

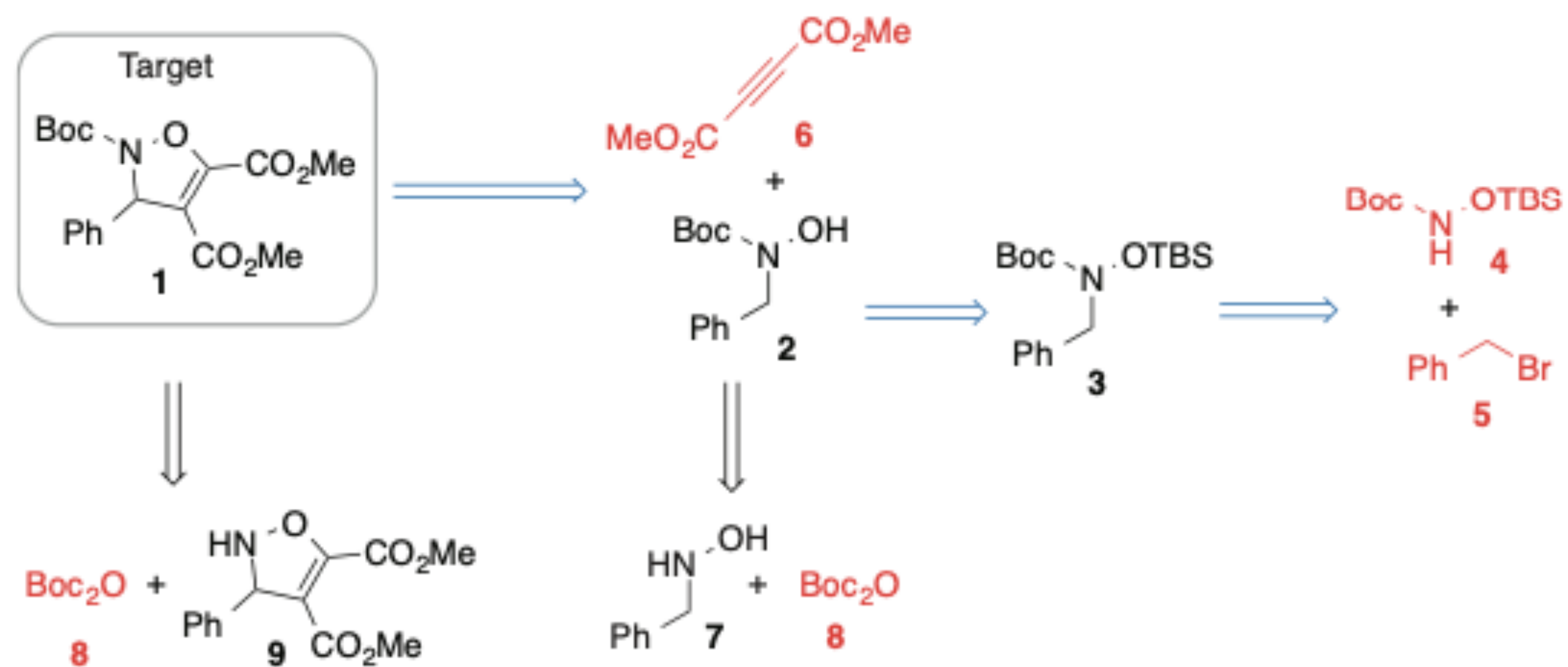
A TRANSFORMER MODEL FOR RETROSYNTHESIS

Karpov P., Godin G., Tetko I.V.: A Transformer Model for Retrosynthesis. In: Artificial Neural Networks and Machine Learning – ICANN 2019: Workshop and Special Sessions: 17th - 19th September 2019 2019; Munich. Springer International Publishing: 817-830.

