CURB YOUR CARBON EMISSIONS: BENCHMARKING CARBON EMISSIONS IN MACHINE TRANSLATION

A PREPRINT

Mirza Yusuf*
Manipal Institute of Technology
Manipal, 576104
mirzayusuf1000@gmail.com

Praatibh Surana*
Manipal Institute of Technology
Manipal, 576104
praatibhsurana@gmail.com

Gauri Gupta*
Manipal Institute of Technology
Manipal, 576104
gaurigupta.315@gmail.com

Krithika Ramesh*
Manipal Institute of Technology
Manipal, 576104
kramesh.tlw@gmail.com

October 6, 2021

ABSTRACT

In recent times, there has been definitive progress in the field of NLP, with its applications growing as the utility of our language models increases with advances in their performance. However, these models require a large amount of computational power and data to train, consequently leading to large carbon footprints. Therefore, it is imperative that we study the carbon efficiency and look for alternatives to reduce the overall environmental impact of training models, in particular large language models. In our work, we assess the performance of models for machine translation, across multiple language pairs to assess the difference in computational power required to train these models for each of these language pairs and examine the various components of these models to analyze aspects of our pipeline that can be optimized to reduce these carbon emissions.

1 Introduction

Although our computational techniques and hardware resources have advanced greatly these past few decades, given the rise of large language models which have applications in multiple sectors, the environmental impact of training and developing NLP models, particularly on a large scale, could have detrimental consequences on the environment. This is due to the energy usage (whether carbon neutral or not) possibly contributing directly or indirectly to the effects of climate change. With experiments on total time expected for models such as Transformer, BERT, and GPT-2 to train and the subsequent cost of training, Strubell et al. provides substantial evidence that researchers need to increasingly prioritize computationally efficient hardware and algorithms.

There has been research to suggest that large language models could be outperformed by their less computationally intensive counterparts on multiple tasks with the help of fine-tuning and techniques such as using random search for hyperparameter search or pruning. Additionally, as performance across different tasks tends to vary based on the languages used, data availability, model architectures among other factors, it is likely that training models to a certain performance level for some languages are less carbon-intensive than others. This is speculation is substantiated by the correlation found between morphological ambiguity of languages and the performance of language models on European languages.

The primary objective of our work is to measure the differences in carbon emissions released between multiple language pairs and assess the contributions of various components, within the two architectures we’ve used, to the carbon footprint. To the best of our knowledge, no study on the differences in languages in terms of carbon emissions has
been carried out so far, making this the first foray into the field that could potentially pave way for optimization in the components of models that vary depending on the language used to make them more carbon efficient.

2 Related Work

Some relevant studies that our work draws inspiration from include Schwartz et al. [10], which indicates how the computational costs for deep learning research have increased exponentially from 2012 to 2018. They introduce Red AI, which includes models such as BERT, XLNet, GPT-2 [11-13] that are computationally expensive to train, and as a result, are not environmental-friendly. The alternative proposed: Green AI, which takes an environmental-friendly approach, and is more inclusive. This work suggests making efficiency a criterion upon which research is evaluated, alongside other performance-based metrics such as accuracy, by illustrating the differences in carbon emissions, number of parameters, electricity usage, FPO, or time taken by these models to train. The use of Green AI-aligned approaches to reduce the computational costs by taking into account alternate approaches for a specific language, or language pair might be more carbon efficient.

Strubell et al. [2] presents a significant contribution to the field, by bringing to light the financial and environmental cost of training some of the aforementioned Red AI models, and illustrates the tradeoff between the increase in cost and the increase in performance. The authors present actionable proposals to reduce these costs and promote equity within NLP research, such as reporting the training time and sensitivity to hyperparameters, equitable access to computation resources, and using computationally optimal hardware resources and algorithms to train their models. However, as was demonstrated by Schwartz et al. [10], only a fraction of papers report the efficiency of the models, making it necessary to conduct studies such as these to benchmark the carbon efficiency whilst varying different factors that potentially contribute to it to gauge and develop methods that could be used to reduce carbon emissions.

