The Green KNIGHT: Green Machine Translation with Knowledge-Distilled, Narrow, Inexpensive, Greedy, Hybrid Transformers

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Abstract

State-of-the-art neural machine translation (NMT) models deliver high-quality translations at the expense of high inference latency and energy consumption, requiring vast GPU fleets and contributing significantly to carbon emissions. To democratize and "green" NMT, we introduce the Green KNIGHT, a hardware-agnostic collection of recipes to optimize translation speed and energy consumption, with only a moderate trade-off in quality. On high-resource En→De and En→Ko benchmarks, we achieve up to 117× CPU speedup and 98.2% energy savings with 9% relative BLEU decrease. On WMT 2014 En→De and En→Fr benchmarks, we obtain up to 140× speedup with 98.7% energy savings, while staying within 10–12% relative BLEU decrease. Our results demonstrate that efficient and environmentally conscious NMT can be realized through optimizations built on well-understood, off-the-shelf techniques with no custom low-level code required, making our approach immediately deployable in real-world translation pipelines.

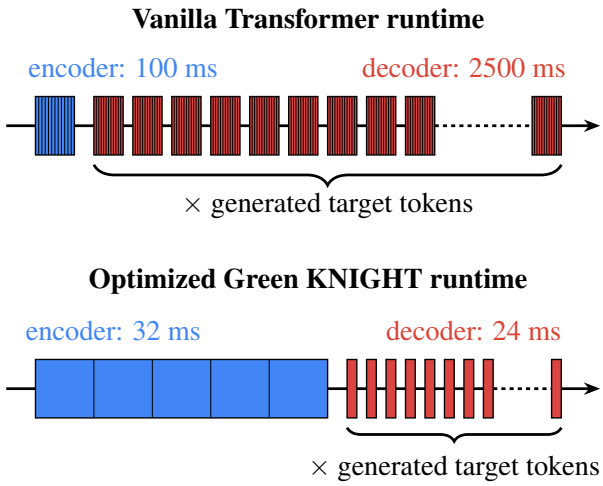

Figure 1: Runtime breakdown for the vanilla Transformer (100 ms encoder + 2500 ms decoder for a single batch, 95% spent in the decoder) versus our optimized Green KNIGHT model. By shifting the workload toward the encoder (32 ms) and drastically reducing decoder cost (24 ms), our design ultimately yields **117× CPU speedup** and **98.2% energy savings** for En→De (unconstrained).

1 Introduction

Neural Machine Translation (NMT) has rapidly become the standard for automated language transfer, achieving human-competitive fluency and adequacy across dozens of language pairs with Transformer architectures (Vaswani et al., 2017). Most research aims at improving model performance, which is typically achieved with larger and in particular deeper models whose inference time and energy consumption grow significantly due to the quadratic dependence on target length of the autoregressive decoder and high cost of beam search.

As shown in Figure 1, the conventional Transformer 'big' model can spend over 95% of its batch runtime in the decoder. This imbalance not only throttles throughput but also drives up energy consumption. Recent years have seen large language models (LLMs) surpass traditional Transformer models in translation quality (Kocmi et al., 2024). However, LLMs tend to be orders of magnitude larger and more expensive to operate than Transformers, which is not matched by the gains in quality. This heavy resource burden renders LLM-based translation even less sustainable for most enterprises and hinders broader deployment. In contrast, we aim at NMT with a better quality-speed/energy trade-off than recent LLMs and therefore focus on improving encoder-decoder models.

Parallel to our goal of making machine translation more efficient, we want to reduce the ecological footprint of machine translation systems in order to reduce carbon emissions—an issue which has been advocated before in the context of general AI (Strubell et al., 2019; Schwartz et al., 2020)

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and NMT systems in particular (Shterionov and Vanmassenhove, 2023), but received only minor attention by the broad NMT community. Hence, we ask the question: How "green" can machine translation become while still being practicable?

To tackle these issues, we aim at gaining as much translation speed and energy savings as possible while trying not to lose more than 10% relative translation quality measured in BLEU and COMET or BLEURT. As a solution we introduce the Green KNIGHT, a recipe to build hardware-agnostic Transformer models for green machine translation. It combines inference-time optimizations such as greedy decoding and dynamic 8-bit quantization with architectural changes to decrease the decoder workload. In particular, we investigate fast hybrid models with RNN (Cho et al., 2014; Bahdanau et al., 2015) and SSRU decoders (Kim et al., 2019), augmented with knowledge distillation (Kim and Rush, 2016).

The main contributions of our work areas follows:

1. A comprehensive analysis of stacked inference and architecture optimizations, measuring quality, speed and energy at each step.

2. A comparison of hybrid translation models under these optimizations and optionally combined with knowledge distillation.

3. Extensive evaluations on real-life English→German and English→Korean tasks, where we achieve translation speedups of up to 117× with 98.2% energy savings. On WMT English→French, we gain a 140× speedup and 98.7% energy savings.

The final model achieves an 18× speedup on CPU over the baseline model run on GPU. When applying only greedy search and quantization, running the model on CPU is already twice as fast as on GPU, with relative drops of only 2.5% BLEU and 0.6% COMET, making it a viable deployment option even in resource-constrained environments. Our work proves that easy-to-implement methods can make MT substantially more time- and energy-efficient, encouraging more research teams to consider Green AI (Schwartz et al., 2020) when developing and deploying NMT systems.

2 Related Work

Kim et al. (2019) introduce a suite of modeling and engineering improvements for fast NMT. They enhance teacher-student training with multi-agent dual learning and noisy back-translation, and replace self-attention in the decoder with a lightweight recurrent unit (SSRU), tying weights between decoder layers, thereby reducing parameters and improving CPU cache efficiency. Their inference optimizations include 8-bit quantization, 16-bit GPU inference, and concurrent GPU streams, all implemented in a custom C++ Marian framework. Their models achieve up to 24× CPU and 14× GPU speedups over their 2018 baselines without BLEU loss. In contrast, our work uses standard PyTorch, explores a broader range of decoder sizes and employs a simpler knowledge distillation approach. We also explore more RNN decoder variants and do not rely on C++-specific optimizations or weight tying.