Hirah 31.07.2021

Retrosynthesis (逆合成路径设计)

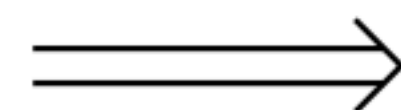
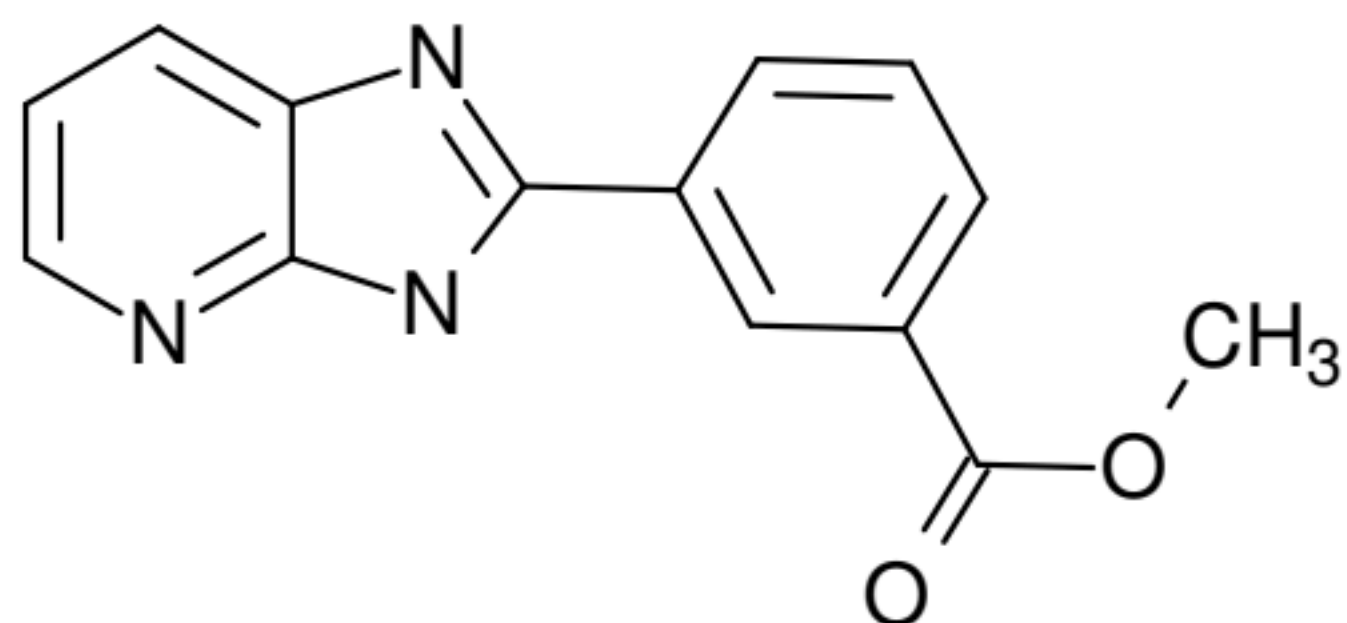
a) Chemical Representation of the Synthesis Plan



