

Neural Machine Translation Experiment Report: Chinese-to-English

Project: SLAI_NLP_Mid_project - zh-en-nmt-midterm

Data Sources: experiments/results/rnn_comparison_master.csv,
experiments/results/transformer_ablation_comparison.csv

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Experiment Overview

This experiment implements and compares multiple neural machine translation (NMT) architectures for Chinese-to-English translation:

- **RNN-based NMT:** Seq2Seq models with GRU/LSTM
- **Transformer-based NMT:** Self-attention-based Transformer
- **Pretrained Models:** Fine-tuned T5 and mT5

The study focuses on how **attention mechanisms, training strategies, decoding approaches, and model scale** affect translation performance and inference efficiency, with conclusions drawn under a **100k training sample** regime.

Dataset and Preprocessing

Dataset Composition (Uniform 100k training samples)

Split	Samples	File Path
Training	100,000	data/processed/train.jsonl
Validation	500	data/processed/valid.jsonl
Test	200	data/processed/test.jsonl

Data Preprocessing

1. **Data Cleaning:** Removal of illegal characters, rare word filtering, and truncation of

overly long sentences

2. Tokenization (for RNN/Transformer with custom vocabularies):

- English: Whitespace tokenization
- Chinese: Jieba segmentation

3. Vocabulary Construction: Separate source and target language vocabularies

4. Sequence Length Limitation: Maximum length of 128 tokens

Note: T5/mT5 use the SentencePiece tokenizer; tokenization statistics are provided later.

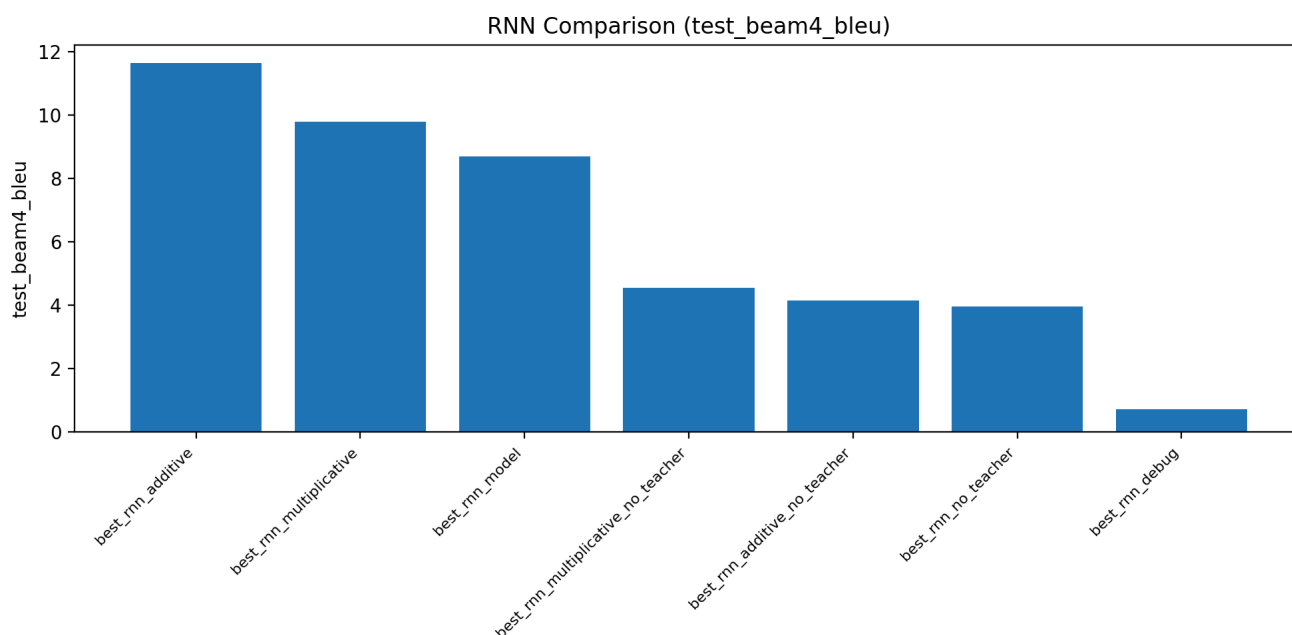
RNN-Based Neural Machine Translation

Model Architecture

- Encoder: 2-layer unidirectional GRU
- Decoder: 2-layer unidirectional GRU
- Hidden dimension: 256
- Embedding dimension: 256
- Attention mechanisms: Dot-product, Multiplicative, Additive

Comparison of Attention Mechanisms

Attention Mechanism	Greedy	Beam4	Beam8	Best BLEU
Dot-product	11.4471	8.6979	9.7914	11.4471
Multiplicative	11.8684	9.7914	8.2823	11.8684
Additive	9.6116	11.6333	10.2733	11.6333