Hsu et al. (2020) empirically combine several known techniques, including multi-agent dual learning for distillation, SSRU and AAN decoders (Zhang et al., 2018), removal of the decoder feed-forward network (FFN), and a deep encoder–shallow decoder structure (12/1 layers). They further reduce parameters by pruning attention heads, achieving 2.2× CPU and 1.7× GPU speedups with 25% fewer parameters, while matching the Transformer "base" quality. Unlike their work, we do not focus on parameter reduction, but rather on maximizing speed and energy efficiency with minimal quality loss. We systematically evaluate various decoder sizes, tune the beam size, and find that removing the decoder's FFN is not beneficial in our setting.

Lin et al. (2021) present a combination of simple, hardware-agnostic techniques for efficient Transformer inference, such as tuning the vocabulary size, using a shallow decoder, pruning attention heads, dropping the decoder FFN, and factorizing the output projection. They also employ weight distillation and "weak" distillation (training without dropout or label smoothing in the shallow decoder). Their approach yields a $\sim 3.5\times$ speedup without quality degradation. In contrast, we achieve much higher speedups (between 84× and 140×) by permitting small quality degradation and incorporating RNN-based decoders.

Lin et al. (2023) present an NMT system optimized for mobile deployment through three key architecture improvements: reducing vocabulary size instead of using embedding factorization, reducing model width rather than using parameter sharing, and employing a deep encoder with a

shallow decoder. Combined with knowledge distillation, dropout removal, and optimization of integer operations, their 10MB model achieves a $\sim$ 47$\times$ speedup while maintaining 88.4% of Transformer-big performance, with 99.5% memory reduction. Their 20MB variant achieves 95.5% baseline performance with a $\sim$ 27.7$\times$ speedup. Unlike their approach, our work does not require custom hardware-specific implementations, and we thoroughly investigate beam size tuning and RNN decoder alternatives.

3 Transformer Models

Since the introduction of the Transformer (Vaswani et al., 2017), this network architecture is the de facto standard for machine translation. The model can be described as being composed of two main parts; an encoder which compresses the input source sentence, and a decoder which autoregressively—i.e. word-by-word—generates the hypothesis in the target language. Both, encoder and decoder consist of a stack of layers which transform dense vector-representations of a fixed model dimension d. The encoder as well as the decoder layers consist of a self-attention component, which scales quadratically in the input sequence length, as well as a feedforward sub-layer. In addition, the decoder also has a cross-attention component of similar complexity as the self-attention.

Despite encoder and decoder having a comparable total number of floating-point operations (roughly weighted 2:3 due to the cross-attention in the decoder), the computations of the encoder can be parallelized while the decoder in this architecture is inherently autoregressive. This effect is further amplified by beam search, and in our case leads to 95% of the total computation time being spent in the decoder, as presented in Figure 1.

4 Inference Optimizations

We commence with optimizing inference as it is independent of any system, i.e. it introduces no retraining burden and can be adopted with minimal engineering effort.

4.1 Greedy Search

To begin with, we reduce the number of candidate hypotheses per time step by shrinking the beam size down to 1. Moreover, by utilizing greedy decoding, we eliminate all overhead due to beam management.

4.2 Quantization

The most expensive operations in the Transformer are vector-matrix multiplications. In our measurements, they take around 55% of the total baseline computation time.

These operations can be sped up by computing them in 8-bit integer arithmetic, with hardware acceleration on recent CPUs (Bhandare et al., 2019). We apply a dynamic post-training quantization scheme which computes ranges of the activations on-the-fly during inference (Tang et al., 2024) and apply it to all major vector-matrix multiplications: the feedforward blocks, the attention key/value/query computation and projection, the softmax, and the RNN cells (in case of the SSRU and LSTM experiments).

5 Architectural Optimizations

As our baseline, we adopt the state-of-the-art Transformer 'big' model, in which the encoder and decoder share the same depth. As previously shown in Figure 1, the decoder dominates the encoder in inference runtime. Hence, our focus lies on applying architectural modifications that shift computation towards the encoder and thus streamline the decoder, as illustrated in Figure 2.

5.1 Layer Reallocation & Reduction

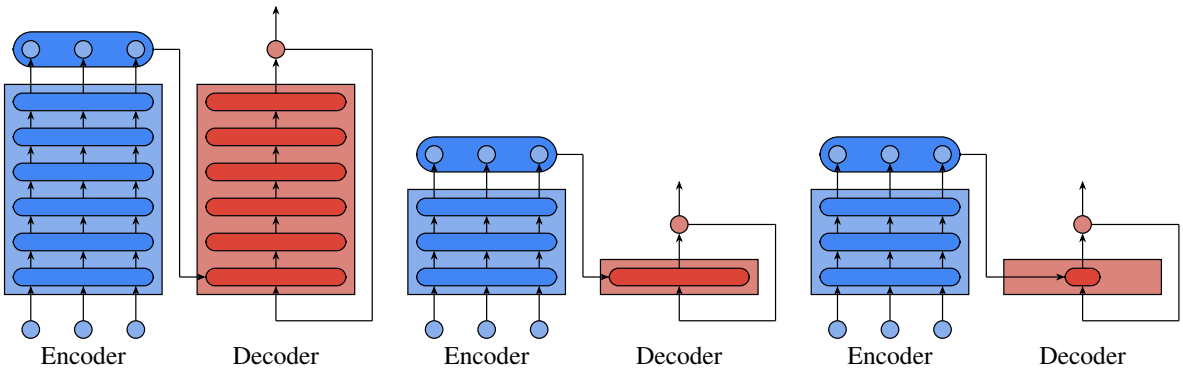
At first, we shift all decoder layers but one to the encoder, leveraging the parallelism in the encoder. The reallocation results in a model comprising $L_{\mathrm{E}} + L_{\mathrm{D}} - 1$ encoder layers and a single-layer decoder.

Moreover, we empirically investigate the trade-off between translation quality and efficiency regarding translation speed and energy consumption. Since the mapping between encoder depth and quality-efficiency ratio is not linear, our focus does not lie on reducing the encoder to as few layers as possible, but rather on finding a good optimum.

The combined effect of both steps is illustrated in Figure 2b. In comparison to the baseline model (Figure 2a), the resulting model contains only a shallow single-layer decoder and an encoder that is significantly less deep.