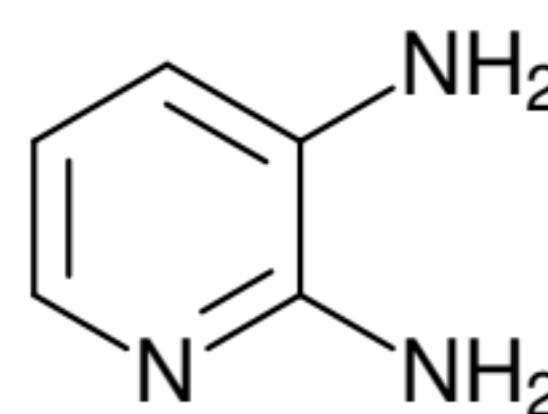
Prediction of Chemical Synthesis 化学反应预测

- SMILES notations & Training Data

COC(=O)c1cccc(-c2nc3cccn3[nH]2)c1

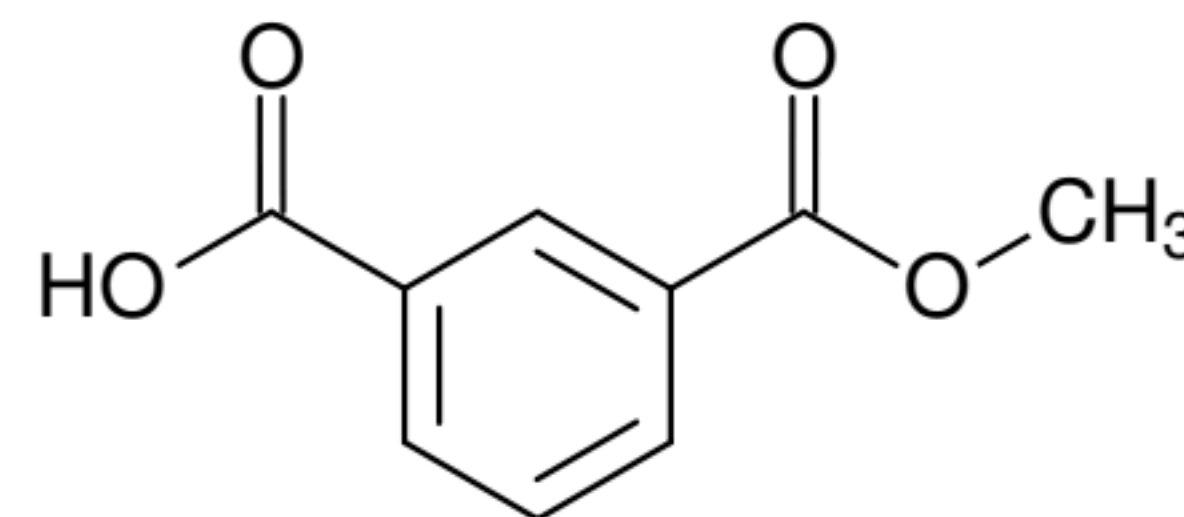


Nc1cccn1N



+

COC(=O)c1cccc(C(=O)O)c1



- COC(=O)c1cccc(-c2nc3cccn3[nH]2)c1 <- Nc1cccn1N.COC(=O)c1cccc(C(=O)O)c1

Analogy between machine translation and retro synthesis

- Target Language 语言A <- Source Language 语言B
- Target Molecule 目标分子 <- Predecessors 反应前体
- Liu, B. et al. Retrosynthetic reaction prediction using neural sequence-to-sequence models. ACS Central Science 3, 1103–1113 (2017).
- Neural sequence-to-sequence (seq2seq) model

