

1 Learned Data Augmentation: Non-Autoregressive Translation

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4 Abstract

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6 1 Introduction

7 Learned models of data are often misspecified. When the goal of modeling is not density estimation,
8 but some alternative objective, this misspecification may lead to undesirable behaviour under the
9 maximum likelihood objective. In this note, we consider learned data augmentation techniques to
10 edit each data point so that the augmented data is more amenable to a particular model class, while
11 hopefully preserving the properties we care about.

12 A concrete example of a setup where maximum likelihood may not be desirable is non-autoregressive
13 translation, which we focus on in this note. In translation, the goal is to translate a source sentence
14 from one language into a sentence in a different target language. The success of translation is mea-
15 sured by the BLEU score between our generated translation and the true reference target sentence.
16 As the BLEU score is not a function of distributional closeness to the true data, translation systems
17 often discard distributional information and output a single translation of a source sentence. How-
18 ever, the training objective is still often maximum likelihood, a function of the model distribution.

19 In the case of non-autoregressive translation, this results in undesirable behaviour. As non-
20 autoregressive models cannot model output dependencies, resulting models trained via maximum
21 likelihood using the true distribution often have pathological errors due to misspecification, and
22 therefore poor BLEU scores. We aim to resolve this via data augmentation.

23 Prior work shows that distillation is a successful data augmentation approach. We instead rely
24 on neural editor models [Guu et al., 2017], which are a trainable alternative to data augmentation
25 [Akyürek et al., 2021].

26 2 Problem Setup

27 Source sentence x , target sentence y . True translation distribution $p(y \mid x)$.

28 We propose to, given a family of student models $q_\theta(y \mid x)$, learn an edit model $q_\phi(\hat{y} \mid y, x)$
 29 whose conditional distribution over \hat{y} is easier for the student model q_θ to learn. Learning an inter-
 30 mediate distribution will allow the student model to focus on only modeling the important aspects
 31 of the true distribution.

To accomplish this, we propose to solve the following optimization problem

$$\operatorname{argmin}_{\phi} D_{\text{KL}} [p(y \mid x) \parallel q_\phi(\hat{y} \mid y, x)] + \min_{\theta} D_{\text{KL}} [q_\phi(\hat{y} \mid y, x) \parallel q_\theta(\hat{y} \mid x)]. \quad (1)$$

This is a bilevel optimization problem, where we want to find the edit model that is able to balance faithfulness to the true data (the first term) as well as learnability of the student model (the second term). We refer to Equation 1 as the outer problem, and the second term as the inner problem:

$$\operatorname{argmin}_{\theta} D_{\text{KL}} [q_\phi(\hat{y} \mid y, x) \parallel q_\theta(\hat{y} \mid x)]. \quad (2)$$

32 **3 Method 1: The Exact Setting**

33 We first make the simplifying assumption that we can solve the inner problem exactly. In order to
 34 then solve the full outer problem, we will differentiate through the solution of the inner problem. In
 35 full generality, this would require an application of the implicit function theorem, or approximations
 36 through sampling or incomplete optimization.

37 **3.1 Experiment: Length-2 Binary Strings + Non-autoregressive Student**

38 Our first experiment will determine whether training an edit model is possible in a very simple
 39 setting, where we can compute the solution to the inner problem (training the student model given
 40 an edit model) in closed form, and subsequently differentiate through that procedure.

We restrict our attention to distributions over target sentences that are binary strings of length 2 without conditioning on a source sentence. In particular, our true distribution takes the form

$$y = b_1[0, 0] + b_2[0, 1] + b_3[1, 0] + b_4[1, 1],$$

where $b \sim \text{Cat}(\lambda)$. As we are interested in disambiguation, we first focus on the case where $b_1, b_4 \approx 0$, and $b_2 < b_3$. The edit model then takes the form

$$q_\phi(\hat{y} \mid y) = [\phi]_{\hat{y}, y},$$

where $\hat{y}, y \in \{0, 1\}^2 = \mathcal{Y}$ and $\phi \in [0, 1]^{\mathcal{Y} \times \mathcal{Y}}$. The student is nonautoregressive, and has the form

$$q_\theta(\hat{y}) = \prod_t q_\theta(\hat{y}_t) = [\theta]_{1, \hat{y}_1} \cdot [\theta]_{2, \hat{y}_2},$$

41 where $\theta \in [0, 1]^{2 \times \mathcal{Y}}$.