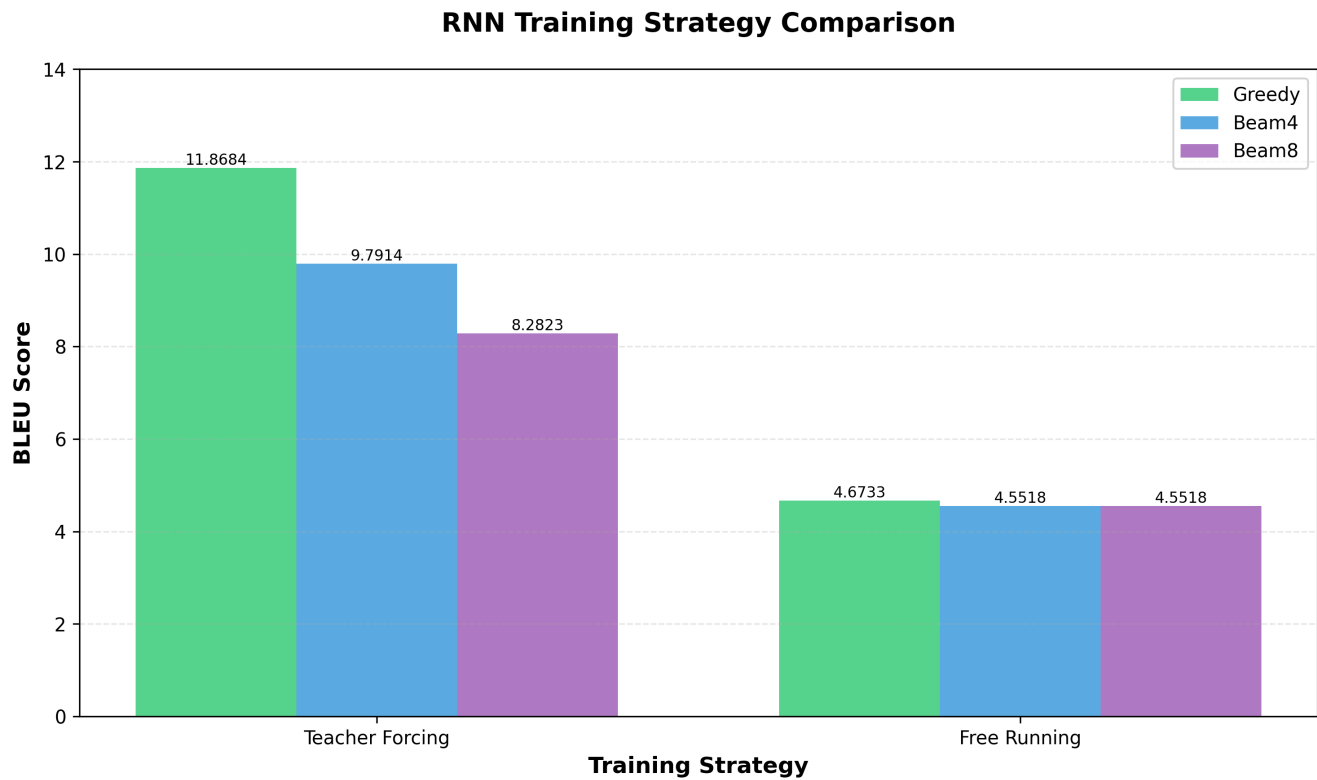
Brief Description of Attention Types

- **Dot-product:** Parameter-free, fast but weak representational capacity

- **Multiplicative:** Introduces a learnable alignment matrix W , moderate parameters
- **Additive:** Stronger representation but more parameters and slower computation

