Fixing exposure bias with imitation learning needs powerful oracles

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Abstract

We apply imitation learning (IL) to tackle the NMT exposure bias problem with errorcorrecting oracles, and evaluate an SMT lattice-based oracle which, despite its excellent performance in an unconstrained oracle translation task, turned out to be too pruned and idiosyncratic to serve as the oracle for IL.

1 Introduction

Catastrophic failures of neural machine translation (NMT) systems – hallucinations, repeated or nonsense outputs – are hypothesized to be caused by the exposure bias (Bengio et al., 2015; Ranzato et al., 2016), which is understood as the inferencetime inability to recover from own errors and that manifests itself in a spectrum of erroneous translations from fluent, but semantically unrelated to the input, to completely non-linguistic outputs (Wang and Sennrich, 2020). One suspected reason is that not all inference-time token decisions are featured in the training data and so there was no training signal to help to recover or to continue from them. This in turn, is believed to be caused by the standard teacher-forcing training algorithm (Williams and Zipser, 1989), which decomposes sequence learning into independent per-token predictions, each conditioned on the golden truth context rather thauan the context the model would have produced.

Several attempts tackle exposure bias by bringing the training and testing objectives closer, most notably with reinforcement learning (RL) (Ranzato et al., 2016; Shen et al., 2015). While RL does improve quality (Shen et al., 2015; Kreutzer et al., 2017), to what extent this can be attributed to exposure bias reduction is not clear, as RL generally replaces the learning algorithm causing the exposure bias, rather than using its proven mitigation. Moreover, fully-fledged RL is slower than maximum likelihood training (MLE) with teacherforcing (Shen et al., 2015), which is a limiting factor in applications.

In this work¹, we attempted to address exposure bias directly via a connection to robotics, where the same underlying problem of catastrophic control failures of behavioral cloning (the equivalent of teacher-forcing) is well understood: behavioral cloning has been theoretically proven to amplify errors (Kääriäinen, 2006; Ross et al., 2011) that explains its failures, and several imitation learning (IL) based mitigation strategies with guarantees exist. Specifically, we are motivated by the result of (Ross et al., 2011), that a system trained with behavioral cloning accumulates errors quadratically with the target length T in the worst case. We further adapt their algorithm AggreVaTe (Ross and Bagnell, 2014) to NMT, that is free from error accumulation. Its major requirement is a powerful oracle capable of correcting arbitrary inference errors on-demand. Once such oracle is available, onthe-fly augmenting training data with the oracle's corrections allows the student NMT to be exposed to (optimal) corrections of its own errors, enjoying only linear worst-case error accumulation.

The bulk of our work is devoted to the construction and evaluation of the oracle. Given an input x and the reference r, it should be able to continue any (potentially, erroneous) partial translation $y_{1:t}$ in a BLEU-optimal way:

$$y_{t+1:T}^* = \underset{T, y_{t+1:T}s.t.y_{1:T} \in L}{\arg\max} \text{BLEU}(y_{1:t} + y_{t+1:T}, r),$$
(1)

where $y_{1:T} = y_{1:t} + y_{t+1:T}$ is the concatenation of the prefix, $y_{1:t}$, and the continuation, $y_{t+1:T}$, and L is the search space which, in our case, will be a statistical machine translation (SMT) lattice.

Token cross-alignments make (1) a hard problem and many possible hypotheses are unreachable in L. However, finding such oracle translations – reachable hypotheses closest to the references – has been studied for SMT, where with the help of linear BLEU approximations (Tromble et al., 2008)

¹See extended report in (Hormann, 2021).

and shortest path algorithms excellent oracle translations, almost doubling BLEU scores vs. regular SMT translations, could be found via a finite-state transducer (FST) representation of search space L (Sokolov et al., 2013). The main idea behind our IL oracle was to repurpose these existing BLEU oracles to solve (1), powered by the observation that there exists a gap of >25 BLEU points between NMT quality and the oracle quality (Figure 3, left).

