

A Distributional Approach to Controlled Text Generation

(ICLR 2021)
(Oral)



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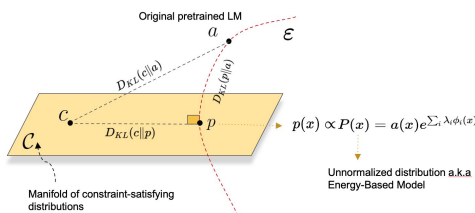
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The first approach to controlled text generation that exploits **distributional** requirements. Through minimization of KL divergence from the original pretrained LM, degeneration is avoided.

MOTIVATIONS

1. Imposing **constraints** on generations from a large pretrained LM.
2. Not only **"pointwise"** constraints on individual sequences, but also **"distributional"** constraints on statistical properties of generated sequences.
3. Avoiding **degeneration**: loss of fluency or diversity of the generated sequences.

APPROACH



- **Moment constraints** over desired generation features
- Manifold C of all LMs satisfying the moment constraints
- We select the LM p which **minimizes KL-divergence** to the original pretrained LM a

Step 1: From constraints to EBM

Desired Moment Constraints

$$\begin{aligned} \mathbb{E}_{x \sim p} \phi_1(x) &= \bar{\mu}_1 \\ \mathbb{E}_{x \sim p} \phi_2(x) &= \bar{\mu}_2 \\ &\vdots \\ \mathbb{E}_{x \sim p} \phi_n(x) &= \bar{\mu}_n \end{aligned}$$

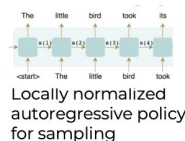
Moment Matching

$$P(x) = a(x)e^{\sum_i \lambda_i \phi_i(x)}$$

$P(x)$ is an unnormalized form of the optimal distribution $p(x)$ i.e an Energy-Based Model

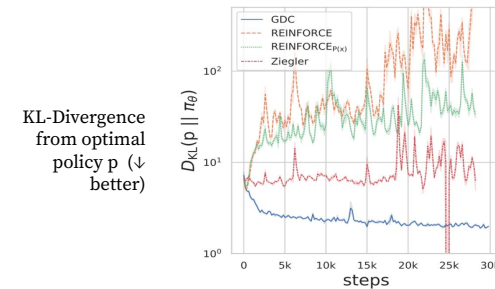
Step 2: From EBM to autoregressive policy

Distributional Policy Gradients

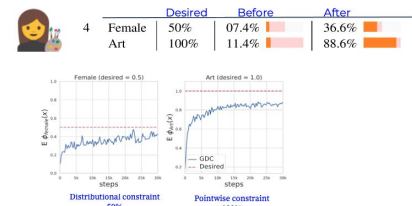


EXPERIMENTS

(1) Pointwise, (2) Distributional, (3) Hybrid Constraints



$$\begin{aligned} \mathbb{E}_{x \sim p} \phi_{she} &= 0.5 \\ \mathbb{E}_{x \sim p} \phi_{art} &= 1.0 \end{aligned}$$



$$\begin{aligned} \mathbb{E}_{x \sim p} \phi_{she} &= 0.5 \\ \mathbb{E}_{x \sim p} \phi_{business} &= 1.0 \end{aligned}$$



A hybrid experiment:

- Pointwise and distributional constraints together
- Application to **de-biasing** the pretrained LM



Paper: <http://bit.ly/DIST-CTRL-ICLR2021>

Code: <https://github.com/naver/gdc>