5.2 Decoder Width Compression

After having shrunk the decoder to just a single layer (see Figure 2b), we aim at further improving translation speed by also reducing the decoder hidden dimension d to a smaller dimension $d' < d$,



(a) Baseline model. (b) Reallocated & reduced layers. (c) Compressed decoder width.

Figure 2: Architecture optimizations.

as pictured in Figure 2c. Accordingly, we also decrease the size of the forward-projections (which in the baseline was chosen as $4d$) to $4d'$. As every component in the Transformer decoder scales with the model dimension, this reduces the computational load of the entire decoder.

5.3 Replacing Transformer with Interleaved RNN Decoder

Finally, we replace the Transformer decoder with a custom lightweight RNN module. First, we experiment with replacing the self-attention layer of the decoder with an RNN layer (Kim et al., 2019; Hsu et al., 2020; Lin et al., 2021). We tested a standard LSTM (Hochreiter and Schmidhuber, 1997) and an optimized SSRU (Kim et al., 2019). Unlike previous work, we use only one decoder layer (see Section 5.1). In our initial experiments with LSTM, we observed a notable decrease in quality, with some smaller models practically diverging (see Table 4). We assume that this is due to the fact that the RNN cell is never exposed to hidden representations of the encoder. Therefore, we rewire the decoder by enriching the hidden state of the RNN cell h_t with a cross-attention to the hidden representation of the encoder H_{enc} (Bahdanau et al., 2015):

$$\begin{aligned} h'_t, c_t &= \text{RNN}(x_t, h_{t-1}, c_{t-1}), \\ h_t &= h'_t + \text{Attention}(H_{enc}, h'_t). \end{aligned} \tag{1}$$

In this way, the RNN cell has a direct information path to the source sentence. We dub this method *interleaving*, as RNN cell and cross-attention computations are interleaved between token positions. As the original SSRU design lacks a hidden state, we integrate one by concatenating the input embedding x_t with the previous output h_t, i.e., $x_t^{\text{new}} := [x_t, h_t]$.

6 Training Optimizations

After improving translation speed and energy consumption by optimizing inference and the model architecture, we address the question of how to optimize the training of our models. Here, the goal is different, as we aim to obtain better models in terms of translation quality rather than making them faster and more energy efficient.

To achieve this goal, we apply sequence-level **knowledge distillation** (KD; Kim and Rush, 2016) using the baseline model as the teacher model p_{T}, which aids the training of the student model p_{S} using the aforementioned optimized architecture. However, instead of using the cross-entropy between student and teacher, we use the Kullback-Leibler divergence $\mathcal{D}_{\text{KL}}(\cdot, \cdot)$ to compute the additional training loss $\mathcal{L}_{\text{KD}}$:

$$\mathcal{L}_{\text{KD}} = -\frac{1}{2}\Big(\mathcal{D}_{\text{KL}}(p_{\text{S}}, p_{\text{T}}) + \mathcal{D}_{\text{KL}}(p_{\text{T}}, p_{\text{S}})\Big). \tag{2}$$

The resulting overall training loss is computed as

$$\mathcal{L} = \alpha \cdot \mathcal{L}_{\text{CE}} + \beta \cdot \mathcal{L}_{\text{KD}}. \tag{3}$$

$\mathcal{L}_{\text{CE}}$ is the cross-entropy loss of the student model and α, β are corresponding hyper parameters.

7 Experiments

We evaluate our findings on four tasks in total: Two general domain translation tasks resembling a industry-typical, *unconstrained* data condition for En→De and En→Ko, as well as the *WMT 2014* datasets for En→De and En→Fr. We provide detailed intermediate results for both unconstrained settings, however moved the intermediate En→Ko results to Appendix B due to limited space.

The overall goal is to build a system that preserves 90% translation quality of the baseline,

while yielding as much translation speed and energy savings as possible.

7.1 Data

For the two unconstrained tasks (En→De/Ko), we trained on a large chunk of data available publicly via OPUS (Tiedemann and Thottingal, 2020). To evaluate the general-domain ability of these models, we chose four test sets of different domains for both tasks respectively. The corresponding training data was selected as a mix of in-domain data matching the test set domains, and general out-of-domain and crawled data.

The unconstrained En→De task is evaluated on four test sets from the movie subtitles (OpenSubtitles 2018 test set), talks (TED tst2018), news (WMT newstest2019), and parliament speech domain (Europarl ST test) (Tiedemann, 2012; Tiedemann and Thottingal, 2020). As for En→Ko, we report on four test sets comprised of subtitles (2018 OpenSubtitles test set), talks (TED tst2018), newswire texts from FBIS (2013 test set), as well as a general-domain test set from the Korean-English treebank (2013 version).

For the WMT 2014 En→De and En→Fr tasks we evaluate on the corresponding newstest2014 test sets (Bojar et al., 2014).

In summary, we obtain these training and evaluation dataset sizes (counting English source words):

Task	Train Sents	Evaluation Sents	Evaluation Words
Unconstrained En→De	90M	9k	154k
Unconstrained En→Ko	28M	10k	123k
WMT 2014 En→De	4M	3k	59k
WMT 2014 En→Fr	32M	3k	62k

Detailed dataset descriptions and statistics can be found in the Appendix C.

7.2 Setup

We train models based on the Transformer architecture and implemented them in PyTorch 2.5 (Paszke et al., 2019). We apply byte-pair encodings (Sennrich et al., 2016; Kudo and Richardson, 2018) to the training data and obtain a source and target vocabulary of 30k and 10k units respecively. Segmentation and casing is encoded via two separate translation factors (Wilken and Matusov, 2019). Our models are trained for 250 sub-epochs of 1M sentences each using the Adam optimizer (Loshchilov and Hutter, 2019) with weight decay 0.01 and base learning rate of $3{\cdot}10^{-4}$, 0.1 label smoothing and 0.1 dropout. For more details we refer to Appendix C.

In the following, we abbreviate a model with L_{E} encoder and L_{D} decoder layers by $L_{\mathrm{E}}/L_{\mathrm{D}}$, e.g. a 12/12 model refers to a system with 12 encoder and decoder layers each.