We report a positive and a negative result: First, the overhead of on-the-fly querying the SMT error-correcting oracle is tolerable and permits efficient IL implementation of NMT training. Second, however: while SMT oracles do find high-BLEU oracle translations when no (or a short) prefix is enforced, even the least pruned lattices are still overly reduced by the SMT decoder to keep only very reasonable translations and exclude many student prefixes which are though required to be in-lattice for the oracle to correct them. Although we implemented a workaround to fix this prefix unreachability problem, it did not lead to corrections improving over the student's own translations.

2 Imitation Learning Training of NMT

We treat an auto-regressive NMT system as a timedependent policy π that specifies a distribution over target tokens conditioned on input x and previously generated prefix $y_{< t}$, both of which will be omitted for clarity: $\pi_t(y) \equiv \pi(y|y_{< t};x)$. This policy is implemented as the output of the last softmax layer and depends functionally on the rest of the network². When training with teacher-forcing, the following loss is minimized under the empirical distribution of parallel sequences in training data \mathcal{D} : $\mathcal{L}_{\text{MLE}}(\pi) = \mathbb{E}_{\mathbf{y}|\mathbf{x} \sim \mathcal{D}}[\sum_{t=1}^{T} \ell(y_t, \pi_t)], \text{ where } \ell(\cdot) \text{ is }$ usually the negative log-likelihood. However, to perform well at test time we are interested instead in $\mathcal{L}(\pi) = \mathbb{E}_{\mathbf{y}|\mathbf{x} \sim \pi}[\sum_{t=1}^T \ell(y_t, \pi_t)]$, i.e. we need to perform well under the learned model distribution. As shown by Ross et al. (2011), the discrepancy between \mathcal{L} and \mathcal{L}_{MLE} can accumulate quadratically with the sequence length T, which in practice could manifest itself as catastrophic translation failures.

To mitigate, Ross and Bagnell (2014) proposed the AggreVaTe algorithm, which is free from such error accumulation and would be an attractive asset for NMT. It, however, relies on an oracle policy π^* that, given the same input x and the partially

generated π 's prefix $y_{< t}$, can produce the full continuation in the task-loss optimal fashion. For NMT, that translates into solving the BLEU optimization task (1), which is our main technical contribution.

AggreVaTe aims to make the student's action-value function Q (here, unnormalized logits before softmax) accurately predict the expert continuation's BLEU score for any action, i.e. vocabulary token. Each training example x is translated by π to get translation y; then an exploration action, a_t , is sampled at a random position t. The prefix $y_{< t}$ is concatenated with a_t and continued by the oracle to obtain the BLEU score of this correction for the particular action a_t given context $y_{< t}$; this score is then used as the target value for Qs.

Algorithm 1: AggreVaTe for NMT

In Algorithm 1, the sigmoid σ scales logits to [0,1] to match the BLEU range (its slope is chosen such that min and max values of Q roughly map to 0 and 1, resp.), I is the indicator testing that the oracle's continuations are of higher BLEU than the student's, and the "reward-to-go" at time t, $\Delta \operatorname{BLEU}(a_t)$, is defined as the contribution of the oracle's suffix $y_{t+1:T}^*$ to the total sequence's score: $\operatorname{BLEU}(y_{< t} + a_t + y_{t+1:T}^*) - \operatorname{BLEU}(y_{< t} + a_t)$).

Exploratory actions. After beam search on π_j produces $y_{1:T}$ and a random t is sampled, we need to generate an exploration action a_t . We evaluated three ways of selecting a_t :

- A uniform random action as in (Ross and Bagnell, 2014). This leads to slower training as most tokens will not influence BLEU, but can eventually help generalization.
- 2. The most probable action as per student's π . This uses the oracle more efficiently, focusing

²We also reuse the notation to denote whole or partial generated sequences as π 's output, e.g. $y_{1:T} = \pi(x)$.

- on correcting student errors that are about to be committed.
- 3. A stochastic mixture of the above two methods with probability β of selecting 1) or 2) otherwise, to balance their trade-offs.

Empirically, mixing with $\beta = 0.1$ worked best.