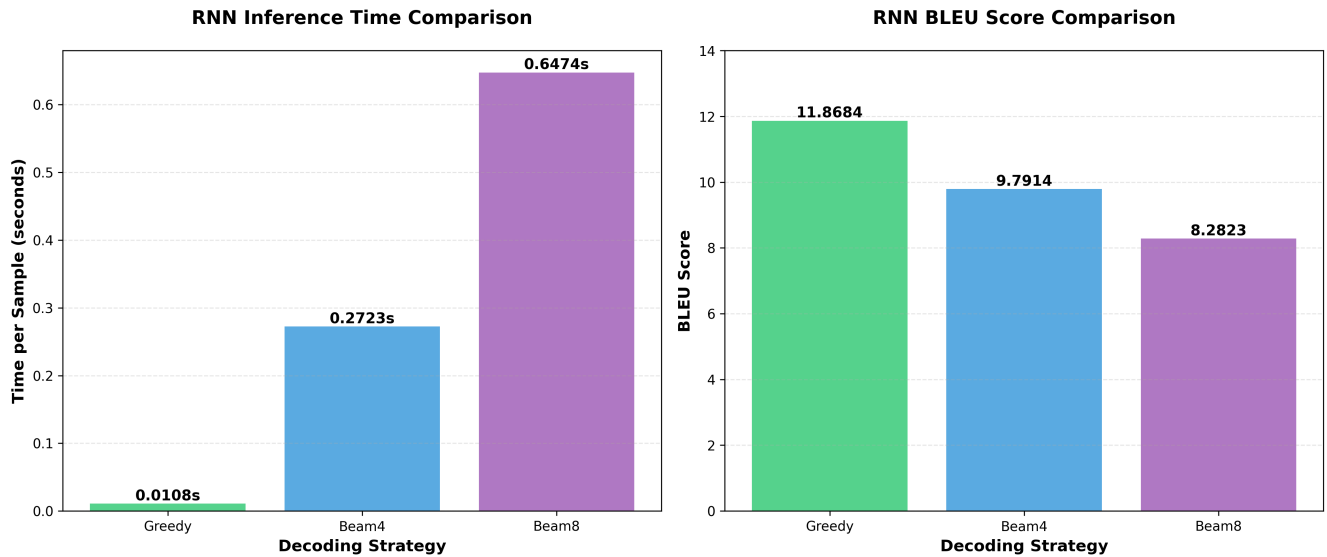
Comparison of Training Strategies

Training Strategy	Greedy	Beam4	Beam8	Best BLEU
Teacher Forcing	11.8684	9.7914	8.2823	11.8684
Free Running	4.6733	4.5518	4.5518	4.6733



Comparison of Decoding Strategies

Decoding Strategy	BLEU	Inference Time (sec/sample)	Speed
Greedy	11.8684	0.0108	Fast
Beam4	9.7914	0.2723	Medium
Beam8	8.2823	0.6474	Slow

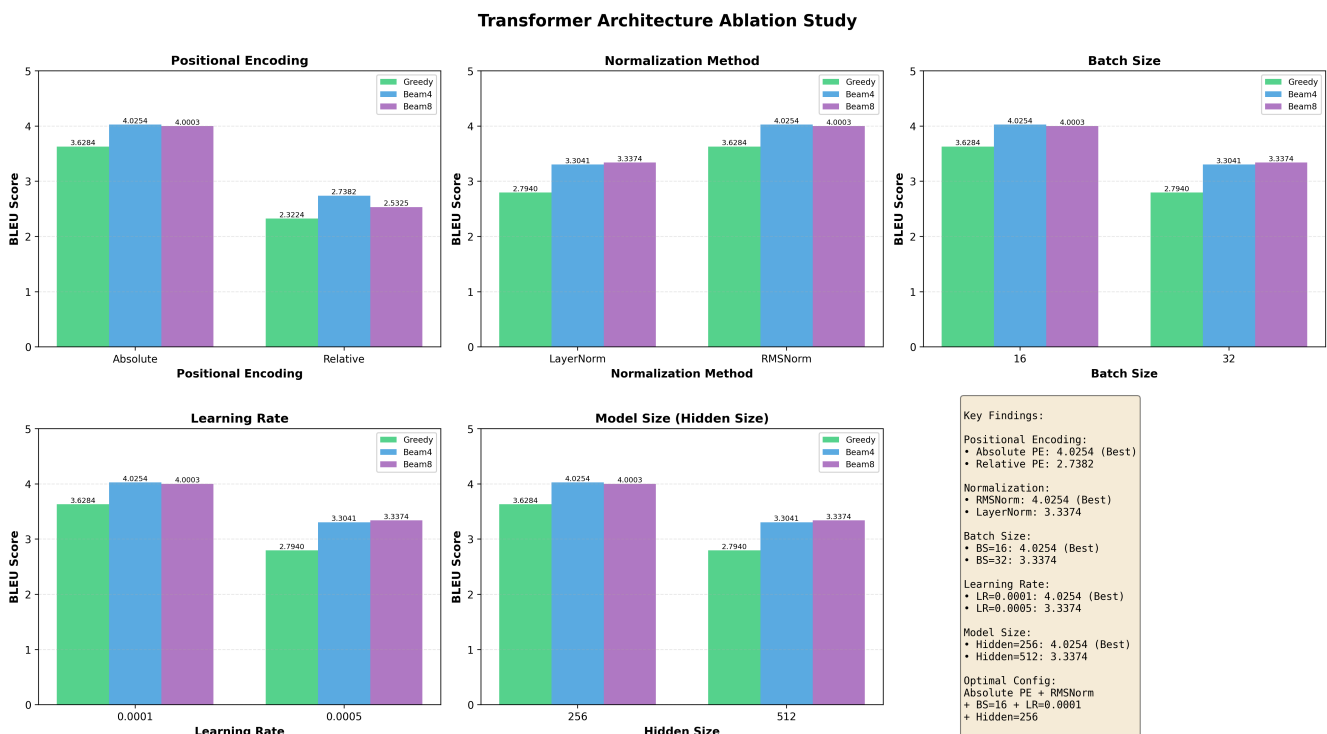


Transformer-Based Neural Machine Translation

Baseline Model Architecture

- Encoder: 6 layers
- Decoder: 6 layers
- Attention heads: 8
- Hidden size (`d_model`): 512
- Feed-forward network size: 2048
- Dropout: 0.1