We evaluate both the translation quality, as well as the inference speed and energy consumption of each of the trained model configurations. For this we compute BLEU (Papineni et al., 2002) and COMET (Rei et al., 2020) for each of the test sets, and in the interest of readability report the average over all four corresponding test sets for the unconstrained tasks. BLEU is computed via Sacrebleu (Post, 2018; $p < 0.005$) with paired approximate randomization (Riezler and III, 2005), COMET uses the checkpoint `Unbabel/wmt22-comet-da` and bootstrap resampling (Koehn, 2004). As the use of whitespaces is inconsistent in Korean, we report character-level BLEU for this language.

Profiling the CPU time and energy is done on a single fixed machine which resembles a server-typical setup with a total of 128 Intel® Xeon® Gold 6438Y+ CPUs (Sapphire Rapid) and 500 GB RAM running Ubuntu 22. We reserve this machine exclusively for the translation executable which we give access to a subset of 8 of these CPUs. For each model, we concatenate the four language-pair specific test sets (unconstrained tasks), and then the total time and energy required for the translation itself. Sequences are sorted by length to reduce the amount of padding. We tune the batch size separately for each experiment for the best decoding speed. Our models are converted into TorchScript and automatically optimized using PyTorch's JIT engine[1]. As it may take longer to translate when the model and data is first loaded, we run a translation of all data once as a warmup phase before profiling the actual runtime and energy usage.

The CPU energy usage is measured in a separate thread by rapidly polling the current power usage[2] and integrating over time. This also includes the passive energy usage by running the node and operation system. As the runtime and energy consumption varies between different executions, we run each inference three times and then report the median to omit outliers. For GPU inference we use one NVIDIA RTX 2080 Ti[3].

[1] Using `torch.jit.optimize_for_inference`

[2] Via s-tui, https://github.com/amanusk/s-tui

[3] Running `nvidia-smi --query-gpu=power.draw` periodically to poll the power usage

Beam Size	BLEU	COMET	WPS	kJ
32	35.3	85.4	18	2.5k
16	35.3	85.3	37	1.1k
12	35.3	85.4	51	894
8	35.3	85.3	76	596
4	35.1	85.3	145	314
2	34.8	85.2	264	172
1	34.3	85.0	477	95.4
greedy	34.3	85.0	629	74.3
+ quantiza	**34.4**	**84.8**	**1.1k**	**42.5**

Table 1: Impact of beam size on quality, speed and energy for the unconstrained En→De 12/12 system. We also investigate greedy search and quantization.

Enc	Dec	BLEU	COMET	WPS	kJ
12	12	34.4	84.8	1.1k	42.5
18	6	34.3	85.0	1.5k	30.2
21	3	34.2	84.9	1.9k	24.9
23	1	33.7	83.4	2.3k	21.1
12	1	33.5	83.0	3.5k	15.3
6	1	33.0	82.3	4.8k	12.8
5	**1**	**32.8**	**82.2**	**5.2k**	**12.3**
4	1	32.3	81.7	5.6k	12.0
3	1	31.8	81.1	6.5k	11.5
2	1	30.9	80.3	7.3k	11.0
1	1	28.7	77.8	7.7k	10.8

Table 2: Impact of layer reallocation and reduction on quality, speed and energy for En→De (unconstrained). All systems here utilize greedy search and quantization.

We report the translation speed measured in untokenized English words per second (WPS), and the energy consumption in kJ for running the complete inference.

7.3 Evaluation: Inference Optimizations

At first, we investigate the effect of the beam size during inference in terms of translation quality, speed and energy. The results for the unconstrained En→De task are presented in Table 1. Starting from the baseline beam size of 8, increasing it stepwise to 32 does not affect quality, but slows down translation from 76 to 18 WPS while also increasing the energy consumption by a factor of 4. This underlines that higher beam sizes yield no improvement (Yang et al., 2018). For each beam size, we tuned the batch size to maximize translation speed: For greedy search and beam size 1, we use 128 sentences per batch; which we then decrease proportionally for higher beam sizes (64 for beam size 2, 32 for beam size 4, etc.).

Moving into the opposite direction, decreasing the beam size down to 1 yields a 6.3× speedup and a 6.2× energy efficiency boost at the cost of 1.0 BLEU and 0.3 COMET. To discard the overhead of beam search, we replace it by a greedy search implementation. This does not affect quality, but further improves speed and energy to 629 WPS and 74.3 kJ, respectively.

Additionally quantizing the model results in a translation speed of 1.1k WPS while consuming 42.5 kJ, which corresponds to improvement factors of 14.5× and 14.0× over the baseline. If not mentioned otherwise, we use greedy search and quantization for all evaluations to follow, carried out on CPU.

7.4 Evaluation: Architectural Optimizations

We then investigate the impact of reallocating layers from the decoder to the encoder (see Table 2, lines 1–4). Starting from the 12/12 baseline model, we can shift 6 or even 9 layers without seeing a degradation in quality, increasing translation speed from 1.1k to 1.9k WPS. Moving all but one layer to the encoder results in the 23/1 model which is 2.1× faster than the 12/12 model at the cost of 0.7 BLEU. The energy consumption is improved by a factor of 2.0. As before, we tuned the batch size for each configuration. For 12/12 and 18/6 systems 128 is optimal, while all other models with further reduced decoder size use batch size 64.

Furthermore, we reduce the number of layers in the decoder to a point that is still acceptable in terms of translation quality, bearing in mind that we also want to improve the decoder width. The results are presented in the bottom part of Table 2. Given our minimum 90% threshold with respect to the baseline, i.e. 31.8 BLEU, the 3/1 model with 6.5k WPS would be still acceptable. However, as we want to have the possibility to further improve the decoder width, we settle with the 5/1 model as trade-off between quality and efficiency. Note that the number of encoder layers has only a minor effect on the energy consumption (lines 4-11).