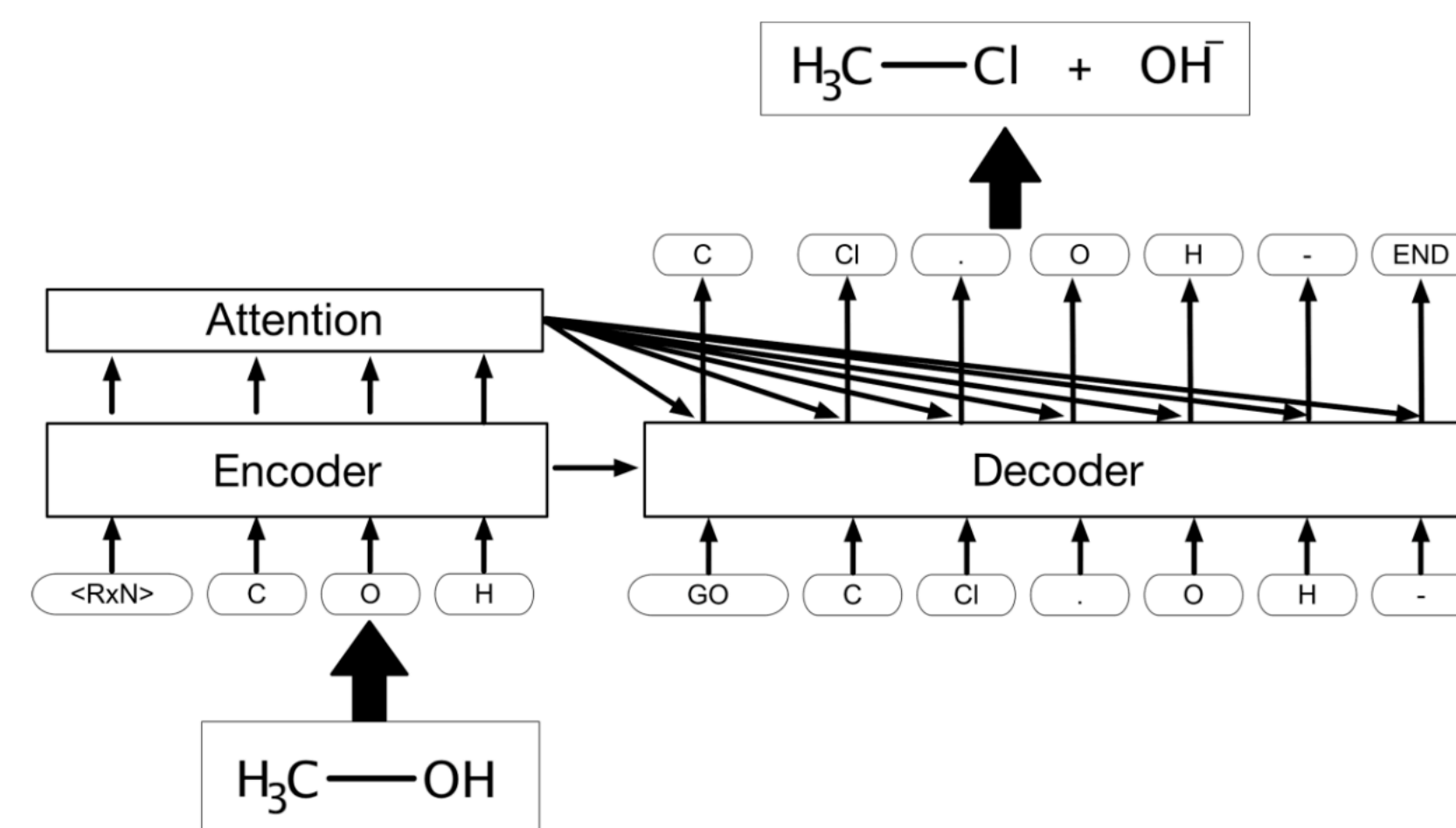


Figure 3: seq2seq model architecture

Transformer model inference

- Explore the internal representation of data
- Estimates the probability of the next symbol over the model's vocabulary (66) given all previous symbols in the string.

- Calculate the logits:

$$z_i = \text{Transformer}(\{x_1, x_2, x_3, \dots, x_L\}, \{y_1, y_2, y_3, \dots, y_{i-1}\})$$

- Convert to probabilities:

$$q_i = \frac{\exp(z_i/T)}{\sum_{j=0}^V \exp(z_j/T)}$$

- Greedy - $y_{\{i\}} = q_{\{l\}}$

- Beam Search 集束搜索：每次保留Top - K个模型推荐的结果

Heuristics for Training A Transformer

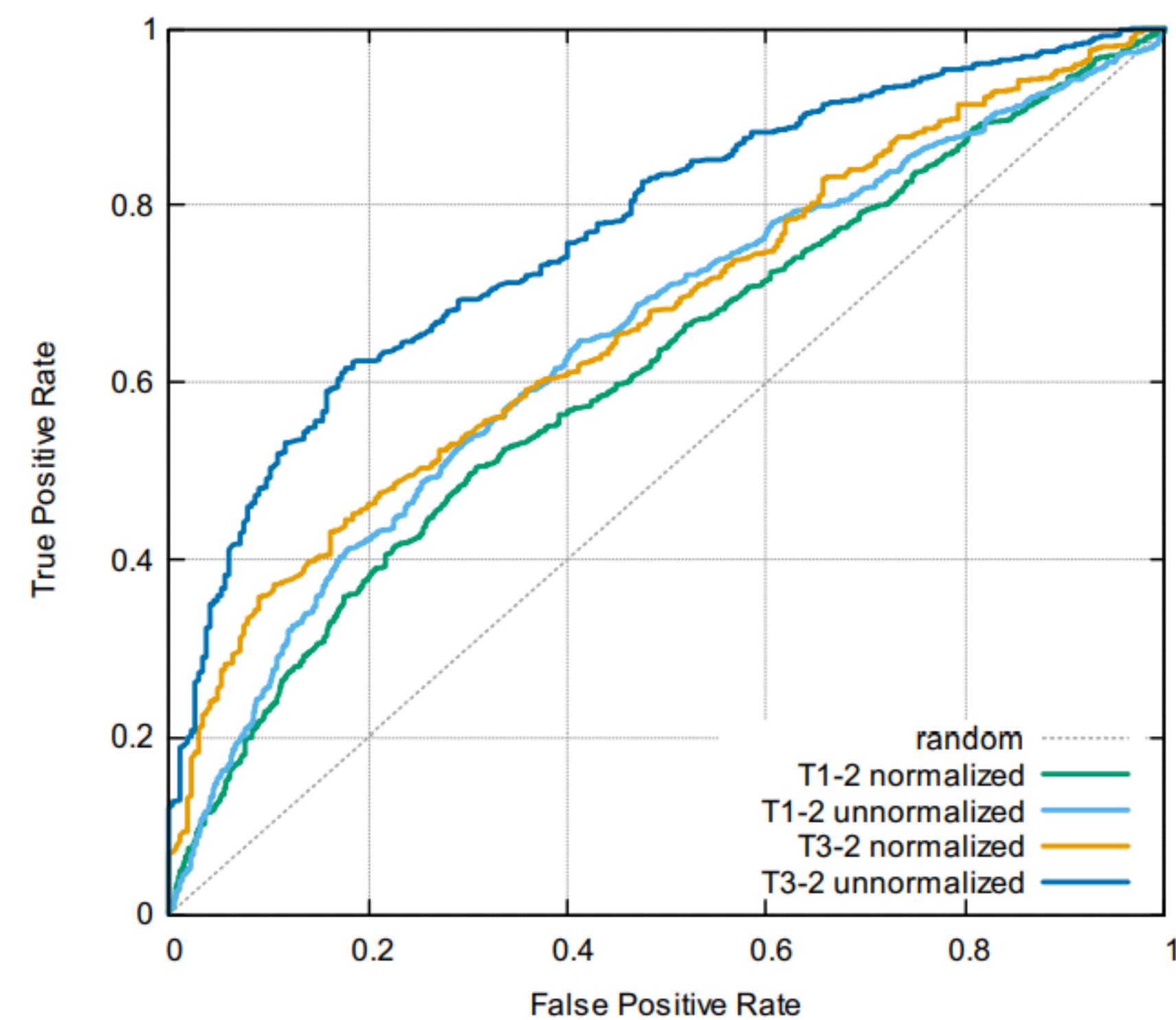
- 使用较大的Batch Size
- 在开始时增加Learning Rate
- Applying Cyclic Learning Rate: 在优化后期增大学习率避免local minima

Results

Table 1: Accuracy (%) of the models on test set when all reactants were correctly predicted.

Model	Greedy	Top-1	Top-3	Top-5	Description
Seq2Seq		37.4	52.4	57.0	Literature result from [17] based on Seq2Seq architecture.
T1	34.4	37.9	57.3	62.7	Transformer Model trained with validation control set (early stopping, ~200 epochs).
T1 ₁	37.3	39.8	59.1	63.9	The same as T1, but without early stopping (1000 epochs).
T2	39.3	41.8	61.3	67.2	Transformer Model trained on both training and validation sets for 1000 epochs.
T3	40.6	42.7	63.9	69.8	Transformer Model trained with cyclic learning rate schedule for 1000 epochs. Averaging cycles 6,7,8,9, and 10.

Results



<https://chemrxiv.org/engage/chemrxiv/article-details/60c7417af96a00cd49286446>

Figure 4: Internal classification performance.