3 Building the BLEU oracle

To build an oracle solving (1), we follow Sokolov et al. (2013), who convert phrase lattices generated by Moses decoder (Koehn et al., 2007) to FSTs and score edges with the linear BLEU approximation from (Tromble et al., 2008): For a hypothesis y and a reference r the log-BLEU is assumed to be approximately linear in n-gram precisions:

BLEU'(y,r) =
$$\theta_0 |y| + \sum_{n=1}^{N} \theta_n \sum_{u \in \Sigma^n} c_u(y) \delta_u(r)$$
, (2)

where $c_u(e)$ is the number of times the n-gram u appears in y, $\delta_u(r)$ is an indicator for presence of u in r; θ_n are further parametrized as $\theta_0 = 1$, $\theta_n = -\left(4p \cdot r^{n-1}\right)^{-1}$, where p and r are grid-sought on a dev set to maximize corpus BLEU (§A).

Given pre-decoded, reweighted with (2) and cached FSTs for every training example, shortest paths on them correspond then to the hypotheses with (approximately) the best BLEU in the FST w.r.t. to the corresponding reference, thus solving (1) from scratch for t = 0. For the IL usecase, however, the oracle must continue hypotheses, rather than create them from scratch, so it must accept an existing prefix $y_{< t}$ and solve (1) with this constrain. Since $y_{< t}$ is not guaranteed to be reachable in L, we perform a two-step procedure: First, make all FST states final to allow termination of shortest paths in any state and set $r = y_{< t}$; then, the shortest path is a reachable partial translation, $y'_{< t}$, closest to $y_{< t}$ as per (2). Second, prune all edges not reachable from $y'_{< t}$ from the original FST and re-solve (1), this time, with the actual reference r.

Since Sokolov et al. (2012) showed that by approximating bi-gram BLEU in (2) only a marginal decrease in corpus BLEU can be traded for an order of magnitude faster computation, we implemented the oracle for N=2 in C++ with Python bindings to enable calls from the fairseq NMT toolkit.

Oracle efficiency. Figure 1 shows that oracle's memory consumption decreases from 50Mb for Moses' lattice beam threshold b = 0.1 (low pruning) to a 1/100th of that (10Kb) for b = 0.9 (high

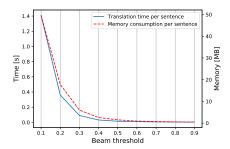


Figure 1: Oracle's average memory consumption and continuation time.

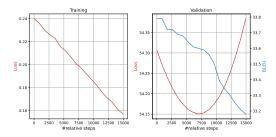


Figure 2: Training and validation loss/BLEU during 15k fine-tuning steps of a converged baseline.

pruning). Increasing b also reduces the oracle continuation time as FSTs have fewer states and transitions: The shortest path takes from about 1 to 0.1 secs, allowing oracle queries on every SGD update. As oracle calls are self-contained and therefore highly parallelizable, time should be further divided by available CPUs.

Oracle quality. Figure 3 (left) illustrates gridsearch results for p and r with reference prefixes. As can be seen, the achievable oracle BLEU on the IWSLT14 EN-DE dev set exceeds the teacherforcing NMT quality (\sim 32 BLEU) by >25 points.

4 Experiments

We experimented with the IWSLT14 DE-EN dataset tokenized, lowercased and cleaned with Moses tools, and jointly BPE-split into 32,000 tokens. Training hyperparameters are given in Table 3 in Appendix. We warm-started fine-tuning with AggreVaTe from the baseline's last checkpoint; the learning rate was reduced to 5×10^{-7} and its schedule changed to "fixed".

Despite the high performance of the oracle and working training loop we failed to improve over the teacher-forcing training. While in Figure 2 the training and validation losses decrease when warm-starting AggreVaTe, this is not mirrored by dev BLEU increase. Moreover, the same behaviour

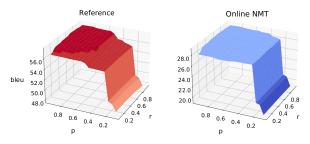


Figure 3: Oracle's BLEU for reference (right) and imperfect (left) prefixes for pruning threshold b=0.1 (other $b\in\{0.2,0.3,0.4\}$ give similar results). Baseline NMT achieves BLEU 32 on the same dev set.

