation for Language

In language translation we take $\beta = \infty$ (softmax $\Rightarrow$ 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

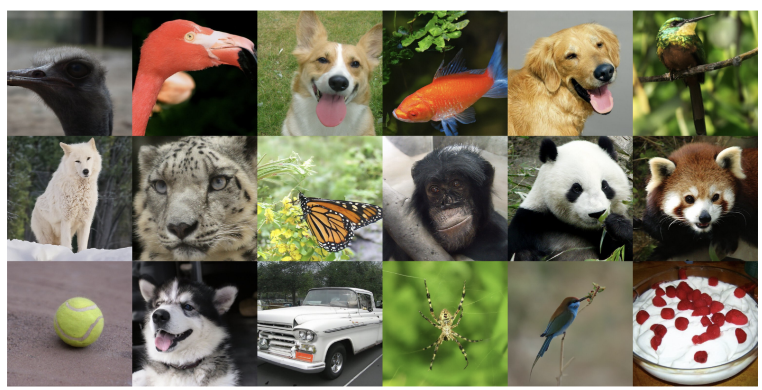
$$z(t - \Delta t) = z(t) + \left(\frac{\hat{E}_\Phi[y|t, z(t)] - z(t)}{t} \right) \Delta t + \frac{1}{\sqrt{\beta}}\, \epsilon \sqrt{\Delta t}$$

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
Dharriwal and Nichol, May 2021

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

$$P^{\beta,\gamma}_{\Phi,\Psi}(y|x) = \operatorname*{softmax}_y \beta(s_\Phi(y)+\gamma s_\Psi(x|y)) \;\propto\; P_\Phi(y)^\beta P_\Psi(x|y)^{\beta+\gamma}$$

Classifier Guidance

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

This is different from, but motivated by,

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

Conditional Diffusion Models

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

panda mad scientist mixing sparkling chemicals, artstation

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

Classifier Free Guidance (Self-Guidance)

Classifier Free Diffusion Guidance
Ho and Salimans, December 2021 (NeurIPS workshop)

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

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

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

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

Guidance

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

$$P_\Phi^\beta(y|x) = \operatorname*{softmax}_y \beta s_\Phi(y|x) - (\beta - 1) s_\Phi(y|\emptyset) \quad \propto \frac{P_\Phi(y|x)^\beta}{P_\Phi(y|\emptyset)^{\beta-1}}$$

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

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

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

$$P_\Phi^\beta(y|x) \approx \operatorname*{softmax}_y \beta(s_\Phi(y|x) - s_\Phi(y|\emptyset)) \;\propto\; \left(\frac{P_\Phi(y|x)}{P_\Phi(y|\emptyset)}\right)^\beta$$

Guidance

$$P_\Phi^\beta(y|x) = \operatorname*{softmax}_y \beta(s_\Phi(y|x) - s_\Phi(y|\emptyset)) \quad \propto \quad \left(\frac{P_\Phi(y|x)}{P_\Phi(y|\emptyset)}\right)^\beta$$

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

Guidance

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

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

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

This will make the generated image sharper.

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

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

Output z_1

Adjusted Generation: Majority Voting

Self-Consistency Improves Chain Of Thought Reasoning In Language Models
Wang et al., March 2023

The answer is taken to be a majority vote over stochastic chain of thought generation.

$$\text{answer}^*(\text{question}) = \underset{\text{answer}}{\text{argmax}} \; E_{\text{thought} \sim P_{\text{LLM}}(\text{thought}|\text{question})} \; P_{\text{LLM}}(\text{answer}|\text{question}; \text{thought})$$

END