Having settled on a quantized 5/1 model with greedy search, we proceed with decoder-width optimization (see Table 3). Starting with a Transformer 'big' decoder, we stepwise halve the decoder dimen-

Decoder	BLEU	COMET	WPS	kJ
'big'	32.8	82.2	5.3k	12.3
'base'	32.3	81.3	6.7k	11.2
'small'	**31.7**	**79.8**	**8.0k**	**10.7**
'tiny'	31.1	78.0	8.4k	10.6

Table 3: Impact of decoder width on quality, speed and energy for the quantized 5/1 system with greedy search (En→De, unconstrained).

sion d until reaching the Transformer 'tiny' model with only $1/8$ dimension width in comparison to Transformer 'big' (where $d = 1024$). The number of attention heads and the feedforward dimension is down-scaled accordingly. Although the quality loss per step is 0.5–0.6 BLEU, the speed gain diminishes as the decoder becomes narrower, while the energy consumption stays basically unaffected. Thus, we choose the Transformer 'small' decoder (decoder model dimension $d = 256$, 4 attention heads, $d_{\text{ff}} = 1024$) for further experiments, as it offers a good trade-off between the speedup and quality loss.

7.5 Evaluation: RNN Decoder Replacement

A common approach to speed up the inference for MT is to replace the decoder with an RNN (Kim et al., 2019; Hsu et al., 2020; Lin et al., 2021). However, existing research has not studied the performance of such hybrid models when they are combined with inference optimizations such as greedy search and quantization—which for themselves already yield a speedup of factor $14\times$ at only minor drop in quality.

In Figure 3 we show that the effect of quantization and beam size reduction varies between different metrics: we compare our hybrid models with Transformer and LSTM decoders (with interleaving). Across all metrics, the hybrid LSTM decoder performs better than the Transformer decoder when using beam search and not applying quantization. However, in BLEU this advantage vanishes when decoding with quantization and greedy search. For COMET and BLEURT, this is not the case.

We proceed to compare different RNN architectures: the standard LSTM (Hochreiter and Schmidhuber, 1997) and the optimized SSRU (Kim et al., 2019); and apply our proposed interleaving approach to both models.

As shown in Table 4, the interleaved SSRU decoder is similarly fast as the LSTM but the quality

Decoder	BLEU	COMET	WPS	kJ
Transformer	**31.7**	79.8	8.0k	10.7
SSRU	30.5†	78.4†	**8.8k**	10.4
+ interleave	30.6†	79.8	**8.8k**	10.5
LSTM	7.6†	43.3†	7.4k	10.9
+ interleave	31.4	**80.5**†	8.7k	10.6

Table 4: Different decoder architectures, applied to the quantized 5/1 model with the 'small' decoder size (En→De, unconstrained). † indicates a statistically significant difference with respect to the Transformer decoder.

Decoder	KD	BLEU	COMET	WPS
Transformer	✗	31.7	79.8	8.0k
	✓	**32.2**	80.5	8.1k
SSRU interl.	✗	30.6	79.8	8.8k
	✓	31.7	81.0	**8.9k**
LSTM interl.	✗	31.4	80.5	8.7k
	✓	32.0	**81.3**	**8.9k**

Table 5: Impact of knowledge distillation (KD) on quality, speed and energy for the quantized 5/1 system with a Transformer 'small' decoder and greedy search (En→De, unconstrained). All systems consume 10.5–10.7 kJ. All three KD systems have pairwise statistically significantly different COMET scores.

is worse. Interleaving proves to be crucial for the LSTM decoder, which offers the best speed-quality trade-off: It has the best COMET score of 80.5, and despite its 31.4 BLEU being slightly lower than the 31.7 BLEU gained with the Transformer decoder, this difference is statistically not significant. At the same time it is **114× faster** than the baseline model.

7.6 Evaluation: Training Optimization

After having improved the model speed and energy consumption, we shift our focus on improving its translation quality through knowledge distillation (KD). We utilize the strongest model—the 12/12 Transformer 'big' baseline—as the teacher and weigh the CE and KD losses with $\alpha = 0.5$ and $\beta = 1.0$, respectively. This setting performed best in prior experiments.

Table 5 presents the performance of the models trained with KD in comparison to their counterparts without. The Transformer system with KD performs best in BLEU with a small 0.2 advantage

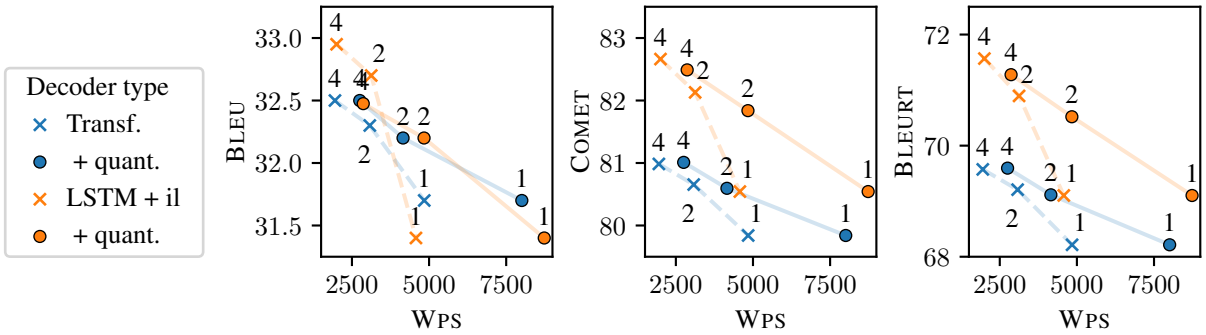


Figure 3: Comparing the decoding quality and speed, with different beam sizes: 4, 2, and 1 (using greedy search). All models use the 5/1 architecture with either a Transformer 'small' or interleaved LSTM 'small' decoder (En→De, unconstrained).

Technique	Unconstrained English → German						Unconstr. English → Korean			
	Quality		CPU		GPU		Quality		CPU	
	BLEU	COMET	WPS	kJ	WPS	kJ	BLEU	COMET	WPS	kJ
Transformer 'big'	35.3	85.3	76	596	484	76	28.1	82.8	92	402
+ greedy search	34.3	85.0	629	74.3	3.4k	10.4	27.3	82.4	544	67.9
+ quantize	34.4	84.8	1.1k	42.5	n.a.	n.a.	27.2	82.4	1.2k	57.2
+ depth opt.	32.8	82.2	5.2k	12.3	16.0k	1.9	25.6	81.0	4.8k	13.0
+ width opt.	31.7	79.8	8.0k	10.7	21.4k	1.3	24.9	79.9	7.4k	11.8
+ LSTM interl.	31.4	80.5	8.7k	10.6	22.5k	1.2	24.7	79.9	7.5k	11.8
+ KD	**32.0**	**81.3**	**8.9k**	**10.5**	**22.6k**	**1.2**	**25.7**	**81.0**	**7.7k**	**11.6**

Table 6: Incrementally applying all proposed techniques to the En→De and En→Ko unconstrained tasks. We report inference speed (WPS) and energy consumption (kJ) on CPU and GPU.

