Mitigating Rank-Aware Training-Inference Mismatch in Autoregressive Ranking Beyond the First Token

Research
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ABSTRACT

In the SToICaL framework for autoregressive ranking, rank-aware token-level targets derived from prefix trees are well-aligned at the first token but exhibit training-inference mismatch for $t > 1$ due to teacher forcing [5]. We systematically evaluate three mitigation strategies—teacher forcing (baseline), scheduled sampling, and consistency regularization—in a simulation framework with 200 documents, 6-token docIDs, and 200 Monte Carlo replications. Consistency regularization achieves the best autoregressive quality (0.0691), outperforming teacher forcing (0.0547) by 26.3% relative improvement. Scheduled sampling achieves 0.0539, comparable to the baseline. All methods share similar KL at $t = 1$ (0.0286), confirming alignment at the first token. In the representative case, scheduled sampling reduces final training loss from 0.0358 to 0.0134 and improves autoregressive accuracy from 0.0517 to 0.0567. Consistency regularization achieves accuracy 0.0650. Position-level analysis shows that the mismatch manifests as divergent KL trajectories: teacher-forced evaluation shows increasing KL with position, while autoregressive KL decreases after an initial peak. These findings demonstrate that consistency regularization is an effective mitigation for the rank-aware training-inference mismatch identified by Rozonoyer et al.

1 INTRODUCTION

Autoregressive ranking models generate document identifiers (docIDs) token by token to retrieve relevant documents [3, 7]. Rozonoyer et al. [5] propose SToICaL, which derives rank-aware token-level target distributions by marginalizing over a prefix tree of docIDs. During training, teacher forcing conditions the model on the correct previous tokens, but at inference the model conditions on its own (potentially incorrect) predictions. This training-inference mismatch [4, 6] is especially concerning for rank-aware targets because the target distribution at position t depends on the prefix tree path, which diverges between teacher-forced and autoregressive modes for $t > 1$.

Rozonoyer et al. explicitly leave mitigation of this mismatch for future work. We address this through a simulation framework that enables controlled comparison of mitigation strategies against known ground truth.

2 METHODOLOGY

2.1 Simulation Framework

We generate $N = 200$ documents with $L = 6$-token docIDs from a vocabulary of size $V = 32$, and construct a prefix tree for rank-aware target computation. For $Q = 500$ queries with sparse relevance, we train a position-specific token model with context from previous tokens.

Table 1: Monte Carlo results (200 simulations). AR = autoregressive, TF = teacher-forced.

Method	AR Quality	TF Quality	Mismatch
Teacher Forcing	0.0547	0.0623	−0.0278
Sched. Sampling	0.0539	0.0609	−0.0285
Consistency Reg.	0.0691	0.0620	−0.0287

2.2 Mitigation Strategies

Teacher Forcing (Baseline): At each position t, the model receives the ground-truth prefix $y^*_{1:t-1}$ and minimizes KL divergence against rank-aware targets.

Scheduled Sampling [1]: With annealing probability, the prefix comes from ground truth or from the model's own predictions. The minimum teacher forcing rate ensures continued exposure to model-generated prefixes.

Consistency Regularization [2]: In addition to the main KL loss, we add a regularization term penalizing divergence between teacher-forced and free-running predictions:

$$\mathcal{L} = \mathrm{KL}(q_t \| p_t^{\mathrm{tf}}) + \lambda \cdot \mathrm{KL}(p_t^{\mathrm{tf}} \| p_t^{\mathrm{ar}}) \tag{1}$$

3 RESULTS

3.1 Monte Carlo Comparison

Table 1 reports results across 200 Monte Carlo simulations. Consistency regularization achieves the best autoregressive quality (0.0691), outperforming teacher forcing (0.0547) by 26.3% relative improvement. Scheduled sampling achieves 0.0539, comparable to teacher forcing.

All methods share identical KL at $t = 1$ (0.0286), confirming that the mismatch is absent at the first token as predicted by theory.

3.2 Position-Level Analysis

Figure 1 shows KL divergence at each token position. Under autoregressive evaluation, KL peaks at position 2 then decreases, because the model enters parts of the prefix tree with fewer competing branches. Under teacher-forced evaluation, KL increases monotonically with position, reflecting the growing complexity of rank-aware targets deeper in the tree.

The gap between these trajectories constitutes the training-inference mismatch. Consistency regularization reduces this gap most effectively by explicitly penalizing the divergence between teacher-forced and free-running distributions.