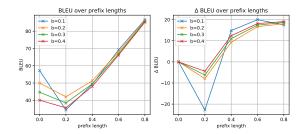


Figure 4: Left: BLEU score over prefix lengths taken from the reference. Right: Difference of BLEU score from one discrete prefix length to the next.

happens even for AggreVaTe on top of an unconverged student (Figure 5 in §B), hinting at systematic low-quality oracle outputs. More evaluations, including other quality metrics, can be found in §B.

Below we hypothesize and verify three related reasons that could explain this oracle failure to correct NMT student's errors despite high BLEU on the unconstrained oracle task.

4.1 Failure analysis

Oracle overfits to references. The oracle achieves high BLEU for oracle translations when finding them from scratch, or when continuing prefixes, that are extracted from references, which are not representative of real student prefixes. To confirm the hypothesis that the SMT oracle search spaces are overly bound to high-scoring translation, and to understand how prefix quality influences the oracle quality, we used an online NMT service to generate good but imperfect translations and derive our prefixes from them.

While the optimal approximation hyperparameters, p and r, did not visibly change when continuing imperfect prefixes, the drop in oracle performance vs. reference prefixes are considerable 20+ BLEU points (Figure 3, right), confirming that oracle on suboptimal prefixes is underperforming.

b	β	s_BLEU	s_GLEU	BLEU	GLEU
0.1	0.1	13.59	11.56	29.16	31.58
	0.5	12.86	10.97	27.19	29.74
0.2	0.1	13.01	11.17	28.23	30.87
	0.5	11.89	10.26	26.12	28.95
0.4	0.1	10.76	9.38	25.95	29.07
	0.5	9.88	8.70	23.88	27.20

Table 1: BLEU/GLEU grouped by beam threshold b and exploration randomness β .

Non-monotonic search spaces. Figure 4 shows the influence of the prefix length and the beam threshold b on corrections' BLEU. As can be seen, less pruning of the lattice (decreasing b) does not lead to improved oracle quality, meaning that, counter-intuitively, not every path that exists in a more pruned lattice (larger b) is also present in it for lower b. We hypothesize that the increased flexibility of larger lattices becomes a problem when the beam search, that drives the pruning, has more options to minimize the *model* score on idiosyncratic paths that, due to model and search errors, do not necessarily maximize BLEU w.r.t. the reference. This corroborates the findings of Sokolov et al. (2013) (Table VIII), who found that smaller b do not lead to a significant oracle BLEU increase despite an explosion of the number of edges.

Unfortunately, this lattice non-monotonicity may disproportionally affect our oracle because of the two-step unreachability mitigation procedure (§3).

Lattices lack diversity. Our final hypothesis is that lattices do not match the diversity of NMT outputs; and so they struggle to correct an underperformant student, finding reachable prefixes $y'_{< t}$ that are wildly different from the actual $y_{< t}$. In Table 1 we measure BLEU and GLEU as a function of b and increased exploration β . As the student should generate better-than-random tokens, replacing them more often with random ones should significantly decrease oracle continuation scores. We observe, however, a relatively modest (for an oracle) drop, pointing to difficulties of continuing reasonable student's prefixes even without random exploration. To make sure that the drop is not due to the inserted random token only and affects the whole continuation, we also report the suffix-BLEU/GLEU (denoted with 's_') that measures the suffix contribution to the total metric (see Δ BLEU (a_t) in Algorithm 1). More results in §C.

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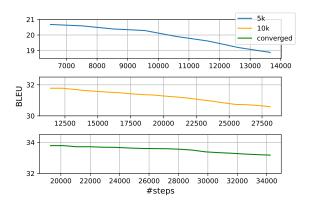


Figure 5: BLEU performance on validation set during fine-tuning with AggreVaTe at different starting points.