Technique	WMT14 English → German				WMT14 English → French			
	Quality		CPU		Quality		CPU	
	BLEU	COMET	WPS	kJ	BLEU	COMET	WPS	kJ
Transformer 'big' (6/6 layers)	29.0	84.4	142	121	41.5	85.9	111	158
Transformer 'big' (12/12 layers)	29.2	84.7	72	240	42.1	86.4	60	289
+ greedy search	28.5	83.9	600	30.0	41.4	85.9	530	34.2
+ quantize	28.4	83.8	965	17.8	41.2	85.8	848	20.6
+ depth opt.	25.5	77.7	4.9k	3.8	38.8	82.8	4.9k	3.6
+ width opt.	23.7	73.4	8.5k	3.7	37.8	80.8	7.5k	3.7
+ LSTM interl.	24.2	75.4	8.5k	3.7	37.5	80.9	8.3k	3.7
+ KD	**25.7**	**78.7**	**8.5k**	**3.6**	**37.7**	**81.4**	**8.4k**	**3.7**

Table 7: Incrementally applying all proposed techniques to models trained on the WMT 2014 tasks in En→De and En→Fr. We measure translation quality, inference speed (WPS) and energy consumption (kJ) on CPU for the `newstest2014` test set.

over the interleaved LSTM with KD, which in turn outperforms the Transformer by 0.8 COMET and is faster by 0.8k WPS. On the other hand, the interleaved SSRU offers the same inference speed as the interleaved LSTM, but its performance is worse by 0.3 BLEU as well as COMET points in comparison to the interleaved LSTM.

Note that the BLEU score of 31.7 gained by the interleaved SSRU with KD corresponds to only 89.8% translation quality with respect to our baseline Transformer system, which does not fulfill our goal to preserve at least 90% quality.

7.7 Evaluation: Summary

In the following, we summarize the final results on the unconstrained En→De and En→Ko tasks as well as the WMT 2014 En→De and En→Fr tasks.

7.7.1 Unconstrained Tasks

Table 6 summarizes the gains by all optimization techniques proposed in this work when applied incrementally for both unconstrained tasks, En→De and En→Ko. Details on all intermediate results for En→Ko are to be found in the Appendix B.

An extended analysis reveals that the speed gains are particularly high for long sequences (see appendix, Figure 4).

On GPU we obtain 47× translation speed and 98.4% energy savings. The final model is 18× faster on CPU than the vanilla Transformer 'big' model on GPU. Moreover, it is 0.4× as fast on CPU as it is on GPU. Note that no GPU kernels exist in PyTorch 2.5 for quantization. Hence, all GPU results are obtained without quantization.

In the En→Ko test sets, there are 1.19 target tokens per source token on average, whereas in the En→De test sets this number is 1.36. As there are fewer target words to be generated per source word in the En→Ko task, there are fewer decoding steps, which explains why for En→Ko the baseline system achieves a translation speed of 92 WPS.

Overall, the **En→Ko speedup is 84-fold** and our final system achieves **97.1% energy savings**, while still reaching 91.5% relative BLEU and 97.8% relative COMET, which underlines the general applicability and gains of our proposed optimizations. However, as there are less decoding steps than in the En→De task on average, there is also less gain to be expected by the proposed techniques.

7.7.2 WMT 2014 Tasks

The WMT2014 En→De and En→Fr results are presented in Table 7. On the **WMT 2014 En→De** task, our approach yields **118× translation speed** and **98.5% energy savings**, which is very similar to the unconstrained task. At the same time, we lose 12.0% and 7.1% relative in BLEU and COMET, respectively.

On the **WMT 2014 En→Fr** task, we even achieve **140× translation speed** and **98.7% energy savings**. This comes at a cost of 10.5% and 5.8% relative in BLEU and COMET, respectively.

Generally speaking, En→Fr translation requires fewer word reorderings than En→De translation, which might explain why our final narrow single-layer decoder model performs better in comparison to the Transformer 'big' (12/12 layers) baseline. However, an actual analysis remains for future work.

8 Conclusion

In this work, we introduced Green KNIGHT, an easy-to-cook recipe that substantially accelerates inference and reduces energy consumption of NMT models while incurring only minimal loss in translation quality. In contrast to specialized low-level or hardware-specific optimizations, Green KNIGHT achieves these gains through widely used and well-understood tools and methods, making it immediately adoptable in production NMT pipelines. Our experiments on two language pairs show that this recipe achieves up to 140× speed-ups and up to 98.7% energy reduction, while maintaining at least 92.9% COMET and 88.0% **Bleu** scores relative to the baseline.

Crucially, the final models achieve the a 18-fold throughput on CPU in comparison to the throughput of the baseline model on GPU, significantly contributing to democratizing NMT. When applied on GPU, our model achieves a 47× speeup over the baseline model while reducing energy consumption by 98.4%.

Limitations

The empirical relevance of this work might be limited by the tasks we report on and the evaluation. We report on four high-resource datasets translating from English as the source language. Although, according to our findings, the encoder (and therefore the source language) does not seem to be the bottleneck, further investigation would be needed

to confirm this. We base our findings on medium and high-resource language pairs and do not investigate low-resource settings or other language pairs.

Due to resource constraints, we were also only able to perform a single training run per reported system and do not account for variability of different training runs. Furthermore, our evaluation relies solely on automatic metrics. We validate our results using a range of automatic metrics (COMET, BLEURT, and BLEU), but we do not perform a human evaluation.

We only reported results measured on a single machine and one specific driver version for the measurement of translation speed and energy. Although the setup used is typical for a server CPU, using different hardware might impact the translation speed and energy consumption. Furthermore, time and energy measurements inherently suffer from some variance between runs, which can depend on exterior factors such as the server temperature or system background jobs. The same holds for the GPU measurements.