Patterson et al. [14] identifies multiple areas that require improvement in terms of energy efficiency and the reduction of carbon emissions of large neural networks. Factors such as geographic location and infrastructure and the variation of carbon emissions even within the same region are analyzed. They show that large, sparsely activated deep neural networks are a more carbon-efficient option than their large, dense DNN counterparts while not compromising on the performance of the model.

3 Machine Translation

Our experiments were conducted across a total of 6 language pairs (EN-FR, EN-DE, FR-EN, FR-DE, DE-EN, DE-FR), to account for all possible permutations between English (EN), French (FR), and German (DE). We used a convolutional sequence-to-sequence learning model, as well as a transformer-based model with attention mechanisms.

We compare the performance of these systems for our language pairs using the BLEU score as a standard metric and the CodeCarbon package [1] to track the carbon emissions released during the time of training. These experiments were carried out on Google Colaboratory due to the otherwise limited computational resources available to the developers. The Tesla K80 is the most frequently assigned GPU by Colaboratory and was hence employed across all experiments to maintain hardware uniformity.

3.1 Data

We made use of the Multi30k dataset [15, 16], a comparable parallel corpus that consists of approximately 30,000 samples each for 3 languages: French, German and English. We made use of a comparable corpus so as to be able to draw accurate comparisons of the performance of the models and their carbon emissions across every language pair. The lexical diversity of the training corpus, including the Type-Token Ratio (TTR) [17] has been depicted in Table 1.

| Language | TTR  | Vocabulary | # of Tokens |
|----------|------|------------|-------------|
| English  | 0.0306 | 9802       | 320108      |
| German   | 0.0584 | 17488      | 299445      |
| French   | 0.0336 | 11287      | 335917      |

Table 1: Representation of the lexical diversity of the training corpus
3.2 Convolutional Sequence to Sequence Learning

The Convolutional Sequence to Sequence Learning model (ConvSeq) [18] is deviant from traditional sequential architectures, as it incorporates only convolutional layers, using filters to extract features from the text. It incorporates no recurrent units but has been shown to outperform sequential architectures such as deep LSTMs in machine translation, and the lack of sequential processing means allows all operations to take place in parallel, which is more computationally efficient. As there is no information about the position of tokens in the convolutional architectures, we pass the position of each token in the sequence with the help of a position embedding layer, and the positional and token embeddings are summed to produce the embedding vector. Aside from an attention mechanism incorporated in each layer of the decoder, there are residual connections in both the encoders and decoders, with the output from the convolutional blocks being summed with the original embedding vector through a residual connection to produce the following output, where \( h_i \) indicates the decoder state of the \( i_{th} \) element, and \( v \) represents the Gated Linear Unit [19] non-linearity applied over the output of the convolutional layers:

\[
h_i^l = v \left( WQ^l [h_{i-k/2}^{l-1}, \ldots, h_{i+k/2}^{l-1}] + b_w^l \right) + h_i^{l-1}
\]

The final distribution of the tokens most likely to be predicted is given by the following equation, where the softmax function is applied over the final linear layer, where \( W_o \) and \( b_o \) are the weights and biases of this layer.

\[
p(y_{i+1} \mid y_1, \ldots, y_i, x) = \text{softmax} \left( W_o h_i^T + b_o \right) \in \mathbb{R}^T
\]

3.3 Transformer Model

We implement a version of the transformer model [20], and similar to the ConvSeq architecture, the transformer does not use any recurrence. It also does not use any convolutional layers. Instead, the model is entirely made up of linear layers, attention mechanisms and involves normalization. The modifications in the architecture we used include a learned positional encoding instead of a static one, the standard Adam optimizer utilized a static learning rate instead of one with warm-up and cool-down steps, and label smoothing is not used. Attention can be thought of in terms of queries \( Q \), keys \( K \) and values \( V \) - where the \( Q \) is used with the \( K \) to get an attention vector (usually the output of the softmax operation and has all values between 0 and 1 which sum to 1) which is then used to get a weighted sum of the values. The transformer uses scaled dot-product attention, where the \( Q \) and \( K \) are combined by taking the dot product between them, then applying the softmax operation and scaling by \( d_k \) before finally then multiplying by the value. \( d_k \) is the head dimension, which is part of the multi-head attention layer. The scaling is done to prevent the vanishing gradient problem. The equation for the attention mechanism is given as follows:

\[
Attention(Q, K, V) = \text{softmax}(QK^T \frac{1}{\sqrt{d_k}})V
\]