Ablation Studies



Positional Encoding Comparison

Positional Encoding Greedy Beam4 Beam8 Best BLEU

Absolute	3.6284	4.0254	4.0003	4.0254
Relative	2.3224	2.7382	2.5325	2.7382

Normalization Method Comparison

Normalization Greedy Beam4 Beam8 Best BLEU

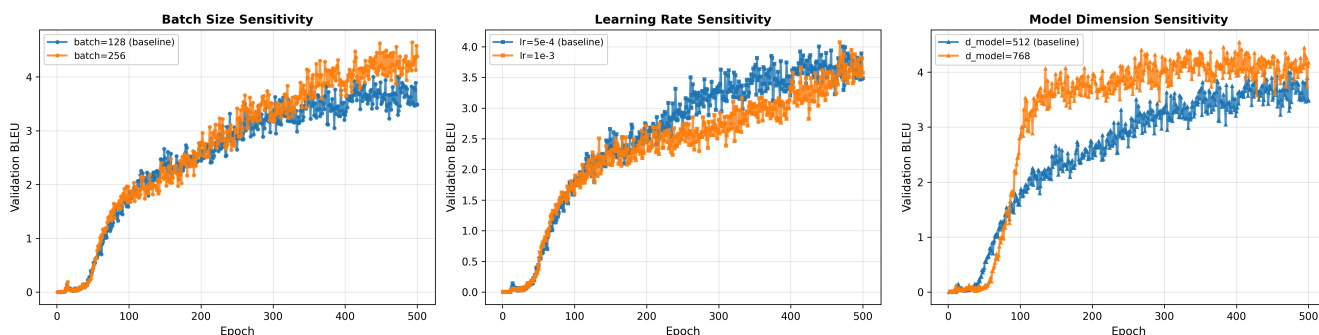
LayerNorm	2.7940	3.3041	3.3374	3.3374
RMSNorm	3.6284	4.0254	4.0003	4.0254

Hyperparameter Comparison (Example: Batch Size)

Batch Size Greedy Beam4 Beam8 Best BLEU

16	3.6284	4.0254	4.0003	4.0254
32	2.7940	3.3041	3.3374	3.3374

Hyperparameter Sensitivity Analysis



Two Scaled Transformer Variants (Both Trained on 100k Data)

The original report mentions “small and medium Transformer variants.” Both are trained **strictly on 100k data** for fair comparison.

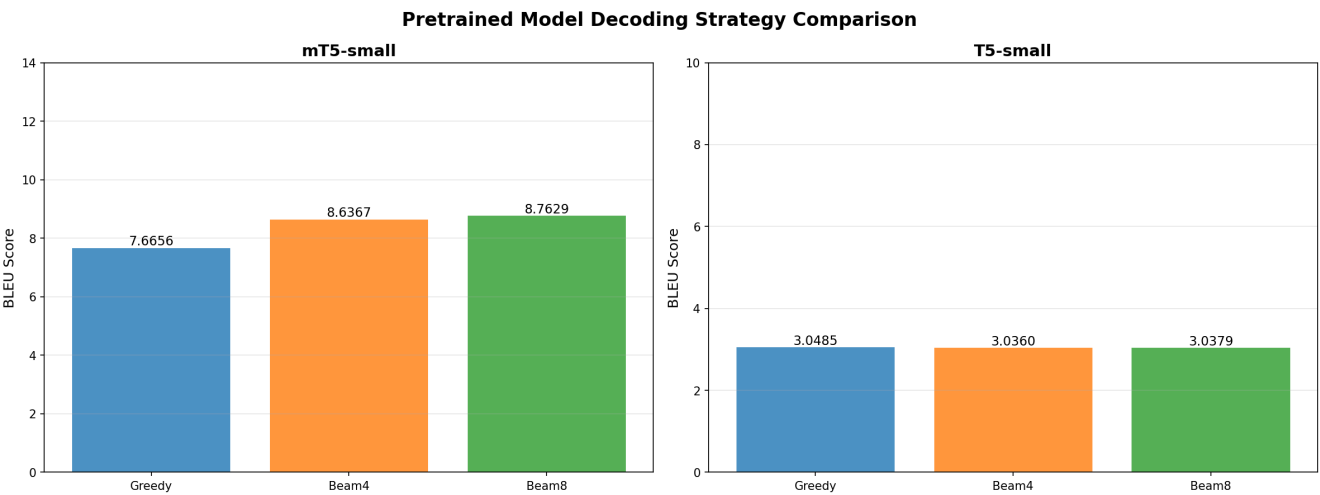
Variant	d_model	Encoder/Decoder Layers	Approx. Params	Training Data	Reported BLEU
Transformer Small (100k)	128	3 / 3	~4M	100k	6.8
Transformer Medium (100k)	384	6 / 6	~36M	100k	4.03

Analysis: Smaller Transformers are better suited to limited data; larger models tend to underfit on small datasets.