Potential Risks

As our primary results are based on automated metrics, they do not necessarily reflect the quality as assessed by humans. This is especially true for neural metrics such as COMET and BLEURT, which are not auditable and may lead to unpredictable results in varying domains and language pairs. Relying blindly on these metrics to make decisions can lead to misjudgments in translation quality.

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Beam Size	BLEU	COMET	WPS	kJ
32	27.8	82.6	22	1645
16	27.9	82.8	46	811
12	27.9	82.8	60	621
8	28.1	82.8	92	402
4	28.1	82.9	180	207
2	27.8	82.8	321	115
1	27.3	82.4	544	67.9
greedy	27.3	82.4	668	57.2
+ quantize	**27.2**	**82.4**	**1.2k**	**30.7**

Table 8: Various beam sizes of En-Ko system with a 12-layer encoder and a 12-layer decoder. We also investigate greedy search and quantization.

Enc	Dec	BLEU	COMET	WPS	kJ
12	12	27.2	82.4	1.2k	30.7
21	3	27.3	82.6	1.8k	20.2
21	1	26.6	81.6	2.3k	18.4
12	1	26.3	81.6	3.0k	15.4
6	1	25.7	81.0	4.2k	13.6
5	**1**	**25.6**	**81.0**	**4.8k**	**13.0**
4	1	25.1	80.7	5.2k	12.8
3	1	24.9	80.4	5.5k	12.5
2	1	24.1	79.7	6.2k	12.2
1	1	22.4	77.8	6.8k	11.8

Table 9: Comparison of En-Ko systems with varying encoder and decoder depth. All investigated systems utilize greedy search with quantization.

Decoder	BLEU	COMET	WPS	kJ
'big'	25.6	81.0	4.8k	13.0
'base'	25.1	80.4	6.1k	12.2
'small'	**24.9**	**79.9**	**7.4k**	**11.8**
'tiny'	24.2	78.8	7.5k	11.6

Table 10: Comparison of En-Ko system with various decoder width. All investigated system utilize a 5-layer Transformer 'big' encoder, a single layer Transformer decoder and greedy search with quantization.

A Relative Speed Improvements per Sequence Length

Figure 4 shows the relative speed improvement, depending on the sequence length. As the baseline inference time is mostly dictated by the decoding steps, it is particularly slow when decoding long sentences. Our improved model shifts computation time towards the encoder, which leads to a particularly high relative speedup for longer sentences.

B Extended Evaluation on Unconstrained English → Korean Task

We present detailed intermediate results on the unconstrained English to Korean task in this section.

The procedure here is exactly the same as for the unconstrained English to German setup. We investigate the beam size first as shown in Table 8. We choose the beam size of 8 as a baseline, as it gives the best BLEU and BLEURT. Then we follow the recipe as described for English to German. We then start with the inference optimization (greedy search and quantization) in Table 8. Then we optimize the architecture, i.e. the depth and width shown in Tables 9, and 10 respectively. We then replace the decoder with our LSTM implementation, and apply knowledge distillation, as shown in Table 11. In each step, the chosen hyperparameters correspond to the same ones as for the unconstrained English → German task.

C Training Details

The statistics of our training and test data are presented in Table 12. For the unconstrained tasks, we mix in-domain and out-of-domain data in a ratio of 1:3. The exact lists of used corpora and their weights are stated in Tables 13a and 13b. For the WMT14 tasks, we train on all released corpora for that year's shared tasks and do not perform additional weighting between corpora.

We apply some simple filtering to our training data based on a set of rules, as well as similarity-based on LaBSE embeddings (Feng et al., 2022).

All models, independently of the configuration, are trained for 250 sub-epochs of 1M samples. Our optimizer is AdamW (Loshchilov and Hutter, 2019) with $\beta = (0.9, 0.98)$, weight decay 0.01 and a

Decoder	BLEU	COMET	WPS	kJ
Transformer	24.9	79.9	7.4k	11.8
+ KD	25.4	80.6	7.4k	11.7
Interl. LSTM	24.7	79.9	7.5k	11.8
+ KD	25.7	81.0	7.7k	11.6

Table 11: Impact of training optimization on quality, speed and energy for the En→Ko quantized 5/1 system with a 'small' decoder and greedy search.

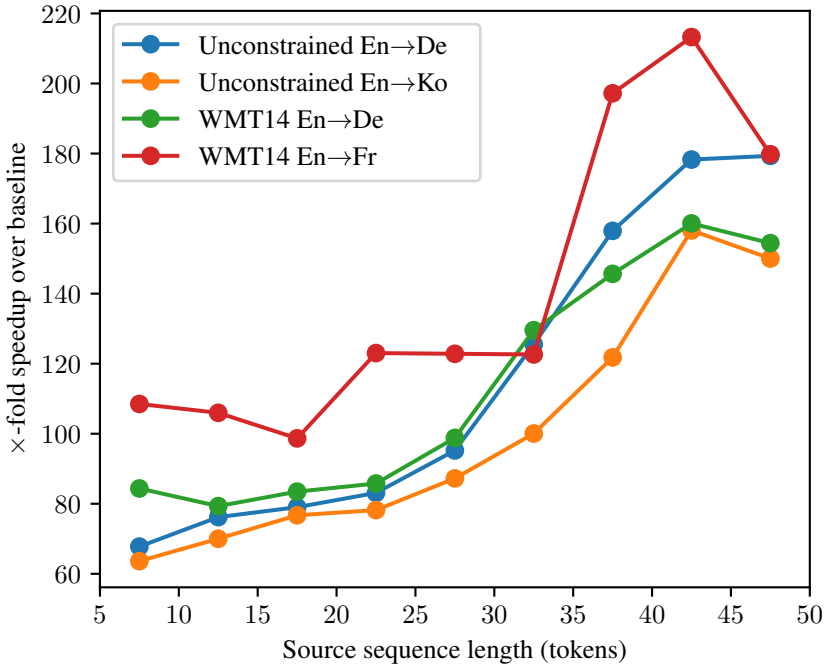

Figure 4: Relative CPU speed up of our optimized model (final row in Tables 6, 7) vs. the Transformer 'big' baseline, binned by source sequence length. While the baseline scales poorly with increasingly long sequences, this effect is mitigated with our optimized models.

learning rate of $3 \cdot 10^{-4}$, which after a warmup of ten epochs is reduced by factor 0.9 if the validation perplexity plateaus. We use 16-bit mixed precision training (Micikevicius et al., 2017) as provided by PyTorch lighting, and an effective batch size of up to 120k source plus target tokens. We apply label smoothing of 0.01 and a training dropout of 0.1 in almost all cases. As the WMT2014 En→De dataset is relatively small, we increased the dropout rate on this task to 0.3 for the models that used a 'big' decoder to prevent overfitting.