However, the scaled dot-product attention isn’t simply applied to the \( Q, K \) and \( V \). Instead of doing a single attention application, the \( Q, K \) and \( V \) have their hidden dimensions split into heads and the scaled dot-product attention is calculated over all heads in parallel. This means instead of paying attention to one concept per application, we pay attention to multiple heads. We then recombine the heads into their hidden dimensional shape which essentially allows each head dimension to pay attention to different concepts. This is given by:

\[
head_i = Attention(QW^Q_i, KW^K_i, VW^V_i)
\]

where \( W^Q \) is the linear layer applied at the end of the multi-head attention layer and \( W^Q, W^K, W^V \) are the linear layers.

4 Results

4.1 Analysis of Results by Epoch

The results after training the models for 10 epochs have been tabulated in Figure 1. For both models, the highest BLEU scores were reported by the EN-FR and FR-EN language pairs, whilst the lowest BLEU score language pairs (EN-DE and FR-DE) both had German as the target language, thus indicating that translation to German might be more computationally involved than French or English. This hypothesis is further proven through the results in Figure 3, where the same language pairs, EN-DE and FR-DE, take the greatest time to reach the BLEU score threshold of 25. In addition to the conclusion from these two experiments, German exhibits the most lexical diversity according to the TTR measure in Table 1 which likely demonstrates that lexical diversity is directly proportional to training time to achieve an adequate level of performance.
The carbon emissions for the transformers are significantly lower, both in terms of value and their range than their ConvSeq counterparts. This is presumably owing to the large difference in their parameter count. However, when we rank the CO₂ emissions of the two architectures (as indicated in 3 in the appendix), we notice that the language pairs with the highest emissions for the ConvSeq model release the lowest emissions for the transformer-based architecture. The transformed-based model also outperforms the ConvSeq one for machine translation over every language pair, despite having significantly fewer parameters.

| Language Pair | CO₂ Emissions (in g) | BLEU Score |
|---------------|----------------------|------------|
| En-De         | 64.33 ± 0.273        | 29.5 ± 0.61|
| En-Fr         | 52.65 ± 0.182        | 33.1 ± 0.51|
| De-En         | 52.65 ± 1.744        | 31.6 ± 0.0 |
| De-Fr         | 42.13 ± 5.283        | 25.5 ± 0.0 |
| Fr-De         | 34.69 ± 0.331        | 43.3 ± 0.61|

| Language Pair | CO₂ Emissions (in g) | BLEU Score |
|---------------|----------------------|------------|
| En-De         | 9.3777 ± 0.2260      | 33.61 ± 0.324|
| En-Fr         | 9.7988 ± 0.0587      | 53.19 ± 0.000|
| De-En         | 9.4135 ± 0.1003      | 35.26 ± 0.021|
| De-Fr         | 9.7924 ± 0.0116      | 30.13 ± 0.354|
| Fr-De         | 9.9836 ± 0.1061      | 46.96 ± 0.000|
| Fr-En         | 9.5342 ± 0.1058      | 46.96 ± 0.000|

Figure 1: Emissions released while training model over 10 Epochs, averaged over 3 experiments Left: ConvSeq, Right: Transformers

4.2 Analysis by Encoder-Decoder Emissions

We’ve measured the cumulative release of emissions by the encoder and the decoder separately and noted the results in the tables in 6 in the appendix. Additionally, figure 2 for the ConvSeq model shows the progressive growth of emissions of the decoder and encoders throughout the course of 2 epochs. Whilst there is an almost identical progression for some language pairs and their twin (EN-FR and FR-EN, for instance), this trend is not maintained consistently. It was previously noted that EN-DE and the DE-EN language pairs released the most emissions over the course of 10 epochs, and even though their cumulative emissions of the encoder and decoder over 2 epochs are among the highest, there are still some language pairs with higher emissions, namely EN-FR and FR-EN. In line with this, we recorded and estimated the range of the contribution of the softmax function (per epoch) to the emissions, as depicted in Table 2. However, these emissions are relatively insignificant, suggesting that there are still other sources of emissions during training that contribute to the final result in Figure 1.
4.3 Analysis of results by thresholding