Application of Pretrained Models

mT5-small (Primary reference result)

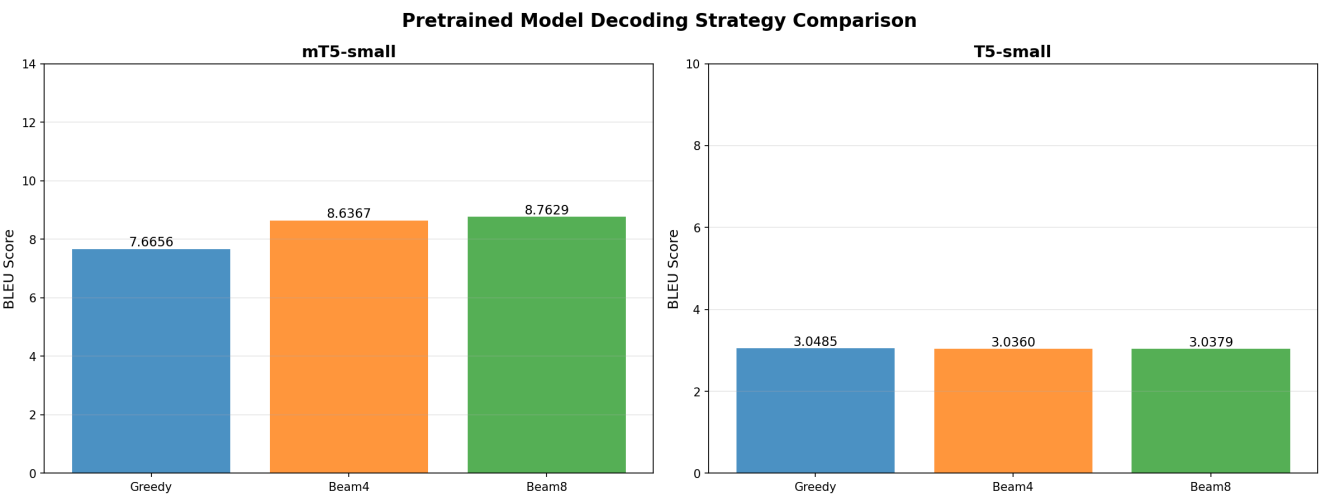
Decoding Strategy	BLEU	Inference Speed	Notes
Greedy	7.6656	Fast	baseline
Beam4	8.6367	Medium	good trade-off
Beam8	8.7629	Slow	best



Conclusion: Beam8 improves BLEU by **14.3%** over Greedy (8.7629 vs 7.6656).