In this setting, we can exactly compute the solution of the inner problem,

$$\operatorname{argmin}_{\theta} \mathbb{E}_y [D_{\text{KL}} [q_{\phi}(\hat{y}) \mid y] \parallel q_{\theta}(\hat{y})] = \operatorname{argmin}_{\theta} \mathbb{E}_y \left[\sum_{\hat{y}} q_{\phi}(\hat{y} \mid y) (\log q_{\phi}(\hat{y} \mid y) - \log q_{\theta}(\hat{y})) \right],$$

and differentiate through it. The minimizer is given by

$$\begin{aligned} [\theta]_{1,0} &= \sum_y \sum_{\hat{y}} p(y) q_{\phi}(\hat{y} \mid y) 1(\hat{y}_1 = 0) \\ [\theta]_{2,0} &= \sum_y \sum_{\hat{y}} p(y) q_{\phi}(\hat{y} \mid y) 1(\hat{y}_2 = 0) \\ [\theta]_{t,1} &= 1 - [\theta]_{t,0}, \end{aligned}$$

42 which is differentiable wrt ϕ .

43 **Results** We find that the editor model is able to disambiguate the true data and produces a new
 44 data distribution with no dependencies across time, resulting in a distribution that is easier for the
 45 student to match. We see the results of training the editor model with the following conditions:

- 46 • $b = [0.001, 0.4, 0.59, 0.001]$
- 47 • Editor is initialized to uniform everywhere except the transitions from $[0,1]$ and $[1,0]$, where
 48 transitions to $[0,0]$ and $[1,1]$ are given low mass in order to speed up training
- 49 • We recompute the parameters of the student by solving the inner problem at every iteration
- 50 • We solve the outer problem via gradient descent (1k iterations, learning rate of 1e-3)

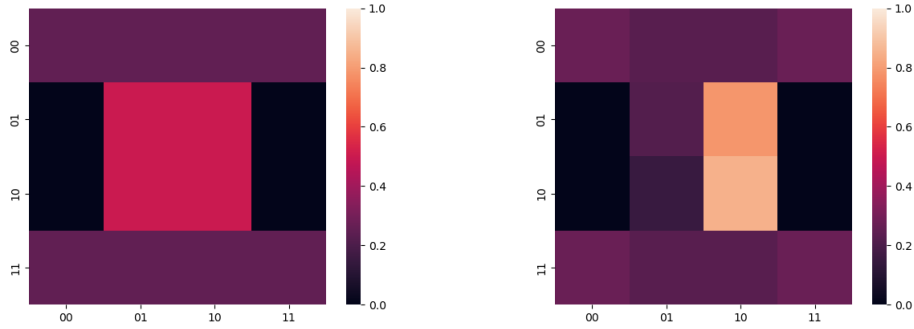


Figure 1: The emission probabilities for the editor model at the start of training (left) and end of training (right).

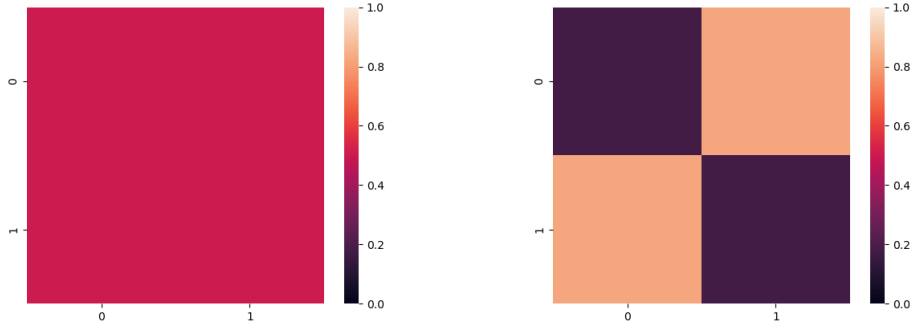


Figure 2: The emission probabilities for the student model at the start of training (left) and end of training (right).

4 Decoding: work back into problem setup later

Given data consisting of (x, y) pairs, our goal is to learn a model $q_\theta(y \mid x)$ such that it maximizes the functional

$$F(q) = \mathbb{E}_{p(x,y)} \left[\operatorname{argmax}_{\hat{y}} d(q_\theta(\hat{y} \mid x), y) \right], \quad (3)$$

where $p(x, y)$ is the data distribution and d is some measure of correctness between our prediction \hat{y} and the true output y .

References

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