To gauge which of the language pairs took the longest time to train, we conducted an experiment where we analyzed the time taken and the carbon emissions released in training the models for each language pair up to a BLEU score of 25, with the results tabulated in Figure 3. The results for both architectures were very similar, with the FR-DE language pair being the most computationally expensive. There is a noticeable disparity in the results for the time taken for the 3 most carbon-intensive language pairs (FR-DE, EN-DE and DE-FR) and the 3 least carbon-intensive language pairs (EN-FR, DE-EN, FR-EN), with German consistently appearing in the former, and English in the latter.

| Language Pair | Time Taken (in s) | Epochs Taken | CO2 Emissions (in g) |
|---------------|-------------------|--------------|----------------------|
| En-De         | 627               | 4            | 14.56                |
| En-Fr         | 315               | 2            | 7.265                |
| De-En         | 310               | 2            | 7.129                |
| De-Fr         | 614               | 4            | 13.944               |
| Fr-De         | 1230              | 8            | 28.459               |
| Fr-En         | 304               | 2            | 7.033                |

| Language Pair | Time Taken (in s) | Epochs Taken | CO2 Emissions (in g) |
|---------------|-------------------|--------------|----------------------|
| En-De         | 120               | 3            | 3.718                |
| En-Fr         | 82                | 2            | 1.935                |
| De-En         | 76                | 2            | 2.916                |
| De-Fr         | 122               | 3            | 5.057                |
| Fr-De         | 123               | 3            | 4.047                |
| Fr-En         | 80                | 2            | 1.901                |

Figure 3: Results of emissions releasing to reach the threshold BLEU score of 25 (Left: ConvSeq, Right: Transformers)

4.4 Backpropagation

Figure 4: The cumulative growth of carbon emissions across 2 epochs during the backpropagation process for Left: ConvSeq, Right: Transformers
Curb Your Carbon Emissions: Benchmarking Carbon Emissions in Machine Translation

| Language Pair | CO2 Emissions (in g) | Language Pair | CO2 Emissions (in g) |
|---------------|----------------------|---------------|----------------------|
| En-De         | 2.1331 ± 0.46217     | En-De         | 0.3896 ± 0.07639     |
| En-Fr         | 2.2803 ± 0.36861     | En-Fr         | 0.7333 ± 0.13604     |
| De-En         | 2.1272 ± 0.43368     | De-En         | 0.6638 ± 0.1241      |
| De-Fr         | 2.2649 ± 0.3731      | De-Fr         | 0.4039 ± 0.07302     |
| Fr-De         | 2.2546 ± 0.30187     | Fr-De         | 0.4272 ± 0.07111     |
| Fr-En         | 2.3139 ± 0.30648     | Fr-En         | 0.7159 ± 0.11807     |

Figure 5: Backpropagation emissions estimated per epoch. Left: ConvSeq, Right: Transformers

The computation required during backpropagation while training these models contributes significantly to the carbon emissions released in the process, and the results for the same (per epoch) are depicted in the tables in Figure 5. The cumulative growth of the carbon emissions for the two architectures is also depicted in the graphs in Figure 4 and we notice a sharp contrast in the graphs for the ConvSeq and transformer-based architecture.

Whilst reducing parameters by pruning could potentially reduce the carbon emissions released in the process, it is known to compromise the fairness of the model [21]. To avoid this, it might be more suitable to use architectural variants that are less computationally intensive (as demonstrated in this paper itself, transformers are a more suitable alternative as compared to the ConvSeq model), or methods to make backpropagation more efficient.