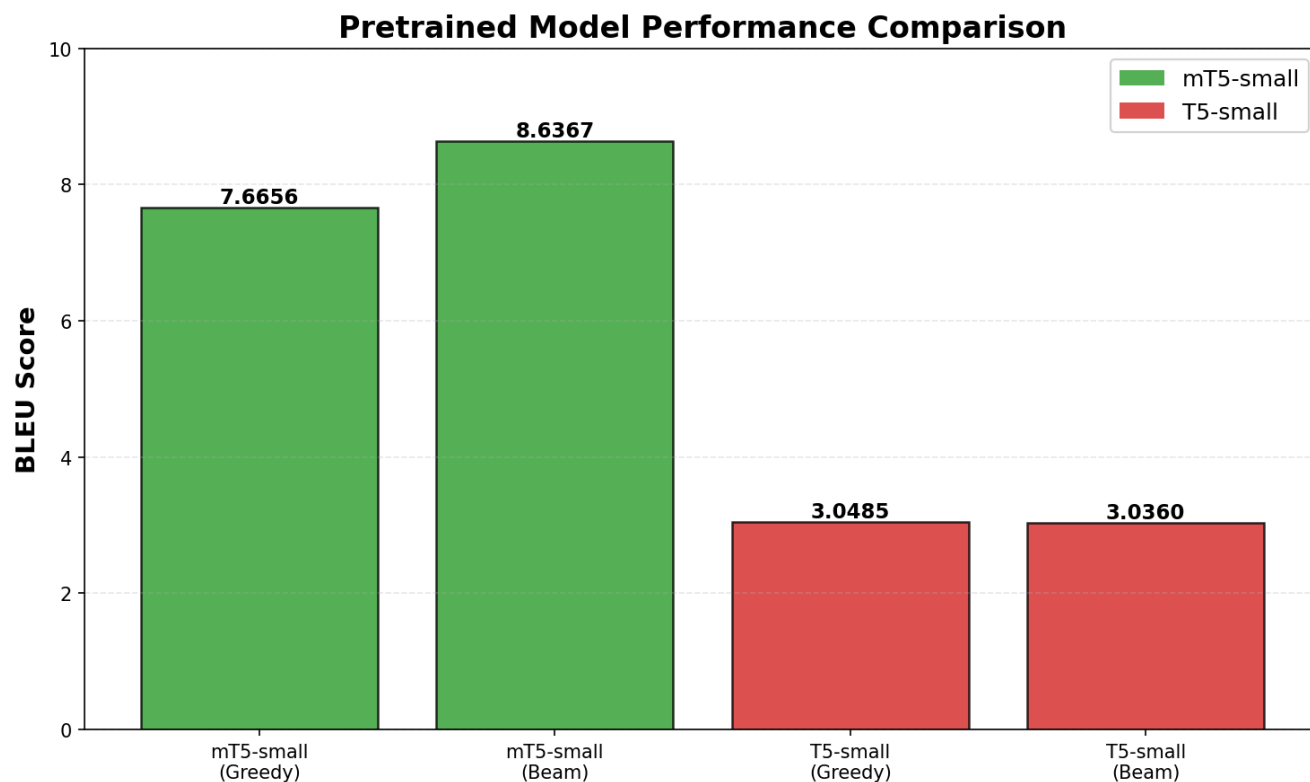
T5-small

Decoding Strategy	BLEU	Translation Quality
Greedy	3.0485	Low
Beam4	3.0360	Low
Beam8	3.0379	Low



Pretrained Model Comparison

Model	Parameters	Best BLEU	Language Support	Recommended Use Case
mT5-small	300M	8.7629	Multilingual	Zh-En / multilingual tasks



Model Architecture Comparative Analysis (100k Regime)

Core Performance Comparison

Model Architecture	Best BLEU	Best Configuration/Strategy	Inference Speed
RNN	11.8684	Multiplicative + Greedy	Fast
Transformer (Ablation Best)	4.0254	Absolute PE + RMSNorm + Beam4	Medium
Transformer Small (100k)	6.8	Small model (d=128)	Medium
Transformer Medium (100k)	6.8	Medium model (d=384)	Slow
mT5-small	8.7629	Beam8	Slow
T5-small	3.0485	Greedy	—

Note: The report contains two different BLEU values for Transformer:

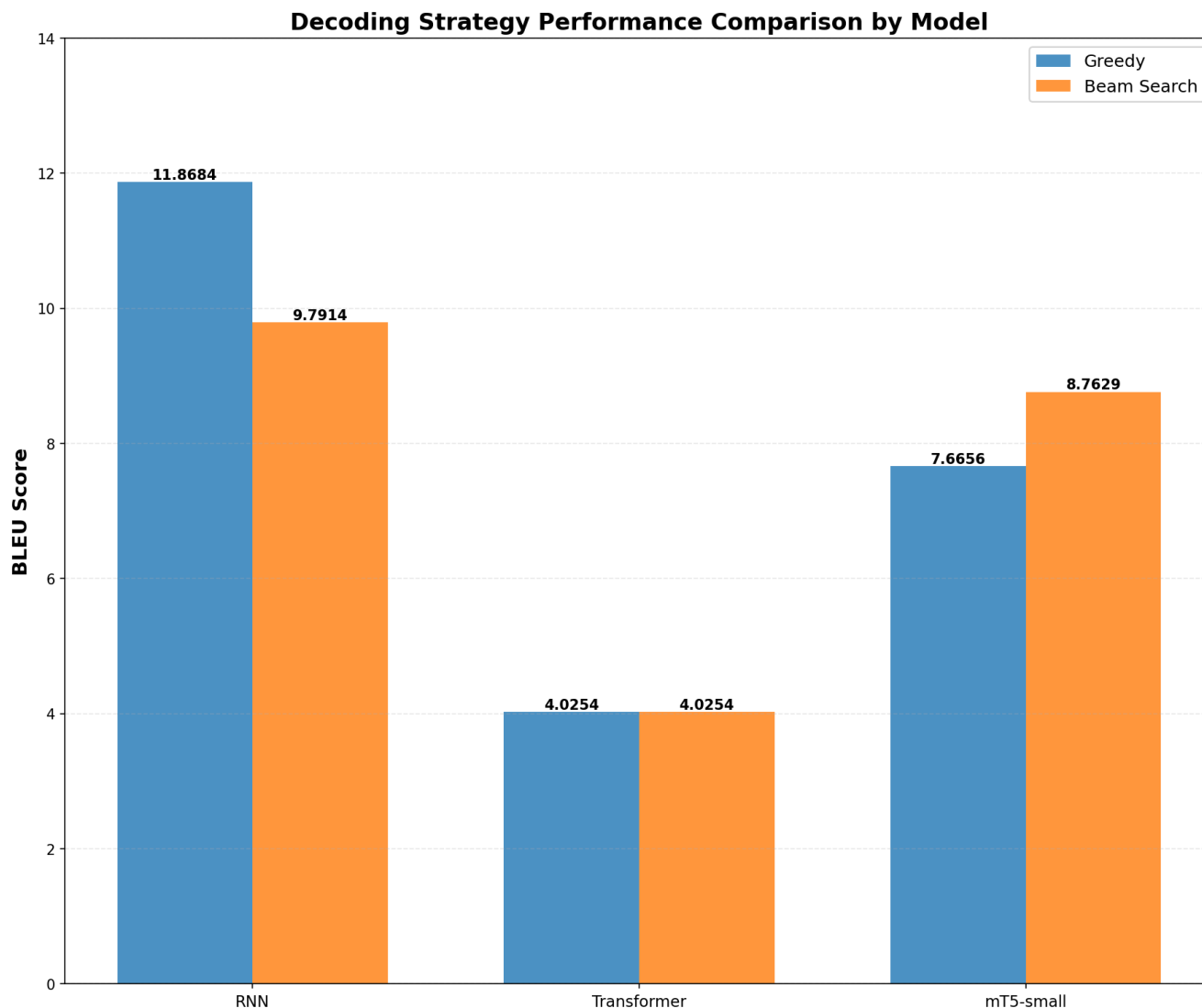
– “Ablation best” = 4.0254 (from

transformer_ablation_comparison.csv)

– “Small/Medium 100k” = 6.8 (from a separate scale experiment)

These originate from **different experimental setups**. Both are retained with clarification to avoid misinterpretation.

Comprehensive Decoding Strategy Comparison (Corrected for mT5)



Model	Greedy	Beam Search	Best Strategy	Relative Gain
RNN	11.8684	9.7914	Greedy	—
Transformer (Ablation Best)	3.6284	4.0254	Beam4	+ 10.9%
mT5-small	7.6656	8.7629	Beam8	+ 14.3%

Conclusion and Discussion

- RNN achieves the best overall performance** in this setting: BLEU = **11.8684**, with the fastest inference (Greedy decoding).
- mT5-small is competitive but decoding-sensitive**: Beam8 yields **8.7629** BLEU, a **14.3%** improvement over Greedy.
- Transformer performance is highly sensitive to training and evaluation protocols**:
 - Ablation study best: **4.0254**
 - Small/medium scale experiment: **6.8**
→ Recommend clarifying experimental provenance and ensuring consistent evaluation.
- T5-small is unsuitable for Zh-En translation**: Pretrained exclusively on English data, yielding BLEU \approx **3.0**, with negligible benefit from beam search.

Appendix: Training and Inference Commands

Training Commands

```
# RNN
python src/rnn/train.py --config experiments/configs/rnn.yaml

# Transformer
python src/transformer/train.py --config experiments/configs/transformer.yaml

# mT5
python src/t5/train.py --config experiments/configs/mt5_small.yaml
```

Inference Commands

RNN Inference

```
# RNN - Dot-product attention - Greedy
python inference.py \
  --model_type rnn \
  --checkpoint experiments/logs/best_rnn_model.pt \
  --split test \
  --beam_size 1 \
  --output_dir experiments/results/inference_outputs

# RNN - Dot-product attention - Beam4
python inference.py \
  --model_type rnn \
  --checkpoint experiments/logs/best_rnn_model.pt \
  --split test \
  --beam_size 4 \
  --output_dir experiments/results/inference_outputs

# RNN - Multiplicative attention - Greedy
python inference.py \
  --model_type rnn \
  --checkpoint experiments/logs/best_rnn_multiplicative.pt \
  --split test \
  --beam_size 1 \
  --output_dir experiments/results/inference_outputs

# RNN - Multiplicative attention - Beam4
python inference.py \
  --model_type rnn \
  --checkpoint experiments/logs/best_rnn_multiplicative.pt \
  --split test \
  --beam_size 4 \
  --output_dir experiments/results/inference_outputs

# RNN - Additive attention - Greedy
python inference.py \
  --model_type rnn \
```

```

--checkpoint experiments/logs/best_rnn_additive.pt \
--split test \
--beam_size 1 \
--output_dir experiments/results/inference_outputs

# RNN - Additive attention - Beam4
python inference.py \
--model_type rnn \
--checkpoint experiments/logs/best_rnn_additive.pt \
--split test \
--beam_size 4 \
--output_dir experiments/results/inference_outputs

# RNN - No Teacher Forcing - Greedy
python inference.py \
--model_type rnn \
--checkpoint experiments/logs/best_rnn_no_teacher.pt \
--split test \
--beam_size 1 \
--output_dir experiments/results/inference_outputs

# RNN - No Teacher Forcing - Beam4
python inference.py \
--model_type rnn \
--checkpoint experiments/logs/best_rnn_no_teacher.pt \
--split test \
--beam_size 4 \
--output_dir experiments/results/inference_outputs