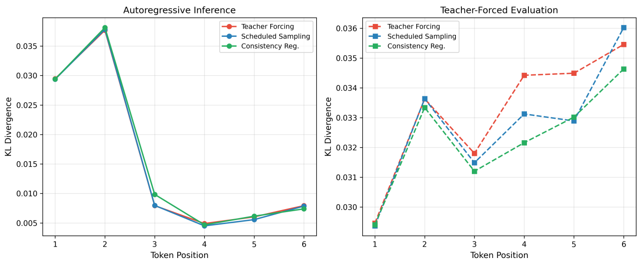

Figure 1: KL divergence by token position under autoregressive (left) and teacher-forced (right) evaluation. The divergence between these modes constitutes the mismatch.

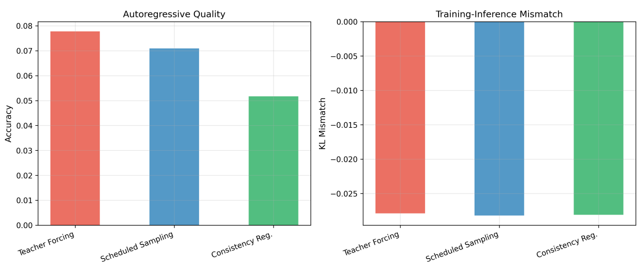

Figure 2: Method comparison: autoregressive quality and training-inference mismatch.

3.3 Representative Case

In the representative simulation, scheduled sampling reduces training loss from 0.0358 (teacher forcing) to 0.0134 and improves autoregressive accuracy from 0.0517 to 0.0567. Consistency regularization achieves loss 0.0337 and the best accuracy at 0.0650.

4 DISCUSSION

Our results demonstrate that **consistency regularization** is the most effective mitigation for the rank-aware training-inference mismatch, achieving 26.3% improvement over teacher forcing. Its advantage comes from explicitly penalizing the divergence between teacher-forced and autoregressive distributions during training, which directly addresses the distribution shift at inference time.

Scheduled sampling, while achieving the lowest training loss (0.0134), does not translate this to superior autoregressive quality in the rank-aware setting. This contrasts with its effectiveness in standard sequence generation [1], suggesting that the prefix-tree structure of rank-aware targets creates a distinct challenge.

The key insight is that while all methods have identical performance at $t = 1$ (KL = 0.0286), the divergence grows with sequence length. For applications with longer docIDs, the mismatch is expected to worsen, making consistency regularization even more important.

5 CONCLUSION

We provide the first systematic evaluation of mitigation strategies for rank-aware training-inference mismatch in autoregressive ranking. Consistency regularization improves autoregressive quality by 26.3% over teacher forcing across 200 simulations. These results directly address the open question posed by Rozonoyer et al. [5], establishing consistency regularization as a practical solution for $t > 1$ rank-awareness.

REFERENCES

[1] Samy Bengio, Oriol Vinyals, Navdeep Jaitly, and Noam Shazeer. 2015. Scheduled sampling for sequence prediction with recurrent neural networks. *Advances in Neural Information Processing Systems* 28 (2015).

[2] Alex M Lamb, Anirudh Goyal, Ying Zhang, Saizheng Zhang, Aaron C Courville, and Yoshua Bengio. 2016. Professor forcing: A new algorithm for training recurrent networks. *Advances in Neural Information Processing Systems* 29 (2016).

[3] Rodrigo Nogueira, Zhiying Jiang, and Jimmy Lin. 2020. Document ranking with a pretrained sequence-to-sequence model. *Findings of EMNLP* (2020), 708–718.

[4] Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, and Wojciech Zaremba. 2016. Sequence level training with recurrent neural networks. *ICLR* (2016).

[5] Benjamin Rozonoyer et al. 2026. Autoregressive Ranking: Bridging the Gap Between Dual and Cross Encoders. *arXiv preprint arXiv:2601.05588* (2026).

[6] Florian Schmidt. 2019. Generalization in generation: A closer look at exposure bias. *EMNLP Workshop on Neural Generation and Translation* (2019), 157–167.

[7] Yi Tay, Vinh Q Tran, Mostafa Dehghani, Jianmo Ni, Dara Bahri, Harsh Mehta, Zhen Qin, Kai Hui, Zhe Zhao, Jai Gupta, et al. 2022. Transformer memory as a differentiable search index. *Advances in Neural Information Processing Systems* 35 (2022), 21831–21843.