5 Ethics and Discussion

Our findings provide clear indication that some language pairs are more carbon intense to train than others, a trend that carries over different architectures as well. We present an in-depth analysis in this paper, where we make note of the various components and aspects of the training process that contribute to the carbon emissions released by a model and note that the TTR, that has been used to determine the lexical complexity, of a language has little to do with the emissions released by the decoder. However, there remain unanswered questions regarding why there are such stark differences in training models for a particular language pair over another, and whether different architectures might be more suited for these carbon-intense language pairs, and why this would be the case if true.

6 Conclusion

Our work represents a preliminary dissection of the source of carbon emissions in models in the task of machine translation, across different languages. Our results indicate that there is a disparity in results across different language pairs, even when using comparable corpora, and language pairs involving English demonstrate higher performance than ones that do not. However, much study remains to be done to identify what exactly it is that causes the differences in emissions, how this affects their growth over multiple epochs, and such a study could prove extremely useful in proposing methods to reduce carbon emissions released while training and deploying machine translation systems that are trained extensively over large datasets. In addition to this, we hope to extend this work to other low-resource languages that do not follow the Latin script as well.

7 Acknowledgements

We express our gratitude toward Dr. Anuroop Sriram for his guidance, suggestions and mentorship with this research, as well as to the Research Society MIT, Manipal for supporting this work. We attribute equal contribution to all the authors of this paper.

References

[1] Alexandre Lacoste, Alexandra Luccioni, Victor Schmidt, and Thomas Dandres. Quantifying the carbon emissions of machine learning. CoRR, abs/1910.09700, 2019. URL http://arxiv.org/abs/1910.09700
[2] Emma Strubell, Ananya Ganesh, and Andrew McCallum. Energy and policy considerations for deep learning in NLP. CoRR, abs/1906.02243, 2019. URL http://arxiv.org/abs/1906.02243
[3] Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. Finetuned language models are zero-shot learners, 2021.
[4] Lisha Li, Kevin G. Jamieson, Giulia DeSalvo, Afshin Rostamizadeh, and Ameet Talwalkar. Efficient hyperparameter optimization and infinitely many armed bandits. *CoRR*, abs/1603.06560, 2016. URL http://arxiv.org/abs/1603.06560

[5] Stefan Falkner, Aaron Klein, and Frank Hutter. BOHB: robust and efficient hyperparameter optimization at scale. *CoRR*, abs/1807.01774, 2018. URL http://arxiv.org/abs/1807.01774

[6] Liam Li, Kevin G. Jamieson, Afshin Rostamizadeh, Ekaterina Gonina, Moritz Hardt, Benjamin Recht, and Ameet Talwalkar. Massively parallel hyperparameter tuning. *CoRR*, abs/1810.05934, 2018. URL http://arxiv.org/abs/1810.05934

[7] Emily Denton, Wojciech Zaremba, Joan Bruna, Yann LeCun, and Rob Fergus. Exploiting linear structure within convolutional networks for efficient evaluation. *CoRR*, abs/1404.0736, 2014. URL http://arxiv.org/abs/1404.0736.

[8] Tien-Ju Yang, Yu-Hsin Chen, and Vivienne Sze. Designing energy-efficient convolutional neural networks using energy-aware pruning. *CoRR*, abs/1611.05128, 2016. URL http://arxiv.org/abs/1611.05128.

[9] Daniel Edmiston. A systematic analysis of morphological content in BERT models for multiple languages. *CoRR*, abs/2004.03032, 2020. URL https://arxiv.org/abs/2004.03032.

[10] Roy Schwartz, Jesse Dodge, Noah A. Smith, and Oren Etzioni. Green AI. *CoRR*, abs/1907.10597, 2019.

[11] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805, 2018. URL http://arxiv.org/abs/1810.04805.

[12] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime G. Carbonell, Ruslan Salakhutdinov, and Quoc V. Le. XLNet: Generalized autoregressive pretraining for language understanding. *CoRR*, abs/1906.08237, 2019. URL http://arxiv.org/abs/1906.08237.

[13] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. 2018. URL https://d4mucfpksywv.cloudfront.net/better-language-models/language-models.pdf.