Metric	Baseline 17.5k	Fine-tuned best 26.3k	Fine-tuned last 34.2k
BLEU	34.34	34.06	33.66
GLEU	0.665	0.663	0.66
METEOR	0.57	0.569	0.564
BLEURT	0.17	0.173	0.172
Perplexity	6.11	6.06	6.11

Table 2: Comparison of the baseline and fine-tuned AggreVaTe models on test set. The best model was selected according to the NLL loss on the validation set.

A Oracle tuning

Grid-searches for p and r were done in [0.1, 0.95] with the step 0.05, the Moses beam pruning threshold b - in [0.1, 0.9] with the step 0.1. Prefixes $y_{< t}$ were randomly cut from references or student translations at length [0%, 80%] with the 20% step.

B More Evaluation Results

Fine-tuning at different stages of convergence. Figure 5 shows the effect of fine-tuning the baseline model from the starting points 5k, 10k and 17.5k steps respectively. The experiments were stopped after 8 hours of fine-tuning. Training is decreasing the BLEU score on the validation set with increasing number of training iterations.

Other metrics. In Table 2 shows the evaluation on the IWSLT14 test set for four additional metrics, known to better correlate with human scores. The *Fine-tuned best* was trained for 26.3k - 17.5k = 8.8k steps and selected by the minimum NLL loss on the validation set from the models during fine-tuning. The *Fine-tuned last* model is fine-tuned for additional 34.2k - 17.5k = 16.7k steps.

In the experiments, the best fine-tuned model exceeds the performance of the last fine-tuned

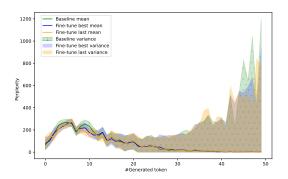


Figure 6: Mean and variance of perplexity over number of generated tokens for baseline and fine-tuned models.

model in all of the measured metrics. Compared to the baseline, the best fine-tuned model performs slightly better in BLEURT and perplexity but fails to improve BLEU, GLEU and METEOR.

Measuring effect on exposure bias. In Figure 6 we measured the mean and variance of the perplexity for each consecutive token for the test setting. All models are pretty certain in the beginning of the sequence and get more uncertain after around 10 tokens, which quantifies the exposure bias phenomenon. For the baseline model, this is expected, among other things, because for initial tokens the self-attention has less tokens to attend to; the increased variance after 30 generated tokens can be explained by inability to correct own errors, as well as the low number of training examples actually reaching that length. As AggreVaTe training failed, we do not observe improvements in perplexity for fine-tuned models.

C Lattice diversity

To investigate the lattice diversity further, we plotted in Figure 7 the following averages: the BLEU score of the oracle (B_o) , student (B_s) , of the oracle's using the student's exploration action (B_{oe}) and the ratio B_o/B_s to show for how many sentences the oracle's continuations were better than the student's inferred sentences (corresponds to the indicator I in Algorithm 1).

As the student's performance gets worse due to training on sub-optimal examples, B_o/B_s increases which is a sign of the student dropping in quality below oracle corrections. However, the B_{oe} curve, which includes the exploration action, is below B_s most of the time, witnessing that the oracle is confused both by the exploration action as well as by the student's prefix (after B_s decreases below B_o or B_{oe} , B_s still does not acquire positive slope).

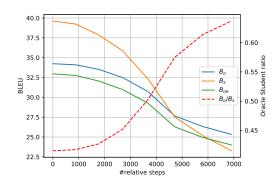


Figure 7: BLEU performance of student (B_s) , oracle (B_o) , oracle with student exploration action (B_{oe}) and the ratio of oracle to student BLEU (B_o/B_s) over the course of fine-tuning.

Parameter	Baseline	Fine-tuning
Learn. Method	Teacher-Forcing	AggreVaTe
Criterion	Cross-Entropy	MSE
Optimizer	Adam (default)	#
Learn. Rate	5×10^{-4}	5×10^{-7}
Learn. Rate Scheduler	Inv. Square Root	Fixed
Dropout	0.3	#
Weight Decay	1×10^{-4}	#
Warmup	4000	0
Tokens per Batch	4096	#

Table 3: Hyperparameters for training the MLE baseline and fine-tuning with AggreVaTe. Unchanged parameters are marked with #.