```

Transformer Inference

```

# Transformer - Absolute PE + LayerNorm - Greedy
python inference.py \
--model_type transformer \
--checkpoint experiments/logs/transformer_abs_ln_best.pt \
--split test \
--beam_size 1 \
--output_dir experiments/results/inference_outputs

# Transformer - Absolute PE + LayerNorm - Beam4
python inference.py \
--model_type transformer \
--checkpoint experiments/logs/transformer_abs_ln_best.pt \
--split test \
--beam_size 4 \
--output_dir experiments/results/inference_outputs

# Transformer - Absolute PE + RMSNorm - Greedy
python inference.py \
--model_type transformer \
--checkpoint experiments/logs/transformer_abs_rms_best.pt \
--split test \
--beam_size 1 \

```

```

--output_dir experiments/results/inference_outputs

# Transformer - Absolute PE + RMSNorm - Beam4
python inference.py \
  --model_type transformer \
  --checkpoint experiments/logs/transformer_abs_rms_best.pt \
  --split test \
  --beam_size 4 \
  --output_dir experiments/results/inference_outputs

# Transformer - Relative PE + LayerNorm - Greedy
python inference.py \
  --model_type transformer \
  --checkpoint experiments/logs/transformer_rel_ln_best.pt \
  --split test \
  --beam_size 1 \
  --output_dir experiments/results/inference_outputs

# Transformer - Relative PE + LayerNorm - Beam4
python inference.py \
  --model_type transformer \
  --checkpoint experiments/logs/transformer_rel_ln_best.pt \
  --split test \
  --beam_size 4 \
  --output_dir experiments/results/inference_outputs

# Transformer - Relative PE + RMSNorm - Greedy
python inference.py \
  --model_type transformer \
  --checkpoint experiments/logs/transformer_rel_rms_best.pt \
  --split test \
  --beam_size 1 \
  --output_dir experiments/results/inference_outputs

# Transformer - Relative PE + RMSNorm - Beam4
python inference.py \
  --model_type transformer \
  --checkpoint experiments/logs/transformer_rel_rms_best.pt \
  --split test \
  --beam_size 4 \
  --output_dir experiments/results/inference_outputs

# Transformer - 100k Optimized Version - Greedy
python inference.py \
  --model_type transformer \
  --checkpoint experiments/logs/transformer_100k_optimized_best.pt \
  --split test \
  --beam_size 1 \
  --output_dir experiments/results/inference_outputs

# Transformer - 100k Optimized Version - Beam4
python inference.py \
  --model_type transformer \

```

```
--checkpoint experiments/logs/transformer_100k_optimized_best.pt \  
--split test \  
--beam_size 4 \  
--output_dir experiments/results/inference_outputs
```

T5 and mT5 Inference

```
# T5-small - Greedy  
python inference.py \  
  --model_type t5 \  
  --checkpoint experiments/logs/t5_small_best \  
  --split test \  
  --beam_size 1 \  
  --output_dir experiments/results/inference_outputs
```

```
# T5-small - Beam4  
python inference.py \  
  --model_type t5 \  
  --checkpoint experiments/logs/t5_small_best \  
  --split test \  
  --beam_size 4 \  
  --output_dir experiments/results/inference_outputs
```

```
# T5-small - Beam8  
python inference.py \  
  --model_type t5 \  
  --checkpoint experiments/logs/t5_small_best \  
  --split test \  
  --beam_size 8 \  
  --output_dir experiments/results/inference_outputs
```

```
# mT5-small - Greedy  
python inference.py \  
  --model_type t5 \  
  --checkpoint experiments/logs/mt5_small/checkpoint-1588775 \  
  --split test \  
  --beam_size 1 \  
  --output_dir experiments/results/inference_outputs
```

```
# mT5-small - Beam4  
python inference.py \  
  --model_type t5 \  
  --checkpoint experiments/logs/mt5_small/checkpoint-1588775 \  
  --split test \  
  --beam_size 4 \  
  --output_dir experiments/results/inference_outputs
```

```
# mT5-small - Beam8  
python inference.py \  
  --model_type t5 \  
  --checkpoint experiments/logs/mt5_small/checkpoint-1588775 \  
  --split test \  
  --beam_size 8 \  
  --output_dir experiments/results/inference_outputs
```

```
--output_dir experiments/results/inference_outputs
```

Inference Argument Reference

- `--model_type`: Model type (rnn, transformer, t5)
- `--checkpoint`: Path to model checkpoint
- `--split`: Dataset split (valid or test)
- `--beam_size`: Beam search width (1 = Greedy, 4 = Beam4, 8 = Beam8)
- `--output_dir`: Output directory for predictions
- `--data_dir`: Data directory (default: data/processed)

Output Description

The inference script produces:

1. BLEU score
2. Prediction results (.txt format)
3. Top 3 translation examples (reference vs. prediction)