For both unconstrained tasks, we compile a held-out validation set that approximately equally represent the four test sets, and use this validation set to select the best checkpoint after each sub-epoch by computing validation BLEURT. For the WMT 2014 tasks, we use the newstest2013 sets as validation data.

Our unconstrained En→De baseline system has 485M trained parameters and was trained on two NVIDIA RTX A6000 GPUs, which took around 103 hours to complete. Other models train faster due to their reduced complexity. All datasets and tools that this work is based on are publicly available.

Dataset	Sentences	Total Words		Vocabulary Words	
		English	German	English	German
Training Data	90.6M	1.6B	1.4B	11.3M	22.9M
Test Data (total)	8984	154.0k	142.7k	29.6k	36.2k
WMT newstest2019	1997	42.0k	42.1k	10.6k	12.4k
TED tst2018	1978	38.0k	35.1k	6.7k	8.4k
Europarl ST	2631	60.4k	52.3k	8.2k	11.2k
OpenSubtitles 2018	2378	13.6k	13.1k	4.0k	4.3k

(a) Unconstrained English to German task.

Dataset	Sentences	Total Words		Vocabulary Words	
		English	Korean	English	Korean
Training Data	27.9M	265M	201M	183.2M	3.4M
Test Data (total)	10483	123.6k	83.4k	16.0k	77.7k
FBIS test 2013	676	21.8k	13.0k	4.7k	12.6k
Korean English treebank	3883	51.5k	36.7k	5.9k	33.7k
TED tst2015	1214	21.2k	15.1k	4.9k	14.4k
OpenSubtitles 2018	4710	29.1k	18.6k	6.0k	16.9k

(b) Unconstrained English to Korean task.

Dataset	Sentences	Total Words		Vocabulary Words	
		English	German	English	German
Training Data	3.9M	86.9M	81.2M	1.4M	2.5M
Test Data (newstest2014)	3003	59.3k	54.9k	14.1k	16.8k

(c) WMT 2014 English to German task.

Dataset	Sentences	Total Words		Vocabulary Words	
		English	French	English	French
Training Data	31.8M	709.4M	809.2M	5.3M	5.2M
Test Data (newstest2014)	3003	62.3k	69.6k	14.4k	15.7k

(d) WMT 2014 English to French task.

Table 12: Total training and test set sizes, without tokenization and cased.

10%	OPUS-OpenSubtitles (16,166,700)
5%	OPUS-TED2020 (162,134)
5%	News-Commentary (317,129), OPUS-GlobalVoices (83,240)
5%	OPUS-Europarl (2,308,549)
65%	pattr (12,183,523), OPUS-CCAligned (10,876,712), OPUS-EuroPat (10,664,245), OPUS-EUbookshop (5,459,744), OPUS-TildeMODEL (3,249,472), OPUS-MultiCCAligned (2,638,152), OPUS-ELRC (2,599,018), OPUS-ParaCrawl (2,551,919), OPUS-DGT (2,240,204), OPUS-JW300 (1,707,885), OPUS-WikiMatrix (1,139,146), OPUS-Wikipedia (1,073,073), rapid (692,934), OPUS-Tatoeba (546,960), CommonCrawl (523,024), OPUS-Tanzil (492,585), WikiTitles (487,528), OPUS-QED (417,637), OPUS-JRC-Acquis (265,780), covost (258,177), OPUS-EMEA (201,860), EUTV (152,233), must-c (115,563), OPUS-KDE4 (100,791), OPUS-MultiUN (63,833), OPUS-ECB (63,277), OPUS-bible-uedin (37,857), OpenOffice (25,980), OPUS-MPC1 (15,794), OPUS-GNOME (12,814), OPUS-Ubuntu (6,971), OPUS-PHP (6,557), OPUS-EUconst (1,928), OPUS-Salome (1,057), OPUS-RF (165)
10%	extracted parallel short phrases and dictionary entries from the above corpora

(a) Unconstrained English to German training data.

10%	OPUS-TED2020 (323,188)
1%	fbis (39,867)
14%	OPUS-OpenSubtitles (947,351)
65%	OPUS-NLLB (13,736,682), OPUS-CCMatrix (3,799,459), OPUS-ParaCrawl (2,267,324), OPUS-CCAligned (2,199,281), OPUS-LinguaTools-WikiTitles (1,533,792), systran (576,744), OPUS-MultiCCAligned (475,984), naver (375,119), OPUS-XLEnt (328,552), taus (315,934), subscene (188,012), jaykim (118,297), OPUS-QED (112,298), OPUS-WikiMatrix (88,069), OPUS-Tanzil (62,991), jhe-park (52,850), joongang (47,555), joint-pubs (42,438), OPUS-bible-uedin (40,161), kaist (30,269), OPUS-KDE4 (23,249), OPUS-wikimedia (18,285), osc translated text (15,813), goodneighbor (14,484), various-book1-johanna (13,513), OPUS-Tatoeba (11,403), donga-ilbo (10,728), various-military (9,202), OPUS-Mozilla-I10n (6,791), OPUS-GlobalVoices (6,108), bible world (4,794), sejong (4,632), OPUS-MDN Web Docs (3,655), kgf (3,442), various-unknown-topic (2,871), nvtc (2,673), OPUS-tldr-pages (1,096), OPUS-ELRC (732), usembassy (575), usfkgovplan (204), various-medical (140), OPUS-PHP (126), social-media (92), OPUS-GNOME (74), OPUS-Ubuntu (13)
10%	extracted parallel short phrases and dictionary entries from the above corpora

(b) Unconstrained English to Korean training data.

Table 13: Training dataset statistics per weight group. Training data is mostly taken from OPUS (Tiedemann and Thottingal, 2020) and then filtered. We report the number of sentences after filtering here.