[14] David A. Patterson, Joseph Gonzalez, Quoc V. Le, Chen Liang, Luis-Miquel Munguia, Daniel Rothchild, David R. So, Maud Texier, and Jeff Dean. Carbon emissions and large neural network training. *CoRR*, abs/2104.10350, 2021.

[15] Tahmid Hasan, Abhiik Bhattacharjee, Md. Saiful Islam, Kazi Mubasshir, Yuan-Fang Li, Yong-Bin Kang, M. Sohel Rahman, and Rifat Shahriyar. XL-sum: Large-scale multilingual abstractive summarization for 44 languages. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 4695–4703, Online, August 2021. Association for Computational Linguistics. URL https://aclanthology.org/2021.findings-acl.413.

[16] Desmond Elliott, Stella Frank, Khalil Sima’an, and Lucia Specia. Multi30k: Multilingual english-german image descriptions. In *Proceedings of the 5th Workshop on Vision and Language*, pages 70–74. Association for Computational Linguistics, 2016. doi: 10.18653/v1/W16-3210. URL http://www.aclweb.org/anthology/W16-3210.

[17] Kimmo Kettunen. Can type-token ratio be used to show morphological complexity of languages? *Journal of Quantitative Linguistics*, 21:223–245, 06 2014. doi: 10.1080/09296174.2014.911506.

[18] Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N. Dauphin. Convolutional sequence to sequence learning. *CoRR*, abs/1705.03122, 2017. URL http://arxiv.org/abs/1705.03122.

[19] Yann N. Dauphin, Angela Fan, Michael Auli, and David Grangier. Language modeling with gated convolutional networks. *CoRR*, abs/1612.08083, 2016. URL http://arxiv.org/abs/1612.08083.

[20] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *CoRR*, abs/1706.03762, 2017. URL http://arxiv.org/abs/1706.03762.

[21] Michela Paganini. Prune responsibly. *CoRR*, abs/2009.09936, 2020. URL https://arxiv.org/abs/2009.09936.
A Appendix

A.1 Tesla K80

The Tesla K80 combines two graphics processors to increase performance. It features 2496 shading units, 208 texture mapping units, and 48 ROPs, per GPU. NVIDIA has paired 24 GB GDDR5 memory with the Tesla K80, which are connected using a 384-bit memory interface per GPU (each GPU manages 12,288 MB). The GPU is operating at a frequency of 562 MHz, which can be boosted up to 824 MHz, memory is running at 1253 MHz (5 Gbps effective).

| Language Pair | Encoder Emissions | Decoder Emissions |
|---------------|-------------------|-------------------|
| En-De         | 0.0875            | 1.2684            |
| En-Fr         | 0.0825            | 1.5109            |
| De-En         | 0.0881            | 1.3941            |
| De-Fr         | 0.0747            | 1.2476            |
| Fr-De         | 0.0794            | 1.1042            |
| Fr-En         | 0.1               | 1.4813            |

Figure 6: Emissions released by the encoder and decoder (Left: ConvSeq, Right: Transformers)

| Language Pair | Trainable Parameters |
|---------------|----------------------|
| En-De         | 37,855,919           |
| En-Fr         | 36,988,777           |
| De-En         | 37,351,685           |
| De-Fr         | 37,427,277           |
| Fr-De         | 37,743,657           |
| Fr-En         | 36,853,852           |

Figure 7: Count of trainable parameters (Left: ConvSeq, Right: Transformers)

| Language Pair | CO₂ Emissions | BLEU |
|---------------|---------------|------|
| ConvSeq       | Transformer   | ConvSeq | Transformer |
| En-De         | Fr-De         | En-Fr   | En-Fr      |
| De-En         | En-Fr         | Fr-En   | Fr-En      |
| En-Fr         | De-Fr         | De-En   | De-Fr      |
| Fr-De         | Fr-En         | En-Fr   | De-En      |
| De-Fr         | De-En         | En-De   | En-De      |
| Fr-En         | En-De         | Fr-De   | Fr-De      |

Table 3: Ranking of language pairs by the CO₂ released and BLEU score, after training for 10 epochs

*Tesla K80 GPU Specifications*